PTE : Predictive Text Embedding through Large-scale Heterogeneous Text Networks

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CS591txt - Text Mining Seminar

University of Illinois, Urbana-Champaign

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Outline

Motivation

Introduction
- The Data Sparseness Problem

Related Work
- Overview
- Information Network Embedding

Predictive Text Embedding
- The Text Representation
- Heterogeneous Text Network Embedding
- Bipartite Network Embedding
- Text Embedding

Experiments
- Statistics of the Dataset
- Results
- Results

Analysis

Conclusion

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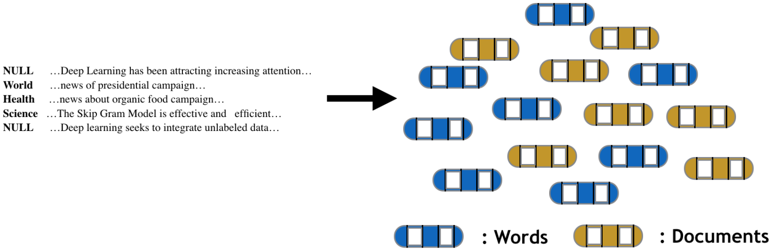
Solving the Problem of Data Sparseness($|V|$) : Text Embedding

- Representing words and documents in low-dimensional space
- Words and documents with similar meanings are embedded closely to each other



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- CBOW (Mikolov et al. 2013)
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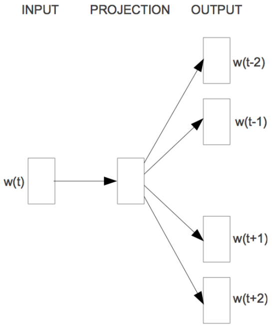

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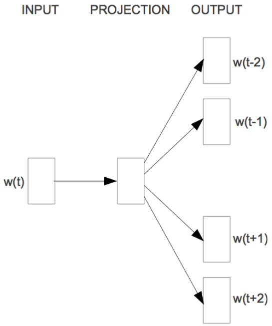

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- Insensitive parameters
- Potential to leverage a large amount of unlabeled data, embeddings are general for different tasks

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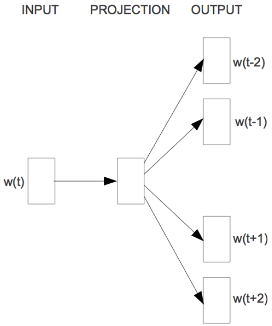

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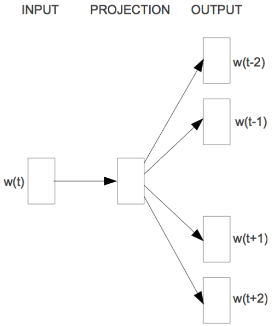

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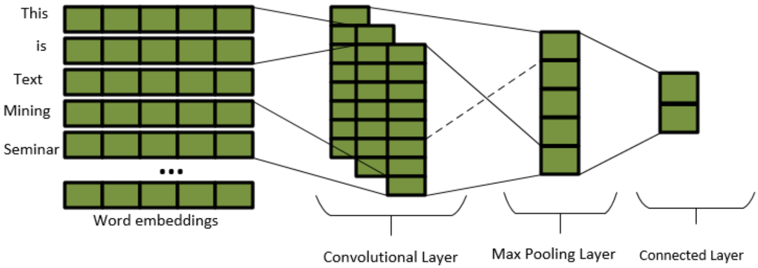
- Recurrent Neural Networks (Mikolov et al. 2010)
- Recursive Neural Networks (Socher et al. 2012)
- Convolutional Neural Network (Kim et al. 2014)



Supervised Learning Model

- Recurrent Neural Networks (Mikolov et al. 2010)
- Recursive Neural Networks (Socher et al. 2012)
- Convolutional Neural Network (Kim et al. 2014)

Pros

- State-of-the-art performance on specific tasks

Cons

- Computationally expensive
- Require a large number of labeled data, hard to leverage unlabeled data
- *Very* sensitive to parameters, difficult to tune
- Potential to leverage a large amount of unlabeled data, embeddings are general for different tasks

Information Network Embedding

- Embedding one instance of some mathematical structure contained within another instance.
- Words that are used together with many similar words are likely to have similar meanings.

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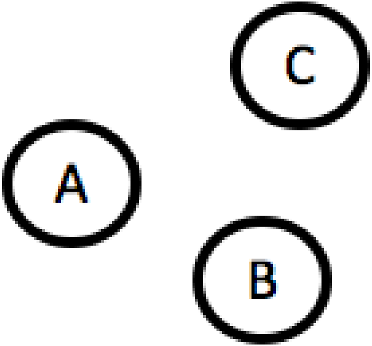

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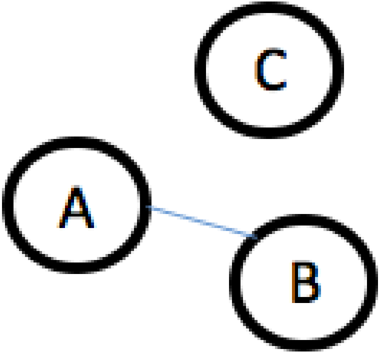

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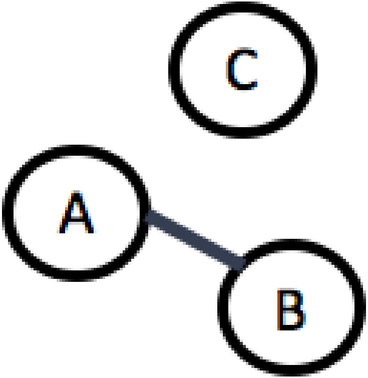

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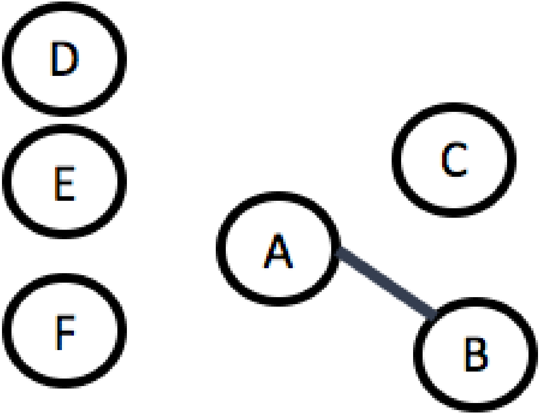

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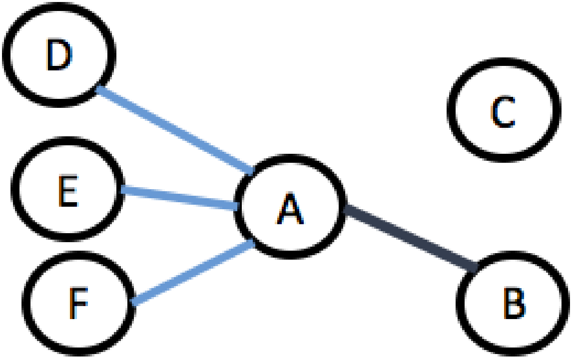

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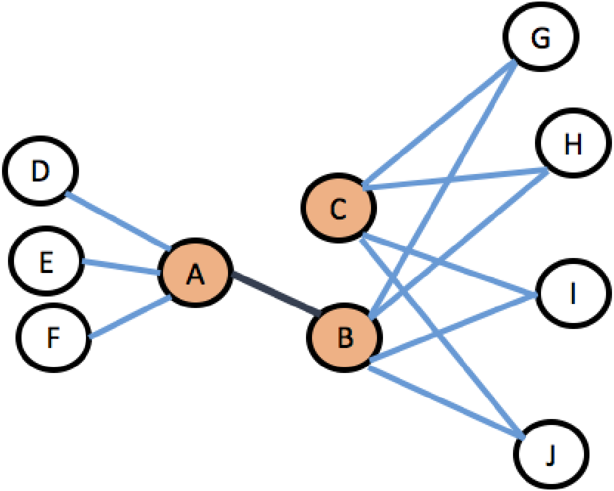

Large-scale Information Network Embedding

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- How to uniformly represent unsupervised and supervised information?

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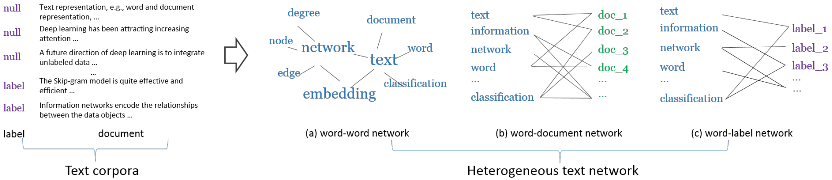
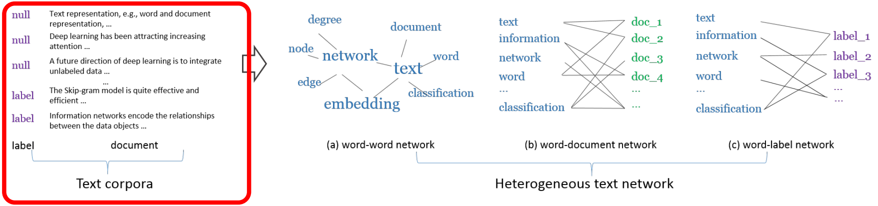
- How to uniformly represent unsupervised and supervised information?
  - Heterogeneous Text Network
- Different Levels of Word Occurrences : *Word-Word Network, Word-Document Network, Word-Label Network*

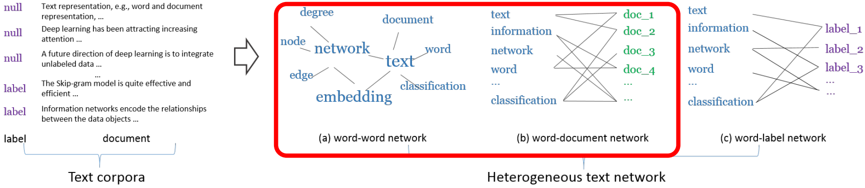
Converting Text Corpora



Partially Labeled Text Corpora



Word-Word and Word-Document Network



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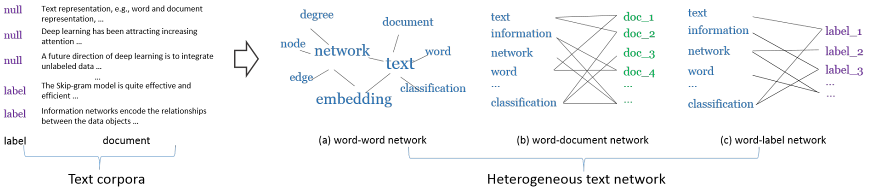

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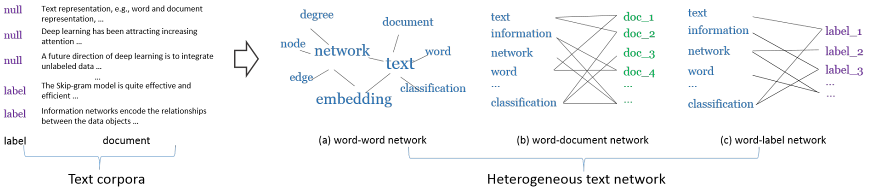

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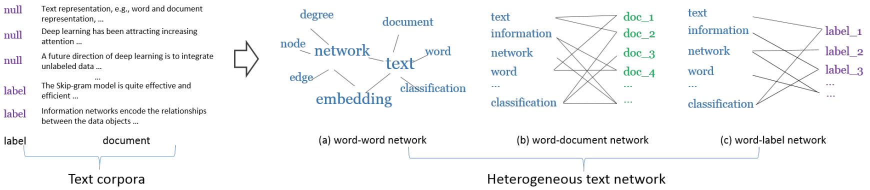

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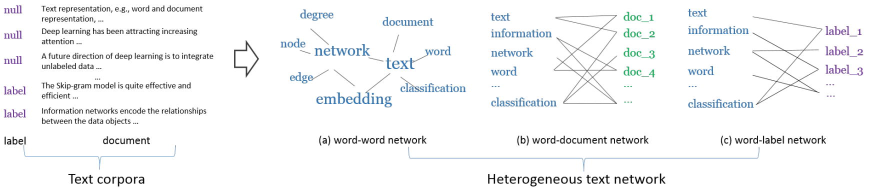

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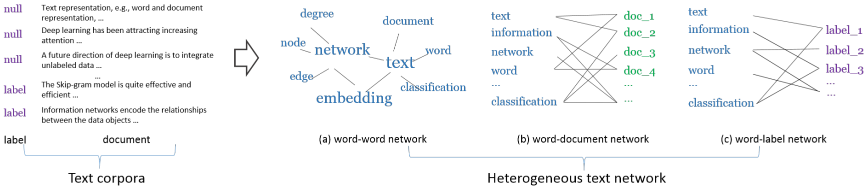

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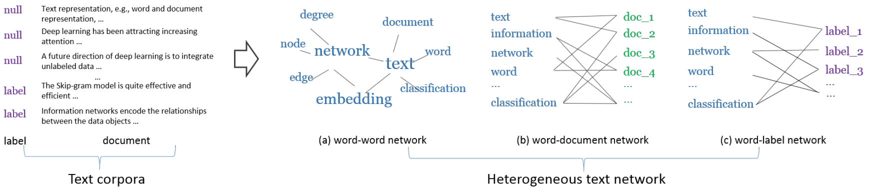

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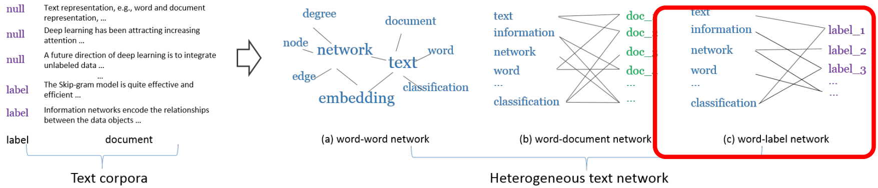
Word Label Network



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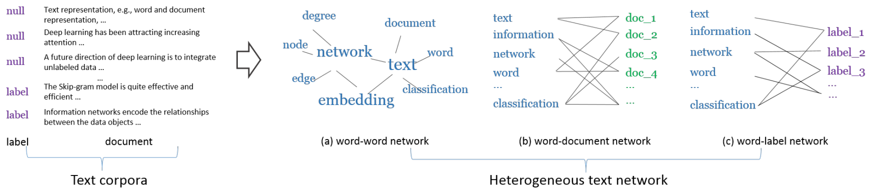

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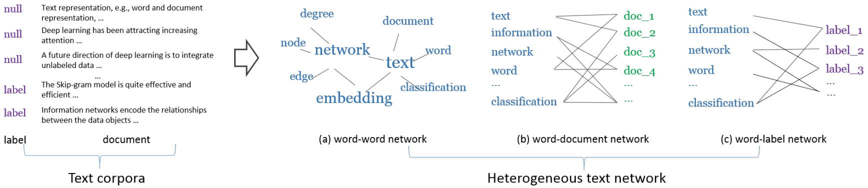

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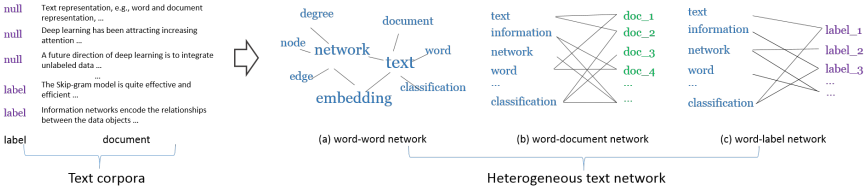

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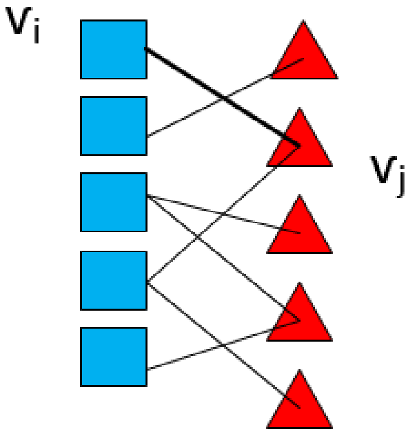
- Three Bipartite Networks : Word-word(word-context), word-document and word-label network
- Encodes different levels of word co-occurency
- Contains both `supervised` and `unsupervised` information
- Embedding a Heterogeneous Text Network, we obtain a very robust and optimized word embeddings for a specific task.

Bipartite Network Embedding



What is the ideal proximity measure?
Hint : It's either **First Order** or **Second Order**

Bipartite Network Embedding(contd.)

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Bipartite Network Embedding : Second-order proximity

– For each edge (v_i, v_j), define a conditional probability:

$$p_2(v_j|v_i) = \frac{e^{\vec{u}_j'^T \cdot \vec{u}_i}}{\sum_{k=1}^{|V|} e^{\vec{u}_k'^T \cdot \vec{u}_i}} \tag{1}$$

$$O_2 = -\sum_{(i,j)\in E} w_{ij} \log p_2(v_j|v_i). \tag{2}$$

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- Objective Function :

$$O_{pte} = O_{ww} + O_{wd} + O_{wl}, \tag{3}$$

where

$$O_{ww} = - \sum_{(i,j) \in E_{ww}} w_{ij} \log p(v_i | v_j) \tag{4}$$

$$O_{wd} = - \sum_{(i,j) \in E_{wd}} w_{ij} \log p(v_i | d_j) \tag{5}$$

$$O_{wl} = - \sum_{(i,j) \in E_{wl}} w_{ij} \log p(v_i | l_j) \tag{6}$$

Optimization

Two different ways of optimization : Depends on when **labeled data(word-label network)** are utilized.

- Joint Training
  - Train the unlabeled data and the labeled data simultaneously
- Pre-training + Fine-Tuning
  - Jointly train the G_{ww} and G_{wd} networks
  - Fine tuning the word embeddings with the word-label network

Learning Word Representations

- *Robust* and *Optimized* word Embeddings for *specific tasks*
  - Containing different levels of word co-occurences.
  - Encoding both supervised and unsupervised data
- Given an arbitrary textpiece $d = w_1 w_2 ... w_n$
- For every w_i, the text embedding is given by $\vec{u}_i$.
- The vector representation of the embedding can be computed as :

$$\vec{d} = \frac{1}{n} \sum_{i}^{n} \vec{u_i} \tag{7}$$

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Task : Text Classification

- Embeddings as Features
- Classifier : Logistic Regression

Compared Algorithms

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- **Predictive Text Embedding : incorporates labels a.k.a Supervised Learning**
  - **CNN**
  - **PTE**

Datasets

	Long Documents							Short Documents		
Name	20NG	WIKI	IMDB	CORPORATE	ECONOMICS	GOVERNMENT	MARKET	DBLP	MR	TWITTER
Train	11,314	1,911,617*	25,000	245,650	77,242	138,990	132,040	61,479	7,108	800,000
Test	7,532	21,000	25,000	122,827	38,623	69,496	66,020	20,000	3,554	400,000
—V—	89,039	913,881	71,381	141,740	65,254	139,960	64,049	22,270	17,376	405,994
Doc. length	305.77	672.56	231.65	102.23	145.10	169.07	119.83	9.51	22.02	14.36
#classes	20	7	2	18	10	23	4	6	2	2

*In the WIKI data set, only 42,000 documents are labeled.

Results of Text Classification Long Documents : Unsupervised

		20NG		Wikipedia		IMDB	
Type	Algorithm	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
Word	BOW	80.88	79.30	79.95	80.03	86.54	86.54
Unsupervised Embedding	Skip-gram	70.62	68.99	75.80	75.77	85.34	85.34
	PVDBOW	75.13	73.48	76.68	76.75	86.76	86.76
	PVDM	61.03	56.46	72.96	72.76	82.33	82.33
	LINE(G_{ww})	72.78	70.95	77.72	77.72	86.16	86.16
	LINE(G_{wd})	79.73	78.40	80.14	80.13	89.14	89.14
	LINE($G_{ww} + G_{wd}$)	78.74	77.39	79.91	79.94	89.07	89.07

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Results on Long Documents : Predictive

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Predictive Embedding	CNN	78.85	78.29	79.72	79.77	86.15	86.15
	CNN(pretrain)	80.15	79.43	79.25	79.32	89.00	89.00
	PTE(G_{wl})	82.70	81.97	79.00	79.02	85.98	85.98
	PTE($G_{ww} + G_{wl}$)	83.90	83.11	81.65	81.62	89.14	89.14
	PTE($G_{wd} + G_{wl}$)	**84.39**	**83.64**	82.29	82.27	89.76	89.76
	PTE(pretrain)	82.86	82.12	79.18	79.21	86.28	86.28
	PTE(joint)	84.20	83.39	**82.51**	**82.49**	**89.80**	**89.80**

Results on Long Documents : Predictive

		20NG		Wikipedia		IMDB	
Type	Algorithm	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
Word	BOW	80.88	79.30	79.95	80.03	86.54	86.54
Predictive Embedding	CNN	78.85	78.29	79.72	79.77	86.15	86.15
	CNN(pretrain)	80.15	79.43	79.25	79.32	89.00	89.00
	PTE(G_{wl})	82.70	81.97	79.00	79.02	85.98	85.98
	PTE($G_{ww} + G_{wl}$)	83.90	83.11	81.65	81.62	89.14	89.14
	PTE($G_{wd} + G_{wl}$)	**84.39**	**83.64**	82.29	82.27	89.76	89.76
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- PTE(joint) $>$ CNN/CNN(pretrain)

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Results on Short Documents : Unsupervised

		DBLP		MR		Twitter	
Type	Algorithm	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
Word	BOW	75.28	71.59	71.90	71.90	75.27	75.27
Unsupervised Embedding	Skip-gram	73.08	68.92	67.05	67.05	73.02	73.00
	PVDBOW	67.19	62.46	67.78	67.78	71.29	71.18
	PVDM	37.11	34.38	58.22	58.17	70.75	70.73
	LINE(G_{ww})	73.98	69.92	71.07	71.06	73.19	73.18
	LINE(G_{wd})	71.50	67.23	69.25	69.24	73.19	73.19
	LINE($G_{ww} + G_{wd}$)	74.22	70.12	71.13	71.12	73.84	73.84

Results on Short Documents : Unsupervised

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	LINE(G_{ww})	73.98	69.92	71.07	71.06	73.19	73.18
	LINE(G_{wd})	71.50	67.23	69.25	69.24	73.19	73.19
	LINE($G_{ww} + G_{wd}$)	74.22	70.12	71.13	71.12	73.84	73.84

– Local context-level word co-occurences : LINE(G_{ww}) $>$ Skip-gram

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- Document-Level word co-occurences
  - LINE(G_{wd}) $>$ PV
  - LINE($G_{ww} + G_{wd}$) $>$ LINE($G_w w$) $>$ LINE($G_w d$)

Results on Short Documents : Predictive

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Type	Algorithm	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1
Word	BOW	75.28	71.59	71.90	71.90	75.27	75.27
Predictive Embedding	CNN	76.16	73.08	72.71	72.69	**75.97**	**75.96**
	CNN(pretrain)	75.39	72.28	68.96	68.87	75.92	75.92
	PTE(G_{wl})	76.45	72.74	73.44	73.42	73.92	73.91
	PTE($G_{ww} + G_{wl}$)	76.80	73.28	72.93	72.92	74.93	74.92
	PTE($G_{wd} + G_{wl}$)	**77.46**	**74.03**	73.13	73.11	75.61	75.61
	PTE(pretrain)	76.53	72.94	73.27	73.24	73.79	73.79
	PTE(joint)	77.15	73.61	**73.58**	**73.57**	75.21	75.21

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Motivation

Introduction
- The Data Sparseness Problem

Related Work
- Overview
- Information Network Embedding

Predictive Text Embedding
- The Text Representation
- Heterogeneous Text Network Embedding
- Bipartite Network Embedding
- Text Embedding

Experiments
- Statistics of the Dataset
- Results
- Results

Analysis

Conclusion

Unsupervised Embedding

Unsupervised Embedding

- Long Documents
  - Documemt-level word co-occurences are more useful than local Context-Level word co-occurences.
  - *No improvement observed* when these two co-occurences are combined.

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- Short Documents
  - Local context-level word co-occurences are more useful than document-Level word co-occurences.
  - Combination further improves the embedding.

Summary

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- Predictive Text Embedding
  - Adapt the advantages of unsupervised text embedding approaches
  - Naturally incorporate the labeled data
- Encode unsupervised and supervised information through Large-scale heterogeneous information networks
- Outperform or comparable to sophisticated methods such as CNN
  - Outperform CNN on long documents
  - Comparable to CNN on short documents

Takeaway

Predictive Text Embedding

Given a large collection of text data with unlabeled and *labeled* information, PTE aims to learn *low-dimensional* representations of words by **embedding** the **heterogeneous** representations of words by embedding the heterogeneous text network constructed from the collection into a low dimensional vector space.

Thank You !