Machine Learning Lecture #7

(Building a Naive Bayes Text Classifier with scikit-learn)

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Naïve Bayes: A Little History





$$P(A|B) = \underline{P(B|A) P(A)}$$

$$P(B)$$



Reverend Bayes



Pierre-Simon Laplace

Naïve Bayes: Advantages and Disavantages

Advantages

- Very simple to implement and fast
- Works well even when the feature independence assumption does not hold as in the case of text
- Deals well with data sets that have very large feature spaces

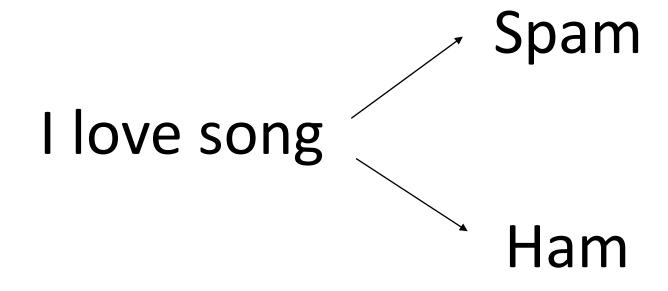
Disadvantages

 Does not work well with expressions that have a combination of words with unique meanings.

Naïve Bayes: The Equation

$$P(y \mid x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots, x_n \mid y)}{P(x_1, \dots, x_n)}$$

Naïve Bayes: An example



Naïve Bayes: An example

	comment	category
0	Check out my you[tube] /#?song Channel?	spam
1	I love song, please like my channel!!!	spam
2	l'm not a fan, :(ham
3	This song is great, I love your channel	ham
4	love love love	ham

I love song

Naïve Bayes: An example

comment	category
---------	----------

0	Check out my you[tube] /#?song Channel?	spam
1	I love song, please like my channel!!!	spam
2	l'm not a fan, :(ham
3	This song is great, I love your channel	ham
4	love love love	ham



Naïve Bayes: The Equation

	channel	check	fan	great	like	love	song	tube	class
0	1	1	0	0	0	0	1	1	spam
1	1	0	0	0	1	1	1	0	spam
2	0	0	1	0	0	0	0	0	ham
3	1	0	0	1	0	1	1	0	ham
4	0	0	0	0	0	3	0	0	ham

I love song

Naïve Bayes: The Equation

	channel	check	fan	great	like	love	song	tube	class	$P(y \mid x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots x_n \mid y)}{P(x_1, \dots, x_n)}$
0	1	1	0	0	0	0	1	1	spam	$P(x_1,\ldots,x_n)$
1	1	0	0	0	1	1	1	0	spam	
2	0	0	1	0	0	0	0	0	ham	
3	1	0	0	1	0	1	1	0	ha R (Spam I love song) = $P(Spam) \times P(I love song Spam)$
4	0	0	0	0	0	3	0	0	ham	P(I love song)

$$P(\mathbf{Ham}|\mathbf{I} \text{ love song}) = \underline{P(\mathbf{Ham}) \times P(\mathbf{I} \text{ love song}|\mathbf{Ham})}$$

$$P(\mathbf{I} \text{ love song})$$

Naïve Bayes: The

Calculating the apriori:

				- 4		
	q	U	18	lt	O	n

	channel	check	fan	great	like	love	song	tube	class	
0	1	1	0	0	0	0	1	1	spam	
1	1	0	0	0	1	1	1	0	spam	
2	0	0	1	0	0	0	0	0	ham	
3	1	0	0	1	0	1	1	0	ham	P(S
4	0	0	0	0	0	3	0	0	ham	

$$= \frac{P(y)P(x_1, \dots x_n \mid y)}{P(x_1, \dots, x_n)}$$

$$P(Ham) = # of Ham comments = 3$$
total comments = 5

Naïve Bayes: The Equation conditional probability

Naïve Bayes: The Equation conditional probability

	channel	check	fan	great	like	love	song	tube	class
0	1	1	0	0	0	0	1	1	spam
1	1	0	0	0	1	1	1	0	spam
2	0	0	1	0	0	0	0	0	ham
3	1	0	0	1	0	1	1	0	ham
4	0	0	0	0	0	3	0	0	ham

$$= \frac{P(y)P(x_1, \dots x_n \mid y)}{P(x_1, \dots, x_n)}$$

P(Spam|love song) =
$$\frac{1}{5} \times \frac{1}{32}$$
 = **0.006**

P(Ham|love song) =
$$\frac{4}{5} \times \frac{1}{16}$$

= 0.05

Naïve Bayes: and now for the

Code

Loading the Dataset

```
In [1]: # Import necessary modules
        import pandas as pd
        import numpy as np
        import glob
In [2]: # Import the data set
        path = r'C:\Users\obiamOneDrive\YouTube-Spam-Collection-v1'
        allFiles = glob.glob(path + "/*.csv")
        frame = pd.DataFrame()
        list = []
        for file_ in allFiles:
            df = pd.read_csv(file_,index_col=None, header=0)
            list .append(df)
        frame = pd.concat(list )
```

Loading the Dataset

CLAS	CONTENT	DATE	AUTHOR	COMMENT_ID		ıt[3]:
	Huh, anyway check out this you[tube] channel:	2013-11-07T06:20:48	Julius NM	LZQPQhLyRh80UYxNuaDWhIGQYNQ96luCg-AYWqNPjpU	0	
	Hey guys check out my new channel and our firs	2013-11-07T12:37:15	adam riyati	LZQPQhLyRh_C2cTtd9MvFRJedxydaVW-2sNg5Diuo4A	1	
	just for test I have to say murdev.com	2013-11-08T17:34:21	Evgeny Murashkin	LZQPQhLyRh9MSZYnf8djyk0gEF9BHDPYrrK-qCczIY8	2	
	me shaking my sexy ass on my channel enjoy $^{\ }$	2013-11-09T08:28:43	ElNino Melendez	z13jhp0bxqncu512g22wvzkasxmvvzjaz04	3	
	$watch?v = vtaRGgvGtWQ\ Check\ this\ out\ .$	2013-11-10T16:05:38	GsMega	z13fwbwp1oujthgqj04chlngpvzmtt3r3dw	4	

Sub-setting

```
In [5]: df = frame.iloc[:,3:5]
            df.head()
                                               CONTENT CLASS
Out[5]:
                Huh, anyway check out this you[tube] channel: ...
               Hey guys check out my new channel and our firs...
                         just for test I have to say murdev.com
            3 me shaking my sexy ass on my channel enjoy ^_^
            4
                       watch?v=vtaRGgvGtWQ Check this out .
In [6]:
            df.shape
Out[6]: (1956, 2)
```

Train/test split

```
In [7]: # Import the necessary modules
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn.model selection import train test split
In [8]: # Create a series to store the comments:x
        x = df['CONTENT']
        # Create a series to store the labels: y
        v = df['CLASS']
         # Create training and test sets
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_state=53)
In [9]: print(x_train.shape,
        x_test.shape,
        y_train.shape,
        y_test.shape)
        (1369,) (587,) (1369,) (587,)
```

Feature extraction: Bag of words approach

Bag of words approach-Training

```
In [11]: # Import the necessary modules
    from sklearn import metrics
    from sklearn.naive_bayes import MultinomialNB

# Instantiate a Multinomial Naive Bayes classifier: nb_classifier
    nb_classifier = MultinomialNB()

# Fit the classifier to the training data
    nb_classifier.fit(count_train, y_train)
```

Bag of Words approach-Testing and Evaluatio

```
In [12]: # Create the predicted tags: pred
    pred = nb_classifier.predict(count_test)

# Calculate the accuracy score: score
    score = metrics.accuracy_score(y_test, pred)
    print(score)

0.9114139693356048
```

```
In [13]: # Calculate the confusion matrix: cm
   cm = metrics.confusion_matrix(y_test, pred,labels=[1, 0])
   print(cm)
[[289 9]
   [ 43 246]]
```

Feature Extraction: TF-IDF Approach

```
In [14]: # Import TfidfVectorizer
         from sklearn.feature extraction.text import TfidfVectorizer
         # Initialize a TfidfVectorizer object: tfidf vectorizer
         tfidf vectorizer = TfidfVectorizer(stop words="english", max df=0.7)
         # Transform the training data: tfidf train
         tfidf train = tfidf vectorizer.fit transform(x train.values)
         # Transform the test data: tfidf test
         tfidf test = tfidf vectorizer.transform(x test.values)
```

TF-IDF Approach: Training

```
In [11]: # Import the necessary modules
    from sklearn import metrics
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# Instantiate a Multinomial Naive Bayes classifier: nb_classifier
    nb_classifier = MultinomialNB()

# Fit the classifier to the training data
    nb_classifier.fit(count_train, y_train)
```

TF-IDF Approach: Testing and Evaluation

```
In [16]: # Create the predicted tags: pred
         pred = nb_classifier.predict(tfidf_test)
         # Calculate the accuracy score: score
         score = metrics.accuracy score(y test, pred)
         print(score)
         0.9148211243611585
In [17]: # Calculate the confusion matrix: cm
         cm = metrics.confusion matrix(y test, pred, labels=[1, 0])
         print(cm)
         [[289 9]
          [ 41 248]]
```

Question?

