

Configuration Manual

MSc Internship
Cyber Security

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Configuration Manual

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1 Introduction

This configuration manual provides the details of the proposed work and model used for intrusion detection system. Hybrid IDS is developed using machine learning approaches. It combines Random Forest classification and K-Means clustering. This will use both mis-use detection and anomaly detection for improving performance of the IDS. These algorithms are evaluated for the four categories of attacks based on accuracy, false-alarm-rate, and detection-rate besides other metrics like precision, recall and F1-score. The technical details of individual machine learning methods can be found in literature such as [1], [2], [3], [4], [5], [6] and [7].

2 System Configuration

This section provides an overview of the system used for the implementation of this model.

Hardware Specification

This project is developed using a laptop running Windows 8 operating system. The system specifications are as shown below.

Operating System: Windows 10.1

Intel i7 CPU with 1.60 GHz

64 bit operating system

3 Software Specification

This section describes details of the tools and technologies used while developing the project.

Tool	Version	Description
Python for Windows ¹	3.7	Python language support.
Anaconda for Windows ²	2019.10	Data science platform with many IDEs.
Jupyter ³	3	Chosen IDE

Table 1: Tools used in this model

4 Working

This section illustrates step by step procedure used for setting up the proposed model and demonstrates its working.

Software Installation

Python data science environment is created using the following URL.

<https://www.anaconda.com/distribution/#download-section>

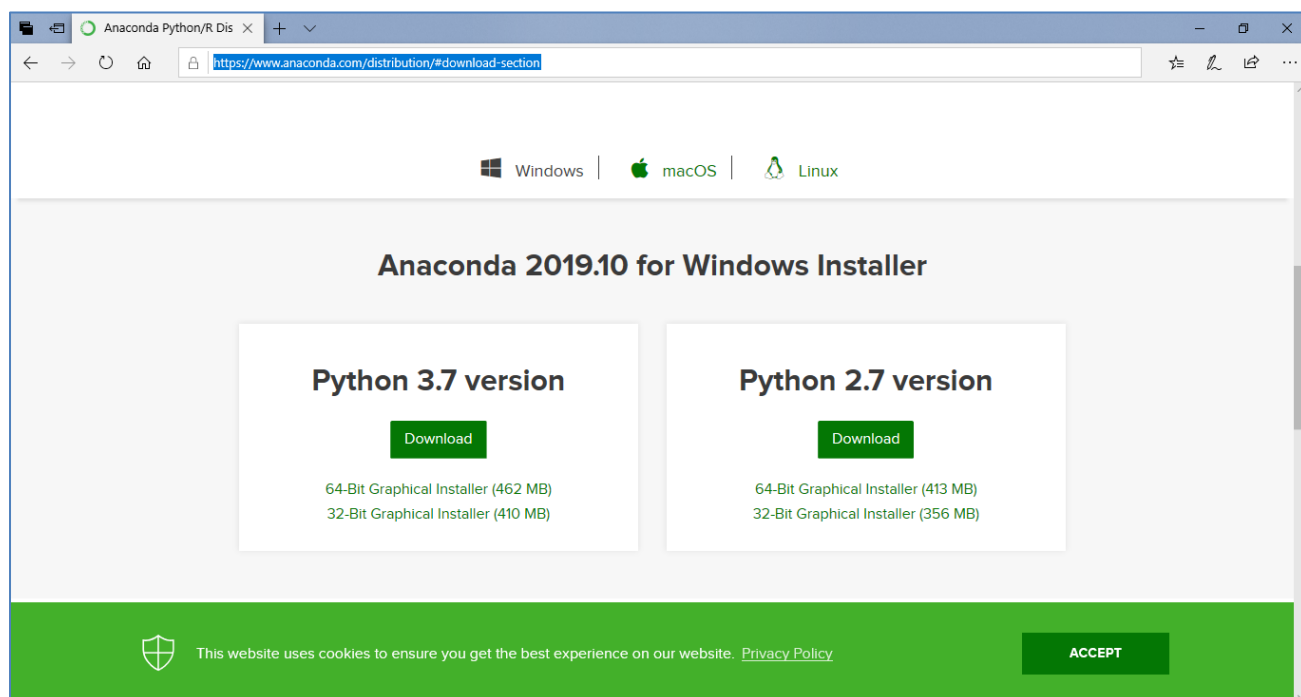


Figure 1: Anaconda installation with Python 3.7

Implementation

¹<https://www.anaconda.com/distribution/#download-section>

²<https://www.anaconda.com/distribution/#download-section>

³<https://www.anaconda.com/distribution/#download-section>

Jupyter IDE is used for the implementation of IDE. It is part of the Anaconda platform based on Python.

To run the project:

1. Open Jupyter
2. Load the project
3. Load the files to run

KMeans clustering with Random Forest Classifiers

```
kmeans_prob_col = 'kmeans_rf_prob'
kmeans_pred_col = 'kmeans_rf_pred'

prob_cols.append(kmeans_prob_col)
pred_cols.append(kmeans_pred_col)
# KMeans clustering
from pyspark.ml.clustering import KMeans

t0 = time()
kmeans_slicer = VectorSlicer(inputCol="indexed_features", outputCol="features",
                             names=list(set(selectFeaturesByAR(ar_dict, 0.1)).intersection(numeric_cols)))

kmeans = KMeans(k=8, initSteps=25, maxIter=100, featuresCol="features", predictionCol="cluster", seed=seed)

kmeans_pipeline = Pipeline(stages=[kmeans_slicer, kmeans])

kmeans_model = kmeans_pipeline.fit(scaled_train_df)

kmeans_train_df = kmeans_model.transform(scaled_train_df).cache()
kmeans_cv_df = kmeans_model.transform(scaled_cv_df).cache()
kmeans_test_df = kmeans_model.transform(scaled_test_df).cache()

print(time() - t0)

# Function for describing the contents of the clusters
def getClusterCrosstab(df, clusterCol='cluster'):
    return (df.crosstab(clusterCol, 'labels2')
            .withColumn('count', col('attack') + col('normal'))
            .withColumn(clusterCol + '_labels2', col(clusterCol + '_labels2').cast('int'))
            .sort(col(clusterCol + '_labels2').asc()))

kmeans_crosstab = getClusterCrosstab(kmeans_train_df).cache()
kmeans_crosstab.show(n=30)
# Function for splitting clusters
def splitClusters(crosstab):
    exp = ((col('count') > 25) & (col('attack') > 0) & (col('normal') > 0))

    cluster_rf = (crosstab
```

```

# Function for splitting clusters
def splitClusters(crosstab):
    exp = ((col('count') > 25) & (col('attack') > 0) & (col('normal') > 0))

    cluster_rf = (crosstab
        .filter(exp).rdd
        .map(lambda row: (int(row['cluster_labels2']), [row['count'], row['attack']/row['count']]))
        .collectAsMap())

    cluster_mapping = (crosstab
        .filter(~exp).rdd
        .map(lambda row: (int(row['cluster_labels2']), 1.0 if (row['count'] <= 25) | (row['normal'] == 0) else 0.0))
        .collectAsMap())

    return cluster_rf, cluster_mapping

kmeans_cluster_rf, kmeans_cluster_mapping = splitClusters(kmeans_crosstab)

print(len(kmeans_cluster_rf), len(kmeans_cluster_mapping))
print(kmeans_cluster_mapping)
kmeans_cluster_rf
from pyspark.ml.classification import RandomForestClassifier

# This function returns Random Forest models for provided clusters
def getClusterModels(df, cluster_rf):
    cluster_models = {}

    labels_col = 'labels2_cl_index'
    labels2_indexer.setOutputCol(labels_col)

    rf_slicer = VectorSlicer(inputCol="indexed_features", outputCol="rf_features",
        names=selectFeaturesByAR(ar_dict, 0.05))

    for cluster in cluster_rf.keys():
        t1 = time()
        rf_classifier = RandomForestClassifier(labelCol=labels_col, featuresCol='rf_features', seed=seed,

```

Visualization via PCA

```
t0 = time()
pca_slicer = VectorSlicer(inputCol="indexed_features", outputCol="features", names=selectFeaturesByAR(ar_dict, 0.05))

pca = PCA(k=2, inputCol="features", outputCol="pca_features")
pca_pipeline = Pipeline(stages=[pca_slicer, pca])

pca_train_df = pca_pipeline.fit(scaled_train_df).transform(scaled_train_df)
print(time() - t0)
t0 = time()
viz_train_data = np.array(pca_train_df.rdd.map(lambda row: [*row['pca_features'], row['labels2_index'], row['labels5_index']]))
plt.figure()
plt.scatter(x=viz_train_data[:,0], y=viz_train_data[:,1], c=viz_train_data[:,2], cmap="Set1")
plt.figure()
plt.scatter(x=viz_train_data[:,0], y=viz_train_data[:,1], c=viz_train_data[:,3], cmap="Set1")
plt.show()
print(time() - t0)
```

Data loading

```
# Creating Local SparkContext with 8 threads and SQLContext based on it
sc = pyspark.SparkContext(master='local[8]')
sc.setLogLevel('INFO')
sqlContext = SQLContext(sc)
from pyspark.sql.types import *
from pyspark.sql.functions import udf, split, col
import pyspark.sql.functions as sql

train20_nsl_kdd_dataset_path = "NSL_KDD_Dataset/KDDTrain+ 20Percent.txt"
train_nsl_kdd_dataset_path = "NSL_KDD_Dataset/KDDTrain+.txt"
test_nsl_kdd_dataset_path = "NSL_KDD_Dataset/KDDTest+.txt"

col_names = np.array(["duration", "protocol_type", "service", "flag", "src_bytes",
    "dst_bytes", "land", "wrong_fragment", "urgent", "hot", "num_failed_logins",
    "logged_in", "num_compromised", "root_shell", "su_attempted", "num_root",
    "num_file_creations", "num_shells", "num_access_files", "num_outbound_cmds",
    "is_host_login", "is_guest_login", "count", "srv_count", "error_rate",
    "srv_error_rate", "rerror_rate", "srv_rerror_rate", "same_srv_rate",
    "diff_srv_rate", "srv_diff_host_rate", "dst_host_count", "dst_host_srv_count",
    "dst_host_same_srv_rate", "dst_host_diff_srv_rate", "dst_host_same_src_port_rate",
    "dst_host_srv_diff_host_rate", "dst_host_error_rate", "dst_host_srv_error_rate",
    "dst_host_rerror_rate", "dst_host_srv_rerror_rate", "labels"])

nominal_inx = [1, 2, 3]
binary_inx = [6, 11, 13, 14, 20, 21]
numeric_inx = list(set(range(41)).difference(nominal_inx).difference(binary_inx))

nominal_cols = col_names[nominal_inx].tolist()
binary_cols = col_names[binary_inx].tolist()
numeric_cols = col_names[numeric_inx].tolist()
# Function to Load dataset and divide it into 8 partitions
def load_dataset(path):
    dataset_rdd = sc.textFile(path, 8).map(lambda line: line.split(','))
    dataset_df = (dataset_rdd.toDF(col_names.tolist()).select(
        col('duration').cast(DoubleType()),
        col('protocol_type').cast(StringType()),
```


Experimental Results

	normal	attack			
normal	13316	12			
attack	26	11779			
Accuracy = 0.998488					
AUC = 0.998449					
False Alarm Rate = 0.00090036					
Detection Rate = 0.997798					
F1 score = 0.99839					
	precision	recall	f1-score	support	
0.0	1.00	1.00	1.00	13328	
1.0	1.00	1.00	1.00	11805	
avg / total	1.00	1.00	1.00	25133	

	normal	attack			
normal	8262	1449			
attack	182	12651			
Accuracy = 0.927653					
AUC = 0.918303					
False Alarm Rate = 0.149212					
Detection Rate = 0.985818					
F1 score = 0.939442					
	precision	recall	f1-score	support	
0.0	0.98	0.85	0.91	9711	
1.0	0.90	0.99	0.94	12833	
avg / total	0.93	0.93	0.93	22544	

	normal	attack
normal	13195	133
attack	2	11803

Accuracy = 0.994629

AUC = 0.994926

False Alarm Rate = 0.00997899

Detection Rate = 0.999831

F1 score = 0.994314

	precision	recall	f1-score	support
0.0	1.00	0.99	0.99	13328
1.0	0.99	1.00	0.99	11805
avg / total	0.99	0.99	0.99	25133

	normal	attack
normal	8367	1344
attack	830	12003

Accuracy = 0.903566

AUC = 0.898462

False Alarm Rate = 0.1384

Detection Rate = 0.935323

F1 score = 0.91696

	precision	recall	f1-score	support
0.0	0.91	0.86	0.89	9711
1.0	0.90	0.94	0.92	12833
avg / total	0.90	0.90	0.90	22544

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