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Considering quasi-real time delivery information in product recommendation

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Abstract. Recommender systems are used in a wide range of applications, such as news, e-learning and travel recommendations. In e-commerce, they have become necessary because of the high diversity of products. Current recommender systems do not consider supply chain constraints in product recommendations. This paper presents a first approach to the consideration of delivery constraints, such as scheduled deliveries, remaining capacity and the physical constraints of items in product recommendations. A methodology and individual case study are presented in this paper.

Keywords: Recommender systems, delivery scheduling, context-aware recommendation, supply chain.

1. Introduction

In the past decade, recommender systems have been largely used by retail companies to promote their products and to increase sales. Studies have shown that recommender systems can be responsible for up to 35% of online sales [22]. Research in the domain of recommendation in general has attracted a lot of interest, especially regarding the accuracy of recommendations. However, very little work has been done concerning the consideration of supply chain constraints in product recommendations [1]. In today's global markets, customers have heightened expectations about companies' services, expecting shorter lead-times and cheaper delivery costs [2]. In order for companies to be able to meet customers' requirements, recommendations that are made should consider the capacity of the network to deliver products to the customer during a defined time window. This paper presents a first approach into the consideration of delivery constraints such as scheduled deliveries, remaining capacities and delivery constraints in product recommendations. The remainder of this paper is structured as follows: Section 2 presents the state of the art regarding recommender systems and delivery constraints in a supply chain. Section 3 presents the problem definition, followed by section 4 with a proposed method depicted in six stages. Section 5 presents a case study. A conclusion is presented in section 5.

2. State of the art

2.1. Recommender systems

Recommender systems are tools that help users receive personalised content to address the problem of information overload. They have been defined as programs that predict a user's interest in an item based on related information about the items, the users and the interactions between items and users [3]. Many approaches and techniques have been presented in classical literature, the most widely used and accepted ones divide them into (a) collaborative filtering, (b) content-based filtering and, (c) hybrid filtering [4], [5], [6].

Collaborative filtering (CF) is a literature choice for e-commerce recommendations [7] and is based on the assumption that a person is more likely to have preferences that are similar to those of people that are considered similar to the active user. CF is usually categorised into memory-based collaborative filtering and model based collaborative filtering, and requires data on the users [3].

Content-based recommender systems (CBF) are based on the characteristics of the products or services consumed by the user [8]; these use data about item descriptions and characteristics and do not require information about the user.

Hybrid recommender systems commonly use both content-based filtering and collaborative filtering, [9] presents seven classes of hybrid recommendation techniques.

Other recommendation techniques have also been developed and are presented in a survey from [3], the methods usually consider social, demographic or contextual data. [3] also presents a hierarchy of data used for the computation of product recommendations. Although a variety of data has been used to compute recommendations, to the best of our knowledge no previous work has considered quasi-real time information about the network state and delivery constraints in product recommendations.

2.2. Delivery constraints in the supply chain

Using e-commerce as a channel for distribution has increased complexity with regards to delivery services. Clients have a variety of options for buying products and can easily switch from one retailer to another, which makes client retention complex. A recent report [10] states that the speed of delivery as well as the rapid availability of products are the main expectations of more than one in two consumers. The efficiency of delivery has become a necessity to be competitive and survive in market conditions [11].

Delivering products to a customer in a time frame that is considered acceptable to the customer is not a new problem; a lot of research is being conducted to minimize both costs and lead-time, whether that is by using traditional pick-up and delivery problems by considering a dedicated fleet [12] or more recent approaches, such as considering crowdsourced and real-time deliveries [13].

Many constraints need to be considered to evaluate the cost of delivering to a customer [14]. Some of the constraints are: the availability and the number of vehicles, the number and locations of pick-up and delivery points, the time windows for delivery, the precision of the time of delivery, physical constraints of products, the capacity of the vehicles, travel distance, vehicle-supported physical constraints, and more.

The delivery problem in e-commerce is usually presented as the dynamic routing problem (DVRP) with pick-up delivery and capacity constraints in a given time. A variety of solutions to this problem have been presented in the literature; depending on the size of the problem, the solution can be optimal or can be found using meta heuristics and heuristics. Solutions obtained through the Dantzig-Wolfe decomposition are leading the field [15]. Near-optimal solutions have also been found using [16],[17],[18],[19],[20].

Results vary in terms of accuracy and computational time and cost [21]. Many techniques are available to compute recommendations and vehicle routing problems with regards to computational time, cost and accuracy. However, a literature review shows that, although recommender systems and delivery problems are well known fields in the literature, these two fields do not intercept.

3. Problem definition

This paper addresses the problem of considering delivery constraints in product recommendations for online retail. The objective is to present recommendation lists that take into consideration the time frame and costs in which the product can be delivered without using additional resources.

In order for the delivery constraints to be considered in recommendations, an evaluation of potential profits from vehicle routing problems need to be performed in a hidden time during the computation of recommendations.

We define the parties involved in the problem as follows:

Customers: clients that made previous purchases or that are known by the company.

Transporters: parties responsible for freight transport (vehicles).

Warehouses: Pick-up points for the retrieval of items.

Delivery points: addresses for deliveries of items.

Delivery list: time and location for picking up and delivering items with required quantities.
Distribution tours: Scheduled paths for pick-ups and deliveries.
For the purpose of this paper, we will consider that pick-ups and deliveries are made by trucks and that the recommendations are performed using collaborative filtering.

4. Methodology

The proposed method is presented in figure 1 and follows four phases. The process starts when a user logs into the system. Recommendation scores are computed for the active user in phase 1. From the ranked recommended items, a list of the top X items with their scores are to be used in the remainder of the phases. Phase 2 considers a user's location and evaluates, from a list of vehicles that have been scheduled, which ones are within a given radius of a user's location. For the active trucks, those that cannot be used to ship the items from the recommendation are removed from the list of active trucks. Phase 3 evaluates potential profits that may result from the pick-up and deliveries of each of the X items of the recommendation list. Phase 4 adjusts the recommendation list scores for the items that can be delivered to the active user with a positive profit. The phases are detailed in the remainder of this section.

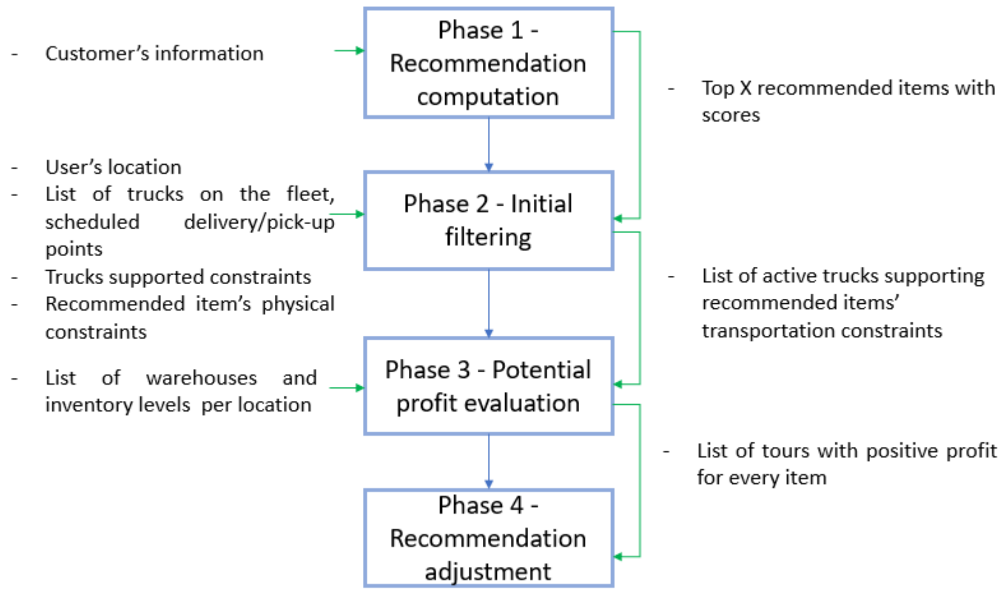

Figure 1 : Methodology for recommendation adjustment based on scheduled tours

4.1. Phase 1: Recommendation computation

In this step, the traditional recommendation process applies. Information about the active user is retrieved and used to compute the utilities of each item in the catalogue.

Input data:
User's information
Input parameter:
Number of items X: top X items (*i*) to consider for recommendation adjustments.

A user profile is created based on all available data about the active user (historical purchases, location, demographic information, social media, clickstream.) Afterwards, recommendations are computed using any recommendation technique that results in a score for each item.
As stated in section 2, collaborative filtering is a state-of-the-art approach for product recommendations in e-commerce, thus, they are used to evaluate the utility of each item for the active user.

Collaborative filtering generates a list of items with the utility of each item for the active user. From the ranked list of the item's utilities, we select the top X items to consider in the remaining phases.

4.2. Phase 2: Initial filtering

In this step, we evaluate which of the products could be delivered within a given time window and radius to the active user, considering the available resources and transportation constraints. If a user's location is unknown and cannot be retrieved, initial recommendation scores are kept unchanged and the remainder of the method does not apply.

Input parameters:

- *Maximum radius (P):* The maximum radius from which a product can be picked-up or from which a truck can be assigned to the delivery,
- *Time window (TW):* The period of time in which the scheduled tour is considered.

Input data:

A user's location, scheduled pick-up/delivery points, the support constraints of trucks, the physical constraints of recommended items.

Considering the input data, a first filter is applied to pick out the trucks that are considered to be close enough to the active user with regards to P and TW. P and TW are defined based on the business environment of the company by implementing the proposed method.

Once the active trucks are selected, a matrix is computed to evaluate the compatibility between the physical constraints of X items from the recommendation list and the vehicles' supported constraints.

There are various physical constraints considered for **items** (*i*), such as: an item's weight, volume, shape, fragility, perishability, need to be placed in a specific orientation, environmental requirements, and more.

Vehicles (*t*) can be characterized by their capacity, configuration of the loading space and unloading possibilities, temperatures, humidity, and more.

This phase is computed to avoid considering all of the constraints in the routing problem for profit evaluation, making it easier and faster to compute. Items that cannot be delivered are not considered in the following phases.

4.3. Phase 3: Potential profit evaluation

Once the X recommended items that could be transported using the active trucks are filtered, we evaluate the availability of the items in the inventory and the location of the warehouses in which each item is available.

Input data: List of warehouses (*e*) and inventory level per item.

The vehicle routing problem (VRP) is considered for profit evaluation. Since the problem has constraints related to pick-ups and deliveries, capacity and time windows with consideration of fixed and variable costs, we propose using a dynamic routing problem (DVRP).

For each item *i* from the filtered recommendation list, we evaluate the marginal profit of adding that item to the already scheduled tour by evaluating the cost of the new tour and subtracting the initial cost of the tour. We consider a pessimistic scenario, in which the user potentially buys one item at a time to evaluate the potential profit and the marginal profit. The marginal profit of adding item *i* from the warehouse *e* in the active truck *t* is evaluated using formula (1).

$$P_{\mathrm{Marginal}} = P_{i;e;t} - P_{\mathrm{init}} \tag{1}$$

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

$P_{i;e;t}$ is 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 phase 2.

4.4. Phase 4: Recommendation adjustment

Once all marginal profits for each item have been calculated, the recommendations are adjusted considering the best potential profit per item. In order to adjust the scores, a threshold P_{min} representing the minimum acceptable profit for a company to update its scheduled tour should be set. The adjusted recommendation score is computed using equation (2)

$$\textit{Adjusted Recommendation score} = \beta.\ \textit{Initial Recommendation score} \quad (2)$$

with $\beta = P_{Marginal}/P_{min}$
β always being superior to 1, if not, the recommendation score remains unchanged since the profit is considered low when considering a company's strategy. The higher that β is, the stronger the priority of the item in the recommendation list and the higher its visibility to 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 of the scores may be low.
Once the scores are adjusted, Y items with the best scores are selected and recommended to the active user. The proposed method never deteriorates the current situation and the effect on logistics and sales is either an improvement or none. If the recommendation is followed by the user, the method will help improve truckload utilization, which could lower operation costs and lessen the number of vehicles used for delivery. If not, the recommendation will remain unchanged.

5. Individual case study

The presented case study is a simulation, considering 20 different locations, 3 warehouses, 100 different items and 5 vehicles. Each item and vehicle is characterised by features retrieved from their description.
An individual case study is presented, because personalised recommendations are always computed for one user at a time. The same approach would be implemented each time a new user logs into the web site.
Phase 1: Recommendation computation
We consider that the recommendation scores are computed using collaborative filtering and customers' information.
In the phase, parameters for the number of items to consider for recommendation adjustments and the number of items for the final recommendation need to be set.
Input parameters:
X =5 items, Y =3.
Table 1 presents the pair of item/scores for the Top X recommendations.

Table 1: Pair of items/scores for the active user

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

In a traditional recommendation, the final recommended items would be the Y items with the highest scores (I1, I2 and I5).

Phase 2: Initial filtering
In this step, a time window and radius are set around an active user. Available resources and transportation constraints are considered to filter items that cannot be shipped using the scheduled vehicles in a given time window.
Input parameters:
- *Maximum radius (P):* 200km,
- *Time window (TW):* 8hours

Input data: A user's location, scheduled pick-up/delivery points, the trucks' supported constraints, the recommended items' physical constraints.
Once a user's location is known, the vehicles for which a pick-up point or delivery is scheduled within the active radius are selected, the two active vehicles with their physical characteristics are presented in table 2. Table 3 represents the 5 items selected at phase 1 with their physical constraints and characteristics.

Table 2: Vehicles' capacities and supported constraints.

Vehicles	Capacity (units)	Capacity (kg)	Supported constraints	Remaining capacity (kg)	Remaining units
Vehicle 1	1 000	24 000	fragile, fixed orientation, isolation	10 710	242
Vehicle 2	1 000	24 000	refrigerated, fragile,fixed orientation, isolation	6 000	442

Table 3: Items' physical characteristics.

Item	Unit price ($)	Loading units	Weight (kg)	Constraint
I1	75	1 or less	5	Fragile
I2	150	1 or less	1	Refrigerated
I3	300	1 or less	0.5	Refrigerated
I4	175	1 or less	5	Extreme value
I5	700	1 or less	8	Fixed orientation

Data about physical characteristics of the vehicles are crossed with an item's physical constraints to create a compatibility matrix between the vehicles and items, as presented in table 4.

Table 4: Matrix of supported physical constraints.

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

Item I4 cannot be delivered by active trucks, thus item 4 is not considered for recommendation adjustments.

Phase 3: Potential profit evaluation

For each item that can be shipped with one of the active vehicles, we evaluate the profit associated with adding the item to the tour, if a sale was to be completed. The software used is presented in [23].

Input data: List of warehouses (e) and inventory level per item.

For each item, the location of the warehouse in which the product needs to be retrieved is evaluated along with the availability of the product. **Table 5** presents which of the warehouses has each item in stock.

Table 5: The item's locations.

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	-

Considering the active radius, only warehouse A and warehouse C are considered for the remainder of the phases. Since warehouse B is out of the active parameters, items I2 and I5 are not evaluated.

The VRP is launched to evaluate the profit associated with the initial tour and the profit associated with the addition of the selected items in the delivery list.

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. (4) Driving parameters are set to: a maximum capacity (loading units) of 1000, a fixed cost per trip of $200.00, variable costs per unit of distance of $0.95, a distance limit of 1000.00km, a driving time limit of 8 hours and a working time limit of 8 hours.

In order to illustrate the results, we present the initial tour and the tour associated with adding Item I3 to the delivery tour. Item I3 is selected because it shows a positive profit. The tour for vehicle 1 is presented in Table 6, while the tour for vehicle 2 is presented in Table 7. Both tables present the initial tour and the adjusted tour. Table 8 presents the total profits for the initial and adjusted tour.

Table 6: Initial and adjusted tour for vehicle 1.

	Initial tour	Adjusted tour
Distance travelled	952.53 km	968.25 km
Driving time	11:09 hours	11:45 hours
End of tour time	19:09	19:45
Duration of tour	11:09 hours	11:45 hours
Profit collected	\$18,075	\$18,075

Table 7: Initial and adjusted tour for vehicle 3.

	Initial tour	Adjusted tour
Distance travelled	190.87 km	343.93 km
Driving time	2:44 hours	4:28 hours
End of tour time	10:44	12:28
Duration of tour	2:44 hours	4:28 hours
Profit collected	\$28,118.68	\$28,800

Table 8: Total for initial and adjusted tour.

	Initial tour	Adjusted tour
Total profit	\$45,088.78	\$45,228
Total distance travelled	1 143.39 km	1 312.18 km

Considering the total profit of the initial and adjusted tour, the marginal profit related to picking up and delivering product I3 is calculated using equation 1.

$$P_{Marginal} = \$45{,}228 - \$45{,}088.78 \quad (2\cancel{1})$$

$$P_{Marginal} = \$139.22$$

The same have been applied to item I1 resulting in a $P_{Marginal}$ = -\$85.35. Since the profit is negative, no adjustment will be made for the score of item I1.

Phase 4: Recommendation adjustment

P_{min} represents the minimum acceptable profit for a company to update its scheduled tour, which is set to \$100.00 for this case study. The recommendation score is adjusted for item I3 using equation (2)

$$\textit{Adjusted Recommendation score} = (139.22/100) \times 0.49 = 0.682$$

Table 8 presents the top three recommendation list with the adjusted score for item I3.

Table 8: Final recommendation list with adjusted scores.

Items	I1	I3	I2
Recommendation score	0.92	**0.682**	0.68

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

6. Conclusion

The proposed approach consists of an adaptation of recommender systems using the vehicle routing problem to evaluate tour costs related to adding items to the delivery tour. The proposed solution dynamically adjusts to the network state by considering quasi-real time information from the information systems and including it in the recommendation systems. The objective is to improve recommendations by allowing it to shift demand toward products that will be delivered in a short time frame with an acceptable profit.

Possible outcomes of this method are: an improvement in truck-load utilization, resulting in customer satisfaction, competitiveness of the seller and a reduction in traffic congestion and pollution in communities. The results of such a method could present a significant opportunity for increased customer satisfaction and profits for the seller. However, the results of the method depend on the accuracy of the recommendation and the efficiency of the VRP. The recommendation technique selected for this paper is collaborative filtering, which implies that a strong base of information about customers also needs to be available.

7. References

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