

Using sentiment analysis for stock market prediction

BIRGER KLEVE



Project Goals

- Increase Machine Learning knowledge
 - Learning real world practice
 - Facing real world problems
 - Optimize algorithm parameters



Project Definition

Hypothesis:

There is a correlation between tweet sentiment from certain people and a stocks movement.

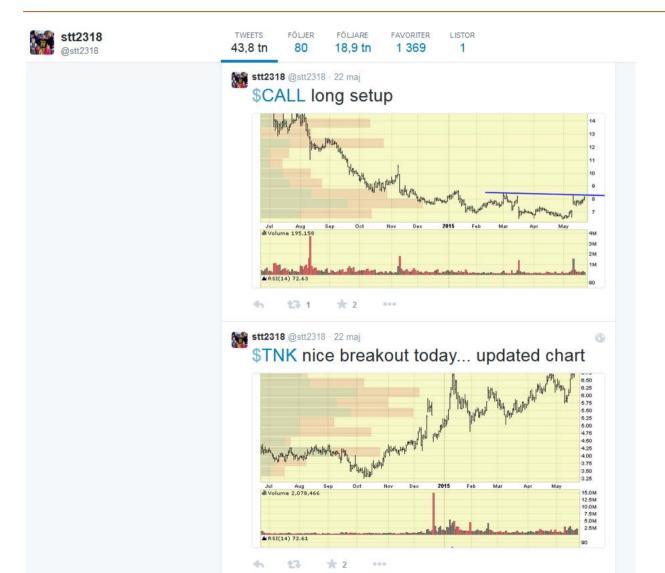
System:

- 1 Find tweets mentioning stocks
- 2 Classify sentiment of the tweet

3 Predict stock movement by processing stock data and tweet sentiment



Availability of Financial data on Twitter





Project Redefinition

 Drop the financial aspect of the project and only focus on the sentiment of tweets



Sentiment Analysis

- Keyword spotting
 - E.g. Happy, sad, bored
- Lexical affinity
 - Affinity (swe: samhörighet) to a certain probability of polarity
- Statistical methods
- Concept-level techniques
 - Semantic analysis of text



Cambria, E. An introduction to Concept-Level Sentiment Analysis. National University of Singapore



- Thumbs up? 2002
- Movie reviews
- Presence of Unigram + Bigram w/ negation

Pang, B. Lee, L. Shivakumar, V. Thumbs up? Sentiment classification using Machine Learning Techniques. Cornell University, IBM Almaden. 2002



Social Media Features

- Words entirely in caps
- Prolonged words like angryyyyy
- Positive/negative emoticons
- Amount of hashtags
- Frequency of different POS tags



Sentiment lexicon

- Look up each word in a sentiment lexicon.
- Lexical affinity
- Use Features:
 - Highest score
 - Total score
 - Mean score



Tokenization and negation

- Change usernames, URLs, hashtags etc. into normalized tokens
- Tag certain words with negation. E.g.

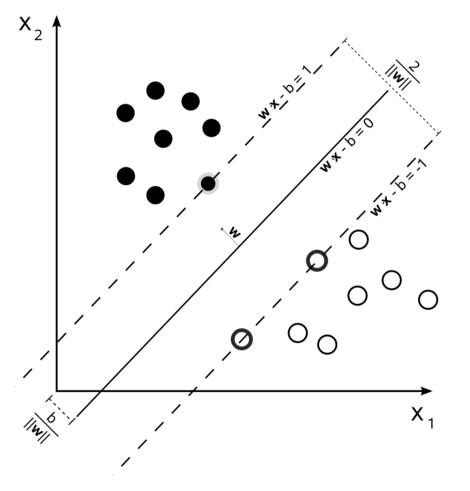
"This horse is not that bad" => "This horse is not that_NOT bad_NOT"

"not quite as great" => "not quite_NOT as great"

• Use the presence of each unigram as a feature



Classifier



- SVM with Linear kernel
- Parameters: C



Training

- Tokenize and collect each unique word in the training data and save it as a vocabulary.
- Fit SVM to the entire training set
- Optimizing parameter C
 - 3-fold Cross Validation
 - Grid Search
 - Test the final classifier against a separate test set



Data

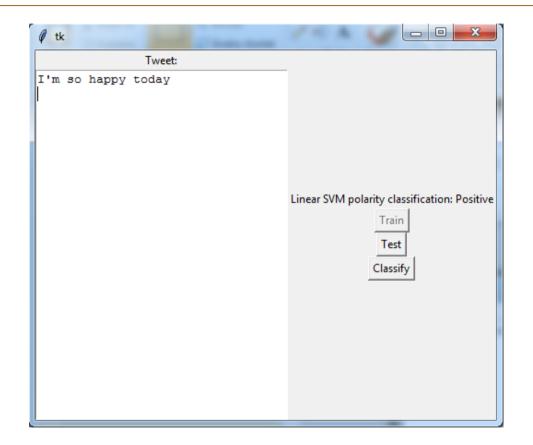
- Training set 1 600 000 automatic classified tweets
 - w/ Keyword search
 - 2 classes: Negative & Positive
- Test set 357 manually classified tweets

Go, A., Bhayani, R., & Huang, L. Twitter sentiment classification using distant supervision. Tech. rep., Stanford University, 2009.

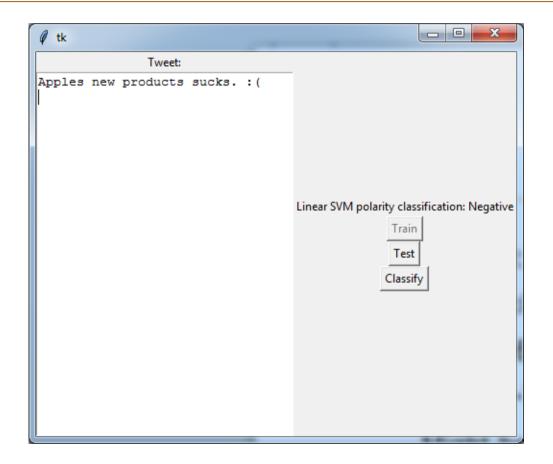
- Sentiment lexicons:
 - Lexical affinity

Kiritchenko, S., Zhu, X., Mohammad, S. Sentiment Analysis of short Informal Texts. Journal of Artificial Intelligence Research, 2014

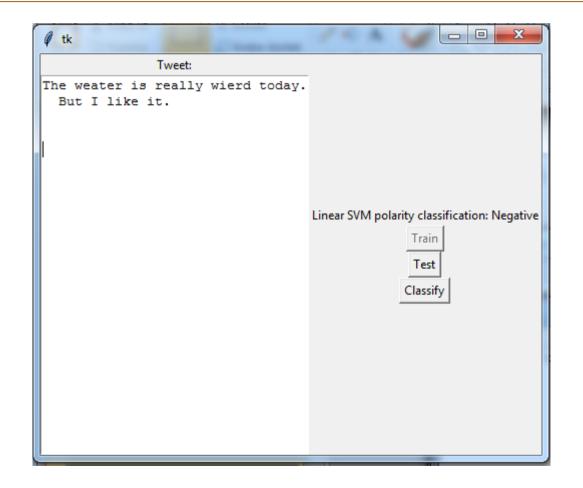














- Using 1.6% of the training data(25600 samples):
 - 54981 features
 - > 12 hours of optimizing
 » DNF
 - 1 hour final training
 - Sparse features => enormous RAM allocation



- Human test: ~80%
- Expected: close to 79%
- My baseline: ~65%
- My Improved: ~75%
 - Might be higher



Tools

- Python's Scikit-learn
- NLTK for POS tagging (as features and to negate context)



What I have learned

- Pitfalls of data collection
- Handling LARGE amount of data
- Using popular machine learning tools
- (SVM, its kernels and their parameters)





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