EECS 498-004: Introduction to Natural Language Processing

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Project proposal (due Feb 15)

- In general, we want to see that you have a clear goal in the project. The technical details can be described in a rough manner, but in principle, you need to show what problem you want to study.
  - **Introduction**: the problem has to be well-defined. What are the input and output. Why this is an important problem to study.
  - **Related work**: put your work in context. Describe what has been done in previous work on the same or related subject. And why what you propose to do here is novel and different.
  - **Datasets**: what data do you want to use? What is the size of it? What information is contained? Why is it suitable for your task?
  - **Methodology**: what models do you want to use? You may change the model as the project goes, but you may want to indicate some type of models that might be suitable for your problem. Is it a supervised learning problem or unsupervised? What classifiers can you start with? Are you making improvements? You don't have to be crystal clear on this section, but it can be used to indicate the direction that your project goes to.
  - **Evaluation**: what metrics do you want to use for evaluating your models?
- Length: 1 page (or more if necessary). Single space if MS word is used. Or you can choose latex templates, e.g. https://www.acm.org/publications/proceedings-template.
- Grading: based on each section described above, 20 points per section. But as you can tell, they're related to each other.
- Each group member will make separate submission with all group members' names indicated.

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Project discussions!

- See Piazza @14 to sign up for meeting times
- Happy to discuss your ideas or just brainstorm together!
- Feb 1, 10:30am-12pm
- Feb 3, 12pm-1pm
- Feb 4, 9pm-10pm

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Outline

- Text Categorization/Classification
- Naïve Bayes
- Evaluation

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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.

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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

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Text Classification

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

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Text Classification: definition

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

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Classification Methods: 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

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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 $(d_1,y_1),\ldots,(d_m,y_m)$, y_i is in C
- *Output:*
  - a learned classifier $y{:}d \rightarrow c$

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Classification Methods: Supervised Machine Learning

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

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Outline

- Text Categorization/Classification
- ➡ Naïve Bayes
- Evaluation

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Naïve Bayes Classifier

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Naïve Bayes Intuition

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

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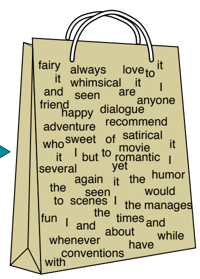
The Bag of Words Representation

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
...	...

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The bag of words representation

γ(

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

)=c

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Bayes' Rule Applied to Documents and Classes

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

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

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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

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Bayes Rule

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

Dropping the denominator

Why we can do this?

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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 $x_1..x_n$

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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

$|X|$ represents the maximum number of possible values for x_i

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

- **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.*

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

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Naïve Bayes Classifier

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

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

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Applying Naive Bayes Classifiers to Text Classification

positions $\leftarrow$ all word positions in test document

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

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Learning for Naïve Bayes Model

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Learning the Naïve Bayes Model

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

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

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

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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 class c_j

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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!

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

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Laplace (add-1) smoothing for Naïve Bayes

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

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

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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 $Text_j$

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

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Naïve Bayes: Learning

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  - For each word w_k in *Vocabulary*
    $n_k \leftarrow$ # of occurrences of w_k in $Text_j$

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

A more general form: add-α smoothing!

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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.

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Each class = a unigram language model

- Assigning each word: P(word | c)
- Assigning each sentence: P(sentence|c)=Π 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	0.01	0.05	0.1

P(sentence | pos) = 0.0000005

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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)

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An Example

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

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

	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) ∝ $3/4 * (3/7)^3 * 1/14 * 1/14$ ≈ 0.0003

P(j|d5) ∝ $1/4 * (2/9)^3 * 2/9 * 2/9$ ≈ 0.0001

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Summary: Naive Bayes is Not So Naive

- Very Fast, low storage requirements
- Robust to Irrelevant Features
  Irrelevant Features cancel each other without affecting results
- Very good in domains with many equally important features
- 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

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Outline

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- ➡ Evaluation

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Evaluation

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The 2-by-2 contingency table (or confusion matrix)

	correct	not correct
selected	tp (true positive)	fp (false positive)
not selected	fn (false negative)	tn (true negative)

For example,
- Which set of documents are related to the topic of NLP?
- Which set of documents are written by Shakespeare?

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The 2-by-2 contingency table

	correct	not correct
selected	tp	fp
not selected	fn	tn

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Precision and recall

- **Precision**: % of selected items that are correct, tp/(tp+fp)
  Recall: % of correct items that are selected, tp/(tp+fn)

	correct	not correct
selected	tp	fp
not selected	fn	tn

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A combined measure: F-measure or F-score

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

$$F = \frac{1}{\alpha \frac{1}{P} + (1-\alpha)\frac{1}{R}}$$

- People usually use balanced F1 measure
  - i.e., $\alpha = ½$, $F = 2PR/(P+R)$

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Text Classification Evaluation

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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

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More Than Two Classes: Sets of binary classifiers

- One-of or multinomial classification
  - 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

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Confusion matrix c

- 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	0	1	2	13	26	5
True trade	0	0	2	14	5	10

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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: $\frac{\sum_i c_{ii}}{\sum_j \sum_i c_{ij}}$

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Micro- vs. Macro-Averaging

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

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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 Avg. Table

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

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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 Avg. Table

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

- Macroaveraged precision: (0.5 + 0.9)/2 = 0.7
- Microaveraged precision: 100/120 = .83

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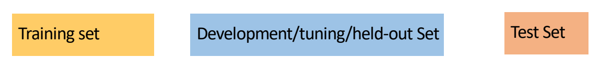
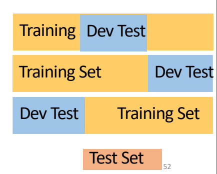
Development Test Sets and Cross-validation



Metric: P/R/F1 or Accuracy

Cross-validation over multiple splits

- Handle sampling errors from different datasets
  - Pool results over each split
  - Compute pooled dev set performance



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