

# Graph-based text representations

Student

Wentao Feng

Thesis supervisors

**Maxime Peyrard** 

**Akhil Arora** 

Thesis advisor

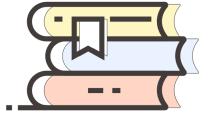
**Robert West** 

External expert

**Andreas Spitz** 



■ Data Science Lab 12 July 2021



### Introduction

Method

Experiment

Conclusion

### **Introduction - Problem**

#### > Text representation

A process converts text into a mathematically computable form

#### > Existing models

Word2Vec, GloVe, Fasttext, etc.

#### > Drawback

Learned representations are not understandable to the human.

EX writings (0.189453, 0.210938, 0.205078, 0.289062, 0.21875, ...) yellow (-0.073242, 0.026367, 0.076171, 0.189453, -0.0471, ...)

### **Introduction - Motivation**



Why do we need an interpretable text representation?



Debug pipeline



**Dimension reduction** 



Improve downstream tasks



## **Introduction - Challenge**

□Interpretable embedding space

Sparse-vector-based methods: one-hot encoding, occurrence matrix

**□** Efficiency

Dense-vector-based methods: Word2Vec, GloVe, etc.

### **Introduction - Previous work**

Wentao Feng

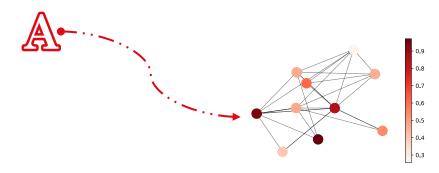
#### SPOWV<sup>1</sup>, SPINE<sup>2</sup>:

Transform dense-vector-based models with sparsity and non-negativity constraint.

- Axis has a topic or concept
- Small capacity of interpretability
- Sub-optimality
- Pre-trained models matter

### **Introduction - Solution**

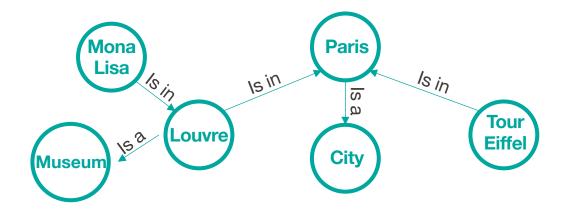
#### Representing word as a distribution on the knowledge graph



#### Method in a nutshell:

- 1. Build Skip-gram dataset.
- 2. Embed word as Gaussian mixture distribution
- 3. Measure the statistical distance between two distributions
- 4. Maximize the objective of negative samplings

### **Introduction - Solution**



#### ■ Naturally interpretable

academia (efficiency: 0.5061 traveling: 0.4707 rookie: 0.4327 upset: 0.4250 ricardo: 0.3571 penalty: 0.3485...)

☐ High efficiency and scalability after relaxations

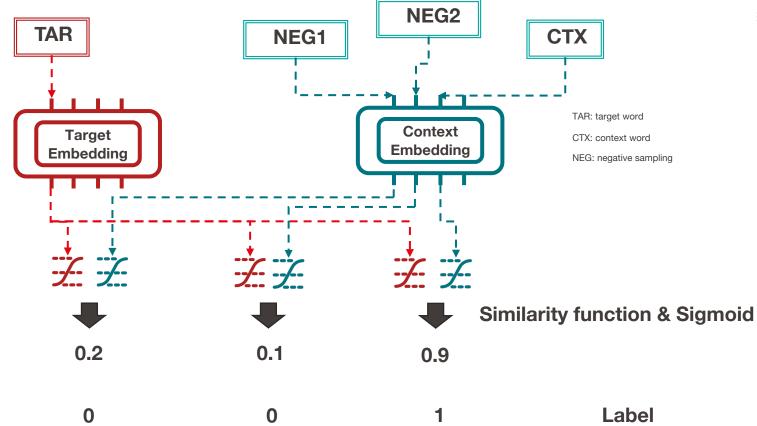
### Introduction

### Method

Experiment

Conclusion

### **Method - Skip-gram**



## **Method - Objective function**

$$\log \sigma(\mathcal{S}(w_j, w_i | \mathcal{G})) + \sum_{k=1}^{K} \mathbb{E}_{w_k \sim p_n(w)} [\log \sigma(-\mathcal{S}(w_k, w_i | \mathcal{G}))]$$

 $w_i$ : target word

 $w_i$ : context word

 $w_k$ : Negative sampling

 $p_n(w)$ : Negative sampling distribution

 $\sigma$ : sigmoid function

*S*: *similarity function* 

G: knowledge graph

### Method - Issue

$$\log \sigma(\mathcal{S}(w_j, w_i | \mathcal{G})) + \sum_{k=1}^{K} \mathbb{E}_{w_k \sim p_n(w)} [\log \sigma(-\mathcal{S}(w_k, w_i | \mathcal{G}))]$$

#### **□** Discrete structure

- Back propagation
- Measure similarity

#### ☐ Efficiency and scalability

Work on large knowledge graph

**Nentao Fen**g

#### **□** Discrete structure

- ⊖ Back propagation→ Node embedding

→ Anchor

- □ Efficiency and scalability
  - Work on large knowledge graph

Node embedding

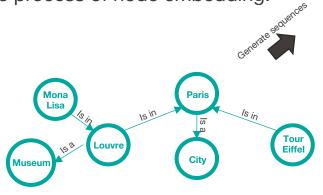
Gaussian mixture model (GMM)

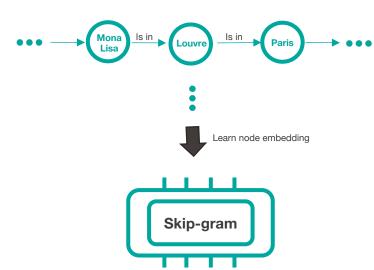
Anchor

Desiderata:

- ☐ Use dense vector represent node.
- □ Preserve structural information and node similarity.

Concise process of node embedding:





Node embedding

Gaussian mixture model (GMM)

Anchor

$$P(x) = \sum_{m=1}^{M} a_m \mathcal{N}(x|\mu_m, \Sigma_m) \quad s.t. \sum_{m=1}^{M} a_m = 1, a_m \ge 0$$

$$\mathcal{N}(x|\mu, \Sigma) = \frac{1}{|\Sigma|^{\frac{1}{2}} (2\pi)^{\frac{d}{2}}} \exp\left(-\frac{1}{2} (x - \mu)^{\top} \Sigma^{-1} (x - \mu)\right)$$

Desiderata:

- ☐ Efficient: closed-form statistical distance
- Expressiveness: more components, more expressive.
- □ Sparse: small area has positive probability density

Anchor

- Node embedding
- Gaussian mixture model (GMM)

Simplify  $\Sigma$  (Positive semidefinite matrix):

- 1. Diagonal matrix.
- 2. Treat as hyperparameter.
- 3. All  $\Sigma$  are the same.

Squared  $l_2$  distance between two mixtures of Gaussian P, Q:

$$\ell_2^2(P,Q) = \sum_{m,m'} a_m a_{m'} \mathcal{N}(\mu_m | \mu_{m'}, \Sigma_m + \Sigma_{m'}) + \sum_{n,n'} b_n b_{n'} \mathcal{N}(\eta_n | \eta_{n'}, \Lambda_n + \Lambda_{n'}) - 2 \sum_{m,n} a_m b_n \mathcal{N}(\mu_m | \eta_n, \Sigma_m + \Lambda_n)$$

**(+)** 

Node embedding

Gaussian mixture model (GMM)

Anchor

**Definition**: An anchor is a carefully selected node (item) whose name (label) is existing in the dictionary, aiming to regulate the word's GMM.

GMM for anchors is non-learnable:

 $\mu$ : node vector

 $\Sigma$ : Diagonal matrix with entries = 1

Anchor selection:

- □k-means++
- □ Sampling with density: k-NN estimates the density
- ☐ High-degree nodes: Hubs as the anchors
- □ Sampling with the degree

### Method - Word2GMM

## ventao reng

https://go.epfl.ch/word2gmm

### Introduction

Method

## **Experiment**

Conclusion

### **Experiment - Setup**

### **Experiment - Word similarity**

#### **>** Similarity

Word2GMM:  $-l_2^2$ 

Word2Vec, SPINE: cosine similarity

#### Datasets

7947 valid pairs of words from 13 datasets.

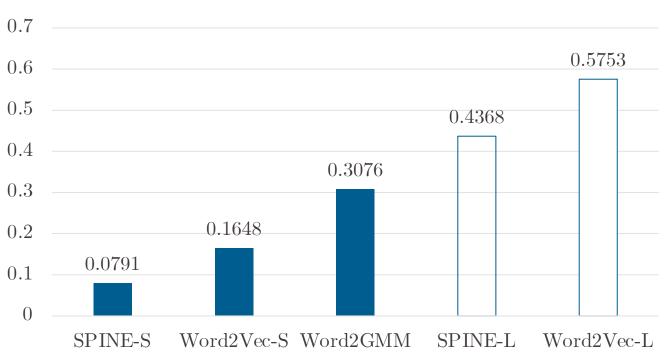
#### > Metric

Spearman's rank correlation coefficient  $r_s$ .

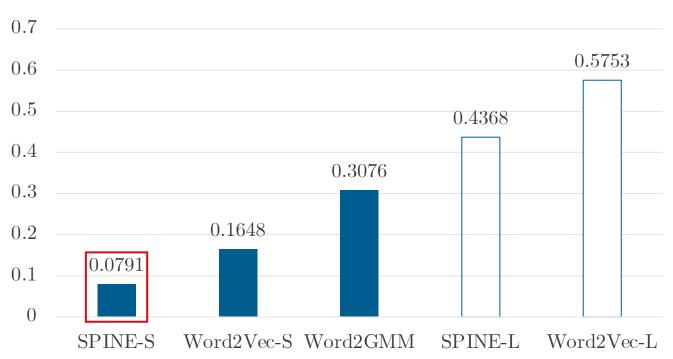
$$r_{\rm S} = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$$

Weighted sum of  $r_s$  from all datasets.

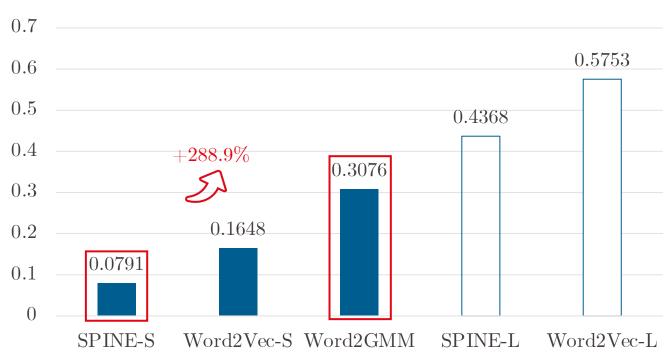
## **Experiment - Word similarity**



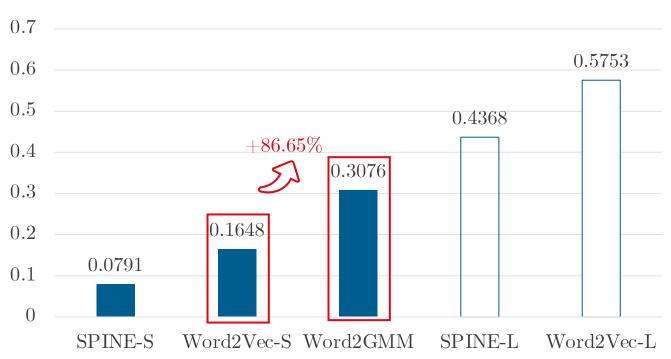
## **Experiment - Word similarity**



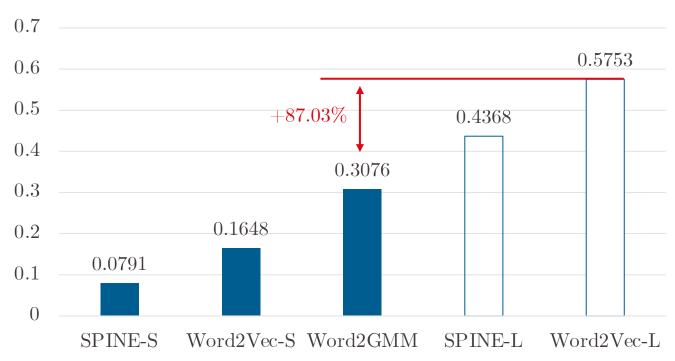
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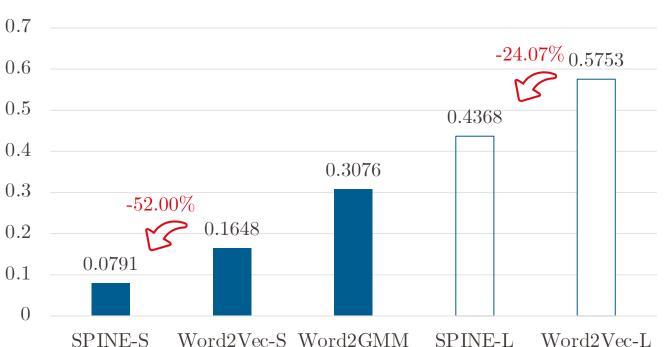
## **Experiment - Word similarity**



## **Experiment - Word similarity**



## **Experiment - Word similarity**



### **Experiment - Word similarity**

#### Word closeness



Word2GMM

Word2Vec-L

build: completion, construction, bas, infrastructure, designated. construct, develop, built, rebuild, establish.

film: movie, films, bros, sitcoms, cartoon, starring.
movie, films, filmmaker, filmmakers, filmmaking.

social: societal, sustainability, deliberation, openness, norms. societal, Carmeta Albarus Lindo, socio, media optimization SMO, cultural.

#### **□** Qualitative assessment

Word2GMM: 5 top-activated nodes

Word2Vec, SPINE: 5 top-activated words

#### ■ Error analysis

The situation when Word2GMM fails to give interpretation.

#### □ Activation pattern analogy

Activation pattern analogy with respect to word similarity.

□ Qualitative assessment

Error analysis

	${f Word2Vec\text{-}S}$	Word2Vec-L
people	bassists, litre, nc	capt, astronomers
people	dispense, daytona	lakers, nec, shootout
government	wafer, quark, ibsen	jacket, consortium
government	ounces, eocene	vaccine, coupe. cigar
water	hotter, newark, bohr	microsoft, sr, bt
water	modernisation, lysander	malaysia, jan
	SPINE-S	SPINE-L
noonlo	SPINE-S mgm, nudity, tensile	SPINE-L viewers, readers, listeners
people		
	mgm, nudity, tensile	viewers, readers, listeners
people government	mgm, nudity, tensile semitone, secretion	viewers, readers, listeners travelers, commuters
	mgm, nudity, tensile semitone, secretion katz, bess, tampa	viewers, readers, listeners travelers, commuters envoy, minister, ministers

	$\operatorname{Word2GMM}$	
	Node	Description
	Schumacher	football player
	Wilde	Argentine city
people	Jonas	football player
	Alexis	football player
	goalkeeper	position in football
	Valencia	electoral district
	Alameda	municipality
government	Monaco	country
	Arenas	municipality
	Algeria	country
	salmon	fish
	lettuce	plant
water	fish	aquatic animal
	tea	drink
	rack	gadget

**□** Qualitative assessment

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■Qualitative assessment

Error analysis

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	SPINE-S	SPINE-L
noonlo	mgm, nudity, tensile	viewers, readers, listeners
people	mgm, nudity, tensile semitone, secretion	viewers, readers, listeners travelers, commuters
		1
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**□** Qualitative assessment

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	semitone, secretion	travelers, commuters
government	katz, bess, tampa	envoy, minister, ministers
	nearing, salisbury	parliament, ambassador
water	tarot, repel, pepys	dam, dams, river
	voltaire, prematurely	rivers, tributary

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# **Experiment - Interpretability**

□ Qualitative assessment

**Error analysis** 

Activation pattern analogy

#### Anchor's contextual meaning is far from Wikidata's description.

EX

London (Q79348): city in Pope County, Arkansas, United States.

	Node	Description
England	garner	American town
	astros	American football team
	blind	type of bet in poker
	linebacker	position in American football
	rochester	American borough

# **Experiment - Interpretability**

□ Qualitative assessment

Error analysis

**Activation pattern analogy** 

#### Activation pattern

Word2GMM: nodes with values  $\geq$  0.01.

SPINE: axes with values  $\geq$  0.01.

Word2Vec: dense vector, not applicable.

#### Datasets

13 datasets are ordered by ground truth score decreasingly.

Similar words: first 10% Dissimilar words: last 10%

#### > Metric

Jaccard index I(A, B)

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

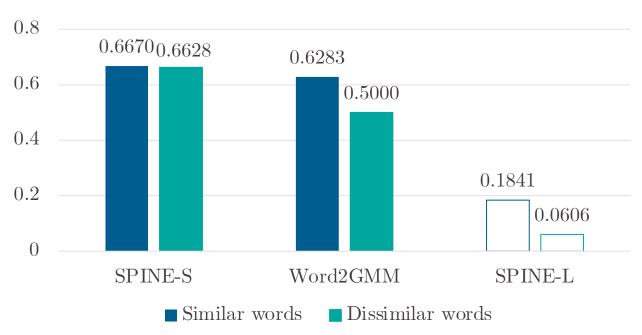
The median of J(A, B) from given set of words.

## **Experiment - Interpretability**

■ Qualitative assessment

Error analysis



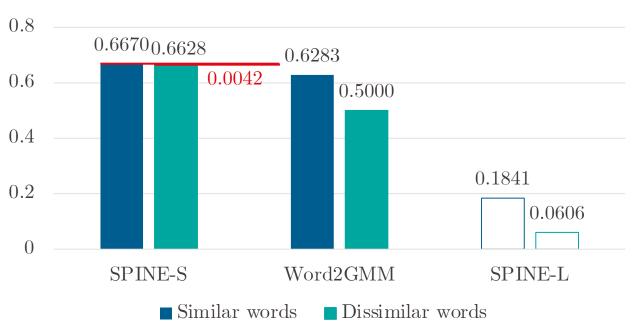


## **Experiment - Interpretability**

■ Qualitative assessment

Error analysis



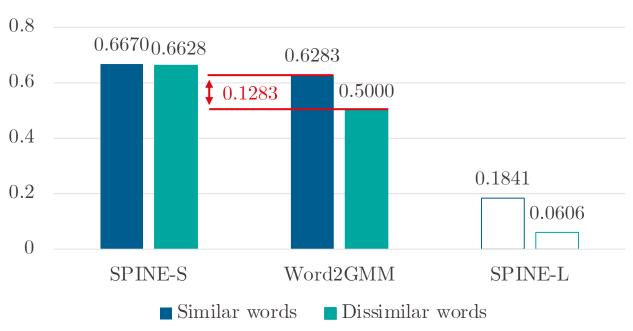


## **Experiment - Interpretability**

☐ Qualitative assessment

Error analysis



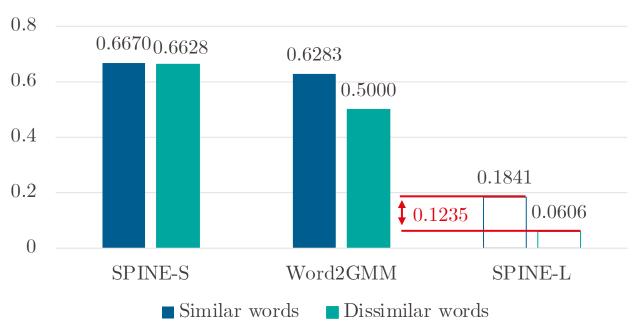


## **Experiment - Interpretability**

□ Qualitative assessment

Error analysis



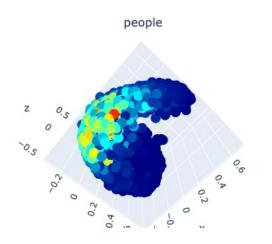


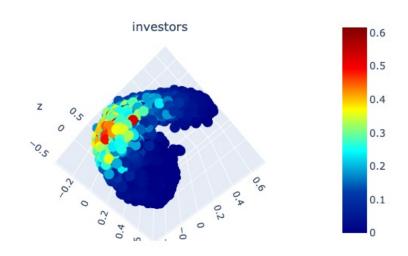
## **Experiment - Interpretability**

☐ Qualitative assessment

Error analysis







Anchor

The number of Gaussian

Covariance matrix

#### Baseline

- ■Anchor selection: sampling with density
- □ Number of anchor: 128
- □ Number of Gaussian: 25
- ☐ Initialize covariance matrix:

Truncated normal distribution with center c=1 and radius r=0

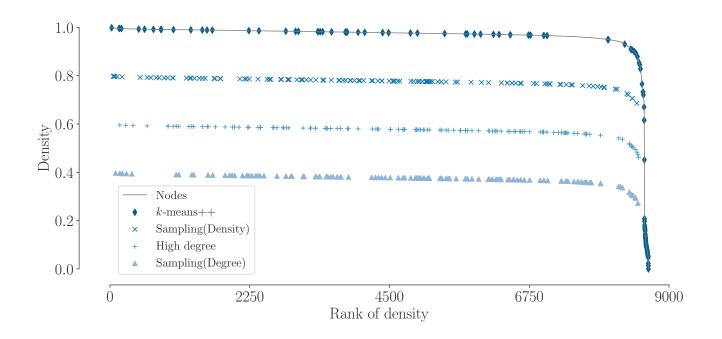
#### > Metric

Word similarity

Relative scores. Baseline = 1

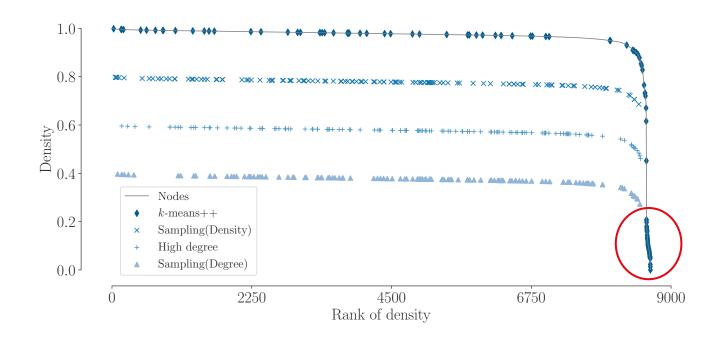
Anchor

The number of Gaussian



Anchor

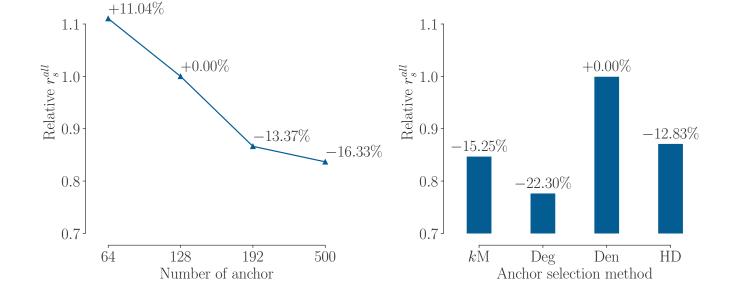
The number of Gaussian



### **Experiment – Parameter influence**

Anchor

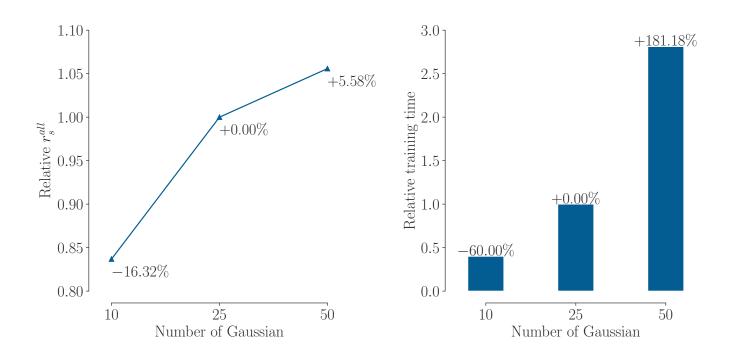
The number of Gaussian



### **Experiment – Parameter influence**

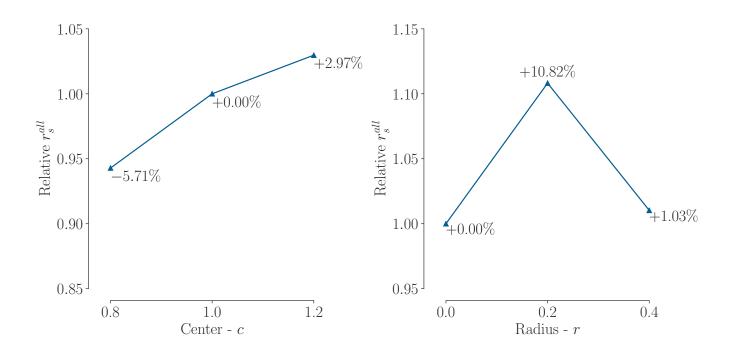
Anchor

The number of Gaussian



Anchor

The number of Gaussian



### **Experiment - Discussion**

# entao ren

#### **Pros**

- Joint learning of two goals
- High-level interpretation
- Good performance on small dataset
- Large capacity of interpretability

#### Cons

- Sensitive to the anchors
- A little less efficient than Word2Vec

#### Introduction

Method

Experiment

### **Conclusion**

#### **Conclusion - Contribution**

#### **■**Word2GMM

New interpretable text representations architecture.

A novel and efficient way to use existing knowledge.

#### ■ Evaluation

Comparison with classical methods.

Analysis of interpretability with the state-of-the-art.

Comprehension of parameter's influence.

#### **Conclusion - Future work**

#### Four aspects need improvement:

- ■Anchor selection
- ☐ Parameter fine-tuning
- ■A large training corpus
- □ Quantitative evaluation on interpretability

#### Thank you for your listening!

#### Reference

- □ Icons: <a href="https://www.iconfinder.com/">https://www.iconfinder.com/</a>
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