# Positive, Negative, or Neutral: Learning an Expanded Opinion Lexicon from Emoticon-annotated Tweets

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# Twitter Sentiment Classification

- Automatically classify a tweet to classes **positive**, **negative**, or **neutral**.

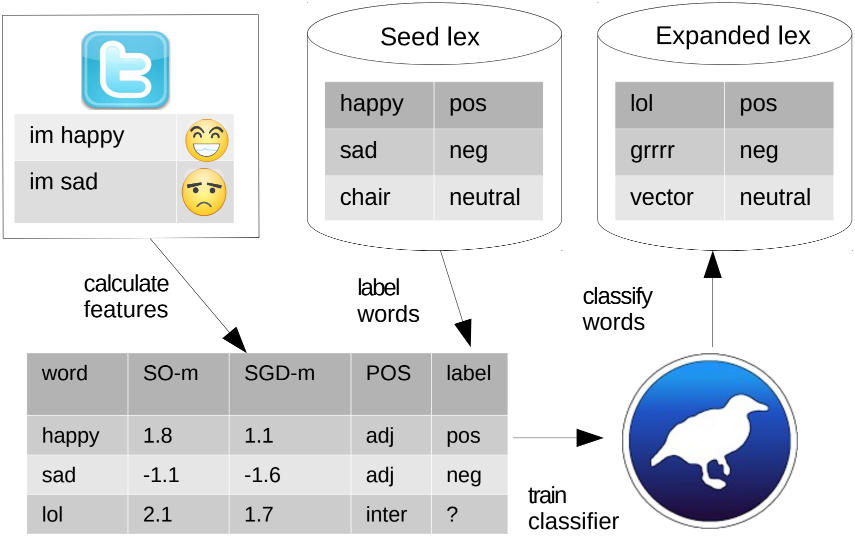
## Approaches

- Most methods rely on opinion lexicons.
- An opinion lexicon is a lists of terms labelled by sentiment.
- They are normally composed of positive and negative words such as **happy, wonderful** and **sad, bad**.
- The words used in Twitter include many abbreviations, acronyms, and misspelled words, e.g., **lol**, **omg**, **hahaha**, **#hatemonday** which are **not** covered by most popular lexicons.

# A Word-level Classification Model

- We propose a **supervised framework** for **Twitter** lexicon expansion from a **seed lexicon**.
- Each expanded word has a **probability distribution**, describing how positive, negative, and neutral it is.
- All the entries of the lexicon are associated with a corresponding **part-of-speech** tag.
- This is useful for word **disambiguation** e.g., apple can be a company or a fruit.

# Methodology



# Obtaining Emoticon-annotated Tweets

- We **require** a collection of tweets with their corresponding **polarity labels**.
- Tweets can be collected from the Twitter API.
- Tweets exhibiting **positive :)** and **negative :(** emoticons are labelled according to the emoticon's polarity.
- We consider **two** collections of tweets covering multiple topics: The **Edinburgh corpus** (ED), and the **Stanford Sentiment corpus** (STS).

| | ED | STS |
|---|---|---|
| Positive | 1,813,705 | 800,000 |
| Negative | 324,917 | 800,000 |
| Total | 2,138,622 | 1,600,000 |

Table : Collection statistics

# Word-level Attributes

- We calculate three type of word-level features to train the word-level classifier.
- **SGD**: Are calculated from the weights of a **linear support vector machine** trained using words as attributes and emoticons as labels.

$$\frac{\lambda}{2}||w||^2 + \sum[1 - y(\mathbf{xw} + b)]_+. \tag{1}$$

- **SO**: Are calculated from the point-wise mutual information between the words and the sentiment labels.

$$\mathrm{PMI}(w_i, y) = \log_2\left(\frac{Pr(w_i \wedge y)}{Pr(w_i)Pr(y)}\right) \tag{2}$$

- **POS**: We also include the POS-tag of the word as a nominal attribute.
- To create training data for machine learning, all the words **matching** the seed lexicon are **labelled** according to the lexicon's polarities.

# Feature Visualisation

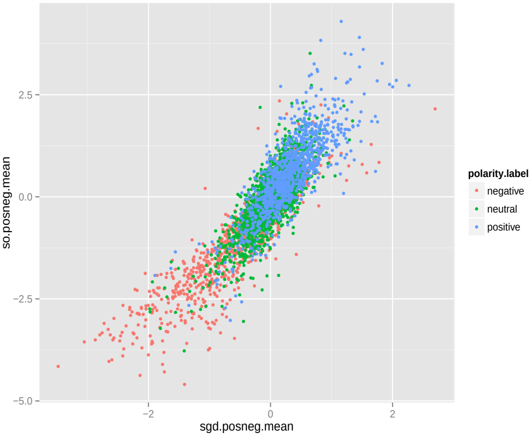



Figure : SO vs SGD scatterplot.

# Word-level Classification Results using RBF SVMs

| Weighted AUC | | |
|---|---|---|
| Dataset | SO | ALL |
| ED-Polarity | $0.62 \pm 0.02$ | $\mathbf{0.65} \pm \mathbf{0.02} \circ$ |
| STS-Polarity | $0.64 \pm 0.02$ | $\mathbf{0.66} \pm \mathbf{0.01} \circ$ |

| Kappa | | |
|---|---|---|
| Dataset | SO | ALL |
| ED-Polarity | $0.28 \pm 0.04$ | $\mathbf{0.33} \pm \mathbf{0.04} \circ$ |
| STS-Polarity | $0.31 \pm 0.04$ | $\mathbf{0.35} \pm \mathbf{0.03} \circ$ |

Table : World-level classification performance.

# Expanded Lexicon

| word | POS | label | negative | neutral | positive |
|---|---|---|---|---|---|
| alrighty | interjection | positive | 0.021 | 0.087 | 0.892 |
| boooooo | interjection | negative | 0.984 | 0.013 | 0.003 |
| lmaoo | interjection | positive | 0.19 | 0.338 | 0.472 |
| french | adjective | neutral | 0.357 | 0.358 | 0.285 |
| handsome | adjective | positive | 0.007 | 0.026 | 0.968 |
| saddest | adjective | negative | 0.998 | 0.002 | 0 |
| same | adjective | negative | 0.604 | 0.195 | 0.201 |
| anniversary | common.noun | neutral | 0.074 | 0.586 | 0.339 |
| tear | common.noun | negative | 0.833 | 0.124 | 0.044 |
| relaxing | verb | positive | 0.064 | 0.244 | 0.692 |
| wikipedia | proper.noun | neutral | 0.102 | 0.644 | 0.254 |

Table : Expanded words example.

# Expanded Lexicon (2)


(a) (b)

Figure : Word clouds of positive and negative words using log odds proportions.

# Message-level Classification

| Weighted AUC | | | |
|---|---|---|---|
| Dataset | Baseline | ED | STS |
| 6-coded | $0.77 \pm 0.03$ | $0.82 \pm 0.03 \circ$ | $0.82 \pm 0.02 \circ$ |
| Sanders | $0.77 \pm 0.04$ | $0.83 \pm 0.04 \circ$ | $\mathbf{0.84} \pm \mathbf{0.04} \circ$ |
| SemEval | $0.77 \pm 0.02$ | $0.81 \pm 0.02 \circ$ | $\mathbf{0.83} \pm \mathbf{0.02} \circ$ |

Table : Message-level polarity classification performance.

# Discussions

- This method could be used to create **domain-specific** lexicons.
- It could also be used to study the **dynamics** of opinion-words.
- This method depends on a collection of **emoticon-annotated tweets**.
- It would be hard to apply to **domains** where emoticons are not **frequently used**.
- Source code and lexicons available at `http://www.cs.waikato.ac.nz/ml/sa/lex.html`.
- Feel free to visit me at poster **#88**.

# Questions?

Thanks for your Attention!


## Acknowledgments

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