# final-project

December 19, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# loading dataset
data = pd.read_csv("C:/Users/brend/OneDrive/Documents/College/STAT 436/Final␣
↪Project/NCAA Champs Data.csv")
# check that it loaded properly
data.head()
```

[1]:

| | Year | SS | Time | Last Lap |
|---|---|---|---|---|
| 0 | 2017 | 0 | 875.60 | 55.76 |
| 1 | 2017 | 0 | 875.88 | 56.19 |
| 2 | 2017 | 0 | 876.23 | 56.41 |
| 3 | 2017 | 0 | 876.57 | 56.31 |
| 4 | 2017 | 0 | 876.78 | 56.69 |

[2]:
```
data.tail()
```

[2]:

| | Year | SS | Time | Last Lap |
|---|---|---|---|---|
| 137 | 2023 | 1 | 868.89 | 65.75 |
| 138 | 2023 | 1 | 870.36 | 64.12 |
| 139 | 2023 | 1 | 877.57 | 70.46 |
| 140 | 2023 | 1 | 885.44 | 68.64 |
| 141 | 2023 | 1 | 889.31 | 71.26 |

[3]:
```
print(data.shape)
# the dataset has 141 entries with 4 features
# each entry is an athlete
# features: Year (the year the athlete competed)
# SS: indicator variable; 0 means the event took place before the release of␣
↪super spikes, 1 means after
# Time: each competitor's time for 5000 meters in seconds
# Last Lap: competitor's time (sec) for the last 400m of the race
```

```
(142, 4)
```

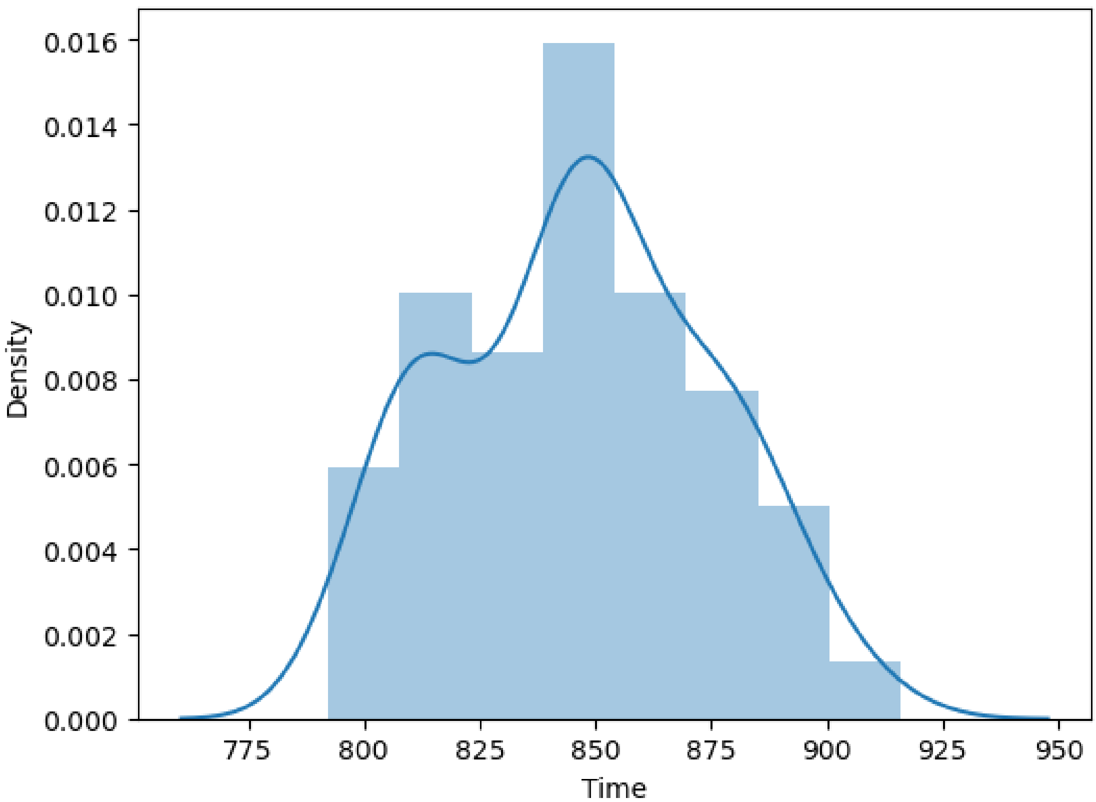
[4]:
```python
print(data.describe())
# the meaningful categories here are time and last lap; the others are labels
# the data is slightly left-skewed (mean < median)
# mean time is 846.74 seconds, or 14:06.74 with standard deviation 28.52 seconds
# median is 848.02 seconds, or 14:08.02
# mean last lap is 61.59 seconds with standard deviation 5.24
```

```
              Year          SS        Time    Last Lap
count   142.000000  142.00000  142.000000  142.000000
mean   2019.985915    0.50000  846.744366   61.586972
std       2.166757    0.50177   28.516079    5.240296
min    2017.000000    0.00000  792.270000   52.910000
25%    2018.000000    0.00000  824.782500   57.635000
50%    2020.000000    0.50000  848.020000   60.925000
75%    2022.000000    1.00000  867.620000   64.487500
max    2023.000000    1.00000  916.000000   75.720000
```

[5]:
```python
# plot the distribution of times run
sns.distplot(data['Time'], kde = True, hist = 1)
# the plot is somewhat symmetrical
# peak is around 850 (14:10), with a smaller peak around 820 (13:40)
```

```
C:\Users\brend\AppData\Local\Temp\ipykernel_1548\3143065218.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data['Time'], kde = True, hist = 1)
```

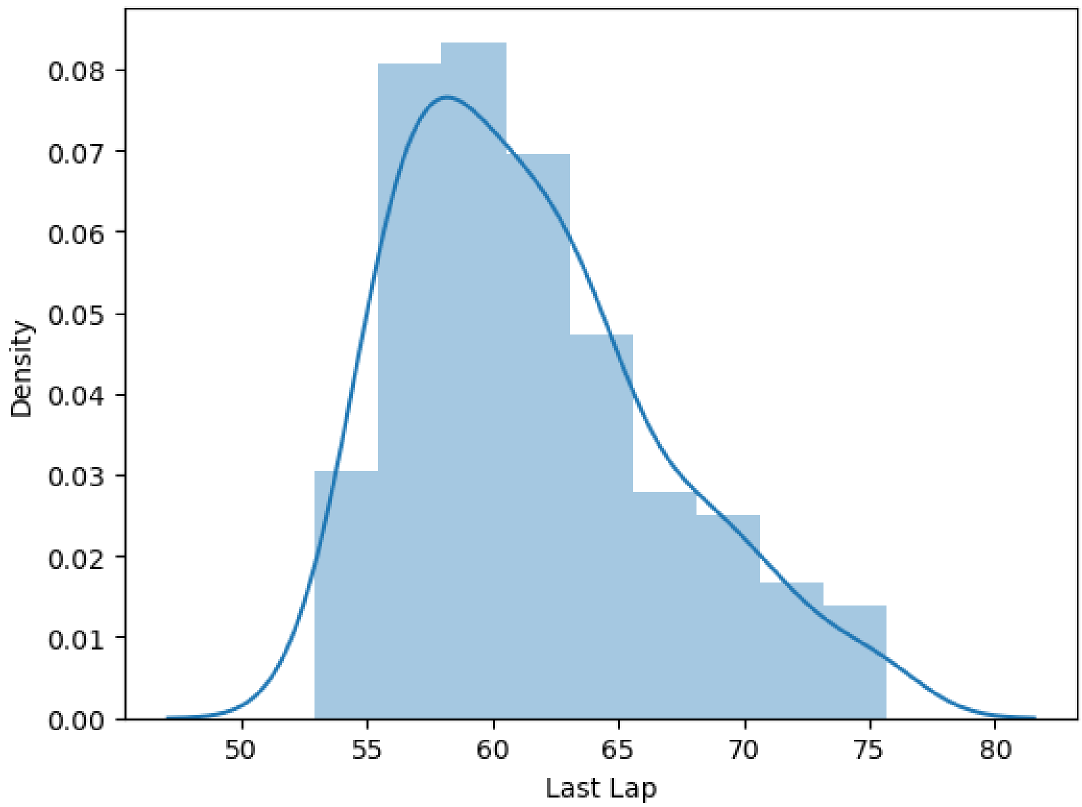
[5]: <Axes: xlabel='Time', ylabel='Density'>




[6]:
```
sns.distplot(data['Last Lap'], kde = True, hist = 1)
# the last lap is right-skewed with a peak around 58 seconds
```

```
C:\Users\brend\AppData\Local\Temp\ipykernel_1548\43024727.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data['Last Lap'], kde = True, hist = 1)
```

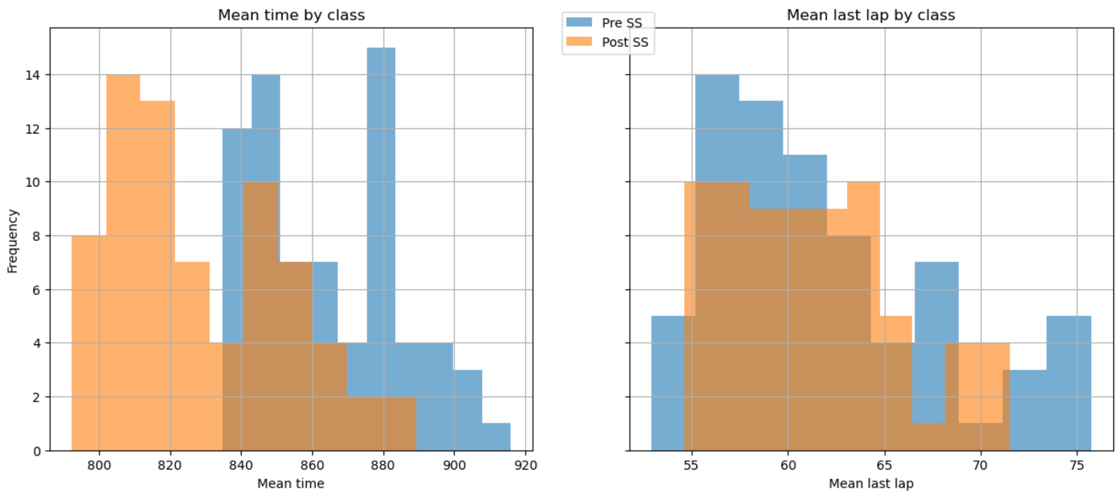
[6]: <Axes: xlabel='Last Lap', ylabel='Density'>




[7]:
```
features = data.drop('Year', axis=1)
x = features.drop('SS', axis=1) # dropping labels to leave only predictive␣
 ↪features in x
y = data['SS']
```

[8]:
```
# plotting histograms of time and last lap separated by pre/post SS
fig1,ax=plt.subplots(nrows=1,ncols=2,figsize=(15,6),sharey=True)
grouped_data=data.groupby("SS")
grouped_data['Time'].hist(alpha=0.6,ax=ax[0])
grouped_data['Last Lap'].hist(alpha=0.6,ax=ax[1])
ax[0].set_title("Mean time by class")
ax[0].set_xlabel("Mean time")
ax[0].set_ylabel("Frequency")
ax[1].set_title("Mean last lap by class")
ax[1].set_xlabel("Mean last lap")
fig1.legend(["Pre SS","Post SS"],bbox_to_anchor=(0.57,0.92))
# lots of overlap in last lap, but total times are noticeably faster post SS
```

[8]:
```
<matplotlib.legend.Legend at 0x2b371d1ab10>
```




[9]:
```
# fitting a k-NN model using cross-validation to find optimal k
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
k_range = list(range(1, 11)) # total dataset is only 141, so k shouldn't be too␣
↪large
k_scores = []
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors = k)
    scores = cross_val_score(knn, x, y, cv=10, scoring='accuracy') # cv=10␣
↪means 10 folds, so 90% train and 10% test each
    k_scores.append(scores.mean())
print(k_scores)
# best score (0.85) is with 2-NN
```

```
[0.7928571428571429, 0.85, 0.8142857142857143, 0.8142857142857143,
0.7642857142857143, 0.8, 0.7714285714285714, 0.7928571428571429,
0.7714285714285716, 0.7785714285714286]
```

[10]:
```
# separate into training and testing dataset
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.1,␣
↪random_state = 10, shuffle = True)
```

[11]:
```
# using the training set for k-NN with 2-NN (2 selected as best k)
knn_model = KNeighborsClassifier(n_neighbors=2)
knn_model.fit(x_train, y_train)
```

[11]:
```
KNeighborsClassifier(n_neighbors=2)
```

[12]:
```python
# testing the 2-NN model
y_pred = knn_model.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_pred)
```

[12]: 0.9333333333333333

[13]:
```python
# fitting a Perceptron model
from sklearn.linear_model import Perceptron
per_model1 = Perceptron(max_iter=500)
per_model1.fit(x_train, y_train)
per_model2 = Perceptron(max_iter=1000)
per_model2.fit(x_train, y_train)
per_model3 = Perceptron(max_iter=10000)
per_model3.fit(x_train, y_train)
```

[13]: Perceptron(max_iter=10000)

[14]:
```python
# testing the Perceptron models
per_scores = []
y_pred = per_model1.predict(x_test)
per_scores.append(accuracy_score(y_test, y_pred))
y_pred = per_model2.predict(x_test)
per_scores.append(accuracy_score(y_test, y_pred))
y_pred = per_model3.predict(x_test)
per_scores.append(accuracy_score(y_test, y_pred))
per_scores
# the model does not improve with more iterations
```

[14]: [0.5333333333333333, 0.5333333333333333, 0.5333333333333333]

[15]:
```python
# fitting a Naive Bayes model
from sklearn.naive_bayes import GaussianNB
gnb_model = GaussianNB()
gnb_model.fit(x_train, y_train)
```

[15]: GaussianNB()

[16]:
```python
# checking parameters of fitted NB model
print("Means:", gnb_model.theta_)
# the pre-ss era has means 863.998 (14:23.998) and 62.027
# the post-ss era has means 830.475 (13:50.475) and 61.416
print("Variances:", gnb_model.var_)
# the pre-ss era has standard deviations 20.992 and 7.837
# the post-ss era has standard deviations 24.513 and 4.553
```

```
Means: [[863.9978125   62.026875  ]
 [830.47460317  61.41587302]]
```

```
Variances: [[440.67799602  36.21404104]
 [600.88861612  20.73022504]]
```

[17]:
```python
# evaluating the Gaussian NB model on the training set
y_train_pred = gnb_model.predict(x_train)
accuracy_score(y_train, y_train_pred)
# not that accurate, only 74.02%
```

[17]:
```
0.7401574803149606
```

[18]:
```python
# evaluating the Gaussian NB model on the test set
y_pred = gnb_model.predict(x_test)
accuracy_score(y_test, y_pred)
# performs much better on the test set- 86.67%
# model is not overfitting; performs better in testing than training
```

[18]:
```
0.8666666666666667
```

[19]:
```python
# fitting a logistic regression model
from sklearn.linear_model import LogisticRegression
lr_model = LogisticRegression()
lr_model.fit(x_train, y_train)
```

[19]:
```
LogisticRegression()
```

[20]:
```python
# evaluating the Logistic Regression model on the training set
y_train_pred = lr_model.predict(x_train)
accuracy_score(y_train, y_train_pred)
# not that accurate, only 66.93%
```

[20]:
```
0.6692913385826772
```

[21]:
```python
# evaluating the Logistic Regression model on the test set
y_pred = lr_model.predict(x_test)
accuracy_score(y_test, y_pred)
# performs much better on the test set- 86.67%
# model is not overfitting; performs better in testing than training
# performs the same as Naive Bayes
```

[21]:
```
0.8666666666666667
```

[22]:
```python
# ranking the models
# 1. k-NN with k=2: accuracy = 0.933333
# 2. Gaussian NB and Logistic Regression: accuracy = 0.866667
# 4. Perceptron: accuracy = 0.533333
# the models, apart from perceptron, do a good job distinguishing between pre␣
↪and post ss times
```

```
# this hints at super spikes improving runners' performance at the NCAA␣
↪Championships
```

[23]:
```
# presentation feedback: setting k as an even number allows for ties
# try an odd number to prevent this
# based on cross-validation from earlier, best odd k is 3 (accuracy 0.814)
knn_oddmodel = KNeighborsClassifier(n_neighbors=3)
knn_oddmodel.fit(x_train, y_train)
```

[23]:
```
KNeighborsClassifier(n_neighbors=3)
```

[24]:
```
# testing the 3-NN model
y_pred2 = knn_oddmodel.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_pred)
```

[24]:
```
0.8666666666666667
```