A Neural Probabilistic Model for Context Based Citation Recommendation

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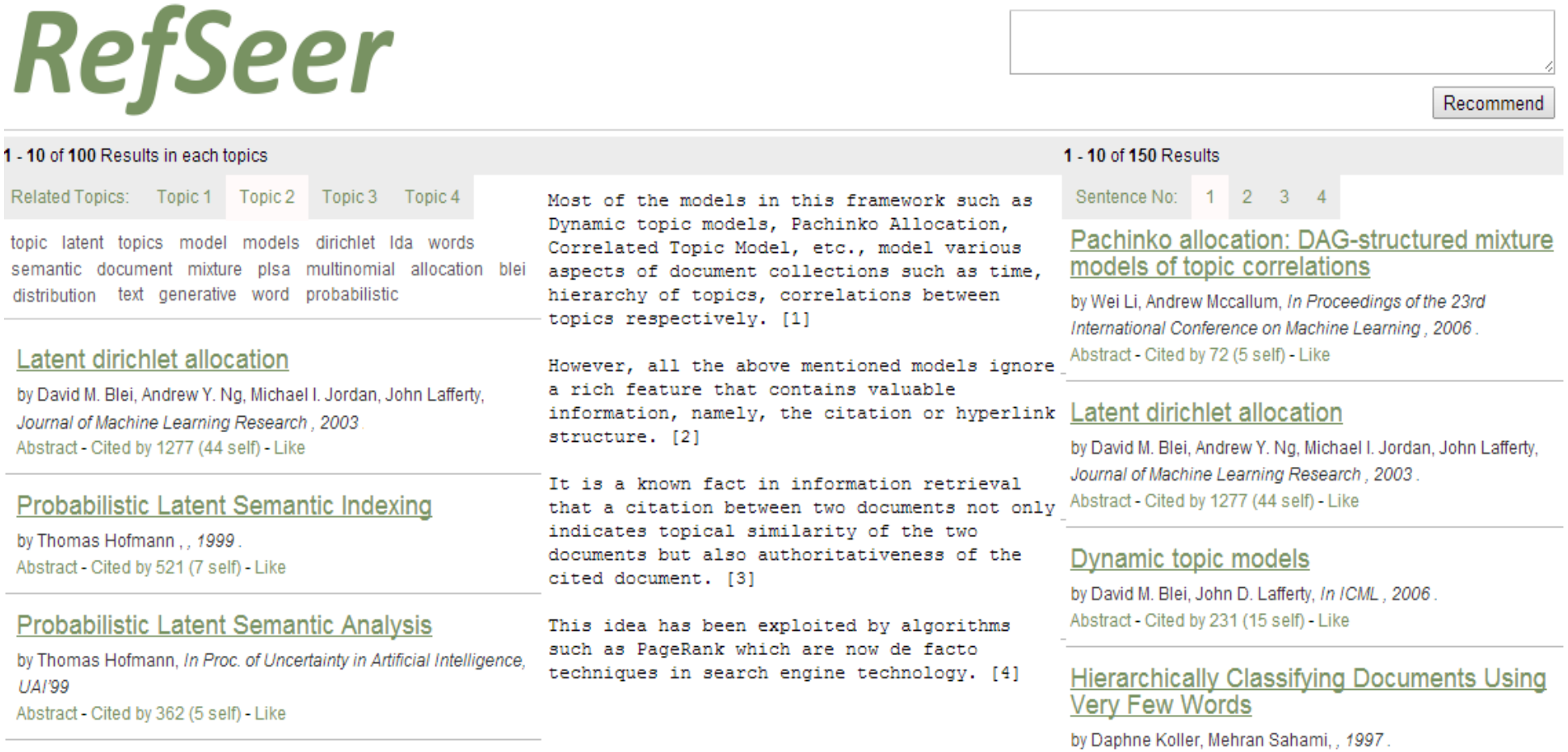
RefSeer

CiteSeerx β

Problem Definition

- What is citation recommendation?
- Two Types of Recommendation: 1) global 2)local



Our Contribution

- We propose a neural probabilistic model that learns the probability of citing a paper given a citation context based on distributed representations of words and documents.

- The model is implemented in RefSeer, ,a citation recommendation engine, for public uses.

- The model was trained and evaluated on the entire CiteSeer dataset which consists of 10,760,318 pairs of citation contexts and cited documents from 1,017,457 papers.

- Compared to other state-of-the-art context-based methods, our model shows significant improvement on various performance metrics, with a 5% gain in recall@10, a 2% gain in MRR and MAP, and a 3% gain in nDCG.

Motivation of this Work

- Authors use different words and phrases when citing the same article.
- The semantics of the cited documents should be close to the citation contexts.

Citation Context Examples	Cited Paper
1. ...For example, PageRank [*] can be applied to the hyperlink structure on domains to obtain domain rank scores... 2. ..., and the unique solution vector r(i) can be expressed as the eigenvector of a matrix [*] or as the stationary probability of a random walk... 3. ... Rank sinks [*] are defined to be a set of nodes which have links between themselves but no links to the other nodes. 4. There is a lot of research work on static information network analysis, including ... , and node ranking [*, *], ...	L. Page, S. Brin, R. Motwani, and T. Winograd. 1998. *The Pagerank Citation Ranking: Bringing Order to the Web.* Technical report, Stanford Digital Library Technologies Project, 1998.

Distributed Representation

- One hit representation:

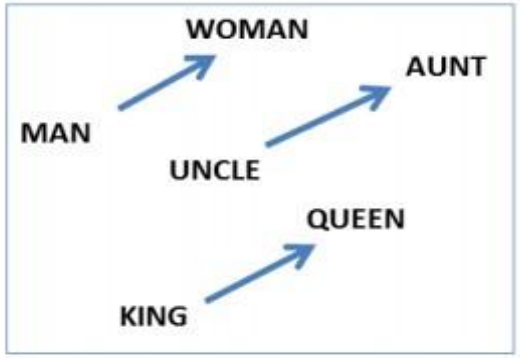
  movie [0 0 0 0 0 0 0 0 1 0 0 0 0] && film [0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

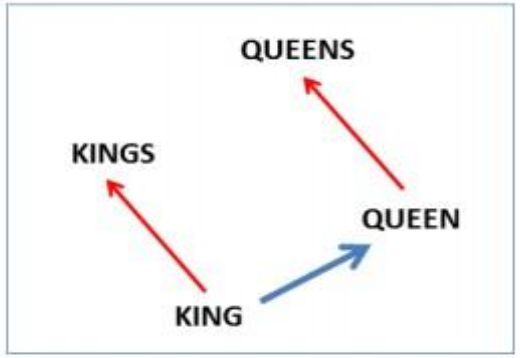
- Distributional similarity based representations
  - Soft clustering word representations
    - LSA/LDA
  - Neural network based distributed representations:
    - Words are projected into n-dimensional continues-valued vectors (n= 50, 100,…)

```
news 0.0937356086753 0.747945120724 -0.0750619884446 -0.226063114311 -1.00569231962 0.516947986429
price 0.287862881268 0.625123596091 0.382014892929 -0.0966298530516 -1.19724365222 0.0196462314248
very 0.323354305535 0.321417782731 0.483145963078 -0.157390738802 -0.962555596754 0.00207746146949
industry 0.0291885988722 0.504720529139 -0.122992000712 0.391162080274 -1.20667627561 0.05815952581
sales 0.141502071535 0.627457134652 0.144504638422 0.00177222515462 -0.971236693536 0.0857220496627
second 0.251871859833 0.65748186686 0.152971131984 -0.350360474704 -0.935662471132 0.167607205076 0
so 0.437489708071 0.637964913163 0.366912669659 -0.049045606276 -0.466581719757 0.373365386391 0.40
```

Distributed Representation

- These representations are good at capturing syntactic and semantic regularities in language, and that each relationship is characterized by a relation-specific vector offset.





$$Vector(Man) - Vector(Woman) \approx Vector(King) - Vector(Queen)$$

$$Vector(Kings) - Vector(King) \approx Vector(Queens) - Vector(Queen)$$

Turian et al. *Word representations: A simple and general method for semi-supervised learning*. ACL, 2010.

Tomas Mikolov, et al. *Linguistic Regularities in Continuous Space Word Representations*. NAACL 2013.

Problem Formulation

- Model the citation context given the cited paper $p(c|d)$. Assume that we have $|C|$ pairs of citation context c_t and cited document d_t. The objective is to maximize the log-likelihood:

$$\text{Maximize} \quad \sum_{t=1}^{|C|} \log p(c_t|d_t)$$

where $p(c_t|d_t) = p\left(w_{t_1}, \cdots, w_{t_{|c_t|}} \middle| d_t\right) = \prod_{i=1}^{|c_t|} p(w_i|d_t)$

- The objective function can be written as:

$$\text{Maximize} \quad \sum_{t=1}^{|C|} \sum_{i=1}^{|c_t|} \log p\left(w_{t_i} \middle| d_t\right)$$

Neural Probabilistic Model

- $p(w|d)$ can be defined using a softmax function:

$$p(w|d) = \frac{\exp(s_\theta(w,d))}{\sum_{i=1}^{|V|} \exp(s_\theta(w_i,d))}$$

where $|V|$ is the size of the word vocabulary.

- $s_\theta(\cdot)$ is the neural network scoring(activate) function. w and d are projected into n-dimensional continues-valued vectors v_w and v_d:

$$s_\theta(w,d) = f(v_w, v_d)$$

where $f(v_w, v_d) = \frac{1}{1+\exp(-v_w \cdot v_d)}$

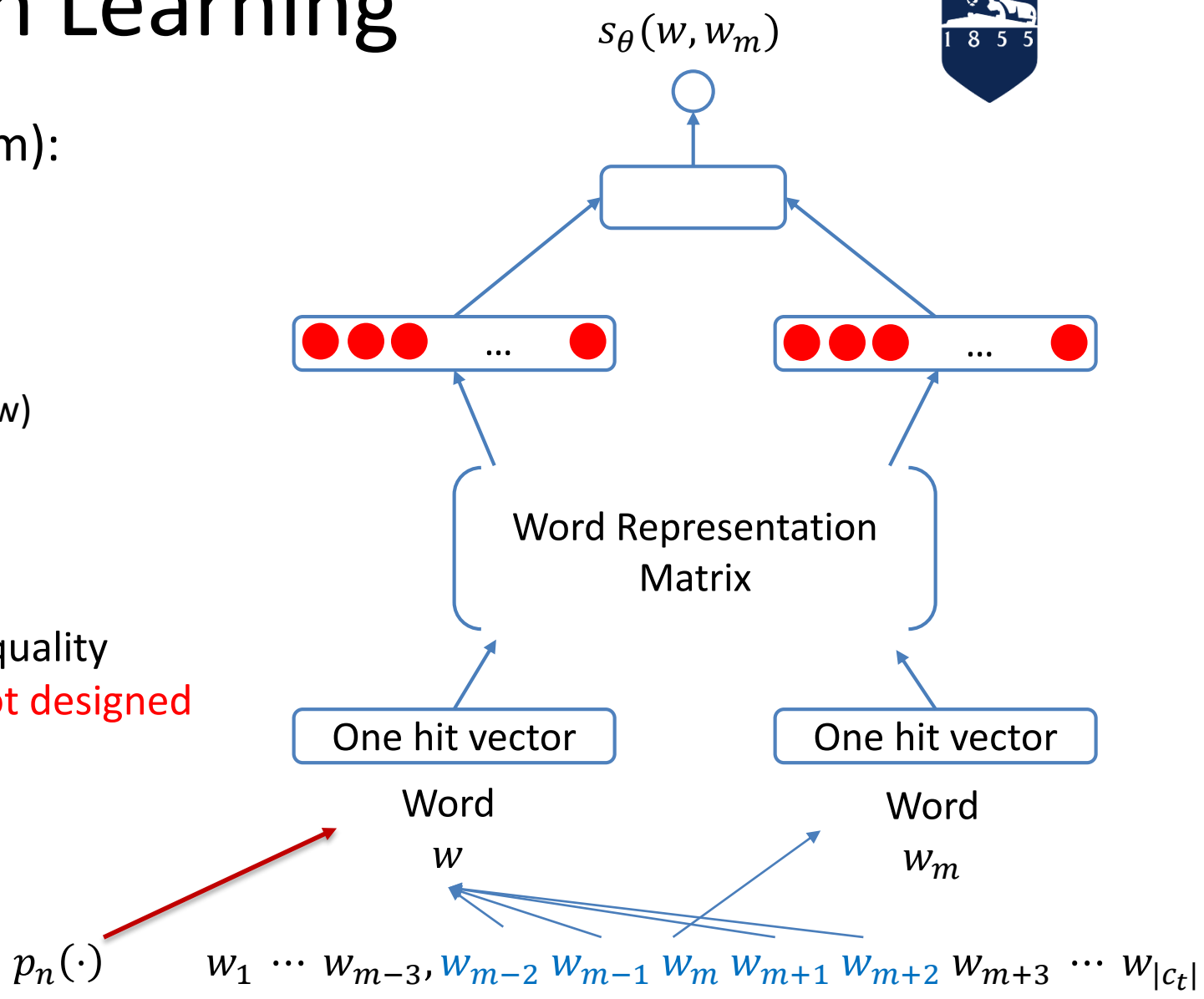
Word Representation Learning

- Google's word2vec model (skip-gram):

$$\ell_m(\theta) = \log s_\theta(w_p, w_m) + \sum_i^k \left[\log\left(1 - s_\theta(w_n, w_m)\right)\right]$$

  - w_p: positive examples (words in the window)
  - w_n: negative example generated by $p_n(\cdot)$
  - k: number of negative examples

- The skip-gram model is able to learn high quality representations of words. However, it is not designed to estimated the conditional probability.

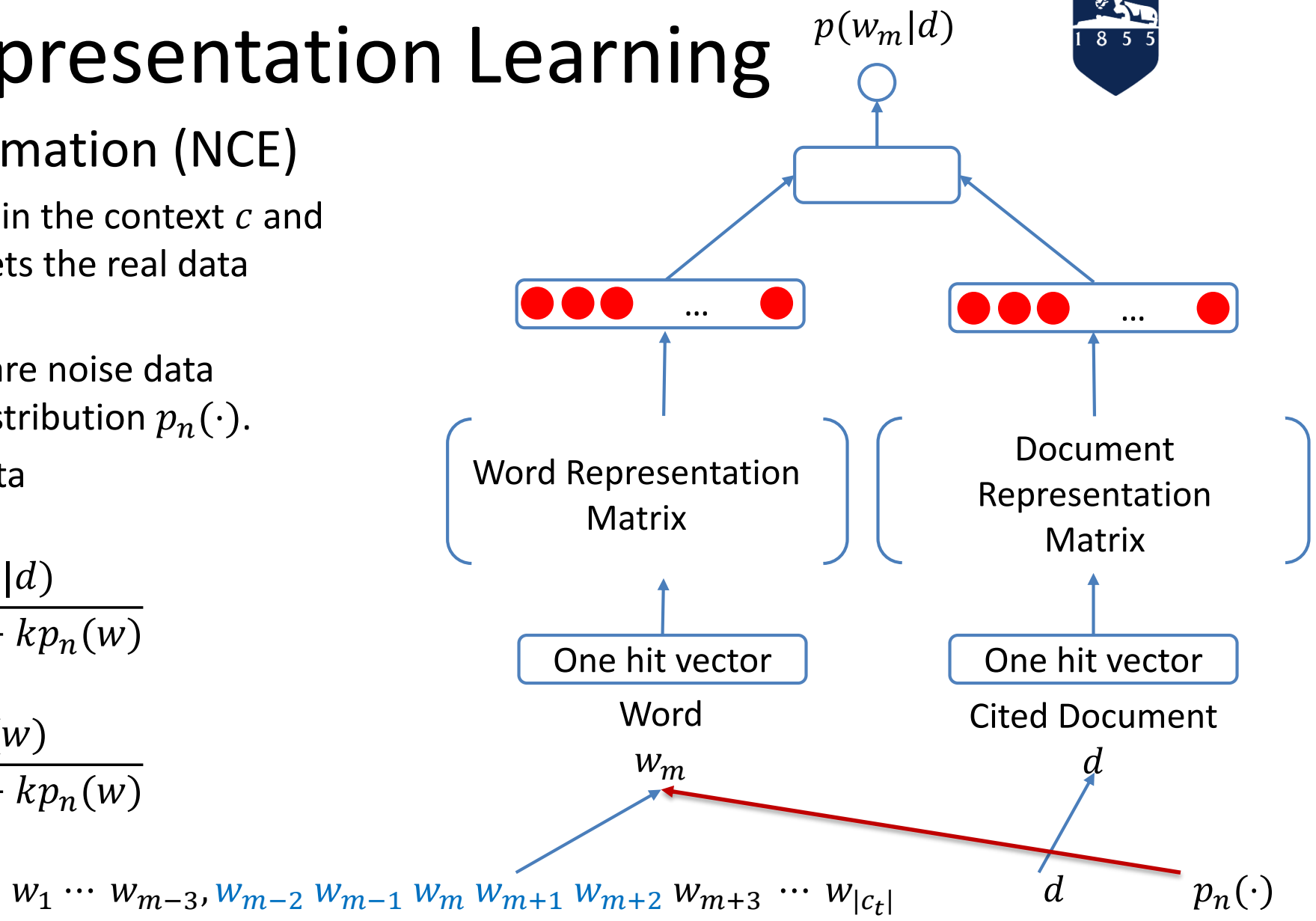


Document Representation Learning

- Noise-contrastive estimation (NCE)
  - Each word w that appears in the context c and the cited document d meets the real data distribution $p_\theta(w|d)$.
  - Any other random words are noise data generated from a noise distribution $p_n(\cdot)$.
  - k times noise than real data

$$p(1|w,d,\theta) = \frac{p_\theta(w|d)}{p_\theta(w|d) + kp_n(w)}$$

$$p(0|w,d,\theta) = \frac{kp_n(w)}{p_\theta(w|d) + kp_n(w)}$$



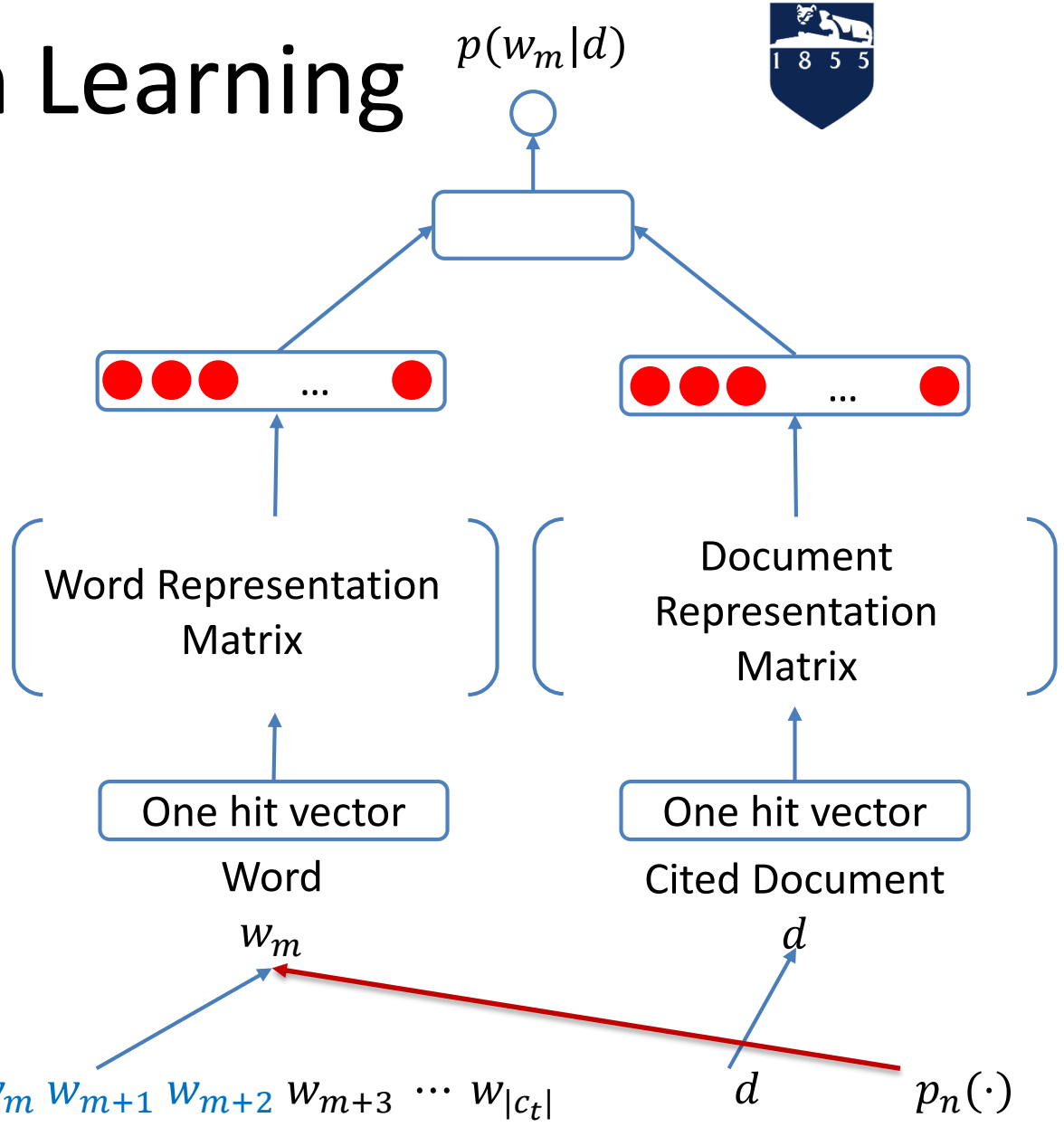
Document Representation Learning

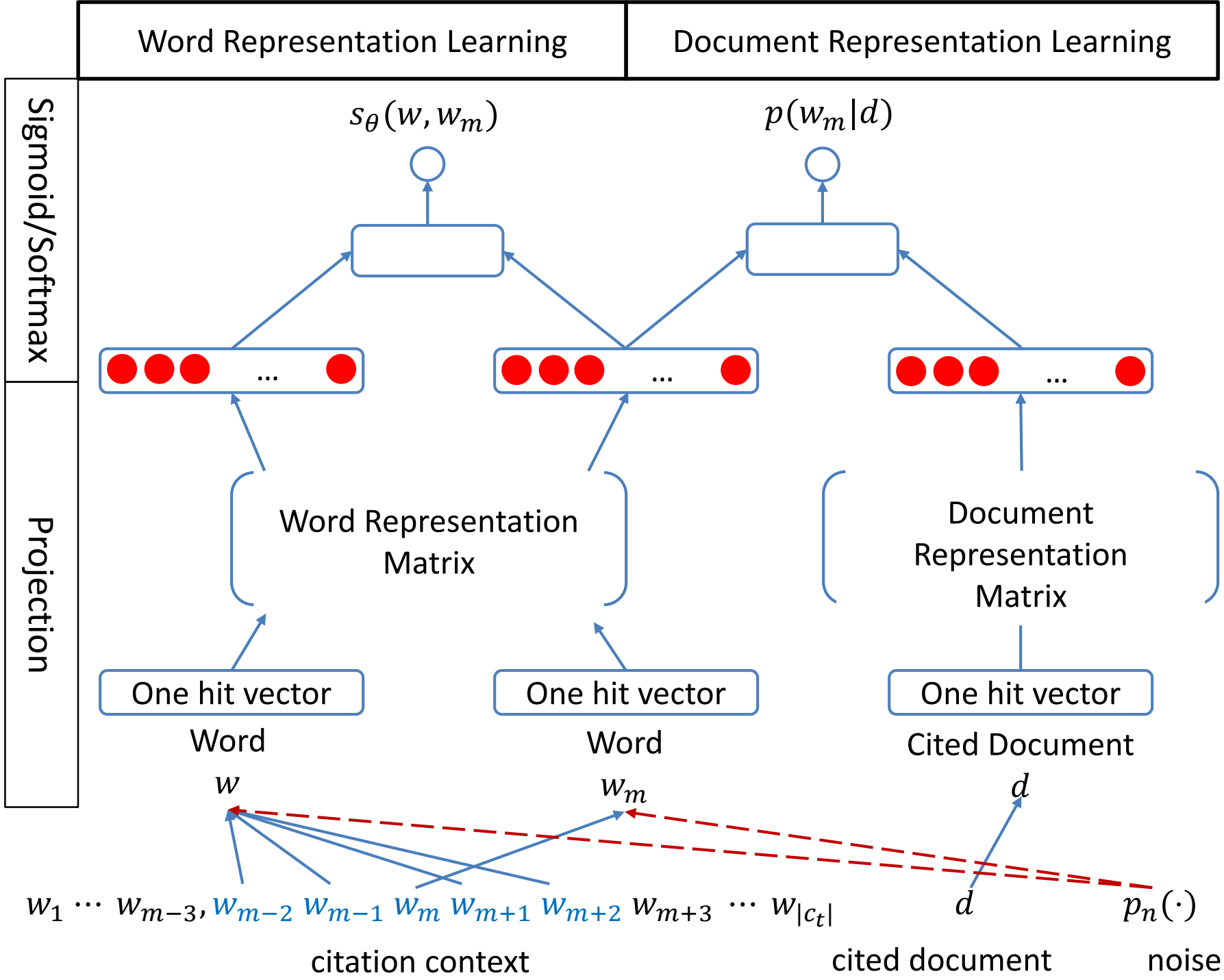
- Noise-contrastive estimation (NCE)
  - The likelihood of binary classification is a Bernoulli distribution.
  - Objective function:

$$\ell_t(\theta) = \log \frac{p_\theta(w|d_t)}{p_\theta(w_{t_i}|d_t) + kp_n(w_{t_i})} + \sum_{i=1}^{k}\left[\log \frac{kp_n(w_{n_i})}{p_\theta(w_{n_i}|d) + kp_n(w_{n_i})}\right]$$

$$p_\theta(w|d) = \exp\big(s_\theta(w,d)\big) \cdot Z(d)$$

The parameters of the neural network are θ and $Z(d)$.




Word Representation Learning
Document Representation Learning
Sigmoid/Softmax
Projection
$s_\theta(w, w_m)$
$p(w_m|d)$
Word Representation Matrix
Document Representation Matrix
One hit vector
One hit vector
One hit vector
Word
Word
Cited Document
w
w_m
d
$w_1 \cdots w_{m-3}, w_{m-2}\ w_{m-1}\ w_m\ w_{m+1}\ w_{m+2}\ w_{m+3} \cdots w_{|c_t|}$
d
$p_n(\cdot)$
citation context
cited document
noise

Citation Recommendation

- Using the fine-tuned word and document representations, we can get the normalized probability distribution $p(w|d)$.

- The table of $p(d|w)$ is pre-calculated using Bayes' rule and stored as an inverted index.

- Given a query $q = [w_1, w_2, \dots, w_{|q|}]$, the task is to recommend a list of document $R = [d_1, d_2, \dots, d_N]$ that need to be cited.

$$p(d_i|q) = \sum_{j=1}^{|q|} p(d_i|w_j) p(w_j|q)$$

where $p(w_j|q)$ can be measured using TF-IDF.

Experiments

- Data:
  - A snapshot of CiteSeer paper and citation database. (Oct. 2013)
    - Training: paper crawled before 2011 (included)
    - Testing: paper crawled after 2011
  - Citations are extracted along with their citation contexts.
    - Training: $|\mathrm{C}| = 8{,}992{,}476$ pairs of citations and citation contexts
    - Testing: $1{,}628{,}698$ pairs.
  - Word vocabulary size: $|V| = 281{,}817$.
  - Cited documents: $|D| = 329{,}365$.

Experiments

- Metrics:
  - Mean average precision(MAP):

$$\text{MAP}=\frac{\sum_{q\in \text{Q}} \text{AveP}(q)}{|Q|} \quad \text{where} \quad \text{AveP}(q) = \frac{\sum_{k=1}^{n} p(k)\cdot \text{rel}(k)}{|\text{correct recommendations}|}$$

  - Recall:

$$\text{Recall} = \frac{|R_g \cap R_r|}{R_g}$$

  - Mean Reciprocal Rank (MRR):

$$\text{MRR} = \frac{1}{|Q|}\sum_{q\in \text{Q}} \frac{1}{\text{rank}_q}$$

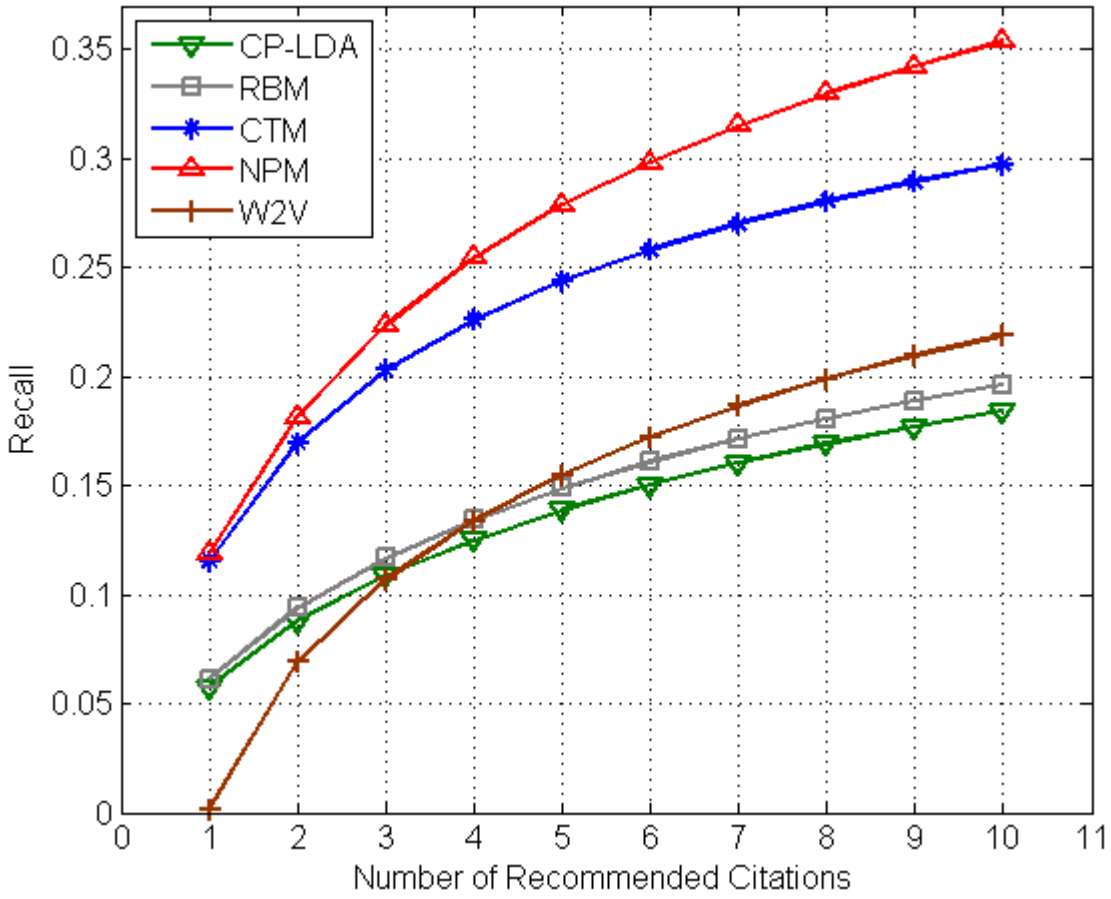
  - Normalized Discounted Cumulative Gain (nDCG):

$$\text{DCG} = rel_1 + \sum_{i=2}^{n} \frac{rel_i}{\log_2 i} \quad \text{and} \quad \text{nDCG}=\frac{\text{DCG}}{\text{IDCG}} \quad \text{where IDCG is idea DCG score}$$

Baselines and Parameter Settings

- Cite-PLSA-LDA (CP-LDA) [Kataria, Mitra, and Bhatia 2010]
  - Number of topic: 600
- Restricted Boltzmann Machine (RBM) [Tang and Zhang 2009]
  - Two layer RBM
  - hidden layer size 600
- Citation Translation Model (CTM) [Huang et al. 2012b]
  - GIZA++ toolkit
  - training iteration: 20
- Word2vec Model(W2V) [Mikolov et al. 2013]
  - Cited documents are regarded as “words” (one document uses a unique token when cited by different papers).
  - Representation vector dimension: 600

Baseline Comparison



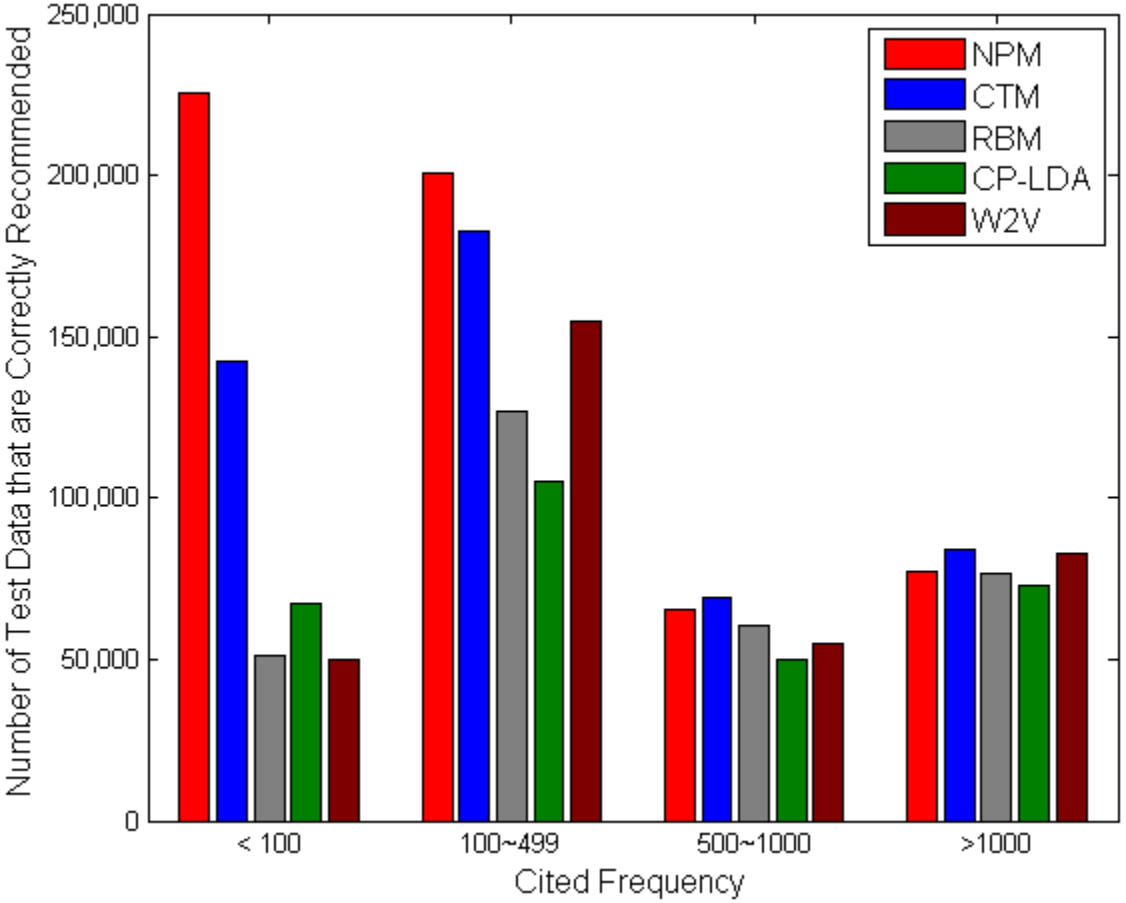
Recall as the number of recommended citations ranges from 1 to 10.

Model	MRR	MAP	nDCG
CP-LDA	0.0916	0.0912	0.1288
RBM	0.0997	0.0982	0.1476
W2V	0.0662	0.0663	0.1356
CTM	0.1687	0.1681	0.2261
NPM	**0.1843***	**0.1835***	**0.2566***

MRR, MAP, nDCG scores for top 10 recommendations; * indicates when NPM better than CTM is statistically significant ($p < 0.001$).

- The proposed model improves the overall recommendation with a 5% gain on Recall@10 and 2% gain on MAP compared to the second best model CTM.
- The proposed model generates better ranked recommendations.
- The significant tests show that the improvements are statistically significant.

Baseline Comparison



Performance versus papers' cited frequency.

- According to the citation counts of the cited documents, we split the test set into four intervals: <100, 100~500, 500~1000, and >1000.
- For each interval, we plot the number of test data that are correctly recommended by each model.
- Our proposed model is particularly good at recommending papers that are not frequently cited (less than 100 citations).
- This result indicates that our model can learn a good representation for documents, even with a small number (less than 100) of training data.

Model Parameters

- Noise Distribution p_n and Number of Samples k

# of Noise k	Uniform Noise	Frequency-based Noise
100	0.3096	0.2913
300	0.3275	0.3165
500	0.3491	0.3297
1,000	**0.3537**	**0.3450**

Recall@10 versus noise distributions and sample size.

- Dimension n

Dimension n	MRR	MAP	nDCG	Recall@10
100	0.1681	0.1692	0.2297	0.3118
300	0.1709	0.1702	0.2372	0.3247
600	**0.1843**	**0.1835**	**0.2566**	**0.3537**

MRR, MAP, nDCG and Recall@10 versus word and document representation dimension.

Recommendation Examples

The query is a citation context extracted from paper ***Fast computation of simrank for static and dynamic information networks***:

There is a lot of research work on static information network analysis, including..., and node ranking[, *]...*

Query and Ground Truth	NPM	CTM	RBM	CP-LDA	W2V
There is a lot of research work on static information network analysis, including ... , and node ranking [1, 2], ... [1] The PageRank citation ranking [2] Authoritative sources in a hyperlinked environment	[O] Authoritative sources in a hyperlinked environment [X] The anatomy of a large-scale hypertextual Web search engine [X] Topic-sensitive PageRank [X] Improved Algorithms for Topic Distillation in Hyperlinked Environments [O] The PageRank citation ranking	[X] Modern Information Retrieval [X] An Efficient Boosting Algorithm for Combining Preferences [X] Optimizing search engines using clickthrough data [X] Learning to rank using gradient descent [X] Chord: A Scalable Peer-to-Peer Lookup Service for Internet Applications	[X] A survey of active network research [X] Statistical mechanics of complex networks [X] How to model an internetwork [X] Network information flow [X] SNORT - lightweight intrusion detection for networks	[X] Network Information Flow [X] Linear network coding [X] Polynomial Time Algorithms for Network Information Flow [X] An algebraic approach to network coding [X] Network Coding for Large Scale Content Distribution	[X] Modern Information Retrieval [X] The anatomy of a large-scale hypertextual Web search engine [X] Chord: A Scalable Peer-to-Peer Lookup Service for Internet Applications [X] A Scalable Content-addressable Network [O] Authoritative sources in a hyperlinked environment

Related Works: Global Recommendation

- Collaborative filtering:
  - McNee, et al. On the recommending of citations for research papers. CSCW '02
    - Recommends citations based on partial list of references
- Text similarity and bibliography similarity:
  - Strohman, et al. Recommending citations for academic papers. SIGIR’07
  - Bethard and Jurafsky. Who should I cite: learning literature search models from citation behavior. CIKM’10
- LDA based model:
  - Kataria, et al. Utilizing context in generative Bayesian models for linked corpus, AAAI’10
    - Recommends topical related documents.

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Related Works: Local Recommendation

- Restricted Boltzmann Machine:
  - Tang and Zhang. A discriminative approach to topic-based citation recommendation. PAKDD'09
- Context-aware model:
  - He, et al. Context-aware citation recommendation. WWW'10
  - He, et al. Citation recommendation without author supervision. WSDM'11
- Translation model:
  - Lu, et al. Recommending citations with translation model. CIKM'11
  - Huang, et al. Recommending citations: Translating papers into references. CIKM'12

Conclusion

- We propose a neural probabilistic model that learns the probability of citing a paper given a citation context based on distributed representations of words and documents.

- The model was trained and evaluated on the entire CiteSeer dataset which consists of 10,760,318 pairs of citation contexts and cited documents from 1,017,457 papers.

- Compared to other state-of-the-art context-based methods, our model shows significant improvement on various performance metrics, with a 5% gain in recall@10, a 2% gain in MRR and MAP, and a 3% gain in nDCG.

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THANK YOU!

RefSeer

We don’t keep query and click data!

DEMO: http://refseer.ist.psu.edu/

Q&A

CiteSeer$^{x}_{\beta}$