Master Thesis Defense

Scalable approach for Learning Word Representations

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Content

Background Knowledge Introduction

Word Vector Representation

Corpus

Representation model

(Local) Euclidean Vector Space

Background Knowledge Introduction

Skip Gram Negative Sampling Word2Vec

$\overbrace{\text{quick brown fox jumps over}}^{\text{window}}$ a lazy dog

central word *w*

context word *c*

$$p(c|w)=\frac{e^{wc}}{\sum_{c'\in V} e^{wc'}}$$

Skip Gram

Background Knowledge Introduction

Skip Gram Negative Sampling Word2Vec

$$p(c|w) = \frac{e^{wc}}{\sum_{c' \in V} e^{wc'}}$$

softmax with a hard-to-solve partition function

$$p(s|d;\theta) = \frac{p(d|s;\theta)}{p(d|s;\theta) + p(d|n;\theta)}$$

Noise-Contrastive Estimation
s for signal
d for input data
n for noise

$$p((w,c)|d;\theta) = \frac{p(d|(w,c);\theta)}{p(c|(w,c);\theta) + p(c|(w,\bar{c});\theta)}$$

Negative Sampling
$\bar{c}$ for negative samples

Background Knowledge Introduction

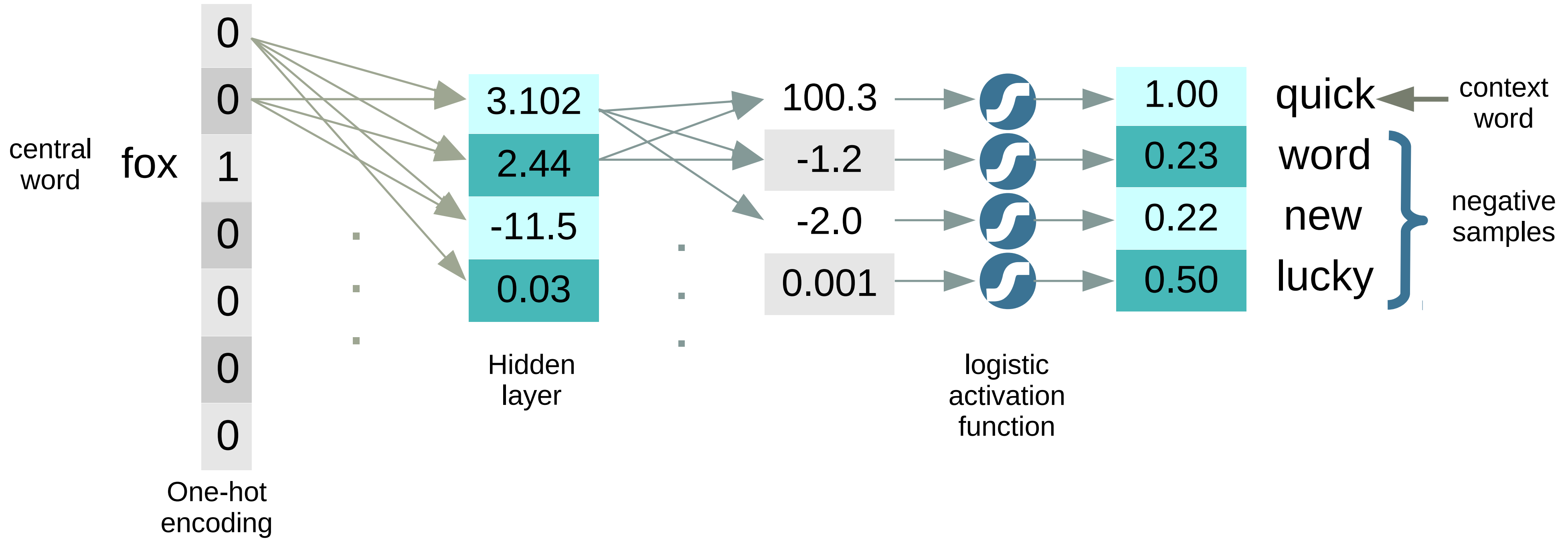
Skip Gram Negative Sampling Word2Vec

Objective function:

$$J(\theta) = \sum_{w \in D} \sum_{c \in l(w)} \left\{ \ln\left[p\left((w, c) \mid \theta \right) \right] + E_{\bar{c} \in V} \ln\left[1 - p\left((w, \bar{c}); \theta \right) \right] \right\}$$

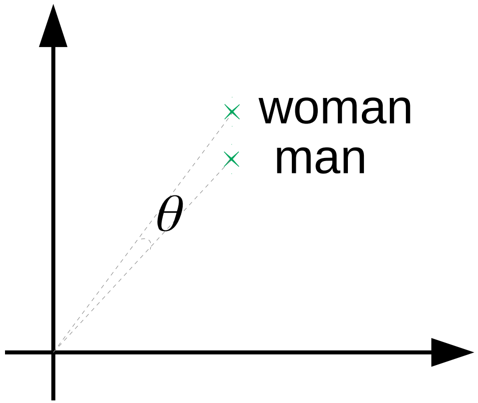
Background Knowledge Introduction

Skip Gram Negative Sampling Word2Vec

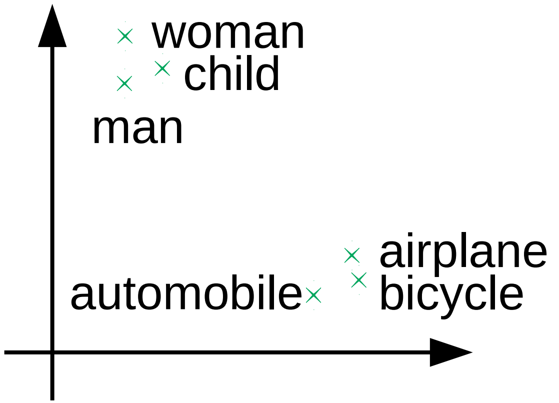


Background Knowledge Introduction

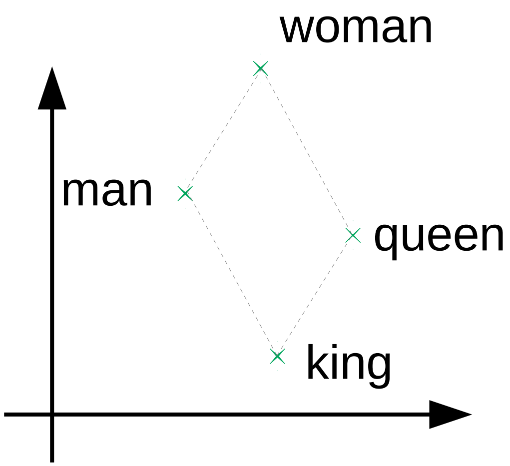
Properties of Word2Vec [1]



$\cos(\theta)$ ~ similarity



categories ⇒ clusters



analogy ⇒ parallelization

[1]: Mikolov T, Yih W, Zweig G.
Linguistic regularities in continuous space word representations
Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2013: 746-751.

Background Knowledge Introduction

Challenge:

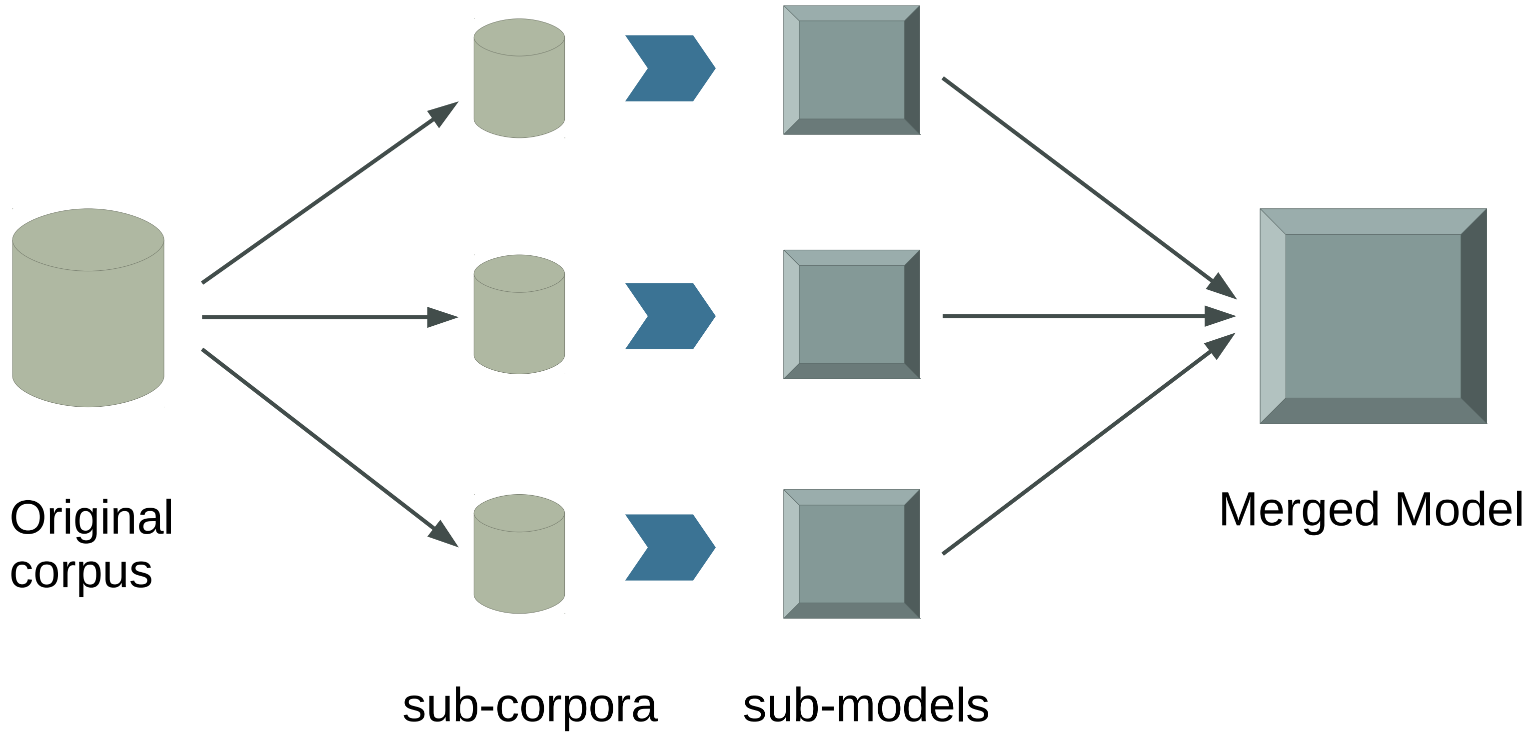
larger corpus: more **expressive**, longer **time**

On 14GB English Wikidump: ≈ **36 hours** !

(dim: 500 Vocabulary: 300k)

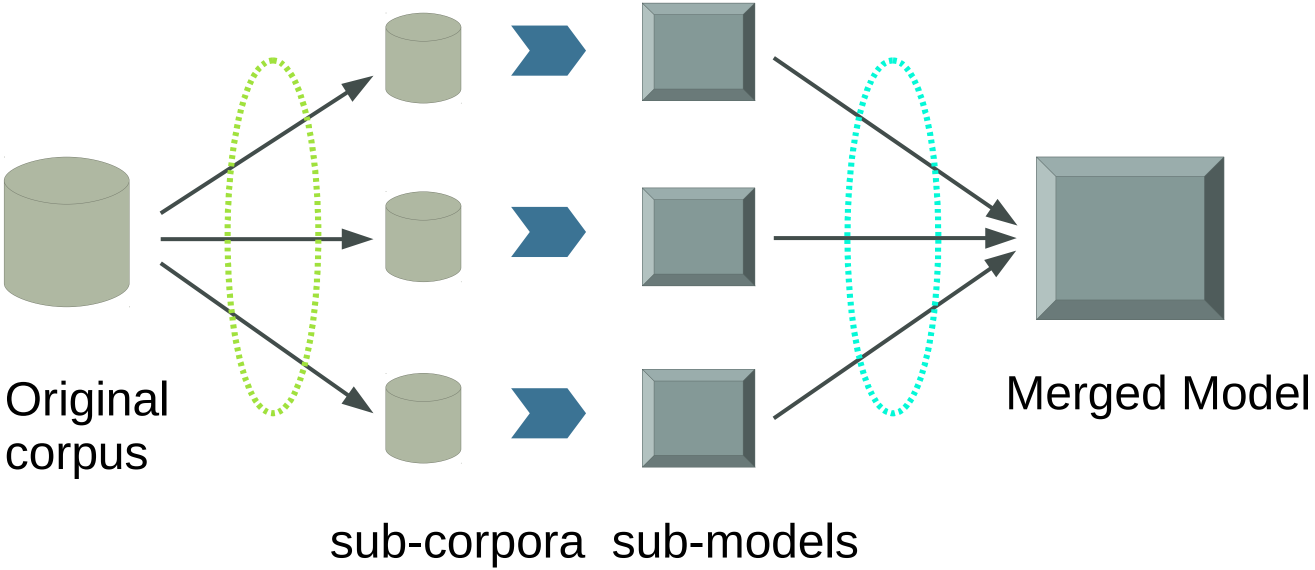
Not **scalable** for large corpus

Structure of our Approach



Structure of our Approach

Research Questions:



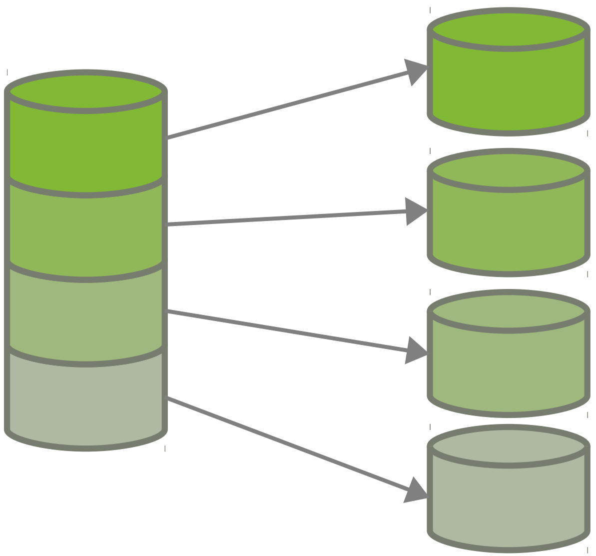
1) How do we sample from the original corpus?

2) How do we combine sub-models?

Original Corpus Division

Trivial approaches: Block-wise partitioning and Stripping

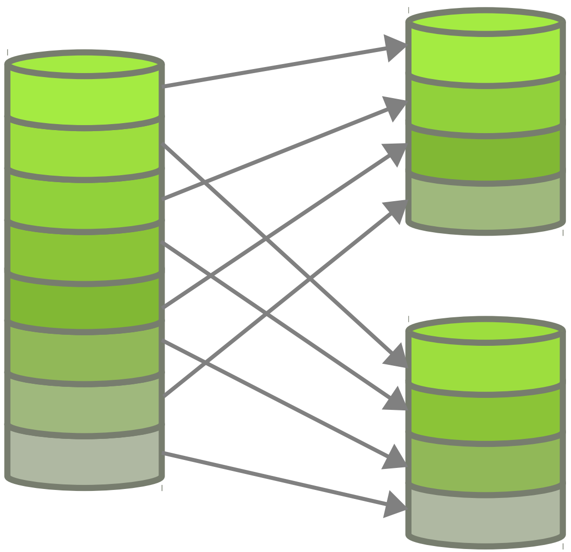
Partitioning:



original
corpus

equisized blocks
in e.g. HDFS

Stripping:



original
corpus

interleaving
stripping

Original Corpus Division

Criterion of Division: “Mimicking” the Original Term Distribution

objective function:

$$J(\theta)=\sum_{w\in D}\sum_{c\in l(w)}\{\ln[p((w,c)|\theta)]+E_{\bar{c}\in V}\ln[1-p((w,\bar{c});\theta)]\}$$

local optimum:

$$\frac{\partial J(\theta)}{\partial \theta}=0$$

final result [1]:

$$\boldsymbol{w}\,\boldsymbol{c}=\log\frac{N\#(w,c)}{\#(w)\#(c)}-\log k$$

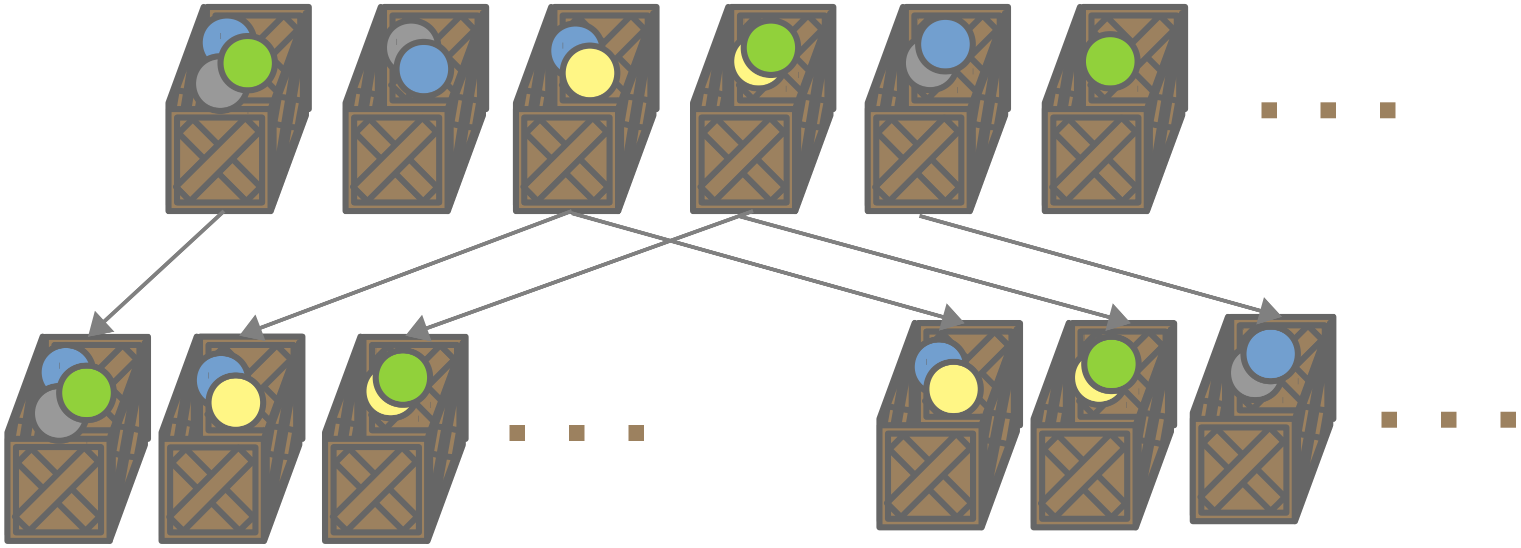
[1]: Levy O, Goldberg Y.
Neural word embedding as implicit matrix factorization
Advances in neural information processing systems. 2014: 2177-2185.

Original Corpus Division

Final Approach: Reservoir Sampling

original dataset
with S “boxes”

Total count of “balls”
≫
Count of “balls” in
each “box”

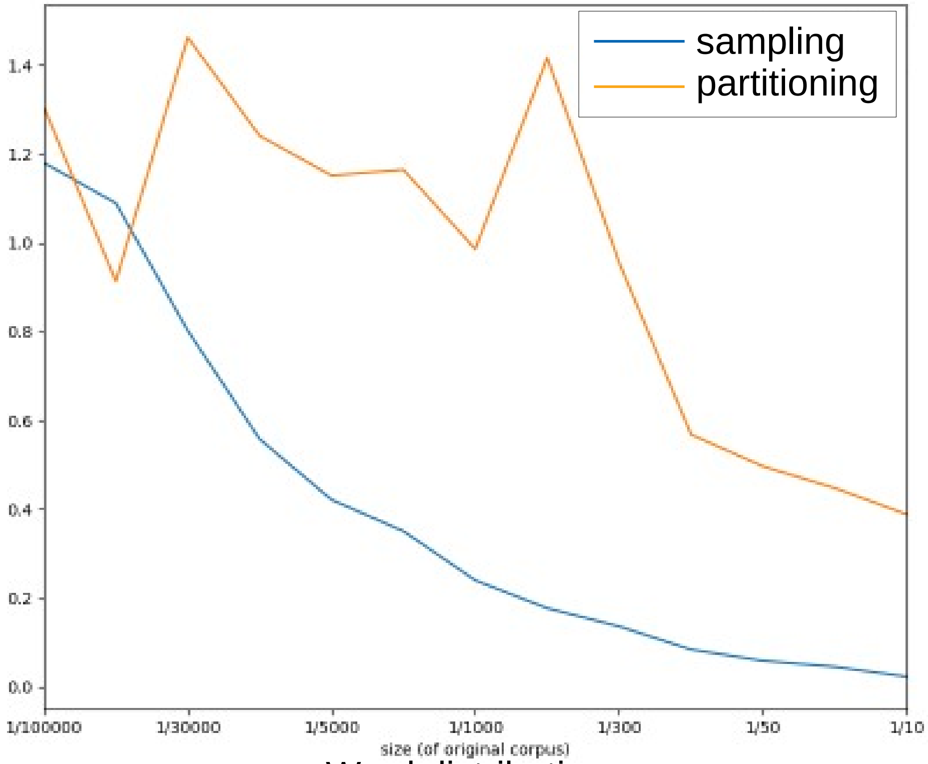


1st “reservoir” with
k “boxes”

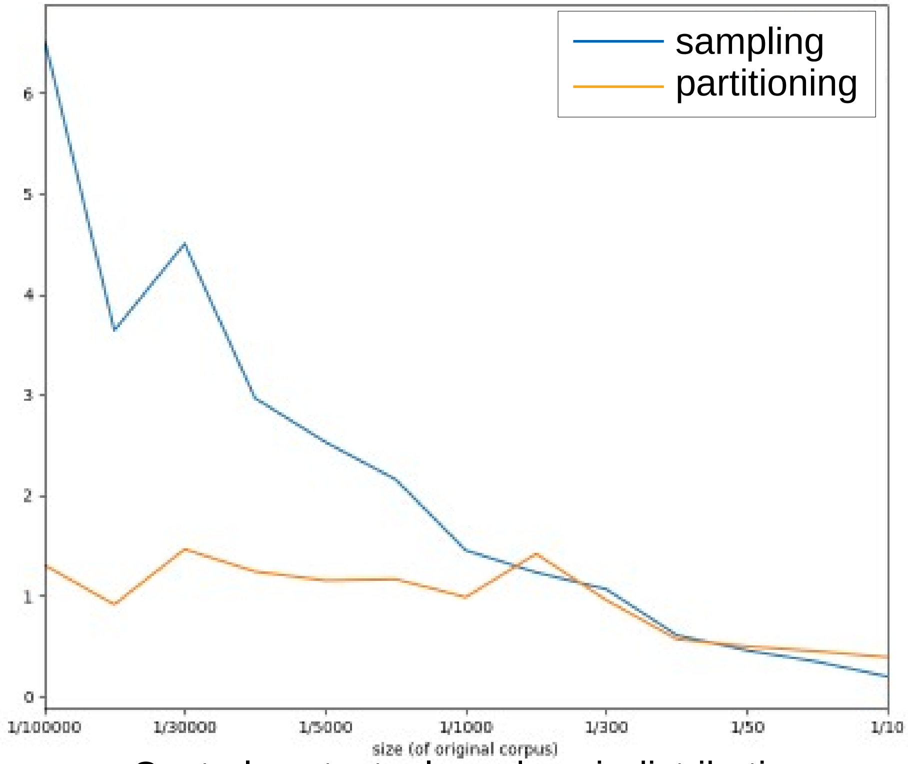
2nd “reservoir” with
k “boxes”

Original Corpus Division

Distribution preservation



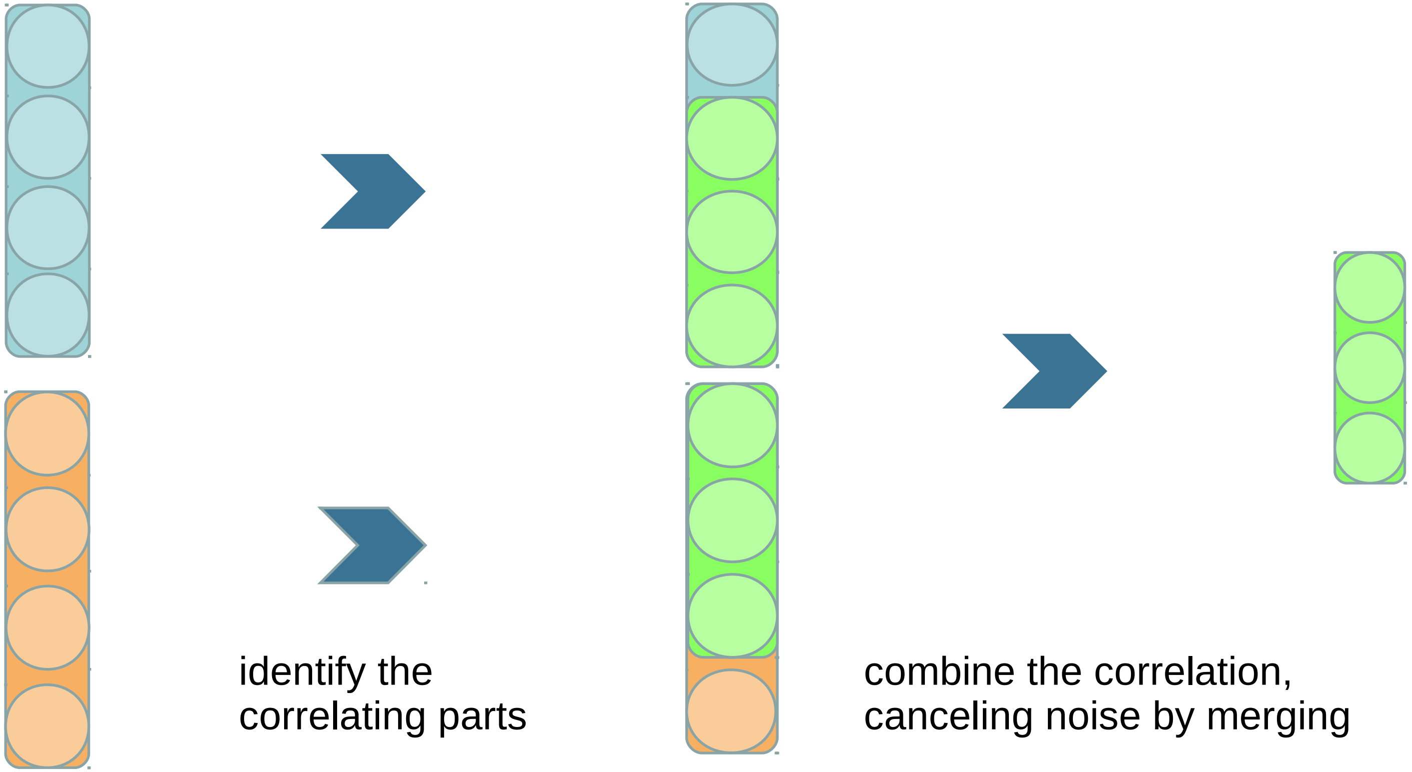
Word distribution



Central contextual words pair distribution

Merging Approaches

Problem so-far:

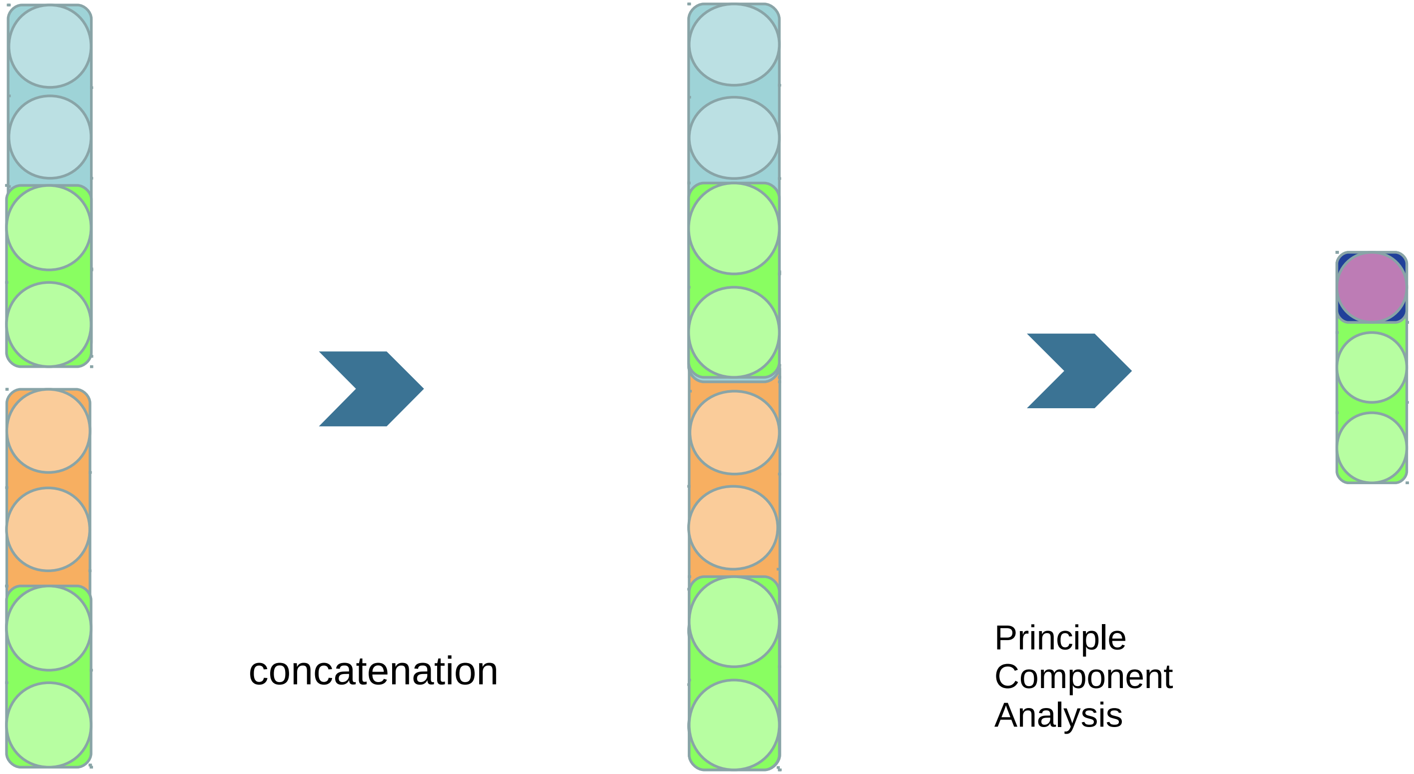


identify the
correlating parts

combine the correlation,
canceling noise by merging

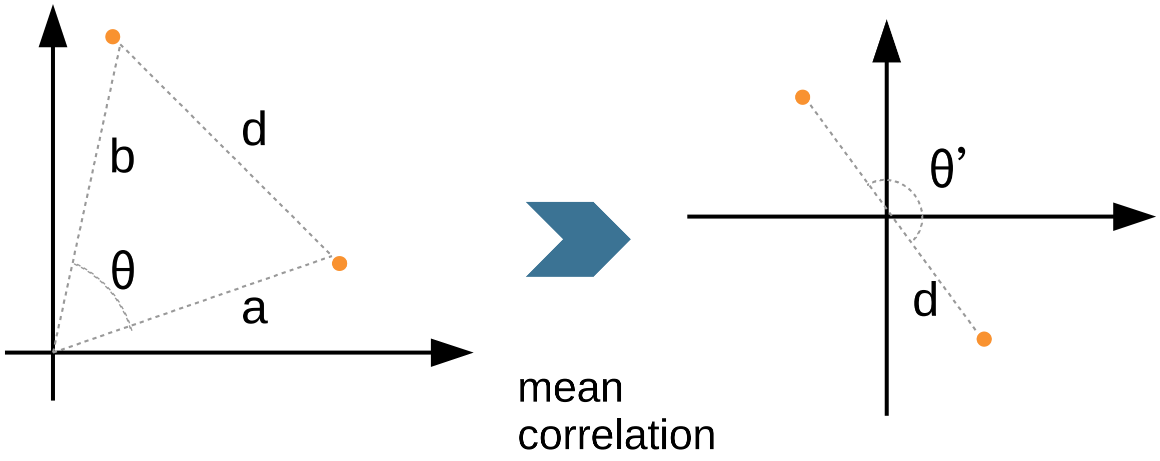
Merging Approaches

1st Approach: Concatenation + Principle Component Analysis



Merging Approaches

Some Comments on PCA [1]



Law of cosines:

$$\|d\|^2 = \|a\|^2 + \|b\|^2 - 2\|a\|\|b\|\cos\theta$$

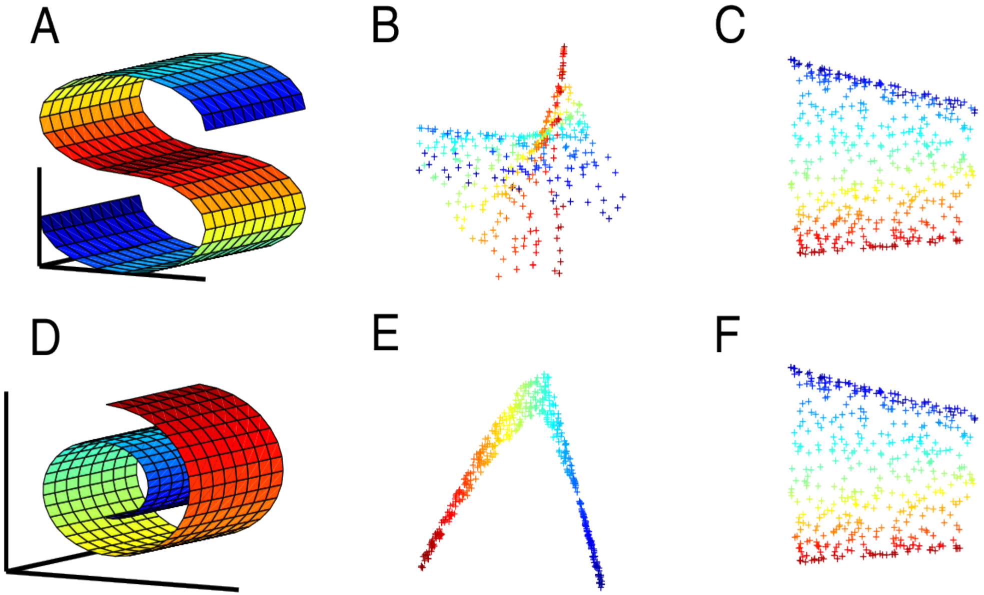
$$\|a\|^2 = \|b\|^2 = 1$$

$$\cos\theta = \frac{2 - \|d\|^2}{2}$$

[1]: Korenius T, Laurikkala J, Juhola M.
On principal component analysis, cosine and Euclidean measures in information retrieval
Information Sciences, 2007, 177(22): 4893-4905.

Merging Approaches

2nd Approach: Manifold Alignment + Vector Averaging

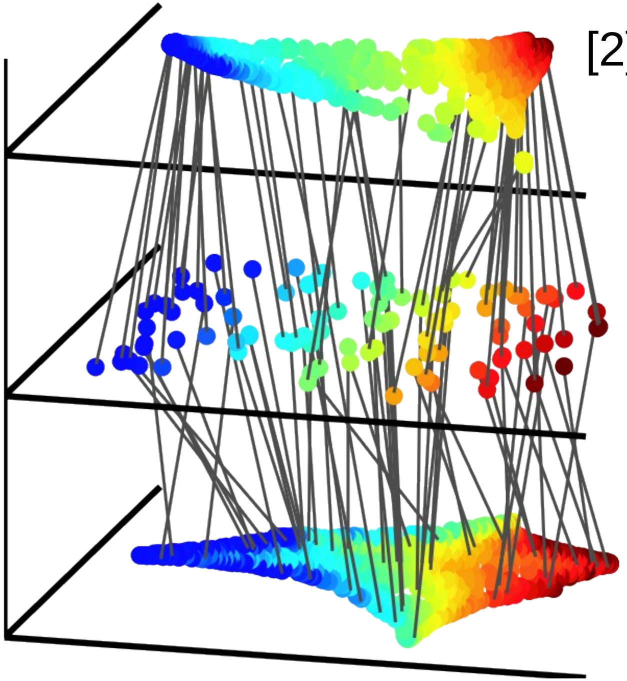


[1]

[1]: Ham, Ji Hun, Daniel D. Lee, and Lawrence K. Saul.
Learning high dimensional correspondences from low dimensional manifolds

Merging Approaches

2nd Approach: Manifold Alignment [1] + Vector Averaging



$$R^{(Y)} = argmin_R \frac{1}{2} \| X - XR \|_F^2 + \lambda \| R \|_*$$

$$F^{(X)}, F^{(Y)} = argmin_{F^X, F^Y} (1-\mu) \sum_{T=\{X,Y\}} \| F^T - R F^T \|_F^2 + \mu \sum_{i=1}^{N} \| F_i^{(X)} - F_i^{(Y)} \|^2$$

$$R^{(Y)} = argmin_R \frac{1}{2} \| Y - YR \|_F^2 + \lambda \| R \|_*$$

[1]: Boucher, Thomas, et al. Aligning Mixed Manifolds AAAI. 2015.

[2]: Ham J, Lee D D, Saul L K. Semisupervised alignment of manifolds AISTATS. 2005: 120-127.

Experiments Setup

Data Set:

- *Original corpus*: English Wikipedia dump file 2016 (14G)
- *Cleaner*: Wikipedia LineSentences cleaner in Gensim
- *Sample/Partition size*: 1%, 10% of the original corpus

Baseline Model:

- *Vocabulary*: 300k words
- *Dimension (size of hidden layer)*: 500
- *Training time*: 36 hours

Benchmarks:

- *Word Similarity*: MEN, RW, RG65, WS353, SimLex999, Mturk
- *Analogy*: Google, SemEval 2012 #2, MSR
- *Categorization*: AP, BLESS, Battig

Performance and Timing

Effect of Dividing (sampling/partitioning):

Approach	AP	Battig	MEN	RG65	RW	WS353	Google	SemEval2012_2
`Partition(1/10,10)`	0.582	0.420	0.719	0.725	**0.232**	0.596	0.615	0.162
`Random(1/10,10)`	**0.604**	**0.435**	**0.740**	**0.757**	0.209	**0.637**	0.654	**0.188**
`Partition(1/100,100)`	0.505	0.358	0.622	0.723	0.203	0.516	0.467	0.129
`Random(1/100,100)`	0.517	0.381	0.644	0.746	0.257	0.542	0.487	0.138
`Baseline`	0.595	0.434	0.736	0.757	**0.299**	0.611	**0.661**	0.181

Table 2: Comparison between `Random(.,.)` and `Partition` sampling approaches at different granularities. PCA is used as the merging method.

Conclusions:

Sampling performs overall better than partitioning

Larger division size makes the performance better, but less scalability

Surprisingly, some of our approaches even outperform the **baseline**!

Performance and Timing

Effect of Merging (concatenation/PCA/LRA):

Approach	AP	Battig	MEN	RG65	RW	WS353	Google	SemEval2012_2
Random(1/10,10) + Concat	0.595	0.429	**0.742**	0.765	0.268	0.611	0.645	0.187
Random(1/10,10) + LRA	0.560	0.327	0.685	**0.785**	0.264	0.606	**0.661**	0.158
Random(1/10,10) + PCA	**0.604**	**0.435**	0.740	0.757	0.209	**0.637**	0.654	**0.188**
Random(1/100,100) + Concat	**0.525**	0.377	0.643	**0.746**	**0.257**	**0.542**	**0.487**	**0.138**
Random(1/100,100) + LRA	–	–	–	–	–	–	–	–
Random(1/100,100) + PCA	0.517	**0.381**	**0.644**	**0.746**	**0.257**	**0.542**	**0.487**	**0.138**
Baseline	0.595	0.434	0.736	0.757	0.299	0.611	0.661	0.181

Table 3: Evaluation results for merging

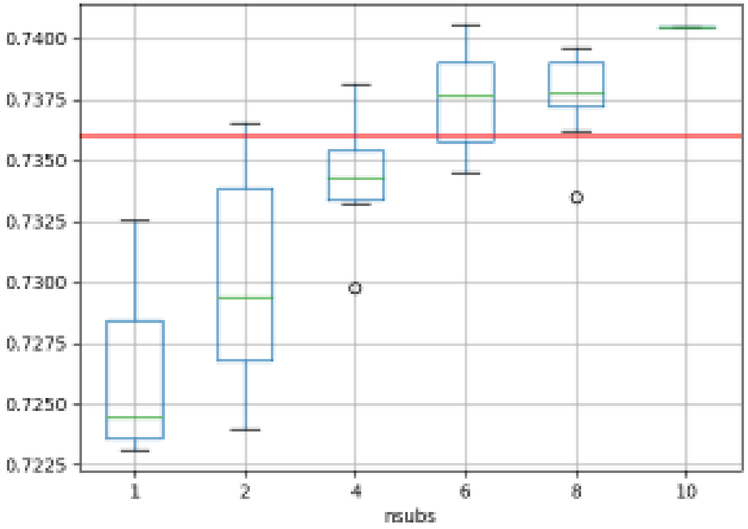
Conclusions:

- PCA performs overall the best
- LRA and Vector average is the slowest
- To see the information loss in the PCA, we added the concatenation as a single line, it performs surprisingly robust, despite its higher dimensionality

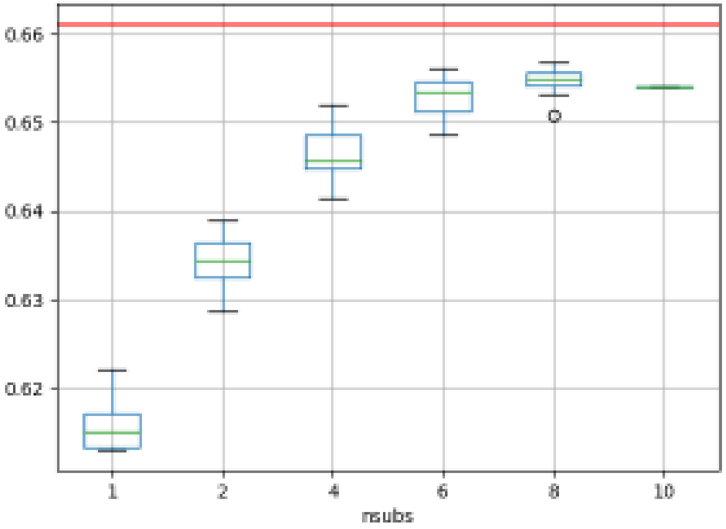
Performance and Timing

Effect of sample count (10% of original corpus):

MEN



Google

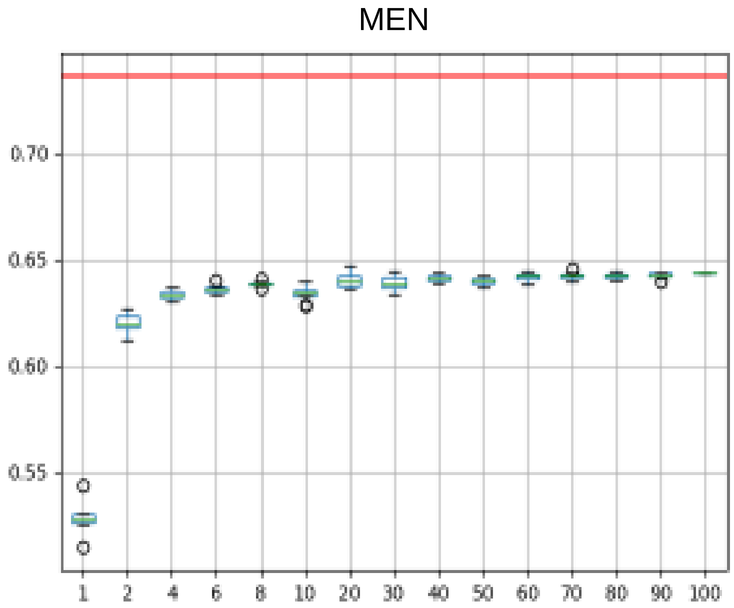


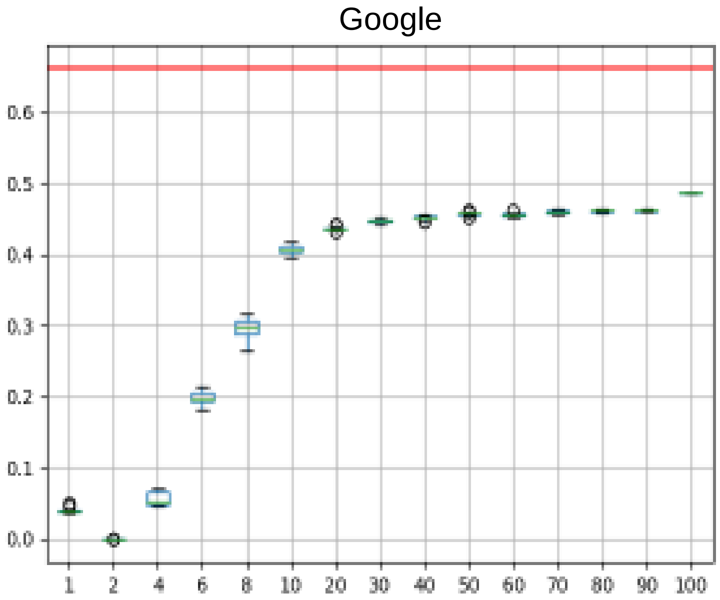
Conclusion:

Larger count of sub-models doesn't help.
8~10 for 10% approach, 20~30 for 1% approach is enough.
After that it goes into flat road.

Performance and Timing

Effect of sample count (1% of original corpus):





Conclusion:

Larger count of sub-models doesn't help.
8~10 for 10% approach, 20~30 for 1% approach is enough.
After that it goes into flat road.

Performance and Timing

Timing:

Subject name	Time Elapse (s)
10% partitioning PCA	10932
1% partitioning PCA	2093
10% sampling PCA	12852
1% sampling PCA	16293
10% sampling LRA	27385
Baseline	129015

Conclusions:

m-part division leads to m-folds speed up

Total training time: from 36h of baseline to 3.6 hours @ 10% and < 1 hour @ 1% approach

Time of merging is in minutes

Conclusion and Future Works

Conclusions:

– Sentence-wise sampling to divide, PCA to merge

– M-fold speed up by M-splitting, sometimes even outperform the baseline.

Future works:

– Works on the go: dealing with missing-word problem between sub-models

Thank you for your attention

Questions and comments are highly appreciated

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Hannover
08. 03. 2018