Sentiment Classification using ML Techniques

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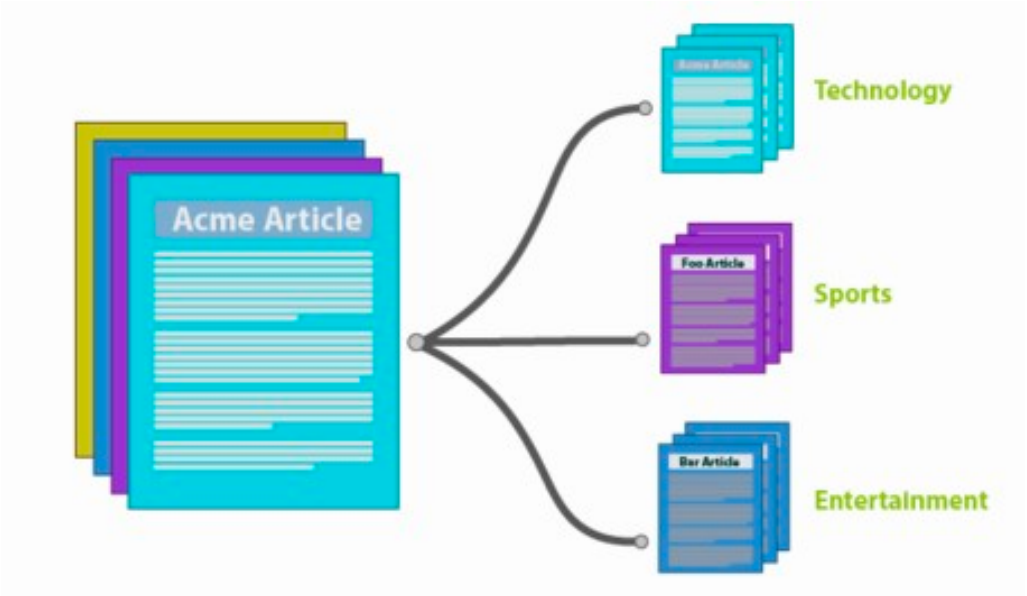
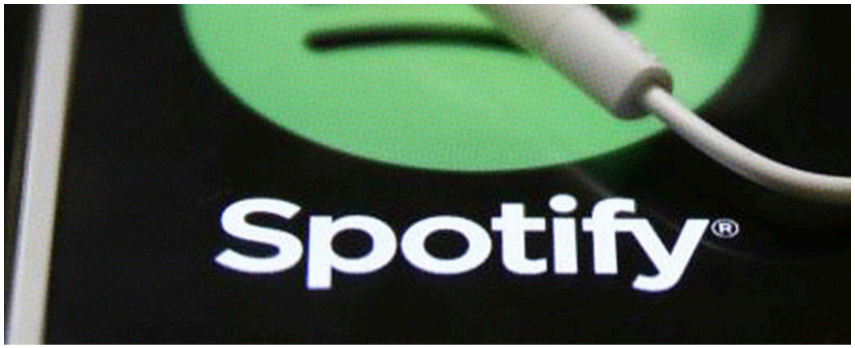
Background

- Back in 2002, when there was no Twitter
- Classify by topic vs Classify by sentiment



Background

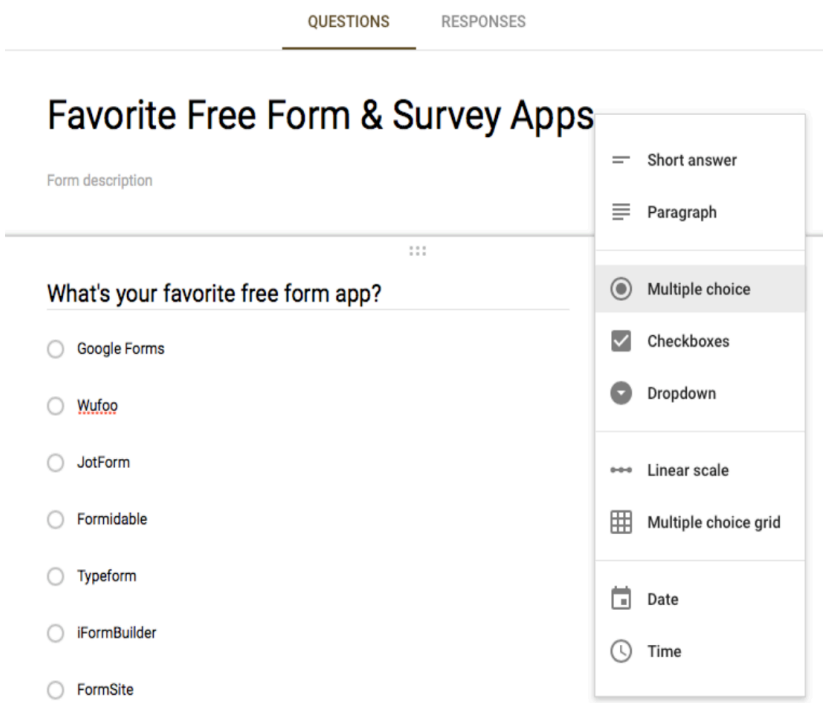
- Classify by sentiment



Spotify's Discover Weekly: How machine learning finds your new music

The science behind personalized music recommendations

This Monday—just like every Monday— over 100 million Spotify users found a fresh new playlist waiting for them. It's a custom mixtape of 30 songs they've never listened to before but will probably love. It's called Discover Weekly, and it's pretty much magic.



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Goal of the paper

Examine the effectiveness of applying ML to sentiment classification problem, in order to understand the inherent difficulty of the task.

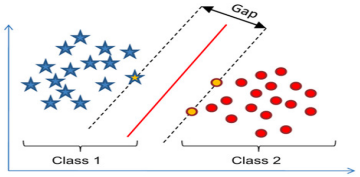
Naïve Bayes

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

Maximum Entropy

$$H(p) = -\sum p(a,b) log p(a,b)$$

SVM



Human

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Challenge

- **express negation without using negative word**

  "How could anyone sit through this presentation?"

  Contains no single word that is obviously negative.

- **Thwarted expectations**

  "Okay, I'm really ashamed of it, but I enjoyed it. I mean, I admit it's a really awful movie ...the ninth floor of hell...The plot is such a mess that it's terrible. But I loved it."

  Sets up a deliberate contrast to earlier discussion.

Sentiment requires more understanding than the usual topic-based classifications

Model

Data Source

- Internet Movie Database(IMDb)
- Select only reviews where the author rating was expressed either with stars or some numerical value. Suitable for our supervised machine learning model
- Ratings are extracted and converted into one of three categories: positive, negative or neutral
- Use corpus of 752 negative and 1301 positive reviews as training set, and 700 positive and 700 negative reviews as test set
- Data set available on http://www.cs.cornell.edu/people/pabo/movie-review-data/

Model

Baseline model

Baseline 1: random choose

- Accuracy 50%

Baseline 2: human classifier

- Ask 2 students to independently choose good indicator words for positive and negative sentiments in movie reviews
- Count the number of the proposed positive and negative words in a given document, to determine the class of the document

	Proposed word lists	Accuracy	Ties
Human 1	positive: *dazzling, brilliant, phenomenal, excellent, fantastic* negative: *suck, terrible, awful, unwatchable, hideous*	58%	75%
Human 2	positive: *gripping, mesmerizing, riveting, spectacular, cool, awesome, thrilling, badass, excellent, moving, exciting* negative: *bad, cliched, sucks, boring, stupid, slow*	64%	39%

Model

Naïve Bayes

Bag-of-feature framework

- $\{f_1,...,f_m\}$ a predefined set of m features; unigram like “still”, bigram like “really stinks”
- $n_i(d)$ the number of times f_i occurs in document d
- $\vec{d} = (n_1(d), n_2(d), ..., n_m(d))$ document vector

Bayes framework

- Given a document, choose the class that can maximize the posterior probability $p(c|d)$
- Bayes formula: $p(c|d) = \frac{p(c)p(d|c)}{p(d)}$
  where

  $p(c)$ frequency of each class in the training set; prior probability

  $p(d|c) = p(f_1,...,f_m|c)$ given a class, the probability to have features

  Naïve Bayes assumption: $p(d|c) = p(f_1|c) \bullet p(f_2|c) \bullet ... \bullet p(f_m|c)$

  $p(d|c)$ measure the contribution of each feature to the class; likelihood

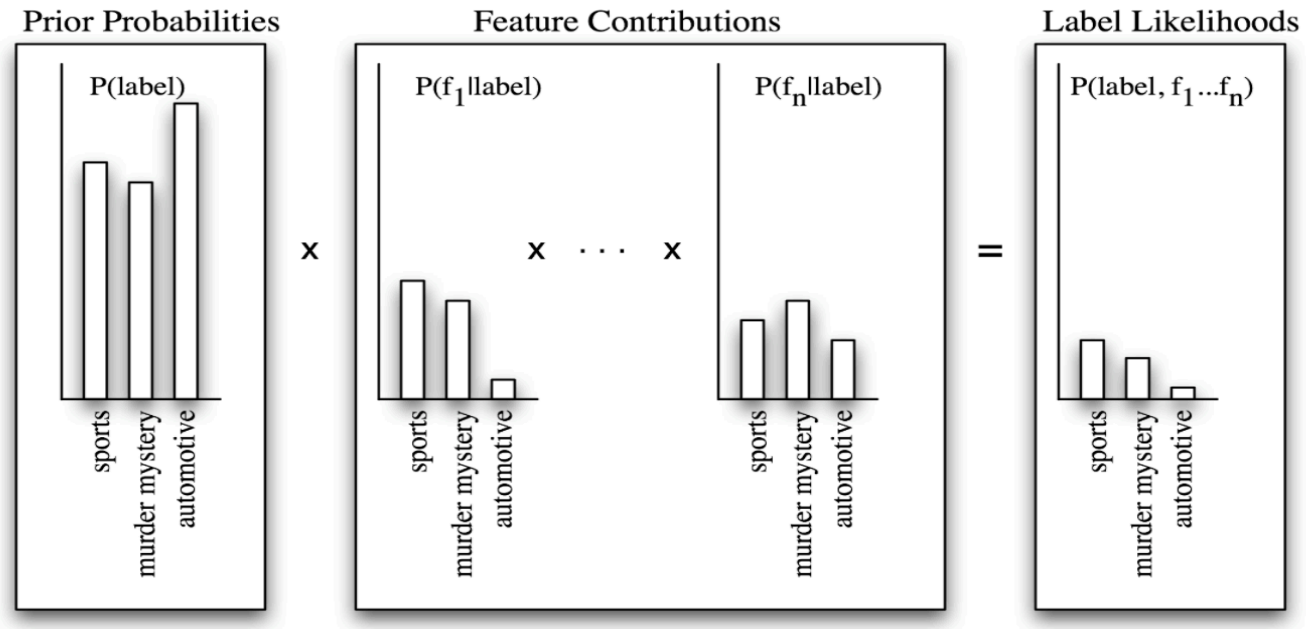
  $p(d)$ the same for every choice of class, does not affect decision; ignore it

Model

Naïve Bayes

- The problem reduces to find the class that maximize

$$p(c) \bullet p(d \mid c)$$
$$= p(c) \bullet p(f_1 \mid c) \bullet p(f_2 \mid c) \bullet \ldots \bullet p(f_m \mid c)$$



Model

Naïve Bayes: a simple example

Let's say we have counted the number of words in a set of labeled training documents. In this set each text document has been labeled as either Positive, Neutral or as Negative. The result will then look like:

Word	Positive Class	Neutral Class	Negative Class	Total
lame	10	20	70	**100**
awesome	70	20	10	**100**
this	50	500	50	**600**
Is	100	600	100	**800**
blog-post	10	90	10	**100**
Total	**240**	**1.230**	**240**	**1.700**

"This blog-post is awesome."

Test set

Model

Naïve Bayes: a simple example

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"This blog-post is awesome."

Class probability

$$P(C_{pos}) = 0.141,$$
$$P(C_{neu}) = 0.723,$$
$$P(C_{neg}) = 0.141.$$

Posterior probability

$$P(C_{pos}) = 0.141 \cdot 50/240 \cdot 10/240 \cdot 100/240 \cdot 70/240 = 1.49 \cdot 10^{-3}$$
$$P(C_{neu}) = 0.723 \cdot 500/1230 \cdot 90/1230 \cdot 600/1230 \cdot 20/1230 = 1.71 \cdot 10^{-4}$$
$$P(C_{neg}) = 0.141 \cdot 50/240 \cdot 10/240 \cdot 100/240 \cdot 10/240 = 2.12 \cdot 10^{-4}$$

Decision

- classified in the positive category

Model

Maximum Entropy

Similar to Naïve Bayes

- Also estimate $p(c|d)$
- The probability that a document belongs to a particular class given a context must maximize the entropy of the classification system
- Distribution should be as uniform as possible; maximize uncertainty of event

ME Framework

- Entropy is measured by $H(p) = -\sum p(a,b) log p(a,b)$

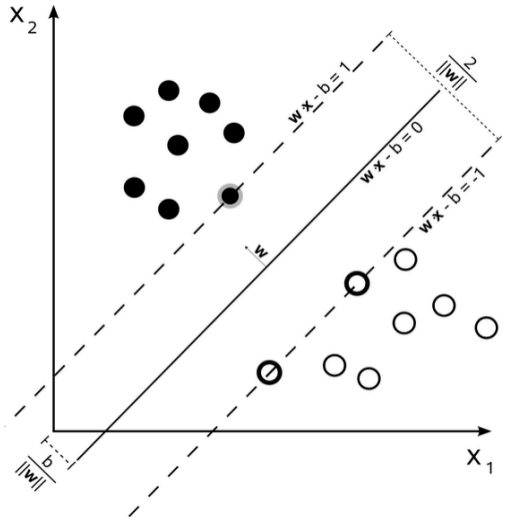
  In our document classification case, it can be shown that the probability distribution has an exponential form: $P(c|d) = \frac{1}{Z(d)} exp(\sum_i \lambda_i f_i(d,c))$

  where $f_i(d,c)$ is a feature function, λ_i is the weight parameter of the feature function and $Z(d)$ is a normalization factor given by $Z(d) = \sum_c exp(\sum_i \lambda_i f_i(d,c))$
- Use Improved Iterative Scaling algorithm to train the model; essentially a gradient descent
- Choose the class that maximize $p(c|d)$

Model

Support Vector Machine

- The SVM tries to find a hyperplane that separates the document vectors in one class from the other as optimally as possible. Here as optimally as possible means that it maximizes the margin between two classes.



- This hyperplane is given by $\langle \vec{\omega} \bullet \vec{d} \rangle + b = 0$; $\vec{\omega}$ is the weight factor defining the hyperplane
- Use the optimization to find the $\vec{\omega}$
- Test data: if $\langle \vec{\omega} \bullet \vec{d} \rangle + b \geq 0$, then the document belongs to positive class.

Compare result

	Features	NB	ME	SVM
(1)	unigrams	81.0	80.4	**82.9**
(2)	bigrams	77.3	**77.4**	77.1
(3)	unigrams + position	81.0	80.1	**81.6**

For Unigrams

- Machine learning algorithms clearly surpass the random-choice baseline of 50%
- Also beat the human-selected-unigram baselines of 58% and 64%
- The topic-based classification utilizing same ML achieve accuracy of 90%

For Bigrams

- Bigrams are not effective in our setting

Position

- Adding position of word information does not help

Conclusion

- The result produced via ML techniques are quite good in comparison to the human-generated baselines
- In terms of relative performance, Naïve Bayes tends to do the worst and SVM tend to do the best, although the differences aren't very large
- On the other hand, we were not able to achieve accuracies on the sentiment classification problem comparable to those reported for topic-based categorization
- Other models like Logistic Regression, Neural Networks and Hidden Markov Models can be used