part-1-machine-learning-nlp

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References used are mentioned whereever required.

Classification objective: To classify insincere quiestion. How can we find insincere question?

Some characteristics that can signify that a question is insincere: (As given in the website)

```
1)Has a non-neutral tone
    Has an exaggerated tone to underscore a point about a group of people
    Is rhetorical and meant to imply a statement about a group of people
2)Is disparaging or inflammatory
    Suggests a discriminatory idea against a protected class of people, or seeks confirmation o
    Makes disparaging attacks/insults against a specific person or group of people
    Based on an outlandish premise about a group of people
    Disparages against a characteristic that is not fixable and not measurable
3)Isn't grounded in reality
    Based on false information, or contains absurd assumptions
Uses sexual content (incest, bestiality, pedophilia) for shock value, and not to seek genuine a
```

```
In [1]: import numpy as np
        import pandas as pd
        import plotly.offline as py
        from plotly.offline import init_notebook_mode,iplot
        init_notebook_mode(connected=True)
        import plotly.graph_objs as go
        from nltk.tokenize import word_tokenize
        from nltk.corpus import stopwords
        from nltk.stem.snowball import SnowballStemmer
        import matplotlib.pyplot as plt
        %matplotlib inline
        from wordcloud import WordCloud
        import string
        from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
        from sklearn.model_selection import train_test_split,GridSearchCV
```

```
from sklearn.metrics import confusion_matrix,f1_score,roc_curve,make_scorer
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB,MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD
from sklearn.manifold import TSNE
import os
import scikitplot as skplt
import seaborn as sns
import time
print(os.listdir("../input"))
stopwords=set(stopwords.words('english'))
stemmer=SnowballStemmer('english')
seed=5
```

```
['train.csv', 'test.csv', 'sample_submission.csv', 'embeddings']
```

```
In [2]: print("Number of stopwords:",len(stopwords))
```

```
Number of stopwords: 179
```

```
In [3]: #This kernel is run on kaggle gpu. Hence loading data online.
        data=pd.read_csv('../input/train.csv')
        test=pd.read_csv('../input/test.csv')
        sub=pd.read_csv('../input/sample_submission.csv')
        data.head() # Lets see some samples
```

```
Out[3]:                     qid                                      question_text  \
        0  00002165364db923c7e6  How did Quebec nationalists see their province...
        1  000032939017120e6e44  Do you have an adopted dog, how would you enco...
        2  0000412ca6e4628ce2cf  Why does velocity affect time? Does velocity a...
        3  000042bf85aa498cd78e  How did Otto von Guericke used the Magdeburg h...
        4  0000455dfa3e01eae3af  Can I convert montra helicon D to a mountain b...

           target
        0       0
        1       0
        2       0
        3       0
        4       0
```

```
In [4]: data.shape
```

```
Out[4]: (1306122, 3)
```

Thus we have quite a large dataset. large enough to train deep learning models. However since the intention of this kernel is to learn existing methods and modern methods. We will also consider ML based models.

```
In [5]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1306122 entries, 0 to 1306121
Data columns (total 3 columns):
qid              1306122 non-null object
question_text    1306122 non-null object
target           1306122 non-null int64
dtypes: int64(1), object(2)
memory usage: 29.9+ MB
```

```
In [6]: data.isnull().sum()
```

```
Out[6]: qid              0
        question_text    0
        target           0
        dtype: int64
```

Therefore, There is no null in the data.

```
In [7]: target_count=data.target.value_counts()
        target_count.index
```

```
Out[7]: Int64Index([0, 1], dtype='int64')
```

```
In [8]: target_count=data.target.value_counts()
        trace1=go.Bar(x=target_count.index,
                     y=target_count.values,
                     name='Target Counts',
                     marker=dict(color='rgba(0,255,255,0.5)',
                                 line=dict(color='rgb(0,0,0)',width=0.5)),
                     text=['Sincere Questions','Insincere Questions'])
        layout=go.Layout(title='Bar plot of target counts',
                        xaxis=dict(title='Target'),
                        yaxis=dict(title='Number of questions'))
        plt_data=[trace1]
        fig=dict(data=plt_data,layout=layout)
        iplot(fig)
```

Clearly the data is highly imbalanced. For the baseline model, even if predict always 0, we would be correct (1225312/1306122)*100 = 93.81 percent of time.!!!

Also, using accuracy as a measure of correctness in such dataset can be higly misleading. F1 score given a more accurate measure in such cases: The references for it are given as follows:

f1 score, precision and recall: 1)https://www.youtube.com/watch?v=Z9NZY3ej9yY 2)https://www.youtube.com/watch?v=dbrRsqlof4w

Data- Pre-processing for Training Machine Learning models. First we fix the data imbalance issue. Since we have sufficient data samples for Target 0. We sample equal amount of sample for Target 1 and create a dataset with a ratio of 50:50 Targets.

```
In [9]: target1=data[data['target']==1]
        target0=data[data['target']==0]
        sampled_size=target1.shape[0]
        sampled_target0=target0.sample(sampled_size,random_state=seed)
        new_data=pd.concat([target1,sampled_target0],axis=0)
        #Shuffling the data
        new_data=new_data.sample(frac=1,random_state=seed).reset_index(drop=True)
```

```
In [10]: sampled_size # For each targets
```

```
Out[10]: 80810
```

```
In [11]: new_data.head() # Combined data with samples shuffled
```

```
Out[11]:                     qid                                       question_text  \
         0  b54dbc3bca0d2780b06e  Why are some people very strange and highly hy...
         1  30ff2ebb239497b194ba  Should I fire someone who unnecessarily wrote ...
         2  fad82a91611d5fa16c1f  Where can I get a SEO article to write and get...
         3  9e66a1060693a5ac1ebe          Why do theists get annoyed with atheists?
         4  48a7e093f2389ae656ca  Have you ever seen a Jew eat something secretl...

            target
         0       0
         1       0
         2       0
         3       1
         4       1
```

1. • – next we tokenize the data. Have a look at what tokenize does.

```
In [12]: word_tokenize("Helloo world world")
```

```
Out[12]: ['Helloo', 'world', 'world']
```

have a look at punctuations

```
In [13]: string.punctuation
```

```
Out[13]: '!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

1. lets see an example of stemming # There are covered in the NLP basics blog linked in the beginning.

```
In [14]: list_words=["walking","versions","goes","mountaineer"]
         print("Before Stemming: After Stemming")
         for i in range(len(list_words)):
             print(list_words[i],":",stemmer.stem(list_words[i]),"\n")
```

```
Before Stemming: After Stemming
walking : walk

versions : version

goes : goe

mountaineer : mountain
```

Joining the filtered(Tokenized and stemmed) words into sentences,eg

```
In [15]: text="hai miss, hope you are doing great. All the best"
         tokenized_words=word_tokenize(text)
         filtered_words=[word.lower() for word in tokenized_words if ((word.lower() not in stri
                                                                      (word.lower() not in stop
         stemmed_words=[stemmer.stem(word) for word in filtered_words]
         print(' '.join(filtered_words))
```

```
hai miss hope great best
```

Finally, we write a general function to do above functions: ie. removing stop words and punctuation, followed by stemming.

```
In [16]: def filter_text(text):
             tokenized_words=word_tokenize(text)
             filtered_words=[word.lower() for word in tokenized_words if ((word.lower() not in
                                                                          (word.lower() not in
             stemmed_words=[stemmer.stem(word) for word in filtered_words]
             return ' '.join(filtered_words)
```

1. Creat a copy and Apply it on the copied data

```
In [17]: trad_data=new_data.copy()
         trad_data['question_text']=trad_data['question_text'].apply(lambda x: filter_text(x))
```

lets Do some Exploratory Data analysis to get some intution/insights on the data. Build a function to show the most frequent words and their magnitude

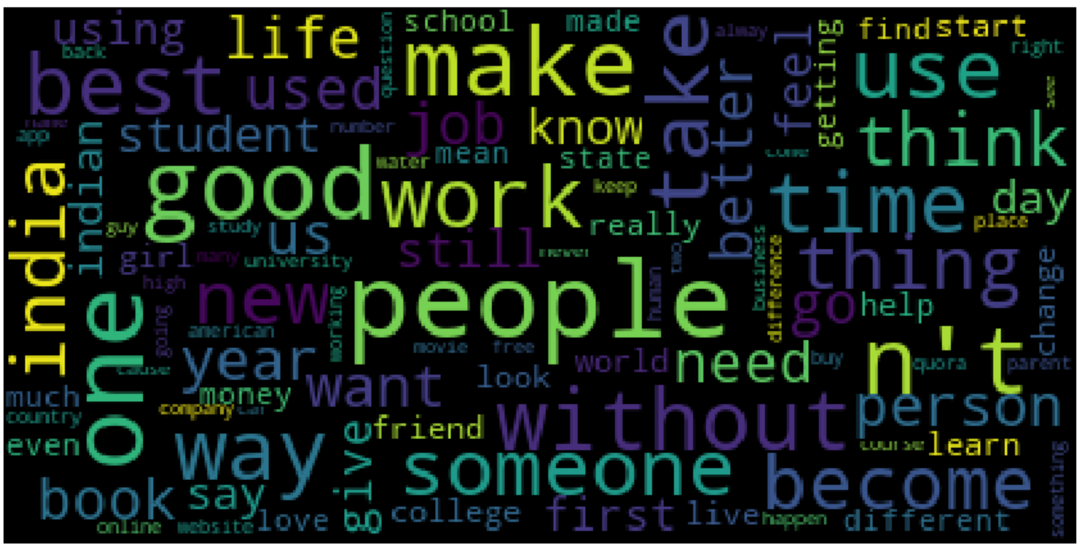
```
In [18]: def plot_wordcloud(text,max_font_size=40,max_words=100):
             plt.figure(figsize=(15,10))
             wordcloud=WordCloud(max_font_size=max_font_size,max_words=max_words,random_state=
             plot=wordcloud.generate(text)
             plt.imshow(plot)
             plt.axis('off')
             plt.show()
```

Combine words from all the sentences of class 0 to create wordcloud. Similarly repeat for class 1 as well . Plot 2 plots for each the targets.

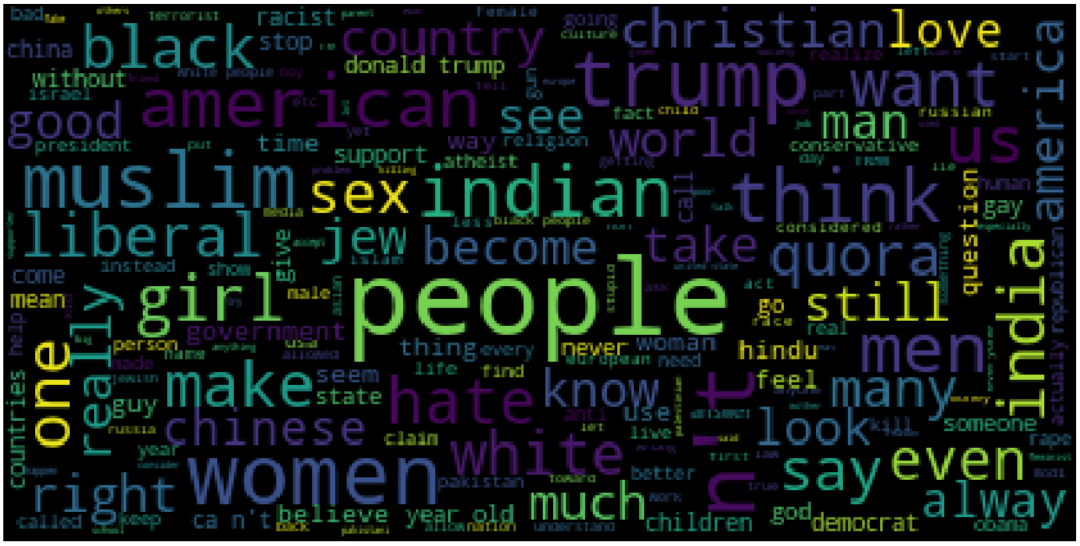
```
In [19]: target0=trad_data[trad_data['target']==0].reset_index(drop=True) #Reset the index onc
         target1=trad_data[trad_data['target']==1].reset_index(drop=True)

         target0_text=''
         target1_text=''
         for i in range(target0.shape[0]):
             target0_text+=target0.question_text[i] # Combine all the words
         for i in range(target1.shape[0]):
             target1_text+=target1.question_text[i]
```

"target0_text" contains all the words in the sentences which have Target 0. Similarly for target 1 as well

```
In [20]: plot_wordcloud(target0_text)
```




```
In [21]: plot_wordcloud(target1_text,max_words=200)
```



Considering mulitple consequetive words can yeild better intution. Lets have a look at N-grams

```
In [22]: def plot_top_ngrams(text,ngrams=(1,1),top=10,max_features=10000,color='rgba(0,255,255
             cv=CountVectorizer(ngram_range=ngrams,max_features=max_features)
             trans_text=cv.fit_transform(text)
             col_sum=trans_text.sum(axis=0)
             word_index=[(word,col_sum[0,idx]) for word,idx in cv.vocabulary_.items()]
             sorted_word_index=sorted(word_index,key=lambda x:x[1],reverse=True)
             top_words_index=sorted_word_index[:top]
             top_words=[element[0] for element in top_words_index]
             counts=[element[1] for element in top_words_index]
             trace1=go.Bar(x=top_words,
                          y=counts,
                          marker=dict(color=color,
                                      line=dict(color='rgb(0,0,0)',width=0.5)))
             layout=go.Layout(title='{}'.format(name),
                             xaxis=dict(title='Ngrams'),
                             yaxis=dict(title='Counts of words'))
             plot_data=[trace1]
             fig=dict(data=plot_data,layout=layout)
             iplot(fig)
```

```
In [23]: plot_top_ngrams(target1.question_text,ngrams=(1,1),top=30,color='rgba(128,0,0,0.5)',na
```

```
In [24]: plot_top_ngrams(target1.question_text,ngrams=(2,2),top=30,name="Top 2-grams for Target
```

```
In [25]: plot_top_ngrams(target1.question_text,ngrams=(3,3),top=30,color='rgba(128,128,128,0.5
```

```
In [26]: plot_top_ngrams(target0.question_text,ngrams=(1,1),top=30,color='rgba(128,0,0,0.5)',na
```

```
In [27]: plot_top_ngrams(target0.question_text,ngrams=(2,2),top=30,name="Top 2-grams for Target
```

```
In [28]: plot_top_ngrams(target0.question_text,ngrams=(3,3),top=30,color='rgba(128,128,128,0.5
```

```
In [29]: trad_data.shape # consists of both targets 0 and 1.
```

```
Out[29]: (161620, 3)
```

Lets create a train-test split

```
In [30]: #Reduce Dataset for testing purpose
         mini_df=trad_data.sample(2000,random_state=seed) #For qucik testing .
         X=trad_data['question_text']
         Y=trad_data['target']

         train_X,val_X,train_y,val_y=train_test_split(X,Y,test_size=0.2,random_state=seed)
```

```
In [31]: print("Train shape",train_X.shape)
         print("Test shape",val_X.shape)
```

```
Train shape (129296,)
Test shape (32324,)
```

For vectorizing: We try out 2 methods: 1)Count 2)TFID

- Lets start with count vectorizer first up: With 3-gram max.

```
In [32]: cv=CountVectorizer(ngram_range=(1,3),analyzer='word')
         train_X_cv=cv.fit_transform(train_X.values)
         val_X_cv=cv.transform(val_X.values)
```

```
In [33]: train_X_cv
```

```
Out[33]: <129296x1377683 sparse matrix of type '<class 'numpy.int64'>'
                 with 2558310 stored elements in Compressed Sparse Row format>
```

Exploring what a Sparse represention is:

```
In [34]: sparse_matrix=cv.fit_transform(["Hi man how are you"])
```

```
In [35]: sparse_matrix
```

```
Out[35]: <1x12 sparse matrix of type '<class 'numpy.int64'>'
                 with 12 stored elements in Compressed Sparse Row format>
```

cv.fit_transform(["Hi man how are you"]) Gernerates <1x12 sparse matrix of type ″ with 12 stored elements in Compressed Sparse Row format>

https://en.wikipedia.org/wiki/Sparse_matrix#Compressed_sparse_row_(CSR,_CRS_or_Yale_format)

In this case the CSR representation contains 13 entries, compared to 16 in the original matrix. The CSR format saves on memory only when NNZ < (m (n 1) 1) / 2. Another example, the matrix

```
( 10 20 0 0 0 0 0 30 0 40 0 0 0 0 50 60 70 0 0 0 0 0 0 80 ) {\displaystyle {\begin{pmatrix}10&2
```

is a 4 Œ 6 matrix (24 entries) with 8 nonzero elements, so

```
A = [ 10 20 30 40 50 60 70 80 ]
```

IA = [0 2 4 7 8] JA = [0 1 1 3 2 3 4 5]

The whole is stored as 21 entries.

```
IA splits the array A into rows: (10, 20) (30, 40) (50, 60, 70) (80);
JA aligns values in columns: (10, 20, ...) (0, 30, 0, 40, ...)(0, 0, 50, 60, 70, 0) (0, 0, 0, (
```

```
In [36]: print(sparse_matrix)
```

```
  (0, 7)	1
  (0, 10)	1
  (0, 4)	1
  (0, 1)	1
  (0, 6)	1
  (0, 9)	1
  (0, 3)	1
  (0, 11)	1
  (0, 0)	1
  (0, 5)	1
  (0, 8)	1
  (0, 2)	1
```

```
In [37]: train_X_cv.shape
```

```
Out[37]: (129296, 1377683)
```

```
In [38]: tsvd=TruncatedSVD(n_components=50,random_state=seed)
         train_X_svd=tsvd.fit_transform(train_X_cv)
         val_X_svd=tsvd.transform(val_X_cv)
         tsne=TSNE(n_components=2,random_state=seed)
         train_X_tsne=tsne.fit_transform(train_X_svd)
```

(model.predict_proba) gives you the probabilities for the target (0 and 1 in your case) in array form.

Confusion matrix: A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

AUC-ROC https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5

In [39]:
```
def get_model(model,train_X,train_y,val_X):
    model.fit(train_X,train_y)
    pred_probs=model.predict_proba(val_X)
    pred_train=model.predict(train_X)
    pred_val=model.predict(val_X)
    score_train=f1_score(train_y,pred_train)
    score_val=f1_score(val_y,pred_val)
    return pred_probs,pred_train,pred_val,score_train,score_val

def get_confusion_matrix(val_y,pred,title):
    cm=confusion_matrix(val_y,pred)
    plt.figure(figsize=(10,5))
    sns.heatmap(cm,annot=True)
    plt.title(title)
    plt.ylabel('True labels')
    plt.xlabel('Predicted labels')
    plt.show()

def get_roc_curve(val_y,pred_probs,title):
    plt.title(title)
    skplt.metrics.plot_roc(val_y,pred_probs)
```

In [40]:
```
models=[LogisticRegression(random_state=seed),MultinomialNB(),DecisionTreeClassifier(r
        AdaBoostClassifier(DecisionTreeClassifier(max_depth=3),n_estimators=100,learni
        RandomForestClassifier(n_estimators=100,max_depth=3,random_state=seed),
        XGBClassifier(random_state=seed)]
model_names=['LR','Multinomial NB','DTC','ABC','RFC','XGBC']
```

In [41]:
```
pred_probs={}
pred_train={}
pred_val={}
score_train={}
score_val={}
k=0
for i in range(len(models)):
    k=k+1
    print("Model Number:",k)
    pred_probs[model_names[i]],pred_train[model_names[i]],pred_val[model_names[i]],\
    score_train[model_names[i]],score_val[model_names[i]]=get_model(models[i],train_X_



scl=StandardScaler()
train_X_scl_cv=scl.fit_transform(train_X_svd)
val_X_scl_cv=scl.transform(val_X_svd)
pred_probs['SVC'],pred_train['SVC'],pred_val['SVC'],\
```

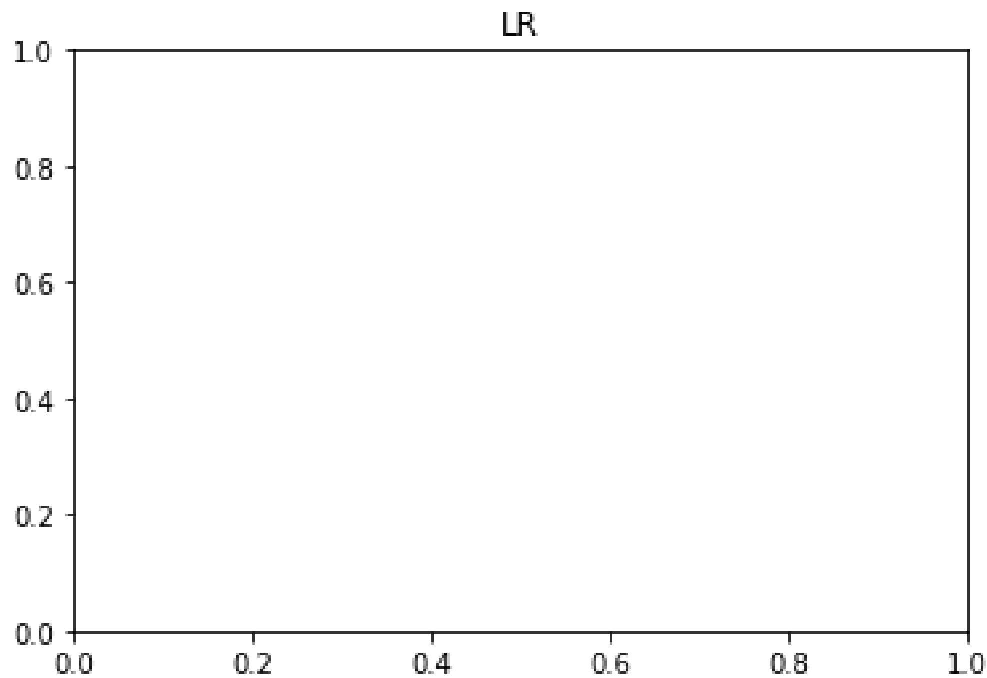
```
score_train['SVC'],score_val['SVC']=get_model(SVC(probability=True,random_state=seed)
                                                      train_X_scl_cv,train_y,val_X_scl
```

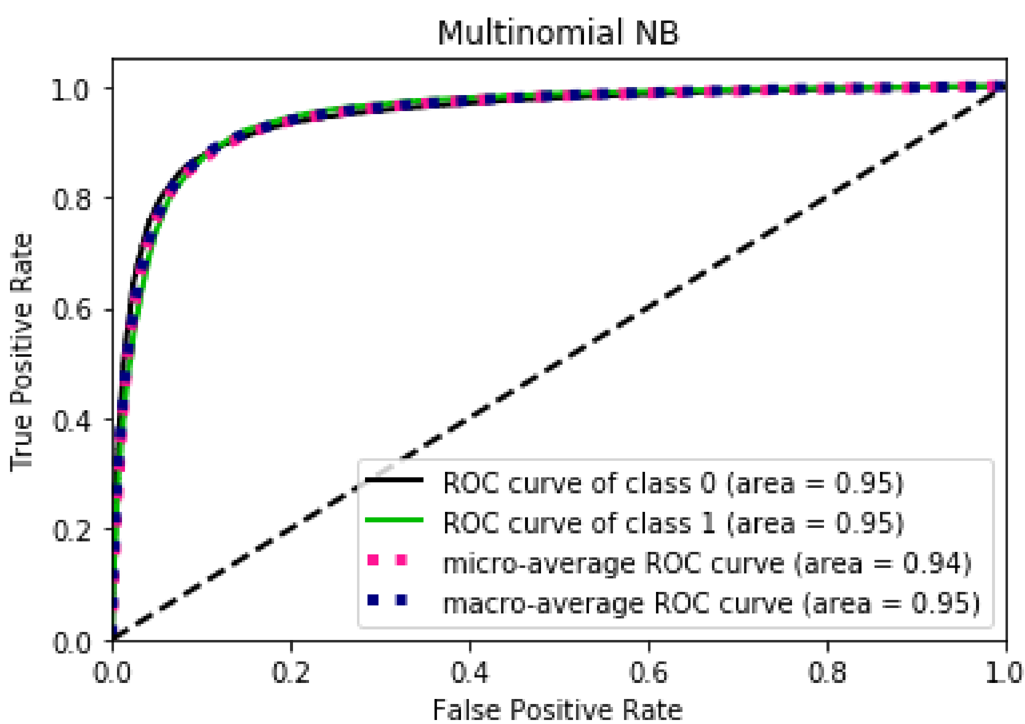
```
Model Number: 1


/opt/conda/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:432: FutureWarning:

Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.



Model Number: 2
Model Number: 3
Model Number: 4
Model Number: 5
Model Number: 6
```

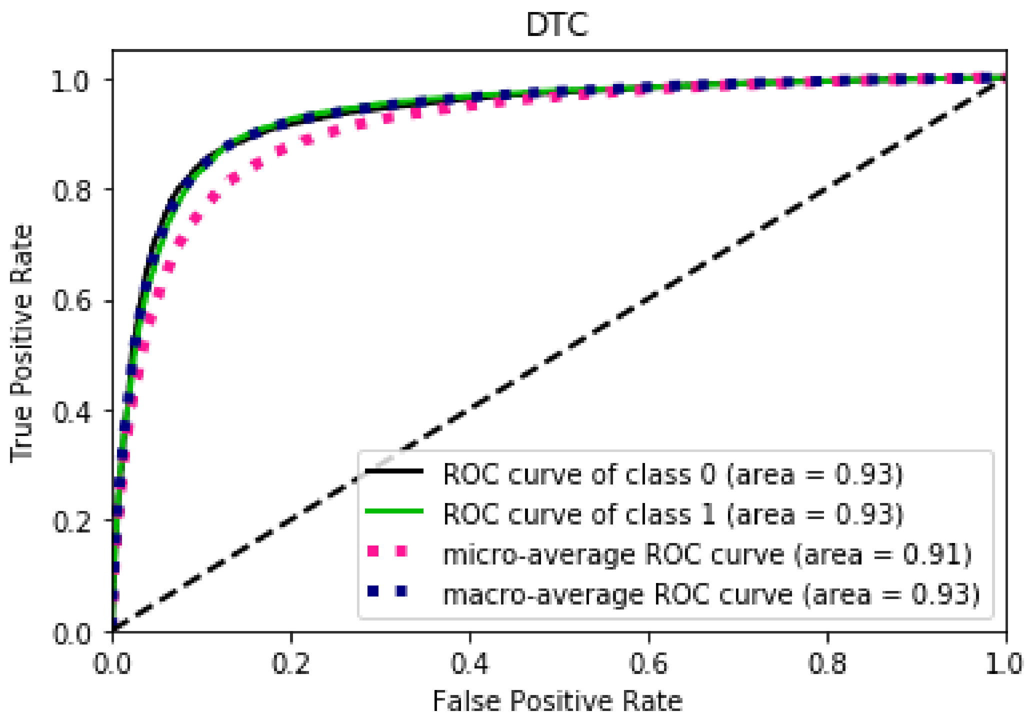
In [42]:
```
trace1=go.Bar(x=list(score_train.keys()),
              y=list(score_train.values()),
             name='Training Score with CV',
             marker=dict(color='rgba(0,255,0,0.5)',
                        line=dict(color='rgb(0,0,0)',width=1.5)))
trace2=go.Bar(x=list(score_val.keys()),
              y=list(score_val.values()),
             name='Validation Score with CV',
             marker=dict(color='rgba(255,255,0,0.5)',
                        line=dict(color='rgb(0,0,0)',width=1.5)))

layout=go.Layout(barmode='group',
                title='Scores of Different Models')
plot_data=[trace1,trace2]
fig=dict(data=plot_data,layout=layout)
iplot(fig)
```

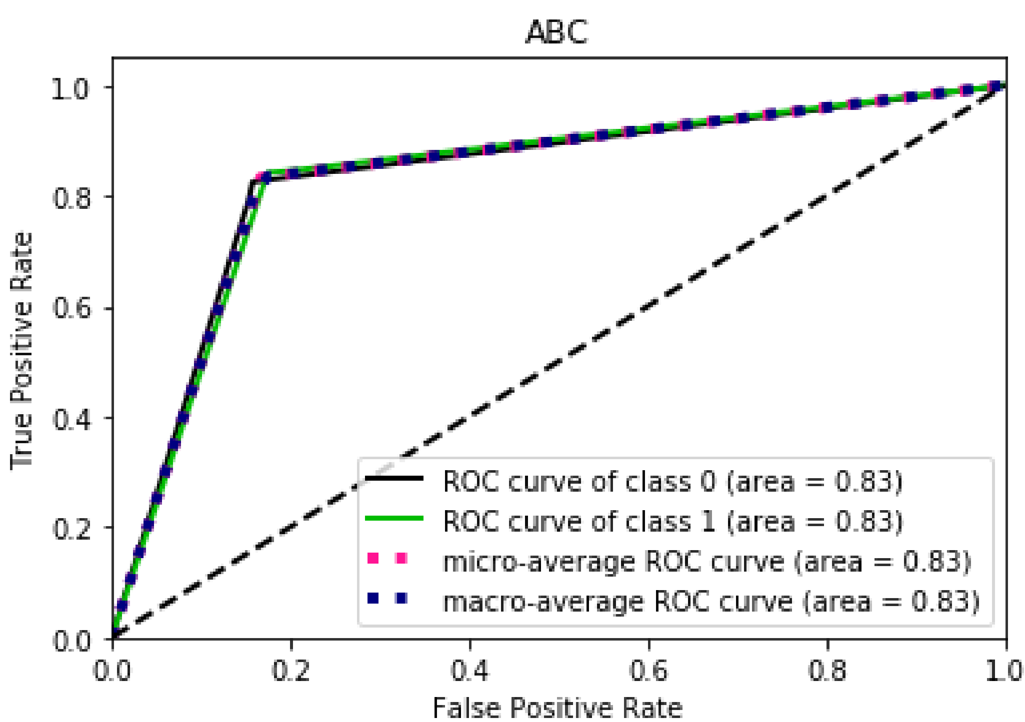
Clearly, LogisticRegression, Multinomial NB and DecisionTree Classifier overfit the data. AdaBoost, RandomForest and XGB Classifiers do not overfit but their scores are low compared to the former 3 models. Regularization and Hyperparameter tuning can surely help to not overfit in case of initial 3 models and can help the latter 3 models to improve their scores,respectively.

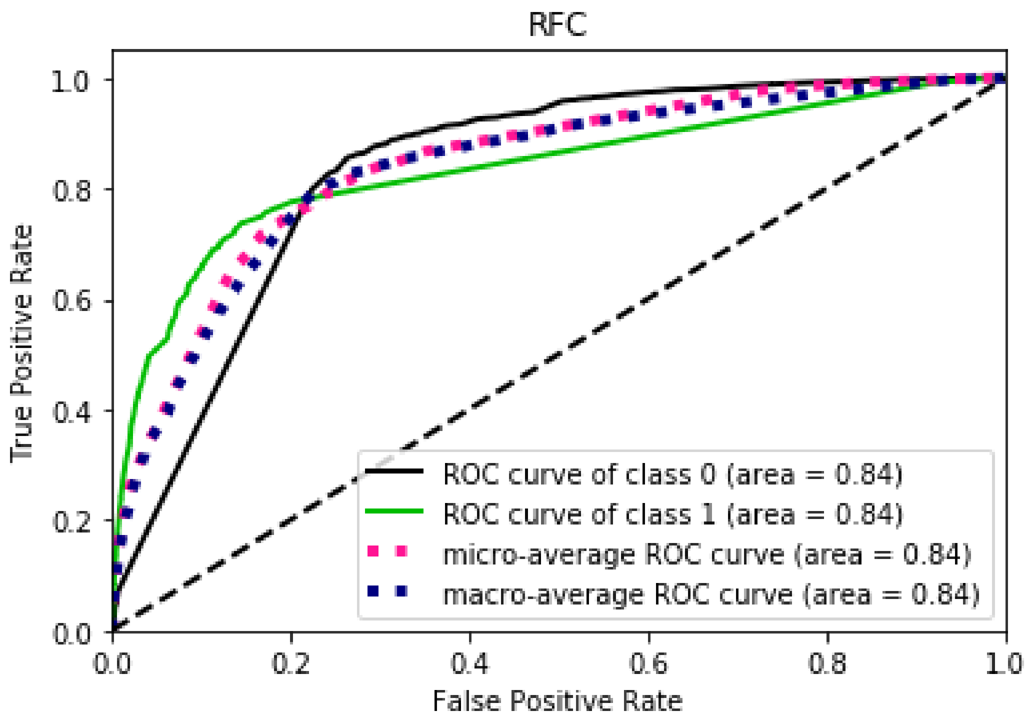
In [43]:
```
for model,probs in pred_probs.items():
    get_roc_curve(val_y,probs,model)
```

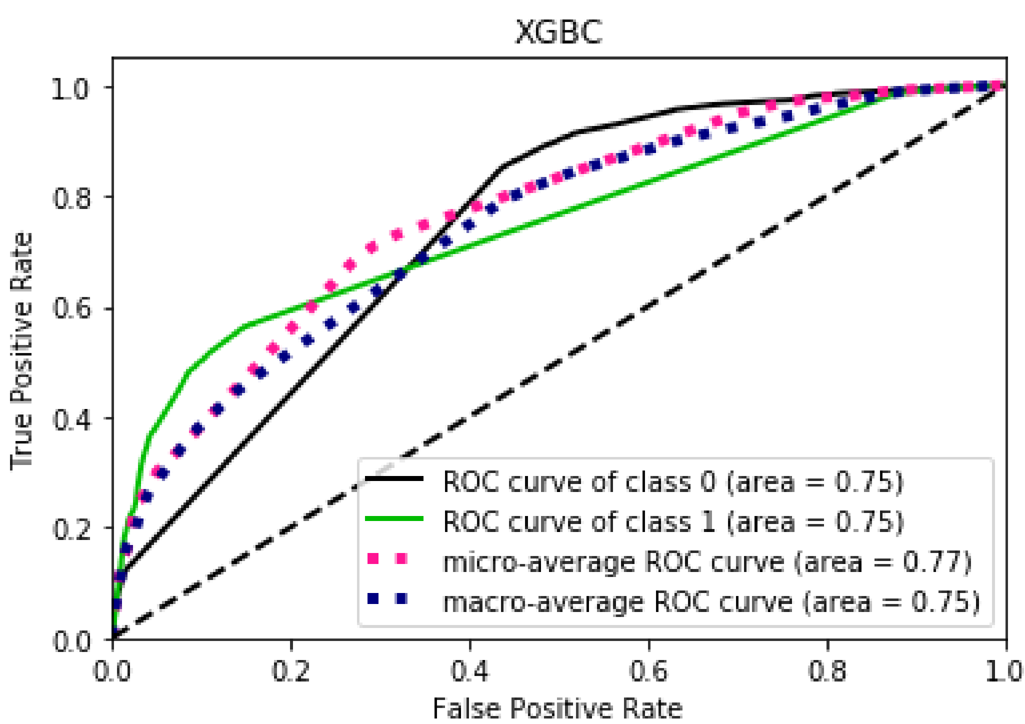

LR
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

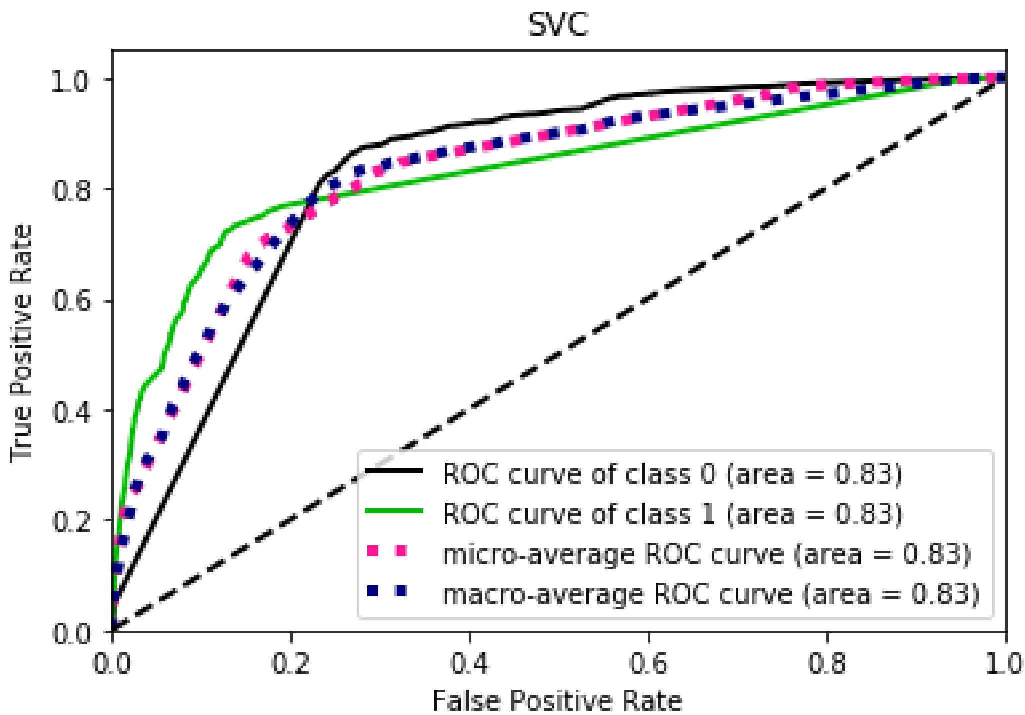

Multinomial NB
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve of class 0 (area = 0.95)
ROC curve of class 1 (area = 0.95)
micro-average ROC curve (area = 0.94)
macro-average ROC curve (area = 0.95)

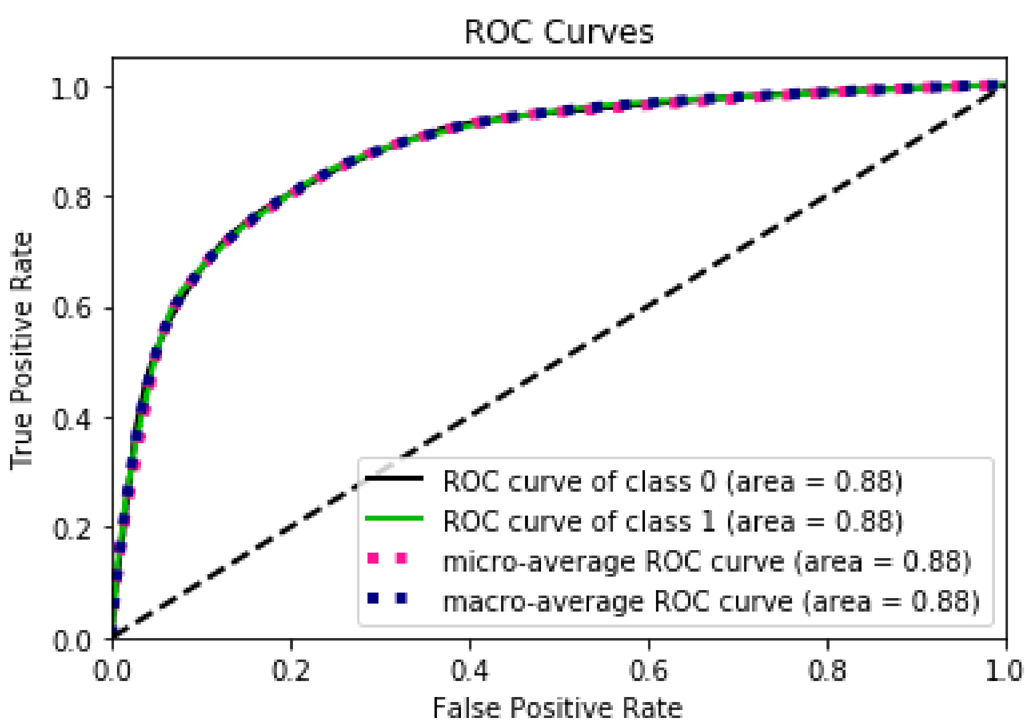

DTC
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve of class 0 (area = 0.93)
ROC curve of class 1 (area = 0.93)
micro-average ROC curve (area = 0.91)
macro-average ROC curve (area = 0.93)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


ABC
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve of class 0 (area = 0.83)
ROC curve of class 1 (area = 0.83)
micro-average ROC curve (area = 0.83)
macro-average ROC curve (area = 0.83)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


RFC
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve of class 0 (area = 0.84)
ROC curve of class 1 (area = 0.84)
micro-average ROC curve (area = 0.84)
macro-average ROC curve (area = 0.84)

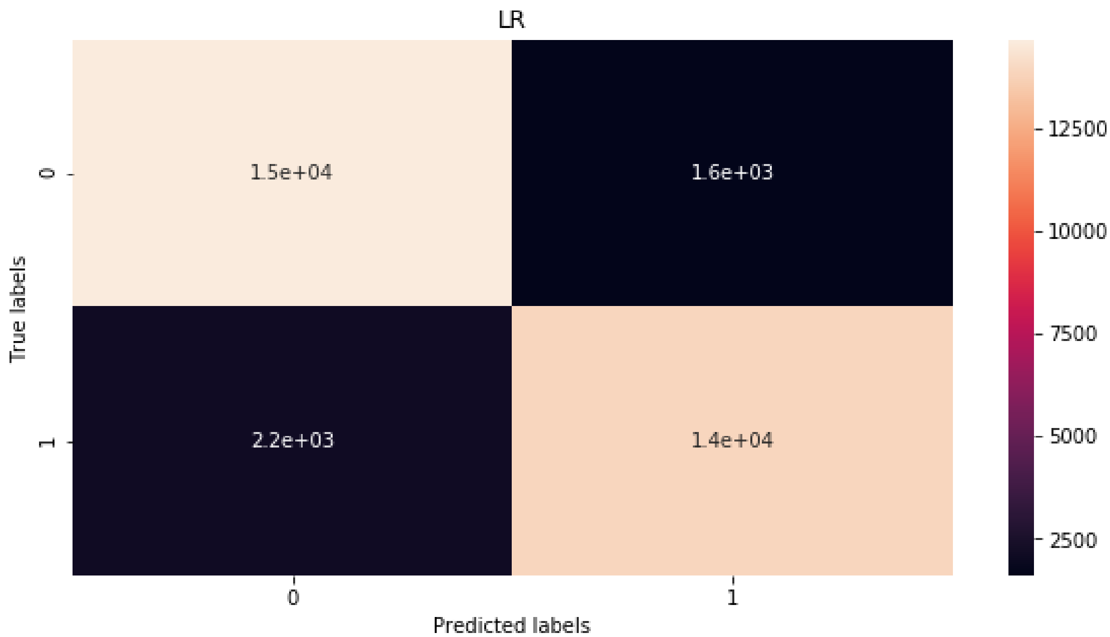

XGBC
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve of class 0 (area = 0.75)
ROC curve of class 1 (area = 0.75)
micro-average ROC curve (area = 0.77)
macro-average ROC curve (area = 0.75)

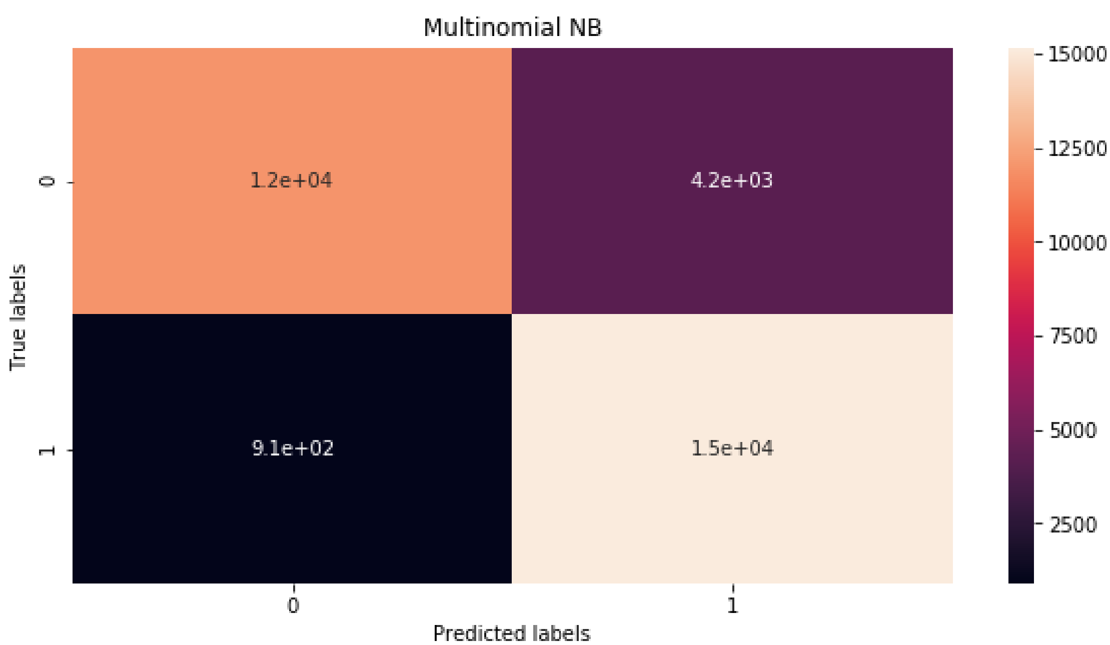

SVC
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve of class 0 (area = 0.83)
ROC curve of class 1 (area = 0.83)
micro-average ROC curve (area = 0.83)
macro-average ROC curve (area = 0.83)

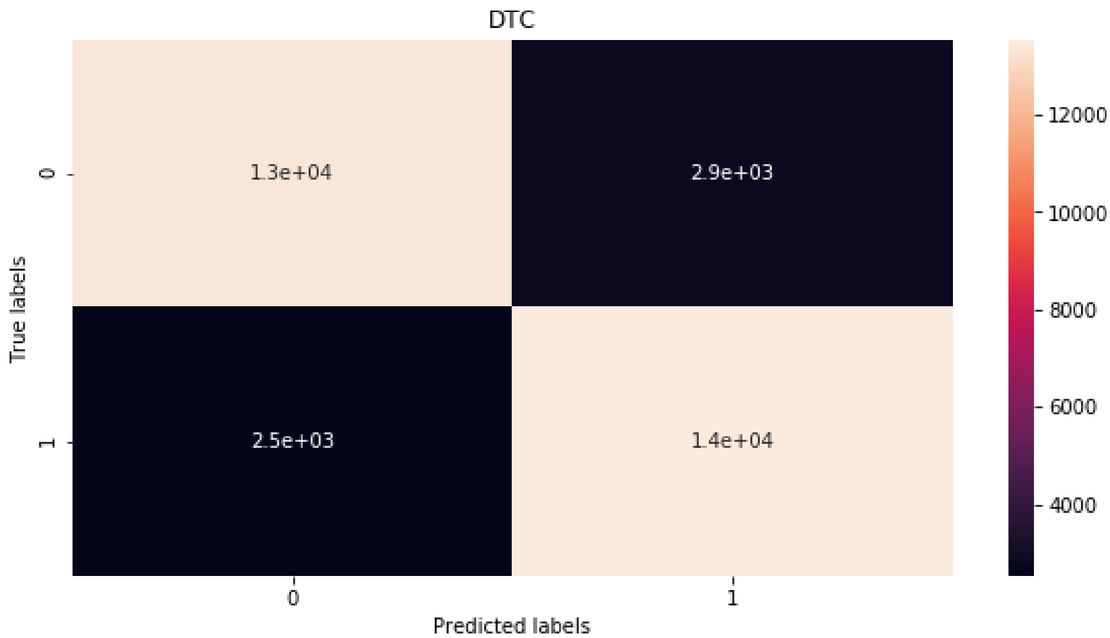

ROC Curves
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve of class 0 (area = 0.88)
ROC curve of class 1 (area = 0.88)
micro-average ROC curve (area = 0.88)
macro-average ROC curve (area = 0.88)

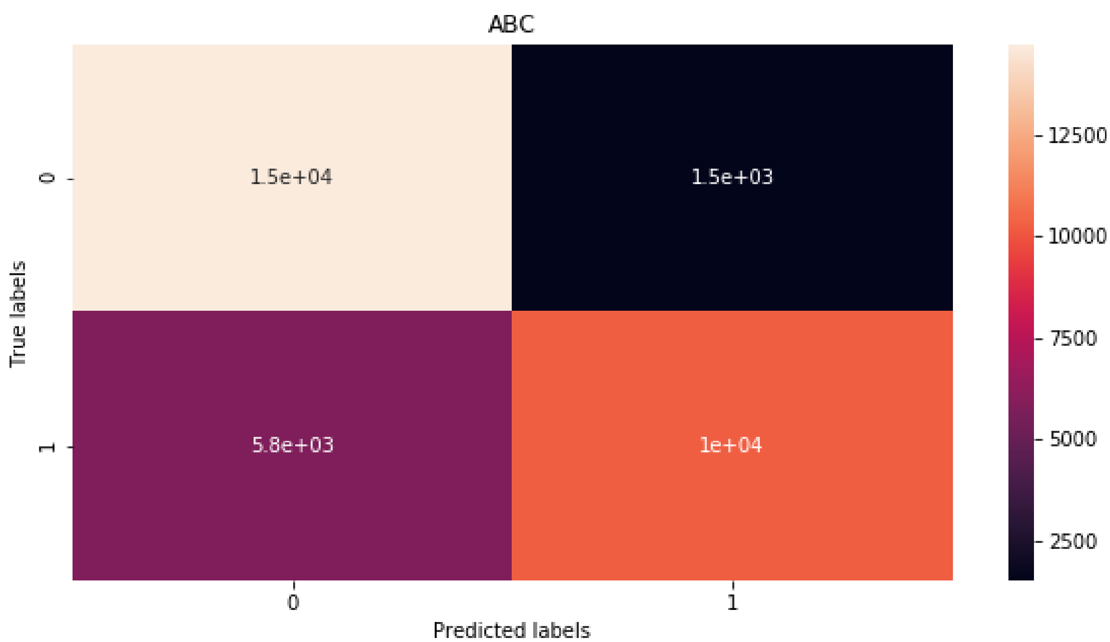
I don't know what is the problem with roc curve for LR. It is printed at the bottom with title ROC Curves. Multinomial NB and Decision Tree Classifier seem to perform best.

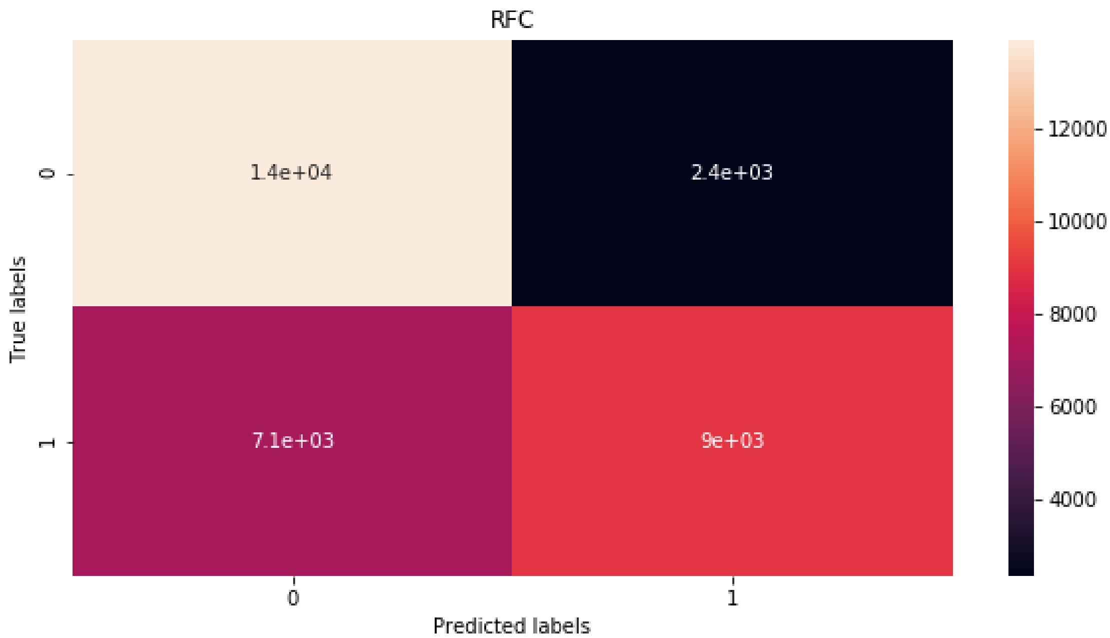
```
In [44]: for model,pred in pred_val.items():
             get_confusion_matrix(val_y,pred,model)
```

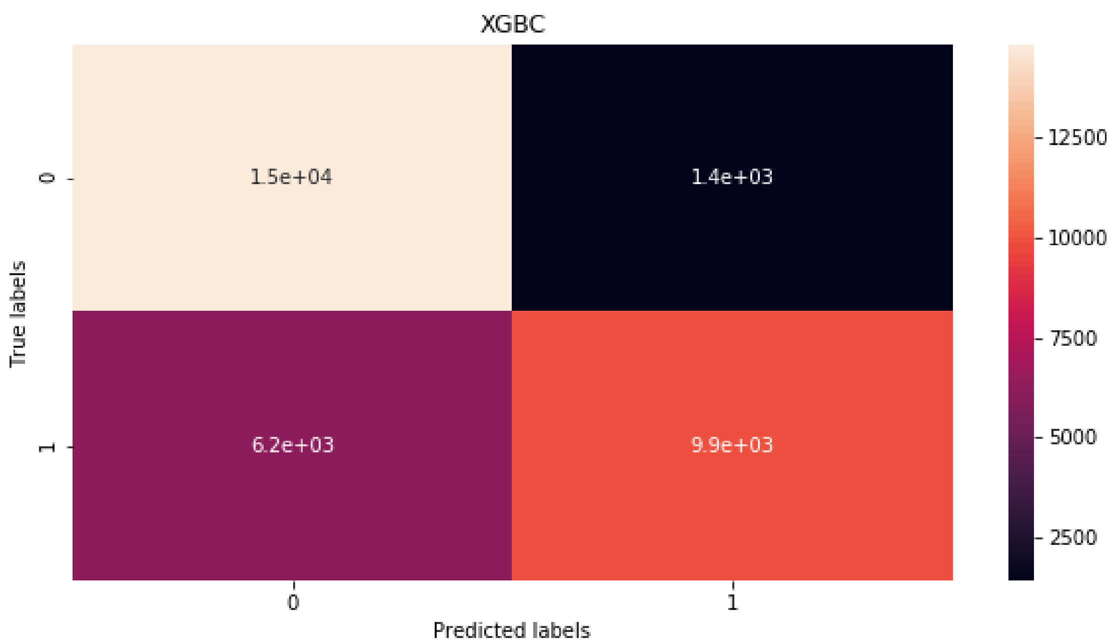


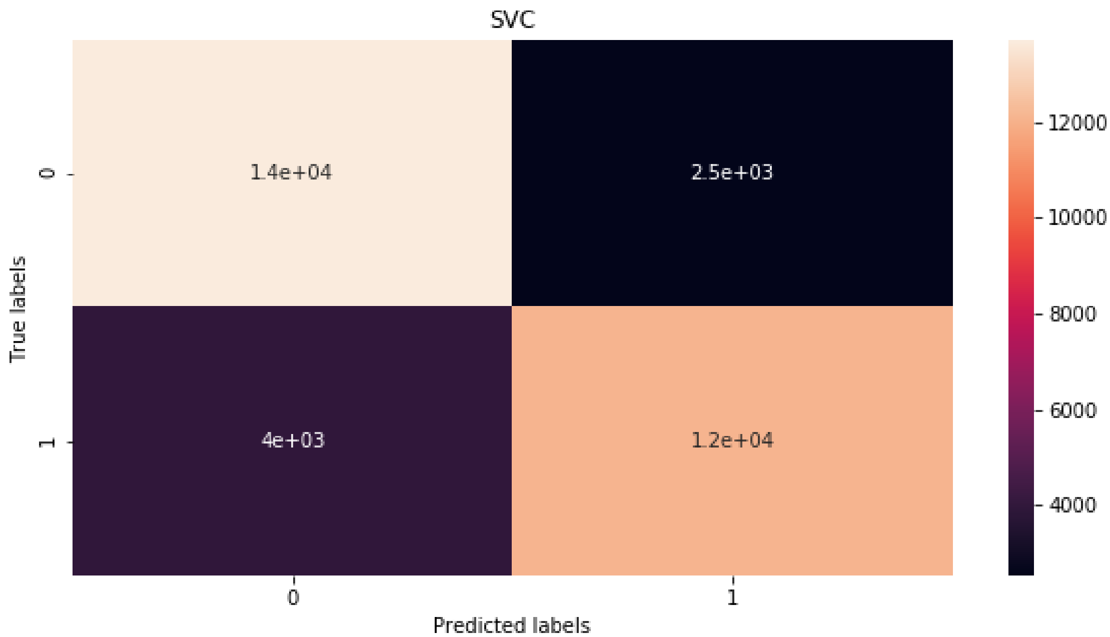



DTC
1.3e+04
2.9e+03
2.5e+03
1.4e+04
True labels
Predicted labels
0
1
12000
10000
8000
6000
4000


ABC
1.5e+04
1.5e+03
5.8e+03
1e+04
True labels
Predicted labels
0
1
12500
10000
7500
5000
2500


RFC
1.4e+04
2.4e+03
7.1e+03
9e+03
True labels
0
1
Predicted labels
12000
10000
8000
6000
4000


XGBC
1.5e+04
1.4e+03
6.2e+03
9.9e+03
True labels
0
1
Predicted labels
12500
10000
7500
5000
2500



From the confusion matrix of Multinomial NB and Decision Tree Classifier, we see that MNB has higher misclassification of 'Sincere Questions' and lower misclassification of 'Insincere Questions' as compared to DTC. DTC has large misclassification of 'Insincere Questions'. This is not at all desired. Practically speaking, it is better to misclassify true 'Sincere Question' than to misclassify true 'Insincere Question'. In case of classification of true 'Insincere Question', MNB performs best while RFC performs worst.

tfv=TfidfVectorizer(ngram_range=(1,3),analyzer='word',min_df=3) train_X_tfv=tfv.fit_transform(train_X.values) val_X_tfv=tfv.transform(val_X.values) tsvd_tfv=TruncatedSVD(n_components=50,random_state=seed) train_X_svd_tfv=tsvd_tfv.fit_transform(train_X val_X_svd_tfv=tsvd_tfv.transform(val_X_tfv) tsne_tfv=TSNE(n_components=2,random_state=seed) train_X_tsne_tfv=tsne_tfv.fit_transform(train_X_svd_tfv)

df=pd.DataFrame() df['tsne1']=pd.Series(train_X_tsne_tfv[:,0]) df['tsne2']=pd.Series(train_X_tsne_tfv[:,1]) df['target']=train_y sns.scatterplot(df['tsne1'],df['tsne2'],hue='target',data=df) plt.show()

pred_probs_tfv={} pred_train_tfv={} pred_val_tfv={} score_train_tfv={} score_val_tfv={}

for i in range(len(models)): pred_probs_tfv[model_names[i]],pred_train_tfv[model_names[i]],pred_val_tfv[m score_train_tfv[model_names[i]],score_val_tfv[model_names[i]]=get_model(models[i],train_X_tfv,train_y,val_X_

scl=StandardScaler() train_X_scl_tfv=scl.fit_transform(train_X_svd_tfv) val_X_scl_tfv=scl.transform(val_X_svd_tfv) pred_probs_tfv['SVC'],pred_train_tfv['SVC'],pred_val_tfv['SVC'], score_train_tfv['SVC'],score_val_tfv['SVC']=get_model(SVC(probability=True,random_state=seed), train_X_scl_tfv,train_y,val_X_scl_tfv)

```
In [45]: trace1=go.Bar(x=list(score_train_tfv.keys()),
                        y=list(score_train_tfv.values()),
                       name='Training Score with TFV',
                       marker=dict(color='rgba(0,255,0,0.5)',
                                   line=dict(color='rgb(0,0,0)',width=1.5)))
         trace2=go.Bar(x=list(score_val_tfv.keys()),
```

```
                  y=list(score_val_tfv.values()),
                 name='Validation Score with TFV',
                 marker=dict(color='rgba(255,255,0,0.5)',
                             line=dict(color='rgb(0,0,0)',width=1.5)))

layout=go.Layout(barmode='group',
                 title='Scores of Different Models')
plot_data=[trace1,trace2]
fig=dict(data=plot_data,layout=layout)
iplot(fig)
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-45-4d67e7e1b3e2> in <module>
----> 1 trace1=go.Bar(x=list(score_train_tfv.keys()),
      2               y=list(score_train_tfv.values()),
      3              name='Training Score with TFV',
      4              marker=dict(color='rgba(0,255,0,0.5)',
      5                          line=dict(color='rgb(0,0,0)',width=1.5)))


NameError: name 'score_train_tfv' is not defined
```

With the use of TfidfVectorizer, overfitting is not observed in LR and Multinomial NB models unlike during usage of CountVectorizer. Overfitting of DTC still remains an issue. Other models aren't overfitting. It looks like Multinomial NB is the best model. But we haven't yet tuned hyperparameters of tree based models. In the following graphs, we compare the training scores of models with CountVectorizer vs with TfidfVectorizer. Same is done for validation scores as well.

trace1=go.Bar(x=list(score_train.keys()), y=list(score_train.values()), name='Training Score with CV', marker=dict(color='rgba(0,0,255,0.5)', line=dict(color='rgb(0,0,0)',width=1.5))) trace2=go.Bar(x=list(score_train_tfv.keys()), y=list(score_train_tfv.values()), name='Training Score with TFV', marker=dict(color='rgba(255,0,0,0.5)', line=dict(color='rgb(0,0,0)',width=1.5)))

layout=go.Layout(barmode='group', title='Training Scores of Different Models') plot_data=[trace1,trace2] fig=dict(data=plot_data,layout=layout) iplot(fig)

```
In [46]: trace1=go.Bar(x=list(score_train.keys()),
                  y=list(score_train.values()),
                 name='Training Score with CV',
                 marker=dict(color='rgba(0,0,255,0.5)',
                             line=dict(color='rgb(0,0,0)',width=1.5)))
         trace2=go.Bar(x=list(score_train_tfv.keys()),
                  y=list(score_train_tfv.values()),
                 name='Training Score with TFV',
                 marker=dict(color='rgba(255,0,0,0.5)',
```

```
                              line=dict(color='rgb(0,0,0)',width=1.5)))

layout=go.Layout(barmode='group',
                 title='Training Scores of Different Models')
plot_data=[trace1,trace2]
fig=dict(data=plot_data,layout=layout)
iplot(fig)
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-46-11afe87a445f> in <module>
  4              marker=dict(color='rgba(0,0,255,0.5)',
  5                          line=dict(color='rgb(0,0,0)',width=1.5)))
----> 6 trace2=go.Bar(x=list(score_train_tfv.keys()),
  7               y=list(score_train_tfv.values()),
  8              name='Training Score with TFV',


NameError: name 'score_train_tfv' is not defined
```

When switched from CountVectorizer to TfidfVectorizer, the training scores of LR and Multinomial NB have decreased, while that of other models it has increased.

trace1=go.Bar(x=list(score_val.keys()), y=list(score_val.values()), name='Validation Score with CV', marker=dict(color='rgba(0,0,255,0.5)', line=dict(color='rgb(0,0,0)',width=1.5))) trace2=go.Bar(x=list(score_val_tfv.keys()), y=list(score_val_tfv.values()), name='Validation Score with TFV', marker=dict(color='rgba(255,0,0,0.5)', line=dict(color='rgb(0,0,0)',width=1.5)))

layout=go.Layout(barmode='group', title='Validation Scores of Different Models') plot_data=[trace1,trace2] fig=dict(data=plot_data,layout=layout) iplot(fig)

When switched from CountVectorizer to TfidfVectorizer, there is either a slight decrease or increase in validation scores. Increase in the validation score of RFC is huge.

for model,probs in pred_probs_tfv.items(): get_roc_curve(val_y,probs,model)

From ROC Curves, it looks like Multinomial NB and DTC are best models. Let us check their confusion matrices.

for model,pred in pred_val_tfv.items(): get_confusion_matrix(val_y,pred,model)

Classification of true 'Insincere Questions' is highest in Multinomial NB and least in RFC. Again, Multinomial NB with TfidfVectorizer seems to be the best model.

Let us try to tune the hyperparameters of XGBClassifier.

start=time.time() params={'n_estimators':[100,500], 'learning_rate':[0.01,0.1], 'subsample':[0.8]}

model=XGBClassifier(random_state=seed) score=make_scorer(f1_score) grid=GridSearchCV(model,params,cv=3,scoring=score) grid.fit(train_X_tfv,train_y)

end=time.time() print('Total time taken: ' + str(end-start))

print(grid.best_params_) print(grid.best_score_) xgb1=grid.best_estimator_ xgb1.fit(train_X_tfv,train_y) pred1=xgb1.predict(val_X_tfv) score1=f1_score(val_y,pred1) print(score1)

Little bit of tuning has increased our score by 4.5%. The best part is, it is not even overfitting.

In [47]:
```
#start=time.time()
#params={'n_estimators':[500,800,1000],
#        'learning_rate':[0.1,0.15,0.2],
#        'subsample':[0.8],
#        'max_depth':[3,5,7],
#        'gamma':[0,10]}

#model=XGBClassifier(random_state=seed)
#score=make_scorer(f1_score)
#grid2=GridSearchCV(model,params,cv=3,scoring=score)
#grid2.fit(train_X_tfv,train_y)

#end=time.time()
#print('Total time taken: ' + str(end-start))

#0.8397122528906257
#{'gamma': 0, 'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 800, 'subsample':
#Total time taken: 8327.329408407211
```

In [48]:
```
#print(grid2.best_score_)
#print(grid2.best_params_)
#xgb2=grid2.best_estimator_
#xgb2.fit(train_X_tfv,train_y)
#pred2=xgb2.predict(val_X_tfv)
#score2=f1_score(val_y,pred2)
#print(score2)

#0.8397122528906257
#{'gamma': 0, 'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 800, 'subsample':
#0.8515138946495231
```

Thus, by further parameter tuning we have increased XGBClassifier score by 7%.

Hence we have analysed various ML models and Tuned one of them. In the next notebook we have a look at Deep Learning based methods.

In [ ]:

In [ ]: