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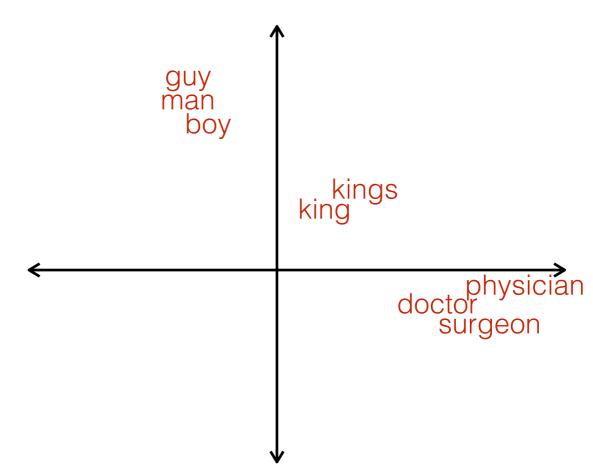
University of Utah School of Computing

NOVEMBER 10<sup>TH</sup> ICDM 2019

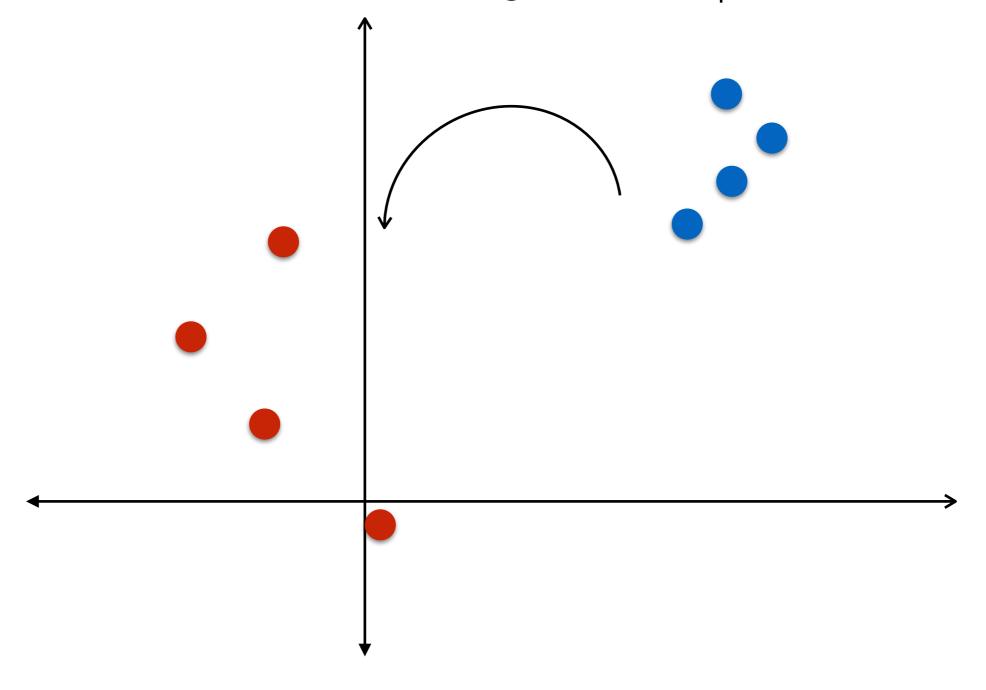


#### Word2Vec, GloVe, FastText

- distributed representations of word vectors
- low dimensional (about ~300 dimensions)
- contain useful semantic and syntactic information and useful linear relationships

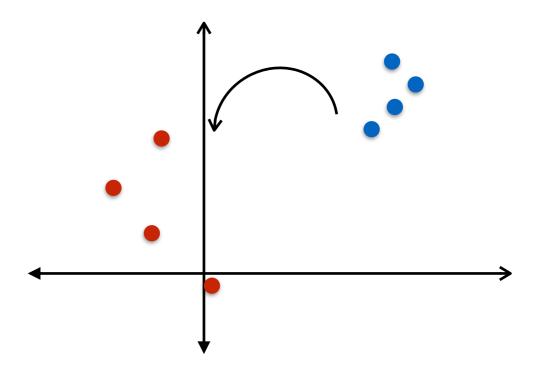


Given two point sets A and B with correspondence between the points a<sub>i</sub> and b<sub>i</sub> known, can we align them in space?



### Why Align Embeddings?

- In word embeddings:
  - Align phrases, extend pools of synonyms
  - Machine Translation
  - Boosting performance
- In Graph and RDF embeddings to align new nodes



Given two point sets A and B with correspondence between respective points a<sub>i</sub> and b<sub>i</sub> known,

$$(R^*, t^*, s^*) = \underset{s \in \mathbb{R}, t \in \mathbb{R}^d, R \in \mathbb{SO}(d)}{\operatorname{argmin}} \sum_{i=1}^n \|a_i - s(b_i - t)R\|^2$$

Hanson and Norris; Analysis of measurements based on the singular value decomposition. SIAM Journal of Scientific and Statistical Computing, 1981

Smith etal; Offline bilingual word vectors, orthogonal transformations and the inverted softmax, ICLR 2017.

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$$R^* = \underset{R \in \mathbb{SO}(d)}{\operatorname{argmin}} \sum_{i=1}^n \|a_i - (b_i R)\|^2.$$
 — rotation

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$$R^* = \operatorname*{argmin}_{R \in \mathbb{SO}(d)} \left( \sum_{i=1}^n \|a_i\|^2 - \sum_{i=1}^n 2\langle a_i, b_i R \rangle + \sum_{i=1}^n \|b_i R\|^2 \right).$$

$$R^* = \underset{R \in \mathbb{SO}(d)}{\operatorname{argmax}} \sum_{i=1}^{n} \langle a_i, b_i R \rangle.$$

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$$\begin{split} H &= \sum_{i=1}^n b_i^T a_i \\ [U, S, V^T] &= \operatorname{svd}(H) \\ R &= UV^T \end{split}$$

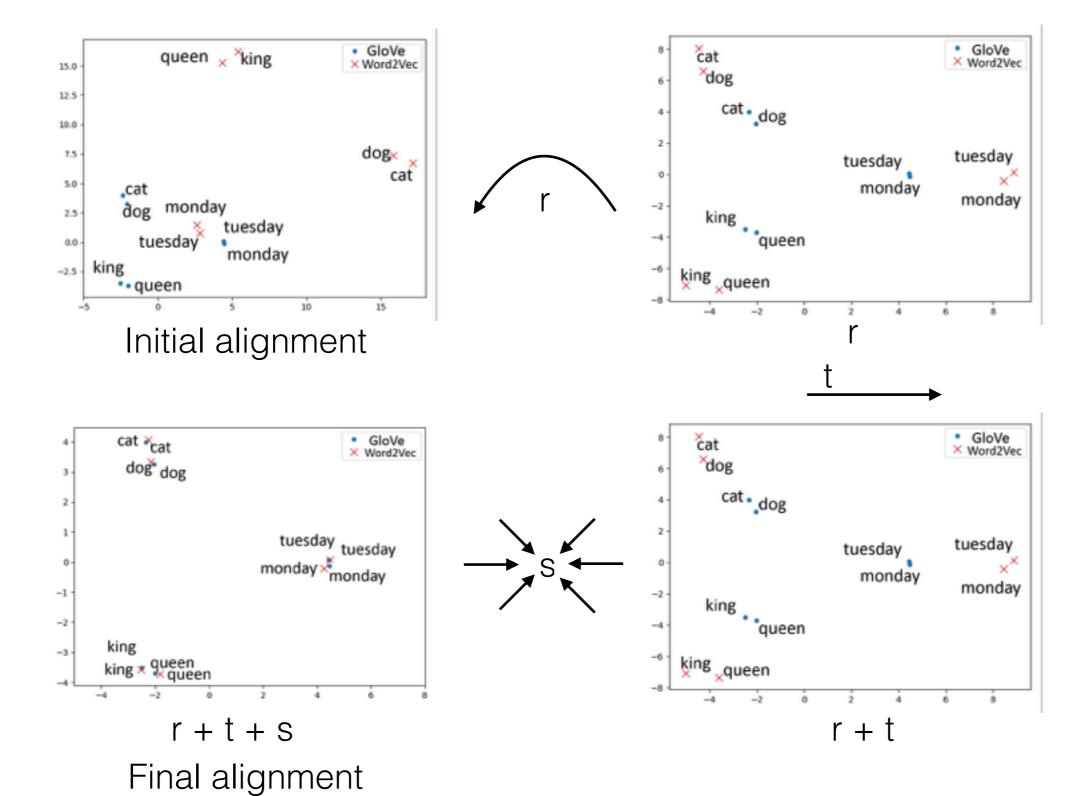
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 — translation

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 — translation

$$s^* = \frac{\sum_{i=1}^n \langle a_i, b_i \rangle}{\sum_{i=1}^n \|b_i\|^2} = \frac{\sum_{i=1}^n \langle a_i, b_i \rangle}{\|B\|_F^2} - \text{scaling}$$



#### Related Techniques

For points  $a_i$  and  $b_i$  in embeddings A and B respectively, and parameter  $\gamma$ ,

$$\underset{M \in \mathbb{R}^{d \times d}}{\operatorname{argmin}} \sum_{i=1}^{n} \|a_i - b_i M\|^2 + \gamma \|M\|_F^2.$$

Bollegela et al ; Learning linear transformations between counting-based and prediction-based word embeddings; PloS ONE, 12(9):3370–3374, 2017

#### Related Techniques

For embeddings A and B respectively, their correspondence matrix C and appropriately chosen λ,

$$M_{A} = \underset{M \in \mathbb{R}^{n \times n}}{\operatorname{argmin}} \frac{1}{2} ||A - AM||_{F}^{2} + \lambda ||M||.$$

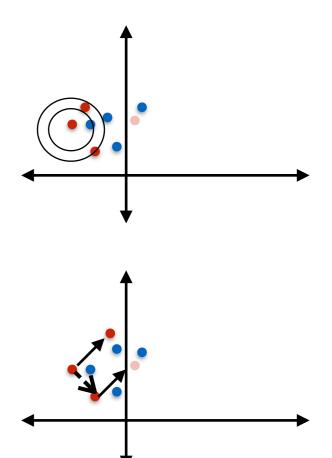
$$M_{B} = \underset{M \in \mathbb{R}^{n \times n}}{\operatorname{argmin}} \frac{1}{2} ||B - BM||_{F}^{2} + \lambda ||M||.$$

$$M = \begin{bmatrix} M_{A} & 0 \\ 0 & M_{B} \end{bmatrix}$$

Sahin et al ; Consistent Alignment of Word Embedding Models. ArXiv e-prints, February 2017

# Related Techniques

Test Sets	LRA	Affine Transformation	Absolute Orientation (10 K words)	Absolute Orientation (100 K words)
RG	0.701	0.301	0.728	0.818
WSIM	0.616	0.269	0.612	0.618
SYN	0.719	0.412	0.722	0.766
SEM	0.327	0.126	0.340	0.343

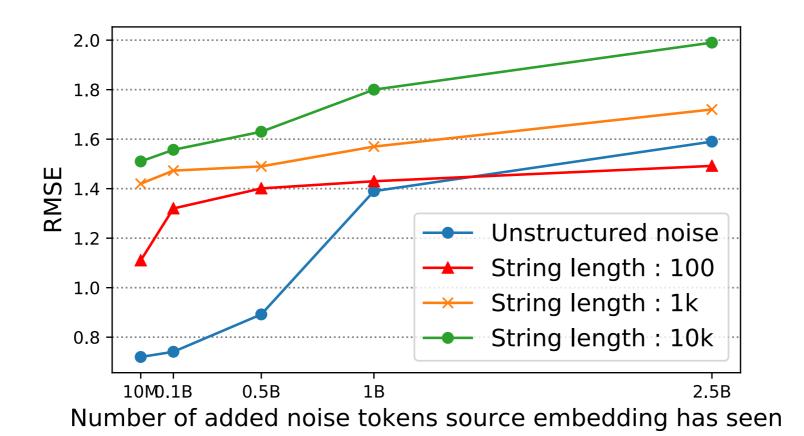


- Resilience of word embeddings
- Relative spatial distribution of words the same across embeddings
- Frequency implies stability

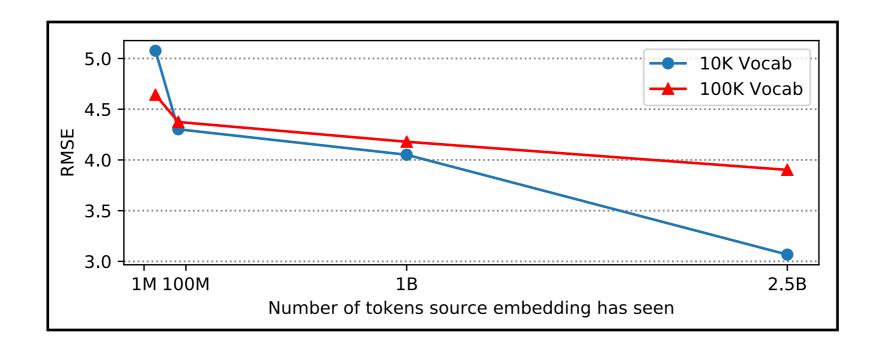
- Resilience of word embeddings
- Relative spatial distribution of words the same across embeddings
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Wendlandt etal; "Factors Influencing the Surprising Instability of Word Embeddings." In Proceedings of NAACL: Human Language Technologies, 2018

### Resilience of Word Embeddings



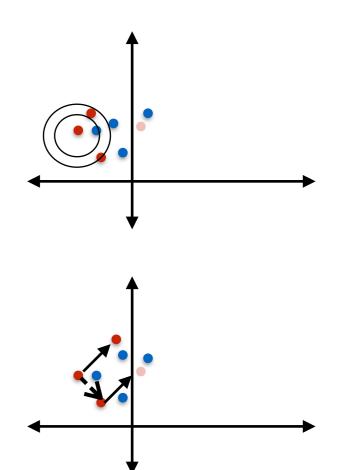
### Resilience of Word Embeddings



- Resilience of word embeddings
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#### Relative Spatial Distribution of Word Vectors

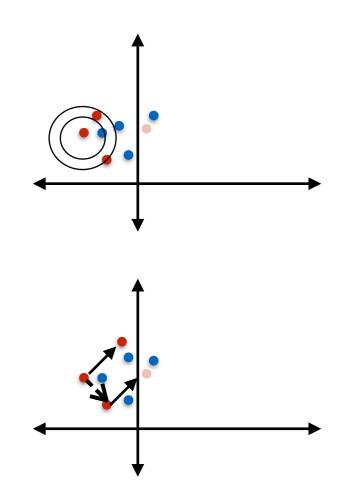
Test Sets	GloVe(Wiki)	word2vec(Wiki)	Original	+r +t + s
RG	0.614	0.696	0.041	0.584
WSIM	0.623	0.659	0.064	0.625
SYN	0.587	0.582	0.0	0.501
SEM	0.691	0.722	0.0	0.624



(higher scores = better performance)

#### Relative Spatial Distribution of Word Vectors

Test Sets	GloVe(Wiki)	GloVe(CC)	Original	+r
RG	0.614	0.696	0.363	0.616
WSIM	0.623	0.659	0.017	0.618
SYN	0.587	0.582	0.0	0.566
SEM	0.691	0.722	0.0	0.676



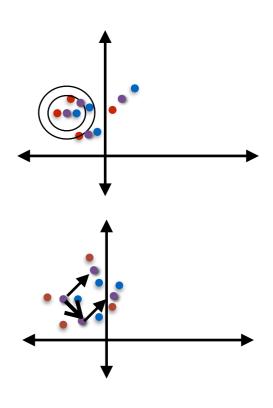
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- Boosting via ensembles
- Translation between languages
- Adding new word vectors inexpensively

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Test Sets	G(Wiki)	W(Wiki)	G(Wiki) + W(Wiki)
RG	0.614	0.696	0.715
WSIM	0.623	0.659	0.697
SYN	0.587	0.582	0.594
SEM	0.691	0.722	0.757



- Boosting via ensembles
- Translation between languages
- Adding new word vectors inexpensively

Word	Neighbors before alignment	Neighbors after alignment
woman	her, young, man, girl, mother	her, girl, <b>mujer</b> , mother, man
week	month, day, year, monday, time	days, <b>semana</b> , year, day, month

- Boosting via ensembles
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	Top 10 accuracy (before)	Top 10 accuracy (after)
EN - ES	0.054	0.848
EN - FR	0.0	0.701

- Boosting via ensembles
- Translation between languages
- Adding new word vectors inexpensively

# Thank You

sunipad@cs.utah.edu github.com/sunipa/Abs-Orientation arxiv.org/abs/1806.01330