COMP9414: Artificial Intelligence

Lecture 6b: Text Classification

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This Lecture

- Probabilistic Formulation of Text Classification
- Rule-Based Text Classification
- Bayesian Text Classification
  - Bernoulli Model
  - Multinomial Naive Bayes
- Evaluating Classifiers

Text Classification Applications

- Spam Detection
- Authorship Analysis
- E-Mail Classification/Prioritization
- News/Scientific Article Topic Classification
- Event Extraction (Event Type Classification)
- Sentiment Analysis
- Recommender Systems (using Product Reviews)

Example Movie Reviews/Ratings

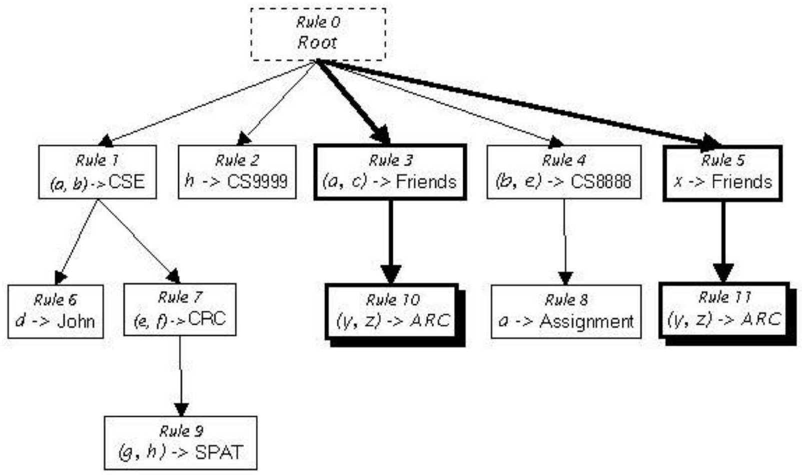
... unbelievably disappointing ...

Full of zany characters and richly applied satire, and some great plot twists.

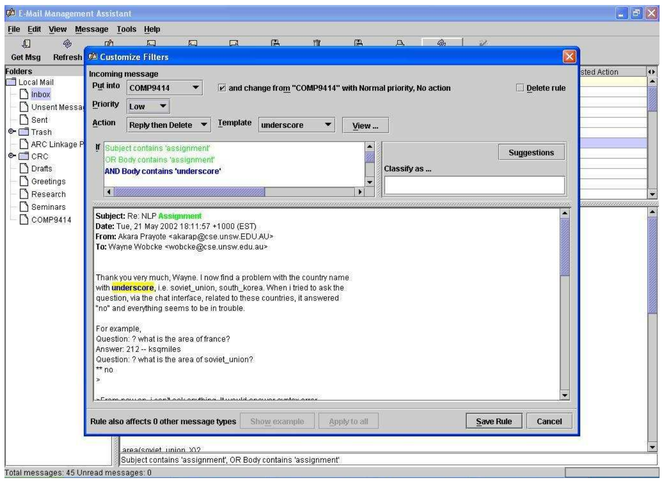
The greatest screwball comedy ever filmed.

It was pathetic. The worst part about it was the boxing scenes.

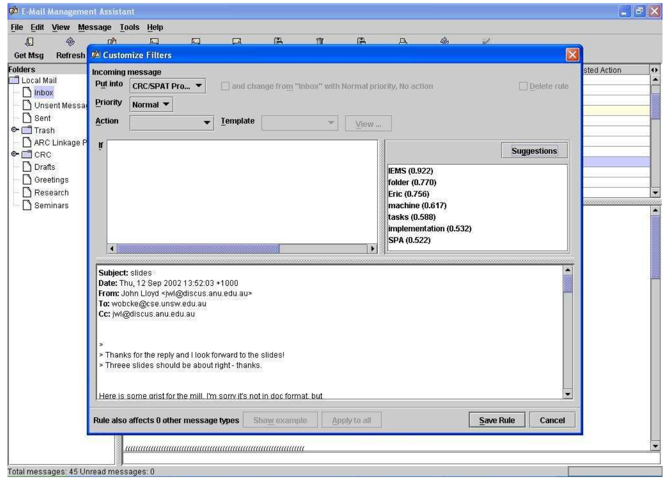
Rule-Based Method



Help User Define Rules



Suggest Features using Naive Bayes



Supervised Learning

- Input: A document (e-mail, news article, review, **tweet**)
- Output: One class drawn from a fixed set of classes
  - So text classification is a multi-class classification problem
  - … and sometimes a multi-label classification problem
- Learning Problem
  - Input: Training set of labelled documents $\{(d_1, c_1), \cdots\}$
  - Output: Learned classifier that maps d to predicted class c

Probabilistic Formulation

- Events: Occurence of features x, occurrence of document with class c
- Given document $x_1, \cdots, x_n$, choose c so that $P(c|x_1, \cdots, x_n)$ is maximixed
- Apply Bayes' Rule
  - $P(c|x_1, \cdots, x_n) = \frac{P(x_1, \cdots, x_n|c).P(c)}{P(x_1, \cdots, x_n)}$
  - Therefore maximize $P(x_1, \cdots, x_n|c).P(c)$

Feature Engineering

Example SpamAssassin (Spam E-Mail)

- Mentions Generic Viagra
- Online Pharmacy
- Mentions millions of (dollar) ((dollar) NN,NNN,NNN.NN)
- Phrase: impress ... girl
- 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

http://spamassassin.apache.org/old/tests_3_3_x.html

Bernoulli Model

Maximize $P(x_1, \cdots, x_n|c).P(c)$

- Features are presence or absence of word w_i in document
- Apply independence assumptions
  - $P(x_1, \cdots, x_n|c) = P(x_1|c). \cdots .P(x_n|c)$
  - Probability of word w (not) in class c independent of context
- Estimate probabilities
  - $P(w|c)$ = #(w in document in class c)/#(documents in class c)
  - $P(\neg w|c) = 1 - P(w|c)$
  - $P(c)$ = #(documents in class c)/#documents

Naive Bayes Classification

w_1	w_2	w_3	w_4	$Class$
1	0	0	1	1
0	0	0	1	0
1	1	0	1	0
1	0	1	1	1
0	1	1	0	0
1	0	0	0	0
1	0	1	0	1
0	1	0	0	1
0	1	0	1	0
1	1	1	0	0

	$Class = 1$	$Class = 0$
$P(Class)$	0.40	0.60
$P(w_1\|Class)$	0.75	0.50
$P(w_2\|Class)$	0.25	0.67
$P(w_3\|Class)$	0.50	0.33
$P(w_4\|Class)$	0.50	0.50

To classify document with w_2, w_3, w_4

- $P(Class = 1|\neg w_1, w_2, w_3, w_4)$
  $= ((1 - 0.75) * 0.25 * 0.5 * 0.5) * 0.4$
  $= 0.00625$
- $P(Class = 0|\neg w_1, w_2, w_3, w_4)$
  $= ((1 - 0.5) * 0.5 * 0.67 * 0.33) * 0.6$
  $= 0.03333$

Bag of Words Model

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

Naive Bayes Classification

Maximize $P(x_1,\cdots,x_n|c).P(c)$

- Features are occurrence of word in positions in document
- Apply independence assumptions
  - $P(w_1,\cdots,w_n|c) = P(w_1|c).\cdots.P(w_n|c)$
  - Position of word w in document doesn't matter
- Estimate probabilities
  - Let V be the vocabulary
  - Let "document" c = concatenation of documents in class c
  - $P(w|c)$ = #(w in document c)/$\Sigma_{w\in V}$#(w in document c)
  - $P(c)$ = #(documents in class c)/#documents

Laplace Smoothing

- What if word in test document has not occurred in training?
- Then $P(w|c) = 0$ and so estimate for class c is 0
- Laplace smoothing
  - Assign small probablity to unseen words
  - $P(w|c)$ = (#(w in document c)+1)/($\Sigma_{w\in V}$#(w in document c)+$|V|$)
  - Don't have to add 1, can be 0.05 or some parameter α

MNB Example

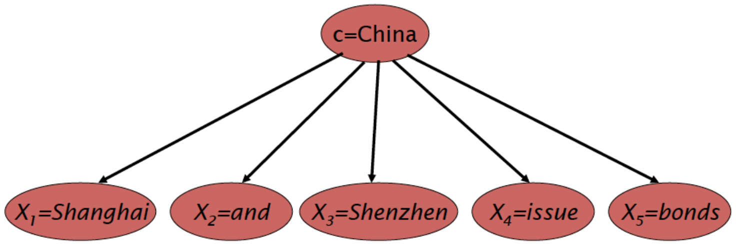
	Words	*Class*
d_1	Chinese Beijing Chinese	c
d_2	Chinese Chinese Shanghai	c
d_3	Chinese Macao	c
d_4	Tokyo Japan Chinese	j
d_5	Chinese Chinese Chinese Tokyo Japan	?

$P(\text{Chinese}|c)$ = (5+1)/(8+6) = 3/7
$P(\text{Tokyo}|c)$ = (0+1)/(8+6) = 1/14
$P(\text{Japan}|c)$ = (0+1)/(8+6) = 1/14
$P(\text{Chinese}|j)$ = (1+1)/(3+6) = 2/9
$P(\text{Tokyo}|j)$ = (1+1)/(3+6) = 2/9
$P(\text{Japan}|j)$ = (1+1)/(3+6) = 2/9

To classify document d_5

- $P(c|d_5) = [(3/7)^3.1/14.1/14].3/4$ ≈ 0.0003
- $P(j|d_5) = [(2/9)^3.2/9.2/9].1/4$ ≈ 0.0001
- Choose *Class c*

Graphical Model for Example



Evaluating Classifiers

2×2 Contingency Table (single class c)

	Class c	not Class c
Predicted c	True Positive	False Positive
Predicted not c	False Negative	True Negative

- Precision (P) = TP/(TP+FP) – you want what you get
  - $\cdots$ but may not get much
- Recall (R) = TP/(TP+FN) – you get what you want
  - $\cdots$ but you might get a lot more (junk)
- F1 = 2PR/(P+R) – harmonic mean of precision and recall

Multiple Classes: Per-Class Metrics

$n \times n$ Confusion Matrix (each instance in one class)

	Predicted c_1	Predicted c_2	$\cdots$
Class c_1	c_{11}	c_{12}	c_{13}
Class c_2	c_{21}	c_{22}	c_{23}
$\cdots$	c_{31}	c_{32}	c_{33}

- Precision (class c_i) = $c_{ii}/\Sigma_j c_{ji}$
  - Proportion of items predicted as c_i correctly classified (as c_i)
- Recall (class c_i) = $c_{ii}/\Sigma_j c_{ij}$
  - Proportion of items in class c_i predicted correctly (as c_i)
- Accuracy = $\Sigma_i c_{ii}/\Sigma_i \Sigma_j c_{ij}$

Multiple Classes: Micro/Macro-Averaging

n (one per class) 2×2 Contingency Tables

- Micro-average = Aggregated measure over all classes
  - micro-precision = $\Sigma_c \mathrm{TP}_c/\Sigma_c(\mathrm{TP}_c + \mathrm{FP}_c)$
  - micro-recall = $\Sigma_c \mathrm{TP}_c/\Sigma_c(\mathrm{TP}_c + \mathrm{FN}_c)$
  - Same when each instance has and is given one and only one label
  - Dominated by larger classes
- Macro-average = Average of per-class measures
  - macro-precision = $\frac{1}{n}\Sigma_c \mathrm{TP}_c/(\mathrm{TP}_c + \mathrm{FP}_c)$
  - macro-recall = $\frac{1}{n}\Sigma_c \mathrm{TP}_c/(\mathrm{TP}_c + \mathrm{FN}_c)$
  - Dominated by smaller classes
  - Fairer for imbalanced data, e.g. sentiment analysis

Summary: Naive Bayes

- 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
  - 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
- Good dependable baseline for text classification