Learning Word Embeddings for Low-resource Languages by PU Learning

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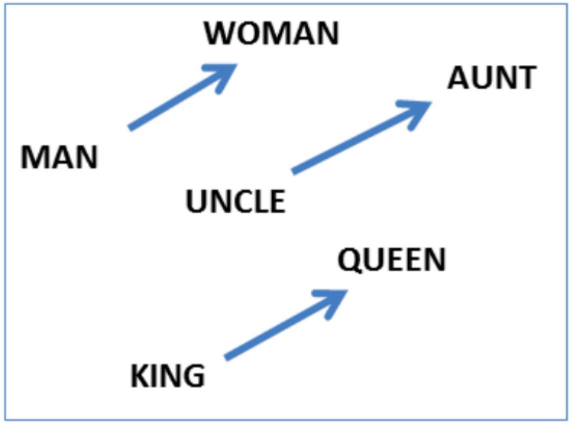
Word Embeddings are useful



- Many successful stories
  - Named entity recognition
  - Document ranking
  - Sentiment analysis
  - Question answering
  - Image captioning
- Pre-trained word vectors have been widely used
  - GloVe [Pennington+14]: **11800+** citations
  - Word2Vec[Mikolov+13]: **18000+** citations

Existing English Embeddings are trained on a large collection of text

- Word2Vec is trained on the Google News dataset.

100 billion tokens

- GloVe is trained on a crawled corpus.

840 billion tokens

How about other language?

How about other language?

- # Wikipedia articles in different languages
  - English: **~ 2.5 M**
  - German: **~ 800 K**
  - French: **~ 700 K**
  - …
  - Czech: **~100 K**
  - Danish: **~95K**
  - …
  - Chichewa: **58**

High-resource languages:
23 languages have more than 100K articles

low-resource languages:
60 languages have 10K ~ 100K articles

very low-resource languages:
183 languages have less than 10K articles

Sparsity of the co-occurrence matrix

- Word Embeddings are trained based on co-occurrence statistics
- When training corpus is small
    - Many word pairs are unobserved
    - Co-occurrence matrix is very sparse
- Example: The text8 data
    - 17,000,000 tokens and 71,000 distinct words
    - Co-occurrence matrix has more than 5,000,000,000 entries, **> 99% are zeros**.

Zeros in the co-occurrence matrix

- True zeros
  - Word pairs which are unlikely to co-occur
- Missing entries
  - Word pairs can co-occur
  - Unobserved in the training data

Center word

context word

	alien	table	…	cake	space
alien	0.8	0.1	-	0	0
table	0	0	-	0	0
…	-	-	-	-	-
cake	**0**	0.2	-	0	0
space	**0**	0	-	0	0.7

True 0

Missing

Motivation

- Small size text corpus
  ⇒ Extremely sparse co-occurrence matrix
- Existing approaches do not use unobserved word pairs effectively
  - E.g., Word2Vec subsamples only some negative word pairs (negative sampling)
- Similar problem is faced by recommendation system
  - User-Product matrix
  - **P**ositive **U**nlabeled learning

Our contributions

1. Propose a PU-Learning framework for training word embedding
2. Design an efficient learning algorithm to deal with all negative pairs
3. Demonstrate that unobserved word pairs provide valuable information

PU-Learning for Training Word Embedding

PU Learning Framework

1. Pre-processing:
   Building co-occurrence matrix

2. Matrix factorization by PU-Learning

3. Post-processing

Step 1 – Building co-occurrence matrix

- Count words co-occurrence statistics
- We follow [Levy+15] to scale the co-occurrence counts by PPMI metric

… the black cat likes milk …

context window

(cat, the)
(cat, black)
(cat, likes)
(cat, milk) …

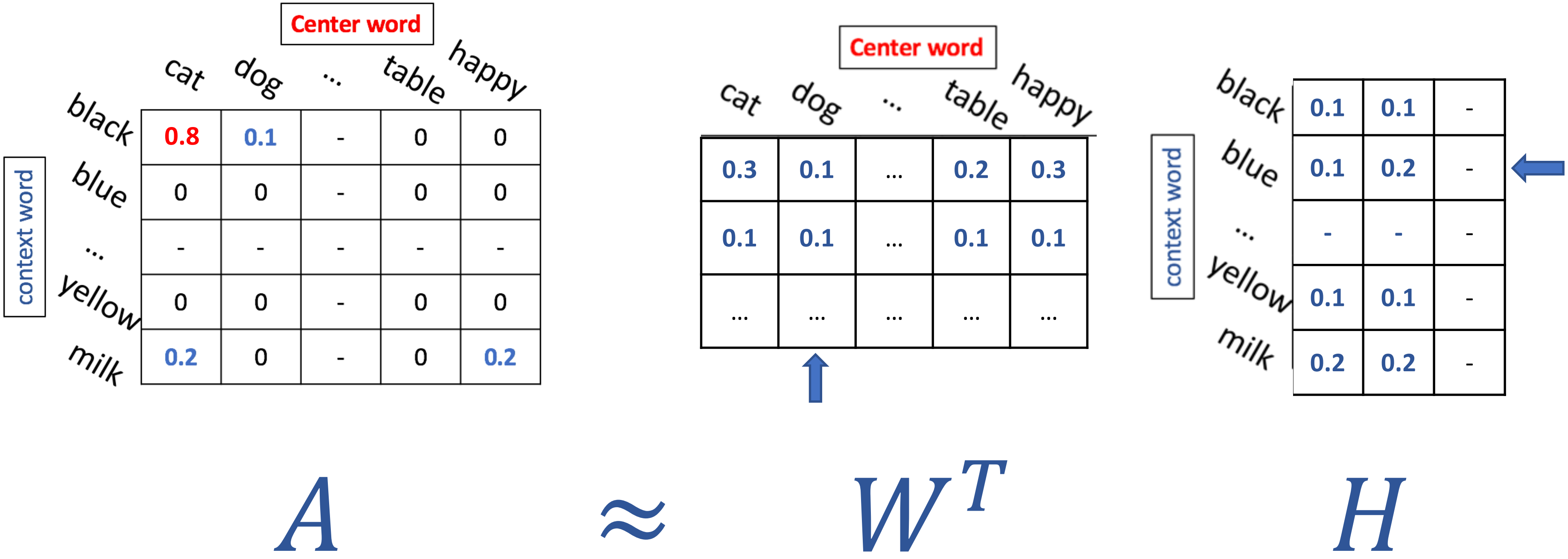
Center word

context word

	cat	dog	…	table	happy
the	**0.8**	**0.1**	-	0	0
black	0	0	-	0	0
…	-	-	-	-	-
likes	0	0	-	0	0
milk	**0.2**	0	-	0	**0.2**

Scaled by PPMI

Step 2 - PU-Learning for matrix factorization



Center word

context word

	cat	dog	...	table	happy
black	0.8	0.1	-	0	0
blue	0	0	-	0	0
...	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

Center word

cat	dog	...	table	happy
0.3	0.1	...	0.2	0.3
0.1	0.1	...	0.1	0.1
...	...	...	...	...

context word

black	0.1	0.1	-
blue	0.1	0.2	-
...	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$A \approx W^T \quad H$$

Step 2 - PU-Learning for matrix factorization

$$A \qquad \approx \qquad W^T \qquad H$$

Center word

context word

	cat	dog	...	table	happy
black	0.8	0.1	-	0	0
blue	0	0	-	0	0
...	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

Center word

cat	dog	...	table	happy
0.3	0.1	...	0.2	0.3
0.1	0.1	...	0.1	0.1
...	...	...	...	...

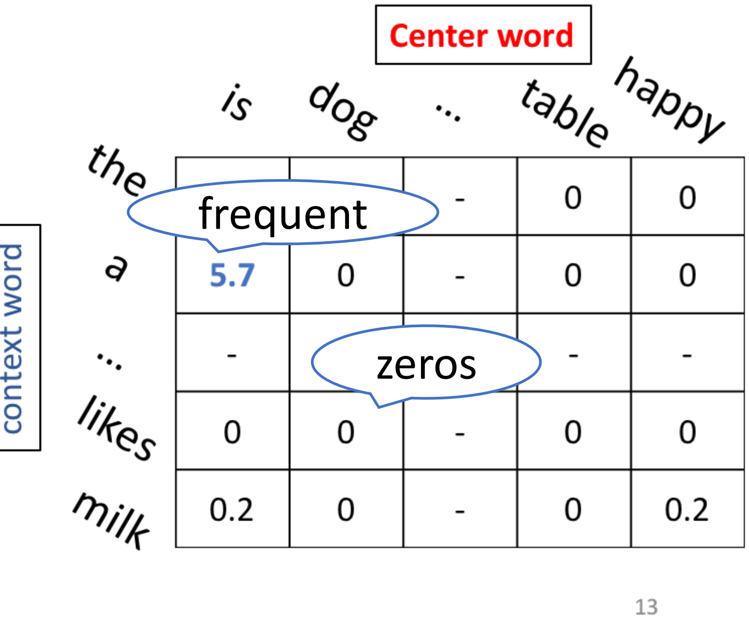
context word

black	0.1	0.1	-
blue	0.1	0.2	-
...	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j\in\Omega} C_{ij} \underbrace{\left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j\right)^2}_{\text{Reconstruction error}} + \underbrace{\sum_{\text{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j \left\|\boldsymbol{h}_j\right\|^2}_{\text{Regularization}}$$

Weighting function

Step 2 – Weighting function



Center word

context word

	is	dog	...	table	happy
the			-	0	0
a	5.7	0	-	0	0
...	-			-	-
likes	0	0	-	0	0
milk	0.2	0	-	0	0.2

frequent

zeros

13

$$A$$

Three types of entries:

1. Co-occurrence count > x_{max}

   $C_{ij} = 1$

2. Co-occurrence count $\leq x_{max}$

   $C_{ij} = \text{count} / x_{max}$

3. Co-occurrence count $= 0$

   $C_{ij} = \rho$

Step 2 - PU-Learning for matrix factorization

$$\min_{W,H} \sum_{i,j\in\Omega} \underset{\text{Weighting function}}{C_{ij}} \underbrace{\left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j\right)^2}_{\text{Reconstruction error}} + \underbrace{\sum_{\mathrm{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j \|\boldsymbol{h}_j\|^2}_{\text{Regularization}}$$

- We consider all entries
  - Both positive and **zero** entries

Step 2 - PU-Learning for matrix factorization

$$A \approx W^T H$$

Center word

context word

	cat	dog	…	table	happy
black	0.8	0.1	-	0	0
blue	0.5	0	-	0	0
…	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

Center word

cat	dog	…	table	happy
0.3	0.1	…	0.2	0.3
0.1	0.1	…	0.1	0.1
…	…	…	…	…

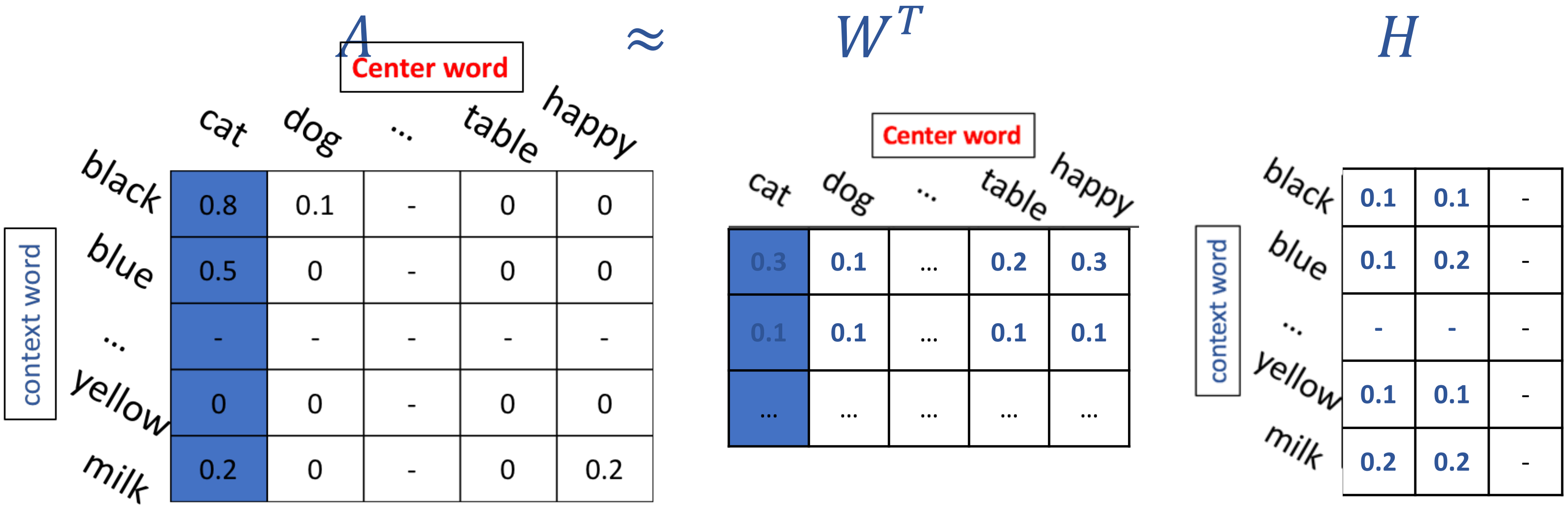
context word

black	0.1	0.1	-
blue	0.1	0.2	-
…	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j\in\Omega} C_{ij}\left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j\right)^2 + \sum_{\mathrm{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j \left\|\boldsymbol{h}_j\right\|^2$$

- We design efficient coordinate descent algorithm (see paper for details)

Step 2 - PU-Learning for matrix factorization



$A \approx W^T H$

A (Center word × context word)

	cat	dog	…	table	happy
black	0.8	0.1	-	0	0
blue	0.5	0	-	0	0
…	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

W^T (Center word)

cat	dog	…	table	happy
0.3	0.1	…	0.2	0.3
0.1	0.1	…	0.1	0.1
…	…	…	…	…

H (context word)

black	0.1	0.1	-
blue	0.1	0.2	-
…	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j\in\Omega} C_{ij}\left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j\right)^2 + \sum_{\mathrm{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_{j} \bar{\lambda}_j \left\|\boldsymbol{h}_j\right\|^2$$

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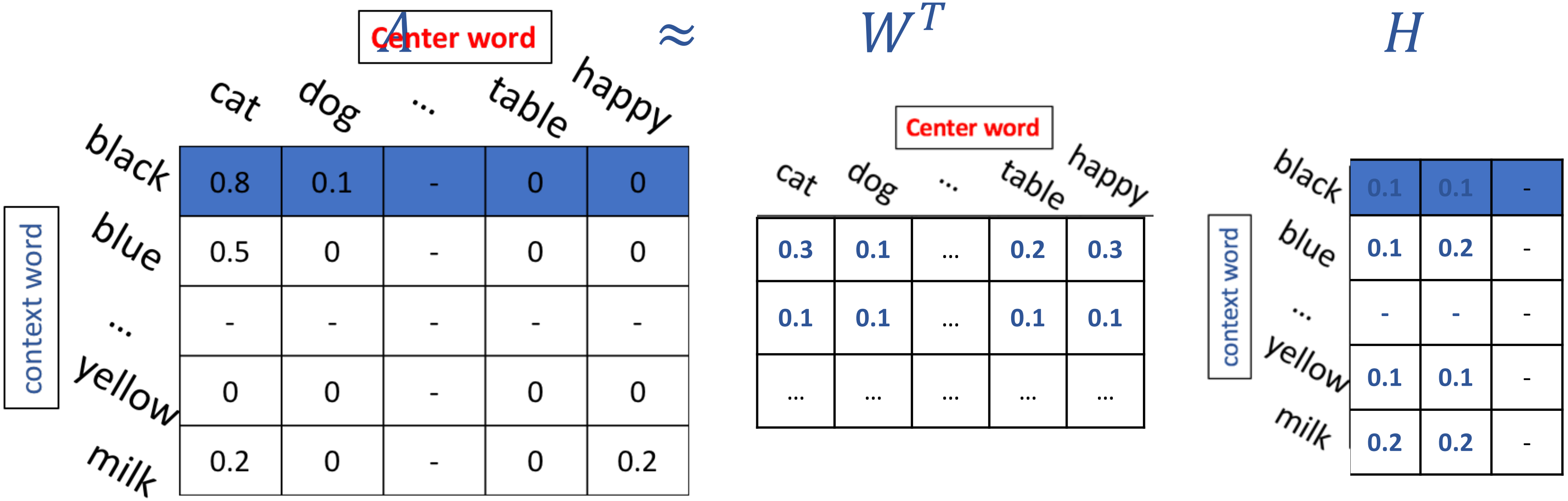
Step 2 - PU-Learning for matrix factorization



	cat	dog	..	table	happy
black	0.8	0.1	-	0	0
blue	0.5	0	-	0	0
..	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

cat	dog	..	table	happy
0.3	0.1	…	0.2	0.3
0.1	0.1	…	0.1	0.1
…	…	…	…	…

black	0.1	0.1	-
blue	0.1	0.2	-
..	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j\in\Omega} C_{ij}\left(A_{ij} - \boldsymbol{w}_i^T\boldsymbol{h}_j - b^i - \hat{b}^j\right)^2 + \sum_{\mathrm{i}} \lambda_i\|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j\left\|\boldsymbol{h}_j\right\|^2$$

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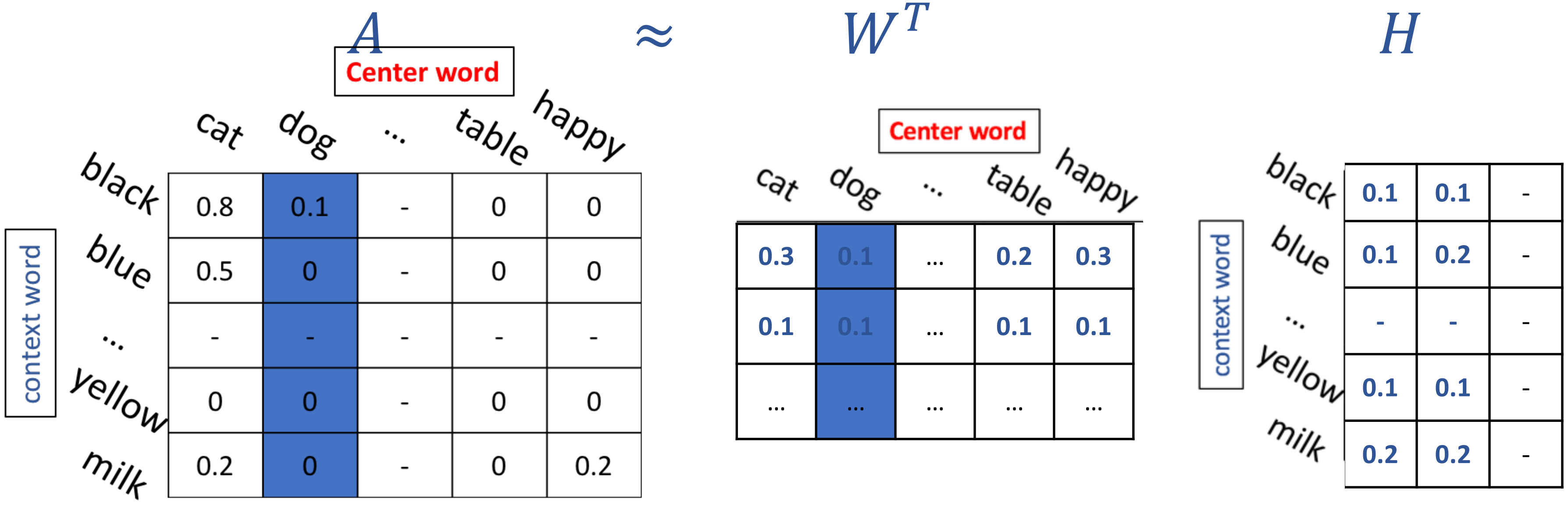
Step 2 - PU-Learning for matrix factorization



$A \approx W^T H$

Center word

context word

	cat	dog	…	table	happy
black	0.8	0.1	-	0	0
blue	0.5	0	-	0	0
…	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

Center word

cat	dog	…	table	happy
0.3	0.1	…	0.2	0.3
0.1	0.1	…	0.1	0.1
…	…	…	…	…

context word

black	0.1	0.1	-
blue	0.1	0.2	-
…	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j\in\Omega} C_{ij}\left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j\right)^2 + \sum_{\mathrm{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j \|\boldsymbol{h}_j\|^2$$

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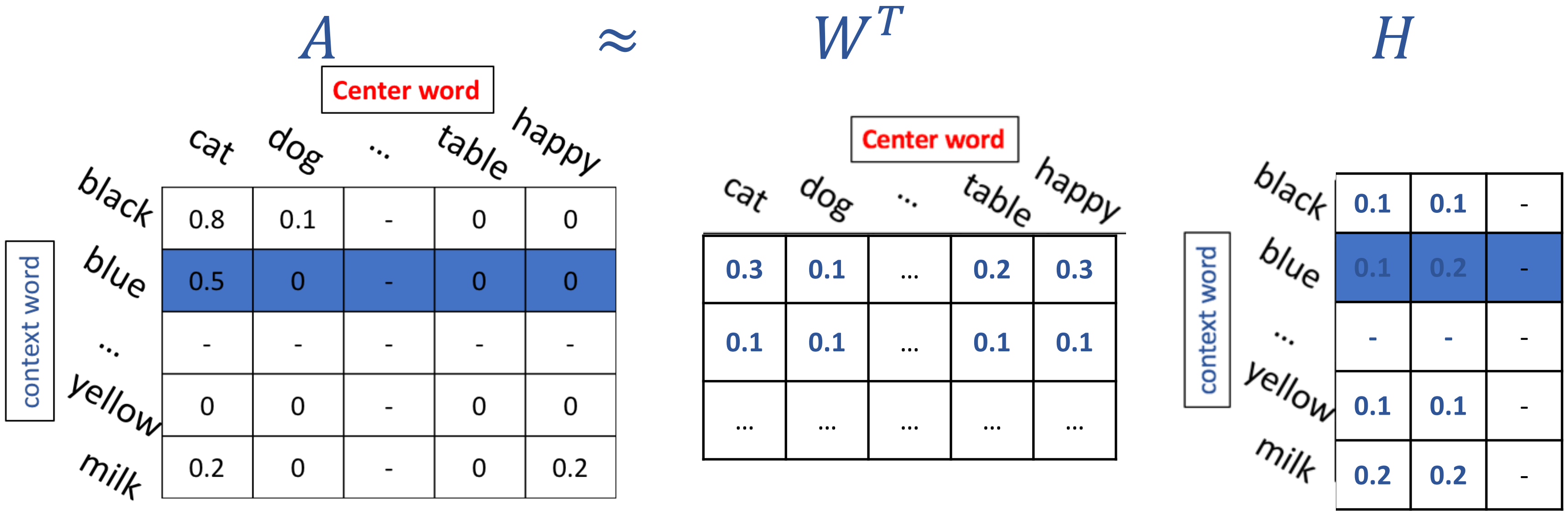
Step 2 - PU-Learning for matrix factorization



$A \approx W^T H$

A

Center word

context word

	cat	dog	...	table	happy
black	0.8	0.1	-	0	0
blue	0.5	0	-	0	0
...	-	-	-	-	-
yellow	0	0	-	0	0
milk	0.2	0	-	0	0.2

W^T

Center word

cat	dog	...	table	happy
0.3	0.1	...	0.2	0.3
0.1	0.1	...	0.1	0.1
...	...	...	...	...

H

context word

black	0.1	0.1	-
blue	0.1	0.2	-
...	-	-	-
yellow	0.1	0.1	-
milk	0.2	0.2	-

$$\min_{W,H} \sum_{i,j \in \Omega} C_{ij} \left(A_{ij} - \boldsymbol{w}_i^T \boldsymbol{h}_j - b^i - \hat{b}^j \right)^2 + \sum_{\mathrm{i}} \lambda_i \|\boldsymbol{w}_i\|^2 + \sum_j \bar{\lambda}_j \left\|\boldsymbol{h}_j\right\|^2$$

- We design efficient coordinate descent algorithm (see paper for details)

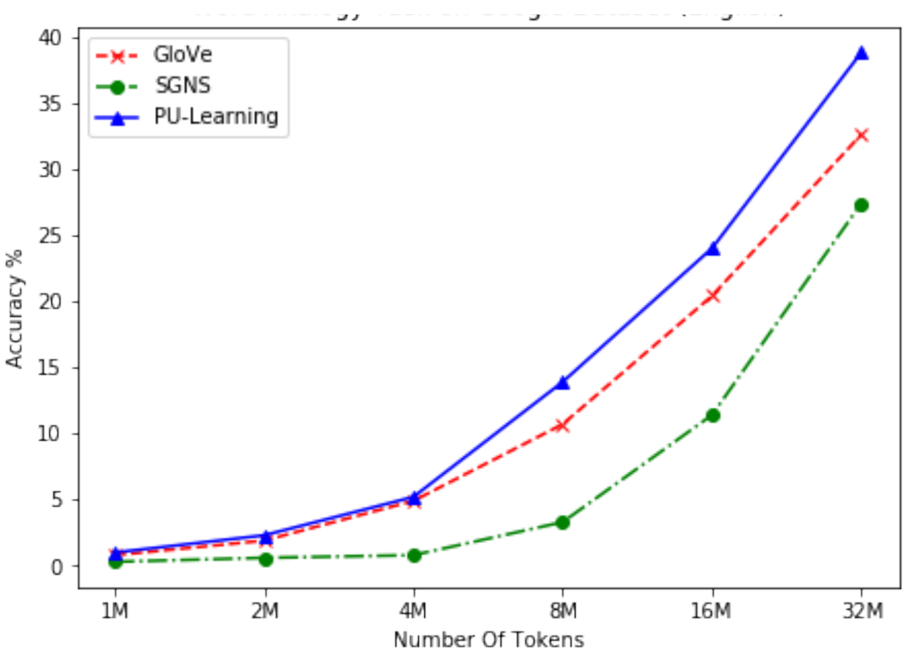
Step 3 -- Post-processing

- Each word is represented by a word vector w_i^T and a context vector h_i
- We follow [Pennington+14, Levy+15] to use the average of w_i^T and h_i as word vector for word i

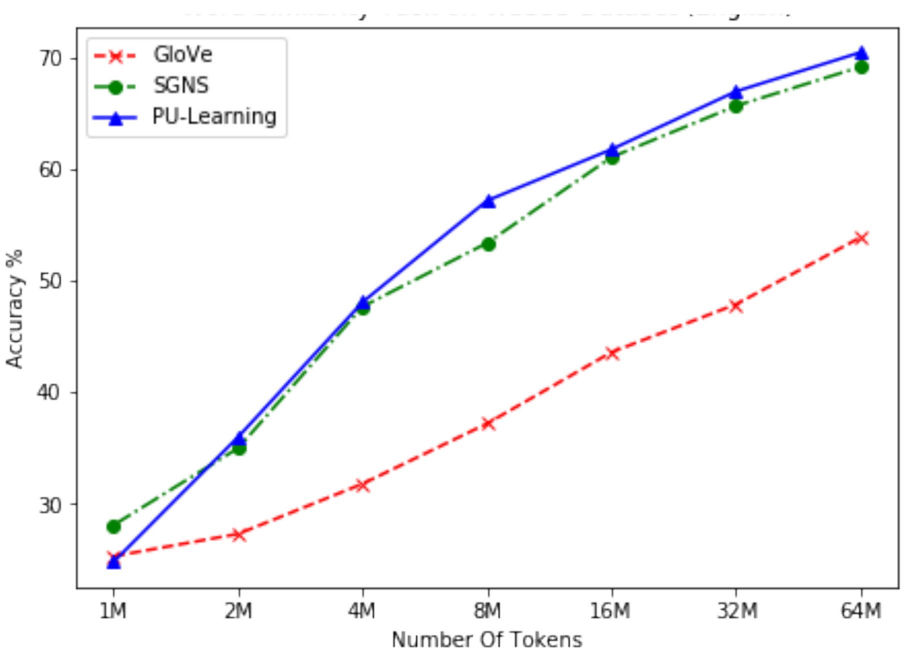
Experiments

Results on English

Simulate the low-resource setting: Embedding is trained on a subset of Wikipedia with 32M tokens



Analogy Task on Google Dataset



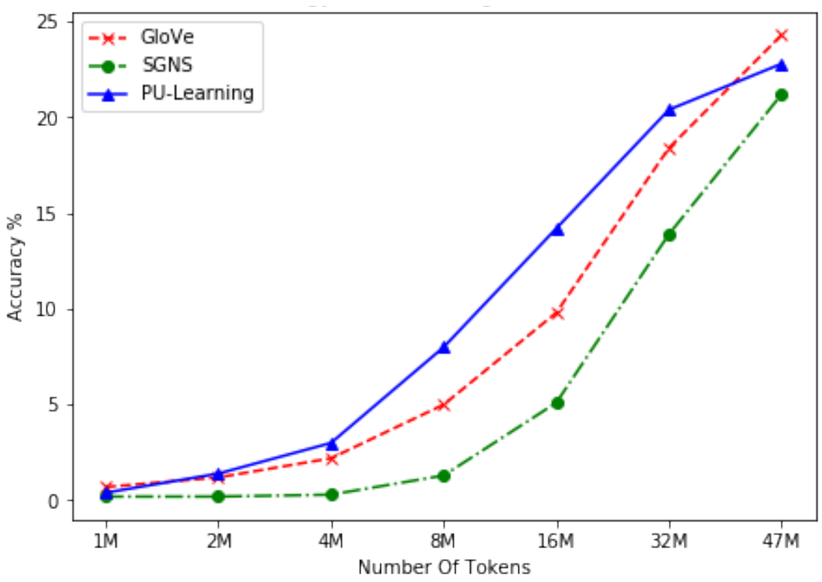
Word Similarity Task on WS353

Results on Danish (more results in paper)

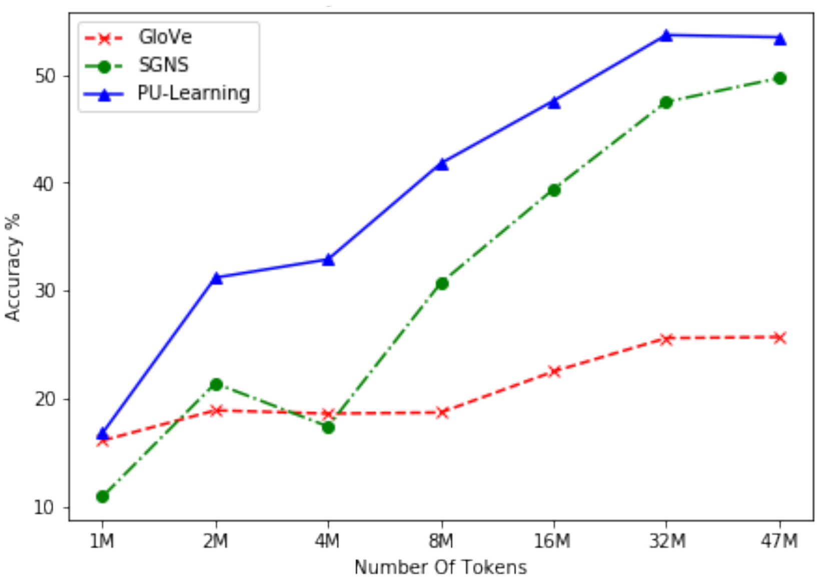
Danish Wikipedia with 64M tokens

Test set are translated by Google translation

(w/ 90% accuracy verified by native speakers)



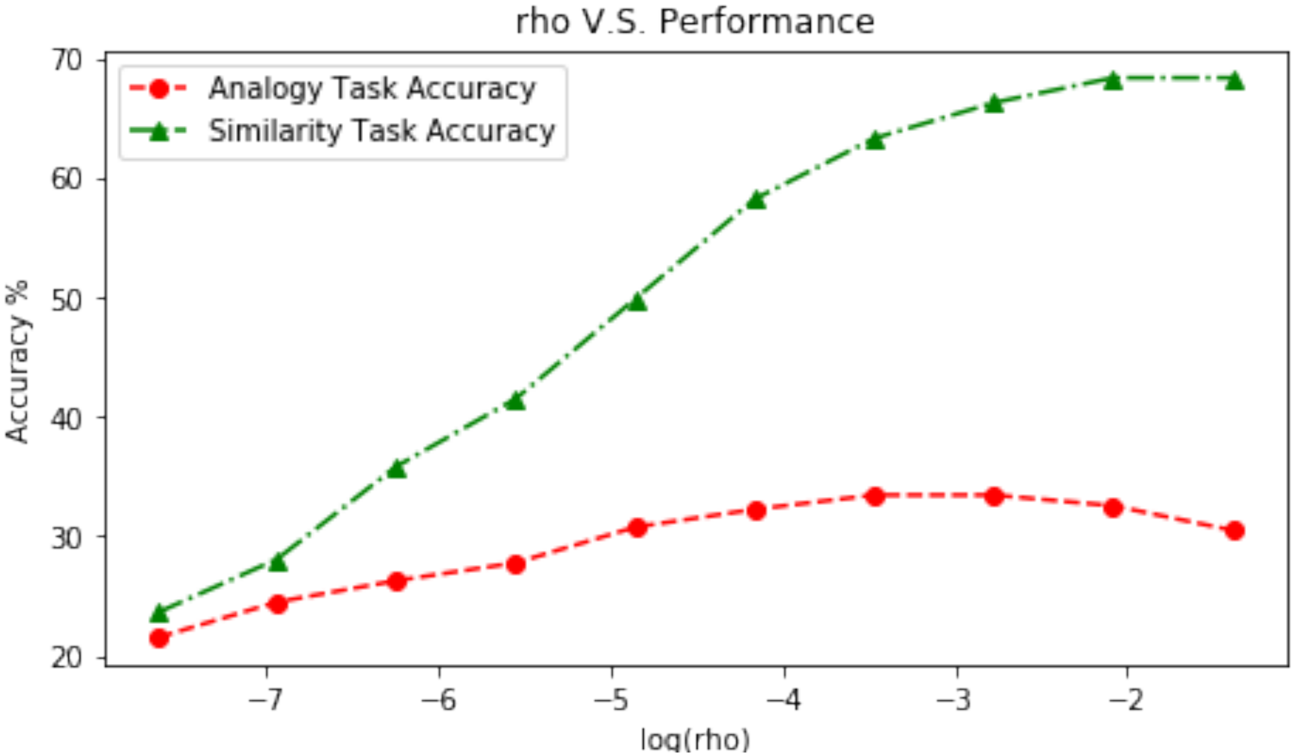
Analogy Task on Google Dataset



Word Similarity Task on WS353

Interpretation of Parameters - ρ

- Weight for zero entries in co-occurrence matrix
- Zero entries can be true 0 or missing
- **ρ reflects how confident that the zero entries are true zero**



Take home messages

- A PU-Learning framework for learning word embedding in the low resource setting
- Unobserved word pairs provide valuable information

Thanks!