Paper2vec: Citation-Context Based Document Distributed Representation for Scholar Recommendation

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Abstract

Due to the availability of references of research papers and the rich information contained in papers, various citation analysis approaches have been proposed to identify similar documents for scholar recommendation. Despite of the success of previous approaches, they are, however, based on co-occurrence of items. Once there are no co-occurrence items available in documents, they will not work well. Inspired by distributed representations of words in the literature of natural language processing, we propose a novel approach to measuring the similarity of papers based on distributed representations learned from the citation context of papers. We view the set of papers as the vocabulary, define the weighted citation context of papers, and convert it to weight matrix similar to the word-word co-occurrence matrix in natural language processing. After that we explore a variant of matrix factorization approach to train distributed representations of papers on the matrix, and leverage the distributed representations to measure similarities of papers. In the experiment, we exhibit that our approach outperforms state-of-the-art citation-based approaches by 25%, and better than other distributed representation based methods.
1. Introduction

Recommender systems have been introduced into many academic services, such as CiteSeerX\(^1\), Google Scholar\(^2\), PubMed\(^3\), and scholar social network such as ResearchGate\(^4\), reference managers such as CiteULike\(^5\), Docear\(^6\), Mendeley\(^7\). Due to the availability of paper references, many approaches based on citation analysis have been proposed to enhance the performance of relevant-document search\(^{[13]}\). Researchers found document retrieval methods using citation linkages are able to find additional relevant documents than conventional word indexing methods\(^{[9]}\). While full text documents are not always open access, citation indexes such as Web of Science, Google Scholar and Microsoft Academic Search can track citation linkage for most papers. Table 1 demonstrates some popular scholar datasets and citation indexes.

|                | WoS  | Scopus | CiteSeerX | DBLP | PMC | arXiv |
|----------------|------|--------|-----------|------|-----|-------|
| Full text availability | No   | No     | Yes       | Yes  | Yes | Yes   |
| Records in millions | ~ 90 | ~ 55   | ~ 6       | ~ 3  | ~ 3 | ~ 1   |

Table 1: List of some popular datasets. Citation index often contains much more records than full-text dataset.

Most of citation based methods view the number of co-occurrence of the citation linkages as similarity measurement via considering different citation linkage types with different weighting schemes. In those approaches, they require that there is at least one item shared in the contexts of two papers in order to calculate their similarity\(^{[2]}\). However, it is common for lots of pairs of documents that are similar but having no shared citation linkages. It may be caused by the fact that they come from different sources: technical reports, books, case-report and so on, or the time span between two papers are too long or too short. Table 2 demonstrates some examples from dataset.

\(^{1}\)http://citeseerx.ist.psu.edu/
\(^{2}\)http://scholar.google.com
\(^{3}\)http://www.ncbi.nlm.nih.gov/pubmed
\(^{4}\)https://www.researchgate.net
\(^{5}\)http://www.citeulike.org
\(^{6}\)http://www.docear.org/
\(^{7}\)https://www.mendeley.com/

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In this paper, we present a novel approach, called Paper2Vec, indicating that each paper is represented by a real valued vector. Inspired by distributed representations of words proposed in the area of NLP, which have recently demonstrated state-of-the-art results across various NLP tasks, we view each scholar paper (or paper ID specifically) as a word, and learn the distributed representations of words based on the citation context of papers, to capture the implicit scholar topics contained in the citation linkage set. Our paper distributed vectors are trained in a stochastic way based on matrix factorization on the citation relations data. And the cosine similarity of vectors is used as the document similarity measurement to find relevant scholar papers. The stochastic training way also makes Paper2vec easy for online learning.

As far as we know, there is no related research based on distributed representation for citation based algorithm. [18] also proposed a way to train documents as vectors under the framework of recent distributed representation models of NLP, however, it’s based on the full text corpus of papers. In summary, our contributions are shown as follows.

- we can calculate the similarity between any pair of document without the need of intersection of citation linkage sets.

- full text is not needed for Paper2vec, which makes it possible to be applied
into scholar databases where full text is not supported.

- the stochastic learning process and the corpus structure make it possible an online learning process. When a new paper is included into the database, it can be transformed into training data and learned immediately.

The paper is organized as follows. In Section 2 we review the related work of Paper2vec, from the citation-based similarity measures (Section 2.1) to the word distributed representation training algorithms (Section 2.2). Section 3 describes Paper2vec in details and the similarity between paper vectors and word vectors. Section 4 contains the details of the evaluation experiment, and Section 5 draws some conclusions and addresses future aspects of our work.

2. Related Work

2.1. Citation-based Algorithms

Many different similarity measures were proposed derived from document citation structure. A lot of research have proved that the search performance can be enhanced by incorporating citation algorithms into IR systems [7]. Among them the most widely used three basic methods are Co-citation, Bibliographic Coupling and Amsler, invented in the 60s and 70s [6]. They calculate the intersection of different citation linkage sets. While Co-citation regards the times two documents are cited together, namely “co-cited”, as the similarity measure, Bibliographic Coupling consider the number of documents they share in their references. To combine the two basic algorithms to get better results, Amsler proposed an algorithm considering the intersection of the union of two citation linkage sets mentioned above. Pairs of documents under all three models cannot be compared without co-occurrence items.

Context information of citation were introduced recently into the co-citation based similarity measure with different weighting schemes to quantify the degree of relevance between co-cited documents. Citation Proximity Analysis (CPA) [8], for instance, takes fixed value reflecting the proximity between two citations in the full text as the strength of the relevance of two co-cited papers, while [5] use another proximity function to get co-citation strength based on document structure. However, they have the same problems as the classical methods do, and the need of full text of such context-based co-citation methods limits their availability in some large datasets such as Web of Science, where full text is not supported.
2.2. Word Distributed Representation Models

The distributed representation for words were initially applied to solve the curse of dimensionality caused in language modeling based on discrete representation of words [4]. Under the hypothesis that words having similar context are similar, which suggests that contextual information nicely approximates word meaning, distributional semantic models (DSMs) use continuous short vectors to keep track of the context information collected in large corpus, namely the word distribution nearby the specific word. [1] classified DSMs into two types, count models and predict models. While count models are the traditional methods to generate distributed vectors by transforming the feature vectors with various specific criteria, predict models build a probabilistic model based on word vectors, which are trained on large corpus to maximize the probability of the occurrences of the contexts of observed words. Because the probability function is smooth and calculated totally by the distributed word vectors instead of discrete word features, the word distributed representation obtained by predict models makes it possible to regard two words similar when the distribution of context word vectors are similar. Evaluation performed in [1] shows context-predicting models are superior than count-based models on several measures.

Among existing predict models, SkipGram uses a simple probability function and achieved promising performance. SkipGram was proposed in [14] and improved in [15], which tries to predict the context of observed words \( P(\text{context} | w) \) across the corpus. The context of word is defined as a window around the word, the window size can be parameterized. Some efficient approximation methods are proposed to accelerate the training process such as hierarchical softmax and negative sampling [14]. The training process is stochastic and iterates several times across the large corpus. [10] proved SkipGram with negative sampling is implicitly factorizing a shifted point-wise mutual information (PMI) transformed word-context occurrence matrix. [14] have also proposed another algorithm named CBOW, which is an approximation version of SkipGram.

Different from SkipGram, GloVe [16] minimize the cost function corresponding to the probabilistic function SkipGram maximizes, which is based on the word-word co-occurrence matrix collected from training corpus. The nonzero elements on the matrix are trained to obtain word representations. This model efficiently leverages global statistical information and connects local context window methods such as SkipGram to the well-established matrix factorization methods, our algorithm is inspired by it.
Algorithm 1 Framework of Paper2vec algorithm

Require: The scholar database of research papers $D$ containing citation relation;
Ensure: Distributed embeddings of research papers contained in $D$, $W$;

1: Build the citation relation network from $D$;
2: Construct the citation linkage weight matrix of research papers from the network;
3: Minimize the cost function stochastically to get the paper vectors $W$;
4: return $W$;

3. Paper2vec

The latent vertex dimensions learned should be continuous and informative of the context. In this section we describe the Paper2vec algorithm, which learns distributed vertex embeddings from matrix factorization on the weighted context definition of node.

3.1. Weighted Citation Link Context

Many citation based similarity measurements are based on the assumption that papers having similar citation relation are similar. If we model the citation relation of papers to a directed graph, where nodes representing the documents, links representing citation relations, a classical similarity measurement approach is to measure the intersection of sets of neighbor nodes of the compared nodes representing the compared documents [6]. The set implicitly demonstrates the semantic content of the target paper. We define the set as “citation link context” of a document because the context set is based on the citation relation of papers.

However, we find that the citation link context is not limited to the direct citation relation, but can extend to papers having indirectly citation relation with the target paper, which also explicit the semantic context, with a weaker weight. Our first task is to define a new weighted citation link context that extends the neighbor nodes, which can help us better measure the similarity between documents.

The weight scheme of citation link context should consider the following characteristics we observe in the scholar dataset:

- Cited papers and citing papers together help predicting the content of the

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8The concept “citation context” has been used to describe the text surrounding the citation position in full text in previous research.
current paper. While cited papers reflect the topics at the publication time, citing papers focus more on the academic significance afterwards.

- Decrease with distance. Papers indirectly cited are not so relevant than the directly cited papers and have smaller weight.

- Transitivity. Weights can be transmitted. Assume paper A cites paper B and paper B cites paper C, weaker the weight of citation link between A and B or B and C, weaker the weight of link between A and C.

To satisfy the above properties, we define a weight scheme based on random walk probability. We don’t treat cited link and the citing link differently. So we can get a undirected graph from the citation relation of dataset. In the graph, we consider the probability randomly walking from node A to node B as the weight of B to A, which implicit the weight scheme is not symmetric. To simplify the calculation, we only concern nodes in a predefined window \( \text{win} \), meaning only taking the nodes having less than \( \text{win} \) steps away from the target node along the link path into account. Farther nodes may have too small to have an impact for the result. We define \( A \) as the transition matrix of nodes, \( A_{ij} \) meaning the probability walking from node \( i \) to node \( j \). The transition matrix only consider the probability between neighbor nodes, and the probability from node to its neighbors are equally allocated. Then the weight can be calculated as follows:

\[
X(j \mid i) = \max(0, \log \left( \sum_{o=1}^{\text{win}} \sum_{k=1}^{o} A_{ij}^k \right) + \lambda)
\]  

(1)

The weight is the shifted positive logarithm of expected time we arrive node \( j \) when random walk from node \( i \) for \( \text{win} \) steps. \( X(j \mid i) \) represents the weight of node \( j \) for node \( i \). We use logarithm function to change the exponential decay of weight with respect to the distance to the target node to linear decay, then we shift it to get positive weights, which are asymmetric and not fixed. The parameter \( \lambda \) should be chose based on the dataset and the window to guarantee most of the weight information are reserved. With the weight scheme we define a new richer citation link context, which can help us find a better similarity measurement.

3.2. Learning Vertex Dimensions with Citation Link Context

Distributed representation have recently demonstrated state-of-the-art results across various NLP tasks. The successful application is based on the assumption
that words having similar context are similar. The similarity between the assump-
tions inspired us to use distributed representation to represent papers, which is
learned from the weighted citation link context we get in the last section. While
word distributed representations can implicit the semantic and syntatic informa-
tion of word, we expect scholar document to be represented by distributed vectors
to capture the implicit scholar topics contained in the citation link set.

Now the question is how to utilize the weighted citation link set. We can
transfer it to a sparse weight matrix $W$, where $W_{ij}$ representing the weight node
$j$ for node $i$. Then matrix factorization approach can be used to obtain vectors
representing nodes. The cost function for training is defined as follows:

$$J = \sum_{i=1}^{V} \sum_{j=1}^{V} f(X(j \mid i))(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - X(j \mid i))^2$$

where $w$ and $\tilde{w}$ are respectively the paper embeddings and the context em-
bodiments. $f(X_{ij})$ controls the weight of elements in the matrix. While small
$X(j \mid i)$ may mean less information and more noise, we give a weighting func-
tion $f(X(i \mid j))$ for every element in the matrix as follows:

$$f(X(j \mid i)) = \left[ \sum_{o=1}^{\text{win}} \sum_{k=1}^{o} A^k_{ij} \right]$$

Notably, we use bias $b$ and $\tilde{b}$ to loose the constraint of $\lambda$ in the weight scheme,
making cost function more flexible. When the cost function is satisfied and ac-
cording to the weight scheme, the exponential of the inner product of the paper
vector and the context vector represents the random walk probability of the con-
text paper:

$$\exp w_i^T \tilde{w}_j = \frac{\left[ \sum_{o=1}^{\text{win}} \sum_{k=1}^{w} A^k_{ij} \right]}{\exp^{b+b-\lambda}}$$

When the window of random walk is set to $\text{win}$, the sum of probability of all
context nodes is $\text{win}$. So the exponential value of inner product represents the

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**Algorithm 2** Paper2vec($i, j, X(i \mid j)$)

1: grad = $2 \cdot f(X(i \mid j))(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - X(i \mid j))$
2: temp$_i = \alpha \cdot \text{grad} \cdot \tilde{w}_j$; temp$_j = \alpha \cdot \text{grad} \cdot w_i$
3: $\tilde{w}_j = \tilde{w}_j + \text{temp}_j$; $w_i = w_i + \text{temp}_i$
probability ratio. The cost function approximates the document embeddings from a different way compared with DeepWalk [17].

Given the definition of context and the weight scheme, we can minimize the cost function to get representations representing the items. We note that the weight is not symmetric, \(X(j | i) \neq X(i | j)\), different from the word-word co-occurrence matrix in the area of NLP, and is often the case for the relationship between items and friends. We tried to average the weight for \(X(j | i)\) and \(X(i | j)\), but the former won. The updating procedure is described in detailed in Algorithm 2.

The complete algorithm of Paper2vec is described in Algorithm 1. The same as GloVe, Paper2vec will use a stochastic learning way to iterate the nonzero items in the matrix. Because the citation corpus is not as redundant as text corpus, the iteration time is often larger than that used in NLP tasks. After training, the context vectors are dropped and we obtain the paper vectors after normalizing, which can be used to measure similarity by calculating the cosine similarity of vectors of two documents as similarity measurement:

\[
paper2vec(d_i, d_j) = p_i^T p_j
\]

4. Experiment

Conducting a nice evaluation experiment is challenging in research-papers recommender system, relating to the lack of datasets and gold standards [2, 13]. Our experiment is conducted based on CITREC, an open evaluation framework for citation-based similarity measures proposed in [13], which provides scholar datasets, baseline measurement and some implementations of previous citation-based algorithms.

4.1. Dataset

CITREC has collected the data from the PubMed Central Open Access Subset (PMCOS) and the TREC Genomics collection. PubMed Central is a repository of full text documents from biomedicine and the life sciences maintained by the U.S. National Library of Medicine (NLM). The NLM offers a subset of 860,000 documents for downloading and processing. TREC Genomics Collection is a test collection used in the Genomics track of the TREC conference 2006, which comprises approx. 160 thousands Open Access biomedical full text articles.

We extracted the citation relation from the full text with the methods CITREC provided and constructed a database with documents, references for both datasets. With reference information collected in full text, we conducted entity
resolution between documents and references based on PubMed ids, titles and authors, et al. We collected 252673 documents and 9379146 references for PM-COS, 160446 documents and 6312425 references for TREC Genomics. In order to make datasets self-containment, we only construct distributed vectors for papers contained in recorded documents. For other baseline methods, we also limit the available references data to the subset of that included in the recorded documents.

4.2. Gold Standards

The standard similarity score is calculated based on the Medical Subject Headings thesaurus (MeSH), which are a poly-hierarchical thesaurus of subject descriptors, maintained by experts at the U.S. National Library of Medicine (NLM), and available for two scholar datasets mentioned above. CITREC include a gold standard suggested by [12] based on MeSH to reflect topical relevance between documents. The similarity measurement demonstrates the proximity of the subject descriptors of two papers across the concept hierarchical tree, which can be considered as a suitable way to measure the semantic similarity between papers [13].

4.3. Baseline Methods

We compare our proposed method to some representative methods for citation-based analysis and network representation learning approaches which can be transferred to this area.

- **Amsler [6]**: This model calculate the intersection of papers having citing or cited relation with the measured pair of papers. The similarity score can be formalized as follows:

\[
amsler(d_i, d_j) = \frac{(P_{d_i} \cup C_{d_i}) \cap (P_{d_j} \cup C_{d_j})}{|(P_{d_i} \cup C_{d_i}) \cup (P_{d_j} \cup C_{d_j})|}
\]  

(6)

\(P_{d_i}\) in the Equation is defined as the paper set citing \(d_i\) and \(C_{d_i}\) the cited paper set of \(d_i\).

- **CPA [8]**: Context information of citation were introduced into the this model to build co-citation based similarity measure with different weighting schemes. To quantify the degree of relevance between co-cited documents, Citation Proximity Analysis (CPA) maps the proximity between two citations in the full text to the strength of the relevance of two co-cited papers. Two papers having more strength of the co-cited relevance are more similar.
• DeepWalk [17]: DeepWalk is a learning algorithm to obtain distributed representation for vertices in a network, which was used in the original paper for relational classification problem. As the paper citation relation is similar to a network while papers can be regard as the vertices, DeepWalk can be easily introduced to get paper vectors. The core idea in DeepWalk is to take random walk paths from network as sentences, while the vertices as words. The built corpus is then dropped to SkipGram to generate corresponding distributed representation of vertices. DeepWalk declared a 10% promotion based on $F_1$ score on relational classification tasks than state-of-the-art methods for social network representations. We transfer the model to learn vectors of papers in citation network for our task.

4.4. Evaluation

With the calculated similarity scores by various algorithms, we can get the rank of the most $K$ similar documents of every document in the database. Because classical similarity methods cannot get the similarity score for every pair arbitrarily, $K$ is not fixed, so we conducted experiment under different $K$ to get a comprehensive result. Intersection ratio are used as evaluation measurement for our experiment for their invariance of $K$. Intersection ratio take the average ratio of intersection between the top-$K$ document sets ranked according to the similarity measure and the Mesh baseline respectively.

4.5. Results

We train 500-dimensional vectors for Paper2vec and DeepWalk and the window size is both set 3. There are several variants of CPA model, we only list the best result around them. The compared result under different $K$ is showed in Figure 1. DeepWalk and Paper2vec are both based on distributed representation and outperform other models significantly, which implies the promising future of distributed representation in this area. Paper2vec is better than DeepWalk on small $K$, meaning it can find better results in the first few documents, which is important for scholar recommendation.

4.6. Model Analysis: Window Size

Larger window should contain richer information about the context and results in better performance. So we look into the relation between the window size $win$ and the performance of the model. We trained Paper2vec model on datasets mentioned above for various training window size $win$. Parameters relating to training are the same as before and we consider the situation $K=10$. The result
Figure 1: Evaluation results on both datasets on different $K$.

Figure 2: Intersection ratio on datasets evaluation as a function of window size of Paper2vec when $K = 10$. 
is showed in Figure 2. We can see a monotonic increase in performance as the window size $win$ increases, since larger context tends to contain more information about current document, as we supposed. With the increasing of window size, the marginal profit of information gained is diminishing and the curve slope is descending. The curve suggests the information distribution among the structure.

4.7. Model Analysis: Novelty

Novelty are highly desirable features for scholar recommendation, for the goal of scholar recommendation system is to help researchers find papers that are relevant but have not be found by themselves. However, models based on cooccurrences of links prefer items having more links. For example, CPA prefers popular papers that are cited frequently and all similar documents found by CPA should at least be cited at once. It is not the case for distributed representation based algorithms, which give every document a vector and just consider the distance between vectors. So we suppose our Paper2vec model tend to be more popularity independent than classical models. Inspired by novelty measurement in [3], we define a similar novelty measurement in a global perspective based on the concept of entropy in information theory. Considering the top-K similar documents found by all documents in the collection, given the collection set $S$, we get,

$$\text{novelty} = - \sum_{i \in S} p_i \log p_i$$  \hspace{1cm} (7)

where,

$$p_i = \frac{|\{j | i \in R_j\}|}{\sum_k |R_k|}$$  \hspace{1cm} (8)

$R_j$ denotes the top-K similar documents found by model for document $j$. The numerator part of the equation denotes the frequency document $i$ appears in other documents’ similar lists. In information theory, the novelty measurement could be seen as the expect value of the information contained in the distribution of documents in the relevant set of all documents in the collection. The maximum value happens when all documents appear in relevant set at the same frequent, which is the ideal situation that there is no popular documents any more. More frequently one of the documents appears than others, smaller the novelty measurement, meaning model prefering some items than others when recommending. The measurement also decreases when the coverage of relevant set decreases. We name this measurement Entropy Novelty for it’s derived from the concept of entropy in information theory. In equation $|R_k|$ is not fixed to $K$ because in cooccurrence model the size of similar documents set for every document is variant.
We calculated the Entropy Novelty for Paper2vec and other models mentioned in the baseline methods section on datasets PMCOS and TREC Genomics. The gold standard measurement MeSH is also calculated as control group. The result is showed on Figure 3. While all distributed representation based models surpass cooccurrence based models apparently, Paper2vec is the best around all models considered in both datasets, which proves distributed representation based models tend to consider semantic similarity of papers without the influence of other effects, such as popularity. This property can help users to find relevant papers that are hard to find by other classical models.

5. Conclusion & Discussion

We proposed Paper2vec, a novel approach for learning latent distributed representations from citation relations between documents reflecting the topics. We define a weighted citation linkage context for papers based on probability, and utilize a variant of matrix factorization to obtain document distributed representation, which can be used for tasks such as document clustering, relational classification, similarity measurement and so on. For paper recommendation, the similarity measure of any pair of documents can be calculated, the full text is not necessary, and the stochastic training process make it possible to update the new papers introduced into the database without training the whole corpus again and easy to be parallelized. The advantages and better performance of Paper2vec make it a promising method combined with text-based method for future scholar recommender systems.

In addition, there are more untapped potential hidden in distributed representation. [14] finds the vector difference of distributed representation can suggest the
similarity of pair of words. For instance, \text{vector}("King") - \text{vector}("Man") + \text{vector}("Woman") results in a vector closed to \text{vector}("Queen"). \cite{1} gave an math explanation of the property. If the paper vectors have the same property, which can be used for finding papers that having a specific topic relation with the input document by simple vector algebraic operation. More research are needed to verify this hypothesis.
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