# Phishing Detection Using Machine Learning

### Practice Module: Pattern Recognition Systems (PRS)

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#Phishing Dataset Source

[Kaggle Phishing Site (https://www.kaggle.com/taruntiwarihp/phishing-site-urls/download)](https://www.kaggle.com/taruntiwarihp/phishing-site-urls/download) - url,label

[Kaggle Malicious URL (https://www.kaggle.com/sid321axn/malicious-urls-dataset)](https://www.kaggle.com/sid321axn/malicious-urls-dataset) - url,label

[OpenPhish (https://OpenPhish.com)](https://OpenPhish.com) - url,label

# Load Packages and File

In [ ]:

```
# from google.colab import drive
# drive.mount('/content/drive')
```

In [ ]:

```
# !pip install tldextract -q
# !pip install scikit-plot
```

In [ ]:

```
import sys
import os
import scipy
import matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from typing import *
import scikitplot as skplt

import tldextract
from urllib.parse import urlparse,urlsplit

from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import export_graphviz
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier


from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score, roc_curv
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

from nltk.tokenize import RegexpTokenizer
from nltk.stem.snowball import SnowballStemmer
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from sklearn.pipeline import make_pipeline
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
import dataframe_image as dfi

# os.chdir('/content/drive/MyDrive/iss/PRSProjectSharedFolder/')
# print("Current working directory:")
# os.getcwd()
#!dir
```

In [5]:

```
# !wget https://openphish.com/feed.txt #500items, feed.txt
```

In [ ]:

```
# !mkdir '/content/phishingURL'
# !unzip -q '/content/drive/MyDrive/iss/PRS_Project/phishing_url.zip' -d '/content/phishing
```

# Machine Classifier - Phishing

## Load Data and Integrate Multiple Datasets

In [3]:

```
# pdPhish1 = pd.read_csv("/content/phishingURL/phishing_site_urls.csv")
pdPhish1 = pd.read_csv("phishing_site_urls.csv")
lines = []
with open('phishFeed.txt', encoding = 'utf-8') as f:
    for line in f:
        line=line.strip()
        if line not in lines:
            lines.append((line,'bad'))
f.close()
openPhishData = np.array(lines)
pdOpenPhish = pd.DataFrame(openPhishData, columns=['url', 'label'])
pdOpenPhish.head()
pdPhish1.rename(columns={'URL':'url', 'Label':'label'}, inplace=True)
#Concat
pdPhishing=pd.DataFrame()
pdPhishing= pdPhishing.append([pdPhish1,pdOpenPhish], ignore_index=True)
```

In [4]:

```
print("Shape: ", pdPhish1.shape, pdOpenPhish.shape, pdPhishing.shape)
print("Null value:\n", pdPhishing.isnull().sum())
print("Label Counts:\n", pdPhishing.label.value_counts())
print(pdPhishing.describe())
pdPhishing.head()

#Good: 392924, Bad: 251547. No Null
```

```
Shape:  (549346, 2) (95125, 2) (644471, 2)
Null value:
 url      0
label    0
dtype: int64
Label Counts:
 good    392924
bad     251547
Name: label, dtype: int64
                                  url   label
count                          644471  644471
unique                         554285       2
top     jhomitevd2abj3fk.tor2web.org/    good
freq                               52  392924
```

Out[4]:

| | url | label |
|---|---|---|
| **0** | nobell.it/70ffb52d079109dca5664cce6f317373782/... | bad |
| **1** | www.dghjdgf.com/paypal.co.uk/cycgi-bin/webscrc... | bad |
| **2** | serviciosbys.com/paypal.cgi.bin.get-into.herf.... | bad |
| **3** | mail.printakid.com/www.online.americanexpress.... | bad |
| **4** | thewhiskeydregs.com/wp-content/themes/widescre... | bad |

## Manual Lexical Features - Data Processing

1. Parse URL (urlparse) into scheme, netloc, path, params, query, fragment
2. Parse URL (tldextract) the domain, subdomain, and suffix
3. Remove corrupted data based on the netloc values
4. Feature Extraction: URL Length, Hostname/Netloc(netloc_length), path_length, fd_length, suffix_length, num_subdomains{from netloc}, count_dir, path_fs_., domain_, url_, path_, domain-, url-, path-, count@, count?, count%, count., count=, count-https_inpath, count-http_inpath, count-www_inpath, count-digits, count-letters

In [5]:

```
''' urlparse
Parse a URL into 6 components:
    <scheme>://<netloc>/<path>;<params>?<query>#<fragment>
    Return a 6-tuple: (scheme, netloc, path, params, query, fragment).
'''
def parse_url(url: str) -> Optional[Dict[str, str]]:
    try:
        no_scheme = not url.startswith('https://') and not url.startswith('http://')
        if no_scheme:
            parsed_url = urlparse(f"http://{url}")
            return {
                "scheme": None, # not established a value for this
                "netloc": parsed_url.netloc,
                "path": parsed_url.path,
                "params": parsed_url.params,
                "query": parsed_url.query,
                "fragment": parsed_url.fragment,
            }
        else:
            parsed_url = urlparse(url)
            return {
                "scheme": parsed_url.scheme,
                "netloc": parsed_url.netloc,
                "path": parsed_url.path,
                "params": parsed_url.params,
                "query": parsed_url.query,
                "fragment": parsed_url.fragment,
            }
    except:
        return None
def tldExtract(url) -> Optional[Dict[str, str]]:
    # extract subdomain, domain, and domain suffix from url
    # if item == '', fill with '<empty>'
    subdomain, domain, domain_suffix = (None if extracted == '' else extracted for extracte
    return {"subdomain": subdomain, "domain": domain, "suffix": domain_suffix}

pdPhishing["parsed_url"] = pdPhishing.url.apply(parse_url)
pdPhishing["tldextract"] = pdPhishing.url.apply(tldExtract)

pdPhishing = pd.concat([pdPhishing.drop(['parsed_url'], axis=1), pdPhishing['parsed_url'].a
pdPhishing = pd.concat([pdPhishing.drop(['tldextract'], axis=1), pdPhishing['tldextract'].a
pdPhishing.head()
```

Out[5]:

| | url | label | scheme | netloc | |
|---|---|---|---|---|---|
| 0 | nobell.it/70ffb52d079109dca5664cce6f317373782/... | bad | None | nobell.it | /70ffb52d0 |
| 1 | www.dghjdgf.com/paypal.co.uk/cycgi-bin/webscrc... | bad | None | www.dghjdgf.com | /paypal.cc |
| 2 | serviciosbys.com/paypal.cgi.bin.get-into.herf.... | bad | None | serviciosbys.com | /pa |
| 3 | mail.printakid.com/www.online.americanexpress.... | bad | None | mail.printakid.com | /w |
| 4 | thewhiskeydregs.com/wp-content/themes/widescre... | bad | None | thewhiskeydregs.com | /wp-cor |

In [6]:

```
#Remove Corrupted Data
print(pdPhishing.netloc.isnull().sum())
for idx, i in enumerate(pdPhishing.netloc.values):
    if type(i) is not str:
        print(idx, pdPhishing.url.values[idx],pdPhishing.label.values[idx])
pdPhishing.shape
#remove null_netloc
pdPhishing=pdPhishing[~pdPhishing.netloc.isnull()].reset_index()
pdPhishing=pdPhishing.drop("index", axis=1)
print(pdPhishing.shape)
```

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(644441, 11)
```

In [7]:

```
# #First Directory Length
def fd_length(url_path):
    try:
        return len(url_path.split('/')[1])
    except:
        return 0

def get_num_subdomains(netloc: str) -> int:
    subdomain = tldextract.extract(netloc).subdomain
    if subdomain == "":
        return 0
    return subdomain.count('.') + 1

pdPhishing['num_subdomains'] = pdPhishing['netloc'].apply(lambda i: get_num_subdomains(i))

def digit_count(url):
    digits = 0
    for i in url:
        if i.isnumeric():
            digits = digits + 1
    return digits

def letter_count(url):
    letters = 0
    for i in url:
        if i.isalpha():
            letters = letters + 1
    return letters

#URL Length, Hostname Length, PathLength
pdPhishing['tot_url_length'] = pdPhishing['url'].apply(lambda i: len((i)))
pdPhishing['netloc_length'] =  pdPhishing['netloc'].apply(lambda i: len((i)))
pdPhishing['path_length'] = pdPhishing['path'].apply(lambda i: len((i)))

pdPhishing['fd_length'] = pdPhishing['path'].apply(lambda i: fd_length(i))
pdPhishing['suffix_length'] = pdPhishing['suffix'].apply(lambda i: len(str(i)))

#CountFeatures

pdPhishing['count_dir'] = pdPhishing['path'].str.count('/')
pdPhishing['path_fsdot'] = pdPhishing['path'].apply(lambda i: i.count('.')) #malicious.com/

pdPhishing['domain_'] = pdPhishing['netloc'].apply(lambda i: i.count('_'))
pdPhishing['countunderscore'] = pdPhishing['url'].apply(lambda i: i.count('_'))
pdPhishing['path_'] = pdPhishing['path'].apply(lambda i: i.count('_'))

pdPhishing['domaindesk'] = pdPhishing['netloc'].apply(lambda i: i.count('-'))
pdPhishing['urldesk'] = pdPhishing['url'].apply(lambda i: i.count('-'))
pdPhishing['pathdesk'] = pdPhishing['path'].apply(lambda i: i.count('-'))


pdPhishing['countat'] = pdPhishing['url'].apply(lambda i: i.count('@'))
pdPhishing['countquest'] = pdPhishing['url'].apply(lambda i: i.count('?'))
pdPhishing['countpercent'] = pdPhishing['url'].apply(lambda i: i.count('%'))
pdPhishing['countdot'] = pdPhishing['url'].apply(lambda i: i.count('.'))
pdPhishing['counteq'] = pdPhishing['url'].apply(lambda i: i.count('='))

pdPhishing['count_http_inpath'] = pdPhishing['path'].apply(lambda i : i.count('http'))
pdPhishing['count_https_inpath'] = pdPhishing['path'].apply(lambda i : i.count('https'))
```

```
pdPhishing['count_www_inpath'] = pdPhishing['path'].apply(lambda i: i.count('www'))

pdPhishing['countdigits']= pdPhishing['url'].apply(lambda i: digit_count(i))
pdPhishing['countletters']= pdPhishing['url'].apply(lambda i: letter_count(i))
```

In [ ]:

```
colList=pdPhishing.columns
for i in colList:
    print(i, " - Null: ", pdPhishing[str(i)].isnull().sum())
display(pdPhishing.head())
```

## CountVectorizer and TFIDF - Tokenize & Stem

In [9]:

```
tokenizer = RegexpTokenizer(r'[A-Za-z]+')
pdPhishing['url_tokenized'] = pdPhishing.url.map(lambda t: tokenizer.tokenize(t))
#SnowballStemmer
#Snowball is a small string processing language, gives root words. More aggressive than por
root_words = SnowballStemmer("english")
pdPhishing['root_words'] = pdPhishing['url_tokenized'].map(lambda l: [root_words.stem(word)
#take all rootwords into sentences to be pass to CountVectorizer
pdPhishing['url_sentence'] = pdPhishing['root_words'].map(lambda l: ' '.join(l))
pdPhishing.head()
```

Out[9]:

| | url | label | scheme | netloc | |
|---|---|---|---|---|---|
| **0** | nobell.it/70ffb52d079109dca5664cce6f317373782/... | bad | None | nobell.it | /70ffb52d0 |
| **1** | www.dghjdgf.com/paypal.co.uk/cycgi-bin/webscrc... | bad | None | www.dghjdgf.com | /paypal.cc |
| **2** | serviciosbys.com/paypal.cgi.bin.get-into.herf.... | bad | None | serviciosbys.com | /pa |
| **3** | mail.printakid.com/www.online.americanexpress.... | bad | None | mail.printakid.com | /w |
| **4** | thewhiskeydregs.com/wp-content/themes/widescre... | bad | None | thewhiskeydregs.com | /wp-cor |

5 rows × 38 columns

###Split Training/Testing Dataset, Scaling (Manual FExt)

In [10]:

```
x = pdPhishing[['tot_url_length',
       'netloc_length', 'path_length', 'fd_length', 'suffix_length',
       'num_subdomains', 'domaindesk', 'urldesk', 'pathdesk', 'domain_', 'countunderscore',
       'path_', 'count_dir', 'path_fsdot', 'countat', 'countquest', 'countpercent',
       'countdot', 'counteq', 'count_http_inpath', 'count_https_inpath',
       'count_www_inpath', 'countdigits', 'countletters']]

le = LabelEncoder()
y=le.fit_transform(pdPhishing.label) #bad=0, good=1
# le.inverse_transform([0])

#Splitting the data into Training, Validation, Test - 0.7, 0.15, 0.15 ratio
x_train, x_valtest, y_train, y_valtest = train_test_split(x, y, test_size=0.3, stratify=y,
x_val, x_test, y_val, y_test = train_test_split(x_valtest, y_valtest, test_size=0.5, strati
scaler = StandardScaler()
scaler.fit(x_train)

x_train_scale = scaler.transform(x_train)
x_val_scale = scaler.transform(x_val)
x_test_scale = scaler.transform(x_test)
```

###Split Training/Testing Dataset - CountVectorizer and TFIDFVectorizer

In [11]:

```
x_train_tkn, x_valtest_tkn, y_train_tkn, y_valtest_tkn = train_test_split(pdPhishing.url_se
x_val_tkn, x_test_tkn, y_val_tkn, y_test_tkn = train_test_split(x_valtest_tkn, y_valtest_tk

y_train_cv, y_train_tf = y_train_tkn, y_train_tkn
y_val_cv, y_val_tf = y_val_tkn, y_val_tkn
y_test_cv, y_test_tf = y_test_tkn, y_test_tkn


cv = CountVectorizer()
tfidf_v =TfidfVectorizer()

cv_f= cv.fit(x_train_tkn)
tfidf_f= tfidf_v.fit(x_train_tkn)

x_train_cv = cv.transform(x_train_tkn)
x_val_cv = cv.transform(x_val_tkn)
x_test_cv = cv.transform(x_test_tkn)

x_train_tf = tfidf_v.transform(x_train_tkn)
x_val_tf = tfidf_v.transform(x_val_tkn)
x_test_tf = tfidf_v.transform(x_test_tkn)
```

# Data Visualisation

In [12]:

```
#split data into two
bad_sites = pdPhishing[pdPhishing.label == 'bad']
good_sites = pdPhishing[pdPhishing.label == 'good']
```

In [13]:

```
## WorldCloud for Good URLS

data = good_sites.url_sentence
data.reset_index(drop=True, inplace=True)
text = str(data)

stopwords = set(STOPWORDS).union({'com','http','www'})
wordcloud = WordCloud(width = 800, height = 800, background_color ='white', stopwords = sto


plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.title("Most common words used in Good Urls", fontdict={'size': 20, 'color': 'navy', 've
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
```

In [14]:

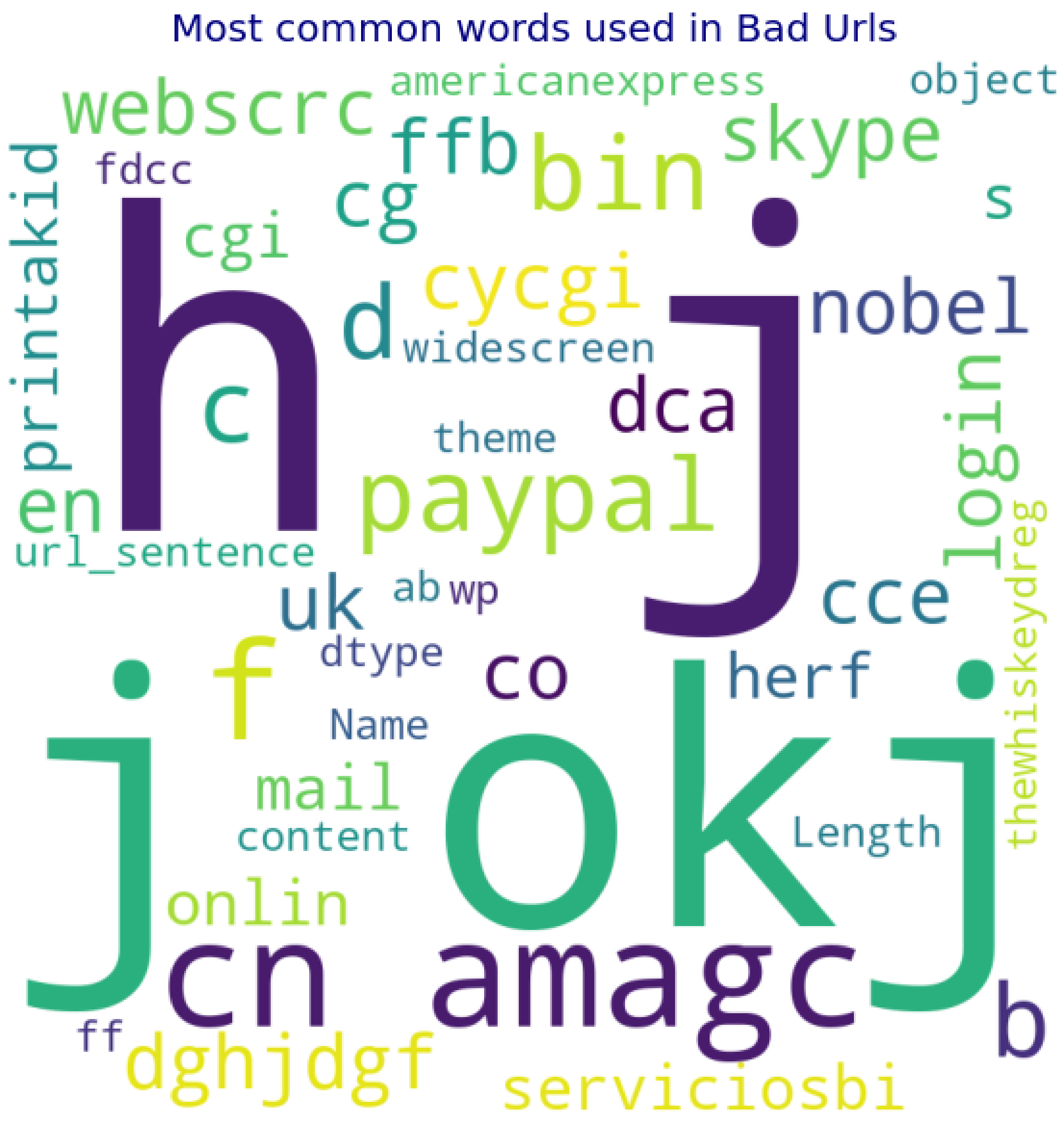
```
#worldcloud for bad url

data = bad_sites.url_sentence
data.reset_index(drop=True, inplace=True)
text = str(data)


stopwords = set(STOPWORDS).union({'com','http','www'})
wordcloud = WordCloud(width = 800, height = 800, background_color ='white', stopwords = sto


plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.title("Most common words used in Bad Urls", fontdict={'size': 20, 'color': 'navy', 'ver
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
```

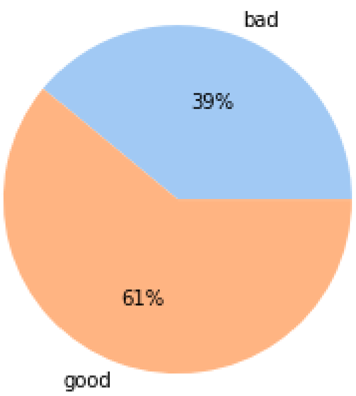


In [72]:

```
#define data
data = [len(pdPhishing[pdPhishing['label']=='bad']), len(pdPhishing[pdPhishing['label']=='g
labels = pdPhishing['label'].unique()

#define Seaborn color palette to use
colors = sns.color_palette('pastel')[0:5]

#create pie chart
plt.pie(data, labels = labels, colors = colors, autopct='%.0f%%')
plt.show()
```



In [61]:

```
#Heatmap
corrmat = pdPhishing.corr()
f, ax = plt.subplots(figsize=(25,19))
sns.heatmap(corrmat, square=True, annot = True, annot_kws={'size':10})

plt.figure(figsize=(15,5))
sns.countplot(x='label',data=pdPhishing)
plt.title("Distribution of Good and Bad Phishing URLs",fontsize=20)
plt.xlabel("Label of URLs",fontsize=18)
plt.ylabel("Number Of URLs",fontsize=18)

print("Percent Of Malicious URLs:{:.2f} %".format(len(pdPhishing[pdPhishing['label']=='bad'
print("Percent Of Benign URLs:{:.2f} %".format(len(pdPhishing[pdPhishing['label']=='good'])

#class imbalance to some extent
plt.figure(figsize=(20,5))
plt.hist(pdPhishing['tot_url_length'],bins=50,color='LightBlue')
plt.title("URL-Length",fontsize=20)
plt.xlabel("Url-Length",fontsize=18)
plt.ylabel("Number Of Urls",fontsize=18)
plt.ylim(0,1000)

plt.figure(figsize=(20,5))
plt.hist(pdPhishing['netloc_length'],bins=50,color='Lightgreen')
plt.title("netloc/hostname-Length",fontsize=20)
plt.xlabel("Length Of Hostname",fontsize=18)
plt.ylabel("Number Of Urls",fontsize=18)
plt.ylim(0,1000)

plt.figure(figsize=(20,5))
plt.hist(pdPhishing['path_length'],bins=50,color='Lightgreen')
plt.title("Path-Length",fontsize=20)
plt.xlabel("Length Of Path",fontsize=18)
plt.ylabel("Number Of Urls",fontsize=18)
plt.ylim(0,1000)

plt.figure(figsize=(15,5))
plt.title("Count of Dir In Url",fontsize=20)
plt.xlabel("Count of Dir",fontsize=18)
sns.countplot(pdPhishing['count_dir'])
plt.ylabel("Number of URLs",fontsize=18)

plt.figure(figsize=(15,5))
plt.title("Count of Dir In Url",fontsize=20)
plt.xlabel("Count of Dir",fontsize=18)
sns.countplot(pdPhishing['count_dir'])
plt.ylabel("Number of URLs",fontsize=18)

plt.figure(figsize=(15,5))
plt.title("Distribution of Count of Dir In URL By Label",fontsize=20)
plt.xlabel("Count Of Dir",fontsize=18)
plt.ylabel("Number of URLs",fontsize=18)
plt.ylim((0,1000))
sns.countplot(pdPhishing['count_dir'],hue='label',data=pdPhishing)
plt.ylabel("Number of URLs",fontsize=18)

plt.figure(figsize=(15,5))
plt.title("Distribution of Use Of HTTP In Path By Label",fontsize=20)
plt.xlabel("Count Of http",fontsize=12)
```

```
plt.ylabel("Number of URLs",fontsize=12)
plt.ylim((0,10000))
sns.countplot(pdPhishing['count_http_inpath'],hue='label',data=pdPhishing)

plt.figure(figsize=(15,5))
plt.title("Distribution of Use Of HTTPS In Path By Label",fontsize=20)
plt.xlabel("Count Of https",fontsize=12)
plt.ylabel("Number of URLs",fontsize=12)
plt.ylim((0,10000))
sns.countplot(pdPhishing['count_https_inpath'],hue='label',data=pdPhishing)

plt.figure(figsize=(15,5))
plt.title("Distribution of Use Of WWW In Path By Label",fontsize=20)
plt.xlabel("Count Of WWW",fontsize=12)
plt.ylabel("Number Of URLs",fontsize=12)
sns.countplot(pdPhishing['count_www_inpath'],hue='label',data=pdPhishing)
plt.ylim(0,10000)
```

```
Percent Of Malicious URLs:39.03 %
Percent Of Benign URLs:60.97 %

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
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C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
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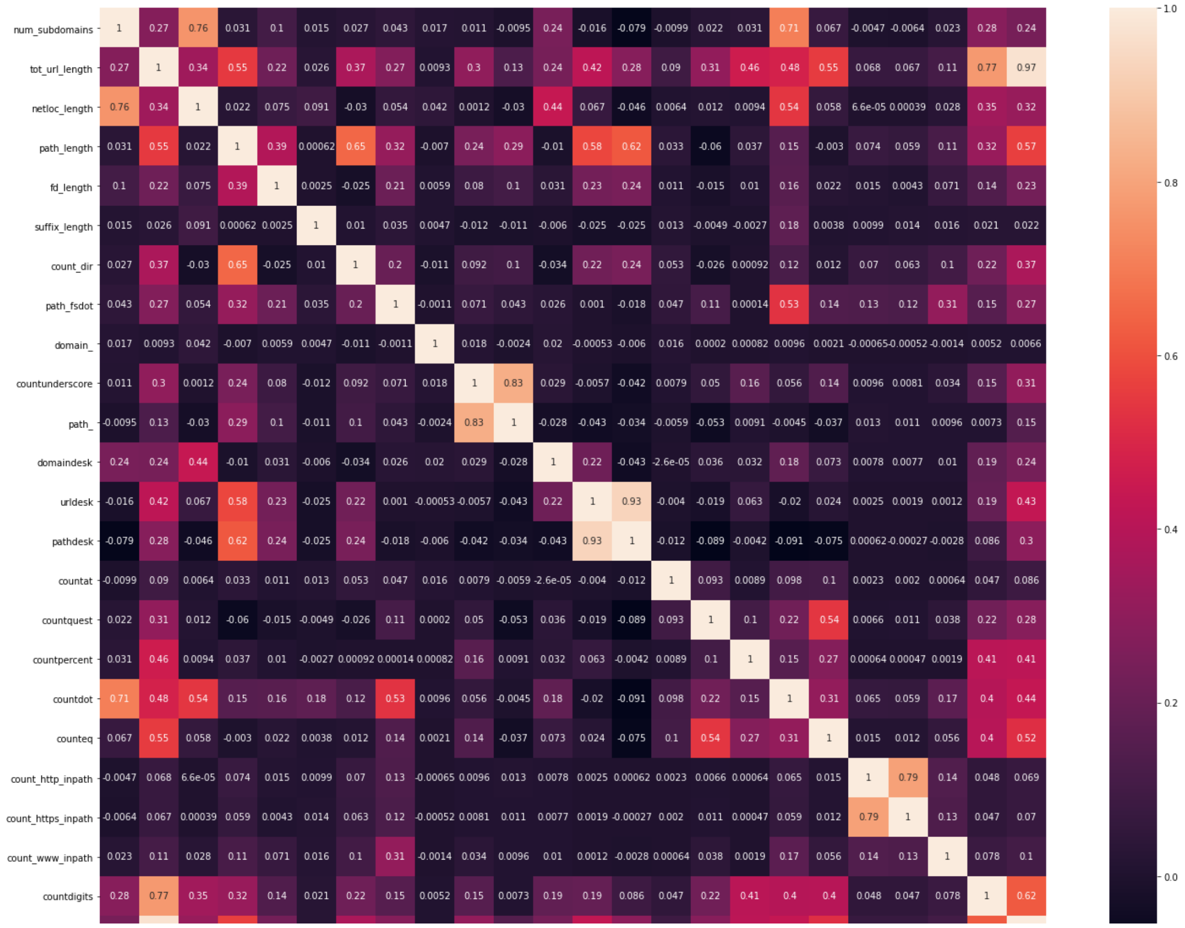
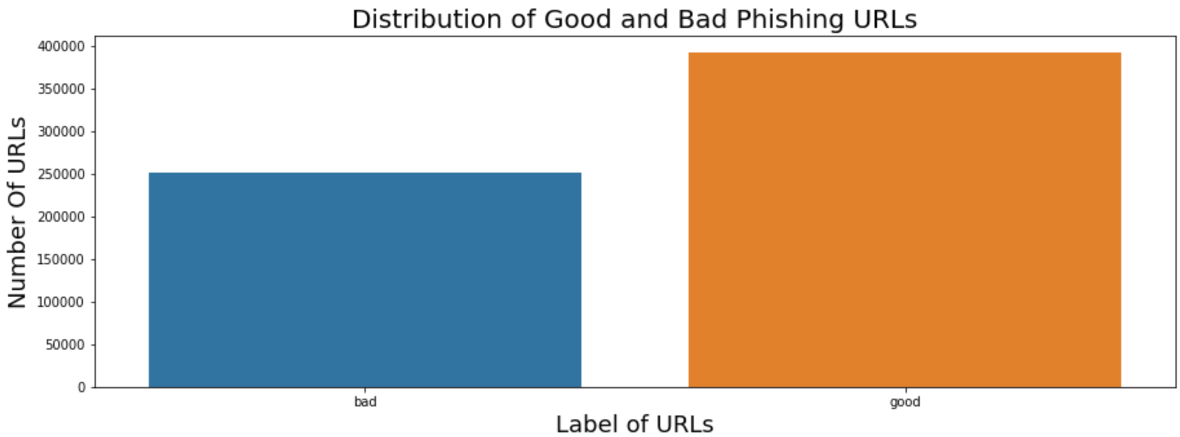
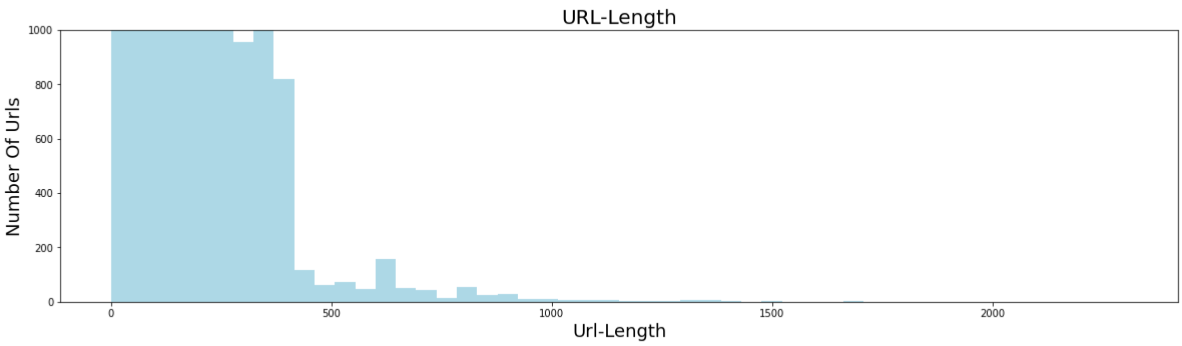
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[61]:

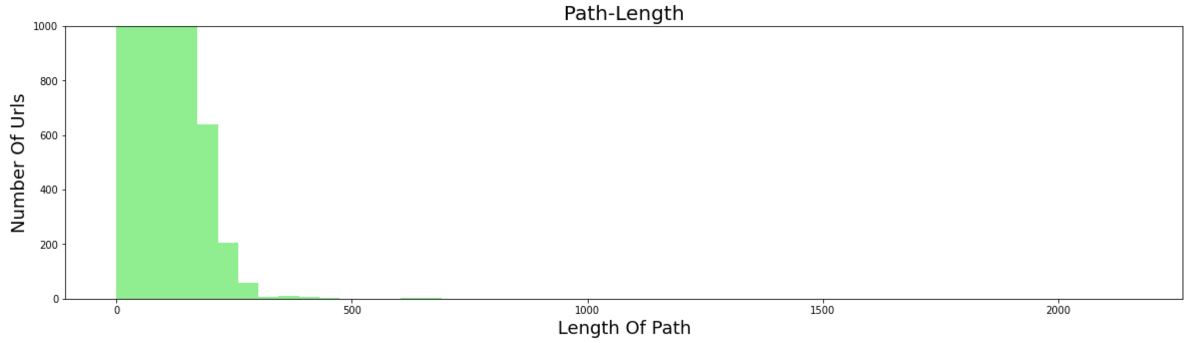
```
(0.0, 10000.0)
```

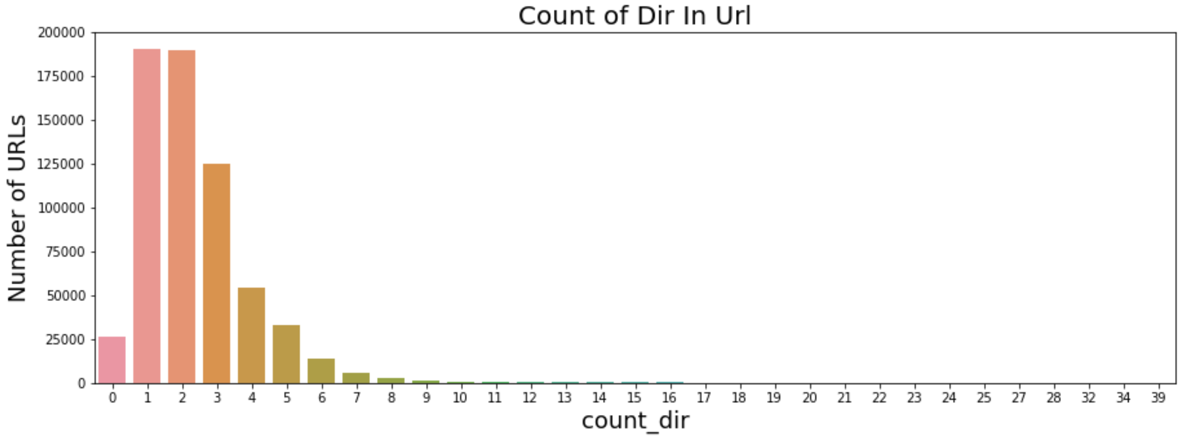

num_subdomains
tot_url_length
netloc_length
path_length
fd_length
suffix_length
count_dir
path_fsdot
domain_
countunderscore
path_
domaindesk
urldesk
pathdesk
countat
countquest
countpercent
countdot
counteq
count_http_inpath
count_https_inpath
count_www_inpath
countdigits
1.0
0.8
0.6
0.4
0.2
0.0

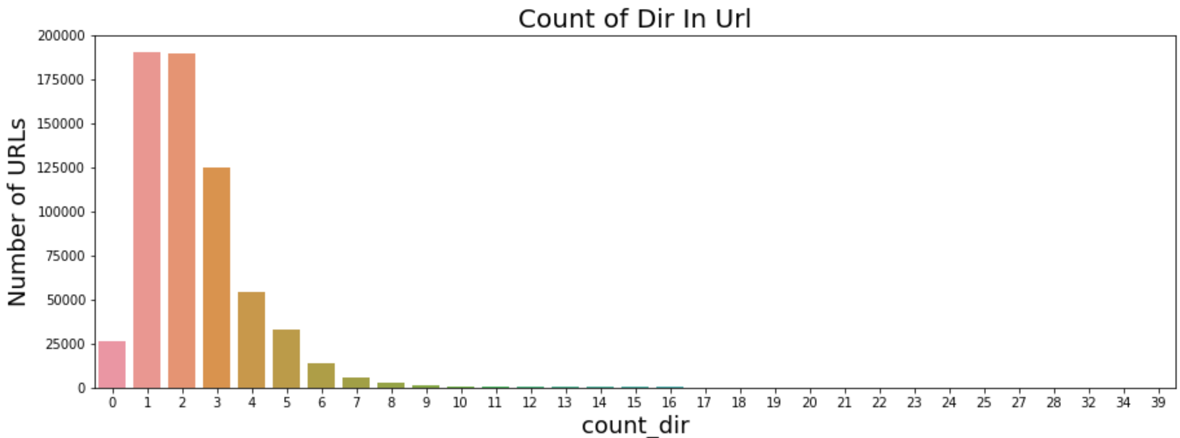

Distribution of Good and Bad Phishing URLs
Number Of URLs
Label of URLs
bad
good
0
50000
100000
150000
200000
250000
300000
350000
400000

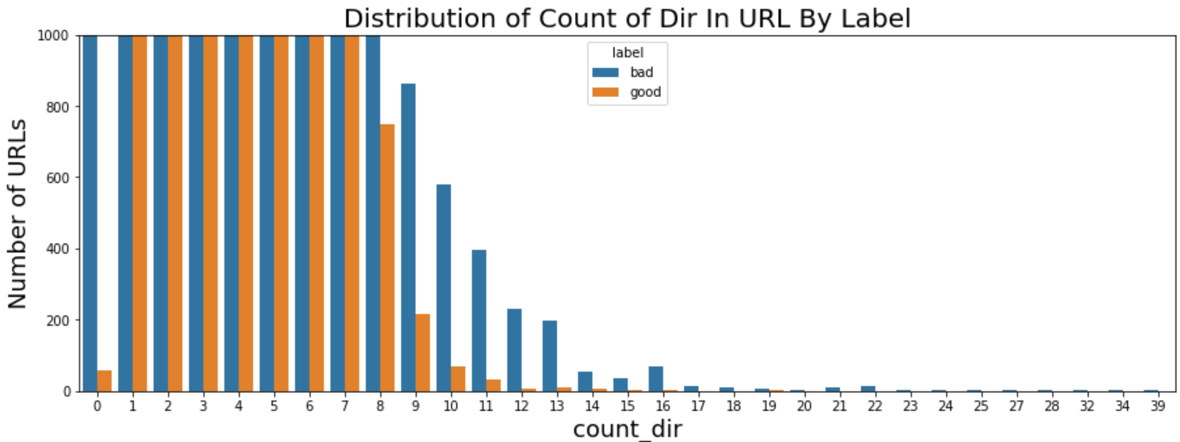

URL-Length
Number Of Urls
Url-Length
0
200
400
600
800
1000
500
1500
2000

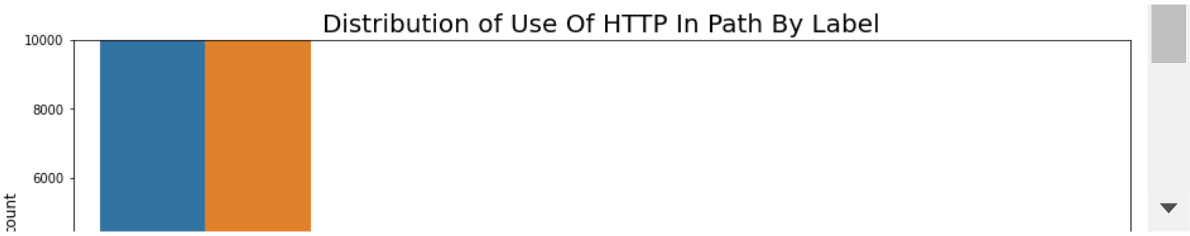
netloc/hostname-Length

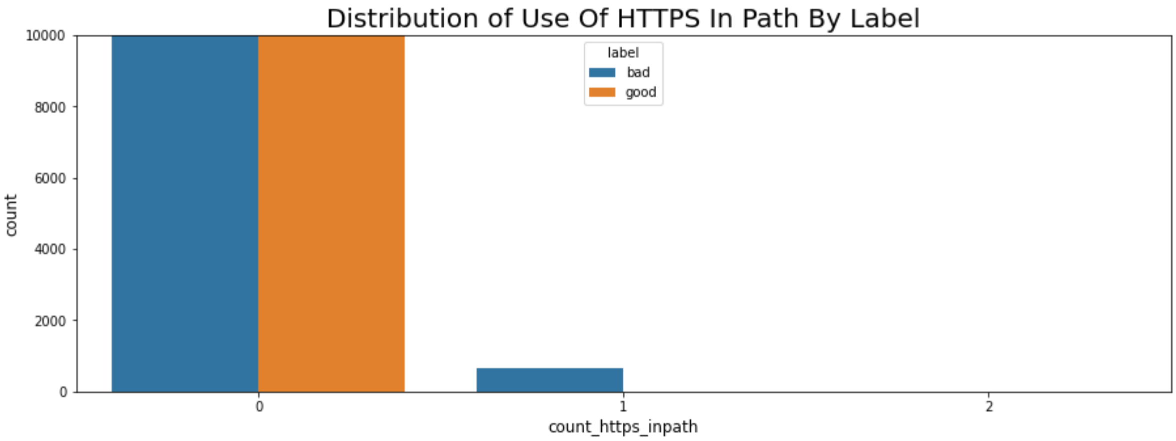


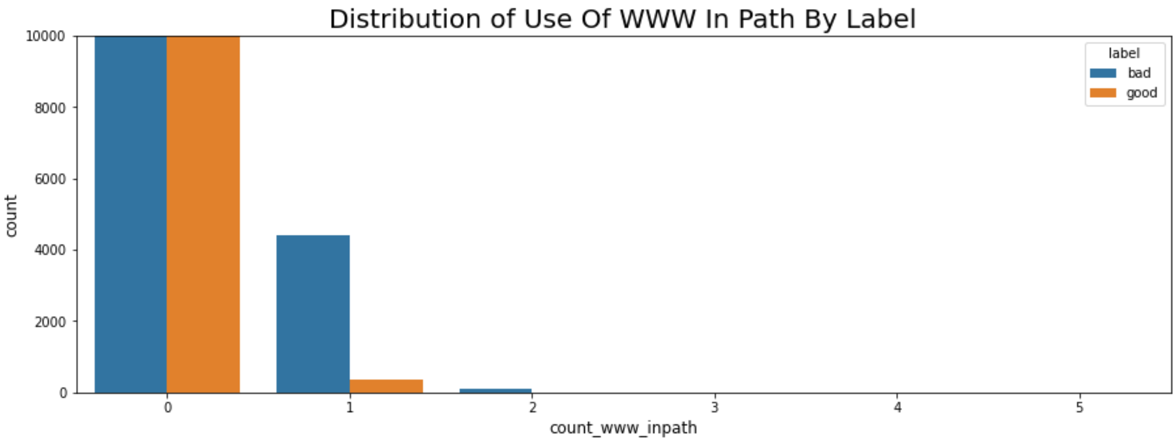






# Function Definition -

## Plotting, Performance, Saving Result

In [116]:

```
def perfResult(x_train, x_test, y_train, y_test, model):
    model.fit(x_train, y_train)
    tr_predict = model.predict(x_train)
    ts_predict = model.predict(x_test)
    tr_accuracy = accuracy_score(y_train, tr_predict)
    ts_accuracy = accuracy_score(y_test, ts_predict)
    modelName = str(model).split("(")[0]
    print(modelName)
    print(f"Train Accuracy Score: {tr_accuracy}")
    print(f"Test Accuracy Score: {ts_accuracy}\n")
    print(confusion_matrix(y_test,ts_predict))
    print(classification_report(y_test,ts_predict))
    saveModel(model, modelName)
    return [tr_predict, ts_predict, tr_accuracy, ts_accuracy]

#plotting ROC Chart
def plotROC_CummGain_Lift(x_train, x_test, y_train, y_test, model):
    y_pred_prob = model.predict_proba(x_test)
    fpr, tpr, _ = roc_curve(y_test, y_pred_prob[:,1])
    auc = roc_auc_score(y_test, y_pred_prob[:,1])
    modelName = str(model).split("(")[0]
    plt.title(modelName + " ROC")
    plt.xlabel("FPR")
    plt.ylabel("TPR")
    plt.plot(fpr,tpr,label=modelName+ ", auc="+str(auc)[:5])
    plt.plot([0,1],[0,1],'r--')
    plt.legend(loc=4)
    plt.show()
    skplt.metrics.plot_cumulative_gain(y_test, y_pred_prob)
    plt.show()
    skplt.metrics.plot_lift_curve(y_test, y_pred_prob)
    plt.show()

#plotting ROC Chart
def plotROC(x_train, x_test, y_train, y_test, model):
    y_pred_prob = model.predict_proba(x_test)
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob[:,1])
    auc = roc_auc_score(y_test, y_pred_prob[:,1])
    modelName = str(model).split("(")[0]
    plt.title(modelName + " ROC")
    plt.xlabel("FPR")
    plt.ylabel("TPR")
    plt.plot(fpr,tpr,label=modelName+ ", roc_auc="+str(auc)[:5])
    plt.plot([0,1],[0,1],'r--')
    plt.legend(loc=4)
    plt.show()
    return (y_pred_prob, fpr, tpr, auc)

#import GridSearchCV
from sklearn.model_selection import GridSearchCV
def gridSearchCV(x_train, x_test, y_train, y_test, model, param, cv_value):
    model_cv=GridSearchCV(model, param, cv=cv_value)
    model_cv.fit(x_train, y_train)
    # print('TrainScore: ', model_cv.score(x_train, y_train))
    # print('TestScore: ', model_cv.score(x_test, y_test))
    best_score = model_cv.best_score_
    best_params = model_cv.best_params_
    print("Best Score:" + str(best_score))
    print("Best Parameters: " + str(best_params))
```

```
    return (best_score, best_params)
```

###SaveModelFunction

In [160]:

```
import pickle
def saveModel(model, modelname):
    pathfolder="model/"
    pickle.dump(model, open(pathfolder+modelname+".pkl", 'wb'))
```

##SAVING

In [75]:

```
# saveModel(scaler, "vectorizer/scaler")
# saveModel(cv, 'vectorizer/cv2')
# saveModel(tfidf_v, 'vectorizer/tfidf_v2')

# with open('/content/drive/MyDrive/iss/PRS_Project/vectorizer/tfidf_v2.pkl', 'rb') as f:
#     tfidf_v = pickle.load(f)
# f.close()

# with open('/content/drive/MyDrive/iss/PRS_Project/vectorizer/cv2.pkl', 'rb') as f:
#     cv = pickle.load(f)
# f.close()
# cvFeatures=cv.transform(pdPhishing.url_sentence)
# tfidfFeatures = tfidf_v.transform(pdPhishing.url_sentence)
# print('The length of vocabulary', len(tfidf_v.get_feature_names()))
```

### Save Cleanup CSV

In [ ]:

```
# compression_opts = dict(method='zip', archive_name='pdPhishing.csv')
# pdPhishing.to_csv("/content/drive/MyDrive/iss/PRS_Project/pdPhishing_oct.zip",index=False
```

### Load CleanCSV

In [ ]:

```
# !mkdir '/content/phishingURL'
# !unzip -q '/content/drive/MyDrive/iss/PRS_Project/pdPhishing_oct.zip' -d '/content/phishi
# pdPhishing = pd.read_csv('/content/phishingURL/pdPhishing.csv')
# pdPhishing.head()
# print("Shape: ", pdPhishing.shape)
# print("Null value:\n", pdPhishing.isnull().sum())
# print("Label Counts:\n", pdPhishing.label.value_counts())
# print(pdPhishing.describe())
# pdPhishing.head()
```

# Build Model (Manual vs CountVect vs TFIDF)

```
Models for comparison
1. KNN
2. Logistic Regression
3. Decision Trees
4. Random Forest
5. AdaBoost
6. NB
7. MLP*
```

####Init|

In [19]:

```
# Initialization
X_labels = ['Manual', 'CountVect', 'TfIdf'] # List of Descriptions of X feature map
X_train = [x_train_scale, x_train_cv, x_train_tf] # List of X feature map for training
X_val = [x_val_scale, x_val_cv, x_val_tf] # List of X feature map for validation
X_test = [x_test_scale, x_test_cv, x_test_tf] # List of X feature map for testing
```

### Logistic Regression

### *Training*

In [78]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Regularization Strength', 'Training Accuracy', 'Validati
reg_str = [3, 2, 1, 0.3, 0.1, 0.03, 0.01, 0.003, 0.001] # different regularization strength
modelname = 'LogisticRegresion'

# Initialize
labels = []
reg = []
tr_acc = []
tv_acc = []
F1 = []
auc = []
fpr = []
tpr = []

for i in range(len(X_labels)):
  for r in reg_str:
    labels.append(X_labels[i])
    reg.append(r)

    lr = LogisticRegression(C=r)
    lr_fit = lr.fit(X_train[i], y_train)

    # Predictions
    lr_trpred = lr.predict(X_train[i])
    lr_tvpred = lr.predict(X_val[i])
    lr_tvprob = lr.predict_proba(X_val[i])

    # Accuracies
    tr_acc.append(accuracy_score(y_train, lr_trpred))
    tv_acc.append(accuracy_score(y_val, lr_tvpred))

    # F1 Score
    F1.append(f1_score(y_val, lr_tvpred))

    # AUC Score
    auc.append(roc_auc_score(y_val, lr_tvprob[:,1]))

# Training Evaluation Results
lr_val_sumarr = np.array([labels, reg, tr_acc, tv_acc, F1, auc]).transpose()
lr_val_sum = pd.DataFrame(lr_val_sumarr, columns=metrics)
for i in metrics[2:]:
  lr_val_sum[i] = lr_val_sum[i].apply(lambda x: round(float(x),3))

# Save Training Evaluation Results
folderpath = 'model/trad_model/hyperparameter_tuning/'
filepath = folderpath + modelname + '.csv'
lr_val_sum.to_csv(filepath, index=False)

display(lr_val_sum)
```

| Input Feature Types | Regularization Strength | Training Accuracy | Validation Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|

| | Input Feature Types | Regularization Strength | Training Accuracy | Validation Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|
| **0** | Manual | 3.000 | 0.723 | 0.719 | 0.793 | 0.792 |
| **1** | Manual | 2.000 | 0.723 | 0.719 | 0.793 | 0.792 |
| **2** | Manual | 1.000 | 0.723 | 0.719 | 0.793 | 0.791 |
| **3** | Manual | 0.300 | 0.723 | 0.719 | 0.793 | 0.791 |
| **4** | Manual | 0.100 | 0.722 | 0.719 | 0.793 | 0.791 |
| **5** | Manual | 0.030 | 0.720 | 0.717 | 0.791 | 0.789 |
| **6** | Manual | 0.010 | 0.717 | 0.715 | 0.790 | 0.788 |
| **7** | Manual | 0.003 | 0.713 | 0.710 | 0.787 | 0.785 |
| **8** | Manual | 0.001 | 0.710 | 0.708 | 0.786 | 0.782 |
| **9** | CountVect | 3.000 | 0.910 | 0.868 | 0.895 | 0.956 |
| **10** | CountVect | 2.000 | 0.907 | 0.868 | 0.895 | 0.957 |
| **11** | CountVect | 1.000 | 0.905 | 0.870 | 0.896 | 0.958 |
| **12** | CountVect | 0.300 | 0.893 | 0.871 | 0.897 | 0.957 |
| **13** | CountVect | 0.100 | 0.880 | 0.869 | 0.896 | 0.954 |
| **14** | CountVect | 0.030 | 0.866 | 0.862 | 0.891 | 0.948 |
| **15** | CountVect | 0.010 | 0.851 | 0.848 | 0.882 | 0.940 |
| **16** | CountVect | 0.003 | 0.835 | 0.833 | 0.872 | 0.928 |
| **17** | CountVect | 0.001 | 0.816 | 0.814 | 0.859 | 0.911 |
| **18** | TfIdf | 3.000 | 0.929 | 0.867 | 0.894 | 0.937 |
| **19** | TfIdf | 2.000 | 0.924 | 0.869 | 0.896 | 0.937 |
| **20** | TfIdf | 1.000 | 0.906 | 0.872 | 0.898 | 0.936 |
| **21** | TfIdf | 0.300 | 0.883 | 0.870 | 0.897 | 0.932 |
| **22** | TfIdf | 0.100 | 0.868 | 0.862 | 0.892 | 0.926 |
| **23** | TfIdf | 0.030 | 0.843 | 0.840 | 0.877 | 0.915 |
| **24** | TfIdf | 0.010 | 0.814 | 0.814 | 0.860 | 0.902 |
| **25** | TfIdf | 0.003 | 0.756 | 0.761 | 0.831 | 0.885 |
| **26** | TfIdf | 0.001 | 0.688 | 0.696 | 0.799 | 0.873 |

#####Tuning

In [103]:

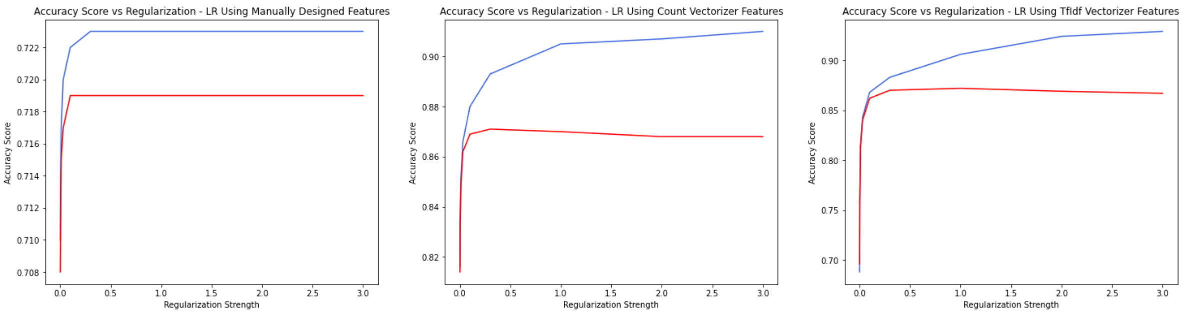
```
# Initialize Plot
plt.figure(figsize=(25,6))

# Plot Accuracies vs Regularization Strength for Logistic Regression using manually designe
plt.subplot(131)
mfd_train_acc = lr_val_sum['Training Accuracy'][lr_val_sum['Input Feature Types'] == 'Manua
mfd_test_acc = lr_val_sum['Validation Accuracy'][lr_val_sum['Input Feature Types'] == 'Manu
plt.plot(reg_str, mfd_train_acc, color='royalblue')
plt.plot(reg_str, mfd_test_acc, color='red')
plt.xlabel('Regularization Strength')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Regularization - LR Using Manually Designed Features')

# Plot Accuracies vs Regularization Strength for Logistic Regression using CountVectorizer
plt.subplot(132)
cv_train_acc = lr_val_sum['Training Accuracy'][lr_val_sum['Input Feature Types'] == 'CountV
cv_test_acc = lr_val_sum['Validation Accuracy'][lr_val_sum['Input Feature Types'] == 'Count
plt.plot(reg_str, cv_train_acc, color='royalblue')
plt.plot(reg_str, cv_test_acc, color='red')
plt.xlabel('Regularization Strength')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Regularization - LR Using Count Vectorizer Features')

# Plot Accuracies vs Regularization Strength for Logistic Regression using Tfidf features m
plt.subplot(133)
tfidf_train_acc = lr_val_sum['Training Accuracy'][lr_val_sum['Input Feature Types'] == 'TfI
tfidf_test_acc = lr_val_sum['Validation Accuracy'][lr_val_sum['Input Feature Types'] == 'Tf
plt.plot(reg_str, tfidf_train_acc, color='royalblue')
plt.plot(reg_str, tfidf_test_acc, color='red')
plt.xlabel('Regularization Strength')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Regularization - LR Using TfIdf Vectorizer Features')

plt.show()
```




#####Evaluate

In [111]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Regularization Strength', 'Training Accuracy', 'Testing
modelname = 'LogisticRegresion'
colors = ['blue', 'orange', 'red'] # indicates the corresponding color to represent in plot

# Using C=0.1 for LR in Manually Designed Features
lr_mfd = LogisticRegression(C=0.1)
lr_mfd_fit = lr_mfd.fit(X_train[0], y_train)
lr_mfd_trpred = lr_mfd.predict(X_train[0])
lr_mfd_tspred = lr_mfd.predict(X_test[0])
lr_mfd_tsprob = lr_mfd.predict_proba(X_test[0])
lr_mfd_tracc = accuracy_score(y_train, lr_mfd_trpred)
lr_mfd_tsacc = accuracy_score(y_test, lr_mfd_tspred)
lr_mfd_f1 = f1_score(y_test, lr_mfd_tspred)
lr_mfd_auc = roc_auc_score(y_test, lr_mfd_tsprob[:,1])
lr_mfd_fpr, lr_mfd_tpr, _ = roc_curve(y_test, lr_mfd_tsprob[:,1])

# Using C=0.3 for LR in CountVectorizer Features
lr_cv = LogisticRegression(C=0.3)
lr_cv_fit = lr_cv.fit(x_train_cv, y_train_tkn)
lr_cv_trpred = lr_cv.predict(x_train_cv)
lr_cv_tspred = lr_cv.predict(x_test_cv)
lr_cv_tsprob = lr_cv.predict_proba(x_test_cv)
lr_cv_tracc = accuracy_score(y_train_tkn, lr_cv_trpred)
lr_cv_tsacc = accuracy_score(y_test_tkn, lr_cv_tspred)
lr_cv_f1 = f1_score(y_test_tkn, lr_cv_tspred)
lr_cv_auc = roc_auc_score(y_test_tkn, lr_cv_tsprob[:,1])
lr_cv_fpr, lr_cv_tpr, _ = roc_curve(y_test_tkn, lr_cv_tsprob[:,1])

# Using C=1 for LR in TfIdf Vectorizer Features
lr_tfidf = LogisticRegression(C=1)
lr_tfidf_fit = lr_tfidf.fit(x_train_tf, y_train_tkn)
lr_tfidf_trpred = lr_tfidf.predict(x_train_tf)
lr_tfidf_tspred = lr_tfidf.predict(x_test_tf)
lr_tfidf_tsprob = lr_tfidf.predict_proba(x_test_tf)
lr_tfidf_tracc = accuracy_score(y_train_tkn, lr_tfidf_trpred)
lr_tfidf_tsacc = accuracy_score(y_test_tkn, lr_tfidf_tspred)
lr_tfidf_f1 = f1_score(y_test_tkn, lr_tfidf_tspred)
lr_tfidf_auc = roc_auc_score(y_test_tkn, lr_tfidf_tsprob[:,1])
lr_tfidf_fpr, lr_tfidf_tpr, _ = roc_curve(y_test_tkn, lr_tfidf_tsprob[:,1])

lr_tracc = [lr_mfd_tracc, lr_cv_tracc, lr_tfidf_tracc]
lr_tsacc = [lr_mfd_tsacc, lr_cv_tsacc, lr_tfidf_tsacc]
lr_f1 = [lr_mfd_f1, lr_cv_f1, lr_tfidf_f1]
lr_auc = [lr_mfd_auc, lr_cv_auc, lr_tfidf_auc]
lr_c = [0.1, 0.3, 1]
lr_labels = ['Manual', 'CountVect', 'TfIdf']
lr_fpr = [lr_mfd_fpr, lr_cv_fpr, lr_tfidf_fpr]
lr_tpr = [lr_mfd_tpr, lr_cv_tpr, lr_tfidf_tpr]

# Displaying final model evaluation
lr_sumarr = np.array([lr_labels, lr_c, lr_tracc, lr_tsacc, lr_f1, lr_auc]).transpose()
lr_sum = pd.DataFrame(lr_sumarr, columns=metrics)
for i in metrics[2:]:
  lr_sum[i] = lr_sum[i].apply(lambda x: round(float(x),3))

# Save Test Dataset Evaluation to File
folderpath = 'model/trad_model/model_evaluation/'
filepath = folderpath + modelname + '.csv'
```

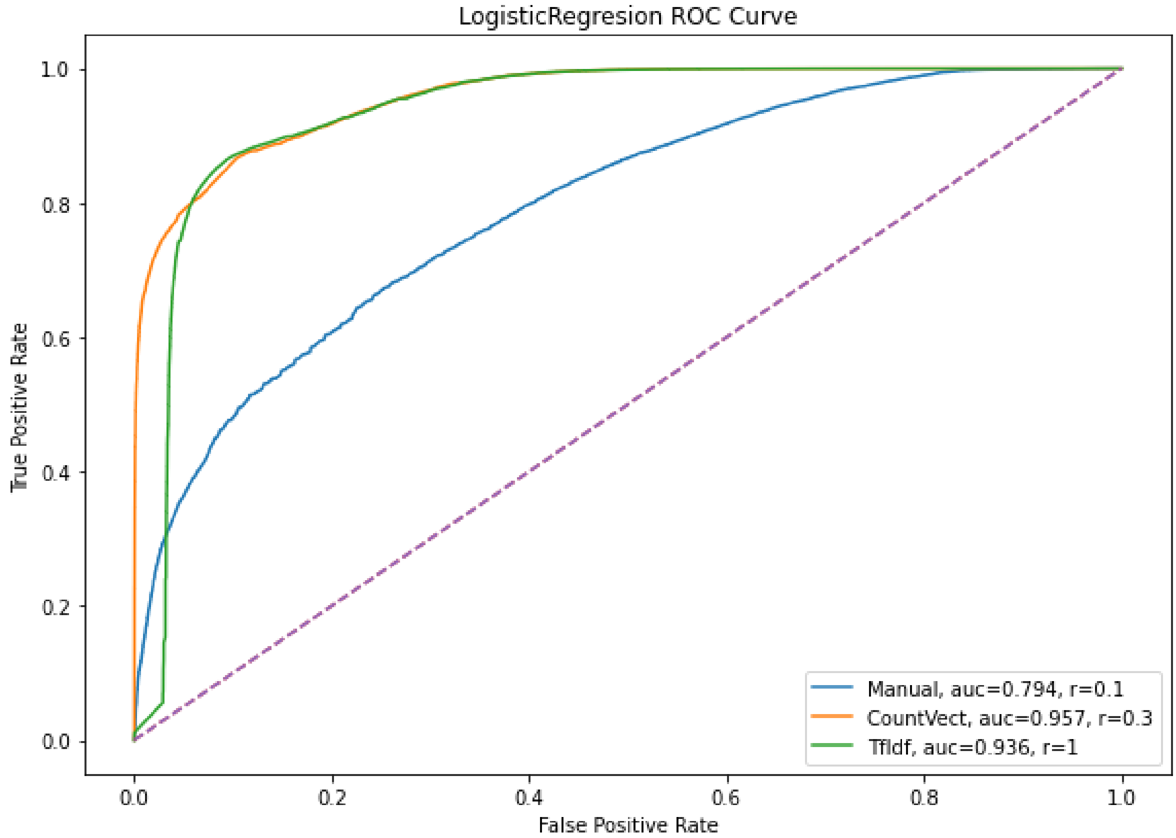
```
lr_sum.to_csv(filepath, index=False)
display(lr_sum)
```

In [ ]:

```
display(lr_sum)

# Plot of ROC Curve
plt.figure(figsize=(10,7))
for i in np.arange(len(X_labels)):
  plt.plot(lr_fpr[i],lr_tpr[i], label=lr_labels[i]+  ", auc="+str(lr_auc[i])[:5] + ", r=" +
plt.plot([(0,0), (1,1)], linestyle="--")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(modelname + ' ROC Curve')
plt.legend()
plt.show()
```

| | Input Feature Types | Regularization Strength | Training Accuracy | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|
| **0** | Manual | 0.1 | 0.722 | 0.721 | 0.794 | 0.794 |
| **1** | CountVect | 0.3 | 0.893 | 0.872 | 0.898 | 0.958 |
| **2** | TfIdf | 1 | 0.906 | 0.873 | 0.899 | 0.936 |




***Saving***

In [ ]:

```
saveModel(lr_mfd, "LR/lr_mfd_79")
saveModel(lr_cv, "LR/lr_cv_89_95") ##
saveModel(lr_tfidf, "LR/lr_tfidf_89_93")
```

#####Others

In [76]:

```
#Logistic Regression MAN
# log_model = LogisticRegression()
log_model = LogisticRegression(C=0.1)
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_scale, x_val_scale,
y_pred_prob, fpr, tpr, auc = plotROC(x_train_scale, x_val_scale,  y_train, y_val, log_model

#Logistic Regression CV
log_modelc = LogisticRegression(C=0.3)
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_cv, x_val_cv, y_train
y_pred_prob, fpr, tpr, auc = plotROC(x_train_cv, x_val_cv, y_train_cv, y_val_cv,log_modelc)

#Logistic Regression TF
log_modelt = LogisticRegression(C=1)
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_tf, x_val_tf, y_train
y_pred_prob, fpr, tpr, auc = plotROC(x_train_tf, x_val_tf, y_train_tf, y_val_tf,log_modelt)
```

**KNN**

#####Training

In [77]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Nearest Neighbors', 'Training Accuracy', 'Validation Acc
n_neighbor = [3, 5, 7] # different number of neighbors to try out
modelname = 'KNN'

colors = ['blue', 'orange', 'red'] # indicates the corresponding color to represent in plot

# Initialize
labels = []
neighbor = []
tr_acc = []
tv_acc = []
F1 = []
auc = []
fpr = []
tpr = []

# for i in range(len(X_labels)):
for i in [1,2]:
  for n in n_neighbor:
    labels.append(X_labels[i])
    neighbor.append(n)

    knn = KNeighborsClassifier(n_neighbors=n)
    knn_fit = knn.fit(X_train[i], y_train)
    saveModel(knn_fit, str(modelname)+str(i)+"_"+str(n))

    # Predictions
    knn_trpred = knn.predict(X_train[i])
    knn_tvpred = knn.predict(X_val[i])
    knn_tvprob = knn.predict_proba(X_val[i])

    # Accuracies
    tr_acc.append(accuracy_score(y_train, knn_trpred))
    tv_acc.append(accuracy_score(y_val, knn_tvpred))

    # F1 Score
    F1.append(f1_score(y_val, knn_tvpred))

    # AUC Score
    auc.append(roc_auc_score(y_val, knn_tvprob[:,1]))

    print(str(modelname) + str(X_labels[i]) + "_n=" + str(n), str(accuracy_score(y_val, knn
          str(roc_auc_score(y_val, knn_tvprob[:,1])))

# Training Evaluation Results
knn_val_sumarr = np.array([labels, neighbor, tr_acc, tv_acc, F1, auc]).transpose()
knn_val_sum = pd.DataFrame(knn_val_sumarr, columns=metrics)
for i in metrics[2:]:
  knn_val_sum[i] = knn_val_sum[i].apply(lambda x: round(float(x),3))

# Save Training Evaluation Results
folderpath = 'model/trad_model/hyperparameter_tuning/'
filepath = folderpath + modelname + '.csv'
knn_val_sum.to_csv(filepath, index=False)

display(knn_val_sum)
```

| | Input Feature Types | Nearest Neighbors | Validation Acc | AUC Score |
|---|---|---|---|---|
| **0** | Manual | 3 | 0.835433 | 0.903900 |
| **1** | Manual | 5 | 0.838951 | 0.922829 |
| **2** | Manual | 7 | 0.842209 | 0.929550 |
| **3** | CountVect | 3 | 0.807000 | 0.900000 |
| **4** | CountVect | 5 | 0.836000 | 0.920000 |
| **5** | CountVect | 7 | 0.841000 | 0.927000 |
| **6** | TfIdf | 3 | 0.757000 | 0.874000 |
| **7** | TfIdf | 5 | 0.713000 | 0.833000 |
| **8** | TfIdf | 7 | 0.688000 | 0.834000 |

#####Tuning

In [99]:

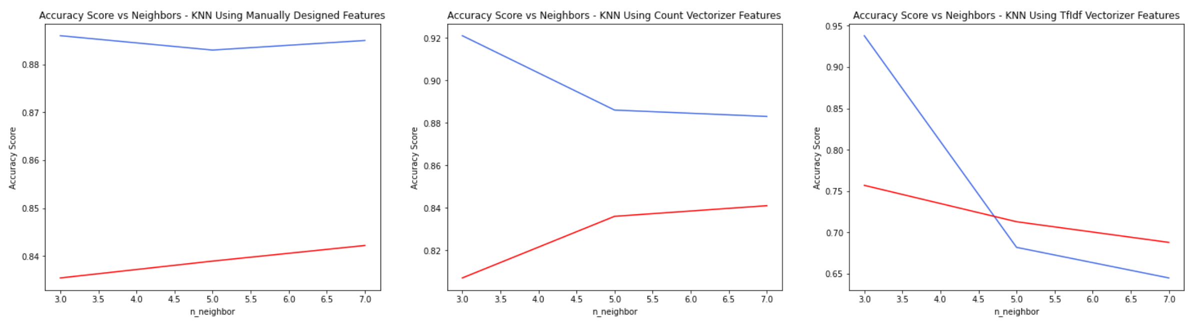
```
# Initialize Plot
plt.figure(figsize=(25,6))

# Plot Accuracies vs Regularization Strength for Logistic Regression using manually designe
plt.subplot(131)
n_neighbor = knn_val_sum['Nearest Neighbors'][knn_val_sum['Input Feature Types'] == 'Manual
mfd_train_acc = knn_val_sum['Training Accuracy'][knn_val_sum['Input Feature Types'] == 'Man
mfd_test_acc = knn_val_sum['Validation Accuracy'][knn_val_sum['Input Feature Types'] == 'Ma
plt.plot(n_neighbor, mfd_train_acc, color='royalblue')
plt.plot(n_neighbor, mfd_test_acc, color='red')
plt.xlabel('n_neighbor')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Neighbors - KNN Using Manually Designed Features')

# Plot Accuracies vs Regularization Strength for Logistic Regression using CountVectorizer
plt.subplot(132)
n_neighbor = knn_val_sum['Nearest Neighbors'][knn_val_sum['Input Feature Types'] == 'CountV
cv_train_acc = knn_val_sum['Training Accuracy'][knn_val_sum['Input Feature Types'] == 'Coun
cv_test_acc = knn_val_sum['Validation Accuracy'][knn_val_sum['Input Feature Types'] == 'Cou
plt.plot(n_neighbor, cv_train_acc, color='royalblue')
plt.plot(n_neighbor, cv_test_acc, color='red')
plt.xlabel('n_neighbor')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Neighbors - KNN Using Count Vectorizer Features')

# Plot Accuracies vs Regularization Strength for Logistic Regression using Tfidf features m
plt.subplot(133)
n_neighbor = knn_val_sum['Nearest Neighbors'][knn_val_sum['Input Feature Types'] == 'TfIdf'
tfidf_train_acc = knn_val_sum['Training Accuracy'][knn_val_sum['Input Feature Types'] == 'T
tfidf_test_acc = knn_val_sum['Validation Accuracy'][knn_val_sum['Input Feature Types'] == '
plt.plot(n_neighbor, tfidf_train_acc, color='royalblue')
plt.plot(n_neighbor, tfidf_test_acc, color='red')
plt.xlabel('n_neighbor')
plt.ylabel('Accuracy Score')
plt.title('Accuracy Score vs Neighbors - KNN Using TfIdf Vectorizer Features')

plt.show()
```




#####Evaluate

In [113]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Nearest Neighbors', 'Training Accuracy', 'Testing Accura
modelname = 'KNN'
colors = ['blue', 'orange', 'red'] # indicates the corresponding color to represent in plot

X_train_mfd, X_train_cv, X_train_tfidf = X_train[0], X_train[1], X_train[2]
X_test_mfd, X_test_cv, X_test_tfidf = X_test[0], X_test[1], X_test[2]

# Using num_neighbor=9 for KNN in Manually Designed Features
# knn_mfd = KNeighborsClassifier(n_neighbors = 9)
# knn_mfd_fit = knn_mfd.fit(X_train_mfd, y_train)
knn_mfd = pickle.load(open("model\KNN\KnnMod\.KNN0_5.pkl", 'rb'))
knn_mfd_trpred = knn_mfd.predict(X_train_mfd)
knn_mfd_tspred = knn_mfd.predict(X_test_mfd)
knn_mfd_tsprob = knn_mfd.predict_proba(X_test_mfd)
knn_mfd_tracc = accuracy_score(y_train, knn_mfd_trpred)
knn_mfd_tsacc = accuracy_score(y_test, knn_mfd_tspred)
knn_mfd_f1 = f1_score(y_test, knn_mfd_tspred)
knn_mfd_auc = roc_auc_score(y_test, knn_mfd_tsprob[:,1])
knn_mfd_fpr, knn_mfd_tpr, _ = roc_curve(y_test, knn_mfd_tsprob[:,1])

y_train = y_train_tkn
y_test = y_test_tkn
# Using num_neighbor=5 for KNN in CountVectorizer Features
# knn_cv = KNeighborsClassifier(n_neighbors = 5)
# knn_cv_fit = knn_cv.fit(X_train_cv, y_train)
knn_cv = pickle.load(open("model\KNN\KnnMod\.KNN1_5.pkl", 'rb'))
knn_cv_trpred = knn_cv.predict(X_train_cv)
knn_cv_tspred = knn_cv.predict(X_test_cv)
knn_cv_tsprob = knn_cv.predict_proba(X_test_cv)
knn_cv_tracc = accuracy_score(y_train, knn_cv_trpred)
knn_cv_tsacc = accuracy_score(y_test, knn_cv_tspred)
knn_cv_f1 = f1_score(y_test, knn_cv_tspred)
knn_cv_auc = roc_auc_score(y_test, knn_cv_tsprob[:,1])
knn_cv_fpr, knn_cv_tpr, _ = roc_curve(y_test, knn_cv_tsprob[:,1])

# Using num_neighbor=5 for KNN in TfIdf Vectorizer Features
# knn_tfidf = KNeighborsClassifier(n_neighbors = 3)
# knn_tfidf_fit = knn_tfidf.fit(X_train_tfidf, y_train)
knn_tfidf = pickle.load(open("model\KNN\KnnMod\.KNN2_3.pkl", 'rb'))
knn_tfidf_trpred = knn_tfidf.predict(X_train_tfidf)
knn_tfidf_tspred = knn_tfidf.predict(X_test_tfidf)
knn_tfidf_ttsprob = knn_tfidf.predict_proba(X_test_tfidf)
knn_tfidf_tracc = accuracy_score(y_train, knn_tfidf_trpred)
knn_tfidf_tsacc = accuracy_score(y_test, knn_tfidf_tspred)
knn_tfidf_f1 = f1_score(y_test, knn_tfidf_tspred)
knn_tfidf_auc = roc_auc_score(y_test, knn_tfidf_tsprob[:,1])
knn_tfidf_fpr, knn_tfidf_tpr, _ = roc_curve(y_test, knn_tfidf_tsprob[:,1])

knn_tracc = [knn_mfd_tracc, knn_cv_tracc, knn_tfidf_tracc]
knn_tsacc = [knn_mfd_tsacc, knn_cv_tsacc, knn_tfidf_tsacc]
knn_f1 = [knn_mfd_f1, knn_cv_f1, knn_tfidf_f1]
knn_auc = [knn_mfd_auc, knn_cv_auc, knn_tfidf_auc]
knn_neighbor = [5,5,3]
knn_labels = ['Manual', 'CountVect', 'TfIdf']
knn_fpr = [knn_mfd_fpr, knn_cv_fpr, knn_tfidf_fpr]
knn_tpr = [knn_mfd_tpr, knn_cv_tpr, knn_tfidf_tpr]

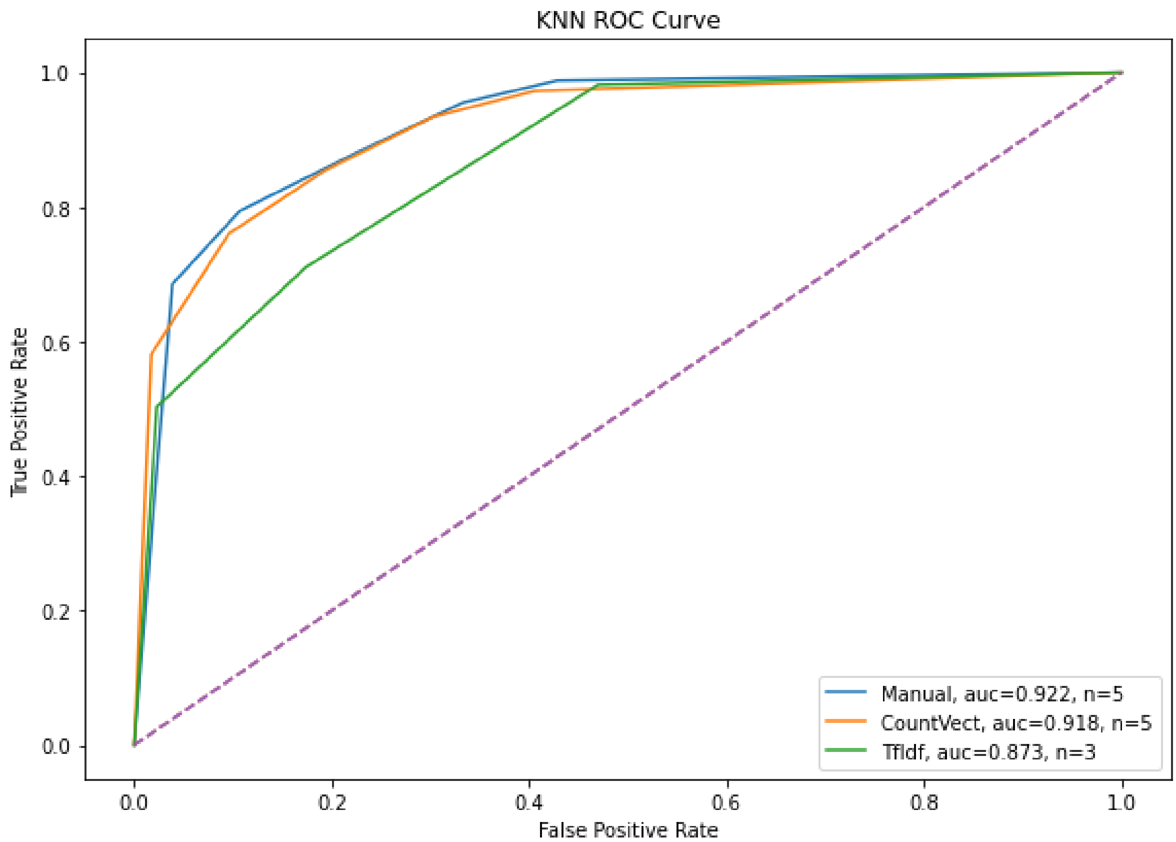
# Displaying final model evaluation
```

```
knn_sumarr = np.array([knn_labels, knn_neighbor, knn_tracc, knn_tsacc, knn_f1, knn_auc]).tr
knn_sum = pd.DataFrame(knn_sumarr, columns=metrics)
for i in metrics[2:]:
  knn_sum[i] = knn_sum[i].apply(lambda x: round(float(x),3))

# Save Test Dataset Evaluation to File
folderpath = 'model/trad_model/model_evaluation/'
filepath = folderpath + modelname + '.csv'
knn_sum.to_csv(filepath, index=False)
display(knn_sum)

# Plot of ROC Curve
plt.figure(figsize=(10,7))
for i in np.arange(len(X_labels)):
  plt.plot(knn_fpr[i],knn_tpr[i], label=knn_labels[i]+  ", auc="+str(knn_auc[i])[:5] + ", n
plt.plot([(0,0), (1,1)], linestyle="--")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(modelname + ' ROC Curve')
plt.legend()
plt.show()
```

| | Input Feature Types | Nearest Neighbors | Training Accuracy | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|
| **0** | Manual | 5 | 0.881 | 0.839 | 0.870 | 0.923 |
| **1** | CountVect | 5 | 0.886 | 0.836 | 0.864 | 0.919 |
| **2** | TfIdf | 3 | 0.938 | 0.756 | 0.780 | 0.873 |



#####Save ModeL

In [94]:

```
saveModel(knn_mfd, "KNN/KNN_Man_5")
saveModel(knn_cv, "KNN/KNN_CV_5") ##
saveModel(knn_tfidf, "KNN/KNN_TF3")
```

#####Others

**Decision Tree**

In [ ]:

```
#perform GridSearchCV
param_grid = {'criterion':['gini', 'entropy'], 'max_depth':np.arange(2,10), 'min_samples_sp
dt_model = DecisionTreeClassifier()
best_score, best_params = gridSearchCV(x_train, x_test, y_train, y_test, dt_model, param_gr
# Best Score:0.7857002239147877
# Best Parameters: {'criterion': 'entropy', 'max_depth': 9, 'min_samples_split': 35}
```

```
Best Score:0.785700223914787
Best Parameters: {'criterion': 'entropy', 'max_depth': 9, 'min_samples_spli
t': 35}
```

In [143]:

```
#Decision Tree 78,86
dt_model = DecisionTreeClassifier(min_samples_split=35, max_depth=9,criterion='entropy')
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train, x_val,  y_train, y_v
y_pred_prob, fpr_man, tpr_man, auc_man = plotROC(x_train, x_val,  y_train, y_val, dt_model)
```

```
DecisionTreeClassifier
Train Accuracy Score: 0.7888044548090479
Test Accuracy Score: 0.7870192208222125

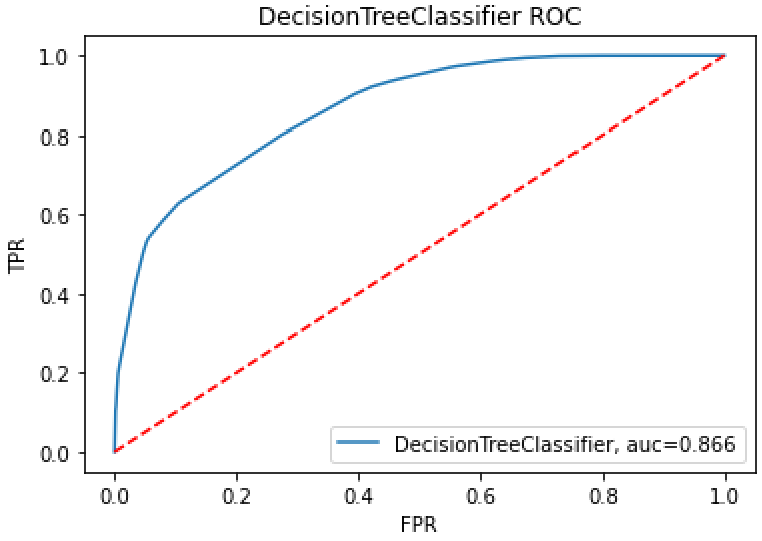
[[21852 15877]
 [ 4711 54226]]
              precision    recall  f1-score   support

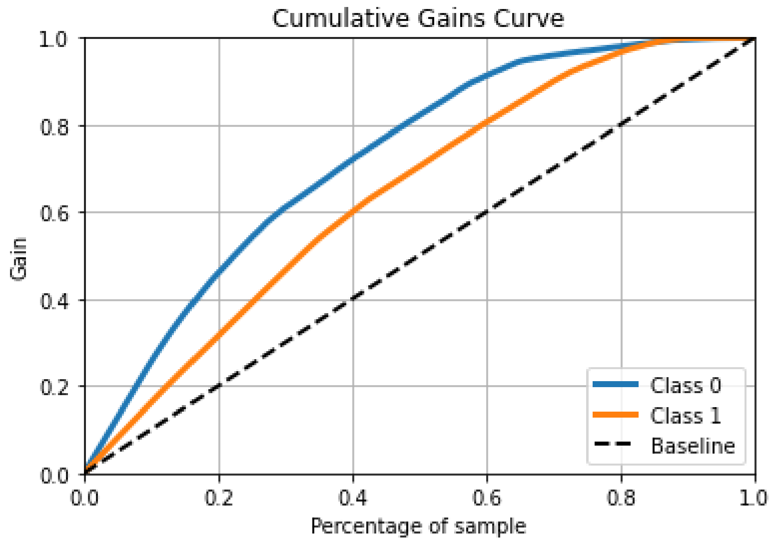
           0       0.82      0.58      0.68     37729
           1       0.77      0.92      0.84     58937

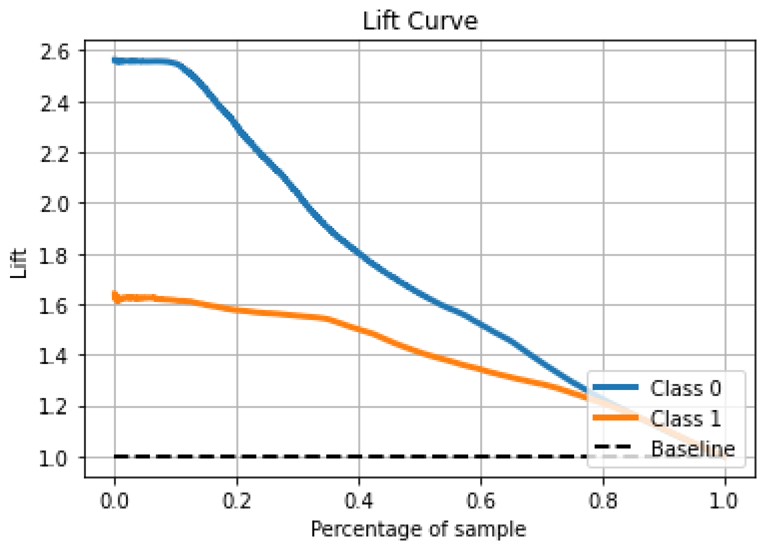
    accuracy                           0.79     96666
   macro avg       0.80      0.75      0.76     96666
weighted avg       0.79      0.79      0.78     96666
```

In [ ]:

```
plotROC_CummGain_Lift(x_train, x_val,  y_train, y_val, dt_model)
```



In [138]:

```
#perform GridSearchCV
param_grid = {'criterion':['gini', 'entropy'], 'max_depth':np.arange(2,10), 'min_samples_sp
dt_model_cv = DecisionTreeClassifier()
best_score, best_params = gridSearchCV(x_train_cv, x_val_cv, y_train_cv, y_val_cv, dt_model
```

In [144]:

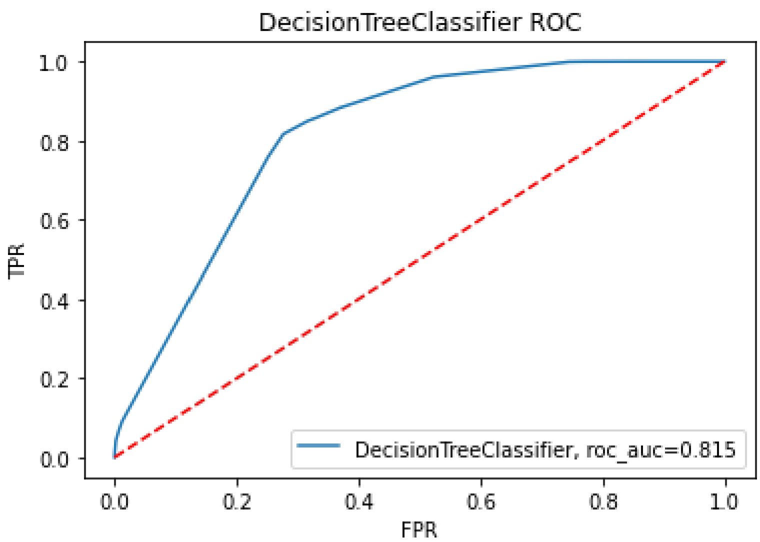
```
#Decision Tree #99,96
dt_model_cv = DecisionTreeClassifier(min_samples_split=35, max_depth=9,criterion='entropy')
# dt_model_cv = DecisionTreeClassifier()
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_cv, x_val_cv, y_train
y_pred_prob, fpr_cv, tpr_cv, auc_cv = plotROC(x_train_cv, x_val_cv, y_train_cv, y_val_cv, d
```

```
DecisionTreeClassifier
Train Accuracy Score: 0.7868647862596096
Test Accuracy Score: 0.7843295471003249

[[23749 13980]
 [ 6868 52069]]
              precision    recall  f1-score   support

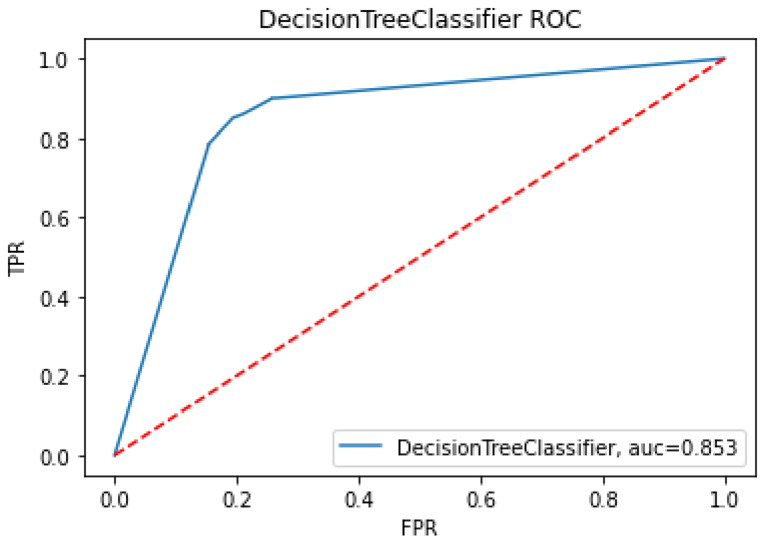
           0       0.78      0.63      0.69     37729
           1       0.79      0.88      0.83     58937

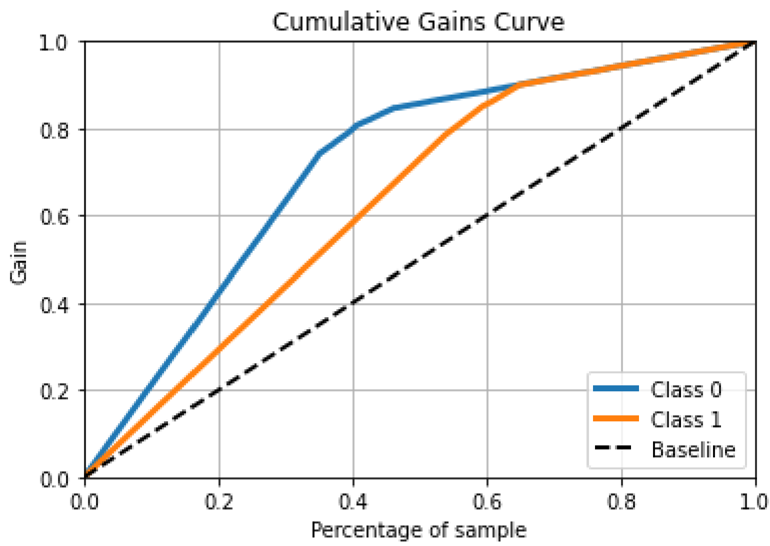
    accuracy                           0.78     96666
   macro avg       0.78      0.76      0.76     96666
weighted avg       0.78      0.78      0.78     96666
```

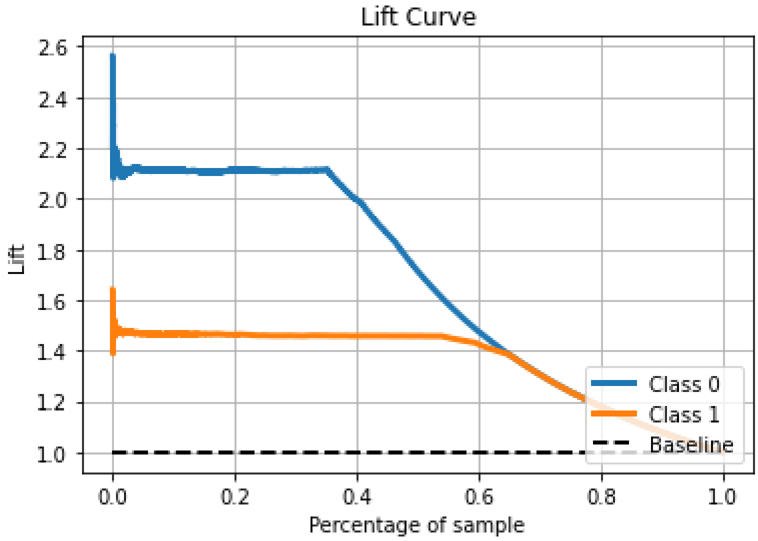


In [121]:

```
plotROC_CummGain_Lift(x_train_cv, x_val_cv, y_train_cv, y_val_cv, dt_model_cv)
```




Lift Curve
Lift
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Percentage of sample
Class 0
Class 1
Baseline

In [145]:

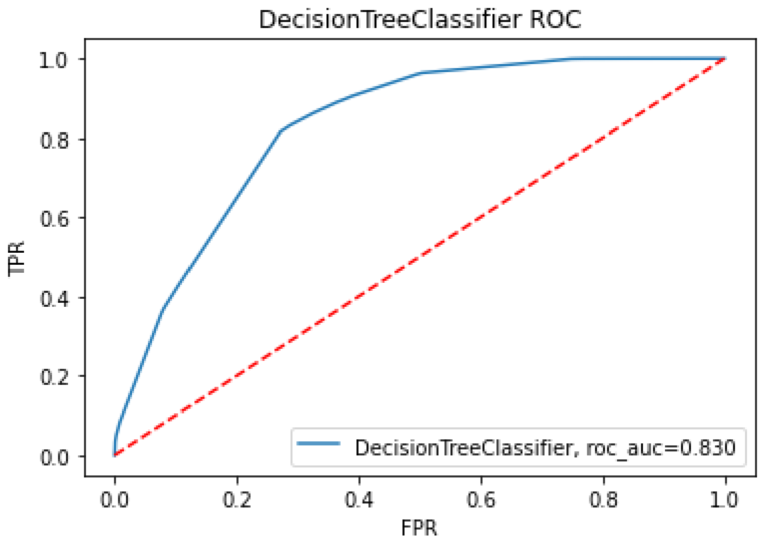
```
dt_model_tf = DecisionTreeClassifier(min_samples_split=50, max_depth=10,criterion='entropy'
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_tf, x_val_tf, y_train
y_pred_prob, fpr_tf, tpr_tf, auc_tf = plotROC(x_train_tf, x_val_tf, y_train_tf, y_val_tf,dt
```

```
DecisionTreeClassifier
Train Accuracy Score: 0.7929431533025351
Test Accuracy Score: 0.7903916578735026

[[23557 14172]
 [ 6090 52847]]
              precision    recall  f1-score   support

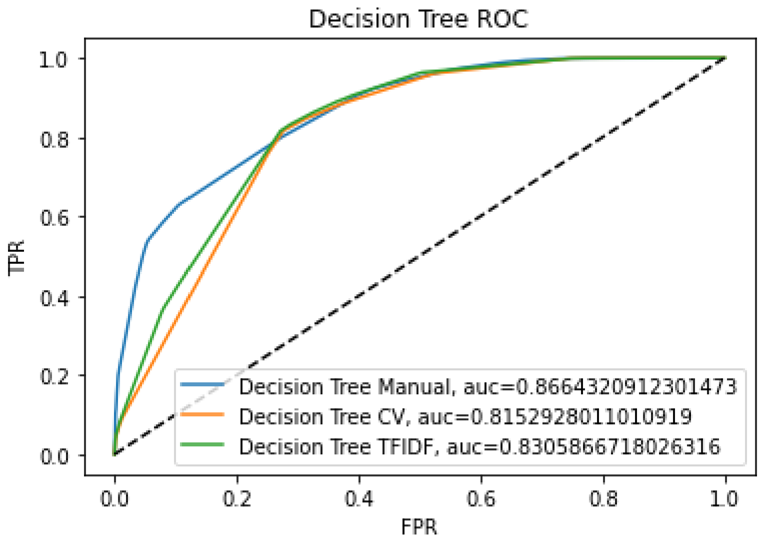
           0       0.79      0.62      0.70     37729
           1       0.79      0.90      0.84     58937

    accuracy                           0.79     96666
   macro avg       0.79      0.76      0.77     96666
weighted avg       0.79      0.79      0.78     96666
```



In [146]:

```
plt.title("Decision Tree" + " ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.plot(fpr_man,tpr_man,label="Decision Tree Manual, auc="+str(auc_man))
plt.plot(fpr_cv,tpr_cv,label="Decision Tree CV, auc="+str(auc_cv))
plt.plot(fpr_tf,tpr_tf,label="Decision Tree TFIDF, auc="+str(auc_tf))
plt.plot([0,1],[0,1],'k--')
plt.legend(loc=4)
plt.show()
```




In [142]:

```
saveModel(dt_model, "dt")
saveModel(dt_model_cv, "dt_cv")
saveModel(dt_model_tf, "dt_tf")
```

**Random Forest**

#####Training

In [152]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Number of Trees', 'Max Features Per Tree', 'Training Acc
n_trees = [3,5,10,25,50] # number of trees in RF to try out
n_features = [4,10,20,50] # number of features per tree to try out
modelname = 'RandomForest'

# Initialize
labels = []
tree = []
feature = []
tr_acc = []
tv_acc = []
F1 = []
auc = []
fpr = []
tpr = []

# Y_train=[y_train, y_train_tkn, y_train_tkn]
# Y_val=[y_val, y_val_tkn, y_train_tkn]
for i in range(len(X_labels)):
  for t in n_trees:
    for f in n_features:
      if f <= X_train[i].shape[1]:
        labels.append(X_labels[i])
        tree.append(t)
        feature.append(f)

        rf = RandomForestClassifier(n_estimators=t, max_features=f)
        rf_fit = rf.fit(X_train[i], Y_train[i])

        # Predictions
        rf_trpred = rf.predict(X_train[i])
        rf_tvpred = rf.predict(X_val[i])
        rf_tvprob = rf.predict_proba(X_val[i])

        # Accuracies
        tr_acc.append(accuracy_score(Y_train[i], rf_trpred))
        tv_acc.append(accuracy_score(Y_val[i], rf_tvpred))

        # F1 Score
        F1.append(f1_score(y_val, rf_tvpred))

        # AUC Score
        auc.append(roc_auc_score(Y_val[i], rf_tvprob[:,1]))

        print(str(modelname) + str(X_labels[i]) + "_tree" + str(t) +
              "_feature" + str(f), str(accuracy_score(Y_train[i], rf_trpred)),
              str(accuracy_score(y_val, rf_tvpred)),
              str(f1_score(Y_val[i], rf_tvpred)),
              str(roc_auc_score(Y_val[i], rf_tvprob[:,1])))


# Training Evaluation Results
rf_val_sum = np.array([labels, tree, feature, tr_acc, tv_acc, F1, auc]).transpose()
rf_val_sum = pd.DataFrame(rf_val_sum, columns=metrics)
for i in metrics[3:]:
  rf_val_sum[i] = rf_val_sum[i].apply(lambda x: round(float(x),3))

# Save Training Evaluation Results
```

```
folderpath = 'model/trad_model/hyperparameter_tuning/'
filepath = folderpath + modelname + '.csv'
rf_val_sum.to_csv(filepath, index=False)

display(rf_val_sum)
```

| | Input Feature Types | n_tree | n_features | Validation Acc | AUC Score |
|---|---|---|---|---|---|
| **0** | Manual | 50 | 10 | 0.837895 | 0.932350 |
| **1** | Manual | 50 | 20 | 0.836954 | 0.932134 |
| **2** | TfIdf | 50 | 4 | 0.849000 | 0.932000 |
| **3** | TfIdf | 50 | 20 | 0.848000 | 0.932000 |
| **4** | Manual | 50 | 4 | 0.838402 | 0.931900 |
| **5** | TfIdf | 50 | 50 | 0.843000 | 0.931000 |
| **6** | Manual | 25 | 10 | 0.837730 | 0.930399 |
| **7** | Manual | 25 | 4 | 0.837554 | 0.929979 |
| **8** | Manual | 25 | 20 | 0.836654 | 0.929886 |
| **9** | TfIdf | 25 | 20 | 0.846709 | 0.929848 |
| **10** | TfIdf | 25 | 4 | 0.844464 | 0.929208 |
| **11** | TfIdf | 25 | 10 | 0.844620 | 0.928823 |
| **12** | TfIdf | 25 | 50 | 0.841899 | 0.928358 |
| **13** | Manual | 10 | 10 | 0.835640 | 0.923913 |
| **14** | Manual | 10 | 20 | 0.834233 | 0.923837 |
| **15** | Manual | 10 | 4 | 0.835547 | 0.923834 |
| **16** | TfIdf | 10 | 20 | 0.842623 | 0.919444 |
| **17** | TfIdf | 10 | 4 | 0.840989 | 0.919026 |
| **18** | TfIdf | 10 | 10 | 0.844620 | 0.918485 |
| **19** | TfIdf | 10 | 50 | 0.840937 | 0.918193 |
| **20** | Manual | 5 | 10 | 0.834202 | 0.914288 |
| **21** | Manual | 5 | 4 | 0.835423 | 0.914161 |
| **22** | Manual | 5 | 20 | 0.834182 | 0.913462 |
| **23** | CountVect | 5 | 10 | 0.844744 | 0.909507 |
| **24** | CountVect | 5 | 20 | 0.844175 | 0.908343 |
| **25** | CountVect | 5 | 50 | 0.840575 | 0.907260 |
| **26** | CountVect | 5 | 4 | 0.841195 | 0.907189 |
| **27** | TfIdf | 5 | 10 | 0.835723 | 0.904676 |
| **28** | TfIdf | 5 | 50 | 0.836602 | 0.904648 |
| **29** | TfIdf | 5 | 20 | 0.835330 | 0.904063 |
| **30** | TfIdf | 5 | 4 | 0.840958 | 0.903906 |
| **31** | Manual | 3 | 10 | 0.832247 | 0.901872 |
| **32** | Manual | 3 | 20 | 0.832402 | 0.901590 |

| | Input Feature Types | n_tree | n_features | Validation Acc | AUC Score |
|---|---|---|---|---|---|
| **33** | Manual | 3 | 4 | 0.830520 | 0.900348 |
| **34** | CountVect | 3 | 20 | 0.838920 | 0.892374 |
| **35** | CountVect | 3 | 50 | 0.841175 | 0.892244 |
| **36** | CountVect | 3 | 4 | 0.834668 | 0.891691 |
| **37** | CountVect | 3 | 10 | 0.835682 | 0.891585 |
| **38** | TfIdf | 3 | 50 | 0.836571 | 0.891052 |
| **39** | TfIdf | 3 | 10 | 0.834668 | 0.890138 |
| **40** | TfIdf | 3 | 4 | 0.835578 | 0.888209 |
| **41** | TfIdf | 3 | 20 | 0.831182 | 0.887426 |

#####Evaluate

In [170]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Number of Trees', 'Max Features Per Tree', 'Training Acc
modelname = 'RandomForest'
colors = ['blue', 'orange', 'red'] # indicates the corresponding color to represent in plot

X_train_mfd, X_train_cv, X_train_tfidf = X_train[0], X_train[1], X_train[2]
X_test_mfd, X_test_cv, X_test_tfidf = X_test[0], X_test[1], X_test[2]

# Using num_tree=50, max_feature=10 for RF in Manually Designed Features
rf_mfd = RandomForestClassifier(n_estimators=50, max_features=10)
rf_mfd_fit = rf_mfd.fit(X_train_mfd, y_train)
rf_mfd_trpred = rf_mfd.predict(X_train_mfd)
rf_mfd_tspred = rf_mfd.predict(X_test_mfd)
rf_mfd_tsprob = rf_mfd.predict_proba(X_test_mfd)
rf_mfd_tracc = accuracy_score(y_train, rf_mfd_trpred)
rf_mfd_tsacc = accuracy_score(y_test, rf_mfd_tspred)
rf_mfd_f1 = f1_score(y_test, rf_mfd_tspred)
rf_mfd_auc = roc_auc_score(y_test, rf_mfd_tsprob[:,1])
rf_mfd_fpr, rf_mfd_tpr, _ = roc_curve(y_test, rf_mfd_tsprob[:,1])


y_train = y_train_tkn
y_test = y_test_tkn

# Using num_tree=5, max_feature=10 for RF in CountVectorizer Features
rf_cv = RandomForestClassifier(n_estimators=10, max_features=20)
rf_cv_fit = rf_cv.fit(X_train_cv, y_train_tkn)
rf_cv_trpred = rf_cv.predict(X_train_cv)
rf_cv_tspred = rf_cv.predict(X_test_cv)
rf_cv_tsprob = rf_cv.predict_proba(X_test_cv)
rf_cv_tracc = accuracy_score(y_train_tkn, rf_cv_trpred)
rf_cv_tsacc = accuracy_score(y_test, rf_cv_tspred)
rf_cv_f1 = f1_score(y_test_tkn, rf_cv_tspred)
rf_cv_auc = roc_auc_score(y_test_tkn, rf_cv_tsprob[:,1])
rf_cv_fpr, rf_cv_tpr, _ = roc_curve(y_test_tkn, rf_cv_tsprob[:,1])

# Using num_tree=50, max_feature=4 for RF in TfIdf Vectorizer Features
rf_tfidf = RandomForestClassifier(n_estimators=50, max_features=4)
rf_tfidf_fit = rf_tfidf.fit(X_train_tfidf, y_train_tkn)
rf_tfidf_trpred = rf_tfidf.predict(X_train_tfidf)
rf_tfidf_tspred = rf_tfidf.predict(X_test_tfidf)
rf_tfidf_tsprob = rf_tfidf.predict_proba(X_test_tfidf)
rf_tfidf_tracc = accuracy_score(y_train_tkn, rf_tfidf_trpred)
rf_tfidf_tsacc = accuracy_score(y_test_tkn, rf_tfidf_tspred)
rf_tfidf_f1 = f1_score(y_test, rf_tfidf_tspred)
rf_tfidf_auc = roc_auc_score(y_test_tkn, rf_tfidf_tsprob[:,1])
rf_tfidf_fpr, rf_tfidf_tpr, _ = roc_curve(y_test_tkn, rf_tfidf_tsprob[:,1])

rf_tracc = [rf_mfd_tracc, rf_cv_tracc, rf_tfidf_tracc]
rf_tsacc = [rf_mfd_tsacc, rf_cv_tsacc, rf_tfidf_tsacc]
rf_f1 = [rf_mfd_f1, rf_cv_f1, rf_tfidf_f1]
rf_auc = [rf_mfd_auc, rf_cv_auc, rf_tfidf_auc]
rf_tree = [50, 5, 50]
rf_feature = [10, 10, 4]
rf_labels = ['Manual', 'CountVect', 'TfIdf']
rf_fpr = [rf_mfd_fpr, rf_cv_fpr, rf_tfidf_fpr]
rf_tpr = [rf_mfd_tpr, rf_cv_tpr, rf_tfidf_tpr]

# Displaying final model evaluation
```

```
rf_sumarr = np.array([rf_labels, rf_tree, rf_feature, rf_tracc, rf_tsacc, rf_f1, rf_auc]).t
rf_sum = pd.DataFrame(rf_sumarr, columns=metrics)
for i in metrics[3:]:
  rf_sum[i] = rf_sum[i].apply(lambda x: round(float(x),3))

# Save Test Dataset Evaluation to File
folderpath = 'model/trad_model/model_evaluation/'
filepath = folderpath + modelname + '.csv'
rf_sum.to_csv(filepath, index=False)
display(rf_sum)

# Plot of ROC Curve
plt.figure(figsize=(10,7))
for i in np.arange(len(X_labels)):
  plt.plot(rf_fpr[i],rf_tpr[i], label=rf_labels[i]+  ", auc="+str(rf_auc[i])[:5] + ", r=" +
plt.plot([(0,0), (1,1)], linestyle="--")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(modelname + ' ROC Curve')
plt.legend()
plt.show()
```

| | Input Feature Types | n_tree | n_features | Validation Accuracy | AUC Score |
|---|---|---|---|---|---|
| **0** | Manual | 50 | 10 | 0.837895 | 0.932350 |
| **1** | CountVect | 5 | 10 | 0.844744 | 0.909507 |
| **2** | TfIdf | 50 | 4 | 0.849000 | 0.932000 |

#####Save

#####Others

In [179]:

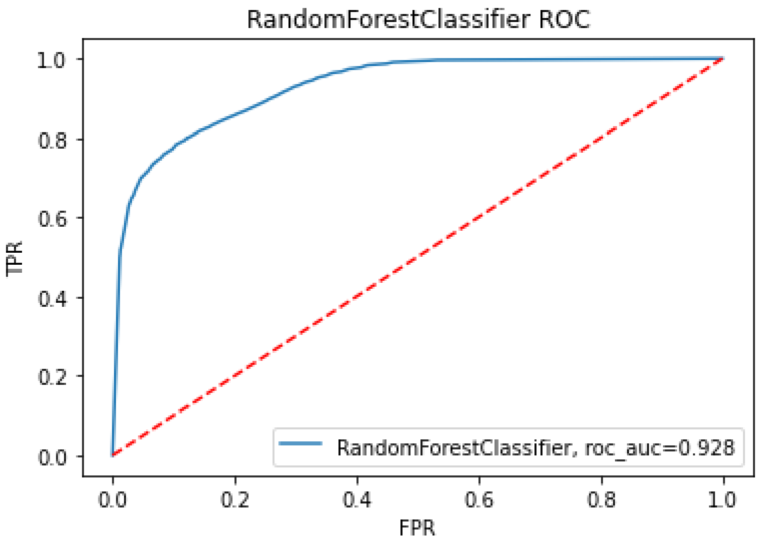
```
rfman = RandomForestClassifier(n_estimators=50, max_features=10)
tr_predict_man, ts_predict_man, tr_accuracy_man, ts_accuracy_man = perfResult(x_train, x_te
y_pred_prob_man, fpr_man, tpr_man, auc_man = plotROC(x_train, x_test,  y_train, y_test, rfm
```

```
RandomForestClassifier
Train Accuracy Score: 0.9175563279746757
Test Accuracy Score: 0.8355591877269388

[[29162  8568]
 [ 7328 51609]]
              precision    recall  f1-score   support

           0       0.80      0.77      0.79     37730
           1       0.86      0.88      0.87     58937

    accuracy                           0.84     96667
   macro avg       0.83      0.82      0.83     96667
weighted avg       0.83      0.84      0.84     96667
```



In [184]:

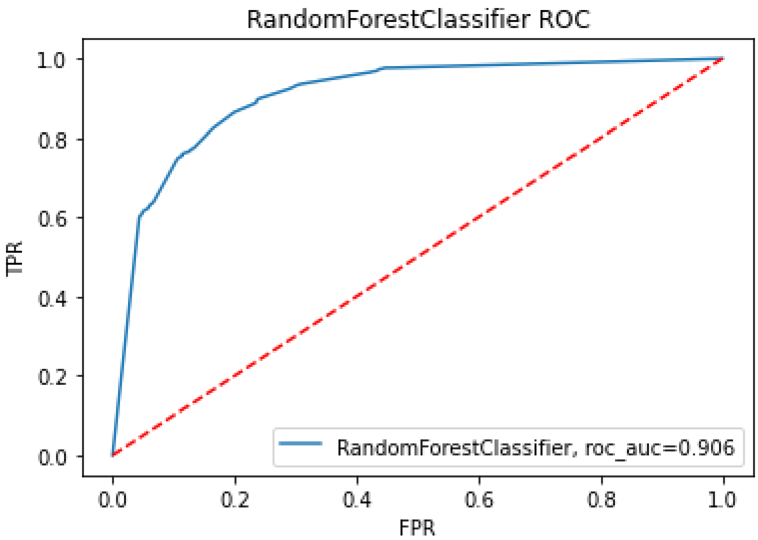
```
rfcv = RandomForestClassifier(n_estimators=5, max_features=10)
tr_predict_cv, ts_predict_cv, tr_accuracy_cv, ts_accuracy_cv = perfResult(x_train_cv, x_tes
y_pred_prob_cv, fpr_cv, tpr_cv, auc_cv = plotROC(x_train_cv, x_test_cv,  y_train_cv, y_test
```

```
RandomForestClassifier
Train Accuracy Score: 0.9405308706562509
Test Accuracy Score: 0.8399557242906059

[[29271  8459]
 [ 7012 51925]]
              precision    recall  f1-score   support

           0       0.81      0.78      0.79     37730
           1       0.86      0.88      0.87     58937

    accuracy                           0.84     96667
   macro avg       0.83      0.83      0.83     96667
weighted avg       0.84      0.84      0.84     96667
```



In [180]:

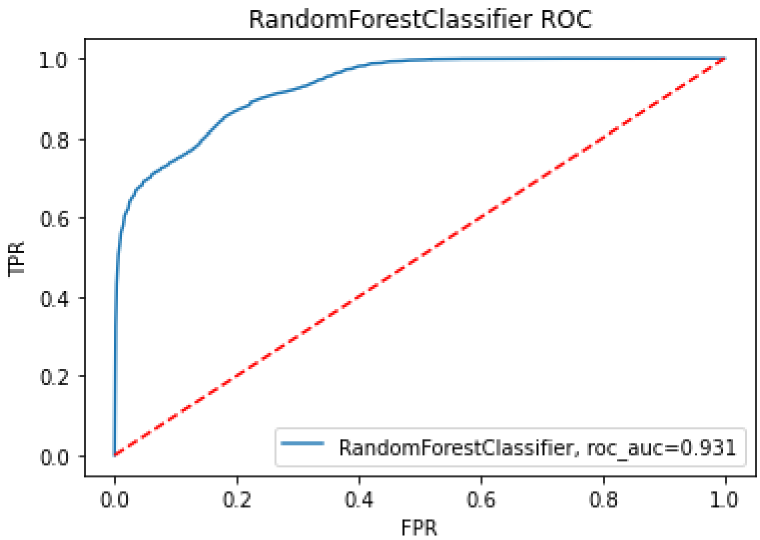
```
rfc2 = RandomForestClassifier(n_estimators=50, max_features=4)
tr_predict_tf, ts_predict_tf, tr_accuracy_tf, ts_accuracy_tf = perfResult(x_train_tf, x_tes
y_pred_prob_tf, fpr_tf, tpr_tf, auc_tf = plotROC(x_train_tf, x_test_tf, y_train_tf, y_test_
```

```
RandomForestClassifier
Train Accuracy Score: 0.9452437110403717
Test Accuracy Score: 0.8457488077627319

[[29334  8396]
 [ 6515 52422]]
              precision    recall  f1-score   support

           0       0.82      0.78      0.80     37730
           1       0.86      0.89      0.88     58937

    accuracy                           0.85     96667
   macro avg       0.84      0.83      0.84     96667
weighted avg       0.84      0.85      0.84     96667
```




In [191]:

```
rfEv = pd.read_csv("model/__RF/RF_Eval.csv")
display(rfEv)
dfi.export(rfEv, 'model/__RF/RF_Eval.png')
```

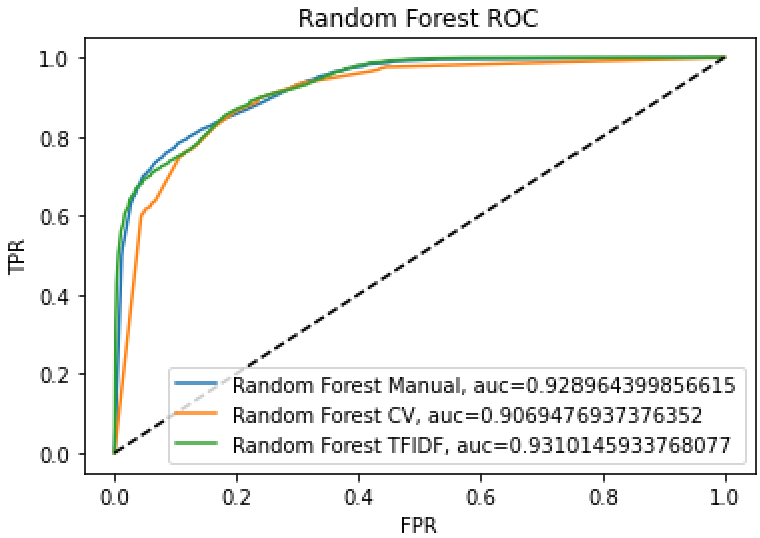
| | Input Feature Types | n_tree | n_features | Training Score | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|---|
| **0** | Manual | 50 | 10 | 0.917 | 0.836 | 0.87 | 0.929 |
| **1** | CountVect | 5 | 10 | 0.941 | 0.840 | 0.87 | 0.907 |
| **2** | TfIdf | 50 | 4 | 0.945 | 0.846 | 0.88 | 0.931 |

In [192]:

```
saveModel(rfman,"__RF/rfman")
saveModel(rfcv, "__RF/rfcv")
saveModel(rftf, "__RF/rftf")
```

In [187]:

```
plt.title("Random Forest" + " ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.plot(fpr_man,tpr_man,label="Random Forest Manual, auc="+str(auc_man))
plt.plot(fpr_cv,tpr_cv,label="Random Forest CV, auc="+str(auc_cv))
plt.plot(fpr_tf,tpr_tf,label="Random Forest TFIDF, auc="+str(auc_tf))
plt.plot([0,1],[0,1],'k--')
plt.legend(loc=4)
plt.show()
```




### Adaboost

#####Training

In [105]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Number of Trees', 'Max Features Per Tree', 'Training Acc
n_trees = [25, 50, 100] # number of trees in AdaBoost to try out
tree_depth = [1,2,4,10] # Depth of the weak learners (Decision Tree)
modelname = 'AdaBoost'

# Initialize
labels = []
tree = []
depth = []
tr_acc = []
tv_acc = []
F1 = []
auc = []
fpr = []
tpr = []

for i in range(len(X_labels)):
  for t in n_trees:
    for d in tree_depth:
      if d <= X_train[i].shape[1]:
        labels.append(X_labels[i])
        tree.append(t)
        depth.append(d)

        base = DecisionTreeClassifier(max_depth=d)
        ad = AdaBoostClassifier(n_estimators=t, base_estimator=base)
        ad_fit = ad.fit(X_train[i], y_train)

        # Predictions
        ad_trpred = ad.predict(X_train[i])
        ad_tvpred = ad.predict(X_val[i])
        ad_tvprob = ad.predict_proba(X_val[i])

        # Accuracies
        tr_acc.append(accuracy_score(y_train, ad_trpred))
        tv_acc.append(accuracy_score(y_val, ad_tvpred))

        # F1 Score
        F1.append(f1_score(y_val, ad_tvpred))

        # AUC Score
        auc.append(roc_auc_score(y_val, ad_tvprob[:,1]))

# Training Evaluation Results
ad_val_sumarr = np.array([labels, tree, depth, tr_acc, tv_acc, F1, auc]).transpose()
ad_val_sum = pd.DataFrame(ad_val_sumarr, columns=metrics)
for i in metrics[3:]:
  ad_val_sum[i] = ad_val_sum[i].apply(lambda x: round(float(x),3))

# Save Training Evaluation Results
folderpath = 'model/trad_model/hyperparameter_tuning/'
filepath = folderpath + modelname + '.csv'
ad_val_sum.to_csv(filepath, index=False)

display(ad_val_sum)
```

| | Input Feature Types | Number of Trees | Max Features Per Tree | Training Accuracy | Validation Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|---|
| **0** | Manual | 25 | 1 | 0.783 | 0.780 | 0.829 | 0.864 |
| **1** | Manual | 25 | 2 | 0.804 | 0.803 | 0.847 | 0.887 |
| **2** | Manual | 25 | 4 | 0.824 | 0.823 | 0.860 | 0.911 |
| **3** | Manual | 25 | 10 | 0.874 | 0.850 | 0.880 | 0.932 |
| **4** | Manual | 50 | 1 | 0.790 | 0.789 | 0.838 | 0.875 |
| **5** | Manual | 50 | 2 | 0.814 | 0.814 | 0.854 | 0.901 |
| **6** | Manual | 50 | 4 | 0.835 | 0.833 | 0.867 | 0.921 |
| **7** | Manual | 50 | 10 | 0.891 | 0.847 | 0.876 | 0.925 |
| **8** | Manual | 100 | 1 | 0.798 | 0.797 | 0.843 | 0.883 |
| **9** | Manual | 100 | 2 | 0.822 | 0.821 | 0.859 | 0.909 |
| **10** | Manual | 100 | 4 | 0.844 | 0.841 | 0.873 | 0.928 |
| **11** | Manual | 100 | 10 | 0.905 | 0.840 | 0.870 | 0.917 |
| **12** | CountVect | 25 | 1 | 0.756 | 0.755 | 0.823 | 0.832 |
| **13** | CountVect | 25 | 2 | 0.806 | 0.804 | 0.847 | 0.875 |
| **14** | CountVect | 25 | 4 | 0.827 | 0.824 | 0.862 | 0.906 |
| **15** | CountVect | 25 | 10 | 0.851 | 0.844 | 0.874 | 0.932 |
| **16** | CountVect | 50 | 1 | 0.804 | 0.802 | 0.846 | 0.871 |
| **17** | CountVect | 50 | 2 | 0.825 | 0.824 | 0.859 | 0.903 |
| **18** | CountVect | 50 | 4 | 0.840 | 0.837 | 0.869 | 0.924 |
| **19** | CountVect | 50 | 10 | 0.863 | 0.853 | 0.882 | 0.940 |
| **20** | CountVect | 100 | 1 | 0.823 | 0.822 | 0.858 | 0.900 |
| **21** | CountVect | 100 | 2 | 0.837 | 0.836 | 0.869 | 0.922 |
| **22** | CountVect | 100 | 4 | 0.853 | 0.849 | 0.880 | 0.937 |
| **23** | CountVect | 100 | 10 | 0.874 | 0.860 | 0.887 | 0.944 |
| **24** | TfIdf | 25 | 1 | 0.779 | 0.778 | 0.827 | 0.832 |
| **25** | TfIdf | 25 | 2 | 0.805 | 0.780 | 0.821 | 0.859 |
| **26** | TfIdf | 25 | 4 | 0.828 | 0.825 | 0.862 | 0.907 |
| **27** | TfIdf | 25 | 10 | 0.852 | 0.840 | 0.873 | 0.925 |
| **28** | TfIdf | 50 | 1 | 0.807 | 0.782 | 0.825 | 0.857 |
| **29** | TfIdf | 50 | 2 | 0.826 | 0.802 | 0.837 | 0.886 |
| **30** | TfIdf | 50 | 4 | 0.840 | 0.836 | 0.869 | 0.923 |
| **31** | TfIdf | 50 | 10 | 0.866 | 0.848 | 0.878 | 0.932 |
| **32** | TfIdf | 100 | 1 | 0.826 | 0.800 | 0.838 | 0.885 |
| **33** | TfIdf | 100 | 2 | 0.839 | 0.835 | 0.868 | 0.921 |
| **34** | TfIdf | 100 | 4 | 0.855 | 0.848 | 0.878 | 0.936 |
| **35** | TfIdf | 100 | 10 | 0.880 | 0.856 | 0.884 | 0.936 |

# Evaluate

In [117]:

```
# Parameters Setup
metrics = ['Input Feature Types', 'Number of Trees', 'Max Features Per Tree', 'Training Acc
modelname = 'AdaBoost'
colors = ['blue', 'orange', 'red'] # indicates the corresponding color to represent in plot

X_train_mfd, X_train_cv, X_train_tfidf = X_train[0], X_train[1], X_train[2]
X_test_mfd, X_test_cv, X_test_tfidf = X_test[0], X_test[1], X_test[2]

# Using num_trees=25, tree_depth=10 for AdaBoost in Manually Designed Features
base_mfd = DecisionTreeClassifier(max_depth=10)
ad_mfd = AdaBoostClassifier(n_estimators=25, base_estimator=base_mfd)
ad_mfd_fit = ad_mfd.fit(X_train_mfd, y_train)
ad_mfd_trpred = ad_mfd.predict(X_train_mfd)
ad_mfd_tspred = ad_mfd.predict(X_test_mfd)
ad_mfd_tsprob = ad_mfd.predict_proba(X_test_mfd)
ad_mfd_tracc = accuracy_score(y_train, ad_mfd_trpred)
ad_mfd_tsacc = accuracy_score(y_test, ad_mfd_tspred)
ad_mfd_f1 = f1_score(y_test, ad_mfd_tspred)
ad_mfd_auc = roc_auc_score(y_test, ad_mfd_tsprob[:,1])
ad_mfd_fpr, ad_mfd_tpr, _ = roc_curve(y_test, ad_mfd_tsprob[:,1])

y_train = y_train_tkn
y_test = y_test_tkn

# Using num_trees=100, tree_depth=10 for AdaBoost in CountVectorizer Features
base_cv = DecisionTreeClassifier(max_depth=10)
ad_cv = AdaBoostClassifier(n_estimators=100, base_estimator=base_cv)
ad_cv_fit = ad_cv.fit(X_train_cv, y_train)
ad_cv_trpred = ad_cv.predict(X_train_cv)
ad_cv_tspred = ad_cv.predict(X_test_cv)
ad_cv_tsprob = ad_cv.predict_proba(X_test_cv)
ad_cv_tracc = accuracy_score(y_train, ad_cv_trpred)
ad_cv_tsacc = accuracy_score(y_test, ad_cv_tspred)
ad_cv_f1 = f1_score(y_test, ad_cv_tspred)
ad_cv_auc = roc_auc_score(y_test, ad_cv_tsprob[:,1])
ad_cv_fpr, ad_cv_tpr, _ = roc_curve(y_test, ad_cv_tsprob[:,1])

# Using num_trees=100, tree_depth=10 for AdaBoost in TfIdf Vectorizer Features
base_tfidf = DecisionTreeClassifier(max_depth=10)
ad_tfidf = AdaBoostClassifier(n_estimators=100, base_estimator=base_tfidf)
ad_tfidf_fit = ad_tfidf.fit(X_train_tfidf, y_train)
ad_tfidf_trpred = ad_tfidf.predict(X_train_tfidf)
ad_tfidf_tspred = ad_tfidf.predict(X_test_tfidf)
ad_tfidf_tsprob = ad_tfidf.predict_proba(X_test_tfidf)
ad_tfidf_tracc = accuracy_score(y_train, ad_tfidf_trpred)
ad_tfidf_tsacc = accuracy_score(y_test, ad_tfidf_tspred)
ad_tfidf_f1 = f1_score(y_test, ad_tfidf_tspred)
ad_tfidf_auc = roc_auc_score(y_test, ad_tfidf_tsprob[:,1])
ad_tfidf_fpr, ad_tfidf_tpr, _ = roc_curve(y_test, ad_tfidf_tsprob[:,1])

ad_tracc = [ad_mfd_tracc, ad_cv_tracc, ad_tfidf_tracc]
ad_tsacc = [ad_mfd_tsacc, ad_cv_tsacc, ad_tfidf_tsacc]
ad_f1 = [ad_mfd_f1, ad_cv_f1, ad_tfidf_f1]
ad_auc = [ad_mfd_auc, ad_cv_auc, ad_tfidf_auc]
ad_tree = [25, 100, 100]
ad_depth = [10, 10, 10]
ad_labels = ['Manual', 'CountVect', 'TfIdf']
ad_fpr = [ad_mfd_fpr, ad_cv_fpr, ad_tfidf_fpr]
ad_tpr = [ad_mfd_tpr, ad_cv_tpr, ad_tfidf_tpr]
```

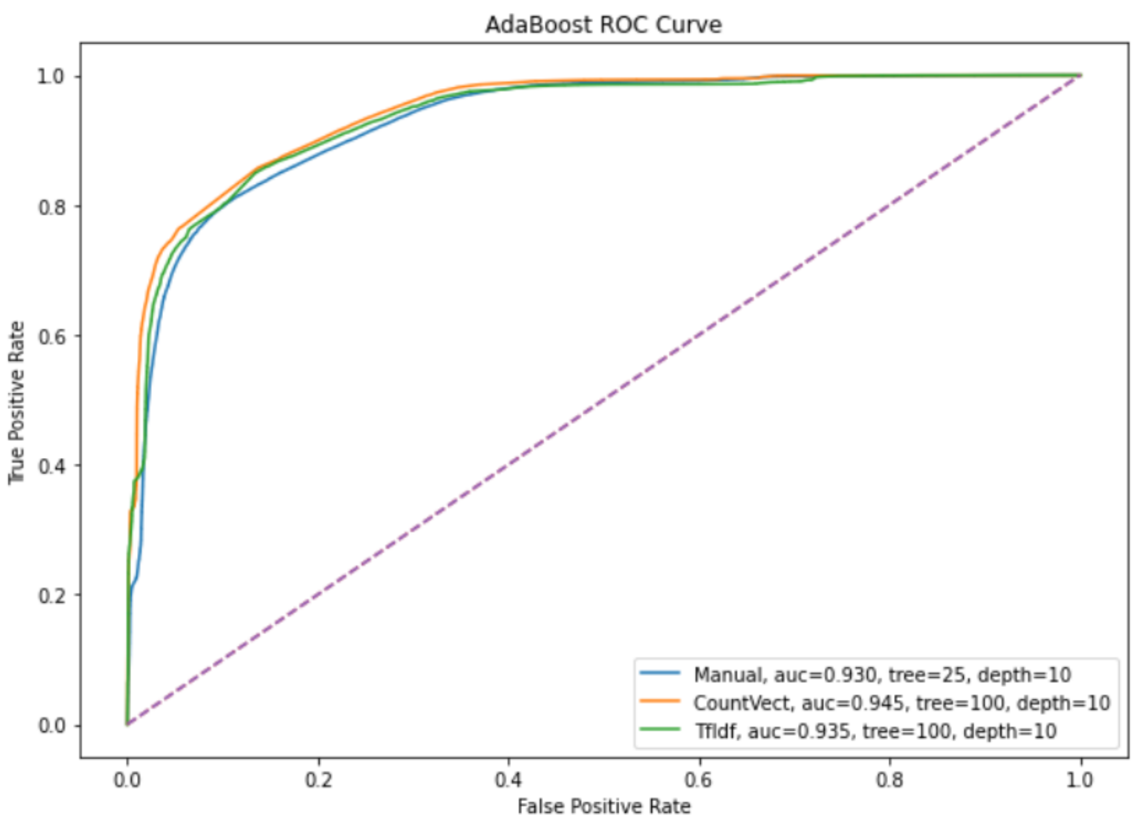
```
# Displaying final model evaluation
ad_sumarr = np.array([ad_labels, ad_tree, ad_depth, ad_tracc, ad_tsacc, ad_f1, ad_auc]).tra
ad_sum = pd.DataFrame(ad_sumarr, columns=metrics)
for i in metrics[3:]:
  ad_sum[i] = ad_sum[i].apply(lambda x: round(float(x),3))

# Save Test Dataset Evaluation to File
folderpath = 'model/trad_model/model_evaluation/'
filepath = folderpath + modelname + '.csv'
ad_sum.to_csv(filepath, index=False)
display(ad_sum)

# Plot of ROC Curve
plt.figure(figsize=(10,7))
for i in np.arange(len(X_labels)):
  plt.plot(ad_fpr[i],ad_tpr[i], label=ad_labels[i]+  ", auc="+str(ad_auc[i])[:5] + ", tree=
plt.plot([(0,0), (1,1)], linestyle="--")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(modelname + ' ROC Curve')
plt.legend()
plt.show()
```

| | Input Feature Types | Number of Trees | Max Features Per Tree | Training Accuracy | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|---|---|
| **0** | Manual | 25 | 10 | 0.875 | 0.848 | 0.878 | 0.930 |
| **1** | CountVect | 100 | 10 | 0.874 | 0.861 | 0.888 | 0.945 |
| **2** | TfIdf | 100 | 10 | 0.878 | 0.856 | 0.884 | 0.936 |

Out[117]:



#####Save

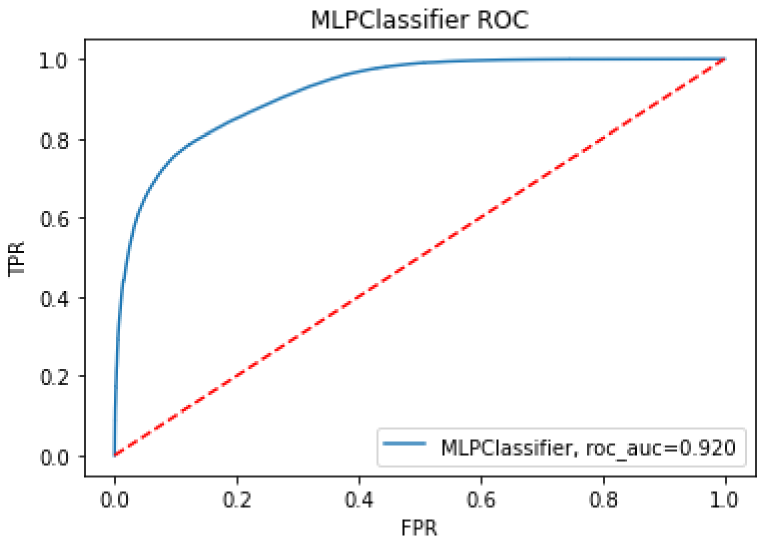
In [108]:

```
# saveModel(ad_mfd, "ad_mfd_85_93")
# saveModel(ad_cv, "ad_cv_86_94") ##
# saveModel(ad_tfidf, "ad_tfidf_85_93")
```

#####MLP

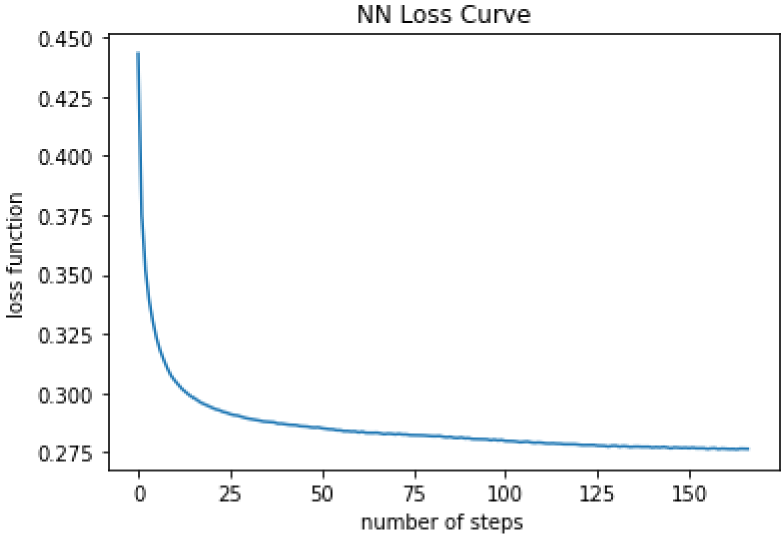
In [ ]:

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(10,10,20,20), max_iter=1000,verbose=0)  #0.83, 0.83
tr_predict, ts_predict, tr_accuracy, ts_accuracy = perfResult(x_train_scale, x_val_scale, y
y_pred_prob, fpr, tpr, auc=plotROC(x_train_scale, x_val_scale, y_train, y_val, mlp)
```



In [ ]:

```
plt.plot(mlp.loss_curve_)
plt.title("NN Loss Curve")
plt.xlabel("number of steps")
plt.ylabel("loss function")
plt.show()
```




**NB**

In [133]:

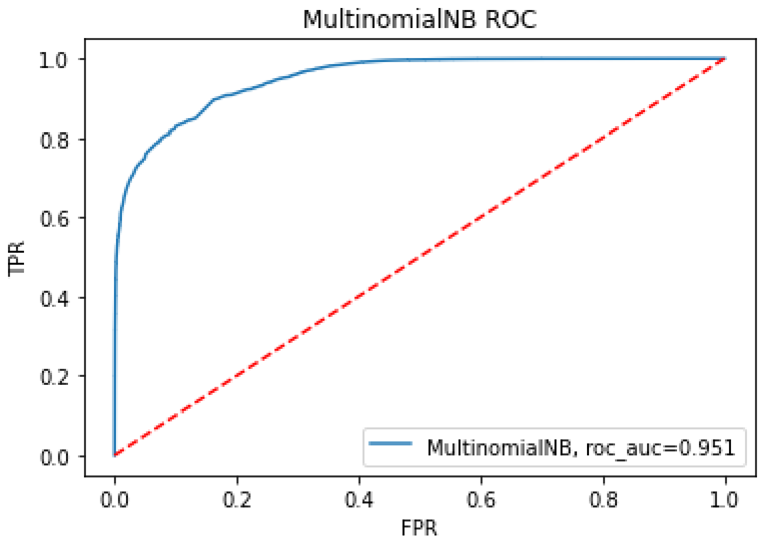
```
#NB
#NB - strong independence assumptions between the features.
NB = MultinomialNB()
tr_predict_cv, ts_predict_cv, tr_accuracy_cv, ts_accuracy_cv = perfResult(x_train_cv, x_val
y_pred_prob_cv, fpr_cv, tpr_cv, auc_cv = plotROC(x_train_cv, x_val_cv, y_train_cv, y_val_cv
```

```
MultinomialNB
Train Accuracy Score: 0.9118038252480559
Test Accuracy Score: 0.8677611569734963

[[29540  8189]
 [ 4594 54343]]
              precision    recall  f1-score   support

           0       0.87      0.78      0.82     37729
           1       0.87      0.92      0.89     58937

    accuracy                           0.87     96666
   macro avg       0.87      0.85      0.86     96666
weighted avg       0.87      0.87      0.87     96666
```



In [134]:

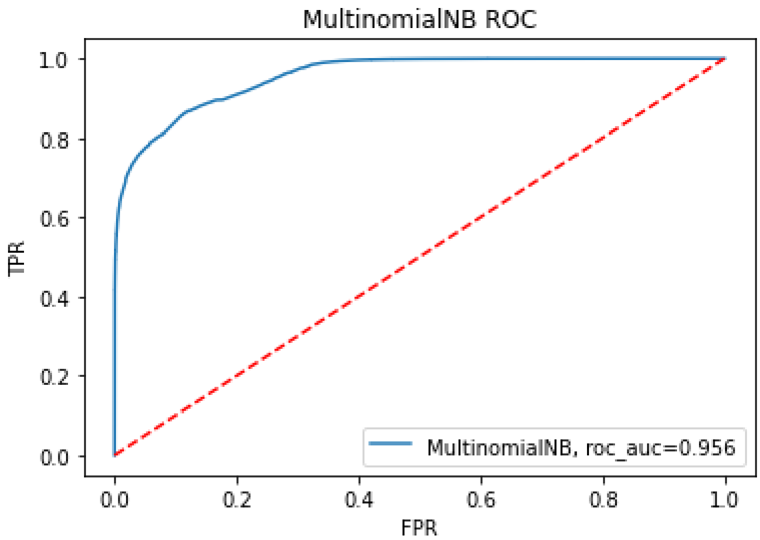
```
NB2 = MultinomialNB()
tr_predict_tf, ts_predict_tf, tr_accuracy_tf, ts_accuracy_tf = perfResult(x_train_tf, x_val
y_pred_prob_tf, fpr_tf, tpr_tf, auc_tf = plotROC(x_train_tf, x_val_tf, y_train_tf, y_val_tf
```

```
MultinomialNB
Train Accuracy Score: 0.9193984589056279
Test Accuracy Score: 0.8659507996606873

[[28784  8945]
 [ 4013 54924]]
              precision    recall  f1-score   support

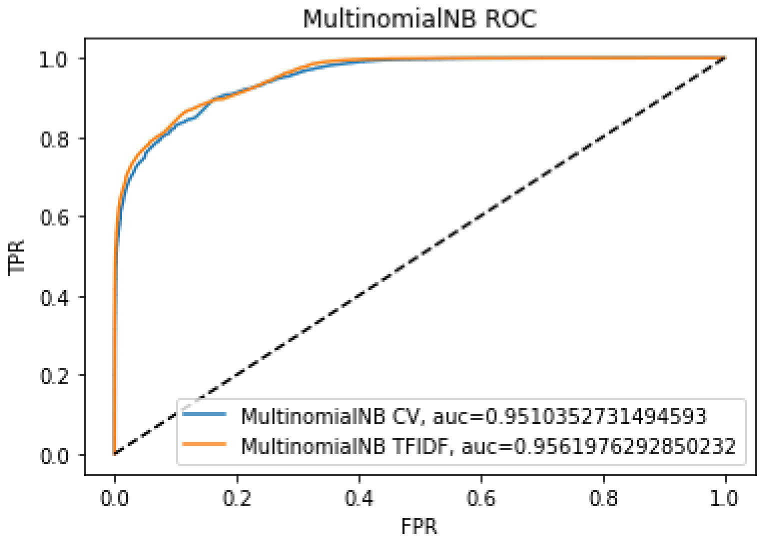
           0       0.88      0.76      0.82     37729
           1       0.86      0.93      0.89     58937

    accuracy                           0.87     96666
   macro avg       0.87      0.85      0.86     96666
weighted avg       0.87      0.87      0.86     96666
```



In [137]:

```
plt.title("MultinomialNB" + " ROC")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.plot(fpr_cv,tpr_cv,label="MultinomialNB CV, auc="+str(auc_cv))
plt.plot(fpr_tf,tpr_tf,label="MultinomialNB TFIDF, auc="+str(auc_tf))
plt.plot([0,1],[0,1],'k--')
plt.legend(loc=4)
plt.show()
```




In [147]:

```
print(tr_accuracy_cv, ts_accuracy_cv)
print(tr_accuracy_tf, ts_accuracy_tf)
```

```
0.9118038252480559 0.8677611569734963
0.9193984589056279 0.8659507996606873
```

In [149]:

```
nb = pd.read_csv("model/NB/NB_Tr.csv")
display(nb)
dfi.export(nb, 'model/NB/NB_Tr.png')
```

| | Input Feature Types | Alpha | Training Acc | Testing Acc | F1-Score | AUC Score |
|---|---|---|---|---|---|---|
| **0** | CountVectorizer | 1 | 0.911804 | 0.867761 | 0.87 | 0.951 |
| **1** | TfIdf | 1 | 0.919398 | 0.865951 | 0.89 | 0.956 |

In [165]:

```
modcom = pd.read_csv("model/model_compare.csv")
display(modcom)

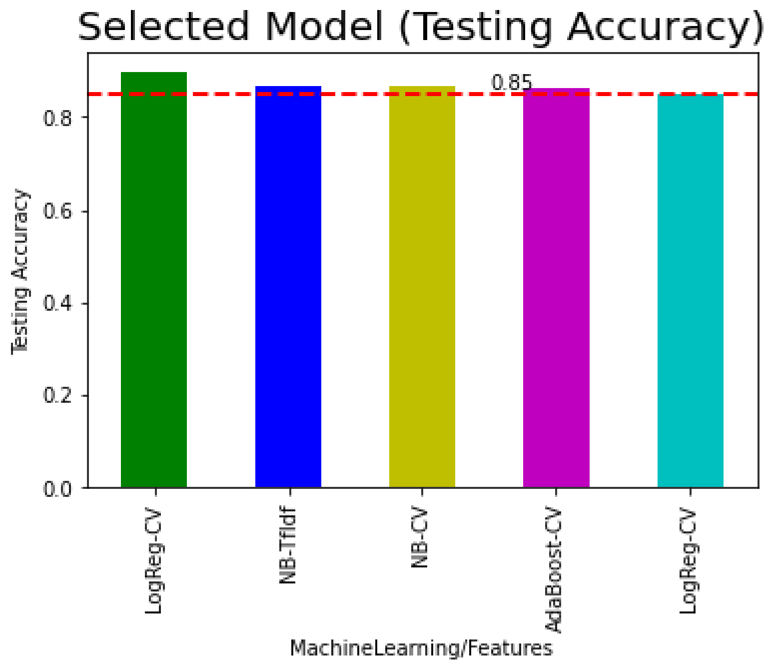
df = pd.Series(list(modcom["Testing Accuracy"]), index=list(modcom["ML-Features"]))
#Set descriptions:
plt.title("Selected Model (Testing Accuracy)", fontsize=20)
plt.ylabel('Testing Accuracy')
plt.xlabel('MachineLearning/Features')
#Set tick colors:
ax = plt.gca()
ax.tick_params(axis='x', colors='black')
ax.tick_params(axis='y', colors='black')
#Plot the data:
color = list('gbymc') #red, green, blue, black, etc.
df.plot(kind='bar',color=color)
plt.axhline(y=0.85, color='r', linestyle='--', linewidth=2)
plt.text(2.5,0.86,'0.85')
plt.show()

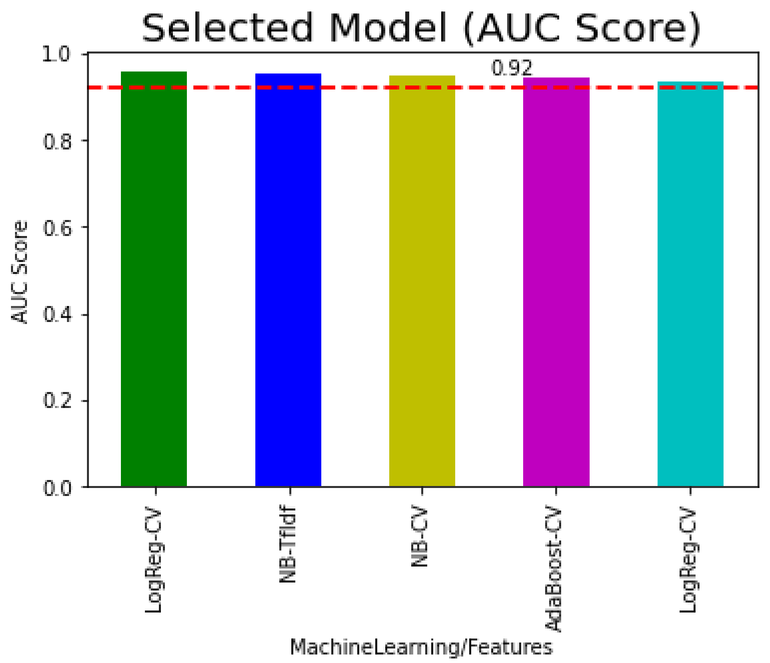
df = pd.Series(list(modcom["AUC Score"]), index=list(modcom["ML-Features"]))
#Set descriptions:
plt.title("Selected Model (AUC Score)", fontsize=20)
plt.ylabel('AUC Score')
plt.xlabel('MachineLearning/Features')
#Set tick colors:
ax = plt.gca()
ax.tick_params(axis='x', colors='black')
ax.tick_params(axis='y', colors='black')
#Plot the data:
color = list('gbymc') #red, green, blue, black, etc.
df.plot(kind='bar',color=color, align='center')
plt.axhline(y=0.92, color='r', linestyle='--', linewidth=2)
plt.text(2.5,0.95,'0.92')
plt.show()

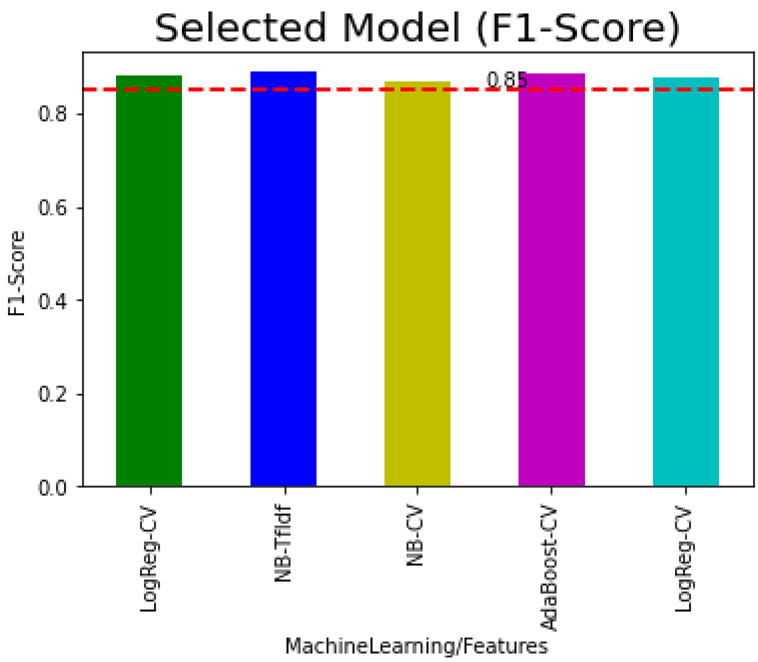
df = pd.Series(list(modcom["F1-Score"]), index=list(modcom["ML-Features"]))
#Set descriptions:
plt.title("Selected Model (F1-Score)", fontsize=20)
plt.ylabel('F1-Score')
plt.xlabel('MachineLearning/Features')
#Set tick colors:
ax = plt.gca()
ax.tick_params(axis='x', colors='black')
ax.tick_params(axis='y', colors='black')
#Plot the data:
color = list('gbymc') #red, green, blue, black, etc.
df.plot(kind='bar',color=color, align='center')
plt.axhline(y=0.85, color='r', linestyle='--', linewidth=2)
plt.text(2.5,0.86,'0.85')
plt.show()
```

| | ML-Features | Training Accuracy | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|
| **0** | LogReg-CV | 0.870000 | 0.896000 | 0.880 | 0.958 |
| **1** | NB-TfIdf | 0.919398 | 0.865951 | 0.890 | 0.956 |
| **2** | NB-CV | 0.911804 | 0.867761 | 0.870 | 0.951 |

| | ML-Features | Training Accuracy | Testing Accuracy | F1-Score | AUC Score |
|---|---|---|---|---|---|
| 3 | AdaBoost-CV | 0.874000 | 0.860000 | 0.887 | 0.944 |
| 4 | LogReg-CV | 0.855000 | 0.848000 | 0.878 | 0.936 |




Selected Model (F1-Score)
F1-Score
0.0
0.2
0.4
0.6
0.8
0.85
LogReg-CV
NB-TfIdf
NB-CV
AdaBoost-CV
LogReg-CV
MachineLearning/Features

In [ ]:

```

```