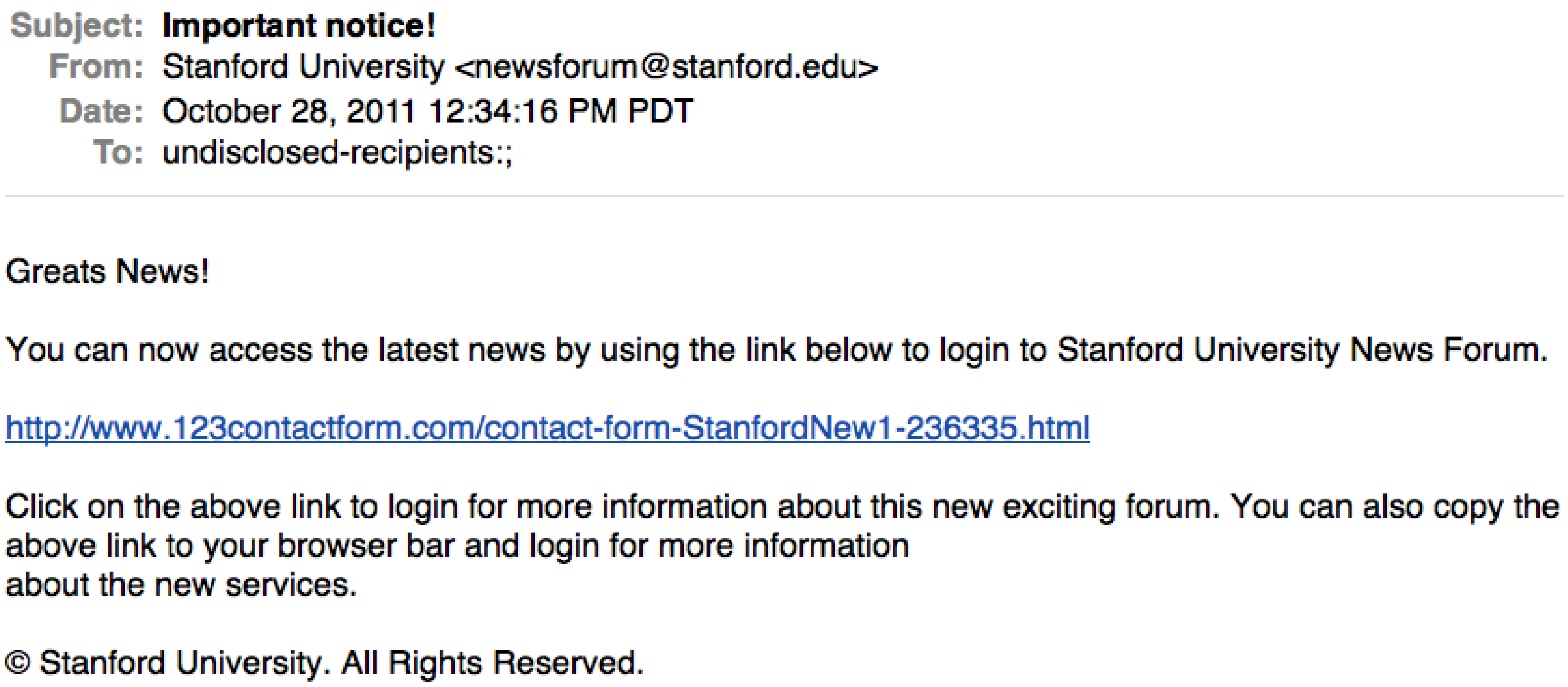
Text Classification

SLP3 Ch 2.1, 4, 5; INLP Ch 2, 4.4

Is this spam?



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Date: October 28, 2011 12:34:16 PM PDT
To: undisclosed-recipients:;

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Positive or negative review?

- + *...zany characters and richly applied satire, and some great plot twists*
- – *It was pathetic. The worst part about it was the boxing scenes...*
- + *...awesome caramel sauce and sweet toasty almonds. I love this place!*
- – *...awful pizza and ridiculously overpriced...*

What is the subject of this medical article?

MEDLINE Article

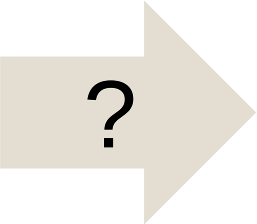
Available online at www.sciencedirect.com

Brain and Cognition

Syntactic frame and verb bias in aphasia: Plausibility judgments of undergoer-subject sentences

Susanne Gahl, Lise Menn, Gail Ramsberger, Daniel S. Jurafsky, Elizabeth Elder, Molly Rewega, and L. Holland Audrey

[illegible]



MeSH Subject Category Hierarchy

Antogonists and Inhibitors

Blood Supply

Chemistry

Drug Therapy

Embryology

Epidemiology

…

Text Classification: Definition

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

Text Classification: Methods

- Rule-based methods
  - Need experts writing rules
  - Regular expression
- Machine learning methods
  - Need annotated training data and computing resource for training
  - Generative classifiers
  - Discriminative classifiers

Regular Expressions

Regular Expressions

- A formal language for specifying text patterns
- We used char-level regular expression in word tokenization
- We may use word-level regular expression for text classification
  - Pattern for positive reviews
    - .*((very)? good|great|awesome|not bad).*
  - Pattern for negative reviews
    - .*(bad|awful|worst|ridiculously overpriced).*

Pattern	Matches
`.`	Any char
`(aaa|bbb)`	Disjunction, “aaa” or “bbb”

Regular Expressions

- Advantages
  - Interpretable
  - Easy to manipulate
  - Do not need (annotated) data and training
- Problems
  - Low coverage
    - hard even for an expert to cover all cases
  - Might be wrong
    - e.g., “not good at all”

Machine Learning Methods

Supervised Machine Learning

- Input:
  - A fixed set of classes $C = \{c_1, c_2, \ldots, c_J\}$
  - A training set of m hand-labeled documents $(d_1, c_1), \ldots, (d_m, c_m)$
- Output:
  - A learned classifier $d \to c$

Generative and Discriminative Classifiers

- Suppose we're distinguishing cat from dog images

Generative Classifier

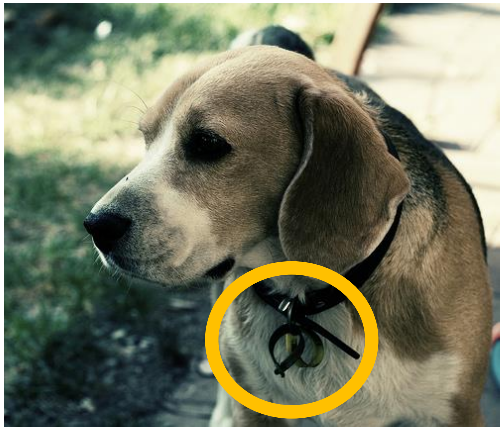
- Build a model of what's in a cat image
  - Knows about whiskers, ears, eyes…
  - Assigns a probability to any image:
    - If you ask someone to draw a cat, how likely he would draw this image?

- Also build a model for dog images

- Now given a new image:
  Run both models and see which one fits better.

Discriminative Classifier

- Just try to distinguish dogs from cats



Oh look, dogs have collars!
Let’s ignore everything else.

Generative and Discriminative Classifiers

- Finding the correct class c of a document d
- Generative classifiers

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d) = \underset{c \in C}{\operatorname{argmax}} \frac{P(d|c)P(c)}{P(d)}$$

$$= \underset{c \in C}{\operatorname{argmax}} \overbrace{P(d|c)}^{\text{likelihood}} \overbrace{P(c)}^{\text{prior}}$$

- Discriminative classifiers

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} \overbrace{P(c|d)}^{\text{posterior}}$$

Machine Learning
-- Generative Classifiers

Generative Classifiers

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

$O(|X|^n \cdot |C|)$ parameters

Could only be estimated if a very, very large number of training examples was available.

How often does this class occur?

We can just count the relative frequencies in a corpus.

Multinomial Naïve Bayes

- Conditional Independence
  - Assume words are independent given the class c.

$$P(x_1, x_2, \ldots, x_n | c) = P_1(x_1|c) P_2(x_2|c) \cdots\ P_n(x_n|c)$$

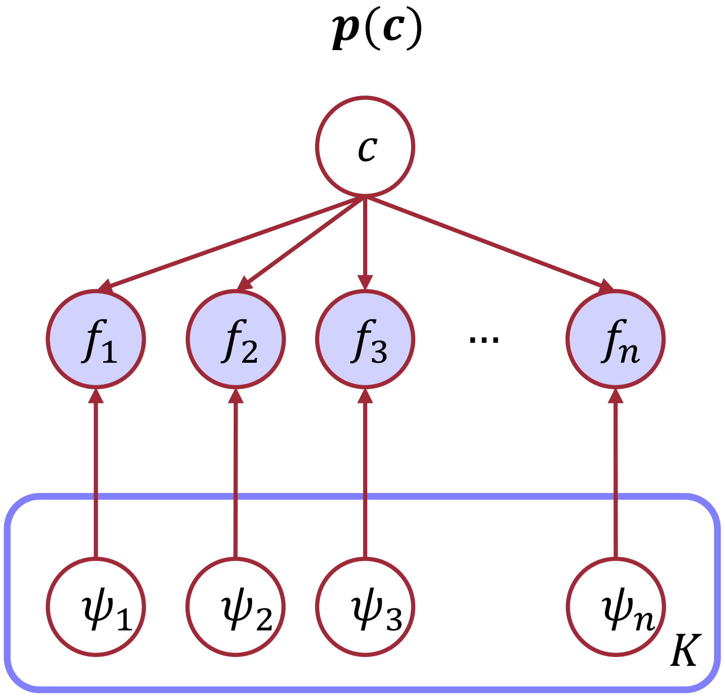
$$C_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i \in \text{positions}} P_i(x_i|c)$$

- Bag of Words assumption
  - Assume position doesn’t matter
  - All the positions share the same conditional distribution

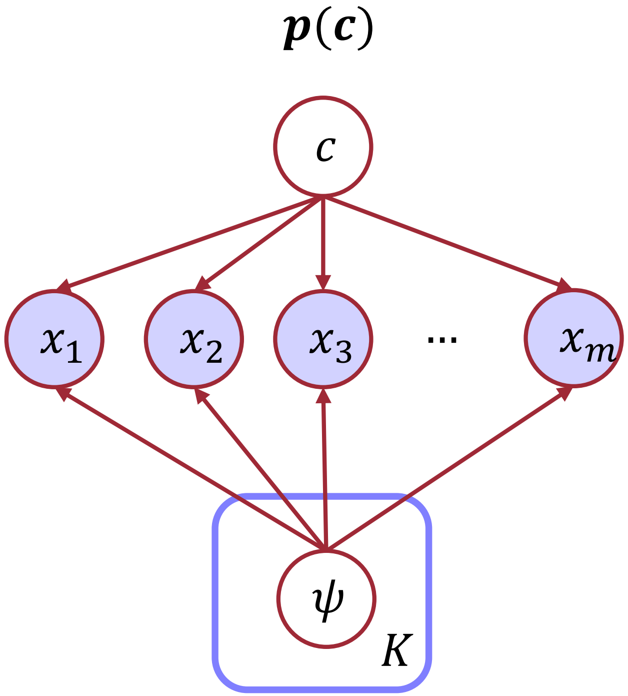
$$\forall i, j\colon\ P_i(x|c) = P_j(x|c)$$

Probabilistic graphical models for Naïve Bayes

- General form: $P(f_i|c;\psi_i)$
- Bag of Word: $P(x_i|c;\psi)$, ψ are irrelative to position.



General form



Bag of word

Learning Multinomial Naïve Bayes

- First attempt: maximum likelihood estimates
  - Simply use the frequencies in the data
  - N_{c_j} is the number of documents with class c; N_{total} is the total number of documents.

$$\hat{p}(c_j) = \frac{N_{c_j}}{N_{total}}$$

  - $count(w, c)$ is the times the word w appears among all words in all documents of topic c.

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

Problem with Maximum Likelihood

- What if we have seen no training documents with the word ***fantastic*** and class ***positive***?

$$\hat{P}(\text{"fantastic"}|\text{positive}) = \frac{count(\text{"fantastic", positive})}{\sum_{w \in V} count(w, \text{positive})} = 0$$

- Zero conditional probability leads to zero posterior, no matter the other evidence!

$$C_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i \in \text{positions}} P(x_i|c)$$

Laplace (add-1) smoothing for Naïve Bayes

Pseudo-count

$$\hat{P}(\text{"fantastic"}|\text{positive}) = \frac{count(\text{"fantastic"},\ \text{positive}) + 1}{\sum_{w \in V}(count(w, \text{positive}) + 1)}$$

$$= \frac{count(\text{"fantastic"},\ \text{positive}) + 1}{(\sum_{w \in V} count(w, \text{positive})) + |V|}$$

Unknown words

- Words that
  - …appear in our test data
  - …but not in our training data or vocabulary
- We **ignore** them
  - Remove them from the test document and pretend they weren't there!
  - Don't include any probability for them at all!
- Why don't we build an unknown word model?
  - It doesn't help: knowing which class has more unknown words is not generally helpful!

Let's do a sentiment example!

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable with no fun

A sentiment example with add-1 smoothing

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable ~~with~~ no fun

1. Prior from training:

$$\hat{P}(c_j) = \frac{N_{c_j}}{N_{total}} \qquad \begin{aligned} P(-) &= 3/5 \\ P(+) &= 2/5 \end{aligned}$$

3. Drop "with"

2. Likelihoods from training:

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

$$P(\text{“predictable”}|-) = \frac{1+1}{14+20} \qquad P(\text{“predictable”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“no”}|-) = \frac{1+1}{14+20} \qquad P(\text{“no”}|+) = \frac{0+1}{9+20}$$

$$P(\text{“fun”}|-) = \frac{0+1}{14+20} \qquad P(\text{“fun”}|+) = \frac{1+1}{9+20}$$

4. Scoring the test set:

$$C_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i \in \text{positions}} P(x_i|c)$$

$$P(-)P(S|-) = \frac{3}{5} \times \frac{2 \times 2 \times 1}{34^3} = 6.1 \times 10^{-5}$$

$$P(+)P(S|+) = \frac{2}{5} \times \frac{1 \times 1 \times 2}{29^3} = 3.3 \times 10^{-5}$$

Machine Learning
-- Discriminative Classifiers

Generative and Discriminative Classifiers

- Finding the correct class c of a document d
- Generative classifiers

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|d) = \underset{c \in C}{\operatorname{argmax}} \frac{P(d|c)P(c)}{P(d)}$$

$$= \underset{c \in C}{\operatorname{argmax}} \ \overbrace{P(d|c)}^{\text{likelihood}} \ \overbrace{P(c)}^{\text{prior}}$$

- Discriminative classifiers

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} \ \overbrace{P(c|d)}^{\text{posterior}}$$

Representing text with feature vectors

- As a sparse feature vector
  - tf-idf
  - n-gram frequencies (n-gram = n-word combination)
  - Task-specific features
- As a dense feature vector
  - Latent Semantic Analysis
  - Computed from the sequence of word embeddings of the input text.

Logistic regression (two classes)

- Make probabilities with Sigmoid.

$$P(y=1)=\sigma(w\cdot x+b)=\frac{1}{1+\exp\big(-(w\cdot x+b)\big)}$$

$$P(y=0)=1-\sigma(w\cdot x+b) \qquad =\sigma\big(-(w\cdot x+b)\big)$$

$$=\frac{\exp\big(-(w\cdot x+b)\big)}{1+\exp\big(-(w\cdot x+b)\big)}$$

$\sigma(-x)=1-\sigma(x)$

- Turning a probability into a classifier

$$f(x)=\begin{cases}1, & \text{if } P(y=1|x)>0.5\\ 0, & \text{otherwise}\end{cases}$$

if $w\cdot x+b>0$

If $w\cdot x+b\leq 0$

Logistic regression (>2 classes)

- Still compute the dot product between weight vector w and input vector x.
- But now we need a separate weight vector for each of the K classes.

$$p(y = c|x) = \frac{\exp(w_c \cdot x + b_c)}{\sum_{j=1}^{k} \exp\left(w_j \cdot x + b_j\right)}$$

- Softmax function
  - Turning a vector $z = [z_1, z_2, \dots, z_k]$ of k arbitrary values into probabilities.

$$\text{softmax}(z) = \left[\frac{\exp z_1}{\sum_{j=1}^{k} \exp z_j}, \frac{\exp z_2}{\sum_{j=1}^{k} \exp z_j}, \dots, \frac{\exp z_k}{\sum_{j=1}^{k} \exp z_j}\right]$$

  - Q: how is softmax related to sigmoid?

Learning in Logistic Regression

- Maximizing conditional log likelihood of the true labels
  - = minimizing cross-entropy loss
  - often with a regularization term to avoid overfitting

$$\mathcal{L} = \overbrace{-\frac{1}{N}\sum_{i \in N} \log p_\theta(y_i^* | x)}^{\mathcal{L}_{CE}} + \lambda \overbrace{R(\theta)}^{\mathcal{L}_{reg}}$$

- Optimized with stochastic gradient descent

More Discriminative Classifiers

- Support vector machines
- Neural networks
- Decision trees
- …

Evaluation

Datasets

Training set

Development Set

Test Set

- Train on training set, tune on dev set, report on test set

The 2-by-2 confusion matrix

		gold standard labels		
		gold positive	gold negative	
system output labels	system positive	true positive	false positive	$\textbf{precision} = \frac{\text{tp}}{\text{tp} + \text{fp}}$
	system negative	false negative	true negative	
		$\textbf{recall} = \frac{\text{tp}}{\text{tp} + \text{fn}}$		$\textbf{accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{fp} + \text{tn} + \text{fn}}$

Why Precision and Recall

- Why don't we just use **accuracy** as our metric?

$$\textbf{accuracy} = \frac{\mathrm{tp} + \mathrm{tn}}{\mathrm{tp} + \mathrm{fp} + \mathrm{tn} + \mathrm{fn}}$$

- Imagine we save 1 million messages.
  - 100 of them talked about "Pie"
  - 999,900 talked about something else
- We could build a dumb classifier that just labels every message "not about pie"
  - It would get 99.99% accuracy!!! Wow!!!
  - But useless! Doesn't return the messages we are looking for!
  - Recall = 0
    - It doesn't get any of the 100 Pie messages.

A combined measure

- F-measure: a single number that combines P and R:

$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

- We almost always use balanced F_1 (i.e., $\beta = 1$)

$$F_1 = \frac{2PR}{P + R}$$

Confusion Matrix for 3-class classification

gold standard labels

system output labels		urgent	normal	spam
	urgent	8	10	1
	normal	5	60	50
	spam	3	30	200

$$\textbf{precision}_u = \frac{8}{8 + 10 + 1}$$

$$\textbf{precision}_n = \frac{60}{5 + 60 + 50}$$

$$\textbf{precision}_s = \frac{200}{3 + 30 + 200}$$

$$\textbf{recall}_u = \frac{8}{8+5+3}$$

$$\textbf{recall}_n = \frac{60}{10+60+30}$$

$$\textbf{recall}_s = \frac{200}{1 + 50 + 200}$$

Combine P/R from 3 classes to get one metric

- Macro-averaging:
  - Compute the performance for each class
  - Then average over classes
- Micro-averaging:
  - Aggregate statistics for all classes into one confusion matrix
  - Compute the precision and recall from that table

Macro-/Micro-averaging

Class 1: Urgent

	true urgent	true not
system urgent	8	11
system not	8	340

$$\text{Precision} = \frac{8}{8+11} = .42$$

Class 2: Normal

	true normal	true not
system normal	60	55
system not	40	212

$$\text{Precision} = .52$$

Class 3: Spam

	true spam	true not
system spam	200	33
system not	51	83

$$\text{Precision} = .86$$

Pooled

	true yes	true no
system yes	268	99
system no	99	635

$$\begin{matrix}\text{micro-average}\\ \text{precision}\end{matrix} = .73$$

$$\begin{matrix}\text{macro-average}\\ \text{precision}\end{matrix} = \frac{.42 + .52 + .86}{3} = .60$$

Summary

Text Classification

- Rule-based methods
  - Regular expression
- Machine learning methods
  - Generative classifiers
    - Naive Bayes
  - Discriminative classifiers
    - Logistic regression
- Evaluation
  - Precision, recall, F-measure
  - Macro-/micro-averaging