Formalization & Learning

Slides borrowed from Stanford with modifications

Formalizing the Naïve Bayes Classifier

Naïve Bayes Intuition

- Simple ("naïve") classification method based on Bayes rule
- Relies on very simple representation of document
 - Bag of words

Bayes' Rule Applied to Documents and Classes

For a document d and a class c

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

Naïve Bayes Classifier (I)

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(c \mid d)$$

MAP is "maximum a posteriori" = most likely class

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

Bayes Rule

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

Dropping the denominator

Naïve Bayes Classifier (II)

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(d \mid c) P(c)$$

$$= \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \dots, x_n \mid c) P(c)$$

Document d represented as features x1..xn

Naïve Bayes Classifier (III)

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

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

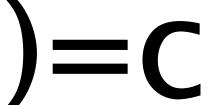
How often does this class occur?

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

We can just count the relative frequencies in a corpus

The bag of words representation

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.



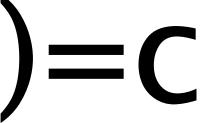




The bag of words representation

Y	

great	2
love	2
recommend	1
laugh	1
happy	1
• • •	• • •







Multinomial Naïve Bayes Independence Assumptions $P(x_1, x_2,...,x_n \mid c)$

- Bag of Words assumption: Assume position doesn't matter
- Conditional Independence: Assume the feature probabilities $P(x_i|c_i)$ are independent given the class c.

$$P(x_1,...,x_n \mid c) = P(x_1 \mid c) \cdot P(x_2 \mid c) \cdot P(x_3 \mid c) \cdot ... \cdot P(x_n \mid c)$$

Applying Multinomial Naive Bayes Classifiers to Text Classification

positions ← all word positions in test document

$$c_{NB} = \underset{c_{j} \in C}{\operatorname{argmax}} P(c_{j}) \prod_{i \in positions} P(x_{i} \mid c_{j})$$

Formalizing the Naïve Bayes Classifier

Naïve Bayes: Learning

Sec.13.3

Learning the Multinomial Naïve Bayes Model

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

$$\hat{P}(c_j) = \frac{doccount(C = c_j)}{N_{doc}}$$

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

Parameter estimation

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$
 fraction of times word w_i appears among all words in documents of topic c_j

- Create mega-document for topic j by concatenating all docs in this topic
 - Use frequency of w in mega-document

Problem with Maximum Likelihood

• What if we have seen no training documents with the word *fantastic* and classified in the topic **positive** (*thumbs-up*)?

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

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

$$c_{MAP} = \operatorname{argmax}_{c} \hat{P}(c) \prod_{i} \hat{P}(x_{i} \mid c)$$

Laplace (add-1) smoothing: unknown words

Add one extra word to the vocabulary, the "unknown word" w_u

$$\hat{P}(w_u \mid c) = \frac{count(w_u, c) + 1}{\left(\sum_{w \in V} count(w, c)\right) + |V + 1|}$$

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

Underflow Prevention: log space

- Multiplying lots of probabilities can result in floating-point underflow.
- Since log(xy) = log(x) + log(y)
 - Better to sum logs of probabilities instead of multiplying probabilities.
- Class with highest un-normalized log probability score is still most probable.

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

Model is now just max of sum of weights

Naïve Bayes: Learning

Multinomial Naïve Bayes: A Worked Example

$$\hat{P}(c) = \frac{N_c}{N}$$
Training 1 Chinese Beijing Chinese Chinese Shanghai C
$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|+1}$$
3 Chinese Macao C
4 Tokyo Japan Chinese Tokyo Japan P
Test 5 Chinese Chinese Tokyo Japan ?

Priors:

$$P(c) = \frac{3}{4} \frac{1}{4}$$

$$P(j) = \frac{3}{4} \frac{1}{4}$$

Conditional Probabilities:

P(Chinese
$$|c|$$
 = (5+1) / (8+7) = 6/15
P(Tokyo $|c|$ = (0+1) / (8+7) = 1/15
P(Japan $|c|$ = (0+1) / (8+7) = 1/15
P(Chinese $|j|$ = (1+1) / (3+7) = 2/10
P(Tokyo $|j|$ = (1+1) / (3+7) = 2/10

P(Japan|j) = (1+1)/(3+7) = 2/10

Choosing a class:

$$P(c|d5) \propto 3/4 * (6/15)^3 * 1/15 * 1/15$$

 ≈ 0.0002

$$P(j|d5) \propto 1/4 * (2/10)^3 * 2/10 * 2/10$$

 ≈ 0.00008

Summary: Naive Bayes is Not So Naive

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
- A good dependable baseline for text classification

Multinomial Naïve Bayes: A Worked Example