Utilizing Crowd Intelligence for Online Detection of Emotional Distress

Master's Thesis Presentation

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March 14, 2013

Outline

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  - Backdrop
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- Theoretical Background
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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

[b] http://www.reddit.com/r/suicidewatch

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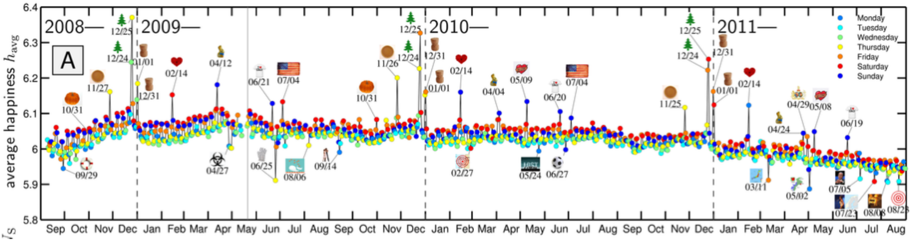
Backdrop



- 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

Problem Definition

Evaluation

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

Machine Learning

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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 $\mathbf{x_n}$

Text Corpus

"I am happy today"

and

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

Document Representation

Text Corpus

"I am happy today"

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$\rightarrow$

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Token dictionary

"I": 1,
"am": 2,
"happy": 3,
"today": 4,
"not": 5,
"but": 6,
"was": 7,
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Document Representation

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$\rightarrow$

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

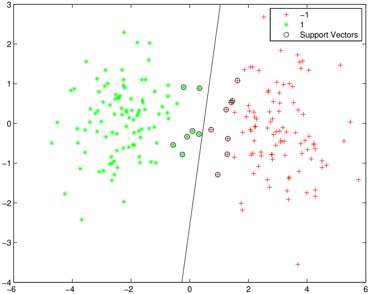

Figure : Binary classification on a dataset using a linear kernel SVM

Kernel functions

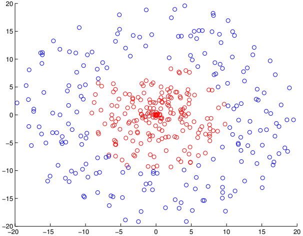

Figure : Dataset in 2D (cannot be classified using a linear kernel SVM)

Kernel functions

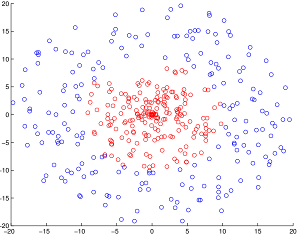

Figure : Dataset in 2D (cannot be classified using a linear kernel SVM)

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

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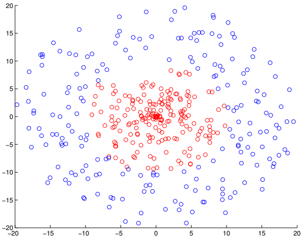

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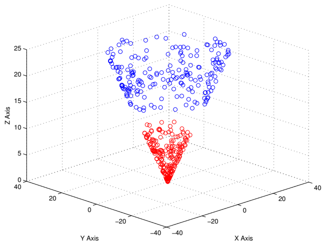

Figure : Dataset transformed to 3D

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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Bagging

- Obtain predictions from all constituent classifiers, and take a majority vote
- Final prediction $= \text{sign}(\sum_{m=1}^{M} y_m(\mathbf{x_n}))$

$$\begin{pmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \cdots & x_{1,N} \\ x_{2,1} & x_{2,2} & x_{2,3} & \cdots & x_{2,N} \\ x_{3,1} & x_{3,2} & x_{3,3} & \cdots & x_{3,N} \\ \vdots & \vdots & \ddots & \vdots & \\ x_{M,1} & x_{M,2} & x_{M,3} & \cdots & x_{M,N} \end{pmatrix}$$

Sample split

$$\begin{pmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \cdots & x_{1,N} \\ x_{2,1} & x_{2,2} & x_{2,3} & \cdots & x_{2,N} \\ x_{3,1} & x_{3,2} & x_{3,3} & \cdots & x_{3,N} \\ \vdots & \vdots & \ddots & \vdots & \\ x_{M,1} & x_{M,2} & x_{M,3} & \cdots & x_{M,N} \end{pmatrix}$$

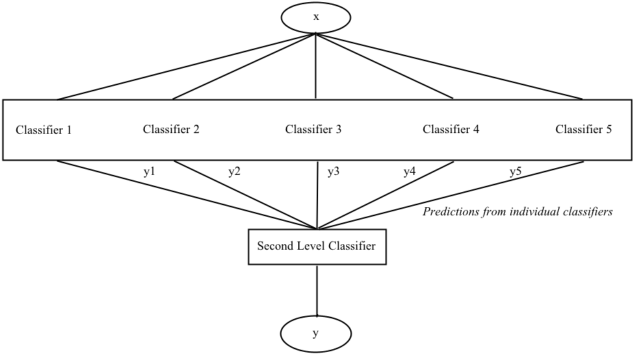
Feature split

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)
- Final prediction $= \operatorname{sign}(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x_n}))$

$$\begin{array}{|c|}\hline \mathbf{x_1} \\ \hline \mathbf{x_2} \\ \hline \mathbf{x_3} \\ \hline \mathbf{x_4} \\ \hline \mathbf{x_5} \\ \hline \end{array} \quad \rightarrow \quad \begin{array}{|c|}\hline \mathbf{x_1} \\ \hline \mathbf{x_2} \\ \hline \mathbf{x_3} \\ \hline \mathbf{x_4} \\ \hline \mathbf{x_5} \\ \hline \end{array} \quad \rightarrow \quad \begin{array}{|c|}\hline \mathbf{x_1} \\ \hline \mathbf{x_2} \\ \hline \mathbf{x_3} \\ \hline \mathbf{x_4} \\ \hline \mathbf{x_5} \\ \hline \end{array}$$

Stacking



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

Experiments

Evaluation of algorithms

Datasets

- Evaluation
  - Comments dataset from a competition on Kaggle
  - 6182 comments, each having a binary label
  - Label depends on whether or not a particular comment insults another user
- Web based system
  - Training data - Reddit
  - Fetch posts from "/r/happy" [1] and "/r/suicidewatch" [2]
  - Prediction data - Twitter
  - Gather tweets from the public streaming API [3]

[1] http://www.reddit.com/r/happy
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[3] https://dev.twitter.com/docs/streaming-apis/streams/public

Data consolidation frequencies

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

Evaluation of algorithms

Approach

- Implement all the models in MATLAB
- Extract n-grams (size upto 2) out of the Kaggle dataset
- Use tf-idf information as feature values
- Input matrix - 6182 rows and 23175 columns
- **SVM**, **Bagging**, **Boosting**, **Stacking** - obtain accuracy (10-fold cross validation) against number of samples
- **SVM** - Growth of number of support vectors with the number of samples
- **Bagging** - Accuracy against number of underlying models
- Start with 100 samples, and continue adding 100 samples in each iteration until no more samples are left

Results

Evaluation of algorithms

Support Vector Machines

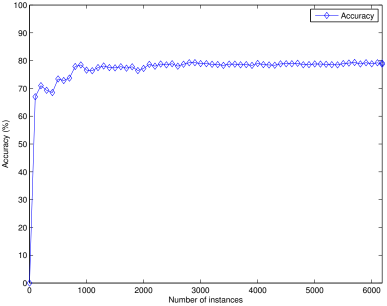

Figure : Accuracy v/s Number of instances

- Linear kernel accuracy - 79.02%
- Polynomial/RBF/Sigmoid kernel accuracy - 34.39%
- Having a large number of features implies less need for a kernel function

Evaluation of algorithms

Support Vector Machines

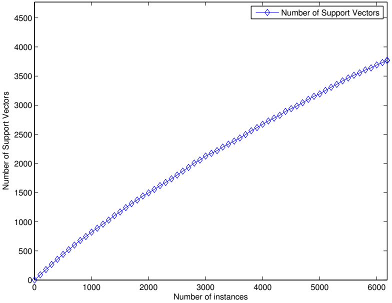

Figure : Number of support vectors v/s Number of instances

- 100 samples - 90% support vectors
- 6182 samples - 60% support vectors
- Less support vectors implies that the classification is easy

Evaluation of algorithms

Bagging

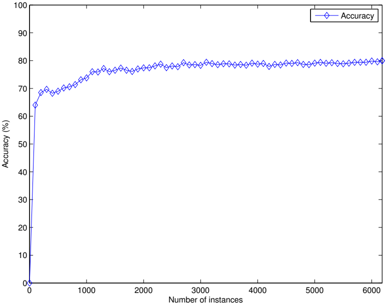

Figure : Accuracy v/s Number of instances

- 9 linear kernel SVMs underneath
- Performance ultimately governed by how SVMs perform
- Average accuracy on all 6182 samples = 79.65%

Bagging

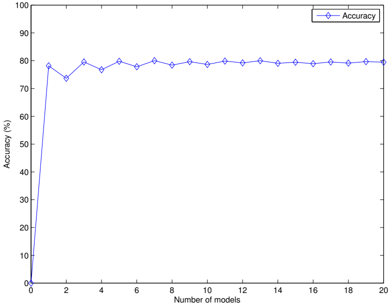

Figure : Accuracy v/s Number of models

- Accuracy "stabilizes" slowly with the number of models
- Each model is trained on a random subset of samples
- Increase in number of models *implies* Subsets overlap *implies* Performance stabilizes

Boosting

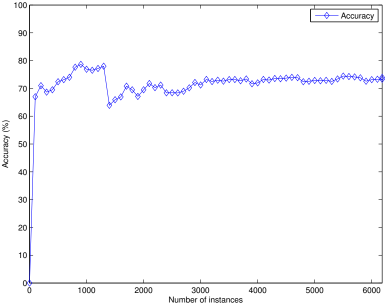

Figure : Accuracy v/s Number of instances

- 9 linear kernel SVMs trained successively on each iteration
- Average accuracy = 72.84%

Stacking

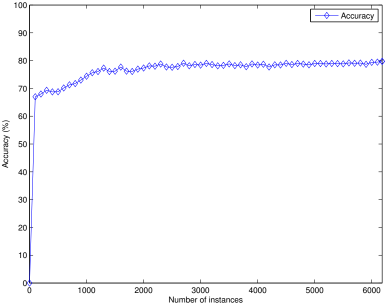

Figure : Accuracy v/s Number of instances

- 9 linear kernel SVMs at first level
- Second level SVM trained using a linear kernel as well
- Average accuracy = 79.48%

Web based system

Approach

- Implement all the models in Python, and web interface in Django
- No training data available => build our own
- Training data
  - Consolidated from Reddit
  - "/r/happy" - users posts their happy moments
  - "/r/suicidewatch" - users post when they want to commit suicide
  - Pull 500 stories from each, every day
- Prediction data
  - Should be the general sentiment of the overall public
  - Hence, pull 100 tweets every 3 hours from Twitter

Web based system

Architecture

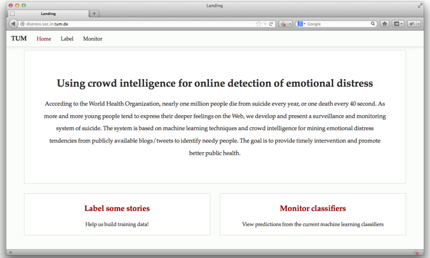

Figure : Landing page

- Two sections - *Ratings* and *Monitoring*
- *Ratings* - used to build the training data
- *Monitoring* - used to monitor the status of the models and check distressed tweets

Ratings module

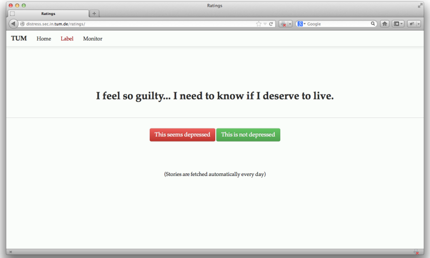

Figure : Landing page of the Ratings module

- Taps into crowd intelligence
- Automated scripts fetch 1000 posts from Reddit every day
- Displays the first unlabelled post
- Users can then assign labels to stories
- This builds the training data

Monitoring module

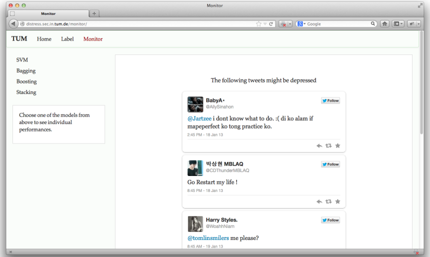

Figure : Landing page of the Monitoring module

- Displays the top few tweets that were classified as depressed by all the classifiers
- Links for checking the status of individual classifiers

Monitoring module

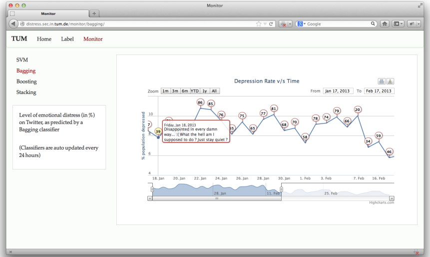

Figure : Statistics of the bagging classifier

For each classifier -

- displays the overall level of distress (in %) on Twitter
- each bubble displays
  - the number of stories that were found depressed on that particular day
  - the first tweet from that day which was depressed (no confidence values, yet)

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

Future Work

- Fetch more tweets
- Increase the crowd intelligence involved
- Relabelling process (decreases wastage of resources)
- Select best performing model
- Store confidence values

Thank you!

Questions?