NATURAL LANGUAGE PROCESSING

Text Classification

TOPICS

- **Text Classification**
  - Naïve Bayes
  - Logistic Regression
  - Practical Issues

IS THIS SPAM?

Subject: **Important notice!**
From: Stanford University <newsforum@stanford.edu>
Date: October 28, 2011 12:34:16 PM PDT
To: undisclosed-recipients:;

Greats News!

You can now access the latest news by using the link below to login to Stanford University News Forum.

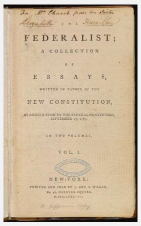
http://www.123contactform.com/contact-form-StanfordNew1-236335.html

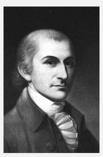
Click on the above link to login for more information about this new exciting forum. You can also copy the above link to your browser bar and login for more information
about the new services.

© Stanford University. All Rights Reserved.

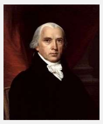
WHO WROTE WHICH FEDERALIST PAPERS?

- 1787-8: anonymous essays try to convince New York to ratify U.S Constitution: Jay, Madison, Hamilton.
- Authorship of 12 of the letters in dispute
- 1963: solved by Mosteller and Wallace using Bayesian methods





John Jay



James Madison

Alexander Hamilton

MALE OR FEMALE AUTHOR?

1. By 1925 present-day Vietnam was divided into three parts under French colonial rule. The southern region embracing Saigon and the Mekong delta was the colony of Cochin-China; the central area with its imperial capital at Hue was the protectorate of Annam…
2. Clara never failed to be astonished by the extraordinary felicity of her own name. She found it hard to trust herself to the mercy of fate, which had managed over the years to convert her greatest shame into one of her greatest assets…

S. Argamon, M. Koppel, J. Fine, A. R. Shimoni, 2003. “Gender, Genre, and Writing Style in Formal Written Texts,” Text, volume 23, number 3, pp. 321–346

POSITIVE OR NEGATIVE MOVIE REVIEW?


- unbelievably disappointing


- Full of zany characters and richly applied satire, and some great plot twists


- this is the greatest screwball comedy ever filmed


- It was pathetic. The worst part about it was the boxing scenes.

WHAT IS THE SUBJECT OF THIS ARTICLE?

MEDLINE Article

?

MeSH Subject Category Hierarchy

- Antogonists and Inhibitors
- Blood Supply
- Chemistry
- Drug Therapy
- Embryology
- Epidemiology
- …

TEXT CLASSIFICATION

- Assigning subject categories, topics, or genres
- Spam detection
- Authorship identification
- Age/gender identification
- Language Identification
- Sentiment analysis
- …

TEXT CLASSIFICATION: DEFINITION

- *Input*:
  - a document d
  - a fixed set of classes $C = \{c_1, c_2, \ldots, c_J\}$
- *Output*: a predicted class $c \in C$

Yanjun Li

9

HAND-CODED RULES

- Rules based on combinations of words or other features
  - spam: black-list-address OR (“dollars” AND “have been selected”)
- Accuracy can be high
  - If rules carefully refined by expert
- But building and maintaining these rules is expensive

Yanjun Li

10

SUPERVISED MACHINE LEARNING

- *Input:*
  - a document *d*
  - a fixed set of classes $C = \{c_1, c_2,\ldots, c_J\}$
  - A training set of *m* hand-labeled documents $(d_1,c_1),\ldots,(d_m,c_m)$
- *Output:*
  - a learned classifier $\gamma: d \rightarrow c$

Yanjun Li

11

SUPERVISED MACHINE LEARNING

- Any kind of classifier
  - Naïve Bayes
  - Logistic regression
  - Support-vector machines
  - k-Nearest Neighbors
  - …

Yanjun Li

12

TOPICS

- Text Classification
  - **Naïve Bayes**
  - Logistic Regression
  - Practical Issues

NAÏVE BAYES INTUITION

- Simple ("naïve") classification method based on Bayes rule
- Relies on very simple representation of document
  - Bag of words

THE BAG OF WORDS REPRESENTATION

γ(

seen	2
sweet	1
whimsical	1
recommend	1
happy	1
...	...

)=c

BAYES' RULE APPLIED TO DOCUMENTS AND CLASSES

- For a document *d* and a class *c*

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

NAÏVE BAYES CLASSIFIER (I)

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(c \mid d)$$

MAP is "maximum a posteriori" = most likely class

$$= \underset{c \in C}{\operatorname{argmax}} \frac{P(d \mid c)P(c)}{P(d)}$$

Bayes Rule

$$= \underset{c \in C}{\operatorname{argmax}} P(d \mid c)P(c)$$

Dropping the denominator

NAÏVE BAYES CLASSIFIER (II)

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(d \mid c)P(c)$$

$$= \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c)P(c)$$

Document d represented as features x1..xn

NAÏVE BAYES CLASSIFIER (IV)

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c) P(c)$$

How often does this class occur?

Could only be estimated if a very, very large number of training examples was available.

We can just count the relative frequencies in a corpus

Yanjun Li

19

MULTINOMIAL NAÏVE BAYES INDEPENDENCE ASSUMPTIONS

$$P(x_1, x_2, \ldots, x_n \mid c)$$

- **Bag of Words assumption**: Assume position doesn't matter
- **Conditional Independence**: Assume the feature probabilities $P(x_i|c_j)$ are independent given the class c.

$$P(x_1, \ldots, x_n \mid c) = P(x_1 \mid c) \bullet P(x_2 \mid c) \bullet P(x_3 \mid c) \bullet \ldots \bullet P(x_n \mid c)$$

Yanjun Li

20

MULTINOMIAL NAÏVE BAYES CLASSIFIER

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c) P(c)$$

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod_{x \in X} P(x \mid c)$$

APPLYING MULTINOMIAL NAIVE BAYES CLASSIFIERS TO TEXT CLASSIFICATION

positions $\leftarrow$ all word positions in test document

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(x_i \mid c_j)$$

Sec.13.3

LEARNING THE MULTINOMIAL NAÏVE BAYES MODEL

- First attempt: maximum likelihood estimates
  - simply use the ***frequencies*** in the data

$$\hat{P}(c_j) = \frac{doccount(C = c_j)}{N_{doc}}$$

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

Yanjun Li

23

PARAMETER ESTIMATION

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

fraction of times word w_i appears among all words in documents of topic c_j

- Create mega-document for topic *j* by concatenating all docs in this topic
  - Use frequency of *w* in mega-document

Yanjun Li

24

Sec.13.3

PROBLEM WITH MAXIMUM LIKELIHOOD

- What if we have seen no training documents with the word ***fantastic*** and classified in the topic **positive** (***thumbs-up)***?

$$\hat{P}(\text{"fantastic"} \mid \text{positive}) = \frac{count(\text{"fantastic", positive})}{\sum_{w \in V} count(w, \text{positive})} = 0$$

- Zero probabilities cannot be conditioned away, no matter the other evidence!

$$c_{MAP} = \text{argmax}_c\, \hat{P}(c) \prod_i \hat{P}(x_i \mid c)$$

LAPLACE (ADD-1) SMOOTHING FOR NAÏVE BAYES

$$\hat{P}(w_i \mid c) = \frac{count(w_i, c) + 1}{\sum_{w \in V} \left(count(w, c) + 1 \right)}$$

$$= \frac{count(w_i, c) + 1}{\left(\sum_{w \in V} count(w, c) \right) + |V|}$$

UNKNOWN WORD

- The solution for unknown words is to ignore them.
  - Remove them from the test document and not include any probability for them at all in the prediction procedure.

MULTINOMIAL NAÏVE BAYES: LEARNING

- From training corpus, extract *Vocabulary*

- Calculate $P(c_j)$ terms
  - For each c_j in C do

    $docs_j \leftarrow$ all docs with class $= c_j$

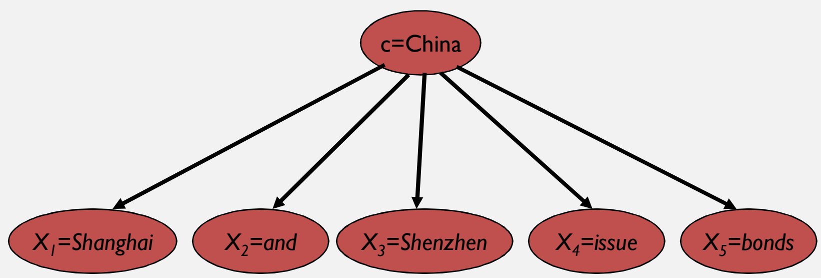
$$P(c_j) \leftarrow \frac{|docs_j|}{|\text{total \# documents}|}$$

- Calculate $P(w_k \mid c_j)$ terms
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word w_k in *Vocabulary*

    $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

$$P(w_k \mid c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha |Vocabulary|}$$

GENERATIVE MODEL FOR MULTINOMIAL NAÏVE BAYES



Yanjun Li

29

NAÏVE BAYES AND LANGUAGE MODELING

- Naïve bayes classifiers can use any sort of feature
  - URL, email address, dictionaries, network features
- But if, as in the previous slides
  - We use **only** word features
  - we use **all** of the words in the text (not a subset)
- Then
  - Naïve bayes has an important similarity to language modeling.

Yanjun Li

30

EACH CLASS = A UNIGRAM LANGUAGE MODEL

Sec.13.2.1

- **Assigning each word: P(word | c)**
- **Assigning each sentence: P(s|c)=$\prod P(word|c)$**

Class *pos*

0.1 I

0.1 love

0.01 this

0.05 fun

0.1 film

…

P(s | pos) = 0.0000005

Yanjun Li

31

NAÏVE BAYES AS A LANGUAGE MODEL

Sec.13.2.1

- Which class assigns the higher probability to s?

Model pos	
0.1	I
0.1	love
0.01	this
0.05	fun
0.1	film

Model neg	
0.2	I
0.001	love
0.01	this
0.005	fun
0.1	film

I	love	this	fun	film
0.1	0.1	0.01	0.05	0.1
0.2	0.001	0.01	0.005	0.1

P(s|pos) > P(s|neg)

Yanjun Li

32

Example

$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{\sum count(w,c)+|V|}$$

	Doc	Words	Class
Training	1	Chinese Beijing Chinese	c
	2	Chinese Chinese Shanghai	c
	3	Chinese Macao	c
	4	Tokyo Japan Chinese	j
Test	5	Chinese Chinese Chinese Tokyo Japan	?

Priors:

$P(c) = \frac{3}{4}$

$P(j) = \frac{1}{4}$

Conditional Probabilities:

P(Chinese|c) = (5+1) / (8+6) = 6/14 = 3/7

P(Tokyo|c) = (0+1) / (8+6) = 1/14

P(Japan|c) = (0+1) / (8+6) = 1/14

P(Chinese|j) = (1+1) / (3+6) = 2/9

P(Tokyo|j) = (1+1) / (3+6) = 2/9

P(Japan|j) = (1+1) / (3+6) = 2/9

Choosing a class:

$P(c|d5) \propto 3/4 * (3/7)^3 * 1/14 * 1/14 \approx 0.0003$

$P(j|d5) \propto 1/4 * (2/9)^3 * 2/9 * 2/9 \approx 0.0001$

Yanjun Li

33

SUMMARY: NAIVE BAYES IS NOT SO NAIVE

- Very Fast, low storage requirements
- Very good in domains with many equally important features
- Optimal if the independence assumptions hold: If assumed independence is correct
- A good dependable baseline for text classification
  - **But we will see other classifiers that give better accuracy**

Yanjun Li

34

EVALUATION OF NB

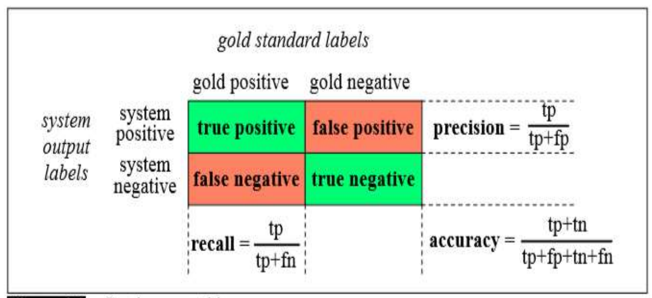


Figure 4.4 Contingency table

A COMBINED MEASURE: F

- A combined measure that assesses the P/R tradeoff is F measure (weighted harmonic mean):

$$F = \frac{1}{\alpha \frac{1}{P} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

- The harmonic mean is a very conservative average; see *IIR* § 8.3
- People usually use balanced F1 measure
  - i.e., with $\beta = 1$ (that is, $\alpha = ½$): *F* = 2*PR*/(*P*+*R*)

Sec.14.5

MORE THAN TWO CLASSES: SETS OF BINARY CLASSIFIERS

- Dealing with any-of or multivalue classification
  - A document can belong to 0, 1, or >1 classes.

- For each class $c \in C$
  - Build a classifier γ_c to distinguish c from all other classes $c' \in C$
- Given test doc d,
  - Evaluate it for membership in each class using each γ_c
  - d belongs to any class for which γ_c returns true

Sec.14.5

MORE THAN TWO CLASSES: SETS OF BINARY CLASSIFIERS

- One-of or multinomial classification (multiclass)
  - Classes are mutually exclusive: each document in exactly one class
- For each class $c \in C$
  - Build a classifier γ_c to distinguish c from all other classes $c' \in C$
- Given test doc d,
  - Evaluate it for membership in each class using each γ_c
  - d belongs to the one class with maximum score

EVALUATION: CLASSIC REUTERS-21578 DATA SET

ec. 15.2.4

- Most (over)used data set, 21,578 docs (each 90 types, 200 toknens)
- 9603 training, 3299 test articles (ModApte/Lewis split)
- 118 categories
  - An article can be in more than one category
  - Learn 118 binary category distinctions
- Average document (with at least one category) has 1.24 classes
- Only about 10 out of 118 categories are large

Common categories (#train, #test)

- Earn (2877, 1087)
- Acquisitions (1650, 179)
- Money-fx (538, 179)
- Grain (433, 149)
- Crude (389, 189)
- Trade (369,119)
- Interest (347, 131)
- Ship (197, 89)
- Wheat (212, 71)
- Corn (182, 56)

REUTERS TEXT CATEGORIZATION DATA SET (REUTERS-21578) DOCUMENT

ec. 15.2.4

<REUTERS TOPICS="YES" LEWISSPLIT="TRAIN" CGISPLIT="TRAINING-SET" OLDID="12981" NEWID="798">

<DATE> 2-MAR-1987 16:51:43.42</DATE>

<TOPICS><D>livestock</D><D>hog</D></TOPICS>

<TITLE>AMERICAN PORK CONGRESS KICKS OFF TOMORROW</TITLE>

<DATELINE> CHICAGO, March 2 - </DATELINE><BODY>The American Pork Congress kicks off tomorrow, March 3, in Indianapolis with 160 of the nations pork producers from 44 member states determining industry positions on a number of issues, according to the National Pork Producers Council, NPPC.

Delegates to the three day Congress will be considering 26 resolutions concerning various issues, including the future direction of farm policy and the tax law as it applies to the agriculture sector. The delegates will also debate whether to endorse concepts of a national PRV (pseudorabies virus) control and eradication program, the NPPC said.

A large trade show, in conjunction with the congress, will feature the latest in technology in all areas of the industry, the NPPC added. Reuter

&#3;</BODY></TEXT></REUTERS>

CONFUSION MATRIX

- For each pair of classes <c_1,c_2> how many documents from c_1 were incorrectly assigned to c_2?
  - $c_{3,2}$: 90 wheat documents incorrectly assigned to poultry

Docs in test set	Assigned UK	Assigned poultry	Assigned wheat	Assigned coffee	Assigned interest	Assigned trade
True UK	95	1	13	0	1	0
True poultry	0	1	0	0	0	0
True wheat	10	90	0	1	0	0
True coffee	0	0	0	34	3	7
True interest	-	1	2	13	26	5
True trade	0	0	2	14	5	10

PER CLASS EVALUATION MEASURES

Recall:

Fraction of docs in class *i* classified correctly: $$\frac{c_{ii}}{\sum_j c_{ij}}$$

Precision:

Fraction of docs assigned class *i* that are actually about class *i*: $$\frac{c_{ii}}{\sum_j c_{ji}}$$

Accuracy: (1 - error rate)

Fraction of docs classified correctly: $$\frac{\sum_i c_{ii}}{\sum_j \sum_i c_{ij}}$$

Sec. 15.2.4

MICRO- VS. MACRO-AVERAGING

- If we have more than one class, how do we combine multiple performance measures into one quantity?
- **Macro-averaging**: Compute performance for each class, then average.
- **Micro-averaging**: Collect decisions for all classes, compute contingency table, evaluate.

Sec. 15.2.4

MICRO- VS. MACRO-AVERAGING: EXAMPLE

Class 1

	Truth: yes	Truth: no
Classifier: yes	10	10
Classifier: no	10	970

Class 2

	Truth: yes	Truth: no
Classifier: yes	90	10
Classifier: no	10	890

Micro Ave. Table

	Truth: yes	Truth: no
Classifier: yes	100	20
Classifier: no	20	1860

- Macro-averaged precision: (0.5 + 0.9)/2 = 0.7
- Micro-averaged precision: 100/120 = .83
- Micro-averaged score is dominated by score on common classes

DEVELOPMENT TEST SETS AND CROSS-VALIDATION

Training set | Development Test Set | Test Set

- Metric: P/R/F1 or Accuracy
- Unseen test set
  - avoid overfitting ('tuning to the test set')
  - more conservative estimate of performance
- Cross-validation over multiple splits
  - Handle sampling errors from different datasets
  - Pool results over each split
  - Compute pooled dev set performance