Text Files to proper csv File.

This section comprises of the following steps:

- **Extracting dataset from compressed rar file.**
- **Getting file-paths of *B* and *M* labelled data.**
- **Reading each text file line-by-line and converting it into one big space seperated line of sys-calls.**
- **Storing this data in a dataframe `final_data` in the format:**
  `(Filename, Sys-Calls, Label (B/M) )`

In [ ]:

```
!unrar x 'App Dataset.rar'   #Extract the Data
```

In [ ]:

```
!ls
```

```
'App Dataset'   'App Dataset.rar'    sample_data
```

In [ ]:

```
#Importing required libraries
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [ ]:

```
B_dataset_path = os.getcwd() + '/App Dataset/Dataset/B/sys'     #Get file paths, for rea
ding
M_dataset_path = os.getcwd() + '/App Dataset/Dataset/M/sys'

files_B = os.listdir(B_dataset_path)
files_M = os.listdir(M_dataset_path)
list_sys_calls = []

for filename in files_B:
    file = open( ( B_dataset_path + '/' + filename ), 'r' )
    sys_calls = file.read().splitlines()
    list_sys_calls.append([filename, ' '.join(sys_calls), 'B'])   #Store and label the d
ata

for filename in files_M:
    file = open( ( M_dataset_path + '/' + filename ), 'r' )
    sys_calls = file.read().splitlines()
    list_sys_calls.append([filename, ' '.join(sys_calls), 'M'])

final_data = pd.DataFrame(list_sys_calls, columns=['File','Calls','Label'])
final_data      #Final dataframe of sys-calls, labeled
```

Out[ ]:

	File	Calls	Label
0	com.chinadeals.apk.sys_names.txt	ioctl pread rt_sigprocmask rt_sigprocmask rt_s...	B
1	chat.cristianogratis.apk.sys_names.txt	dup fcntl close epoll_ctl ioctl ioctl getuid e...	B
2	com.eterno.apk.sys_names.txt	futex ioctl epoll_pwait read recvfrom writev s...	B
3	com.andromo.dev551559.app531086.apk.sys_names.txt	read writev write read read write read read re...	B
4	com.blinkslabs.blinkist.android.apk.sys_names.txt	read read ioctl ioctl writev futex ioctl ioctl...	B

...	File	Calls	Label
5817	a0bffc11168c65beb59c326d88f144f0d750634252a507...	newfstatat ioctl ioctl getuid newfstatat newfs...	M
5818	02c9bddf966b59a8850a7395e7ce5af21ca16c442a0389...	recvfrom recvfrom writev sendto getuid epoll_p...	M
5819	6113bc8bbbdfe89114a12ddfa25ad54eed63367cf21462...	dup fcntl close epoll_ctl ioctl ioctl getuid e...	M
5820	3ddcdc882166b87d3db9d5cc21ccd4c7009e1f134edeeb...	ioctl ioctl faccessat mprotect mprotect mprote...	M
5821	66d6c067ca2c6e500caac92977f19c513436b2ae276ab9...	getuid epoll_pwait getuid epoll_pwait read new...	M

5822 rows × 3 columns

Task 1 - Analysis of Sys-Calls with different Unigram Models

In this task, we analyse different models for representation of features, sys-calls. Sys-Calls are taken one at a time, hence they're Unigram Models.

For each data model, i.e., `Bag of Words`, `Boolean Occurrence` and `TF-IDF` the following steps are performed:

- Data is prepared by extracting the sys-calls from `final_data` and vectorizing it. The `CountVectorizer` is used for the first two models and `TfidfVectorizer` is used for TF-IDF.
- After this, the data is fit and transformed using the vectorizer. This data serves as the input variables, `X`. The Labels, `Y`, are extracted from `final_data`, being either `B/M` for each input.
- Data is split into train and test data.
- Three different SVM Kernels, `Linear`, `Polynomial` and `RBF` are trained and analysed.

Bag of Words (No. of Occurrences of Calls)

This data model counts the occurence of a particular feature in the dataset.

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
text = final_data['Calls']
print(text)
```

```
0       ioctl pread rt_sigprocmask rt_sigprocmask rt_s...
1       dup fcntl close epoll_ctl ioctl ioctl getuid e...
2       futex ioctl epoll_pwait read recvfrom writev s...
3       read writev write read read write read read re...
4       read read ioctl ioctl writev futex ioctl ioctl...
                              ...
5817    newfstatat ioctl ioctl getuid newfstatat newfs...
5818    recvfrom recvfrom writev sendto getuid epoll_p...
5819    dup fcntl close epoll_ctl ioctl ioctl getuid e...
5820    ioctl ioctl faccessat mprotect mprotect mprote...
5821    getuid epoll_pwait getuid epoll_pwait read new...
Name: Calls, Length: 5822, dtype: object
```

In [ ]:

```
vectorizer = CountVectorizer()
transformed_text = vectorizer.fit_transform(text)
vectorizer.get_feature_names()[:5]       #First five features
```

Out[ ]:

```
['_llseek', 'bind', 'capget', 'clock_gettime', 'clone']
```

In [ ]:

```
from sklearn import preprocessing
X = transformed_text.toarray()
X = preprocessing.normalize(X)
X
```

Out[ ]:

```
array([[0.        , 0.        , 0.        , ..., 0.        , 0.26287891,
        0.11385516],
       [0.        , 0.        , 0.        , ..., 0.        , 0.16569688,
        0.1347668 ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.18283549,
        0.09310442],
       ...,
       [0.        , 0.        , 0.        , ..., 0.        , 0.19940531,
        0.17339592],
       [0.        , 0.        , 0.        , ..., 0.        , 0.53886354,
        0.06260463],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.01377167]])
```

In [ ]:

```
from sklearn import model_selection, svm        #Split the data
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

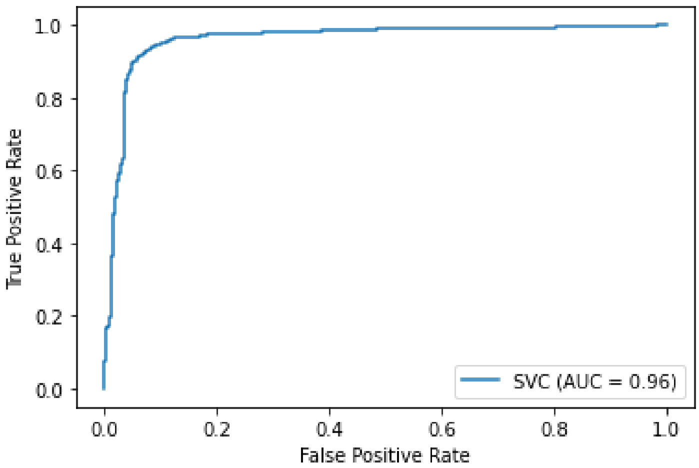
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9218884120171674

Confusion matrix:

[[480  30]
 [ 61 594]]

Classification Report:

              precision    recall  f1-score   support

           B       0.89      0.94      0.91       510
```

```
           M       0.95      0.91      0.93       655

    accuracy                           0.92      1165
   macro avg       0.92      0.92      0.92      1165
weighted avg       0.92      0.92      0.92      1165


ROC Plot
```



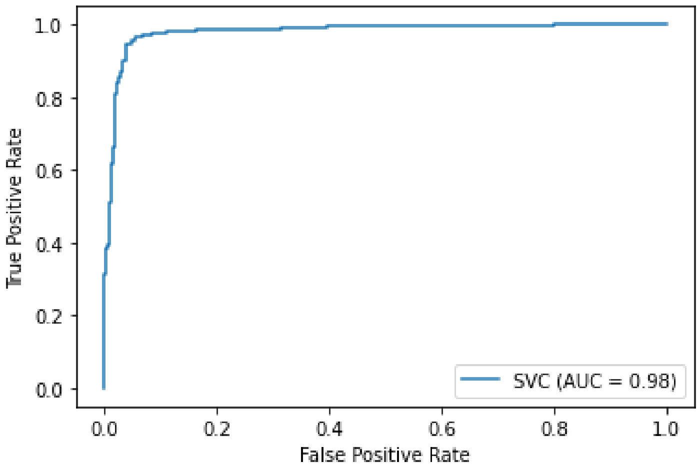
Polynomial SVM Kernel

In [ ]:

```python
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9536480686695279

Confusion matrix:

[[486  24]
 [ 30 625]]

Classification Report:

              precision    recall  f1-score   support

           B       0.94      0.95      0.95       510
           M       0.96      0.95      0.96       655

    accuracy                           0.95      1165
```

```
    accuracy                           0.95      1165
   macro avg       0.95      0.95      0.95      1165
weighted avg       0.95      0.95      0.95      1165


ROC Plot
```



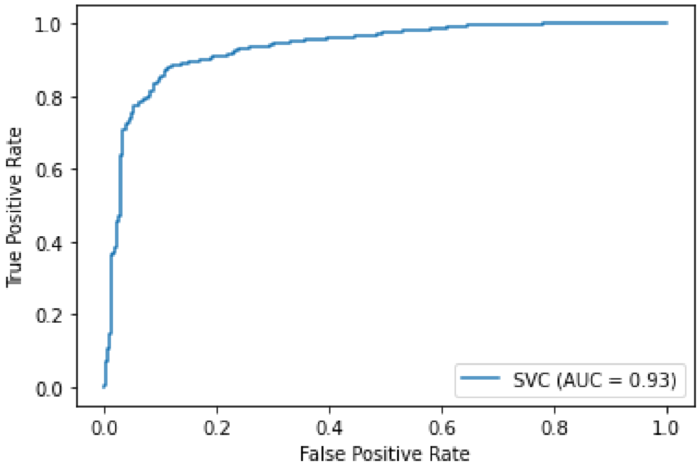
RBF SVM Kernel

In [ ]:

```python
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1.5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.855793991416309

Confusion matrix:

[[468  42]
 [126 529]]

Classification Report:

              precision    recall  f1-score   support

           B       0.79      0.92      0.85       510
           M       0.93      0.81      0.86       655

    accuracy                           0.86      1165
   macro avg       0.86      0.86      0.86      1165
weighted avg       0.87      0.86      0.86      1165
```

ROC Plot



Boolean Occurrence

Prepare the Data

In [ ]:

```
X = np.where(transformed_text.toarray() >= 1,1,0)        #Same as Bag of words, but Boole
an. So all values >=1 are replaced with 1.
X
```

Out[ ]:

```
array([[0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       ...,
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 0, 1]])
```

In [ ]:

```
from sklearn import model_selection, svm        #Split the data
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

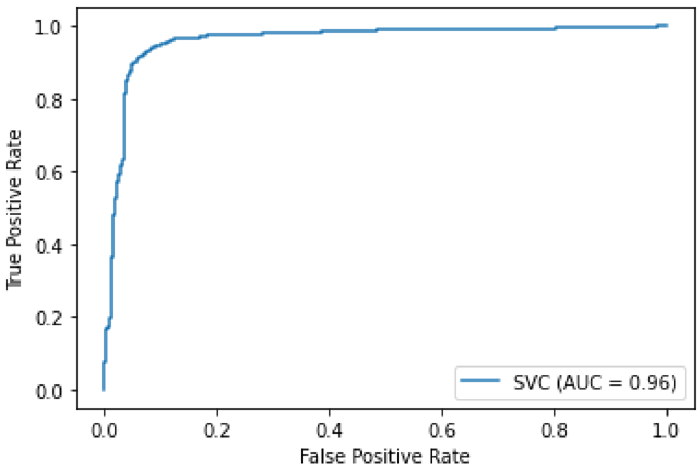
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
```

```
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9218884120171674

Confusion matrix:

[[480  30]
 [ 61 594]]

Classification Report:

              precision    recall  f1-score   support

           B       0.89      0.94      0.91       510
           M       0.95      0.91      0.93       655

    accuracy                           0.92      1165
   macro avg       0.92      0.92      0.92      1165
weighted avg       0.92      0.92      0.92      1165


ROC Plot
```



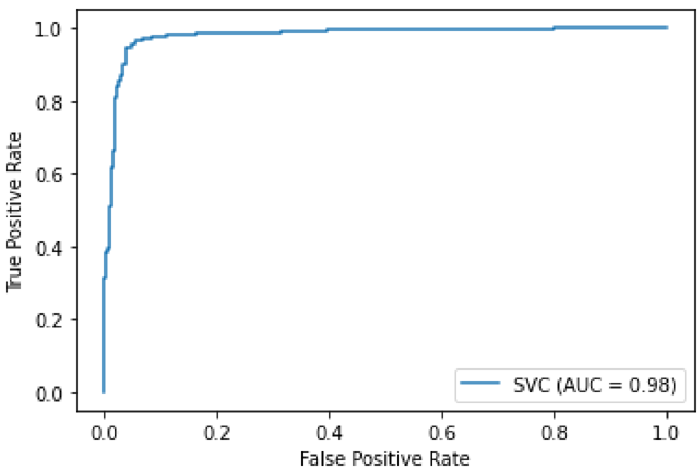
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))
```

```
#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9536480686695279

Confusion matrix:

[[486  24]
 [ 30 625]]

Classification Report:

              precision    recall  f1-score   support

           B       0.94      0.95      0.95       510
           M       0.96      0.95      0.96       655

    accuracy                           0.95      1165
   macro avg       0.95      0.95      0.95      1165
weighted avg       0.95      0.95      0.95      1165


ROC Plot
```



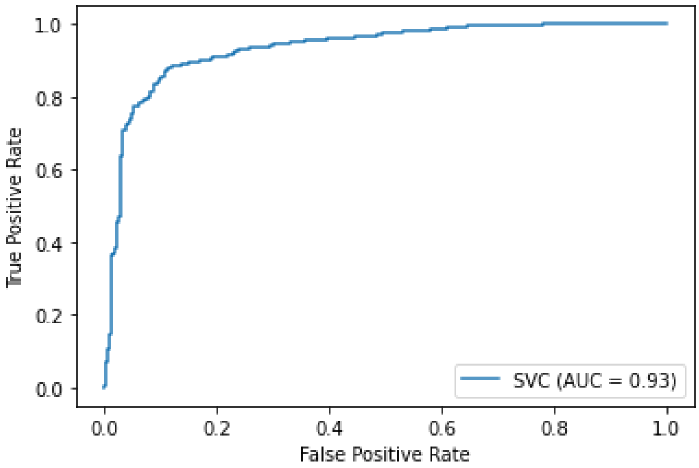
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1.5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
```

```
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.855793991416309

Confusion matrix:

[[468  42]
 [126 529]]

Classification Report:

              precision    recall  f1-score   support

           B       0.79      0.92      0.85       510
           M       0.93      0.81      0.86       655

    accuracy                           0.86      1165
   macro avg       0.86      0.86      0.86      1165
weighted avg       0.87      0.86      0.86      1165


ROC Plot
```



TF-IDF

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(text).toarray()

# print(X)
# print(vectorizer.vocabulary_)
```

In [ ]:

```
from sklearn import model_selection, svm          #Split the data

X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

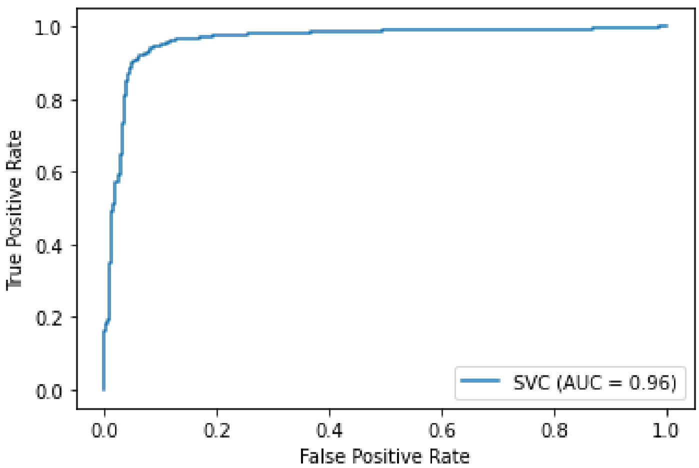
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve
```

```
#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9218884120171674

Confusion matrix:

[[480  30]
 [ 61 594]]

Classification Report:

              precision    recall  f1-score   support

           B       0.89      0.94      0.91       510
           M       0.95      0.91      0.93       655

    accuracy                           0.92      1165
   macro avg       0.92      0.92      0.92      1165
weighted avg       0.92      0.92      0.92      1165


ROC Plot
```



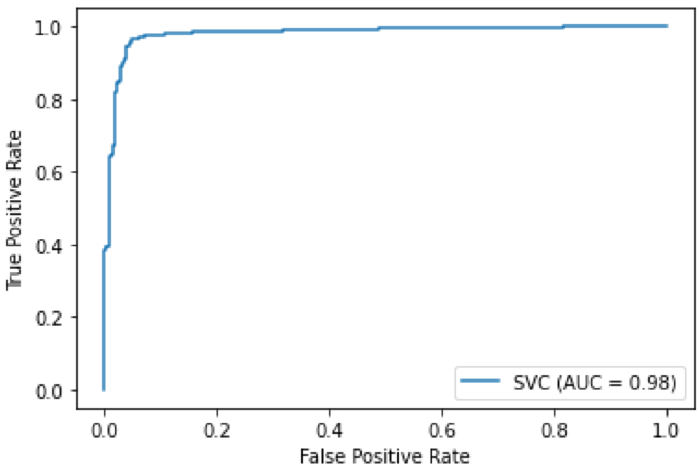
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
```

```
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9545064377682403

Confusion matrix:

[[487  23]
 [ 30 625]]

Classification Report:

              precision    recall  f1-score   support

           B       0.94      0.95      0.95       510
           M       0.96      0.95      0.96       655

    accuracy                           0.95      1165
   macro avg       0.95      0.95      0.95      1165
weighted avg       0.95      0.95      0.95      1165


ROC Plot
```



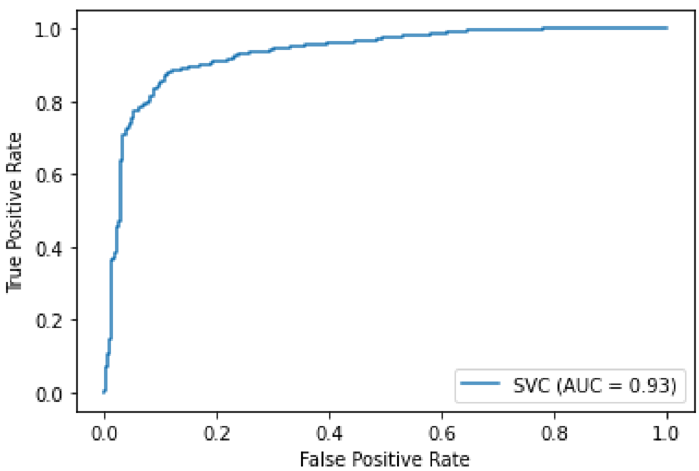
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1.5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)
```

```
#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.855793991416309

Confusion matrix:

[[468  42]
 [126 529]]

Classification Report:

              precision    recall  f1-score   support

           B       0.79      0.92      0.85       510
           M       0.93      0.81      0.86       655

    accuracy                           0.86      1165
   macro avg       0.86      0.86      0.86      1165
weighted avg       0.87      0.86      0.86      1165


ROC Plot
```



Task 2 - Bigram Model

In this task, we now analyse two sequence of sys-calls. This task in therefore similar to the first task, the only difference being that we now use bigram models.

For each `vectorizer`, we add a constraint - `ngram_range=(2,2)`.

Bag of Words

This data model counts the occurence of a particular feature in the dataset.

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
text = final_data['Calls']
print(text)
```

```
0       ioctl pread rt_sigprocmask rt_sigprocmask rt_s...
1       dup fcntl close epoll_ctl ioctl ioctl getuid e...
2       futex ioctl epoll_pwait read recvfrom writev s...
3       read writev write read read write read read re...
4       read read ioctl ioctl writev futex ioctl ioctl...
                              ...
5817    newfstatat ioctl ioctl getuid newfstatat newfs...
5818    recvfrom recvfrom writev sendto getuid epoll_p...
5819    dup fcntl close epoll_ctl ioctl ioctl getuid e...
5820    ioctl ioctl faccessat mprotect mprotect mprote...
5821    getuid epoll_pwait getuid epoll_pwait read new...
Name: Calls, Length: 5822, dtype: object
```

In [ ]:

```
vectorizer = CountVectorizer(ngram_range=(2,2))
transformed_text = vectorizer.fit_transform(text)
vectorizer.get_feature_names()[:5]      #First five features
```

Out[ ]:

```
['_llseek _llseek',
 '_llseek clock_gettime',
 '_llseek close',
 '_llseek faccessat',
 '_llseek fcntl64']
```

In [ ]:

```
from sklearn import preprocessing
X = transformed_text.toarray()
X = preprocessing.normalize(X)
X
```

Out[ ]:

```
array([[0.        , 0.        , 0.        , ..., 0.        , 0.00826803,
        0.0950823 ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.00446945,
        0.14469859],
       [0.        , 0.        , 0.        , ..., 0.        , 0.01349764,
        0.05736499],
       ...,
       [0.        , 0.        , 0.        , ..., 0.        , 0.01105867,
        0.14376274],
       [0.        , 0.        , 0.        , ..., 0.        , 0.00649589,
        0.04929233],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ]])
```

In [ ]:

```
from sklearn import model_selection, svm        #Split the data
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

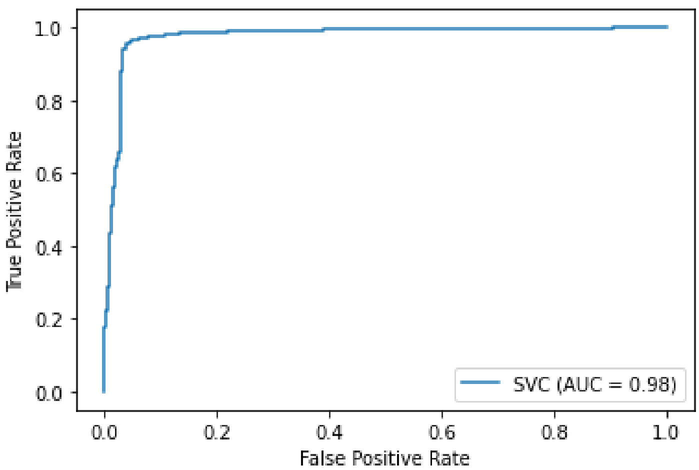
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
```

```
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9493562231759657

Confusion matrix:

[[494  16]
 [ 43 612]]

Classification Report:

              precision    recall  f1-score   support

           B       0.92      0.97      0.94       510
           M       0.97      0.93      0.95       655

    accuracy                           0.95      1165
   macro avg       0.95      0.95      0.95      1165
weighted avg       0.95      0.95      0.95      1165


ROC Plot
```



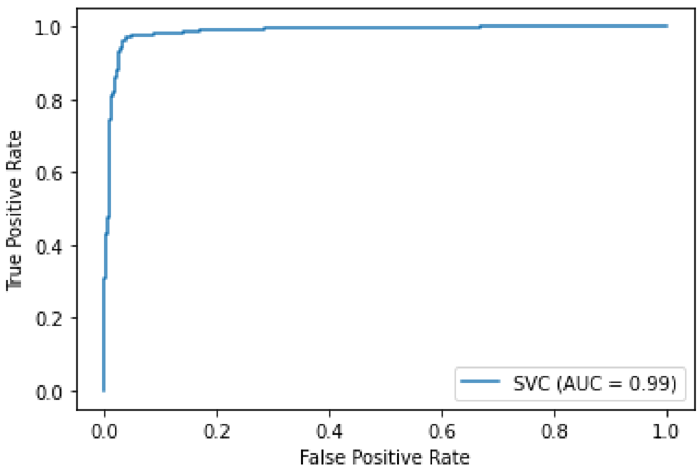
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
```

```
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9648068669527897

Confusion matrix:

[[491  19]
 [ 22 633]]

Classification Report:

              precision    recall  f1-score   support

           B       0.96      0.96      0.96       510
           M       0.97      0.97      0.97       655

    accuracy                           0.96      1165
   macro avg       0.96      0.96      0.96      1165
weighted avg       0.96      0.96      0.96      1165


ROC Plot
```



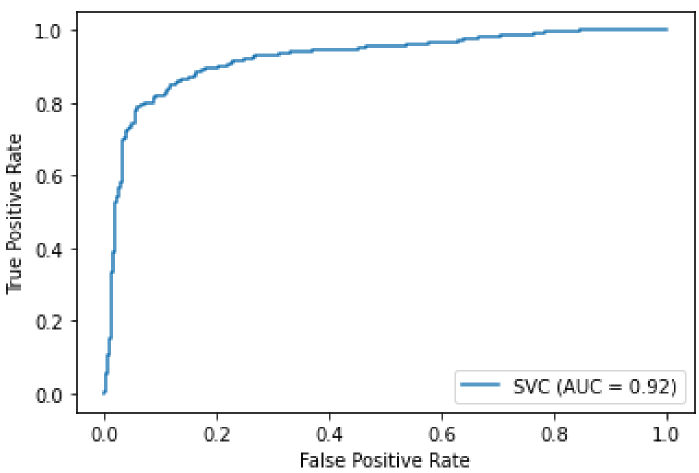
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)
```

```
#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.8566523605150215

Confusion matrix:

[[460  50]
 [117 538]]

Classification Report:

              precision    recall  f1-score   support

           B       0.80      0.90      0.85       510
           M       0.91      0.82      0.87       655

    accuracy                           0.86      1165
   macro avg       0.86      0.86      0.86      1165
weighted avg       0.86      0.86      0.86      1165


ROC Plot
```



Boolean Occurrence

Prepare the Data

In [ ]:

```
X = np.where(transformed_text.toarray() >= 1,1,0)        #Same as Bag of words, but Boole
an. So all values >=1 are replaced with 1.
X
```

Out[ ]:

```
array([[0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       ...,
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 0, 0]])
```

In [ ]:

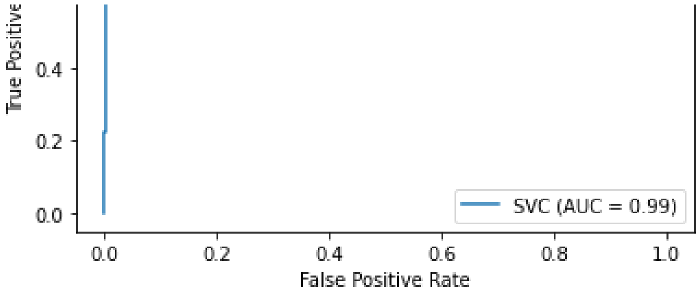
```
from sklearn import model_selection, svm        #Split the data
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9682403433476395

Confusion matrix:

[[499  11]
 [ 26 629]]

Classification Report:

              precision    recall  f1-score   support

           B       0.95      0.98      0.96       510
           M       0.98      0.96      0.97       655

    accuracy                           0.97      1165
   macro avg       0.97      0.97      0.97      1165
weighted avg       0.97      0.97      0.97      1165


ROC Plot
```

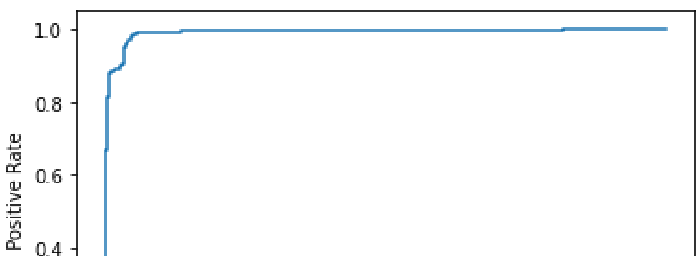


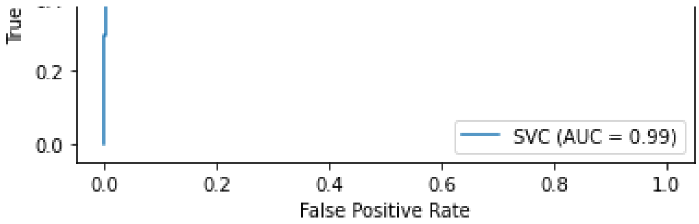
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9682403433476395

Confusion matrix:

[[480  30]
 [  7 648]]

Classification Report:

              precision    recall  f1-score   support

           B       0.99      0.94      0.96       510
           M       0.96      0.99      0.97       655

    accuracy                           0.97      1165
   macro avg       0.97      0.97      0.97      1165
weighted avg       0.97      0.97      0.97      1165


ROC Plot
```



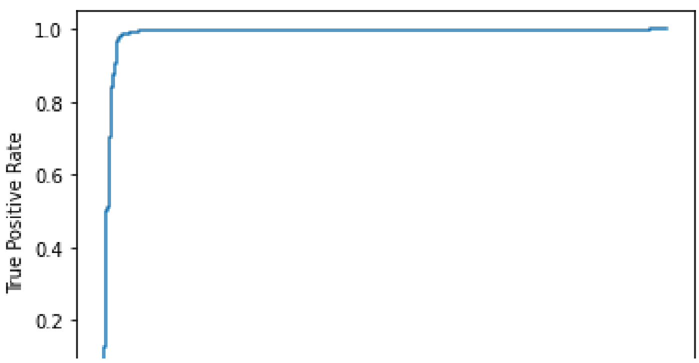


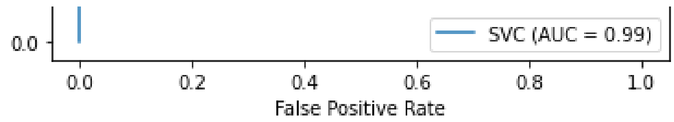
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1.5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.975107296137339

Confusion matrix:

[[489  21]
 [  8 647]]

Classification Report:

              precision    recall  f1-score   support

           B       0.98      0.96      0.97       510
           M       0.97      0.99      0.98       655

    accuracy                           0.98      1165
   macro avg       0.98      0.97      0.97      1165
weighted avg       0.98      0.98      0.98      1165


ROC Plot
```





TF-IDF

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(ngram_range=(2,2))
X = vectorizer.fit_transform(text).toarray()

# print(X)
# print(vectorizer.vocabulary_)
```

In [ ]:

```
from sklearn import model_selection, svm         #Split the data

X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

Linear SVM Kernel

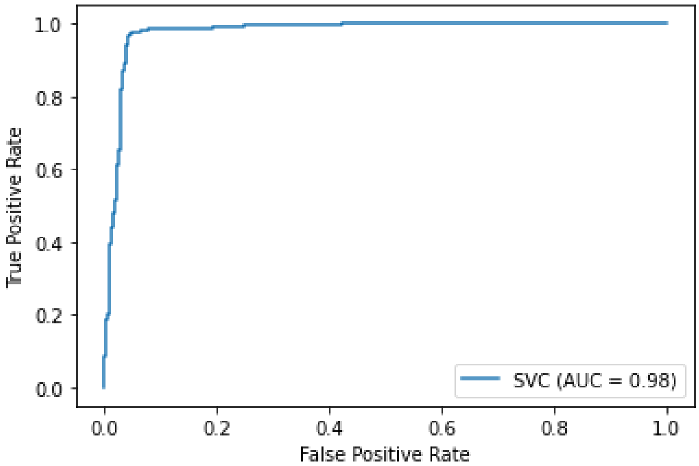
In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9390557939914163

Confusion matrix:

[[490  20]
 [ 51 604]]

Classification Report:

              precision    recall  f1-score   support
```

```
           B       0.91      0.96      0.93       510
           M       0.97      0.92      0.94       655

    accuracy                           0.94      1165
   macro avg       0.94      0.94      0.94      1165
weighted avg       0.94      0.94      0.94      1165
```

ROC Plot



Polynomial SVM Kernel

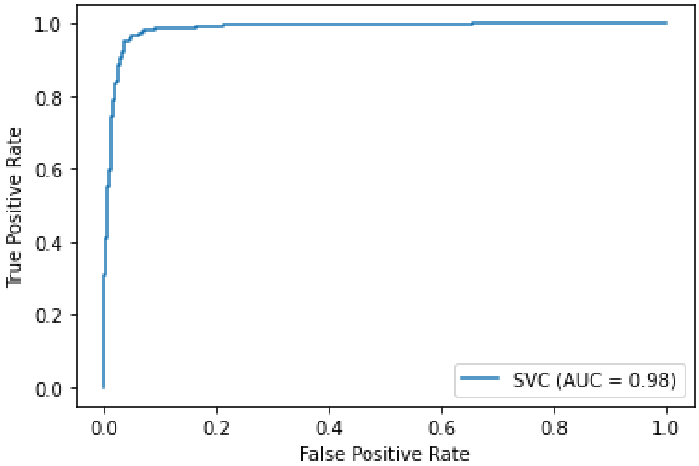
In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1, kernel='poly', degree=3)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9553648068669528

Confusion matrix:

[[489  21]
 [ 31 624]]

Classification Report:

              precision    recall  f1-score   support

           B       0.94      0.96      0.95       510
           M       0.97      0.95      0.96       655
```

```
    accuracy                           0.96      1165
   macro avg       0.95      0.96      0.95      1165
weighted avg       0.96      0.96      0.96      1165
```

```
ROC Plot
```



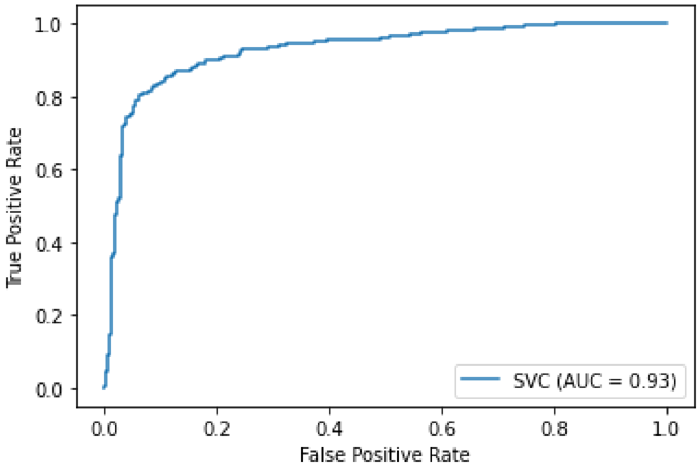
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=5, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.8600858369098713

Confusion matrix:

[[468  42]
 [121 534]]

Classification Report:

              precision    recall  f1-score   support

           B       0.79      0.92      0.85       510
           M       0.93      0.82      0.87       655

    accuracy                           0.86      1165
   macro avg       0.86      0.87      0.86      1165
weighted avg       0.87      0.86      0.86      1165
```

ROC Plot



Task 2 - Tigram Model

We now analyse three sequence of sys-calls.
We change `ngram_range` to `(3,3)` and repeat the steps in the earlier tasks.

Bag of Words (No. of Occurrences of Calls)

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
text = final_data['Calls']
print(text)
```

```
0       ioctl pread rt_sigprocmask rt_sigprocmask rt_s...
1       dup fcntl close epoll_ctl ioctl ioctl getuid e...
2       futex ioctl epoll_pwait read recvfrom writev s...
3       read writev write read read write read read re...
4       read read ioctl ioctl writev futex ioctl ioctl...
                              ...
5817    newfstatat ioctl ioctl getuid newfstatat newfs...
5818    recvfrom recvfrom writev sendto getuid epoll_p...
5819    dup fcntl close epoll_ctl ioctl ioctl getuid e...
5820    ioctl ioctl faccessat mprotect mprotect mprote...
5821    getuid epoll_pwait getuid epoll_pwait read new...
Name: Calls, Length: 5822, dtype: object
```

In [ ]:

```
vectorizer = CountVectorizer(ngram_range=(3,3))
transformed_text = vectorizer.fit_transform(text)
vectorizer.get_feature_names()[:5]       #First five features
```

Out[ ]:

```
['_llseek _llseek _llseek',
 '_llseek _llseek clock_gettime',
 '_llseek _llseek close',
 '_llseek _llseek fcntl64',
 '_llseek _llseek futex']
```

In [ ]:

```
from sklearn import preprocessing
X = transformed_text.toarray()
```

```
X = preprocessing.normalize(X)
X
```

Out[ ]:

```
array([[0.        , 0.        , 0.        , ..., 0.        , 0.00053259,
        0.0958666 ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.15532401],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.05505922],
       ...,
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.15491933],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.05260622],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ]])
```

In [ ]:

```
from sklearn import model_selection, svm        #Split the data
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

Linear SVM Kernel

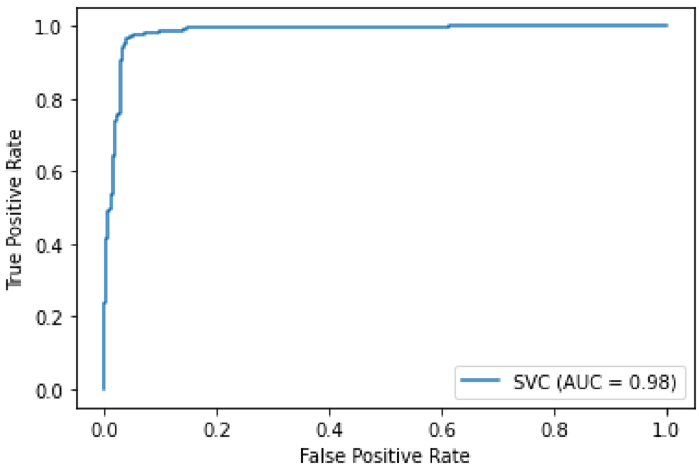
In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9570815450643777

Confusion matrix:

[[492  18]
 [ 32 623]]

Classification Report:

              precision    recall  f1-score   support

           B       0.94      0.96      0.95       510
           M       0.97      0.95      0.96       655

    accuracy                           0.96      1165
   macro avg       0.96      0.96      0.96      1165
```

```
weighted avg       0.96      0.96      0.96      1165
```

ROC Plot



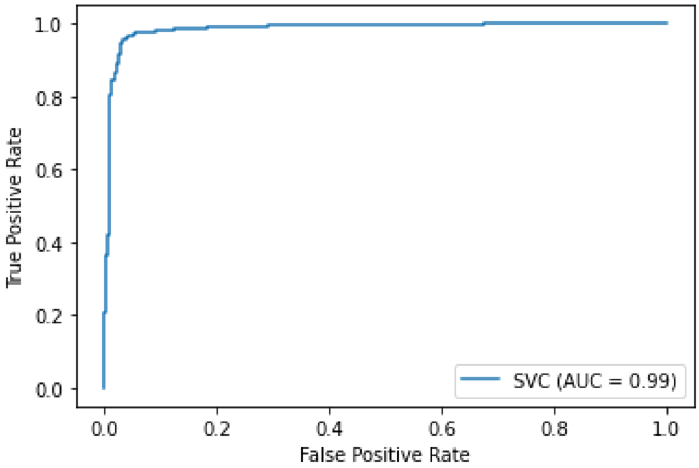
Polynomial SVM Kernel

In [ ]:

```python
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9605150214592275

Confusion matrix:

[[489  21]
 [ 25 630]]

Classification Report:

              precision    recall  f1-score   support

           B       0.95      0.96      0.96       510
           M       0.97      0.96      0.96       655

    accuracy                           0.96      1165
   macro avg       0.96      0.96      0.96      1165
weighted avg       0.96      0.96      0.96      1165
```

ROC Plot



RBF SVM Kernel

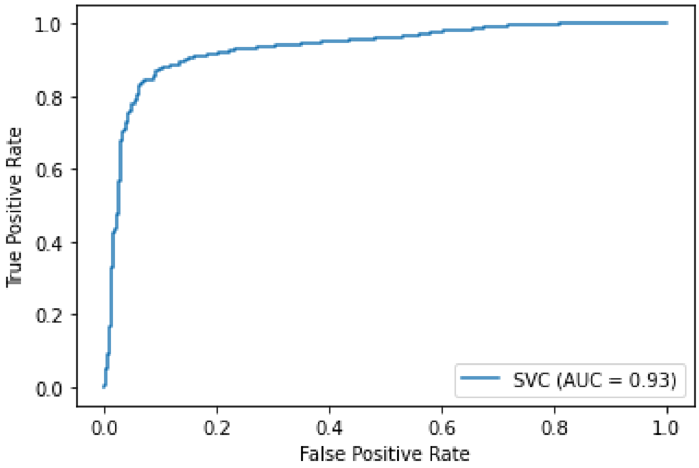
In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.5622317596566524

Confusion matrix:

[[   0 510]
 [   0 655]]

Classification Report:

              precision    recall  f1-score   support

           B       0.00      0.00      0.00       510
           M       0.56      1.00      0.72       655

    accuracy                           0.56      1165
   macro avg       0.28      0.50      0.36      1165
weighted avg       0.32      0.56      0.40      1165


ROC Plot
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: Undefined
```

```
MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Boolean Occurrence

Prepare the Data

In [ ]:

```
X = np.where(transformed_text.toarray() >= 1,1,0)
X
```

Out[ ]:

```
array([[0, 0, 0, ..., 0, 1, 1],
       [0, 0, 0, ..., 0, 0, 1],
       [0, 0, 0, ..., 0, 0, 1],
       ...,
       [0, 0, 0, ..., 0, 0, 1],
       [0, 0, 0, ..., 0, 0, 1],
       [0, 0, 0, ..., 0, 0, 0]])
```

In [ ]:

```
from sklearn import model_selection, svm
X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Labe
l'], test_size=0.2 , random_state=45 )
```

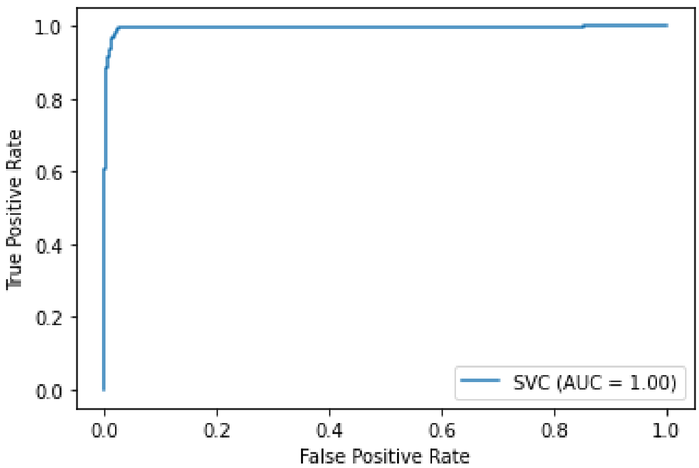
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
```

```
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9836909871244636

Confusion matrix:

[[498  12]
 [  7 648]]

Classification Report:

              precision    recall  f1-score   support

           B       0.99      0.98      0.98       510
           M       0.98      0.99      0.99       655

    accuracy                           0.98      1165
   macro avg       0.98      0.98      0.98      1165
weighted avg       0.98      0.98      0.98      1165


ROC Plot
```



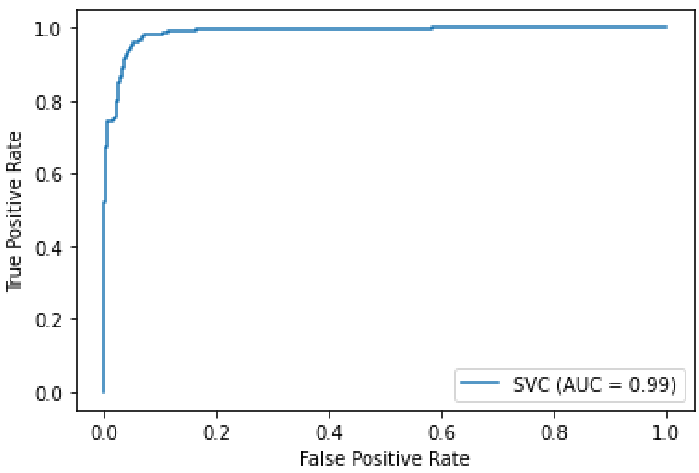
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))
```

```
#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.944206008583691

Confusion matrix:

[[455  55]
 [ 10 645]]

Classification Report:

              precision    recall  f1-score   support

           B       0.98      0.89      0.93       510
           M       0.92      0.98      0.95       655

    accuracy                           0.94      1165
   macro avg       0.95      0.94      0.94      1165
weighted avg       0.95      0.94      0.94      1165


ROC Plot
```



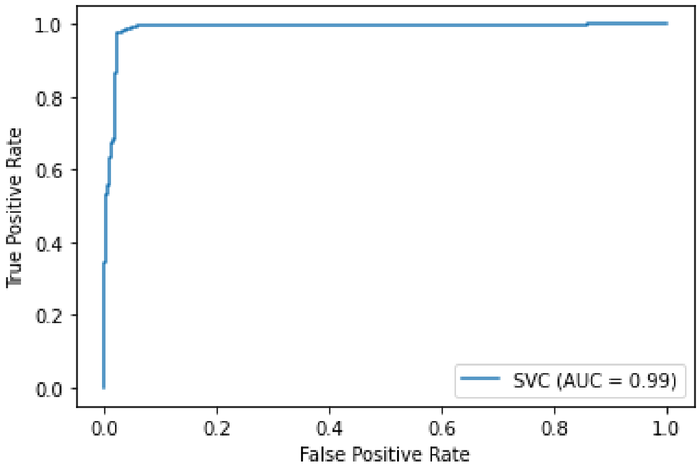
RBF SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)

#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
```

```
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.9725321888412017

Confusion matrix:

[[486  24]
 [  8 647]]

Classification Report:

              precision    recall  f1-score   support

           B       0.98      0.95      0.97       510
           M       0.96      0.99      0.98       655

    accuracy                           0.97      1165
   macro avg       0.97      0.97      0.97      1165
weighted avg       0.97      0.97      0.97      1165


ROC Plot
```



TF-IDF

Prepare the Data

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(ngram_range=(3,3))
X = vectorizer.fit_transform(text).toarray()

# print(X)
# print(vectorizer.vocabulary_)
```

In [ ]:

```
from sklearn import model_selection, svm

X_train, X_test, Y_train, Y_test = model_selection.train_test_split( X, final_data['Label'], test_size=0.2 , random_state=45 )
```

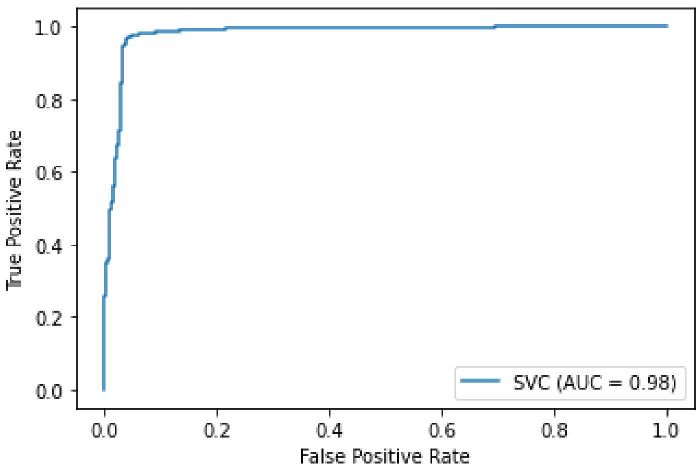
Linear SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot_roc_curve
```

```
#train model
Linear_Kernel = svm.SVC(C=1.5, kernel='linear', gamma='auto')
Linear_Kernel.fit(X_train,Y_train)

#predictions
Linear_Kernel_Predictions = Linear_Kernel.predict(X_test)

#accuracy score
print("Linear Kernel accuracy is ", accuracy_score(Linear_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Linear_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Linear_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Linear_Kernel, X_test, Y_test)
plt.show()
```

```
Linear Kernel accuracy is  0.9545064377682403

Confusion matrix:

[[493  17]
 [ 36 619]]

Classification Report:

              precision    recall  f1-score   support

           B       0.93      0.97      0.95       510
           M       0.97      0.95      0.96       655

    accuracy                           0.95      1165
   macro avg       0.95      0.96      0.95      1165
weighted avg       0.96      0.95      0.95      1165


ROC Plot
```



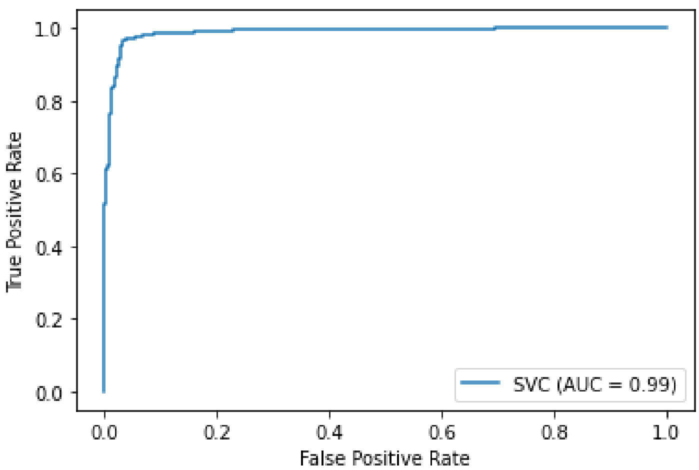
Polynomial SVM Kernel

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
Polynomial_Kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
```

```
Polynomial_Kernel.fit(X_train,Y_train)

#predictions
Polynomial_Kernel_Predictions = Polynomial_Kernel.predict(X_test)

#accuracy score
print("Polynomial Kernel accuracy is ", accuracy_score(Polynomial_Kernel_Predictions, Y_t
est))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,Polynomial_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,Polynomial_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(Polynomial_Kernel, X_test, Y_test)
plt.show()
```

```
Polynomial Kernel accuracy is  0.9639484978540772

Confusion matrix:

[[494  16]
 [ 26 629]]

Classification Report:

              precision    recall  f1-score   support

           B       0.95      0.97      0.96       510
           M       0.98      0.96      0.97       655

    accuracy                           0.96      1165
   macro avg       0.96      0.96      0.96      1165
weighted avg       0.96      0.96      0.96      1165


ROC Plot
```



RBF SVM Kernel

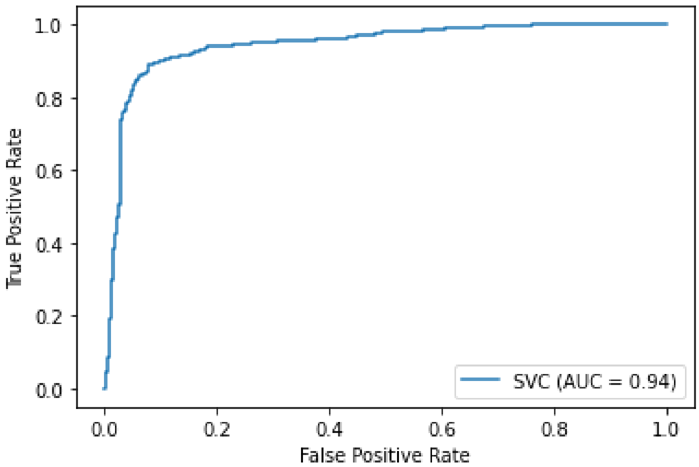
In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
RBF_Kernel = svm.SVC(C=1, kernel='rbf', gamma='auto')
RBF_Kernel.fit(X_train,Y_train)
```

```
#predictions
RBF_Kernel_Predictions = RBF_Kernel.predict(X_test)

#accuracy score
print("RBF Kernel accuracy is ", accuracy_score(RBF_Kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,RBF_Kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,RBF_Kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(RBF_Kernel, X_test, Y_test)
plt.show()
```

```
RBF Kernel accuracy is  0.5622317596566524

Confusion matrix:

[[  0 510]
 [  0 655]]

Classification Report:

              precision    recall  f1-score   support

           B       0.00      0.00      0.00       510
           M       0.56      1.00      0.72       655

    accuracy                           0.56      1165
   macro avg       0.28      0.50      0.36      1165
weighted avg       0.32      0.56      0.40      1165


ROC Plot
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: Undefined
MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with
no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Task 3 - Feature Selection

This task is an attempt to find the best features in two and three sequence models of sys-calls.
For both these data models, the following steps are performed:

- **The data is vectorized using the `TfidfVectorizer` with `ngram_range` being `(2,2)` and `(3,3)` for bigram and trigram respectfully.**
- **A light-weight model, `DecisionTreeClassifier` is trained with `max-features = 30`. This is to find the**

features with most **Feature Importance**.
- Finally, a bar graph is plot between the top 30 features and their feature importance.

Additionally, for the 2 sequence data model, a Polynomial SVM Kernel is trained and analysed.

Feature selection for 2 sequence

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

text = final_data['Calls']
vectorizer = TfidfVectorizer(ngram_range=(2,2))
X = vectorizer.fit_transform(text)
X
```

Out[ ]:

```
<5822x2425 sparse matrix of type '<class 'numpy.float64'>'
 with 1192807 stored elements in Compressed Sparse Row format>
```

In [ ]:

```
bigram_features = list(vectorizer.vocabulary_.keys())
print(bigram_features[:7])
```

```
['ioctl pread', 'pread rt_sigprocmask', 'rt_sigprocmask rt_sigprocmask', 'rt_sigprocmask openat', 'openat ioctl', 'ioctl ioctl', 'ioctl mmap']
```

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
Y = final_data['Label']

model = DecisionTreeClassifier(max_features=30)
model.fit(X,Y)

feature_df = pd.DataFrame(list(zip(model.feature_importances_,bigram_features)), columns = ['Feature Importance', 'Features'])
feature_df = feature_df.sort_values(by='Feature Importance',ascending=False)
print("Top 30 features (2 Sequence):")
feature_df.head(n=30)
```

```
Top 30 features (2 Sequence):
```

Out[ ]:

	Feature Importance	Features
1805	0.202945	fcntl64 ftruncate
1101	0.107995	fstat64 close
1400	0.072044	sendto getrlimit
2355	0.058309	clone prctl
1817	0.056940	ioctl geteuid
1206	0.039688	sendmsg getuid
1025	0.032005	geteuid32 openat
1035	0.022775	prctl clock_gettime
2320	0.020981	openat readlinkat
1019	0.019145	mmap2 faccessat
1236	0.016981	read rt_sigreturn
235	0.014451	write mprotect
102	0.011937	ioctl write

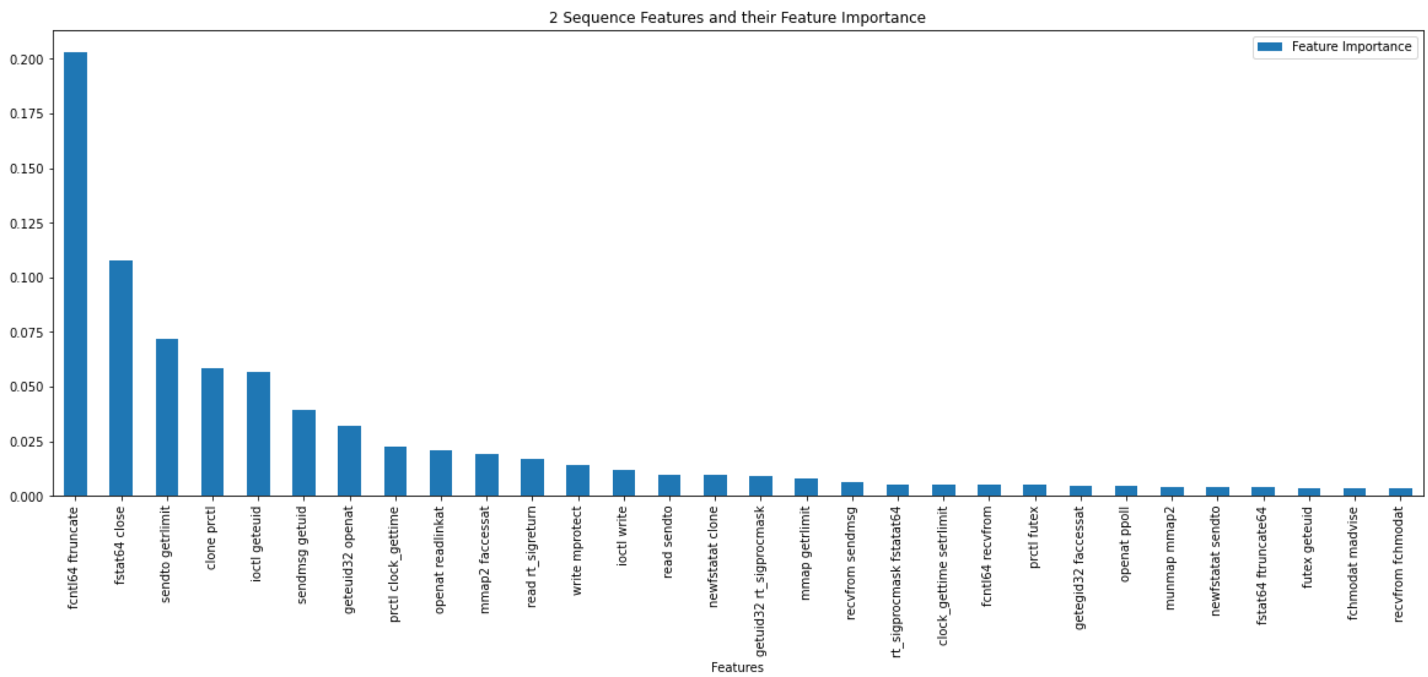
	Feature Importance	Features
231	0.009610	read sendto
1041	0.009583	newfstatat clone
1478	0.009254	getuid32 rt_sigprocmask
2339	0.008020	mmap getrlimit
2077	0.006301	recvfrom sendmsg
1783	0.005343	rt_sigprocmask fstatat64
1678	0.005339	clock_gettime setrlimit
1018	0.005250	fcntl64 recvfrom
320	0.005167	prctl futex
1991	0.004847	getegid32 faccessat
1089	0.004743	openat ppoll
720	0.004307	munmap mmap2
1422	0.004296	newfstatat sendto
1000	0.003961	fstat64 ftruncate64
1319	0.003848	futex geteuid
1537	0.003812	fchmodat madvise
1526	0.003811	recvfrom fchmodat

In [ ]:

```
feature_df.iloc[:30].plot(x = 'Features', y = 'Feature Importance', kind = 'bar', figsiz
e = (20,7), title = '2 Sequence Features and their Feature Importance')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9bcdb40550>
```



Model for 2 sequence based on top 30 features

Prepare the Data

In [ ]:

```
bigram_tfidf_data = pd.DataFrame(X.toarray(),columns = vectorizer.get_feature_names())
bigram_tfidf_data['File'] = final_data['File']
cols = list(bigram_tfidf_data.columns)
```

```
cols = [cols[-1]] + cols[:-1]
bigram_tfidf_data = bigram_tfidf_data[cols]
```

In [ ]:

```
bigram_tfidf_data
```

Out[ ]:

	File	_llseek _llseek	_llseek clock_gettime	_llseek close	_llseek faccessat	_llseek fcntl64	_llseek fstat64	_lls fstata
0	com.chinadeals.apk.sys_names.txt	0.0	0.0	0.0	0.0	0.0	0.0	
1	chat.cristianogratis.apk.sys_names.txt	0.0	0.0	0.0	0.0	0.0	0.0	
2	com.eterno.apk.sys_names.txt	0.0	0.0	0.0	0.0	0.0	0.0	
3	com.andromo.dev551559.app531086.apk.sys_names.txt	0.0	0.0	0.0	0.0	0.0	0.0	
4	com.blinkslabs.blinkist.android.apk.sys_names.txt	0.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	
5817	a0bffc11168c65beb59c326d88f144f0d750634252a507...	0.0	0.0	0.0	0.0	0.0	0.0	
5818	02c9bddf966b59a8850a7395e7ce5af21ca16c442a0389...	0.0	0.0	0.0	0.0	0.0	0.0	
5819	6113bc8bbbdfe89114a12ddfa25ad54eed63367cf21462...	0.0	0.0	0.0	0.0	0.0	0.0	
5820	3ddcdc882166b87d3db9d5cc21ccd4c7009e1f134edeeb...	0.0	0.0	0.0	0.0	0.0	0.0	
5821	66d6c067ca2c6e500caac92977f19c513436b2ae276ab9...	0.0	0.0	0.0	0.0	0.0	0.0	

5822 rows × 2426 columns

In [ ]:

```
a = list(feature_df['Features'].head(n=30))
top30_bigram_tfidf_data = bigram_tfidf_data[a]
top30_bigram_tfidf_data
```

Out[ ]:

	fcntl64 ftruncate	fstat64 close	sendto getrlimit	clone prctl	ioctl geteuid	sendmsg getuid	geteuid32 openat	prctl clock_gettime	openat readlinkat	mmap2 faccessat	read rt_sigreturn	mpr
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
...	...	...	...	...	...	...	...	...	...	...	...	
5817	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
5818	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
5819	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
5820	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00
5821	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00

5822 rows × 30 columns

Train the model on top 30 features

In [ ]:

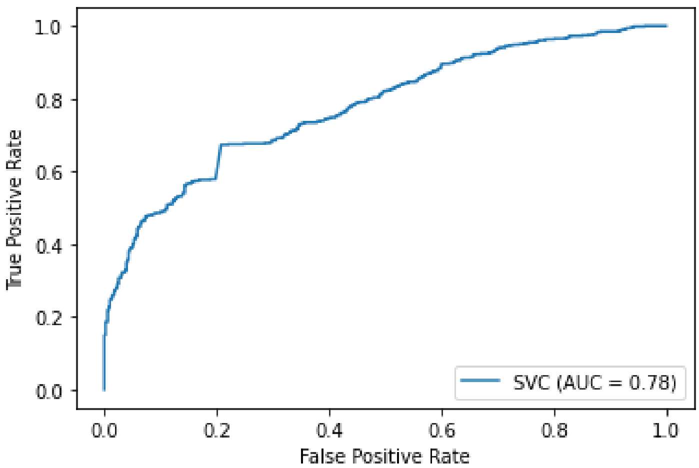
```
from sklearn import model_selection, svm
```

```
from sklearn import model_selection, svm

X_train, X_test, Y_train, Y_test = model_selection.train_test_split( top30_bigram_tfidf_
data, final_data['Label'], test_size=0.2 , random_state=45 )
```

In [ ]:

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, plot
_roc_curve

#train model
top30_feature_kernel = svm.SVC(C=1.5, kernel='poly', degree=4)
top30_feature_kernel.fit(X_train,Y_train)

#predictions
top30_feature_kernel_Predictions = top30_feature_kernel.predict(X_test)

#accuracy score
print("For Polynomial Kernel trained on top30, features accuracy is ", accuracy_score(top
30_feature_kernel_Predictions, Y_test))

#Confusion Matrix
print("\nConfusion matrix:\n")
print(confusion_matrix(Y_test,top30_feature_kernel_Predictions))

#Classification Report for the rest of the metrics
print("\nClassification Report:\n")
print(classification_report(Y_test,top30_feature_kernel_Predictions))

#ROC Plot
print("\nROC Plot")
plot_roc_curve(top30_feature_kernel, X_test, Y_test)
plt.show()
```

```
For Polynomial Kernel trained on top30, features accuracy is  0.5871244635193134

Confusion matrix:

[[ 33 477]
 [  4 651]]

Classification Report:

              precision    recall  f1-score   support

           B       0.89      0.06      0.12       510
           M       0.58      0.99      0.73       655

    accuracy                           0.59      1165
   macro avg       0.73      0.53      0.43      1165
weighted avg       0.71      0.59      0.46      1165


ROC Plot
```



Feature selection for 3 sequence

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

text = final_data['Calls']
vectorizer = TfidfVectorizer(smooth_idf=False, sublinear_tf=False, norm=None, analyzer='
word',ngram_range=(3,3))
X = vectorizer.fit_transform(text)
X
```

Out[ ]:

```
<5822x23331 sparse matrix of type '<class 'numpy.float64'>'
 with 3442893 stored elements in Compressed Sparse Row format>
```

In [ ]:

```
trigram_features = list(vectorizer.vocabulary_.keys())
print(trigram_features[:7])
```

```
['ioctl pread rt_sigprocmask', 'pread rt_sigprocmask rt_sigprocmask', 'rt_sigprocmask rt_
sigprocmask rt_sigprocmask', 'rt_sigprocmask rt_sigprocmask openat', 'rt_sigprocmask open
at ioctl', 'openat ioctl ioctl', 'ioctl ioctl mmap']
```

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
Y = final_data['Label']

model = DecisionTreeClassifier(max_features=15)
model.fit(X,Y)

feature_df = pd.DataFrame(list(zip(model.feature_importances_,trigram_features)), columns
= ['Feature Importance', 'Features'])
feature_df = feature_df.sort_values(by='Feature Importance',ascending=False)
print("Top 30 features (3 Sequence):")
feature_df.head(n=15)
```

```
Top 30 features (3 Sequence):
```

Out[ ]:

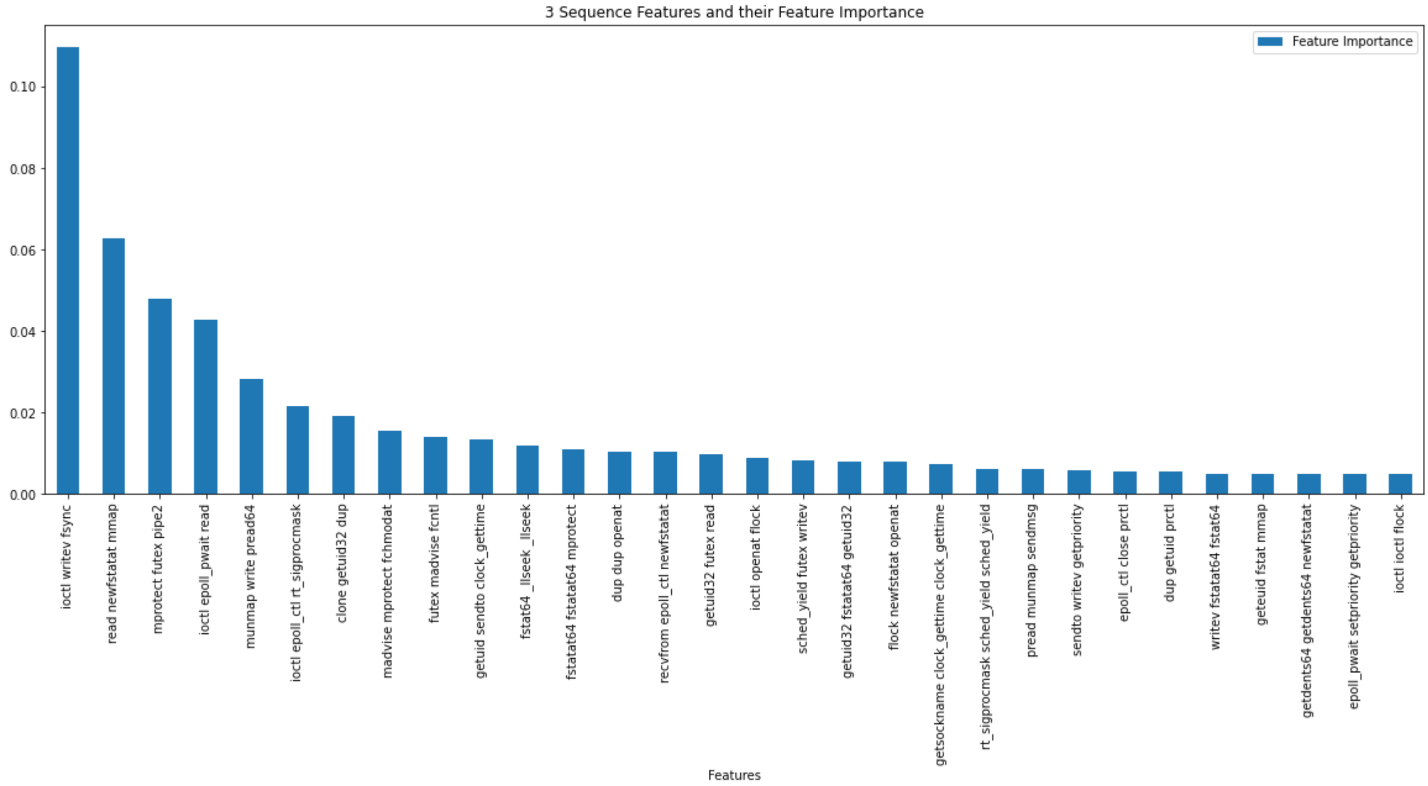
	Feature Importance	Features
22452	0.109745	ioctl writev fsync
20601	0.062664	read newfstatat mmap
9315	0.047965	mprotect futex pipe2
479	0.042854	ioctl epoll_pwait read
10624	0.028177	munmap write pread64
21798	0.021520	ioctl epoll_ctl rt_sigprocmask
13829	0.019237	clone getuid32 dup
17760	0.015724	madvise mprotect fchmodat
11238	0.014135	futex madvise fcntl
21807	0.013475	getuid sendto clock_gettime
3330	0.011935	fstat64 _llseek _llseek
3689	0.010983	fstatat64 fstatat64 mprotect
14929	0.010563	dup dup openat
13804	0.010319	recvfrom epoll_ctl newfstatat
17460	0.009827	getuid32 futex read

In [ ]:

```
feature_df.iloc[:30].plot(x = 'Features', y = 'Feature Importance', kind = 'bar', figsiz
e = (20,7), title = '3 Sequence Features and their Feature Importance')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9bb012d940>
```



Task 4 - Clustering Techniques

This task is an attempt to understand three different clustering methods, namely - `K Means`, `Hierarchial Clustering` and `DBSCAN`.
This task has been performed in the following steps -

- **First, the data has been prepared. The sys-calls have been vectorized, fit and transformed using `TfidfVectorizer`. This is stored in a DataFrame `unigram_tfidf_data`. Then, we find the top 30 features by training this data using `ExtraTreesClassifier` and . Finally, we extract the data of these top 30 features from `X` and store it in a DataFrame, `top30_features_data`.**
- **`K Means` clustering is performed on data from `top30_features_data`. A `KMeans` model is fit with number of clusters from 1 to 5. Then, a graph of `Number of Clusters` vs `Within Cluster Sum of Squares`. This is done to find optimum number of clusters, i.e., The Elbow Method. Finally, a graph is plotted for two random features and their cluster number.**
- **`Hierarchial Clustering` is performed. The data from `top30_features_data` is trained on an `AgglomerativeClustering` model and optimum number of clusters are found. and a graph is plotted for two random features and their cluster number.**
- **`DBSCAN` clustering is performed. The data from `top30_features_data` is trained on a `DBSCAN` model and optimum number of clusters are found. Finally, a graph is plotted for two random features and their cluster number.**

Preparing the Data

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

text = final_data['Calls']
```

```
vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(text)
```

In [ ]:

```
features = list(vectorizer.vocabulary_.keys())
print(features[:7])
```

```
['ioctl', 'pread', 'rt_sigprocmask', 'openat', 'mmap', 'close', 'mprotect']
```

In [ ]:

```
from sklearn.ensemble import ExtraTreesClassifier
Y = final_data['Label']

model = ExtraTreesClassifier(n_estimators=10)
model.fit(X,Y)

feature_df = pd.DataFrame(list(zip(model.feature_importances_,features)), columns = ['Fea
ture Importance', 'Features'])
feature_df = feature_df.sort_values(by='Feature Importance',ascending=False)
print("Top 30 features:")
feature_df.head(n=30)
```

```
Top 30 features:
```

Out[ ]:

	Feature Importance	Features
70	0.162134	ftruncate
65	0.072768	connect
100	0.072081	eventfd2
45	0.043114	lseek
49	0.042371	rt_sigaction
25	0.032815	setpriority
10	0.032499	futex
40	0.031677	pipe2
43	0.031334	getdents64
3	0.026308	openat
72	0.025985	tgkill
81	0.025618	stat64
55	0.023089	mmap2
34	0.022299	unlinkat
75	0.020741	mknodat
66	0.020246	gettid
7	0.019560	madvise
9	0.018031	epoll_pwait
83	0.015769	setsockopt
61	0.014429	fstatat64
53	0.014157	clock_gettime
62	0.013475	geteuid32
33	0.012164	fchmodat
59	0.011870	_llseek
5	0.011279	close
8	0.011176	getuid
41	[illegible]	[illegible]

	Feature Importance	Features
41	0.010527	epoll_create1
71	0.010222	getcwd
4	0.009361	mmap
101	0.009048	ugetrlimit

In [ ]:

```
unigram_tfidf_data = pd.DataFrame(X.toarray(), columns = features)
unigram_tfidf_data
```

Out[ ]:

	ioctl	pread	rt_sigprocmask	openat	mmap	close	mprotect	madvise	getuid	epoll_pwait	futex	munmap
0	0.0	0.0	0.0	0.0	0.000593	0.027595	0.0	0.007276	0.000000	0.015406	0.486590	0.0
1	0.0	0.0	0.0	0.0	0.000730	0.019107	0.0	0.007357	0.000000	0.018643	0.317636	0.0
2	0.0	0.0	0.0	0.0	0.005048	0.021287	0.0	0.003402	0.000000	0.009913	0.207178	0.0
3	0.0	0.0	0.0	0.0	0.009158	0.047608	0.0	0.011388	0.000873	0.011964	0.509608	0.0
4	0.0	0.0	0.0	0.0	0.005554	0.068540	0.0	0.014597	0.000000	0.032828	0.316841	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...
5817	0.0	0.0	0.0	0.0	0.007177	0.065576	0.0	0.044014	0.000000	0.006318	0.374608	0.0
5818	0.0	0.0	0.0	0.0	0.000701	0.016487	0.0	0.007774	0.000000	0.007195	0.470133	0.0
5819	0.0	0.0	0.0	0.0	0.020579	0.094020	0.0	0.027045	0.000000	0.027176	0.281335	0.0
5820	0.0	0.0	0.0	0.0	0.000544	0.049521	0.0	0.017649	0.000000	0.022527	0.203664	0.0
5821	0.0	0.0	0.0	0.0	0.000000	0.136429	0.0	0.000000	0.000000	0.000000	0.067378	0.0

5822 rows × 102 columns

In [ ]:

```
top30_features = feature_df['Features'].head(n=30)
pd.DataFrame(top30_features)
```

Out[ ]:

	Features
70	ftruncate
65	connect
100	eventfd2
45	lseek
49	rt_sigaction
25	setpriority
10	futex
40	pipe2
43	getdents64
3	openat
72	tgkill
81	stat64
55	mmap2
34	unlinkat
75	mknodat
66	gettid

	Features
7	madvise
9	epoll_pwait
83	setsockopt
61	fstatat64
53	clock_gettime
62	geteuid32
33	fchmodat
59	_llseek
5	close
8	getuid
41	epoll_create1
71	getcwd
4	mmap
101	ugetrlimit

In [ ]:

```
top30_features_data = unigram_tfidf_data[top30_features]
top30_features_data
```

Out[ ]:

	ftruncate	connect	eventfd2	lseek	rt_sigaction	setpriority	futex	pipe2	getdents64	openat	tgkill	st
0	0.180168	0.001213	0.267231	0.363398	0.007414	0.031091	0.486590	0.354401	0.0	0.0	0.518655	0.31
1	0.101963	0.000000	0.166216	0.259153	0.001574	0.032454	0.317636	0.146693	0.0	0.0	0.646377	0.57
2	0.054056	0.001190	0.182486	0.232233	0.018742	0.038095	0.207178	0.184826	0.0	0.0	0.672197	0.60
3	0.035253	0.000906	0.081974	0.356077	0.017824	0.083732	0.509608	0.539019	0.0	0.0	0.355259	0.29
4	0.067061	0.001622	0.156857	0.513908	0.005471	0.163663	0.316841	0.309751	0.0	0.0	0.435994	0.35
...	...	...	...	...	...	...	...	...	...	...	...	
5817	0.523352	0.000000	0.429397	0.528391	0.024743	0.042127	0.374608	0.244462	0.0	0.0	0.124806	0.00
5818	0.354499	0.000239	0.380667	0.279326	0.049914	0.060897	0.470133	0.487238	0.0	0.0	0.304561	0.26
5819	0.170535	0.031548	0.205216	0.493704	0.008869	0.017257	0.281335	0.305562	0.0	0.0	0.026841	0.00
5820	0.493119	0.001947	0.548576	0.352653	0.034256	0.004794	0.203664	0.193298	0.0	0.0	0.350787	0.31
5821	0.006607	0.000000	0.000000	0.427389	0.000000	0.060170	0.067378	0.065457	0.0	0.0	0.000000	0.00

5822 rows × 30 columns

K-Means

Finding optimum number of clusters using elbow method

In [ ]:

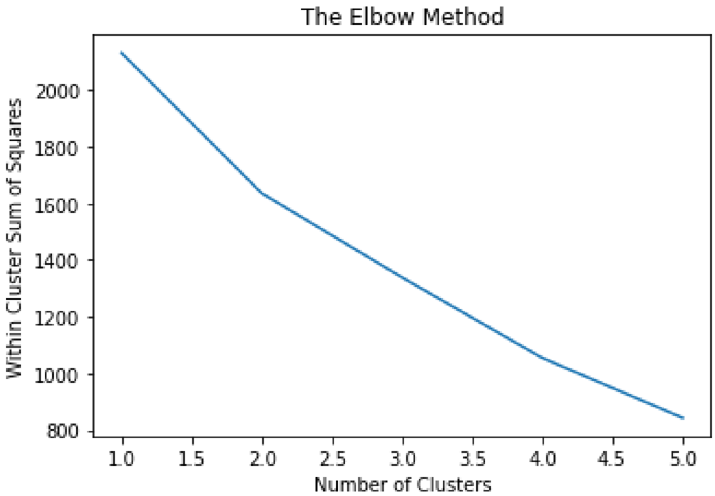
```
from sklearn.cluster import KMeans
WCSS = []

for cluster in range(1,6):
    kmeans = KMeans(n_clusters= cluster, init='k-means++', random_state=0)
    kmeans.fit(top30_features_data)
    print("Cluster", cluster, "done!")
    WCSS.append(kmeans.inertia_)
```

Cluster 1 done!

```
Cluster 1 done!
Cluster 2 done!
Cluster 3 done!
Cluster 4 done!
Cluster 5 done!
```

In [ ]:

```
plt.plot(range(1,6), WCSS)
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Within Cluster Sum of Squares')
plt.show()       #Elbow is at 2, therefore 2 is the optimum number of clusters
```



Model Creation with optimum number of clusters

In [ ]:

```
two_cluster_kmeans = KMeans(n_clusters= 2, init='k-means++', random_state=0)
random_two_features = top30_features_data.iloc[:,[6,9]]
random_two_features_model = two_cluster_kmeans.fit(random_two_features)
random_two_features
```

Out[ ]:

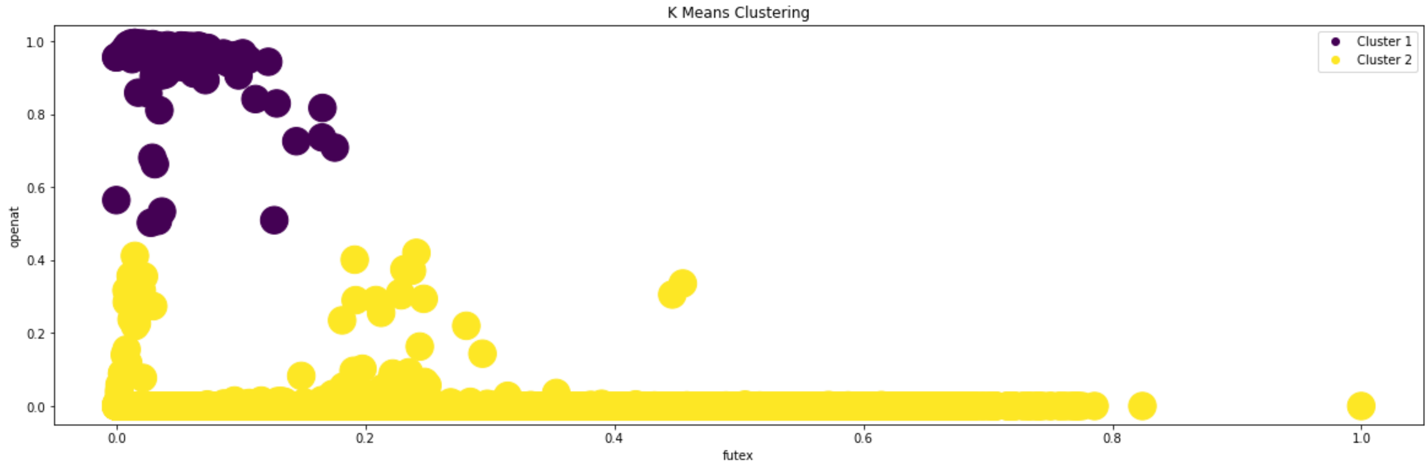
	futex	openat
0	0.486590	0.0
1	0.317636	0.0
2	0.207178	0.0
3	0.509608	0.0
4	0.316841	0.0
...	...	...
5817	0.374608	0.0
5818	0.470133	0.0
5819	0.281335	0.0
5820	0.203664	0.0
5821	0.067378	0.0

5822 rows × 2 columns

In [ ]:

```
# random_two_features
plt.figure(figsize=(20, 6))
plt.scatter(random_two_features['futex'], random_two_features['openat'], c=random_two_fea
```

```
tures_model.labels_.astype(float), label=['Cluster1','Cluster2'], s=500)
plt.legend(handles=scatter.legend_elements()[0], labels=['Cluster 1', 'Cluster 2'])
plt.xlabel('futex')
plt.ylabel('openat')
plt.title('K Means Clustering')
plt.show()
```



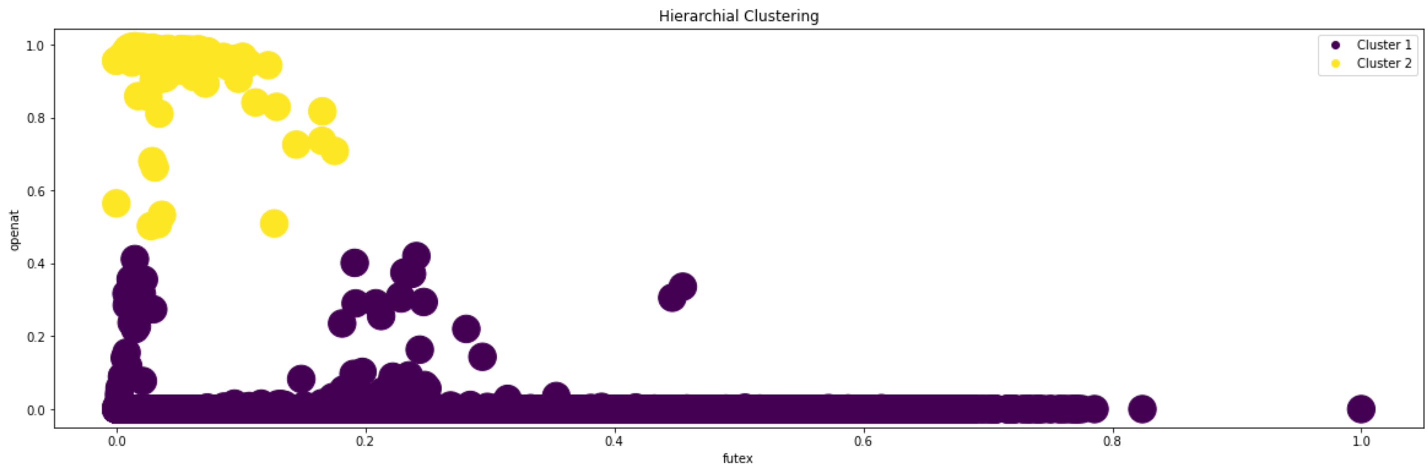
Hierarchial Clustering

In [ ]:

```
from sklearn.cluster import AgglomerativeClustering

two_cluster_HC = AgglomerativeClustering(n_clusters = 2, affinity = 'euclidean', linkage
= 'ward')
two_cluster_HC_model = two_cluster_HC.fit(random_two_features)
```

In [ ]:

```
# random_two_features
plt.figure(figsize=(20, 6))
plt.scatter(random_two_features['futex'], random_two_features['openat'], c=two_cluster_HC
_model.labels_.astype(float), label=['Cluster1','Cluster2'], s=500)
plt.legend(handles=scatter.legend_elements()[0], labels=['Cluster 1', 'Cluster 2'])
plt.xlabel('futex')
plt.ylabel('openat')
plt.title('Hierarchial Clustering')
plt.show()
```



DBSCAN

In [ ]:

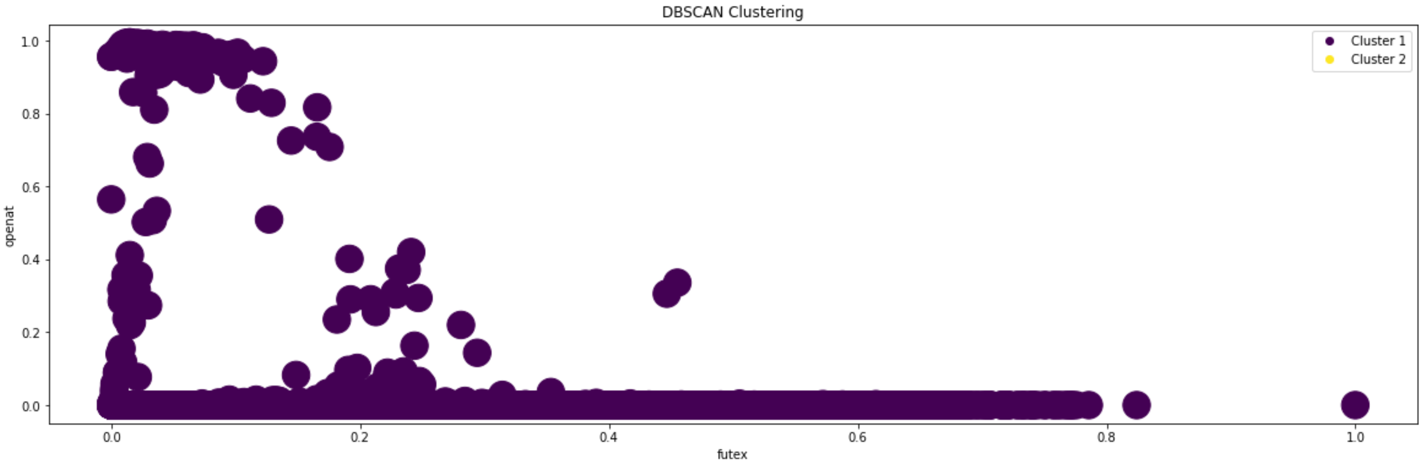
```
from sklearn.cluster import DBSCAN
two_feature_DB=DBSCAN(eps=10,min_samples=5,metric='euclidean')
two_feature_DB.fit(random_two_features)
```

```
print("Optimum No. of clusters, according to DBSCAN = ", len(set(two_feature_DB.labels_))
)
```

```
Optimum No. of clusters, according to DBSCAN =  1
```

In [ ]:

```
# random_two_features
plt.figure(figsize=(20, 6))
plt.scatter(random_two_features['futex'], random_two_features['openat'], c=two_feature_DB
.labels_.astype(float), label=['Cluster1','Cluster2'], s=500)
plt.legend(handles=scatter.legend_elements()[0], labels=['Cluster 1', 'Cluster 2'])
plt.xlabel('futex')
plt.ylabel('openat')
plt.title('DBSCAN Clustering')
plt.show()
```



Conclusion

In this series of tasks, analysis of sys-calls has been done. A sequence of sys-calls is either labeled as B/M.

In the first two tasks, we see that the two sequence/bigram models produce the most convincing results, with `TF-IDF` being the most effective vectorizing technique.
Trigram models take significantly longer time to train, with marginal better accuracy in some cases. Some RBF models crashed the runtime while training, which is the reason for some errors in `classification_report`.

In the third task, we find the top features in two sequence and three sequence models. These features are plot to analyse visually. The model prepared with the top 30 two sequence features gives un-satisfactory output. Bigram models trained on all features are still the better models.

In the last task, we use three different clustering techniques to cluster sys-calls sequences into clusters. From the three techniques performed, we find that two clusters are the ideal number of clusters in the data.