

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

**Intégration de contraintes industrielles dans la recommandation de produits
pour la prise en compte de la capacité à répondre à la demande**

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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Cette thèse intitulée :

**Intégration de contraintes industrielles dans la recommandation de produits
pour la prise en compte de la capacité à répondre à la demande**

présentée par **Camélia DADOUCHI**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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DÉDICACE

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RÉSUMÉ

Les systèmes de recommandations (SRs) ont été développés pour prédire les intérêts des utilisateurs et les assister quant à la surcharge d'informations à laquelle ils peuvent être exposés lors de leurs processus d'achat. De façon spécifique, en vente de détail, ils ont été développés pour personnaliser l'affichage des produits en fonction des prédictions des intérêts des clients en se basant sur leurs comportements passés. Les SRs orientent donc les clients vers des produits spécifiques. Cependant, ils ne tiennent pas compte de la capacité de l'entreprise à répondre à la demande qu'ils induisent. Ainsi, l'objectif de cette thèse est d'améliorer les systèmes de recommandations pour tenir compte de la capacité de l'entreprise à répondre à la demande. Les trois problématiques relatives à la prise en compte de la demande dans la recommandation de produits sont les suivantes : (1) tenir compte de la disponibilité des produits en inventaire, en contexte de e-commerce, (2) tenir compte de la capacité de l'entreprise à livrer les produits dans un délai prédéterminé, en contexte de e-commerce et (3) tenir compte de la disponibilité des produits, en contexte de vente stationnaire et de démarrage à froid.

La première contribution propose une méthode d'ajustement des scores de recommandations pour réorienter la demande, en fonction des niveaux de stock des produits et de l'importance perçue des clients pour l'entreprise. La deuxième contribution propose d'ajuster les scores de recommandation en tenant compte des tournées des véhicules programmées et de la localisation des stocks au moment de la recommandation. Et finalement la troisième contribution présente une nouvelle technique de recommandation tenant compte de manière interactive des exigences et des appréciations du client, mais également des données logistiques. Elle permet d'un côté de réaliser des recommandations en contexte de démarrage à froid, et d'un autre côté de tenir compte des contraintes d'approvisionnement de produits.

Ces trois contributions permettent d'améliorer les performances des SRs actuels en tenant compte des contraintes logistiques dans la recommandation de produits et donc de ne pas générer de demande qui ne peut être comblée. Les méthodes présentées permettent également d'utiliser les systèmes de recommandations pour augmenter l'agilité de la gestion de la demande. L'utilisation des systèmes de recommandations pour réorienter la demande permet de limiter l'impact potentiel de ruptures ou de surcharges de stock, d'améliorer le taux de remplissage des camions, d'augmenter la satisfaction des clients et d'améliorer la compétitivité de l'entreprise.

ABSTRACT

Recommendation systems have been developed to predict users' interests and assist them with the information overload they may face. Specifically for retail, they have been developed to customize the display of products based on predictions of customer interests based on their past behavior. Recommendation systems therefore direct customers to specific products. However, they do not take into account the ability of the company to meet the demand that it induces.

Thus, the objective of this thesis is to improve the recommendation systems to take into account the capacity of the company through its logistic network to meet the demand. The three issues relating to the consideration of demand in the product recommendation are as follows: (1) Take into account the availability of products in inventory, in the context of e-commerce. (2) Take into account company's ability to deliver products within a pre-determined period, in the context of e-commerce. (3) Take into account the availability of products in the context of brick and mortar while facing cold start.

The first contribution proposes a method of adjusting recommendation scores to redirect demand based on product inventory levels and on the perceived importance of customers for the company. The second contribution proposes to adjust the recommendation scores taking into account scheduled vehicle tours and product locations. And finally the third contribution presents a new technique of recommendation taking into account, through the interaction with the customer, his requirements and his appreciations in the recommendation of products. It allows on one side to perform recommendations in a cold start context, and on the other side to take into account the constraints of supply chain.

These three contributions make it possible to take into account supply chain constraints in the product recommendation and thus avoid inducing product demand that cannot be filled. The methods presented also allow the use of recommender systems to increase agility in demand management. The use of recommender systems to redirect demand limits the impact of stockouts or potential inventory overloads, improves truckload rates, increases customer satisfaction and improves competitiveness for the company.

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LISTE DES SIGLES ET ABRÉVIATIONS

SRs	Systèmes de recommandations
CB	Basé sur le contenu
CF	Filtrage collaboratif
RMSE	Root mean squared error
MAE	Mean absolute Error
PCC	Coefficient de corrélation de Pearson
TF-IDF	Term Frequency /Inverse document frequency
SCM	Gestion de la chaîne logistique
BDBA	Big Data Business Analytics

CHAPITRE 1 INTRODUCTION

Dans les dernières décennies, la révolution de l'information a fondamentalement changé nos façons d'interagir, de travailler, d'apprendre, d'acheter, de nous rencontrer, etc. Chaque jour, à travers l'utilisation de nos ordinateurs, nos téléphones portables, nos voitures intelligentes, et autres objets connectés, nous générons pas moins de 2.5 quintillions d'octets (Marr, Bernard, 2018), un chiffre faramineux ! Cette révolution n'a pas épargné la façon dont les entreprises interagissent avec les clients. Au Québec, les ventes réalisées en ligne représentent en moyenne 20 % des ventes totales annuelles des entreprises sondées dans un rapport récent du CEFRIIO (Beaudoin et al., 2018). L'adoption massive du web comme plateforme de commerce a permis de toucher un public plus large et plus diversifié, ce qui a ouvert les portes à une compétition féroce. Cette compétitivité du marché a poussé les entreprises à tenter de se différencier les unes des autres à travers l'expérience client qu'elles offrent (Demiriz, 2004). Parmi les outils développés à cet effet, on trouve les systèmes de recommandations (SRs). Les SRs aident les utilisateurs à faire face à la surcharge d'informations qu'ils peuvent subir, en personnalisant le contenu qui leur est présenté (Ricci et al., 2011), minimisant ainsi le temps associé à la recherche et maximisant les chances de découverte de produits nouveaux.

La définition des systèmes de recommandations diffère d'un domaine à l'autre, mais se concentre sur l'établissement d'une liste d'éléments à recommander à un utilisateur spécifique (Burke et al., 2011). Ces systèmes se basent sur des algorithmes de différentes disciplines pouvant prédire le niveau d'intérêt d'un utilisateur pour une liste de produits et suggérer, parmi un large éventail d'articles, ceux qui peuvent répondre aux besoins spécifiques des utilisateurs (Ricci et al., 2011). Au cours des trois dernières décennies, la recherche sur les SRs s'est concentrée sur les différents algorithmes et techniques permettant de traiter les données de manière efficiente (consommation de mémoire et vitesse de calcul), afin d'obtenir les prédictions les plus précises possibles des préférences d'un utilisateur pour une liste d'items (Burke, 2002), (Bobadilla et al., 2012). Dans le contexte des ventes, les systèmes de recommandations permettent de proposer au client actif, des produits qui pourraient l'intéresser, dans le but d'assurer une vente. Un objectif qui s'est révélé atteint. En effet, des études antérieures ont révélé plusieurs résultats notables sur l'impact des systèmes de recommandations sur les ventes, confirmant que ces systèmes ont une incidence positive sur celles-ci (Lin, 2014), (Pathak et al., 2010). Une enquête récente a révélé que 94% des plus grandes entreprises de commerce électronique reconnaissent que la personnalisation est essentielle à leur succès en ligne. Ils indiquent également que les recommandations ont un impact majeur sur le choix des consommateurs (Lee and Hosanagar, 2019) - par exemple, près de 35% des ventes chez

Amazon (Lamere, P and Green, S , 2008) proviennent des recommandations. Ces affirmations nous permettent de déduire que les systèmes de recommandations ont une incidence directe sur la demande des clients.

Cependant, les systèmes de recommandations ne tiennent pas compte de la capacité d'une entreprise à répondre à la demande qu'ils induisent. En effet, recommander des produits que l'entreprise ne peut fournir aux clients peut nuire à sa crédibilité, à son image de marque et à ses performances de ventes. De ce fait, il serait judicieux, avant d'orienter la demande vers certains produits, d'évaluer la capacité de l'entreprise à répondre à cette demande.

La capacité d'une entreprise à répondre à la demande dépend non seulement, de la performance de la chaîne logistique, mais également de son adéquation aux attentes des clients. Selon le rapport du Centre Francophone d'Informatisation des Organisations (CEFRIO), la rapidité de livraison de même que la disponibilité rapide des produits seraient les principales attentes de plus d'un consommateur sur deux (Beaudoin et al., 2018).

Dans cette thèse, nous proposons une méthode d'amélioration des systèmes de recommandations pour tenir compte de la capacité à satisfaire la demande, considérant certaines contraintes logistiques impactant la disponibilité des produits et la rapidité de livraison des produits.

Pour cela, nous tenons compte de trois aspects à intégrer dans la recommandation de produits et présentons des cas d'application en contexte de vente en ligne et en contexte de vente stationnaire.

La première contribution de cette thèse tient compte de la disponibilité des produits en inventaire dans la recommandation de produits, en contexte de e-commerce. La méthode proposée permet de réorienter la demande, en ajustant les scores de recommandations pour considérer les niveaux de stock des produits et l'importance perçue des clients pour l'entreprise. De cette façon, elle permet de limiter l'impact de ruptures de stock ou de surcharges de stock qui pourraient survenir.

La deuxième contribution tient compte de la capacité de l'entreprise à livrer les produits dans un délai prédéterminé, en contexte de e-commerce. La méthode proposée permet de réorienter la demande, en ajustant les scores de recommandations pour tenir compte des tournées des véhicules programmées et de la localisation des stocks. De cette façon, elle permet d'augmenter les produits de la liste de recommandations qui peuvent être livrés dans les délais requis par les clients. D'autres avantages de la méthode incluent, une amélioration du taux de remplissage des camions, une augmentation de la satisfaction client et une meilleure compétitivité pour l'entreprise.

La dernière contribution quant à elle, propose une nouvelle technique de recommandations interactive basée sur les connaissances métier et sensible au contexte logistique. Cette technique a été élaborée pour une utilisation en contexte de vente stationnaire de produits à haute valeur. Ce contexte se traduit souvent par un manque d'information concernant les clients, un problème connu sous le nom de "démarrage à froid". La méthode proposée tient compte, à travers l'interaction avec le client, de ses exigences et de ses appréciations des caractéristiques des produits, pour produire une recommandation tenant compte de la capacité à répondre à la demande en contexte de démarrage à froid. Les avantages de cette méthode incluent la capacité à réaliser des recommandations dans un contexte de démarrage à froid, la capacité à tenir compte des contraintes logistiques lors de la recommandation de produits, l'augmentation des chances de clore une vente et l'amélioration de l'expérience client.

La combinaison des différentes solutions a permis de répondre à la problématique globale et de démontrer que les systèmes de recommandations peuvent être améliorés pour tenir compte des différentes contraintes qui influencent la capacité à répondre à la demande et ce, en contexte de vente en ligne et en contexte de vente stationnaire. Cette thèse propose deux approches, l'une à travers l'ajustement de recommandations émanant d'un système de recommandations existant et l'autre à travers le développement d'un système de recommandations personnalisé au secteur d'activité dans lequel il est déployé. Cette thèse démontre également que l'amélioration des systèmes de recommandations peut être utilisée pour augmenter l'agilité d'une chaîne logistique à travers la réorientation de la demande, en fonction des stratégies de l'entreprise et de ses objectifs opérationnels.

Le chapitre 2 de cette thèse propose une revue de littérature dans laquelle les systèmes de recommandations sont présentés au côté des chaînes logistiques, une synthèse discutant les aspects pertinents de la logistique qui peuvent être considérés dans les systèmes de recommandations clôt le chapitre. Ensuite, la problématique et le cadre global de recherche dans lequel s'imbriquent nos contributions sont présentés au chapitre 3. Le chapitre 4 et le chapitre 5 présentent des méthodes d'ajustement des recommandations pour tenir compte respectivement de la disponibilité des produits et de la capacité du réseau logistique à livrer les produits au client, en contexte de e-commerce. Le chapitre 6 présente la dernière contribution de cette thèse, et ce, à travers la présentation d'une nouvelle technique de recommandations qui permet de résoudre le problème de démarrage à froid, tout en tenant compte du ratio de disponibilité des produits en contexte de vente stationnaire. La thèse se poursuit au travers d'une discussion générale présentée au chapitre 7 et se clôt par une conclusion présentée au chapitre 8.

CHAPITRE 2 REVUE DE LITTÉRATURE

Le chapitre précédent a expliqué l'importance des systèmes de recommandations dans le contexte actuel de surcharge d'information de façon générale et pour la vente de produits en ligne spécifiquement. Tel qu'énoncé précédemment, la logistique de livraison des produits aux clients, dans les délais qu'ils exigent, impacte grandement la capacité à répondre à la demande.

Dans ce chapitre, nous présentons une revue de littérature traitant des systèmes de recommandations présentant les différentes fonctionnalités des systèmes de recommandation ainsi que les techniques de recommandations qui permettent de répondre à l'objectif de recommandation. La section présente également les défis majeurs auxquels font face les systèmes de recommandations et les métriques permettant l'évaluation de leurs performances.

2.1 Systèmes de recommandations

Les systèmes de recommandations sont utilisés dans plusieurs disciplines, telles : e-government, e-business, e-commerce, e-learning, e-tourisme, e-resource services, e-group activities. etc. Une revue de littérature dans ce sens a été fournie par (Lu et al., 2015). Les auteurs illustrent les différents rôles que jouent les SRs dans les différentes disciplines tout en expliquant les techniques de recommandations utilisées par discipline. Dans le contexte des travaux présentés, les champs d'application pour nos recherches seront le e-commerce et le e-business étant donné que nous recommanderons des produits physiques à des clients. En recommandation de produits, les systèmes de recommandations aident (1) à décider quels produits offrir à un client déterminé dans un domaine où il dispose de peu d'informations pour trier et évaluer les alternatives possibles, (2) à augmenter les ventes croisées en proposant des produits supplémentaires aux clients, et (3) à améliorer la fidélité des consommateurs, car ceux-ci ont tendance à revenir vers les sites qui répondent le mieux à leurs besoins (Lü et al., 2012).

Pour la suite du document, nous définirons :

Item comme étant tout objet/service/bien/relation, pouvant être recommandé. Exemple d'items : films, musiques, livres, articles scientifiques, restaurants, produits, services financiers, amis, emplois. . .

Utilisateur comme étant l'individu pour lequel la recommandation est effectuée.

Dans cette section, nous allons présenter un état de l'art sur les systèmes de recommanda-

tions. Nous commencerons par définir les systèmes de recommandations avant de passer à leurs fonctionnalités. Nous présenterons par la suite les catégorisations traditionnelles des systèmes de recommandations, les données utilisées par ceux-ci ainsi que les différentes techniques de recommandations. Cette section présente un aperçu non exhaustif des techniques de recommandations existantes. En effet, grâce aux plateformes open source et aux forums spécialisés, différentes communautés d'utilisateurs du web (programmeurs, physiciens, statisticiens, économistes...), développent de nouvelles méthodes et les partagent sur le web, continuellement et sans restriction, sans pour autant les publier.

2.2 Définitions des systèmes de recommandations

On trouve différentes définitions des systèmes de recommandations dans la littérature. Certaines expliquent que les systèmes de recommandations sont des outils qui assistent les utilisateurs face aux problèmes de surcharge croissante d'informations et améliorent la gestion de la relation client en fournissant aux utilisateurs des recommandations personnalisées de produits ou de services (Lu et al., 2015). D'autres, considèrent les SRs comme étant une sous-classe de système de filtrage d'informations qui tente de prédire les « évaluations » ou les « préférences » que les utilisateurs attribueraient à un produit, en collectionnant des informations sur leurs préférences pour un ensemble d'items (Ricci et al., 2011). On trouve également des définitions, comme celle fournie par Adomavicius and Tuzhilin (2005), qui expliquent que les systèmes de recommandations tentent de prédire les évaluations pour les produits inconnus, pour chaque utilisateur, souvent en utilisant les évaluations des autres utilisateurs, et recommandent les N meilleurs items ayant la plus haute valeur d'évaluation prédite. Adomavicius a aussi donné une définition plus formelle, qu'il a exprimée comme suit :

"Soit C l'ensemble de tous les utilisateurs et S l'ensemble de tous les éléments possibles pouvant être recommandés, tels que les livres, les films ou les restaurants. L'espace S des items possibles, peut être très vaste, allant de centaines de milliers à des millions d'items dans certains cas, comme la recommandation de livres ou de films. De façon similaire l'espace C des clients peut également être très large allant jusqu'à plusieurs millions d'utilisateurs dans certains cas. Soit u la fonction d'utilité qui mesure l'utilité d'un item s pour un utilisateur c , ex : $u : C * S = R$, avec R un ensemble ordonné (ex : des entiers non négatifs ou des réels faisant parties d'un intervalle). Ensuite, pour chaque utilisateur $c \in C$, nous voulons choisir cet élément $s' \in S$ qui maximise l'utilité. L'équation 2.1 le présente de manière plus formelle :"

$$\forall c \in C, S'_c = \operatorname{argmax}_{s \in S} u(c, s) \quad (2.1)$$

Dans une édition de 2011 de l'Association de l'Avancement de l'Intelligence Artificielle, les auteurs considèrent que les différentes définitions s'accordent sur deux traits distinctifs des systèmes de recommandations. On peut lire dans (Burke et al., 2011) les deux affirmations suivantes :

- Un système de recommandations est personnalisé. Les recommandations qu'il produit visent à optimiser l'expérience d'un utilisateur et non à représenter un consensus de groupe pour tous.
- Un système de recommandations est conçu pour aider l'utilisateur à choisir parmi des options discrètes. En règle générale, les éléments sont déjà connus à l'avance et ne sont pas générés de manière personnalisée.

Les définitions pour les systèmes de recommandations diffèrent d'une communauté à une autre, mais restent tout de même toutes axées sur l'établissement d'une liste d'items à recommander aux utilisateurs, en se basant sur des algorithmes issus de différentes disciplines qui permettent de prédire l'appréciation d'un utilisateur pour une liste de produits inconnus et de lui suggérer, parmi un large éventail d'items, ceux qui sauront répondre à des besoins spécifiques.

2.3 Fonctionnalités des systèmes de recommandations

Dans sa thèse de doctorat, Meyer (2012) fait un découpage des systèmes de recommandations selon les fonctions qu'ils accomplissent. Il en relève 4, qui sont énoncées ci-dessous :

- Aide à la décision : prédire la note d'un utilisateur pour un item.
- Aide à la comparaison : ordonne les listes d'items dans un ordre personnalisé pour l'utilisateur.
- Aide à l'exploration : présente des items similaires à un item cible donné.
- Aide à la découverte : fournit à un utilisateur des items inconnus qu'il pourrait apprécier.

Nous adapterons et enrichirons le modèle de Meyer (2012) et expliquerons les fonctionnalités attendues des systèmes de recommandations de façon conceptuelle dans les sous-sections suivantes. L'aide à la découverte et l'aide à l'exploration ont été regroupées à la section 2.3.3.

2.3.1 Aide à la décision

Pour l'utilisateur du système de recommandations, il existe une variété de produits disponibles à l'achat. Dans la littérature, ces produits sont classifiés en trois catégories en fonction de la capacité de l'utilisateur à en évaluer la qualité avant ou après l'achat. « Search goods

» sont les produits dont il est possible d'évaluer la qualité avant l'achat (des fleurs), « experience goods » sont les produits dont il est possible d'évaluer la qualité après l'utilisation (shampooing) et « credence goods » sont des produits dont il est difficile d'évaluer la qualité à court terme (les comprimés de vitamines), généralement les décisions d'achats pour ce type de produits se prennent en se basant sur la réputation du fournisseur (Pathak et al., 2010). Les systèmes de recommandations sont des outils qui aident l'utilisateur à prendre une décision quand il n'est pas sûr de son choix ou qu'il n'a pas assez de connaissance ou de moyen pour évaluer lui-même des items. En faisant la prédiction de l'appréciation d'un utilisateur pour une liste de produits, on l'aide à choisir l'item qui est le plus adapté pour lui. Cette fonctionnalité est intéressante, car l'utilisateur lui-même pourrait ignorer des attributs essentiels quand il est novice dans un domaine, chose que le système de recommandations aide à pallier en accumulant des informations sur les utilisateurs, en se basant sur le contenu créé par ceux-ci (Meyer, 2012).

2.3.2 Aide à la comparaison

En plus de faire des prédictions d'appréciation d'items, le système de recommandation peut aussi faire le classement de ceux-ci par pertinence pour l'utilisateur. L'item au premier rang devrait être plus pertinent pour l'utilisateur que celui au dernier rang. Ceci permet à l'utilisateur de comparer différents produits qui pourraient tous être adaptés à ses intérêts. Cette fonctionnalité est particulièrement intéressante lorsque les données dont on dispose sont des données implicites qui ne fournissent pas le degré d'appréciation pour un item (nous savons si un utilisateur a apprécié un item, mais pas à quel point celui-ci l'a apprécié) (Meyer, 2012).

2.3.3 Aide à la découverte et à l'exploration

Cette fonctionnalité des systèmes de recommandations permet aux utilisateurs de découvrir des produits dont ils ne connaissaient peut-être pas l'existence. Ces produits peuvent être nouveaux ou juste spécialisés. L'aide à la découverte est un des challenges auxquels font face les systèmes de recommandations. Cette fonctionnalité est très pertinente quand il s'agit de recommandation de produits niches, car elle permet d'explorer différents types d'items. Il n'est pas pertinent de recommander les produits populaires, car l'utilité est d'avoir une large couverture du catalogue de produits. Le magazine « Wired » a proposé d'utiliser la longue traîne « Long Tail » pour décrire le modèle de e-commerce d'entreprises comme Amazon (Anderson, 2006). La théorie de la longue traîne, comme la décrivent Chunfang and Zhongliang (2015), peut être illustrée par le vocabulaire utilisé par l'humain, il y a un petit nombre de mots utilisés fréquemment qui occupe beaucoup d'espace dans notre mémoire à court terme,

puis il y a un grand nombre de mots très peu utilisés. Un large éventail de produits malgré la faible fréquence d'achats pour certains items peut générer beaucoup de profit. La liste d'items proposés à l'utilisateur pour l'aide à la découverte doit remplir certains critères comme : être pertinente, être utile, être crédible. Cependant, pour faire de la "recommandation de découverte" pertinente, il faut avoir cumulé assez d'informations sur les intérêts des utilisateurs (historique d'achats/navigations/clic stream/scores...). Dans le cas contraire, il serait risqué de proposer des produits niches, surtout si le système est en « boîte noire » et que l'utilisateur n'a pas de visibilité sur le mécanisme de fonctionnement de la recommandation, cela pourrait nuire à la crédibilité du système (He et al., 2016). On peut donc distinguer deux types de recommandations : la recommandation pour l'exploration et la recommandation pour la découverte de nouveaux produits. L'exploration serait utilisée quand l'utilisateur est nouveau sur la plateforme ou qu'il n'y a pas assez d'information sur ses préférences, qu'elles soient implicites ou explicites. Dans ce cas, il faudra se contenter d'une recommandation item à item. Dans le cas le plus répandu, la recommandation se fait en deux étapes, on commence par fournir des produits de la catégorie des meilleurs vendeurs, ensuite en fonction des produits dont l'utilisateur a visité la page, une recommandation pourra être faite en proposant des items similaires à celui préféré par l'utilisateur (Meyer, 2012).

2.4 Données dans les systèmes de recommandations

Dans cette section, nous commençons par faire état du type de données utilisées dans la recommandation et leurs spécificités.

Dans un premier temps, il est nécessaire de différencier entre :

Les données explicites et les données implicites :

Les données explicites : sont des données qui n'ont pas été interprétées, l'utilisateur nous les fournit directement. Généralement ce sont des données comme celles sur l'appréciation (ratings) de l'utilisateur pour un produit. Des systèmes de recommandations interactifs plus récents recueillent des informations explicites à travers une interface où l'utilisateur est sollicité à fournir des renseignements sur ses préférences (Ricci et al., 2015).

Les données implicites : sont des données qui ne requièrent pas d'intervention spécifique de l'utilisateur. Généralement, ces données sont recueillies à travers la surveillance des actions des utilisateurs sur la plateforme qu'ils utilisent. Typiquement des données sur le clic stream (données représentant le parcours de l'utilisateur sur un site web), les téléchargements, sites web visités, l'historique des achats, les coordon-

nées GPS, les données de transactions, les quantités de produits achetés, etc. (Ricci et al., 2015).

Les données implicites englobent également les données sociodémographiques, les données recueillies sur les réseaux sociaux et plus récemment les données recueillies à partir des objets connectés (internet of things) (Wei et al., 2007).

Les données sur les usagers et les données sur les items : Il est important de différencier les données sur les items de celles sur les usagers pour le calcul des recommandations. Selon les méthodes, les calculs peuvent être effectués sur différentes combinaisons de données items/utilisateurs. Meyer (2012) présente quatre combinaisons et leurs usages dans la littérature :

Item à item : pas de connaissances nécessaires sur l'utilisateur. Utilisé principalement pour la vente en ligne pour découvrir et explorer les produits.

Utilisateur à item : assume que le SRs connaît le profil du client. Utilisé principalement pour les campagnes de courriels ciblés ou pour l'aide à la décision d'achat de produits en ligne.

Utilisateur à utilisateur : pas d'item considéré. Utilisé pour la recommandation d'utilisateur principalement sur les réseaux sociaux.

Item à utilisateur : assume que le SRs connaît le profil du client. Utilisé principalement pour les campagnes de marketing pour déterminer quel public sera intéressé par un item spécifique.

Bobadilla et al. (2013) présentent une classification des données selon leur nature ainsi que comment les caractéristiques des données s'imbriquent. Cette classification se base sur trois axes; (1) la cible des données : utilisateur ou item, (2) le mode d'acquisition : implicite ou explicite, et (3) le niveau d'information : basée sur la mémoire, sur le contenu, sur le niveau social (nombre d'amis, de suiveurs, de tags, de postes, de tweets, etc.) et sur le contexte (données démographiques, données de description d'items, de localisation, etc.).

2.5 Catégories de systèmes de recommandations

Afin de répondre aux fonctionnalités attendues des systèmes de recommandations, plusieurs méthodes existent. La littérature propose plusieurs typologies. La typologie traditionnelle a été établie par Adomavicius and Tuzhilin (2005). Ils considèrent trois types de systèmes de recommandation :

Filtrage basé sur le contenu (CB) : L'utilisateur se fera recommander des items similaires à ceux qu'il a préférés dans le passé.

Filtrage collaboratif (CF) : L'utilisateur se fera recommander des items que des personnes avec des goûts et des préférences semblables ont appréciés dans le passé.

Filtrages hybrides : Ces méthodes combinent les deux méthodes précédentes.

Une autre classification bien répandue est celle proposée par Su and Khoshgoftaar (2009) qui se base sur les méthodes de recommandation.

Memory-based CF techniques : Les algorithmes de filtrage collaboratif basés sur la mémoire utilisent la totalité ou un échantillon de la base de données item/utilisateur pour générer des prédictions. Chaque utilisateur fait partie d'un groupe de personnes qui a des intérêts similaires. En identifiant les « voisins » de l'utilisateur actif, une prédiction des préférences par rapport à de nouveaux items peut être produite.

Model-based CF techniques : Le design et le développement de modèles peuvent permettre au système d'apprendre à reconnaître des modèles complexes dans les données d'apprentissage. Une fois que le modèle est appris, le SRs pourra faire des prédictions intelligentes sur de nouvelles données. Les algorithmes collaboratifs basés sur les modèles aident à contourner plusieurs des lacunes auxquelles ont fait face les systèmes collaboratifs basés sur la mémoire.

Hybrid CF techniques : Les CFs hybrides combinent les recommandations CF avec d'autres techniques de recommandations comme les recommandations basées sur le contenu.

Ces typologies ont été la base de plusieurs autres classifications de systèmes de recommandations. Une classification enrichie et plus récente incluant les deux classifications précédentes est présentée dans (Candillier et al., 2007).

2.6 Fonctionnement des catégories des systèmes de recommandations

Dans cette section, nous expliquons le fonctionnement de chacune des catégories des systèmes de recommandations présentée à la section 2.5.

2.6.1 Filtrage basé sur le contenu

De façon très simple, la recommandation basée sur le contenu (content-based filtering - CBF) tente de définir les préférences des utilisateurs et de les comparer avec les caractéristiques des items disponibles. Comme on peut le lire dans (Bobadilla et al., 2013) : le filtrage basé sur le

contenu fait des recommandations basées sur les choix de l'utilisateur effectués dans le passé. Il utilise le contenu d'items du catalogue pour la recommandation. Par conséquent, certains contenus peuvent être analysés, tels que le texte, les images et le son. À partir de cette analyse, une similarité peut être établie entre les objets afin de recommander des éléments similaires à ceux composant le profil de l'utilisateur.

Cette approche se fait donc en trois étapes (Sharma and Mann, 2013), dans un premier temps : il faut former les profils des items et les profils des utilisateurs. Les profils des items sont composés de leurs caractéristiques. Les profils des utilisateurs sont composés par les caractéristiques des items précédemment appréciés par les utilisateurs. Dans un deuxième temps, on effectue la prédiction de l'appréciation de l'utilisateur pour tous les items non évalués par celui-ci. Finalement, on construit la liste de recommandations avec les N items ayant les meilleures prédictions. Les caractéristiques des items sont généralement tirées de contenu textuel (description de produits, articles de journaux, site internet...), ce qui explique que le CBF découle principalement de deux disciplines : la recherche d'information et le filtrage d'information. Ces disciplines permettent d'établir les profils des items à partir de contenu textuel. La « Term Frequency /Inverse Document Frequency (TF-IDF) » est la méthode la plus utilisée pour la découverte de caractéristiques à partir de textes. Elle calcule la valeur de chaque mot d'un document selon une proportion inverse de la fréquence du mot d'un document donné par rapport au pourcentage de documents dans lequel le mot apparaît (Ramos, 2003).

Comme expliqué précédemment, la deuxième étape du CBF est d'utiliser les profils des utilisateurs pour estimer l'appréciation de ceux-ci pour les items non évalués dans le passé (Bobadilla et al., 2013).

Adomavicius and Tuzhilin (2005) présentent deux façons d'effectuer cette étape :

- Soit, des heuristiques se basant sur la similarité entre les caractéristiques des items déjà consultés/acquis/évalués et tous les autres items disponibles.
- Soit, des méthodes de prédictions sophistiquées comme les classificateurs bayésiens, les analyses de grappes, les arbres de décision et les réseaux de neurones artificiels qui calculent la probabilité que l'utilisateur cible apprécie chacun des items.

La différence entre les deux méthodes est que l'une calcule les prédictions grâce à des heuristiques comme les mesures de similarités. Tandis que les autres techniques se basent sur l'apprentissage de modèles à partir des données disponibles en utilisant des modèles statistiques et des algorithmes d'apprentissage machine. Adomavicius and Tuzhilin (2005) fournissent également un résumé des méthodes les plus utilisées pour la recommandation basée sur le contenu, ainsi que les recherches significatives effectuées dans la littérature traditionnelle.

La méthode de recommandation basée sur le contenu est rarement utilisée seule dans les systèmes de recommandations commerciaux (Wang and Zhang, 2011). Généralement, elle est utilisée en combinaison avec d'autres méthodes de recommandations (Burke, 2002), car elle nécessite des données précises sur les caractéristiques des items, ce qui n'est pas nécessairement disponible pour tous les produits proposés en e-commerce.

2.6.2 Filtrage collaboratif

Le filtrage collaboratif (CF) est la méthode la plus répandue dans le monde de la recommandation (Wei et al., 2007). Comme son nom l'indique, cette approche est à caractère collaboratif. Elle se base sur l'hypothèse du « stéréotype » qui implique qu'un utilisateur faisant partie d'un groupe de personnes ayant eu des préférences semblables dans le passé aura des goûts semblables aux leurs (Sarwar et al., 2003). Le CF tente donc de prédire l'appréciation d'un utilisateur type pour des items en se basant sur les préférences passées d'autres utilisateurs qui sont considérés semblables à lui. Cette méthode permet de faire des recommandations sans connaître les caractéristiques des items ou des utilisateurs, ce qui rend son implantation bien plus simple que celle du filtrage basé sur le contenu quand les données le permettent (Bobadilla et al., 2013).

Breese et al. (1998) proposent une taxonomie largement acceptée aujourd'hui, qui divise les méthodes de recommandation du filtrage collaboratif en deux catégories soit : le contenu collaboratif basé sur la mémoire (Memory-based Collaborative Filtering) et le contenu collaboratif basé sur les modèles (Model-based Collaborative Filtering).

2.6.2.1 Méthodes basées sur la mémoire / Méthodes heuristiques

Les méthodes basées sur la mémoire sont des méthodes qui n'agissent que sur la matrice des notes des utilisateurs pour les items (user x item) et utilisent toute évaluation (rating/preference) générée avant le processus de recommandation (la matrice doit régulièrement être mise à jour avant la compilation) (Bobadilla et al., 2013). On peut voir un utilisateur comme un vecteur dont les caractéristiques sont des items et dont les appréciations (implicites ou explicites) sont les valeurs données aux caractéristiques (Grčar et al., 2005). Pour ce type de recommandation, les méthodes utilisées sont des heuristiques se basant sur le calcul des similarités, des corrélations ou des distances pour recommander à l'utilisateur cible les items qui sont les plus appréciés par les utilisateurs les plus proches de celui-ci (Adomavicius and Tuzhilin, 2005). Afin que les résultats ne soient pas biaisés par les différences de perceptions dans les jugements (certains utilisateurs ont tendance à sous-évaluer ou à surévaluer), on corrige les prédictions pour tenir compte du biais. L'équation 2.2 présente une façon de

calculer une prédiction en éliminant le biais (Grčar et al., 2005).

$$p_{u,i} = \overline{u_u} + k \sum_i^n w(u,i)(v_{j,i} - \overline{v_i}) \quad (2.2)$$

$\overline{u_u}$ étant la moyenne des évaluations pour l'utilisateur cible.

k est un facteur de normalisation dont la somme est égale à 1.

n est le nombre d'utilisateurs considéré pour la recommandation.

$w(u,i)$ sont les poids des évaluations qui peuvent être la similarité, la corrélation ou la distance.

$v_{j,i}$ sont les appréciations de l'utilisateur i pour l'item j .

$\overline{v_i}$ est la moyenne des appréciations de chacun des utilisateurs.

De cette façon, peu importe la tendance de l'utilisateur, le fait de considérer les biais permet d'améliorer les prédictions.

La distinction entre le filtrage basé sur le contenu et le filtrage basé sur la mémoire est que le premier crée un profil pour l'utilisateur et calcule les similarités entre le profil de l'utilisateur cible et tous les items disponibles en se basant sur les caractéristiques des items. Tandis que le deuxième, utilise une matrice Items x Utilisateurs pour le calcul des similarités entre les utilisateurs en se basant sur leurs appréciations des items. Suite à cela, une prédiction des appréciations pour les items est estimée par une moyenne pondérée des appréciations des utilisateurs avoisinants l'utilisateur cible (Bobadilla et al., 2013).

Les approches basées sur la mémoire peuvent être classées en deux types principaux (Sharma and Mann, 2013) :

les systèmes basés sur l'utilisateur (user-based systems) : la similarité entre les utilisateurs est calculée en comparant leurs évaluations du même item. L'appréciation pour l'élément j par l'utilisateur i est donc calculée en tant que moyenne pondérée des appréciations de j par des utilisateurs similaires à l'utilisateur i .

Les systèmes basés sur les items (item-based systems) : la similarité entre deux éléments est déterminée en comparant la note du même utilisateur i pour les items. Ensuite, l'appréciation prédite de l'item j par l'utilisateur i est obtenue en tant que moyenne pondérée des appréciations de i pour les items, pondérée par la similarité entre ces items.

2.6.2.2 Méthodes basées sur le modèle

Les méthodes basées sur le modèle fournissent des recommandations en estimant les paramètres de modèles d'apprentissage. Dans un premier temps, les appréciations passées des utilisateurs pour des items sont collectées et utilisées pour apprendre un modèle. Ce modèle est ensuite utilisé pour faire des prévisions d'appréciation qui sont généralement rapides et précises (Sarwar et al., 2003), (Sharma and Mann, 2013). Parmi les modèles les plus utilisés, il y a les classificateurs bayésiens, les réseaux de neurones, les systèmes de logiques floues (fuzzy systems), les algorithmes génétiques, les factorisations de matrice (matrix factorization), et les facteurs latents (latent features) (Adomavicius and Tuzhilin, 2005), (Sharma and Mann, 2013).

Différence entre les méthodes basées sur la mémoire et les méthodes basées sur le modèle

La distinction principale entre les deux méthodes est que celle basée sur la mémoire utilise toujours toutes les données pour faire les prédictions (ce qui est coûteux dans le cas de bases de données volumineuses), tandis que celle basée sur le modèle utilise les paramètres définis grâce à l'apprentissage pour des prédictions. Ce qui se traduit, pour les méthodes basées sur la mémoire, par une utilisation importante de l'espace de stockage en tout temps. Tandis que pour les méthodes basées sur le modèle, les prédictions se font grâce au modèle préalablement appris, ce qui se traduit par une utilisation des données bien moins conséquente et donc des résultats plus rapides. Cependant, pour bâtir des modèles performants, il est nécessaire d'avoir un gros volume de données pour créer le modèle d'apprentissage.

2.6.3 Méthodes hybrides

Souvent, pour avoir des systèmes plus performants en recommandations, il est plus intéressant de combiner différentes méthodes. Les systèmes de recommandations récents sont souvent une combinaison des deux méthodes ou plus avec des choix de paramètres différents selon les besoins. La combinaison de systèmes de recommandations permet également de pallier à plusieurs des problèmes types auxquels font face les systèmes de recommandations présentés à la section 2.7.

Les approches peuvent être mises en oeuvre de différentes manières (Thorat et al., 2015) :

- Implémenter des méthodes collaboratives et basées sur le contenu individuellement et agréger leurs prévisions.
- Intégrer certaines caractéristiques de la recommandation basée sur le contenu dans une approche collaborative.

- Intégrer certaines caractéristiques de filtrage collaboratif dans une approche basée sur le contenu.
- Construire un modèle de consolidation générale intégrant à la fois des caractéristiques de contenu et de collaboration.

Burke (2002) présente une taxonomie des systèmes hybrides qu'il classifie en sept classes :

Pondération : Cette technique utilise plusieurs méthodes de recommandation séparément. La recommandation des items est faite en faisant la moyenne des scores attribués à chaque item existant dans chacune des listes de recommandation produites. Les items ayant les meilleurs scores sont choisis pour la recommandation finale.

Alternance : Cette technique ne combine pas différents résultats de systèmes de recommandations, mais choisit un système à la fois de façon dynamique selon un critère relatif au type de recommandation que l'on veut produire (exemple : recommandation à court terme VS recommandation à long terme). Ce critère peut être difficile à déterminer. On peut également choisir l'approche selon un critère de confiance de la recommandation, s'il y a lieu.

Mix : Cette technique utilise plusieurs méthodes de recommandations en parallèle et présente un mélange des items recommandés par les différentes méthodes. La sélection des items candidats se fait en demandant à chaque système de délivrer à ses candidats une note associée, une note prédite et/ou un indice de confiance. Ensuite, un module spécifique effectue un mélange de ces recommandations avec un tri et une sélection basés sur les scores associés aux éléments candidats. Cette méthode d'hybridation est seulement citée par (Burke, 2007) et n'est pas évaluée.

Combinaison des caractéristiques : Cette technique utilise des données normalement utilisées pour un type de système de recommandations dans un autre contexte. Par exemple, on peut utiliser les données des évaluations des utilisateurs sur les éléments normalement traités par un système basé sur le contenu.

Augmentation des caractéristiques : Cette méthode rajoute des données caractéristiques des utilisateurs et des items avant de les utiliser comme données d'entrée d'un système de recommandations.

Cascade : Le procédé d'hybridation en cascade est une méthode hiérarchique dans laquelle chaque méthode de SRs raffine une recommandation obtenue par une méthode de recommandation utilisée précédemment. Par exemple, le système EntreeC (Burke, 2002), qui fournissait trop d'items avec des scores identiques, a été amélioré en ajoutant un post-classement basé sur une recommandation collaborative.

Meta-niveau : Cette méthode utilise comme entrée un modèle fait par un autre SRs.

Comparé à la méthode d’augmentation des caractéristiques, cette méthode nécessite un remplacement total du modèle d’entrée par la sortie de la recommandation précédente.

Il existe d’autres méthodes de recommandations qui ont été utilisées dans les différentes études. Ces recommandations sont généralement des sous-types des recommandations présentées précédemment. Des exemples seraient : La recommandation démographique (Bobadilla et al., 2013), la recommandation basée sur l’utilité et la recommandation basée sur la connaissance (Burke, 2002), la recommandation basée sur le contexte (Adomavicius and Tuzhilin, 2011) ainsi que la recommandation sociale (Ruffo and Schifanella, 2009).

2.7 Défis

Malgré la diversité des techniques des recommandations présentées précédemment, certains défis persistent. Dans cette section, adaptée de (Lü et al., 2012). Nous présentons un découpage des défis les plus importants en incluant les conclusions de Adomavicius and Tuzhilin (2005) et de Bobadilla et al. (2013) dans leurs revues de littératures respectives.

2.7.1 Clairsemance des données

L’une des caractéristiques du e-commerce est que la diversité des produits existants est impressionnante. Les produits offerts sur le catalogue d’un site de e-commerce peuvent se compter par millions. La problématique liée à cela est que dans tous les systèmes de recommandations, les items que l’on tente d’évaluer sont bien plus nombreux que ceux qui le sont déjà. Ce qui implique que les données sont clairsemées (sparse data). ceci rend la tâche de calcul de similarité très difficile et influence grandement la qualité des recommandations. Pour pallier à ce problème, une des solutions serait d’utiliser les profils des utilisateurs pour calculer les similarités. Les profils peuvent être incrémentés par différentes informations disponibles sur l’utilisateur. Des exemples de ces données seraient les données sociodémographiques. La prise en compte de ces données permet de faire des recommandations basées non seulement sur les appréciations communes, mais également sur le contexte sociodémographique. Les recommandations utilisant ces informations sont celles que nous avons nommées précédemment « le filtrage démographique ». Une seconde manière serait d’utiliser une méthode de réduction de dimension comme la Singular Value décomposition (Golub and Reinsch, 1970). D’autres méthodes existent comme celle présentée par (Huang et al., 2004) qui propose de rajouter d’autres données à la matrice utilisateur/item, en explorant « les relations d’interaction transitive », pour l’éviter le problème de clairsemance (sparsness) .

2.7.2 Démarrage à froid

Le problème de démarrage à froid (cold start) est le phénomène qui survient quand un SRs peine à fournir des recommandations dues à un manque d'informations initiales sur les appréciations des utilisateurs. Il touche principalement le filtrage collaboratif. Il existe différents types de problèmes de démarrage à froid. Les plus communs sont les problèmes de démarrages à froid de : nouvelle communauté (New community), nouvel utilisateur (new user), nouvel item (new item). Généralement, la solution à ces problèmes est de combiner plusieurs méthodes de recommandations (CF-content based RS, CF-demographic based RS, CF-social based RS). En guise d'exemple, la combinaison du filtrage basé sur le contenu et du filtrage collaboratif peut être utilisée pour inclure les caractéristiques des items et les évaluations simultanément dans le calcul des recommandations. Des questions explicites peuvent aussi être posées aux utilisateurs pour avoir des informations générales sur ces derniers. Un suivi des comportements des utilisateurs sur d'autres sites est également possible si l'on veut acquérir des données sur les utilisateurs chez des tiers partis tels « syndicated data suppliers » ou « internet service providers » (User-centric clickstream) (Bucklin and Sismeiro, 2009). L'exploration des interactions transitives présentées comme solution au problème de clairseance des données peut aussi être une solution au cold start (Huang et al., 2004).

2.7.3 Coût de traitement des données

Le coût de traitement des données (scalability) est un facteur important pour la réussite d'un système de recommandations. En effet, la majorité des sites de e-commerce proposent des millions d'items à des millions de clients différents. Le volume de données à traiter est donc extrêmement élevé. La solution à ce problème est d'utiliser des algorithmes peu demandant en puissance de calcul et/ou de paralléliser le traitement des données. Une autre approche serait d'utiliser des algorithmes incrémentaux qui n'utilisent pas la totalité des données à chaque itération des recommandations (Sarwar et al., 2002).

2.7.4 Diversité et précision

L'un des buts principaux des systèmes de recommandations commerciaux, si ce n'est le but ultime, est l'augmentation des ventes. La diversité des produits est un facteur important pour l'augmentation des ventes. Si les produits niches ne sont pas recommandés, le but du système de recommandations n'est pas atteint (Schafer et al., 1999). Pour créer une diversité dans le catalogue de produits à recommander, il faut éviter de recommander uniquement les produits populaires. Des recommandations intéressantes doivent contenir des produits moins évidents

qui sont difficilement accessibles aux utilisateurs et qui n'auraient probablement pas été considérés par ses derniers (McNee et al., 2006). La diversité des SRs peut être forcée par des études plus poussées des préférences des utilisateurs. Une méthode est présentée par (Ziegler et al., 2005), qui balance et diversifie les recommandations personnalisées dans le but de refléter le spectre complet des intérêts de l'utilisateur. L'utilisation de SRs hybrides apporte encore une fois une solution à ce problème en proposant des recommandations découlant de plusieurs techniques différentes (Burke, 2002).

2.7.5 La valeur du temps

Un des défis les plus importants de la recommandation est de faire les bonnes recommandations au bon moment. La plupart des SRs négligent cet aspect critique de la recommandation qui varie grandement selon le type de produit à suggérer. Prenons l'exemple de la recommandation de voyage, elle se base sur des intérêts à court terme (beaucoup d'intérêt pour la Thaïlande avant le voyage, plus d'intérêt au retour de voyage). Les recommandations d'informations sur un journal électronique se basent principalement sur des intérêts à long terme (une personne qui s'est beaucoup intéressée à la politique dans le passé devrait s'y intéresser longtemps). La prise en compte du temps dans les recommandations est un sujet de recherche d'actualités (Feng et al., 2015), (Rezaeimehr et al., 2018).

2.7.6 Interface / Interactivité

Une interface de recommandation peut jouer un rôle important dans l'acceptation des utilisateurs des recommandations. En effet, des études ont démontré que la transparence dans les recommandations était un facteur clé dans l'acceptation de celle-ci. Les utilisateurs sont plus ouverts aux recommandations quand ils sont capables de comprendre pourquoi un item spécifique leur a été recommandé (Sinha and Swearingen, 2002). He et al. (2016), dans leur état de l'art sur les interfaces des systèmes de recommandations, donnent un aperçu du rôle que les interfaces et les visualisations des recommandations peuvent jouer dans l'acceptation des recommandations. De plus, ils démontrent que les interfaces ont un impact significatif sur certaines métriques de performances des systèmes de recommandations.

2.8 Métriques d'évaluations

Les métriques d'évaluations des systèmes de recommandations évaluent généralement : les prédictions, les ensembles de recommandations ou le classement des listes de recommandations. Dans cette section nous présentons les différentes métriques utilisées : les métriques de

précision des évaluations, les métriques de comparaisons, les métriques du rang dans la liste de recommandations et d'autres métriques.

2.8.1 Métriques de précision des évaluations

Les systèmes de recommandations sont généralement mis en place pour prédire les intérêts futurs des utilisateurs. Il existe plusieurs méthodes pour évaluer les performances du système de recommandations, les deux métriques les plus utilisées sont la Mean Absolute Error (MAE) et la Root Mean Squared Error (RMSE) (Herlocker et al., 2004) et (Lü et al., 2012). Elles permettent de comparer les prédictions aux résultats réels : si $r_{i\alpha}$ est la vraie valeur de l'appréciation de l'utilisateur i pour l'objet α . $\tilde{r}_{i\alpha}$ est la valeur prédite de l'évaluation et E^p est l'ensemble des évaluations non utilisées pour l'apprentissage, MAE et RMSE sont définies comme suit :

Mean absolute error :

$$MAE = \frac{1}{|E^p|} \sum_{i,\alpha \in E^p} (|r_{i\alpha} - \tilde{r}_{i\alpha}|) \quad (2.3)$$

Root mean squared error :

$$RMSE = \sqrt{\frac{1}{|E^p|} \sum_{i,\alpha \in E^p} |r_{i\alpha} - \tilde{r}_{i\alpha}|^2} \quad (2.4)$$

Plus les MAE et RMSE sont faibles, meilleure est la précision de l'évaluation. Ces métriques ne sont pas optimales quand il s'agit d'aide à la découverte, car toutes les évaluations sont traitées de la même façon peu importe leurs positionnements (ranking) sur la liste de recommandations. Elles sont tout de même très utilisées vu leur simplicité (Lü et al., 2012).

Une autre façon d'évaluer la précision d'une prédiction est de calculer la corrélation entre les valeurs prédites et les évaluations réelles. Les trois méthodes les plus connues sont la corrélation de Pearson (Pearson, 1896) (Pearson product-moment correlation coefficient), la corrélation de Spearman (Spearman, 1904) et la corrélation de Kendall (Kendall, 1938).

Le coefficient de corrélation de Pearson mesure l'étendu de la relation linéaire présente entre deux ensembles d'évaluations. Il est présentée dans l'équation 2.5.

$$PCC = \frac{\sum_{\alpha} (\tilde{r}_{\alpha} - \bar{\tilde{r}})(r_{\alpha} - \bar{r})}{\sqrt{\sum_{\alpha} (\tilde{r}_{\alpha} - \bar{\tilde{r}})^2} \sqrt{\sum_{\alpha} (r_{\alpha} - \bar{r})^2}} \quad (2.5)$$

Avec r_{α} : valeur réelle d'évaluation, $\tilde{r}_{\alpha}$: valeur prédite de l'évaluation, $\bar{\tilde{r}}$: valeur moyenne prédite des évaluations et $\bar{r}$: valeur moyenne des évaluations.

Le coefficient de corrélation de Spearman quant à lui est défini de la même manière que la corrélation de Pearson, excepté que r_α et $\tilde{r}_\alpha$ sont remplacés par le classement des items respectifs. Spearman et Kendall, mesurent l'étendue de l'accord des deux classements sur l'exactitude des valeurs des évaluations. Le coefficient de Kendall quant à lui est défini comme suit :

$$\tau = (C - D)/(C + D) \quad (2.6)$$

C est le nombre de paires concordantes d'objets que le système prédit dans l'ordre classé correct. D le nombre de paires-paires discordantes que le système prédit dans le mauvais ordre.

$\tau = 1$ lorsque les classements vrai et prédit sont identiques et $\tau = -1$ quand ils sont exactement opposés.

2.8.2 Métriques de comparaison

Il existe également d'autres métriques qui permettent d'évaluer la recommandation en comparant les différents items à recommander. Ces métriques sont principalement utilisées quand il n'y a pas d'évaluations explicites « ratings », c'est-à-dire que les données d'entrées sont implicites. En d'autres termes, ces métriques sont utilisées quand nous sommes capables de savoir quels objets ont été préférés par les utilisateurs, sans pour autant connaître le degré d'appréciation (Lü et al., 2012). Les métriques les plus connues sont Precision and Recall qui sont généralement utilisées en même temps dans une même métrique appelée la F1-score ou la Area Under ROC Curve.

La précision est définie comme le ratio du nombre d'éléments pertinents sélectionnés dans la liste de recommandations (N_{rs}) sur le nombre d'éléments de la liste de recommandations (N_s) tel que présenté à l'équation 2.7 . Elle représente la probabilité qu'un item sélectionné soit pertinent (Herlocker et al., 2004).

$$Precision = \frac{N_{rs}}{N_s} \quad (2.7)$$

Le rappel est défini comme le ratio du nombre d'éléments pertinents de la liste de recommandation (N_{rs}) sur l'ensemble des items pertinents dans l'ensemble des produits disponibles dans le catalogue (N_r) tel que présenté dans l'équation 2.8. Il représente la probabilité qu'un item soit sélectionné (Herlocker et al., 2004).

$$Rappel = \frac{N_{rs}}{N_r} \quad (2.8)$$

En faisant la moyenne de la précision et du rappel sur tous les utilisateurs qui ont au moins un objet significatif dans la liste de recommandations, on obtient la précision et le rappel moyens (Lü et al., 2012).

La précision et le rappel peuvent porter à confusion quand il s'agit de comparer l'efficacité de différents systèmes de recommandations, vu qu'ils sont sensibles à la taille de la liste de recommandations. Ceci pousse à l'utilisation d'une métrique combinatoire qui est moins dépendante de la taille de la liste de recommandations. Cette métrique présentée par Yang et al. (1999) est appelée "F1-score", elle combine la précision et le rappel en un seul chiffre, plus simple à interpréter, présenté par l'équation 2.9 :

$$F1 - score = \frac{2 * Rappel * Precision}{(Rappel + Precision)} \quad (2.9)$$

F1-score est calculé individuellement pour chaque utilisateur avant d'en faire la moyenne pour tous les utilisateurs et de l'utiliser comme métrique de comparaison de systèmes de recommandations.

La Area under roc curve (AUC) tente d'évaluer la capacité d'un système de recommandations à distinguer entre un item pertinent à l'utilisateur et un item non pertinent. Comme la précision et le rappel, elle est utilisée sur des données binaires quand les appréciations ne sont pas disponibles. Elle représente la probabilité que le système puisse choisir correctement entre deux éléments, l'un sélectionné aléatoirement parmi les items considérés non pertinents à l'utilisateur et l'autre choisi aléatoirement parmi l'ensemble des éléments considérés pertinents à celui-ci.

La Area under roc curve est la plus appropriée à utiliser quand il y a une relation de pertinence binaire claire et quand l'objectif est de trouver "les bons items" à recommander à l'utilisateur, c'est à dire que la liste de recommandations comporte le maximum possible d'items qui lui sont pertinents.

2.8.3 Métriques du rang dans la liste de recommandations

Il existe également des métriques qui considèrent le rang d'un item dans un classement. Ces métriques partent de l'hypothèse que tous les utilisateurs ne prennent pas le temps d'inspecter toute la liste de recommandations. Il est donc important de mesurer la satisfaction en tenant compte de la position de chaque item pertinent dans la liste de recommandations et d'attribuer des pondérations selon le classement. Il existe plusieurs métriques pour évaluer cet aspect dont : la métrique "half life utility", la métrique "discounted cumulative gain", et la métrique "rank biased precision", présentées et discutées en détail, respectivement dans

(Breese et al., 1998), (Järvelin and Kekäläinen, 2002) et (Moffat and Zobel, 2008).

2.8.4 Autres métriques

Il existe également d'autres métriques d'évaluation tels : les métriques tenant compte de l'impact sur les performances relatives aux ventes, le développement et les maintiens des relations avec la clientèle (Pathak et al., 2010) ou encore sur l'impact sur la prise de décisions d'achats par les utilisateurs (Senecal et al., 2005). Une autre métrique populaire est la couverture (Coverage), elle mesure le pourcentage d'objets proposés sur le catalogue d'items qui sont recommandés par le système (Burke, 2002).

2.8.5 Synthèse

Cette section a présenté les systèmes de recommandations traditionnels, leurs fonctionnalités, les données qu'ils utilisent, les différentes méthodes de recommandations classiques, les défis auxquels ces systèmes de recommandations font face et les métriques classiques d'évaluation des recommandations. On peut remarquer, à travers le contenu de cette section, que les systèmes de recommandations sont conçus pour répondre aux intérêts commerciaux des compagnies à travers la prédiction des intérêts des clients. Cependant, malgré des performances de plus en plus élevées au niveau des prédictions des intérêts des clients, les systèmes de recommandations traditionnels ne prévoient pas l'évaluation de la capacité de répondre à la demande. La capacité de réponse à la demande est grandement liée aux contraintes logistiques et aux contraintes de production. Cette thèse présente un travail visant à améliorer l'adaptabilité de ceux-ci au contexte logistique dans lequel ils sont utilisés.

Des revues de littératures spécifiques aux sous-problématiques traitées dans cette thèse sont présentées dans les chapitres 4, 5 et 6.

CHAPITRE 3 DÉMARCHE ET ORGANISATION

3.1 Les problématiques de recherche

Les systèmes de recommandations se sont montrés extrêmement utiles dans les dernières années. Dans la vente de détail, l'efficacité de ces systèmes a été très vite démontrée à travers les réussites impressionnantes de géants comme Amazon. Amazon aurait augmenté ses ventes de 21% en une semaine en apportant des améliorations à son système de recommandations (Hill et al., 2017).

Les systèmes de recommandations dans un contexte de vente de détail permettent d'accroître la visibilité de certains produits, ce qui augmente leurs probabilités de vente à travers l'augmentation de la demande. Cependant, l'augmentation de la demande est inutile si celle-ci ne peut être convertie en vente. Une demande non comblée peut générer des ventes perdues, porter atteinte à l'image de marque de l'entreprise et engendrer des pertes à long terme.

Les systèmes de recommandations existants ne tiennent pas compte de la capacité de l'entreprise à répondre à la demande. Tel que présenté dans la littérature, les attentes des clients en termes de délais de livraison sont de plus en plus élevées, se traduisant par une compétitivité dépendante de celle de la chaîne logistique (Anand and Grover, 2015). Comme la demande est souvent conditionnelle aux délais de livraison, la capacité à répondre à celle-ci se retrouve grandement conditionnée par les contraintes de la chaîne logistique relatives à la disponibilité de produits et aux contraintes de transport et de manutention des produits.

Notre question de recherche peut donc se formuler comme suit :

« Comment améliorer les systèmes de recommandations pour tenir compte de la satisfaction de la demande considérant plusieurs contraintes de la chaîne logistique ? »

Notre problème n'est donc pas d'améliorer la précision des systèmes de recommandations, mais d'améliorer l'adaptabilité de ceux-ci au contexte logistique dans lequel ils sont utilisés. Nous considérons trois aspects dont il faut tenir compte lors de la recommandation de produits pour pouvoir satisfaire la demande :

1. La disponibilité des produits en inventaire, en contexte de e-commerce.
2. La capacité de livraison des produits, en fonction des tournées de véhicules program-

mées dans une fenêtre de temps donnée, en contexte de e-commerce.

3. La disponibilité des produits en fonction du réseau d’approvisionnement, en contexte de vente stationnaire.

La contribution de cette recherche ne réside pas dans l’élaboration d’une nouvelle théorie, mais dans la proposition d’un nouveau cadre conceptuel qui intègre les contraintes logistiques dans les systèmes de recommandations.

3.2 Cadre de recherche et contributions

Tels qu’énoncé dans la littérature, les systèmes de recommandations, dans leur état actuel, ne tiennent pas compte de la capacité de la chaîne d’approvisionnement à répondre à la demande. De ce fait, certaines recommandations de produits peuvent impacter l’image de marque de l’entreprise et mener à des pertes de rentabilité lorsque la demande qui y est associée n’est pas satisfaite. Cette thèse propose une approche qui permet une intégration adéquate de plusieurs contraintes logistiques dans la recommandation des produits.

Afin d’évaluer la capacité à répondre à une demande, un éventail de données logistiques doit être extrait (les données sur l’inventaire des produits, sur la capacité et les caractéristiques de la flotte, sur les coûts de livraison d’un produit, sur les contraintes de manutention des produits, etc.). L’information contenue dans ces données doit être transformée de façon à être exploitable par le système de recommandations, étant donné que la majorité des algorithmes de recommandations se basent sur le calcul de scores de recommandations. Une façon d’inclure la capacité de la chaîne logistique à répondre à la demande serait d’ajuster les scores par un ratio qui permet de réarranger la liste de recommandations en fonction de la facilité logistique de satisfaction de la demande. La réorganisation de la liste permet d’éviter l’hyper visualisation d’un produit dont la demande ne peut être satisfaite. Recommander un produit qui ne peut être fourni est une perte garantie.

Pour bien visualiser comment les trois problématiques de recherches s’inscrivent dans notre problématique globale, nous présentons la figure 3.1 qui illustre les interactions entre les différents éléments de la problématique. Le cadre général est celui des systèmes de recommandations traditionnels, qui utilisent comme données d’entrées, les données sur les items et les données sur les clients. Le cadre spécifique est celui de la recommandation basée sur la connaissance. Les connaissances métiers liées à la gestion de la chaîne logistique sont considérées à travers l’utilisation de données liées à la chaîne logistique et aux ventes. Dans chacun des chapitres, des données différentes sont considérées. Les éléments d’un même chapitre sont identifiés par une couleur unique, le bleu ciel, étant associée au chapitre 4, le vert, au chapitre

5 et l'orange, au chapitre 6.

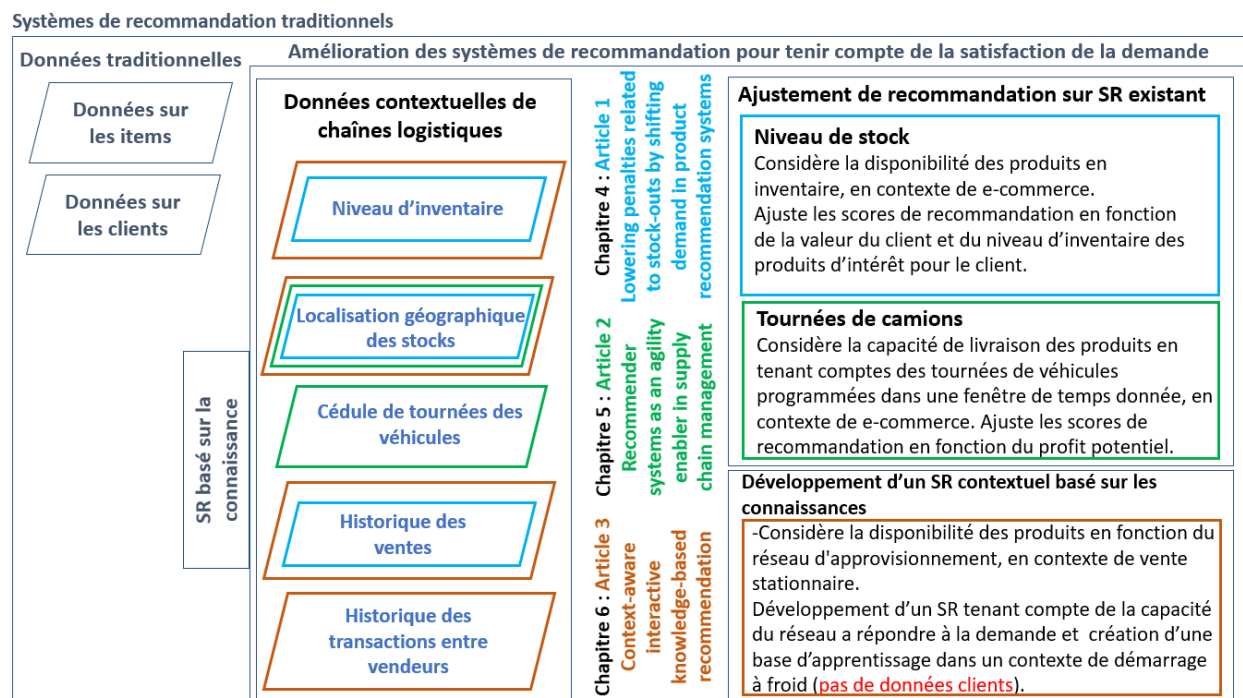


Figure 3.1 Amélioration des systèmes de recommandations pour tenir compte de la satisfaction de la demande

Concernant la problématique présentée au chapitre 4, nous proposons une méthode conçue pour tenir compte du **niveau de stock** suite au processus de recommandations classiques afin de transférer la demande vers des produits spécifiques pour un utilisateur spécifique en fonction de la disponibilité des produits à recommander en contexte de e-commerce. Nous pouvons voir à la figure 3.1, que les éléments liés à ce chapitre sont identifiés en **bleu ciel**. Les données d'entrées sont **l'historique des ventes et le niveau d'inventaire des produits**. La méthode s'articule autour de deux phases ; la première est une catégorisation des clients basée sur l' historique des ventes, et la seconde est une actualisation des scores de recommandations des produits pour tenir compte de la catégorisation des clients et de la stratégie de l'entreprise en matière d'assignation des stocks en fonction du **niveau d'inventaire**. Les produits à faible inventaire ne seront recommandés qu'aux clients à valeur de vie élevée, et les produits à inventaire élevé seront recommandés plus agressivement. Comme on peut le voir à la figure 3.1, ce chapitre rentre dans le cadre de l'ajustement des recommandations des SRs existants.

Pour ce qui est de la problématique traitée au chapitre 5, nous tenons compte des **tournées des véhicules** suite au processus de recommandations classiques afin de transférer la de-

mande vers les produits ayant un délai de livraison rapide et rentable, en tenant compte de la localisation géographique des stocks. Nous pouvons voir à la figure 3.1, que les éléments liés à ce chapitre sont identifiés en **vert**. Les données d'entrées sont **la localisation géographique des stocks** et **la cédule de tournées des véhicules**. Cette méthode suit deux étapes : la première étape est le calcul de la recommandation et la seconde étape est l'ajustement de la recommandation en 4 phases : (1) l'évaluation des camions en activité, (2) l'évaluation des contraintes physiques de transport, (3) l'évaluation des bénéfices associés à l'ajout de points de collecte et/ou livraison à une tournée programmée pour chaque article recommandé et (4) l'ajustement des scores de recommandation. Seuls les produits générant un profit considéré comme étant acceptable seront recommandés en priorité. Comme on peut le voir à la figure 3.1 ce chapitre rentre également dans le cadre de l'ajustement de recommandations des SRs existants.

Dans le chapitre 6 de cette thèse, nous **développons un SRs contextuel basé sur les connaissances** tenant compte de la disponibilité des produits à recommander en contexte de vente stationnaire. Nous présentons une nouvelle technique de recommandations interactive basée sur les connaissances et sensible au contexte. Cette technique a été élaborée pour une utilisation en contexte de vente stationnaire. Elle permet de créer une base d'apprentissage des profils de clients dans des contextes de démarrage à froid. Nous pouvons voir à la figure 3.1, que les éléments liés à ce chapitre sont identifiés en **orange**. Les données d'entrées sont **le niveau d'inventaire**, **la localisation géographique des stocks**, **l'historique des ventes** et **l'historique des transactions** entre vendeurs. La méthode débute par une première phase d'exploration interactive et finit par une recommandation basée sur le contexte tenant compte des contraintes de la chaîne d'approvisionnement en tenant compte du taux de disponibilité des produits. Un pré-filtrage basé sur la connaissance est effectué avant l'utilisation d'une approche basée sur le contenu pour calculer les scores de recommandations en utilisant une méthode basée sur la mémoire avec une inclusion dynamique de l'appréciation des caractéristiques basée sur les commentaires explicites de l'utilisateur.

CHAPITRE 4 ARTICLE 1 : LOWERING PENALTIES RELATED TO STOCK-OUTS BY SHIFTING DEMAND IN PRODUCT RECOMMENDATION SYSTEMS

Abstract - *Recommender systems focus on the various algorithms and techniques to get the most accurate prediction of users' preferences. We propose a method designed to consider actual stock levels in the recommendation process in order to shift demand toward specific products for a specific user. The method is displayed in two phases; the first is a categorization of customers, and in the second, item scores are corrected to take into account customer categorization and a company's strategy in stock allocation. Low inventory products will be recommended only to high lifetime value customers, and high inventory products will be recommended more often to all users. Based on a real situation from an industrial partner in a B2B context, experiments were conducted on simulated data representing recommender systems' scores modeled over data. Results indicate that penalties resulting from the recommendation of stock-out products are lowered.*

4.1 Introduction

The information revolution led to a massive adoption of the web as a trading platform. Traditional tools of gaining and retaining customers have evolved to meet new challenges. Recommender systems (RSs) are among the tools used for managing customer relationships (Demiriz, 2004).

The definition of RSs differs from one area to another, but is focused on establishing a list of items to recommend to a specific user (Burke et al., 2011), based on algorithms from different disciplines that can predict a user's interest level in a list of products (Ricci et al., 2011) and suggests, among a wide range of items, those that can meet their specific needs.

In the past three decades, research on RSs focused on the various algorithms and techniques to process data in the most efficient way (memory consumption and speed of computation), in order to obtain the most accurate prediction of a users' preferences (Burke, 2002; Bobadilla et al., 2012). To the best of our knowledge, there has, as of now, been no RS that considers supply chain constraints and strategies. Nevertheless, previous studies have uncovered several notable findings on the impact of recommender systems on sales, confirming that recommender systems positively affect sales (Lin, 2014; Pathak et al., 2010).

Current RSs emphasize supply chain management problems by suggesting items that may be

out of stock, or close to being out of stock. This results in long-term consequences such as negative word-of-mouth, loss of patronage, customer dissatisfaction and loss of market share (Fitzsimons, 2000; Zinn and Liu, 2001). Research in the field of inventory management is consistent and many tools have been successfully implemented to a certain extent, but none is the ultimate solution to stock management (Wild, 2017).

Existing RSs focus on customers’ interests by helping the customer to decide, compare, discover and explore the products by offering the “right product”, to the “right customer” and increase sales (Meyer, 2012). Furthermore, supply chain constraints are not taken into consideration to improve recommendations from a business point of view.

We propose a methodology that takes into account some supply chain constraints in RSs. We consider stock levels to diminish the occurrence of inventory management issues (out of stock/overstock) by prioritizing customers, based on their value. The contribution of this research is not in the development of a new theory, but in the proposal of a new conceptual framework that brings RSs into supply chain and inventory management.

The remainder of this article is structured as follows: Section 4.2 describes RSs foundations including definitions, objectives, techniques and challenges. The current situation of stock management and demand-shaping is also depicted, followed by a brief synthesis. Section 4.3 describes the proposed method in 2 phases: (1) customer categorization and (2) product recommendation correction. Section 4.4 elaborates upon a case study that evaluates improvements resulting from the proposed methodology. Section 4.5 presents experimental results on the penalties related to stock-outs. The concluding section summarizes the purpose of considering stocks in RSs and indicates new areas to focus on in the near future.

4.2 State of the art

4.2.1 Recommender System

Different definitions of RSs exist, but all agree that recommender systems are tools developed in order to assist **users** (Bobadilla et al., 2012; Dadouchi and Agard, 2017). In (Burke et al., 2011), the authors consider that the different definitions agree on two distinctive features:

- *A recommender system is personalized. The recommendations it produces are meant to optimize the experience of one user, not to represent group consensus for all.*
- *A recommender system is intended to help the user select among discrete options. Generally, the items are already known in advance and not generated in a bespoke fashion.*

The definitions of RSs focus on establishing a list of items (object / service / good / etc.) to

recommend to users. RSs predict a user's appreciation for a list of unknown products and suggest a wide range of items that will meet their specific needs. The **user** is the center of the system.

RSs are used in several disciplines, such as government, business, commerce, learning, tourism, e-resource services and group activities (Lu et al., 2015).

In addition to the two former points, other objectives can be identified: recommender systems may also help to increase cross selling and to improve consumer loyalty (Lu et al., 2015; Shardanand and Maes, 1995; Resnick and Varian, 1997). (Meyer, 2012) noted the four main functions below: (1) Help to Decide (predicting a rating for a user for an item), (2) Help to Compare (rank a list of items in a personalized way for a user), (3) Help to Discover (provide a user with unknown items that would appreciate) and (4) Help to Explore (provide items similar to a given target item).

To meet those functionalities, three types of recommender systems are identified (Adomavicius and Tuzhilin, 2005): (1) Content-based recommendations/filtering recommend items similar to those that the user preferred in the past; (2) Collaborative recommendations/filtering recommend items that people with similar tastes and preferences have appreciated in the past; and (3) Hybrid approaches/filtering combine the two previous ones.

(Su and Khoshgoftaar, 2009) made a classification based on the methods of recommendation: (1) memory-based collaborative filtering (CF) techniques: each user is part of a group of people with similar interests and by identifying the "neighbors" of the active user, a prediction for a preference over new items can be produced; (2) model-based CF techniques: models learn to recognize patterns in previous sales and then make predictions for new data; and (3) Hybrid CF techniques: combine CF recommendations with other recommendation techniques such as content-based recommendations.

These typologies have been the basis of other classifications (Candillier et al., 2007). An enhanced and more recent classification, including recently-developed advanced methods such as fuzzy set-based, social network-based, trust-based, context awareness-based and group recommendation approaches, is proposed by (Lu et al., 2015). For all of the techniques presented, two types of data can be used: **Explicit data**, such as user-provided item evaluations (these are generally continuous or ordered data) or **Implicit data** such as data collected from a user's historical profile (these are often binary data, for example the history of the purchases of a user).

(Bauer and Nanopoulos, 2014) provided a comparison of recommender systems by summarizing their advantages and disadvantages. Recommendation methods perform the best on

explicit (continuous) data, and are not effective on implicit (discrete) data. In B2B, explicit information may not be accessible and available data consists mostly of historical purchases (Gatzioura and Sánchez-Marrè, 2015).

Currently, recommendation systems are not geared to respond to industrial problems, but rather to commercial interests such as increased sales. The latter is reached by attempting to predict which products each user will be more likely to buy. Some studies have focused on the interests of users according to price by product categories (Guo et al., 2018) and others on the profits generated by the seller (Chen et al., 2008). Supply chain constraints remain poorly covered in actual RSs, according to our research.

4.2.2 Inventory Management

According to (IHL-group, 2015). retailers worldwide lose \$1.75 trillion annually due to the cost of overstock, out of stock items, and sales returns. Stock problems are not a new issue and researchers have been working on this challenge for decades.

Inventory management is a crucial part of a company’s performance. Product demand variability can be identified as one of the key sources of uncertainty in any supply chain. Failure to account for significant product demand fluctuations may lead to poor inventory management that affects different aspects of the supply chain (Wild, 2017).

In addition, this does not only involve production constraints but also capital management. Dealing with stocks is a delicate task and despite the advances in supply chain management and increased investments in inventory-tracking systems, stock outs have been an endemic problem in retail (Corsten and Gruen, 2003). This is especially true as the web has become one of the main channels of distribution, increasing the long-term consequences of mismanagement from missed sales: store, item or brand switch (Sloot et al., 2005) eventually leading to the loss of market share, customer dissatisfaction, loss of patronage, and negative word-of-mouth (Fitzsimons, 2000; Zinn and Liu, 2001).

Most grocery shoppers perceive stock outs to be an irritating situation, and evidence suggests that the impact of out-of-stock (OOS) items is enduring and influences future profits (Kim and Lennon, 2011). Dealing with stock is still a persistent industrial problem to solve on as many grounds as possible. In the area of production, two main strategies can be used to manage uncertainty: gradually building inventory to hedge against possible future shortages or temporarily increasing capacity by purchasing extra capacity (Cinar and Gollu, 2012). An additional way to deal with this is to predict customers’ interests and redirect those interests into products that will help manage inventory. Recommender systems can therefore be used

in such a way to influence demand for a product and limit the costs of mismanagement of stocks. This is the topic of this article.

The use of an online channel allows an organization to reach a larger customer base; it also amplifies demand variance and operational risk. Matching supply and demand becomes then even more demanding (Wu and Wu, 2015) and managing the unforeseen becomes of great value. An important technique to respond to this, is demand shifting (steering); this refers to the ability to promote a substitute for a product when it is OOS, and/or move a sale and marketing tactic from one period to another to accommodate supply constraints. It can do so (1) at the point of sales, by influencing a customer to purchase an alternative product using sales and marketing incentives; or (2) at the point of supply, when the operations planning and manufacturing teams negotiate to shift unconstrained demand into the future due to supply capacity constraints (Wu and Wu, 2015).

One of the most famous business best practices of demand shifting in a web based context is the demand shaping done by Dell (Lapide, 2013). Dell “consigns” inventories of components at supplier warehouses. If they uncover components that have excessive inventories, the team would alter the daily list of specially promoted items to include computer configurations that include these components. In contrast, if they uncover components that had inventory shortages, the team would “de-promote” them. This means taking them off the daily list of specially promoted items, raising their prices, and increasing their delivery lead times (Lapide, 2005).

4.3 The proposed method

As presented, RSs, in their structure, do not consider inventory levels. Thus, we suggest an approach to help consider this constraint based on a 2-phase approach to (1) categorize each user, and (2) correct RSs outputs based on the user’s categorization and on the company’s strategy.

4.3.1 Phase 1: Categorization of users

Customer satisfaction leads to customer retention. Making a sale with a new customer is estimated to be up to 5 times more difficult than making an additional sale to an existing customer (Hart et al., 1990). Thus, customer defections are among the worst economic events that can happen to a business, and keeping customers with the highest customer value is a business priority.

Categorization of users can be quantitative using metrics such as customer value or qualitative

based on a company's strategy. We propose using a classification to set different classes of customers in order to adapt recommendations for priorities. The classification is based on Customer Lifetime Value (CLV), except when legal or ethical constraints are noted, in which case, customer class can be forced to any required specific category. Customers identified as **CAT 1** will be high CLV customers or customers with binding contracts and ethical priority. Customers in **CAT 2** will be the rest of the customers. It is possible to make sub-distinctions in those (ex: between customers making multiple purchases of low profit items and those making very few purchases).

CLV over a period of time is calculated with formula 4.1 from (Berger and Nasr, 1998).

$$CLV = GC * \sum_{i=0}^{p.n} \frac{r^i}{(1+d)^{\frac{i}{p}}} - M * \sum_{i=1}^{p.n} \frac{r^{i-1}}{(1+d)^{\frac{i+0.5}{p}}} \quad (4.1)$$

For i in 0 to p , representing a period,

GC is the (expected) gross contribution margin per customer per sales cycle,

M is the promotion costs per customer per sales cycle,

r is the retention rate per sales cycle,

n is the length, in years, of the period over which cash flows are to be projected,

d is the yearly discount rate (appropriate for marketing investments),

p is the number of periods (it is not necessary that p to be as an integer).

4.3.2 Phase 2: Correct recommendations

Customer categorization helps determine which customers will have priority when it comes to inventory management. Recommendations do not always result in a purchase, but recommendations highlight items that are predicted to be of interest to a user. Highlighting an item that is low inventory to a low CLV user may go against the company's interests. When recommending items without considering stock level, as is the case for current RSs, a user with a low CLV may be recommended with an item soon to be OOS, but this item may be highly critical for another user with high CLV. Hence, since the recommendation is in real time, if the low CLV user buys the item, then the user with a high CLV could be the one facing the OOS situation. This could be partly avoided by redirecting interest of low CLV user to another item.

In order to correct recommendations based on stock levels it is important to use accurate,

up-to-date information. Nowadays, many Advanced Planning Systems allow full visibility of the supply chain and assist in the coordination and decision making in the supply chain (Stadtler H., 2015). Multiple inventory counting systems can be implemented to monitor current levels of each item keeping track of all removals and replenishments from inventory (Stevenson, 2007). For the purpose of this paper we consider the data that monitor current levels of each item. Advanced planning systems usually include modules that allow safety stocks and the expected demand per item to be calculated. Safety stocks along a supply chain have been described by (Graves and Willems, 2000) as the minimum level of stock to absorb demand uncertainties and to avoid lost sales and backorders. Because of the different replenishment cycles, the demand can be met without losing the sale or having backorders, if a replenishment is expected in the time window in which the retailers can secure the sale. In this case, the items with low inventory that expect a replenishment are considered in the normal range of stock levels, and taken into account in **Step 7**. Also, expected stock levels can be defined as the remaining stock calculated based on the expected demand. Expected demand is a forecast of demand on a period of time. Those two quantities define the range in which the stock level is expected to be. Reaching the safety stock level implies risks for inventory management; likewise, a stock level that is higher than the “expected stock” may result in excess stock. Stock slows the cash flow (Fernandes et al., 2010) and can lead to losses, especially for perishable items. This results in grocery retailers losing up to 15% as a result of damage and spoilage (Ferguson and Ketzenberg, 2006); therefore, having a contingency plan using recommender systems to act upon short-term to shift demand may help avoid shortage or excessive stock.

Phase 2 is supported by 9 steps, as depicted in Figure 4.1. This figure gives an overview of the proposed method to adapt recommendations to stock levels and a user’s categorization. Depending on stock levels and a customer’s categorization, constants A and B permit reordering recommended items.

Multiplying the score of an item in the list by a high constant makes the recommendation of the given item in the first rank of the recommendation list. Constant A must remain superior to the other constants used for a given user. Thus, items at risk of being OOS will always be recommended at the top of the list. Multiplying the scores for items that are out of stock by is a way to disfavor the items’ recommendations, since the item is currently unavailable.

Constant B is used to give the item a higher rank in the recommendation list compared to items with a normal range of stock in order to promote sale. B is a constant that is higher than 1 but inferior to A in order to make items from step 5 second priority. B is calculated based on how important the overstock is by using a calculated rate that could, for example,

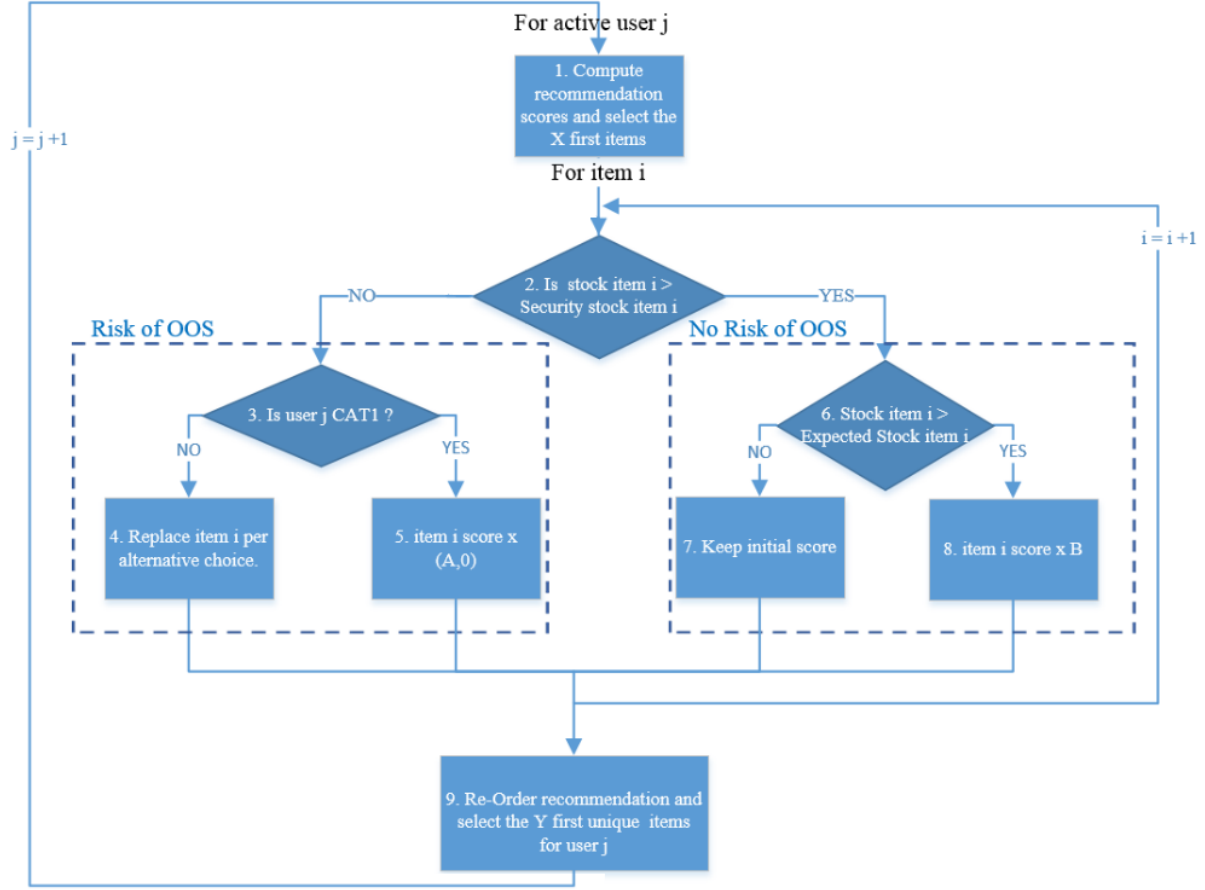


Figure 4.1 Recommendation adjustment based on stock levels and customer categories

use formula 4.2.

$$B(i) = \frac{Actualstock(i)}{Predictedsales(i)} \quad (4.2)$$

Alternative choices are considered for the first Y items that are proposed to user j . An alternative item could be the next item in the X recommended items for user j , or an item supposed to be equivalent to i . If an alternative item is OOS, it is proposed to select the next available alternative item from the X first recommendations. If all of the alternatives are low in stock, we recommend a different item that is not out-of-stock. If all of the items are OOS, then it recommends one of the remaining items with the highest scores.

4.4 Pedagogical case study

In this section, we validate the results and improvements permitted by the proposed method. Section 4.4.1 exposes the context of the case study. Section 4.4.2 presents a data description and a company’s strategy used for the case study. Section 4.4.3 presents the status quo results using an actual recommender system, section 4.4.4 shows the results from the proposed methodology and compares the performance with results from section 4.4.3.

4.4.1 Context

This study is based on a real-life situation with our industrial partner. The partner uses two coexisting distribution channels: store-based and website-based. The company is specialized in business to business commerce with different customers from various fields and levels of importance.

The industrial partner uses a classical recommender system, which suggests items without considering stock levels. This may result in the recommendation of out-of-stock items. Currently, the importance of certain users and the fields of activity are not used to prioritize recommendations when stock levels are low. Here, we compare the benefits resulting from the execution of their current RSs and from our proposed methodology.

4.4.2 Data description

In order to illustrate the implementation of this method, we simulated and scaled data to a smaller sample, keeping a similar structure as the existing one with our industrial partner. 17 items are separated into 8 categories. Each category is represented by a single capital letter (A – H). Items from the same category are supposed to have similar usefulness and are considered interchangeable. 10 users with different profiles will make orders. Table 4.1 presents recommendation scores for the 10 users and 17 items.

Table 4.1 Simulated recommender systems’ scores

Cat	A					B				C		D	E	F		G	H
Ids	a1	a2	a3	a4	a5	b1	b2	b3	b4	c1	c2	d	e	f1	f2	g	h
User 1	0.491	0.2	0.238	0.677	0.874	0.741	0.029	0.949	0.632	0.604	0.156	0.701	0.036	0.134	0.142	0.606	0.759
User 2	0.314	0.886	0.058	0.539	0.408	0.559	0.153	0.811	0.565	0.245	0.727	0.218	0.815	0.335	0.854	0.918	0.108
User 3	0.016	0.253	0.828	0.942	0.084	0.977	0.473	0.466	0.935	0.802	0.298	0.256	0.096	0.238	0.323	0.299	0.07
User 4	0.259	0.759	0.138	0.724	0.912	0.532	0.08	0.816	0.757	0.358	0.839	0.315	0.945	0.738	0.876	0.035	0.397
User 5	0.467	0.472	0.65	0.42	0.986	0.381	0.619	0.895	0.926	0.825	0.578	0.393	0.956	0.599	0.078	0.851	0.711
User 6	0.452	0.338	0.671	0.84	0.792	0.881	0.538	0.544	0.26	0.149	0.692	0.757	0.181	0.851	0.497	0.794	0.798
User 7	0.348	0.118	0.16	0.781	0.517	0.624	0.093	0.933	0.113	0.815	0.579	0.16	0.396	0.382	0.735	0.092	0.442
User 8	0.865	0.737	0.454	0.85	0.59	0.873	0.804	0.827	0.149	0.932	0.852	0.315	0.636	0.014	0.444	0.38	0.598
User 9	0.124	0.814	0.464	0.045	0.119	0.856	0.572	0.222	0.649	0.171	0.111	0.356	0.613	0.723	0.822	0.641	0.969
User 10	0.916	0.434	0.827	0.143	0.501	0.276	0.476	0.863	0.846	0.384	0.789	0.016	0.075	0.768	0.699	0.296	0.75

For the case study, we consider the top 3 items with the highest score for each user ($Y = 3$) and we keep a total of the top 6 items ($X = 6$) to improve recommendations. In Table 4.1, for each user, the 3 items with the highest scores are in bold. For example, for user 1, the suggested items are b3, a5 and h, which have the highest scores for user 1.

Table 4.2 shows for each item, the inventory levels (Stock), safety stock levels (SS) and expected stock (Exp. Stock), at the initial time. In order to facilitate the reader's understanding, information about stock level is fixed for the period that is considered. In a real application, stock levels may vary pending on other sales made outside the RS and replenishments. Thus, stock levels should be retrieved directly from the inventory system at each evaluation of step 2 and step 6. For example, for item a1, initial stock level is 0, safety stock level is 5, and expected remaining stock is 8.

Table 4.2 Product inventory levels (Stock), safety stock levels (SS) and expected stock (Exp. Stock), at initial time

Item	Stock	SS	Exp. stock	Item	Stock	SS	Exp. stock
a1	0	5	8	c1	4	5	8
a2	8	5	8	c2	6	2	6
a3	30	20	35	d	10	8	15
a4	4	5	10	e	6	5	10
a5	8	5	10	f1	30	5	15
b1	2	5	10	f2	5	10	15
b2	10	8	12	g	20	15	30
b3	2	5	12	h	5	3	6
b4	1	10	5				

Phase 1: Categorization of the users

Customers are separated into categories. *CAT1: high priority customer*, includes customers with the highest CLV, customers with binding contracts for priority delivery, customers with ethical requirements for delivery (i.e. hospitals), or other priorities, depending on the company's strategy. **CAT2: medium or low priority customers** are subdivided in **CAT2.1:** medium priority customers, and **CAT2.2:** low priority customers.

For the simulation, we consider that each user belongs to a category as provided in 4.3. Similar to the real dataset, the proportions were set as follows: 20% of the customers were CAT 1 and the remaining 80% are randomly separated between CAT2.1 and CAT2.2.

We allocate different penalties for each category of unsatisfied users (See Table 4.4): Penalty is the loss in the long-run of average demand rate, which is affected by backorders (Liberopoulos et al., 2010). The loss of a customer in category CAT1 is estimated to cause a damage of 100

Table 4.3 Categorization of users

Users	CAT	Users	CAT
User 1	CAT2.2	User 6	CAT2.2
User 2	CAT2.1	User 7	CAT2.2
User 3	CAT2.2	User 8	CAT1
User 4	CAT2.1	User 9	CAT2.2
User 5	CAT1	User 10	CAT2.1

Table 4.4 Penalties based on clients' categories

Categories	Penalties
CAT1	100
CAT2.1	10
CAT2.2	5

The data described in this section will be used independently in sections 4.4.3 and 4.4.4 to evaluate the results of the use in a state of the art system and to simulate the impact of the use of the proposed method. Recommendations in real life are made in real time, customer by customer. In order to illustrate the situation, we consider:

1. Customers come in the chronological order depicted in Table 4.3.
2. Customers buy all of the recommended items ($X=3$ for the example). This represents a worst-case scenario for OOS evaluation.
3. Customers only buy one of each recommended item.

4.4.3 Status quo: Results from actual systems

This section presents inventory variations related to the use of traditional RSs. Data from Tables 4.1 to 4.4 are considered. Each user receives a recommendation of the three highest ranked items in Table 4.1. So User 1 is recommended items b3, a5 and h. Considering he buys the recommended items, the stock will diminish for each of those items and become b3: 1, a5: 7 and h: 4, before going to the next user.

By going this way, from one user to another and simulating the effect of a purchase for each possible recommended item, it is apparent that some recommendations will include OOS items. The final results is provided in Table 4.5. This shows, for each costumer, the recommended items and how the stock levels evolved. Items that are out of stock are identified with (-1). This leads to some unsatisfied users and to penalties. The total penalty equals 335 with this strategy. The following section will show how the proposed method decreases penalties related to stock mismanagement by adapting the recommendations based on stock levels.

Table 4.5 Penalties related to the OOS for each user

Users	CAT	i1	i2	i3	Penalty
User 1	CAT2.2	b3: 1	a5: 7	h: 4	100
User 2	CAT2.1	g: 19	a2: 7	f2: 4	
User 3	CAT2.2	b1: 1	a4: 3	b4: 0	
User 4	CAT2.1	e: 5	a5: 6	f2: 3	
User 5	CAT1	a5: 5	e: 4	b4: -1	
User 6	CAT2.2	b1: 0	f1: 29	a4: 2	200
User 7	CAT2.2	b3: 0	c1: 3	a4: 1	
User 8	CAT1	c1: 2	b1: - 1	a1: -1	5
User 9	CAT2.2	h: 3	b1: -1	f2: 2	
User 10	CAT2.1	a1: -1	b3: -1	b4: - 1	30
Total					335

4.4.4 Results of the proposed methodology

The same data from Tables 4.1 to 4.4 are considered with the methodology proposed in section 4.3.2. Each user is processed and each stock level is updated. As an example, we selected Y=6 items in the list of possible suggested items. A detailed step by step application of the method is presented for all users. Users 1, 2, 5 and 6 enable showing all possible options covered by the methodology.

For user 1

Step 1: We extract the Y=6 top items from Table 4.1. Products b3, a5, h, b1, d, and a4 are considered.

Step 2: For each item, we extract product inventory information from Table 4.2 and if the quantity in stock is lower than the safety stock we go to **Step 3** (this is for items b3, b1 and a4), or else we will go to **Step 6** (this is for items a5, h and d).

Step 3: There is a risk of OOS for b3, b1 and a4, but only b3 is in the X=3 best items. Active user1 is CAT2.2 (see Table 4.3) so go to **Step 4**.

Step 4: We need alternative choices for b3. b1 is an alternative to b3 in the recommendation list, but b1 is also at risk for OOS. b1 is not an option, so we take the next in line, which is d. d takes the place and score of b3.

Step 6: For items a5 and h, the quantity in stock is inferior to the expected stock (see Table 4.2), the next step is **Step 7**.

Step 7: No changes in the score for a5 and h. Go to **Step 9**.

Step 9: Recommend a re-ordered list of 3 unique first items.

Initial and adapted recommendations for user 1 are presented in Table 4.6, only the X=3 first items are presented to the user.

Table 4.6 Recommendation summary for user 1

Initial recommendation		Adapted recommendation	
Item	Rec scores	Item	Rec scores
b3	0.949	d	0.949
a5	0.874	a5	0.874
h	0.759	h	0.759
b1	0.741	b1	0.741
d	0.701	~~d~~	~~0.701~~
a4	0.677	a4	0.677

Following our hypothesis, user 1 takes items d, a5 and h, quantities in stock for those items that are updated: d: 9, a5: 7 , h: 4

For user 2

Step 1: We extract the Y=6 top items from Table 4.1. Products g, a2, f2, e, b3, and c2 are considered.

Step 2: For each item, we extract product inventory information from Table 4.2, updated from previous sales, and if the quantity in stock is lower than the safety stock we go to **Step 3** (it is for items f2 and b3) or else we go to **Step 6** (this is for items g, a2, e, and c2).

Step 3: There is a risk of OOS for f2 and b3, but only f2 is in the X=3 best items. Active user2 is CAT2.1 (see Table 4.3) go to **Step 4** .

Step 4: We need alternative choices for f2. An alternative from the list of the 6 top recommendations, with a stock that is superior to Safety Stock level, is e. We replace f2 with e and keep f2's score.

Step 6: For item a2 and g, quantity in stock is higher than the expected stock go to **Step 7**.

Step 7: No changes in score for a2 and g. Go to **Step 9**.

Step 9: Recommend a re-ordered list of 3 unique first items.

Initial and adapted recommendations for user 1 are presented in Table 4.7, only the X=3 first items are presented to the user.

Following our hypothesis, user 2 takes items g, a2 and e; the quantities in stock for those

Table 4.7 Recommendation summary for user 2

Initial recommendation		Adapted recommendation	
Item	Rec scores	Item	Rec scores
g	0.918	g	0.918
a2	0.886	a2	0.886
f2	0.854	e	0.854
e	0.815	e	0.815
b3	0.811	b3	0.811
c2	0.727	c2	0.727

items that are updated are: g: 19, a2: 7 , e: 5

For users 3 and 4

The same procedure applies to users 3 and 4. The users are from CAT2, presented with recommendations of items with normal to low stock levels. The recommendation scores are kept the same and items are replaced with alternatives for low inventory items. Alternative choices at Step 4 are either the next item available in a large enough quantity to be recommended ($>SS$) or an item from the same category as the replaced item.

User 3 takes items a3, a5 and b2, quantities in stock for those items are updated: a3: 29, a5: 6, b2: 9, and user 4 takes items c2, a5 and a2, quantities in stock for those items are updated: c2:5, a5: 5, a2: 6.

For user 5

This user goes to **Step 5** for items a5, e, b4, b3, g, and c1. The recommendation scores are adapted using constant A in order to prioritize the items with low inventory for users in CAT1. For items that are out of stock, the score is set to 0 so the item is never recommended. Constant A has to be higher than the highest ratio of (stock to expected stock). In this example, A is set to 10. Recommendations for user 5 are in Table 4.8, and user 5 takes items g, a2 and e, quantities in stock for those items that are updated: a5: 4, e:4, b4: 0.

For user 6

User 6 goes to **Step 8** for item f1. We will multiply the f1 score of the item by constant B.

$$B(f1) = \frac{Actualstock(f1)}{Predictedsales(f1)} = \frac{30}{15} = 2$$

Table 4.8 Recommendation summary for user 5

Initial recommendation		Adapted recommendation	
Items	Rec Scores	Items	Rec Scores
a5	0.986	a5	$0.986 \times 10 = 9.86$
e	0.956	e	$0.956 \times 10 = 9.56$
b4	0.926	b4	$0.926 \times 10 = 9.26$
b3	0.895	b3	0.895
g	0.851	g	0.851
c1	0.825	c1	$0.825 \times 10 = 8.25$

The new score for $f1 = 0.851 * 2 = 1.70$. User 6 takes items f1, h and g, and the quantities in stock for those items are updated: f1:29, h:3, g:18.

For users 7 through the end

In presenting users 1 to 6, all possibilities of the proposed methodology are covered, and each step in the method has been presented. User 7 takes items b2, c2 and a3. User 8 takes items c1, b1 and c2. User 9 takes f1, h and b2. User 10 takes f1, h and b2.

The new recommendation list contains no OOS items; thus, no penalties have been applied to the company. For example, instead of assigning item b1 to a user with low value to the company, it was only recommended to high value customers; that way, the penalty is lower, thanks to the better allocation of stock.

4.5 Experimental Results

In order to visualize the effects of the implementation of our method on the penalties related to stock-outs, as well as to review the accuracy of the recommendations, we conducted an experiment on a larger set of products and users and compared the proposed method to the traditional method.

The data used in the experimental example has been inspired from an industrial partner dataset (that cannot be published) and contains its main characteristics. Historical purchases lead to a very sparse matrix and different recommender systems that were tested on that data, resulting in a list of items with a recommendation score. Since the recommendation score is only input data, and no specific recommender system is linked to the methodology, we generated scores that represent a RS output. In addition, exploratory data analyses on the real dataset reveal customers' behaviours and items' categories that led to the characteristics used in the simulated data: (1) Items from the catalogue are segmented

into 16 different categories each one representing an industrial field; (2) a limited number of customers generated 20% of the company’s revenue. After testing the method with many examples, we concluded that if kept in the same proportions (those of the industrial partners), the size of the sample does not impact the effect on the penalties and accuracy of recommendations, and therefore the conclusions remain the same.

4.5.1 Data description

To evaluate the method, we selected the following parameters:

- 500 items are separated into 5 categories. Each category is represented by a single capital letter (A – E). Items from the same category are used in the same field (i.e., Medical, Industrial, Agriculture, etc.).
- We have 1000 users with different profiles. From those, we randomly and chronologically generate 1500 entrances in the recommender system, that means that the same user can appear more than once and simulates the fact that a user can purchase more than once and also that some users may make no purchase at all.
- For the proposed method: $X = 6$, $Y = 15$, $B_{\max} = 100$ and $A = 1000$.

4.5.2 Results

All of the hypotheses presented in sections 4.3 and 4.4 remain unchanged. Using Rstudio (RStudio Team, 2015), we run the methods on the data presented above and get the following results.

The graph presented in Figure 4.2 shows the cumulative penalties related to stock-outs with the two methods. The blue line represents the penalties related to the traditional recommendation technique and the red line represents the penalties related to the proposed method, with consideration made to stock levels and the customer category.

The graph shows three phases, in the first (P1), the slope of the penalties curve for the traditional recommendation (blue) is positive but small compared to the proposed method (red), which shows a neutral slope. This can be explained by the fact that, at the beginning of the recommendation process, the majority of the items have sufficient stock levels; only few products are out of stock, and thus the difference between the two methods is small. However, no OOS are recommended using the proposed method.

In the second phase (P2), the gap between the two methods starts to get larger. The penalties increase steadily for the traditional RS (blue) in contrast with the proposed method (red), which maintains the penalties to 0 all along P2. This can be explained by the fact that

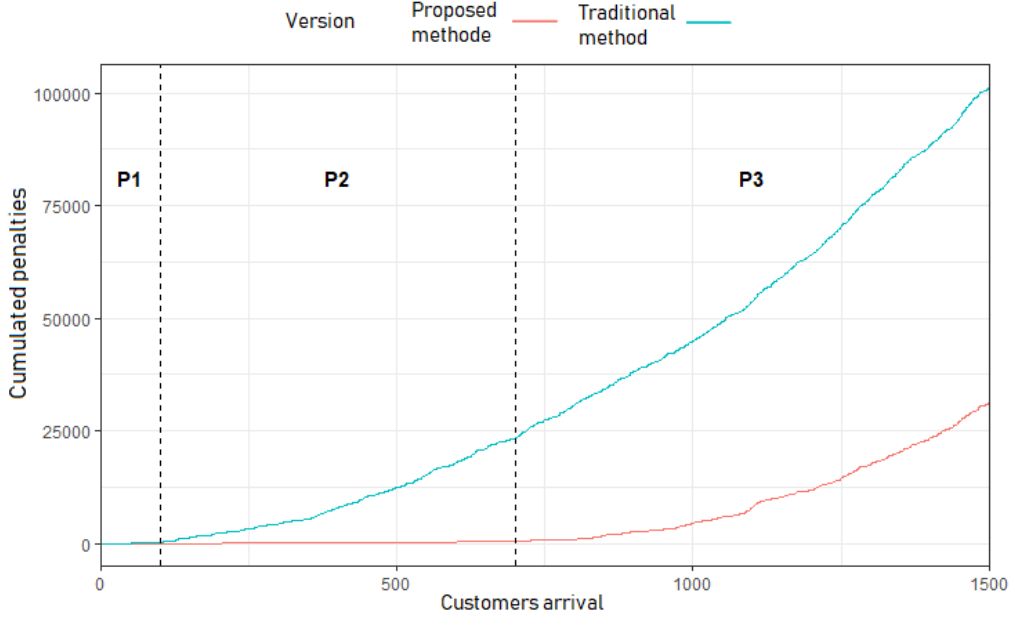


Figure 4.2 Cumulative penalties according to customers' arrivals, for both methods

the second method presents alternatives for items that demonstrate low stock, delaying the stock-outs and shifting demand to other products instead of highlighting the ones that are already low in stock. At this step, we can argue that the accuracy of the recommendation will get lower when presenting alternatives to the products. Figure 4.3 presents the effect on the recommendation scores. Although accuracy decreases, it is important to remember the objectives behind the recommendations presented in (section 4.2.1) such as (2) **increasing cross selling** by offering additional products to customers, and (3) **improving consumer loyalty** (Lu et al., 2015; Shardanand and Maes, 1995; Resnick and Varian, 1997).

Since a product that is OOS cannot be sold, making a 100% accurate recommendation for a product, but not being able to meet user's need for that product, is useless. Consequently, having an accurate recommendation may be irrelevant in some situations, such as when dealing with shortages. By suggesting products that are low in stock to all customers, we sell products that are in high demand to random customers without favoring those with high value, making the occurrence of the OOS random. Also, when a product is OOS, neither (2) nor (3) can be achieved, and the cost of a stock out on the business is not controlled.

In the third phase (P3), we can see that both methods have the same increasing tendency in the slope of the curve. This can be explained by the fact that more items are out of stock and the alternatives are more limited. Although the slope is positive for both methods, the one we recommend keeps the penalties lower. Also, by postponing the occurrence of a stock out, we get more time to deal with the issue and replenish the stocks (the arrival of customers is

also implicitly the time stamp).

Figure 4.3 presents a parallel between cumulative penalties presented in (Figure 4.2), the difference between the cumulative penalties incurred by each method, and a comparison of the mean score of recommendations for all users.

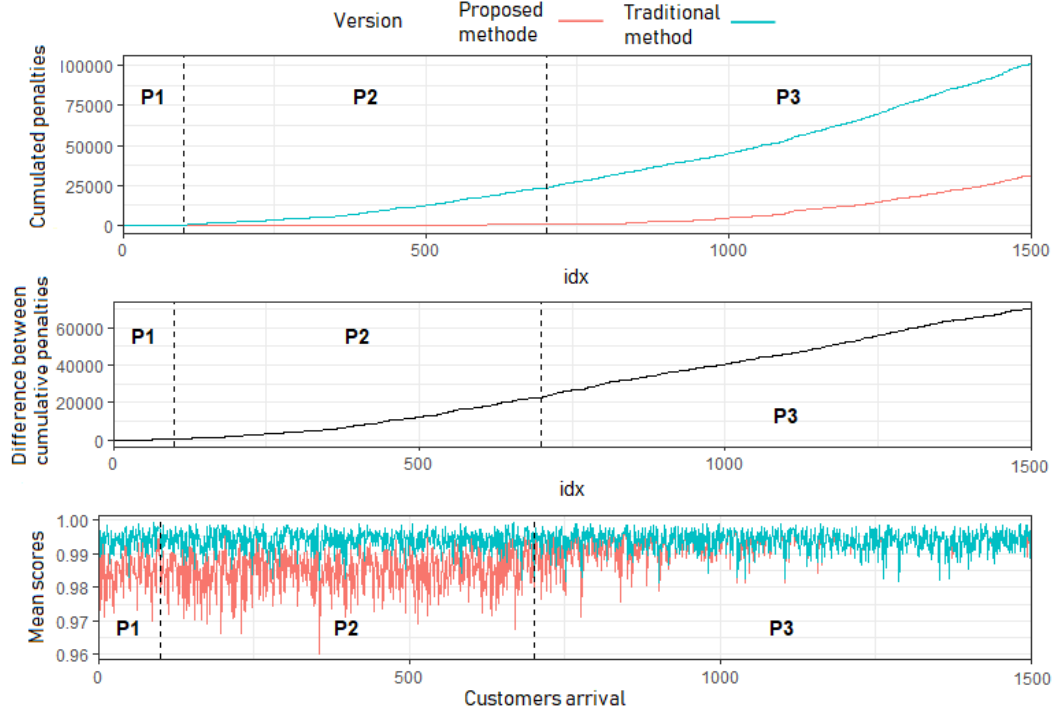


Figure 4.3 Impacts of the proposed method on recommendation scores

It is observed that in the first phase (P1), the difference between the two methods is the highest, the difference between the penalties increases in (P1) and (P2) and stabilises in (P3), the same occurs with regards to the accuracy of the recommendation. We can see that, in (P1), there is a notable difference in the scores of the recommended products. Since we suggest alternatives for products that are low in stock, the scores of the recommendations are lower. In order to keep the recommendations relatively good, we only select alternatives from the top 15 recommendations and not from all available items. Although the recommendation scores are lower than those from the traditional method, they are still relatively close and stabilize completely in (P3). This is because both methods present the same products as a result of a lack of viable alternatives with sufficient stock.

After testing our method with different sizes of products, users, recommendation sizes and families, we have concluded that if kept in the same proportions (based on the data presented by our industrial partners), the size of the sample will not impact the effect on the penalties and accuracy of recommendations and therefore the conclusions remain the same.

4.6 Conclusion

The proposed approach consists of an adaptation of recommender systems, using well-established customer relationship management concepts. The focus is to help companies shape demand with an execution process by acting upon short-term demands to recover from excess and short inventory positions and limit the consequences of the mismanagement of stocks.

Recommendation systems have become essential in e-commerce; they collect and process intelligence gathered about customers by the company. These systems have been used to allow a user to reduce search time and improve the user experience, which in turns helps in the retention of the user for the company. Recommender systems are also used to increase cross-selling. Some customized RSs can even consider the profits on items and maximize the profit potential of a recommendation.

However, the development of RSs mainly focuses on commercial interests of the customers. Our goal has been to develop an area of RSs that can meet industrial interests at the same time. Our attempt at doing so has been by adapting recommendations according to categorization of customers. The importance of a customer is variable and depends on the area of activity of a company, its strategies and policies. Different indicators of customer importance can be used and incorporated into Step 1 of our method. Those categories of customers enable favoring certain customers over regular customers, and make sure that the long-term impact on the company is monitored.

However, the proposed approach relies on the accuracy of recommendations and stock management.

Limitations and perspectives

Recommender systems are based on many different techniques. As stated in the state of the art, those techniques lead to different kinds of recommendations, depending on the available data and the purpose behind the recommendation. Using recommender systems is not trivial and making the right choices directly influences the accuracy of the recommended items. It is of high importance to obtain a customized recommender system in order to align with businesses interests without altering the perceived customer trust in the technology, since it is considered a key component in marketing and e-commerce literature (Beatty et al., 1996). Trust formation can be described in terms of six dimensions: consumer behavioral, institutional, information, product, transaction, and technology. By manipulating the recommender system, information and technology are impacted (Jarvenpaa et al., 2000). Making bad recommendations will result in a mistrust of the system, and will be of no use for demand

shifting.

Most companies track stock, whether it is online or on ERPs. Therefore, getting a good approximation of the current inventory is usually possible in most cases. Our aim is not to improve inventory management systems, but to deal with the consequences of stock mismanagement in real time. Thus, we consider that the existing system considers demand, seasonality, average replenishment time, while determining safety stocks. If the safety stocks and the prediction of stock consumption is not calculated effectively, it can lead to unnecessary actions on recommendations that can lower accuracy without helping the business.

Future work includes developing a better way of choosing alternative items at (Step 4) in our proposed method. Considering the similarities in terms of the usefulness of the items, or the similarities of an item’s features, could be used to improve alternative choices and make them systematic. In addition, we consider only the customer categories and the stock information for an item; many other supply chain constraints could be considered, such as logistic constraints on stock location, delivery points, warehouse storage capacity, trends in raw material prices and the margin of products.

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CHAPITRE 5 ARTICLE 2: RECOMMENDER SYSTEMS AS AN AGILITY ENABLER IN SUPPLY CHAIN MANAGEMENT

Abstract - *Recommender systems have widely been used as prediction tools for customer interest, designed to help customers decide, compare, discover and explore products (Meyer, 2012). Accordingly, they do not take into consideration supply chain constraints for deliveries. This paper addresses the problem of considering delivery constraints in product recommendation. The objective is to shift demand toward products that can be delivered using the current network state without additional resources in a given time window, perimeter and with a minimum acceptable profit, in the context of e-commerce. To achieve this goal, we propose a methodology to adjust product recommendations in order to shift customers' interests towards particular products with consideration for remaining unit loads of scheduled deliveries. For this, quasi-real-time information about the supply chain is taken into consideration to improve the number of shippable products in the recommendation list, resulting in the possible improvement of truck-load utilization, lower operation costs and reduced lead-times for delivery. This method works in two stages: the first stage is the computation of the recommendation with traditional recommendation systems, and the second stage is recommendation adjustments in 4 phases that consider the evaluation of active trucks, evaluation of physical constraints for transportation, evaluation of the profits associated with adding a pickup/delivery to a scheduled tour for each recommended item and adjustment of recommendation scores. Various experimental results prove that the method permits increasing the number of recommended products that can be shipped using the available resources within a given perimeter radius, time window and minimum profit.*

5.1 Introduction

In the fierce, changing and competitive environment of global markets, with the introduction of products with shorter life cycles and the heightened expectations of customers, firms need to be responsive to customers' unique and rapidly changing needs (Simchi-Levi et al., 2008). Therefore, companies are strongly encouraged to invest in, and pay attention to, the development of cost-effective solutions for organizations and facilities that are highly flexible and responsive to changing market and customer requirements (Gunasekaran et al., 2008), (Van der Vorst, 2004). Organizations are using big data to reap the benefits from analyzing this massive influx. Big data can provide unique insights into, inter alia, market trends, customer buying patterns, and maintenance cycles, as well as into ways of lowering costs and

enabling more targeted business decisions (Wang et al., 2016).

One of the main techniques used to respond to customers' needs in e-commerce is recommender systems (RSs) (Jiang et al., 2010). RSs are tools that use algorithms from different disciplines to anticipate a user's level of interest for a list of items (object, service, good, etc.) and recommend the item with the highest potential of sale (Burke, 2002). The recommendation is personalized to each user and is based on data such as historical purchases, the user's profile and demographics, click stream, and so forth (Schafer et al., 1999).

RSs are customer oriented and focus on helping the customer decide, compare, discover and explore the products (Meyer, 2012). Furthermore, current RSs do not take into consideration supply chain constraints such as stock levels, which may lead to sub efficient recommendations from the company's perspective (Dadouchi and Agard, 2018). Lead time, truckload utilization and traveled distance per item could all be considered to improve recommendation systems' response to industrial needs.

A recent report for thirteen European countries reveals that, on about 30% of all trips made, trucks are empty, while the percentage of a truck's carrying capacity filled with a cargo (the load factor) remained stable at an average of 50 per cent over the period 1990–2008 (European Environmental Agency, 2010) as cited in (Abate, 2014). In Canada, the Québec Transport Ministry issued a report in which the truckload rate was estimated to be 61% round-trip and the rate of empty round-trips was estimated to be 30%. Moving toward possible opportunities for improvement (Montreuil, 2011) highlighted that the way physical objects are currently transported, handled, stored, realized, supplied, and used throughout the world is not sustainable economically, environmentally, or socially. Trucks, wagons, and containers are often half empty at departure, with a large portion of the non-emptiness being filled by packaging (Levinson, 2016). Overall, the global transport efficacy has been estimated to be lower than 10% (Ballot et al., 2008). Furthermore, vehicles leaving loaded get emptier and emptier as their route unfolds from delivery point to delivery point. These studies highlight the environmental shortfalls of land transportation, making it clear that corrective measures need to be put into place (Barla et al., 2006). Physical Internet is a concept proposing a solution to the previously presented problem by progressively integrating currently dedicated logistics networks into a universally interconnected system that targets intermodal less-than-truckload transport to be nearly at the same price, speed, and reliability as current single-mode full truckload. The Physical Internet combines standardized, modular and intelligent containers with new logistics protocols and business models, resulting in a collaborative, highly distributed and leveraged logistics and distribution system (Montreuil, 2011).

Supply chain excellence is the ultimate source for a competitive advantage and today the competition is not only among the products themselves but between one supply chain and another (Anand and Grover, 2015). Using supply chain constraints in recommendations can be a win-win situation in which the customer benefits from products of potential interest in a short time window, and where the business benefits from cost reduction and from increased performance in logistics. Availability and delivery time are considered the most important logistics services and critical to achieve high levels of performance in customer satisfaction (Sharma et al., 1995). (Kumar et al., 2011) also argued that operations performance of service delivery can positively affect customer satisfaction, and that operations performance is a direct determinant of customer loyalty.

To achieve successful supply chain management (SCM), possible gaps between planning and execution need to be minimized (Stadtler, 2005). It is not possible to entirely remove such gaps from one's supply chain (Chae, 2009); yet, using a RS with a real-time corrective measure that adjusts a product's visibility may help shift demand from one item to another with regards to the supply chain.

Our approach acknowledges the need to address the transport efficiency problem and can be used in the context of the Physical Internet. However, our approach differs from it, by considering that the list of items to be delivered may be completed during the delivery process. We propose highlighting products of interest to customers with consideration for remaining unit loads, for scheduled deliveries, in order to influence the demand in favor of those products in real-time. If the customer decides to proceed with the recommendation, a local improvement to the efficiency of the transport can be noted, otherwise the situation remains the same.

This paper addresses the **problem** of considering delivery constraints in product recommendation. The **objective** is to shift demand toward products that can be delivered using the current network state without additional resources in a given time window, perimeter and with a minimum acceptable profit, in a context of e-commerce. To achieve this goal, we propose a **methodology** to adjust product recommendations in order to shift customers' interests towards particular products with consideration for remaining unit loads of scheduled deliveries. Our intent is not to fulfill the logistics KPI but to choose a number of items that are considered relevant to the customer and improve their ranking based on supply chain constraints. Selected products are highlighted because of possible same-day delivery without excessive supplementary cost. For that, quasi-real-time information about the supply chain is taken into consideration to improve the number of shippable products in the recommendation list. If the new recommendation is pertinent to the customer then he may order a product

that will be delivered in a specific time frame, using actual available remaining transport capacity. Therefore, the proposed method also creates the opportunity to improve truckload utilization and delivery time. Other consequences, linked to improved truckload utilization and delivery time, are lower operation cost, increased revenue, smaller number of trucks used, higher client satisfaction and retention of customers (Kumar et al., 2011), as well as reduced congestion and pollution for society (Wong et al., 2018). If the new recommendation is not selected and the customers keeps his focus on other products, it will simply run as usual, which still permits taking advantage of existing transport capacity sharing, platforms are Saloodo! and QuiCargo in Europe, Freightos, Convoy, and Loadsmart in the U.S., and Huochebang in China (Van Duin et al., 2018).

The remainder of this article is structured as follows: Section 5.2 is a state of the art presenting supply chain management, along with a brief overview of key performance indicators for delivery in a supply chain and the importance of agility in a supply chain. Current recommender systems are also depicted and a brief synthesis concludes the section. Section 5.3 presents the problem definition and the premises made. Section 5.4 presents the proposed method, depicted in two stages and four phases. Section 5.5 presents a case study applying the method to a planned delivery. The conclusion includes the contribution and key findings, summarizes the purpose of considering supply chain constraints and indicates new areas to focus on in the near future.

5.2 The state of the art

5.2.1 Supply chain management

Supply chain management (SCM) is defined by (Christopher, 2016) as the management of upstream and downstream relationships with suppliers and customers in order to deliver superior customer value at less cost to the supply chain as a whole. There are many specific objectives to SCM, such as improving profitability, competitive advantages, and the customer value and satisfaction with a supply chain and its participants (Mentzer et al., 2001). The source of competitive advantage is found firstly in the ability of the organization to differentiate itself positively, in the eyes of the customer, from its competition and secondly by operating at a lower cost and hence at a greater profit (Christopher, 2016). The literature clearly demonstrates that cost is considered to be a very important matter and is given significant attention in SCM. According to (Thomas and Griffin, 1996) the single largest cost component of logistics is transportation costs, often comprising half of the total logistics costs. (Rushton & Oxley, 1991) as cited in (Gunasekaran et al., 2001) demonstrated that

trucking costs are always the highest among all of the costs in total distribution cost. Costs generally depend on the nature of the network, characterized by its location, distances and number of nodes; the intensity of activities in the network characterized by its use; the efficiency of services, and the prices of inputs. Although costs are an important indicator of the efficiency of a supply chain, other indicators need to be defined to evaluate the performance of the supply chain and to determine the necessary improvements.

5.2.1.1 Key performance indicators in supply chain

Improving supply chain performance has become one of the most critical issues for companies to gain competitive advantages (Cai et al., 2009). Performance measurement is critical for companies to improve supply chain effectiveness and efficiency (Shepherd and Günter, 2010). It has been argued that measuring supply chain performance can facilitate a better understanding of the supply chain, positively influence the behaviour of actors, and improve its overall performance (Chen et al., 2004). The managers in a supply chain usually identify KPIs according to their objective requirements and practical experiences. However, to obtain a systematic performance measurement, they often turn to some widely recognized models, such as Balanced Scorecard (BSC) and Supply Chain Operations Reference (SCOR) (Cai et al., 2009). Considering the complex supply chain characteristics, we resort to a process-oriented SCOR-model to identify the basic performance measures.

- Individual measures of supply chain performance have typically been categorized into four groups: quality, time, cost and flexibility. Furthermore, the measures have been classified as quality and quantity, cost and non-cost and strategic/operational/tactical supply chain processes (Shepherd and Günter, 2010),(Gunasekaran et al., 2001),(Huan et al., 2004).
- Subsequently, (Chae, 2009) categorized KPIs as primary and secondary. The primary metrics (i.e. forecast accuracy, on time delivery) represent a company's overall supply chain performance. The secondary metrics offer a detailed view of the supply chain and explain primary metrics levels.

(Shepherd and Günter, 2010) outlined results from (Beamon, 1999), who explained that the overall proportion of the measures identified substantiates the argument that there remains a disproportionate focus on cost (42%) over non-cost measures such as quality (28%), time (19%), flexibility (10%), and innovativeness (1%).

In addition to performance measures, a supply chain needs to adapt to a continuously moving environment in an agile and responsive way.

5.2.1.2 Agile and responsive supply chain

Agility has been identified as one of the most salient issues in contemporary supply chain management (Gligor and Holcomb, 2012). It is defined by (Braunscheidel and Suresh, 2009) and (Gligor et al., 2013) as a firm's ability to quickly adjust its supply chain tactics and operations. Agility is a business-wide capability that embraces organizational structures, information systems, logistics processes, and, in particular, mindsets. A key characteristic of an agile organization is flexibility. (Gligor et al., 2015) confirm that as the level of supply chain agility (FSCA) increases, so does the firm's ability to effectively meet customers' requirements in a cost-efficient manner. The key to the success of a responsive supply chain has been summarized by (Gunasekaran et al., 2008) as the following: timely information sharing, shortening the total cycle time, coordinating the workflow at different tiers of the supply chain, good decision support systems, reducing lead times for information and material flows, integrating information about operations, reducing redundant echelons, and flexible capacity. (Gunasekaran and Yusuf, 2002) highlighted the need to support it with flexible people, processes and technologies. (Wang et al., 2016) stressed the importance of the use of big data business analytics (DBDA) in supply chain as a strategic asset to be understood and integrated holistically to achieve the success of an organization. Companies need to develop agile supply chain analytics capabilities to cope with high uncertainties in supply chains operations and gain competitive advantage. Real time monitoring of supply chains can contribute towards uncertainty reduction, flexibility and speed in addressing changing customer demands, and short lead times related to the transformation of supply chains. Big data business analytics can be used to influence demand toward particular products using machine learning tools such as recommender systems.

5.2.2 Recommender systems

Recommender systems (RSs) can be defined as programs that use big data and attempt to recommend the most suitable items (products or services) to particular users (individuals or businesses) by predicting a user's interest in an item based on related information about the items, the users and the interactions between items and users (Bobadilla et al., 2013). The purpose of a recommender system from a user's perspective is to enable higher efficiency in finding preferential items, more confidence in making a purchase decision, and the potential to discover something new. From the marketer's perspective, this technology can significantly enhance a user's likelihood of buying the items recommended to them and their overall satisfaction and loyalty, increasing the likelihood of users returning to the site (Pu et al., 2011). In order to implement its core function, which is identifying the useful items for the

user, a RS must predict that an item is worth recommending. In order to do this, the system must be able to predict the utility of some of them, or at least compare the utility of some items, and then decide what items to recommend (Ricci et al., 2015). There are a variety of RS methods; (Adomavicius and Tuzhilin, 2005) presented the traditional approaches and give the following divisions:

- **Content-based filtering** is based on the characteristics of the products or services consumed by the user (Wu et al., 2014).
- **Collaborative-filtering (CF)** is the most important filtering approach in the RS (Yang et al., 2016) . Each active user receives a recommendation based on the preferences of his/her neighbours: users with similar preferences as the active user. CF is based on the way in which humans have made decisions throughout history: besides our own experiences, we also base our decisions on the experiences and knowledge that reach each of us from a relatively large group of acquaintances (Bobadilla et al., 2013).
- **Hybrid recommender systems** commonly use a combination of CF with demographic filtering as in (Vozalis and Margaritis, 2007) or CF with content-based filtering in (Barragáns-Martínez et al., 2010) and in (Choi et al., 2012) to exploit merits of each one of these techniques as presented in (Burke, 2002). This is e-commerce’s favourite system, as it takes several types of data filtering and performs an aggregation of the results.

There are more recent techniques that have been presented in the literature, as provided in (Bobadilla et al., 2013), such as:

- **Demographic-filtering** that is justified on the principle that individuals with certain common personal attributes (sex, age, country, etc.) will also have common preferences.
- **Social-filtering** exploits the social information (followers, followed, likes) to recommend to a user based on the preferences of her social environment (Ruffo and Schifanella, 2009).
- **Context-based filtering** focuses on additional contextual information, such as time, location, and wireless sensor networks, usually implicitly obtained from GPS coordinates, RFID signals, IoT data (Adomavicius and Tuzhilin, 2011).

Currently, recommendation systems are not geared to respond to industrial problems (Dadouchi and Agard, 2018), but rather to commercial interests such as increased sales. Some studies have focused on the interests of users according to price by product categories (Guo et al., 2018) and others on the profits generated by the seller (Chen et al., 2008). Supply chain remains poorly covered in current RSs, although its performance highly affects the competi-

tiveness of a company.

5.2.3 Synthesis

Supply chain management is an integral part of most businesses and an important part of a company's success. In order to be efficient, key performance indicators need to be defined and actions toward meeting performance, agility and responsiveness of a supply chain need to be implemented. In the last decade, the digital area has been developing to an extent where almost every data created is valued. Using big data and machine learning to address supply chain problems is becoming a necessity in today's fast-moving environment. Recommender systems (RSs) are specific tools developed to predict customers' interests. However, RSs have been created from a marketing perspective, with a focus on volume and diversity, independently from the operations and logistics. Considering that RSs are used to increase sales by highlighting products of interest to the user, they can have a direct impact on demand, distribution costs and lead-times. The literature shows no overlap between supply chain management and recommender systems.

In the following, we propose a methodology that improves both the operations and the RSs by making product recommendations in order to shift customers' interests towards particular products with regards for supply chain planning and costs. The contribution of this research is not in the development of a new theory, but in the proposal of a new conceptual framework that brings RSs into supply chain and inventory management.

The methodology was developed in the framework of an industrial partnership. The company has a traditional recommender system that is being enhanced with new techniques and data from different departments, such as marketing, with customer relationship management data, which keeps track of purchase history. The company also has data on its supply chain, such as fleet characteristics (truck capacity, fuel consumption, various costs), product characteristics, stock levels and locations. Tour scheduling and real-time locations are also available.

5.3 Problem definition

The problem in this paper is to consider delivery constraints in product recommendation. The objective is to shift demand toward products that can be delivered using the current network state without additional resources in a given time window, perimeter and with a minimum acceptable profit, in a context of e-commerce. As a consequence, the proposed method also creates the opportunity to help distributors benefit from the convenience of improving truckload utilization, lowering operation costs, increasing revenue, lessening the

number of trucks used, and helping benefit customers by shortening the delivery time and reducing congestion and pollution for society in general (Wong et al., 2018).

The parties involved and vocabulary used for the information flow is explained in section 5.3.1, followed with the premises in section 5.3.2.

5.3.1 Situation

The parties involved in the distribution of the products to the customers are presented in a simplified network in Figure 5.1, the terms used for the remainder of the article are also presented below.

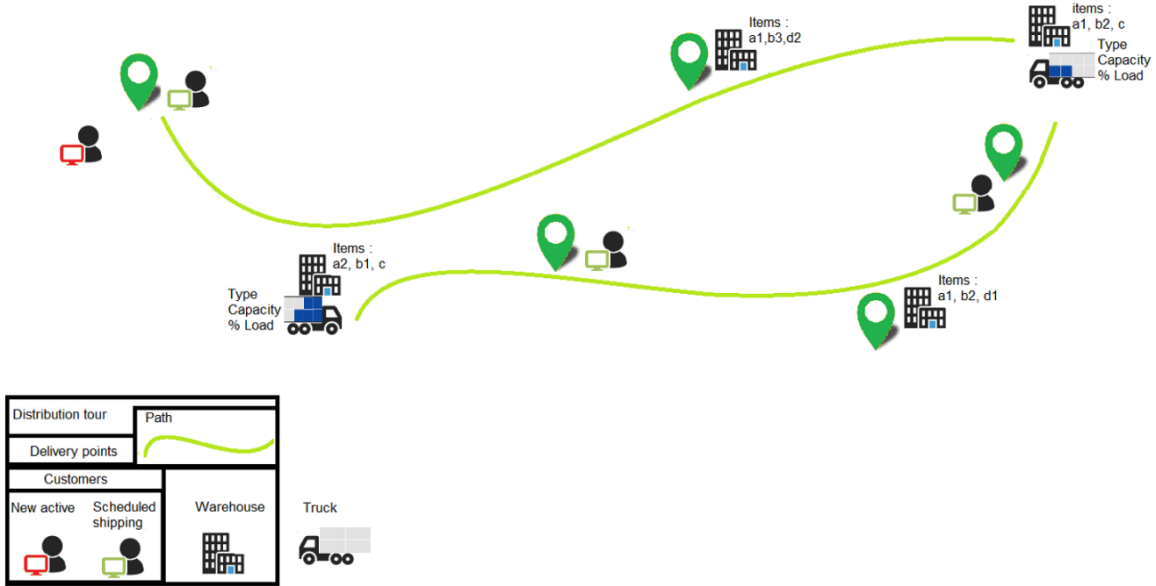


Figure 5.1 Simplified road transport network

Figure 5.1 presents a simplified road transport network composed of two trucks and four customers with scheduled deliveries organized in a distribution tour based on a delivery list, composed of orders that need to ship from/to a delivery point. Each truck starts a distribution tour from a warehouse. Each warehouse has a number of available items in store. The trucks have the capacity and load known for the scheduled tours.

We define the following:

- **Customers:** the clients that are identified in the database as a result of previous purchases. (Dissociated from the users of the RS; users can become customers).
- **Transporters:** the parties responsible for the transport of the freight, we will refer to them as trucks.

- **Warehouses:** the pick-up points for items.
- **Delivery list:** a list of orders that need to be shipped to a delivery point on a certain Distribution tour, they indicate the quantity of each article, product or service that is required.
- **Delivery points:** Addresses that are on the delivery list with the times when and the locations where to pick up, deliver and provide the required quantities.
- **Distribution tours:** The scheduled paths for pick ups and deliveries.

5.3.2 Premises

In order to clearly understand the framework, the following premises are considered:

1. We focus on the distribution phase of the supply chain. Data used as an input to the methodology is derived from the already-scheduled deliveries.
2. Distribution is done by trucks, considering that each truck creates some degree of fixed costs that arise for transportation from one point to another. The truck load determines the cost per unit shipped. Therefore, it is cheaper to batch transportation quantities up to a full load and to ship them together (Stadtler, 2008). Adapting the method to other transportation means and networks can be easily made as long as departure, stops and arrivals are known in advance.
3. We consider that the recommendation method is based on collaborative filtering methods (Su and Khoshgoftaar, 2009), using historical data of purchases, and provides a score to list pertinent items. Selected RS provides input data for adjustments; the selection of a specific recommendation technique does not impact the proposed method.
4. The customer may or may not buy the recommended products. Using a recommender system is a way to highlight an item's visibility and consequently the sale potential. However, the customer may still prefer other items and purchase different items that are not impacted by the method. If the customer purchases a product highlighted by the proposed method, benefits will appear, otherwise the previous (current) situation remains the same and is not impacted at all.
5. Logistic costs: Only internal costs such as the operators' costs of moving units between shippers and receivers are considered.

5.4 Methodology

The main processes for recommendation adjustments are presented in figure 5.2. The process starts with Stage 1 (section 5.4.1), when a user logs into the system, the customer's

information is retrieved and used as input for the calculation of the X best recommendation scores. Stage 2 (section 5.4.2) uses previous recommendation scores as an input and adjusts those scores based on the supply chain's constraints. The top Y recommendations are then selected from the adjusted recommendation list and presented to the active user. X and Y are the general parameters for the methodology:

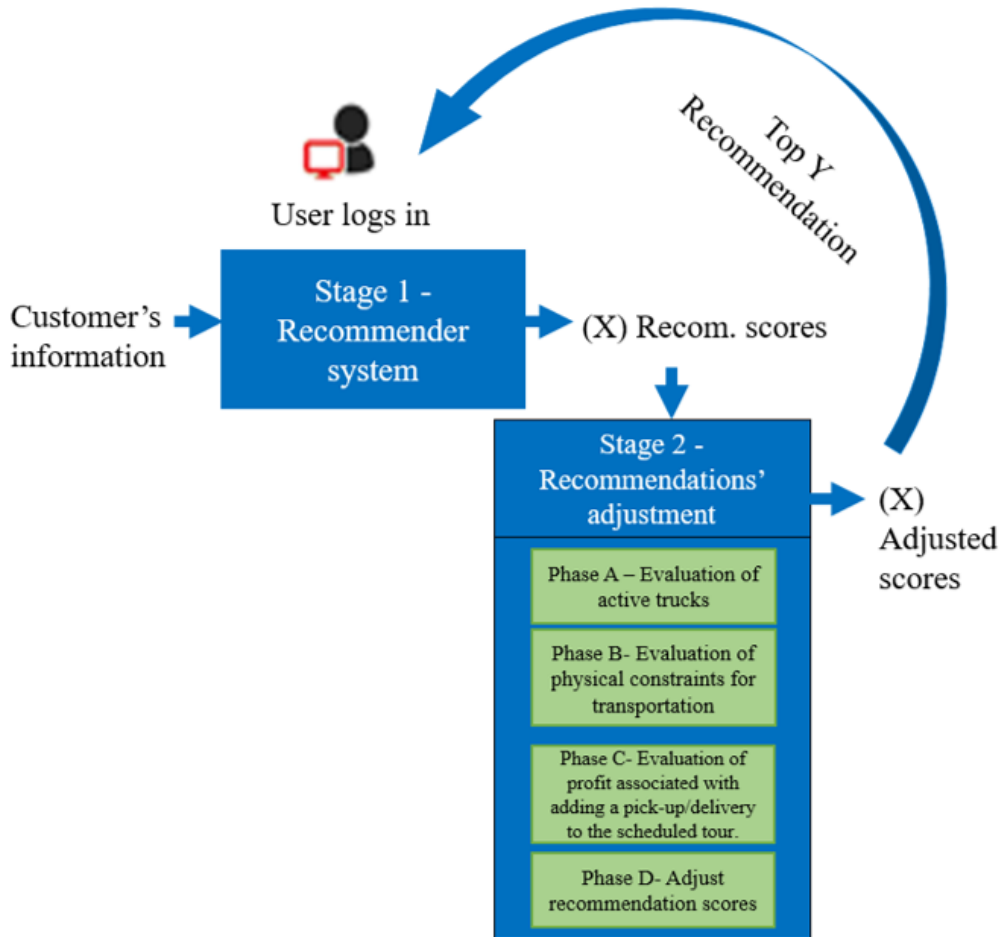


Figure 5.2 Main processes for recommendation adjustments

X : Number of items to be considered for the recommendation system. This number enables the selection the X best items relevant to the user. The adjustment method will consider all X items.

Y : Number of selected items from the recommendation list. This number is smaller than X , it represents the number of items that will be proposed to the user. This number depends on the template of the system where the recommendation appears.

The methodology is initiated at Stage 1 in section 5.4.1 when a user logs into the platform. Recommendations are computed individually for each user. Logistic parameters used for recommendation adjustment in Stage 2 will be presented in the pertinent place in section

5.5.2

5.4.1 Stage 1: Recommender system

The traditional process for using a recommendation system is applied:

1. A user logs into the system, the customer's information is retrieved. A user profile is created based on the customer's available information, for example: historical purchases, location, clickstream, demographic information and others.
2. Recommendation scores are calculated based on users' profiles and available information about the products and/or about other users. In order for our method to be implemented, we need a recommender system that will predict the utility of the items for the user. Collaborative filtering is one of the most widely adopted and successful recommendation approaches for e-commerce recommendation (Huang et al., 2007). It models the utility of the user u for the item i as a (real valued) function $R(u, i)$, by considering the appreciation of users for items. Then the fundamental task of a collaborative filtering RS is to predict the value of the appreciation R over pairs of users and items, i.e., to compute $R^*(u, i)$, where we denote with R^* the estimation, computed by the RS, of the true function R . Consequently, having computed this prediction for the active user u on a set of items, i.e., $R^*(u, i_1), \dots, R^*(u, i_n)$ the system will recommend the items $ij_1, \dots, ij_K$ ($K \leq N$) with the largest predicted utility (Ricci et al., 2015). Popular heuristic based techniques are: nearest neighbor, clustering and graph theory. Whereas, popular model based techniques are: Bayesian networks, clustering, artificial neural network, probabilistic models, deep learning (Wang et al., 2015). The choice of the recommendation technique remains highly dependent on the available data and on the purpose of the recommendation (decide, compare, discover and explore). However, for our method to be used, the output of the recommendation system needs to be a prediction (recommendation score) or user's utility for items and not a ranking.
3. Recommendation scores for X best items are provided.

For example: consider user 1 logs into the system. User 1's information is retrieved, recommendation scores are computed for the catalogue of products and the ($X=5$) highest recommendation scores are selected. Eventually those scores will be adjusted in Stage 2. Table 5.1 represents the pair of items/scores for the ($X=5$) selected items for user 1.

Table 5.1 Pair of items/scores for user 1

Items	I1	I2	I3	I4	I5
Recommendation score	0.92	0.68	0.49	0.47	0.6

5.4.2 Stage 2: Adjustment of recommendations

Recommendation adjustments depend on the availability of location information.

If users' locations cannot be retrieved, the proposed recommendation adjustments described below do not apply, then the system will classically propose the Y top items with the highest recommendation scores for recommendation. In this case, the proposed methodology does not change anything from current practice. For example, if we select $Y=3$, the recommendation method would simply suggest the ($Y = 3$) items with the highest score (Table 5.2). The final recommendation for a user with no location would be: Item 1, Item 2 and Item 5.

Table 5.2 Recommended items (with resp. score) for user 1 if no location information is available

Items	I1	I2	I5
Recommendation score	0.92	0.68	0.6

If a user's profile information contains location information, then adjustments to the recommendations could be made to take into consideration a supply chain's constraints for an item's distribution. The recommendation adjustment algorithm adjusts the score for the X items and then recommends the Y items with the highest score. The proposed adjustment is based on supply chain information. The algorithm presented in Figure 5.3 takes input information on a fleet's scheduled deliveries and pick ups, an active truck's supported constraints, an item's physical constraints, a list of warehouses and their locations and chooses which items are the most valuable to ship considering the status quo of the network. The algorithm presents 4 phases (A to D):

Phase (A) : "Evaluation of active trucks" determines the list of active trucks in a (P) radius and a (TW) time window. Active perimeter radius (P) represents the distance to be considered around the active user for truck selection, and time window (TW) is defined as a period of time in which the delivery and pick up points are considered, starting from the moment the user logs into the system.

It helps pick out the trucks that will be passing through the area surrounding the current user's location in a specific time frame. **The goal is** to select the list of active trucks from all the trucks in the fleet **with consideration** for scheduled delivery and pick up points.

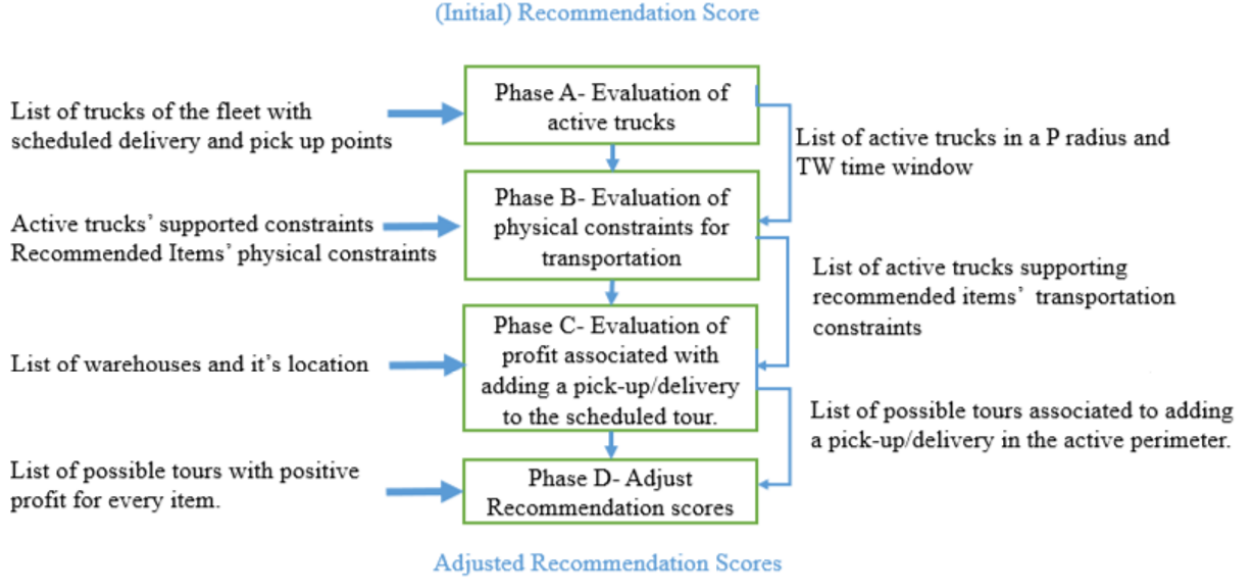


Figure 5.3 Adjustment algorithm for recommendation considering supply chain constraints

Phase (B) : “Evaluation of physical constraints for transportation” selects the list of active trucks supporting the recommended items’ transportation constraints. **The goal** is to select the list of active trucks supporting the recommended items’ transportation constraints **from** the list of active trucks **with consideration** of the trucks’ supported constraints and recommended items’ physical constraints.

Phase (C) : “Evaluation of profit associated with adding a pick-up/ delivery to the scheduled tour” determines the list of profit associated to adding each item to be delivered to the active user **from** the list of trucks supporting the recommended items’ transportation constraints **with consideration** of warehouse locations.

Phase (D) : “Adjust Recommendation scores” determines a new score associated with each item **with consideration** of the list of possible tours, with a positive profit **from** the list of possible tours associated with adding a pick-up/delivery in the active perimeter.

The output of the adjustment algorithm is a list of adjusted recommendation scores for all X items. Each phase is further explained in the following subsections.

5.4.2.1 Phase A: Evaluation of active trucks

The adjustment algorithm (Algorithm 1) starts with the identification of active trucks. This phase’s main purpose is to select the active trucks from all of the trucks in the fleet with consideration for scheduled delivery and pick up points. The parameters used for this step

are: active perimeter radius (P) around the location of the active user and the time window (TW).

Data: List of trucks in the fleet with scheduled delivery and pick up points

Result: List of active trucks in an active perimeter during a given time window.

Initialization: list of active trucks = {};

for *each truck in the fleet* **do**

 Evaluate whether one of the scheduled pick up and delivery points is in the active perimeter during a fixed time window;

if *One of the pick up and delivery points of a truck is within the active parameter during a fixed time window = TRUE* **then**

 The truck is added to the list of active trucks;

end

end

Algorithm 1: Evaluation of active trucks

5.4.2.2 Phase B: Evaluation of physical constraints for transportation

Once the trucks that could deliver the user are picked out, physical constraints need to be evaluated. Customer demand consists of sets of items which are characterized not only by a weight but also by a volume, a shape, fragility, orientation issues, environmental requirements (temperature, humidity), perishability, hazard and contamination potential or extreme value (i.e. financial, historical, artistic) (Iori and Martello, 2010) (Farahani et al., 2011). The fragility and shape of items may bear on the loading possibilities into a container. Items may have specific orientation constraints, i.e. several require a fixed orientation with respect to height. This means they cannot be placed upside down but have a pre-determined top (Pollaris et al., 2015). On the other hand, vehicle fleets are characterized by their capacity, configuration of the loading space and unloading possibilities (Ruan et al., 2013). The capacity of vehicles may be specified in terms of weight, number of items and/or volume. The loading space of the vehicle often influences the capacity. The loading space is determined by the measurements of the vehicle such as length, width and height, and may have a specific configuration (Pollaris et al., 2015). Furthermore, certain products are not allowed to be transported together in the same vehicle or vehicle compartment (isolation). Others are required to be transported in adapted containers or container compartments (i.e., frozen or refrigerated items or liquid products). Thus, compatibility between items and trucks needs to be considered. Algorithm 2 tests the compatibility between the X recommended items physical constraints and the truck's supported constraints. We compare the supported constraints of the trucks with the list resulting from phase A (section 5.4.2.1) to the physical constraints of items from the top X recommendations presented in Stage 1 (section 5.4.1).

Data: list of trucks' supported constraints and list of recommended items' physical constraints

Result: Matrix of items supported by each truck

initialization;

for each item i in the recommendation list **do**

 Evaluate whether one of the scheduled pick up and delivery points is in the active parameter during a fixed time window;

if $\left(\begin{array}{l} ConstraintsSupported(i, t) = TRUE \\ Weight < RemainingRapacity \\ LoadUnitsNeeded < RemainingLoadUnits \end{array} \right)$ **then**

 Go to Phase C;

end

end

Algorithm 2: Evaluation of supported constraints

5.4.2.3 Phase C: Evaluation of the profits associated with adding a pickup/delivery to a scheduled tour for each recommended item

When the supported items are selected, an evaluation of the economic interest for each item is needed. The selected items are stored in warehouses, then an evaluation of the potential profit related to picking up and delivering them for each active truck needs to be evaluated.

Step 1: Evaluate the location of items

We evaluate the availability of the items by searching the inventory of warehouses in the active perimeter in which the user is located. The output of this step is a matrix (Items x Warehouses), representing the availability of a given item at a given warehouse.

Step 2: Evaluate the potential profit

Once the availability of the items in all warehouses has been determined, the potential profit of adding an item i from a warehouse e to the active tours needs to be evaluated. Depending on the company's strategy, the best route can be evaluated based on marginal time or marginal cost/profit of adding a stop to the planned route instead of considering the distance. Considering the fastest route that maximizes the profit collected and delivered. The profit is calculated based on costs. The American Transportation Research Institute's (ATRI's) reports that operation costs include : fuel, truck/trailer lease or purchase payments, repair and maintenance, truck insurance premiums, permits and special licenses, tolls, wages and benefits of drivers. Those costs can be impacted by a number of underlying influences and externalities. These may include fuel and tire costs. Alternatively, costs such as labor can be impacted by driver experience, performance and differing compensation models. Based on data

collected from motor carrier survey respondents, the average carrier cost per mile in 2017 was 1.691 \$, an approximately 6 percent increase from 2016 costs. The average carrier cost per hour was 66.65\$ versus 63.66\$ in 2016. Driver wages and benefits represent 43% of total average marginal costs and fuel costs represent 22% (Hooper and Murray, 2018). Operational costs considered in the VRP are usually separated into fixed costs and variable costs. Tools are available to help determine those costs such as 'Freight metrics', which gives an approximation per country of the fuel cost per vehicle type; an estimation of vehicle costs such as stamp duty, miscellaneous costs, loans; an estimation of other costs per vehicle such as insurance, registration, accounting, rent of vehicle, driver wage per day, mobile costs, road tolls paid; service and maintenance costs and tire wear are also considered. The profit generated by a tour will be evaluated using the dynamic routing problem (DVRP) with pick-up deliveries and capacity constraints in a given time window with consideration to fixed and variable costs.

The literature presents a variety of solutions for the problem that are considered NP hard; some are optimal algorithms for small problems and others are meta heuristics and heuristics. Results vary in terms of accuracy and computational time and cost (Cordeau et al., 2002). Presently, optimal algorithms using branching and cutting on solutions obtained through Dantzig-Wolfe decomposition are leading the field (Kohl et al., 1999), (Kallehauge et al., 2005). Metaheuristics have led the way in generating near optimal solutions as illustrated by the results of (Rochat and Taillard, 1995), (Homberger and Gehring, 1999), (Cordeau et al., 2001), (Soonpracha et al., 2015) and (Calvet et al., 2016) among others. Recent composite heuristics, such as that of (Polat et al., 2015) are also showing promise. For each item i , the maximal potential profit associated with picking up and delivering it in the active perimeter in the current prescheduled tour is evaluated, using a VRP over all of the distribution points of the pre-scheduled tours first. The maximal potential profits take into account fixed costs and variable costs previously cited. A plausible assumption about the quantity ordered for each item would be the mean quantity ordered for historical purchases. However, using this assumption would must likely give better results for profits and for truckload improvement. We will consider that the user is only buying one of the proposed items, thus the VRP is estimated based on one item at a time for each client.

Step 3: Evaluate Marginal Profit

In the literature, the problem of evaluating the profitability of adding a product to a scheduled tour falls under demand management which is an important side of the fleet management problem. The evaluation of marginal profits helps to decide whether to

accept or reject a load (pick-up/delivery). It requires being able to quickly evaluate the profitability of loads (Powell, 1996). In the literature, when various options of loads are to be considered, various solutions for new incoming requests need to be evaluated. The opportunity value of the new request is calculated as the sum of the differences over all acceptable solutions with and without the insertion of the new request. Only feasible solutions contribute to the summation (Azi et al., 2012). In our case, only one potential load request is considered at a time. Thus, the marginal profit is the difference between the solution with and without the potential delivery. Marginal profit includes only costs that were not considered in the initial scheduling tour. Those variable costs are usually related to the additional labor time and fuel. Other fixed costs such as insurance, registration, accounting, rent of vehicle, driver wage per day, road tolls paid, service and maintenance costs are part of the costs related to the initial scheduled tour, thus, they are suppressed by the subtraction of the evaluation of marginal profit. The marginal profit of adding item i from the warehouse e in the active truck t is evaluated using formula (5.1)

$$MProfit_i = P_{i,e,t} - P_{init} \quad (5.1)$$

P_{init} is the profit from the previously scheduled plan for the active truck.

$P_{i,e,t}$ is the profit generated by picking item i from the warehouse e in a truck t .

If the new request cannot be incorporated into the solution due to delivery constraints, it is automatically rejected while evaluating the route at step 2. Otherwise, if this value is positive then the new profit is considered at Phase D, otherwise it is not considered for recommendation score adjustment.

5.4.2.4 Phase D: Adjust recommendation scores

Once all items have been tested and all marginal costs calculated, the recommendation adjustment follows. It is meant to reflect the value of adding a product to the scheduled deliveries. A threshold β could be fixed, depending on a company's strategy.

We propose the following Adjusted Recommendation Score to be calculated using equation (5.2).

$$Adjusted\ Recommendation\ Score = \beta \cdot Recommendation\ Score \quad (5.2)$$

with $\beta = MProfit/Prof_{min}$ and $Prof_{min}$ being the threshold based on the company's strategy.

We want β to be always superior to 1. It represents how aggressive we want the recommen-

dation to be. The higher the β , the stronger the priority of the item in the recommendation list and the higher its visibility for the customer. β is correlated to the minimum profit for which a company would accept changing its delivery schedule. If the company requires high profits, adjustments may be low, if the marginal profit is not high enough.

A sensitivity analysis to the minimum acceptable profit is presented in figure 5.9. It is important to note that recommendation scores will not be adjusted for all items. Only the items considered to accommodate logistics purposes will be adjusted. Our method does not claim to improve supply chain agility on its own, but wishes to contribute to the solution by acting on shifting demand when such demand is probable toward items that are of interest to the customer (Top N recommended items) by ranking them considering supply chain constraints and consequently improving truck-load utilization and delivery time. The proposed method never deteriorates the current situation, the effect on logistics and sales is either improvement or none.

5.5 Individual case study

The case study presents an application of the proposed method on real data from an industrial partner using the VRP presented by (Erdougan, 2017). The VRP used can solve more than 64 variants of the VRP, based on features related to selective visits to customers, simultaneous pickups and deliveries, time windows, fleet composition, distance constraint, and the final destination of the vehicles. Since recommendations and adjustments are computed individually, the presented case will present one user. For studies evaluating the impact of recommendation systems, the reader may refer to (Pathak et al., 2010) and (Shani and Gunawardana, 2011).

For the demonstration, parameters in Table 5.3 are fixed:

Table 5.3 Parameters for the case study

Number of items to be considered for recommendation	$X = 5$
Number of selected items from the recommendation list	$Y = 3$
Active perimeter radius	$P = 350km$
Time window	$TW = 11h59min$

The process starts when user 1 logs into the system.

5.5.1 Stage 1: Recommender system

The customer's information is retrieved and used as input to calculate recommendation scores. Here, we consider that recommendation scores are the output of a collaborative

filtering algorithm based on a customer's historical purchases. Table 5.4 represents a pair of simulated items/scores for user 1.

Table 5.4 Pair of item/score for user 1

Items	I1	I2	I3	I4	I5
Recommendation score	0.92	0.68	0.49	0.47	0.6

5.5.2 Stage 2: Recommendation adjustments

If the location for user 1 is not available, the adjustment algorithm stops and the $Y=3$ best items I1, I2 and I5 are recommended.

Here, we consider that user 1's location information was retrieved, making it possible to apply the methodology as detailed below.

Phase (A): The list of active trucks is determined based on selected parameters.

Figure 5.4 presents the situation around user 1 (represented with a yellow star). Three warehouses (black squares A, B, C), 20 delivery points (customers, green points) and three scheduled tours (lines) are depicted. A perimeter with a radius of 350km around user 1 is presented in blue. We suppose each scheduled tour is served by a single truck (Truck 1 in red, Truck 2 in purple and Truck 3 in orange).

For every truck in the fleet, we verify whether one of the scheduled pick up or delivery points is in the active area ($P=350$ km around user 1) during the selected time window ($TW = 11h59$ after user 1 logged into the system). Only Truck 1 and Truck 3 remain.

Phase (B): The compatibility between the X recommended item's physical constraints and the truck-supported constraints is tested. Table 5.5 presents truck capacities, supported constraints and remaining capacity in kg and loading units for the selected trucks.

Table 5.5 Trucks' capacities and supported constraints

Truck	Capacity (units)	Capacity (kg)	Supported constraints	Remaining capacity (kg)	Remaining units
Truck 1	1 000	24 000	fragile, fixed orientation, isolation	10 710	242
Truck 3	1 000	24 000	refrigerated, fragile, fixed orientation, isolation	6 000	442

The first line of table 5.5 would be read as follows: Truck 1 has total supported loading units of 1000 loading units, with a maximum capacity of 24 000 kg when empty. The

Each item is tested to see whether the physical constraints are supported by each of the active trucks. Table 5.7 presents which items are supported by each truck.

Table 5.7 Matrix of physical supported constraints

Items	I1	I2	I3	I4	I5
Truck 1	Supported	-	-	-	Supported
Truck 3	Supported	Supported	Supported	-	Supported

Knowing the two active trucks and the supported constraints, Item 1 and Item 5 can be transported by both available trucks and Item 2 and Item 3 can only be transported by Truck 3. Item 4 cannot be transported by either available truck.

Phase (C): An evaluation of the economic interest is to be completed for each item. The first step is to locate each of the items of interest.

Step 1: Evaluate the locations of items

Input: Inventory and stock levels for every warehouse

Output: Matrix of an item's location (Table 5.8) representing the warehouses in which each item of interest is stocked.

Table 5.8 Item's location

Items	Warehouse A	Warehouse B	Warehouse C
I1	e1,1	e1,2	e1,3
I2	-	-	-
I3	e2,1	e2,1	e2,1
I5	-	e5,3	-

Item 1 and Item 3 are available in all warehouses, with quantities $e_{i,j}$. Item 5 is available only in warehouse B. Item 2 is not available in any of the warehouses of the active perimeter. In the next step, the potential profit of delivering Item 1, Item 3 and Item 5 to the active user is evaluated.

Step 2: Evaluate the potential profit

Initial situation:

In order to evaluate the potential profit related to picking up and delivering an item located at a specific warehouse, a benchmark of the current solution needs to be set. To do so, tour scheduling information is needed.

We used the following tour scheduling parameters: (1) geographical information was retrieved from Microsoft Bing maps, (2) average speed was set to 70km/h, (3) the selected algorithm was VRP with a return to the warehouse using the fastest route. and (4) driving parameters are provided in Table 5.9.

Table 5.9 Driving parameters

Capacity (loading units)	1000
Fixed cost per trip	200.00
Cost per unit distance	0.95
Distance limit	1000.00
Work start time	08:00
Driving time limit	11:59
Working time limit	11:59

We consider that items on the prescheduled delivery list are available in all of the warehouses of the active zone.

The initial scheduled tour is presented in Figure 5.4. Three tours are scheduled.

Initial tour already scheduled for Truck 1 contains the following sequence of deliveries (by Location IDs): B-14-13-12-11-3-5-4-2-1-15-B.

The main characteristics of the tour are presented in Table 5.10:

Table 5.10 Truck 1, already scheduled

Distance travelled	952.53 km
Driving time	11:09 hours
End of tour time	19:09
Duration of tour	11:09 hours
Profit collected	\$18,075

An initial tour already scheduled for Truck 3 contains the following sequence of deliveries A-18-17-20-19-A. The main characteristics of the tour are presented in Table 5.11:

Table 5.11 Truck 3, already scheduled

Distance travelled	190.87 km
Driving time	2:44 hours
End of tour time	10:44
Duration of tour	2:44 hours
Profit collected	\$28,118.68

The results of the already scheduled tour for Trucks 1 and 3 presented in Figure 5.4 produce the following results (table 5.12):

Table 5.12 Total, already scheduled

Total profit	\$45,088.78
Total distance travelled	1 143.39 km

Potential profit for pick-up/delivery of new items:

A new VRP problem is solved considering items 1, 3, 5 and Warehouse A, B, C. The results of the new tours if the user orders one of the items is presented in figure 5.5. Potential profits for including each new item is considered one by one.



Figure 5.5 Potential tours considering the delivery for user 1 from Warehouse B

Item 1: It is available at all warehouses and the related profit is \$75.

A new sequence of deliveries for Truck 1 by Location IDs is: B-13-11-3-5-4-2-1-user1-12-14-B. The main characteristics of the new tour are presented in table 5.13:

Table 5.13 Truck 1, new schedule

Distance travelled	968.25 km
Driving time	11:45 hours
End of tour time	19:45
Duration of tour	11:45 hours
Profit collected	\$18,075

A new sequence of deliveries for Truck 3 by Location IDs is: A-18-17-20-15-19-

A.

The main characteristics of the new tour are presented in Table 5.14.

Table 5.14 Truck 3, new schedule

Distance travelled	343.93 km
Driving time	4:28 hours
End of tour time	12:28
Duration of tour	4:28 hours
Profit collected	\$28,575

This time, the total results of the new scheduled tour for Trucks 1 and 3 presented in Figure 5.5 produce the results presented in Table 5.15.

Table 5.15 Total, new schedule

Total profit	\$45,003.43
Total distance travelled	1 312.18 km

When a new pick up or delivery is launched, the VRP is recalculated considering all of the trucks in the active parameter. Because of constraints involving driving time, maximum driving distance, maximum driving hours, finding the best solution should consider all of the available trucks in the area.

The reason the scheduled tour for Truck 3 changed is because the drive time was too long for Truck 1; therefore, Truck 3 had to deliver to some of the customers that Truck 1 originally delivered to. The overall profit and truckload were globally improved.

Item 3: Item 3 is available at all warehouses and its related profit is \$300. The tours for Item 3 change in the same way as the tour for Item 1. Since the profit generated by Item 3 is different, the profit becomes \$45,228.43.

Item 5: Item 5 is only available in Warehouse B. Warehouse B is out of the active perimeter. The recommendation for Item 5 is not adjusted.

Step 3: Marginal profit is evaluated with Formula (5.1)

For Item 1:

$$MProfit_1 = 45,003.43 - 45,088.78 = \$ - 85.35$$

For Item 3:

$$MProfit_3 = 45,228 - 45,088.78 = \$139.22$$

The profit for Item 1 is negative and for Item 3, the profit is positive.

Phase (E): Adjust the recommendation scores.

The adjusted recommendation scores are meant to reflect the value of adding the product to the scheduled deliveries. A threshold needs to be fixed, depending on the company's strategy to evaluate whether the profit of adding a product is considered acceptable. Here, we set the threshold to \$100.

For **Item 1**, the marginal profit is negative, thus the recommendation score is not adjusted.

For **Item 3**, the marginal profit is positive, the adjusted recommendation score for Item 3 becomes: $0.49 * 139.22/100 = 0.682$

The scores for the remaining items remain unchanged; the final adjusted recommendation scores are then presented in table 5.16.

Table 5.16 Adjusted recommendation scores

Items	I1	I2	I3	I4	I5
Recommendation score	0.92	0.68	0.682	0.47	0.6

User 1 will be presented with the following final recommendations:

Table 5.17 New recommended items with new scores

Items	I1	I3	I2
Recommendation score	0.92	0.682	0.68

We can see that the final Y recommendations have changed and that Item 3 was favoured over Item 5, which no longer appears in the recommendation. Item 3 was also ranked before Item 2, changing the overall ranking of the recommendation.

5.6 Validation

In this section, we evaluate the impact of the recommendation adjustment on the recommendation list. Sensitivity to parameters is evaluated for each of the parameters of the method: time window (TW), Perimeter radius (P) and minimum acceptable profit ($Prof_{min}$). We consider a list of a 1000 inventory products. We simulate product ratings and a list of 50 products with the highest scores are selected for each user. For each of the 50 selected products, we simulate which of the products in the recommendation list can be shipped within the selected parameters' constraints. We consider that the capacity of shipping depends on the current state of the network (trucks, scheduling), distance from the user, the selected time window and the marginal profit accepted by the company. For the traditional method, a recommendation of 20 of the products with the highest rating is presented to each of the

users. For the proposed recommendation method, we consider that the list is adjusted based on the parameter β as presented in section 5.4. For each method, we evaluate the products from the recommendation list that can be shipped within specific constraints.

Figure 5.6 presents the number of shippable products per recommendation list within $TW = 12$ hours, in a perimeter radius of $P=300\text{km}$ and a minimum profit of $Prof_{min} = 100\$$ per product. The abscissa represents recommendation lists per customer arrival and the ordinate presents the number of products that can be shipped if purchased by the user considering the delivery constraints. The Old RS in yellow presents the number of shippable products using the traditional recommendation technique and the New RS in green presents the number of shippable products using the proposed method.

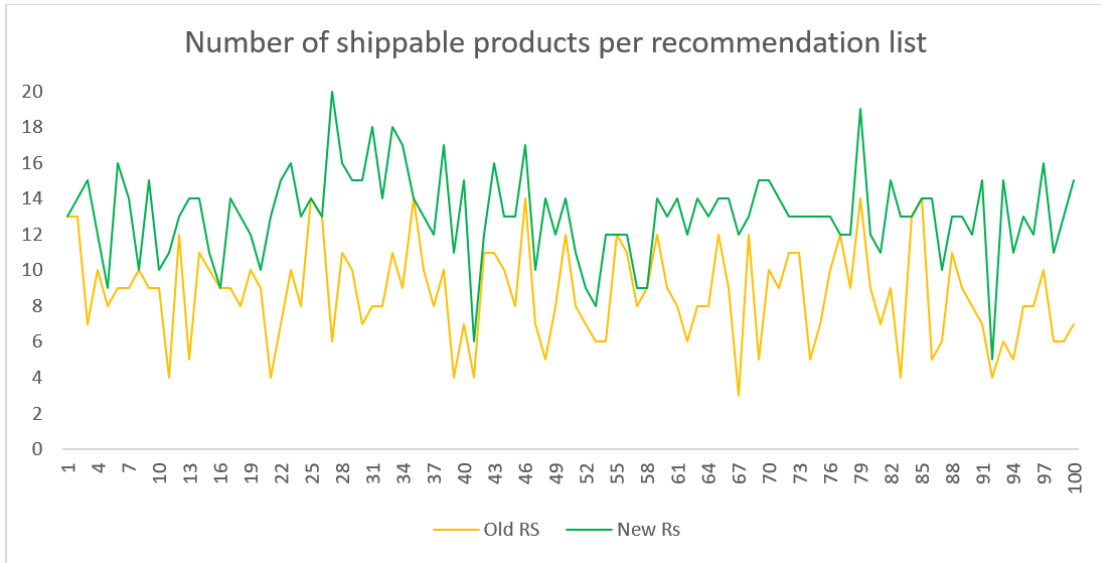


Figure 5.6 Number of shippable products per recommendation type

In order to illustrate the impact of the variation of the parameters, we present the sensitivity of each of the parameters over the number of shippable products.

Figure 5.7 represents the sensitivity to the chosen diameter of the perimeter from which products can be picked. Time window is fixed to 12 hours and minimum profit is fixed to \$100. We can see that for both methods a wider area of procurement implies more shippable products.

Figure 5.8 represents the sensitivity to the chosen time window in which products can be picked up and delivered. The diameter is fixed to 300km and minimum profit is fixed to \$100. We can see that the proposed method gives better results in term of the number of shippable products from 8 hours to 14 hours. However, within 24 hours the methods become comparable since almost all products can be shipped the following day.

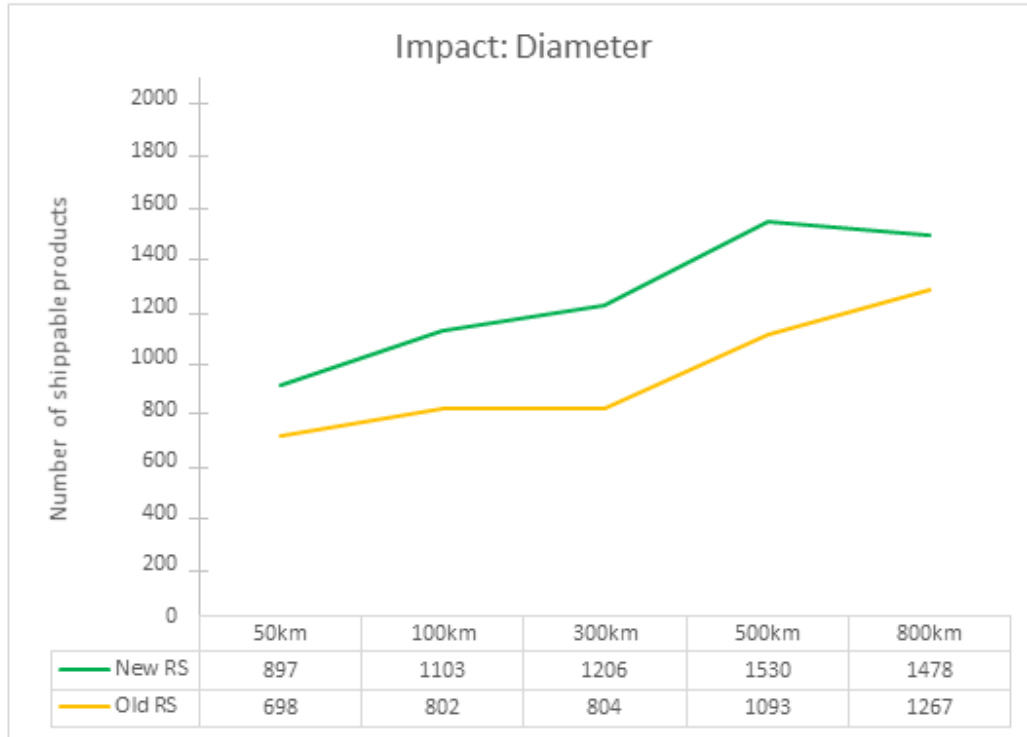


Figure 5.7 Sensitivity of the number of shippable products per recommendation type to diameter variation

For both figure 5.7 and figure 5.8, the proposed method has higher shippable products compared to the traditional recommendation since the recommendation list for each of the users will be adjusted to favor products that can be shipped, whereas traditional recommendation do not take it into consideration.

Figure 5.9 presents the sensitivity to the minimum profit for which a product is considered worth the pick-up/delivery. Diameter is fixed to 300 km and time window is fixed to 12 hours. We can see that the higher the minimum profit, the fewer the shippable items there are in the recommendation list.

As shown in the validation, our method improves the number of shippable items within the recommendation list. Such improvement increases the chances of shifting demand toward products that can be delivered within the chosen time window. Delivering products using no additional resources potentially helps improve truck-load utilization, delivery time, client satisfaction and retention while improving recommendation systems to adjust to current state of supply chain network.

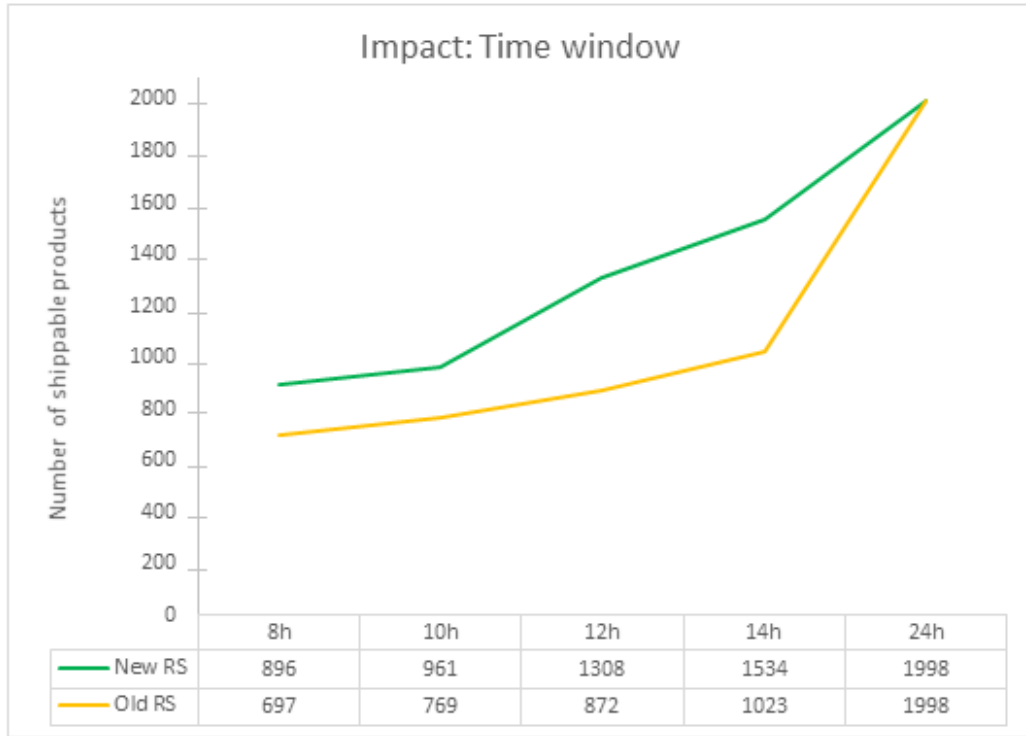


Figure 5.8 Sensitivity of the number of shippable products per recommendation type to time window variation

5.7 Conclusion

The proposed approach consists of an adaptation of recommender systems using well-established supply chain concepts. The focus is to improve recommendations by allowing it to shift demand toward items that would be of interest to the user, while being profitable to deliver during a given time window. The contribution of this study is to consider scheduled tours, physical characteristics of products, trucks' supported constraints, truck loads and supply chain network in the recommendation of products. We found that using the proposed method helps improve truckload utilization in real-time by proposing a solution that dynamically adjusts to the network state. Delivery costs, lead-times, agility and responsiveness of the supply chain are improved by making it possible to shift demand toward specific products. If the recommendation is followed by the customer and a sale is secured, truck-load utilization is improved, resulting in customer satisfaction, competitiveness of the seller and a reduction of congestion and pollution for society. If the available items are not of interest to the customer or the profit is not high enough for the supplier, no actions are taken, and the status quo is maintained. We presented a validation section that shows the impact of using the proposed method on the number of shippable items in a recommendation list. Sensitivity to method

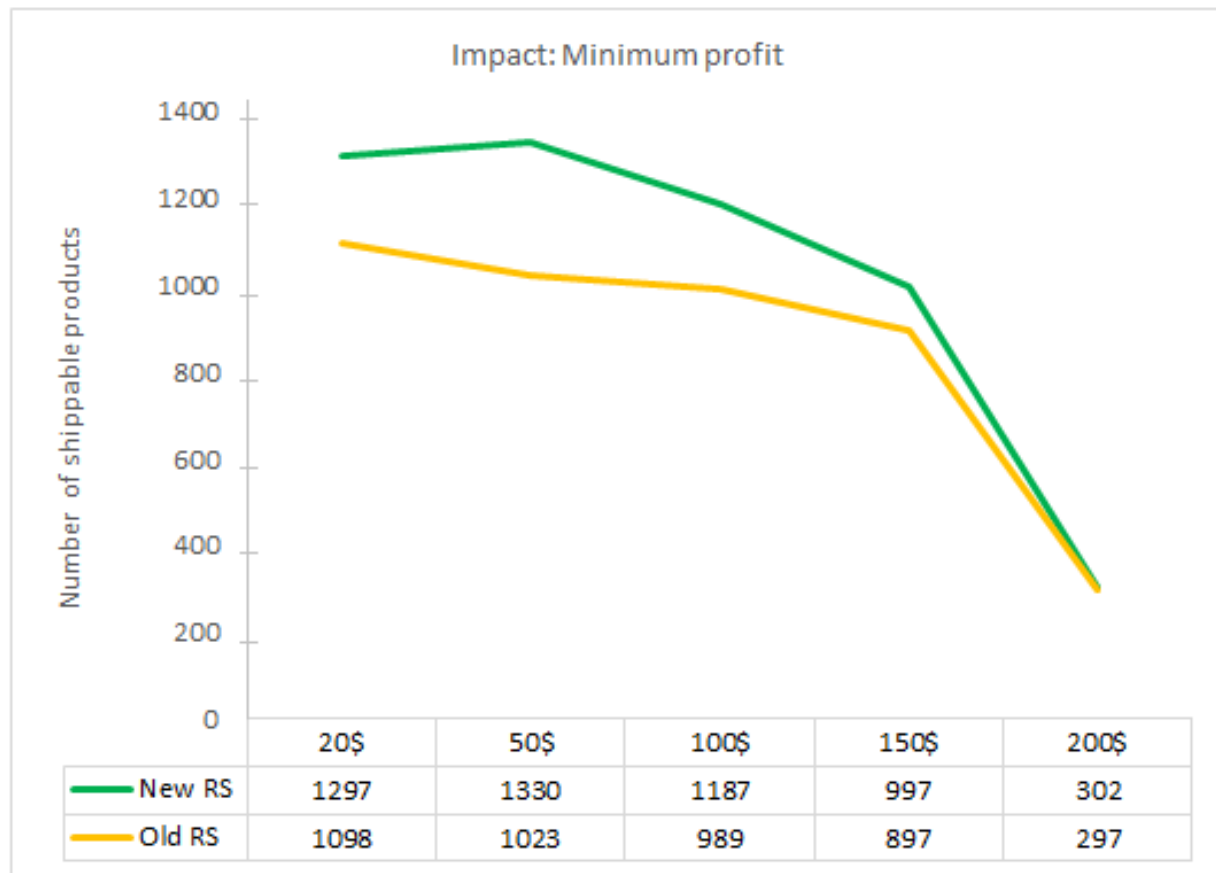


Figure 5.9 Sensitivity of the number of shippable products per recommendation type to minimum profit variation

parameters have also been included. This confirms that our method could help shift demand with consideration to the supply chain network state. The decision of considering the number of product on the recommendation list results in the fact that customers' behaviours are hard to predict and making assumptions about sales would lead to less accurate results.

Recommender systems are tools designed to make personalised recommendations, thus customers are treated individually. The results of such a method could provide a significant opportunity for increased customer satisfaction and increased profits for the seller. The same would be true in the context of a universally interconnected system. However, the results of the method depend on the accuracy of the recommendation and the efficiency of the VRP. The recommendation technique chosen for this paper is collaborative filtering, which implies that a strong base of information about customers is available. Nevertheless, in many cases, a cold start is an issue and making a recommendation with no information about the client leads to poor results. Tackling the cold-start using interactive recommendations and creating

a learning base is an active research field. A better understanding of customers' specific interests could be a great insight to make improvements in the supply chain and the creation of a learning base to improve future recommendations. Also, since both approximate and exact VRP methods demand a significant computational effort (Rey et al., 2018), it is important to make sure that the computation time of the VRP can be hidden in the recommendation's computation time. This also is an active research field and the problem has been tackled by using GPUs in (Benaini et al., 2017) and (Rey et al., 2018). Future perspectives would be to take into consideration other constraints such as network and inventory levels for every location, crossdocking when optimizing the distribution tours, categorization of clients based on their delivery time flexibility or their preferred time window for delivery, trends in raw material prices and the margin of products. Other intangible profits related to fast delivery for client retention and trademark could be considered in the profit evaluation. A comparison of potential profit that could be generated in another time window could also be included when adjusting recommendations.

Acknowledgments

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CHAPITRE 6 ARTICLE 3: CONTEXT-AWARE INTERACTIVE KNOWLEDGE-BASED RECOMMENDATION SYSTEM

Abstract - Recommender systems have widely been used in the past few years as a recipe to success in e-commerce. Already, 35 percent of what consumers purchase on Amazon and 75 percent of what they watch on Netflix come from product recommendation (MacKenzie, Ian and Meyer, Chris and Noble, Steve, 2013). However, in the context of high-end products such as cars, computers, apartments, or financial services, traditional approaches are not the best choice since it is as of now infeasible to collect enough customer behavioural information or feedback over numerous items Burke et al. (2011). Accordingly, since brick and mortar outlets remain the channel of choice for those kinds of products, recommender systems need to adjust to a context in which inventory and customer information are limited. To achieve this goal, we propose a context-aware interactive knowledge-based recommendation system in order to make recommendations to customers who walk into a store, even when no previous information about the customers is available. The proposed approach works in 3 stages: Stage 1: Contextual pre-filtering, Stage 2: Interactive exploration, and Stage 3: Constraint-based recommendation. The methodology was developed based on a real life problem of in-store recommendation, when no information about the customer is available. It was developed with an industrial partner in the domain of sport vehicles. The methodology is illustrated step by step with an example inspired from this partnership. The method enables an iterative exploration of the products in-store, and recommends a product available in the supply network for a new customer.

6.1 Introduction

Traditional recommendation approaches (content-based filtering and collaborative filtering) are well-suited for the recommendation of products based on quality and personal taste, such as books, movies, or news. However, especially in the context of products such as cars, computers, apartments, or financial services, those approaches are not the best choice since it is as of now infeasible to collect enough customer behavioural information or feedback over numerous items (Burke et al., 2011). Moreover, in industries such as these where the monetary value of products is high, customers have a higher perceived risk, insisting more over the notion of assurance that brings a feeling of security in the minds of customers. Traditionally, brick and mortar outlets have been associated with these dimensions of assurance motivation because of their more tangible nature and the presence of human interaction (Rajamma

et al., 2007). When a customer walks into a brick and mortar outlet to make a rare purchase, the dealer has often no previously relevant history about the customer, making it hard to assess customers’ interests, especially when a large selection of products is offered. Although the field has been researched extensively, there are still important challenges that need to be addressed (He et al., 2016) such as the cold start for new users or customers (Burke et al., 2011), difficulties for the user in understanding a recommendation process resulting in trust issues (Herlocker et al., 2000), lack of rich contextual interaction capabilities preventing a user from providing interactive and iterative input (Adomavicius and Tuzhilin, 2011).

Interactive recommender systems have been developed to continuously refine recommendations by receiving feedback on items, making it possible for the user to enjoy sequential recommendations. Most existing solutions model the interactive recommendation problem as a contextual bandit problem to address the explore-exploit dilemma at a per-user basis. Unfortunately, these approaches require a large number of user interactions Shen et al. (2018). Knowledge-based recommender technologies have helped to tackle these challenges by exploiting explicit user requirements and deep knowledge about the underlying product domain for the calculation of recommendations Felfernig (2007). However, knowledge-based recommender technologies only consider precise requirements, and do not support degrees of appreciations for features. In the context of expensive, infrequently bought products, tastes and appreciations need to be acquired to better explore a customer’s options and to make recommendations. In this work, we present a context-aware interactive knowledge-based recommendation that can be used in-store to create a learning base of customer profiles, make an interactive exploration phase in-store and a final context-based recommendation, considering supply chain constraints through the product availability state (Montreuil and Derhami, 2019) of the supply network. A knowledge-based pre-filtering of a user’s feedback on discriminant features is made before using a content-based approach to compute recommendation scores with a dynamic inclusion of a feature’s appreciations, based on user’s explicit feedback.

The remainder of this article is structured as follows: Section 2 describes work related to recommender systems, including classical recommendation techniques, context-aware recommendations, knowledge-based recommendations and interactive recommendations. The context of the study is then presented, along with a description of the data in section 3. Section 4 describes the proposed method for the implementation of a context-aware interactive knowledge-based recommendation system in 3 stages: Stage 1: Contextual pre-filtering, Stage 2: Interactive exploration and Stage 3: Constraints based recommendation. The methodology is illustrated step by step with an example inspired from an industrial partnership. Section 5 presents computational performance. The concluding section summarizes the purpose of using our method in a cold-start context with consideration for the supply

network.

6.2 Related work

6.2.1 Recommender Systems

A tremendous amount of research has been conducted in the field of recommendation systems. With the development of recommendation approaches and techniques, more and more recommender systems (software) have been implemented and many real-world recommender system applications have been developed (Lu et al., 2015). Numerous literature reviews have been presented, providing different classifications. The most widely used classification Adomavicius and Tuzhilin (2005), Candillier et al. (2007), Schafer et al. (2007) divides the filtering algorithms that characterize internal functions into (a) collaborative filtering, (b) demographic filtering, (c) content-based filtering and (d) hybrid filtering. A widely accepted taxonomy divides recommendation methods into memory-based and model-based method categories Bobadilla et al. (2013). Traditionally recommender systems deal with applications that have only two types of entities, users and items, and do not put them into a context when providing recommendations. However, in many applications, it is important to incorporate the contextual information into the recommendation process in order to recommend items to users under certain circumstances. The context-aware recommendation process can take one of the following three forms : contextual pre-filtering, contextual post-filtering and contextual modeling, based on how the contextual information is used, as shown in Adomavicius and Tuzhilin (2011).

6.2.1.1 Context-aware recommendation

Generally, context is an information halo that is used to characterize the situations pertaining to the objects of interest Abbas et al. (2015). From an operational perspective, it is often defined as an aggregate of various categories that describe the setting in which a recommender is deployed, such as the location, current activity, and available time Verbert et al. (2012). Context can be described using a set of observable attributes that are known a priori. Adomavicius and Tuzhilin (2011) presents:

Contextual pre-filtering (or contextualization of recommendation input) uses information about the current context to select only the relevant set of data, and scores are computed using any traditional recommender system on the selected data.

Contextual post-filtering (or contextualization of recommendation output) initially ignores contextual information and scores are predicted using any traditional recom-

mender system on the entire data. Then, the resulting set of recommendations is adjusted (contextualized) for each user using the contextual information.

Contextual modeling (or contextualization of recommendation function) directly uses contextual information in the modeling technique as part of the rating estimation. In addition to contextual information, domain knowledge can highly affect the type of recommendation filtering that can be used and its performance. Most of the techniques in the literature must be initialized with a large amount of data. However, knowledge-based recommender systems overcome that issue.

6.2.1.2 Knowledge-based recommender systems

Knowledge-based recommender systems do not depend on large bodies of statistical data about particular rated items or particular users, since we only need enough knowledge to judge items as similar to each other Burke (2000). Knowledge-based advisors (Burke (2000); Felfernig and Kiener (2005); Jiang et al. (2005); Thompson et al. (2004)) exploit deep product domain knowledge in order to determine solutions that suit the wishes and needs of a customer. Two basic aspects have to be considered when implementing a knowledge-based recommender system. First, the relevant product, marketing and sales knowledge has to be acquired and transformed into a formal representation, i.e., a recommender knowledge base Felfernig and Kiener (2005) has to be defined. Such a knowledge base consists of a formal description of the relevant set of products, possible customer requirements and constraints defining allowed combinations of customer requirements and product properties Felfernig (2007). Knowledge-based recommender systems are prone to the drawback of all knowledge-based systems: the so-called knowledge acquisition bottleneck in the sense that knowledge engineers must work hard to convert the knowledge possessed by domain experts into formal, executable representations Felfernig (2007). There are three types of knowledge that are involved in such a system Adomavicius and Tuzhilin (2011):

Catalog knowledge: Knowledge about the objects being recommended and their features. For example, the recommender system should know that 'Thai' cuisine is a kind of 'Asian' cuisine.

Functional knowledge: The system must be able to map between the user's needs and the objects that might satisfy those needs. For example, a recommender system knows that a need for a romantic dinner spot could be met by a restaurant that is 'quiet with an ocean view'.

User knowledge: To provide good recommendations, the system must have some knowledge about the user. This might take the form of general demographic information or

specific information about the need for which a recommendation is sought.

Of these knowledge types, the last is the most challenging, as it is, in the worst case, an instance of the general user-modeling problem Towle and Quinn (2000).

Knowledge-based techniques are good candidates for hybridization since they are not subject to ramp-up problems. Further, knowledge-based recommender systems actually help users explore and thereby understand an information space. Users are an integral part of the knowledge discovery process, elaborating their information needs in the course of interacting with the system Burke (2000).

6.2.1.3 Interactive recommender systems

Interactive recommender systems are an active field of research. These systems usually rely on an online learning algorithm that gradually learns users' preferences. At each step of the interaction, the system generates a list of recommendations and observes the user's feedback on the recommended items indicating the utility of the recommendations. The goal of such a system is to maximize the total utility obtained over the whole interaction session Hariri et al. (2014). A successful algorithm for interactive recommendation should continuously detect/learn the user profile while trying to satisfy the user at the same time. The dilemma of whether, for each interaction, we should try to satisfy the user's interest with the best-guessed item based on current knowledge, or whether we should try some sub-optimal yet discriminative items to gain more knowledge about the user, have been called the exploit-explore dilemma Yu et al. (2019). Most of the existing solutions model the interactive recommendation problem as a contextual bandit problem to address the explore-exploit dilemma at a per-user basis Shen et al. (2018).

The Multi-Armed Bandit (MAB) problem is defined as a sequential Markov decision process of an agent that tries to optimize its actions while improving its knowledge on the arms. The fundamental challenge in bandit problems is the need for balancing exploration and exploitation. In the context of online recommender systems, each arm represents an item to be recommended to a user, and the reward corresponds to whether the user clicked the suggested item or not Lacerda (2017). Unfortunately, these approaches require a large number of user interactions Shen et al. (2018).

To the best of our knowledge, no hybrid interactive context-aware recommendation technique has made the distinction between features' appreciation type (discriminant and appreciable) while considering the state and constraints of the supply chain in the context of high-end products. As presented in the literature, interactive recommender systems have mainly used reinforcement learning such as MAB. Such an approach needs a large learning base about

customers' behaviours. MAB does not consider the difference in customer perception of feature and requires a large amount of interaction. Knowledge-based recommendation has been used to tackle the cold-start. We present an interactive context-aware knowledge-based recommender system to create a learning base about customers, while exploring products and iteratively exploiting feedback.

6.3 Context

In industries such as the vehicle industry, for which the prices of products is high and the buying frequency is low, customers have a higher perceived risk. Perceived risk is defined by Cunningham (1967) as a feeling of certainty that the consequences will be unfavourable. Customers tend to research information more thoroughly, from multiple sources, as compared to the products or services that any consumer buys on a regular basis Munthiu (2009). The consumer usually has to learn about the product. A high price may result in financial loss, the highly expressive nature of the product may result in significant psycho-social loss, and the infrequent purchase and lack of product category knowledge will result in increased uncertainty and complex buying behaviours Mitchell (1992). These behaviors, on the part of a consumer who is experiencing increased risk perception, come with more insistence on the notion of assurance that captures dimensions such as confidentiality, shopping security, complaint resolution, solution to problems, warranties, interaction with the seller, and customer service Bitner (1992); Kotler (1973); Solomon et al. (1985); Crosby and Stephens (1987); Crosby et al. (1990). Brick and mortar outlets usually attempt to generate that assurance Rajamma et al. (2007). Unless prices are 8-22% lower online (depending on the product category), consumers prefer to buy those kinds of expensive products from traditional stores than from online stores Kacen et al. (2013).

The present study is based on a real-life situation with an industrial partner in the domain of sport vehicles. The industrial partner disposes of a variety of data about its network and supply chain, stores, sales, products features and product similarities. However, since the buying frequency is low, almost any information about customers is obsolete and useless for the creation of customer profiles for the recommendation process. Also, the industrial partner does not allow sales online, making in-store sales the only available option for product acquirement. In this context, it is important for our industrial partner to be able to evaluate its capacity to meet customer demand in a reasonable time. Thus, a supply chain performance indicator has been developed to do so by (Montreuil and Derhami, 2019) : the product availability ratio (PAR) is a customer-centric demand-driven performance indicator. It was developed to measure the current readiness of a dealer to satisfy demand for the forthcoming

customers. Measuring PAR considers the availability of each product, or an acceptable substitute in its inventory or by shipment in an acceptable time from another dealer or from another replenishment site.

We present an interactive knowledge-based recommendation that can be used in-store by interactively exploring the products in-store to create a learning base of customer profiles, and make a final context-based recommendation taking into consideration supply chain induced constraints and opportunities.

6.4 The proposed method

As have been previously presented, an interactive RS needs a learning base about users for its model-based algorithm in order to perform a recommendation. Since no data about the customers is available in our context, we cannot use a model-based recommendation because no feature extraction is possible to make personalised recommendations for the in-store customer. We suggest a memory based interactive recommendation technique to learn about the customer's interests and create a learning base for future purposes using available data about products and their features. For providing personalized recommendations, we find in the literature that there are two ways to receive users' preferences: implicit and explicit. First, the implicit method collects users' behavior to infer their preferences. When detecting changes, these user preference data change simultaneously. Second, the explicit method filters and analyzes interactions and feedback to infer users' specifications (Li et al., 2013).

In this paper, we also distinguish two types of product features for which the customer will give feedback:

Discriminant features: features for which the choice of an attribute cancels all other possible alternative choices. As examples of discriminant features, we offer functionality and availability. Functionality may result from a set of business-specific features (for example: Seating) and availability may be a function of the waiting time accepted by the customer considering the possible transfer of products from a partner store at a certain distance. The discriminant features represent the constraints of the customer. Discriminant features can serve as preliminary filtering of the products to be presented to the customer. They are usually easily deductible through business knowledge.

Appreciable features: features for which the appreciation is neither categorical nor exclusive. The customer may have preferences whose importance varies according to

the feature. The color is an example of an appreciable feature on which a compromise could be easy. The appreciable features representing the tastes of the customer will be deduced during the creation of a customer's profile.

Figure 6.1 gives an overview of the proposed method. First, a contextual pre-filtering is conducted over the products, based on the discriminant features provided by the customer. Afterward, an interactive exploration of the products begins, in order to collect explicit feedback from the customer about his/her appreciation of the attributes for some features of the products presented to him/her. The process ends with a constraint-based recommendation considering supply chain constraints through the product availability ratio performance indicator (Montreuil and Derhami, 2019) in a content-based recommendation.

The proposed method is based on six phases clustered in three stages, with phase 4 corresponding to three steps.

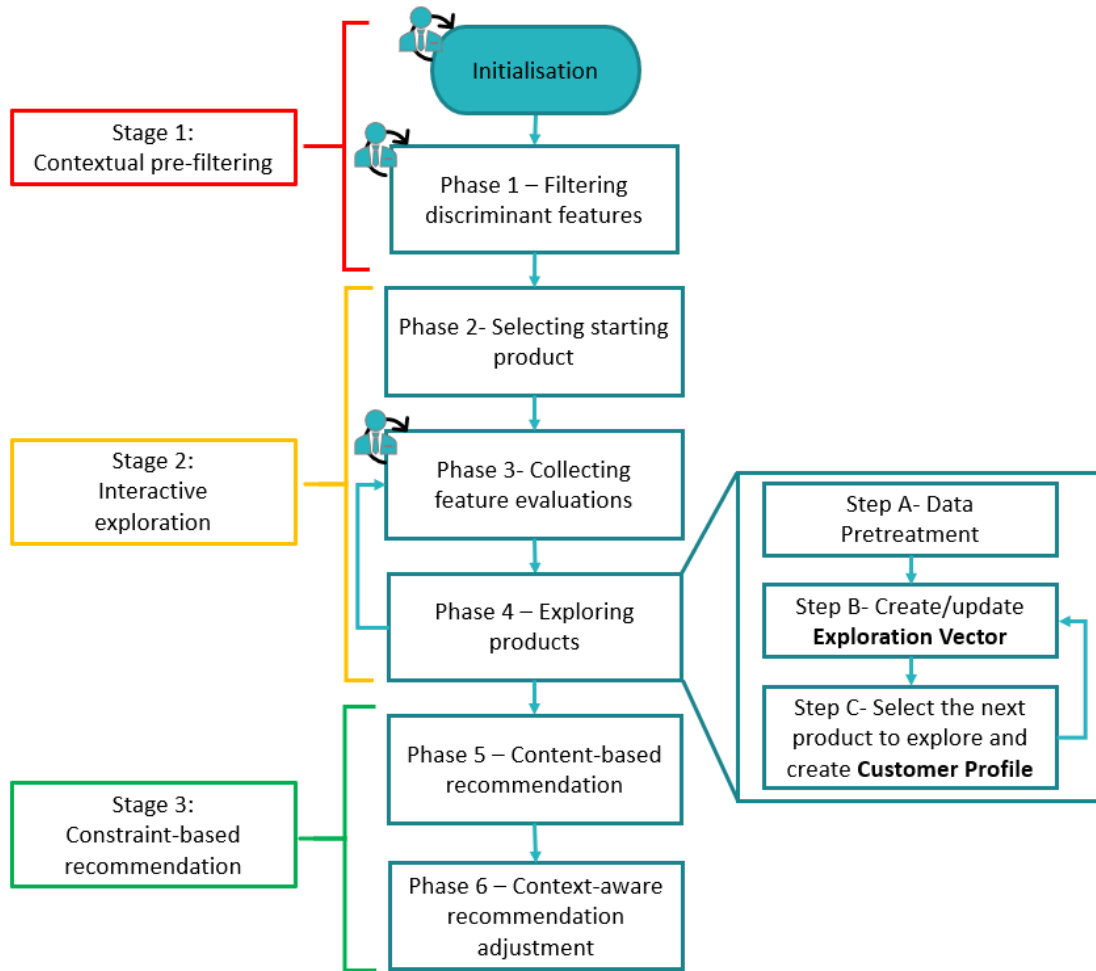


Figure 6.1 Context-aware interactive knowledge-based recommendation method

Figure 6.1 presents the 3 stages on the left, each stage is highlighted in a specific color and

points to the phases it contains. Phase 4 also points to the 3 steps it includes. The symbol with a graphic icon representing a user and a black arrow denoted at initialisation, phase 1 and phase 3 require customer interaction. The remainder of the section presents the detail of each phase. A pedagogical illustration of the method is presented along each phase.

6.4.1 Stage 1: Contextual pre-filtering

A contextual pre-filtering approach uses contextual information to select the most relevant data for generating recommendations. A study on how context can be defined and used in recommender systems in order to create more intelligent and useful recommendations is presented in Adomavicius and Tuzhilin (2011). Relevant contextual information is defined here based on the functionality of the product. Business knowledge is required to define relevant features for utility. Contextual pre-filtering is composed of the initialisation and phase 1: Filtering discriminant features.

6.4.1.1 Initialization

This phase collects information about the customer's willingness to wait for the product to be delivered and about the time available by the customer for product exploration.

Customer's willingness to wait (TW) helps to determine which locations from the neighboring network can provide a product in an acceptable time window. The time available to spend in store by the customer approximates the number of vehicles (N) the customer can assess during the period. Once the data has been retrieved and interpreted, we go to **phase 1**, section 6.4.1.2.

In the context of our case study, the customer is asked two questions:

- How long is he willing to wait for his product to be delivered?
- How much time does he have to spend for in-store exploration of the product features?

In our illustrative example, we suppose that:

- The customer would like to get his vehicle to be delivered in a maximum of $TW = 4$ *days*.
- The customer has 30 minutes available in-store. For an exploration of approximately 5 minutes per vehicle, up to $N = 6$ products can be exposed to the customer.

6.4.1.2 Phase 1: Filtering discriminant features

The literature presents various traditional feature selection techniques such as filter, wrapper, or embedded methods, to determine the importance of each feature. The more important a

feature is, the higher the accuracy that can be achieved when using it in a learning base for model-based recommender systems Li et al. (2018).

Discriminant features are highly correlated with the type of products the customer wants to buy. In the context of high-end products, customers usually present a complex buying behaviour. Various information are gathered before making a purchase decision, which makes it common for customers to have a strong opinion about specific functionalities. Dealers are often faced with requirements that they need to translate into product suggestions with specific features Salvador and Forza (2007). Dealers develop a domain knowledge about the specific set of features for which customers usually have very little flexibility. Those features are considered here as discriminant. Customers are asked direct questions about their requirements for those features and a filter is applied over the offered products. It helps decrease the size of the data to be considered at the exploration phase, which results in making computation faster and avoids the recommendation of products for which the customer has no interest.

The customer is asked questions about features that have been considered discriminant by domain experts. He answers that he would like a vehicle in order to go hunting in the woods with his two kids. The dealer understands that the customer needs:

- a vehicle that can be used off-road,
- a vehicle that can seat at least three persons.

Afterward, all products from the catalogue are filtered to select those that correspond to the constraints of the customer (see Table 6.1).

Table 6.1 Filtered products - F_i

Product	Seating (persons)	Type	Color	Engine	Package	Wheels
P1	3	Off-road	Green	1000	WX03	Bronze
P2	4	Off-road	Yellow	800	WM39	Titan
P3	4	Off-road	Blue	1000	MWX0	Bronze
P4	3	Off-road	Orange	1500	PXK3	Gold-Rose
...	...	...	...	...	...	...
P30	6	Off-road	Green	1000	PLP30	Gold

Table 6.1 presents products from the catalogue that are off-road vehicles with a seating capacity of three persons or more. We can observe products that can seat 3 to 6 persons, in different colors, with various engine, package and wheel options. Once this step is complete, we proceed to **stage 2** described in section 6.4.2.

6.4.2 Stage 2: Interactive exploration

This stage evaluates which of the in-store products should be presented to the customer for gathering information about his appreciation for certain features. As the customer generates feedback over the attributes of the products he is presented with, the system selects the next product to explore. Interactive exploration is composed by Phase 2: Selecting starting product, Phase 3: Collecting feature evaluations, and by Phase 4: Exploring products.

6.4.2.1 Phase 2: Selecting the starting product

Phase 2 starts the exploration process by choosing an initial product (P_{init}) to present to the customer. Only in-store products are considered in this phase. Table 6.2 presents in-store filtered products and results from table 6.1 and data about in-store inventory. Note that in Table 2, products such as P3 and P4 of Table 1 are eliminated for this step as they are not available in store.

Table 6.2 Filtered products available in-store

ID	Product	Seating (persons)	Type	Color	Engine	Package	Wheels
1	P1	3	Off-road	Green	1000	WX03	Bronze
2	P2	4	Off-road	Yellow	800	WM39	Titan
3	P7	6	Off-road	Orange	800	MWO0	Gold
4	P12	5	Off-road	Orange	1500	MWX0	Bronze
5	P13	3	Off-road	Blue	1500	MWZ0	Bronze
6	P15	4	Off-road	Yellow	800	WM39	Titan
7	P18	3	Off-road	Grey	800	PXK3	Silver
8	P21	4	Off-road	Green	1500	QWP30	Gold
9	P24	6	Off-road	Green	1000	PLP30	Gold-Rose
10	P26	3	Off-road	Orange	1500	WM39	Titan
11	P28	3	Off-road	Blue	800	WX03	Silver
12	P29	6	Off-road	Grey	1000	PXK0	Bronze

The initial product (P_{init}) to present to the customer is the one with the highest probability of sale, which depends on ongoing promotions and product demand shares. It can also be the first product that the customer shows interest for when walking into the store. Once an initial product to be presented to the customer is selected by the dealer, we proceed to **phase 3** section 6.4.2.2.

For illustrative purposes, let us consider that the dealer selects P1 from Table 6.2 ($P_{init} = P1$) and presents it to the customer. P1 (see Table 6.3) is a green off-road vehicle with 3-person seating capacity (3-seater), high-performance 1000 engine, luxury package WX03, and bronze

wheels.

Table 6.3 Selected product - $P_{init} = P1$

Product	Seating (persons)	Type	Color	Engine	Package	Wheels
P1	3	Off-road	Green	1000	WX03	Bronze

6.4.2.2 Phase 3: Collecting feature evaluations

In this phase, the customer is asked to rate some attributes of pertinent features of the active product. The customer gives an appreciation for each attribute and a table of attributes' appreciations is created. The overall method works whether the rating is between 0 and 1, 0 and 10, etc.

Table 6.4 presents the appreciations generated by the customer for certain attributes of the selected product.

Table 6.4 Customer's rating of product P1 attributes

Green	1000	WX03	Bronze
8/10	9/10	5/10	2/10

Once the ratings are collected and stored in Table 6.4 , we proceed to **phase 4** section 6.4.2.3.

6.4.2.3 Phase 4: Exploring products

In this phase the objective is to iteratively select the next product to present to the customer while considering the feedback we collected at phase 3 section 6.4.2.2 as it becomes available. At each iteration one product is selected based on the collected feedback of the previously explored products.

To do so, we make the assumption that an explicit feedback generated by a customer as a rating for an attribute has a dual interpretation that can be exploited to deduce an appreciation for another attribute of the same feature. By deducing an additional appreciation from user feedback, we improve the chances of converging toward attributes that the customer may like. Adding appreciation to the exploration vector also double it's density, which enhances the exploitation of the information given by the customer. Improving the density of the vector helps in the computation of similarities, while exploiting the deduced feedback helps find products with attributes that are more likely to be appreciated by the customer. Phase 4 is detailed in 3 steps: Step A: Data pre-treatment, Step B: Create/update exploration vector and Step C: Select the next product to explore and create a Customer Profile,

as presented in Figure 6.1. The different data structures that are created in this phase are hereafter highlighted in bold and explained as we move into the steps.

6.4.2.3.1 Step A - Data pretreatment In order to use a content-based approach to evaluate similarities between the vectors representing customers' interests and products, the input data needs to be a vector containing all possible attributes of all the products for every selected feature.

We create a **Features' vector** (F_i), for each product. Each attribute describing the product is assigned 1 and all the other attributes that are not present in the active product are given a 0.

Table 6.5 gives an overview of the features' vector F_1 representing P1. Here, the demonstration is limited to 3 features, namely : Color, Engine and Wheels.

Table 6.5 F_1 features' vector for P1

Product	Color				Engine				Wheels			
	Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
P1	0	0	1	...	0	1	0	...	0	1	0	...

Afterward, we construct a Content-based **preference vector** (R_i) per product, presenting all explicit feedback generated during the interaction with the customer. The ratings collected at phase 6.4.2.2 for each attribute of the i_{th} explored product are assigned to the cell of the vector associated to the rated attribute, as shown in Table 6.6 for the first explored product P1.

Table 6.6 Preference vector (R_1)- P1

	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
R_1	P1	0	0	0.8	...	0	0.9	0	...	0	0.2	0	...

Afterward, a table of Preference vectors (R_{tab}) is constructed to store the R_i created during the exploration phase for all the explored products. The table is initially created empty with a length of N (the number of products to present to the customer). For each iteration of step 3 and step 4, a row is filled in the table. The R_{tab} will be used to create the exploration vector (E) and Customer Profile (CP) in **step B** and **step C** respectively.

6.4.2.3.2 Step B: Create/update exploration vector In this step, we create the exploration vector at the first iteration of this step and we update it afterward. To do so

we start by creating E_i as the enhanced vector of ratings and appreciations. The vector is filled by the customer explicit ratings and deduced appreciations for a given product. It is based on R_i the preference vector created in step A section 6.4.2.3.1. For each rated attribute of a feature from R_i , we deduce an appreciation for an attribute of the same feature. To illustrate the value of doing so let's consider that a customer badly rated an attribute. The next products to be explored and presented to the customer should not display the disliked attribute. A product with a dissimilar attribute should be favored over a similar one. This can be achieved using rating complements.

For example, for the feature Color, if a customer gives a very bad rating (i.e.: 0.1) to an attribute (i.e.: black), we deduce that he would most likely prefer something completely different (i.e.: white) and we would give the complement rating ($1 - 0.1 = 0.9$) to the attribute (white) that is the least similar to the initially rated attribute (black).

For that purpose, a substitution matrix that contains the substitution degree between each pair of attributes that a specific feature can take is considered. A substitution matrix for each feature is needed and is provided by experts of the application domain. For the demonstration, Table 6.7 shows the substitution matrix for the feature Color. For example, it displays that the experts have estimated that for customers Green is more similar to Blue and Yellow than to Red. In this case, the matrix is symmetric, thus only the upper side is filled.

Table 6.7 Substitution matrix between the different attributes of the Color feature

Colors	Green	Blue	Orange	Yellow	Mauve	Red
Green	1	0.78	0.31	0.80	0.30	0.22
Blue		1	0.12	0.18	0.78	0.42
Orange			1	0.90	0.21	0.8
Yellow				1	0.32	0.55
Mauve					1	0.86
Red						1

To select the attribute for which an implicit appreciation will be deduced, we extract and order the substitution degree between the active attribute (Green for P1) and all other attributes from the substitution matrix (table 6.7). The resulting table 6.8 is ordered in a decreasing order of substitution degree and an ID is associated for each position. ID = 1 corresponds to the explicitly rated attribute.

Table 6.8 is completed with the popularity of each attribute. The popularity for each attribute is determined as the frequency of demand per attribute among all the products. This results in table 6.9 are presented for the feature Color and the Green attribute. This table is defined as tab_{ranked} .

Table 6.8 Feature Color - Green : Ordered substitution degrees

ID	Color	Substitution degree
1	Green	1
2	Yellow	0.81
3	Blue	0.78
4	Orange	0.31
5	Mauve	0.30
6	Red	0.22

Table 6.9 Ranked table of substitution degrees with green - Feature Color

ID	Color	Substitution degree	Popularity
1	Green	1	400
2	Yellow	0.81	320
3	Blue	0.78	1030
4	Orange	0.31	503
5	Mauve	0.30	892
6	Red	0.22	987

We call att_{imp} the ID associated with the attribute to be implicitly rated. By selecting an ID from a table ranked based on the substitution degree, we draw a parallel with how different the attribute to be rated is from the explicitly rated attribute (Green). The higher the ID, the lower the substitution degree with the active attribute and vice versa .

att_{imp} is evaluated using equation 6.1 :

$$att_{imp} = \left\lfloor n(tab_{ranked}) * (1 - R) + 1 \right\rfloor \quad (6.1)$$

$\lfloor - \rfloor$: returns the closest integer,

$n(-)$: returns the length of the matrix (number of rows),

R : rating ratio of initial attribute from the R_i . The value of R ranges between 0 and 1,

tab_{ranked} is table with IDs, attributes, Substitution degree and popularity,

att_{imp} is the attribute associated to the ID.

For the initially selected attribute Green, the att_{imp} is evaluated as follows:

$att_{imp} = Round\left(6 * (1 - 0.8) + 1\right)$. Here, $att_{imp} = 2$, which corresponds to Yellow.

If the substitution degree of the att_{imp} selected is close to another attribute's substitution

degree (the two features may be equally preferred), we select the attribute with the highest popularity. Closeness is defined by domain experts for each feature. Attributes of a feature can be considered to be very similar if the differences in their substitution degree is lower than a range specified by experts. For the feature Color, domain experts consider an acceptable range of substitution degree difference equivalent to 0.25. Yellow and Blue are the only colors in the acceptable range. Since Blue has a higher popularity than Yellow. The selected attribute for the implicit appreciation is Blue.

The implicit appreciation A^* is the complement to the initial rating, and is assigned to the selected attribute, it is evaluated with equation 6.2:

$$A^* = 1 - R \quad (6.2)$$

The appreciation is assigned to the attribute Blue ($A^* = 1 - 0.8 = 0.2$). The position in E_1 corresponding to Blue is given the appreciation A^* as shown in table 6.10.

Table 6.10 Composition in progress of E_1 - implicit evaluation for feature Color

	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
E_1	P1	0.2	0	0.8	...	0	0.9	0	...	0	0.2	0	...

The ratings are deduced in the same manner for each explicitly rated attribute to complete an instance of E_i . Table 6.11 presents E_1 which is the first iteration of the E_i completed with implicit appreciations for all the rated features of product P1. Highlighted in bold, are the attributes that have been assigned an implicit appreciation, while the explicitly rated attributes are in italic.

Table 6.11 Complete E_1 for product 1

	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
E_1	P1	0.2	0	<i>0.8</i>	...	0	<i>0.9</i>	0.1	...	0	<i>0.2</i>	0.8	...

Each time a E_i is created it is stored in a table of exploration vectors E_{tab} .

Let us illustrate the construction of E . In the first iteration, E_{tab} is filled with one line. E is the mean E_i stored in E_{tab} . The mean of E_1 is itself thus $E = E_1$.

This vector is used to select the next product to be presented to the customer in step C section 6.4.2.3.3. Note that the remaining of this step is represented to explain how E is update at each iteration of this step.

Let's consider Table 6.12, following the same steps as for the creation of E_1 . First, the user rates the attributes of the second product that was presented to him (P2) then, implicit appreciations are deduced resulting in E_2 .

Table 6.12 Complete E_2 for product 2

	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
E_2	P2	0.9	<i>0.1</i>	0	...	0	0	0	...	<i>0.7</i>	0.3	0	...

Once E_2 is created, E_{tab} is updated and the second line is filled.

E is computed as the mean of nonzero observations of E_{tab} . Table 6.13 presents the resulting E for the first two products explored.

Table 6.13 Example of E - second iteration

Product	Color				Engine				Wheels			
	Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
E	0.55	0.1	0.8	...	0	0.9	0.45	...	0.7	0.25	0.8	...

A final version of E_{tab} would look like table 6.14, if all the products to explore were visited. Values in italic are the ratings explicitly given by the customer, those in bold are the implicit appreciations.

Table 6.14 Table of exploration vectors E_{tab} - Completed

E_i	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
E_1	P1	0.2	0	<i>0.8</i>	...	0	<i>0.9</i>	0.1	...	0	<i>0.2</i>	0.8	...
E_2	P2	0.9	<i>0.1</i>	0	...	0	0	0	...	<i>0.7</i>	0.3	0	...
E_3	P24	0	0	0	...	0	0	<i>0.8</i>	...	0	0	0	...
E_4	P18	0	0	0	...	0.1	0	0	...	0	0	<i>0.9</i>	...
E_5	P21	<i>0.9</i>	0	0.1	...	0	0	0	...	0	0	0	...

E is computed $N - 1$ times to select $N - 1$ products to present to the user (the first product is selected in phase 2 section 6.4.2.1).

Every time E is computed, we go to step C, to select the next product to present to the customer.

6.4.2.3.3 Step C: Select the next product to explore and create Customer Profile In this step, we select the next product to propose to the customer considering his anterior feedback (summarized in E). To evaluate which products correspond the best to the

customer, we compute the similarities between E (a vector of rating ratios, i.e. E presented in table 6.13) and all of the features' vectors (a binary vector representing the attributes of products, i.e. F_1 vector presented in table 6.5).

Those similarities are evaluated using cosine similarity. Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them (Gomaa and Fahmy, 2013). Pearson (Pearson, 1896) was not used since we only have one customer at a time, no bias needs to be considered. Cosine similarity formula is given by equation 6.3 .

$$\cos(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \cdot \|\mathbf{b}\|} = \frac{\sum_{i=1}^n \mathbf{a}_i \mathbf{b}_i}{\sqrt{\sum_{i=1}^n (\mathbf{a}_i)^2} \sqrt{\sum_{i=1}^n (\mathbf{b}_i)^2}} \quad (6.3)$$

With a and b being the two vectors between which we want to evaluate the similarity. a_i and b_i , represent the attributes of vector a and vector b respectively (i.e. E and F_2 features' vector of product P2).

Table 6.15 presents the table of similarity computed after the first iteration of E and each product available in-store (table 6.2).

Table 6.15 Table of similarities between first iteration of E and all F_i vectors of products available in-store.

Product	P1	P2	P7	P12	P13	P15	P18	P21	P24	P26	P28	P29
Similarity	0.221	0.678	0.53	0.37	0.65	0.39	0.43	0.19	0.321	0.54	0.09	0.14

We create table $tab_{ranked2}$ a ranked table of similarities based on table 6.15 and that includes estimated product demand shares, which are used to select the next product to present to the customer. $tab_{ranked2}$ is presented in table 6.16.

Table 6.16 Ranked table of similarities between first iteration of E and all F_i vectors of products available in-store with product demand shares

Product	P2	P13	P26	P7	P18	P15	P12	P24	P1	P21	P29	P28
Similarity	0.678	0.65	0.54	0.53	0.43	0.39	0.37	0.321	0.221	0.19	0.14	0.09
Demand Share	12%	3%	8%	4.5%	0.8%	0.5%	15%	2.4%	21.2%	13%	19%	2%

In order to evaluate which product to present to the customer we select the product with highest demand share within an acceptable range of similarity with E . The assumption here is the same as in **step B** section 6.4.2.3.2, domain experts set a maximum acceptable range in which products are considered to have close similarities with E .

Based on table 6.15, product P2 is selected. Then we consider Table 6.16 to take demand shares into consideration. Domain experts set the acceptable similarity range to 0.15. We

evaluate whether other products in that similarity range compared to the similarity of P2 have higher demand shares. Table 6.16 presents no products similar to product P2 with higher demand shares within the acceptable similarity range. Thus, Product P2 is the next product to be presented to the customer at **step B**, section 6.4.2.3.2.

The selected product is used as an input in **step B** until N products have been iteratively visited. As mentioned in step B section 6.4.2.3.2, each time a product is visited and rated, a line is added to R_{tab} creating a table of all explicit feedback generated during the exploration phase. Besides, each time a product is presented to the customer, it is removed from table 6.2 of products in store, so no product is visited twice.

Once the N products have been explored, we create a customer profile that is based on all the explicit feedback generated during this phase. **Customer profile (CP)** is the mean of nonzero explicit ratings of R_{tab} .

For our demonstration, the last iteration of R_{tab} is presented in table 6.17 and CP is presented in table 6.18.

Table 6.17 Preference vectors table - R_{tab} - Completed

R_i	P	Color				Engine				Wheels			
		Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
R_1	P1	0	0	0.8	...	0	0.9	0	...	0	0.2	0	...
R_2	P2	0	0.1	0	...	0	0	0	...	0.7	0	0	...
R_3	P24	0	0	0	...	0	0	0.8	...	0	0	0	...
R_4	P18	0	0	0	...	0	0	0	...	0	0	0.9	...
R_5	P21	0.9	0	0	...	0	0	0	...	0	0	0	...
R_6	P7	0	0	0	...	0.1	0	0	...	0	0	0	...

Table 6.18 Customer Profile (CP)

CP	Color				Engine				Wheels			
	Blue	Yellow	Green	...	800	1000	1500	...	Titan	Bronze	Silver	...
CP	0.9	0.1	0.8	...	0.1	0.9	0.8	...	0.7	0.2	0.9	...

Once the customer profile (CP) is created, we go to **stage 3** section 6.4.3.

6.4.3 Stage 3: Constraint-based recommendation

This phase is the contextualization of the recommendation output. We start by making recommendations with no consideration for the context. Then, the resulting recommendation list is adjusted (contextualized) for each customer using the contextual information Adomavicius and Tuzhilin (2011).

Contextualization here is based on an adaptation of the concept of product availability ratio (PAR). The concept is introduced by (Montreuil and Derhami, 2019), as a customer-centric demand-driven performance indicator. It was developed to measure the current readiness of a dealer to satisfy demand for the forthcoming customers. It shows the availability of each product or an acceptable substitute in its inventory or by shipment in acceptable time from another dealer or from another replenishment site. That indicator is especially relevant for high end products such as cars or boats. Product availability ratio takes into consideration six aspects as presented in (Montreuil and Derhami, 2019):

Customer Willingness to wait: The expected proportion of customers willing to wait up to a given time to receive their requested product.

Network Availability: Acceptable alternatives available at the dealer, other dealers, depots or factories.

Customer Buying Probability: Probability that a customer will buy a substitute product given substitution fitness between the requested and offered product.

Showcasing-based Consideration Probability: Probability that a customer will buy a targeted substitute product out-of-stock at the dealer given the model showcasing at the dealer.

Substitution Inertia Exclude similar items that do not increase customer satisfaction enough to justify longer inventory transshipment for dealers. Shelf-time (duration of time in inventory) is also considered. A dealer who knows that he will be able to sell a product and obtain a full profit may be reluctant to agree to a transshipment.

Product Demand Share Current expected probability that a forthcoming customer would request a specific product out of all products in the portfolio.

Evaluation of PAR is presented in detail in (Montreuil and Derhami, 2019).

The constraint-based recommendation stage is composed of **phase 5** section 6.4.3.1 and **phase 6** section 6.4.3.2.

6.4.3.1 Phase 5- Content-based recommendation

In this step, recommendation is computed using content-based recommendation technique between the Customer profile (CP) generated at the interactive exploration stage section 6.4.2 and all products available in the **accessible** network inventory. Accessibility in this step is defined as the ability to ship a product in the time window (TW) that the customer is willing to wait (evaluated section 6.4.1.1). Filtering the products that cannot be sold, lowers the computational costs for similarities.

Cosine similarity computation is made in the same manner as in **section C** by replacing E with CP , resulting in a similarity table as shown in Table 6.19. Products' scores are equivalent to product similarities. Table 6.20 presents the initial recommendation table of the top N products and their recommendation scores (similarities with CP).

Table 6.19 Table of similarities between the customer profile CP and the feature vector F_i for all the products available in the network

Product	P1	P2	P3	P4	P5	P6	P7	...	P29	P30
Similarity	0.34	0.65	0.39	0.37	0.20	0.321	0.69	...	0.54	0.87

Once the similarities are computed, we rank table 6.19 and select the top N rated products to create the initial recommendation table presented in table 6.20

Table 6.20 Initial recommendation table with scores for $N = 5$

Product	Score
P30	0.87
P8	0.76
P7	0.69
P20	0.59
P15	0.57

Once the initial scores are computed, other aspects of the PAR need to be evaluated to assess the capacity of the network to deliver the product in an acceptable time window as presented in **Phase 6** section 6.4.3.2.

6.4.3.2 Phase 6- Context-aware recommendation adjustment

In this phase, showcasing-based probability of sale, substitution inertia of dealers and product demand share are computed as a ratio for each product from the recommendation list. Ratings are adjusted by multiplying recommendation initial recommendation scores and PAR ratios. Top N recommendations for the customer are re-ranked based on their new ratings. If the product is in-store, the PAR ratio is 100%, which would not affect the recommendation score; otherwise, the recommendation score is lowered based on the product availability ratio.

Table 6.21 presents the adjusted scores considering the PAR ratio for each product.

The dealer gets a recommendation list ranked from the most likely to be sold due to its availability in the acceptable time window required by the customer. The dealer decides which of the products from the ranked table he should recommend to the client. In this case, dealer will recommend product P7 since it is an in-store product that has the highest recommendation score.

Table 6.21 Recommendation table with PAR and adjusted scores

Product	Score	PAR	Adjusted Score
P7	0.69	1	0.69
P15	0.57	1	0.57
P20	0.59	0.9	0.531
P8	0.76	0.60	0.456
P30	0.87	0.23	0.20

6.5 Computational performance:

Our proposition has been validated with the data of our industrial partner and the recommendations that have been generated are plausible. Due to confidentiality reasons, the data cannot be published.

We validated our model on a network of about 1000 dealerships, about 350 vehicles, more than 100,000 sales were considered to evaluate the popularity and product availability ratio. - Similarities between products ranged between 0.05 and 0.98. - 136 attributes were considered for 7 features.

The computation time on a processor **intel® Core™ i7-45100 CPU @ 2.00GHz 2.60 GHz** in **Rstudio** for the product selection at the exploration phase is 0.108866 secs for each set of acquired ratings and the final recommendation time is 0.91308 secs. Thus, our method can be implemented in store and it generates quasi-instant recommendations while creating a learning base.

6.6 Conclusion

The proposed work presents a context-aware interactive knowledge-based recommendation in-store. The focus is to help make a recommendation to customers in a context where no information about the client is available and product availability often depends on the supply network. The proposed recommender system not only evaluates customers' interests, but also the dealer's capability to fill the demand for products based on customers requirements and the state of the supply network. We validated the feasibility of our proposition on our industrial partners' data. Recommendations created by the system are consistent with users' feedback. We believe the recommendations will facilitate interaction with the client and increase the chances of recommending products satisfying the needs and expectations of that particular customer and inducing with high chance a potential sale. The system can be implemented using mobile devices such as tablets and smartphones, since no high computation cost is necessary. Customers can use the tablets with the dealer and explore the

products together or they can be directed in the retail store site by the tablet to explore the products when the dealer is unavailable due to high demand. This paper falls in the same category as our previous work Dadouchi and Agard (2018), in which we attempt to adjust recommender systems to not only focus on commercial interests of the customers, but also take into consideration industrial constraints, here supply chain constraints.

The presented recommender system has the same limitation as all knowledge-based recommender systems, the so-called knowledge acquisition bottleneck in the sense that knowledge engineers must work hard to convert the knowledge possessed by domain experts into formal, executable representations such as the differentiation between discriminant features and appreciable features or the creation of the similarity matrices needed for the implementation of the method Felfernig (2007).

The presented recommender system is highly dependent on the availability and the validity of the similarity matrices between attributes of each feature. Another limitation is related to the retrieval of customers' appreciation for features; we used the exact rating the customer gave us, using fuzzy logic to assess customers' interest could have been a better choice since appreciation is not a precise value. Also, based on the fact that our purpose is to create a learning base and that it is supposed to work when no available data about the customer exists, testing our method cannot be done by comparing it to other algorithms on a historical database that does not exist. The only efficient way is to implement it in-store and assess a dealer's feedback about the system.

Further work would be to valorise the data created by the system while making recommendations and evaluating the output of the interaction. Information about lost sales could be retrieved, making future predictions of demand more accurate. Demand for features could be evaluated and used to help in product design. Data created by the system could also be used as a learning base to tune the existing recommender system or to switch to a more performant recommendation technique once the cold start issue has been overcome.

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CHAPITRE 7 DISCUSSION GÉNÉRALE

La problématique de cette thèse a été d'améliorer l'adaptabilité des systèmes de recommandation pour tenir compte de la capacité de la chaîne logistique à satisfaire la demande qu'ils induisent.

La problématique globale de la thèse a été traitée en trois sous-problèmes qui ont mené à trois contributions. Chacune, proposant une méthode appliquée à un exemple qui illustre l'implémentation de celle-ci. La première contribution est publiée tandis que les deux autres sont soumises à des journaux. Les deux premières contributions ont présenté des méthodes pour adapter un système de recommandation existant à des contraintes logistiques différentes, à savoir : le niveau d'inventaire des produits et l'état du réseau de distribution. La troisième et dernière contribution présente un système de recommandation adapté à un contexte de vente stationnaire présentant un problème de démarrage à froid. Le système de recommandation proposé considère également le ratio de disponibilité des produits dans la sélection des produits à recommander.

Tel qu'énoncé dans la littérature, malgré l'existence de plusieurs techniques de recommandation et le développement d'algorithmes de plus en plus performants au niveau de la prédiction des intérêts des clients, très peu de recherches se sont penchées sur la prise en compte de facteurs apportant des améliorations autres qu'une meilleure précision des prédictions. De plus, au meilleur de nos connaissances, aucune recherche ne traite la problématique de la capacité à répondre à la demande liée aux recommandations de produits. Plus spécifiquement aucune recherche ne tient compte de l'état de la chaîne logistique dans la recommandation de produits. Ignorer l'état du réseau et le niveau d'inventaire des produits lors de la recommandation revient à ignorer la capacité de réponse à la demande, ce qui peut impacter l'image de marque de l'entreprise et mener à des pertes de rentabilité due à la non-satisfaction des clients (disponibilité de produit, délais de livraison, coûts de livraison), si cette demande ne peut être pourvue. Le rapport présenté par le CEFRIO présente les enjeux de la logistique pour les entreprises de vente en ligne québécoise et met à l'avant trois points cruciaux qui représentent un défi pour l'entreprise québécoise soit : les délais de livraison, la variabilité de la demande et les frais de livraisons Beaudoin et al. (2018). Des enjeux dont nous avons tenu compte dans nos contributions.

La première contribution présentée au chapitre 4 a démontré comment tenir compte de la capacité à répondre à la demande dans la recommandation de produits en les priorisant en fonction de leurs niveaux d'inventaire et de la valeur à long terme du client pour lequel la

recommandation est performée. La méthode proposée dans cette contribution s'est articulée autour de deux phases ; la première phase a été la catégorisation des clients qui s'est basée sur l'historique des ventes et qui a permis d'évaluer la valeur à long terme des clients. La seconde phase a permis d'intégrer une stratégie d'assignation des stocks en se basant sur la catégorie du client actif évaluée à la première phase et le **niveau d'inventaire** des produits, pour ajuster les listes de recommandations de produit. La stratégie utilisée pour cette contribution, a été d'une part, de recommander les produits ayant un faible inventaire uniquement aux clients dont la valeur à long terme a été considérée comme étant élevée, et d'autre part, à recommander plus agressivement les produits à inventaire élevé à tous les utilisateurs. En effet, plus le niveau d'inventaire excède le niveau d'inventaire prévu à une période donnée, plus les recommandations pour ces produits sont agressives. Les résultats des analyses menées sur des données simulées ont démontré que les pénalités résultant de la recommandation de produits en rupture de stock ont été réduites, car les clients dont l'impact est le plus coûteux sont les derniers à subir les ruptures de stock. La méthode a également permis de maximiser les chances d'écoulement des stocks en tentant de diriger la demande vers les produits en excès de stock. Cette contribution permet donc de limiter l'impact de la **variabilité de la demande** dont souffre l'entreprise québécoise.

Pour la deuxième contribution, présentée au chapitre 5, nous avons tenté de considérer d'autres enjeux de la logistique contemporaine qui sont **le délai et le coût de livraison**. Cette contribution nous a permis de proposer une méthodologie d'ajustement de scores de recommandation en fonction de la disponibilité de produits à livraison rapide. En appliquant la méthode, on se retrouve avec des listes de recommandations de produits tenant compte de la capacité à répondre à la demande dans des délais de livraison rapide et à un coût rentable. La méthode développée suit deux étapes : la première étape est le calcul de la recommandation avec algorithme classique de la littérature, et la seconde étape est l'ajustement des scores de recommandation en 4 phases : (1) l'évaluation des camions en activité, (2) l'évaluation des contraintes physiques de transport, (3) l'évaluation des bénéfices associés à l'ajout de points de collecte et/ou de livraison à une tournée programmée pour chaque article recommandé et (4) l'ajustement des scores de recommandation. Seuls les produits générant un profit considéré comme étant acceptable ont été recommandés en priorité aux clients. Les résultats de ce chapitre ont permis de démontrer sur des données simulées que la méthode proposée augmente le nombre de produits dans la liste de recommandation pour lesquels une livraison est possible dans un délai préétabli. D'autres retombées possibles de la méthode, si l'utilisateur choisit de suivre la recommandation, sont l'amélioration du taux de remplissage des camions, une augmentation de la satisfaction client liée à des délais de livraison courts, une meilleure compétitivité de l'entreprise.

Enfin, la troisième contribution présentée au chapitre 6 a permis d'intégrer plusieurs contraintes logistiques dans la recommandation de produits à travers le développement d'un système de recommandation capable de performer dans un contexte de démarrage à froid. Nous avons appliqué notre méthode sur des données réelles, en tenant compte de **la disponibilité des produits à recommander en contexte de vente stationnaire**. Dans ce chapitre une nouvelle technique de recommandation interactive basée sur les connaissances et sensible au contexte est développée. Cette technique a été élaborée pour une utilisation en contexte de vente stationnaire. Elle a été pensée pour créer une base d'apprentissage des profils de clients dans un contexte de démarrage à froid. La méthode débute par une première phase de préfiltrage basée sur le contexte, elle se poursuit avec une étape d'exploration interactive des produits en magasin et se clôt par une recommandation basée sur les contraintes logistiques. Le système de recommandation proposé évalue non seulement les intérêts des clients, mais également la capacité du revendeur à répondre à la demande en fonction des besoins des clients et de l'état du réseau d'approvisionnement. Nous avons validé la faisabilité de notre proposition sur les données de notre partenaire industriel. Les recommandations fournies par le système sont cohérentes avec les appréciations fournies par les utilisateurs. De ce fait, nous pensons que le système de recommandation proposé facilitera l'interaction entre le vendeur et le client et augmentera les chances de recommander des produits susceptibles d'être vendus de façon personnalisée à chaque client utilisant le système.

Les trois contributions ont permis de fournir des solutions concrètes à la prise en compte de la capacité de répondre à la demande, en fonction des contraintes logistiques, dans la recommandation de produits. Dans les deux premières contributions, à travers l'ajustement des scores de systèmes de recommandations existants. Dans la troisième contribution, à travers le développement d'une nouvelle technique de recommandation interactive.

À travers cette thèse nous avons démontré les avantages de la prise en compte des contraintes logistiques dans la recommandation de produits. La principale force de cette proposition est qu'elle tient compte de l'effet induit par le système de recommandation sur la demande et par conséquent sur la chaîne logistique. La méthode est bénéfique pour les systèmes de recommandations, car ils présentent uniquement des produits dont la demande peut être comblée, tout en étant bénéfiques pour la chaîne logistique qui peut utiliser les SRs comme un outil permettant d'influencer la demande pour régler des problèmes opérationnels de façon réactive.

CHAPITRE 8 CONCLUSION ET RECOMMANDATIONS

Dans cette thèse, nous avons présenté un état de l'art sur les systèmes de recommandations dans lequel nous avons identifié qu'une des limites des systèmes de recommandations est qu'ils ne tiennent pas compte des contraintes logistiques qui influencent la capacité à répondre à la demande qu'ils induisent. Pour répondre à cette problématique, nous avons présenté trois sous problématiques. La première considère la disponibilité des produits en inventaire en contexte de e-commerce. La deuxième considère la capacité de livraison des produits, en fonction des tournées de véhicules programmées dans une fenêtre de temps donnée, en contexte de e-commerce. La troisième considère la disponibilité des produits en fonction du réseau d'approvisionnement, en contexte de vente stationnaire. Pour chacune des sous-problématiques, nous avons proposé une méthodologie présentant une solution qui a été implémentée sur des données réelles ou simulées. Dans cette section nous ferons une synthèse des contributions de cette thèse, présenterons les limites de chacune des solutions proposées et quelques perspectives de travaux futurs.

Dans la première contribution de cette thèse, nous avons présenté une approche qui consiste à tenir compte de la capacité du système de recommandation à répondre à la demande en fonction des niveaux d'inventaires des produits. La méthode tient également compte de l'importance perçue des clients pour l'entreprise lors de l'ajustement des scores de recommandation pour influencer l'assignation des stocks à travers la réorientation personnalisée de la demande. En utilisant la méthode proposée dans cette contribution, nous avons pu prévenir ou retarder l'occurrence de rupture de stock et limiter leurs impacts sur l'entreprise. La méthode permet également de favoriser l'écoulement des produits en excès de stock.

Les limites de cette contribution sont liées à la dépendance de la méthode envers la fiabilité des recommandations initiales utilisées et envers la fiabilité des données liées à la gestion de l'inventaire. Le choix de la technique de recommandation a une influence directe sur l'utilité des recommandations pour l'utilisateur et donc sur l'impact des recommandations sur la demande. De plus, la méthode proposée dépend grandement de l'accès à l'information sur l'état des stocks en temps réel. Si cette information est inexistante ou que les données recueillies ne sont pas fiables, la méthode proposée ne peut être utilisée. L'utilisation non adéquate de paramètres de stocks de sécurités et de prévisions de consommation des stocks, peut également mener à des ajustements de recommandations inutiles qui risquent de réduire la précision des systèmes de recommandation, sans améliorer la performance opérationnelle de la chaîne logistique.

La deuxième contribution tient compte de la capacité du système de recommandation à répondre à la demande en fonction de la capacité de livraison des produits en tenant compte des tournées de véhicules programmées dans une fenêtre de temps donnée, en contexte de e-commerce. La méthode permet de réorienter la demande vers des produits pouvant être livrés en tenant compte de contraintes de temps, de distance et de profit en utilisant le VRP. Elle permet également de présenter des listes de recommandation avec un ratio de produits ayant un potentiel de livraisons rapides et rentables plus élevé.

Parmi les limites de cette contribution on trouve que les résultats de la méthode dépendent grandement de la capacité à évaluer la rentabilité des livraisons à travers l'utilisation des VRP, ce qui implique que la précision de la méthode dépend de la précision des calculs de VRP. De plus, étant donné que les recommandations de produits se font en temps réel, il est nécessaire d'utiliser des méthodes de calcul de VRP induisant un temps de calcul très faible. Plusieurs recherches récentes tentent d'améliorer les temps de calcul des VRP telles celles présentées par Benaini et al. (2017) et par Rey et al. (2018).

La dernière contribution de cette thèse a traité de la capacité à répondre à la demande dans un contexte de recommandation différent des deux contributions précédentes. En effet, nous nous sommes positionnés dans un contexte de vente stationnaire présentant un problème de démarrage à froid lié à un manque d'informations sur les clients. Un problème réel auquel fait face notre partenaire industriel. Dans cette contribution nous avons développé un système de recommandations interactif, basé sur la connaissance et sensible au contexte logistique. Le système de recommandation proposé permet non seulement de tenir compte de la capacité du réseau d'approvisionnement à répondre à la demande, mais également d'apporter une solution au démarrage à froid tout en tenant compte du ratio de disponibilité des produits. Les données recueillies lors du processus d'exploration permettent également de bâtir une base d'apprentissage sur les clients. Base qui peut être valorisée par la suite et qui peut permettre d'améliorer la recommandation. Un prototype du système de recommandation a été implémenté sur les données de notre partenaire industriel. La première limite de cette contribution est que les données d'entrées nécessaires à son implémentation se basent sur des connaissances métier. Or, la formalisation des connaissances métier en données exploitables est une tâche reconnue comme étant complexe (Felfernig, 2007). Une autre limite de cette méthode est que les appréciations des utilisateurs pour les caractéristiques des produits, ont été recueillies en logique classique (notes exactes) or, les appréciations fournies par les clients devraient être considérées de façon plus flexible, car les intérêts des utilisateurs sont souvent imprécis et peuvent varier au fur et à mesure qu'ils découvrent d'autres attributs. L'utilisation de la logique floue pour évaluer les attributs des produits pourrait être une solution intéressante.

De façon globale, la contribution de cette thèse a été de proposer un nouveau cadre d'analyse des systèmes de recommandation afin de les améliorer en tenant compte de certaines contraintes logistiques considérées importantes dans un marché où la compétitivité passe par l'efficacité logistique. L'amélioration des systèmes de recommandation pour tenir compte des contraintes logistiques permet également d'augmenter l'agilité de la chaîne logistique. En effet, les systèmes de recommandation peuvent être utilisés comme un outil permettant d'être réactif face aux incertitudes liées à la demande en la réorientant pour améliorer la performance opérationnelle de la chaîne logistique.

Cependant, cette approche globale présente des limites. En effet, l'impact des ajustements de recommandation sur les ventes reste inconnu, malgré le fait que nous avons démontré au chapitre 4 que l'impact sur les scores de recommandation est faible, nous ne pouvons prédire l'impact réel sur les recommandations converties en ventes. En effet, les jeux de données existants en systèmes de recommandations pour l'évaluation des performances se tournent principalement sur des données dont les items ne sont pas des objets physiques et ne contiennent pas de données sur la logistique et la gestion des inventaires, rendant la contribution scientifique des modèles proposés très difficile à évaluer. Aussi, en utilisant les modèles proposés et en réorientant la demande il est possible d'affecter l'ordonnancement des opérations en affectant la capacité à prédire la demande de façon convenable. Relativement au cas d'application, l'ajustement des scores de recommandation reste lié au secteur d'activité de l'entreprise qui souhaite l'implémenter de la même façon que le choix du système de recommandation utilisé. Il est donc important de bien choisir le système de recommandation à utiliser ainsi que de bien choisir l'ajustement à apporter pour impacter positivement l'agilité de la chaîne logistique.

Au niveau des perspectives liées à la première contribution, il serait intéressant de trouver une meilleure façon d'évaluer les alternatives de produits à proposer aux utilisateurs du système. En effet, le chapitre 4 propose de choisir le prochain item sur la liste de recommandation, cependant, le choix de l'alternative pourrait se baser sur la prise en compte de similarités en terme de fonctionnalité de produits, de similarités au niveau des attributs des produits qui pourraient inclure la famille de produits ou la marque du produit. Cette perspective pourrait systématiser le choix de l'alternative à proposer au client et améliorer les chances de conversion de la recommandation en demande. De plus, l'ajustement des recommandations dans cette contribution tient compte uniquement des catégories de clients et des informations sur les stocks des produits ; or, de nombreuses autres contraintes liées à la chaîne logistique pourraient être prises en compte, telles que les contraintes logistiques sur l'emplacement des stocks, la contrainte de capacité de stockage des entrepôts, les tendances des prix des matières premières, les marges de profits des produits, etc.

Dans la deuxième contribution, il serait intéressant d'utiliser un VRP dynamique pour l'évaluation des profits liés à l'ajout d'un produit à livrer à une tournée existante. En effet, notre évaluation du profit est estimée en utilisant un VRP statique qui évalue le profit marginal à travers la réévaluation du coup de la tournée en tenant compte des changements liés à l'ajout d'un produit à une tournée existante (ajout d'un point de cueillette et d'un point de livraison). La méthode pourrait également favoriser les recommandations non seulement en fonction du profit potentiel lié à un achat dans une seule fenêtre de temps, mais également comparer les profits dans d'autres fenêtres de temps. Afin que le calcul des profits liés aux ventes des produits recommandés soit plus précis, il serait également intéressant d'y considérer les profits intangibles dont la compagnie bénéficiera au niveau de sa rétention de clients et de son image de marque.

Pour ce qui est de la troisième contribution proposée, de futurs travaux avec notre partenaire industriel seraient envisageables au niveau de la valorisation des données recueillies. Le croisement et la valorisation des données sur les clients, sur les recommandations et sur les ventes permettraient entre autres de développer des connaissances en rapport avec l'efficacité des recommandations et la réduction des ventes perdues. Ces données pourraient également être utilisées pour améliorer les prévisions de la demande en tenant compte des ventes perdues et pour améliorer le système de recommandation. La valorisation des données sur les appréciations des attributs pourrait également aider à la conception de nouveaux modèles de produits.

De manière générale, cette thèse présente une manière de tenir compte de la capacité à répondre à la demande dans la recommandation de produits et de participer à l'amélioration de la chaîne logistique à travers la création d'un moyen pour réorienter la demande en tenant compte des contraintes logistiques au niveau opérationnel. Cependant, cette méthode ne permet pas de déterminer les contraintes dont il faut tenir compte en fonction de l'environnement de recommandation et du secteur d'activité pour l'évaluation de la capacité à répondre à la demande. Déterminer les contraintes pertinentes de façon systématique afin de les intégrer dans la recommandation serait un bel ajout à ce travail. De plus, nous avons considéré les ajustements de scores de façon équivalente, indépendamment de la contrainte prise en compte, or, cela n'est pas nécessairement vrai en fonction de l'importance de la contrainte dans le contexte d'application.

La méthodologie proposée dans cette thèse a été validée au travers des trois contributions par des exemples appliqués à des données simulées pour les deux premières contributions et à des données réelles pour la dernière contribution. De ce fait, nous avons répondu à l'objectif général de la thèse qui est d'améliorer l'adaptabilité des systèmes de recommandation au

contexte logistique dans lequel ils sont utilisés à travers trois contributions soit l'intégration des contraintes liées au niveau d'inventaire, de contraintes liés aux tournées de véhicules planifiées et aux contraintes liées à la disponibilité des produits dans le réseau.

Nous avons également tenu compte du contexte de vente en ligne et du contexte de vente stationnaire. La méthode proposée reste tout de même limitée par le contexte dans laquelle elle a été développée (vente de détail) et requièrent plus de raffinements et de tests pour pouvoir être exploitée dans d'autres contextes de recommandations.

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