Utilizing Crowd Intelligence for Online Detection of Emotional Distress

Master's Thesis Presentation

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Technische Universität München

March 14, 2013

Outline

- Introduction
  - Backdrop
  - Motivation
  - Problem Definition
- Theoretical Background
  - Machine Learning and Text Classification
  - Support Vector Machines
  - Ensemble Learning methods
- Experiments
- System
- Conclusion and Future Work
- Q/A

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Introduction

Backdrop

Depression and Suicide

- Nearly one million people die every year because of suicide
- Most people are between 15 to 29 years old

Social Media

- Rise of Twitter, Facebook, Reddit, Wordpress
- Sections of interest
  - Reddit - "/r/happy" [a] and "/r/suicidewatch" [b]
  - Twitter - the entire website

[a] http://www.reddit.com/r/happy
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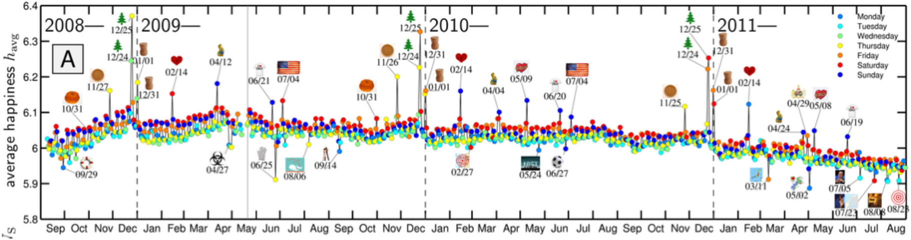
Backdrop



- Study conducted in 2011
- 46 billion words collected over 33 months
- Negativity on Twitter has been on the rise
- Words include *death*, *hate*, and even *suicide*

Motivation

- **Direct** - *"thoughts of suicide make me happy"*, *"I have a rope around my neck"*
- **Indirect** - *"I don't know anything anymore"*, *"Need someone to talk to"*
- Some accounts have lots of followers, some don't
- Lives can be saved if there is a surveillance system of suicide
- Public sentiment information available on the web + No analysis possible = Disconnect

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Problem Definition

Experiments

Evaluate machine learning algorithms that can be used for identifying depressed emotions in pieces of text

System

Build a web based system that can

- tap into crowd intelligence to incrementally improve the classifiers
- detect content on the web that indicates that its author may be depressed or suicidal

Theoretical Background

Machine Learning

- Algorithms that can learn from data
- Construct a model from a given dataset, and then perform the required task on another dataset
- **Supervised learning** - Train the models on the training data, and predict on the test data
- **Unsupervised learning** - No distinction between training and test data

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Text Classification

Formal definition

Given a dataset $\{(\mathbf{x_n}, y_n)\}_{n=1}^{N}$ containing N instances, where each instance $(\mathbf{x_n}, y_n)$ is of the form $[(x_{n,1}, x_{n,2}, ..., x_{n,D}), y_n]$, calculate the y_n values.

- Given some pieces of text, put unseen pieces of text into two or more categories
- **Supervised** - calculate y_n of test data given information about y_n from training data
- **Unsupervised** - calculate y_n given only information about $\mathbf{x_n}$

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Document Representation

Text Corpus

"I am happy today"

and

"I am not happy today, but I was happy yesterday"

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Token dictionary

"I": 1,
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Vector Space Representation

$1, 1, 1, 1, 0, 0, 0, 0$

and

$2, 1, 2, 1, 1, 1, 1, 1$

Support Vector Machines

- Fairly popular class of algorithms used for binary classification
- Given training data in some D dimensional space, find a decision boundary (hyperplane) that separates the two classes
- Hyperplane ($\mathbf{w} \cdot \mathbf{x} - b = 0$) should have maximum distance from any data point
- Solution for linear classifiers: $\mathbf{w} = \sum_{i=1}^{S} \alpha_i \mathbf{x_i}$
- Replace $\mathbf{x_i} \cdot \mathbf{x}$ with $k(\mathbf{x_i}, \mathbf{x}) \implies$ represents the dot product of two vectors in higher dimensions (kernel function)

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Linear kernel SVM

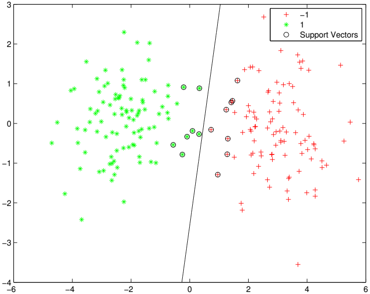

Figure : Binary classification on a dataset using a linear kernel SVM

Kernel functions

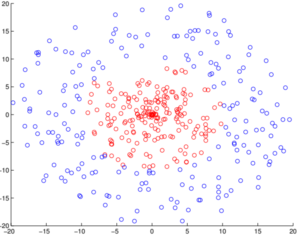

Figure : Dataset in 2D (cannot be classified using a linear kernel SVM)

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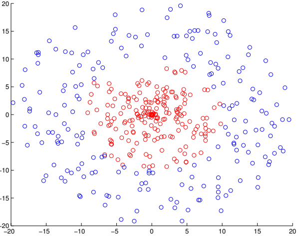

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$$\xrightarrow{x_3 = \sqrt{x_1^2 + x_2^2}}$$

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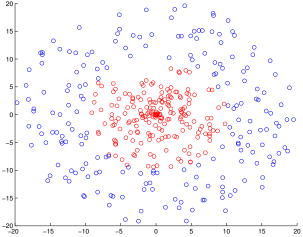

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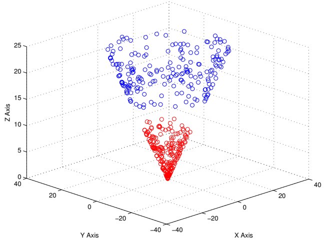

Figure : Dataset transformed to 3D

Ensemble Learning

- Class of machine learning methods that combine models to obtain better predictions
- Various strategies to combine models - *select best*, *voting (bagging)*, *boosting*, *stacking*
- Performance not guaranteed to be better than constituent classifiers
- Ensemble methods still usually outperform individual classifiers
- Soft requirement - underlying models should be diverse

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Sample split

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Feature split

Boosting

- Assign each sample a weight value (same for all samples in the beginning), and train M classifiers successively
- For each classifier, calculate ϵ (measure of error) and α (decreases with ϵ)
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$\xrightarrow{Classifier1}$

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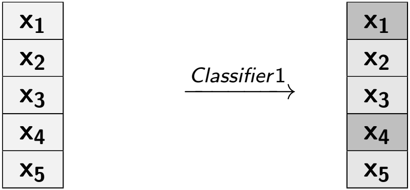

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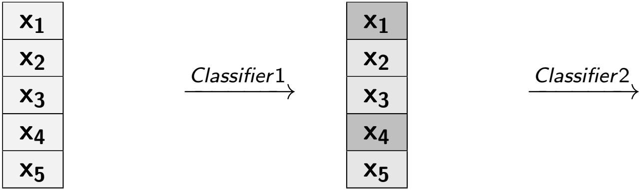

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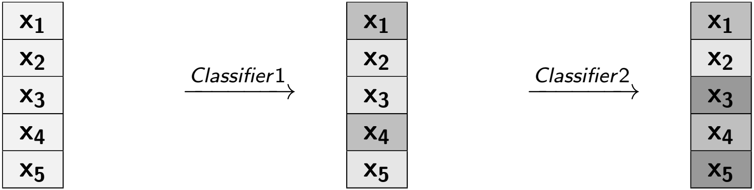
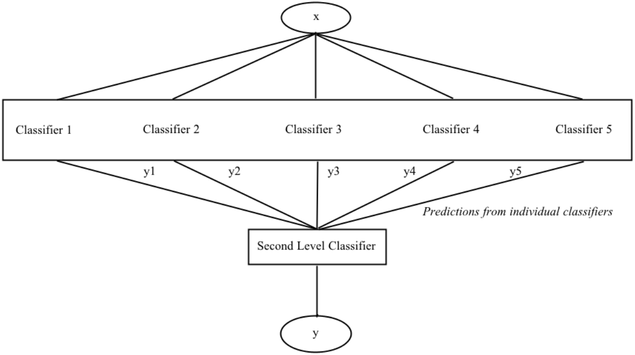


Stacking



- Outputs from first layer form the input for second layer
- Layer-1 classifiers can be trained using bootstrapping or selecting random features

Experiments

Dataset

- List of 6182 comments from the internet - Kaggle [1]
- label | timestamp | comment
- Examples
  - 1 - How arrogant you are
  - 1 - you are human garbage
  - 0 - i really don't understand your point. It seems you are mixing apples and oranges.
  - 0 - you may be right

[1] `http://www.kaggle.com/c/detecting-insults-in-social-commentary`

Experiments

Approach

- Extract n-grams upto size 2 and use tf-idf information as feature values
- Input matrix - 6182 rows and 23175 columns
- Implement all models in MATLAB
- Start with 100 samples, and continue adding 100 samples in each iteration until no more samples are left

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Name	Accuracy	Support Vector Count	Model Count
SVM	✓	✓	✗
Bagging	✓	✗	✓
Boosting	✓	✗	✗
Stacking	✓	✗	✗

Support Vector Machines

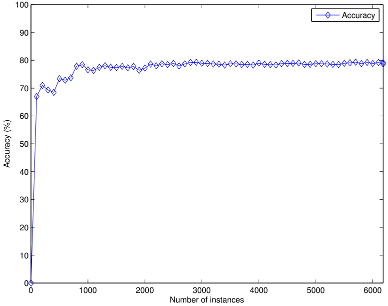


Figure : Accuracy

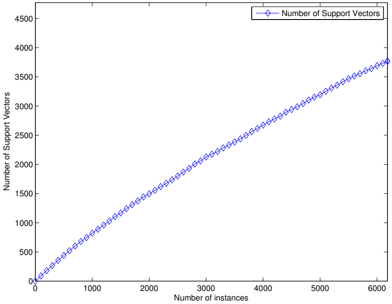


Figure : Support Vector count

79.02% for linear kernel, and 34.39% for Polynomial/RBF/Sigmoid kernels

Number of support vectors decreases from 90% to 60%

Experiments

Bagging

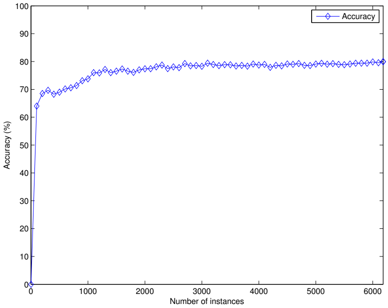


Figure : Accuracy v/s Number of instances

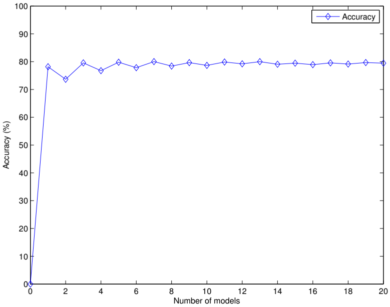


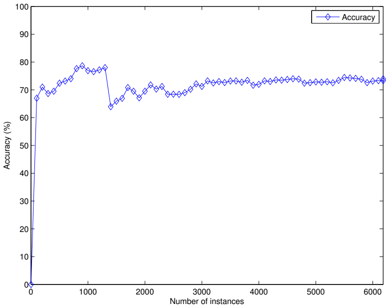
Figure : Accuracy v/s Number of models

79.65% (9 linear kernel SVMs)

Models increase → Subsets overlap → Accuracy Stabilizes

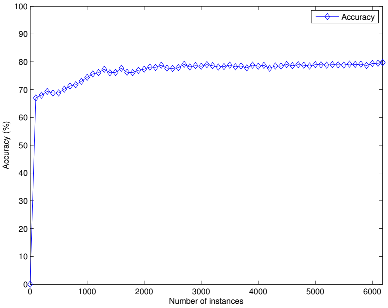
Experiments

Boosting



Average accuracy of 72.84%

Stacking



Average accuracy of 79.48%

All using linear kernel SVMs

System

System

Dataset

- **Training data** - Reddit
- Fetch posts from "/r/happy" [2] and "/r/suicidewatch" [3]
- **Prediction data** - Twitter
- Gather tweets from the public streaming API [4]

[2] http://www.reddit.com/r/happy
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Task	Frequency
Fetch 1000 posts from Reddit	24 hours
Fetch 100 tweets from Twitter	3 hours
Re-assign labels to previous tweets and update statistics	24 hours

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- Implement all classifiers in Python, and web interface in Django
- No training data available → build our own
- Training data (Reddit)
  - "/r/happy" - people posts their happy moments
  - "/r/suicidewatch" - people post when they want to commit suicide
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  - General sentiment of the overall public
  - Pull 100 tweets every 3 hours from Twitter

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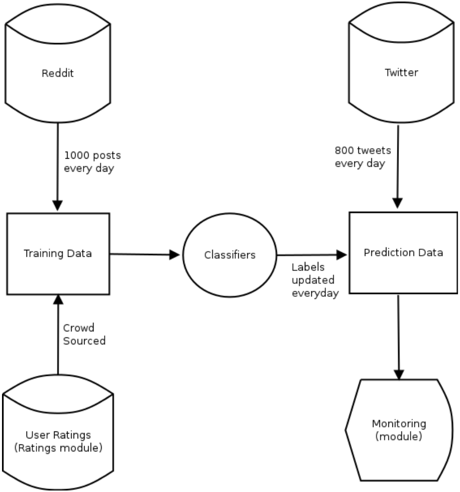
Architecture



- **Ratings** - allows users to assign labels to stories (crowd intelligence), building the training data
- **Monitoring** - displays predictions of classifiers in the form of depressed tweets and individual statuses of classifiers

Demo

Conclusion and Future Work

Conclusion

- An evaluation of Support Vector Machines and Ensemble Learning methods (Bagging/Boosting/Stacking) in the domain of text classification
- Bagging outperformed Stacking outperformed SVM outperformed Boosting
- A web based system that can detect emotional distress on Twitter
- No labels implies qualitative evaluation is difficult except observation
- Observed results seem to be reasonable

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- Relabelling process (decreases wastage of resources)
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Thank you!

Questions?