

COM6115: Text Processing

Sentiment Analysis: Approaches and Evaluation

Chenghua Lin

Department of Computer Science
University of Sheffield

- Definition of the problem of sentiment analysis
- **Approaches to sentiment analysis**
- **Evaluation of sentiment analysis approaches**

Two approaches to SA

- Lexicon-based
 - ◊ Binary
 - ◊ Gradable
- **Corpus-based (machine learning)**

By the end of the SA sessions, you will be able to:

- Explain the relevance of the topic
- Differentiate between objective and subjective texts
- List the main elements in a sentiment analysis system
- Provide a critical summary of the main approaches for the problem
- Explain how sentiment analysis systems are evaluated.

*All models are wrong
but some are useful*



George E.P. Box

Two Event Models for Naive Bayes

- Today we learn about Naïve Bayes classifier:
 - ◊ How to turn Bayes rule into a classifier
 - ◊ A supervised probabilistic model of the observed data
 - ◊ Can be used to predict the class label of new/unseen data
- Multi-variate Bernoulli Model: a document is a binary vector over the space of words
- Multinomial Model: captures word frequency information in documents

Two Event Models for Naive Bayes

A Comparison of Event Models for Naive Bayes Text Classification

Andrew McCallum^{††}
mccallum@justresearch.com

[†]Just Research
4616 Henry Street
Pittsburgh, PA 15213

Kamal Nigam[†]
knigam@cs.cmu.edu

[†]School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213

Abstract

Recent approaches to text classification have used two different first-order probabilistic models for classification, both of which make the *naive Bayes assumption*. Some use a multi-variate Bernoulli model, that is, a Bayesian Network with no dependencies between words and binary word features (*e.g.* Larkey and Croft 1996; Koller and Sahami 1997). Others use a multinomial model, that is, a generalized Bayesian model with integer

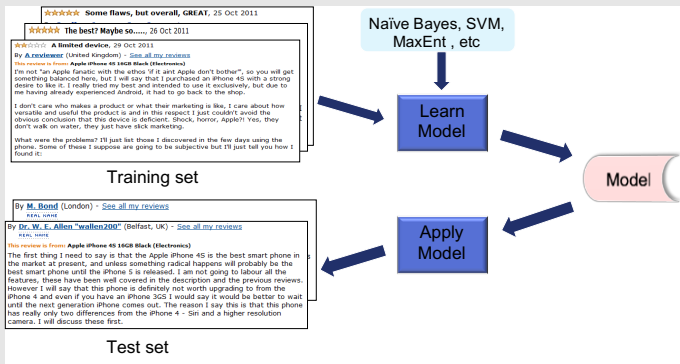
learning, especially when the number of attributes is large.

Document classification is just such a domain with a large number of attributes. The attributes of the examples to be classified are words, and the number of different words can be quite large indeed. While some simple document classification tasks can be accurately performed with vocabulary sizes less than one hundred, many complex tasks on real-world data, from

Supervised Classification

- **Supervised learning:** the machine learning task of inferring a function from labeled training data
- Given:
 - ◇ **Target:** a fixed set of **classes**: $Y = y_1, y_2, \dots, y_n$, e.g. {sports, politics, ..., music}
 - ◇ **Training data:** a collection of data objects X with known classes Y , i.e. $(X, Y) = (x_1, y_1), (x_2, y_2) \dots (x_n, y_n)$. E.g {(d1, sports), (d2, sports), (d3, music) ... }.
 - ◇ **Testing data:** a description of an unseen instance, D_{new} e.g. a new document without class label information
- Goal:
 - ◇ Predict the category/class of $D_{new} : y(x) \in Y$, where $y(x)$ is a *classification function*, aka *trained model*, whose domain is X and whose range is Y .

Supervised Classifier



- Rely on syntactic or co-occurrence patterns in large text corpora

The Bayes Rule

The diagram shows the Bayes' Rule formula:
$$p(Y | X_1, \dots, X_n) = \frac{P(X_1, \dots, X_n | Y)P(Y)}{P(X_1, \dots, X_n)}$$
 The formula is enclosed in an orange rectangular box. Four labels with arrows point to parts of the formula: 'Posterior' (blue) points to the left side of the equation; 'Likelihood' (blue) points to the numerator's first term; 'Prior' (purple) points to the numerator's second term; and 'Normalization Constant' (green) points to the denominator.

- $P(Y)$: Prior belief (probability of hypothesis Y before seeing any data)
- $P(X_1, \dots, X_n | Y)$: Likelihood (probability of the data if the hypothesis Y is true)
- $P(X_1, \dots, X_n)$: Data evidence (marginal probability of data)
- $P(Y | X_1, \dots, X_n)$: Posterior (probability of hypothesis Y after having seen the data)

The Independence Assumption

- Assume A and B are Boolean Random variables. Then

“ A and B are independent”

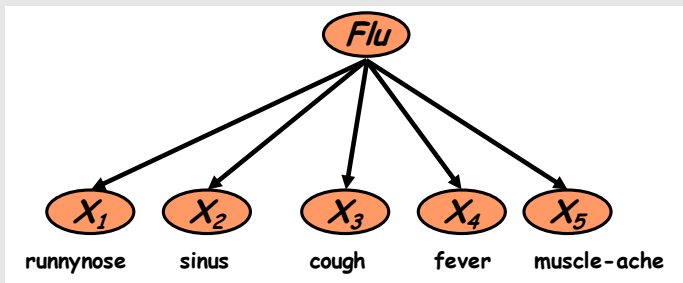
if and only if

$$P(A|B) = P(A)$$

“ A and B are independent” is often notated as

$$A \perp B$$

The Independence Assumption



- Features (term presence) are *independent* of each other given the class:

$$P(X_1, \dots, X_5|Y) = P(X_1|Y) \bullet P(X_2|Y) \bullet \dots \bullet P(X_5|Y)$$

Naive Bayes classifier: estimate the probability of each class given a text:

- Compute the posterior probability (Bayes rule) of each class c_i for text segment T

$$P(c_i|T) = \frac{P(T|c_i)P(c_i)}{P(T)}$$

- Assumption of independence between features (“naive” assumption)

$$P(T|c_i) = P(t_1, t_2, \dots, t_j|c_i) \approx \prod_{j=1}^n P(t_j|c_i)$$

where T is described by a number of attributes or features t_1, \dots, t_j

I.e. joint probability of the features given the class is approximated by the product of the probabilities of each feature given the class.

A corpus-based approach to SA - Machine Learning

A Naive Bayes classifier (ctd)

- **Likelihood:** product of probabilities of each feature value of segment occurring with class c_i

$$\prod_{j=1}^n P(t_j|c_i)$$

- **Prior:** probability of segment having class c_i

$$P(c_i)$$

- **Evidence:** product of probabilities of features of segment – **constant term for all classes, so can be disregarded:**

$$\prod_{j=1}^n P(t_j)$$

Final decision:

$$\operatorname{argmax}_{c_i} \prod_{j=1}^n P(t_j|c_i) P(c_i) = \operatorname{argmax}_{c_i} P(c_i) \prod_{j=1}^n P(t_j|c_i)$$

A corpus-based approach to SA - Machine Learning

A Naive Bayes classifier - a worked out example

- Corpus of movie reviews: 7 examples for **training**

Doc	Words	Class
1	Great movie, excellent plot, renowned actors	Positive
2	I had not seen a fantastic plot like this in good 5 years. Amazing!!!	Positive
3	Lovely plot, amazing cast, somehow I am in love with the bad guy	Positive
4	Bad movie with great cast, but very poor plot and unimaginative ending	Negative
5	I hate this film, it has nothing original	Negative
6	Great movie, but not...	Negative
7	Very bad movie, I have no words to express how I dislike it	Negative

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A Naive Bayes classifier - a worked out example (ctd)

- **Features:** adjectives (bag-of-words)

Doc	Words	Class
1	Great movie, excellent plot, renowned actors	Positive
2	I had not seen a fantastic plot like this in good 5 years. amazing !!!	Positive
3	Lovely plot, amazing cast, somehow I am in love with the bad guy	Positive
4	Bad movie with great cast, but very poor plot and unimaginative ending	Negative
5	I hate this film, it has nothing original. Really bad	Negative
6	Great movie, but not...	Negative
7	Very bad movie, I have no words to express how I dislike it	Negative

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Relative frequency in corpus is the simplest approach to estimating probabilities:

Priors:

$$P(\textit{positive}) = \textit{count}(\textit{positive})/N = 3/7 = 0.43$$

$$P(\textit{negative}) = \textit{count}(\textit{negative})/N = 4/7 = 0.57$$

where N = total training examples

Assume standard pre-processing: tokenisation, lowercasing, punctuation removal (except special punctuation like !!!)

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Likelihoods:

$$P(t_j|c_i) = \frac{\text{count}(t_j, c_i)}{\text{count}(c_i)}$$

Count word t_j in class c_i / total words in that class

$P(\text{amazing} \text{positive})$	$= 2/10$	$P(\text{amazing} \text{negative})$	$= 0/8$
$P(\text{bad} \text{positive})$	$= 1/10$	$P(\text{bad} \text{negative})$	$= 3/8$
$P(\text{excellent} \text{positive})$	$= 1/10$	$P(\text{excellent} \text{negative})$	$= 0/8$
$P(\text{fantastic} \text{positive})$	$= 1/10$	$P(\text{fantastic} \text{negative})$	$= 0/8$
$P(\text{good} \text{positive})$	$= 1/10$	$P(\text{good} \text{negative})$	$= 0/8$
$P(\text{great} \text{positive})$	$= 1/10$	$P(\text{great} \text{negative})$	$= 2/8$
$P(\text{lovely} \text{positive})$	$= 1/10$	$P(\text{lovely} \text{negative})$	$= 0/8$
$P(\text{original} \text{positive})$	$= 0/10$	$P(\text{original} \text{negative})$	$= 1/8$
$P(\text{poor} \text{positive})$	$= 0/10$	$P(\text{poor} \text{negative})$	$= 1/8$
$P(\text{renowned} \text{positive})$	$= 1/10$	$P(\text{renowned} \text{negative})$	$= 0/8$
$P(\text{unimaginative} \text{positive})$	$= 0/10$	$P(\text{unimaginative} \text{negative})$	$= 1/8$
$P(!!! \text{positive})$	$= 1/10$	$P(!!! \text{negative})$	$= 0/8$

A corpus-based approach to SA - Machine Learning

- Relative frequencies for prior ($P(c_i)$) and likelihood ($P(t_j|c_i)$) make the **model** in a Naive Bayes classifier.
- At decision (test) time, given a new segment to classify, this model is applied to find the most likely class for the segment:

$$\operatorname{argmax}_{c_i} P(c_i) \prod_{j=1}^n P(t_j|c_i)$$

A corpus-based approach to SA - Machine Learning

Given a new segment to classify (**test time**):

Doc	Words	Class
8	This was a fantastic story, good, lovely	???

Final decision

$$\operatorname{argmax}_{c_i} P(c_i) \prod_{j=1}^n P(t_j | c_i)$$

$$P(\text{positive}) * P(\text{fantastic} | \text{positive}) * P(\text{good} | \text{positive}) * P(\text{lovely} | \text{positive})$$

$$3/7 * 1/10 * 1/10 * 1/10 = 0.00043$$

$$P(\text{negative}) * P(\text{fantastic} | \text{negative}) * P(\text{good} | \text{negative}) * P(\text{lovely} | \text{negative})$$

$$4/7 * 0/8 * 0/8 * 0/8 = 0$$

So: sentiment = positive

A corpus-based approach to SA - Machine Learning

What if the new segment to classify (**test time**) is:

Doc	Words	Class
10	Lovely plot, excellent cast, amazing everything	???

Final decision

$$P(\text{positive}) * P(\text{lovely}|\text{positive}) * P(\text{excellent}|\text{positive}) * P(\text{amazing}|\text{positive})$$

$$3/7 * 1/10 * 1/10 * 1/10 = 0.00043$$

$$P(\text{negative}) * P(\text{lovely}|\text{negative}) * P(\text{excellent}|\text{negative}) * P(\text{amazing}|\text{negative})$$

$$4/7 * 0/8 * 0/8 * 0/8 = 0$$

So: *sentiment = positive*

A corpus-based approach to SA - Machine Learning

Given a new segment to classify (**test time**):

Doc	Words	Class
9	Great plot, great cast, great everything	???

Final decision

$$P(\text{positive}) * P(\text{great}|\text{positive}) * P(\text{great}|\text{positive}) * P(\text{great}|\text{positive})$$

$$3/7 * 1/10 * 1/10 * 1/10 = 0.00043$$

$$P(\text{negative}) * P(\text{great}|\text{negative}) * P(\text{great}|\text{negative}) * P(\text{great}|\text{negative})$$

$$4/7 * 2/8 * 2/8 * 2/8 = 0.00893$$

So: *sentiment = negative*

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But if the new segment to classify (**test time**) is:

Doc	Words	Class
11	Boring movie, annoying plot, unimaginative ending	???

Final decision

$$P(\text{positive}) * P(\text{boring}|\text{positive}) * P(\text{annoying}|\text{positive}) * P(\text{unimaginative}|\text{positive})$$

$$3/7 * 0/10 * 0/10 * 0/10 = 0$$

$$P(\text{negative}) * P(\text{boring}|\text{negative}) * P(\text{annoying}|\text{negative}) * P(\text{unimaginative}|\text{negative})$$

$$4/7 * 0/8 * 0/8 * 1/8 = 0$$

So: *sentiment* = ???

A corpus-based approach to SA - Machine Learning

Add smoothing to feature counts (add 1 to every count). **Likelihoods** =

$$P(t_j|c_i) = \frac{\text{count}(t_j, c_i) + 1}{\text{count}(c_i) + |V|}$$

where $|V|$ is the number of distinct attributes in training (all classes) = **12**

Doc	Words	Class
12	Boring movie, annoying plot, unimaginative ending	???

Final decision

$$P(\text{positive}) * P(\text{boring}|\text{positive}) * P(\text{annoying}|\text{positive}) * P(\text{unimaginative}|\text{positive})$$

$$3/7 * ((0 + 1)/(10 + 12)) * ((0 + 1)/(10 + 12)) * ((0 + 1)/(10 + 12)) = 0.000040$$

$$P(\text{negative}) * P(\text{boring}|\text{negative}) * P(\text{annoying}|\text{negative}) * P(\text{unimaginative}|\text{negative})$$

$$4/7 * ((0 + 1)/(8 + 12)) * ((0 + 1)/(8 + 12)) * ((1 + 1)/(8 + 12)) = 0.000143$$

So: *sentiment = negative*

A corpus-based approach to SA - Machine Learning

Given a trained classifier that classifies arbitrary segments of text we can use it to:

- Classify **entire documents**, e.g. an entire review.
- Classify **sentences** in a document (perhaps just those identified as subjective) and then compute a classification of the document by aggregating the sentiments of individual sentences, according to some function.
- Classify **sentences or phrases identified as discussing an aspect/feature** of a target object (e.g. a sentence discussing battery life of a phone) and interpret the sentiment as the sentiment of opinion holder towards the specific aspect under discussion

Questions:

- Is this a good solution? Is it robust?
- What is the role of the **prior**?
- How can we improve this solution?
 - ◇ Other **features**? Are we missing out critical information?
 - ◇ Other **algorithms**?
- What about **non-binary classification** (e.g. 5-grades of sentiment)?

A corpus-based approach to SA - Machine Learning

Questions:

- Is this a good solution? Is it robust?
 - It's simple and will work well if data is not sparse
- What is the role of the **prior**?
 - Prior is very important esp. on biased cases
- How can we improve this solution?
 - ◇ Other **features**? Are we missing out critical information?
 - Using all words (in Naive Bayes) works well in some tasks
 - Finding subsets of words may help in other tasks
 - Using only adjectives can be limiting. Verbs like **hate**, **dislike**; nouns like **love**; words for inversion like **not**; intensifiers like **very**
 - Pre-built polarity lexicons can be helpful
 - Negation is important
 - ◇ Other **algorithms**?
 - MaxEnt & SVM tend to do better than Naive Bayes
- What about **non-binary classification** (e.g. 5-grades of sentiment)?
 - 5-class ordinal classification or regression algorithms can be used

Can contrast **direct opinions** versus more complex **comparative opinions**:

- Direct sentiment expressions on target objects
 - ◇ e.g., *"the picture quality of this camera is great."*
- Comparisons expressing similarities or differences between objects,
 - ◇ e.g., *"car x is cheaper than car y."*

Bing Liu distinguishes 4 types of comparative relations:

- 1 **Gradable** Non-equal gradable: Relations of the type greater or less than. E.g.: *“lenses of camera A are better than those of camera B”*
- 2 **Equative**: Relations of the type equal to. E.g.: *“camera A and camera B both come in 7MP”*
- 3 **Superlative**: Relations of the type greater or less than all others. E.g.: *“camera A is the cheapest camera available in market”*
- 4 **Non-gradable comparisons**: Relations that compare aspects of two or more entities, but do not grade them. e.g., *“Coke tastes differently from Pepsi.”*

Evaluation

How do we quantify how well our Sentiment Analysis systems work?

- Create experimental datasets (aka test corpora): i.e., text segments that have been classified by humans, e.g. positive vs negative
- Compare (positive vs negative) system to human classifications
- Compute metrics like

$$\text{Accuracy} = \frac{\# \text{ correctly classified texts}}{\# \text{ texts}}$$

$$\text{Precision Pos} = \frac{\# \text{ texts correctly classified as positive}}{\# \text{ texts classified as positive}}$$

$$\text{Recall Pos} = \frac{\# \text{ texts correctly classified as positive}}{\# \text{ positive texts}}$$

$$\text{F-measure Pos} = \frac{2 * \text{Precision Pos} * \text{Recall Pos}}{\text{Precision Pos} + \text{Recall Pos}}$$

Same for **negative** class.

Baseline: most frequent class in the training set.

- Naïve Bayes classifier:
 - ◊ Really easy to implement and often works well
 - ◊ Often a good first thing to try
- Actually, the Naïve Bayes assumption is almost never true
- Still, Naïve Bayes often performs surprisingly well even when its assumption does not hold
- SA is an exciting topic, many applications, huge market for systems, particularly in focused domains.
- Promising results with simple techniques, but many interesting research challenges to be addressed for high accuracy.

Bing Liu and Lei Zhang (2012). A survey on opinion mining and sentiment analysis. Kluwer Academic Publishers:

http://www.cs.uic.edu/~lzhang3/paper/opinion_survey.pdf

Bing Liu (2012). Sentiment Analysis and Opinion Mining. Morgan and Claypool Publishers. Draft on line at: <https://www.cs.uic.edu/~liub/FBS/SentimentAnalysis-and-OpinionMining.pdf>

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