Sentiment Knowledge Discovery in Twitter Streaming Data

Albert Bifet and Eibe Frank (2010)

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1. Introduction
2. Methods
3. Results
4. Discussion

Twitter

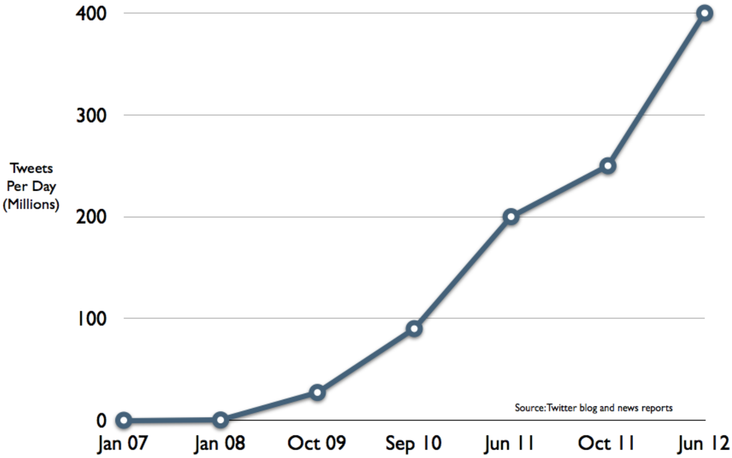
iPhoneAppCafe @iPhoneAppCafe 19m
iOS 6.0.1 jailbreak misery after iOS 6 on **iPhone** 5, 4S - Product Reviews: Product ReviewsiOS 6.0.1 jailbreak mis... bit.ly/Z2gozs
Öffnen

Andreas Heuer @DubaiHeuer 19m
hat ein @runtastic Livetracking gestartet. Schau dir an wo ich bin und feuere mich an. - bit.ly/Uf511r #runtastic #iphone
Öffnen

iStore Balikpapan @iStoreBPN 23m
#iPhone5 iOS 6.0.1 jailbreak misery after iOS 6 on **iPhone** 5, 4S - Product Reviews ow.ly/2t8tJq

- Social networking - microblogging service
- Tweets
  - up to 140 characters long text message
  - **@runtastic**: user name
  - **#iPhone**: subject or category
  - **RT** *I like my iPhone*: retweet - repetition of tweet

Twitter: Tweets per day



Source: Twitter blog and news reports

Twitter: Statistics

Statistics

- More than 140 mil users
- More than 400 mil tweets per day
- Exponential growth

Makes Twitter attractive for

- Companies
- Politicians
- **Data mining**

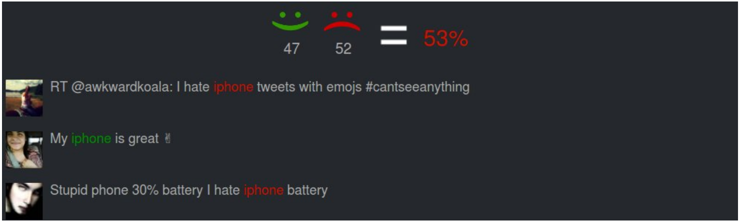
Sentiment analysis

Definition (Sentiment analysis)

- Given a tweet
- Predict its sentiment
  - positive
  - (neutral)
  - negative

Twitter sentiment analysis

- sentiment140.com
- tweetfeel.com
- tweettone.com



RT @awkwardkoala: I hate iphone tweets with emojs #cantseeanything

My iphone is great ✌

Stupid phone 30% battery I hate iphone battery

Challenges learning from Twitter streams

- Twitter API provides access to all tweets
- Incremental learning instead of Batch learning required

1. **Time efficiency**: samples arrive with high rate
2. **Memory efficiency**: infinite training set
3. **Concept drift**: sentiments change dynamically
4. **Evaluation**: concept drift and unbalanced classes

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Classification

Problem description

- **Given**: training set $\left\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\right\}$
  - $x^{(i)}$: data (unigram, bigram)
  - $y^{(i)}$: class ($y^{(i)} = +1$: positive, $y^{(i)} = -1$: negative)
- **Wanted**: hypothesis $h_\theta(x) \rightarrow y$
  - minimizes some cost function $J(\theta)$

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Models for sentiment classification

- Naïve Bayes
- SVM
- Hoeffding tree
- Logistic regression
- ...

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Models for sentiment classification

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Naïve Bayes

Prediction

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} \propto \prod_{j=1}^{n} P(w_j|y)^{x_j} P(y)$$

$$h_\theta(x) = \text{argmax}_{y'} P(y'|x)$$

Training

$P(w_j\|y)$	Prob. of word w_j in tweet with sentiment y
$P(y)$	Prior prob. of sentiment y

- Can be easily approximated by the relative frequency
- Count word w_j sentiment y
- ⇒ Simple incremental implementation

Batch Gradient Descent

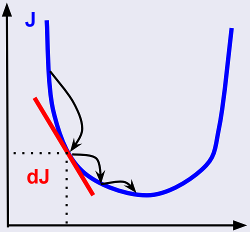
Idea

- Minimize cost function $J(\theta) = \sum_{i=1}^{m} l(x^{(i)}, y^{(i)}, \theta)$
- Go into direction of steepest descent $\nabla J(\theta)$

Algorithm

- Initialize θ^0 randomly
- Loop until convergence:

$$\theta^{t+1} = \theta^t - \alpha \nabla J(\theta^t)$$
$$= \theta^t - \alpha \sum_{i=1}^{m} \nabla l(x^{(i)}, y^{(i)}, \theta^t)$$



Stochastic Gradient Descent

Idea

- Compute gradient of a single random sample
- More efficient than Batch Gradient Descent

Algorithm

- Initialize θ^0 randomly
- Loop until convergence:
  - Shuffle training set randomly
  - for $i = 1$ to m

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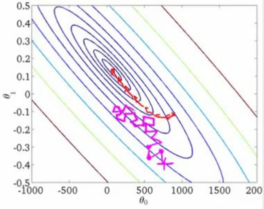

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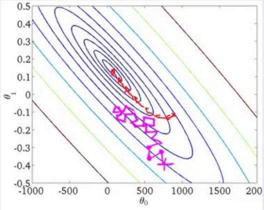


$\Rightarrow$ Simple incremental update for new $(x^{(i)}, y^{(i)})$

SVM: Support Vector Machine

Prediction

Given weight vector θ

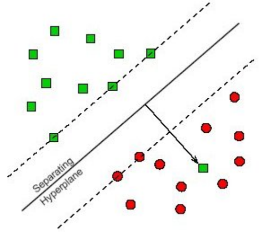
$$h_\theta(x) = \begin{cases} +1 & \theta^T x \geq 0 \\ -1 & \theta^T x < 0 \end{cases}$$

Training

- Hinge loss function:

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} max \left\{ 1 - y^{(i)} \theta^T x^{(i)}, 0 \right\}$$

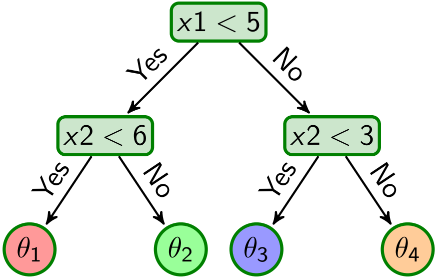
- θ can be updated incrementally via SGD

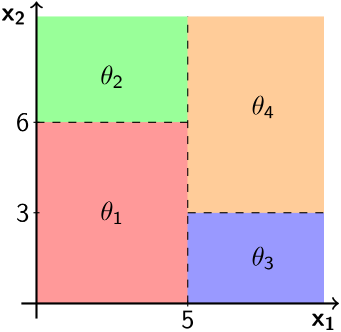


Hoeffding Tree

Prediction

- Each node tests an attribute
- Each edge refers to an attribute value
- $h_\theta(x) =$ *'label y of leaf to which x is assigned to'*





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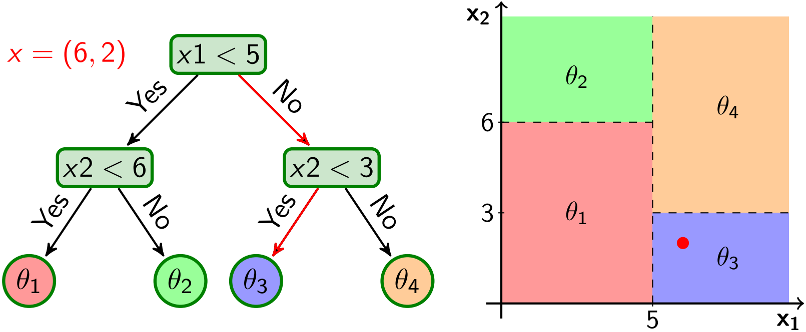
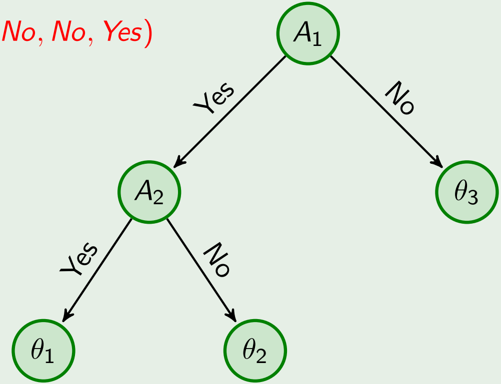


Hoeffding Tree

Incremental tree induction

Top-down model tree induction

$x = (No, No, Yes)$



Hoeffding Tree

Incremental tree induction

1. Assign (x, y) to leaf

Top-down model tree induction

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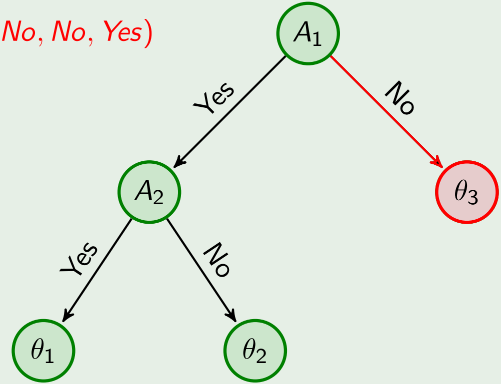

Hoeffding Tree

Incremental tree induction

1. Assign (x, y) to leaf
2. Use Hoeffding bound as split criterion

Top-down model tree induction

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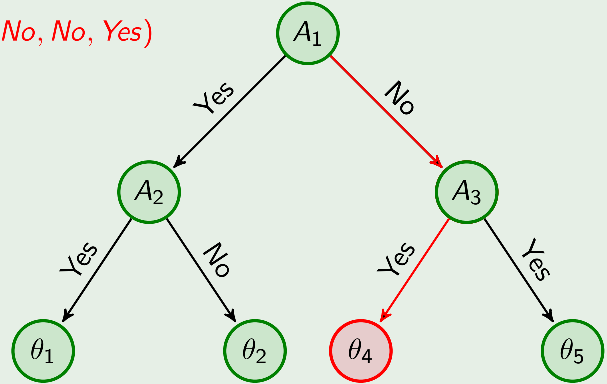

Hoeffding Tree

Incremental tree induction

1. Assign (x, y) to leaf
2. Use Hoeffding bound as split criterion

$$\Delta G = G(X_a) - G(X_b) > \epsilon$$

$$\epsilon = \ln \sqrt{\frac{R^2 ln(1/\alpha)}{2n}}$$

$\Rightarrow$ **Hypothesis testing with significance level** α

Labeling tweets

Question

How to label millions of tweets?

Labeling tweets

Question

How to label millions of tweets?

Answer

Emoticons :-)

Positive sentiment

- $x =$ '*I love my iPhone more than my girlfriend* **:-)**'
- $y = +1$

Negative sentiment

- $x =$ '*My iPhone is broken* **:-(**'
- $y = -1$

Data preparation (Go et al., sentiment140.com)

1. Retrieve tweets via Twitter API
2. Discard tweets without emoticons
3. Define $y = +1/-1$ with positive/negative emoticon
4. Feature reduction
    - Remove emoticons
    - @john → USER
    - www.google.com → URL
    - heeeello → hello
5. Define x with unigrams/bigrams

Training and Test set

Holdout validation

Prequential / Interleaved test-then-train

Training and Test set

Holdout validation

1. Divide data into training set (60%) and test set (40%)
2. Train model on training set
3. Measure performance on test set

⇒ Static test set

Prequential / Interleaved test-then-train

Training and Test set

Holdout validation

1. Divide data into training set (60%) and test set (40%)
2. Train model on training set
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⇒ Static test set

Prequential / Interleaved test-then-train

New sample (x, y) arrives...

1. Test $h_\theta(x) \overset{?}{=} y$ and update performance metric
2. Update θ with (x, y)

⇒ Dynamic test set

Accuracy

$$\begin{array}{cc|c|c|c|c}
 & & \multicolumn{3}{c}{f(x)} & \\
 & & 1 & \cdots & L & \\
\hline
 & 1 & o_{1,1} & \cdots & o_{1,L} & r_1 \\
\hline
h_\theta(x) & \vdots & \vdots & \ddots & \vdots & \vdots \\
\hline
 & L & o_{L,1} & \cdots & o_{L,L} & r_L \\
\hline
 & & c_1 & \cdots & c_L & m
\end{array}$$

Definition (Accuracy)

$$p_0 = \frac{1}{m} \sum_{i=1}^{L} o_{i,i}$$

$\Rightarrow$ Fraction of correct predictions

Accuracy

Unbalanced classes

- Unbalanced (skewed) class distribution
- Can lead to high accuracy

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Cancer prediction

- $y = -1$: person has no cancer (99%)
- $y = +1$: person has cancer (1%)

- $h_\theta(x) = -1$, i.e. predict always *no cancer*
- $\Rightarrow p_0 = 99\%$

κ statistic (Cohen, 1960)

Definition (*kappa* statistic)

$$\frac{r_i}{m} = \text{predicted frequency of class } i$$

$$\frac{c_i}{m} = \text{actual frequency of class } i$$

$$p_c = \sum_{i=1}^{L} \frac{r_i}{m} \frac{c_i}{m} = \text{probability of being correct by chance}$$

$$\kappa = \frac{p_0 - p_c}{1 - p_c}$$

κ: accuracy relative to change prediction

- $p_o = p_c \to \kappa = 0$
- $p_o = 1 \to \kappa = 1$

κ statistic

Cancer prediction

- $y = -1$: person has no cancer (99%)
- $y = +1$: person has cancer (1%)

- $h_\theta(x) = -1$, i.e. predict always *no cancer*
- $p_0 = 0.99$
- $p_c = 1.00 * 0.99 + 0.00 * 0.01 = 0.99$
- $\Rightarrow \kappa = \frac{p_0 - p_c}{1 - p_c} = 0.0$

κ statistic

Incremental update

Variables

Only $2L + 1$ variables

- r_i, c_i for $i = 1, ..., L$: row, column sums
- p_0: accuracy

Can be updated incrementally for a new (x, y)

Only consider most recent samples

- **Sliding window**: store last w samples
- **Fading factors**: down weight older samples

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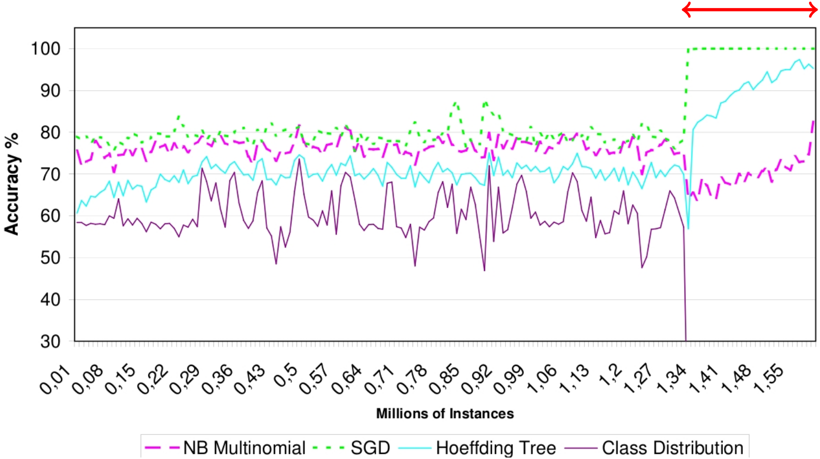
Training sets

- sentiment140.com (Go et al.)
    - 800.000 positive tweets
    - 800.000 negative tweets
    - Balanced classes - not representative
- Edinburgh corpus
    - 1.800.000 positive tweets
    - 325.000 negative tweets
    - Unbalanced classes - representative

sentiment140.com

Accuracy

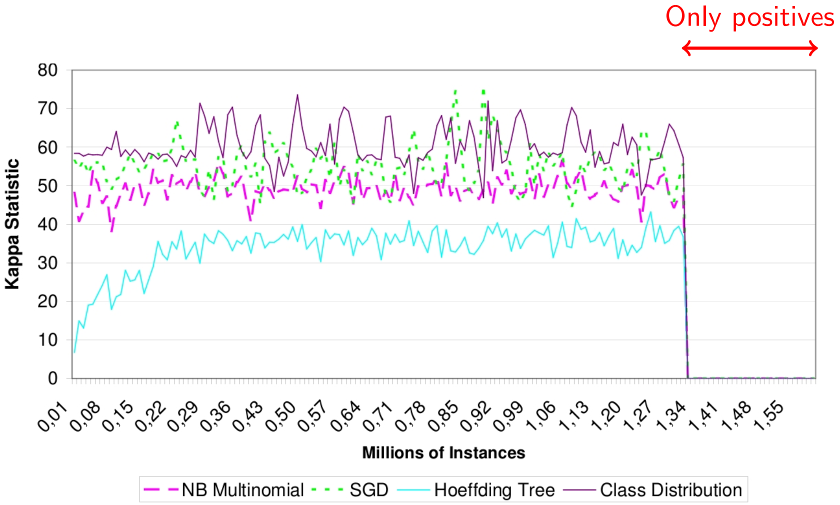


Only positives

⇒ **High accuracy for unbalances classes**

sentiment140.com

κ statistic



$\Rightarrow$ κ **statistic detects unbalanced classes**

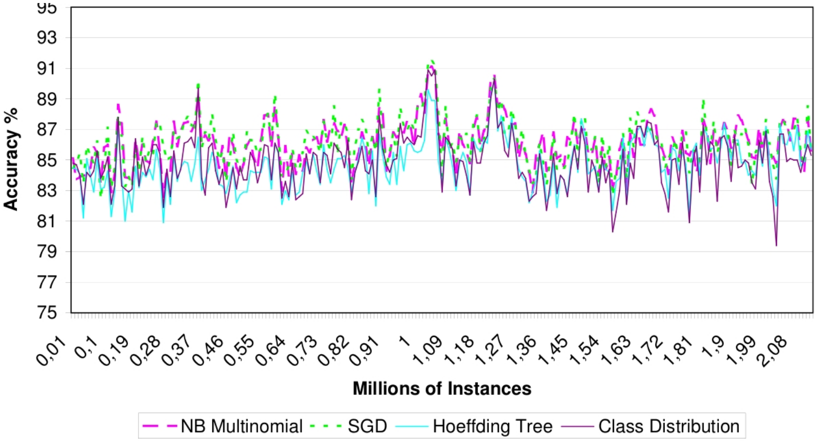
sentiment140.com

		Accuracy	κ	Time
1	SGD	86.80%	62.60%	219.54 sec.
2	Naïve Bayes	75.05%	50.10%	116.62, sec.
3	Hoeffding Tree	73.11%	46.23%	5525.51 sec.

- SGD scores best (Accuracy, κ)
- Hoeffding tree scores worst (Accuracy, κ, Time)

Edinburgh corpus

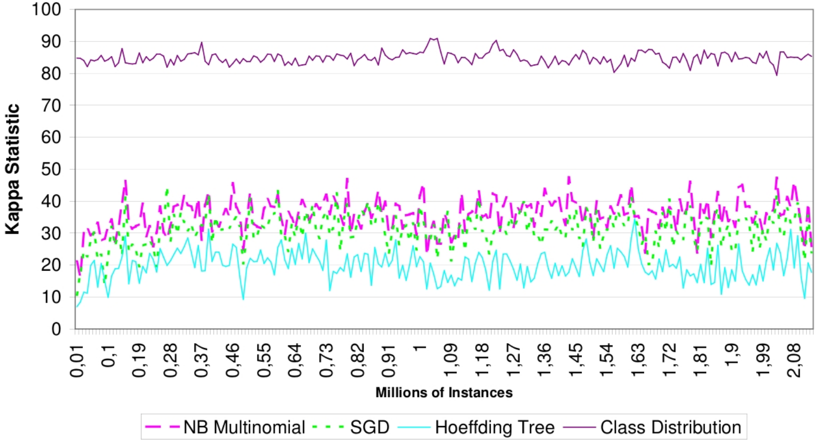
Accuracy



⇒ **Similar accuracy**

Edinburgh corpus

κ statistic



$\Rightarrow$ κ **discriminates better**

Edinburgh corpus

		Accuracy	κ	Time
1	Naïve Bayes	86.11%	36.15%	173.28, sec.
2	SGD	86.26%	31.88%	293.98 sec.
3	Hoeffding Tree	84.76%	20.40%	6151.51 sec.

- Naïve Bayes scores best (κ, Time)
- Hoeffding tree scores worst (Accuracy, κ, Time)
- κ lower than sentiment140.com due to unbalanced classes

Changing feature weights

Tag	Middle	End	Variance
apple	0.3	0.7	0.4
microsoft	-0.4	-0.1	0.3
facebook	-0.3	0.4	0.7
mcdonalds	0.5	0.1	-0.4
google	0.3	0.6	0.3
disney	0.0	0.0	0.0
bmw	0.0	-0.2	-0.2
pepsi	0.1	-0.6	-0.7
dell	0.2	0.0	-0.2
gucci	-0.4	0.6	1.0
amazon	-0.1	-0.4	-0.3

- High weight: more frequent in positive tweets
- Low weight: more frequent in negative tweets

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κ statistic

Pros

- Suitable for unbalanced classes
- Simple computation
- Suitable for incremental learning

Cons

- Independence assumption for computing p_c often invalid
- Conservative estimate

Furture improvements

- Additional features
    - Emoticons
    - Number of friends/followers
- Different languages
- Neural sentiments (three classes)
- Semantics
    - Foo beats Bar
    - Bar beats Foo

Sources

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Twitter Sentiment Classification using Distant Supervision.

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J. Cohen (1960)
A coefficient of agreement for nominal scales.