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

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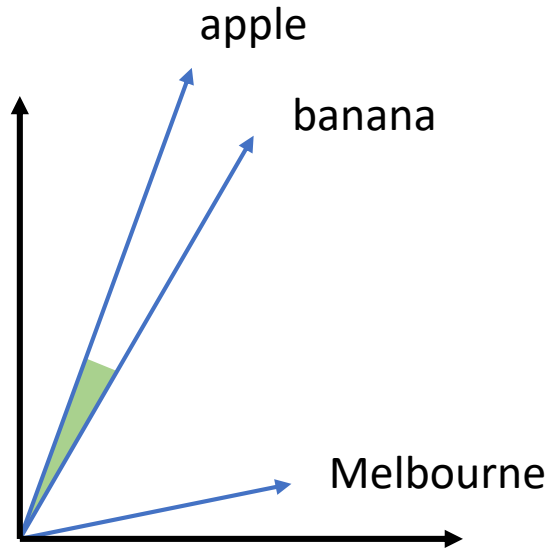
Word Embeddings

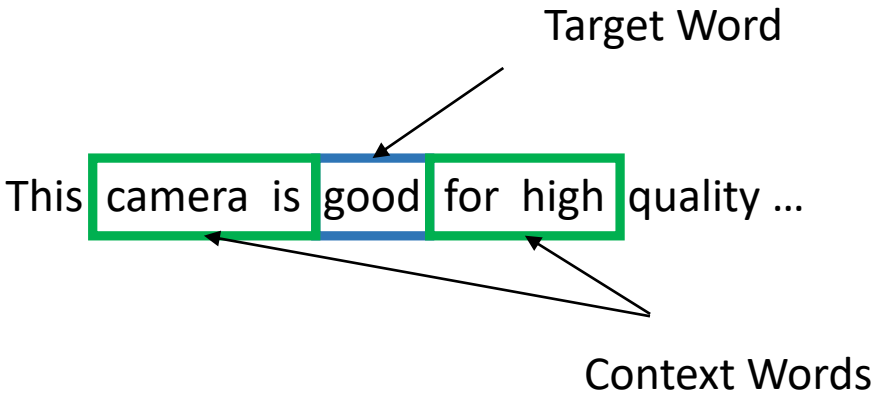
- Dense vectors of words
- Unsupervised training: GloVe, **Word2Vec**
- Words in similar context tend to have similar meaning

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

- Words with similar meanings tend to be close in embedding space



Training Word Embeddings



Counting Contexts

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

Reducing Dimensionality

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

Different Input Corpora

?

amazon

Counting Contexts

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

Reducing Dimensionality

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

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

Objective Embeddings (OE)

amazon

Subjective Embeddings (SE)

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

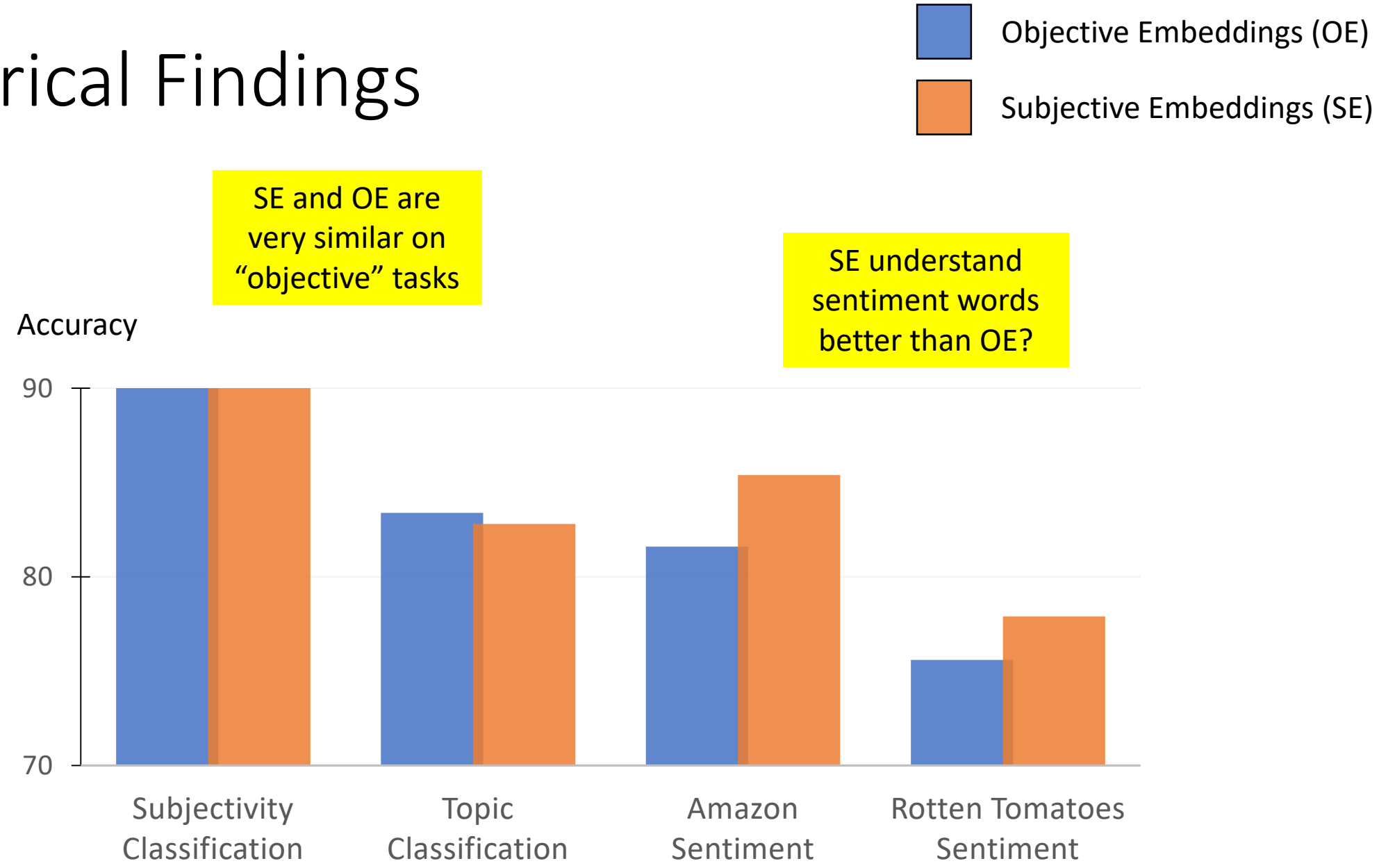
"The story needs more dramatic meat" vs. "She's an artist"

- 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



Top Words Similar to “good”

Objective Embeddings

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

amazon

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 + Lexical 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.

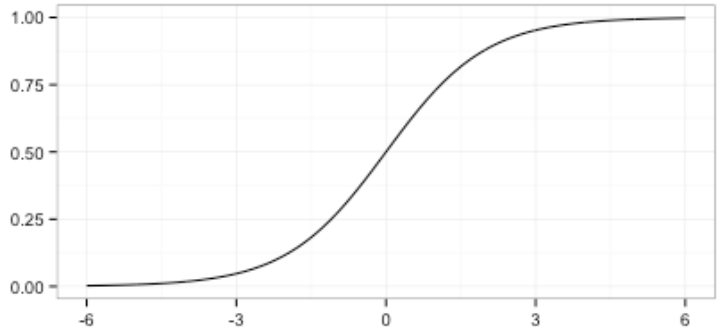
Random Noise
(good, frog)
(good, duck)
…

Lexical objective of SentiVec (two classes)

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

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

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



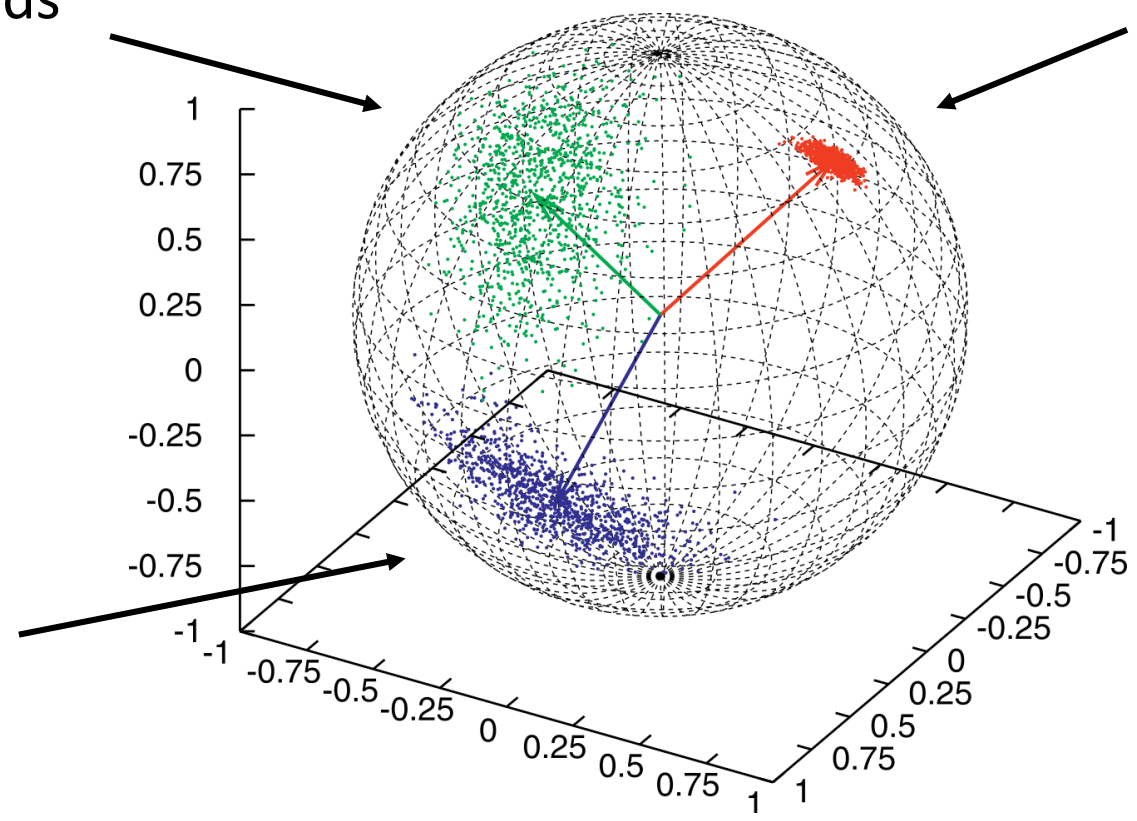
Spherical SentiVec

Positive Words

$\phi_{POSITIVE}$

Negative Words

$\phi_{NEGATIVE}$

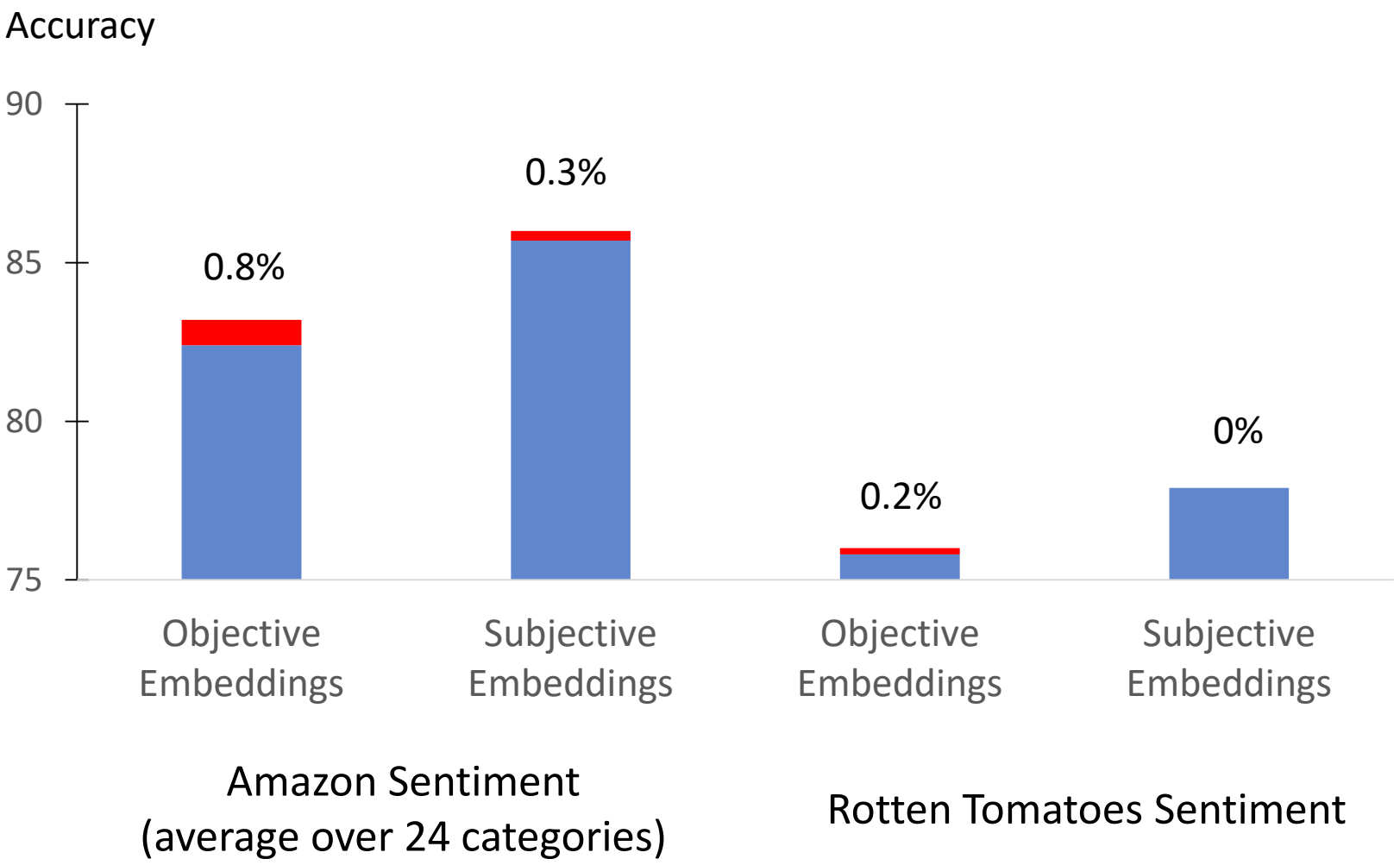


Neutral Words

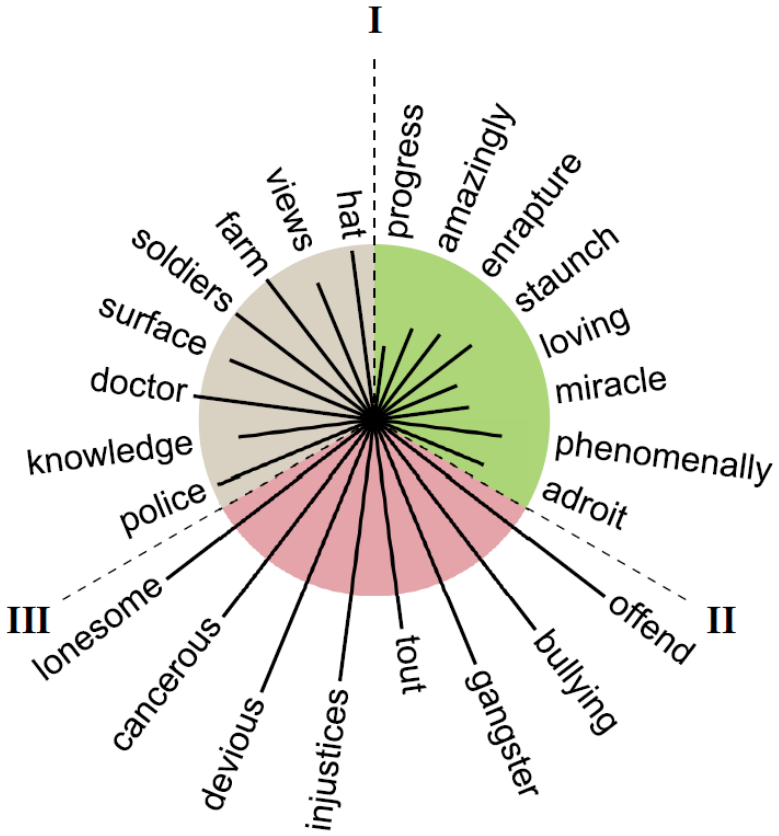
$\phi_{NEUTRAL}$

Empirical Findings

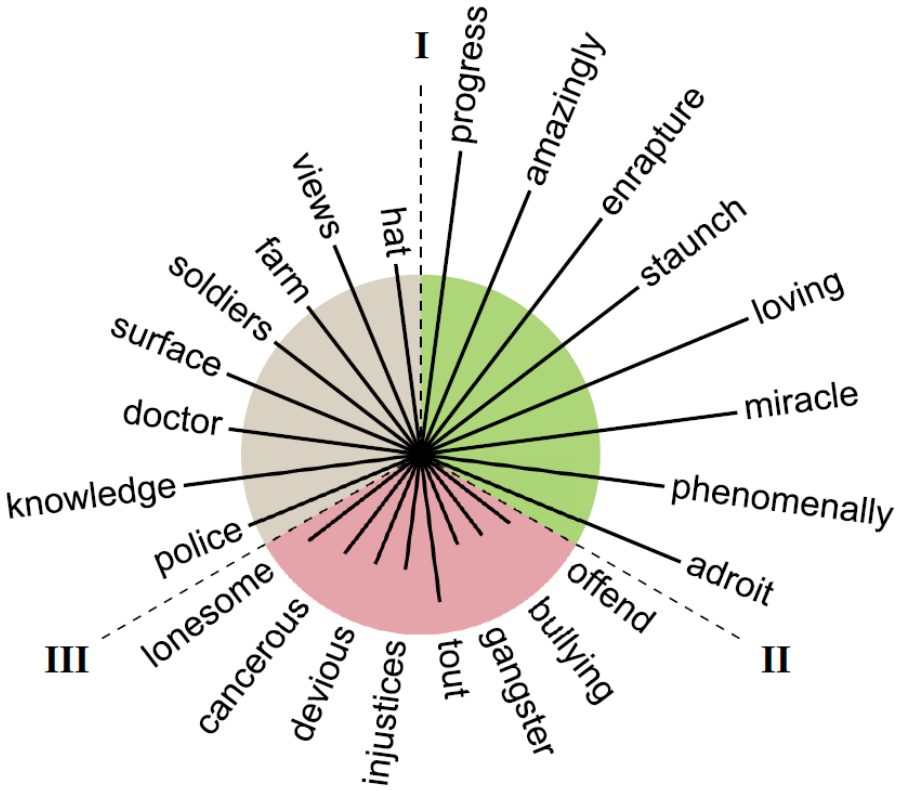
SentiVec does not affect
“objective” classification tasks



Changes in Similarity



Target Word: Good



Target Word: Bad

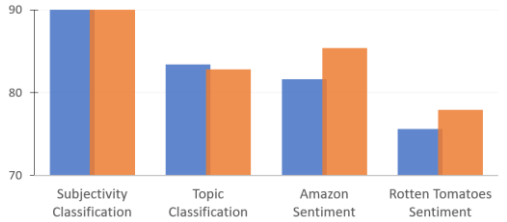
Positive Words

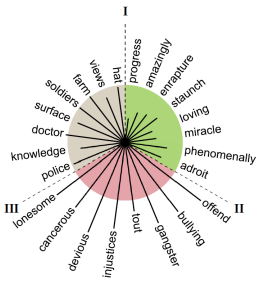
Negative Words

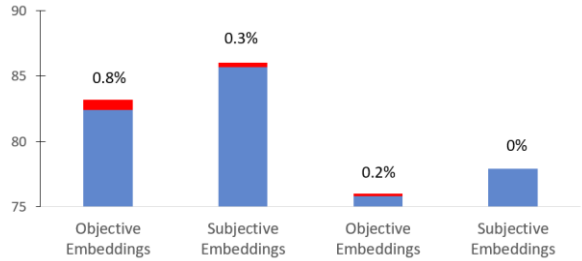
Neutral Words

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







Pre-trained Word Embeddings & Code: https://sentivec.preferred.ai/