Sentiment and Emotion on Social Media

EECS 510 : Social Media Mining - Paper Presentation

Compass: Spatio Temporal Sentiment Analysis of US Election

Introduction

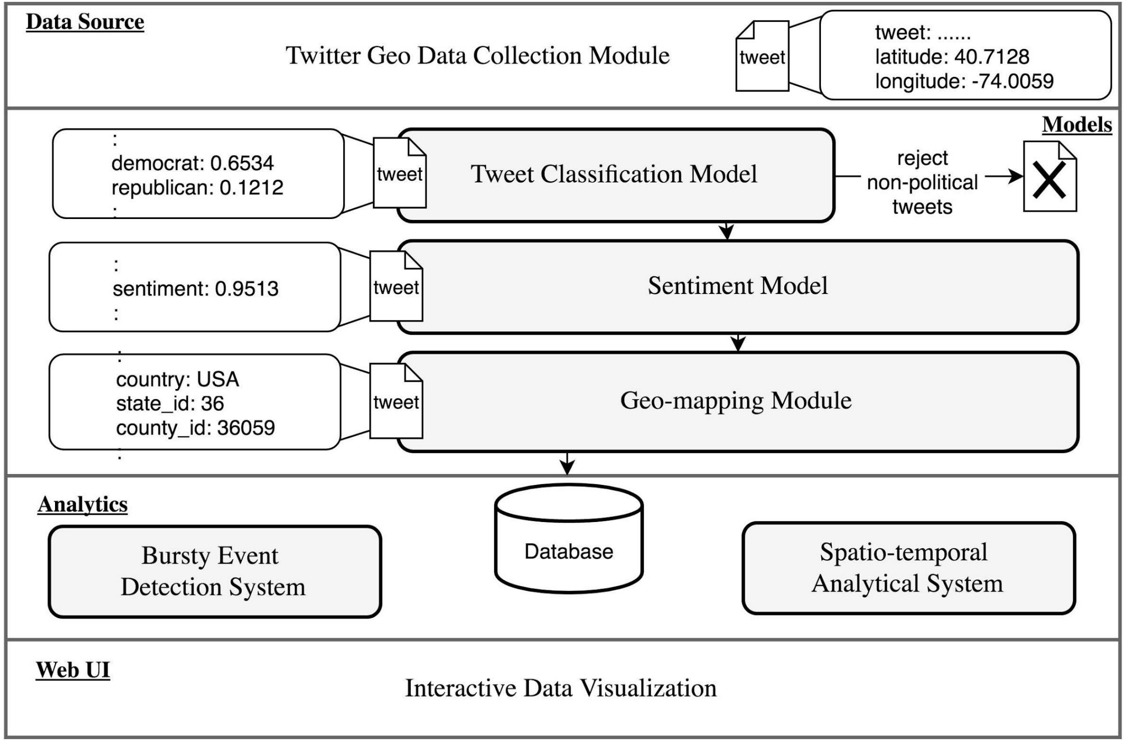
Motivation: social media can offer understanding of important social issues and events

Challenge: social media data is unstructured, noisy and big

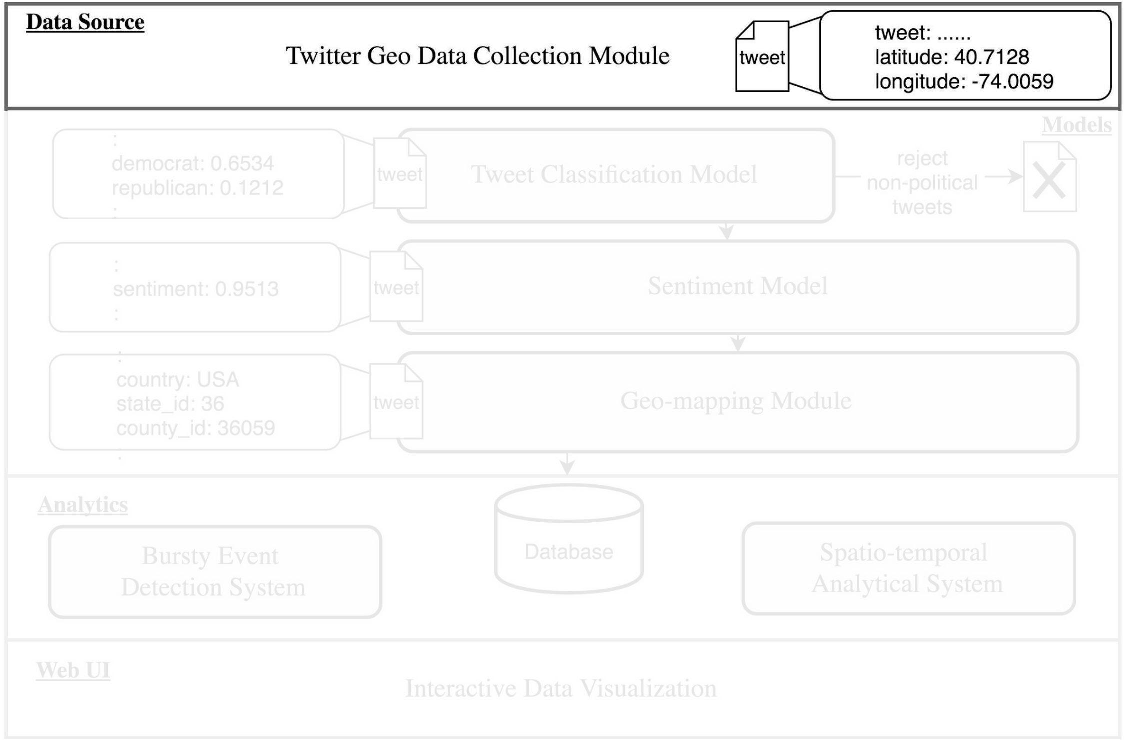
Proposal: create a system that generates spatio-temporal sentiment analysis from large-scale social media data

<u>Comp</u>rehensive <u>A</u>nalytics on <u>S</u>entiment for <u>S</u>patiotemporal Data

<u>COMPASS</u>

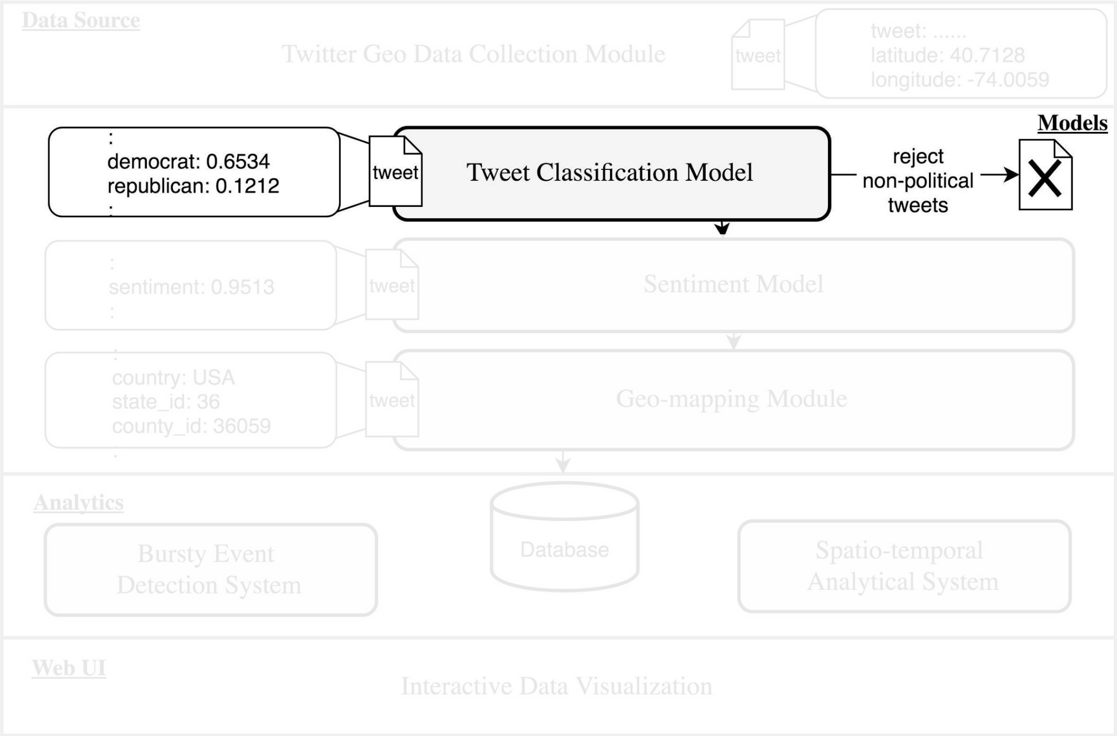


Data Source
Twitter Geo Data Collection Module
tweet
tweet: ......
latitude: 40.7128
longitude: -74.0059
Models
democrat: 0.6534
republican: 0.1212
tweet
Tweet Classification Model
reject
non-political
tweets
sentiment: 0.9513
tweet
Sentiment Model
country: USA
state_id: 36
county_id: 36059
tweet
Geo-mapping Module
Analytics
Bursty Event
Detection System
Database
Spatio-temporal
Analytical System
Web UI
Interactive Data Visualization



Collection of geo-tagged tweets

Partitioning search locations by bounding boxes based on expected volumes of tweets (New York City versus Utah)

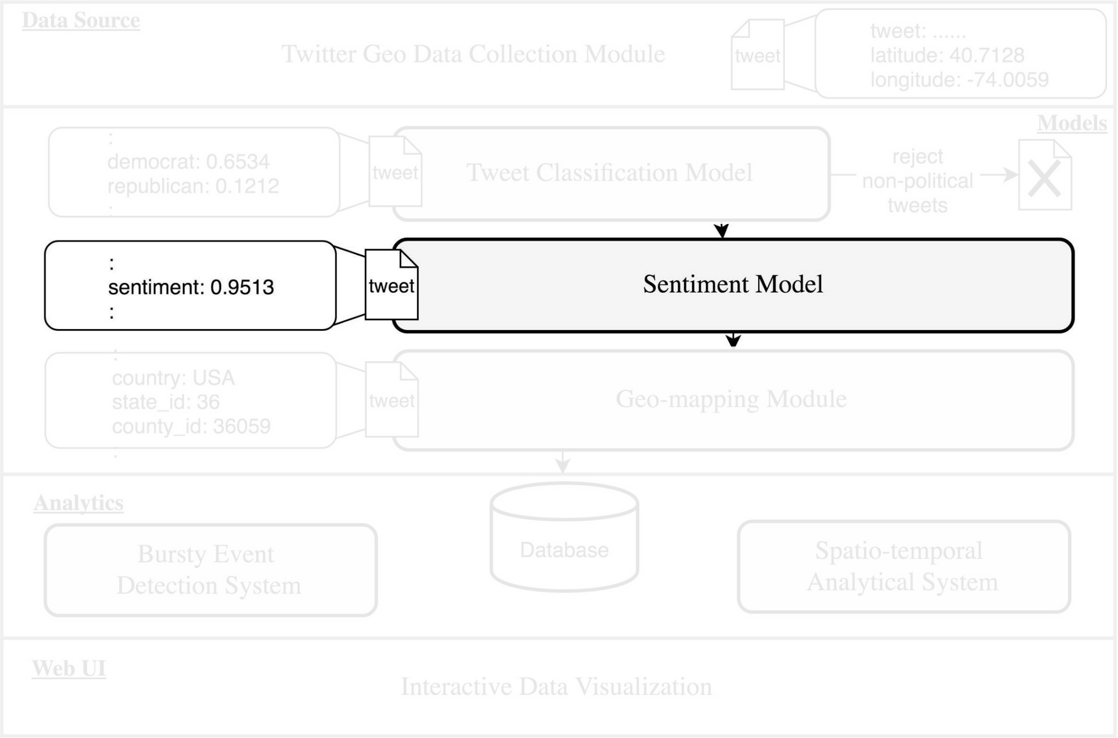


Classification model collects news articles (NYTimes, Fox News, CNN etc).

Feeds them to a Latent Dirichlet Allocation (LDA) topic modeling algorithm to find the keywords related to politics

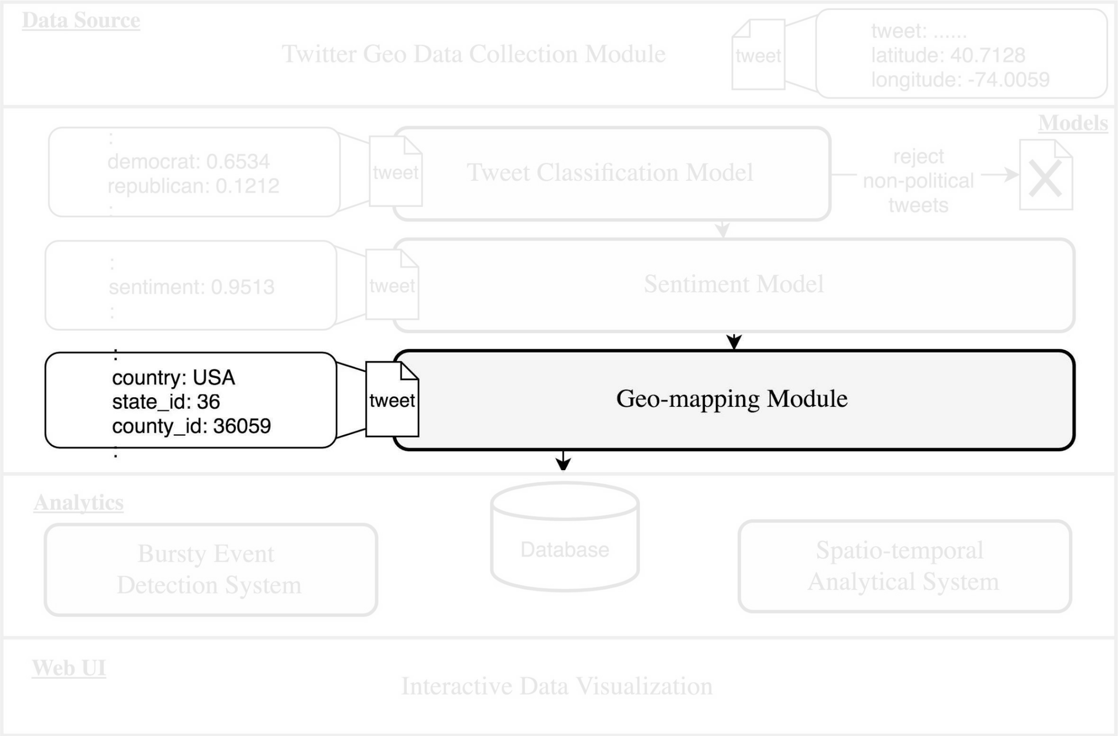
Language used on Twitter ≠ from news articles; used Word2Vec to expand that lexicon

Compass takes tweets and classifies them as Democrat, Republican, both or none, with the last two being excluded



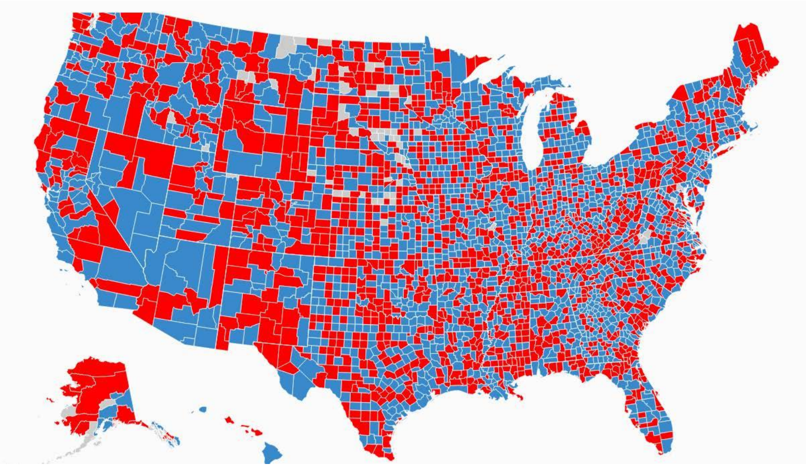
Uses Stanford Twitter Sentiment (STS) corpus model "to figure out whether a particular tweet in a group is for or against that group"

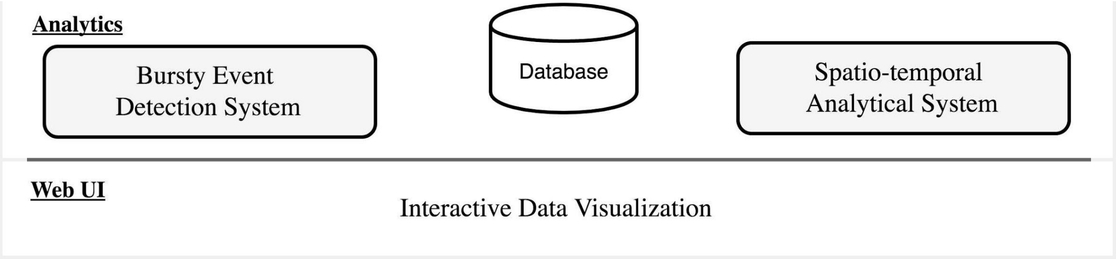
"For example, *Go Hillary. I'm with her!* will be classified into the Democrat group, and its sentiment score will be close to 1; whereas *Email leak is a crime!* will also be classified into the Democrat group, but with a very low sentiment score"



Coordinates of the geotag of each tweet to to counties

GeoJSON to delineate features, finds a point within a polygon





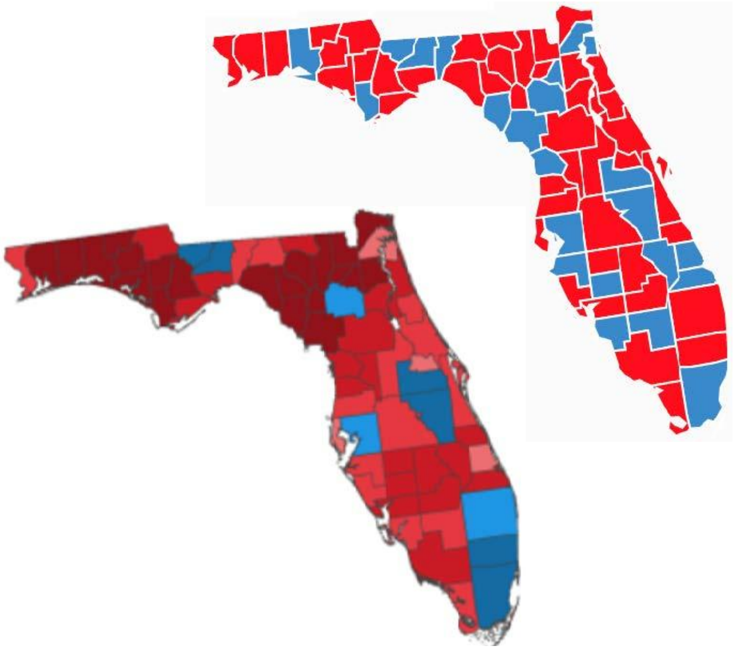
Bursty Event Detection System: "Bursty events gain popularity in a short time but might not be prevalent for longer time hence usually get overlooked by trending topics"

Spatio-temporal Analysis: using the county map

Visualization: Built with D3.js

Results

- Collected 286 million tweets from June-October 2016
- Identified 2 million geo-tagged tweets related to US politics: 822,062 republican-related, 702,042 democrat-related
- Bursty: "Early detection of significant events throughout the election season"
- Geospatial: "sentiment map matches to the election result to an extent"



Social Emotion Mining Techniques for Facebook Posts Reaction Prediction

Introduction

Collecting customer feedback and acting upon it is a must for any business that offers products or services to it users.

People are using social media to share opinions, thoughts and is increasingly being used to measure customer satisfaction.

Motivation

Utilize available information from social media to

- Enhance customer experience from marketing perspective
- Influence future purchases and decisions
- Contribute to the development of various fields of behavioral research, marketing, political science, education, etc.

Goals & Contribution

- Provide a dataset to study reaction of Facebook posts
- Perform sentiment analysis and emotion mining to Facebook posts

Data Collection

Data Treatment

- Included posts, comments and reactions
- Excluded ‘Like’ posts from the dataset

Pre Processing

- Used Standard core NLP parser to standardise and normalize data
- Convert to lower case
- Remove hashtag reference
- Replace three or more occurrences of one character in a row with the character itself (e.g.“looooove” becomes ”love”)

Reaction Distribution Prediction System

Emotion Mining Lexicon EmoLex and WordNet make a corpus of 31,485 words.

Table 1: Examples from EmoLex showing the emotion association to the words abuse and shopping.

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
abuse	1	0	1	1	0	1	0	0
shopping	0	1	0	0	1	0	1	1

Reaction Distribution Prediction System

- Negation Handling
  - Detecting negations in a sentence followed by emotion.
  - Detecting negations in a sentence to handle adverbs and Part of speech
- Sentence Similarity Measures
  - Used to calculate similarities between sentences and annotate them using word vectors. This was deemed unsuccessful sentences with similar structure were incorrectly measured as similar
  - Failed primarily due to inability to correctly identify underlying sentiment.
- SVM for unannotated sentences
  - Used to estimate emotions using one versus all classifier and TF-IDF. Input consists of array of 8 values representing emotions as a label.

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shopping	0	1	0	0	1	0	1	1

```
Sentence 1: "I really love your car."
Sentence 2: "I really hate your car."
Sentence2Vec similarity: 0.9278
Avg vector similarity: 0.9269
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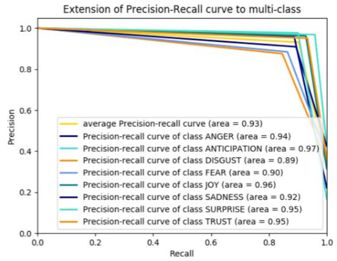
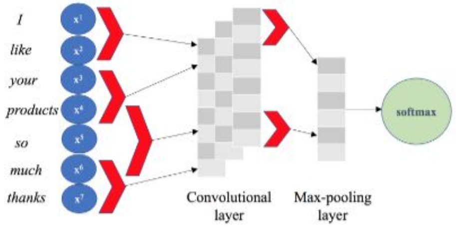


Reaction Distribution Predictor

Convolutional Neural Networks

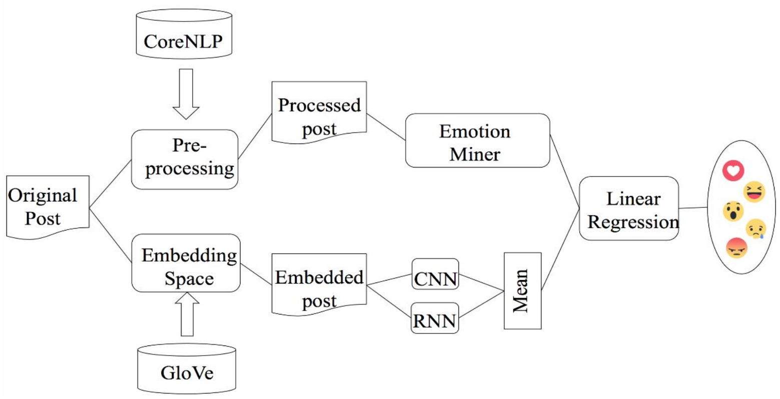
- Variable length input sentences are padded
- Each word represented by equivalent word vector
- Convolution operation is applied to extract common patterns
- Pooling layer reduces the spatial dimensions and produces a softmax output.
- A probability distribution over all reactions(except 'Like')



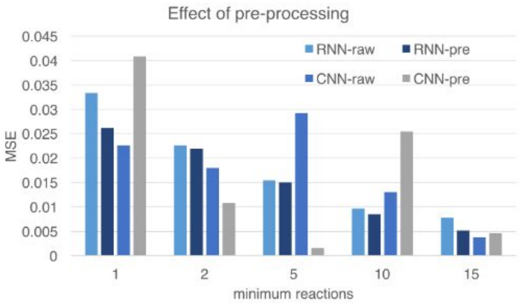
Reactio Distribution Predictor

Reaction Distribution Predictor

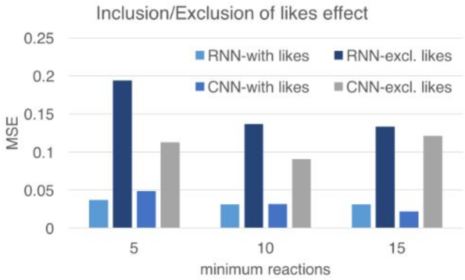
The final prediction reaction ratio is computed by combining neural networks and emotions on Facebook posts/comments. The ratio for emotion and averaged networks is combined into a single vector and regressed over a linear model.



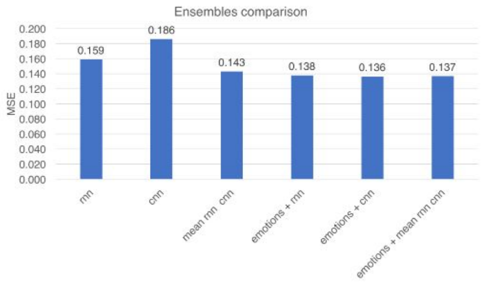
Experiments



Raw vs Pre-processed Input



Exclusions of ‘Like’ reactions



Neural Network Performance

Conclusions

Emotion miners can be used to detect sentiment/emotion associated with a social media post.

Emotion mining together with neural networks works better to improve the overall prediction and reduce mean squared error.

Vast amount of data is available on social media as people continue to share feedback about products and their experiences. While this is one of the first steps in exploring emotion mining, Big Data, Real Time, Accuracy, and visualization are list of challenges faced in area of emotion mining in online social network.

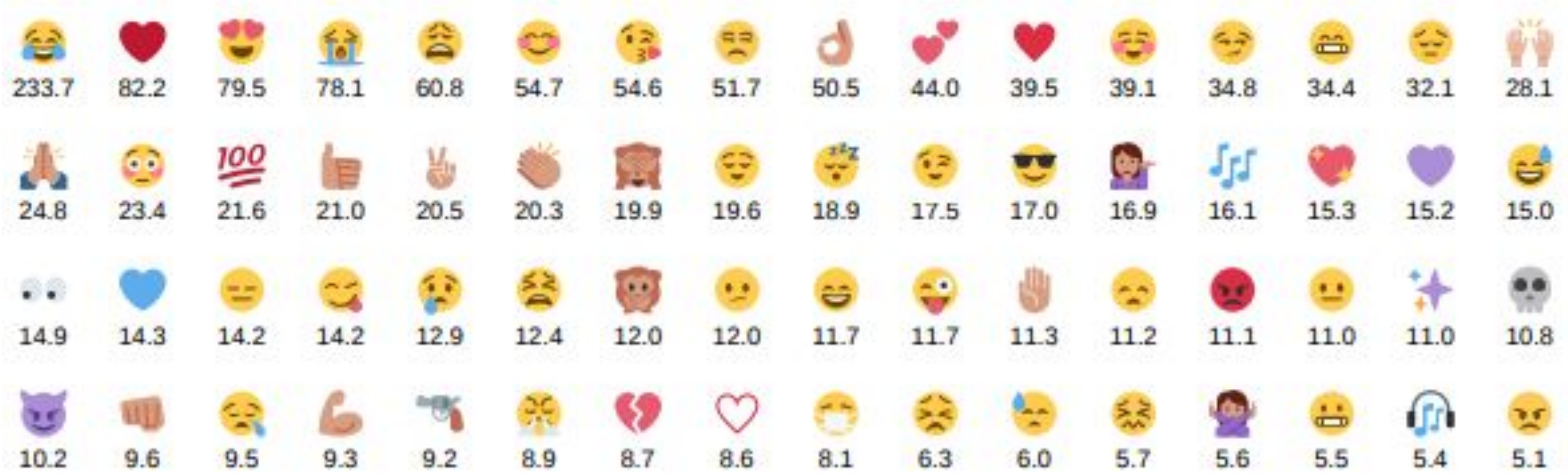
Using emoji for detecting sentiment, emotion and sarcasm

The Idea

Improve on existing sentiment-analysis algorithms for classifying text based on emoji/emoticon by using a wider variety of emojis and implementing a new training method

The Data

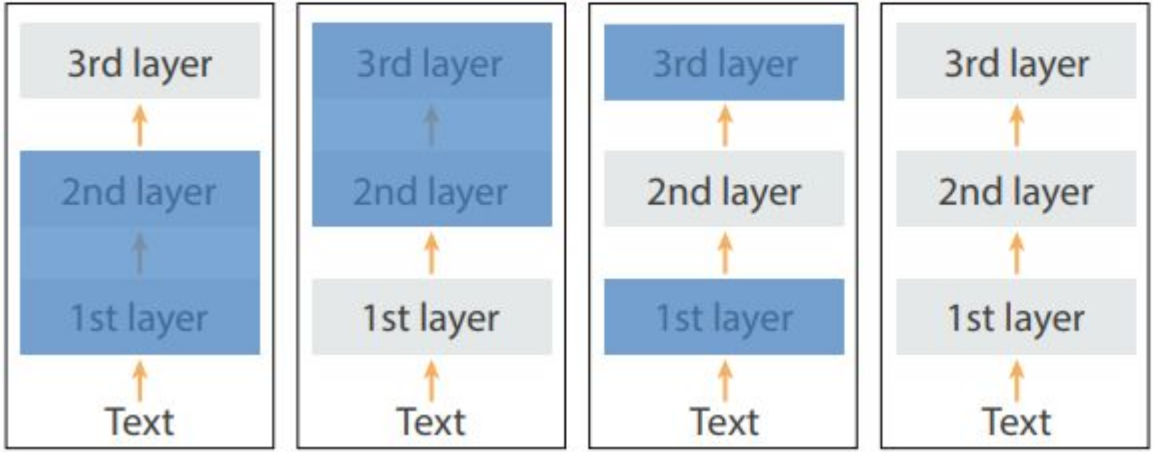
- 56.6 billion tweets
  - Minus all tweets not in english
  - Minus all tweets with URLs
  - Minus all tweets that only contain punctuation, emojis, numbers, or @mentions
- 1.2 billion tweets
  - Plus tweet copies with multiple different emojis, used as distinct tweets
- **1.6 billion tweets**


233.7 82.2 79.5 78.1 60.8 54.7 54.6 51.7 50.5 44.0 39.5 39.1 34.8 34.4 32.1 28.1
24.8 23.4 21.6 21.0 20.5 20.3 19.9 19.6 18.9 17.5 17.0 16.9 16.1 15.3 15.2 15.0
14.9 14.3 14.2 14.2 12.9 12.4 12.0 12.0 11.7 11.7 11.3 11.2 11.1 11.0 11.0 10.8
10.2 9.6 9.5 9.3 9.2 8.9 8.7 8.6 8.1 6.3 6.0 5.7 5.6 5.5 5.4 5.1

The Model

- Embedding layer projects each word in the tweet into vector-space
- Two Long Short-Term Memory layers to get the context of each word
- Attention layer for weighting the importance of each word in the classifying task

The Training



"Chain-thaw" training: Pre-train each layer individually, "freezing" the others until the very end when the entire model is trained together

Results

Table 5: Comparison across benchmark datasets. Reported values are averages across five runs. Variations refer to transfer learning approaches in §3.3 with 'new' being a model trained without pretraining.

Dataset	Measure	State of the art	DeepMoji (new)	DeepMoji (full)	DeepMoji (last)	DeepMoji (chain-thaw)
SE0714	F1	.34 [Buechel]	.21	.31	.36	**.37**
Olympic	F1	.50 [Buechel]	.43	.50	**.61**	**.61**
PsychExp	F1	.45 [Buechel]	.32	.42	.56	**.57**
SS-Twitter	Acc	.82 [Deriu]	.62	.85	.87	**.88**
SS-Youtube	Acc	.86 [Deriu]	.75	.88	.92	**.93**
SE1604	Acc	.51 [Deriu][3]	.51	.54	**.58**	**.58**
SCv1	F1	.63 [Joshi]	.67	.65	.68	**.69**
SCv2-GEN	F1	.72 [Joshi]	.71	.71	.74	**.75**

Even More Results!

Table 8: Comparison of agreement between classifiers and the aggregate opinion of Amazon Mechanical Turkers on sentiment prediction of tweets.

	Agreement
Random	50.1%
fastText	71.0%
MTurk	76.1%
DeepMoji	**82.4%**

Questions?