

Fantasy_Football_ML

October 14, 2024

```
[1]: # Imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.decomposition import PCA
import numpy as np
import re
```

```
[2]: # Week 2 Start: Ingestion of the Dataset
```

```
# File paths for each year
file_2019 = 'FFRank 2019.csv'
file_2020 = 'FFRank 2020.csv'
file_2021 = 'FFRank 2021.csv'
file_2022 = 'FFRank 2022.csv'
```

```
[3]: # Read each CSV file into a pandas DataFrame
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```
df_2019 = pd.read_csv(file_2019)
df_2020 = pd.read_csv(file_2020)
df_2021 = pd.read_csv(file_2021)
df_2022 = pd.read_csv(file_2022)
```

```
[4]: # Display the first few rows of each dataset to ensure they loaded correctly
```

```
print("2019 Data Preview:\n", df_2019.head())
print("2020 Data Preview:\n", df_2020.head())
print("2021 Data Preview:\n", df_2021.head())
print("2022 Data Preview:\n", df_2022.head())
```

2019 Data Preview:

	Rank	Player	Team	Position	Age	Games Played	\
0	1	Christian McCaffrey	CAR	RB	23	16	
1	2	Lamar Jackson	BAL	QB	22	15	
2	3	Derrick Henry	TEN	RB	25	15	

3	4	Aaron Jones	GNB	RB	25	16
4	5	Ezekiel Elliott	DAL	RB	24	16

	Passing Completion	Passing Attempts	Passing Yards	Passing TDs	...	\
0	0	2	0	0	...	
1	265	401	3127	36	...	
2	0	0	0	0	...	
3	0	0	0	0	...	
4	0	0	0	0	...	

	Rushing TDs	Targets	Recepotions	Receiving Yards	Yards per Reception	\
0	15	142	116	1005	8.66	
1	7	0	0	0	NaN	
2	16	24	18	206	11.44	
3	16	68	49	474	9.67	
4	12	71	54	420	7.78	

	Receiving TDs	Fumbles Lost	Total TD	Fantasy Points	PPR Fantasy Points
0	4	0	19	355	471.2
1	0	2	7	416	415.7
2	2	3	18	277	294.6
3	3	2	19	266	314.8
4	2	2	14	258	311.7

[5 rows x 24 columns]

2020 Data Preview:

	Rank	Player	Team	Position	Age	Games Played	Passing Completions	\
0	1	Derrick Henry	TEN	RB	26	16	0	
1	2	Alvin Kamara	NOR	RB	25	15	0	
2	3	Dalvin Cook	MIN	RB	25	14	0	
3	4	Davante Adams	GNB	WR	28	14	0	
4	5	Travis Kelce	KAN	TE	31	15	1	

	Passing Attempts	Passing Yards	Passing TD	...	Rushing TD	Targets	\
0	0	0	0	...	17	31	
1	0	0	0	...	16	107	
2	0	0	0	...	16	54	
3	0	0	0	...	0	149	
4	2	4	0	...	0	145	

	Receptions	Receiving Yards	Yards Per Reception	Receiving TD	\
0	19	114	6.00	0	
1	83	756	9.11	5	
2	44	361	8.20	1	
3	115	1374	11.95	18	
4	105	1416	13.49	11	

Fumbles Lost	Total TD	Fantasy Points	PPR Points
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0	2	17	314	333.1
1	0	21	295	377.8
2	3	17	294	337.8
3	1	18	243	358.4
4	1	11	208	312.8

[5 rows x 24 columns]

2021 Data Preview:

	Rank	Player	Team	Position	Age	Games Played	\
0	1	Jonathan Taylor	IND	RB	22	17	
1	2	Cooper Kupp	LAR	WR	28	17	
2	3	Deebo Samuel	SFO	WR	25	16	
3	4	Josh Allen	BUF	QB	25	17	
4	5	Austin Ekeler	LAC	RB	26	16	

	Passing Completions	Passing Attempts	Passing Yards	Passing TDs	...	\
0	0	0	0	0	...	
1	0	1	0	0	...	
2	1	2	24	1	...	
3	409	646	4407	36	...	
4	0	0	0	0	...	

	Rushing TDs	Target	Receptions	Receiving Yards	Yards Per Reception	\
0	18	51	40	360	9.00	
1	0	191	145	1947	13.43	
2	8	121	77	1405	18.25	
3	6	0	0	0	NaN	
4	12	94	70	647	9.24	

	Receiving Yards.1	Fumbles Lost	Total TDs	Fantasy Points	PPR Points
0	2	2	20	333	373.1
1	16	0	16	295	439.5
2	6	2	14	262	339.0
3	0	3	6	403	402.6
4	8	3	20	274	343.8

[5 rows x 24 columns]

2022 Data Preview:

	Rank	Player	Team	Position	Age	Games Played	\
0	1	Patrick Mahomes	KAN	QB	27	17	
1	2	Josh Jacobs	LVR	RB	24	17	
2	3	Christian McCaffrey	2TM	RB	26	17	
3	4	Derrick Henry	TEN	RB	28	16	
4	5	Justin Jefferson	MIN	WR	23	17	

	Passing Completions	Passing Attempts	Passing Yards	Passing Touchdowns	\
0	435	648	5250	41	
1	0	0	0	0	

2	1	1	34	1
3	2	2	4	1
4	2	2	34	0

	Rushing TD	Targets	Receptions	Receiving Yards	\
0	4	1	1	6	
1	12	64	53	400	
2	8	108	85	741	
3	13	41	33	398	
4	1	184	128	1809	

	Yards per Receptions	Receiving Touchdowns	Fumbles Lost	Total TD2	\
0	6.00	0	5	4	
1	7.55	0	3	12	
2	8.72	5	1	13	
3	12.06	0	6	13	
4	14.13	8	0	9	

	Fantasy Points	PPR Fantasy Points
0	416	417.4
1	275	328.3
2	271	356.4
3	270	302.8
4	241	368.7

[5 rows x 24 columns]

```
[5]: # Check for missing values and data types for each year
print("2019 Data Information:")
print(df_2019.info())
print("\n2020 Data Information:")
print(df_2020.info())
print("\n2021 Data Information:")
print(df_2021.info())
print("\n2022 Data Information:")
print(df_2022.info())
```

2019 Data Information:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 200 entries, 0 to 199

Data columns (total 24 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Rank	200 non-null	int64
1	Player	200 non-null	object
2	Team	200 non-null	object
3	Position	200 non-null	object
4	Age	200 non-null	int64

5	Games Played	200 non-null	int64
6	Passing Completion	200 non-null	int64
7	Passing Attempts	200 non-null	int64
8	Passing Yards	200 non-null	int64
9	Passing TDs	200 non-null	int64
10	Interceptions	200 non-null	int64
11	Rushing Attempts	200 non-null	int64
12	Rushing Yards	200 non-null	int64
13	Yards per Attempt	156 non-null	float64
14	Rushing TDs	200 non-null	int64
15	Targets	200 non-null	int64
16	Receptions	200 non-null	int64
17	Receiving Yards	200 non-null	int64
18	Yards per Reception	167 non-null	float64
19	Receiving TDs	200 non-null	int64
20	Fumbles Lost	200 non-null	int64
21	Total TD	200 non-null	int64
22	Fantasy Points	200 non-null	int64
23	PPR Fantasy Points	200 non-null	float64

dtypes: float64(3), int64(18), object(3)
memory usage: 37.6+ KB
None

2020 Data Information:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 200 entries, 0 to 199

Data columns (total 24 columns):

#	Column	Non-Null Count	Dtype
0	Rank	200 non-null	int64
1	Player	200 non-null	object
2	Team	200 non-null	object
3	Position	200 non-null	object
4	Age	200 non-null	int64
5	Games Played	200 non-null	int64
6	Passing Completions	200 non-null	int64
7	Passing Attempts	200 non-null	int64
8	Passing Yards	200 non-null	int64
9	Passing TD	200 non-null	int64
10	Interceptions	200 non-null	int64
11	Rushing Attempts	200 non-null	int64
12	Rushing Yards	200 non-null	int64
13	Yards Per Attempt	155 non-null	float64
14	Rushing TD	200 non-null	int64
15	Targets	200 non-null	int64
16	Receptions	200 non-null	int64
17	Receiving Yards	200 non-null	int64
18	Yards Per Reception	172 non-null	float64

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19 Receiving TD          200 non-null    int64
20 Fumbles Lost          200 non-null    int64
21 Total TD              200 non-null    int64
22 Fantasy Points        200 non-null    int64
23 PPR Points            200 non-null    float64
dtypes: float64(3), int64(18), object(3)
memory usage: 37.6+ KB
None

```

2021 Data Information:

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 24 columns):
#   Column                      Non-Null Count  Dtype
---  -
0   Rank                        200 non-null    int64
1   Player                     200 non-null    object
2   Team                       200 non-null    object
3   Position                   200 non-null    object
4   Age                        200 non-null    int64
5   Games Played               200 non-null    int64
6   Passing Completions        200 non-null    int64
7   Passing Attempts           200 non-null    int64
8   Passsing Yards             200 non-null    int64
9   Passing TDs                200 non-null    int64
10  Interceptions              200 non-null    int64
11  Rushing Attempts           200 non-null    int64
12  Rushing Yards              200 non-null    int64
13  Yards Per Attempt          162 non-null    float64
14  Rushing TDs                200 non-null    int64
15  Target                     200 non-null    int64
16  Receptions                 200 non-null    int64
17  Receiving Yards            200 non-null    int64
18  Yards Per Reception        164 non-null    float64
19  Receiving Yards.1          200 non-null    int64
20  Fumbles Lost               200 non-null    int64
21  Total TDs                  200 non-null    int64
22  Fantasy Points             200 non-null    int64
23  PPR Points                 200 non-null    float64
dtypes: float64(3), int64(18), object(3)
memory usage: 37.6+ KB
None

```

2022 Data Information:

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 24 columns):
#   Column                      Non-Null Count  Dtype

```

```

---  -----
0   Rank                200 non-null    int64
1   Player              200 non-null    object
2   Team                200 non-null    object
3   Position            200 non-null    object
4   Age                 200 non-null    int64
5   Games Played        200 non-null    int64
6   Passing Completions 200 non-null    int64
7   Passing Attempts    200 non-null    int64
8   Passing Yards       200 non-null    int64
9   Passing Touchdowns  200 non-null    int64
10  Interceptions       200 non-null    int64
11  Rushing Attempts    200 non-null    int64
12  Rushing Yards       200 non-null    int64
13  Yards per Attempt    157 non-null    float64
14  Rushing TD          200 non-null    int64
15  Targets             200 non-null    int64
16  Receptions          200 non-null    int64
17  Receiving Yards     200 non-null    int64
18  Yards per Receptions 166 non-null    float64
19  Reciving Touchdowns 200 non-null    int64
20  Fumbles Lost        200 non-null    int64
21  Total TD2           200 non-null    int64
22  Fantasy Points      200 non-null    int64
23  PPR Fantasy Points  200 non-null    float64
dtypes: float64(3), int64(18), object(3)
memory usage: 37.6+ KB
None

```

```

[6]: # Basic statistics for numerical columns (mean, min, max, etc.)
print("\n2019 Summary Statistics:")
print(df_2019.describe())
print("\n2020 Summary Statistics:")
print(df_2020.describe())
print("\n2021 Summary Statistics:")
print(df_2021.describe())
print("\n2022 Summary Statistics:")
print(df_2022.describe())

```

2019 Summary Statistics:

	Rank	Age	Games Played	Passing Completion \
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	26.330000	14.105000	51.680000
std	57.879185	3.846437	2.460538	115.946174
min	1.000000	21.000000	3.000000	0.000000
25%	50.750000	24.000000	13.000000	0.000000
50%	100.500000	25.500000	15.000000	0.000000

75%	150.250000	28.000000	16.000000	0.000000
max	200.000000	42.000000	17.000000	408.000000

	Passing Attempts	Passing Yards	Passing TDs	Interceptions \
count	200.000000	200.000000	200.000000	200.000000
mean	80.795000	592.350000	3.775000	1.755000
std	181.237935	1334.654668	8.575082	4.454682
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	0.000000	0.000000
max	626.000000	5109.000000	36.000000	30.000000

	Rushing Attempts	Rushing Yards	...	Rushing TDs	Targets \
count	200.000000	200.000000	...	200.000000	200.000000
mean	55.970000	246.340000	...	1.960000	59.705000
std	81.342066	366.605212	...	3.163612	44.292404
min	0.000000	-12.000000	...	0.000000	0.000000
25%	1.000000	0.000000	...	0.000000	21.750000
50%	9.000000	40.500000	...	0.000000	56.500000
75%	82.250000	374.250000	...	3.000000	90.250000
max	303.000000	1540.000000	...	16.000000	185.000000

	Receptions	Receiving Yards	Yards per Reception	Receiving TDs \
count	200.000000	200.000000	167.000000	200.000000
mean	40.120000	471.120000	11.116766	3.055000
std	29.785086	388.879547	3.683657	2.760448
min	0.000000	-4.000000	-4.000000	0.000000
25%	14.750000	118.750000	8.325000	0.000000
50%	39.000000	424.500000	11.180000	3.000000
75%	59.000000	715.250000	13.720000	5.000000
max	149.000000	1725.000000	20.690000	11.000000

	Fumbles Lost	Total TD	Fantasy Points	PPR Fantasy Points
count	200.000000	200.000000	200.000000	200.000000
mean	1.090000	5.040000	135.945000	176.032000
std	1.585709	3.275982	70.621448	73.096789
min	0.000000	0.000000	55.000000	58.100000
25%	0.000000	3.000000	79.750000	113.575000
50%	1.000000	5.000000	118.500000	164.550000
75%	2.000000	7.000000	168.000000	225.500000
max	11.000000	19.000000	416.000000	471.200000

[8 rows x 21 columns]

2020 Summary Statistics:

	Rank	Age	Games Played	Passing Completions \
count	200.000000	200.000000	200.000000	200.000000

mean	100.500000	26.345000	14.040000	54.08000
std	57.879185	3.932339	2.598492	118.08405
min	1.000000	21.000000	3.000000	0.00000
25%	50.750000	24.000000	13.000000	0.00000
50%	100.500000	25.000000	15.000000	0.00000
75%	150.250000	28.000000	16.000000	0.25000
max	200.000000	43.000000	16.000000	407.00000

	Passing Attempts	Passing Yards	Passing TD	Interceptions	\
count	200.000000	200.000000	200.000000	200.000000	
mean	82.13500	601.650000	4.085000	1.715000	
std	178.39076	1325.122438	9.709229	3.758244	
min	0.00000	0.000000	0.000000	0.000000	
25%	0.00000	0.000000	0.000000	0.000000	
50%	0.00000	0.000000	0.000000	0.000000	
75%	1.00000	1.000000	0.000000	0.000000	
max	626.00000	4823.000000	48.000000	15.000000	

	Rushing Attempts	Rushing Yards	...	Rushing TD	Targets	\
count	200.000000	200.000000	...	200.000000	200.000000	
mean	54.825000	248.605000	...	2.335000	59.025000	
std	74.243687	351.093982	...	3.442678	44.046508	
min	0.000000	-8.000000	...	0.000000	0.000000	
25%	1.000000	0.000000	...	0.000000	19.000000	
50%	11.500000	47.500000	...	1.000000	59.000000	
75%	97.000000	429.500000	...	3.000000	92.250000	
max	378.000000	2027.000000	...	17.000000	166.000000	

	Receptions	Receiving Yards	Yards Per Reception	Receiving TD	\
count	200.00000	200.000000	172.000000	200.00000	
mean	40.38000	459.670000	10.541744	3.22000	
std	29.97764	385.912234	3.943376	3.32821	
min	0.00000	-6.000000	-6.000000	0.00000	
25%	16.00000	122.250000	7.740000	0.00000	
50%	38.00000	418.000000	10.760000	3.00000	
75%	59.00000	723.750000	13.222500	5.00000	
max	127.00000	1535.000000	20.910000	18.00000	

	Fumbles Lost	Total TD	Fantasy Points	PPR Points
count	200.00000	200.000000	200.000000	200.000000
mean	0.93000	5.580000	140.285000	180.623500
std	1.39457	3.631742	74.926052	75.091079
min	0.00000	0.000000	63.000000	64.300000
25%	0.00000	3.000000	86.000000	126.875000
50%	0.00000	5.000000	116.000000	164.200000
75%	1.00000	7.000000	166.000000	223.725000
max	8.00000	21.000000	395.000000	396.100000

[8 rows x 21 columns]

2021 Summary Statistics:

	Rank	Age	Games Played	Passing Completions \
count	200.000000	200.000000	200.000000	200.00000
mean	100.500000	26.270000	14.570000	55.75000
std	57.879185	3.663908	2.852329	123.65529
min	1.000000	21.000000	6.000000	0.00000
25%	50.750000	24.000000	13.000000	0.00000
50%	100.500000	26.000000	16.000000	0.00000
75%	150.250000	28.000000	17.000000	0.25000
max	200.000000	44.000000	17.000000	485.00000

	Passing Attempts	Passsing Yards	Passing TDs	Interceptions \
count	200.000000	200.000000	200.000000	200.000000
mean	85.710000	614.010000	3.935000	1.945000
std	188.009798	1365.233155	9.389975	4.304021
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	1.000000	0.000000	0.000000
max	719.000000	5316.000000	43.000000	17.000000

	Rushing Attempts	Rushing Yards ...	Rushing TDs	Target \
count	200.000000	200.000000 ...	200.000000	200.000000
mean	59.350000	263.215000 ...	2.190000	60.150000
std	77.035184	342.780954 ...	3.20237	46.423737
min	0.000000	0.000000 ...	0.000000	0.000000
25%	1.000000	5.000000 ...	0.000000	20.000000
50%	17.500000	78.500000 ...	1.000000	57.500000
75%	104.250000	435.250000 ...	3.000000	92.250000
max	332.000000	1811.000000 ...	18.000000	191.000000

	Receptions	Receiving Yards	Yards Per Reception	Receiving Yards.1 \
count	200.000000	200.000000	164.000000	200.000000
mean	41.16500	465.720000	10.696951	3.015000
std	30.97718	401.140274	3.520453	3.224401
min	0.000000	-4.000000	-4.000000	0.000000
25%	18.000000	128.750000	7.977500	0.000000
50%	41.000000	430.500000	10.690000	2.000000
75%	61.000000	705.000000	13.122500	5.000000
max	145.00000	1947.000000	19.540000	16.000000

	Fumbles Lost	Total TDs	Fantasy Points	PPR Points
count	200.000000	200.000000	200.000000	200.000000
mean	0.960000	5.220000	139.775000	180.869000
std	1.306497	3.691849	73.146335	75.794843
min	0.000000	0.000000	59.000000	62.500000

25%	0.000000	3.000000	85.000000	121.700000
50%	1.000000	5.000000	116.500000	164.200000
75%	1.000000	7.000000	172.000000	227.350000
max	6.000000	20.000000	403.000000	439.500000

[8 rows x 21 columns]

2022 Summary Statistics:

	Rank	Age	Games Played	Passing Completions \
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	26.385000	14.585000	50.680000
std	57.879185	3.438881	2.760594	114.872346
min	1.000000	21.000000	6.000000	0.000000
25%	50.750000	24.000000	13.000000	0.000000
50%	100.500000	26.000000	16.000000	0.000000
75%	150.250000	28.000000	17.000000	0.000000
max	200.000000	45.000000	17.000000	490.000000

	Passing Attempts	Passing Yards	Passing Touchdowns	Interceptions \
count	200.000000	200.000000	200.000000	200.000000
mean	78.235000	558.965000	3.445000	1.675000
std	175.443014	1256.461792	8.089759	3.744259
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	0.000000	0.000000
max	733.000000	5250.000000	41.000000	15.000000

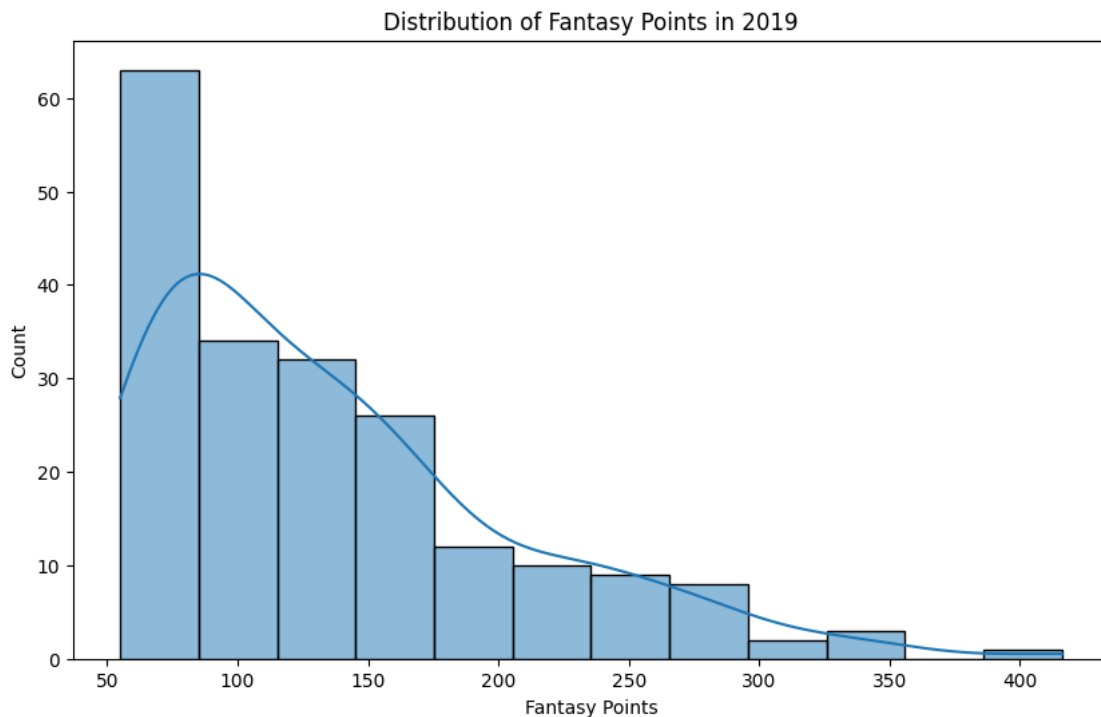
	Rushing Attempts	Rushing Yards	...	Rushing TD	Targets \
count	200.000000	200.000000	...	200.000000	200.000000
mean	60.630000	274.515000	...	2.110000	59.965000
std	83.747845	388.655432	...	3.210833	45.957089
min	0.000000	-15.000000	...	0.000000	0.000000
25%	1.000000	0.000000	...	0.000000	18.000000
50%	10.000000	53.500000	...	1.000000	59.000000
75%	95.000000	462.250000	...	3.000000	92.250000
max	349.000000	1653.000000	...	17.000000	184.000000

	Receptions	Receiving Yards	Yards per Receptions	Receiving Touchdowns \
count	200.000000	200.000000	166.000000	200.000000
mean	40.730000	456.14500	10.348193	2.765000
std	30.634613	396.47656	3.571122	2.867208
min	0.000000	-10.00000	-5.000000	0.000000
25%	15.750000	95.75000	7.682500	0.000000
50%	40.000000	423.50000	10.585000	2.000000
75%	60.250000	710.75000	12.872500	4.000000
max	128.000000	1809.00000	18.080000	14.000000

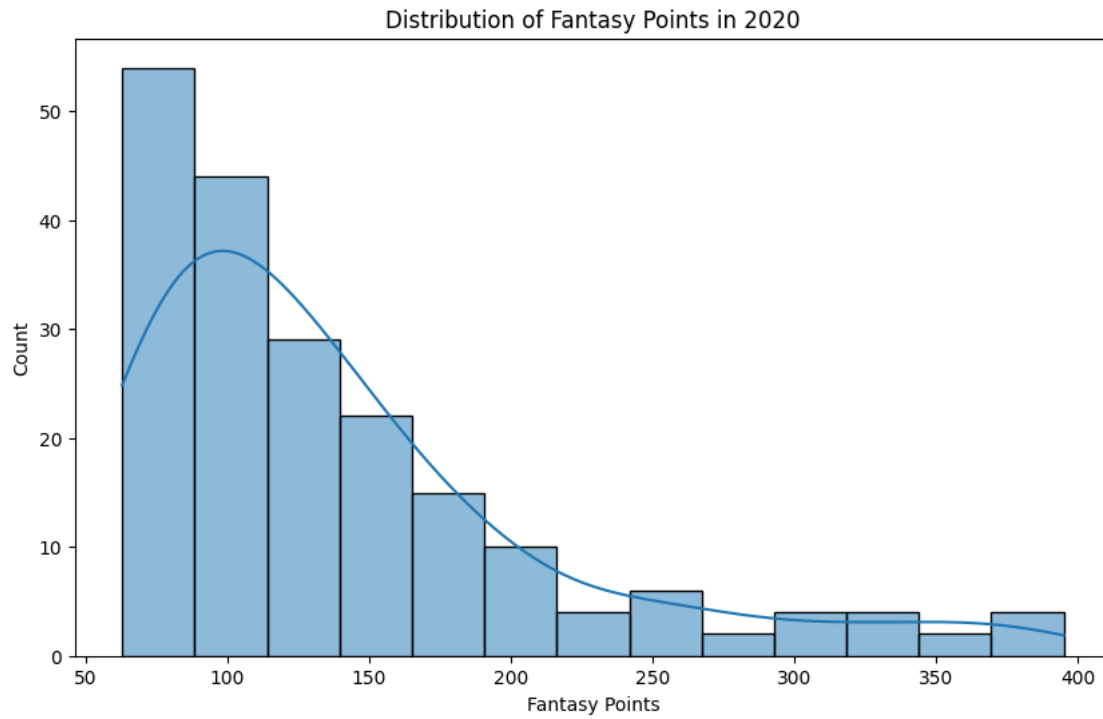
	Fumbles Lost	Total TD2	Fantasy Points	PPR Fantasy Points
count	200.00000	200.000000	200.00000	200.000000
mean	2.11000	4.905000	134.09000	174.766000
std	2.79229	3.319801	71.48962	74.628082
min	0.00000	0.000000	57.00000	56.600000
25%	0.00000	3.000000	79.75000	115.100000
50%	1.00000	4.000000	115.00000	162.600000
75%	3.00000	6.000000	165.75000	219.550000
max	16.00000	18.000000	416.00000	417.400000

[8 rows x 21 columns]

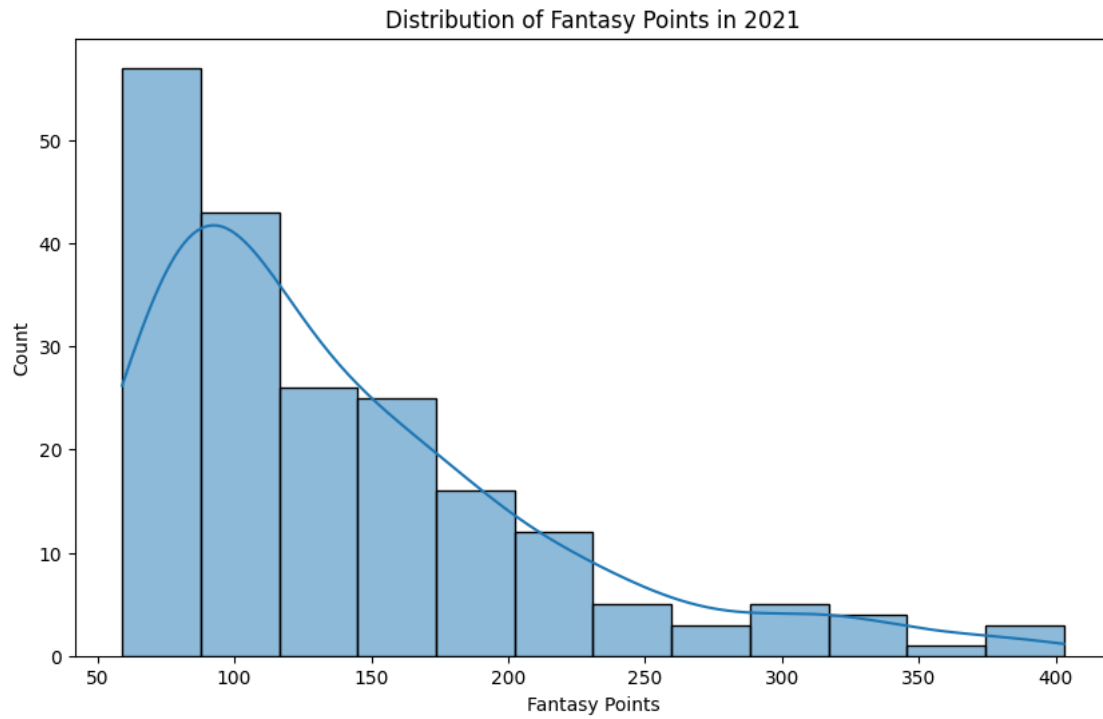
```
[7]: # Plot distribution of fantasy points
plt.figure(figsize=(10, 6))
sns.histplot(df_2019['Fantasy Points'], kde=True)
plt.title('Distribution of Fantasy Points in 2019')
plt.show()
```



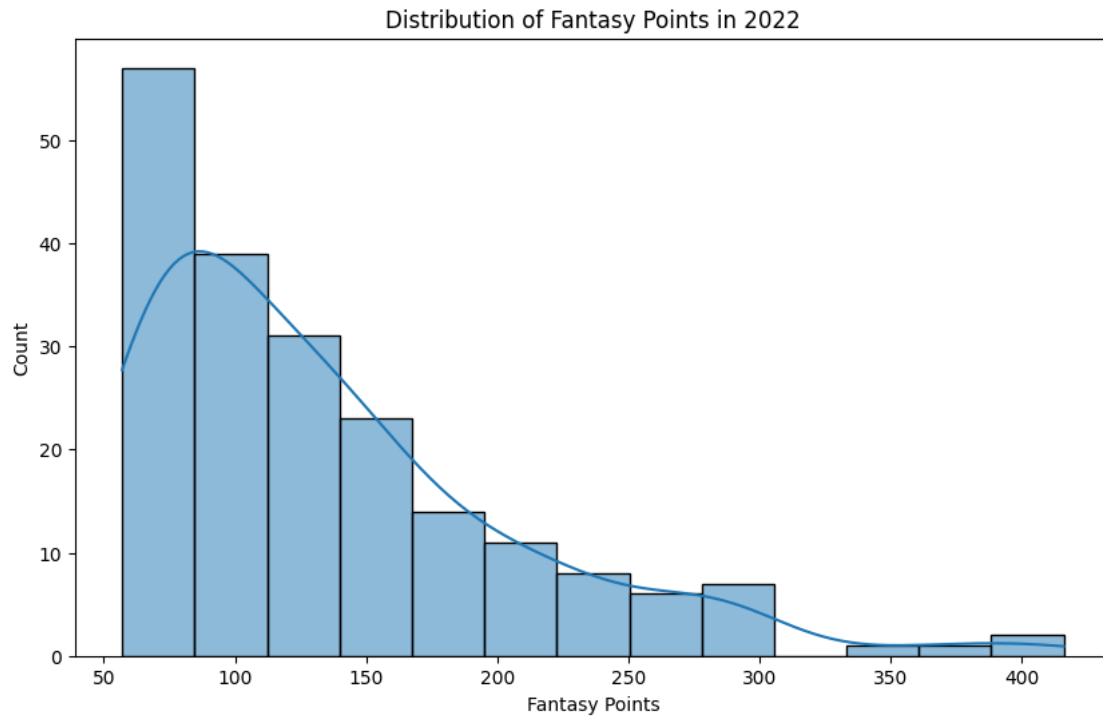
```
[8]: # Plot distribution of fantasy points
plt.figure(figsize=(10, 6))
sns.histplot(df_2020['Fantasy Points'], kde=True)
plt.title('Distribution of Fantasy Points in 2020')
plt.show()
```



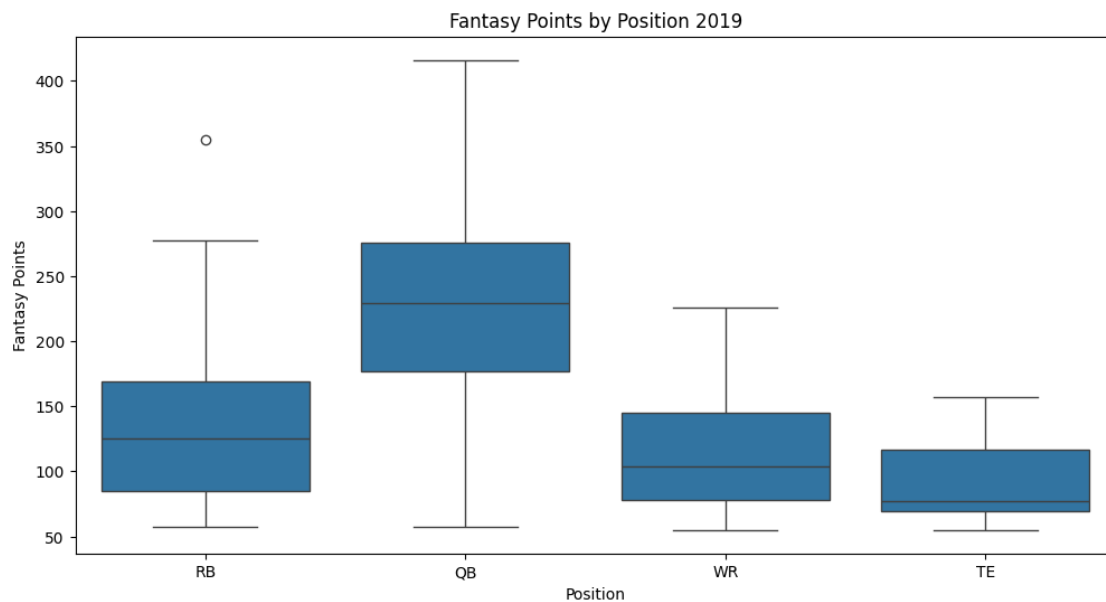
```
[9]: # Plot distribution of fantasy points
plt.figure(figsize=(10, 6))
sns.histplot(df_2021['Fantasy Points'], kde=True)
plt.title('Distribution of Fantasy Points in 2021')
plt.show()
```



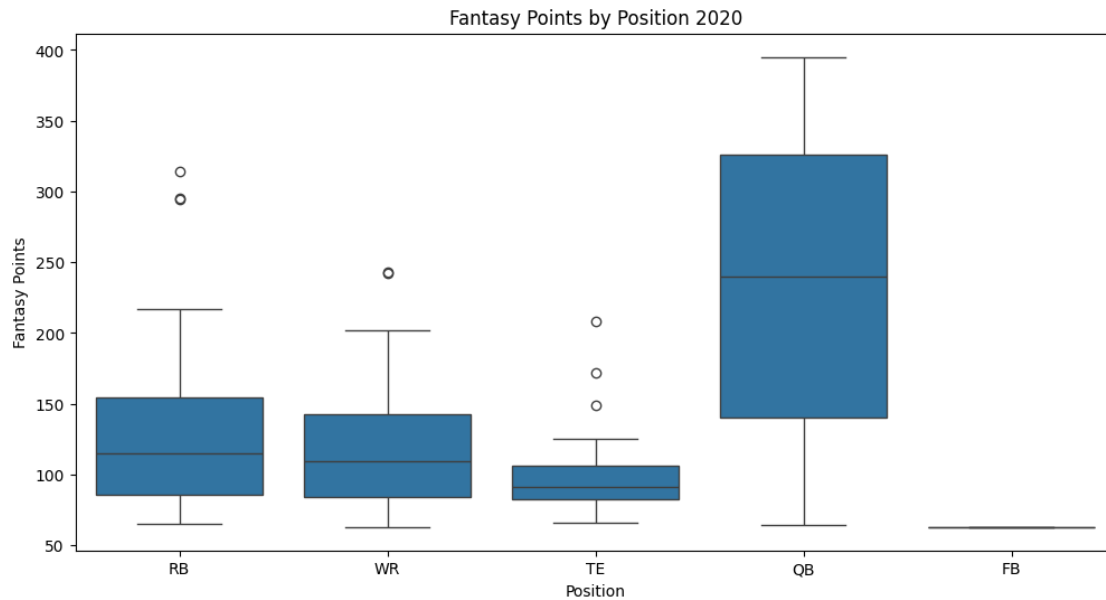
```
[10]: # Plot distribution of fantasy points
plt.figure(figsize=(10, 6))
sns.histplot(df_2022['Fantasy Points'], kde=True)
plt.title('Distribution of Fantasy Points in 2022')
plt.show()
```



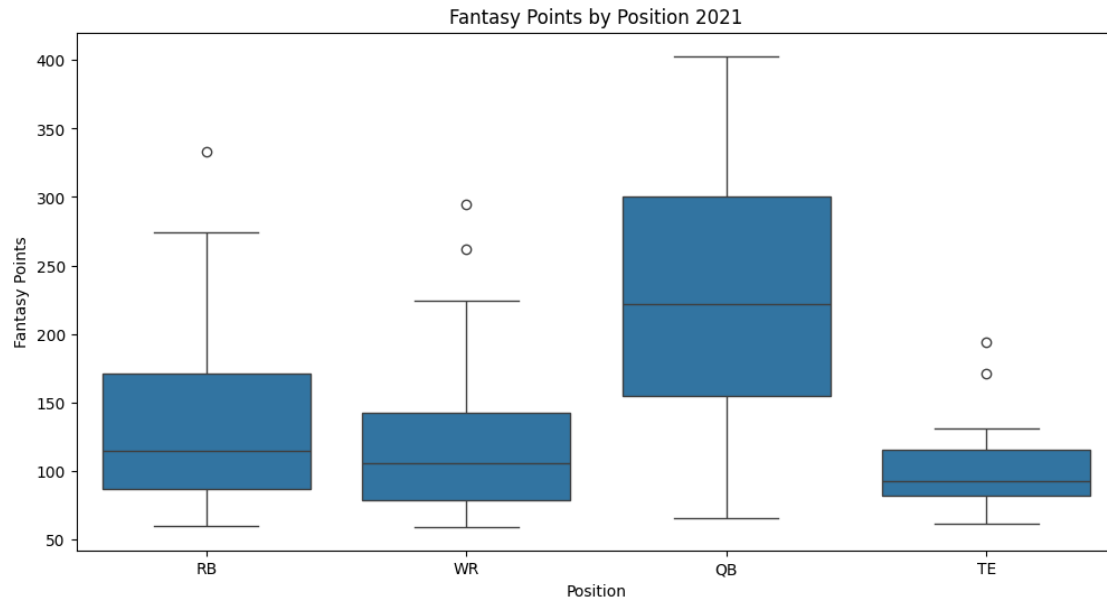
```
[11]: # Boxplot to compare fantasy points across positions
plt.figure(figsize=(12, 6))
sns.boxplot(x='Position', y='Fantasy Points', data=df_2019)
plt.title('Fantasy Points by Position 2019')
plt.show()
```



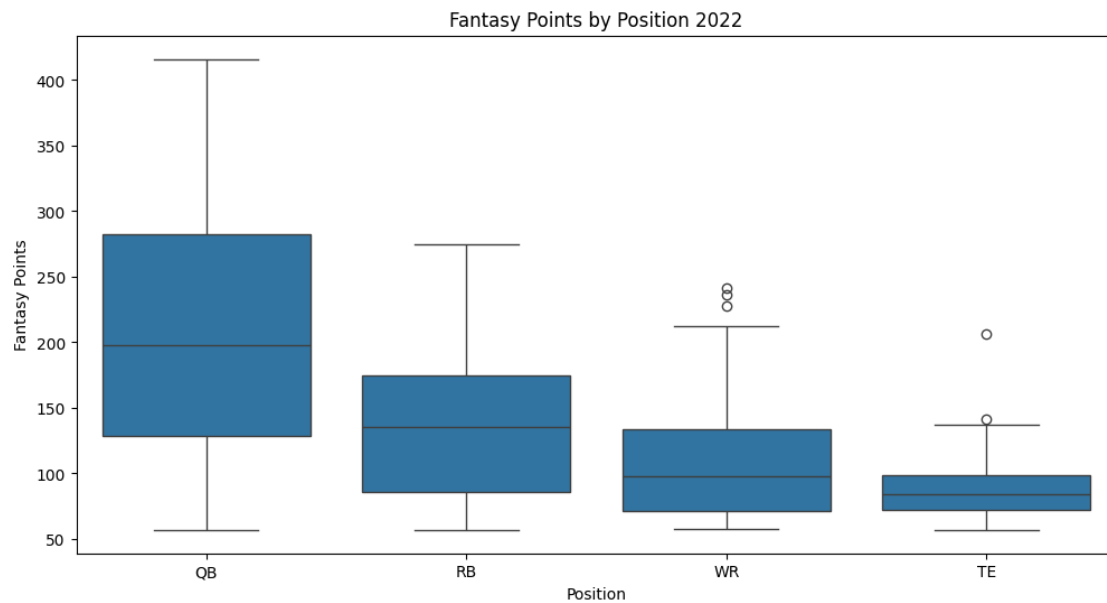
```
[12]: # Boxplot to compare fantasy points across positions
plt.figure(figsize=(12, 6))
sns.boxplot(x='Position', y='Fantasy Points', data=df_2020)
plt.title('Fantasy Points by Position 2020')
plt.show()
```



```
[13]: # Boxplot to compare fantasy points across positions
plt.figure(figsize=(12, 6))
sns.boxplot(x='Position', y='Fantasy Points', data=df_2021)
plt.title('Fantasy Points by Position 2021')
plt.show()
```

```
[14]: # Boxplot to compare fantasy points across positions
plt.figure(figsize=(12, 6))
sns.boxplot(x='Position', y='Fantasy Points', data=df_2022)
plt.title('Fantasy Points by Position 2022')
plt.show()
```



```
[15]: # Week 3 Start

# Concatenate all dataframes into a single dataframe
combined_df = pd.concat([df_2019, df_2020, df_2021, df_2022], ignore_index=True)

# Clean player names by removing special characters
combined_df['Player'] = combined_df['Player'].str.replace(r'[^a-zA-Z.\s]', '',
    ↪ regex=True)

# Group by 'Player' and aggregate relevant numerical columns
aggregated_df = combined_df.groupby('Player').agg({
    'Rushing Yards': 'sum',
    'Receiving Yards': 'sum',
    'Passing Yards': 'sum',
    'Total TD': 'sum',
    'Fantasy Points': 'sum',
    'Games Played': 'sum',
    'Position': 'first', # Get the first non-null position
}).reset_index()

# Calculate Yards from Scrimmage and Total Yards
aggregated_df['Yards_from_Scrimmage'] = aggregated_df['Rushing Yards'] +
    ↪ aggregated_df['Receiving Yards']
aggregated_df['Total_Yards'] = aggregated_df['Yards_from_Scrimmage'] +
    ↪ aggregated_df['Passing Yards']

# Calculate averages for aggregated statistics
aggregated_df['Avg_TD'] = aggregated_df['Total TD'] / aggregated_df['Games
    ↪ Played']
aggregated_df['Avg_Yards_from_Scrimmage'] =
    ↪ aggregated_df['Yards_from_Scrimmage'] / aggregated_df['Games Played']
aggregated_df['Avg_Passing_Yards'] = aggregated_df['Passing Yards'] /
    ↪ aggregated_df['Games Played']
aggregated_df['Avg_Total_Yards'] = aggregated_df['Total_Yards'] /
    ↪ aggregated_df['Games Played']

# Save the aggregated data to a new CSV file
aggregated_df.to_csv('aggregated_fantasy_data.csv', index=False)

[16]: # Split Data (Train/Test)
X = aggregated_df[['Yards_from_Scrimmage', 'Passing Yards', 'Total TD',
    ↪ 'Total_Yards']]
y = aggregated_df['Fantasy Points']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪ random_state=42)
```

```

# Confirm the split sizes
print("Train Feature Set Shape:", X_train.shape)
print("Test Feature Set Shape:", X_test.shape)
print("Train Target Set Shape:", y_train.shape)
print("Test Target Set Shape:", y_test.shape)

# Correlation heatmap
plt.figure(figsize=(8, 6))
corr = aggregated_df[['Yards_from_Scrimmage', 'Passing Yards', 'Total TD', 'Total_Yards', 'Fantasy Points']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()

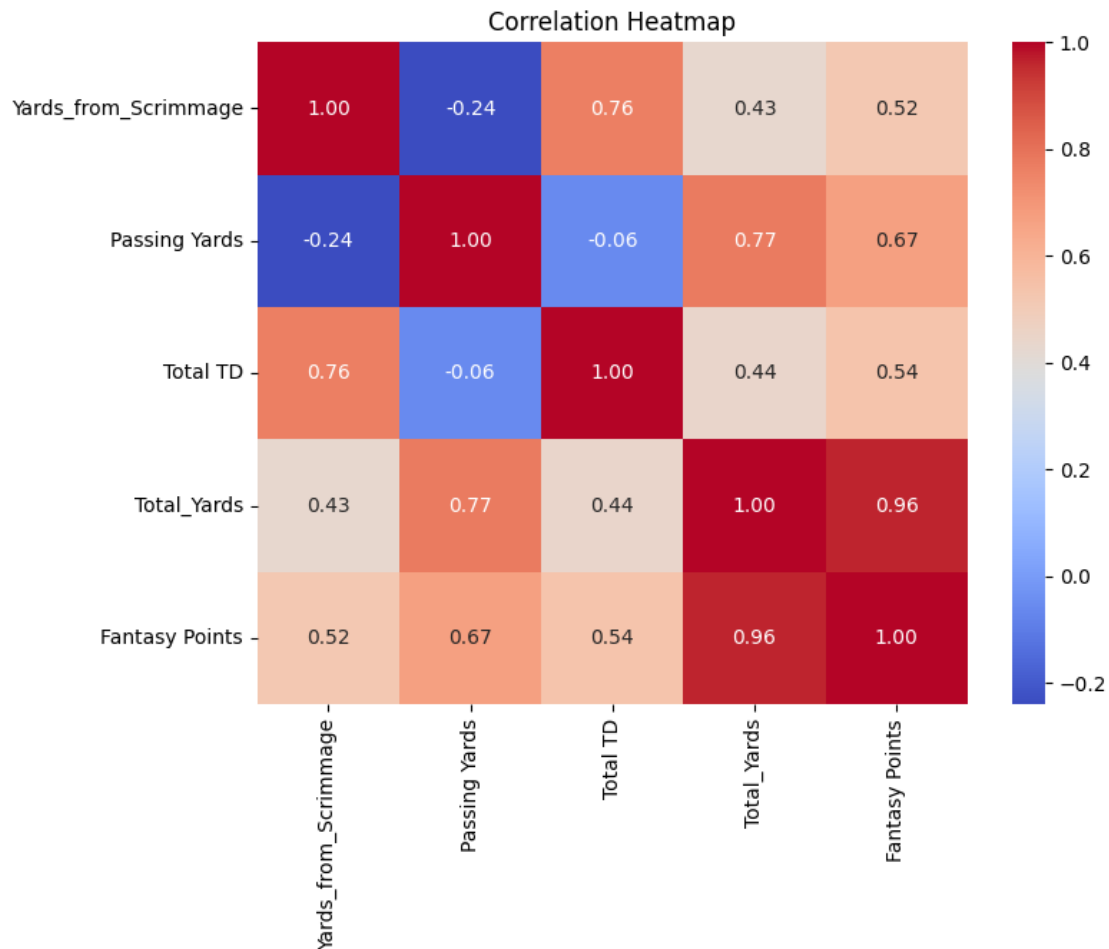
```

Train Feature Set Shape: (288, 4)

Test Feature Set Shape: (72, 4)

Train Target Set Shape: (288,)

Test Target Set Shape: (72,)



```
[17]: ##### Start of Week 4 #####
# Data Cleaning: Remove special characters from 'Player' column
aggregated_df['Player'] = aggregated_df['Player'].str.replace(r'[^a-zA-Z.\s]', ' ',
    ↪ regex=True)

[18]: # Handle missing data
imputer = SimpleImputer(strategy='mean') # You can change the strategy based
    ↪ on needs (mean, median, etc.)
aggregated_df['Fantasy Points'] = imputer.fit_transform(aggregated_df[['Fantasy
    ↪ Points']])

[19]: # Outlier Treatment: Using IQR to detect and remove outliers in Fantasy Points
Q1 = aggregated_df['Fantasy Points'].quantile(0.25)
Q3 = aggregated_df['Fantasy Points'].quantile(0.75)
IQR = Q3 - Q1
# Filtering out outliers beyond 1.5*IQR
aggregated_df = aggregated_df[~((aggregated_df['Fantasy Points'] < (Q1 - 1.5 *
    ↪ IQR)) | (aggregated_df['Fantasy Points'] > (Q3 + 1.5 * IQR)))]

[20]: # Normalize and Standardize numerical features
scaler = StandardScaler()
numerical_features = ['Yards_from_Scrimmage', 'Passing Yards', 'Total TD',
    ↪ 'Fantasy Points']
aggregated_df[numerical_features] = scaler.
    ↪ fit_transform(aggregated_df[numerical_features])

# One-hot Encoding for categorical variables
encoder = OneHotEncoder(sparse_output=False, drop='first') # Dropping first to
    ↪ avoid multicollinearity
encoded_position = encoder.fit_transform(aggregated_df[['Position']])
encoded_df = pd.DataFrame(encoded_position, columns=encoder.
    ↪ get_feature_names_out(['Position']))
aggregated_df = pd.concat([aggregated_df, encoded_df], axis=1)

[21]: # Remove unnecessary columns (e.g., 'Team' column if not needed)
aggregated_df.drop(columns=['Team'], inplace=True, errors='ignore')

# Handle duplicates by removing any duplicate rows
aggregated_df.drop_duplicates(inplace=True)

[22]: # Text Data Cleaning (if applicable): removing stop words, punctuation,
    ↪ lowercasing
# This is included as an example in case you have text data, modify if needed
```

```

aggregated_df['Player'] = aggregated_df['Player'].str.lower().str.
    ↪replace(r'[\w\s]', '', regex=True).str.strip()

# Aggregating relevant statistics (already done previously, no changes needed,
    ↪for now)
aggregated_df = aggregated_df.groupby('Player').agg({
    'Rushing Yards': 'sum',
    'Receiving Yards': 'sum',
    'Passing Yards': 'sum',
    'Total TD': 'sum',
    'Fantasy Points': 'sum',
    'Games Played': 'sum',
    'Position': 'first',
}).reset_index()

```

```

[23]: # Save processed data to a new CSV
aggregated_df.to_csv('processed_fantasy_data.csv', index=False)

print("Data processing complete. Here's the head of the cleaned dataframe:")
print(aggregated_df.head())

```

Data processing complete. Here's the head of the cleaned dataframe:

	Player	Rushing Yards	Receiving Yards	Passing Yards	Total TD	\
0	aaron jones	2987.0	1615.0	-0.311467	4.027857	
1	adam thielen	23.0	2785.0	-0.311467	2.532938	
2	adrian peterson	1502.0	243.0	-0.311467	1.038018	
3	aj brown	70.0	4491.0	-0.311467	2.532938	
4	aj dillon	803.0	519.0	-0.311467	-0.955208	

	Fantasy Points	Games Played	Position
0	2.730606	62.0	RB
1	1.126495	55.0	WR
2	-0.126419	31.0	RB
3	1.914313	60.0	WR
4	0.106129	34.0	RB

```

[24]: ##### Start of Week 5 #####
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Load your dataset
df = pd.read_csv('aggregated_fantasy_data.csv')

```

```

# Feature 1: Create a new feature 'Total_Yards' by adding rushing and receiving
↳yards
df['Total_Yards'] = df['Rushing Yards'] + df['Receiving Yards']

# Feature 2: Create 'Touchdown_Efficiency' by dividing total touchdowns by
↳total yards
df['Touchdown_Efficiency'] = df['Total TD'] / df['Total_Yards']

# Feature 3: Create 'Fantasy Points per Game (FP_per_Game)' by dividing fantasy
↳points by games played
df['FP_per_Game'] = df['Fantasy Points'] / df['Games Played']

# Drop NaN or infinite values that may result from division
df['Touchdown_Efficiency'].replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(subset=['Touchdown_Efficiency'], inplace=True)

# View the new columns added
df[['Player', 'Rushing Yards', 'Receiving Yards', 'Total_Yards', 'Total TD',
↳'Touchdown_Efficiency', 'FP_per_Game']].head()

```

/tmp/ipykernel_3833786/2416030159.py:21: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
df['Touchdown_Efficiency'].replace([np.inf, -np.inf], np.nan, inplace=True)
```

```
[24]:
```

	Player	Rushing Yards	Receiving Yards	Total_Yards	Total TD	\
0	A.J. Brown	70.0	4491	4561.0	21.0	
1	A.J. Green	0.0	1371	1371.0	2.0	
2	AJ Dillon	803.0	519	1322.0	0.0	
3	Aaron Jones	2987.0	1615	4602.0	30.0	
4	Aaron Rodgers	433.0	-10	423.0	4.0	

	Touchdown_Efficiency	FP_per_Game
0	0.004604	11.216667
1	0.001459	5.218750
2	0.000000	8.588235
3	0.006519	13.629032
4	0.009456	18.938462

```

[30]: # Select only numeric features (excluding player names or other categorical
      ↪ features)
      numeric_columns = df.select_dtypes(include=['number']).columns

[31]: # Week 6: PCA

df = pd.read_csv('aggregated_fantasy_data.csv')
df['Total_Yards'] = df['Rushing Yards'] + df['Receiving Yards']
# Avoid division by zero
df['Touchdown_Efficiency'] = np.where(df['Total_Yards'] != 0, df['Total TD'] /
      ↪ df['Total_Yards'], 0)
df['FP_per_Game'] = df['Fantasy Points'] / df['Games Played']

# Split data first to prevent leakage
X = df[numeric_columns].drop(columns=['Fantasy Points'])
y = df['Fantasy Points']
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
      ↪ random_state=42)

# Feature Scaling and PCA
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train.select_dtypes(include=['int64',
      ↪ 'float64']))
X_val_scaled = scaler.transform(X_val.select_dtypes(include=['int64',
      ↪ 'float64']))

pca = PCA(n_components=5)
X_train_pca = pca.fit_transform(X_train_scaled)
X_val_pca = pca.transform(X_val_scaled)

# Model
rf = RandomForestRegressor(random_state=42)
param_grid = {'n_estimators': [100, 200, 300], 'max_depth': [10, 20, None],
      ↪ 'min_samples_split': [2, 5, 10]}
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=3,
      ↪ scoring='r2', n_jobs=-1, verbose=2)
grid_search.fit(X_train_pca, y_train)

# Evaluate the model
y_val_pred = grid_search.best_estimator_.predict(X_val_pca)
val_rmse = np.sqrt(mean_squared_error(y_val, y_val_pred))
val_r2 = r2_score(y_val, y_val_pred)

print(f"Validation RMSE: {val_rmse}")
print(f"Validation R^2: {val_r2}")

```

Fitting 3 folds for each of 27 candidates, totalling 81 fits

Validation RMSE: 159.2263800401631
Validation R²: 0.7018433605794435

```
[32]: from sklearn.ensemble import RandomForestRegressor
      from sklearn.metrics import mean_squared_error, r2_score
      import numpy as np

      # Base model
      rf_base = RandomForestRegressor(random_state=42)
      rf_base.fit(X_train, y_train)

      # Predictions
      y_train_pred_base = rf_base.predict(X_train)
      y_val_pred_base = rf_base.predict(X_val)

      # Metrics calculation
      train_rmse_base = np.sqrt(mean_squared_error(y_train, y_train_pred_base))
      val_rmse_base = np.sqrt(mean_squared_error(y_val, y_val_pred_base))

      train_r2_base = r2_score(y_train, y_train_pred_base)
      val_r2_base = r2_score(y_val, y_val_pred_base)

      print(f"Base Model - Training RMSE: {train_rmse_base}, Validation RMSE:␣
            ↳{val_rmse_base}")
      print(f"Base Model - Training R2: {train_r2_base}, Validation R2:␣
            ↳{val_r2_base}")
```

Base Model - Training RMSE: 18.48719200028916, Validation RMSE:
30.64079352395721
Base Model - Training R²: 0.9950859234251188, Validation R²: 0.9889588462379747

```
[33]: from sklearn.model_selection import GridSearchCV

      # Define hyperparameters to tune
      param_grid = {
          'n_estimators': [100, 200, 300],
          'max_depth': [10, 20, None],
          'min_samples_split': [2, 5, 10]
      }

      # Grid Search
      rf_tuned = RandomForestRegressor(random_state=42)
      grid_search = GridSearchCV(estimator=rf_tuned, param_grid=param_grid, cv=3,␣
            ↳scoring='r2', n_jobs=-1, verbose=2)
      grid_search.fit(X_train, y_train)

      # Predictions
```



```

y_train_pred_tuned = grid_search.best_estimator_.predict(X_train)
y_val_pred_tuned = grid_search.best_estimator_.predict(X_val)

# Metrics calculation
train_rmse_tuned = np.sqrt(mean_squared_error(y_train, y_train_pred_tuned))
val_rmse_tuned = np.sqrt(mean_squared_error(y_val, y_val_pred_tuned))

train_r2_tuned = r2_score(y_train, y_train_pred_tuned)
val_r2_tuned = r2_score(y_val, y_val_pred_tuned)

print(f"Tuned Model - Training RMSE: {train_rmse_tuned}, Validation RMSE:␣
↪{val_rmse_tuned}")
print(f"Tuned Model - Training R²: {train_r2_tuned}, Validation R²:␣
↪{val_r2_tuned}")

```

Fitting 3 folds for each of 27 candidates, totalling 81 fits

Tuned Model - Training RMSE: 16.94819532653518, Validation RMSE:

30.67567504124581

Tuned Model - Training R²: 0.9958700296141166, Validation R²: 0.9889336934028812

```

[34]: from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Standardize features before applying PCA
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Apply PCA
pca = PCA(n_components=5)
X_train_pca = pca.fit_transform(X_train_scaled)
X_val_pca = pca.transform(X_val_scaled)

# Train Random Forest on PCA-transformed data
rf_pca = RandomForestRegressor(random_state=42)
rf_pca.fit(X_train_pca, y_train)

# Predictions
y_train_pred_pca = rf_pca.predict(X_train_pca)
y_val_pred_pca = rf_pca.predict(X_val_pca)

# Metrics calculation
train_rmse_pca = np.sqrt(mean_squared_error(y_train, y_train_pred_pca))
val_rmse_pca = np.sqrt(mean_squared_error(y_val, y_val_pred_pca))

train_r2_pca = r2_score(y_train, y_train_pred_pca)
val_r2_pca = r2_score(y_val, y_val_pred_pca)

```

```
print(f"PCA Model - Training RMSE: {train_rmse_pca}, Validation RMSE: {val_rmse_pca}")
print(f"PCA Model - Training R²: {train_r2_pca}, Validation R²: {val_r2_pca}")
```

PCA Model - Training RMSE: 30.30089734988608, Validation RMSE:
159.26648103711102

PCA Model - Training R²: 0.9867988733775771, Validation R²: 0.7016931607936405

[]: