Learning Representations from Product Titles for Modeling Shopping Transactions

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ABSTRACT
Shopping transaction analysis is important for understanding the shopping behaviors of customers. Existing models such as association rules are poor at modeling products that have short purchase histories and cannot be applied to new products (the cold-start problem). In this paper, we propose BASTEXT, an efficient model of shopping baskets and the texts associated with the products (e.g., product titles). The model’s goal is to learn the product representations from the textual contents to capture the relationships between the products in the baskets. Given the products already in a basket, a classifier identifies whether a potential product is relevant to the basket based on their vector representations. This relevancy enables us to learn high-quality representations of the products. The experiments demonstrate that BASTEXT can efficiently model millions of baskets and that it outperforms the state-of-the-art methods in the next product recommendation task. We also show that BASTEXT is a strong baseline for keyword-based product search.

1 INTRODUCTION
With the rapid development of the internet and online shopping services, modern consumers are able to access a large number of products. During interactions with the system, consumers leave footprints such as purchase data. Such data is valuable in developing recommender systems that can suggest products that meet the needs of customers.

In this work, we focus on shopping transaction data. A shopping transaction, also known as a shopping basket, or a basket, is a set of products that a customer buys on a single shopping trip. Such data could help reveal the relationships between products, and these relationships are crucial to making recommendations in a given context. For example, when a customer examines a mobile phone case, it is useful to recommend other mobile phone cases or other accessories such as screen protectors, while it does not make sense to show, for instance, a T-shirt in that context.

A common approach to shopping basket analysis is to use association rules [1]. This approach discovers the rules in the form: “Consumers who buy diapers are likely to buy baby food.” However, in a system with a large number of products, many relevant products never co-occur in a basket, so the relationships between such products cannot be discovered by association rules. Another approach to context-based recommendation is neighborhood-based methods [12, 17]. This approach relies on the similarities between products. However, a drawback of this approach is that it only considers the last product and ignores previous products that are also valuable for predicting the next products. For example, suppose that {milk, sugar, eggs} are in the current shopping basket. Considering all three products is a better indication of buying flour than considering only eggs, the last product. Moreover, since both these approaches rely on purchase data, they cannot model new products, an issue known as the cold-start problem.

Addressing the cold-start problem using textual contents has been extensively studied, particularly in recommender systems [11, 21, 22]. These methods are a combination of a text model such as a variational autoencoder [11] and a matrix factorization-based model [16]. These approaches learn item representations from texts that are useful for predicting the elements of a user-item matrix. However, these models are more suitable for modeling long-term preferences of users rather than modeling the relationships between products in shopping baskets.

Recently, neural network-based approaches have achieved tremendous success in learning text representations [3, 10]. However, although these models are effective in learning text representations, they are not appropriate for understanding shopping baskets, because the text representations learned by these models can capture the semantic similarities of the texts but not the relationships between texts that co-occur in baskets. For example, they cannot identify that milk and flour often co-occur in baskets because there is no semantic similarity between the titles of these products.

This paper: To address the aforementioned problems, we propose BASTEXT, a novel model for learning product representations from the textual contents that are useful in explaining shopping baskets. By learning such representations, BASTEXT enables us to make different types of recommendations such as the products to be added to the current basket and the products that are often purchased together with a specific product.

Technically, BASTEXT consists of two text encoders that map the textual contents of the products in a basket and a potential product into fixed-size vector representations. A classifier identifies whether the potential product is relevant to the basket based on their vector representations. This identification enables us to learn product representations that are strong in identifying which products are likely to be in the same basket. Because the basket data is not an obvious dataset for training a classifier, we show how to form such data from the baskets.

The advantages of BASTEXT are as follows.
• It is a scalable model. Because the classifier operates on low-dimensional vector representations, it can model millions of baskets efficiently.
• It is a flexible model. It allows various types of text encoders to be used and enables the use of pretrained word vectors for learning better recommendations.
It is a multipurpose model. It can recommend the products in various scenarios and is a strong baseline for keyword-based product search.

2 RELATED WORK

2.1 Recommender Systems

Most of the existing recommender systems rely on collaborative filtering (CF), learning user preferences from their prior behaviors such as ratings, purchases, or clicks. One of the most efficient methods for CF is matrix factorization (MF), which models user preferences based on the user-item matrix [16]. However, MF is strong in identifying users’ long-term preferences rather than making recommendations in a given context. Another method of recommendation is sequential recommendation, which considers the interactions of users with items as a sequence with an explicit order, e.g., a sequence of clicks. A common approach to this problem is Markov chain-based methods [4, 18]. Recently, recurrent neural networks (RNNs) have been applied to this problem [6]. However, our problem is different from sequential recommendation. In shopping basket modeling, there is no explicit order in which the products are added to the baskets. Although a customer adds products to the basket sequentially, the order in which the products are added does not change the nature of the basket.

2.2 Shopping Basket Analysis

The most common approach to shopping basket analysis is association rules, which discovers the rules in the form: "Consumers who buy diapers are likely to buy baby food". Formally, such rules can be expressed as \( B \Rightarrow i \), where \( B \) is a set of products and \( i \) is a product not contained in \( B \). Such rules are useful in making recommendations given the products currently in the basket. However, association rules cannot discover the relationships between products that are relevant but have never co-occurred in the same basket.

Another method of basket analysis is next basket recommendations [15, 23, 25], which suggests a whole basket to a specific customer, given his or her previous shopping baskets. Again, our task differs because it does not focus on recommending the next basket. Instead, we focus on recommending the next product to add to the current basket.

2.3 Text Representation Learning

Neural approaches for learning text representations range from simple composition of the word vectors [13, 14] to more complicated networks such as doc2vec [10], convolutional neural network (CNN)-based approaches [7, 24], and RNN-base approaches [20]. Skip-thought vectors [9] are another model that learns sentence representations by predicting the surrounding sentences of a given sentence.

Although these approaches are effective in learning text representations, they may not be appropriate for understanding shopping baskets because the goal of these approaches is to learn the text representations that capture the similarities between texts; however, in shopping basket modeling, we need to capture the similarities between texts and the relationships between texts that co-occur in baskets.

2.4 Problem Formulation

Suppose that we have a collection of \( T \) shopping baskets. The products in the baskets come from a set of \( M \) products that are denoted by their indices 1, 2, ..., \( M \). For each product \( i \), there is a text \( s_i \) (e.g., product title, product description, or set of tags) associated with it. We also use \( w_i \) to denote the input vector of the \( i^{th} \) word. Table 1 lists the relevant notations used throughout this paper.

**Table 1: The notations used throughout the paper.**

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T )</td>
<td>the number of shopping baskets</td>
</tr>
<tr>
<td>( M )</td>
<td>the number of products</td>
</tr>
<tr>
<td>( s_i )</td>
<td>the text associated with the ( i^{th} ) product</td>
</tr>
<tr>
<td>( B )</td>
<td>a basket</td>
</tr>
<tr>
<td>( w_i )</td>
<td>the input vector of the ( i^{th} ) word</td>
</tr>
<tr>
<td>( K )</td>
<td>the embedding size</td>
</tr>
<tr>
<td>( h_i )</td>
<td>the embedding vector of product ( i )</td>
</tr>
<tr>
<td>( h'_i )</td>
<td>the context vector of product ( i )</td>
</tr>
<tr>
<td>( h_B )</td>
<td>the average of the context vectors of the products currently in basket ( B )</td>
</tr>
<tr>
<td>( D^+ )</td>
<td>the set of positive examples</td>
</tr>
<tr>
<td>( D^- )</td>
<td>the set of negative examples</td>
</tr>
<tr>
<td>( D )</td>
<td>the set of all examples: ( D = D^+ \cup D^- )</td>
</tr>
<tr>
<td>( n )</td>
<td>the negative sampling ratio</td>
</tr>
</tbody>
</table>

3 BASTEXT: THE SHOPPING BASKET MODEL

3.1 Notations and Definitions

Suppose that we have a collection of \( T \) shopping baskets. The products in the baskets come from a set of \( M \) products that are denoted by their indices 1, 2, ..., \( M \). For each product \( i \), there is a text \( s_i \) (e.g., product title, product description, or set of tags) associated with it. We also use \( w_i \) to denote the input vector of the \( i^{th} \) word. Table 1 lists the relevant notations used throughout this paper.

**Problem 1.** *(Next product recommendation)* The task is to recommend the next product to add to the current shopping basket given the products already in the basket.

3.2 Proposed Model

First, we present the decision process of how a customer chooses a product to add to the current basket. We assume the customer identity is anonymous because many websites allow shopping without account registration. We posit that the customer adds products into the basket sequentially. At each step, the customer chooses one product from the available products, conditioned by the products already in the basket.

The general architecture is shown in Fig. 1. Given the texts of the products currently in a basket \( B \) (the left side) and the text of a potential product \( i \) (the right side), the model predicts whether \( i \) will be added to the \( B \). First, the texts of the products are encoded into fixed-sized vectors. Then, we apply the mean pooling operation to the vector representations of the products in \( B \) to obtain the vector representation of the basket. Second, a classifier identifies whether the potential product \( i \) should be added into basket \( B \).

Here, we use two text encoders, \( f_E \) and \( f_C \), for encoding the text \( s_i \) of the potential product \( i \) and the text \( s_j \) of each product \( j \) in the basket \( B \), respectively. These encoders have the same architecture...
but different weights.
\[ h_i = f_E(s_i) \in \mathbb{R}^K, \quad h'_i = f_C(s_j) \in \mathbb{R}^K \] (1)

Formally, the probability that \( i \) will be added to \( B \) is formulated as
\[ p(\text{next} = i | B) = \sigma(h_i^T \bar{h}_B) \] (2)

where \( \bar{h}_B = \frac{1}{|B|} \sum_{j \in B} h'_j \).

While we can use one encoder, there is an advantage in using two encoders. If only one encoder is used, each product is represented by one vector and thus can represent only one aspect of the product (e.g., the product’s attribute). In contrast, when two encoders are used, each product will be represented by two vectors: the embedding vector \( h_i \) and the context vector \( h'_i \). The embedding vector identifies the attributes of the product, while the context vector identifies the products that often co-occur with it in the same basket. Consequently, BASTEXT can identify two types of relationships between products: “similar products” and “also-buy products”, as demonstrated in the experiments.

The architecture of a text encoder is a modeling choice. It can be simply the average of the vector representations of its words, a CNN, or an RNN. In this paper, we implemented two types of text encoders: (1) a mean of vectors (MoV)-based text encoder, and (2) a CNN-based text encoder.

**MoV-based text encoder.** The representation of text is simply the mean of the representations of the words contained in it. Then, to introduce nonlinearity, we added ReLU after the average layer, and the formal specification of the MoV-based text encoder is
\[ f(s) = \text{ReLU}\left(\frac{1}{|s|} \sum_{l} w_l^T W\right) \] (3)

where \( W \) is the connection matrix of the embedding layer.

Although this network is simple, it has two advantages: (1) it is very efficient in computational cost, and (2) it can be used when there is no explicit order of the words in a text, e.g., when the text is a set of tags associated with a product.

**CNN-based text encoder.** Although the MoV-based text encoder is simple and efficient, it ignores the order of words in sentences. To verify the effectiveness of the word order, we implement a CNN-based text encoder that considers the order of the words in a text. While using an RNN is common in modeling sentences, we use a CNN because of its efficiency in computational cost. In addition, we use the CNN architecture proposed in [7].

### 3.3 Forming the Training Data
We now present how to form the training data from a collection of shopping baskets. Each training example is a tuple: \((B, i, L)\) where \(B\) is the set of products currently in the basket, \(i\) is a potential product, and \(L\) is the label + or – to indicate whether \(i\) was chosen.

**Positive examples.** For each basket, we select each product in turn and use as the potential product, and the remaining products are interpreted as the products currently in the basket. In this manner, we obtain \(m_B\) positive examples, where \(m_B\) is the number of products in the basket \(B\), and we use \(D^+\) to denote the set of positive examples.

**Negative examples.** Since negative examples are not available, we obtain them by negative sampling by using the uniform sampling method. Other strategies are left for future work. For each positive example, \((B, i, +)\), we randomly select a product \(j\) that is not in \(B\) to form a negative example, \((B, j, –)\). For each positive example, we repeat this procedure \(n\) times to obtain \(n\) negative examples, and we use \(D^–\) to denote the set of negative examples.

### 3.4 Parameter Learning
After forming the training data, we have a set of examples \(D\) where each example is in the form \((B, i, L)\), where \(L\) is – or +. The objective function is the negative log likelihood over all examples in the training set formulated as
\[ \mathcal{L}(\theta) = \sum_{(B, i) \in D^+} \log \mu_{B,i} - \sum_{(B, i) \in D^-} (1 - \log \mu_{B,i}) \] (4)

where \(\mu_{B,i} = \sigma(h_i^T \bar{h}_B)\).

Training the BASTEXT model can be efficiently performed by back-propagation using stochastic gradient descent with mini-batches. In the experiments, we use Adam [8], and we do not perform negative sampling in advance. Instead, we use negative sampling at each mini-batch for obtaining diverse negative examples.

### 4 EXPERIMENTS

#### 4.1 Datasets
We use two public datasets of varying sizes.

- **OnlineRetail** [2]: this dataset contains about 20,000 shopping baskets. The average number of products in a basket is 26.7, and the average length of the product descriptions is 4.3 words.
Table 2: Statistical information of the datasets

(a) Warm-start splitting

<table>
<thead>
<tr>
<th>Data</th>
<th>OnlineRetail</th>
<th>Instacart</th>
</tr>
</thead>
<tbody>
<tr>
<td># training baskets</td>
<td>17K</td>
<td>2.7M</td>
</tr>
<tr>
<td># validation baskets</td>
<td>1K</td>
<td>159K</td>
</tr>
<tr>
<td># test baskets</td>
<td>1.9K</td>
<td>318K</td>
</tr>
<tr>
<td># test cases</td>
<td>51K</td>
<td>3.3M</td>
</tr>
</tbody>
</table>

(b) Cold-start splitting

<table>
<thead>
<tr>
<th>Data</th>
<th>OnlineRetail</th>
<th>Instacart</th>
</tr>
</thead>
<tbody>
<tr>
<td># training baskets</td>
<td>16K</td>
<td>2.3M</td>
</tr>
<tr>
<td># validation baskets</td>
<td>988</td>
<td>138K</td>
</tr>
<tr>
<td># test baskets</td>
<td>1.7K</td>
<td>312K</td>
</tr>
<tr>
<td># test cases</td>
<td>13.6K</td>
<td>2.3M</td>
</tr>
</tbody>
</table>

- Instacart: this dataset contains 3.2 million orders, and the average number of products per order is 10.6. Each product is associated with a product title whose average length is 4.7 words.

4.2 Experimental Setup

We randomly split the baskets into three sets: training baskets, validation baskets, and test baskets, with proportions 85%, 5%, and 10%, respectively. Then, we form the training set, validation set, and test set as warm-start and cold-start. Details of data splitting are given in Table 2a and Table 2b.

Warm-start. In this setting, we ensure that every product in the test set appears in the training set. We therefore remove from the test baskets the products that do not appear in the training baskets before forming the training set, the validation set, and the test set.

Cold-start. In this setting, we ensure that every product in the test set is absent from the training set, and we randomly select 10% of products from the test baskets and call these test products. We remove these products from training baskets. Then, we form the test cases in which the potential products come from the test products. The validation set and training set are formed with the warm-start setting.

Evaluation. For each basket in the test set, we predict the relevant scores for all the remaining products and rank these products according to their relevance scores. Then, we select the N products that have the highest scores to form a recommendation list. We use common rank-based metrics, Recall@N and MRR@N (mean reciprocal rank) for evaluating the models.

Competing methods. In evaluating the predictive performance, we compare the following methods (including ours). We do not compare with MF-based methods because they are not appropriate for modeling shopping baskets.

- POP (popular products): this model recommends the most popular products in the training set. Although POP is simple, it is often a strong baseline in certain domains.
- ItemKNN: this model is based on the co-occurrences of products in the baskets and is one of the most common item-to-item recommendations in the form “users who bought X also bought Y”.
- prod2vec: a word2vec version for learning the product representations by corresponding a basket as a sentence and a product in the basket as a word. A basket’s representation is calculated as the mean of the products contained in the basket. Given a basket, we compute the cosine similarities between its representation and all potential products and select the top N similar products.
- doc2vec: a model for learning text representations. We apply doc2vec to obtain the product representations from their titles. A basket’s representation is calculated as the mean of the products contained in it. Given a basket, we calculate the cosine similarities between the basket’s representation and all potential products and select the top-N similar products.
- BASTEXT-Avg: the BASTEXT model where the MoV-based text encoders are used for learning text representations. The word input vectors are one-hot vectors.
- BASTEXT-Avg+ (our): the BASTEX-Avg model where the input vector for each word is the pretrained word vector.
- BASTEXT-Conv (our): the BASTEXT model where the CNN-based text encoder is used for learning the representations of texts. The input vector for each word is its one-hot vector.
- BASTEXT-Conv+ (our): the BASKET-Conv model where the input vector for each word is the pretrained word vector.

4.3 Implementation Detail

All BASTEXT variants are trained by optimizing the binary cross-entropy loss in Eq. 4. We use dropout for hidden layers to avoid overfitting. To speed up the training process, we exploit the power of the GPU. In dividing the training data into mini-batches, we choose the mini-batch sizes that fit the GPU memory. The mini-batch size is 10,000 for OnlineRetail data and 5,000 for Instacart data.

4.4 Comparison over Baselines

Table 3 and Table 4 show the performances of the next product prediction task. We can see that all variants of BASTEXT significantly outperformed the other methods. We can make the following observations.

As expected, POP does not achieve good performance because it cannot capture the context of the shopping trips. Therefore, it is easily beaten by ItemKNN and prod2vec. We also see that ItemKNN and prod2vec outperform doc2vec, which uses content only, indicating that the basket data is more valuable than the contents in capturing the shopping behaviors. In the warm-start setting, BASTEXT-Avg significantly outperforms prod2vec (8.4% and 19% for OnlineRetail and Instacart, respectively), indicating that introducing textual contents significantly improves the performances.

In the cold-start setting, only doc2vec and the variants of BASTEXT achieve good performance. The performances of doc2vec are almost the same as the warm-start setting because doc2vec uses content only. BASTEXT-Avg performs slightly better than doc2vec,
indicating that jointly training the texts with purchase data improves the performance.

Impact of the text encoder model. Table 3 and 4 show that BASTEXT-Conv and BASTEXT-Conv+ perform slightly better than their counterparts (BASTEXT-Avg and BASTEXT-Avg+). These results indicate that considering the order of words in texts can improve the representations. However, such minor improvements suggest that using the MoV-based text encoder is also effective, given that its complexity is cheaper than a CNN.

Impact of the pretrained word vectors. One advantage of BASTEXT is that it can use the pretrained word embedding vectors as its input. Thus, we can study the impact of using pretrained word embedding vectors on the performance of BASTEXT, and to this end we use the pretrained vectors of GloVe [14].

Table 3 and 4 show marginal improvements of BASTEXT-Avg and BASTEXT-Conv+ over their counterparts (BASTEXT-Avg and BASTEXT-Conv). The improvement is due to the very short product titles; they are therefore poor at capturing the semantic meaning of the texts. Instead, using pretrained word vectors improves the representations of short texts.

### 4.5 Product-based Recommendation

Making recommendations in the context of a specific product is a typical scenario. Here, we consider two kinds of such recommendations: similar product and also-buy product recommendations.

Similar product recommendation. This is useful when a customer is examining a product. For example, if the customer is examining a skirt, it makes sense to show her some other skirts so that she can compare before deciding.

Also-buy product recommendation. Here, products are recommended that are frequently purchased together with a specific product. This scenario is useful when a customer has added a product to the shopping basket.

Given two products $i$ and $j$, we compute how likely $i$ is bought given that the customer has already bought $j$ as the inner product of the context vector $h_i$ and $h_j'$:

$$\text{Also\_buy}(i, j) = h_i^\top h_j'. \tag{6}$$

Fig. 3 shows some examples of also-buy product recommendations. In each row, the leftmost example is a “query” product, and the three products to the right are the top-3 “similar” products, as calculated by Eq. 5.

The similarity between two products $i$ and $j$ is defined as the cosine similarity between their embedding vectors:

$$\text{sim}(i, j) = \cosine(h_i, h_j). \tag{5}$$

Fig. 2 shows some examples of similar product recommendations. In each row, the leftmost example is a “query” product, and the three products to the right are the top-3 “similar” products, as calculated by Eq. 5.
Table 5: Product search results on Instacart data. The top line contains the query (in boldface). Below the query are the top-5 answers according to BASTEXT-Avg and word2vec. Inside the parentheses () are the categories of the returned products, and the underlined words are words that appear in the query.

<table>
<thead>
<tr>
<th>query</th>
<th>organic tea</th>
<th>natural herb cough drops</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASTEXT</td>
<td>organic honeybush tea (tea)</td>
<td>cough drop (cold flu allergy)</td>
</tr>
<tr>
<td></td>
<td>organic chamomile lemon tea (tea)</td>
<td>honey/lemon cough drops (cold flu allergy)</td>
</tr>
<tr>
<td></td>
<td>organic white rose white tea (tea)</td>
<td>defense vitamin c, cold flu allergy (cold flu allergy)</td>
</tr>
<tr>
<td></td>
<td>Chinese breakfast black tea (tea)</td>
<td>natural throat drops honey &amp; pomegranate (cold flu allergy)</td>
</tr>
<tr>
<td>doc2vec</td>
<td>organic English breakfast black tea (tea)</td>
<td>ultra thin crust cheese lovers pizza (frozen pizza)</td>
</tr>
<tr>
<td></td>
<td>lemon sweet tea iced tea mix (tea)</td>
<td>homemade pizza sauce (pasta sauce)</td>
</tr>
<tr>
<td></td>
<td>bags organic turmeric ginger green tea (tea)</td>
<td>authentic deep dish sausage pizza (frozen pizza)</td>
</tr>
<tr>
<td></td>
<td>half sweet tea pink lemonade (tea)</td>
<td>Colby Jack cheese (packaged cheese)</td>
</tr>
</tbody>
</table>

Product search. Given a query \( s \) in the form of keywords, the task is to retrieve the products relevant to the query. We compare BASTEXT with doc2vec [10].

First, we infer the vector representations of the query using two models BASTEXT-Avg and doc2vec. For BASTEXT, we use the text encoder \( f_E \) and then compute the cosine similarity query’s vector representation with the embedding vector of every product in the dataset. The top-5 similar products are reported in Table 5.

We observe that BASTEXT retrieves more relevant products than doc2vec. In particular, for the second query, natural herb cough drops, BASTEXT can return relevant products while doc2vec completely misunderstands the query. We found that the keywords of this query rarely appear in the titles; therefore, doc2vec cannot learn good representations. In contrast, BASTEXT can learn effective representations by leveraging the basket data. This experiment suggests that BASTEXT is a potential baseline for product search, especially when the product titles are short.

Category classification. We also investigated the effectiveness of the product representations of BASTEXT, prod2vec, and doc2vec by performing category classification on the Instacart dataset. To this end, we used the embedding vectors of the products learned by these models as the feature vectors and used a support vector machine as the classifier. We performed fivefold cross-validation and report the classification accuracies. The products used in the test are from two groups. The first group contains five most active categories (categories that are most frequently purchased): (H1) Produce, (H2) Dairy/eggs, (H3) Snacks, (H4) Beverages, (H5) Frozen. The second group contains five least active categories (categories that are less frequently purchased): (L1) Personal care, (L2) Babies, (L3) (International), (L4) Alcohol, (L5) Pets.

The result is shown in Fig. 4. The accuracy of doc2vec is almost the same across the categories, which is as expected because doc2vec uses only the textual content. In the least active categories (L1–L5),
BASTEXT and prod2vec perform better than doc2vec. Although not large, the differences between BASTEXT and prod2vec with doc2vec increase in the most active categories (H1–H5), indicating the important role of purchase data in the performance. In the most active categories, BASTEXT still performs better than prod2vec, implying that introducing textual contents improves the effectiveness of the representations.

4.7 Hyperparameter Sensitivity
In this section, we study the impact of hyperparameters on the performance of the next product prediction task.

Impact of the negative sampling ratio. Fig. 5 shows the performance of BASTEXT-Avg’s next product prediction with different negative sampling ratios n. The results show that Recall@20 increases when the negative ratio n increases until a certain value of n (8–10) before becoming stable. Therefore, we do not need to sample more negative examples than this value of n.

Impact of the embedding size. Fig. 6 shows the performance of BASTEXT-Avg’s next product prediction with different embedding sizes K. The results show that the performance increases when K increases until a threshold of K (around 64). Then, the performances decrease (OnlineRetail data) or do not significantly increase (Instacart data). These observations suggest that the embedding size around K = 64 will balance performance and computational complexity.

5 CONCLUSIONS
We introduced BASTEXT, a model of texts and shopping basket data. BASTEXT uses the texts to address the cold-start problem and basket data to improve the performance of text representations. The experiments show that BASTEXT is effective in various tasks such as next product recommendation, similar product recommendation, also-buy product recommendation, and product search.

There are several directions for future work. One is to use data such as click data, in addition to the purchasing data. Another direction is to use other auxiliary data such as product images or user reviews in modeling the products.

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