Text Categorization using Naïve Bayes

Mausam

(based on slides of Dan Weld, Prabhakar Raghavan, Hinrich Schutze, Guillaume Obozinski, David D. Lewis)

Categorization

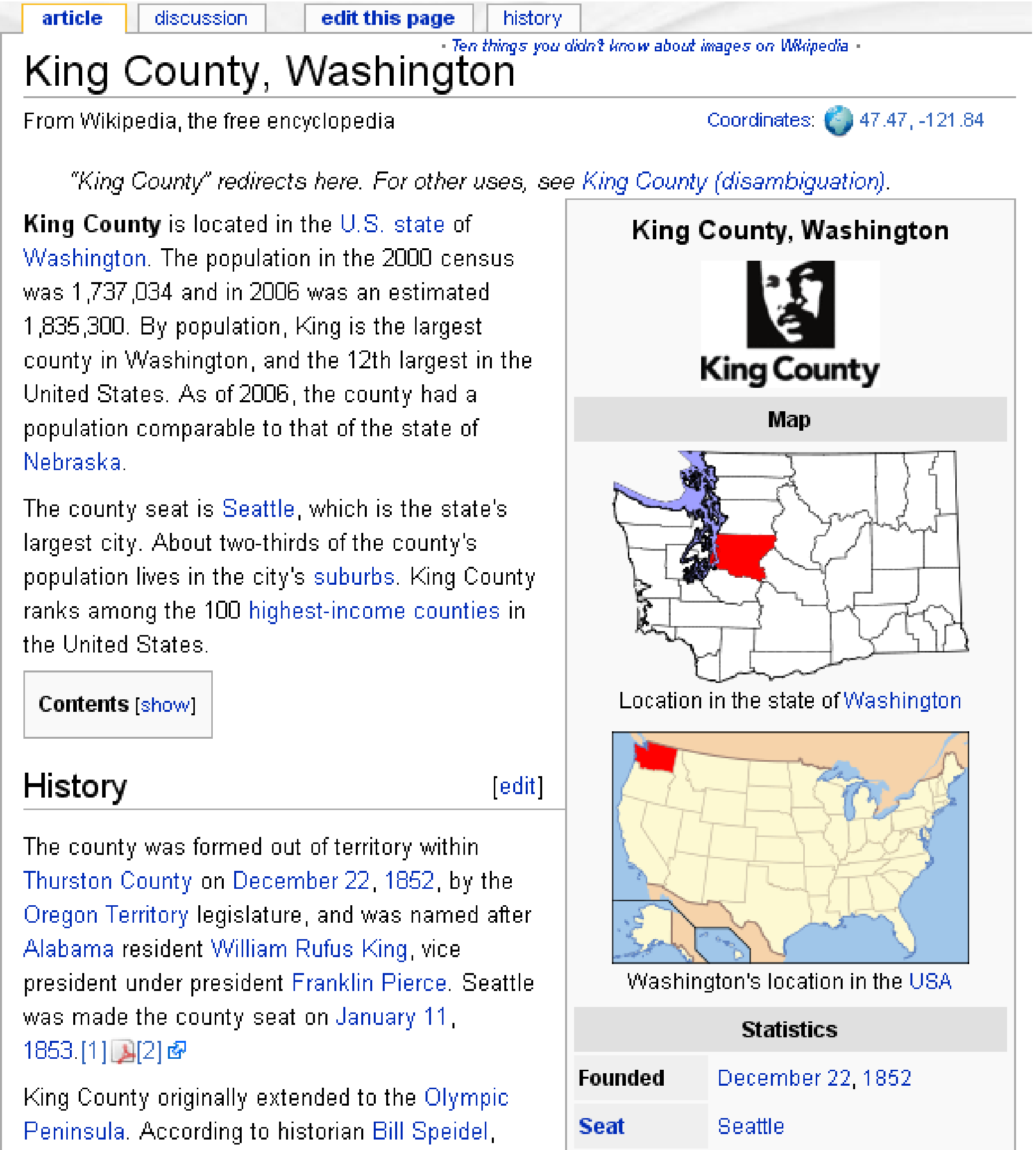
- Given:
  - A **description of an instance**, $x \in X$, where X is the *instance language* or *instance space*.
  - A **fixed set of categories**: $C = \{c_1, c_2, \ldots c_n\}$
- Determine:
  - The **category of *x***: $c(x) \in C$, where $c(x)$ is a categorization function whose domain is X and whose range is C.

Sample Category Learning Problem

- Instance language: <size, color, shape>
  - size ∈ {small, medium, large}
  - color ∈ {red, blue, green}
  - shape ∈ {square, circle, triangle}
- C = {**positive**, negative}
- D:

Example	Size	Color	Shape	Category
1	**small**	**red**	**circle**	**positive**
2	**large**	**red**	**circle**	**positive**
3	small	red	triangle	negative
4	large	blue	circle	negative

Another Example: County *vs.* Country?



King County, Washington

From Wikipedia, the free encyclopedia

Coordinates: 47.47, -121.84

"King County" redirects here. For other uses, see King County (disambiguation).

King County is located in the U.S. state of Washington. The population in the 2000 census was 1,737,034 and in 2006 was an estimated 1,835,300. By population, King is the largest county in Washington, and the 12th largest in the United States. As of 2006, the county had a population comparable to that of the state of Nebraska.

The county seat is Seattle, which is the state's largest city. About two-thirds of the county's population lives in the city's suburbs. King County ranks among the 100 highest-income counties in the United States.

Contents [show]

King County, Washington

Map

Location in the state of Washington

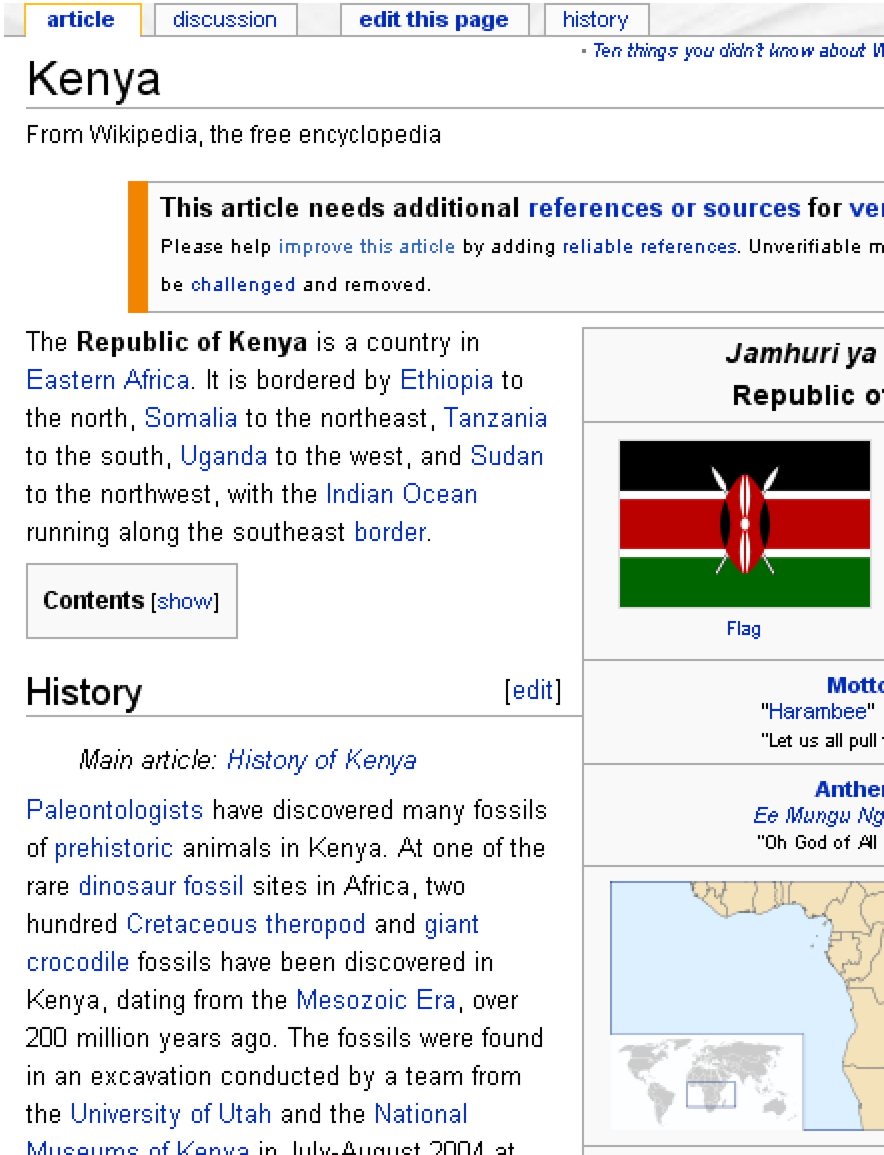
Washington's location in the USA

Statistics	
Founded	December 22, 1852
Seat	Seattle

History [edit]

The county was formed out of territory within Thurston County on December 22, 1852, by the Oregon Territory legislature, and was named after Alabama resident William Rufus King, vice president under president Franklin Pierce. Seattle was made the county seat on January 11, 1853.[1] [2]

King County originally extended to the Olympic Peninsula. According to historian Bill Speidel,



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Jamhuri ya
Republic o

Flag

Motto
"Harambee"
"Let us all pull

Anthem
Ee Mungu Ng
"Oh God of All

History [edit]

Main article: History of Kenya

Paleontologists have discovered many fossils of prehistoric animals in Kenya. At one of the rare dinosaur fossil sites in Africa, two hundred Cretaceous theropod and giant crocodile fossils have been discovered in Kenya, dating from the Mesozoic Era, over 200 million years ago. The fossils were found in an excavation conducted by a team from the University of Utah and the National Museums of Kenya in July-August 2004 at

Example: County *vs.* Country?

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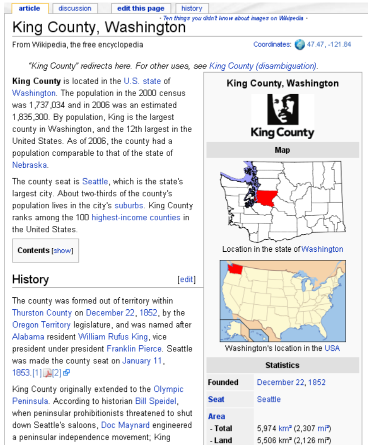

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King County, Washington

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Location in the state of Washington

Washington's location in the USA

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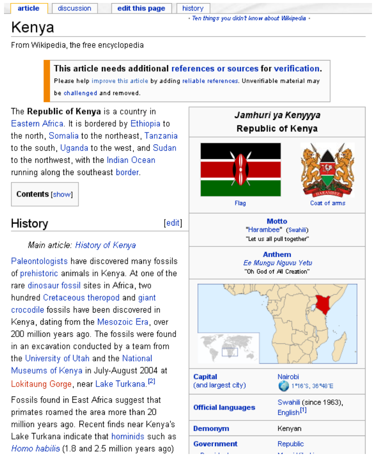
Area	
- **Total**	5,974 km² (2,307 mi²)
- **Land**	5,506 km² (2,126 mi²)



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Fossils found in East Africa suggest that primates roamed the area more than 20 million years ago. Recent finds near Kenya's Lake Turkana indicate that hominids such as *Homo habilis* (1.8 and 2.5 million years ago)

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Republic of Kenya

Flag

Coat of arms

Motto
"Harambee" (Swahili)
"Let us all pull together"

Anthem
Ee Mungu Nguvu Yetu
"Oh God of All Creation"

Capital (and largest city)	Nairobi 1°16′S, 36°48′E
Official languages	Swahili (since 1963), English[1]
Demonym	Kenyan
Government	Republic

Text Categorization

- Assigning documents to a fixed set of categories, *e.g.*
- Web pages
  - Yahoo-like classification
- What else?
- Email messages
  - Spam filtering
  - Prioritizing
  - Folderizing
- News articles
  - Personalized newspaper
- Web Ranking
  - Is page related to selling something?

Procedural Classification

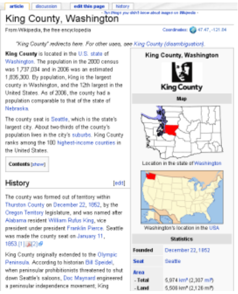
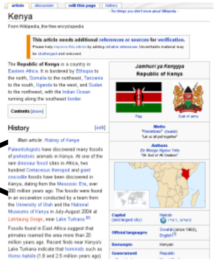
- Approach:
  - Write a procedure to determine a document’s class
  - E.g., Spam?

Learning for Text Categorization

- Hard to construct text categorization functions.
- Learning Algorithms:
  - **Bayesian (naïve)**
  - Neural network
  - Relevance Feedback (Rocchio)
  - Rule based (C4.5, Ripper, Slipper)
  - Nearest Neighbor (case based)
  - Support Vector Machines (SVM)

Learning for Categorization

- A ***training example*** is an instance $x \in X$, paired with its correct category $c(x)$: $<x, c(x)>$ for an unknown categorization function, c.
- Given a set of training examples, D.

{<  , county>, <  , country>,…

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- Find a hypothesized categorization function, $h(x)$, such that: $\forall < x, c(x) > \in D : h(x) = c(x)$

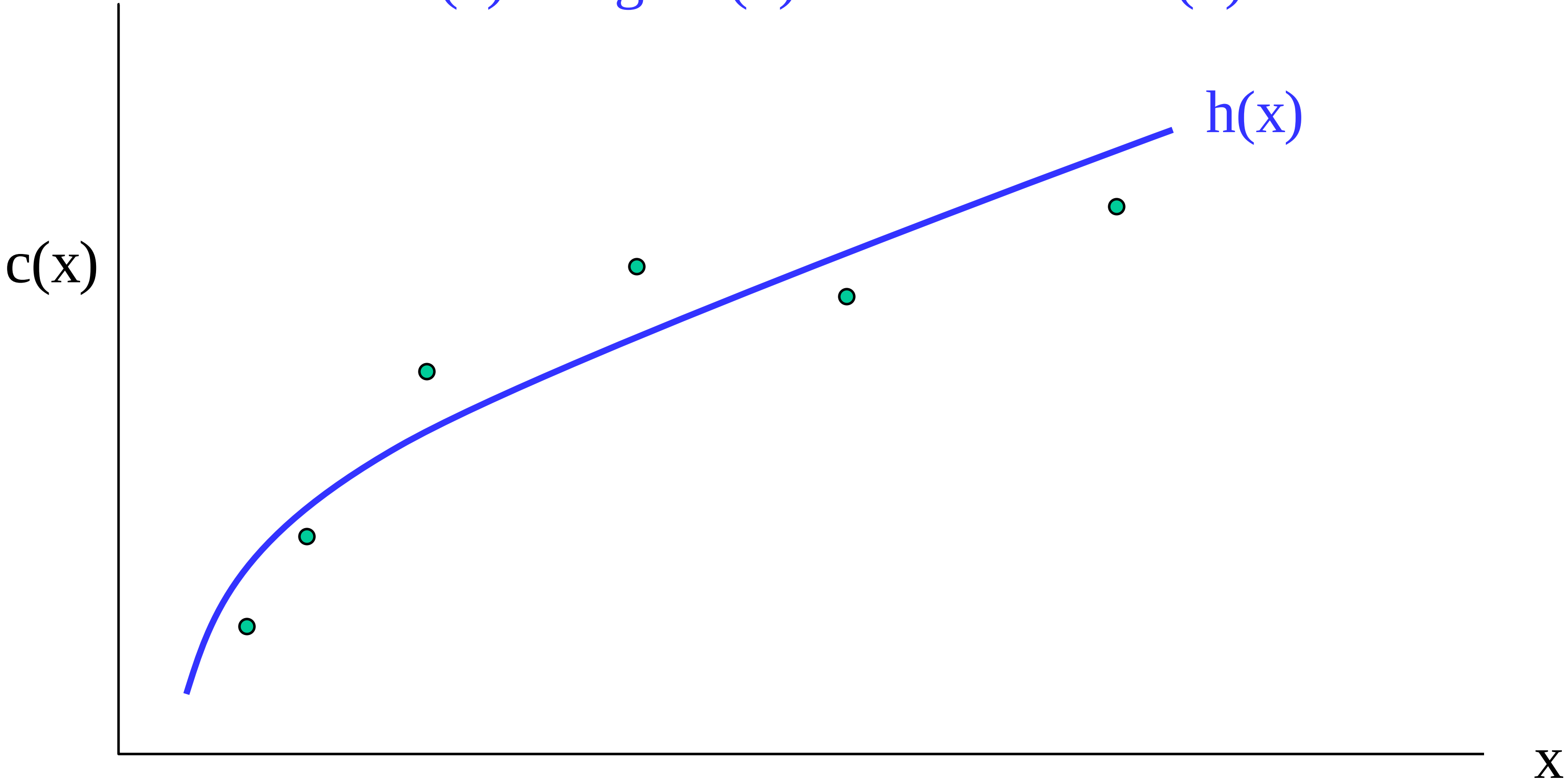
Consistency

Function Approximation

May not be any perfect fit

Classification ~ discrete functions

$h(x) = \text{nigeria}(x) \wedge \text{wire-transfer}(x)$



General Learning Issues

- Many hypotheses consistent with the training data.
- **Bias**
  - Any criteria other than consistency with the training data that is used to select a hypothesis.
- Classification accuracy
  - % of instances classified correctly
  - (Measured on independent test data.)
- Training time
  - Efficiency of training algorithm
- Testing time
  - Efficiency of subsequent classification

Generalization

- Hypotheses must ***generalize*** to correctly classify instances not in the training data.

- Simply memorizing training examples is a consistent hypothesis ***that does not generalize***.

Why is Learning Possible?

Experience alone never justifies any conclusion about any unseen instance.

Learning occurs when

PREJUDICE meets DATA!

Bias

- The nice word for prejudice is “bias”.

- What kind of hypotheses will you ***consider***?
  - What is allowable ***range*** of functions you use when approximating?
- What kind of hypotheses do you ***prefer***?

Bayesian Methods

- Learning and classification methods based on probability theory.
  - Bayes theorem plays a critical role in probabilistic learning and classification.
  - Uses *prior* probability of each category given no information about an item.
- Categorization produces a ***posterior*** probability distribution over the possible categories given a description of an item.

Bayesian Categorization

- Let set of categories be $\{c_1, c_2, \ldots c_n\}$
- Let E be description of an instance.
- Determine category of E by determining for each c_i

$$P(c_i \mid E) = \frac{P(c_i)P(E \mid c_i)}{P(E)}$$

- P(E) can be ignored since is factor ∀ categories

$$P(c_i \mid E) \sim P(c_i)P(E \mid c_i)$$

Bayesian Categorization

$$P(c_i \mid E) \sim P(c_i)P(E \mid c_i)$$

- Need to know:
  - Priors: P(c_i)
  - Conditionals: P(E | c_i)
- P(c_i) are easily estimated from data.
  - If n_i of the examples in D are in c_i,then P(c_i) = n_i / |D|
- Assume instance is a conjunction of binary features:

$$E = e_1 \wedge e_2 \wedge \cdots \wedge e_m$$

- Too many possible instances (exponential in m) to estimate all P(E | c_i)

Problem!

Naïve Bayesian Motivation

- Problem: Too many possible instances (exponential in *m*) to estimate all P(E | c_i)

- If we assume features of an instance are independent given the category (c_i) (*conditionally independent*).

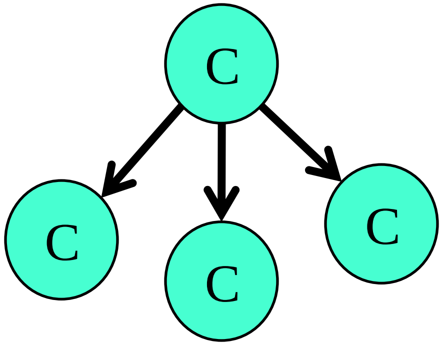
$$P(E \mid c_i) = P(e_1 \wedge e_2 \wedge \cdots \wedge e_m \mid c_i) = \prod_{j=1}^{m} P(e_j \mid c_i)$$

- Therefore, we then only need to know P(e_j | c_i) for each feature and category.

Naïve Bayes Example

- C = {allergy, cold, well}
- e_1 = sneeze; e_2 = cough; e_3 = fever
- E = {sneeze, cough, ¬fever}

Prob	**Well**	**Cold**	**Allergy**
P(c_i)	0.9	0.05	0.05
P(sneeze|c_i)	0.1	0.9	0.9
P(cough|c_i)	0.1	0.8	0.7
P(fever|c_i)	0.01	0.7	0.4



Naïve Bayes Example (cont.)

Probability	**Well**	**Cold**	**Allergy**
P(c_i)	0.9	0.05	0.05
P(sneeze | c_i)	0.1	0.9	0.9
P(cough | c_i)	0.1	0.8	0.7
P(fever | c_i)	0.01	0.7	0.4

E={sneeze, cough, ¬fever}

P(well | E) = (0.9)(0.1)(0.1)(0.99)/P(E)=0.0089/P(E)

P(cold | E) = (0.05)(0.9)(0.8)(0.3)/P(E)=0.01/P(E)

P(allergy | E) = (0.05)(0.9)(0.7)(0.6)/P(E)=0.019/P(E)

Most probable category: allergy

P(E) = 0.089 + 0.01 + 0.019 = 0.0379

P(well | E) = 0.23

P(cold | E) = 0.26

P(allergy | E) = 0.50

Learning Probabilities

- Normally, probabilities are estimated based on observed frequencies in the training data.
- If *D* contains n_i examples in category c_i, and n_{ij} of these n_i examples contains feature e_j, then:

$$P(e_j \mid c_i) = \frac{n_{ij}}{n_i}$$

- However, estimating such probabilities from small training sets is error-prone.
- If due only to chance, a rare feature, e_k, is always false in the training data, $\forall c_i : \mathrm{P}(e_k \mid c_i) = 0$.
- If e_k then occurs in a test example, *E*, the result is that $\forall c_i$: $\mathrm{P}(E \mid c_i) = 0$ and $\forall c_i$: $\mathrm{P}(c_i \mid E) = 0$

Smoothing

- To account for estimation from small samples, probability estimates are adjusted or *smoothed*.
- Laplace smoothing using an *m*-estimate assumes that each feature is given a prior probability, *p*, that is assumed to have been previously observed in a "virtual" sample of size *m*.

$$P(e_j \mid c_i) = \frac{n_{ij} + mp}{n_i + m} \qquad = (\mathrm{n}_{\mathrm{ij}} + 1) / (\mathrm{n}_{\mathrm{i}} + 2)$$

- For binary features, *p* is simply assumed to be 0.5.

Naïve Bayes for Text

- Modeled as generating a bag of words for a document in a given category by repeatedly sampling with replacement from a vocabulary $V = \{w_1, w_2, \ldots w_m\}$ based on the probabilities $P(w_j \mid c_i)$.
- Smooth probability estimates with Laplace *m*-estimates assuming a uniform distribution over all words ($p = 1/|V|$) and $m = |V|$
  - Equivalent to a virtual sample of seeing each word in each category exactly once.

Text Naïve Bayes Algorithm (Train)

```
Let $V$ be the vocabulary of all words in the documents in $D$
For each category $c_i \in C$
    Let $D_i$ be the subset of documents in $D$ in category $c_i$
    $P(c_i) = |D_i| / |D|$
    Let $T_i$ be the concatenation of all the documents in $D_i$
    Let $n_i$ be the total number of word occurrences in $T_i$
    For each word $w_j \in V$
        Let $n_{ij}$ be the number of occurrences of $w_j$ in $T_i$
        Let $P(w_i \mid c_i) = (n_{ij} + 1) / (n_i + |V|)$
```

Text Naïve Bayes Algorithm
(Test)

Given a test document X

Let n be the number of word occurrences in X

Return the category:

$$\underset{c_i \in C}{\operatorname{argmax}}\ P(c_i)\prod_{i=1}^{n} P(a_i \mid c_i)$$

where a_i is the word occurring the ith position in X

Naïve Bayes Time Complexity

- Training Time: O($|D|L_d + |C||V|$)) where L_d is the average length of a document in D.
  - Assumes V and all D_i , n_i, and n_{ij} pre-computed in O($|D|L_d$) time during one pass through all of the data.
  - Generally just O($|D|L_d$) since usually $|C||V| < |D|L_d$
- Test Time: O($|C|\ L_t$) where L_t is the average length of a test document.
- Very efficient overall, linearly proportional to the time needed to just read in all the data.

Easy to Implement

- But…

- If you do… it probably won’t work…

Probabilities: Important Detail!

- $P(\text{spam} \mid E_1 \ldots E_n) = \prod_i P(\text{spam} \mid E_i)$

Any more potential problems here?

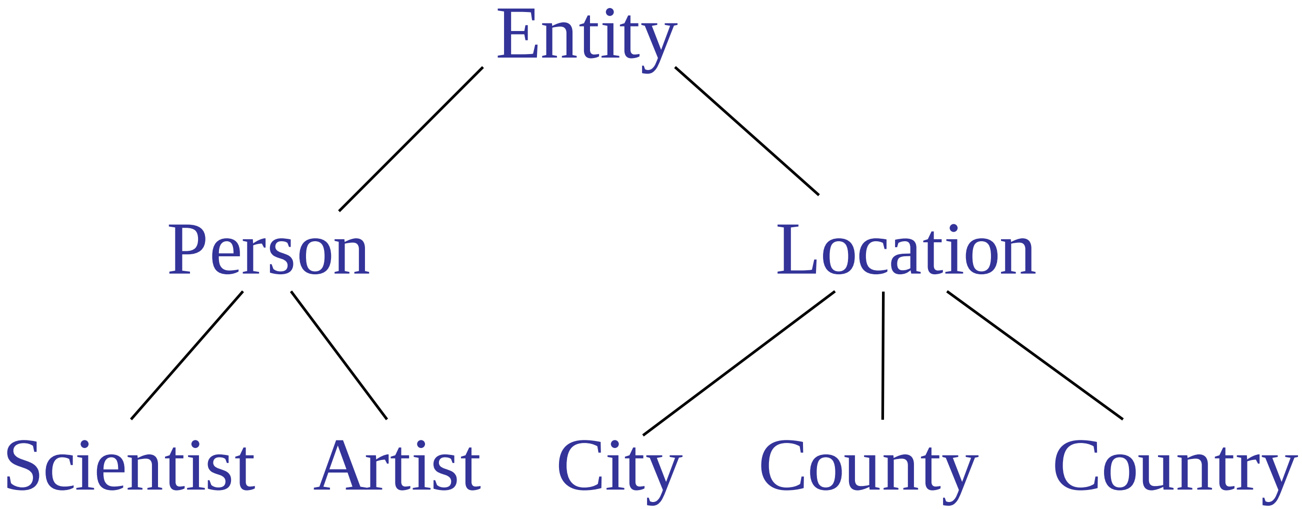
- We are multiplying lots of small numbers
  Danger of underflow!
  - $0.5^{57} = 7 \text{ E } {-18}$
- Solution? Use logs and add!
  - $p_1 * p_2 = e^{\log(p1)+\log(p2)}$
  - Always keep in log form

Multi-Class Categorization

- Pick the category with max probability
- One-vs-all (OVA) Create many 1 vs other classifiers
  - Classes = City, County, Country
  - Classifier 1 = {City} {County, Country}
  - Classifier 2 = {County} {City, Country}
  - Classifier 3 = {Country} {City, County}
- **All-vs-all (AVA)** For each pair of classes build a classifier
  - {City vs. County}, {City vs Country}, {County vs. Country}

Multi-Class Categorization

- Pick the category with max probability
- Create many OVA/AVA classifiers
- Use a hierarchical approach (wherever hierarchy available)



Advantages

- Simple to implement
  - No numerical optimization, matrix algebra, etc
- Efficient to train and use
  - Easy to update with new data
  - Fast to apply
- Binary/multi-class
- Independence allows parameters to be estimated on different datasets
- Comparitively good effectiveness with small training sets

Disadvantages

- Independence assumption wrong
  - Absurd estimates of class probabilities
    - Output probabilities close to 0 or 1
  - Thresholds must be tuned; not set analytically

- Generative model
  - Generally lower effectiveness than discriminative techniques
  - Improving parameter estimates can hurt classification effectiveness

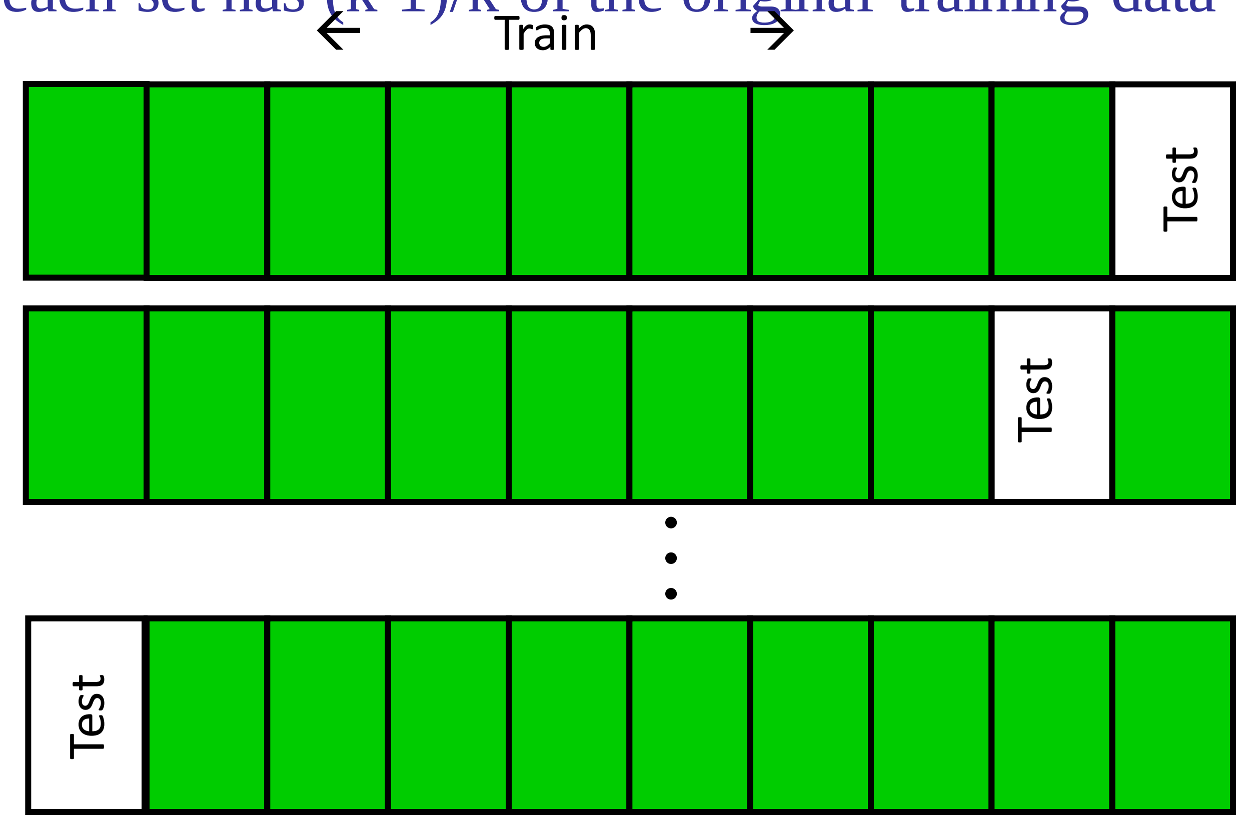
Experimental Evaluation

Question: How do we estimate the performance of classifier on unseen data?

- Can’t just at accuracy on training data – this will yield an over optimistic estimate of performance
- Solution: Cross-validation
- Note: this is sometimes called estimating how well the classifier will generalize

Evaluation: Cross Validation

- Partition examples into *k* disjoint sets
- Now create *k* training sets
  - Each set is union of all equiv classes ***except one***
  - So each set has (k-1)/k of the original training data



Cross-Validation (2)

- Leave-one-out
  - Use if < 100 examples (rough estimate)
  - Hold out one example, train on remaining examples

- 10-fold
  - If have 100-1000’s of examples

- M of N fold
  - Repeat M times
  - Divide data into N folds, do N fold cross-validation

Evaluation Metrics

- Accuracy: no. of questions correctly answered

- Precision (for one label): accuracy when classification = label

- Recall (for one label): measures how many instances of a label were missed.

- F-measure (for one label): harmonic mean of precision & recall.

- Area under Precision-recall curve (for one label): vary parameter to show different points on p-r curve; take the area

Precision & Recall

Two class situation

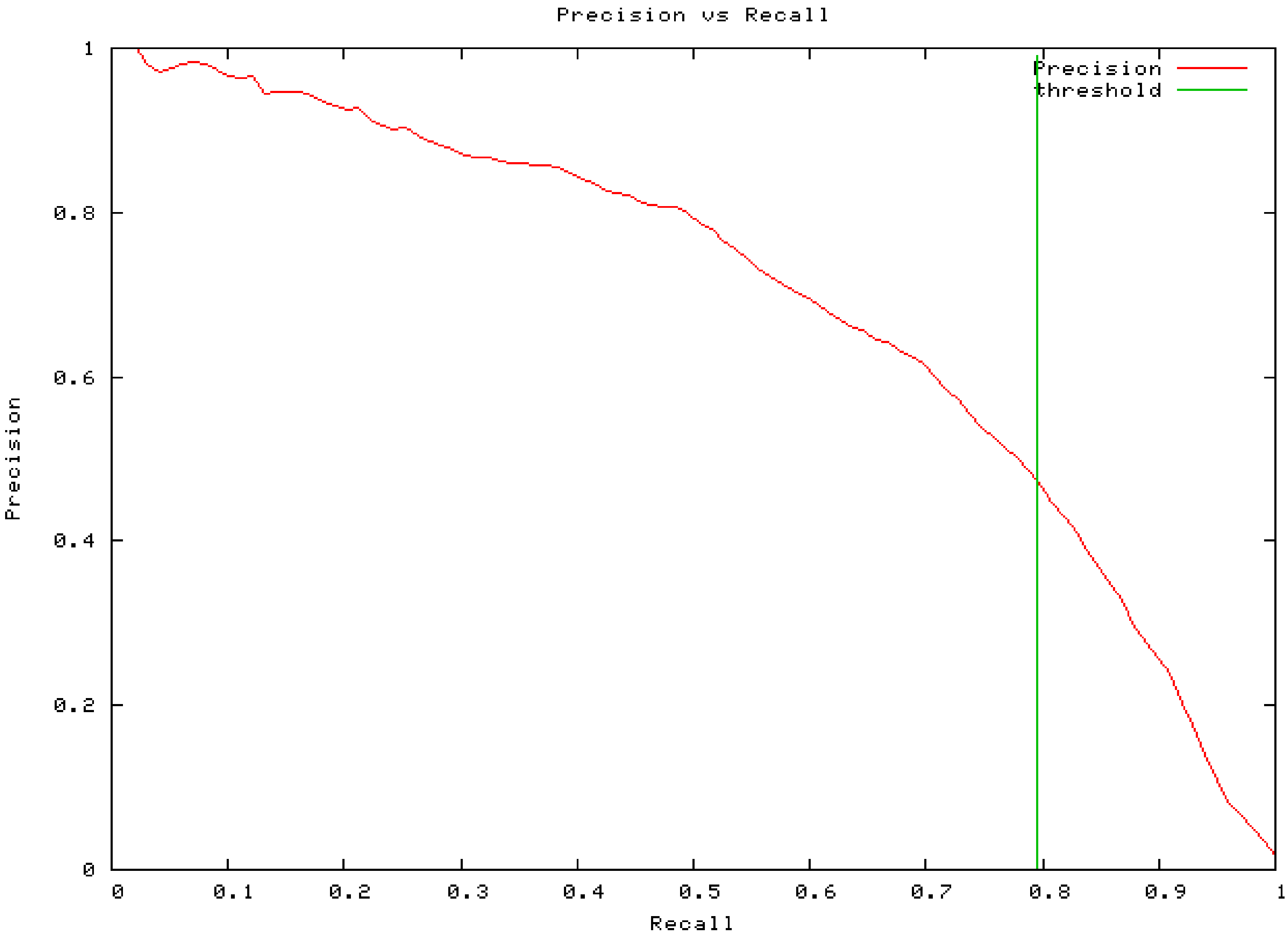
		Predicted	
Actual		**“P”**	**“N”**
	P	**TP**	**FN**
	N	**FP**	**TN**

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F-measure = 2pr/(p+r)

A typical precision-recall curve

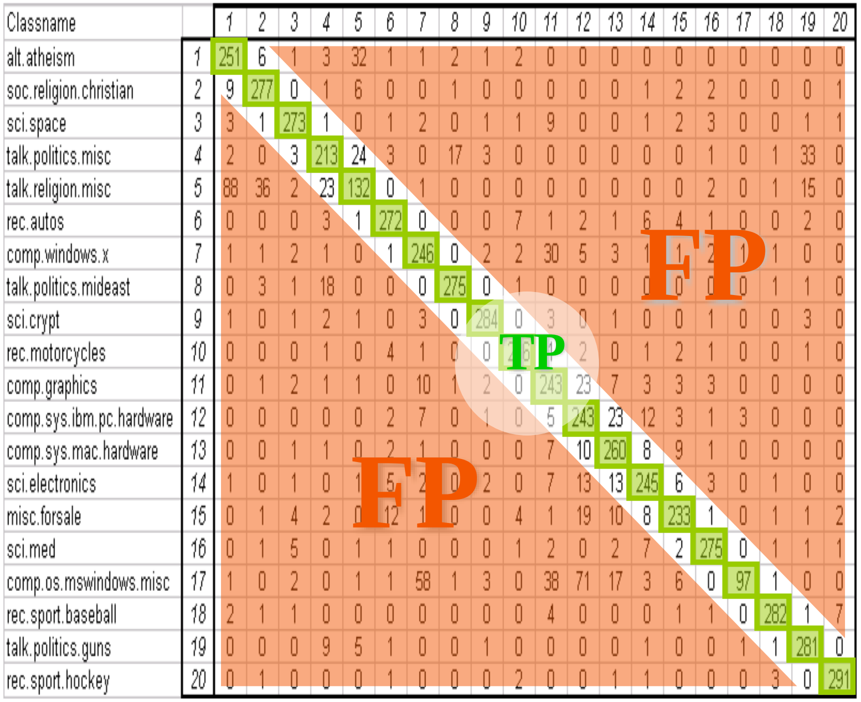


Precision & Recall

Two class situation

		Predicted	
		“P”	“N”
Actual	P	TP	FN
	N	FP	TN

Multi-class situation:



Classname		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
alt.atheism	1	251	6	1	3	32	1	1	2	1	2	0	0	0	0	0	0	0	0	0	0
soc.religion.christian	2	9	277	0	1	6	0	0	1	0	0	0	0	0	1	2	2	0	0	0	1
sci.space	3	3	1	273	1	0	1	2	0	1	1	9	0	0	1	2	3	0	0	1	1
talk.politics.misc	4	2	0	3	213	24	3	0	17	3	0	0	0	0	0	0	1	0	1	33	0
talk.religion.misc	5	88	36	2	23	132	0	1	0	0	0	0	0	0	0	0	2	0	1	15	0
rec.autos	6	0	0	0	3	1	272	0	0	0	7	1	2	1	6	4	1	0	0	2	0
comp.windows.x	7	1	1	2	1	0	1	246	0	2	2	30	5	3	1	1	2	1	1	0	0
talk.politics.mideast	8	0	3	1	18	0	0	0	275	0	1	0	0	0	0	0	0	0	1	1	0
sci.crypt	9	1	0	1	2	1	0	3	0	284	0	3	0	1	0	0	1	0	0	3	0
rec.motorcycles	10	0	0	0	1	0	4	1	0	0	[illegible]	1	2	0	1	2	1	0	0	1	0
comp.graphics	11	0	1	2	1	1	0	10	1	2	0	243	23	7	3	3	3	0	0	0	0
comp.sys.ibm.pc.hardware	12	0	0	0	0	0	2	7	0	1	0	5	243	23	12	3	1	3	0	0	0
comp.sys.mac.hardware	13	0	0	1	1	0	2	1	0	0	0	7	10	260	8	9	1	0	0	0	0
sci.electronics	14	1	0	1	0	1	5	2	0	2	0	7	13	13	245	6	3	0	1	0	0
misc.forsale	15	0	1	4	2	0	12	1	0	0	4	1	19	10	8	233	1	0	1	1	2
sci.med	16	0	1	5	0	1	1	0	0	0	1	2	0	2	7	2	275	0	1	1	1
comp.os.mswindows.misc	17	1	0	2	0	1	1	58	1	3	0	38	71	17	3	6	0	97	1	0	0
rec.sport.baseball	18	2	1	1	0	0	0	0	0	0	0	4	0	0	0	1	1	0	282	1	7
talk.politics.guns	19	0	0	0	9	5	1	0	0	1	0	0	0	0	1	0	0	1	1	281	0
rec.sport.hockey	20	0	1	0	0	0	1	0	0	0	2	0	0	1	1	0	0	0	3	0	291

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F-measure = 2pr/(p+r)

Assignment 4

- 20 newsgroups data
- Use Weka to learn a multi-class classifier

- Evaluation accuracy
  - Output a label for each document

Construct Better Features

- Key to machine learning is having good features

- In industrial data mining, large effort devoted to constructing appropriate features

- Ideas??

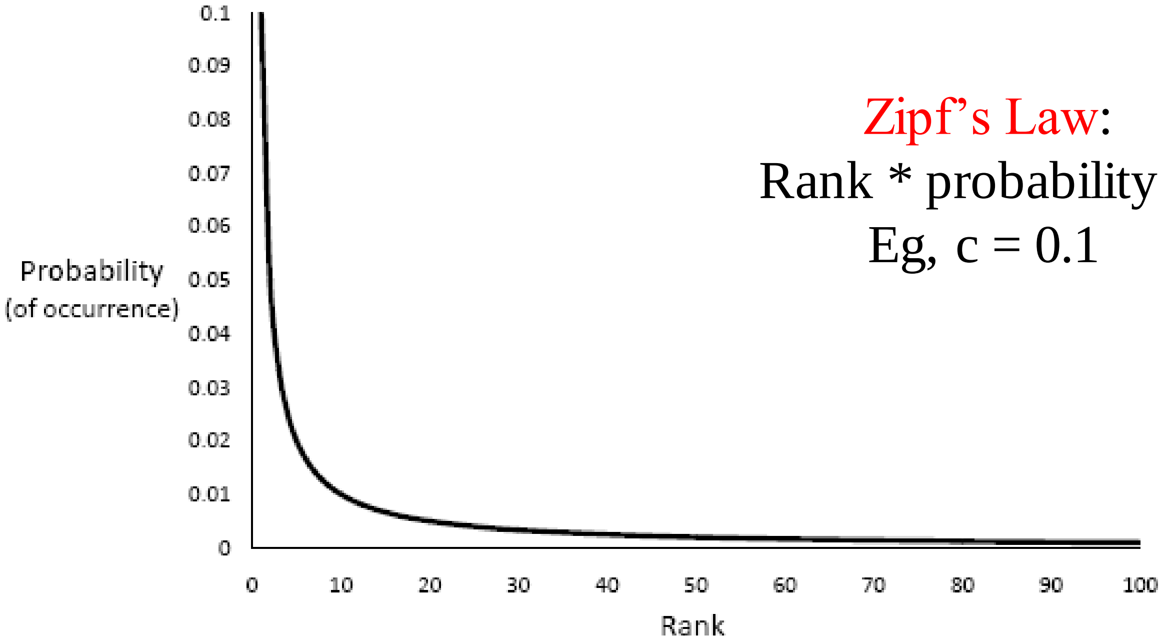
Possible Feature Ideas

- Look at capitalization (may indicated a proper noun)

- Look for commonly occurring sequences
  - E.g. New York, New York City
  - Limit to 2-3 consecutive words
  - Keep all that meet minimum threshold (e.g. occur at least 5 or 10 times in corpus)

Properties of Text

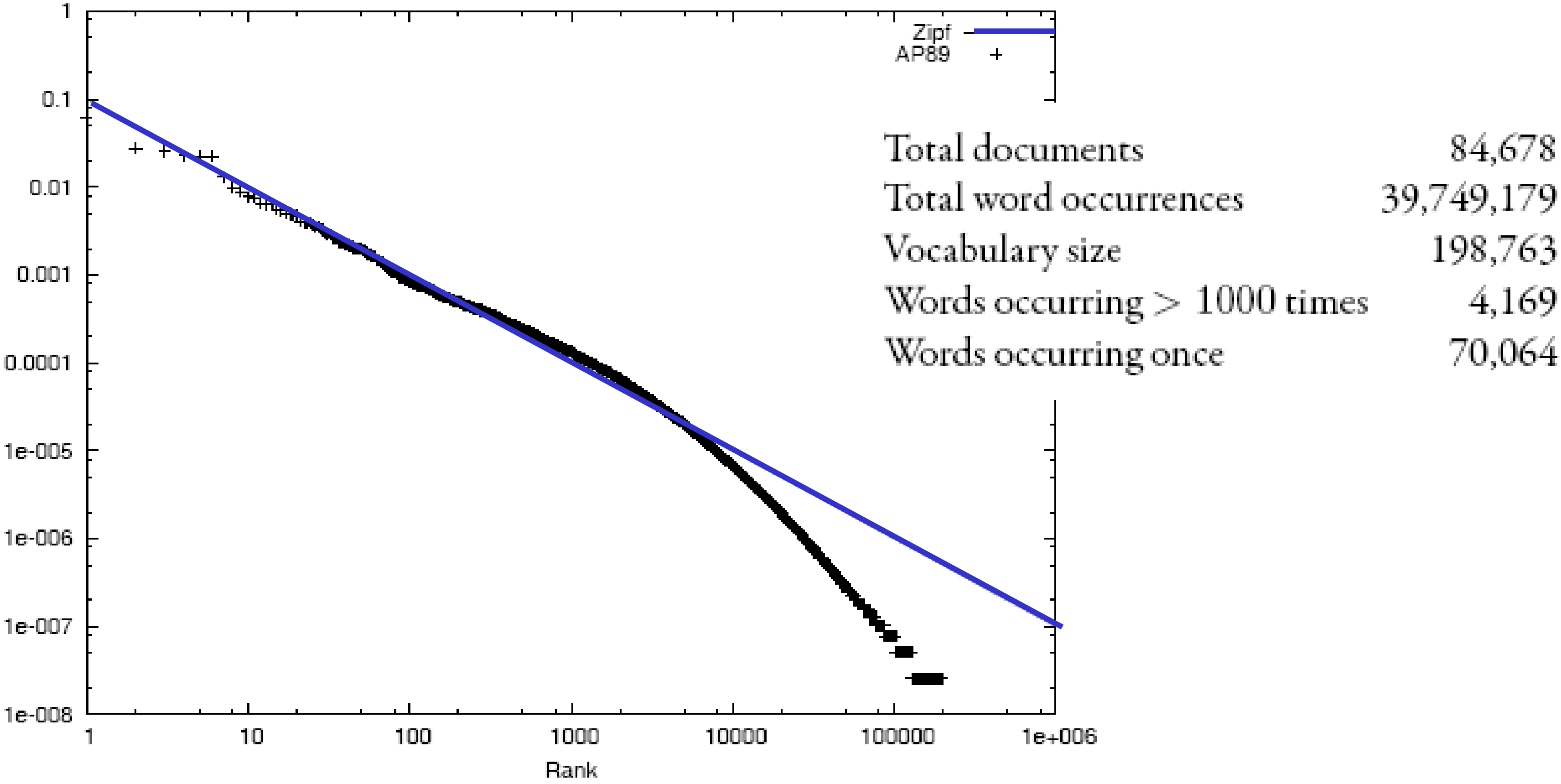
- Word frequencies - skewed distribution
- `The’ and `of’ account for 10% of all words
- Six most common words account for 40%



Zipf’s Law:
Rank * probability = c
Eg, c = 0.1

From [Croft, Metzler & Strohman 2010]

Associate Press Corpus `AP89’



Total documents	84,678
Total word occurrences	39,749,179
Vocabulary size	198,763
Words occurring > 1000 times	4,169
Words occurring once	70,064

From [Croft, Metzler & Strohman 2010]

Middle Ground

- Very common words → bad features
  - Language-based stop list:

    words that bear little meaning

    20-500 words

    http://www.dcs.gla.ac.uk/idom/ir_resources/linguistic_utils/stop_words
  - Subject-dependent stop lists

- Very rare words *also* bad features

Drop words appearing less than k times / corpus

Stemming

- Are there different index terms?
  - retrieve, retrieving, retrieval, retrieved, retrieves…
- Stemming algorithm:
  - (retrieve, retrieving, retrieval, retrieved, retrieves) ⇨ retriev
  - Strips prefixes of suffixes (-s, -ed, -ly, -ness)
  - Morphological stemming

Stemming Continued

- Can reduce vocabulary by ~ 1/3
- C, Java, Perl versions, python, c#

  www.tartarus.org/~martin/PorterStemmer
- Criterion for removing a suffix
  - Does "a document is about w_1" mean the same as
  - a "a document about w_2"
- Problems: sand / sander & wand / wander

- Commercial SEs use giant in-memory tables

Word Frequency

- Which word is more indicative of document similarity?
  - ‘book,’ or ‘Rumplestiltskin’?
  - Need to consider “document frequency”--- how frequently the word appears in doc collection.
- Which doc is a better match for the query “Kangaroo”?
  - One with a single mention of Kangaroos… or a doc that mentions it 10 times?
  - Need to consider “term frequency”--- how many times the word appears in the current document.

TF x IDF

$$w_{ik} = tf_{ik} * \log(N / n_k)$$

$$T_k = term\ k\ in\ document\ D_i$$

$$tf_{ik} = frequency\ of\ term\ T_k\ in\ document\ D_i$$

$$idf_k = inverse\ document\ frequency\ of\ term\ T_k\ in\ C$$

$$idf_k = \log\left(\frac{N}{n_k}\right)$$

$$N = total\ number\ of\ documents\ in\ the\ collection\ C$$

$$n_k = the\ number\ of\ documents\ in\ C\ that\ contain\ T_k$$

Inverse Document Frequency

- IDF provides high values for rare words and low values for common words

$$\log\left(\frac{10000}{10000}\right) = 0$$

$$\log\left(\frac{10000}{5000}\right) = 0.301$$

$$\log\left(\frac{10000}{20}\right) = 2.698$$

$$\log\left(\frac{10000}{1}\right) = 4$$

TF-IDF normalization

- Normalize the term weights
  - so longer docs not given more weight (fairness)
  - force all values to fall within a certain range: [0, 1]

$$w_{ik} = \frac{tf_{ik} \log(N / n_k)}{\sqrt{\sum_{k=1}^{t} (tf_{ik})^2 [\log(N / n_k)]^2}}$$

Assignment 4

- 20 newsgroups data
- Use Weka to learn a multi-class classifier

- Use any of these ideas or more
  - Stop words/rare words
  - Stemming
  - Tf-idf
  - POS enhanced features
  - Different classifiers
  - Parameter search
  - etc