Lecture 11:
Naïve Bayes Classifier

Ling 1330/2330 Intro to Computational Linguistics

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Overview

- Text classification; Naïve Bayes classifier
  - *Language and Computers*: Ch.5 Classifying documents
  - NLTK book: Ch.6 Learning to classify text

  - Exercise 6 review

Automatic classification

- A ***classifier*** is an algorithm that processes a linguistic input and assigns it a **class** from a user-defined set.
  - It usually denotes a statistical model induced through machine learning.
  - The algorithm works off a set of weighted contextual features.

Classifier examples

Example	Unit of linguistic input	What type of classes	Class labels
POS-tagging a text	word		
Grammar error checker	sentence		
Pronoun resolution	NP + pronoun		
Spam filter	document (email)		
Language identifier	document		
Sentiment analysis	document		
Automatic essay grader	document (essay)		
Military intelligence	document (message)		

Classifier examples

Example	Unit of linguistic input	What type of classes	Class labels
POS-tagging a text	word	Part-of-speech	Noun, Verb, Adj, Det...
Grammar error checker	sentence	Grammaticality	grammatical/not
Pronoun resolution	NP + pronoun	Co-reference	co-refers/not
Spam filter	document (email)	Spam or not	Spam/Ham
Language identifier	document	Which language	ENG, SPA, FRN, JAP, CHI, KOR, ...
Sentiment analysis	document	What "sentiment"	Positive, (neutral), negative
Automatic essay grader	document (essay)	Quality of writing	5, 4, 3, 2, 1, 0
Military intelligence	document (message)	Threat assessment	Contains a threat/not

Example: movie reviews (Exercise #6)

all of this , of course , leads up to the predictable climax . but as foreseeable as the ending is , it's so damn cute and well-done that i doubt any movie in the entire year contains a scene the evokes as much pure joy as this part does . when ryan discovers the true identity of her online love , i was filled with such , for lack of a better word , happiness that for the first time all year , i actually left the theater smiling .

the acting is below average , even from the likes of curtis .. sutherland is wasted and baldwin , well , he's acting like a baldwin , of course . the real star here are stan winston's robot design , some schnazzy cgi , and the occasional good gore shot , like picking into someone's brain . so , if robots and body parts really turn you on , here's your movie . otherwise , it's pretty much a sunken ship of a movie .

- Classify each document as "positive" or "negative"

  ← A type of **sentiment analysis**

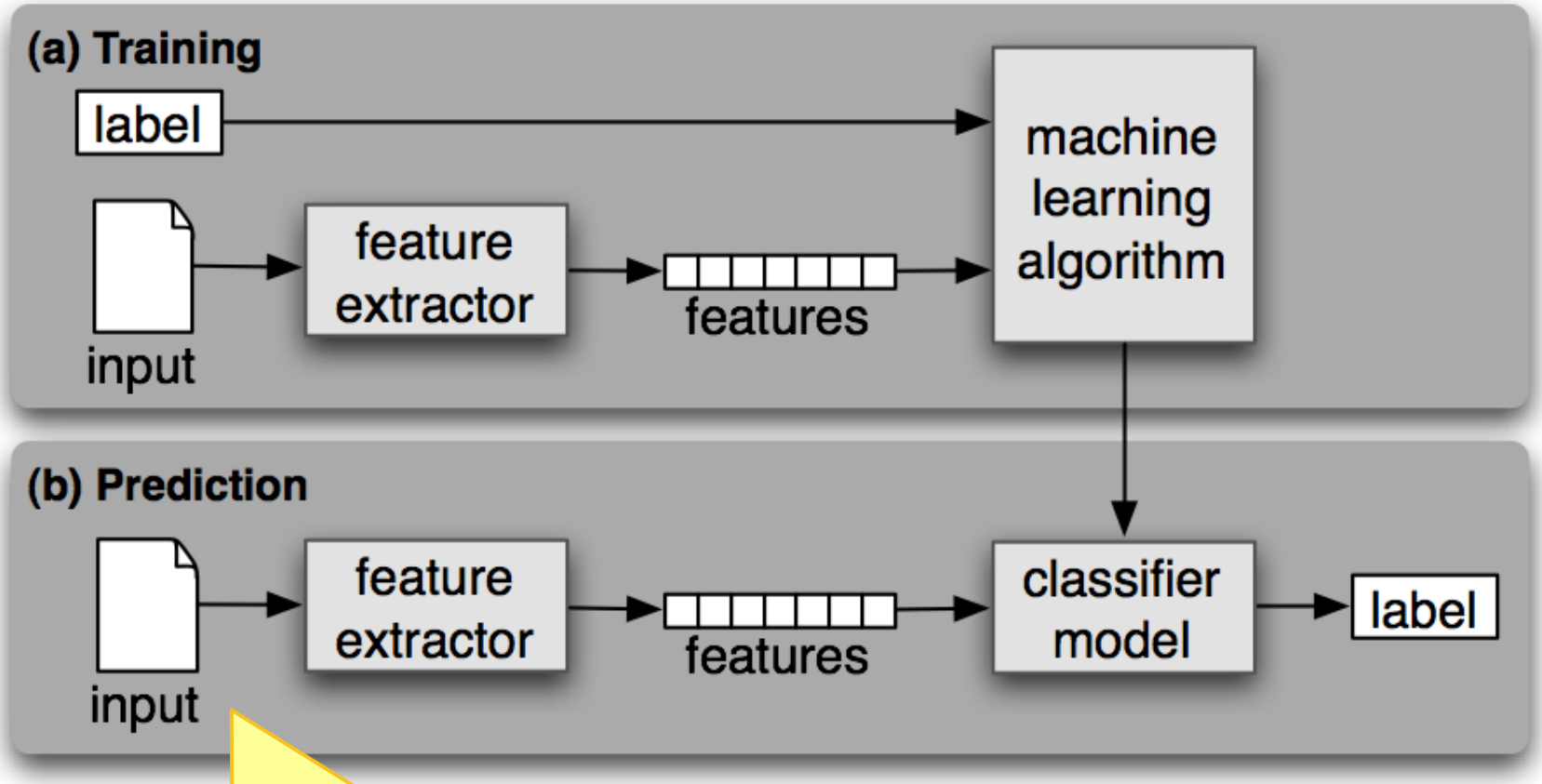
- What "features" can we use?
  - Words themselves
  - N-grams, length, ...

How computers "learn"

- Document classification is an example of computer science engineering called **machine learning**
  - Just like humans learn from "experience", a computer algorithm *learns* from data
    - Learns what exactly? → Statistical patterns
  - Machine learning is not limited to linguistic data
    - Example?
- Machine learning requires:
  - *Training* data, often lots of them
  - *Testing* data for evaluation

    (Also: sometimes *development test data* for error analysis)

Machine learning (supervised)



If testing, correct labels are known → can calculate model's **accuracy**

Source: NLTK book

Features and evidence

- A classification decision must rely on some observable evidence: **features**
  - Female or male names?
    - The last letter of the name: 'a', 'k', etc.
  - What POS is *park*? What about *carbingly*?
    - Is *park* preceded by *the*? *to*?
    - Does *carbingly* end with 'ly'? 'ness'?
  - Is this document SPAM or HAM?
    - Does it contain the word *enlargement*?
    - Does it contain *linguistics*?

Feature engineering

- Deciding what features are relevant. Two types:
- **Kitchen sink** strategy
  - Throw a set of features to the machine learning algorithm, see what features are given greater weight and what gets ignored
  - Example: using each word in a document as a feature:
    - 'has-*cash*': True, 'has-*the*': True, 'has-*linguistics*': False, ..
- **Hand-crafted** strategy
  - Utilizing expert knowledge, determine a small set of features that are likely to be relevant
  - Example: grammatical error detection
    - For each sentence, determine grammatical/ungrammatical
    - Hand-coded features:
      - Subject-verb agreement, fragment or not, etc.

Weighting the evidence

- A classification decision involves reconciling multiple features with different levels of predictive power.

  ⬅Different types of classifiers use different algorithms for:

  1. Determining the **weights of individual features** in order to maximize its labeling success in the training data
  2. When given an input, using the feature weights to **compute the likelihood of a label**

- Popular machine learning methods:
  - **Naïve Bayes**
  - Decision tree
  - Maximum entropy (ME)
  - Hidden Markov model (HMM)
  - Neural network → Deep learning (!!)
  - Support vector machine (SVM)

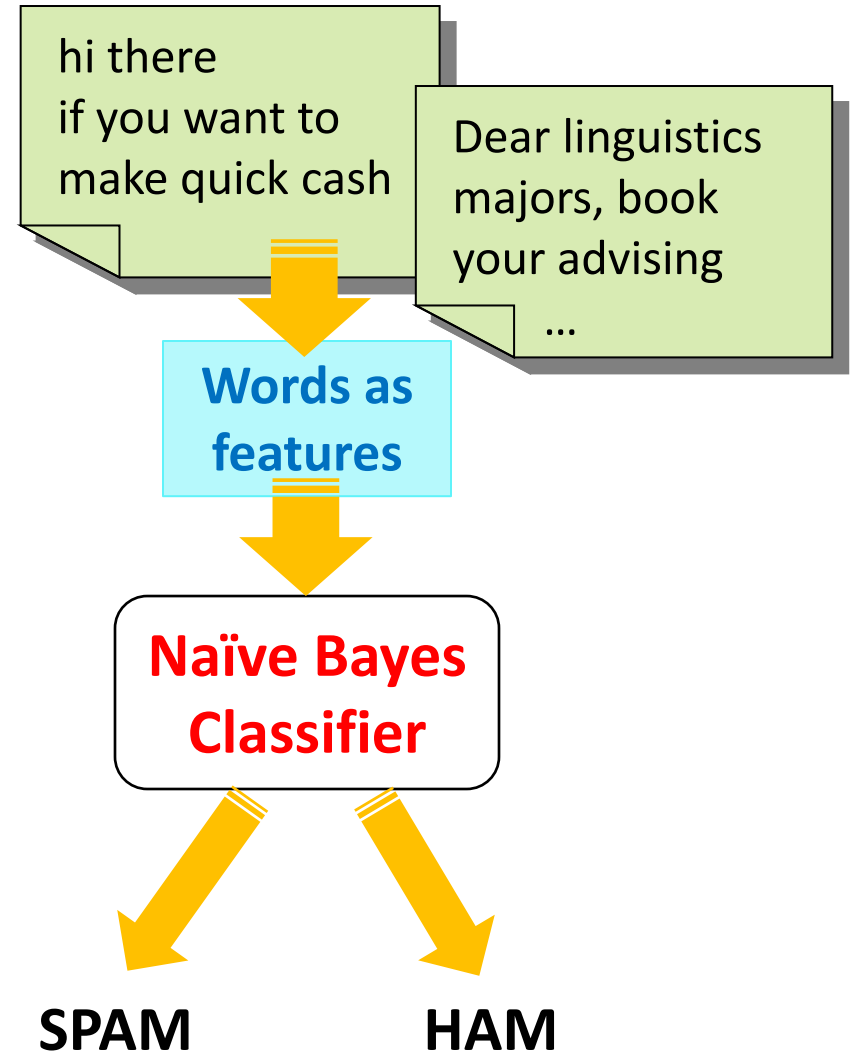
A spam filter as a Naïve Bayes model

- Unit of linguistic input:
  - A document (email text)
  - Features: Words in document (kitchen sink strategy)
  - A document is reduced to **the set of words it contains**

    ← "Bag of words" assumption

- Classifier type:
  - Naïve Bayes

- Class labels:
  - SPAM/HAM



Bag of words + feature independence

P(Document)
= P('a', 'boring', 'movie', 'really', 'terrible', 'this', 'was', 'what', ',', '.')❶
= P('a') * P('boring') * P('movie') * P('really') * P('terrible') * P('this') * P('was') * P('what') * P(',') * P('.')❷

This was a really boring movie. What a terrible, terrible movie.

❶ **"Bag of words" assumption**: a document is reduced to the set of words it contains.

❷ **Feature independence assumption**: features are independent of each other (obviously false)

- The overall probability of this particular document P(Document) is then calculated as the product of the probabilities of each word occurring.
- How to calculate P('boring')?
  - 2,000 movie review documents, 'boring' found in 217 of them
    ➔ 217/2000 = 0.1085
  - cf. P('really') = 867/2000 = 0.4335
  - cf. P('a') = 1996/2000 = 0.998

The Naïve Bayes Classifier

- A rough sketch of a Naïve Bayes algorithm:
  - Given an email document (D), process each piece of evidence (f_1, f_2, f_3... f_n) to support the two hypothesis:

    H_1: D is a SPAM.

    H_2: D is a HAM.

1. It starts with the **base probabilities**, also known as **priors**.

Suppose 70% of all email in the training data is SPAM:

H_1: D is a SPAM: 70%

H_2: D is a HAM: 30%.

2. Each piece of evidence (=feature) will strengthen one hypothesis and weaken the other.
   - `'contains-cash:YES'` → H_1 is now 85%, H_2 15%.
3. Repeat 2. for all features.
4. When done, rule for hypothesis with higher probability.

Inducing feature weights

- But how is the feature weight determined?

  `f1: 'contains-cash:YES'`

  ←Weight for SPAM hypothesis: P(f1|SPAM) ❶

  = the probability of 'cash' occurring, given a spam document

  ←Weight for HAM hypotheses: P(f1|HAM) ❷

  = the probability of 'cash' occurring, given a ham document

- In the training data:

	SPAM (n=140)	HAM (n=60)
day	20	20
linguistics	1	15
cash	90	3
Viagra	20	0
the	138	60
from	70	29

❶ = 90/140 = 0.64

❷ = 3/60 = 0.05

SPAM-to-HAM **odds ratio** of f1:

❶/❷ = 12.8 ← Feature strength

How about *linguistics* (f2)?

❶ P(f2|SPAM) = 1/140 = 0.007

❷ P(f2|HAM) = 15/60 = 0.25

HAM-to-SPAM odds ratio: **35.7**

Inducing feature weights

- But how is the feature weight determined?

  `f1: 'contains-cash:YES'`

  ←Weight for SPAM hypothesis: P(f1|SPAM) ❶

  = the probability of 'cash' occurring, given a spam document

  ←Weight for HAM hypotheses: P(f1|HAM) ❷

  = the probability of 'cash' occurring, given a ham document

- In the training data:

	SPAM (n=140)	HAM (n=60)
day	20	20
linguistics	1	15
cash	90	3
Viagra	20	0
the	138	60
from	70	29

How about weights of *the*?

❶ = 138/140 = 0.98

❷ = 60/60 = 1.00

SPAM-to-HAM odds ratio: ❶/❷ = 1

How about *from*?

❶ = 70/140 = 0.5

❷ = 29/60 = 0.48

SPAM-to-HAM odds ratio: ❶/❷ = 1

Both are *neutral* features!

Smoothing

- We have to account for cases where a feature is never observed with a label.

	SPAM (n=140)	HAM (n=60)
day	20	20
linguistics	1	15
cash	90	3
Viagra	20	0
the	138	60
from	70	29

- 'Viagra' never occurred in a HAM document.
  - ❶ P(f3|SPAM) = 20/140 = 0.14
  - ❷ P(f3|HAM) = 0/60 = 0
- SPAM-HAM odds ratio = 0.14/0 ← !!!
- HAM-SPAM odds ratio = 0/0.14 = 0

  ← Not good, because it single-handedly renders P(HAM|D) to 0, regardless of what other features are present

- Just because we haven't seen a feature/label combination occur in the training set, doesn't mean it's impossible for that combination to occur.
- **Smoothing** is a process through which a very small probability is assigned to such features.

Probabilities of the entire document

H_1 "D is a SPAM" is closely related to P(D, SPAM):

The probability of document D occurring *and* it being a spam

= P(SPAM) * P(D|SPAM)

= P(SPAM) * $P(f_1, f_2, \ldots, f_n | SPAM)$ ❶

= P(SPAM) * $P(f_1|SPAM) * P(f_2|SPAM) * \ldots * P(f_n|SPAM)$ ❷

- We have all the pieces to compute this.
- "Bag-of-words" assumption ❶
- "Naïve" Bayes because ❷ assumes **feature independence**.

  ← Why is this assumption naïve/unreasonable?
- If all we're going to do is rule between SPAM and HAM, we can simply compare P(D, SPAM) and P(D, HAM) and choose one with higher probability.
- But we may also be interested in answering:

  "Given D, what are the *chances* of it being a SPAM? 70%? 5%?"

  ← This is P(SPAM|D).

Given D, chance of Spam?

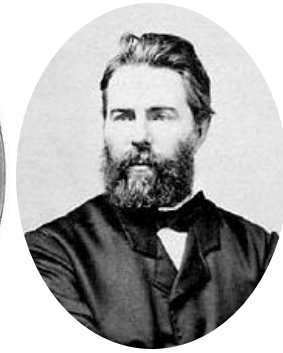
$$P(SPAM \mid D) = \frac{P(SPAM, D)}{P(D)} = \frac{P(SPAM, D)}{P(SPAM, D) + P(HAM, D)}$$

P(SPAM|D): the probability of a given document D being SPAM

(ex: "This email looks sketchy: 97% chance of spam, 3% benign…")

- Can be calculated from P(SPAM, D) and P(HAM, D)
- More next class… **Bayes Theorem**!

Homework 4: Who Said It?



- Jane Austen or Herman Melville?
  - *I never met with a disposition more truly amiable.*
  - *But Queequeg, do you see, was a creature in the transition stage -- neither caterpillar nor butterfly.*
  - *Oh, my sweet cardinals!*

- Task: build a Naïve Bayes classifier and explore it
- Do three-way partition of data:
  - test data
  - development-test data
  - training data

1,000 **Test**	1,000 **Dev-test**	15,152 sents **Training**

Wrapping up

- HW 4 out
  - Week-long
    - 10/5 (Thu): [PART A], report on classifier performance
    - 10/10 (Tue): everything due
  - **Don't procrastinate** – start now!
  - This is likely the single most challenging HW!

- PyLing tomorrow! ➔ Next slide

- Next class (Thu)
  - Bayes Theorem
  - Evaluating performance of a classifier

- Midterm exam (next Thursday) ➔ Next next slide

Come join PyLing!

- "Pitt Python Linguistics Group"
- Everyone at Pitt & CMU studying computational linguistics and Python
- Celebrating 10 years!

- Meeting tomorrow:
  - 6pm (-7:15pm)
  - CL 2818 (linguistics conference room)
  - TTS (text-to-speech) hands-on!

Midterm exam: what to expect

- 10/12 (Thursday)
  - 75 minutes.
  - At LMC's PC Lab (G17 CL)
- Exam format:
  - Closed book. All pencil-and-paper.
  - Topical questions: "what is/discuss/analyze/find out/calculate…"
  - Bring your calculator! →

- A letter-sized cheat sheet allowed.
  - Front and back.
  - Hand-written only.