Text Classification and Naive Bayes

The Task of Text Classification
Is this spam?

Good morning Dan,

Please familiarize yourself with the attached file.
Reply here if you have any questions.

Thank you.

John and Mike,

Appreciate your flexibility this week, as the team navigates the sensitivities surrounding some of the project work taking place at the sites. Please tentatively plan for mobilization on Ø5/16/2022, in order to begin the final stages of the upgrade.

I will follow-up tomorrow with a confirmation if all indications are we will be given the “all-clear” before EOB Wednesday/SOB Thursday.

Appreciate your support.

Regards,

Judy Sewell
Project Manager
Who wrote which *Federalist Papers*?

1787-8: essays anonymously written by:

**Alexander Hamilton, James Madison, and John Jay**

to convince New York to ratify U.S Constitution

Authorship of 12 of the letters unclear between:

Alexander Hamilton    James Madison

1963: solved by Mosteller and Wallace using Bayesian methods
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

Antagonists and Inhibitors
Blood Supply
Chemistry
Drug Therapy
Embryology
Epidemiology
...
Text Classification

Assigning subject categories, topics, or genres
Spam detection
Authorship identification (who wrote this?)
Language Identification (is this Portuguese?)
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 $c \in C$
Basic Classification Method: 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
  - In very specific domains
  - If rules are carefully refined by experts

But:
  - building and maintaining rules is expensive
  - they are too literal and specific: "high-precision, low-recall"
Classification Method:
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

Many kinds of classifiers!
• Naïve Bayes (this lecture)
• Logistic regression
• Neural networks
• $k$-nearest neighbors
• …

We can also use pretrained large language models!
• Fine-tuned as classifiers
• Prompted to give a classification
The Naive Bayes Classifier
Naive Bayes Intuition

Simple ("naive") classification method based on Bayes rule

Relies on very simple representation of document
  ◦ Bag of words
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!
The bag of words representation

\[ \gamma(\ ) = C \]

<table>
<thead>
<tr>
<th>Word</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>seen</td>
<td>2</td>
</tr>
<tr>
<td>sweet</td>
<td>1</td>
</tr>
<tr>
<td>whimsical</td>
<td>1</td>
</tr>
<tr>
<td>recommend</td>
<td>1</td>
</tr>
<tr>
<td>happy</td>
<td>1</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Bayes’ Rule Applied to Documents and Classes

• For a document $d$ and a class $c$

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$
Naive Bayes Classifier (I)

\[ c_{MAP} = \arg\max_{c \in C} P(c \mid d) \]

\[ = \arg\max_{c \in C} \frac{P(d \mid c)P(c)}{P(d)} \]

\[ = \arg\max_{c \in C} P(d \mid c)P(c) \]

MAP is “maximum a posteriori” = most likely class

Bayes Rule

Dropping the denominator
Naive Bayes Classifier (II)

\[ c_{MAP} = \arg\max_{c \in C} P(d \mid c)P(c) \]

\[ = \arg\max_{c \in C} P(x_1, x_2, \ldots, x_n \mid c)P(c) \]

"Likelihood"  "Prior"

Document d represented as features \(x_1 \ldots x_n\)
Naïve Bayes Classifier (IV)

\[ c_{MAP} = \arg \max_{c \in C} P(x_1, x_2, \ldots, x_n \mid c)P(c) \]

\[ O(|X|^n \cdot |C|) \text{ parameters} \]

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 Naive 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 \( P(x_i \mid c_j) \) are independent given the class \( c \).

\[ P(x_1, \ldots, x_n \mid c) = P(x_1 \mid c) \cdot P(x_2 \mid c) \cdot P(x_3 \mid c) \cdot \ldots \cdot P(x_n \mid c) \]
Multinomial Naive Bayes Classifier

\[ c_{MAP} = \operatorname{arg\,max}_{c \in C} P(x_1, x_2, \ldots, x_n \mid c) P(c) \]

\[ c_{NB} = \operatorname{arg\,max}_{c \in C} P(c_j) \prod_{x \in X} P(x \mid c) \]
Applying Multinomial Naive Bayes Classifiers to Text Classification

\[ c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(x_i | c_j) \]

\( \text{positions} \leftarrow \text{all word positions in test document} \)
Problems with multiplying lots of probs

There's a problem with this:

\[ c_{NB} = \text{argmax} \ P(c_j) \prod_{i \in \text{positions}} P(x_i \mid c_j) \]

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

\[ .0006 \times .0007 \times .0009 \times .01 \times .5 \times .000008 \ldots \]

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:

\[ c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(x_i | c_j) \]

This:

\[ c_{NB} = \arg\max_{c_j \in C} \left[ \log P(c_j) + \sum_{i \in \text{positions}} \log P(x_i | c_j) \right] \]

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 \textbf{linear} function of the inputs
   So naive bayes is a \textbf{linear classifier}
Text Classification and Naive Bayes

The Naive Bayes Classifier
Text Classification and Naïve Bayes

Naive Bayes: Learning
Learning the Multinomial Naive Bayes Model

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

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

\[
\hat{P}(w_i \mid c_j) = \frac{\text{count}(w_i, c_j)}{\sum_{w \in V} \text{count}(w, c_j)}
\]
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 \textit{fantastic} and classified in the topic \textbf{positive} (\textit{thumbs-up})?

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

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

\[
c_{MAP} = \arg\max_c \hat{P}(c) \prod_i \hat{P}(x_i | c)
\]
Laplace (add-1) smoothing for Naïve Bayes

\[
\hat{P}(w_i | c) = \frac{\text{count}(w_i, c) + 1}{\sum_{w \in V} (\text{count}(w, c) + 1)}
\]

\[
= \frac{\text{count}(w_i, c) + 1}{\left( \sum_{w \in V} \text{count}(w, c) \right) + |V|}
\]
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** $P(w_k | c_j)$ 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 $Text_j$

  $$P(w_k | c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha |\text{Vocabulary}|}$$
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
Naive Bayes: Learning
Sentiment and Binary Naive Bayes
Let's do a worked sentiment example!

<table>
<thead>
<tr>
<th>Cat</th>
<th>Documents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training-</td>
<td>just plain boring</td>
</tr>
<tr>
<td>-</td>
<td>entirely predictable and lacks energy</td>
</tr>
<tr>
<td>-</td>
<td>no surprises and very few laughs</td>
</tr>
<tr>
<td>+</td>
<td>very powerful</td>
</tr>
<tr>
<td>+</td>
<td>the most fun film of the summer</td>
</tr>
<tr>
<td>Test</td>
<td>?</td>
</tr>
<tr>
<td></td>
<td>predictable with no fun</td>
</tr>
</tbody>
</table>
4.4 Optimizing for Sentiment Analysis

A worked sentiment example with add-1 smoothing

<table>
<thead>
<tr>
<th>Cat</th>
<th>Documents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>- just plain boring</td>
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<td>- no surprises and very few laughs</td>
</tr>
<tr>
<td></td>
<td>+ very powerful</td>
</tr>
<tr>
<td></td>
<td>+ the most fun film of the summer</td>
</tr>
<tr>
<td>Test</td>
<td>? predictable with no fun</td>
</tr>
</tbody>
</table>

### 1. Prior from training:

\[ P(c_j) = \frac{N_{cj}}{N_{total}} \]

- \( P(-) = \frac{3}{5} \)
- \( P(+) = \frac{2}{5} \)

### 2. Drop "with"

### 3. Likelihoods from training:

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

\[ P(\text{"predictable"}|-) = \frac{1+1}{14+20} \]
\[ P(\text{"predictable"}|+) = \frac{0+1}{9+20} \]
\[ P(\text{"no"}|-) = \frac{1+1}{14+20} \]
\[ P(\text{"no"}|+) = \frac{0+1}{9+20} \]
\[ P(\text{"fun"}|-) = \frac{0+1}{14+20} \]
\[ P(\text{"fun"}|+) = \frac{1+1}{9+20} \]

### 4. Scoring the test set:

\[ P(-)P(S|-) = \frac{3}{5} \times \frac{2 \times 2 \times 1}{34^3} = 6.1 \times 10^{-5} \]
\[ P(+)P(S|+) = \frac{2}{5} \times \frac{1 \times 1 \times 2}{29^3} = 3.2 \times 10^{-5} \]
Optimizing for sentiment analysis

For tasks like sentiment, word \textit{occurrence} seems to be more important than word \textit{frequency}.

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

\textbf{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 $C$
  - $docs_j \leftarrow$ all docs with class $=c_j$
  - $P(c_j) \leftarrow \frac{|docs_j|}{|\text{total # documents}|}$

Calculate $P(w_k | c_j)$ terms
- Remove single doc containing all $docs_j$
- For each word type $w_k$ in Vocabulary
  - $n_k \leftarrow$ # of occurrences of $w_k$ in $Text_j$
  - $P(w_k | c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha |Vocabulary|}$
Binary Multinomial Naive Bayes on a test document $d$

First remove all duplicate words from $d$

Then compute NB using the same equation:

$$c_{NB} = \arg\max_{c_j \in C} P(c_j) \prod_{i \in \text{positions}} P(w_i | c_j)$$
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 multinomial 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

<table>
<thead>
<tr>
<th></th>
<th>NB Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+</td>
</tr>
<tr>
<td>and</td>
<td>2</td>
</tr>
<tr>
<td>boxing</td>
<td>0</td>
</tr>
<tr>
<td>film</td>
<td>1</td>
</tr>
<tr>
<td>great</td>
<td>3</td>
</tr>
<tr>
<td>it</td>
<td>0</td>
</tr>
<tr>
<td>no</td>
<td>0</td>
</tr>
<tr>
<td>or</td>
<td>0</td>
</tr>
<tr>
<td>part</td>
<td>0</td>
</tr>
<tr>
<td>pathetic</td>
<td>0</td>
</tr>
<tr>
<td>plot</td>
<td>1</td>
</tr>
<tr>
<td>satire</td>
<td>1</td>
</tr>
<tr>
<td>scenes</td>
<td>1</td>
</tr>
<tr>
<td>the</td>
<td>0</td>
</tr>
<tr>
<td>twists</td>
<td>1</td>
</tr>
<tr>
<td>was</td>
<td>0</td>
</tr>
<tr>
<td>worst</td>
<td>0</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>NB</th>
<th>Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>+</td>
<td>−</td>
</tr>
<tr>
<td>and</td>
<td>2 0</td>
</tr>
<tr>
<td>boxing</td>
<td>0 1</td>
</tr>
<tr>
<td>film</td>
<td>1 0</td>
</tr>
<tr>
<td>great</td>
<td>3 1</td>
</tr>
<tr>
<td>it</td>
<td>0 1</td>
</tr>
<tr>
<td>no</td>
<td>0 1</td>
</tr>
<tr>
<td>or</td>
<td>0 1</td>
</tr>
<tr>
<td>part</td>
<td>0 1</td>
</tr>
<tr>
<td>pathetic</td>
<td>0 1</td>
</tr>
<tr>
<td>plot</td>
<td>1 1</td>
</tr>
<tr>
<td>satire</td>
<td>1 0</td>
</tr>
<tr>
<td>scenes</td>
<td>1 2</td>
</tr>
<tr>
<td>the</td>
<td>0 2</td>
</tr>
<tr>
<td>twists</td>
<td>1 1</td>
</tr>
<tr>
<td>was</td>
<td>0 2</td>
</tr>
<tr>
<td>worst</td>
<td>0 1</td>
</tr>
</tbody>
</table>

Figure 4.3 An example of binarization for the binary naive Bayes algorithm.

A second important addition commonly made when doing text classification for sentiment is to deal with negation. Consider the difference between I really like this movie (positive) and I didn’t like this movie (negative). The negation expressed by didn’t completely alters the inferences we draw from the predicate like. Similarly, negation can modify a negative word to produce a positive review (don’t dismiss this film, doesn’t let us get bored).

A very simple baseline that is commonly used in sentiment analysis to deal with negation is the following: during text normalization, prepend the prefix NOT to every word after a token of logical negation (n’t, not, no, never) until the next punctuation mark. Thus the phrase didn’t like this movie, but I becomes didn’t NOT_like NOT_this NOT_movie, but I.

Newly formed ‘words’ like NOT_like, NOT_recommend will thus occur more often in negative document and act as cues for negative sentiment, while words like NOT_bored, NOT_dismiss will acquire positive associations. We will return in Chapter 16 to the use of parsing to deal more accurately with the scope relationship between these negation words and the predicates they modify, but this simple baseline works quite well in practice.

Finally, in some situations we might have insufficient labeled training data to train accurate naive Bayes classifiers using all words in the training set to estimate positive and negative sentiment. In such cases we can instead derive the positive
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

Counts can still be 2! Binarization is within-doc!
Text Classification and Naive Bayes

Sentiment and Binary Naive Bayes
Text Classification and Naive 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


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


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


- 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 $(dollar) ((dollar) \text{ NN,NNN,NNN.NN})$
- 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
Text Classification and Naive Bayes

More on Sentiment Classification
Text Classification and Naïve Bayes

Naïve Bayes: Relationship to Language Modeling
Generative Model for Multinomial Naïve Bayes

\[ c = \text{China} \]

\[ X_1 = \text{Shanghai} \quad X_2 = \text{and} \quad X_3 = \text{Shenzhen} \quad X_4 = \text{issue} \quad X_5 = \text{bonds} \]
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: $P(\text{word} \mid c)$
- Assigning each sentence: $P(s \mid c) = \prod P(\text{word} \mid c)$

**Class pos**

<table>
<thead>
<tr>
<th>Class</th>
<th>pos</th>
<th>$P(s \mid \text{pos})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>I</td>
<td>0.0000005</td>
</tr>
<tr>
<td>0.1</td>
<td>love</td>
<td>0.1 0.1 .05 0.01 0.1</td>
</tr>
<tr>
<td>0.01</td>
<td>this</td>
<td></td>
</tr>
<tr>
<td>0.05</td>
<td>fun</td>
<td></td>
</tr>
<tr>
<td>0.1</td>
<td>film</td>
<td></td>
</tr>
</tbody>
</table>

$P(s \mid \text{pos}) = 0.0000005$
Naïve Bayes as a Language Model

- Which class assigns the higher probability to $s$?

\[
P(s|\text{pos}) > P(s|\text{neg})
\]
Text Classification and Naïve Bayes

Naïve Bayes: Relationship to Language Modeling
Text Classification and Naive Bayes

Precision, Recall, and F1
Evaluating Classifiers: How well does our classifier work?

Let's first address binary classifiers:

• Is this email spam?
  spam (+) or not spam (-)

• Is this post about Delicious Pie Company?
  about Del. Pie Co (+) or not about Del. Pie Co(-)

We'll need to know

1. What did our classifier say about each email or post?
2. What should our classifier have said, i.e., the correct answer, usually as defined by humans ("gold label")
First step in evaluation: The confusion matrix

<table>
<thead>
<tr>
<th>Gold Standard Labels</th>
<th>System Output Labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gold Positive</td>
<td>System Positive</td>
</tr>
<tr>
<td>Gold Positive</td>
<td>True Positive</td>
</tr>
<tr>
<td>Gold Negative</td>
<td>False Positive</td>
</tr>
<tr>
<td>False Positive</td>
<td>False Negative</td>
</tr>
<tr>
<td>True Negative</td>
<td>True Negative</td>
</tr>
</tbody>
</table>
Accuracy on the confusion matrix

<table>
<thead>
<tr>
<th></th>
<th>gold positive</th>
<th>gold negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>system output</td>
<td>true positive</td>
<td>false positive</td>
</tr>
<tr>
<td>labels</td>
<td>false negative</td>
<td>true negative</td>
</tr>
</tbody>
</table>

\[
\text{accuracy} = \frac{tp+tn}{tp+fp+tn+fn}
\]

\[
\text{recall} = \frac{tp}{tp+fn}
\]

\[
\text{precision} = \frac{tp}{tp+fp}
\]
Why don't we use accuracy?

Accuracy doesn't work well when we're dealing with uncommon or imbalanced classes

Suppose we look at 1,000,000 social media posts to find Delicious Pie-lovers (or haters)

• 100 of them talk about our pie
• 999,900 are posts about something unrelated

Imagine the following simple classifier

Every post is "not about pie"
Accuracy re: pie posts

100 posts are about pie; 999,900 aren't

<table>
<thead>
<tr>
<th>gold standard labels</th>
<th>gold positive</th>
<th>gold negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>system output labels</td>
<td>system positive</td>
<td>false positive</td>
</tr>
<tr>
<td></td>
<td>true positive</td>
<td>false negative</td>
</tr>
<tr>
<td></td>
<td>true negative</td>
<td></td>
</tr>
</tbody>
</table>

\[
\text{accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{fp} + \text{tn} + \text{fn}}
\]
Why don't we use accuracy?

Accuracy of our "nothing is pie" classifier

999,900 true negatives and 100 false negatives

Accuracy is 999,900/1,000,000 = 99.99%!

But useless at finding pie-lovers (or haters)!!

Which was our goal!

Accuracy doesn't work well for unbalanced classes

Most tweets are not about pie!
Instead of accuracy we use precision and recall

\[ \text{gold standard labels} \]

\[
\begin{array}{c|c|c|c}
& \text{gold positive} & \text{gold negative} \\
\hline
\text{system output labels} & \text{true positive} & \text{false positive} \\
\hline
\text{system positive} & \text{false negative} & \text{true negative} \\
\text{system negative} & & \\
\hline
\end{array}
\]

\[
\text{precision} = \frac{tp}{tp+fp}
\]

\[
\text{recall} = \frac{tp}{tp+fn}
\]

\[
\text{accuracy} = \frac{tp+tn}{tp+fp+tn+fn}
\]

**Precision**: % of selected items that are correct

**Recall**: % of correct items that are selected
Precision/Recall aren't fooled by the "just call everything negative" classifier!

Stupid classifier: Just say no: every tweet is "not about pie"
- 100 tweets talk about pie, 999,900 tweets don't
- Accuracy = 999,900/1,000,000 = 99.99%

But the Recall and Precision for this classifier are terrible:

\[
\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}
\]

\[
\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}
\]
A combined measure: F1

F1 is a combination of precision and recall.

\[ F_1 = \frac{2PR}{P + R} \]
F1 is a special case of the general "F-measure"

F-measure is the (weighted) harmonic mean of precision and recall

\[
\text{HarmonicMean}(a_1, a_2, a_3, a_4, \ldots, a_n) = \frac{n}{\frac{1}{a_1} + \frac{1}{a_2} + \frac{1}{a_3} + \ldots + \frac{1}{a_n}}
\]

\[
F = \frac{1}{\alpha \frac{1}{P} + (1 - \alpha) \frac{1}{R}} \quad \text{or} \quad \left( \frac{\text{with } \beta^2 = \frac{1 - \alpha}{\alpha}} \right) \quad F = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}
\]

F1 is a special case of F-measure with \(\beta=1, \alpha=\frac{1}{2}\)
Suppose we have more than 2 classes?

Lots of text classification tasks have more than two classes.  
- Sentiment analysis (positive, negative, neutral), named entities (person, location, organization)

We can define precision and recall for multiple classes like this 3-way email task:

<table>
<thead>
<tr>
<th>gold labels</th>
<th>urgent</th>
<th>normal</th>
<th>spam</th>
</tr>
</thead>
<tbody>
<tr>
<td>system output</td>
<td>urgent</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>normal</td>
<td>5</td>
<td>60</td>
<td>50</td>
</tr>
<tr>
<td>spam</td>
<td>3</td>
<td>30</td>
<td>200</td>
</tr>
</tbody>
</table>

**Recall**

- \( \text{recall}_u = \frac{8}{8+5+3} \)
- \( \text{recall}_n = \frac{60}{10+60+30} \)
- \( \text{recall}_s = \frac{200}{1+50+200} \)

**Precision**

- \( \text{precision}_u = \frac{8}{8+10+1} \)
- \( \text{precision}_n = \frac{60}{5+60+50} \)
- \( \text{precision}_s = \frac{200}{3+30+200} \)
How to combine P/R values for different classes: Microaveraging vs Macroaveraging

<table>
<thead>
<tr>
<th>Class 1: Urgent</th>
<th>Class 2: Normal</th>
<th>Class 3: Spam</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>true</td>
<td>true</td>
<td>true</td>
</tr>
<tr>
<td></td>
<td>urgent</td>
<td>not</td>
<td>true</td>
</tr>
<tr>
<td>system</td>
<td></td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>urgent</td>
<td>8</td>
<td>11</td>
<td>200</td>
</tr>
<tr>
<td>system not</td>
<td>8</td>
<td>340</td>
<td>99</td>
</tr>
<tr>
<td>system</td>
<td></td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>urgent</td>
<td>6</td>
<td>55</td>
<td>33</td>
</tr>
<tr>
<td>system normal</td>
<td>60</td>
<td>51</td>
<td>268</td>
</tr>
<tr>
<td>system not</td>
<td>40</td>
<td>212</td>
<td>99</td>
</tr>
<tr>
<td>system</td>
<td></td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>spam</td>
<td>200</td>
<td>51</td>
<td>268</td>
</tr>
<tr>
<td>system normal</td>
<td>200</td>
<td>83</td>
<td>635</td>
</tr>
<tr>
<td>system not</td>
<td>51</td>
<td>83</td>
<td>635</td>
</tr>
<tr>
<td>system</td>
<td></td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>yes</td>
<td>200</td>
<td>33</td>
<td>268</td>
</tr>
<tr>
<td>system no</td>
<td>51</td>
<td>83</td>
<td>99</td>
</tr>
<tr>
<td>no</td>
<td>99</td>
<td>635</td>
<td>635</td>
</tr>
</tbody>
</table>

precision = \[
\frac{8}{8+11} = .42
\]

precision = \[
\frac{60}{60+55} = .52
\]

precision = \[
\frac{200}{200+33} = .86
\]

microaverage precision = \[
\frac{268}{268+99} = .73
\]

macroaverage precision = \[
\frac{.42+.52+.86}{3} = .60
\]
Text Classification and Naive Bayes

Precision, Recall, and F1
Text Classification and Naive Bayes

Avoiding Harms in Classification
Harms of classification

Classifiers, like any NLP algorithm, can cause harms. This is true for any classifier, whether Naive Bayes or other algorithms.
Representational Harms

• Harms caused by a system that demeans a social group
  • Such as by perpetuating negative stereotypes about them.

• Kiritchenko and Mohammad 2018 study
  • Examined 200 sentiment analysis systems on pairs of sentences
  • Identical except for names:
    • common African American (Shaniqua) or European American (Stephanie).
    • Like "I talked to Shaniqua yesterday" vs "I talked to Stephanie yesterday"

• Result: systems assigned lower sentiment and more negative emotion to sentences with African American names

• Downstream harm:
  • Perpetuates stereotypes about African Americans
  • African Americans treated differently by NLP tools like sentiment (widely used in marketing research, mental health studies, etc.)
Harms of Censorship

- **Toxicity detection** is the text classification task of detecting hate speech, abuse, harassment, or other kinds of toxic language.
  - Widely used in online content moderation

- Toxicity classifiers incorrectly flag non-toxic sentences that simply mention minority identities (like the words "blind" or "gay")
  - women (Park et al., 2018),
  - disabled people (Hutchinson et al., 2020)
  - gay people (Dixon et al., 2018; Oliva et al., 2021)

- Downstream harms:
  - Censorship of speech by disabled people and other groups
  - Speech by these groups becomes less visible online
  - Writers might be nudged by these algorithms to avoid these words making people less likely to write about themselves or these groups.
1. Text classifiers perform worse on many languages of the world due to lack of data or labels.

2. Text classifiers perform worse on varieties of even high-resource languages like English.
   - Example task: language identification, a first step in NLP pipeline ("Is this post in English or not?")
   - English language detection performance worse for writers who are African American (Blodgett and O'Connor 2017) or from India (Jurgens et al., 2017)
Harms in text classification

• **Causes:**
  • Issues in the data; NLP systems amplify biases in training data
  • Problems in the labels
  • Problems in the algorithms (like what the model is trained to optimize)

• **Prevalence:** The same problems occur throughout NLP (including large language models)

• **Solutions:** There are no general mitigations or solutions
  • But harm mitigation is an active area of research
  • And there are standard benchmarks and tools that we can use for measuring some of the harms
Text Classification and Naive Bayes

Avoiding Harms in Classification