MACHINE LEARNING

Text Classification Using Naive Bayes: Theory & A Working Example

In this article, I explain how the Naive Bayes works and I implement a multi-class text classification problem step-by-step in Python.

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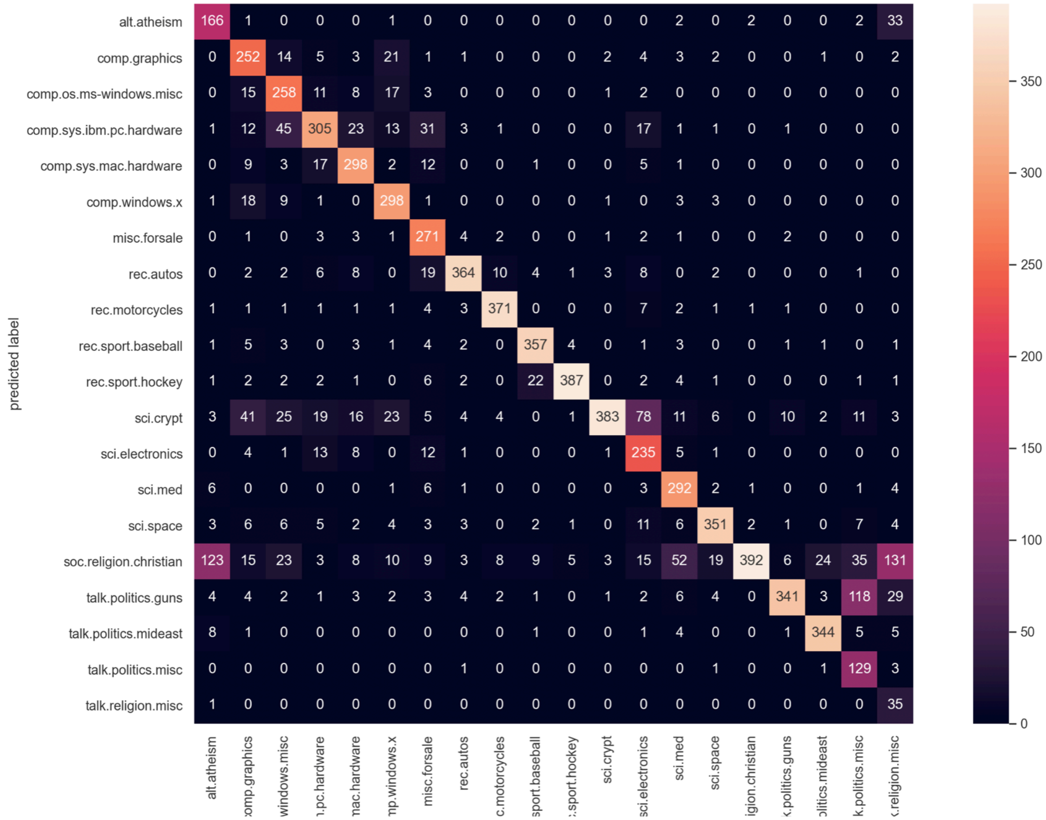
Getting Started




```python
def my_predictions(my_sentence, model):
    all_categories_names = np.array(data.target_names)
    prediction = model.predict([my_sentence])
    return all_categories_names[prediction]

my_sentence = "jesus"
print(my_predictions(my_sentence, model))

my_sentence = "Are you an atheist?"
print(my_predictions(my_sentence, model))
```

```
['soc.religion.christian']
['alt.atheism']
```

Figure created by the author.

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1. Introduction

Naive Bayes classifiers are a collection of Classification algorithms based on **Bayes' Theorem**. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

Naive Bayes classifiers have been heavily used for **text classification** and **text analysis** machine learning **problems**.

Text Analysis is a major application field for Machine Learning algorithms. However the raw data, a sequence of symbols (i.e. strings) cannot be fed directly to the algorithms themselves as most of them expect numerical feature vectors with a fixed size rather than the raw text documents with variable length.

In this article I explain a) how **Naive Bayes** works**,** b) how we can use **text data** and **fit** them into a **model** after transforming them into a more appropriate form. Finally, I **implement** a **multi-class text classification problem step-by-step in Python**.

Let’s get started !!!

- **NEW**: After a great deal of hard work and staying behind the scenes for quite a while, we’re excited to now offer our expertise through a platform, the "**Data Science Hub**" on Patreon (https://www.patreon.com/TheDataScienceHub). This hub is our way of providing you with **bespoke consulting services** and comprehensive **responses to all your inquiries**, ranging from Machine Learning to strategic data analytics planning.

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2. The Naive Bayes algorithm

Naive Bayes classifiers are a collection of classification algorithms based on **Bayes’ Theorem**. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

The dataset is divided into two parts, namely, **feature matrix** and the **response/target vector**.

- The **Feature matrix** (X) contains all the vectors(rows) of the dataset in which each vector consists of the value of **dependent features**. The number of features is **d** i.e. **X = (x1,x2,x2, xd).**
- The **Response/target vector** (y) contains the value of **class/group variable** for **each row of feature matrix.**

2.1. The main two assumptions of Naive Bayes

Naive Bayes assumes that **each feature/variable** of the same class makes an:

- **independent**
- **equal**

contribution to the outcome.

Side Note: The assumptions made by Naive Bayes are not generally correct in real-world situations. In-fact, the independence assumption is often not met and this is why it is called "**Naive**" i.e. because it assumes something that might not be true.

2.2. The Bayes' Theorem

Bayes' Theorem finds the Probability of an event occurring given the probability of another event that has already occurred. Bayes' theorem is stated mathematically as follows:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

Figure created by the author.

where:

- **A** and **B** are called **events.**
- P(A | B) is the probability of event A, given the event B is true (has occured). Event B is also termed as **evidence**.
- P(A) is the **priori** of A (the prior independent probability, i.e. probability of event before evidence is seen).
- P(B | A) is the probability of B given event A, i.e. probability of event B after evidence A is seen.

Summary

$$\begin{aligned} A, B \quad &= \text{events} \\ P(A \mid B) \quad &= \text{probability of A given B is true} \\ P(B \mid A) \quad &= \text{probability of } B \text{ given } A \text{ is true} \\ P(A), P(B) &= \text{the independent probabilities of A and B} \end{aligned}$$

Figure created by the author.

2.3. The Naive Bayes Model

Given a data matrix **X** and a target vector **y,** we state our problem as:

$$P(y \mid X) = \frac{P(X \mid y)P(y)}{P(X)}$$

Figure created by the author.

where, **y** is **class variable** and **X** is a **dependent feature vector with dimension d i.e. X = (x1,x2,x2, xd),** where **d** is the number of variables/features of the sample.

- P(y|X) is the probability of observing the class **y** given the sample **X** with **X = (x1,x2,x2, xd),** where **d** is the number of variables/features of the sample.

Now the "naïve" conditional independence assumptions come into play: assume that all features in **X** are mutually independent, conditional on the category **y**:

$$P(y \mid x_1, \ldots, x_d) = \frac{P(y)\prod_{i=1}^{d} P(x_i|y)}{P(x_1)P(x_2)\ldots P(x_d)}$$

The denominator remains constant for a given input, so we can remove that term:

$$P(y \mid x_1, \ldots, x_d) \propto P(y)\prod_{i=1}^{d} P(x_i \mid y)$$

Figure created by the author.

Finally, to find the probability of a given **sample** for all possible values of the class variable ***y***, we just need to find the output with maximum probability:

$$y = \operatorname{argmax}_y P(y) \prod_{i=1}^{n} P(x_i \mid y)$$

Figure created by the author.

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3. Dealing with text data

One question that arises at this point is the following:

> How are we going to use the raw text data to train the model ? The raw data is a collection of strings !

Text Analysis is a major application field for machine learning algorithms. **However the raw data, a sequence of symbols (i.e. strings) cannot be fed directly to the algorithms themselves as most of them expect numerical feature vectors with a fixed size rather than the raw text documents with variable length.**

In order to address this, scikit-learn provides utilities for the most common ways to extract numerical features from text content, namely:

- **tokenizing** strings and giving an integer id for each possible token, for instance by using white-spaces and punctuation as token separators.
- **counting** the occurrences of tokens in each document.

In this scheme, features and samples are defined as follows:

- each **individual token occurrence frequency** is treated as a **feature**.
- the vector of all the token frequencies for a given **document** is considered a multivariate **sample**.

"Counting" Example (to really understand this before we move on):

```
from sklearn.feature_extraction.text import CountVectorizer
corpus = [
    'This is the first document.',
    'This document is the second document.',
    'And this is the third one.',
    'Is this the first document?',
]

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(corpus)

print(vectorizer.get_feature_names())
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']

print(X.toarray())
[[0 1 1 1 0 0 1 0 1]
 [0 2 0 1 0 1 1 0 1]
 [1 0 0 1 1 0 1 1 1]
 [0 1 1 1 0 0 1 0 1]]
```

In the above toy example, we have a collection of strings stored into the variable **corpus.** Using the **text transformer**, we can see that we have a specific number of unique strings (vocabulary) in our data.

This can be seen by printing the **vectorizer.get_feature_names()** variable**.** We observe that we have **9 unique words**.

Next, we printed the transformed data (**X**) and **we observe the following**:

- We have 4 rows in X as the number of our text strings (**we have the same number of samples after the transformation**).
- **We have the same number of columns** (features/variables) in the transformed data (**X**) f**or all the samples (**this was not the case before that transformation i.e. the individual strings had different lengths).
- The values 0,1,2, encode the **frequency** of a **word** that **appeared** in the **initial text data.**

E.g. The first transformed row is **[0 1 1 1 0 0 1 0 1]** and ** **th**e unique vocabulary **i**s [‘and’, ‘document’, ‘first’, ‘is’, ‘one’, ‘second’, ‘the’, ‘third’, ‘this’],** thus this means that the words "document", "first", "is", "the" and "this" appeared 1 time each in the initial text string (i.e. ‘This is the first document.’).

Side note: This is the counting approach. The term-frequency transform is nothing more than a transformation of a count matrix into a normalized term-frequency matrix.

Hope everything is clear now. If not, read this paragraph as many times as it is needed in order to really grasp the idea and understand this transformation. **It is a fundamental step.**

4. Working example in Python

Now that you understood how the Naive Bayes and the Text Transformation work, it's time to start coding !

Problem Statement

As a working example, we will use some **text data** and we will build a **Naive Bayes** model to **predict** the **categories** of the **texts**. This is a **multi-class (20 classes) text classification problem**.

Let's start (I will walk you through). First, we will **load all the necessary libraries**:

```
import numpy as np, pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
from sklearn.metrics import confusion_matrix, accuracy_score

sns.set() # use seaborn plotting style
```

Next, **let's load the data** (**training** and **test** sets):

```
# Load the dataset
data = fetch_20newsgroups()

# Get the text categories
text_categories = data.target_names

# define the training set
train_data = fetch_20newsgroups(subset="train", categories=text_categories)

# define the test set
test_data = fetch_20newsgroups(subset="test", categories=text_categories)
```

Let's find out **how many classes** and **samples** we have:

```
print("We have {} unique classes".format(len(text_categories)))
print("We have {} training samples".format(len(train_data.data)))
print("We have {} test samples".format(len(test_data.data)))
```

The above prints:

```
We have 20 unique classes
We have 11314 training samples
We have 7532 test samples
```

So, this is a **20-class text classification problem** with n_train = **11314 training samples** (text sentences) and n_test = **7532 test samples** (text sentences).

Let’s visualize the 5th training sample:

```
# let's have a look as some training data
print(test_data.data[5])
```

As mentioned previously, our data are **texts** (more specifically, **emails**) so you should see something like the following printed out:

```
In [12]: print(test_data.data[5])
From: banschbach@vms.ocom.okstate.edu
Subject: Re: Candida(yeast) Bloom, Fact or Fiction
Organization: OSU College of Osteopathic Medicine
Lines: 91
Nntp-Posting-Host: vms.ocom.okstate.edu

In article <1rp8p1$2d3@usenet.INS.CWRU.Edu>, esd3@po.CWRU.Edu (Elisabeth S. Davidson) writ
es:
>
> In a previous article, banschbach@vms.ocom.okstate.edu () says:
>>least a few "enlightened" physicians practicing in the U.S.  It's really
>>too bad that most U.S. medical schools don't cover nutrition because if
>>they did, candida would not be viewed as a non-disease by so many in the
>>medical profession.
>
> Case Western Reserve Med School teaches nutrition in its own section as
> well as covering it in other sections as they apply (i.e. B12
> deficiency in neuro as a cause of neuropathy, B12 deficiency in
> hematology as a cause of megaloblastic anemia), yet I sill
> hold the viewpoint of mainstream medicine:  candida can cause
> mucocutaneous candidiasis, and, in already very sick patients
> with damaged immune systems like AIDS and cancer patients,
> systemic candida infection.  I think "The Yeast Connection" is
> a bunch of hooey.  What does this have to do with how well
> nutrition is taught, anyway?
```

Figure created by the author.

The next step consists of building the **Naive Bayes classifier** and finally **training** the **model.** In our example, we will convert the collection of text documents (train and test sets) into a matrix of token counts (I explained how this works in **Section 3**).

> To implement that text transformation we will use the **make_pipeline** function. This will internally transform the text data and then the model will be fitted **using the transformed data**.

```
# Build the model
model = make_pipeline(TfidfVectorizer(), MultinomialNB())

# Train the model using the training data
model.fit(train_data.data, train_data.target)

# Predict the categories of the test data
predicted_categories = model.predict(test_data.data)
```

The last line of code **predicts the labels of the test set**.

Let's see the predicted categories names:

```
print(np.array(test_data.target_names)[predicted_categories])
array(['rec.autos', 'sci.crypt', 'alt.atheism', ..., 'rec.sport.baseball', 'comp.sys.ibm.p
```

Finally, let's build the **multi-class confusion matrix** to see if the model is good or if the model predicts correctly only specific text categories.

```
# plot the confusion matrix
mat = confusion_matrix(test_data.target, predicted_categories)
sns.heatmap(mat.T, square = True, annot=True, fmt = "d", xticklabels=train_data.target_nam
plt.xlabel("true labels")
plt.ylabel("predicted label")
plt.show()

print("The accuracy is {}".format(accuracy_score(test_data.target, predicted_categories)))
```

```
The accuracy is 0.7738980350504514
```

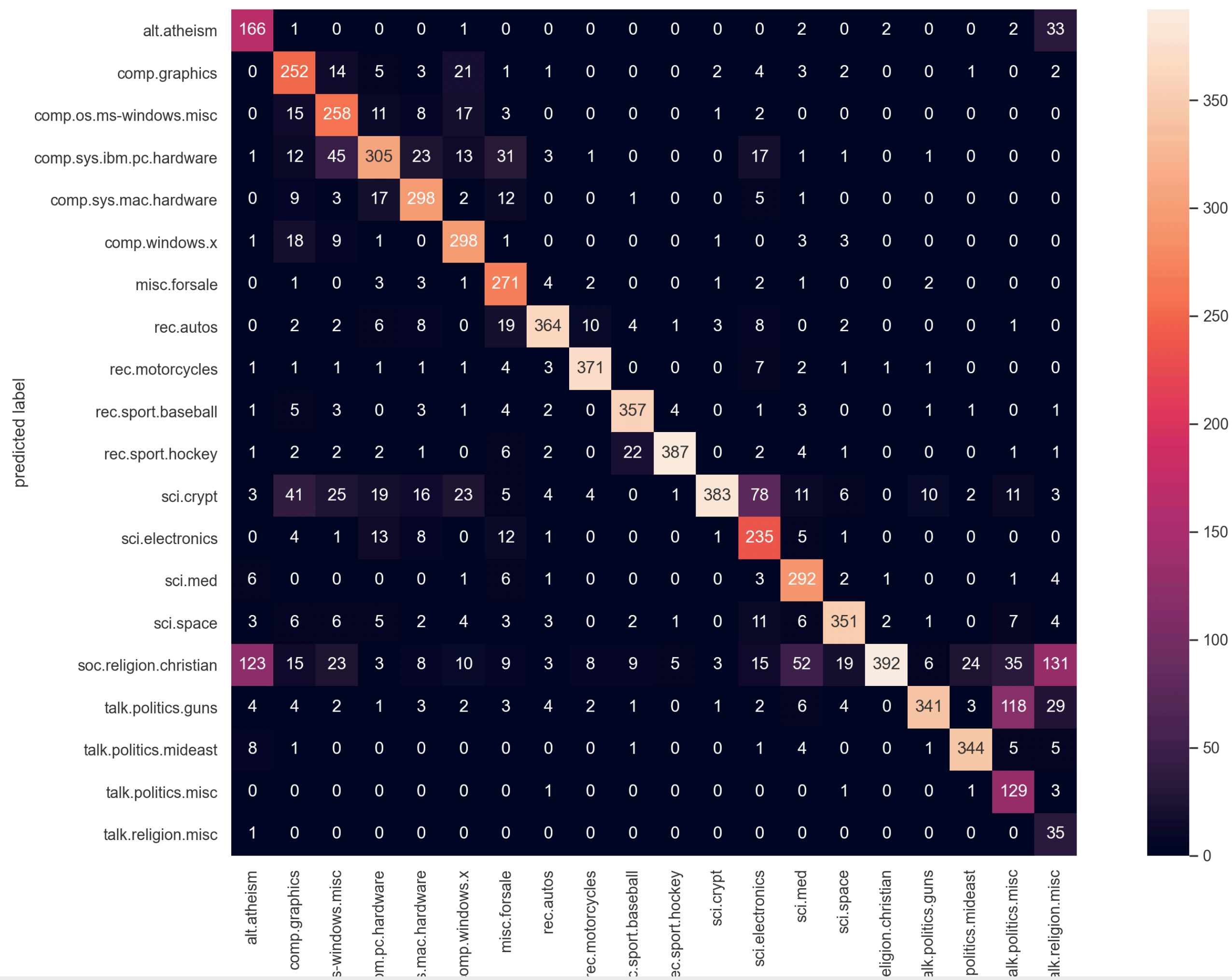

Figure created by the author.

Note: If you're passionate about diving deeper into machine learning with Python and sklearn, I highly recommend checking out **this book**; it's a game-changer in breaking down complex topics into digestible insights.

[Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques...]()

5. Bonus: Having fun with the model

Let's have some fun using the trained model. Let's classify whatever sentence we like 😄 .

```
# custom function to have fun
def my_predictions(my_sentence, model):
    all_categories_names = np.array(data.target_names)
    prediction = model.predict([my_sentence])
    return all_categories_names[prediction]



my_sentence = "jesus"
print(my_predictions(my_sentence, model))
['soc.religion.christian']

my_sentence = "Are you an atheist?"
print(my_predictions(my_sentence, model))
['alt.atheism']
```

We inserted the string "jesus" to the model and it predicted the class "['soc.religion.christian']".

Change the "my_sentence" into other stings and **play with the model** 😃 .

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6. Conclusions

We saw that **Naive Bayes is a very powerful algorithm** for **multi-class text classification problems.**

Side Note: *If you want to know more about the confusion matrix (and the ROC curve) read this:*

> **ROC Curve Explained using a COVID-19 hypothetical example: Binary & Multi-Class Classification...**

Interpreting the confusion matrix

From the above **confusion matrix**, we can verify that the model is really good.

- It is able to correctly predict all 20 classes of the text data (most values are on the diagonal and few are off-the-diagonal).
- We also notice that the highest miss-classification (value off-the-diagonal) is **131** (5 lines from the end, last column at the right). The value 131 means that 131 documents that belonged to

the "**religion miscellaneous** " category were miss-classified as belonging to the "**religion christian**" category.

Interesting thing that these 2 categories are really similar and actually one could characterize these as 2 subgroups of a larger group e.g. "religion" in general.

Finally, the **accuracy** on the **test** set is **0.7739** which is quite good for a **20-class text classification problem** 🚀 .

That's all folks! Hope you liked this article.

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