The Deep Journey from Content to Collaborative Filtering

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ABSTRACT

In Recommender Systems research, algorithms are often characterized as either Collaborative Filtering (CF) or Content Based (CB). CF algorithms are trained using a dataset of user explicit or implicit preferences while CB algorithms are typically based on item profiles. These approaches harness very different data sources hence the resulting recommended items are generally also very different. This paper presents a novel model that serves as a bridge from items content into their CF representations. We introduce a multiple input deep regression model to predict the CF latent embedding vectors of items based on their textual description and metadata. We showcase the effectiveness of the proposed model by predicting the CF vectors of movies and apps based on their textual descriptions. Finally, we show that the model can be further improved by incorporating metadata such as the movie release year and tags which contribute to a higher accuracy.

Keywords
Recommender Systems, Collaborative Filtering, Neural Embedding, Multi-view Representation Learning, Item2vec, Skip-Gram, Word2vec, Cold Start, Content Based Filtering, Item Similarity

1. INTRODUCTION

In Recommender Systems research, CF models are commonly used for a variety of personalization tasks [9]–[11]. A common approach in CF is to learn a low-dimensional latent space that captures the user’s preference patterns or “taste”. For example, Matrix Factorization (MF) models [8] are commonly used to map users and items into a dense manifold using a dataset of usage patterns or explicit ratings. An alternative to the CF approach is the Content Based (CB) approach which uses item profiles such as metadata and item descriptions, etc. CF approaches are generally accepted to more accurate than CB approaches [32].

Our goal is to predict the CF representation of items based on their CB profiles. The CB profiles are obtained from multiple sources such as item tags, numeric values and textual descriptions. Hence, the CB profiles are a mix of categorical, continuous and unstructured data. For example, the CB representation of a movie contains tags (genres, actors, director, languages), numeric values (release year) and textual description (plot summary). To obtain the CF representations, we have used the item2vec [12] algorithm. Finally, to learn a mapping from items CB representation to their CF representation, we propose a novel multiple input deep regression model that receives the CB representation as input and uses the CF latent vectors as labels.

We demonstrate the application of the proposed model for movies and apps recommender systems. We utilize a CNN on top of word2vec representation to learn a mapping from textual description of items (movie plots or app descriptions) to their CF latent vectors based on item2vec. We note that the approach in this paper is not restricted to item2vec and can be trivially extended to any CF algorithm that is based on a low-dimensional latent embedding such as most common MF models [8].

Beyond the textual descriptions, the model can be enhanced by adding different types of structured metadata as input. This metadata can be used as additional input along the textual descriptions to produce a mapping which is more accurate than when using each information source separately.

This paper makes several contributions: First, we introduce a model for bridging the gap between items’ CB profiles and their CF representations. This can be particularly useful for recommending new items where usage and preference data is not available (the items “cold-start” problem). Second, we present a multi-source architecture that supports a combination of categorical, continuous and unstructured data as an input. Finally, we investigate the contribution of each information source with respect to the ultimate CF prediction task.

The remainder of this paper is organized as follows: Section 2 describes related work and contrasts it with the current one. Section 3 explains the proposed model in detail. Section 4, presents the experimental setup, the datasets used in this paper and provides both quantitative and qualitative results. Finally, Section 5 concludes and discusses future research.

2. RELATED WORK

Deep learning models are being applied in a growing number of machine learning applications. Considerable technological advancements have been achieved in the fields of computer vision [1] and speech recognition [2]. In Natural Language Processing (NLP), deep learning methods have been mostly focused on learning word vector representations [3]–[6], [30]. Specifically, Skip-Gram with Negative Sampling (SGNS) [5], known also as word2vec, has drawn much attention for its versatile uses in several linguistic tasks.

Word2vec maps a sparse 1-of-V encoding (where V is the size of the vocabulary) into a dense low-dimensional latent space which encodes semantic information. The resulting word representations span a manifold in which semantically related words are close to each other. A recent work by Kim [7] has further enhanced this approach by applying a convolutional neural network (CNN) on top...
of the latent word representations to glean more information from unstructured textual data.

The first part of our model starts from a very similar architecture: First, a word2vec model is established in order to map words taken from the item descriptions into a latent semantic manifold. Then, a CNN model is placed in cascade in order to utilize the semantic information for predicting the CF representation of the items. Therefore, the model in this paper serves as a mapping between the content profiles of items and their CF representations.

An interesting observation is that the principle behind CF models such as MF models bears much similarity to SGNs models: both approaches work by “summarizing” a large dataset of sparse entities into a dense manifold that facilitates extraction of useful information. In the case of a word2vec model, the manifold encodes semantic information, while in MF the manifold encodes user preference information. Moreover, a simple neural network that maps a sparse 1-of-M encoding of users (where M is the number of users) into a sparse encoding of N items using a single hidden layer is in fact identical to a MF model: The weight parameters on the incoming and outgoing edges of the hidden layer are respectively equivalent to the user and items vectors of a MF model. The similarity of SGNs to MF has been thoroughly studied in [24].

Item2vec [12] is a variant of the SGNs with a modified objective aimed at learning item representations for CF tasks. Training is performed using sets of items that were co-purchased or co-consumed by users. Unlike MF models, in item2vec the users are not modeled directly in the latent space. Instead, in item2vec, users are treated as sets of items that are analogous to sentences in word2vec – these users are the “glue” that indicates relevance between co-occurring items.

Many attempts have been taken to leverage multiple views for representation learning. Ngiam et al. [25] proposed a ‘split autoencoder’ approach to extract a joint representation by reconstructing both views from a single view. Andrew et al. [26] introduce a deep variant of Canonical Correlation Analysis (CCA) [29] dubbed Deep CCA (DCCA). In DCCA, two deep neural networks were trained in order to extract representations for two views, where the canonical correlation between the representations is maximized. Other variants of DCCA are investigated in [27, 28].

In the context of Recommender Systems, Wang et al. [20] proposed a hierarchical Bayesian model for learning a joint representation for content information and collaborative filtering ratings. Djuric et al. [21] introduced hierarchical neural language models for joint representation of streaming documents and their content with application to personalized recommendations. Xiao and Quan [22] suggested a hybrid recommendation algorithm based on collaborative filtering and word2vec, where recommendations scores are computed by a weighted combination of CF and CB scores.

This paper differs from the aforementioned works by several aspects: first, we do not learn a joint representation for both CF and CB views nor do we optimize CCA variants. Instead, we learn a mapping from the CB view directly into the CF view. Second, we introduce a flexible model architecture that supports a combination of various types of input, simultaneously. Third, our model does not produce representation for users, as our task is to predict the CF representation of items. To the best of our knowledge, this is the first work to introduce such a setup, hence a direct comparison of these models is not valid.

3. MULTIPLE INPUT DEEP REGRESSION

In this section we provide a detailed description of the proposed model. Our task is to predict the CF representation for each item from its content (textual description / metadata). Given an effective finite set of items $I = \{k\}_{k=1}^{K} \subset \mathbb{N}$ and co-occurrences matrix $A \in \{0,1\}^{K \times K}$, we first employ item2vec [12] to produce a mapping $M_{\text{CF}} : I \rightarrow \mathbb{R}^r$ from an item $k$ to a CF vector $v_k$.

The CB profile of an item $k$ is obtained by using different mappings for different information sources. For the textual descriptions (e.g. movie plot summaries), we consider two different mappings: $M_{\text{w1}} : I \rightarrow \mathbb{R}^{m \times w}$ is a mapping from an item to a matrix that consists of $l$ rows, where each row is an $m$-dimensional word vector obtained by word2vec [5]. This matrix corresponds to the first $l$ words in the textual description of the item. If the number of words is less than $l$, we pad the matrix with zero rows. $M_{\text{w2}}$ is used to generate the input for the CNN-based text component (Section 3.1).

The second mapping for textual data maps an item to its bag of words (BOW) representation denoted by $M_{\text{bow}} : I \rightarrow [0,1]^T$. This mapping is obtained by first applying k-means clustering on the word2vec representations of the entire vocabulary. We denote the number of clusters by $b$. Then, given the item’s description text, soft alignment is applied between each word vector in the text and the $b$ centroids. The result is a histogram vector, which is then normalized into probabilities to form the BOW representations. This approach is inspired by prominent BOW models in computer vision [15].

For CB information in the form of tags / categories we define a mapping $M_{\text{tags}} : I \rightarrow \{0,1\}^c$ from an item to binary vector in size $T$, where $T$ is the size of available tags. Each entry in the binary vector corresponds to a different tag and the value indicates whether the tag related to the item or not.

The last mapping we applied is used for numerical inputs and denoted by $M_{\text{num}} : I \rightarrow \mathbb{R}^r$. This mapping maps an item to a $c$-dimensional vector, where each element corresponds to one of $c$ continuous features. In the examples we have used, the only numeric feature was a movie’s release year. Therefore, in this case $M_{\text{num}}$ is reduced to $M_{\text{num}} : I \rightarrow \mathbb{N}^c$.

In order to harness the different information sources, we utilize a multiple input deep regression model consisting of three distinct types of components corresponding to each type of information source: textual, tags and numeric information. In what follows, we describe this architecture in detail.

3.1 Text Components

The text components are designed to receive raw text as input and output a fixed size vector. In this work, we implement two different types of text components: dubbed ‘CNN’ and ‘BOW’ (marked red in Fig. 1). The CNN approach follows Kim’s ‘CNN non-static’ model from [7]. As explained earlier, using $M_{\text{w2}}$, we map the sequence of words in the textual input to a matrix which serves as the input to a CNN network. An illustration of this approach (taken from [7]) appears in Fig. 1(d). We note that the backpropagation process continues through the CNN onto the initial word2vec representations allowing the word embedding to freely adjust with respect to the CF prediction task at hand. Hence, the initial mapping $M_{\text{w2}}$ is fine-tuned throughout the training process.

Our CNN consists of a single 1D convolutional layer with a filter length of 3 and L2 regularization on its weights. This is followed by a global max pooling layer (convolution and pooling are applied over the time axis) and an additional fully connected (FC) layer. In contrast to [7], we did not apply parallel convolutional layers with different filter lengths. We did experiment with multiple filter
lengths (2-12), but these attempts failed to materialize into any gains with respect to our objective. A similar observation was also made in [31].

We applied a random dropout of words before feeding them into the CNN. This technique was instrumental in improving the model’s generalization capability and avoiding overfitting. The probability for dropping words can be either fixed or proportional to the words’ frequency. We found that both methods yield similar results and therefore resulted to using a fixed dropping probability of 0.2.

We considered several additional variants of CNN-based models as in [7]: (1) the ‘CNN random’ model learns the word representation \( M_{w, 2} \) from scratch by using random initialization of the word vectors; (2) the ‘CNN static’ model that keeps the word2vec representation \( M_{w, 2} \) fixed during the entire training process; (3) the ‘CNN multichannel’ model, which is a combination of both the ‘non-static’ and ‘static’ models. However, the ‘CNN non-static’ variant outperformed all the rest. In the remainder of this paper we refer to this variant as our CNN component.

Our second approach for utilizing textual information is based on a Bag of Words (BOW) on top of the word2vec representations. The BOW representation is computed by \( M_{bow} \) and is fed into a neural network with two FC layers and dropout in between. The BOW network architecture is presented in Fig. 1(c).

### 3.2 Tags Components

Beyond the textual information, it might be useful to utilize tags metadata which is associated with each item. The tags network component is a binary input vector in the dimension of number of tags and a single FC hidden layer with L2 regularization on its weights. No further improvement was gained by including additional layers. The input for the tags component is given by \( M_{tags} \). The tags component is illustrated in Fig 1(a).

In the movies examples, we used different tags components for different types of tags: genres, actors, directors and language tags. The hidden layer dimension is determined for each component according to the number of tags and their available combinations. For example, the actors component might be assigned with a higher output dimension than the language component. This is due to the fact that the number of actors is much larger than the number of languages. Moreover, movies usually contain multiple actors, but a single language.

### 3.3 Numeric Components

Numeric components are designed to handle numeric structured data represented as a continuous feature vectors. In this work, the only numeric values available were the movies’ release years. Therefore, the numeric component was simply chosen to be a network with a single input neuron (Fig. 1(b)). This input is given by \( M_{num} \).
3.4 A Combiner Component

The combiner component aims at combining multiple outputs from different components in order to predict into the CF space. The combiner component (illustrated in Fig. 1(e)) consists of a multiple input layers that are fully connected to a hidden layer with L2 regularization. This is followed by a final FC output layer with the same dimension of the CF space.

3.5 The Full Model

The full model is illustrated in Fig. 2. In accordance with Fig. 1, tags, text and numeric components are colored in blue, red and green respectively. The combiner component is colored in yellow. Fig. 2 exemplifies the application of the presented model for the movie similarity task, specifically for the ‘Pulp Fiction’ movie. Genres, actors, directors and languages are modeled as tags components, the movie plot summary is modeled as text component. In this implementation, the text component can be either CNN or BOW network. The release year is modeled as a numeric component. The combiner receives the outputs from all components and outputs a vector that is compared against the original ‘Pulp Fiction’ CF vector (produced by item2vec) using the MSE loss function.

4. EXPERIMENTAL SETUP AND RESULTS

The quantitative evaluation results in this paper are based on a 10-fold cross validation processes. We supplement these quantitative results with qualitative results to gain a better “feel” of the model. Recall that our goal is to predict for each item its CF vector from its content profile. Hence, the CF representation is considered as the ground truth in all of our experiments. Furthermore, since our model and the experimental setup are substantially different from previous other work [20]-[22], a direct comparison between these models to ours cannot be made (as explained in Section 2).

Next, we describe in detail the datasets, evaluated systems, parameter configurations, evaluation measures and present results.

4.1 Datasets

We exemplify the model by mapping CB to CF in two domains: movie recommendations based on a public dataset and Windows Apps recommendations using a proprietary dataset.

4.1.1 Word2vec dataset

We used a subset of the dataset from [14] in order to establish a word2vec model. Specifically, we kept only the top 50K most frequent words. We also mapped all numbers to the digit 9 and removed punctuation characters. Then, we randomly sampled 9.2M sentences that formed a total text length of 217M words for training the word2vec model according to [5].

4.1.2 Movies dataset

The movies dataset is publicly available and contains both CF and CB data for movies. The CF data is based on the latest MovieLens dataset [18] containing 22,884,377 ratings collected during 1995-2016 from 247,753 users that watched 34,208 movies. The movies are rated using a 5-star scale with half-star increments (0.5 - 5.0). From each user’s rating list, we consider all the movies with ratings above 3.5 as a set of co-occurring movies. We further discard all sets of size < 2. This results in 173,266 sets that contain 11,108 unique items (movies) as the effective training data for learning the item2vec model [12].
For each movie, we collected metadata from IMDB [33]. Three types of information sources are collected: movie plot (given as raw text), genres / actors / directors / languages (given as tags) and release year (given as a natural number). In the metadata tags, we filtered tags that with less than 5 occurrences resulting in a remainder of 23 genres, 1526 actors, 470 directors and 72 languages.

We created movie CB profiles as follows: First, we represented each movie’s plot summary by taking the first 500 words with word2vec mapping. We used zero padding for the plot descriptions shorter than 500 words. Then, the metadata fields from above were added to the movie profiles. Note that some of the movies had missing information. In this case, we set the plot or the missing tags to a special word / tag ‘n/a’. Missing values for the release year are set to the mean year of all movies (1993).

4.1.3 Windows apps dataset
The second dataset is a propriety dataset containing CF and CB data for apps from the Microsoft Windows Store. We generated CF profiles for the items using a dataset of users activity containing 5M user sessions. Each user session contains a list of items that were clicked by the same user in the same activity session. This dataset consisted of 33K unique items (apps) which were used to procure an item2vec model of representative CF vectors.

For each app, we created textual profiles based on the app description in the same manner as we did with the movies data (first 500 words that have word2vec representation are saved for each app as its textual description). In this case, no further metadata was used beyond the textual descriptions.

4.2 Evaluated Systems
In order to quantify the relative contribution of each data source in our model, we trained different configurations of the model, each time connecting a single component to the combiner and disconnecting all other components. For tags components we trained separate models for genres, actors, director and language. When presenting results, we intuitively dubbed each of these models according to their information sources i.e., ‘Genres’, ‘Actors’, ‘Director’ and ‘Language’ respectively. For the text components we trained separate models for CNN and BOW as explained above and dubbed them ‘CNN’ and ‘BOW’. For the numeric component we trained a separate model for the release year and dubbed it ‘Year’.

In order to quantify the relative contribution of each combination, we further trained models for the following combinations of components: ‘Tags’ – a combination of ‘Genres’, ‘Actors’, ‘Director’ and ‘Language’. ‘Tags+Year’ – a combination of ‘Tags’ and ‘Year’. ‘Tags+CNN’ – a combination of ‘CNN’ and ‘Tags’. ‘CNN+Year’ – a combination of ‘CNN’ and ‘Year’. ‘CNN+Tags+Year’ – a combination of ‘CNN’, ‘Tags’ and ‘Year’. which is the ‘full’ model (Section 3.5). Note that we did not include the ‘BOW’ component in the combinations since we found its contribution to be marginal once ‘CNN’ is included.

4.3 Parameter Configuration
The system parameters were determined according to a separate validation set.

The item2vec models (for both movies and apps) were trained for 100 epochs with a target dimension n = 40, negative to positive ratio 15 and subsampling parameter 1e-4.

The word2vec model was trained for 100 epochs with a target dimension n = 100, window size 4, subsampling parameter 1e-5 and negative to positive ratio 15.

For the ‘Genres’, ‘Actors’, ‘Director’ and ‘Language’ components, we used hidden layers with dimensions 100, 100, 40 and 20, respectively.

The ‘CNN’ components (for both movies and apps) uses 300 filters with a length 3 (each filter’s dimensions are in size of 3×100). The input shape for the ‘CNN’ was set to a matrix in size of 500×100. This matrix contains the first 500 words from the movie plot / app description, where each word vector is in dimension 100. For the ‘BOW’ component, we used hidden layers of dimension 256. The number of centroids in k-means was set to b=250. For the combiner component, we used a hidden layer of dimension 256.

Each system was trained to minimize the MSE loss function. We used the Adam optimizer [17] with a mini-batch size of 32 and applied an early stopping procedure [19]. When applied, the L2 regularization and dropout probability values were set to 1e-4 and 0.2, respectively.

4.4 Evaluation Measures
The first evaluation measure used in this paper is the Mean Squared Error (MSE) as measured by the difference of the predicted CF vectors from their original (item2vec) CF vectors. Formally, MSE is measured as follows: \[ MSE = \frac{1}{|T|} \sum_{i \in T} (v_i - \tilde{v}_i)^2, \] where T is the set of all test set items, v_i is the original CF vector, and \( \tilde{v}_i \) is the predicted vector. Minimizing the MSE is the objective of all the systems in this paper. It quantifies the ability of the different systems to reconstruct the original CF vectors. However, MSE does not have any direct business interpretation with regard to the ultimate collaborative filtering task. Hence, our next evaluation measures are borrowed from the field of CF research and directly quantify the quality of the predicted vectors with regard to the CF task.

Our second measure quantifies the quality of the predicted vectors in terms of item similarities in the CF latent manifold. For each predicted CF vector, we compute item similarities to all other items as well as to its own original CF vector. Then, we measure the Mean Percentile Rank (MPR) of the original item with respect to all other items. Formally, we denote by \( r_i \) the ranked position of the original item, when measured against the other items based on similarity to the predicted vector. For a dataset of M items, the best possible rank is \( r_i = 0 \) and the worst is \( r_i = M - 1 \). The MPR measure is computed according to \[ MPR = \frac{1}{|T|} \sum_{i \in T} \frac{1}{r_i}. \] Note that \( 0 \leq MPR \leq 1 \), where MPR = 0 is the optimal value and MPR = 0.5 can be achieved by random predictions.

Our final evaluation measure was chosen to quantify the ability of the predicted vectors to maintain the original item similarities. Specifically, we care more about the ability to find the most relevant item to each test item. Hence, we chose to use the Normalized Discounted Cumulative Gain for the top K most similar items or NDCG(K). This measure is computed by finding the K items most similar to the predicted vector, and summing their discounted relevance scores based on the original item vector. Formally, for the \( i \)’th test item the Discounted Cumulative Gain at \( K \) is given by \[ DCG_i(K) = \frac{1}{|K|} \sum_{j=1}^{K} \frac{rel_{i,j}}{\log(2 + j)}, \] where \( rel_{i,k} \) is the relevance score of the \( k \)’th retrieved item to the \( i \)’th test item. The relevance scores are simply the similarities of the retrieved items to the test item based on its original vector. Then, the normalized discounted commutative gain at \( K \) is computed by normalizing the item’s \( DCG_i(K) \) score by its maximum possible value also known as the Ideal Discounted Commutative Gain at \( K \) or IDCG(K). The IDCG(K) is achieved by ranking the items according to the original (item2vec) CF vector and taking the \( K \) most similar items. The final measure is computed by averaging over all the test set
Table 1: Average MSE (x100) and MPR (x100) values obtained by different systems for the movies dataset

| System       | MSE / MPR |
|--------------|-----------|
| Language     | 23.1 / 40.8 |
| Director     | 22.2 / 34.3 |
| Actors       | 21.6 / 25.5 |
| Genres       | 21.3 / 21.4 |
| BOW          | 21.2 / 19.2 |
| CNN          | 20.3 / 17.2 |
| Year         | 19.8 / 15.4 |
| Tags         | 19.2 / 12.4 |
| CNN + Tags   | 18.6 / 11.2 |
| CNN + Year   | 17.4 / 7.6  |
| Tags + Year  | 17.1 / 6.7  |
| CNN + Tags + Year | 16.5 / 5.4 |

Table 2: Average MPR (x100) and NDCG(10) values obtained for apps dataset

| System     | MPR / NDCG(10) |
|------------|----------------|
| CNN        | 2.35 / 0.86    |

items as follows: \( NDCG(K) = \frac{1}{|I|} \sum_{i \in I} \frac{DCG(i)}{DCG^*(i)} \). Note that \( 0 \leq NDCG(K) \leq 1 \) and \( NDCG(K) = 1 \) indicates a “perfect” prediction for the top \( K \) most similar items.

4.5 Quantitative Results

4.5.1 Movies data

Table 1 depicts the MSE and MPR values and Fig. 3 depicts NDCG(K) for the systems described in Section 4.2. All values are averaged using 10 fold cross validation. In most cases, the three evaluation measures are highly correlated. In what follows, we identify common trends across all evaluation measures and provide interpretations to these trends.

First, let us consider the ‘BOW’ vs. the ‘CNN’ systems. Both systems are based purely on the movie textual descriptions. Our results show that ‘CNN’ approach achieves better results than the ‘BOW’ approach. This showcases the ability of the ‘CNN’ model to benefit from the semantic information encoded in the word2vec representations as well as the ability of the ‘CNN’ filters to pick up the semantical context encoded by word propagation in the text. Next, we turn to consider the tags data. As explained in Section 3.2, there are four types of tags based systems: ‘Genres’, ‘Actors’, ‘Directors’, and ‘Language’ and we consider each system separately. Table 1 and Fig. 3 show that these systems were outperformed by ‘CNN’ across all measures. This indicates the ability of the ‘CNN’ system to utilize the textual information even beyond these very informative data sources.

The ‘Year’ system, based on movies release year, outperforms each of the previous systems including the ‘CNN’. Clearly, a movie’s release year alone cannot make for a good recommender system. Nevertheless, it captures a key pattern in the MovieLens dataset, which is characterized by many users who watch movies with adjacent release dates. Typically, movies are heavily promoted during their release period and much of the viewing patterns recorded in the MovieLens dataset occur during that period. Many MovieLens users watch multiple movies with close release dates. Hence, a movie’s release date explains a very dominant pattern in the dataset.

Finally, we turn to consider systems in which different information sources are combined. We notice that each combined model generates a considerable performance boost over its respective systems. Ultimately, the ‘CNN+Tags+Year’ system (the ‘full’ model) outperformed all the rest by combining all these information sources together.

4.5.2 Windows apps data

Table 2 presents MPR and NDCG values obtained by the ‘CNN’ system on the apps dataset. As we can see, the MPR value obtained by the ‘CNN’ model is significantly lower than the best result obtained by the ‘full’ model for the movies data (2.35 vs 5.4). We believe this is due to fact the apps dataset contains more training examples than the movies dataset (30K vs 11K) that enables a better fine-tuning of the word vectors with respect to the prediction task.

4.6 Qualitative Results

4.6.1 Movies data

Table 2 presents movie recommendations based on nearest neighbor search (with cosine similarity) in the CF and predicted space with respect to test queries. All queries contain items from the test set. The second column presents recommendations that were produced using the original CF vectors based on item2vec. The third column presents recommendations produced by the ‘CNN+Tags+Year’ system (the ‘full’ model) that utilizes all information sources. The last column presents recommendations produced by the ‘CNN’ system that leverages textual description of movies (plots) solely.

Three well-known movies from the test set are considered: ‘Shrek’ (2001), ‘The Hangover’ (2011) and ‘Gladiator’ (2000). We notice the tendency of the CF based recommendations to prefer popular movies. The ‘full’ model tends to pick recommendations from adjacent years having the same genre / actors and with similar plots. The ‘CNN’ model produces recommendations that are not restricted to a specific year. Therefore, it contains the recommendations ‘Shrek the Third’ and ‘Shrek Forever After’ that are the third and fourth movies in the ‘Shrek’ series released in later years (2007 and 2010). The ‘CNN’ model exhibits the same behavior, when recommending the third movie in ‘The Hangover’ series. This showcases the ability of the ‘CNN’ model to accurately identify the movie type in the query by analyzing its plot and provide recommendations that are competitive with the other two models.
relationship is applied to a new actor by adding the distance vector between their representations. In the right column, this presents a relationship between actors captured by the distance between their respective vector representations (Fig. 2 in [5]). Inspired by this work, we demonstrate the ability of our model to encode relationships between actors. Representations for actors are produced by setting the corresponding entry of the actor in the ‘Actors’ component to 1 and setting all other entries to 0.

Table 4 presents the learned relationships. The left column presents a relationship between actors captured by the distance vector between their representations. In the right column, this relationship is applied to a new actor by adding the distance vector to a new origin. The closest artist is then retrieved (according to cosine similarity) and presented as the result of the summation.

The first example demonstrates a relationship based on a generational (~ 20 years) gap between actors that play in movies from the same genres. The second example demonstrates a transition from versatile actors to more comedy oriented actors in both genders. Finally, the third example demonstrates a transition from American to British actors across different genres.

Figure 4 depicts a t-SNE [13] embedding of the original (item2vec) CF vectors (a) and the predicted vectors by our ‘full’ model (b) for a random pick of 900 movies from the top six genres in the test set. For movies with multiple genre tags, we depict the first tag as their genre. Figure 4 shows that genre clustering exists both in the original CF space and even more so in the predicted space.

Figure 5 depicts a random pick of 1100 movies from the test set and the t-SNE embedding of their original CF vectors (a) and the vectors predicted by our model (b). This figure investigates the importance of a movie release dates in finding similar items. In accordance with the evaluation measures, Fig. 5 indicates that a release date is an important factor in the original CF similarities as well as in the resulting predictions.
4.6.2 Windows apps data
Table 3 presents apps recommendations produced according to a similar setting as in Table 2. The second column presents recommendations that were produced using the original CF vectors based on item2vec. The third column presents recommendations produced by the ‘CNN’ system. As we can see, the ‘CNN’ system manages to provide accurate recommendations with respect to the given seed item based on textual description of apps solely.

5. CONCLUSION AND FUTURE WORK
In this paper, we introduce a novel model that maps content based item information to its CF representation. We focus on movie and app recommendations and show a network architecture that maps movie structured metadata as well as unstructured textual descriptions into their latent CF representations. The textual descriptions were processed using a word2vec model followed by a CNN that scans the text in a similar fashion to latest NLP models [7]. In our evaluation, we show the effectiveness of the system in predicting useful movie and app recommendations and explore the contribution of each of its components.

In the future, we plan to investigate additional directions. Specifically, we plan to train a model to predict both metadata tags and the CF representation, simultaneously, from textual descriptions. This model will use a hybrid loss function that consists of classification and regression losses. We also plan to expand the model presented in this paper to include additional information sources such as audio, image and video. We further plan to apply the same ideas to books and music datasets.

Figure 4: TSNE visualization of the ground truth CF representation produced by item2vec (a) and the representation produced by our full model ‘CNN+Tags+Year’ (b) for 900 movies. Movies are colored according to their genres.

Figure 5: TSNE visualization of the ground truth CF representation produced by item2vec (a) and the representation produced by our full model ‘CNN+Tags+Year’ (b) for random set of 1100 movies. Movies are colored according to their release date.
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