On the Downstream Performance of Compressed Word Embeddings

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Word Embeddings

Pretraining

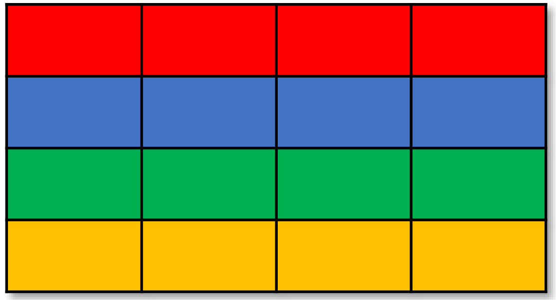
Downstream models

Apple

Pear

Cat

Dog



Word embeddings

2

Word embedding is a memory-intensive feature representation

1. Freepik 2. slideshare

Word Embedding Compression

Critical for deployment **under memory constraints**

- Deep compositional code learning (DCCL)[1]
- Kmeans[2]
- Uniform quantization[3]
- Dimension reduction (e.g. PCA)[4]

1. Shu et al. 2017
2. Andrews et al. 2015
3. Gersho et al. 1977
4. Pearson et al. 1901

What determines the ***model accuracy*** attained by different ***compressed word embeddings?***

&

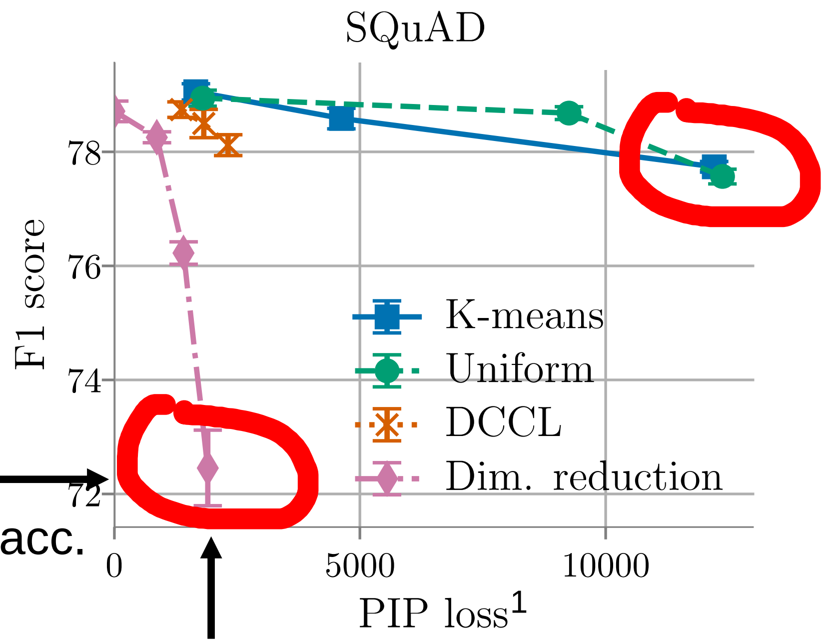
Can the insights guide the selection of ***compressed word embeddings*** under ***memory constraints?***

Existing quality measures

Can’t explain the relative model accuracy **across compression methods**

Higher model acc.

Low model acc.



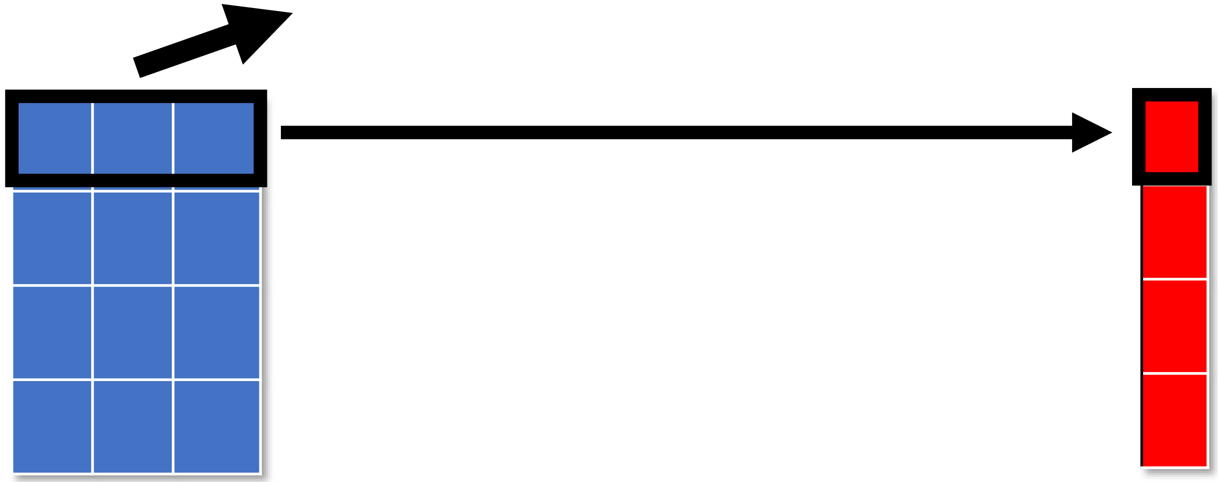
High quality

Lower quality

1. Yin et al. 2018

Setting to derive a new quality measure

Word vector as feature



Compressed word embedding
$X \in \mathbb{R}^{n \times d}$

Regression label
$y \in \mathbb{R}^{n}$

Model accuracy

Test mean square error (MSE) rel. to uncompressed embedding

In the setting of *linear regression*

Fixed design linear regression (simple and classic setup):[1,2,3]
Same set of data points for train and test; noisy training label; noiseless test label

Test time prediction $= UU^T y$

Compressed word embedding $X \in \mathbb{R}^{n \times d}$

SVD $X = U \Lambda V^T$

Training label $y \in \mathbb{R}^n$

Observation

Prediction highly depends on ***U, the left singular vectors***

1. Avron et al. 2018 2. Bach et al. 2013 3. Cortes et al. 2010

A new quality measure of compression word embedding

Eigenspace overlap (EO)

$$\mathcal{E}(X, \tilde{X}) := \frac{1}{\max(d,k)} \|U^T \tilde{U}\|_F^2$$

Compressed $X \in \mathbb{R}^{n \times d}$ uncompressed $\tilde{X} \in \mathbb{R}^{n \times k}$

SVD $X = U \Lambda V^T, \tilde{X} = \tilde{U} \tilde{\Lambda} \tilde{V}^T$

Intuition

More ***similar left singular vectors***,
better model acc. relative to uncompressed embeddings

In the setting of *linear regression*

Test MSE rel. to uncompressed embedding

$$\mathbb{E}_{\bar{y}}\left[\underbrace{\mathcal{R}_{\bar{y}}(\tilde{X}) - \mathcal{R}_{\bar{y}}(X)}\right] = \mathcal{O}\Big(1 - \mathcal{E}(X, \tilde{X})\Big)$$

Target label vector sampled from $\mathrm{Span}(U)$

Uncompressed embedding X

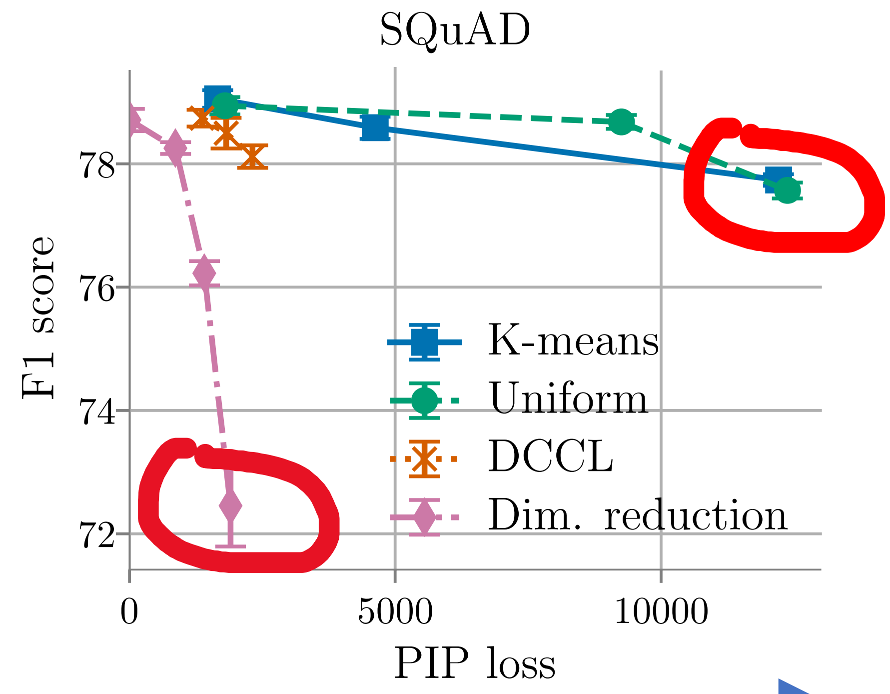
Compressed embedding $\tilde{X}$

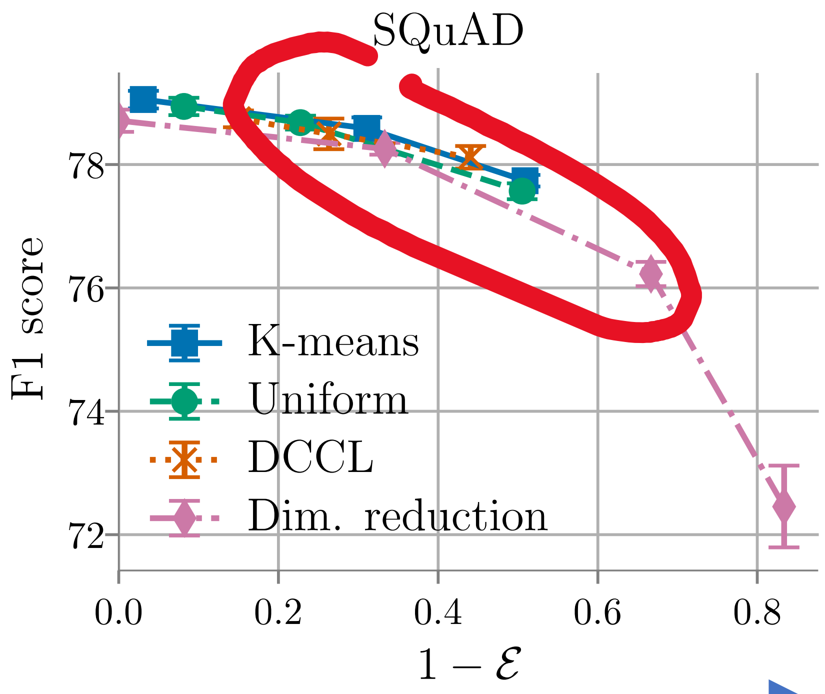
Theory connection (sketch)

Model acc. can be bounded in terms of ***eigenspace overlap***

Empirical correlation beyond *the regression setting*

Higher model acc.





Lower quality

Lower quality

Empirical correlation

EO attains ***better correlation*** with downstream ***model acc.***

What determines the ***model accuracy*** attained by different ***compressed word embeddings?***

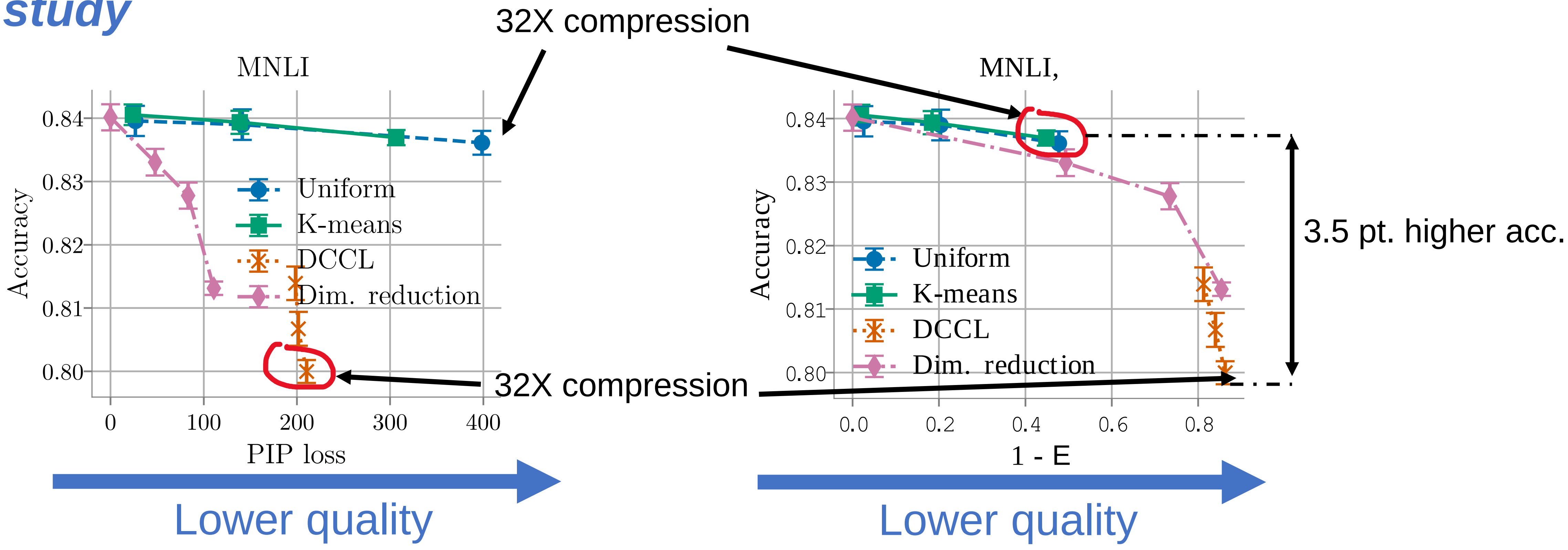
&

Can the insights guide the selection of ***compressed word embeddings*** under ***memory constraints?***

Eigenspace overlap as a selection criterion

Selecting the right embedding → **better model acc.** under **memory budgets**

Case study

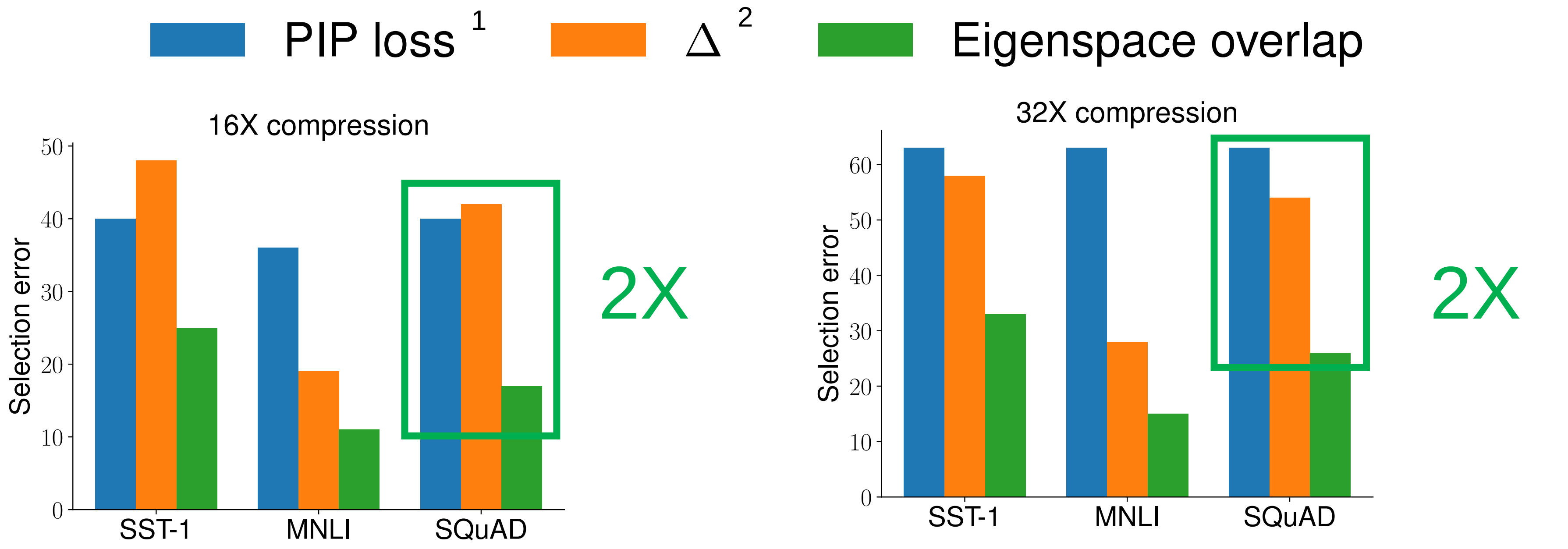


Eigenspace overlap vs. PIP loss → ***higher acc.*** at ***32X compression***

Eigenspace overlap as a selection criterion

Selection error

Fraction of cases when ***failing to select*** the embedding with ***better model acc.***



Utility under memory budgets

Up to **2X lower selection error** at up to 32X compression

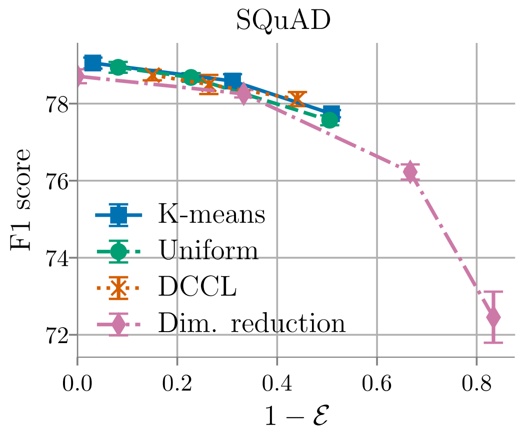
1. Yin et al. 2018 2. Avron et al. 2018

Summary

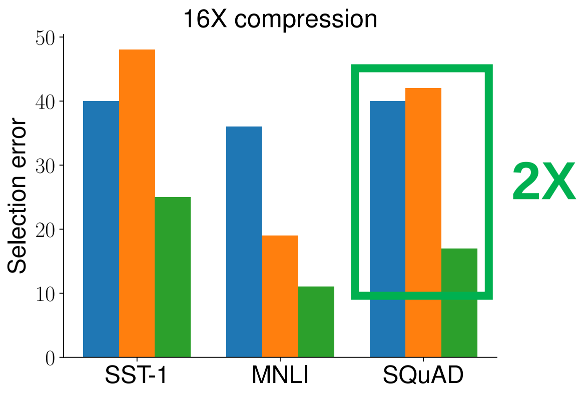
Theoretical connection ***in a regression setting***

$$\mathbb{E}_{\bar{y}}\left[\mathcal{R}_{\bar{y}}(\tilde{X}) - \mathcal{R}_{\bar{y}}(X)\right] = \mathcal{O}\Big(1 - \mathcal{E}(X, \tilde{X})\Big)$$

Empirical correlations in ***a wide range of models / tasks***



Guide the ***selection*** of compressed word embeddings



Left singular vector is important, EO captures it

Utility under memory constraints

THANK YOU!

Spotlight: Thursday, Dec 12, 4:05 pm
Poster: Thursday, Dec 12, 5-7 pm