Python project

Project name – detection of malicious content/web links related to cyber frauds

Project description- detection of malicious ontent/web links related to cyber frauds for ex: fake offers in name of puma, adidas, banking sites

Project output- user should be able to enter url and check whether is legitimate

Outline:

- Initial Setup
- Tokenization
- Load Training Data
- Vectorize Training Data
- Load Testing Data
- Train and Evaluate Models

We'll start by downloading the data and loading the needed libraries.

Step 1- data are download from internet and I add this line in my code itself so just continue with my code

```
# Download data from Github
! git clone https://github.com/NetsecExplained/Machine-Learning-for-Security-Analysts.git

# Install dependencies
! pip install nltk sklearn pandas matplotlib seaborn
data_dir = "Machine-Learning-for-Security-Analysts/Malicious URLs.csv"
```

```
Cloning into 'Machine-Learning-for-Security-Analysts'...
remote: Enumerating objects: 4186, done.
remote: Total 4186 (delta 0), reused 0 (delta 0), pack-reused 4186
Receiving objects: 100% (4186/4186), 14.75 MiB | 20.58 MiB/s, done.
Resolving deltas: 100% (60/60), done.
Requirement already satisfied: nltk in /usr/local/lib/python3.6/dist-packages (3.2.5)
Requirement already satisfied: sklearn in /usr/local/lib/python3.6/dist-packages (0.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (1.1.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (3.2.2)
Requirement already satisfied: seaborn in /usr/local/lib/python3.6/dist-packages (0.11.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from nltk) (1.15.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from sklearn) (0.22.2.post1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dist-packages (from pandas) (2.8.1)
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.6/dist-packages (from pandas) (1.19.4)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib) (0.10.0)
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.6/dist-packages (from seaborn) (1.4.1)
```

Step 2- **install needed libraries for this project**

1- Pandas . **is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language here we use csv file so need to use pandas module to add that data file**
2- **matplotlib**. **pyplot** is a collection of functions that make **matplotlib** work like MATLAB. Each **pyplot** function makes some change to a figure and e, plots some lines in a plotting area, decorates the **plot** with labels, etc

3- . The **random** module gives access to various useful functions and one of them being able to generate **random** floating numbers
4- A **regular expression** (or **RE**) specifies a set of strings that matches it; the functions in this module let you check if a particular string matches a given **regular expression**

Scikit_learn helper function specifically trained test split, tfidfVectorizer and CountVectorizer

LoogisticRegression and MultinomialNB symmetrix funcction

```
# Common imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
import re

%matplotlib inline

# Import Scikit-learn helper functions
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer

# Import Scikit-learn models
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB

# Import Scikit-learn metric functions
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns


print("now the libery are installed correctly")
```

```
now the libery are installed correctly
```

Load the dataset

With this set, we first need to load our CSV data

Use pandas read csv and we going to define a test URL as just random URL in data set

Step 1- .

```
# Load the training data
print("- Loading CSV Data -")
url_df = pd.read_csv(data_dir)

test_url = url_df['URLs'][4]

print("\n### CSV Data Loaded ###\n")
```

```
- Loading CSV Data -

### CSV Data Loaded ###
```

Step 2-

```
# Let's see what our training data looks like
print(url_df)
```

```
                                                  URLs Class
0                     freebase.com/view/en/bob_sirois  good
1                      en.wikipedia.org/wiki/Joie_Lee  good
2               pipl.com/directory/people/Rejean/Beaudin  good
3         flickr.com/photos/teneyck/sets/72157610336209297/  good
4         ussoccer.com/News/Federation-Services/2009/06/...  good
...                                                    ...   ...
420459    ourorigins.org/genealogielistfirstname.aspx?an...  good
420460      simira.co.id/cifk/live.com/Account_Verified.htm   bad
420461    kstatesports.com/sports/w-baskbl/spec-rel/ksu-...  good
420462    vh1.com/video/living-colour/9128/cult-of-perso...  good
420463       absoluteastronomy.com/topics/SummerSlam_(1990)  good

[420464 rows x 2 columns]
```

Well this is not output this is how our data look like and csv have 2 kind one for URL and another for class labels

Step 3- data is not ready split for traning and testing so for the task we use spkit learn train test split function

That simple function that randomly sample a certain percentage of your data and splits it up into traning and testing

```
# Perform Train/Test split
test_percentage = .2

train_df, test_df = train_test_split(url_df, test_size=test_percentage, random_state=42)

labels = train_df['Class']
test_labels = test_df['Class']

print("\n### Split Complete ###\n")
```

```
### Split Complete ###
```

In case 1 set the testing percentage to be 20% and remaing 80% for traning

To do this we find the function the full data set and then the testing size that we want it even has the ability to enter in a random seed

Step 4

```
# Print counts of each class
print("- Counting Splits -")
print("Training Samples:", len(train_df))
print("Testing Samples:", len(test_df))

# Graph counts of each class, for both training and testing
count_train_classes = pd.value_counts(train_df['Class'])
count_train_classes.plot(kind='bar', fontsize=16)
plt.title("Class Count (Training)", fontsize=20)
plt.xticks(rotation='horizontal')
plt.xlabel("Class", fontsize=20)
plt.ylabel("Class Count", fontsize=20)

plt.show()

count_test_classes = pd.value_counts(test_df['Class'])
count_test_classes.plot(kind='bar', fontsize=16, colormap='ocean')
plt.title("Class Count (Testing)", fontsize=20)
plt.xticks(rotation='horizontal')
plt.xlabel("Class", fontsize=20)
plt.ylabel("Class Count", fontsize=20)

plt.show()
```

```
- Counting Splits -
Training Samples: 336371
Testing Samples: 84093
```

In this case 400,000 URL in totel and looking at class count we have significantly more good URL then we do bad URL normaly would consider these count to be unbalanced classes

Tokenization

Create our tokenizer by splitting URLs into their domains, subdomains, directories, files, and extensions.

```python
#   The purpose of a tokenizer is to separate the features from the raw data


def tokenizer(url):
  """Separates feature words from the raw data
  Keyword arguments:
    url ---- The full URL

  :Returns -- The tokenized words; returned as a list
  """

  # Split by slash (/) and dash (-)
  tokens = re.split('[/-]', url)

  for i in tokens:
    # Include the splits extensions and subdomains
    if i.find(".") >= 0:
      dot_split = i.split('.')

      # Remove .com and www. since they're too common
      if "com" in dot_split:
        dot_split.remove("com")
      if "www" in dot_split:
        dot_split.remove("www")

      tokens += dot_split

  return tokens

print("\n### Tokenizer defined ###\n")
```

Define our tokenizer to tell our function how to pre-process the data

Now time it gonna be a little different based on out data being url and split up the url whenever there is forward slash and a hyphen

We also gonna split up the domain subdomains and extension by splitting up wherever there is a that this give us the taken sub domain

Subdamain example.com – subdamain, example, com

And remove com and www

Tokenize a URL

1. Print the full URL, **test_url**
2. Print the results of **tokenizer(test_url)**

```
# Let's see how our tokenizer changes our URLs

print("\n- Full URL -\n")
# (Write code here)
print(test_url)



# Tokenize test URL
print("\n- Tokenized Output -\n")
# (Write code here)
tokenized_url = tokenizer(test_url)
print(tokenized_url)
```

```
URL -

er.com/News/Federation-Services/2009/06/University-Of-Miami-President-Donna-E-Shalala-Joins-Team-To-Bring-FIFA-World-Cup-To-United-States-In.aspx

nized Output -

ccer.com', 'News', 'Federation', 'Services', '2009', '06', 'University', 'Of', 'Miami', 'President', 'Donna', 'E', 'Shalala', 'Joins', 'Team', 'To', 'Bring', 'FIFA', 'World', 'Cup', 'To', 'United', 'States
```

Vectorize the Data

Now that the training data has been loaded, we'll train the vectorizers to turn our features into numbers

Train the vectorizers

1. Create the count vectorizer **cVec** using the **CountVectorizer** function
2. Configure *cVec* to use the *tokenizer* function from earlier
3. Perform **fit_transform** on *cVec* to train the vectorizer with the *training URLs*
   a. Save the result as **count_X**

4. Create the TF-IDF vectorizer **tVec** using the **TfidfVectorizer** function
5. Configure *tVec* to use the *tokenizer* function from earlier
6. Perform **fit_transform** on *tVec* to train the vectorizer with the *training URLs*
   a. Save the result as **tfidf_X**

```python
# Vectorizer the training inputs -- Takes about 30 seconds to complete
#   There are two types of vectors:
#     1. Count vectorizer
#     2. Term Frequency-Inverse Document Frequency (TF-IDF)

print("- Training Count Vectorizer -")
# (Write code here)
cVec = CountVectorizer(tokenizer= tokenizer)
count_X = cVec.fit_transform(train_df['URLs'])



print("- Training TF-IDF Vectorizer -")
# (Write code here)

tVec = TfidfVectorizer(tokenizer= tokenizer)
tfidf_X = tVec.fit_transform(train_df['URLs'])
#_______________________________________________________________________________
# (Keep the following lines)
print("\n### Vectorizing Complete ###\n")
```

```
- Training Count Vectorizer -
- Training TF-IDF Vectorizer -

### Vectorizing Complete ###
```

Count the test URL tokens

1. Print the count of each *token* from **test_url**

```python
# Manually perform term count on test_url
# (Write code here)

for token in list(dict.fromkeys(tokenized_url)):
  print("{} - {}".format(tokenized_url.count(token),token))
```

```
1 - ussoccer.com
1 - News
1 - Federation
1 - Services
1 - 2009
1 - 06
1 - University
1 - Of
1 - Miami
1 - President
1 - Donna
1 - E
1 - Shalala
1 - Joins
1 - Team
2 - To
1 - Bring
1 - FIFA
1 - World
1 - Cup
1 - United
1 - States
1 - In.aspx
1 - ussoccer
1 - In
1 - aspx
```

View the test URL vectorizers

1. Create a new **CountVectorizer** and **TfidfVectorizer** for demonstration
2. Train the new vectorizers on **test_url** using **fit_transform**
3. Print the results of each *transform*

CountVectorizer is a great tool provided by the scikit-learn library in **Python**. It is used to transform a given text into a vector on the basis of the frequency (count) of each word that occurs in the entire text

The **TfidfVectorizer** will tokenize documents, learn the vocabulary and inverse document frequency weightings, and allow you to encode new documents.

Here compare to count vectorizer the TFIDF vectorizer provide more acqurate

```
print("\n- Count Vectorizer (Test URL) -\n")
# (Write code here)
exvec = CountVectorizer(tokenizer=tokenizer)
exx = exvec.fit_transform([test_url])
print(exx)
# (Keep the following lines)
print()
print("=" * 50)
print()

print("\n- TFIDF Vectorizer (Test URL) -\n")
# (Write code here)
exvec = TfidfVectorizer(tokenizer=tokenizer)
exx = exvec.fit_transform([test_url])
print(exx)
```

```
- Count Vectorizer (Test URL) -

  (0, 24)	1
  (0, 13)	1
  (0, 7)	1
  (0, 16)	1
  (0, 1)	1
  (0, 0)	1
  (0, 22)	1
  (0, 14)	1
  (0, 12)	1
  (0, 15)	1
  (0, 5)	1
  (0, 6)	1
  (0, 17)	1
  (0, 11)	1
  (0, 19)	1
  (0, 20)	2

==================================================


- TFIDF Vectorizer (Test URL) -

  (0, 2)	0.18569533817705186
  (0, 9)	0.18569533817705186
  (0, 23)	0.18569533817705186
  (0, 10)	0.18569533817705186
  (0, 18)	0.18569533817705186
  (0, 21)	0.18569533817705186
  (0, 4)	0.18569533817705186
  (0, 25)	0.18569533817705186
  (0, 8)	0.18569533817705186
  (0, 3)	0.18569533817705186
  (0, 20)	0.3713906763541037
  (0, 19)	0.18569533817705186
  (0, 11)	0.18569533817705186
  (0, 17)	0.18569533817705186
  (0, 6)	0.18569533817705186
  (0, 5)	0.18569533817705186
  (0, 15)	0.18569533817705186
  (0, 12)	0.18569533817705186
  (0, 14)	0.18569533817705186
  (0, 22)	0.18569533817705186
  (0, 0)	0.18569533817705186
  (0, 1)	0.18569533817705186
  (0, 16)	0.18569533817705186
  (0, 7)	0.18569533817705186
  (0, 13)	0.18569533817705186
  (0, 24)	0.18569533817705186
```

Test and Evaluate the Models

OK, we have our training data loaded and our testing data loaded. Now it's time to train and evaluate our models.

But first, we're going to define a helper function to display our evaluation reports.

Vectorize the testing data

1. Use **cVec** to *transform* **test_df['URLs']**
   a. Save the result as **test_count_X**
2. Use **tVec** to *transform* **test_df['URLs']**
   a. Save the result as **test_tfidf_X**

```
# Vectorize the testing inputs
#   Use 'transform' instead of 'fit_transform' because we've already trained our vectorizers

print("- Count Vectorizer -")
# (Write code here)
test_count_X = cVec.transform(test_df['URLs'])



print("- TFIDF Vectorizer -")
# (Write code here)
test_count_X = tVec.transform(test_df['URLs'])

print("\n### Vectorizing Complete ###\n")
```

```
- Count Vectorizer -
- TFIDF Vectorizer -

### Vectorizing Complete ###
```

```
def generate_report(cmatrix, score, creport):
  """Generates and displays graphical reports
  Keyword arguments:
    cmatrix - Confusion matrix generated by the model
    score --- Score generated by the model
    creport - Classification Report generated by the model

  :Returns -- N/A
  """

  # Transform cmatrix because Sklearn has pred as columns and actual as rows.
  cmatrix = cmatrix.T

  # Generate confusion matrix heatmap
  plt.figure(figsize=(5,5))
  sns.heatmap(cmatrix,
              annot=True,
              fmt="d",
              linewidths=.5,
              square = True,
              cmap = 'Blues',
              annot_kws={"size": 16},
              xticklabels=['bad', 'good'],
              yticklabels=['bad', 'good'])

  plt.xticks(rotation='horizontal', fontsize=16)
  plt.yticks(rotation='horizontal', fontsize=16)
  plt.xlabel('Actual Label', size=20);
  plt.ylabel('Predicted Label', size=20);

  title = 'Accuracy Score: {0:.4f}'.format(score)
  plt.title(title, size = 20);

  # Display classification report and confusion matrix
  print(creport)
  plt.show()


print("\n### Report Generator Defined ###\n")
```

Train and evaluate the MNB-Count model

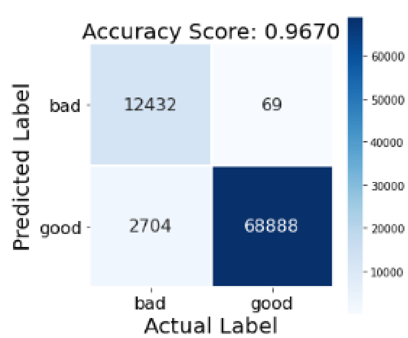
1. Create **mnb_count** as a **MultinomialNB()** constructor
2. Use **fit** to train *mnb_count* on the training data (*count_X*) and training labels (*labels*)

3. Evaluate the model with the testing data (*test_count_X*) and testing labels (*test_labels*):
a. Use the **score** function in *mnb_count* to calculate model accuracy; save the results as **score_mnb_count**
b. Use the **predict** function in *mnb_count* to generate model predictions; save the results as **predictions_mnb_count**
c. Generate the confusion matrix with **confusion_matrix**, using the predictons and labels; save the results as **cmatrix_mnb_count**
d. Generate the classification report with **classification_report**, using the predictions and labels; save the results as **creport_mnb_count**

```
# Multinomial Naive Bayesian with Count Vectorizer

# Train the model
# (Write code here)

mnb_tfidf = MultinomialNB()
mnb_tfidf.fit(tfidf_X, labels)

# Test the mode (score, predictions, confusion matrix, classification report)
# (Write code here)


score_mnb_count = mnb_tfidf.score(test_count_X, test_labels)
predictions_mnb_tfidf = mnb_tfidf.predict(test_count_X)
cmatrix_mnb_count = confusion_matrix(test_labels, predictions_mnb_tfidf)
creport_mnb_count = classification_report(test_labels, predictions_mnb_tfidf)

# (Keep the following lines)
print("\n### Model Built ###\n")
generate_report(cmatrix_mnb_count, score_mnb_count, creport_mnb_count)
```

```
### Model Built ###

              precision    recall  f1-score   support

         bad       0.99      0.82      0.90     15136
        good       0.96      1.00      0.98     68957

    accuracy                           0.97     84093
   macro avg       0.98      0.91      0.94     84093
weighted avg       0.97      0.97      0.97     84093
```

Accuracy Score: 0.9670



Recall and precision both are important

Recall and precision as being balancing act between “how many time you label a particular event correctly” vs “how many time you incorrectly things as begin part of that event”

Precision Bad url are 0.99 and recall bad are 0.82 but Precision good url are 0.96 and recall good are 100 and accuracy score 96.70

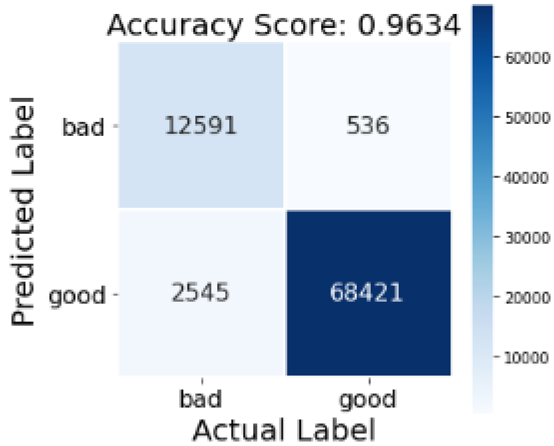
If you want to increase the accuracy use “alpha = .2” then accuracy are increased

Train and evaluate the LGS-Count model

1. Create **lgs_count** as a **LogisticRegression()** constructor, using the **lbfgs** *solver*
2. Use **fit** to train *lgs_count* on the training data (*count_X*) and training labels (*labels*)
3. Evaluate the model with the testing data (*test_count_X*) and testing labels (*test_labels*):
   a. Use the **score** function in *lgs_count* to calculate model accuracy; save the results as **score_lgs_count**
   b. Use the **predict** function in *lgs_count* to generate model predictions; save the results as **predictions_lgs_count**
   c. Generate the confusion matrix with **confusion_matrix**, using the predictons and labels; save the results as **cmatrix_lgs_count**
   d. Generate the classification report with **classification_report**, using the predictions and labels; save the results as **creport_lgs_count**

```
# Logistic Regression with Count Vectorizer

# Train the model

lgs_tfidf = LogisticRegression(solver='lbfgs')
lgs_tfidf.fit(tfidf_X, labels)

# Test the mode (score, predictions, confusion matrix, classification report)
# (Write code here)
score_lgs_count = lgs_tfidf.score(test_count_X, test_labels)
predictions_lgs_tfidf = lgs_tfidf.predict(test_count_X)
creport_lgs_count = classification_report(test_labels, predictions_lgs_tfidf)
cmatrix_lgs_count = confusion_matrix(test_labels, predictions_lgs_tfidf)

# (Keep the following lines)
print("\n### Model Built ###\n")
generate_report(cmatrix_lgs_count, score_lgs_count, creport_lgs_count)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

### Model Built ###

              precision    recall  f1-score   support

         bad       0.96      0.83      0.89     15136
        good       0.96      0.99      0.98     68957

    accuracy                           0.96     84093
   macro avg       0.96      0.91      0.93     84093
weighted avg       0.96      0.96      0.96     84093
```



Here the accuracy score are 96%

Finding the malicious link is not enough we need to find the content which is true or false so that we develop a application that detect the given text true or false

By using pickle library **Python pickle module** is used for serializing and de-serializing a **Python** object structure. Any object in **Python** can be **pickled** so that it can be saved on disk

```
import pickle
var = input("Please enter the news text you want to verify: ")
print("You entered: " + str(var))


# function to run for prediction
def fakenews(var):
# retrieving the best model for prediction call
    load_model = pickle.load(open('/content/model.sav', 'rb'))
    prediction = load_model.predict([var])
    prob = load_model.predict_proba([var])

    return (print("The given statement is ",prediction[0]),
        print("The truth probability score is ",prob[0][1]))



fakenews(var)
```

```
Please enter the news text you want to verify: 1 is a number
You entered: 1 is a number
The given statement is  True
The truth probability score is  0.6832222557351969
/usr/local/lib/python3.6/dist-packages/sklearn/base.py:318: UserWarning: Trying to unpickle estimator TfidfTransformer from version 0.18.1 when using version 0.22.2.post1. This might
  UserWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/base.py:318: UserWarning: Trying to unpickle estimator TfidfVectorizer from version 0.18.1 when using version 0.22.2.post1. This might
  UserWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/base.py:318: UserWarning: Trying to unpickle estimator LogisticRegression from version 0.18.1 when using version 0.22.2.post1. This mig
  UserWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/base.py:318: UserWarning: Trying to unpickle estimator Pipeline from version 0.18.1 when using version 0.22.2.post1. This might lead to
  UserWarning)
(None, None)
```