

Searching for the X-Factor: Exploring Corpus Subjectivity for Word Embeddings

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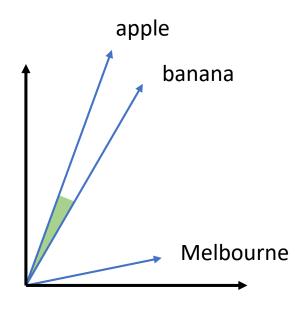
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Word Embeddings

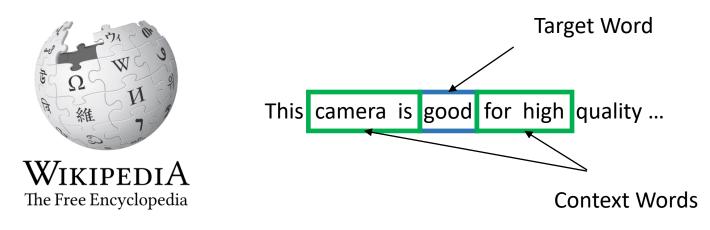
- Dense vectors of words
- Unsupervised training: GloVe, Word2Vec
- Words in similar context tend to have similar meaning

$$good \rightarrow (... \ 0.0335, -0.1018, 0.2300, ...) \in R^{300}$$

 Words with similar meanings tend to be close in embedding space



Training Word Embeddings





good \rightarrow (... 8321, 235, 63444, ...) $\in R^{\text{Vocabulary Size}} (\approx 300k)$



 $good \rightarrow (... \ 0.0335, -0.1018, 0.2300, ...) \in R^{300}$

Different Input Corpora







good \rightarrow (...?, ?, ...) $\in R^{\text{Vocabulary Size}} (\approx 300k)$



Reducing Dimensionality

 $good \rightarrow (...?, ?, ?, ...) \in R^{300}$



An article must be written from a neutral point of view, which among other things means "representing fairly, proportionately, and, as far as possible, without editorial bias, all of the significant views that have been published by reliable sources on a topic."



"Amazon values diverse opinions" and that "content [customer reviews] you submit should be relevant and based on your own honest opinions and experience."

Subjectivity Scale

More Objective

More Subjective





Subjective Embeddings (SE)

Objective Embeddings (OE)

Binary Classification Tasks

- Sentiment Classification (positive vs. negative):
 - Amazon Reviews (24 categories) + Rotten Tomatoes Reviews

"A very funny movie" vs. "One lousy movie"

- Subjectivity Classification (subjective vs. objective)
 - Rotten Tomatoes Reviews

"The story needs more dramatic meat" vs. "She's an artist"

- Topic Classification (in-topic vs. out-of-topic)
 - Newsgroups Dataset (6 categories)

Methodology

Cross-validation on balanced samples

Binary logistic regression classifier

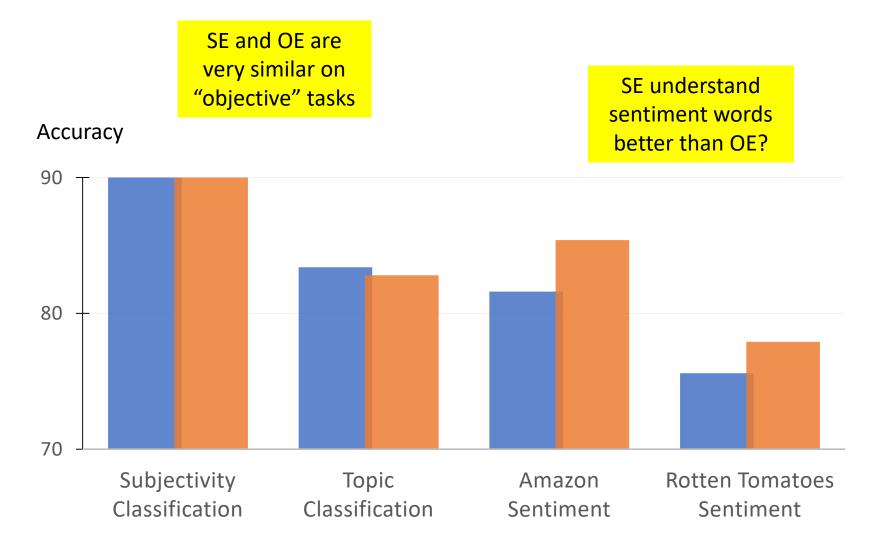
Sentence embedding = average of word embeddings

• The same number of sentences and the same vocabulary when training embeddings

Empirical Findings

Objective Embeddings (OE)

Subjective Embeddings (SE)



Top Words Similar to "good"



Objective Embeddings

Word	Similarity
bad	0.68
decent	0.67
nice	0.62
poor	0.61
•••	•••



Subjective Embeddings

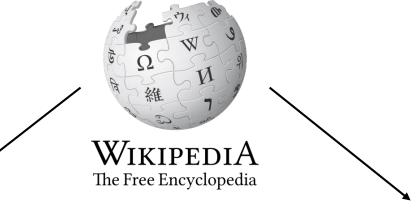
Word	Similarity
decent	0.78
great	0.76
nice	0.69
terrific	0.64
•••	•••

Sentiment Words Still Cause Troubles!

amazon Subjective Embeddings

Word A	Word B	Their Similarity
waste	Save	0.51
love	hate	0.60
loves	hates	0.68
easy	difficult	0.56
•••		•••

SentiVec Embeddings



Objective Word2Vec Embeddings

Similar to "good"	Similarity
bad	0.68
decent	0.67
nice	0.62
poor	0.61
	•••

Objective SentiVec Embeddings

Similar to "good"	Similarity
decent	0.79
nice	0.76
perfect	0.75
excellent	0.73
	•••

SentiVec: Infusing Sentiment

SentiVec = Word2Vec + Resource

- Predicts context words as in Word2Vec Skip-gram
- Predicts word category

Negative: waste, junk, horrible, defective, ...

Positive: love, great, recommend, easy, ...

Logistic SentiVec

This camera is good for high quality ...

Word2Vec Skip-gram objective

(good, camera)

(good, is)

(good, for)

(good, high)

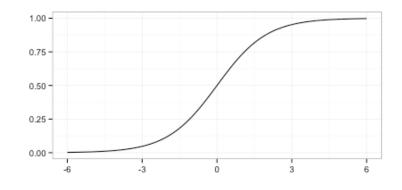
VS.

Random Noise (good, frog) (good, duck) Lexical objective of SentiVec (two classes)

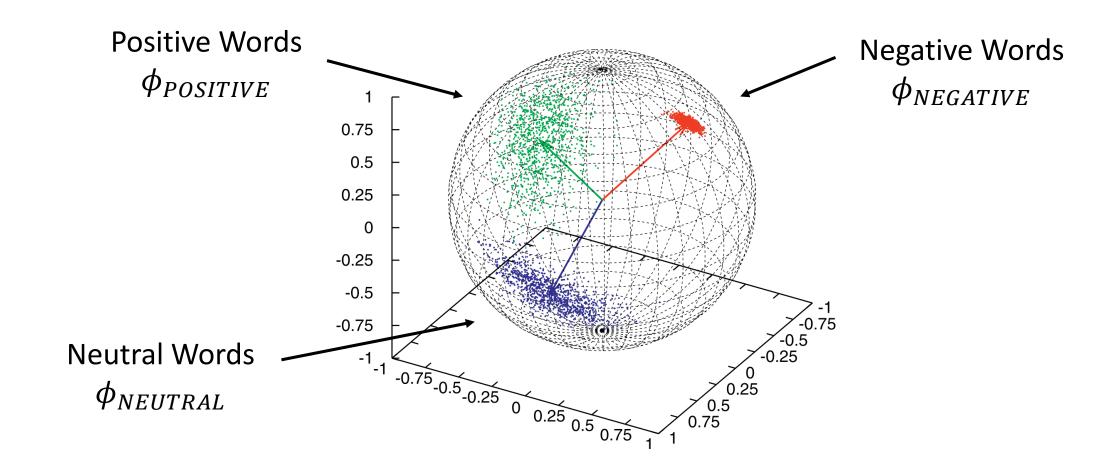
 $P(\text{good } is POSITIVE) = \sigma \left(\overrightarrow{\text{good}} \cdot \phi \right)$

 $P(\text{good } is \, NEGATIVE) = 1 - P(\text{good } is \, POSITIVE)$

 $P(\text{good } is POSITIVE) \rightarrow MAXIMIZE$

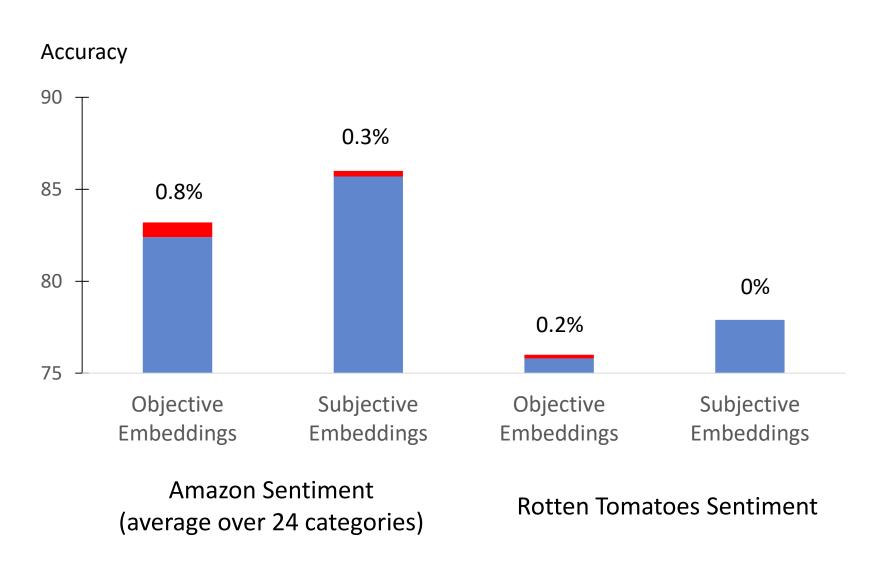


Spherical SentiVec

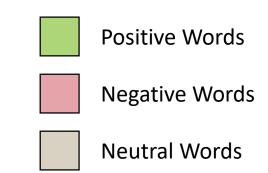


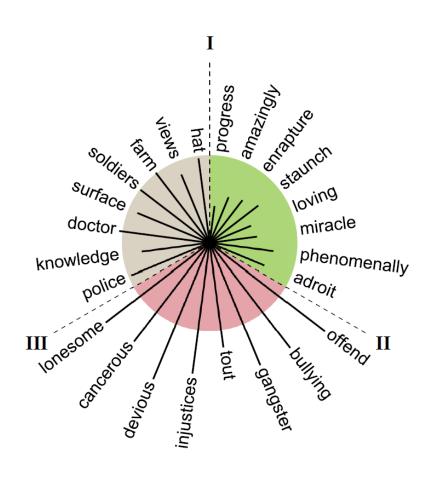
Empirical Findings

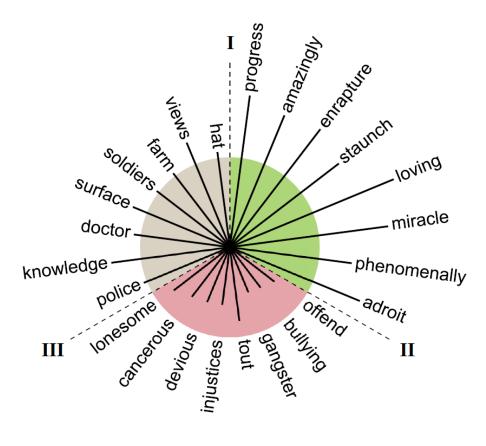
SentiVec does not affect "objective" classification tasks



Changes in Similarity





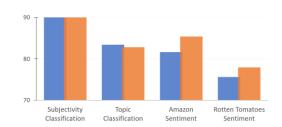


Target Word: Good

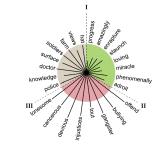
Target Word: Bad

Conclusion

 Explored effects of corpus subjectivity for word embeddings



 SentiVec, a method for infusing lexical information into word embeddings



 Sentiment-infused SentiVec embeddings space facilitate better sentiment-related similarity

