ADIKAVI NANNAYA UNIVERSITY UNIVERSITY COLLEGE OF ENGINEERING



INTRUSION DETECTION SYSTEM

PROJECT GUIDE,
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INTRODUCTION

- What is Intrusion?
- Types of intruders
 - Masquerader (Not authorized)
 - Misfeasor(Misuses privileges)
 - Clandestine(Seizes Supervisory Control)
- Types of Intrusion detection system:
 - Network IDS
 - Host IDS
 - Protocol-based IDS
 - Application protocol –based IDS
 - Hybrid IDS

Continue...

- Classification of IDS:
 - Signature based IDS
 - Anomaly based IDS

OBJECTIVE

- To reduce the human intervention.
- To detect intrusions.
- To experiment machine learning algorithm in the domain of Cyber security.

REQUIREMENTS

- Software Requirements:
 - Python programming language.
 - Jupyter Notebook (Python editor).
 - Windows OS/unix.
- Hardware Requirements:
 - Fluently working Laptops (64 bit preferable).
 - RAM minimum 6GB.

IMLEMENTATION

• The system under following steps:

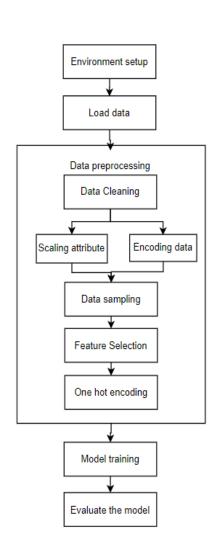
Environment Setup

Load Data

Data Preprocessing

Model Training

Evaluate the model



Continue....

- Environment Setup:
 - Setting Jupyter notebook
 - Installing and importing the packages
 - Numpy (Numerical and Mathematical Operations)
 - Seaborn (Data visualization library)
 - Padas (Data Frames)
 - Matplotlib (plots)
 - Sklearn (tools for machine learning)
 - Imblearn (re-sampling techniques)

Ex: import Numpy

- Load Dataset:
 - Kaggel
 - Test Dataset (125973 *42)
 - Train Dataset(22544 *42)
 - Some attributes are
 - count
 - dst_host_srv_count
 - Src_bytes
 - Srv_count
 - dst_host_serror_rate etc......

Pd.read_csv('Train.csv')

- Data Preprocessing
 - Data Cleaning
 - Missing values
 - Dummy attributes

drop()

- Scaling numerical attribute
 - Standardization (sklaern)
 - Mean=0 and Standard deviation =1
 - Z=x-M/SD

```
scaler = StandardScaler()
scaler.fit_transform(df_train.select_dtypes(include=['float64','int64']))
```

- Encoding the categorical data
 - Label Encoder (sklearn)
 - Categorical values to numerical labels
 - Alphabetical order

Labels	Dos	Normal	Probe
Label after encoding	0	1	2

```
encoder = LabelEncoder()
cattrain = df_train.select_dtypes(include=['object']).copy()
traincat = cattrain.apply(encoder.fit_transform)
```

Continue.....

- Data Sampling
 - Solve the class imbalance problem
 - Random oversampling (imblearn)

```
ros = RandomOverSampler(random_state=42)
X_res, y_res = ros.fit_sample(X, y)
```

- Feature Selection
 - Random forest
 - Important features only
 - Performance
 - Recursive feature elimination

```
rfe = RFE(rfc, n_features_to_select=10)
rfe = rfe.fit(X_res, y_res)
```

'src_bytes', 'dst_bytes', 'logged_in', 'count', 'srv_count', 'dst_host_srv_count',
 'dst_host_diff_srv_rate', 'dst_host_same_src_port_rate', 'dst_host_serror_rate', 'service'

Continue....

- One hot Encoding
 - Draw back on label encoding
 - Interger label to binary label

Label encoding

Dos	0
Normal	1
Probe	2



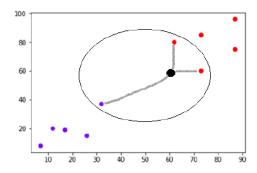
one hot encoding

Dos	Normal	Probe
1	0	0
0	1	0
0	0	1

- Model training
 - K-NearestNeighbour classifier
 - Logistic Regression

Continue....

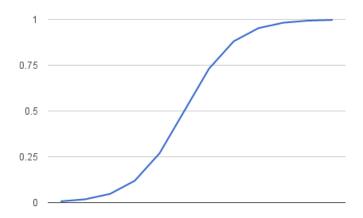
- K-Nearest Neighbor:
 - Non parametric ,Lazy learning
 - Distance Euclidean ,Hamming distance etc......
 - Algorithm:
 - Initialize the value of k
 - for i=0 to m: Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it's the most popular method.
 - Sort the calculated distances in ascending order based on distance values
 - Get top k rows from the sorted array
 - Return the majority label among S.



KNN_Classifier = KNeighborsClassifier(n_jobs=-1) KNN_Classifier.fit(X_train, Y_train);

Continue...

- Logistic Regression:
 - Probability based (0-1)
 - Sigmoid function: $1/1+e^{x}$
 - Developed from linear regression.



LGR_Classifier = LogisticRegression(n_jobs=-1, random_state=0) LGR_Classifier.fit(X_train, Y_train);

- Evaluating the model
 - Accuracy Score:
 - Number of correct predictions / Total number of predictions

accuracy = metrics.accuracy_score(Y_test, v.predict(X_test))

- Confusion matrix:
 - Accuracy=(true postive +true negative)*100/total samples

confusion_matrix = metrics.confusion_matrix(Y_test, v.predict(X_test))

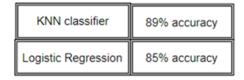
- Classification Report:
 - Precission: percent of correct prediction by model =TP/(TP+FP)
 - Recall:fraction of positive that are correctly identified by the classifier =TP/(TP+FN)
 - F1-Score:weighted mean of persision and recall = (2*Recall*percision)/(recall+Percission)

classification = metrics.classification_report(Y_test, v.predict(X_test))

Model Evaluation				Model Evaluation					
Model Accuracy: 0.8946356805871046					Model Accuracy: 0.8525248995282194				
Confusion mat [[5893 1565] [244 9467]]					Confusion matr [[5843 1615] [917 8794]]	rix:			
Classificatio	n report: precision	recall	f1-score	support	Classification	report: precision	recall	f1-score	support
0.0	0.96	0.79	0.87	7458					
1.0	0.86	0.97	0.91	9711	0.0	0.86	0.78	0.82	7458
					1.0	0.84	0.91	0.87	9711
accuracy			0.89	17169					
macro avg	0.91	0.88	0.89	17169	accuracy			0.85	17169
weighted avg	0.90	0.89	0.89	17169	macro avg	0.85	0.84	0.85	17169
					weighted avg	0.85	0.85	0.85	17169

CONCLUSION

 The system got the accuracy of 89% through KNN and 85% through Logistic regression



- A similar system is implemented by J.S.Sirisha (178297601004) and obtained an accuracy of 82.88% using decision tree algorithm and 86.97% using Naive Bayes algorithm.
- From the results KNN got the higher accuracy.

• What I look forward to use:

- Boosting techniques
- Implementation is done using real life packets.
- Advance algorithms and technologies.
- Mainly your suggestions

Thank you