Utilizing Crowd Intelligence for Online Detection of Emotional Distress

Master's Thesis Presentation

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March 12, 2013

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Introduction

Backdrop

- Millions of people die every year because of suicide
- Most people are between 15 to 29 years old
- Rise of social media - Twitter, Facebook, Reddit, Wordpress
- Reddit - "/r/happy" [1] and "/r/suicidewatch" [2]
- People are not afraid of posting their inner feelings on the web

[1] http://www.reddit.com/r/happy
[2] http://www.reddit.com/r/suicidewatch

Backdrop

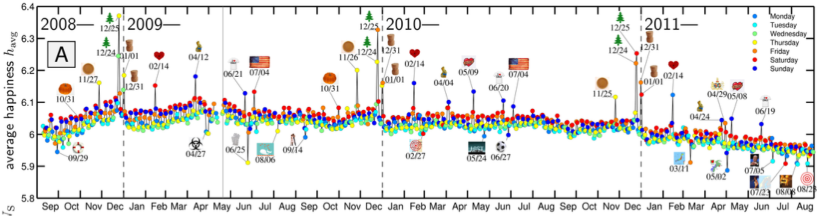

Figure : Happiness on Twitter as a function of time

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

Motivation

Figure : Last tweet of Twitter user "@CapitalSTEEZ_"[3]

- 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

[3] http://twitter.com/CapitalSteez_

Problem Definition

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

Text Classification

- Subset of machine learning algorithms (we focus on supervised text classification)
- Given some pieces of text, put future pieces of text into two or more categories
- Dataset $(\mathbf{x_n}, y_n)_{n=1}^{N}$ containing N instances
- Each instance $(\mathbf{x_n}, y_n)$ is of the form $[(x_{n,1}, x_{n,2}, ..., x_{n,D}), y_n]$
- Supervised learning - calculate y_n of test data given information about y_n from training data
- Unsupervised learning - calculate y_n given only information about $\mathbf{x_n}$

Support Vector Machines

- Fairly popular class of algorithms in binary classification
- Given training data in D dimensional space, find a decision boundary (hyperplane) that separates the two classes
- Maximize the distance of the boundary from any data point
- Decision function depends on a (usually small) subset of points called support vectors
- Distance function between two points is calculated using a kernel function

Linear kernel SVM

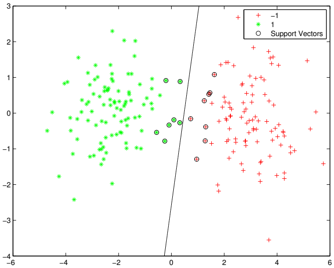

Figure : Classifying two subsets of a dataset using a linear kernel SVM

Kernel functions

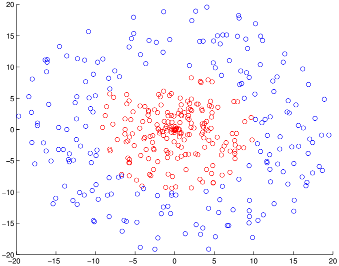

Figure : A dataset that cannot be classified using a linear kernel SVM

Kernel functions

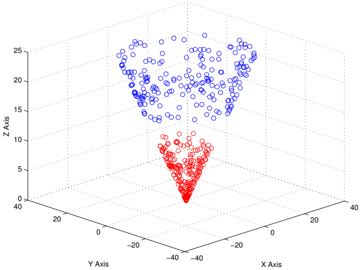

Figure : Add the third dimension as $\sqrt{x_1^2 + x_2^2}$ to transform the dataset into 3D

Ensemble Learning

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

Bagging

- Combine M classifiers to form a single classifier
- To predict, obtain predictions from all constituent classifiers, and take majority vote
- Requirement - classifiers should change for even small changes in underlying classifiers
- Two main approaches for training individual classifiers
  - Sample split - each classifier is trained using a random subset of the samples
  - Feature split - each classifier is trained using a random subset of the features

Boosting

- Assign each sample a weight value (same for all samples in the beginning)
- Train M classifiers successively
- Each classifier focuses more on samples that the previous classifier classified incorrectly
- For each classifier, calculate ϵ (measure of error) and α (decreases with ϵ)
- Final prediction $= \mathrm{sign}(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x_n}))$

Stacking

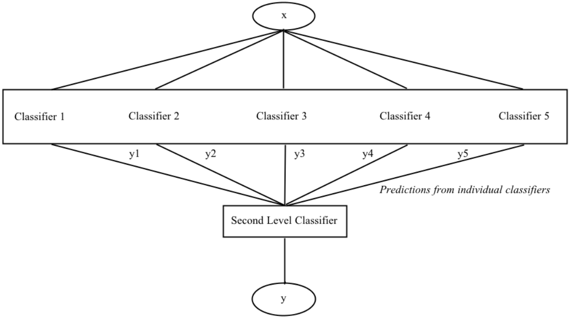

Figure : Prediction using a stacking ensemble

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