Zach_Yek_Submission

April 21, 2023

1 Import Dependencies

We begin by importing the necessary libraries.

[1]:
```
# System & OS
import os

# Data analysis
import numpy as np
import pandas as pd
pd.options.display.max_columns = None

# ML
from sklearn.cluster import KMeans

# Data visualization
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
sns.set_style('white')
```

2 Reproducibility

Set the seed to ensure our results are reproducible.

[2]:
```
def set_seed(seed):
    np.random.seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)

SEED = 11
set_seed(SEED)
```

3 Data Cleaning

Next, read in the `Pitching` dataframe from the `Lahman` package. Note, a separate R script was used to export the data into a CSV file.

[3]:
```
# Read data & drop irrelevant columns
df = pd.read_csv('../data/pitching_df.csv')
df.drop(columns=['Unnamed: 0'], inplace=True)

# Display results
df.head()
```

[3]:
```
    playerID  yearID  stint teamID lgID   W   L   G  GS  CG  SHO  SV  IPouts  \
0  bechtge01    1871      1    PH1  NaN   1   2   3   3   2    0   0      78
1  brainas01    1871      1    WS3  NaN  12  15  30  30  30    0   0     792
2  fergubo01    1871      1    NY2  NaN   0   0   1   0   0    0   0       3
3  fishech01    1871      1    RC1  NaN   4  16  24  24  22    1   0     639
4  fleetfr01    1871      1    NY2  NaN   0   1   1   1   1    0   0      27

     H   ER  HR  BB  SO  BAOpp    ERA  IBB  WP  HBP  BK     BFP  GF    R  SH  \
0   43   23   0  11   1    NaN   7.96  NaN   7  NaN   0   146.0   0   42 NaN
1  361  132   4  37  13    NaN   4.50  NaN   7  NaN   0  1291.0   0  292 NaN
2    8    3   0   0   0    NaN  27.00  NaN   2  NaN   0    14.0   0    9 NaN
3  295  103   3  31  15    NaN   4.35  NaN  20  NaN   0  1080.0   1  257 NaN
4   20   10   0   3   0    NaN  10.00  NaN   0  NaN   0    57.0   0   21 NaN

   SF  GIDP
0 NaN   NaN
1 NaN   NaN
2 NaN   NaN
3 NaN   NaN
4 NaN   NaN
```

Apply the following cleaning steps:

- only consider entries from the past 12 seasons (since 2010)
- only consider entries with more than 20 games played
- select the following features: `W`, `L`, `G`, `GS`, `SV`

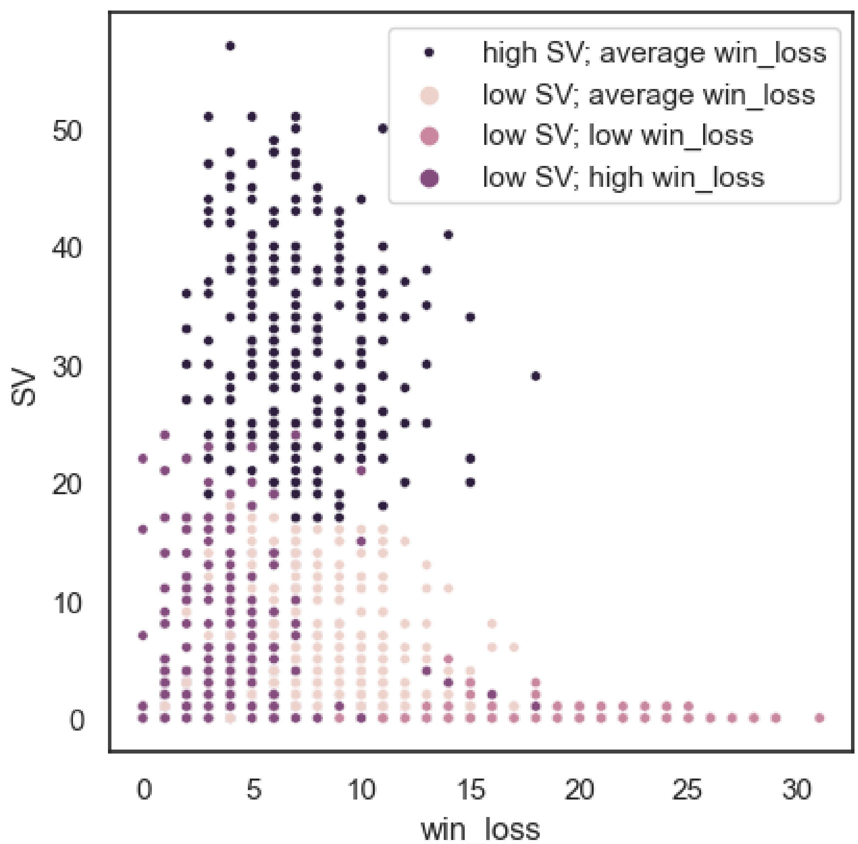
[4]:
```
# Filter rows with year >= 2010 and games played >= 20
df = df[(df['yearID'] >= 2010) & (df['G'] >= 20)].reset_index(drop=True)

# Use only the specified features
df = df[['W', 'L', 'G', 'GS', 'SV']]

# Display results' dimensions
df.shape
```

[4]:
```
(4697, 5)
```

4 K-Means Clustering

It remains to perform k-means clustering on the dataframe. After testing a couple different values of `k` off-screen, we'll opt for `k=4` clusters. Note, the model is fit to the dataframe as is, while the scatterplot is visualized by aggregating `W` and `L` into one of the coordinate axes `win_loss = W + L`.

[5]:
```
# Create figure
fig, ax = plt.subplots(figsize=(5, 5))
# Fit the k-means clustering model to df
kmeans = KMeans(n_clusters=4, n_init='auto', random_state=SEED).fit(df)
# Extract cluster labels
df['cluster'] = kmeans.labels_
# Create x-axis
df['win_loss'] = df['W'] + df['L']
# Create scatter plot
sns.scatterplot(data=df, x='win_loss', y='SV', hue='cluster', s=15)
# Create legend
ax.legend(['high SV; average win_loss', 'low SV; average win_loss', 'low SV;␣
↪low win_loss', 'low SV; high win_loss'])
# Display results
plt.show()
```



As we can see, the model does a fairly good job at identifying 4 distinct clusters in the data. The low `SV` high `win_loss` cluster likely represents starting pitchers; high `SV` average `win_loss` likely represents closers; etc. With our limited understanding of baseball, that's about as far as we're able to interpret the results, though an individual with a more insightful knowledge base on the subject may be able to decipher these results further.