# pulsar5

November 4, 2022

- 1 Pulsar Emission Data Analysis
- 2 All Imports that may or may not be needed and used for the notebook

```
[]: #currently including any and all Imports that maybe needed for the project.
     import pandas as pd
     import numpy as np
     import seaborn as sns
     import matplotlib.pyplot as plt
     %matplotlib inline
     from sklearn.model_selection import train_test_split
     from sklearn import linear_model
     from sklearn.metrics import r2_score, mean_squared_error
     from sklearn.linear_model import LogisticRegression, LinearRegression
     from sklearn.metrics import confusion_matrix, accuracy_score
     from sklearn.feature_selection import RFE
     import datetime as dt
     from sklearn.cluster import KMeans
     from sklearn.metrics import pairwise_distances
     from scipy.cluster.hierarchy import linkage, dendrogram, cut_tree
     from scipy.spatial.distance import pdist
     from sklearn.feature extraction.text import TfidfVectorizer
     import matplotlib.dates as mdates
     from scipy.stats import pearsonr
     from scipy import stats
     import statistics
     import math
     from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
     from statsmodels.tsa.stattools import acf, pacf
     from statsmodels.tsa.tsatools import lagmat
     from numpy import array
     from sklearn.model_selection import train_test_split
     from keras.models import Sequential
     from keras.layers import LSTM
     from keras.layers import Dense
     from keras.layers import Bidirectional
```

# 3 Section for extracting from a tar file.

### Currently implemented for original TAR File structure.

```
[]: #This is also found in the main file under tarunzip.py
import tarfile
import os
import sys

#tar = tarfile.open("pulseTarFile.tar")
#tar.extractall('./Data')
#tar.close()
```

# 3.1 Beginning of Exploration

## 3.1.1 Examining the data

In this section we are determining the total integrity of the data to determine if further comprehensive data cleaning and uniforming processes are needed.

```
[]: colnames = ['Pulse Number', 'Brightness', 'Uncertainty']

pulsar = pd.read_csv("Data/J1456-6843.pulses", sep = ' ', header = None, names

→= colnames)
```

```
[]: pulsar.shape
```

[]: (1219, 3)

```
[]: pulsar.head(25)
```

```
[]:
         Pulse Number
                         Brightness
                                      Uncertainty
                           0.053904
                                         0.005560
     0
                      1
                      2
                           0.058653
                                         0.004821
     1
     2
                      3
                           0.110208
                                         0.005196
     3
                      4
                           0.034716
                                         0.004729
                      5
     4
                                         0.004619
                           0.056101
     5
                      6
                           0.046168
                                         0.005074
     6
                      7
                           0.055648
                                         0.004916
     7
                      8
                           0.060890
                                         0.004581
     8
                      9
                           0.024388
                                         0.004922
     9
                    10
                           0.039370
                                         0.004633
                    11
                                         0.004581
     10
                           0.009141
     11
                    12
                           0.145273
                                         0.005053
     12
                    13
                           0.039953
                                         0.004938
     13
                    14
                          -0.002554
                                         0.004409
     14
                    15
                           0.035696
                                         0.004903
     15
                    16
                           0.046869
                                         0.004706
     16
                    17
                           0.082637
                                         0.004596
     17
                           0.349419
                                         0.006828
                    18
     18
                    19
                           0.058343
                                         0.004650
```

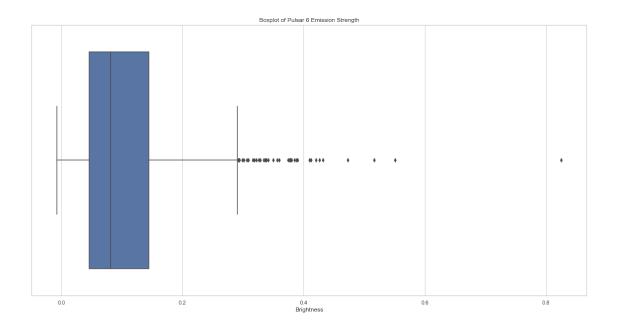
```
20
                   21
                         0.120429
                                       0.005141
     21
                   22
                         0.209730
                                       0.005389
     22
                   23
                         0.088045
                                       0.004945
     23
                   24
                         0.203736
                                       0.008553
     24
                   25
                         0.024098
                                       0.004641
    pulsar.describe()
[]:
            Pulse Number
                            Brightness
                                        Uncertainty
     count
             1219.000000
                          1219.000000
                                        1219.000000
     mean
              610.000000
                              0.104176
                                           0.005410
     std
              352.039297
                              0.081916
                                           0.001282
    min
                1.000000
                            -0.007285
                                           0.001075
     25%
              305.500000
                              0.045763
                                           0.004728
     50%
              610.000000
                              0.081228
                                           0.004966
     75%
              914.500000
                              0.144228
                                           0.005541
             1219.000000
                              0.825366
     max
                                           0.016201
[]: nullBoolBrightness = pd.isnull(pulsar["Brightness"])
     pulsar[nullBoolBrightness]
[]: Empty DataFrame
     Columns: [Pulse Number, Brightness, Uncertainty]
     Index: []
[]: pulsar["Brightness"].describe()
[]: count
              1219.000000
     mean
                 0.104176
     std
                 0.081916
    min
                -0.007285
     25%
                 0.045763
     50%
                 0.081228
     75%
                 0.144228
                 0.825366
    max
     Name: Brightness, dtype: float64
[]: plt.figure(figsize=(20,10))
     sns.set_theme(style="whitegrid")
     ax = sns.boxplot(x=pulsar["Brightness"]).set_title("Boxplot of Pulsar 6")
      →Emission Strength")
```

0.005068

19

20

0.090261



```
[]: medianpulse6 = pulsar["Brightness"].median()
print("Median of Pulsar6: ", medianpulse6)
pulsar['Binary'] = np.where(pulsar['Brightness'] > medianpulse6, 1, 0)
```

Median of Pulsar6: 0.081228

## []: pulsar

[]:		Pulse Number	Brightness	Uncertainty	Binary
	0	1	5.390386e-02	0.005560	0
	1	2	5.865279e-02	0.004821	0
	2	3	1.102083e-01	0.005196	1
	3	4	3.471609e-02	0.004729	0
	4	5	5.610133e-02	0.004619	0
		•••	***		
	1214	1215	4.321559e-02	0.004991	0
	1215	1216	1.830750e-02	0.004578	0
	1216	1217	1.155671e-01	0.005212	1
	1217	1218	1.562609e-02	0.004686	0
	1218	1219	-1.137418e-08	0.001075	0

[1219 rows x 4 columns]

```
[]: plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar.Brightness.values
plt.style.use('ggplot')
```

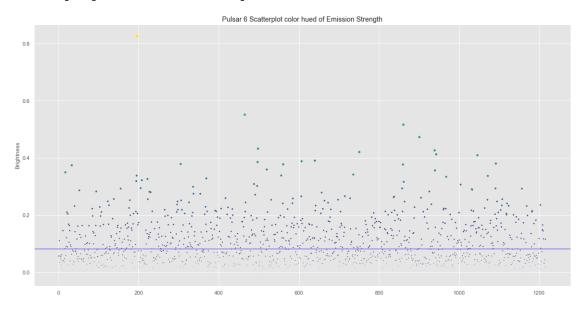
```
ax = sns.scatterplot(data=pulsar["Brightness"], s= strength*50, c=strength, 

⇒cmap="viridis", marker="o").set_title('Pulsar 6 Scatterplot color hued of 

⇒Emission Strength')

ax= plt.axhline( y=0.081228, ls='-',c='mediumslateblue')
```

C:\Users\tajki\anaconda3\lib\site-packages\matplotlib\collections.py:1003:
RuntimeWarning: invalid value encountered in sqrt
 scale = np.sqrt(self.\_sizes) \* dpi / 72.0 \* self.\_factor

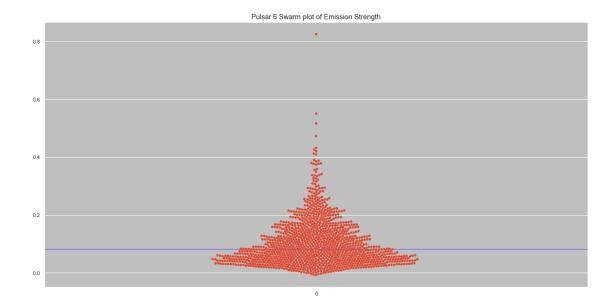


```
[ ]: print(len(pulsar[(pulsar.Brightness > 0.081228)]))
print(len(pulsar[(pulsar.Brightness < 0.081228)]))</pre>
```

609 609

```
[]: plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar.Brightness.values
ax = plt.axhline( y=0.081228, ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=pulsar["Brightness"], c="blue").set_title('Pulsar 6

→Swarm plot of Emission Strength')
```

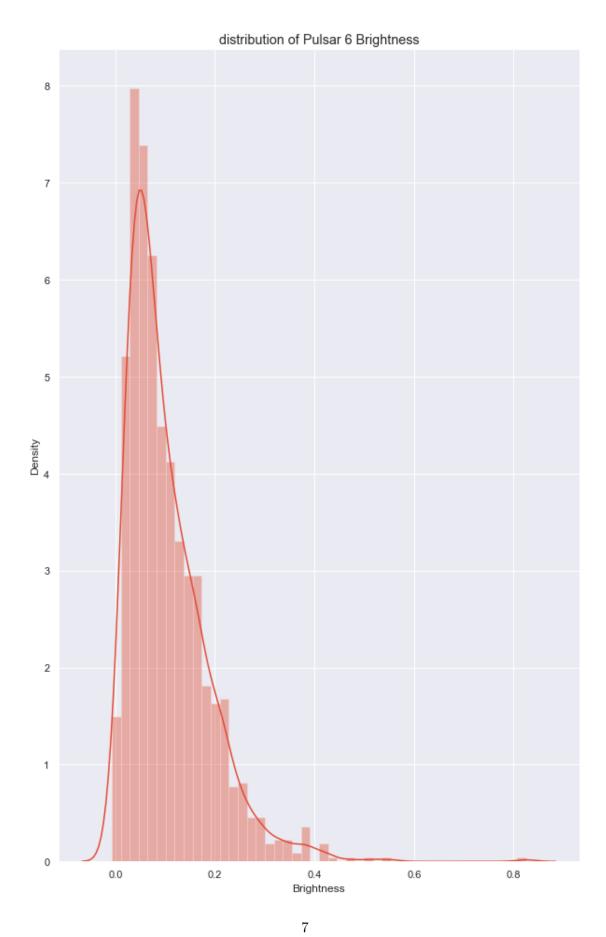


```
[]: plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar.Brightness)
plt.title("distribution of Pulsar 6 Brightness")
```

C:\Users\tajki\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

[]: Text(0.5, 1.0, 'distribution of Pulsar 6 Brightness')



```
[]: plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
        sns.distplot(pulsar.Binary)
plt.title("distribution of Pulsar 6 binary assignments")
```

C:\Users\tajki\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

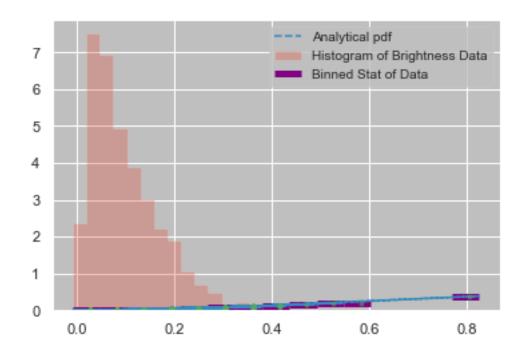
warnings.warn(msg, FutureWarning)

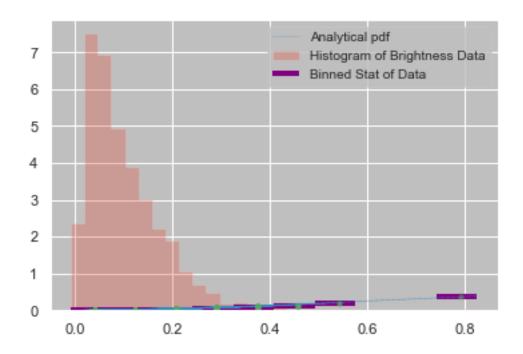
[]: Text(0.5, 1.0, 'distribution of Pulsar 6 binary assignments')



4 Rolling Medians, Rolling Means, Binned Medians and Binned Mean analysis.

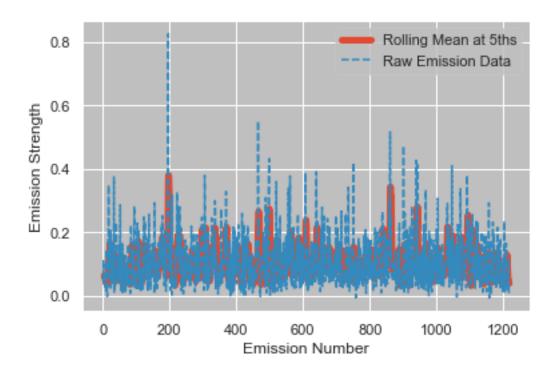
```
[]: data = pulsar["Brightness"]
     data
[]: 0
            5.390386e-02
            5.865279e-02
     1
     2
            1.102083e-01
     3
            3.471609e-02
            5.610133e-02
     1214
            4.321559e-02
            1.830750e-02
     1215
     1216
           1.155671e-01
     1217
            1.562609e-02
     1218
           -1.137418e-08
    Name: Brightness, Length: 1219, dtype: float64
[ ]: dataPDF = stats.maxwell.pdf(data)
     bin_means, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
            statistic='mean', bins=15)
     bin_width = (bin_edges[1] - bin_edges[0])
     bin_centers = bin_edges[1:] - bin_width/2
     plt.figure()
     plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,
     →label='Histogram of Brightness Data')
     plt.plot(data, dataPDF, '--', label = "Analytical pdf")
     plt.hlines(bin_means, bin_edges[:-1], bin_edges[1:], colors='purple', lw=5,__
      →label='Binned Stat of Data')
     plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
     plt.legend(fontsize=10)
     plt.show()
```

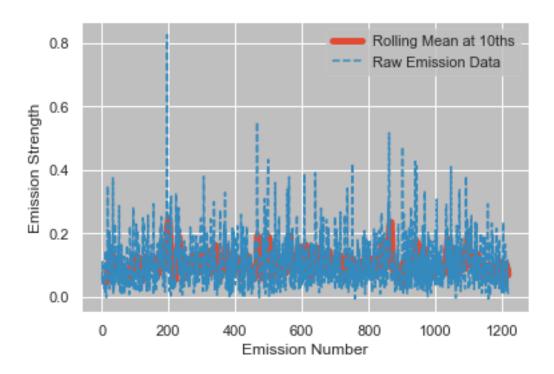


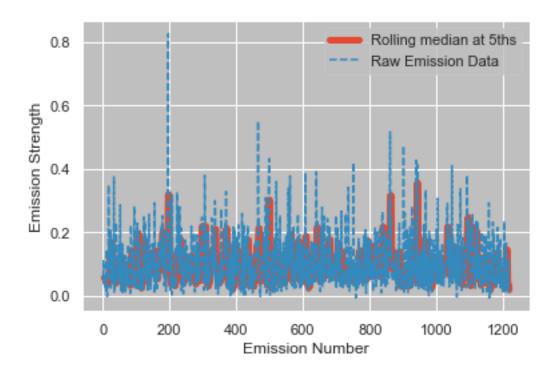


```
pulsar['RollingMeanEmissions5ths'] = pulsar["Brightness"].rolling(5).mean()

plt.plot(pulsar['RollingMeanEmissions5ths'], label="Rolling Mean at 5ths", lw=5)
plt.plot(pulsar['Brightness'], label= "Raw Emission Data", linestyle='--')
plt.legend()
plt.ylabel('Emission Strength')
plt.xlabel('Emission Number')
plt.show()
```







```
[]: pulsar['RollingMedianEmissions10ths'] = pulsar["Brightness"].rolling(10).

→ median()

plt.plot(pulsar['RollingMedianEmissions10ths'], label="Rolling median at_u"

→ 10ths", lw=5)

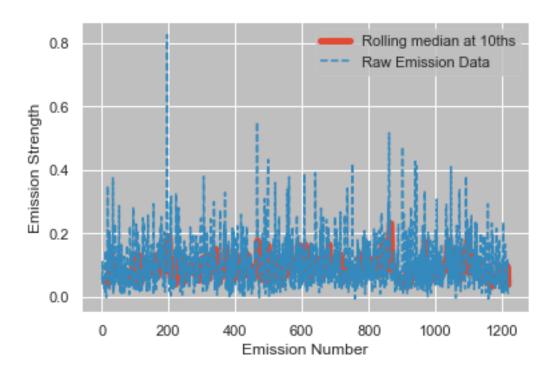
plt.plot(pulsar['Brightness'], label= "Raw Emission Data", linestyle='--')

plt.legend()

plt.ylabel('Emission Strength')

plt.xlabel('Emission Number')

plt.show()
```



[]:	pulsar.head(25)							
[]:	Pulse	Number	Brightness	Uncertainty	Binary	RollingMeanEmissions5ths	\	
	0	1	0.053904	0.005560	0	NaN		
	1	2	0.058653	0.004821	0	NaN		
	2	3	0.110208	0.005196	1	NaN		
	3	4	0.034716	0.004729	0	NaN		
	4	5	0.056101	0.004619	0	0.062716		
	5	6	0.046168	0.005074	0	0.061169		
	6	7	0.055648	0.004916	0	0.060568		
	7	8	0.060890	0.004581	0	0.050705		
	8	9	0.024388	0.004922	0	0.048639		
	9	10	0.039370	0.004633	0	0.045293		
	10	11	0.009141	0.004581	0	0.037888		
	11	12	0.145273	0.005053	1	0.055813		
	12	13	0.039953	0.004938	0	0.051625		
	13	14	-0.002554	0.004409	0	0.046237		
	14	15	0.035696	0.004903	0	0.045502		
	15	16	0.046869	0.004706	0	0.053048		
	16	17	0.082637	0.004596	1	0.040520		
	17	18	0.349419	0.006828	1	0.102413		
	18	19	0.058343	0.004650	0	0.114593		
	19	20	0.090261	0.005068	1	0.125506		
	20	21	0.120429	0.005141	1	0.140218		

```
21
               22
                                    0.005389
                                                                          0.165637
                      0.209730
                                                     1
22
               23
                      0.088045
                                    0.004945
                                                     1
                                                                          0.113362
                                    0.008553
23
               24
                                                     1
                      0.203736
                                                                          0.142440
24
                                                     0
               25
                      0.024098
                                    0.004641
                                                                          0.129208
    RollingMeanEmissions10ths
                                  RollingMedianEmissions5ths
0
                            NaN
                                                           NaN
1
                            NaN
                                                           NaN
2
                            NaN
                                                           NaN
3
                            NaN
                                                           NaN
4
                            NaN
                                                      0.056101
5
                            NaN
                                                      0.056101
6
                            NaN
                                                      0.055648
7
                            NaN
                                                      0.055648
8
                            NaN
                                                      0.055648
9
                       0.054005
                                                      0.046168
10
                       0.049528
                                                      0.039370
11
                       0.058190
                                                      0.039370
12
                       0.051165
                                                      0.039370
13
                       0.047438
                                                      0.039370
14
                       0.045397
                                                      0.035696
15
                       0.045468
                                                      0.039953
16
                       0.048166
                                                      0.039953
17
                       0.077019
                                                      0.046869
18
                       0.080415
                                                      0.058343
19
                       0.085504
                                                      0.082637
20
                                                      0.090261
                       0.096633
21
                       0.103078
                                                      0.120429
22
                                                      0.090261
                       0.107888
23
                                                      0.120429
                       0.128517
24
                       0.127357
                                                      0.120429
    RollingMedianEmissions10ths
0
                               NaN
1
                               NaN
2
                               NaN
3
                               NaN
4
                               NaN
5
                               NaN
6
                               NaN
7
                               NaN
8
                               NaN
9
                         0.054776
10
                         0.050908
11
                         0.050908
12
                         0.043061
13
                         0.043061
```

```
14
                            0.039662
     15
                            0.039662
     16
                            0.039662
     17
                            0.039662
     18
                            0.043411
     19
                            0.052606
     20
                            0.070490
    21
                            0.070490
     22
                            0.085341
     23
                            0.089153
     24
                            0.089153
    4.1 Binary Classification
[]: X = pulsar[['Brightness', 'Uncertainty']]
     y = pulsar['Binary']
[]: X.head()
[]:
        Brightness Uncertainty
          0.053904
                       0.005560
     1
          0.058653
                       0.004821
     2
          0.110208
                       0.005196
     3
          0.034716
                       0.004729
     4
          0.056101
                       0.004619
[]: y.head()
[]: 0
          0
          0
     1
     2
          1
     3
          0
     4
          0
     Name: Binary, dtype: int32
[]: from sklearn.model_selection import train_test_split
     X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)
[]: from sklearn.preprocessing import StandardScaler
     train_scaler = StandardScaler()
     X_train = train_scaler.fit_transform(X_train)
     test scaler = StandardScaler()
```

X\_test = test\_scaler.fit\_transform(X\_test)

```
[]: model = LogisticRegression()
    model.fit(X_train, y_train)
[]: LogisticRegression()
[ ]: predictions = model.predict(X_test)
[]: from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_test, predictions)
    TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()
    print('True Positive(TP) = ', TP)
    print('False Positive(FP) = ', FP)
    print('True Negative(TN) = ', TN)
    print('False Negative(FN) = ', FN)
    True Positive(TP) = 109
    False Positive(FP) = 6
    True Negative(TN) = 129
    False Negative(FN) = 0
[]: accuracy = (TP + TN) / (TP + FP + TN + FN)
    print("Accuracy of the model is ", accuracy)
    Accuracy of the model is 0.9754098360655737
    4.2 Bidirectional LSTM Model
[]: # making a list with the brightness and uncertainty values
    values_list = pulsar[['Brightness', 'Uncertainty']].values.tolist()
    values_list[:10]
[]: [[0.05390386, 0.005559608],
      [0.05865279, 0.004821059],
      [0.1102083, 0.005195663],
      [0.03471609, 0.004728795],
      [0.05610133, 0.00461856],
      [0.04616798, 0.005074086],
      [0.05564797, 0.004915987],
      [0.06089036, 0.004580757],
      [0.02438825, 0.00492155],
      [0.0393704, 0.004633388]]
```

```
[]: from sklearn import preprocessing
    # normalizing the values
    values_list = preprocessing.normalize(values_list)
[]: # function for spliting a list in a format we can use in the model
    def split list(blist, steps):
        X, y = list(), list()
        for i in range(len(blist)):
            end_ix = i + steps
            if end_ix > len(blist)-1:
                break
            list_x, list_y = blist[i:end_ix], blist[end_ix][0]
            X.append(list_x)
            y.append(list_y)
        return array(X), array(y)
[]: # splitting the list
    X, y = split_list(values_list, 100)
    # reshaping the list to feed the model
    X = X.reshape((X.shape[0], X.shape[1], 2))
[]: # splitting the list into train and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)
[]: X_train.shape
[]: (895, 100, 2)
[]: | # setting the parameters for the lstm model and compiling it
    model = Sequential()
    model.add(Bidirectional(LSTM(50, activation='relu'), input_shape=(100, 2)))
    model.add(Dense(25, activation='relu'))
    model.add(Dense(12, activation='relu'))
    model.add(Dense(6, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam',_

→metrics=['accuracy'])
[]: # training the model
    history = model.fit(X_train, y_train, epochs=50, verbose=1,_
     →batch_size=(int(X_train.shape[0]/50)))
    Epoch 1/50
    0.0000e+00
    Epoch 2/50
```

```
0.0000e+00
Epoch 3/50
0.0000e+00
Epoch 4/50
0.0000e+00
Epoch 5/50
0.0000e+00
Epoch 6/50
0.0000e+00
Epoch 7/50
0.0000e+00
Epoch 8/50
0.0000e+00
Epoch 9/50
0.0000e+00
Epoch 10/50
0.0000e+00
Epoch 11/50
0.0000e+00
Epoch 12/50
0.0000e+00
Epoch 13/50
0.0000e+00
Epoch 14/50
0.0000e+00
Epoch 15/50
0.0000e+00
Epoch 16/50
0.0000e+00
Epoch 17/50
0.0000e+00
Epoch 18/50
```

```
0.0000e+00
Epoch 19/50
0.0000e+00
Epoch 20/50
0.0000e+00
Epoch 21/50
0.0000e+00
Epoch 22/50
0.0000e+00
Epoch 23/50
0.0000e+00
Epoch 24/50
0.0000e+00
Epoch 25/50
0.0000e+00
Epoch 26/50
0.0000e+00
Epoch 27/50
0.0000e+00
Epoch 28/50
0.0000e+00
Epoch 29/50
0.0000e+00
Epoch 30/50
0.0000e+00
Epoch 31/50
0.0000e+00
Epoch 32/50
0.0000e+00
Epoch 33/50
0.0000e+00
Epoch 34/50
```

```
0.0000e+00
Epoch 35/50
0.0000e+00
Epoch 36/50
0.0000e+00
Epoch 37/50
0.0000e+00
Epoch 38/50
0.0000e+00
Epoch 39/50
0.0000e+00
Epoch 40/50
0.0000e+00
Epoch 41/50
0.0000e+00
Epoch 42/50
0.0000e+00
Epoch 43/50
0.0000e+00
Epoch 44/50
0.0000e+00
Epoch 45/50
0.0000e+00
Epoch 46/50
0.0000e+00
Epoch 47/50
0.0000e+00
Epoch 48/50
0.0000e+00
Epoch 49/50
0.0000e+00
Epoch 50/50
```

```
0.0000e+00
[]: # predicting the y/brightness values for the test set
   y_pred = model.predict(X_test, verbose=0)
   y_pred[:10]
[]: array([[0.9813596],
        [0.9805201],
        [0.98130524],
        [0.97970897],
        [0.9797267],
        [0.98002166],
        [0.9799235],
        [0.9785363],
        [0.9804213],
        [0.97794783]], dtype=float32)
[]: # evaluating the model
   model.evaluate(X_test, y_test)
   0.0000e+00
[]: [0.0934809073805809, 0.0]
```

#### 4.3 ML Evaluation.

#### 4.3.1 Logistic Regression

Rewards no significant results for this type of analysis and is dropped for a LSTM attempt

#### 4.3.2 Bidirectional LSTM

Loss is low so the model is performing well. But the accuracy is low therefore unable to obtain trend and therefore not rewarding any information. This means we cannot predict any of the values with confidence.

# 5 Preliminary runs test

### 5.0.1 Math Logic

$$Z = \frac{R - \tilde{R}}{s_R}$$
 
$$\tilde{R} = \frac{2_{n1n2}}{n1 + n2} + 1$$

$$s_R^2 = \frac{2nn2(2n1n2 - n1 - n2)}{(n1 + n2)^2(n1 + n2 - 1)}$$

link to resource: https://www.geeksforgeeks.org/runs-test-of-randomness-in-python/

 $Z_{\text{critical}} = 1.96$  s as the confidence interval level of 95% thus this is a 2 tailed test. If the probability as corrosponding to this confidence interval  $H_{\text{null}}$  will be rejected as it is not statistically significant as denoted by  $|Z| > Z_{\text{critical}}$ 

There is also code attempting to change it from a z-score probability to a P-score for ease of understanding and clarity.

# 6 FUNCTION CODE FOR RUNS TEST

```
[]: binaryData1 = pulsar['Binary'].tolist()
print("pulsar6 original: ",binaryData1)
```

```
pulsar6 original: [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1,
1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1,
0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0,
0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0,
0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0,
1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0,
1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1,
0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0,
0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0,
0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,
0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0,
0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1,
1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1,
0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1,
0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0,
0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0,
0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1,
0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0,
1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1,
1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0,
0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1,
1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0,
0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1,
1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0,
0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0,
1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1,
1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1,
0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0,
0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0,
```

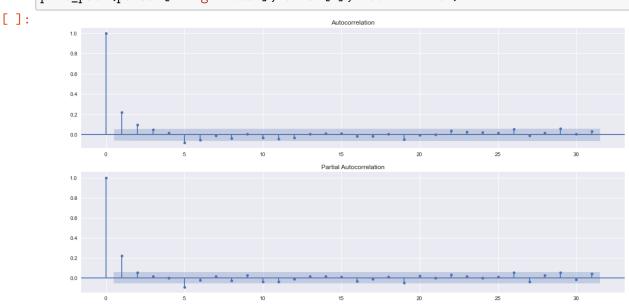
# 7 Below we begin autocorrelation and autocovariance analysis

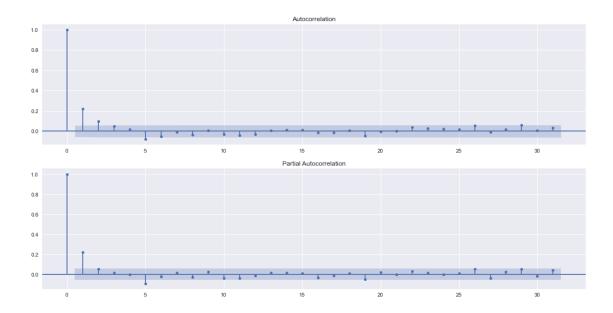
To get started with this I am playing around with guide from: https://towardsdatascience.com/a-step-by-step-guide-to-calculating-autocorrelation-and-partial-autocorrelation-8c4342b784e8

```
[]: plt.style.use("seaborn")
  plt.rcParams["figure.figsize"] = (18, 9)

fig, ax = plt.subplots(2,1)

plot_acf(pulsar['Brightness'], ax=ax[0])
  plot_pacf(pulsar['Brightness'], ax=ax[1], method="ols")
```





```
[]: acf(pulsar['Brightness'], nlags=10)
```

C:\Users\tajki\anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:667:
FutureWarning: fft=True will become the default after the release of the 0.12
release of statsmodels. To suppress this warning, explicitly set fft=False.
 warnings.warn(

```
[]: array([1. , 0.22161581, 0.09940415, 0.04669096, 0.01876941, -0.07818365, -0.0539178 , -0.01220963, -0.03566829, 0.00520742, -0.03014362])
```

```
[]: acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar['Brightness'].shift(lag)
acfpulsar
```

```
[]:
                B_lag_0
                                                         B_lag_4
                                                                   B_lag_5
                          B_lag_1
                                    B_lag_2
                                               B_lag_3
           5.390386e-02
                                                             NaN
                                                                       NaN
     0
                              NaN
                                        {\tt NaN}
                                                   NaN
           5.865279e-02 0.053904
     1
                                        {\tt NaN}
                                                   NaN
                                                             NaN
                                                                       NaN
     2
           1.102083e-01
                         0.058653
                                   0.053904
                                                   NaN
                                                             NaN
                                                                       NaN
     3
           3.471609e-02 0.110208
                                   0.058653
                                             0.053904
                                                             NaN
                                                                       NaN
     4
           5.610133e-02 0.034716
                                   0.110208
                                             0.058653
                                                        0.053904
                                                                       NaN
     1214 4.321559e-02 0.031916 0.030713
                                             0.116777
                                                        0.144606
                                                                  0.165039
     1215 1.830750e-02 0.043216
                                   0.031916
                                             0.030713
                                                                  0.144606
                                                        0.116777
     1216 1.155671e-01 0.018308 0.043216
                                             0.031916
                                                        0.030713 0.116777
```

```
1217 1.562609e-02 0.115567 0.018308 0.043216
                                                 0.031916 0.030713
1218 -1.137418e-08  0.015626  0.115567  0.018308
                                                 0.043216 0.031916
      B_lag_6
                B_lag_7
                          B_lag_8
                                    B_lag_9 B_lag_10
0
          NaN
                    NaN
                              NaN
                                        NaN
                                                  NaN
1
          NaN
                    NaN
                              NaN
                                        NaN
                                                  NaN
2
          NaN
                    NaN
                              NaN
                                        NaN
                                                  NaN
3
          NaN
                    NaN
                              NaN
                                        NaN
                                                  NaN
4
          NaN
                    NaN
                              NaN
                                        NaN
                                                  NaN
1214
     0.148642
               0.071752
                         0.008108
                                   0.038793 0.084002
1215 0.165039
               0.148642 0.071752
                                  0.008108 0.038793
1216
     0.144606 0.165039
                         0.148642 0.071752 0.008108
1217
     0.116777
               0.144606 0.165039
                                   0.148642 0.071752
1218 0.030713 0.116777 0.144606 0.165039 0.148642
```

[1219 rows x 11 columns]

```
[]: acfpulsar.corr()["B_lag_0"].values
```

```
[]: array([1. , 0.22179701, 0.09954441, 0.04675654, 0.01880625, -0.07839106, -0.05409556, -0.01226841, -0.03581717, 0.00521062, -0.03030331])
```

- 7.0.1 Getting every 5th as per the auto correlation
- 7.0.2 Creating a new set of discrete 100 sets and examining them specifically
- 7.0.3 Further Random testing to move into extensive testing

#### Getting every 5th as per the auto correlation

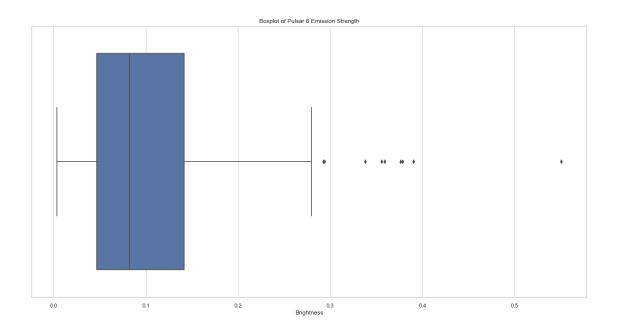
```
[]: held5ths = pulsar[pulsar.index % 5 == 0] held5ths
```

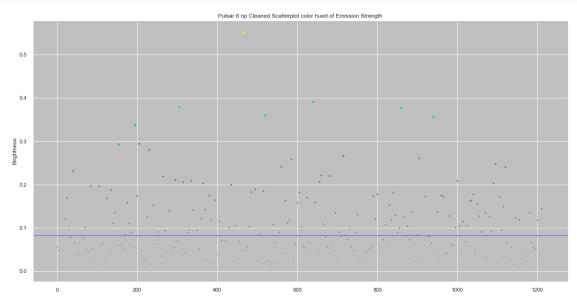
[]:	Pulse Number	Brightness	Uncertainty	Binary	${\tt Rolling Mean Emissions 5 ths}$	\
0	1	0.053904	0.005560	0	NaN	
5	6	0.046168	0.005074	0	0.061169	
10	) 11	0.009141	0.004581	0	0.037888	
15	5 16	0.046869	0.004706	0	0.053048	
20	21	0.120429	0.005141	1	0.140218	
•••	•••	•••				
11	1196	0.049626	0.004631	0	0.072716	
12	200 1201	0.117575	0.005117	1	0.055436	
12	205 1206	0.038793	0.004621	0	0.079521	
12	210 1211	0.144606	0.005046	1	0.107629	
12	215 1216	0.018308	0.004578	0	0.048186	

 ${\tt Rolling Mean Emissions 10 ths} \quad {\tt Rolling Median Emissions 5 ths} \quad {\tt \ \ }$ 

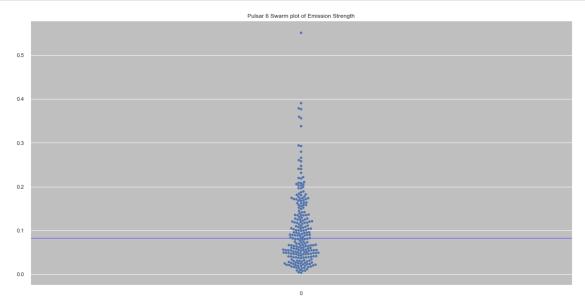
```
0
                                   NaN
                                                                 NaN
     5
                                   NaN
                                                           0.056101
                             0.049528
     10
                                                           0.039370
     15
                             0.045468
                                                           0.039953
     20
                             0.096633
                                                           0.090261
     1195
                             0.079188
                                                           0.049626
     1200
                             0.064076
                                                           0.050588
     1205
                             0.067478
                                                           0.038793
     1210
                             0.093575
                                                           0.144606
     1215
                             0.077908
                                                           0.031916
           RollingMedianEmissions10ths
     0
                                     NaN
     5
                                     NaN
     10
                               0.050908
     15
                               0.039662
     20
                               0.070490
     1195
                               0.056310
     1200
                               0.050107
     1205
                               0.044691
     1210
                               0.077877
     1215
                               0.057484
     [244 rows x 8 columns]
[]: medianheld5ths = held5ths["Brightness"].median()
     medianheld5ths
[]: 0.08254402
[]: plt.figure(figsize=(20,10))
     sns.set_theme(style="whitegrid")
     ax = sns.boxplot(x=held5ths["Brightness"]).set_title("Boxplot of Pulsar <math>6_{\sqcup})
```

→Emission Strength")





```
[]: plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = held5ths.Brightness.values
ax = plt.axhline( y=0.08254402, ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=held5ths["Brightness"], c="blue").set_title('Pulsar 6⊔
→Swarm plot of Emission Strength')
```



```
[]: print(len(held5ths[(held5ths.Brightness > 0.08254402)]))
print(len(held5ths[(held5ths.Brightness < 0.08254402)]))
```

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## Randomness testing

```
[]: np.savetxt(r'every5thbinarypulsar5.txt', held5ths.Binary, fmt='%d', u

delimiter='')

np.savetxt(r'allpulsar5.txt', pulsar.Binary, fmt='%d', delimiter='')
```

## []: pulsar.Binary

```
[]: 0 0
1 0
2 1
3 0
4 0
...
1214 0
1215 0
```

```
1216 1
1217 0
1218 0
```

Name: Binary, Length: 1219, dtype: int32