

Spam Detection with Machine Learning



Rapport de projet de fin d'année

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Introduction

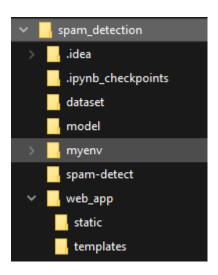
We are going to build an SMS spam detection web application. This application will be built with Python using the Flask framework and will include a machine learning model that we will train to detect SMS spam.

1. Prerequisites

We will need:

- Python 3. The Anaconda distribution includes a number of useful libraries for data science.
- Flask, HTML, and CSS.

2. File Structure



3. Set Up a Python Virtual Environment

Creating a new Python virtual environment

C:\Users\viet\spam_detection>conda create -n myenv python=3.6

Activating the environment

C:\Users\viet\spam_detection>conda activate myenv

Creating a new virtual environment

(myenv) C:\Users\viet\spam_detection>python -m venv myenv

Activating the new environment

(myenv) C:\Users\viet\spam_detection>myenv\Scripts\activate

Our prompt has been modified to look like the following:

(myenv) (myenv) C:\Users\viet\spam_detection>

4. Install Required Packages

Next, we will install all the packages needed for this tutorial:

(myenv) (myenv) C:\Users\viet\spam_detection>pip install jupyterlab Flask lightgbm nexmo matplotlib plotly plotly-expr ss python-dotenv nltk numpy pandas regex scikit-learn wordcloud

Here are some details about these packages:

- jupyterlab is for model building and data exploration.
- flask is for creating the application server and pages.
- lightgbm is the machine learning algorithm for building our model
- nexmo is a Python library for interacting with your Vonage account
- matplotlib, plotly, plotly-express are for data visualization
- python-dotenv is a package for managing environment variables such as API keys and other configuration values.
- nltk is for natural language operations
- numpy is for arrays computation
- pandas is for manipulating and wrangling structured data.
- regex is for regular expression operations
- scikit-learn is a machine learning toolkit
- wordcloud is used to create word cloud images from text

After installation, we will start our Jupyter lab by running:

(myenv) (myenv) C:\Users\viet\spam_detection>jupyter lab

5. Build and Train the SMS Detection Model

Now that your environment is ready, you're going to download the SMS training data and build a simple machine learning model to classify the SMS messages.

We downloaded the spam dataset for this project from here:

https://www.kaggle.com/uciml/sms-spam-collection-dataset

The datasets contain 5574 messages with respective labels of spam and ham (legitimate), With this data, we will train a machine learning model that can correctly classify SMS as ham or spam. These procedures will be carried out in a Jupyter notebook, which from our file directory is named 'project_notebok'.

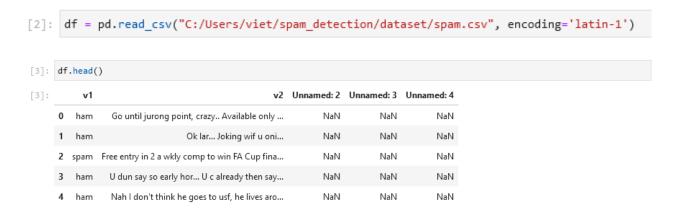
6.Exploratory Data Analysis (EDA)

Here, we will apply a variety of techniques to analyze the data and get a better understanding of it.

a. Import Libraries and Data

```
[1]: import pandas as pd
  import numpy as np
  import matplotlib.pyplot as plt
  import plotly_express as px
  import wordcloud
  import nltk
  import warnings
  warnings.filterwarnings('ignore')
```

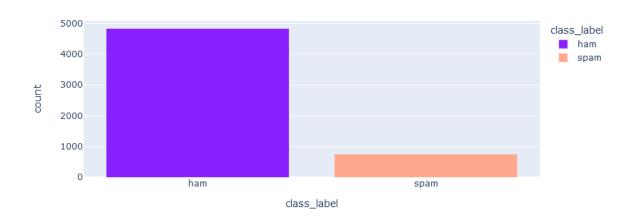
The spam dataset located in the dataset directory named spam.csv can be imported as follows:



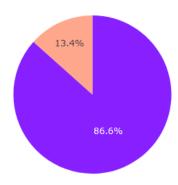
```
[4]: df.drop(columns=['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], inplace=True)
df.rename(columns = {'v1':'class_label','v2':'message'},inplace=True)
df.head()
```

[4]:		class_label	message									
	0	ham	Go until jurong point, crazy Available only									
	1	ham	Ok lar Joking wif u oni									
	2	spam	Free entry in 2 a wkly comp to win FA Cup fina									
	3	ham	U dun say so early hor U c already then say									
	4	ham	Nah I don't think he goes to usf, he lives aro									

```
[5]: fig = px.histogram(df, x="class_label", color="class_label", color_discrete_sequence=["#871fff","#ffa78c"])
fig.show()
```



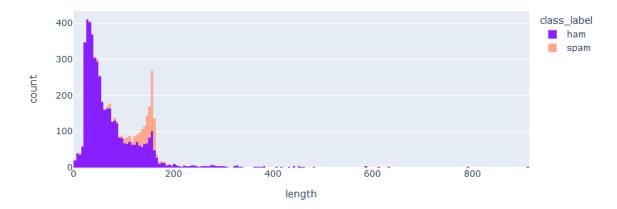




[7]: class_label message length 0 ham Go until jurong point, crazy.. Available only ... 111 1 Ok lar... Joking wif u oni... 29 ham 2 spam Free entry in 2 a wkly comp to win FA Cup fina... 155 3 U dun say so early hor... U c already then say... 49 ham 4 Nah I don't think he goes to usf, he lives aro... ham 61

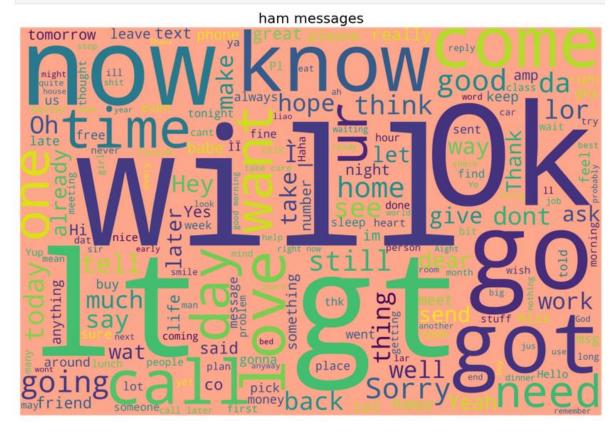
length	message	class_label	[8]:
. 111	Go until jurong point, crazy Available only	0 ham	
. 29	Ok lar Joking wif u oni	1 ham	
155	Free entry in 2 a wkly comp to win FA Cup fina	2 spam	
. 49	U dun say so early hor U c already then say	3 ham	
. 61	Nah I don't think he goes to usf, he lives aro	4 ham	

```
[9]: fig = px.histogram(df, x="length", color="class_label", color_discrete_sequence=["#871fff","#ffa78c"] )
fig.show()
```





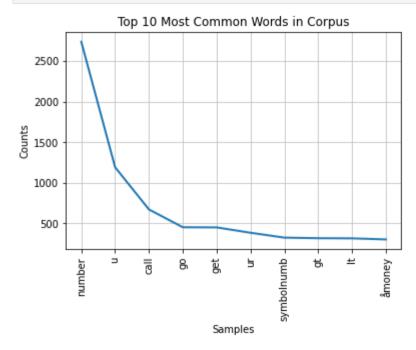
[12]: show_wordcloud(data_ham, "ham messages")



```
[13]: df['class_label'] = df['class_label'].map( {'spam': 1, 'ham': 0})
```

```
[14]: # Replace email address with 'emailaddress'
               df['message'] = df['message'].str.replace(r'^.+@[^\.].*\.[a-z]{2,}$', 'emailaddress')
               # Replace urls with 'webaddress'
                df['message'] = df['message'].str.replace(r'^http\://[a-zA-Z0-9\-\.]+\.[a-zA-Z]\{2,3\}(/\S*)?\$', 'webaddress') 
               # Replace money symbol with 'money-symbol'
               df['message'] = df['message'].str.replace(r'f|\$', 'money-symbol')
               # Replace 10 digit phone number with 'phone-number'
                df['message'] = df['message'].str.replace(r'^(?[\d]{3}\)?[\s-]?[\d]{4}$', 'phone-number') 
               # Replace normal number with 'number'
               df['message'] = df['message'].str.replace(r'\d+(\.\d+)?', 'number')
               # remove punctuation
               df['message'] = df['message'].str.replace(r'[^\w\d\s]', ' ')
               # remove whitespace between terms with single space
               df['message'] = df['message'].str.replace(r'\s+', ' ')
               # remove leading and trailing whitespace
               df['message'] = df['message'].str.replace(r'^\s+|\s*?$', ' ')
               # change words to lower case
               df['message'] = df['message'].str.lower()
[15]: from nltk.corpus import stopwords
              stop_words = set(stopwords.words('english'))
             \label{eq:df'message'} df'' (\mbox{"message'}) = df'' (\mbox{"messag
 [16]: ss = nltk.SnowballStemmer("english")
                 df['message'] = df['message'].apply(lambda x: ' '.join(ss.stem(term) for term in x.split()))
  [17]: import nltk
                  nltk.download('punkt')
                  sms_df = df['message']
                  from nltk.tokenize import word_tokenize
                  # creating a bag-of-words model
                  all_words = []
                  for sms in sms_df:
                            words = word_tokenize(sms)
                            for w in words:
                                      all_words.append(w)
                  all_words = nltk.FreqDist(all_words)
 [18]: print('Number of words: {}'.format(len(all_words)))
                   Number of words: 6526
```

```
[19]: all_words.plot(10, title='Top 10 Most Common Words in Corpus');
```



```
[23]: from sklearn.feature_extraction.text import TfidfVectorizer
    tfidf_model = TfidfVectorizer()
    tfidf_vec=tfidf_model.fit_transform(sms_df)
    import pickle
    #serializing our model to a file called model.pkl
    pickle.dump(tfidf_model, open("C:/Users/viet/spam_detection/model/tfidf_model.pkl","wb"))
    tfidf_data=pd.DataFrame(tfidf_vec.toarray())
    tfidf_data.head()
```

[23]:		0	1	2	3	4	5	6	7	8	9	 6496	6497	6498	6499	6500	6501	6502	6503	6504	6505
	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 6506 columns

```
[24]: ### Separating Columns
df_train = tfidf_data.iloc[:4457]
df_test = tfidf_data.iloc[4457:]

target = df['class_label']
df_train['class_label'] = target

Y = df_train['class_label']
X = df_train.drop('class_label',axis=1)

# splitting training data into train and validation using sklearn
from sklearn import model_selection
X_train,X_test,y_train,y_test = model_selection.train_test_split(X,Y,test_size=.2, random_state=42)
```

```
import lightgbm as lgb
from sklearn.metrics import f1_score

def train_and_test(model, model_name):
    model.fit(X_train, y_train)
    pred = model.predict(X_test)
    print(f'F1 score is: {f1_score(pred, y_test)}')

for depth in [1,2,3,4,5,6,7,8,9,10]:
    lgbmodel = lgb.LGBMClassifier(max_depth=depth, n_estimators=200, num_leaves=40)
    print(f"Max_Depth_{depth}")
    print(" ")
    print(" ")
    train_and_test(lgbmodel, "Light_GBM")
```

```
Max Depth 1
```

F1 score is: 0.8870292887029289 Max Depth 2

F1 score is: 0.9236947791164659 Max Depth 3

F1 score is: 0.9149797570850203 Max Depth 4

F1 score is: 0.912 Max Depth 5

F1 score is: 0.9133858267716536 Max Depth 6

F1 score is: 0.9098039215686274

Max Depth 7

F1 score is: 0.9133858267716536 Max Depth 8

F1 score is: 0.9169960474308301 Max Depth 9

F1 score is: 0.9206349206349207

Max Depth 10

F1 score is: 0.9206349206349207

```
[28]: from sklearn.model selection import RandomizedSearchCV
      lgbmodel_bst = lgb.LGBMClassifier(max_depth=6, n_estimators=200, num_leaves=40)
      param_grid = {
          'num_leaves': list(range(8, 92, 4)),
          'min_data_in_leaf': [10, 20, 40, 60, 100],
          'max_depth': [3, 4, 5, 6, 8, 12, 16, -1],
          'learning_rate': [0.1, 0.05, 0.01, 0.005],
          'bagging_freq': [3, 4, 5, 6, 7],
          'bagging_fraction': np.linspace(0.6, 0.95, 10),
          'reg_alpha': np.linspace(0.1, 0.95, 10),
          'reg_lambda': np.linspace(0.1, 0.95, 10),
          "min_split_gain": [0.0, 0.1, 0.01],
          "min_child_weight": [0.001, 0.01, 0.1, 0.001],
          "min child samples": [20, 30, 25],
          "subsample": [1.0, 0.5, 0.8],
      }
      model = RandomizedSearchCV(lgbmodel_bst, param_grid, random_state=1)
      search = model.fit(X_train, y_train)
      search.best_params_
[28]: {'verbose': -1,
        'subsample': 0.5,
        'reg lambda': 0.47777777777777,
        'reg alpha': 0.572222222222222,
        'num leaves': 88,
        'min split gain': 0.01,
        'min data in leaf': 10,
        'min_child_weight': 0.01,
        'min child_samples': 30,
        'max depth': 3,
        'learning_rate': 0.1,
        'bagging freq': 3,
        'bagging_fraction': 0.6}
```

```
[29]: best_model = lgb.LGBMClassifier(subsample=0.5,
                                  reg lambda= 0.47777777777777,
                                  reg_alpha= 0.572222222222222,
                                  num_leaves= 88,
                                  min_split_gain= 0.01,
                                  min_data_in_leaf= 10,
                                  min_child_weight= 0.01,
                                  min_child_samples= 30,
                                  max_depth= 3,
                                  learning_rate= 0.1,
                                  bagging_freq= 3,
                                  bagging_fraction= 0.6,
                                  random_state=1)
      best_model.fit(X_train,y_train)
[29]: LGBMClassifier(bagging_fraction=0.6, bagging_freq=3, max_depth=3,
                     min_child_samples=30, min_child_weight=0.01, min_data_in_leaf=10,
                     min_split_gain=0.01, num_leaves=88, random_state=1,
                     reg_alpha=0.572222222222222, reg_lambda=0.477777777777775,
                     subsample=0.5)
[1]: prediction = best_model.predict(X_test)
      print(f'F1 score is: {f1_score(prediction, y_test)}')
       F1 score is: 0.891566265060241
[32]: best_model.fit(tfidf_data, target)
      pickle.dump(best_model, open("C:/Users/viet/spam_detection/model/spam_model.pk1","wb"))
```