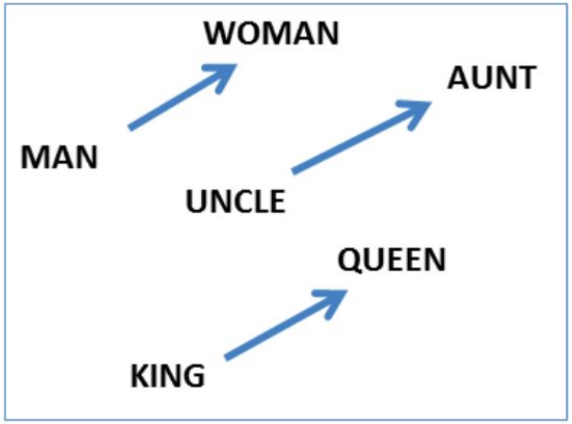
# Learning Word Embeddings for Low-resource Languages by PU Learning

Chao Jiang, Hsiang-Fu Yu, Cho-Jui Hsieh, Kai-Wei Chang

# 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]: **3900+** citations
  - Word2Vec[Mikolov+13]: **7600+** 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

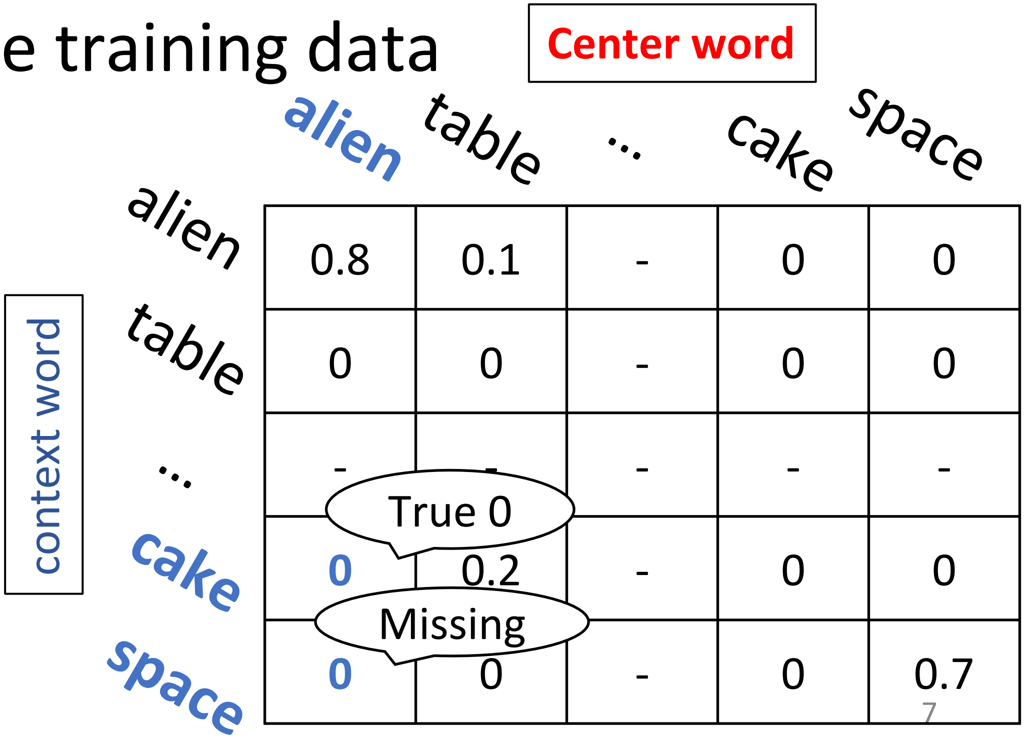
**very low-resource languages:**
183 languages have less than 10K articles

# 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 |

# 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

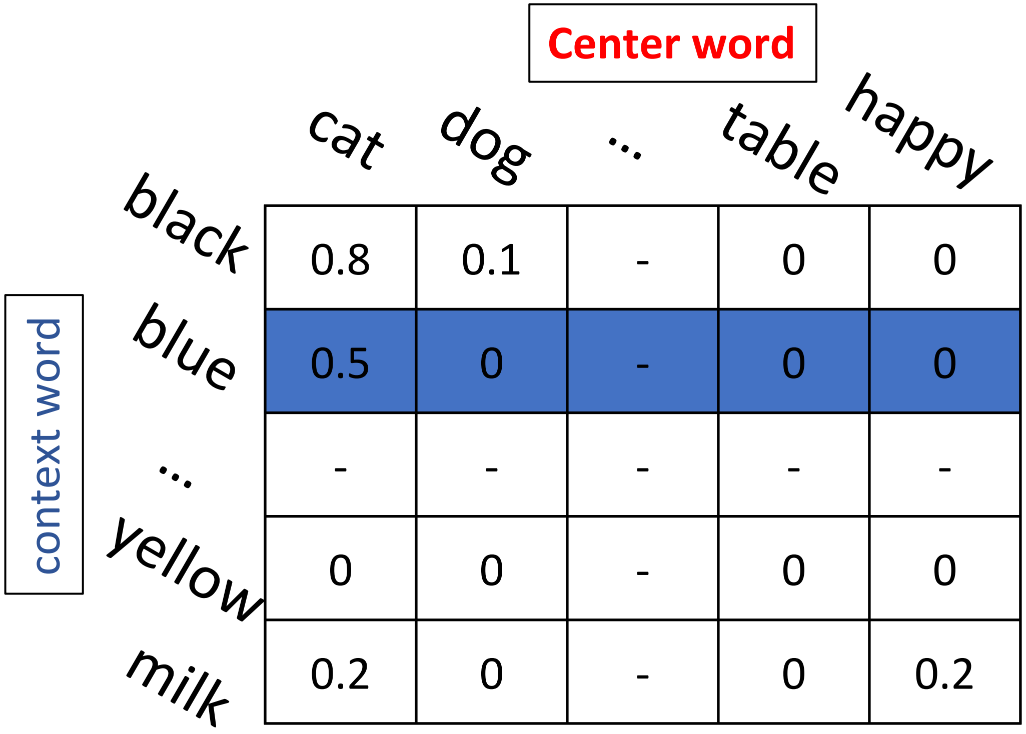
(cat, the)
(cat, black)
(cat, likes)
(cat, milk) ...

**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



**Center word**

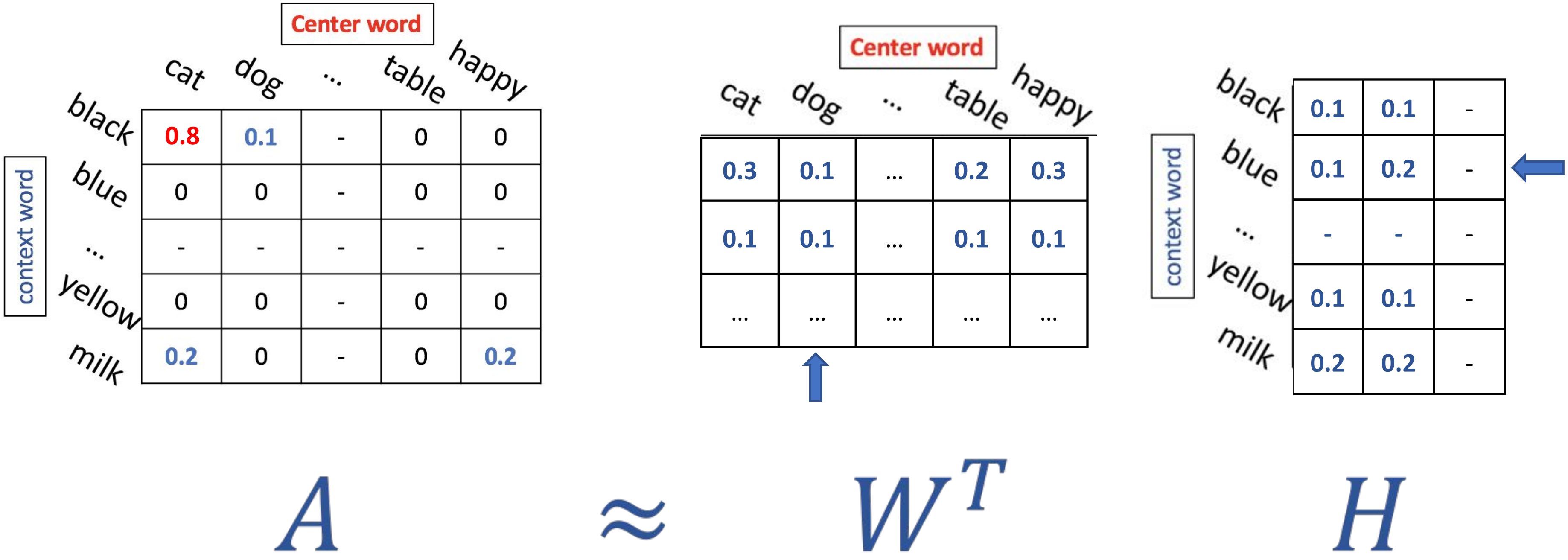
context word

| | 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 |

zeros

frequent

# 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

$A \approx W^T \quad H$

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 |
| … | … | … | … | … |

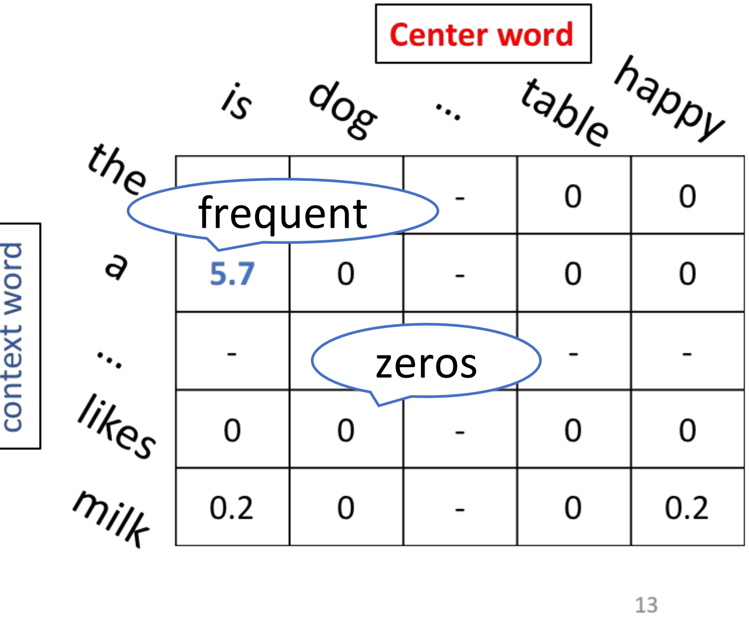
context word

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

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

Weighting function

# Step 2 – Weighting function



| | 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 |

$A$

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

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

Weighting function

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

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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 |
| … | … | … | … | … |

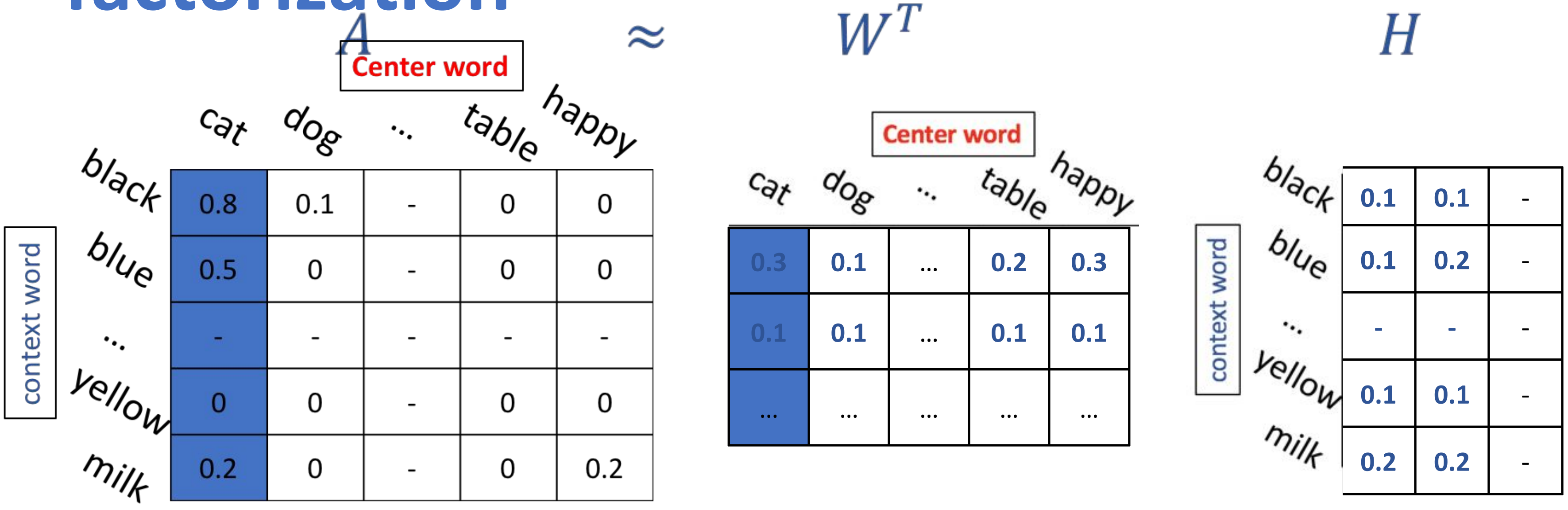
$H$

| 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 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 | - |

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

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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 |

$W^T$

Center word

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

$H$

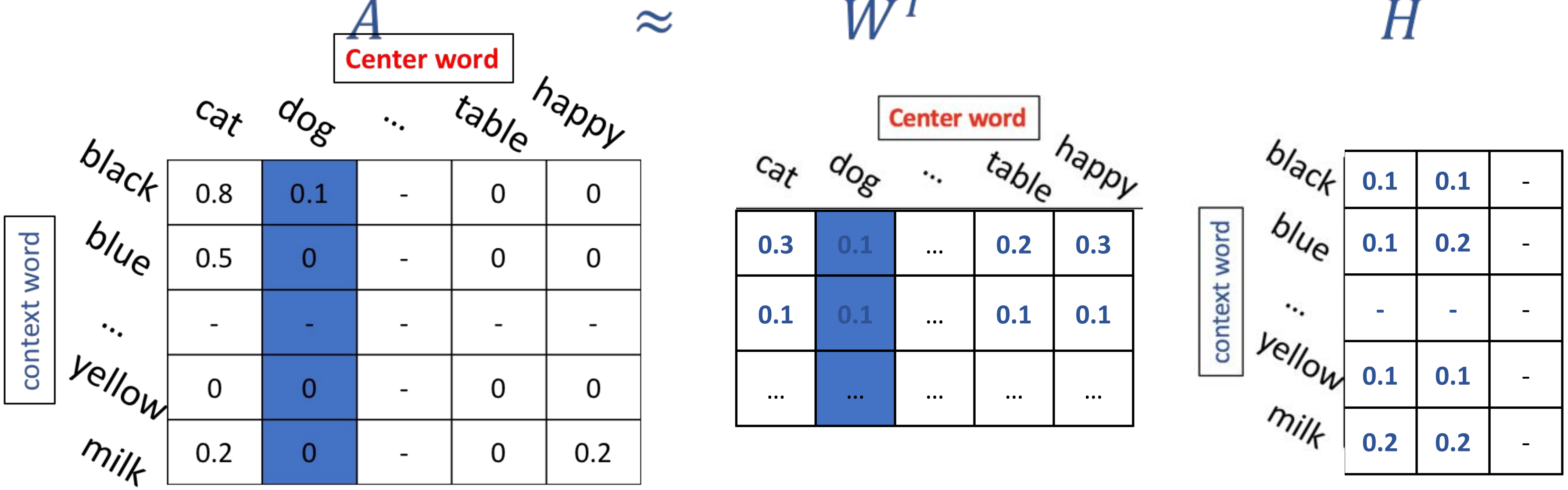
context word

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

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

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

# Step 2 - PU-Learning for matrix factorization



$$A \approx W^T H$$

$A$

| | 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 |

$W^T$

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

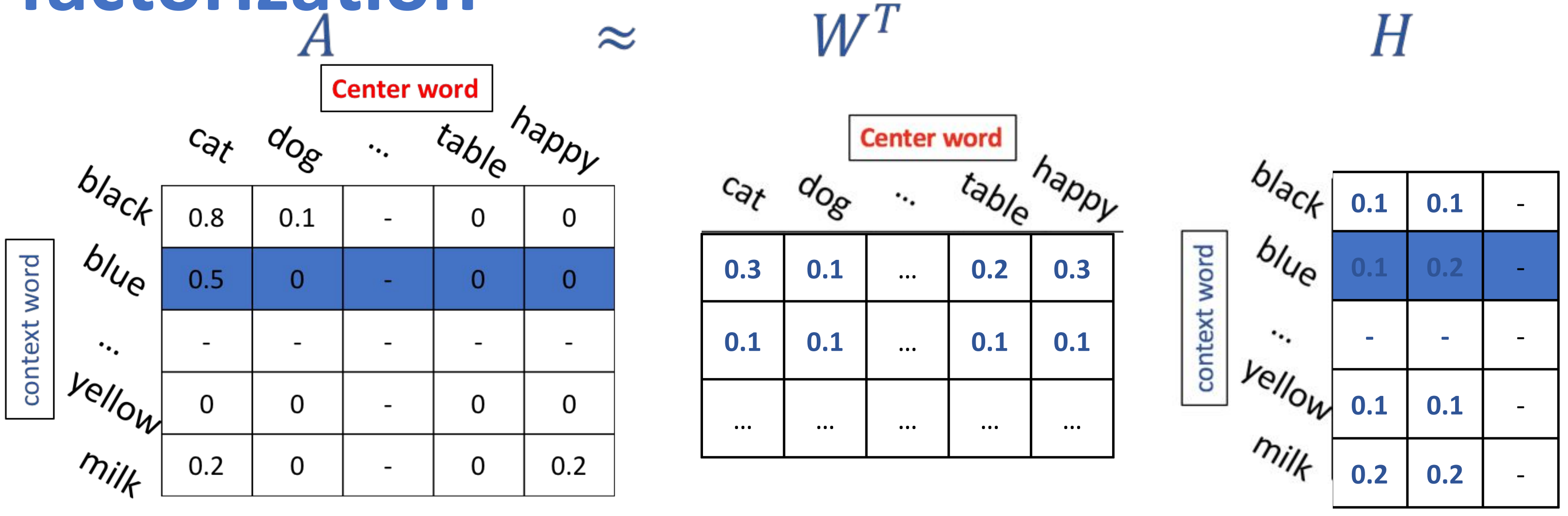
$H$

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

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

- 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 | - |

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

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

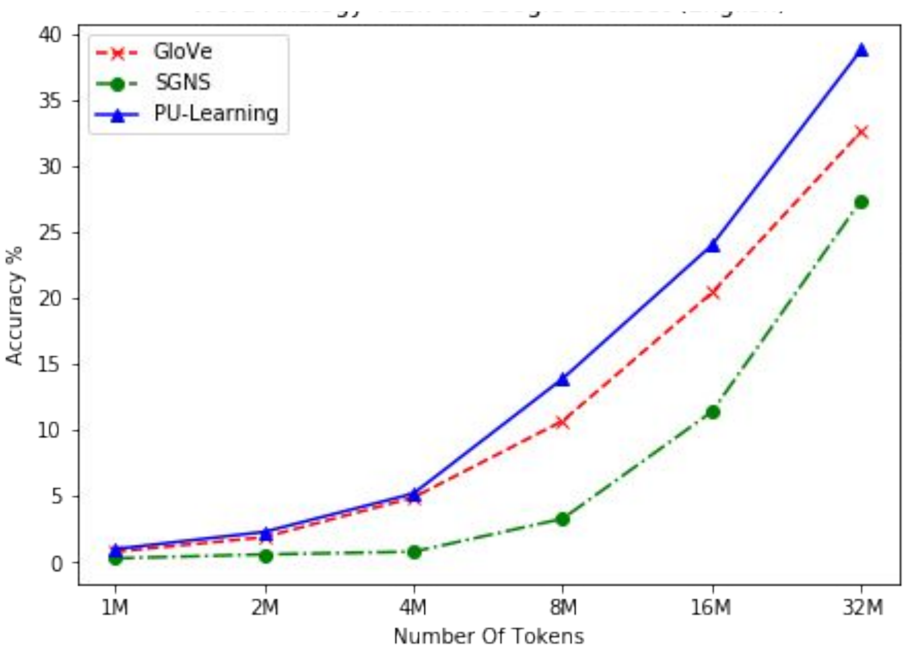
# Step 3 -- Post-processing

- 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 $i$

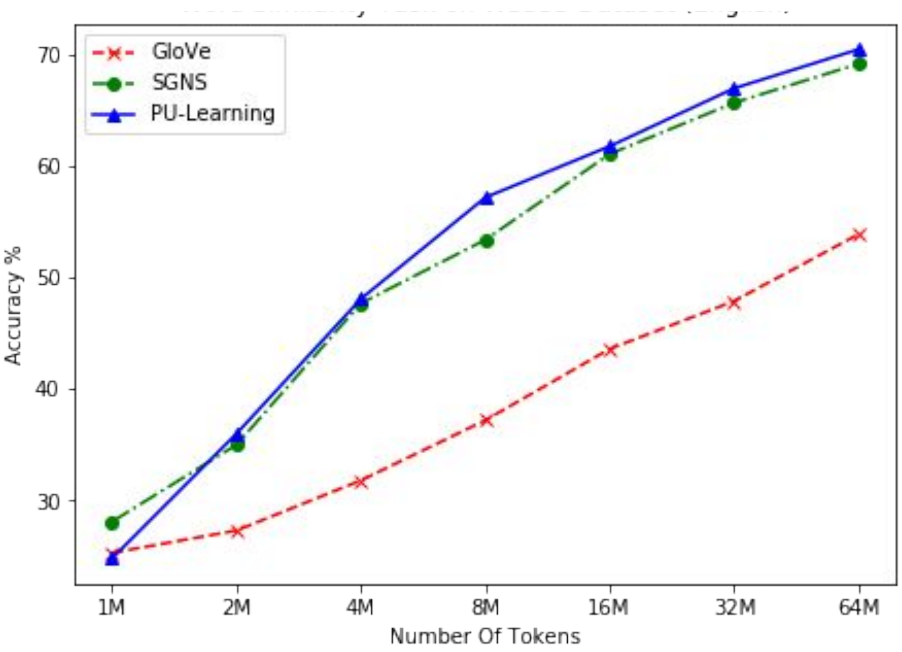
# Experiments

# Results on English

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



Analogy Task on Google Dataset

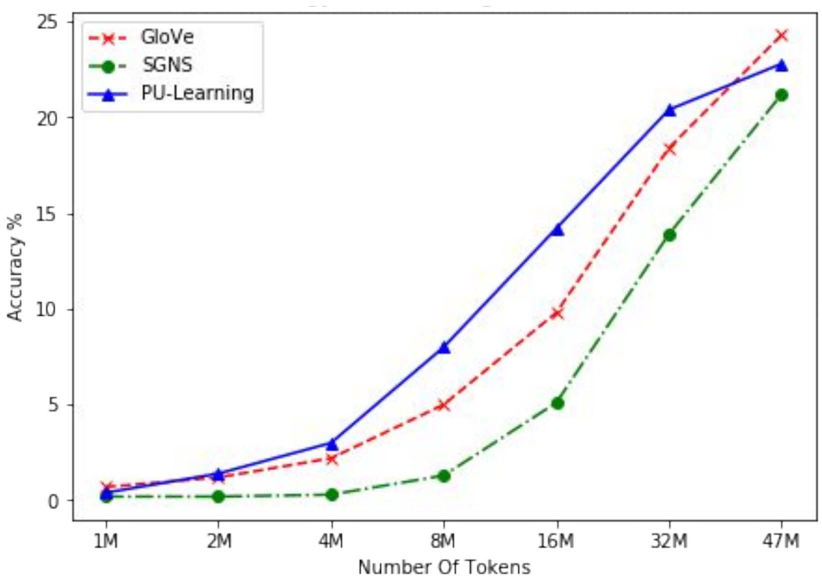


Word Similarity Task on WS353

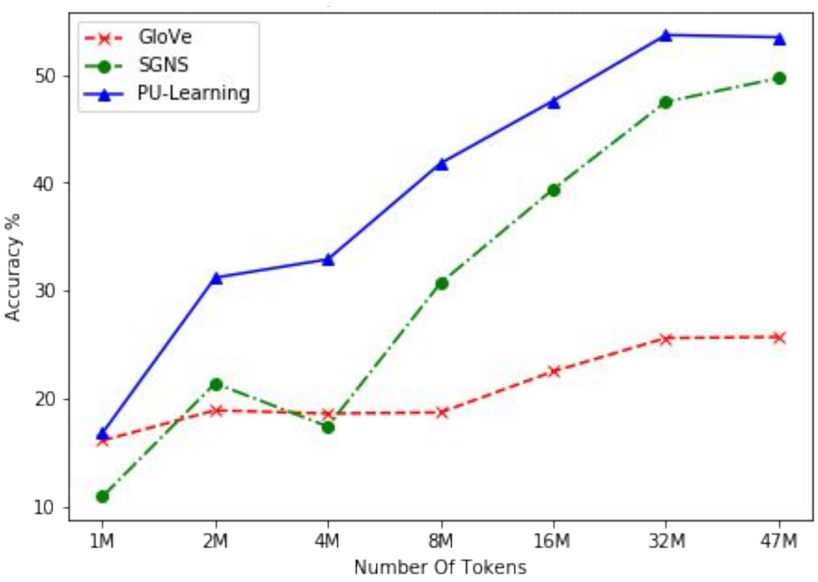
# Results on Danish (more results in paper)

Danish Wikipedia with 64M tokens

Test set are translated by Google translation (w/ 90% accuracy verified by native speakers)



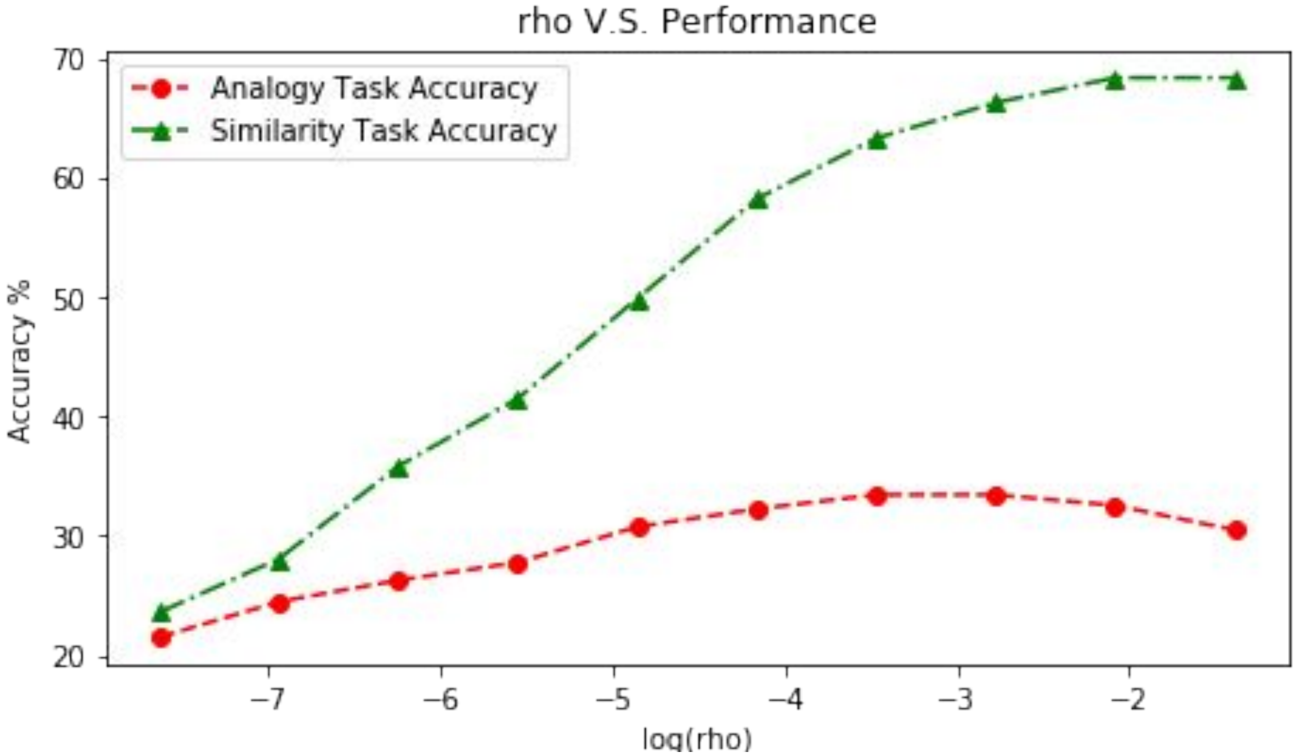
Analogy Task on Google Dataset



Word Similarity Task on WS353

# Interpretation of Parameters- $\rho$

- Weight for zero entries in co-occurrence matrix
- Zero entries can be true 0 or missing
- **$\varrho$ 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!