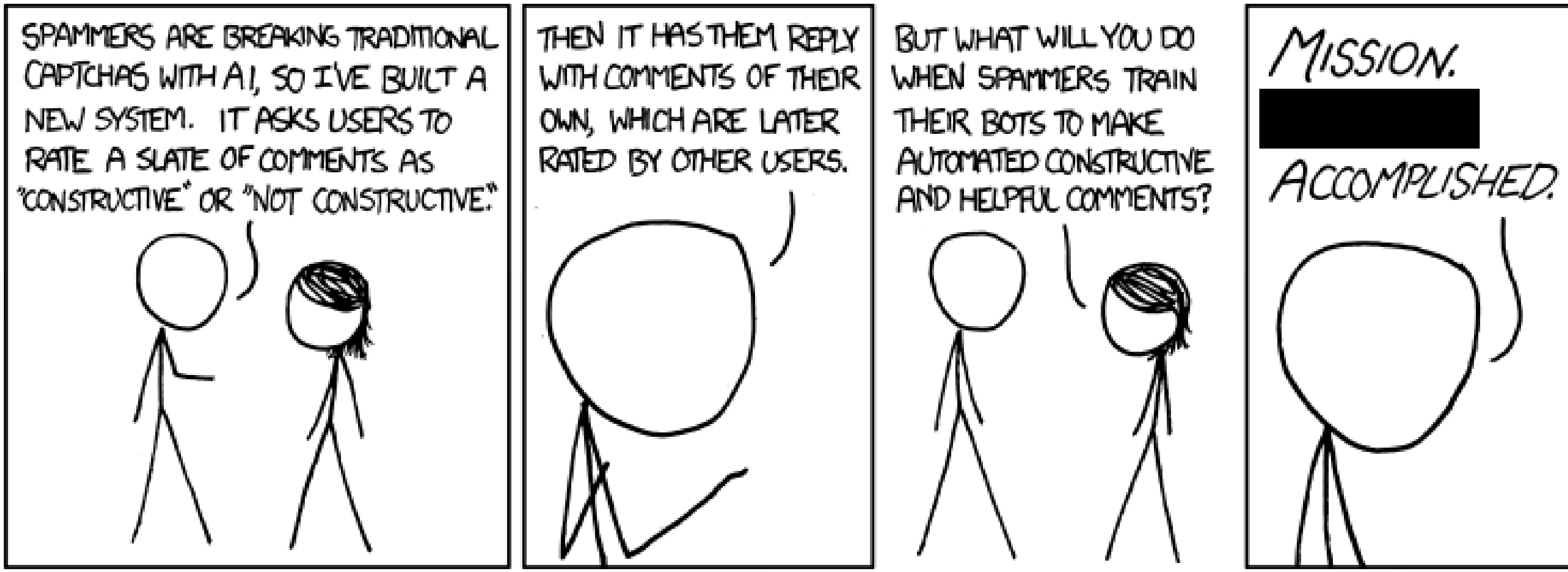
UNIVERSITY of WASHINGTON

Data Science UW Methods for Data Analysis

Intro to Natural Language Processing
Lecture 9
Nick McClure


SPAMMERS ARE BREAKING TRADITIONAL CAPTCHAS WITH AI, SO I'VE BUILT A NEW SYSTEM. IT ASKS USERS TO RATE A SLATE OF COMMENTS AS "CONSTRUCTIVE" OR "NOT CONSTRUCTIVE."
THEN IT HAS THEM REPLY WITH COMMENTS OF THEIR OWN, WHICH ARE LATER RATED BY OTHER USERS.
BUT WHAT WILL YOU DO WHEN SPAMMERS TRAIN THEIR BOTS TO MAKE AUTOMATED CONSTRUCTIVE AND HELPFUL COMMENTS?
MISSION. [redacted] ACCOMPLISHED.

Topics

> Review
> Natural Language Processing
  - Text Normalization
  - Text Distances
  - Corpus/Dictionaries
  - Naïve Bayes
  - Word Frequencies
  - Latent Dirichlet Allocation

Review

- Bayesian Statistics
  - Bayesian Inference
  - MCMC distributions
- Computational Statistics
  - Bootstrapping
  - Generating P-values via simulating the Null Hypothesis
  - Cross Validation

Why Text?

- How much data?
  - Twitter has more text data recorded than all that has been written in print in the history of mankind. (http://www.internetlivestats.com/twitter-statistics/)
  - Most of the world's data is unstructured:
    - 2009 HP Survey: 70%
    - Gartner: 80%
    - Teradata: 85%
- Why use text?
  - Structured (numerical/categorical) data very often misses elements critical to modeling.
    - Un-transcribed notes, comments, logs
    - Surveys, medical charts

Measuring Text Distance

- Hamming Distance
  - Line up strings, count number of positions that are the different.
  - Assumes strings are of the same length.

$Hamming(beer, bear) = 1$ $Hamming(101101, 100011) = 3$

- Levenshtein distance
  - Measures edit distance between two strings (insertion, deletion, substitution only)

$Lev(beer, bear) = 1$ $Lev(banana, ban) = 3$

Measuring Text Differences

- Jaccard index
  - Size of intersection of characters divided by size of union of characters.

$$J(A,B) = 1 - \frac{|A \cap B|}{|A \cup B|}$$

$$J(beer, bear) = 1 - \frac{3}{4} \qquad J(banana, ban) = 1 - \frac{3}{3}$$

- Weighted Jaccard Index
  - For each letter, calculate the minimum times it appears, $m_i$and the max, M_i

$$J'(A,B) = 1 - \frac{\sum m_i}{\sum M_i}$$

$$J(beer, bear) = 1 - \frac{m_a + m_b + m_e + m_r}{M_a + M_b + M_e + M_r} \qquad J(banana, ban) = 1 - \frac{m_a + m_b + m_n}{M_a + M_b + M_n}$$

$$J(beer, bear) = 1 - \frac{0+1+1+1}{1+1+2+1} = 1 - \frac{3}{5} \qquad J(banana, ban) = 1 - \frac{1+1+1}{3+1+2}$$

- R demo

Text Normalization (Pre processing)

- Strip extra white space:

I <3 statistics, it’s my \u1072   fAvoRitE!! 11!!! → I <3 statistics, it’s my \u1072 fAvoRitE!! 11!!!

- Remove Unicode text

I <3 statistics, it’s my \u1072 fAvoRitE!! 11!!! → I <3 statistics, it’s my fAvoRitE!! 11!!!

- Lower case

I <3 statistics, it’s my fAvoRitE!! 11!!! → i <3 statistics, it’s my favorite!! 11!!!

- Remove punctuation

i <3 statistics, it’s my favorite!! 11!!! → i 3 statistics its my favorite 11

- Remove numbers

i 3 statistics its my favorite 11 → i statistics its my favorite

- Remove stop words

i statistics its my favorite → statistics favorite

- Stem words (optional)

statistics favorite → statisti favori

- R-demo

Dictionary Creation

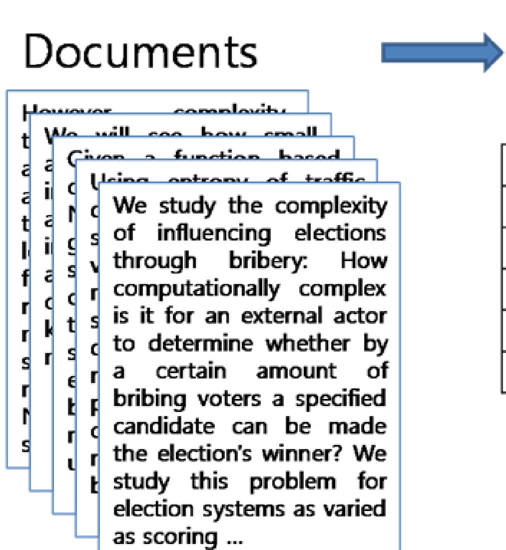
> Usually we have a whole bunch of entries, each entry is a sequence of variable length text.

> A <u>document</u> is just one entry.

> A collection of documents is called a <u>corpus.</u>

> We can represent that corpus many ways.

> Term document matrix (shown below) or a Document term matrix (transpose).



	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Term-document matrix

Naïve Bayes!

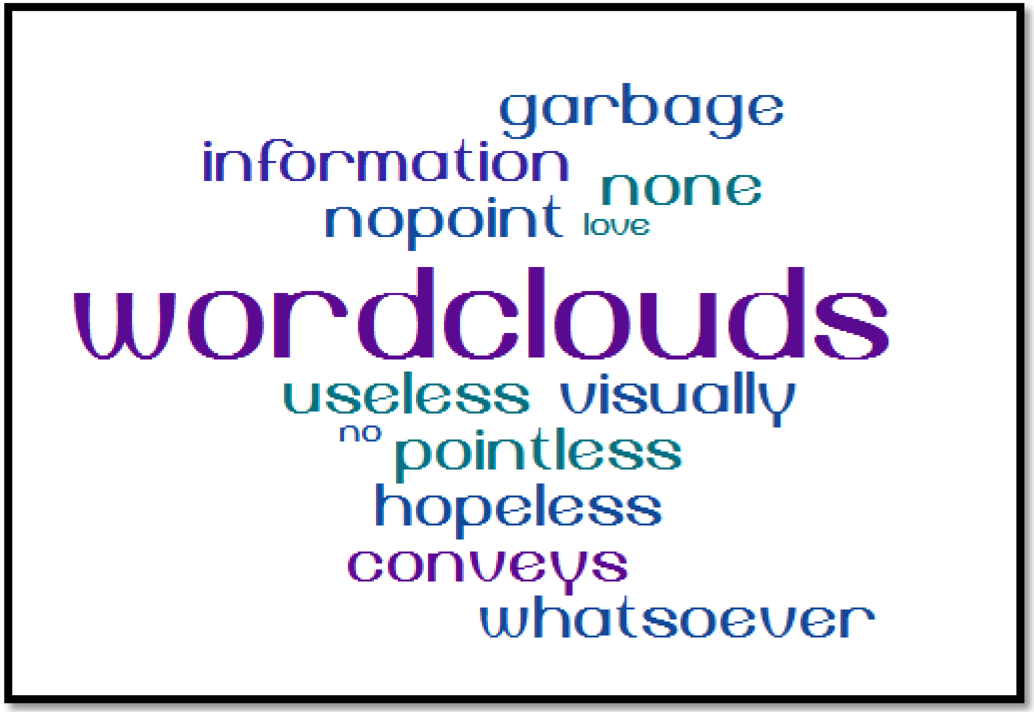
- Now we have a numeric representation of key words in our documents.
- We can use this in our Naïve Bayes algorithm to classify documents.

- R-demo

Wordclouds

> Completely useless display of information that people love to see.

> R demo



Creating Features

- Text Frequency: Word frequency or TF
  - Count how many times a word appears in a single document.
  - Terms that occur in fewer documents are more descriptive and may contain more information (Rarity matters).
- Inverse Document Frequency (IDF)
  - Inverse of the proportion of documents containing term in the whole collection.
  - #documents / #documents with word might be too severe.
    - A word appearing twice instead of once shouldn't have twice the impact

$$IDF = \log\left(\frac{\#Documents}{\#Documents\ with\ Word}\right)$$

- Maybe we should tie these together:
- TF-IDF: Rare terms in whole collection that appear frequently in some documents maybe very important!
  - Multiply these two

How to Use TF-IDF

$$TF - IDF = \log\left(\frac{\#Documents}{\#Documents\ with\ Word}\right) \times f(Word)$$

- > Finding important words to describe the document collections or subgroups of collections.
- > Using the count of important words as a feature in a model.
- > Using the distribution of a document's TF-IDF values.
  - – Characterize writing styles
  - – Comparing authors
  - – Determining original authors
  - – Finding plagiarism
- > R-demo

Latent Dirichlet Allocation

- Creates k-subtopics and determines which topics apply to which document (multiple allowed) with a probability.
- In other words, each document is considered to be generated by drawing words from a mixture of topics.
- Steps:
  - Initialize the number of topics. Use informed estimate or use trial-and error, choosing the number that results in the most interpretable topics.
  - Assign every word to a random topic in each document.
  - Iterate and update topic assignments via:
    - How common is that word across topics (for all documents)?
    - How common is that topic in that document.
- We are trying to estimate the distribution of topics…
  - Via MCMC!!!! (prior = Dirichlet distribution)

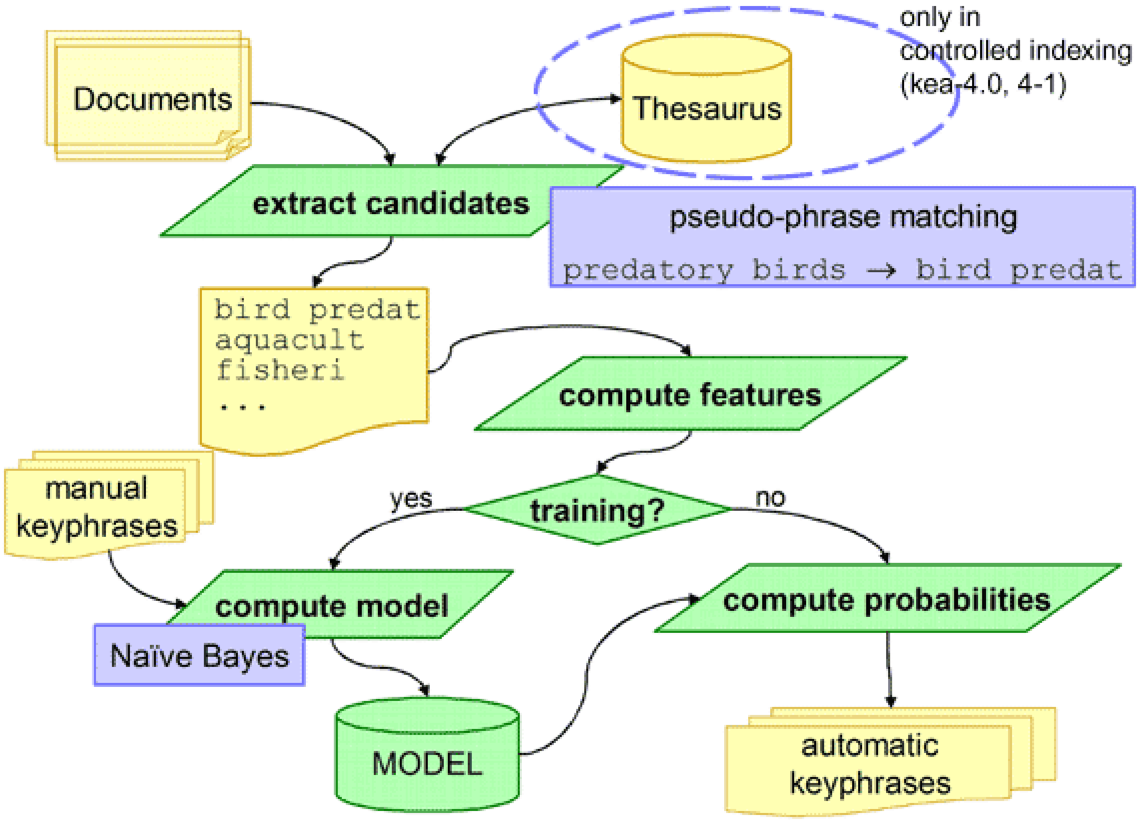
- R-demo

RAKE: Rapid Automatic Keyword Extraction

- LDA is computationally hard and to apply this to many documents is quite time and memory consuming.
- Tweets come in at up to 500k per minute.
- If we can give our algorithm an idea of what to look for:
  - TF-IDF: Keywords will have higher TF-IDF values.
  - First occurrence: Keywords will tend to appear in the beginning of the document, so we calculate the % of document before the first occurrence.
  - Length: Long keywords are not preferred, we know that in English, 3-8 letter words are preferred.
  - Node Degree: Number of phrases (synonyms, rearrangements, stems) that are related to other candidate phrases.

RAKE: Rapid Automatic Keyword Extraction

- After candidates are computed, we use a Naïve Bayes model to predict other keywords in the model.



- R-demo

Further interesting links

- Microsoft Research 2008: Bayesian Inference in Traffic Patterns. http://research.microsoft.com/pubs/101948/TAinfer.pdf
- Google Analytics (Multi armed bandit experiments for AB testing): https://support.google.com/analytics/answer/2844870?hl=en
- Google Research: Voice recognition: http://static.googleusercontent.com/media/research.google.com/en//pubs/archive/37567.pdf
- CNA: Forecasting insurance loss: http://www.casact.org/education/annual/2010/handouts/C4-Zhang.pdf
- Swype texting: http://static.googleusercontent.com/media/research.google.com/en//pubs/archive/39190.pdf

Class Overview

> Hypothesis Testing

Parametric/Well Defined High-Powered Higher Bias	More-Less Assumptions ⟷	Non-Parametric/Computational Low-Powered Higher Variance

> Linear Regression
  - Ordinary Linear Regression, Multiple Linear Regression, Logistic Regression, Ridge Regression, Lasso Regression, SVD

> Graph Algorithms, Spatial Statistics and Time Series

> Bayesian Statistics and Computational Statistics

Less Models Higher Bias	Test/Train Cross Validation ⟷	More Models Higher Variance

> N.L.P.

Class Overview

- Remember this class is an overview of many methods.
- Hopefully you will know what and where to lookup subjects that you may need for work, projects, fun dinner party jokes, etc…
- This certification class is a great step in the right direction.
  - It shows employers and colleagues that you are serious about the analytical field and have had formal training.
- You are now (and have been) a resource for others.
- Last piece of advice:
  - Don’t ever stop learning. The day we stop learning for/at our jobs is the day we should be looking for a new job.