Learning Compatibility Across Categories for Heterogeneous Item Recommendation

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Abstract—Identifying relationships between items is a key task of an online recommender system, in order to help users discover items that are functionally complementary or visually compatible. In domains like clothing recommendation, this task is particularly challenging since a successful system should be capable of handling a large corpus of items, a huge amount of relationships among them, as well as the high-dimensional and semantically complicated features involved. Furthermore, the human notion of “compatibility” goes beyond mere similarity: For two items to be compatible—whether jeans and a t-shirt, or a laptop and a charger—they should be similar in some ways, but systematically different in others.

In this paper we propose a novel method, Monomer, to learn complicated and heterogeneous relationships between items in product recommendation settings. Recently, scalable methods have been developed that address this task by learning similarity metrics on top of the content of the products involved. Here our method relaxes the metricity assumption inherent in previous work and models multiple localized notions of ‘relatedness,’ so as to uncover ways in which related items should be systematically similar, and systematically different. Quantitatively, we show that our system achieves state-of-the-art performance on large-scale compatibility prediction tasks, especially in cases where there is substantial heterogeneity between related items. Qualitatively, we demonstrate that richer notions of compatibility can be learned that go beyond similarity, and that our model can make effective recommendations of heterogeneous content.

Keywords—Recommender Systems; Visual Compatibility; Metric Learning

I. INTRODUCTION

Identifying and understanding relationships between items is a key component of any modern recommender system. Knowing which items are ‘similar,’ or which otherwise may be substitutable or complementary, is key to building systems that can understand a user’s context, recommend alternative items from the same style [11], or generate bundles of items that are compatible [18, 22, 34].

Typically, identifying these relationships means defining (or otherwise learning from training data) an appropriate distance or similarity measure between items. This is appropriate when the goal is to learn some notion of ‘equivalence’ between items, e.g. in order to recommend an item that may be a natural alternative to the one currently being considered. However, identifying such a similarity measure may be insufficient when there is substantial heterogeneity between the items being considered. For example, the characteristics that make clothing items, electronic components, or even romantic partners compatible exhibit substantial heterogeneity: for a pair of such items to be compatible they should be systematically similar in some ways, but systematically different in others.

Recently, a line of work has aimed to model such heterogeneous relationships, e.g. to model co-purchasing behavior between products based on their visual appearance or textual descriptions [21, 22, 31]. In spite of the substantial heterogeneity in the data used for training (a large dataset of co-purchase ‘dyads’ from Amazon) and the complexity of the models used, these works ultimately follow an established metric-learning paradigm: (1) Collect a large dataset of related (and unrelated) items; (2) Propose a parameterized similarity function; and (3) Train the parameterized function such that related items are more similar than non-related items. Such metric-learning approaches can be incredibly flexible and powerful, and have been used to identify similarities between items ranging from music [27] to members of the same tribe [7]. Such methods work to some extent even in the presence of heterogeneity, since they learn to ‘ignore’ dimensions where similarity should not be preserved. But we argue that ignoring such dimensions discards valuable information that ought to be used for prediction and recommendation.

In this paper, we propose new models and algorithms to identify relationships between items in product recommendation settings. In particular, we relax the metricity assumption present in recent work, by proposing more flexible notions of ‘relatedness’ while maintaining the same levels of speed and scalability. Specifically, we hope to overcome the following limitations of previous work:

• The similarity measures learned by previous approaches ultimately project categories as clusters into a metric space (albeit potentially via a complex embedding), since an item is inherently more similar to those from the same category than others (as we show later in Figure 5). This means that cross-category recommendations can only be made by exploiting an explicit category tree (e.g. ‘find the shoes nearest to these jeans’). Not only do such approaches require explicit category labels, but they are also subject to any noise or deficiencies in the category data. Our method can make cross-category recommendations without any depen-
Mixtures-of-experts type framework, determining to what extent each of the \( N \) embeddings is ‘relevant’ to a particular query.

Note in particular that the method described in Figure 1 can learn non-metric relationships since we are measuring the distance between two different embeddings. The learned relationships are not necessarily symmetric, nor do identity and transitivity necessarily hold; on the other hand the model is flexible enough such that a metric embedding could be learned if that was what the data supported.

For clarity, our contributions are summarized as follows:

1) We propose a new scalable method, Monomer, for heterogeneous item-to-item recommendation. The presented mixtures-of-embeddings framework allows it to learn non-metric relationships, thereby overcoming multiple limitations present in existing work.

2) We demonstrate quantitatively that Monomer is effective at learning notions of ‘relatedness’ from heterogeneous dyads of co-purchases from Amazon, and in particular that it does so more accurately than recent approaches based on metric/similarity learning.

3) We qualitatively show that Monomer can effectively learn multiple, semantically complex notions of ‘relatedness,’ and that these can be useful to generate rich, heterogeneous, and diverse sets of recommendations.

Code and data can be found at https://sites.google.com/a/eng.ucsd.edu/ruining-he/.

II. Related Work

The most closely related branches of work to ours are (1) Those that deal with the item-to-item recommendation problem, e.g. systems that generate recommendations by modeling relationships between items; and (2) Works that deal with metric (or relationship) learning in general, whether or not for recommendation.

Item-to-Item Recommendation. Identifying relationships among items is a fundamental part of many real-world recommender systems, e.g. to generate recommendations of the form ‘people who viewed \( x \) also viewed \( y \)’ on Amazon. Such methods may be based on collaborative filtering, e.g. counting the overlap between users who have clicked on / bought both items, as in Amazon’s own solution [18]. Latent-factor approaches aim to model user-item relationships in terms of low-dimensional factors, such that ‘similar’ items are those with close embeddings. See (e.g.) [1, 17] for surveys, and [18], [11], and [34] for specific systems that make use of Amazon, Etsy, and Ebay data.

Of more interest to us are systems that predict item-to-item relationships based on the content (e.g. images/text/metadata) of the items themselves. Various systems have been proposed to address specific settings, e.g. to identify relationships between members of ‘urban tribes’ [25], tweets [28], text [2, 4], or music [27]. Several methods have also been used to model visual data [3, 9, 15, 26, 32],

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Figure 1: Illustration of the high-level ideas of Monomer. The query item (a t-shirt) is embedded into visual space 0 (the anchor space) whose position we superimpose into the other spaces. The potential match (a shoe) is embedded to \( \sum_{k=1}^{N} \text{Prob}(\text{Space} = k) \cdot d_k \).
though typically in settings where the metric assumption is well-founded (e.g. similar image retrieval).

Our work follows recent examples that aim to model copurchase and co-browsing relationships, using a recently introduced dataset from Amazon [21, 22, 31]. While we extend (and compare quantitatively against) such work, our main contribution here is that we substantially relax the model assumptions to allow for more complex relationships than mere similarity between items.

Also of interest are a few works that model clothing data, particularly in recommendation settings, e.g. a few recent works that aim to capture some notion of ‘style’ include [8, 10, 13, 16, 19, 33]. However the specific tasks considered there are quite different from the item-to-item recommendation task in which we are interested.

**Metric (and non-metric) Learning.** Outside of the recommendation scenarios considered here, learning the features that describe relationships between objects is a vast topic. Typically, one is given some collection of putative relationships between items (i.e., a training set), and the goal is then to identify a (parameterized) function that can be tuned to fit these relationships, i.e., to assign observed relationships a higher likelihood or score than non-relationships. State-of-the-art methods identify hidden variables or factors that describe relationships between objects (i.e., a training set), and the goal is then to identify a (parameterized) function that can be tuned to fit these relationships among items [7, 29], e.g. by factorizing the matrix of links between items [23]. Again, the main contributions we hope to make over such approaches are (1) to relax the assumption of metricity, and (2) to allow for multiple notions of ‘relatedness’ to compete and interact. While a few approaches have recently been proposed to learn non-metric relationships (e.g. [5]), we are unaware of any that allow for the scale of the data (thousands of features, millions of items and relationships) that we consider.

### III. THE MODEL

Formally, we are given a dataset $\mathcal{D}$ comprising a large corpus of objects (or ‘items’) and the pairwise relationships $\mathcal{R}$ between items from different subcategories, i.e., if $(x, y) \in \mathcal{R}$ then (1) item $x$ and $y$ are related, and (2) $x$ and $y$ are not from the same subcategory (e.g. a shirt and a matching pair of pants). We choose such cross-category recommendations to highlight the ability of our model to generate recommendations between heterogeneous pairs of items. This matches the training instance selection approach from [31]. Additionally, a high-dimensional feature vector $f_x$ associated with each item $x$ is also provided (encoding e.g. its image or the text of its reviews). We seek a scalable method to model such relationships with a set of parameterized transform functions $d(x, y)$ such that related objects $((x, y) \in \mathcal{R})$ are assigned higher probabilities than non-related ones $((x, y) \notin \mathcal{R})$. Notation used throughout the paper is summarized in Table I.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{R}$</td>
<td>relationships between a corpus of items</td>
</tr>
<tr>
<td>$(x, y)$</td>
<td>an (ordered) item pair</td>
</tr>
<tr>
<td>$P((x, y) \in \mathcal{R})$</td>
<td>probability that $x$ and $y$ are related</td>
</tr>
<tr>
<td>$F$</td>
<td>dimensionality of the feature vector</td>
</tr>
<tr>
<td>$f_x, f_y$</td>
<td>feature vectors of $x$ and $y$ respectively ($F \times 1$)</td>
</tr>
<tr>
<td>$K$</td>
<td>rank of the Mahalanobis embedding matrix</td>
</tr>
<tr>
<td>$M$</td>
<td>Mahalanobis matrix ($F \times F$)</td>
</tr>
<tr>
<td>$\mathbf{E}_k$</td>
<td>low-rank Mahalanobis matrix ($F \times K$)</td>
</tr>
<tr>
<td>$N$</td>
<td>no. of Mahalanobis embeddings (i.e., learners)</td>
</tr>
<tr>
<td>$k$</td>
<td>index of the $N$ learners ($k \in {1, 2, ..., N}$)</td>
</tr>
<tr>
<td>$\mathbf{D}_k(x, y)$</td>
<td>distance from $x$ to $y$ predicted by learner $k$</td>
</tr>
<tr>
<td>$\bar{d}(x, y)$</td>
<td>distance from $x$ to $y$ (can be directed)</td>
</tr>
<tr>
<td>$\sigma_c(z)$</td>
<td>shifted sigmoid function $(1/(1 + \exp(-z - c)))$</td>
</tr>
</tbody>
</table>

### A. Preliminaries

**Visual Features.** In this paper, we mainly consider the case of using high-level visual features for relationship prediction. This is particularly useful for clothing recommendation (for example), a natural domain in which learning heterogeneous relationships between items across categories is particularly important.

Our visual features are extracted from a deep convolutional neural network pre-trained on 1.2 million ImageNet (ILSVRC2010) images. In particular, we used the Caffe reference model [14], which has 5 convolutional layers followed by 3 fully-connected layers, to extract $F = 4096$ dimensional visual features from the second fully-connected layer (i.e., FC7).

Note however that our proposed method is agnostic to the type of features used, and as we show later can handle other types of features (e.g. text) in order to address more general settings.

**Mahalanobis Transform.** In order to model subtle notions like ‘compatibility’ upon the raw visual features, we need expressive transformations that are capable of relating feature dimensions to explain the relationships between pairs of items. To this end, we follow the approach from [22]: there, a *Mahalanobis Distance* is used to measure the distance (or ‘dissimilarity’) between items within the feature space according to the knowledge of how different feature dimensions relate to each other. Let $M$ denote the matrix that parameterizes the Mahalanobis Distance, then the distance between an item pair $(x, y)$ is defined by

$$d_M(x, y) = (f_x - f_y)^T M (f_x - f_y),$$

where $f_x$ and $f_y$ are the features vectors of $x$ and $y$ respectively. Although such an approach defines a distance function (and therefore suffers from the issues we are hoping to address), we use this method as a building block and ultimately relax its limitations.
Mixtures-of-Experts. Mixtures of experts (MoEs) are a classical machine learning method to aggregate the predictions of a set of ‘weak’ learners, known as experts [12]. What is particularly elegant about this approach is that it allows each learner to ‘focus’ on classifying instances about which it is relevant (i.e., expert), without being penalized for making classifications elsewhere.

For regression tasks such as the one we consider, each learner (denoted by \( l \)) outputs a prediction value \( \text{Pred}_l(X) \) for the given input \( X \). These predictions are then aggregated to generate the final prediction by associating weighted ‘confidence’ scores with each learner. Here we are interested in probabilistically modeling such confidences to be proportional to the expertise of the learners:

\[
\text{confidence in } l’s \text{ expertise} = \sum_l P(l|X) \cdot \text{Pred}_l(X).
\]

In our model, each ‘expert’ shall correspond to a single notion of ‘relatedness’ between items. Thus, for a given pair of items that are potentially related, we can determine (a) which notions of relatedness are relevant for these items \( P(l|X) \); and (b) whether or not they are related according to that notion \( \text{Pred}_l(X) \). These two functions are learned jointly, such that the model automatically uncovers multiple notions of ‘relatedness’ simultaneously.

B. Model Specifics

First we describe how Mahalanobis transforms have previously been applied to this task, and can be used as a building block for this task, before describing our proposed non-metric method.

1) Low-rank Mahalanobis Metric: Considering the high dimensionality of the visual features we are modeling (feature dimension \( F = 4096 \) in our case), learning a full rank positive semi-definite matrix \( M \) as in Eq. (1) is neither computationally tractable for existing solvers nor practical given the size of the dataset.

Recently it was shown in [22] that a low-rank approximation of a Mahalanobis matrix works very well on visual datasets for the tasks considered in this paper. Specifically, the \( F \times F \) Mahalanobis matrix is approximated by \( M = \sum_{k=1}^{N} E_k E_k^T \), where \( E \) is an \( F \times K \) matrix and \( K \ll F \). Then the distance between a pair \((x, y)\) is calculated by

\[
d_E(x, y) = (f_x - f_y)^T E E^T (f_x - f_y) = ||E^T f_x - E^T f_y||^2_2.
\]

This can be viewed as embedding the high-dimensional feature space \((F \times d)\) into a much lower-dimensional one \((K \times d)\) within which the Euclidean distance is measured. Note that the low rank property reduces the number of model parameters and increases the training efficiency significantly.

2) Multiple, Non-Metric Embeddings: There are two key limitations from using a low-rank Mahalanobis embedding approach like the one above. First, it can capture only a single set of dimensions (or the ‘statistically dominant reason’) that determines whether two given items are related or not. However, there might be multiple reasons relevant to the link discrimination task in question. For example, a shirt and a pair of pants might go well together due to complementary colors, compatible textures, or simply some common characteristics they share (such as both having pockets/buttons, etc.). This drives us to use a group of embeddings, parameterized by \( N \) matrices \( E_1, \ldots, E_N \) each with dimensionality \( F \times K \) for the prediction task, with each capturing a different set of factors or ‘reasons’ that items may be related.

Another limitation of the single Mahalanobis embedding method, or more generally any metric-based method, is that it assumes that the closest neighbor of a given item is always itself, which is inappropriate for our task of placing many different categories of items close to the target. To overcome this shortcoming, we propose to use an anchor embedding (denoted by \( E_0 \), again, with dimensionality \( F \times K \)) to learn the feature mappings in a non-metric manner.

In our model, \( E_0 \) projects item \( x \) to a reference point \( E_0^T f_x \) in the corresponding space, referred to as the anchor space as it will be used as the basis for further comparisons. Next, embeddings \( E_k \) (for \( k = 1, 2, \ldots, N \)) map the potential match \( y \) and correspond to a particular notion of relatedness, such that \( E_k^T f_x \) will be close to \( E_k^T f_y \) (for some \( k \)) if \( x \) and \( y \) are related.

That is, the predicted distance \( d_k(x, y) \) by the \( k \)-th learner is

\[
d_k(x, y) = ||E_0^T f_x - E_k^T f_y||^2_2.
\]

For clarity, we call the \( N \) spaces defined by \( E_k \) (\( k > 0 \)) ‘pseudo’ spaces as all distance calculations are still performed within one actual space, i.e., the anchor space.

The above definition supports learning directed relationships as the model is not required to be symmetric; but, it is flexible enough to learn symmetric (or even metric) embeddings if such structures are exhibited by the data.

3) Probabilistic Mixtures of Embeddings: Now we introduce how we aggregate the predictions from different embeddings. Given an item pair \((x, y)\), we build our model upon the MoE framework to learn a probabilistic gating function to ‘switch’ among different embeddings. Considering our asymmetric setting where the query item \( x \) in the pair is used as the reference point, we model the probability that the \( k \)-th embedding is used for the given pair \((x, y)\)
with a softmax formulation:
\[
P(k|(x, y)) = \frac{P(k|x)}{\sum_i \exp(U^T_{ik}f_x)}, \tag{5}
\]
where \( U \) is a newly-introduced \( F \times N \) parameter matrix with \( U_{ik} \) being its \( k \)-th column. Briefly, the idea is to compute the probability distribution over the \( N \) learners given the characteristics of the ‘pivot’ item \( x \). Note that our formulation is efficient as it only introduces a small number of parameters given that \( N \) is usually a small number (e.g. on the order of 4 or 5 in our experiments).

Finally, our model calculates the ‘distance’ of an item pair \((x, y)\) by the probabilistic expectation:
\[
d(x, y) = \sum_k P(k|(x, y)) \cdot d_k(x, y). \tag{6}
\]

Note that our ‘distance’ definition is a non-metric method as it only preserves the non-negativity and is relaxing the symmetry, identity, and triangle inequality properties.

C. Learning the Model

With the ‘distance’ function defined above, we model the probability that a pair is related by a shifted sigmoid function (in a way similar to \([22]\)):
\[
P((x, y) \in R) = \sigma_c(-d(x, y)) = \frac{1}{1 + \exp(d(x, y) - c)}. \tag{7}
\]
Next, we need to randomly select a negative set of relationships \( \bar{R} \). To this end, we use a procedure from \([24]\) which randomly rewires the positive set in such a way that (1) the degree sequence of items is preserved and (2) each negative pair consists of items from two categories.

Then we proceed by fitting the parameters by maximizing the log-likelihood of the training corpus:
\[
\hat{(\Theta)} = \arg \max_{\Theta} L(R, \bar{R}|\Theta) = \sum_{(x, y) \in R} \log(P((x, y) \in R)) + \sum_{(x, y) \in \bar{R}} \log(1 - P((x, y) \in R)) + \Omega(\Theta), \tag{8}
\]

where \( \Theta \) is the full parameter set \( \{E_0, E_1, \ldots, E_N, U, c\} \), and \( \Omega(\Theta) \) is an \( L_2 \)-regularizer to avoid overfitting. The total number of parameters is \( F \times (N \times K + K + N) + 1 \). Since \( N \) and \( K \) are small numbers (see Section IV), the log-likelihood as well as the derivatives can be computed efficiently.

Monomer is learned with L-BFGS \([20]\), a quasi-Newton method for non-linear optimization of problems with a large number of variables. Our log-likelihood and the full derivative computations can be naїvely parallelized over all training pairs \((x, y) \in \mathcal{R} \cup \mathcal{R}\). This means the optimization can easily benefit from multi-threading and even parallelization across multiple machines (e.g. [6]). Note that Monomer and the single-embedding method share the same time complexity when using the same amount of embedding parameters (see Appendix for a detailed analysis).

IV. Experiments

A. Dataset

To fully evaluate the ability of Monomer to handle real-world tasks, we want to experiment on the largest dataset available. To this end, we adopt the dataset from Amazon recently introduced by \([22]\). We focus on five large top-level categories under the category tree rooted with ‘Clothing Shoes & Jewelry’, i.e., Men’s, Women’s, Boys’, Girls’, and Baby’s Clothing & Accessories. Statistics are shown in Table II.

For each of the above categories, we experiment with two important types of relationships: ‘users who bought \( x \) also bought \( y \)’, and ‘users who viewed \( x \) also viewed \( y \)’, denoted by ‘also bought’ and ‘also viewed’ respectively for brevity. Such relationships are a key source of data to learn from in order to recommend items of potential interests to customers. Ground-truth for these relationships is also introduced in \([22]\), and are originally derived from co-purchase and co-browsing data from Amazon.

Recall that our objective is to learn heterogeneous relationships so as to support cross-category recommendation. Across the entire dataset, such relationships are noisy, sparse, and not always meaningful. To address issues of noise and sparsity to some extent, it’s sensible to focus on the relationships within the scope of a particular top-level category, e.g. Women’s Clothing, Men’s Clothing etc. We then consider relationships between ‘2nd-level’ categories, e.g. women’s shirts, women’s shoes, etc.

In summary, our evaluation protocol is as follows:

1) A single experiment consists of a specific category (e.g. Men’s Clothing) and a graph type (e.g. ‘also bought’).

2) For each experiment, the relationships \((\mathcal{R})\) and a random sample of non-relationships \((\mathcal{R}^\prime)\) and \((\mathcal{R}^\prime)\) are pairs of items connecting different subcategories of the category we are experimenting on. Note
that $|\mathcal{R}| = |\mathcal{R}|$ and they share the same distribution over the items.

3) For each experiment, we use an 80/10/10 random split of the dataset ($\mathcal{R} \cup \mathcal{R}$) with the training set being at most two million pairs. Our goal is then to predict the relationships and non-relationships correctly, i.e., link prediction.

4) For all methods, the validation set is used for tuning the regularization hyperparameters, and finally the learned models are evaluated on the test set in terms of error/misclassification rate.

For example, one experiment is to predict ‘also_bought’ relationships for Men’s Clothing. There are 56 subcategories under Men’s Clothing (see Table II), so our goal is to distinguish edges from non-edges connecting items from among these subcategories.

All experiments were performed on a single machine with 64GB memory and 8 cores. Our largest experiment required around 40 hours to train, though most were completed in a few hours.

B. Comparison Methods

Weighted Nearest Neighbor (WNN): This method uses a weighted Euclidean distance in the raw feature space to measure similarity between items: $d_w(x, y) = \| w \odot (f_x - f_y) \|_2^2$. Here $\odot$ is the Hadamard product and $w$ is a weighting vector that is learned from the data.

Category Tree (CT): This method computes a matrix of co-occurrences between subcategories from the training data. Then a pair $(x, y)$ is predicted to be positive if the subcategory of $y$ is one of the top 50% most commonly connected subcategories to the subcategory of $x$.

Low-rank Mahalanobis Transform (LMT): LMT [22] is a state-of-the-art method for learning visual similarities among different items (possibly between categories) on large-scale datasets. LMT learns a single low-rank Mahalanobis embedding matrix to embed all items into a low-dimensional space. Then it predicts the links between a given pair based on the Euclidean distance within the embedded space (i.e., Eq. (3)).

Mixtures of Non-metric Embeddings (Monomer): Our method. This method learns a mixture of low-rank transforms/embeddings to uncover groups of underlying reasons that explain the relationships between items. It measures the ‘distance’ (or dissimilarity) between items in a non-metric manner (i.e., Eq. (6)).

Ultimately, our baselines are designed to demonstrate that (a) the raw feature space is not directly suitable for learning the notions of relationships (WNN); (b) using category metadata directly and not using other features (CT) results in relatively poor performance; and that (c) our proposed model is an improvement over the state-of-the-art method on our task (LMT).

### Table III: Test errors of the link prediction task (i.e., predicting ‘also_bought’ and ‘also_viewed’ relationships between items) using visual features (4096-d) for each edge type on clothing categories of the Amazon dataset. The best performing method in each case is boldfaced. Lower is better.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Graph</th>
<th>(a) Monomer</th>
<th>(b) CT</th>
<th>(c) LMT</th>
<th>(d) % impr. vs. c</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>also_bought</td>
<td>34.95%</td>
<td>47.71%</td>
<td>9.20%</td>
<td>6.48%</td>
</tr>
<tr>
<td></td>
<td>also_viewed</td>
<td>18.98%</td>
<td>47.40%</td>
<td>6.78%</td>
<td>6.58%</td>
</tr>
<tr>
<td>Women</td>
<td>also_bought</td>
<td>30.50%</td>
<td>49.73%</td>
<td>11.52%</td>
<td>7.87%</td>
</tr>
<tr>
<td></td>
<td>also_viewed</td>
<td>20.50%</td>
<td>49.48%</td>
<td>7.90%</td>
<td>7.34%</td>
</tr>
<tr>
<td>Boys</td>
<td>also_bought</td>
<td>31.16%</td>
<td>46.02%</td>
<td>8.80%</td>
<td>5.71%</td>
</tr>
<tr>
<td></td>
<td>also_viewed</td>
<td>21.52%</td>
<td>46.22%</td>
<td>6.72%</td>
<td>5.35%</td>
</tr>
<tr>
<td>Girls</td>
<td>also_bought</td>
<td>31.10%</td>
<td>47.63%</td>
<td>8.33%</td>
<td>5.78%</td>
</tr>
<tr>
<td></td>
<td>also_viewed</td>
<td>22.36%</td>
<td>46.43%</td>
<td>6.46%</td>
<td>5.62%</td>
</tr>
<tr>
<td>Baby</td>
<td>also_bought</td>
<td>37.26%</td>
<td>48.01%</td>
<td>12.48%</td>
<td>7.94%</td>
</tr>
<tr>
<td></td>
<td>also_viewed</td>
<td>30.89%</td>
<td>47.72%</td>
<td>11.88%</td>
<td>9.25%</td>
</tr>
<tr>
<td>Avg.</td>
<td></td>
<td>27.92%</td>
<td>47.64%</td>
<td>9.00%</td>
<td>6.79%</td>
</tr>
</tbody>
</table>

C. Performance & Quantitative Analysis

Error rates on the test set for all experiments are reported in Table III. To perform a fair comparison between LMT and Monomer, the following setting is used for all experiments in this paper:

1) It has been shown by [22] that LMT can achieve better accuracy when using a reasonably large number of embedding dimensions ($K$). Therefore in all cases we choose $K$ large enough such that LMT obtains the best possible (validation) performance.

2) In all cases we try to compare LMT and Monomer under the same total number of model parameters. For example, if we set the number of dimensions $K$ to 100 for LMT, then a fair setting for Monomer would be $K = 20$ and $N = 4$. This way both of them are using 100$F$ embedding parameters. Recall that $N$ is the number of embeddings (excluding the anchor embedding).

For experiments on ‘also_bought’ relationships, LMT uses $K = 100$ dimensions and Monomer uses $K = 20$ and $N = 4$. While for experiments on ‘also_viewed’ relationships, $K$ is set to 50 for LMT and $K = 10$ and $N = 4$ for Monomer. Note that ‘also_viewed’ relationships are almost twice as sparse as ‘also_bought’ relationships (and thus a model with fewer parameters performed better at validation time), as shown in Table II. We make a few observations to explain and understand our findings as follows:

1) WNN is particularly inaccurate for our task. We also observed relatively high training errors with this method for most experiments. This confirms our conjecture that raw similarity is inappropriate for our task, and that in order to learn the relationships across
Query Image

Figure 2: Visualization of *Monomer* trained on Women’s Clothing for ‘also bought’ prediction. Each visual space is demonstrated by a 2-d t-SNE grid view [30] (each cell randomly selects one image in overlapping cases). According to our ‘distance’ function (i.e., Eq. (6)), *Monomer* recommends the nearest neighbors of the query within each visual space, based on the associated ‘reasons’ learned from data. Note that each visual space exhibits different category ‘clusters’ at the query image’s location, allowing us to recommend diverse sets of items from the most closely-related categories.

2) The counting method (CT) performs considerably worse than other methods. This reveals that the predictive information used by the other models goes beyond the categories of the products, i.e., that the image-based models are learning relationships between finer-grained attributes.

3) Note that all models perform better at predicting ‘also viewed’ than ‘also bought’ relationships. This is reasonable since intuitively items that are “also viewed” indeed tend to share more common characteristics compared to the “also bought” scenario. The greater heterogeneity between training pairs in the latter task makes it comparatively harder to address.

4) *Monomer* outperforms LMT significantly for all experiments, especially for the harder task of predicting co-purchase dyads.

**D. Visualization of the Embeddings**

Next, we proceed by demonstrating the embeddings learned from our largest dataset, Women’s Clothing, by *Monomer*. We take the same model trained on co-purchase relationships from the previous subsection and visualize it in Figure 2. In this figure, we show each of the 5 visual spaces by a 2-d visualization with t-SNE [30]. Images are a random sample of size 50,000 from the Women’s Clothing dataset and projected (using the learned embedding matrices) to each visual space to demonstrate the underlying structure.

As analyzed in Section III, each embedding (i.e., learner) is capturing a specific notion of relatedness that explains the relationships of pairs of items in the corpus. In other words, it means that the nearest neighbors in each of the $N$ ‘pseudo’ spaces should be related to the query according to the specific notion captured. Therefore those neighbors should be recommended as potential matches to the query item, as shown by the example in Figure 2. For the query image (a t-shirt) in this example, *Monomer* recommends bundles of similar t-shirts, pants, shoes, and accessories (watches etc.) that resemble the query in terms of patterns (e.g. space 1), colors (e.g. space 2), and more generally ‘styles’ (e.g. space 3 and 4).¹ Such matching between a query image and nearby items in alternate spaces directly facilitates the task of recommending visually consistent outfits, where modeling and understanding the visual compatibility across categories is essential.

**E. Visualization of the Visual Dimensions**

Next we demonstrate the visual dimensions learned by *Monomer*, i.e., what kind of characteristics the model is capturing to explain the relationships among items. A simple way to visualize these dimensions is to show items that exhibit maximal values for each dimension. In other words, we select items according to

$$\arg \max_x E^T_{n,i} f_x.$$

¹The second patch actually contains a few men’s clothing items due to data deficiency—an intrinsic problem suffered by *Amazon*.
where $E_{:,i}$ is the $i$-th column of the embedding matrix $E$, corresponding to a visual dimension $i$. Intuitively, this informs us of items that are most representative of a particular visual aspect discovered by the model.

We trained Monomer on Men’s Clothing ($K = 10, N = 4$), predicting co-purchase relationships. Due to limited space, we randomly select one embedding and demonstrate its 10 visual dimensions in Figure 3. From the figure we can see that (1) Monomer seems to uncover meaningful visual dimensions, each of which highlights certain fine-grained item types (e.g., plaid tees and jeans in row 1 and 5); (2) human notions seem to have been captured, e.g., casual versus formal in rows 2 and 9; and (3) subtle differences between different characteristics can be distinguished (e.g., tees in rows 2 and 6). Monomer’s ability to discover and model the correlations among visual characteristics explains its success.

F. Visual Recommendation & Analysis

Beyond achieving high prediction accuracy, we want to test the ability of Monomer to generate useful recommendations. Again, we mainly compare to the state-of-the-art metric-based method, LMT. Both methods are able to learn relationships from the data, so one common setting is to retrieve ‘similar’ items (i.e., maximum probability of being related) to a given query.

First we train LMT and Monomer on Women’s Clothing to predict ‘also_bought’ relationships, under the same setting as in Table III. This way the two models will learn their own similarity (or distance) functions from the data. Next, from Women’s Clothing we randomly select a few query items, for each of which LMT and Monomer will retrieve its highest-probability links according to their own similarity functions. Figure 4 demonstrates such queries and the retrieved connections (in all cases ranked in decreasing order in terms of the probability of the link) by the two models.
women’s clothing, and then bought also. Indeed it bought also.

Be problematic especially for recommending related items to become ‘clusters’ in the embedded space. This can show results on two representative datasets, Men’s and a unique color to each subcategory in the dataset. Figure 5

Subcategories of items over the space. Therefore we assign are particularly interested in the distribution of different visualization, we use t-SNE [30] to further embed this space into 2-d. In each subgraph, a color represents a specific subcategory within the corresponding dataset. The main finding is that LMT tends to project subcategories to be ‘clusters’ in the embedded space, which may cause a ‘limited coverage’ problem for the recommendation task.

As shown in Figure 4, the metric-based method (LMT) tends to recommend items that are very similar to the query, even though for this task it is trained to predict complementary relationships (i.e., ‘also bought’). Indeed it is very difficult for a metric-based method to project items from different subcategories to be nearer than items from the same category; presumably such methods are limited by their underlying assumption that the most similar item to a given query is always itself. In [22] this was addressed to some extent by making explicit use of the category information at test time (e.g. ‘find the shirt closest to this pair of shoes’), though our model is able to make diverse sets of recommendations without such a dependence on explicit category information.

Recall that LMT learns an embedding within which the Euclidean distance is used to distinguish relationships from non-relationships. Visualizing such spaces can help understand the behavior of LMT. Again we uniformly sample 10,000 items from the dataset and use t-SNE [30] to visualize their positions in the embedded space. We are particularly interested in the distribution of different subcategories of items over the space. Therefore we assign a unique color to each subcategory in the dataset. Figure 5 shows results on two representative datasets, Men’s and Women’s Clothing.

From Figure 5 we find that subcategories of items tend to become ‘clusters’ in the embedded space. This can be problematic especially for recommending related items across subcategories:

1) From a recommendation perspective, there will be a ‘limited coverage’ issue because given a query LMT tends to recommend only those items on the boundaries of the clusters. There is no way that items located near the center of a cluster will ever be recommended, since the closest item outside the query’s own category cluster will be on the fringe of a different category cluster.

2) Recommendations will suffer from ‘mislabeling’ issues. Note that LMT relies heavily on the taxonomy metadata at test time to filter out items from the same subcategory as the query. However, even a tiny number of mislabeled items in the dataset can poison recommendations, and certainly some such examples exist in the Amazon dataset [31]. Unexpected items may appear on the recommendation list when there are mislabeled items that actually come from the same subcategory as the query.

Note that Monomer doesn’t suffer from either of above issues since it has already successfully ‘blended’ different subcategories, as shown by the nearest neighbors in Figure 4.

G. Learning Compatibility from Textual Features

In previous sections, we have shown that Monomer not only performs very well on link prediction tasks but also that it recommends highly diverse sets of items. However, above we only considered scenarios in which relationships like co-purchasing can be predicted from visual features. Following this, a natural question would be “Is Monomer able to learn relationships from non-visual features and achieve similarly competitive performance?”

To answer the above question, we perform further experiments on Bag-of-Words (BoW) features extracted from the text of product reviews, which are also available in the Amazon dataset. In particular, we experiment with a variety of top-level Amazon categories, i.e., Electronics, Automotive, Video Games, Movies & TV, Office Products, Home & Kitchen, and Cell Phones & Accessories (denoted by ‘Elect’, ‘Auto’, ‘Games’, ‘Movies’, ‘Office’, ‘Home’, and ‘Phones’ resp.). Statistics of these datasets are shown in Table IV.

For each category (e.g. Electronics) we use the following procedure to generate BoW features for all its items: (1) Remove stop-words and construct a dictionary. Our dictionary consists of 5000 nouns or adjectives or adjective-noun bigrams that appear most frequently in the review corpus being considered. (2) For each item i, a document di is generated by bagging all the reviews it has received. (3) The
of non-metric embeddings, which allows us to relax the identity and symmetry assumptions of existing metric-based methods. The proposed scalable approach generates diverse and cross-category recommendations effectively that capture more complex relationships than mere visual similarity. We showed quantitatively that Monomer is accurate at link prediction tasks using co-purchase and co-browsing dyads from Amazon, and qualitatively that it is able to generate diverse recommendations that are consistent with a particular visual style.

APPENDIX

Complexity Analysis: In Monomer, each embedding matrix has \( F \times K \) parameters, which means there are in total \( F \times K \times (N+1) \) embedding parameters. Since Monomer doesn’t need to use more embedding parameters to outperform LMT (see Section IV), we focus on comparing Monomer and LMT under the same total number of embedding parameters, in terms of the amount of multiplications involved.

For complete clarity, we denote the embedding dimension of LMT and Monomer by \( K' \) and \( K \) respectively \((F \times K' = F \times K \times (N+1))\). For each training pair \((x, y)\), LMT takes \( \mathcal{O}(F \times K') \) to compute the distance between them and the corresponding derivatives. While for Monomer, it takes \( \mathcal{O}(F \times K') \) to project \( x \) and \( y \) to the multiple spaces. Afterwards the ‘distance’ will be calculated in \( \mathcal{O}(N \times K') + \mathcal{O}(N \times F) \), where the former is for computing \( N \) distance components and the latter is spent on the probabilistic weights. In total, it takes \( \mathcal{O}(F \times K') + \mathcal{O}(N \times K') + \mathcal{O}(N \times F) = \mathcal{O}(F \times K') \) for Monomer to finish ‘distance’ computation. Likewise, it’s easy to verify that the corresponding derivatives can also be computed in \( \mathcal{O}(F \times K') \) time. To sum up, training Monomer and LMT will have the same time complexity when using the same amount of embedding parameters.

REFERENCES


