Beyond Modeling Private Actions: Predicting Social Shares

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ABSTRACT
We study the problem of predicting sharing behavior from e-commerce sites to friends on social networks via share widgets. The contextual variation in an action that is private (like rating a movie on Netflix), to one shared with friends online (like sharing an item on Facebook), to one that is completely public (like commenting on a Youtube video) introduces behavioral differences that pose interesting challenges. In this paper, we show that users’ interests manifest in actions that spill across different types of channels such as sharing, browsing, and purchasing. This motivates leveraging all such signals available from the e-commerce platform. We show that carefully incorporating signals from these interactions significantly improves share prediction accuracy.

Categories and Subject Descriptors
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Keywords
Recommender systems; e-commerce; user behavior analysis

1. INTRODUCTION
Social media platforms provide an outlet for expressing personal preferences or generic opinions with friends through features like ‘share’. Increasingly, these ‘social signals’ include events, products, and services. Shares pertaining to commerce are particularly relevant from a monetization standpoint. Share widgets are being rolled out on platforms like Amazon and eBay in the hope that they increase sales through network marketing. There however remains little understanding on how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces. There has been a vast body of work on understanding how users actually engage with these share widgets on such marketplaces.

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where $\Omega$ is the set of observed shares in $S$; $\lambda$ is the regularization parameter for both $W_S$ and $H_S$. The share matrix $S$ is approximated by $W_S H_S^T$ and the number of shares the user $i$ makes for $j$-th category is predicted as $w_i^T h_j^T$. Similarly, we can solve the Problem (1) to approximate $P$ by $W_P H_P^T$ and $B$ by $W_B H_B^T$.

Based on that, we can predict $P_{ij}$ and $B_{ij}$ accordingly. A simple way to use this information is to combine the interactions together as follows, named Augmented Matrix Factorization (AMF):

$$\bar{S}_{ij} = \alpha_s w_i^T h_j^T + \alpha_p w_i^T h_j^T + \alpha_b w_i^T h_j^T,$$

where $w_i^T$ and $h_j^T$ are the $i$-th row for $W_P$ and $j$-th row for $H_P$ respectively; $w_i^T$ and $h_j^T$ are the $i$-th row for $W_B$ and $j$-th row for $H_B$ respectively; and $\alpha_s$, $\alpha_p$, and $\alpha_b$ are weights learned from the share matrix $S$. These three scores show the likelihood of user $i$ sharing, purchasing, and clicking on the items in $j$-th category. So the combination of these three shows combined interaction of user $i$.

In Figure 2, we show the benefit of using auxiliary information from pageviews and purchases to improve the share prediction. In this figure, we compare AMF with performing matrix factorization on $S$ alone(MF) and the neighborhood based approach(NN), which predicts the number of shares based on the neighbors of the user. We can clearly see that both MF and AMF perform better than NN, showing that the matrix factorization based methods perform better than neighborhood-based approaches for share prediction. Furthermore, using just purchases (in AMF(S+B)) or just pageviews (in AMF(S+P)) is not sufficient to derive the full predictive accuracy. The figure also shows that AMF is robust to varying $k$.

3. RELATED WORK

There are studies that investigate effects of integrating social networks into e-commerce websites[2, 7]. The goal of providing users with the flexibility to share their interests is to increase consumption based on the belief that social influence is a strong promoter for the consumption. Studies [7, 1, 3] show that while social links are sparse, transactions between friends’ friends in the network usually correlate with higher user satisfaction, and take this to indicate the positive impact of social media. Integration of recommender systems in e-commerce marketplaces to foster and leverage social interaction has shown some success [6, 5].

4. REFERENCES