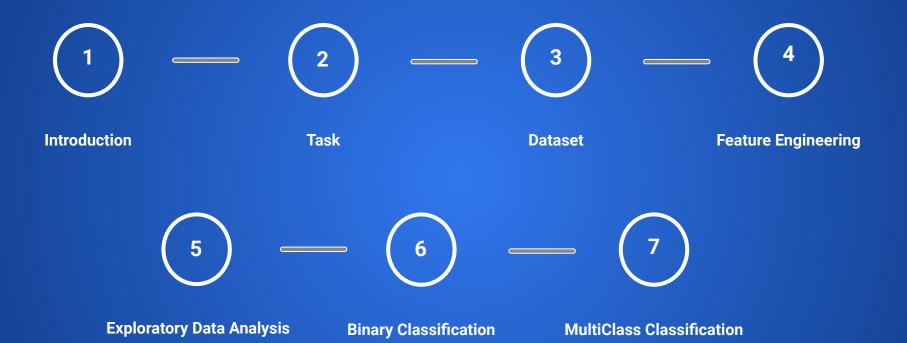
Malicious Url Detection with PySpark

Big Data Computing - Final Project - 2021/2022

Clizia Giorgia Manganaro 2017897



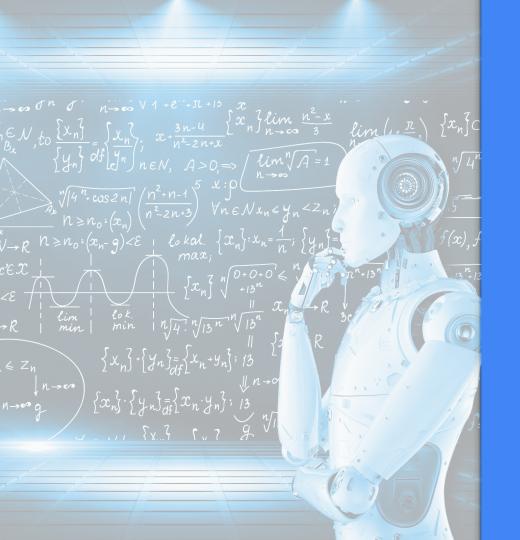
Introduction

Malicious URLs or malicious website is a very serious threat to cybersecurity.

The Web has long become a major platform for online criminal activities. URLs are used as the main vehicle in this domain.







Task

Classification Task:

- Binary classification
- MultiClass classification

Datasets



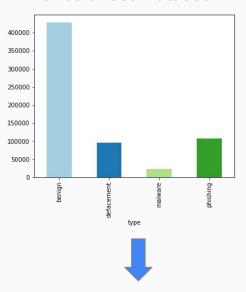
schema → (url, type)

14268 phishing url

651206 urls

defacement: 96457
phishing: 94108
malware: 32520
benign: 428103

Unbalanced Dataset



Undersampling Benign urls

type	count
malware	23645
defacement	95308
phishing	107119
benign	226309

452.381 urls

Feature Engineering

- 28 new features have been added.
- The new dataset will consist of:
 - 23 numerical features
 - 4 categorical features
 - target variable.

http://www.example.com





- Counts signs in url
- URL length
- Domain length



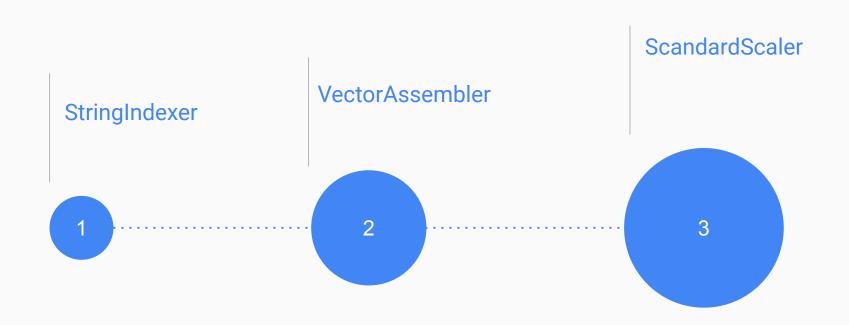
Categorical features

- is_short: is URL shortened
- domain_in_ip: URL domain in IP address format
- email_in_url: Is an email present in url
- server_client_domain: "server" or "client" word in domain

Exploratory Data Analysis:

- Visualizing the distribution of the Numerical Features
- 2. Histograms of individual categorical features
- 3. Correlation Matrix

ML Pipeline



Binary Classification

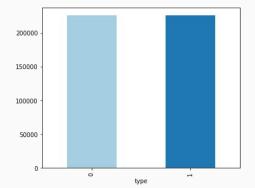
type	count
malware	23645
defacement	95308
phishing	107119
benign	226309

type	count
malicious	226072
benign	226309

Dataset Splitting: Training and Test Set

Training set: 80% of the total number of instances

• **Test set**: 20% of instances



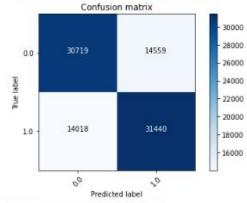
Four classification models:

- Logistic regression
- Decision tree
- 3. Random forest.
- 4. Gradient boosted decision tree

Results:

Logistic Regression

metrics: log_reg_malben_std Confusion matrix without normalization

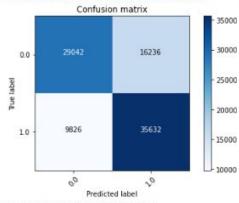


Accuracy: 0.6850533415623347 Precision: 0.6850753479591554 Recall: 0.6850402741007038 F1-score: 0.6850578105809983

Test Under ROC Curve (ROC AUC):: 0.759
Area Under Precision-Recall Curve: 0.761

Decision Tree

Metrics decision_tree_malben_std Confusion matrix without normalization

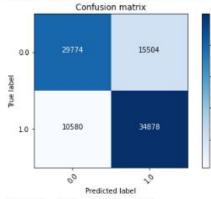


Accuracy : 0.7127711162052548 Precision : 0.7170851322074618 Recall : 0.7126298423405601 F1-score : 0.7148505454680736

Test Under ROC Curve (ROC AUC):: 0.651
Area Under Precision-Recall Curve: 0.594

Random Forest

Metrics random_forest_malben_std Confusion matrix without normalization

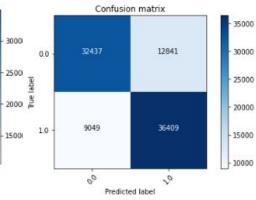


Accuracy: 0.712528654558279 Precision: 0.7150456698069648 Recall: 0.7124198685463711 F1-score: 0.7137303541158223

Test Under ROC Curve (ROC AUC):: 0.803
Area Under Precision-Recall Curve: 0.830

Gradient Boosted Decision Tree

Metrics gradient_malben_std Confusion matrix without normalization



Accuracy: 0.7587506612590372 Precision: 0.7605736297560843 Recall: 0.758666806360925 F1-score: 0.7596190214159675

Test Under ROC Curve (ROC AUC):: 0.852
Area Under Precision-Recall Curve: 0.866

Multiclass Classification

Problem: Unbalanced Dataset

Solutions:

1- Random Stratified Sampling

2- Prefer other evaluation metrics over accuracy, so f1-score, precision and recall

Three Multiclassification models:

- Logistic regression
- Decision tree
- Random forest.

type	count
malware	23645
defacement	95308
phishing	107119
benign	226309

Random Stratified Sampling

TRAIN	
type	count
malware	18925
defacement	76343
phishing	85865
benign	181239

TEST	
type	count
malware	4720
defacement	18965
phishing	21254
benign	45070

Results:

Logistic Regression	
Precision	0.72
Recall	0.53
F1-Score	0.60
ROC AUC	0.60

Decision Tree	
Precision	0.83
Recall	0.52
F1-Score	0.64
ROC AUC	0.60

Random Forest		
Precision	0.85	
Recall	0.53	
F1-Score	0.65	
ROC AUC	0.62	

Conclusion and Future works:

- Tuning Hyperparameters (with K-fold Cross Validation)
- Increase the amount of data of minority classes by using the SMOTE technique