Natural Language Processing (NLP)

Bag of words
Sentiment analysis
- Product reviews, Yelp
Naïve Bayes
LDA
Deep learning

NLP pipeline

- **Tokenization**
  - "Yesterday, I didn't walk 3.14 miles to Penn Engineering."
  - *Yesterday , I didn't walk 3.14 miles to Penn Engineering .*
- **Named Entity recognition**
  - Penn_Engineering
- **Bag of words vs. sequential models**
- **Optionally: word embedding**

Naïve Bayes for Text Classification

adapted by Lyle Ungar from slides by Mitch Marcus, which were adapted from slides by Massimo Poesio, which were adapted from slides by Chris Manning :)

Example: Is this spam?

How do you know?

From: "" <takworlld@hotmail.com>
Subject: real estate is the only way... gem oalvgkay

Anyone can buy real estate with no money down

Stop paying rent TODAY !

There is no need to spend hundreds or even thousands for similar courses

I am 22 years old and I have already purchased 6 properties using the methods outlined in this truly INCREDIBLE ebook.

Change your life NOW !

===

Click Below to order:

http://www.wholesaledaily.com/sales/nmd.htm

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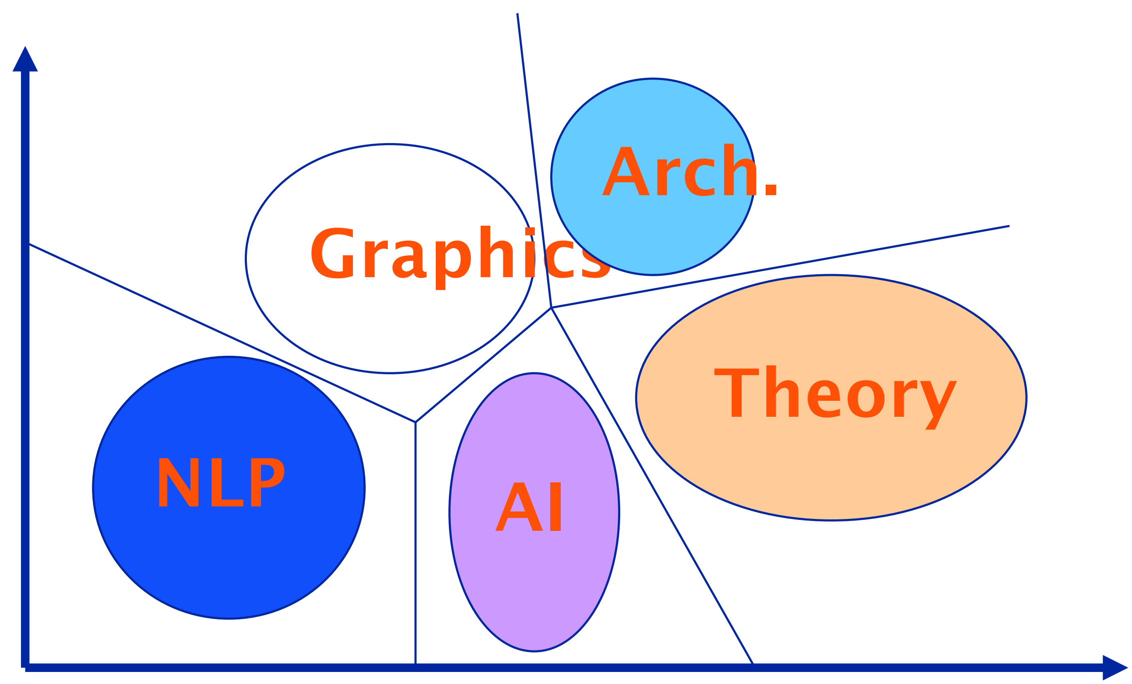
Classification

- **Given**
  - A vector , $x \in X$ describing an instance
    - *Issue: how to represent text documents as vectors?*
  - A fixed set of categories: $C = \{c_1, c_2, \dots, c_k\}$
- **Determine**
  - An optimal *classifier* $c(x)$: $X \rightarrow C$

A Graphical View of Text Classification



Examples of text categorization

- **Spam**
  - “spam” / “not spam”
- **Topics**
  - “finance” / “sports” / “asia”
- **Author**
  - “Shakespeare” / “Marlowe” / “Ben Jonson”
  - The Federalist papers author
  - Male/female
  - Native language: English/Chinese,…
- **Opinion**
  - “like” / “hate” / “neutral”
- **Emotion**
  - “angry”/”sad”/”happy”/”disgusted”/…

Conditional models

$p(Y=y|\mathbf{X}=\mathbf{x};\ \mathbf{w}) \sim \exp(-||\mathbf{y}-\mathbf{x}\cdot\mathbf{w}||^2/2\sigma^2)$ **linear regression**

$p(Y=y|\mathbf{X}=\mathbf{x};\ \mathbf{w}) \sim 1/(1+\exp(-\mathbf{x}\cdot\mathbf{w}))$ **logistic regression**

- **Or derive from full (‘generative’) model**
  - $p(y|x) = p(x,y)/p(x)$
  - Making some assumptions about the distribution of (x,y)

Bayesian Methods

- Use *Bayes theorem* to build a *generative model* that approximates how data are produced
- Use *prior probability* of each category
- Produce a *posterior probability* distribution over the possible categories given a description of an item.

Bayes’ Rule once again

$$P(C \mid D) = \frac{P(D \mid C)P(C)}{P(D)}$$

Maximum a posteriori (MAP)

$$c_{MAP} \equiv \underset{c \in C}{\operatorname{argmax}}\, P(c \mid D)$$

$$= \underset{c \in C}{\operatorname{argmax}} \frac{P(D \mid c) P(c)}{P(D)}$$

$$= \underset{c \in C}{\operatorname{argmax}}\, P(D \mid c) P(c)$$

As *P(D)* is constant

Maximum likelihood

If all hypotheses are *a priori* equally likely, we only need to consider the P(D|c) term:

$$c_{ML} \equiv \underset{c \in C}{\operatorname{argmax}}\, P(D \mid c)$$

Maximum Likelihood Estimate ("MLE")

Naive Bayes Classifiers

Task: Classify a new instance $\underline{x}$ based on a tuple of attribute values $x = (x_1 \ldots x_p)$ into one of the classes $c_j \in C$

$$c_{MAP} = \arg\max_c p(c|x_1, ..x_p)$$

$$= \arg\max_c p(x_1, ..x_p|c)\, p(c) \,/\, p(x_1, ..x_p)$$

$$= \arg\max_c p(x_1, ..x_p|c)\, p(c)$$

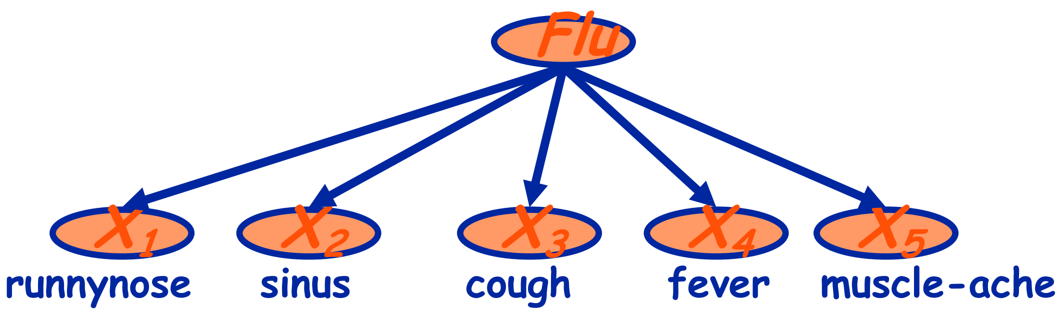
Naïve Bayes Classifier: Assumption

- ***$P(c_j)$***
  - Estimate from the training data.
- ***$P(x_1,x_2,\ldots,x_p|c_j)$***
  - $O(|X|^p \cdot |C|)$ parameters
  - Could only be estimated if a very, very large number of training examples was available.

Naïve Bayes assumes Conditional Independence:

- Assume that the probability of observing the conjunction of attributes is equal to the product of the individual probabilities $P(x_i|c_j)$.

The Naïve Bayes Classifier

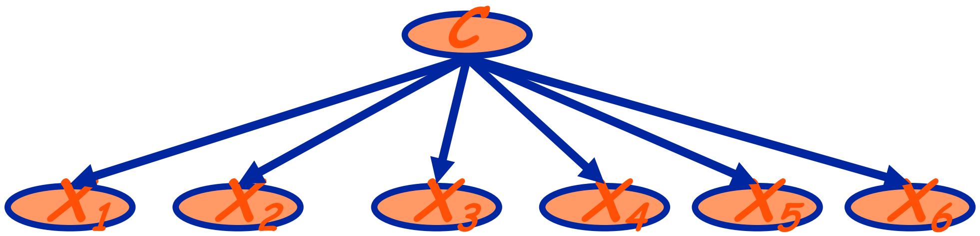


- Conditional Independence Assumption: **Features are independent of each other given the class:**

$$P(X_1,\ldots,X_5 \mid C) = P(X_1 \mid C) \bullet P(X_2 \mid C) \bullet \cdots \bullet P(X_5 \mid C)$$

- **This model is appropriate for binary variables**
  - Similar models work more generally (“Belief Networks”)

Learning the Model

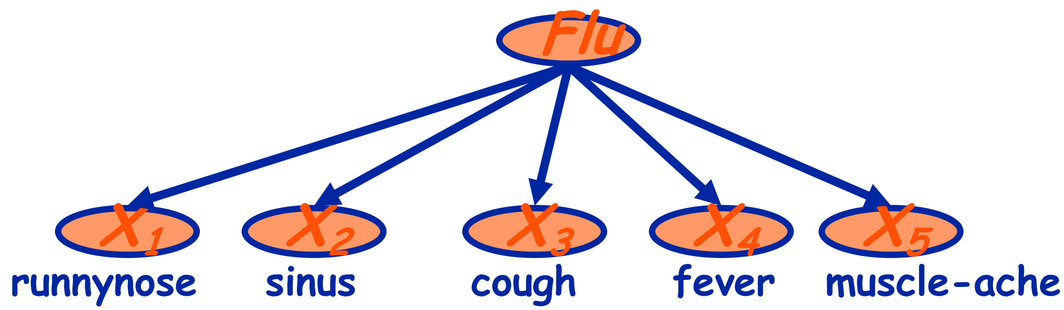


- **First attempt: maximum likelihood estimates**
  - simply use the frequencies in the data

$$\hat{P}(c_j) = \frac{N(C = c_j)}{N}$$

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j)}{N(C = c_j)}$$

Problem with Max Likelihood



- What if we have seen no training cases where patient had no flu and muscle aches?

$$P(X_1,\ldots,X_5 \mid C) = P(X_1 \mid C) \bullet P(X_2 \mid C) \bullet \cdots \bullet P(X_5 \mid C)$$

$$\hat{P}(X_5 = t \mid C = flu) = \frac{N(X_5 = t, C = flu)}{N(C = flu)} = 0$$

- Zero probabilities cannot be conditioned away, no matter the other evidence!

$$\ell = \arg\max_c \hat{P}(c) \prod_i \hat{P}(x_i \mid c)$$

MLE Estimate

$$P(x_i|c_j) = N(X_i\!=\!true,\ C\!=\!c_j) \;/\; N(C\!=\!c_j)$$

Where
$N(C=c_j)$ = # of docs in class c_j
$N(X_i=true,\ C=c_j)$ = # of docs in class c_j containing word x_i,

MAP Estimate

- Add one document to each class with a single count of each word

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = true, C = c_j) + 1}{N(C = c_j) + v}$$

- Somewhat more subtle version

overall fraction of docs containing x_i

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = true, C = c_j) + mp_i}{N(C = c_j) + m}$$

extent of “smoothing”

Now
$N(C=c_j)$ = # of docs in class c_j
$N(X_i=true, C=c_j)$ = # of docs in class c_j containing word x_i,
v = vocabulary size
p_i = probability that word i is present in a document, ignoring class labels

Naïve Bayes: Learning

- From training corpus, extract *Vocabulary*

- Estimate $P(c_j)$ and $P(x_k \mid c_j)$
  - For each c_j in C do

    $docs_j \leftarrow$ documents labeled with class c_j

    $$P(c_j) \leftarrow \frac{|docs_j|}{|\text{total \# documents}|}$$

  - For each word x_k in *Vocabulary*

    $n_k \leftarrow$ number of occurrences of x_k in all $docs_j$

    $$P(x_k \mid c_j) \leftarrow \frac{n_k + 1}{|docs_j| + |Vocabulary|}$$

"Laplace" smoothing

Naïve Bayes: Classifying

- For all words x_i in current document
- Return c_{NB}, where

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in documant} P(x_i \mid c_j)$$

What is the implicit assumption hidden in this?

Naïve Bayes for text

- **The "correct" model would have a probability for each word observed and one for each word *not* observed.**
  - Naïve Bayes for text assumes that there is no information in words that are not observed – since most words are very rare, their probability of *not* being seen is close to 1.

Naive Bayes is not so dumb

- **A good baseline for text classification**
- **Optimal if the independence assumptions hold:**
- **Very fast:**
  - Learns with one pass over the data
  - Testing linear in the number of attributes and of documents
  - Low storage requirements

Technical Detail: Underflow

- Multiplying lots of probabilities, which are between 0 and 1 by definition, can result in floating-point underflow.
- Since *log(xy) = log(x) + log(y),* it is better to perform all computations by summing logs of probabilities rather than multiplying probabilities.
- Class with highest final un-normalized log probability score is still the most probable.

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} \log P(c_j) + \sum_{i \in positions} \log P(x_i \mid c_j)$$

More Facts About Bayes Classifiers

- **Bayes Classifiers can be built with real-valued inputs**
  - Or many other distributions
- **Bayes Classifiers don't try to be maximally discriminative**
  - They merely try to honestly model what's going on
- **Zero probabilities give stupid results**
- **Naïve Bayes is wonderfully cheap**
  - And handles 1,000,000 features cheerfully!

Naïve Bayes – MLE

word	topic	count
a	sports	0
ball	sports	1
carrot	sports	0
game	sports	2
I	sports	2
saw	sports	2
the	sports	3

P(a | sports) = 0/5
P(ball | sports) = 1/5

Assume 5 sports documents

Counts are number of documents on the sports topic containing each word

Naïve Bayes – prior (noninformative)

Word	topic	count
a	sports	0.5
ball	sports	0.5
carrot	sports	0.5
game	sports	0.5
I	sports	0.5
saw	sports	0.5
the	sports	0.5

Assume 5 sports documents

Adding a count of 0.5
beta(0.5,0.5) is a *Jeffreys* prior.

A count of 1
beta(1,1) is *Laplace smoothing.*

Pseudo-counts to be added to the observed counts

We did 0.5 here; before in the notes it was 1; either is fine

Naïve Bayes – posterior (MAP)

Word	topic	count
a	sports	0.5
ball	sports	1.5
carrot	sports	0.5
game	sports	2.5
I	sports	2.5
saw	sports	2.5
the	sports	3.5

P(a | sports) = 0.5/8.5

P(ball | sports) = 1.5/8.5

Assume 5 sports documents,

$$P(\text{word}|\text{topic}) = \frac{N(\text{word},\text{topic})+0.5}{N(\text{topic}) + 0.5\ k}$$

Pseudo count of docs on topic=sports is (5 + 0.5*7=8.5)

posterior

But words have different 'base rates'

word	topic	count	topic	count	p(word)
a	sports	0	politics	2	2/11
ball	sports	1	politics	0	1/11
carrot	sports	0	politics	0	0/11
game	sports	2	politics	1	3/11
I	sports	2	politics	5	7/11
saw	sports	2	politics	1	3/11
the	sports	3	politics	5	8/11

Assume 5 sports docs and 6 politics docs 11 total docs

Naïve Bayes – posterior (MAP)

$$P(\text{word},\text{topic}) = \frac{N(\text{word},\text{topic}) + m\, P_{\text{word}}}{N(\text{topic}) + m}$$

Arbitrarily pick m=4 as the strength of our prior

P(a | sports) = (0 + 4*(2/11))/(5 + 4) = 0.08

P(ball | sports) = (1 + 4*(1/11))/(5 + 4) = 0.15

…

What you should know

- **Applications of document classification**
  - Sentiment analysis, topic prediction, email routing, author ID, Naïve Bayes
  - **As MAP estimator** (uses prior for smoothing)
    - Contrast MLE
  - **For document classification**
    - Use bag of words
    - Could use richer feature set