CS145: INTRODUCTION TO DATA MINING

Text Data: Naïve Bayes

Instructor: Yizhou Sun

yzsun@cs.ucla.edu

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Methods to be Learnt

	Vector Data	Set Data	Sequence Data	Text Data
Classification	Logistic Regression; Decision Tree; KNN; SVM; NN			Naïve Bayes for Text
Clustering	K-means; hierarchical clustering; DBSCAN; Mixture Models			PLSA
Prediction	Linear Regression GLM*			
Frequent Pattern Mining		Apriori; FP growth	GSP; PrefixSpan	
Similarity Search			DTW	

Naïve Bayes for Text

- Text Data
- Revisit of Multinomial Distribution
- Multinomial Naïve Bayes
- Summary

Text Data

- Word/term
- Document
  - A sequence of words
- Corpus
  - A collection of documents

Cancer effort honored

Handsworth memorial award set up

LIFESTYLE

The geek grew up

New Amanda Welliver helps teens bully-proof themselves

News, Thursday, March 15, 2012

Raven in his 80s set to see again after op

Tarquin's blind, has only one eye but has mate 70 years his junior

It's man vs burger

Monster meal deals hard to digest

INDIANAPOLIS NEWS

HUNDREDS IN STATE SEE 'FLYING SAUCERS'

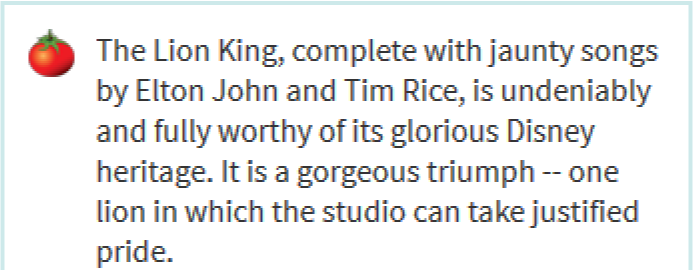
Franklin 'Dogfight' Alerts State Troopers

Text Classification Applications

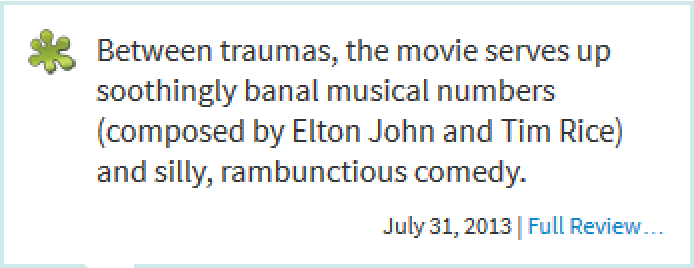
- Spam detection

From: airak@medicana.com.tr
Subject: Loan Offer
Do you need a personal or business loan urgent that can be process within 2 to 3 working days? Have you been frustrated so many times by your banks and other loan firm and you don't know what to do? Here comes the Good news Deutsche Bank Financial Business and Home Loan is here to offer you any kind of loan you need at an affordable interest rate of 3% If you are interested let us know.

- Sentiment analysis



The Lion King, complete with jaunty songs by Elton John and Tim Rice, is undeniably and fully worthy of its glorious Disney heritage. It is a gorgeous triumph -- one lion in which the studio can take justified pride.



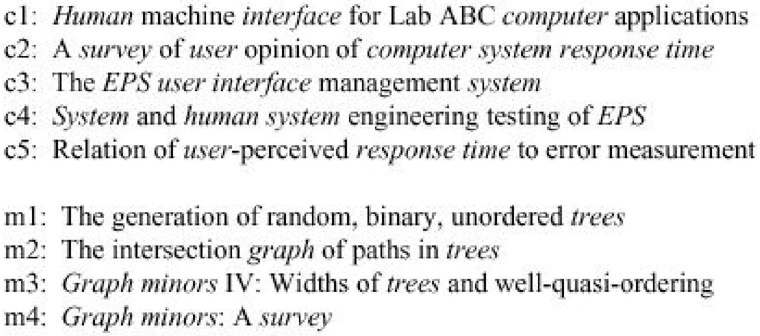
Between traumas, the movie serves up soothingly banal musical numbers (composed by Elton John and Tim Rice) and silly, rambunctious comedy.

July 31, 2013 | Full Review…

Represent A Document

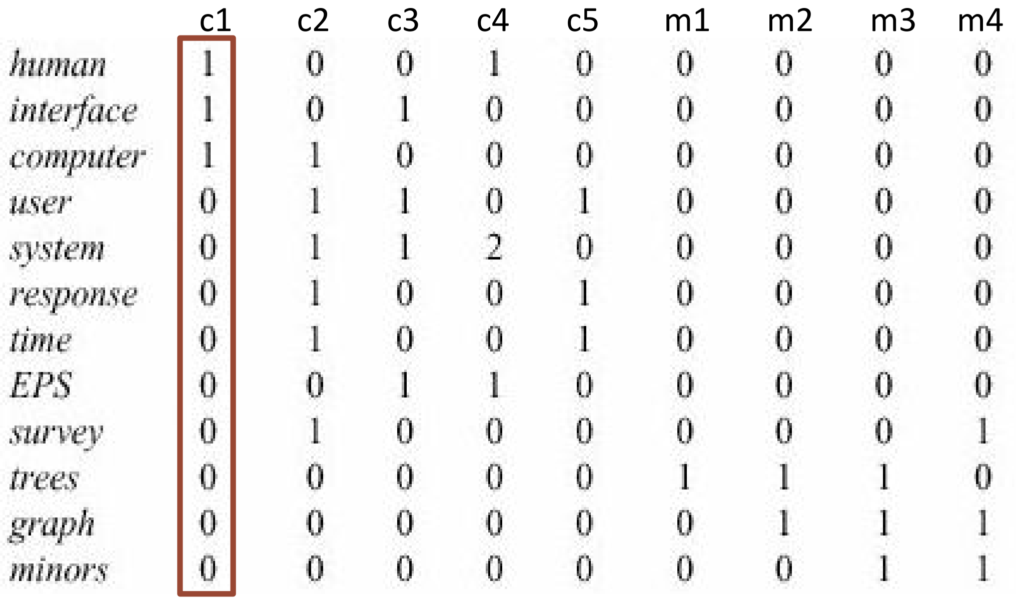
- A document d is represented by a sequence of words selected from a vocabulary
  - $\boldsymbol{w}_d = \left(w_{d1}, w_{d2}, \dots, w_{dN_d}\right)$, where w_{di} is the id of i-th word in document d and N_d is the length of document d
- A bag-of-words representation
  - $\boldsymbol{x}_d = (x_{d1}, x_{d2}, \dots, x_{dN})$, where x_{dn} is the number of words for nth word in the vocabulary
  - $x_{dn} = \sum_i 1(w_{di} == n)$

Example



c1: *Human* machine *interface* for Lab ABC *computer* applications
c2: A *survey* of *user* opinion of *computer system response time*
c3: The *EPS user interface* management *system*
c4: *System* and *human system* engineering testing of *EPS*
c5: Relation of *user*-perceived *response time* to error measurement

m1: The generation of random, binary, unordered *trees*
m2: The intersection *graph* of paths in *trees*
m3: *Graph minors* IV: Widths of *trees* and well-quasi-ordering
m4: *Graph minors*: A *survey*



	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

$\boldsymbol{x}_d$

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Bernoulli and Categorical Distribution

- Bernoulli distribution
  - Discrete distribution that takes two values $\{0,1\}$
    - $P(X=1)=p$ and $P(X=0)=1-p$
    - E.g., toss a coin with head and tail

- Categorical distribution
  - Discrete distribution that takes more than two values, i.e., $x \in \{1, \dots, K\}$
    - Also called generalized Bernoulli distribution, multinoulli distribution
    - $P(X=k)=p_k \; and \; \sum_k p_k = 1$
    - E.g., get 1-6 from a dice with 1/6

Binomial and Multinomial Distribution

- Binomial distribution
  - Number of successes (i.e., total number of 1's) by repeating n trials of independent Bernoulli distribution with probability p
    - $x: number\ of\ successes$
    - $P(X = x) = \binom{n}{x} p^x (1-p)^{n-x}$
- Multinomial distribution (multivariate random variable)
  - Repeat n trials of independent categorical distribution
    - Let x_k be the number of times value k has been observed, note $\sum_k x_k = n$
    - $P(X_1 = x_1, X_2 = x_2, \dots, X_K = x_K) = \frac{n!}{x_1! x_2! \dots x_K!} \prod_k p_k^{x_k}$

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Bayes' Theorem: Basics

- Bayes' Theorem: $P(h|\mathbf{X}) = \frac{P(\mathbf{X}|h)P(h)}{P(\mathbf{X})}$
  - Let **X** be a data sample ("*evidence*")
  - Let h be a *hypothesis* that X belongs to class C
  - P(h) (*prior probability*): the probability of hypothesis h
    - E.g., the probability of "spam" class
  - P(**X**|h) (*likelihood*): the probability of observing the sample **X**, given that the hypothesis holds
    - E.g., the probability of an email given it's a spam
  - P(**X**): marginal probability that sample data is observed
    - $P(X) = \sum_h P(X|h)\,P(h)$
  - P(h|**X**), (i.e., *posterior probability*): the probability that the hypothesis holds given the observed data sample **X**

Classification: Choosing Hypotheses

- *Maximum a posteriori* (maximize the posterior):
  - Useful observation: it does not depend on the denominator P(X)

$$h_{MAP} = \arg\max_{h \in H} P(h \mid X) = \arg\max_{h \in H} P(X \mid h) P(h)$$

Classification by Maximum A Posteriori

- Let D be a training set of tuples and their associated class labels, and each tuple is represented by an p-D attribute vector **x** = (x_1, x_2, …, x_p)
- Suppose there are *m* classes y∈{1, 2, …, m}
- Classification is to derive the maximum posteriori, i.e., the maximal P(y=j|**x**)
- This can be derived from Bayes' theorem

$$p(y=j|\boldsymbol{x}) = \frac{p(\boldsymbol{x}|y=j)p(y=j)}{p(\boldsymbol{x})}$$

- Since p(**x**) is constant for all classes, only $p(\boldsymbol{x}|y)p(y)$ needs to be maximized

Now Come to Text Setting

- A document is represented as
  - $\boldsymbol{w}_d = (w_{d1}, w_{d2}, \dots, w_{dN_d})$
  - w_{di} is the i-th word of d and N_d is the length of document d
- Model $p(\boldsymbol{w}_d|y)$ for class y
  - Each word in the sequence w_{di} is sampled from multinoulli distribution with parameter vector $\boldsymbol{\beta}_y = (\beta_{y1}, \beta_{y2}, \dots, \beta_{yN})$ independently
    - $p(w_{di}|y) = \beta_{yw_{di}}$ and $p(\boldsymbol{w}_d|y) = \prod_i \beta_{yw_{di}} = \prod_n \beta_{yn}^{x_{dn}}$
    - Where x_{dn} is the number of words for nth word in the vocabulary
- Model $p(y = j)$
  - Follow categorical distribution with parameter vector $\boldsymbol{\pi} = (\pi_1, \pi_2, \dots, \pi_m)$, i.e.,
    - $p(y = j) = \pi_j$

Classification Process Assuming Parameters are Given

- Find y that maximizes $p(y|\boldsymbol{x}_d)$, which is equivalently to maximize

$$y^* = argmax_y \; p(\boldsymbol{x}_d, y)$$

$$= argmax_y \; p(\boldsymbol{x}_d|y)p(y)$$

$$= argmax_y \prod_n \beta_{yn}^{x_{dn}} \times \pi_y$$

$$= argmax_y \prod_n \beta_{yn}^{x_{dn}} \times \pi_y$$

$$= argmax_y \sum_n x_{dn} log\beta_{yn} + log\pi_y$$

Parameter Estimation via MLE

- Given a corpus and labels for each document
  - $D = \{(\boldsymbol{x}_d, y_d)\}$
  - Find the MLE estimators for $\Theta = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \dots, \boldsymbol{\beta}_m, \boldsymbol{\pi})$
- The log likelihood function for the training dataset

$$logL = log \prod_d p(\boldsymbol{x}_d, y_d | \Theta) = \sum_d log\, p(\boldsymbol{x}_d, y_d | \Theta)$$

$$= \sum_d log\, p(\boldsymbol{x}_d | y_d) p(y_d) = \sum_d (x_{dn} log \beta_{y_d n} + log \pi_{y_d})$$

- The optimization problem

$$\max_{\Theta} \log L$$

$$s.t.$$

$$\pi_j \geq 0\ and\ \sum_j \pi_j = 1$$

$$\beta_{jn} \geq 0\ and\ \sum_n \beta_{jn} = 1\ for\ all\ j$$

Solve the Optimization Problem

- Use the Lagrange multiplier method
- Solution
  - $\hat{\beta}_{jn} = \frac{\sum_{d:y_d=j} x_{dn}}{\sum_{d:y_d=j} \sum_{n'} x_{dn'}}$
    - $\sum_{d:y_d=j} x_{dn}$: total count of word n in class j
    - $\sum_{d:y_d=j} \sum_{n'} x_{dn'}$: total count of words in class j
  - $\hat{\pi}_j = \frac{\sum_d 1(y_d==j)}{|D|}$
    - $1(y_d = j)$ is the indicator function, which equals to 1 if $y_d = j$ holds
    - |D|: total number of documents

Smoothing

- What if some word n does not appear in some class j in training dataset?
  - $\hat{\beta}_{jn} = \frac{\sum_{d:y_d=j} x_{dn}}{\sum_{d:y_d=j} \sum_{n'} x_{dn'}} = 0$
  - $\Rightarrow p(\boldsymbol{x}_d | y = j) \propto \prod_n \beta_{yn}^{x_{dn}} = 0$
  - But other words may have a strong indication the document belongs to class j
- Solution: add-1 smoothing or Laplacian smoothing
  - $\hat{\beta}_{jn} = \frac{\sum_{d:y_d=j} x_{dn} + 1}{\sum_{d:y_d=j} \sum_{n'} x_{dn'} + N}$
  - $N: total\ number\ of\ words\ in\ the\ vocabulary$
  - Check: $\sum_n \hat{\beta}_{jn} = 1$?

Example

- Data:

	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	?

- Vocabulary:

Index	1	2	3	4	5	6
Word	Chinese	Beijing	Shanghai	Macao	Tokyo	Japan

- Learned parameters (with smoothing):

$$\hat{\beta}_{c1} = \frac{5+1}{8+6} = \frac{3}{7}$$
$$\hat{\beta}_{c2} = \frac{1+1}{8+6} = \frac{1}{7}$$
$$\hat{\beta}_{c3} = \frac{1+1}{8+6} = \frac{1}{7}$$
$$\hat{\beta}_{c4} = \frac{1+1}{8+6} = \frac{1}{7}$$
$$\hat{\beta}_{c5} = \frac{0+1}{8+6} = \frac{1}{14}$$
$$\hat{\beta}_{c6} = \frac{0+1}{8+6} = \frac{1}{14}$$

$$\hat{\beta}_{j1} = \frac{1+1}{3+6} = \frac{2}{9}$$
$$\hat{\beta}_{j2} = \frac{0+1}{3+6} = \frac{1}{9}$$
$$\hat{\beta}_{j3} = \frac{0+1}{3+6} = \frac{1}{9}$$
$$\hat{\beta}_{j4} = \frac{0+1}{3+6} = \frac{1}{9}$$
$$\hat{\beta}_{j5} = \frac{1+1}{3+6} = \frac{2}{9}$$
$$\hat{\beta}_{j6} = \frac{1+1}{3+6} = \frac{2}{9}$$

$$\hat{\pi}_c = \frac{3}{4}$$
$$\hat{\pi}_j = \frac{1}{4}$$

Example (Continued)

- Classification stage
  - For the test document d=5, compute
  - $p(y = c|\boldsymbol{x}_5) \propto p(y = c) \times \prod_n \beta_{cn}^{x_{5n}} = \frac{3}{4} \times \left(\frac{3}{7}\right)^3 \times \left(\frac{1}{14}\right) \times \left(\frac{1}{14}\right) \approx 0.0003$
  - $p(y = j|\boldsymbol{x}_5) \propto p(y = j) \times \prod_n \beta_{jn}^{x_{5n}} = \frac{1}{4} \times \left(\frac{2}{9}\right)^3 \times \left(\frac{2}{9}\right) \times \left(\frac{2}{9}\right) \approx 0.0001$
  - Conclusion: $\boldsymbol{x}_5$ should be classified into c class

A More General Naïve Bayes Framework

- Let D be a training set of tuples and their associated class labels, and each tuple is represented by an p-D attribute vector **x** = (x_1, x_2, …, x_p)
- Suppose there are *m* classes y∈{1, 2, …, m}
- Goal: Find y $\max_y P(y|\boldsymbol{x}) = P(y,\boldsymbol{x})/P(\boldsymbol{x}) \propto P(\boldsymbol{x}|y)P(y)$
- A simplified assumption: attributes are conditionally independent given the class (class conditional independency):
  - $p(\boldsymbol{x}|y) = \ \prod_k p(x_k|y)$
  - $p(x_k|y)$ can follow any distribution, e.g., Gaussian, Bernoulli, categorical, …

Generative Model vs. Discriminative Model

- Generative model
  - *model joint probability* $p(\boldsymbol{x}, y)$
  - E.g., naïve Bayes
- Discriminative model
  - *model conditional probability* $p(y|\boldsymbol{x})$
  - E.g., logistic regression

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Summary

- Text data
  - Bag of words representation
- Naïve Bayes for Text
  - Multinomial naïve Bayes