# 02 - Supervised Learning - Classification - Naive Bayesian - Multinomial(Solution)_st122097_Thantham

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# 1 Supervised Learning - Classification - Naive Bayesian - Multinomial

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## 1.3 TASK

- Put **Multinomial Naive Classification** into a class that can **transform the data**, **fit** the model and do **prediction**.
- In the class, allow users to choose whether to use **CountVectorizer** or **TFIDFVectorizer** to transform the data.
- **Show** both classifications in the ways of **different Vectorization methods**
- **Learn about TFidfVectorizer**

Firstly, just simply import neccessary packages

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
```

## 1.4 1. Prepare Dataset

Dataset to be used in this lab work excercise is 20 new groups. This dataset is basically 18,000 text documents which were categorized into 20 groups. Moreover, we can define data extraction by train subset and test sibset via packages.

[2]:
```
from sklearn.datasets import fetch_20newsgroups
```

We can filter dataset to select only some categories of new group classes by put list of target classes into the function. However, Lab tutorial already used 4 target classes. **In this lab work, I strongly attempt to use full form dataset that contains mentioned dataset information**

[3]:
```
train = fetch_20newsgroups(subset='train')
test = fetch_20newsgroups(subset='test')
```

We further try to extract **X** and **y** from raw one, and do the same for train and test set

[4]:
```python
X_train = train.data
X_test = test.data
y_train = train.target
y_test = test.target
```

Also, this step, we are not able to put them into the model yet. However, we can show the **datatype** of the dataset by following

[5]:
```python
print(f'data type of X_train is {type(X_train)} With {len(X_train)} samples')
print(f'data type of y_train is {type(y_train)} With {len(y_train)} samples')

print(f'data type of X_train is {type(X_test)} With {len(X_test)} samples')
print(f'data type of y_train is {type(y_test)} With {len(y_test)} samples')
```

```
data type of X_train is <class 'list'> With 11314 samples
data type of y_train is <class 'numpy.ndarray'> With 11314 samples
data type of X_train is <class 'list'> With 7532 samples
data type of y_train is <class 'numpy.ndarray'> With 7532 samples
```

From above, we would see that X data are list of textual document by **11,314 and 7,532 as train and test** respectively, along with y data. To prove that, Example of texual document can be show as below

[6]:
```python
print(f'Example of X_train: \n {X_train[0]}')
```

```
Example of X_train:
 From: lerxst@wam.umd.edu (where's my thing)
Subject: WHAT car is this!?
Nntp-Posting-Host: rac3.wam.umd.edu
Organization: University of Maryland, College Park
Lines: 15

 I was wondering if anyone out there could enlighten me on this car I saw
the other day. It was a 2-door sports car, looked to be from the late 60s/
early 70s. It was called a Bricklin. The doors were really small. In addition,
the front bumper was separate from the rest of the body. This is
all I know. If anyone can tellme a model name, engine specs, years
of production, where this car is made, history, or whatever info you
have on this funky looking car, please e-mail.

Thanks,
- IL
   ---- brought to you by your neighborhood Lerxst ----
```

Also, **y data is numerical** interger label that indicates classes

[7]:
```
print(f'Example of y_train: {y_train[0]} which is {train.
↪target_names[y_train[0]]}')
```

```
Example of y_train: 7 which is rec.autos
```

To expand full categories of y, y textual classes as below

[8]:
```
labels = train.target_names
print(f'all target names are \n {labels}')
```

```
all target names are
 ['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc',
'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x',
'misc.forsale', 'rec.autos', 'rec.motorcycles', 'rec.sport.baseball',
'rec.sport.hockey', 'sci.crypt', 'sci.electronics', 'sci.med', 'sci.space',
'soc.religion.christian', 'talk.politics.guns', 'talk.politics.mideast',
'talk.politics.misc', 'talk.religion.misc']
```

## 1.5 2. Naives Bayes Multinomial classification

Referring to previous excercise, we prepared texual documents contains a lot of vocabulary as raw. But, it is unreadable form for machine. we should convert them into machine-readable or numerical form before let them run. To do this, I will point the steps.

### 1.5.1 1) Convert textual document into Sparse Matrix

This step is firstly to count each unique word in all document which occur in document i. this step we would count each word $w_i$ into each feature of X. The simple example of this is

$$\mathtt{X} = \begin{bmatrix} & w_i & ... & w_n \\ 1 & 1 & 0 & 2 \\ ... & 2 & 0 & 3 \\ m & 0 & 1 & 0 \end{bmatrix} \tag{1}$$

Thus, we can easily call Count Vectorizer imported sklearn.feature_extraction.text and fit & transform. Then we can get Sparse Matrix that caontains count of each word as feature of X. This is machine readable to further calcualate into model.

### 1.5.2 2) Calculate $P(y = k)$

From the equation:

$$P(y|w) = \frac{P(w|y)P(y)}{P(w)}$$

we aim to find Possibility of y occur whether w is given. This step we would calcualate $P(y)$ first for each class by equation:

$$P(y=k) = \frac{\Sigma_{i=1}^{m} 1(y=k)}{m}$$

### 1.5.3 3) Calculate Likelihood $P(w|y)$

This step is to calculate possibility of $w$ when &y& is a given target class. To calculate it, we will use likelihood which will count unique word occuring at $y$ class in document $i$ and divided by all number of $w_i$ in all document from given $y$ class. However, some words moght nerver be counted (very low frequency). This cuases likelihood output is 0. So, we use **Laplace Smoothing** to make likelihood is more suitable to be calculated by put +1 for every $w_i$ count with +n for smoothening likelihood

$$P(w_i \in train \mid y=k) = \frac{count(w_i \in train, k) + 1}{\sum_{i=1}^{n} count(w_i \in train, k) + n}$$

### 1.5.4 4) Predict y hat

Prediction step is to implement trained **priors** and **likelihood** to calculate the possibility of $\hat(y)$ given when X_test calculated. we can use this equation:

$$P(y=k) \prod_{i=1}^{n} p(w_i \in test \mid y=k)^{\text{freq of } w_i \in test}$$

However, the product of given equation provides very low of possibility form. Consequently, we simply implement **Monotically Increasing Function** to enhance possibility of product by

$$\log\ P(y=k) + (\text{freq of } w_i \in test) * \sum_{i=1}^{n} \log\ p(w_i \in test \mid y=k)$$

Then we will get array of enhanced possibility of $P(y|w)$. and we can implment np.argmax to get index of maximum value which from possiblity given each classes

Then Construct the model

[9]:
```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

class NaivesBayes_multinomial:

    def __init__(self, vectorize_method='counter', alpha=1):

        self.vectorize_method = vectorize_method # Selective Vectorize Method␣
↪between : 'count','tfidf'
        self.laplace = alpha # stand for Laplace parameter

    def fit(self, X, y):

        # 1) Select Vectorize Method
```

```
        if self.vectorize_method == 'count': # if define 'count'
            self.vectorizer = CountVectorizer() # just create instance␣
↪CountVectorizer
        elif self.vectorize_method == 'tfidf': # if define 'tfidf'
            self.vectorizer = TfidfVectorizer() # just create instance␣
↪TfidfVectorizer
        else: # otherwise raise value error
            raise ValueError("Unavailable vcetorize method. {'count', 'tfid'}")

        # 1-2) Vectorize it
        X = self.vectorizer.fit_transform(X)

        # Init reuse values
        self.m = X.shape[0]
        self.n = X.shape[1]
        class_list = np.unique(y)
        k = len(class_list)

        # init priors and likelihood by the number of target classes
        self.priors = np.zeros(k)
        self.likelihoods = np.zeros((k, self.n))

        # 2) and 3) Looping each target class to calculate prior and likelihood
        for class_idx, class_label in enumerate(class_list):

            X_at_class = X[y == class_label] # get X_train at that class
            self.priors[class_idx] = self.prior(X_at_class) # calcualte prior␣
↪and record in priors list
            self.likelihoods[class_idx, :] = self.likelihood(X_at_class) #␣
↪calculate likelihood and record in likelihoods list


    def likelihood(self,X_at_class):

        return ((X_at_class.sum(axis=0)) + self.laplace) / (np.sum(X_at_class.
↪sum(axis=0)) + self.n) # (count(w_i)+ laplace) / (all(w_i) + n)

    def prior(self, X_class):

        p_y = X_class.shape[0] / self.m # Just count y_k / m

        return p_y

    def predict(self, X_test):
```

```
        X_test = self.vectorizer.transform(X_test) # Transform X_test using␣
↪pre-difined vectorizer

        py_xtest = np.log(self.priors) + X_test @ np.log(self.likelihoods.T) #␣
↪implement monitically increasing function log to get enhanced product

        return np.argmax(py_xtest, axis=1) # simply return idx of maximum value␣
↪of probrabilistic as integer target classes
```

**REMARK: I HAVE USED TFIDFVECTORIZER AS OPTION BECAUSE I WILL EXPLAIN ON TFIDF METHOD IN NEXT SECTION**

## 1.6 3-1 Implement Model and Predict using 'CountVectorizer'

Next step is just to use the contructed model with prepared data. However, The data put into model should be raw textual because we already implement model option to select vectorization method

[10]:
```
import time

model_count = NaivesBayes_multinomial(vectorize_method='count') # Create model␣
 ↪instance with parameter 'count'

start_time = time.time() # start timing

model_count.fit(X_train, y_train) # fitting

print(f'fitting time: {np.round(time.time()-start_time, 2)} seconds') # show␣
 ↪fitting time
```

```
fitting time: 2.24 seconds
```

After fitting, we can simply predict the y hat use model function. The **output** comes from the function is already **interger** form of target classes

[11]:
```
start_time = time.time() # start timing

yhat_count = model_count.predict(X_test) # predict

print(f'predicting time: {np.round(time.time()-start_time, 2)} seconds') # show␣
 ↪predict time
print(f'predicted y example: {yhat_count[:20]}') # show first 20 predicted
```

```
predicting time: 1.3 seconds
predicted y example: [ 7 11  0 17  0 13 15 15  5  1  1  5 17  8 15  3  4  1 12
16]
```

For that predicted classes, we can investigate texual label of each prediected class as following

[12]:
```
print(f'predicted y label classes example: {[labels[i] for i in yhat_count[:
↪20]]}')
```

```
predicted y label classes example: ['rec.autos', 'sci.crypt', 'alt.atheism',
'talk.politics.mideast', 'alt.atheism', 'sci.med', 'soc.religion.christian',
'soc.religion.christian', 'comp.windows.x', 'comp.graphics', 'comp.graphics',
'comp.windows.x', 'talk.politics.mideast', 'rec.motorcycles',
'soc.religion.christian', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware',
'comp.graphics', 'sci.electronics', 'talk.politics.guns']
```

### 1.7 4-1 Model Evaluation using 'CountVectorizer'

[13]:
```
from sklearn.preprocessing import label_binarize
from sklearn.metrics import average_precision_score, classification_report

n_classes = len(np.unique(y_test))

print('>>>>>>>>>>>>> CountVectorization <<<<<<<<<<<<<<<')

print(f"\n######### Accuracy: {np.sum(yhat_count == y_test)/len(y_test)}")

print("\n\n###############Average precision score###############\n")
y_test_binarized = label_binarize(y_test, classes=np.unique(y_test))
yhat__countbinarized = label_binarize(yhat_count, classes=np.unique(y_test))

for i in range(n_classes):
    class_score = average_precision_score(y_test_binarized[:, i],␣
↪yhat__countbinarized[:, i])
    print(f"Class {i} -> {labels[i]} score: ", class_score)

print("\n\n\n################Classification Report################\n")
print("Report: \n", classification_report(y_test, yhat_count,␣
↪target_names=labels))
```

```
>>>>>>>>>>>>> CountVectorization <<<<<<<<<<<<<<<

######### Accuracy: 0.7728359001593202


###############Average precision score###############

Class 0 -> alt.atheism score:  0.6168123096804696
Class 1 -> comp.graphics score:  0.5059736181999389
Class 2 -> comp.os.ms-windows.misc score:  0.052684990740016875
Class 3 -> comp.sys.ibm.pc.hardware score:  0.4389651771489265
Class 4 -> comp.sys.mac.hardware score:  0.6415504370636098
Class 5 -> comp.windows.x score:  0.5555174520045655
```

```
Class 6 -> misc.forsale score:  0.6238187316919536
Class 7 -> rec.autos score:  0.793388588390156
Class 8 -> rec.motorcycles score:  0.887590227018324
Class 9 -> rec.sport.baseball score:  0.8443650028354411
Class 10 -> rec.sport.hockey score:  0.8970183217707456
Class 11 -> sci.crypt score:  0.6377643688825713
Class 12 -> sci.electronics score:  0.5443819973224954
Class 13 -> sci.med score:  0.726442033125988
Class 14 -> sci.space score:  0.7466873954213826
Class 15 -> soc.religion.christian score:  0.6724043723058492
Class 16 -> talk.politics.guns score:  0.6343579136574636
Class 17 -> talk.politics.mideast score:  0.8021708326833523
Class 18 -> talk.politics.misc score:  0.38142129450054985
Class 19 -> talk.religion.misc score:  0.3212311486700287



#################Classification Report################

Report:
                           precision    recall  f1-score   support

             alt.atheism       0.79      0.77      0.78       319
           comp.graphics       0.67      0.74      0.70       389
 comp.os.ms-windows.misc       0.20      0.00      0.01       394
comp.sys.ibm.pc.hardware       0.56      0.77      0.65       392
   comp.sys.mac.hardware       0.84      0.75      0.79       385
          comp.windows.x       0.65      0.84      0.73       395
            misc.forsale       0.93      0.65      0.77       390
               rec.autos       0.87      0.91      0.89       396
         rec.motorcycles       0.96      0.92      0.94       398
      rec.sport.baseball       0.96      0.87      0.91       397
        rec.sport.hockey       0.93      0.96      0.95       399
               sci.crypt       0.67      0.95      0.78       396
         sci.electronics       0.79      0.66      0.72       393
                 sci.med       0.87      0.82      0.85       396
               sci.space       0.83      0.89      0.86       394
  soc.religion.christian       0.70      0.96      0.81       398
      talk.politics.guns       0.69      0.91      0.79       364
   talk.politics.mideast       0.85      0.94      0.89       376
      talk.politics.misc       0.58      0.63      0.60       310
      talk.religion.misc       0.89      0.33      0.49       251

                accuracy                           0.77      7532
               macro avg       0.76      0.76      0.75      7532
            weighted avg       0.76      0.77      0.75      7532
```

To see how much each class was predicted properly. **Confusion Matrix** is proper way to visualize

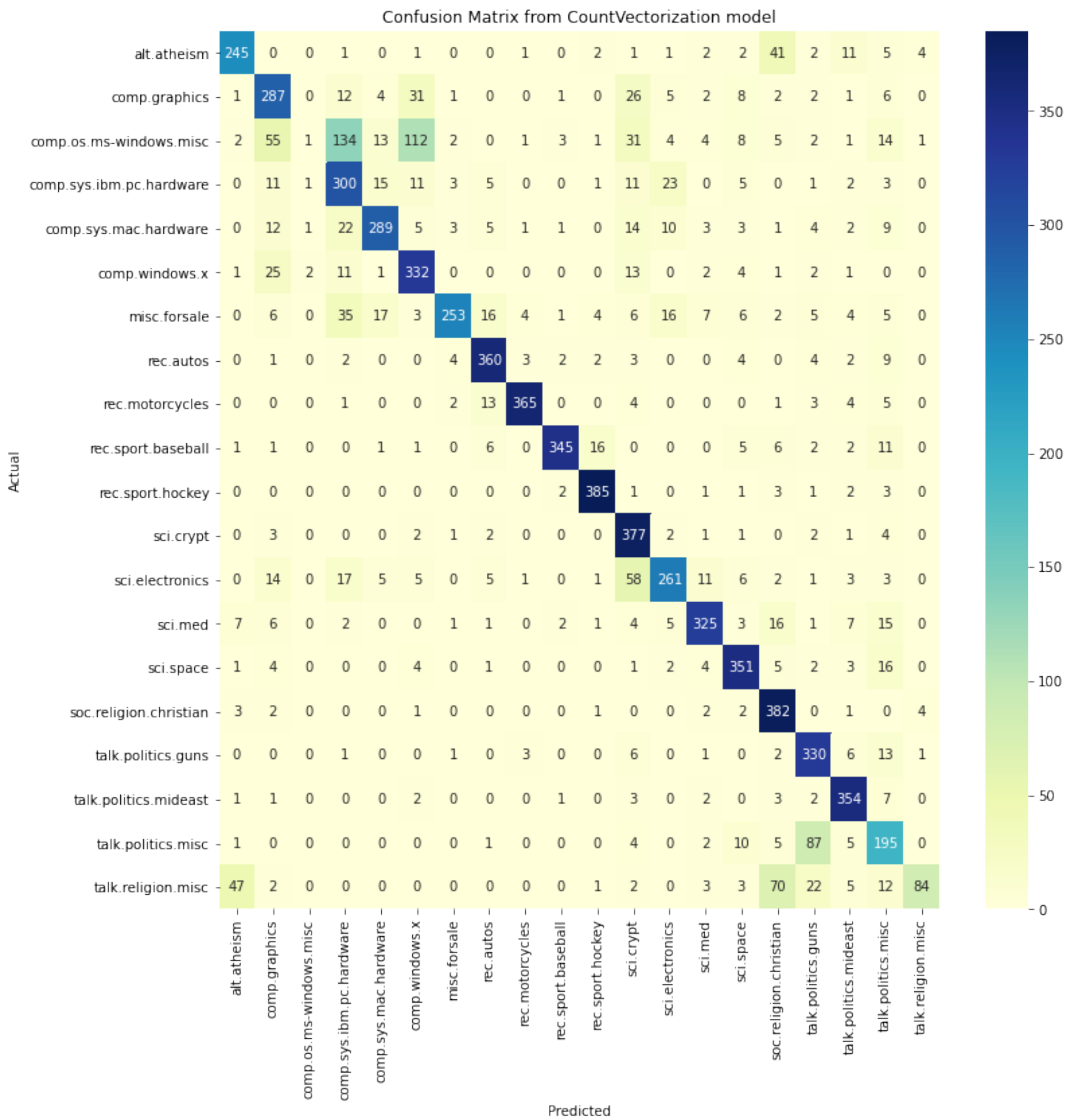
[14]:
```
from sklearn.metrics import confusion_matrix

c = confusion_matrix(y_test, yhat_count)

import seaborn as sns

plt.rcParams["figure.figsize"] = (12,12)
sns.heatmap(c, annot=True, fmt="d", cmap="YlGnBu",
           xticklabels=train.target_names, yticklabels=train.target_names)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix from CountVectorization model')
```

[14]:
```
Text(0.5, 1.0, 'Confusion Matrix from CountVectorization model')
```




## 1.8 3-2 Implement Model and Predict using 'TfidfVectorizer'

Furthermore, I try to convince that **TfidfVectorizer** is able to be used for fitting model also along with **CountVectorizer** availability. And, let me show

### 1.8.1 Create model instance and fitting

[15]:
```
import time

model_tfidf = NaivesBayes_multinomial(vectorize_method='tfidf') # Create model␣
↪instance with parameter 'tfidf'
```

```
start_time = time.time() # start timing

model_tfidf.fit(X_train, y_train) # fitting

print(f'fitting time: {np.round(time.time()-start_time, 2)} seconds') # show␣
↪fitting time
```

```
fitting time: 2.24 seconds
```

### 1.8.2 Predicting

[16]:
```
start_time = time.time() # start timing

yhat_tfidf = model_tfidf.predict(X_test) # predict

print(f'predicting time: {np.round(time.time()-start_time, 2)} seconds') # show␣
↪predict time
print(f'predicted y example: {yhat_tfidf[:20]}') # show first 20 predicted
```

```
predicting time: 1.42 seconds
predicted y example: [ 7 11  0 17  0 13 15 15  5  1  2  5 17  8 15  3  2  1 12
16]
```

## 1.9 4-2 Model Evaluation using 'TfidfVectorizer'

### 1.9.1 Model evaluation

[17]:
```
from sklearn.preprocessing import label_binarize
from sklearn.metrics import average_precision_score, classification_report

n_classes = len(np.unique(y_test))

print('>>>>>>>>>>>>>>>>>>>> TfidfVectorization <<<<<<<<<<<<<<<<<<<<<<<<')

print(f"\n######### Accuracy: {np.sum(yhat_tfidf == y_test)/len(y_test)}")

print("\n\n###############Average precision score###############\n")
y_test_binarized = label_binarize(y_test, classes=np.unique(y_test))
yhat_tfidf_binarized = label_binarize(yhat_tfidf, classes=np.unique(y_test))

for i in range(n_classes):
    class_score = average_precision_score(y_test_binarized[:, i],␣
↪yhat_tfidf_binarized[:, i])
    print(f"Class {i} -> {labels[i]} score: ", class_score)

print("\n\n\n################Classification Report################\n")
```

```python
print("Report: \n", classification_report(y_test, yhat_tfidf,␣
↪target_names=labels))
```

```
>>>>>>>>>>>>>>>>>>> TfidfVectorization <<<<<<<<<<<<<<<<<<<<<<<<

######### Accuracy: 0.7738980350504514


###############Average precision score##############

Class 0 -> alt.atheism score:  0.43761982805890226
Class 1 -> comp.graphics score:  0.5431066076841845
Class 2 -> comp.os.ms-windows.misc score:  0.5543869675509703
Class 3 -> comp.sys.ibm.pc.hardware score:  0.5342570461687778
Class 4 -> comp.sys.mac.hardware score:  0.6743660625150177
Class 5 -> comp.windows.x score:  0.6839836188820012
Class 6 -> misc.forsale score:  0.6629135397023337
Class 7 -> rec.autos score:  0.7823551874386144
Class 8 -> rec.motorcycles score:  0.8768969736703386
Class 9 -> rec.sport.baseball score:  0.8348461439653506
Class 10 -> rec.sport.hockey score:  0.8664800738934689
Class 11 -> sci.crypt score:  0.5760310353636195
Class 12 -> sci.electronics score:  0.5210541338462026
Class 13 -> sci.med score:  0.693028988010987
Class 14 -> sci.space score:  0.755572028759291
Class 15 -> soc.religion.christian score:  0.433148731360181
Class 16 -> talk.politics.guns score:  0.6057957070635053
Class 17 -> talk.politics.mideast score:  0.854852334849171
Class 18 -> talk.politics.misc score:  0.42166521051399336
Class 19 -> talk.religion.misc score:  0.16424647782858062



################Classification Report###############

Report:
                           precision    recall  f1-score   support

             alt.atheism       0.80      0.52      0.63       319
           comp.graphics       0.81      0.65      0.72       389
 comp.os.ms-windows.misc       0.82      0.65      0.73       394
comp.sys.ibm.pc.hardware       0.67      0.78      0.72       392
   comp.sys.mac.hardware       0.86      0.77      0.81       385
          comp.windows.x       0.89      0.75      0.82       395
            misc.forsale       0.93      0.69      0.80       390
               rec.autos       0.85      0.92      0.88       396
         rec.motorcycles       0.94      0.93      0.93       398
```

```
     rec.sport.baseball       0.92      0.90      0.91       397
       rec.sport.hockey       0.89      0.97      0.93       399
              sci.crypt       0.59      0.97      0.74       396
        sci.electronics       0.84      0.60      0.70       393
                sci.med       0.92      0.74      0.82       396
              sci.space       0.84      0.89      0.87       394
 soc.religion.christian       0.44      0.98      0.61       398
     talk.politics.guns       0.64      0.94      0.76       364
  talk.politics.mideast       0.93      0.91      0.92       376
     talk.politics.misc       0.96      0.42      0.58       310
     talk.religion.misc       0.97      0.14      0.24       251

               accuracy                           0.77      7532
              macro avg       0.83      0.76      0.76      7532
           weighted avg       0.82      0.77      0.77      7532
```

### 1.9.2

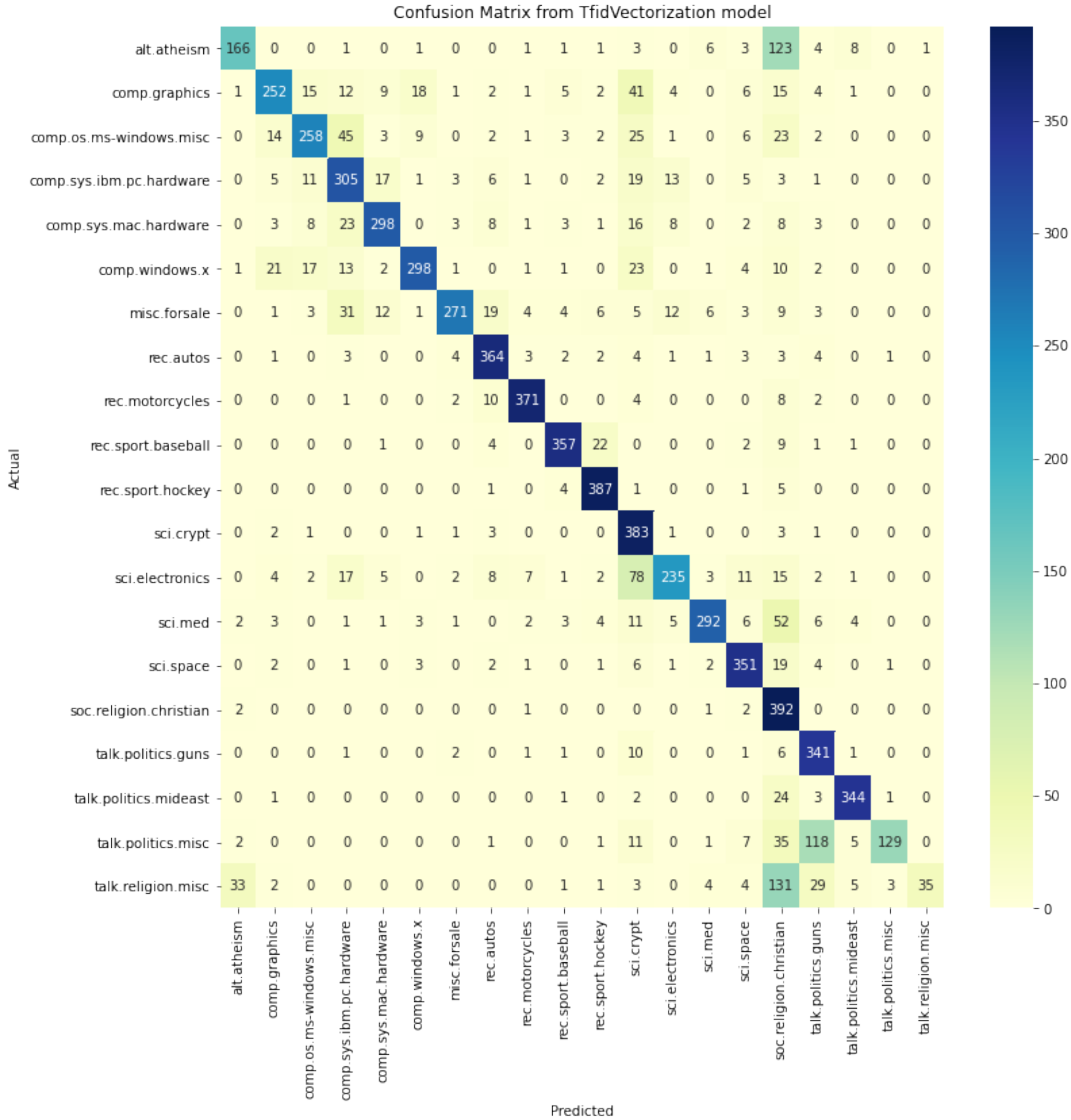
[18]:
```
from sklearn.metrics import confusion_matrix

c = confusion_matrix(y_test, yhat_tfidf)

import seaborn as sns

plt.rcParams["figure.figsize"] = (12,12)
sns.heatmap(c, annot=True, fmt="d", cmap="YlGnBu",
           xticklabels=train.target_names, yticklabels=train.target_names)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix from TfidVectorization model')
```

[18]:
```
Text(0.5, 1.0, 'Confusion Matrix from TfidVectorization model')
```




## 2 Tfid Vectorization

From previous lesson, we have learned about counter vectorizer which performs counting $w_i$ as the number of vocab occuring in a document. the output of it is sparse matrix which contains counted vocab as features (n) in each document (m). the shape represented as (m, n). This section will demonstrateon on how Tfidf works and construct it into function to be useful in the future.

#### 2.0.1 Extract Example of X

First, we just extract 10 samples as example. These are just raw documents.

[19]:
```
X = train.data[:10]
```

### 2.0.2 Create instance of Count Vectorizer

Then, we create **CountVectorizer** instance from sklearn package.

[20]:
```
countervect = CountVectorizer()
```

### 2.0.3 Basically implement Count Vectorizer

Next, we can convert raw document into count vectorized form which contain count number of each unique word in all documents

[21]:
```
X_countvect = countervect.fit_transform(X)

X_countvect = X_countvect.toarray()

print(f'X from CountVectorization: \n {X_countvect}')
print(f'shape of X now is: {X_countvect.shape}')
print(f'This means that there are {X_countvect.shape[0]} documents with all␣
↪{X_countvect.shape[1]} unique words')
```

```
X from CountVectorization:
 [[0 0 0 … 0 2 1]
 [0 0 0 … 0 1 1]
 [0 0 0 … 0 1 0]
 …
 [0 0 4 … 0 3 1]
 [0 1 0 … 0 0 0]
 [0 0 0 … 0 1 0]]
shape of X now is: (10, 881)
This means that there are 10 documents with all 881 unique words
```

From above, we examined that X now contains 10 documents with 881 words count

Sequently, Tfidf can possibly perform transformation directly on sparse matrix obtained from above step.

The full formula of TF-IDF is

$$\text{TF-IDF} = \text{TF} * \text{IDF}$$

The steps to complete calculation as following,

1) Calculate

$$\text{TF}_t = \frac{\text{Count of words t in that document}}{\text{Total count of words in that document}}$$

2) Calculate

$$\text{IDF} = \log\left(\frac{\text{Number of documents}}{\text{Number of documents containing that word}}\right) + 1$$

3) Calculate

$$norm(t_i) = \frac{t_i}{\sqrt{t_1^2 + t_2^2 + .... + t_n^2}}$$

I have summarized all steps into the function as:

[22]:
```
def TfidfVectorize(X_counted):

    # 1) calc TF
    sum_word = np.sum(X_counted, axis=1).reshape(-1, 1) # cal sum of all word␣
↪in each doc
    tf = X_counted / sum_word # divide -> count(w_i) / all_word in doc_i

    # 2) calc IDF
    idf = np.log(X_counted.shape[0] / np.count_nonzero(X_counted, axis=0))+1 #␣
↪cal idf = log[ (# doc)/(# of doc contain w_i) ]+1

    tf_idf = tf * idf # simply multiply

    # 3) calc norm(t_i)
    norm_factor = np.sqrt(np.sum(np.square(tf_idf), axis=1)).reshape(-1,1) #␣
↪cal norm factor
    norm_tfidf = np.array([tf_idf[i, :] / norm_factor[i] for i in range(tf_idf.
↪shape[0])]) # divide tf_idf with norm_factor

    return norm_tfidf
```

Now, let it do the job by putting X_countvect which is sparse matrix (converted to np.array) to function

[23]:
```
X_tfidfvectorized = TfidfVectorize(X_countvect) # just use new function for␣
↪TF-IDF vectirization from scratch
```

We can examine the output from the function as:

[24]:
```
print(f'output from TfidfVectorize function (new created) is: \n␣
↪{X_tfidfvectorized}') # print it as array
```

```
output from TfidfVectorize function (new created) is:
 [[0.         0.         0.         … 0.         0.07133334 0.0642675 ]
 [0.         0.         0.         … 0.         0.02867802 0.05167471]
 [0.         0.         0.         … 0.         0.01976823 0.        ]
 …
 [0.         0.         0.10121014 … 0.         0.0281131  0.01688559]
 [0.         0.17275465 0.         … 0.         0.         0.        ]
 [0.         0.         0.         … 0.         0.01972337 0.        ]]
```

I will prove output from the created function using **TfidfTransformer** imported from sklearn:

[25]:
```
from sklearn.feature_extraction.text import TfidfTransformer # import␣
↪Transformer

transformer = TfidfTransformer() # create instance
X_countvert_tfidtransform = transformer.fit_transform(X_countvect) # fit and␣
↪transform X_countvect

print(f'output from TfidfTranformation is: \n {X_countvert_tfidtransform.
↪toarray()}') # print it as array
```

```
output from TfidfTranformation is:
 [[0.         0.         0.         … 0.         0.08122347 0.06804081]
 [0.         0.         0.         … 0.         0.03372889 0.0565093 ]
 [0.         0.         0.         … 0.         0.02207828 0.        ]
 …
 [0.         0.         0.09856823 … 0.         0.03281673 0.01832703]
 [0.         0.16574254 0.         … 0.         0.         0.        ]
 [0.         0.         0.         … 0.         0.02258813 0.        ]]
```

However, Prof.Chaklam has mentioned about not exactly the same result due to the digit precision produced from our calculation and configurated in sklearn package.

Eventhough, it was like that, the function did the job properly. I have used **TfidfVectorizer** into the **Navies Bayes** class because it might take less time rather than new constructed function.

[ ]:
```

```