Recommender Systems at the Long Tail

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ABSTRACT

Recommender systems form the core of e-commerce systems. In this paper we take a top-down view of recommender systems and identify challenges, opportunities, and approaches in building recommender systems for a marketplace platform. We use eBay as an example where the elaborate interaction offers a number opportunities for creative recommendations. However, eBay also poses complexities resulting from high sparsity of relationships. Our discussion can be generalized beyond eBay to other marketplaces.

Categories and Subject Descriptors

H.3 [**Information Storage and Retrieval**]: Miscellaneous

Keywords

e-commerce, recommender systems, long tail, user interface, sparsity

General Terms

Algorithms, Economics, Human Factors, Measurement

1. INTRODUCTION

The explosive growth of online content, advertising, and commerce has resulted in extensive research and development in recommender systems over the past decade. Commerce sites like eBay, Amazon, and Netflix, content providers like Yahoo, and video and music sites like You tube, spotify, and lastfm incorporate recommenders in their online experience. Recommender systems are information filtering systems where users are recommended "relevant" information items (products, content, services) or social items (friends, events) at the right context at the right time with the goal of pleasing the user and generating revenue for the system. Recommender systems are typically discussed under the umbrella of "People who performed action X also performed action Y" where the action X and Y might be search, view or purchase of product, or seek a friend or connection.

The last decade has seen an explosive growth in research and use of recommender systems [19, 11]. The Netflix challenge has fuelled more recent research in this area [2, 10]. Making recommendations based on a category of goods, in a complementary or substitute context from an economics standpoint is discussed in [23]. Content-based models, neighborhood based systems, and collaborative filtering systems using matrix factorization are well known approaches to building recommenders[6].

The eBay e-commerce platform offers a rich and dynamic arena for recommender systems. The platform affords great avenues for recommendations given the engaging user flow and interaction in the system. At the same time, the diversity of the users that includes collectors, value shoppers, resellers, and the complexities in shopping caused by the gap between buyer and seller languages and diverse trading formats pose challenges. Sellers trying to differentiate themselves from other sellers introduce challenges in creating cataloged items causing the item space to be large and sparse. Additionally, diversity in buyer preferences for sellers (some prefer highly reputed sellers whereas other value shoppers prefer otherwise) add new dimensions towards a tensor space beyond the (item, user) matrices common in collaborative systems.

Online vendors think about recommender systems in terms of increasing the shopping cart size beyond what the customer purchases. These can be thought of in terms of substitutes and complements In Micro-economic theory substitutes and complements are discussed in the context of demand, supply, and pricing[3]. Substitutes are equivalent products (coke and pepsi, for instance). Complements are products that are often bought together (an ipod and an ipod faceplate, for instance). Differentiating between these help us understand the nature of additional purchases. For instance, collectors should be typically recommended substitutes but at the end of a purchase cycle a typical buyer should be recommended complements. Shoppers who are brand-aware often look for products of the same brand even when buying complements. But if the recommender algorithm works along the brand dimension, it can recommend brand substitutions when supply is low or price is unfavorable.

In the following sections we discuss recommender systems for a marketplace like eBay. We start in section 2 with the discussion of the eBay Marketplace - the scale, the diversity, the product taxonomy, and buyer and seller dimensions. In section 3 we discuss recommender systems at the top level by classifying the aspects into 5 Ws and an H - What, When, Why, Who, Where, and How[1]. In section 4 we discuss the challenges and opportunities to building a recommender system in eBay. We conclude in section 5.

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[1]Inspired by Rudyard Kipling's opening poem in *The Elephant's Child: I keep six honest serving men; (They taught me all I knew); Their names are What and Why and When; And How and Where and Who.*

2. THE MARKET PLACE

eBay's Marketplace, now sixteen years old, started primarily as an auction format site. Today sellers list their ware typically using a seven word title which is augmented with description and pictures. Items can be mainly in one of two formats, auctions and fixed price, with variations in these formats. Most sellers pay a listing fee and items are listed in one of the large number of available categories. Buyers typically find these items through a search interface which include browsing over the categories, or searching by keywords. Buyers are also brought to the items through off-eBay advertising and also through other personalized or non-personalized recommendations on the site.

2.1 The Scale

The marketplace is vibrant with nearly 100 million buyers and sellers, and with over 10 million items listed for sale on a daily basis. Items are listed in explicitly defined hierarchy of categories and there are over 30,000 nodes in this category tree. Hundreds of millions of searches are done on a daily basis. Only a fraction of the items are cataloged.

2.2 Product Dimension

While eBay has policies on what can and cannot be listed on the site, the nature of the inventory is quite diverse. Barring prohibited items like arms, alcohol, cigarettes, body parts, and services, the site goes way beyond commodity products. Even for commodity products, a seller personalize to differentiate his or her ware from those of other sellers soliciting better exposure or higher price. While eBay has catalogs and incents sellers to list products in catalogs, products that are used, refurbished, vintage, broken are bought and sold. The terms vintage, collectible, antique may be sometimes used to euphemize item condition as collectible. Even for new products, variations like new in box or without box, new with or without tags, and other slight variations on new products offer great price advantage to buyers who are willing to compromise on perceived quality. Also, by the nature of the auction format, items are transient. Auction items have a fixed life of 1/3/7/10 days depending on the listing. Fixed price items can be listed for up to 30 days but can disappear once they are bought. Multi-quantity items alleviate this problem a bit but sellers stage items across auctions thus not revealing their entire inventory.

2.3 Buyer Dimension

As products on eBay are not necessarily cataloged, buyers have strategies beyond just visiting the site and buying products/items at the posted prices. For auctions, this involves strategies on when to bid, how much to bid etc. Another format includes "Make an offer" where buyers could negotiate a price with the sellers. Diversity in the product dimension, like new versus used or local versus long distance, influences the buying decision. Diversity in buyers - casual shoppers, impulsive shoppers, value-driven shoppers, collectors, flippers (buyers who buy at some price and resell at a higher price) - determine how they buy on eBay. There's also a strong category affinity for experienced buyers.

2.4 The Seller Dimension

Sellers typically specialize in one category. Experienced sellers who understand the market and the buyer behavior better may have the tools and means to track the market, to experiment, and to manage inventory and prices effectively. They are aware of when, in what format, at what price, and in what quantity to list the inventory.

2.5 Buyer-Seller Handshake

Buyers who search for products may use a different language than sellers. The gap in the language helps buyers who understand the seller language and the savvy buyers who are better at finding listings from inexperienced sellers and savvy sellers who are aware of inexperienced buyers and can list products to attract them as well. While this gap introduces additional stress in the search system, it opens up opportunities for recommender system to fill the gap in the buyer-seller language by using the knowledge mined from savvy buyers (and sellers) and helping other buyers (sellers).

2.6 Opportunities and Challenges

The buying and selling process on eBay is elaborate. A buyer persists on the site across multiple sessions, through a number of stages searching, finding, watching, revisiting, bidding, buying, and paying for items of interest. Each of these stages offer opportunities for the recommender system which can use of knowledge of user information and state of commitment and use it to make appropriate recommendations. These recommendations may involve queries, categories, products or items or even sellers to buyers (and buyers to sellers). However, building an effective recommender system on eBay pose several challenges like the long tail and transient nature of the inventory, the diversity in condition and format, multi-seller market (which makes recommending complements a challenge as it may involve additional cost to the buyer in terms of shipping). All of these introduce super sparsity in any relationship matrix and applying well-known recommender algorithms as is (content-based or collaborative or neighborhood algorithms) difficult.

3. SIX SENSES: 5 WS AND AN H

As discussed before, recommenders fill the gap between what the buyer needs, says what she needs, and what is available. In order to address the opportunities offered due to the elaborate shopping mechanism and challenges posed by the long tail nature of the market we discuss this along the dimensions of 5 Ws and an H - What, Where, When, Why, Who, and How[1].

3.1 The What

On a marketplace platform like eBay dealing with the vocabulary and language gap between buyers and sellers is a challenge[20]. Recommender systems augment search by bridging this gap. On the home page of eBay past purchase information or popularity information can be used to attract or remind buyers about potential purchases. The recommended entities could be queries that correct or assist with user queries, categories of purchases, items or products, brands, or even sellers for the buyers. For a buyer who bookmarks an item, then revisits the item and purchases it, the recommendation made(a complementary product that goes with the current item) is different from the one made to the user who visits an item that has expired or on which he/she has lost the auction (where we recommend substitutable items through "similar item merchandizing"[8]).

3.2 The Where

The right context determines the right recommendation. Unlike in web search, typical user visits in e-commerce sites have longer user engagement and workflows. This gives a number of contexts for recommending products -The home page, the results page, the product or item view page, the "my" personal page, the purchase intent (bid) page, the purchase page and the checkout page. Each of these contexts have information about the user's state of mind and phase of the purchase process. For instance, on the search results page information about the query that was typed in along with the session history and past history, the quality of results will indicate the users level of engagement (or frustration). There may be too many results or too few or no results that require different forms of recommendations[20]. On the bid page the user may be more committed to buy but the information about the user's past bid activity and even the likelihood of the user winning the item can influence what is recommended. In the checkout page the user may be recommended a complement product. In a post-transaction scenario the user may be welcome to upgrade the product, buy an accessory, or even sell it back into the marketplace. Even in a non-transaction flow, simple reminders about items viewed or watched by the user can create buying activity that may be otherwise missed.

3.3 The When

This dimension addresses the time factor related a certain user action. For instance, recommendations immediately after the user purchases or a user losing or winning an auction, a few days after the user purchases, weeks or months after the user purchases or loses an auction the recommendation could be different. In order to incorporate this dimension in a recommender system model we incorporate a time window factor into the standard recommender system model. The time window factor indicates the time difference between the purchase time and the recommendation time. This time difference can be easily set to be predefined time windows of a day, a week, a month and, so on. If the time between the purchased item and the active item is within this time window then the active item is considered else it is decayed using a decay factor[5]. Figure 1 shows how as the time progresses from the time of purchase of products on eBay in a certain category the probability of purchase of a related item varies. More details of this work discussed in [22].

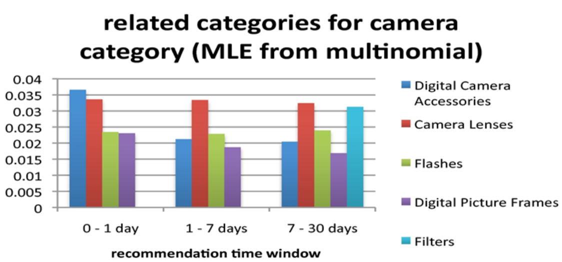

Figure 1: A category recommendations for the camera category in 3 time windows within the first 30 days. Immediately after the purchase camera accessories like bags and tripods are purchased but as time progresses products like lens filters are bought whereas lenses are bought at the same scale across the time range.

3.4 The Why

This dimension of recommender system addresses the transparency aspect of a recommender system. Since recommendations are not sought out or expected by the user the Why dimension is required to reason to the user why certain recommendations are presented. For instance, given the same recommender algorithm, at the point of recommendation, adding informative text like "people who bought this also bought that" versus "80% of the people who bought this also bought that" has a better effect on the user. A more personalized message of "60% of the people like you who bought this also bought that" is likely to have an even better effect on the user. User research study has shown that transparency improves the performance of recommender systems[21].

3.5 The Who

This dimension addresses the personalization aspect of recommender systems. For instance, recommending to a power buyer or seller might be unnecessary and even unfavorable as compared to a inexperienced buyer. Our own study in eBay has shown that for casual buyers recommender systems work much better than for a power buyer. Over-recommending is likely to cause user fatigue. Hence, if the recommender system can be viewed to have a budget constraint (since it is an intrusive system the system could restrict that only a certain number of recommender impressions that can be shown per day or per buyer) and targeting the users this way can be more effective in achieving better purchase-through-rates. Capturing appropriate buyer dimension into the recommender system becomes important. For instance, collectors tend to buy "more of the same" or even warm up to the recommendation of a new class of recommendation of collectible items whereas "accessory recommendations" are beneficial to typical online shoppers. Recommending with sensitivity to price is important to a value buyer. Typical personalization in recommender systems use supervised or semi-supervised approaches to fit the model parameters to some predefined user profile attributes.

3.6 The How

The How dimension is really focusing on designing algorithms and systems that make the different 'Ws' discussed above effective. Recommender systems typically use content models, neighborhood models, matrix factorization models or hybrid approaches to complete the user-item matrix space[6]. For matrix factorization, often these matrices tend to be very sparse. To deal with high sparsity directly modeling on the observed data is preferable to performing SVD decomposition [2, 10]. Matrix factorization involves mapping users and items as a latent factor space (of dimensionality σ) and then modeling the user-item interactions as inner products. To map items and users into the latent space, each item v is represented by a vector q_v in R^σ representing the extent to which the item has the different features in R^σ and each user u is represented by a vector p_u in R^σ representing the extent to which the user is interested in different features in R^σ . Preference for item v by user u, r_{uv} is computed as the dot-product $q_v^T p_u$. The major task is computing the mapping of each item and user to the corresponding factor vectors in R^σ . To learn the factor vectors q_v and p_u we minimize the regularized square error on the known observations:

$$min_{q,p} \sum_{(u,v)\in\kappa} (r_{uv} - q_v^T p_u)^2 + \lambda(\|q_v\|^2 + \|p_u\|^2)$$

$$where\ r_{uv}\ is\ known\ for\ \kappa$$

This minimization equation is solved using for e.g. Stochastic Gradient Descent or Alternating Least Squares.

In the case of eBay, the q space of items is extremely large and volatile. There's very little overlap between buyer interests/purchases and actual items. Scale, super-sparsity, and volatility of items play a huge role in how these are designed in eBay. For instance, the MovieLens data has 10 million ratings of 10,000 movies over 70,000 users. The Netflix prize challenge data has 100 million ratings of 10,000 movies and 500,000 users. While eBay doesn't have explicit ratings we derive the ratings from hundreds of millions of searches a day, bids (over 5 million a day), purchases (over 2 million a day), and 100 million buyers and sellers. The (user, item) matrix sparsity is at least 100X more than what was observed in the Netflix data. However, the space of user queries is fairly static (even though in the millions). We can map the user space to queries

(queries typed in by users) and item space to queries (items are matched to queries by the search engine). The we use explicit feature vectors on the user and item space q_v p_u then optimizing to discover a weight matrix W in q_v W p_u. Alternatively, Latent Topic Models (LDA, for instance) can be used to map users to latent topics, and latent topics to search queries[12]. Every topic is represented by a multinomial probability distribution over vocabulary of all queries. Every user is represented by a multinomial probability distribution over the set of topics. Only queries are observable, topics and distributions are not. A generative user model assumes that the user set of queries and topics of interest can be known based upon which user interest in queries. The generative item model can assume that items are covered by the topic intentions of all the users. In other words, a given item-query pair has an underlying latent topic. Then we can estimate the probability of query given topic without observing user behavior. In our objective function the feature space is the space of the topics of user interest. This works because, in eBay, the item space is volatile whereas the query space is fairly static. So model recomputation is required only whern new queries appear. This can be further delayed by providing fallbacks for queries (if a query is too specific falling back to a generic version of it[14]).

Other variations to this approach have been used in eBay like clustering the item space into pseudo products by using standard clustering techniques using the title, price, and attributes dimensions of the products. By using different probability distributions of these dimensions a latent product is represented as a vector of probabilities and the membership of an item to a cluster is stochastically modeled as a generative process. K-means clustering with a probabilistic distance measure is used. In the reduced space of latent products, the probability of two products to be likely to be purchased together is computed (since this space is sparse other indications like views, watches, and bids are used to smooth and fill the matrix). Finally, item-item scoring is achieved by factorizing a markov chain going from item to product, product to product, and product to item space. Items are painted with their cluster memberships. See [4] for more details. One of the downsides of this approach is fast model degradation and retraining the model frequently and repainting the items.

Another approach is to use a content-based clustering model for clustering items into heterarchical clusters (items could belong to more than one cluster, clusters are arranged in a hierarchy) thus reducing item space sparsity. Here the content-based clustering model takes advantage of any indication of aspect commonality through item titles or item attributes like brand, size, color, or price. These pseudo products are stored as complex query templates. Here pseudo products are indexed as heterarchical clusters. Since the query space is relatively static this approach does not require frequent reclustering[7]. Even though eBay queries are in the billions and also exhibit a long tail nature (a large number of queries repeat very few times[20]) this is still the best static proxy available for products. Inter-cluster relations are captured using collaborative filtering. Due to the hierarchy in the cluster structure, sparsity is resolved by falling back to parent clusters when there is no strong correlation between clusters. Besides purchases, auction bids, views, user-saved views are used to score these relations. They are weighted differently; purchases are stronger than views, for instance.

Our observation is that content-based models helped the system wherever there are cold-start issues with little behavioral data. In a real deployment in eBay, it performed better where there was more structural information on items avialable. In eBay's volatile item space environment it avoided the need for frequent reclustering. A real deployment of these systems in eBay revealed better performance of the probablistic models in categories that had poorer structure information and better performance of the content based model where it could take advantage of structural information like attributes and fitment information. Another lesson was that the performance varied signifcantly by user segments; experienced users reacted differently from inexperienced ones. This makes personalization by segments an important consideration. The next section discusses more eBay-specific issues like buyer diversity, trust, and category-specificity.

4. THE EBAY SPACE

In this section we discuss additional features - Trust, user expertise, category structure, popularity and serendipity - features particular to the eBay marketplace.

4.1 Trust

Trust in recommendations is important especially in a marketplace of diverse buyers and sellers. Recommenders, unlike explicit search systems, provide suggestions proactively rather than respond to a user query. This requires the system to promote (products from) trusted sellers. On the other hand aspects of trust are subjective, the personalization aspect discussed in section 3.5 has to address the fact that buyers who are more knowledgable of the product are likely to seek bargains from sellers who may not be highly reputed. Also, sellers with top reputations might demand trust premium in the price of items they sell.

4.2 The Robinhood Approach

We discussed how the relationship matrices are super-sparse due to the nature of the inventory and the infrequency of purchases. We discussed user diversity and varying expertise. Another way to smooth is to take advantage of the user expertise. On a platform like eBay passionate power users leave quality information trails like queries, navigation paths, products they buy or sell. This can be used to the benefit of inexperienced users. Consider the following use case where fashion oriented users shop by product brands[17]. The goal is be to recommend substitutable brands. Advanced users use conjunctions, disjunctions, regular expressions, and negations to refine and expand their specific queries. By mining advanced queries over the terms occurring as operands supported by conjunctive or disjunctive operators we can expand the brand correlation list. The table below shows the affinity between brands discovered through mining advanced queries. More details on the algorithm can be found in [16].

Table 1: Brands Discovered using Advanced User Query Mining.

Seed Brand	Brands Discovered (Co-occurrence % with seed brand)
Prada	Gucci(11.98) chanel(4.74) miu(3.89) dior(3.79) coach(3.38) miu miu(3.17) dolce(2.65) versace(2.08) fendi(2.08) chloe(2.00) marc jacobs(1.83)
Panasonic	Sony(13.19) samsung(4.51) digital(0.55) alpine(0.51) fuji(0.46) pelco(0.46) kodak(0.34)

Another source of information is user typed queries within the sessions. Simply by relating queries that are typed in the same session a graph of query relationships is built. By using co-occurring terms typed in a query as signals for relationships spurious relationships are removed. The graph mining combines linguistic and behavioral relationship between queries accounting for user expertise. For instance, "apple ipod mp3 player" and "creative mp3 player" links "apple ipod" and "creative" while separating out "apple ipod" from "apple dishes" as the co-occurring terms are different. Some examples of query pairs and the value of the semantic similarity are described below in Table 2. More details on the algorithms can be found in [14]. The brand recommendations can be seen in figure 2.

Table 2: Table showing the value of calculated Semantic Similarity for some representative query-query pairs.

Query 1	Query 2	relationship	L_2 norm
jessica alba	sandra bullock	celebrities	0.856
zune	black zune	general/specific	0.918
harry potter	j k rowling	character/author	0.631
ps2	playstation 2	acronym/expansion	0.891
jessica simpson	shoes	brand/product	0.796
coach bags	coach tote	Synonyms	0.838

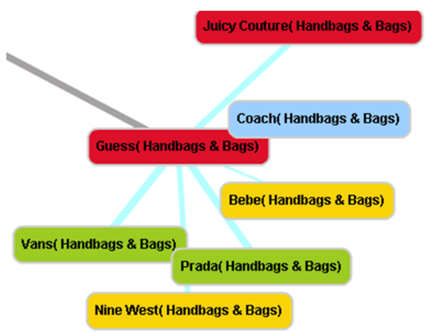

Figure 2: Figure indicating alternate brand recommendations for Guess (Handbags & Bags). The recommendation score is reflected in the thickness of the edges.

4.3 Cross-Category Recommendation

There is big diversity across categories in the nature of the products, catalog adoption, popular formats(collectibles, stamps and coins favor auction formats while commodity items like electronics are often sold at fixed price, for instance), user purchase patterns and buyer-seller affinity. Independent models can be built on a per category basis. Cross-category content relationships[18] or purchase affinities[15] can be discovered and where such relationships exist models for cross-category recommendations can be built. Forcing these category relationship is another way to reduce sparsity.

4.4 Of Populars and the Serendipitous

Offline events like new product releases, or a celebrity or political event often create buzz and trends that cause topical inventory. Recommending buzzing, trending or popular inventory can generate buying activity[14]. Also, the unique one-of-a-kind nature of the inventory lends itself to building novel serendipitous experience. These recommendations of the user is looking for but might be interested in these can also be used to create user engagement.

4.5 The Elephant helps scale

Given the scale of data that needs to be processed over days and months to build the models, all of our algorithms are built over a large scale Hadoop Map-Reduce infrastructure.[1]Also with large amount of data we can use simple methods prove highly effective[9]. Hadoop helps making it easy to break down large data sets equivalent coarse grained task onto individual nodes for processing through a Map (scatter) operation and aggregating the partial results over a Reduce (gather) operation. More recently, there has been great progress in using the graphics card GPU processors on workstations to address scale and parallelism[13]. Since most matrix operations and reduction operations are data-parallelizable it is possible to combine Hadoop with such GPU-based data-parallel local compute-intensive operations.

5. CONCLUDING REMARKS

Recommender systems form an integral part of any e-commerce platform. Long tail marketplaces like eBay provide unique opportunities for recommendations but also introduce a number of challenges. Recommendations are not only for products and items, but categories of items, related query suggestions, and brands. Even connecting buyers and sellers through a recommender system in a targeted way is useful. We recognize the problems in recommender systems are beyond just cross-merchandizing as it is often seen and in that spirit we discussed the 5 Ws and H of recommender system that includes the Who, What, Why, Where, When, and How of recommendations. As e-commerce grows more social and mobile, new dimensions get added like location-aware or app-based or game-based recommender system. The future for this space is bright and vibrant and should provide amazing research opportunities.

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