Chap. 4: Naïve Bayes and Sentiment Classification

Outline

- The task of text classification
- The Naïve Bayes Classifier
- Naïve Bayes: Learning
- Sentiment and Binary Naïve Bayes
- More on Sentiment Classification
- Naïve Bayes: Relationship to Language Modeling
- Precision, Recall, and F-Measure
- Evaluation with more than two classes
- Statistical Significance Testing
- The Paired Bootstrap Test
- Avoiding harms in classification

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.

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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


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

What is the subject of this article?

MEDLINE Article


Brain and Cognition

Syntactic frame and verb bias in aphasia: Plausibility judgments of undergoer-subject sentences

?

MeSH Subject Category Hierarchy

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

Positive or negative movie review?

- \+ *...zany characters and richly applied satire, and some great plot twists*
- – *It was pathetic. The worst part about it was the boxing scenes...*
- \+ *...awesome caramel sauce and sweet toasty almonds. I love this place!*
- – *...awful pizza and ridiculously overpriced...*

Positive or negative movie review?

+ *...zany characters and **richly** applied satire, and some **great** plot twists*

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

+ *...**awesome** caramel sauce and sweet toasty almonds. I **love** this place!*

– *...**awful** pizza and **ridiculously** overpriced...*

Why sentiment analysis?

- *Movie*: is this review positive or negative?
- *Products*: what do people think about the new iPhone?
- *Public sentiment*: how is consumer confidence?
- *Politics*: what do people think about this candidate or issue?
- *Prediction*: predict election outcomes or market trends from sentiment

Scherer Typology of Affective States

- **Emotion**: brief organically synchronized … evaluation of a major event
  - *angry, sad, joyful, fearful, ashamed, proud, elated*
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - *cheerful, gloomy, irritable, listless, depressed, buoyant*
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*
- **Attitudes**: enduring, affectively colored beliefs, dispositions towards objects or persons
  - *liking, loving, hating, valuing, desiring*
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - *nervous, anxious, reckless, morose, hostile, jealous*

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Basic Sentiment Classification

- Sentiment analysis is the detection of **attitudes**
- Simple task we focus on in this chapter
  - Is the attitude of this text positive or negative?
- We return to affect classification in later chapters

Summary: Text Classification

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

Text Classification: definition

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

- *Output*: a predicted class $c \in C$

Classification Methods: Hand-coded rules

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

Classification Methods: 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 $\gamma: d \rightarrow c$

Classification Methods: Supervised Machine Learning

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

Text Classification and Naïve Bayes

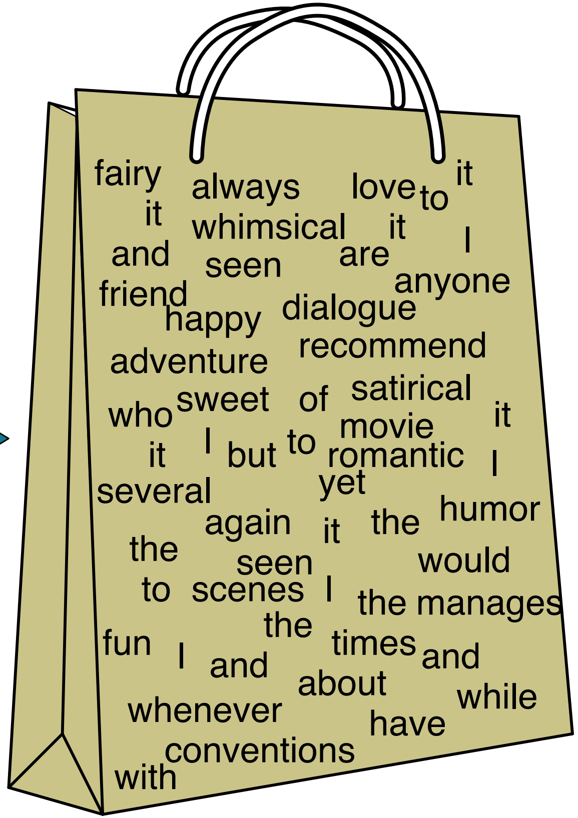
Naïve Bayes Classifier

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

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

The bag of words representation

$\gamma($

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)

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

$O(|X|^n \bullet |C|)$ parameters

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

How often does this class occur?

We can just count the relative frequencies in a corpus

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.

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

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

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

Problems with multiplying lots of probs

- There's a problem with this:

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

- Multiplying lots of probabilities can result in floating-point underflow!

  .0006 * .0007 * .0009 * .01 * .5 * .000008….

- Idea: Use logs, because log(*ab*) = log(*a*) + log(*b*)

  We'll sum logs of probabilities instead of multiplying probabilities!

We actually do everything in log space

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

This: $$c_{\text{NB}} = \underset{c_j \in C}{\operatorname{argmax}} \left[\log P(c_j) + \sum_{i \in \text{positions}} \log P(x_i | c_j) \right]$$

Notes:

1) Taking log doesn't change the ranking of classes!

    The class with highest probability also has highest log probability!

2) It's a linear model:

    Just a max of a sum of weights: a **linear** function of the inputs

    So naive bayes is a **linear classifier**

Text Classification and Naïve Bayes

Naïve Bayes: Learning

Learning the Multinomial Naïve Bayes Model

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

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

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

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

Problem with Maximum Likelihood

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

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

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

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

Laplace (add-1) smoothing for Naïve Bayes

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

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

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 $= c_j$

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

- 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 $Text_j$

$$P(w_k \mid c_j) \neg \frac{n_k + a}{n + a\,|Vocabulary|}$$

Unknown words

- What about unknown words
  - that appear in our test data
  - but not in our training data or vocabulary?
- We **ignore** them
  - Remove them from the test document!
  - Pretend they weren't there!
  - Don't include any probability for them at all!
- Why don't we build an unknown word model?
  - It doesn't help: knowing which class has more unknown words is not generally helpful!

Stop words

- Some systems ignore stop words
  - **Stop words:** very frequent words like *the* and *a*.
    - Sort the vocabulary by word frequency in training set
    - Call the top 10 or 50 words the **stopword list**.
    - Remove all stop words from both training and test sets
      - As if they were never there!
- But removing stop words doesn't usually help
  - So in practice most NB algorithms use **all** words and **don't** use stopword lists

Text Classification and Naïve Bayes

Sentiment and Binary Naïve Bayes

Let's do a worked sentiment example!

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable with no fun

A worked sentiment example with add-1 smoothing

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable ~~with~~ no fun

1. Prior from training:

$$\hat{P}(c_j) = \frac{N_{c_j}}{N_{total}}$$

P(-) = 3/5
P(+) = 2/5

2. Drop "with"

3. Likelihoods from training:

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

$$P(\text{“predictable”}|-) = \frac{1+1}{14+20} \qquad P(\text{“predictable”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“no”}|-) = \frac{1+1}{14+20} \qquad P(\text{“no”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“fun”}|-) = \frac{0+1}{14+20} \qquad P(\text{“fun”}|+) = \frac{1+1}{9+20}$$

4. Scoring the test set:

$$\boxed{P(-)P(S|-) = \frac{3}{5} \times \frac{2 \times 2 \times 1}{34^3} = 6.1 \times 10^{-5}}$$

$$P(+)P(S|+) = \frac{2}{5} \times \frac{1 \times 1 \times 2}{29^3} = 3.2 \times 10^{-5}$$

Optimizing for sentiment analysis

For tasks like sentiment, word **occurrence** seems to be more important than word **frequency**.

- The occurrence of the word *fantastic* tells us a lot
- The fact that it occurs 5 times may not tell us much more.

Binary multinominal naive bayes, or **binary NB**

- Clip our word counts at 1
- Note: this is different than Bernoulli naive bayes; see the textbook at the end of the chapter.

Binary 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
  - Remove duplicates in each doc:
    - For each word type w in doc_j
      - Retain only a single instance of w
  - $Text_j \leftarrow$ single doc containing all $docs_j$
  - For each word w_k in *Vocabulary*

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

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

Binary Multinomial Naive Bayes on a test document *d*

- First remove all duplicate words from *d*
- Then compute NB using the same equation:

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

Binary multinominal naive Bayes

Four original documents:

- – it was pathetic the worst part was the boxing scenes
- – no plot twists or great scenes
- \+ and satire and great plot twists
- \+ great scenes great film

Binary multinominal naive Bayes

Four original documents:

- – it was pathetic the worst part was the boxing scenes
- – no plot twists or great scenes
- + and satire and great plot twists
- + great scenes great film

	NB Counts	
	+	−
and	2	0
boxing	0	1
film	1	0
great	3	1
it	0	1
no	0	1
or	0	1
part	0	1
pathetic	0	1
plot	1	1
satire	1	0
scenes	1	2
the	0	2
twists	1	1
was	0	2
worst	0	1

Binary multinominal naive Bayes

Four original documents:

- – it was pathetic the worst part was the boxing scenes
- – no plot twists or great scenes
- + and satire and great plot twists
- + great scenes great film

After per-document binarization:

- – it was pathetic the worst part boxing scenes
- – no plot twists or great scenes
- + and satire great plot twists
- + great scenes film

	NB Counts	
	+	–
and	2	0
boxing	0	1
film	1	0
great	3	1
it	0	1
no	0	1
or	0	1
part	0	1
pathetic	0	1
plot	1	1
satire	1	0
scenes	1	2
the	0	2
twists	1	1
was	0	2
worst	0	1

Binary multinominal naive Bayes

Four original documents:

– it was pathetic the worst part was the boxing scenes
– no plot twists or great scenes
+ and satire and great plot twists
+ great scenes great film

After per-document binarization:

– it was pathetic the worst part boxing scenes
– no plot twists or great scenes
+ and satire great plot twists
+ great scenes film

	NB Counts +	NB Counts −	Binary Counts +	Binary Counts −
and	2	0	1	0
boxing	0	1	0	1
film	1	0	1	0
great	3	1	2	1
it	0	1	0	1
no	0	1	0	1
or	0	1	0	1
part	0	1	0	1
pathetic	0	1	0	1
plot	1	1	1	1
satire	1	0	1	0
scenes	1	2	1	2
the	0	2	0	1
twists	1	1	1	1
was	0	2	0	1
worst	0	1	0	1

Counts can still be 2! Binarization is within-doc!

Text Classification and Naïve Bayes

More on Sentiment Classification

Sentiment Classification: Dealing with Negation

- I really like this movie

I really **don't** like this movie

Negation changes the meaning of "like" to negative.

Negation can also change negative to positive-ish

- **Don't** dismiss this film
- **Doesn't** let us get bored

Sentiment Classification: Dealing with Negation

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA).
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Simple baseline method:

Add NOT_ to every word between negation and following punctuation:

```
didn't like this movie , but I
```

```
didn't NOT_like NOT_this NOT_movie but I
```

Sentiment Classification: Lexicons

- Sometimes we don't have enough labeled training data
- In that case, we can make use of pre-built word lists
- Called **lexicons**
- There are various publically available lexicons

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: https://mpqa.cs.pitt.edu/lexicons/subj_lexicon/
- 6885 words from 8221 lemmas, annotated for intensity (strong/weak)
  - 2718 positive
  - 4912 negative
- + : *admirable, beautiful, confident, dazzling, ecstatic, favor, glee, great*
- − : *awful, bad, bias, catastrophe, cheat, deny, envious, foul, harsh, hate*

The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
  - Positiv (1915 words) and Negativ (2291 words)
  - Strong vs Weak, Active vs Passive, Overstated versus Understated
  - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use

Using Lexicons in Sentiment Classification

Add a feature that gets a count whenever a word from the lexicon occurs

- E.g., a feature called "**this word occurs in the positive lexicon**" or "**this word occurs in the negative lexicon**"

Now all positive words (*good, great, beautiful, wonderful*) or negative words count for that feature.

Using 1-2 features isn't as good as using all the words.

- But when training data is sparse or not representative of the test set, dense lexicon features can help

Naive Bayes in Other tasks: Spam Filtering

- SpamAssassin Features:
  - Mentions millions of (dollar) ((dollar) NN,NNN,NNN.NN)
  - From: starts with many numbers
  - Subject is all capitals
  - HTML has a low ratio of text to image area
  - "One hundred percent guaranteed"
  - Claims you can be removed from the list

Naive Bayes in Language ID

- Determining what language a piece of text is written in.

Features based on character n-grams do very well

- Important to train on lots of varieties of each language

  (e.g., American English varieties like African-American English, or English varieties around the world like Indian English)

Summary: Naive Bayes is Not So Naive

- Very Fast, low storage requirements
- Work well with very small amounts of training data
- Robust to Irrelevant Features

  Irrelevant Features cancel each other without affecting results
- Very good in domains with many equally important features

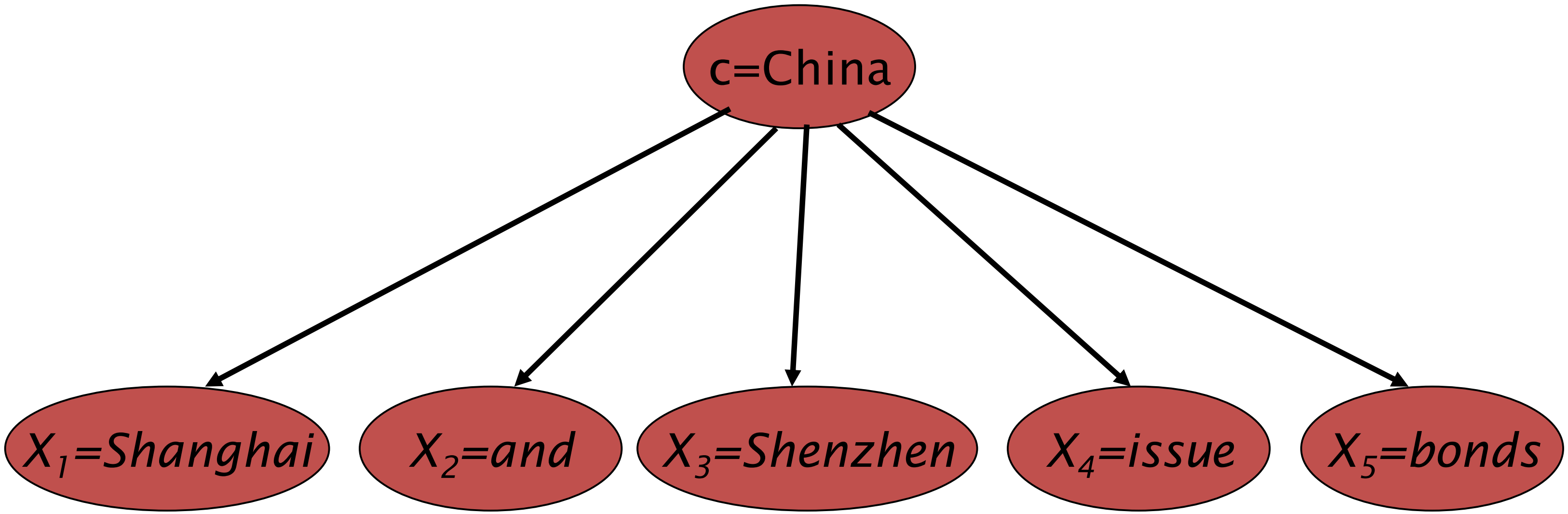
  Decision Trees suffer from *fragmentation* in such cases – especially if little data
- Optimal if the independence assumptions hold: If assumed independence is correct, then it is the Bayes Optimal Classifier for problem
- A good dependable baseline for text classification
  - **But we will see other classifiers that give better accuracy**

Slide from Chris Manning

Text Classification and Naïve Bayes

Naïve Bayes: Relationship to Language Modeling

Generative Model for Multinomial Naïve Bayes



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.

Each class = a unigram language model

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

Class *pos*

0.1	I
0.1	love
0.01	this
0.05	fun
0.1	film

I	love	this	fun	film
0.1	0.1	.05	0.01	0.1

P(s | pos) = 0.0000005

Naïve Bayes as a Language Model

- 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

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

Text Classification and Naïve Bayes

Precision, Recall, and the F measure

Evaluation

- Let's consider just binary text classification tasks
- Imagine you're the CEO of Delicious Pie Company
- You want to know what people are saying about your pies
- So you build a "Delicious Pie" tweet detector
  - Positive class: tweets about Delicious Pie Co
  - Negative class: all other tweets

The 2-by-2 confusion matrix

gold standard labels

system output labels		gold positive	gold negative	
	system positive	**true positive**	**false positive**	$\textbf{precision} = \frac{tp}{tp+fp}$
	system negative	**false negative**	**true negative**	
		$\textbf{recall} = \frac{tp}{tp+fn}$		$\textbf{accuracy} = \frac{tp+tn}{tp+fp+tn+fn}$

Evaluation: Accuracy

- Why don't we use **accuracy** as our metric?
- Imagine we saw 1 million tweets
  - 100 of them talked about Delicious Pie Co.
  - 999,900 talked about something else
- We could build a dumb classifier that just labels every tweet "not about pie"
  - It would get 99.99% accuracy!!! Wow!!!!
  - But useless! Doesn't return the comments we are looking for!
  - That's why we use **precision** and **recall** instead

Evaluation: Precision

- % of items the system detected (i.e., items the system labeled as positive) that are in fact positive (according to the human gold labels)

$$\textbf{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

Evaluation: Recall

- % of items actually present in the input that were correctly identified by the system.

$$\textbf{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Why Precision and recall

- Our dumb pie-classifier
  - Just label nothing as "about pie"

Accuracy=99.99%

but

Recall = 0

- (it doesn't get any of the 100 Pie tweets)

Precision and recall, unlike accuracy, emphasize true positives:

- finding the things that we are supposed to be looking for.

A combined measure: F

- F measure: a single number that combines P and R:

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

- We almost always use balanced F_1 (i.e., $\beta = 1$)

$$\mathrm{F}_1 = \frac{2PR}{P + R}$$

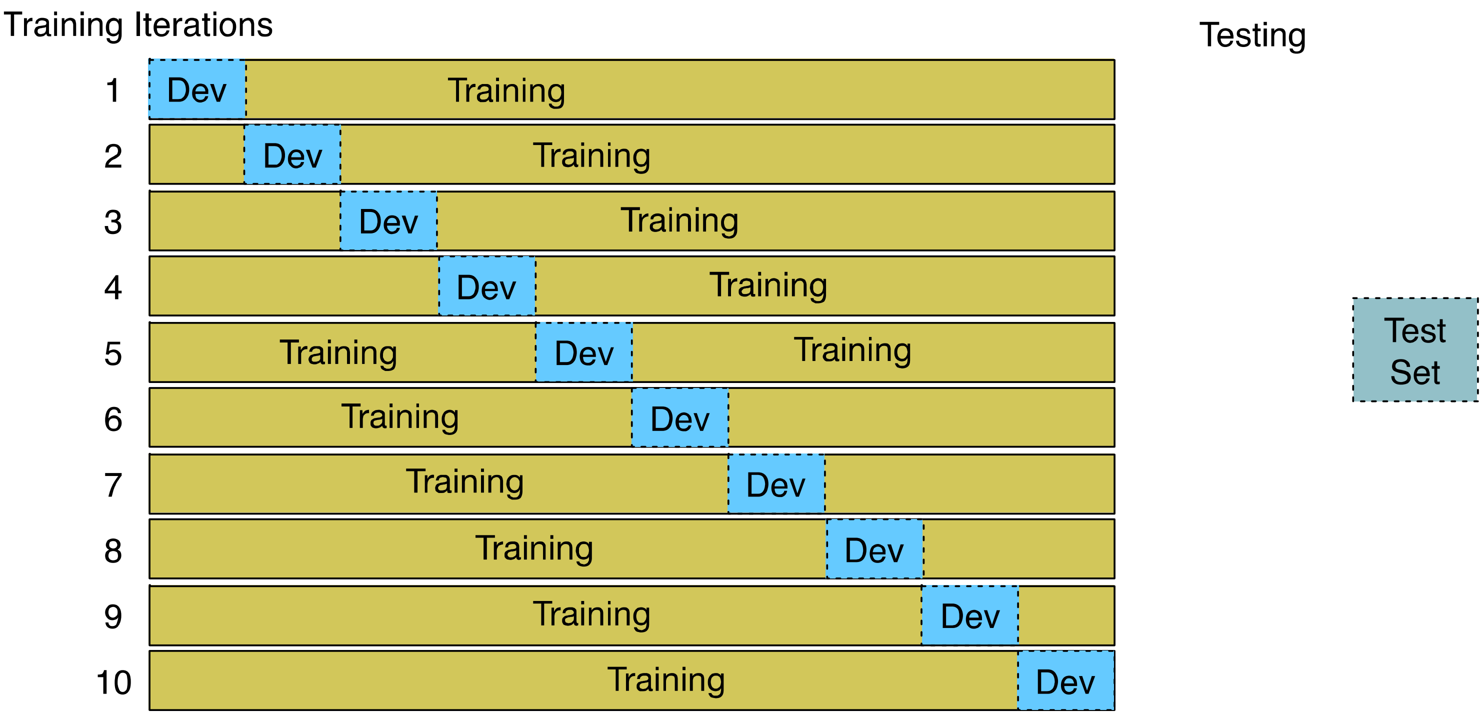
Development Test Sets ("Devsets") and Cross-validation

Training set | Development Test Set | Test Set

- Train on training set, tune on devset, report on testset
  - This avoids overfitting (‘tuning to the test set’)
  - More conservative estimate of performance
  - But paradox: want as much data as possible for training, and as much for dev; how to split?

Cross-validation: multiple splits

- Pool results over splits, Compute pooled dev performance



Text Classification and Naïve Bayes

Text Classification: Evaluation with more than two classes

Confusion Matrix for 3-class classification

		gold labels urgent	normal	spam	
system output	urgent	8	10	1	$\textbf{precision}_{u} = \frac{8}{8+10+1}$
	normal	5	60	50	$\textbf{precision}_{n} = \frac{60}{5+60+50}$
	spam	3	30	200	$\textbf{precision}_{s} = \frac{200}{3+30+200}$
		$\textbf{recall}_{u} = \frac{8}{8+5+3}$	$\textbf{recall}_{n} = \frac{60}{10+60+30}$	$\textbf{recall}_{s} = \frac{200}{1+50+200}$	

How to combine P/R from 3 classes to get one metric

- Macroaveraging:
  - compute the performance for each class, and then average over classes
- Microaveraging:
  - collect decisions for all classes into one confusion matrix
  - compute precision and recall from that table.

Macroaveraging and Microaveraging

Class 1: Urgent

	true urgent	true not
system urgent	8	11
system not	8	340

$$\text{precision} = \frac{8}{8+11} = .42$$

Class 2: Normal

	true normal	true not
system normal	60	55
system not	40	212

$$\text{precision} = \frac{60}{60+55} = .52$$

Class 3: Spam

	true spam	true not
system spam	200	33
system not	51	83

$$\text{precision} = \frac{200}{200+33} = .86$$

Pooled

	true yes	true no
system yes	268	99
system no	99	635

$$\begin{array}{c}\text{microaverage}\\\text{precision}\end{array} = \frac{268}{268+99} = \mathbf{.73}$$

$$\begin{array}{c}\text{macroaverage}\\\text{precision}\end{array} = \frac{.42+.52+.86}{3} = \mathbf{.60}$$

Text Classification and Naive Bayes

Statistical Significance Testing

How do we know if one classifier is better than another?

- Given:
  - Classifier A and B
  - Metric M: M(A,x) is the performance of *A* on testset *x*
  - δ(x): the performance difference between A, B on x:
    - $\delta(x) = M(A,x) - M(B,x)$

  - We want to know if $\delta(x) > 0$, meaning A is better than B
  - δ(x) is called the **effect size**
  - Suppose we look and see that δ(x) is positive. Are we done?
  - No! This might be just an accident of this one test set, or circumstance of the experiment. Instead:

Statistical Hypothesis Testing

- Consider two hypotheses:
  - Null hypothesis: A isn't better than B
  - A is better than B

$$H_0 \ : \ \delta(x) \leq 0$$
$$H_1 \ : \ \delta(x) > 0$$

- We want to rule out H_0
- We create a random variable X ranging over test sets
- And ask, how likely, if H_0 is true, is it that among these test sets we would see the δ(x) we did see?
  - Formalized as the p-value:

$$P(\delta(X) \geq \delta(x) | H_0 \text{ is true})$$

Statistical Hypothesis Testing

$$P(\delta(X) \geq \delta(x) | H_0 \text{ is true})$$

- In our example, this p-value is the probability that we would see $\delta(x)$ assuming H_0 (=*A* is not better than *B)*.
  - If H_0 is true but $\delta(x)$ is huge, that is surprising! Very low probability!
- A very small p-value means that the difference we observed is very unlikely under the null hypothesis, and we can reject the null hypothesis
- Very small: .05 or .01
- A result(e.g., "*A* is better than *B*") is **statistically significant** if the δ we saw has a probability that is below the threshold and we therefore reject this null hypothesis.

Statistical Hypothesis Testing

- How do we compute this probability?
- In NLP, we don't tend to use parametric tests (like t-tests)
- Instead, we use non-parametric tests based on sampling: artificially creating many versions of the setup.
- For example, suppose we had created zillions of testsets x'.
  - Now we measure the value of δ(x') on each test set
  - That gives us a distribution
  - Now set a threshold (say .01).
  - So if we see that in 99% of the test sets $\delta(x) > \delta(x')$
    - We conclude that our original test set delta was a real delta and not an artifact.

Statistical Hypothesis Testing

- Two common approaches:
  - approximate randomization
  - bootstrap test
- Paired tests:
  - Comparing two sets of observations in which each observation in one set can be paired with an observation in another.
  - For example, when looking at systems A and B **on the same test set**, we can compare the performance of system *A* and *B* on each same observation x_i

Text Classification and Naive Bayes

The Paired Bootstrap Test

Bootstrap test

Efron and Tibshirani, 1993

Can apply to any metric (accuracy, precision, recall, F1, etc).

Bootstrap means to repeatedly draw large numbers of smaller samples with replacement (called **bootstrap samples**) from an original larger sample.

Bootstrap example

Consider a baby text classification example with a test set x of 10 documents, using accuracy as metric.

Suppose these are the results of systems A and B on x, with 4 outcomes (A & B both right, A & B both wrong, A right/B wrong, A wrong/B right):

either A+B both correct, or

	1	2	3	4	5	6	7	8	9	10	A%	B%	*d*()
x	AB	AB	AB	~~A~~B	AB	~~A~~B	AB	AB	~~A~~B	AB	.70	.50	.20

Bootstrap example

- Now we create, many, say, b=10,000 virtual test sets $x(i)$, each of size n = 10.
- To make each $x(i)$, we randomly select a cell from row x, with replacement, 10 times:

	1	2	3	4	5	6	7	8	9	10	A%	B%	$d()$
x	AB	AB	AB	~~A~~B	AB	~~A~~B	AB	AB	~~A~~B	AB	.70	.50	.20
$x^{(1)}$	AB	AB	AB	~~A~~B	~~A~~B	AB	~~A~~B	AB	~~A~~B	AB	.60	.60	.00
$x^{(2)}$	AB	AB	~~A~~B	~~A~~B	~~A~~B	AB	~~A~~B	AB	AB	AB	.60	.70	-.10
...													
$x^{(b)}$													

Bootstrap example

- Now we have a distribution! We can check how often A has an **accidental** advantage, to see if the original δ(x) we saw was very common.
- Now assuming H_0, that means normally we expect δ(x')=0
- So we just count how many times the δ(x') we found exceeds the expected 0 value by δ(x) or more:

$$\text{p-value}(x) = \sum_{i=1}^{b} \mathbb{1}\left[d(x^{(i)}) - d(x) \geq 0 \right]$$

Bootstrap example

- Alas, it's slightly more complicated.
- We didn't draw these samples from a distribution with 0 mean; we created them from the original test set *x*, which happens to be biased (by .20) in favor of *A*.
- So to measure how surprising is our observed δ(*x*), we actually compute the p-value by counting how often δ(*x'*) exceeds the expected value of δ(*x*) by δ(*x*) or more:

$$\text{p-value}(x) = \sum_{i=1}^{b} \mathbb{1}\left(d(x^{(i)}) - d(x) \geq d(x) \right)$$

$$= \sum_{i=1}^{b} \mathbb{1}\left(d(x^{(i)}) \geq 2d(x) \right)$$

Bootstrap example

- Suppose:
  - We have 10,000 test sets $x(i)$ and a threshold of .01
  - And in only 47 of the test sets do we find that $\delta(x(i)) \geq 2\delta(x)$
  - The resulting p-value is .0047
  - This is smaller than .01, indicating $\delta(x)$ is indeed sufficiently surprising
  - And we reject the null hypothesis and conclude *A* is better than *B*.

Paired bootstrap example

After Berg-Kirkpatrick et al (2012)

function BOOTSTRAP(test set x, num of samples b) **returns** *p-value*(x)

Calculate $\delta(x)$ # how much better does algorithm A do than B on x

$s = 0$

for $i =$ 1 **to** b **do**

  for $j = 1$ **to** n **do** # Draw a bootstrap sample $x^{(i)}$ of size n

    Select a member of x at random and add it to $x^{(i)}$

  Calculate $\delta(x^{(i)})$ # how much better does algorithm A do than B on $x^{(i)}$

  $s \leftarrow s + 1$ **if** $\delta(x^{(i)}) > 2\delta(x)$

p-value(x) $\approx \frac{s}{b}$ # on what % of the b samples did algorithm A beat expectations?

return p-value(x) # if very few did, our observed δ is probably not accidental

Text Classification and Naive Bayes

Avoiding Harms in Classification

Harms in sentiment classifiers

- Kiritchenko and Mohammad (2018) found that most sentiment classifiers assign lower sentiment and more negative emotion to sentences with African American names in them.
- This perpetuates negative stereotypes that associate African Americans with negative emotions

Harms in toxicity classification

- Toxicity detection is the task of detecting hate speech, abuse, harassment, or other kinds of toxic language
- But some toxicity classifiers incorrectly flag as being toxic sentences that are non-toxic but simply mention identities like blind people, women, or gay people.
- This could lead to censorship of discussion about these groups.

What causes these harms?

- Can be caused by:
  - Problems in the training data; machine learning systems are known to amplify the biases in their training data.
  - Problems in the human labels
  - Problems in the resources used (like lexicons)
  - Problems in model architecture (like what the model is trained to optimized)
- Mitigation of these harms is an open research area
- Meanwhile: **model cards**

Model Cards (Mitchell et al., 2019)

- For each algorithm you release, document:
  - training algorithms and parameters
  - training data sources, motivation, and preprocessing
  - evaluation data sources, motivation, and preprocessing
  - intended use and users
  - model performance across different demographic or other groups and environmental situations

Thanks for Your Attention!