Generating and Personalizing Bundle Recommendations on *Steam*

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ABSTRACT

Many websites offer promotions in terms of bundled items that can be purchased together, usually at a discounted rate. 'Bundling' may be a means of increasing sales revenue, but may also be a means for content creators to expose users to new items that they may not have considered in isolation. In this paper, we seek to understand the semantics of what constitutes a 'good' bundle, in order to recommend existing bundles to users on the basis of their constituent products, as well the more difficult task of generating new bundles that are personalized to a user. To do so we collect a new dataset from the *Steam* video game distribution platform, which is unique in that it contains both 'traditional' recommendation data (rating and purchase histories between users and items), as well as bundle purchase information. We assess issues such as bundle size and item compatibility, and show that these features, when combined with traditional matrix factorization techniques, can lead to highly effective bundle recommendation and generation.

1 INTRODUCTION

The basic goal of a *Recommender System* is to understand relationships between users and the items they consume. Typically, this is cast as estimating compatible user/item (or item/item) pairs, and surfacing these as recommendations. An inherently more challenging task is to understand the semantics that describe relationships between *sets* of items, in terms of what factors make them mutually compatible and mutually desirable to a user. One area where such semantics are important is for recommending *bundles*, or sets of items that can be simultaneously co-purchased.

In this paper, we seek to apply recommender systems techniques to bundle generation and recommendation tasks. Bundles are ubiquitous on e-commerce platforms, though the semantics of how to compose and recommend them have rarely been studied. One reason for the relative scarcity of work in this area may simply be the lack of suitable data to explore users' interactions with bundles. Here we contribute a dataset extracted from the *Steam* video game distribution platform, which offers detailed information both in terms of user/item interactions (including what games users purchased, whether they played them or not after purchase, and how they rated them), as well bundle promotions, and sufficient information to extract what bundles were purchased by each user.

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Together, the features of our data allow us to assess how the semantics of bundle recommendation differ from traditional item recommendation problems. We build on traditional techniques for item-to-user recommendation, in order to assess the extent to which items that are bundled together should be mutually compatible, desirable, or diverse in their features. Beyond personalized bundle recommendation, we can use the learned objective to *generate* new bundles, in order to surface personalized promotions to a user.

2 RELATED WORK

We build upon latent factor models, and in particular Bayesian Personalized Ranking (BPR) [11], which is trained using *implicit feedback* (i.e., purchases vs. non-purchases) in order to estimate rankings of items that are likely to be interacted with.

Also related are systems that recommend items to *groups* of users (i.e., recommending items to sets of users, as opposed to recommending sets of items to users). For example, group recommendation can be addressed by developing techniques that aggregate preferences of individuals within groups. [2, 3, 5, 7]. Bundling products for groups is also considered in [10], though their main focus is item-to-group compatibility. Although the formulations vary, such methods essentially work by maximizing item relevance while minimizing disagreements between group members.

We also build on systems that consider item aggregate diversity. Adomavicius and Kwon [1] study the importance of balancing accuracy and aggregate diversity for ranking tasks, and Nieman and Wolpers [9] study the relationship between aggregate diversity and item co-occurrence.

Finally, given that our goal is to generate sets of items, our work is related to papers that study basket recommendation and item compatibility. This includes both classical works on *market baskets* (and itemset/association rule mining), as well as more modern works that learn substitute and complement relationships [6, 13]. Our work differs from typical bundling scenarios (e.g. grocery shopping) where similar sets of items can be recommended repeatedly. Few recent works consider related forms of 'bundling' [4, 12, 14], though differ in terms of problem formulation, or lack actual bundle sales data and therefore rely on heuristics for evaluation.

3 DATASET AND ANALYSIS

We use data from the *Steam* video game distribution network for training purposes.[1] We focus on the Australian Steam community, by crawling users from the 'GameAus' community. In total, this resulted in a network of 88,310 gamers and 10,978 games they purchased. Basic statistics are shown in Table 1.

Among the 615 bundles available on *Steam* at the time of our experiments, we found that 29,634 gamers (around 33%) purchased

[1]All code and data is available at http://cseweb.ucsd.edu/~jmcauley/

Table 1: Australian Community Data

Users	88,310
Total games	10,978
Total game purchases	902,967
Total bundles	615
Total bundle purchases	87,565
Users who purchased at least one bundle	29,634
Games that appear in at least one bundle	2,819
Average bundle size	5.73

one or more bundles, among 87,565 bundles purchased. This suggests a significant demand for bundles, and a high potential for personalized recommendation and bundle creation. The average bundle size is 5.63 games, and 2,819 (around 25%) of games appeared in at least one bundle. Typically the bundled items are more popular games: even though only 25% of items appear in any bundle, around 70% of *purchases* are over items that appear in a bundle. In practice, this means that users often purchase bundles containing some items they already own, suggesting a need to modify or personalize bundles toward a particular user.

4 PROBLEM FORMULATION

Before describing our approach to bundle recommendation, we introduce some basic notation. Let $U = \{u_1, \dots, u_{|U|}\}$ be a set of users, $I = \{i_1, \dots, i_{|I|}\}$ a set of items and $B = \{b_1, \dots, b_{|B|}\}$ a set of bundles, such that each $b_i \subseteq I$. Personalized *item* ranking (*item BPR*) can then be cast as creating a personalized ranking $>_u \subset I^2$ over all pairs of items for a user u. Similarly, personalized *bundle* ranking can be formalized as $>_u \subset B^2$ over all pairs of bundles.

5 BUNDLE RANKING

We first provide methods for personalized ranking of *existing* bundles to Steam users via Bayesian Personalized Ranking (BPR) [11]. We use a graph sampling technique to create a balanced training set (as described below), then learn users' preferences over individual items using an *item BPR* model. The representation learned by the *item BPR* model can be used to estimate user-to-item compatibility when personalizing bundles in the following stage, i.e., they can be used as parameters in a *bundle BPR* model. Both the *item BPR* and *bundle BPR* models are evaluated by computing the AUC metric, which BPR methods approximately optimize.

Data Sampling. The training data for *item BPR*, D_{item}, should be a list of triplets (u, i_p, i_n), where i_p is an item the user has purchased (positive item) and i_n is an item the user hasn't purchased (negative item). Similarly, the training data for the *bundle BPR* model, D_{bundle}, should be a list of triplets (u, b_p, b_n), where b_p and b_n are positive and negative bundles for the user u. Since our dataset follows a power-law (i.e., a small number of items/bundles are purchased by a large fraction of the users), uniformly sampling negative items (or bundles) i_n results in a method that is heavily biased toward popular items, both for recommendation and generation, and leads to qualitatively poor results. To overcome this problem of data skew, we use a graph sampling algorithm [8] that creates D_{item} and D_{bundle} such that their negative items and bundles follow the same degree distribution as their positive items and bundles.[2] What this means in practice is that it is not possible to distinguish positive versus negative items/bundles based only on their popularity, forcing the model to learn a richer notion of compatibility.

5.1 Bayesian Personalized Ranking (BPR)

The goal of BPR is to derive a *personalized* ranking $>_u$ over items (or bundles). To model the ranking, we assume an estimator $\hat{x} : U \times I \to \mathbb{R}$ encoding the compatibility between a user and an item, which is used to define the ranking

$$i_p >_u i_n \leftrightarrow \hat{x}_{u,i_p} >_{\mathbb{R}} \hat{x}_{u,i_n}.$$

The optimization criterion for BPR, *BPROpt*, as derived in [11] is:

$$BPROpt(\theta) = \sum_{(u,i_p,i_n)\in D} \log(\sigma(\hat{x}_{u,i_p}(\theta) - \hat{x}_{u,i_n}(\theta))) - \lambda\, \|(\theta)\|^2$$

where, σ is the sigmoid function, θ is the parameter vector of the compatibility function, D represents the training set, λ is the regularization hyper-parameter, $\hat{x}_{u,p}$ and $\hat{x}_{u,n}$ represent compatibility estimates that the user u would purchase item p and n respectively. Recall that i_p and i_n are a positive and a negative item, so the expression $\sigma(\hat{x}_{u,i_p}(\theta) - \hat{x}_{u,i_n}(\theta))$ essentially captures the probability that the purchased item is correctly identified as being more compatible than the non-purchased one.

We use different predictors $\hat{x}_{u,i}$ and $\hat{x}_{u,b}$ when considering item and bundle recommendation, as described below.

5.1.1 *Item BPR.*

The estimator function for the *item BPR* model is based on matrix factorization:

$$\hat{x}_{u,i} = \beta_i + P_u \cdot Q_i$$

where β_i is an item parameter, and P_u and Q_i are k-dimensional latent parameter vectors for user u and item i respectively, to be learned by optimizing *BPROpt* over D_{item}.

5.1.2 *Bundle BPR.*

The *bundle BPR* model makes use of the parameters learned through the *item BPR* model to estimate the preference of a user toward a bundle as shown below:

$$\hat{x}_{u,b} = \frac{1}{|B_b|} \sum_{i \in B_b} [\kappa\beta_i + (\mu P_u).(\omega Q_i)] + Cc_b + N_b$$

where β, P, and Q are learned from the *item BPR* model. μ and ω are $k \times k$ dimensional matrix adjustment parameters for P and Q respectively. c_b represents the bundle correlation, which is the mean pair-wise Pearson correlation of the items, represented using their latent features Q_i, present in the bundle. N is a $\max_{j\in B} |B_j|$ dimensional parameter that rewards or penalizes bundles of certain sizes (to prevent the system from generating arbitrarily large bundles). The remaining parameters are scalars that trade-off various terms. All parameters are learned by optimizing *BPROpt* on D_{bundle}.

[2]The scheme itself is a simple randomized 'rewiring' procedure on the original user-item or user-bundle purchase graphs, which has previously been used to correct skew when training recommender systems [6].

5.1.3 *Cold Bundle Problem.*

We define 'cold' bundles as those which contain at least one item $i \in I$ which is not observed in any of the existing bundles in the dataset. Because of the way we have trained the *bundle BPR* model (as a function of parameters of the *item BPR* model), our model is robust to cold bundles, i.e. it can rank any bundle containing items $I' \subset I$.

5.2 Evaluation

We compute the AUC to evaluate both *item BPR* and *bundle BPR*. The AUC is given by:

$$AUC = \frac{1}{|T|} \sum_{(u,p,n) \in T} \delta(\hat{x}_{u,i_p} - \hat{x}_{u,i_n} > 0)$$

where δ is the indicator function and T is the fraction of the data withheld for testing. In other words, we are counting the fraction of times the model correctly ranks p higher than n.

6 PERSONALIZED BUNDLE GENERATION

So far, we have considered recommending bundles that already exist within the system. Next, we present a greedy algorithm that uses the learned parameters to generate new bundles.

6.1 Greedy Algorithm

The algorithm is described below. We start with an initial bundle (of size $S = 3$) and select $k = 10$ neighbors in every iteration. The size of the neighbor set, k, is inversely related to the aggregate diversity of the generated bundle, i.e., as k increases the method will tend to favor popular items in generated bundles.

(1) Start with a bundle b containing S randomly-chosen items.
(2) Randomly select a set of k items $I_* \subset I \setminus \{i \in b\}$ and form a set of new bundles B_* by adding, deleting, and substituting items from I_*.
(3) Let b_* be the most preferred bundle (by a user u) among all bundles in B_* and P be the corresponding preference score, i.e., $b_* = \arg\max_{b' \in B_*}(\hat{x}_{u,b'} - \hat{x}_{u,b})$, and $P = \max(\hat{x}_{u,b'} - \hat{x}_{u,b})$.
(4) If $P > 0$, then accept b_* as the new bundle, otherwise accept b_* with diminishing probability (following an annealing schedule).
(5) Repeat steps 2 to 4 until convergence.

6.2 Evaluation

We evaluate the generated bundles for a set of users using two criteria. First, we consider how the generated bundle *ranks* compared to existing bundles, according to our *bundle BPR* model. Second, we consider the *aggregate diversity* of the generated bundles, in order to assess the coverage of items within the system:

$$\text{aggregate diverstiy} = \frac{\text{\#of distinct items across generated bundles}}{\text{\# of items}}$$

The former of these evaluation measures is a simple sanity check to ensure the greedy approach finds local minima with high compatibility; the latter is a qualitative assessment to assess whether a diverse variety of bundles are recommended.

7 EXPERIMENTS

We consider items that occur in at least one existing bundle, resulting in an item set of size 2,819. Using the sampling method described in Section 5, we create bundle and item data samples of sizes $1,016,646$ and $26,717,059$ (respectively) which we partition into 70%/10%/20% training/validation/test splits. We report performance on the test set for the model that performs best on the validation set.

Table 2: Comparison of different bundle recommendation models (left), and comparison of *bundle BPR* on cold bundles (right)

Model	AUC
BPR	0.8624
I-BPR	0.82212
BR	0.8519
BR + N	0.89447
BR + N + C	0.90276

Model	AUC
BR	0.81203
BR + N	0.81928
BR + N + C	0.84669

7.1 Bundle Ranking

We compare the performance of our bundle ranking model against several baselines: (1) Regular BPR (*BPR*); (2) Bundle BPR using item features (*I-BPR*); (3) Our 'vanilla' model without bundle size and bundle correlation (*BR*); and (4) *BR* with bundle size (*BR + N*). Finally we report (5) our proposed model including size and bundle correlation (*BR + N + C*).

Performance in terms of the AUC is shown in Table 2 (left). *BPR* performs well but cannot be used for bundle generation as it uses only bundle features and not item features. *I-BPR* overcomes this limitation by using the mean over the item features to estimate the preference of a user towards a bundle at the cost of reduced AUC. Our vanilla model (*BR*)—without bundle correlation and bundle size terms—has AUC close to that of *BPR* while using only item features. The main difference between *BR* and *BPR* is that the parameters β, P and Q in *BR* are constants learned from the *item BPR* model. When we add bundle correlation and bundle size terms in *BR* it substantially outperforms *BPR*.

Cold Bundles. In Section 5.1.3, we suggested that our model is robust to the cold bundle problem. To validate this we create a reduced item set, I_*, by randomly removing 219 items from I and re-sampling the training data, D_{bundle}, such that bundles only contain items present in the reduced item set, I_*, where $|I_*| = 2600$. The test set then consists of triplets (u, b_p, b_n) such that b_p is a 'cold' bundle (containing at least one of the removed items) and b_n is not. It should be noted that the data for the *item BPR* model remains unaltered as we are dealing with the cold *bundle* problem and not the cold *item* problem. We observe in Table 2 (right) that when we test our *bundle BPR* model on the test set we observe only a modest reduction in AUC in spite of the presence of cold bundles.

7.2 Bundle Generation

We generate new bundles using the greedy algorithm described in Section 6.1 for 1000 randomly selected users (Table 3). The *BR* model doesn't have bundle size and bundle correlation as features and hence reduces to an average of *item BPR* features; for this model we set the minimum bundle size to 2, otherwise the model tends to

Table 3: Comparison of models for bundle generation.

	Average Rank	Bundle Size	Aggregate Diversity
Random	348.60	4.46	0.824
BR	1.49	2.00	0.505
BR + N	3.35	4.32	0.307
BR + N + C	2.66	4.49	0.374

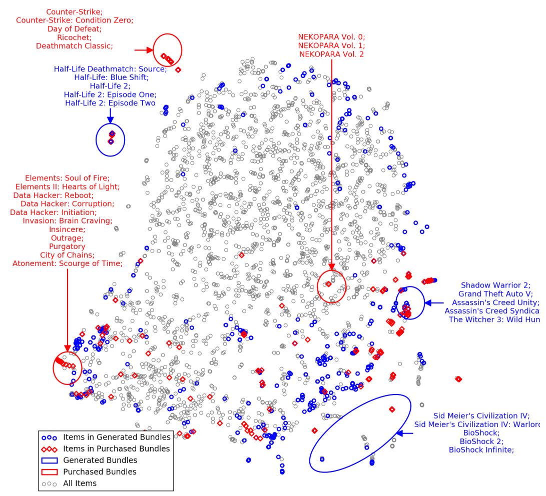


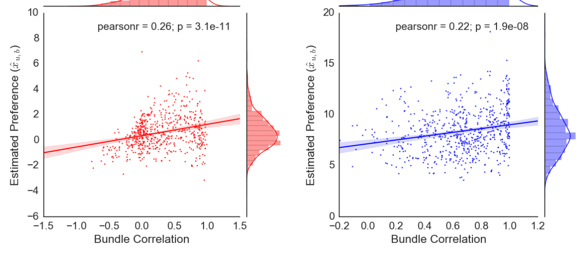
Figure 1: t-SNE embedding of item latent factors. Some generated (blue) and purchased (red) bundles are highlighted.

generate bundles of size 1 (as the maximum compatibility is always greater than or equal to the average). Once we add the bundle size as a feature we start to observe a range of bundle sizes (generally between 3 and 8), though this has the effect of increasing the average rank. Average rank and aggregate diversity both improve slightly after including bundle correlation as a feature.

Our final model with bundle correlation is able to generate bundles that are qualitatively similar to those preferred by *Steam* users. Figure 1 shows a t-SNE embedding of latent representations for all items such that similar items are close to each other, as well as a sample of real and generated bundles. Our generated bundles seem to consist primarily of three types of bundles: those in which all items are similar (e.g. the series of Half Life games); those consisting of multiple series collected together (e.g. multiple Bioshock games along with multiple Sid Meier games); and bundles of different games with similar types (e.g. Shadow Warrior, Grand Theft Auto, Assasin's Creed, and The Witcher).

In general, bundles with correlated games (in terms of their *item BPR* representations) receive higher scores than those with uncorrelated or negatively correlated items (Figure 2). Each point in Figure 2a represents the mean bundle score ($\bar{\hat{x}}_{u,b}$) for 500 users and bundle correlation, whereas each point in Figure 2b represents the bundle score and correlation of the top bundle *generated* for a user. Both figures suggest a *positive* relationship between bundle correlation (c_b) and bundle score ($\hat{x}_{u,b}$).

Surprisingly, we find that few of the generated (or real) bundles are particularly diverse; rather they tend to consist of closely related



(a) Existing Bundles **(b) Generated Bundles**

Figure 2: Variation of estimated preference $\hat{x}_{u,b}$ with bundle correlation c_b. Bundles with highly correlated items are usually preferred.

games. Indeed, our best models identified *positive* bundle correlation terms, indicating that diversity is a feature that is penalized when considering users' preferences toward real bundles.

8 CONCLUSION

We have shown a method to generate and evaluate personalized bundle recommendation on the *Steam* video game subscriber network. We developed a *bundle BPR* model which used the trained features of an item recommendation model in order to learn personalized rankings over bundles. We showed that our model is robust to cold bundles, and that new bundles can be generated effectively via a greedy algorithm.

As future work, we intend to adapt these approaches to generate recommendations for user populations (rather than individuals), and to investigate the role that pricing (and in particular, discount rate) has on users' preferences toward bundles.

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