Master Notebook

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1 Pulsar Emission Data Analysis

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1.0.1 Introduction

Random number generators are crucial for many processes and algorithms in society, including cryptographic, commercial, and defence uses. Therefore, having a source of publicly verifiable randomness (PVR) ensures that any two parties have access to the same, unbiased number sequence. Currently, random number generation is computed using number theory, leaving these sequences susceptible to the interference of quantum computers. Therefore, there is great motivation to find another source that cannot be replicated, with a particular interest in sequences produced by natural phenomena.

This is where we start to look into pulsars. Pulsars are highly magnetised neutron stars that rapidly spin, emitting light beams of varying intensities. Their practical use is of interest to us, as their measure of pulse brightness appears to be random. As a result, pulsars may potentially provide us with a publicly-verifiable random number sequence. For this project, our sponsors Jo and George from the CSIRO tasked us with determining the randomness of 6 pulsars, aiming to arrive at a conclusion of whether these specific pulsars are viable for further randomness studies.

The challenge that surrounds our investigation involves the time-scale correlation that is observed between some pulses. That is, for each individual pulse, the adjacent pulses are correlated - and therefore, not random. We want to remove this observed correlation, as it is likely to impact our tests for true randomness. To do this, we will extract a subset from the data as determined by their autocorrelation function, and run them through our randomness tests. From here, we will be able to conclude whether the brightness emitted from each pulsar is truly random.

Importing required libraries:

[ ]:
```
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 tensorflow import keras
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
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import math
```

[ ]:
```
import warnings
warnings.filterwarnings('ignore')
```

Importing the data:

[ ]:
```
colnames = ['Pulse Number', 'Brightness', 'Uncertainty']
pulsar1 = pd.read_csv("Data/J0437-4715.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
pulsar2 = pd.read_csv("Data/J0953+0755.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
pulsar3 = pd.read_csv("Data/J0835-4510.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
pulsar4 = pd.read_csv("Data/J1243-6423.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
```

```
pulsar5 = pd.read_csv("Data/J1456-6843.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
pulsar6 = pd.read_csv("Data/J1644-4559.pulses", sep = ' ', header = None, names␣
 ↪= colnames)
```

1.0.2 Data Exploration

Pulsar 1 (J0437-4715):

[ ]:
```
obs, cols = pulsar1.shape
print("Number of Observations in Pulsar 1: ", obs)
```

```
Number of Observations in Pulsar 1:  27000
```

Having a look at the first 15 observations:

[ ]:
```
pulsar1.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty
0	1	0.598393	0.056431
1	2	0.590859	0.055182
2	3	0.449643	0.063632
3	4	0.682860	0.056269
4	5	0.490026	0.046830
5	6	0.586071	0.052649
6	7	0.150353	0.056483
7	8	0.384684	0.052567
8	9	0.429094	0.055569
9	10	0.995865	0.075811
10	11	0.670907	0.049539
11	12	0.465406	0.047461
12	13	0.242442	0.050653
13	14	0.500057	0.050163
14	15	0.658159	0.050743

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

[ ]:
```
pulsar1.describe([], exclude=int)
```

[ ]:

	Brightness	Uncertainty
count	27000.000000	27000.000000
mean	0.536400	0.062556
std	0.413764	0.056313
min	-5.114133	0.015426
50%	0.423816	0.056856
max	18.722410	3.049559

Null or missing values: Checking for any null or missing values:

[ ]:
```python
nullBoolBrightness = pd.isnull(pulsar1["Brightness"])

pulsar1[nullBoolBrightness]
```

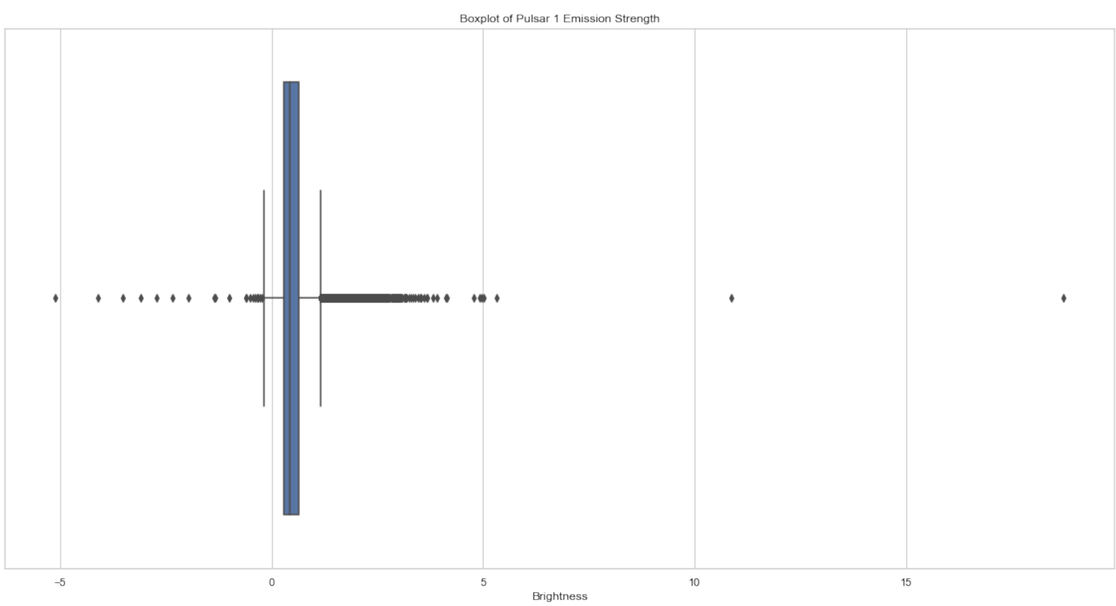
[ ]:
```
Empty DataFrame
Columns: [Pulse Number, Brightness, Uncertainty]
Index: []
```

[ ]:
```python
if len(pulsar1[nullBoolBrightness]) > 0:
    print("There are", len(pulsar1[nullBoolBrightness]), "missing values for␣
↪brightness")
else:
    print("There are no missing brightness values")
```

```
There are no missing brightness values
```

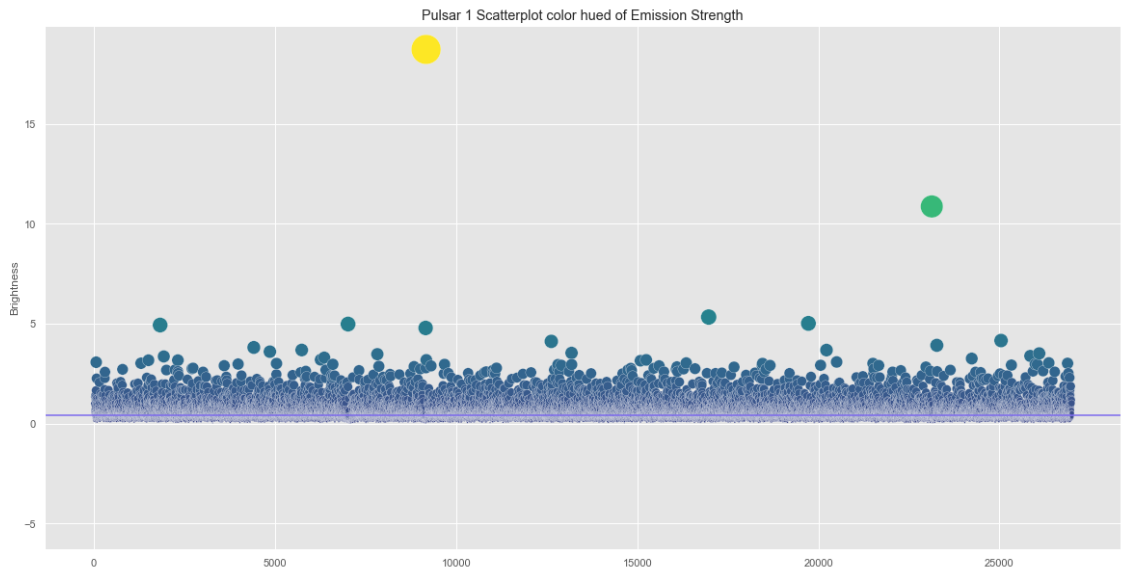
Boxplot Looking at a boxplot of the brightness we can see that most brightness observations are between 0.1 and 0.6, and there appears to be two outliers at roughly 11 and 19 brightness

[ ]:
```python
plt.figure(figsize=(20,10))
sns.set_theme(style="whitegrid")
ax = sns.boxplot(x=pulsar1["Brightness"]).set_title("Boxplot of Pulsar 1␣
↪Emission Strength")
```



Scatterplot Looking at the scatterplot of Pulsar 1's brightness observations, there appears to be a random scatter, with two outliers, marked in yellow and green with readings of roughly 19 and 11 brightness, respectively.

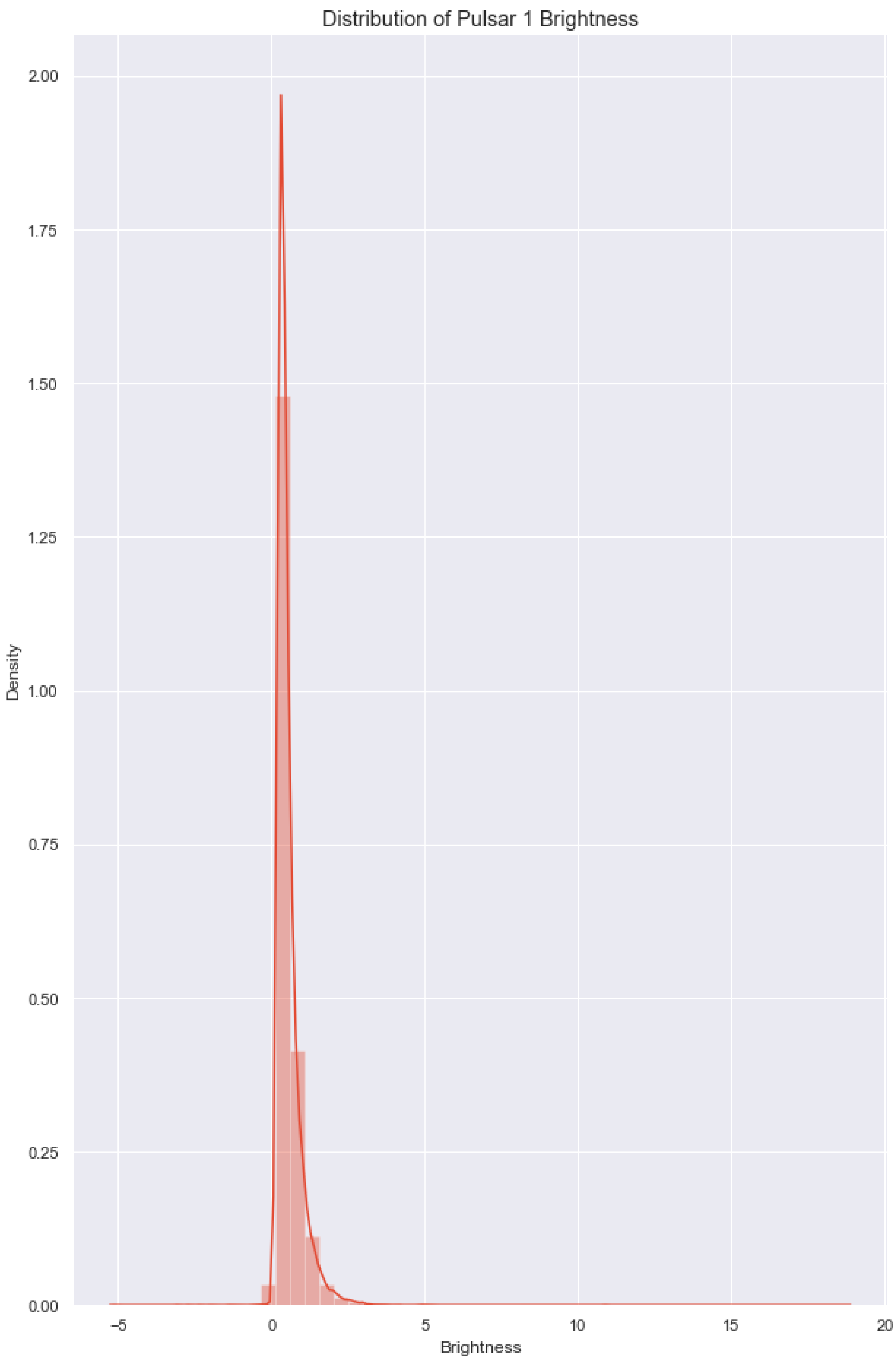
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar1.Brightness.values
plt.style.use('ggplot')
ax = sns.scatterplot(data=pulsar1["Brightness"], s= strength*50, c=strength,␣
 ↪cmap="viridis", marker="o").set_title('Pulsar 1 Scatterplot color hued of␣
 ↪Emission Strength')
ax= plt.axhline( y=pulsar1["Brightness"].median(), ls='-',c='mediumslateblue')
```



Distribution Looking at the distribtuion of Pulsar 1's brightness, there appears to be a moderate positive skew with a peak around 0.4

[ ]:
```
plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar1.Brightness)
plt.title("Distribution of Pulsar 1 Brightness")
```

[ ]: Text(0.5, 1.0, 'Distribution of Pulsar 1 Brightness')


Distribution of Pulsar 1 Brightness
Density
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−5
0
5
10
15
20
Brightness

Pulsar 2 (J0953+0755):

[ ]:
```
obs, cols = pulsar2.shape
print("Number of Observations in Pulsar 2: ", obs)
```

```
Number of Observations in Pulsar 2:  14329
```

Having a look at the first 15 observations:

[ ]:
```
pulsar2.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty
0	1	0.334330	0.015570
1	2	-0.098659	0.014051
2	3	0.123514	0.011901
3	4	0.443923	0.014365
4	5	1.590446	0.057785
5	6	1.233848	0.018692
6	7	0.857876	0.022208
7	8	0.254255	0.018185
8	9	0.292077	0.021672
9	10	0.439929	0.046293
10	11	0.824310	0.036243
11	12	1.443460	0.088372
12	13	0.127981	0.018070
13	14	0.327896	0.012362
14	15	2.473663	0.099205

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

[ ]:
```
pulsar2.describe([], exclude=int)
```

[ ]:

	Brightness	Uncertainty
count	14329.000000	14329.000000
mean	0.994458	0.034561
std	1.211127	0.029641
min	-0.219110	0.010120
50%	0.481894	0.021999
max	8.552022	0.242041

Null or missing values: Checking for any null or missing values:

[ ]:
```
nullBoolBrightness2 = pd.isnull(pulsar2["Brightness"])

pulsar2[nullBoolBrightness2]
```

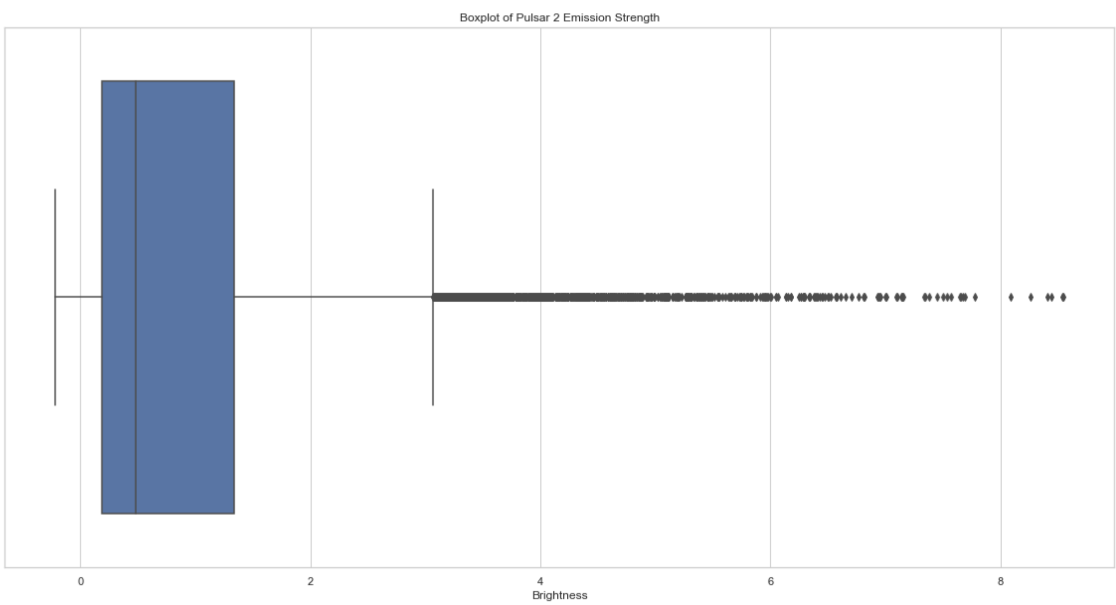
[ ]: Empty DataFrame
Columns: [Pulse Number, Brightness, Uncertainty]
Index: []

[ ]:
```
if len(pulsar2[nullBoolBrightness2]) > 0:
    print("There are", len(pulsar2[nullBoolBrightness2]), "missing values for␣
↪brightness")
else:
    print("There are no missing brightness values")
```

There are no missing brightness values

Boxplot Looking at a boxplot of the brightness we can see that most values fall in the 0.2 to 1.5 range and a lot of large observations, but not quite outliers.

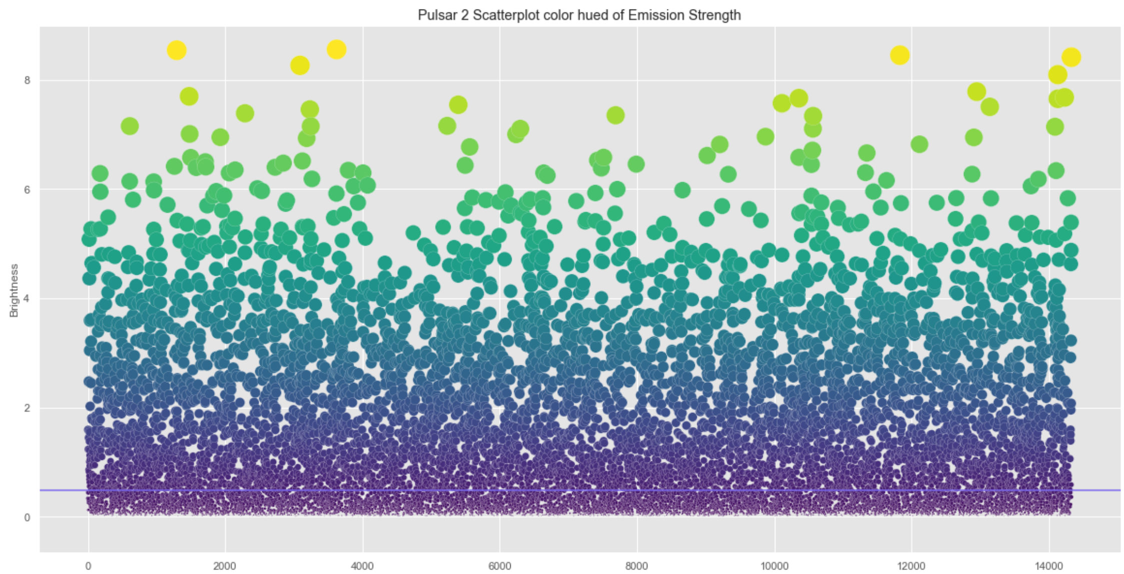
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_theme(style="whitegrid")
ax = sns.boxplot(x=pulsar2["Brightness"]).set_title("Boxplot of Pulsar 2␣
↪Emission Strength")
```



Scatterplot Looking at the scatterplot of Pulsar 2's brightness observations, there appears to be a random scatter

[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar2.Brightness.values
plt.style.use('ggplot')
```

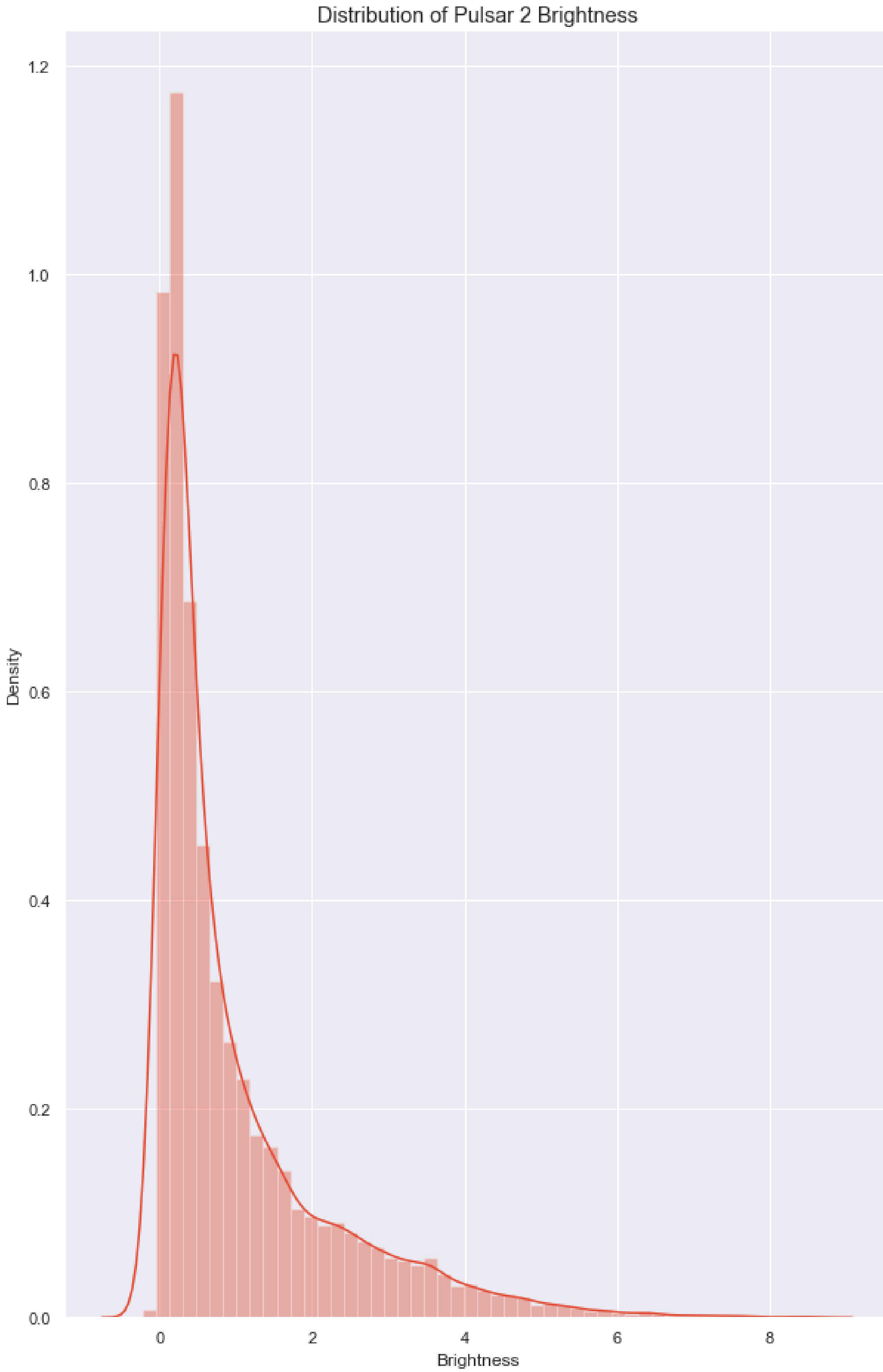
```
ax = sns.scatterplot(data=pulsar2["Brightness"], s= strength*50, c=strength,␣
↪cmap="viridis", marker="o").set_title('Pulsar 2 Scatterplot color hued of␣
↪Emission Strength')
ax= plt.axhline( y=pulsar2["Brightness"].median(), ls='-',c='mediumslateblue')
```



Distribution Looking at the distribtuion of Pulsar 2's brightness, there appears to be a strong positive skew

```
[ ]: plt.figure(figsize=(10, 16))
     with sns.axes_style('darkgrid'):
         sns.distplot(pulsar2.Brightness)
     plt.title("Distribution of Pulsar 2 Brightness")
```

```
[ ]: Text(0.5, 1.0, 'Distribution of Pulsar 2 Brightness')
```


Distribution of Pulsar 2 Brightness
Density
Brightness
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8

Pulsar 3 (J0835-4510):

[ ]:
```
obs, cols = pulsar3.shape
print("Number of Observations in Pulsar 3: ", obs)
```

```
Number of Observations in Pulsar 3:  1331
```

Having a look at the first 15 observations:

[ ]:
```
pulsar3.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty
0	1	0.984043	0.053831
1	2	2.487928	0.048796
2	3	1.690295	0.025639
3	4	1.196142	0.039539
4	5	1.979783	0.041460
5	6	2.297645	0.054210
6	7	2.322135	0.043554
7	8	2.289047	0.049957
8	9	2.442574	0.025110
9	10	2.136332	0.022712
10	11	1.976790	0.037551
11	12	2.445764	0.047004
12	13	1.937017	0.028561
13	14	2.315184	0.045216
14	15	2.584888	0.040232

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

[ ]:
```
pulsar3.describe([], exclude=int)
```

[ ]:

	Brightness	Uncertainty
count	1331.000000	1331.000000
mean	2.248107	0.039495
std	0.591161	0.013056
min	0.633413	0.012888
50%	2.255182	0.037513
max	4.050718	0.098902

Null or missing values: Checking for any null or missing values:

[ ]:
```
nullBoolBrightness3 = pd.isnull(pulsar3["Brightness"])

pulsar3[nullBoolBrightness3]
```

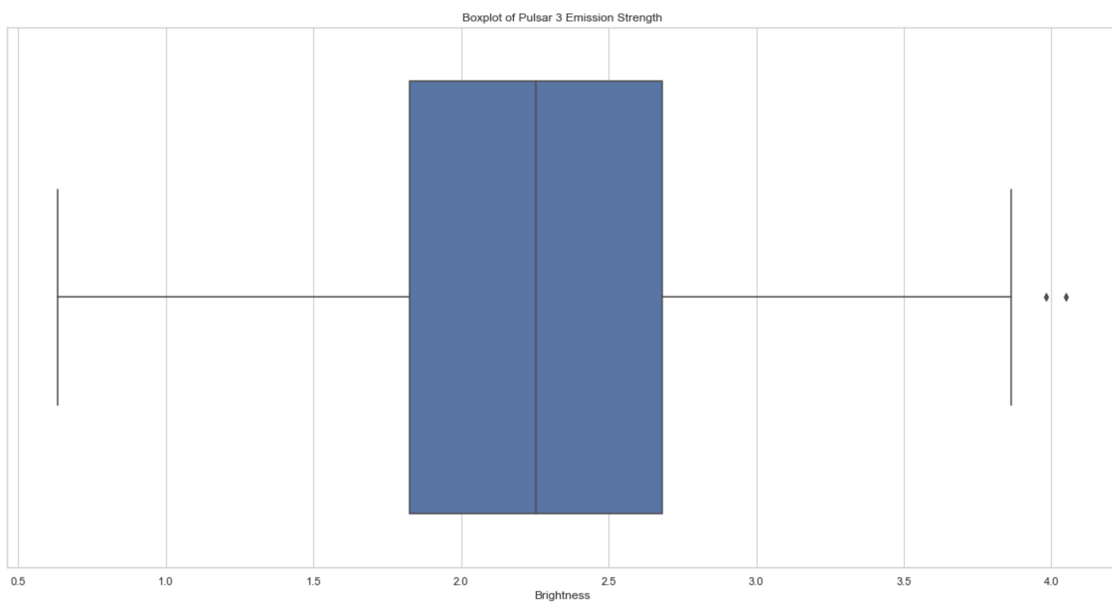
[ ]: Empty DataFrame
Columns: [Pulse Number, Brightness, Uncertainty]
Index: []

```
[ ]: if len(pulsar3[nullBoolBrightness3]) > 0:
         print("There are", len(pulsar3[nullBoolBrightness3]), "missing values for␣
      ↪brightness")
     else:
         print("There are no missing brightness values")
```

There are no missing brightness values

Boxplot Looking at a boxplot of the brightness we can see that most values are within the 1.8 to 2.7 range, but once again no obvious outliers present

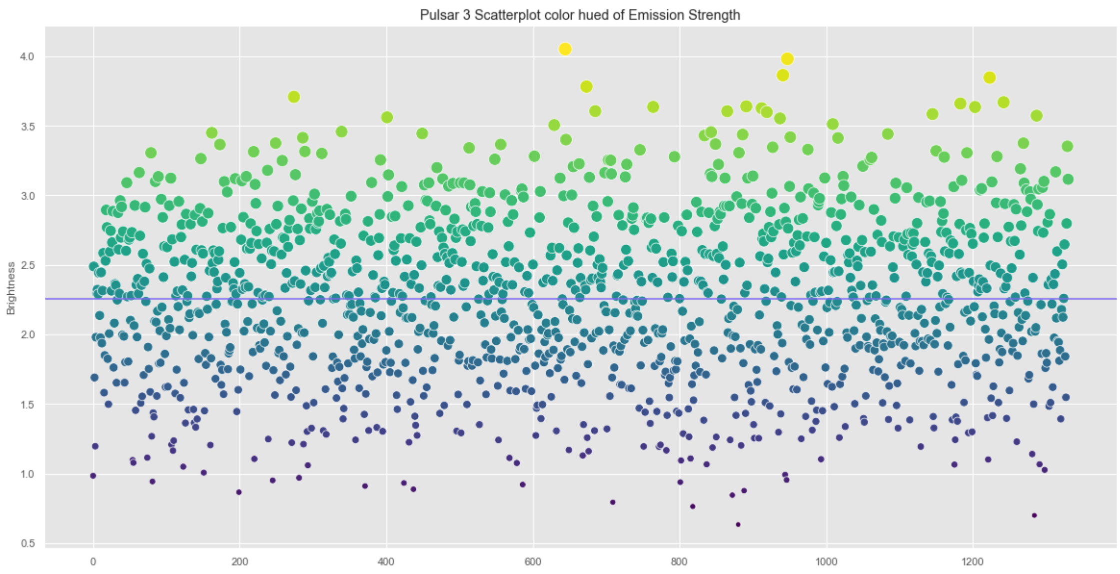
```
[ ]: plt.figure(figsize=(20,10))
     sns.set_theme(style="whitegrid")
     ax = sns.boxplot(x=pulsar3["Brightness"]).set_title("Boxplot of Pulsar 3␣
      ↪Emission Strength")
```



Scatterplot Looking at the scatterplot of Pulsar 3's brightness observations, there appears to be no discernable pattern, that is, it appears to be a random scatter

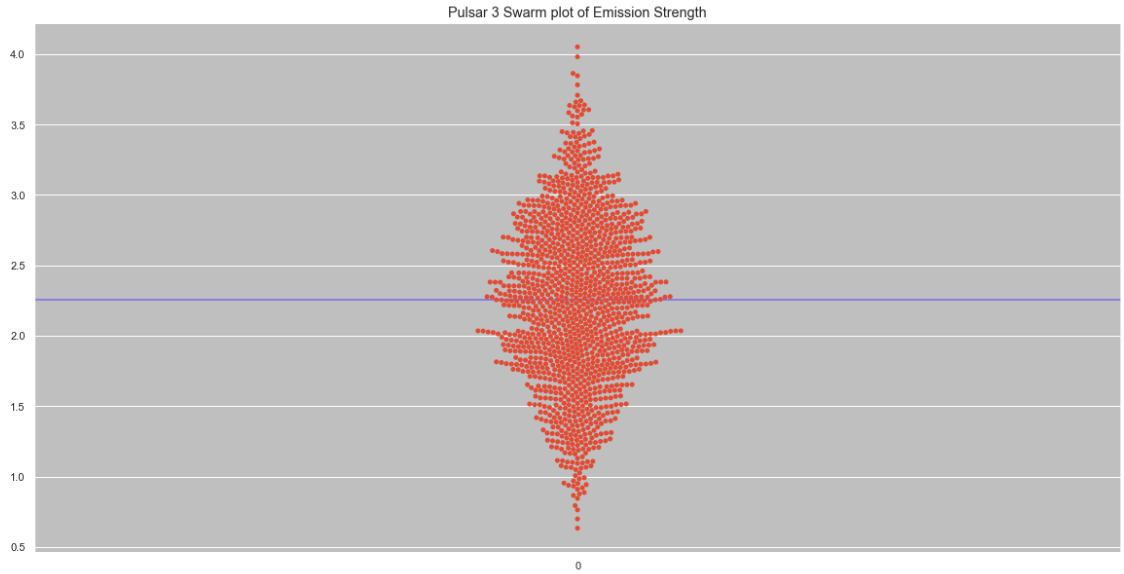
```
[ ]: plt.figure(figsize=(20,10))
     sns.set_style("darkgrid", {"axes.facecolor": ".75"})
     strength = pulsar3.Brightness.values
     plt.style.use('ggplot')
```

```
ax = sns.scatterplot(data=pulsar3["Brightness"], s= strength*50, c=strength,␣
↪cmap="viridis", marker="o").set_title('Pulsar 3 Scatterplot color hued of␣
↪Emission Strength')
ax= plt.axhline( y=pulsar3["Brightness"].median(), ls='-',c='mediumslateblue')
```



Swarm Plot

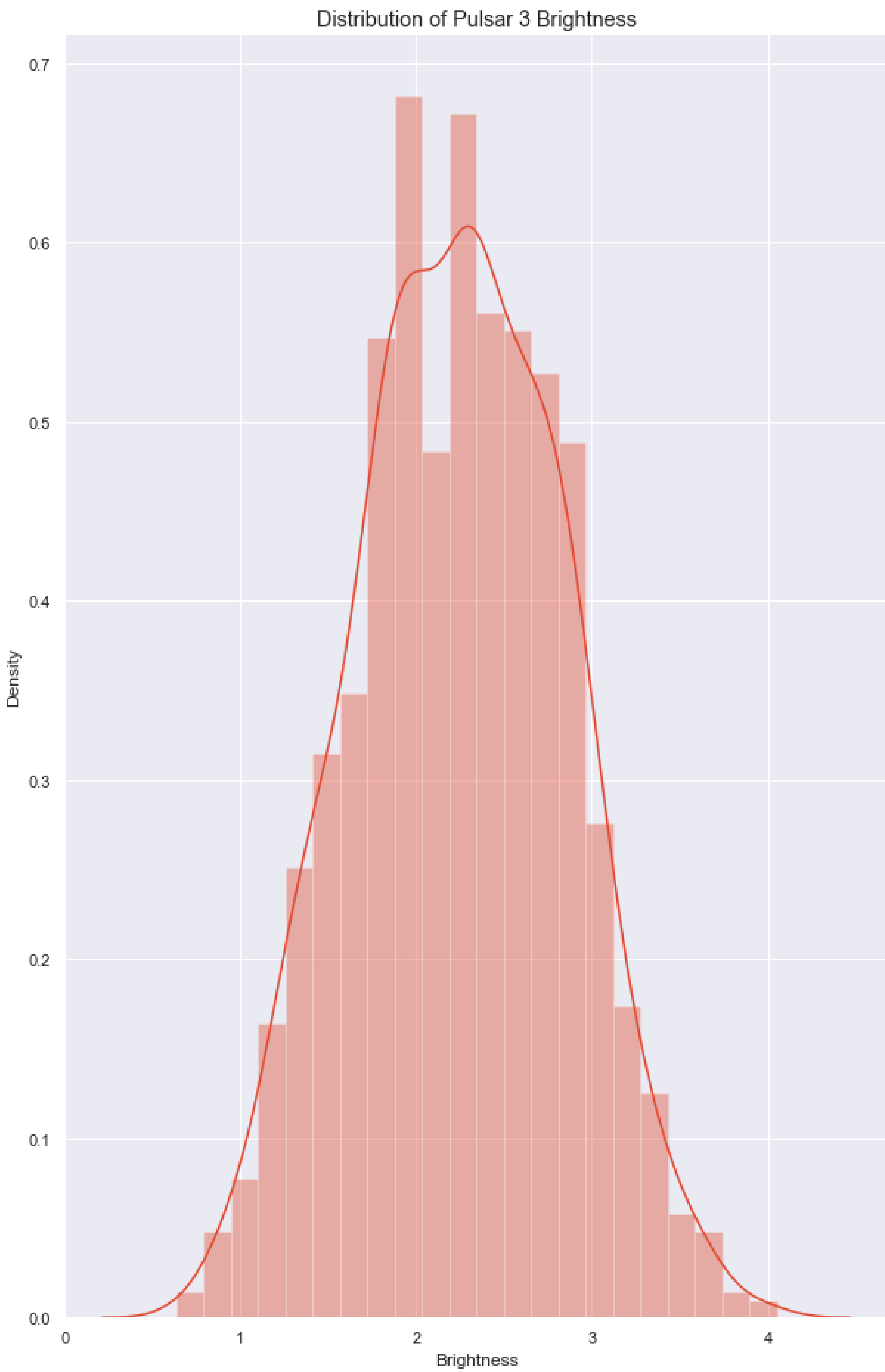
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar3.Brightness.values
ax = plt.axhline( y=pulsar3["Brightness"].median(), ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=pulsar3["Brightness"], c="blue").set_title('Pulsar 3␣
↪Swarm plot of Emission Strength')
```



Distribution Looking at the distribtuion of Pulsar 3's brightness, it appears to follow very closely to a normal distribution, however it does appear to be bimodal.

[ ]:
```
plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar3.Brightness)
plt.title("Distribution of Pulsar 3 Brightness")
```

[ ]: Text(0.5, 1.0, 'Distribution of Pulsar 3 Brightness')



Distribution of Pulsar 3 Brightness
Density
Brightness
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
1
2
3
4

Pulsar 4 (J1243-6423):

[ ]:
```
obs, cols = pulsar4.shape
print("Number of Observations in Pulsar 4: ", obs)
```

```
Number of Observations in Pulsar 4:  1819
```

Having a look at the first 15 observations:

[ ]:
```
pulsar4.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty
0	1	0.101127	0.001893
1	2	0.012166	0.001814
2	3	0.021918	0.001835
3	4	0.181179	0.002183
4	5	0.000240	0.001725
5	6	0.085866	0.001723
6	7	0.067280	0.001778
7	8	0.092884	0.002438
8	9	0.083350	0.002101
9	10	0.087871	0.001941
10	11	0.123529	0.002026
11	12	0.097413	0.001878
12	13	0.100649	0.001820
13	14	0.058025	0.001724
14	15	0.116164	0.001948

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

[ ]:
```
pulsar4.describe([], exclude=int)
```

[ ]:

	Brightness	Uncertainty
count	1819.000000	1819.000000
mean	0.075070	0.001958
std	0.057006	0.000306
min	-0.004643	0.001532
50%	0.076660	0.001872
max	0.269903	0.005952

Null or missing values: Checking for any null or missing values:

[ ]:
```
nullBoolBrightness4 = pd.isnull(pulsar4["Brightness"])

pulsar4[nullBoolBrightness4]
```

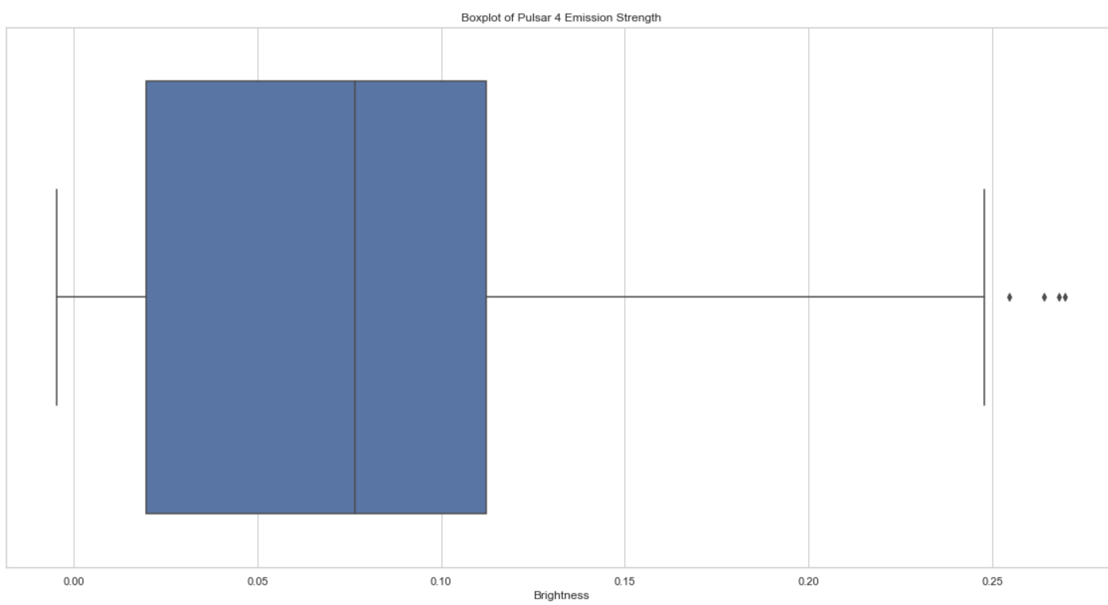
[ ]: Empty DataFrame
Columns: [Pulse Number, Brightness, Uncertainty]
Index: []

```
[ ]: if len(pulsar4[nullBoolBrightness4]) > 0:
         print("There are", len(pulsar4[nullBoolBrightness4]), "missing values for␣
      ↪brightness")
     else:
         print("There are no missing brightness values")
```

There are no missing brightness values

Boxplot Looking at a boxplot of the brightness we can see that most values fall within the 0.02 to 0.12 range, with no extreme outliers

```
[ ]: plt.figure(figsize=(20,10))
     sns.set_theme(style="whitegrid")
     ax = sns.boxplot(x=pulsar4["Brightness"]).set_title("Boxplot of Pulsar 4␣
      ↪Emission Strength")
```



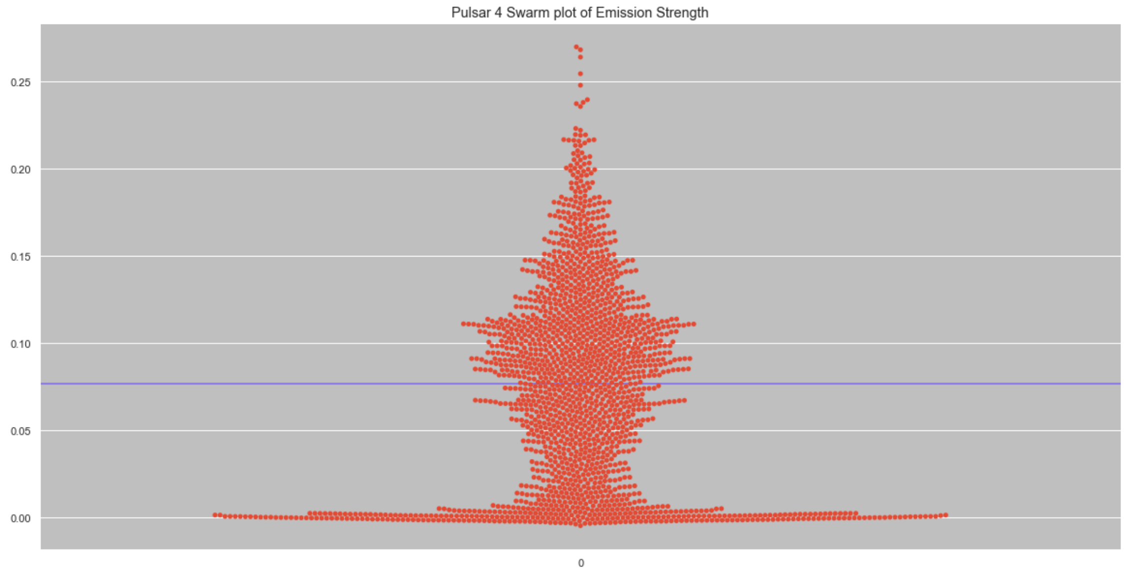
Scatterplot Looking at the scatterplot of Pulsar 4's brightness observations, there is no visible pattern in the data, lending to the idea that it appears random

```
[ ]: plt.figure(figsize=(20,10))
     sns.set_style("darkgrid", {"axes.facecolor": ".75"})
     strength = pulsar4.Brightness.values
     plt.style.use('ggplot')
```

```
ax = sns.scatterplot(data=pulsar4["Brightness"], s= strength*500, c=strength,␣
↪cmap="viridis", marker="o").set_title('Pulsar 4 Scatterplot color hued of␣
↪Emission Strength')
ax= plt.axhline( y=pulsar4["Brightness"].median(), ls='-',c='mediumslateblue')
```

Swarm Plot

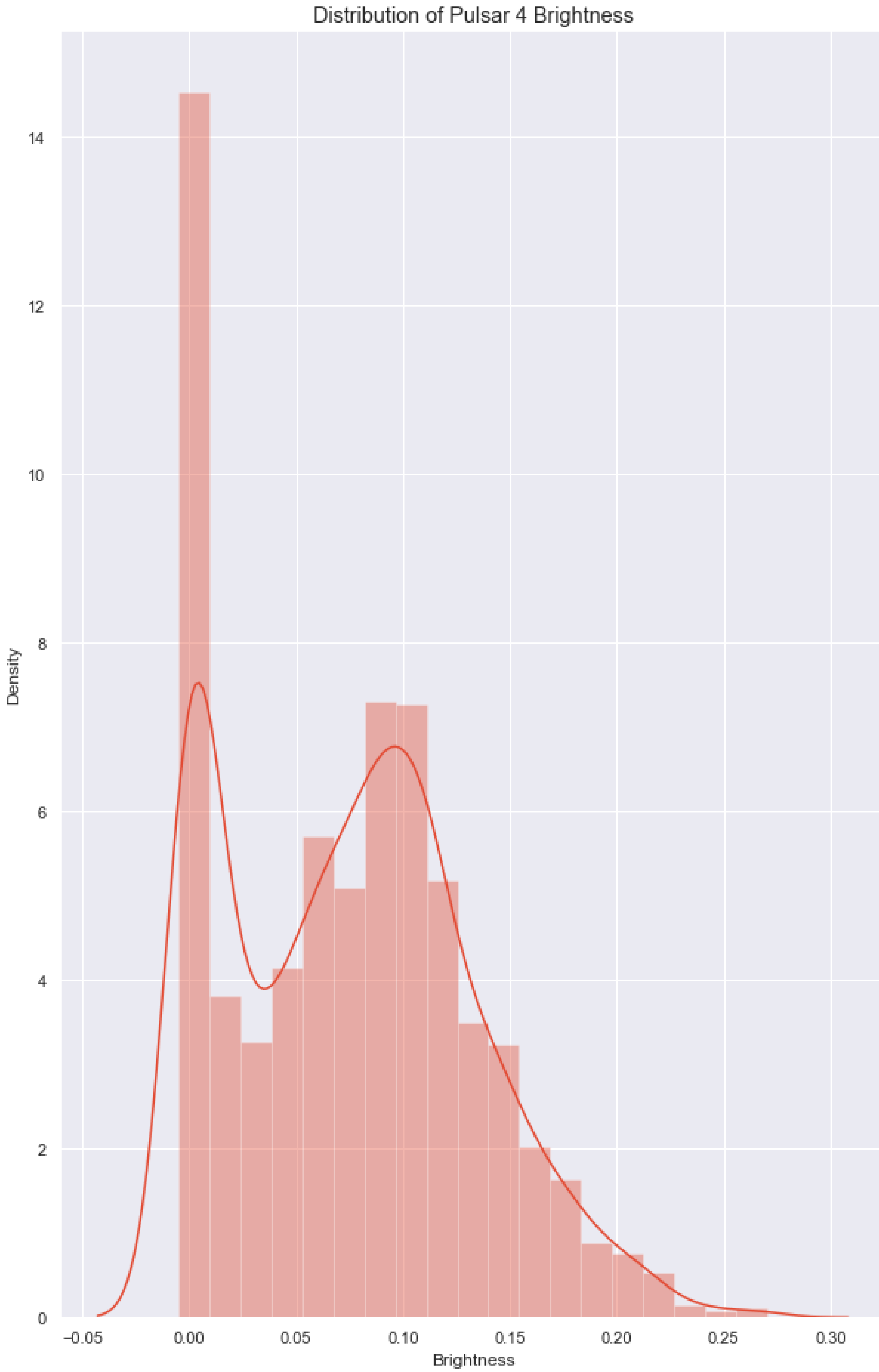
```
[ ]: plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar4.Brightness.values
ax = plt.axhline( y=pulsar4["Brightness"].median(), ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=pulsar4["Brightness"], c="blue").set_title('Pulsar 4␣
↪Swarm plot of Emission Strength')
```



Distribution Looking at the distribtuion of Pulsar 4's brightness, it is bimodal with a moderate positive skew

[ ]:
```
plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar4.Brightness)
plt.title("Distribution of Pulsar 4 Brightness")
```

[ ]:
```
Text(0.5, 1.0, 'Distribution of Pulsar 4 Brightness')
```


Distribution of Pulsar 4 Brightness
Density
Brightness
0
2
4
6
8
10
12
14
−0.05
0.00
0.05
0.10
0.15
0.20
0.25
0.30

Pulsar 5 (J1456-6843):

```
[ ]: obs, cols = pulsar5.shape
     print("Number of Observations in Pulsar 5: ", obs)
```

```
Number of Observations in Pulsar 5:  1219
```

Having a look at the first 15 observations:

```
[ ]: pulsar5.head(15)
```

```
[ ]:     Pulse Number  Brightness  Uncertainty
     0              1    0.053904     0.005560
     1              2    0.058653     0.004821
     2              3    0.110208     0.005196
     3              4    0.034716     0.004729
     4              5    0.056101     0.004619
     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
     10            11    0.009141     0.004581
     11            12    0.145273     0.005053
     12            13    0.039953     0.004938
     13            14   -0.002554     0.004409
     14            15    0.035696     0.004903
```

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

```
[ ]: pulsar5.describe([], exclude=int)
```

```
[ ]:         Brightness  Uncertainty
     count  1219.000000  1219.000000
     mean      0.104176     0.005410
     std       0.081916     0.001282
     min      -0.007285     0.001075
     50%       0.081228     0.004966
     max       0.825366     0.016201
```

Null or missing values: Checking for any null or missing values:

```
[ ]: nullBoolBrightness5 = pd.isnull(pulsar5["Brightness"])

     pulsar5[nullBoolBrightness5]
```

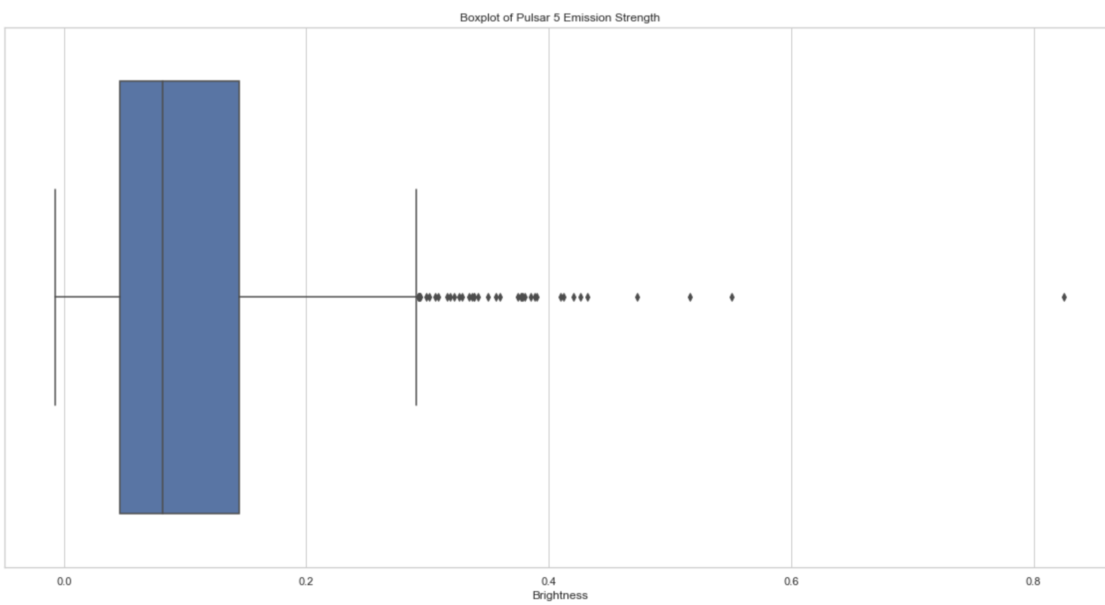
[ ]:
```
Empty DataFrame
Columns: [Pulse Number, Brightness, Uncertainty]
Index: []
```

[ ]:
```
if len(pulsar5[nullBoolBrightness5]) > 0:
    print("There are", len(pulsar5[nullBoolBrightness5]), "missing values for␣
↪brightness")
else:
    print("There are no missing brightness values")
```

```
There are no missing brightness values
```

Boxplot Looking at a boxplot of the brightness we can see that most values fall within the 0.05 to 0.15 range, with an outlier around 0.82

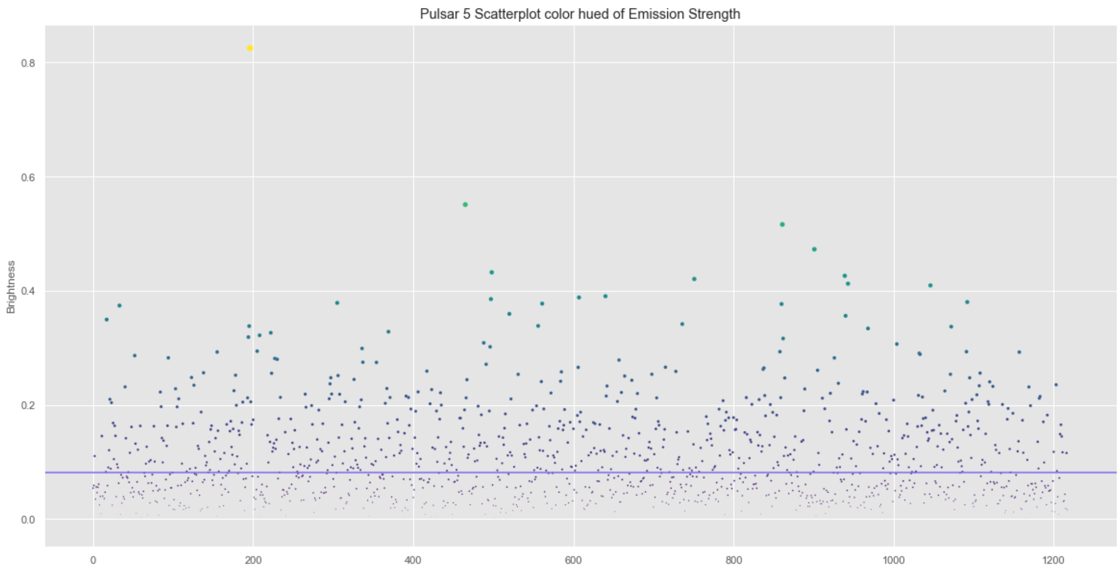
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_theme(style="whitegrid")
ax = sns.boxplot(x=pulsar5["Brightness"]).set_title("Boxplot of Pulsar 5␣
↪Emission Strength")
```



Scatterplot Looking at the scatterplot of Pulsar 5's brightness observations, there appears to be a random scatter

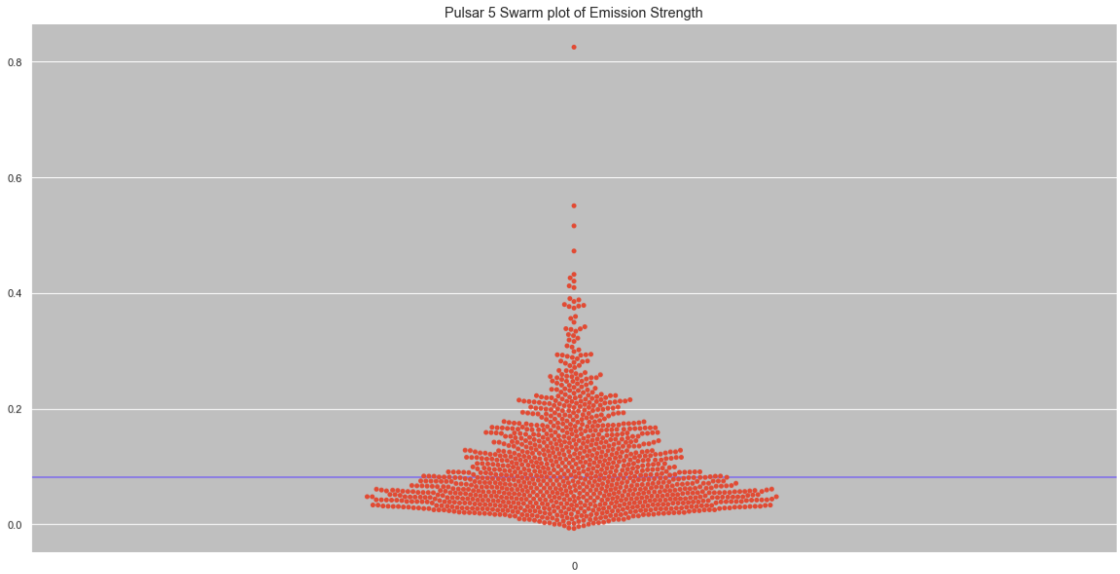
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar5.Brightness.values
plt.style.use('ggplot')
```

```
ax = sns.scatterplot(data=pulsar5["Brightness"], s= strength*50, c=strength,␣
↪cmap="viridis", marker="o").set_title('Pulsar 5 Scatterplot color hued of␣
↪Emission Strength')
ax= plt.axhline( y=pulsar5["Brightness"].median(), ls='-',c='mediumslateblue')
```



Swarm Plot

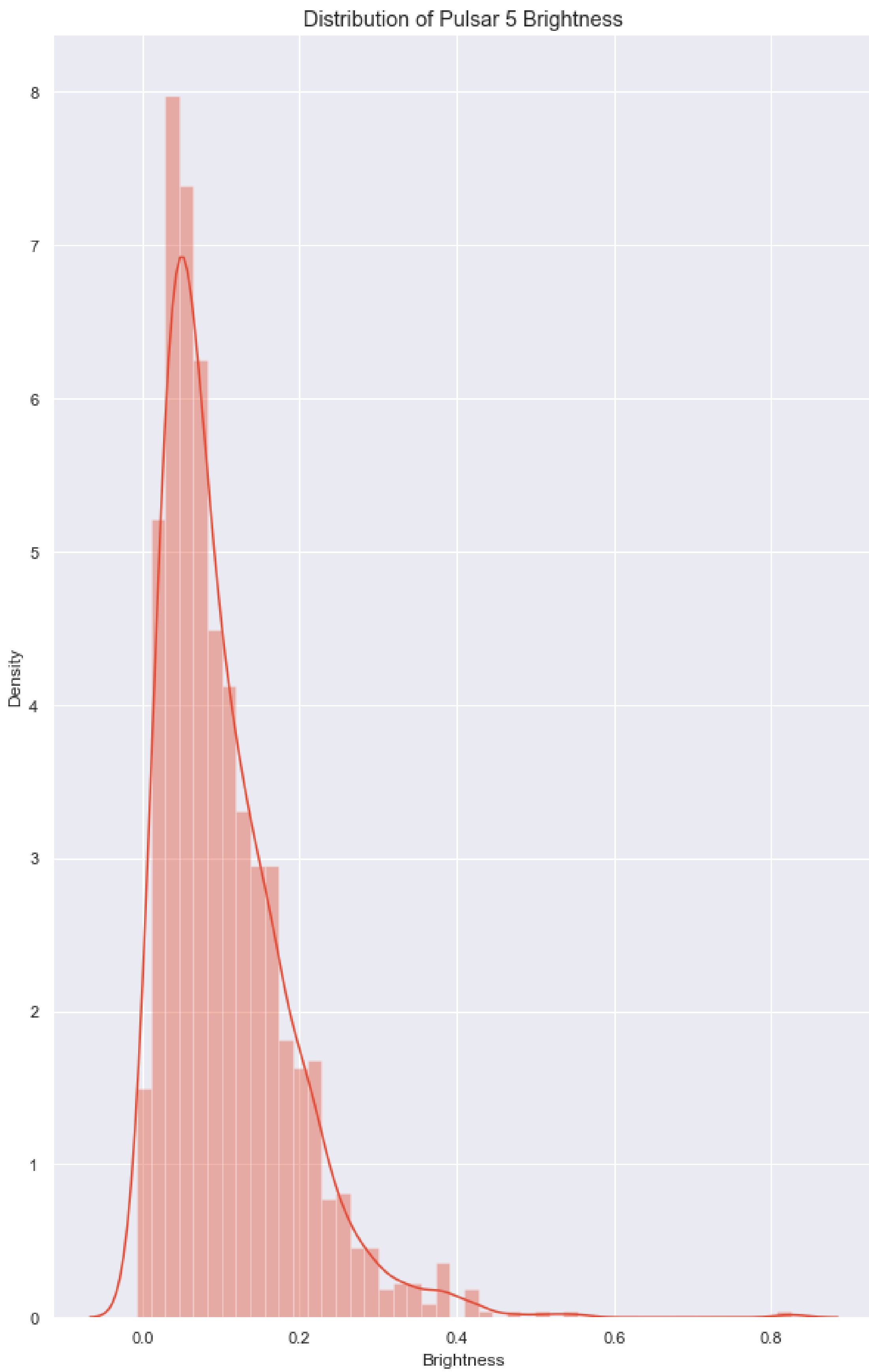
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar5.Brightness.values
ax = plt.axhline( y=pulsar5["Brightness"].median(), ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=pulsar5["Brightness"], c="blue").set_title('Pulsar 5␣
↪Swarm plot of Emission Strength')
```



Distribution Looking at the distribtuion of Pulsar 5's brightness, there is a strong positive skew, with a peak around 0.05

[ ]:
```
plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar5.Brightness)
plt.title("Distribution of Pulsar 5 Brightness")
```

[ ]:
```
Text(0.5, 1.0, 'Distribution of Pulsar 5 Brightness')
```



Distribution of Pulsar 5 Brightness
Density
Brightness
0
1
2
3
4
5
6
7
8
0.0
0.2
0.4
0.6
0.8

Pulsar 6 (J1644-4559):

[ ]:
```python
obs, cols = pulsar6.shape
print("Number of Observations in Pulsar 6: ", obs)
```

```
Number of Observations in Pulsar 6:  698
```

Having a look at the first 15 observations:

[ ]:
```python
pulsar6.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty
0	1	0.634671	0.002761
1	2	0.736945	0.005207
2	3	0.693834	0.002706
3	4	1.021866	0.010184
4	5	0.673845	0.006236
5	6	0.676883	0.004763
6	7	0.527039	0.002422
7	8	0.673417	0.003174
8	9	0.357076	0.002848
9	10	0.661704	0.005588
10	11	0.545564	0.003835
11	12	0.494655	0.003145
12	13	0.804260	0.005258
13	14	0.513362	0.005700
14	15	0.477025	0.002945

Descriptive Statistics Generating descriptive statistics for Brightness and Uncertainty variables

[ ]:
```python
pulsar6.describe([], exclude=int)
```

[ ]:

	Brightness	Uncertainty
count	698.000000	698.000000
mean	0.654319	0.004445
std	0.163945	0.001855
min	0.007642	0.002129
50%	0.658295	0.003951
max	1.159334	0.016097

Null or missing values: Checking for any null or missing values:

[ ]:
```python
nullBoolBrightness6 = pd.isnull(pulsar6["Brightness"])

pulsar6[nullBoolBrightness6]
```

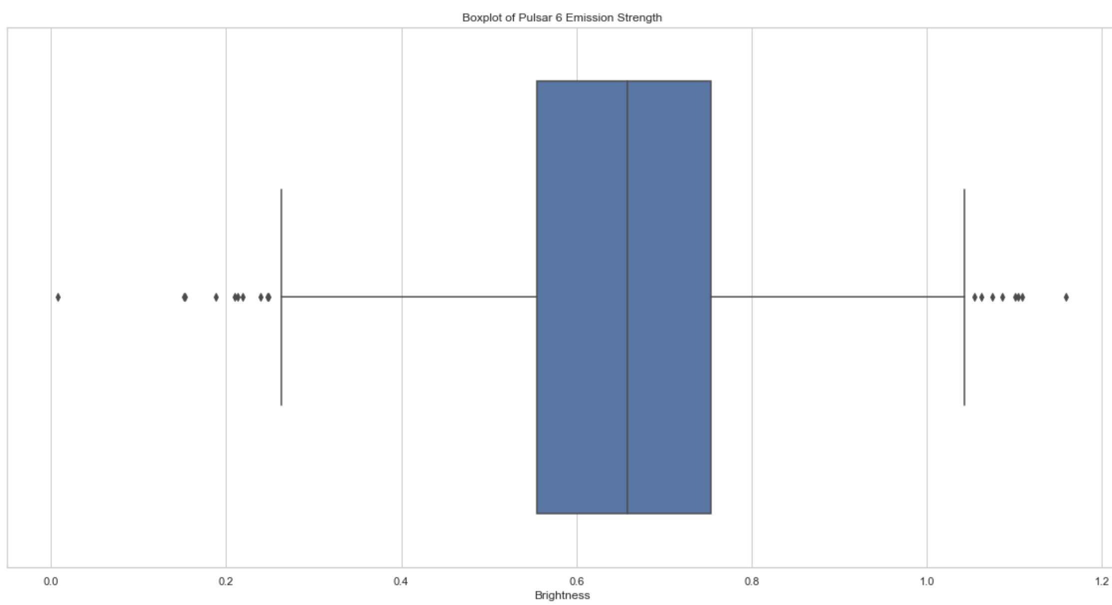
```
[ ]: Empty DataFrame
     Columns: [Pulse Number, Brightness, Uncertainty]
     Index: []
```

```
[ ]: if len(pulsar6[nullBoolBrightness6]) > 0:
         print("There are", len(pulsar6[nullBoolBrightness6]), "missing values for␣
      ↪brightness")
     else:
         print("There are no missing brightness values")
```

```
There are no missing brightness values
```

Boxplot Looking at a boxplot of the brightness we can see that most values are within 0.5 to 0.7, with no obvious outliers to be removed

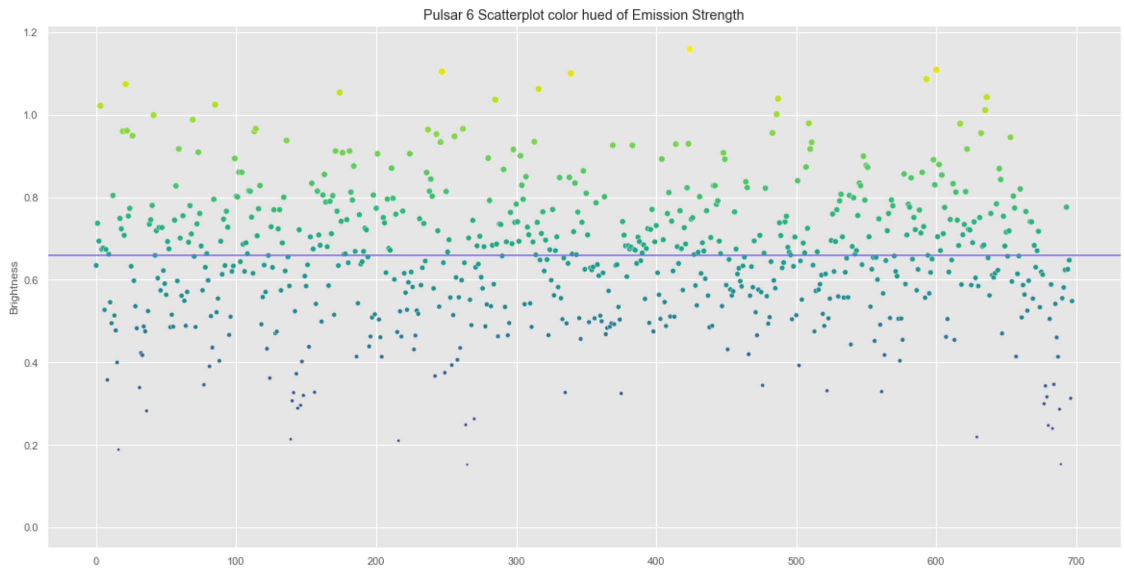
```
[ ]: plt.figure(figsize=(20,10))
     sns.set_theme(style="whitegrid")
     ax = sns.boxplot(x=pulsar6["Brightness"]).set_title("Boxplot of Pulsar 6␣
      ↪Emission Strength")
```



Scatterplot Looking at the scatterplot of Pulsar 6's brightness observations, there brightness appears to have a random scatter, with no pattern distinguishable

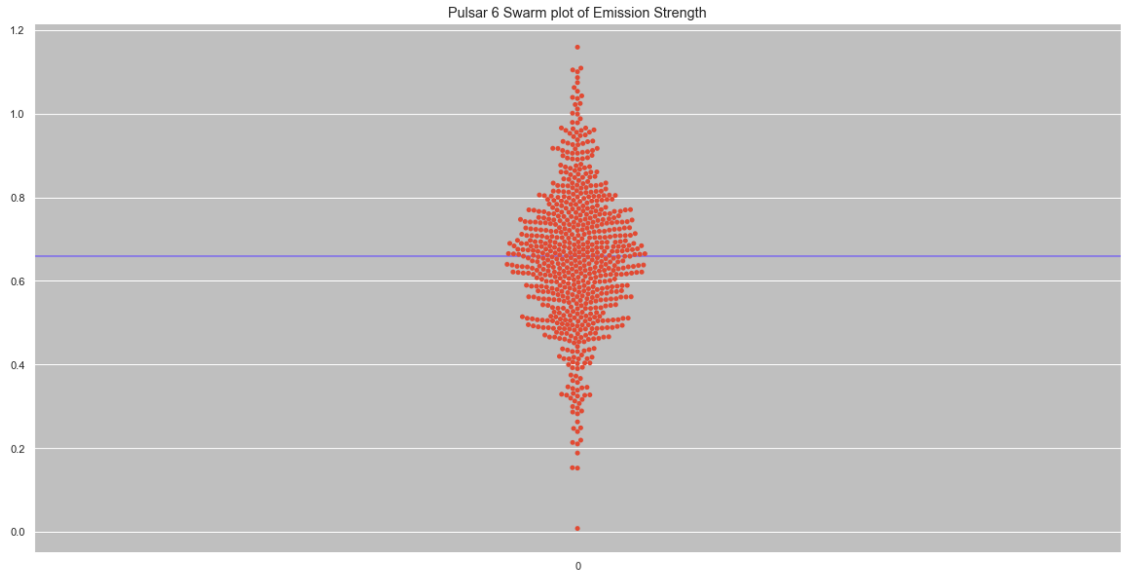
```
[ ]: plt.figure(figsize=(20,10))
     sns.set_style("darkgrid", {"axes.facecolor": ".75"})
     strength = pulsar6.Brightness.values
     plt.style.use('ggplot')
```

```
ax = sns.scatterplot(data=pulsar6["Brightness"], s= strength*50, c=strength,␣
↪cmap="viridis", marker="o").set_title('Pulsar 6 Scatterplot color hued of␣
↪Emission Strength')
ax= plt.axhline( y=pulsar6["Brightness"].median(), ls='-',c='mediumslateblue')
```



Swarm Plot

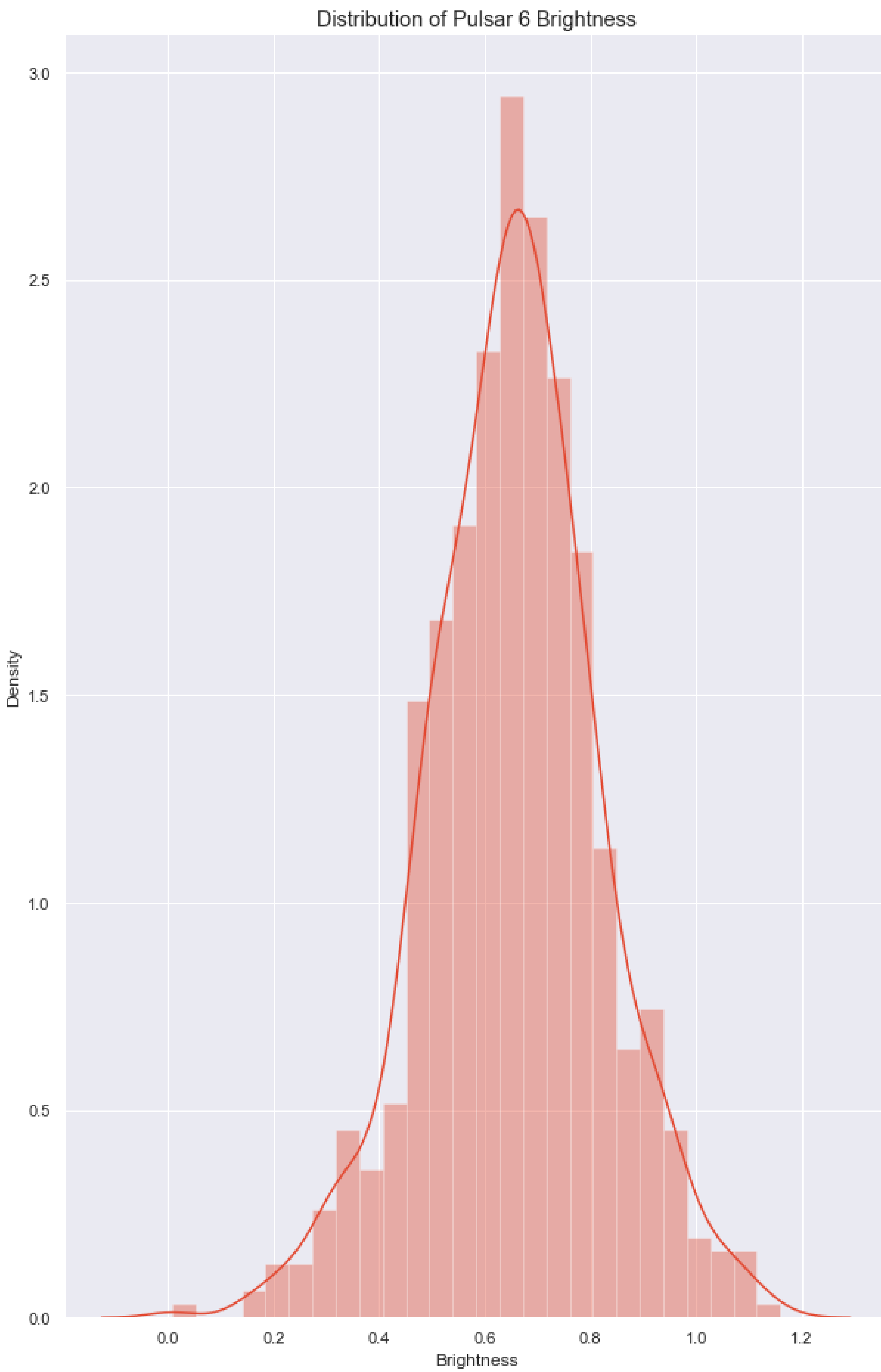
[ ]:
```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid", {"axes.facecolor": ".75"})
strength = pulsar6.Brightness.values
ax = plt.axhline( y=pulsar6["Brightness"].median(), ls='-',c='mediumslateblue')
ax = sns.swarmplot(data=pulsar6["Brightness"], c="blue").set_title('Pulsar 6␣
↪Swarm plot of Emission Strength')
```



Distribution Looking at the distribtuion of Pulsar 6's brightness, it appears very closely follow a normal distribution

[ ]:
```
plt.figure(figsize=(10, 16))
with sns.axes_style('darkgrid'):
    sns.distplot(pulsar6.Brightness)
plt.title("Distribution of Pulsar 6 Brightness")
```

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



Distribution of Pulsar 6 Brightness
Density
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Brightness

1.0.3 Generating a Binary Data Sequence for Machine Learning Algorithms and Randomness Testing

A 'Binary' column is generated based on whether the Brightness for the current observation is higher or lower than the median Brightness. If the observed Brightness is greater than the median, assign 1, if less than, assign 0.

Pulsar 1 (J0437-4715):

[ ]:
```
medianpulse1 = pulsar1["Brightness"].median()
print("Median of Pulsar 1: ", medianpulse1)
pulsar1['Binary'] = np.where(pulsar1['Brightness'] > medianpulse1, 1, 0)
```

```
Median of Pulsar 1:  0.42381595
```

[ ]:
```
pulsar1.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.598393	0.056431	1
1	2	0.590859	0.055182	1
2	3	0.449643	0.063632	1
3	4	0.682860	0.056269	1
4	5	0.490026	0.046830	1
5	6	0.586071	0.052649	1
6	7	0.150353	0.056483	0
7	8	0.384684	0.052567	0
8	9	0.429094	0.055569	1
9	10	0.995865	0.075811	1

[ ]:
```
print("Number of observations assigned 1: ", len(pulsar1[(pulsar1.Brightness >␣
↪medianpulse1)]))
print("Number of observations assigned 0: ", len(pulsar1[(pulsar1.Brightness <␣
↪medianpulse1)]))
```

```
Number of observations assigned 1:  13500
Number of observations assigned 0:  13500
```

Pulsar 2 (J0953+0755):

[ ]:
```
medianpulse2 = pulsar2["Brightness"].median()
print("Median of Pulsar 2: ", medianpulse2)
pulsar2['Binary'] = np.where(pulsar2['Brightness'] > medianpulse2, 1, 0)
```

```
Median of Pulsar 2:  0.4818942
```

[ ]:
```
pulsar2.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.334330	0.015570	0
1	2	-0.098659	0.014051	0
2	3	0.123514	0.011901	0
3	4	0.443923	0.014365	0
4	5	1.590446	0.057785	1
5	6	1.233848	0.018692	1
6	7	0.857876	0.022208	1
7	8	0.254255	0.018185	0
8	9	0.292077	0.021672	0
9	10	0.439929	0.046293	0

[ ]:

```
print("Number of observations assigned 1: ", len(pulsar2[(pulsar2.Brightness >␣
 ↪medianpulse2)]))
print("Number of observations assigned 0: ", len(pulsar2[(pulsar2.Brightness <␣
 ↪medianpulse2)]))
```

```
Number of observations assigned 1:  7164
Number of observations assigned 0:  7164
```

Pulsar 3 (J0835-4510):

[ ]:

```
medianpulse3 = pulsar3["Brightness"].median()
print("Median of Pulsar 3: ", medianpulse3)
pulsar3['Binary'] = np.where(pulsar3['Brightness'] > medianpulse3, 1, 0)
```

```
Median of Pulsar 3:  2.255182
```

[ ]:

```
pulsar3.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.984043	0.053831	0
1	2	2.487928	0.048796	1
2	3	1.690295	0.025639	0
3	4	1.196142	0.039539	0
4	5	1.979783	0.041460	0
5	6	2.297645	0.054210	1
6	7	2.322135	0.043554	1
7	8	2.289047	0.049957	1
8	9	2.442574	0.025110	1
9	10	2.136332	0.022712	0

[ ]:

```
print("Number of observations assigned 1: ", len(pulsar3[(pulsar3.Brightness >␣
 ↪medianpulse3)]))
print("Number of observations assigned 0: ", len(pulsar3[(pulsar3.Brightness <␣
 ↪medianpulse3)]))
```

```
Number of observations assigned 1:  665
Number of observations assigned 0:  665
```

Pulsar 4 (J1243-6423):

[ ]:
```
medianpulse4 = pulsar4["Brightness"].median()
print("Median of Pulsar 4: ", medianpulse4)
pulsar4['Binary'] = np.where(pulsar4['Brightness'] > medianpulse4, 1, 0)
```

```
Median of Pulsar 4:  0.07665979
```

[ ]:
```
pulsar4.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.101127	0.001893	1
1	2	0.012166	0.001814	0
2	3	0.021918	0.001835	0
3	4	0.181179	0.002183	1
4	5	0.000240	0.001725	0
5	6	0.085866	0.001723	1
6	7	0.067280	0.001778	0
7	8	0.092884	0.002438	1
8	9	0.083350	0.002101	1
9	10	0.087871	0.001941	1

[ ]:
```
print("Number of observations assigned 1: ", len(pulsar4[(pulsar4.Brightness >␣
 ↪medianpulse4)]))
print("Number of observations assigned 0: ", len(pulsar4[(pulsar4.Brightness <␣
 ↪medianpulse4)]))
```

```
Number of observations assigned 1:  909
Number of observations assigned 0:  909
```

Pulsar 5 (J1456-6843):

[ ]:
```
medianpulse5 = pulsar5["Brightness"].median()
print("Median of Pulsar 5: ", medianpulse5)
pulsar5['Binary'] = np.where(pulsar5['Brightness'] > medianpulse4, 1, 0)
```

```
Median of Pulsar 5:  0.081228
```

[ ]:
```
pulsar5.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.053904	0.005560	0
1	2	0.058653	0.004821	0
2	3	0.110208	0.005196	1
3	4	0.034716	0.004729	0
4	5	0.056101	0.004619	0
5	6	0.046168	0.005074	0
6	7	0.055648	0.004916	0
7	8	0.060890	0.004581	0
8	9	0.024388	0.004922	0

```
9          10    0.039370    0.004633      0
```

```
[ ]: print("Number of observations assigned 1: ", len(pulsar5[(pulsar5.Brightness >␣
     ↪medianpulse5)]))
     print("Number of observations assigned 0: ", len(pulsar5[(pulsar5.Brightness <␣
     ↪medianpulse5)]))
```

```
Number of observations assigned 1:  609
Number of observations assigned 0:  609
```

Pulsar 6 (J1644-4559):

```
[ ]: medianpulse6 = pulsar6["Brightness"].median()
     print("Median of Pulsar 6: ", medianpulse6)
     pulsar6['Binary'] = np.where(pulsar6['Brightness'] > medianpulse6, 1, 0)
```

```
Median of Pulsar 6:  0.65829515
```

```
[ ]: pulsar6.head(10)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary
0	1	0.634671	0.002761	0
1	2	0.736945	0.005207	1
2	3	0.693834	0.002706	1
3	4	1.021866	0.010184	1
4	5	0.673845	0.006236	1
5	6	0.676883	0.004763	1
6	7	0.527039	0.002422	0
7	8	0.673417	0.003174	1
8	9	0.357076	0.002848	0
9	10	0.661704	0.005588	1

```
[ ]: print("Number of observations assigned 1: ", len(pulsar6[(pulsar6.Brightness >␣
     ↪medianpulse6)]))
     print("Number of observations assigned 0: ", len(pulsar6[(pulsar6.Brightness <␣
     ↪medianpulse6)]))
```

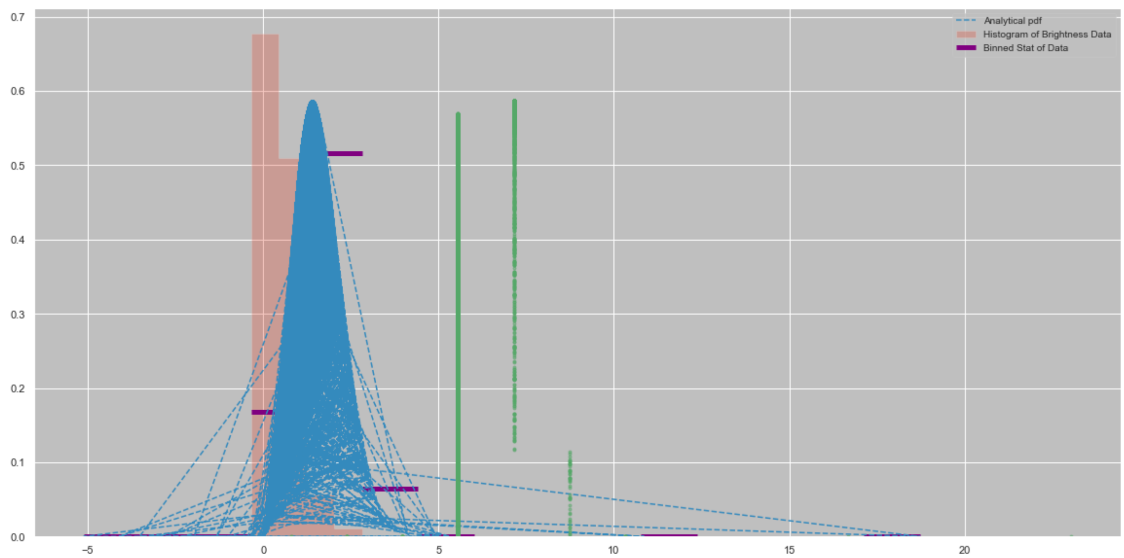
```
Number of observations assigned 1:  349
Number of observations assigned 0:  349
```

1.0.4 Deriving Rolling Median and Mean statistics. With Binned Visualisations

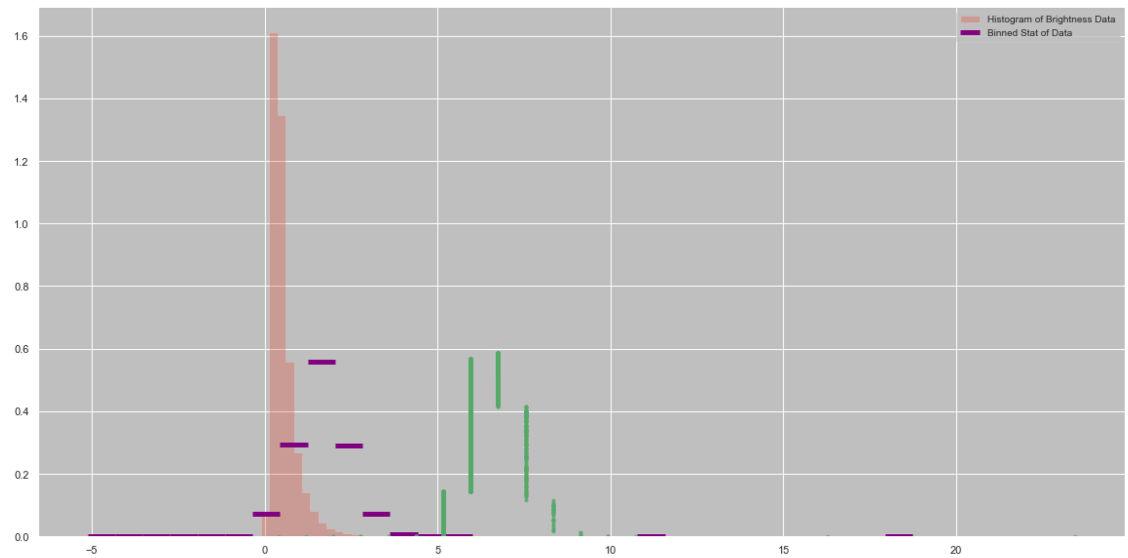
Pulsar 1 (J0437-4715):

```
[ ]: data = pulsar1["Brightness"]
     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
```

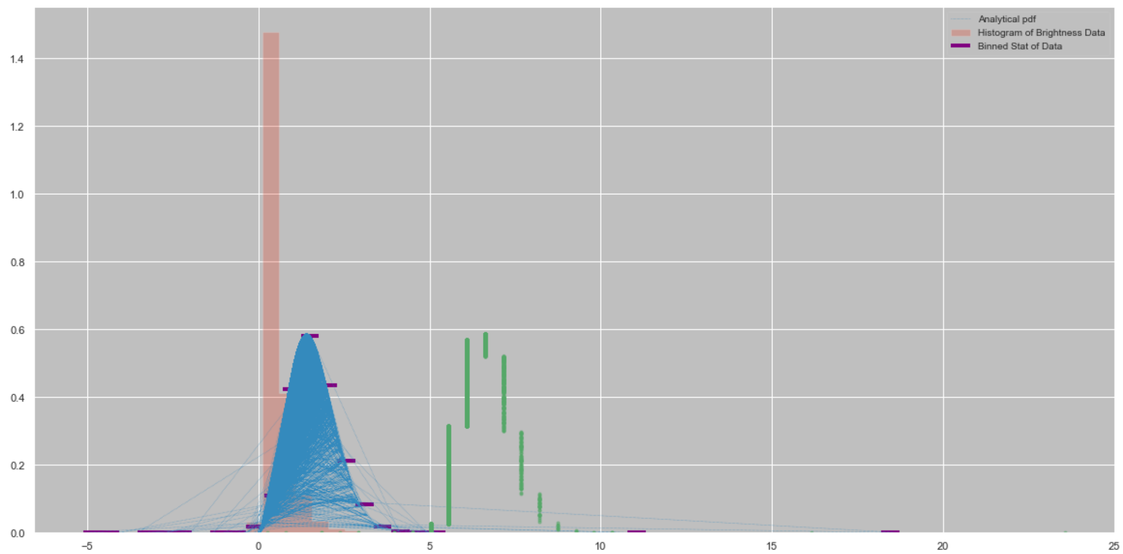
```
plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.plot(data, dataPDF, '--', label = "Analytical pdf")
plt.hlines(bin_means, bin_edges[:-1], bin_edges[1:], colors='purple', lw=5,␣
 ↪label='Binned Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



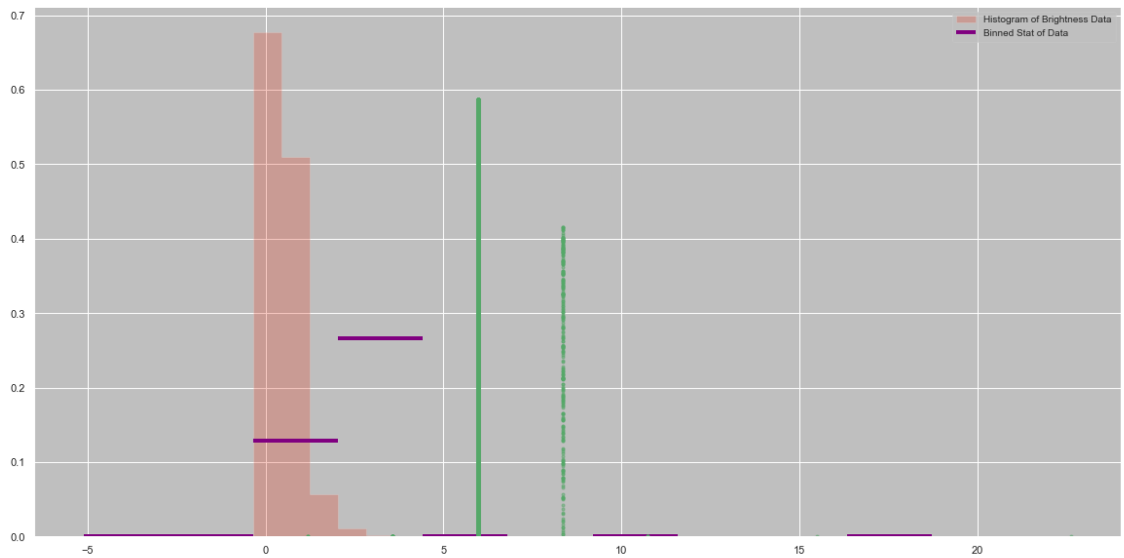
[ ]:
```
dataPDF = stats.maxwell.pdf(data)
bin_means, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='mean', bins=30)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=100, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
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()
```



[ ]:
```
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=45)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=50, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.plot(data, dataPDF, ':', label = "Analytical pdf", lw=0.5)
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], colors='purple', lw=4,␣
 ↪label='Binned Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



[ ]:
```python
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=10)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], colors='purple', lw=4,␣
 ↪label='Binned Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



Here we begin to add in the moving averages for further potential data work

[ ]:
```
pulsar1['RollingMeanEmissions5ths'] = pulsar1["Brightness"].rolling(5).mean()
pulsar1['RollingMeanEmissions10ths'] = pulsar1["Brightness"].rolling(10).mean()
pulsar1['RollingMedianEmissions5ths'] = pulsar1["Brightness"].rolling(5).
↪median()
pulsar1['RollingMedianEmissions10ths'] = pulsar1["Brightness"].rolling(10).
↪median()
pulsar1.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary	RollingMeanEmissions5ths \
0	1	0.598393	0.056431	1	NaN
1	2	0.590859	0.055182	1	NaN
2	3	0.449643	0.063632	1	NaN
3	4	0.682860	0.056269	1	NaN
4	5	0.490026	0.046830	1	0.562356
5	6	0.586071	0.052649	1	0.559892
6	7	0.150353	0.056483	0	0.471791
7	8	0.384684	0.052567	0	0.458799
8	9	0.429094	0.055569	1	0.408046
9	10	0.995865	0.075811	1	0.509214
10	11	0.670907	0.049539	1	0.526181
11	12	0.465406	0.047461	1	0.589191
12	13	0.242442	0.050653	0	0.560743
13	14	0.500057	0.050163	1	0.574935
14	15	0.658159	0.050743	1	0.507394

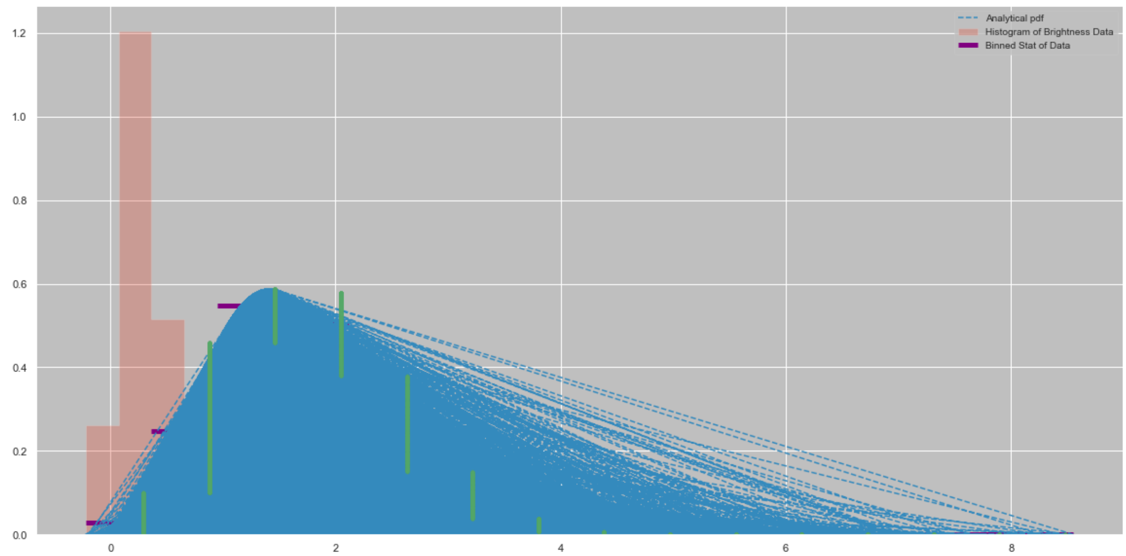
	RollingMeanEmissions10ths	RollingMedianEmissions5ths \
0	NaN	NaN

```
1                          NaN                           NaN
2                          NaN                           NaN
3                          NaN                           NaN
4                          NaN                      0.590859
5                          NaN                      0.586071
6                          NaN                      0.490026
7                          NaN                      0.490026
8                          NaN                      0.429094
9                     0.535785                      0.429094
10                    0.543036                      0.429094
11                    0.530491                      0.465406
12                    0.509771                      0.465406
13                    0.491490                      0.500057
14                    0.508304                      0.500057

    RollingMedianEmissions10ths
0                           NaN
1                           NaN
2                           NaN
3                           NaN
4                           NaN
5                           NaN
6                           NaN
7                           NaN
8                           NaN
9                      0.538048
10                     0.538048
11                     0.477716
12                     0.477716
13                     0.477716
14                     0.482731
```

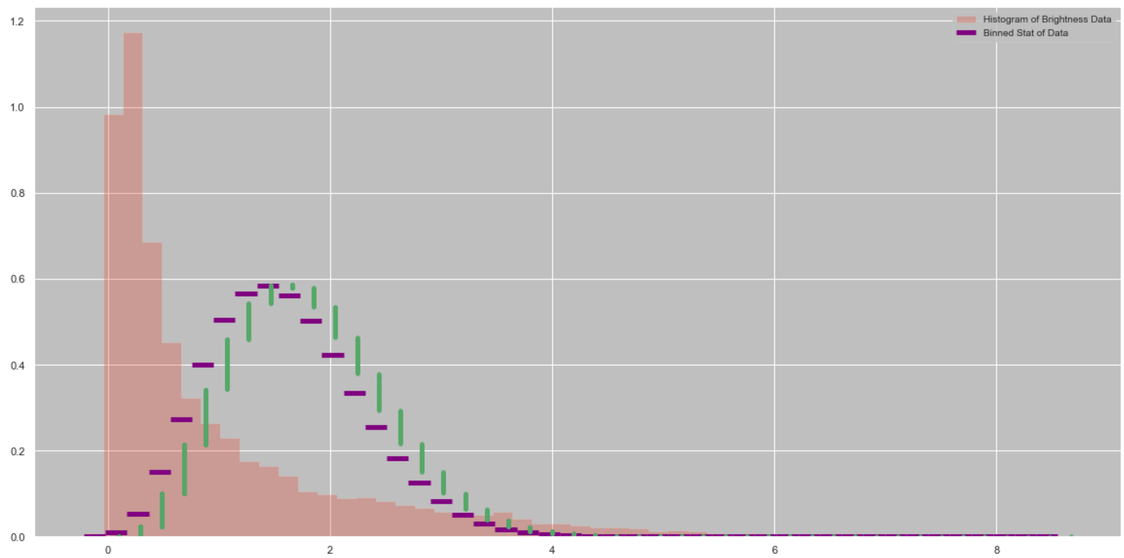
Pulsar 2 (J0953+0755):

[ ]:
```
data = pulsar2["Brightness"]
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(figsize=(20,10))
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')
```

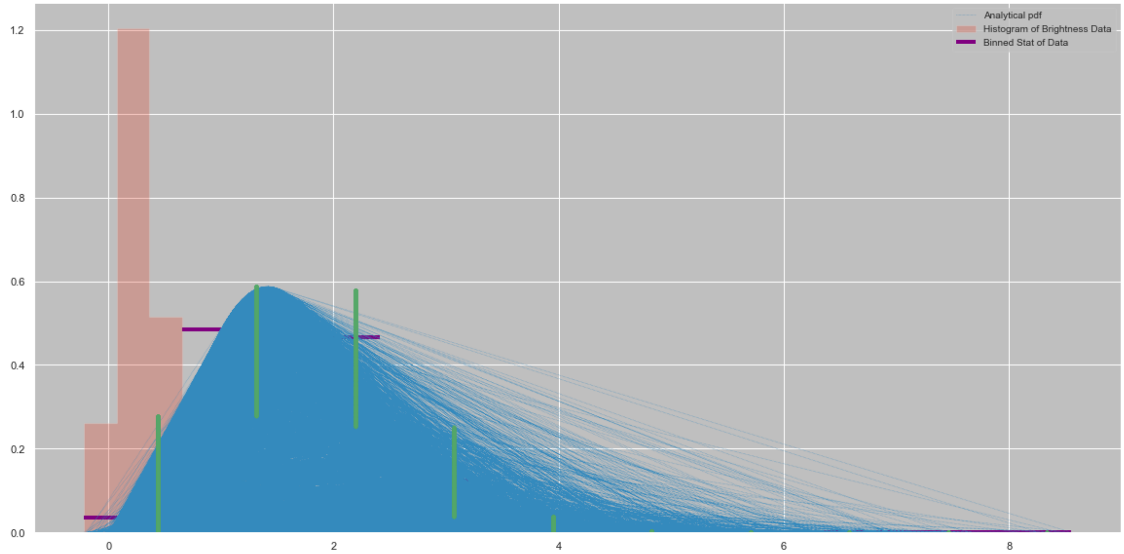
```
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



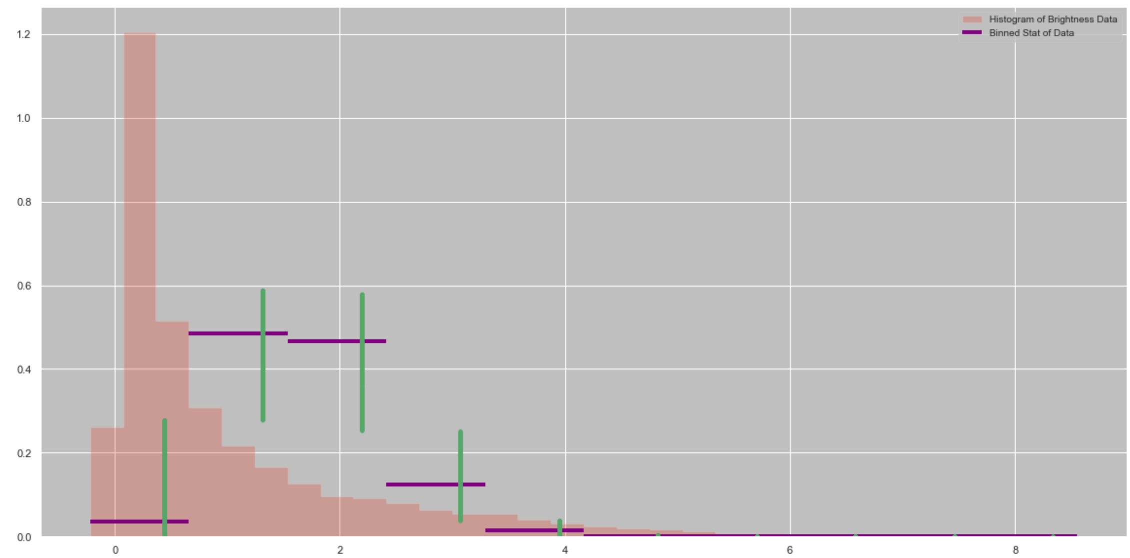

```
[ ]: dataPDF = stats.maxwell.pdf(data)
     bin_means, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
             statistic='mean', bins=45)
     bin_width = (bin_edges[1] - bin_edges[0])
     bin_centers = bin_edges[1:] - bin_width/2

     plt.figure(figsize=(20,10))
     plt.hist(data, bins=50, density=True, histtype='stepfilled', alpha=0.3,␣
      ↪label='Histogram of Brightness Data')
     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()
```




```
[ ]: bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
             statistic='median', bins=10)
     bin_width = (bin_edges[1] - bin_edges[0])
     bin_centers = bin_edges[1:] - bin_width/2

     plt.figure(figsize=(20,10))
     plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
      ↪label='Histogram of Brightness Data')
     plt.plot(data, dataPDF, ':', label = "Analytical pdf", lw=0.5)
     plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], colors='purple', lw=4,␣
      ↪label='Binned Stat of Data')
     plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
     plt.legend(fontsize=10)
     plt.show()
```



[ ]:
```
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=10)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], colors='purple', lw=4,␣
 ↪label='Binned Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



Here we begin to add in the moving averages for further potential data work

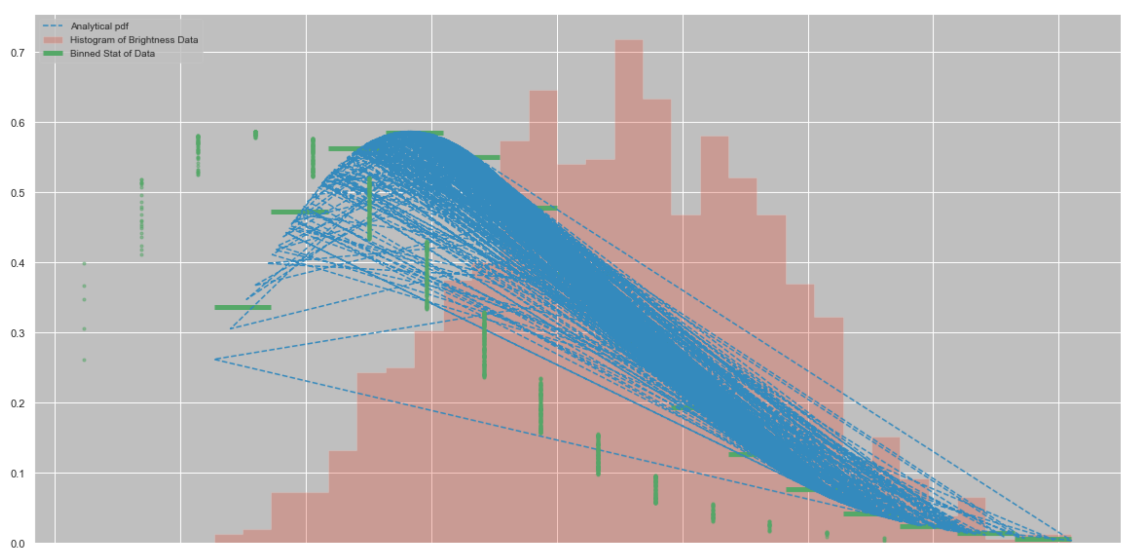
[ ]:
```
pulsar2['RollingMeanEmissions5ths'] = pulsar2["Brightness"].rolling(5).mean()
pulsar2['RollingMeanEmissions10ths'] = pulsar2["Brightness"].rolling(10).mean()
pulsar2['RollingMedianEmissions5ths'] = pulsar2["Brightness"].rolling(5).
 ↪median()
pulsar2.head(15)
```

[ ]:
```
    Pulse Number  Brightness  Uncertainty  Binary  RollingMeanEmissions5ths  \
0              1    0.334330     0.015570       0                       NaN
1              2   -0.098659     0.014051       0                       NaN
2              3    0.123514     0.011901       0                       NaN
3              4    0.443923     0.014365       0                       NaN
4              5    1.590446     0.057785       1                  0.478711
5              6    1.233848     0.018692       1                  0.658614
6              7    0.857876     0.022208       1                  0.849921
7              8    0.254255     0.018185       0                  0.876070
8              9    0.292077     0.021672       0                  0.845700
9             10    0.439929     0.046293       0                  0.615597
10            11    0.824310     0.036243       1                  0.533689
11            12    1.443460     0.088372       1                  0.650806
12            13    0.127981     0.018070       0                  0.625551
13            14    0.327896     0.012362       0                  0.632715
14            15    2.473663     0.099205       1                  1.039462

    RollingMeanEmissions10ths  RollingMedianEmissions5ths
0                         NaN                         NaN
1                         NaN                         NaN
2                         NaN                         NaN
```

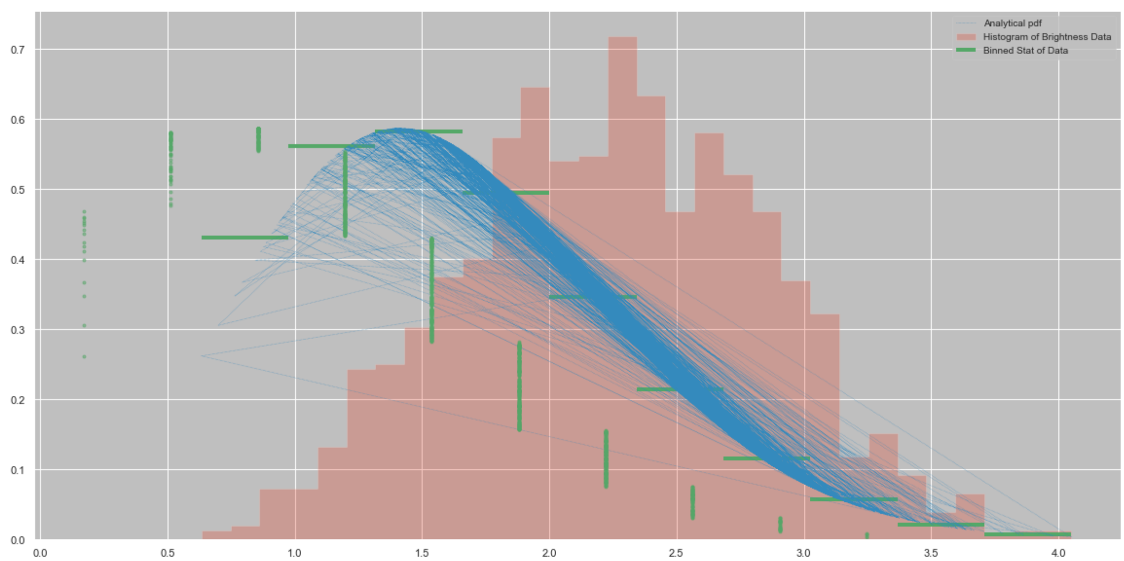
3	NaN	NaN
4	NaN	0.334330
5	NaN	0.443923
6	NaN	0.857876
7	NaN	0.857876
8	NaN	0.857876
9	0.547154	0.439929
10	0.596152	0.439929
11	0.750364	0.439929
12	0.750810	0.439929
13	0.739208	0.439929
14	0.827529	0.824310

Pulsar 3 (J0835-4510):

[ ]:
```
data = pulsar3["Brightness"]
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(figsize=(20,10))
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:], 'g', 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()
```



[ ]:
```python
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=10)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.plot(data, dataPDF, ':', label = "Analytical pdf", lw=0.5)
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], 'g', lw=4, label='Binned␣
 ↪Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



Here we begin to add in the moving averages for further potential data work

[ ]:
```python
pulsar3['RollingMeanEmissions5ths'] = pulsar3["Brightness"].rolling(5).mean()
pulsar3['RollingMedianEmissions5ths'] = pulsar3["Brightness"].rolling(5).
 ↪median()
pulsar3['RollingMedianEmissions10ths'] = pulsar3["Brightness"].rolling(10).
 ↪median()
pulsar3.head(15)
```

[ ]:
```
    Pulse Number  Brightness  Uncertainty  Binary  RollingMeanEmissions5ths  \
0              1    0.984043     0.053831       0                       NaN
```

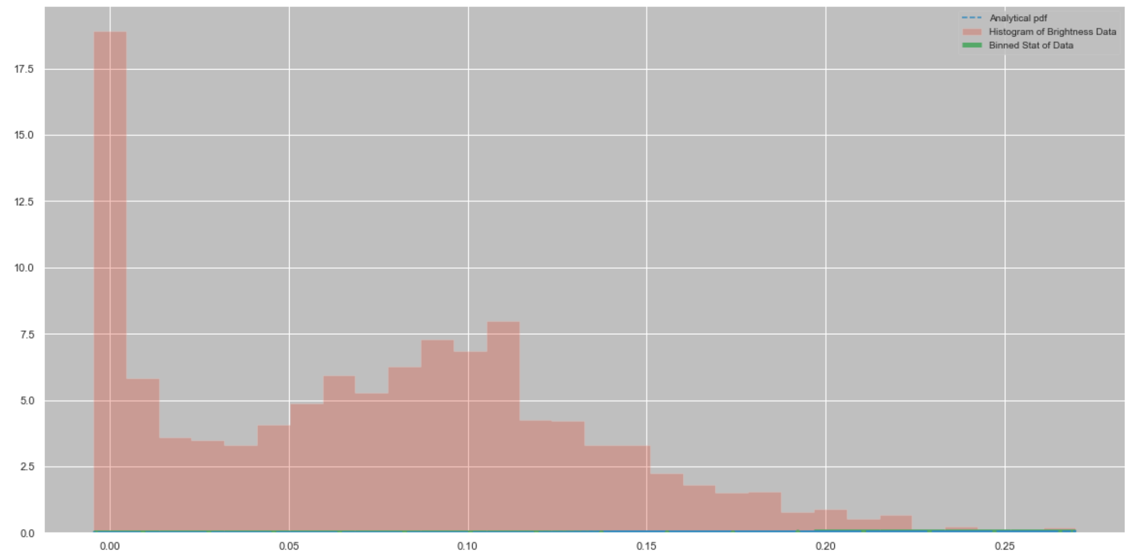
```
1           2    2.487928    0.048796     1                 NaN
2           3    1.690295    0.025639     0                 NaN
3           4    1.196142    0.039539     0                 NaN
4           5    1.979783    0.041460     0            1.667638
5           6    2.297645    0.054210     1            1.930359
6           7    2.322135    0.043554     1            1.897200
7           8    2.289047    0.049957     1            2.016950
8           9    2.442574    0.025110     1            2.266237
9          10    2.136332    0.022712     0            2.297547
10         11    1.976790    0.037551     0            2.233376
11         12    2.445764    0.047004     1            2.258101
12         13    1.937017    0.028561     0            2.187695
13         14    2.315184    0.045216     1            2.162217
14         15    2.584888    0.040232     1            2.251929
```

```
    RollingMedianEmissions5ths  RollingMedianEmissions10ths
0                          NaN                          NaN
1                          NaN                          NaN
2                          NaN                          NaN
3                          NaN                          NaN
4                     1.690295                          NaN
5                     1.979783                          NaN
6                     1.979783                          NaN
7                     2.289047                          NaN
8                     2.297645                          NaN
9                     2.297645                     2.212689
10                    2.289047                     2.212689
11                    2.289047                     2.212689
12                    2.136332                     2.212689
13                    2.136332                     2.293346
14                    2.315184                     2.306414
```

Pulsar 4 (J1243-6423):

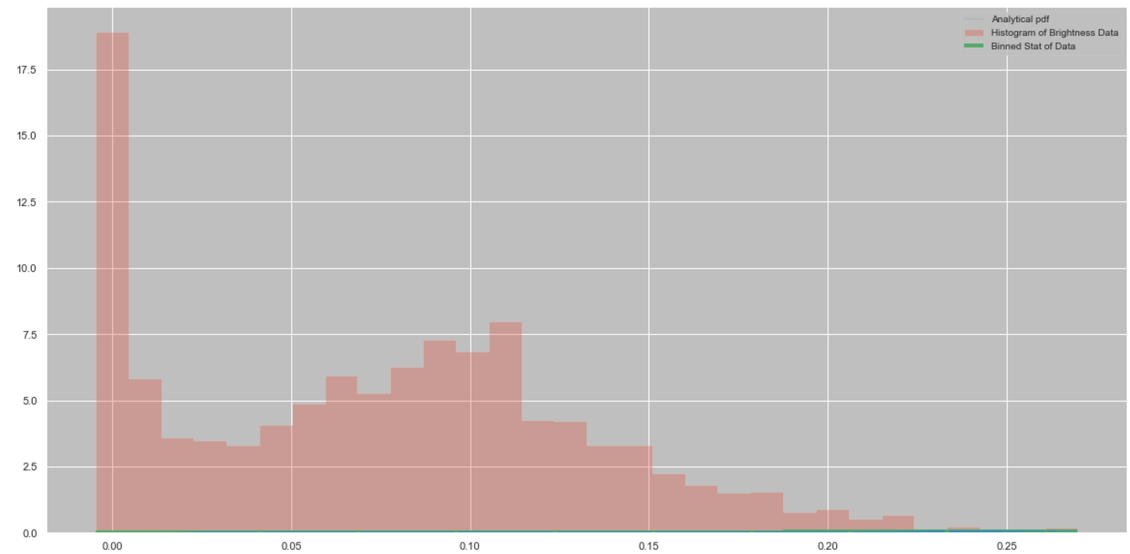
[ ]:
```
data = pulsar4["Brightness"]
dataPDF = stats.maxwell.pdf(data)
bin_means, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='mean', bins=15)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
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:], 'g', lw=5, label='Binned␣
 ↪Stat of Data')
```

```python
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



[ ]:

```python
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=10)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.plot(data, dataPDF, ':', label = "Analytical pdf", lw=0.5)
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], 'g', lw=4, label='Binned␣
 ↪Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



Here we begin to add in the moving averages for further potential data work

[ ]:
```
pulsar4['RollingMeanEmissions5ths'] = pulsar4["Brightness"].rolling(5).mean()
pulsar4['RollingMeanEmissions10ths'] = pulsar4["Brightness"].rolling(10).mean()
pulsar4['RollingMedianEmissions5ths'] = pulsar4["Brightness"].rolling(5).
 ↪median()
pulsar4['RollingMedianEmissions10ths'] = pulsar4["Brightness"].rolling(10).
 ↪median()
pulsar4.head(15)
```

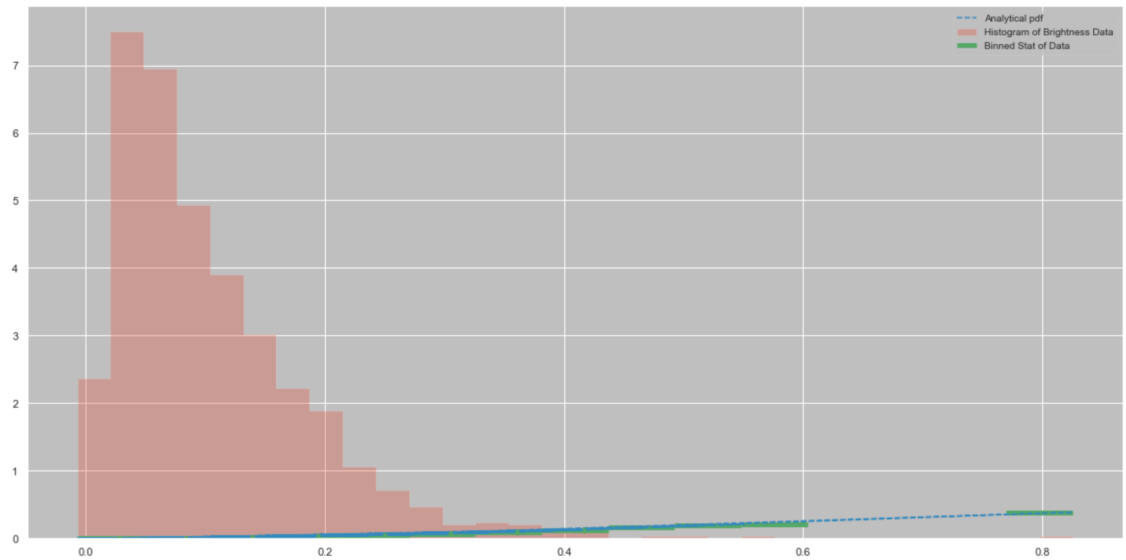
[ ]:
```
    Pulse Number  Brightness  Uncertainty  Binary  RollingMeanEmissions5ths  \
0              1    0.101127     0.001893       1                       NaN
1              2    0.012166     0.001814       0                       NaN
2              3    0.021918     0.001835       0                       NaN
3              4    0.181179     0.002183       1                       NaN
4              5    0.000240     0.001725       0                  0.063326
5              6    0.085866     0.001723       1                  0.060274
6              7    0.067280     0.001778       0                  0.071297
7              8    0.092884     0.002438       1                  0.085490
8              9    0.083350     0.002101       1                  0.065924
9             10    0.087871     0.001941       1                  0.083450
10            11    0.123529     0.002026       1                  0.090983
11            12    0.097413     0.001878       1                  0.097009
12            13    0.100649     0.001820       1                  0.098562
13            14    0.058025     0.001724       0                  0.093498
14            15    0.116164     0.001948       1                  0.099156

    RollingMeanEmissions10ths  RollingMedianEmissions5ths  \
0                         NaN                         NaN
```

```
1                     NaN                       NaN
2                     NaN                       NaN
3                     NaN                       NaN
4                     NaN                  0.021918
5                     NaN                  0.021918
6                     NaN                  0.067280
7                     NaN                  0.085866
8                     NaN                  0.083350
9                0.073388                  0.085866
10               0.075628                  0.087871
11               0.084153                  0.092884
12               0.092026                  0.097413
13               0.079711                  0.097413
14               0.091303                  0.100649

    RollingMedianEmissions10ths
0                          NaN
1                          NaN
2                          NaN
3                          NaN
4                          NaN
5                          NaN
6                          NaN
7                          NaN
8                          NaN
9                     0.084608
10                    0.084608
11                    0.086868
12                    0.090377
13                    0.086868
14                    0.090377
```

Pulsar 5 (J1456-6843):

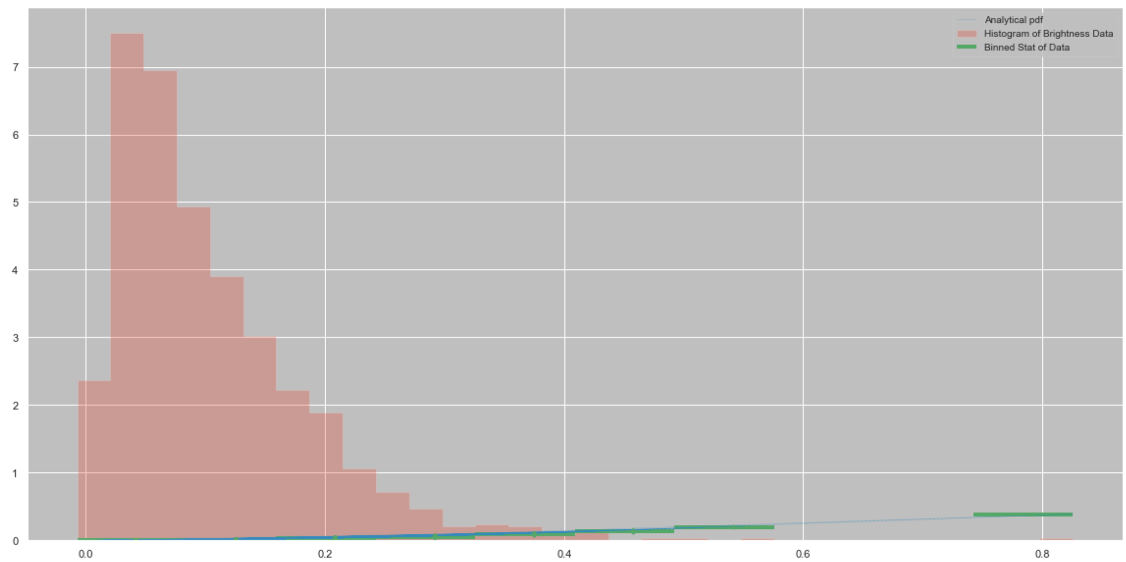
[ ]:
```
data = pulsar5["Brightness"]
dataPDF = stats.maxwell.pdf(data)
bin_means, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='mean', bins=15)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
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:], 'g', 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()
```



[ ]:

```
bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
        statistic='median', bins=10)
bin_width = (bin_edges[1] - bin_edges[0])
bin_centers = bin_edges[1:] - bin_width/2

plt.figure(figsize=(20,10))
plt.hist(data, bins=30, density=True, histtype='stepfilled', alpha=0.3,␣
 ↪label='Histogram of Brightness Data')
plt.plot(data, dataPDF, ':', label = "Analytical pdf", lw=0.5)
plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], 'g', lw=4, label='Binned␣
 ↪Stat of Data')
plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
plt.legend(fontsize=10)
plt.show()
```



Here we begin to add in the moving averages for further potential data work

[ ]:
```
pulsar5['RollingMeanEmissions5ths'] = pulsar5["Brightness"].rolling(5).mean()
pulsar5['RollingMeanEmissions10ths'] = pulsar5["Brightness"].rolling(10).mean()
pulsar5['RollingMedianEmissions5ths'] = pulsar5["Brightness"].rolling(5).
 ↪median()
pulsar5['RollingMedianEmissions10ths'] = pulsar5["Brightness"].rolling(10).
 ↪median()
pulsar5.head(15)
```

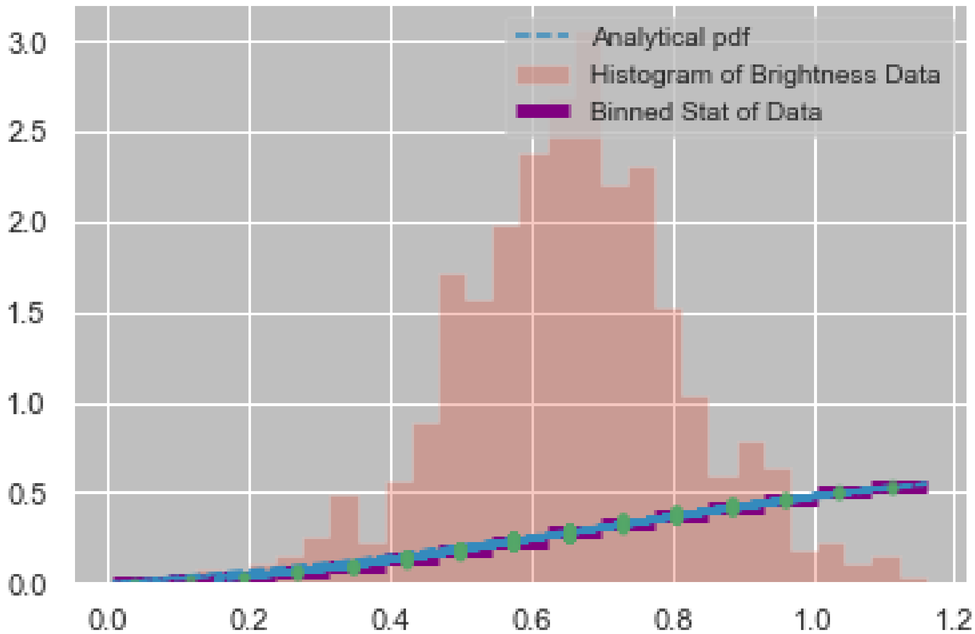
[ ]:
```
    Pulse Number  Brightness  Uncertainty  Binary  RollingMeanEmissions5ths  \
0              1    0.053904     0.005560       0                       NaN
1              2    0.058653     0.004821       0                       NaN
2              3    0.110208     0.005196       1                       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

    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

    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
```

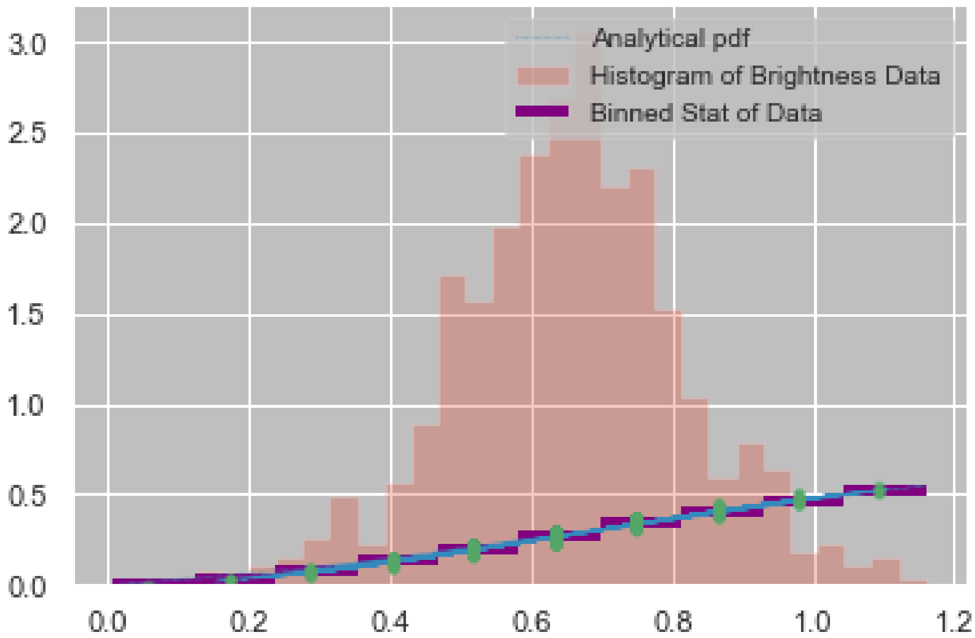
Pulsar 6 (J1644-4559):

[ ]:
```
data = pulsar6["Brightness"]
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()
```




```
[ ]: bin_median, bin_edges, binnumber = stats.binned_statistic(data, dataPDF,
             statistic='median', bins=10)
     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", lw=0.5)
     plt.hlines(bin_median, bin_edges[:-1], bin_edges[1:], colors='purple', lw=4,␣
      ↪label='Binned Stat of Data')
     plt.plot((binnumber - 0.5) * bin_width, dataPDF, 'g.', alpha=0.5)
     plt.legend(fontsize=10)
     plt.show()
```



Here we begin to add in the moving averages for further potential data work

[ ]:
```
pulsar6['RollingMeanEmissions5ths'] = pulsar6["Brightness"].rolling(5).mean()
pulsar6['RollingMeanEmissions10ths'] = pulsar6["Brightness"].rolling(10).mean()
pulsar6['RollingMedianEmissions5ths'] = pulsar6["Brightness"].rolling(5).
 ↪median()
pulsar6['RollingMedianEmissions10ths'] = pulsar6["Brightness"].rolling(10).
 ↪median()
pulsar6.head(15)
```

[ ]:

	Pulse Number	Brightness	Uncertainty	Binary	RollingMeanEmissions5ths \
0	1	0.634671	0.002761	0	NaN
1	2	0.736945	0.005207	1	NaN
2	3	0.693834	0.002706	1	NaN
3	4	1.021866	0.010184	1	NaN
4	5	0.673845	0.006236	1	0.752232
5	6	0.676883	0.004763	1	0.760675
6	7	0.527039	0.002422	0	0.718693
7	8	0.673417	0.003174	1	0.714610
8	9	0.357076	0.002848	0	0.581652
9	10	0.661704	0.005588	1	0.579224
10	11	0.545564	0.003835	0	0.552960
11	12	0.494655	0.003145	0	0.546483
12	13	0.804260	0.005258	1	0.572651
13	14	0.513362	0.005700	0	0.603909
14	15	0.477025	0.002945	0	0.566973

```
    RollingMeanEmissions10ths  RollingMedianEmissions5ths  \
0                         NaN                         NaN
1                         NaN                         NaN
2                         NaN                         NaN
3                         NaN                         NaN
4                         NaN                    0.693834
5                         NaN                    0.693834
6                         NaN                    0.676883
7                         NaN                    0.673845
8                         NaN                    0.673417
9                    0.665728                    0.661704
10                   0.656817                    0.545564
11                   0.632588                    0.545564
12                   0.643631                    0.545564
13                   0.592780                    0.545564
14                   0.573098                    0.513362

    RollingMedianEmissions10ths
0                           NaN
1                           NaN
2                           NaN
3                           NaN
4                           NaN
5                           NaN
6                           NaN
7                           NaN
8                           NaN
9                      0.673631
10                     0.673631
11                     0.667561
12                     0.667561
13                     0.603634
14                     0.536301
```

1.0.5 Machine Learning Both Logistic then Bi-Directional LSTM

Pulsar 1 (J0437-4715): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar1[['Brightness', 'Uncertainty']]
y = pulsar1['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
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)  =  2716
False Positive(FP) =  45
True Negative(TN)  =  2639
False Negative(FN) =  0
```

[ ]:
```
score=model.score(X_test,y_test)
print(score)
```

```
0.9916666666666667
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar1[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
```

```
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=5, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/5
51/51 [==============================] - 15s 258ms/step - loss: 0.0606 - mse:
0.0606 - val_loss: 0.0041 - val_mse: 0.0041
Epoch 2/5
51/51 [==============================] - 13s 263ms/step - loss: 0.0030 - mse:
0.0030 - val_loss: 0.0034 - val_mse: 0.0034
Epoch 3/5
51/51 [==============================] - 14s 277ms/step - loss: 0.0029 - mse:
0.0029 - val_loss: 0.0034 - val_mse: 0.0034
Epoch 4/5
51/51 [==============================] - 14s 283ms/step - loss: 0.0029 - mse:
0.0029 - val_loss: 0.0034 - val_mse: 0.0034
Epoch 5/5
51/51 [==============================] - 15s 295ms/step - loss: 0.0028 - mse:
0.0028 - val_loss: 0.0034 - val_mse: 0.0034
```

[ ]:
```
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  0.05848320013973063
MAE:  0.014415606644854041
RSE:  0.12006501007726623
```

[ ]:
```
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

Evaluation Logistic Regression

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

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.

Pulsar 2 (J0953+0755): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar2[['Brightness', 'Uncertainty']]
y = pulsar2['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
cm = confusion_matrix(y_test, predictions)

TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()

score=model.score(X_test,y_test)

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)

print(score)
```

```
True Positive(TP)  =  1394
False Positive(FP) =  1
True Negative(TN)  =  1449
False Negative(FN) =  22
0.9919748778785764
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar2[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
```

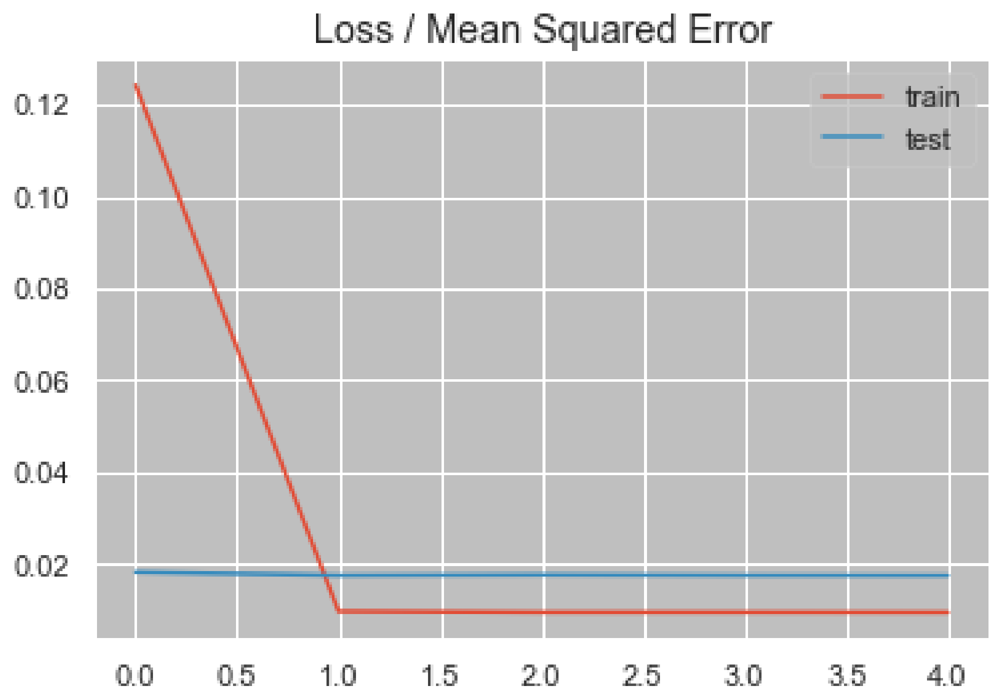
```
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=5, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/5
51/51 [==============================] - 8s 117ms/step - loss: 0.1242 - mse:
0.1242 - val_loss: 0.0182 - val_mse: 0.0182
Epoch 2/5
51/51 [==============================] - 5s 106ms/step - loss: 0.0097 - mse:
0.0097 - val_loss: 0.0175 - val_mse: 0.0175
Epoch 3/5
51/51 [==============================] - 6s 128ms/step - loss: 0.0095 - mse:
0.0095 - val_loss: 0.0176 - val_mse: 0.0176
Epoch 4/5
51/51 [==============================] - 7s 129ms/step - loss: 0.0095 - mse:
0.0095 - val_loss: 0.0175 - val_mse: 0.0175
Epoch 5/5
51/51 [==============================] - 7s 131ms/step - loss: 0.0095 - mse:
0.0095 - val_loss: 0.0175 - val_mse: 0.0175
```

[ ]:
```
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  -0.008593979702192556
MAE:  0.02869650111569234
RSE:  0.1694004165156991
```

[ ]:
```
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



Evaluation Logistic Regression

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

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.

Pulsar 3 (J0835-4510): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar3[['Brightness', 'Uncertainty']]
y = pulsar3['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
cm = confusion_matrix(y_test, predictions)

TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()

score=model.score(X_test,y_test)

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)

print(score)
```

```
True Positive(TP)  =  121
False Positive(FP) =  7
True Negative(TN)  =  139
False Negative(FN) =  0
0.9737827715355806
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar3[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
```

```
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=5, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/5
52/52 [==============================] - 4s 37ms/step - loss: 0.0932 - mse:
0.0932 - val_loss: 0.0015 - val_mse: 0.0015
Epoch 2/5
52/52 [==============================] - 1s 26ms/step - loss: 1.6445e-04 - mse:
1.6445e-04 - val_loss: 2.0977e-07 - val_mse: 2.0977e-07
Epoch 3/5
52/52 [==============================] - 1s 26ms/step - loss: 8.9532e-07 - mse:
8.9532e-07 - val_loss: 1.8486e-07 - val_mse: 1.8486e-07
Epoch 4/5
52/52 [==============================] - 1s 26ms/step - loss: 1.7457e-07 - mse:
1.7457e-07 - val_loss: 1.6213e-07 - val_mse: 1.6213e-07
Epoch 5/5
52/52 [==============================] - 1s 25ms/step - loss: 1.6655e-07 - mse:
1.6655e-07 - val_loss: 1.5735e-07 - val_mse: 1.5735e-07
```

[ ]:
```
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  -5.232615484563366
MAE:  0.0003007963990194052
RSE:  0.01734348289760177
```

[ ]:
```
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

Evaluation Logistic Regression

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

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.

Pulsar 4 (J1243-6423): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar4[['Brightness', 'Uncertainty']]
y = pulsar4['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
cm = confusion_matrix(y_test, predictions)

TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()

score=model.score(X_test,y_test)

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)

print(score)
```

```
True Positive(TP)  =  165
False Positive(FP) =  7
True Negative(TN)  =  192
False Negative(FN) =  0
0.9807692307692307
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar4[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
```

```
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=5, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/5
51/51 [==============================] - 4s 37ms/step - loss: 0.1486 - mse:
0.1486 - val_loss: 0.1051 - val_mse: 0.1051
Epoch 2/5
51/51 [==============================] - 1s 26ms/step - loss: 0.0920 - mse:
0.0920 - val_loss: 0.1006 - val_mse: 0.1006
Epoch 3/5
51/51 [==============================] - 1s 26ms/step - loss: 0.0922 - mse:
0.0922 - val_loss: 0.1014 - val_mse: 0.1014
Epoch 4/5
51/51 [==============================] - 1s 25ms/step - loss: 0.0930 - mse:
0.0930 - val_loss: 0.1087 - val_mse: 0.1087
Epoch 5/5
51/51 [==============================] - 1s 28ms/step - loss: 0.0930 - mse:
0.0930 - val_loss: 0.1016 - val_mse: 0.1016
```

[ ]:
```
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  0.4683583734968013
MAE:  0.18574819977548918
RSE:  0.4309851502957952
```

[ ]:
```
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

Evaluation Logistic Regression

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

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.

Pulsar 5 (J1456-6843): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar5[['Brightness', 'Uncertainty']]
y = pulsar5['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
cm = confusion_matrix(y_test, predictions)

TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()

score=model.score(X_test,y_test)

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)

print(score)
```

```
True Positive(TP)  =  123
False Positive(FP) =  0
True Negative(TN)  =  110
False Negative(FN) =  11
0.9549180327868853
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar5[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
```

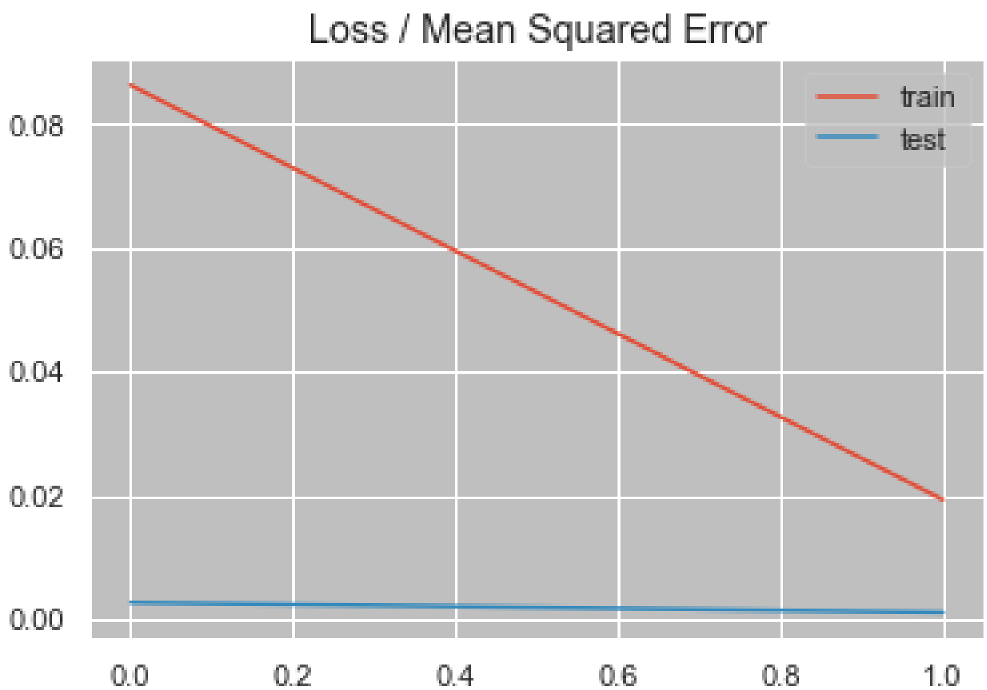
```
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=2, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/2
53/53 [==============================] - 5s 44ms/step - loss: 0.0862 - mse:
0.0862 - val_loss: 0.0027 - val_mse: 0.0027
Epoch 2/2
53/53 [==============================] - 2s 29ms/step - loss: 0.0193 - mse:
0.0193 - val_loss: 0.0011 - val_mse: 0.0011
```

[ ]:
```
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  -6.505993418621036
MAE:  0.02551917383260615
RSE:  0.15974721854419296
```

[ ]:
```
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



Evaluation Logistic Regression

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

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.

Pulsar 6 (J1644-4559): Logistic Regression (Classification Model)

[ ]:
```
X = pulsar6[['Brightness', 'Uncertainty']]
y = pulsar6['Binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.20)

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)

predictions = model.predict(X_test)
```

[ ]:
```
cm = confusion_matrix(y_test, predictions)

TN, FP, FN, TP = confusion_matrix(y_test, predictions).ravel()

score=model.score(X_test,y_test)

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)

print(score)
```

```
True Positive(TP)  =  65
False Positive(FP) =  9
True Negative(TN)  =  66
False Negative(FN) =  0
0.9357142857142857
```

Bi-Directional LSTM (Regression Model)

[ ]:
```
values_list = pulsar6[['Brightness', 'Uncertainty']].values.tolist()
values_list = preprocessing.normalize(values_list)
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)
# setting the parameters for the lstm model and compiling it
model = Sequential()
model.add(Bidirectional(LSTM(50), input_shape=(100, 2)))
model.add(Dense(25))
model.add(Dense(12))
```

```python
model.add(Dense(6))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse', metrics=['mse'])
# training the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
 ↪epochs=5, verbose=1, batch_size=(int(X_train.shape[0]/50)))
# predicting the y/brightness values for the test set
y_pred = model.predict(X_test, verbose=0)
```

```
Epoch 1/5
54/54 [==============================] - 4s 37ms/step - loss: 0.0851 - mse:
0.0851 - val_loss: 0.0011 - val_mse: 0.0011
Epoch 2/5
54/54 [==============================] - 1s 25ms/step - loss: 1.4379e-04 - mse:
1.4379e-04 - val_loss: 3.2544e-06 - val_mse: 3.2544e-06
Epoch 3/5
54/54 [==============================] - 1s 26ms/step - loss: 6.9280e-07 - mse:
6.9280e-07 - val_loss: 4.0650e-07 - val_mse: 4.0650e-07
Epoch 4/5
54/54 [==============================] - 1s 26ms/step - loss: 2.7915e-07 - mse:
2.7915e-07 - val_loss: 4.2872e-07 - val_mse: 4.2872e-07
Epoch 5/5
54/54 [==============================] - 1s 26ms/step - loss: 2.5502e-07 - mse:
2.5502e-07 - val_loss: 4.4464e-07 - val_mse: 4.4464e-07
```

[ ]:
```python
print('R2 Score: ', r2_score(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('RSE: ', math.sqrt(mean_absolute_error(y_test, y_pred)))
```

```
R2 Score:  -810.5787647885551
MAE:  0.0003299506848209353
RSE:  0.01816454471823985
```

[ ]:
```python
plt.title('Loss / Mean Squared Error')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

Evaluation Logistic Regression

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

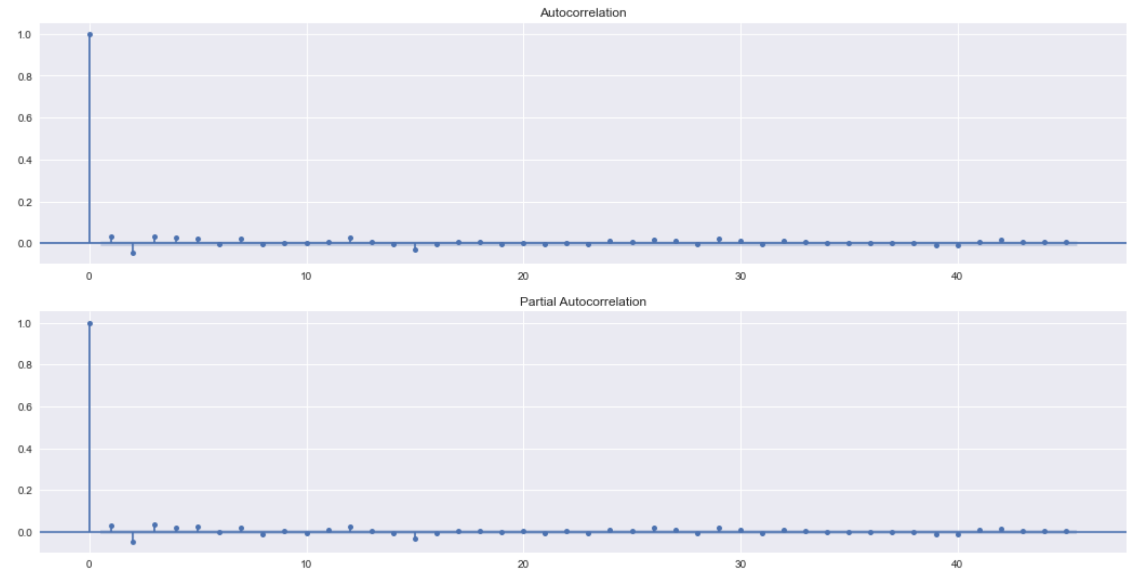
Bidirectional LSTM

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.

1.0.6 Auto Correlation and Covariance with Export of pulsar with correlated dataset.

Pulsar 1 (J0437-4715):

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

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

acf = plot_acf(pulsar1['Brightness'], ax=ax[0])
pacf = plot_pacf(pulsar1['Brightness'], ax=ax[1], method="ols")
```



[ ]:
```python
acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar1['Brightness'].shift(lag)

acfpulsar
```

[ ]:
```
         B_lag_0   B_lag_1   B_lag_2   B_lag_3   B_lag_4   B_lag_5   B_lag_6  \
0       0.598393       NaN       NaN       NaN       NaN       NaN       NaN
1       0.590859  0.598393       NaN       NaN       NaN       NaN       NaN
2       0.449643  0.590859  0.598393       NaN       NaN       NaN       NaN
3       0.682860  0.449643  0.590859  0.598393       NaN       NaN       NaN
4       0.490026  0.682860  0.449643  0.590859  0.598393       NaN       NaN
…            …         …         …         …         …         …         …
26995   0.539079  0.396929  1.014446  0.659313  1.173766  0.606806  0.500412
26996   0.324070  0.539079  0.396929  1.014446  0.659313  1.173766  0.606806
26997   0.291341  0.324070  0.539079  0.396929  1.014446  0.659313  1.173766
26998   0.346267  0.291341  0.324070  0.539079  0.396929  1.014446  0.659313
26999   0.513315  0.346267  0.291341  0.324070  0.539079  0.396929  1.014446

         B_lag_7   B_lag_8   B_lag_9  B_lag_10
0            NaN       NaN       NaN       NaN
1            NaN       NaN       NaN       NaN
2            NaN       NaN       NaN       NaN
3            NaN       NaN       NaN       NaN
4            NaN       NaN       NaN       NaN
…            …         …         …         …
26995   0.409631  0.698172  0.262350  0.447577
26996   0.500412  0.409631  0.698172  0.262350
```

```
26997  0.606806  0.500412  0.409631  0.698172
26998  1.173766  0.606806  0.500412  0.409631
26999  0.659313  1.173766  0.606806  0.500412

[27000 rows x 11 columns]
```

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

[ ]:
```
array([ 1.00000000e+00,  3.02297663e-02, -4.45598682e-02,  3.11938480e-02,
        2.59227920e-02,  2.29443159e-02, -2.72489307e-03,  2.17154085e-02,
       -5.63853223e-03,  1.61145686e-03, -7.10263111e-04])
```

Based on the auctocorrlation function (ACF) and partial autocorrelation function (PACF) above, we take every 5th observation and create a new dataset that removes some of the autocorrelation present and hopefully provides a data set that is random

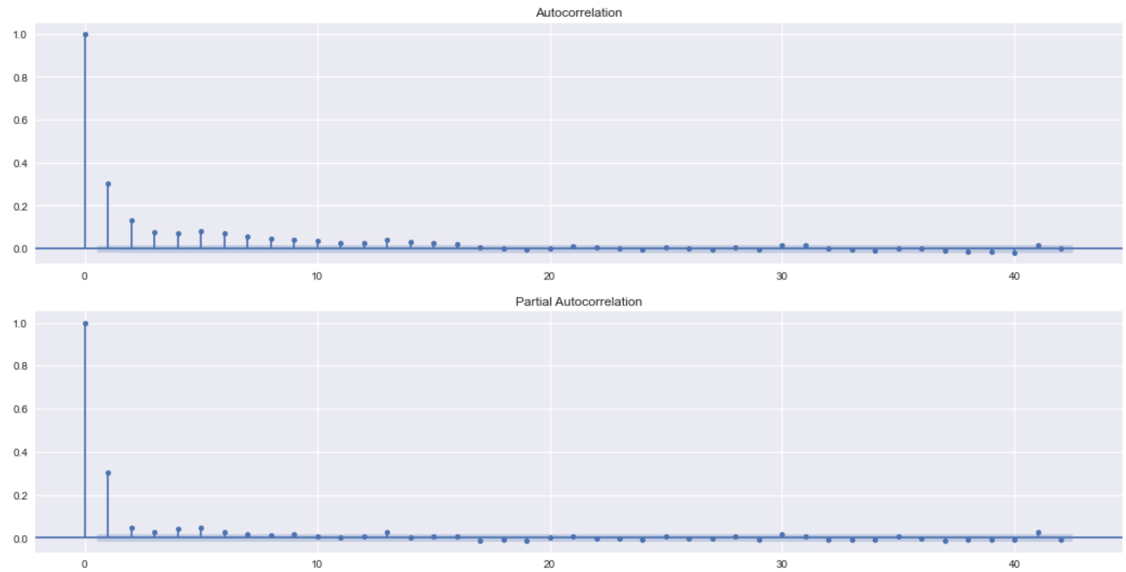
[ ]:
```
held5ths = pulsar1[pulsar1.index % 5 == 0]
```

Then creating a binary column for this new dataset

[ ]:
```
np.savetxt(r'every5thbinarypulsar1.txt', held5ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar15thsbinary = held5ths.Binary.to_list()
np.savetxt(r'allpulsar1.txt', pulsar1.Binary, fmt='%d', delimiter='')
```

Pulsar 2 (J0953+0755):

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

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

acf = plot_acf(pulsar2['Brightness'], ax=ax[0])
pacf = plot_pacf(pulsar2['Brightness'], ax=ax[1], method="ols")
```




```
[ ]: acfpulsar = pd.DataFrame()
     for lag in range(0,11):
         acfpulsar[f"B_lag_{lag}"] = pulsar2['Brightness'].shift(lag)

     acfpulsar
```

```
[ ]:        B_lag_0   B_lag_1   B_lag_2   B_lag_3   B_lag_4   B_lag_5   B_lag_6  \
     0      0.334330       NaN       NaN       NaN       NaN       NaN       NaN
     1     -0.098659  0.334330       NaN       NaN       NaN       NaN       NaN
     2      0.123514 -0.098659  0.334330       NaN       NaN       NaN       NaN
     3      0.443923  0.123514 -0.098659  0.334330       NaN       NaN       NaN
     4      1.590446  0.443923  0.123514 -0.098659  0.334330       NaN       NaN
     …          …        …        …        …        …        …        …
     14324  4.876881  5.386421  3.224787  1.953645  4.624813  0.225158  1.502603
     14325  2.074136  4.876881  5.386421  3.224787  1.953645  4.624813  0.225158
     14326  0.585504  2.074136  4.876881  5.386421  3.224787  1.953645  4.624813
     14327  0.360930  0.585504  2.074136  4.876881  5.386421  3.224787  1.953645
     14328  8.409811  0.360930  0.585504  2.074136  4.876881  5.386421  3.224787

            B_lag_7   B_lag_8   B_lag_9  B_lag_10
     0          NaN       NaN       NaN       NaN
     1          NaN       NaN       NaN       NaN
     2          NaN       NaN       NaN       NaN
     3          NaN       NaN       NaN       NaN
     4          NaN       NaN       NaN       NaN
     …          …        …        …        …
     14324  1.389349  1.592995  2.913151  0.181665
     14325  1.502603  1.389349  1.592995  2.913151
```

```
14326  0.225158  1.502603  1.389349  1.592995
14327  4.624813  0.225158  1.502603  1.389349
14328  1.953645  4.624813  0.225158  1.502603

[14329 rows x 11 columns]
```

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

```
[ ]: array([1.        , 0.30191886, 0.13272532, 0.07726788, 0.07374568,
           0.08110522, 0.07062283, 0.0556971 , 0.04374889, 0.04288793,
           0.0367024 ])
```

Based on the auctocorrlation function (ACF) and partial autocorrelation function (PACF) above, we take every 5th observation and create a new dataset that removes some of the autocorrelation present and hopefully provides a data set that is random

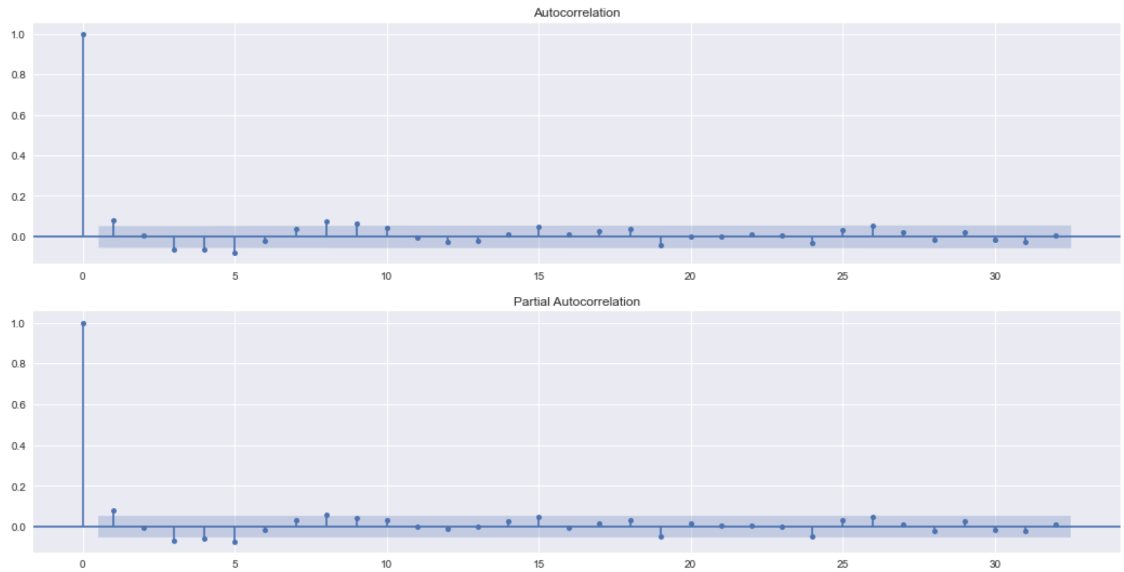
```
[ ]: held5ths = pulsar2[pulsar2.index % 5 == 0]
```

Then creating a binary column for this new dataset

```
[ ]: np.savetxt(r'every5thbinarypulsar2.txt', held5ths.Binary, fmt='%d',␣
      ↪delimiter='')
     pulsar25thsbinary = held5ths.Binary.to_list()
     np.savetxt(r'allpulsar2.txt', pulsar2.Binary, fmt='%d', delimiter='')
```

Pulsar 3 (J0835-4510):

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

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

     acf = plot_acf(pulsar3['Brightness'], ax=ax[0])
     pacf = plot_pacf(pulsar3['Brightness'], ax=ax[1], method="ols")
```



[ ]:
```python
acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar3['Brightness'].shift(lag)

acfpulsar
```

[ ]:
```
        B_lag_0   B_lag_1   B_lag_2   B_lag_3   B_lag_4   B_lag_5   B_lag_6  \
0      0.984043       NaN       NaN       NaN       NaN       NaN       NaN
1      2.487928  0.984043       NaN       NaN       NaN       NaN       NaN
2      1.690295  2.487928  0.984043       NaN       NaN       NaN       NaN
3      1.196142  1.690295  2.487928  0.984043       NaN       NaN       NaN
4      1.979783  1.196142  1.690295  2.487928  0.984043       NaN       NaN
…          …        …        …        …        …        …        …
1326   1.842016  2.646750  2.258860  2.123736  2.503202  2.178636  1.392491
1327   1.547695  1.842016  2.646750  2.258860  2.123736  2.503202  2.178636
1328   2.797312  1.547695  1.842016  2.646750  2.258860  2.123736  2.503202
1329   3.351977  2.797312  1.547695  1.842016  2.646750  2.258860  2.123736
1330   3.115255  3.351977  2.797312  1.547695  1.842016  2.646750  2.258860

        B_lag_7   B_lag_8   B_lag_9  B_lag_10
0           NaN       NaN       NaN       NaN
1           NaN       NaN       NaN       NaN
2           NaN       NaN       NaN       NaN
3           NaN       NaN       NaN       NaN
4           NaN       NaN       NaN       NaN
…          …        …        …        …
1326   1.886326  1.810641  1.943447  1.950708
1327   1.392491  1.886326  1.810641  1.943447
```

```
1328  2.178636  1.392491  1.886326  1.810641
1329  2.503202  2.178636  1.392491  1.886326
1330  2.123736  2.503202  2.178636  1.392491

[1331 rows x 11 columns]
```

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

[ ]:
```
array([ 1.        ,  0.0811623 ,  0.00414645, -0.06751767, -0.06595236,
       -0.08029629, -0.02066581,  0.0379259 ,  0.07664111,  0.06149054,
        0.04473245])
```

Based on the auctocorrlation function (ACF) and partial autocorrelation function (PACF) above, we take every 5th observation and create a new dataset that removes some of the autocorrelation present and hopefully provides a data set that is random

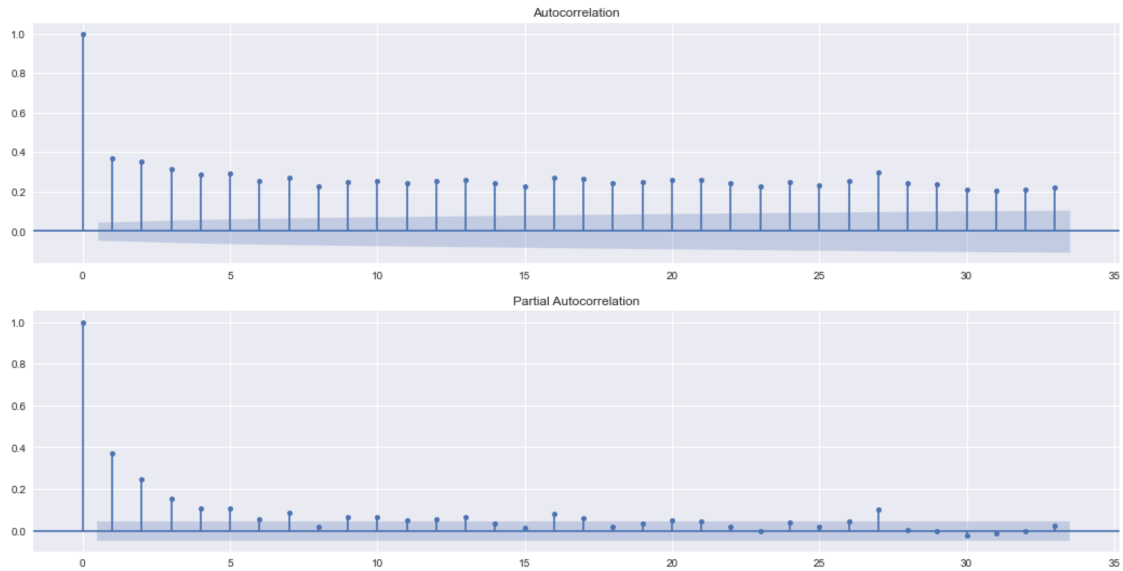
[ ]:
```
held5ths = pulsar3[pulsar3.index % 5 == 0]
```

Then creating a binary column for this new dataset

[ ]:
```
np.savetxt(r'every5thbinarypulsar3.txt', held5ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar35thsbinary = held5ths.Binary.to_list()
np.savetxt(r'allpulsar3.txt', pulsar3.Binary, fmt='%d', delimiter='')
```

Pulsar 4 (J1243-6423):

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

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

acf = plot_acf(pulsar4['Brightness'], ax=ax[0])
pacf = plot_pacf(pulsar4['Brightness'], ax=ax[1], method="ols")
```



[ ]:
```
acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar4['Brightness'].shift(lag)

acfpulsar
```

[ ]:
```
       B_lag_0   B_lag_1   B_lag_2   B_lag_3   B_lag_4   B_lag_5   B_lag_6  \
0     0.101127       NaN       NaN       NaN       NaN       NaN       NaN
1     0.012166  0.101127       NaN       NaN       NaN       NaN       NaN
2     0.021918  0.012166  0.101127       NaN       NaN       NaN       NaN
3     0.181179  0.021918  0.012166  0.101127       NaN       NaN       NaN
4     0.000240  0.181179  0.021918  0.012166  0.101127       NaN       NaN
…          …         …         …         …         …         …         …
1814  0.105178  0.008539  0.053246  0.024587  0.004085  0.000947  0.044895
1815  0.064272  0.105178  0.008539  0.053246  0.024587  0.004085  0.000947
1816  0.000171  0.064272  0.105178  0.008539  0.053246  0.024587  0.004085
1817 -0.000924  0.000171  0.064272  0.105178  0.008539  0.053246  0.024587
1818  0.000001 -0.000924  0.000171  0.064272  0.105178  0.008539  0.053246

       B_lag_7   B_lag_8   B_lag_9  B_lag_10
0          NaN       NaN       NaN       NaN
1          NaN       NaN       NaN       NaN
2          NaN       NaN       NaN       NaN
3          NaN       NaN       NaN       NaN
4          NaN       NaN       NaN       NaN
…          …         …         …         …
1814  0.007906  0.048652  0.013009  0.006294
1815  0.044895  0.007906  0.048652  0.013009
```

```
1816  0.000947  0.044895  0.007906  0.048652
1817  0.004085  0.000947  0.044895  0.007906
1818  0.024587  0.004085  0.000947  0.044895

[1819 rows x 11 columns]
```

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

[ ]:
```
array([1.        , 0.37158343, 0.35041747, 0.31258703, 0.28752434,
       0.29153195, 0.25533259, 0.27276504, 0.22759855, 0.2492633 ,
       0.25277541])
```

The autocorrelation function (ACF) above suggests that their is autocorrelation present for at least 35 lags, giving early evidence that the brightness for this particular pulsar may not be random. Looking at the partial autocorrelation function (PACF) it suggests strong partial autocorrelation exists for about 5 lags, but also shows moderate partial correlation up to about 10 lags. Hence based off the PACF, 2 more datasets are created for Pulsar 4, one with every 5th observation and one with every 10th observation.

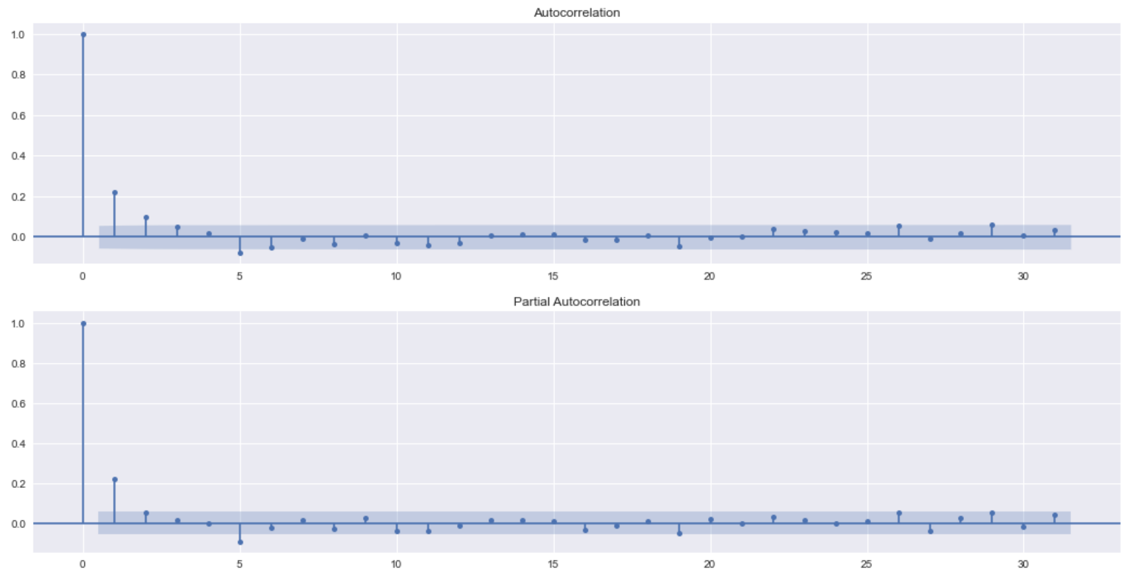
[ ]:
```
held5ths = pulsar4[pulsar4.index % 5 == 0]
held10ths = pulsar4[pulsar4.index % 10 == 0]
```

Then creating a binary column for these new datasets

[ ]:
```
np.savetxt(r'every5thbinarypulsar4.txt', held5ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar45thsbinary = held5ths.Binary.to_list()
np.savetxt(r'allpulsar4.txt', pulsar4.Binary, fmt='%d', delimiter='')
np.savetxt(r'every10thbinarypulsar4.txt', held10ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar410thsbinary = held10ths.Binary.to_list()
```

Pulsar 5 (J1456-6843):

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

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

acf = plot_acf(pulsar5['Brightness'], ax=ax[0])
pacf = plot_pacf(pulsar5['Brightness'], ax=ax[1], method="ols")
```



[ ]:
```python
acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar5['Brightness'].shift(lag)

acfpulsar
```

[ ]:
```
           B_lag_0   B_lag_1   B_lag_2   B_lag_3   B_lag_4   B_lag_5  \
0     5.390386e-02       NaN       NaN       NaN       NaN       NaN
1     5.865279e-02  0.053904       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  0.116777  0.144606
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])
```

Based on the auctocorrlation function (ACF) and partial autocorrelation function (PACF) above, we take every 5th observation and create a new dataset that removes some of the autocorrelation present and hopefully provides a data set that is random

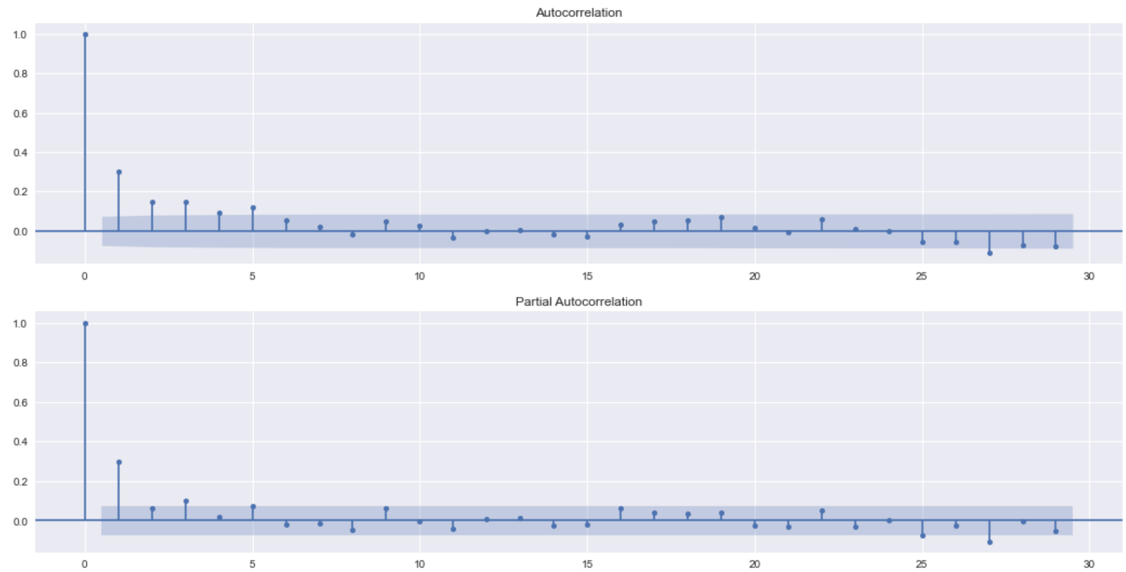
[ ]:
```
held5ths = pulsar5[pulsar5.index % 5 == 0]
```

Then creating a binary column for this new dataset

[ ]:
```
np.savetxt(r'every5thbinarypulsar5.txt', held5ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar55thsbinary = held5ths.Binary.to_list()
np.savetxt(r'allpulsar5.txt', pulsar5.Binary, fmt='%d', delimiter='')
```

Pulsar 6 (J1644-4559):

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

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

acf = plot_acf(pulsar6['Brightness'], ax=ax[0])
pacf = plot_pacf(pulsar6['Brightness'], ax=ax[1], method="ols")
```



[ ]:
```python
acfpulsar = pd.DataFrame()
for lag in range(0,11):
    acfpulsar[f"B_lag_{lag}"] = pulsar6['Brightness'].shift(lag)

acfpulsar
```

[ ]:

	B_lag_0	B_lag_1	B_lag_2	B_lag_3	B_lag_4	B_lag_5	B_lag_6 \
0	0.634671	NaN	NaN	NaN	NaN	NaN	NaN
1	0.736945	0.634671	NaN	NaN	NaN	NaN	NaN
2	0.693834	0.736945	0.634671	NaN	NaN	NaN	NaN
3	1.021866	0.693834	0.736945	0.634671	NaN	NaN	NaN
4	0.673845	1.021866	0.693834	0.736945	0.634671	NaN	NaN
..	…	…	…	…	…	…	…
693	0.776083	0.623757	0.581248	0.555266	0.152886	0.286132	0.413354
694	0.625382	0.776083	0.623757	0.581248	0.555266	0.152886	0.286132
695	0.647559	0.625382	0.776083	0.623757	0.581248	0.555266	0.152886
696	0.312449	0.647559	0.625382	0.776083	0.623757	0.581248	0.555266
697	0.548353	0.312449	0.647559	0.625382	0.776083	0.623757	0.581248

	B_lag_7	B_lag_8	B_lag_9	B_lag_10
0	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN
..	…	…	…	…
693	0.460095	0.541486	0.346502	0.239302
694	0.413354	0.460095	0.541486	0.346502

```
695  0.286132  0.413354  0.460095  0.541486
696  0.152886  0.286132  0.413354  0.460095
697  0.555266  0.152886  0.286132  0.413354

[698 rows x 11 columns]
```

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

[ ]:
```
array([ 1.        ,  0.29938402,  0.14710414,  0.15003691,  0.09455452,
        0.11800036,  0.05537751,  0.02179885, -0.01724535,  0.04863954,
        0.02621294])
```

Based on the auctocorrlation function (ACF) and partial autocorrelation function (PACF) above, we take every 5th observation and create a new dataset that removes some of the autocorrelation present and hopefully provides a data set that is random

[ ]:
```
held5ths = pulsar6[pulsar6.index % 5 == 0]
```

Then creating a binary column for this new dataset

[ ]:
```
np.savetxt(r'every5thbinarypulsar6.txt', held5ths.Binary, fmt='%d',␣
 ↪delimiter='')
pulsar65thsbinary = held5ths.Binary.to_list()
np.savetxt(r'allpulsar6.txt', pulsar6.Binary, fmt='%d', delimiter='')
```

1.0.7 RandTest and export

Running the RandTest on our 11 datasets:

[ ]:
```
import randtest

pulsar1binary = pulsar1.Binary.to_list()
pulsar2binary = pulsar2.Binary.to_list()
pulsar3binary = pulsar3.Binary.to_list()
pulsar4binary = pulsar4.Binary.to_list()
pulsar5binary = pulsar5.Binary.to_list()
pulsar6binary = pulsar6.Binary.to_list()

randtest_pulsar1 = randtest.random_score(pulsar1binary)
randtest_pulsar2 = randtest.random_score(pulsar2binary)
randtest_pulsar3 = randtest.random_score(pulsar3binary)
randtest_pulsar4 = randtest.random_score(pulsar4binary)
randtest_pulsar5 = randtest.random_score(pulsar5binary)
randtest_pulsar6 = randtest.random_score(pulsar6binary)

randtest_pulsar1_5ths = randtest.random_score(pulsar15thsbinary)
randtest_pulsar2_5ths = randtest.random_score(pulsar25thsbinary)
randtest_pulsar3_5ths = randtest.random_score(pulsar35thsbinary)
randtest_pulsar4_5ths = randtest.random_score(pulsar45thsbinary)
```

```python
randtest_pulsar5_5ths = randtest.random_score(pulsar55thsbinary)
randtest_pulsar6_5ths = randtest.random_score(pulsar65thsbinary)

randtest_pulsar4_10ths = randtest.random_score(pulsar410thsbinary)

print('\033[1m' + "Pulsar 1 RandTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar1)
print("Every 5th Observation:", randtest_pulsar1_5ths)
print("\n")

print('\033[1m' + "Pulsar 2 RantTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar2)
print("Every 5th Observation:", randtest_pulsar2_5ths)
print("\n")

print('\033[1m' + "Pulsar 3 RantTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar3)
print("Every 5th Observation:", randtest_pulsar3_5ths)
print("\n")

print('\033[1m' + "Pulsar 4 RantTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar4)
print("Every 5th Observation:", randtest_pulsar4_5ths)
print("Every 10th Observation:", randtest_pulsar4_10ths)
print("\n")

print('\033[1m' + "Pulsar 5 RantTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar5)
print("Every 5th Observation:", randtest_pulsar5_5ths)
print("\n")

print('\033[1m' + "Pulsar 6 RantTest Results:" + '\033[0m')
print("Every Observation:", randtest_pulsar6)
print("Every 5th Observation:", randtest_pulsar6_5ths)

randtestAll = [randtest_pulsar1, randtest_pulsar2, randtest_pulsar3,␣
 ↪randtest_pulsar4, randtest_pulsar5, randtest_pulsar6]
randtest5ths = [randtest_pulsar1_5ths, randtest_pulsar2_5ths,␣
 ↪randtest_pulsar3_5ths, randtest_pulsar4_5ths, randtest_pulsar5_5ths,␣
 ↪randtest_pulsar6_5ths]
randtestElse = ["Null", "Null", "Null", randtest_pulsar4_10ths, "Null", "Null"]

randTestAll = pd.Series(randtestAll)
randTest5ths = pd.Series(randtest5ths)
randTestElse = pd.Series(randtestElse)
```

```
Pulsar 1 RandTest Results:
Every Observation: True
Every 5th Observation: True


Pulsar 2 RantTest Results:
Every Observation: True
Every 5th Observation: True


Pulsar 3 RantTest Results:
Every Observation: True
Every 5th Observation: True


Pulsar 4 RantTest Results:
Every Observation: True
Every 5th Observation: True
Every 10th Observation: True


Pulsar 5 RantTest Results:
Every Observation: True
Every 5th Observation: True


Pulsar 6 RantTest Results:
Every Observation: True
Every 5th Observation: True
```

[ ]:
```
frame = {'RandTestAll' : randTestAll, 'RandTest5ths' : randTest5ths,␣
 ↪'RandTestElse' : randTestElse}
RandtestResults = pd.DataFrame(frame)
RandtestResults.to_csv('RandTestResults.csv', index=False)
```

1.0.8 NIST CSV Results Import

Importing the results of running the external NIST test suite so the result can be displayed within this report

[ ]:
```
pulsar1_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR1_Tested_All.csv")
pulsar1_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR1_Tested_5ths.csv")
pulsar2_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR2_Tested_All.csv")
pulsar2_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR2_Tested_5ths.csv")
pulsar3_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR3_Tested_All.csv")
pulsar3_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR3_Tested_5ths.csv")
pulsar4_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR4_Tested_All.csv")
pulsar4_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR4_Tested_5ths.csv")
```

```
pulsar5_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR5_Tested_All.csv")
pulsar5_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR5_Tested_5ths.csv")
pulsar4_10th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR4_Tested_10ths.
 ↪csv")
pulsar6_all = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR6_Tested_All.csv")
pulsar6_5th = pd.read_csv("pulsaryBinaryDataResultsCSV/PULSAR6_Tested_5ths.csv")
```

1.0.9 NIST Randomness Tests Results

Viewing the results of NIST test suite for each pulsar

Pulsar 1 (J0437-4715):

[ ]:
```
pulsar1_all
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	1.000000e+00	Absolute
1	Frequency Test within a Block	9.050000e-08	Non-Random
2	Run Test	3.353164e-03	Non-Random
3	Longest Run of Ones in a Block	4.782901e-02	Random
4	Binary Matrix Rank Test	1.020085e-01	Random
5	Discrete Fourier Transform (Spectral) Test	5.765222e-01	Random
6	Non-Overlapping Template Matching Test	4.860000e-07	Non-Random
7	Overlapping Template Matching Test	5.365440e-04	Non-Random
8	Maurer's Universal Statistical Test	-1.000000e+00	Error
9	Linear Complexity Test	8.177284e-01	Random
10	Serial Test A	2.420000e-19	Non-Random
11	Serial Test B	1.600000e-06	Non-Random
12	Approximate Entropy Test	1.840000e-13	Non-Random
13	Cumulative Sums (Forward) Test	6.250000e-01	Random
14	Cumulative Sums (Reverse) Test	6.250000e-01	Random
15	Random Excursions Test State -4	1.210000e-01	Random
16	Random Excursions Test State -3	3.158609e-01	Random
17	Random Excursions Test State -2	3.590000e-01	Random
18	Random Excursions Test State -1	7.280000e-01	Random
19	Random Excursions Test State +1	2.730000e-01	Random
20	Random Excursions Test State +2	1.640000e-01	Random
21	Random Excursions Test State +3	3.070000e-01	Random
22	Random Excursions Test State +4	1.160000e-01	Random
23	Random Exursions Variant Test State -9	1.503674e-01	Random
24	Random Exursions Variant Test State -8	2.508288e-01	Random
25	Random Exursions Variant Test State -7	2.850494e-01	Random
26	Random Exursions Variant Test State -6	2.685964e-01	Random
27	Random Exursions Variant Test State -5	4.008621e-01	Random
28	Random Exursions Variant Test State -4	7.261831e-01	Random
29	Random Exursions Variant Test State -3	9.471395e-01	Random
30	Random Exursions Variant Test State -2	7.808785e-01	Random
31	Random Exursions Variant Test State -1	9.114677e-01	Random

32	Random Exursions Variant Test State +1	7.110000e-01	Random
33	Random Exursions Variant Test State +2	7.320000e-01	Random
34	Random Exursions Variant Test State +3	6.430000e-01	Random
35	Random Exursions Variant Test State +4	5.100000e-01	Random
36	Random Exursions Variant Test State +5	8.140000e-01	Random
37	Random Exursions Variant Test State +6	9.820000e-01	Random
38	Random Exursions Variant Test State +7	9.340000e-01	Random
39	Random Exursions Variant Test State +8	6.670000e-01	Random
40	Random Exursions Variant Test State +9	7.260000e-01	Random

[ ]:
```
pulsar1_5th
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.096872	Random
1	Frequency Test within a Block	0.273011	Random
2	Run Test	0.295998	Random
3	Longest Run of Ones in a Block	0.143727	Random
4	Binary Matrix Rank Test	0.858290	Random
5	Discrete Fourier Transform (Spectral) Test	0.453695	Random
6	Non-Overlapping Template Matching Test	0.424735	Random
7	Overlapping Template Matching Test	0.418207	Random
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	0.757153	Random
10	Serial Test A	0.148533	Random
11	Serial Test B	0.445237	Random
12	Approximate Entropy Test	0.000145	Non-Random
13	Cumulative Sums (Forward) Test	0.072222	Random
14	Cumulative Sums (Reverse) Test	0.193743	Random
15	Random Excursions Test State -4	0.997903	Random
16	Random Excursions Test State -3	0.995330	Random
17	Random Excursions Test State -2	0.984748	Random
18	Random Excursions Test State -1	0.849145	Random
19	Random Excursions Test State +1	0.156236	Random
20	Random Excursions Test State +2	0.000354	Non-Random
21	Random Excursions Test State +3	0.000475	Non-Random
22	Random Excursions Test State +4	0.369569	Random
23	Random Exursions Variant Test State +1	0.317311	Random
24	Random Exursions Variant Test State +2	0.386476	Random
25	Random Exursions Variant Test State +3	0.013906	Random
26	Random Exursions Variant Test State +4	0.000670	Non-Random
27	Random Exursions Variant Test State +5	0.007661	Non-Random
28	Random Exursions Variant Test State +6	0.000526	Non-Random
29	Random Exursions Variant Test State +7	0.002282	Non-Random
30	Random Exursions Variant Test State +8	0.038867	Random
31	Random Exursions Variant Test State +9	0.015293	Random

Pulsar 2 (J0953+0755):

```
[ ]: pulsar2_all
```

```
[ ]:                                    Test Name       P-Value     Outcome
0                    Frequency Test (Monobit)  9.933346e-01      Random
1               Frequency Test within a Block  9.910000e-12  Non-Random
2                                    Run Test  3.200000e-94  Non-Random
3              Longest Run of Ones in a Block  3.810000e-36  Non-Random
4                      Binary Matrix Rank Test  2.570000e-01      Random
5    Discrete Fourier Transform (Spectral) Test  6.140000e-05  Non-Random
6        Non-Overlapping Template Matching Test  3.830000e-26  Non-Random
7            Overlapping Template Matching Test  4.630000e-13  Non-Random
8          Maurer's Universal Statistical Test -1.000000e+00       Error
9                     Linear Complexity Test  5.807496e-01      Random
10                               Serial Test A  2.350000e-17  Non-Random
11                               Serial Test B  9.520000e-01      Random
12                    Approximate Entropy Test  8.310000e-34  Non-Random
13              Cumulative Sums (Forward) Test  5.600000e-01      Random
14              Cumulative Sums (Reverse) Test  5.530000e-01      Random
15             Random Excursions Test State -4  2.050000e-01      Random
16             Random Excursions Test State -3  7.680000e-03  Non-Random
17             Random Excursions Test State -2  1.610000e-03  Non-Random
18             Random Excursions Test State -1  1.780000e-02      Random
19             Random Excursions Test State +1  3.980000e-01      Random
20             Random Excursions Test State +2  4.020000e-01      Random
21             Random Excursions Test State +3  1.520000e-01      Random
22             Random Excursions Test State +4  4.760000e-01      Random
23      Random Exursions Variant Test State -9  8.054226e-01      Random
24      Random Exursions Variant Test State -8  8.514120e-01      Random
25      Random Exursions Variant Test State -7  9.198637e-01      Random
26      Random Exursions Variant Test State -6  9.651054e-01      Random
27      Random Exursions Variant Test State -5  9.037602e-01      Random
28      Random Exursions Variant Test State -4  6.808479e-01      Random
29      Random Exursions Variant Test State -3  5.164123e-01      Random
30      Random Exursions Variant Test State -2  3.147768e-01      Random
31      Random Exursions Variant Test State -1  1.467931e-01      Random
32      Random Exursions Variant Test State +1  3.100000e-01      Random
33      Random Exursions Variant Test State +2  7.060000e-01      Random
34      Random Exursions Variant Test State +3  8.460000e-01      Random
35      Random Exursions Variant Test State +4  9.560000e-01      Random
36      Random Exursions Variant Test State +5  7.170000e-01      Random
37      Random Exursions Variant Test State +6  8.100000e-01      Random
38      Random Exursions Variant Test State +7  9.680000e-01      Random
39      Random Exursions Variant Test State +8  9.550000e-01      Random
40      Random Exursions Variant Test State +9  8.880000e-01      Random
```

```
[ ]: pulsar2_5th
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.736699	Random
1	Frequency Test within a Block	0.753000	Random
2	Run Test	0.018694	Random
3	Longest Run of Ones in a Block	0.092363	Random
4	Binary Matrix Rank Test	0.481248	Random
5	Discrete Fourier Transform (Spectral) Test	0.565809	Random
6	Non-Overlapping Template Matching Test	0.526000	Random
7	Overlapping Template Matching Test	0.248594	Random
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	0.543779	Random
10	Serial Test A	0.123000	Random
11	Serial Test B	0.224000	Random
12	Approximate Entropy Test	0.000025	Non-Random
13	Cumulative Sums (Forward) Test	0.604000	Random
14	Cumulative Sums (Reverse) Test	0.904000	Random
15	Random Excursions Test State -4	0.332000	Random
16	Random Excursions Test State -3	0.161000	Random
17	Random Excursions Test State -2	0.625000	Random
18	Random Excursions Test State -1	0.719000	Random
19	Random Excursions Test State +1	0.008430	Non-Random
20	Random Excursions Test State +2	0.000040	Non-Random
21	Random Excursions Test State +3	0.152000	Random
22	Random Excursions Test State +4	0.383000	Random
23	Random Exursions Variant Test State -5	0.226919	Random
24	Random Exursions Variant Test State -4	0.237548	Random
25	Random Exursions Variant Test State -3	0.263552	Random
26	Random Exursions Variant Test State -2	0.193931	Random
27	Random Exursions Variant Test State -1	0.133614	Random
28	Random Exursions Variant Test State +1	0.261000	Random
29	Random Exursions Variant Test State +2	0.516000	Random
30	Random Exursions Variant Test State +3	0.576000	Random
31	Random Exursions Variant Test State +4	0.450000	Random
32	Random Exursions Variant Test State +5	0.739000	Random
33	Random Exursions Variant Test State +6	0.792000	Random
34	Random Exursions Variant Test State +7	0.533000	Random
35	Random Exursions Variant Test State +8	0.561000	Random
36	Random Exursions Variant Test State +9	0.649000	Random

Pulsar 3 (J0835-4510):

[ ]:
```
pulsar3_all
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.978133	Random
1	Frequency Test within a Block	0.843000	Random
2	Run Test	0.051600	Random
3	Longest Run of Ones in a Block	0.206000	Random

```
4                        Binary Matrix Rank Test  0.694000  Random
5   Discrete Fourier Transform (Spectral) Test  0.655000  Random
6         Non-Overlapping Template Matching Test  0.771000  Random
7             Overlapping Template Matching Test  0.887000  Random
8          Maurer's Universal Statistical Test -1.000000   Error
9                         Linear Complexity Test  0.320837  Random
10                                 Serial Test A  0.876000  Random
11                                 Serial Test B  0.553000  Random
12                      Approximate Entropy Test  0.767000  Random
13                Cumulative Sums (Forward) Test  0.943000  Random
14                Cumulative Sums (Reverse) Test  0.926000  Random
15               Random Excursions Test State -4  0.339000  Random
16               Random Excursions Test State -3  0.590000  Random
17               Random Excursions Test State -2  0.573000  Random
18               Random Excursions Test State -1  0.590000  Random
19               Random Excursions Test State +1  0.491000  Random
20               Random Excursions Test State +2  0.565000  Random
21               Random Excursions Test State +3  0.448000  Random
22               Random Excursions Test State +4  0.643000  Random
23        Random Exursions Variant Test State -9  0.215330  Random
24        Random Exursions Variant Test State -8  0.180652  Random
25        Random Exursions Variant Test State -7  0.150421  Random
26        Random Exursions Variant Test State -6  0.174968  Random
27        Random Exursions Variant Test State -5  0.232254  Random
28        Random Exursions Variant Test State -4  0.286278  Random
29        Random Exursions Variant Test State -3  0.322716  Random
30        Random Exursions Variant Test State -2  0.332797  Random
31        Random Exursions Variant Test State -1  0.541866  Random
32        Random Exursions Variant Test State +1  0.493000  Random
33        Random Exursions Variant Test State +2  0.509000  Random
34        Random Exursions Variant Test State +3  0.759000  Random
35        Random Exursions Variant Test State +4  0.863000  Random
36        Random Exursions Variant Test State +5  0.780000  Random
37        Random Exursions Variant Test State +6  0.629000  Random
38        Random Exursions Variant Test State +7  0.410000  Random
39        Random Exursions Variant Test State +8  0.288000  Random
40        Random Exursions Variant Test State +9  0.309000  Random
```

[ ]:
```
pulsar3_5th
```

[ ]:
```
                                     Test Name   P-Value     Outcome
0                     Frequency Test (Monobit)  0.951201      Random
1                Frequency Test within a Block  0.925000      Random
2                                     Run Test  0.126000      Random
3               Longest Run of Ones in a Block  0.957000      Random
4                      Binary Matrix Rank Test -1.000000       Error
5   Discrete Fourier Transform (Spectral) Test  0.003660  Non-Random
```

6	Non-Overlapping Template Matching Test	1.000000	Random
7	Overlapping Template Matching Test	-1.000000	Error
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	-1.000000	Error
10	Serial Test A	0.499000	Random
11	Serial Test B	0.499000	Random
12	Approximate Entropy Test	1.000000	Absolute
13	Cumulative Sums (Forward) Test	0.763000	Random
14	Cumulative Sums (Reverse) Test	0.705000	Random
15	Random Excursions Test State -4	0.886000	Random
16	Random Excursions Test State -3	0.347000	Random
17	Random Excursions Test State -2	0.735000	Random
18	Random Excursions Test State -1	0.700000	Random
19	Random Excursions Test State +1	0.659000	Random
20	Random Excursions Test State +2	0.258000	Random
21	Random Excursions Test State +3	0.018600	Random
22	Random Excursions Test State +4	0.783000	Random
23	Random Exursions Variant Test State -9	0.490920	Random
24	Random Exursions Variant Test State -8	0.463355	Random
25	Random Exursions Variant Test State -7	0.410205	Random
26	Random Exursions Variant Test State -6	0.413686	Random
27	Random Exursions Variant Test State -5	0.438578	Random
28	Random Exursions Variant Test State -4	0.406813	Random
29	Random Exursions Variant Test State -3	0.603332	Random
30	Random Exursions Variant Test State -2	0.765594	Random
31	Random Exursions Variant Test State -1	0.605577	Random
32	Random Exursions Variant Test State +1	0.699000	Random
33	Random Exursions Variant Test State +2	0.502000	Random
34	Random Exursions Variant Test State +3	0.326000	Random
35	Random Exursions Variant Test State +4	0.262000	Random
36	Random Exursions Variant Test State +5	0.263000	Random
37	Random Exursions Variant Test State +6	0.259000	Random
38	NaN	NaN	NaN
39	NaN	NaN	NaN
40	NaN	NaN	NaN

Pulsar 4 (J1243-6423):

[ ]:
```
pulsar4_all
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	9.812939e-01	Random
1	Frequency Test within a Block	3.910000e-53	Non-Random
2	Run Test	3.420000e-21	Non-Random
3	Longest Run of Ones in a Block	3.930000e-08	Non-Random
4	Binary Matrix Rank Test	6.940000e-01	Random
5	Discrete Fourier Transform (Spectral) Test	1.820000e-02	Random
6	Non-Overlapping Template Matching Test	7.120000e-02	Random

```
7           Overlapping Template Matching Test  2.960000e-01      Random
8         Maurer's Universal Statistical Test -1.000000e+00       Error
9                      Linear Complexity Test  4.620000e-01      Random
10                              Serial Test A  0.000000e+00  Non-Random
11                              Serial Test B  0.000000e+00  Non-Random
12                    Approximate Entropy Test  2.100000e-12  Non-Random
13               Cumulative Sums (Forward) Test  1.040000e-09  Non-Random
14               Cumulative Sums (Reverse) Test  8.930000e-10  Non-Random
15              Random Excursions Test State -4  9.730000e-01      Random
16              Random Excursions Test State -3  9.450000e-01      Random
17              Random Excursions Test State -2  8.490000e-01      Random
18              Random Excursions Test State -1  3.060000e-01      Random
19              Random Excursions Test State +1  9.310000e-01      Random
20              Random Excursions Test State +2  5.080000e-01      Random
21              Random Excursions Test State +3  1.770000e-01      Random
22              Random Excursions Test State +4  1.180000e-02      Random
23      Random Exursions Variant Test State -1  5.637029e-01      Random
24      Random Exursions Variant Test State +1  3.860000e-01      Random
25      Random Exursions Variant Test State +2  6.170000e-01      Random
26      Random Exursions Variant Test State +3  6.990000e-01      Random
27      Random Exursions Variant Test State +4  8.270000e-01      Random
28      Random Exursions Variant Test State +5  8.470000e-01      Random
29      Random Exursions Variant Test State +6  7.280000e-01      Random
30      Random Exursions Variant Test State +7  8.100000e-01      Random
31      Random Exursions Variant Test State +8  8.810000e-01      Random
32      Random Exursions Variant Test State +9  8.340000e-01      Random
```

[ ]:
```
pulsar4_5th
```

[ ]:
```
                                    Test Name       P-Value     Outcome
0                   Frequency Test (Monobit)  8.339354e-01      Random
1               Frequency Test within a Block  3.340000e-03  Non-Random
2                                    Run Test  3.350000e-03  Non-Random
3               Longest Run of Ones in a Block  4.350000e-01      Random
4                      Binary Matrix Rank Test -1.000000e+00       Error
5   Discrete Fourier Transform (Spectral) Test  3.120000e-01      Random
6       Non-Overlapping Template Matching Test  1.000000e+00    Absolute
7           Overlapping Template Matching Test -1.000000e+00       Error
8         Maurer's Universal Statistical Test -1.000000e+00       Error
9                      Linear Complexity Test -1.000000e+00       Error
10                              Serial Test A  0.000000e+00  Non-Random
11                              Serial Test B  0.000000e+00  Non-Random
12                    Approximate Entropy Test  1.000000e+00    Absolute
13               Cumulative Sums (Forward) Test  3.970000e-03  Non-Random
14               Cumulative Sums (Reverse) Test  7.880000e-03  Non-Random
15              Random Excursions Test State -4  9.980000e-01      Random
16              Random Excursions Test State -3  9.950000e-01      Random
```

17	Random Excursions Test State -2	9.850000e-01	Random
18	Random Excursions Test State -1	8.490000e-01	Random
19	Random Excursions Test State +1	6.840000e-03	Non-Random
20	Random Excursions Test State +2	2.980000e-04	Non-Random
21	Random Excursions Test State +3	3.550000e-04	Non-Random
22	Random Excursions Test State +4	1.220000e-04	Non-Random
23	Random Exursions Variant Test State +1	1.240000e-02	Random
24	Random Exursions Variant Test State +2	1.490000e-05	Non-Random
25	Random Exursions Variant Test State +3	2.700000e-07	Non-Random
26	Random Exursions Variant Test State +4	1.570000e-04	Non-Random
27	Random Exursions Variant Test State +5	6.680000e-02	Random
28	Random Exursions Variant Test State +6	1.320000e-01	Random
29	Random Exursions Variant Test State +7	3.750000e-02	Random
30	Random Exursions Variant Test State +8	5.280000e-02	Random
31	Random Exursions Variant Test State +9	2.750000e-01	Random

[ ]:
```
pulsar4_10th
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.656501	Random
1	Frequency Test within a Block	0.021600	Random
2	Run Test	0.001920	Non-Random
3	Longest Run of Ones in a Block	0.326000	Random
4	Binary Matrix Rank Test	-1.000000	Error
5	Discrete Fourier Transform (Spectral) Test	0.760000	Random
6	Non-Overlapping Template Matching Test	1.000000	Absolute
7	Overlapping Template Matching Test	-1.000000	Error
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	-1.000000	Error
10	Serial Test A	0.000000	Non-Random
11	Serial Test B	0.000000	Non-Random
12	Approximate Entropy Test	1.000000	Absolute
13	Cumulative Sums (Forward) Test	0.023500	Random
14	Cumulative Sums (Reverse) Test	0.075900	Random
15	Random Excursions Test State -4	0.905000	Random
16	Random Excursions Test State -3	0.324000	Random
17	Random Excursions Test State -2	0.768000	Random
18	Random Excursions Test State -1	0.394000	Random
19	Random Excursions Test State +1	0.836000	Random
20	Random Excursions Test State +2	0.481000	Random
21	Random Excursions Test State +3	0.331000	Random
22	Random Excursions Test State +4	0.067000	Random
23	Random Exursions Variant Test State -3	0.504501	Random
24	Random Exursions Variant Test State -2	0.711923	Random
25	Random Exursions Variant Test State -1	0.831170	Random
26	Random Exursions Variant Test State +1	1.000000	Absolute
27	Random Exursions Variant Test State +2	0.902000	Random

28	Random Exursions Variant Test State +3	0.924000	Random
29	Random Exursions Variant Test State +4	0.872000	Random
30	Random Exursions Variant Test State +5	0.570000	Random
31	Random Exursions Variant Test State +6	0.563000	Random
32	Random Exursions Variant Test State +7	0.636000	Random
33	Random Exursions Variant Test State +8	0.741000	Random
34	Random Exursions Variant Test State +9	0.796000	Random

Pulsar 5 (J1456-6843):

[ ]:
```
pulsar5_all
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.977150	Random
1	Frequency Test within a Block	0.039800	Random
2	Run Test	0.000020	Non-Random
3	Longest Run of Ones in a Block	0.085500	Random
4	Binary Matrix Rank Test	0.694000	Random
5	Discrete Fourier Transform (Spectral) Test	0.064800	Random
6	Non-Overlapping Template Matching Test	0.032300	Random
7	Overlapping Template Matching Test	0.296000	Random
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	0.029600	Random
10	Serial Test A	0.853000	Random
11	Serial Test B	0.963000	Random
12	Approximate Entropy Test	0.956000	Random
13	Cumulative Sums (Forward) Test	0.761000	Random
14	Cumulative Sums (Reverse) Test	0.761000	Random
15	Random Excursions Test State -4	0.000254	Non-Random
16	Random Excursions Test State -3	0.019100	Random
17	Random Excursions Test State -2	0.162000	Random
18	Random Excursions Test State -1	0.067300	Random
19	Random Excursions Test State +1	0.941000	Random
20	Random Excursions Test State +2	0.951000	Random
21	Random Excursions Test State +3	0.155000	Random
22	Random Excursions Test State +4	0.027100	Random
23	Random Exursions Variant Test State -9	0.867859	Random
24	Random Exursions Variant Test State -8	0.790482	Random
25	Random Exursions Variant Test State -7	0.668588	Random
26	Random Exursions Variant Test State -6	0.569494	Random
27	Random Exursions Variant Test State -5	0.331137	Random
28	Random Exursions Variant Test State -4	0.194835	Random
29	Random Exursions Variant Test State -3	0.145052	Random
30	Random Exursions Variant Test State -2	0.092327	Random
31	Random Exursions Variant Test State -1	0.229949	Random
32	Random Exursions Variant Test State +1	0.170000	Random
33	Random Exursions Variant Test State +2	0.166000	Random
34	Random Exursions Variant Test State +3	0.645000	Random

```
35      Random Exursions Variant Test State +4  1.000000    Absolute
36      Random Exursions Variant Test State +5  0.775000      Random
37      Random Exursions Variant Test State +6  0.642000      Random
38      Random Exursions Variant Test State +7  0.812000      Random
39      Random Exursions Variant Test State +8  0.965000      Random
40      Random Exursions Variant Test State +9  0.835000      Random
```

[ ]:
```
pulsar5_5th
```

[ ]:

	Test Name	P-Value	Outcome
0	Frequency Test (Monobit)	0.898120	Random
1	Frequency Test within a Block	0.860000	Random
2	Run Test	0.095800	Random
3	Longest Run of Ones in a Block	0.693000	Random
4	Binary Matrix Rank Test	-1.000000	Error
5	Discrete Fourier Transform (Spectral) Test	0.217000	Random
6	Non-Overlapping Template Matching Test	1.000000	Absolute
7	Overlapping Template Matching Test	-1.000000	Error
8	Maurer's Universal Statistical Test	-1.000000	Error
9	Linear Complexity Test	-1.000000	Error
10	Serial Test A	0.853000	Random
11	Serial Test B	0.932000	Random
12	Approximate Entropy Test	1.000000	Absolute
13	Cumulative Sums (Forward) Test	0.894000	Random
14	Cumulative Sums (Reverse) Test	0.786000	Random
15	Random Excursions Test State -4	0.728000	Random
16	Random Excursions Test State -3	0.900000	Random
17	Random Excursions Test State -2	0.755000	Random
18	Random Excursions Test State -1	0.968000	Random
19	Random Excursions Test State +1	0.383000	Random
20	Random Excursions Test State +2	0.542000	Random
21	Random Excursions Test State +3	0.568000	Random
22	Random Excursions Test State +4	0.796000	Random
23	Random Exursions Variant Test State -9	0.638822	Random
24	Random Exursions Variant Test State -8	8.415830	Random
25	Random Exursions Variant Test State -7	0.382103	Random
26	Random Exursions Variant Test State -6	0.500924	Random
27	Random Exursions Variant Test State -5	0.630192	Random
28	Random Exursions Variant Test State -4	0.655119	Random
29	Random Exursions Variant Test State -3	0.597154	Random
30	Random Exursions Variant Test State -2	0.820090	Random
31	Random Exursions Variant Test State -1	0.599426	Random
32	Random Exursions Variant Test State +1	0.237000	Random
33	Random Exursions Variant Test State +2	0.225000	Random
34	Random Exursions Variant Test State +3	0.159000	Random
35	Random Exursions Variant Test State +4	0.234000	Random
36	Random Exursions Variant Test State +5	0.294000	Random

```
37      Random Exursions Variant Test State +6  0.285000    Random
38      Random Exursions Variant Test State +7  0.382000    Random
39      Random Exursions Variant Test State +8  0.416000    Random
40      Random Exursions Variant Test State +9  0.390000    Random
```

Pulsar 6 (J1644-4559):

[ ]:
```
pulsar6_all
```

[ ]:
```
                                      Test Name   P-Value     Outcome
0                      Frequency Test (Monobit)  1.000000    Absolute
1                 Frequency Test within a Block  0.836000      Random
2                                      Run Test  0.000011  Non-Random
3                Longest Run of Ones in a Block  0.000178  Non-Random
4                       Binary Matrix Rank Test -1.000000       Error
5   Discrete Fourier Transform (Spectral) Test  0.218000      Random
6       Non-Overlapping Template Matching Test  0.087500      Random
7           Overlapping Template Matching Test -1.000000       Error
8          Maurer's Universal Statistical Test -1.000000       Error
9                        Linear Complexity Test -1.000000       Error
10                                Serial Test A  0.356000      Random
11                                Serial Test B  0.697000      Random
12                     Approximate Entropy Test  1.000000    Absolute
13               Cumulative Sums (Forward) Test  0.679000      Random
14               Cumulative Sums (Reverse) Test  0.679000      Random
15              Random Excursions Test State -4  0.196000      Random
16              Random Excursions Test State -3  0.398000      Random
17              Random Excursions Test State -2  0.760000      Random
18              Random Excursions Test State -1  0.845000      Random
19              Random Excursions Test State +1  0.272000      Random
20              Random Excursions Test State +2  0.135000      Random
21              Random Excursions Test State +3  0.076700      Random
22              Random Excursions Test State +4  0.002160  Non-Random
23      Random Exursions Variant Test State -9  0.324324      Random
24      Random Exursions Variant Test State -8  0.338728      Random
25      Random Exursions Variant Test State -7  0.388747      Random
26      Random Exursions Variant Test State -6  0.449177      Random
27      Random Exursions Variant Test State -5  0.449063      Random
28      Random Exursions Variant Test State -4  0.366256      Random
29      Random Exursions Variant Test State -3  0.335979      Random
30      Random Exursions Variant Test State -2  0.407626      Random
31      Random Exursions Variant Test State -1  0.719918      Random
32      Random Exursions Variant Test State +1  0.720000      Random
33      Random Exursions Variant Test State +2  0.730000      Random
34      Random Exursions Variant Test State +3  0.364000      Random
35      Random Exursions Variant Test State +4  0.442000      Random
36      Random Exursions Variant Test State +5  0.605000      Random
37      Random Exursions Variant Test State +6  0.719000      Random
```

```
38      Random Exursions Variant Test State +7  0.947000      Random
39      Random Exursions Variant Test State +8  0.975000      Random
40      Random Exursions Variant Test State +9  0.908000      Random
```

[ ]:
```
pulsar6_5th
```

[ ]:
```
                                    Test Name   P-Value   Outcome
0                    Frequency Test (Monobit)  0.498962    Random
1                Frequency Test within a Block  0.596000    Random
2                                     Run Test  0.835000    Random
3                Longest Run of Ones in a Block  0.833000    Random
4                      Binary Matrix Rank Test -1.000000     Error
5    Discrete Fourier Transform (Spectral) Test  0.698000    Random
6       Non-Overlapping Template Matching Test  1.000000    Random
7           Overlapping Template Matching Test -1.000000     Error
8          Maurer's Universal Statistical Test -1.000000     Error
9                      Linear Complexity Test -1.000000     Error
10                               Serial Test A  0.499000    Random
11                               Serial Test B  0.098400    Random
12                     Approximate Entropy Test  1.000000  Absolute
13               Cumulative Sums (Forward) Test  0.473000    Random
14               Cumulative Sums (Reverse) Test  0.849000    Random
15              Random Excursions Test State -4  0.431000    Random
16              Random Excursions Test State -3  0.494000    Random
17              Random Excursions Test State -2  0.221000    Random
18              Random Excursions Test State -1  0.149000    Random
19              Random Excursions Test State +1  0.570000    Random
20              Random Excursions Test State +2  0.801000    Random
21              Random Excursions Test State +3  0.924000    Random
22              Random Excursions Test State +4  0.963000    Random
23      Random Exursions Variant Test State -9  0.845815    Random
24      Random Exursions Variant Test State -8  0.944984    Random
25      Random Exursions Variant Test State -7  0.766848    Random
26      Random Exursions Variant Test State -6  0.808976    Random
27      Random Exursions Variant Test State -5  0.929013    Random
28      Random Exursions Variant Test State -4  0.613505    Random
29      Random Exursions Variant Test State -3  0.473289    Random
30      Random Exursions Variant Test State -2  0.643429    Random
31      Random Exursions Variant Test State -1  0.422678    Random
32      Random Exursions Variant Test State +1  0.109000    Random
```

[ ]:
```
# Code for results table
index = pd.MultiIndex.from_product([['Pulsar 1', 'Pulsar 2', 'Pulsar 3',␣
 ↪'Pulsar 4', 'Pulsar 5', 'Pulsar 6']])
columns = ['Every Observation','Every 5th Observation', "Every 10th␣
 ↪Observation"]
data = [["Not Random", "Random", "N/A"],
```

```
        ["Not Random", "Random", "N/A"],
        ["Random", "Random", "N/A"],
        ["Not Random", "Not Random", "Random"],
        ["Random", "Random", "N/A"],
        ["Not Random", "Random", "N/A"]]
all_df = pd.DataFrame(data, index=index, columns=columns)
def highlight_cells(s):

    if s == 'Random':
        color = '#71b06b' # green
    elif s == 'Not Random':
        color = '#cf7672' # red
    else:
        color = '#999999' # grey
    return 'background-color: % s' % color
```

1.1 Conclusion

To determine the randomness in pulsar emissions, the data collected by the CSIRO from the Parkes Observatory was explored, and then manipulated into binary sequences based on each pulsar's median. Furthermore, the autocorrelation function (ACF) was analysed for each pulsar to determine if there was any autocorrelation in the brightness that would effect the randomness of the observations. To remove this autocorrelaton, and hopefully achieve more random data, more datasets were created with every nth observation, where n was adjusted based on findings from the ACF. These sequences were then run through the NIST statistical suite as well as RandTest to determine whether they were truly random.

The results of these randomness tests have been studied and an overall determination of the randomness of each dataset on each of the 6 pulsars has been outlined below.

```
[ ]: display(all_df.style.applymap(highlight_cells))
```

```
<pandas.io.formats.style.Styler at 0x24d8cfdda90>
```

It can be observed that for the tests performed on all observations, only Pulsar 3 and Pulsar 5 were deemed to be random. In comparison, Pulsar 1, 2, 3, 5, and 6 were determined to be random when taking every 5th observation, with Pulsar 4 still being non-random. However, when taking every 10th observation for Pulsar 4, we do see a sequence that can be considered random. Hence, by finding the appropriate time scale correlation for each pulsar, we were able to produce a sequence that is random.

This investigation focuses on utilising the measure of pulsar emission intensities to generate random number sequences that can be used for cryptographic, commercial, and defence purposes. Through this study, it has been found that the given pulsars do pass statistical randomness testing when accounting for their correlation scale, and therefore, may provide an unbiased source for random number generation.

```
[ ]:
```