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ABSTRACT

We introduce a novel latent vector space model that jointly learns the latent representations of words, e-commerce products and a mapping between the two without the need for explicit annotations. The power of the model lies in its ability to directly model the discriminative relation between products and a particular word. We compare our method to existing latent vector space models (LSI, LDA and word2vec) and evaluate it as a feature in a learning to rank setting. Our latent vector space model achieves its enhanced performance as it learns better product representations. Furthermore, the mapping from words to products and the representations of words benefit directly from the errors propagated back from the product representations during parameter estimation. We provide an in-depth analysis of the performance of our model and analyze the structure of the learned representations.

Keywords

Entity retrieval; Latent space models; Representation learning

1. INTRODUCTION

Retail through online channels has become an integral part of consumers’ lives [40]. In addition to using these online platforms that generate hundreds of billions of dollars in revenue [22], consumers increasingly participate in multichannel shopping where they research items online before purchasing them in brick-and-mortar stores. Search engines are essential for consumers to be able to make sense of these large collections of products available online [30]. In the case of directed searching (in contrast to exploratory browsing), users formulate queries using characteristics of the product they are interested in (e.g., terms that describe the product’s category) [51]. However, it is widely known that there exists a mismatch between queries and product representations where both use different terms to describe the same concepts [43]. Thus, there is an urgent need for better semantic matching methods.

Product search is a particular example of the more general entity finding task that is increasingly being studied. Other entity finding tasks considered recently include searching for people [6], books [23] and groups [55]. Products are retrievable entities where every product is associated with a description and one or more user reviews. Therefore, we use the terms “product” and “entity” interchangeably in this paper. However, there are two important differences between product search and the entity finding task as defined by de Vries et al. [14]. First, in entity finding one retrieves entities of a particular type from large broad coverage multi-domain knowledge bases such as Wikipedia [3, 14]. In contrast, product search engines operate within a single domain which can greatly vary in size. Second, user queries in product search consist of free-form text [51], as opposed to the semi-structured queries with additional type or relational constraints being used in entity finding [5, 14].

In this paper we tackle the problem of discriminating between products based on the language (i.e., descriptions and reviews) they are associated with. Existing methods that are aimed at discriminating between entities based on textural data learn word representations using a language modeling objective or heuristically construct entity representations [15, 57]. Our approach directly learns two things: a unidirectional mapping between words and entities, as well as distributed representations of both words and entities. It does so in an unsupervised and automatic manner such that words that are strongly evidential for particular products are projected nearby those products. While engineering of representations is important in information retrieval [2, 10, 12, 16, 25, 61], unsupervised joint representation learning of words and entities has not received much attention. We fill this gap. Our focus on learning representations for an end-to-end task such as product search is in contrast to the large volume of recent literature on word representation learning [56] that has a strong focus on upstream components such as distributional semantics [42, 59], parsing [13, 56] and information extraction [13, 56]. In addition, our focus on unsupervised representation learning is in contrast to recent entity representation learning methods [10, 61] that heavily depend on precomputed entity relationships and cannot be applied in their absence.

In recent years, significant progress has been made concerning semantic representations of entities. We point out three key insights on which we build: (1) Distributed representations [27] learned by discriminative neural networks reduce the curse of dimensionality and improve generalization. Latent features encapsulated by the model are shared by different concepts and, consequently, knowledge about one concept influences knowledge about others. (2) Discriminative approaches outperform generative models if enough training data is available [4, 29] as discriminative models solve the classification problem directly instead of solving a more general problem first [59]. (3) Recently proposed unsu-
pervised neural retrieval models [57] do not scale as they model a
distribution over all retrievable entities; the approach is infeasible
during training if the collection of retrievable entities is large.

Building on these insights, we introduce Latent Semantic Enti-
ties (LSE), a method that learns separate representations of words
and retrievable objects jointly for the case where mostly unstruc-
tured documents are associated with the objects (i.e., descriptions
and user reviews for products) and without relying on predefined
relationships between objects (e.g., knowledge graphs). LSE learns
to discriminate between entities for a given word sequence by map-
ning the sequence into the entity representation space. Contrary to
heuristically constructed entity representations [16], LSE learns the
relationship between words and entities directly using gradient de-
scent. Unlike [57], we avoid computing the full probability distri-
bution over entities; we do so by using noise-contrastive estimation.

Our research questions are as follows: (1) How do the param-
eters of LSE influence its efficacy? (2) How does LSE compare to
latent vector models based on LDA, LSI and word2vec? (3) How
does LSE compare to a smoothed language model that applies lex-
ical term matching? (4) What is the benefit of incorporating LSE
as a feature in a learning-to-rank setting?

We contribute: (1) A latent vector model, LSE, that jointly
learns the representations of words, entities and the relationship be-
tween the former, together with an open-source implementation.
(2) A study of the influence of LSE’s parameters and how these
influence its ability to discriminate between entities. (3) An in-depth
comparative analysis of the entity retrieval effectiveness of latent
vector models. (4) Insights in how LSE can improve retrieval per-
formance in entity-oriented search engines. (5) An analysis of the
differences in performance between latent vector models by exam-
ining entity representations and mappings from queries to entity
space.

2. RELATED WORK

2.1 Product retrieval

Product search engines are an important source of traffic in the
e-commerce market [30]. Specialized solutions are needed to max-
imize the utilization of these platforms. Nurmi et al. [45] note a
discrepancy between buyers’ shopping lists and how retail stores
maintain information. They introduce a grocery retrieval system
that retrieves products using shopping lists written in natural lan-
guage. Product resolution [11] is an important task for e-commerce
aggregation platforms, such as verticals of major web search en-
dines and price comparison websites. Duan et al. [19] propose a
probabilistic mixture model for the attribute-level analysis of prod-
uct search logs. They focus on structured aspects of product en-
tities, while in this work we learn representations from unstruc-
tured documents. Duan et al. [20] extend the language modeling
approach to product databases by incorporating the ability to con-
dition on specification (e.g., lightweight products only). They note
that while languages such as SQL can be used effectively to query
these databases, their use is difficult for non-experienced end users.
Duan and Zhai [18] study the problem of learning query intent rep-
resentation for structured product entities. They emphasize that ex-
isting methods focus only on the query space and overlook critical
information from the entity space and the connection in between.

We agree that modeling the connection between query words and
entities and propagating information from the entity representations
back to words is essential. In contrast to their work, we consider
the problem of learning representations for entities based on their
associations with unstructured documents.

https://github.com/cvangysel/SERT

2.2 Latent semantic information retrieval

The mismatch between queries and documents is a critical chal-
enge in search [54]. Latent Semantic Models (LSMs) enable re-
trieval based on conceptual content, instead of exact word matches.
LSMs have become popular through the introduction of Latent Se-
matic Indexing (LSI) [15], followed by probabilistic LSI (pLSI)
[29]. Salakhutdinov and Hinton [52] use a deep auto-encoder for
the unsupervised learning of latent semantic document bit patterns.
Deep Structured Semantic Models [29, 54] employ click data to
predict a document’s relevance to a query. Methods based on neu-
ral networks have also been used for machine-learned ranking [11]
[17, 36]. Van Gysel et al. [57] introduce an LSM for entity retrieval,
with an emphasis on expert finding; they remark that training the
parameters of their model becomes infeasible when the number of
differences in performance between latent vector models by exam-
nining entity representations and mappings from queries to entity
space.

2.3 Representation learning

Recently, there has been a growing interest in neural probabilis-
tic language models (LMs) for the modeling of word sequences
[8, 43, 44]. Distributed representations [27] of words learned by
neural LMs, also known as word embeddings, incorporate syntac-
tic and semantic information [42, 55, 49] as a side-effect of their
ability to reduce the dimensionality. Feed-forward [13] and recur-
rent [42] neural networks perform well in various NLP tasks. Very
recently, there has been an increased interest in multimodal neural
language models [33], which are used for the task of automated
image captioning, amongst others. Learning representations of en-
tities is not new. Bordes et al. [10] leverage structured relations
captured in Knowledge Bases (KB) for entity representation learn-
ning and evaluate their representations on the link prediction task.
Our approach has a strong focus on modeling the language of all
entities collaboratively, without the need for explicit entity relations
during training. Zhao et al. [61] employ matrix factorization meth-
ods to construct low-dimensional continuous representations of en-
tities, categories and words for determining similarity of Wikipedia
entities. They employ a word pair similarity evaluation set and only
evaluate on pairs referring to Wikipedia entities; they learn a single
semantic space for widely-differing concepts (entities, categories
and words) of different cardinalities and make extensive use of an
underlying Knowledge Graph (KG) to initialize their parameters.
In contrast, we model representations of words and entities jointly
in separate spaces, in addition to a mapping from word to entity
representations, in an unsupervised manner.

We tackle the task of learning latent continuous vector repres-
tations for e-commerce products for the purpose of product search.
The focus of this work lies in the language modeling and represen-
tation learning challenge. We learn distributed representations [27]
of words and entities and a mapping between the two. At retrieval
time, we rank entities according to the similarity of their latent rep-
resentations to the projected representation of a query. Our model
LSE is compared against existing entity-oriented latent vector rep-
resentations that have been created using LSI, LDA and word2vec.
We provide an analysis of model parameters and give insight in the
quality of the joint representation space.
3. LATENT VECTOR SPACES FOR ENTITY RETRIEVAL

We first introduce a generalized formalism and notation for entity-oriented latent vector space models. After that, in §3.2 we introduce Latent Semantic Entities, a latent vector space model that jointly learns representations of words, entities, and a mapping between the two directly, based on the idea that entities are characterized by the words they are associated with and vice versa. Product representations are constructed based on the n-grams the products are likely to generate based on their description and reviews, while word representations are based on the entities they are associated with and the context they appear in. We model the relation between word and product representations explicitly so that we can predict the product representation for a previously unseen word sequence.

3.1 Background

We focus on a product retrieval setting in which a user wants to retrieve the most relevant products on an e-commerce platform. As in typical information retrieval scenarios, the user encodes their information need as a query \( q \) and submits it to a search engine. Product search queries describe characteristics of the product the user is searching for, such as a set of terms that describe the product’s category \([51]\).

Below, \( X \) denotes the set of entities that we consider. For every \( x_i \in X \) we assume to have a set of associated documents \( D_{x_i} \). The exact relation between the entity and its documents depends on the problem setting. In this paper, entities are products \([18, 48]\) and documents associated with these products are descriptions and product reviews.

Latent vector space models rely on a function \( f : V^+ \rightarrow E \) that maps a sequence of words (e.g., a query \( q \) during retrieval) from a vocabulary \( V \) to a \( e_E \)-dimensional continuous entity vector space \( E \subseteq \mathbb{R}^{e_E} \). Every entity \( x_i \in X \) has a corresponding vector representation \( e_i \in E \). Let \( S_c : E \times E \rightarrow \mathbb{R} \) denote the cosine similarity between vectors in \( E \). For a given query \( q \), entities \( x_i \) are ranked in decreasing order of the cosine similarity between \( e_i \) and the query projected into the space of entities, \( f(q) \). Fig. 1 illustrates how entities are ranked according to a projected query. For LSI, \( f \) is defined as the multiplication of the term-frequency vector representation of \( q \) with the rank-reduced term-concept matrix and the inverse of the rank-reduced singular value matrix \([15]\). In the case of LDA, \( f \) becomes the distribution over topics conditioned on \( q \) \([9]\). This distribution is computed as the sum of the topic distributions conditioned on the individual words of \( q \). In this paper, the embedding \( f \) is learned; see §3.3 below.

Traditional vector space models operate on documents instead of entities. Demartini et al. \([16]\) extend document-oriented vector spaces to entities by representing an entity as a weighted sum of the representations of their associated documents:

\[
e_i = \sum_{d_j \in D_{x_i}} r_{i,j} f(d_j)
\]

(1)

where \( f(d_j) \) is the vector representation of \( d_j \) and \( r_{i,j} \) denotes the relationship weight between document \( d_j \) and entity \( x_i \). In this work we put \( r_{i,j} = 1 \) whenever \( d_j \in D_{x_i} \), for a particular \( x_i \in X \) and \( r_{i,j} = 0 \) otherwise, as determining the relationship weight between entities and documents is a task in itself.

3.2 Latent semantic entities

While Eq. 1 adapts document-oriented vector space models to entities, in this work we define \( f \) by explicitly learning \((4, 3)\) the mapping between word and entity representations and the representations themselves:

\[
f(s) = \tanh \left( W \cdot \left( W_e \cdot \frac{1}{|w|} \sum_{w_j \in s} \delta_i + b \right) \right)
\]

(2)

for a string \( s \) of constituent words \( w_1, \ldots, w_{|s|} \) (an n-gram extracted from a document or a user-issued query), where \( W_e \) is the \( e_E \times |V| \) projection matrix that maps the averaged one-hot representations (i.e., a \( |V| \)-dimensional vector with element \( i \) turned on and zero elsewhere) of word \( w_i \), \( \delta_i \), to its \( e_E \)-dimensional distributed representation. This is equivalent to taking the embeddings of the words in \( s \) and averaging them. In addition, \( b \) is an \( e_E \)-dimensional bias vector, \( W \) is the \( e_E \times |V| \) matrix that maps averaged word embeddings to their corresponding position in entity space \( E \) and \( \tanh \) is the element-wise smooth hyperbolic tangent with range \((-1, 1)\). This transformation allows word embeddings and entity embeddings to be of a different dimensionality.

In other words, for a given string of words we take the representation of this string to be the average of the representations of the words it contains \([42, 50]\). This averaged word representation is then transformed using a linear map \((W)\) and afterwards translated using \( b \). We then apply the hyperbolic tangent as non-linearity such that every component lies between \(-1 \) and \( 1 \). First of all, this regularizes the domain of the space and avoids numerical instability issues that occur when the magnitude of the vector components be-
comes too large. Secondly, by making the function non-linear we are able to model non-linear class boundaries in the optimization objective that we introduce in the next section. We use $W_e$ to denote the $|X| \times e_E$ matrix that holds the entity representations. Row $i$ of $W_e$ corresponds to the vector representation, $e_i$, of entity $x_i$. Fig. 2 depicts a schematic overview of the proposed model. The parameters $W_e, W_b$ and $W_c$ will be learned automatically using function approximation methods as explained below.

The model proposed in this section shares similarities with previous work on word embeddings and unsupervised neural retrieval models [42, 57]. However, its novelty lies in its ability to scale to large collections of entities and its underlying assumption that words and entities are embedded in spaces of different dimensionality: (1) The model of [42] has no notion of entity retrieval as it estimates a language model for the whole corpus. (2) Similar to [42], Eq. 2 aggregates words $w_i \in s$ to create a single phrase representation of $s$. However, in [57], a distribution $P(X \mid w_t)$ is computed for every $w_t$ independently and aggregation occurs using the factor product. This is infeasible during model training when the collection of retrievable objects becomes too large, as is the case for product search. In the next section (3.3) we solve this problem by sampling. (3) In both [42, 57] two sets of representations of the same dimensionality are learned for different types of objects with potentially different latent structures (e.g., words, word contexts and experts). As mentioned earlier, Eq. 2 alleviates this problem by transforming one latent space to the other.

### 3.3 Parameter estimation

For a particular document $d \in D_{x_t}$ associated with entity $x_t$, we generate n-grams $w_{j,1}, \ldots, w_{j,n}$ where $n$ (window size) remains fixed during training. For every n-gram $w_{j,1}, \ldots, w_{j,n}$, we compute its projected representation $f(w_{j,1}, \ldots, w_{j,n})$ in $E$ using $f$ (Eq. 2). The objective, then, is to directly maximize the similarity between the vector representation of the entity $e_t$ and the projected n-gram $f(w_{j,1}, \ldots, w_{j,n})$ with respect to $S_i$ (3.1), while minimizing the similarity between $f(w_{j,1}, \ldots, w_{j,n})$ and the representations of non-associated entities. This allows the model to learn relations between neighboring words in addition to the associated entity and every word.

However, considering the full set of entities for the purpose of discriminative training can be costly when the number of entities $|X|$ is large. Therefore, we apply a variant of Noise-Contrastive Estimation (NCE) [26, 41, 45, 46] where we sample negative instances from a noise distribution with replacement. We use the uniform distribution over entities as noise distribution. Define

$$P(S \mid e_t, f(w_{j,1}, \ldots, w_{j,n})) = \sigma(e_t \cdot f(w_{j,1}, \ldots, w_{j,n}))$$

as the similarity of two representations in latent entity space, where

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

denotes the sigmoid function and $S$ is an indicator binary random variable that says whether $x_i$ is similar to $f(w_{j,1}, \ldots, w_{j,n})$.

We then approximate the probability of an entity $x_i$ given an n-gram by randomly sampling $z$ contrastive examples:

$$\log \tilde{P}(x_i \mid w_{j,1}, \ldots, w_{j,n}) = \log P(S \mid e_t, f(w_{j,1}, \ldots, w_{j,n})) + \sum_{k=1}^{z} \log (1 - P(S \mid e_k, f(w_{j,1}, \ldots, w_{j,n})))$$

where $U(X)$ denotes the uniform distribution over entities $X$, the noise distribution used in NCE [26]. Eq. 4 avoids iterating over all entities during parameter estimation as we stochastically sample $z$ entities uniformly as negative training examples.

During model construction we maximize the log-probability (4) using batched gradient descent. The loss function for a single batch of $m$ instances $(w_{k,1}, \ldots, w_{k,n}, x_k)$ consisting of n-grams sampled from documents $D_{x_k}$ (see §2) and associated entity $x_k$ is as follows:

$$L(W_e, W_b, W_c, b) = -\frac{1}{m} \sum_{k=1}^{m} \log \tilde{P}(x_k \mid w_{k,1}, \ldots, w_{k,n})$$

$$+ \frac{\lambda}{2m} \left( \sum_{i,j \in E} W_{e_{i,j}}^2 + \sum_{i,j \in E} W_{c_{i,j}}^2 + \sum_{i,j \in E} W_{b_{i,j}}^2 \right),$$

where $\lambda$ is a weight regularization parameter. Instances are shuffled before batches are created. The update rule for a particular parameter $\theta (W_e, W_b, W_c$ or $b)$ given a single batch of size $m$ is:

$$\theta^{(t+1)} = \theta^{(t)} - \frac{\alpha^{(t)}}{\partial L_{\theta}} (W_e^{(t)}, W_c^{(t)}, W_b^{(t)}, b^{(t)}),$$

where $\alpha^{(t)}$ and $\theta^{(t)}$ denote the per-parameter learning rate and parameter $\theta$ at time $t$, respectively. The learning rate $\alpha$ consists of the same number of elements as there are parameters; in the case of a global learning rate, all elements of $\alpha$ are equal to each other. The derivatives of the loss function (5) are given in the Appendix.

### 4. EXPERIMENTAL SETUP

#### 4.1 Research questions

In this paper we investigate the problem of constructing a latent vector model of words and entities by directly modeling the discriminative relation between entities and word context. We seek to answer the following research questions:

**RQ1** How do the parameters of LSE influence its efficacy?

In §4 we introduced various hyper-parameters along with the definition of Latent Semantic Entities. We have the size of word representations $e_W$ and the dimensionality of the entity representations $e_E$. During parameter estimation, the window size $n$ influences the context width presented as evidence for a particular entity. What is the influence of these parameters on the effectiveness of LSE and can we identify relations among parameters?

**RQ2** How does LSE compare to latent vector models based on LDA, LSI and word2vec?

Is there a single method that always performs best or does effectiveness differ per domain? Does an increase in the vector space dimensionality impact the effectiveness of these methods?

**RQ3** How does LSE compare to a smoothed language model that applies lexical term matching?

How does LSE compare to language models on a per-topic basis? Are there particular topics that work especially well with either type of ranker?

**RQ4** What is the benefit of incorporating LSE as a feature in a learning-to-rank setting?

We exploit the special nature of our evaluation scenario where we know the unique association between documents and entities. The setup can easily be adapted to the more general case where a document is associated with multiple entities by extracting the same word sequences from the document for every associated entity.
What if we combine popularity-based, exact matching and latent vector space features in a linear learning-to-rank setting? Do we observe an increase in effectiveness if we combine these features?

4.2 Experimental design

To answer the research questions posed in §4.1 we evaluate LSE in an entity retrieval setting organized around Amazon products (see §4.3). We choose to experiment with samples of Amazon product data [38, 39] for the following reasons: (1) The collection contains heterogeneous types of evidential documents associated with every entity: descriptions as well as reviews. (2) Every department (e.g., Home & Kitchen) constitutes a separate, self-contained domain. (3) Within each department there is a hierarchical taxonomy that partitions the space of entities in a rich structure. We can use the labels associated with these partitions and the partitions themselves as ground truth during evaluation. (4) Every department consists of a large number of products categorized over a large number of categories. Importantly, this allows us to construct benchmarks with an increasing number of entities. (5) Every product has a variety of attributes that can be used as popularity-based features in a learning-to-rank setting.

To answer RQ1 we investigate the relation between the dimensionality of the entity representations \( e_E \) and window size \( n \). The latter, the window size \( n \), controls the context width the model can learn from, while the former, the dimensionality of the entity representations \( e_E \), influences the number of parameters and expressive power of the model. We sweep exponentially over \( n \) (2\(^i \) for \( 0 \leq i < 6 \)) and \( e_E \) (2\(^i \) for \( 6 \leq i < 11 \)). RQ2 is answered by comparing LSE with latent vector space model baselines [45] for an increasing entity space dimensionality \( e_E \) (2\(^i \) for \( 6 \leq i < 11 \)). For RQ3 we compare the per-topic paired differences between LSE and a lexical language model. In addition, we investigate the correlation between lexical matches in relevant entity documents and ranker preference. We address RQ4 by evaluating LSE as a feature in a machine-learned ranking in addition to query-independent and lexical features.

The number of \( n \)-grams sampled per entity \( x \in X \) from associated documents \( D_x \) in every epoch (i.e., iteration of the training data) is equal to \[ \left\lfloor \frac{1}{k^2} \sum_{d \in D} \max \{ |d| - n + 1, 0 \} \right\rfloor, \] where the \( \lfloor \cdot \rfloor \) operator is used interchangeably for the size of set \( X \) and the number of tokens in documents \( d \in D \). This implicitly imposes a uniform prior over entities (i.e., stratified sampling where every entity is of equal importance). The word vocabulary \( V \) is created for each benchmark by ignoring punctuation, stop words and case; numbers are replaced by a numerical placeholder token. We prune \( V \) by only retaining the \( 2^{16} \) most-frequent words so that each word can be encoded by a 16-bit unsigned integer. In terms of parameter initialization of the Latent Semantic Entities model, we sample the initial matrices \( W_o, W \) (Eq. 2) and \( W_e \) uniformly in the range \[ -\sqrt{\frac{0.07}{m \cdot n}}, \sqrt{\frac{0.07}{m \cdot n}} \] for an \( m \times n \) matrix, as this initialization scheme is known to improve model training convergence [24], and take the bias vector \( b \) to be null. The number of word features is set to \( e_V = 300 \), similar to [41]. We take the number of negative examples \( z = 10 \) to be fixed. Mikolov et al. [41] note that a value of \( z \) between 10 and 20 is sufficient for large data sets [45].

We used Adam ([5] \( \alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999 \)) with batched gradient descent (\( m = 4096 \)) and weight decay \( \lambda = 0.01 \) during training on NVidia Titan X GPUs. Adam has been designed specifically for non-stationary, stochastic cost functions like the one we defined in Eq. 4. For every model, we iterate over the training data 15 times and choose the best epoch based on the validation sets (Table 1).

4.3 Product search benchmarks

We evaluate on four samples from different product domains (Amazon departments), each with of an increasing number of products: Home & Kitchen (8,192 products), Clothing, Shoes & Jewelry (16,384 products), Pet Supplies (32,768 products) and Sports & Outdoors (65,536 products); see Table 1. The documents associated with every product consist of the product description plus reviews provided by Amazon customers. Rowley [51] p. 24] describes directed product search as users searching for “a producer’s name, a brand or a set of terms which describe the category of the product.” Following this observation, the test topics \( c_t \) are extracted from the categories each product belongs to. Category hierarchies of less than two levels are ignored, as the first level in the category hierarchy is often non-descriptive for the product (e.g., in Clothing, Shoes & Jewelry this is the gender for which the clothes are designated). Products belonging to a particular category hierarchy are considered as relevant for its extracted topic. Products can be relevant for multiple topics. Textual representations \( q_e \) of the topics based on the categories are extracted as follows. For a single hierarchy of categories, we tokenize the titles of its sub-categories and remove stopwords and duplicate words. For example, a digital camera lens found in the Electronics department under the categorical topic Camera & Photo \( \rightarrow \) Digital Camera Lenses will be relevant for the textual query “photo camera lenses digital.” Thus, we only have two levels of relevance. We do not index the categories of the products as otherwise the query would match the category and retrieval would be trivial.

4.4 Evaluation measures and significance

To measure retrieval effectiveness, we report Normalized Discounted Cumulative Gain (NDCG). For RQ4 we additionally report Precision@k (\( k = 5, 10 \)). Unless mentioned otherwise, significance of observed differences is determined using a two-tailed paired Student’s t-test [55] (** \( p < 0.01 \); * \( p < 0.05 \); * \( p < 0.1 \).

4.5 Methods used in comparisons

We compare Latent Semantic Entities to state-of-the-art latent vector space models for entity retrieval that are known to perform semantic matching [44]. We also conduct a contrastive analysis between LSE and smoothed language models with exact matching capabilities. Vector Space Models for entity finding. Demartini et al. [16] propose a formal model for finding entities using document vector space models [31]. We compare the retrieval effectiveness of LSE with baseline latent vector space models created using (1) Latent Semantic Indexing (LSI) [15] with TF-IDF term weighting, (2) Latent Dirichlet Allocation (LDA) [9] with \( \alpha = \beta = 0.1 \), where a document is represented by its topic distribution, and (3) word2vec [12] with CBOW and negative sampling, where a query/document is represented by the average of its word embeddings (same for queries in LSE). Similar to LSE, we train word2vec for 15 iterations and select the best-performing model using the validation sets (Table 1). Query-likelihood Language Model. For every entity a profile-based statistical language model is constructed using maximum-likelihood estimation [4] [37] [58], which is then smoothed by the language model of the entire corpus. The retrieval score of entity \( x \) for query \( q \) is defined as \[ \hat{P}(q \mid x) = \prod_{t_i \in q} P(t_i \mid \theta_x), \]
where $P(t \mid x_i)$ is the probability of term $t$ occurring in the smoothed language model of $x$ (Jelinek-Mercer smoothing [60]). Given a query $q$, entities are ranked according to $P(q \mid x)$. For the experiment investigating LSE as a feature in machine-learned ranking in §5.2 we construct training examples by using the relevant entities as positive examples. Negative instances are generated by sampling from the non-relevant entities with replacement until the class distribution is uniform.

5. RESULTS AND DISCUSSION

We now investigate the use of LSE as a feature in a learning to rank setting [36]. Latent vector space models are known to provide a means of semantic matching as opposed to a purely lexical match. To determine to which degree this is indeed the case, we first perform a topic-wise comparison between LSE and a learning to rank method [34, 57]. To determine to which degree this is indeed the case, we first perform a topic-wise comparison between LSE and a learning to rank method [34, 57]. We optimize the parameters of LSE and QLM in terms of NDCG. A negative correlation coefficient implies that queries consisting of more specific terms (i.e., low document freq.) that occur exactly in documents associated with relevant entities are more likely to benefit from QLM, whereas other queries (with less specific terms or less exact matches) gain more from LSE. Significance is achieved for all benchmarks ($p < 0.01$) using a permutation test.

### Table 2: Correlation coefficients between average IDF of lexically matched terms in documents associated with relevant entities and NDCG.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Spearman $R$</th>
<th>Pearson $R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home &amp; Kitchen</td>
<td>−0.30</td>
<td>−0.35</td>
</tr>
<tr>
<td>Clothing, Shoes &amp; Jewelry</td>
<td>−0.40</td>
<td>−0.37</td>
</tr>
<tr>
<td>Pet Supplies</td>
<td>−0.17</td>
<td>−0.17</td>
</tr>
<tr>
<td>Sports &amp; Outdoors</td>
<td>−0.34</td>
<td>−0.36</td>
</tr>
</tbody>
</table>

where $\triangle$ is the number of documents per entity. However, as the training corpora become larger (in smaller benchmarks (Fig. 4a, 4b), we see LSI as the main competitor of LSE. However, as the training corpora become larger (in Fig. 4c, 4d), word2vec outperforms LSI and becomes the main competitor of LSE. On all benchmarks, LSE peaks when the entity representations are low-dimensional (128- or 256-dimensional) and afterwards (for a higher dimensionality) performance decreases. On the other hand, word2vec stagnates in terms of NDCG around representations of 512 dimensions and never achieves the same level as LSE did for one or two orders of magnitude (base 2) smaller representations. This is a beneficial trait of LSE, as high-dimensional vector spaces are undesirable due to their high computational cost during retrieval [59].

5.2 A feature for machine-learned ranking

We now investigate the use of LSE as a feature in a learning to rank setting [36]. Latent vector space models are known to provide a means of semantic matching as opposed to a purely lexical matching [34, 57]. To determine to which degree this is indeed the case, we first perform a topic-wise comparison between LSE and a learning to rank method [34, 57]. To determine to which degree this is indeed the case, we first perform a topic-wise comparison between LSE and a learning to rank method [34, 57]. We optimize the parameters of LSE and QLM in terms of NDCG. A negative correlation coefficient implies that queries consisting of more specific terms (i.e., low document freq.) that occur exactly in documents associated with relevant entities are more likely to benefit from QLM, whereas other queries (with less specific terms or less exact matches) gain more from LSE. Significance is achieved for all benchmarks ($p < 0.01$) using a permutation test.

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### Table 1: Overview of the Home & Kitchen, Clothing, Shoes & Jewelry, Pet Supplies and Sports & Outdoors product search benchmarks. T and V denote the test and validation sets, respectively. Arithmetic mean and standard deviation are reported wherever applicable.

<table>
<thead>
<tr>
<th>Corpus (train)</th>
<th>Home &amp; Kitchen</th>
<th>Clothing, Shoes &amp; Jewelry</th>
<th>Pet Supplies</th>
<th>Sports &amp; Outdoors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of documents</td>
<td>88,130</td>
<td>94,024</td>
<td>416,993</td>
<td>502,313</td>
</tr>
<tr>
<td>Document length</td>
<td>$70.02 \pm 73.82$</td>
<td>$58.41 \pm 61.90$</td>
<td>$77.48 \pm 78.44$</td>
<td>$72.52 \pm 81.47$</td>
</tr>
<tr>
<td>Number of entities</td>
<td>8,192</td>
<td>16,384</td>
<td>32,768</td>
<td>65,536</td>
</tr>
<tr>
<td>Documents per entity</td>
<td>$10.76 \pm 52.01$</td>
<td>$5.74 \pm 18.60$</td>
<td>$12.73 \pm 55.98$</td>
<td>$7.66 \pm 30.38$</td>
</tr>
<tr>
<td>Topics (test)</td>
<td>657 (T)</td>
<td>750 (T)</td>
<td>385 (T)</td>
<td>1,879 (T)</td>
</tr>
<tr>
<td>Topics</td>
<td>72 (V)</td>
<td>83 (V)</td>
<td>42 (V)</td>
<td>208 (V)</td>
</tr>
<tr>
<td>Terms per topic</td>
<td>$5.11 \pm 1.79$</td>
<td>$4.10 \pm 1.86$</td>
<td>$3.73 \pm 1.62$</td>
<td>$4.64 \pm 1.68$</td>
</tr>
<tr>
<td>Relevant entities per topic</td>
<td>$10.92 \pm 32.41$ (T)</td>
<td>$20.15 \pm 57.78$ (T)</td>
<td>$75.96 \pm 194.44$ (T)</td>
<td>$29.27 \pm 61.71$ (T)</td>
</tr>
<tr>
<td>Relevant entities per topic</td>
<td>$10.29 \pm 15.66$ (V)</td>
<td>$12.13 \pm 19.85$ (V)</td>
<td>$57.40 \pm 88.91$ (V)</td>
<td>$38.25 \pm 157.34$ (V)</td>
</tr>
</tbody>
</table>
method performs substantially better than the other, suggesting that the two are complementary. To further quantify this, we investigate the relation between specific topic terms and their occurrence in documents relevant to these topics. That is, we measure the correlation between the per-topic $\triangle$NDCG (as described above) and the average inverse document frequency (IDF) of exact/lexically matched terms in the profile-based language model. In Table 2 we observe that queries that contain specific tokens (i.e., with high inverse document frequency) and occur exactly in documents associated with relevant products, benefit more from QLM (lexical matches). Conversely, queries with less specific terms or without exact matches in the profiles of relevant products gain more from LSE (semantic matches).

This observation motivates the use of LSE as a ranking feature in addition to traditional language models. Specifically, we now evaluate the use of LSE as a feature in a linear RankSVM (5). Following Fang et al. (21), we consider query-independent (Q) popularity-based features in addition to features provided by LSE and QLM. This allows us to consider the effect of the query-dependent features independent from their ability to model a popularity prior over entities. Table 3 lists the feature sets.

Table 4 shows the results for different combinations of feature sets used in a machine-learned ranker, RankSVM. The experiment was performed using 10-fold cross validation on the test sets (Table 1). The combination using all features outperforms smaller subsets of features, on all metrics. We conclude that Latent Semantic Entities adds a signal that is complementary to traditional (lexical) language models, which makes it applicable in a wide range of entity-oriented search engines that use ranker fusion techniques.
Table 3: Overview of the feature sets used in the machine-learned ranking experiments.

<table>
<thead>
<tr>
<th>Features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>QI</td>
<td>Query-independent features: (1) product price; (2) product description length; (3) reciprocal of the Amazon sales rank; and (4) product PageRank scores based on four related product graphs (also bought, also viewed, bought together, buy after viewing).</td>
</tr>
<tr>
<td>QLM</td>
<td>Query-likelihood Language Model using Jelinek-Mercer smoothing with $\lambda$ optimized on the validation set (Table 1). Posterior $P(q</td>
</tr>
<tr>
<td>LSE</td>
<td>Latent Semantic Entities optimized on the validation set (Table 4, Fig. 3). Similarity $S_e(f(q), e)$ is used as a feature for entity $x$, with vector representation $e$, and query $q$.</td>
</tr>
</tbody>
</table>

6. ANALYSIS OF REPRESENTATIONS

Next, we analyze the entity representations $e_i$ of the vector space models independent of the textual representations by providing empirical lower-bounds on their maximal retrieval performance, followed by a comparison with their actual performance so as to measure the effectiveness of word-to-entity mapping $f$.

Fig. 2 and 3 show which levels of performance may be achieved by using the latent models to generate a ranking from textual queries (Eq. 2). But this is only one perspective. As entities are ranked according to their similarity with the projected query vector $f(q_c)$, the performance for retrieving entities w.r.t. the textual representation of a topic $c$ depends on the structure of the entity space $E$, the ideal retrieval vector $e^*_c \in E$ (i.e., the vector that optimizes retrieval performance), and the similarity between $f(q_c)$ and $e^*_c$.

How can we determine the ideal vector $e^*_c$? First, we define it to be the vector for which the cosine similarity with each of the entity embeddings results in a ranking where relevant entities are ranked higher than non-relevant or unjudged entities. We approximate $e^*_c$ by optimizing the pairwise SVM objective $\mathcal{L}_{\text{svm}}$. That is, for every topic $c$ we construct a separate RankSVM model based on its ground-truth as follows. We only consider topics with at least two relevant entities, as topics with a single relevant entity have a trivial optimal retrieval vector (the entity representation of the single relevant entity). Using the notation of $\mathcal{L}_{\text{svm}}$, the normalized entity representations are used as features, and hence the feature mapping $\phi$ is defined as

$$ \phi(c, x_i) = \frac{e_i}{\|e_i\|_2} \text{ for all } x_i \in X. $$

The target ranking $r^*_c$ is given by the entities relevant to topic $c$. Thus, the features for every entity become the entity’s normalized representation and its label is positive if it is relevant for the topic and negative otherwise. The pair-wise objective then finds a weight vector such that the ranking generated by ordering according to the vector scalar product between the weight vector and the normalized entity representations correlates with the target ranking $r^*_c$. Thus, our approximation of the ideal vector, $\hat{e}^*_c$, is given by the weight vector $w_c$ for every $c$.

What is the approximation of this approximately ideal vector representation? And how far are our representations removed from it? Fig. 6 shows the absolute performance of $\hat{e}^*_c$ (dashed curves) and $f(q)$ (solid curves) in terms of NDCG. Comparing the (absolute) difference between every pair of dashed and solid curves for a single latent model gives an intuition of how much performance in terms of NDCG there is to gain by improving the projection function $f$ for that method. The approximately ideal vectors $\hat{e}^*_c$ discovered for LSE outperform all baselines significantly. Interestingly, for representations created using LDA, the optimal performance goes up while the actual performance stagnates. This indicates that a higher vector space dimensionality renders better representations using LDA, however, the projection function $f$ is unable to keep up in the sense that projected query vectors are not similar to the representations of their relevant entities. The latent models with the best representations (LSE and LSI) also have the biggest gap between $f(q)$ and $\hat{e}^*_c$ in terms of achieved NDCG.

We interpret the outcomes of our analysis as follows. The entity space $E$ has more degrees of freedom to cluster entities more appropriately as the dimensionality of $E$ increases. Consequently, the query projection function $f$ is expected to learn a more complex function. In addition, as the dimensionality of $E$ increases, so does the modeling capacity of the projection function $f$ in the case of LSE and LSI (i.e., the transformation matrices become larger) and therefore more parameters have to be learned. We conclude that our method can more effectively represent entities in a lower-dimensional space than LSI by making better use of the vector space capacity. This is highly desirable, as the asymptotic runtime complexity of many algorithms operating on vector spaces increases at least linearly $\mathcal{O}(n^2)$ with the size of the vectors.
Figure 6: Comparison of the approximately ideal retrieval vector $e^*_c$ with the projected query retrieval vector $f(q)$ for latent entity models built using LSE, LSI, LDA and word2vec on Home & Kitchen and Pet Supplies product search benchmarks (§4.3) and evaluated on the test sets. The plots for Clothing, Shoes & Jewelry and Sports & Outdoors product search benchmarks are qualitatively similar to the ones shown. The figures show the absolute performance in terms of NDCG of $e^*_c$ (dashed curves) and $f(q)$ (solid curves); significance ($\ddagger$) for the results for the approximately ideal retrieval vectors $e^*_c$ is computed between LSE and the best-performing baseline for each vector space size and indicated along the x-axis.

7. CONCLUSIONS

We have introduced Latent Semantic Entities, an unsupervised latent vector space model for product search. It jointly learns a unidirectional mapping between, and latent vector representations of, words and products. We have also defined a formalism for latent vector space models where latent models are decomposed into a mapping from word sequences to the product vector space, representations of products in that space, and a similarity function. We have evaluated our model using Amazon product data, and compared it to state-of-the-art latent vector space models for product ranking (LSI, LDA and word2vec). LSE outperforms all baselines for lower-dimensional vector spaces.

In an analysis of the vector space models, we have compared the performance achieved with the ideal performance of the proposed product representations. We have shown that LSE constructs better product representations than any of the baselines. In addition, we have obtained important insights w.r.t. how much performance there is to gain by improving the individual components of latent vector space models. Future work can focus on improving the mapping from words to products by incorporating specialized features or increasing the mapping’s complexity. In addition, semi-supervised learning may help specialize the vector space and mapping function for particular retrieval settings.

A comparison of LSE with a smoothed lexical language model unveils that the two methods make very different errors. Some directed product search queries require lexical matching, others benefit from the semantic matching capabilities of latent models. We have evaluated LSE as a feature in a machine-learned ranking setting and found that adding LSE to language models and popularity-based features significantly improves retrieval performance.

As to future work, in this paper we focus on the unsupervised setting where we have a description and a set of reviews associated with every product. Fig. 6 shows that there is a lot of performance to gain by improving the query projection function $f$. In a semi-supervised setting, the difference between $e^*_c$ and $f(q)$ can be minimized according to pairs of queries and ideal rankings. As an additional step, query-relevance training data could be incorporated during estimation of the entity space $E$. Moreover, as mentioned in §6, the query projection function $f$ is expected to learn a more complicated mapping. Hence, it may be beneficial to consider incorporating additional hierarchical depth using multiple non-linear transformations in the construction of $f$. More generally, the obtained product representations can be beneficial for various entity-oriented prediction tasks such as entity disambiguation or related entity finding. While we have focused on product retrieval in this work, the proposed model, insights and ideas can be applied in broader settings, such as entity finding and ad-hoc retrieval.

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REFERENCES


APPENDIX

Denote \( p_s = \hat{P}(x_k | w_{k,1}, \ldots, w_{k,n}) \). The derivative of \( \delta \) w.r.t. bias term \( b \) equals

\[
\frac{\partial \delta}{\partial b}(W, W, W, b) = -\frac{1}{m} \sum_{i=1}^{m} \delta_i \cdot \sum_{j=1}^{n} W_{i,j} \cdot w_{k,j,1} \cdot w_{k,j,2} \ldots \cdot w_{k,j,n}
\]

and w.r.t. an arbitrary matrix parameter \( \theta \) (\( W_1 \), \( W_2 \), or \( W \)):

\[
\frac{\partial \delta}{\partial \theta}(W, W_1, W_2, \theta) = \frac{1}{m} \sum_{i=1}^{m} \delta_i \cdot \sum_{j=1}^{n} W_{i,j,1} \cdot W_{i,j,2} \ldots \cdot W_{i,j,n}
\]

Ignoring the subscripts for batch instances and word positions for ease of notation, for a single instance we denote \( z^+ \) as the target entity and \( X^- \) as the sample of \( z \) contrastive negative examples. We have

\[
p = \frac{P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n-1}))}{P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n-1}), \lambda)} \prod_{s \in X^-} (1 - P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n-1})))
\]

where application of the product rule in the computation of \( \frac{\partial \delta}{\partial \theta} \) is omitted due to space constraints.

For \( \theta \) (\( W_1 \), \( b \), \( W_2 \) or \( W \)) we observe

\[
\frac{\partial P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n}))}{\partial \theta_W} = P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n})) - P(S | e, f(w_{1,j,1}, \ldots, w_{1,j,n-1}, \lambda))
\]

For a single entity representation \( e \) (a row of matrix \( W_1 \)),

\[
\frac{\partial x_{\delta_k}}{\partial \theta_W} = f(w_{1,j,1}, \ldots, w_{1,j,n})
\]

where we observe that the update to an entity representation is the projected representation of the input n-gram multiplied by a scalar.

The symbolic derivative of the dot product between the entity representation and the projected n-gram w.r.t. bias term \( b \), linear map \( W \) and word representations \( W_2 \), respectively are:

\[
\frac{\partial x_{\delta_k}}{\partial b} = \frac{\partial x_{\delta_k}}{\partial \theta_W} = f(w_{1,j,1}, \ldots, w_{1,j,n})
\]

in which the subscripts for batch instances and word positions are omitted for ease of notation.


\[ A. \text{ Y. Ng and M. I. Jordan. On discriminative vs. generative classifiers: A comparison of logistic regression and naive bays. In NIPS, pages 841–848, 2002.} \]