Marathon

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```
"""
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CLASS: ISTA 421 - Machine Learning
DESCRIPTION: This file contains all of the code for a machine learning model
developed for marathon runners. This file includes every step of the process,
from the problem statement to conclusions.
"""
```

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1. Problem Formulation and Significance

Problem Statement:

The Boston Marathon is one of the most prestigious marathons in the world, but marathon runners as a whole may fail to realize the significance of using machine learning methods to improve their times.

Significance:

Using data from a previous year, we can identify patterns and predictors of better times that could be used in helping future runners achieve faster runs.

Dataset Description:

The data was collected from 2015, and contains 26,598 rows and 25 columns. The columns include split times every 5K, demographics such as age and gender, and overall/gender finish time. All 26,598 rows represent a runner who finished the race.

2. Exploratory Data Analysis

Data Exploration

```
import pandas as pd
import numpy as np
```

```
# Read in data, sometimes "-" is used instead of NA
marathon = pd.read_csv("marathon_results_2015.csv", na_values=["-"])
```

I noticed that a lot of columns didn't use NA values, but instead used "-" to show empty values.

```
print("Shape: ", marathon.shape)
#print("Data Types for each column: ",marathon.dtypes)
#print("NA counts: \n", marathon.isnull().sum())
```

```
Shape:  (26598, 25)
```

```
def time_to_sec(time):
  if pd.isna(time):
    return np.nan
  else:
    time = str(time)
    lst = time.split(":")
    return int(lst[0])*3600 + int(lst[1])*60 + int(lst[2])

time_cols = ['5K', '10K', '15K', '20K', 'Half', '25K',
             '30K', '35K', '40K', 'Official Time']

for col in time_cols:
  marathon[col] = marathon[col].apply(time_to_sec)
```

The values of the split times were in H:MM:SS format, and have to be converted to numeric values to be used in models.

```
marathon = marathon.drop(columns=['Unnamed: 0', 'Bib', 'Name', 'City', 'State', 'Country', '(
```

Drop columns with either too many NA values, or not relevant to the problem.

```
marathon.describe().T.round(1)
```

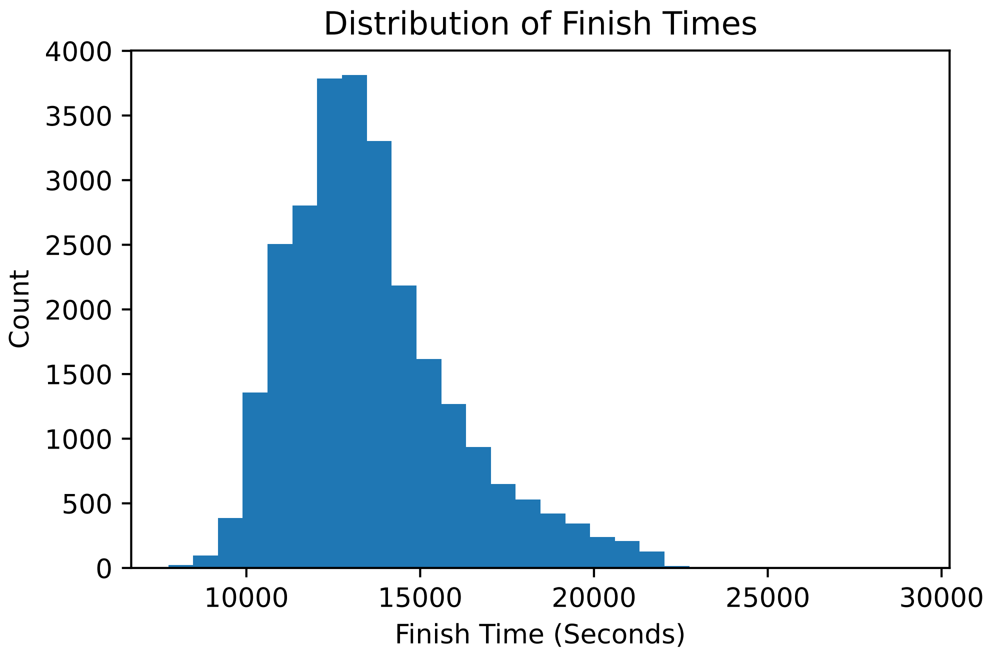
	count	mean	std	min	25%	50%	75%	max
Age	26598.0	42.1	11.3	18.0	33.0	42.0	50.0	82.0
5K	26446.0	1532.1	242.4	883.0	1356.0	1498.0	1658.0	3183.0
10K	26567.0	3045.6	478.8	1783.0	2702.0	2979.0	3299.0	6436.0
15K	26580.0	4575.8	728.7	2697.0	4057.0	4469.0	4958.0	9705.0
20K	26569.0	6139.5	1001.0	3628.0	5434.0	5985.0	6649.0	13027.0
Half	26570.0	6478.3	1057.5	3841.0	5733.0	6315.0	7017.0	13701.0
25K	26567.0	7729.4	1294.7	4565.0	6823.0	7521.0	8374.0	16566.0
30K	26559.0	9396.8	1622.3	5519.0	8262.0	9125.0	10190.0	20624.0
35K	26547.0	11119.7	1961.9	6479.0	9754.0	10791.0	12074.5	24691.0
40K	26542.0	12834.6	2290.9	7359.0	11255.0	12448.0	13956.8	27688.0
Official Time	26598.0	13585.6	2428.1	7757.0	11918.0	13180.0	14785.0	29161.0

This shows the summary statistics of the numeric data. This can be used to see the means, standard deviations, and distributions of data such as min/max and percentiles.

Data Visualization

```
import matplotlib.pyplot as plt

plt.figure()
plt.hist(marathon["Official Time"], bins=30)
plt.xlabel("Finish Time (Seconds)")
plt.ylabel("Count")
plt.title("Distribution of Finish Times")
plt.show()
```



Here is a plot of the distribution of finish times. It is interesting to see how this is right skewed.

Handling of Missing/Imbalanced Data

```
print("NA counts: \n", marathon.isnull().sum())
```

```
NA counts:
 Age              0
M/F             0
5K            152
10K            31
15K            18
20K            29
Half           28
25K            31
30K            39
35K            51
40K            56
Official Time   0
dtype: int64
```

```
marathon = marathon.dropna(subset=time_cols)
```

With over 25000 observations, we can simply remove the split times with incomplete values, without it causing too much harm to the model. It is important to note that I am dropping the whole row when removing the NA values, even if a runner only had one incomplete data point.

```
#Check
#print("NA counts: \n", marathon.isnull().sum())
```

3. Model Selection, Application, and Evaluation

Justify Model Choice

Decision Trees: By classifying runners into brackets (Under 3 hours and over 5 hours) based on splits and demographic data, we can create a blueprint that future runners can use to achieve a goal. While a majority of the runners will fall into the between 3-5 hours category, they can use this model (or change the brackets) to see what they can do to improve.

Method Applications

```
def time_bracket(sec):
   if sec < (3*3600):
     return 'Under 3'
   elif sec > (5*3600):
      return 'Over 5'
   else:
      return 'Between 3-5'

marathon['Bracket'] = marathon['Official Time'].apply(time_bracket)
```

```
# If/else statement assigning 1 to Male, 0 to Female
marathon["M/F"] =np.where(marathon["M/F"] == 'M', 1, 0)
```

```
# Select features
features = ['Age', 'M/F', '5K', '15K', 'Half', '25K', '35K']
x= marathon[features]
y= marathon['Bracket']
```

```python
#Imports from previous time using trees, not all may be necessary
import sklearn.model_selection as skm
from ISLP.models import ModelSpec as MS
from sklearn.tree import (DecisionTreeClassifier as DTC,
                          plot_tree,
                          export_text)
from sklearn.metrics import (accuracy_score,
                             log_loss)
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier


# Get training and test data, using 20% test data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1000)
```

Decision Tree

```python
tree = DTC(max_depth=4, random_state=1000)
tree.fit(x_train, y_train)
```

```
DecisionTreeClassifier(max_depth=4, random_state=1000)
```

```python
print(export_text(tree, feature_names=features, show_weights=True))
```

```
|--- 35K <= 8949.50
|   |--- 35K <= 8798.00
|   |   |--- 35K <= 8654.50
|   |   |   |--- 35K <= 8462.50
|   |   |   |   |--- weights: [2.00, 0.00, 854.00] class: Under 3
|   |   |   |--- 35K >  8462.50
|   |   |   |   |--- weights: [10.00, 0.00, 417.00] class: Under 3
|   |   |--- 35K >  8654.50
|   |   |   |--- 25K <= 5998.00
|   |   |   |   |--- weights: [15.00, 0.00, 2.00] class: Between 3-5
|   |   |   |--- 25K >  5998.00
|   |   |   |   |--- weights: [26.00, 0.00, 355.00] class: Under 3
|   |--- 35K >  8798.00
|   |   |--- Half <= 5220.50
|   |   |   |--- 35K <= 8840.50
```

```
|   |   |   |   |--- weights: [26.00, 0.00, 28.00] class: Under 3
|   |   |   |--- 35K >  8840.50
|   |   |   |   |--- weights: [63.00, 0.00, 9.00] class: Between 3-5
|   |   |--- Half >  5220.50
|   |   |   |--- 35K <= 8887.50
|   |   |   |   |--- weights: [32.00, 0.00, 238.00] class: Under 3
|   |   |   |--- 35K >  8887.50
|   |   |   |   |--- weights: [93.00, 0.00, 144.00] class: Under 3
|--- 35K >  8949.50
|   |--- 35K <= 14786.00
|   |   |--- 35K <= 14567.50
|   |   |   |--- 35K <= 9010.50
|   |   |   |   |--- weights: [186.00, 0.00, 43.00] class: Between 3-5
|   |   |   |--- 35K >  9010.50
|   |   |   |   |--- weights: [17037.00, 38.00, 11.00] class: Between 3-5
|   |   |--- 35K >  14567.50
|   |   |   |--- 25K <= 9965.50
|   |   |   |   |--- weights: [15.00, 38.00, 0.00] class: Over 5
|   |   |   |--- 25K >  9965.50
|   |   |   |   |--- weights: [93.00, 24.00, 0.00] class: Between 3-5
|   |--- 35K >  14786.00
|   |   |--- 35K <= 15076.50
|   |   |   |--- 25K <= 10330.50
|   |   |   |   |--- weights: [13.00, 108.00, 0.00] class: Over 5
|   |   |   |--- 25K >  10330.50
|   |   |   |   |--- weights: [35.00, 27.00, 0.00] class: Between 3-5
|   |   |--- 35K >  15076.50
|   |   |   |--- 35K <= 15274.00
|   |   |   |   |--- weights: [4.00, 118.00, 0.00] class: Over 5
|   |   |   |--- 35K >  15274.00
|   |   |   |   |--- weights: [1.00, 933.00, 0.00] class: Over 5
```

This looks nice, but this barely uses any predictors

Random Forest

```python
rf = RandomForestClassifier(n_estimators=100,max_depth=10, random_state=1000)
rf.fit(x_train, y_train)
```

```
RandomForestClassifier(max_depth=10, random_state=1000)
```

Model Evaluation

```
validation = skm.ShuffleSplit(n_splits=1, test_size=200, random_state=0)

results = skm.cross_validate(tree, x, y, cv=validation)

print("Test Score:",results['test_score'])
```

```
Test Score: [0.975]
```

```
validation = skm.ShuffleSplit(n_splits=1, test_size=200, random_state=0)

results = skm.cross_validate(rf, x, y, cv=validation)

print("Test Score:",results['test_score'])
```

```
Test Score: [0.985]
```

The decision tree is more intuitive, but slightly less accurate than the random forest.

4. Results, Conclusions, and Real-World Implications

Results Presentation

Conclusions