GNR-652 Project: Classifying Spam & Pishing URLs Using var

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Problem Statement:

To use machine learning to classify Spam/Pishing URLs using various ML methods. This would not o allowing the crawler to bypass spam urls, but it would also remove the possibility of that spam url fro thereby improving the quality of search results.

Introduction:

- Spam (harmful) websites are great problem nowadays, getting in consider the frequency of inte
- "Spam technology" is advancing and has opportunities to keep your site high ranks in search res
- The motive for detection by URL is reducing visiting opportunities pages if based on a URL can

Types of Spams included in this project:

- ***Phishing*** - identity theft (personal data), most often via special email or chat. These days many threats
- ***Malware*** - software which is intended to cause damage to computer and computer networks
- ***Defacement*** - change the look (content) existing web pages

> **Spam in the narrow sense** - sending spam mass messages without any criteria

Brief description of the process:

- Processing URLs for retrieval significant information
- Text data processing via specialized algorithms - CountVectorizer, Multinomial Naive Bayes
- Classification using algorithms LinearSVM, SVM with RBF kernel, RandomForest

Data:

- The data set consists of about 89,000 URLs, of which good (not harmful) make up about 40%
- The dataset is obtained from the [Canadian site Institute for Cybersecurity]

- **Benign URLs:** Over 35,300 benign URLs were collected from Alexa top websites. The domains h crawler to extract the URLs.
- **Spam URLs:** : Around 12,000 spam URLs were collected from the publicly available WEBSPAM-U
- **Phishing URLs:** Around 10,000 phishing URLs were taken from OpenPhish which is a repository
- **Malware URLs:** More than 11,500 URLs related to malware websites were obtained from DNS-B malware sites.
- **Defacement URLs:** More than 45,450 URLs belong to Defacement URL category. They are Alexa fraudulent or hidden URL that contains both malicious web pages

Run this cell to download the dataset

```
!wget -q --no-check-certificate 'https://docs.google.com/uc?export=download&id=1zklUuH8n8u
!unzip dataset.zip
```

```
Archive:  dataset.zip
  inflating: Benign_list_big_final.csv
  inflating: __MACOSX/._Benign_list_big_final.csv
  inflating: DefacementSitesURLFiltered.csv
  inflating: __MACOSX/._DefacementSitesURLFiltered.csv
  inflating: Malware_dataset.csv
  inflating: __MACOSX/._Malware_dataset.csv
  inflating: phishing_dataset.csv
  inflating: __MACOSX/._phishing_dataset.csv
  inflating: rf_model.txt
  inflating: __MACOSX/._rf_model.txt
  inflating: spam_dataset.csv
  inflating: __MACOSX/._spam_dataset.csv
  inflating: svm_model.txt
  inflating: __MACOSX/._svm_model.txt
```

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn import linear_model, model_selection, metrics, svm
from urllib.parse import urlparse
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_predict, cross_val_score
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, roc_c
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from google.colab import files
import pickle
np.set_printoptions(3,suppress=True)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
  import pandas.util.testing as tm
```

Non Spam Data Set

Label all of them to 0

```
ds_benign= pd.read_csv('Benign_list_big_final.csv', header = None, names=['url'])
ds_benign.info()
ds_benign['label'] = 0
ds_benign.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35378 entries, 0 to 35377
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   url     35378 non-null  object
dtypes: object(1)
memory usage: 276.5+ KB
```

	url	label
0	http://1337x.to/torrent/1048648/American-Snipe...	0
1	http://1337x.to/torrent/1110018/Blackhat-2015-...	0
2	http://1337x.to/torrent/1122940/Blackhat-2015-...	0
3	http://1337x.to/torrent/1124395/Fast-and-Furio...	0
4	http://1337x.to/torrent/1145504/Avengers-Age-o...	0

Spam Data Set

Label all of them to 1

```
ds_spam = pd.read_csv('spam_dataset.csv', header = None, names=['url'])
ds_spam.info()
ds_spam['label'] = 1
ds_spam.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12000 entries, 0 to 11999
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   url     12000 non-null  object
dtypes: object(1)
memory usage: 93.9+ KB
```

	url	label

Malware Data Set

2	http://appbasic.jettons.co.uk/links/index.html	1

label them 1 (for malware here)

```
ds_malware = pd.read_csv('Malware_dataset.csv', header = None, names=['url'])
ds_malware.info()
ds_malware['label'] = 1
ds_malware.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11566 entries, 0 to 11565
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   url     11566 non-null  object
dtypes: object(1)
memory usage: 90.5+ KB
```

	url	label
0	http://gzzax.livechatvalue.com/chat/chatClient...	1
1	http://gzzax.livechatvalue.com/chat/chatClient...	1
2	http://gzzax.livechatvalue.com/chat/chatClient...	1
3	http://gzzax.livechatvalue.com/chat/chatClient...	1
4	http://mtsx.com.cn/UploadFiles/2011-08/admin/%...	1

Pishing Mail URL Data Set

label them 1 for being pishing URLs

```
ds_phishing = pd.read_csv('phishing_dataset.csv', header = None, names = ['url'])
ds_phishing.info()
ds_phishing['label'] = 1
ds_phishing.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9965 entries, 0 to 9964
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   url     9965 non-null   object
dtypes: object(1)
memory usage: 78.0+ KB
```

	url	label
0	http://v2.email-marketing.adminsimple.com/trac...	1
1	http://bid.openx.net/json?amp;amp;amp;amp;cid;...	1
2	http://webmail2.centurytel.net/hwebmail/servic...	1
3	http://www.google.com.ng/imgres?imgurl=http://...	1
4	http://webmail2.centurytel.net/hwebmail/servic...	1

Filtered defacement URLs Data Set

again label them 1

```
ds_defacement = pd.read_csv('DefacementSitesURLFiltered.csv', header = None, names=['url']
ds_defacement.info()
ds_defacement['label'] = 1
ds_defacement.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 96457 entries, 0 to 96456
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   url     96457 non-null  object
dtypes: object(1)
memory usage: 753.7+ KB
```

	url	label
0	http://www.sinduscongoias.com.br/index.html	1
1	http://www.sinduscongoias.com.br/index.php/ins...	1
2	http://www.sinduscongoias.com.br/index.php/ins...	1
3	http://www.sinduscongoias.com.br/index.php/ins...	1
4	http://www.sinduscongoias.com.br/index.php/ins...	1

shuffle the dataset to randomise data, because we will only take 40k of ~90k rows

```
np.random.seed(42)
ds_defacement = ds_defacement.sample(frac=1).reset_index(drop=True)
ds_defacement.head()
```

	url	label
0	http://www.ijsbaanapeldoorn.nl/fotos-videos.ht...	1
1	http://www.rigsolutions.nl/index.php/nl/compon...	1
2	http://www.userp.org.br/index.php?option=com_c...	1
3	http://www.feilonline.com/index.php/news-mediz...	1
4	http://onlineigri.net/podbrani-top-igri	1

```
ds_defacement = ds_defacement[:40000]
```

Now combine and shuffle the data set

```
ds_comb = pd.concat([ds_benign,ds_spam,ds_malware,ds_phishing,ds_defacement],axis=0)
np.random.seed(42)
ds_comb = ds_comb.sample(frac=1).reset_index(drop=True)
ds_comb['label'].value_counts(normalize=True)*100
```

```
1    67.516
0    32.484
Name: label, dtype: float64
```

Get deep URL part from the URLs

```
def get_deep_url_from_url(url):  # This function will help in getting the final URL part
  path = urlparse(url)
  if path.query:
    return str(path.path) + '?' + str(path.query)
  else:
    return str(path.path)

ds_comb['deep url'] = ds_comb['url'].apply(lambda x : get_deep_url_from_url(x))
ds_comb['len deep url'] = ds_comb['deep url'].apply(lambda x : len(x))
ds_comb.head()
```

	url	label	
0	http://astore.amazon.co.uk/allezvinsfrenchr/de...	1	/allezvinsfrenchr/detail/00
1	http://torcache.net/torrent/62E0C4EDCA7BF75638...	0	/torrent/62E0C4EDCA7BF756384(

We'll use the deep URL part as a feature

- Deep url is parsed on words separated by delimiters, regex: ‘| . | \ / | \ / \ / |: | - | _ |% | ? | = |; | <|> |
- Words are first processed using CountVectorizer
- The probabilities predicted by the Multinomial Naive Bayes (MNB) will be used as as attributes i

```
import re
def split_deep_url(url):
    word_list = re.compile(r'[\:/?=\-&$~<>;%_\.\+\\]+',re.UNICODE).split(url)
    word_list1 = [elem for elem in word_list if len(elem) > 2]
    words_string = ' '.join(word_list1)
    return str(words_string)

ds_comb['deep url'] = ds_comb['deep url'].apply(lambda x : split_deep_url(x))
ds_comb.head()
```

	url	label	
0	http://astore.amazon.co.uk/allezvinsfrenchr/de...	1	allezvinsfrenchr detail 006090(
1	http://torcache.net/torrent/62E0C4EDCA7BF75638...	0	torrent 62E0C4EDCA7BF7563840B4D2
2	http://twitter.com/home?status=%E3%83%8C%E3%81...	0	home status http 2Fero video n
3	http://metro.co.uk/2015/01/30/today-is-the-50t...	0	2015 today the 50th anniver
4	http://szgs.ru/object.php?object=ຮກ\320%9F\320...	1	object php object 320 320 320 9

```
x = ds_comb['deep url']
y = ds_comb['label']
```

```
x_train, x_test, y_train, y_test = model_selection.train_test_split(x, y, test_size=0.33,
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(72969,)
(72969,)
(35940,)
(35940,)
```

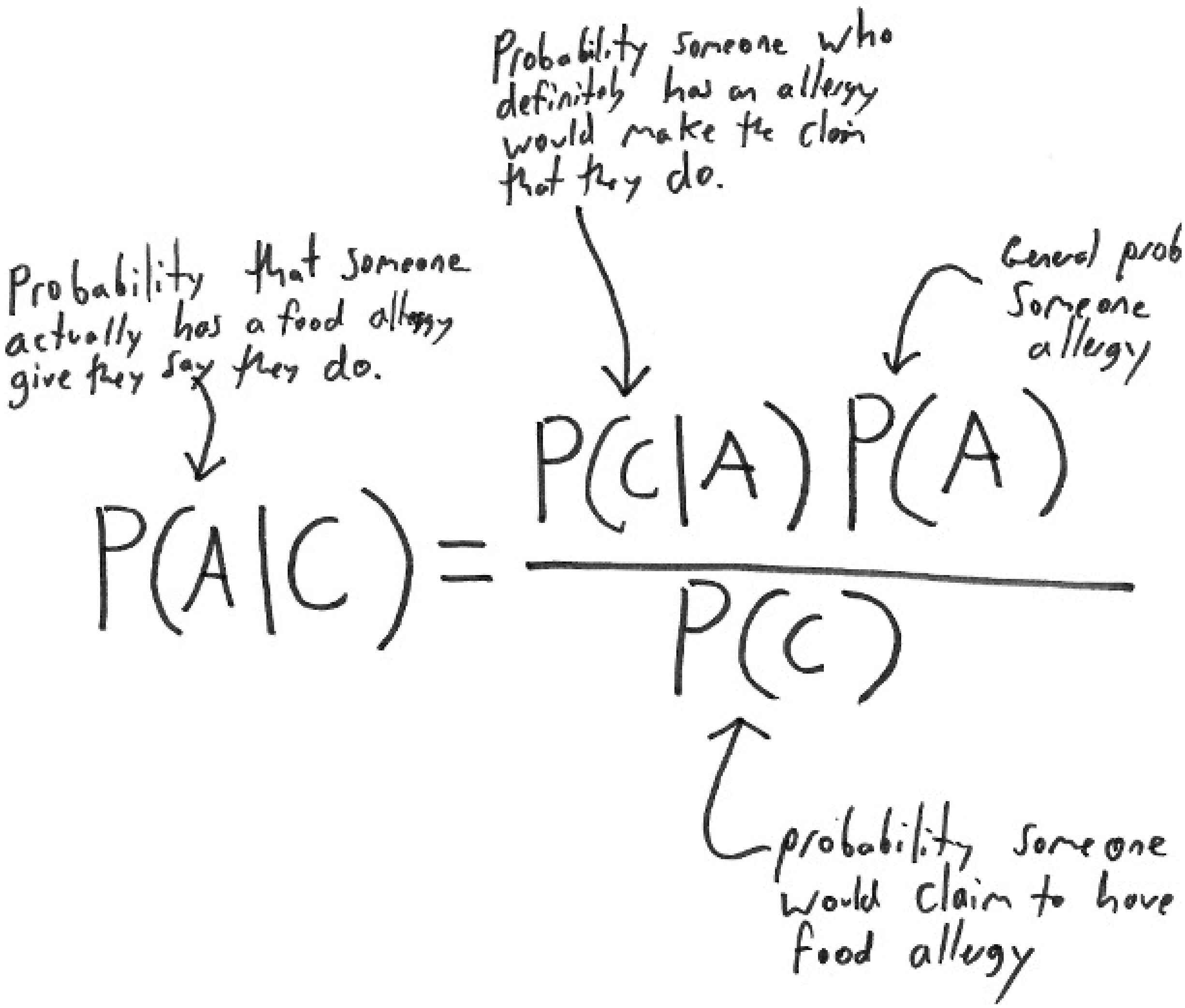
Save the indices to get back our train, test sets later

```
indices_train = x_train.index
indices_test = x_test.index
```

we apply CountVectorizer to have input for MultinomialDB, this will print out dictionary corresponding

Method 1: Naive bayes classifier

Naïve Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theo
assumptions between the features. They are among the simplest Bayesian network models.



In this part we have used Multinomial Naive Bayes. MultinomialNB implements the naive Bayes algori
and is one of the two classic naive Bayes variants used in text classification (where the data are typic
although tf-idf vectors are also known to work well in practice).

[Documentation](#) of Multinomial Naive bayes.

```
from sklearn import feature_extraction
```

```
vectorized = feature_extraction.text.CountVectorizer()
x_train_t = vectorized.fit_transform(x_train)
# vectorized.vocabulary_   # contains ~75k words
```

```
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
nb.fit(x_train_t, y_train)
x_test_t = vectorized.transform(x_test)
y_train_pred = nb.predict(x_train_t)
y_pred = nb.predict(x_test_t)

print("Train set accuracy of NB classifier is: {:.2f} %".format(metrics.accuracy_score(y_t
print("Test set accuracy of NB classifier is: {:.2f} %".format(metrics.accuracy_score(y_te
```

```
Train set accuracy of NB classifier is: 97.17 %
Test set accuracy of NB classifier is: 96.17 %
```

```
print("Confusion matrix:")
metrics.confusion_matrix(y_test, y_pred)
```

```
Confusion matrix:
array([[11044,   631],
       [  747, 23518]])
```

The **predicted probabilities** of our Multinomial Naive Bayes are taken over the **whole dataset** and thes
models

```
x_t = vectorized.transform(x)
```

```
y_pred_proba = nb.predict_proba(x_t) # x_t is vectorized transform of x, our whole set of
pd.DataFrame(y_pred_proba, columns=['class 0 : benign', 'class 1 : spam']).head()
```

	class 0 : benign	class 1 : spam
0	6.242518e-11	1.000000e+00
1	1.000000e+00	1.926474e-22
2	1.000000e+00	1.236210e-16
3	9.999999e-01	9.700286e-08
4	1.498135e-20	1.000000e+00

final_ds will contain the predicted probabilities columns of our NB classifier alongwith the original dat

```
final_ds = ds_comb.copy()
final_ds['label_proba_0'] = y_pred_proba[:,0]
final_ds['label_proba_1'] = y_pred_proba[:,1]
```

```
final_ds['label_proba_1'] = y_pred_proba[:,1]
final_ds.head()
```

	url	label	
0	http://astore.amazon.co.uk/allezvinsfrenchr/de...	1	allezvinsfrenchr detail 0060906
1	http://torcache.net/torrent/62E0C4EDCA7BF75638...	0	torrent 62E0C4EDCA7BF7563840B4D2
2	http://twitter.com/home?status=%E3%83%8C%E3%81...	0	home status http 2Fero video n
3	http://metro.co.uk/2015/01/30/today-is-the-50t...	0	2015 today the 50th anniver
4	http://szgs.ru/object.php?object=ะก\320%9F\320...	1	object php object 320 320 320 9

```
!pip -q install tldextract
```

```
     |████████████████████████████████| 51kB 1.6MB/s
```

Adding columns for domain length and suffix

```
import tldextract
def get_len_of_domain_url(url):
  ext = tldextract.extract(url)
  return len(ext.domain)

def get_suffix_url(url):
  ext = tldextract.extract(url)
  return str(ext.suffix)

final_ds['len of domain'] = final_ds['url'].apply(lambda x : get_len_of_domain_url(x))
final_ds['suffix'] = final_ds['url'].apply(lambda x : get_suffix_url(x))
```

Analysis of top level domain and deep url length for good and bad urls

```
final_ds['suffix'].value_counts()
```

```
com         42586
co.uk       10789
net          7332
de           4988
info         4328
            ...
ad              1
edu.ec          1
org.rs          1
lutsk.ua        1
vg              1
Name: suffix, Length: 262, dtype: int64
```

suffix column (top level domain-tld in operation) has too many different values and a cutoff is done fo

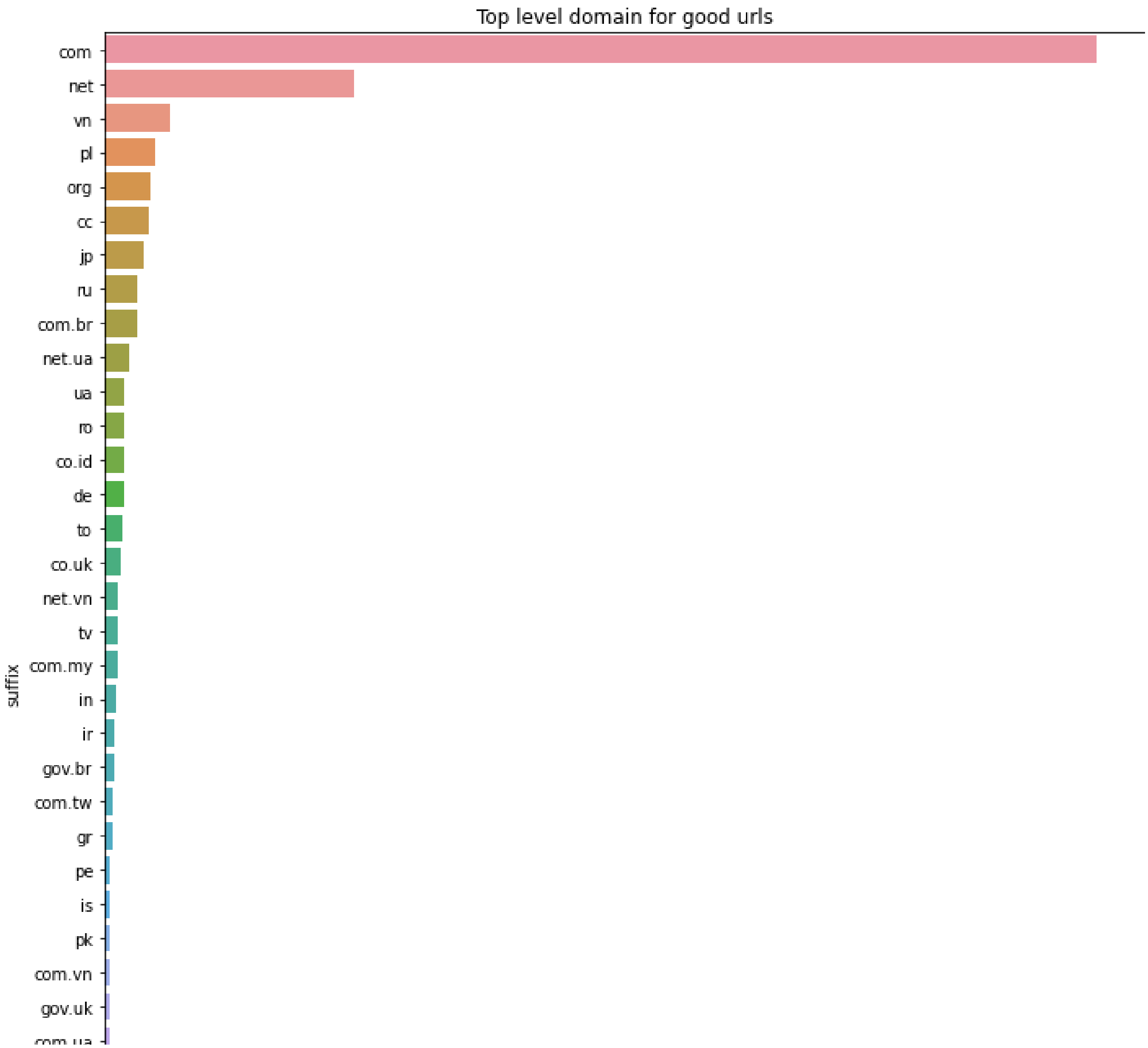
```
final_ds_copy = final_ds.copy() # cutoff only done for frequency analysis, the whole set h
minFreq = 50
suffix_values = final_ds_copy['suffix'].value_counts() # Specific column
to_remove = suffix_values[suffix_values <= minFreq].index
final_ds_copy['suffix'].replace(to_remove, np.nan, inplace=True)
```

we now have the missing values (nan) in the suffix column, so we throw out such rows and reset the i

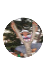
```
final_ds_copy = final_ds_copy.dropna()
final_ds_copy = final_ds_copy.reset_index(drop=True)
final_ds_copy['suffix'].value_counts()
```

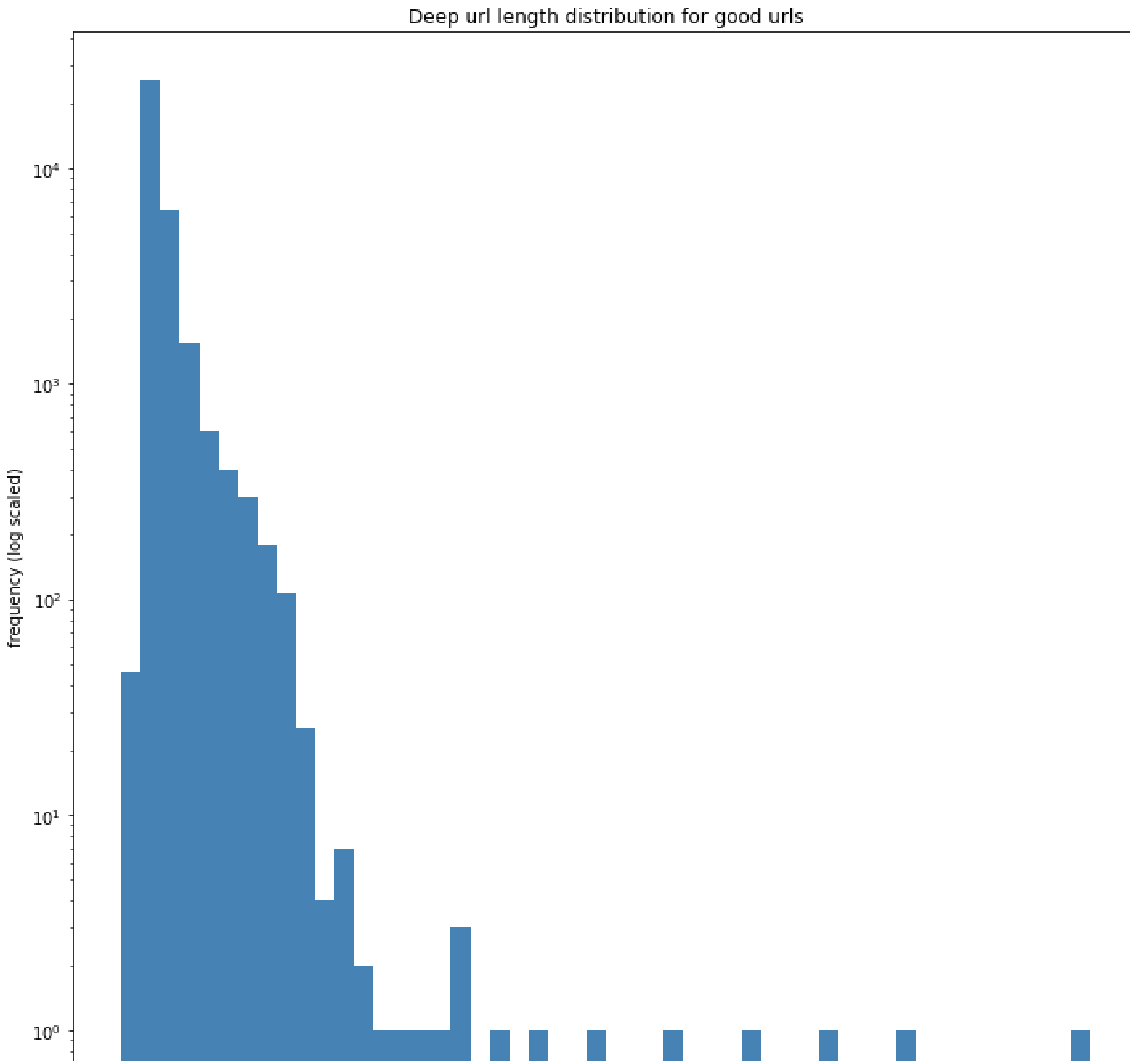
```
com          42586
co.uk        10789
net           7332
de            4988
info          4328
             ...
travel.pl       58
lu              56
com.gr          54
co.nz           52
org.cn          51
Name: suffix, Length: 79, dtype: int64
```

```
fig = plt.figure(figsize=(20,12))
fig.add_subplot(1,2,1)
plt.title('Top level domain for good urls')
sns.countplot(y = final_ds_copy[final_ds_copy['label']==0]['suffix'], order = final_ds_cop
fig.add_subplot(1,2,2)
plt.title('Top level domain for harmful urls')
sns.countplot(y = final_ds_copy[final_ds_copy['label']==1]['suffix'],order = final_ds_copy
plt.tight_layout()
plt.show()
```




```
fig = plt.figure(figsize=(20,10))
fig.add_subplot(1,2,1)
plt.title('Deep url length distribution for good urls')
plt.hist(final_ds[final_ds['label']==0]['len deep url'], log = True, color = 'steelblue',
plt.ylabel("frequency (log scaled)")
plt.xlabel("length of deep url")
fig.add_subplot(1,2,2)
plt.title('Deep url length distribution for malicious urls')
plt.hist(final_ds[final_ds['label']==1]['len deep url'], log = True, color = 'steelblue',
plt.ylabel("frequency (log scaled)")
plt.xlabel("length of deep url")
plt.tight_layout()
plt.show()
```





we throw out unnecessary columns (url, deep url) and encode the categorical variable suffix

```
final_ds = final_ds.drop(['url', 'deep url'], axis = 1)
final_ds = pd.get_dummies(final_ds, prefix = ['suffix'], columns = ['suffix'])
final_ds.head()
```

```
  for n in n_estimators:
      for max_d in max_depths:
        rf = RandomForestClassifier(n_estimators = n, max_depth = max_d)
        rf.fit(X_train, y_train)
        y_pred = rf.predict(X_valid)
        score = metrics.accuracy_score(y_valid, y_pred)
        if score>best_score:
            best_score = score
            best_estimator = rf
            best_params = [n,max_d]
  return best_estimator, best_params, best_score
```

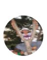
```
# best_rf, best_params_rf, best_score_rf = get_best_model_rf(X_train, y_train, X_valid, y_
```

```
# # this cell pickles our generated model
# rf_model = {'best_rf':best_rf,'best_params_rf':best_params_rf,'best_score_rf':best_score
# f = open('rf_model.txt','wb')
# pickle.dump(rf_model,f)
# f.close()
```

```
# this cell loads our pickled model
f = open('rf_model.txt','rb')
rf_model = pickle.load(f)
best_rf = rf_model['best_rf']
best_params_rf = rf_model['best_params_rf']
best_score_rf = rf_model['best_score_rf']
f.close()
```

```
print(f"Best parameters:\n\tn_estimators: {best_params_rf[0]}\n\tmax_depth: {best_params_r
print(f"\nBest validation accuracy: {best_score_rf*100} %\n")
best_rf.fit(X_train_valid, y_train_valid)

y_train_valid_pred = best_rf.predict(X_train_valid)
y_test_pred = best_rf.predict(X_test)
print(f'Test set accuracy: {metrics.accuracy_score(y_test, y_test_pred)*100} %')
print('Train set report:\n {}'.format(metrics.classification_report(y_train_valid, y_train
print('Test set report:\n {}'.format(metrics.classification_report(y_test, y_test_pred)))
```



	label	len deep url	label_proba_0	label_proba_1	len of domain	suffix_	suffix_ab.ca	suffix_ac

```
df_train = final_ds.loc[indices_train,:]
df_test = final_ds.loc[indices_test,:]

X_train_valid = df_train.drop(['label'], axis=1)
y_train_valid = df_train['label']
X_train, X_valid, y_train, y_valid = train_test_split(X_train_valid, y_train_valid, test_s
# 20% of train set is taken for validation
X_test = df_test.drop(['label'], axis=1)
y_test = df_test['label']
```

Standardise all columns except one-hot encoded ones

```
# train set statistics applied to validation set
ss1 = StandardScaler()
X_train.iloc[:,:4] = ss1.fit_transform(X_train.iloc[:,:4])
X_valid.iloc[:,:4] = ss1.transform(X_valid.iloc[:,:4])

# whole training set statistics (includes validation set) applied to test set
ss2 = StandardScaler()
X_train_valid.iloc[:,:4] = ss2.fit_transform(X_train_valid.iloc[:,:4])
X_test.iloc[:,:4] = ss2.transform(X_test.iloc[:,:4])
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:966: SettingWithCopyWarni
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  self.obj[item] = s
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:966: SettingWithCopyWarni
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  self.obj[item] = s
```

Method 2: Random Forest

```
def get_best_model_rf(X_train, y_train, X_valid, y_valid):
  np.random.seed(42)
  n_estimators = np.random.randint(50, high=100, size=(5,))
  max_depths = np.random.randint(50, high=75, size=(5,))
  best_score = 0
  best_estimator, best_params = None, []
```

```
Best parameters:
        n_estimators: 78
        max_depth: 60

Best validation accuracy: 99.71906262847746 %

Test set accuracy: 99.29326655537007 %
Train set report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     23703
           1       1.00      1.00      1.00     49266

    accuracy                           1.00     72969
   macro avg       1.00      1.00      1.00     72969
weighted avg       1.00      1.00      1.00     72969
```

```
confusion_matrix(y_test, y_test_pred)
```

```
array([[11514,   161],
       [   93, 24172]])
```

15 most important features according to our random forest model alongwith their percentages are as

```
weighted avg       0.99      0.99      0.99     35940
```

```
feature_importances = zip(list(X_train), best_rf.feature_importances_*100)
feature_importances_sorted = sorted(feature_importances, key=lambda x: x[1], reverse=True)
for feature in feature_importances_sorted[:15]:
    print(feature)
```

```
('label_proba_1', 38.22204303617866)
('label_proba_0', 37.479463340831124)
('len deep url', 11.93243819523408)
('len of domain', 3.8430349893701)
('suffix_co.uk', 1.3278298714824788)
('suffix_com', 1.3138298906282377)
('suffix_net', 1.0667911267259529)
('suffix_vn', 0.541653935742985)
('suffix_info', 0.5059103352679813)
('suffix_jp', 0.49035731635762475)
('suffix_cc', 0.31053744732707816)
('suffix_tv', 0.29229789412264434)
('suffix_ua', 0.261701341904223)
('suffix_ac.uk', 0.24519333524004708)
('suffix_nl', 0.23338296465245364)
```

Method 3: SVM using RBF kernel

```
def get_best_model_svm(X_train, y_train, X_valid, y_valid):
  np.random.seed(42)
```

```
Cs = [10**i for i in range(-1,4)]
gammas = [10**i for i in range(-3,2)]
best_score = 0
best_estimator, best_params = None, []
for C in Cs:
    for gamma in gammas:
      rbf = svm.SVC(C=C, gamma=gamma, kernel='rbf', random_state=42)
      rbf.fit(X_train, y_train)
      y_pred = rbf.predict(X_valid)
      score = metrics.accuracy_score(y_valid, y_pred)
      if score>best_score:
          best_score = score
          best_estimator = rbf
          best_params = [C, gamma]
return best_estimator, best_params, best_score
```

It takes $\approx$ 10 mins per model configuration to run.

Avoid running the below cells and load the best model which is saved

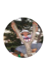
```
# best_svm, best_params_svm, best_score_svm = get_best_model_svm(X_train, y_train, X_valid
# best_svm.fit(X_train_valid, y_train_valid) # fit the best model on the whole training se
```

```
# # this cell pickles our generated model
# svm_model = {'best_svm':best_svm,'best_params_svm':best_params_svm,'best_score_svm':best_
# f = open('svm_model.txt','wb')
# pickle.dump(svm_model,f)
# f.close()
```

```
# this cell loads our pickled model
f = open('svm_model.txt','rb')
svm_model = pickle.load(f)
best_svm = svm_model['best_svm']
best_params_svm = svm_model['best_params_svm']
best_score_svm = svm_model['best_score_svm']
f.close()
```

```
print(f"Best parameters:\n\tC: {best_params_svm[0]}\n\tgamma: {best_params_svm[1]}")
print(f"\nBest validation accuracy: {best_score_svm*100} %\n")

y_train_valid_pred = best_svm.predict(X_train_valid)
y_test_pred = best_svm.predict(X_test)
print(f'Test set accuracy: {metrics.accuracy_score(y_test, y_test_pred)*100} %')
print('Train set report:\n {}'.format(metrics.classification_report(y_train_valid, y_train_
print('Test set report:\n {}'.format(metrics.classification_report(y_test, y_test_pred)))
```



```
Best parameters:
        C: 100
        gamma: 0.01

Best validation accuracy: 99.38330820885295 %

Test set accuracy: 96.46911519198665 %
Train set report:
               precision    recall  f1-score   support

           0       0.97      0.95      0.96     23703
           1       0.97      0.99      0.98     49266

    accuracy                           0.97     72969
   macro avg       0.97      0.97      0.97     72969
weighted avg       0.97      0.97      0.97     72969

Test set report:
               precision    recall  f1-score   support

           0       0.96      0.93      0.94     11675
           1       0.97      0.98      0.97     24265

    accuracy                           0.96     35940
   macro avg       0.96      0.96      0.96     35940
weighted avg       0.96      0.96      0.96     35940
```

```
confusion_matrix(y_test, y_test_pred)
```

```
array([[10877,   798],
       [  471, 23794]])
```

Method 4: Neural Network

```
import torch
from torch.utils.data import TensorDataset,DataLoader

xtrain = torch.tensor(X_train_valid.to_numpy()).float()
ytrain = torch.tensor(y_train_valid.to_numpy())
xtest = torch.tensor(X_test.to_numpy()).float()
ytest = torch.tensor(y_test.to_numpy())

train_loader = DataLoader(TensorDataset(xtrain, ytrain), batch_size= 1000)
```

```
from torch import nn, optim
import torch.nn.functional as F

hidden_1 = 250
hidden_2 = 200
hidden_3 = 150
layers = [
```

```
        nn.Linear(xtrain.shape[1], hidden_1), nn.ReLU(), nn.BatchNorm1d(hidden_1),
        nn.Linear(hidden_1, hidden_2), nn.ReLU(), nn.BatchNorm1d(hidden_2),
        nn.Linear(hidden_2, hidden_3), nn.ReLU(), nn.BatchNorm1d(hidden_3),
        nn.Linear(hidden_3, hidden_3), nn.ReLU(), nn.BatchNorm1d(hidden_3),
        nn.Linear(hidden_3, 2)
]
model = nn.Sequential(*layers)
learning_rate = 1e-3
optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9 ,nesterov=True)
```

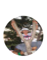
```
def get_num_correct(ypred, ytrue):
    preds = ypred.argmax(axis=1)
    return (preds == ytrue).sum()

n_epochs = 50

for epoch in range(n_epochs):
    num_correct, num_samples = 0, 0
    for xbatch, ybatch in train_loader:
        optimizer.zero_grad()
        y_pred = model(xbatch)
        loss = F.cross_entropy(y_pred,ybatch)
        loss.backward()
        optimizer.step()
        num_correct += get_num_correct(y_pred,ybatch)
        num_samples += xbatch.size(0)

    if epoch%5 == 0:
        acc = float(num_correct) / num_samples
        print(f"Epoch: {epoch}")
        print("\tTraining accuracy: {:.4f} %".format(acc*100))
        with torch.no_grad():
            preds = model(xtest)
            acc = float(get_num_correct(preds,ytest))/preds.size(0)
            print("\tTest accuracy: {:.4f} %".format(acc*100))

```



```
Epoch: 0
        Training accuracy: 90.6303 %
        Test accuracy: 98.0774 %
Epoch: 5
        Training accuracy: 98.7200 %
        Test accuracy: 98.1803 %
Epoch: 10
        Training accuracy: 98.9681 %
        Test accuracy: 98.5364 %
Epoch: 15
        Training accuracy: 99.2161 %
        Test accuracy: 98.2387 %
Epoch: 20
        Training accuracy: 99.2709 %
        Test accuracy: 98.4474 %
Epoch: 25
```

```
with torch.no_grad():
    y_train_pred = model(xtrain).squeeze().numpy().argmax(axis=1)
    y_test_pred = model(xtest).squeeze().numpy().argmax(axis=1)
print('Train set report:\n {}'.format(metrics.classification_report(ytrain, y_train_pred))
print('Test set report:\n {}'.format(metrics.classification_report(ytest, y_test_pred)))
```

```
Train set report:
               precision    recall  f1-score   support

           0       0.99      0.98      0.99     23703
           1       0.99      1.00      0.99     49266

    accuracy                           0.99     72969
   macro avg       0.99      0.99      0.99     72969
weighted avg       0.99      0.99      0.99     72969

Test set report:
               precision    recall  f1-score   support

           0       0.98      0.97      0.98     11675
           1       0.99      0.99      0.99     24265

    accuracy                           0.99     35940
   macro avg       0.98      0.98      0.98     35940
weighted avg       0.99      0.99      0.99     35940
```

Random Forest without Naive bayes classifier as attributes

Here we take the best classifier from the above ones and don't consider the probabilites predicted by

```
X_train_valid.drop(['label_proba_0','label_proba_1'], axis=1, inplace=True)
X_test.drop(['label_proba_0','label_proba_1'], axis=1, inplace=True)
```

```
X_test.head()
```

```
X_test.head()
```

	len deep url	len of domain	suffix_	suffix_ab.ca	suffix_ac	suffix_ac.cr	suffix_ac.
47130	0.898187	-0.962250	0.0	0.0	0.0	0.0	
17786	-0.538912	-2.501851	0.0	0.0	0.0	0.0	
29868	-1.030551	-3.271652	0.0	0.0	0.0	0.0	
101020	0.746913	-3.271652	0.0	0.0	0.0	0.0	
7578	223.000000	13.000000	1.0	0.0	0.0	0.0	

5 rows × 264 columns

```
best_rf, best_params_rf, best_score_rf = get_best_model_rf(X_train, y_train, X_valid, y_va
```

```
print(f"Best parameters:\n\tn_estimators: {best_params_rf[0]}\n\tmax_depth: {best_params_r
print(f"\nBest validation accuracy: {best_score_rf*100} %\n")
best_rf.fit(X_train_valid, y_train_valid)

y_train_valid_pred = best_rf.predict(X_train_valid)
y_test_pred = best_rf.predict(X_test)
print(f'Test set accuracy: {metrics.accuracy_score(y_test, y_test_pred)*100} %')
print('Train set report:\n {}'.format(metrics.classification_report(y_train_valid, y_train
print('Test set report:\n {}'.format(metrics.classification_report(y_test, y_test_pred)))
```

```
Best parameters:
        n_estimators: 78
        max_depth: 50

Best validation accuracy: 99.71221049746471 %

Test set accuracy: 94.39343350027825 %
Train set report:
              precision    recall  f1-score   support

           0       0.90      0.96      0.93     23703
           1       0.98      0.95      0.97     49266

    accuracy                           0.95     72969
   macro avg       0.94      0.96      0.95     72969
weighted avg       0.96      0.95      0.95     72969

Test set report:
              precision    recall  f1-score   support

           0       0.89      0.95      0.92     11675
           1       0.97      0.94      0.96     24265

    accuracy                           0.94     35940
   macro avg       0.93      0.94      0.94     35940
weighted avg       0.95      0.94      0.94     35940
```