Entity-Based Sentiment Analysis on Tweets

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Outline

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Project Overview

Evaluate Sentiment of Entities

- Identify the sentiment for entities in Twitter corpus
- Apply method to a recent event
- Utilize a two-dimensional sentiment analysis in our method

Data

Evaluation Dataset

STS-Gold Sentiment Corpus

- Subset of Stanford Twitter Sentiment Corpus
- Positive/negative polarity of tweet text
- Entity-level sentiment labeled tweets
  - negative/positive/neutral/mixed/other for the entity
- 2034 tweets (632 pos / 1402 neg) human-annotated by PhD students

	Negative Entities	Positive Entities	Neutral Entities
Total Number	13	29	16
Examples	Cancer Lebron James Flu Wii Dominique Wilkins	Lakers Katy Perry Omaha Taylor Swift Jasmine Tea	Obama Sydney iPhone Youtube Vegas

Experimental Dataset

Joint Address Tweets

- Collected 70,412 tweets about Biden's Joint Address on 4/28/2021
  - #jointaddress, #jointsession, #presidentialaddress, #bidenaddress, sotu, "state of the union", "joint address"
  - Limited to tweets between noon on the 28th and noon on the 29th
- Entities will be selected and data will be filtered
- About 100 tweets will be hand-annotated

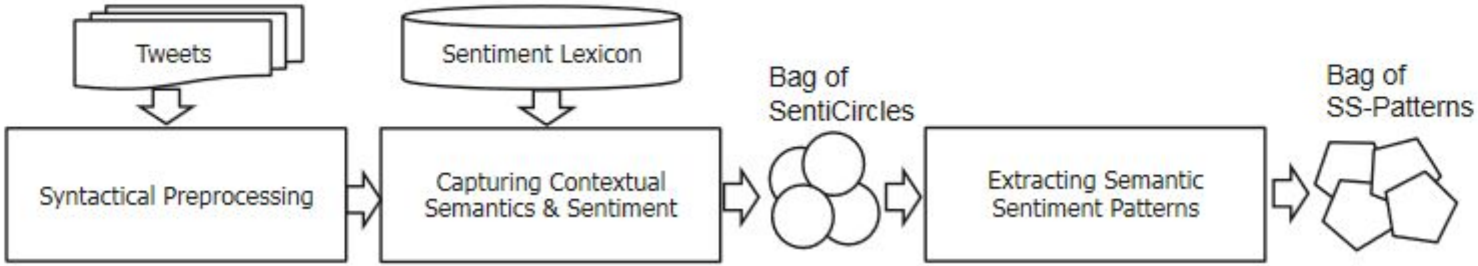
Methodology

Context paper 1: Tweet sentiment analysis with classifier ensembles

- Task: Sentiment Detection (pos/neg)
- Data: 4 publicly available Twitter sentiment datasets
  - Sanders, Stanford, Obama-McCain Debate, and Healthcare Reform
- Method: Ensemble of multinomial naive bayes, SVM, random forest, and logistic regression models
  - Also compared bag-of-words to feature hashing
- Result: Ensemble method improves accuracy compared to individual models
  - Feature hashing is more computationally efficient, but BOW is more accurate

Context Paper 2: Semantic Patterns for Sentiment Analysis of Twitter

- Task: Entity-Level Sentiment Detection (pos/neg/neu)
- Data: STS-Gold
- Baselines: Twitter features, POS features, lexicon features, semantic concept features, LDA-topic features
- Method: Preprocessing, contextual semantics with sentiment lexicon.....

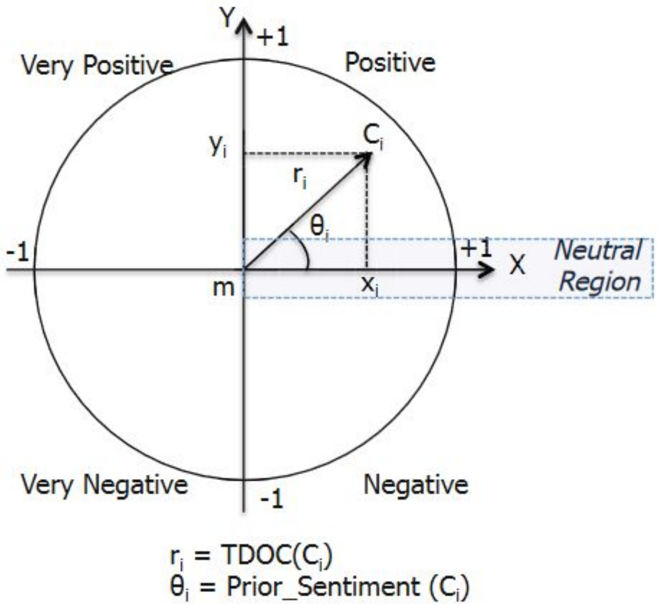


SentiCircles

$$x_i = r_i \cos(\theta_i * \pi) \qquad y_i = r_i \sin(\theta_i * \pi)$$

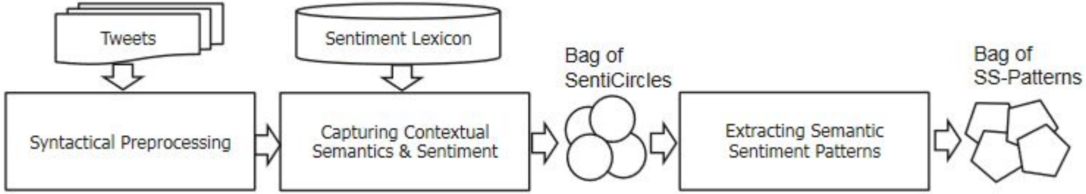
- Sentiment orientation and sentiment strength in unit circle
- Y-axis sentiment orientation
- X-axis sentiment strength
- Θi - polar angle of prior sentiment of ci
- Θi ~ 0 - neutral region
- Sentiment median determines sentiment of term

$$r_i = \mathrm{TDOC}\,(m, c_i)$$
$$\theta_i = \mathrm{Prior\_Sentiment}\,(c_i) * \pi$$



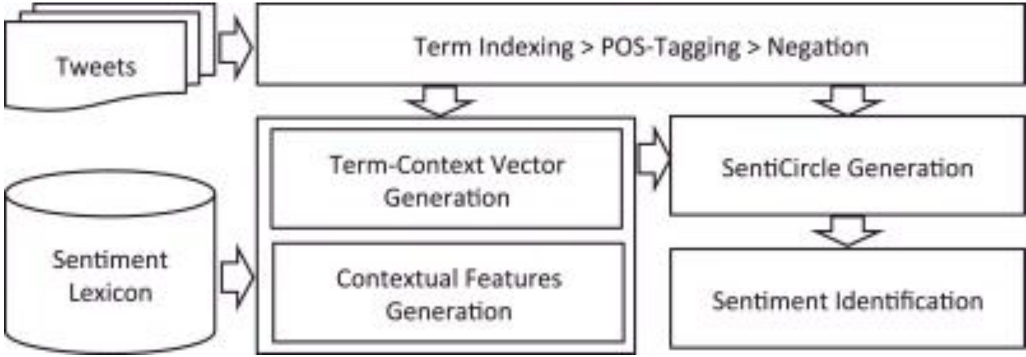
Context Paper 2: Semantic Patterns for Sentiment Analysis of Twitter - Continued

- Method: Preprocessing, contextual semantics with sentiment lexicon, **SS-patterns, classification features for entity-level sentiment classifier (MLE)**
- K-means clusters of three dimensions for each term to create semantic sentiment pattern
  - Geometry: X,Y of SentiMedian vector
  - Density: #pts in SentiCircle_i / #pts in all SentiCircles
  - Dispersion: mean absolute deviation of context terms in SentiCircle
- Classification (MLE)
  - P(c|e) =N(e,c)/N(e)
  - R_e=P(c=Positive|e)/P(c=Negative|e)
- Result: Improves on baseline



Context paper 3: Contextual Semantics for Sentiment Analysis of Twitter

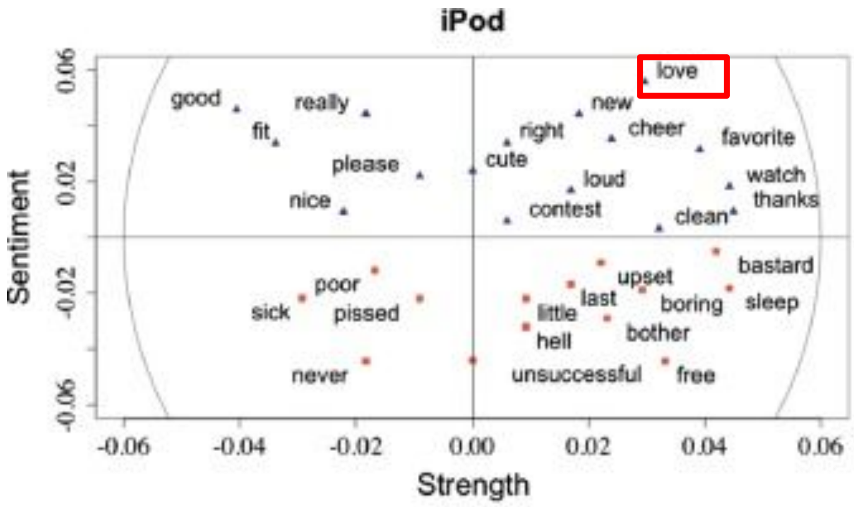
- Task: Entity-Level Sentiment Detection (pos/neg/neu)
- Data: STS-Gold
- Method: Preprocessing
- Term-Context Vector Generation
  - Prior sentiment of context word given POS tag and external lexicon
  - Term degree of correlation
- SentiCircles



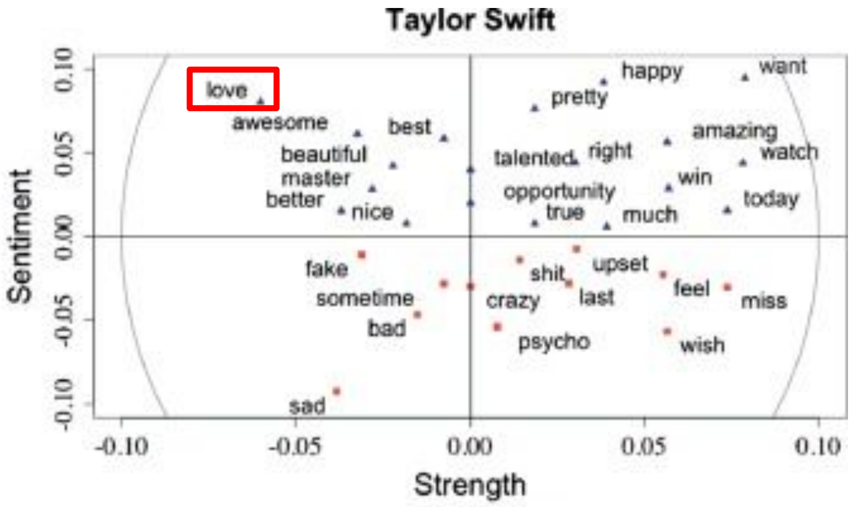
$$\mathrm{TDOC}\left(m, c_i\right) = f\left(c_i, m\right) \times APTARANORMAL \log \frac{N}{N_{c_i}}$$

SentiCircles Example

- “Love” related to the entity iPod not as high strength as for Taylor Swift



(a) iPod.



(b) Taylor Swift.

SentiCircles Advancements

- SentiMedian of context terms to determine positive, negative, neutral sentiment per entity
- Dropped K-means clustering from previous work
- Three different lexicons - SentiWordNet, MPQA, Thelwall-Lexicon
  - Many words updated by SentiCircle ->
- <u>Result:</u> SentiMedian with SentiWordNet had best performance, vastly improving on baseline lexicon-based methods

	SentiWordNet	MPQA	Thelwall-Lexicon	Average
Words found in the lexicon	54.86	16.81	9.61	27.10
Hidden words	45.14	83.19	90.39	72.90
Words flipped their sentiment orientation	65.35	61.29	53.05	59.90
Words changed their sentiment strength	29.30	36.03	46.95	37.43
New opinionated words	49.03	32.89	34.88	38.93

Our Method: Preprocessing

- Remove retweets and close duplicates
- Remove hyperlinks
- Convert emojis to text description
- Remove non-entity usernames
    - e.g. @POTUS will be kept, but @user1234 will be removed
- Tokenize using nltk TweetTokenizer
- Tag parts of speech using nltk pos_tag

Our Method: Sentiment Detection

- Apply SentiCircles and ensemble methods to evaluation and experimental datasets
- Look for sentiment drift over the course of our experimental dataset
  - Create time series using probability of positive/negative label on important entities in our corpus
- Determine most important terms related to entities in the corpus using SentiCircles
- Baseline: majority rule given an opinion lexicon

Expected Results

Replicating SentiCircles

- Achieve similar performance in our replication of the SentiCircles method
- Achieve better performance than our baseline method
- We expect SentiWordNet to be the best lexicon
- Hand annotating sample of tweets to confirm accuracy of entities’ sentiment in our experimental dataset
  - We expect Democrats to have more positive sentiment than Republicans since a Democrat is giving the Joint Address and setting the topic
- Time series hypothesis:
  - Biden will be viewed more positively during his address, but more negatively during Tim Scott’s rebuttal

Any Questions?

References

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