1-Objective

The goal of this analysis was to determine which team-level performance metrics most strongly explain season-long success in the EuroLeague, measured by Wins (W). Data was collected programmatically for four consecutive seasons and explored through descriptive statistics, correlation matrices, and targeted scatter analyses.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 2000)

#uploading cvs's
season_files = {
    "2024_2025": "2024_2025_stats.csv",
    "2023_2024": "2023_2024_stats.csv",
    "2022_2023": "2022_2023_stats.csv",
    "2021_2022": "2021_2022_stats.csv"
}


seasons = {season: pd.read_csv(path) for season, path in season_file

numeric_cols = seasons["2024_2025"].columns.drop("TEAM")

seasons
```

```
 7                  FC Bayern Munich  19  15  2965  616  1058  426
1091  1042  2149  455  348  741  641  456  224   41
 8                  Paris Basketball  19  15  2940  691  1270  362
1025  1053  2295  472  402  785  540  352  223   68
 9                  KK Crvena zvezda  18  16  2814  676  1239  323
882   999  2121  493  378  770  677  420  213   62
 10                   Olimpia Milano  17  17  2905  647  1198  339
858   986  2056  594  300  785  587  410  218   68
 11                      KK Partizan  16  18  2780  703  1297  305
817  1008  2114  459  368  732  610  367  246  101
 12                      BC Zalgiris  15  19  2632  577  1106  325
948   902  2054  503  375  775  519  431  203   92
```

```
 13         Baskonia Vitoria-Gasteiz  14  20  2807  713  1305  306
888  1019  2193  463  417  813  617  411  185  100
 14              ASVEL Villeurbanne  13  21  2751  640  1186  309
847   949  2033  544  344  766  605  469  223   81
 15             Maccabi Tel Aviv BC  11  23  2921  782  1432  274
765  1056  2197  535  413  788  646  444  209   53
 16                  Virtus Bologna   9  25  2693  688  1251  258
827   946  2078  543  338  756  630  407  209   79
 17                     ALBA Berlin   5  29  2673  768  1406  246
818  1014  2224  399  398  772  669  526  219   70,
 '2023_2024':                              TEAM   W   L   PTS
2PM   2PA  3PM  3PA   FGM   FGA  FTM  ORB  DRB  AST  TOV   ST  BLK
 0                      Real Madrid  27   7  2999  711  1240  343
918  1054  2158  548  335  916  696  422  215  119
 1                 AS Monaco Basket  23  11  2785  743  1403  269
763  1012  2166  492  383  782  547  340  236   61
 2   Panathinaikos Athlitikos Omilos  23  11  2774  676  1240  305
801   981  2041  507  337  803  562  433  244   92
 3                     FC Barcelona  22  12  2812  759  1352  292
798  1051  2150  418  384  840  659  433  210   83
 4              Olympiacos Piraeus  22  12  2685  641  1152  320
857   961  2009  443  320  777  657  386  238   96
 5                    Fenerbahçe SK  20  14  2894  649  1151  382
976  1031  2127  450  344  790  616  408  196   82
 6             Maccabi Tel Aviv BC  20  14  2983  781  1464  295
810  1076  2274  536  443  782  666  418  249  106
 7         Baskonia Vitoria-Gasteiz  18  16  2864  664  1197  353
963  1017  2160  477  351  847  640  423  185   79
 8                   Virtus Bologna  17  17  2728  666  1227  319
882   985  2109  439  320  782  640  411  224   85
 9            Anadolu Efes Istanbul  17  17  2928  735  1309  339
911  1074  2220  441  345  754  610  351  237  105
 10                     KK Partizan  16  18  2822  750  1282  273
755  1023  2037  503  310  741  514  423  223   79
 11                  Olimpia Milano  15  19  2659  615  1116  341
930   956  2046  406  302  791  554  423  238   72
 12                 Valencia Basket  14  20  2582  686  1309  247
754   933  2063  469  345  823  550  463  220   62
 13                     BC Zalgiris  14  20  2702  646  1217  331
851   977  2068  417  331  753  532  428  221   59
 14               FC Bayern Munich  13  21  2674  649  1215  336
938   985  2153  368  364  840  547  443  206   89
 15               KK Crvena zvezda  11  23  2764  680  1239  314
920   994  2159  462  403  777  629  411  224   84
 16              ASVEL Villeurbanne   9  25  2674  744  1389  244
723   988  2112  454  350  805  605  440  205   55
 17                     ALBA Berlin   5  29  2591  641  1261  302
```

2- Methods
For each season: Core team statistics were loaded from cleaned CSV files.
Descriptive summaries were generated to understand distribution ranges.
Correlation matrices were computed to quantify the relationship between each metric and Wins.
To avoid noise, only the top 3 positively correlated metrics and the strongest non-trivial negative metric (excluding Losses) were visualized with scatter plots.
Results were compared across seasons to identify consistent patterns.

```
numeric_cols = seasons["2024_2025"].columns.drop("TEAM")
numeric_cols
```

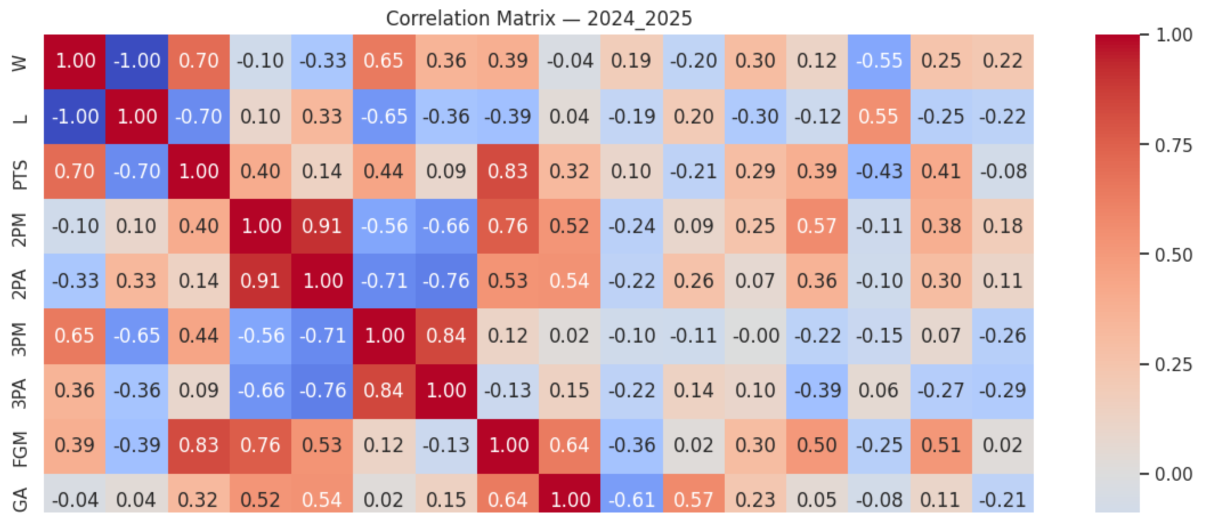
```
Index(['W', 'L', 'PTS', '2PM', '2PA', '3PM', '3PA', 'FGM', 'FGA',
'FTM', 'ORB', 'DRB', 'AST', 'TOV', 'ST', 'BLK'], dtype='object')
```

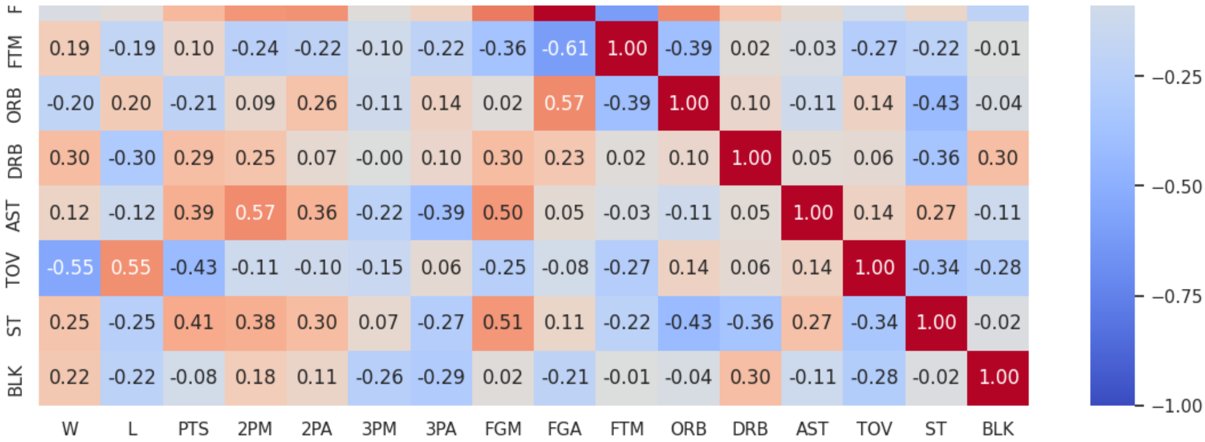
```
for season, df in seasons.items():
    corr = df[numeric_cols].corr()["W"].sort_values(ascending=False)
    print(f"\n=== {season} — W and Correlation ===")
    print(corr)
```

```
L     -1.000000
Name: W, dtype: float64

=== 2023_2024 — W and Correlation ===
W      1.000000
PTS    0.644325
FTM    0.564362
BLK    0.539193
FGM    0.520154
DRB    0.474084
AST    0.447354
2PM    0.272924
3PM    0.236533
FGA    0.084289
ST     0.063067
3PA    0.047684
2PA    0.021683
ORB   -0.039471
TOV   -0.558947
L     -1.000000
Name: W, dtype: float64

=== 2022_2023 — W and Correlation ===
W      1.000000
PTS    0.652519
FGM    0.605009
2PM    0.505996
```

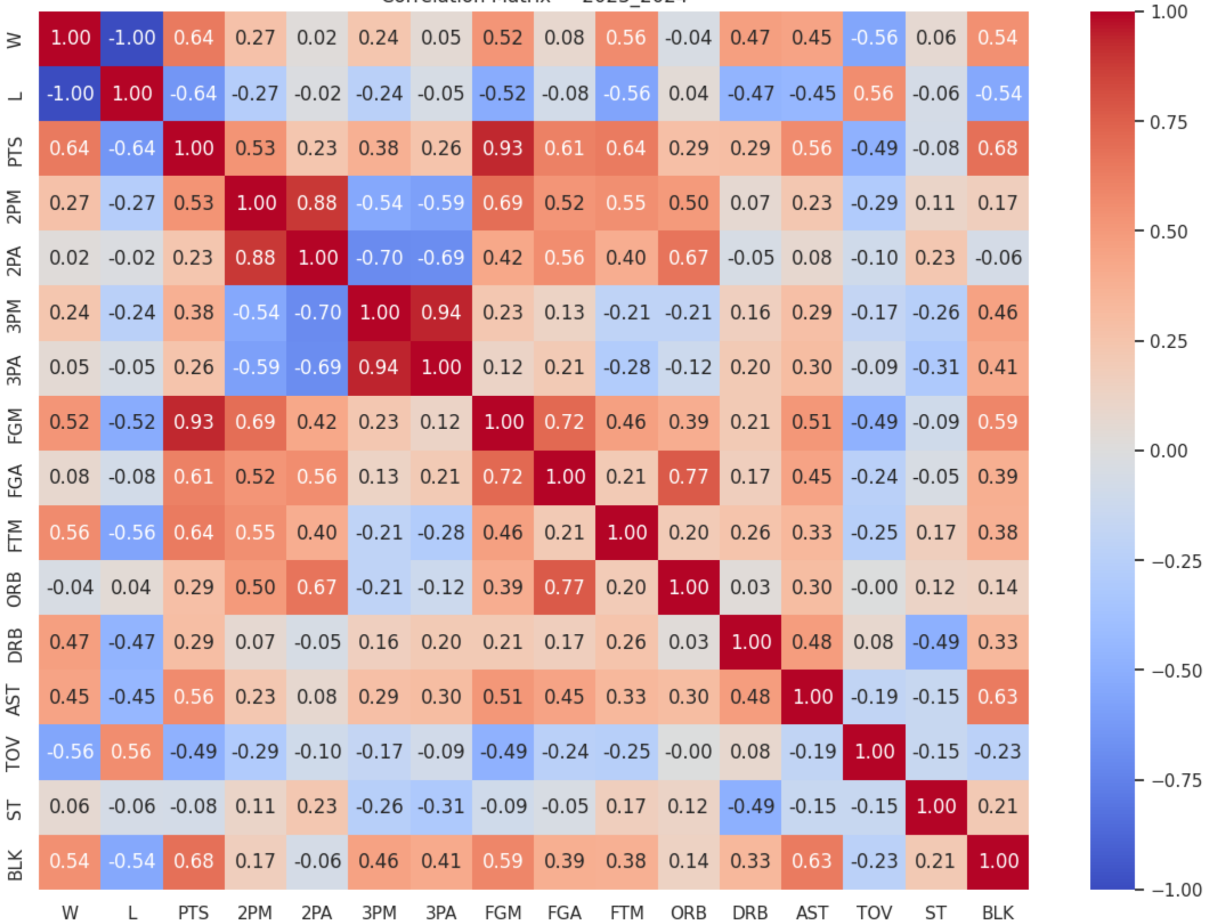
```
AST    0.417378
DRB    0.306056
FTM    0.290993
BLK    0.203811
ORB    0.189095
3PM    0.134864
2PA    0.122237
ST     0.040370
FGA    0.026218
3PA   -0.096461
TOV   -0.283204
L     -1.000000
Name: W, dtype: float64

=== 2021_2022 — W and Correlation ===
W      1.000000
3PM    0.540085
FTM    0.468763
PTS    0.463864
DRB    0.413464
FGM    0.405740
AST    0.404177
3PA    0.373123
ORB    0.357646
FGA    0.297338
2PM    0.268923
ST     0.201749
2PA    0.179730
BLK    0.097754
TOV    0.095683
L     -0.762121
Name: W, dtype: float64
```

```
for season, df in seasons.items():
    plt.figure(figsize=(14, 10))
    sns.heatmap(df[numeric_cols].corr(), annot=True, cmap="coolwarm"
    plt.title(f"Correlation Matrix — {season}")
    plt.show()
```

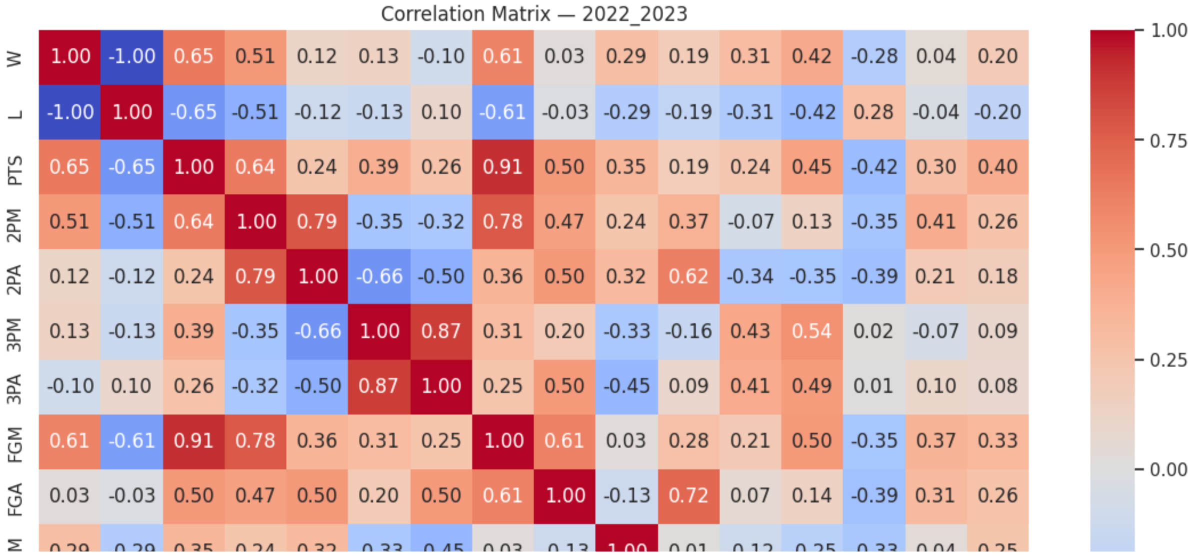


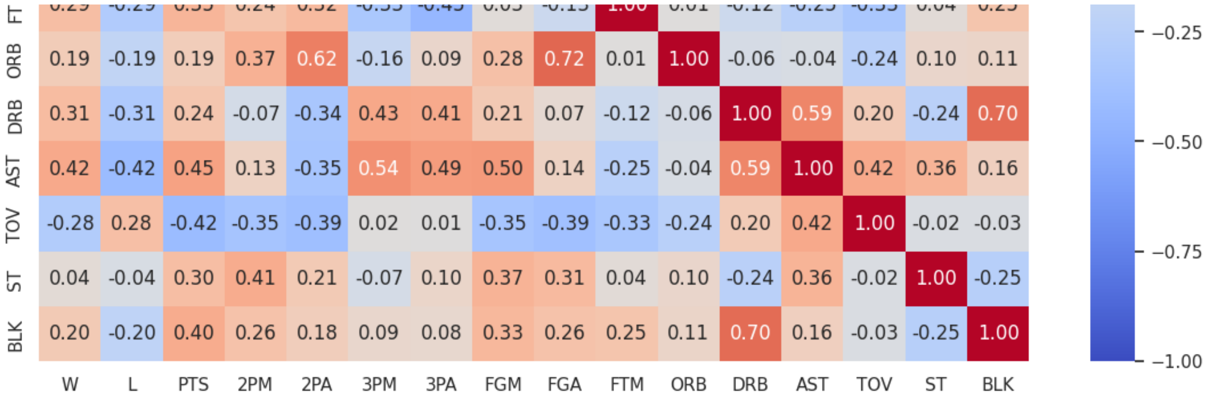


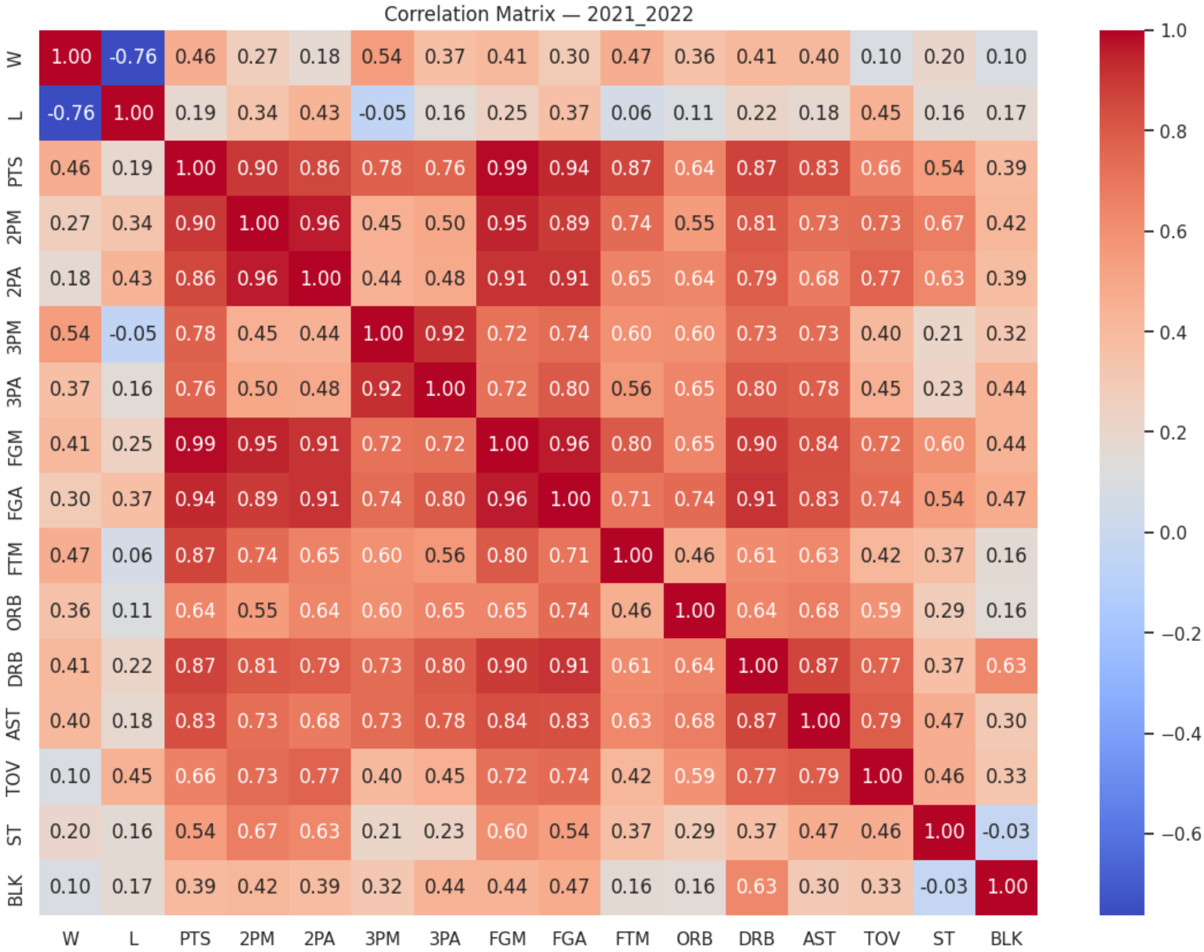
Correlation Matrix — 2023_2024



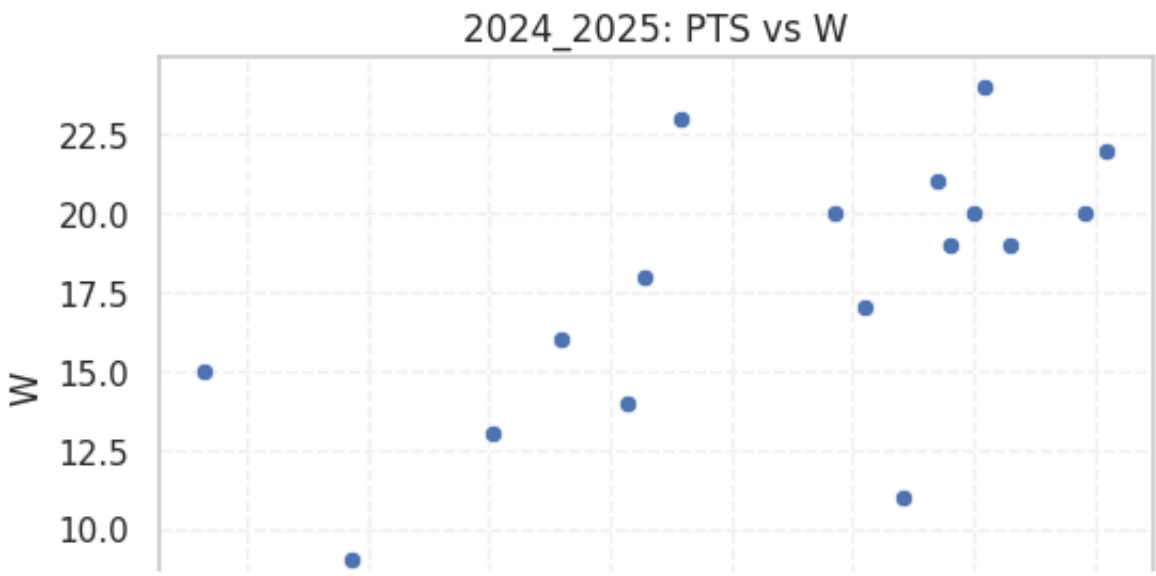
Correlation Matrix — 2022_2023

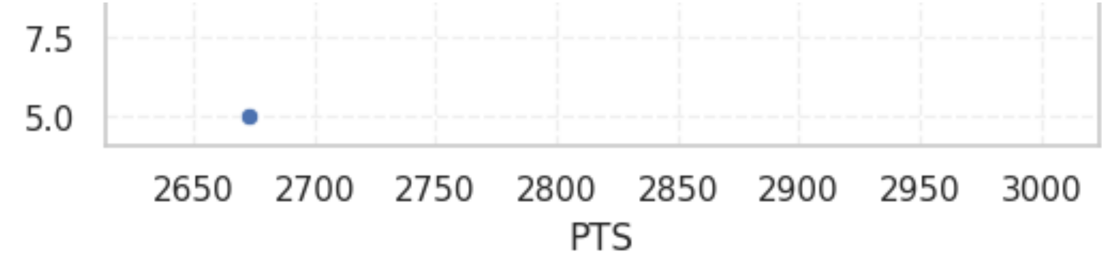


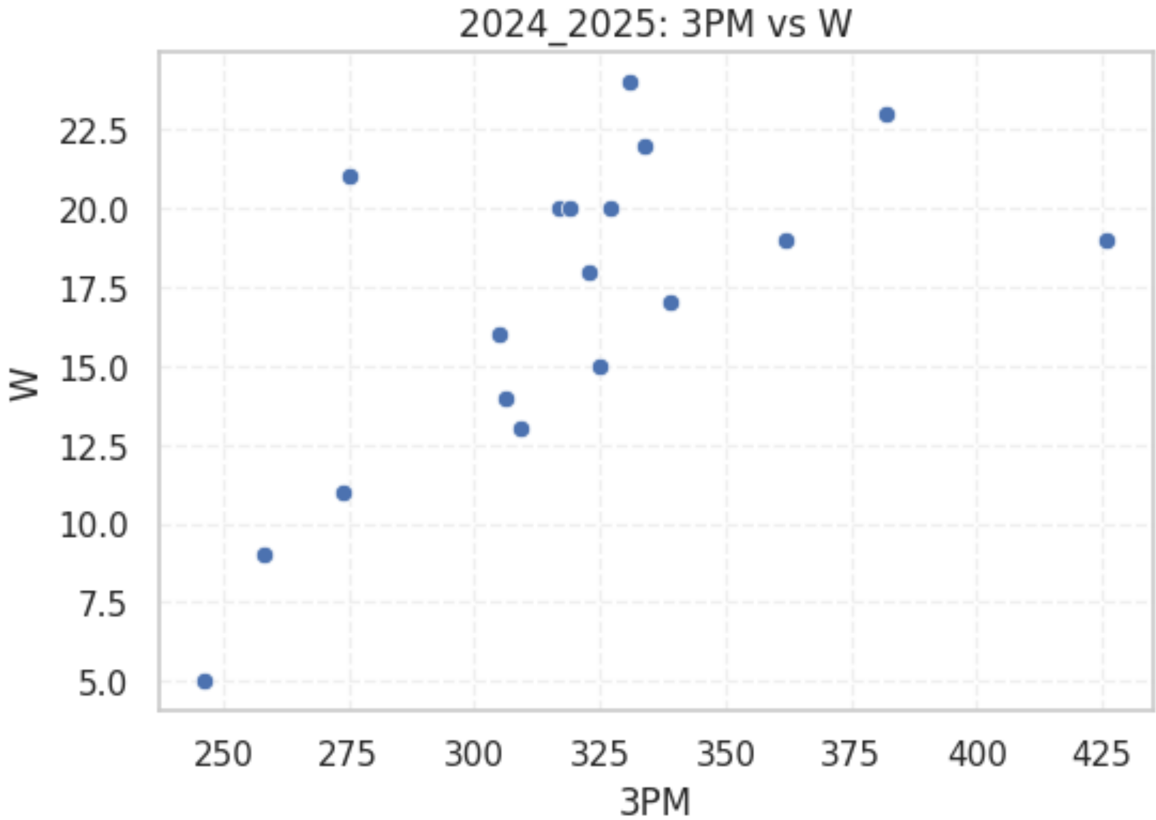

ORB 0.19 -0.19 0.19 0.37 0.62 -0.16 0.09 0.28 0.72 0.01 1.00 -0.06 -0.04 -0.24 0.10 0.11
DRB 0.31 -0.31 0.24 -0.07 -0.34 0.43 0.41 0.21 0.07 -0.12 -0.06 1.00 0.59 0.20 -0.24 0.70
AST 0.42 -0.42 0.45 0.13 -0.35 0.54 0.49 0.50 0.14 -0.25 -0.04 0.59 1.00 0.42 0.36 0.16
TOV -0.28 0.28 -0.42 -0.35 -0.39 0.02 0.01 -0.35 -0.39 -0.33 -0.24 0.20 0.42 1.00 -0.02 -0.03
ST 0.04 -0.04 0.30 0.41 0.21 -0.07 0.10 0.37 0.31 0.04 0.10 -0.24 0.36 -0.02 1.00 -0.25
BLK 0.20 -0.20 0.40 0.26 0.18 0.09 0.08 0.33 0.26 0.25 0.11 0.70 0.16 -0.03 -0.25 1.00
W L PTS 2PM 2PA 3PM 3PA FGM FGA FTM ORB DRB AST TOV ST BLK
−0.25
−0.50
−0.75
−1.00

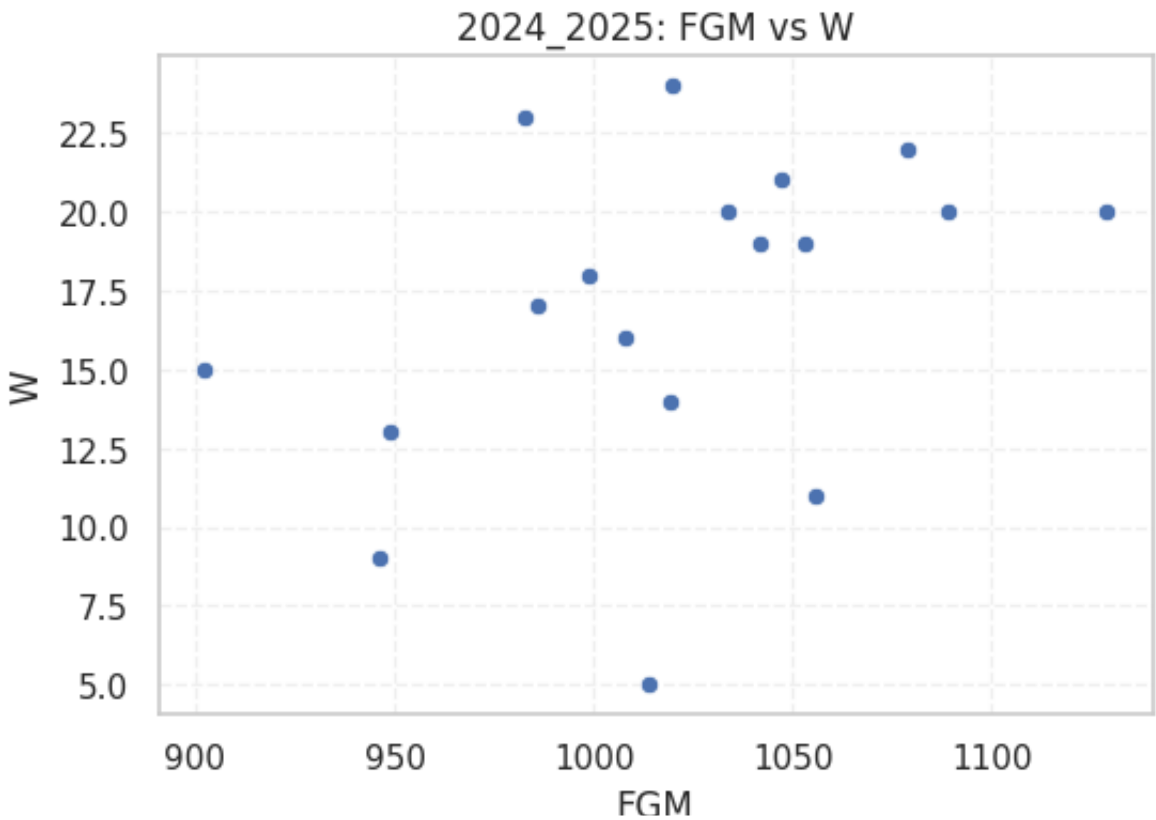

Correlation Matrix — 2021_2022
W 1.00 -0.76 0.46 0.27 0.18 0.54 0.37 0.41 0.30 0.47 0.36 0.41 0.40 0.10 0.20 0.10
L -0.76 1.00 0.19 0.34 0.43 -0.05 0.16 0.25 0.37 0.06 0.11 0.22 0.18 0.45 0.16 0.17
PTS 0.46 0.19 1.00 0.90 0.86 0.78 0.76 0.99 0.94 0.87 0.64 0.87 0.83 0.66 0.54 0.39
2PM 0.27 0.34 0.90 1.00 0.96 0.45 0.50 0.95 0.89 0.74 0.55 0.81 0.73 0.73 0.67 0.42
2PA 0.18 0.43 0.86 0.96 1.00 0.44 0.48 0.91 0.91 0.65 0.64 0.79 0.68 0.77 0.63 0.39
3PM 0.54 -0.05 0.78 0.45 0.44 1.00 0.92 0.72 0.74 0.60 0.60 0.73 0.73 0.40 0.21 0.32
3PA 0.37 0.16 0.76 0.50 0.48 0.92 1.00 0.72 0.80 0.56 0.65 0.80 0.78 0.45 0.23 0.44
FGM 0.41 0.25 0.99 0.95 0.91 0.72 0.72 1.00 0.96 0.80 0.65 0.90 0.84 0.72 0.60 0.44
FGA 0.30 0.37 0.94 0.89 0.91 0.74 0.80 0.96 1.00 0.71 0.74 0.91 0.83 0.74 0.54 0.47
FTM 0.47 0.06 0.87 0.74 0.65 0.60 0.56 0.80 0.71 1.00 0.46 0.61 0.63 0.42 0.37 0.16
ORB 0.36 0.11 0.64 0.55 0.64 0.60 0.65 0.65 0.74 0.46 1.00 0.64 0.68 0.59 0.29 0.16
DRB 0.41 0.22 0.87 0.81 0.79 0.73 0.80 0.90 0.91 0.61 0.64 1.00 0.87 0.77 0.37 0.63
AST 0.40 0.18 0.83 0.73 0.68 0.73 0.78 0.84 0.83 0.63 0.68 0.87 1.00 0.79 0.47 0.30
TOV 0.10 0.45 0.66 0.73 0.77 0.40 0.45 0.72 0.74 0.42 0.59 0.77 0.79 1.00 0.46 0.33
ST 0.20 0.16 0.54 0.67 0.63 0.21 0.23 0.60 0.54 0.37 0.29 0.37 0.47 0.46 1.00 -0.03
BLK 0.10 0.17 0.39 0.42 0.39 0.32 0.44 0.44 0.47 0.16 0.16 0.63 0.30 0.33 -0.03 1.00
W L PTS 2PM 2PA 3PM 3PA FGM FGA FTM ORB DRB AST TOV ST BLK
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

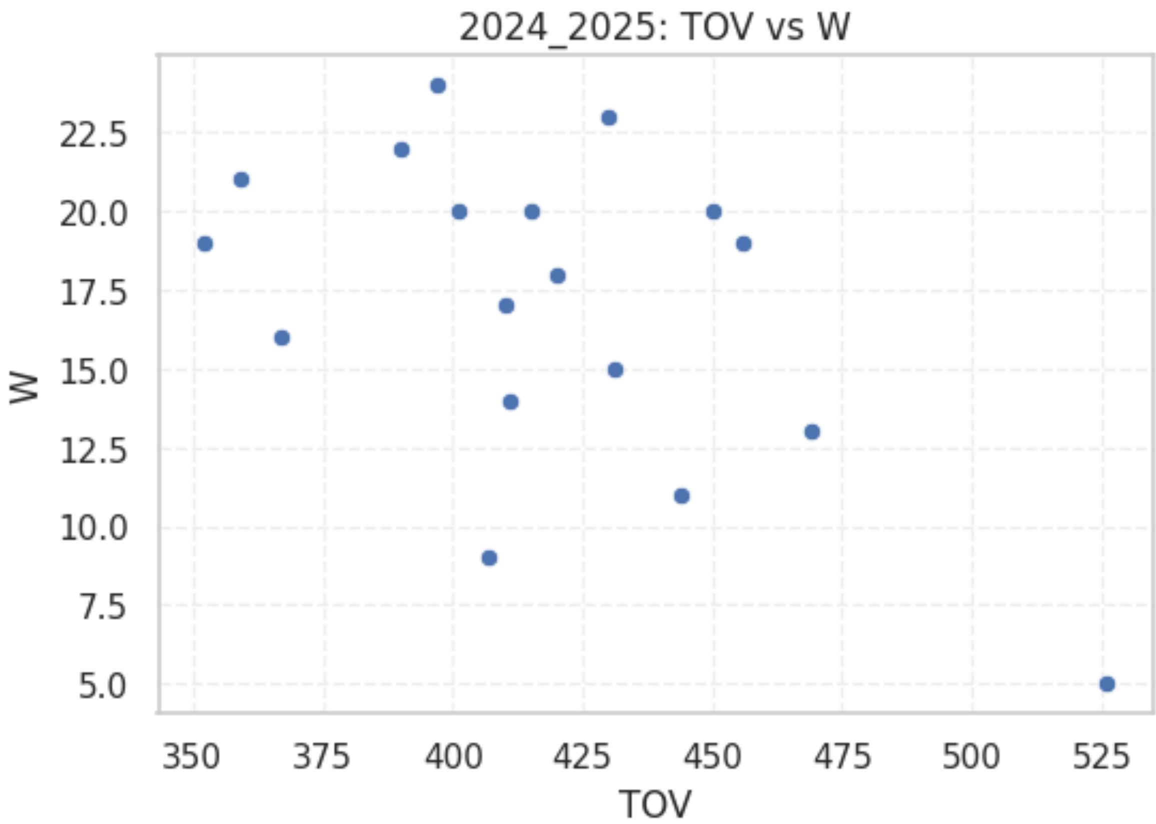
```
import matplotlib.pyplot as plt
import seaborn as sns

def plot_top_correlations(df, season_name):

    numeric_df = df.drop(columns=["TEAM"])

    corrs = numeric_df.corr()["W"].drop("W")

    corrs_no_L = corrs.drop("L")

    top_pos = corrs_no_L.sort_values(ascending=False).head(3)

    top_neg = corrs_no_L.sort_values().head(1)


    metrics = list(top_pos.index) + list(top_neg.index)


    for m in metrics:
        plt.figure(figsize=(6,4))
        sns.scatterplot(data=df, x=m, y="W")
        plt.title(f"{season_name}: {m} vs W")
        plt.xlabel(m)
        plt.ylabel("W")
        plt.grid(True, linestyle="--", alpha=0.3)
        plt.show()



for season_name, df in seasons.items():
    plot_top_correlations(df, season_name)
```

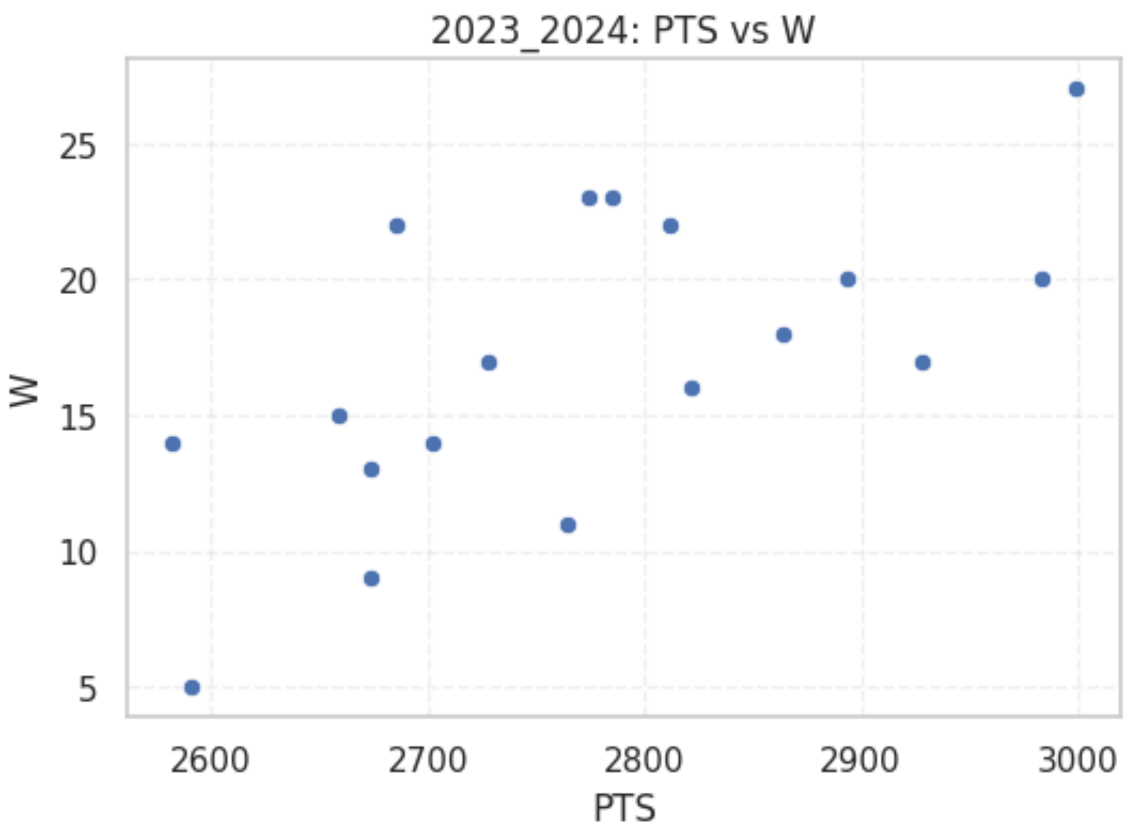



7.5
5.0
2650
2700
2750
2800
2850
2900
2950
3000
PTS

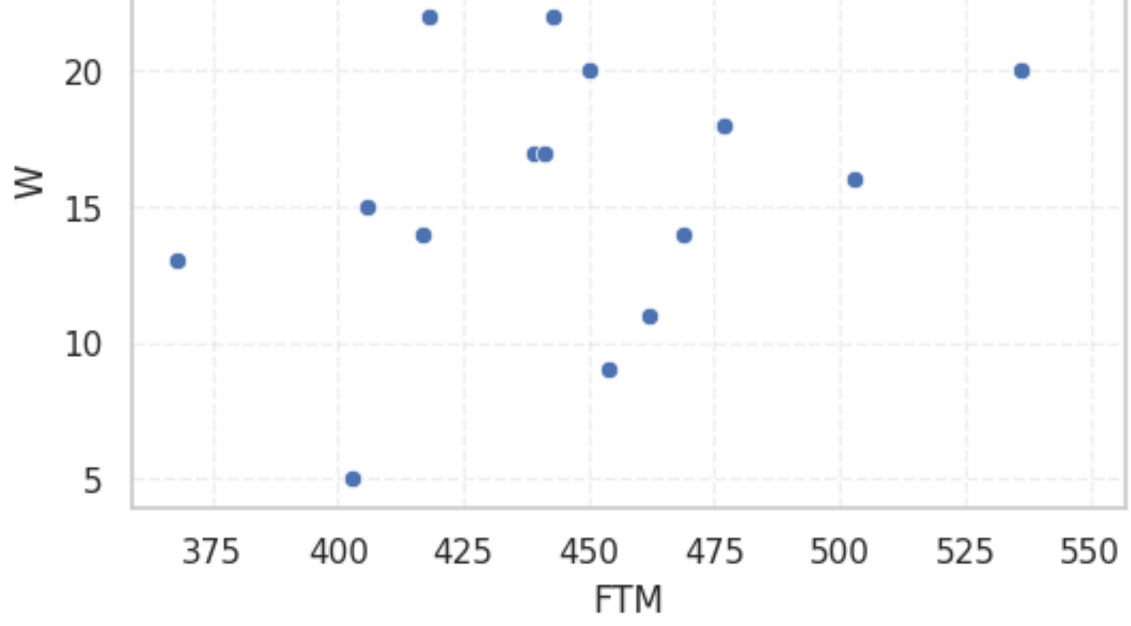

2024_2025: 3PM vs W
W
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
250
275
300
325
350
375
400
425
3PM

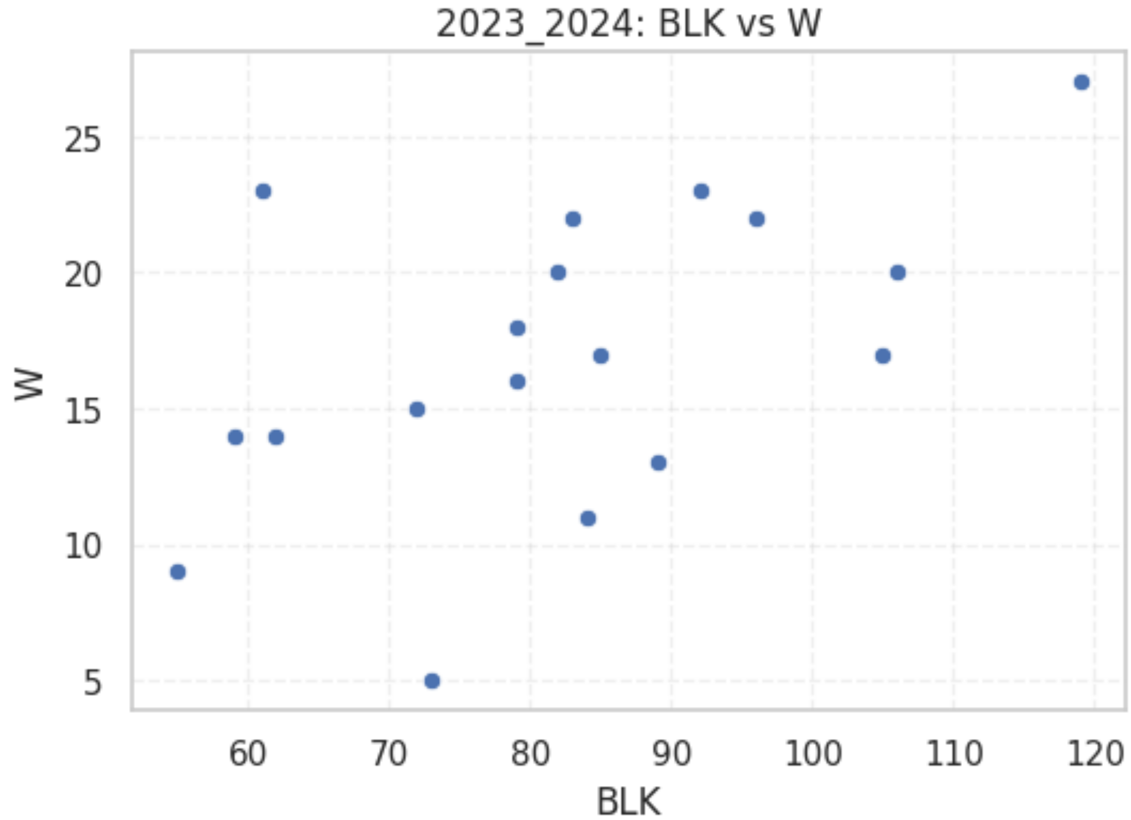

2024_2025: FGM vs W
W
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
900
950
1000
1050
1100
FGM

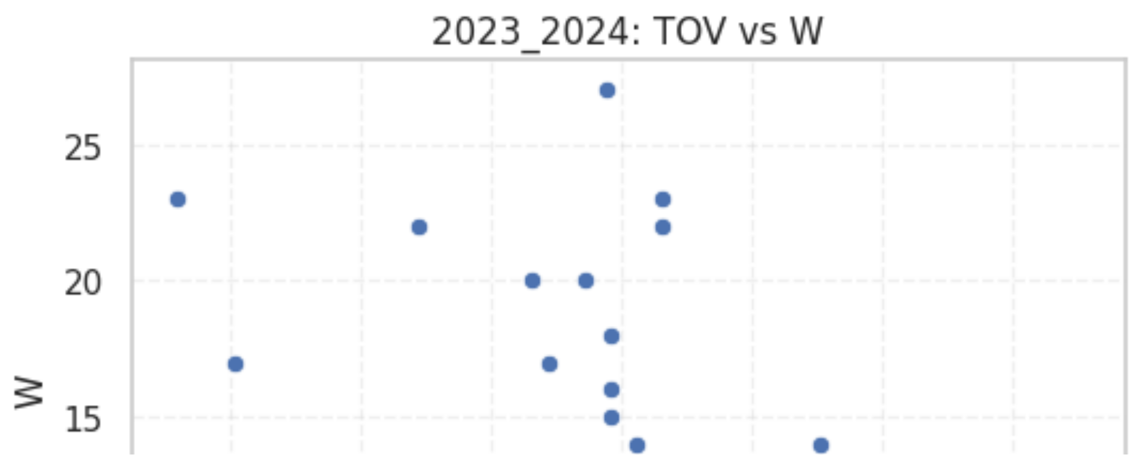

2024_2025: TOV vs W
W
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
350 375 400 425 450 475 500 525
TOV

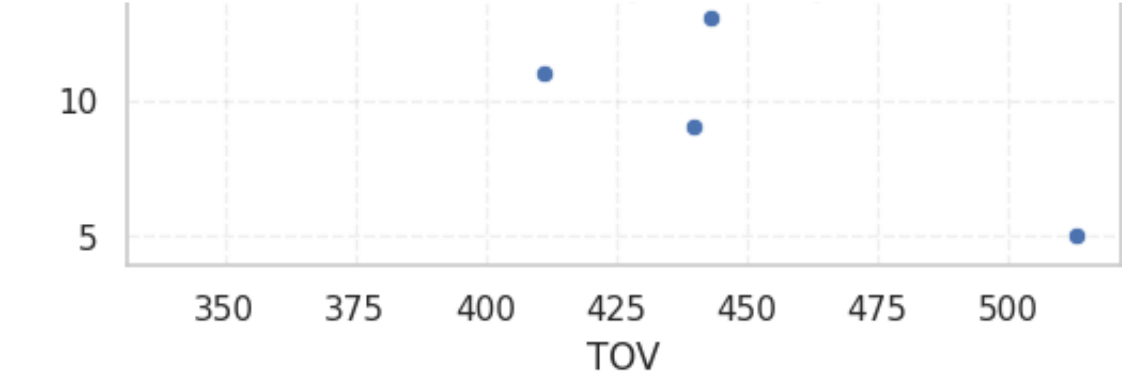

2023_2024: PTS vs W
W
25
20
15
10
5
2600 2700 2800 2900 3000
PTS

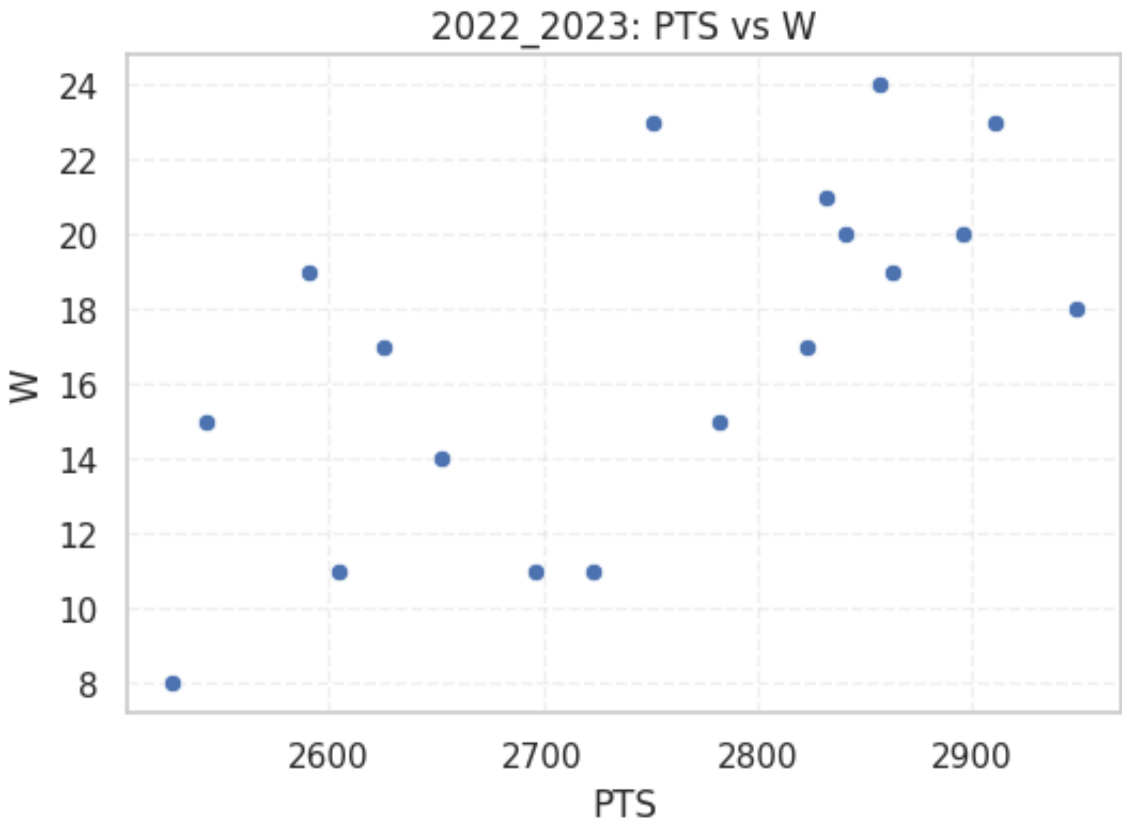

2023_2024: FTM vs W
25

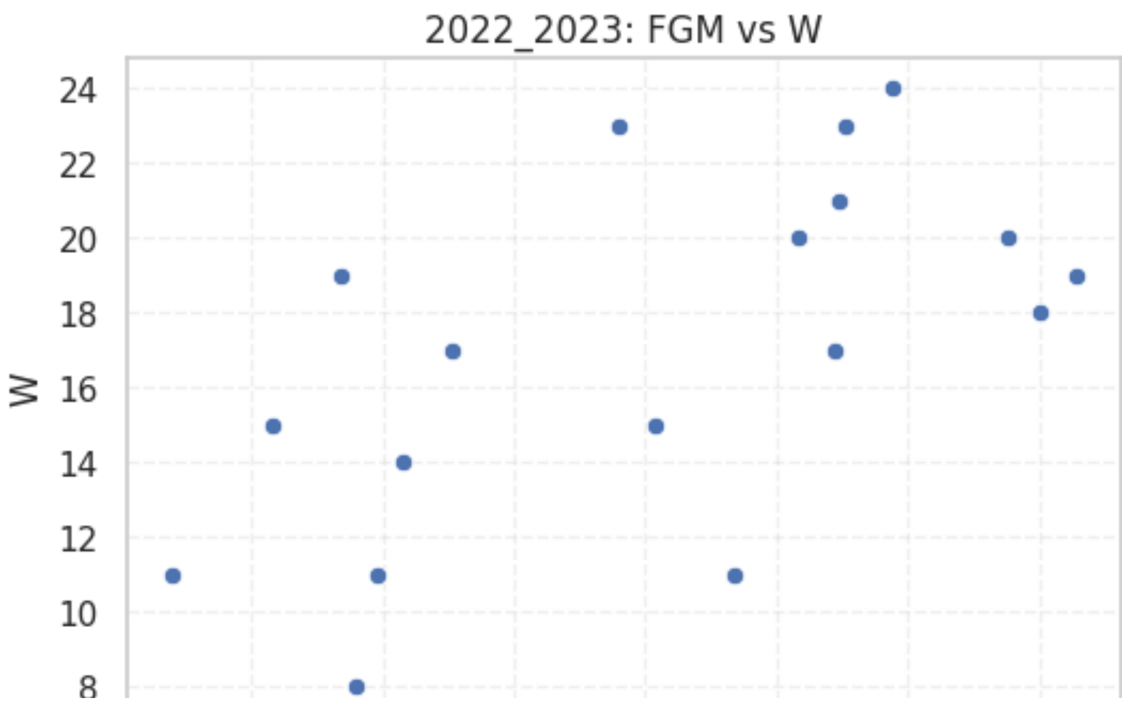

W
20
15
10
5
375
400
425
450
475
500
525
550
FTM

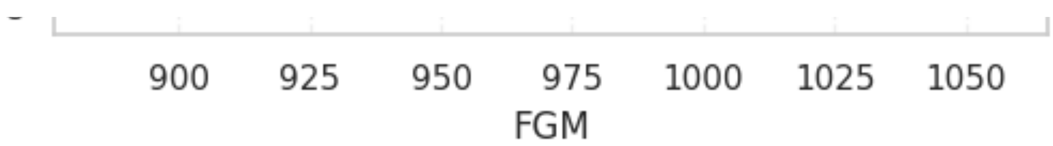

2023_2024: BLK vs W
W
25
20
15
10
5
60
70
80
90
100
110
120
BLK

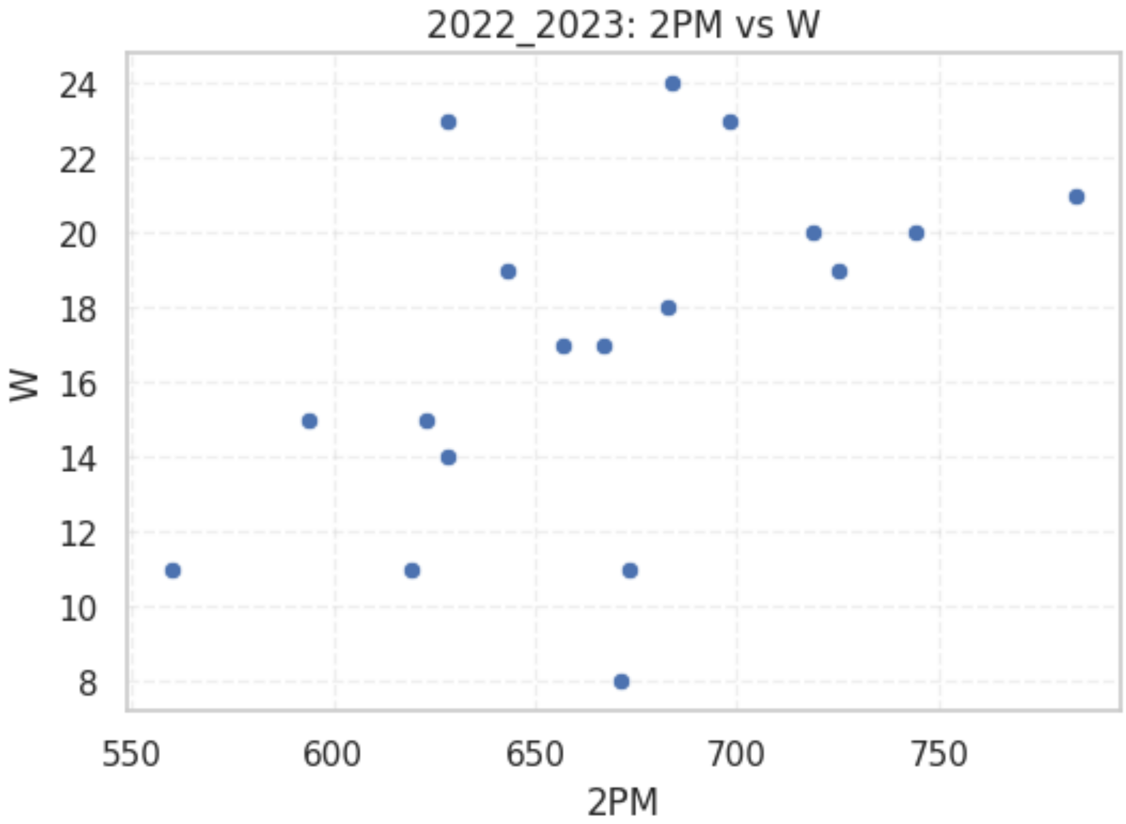

2023_2024: TOV vs W
W
25
20
15

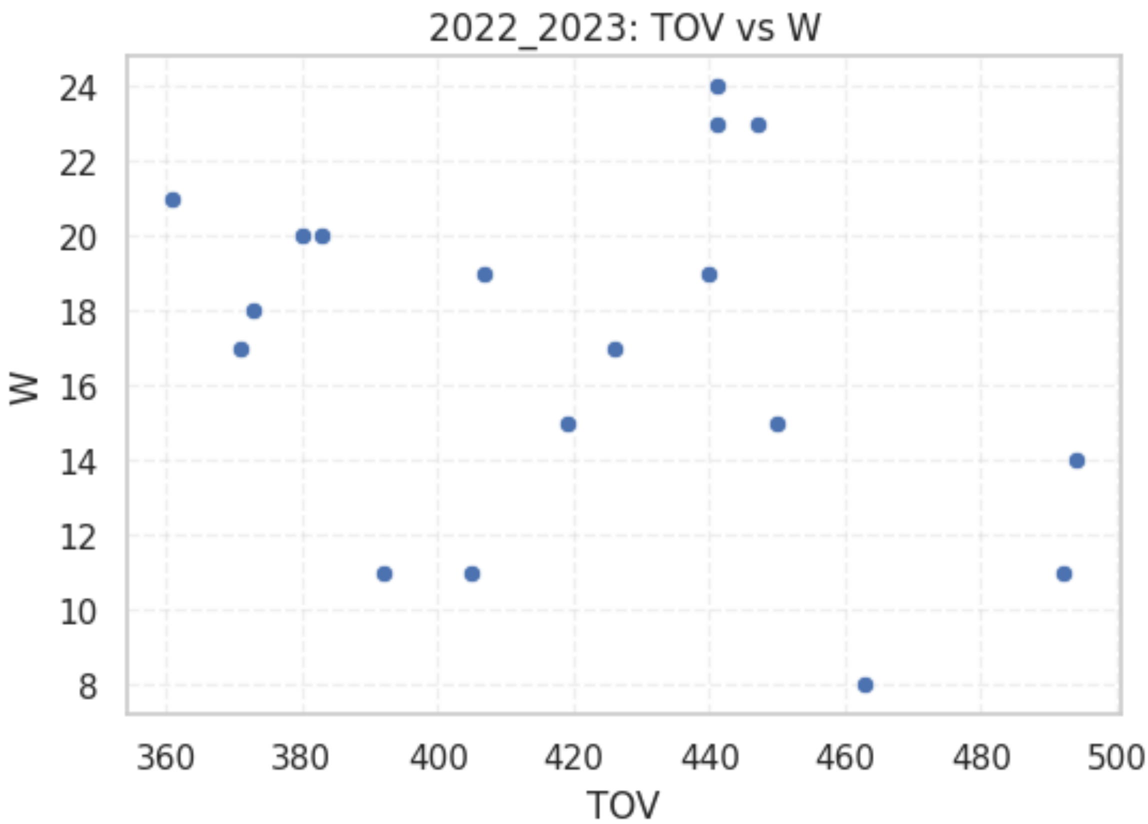

10
5
350
375
400
425
450
475
500
TOV


2022_2023: PTS vs W
24
22
20
18
W
16
14
12
10
8
2600
2700
2800
2900
PTS

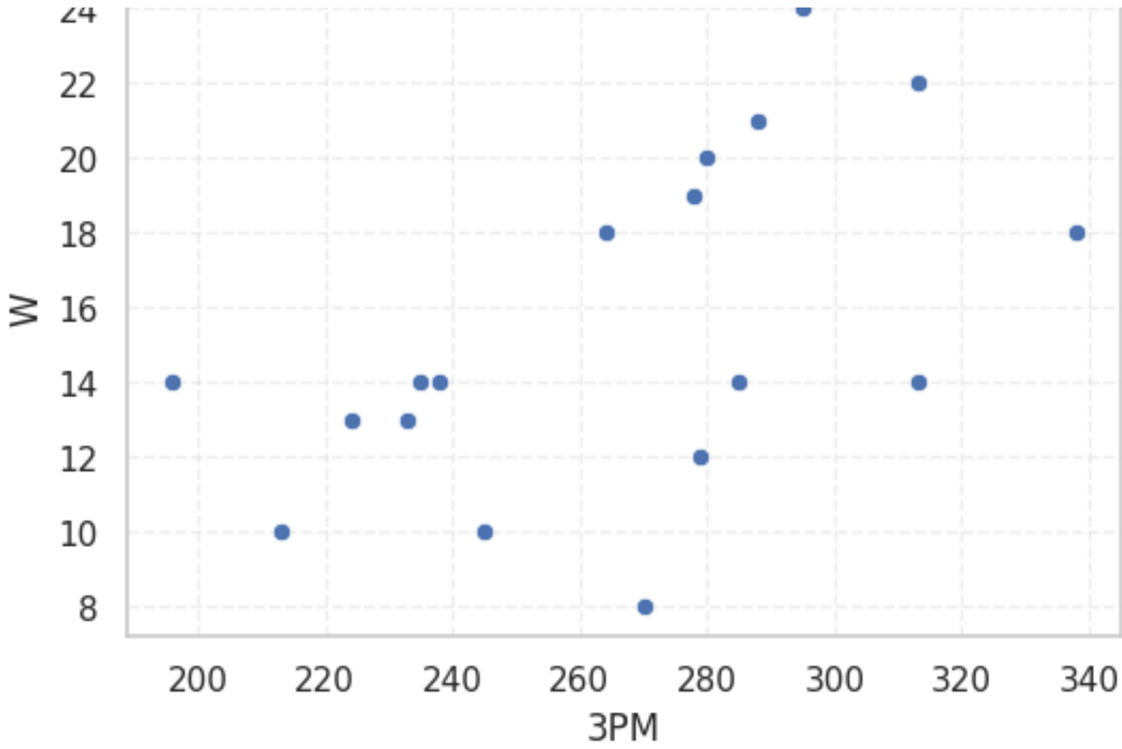

2022_2023: FGM vs W
24
22
20
18
W
16
14
12
10
8


900
925
950
975
1000
1025
1050
FGM

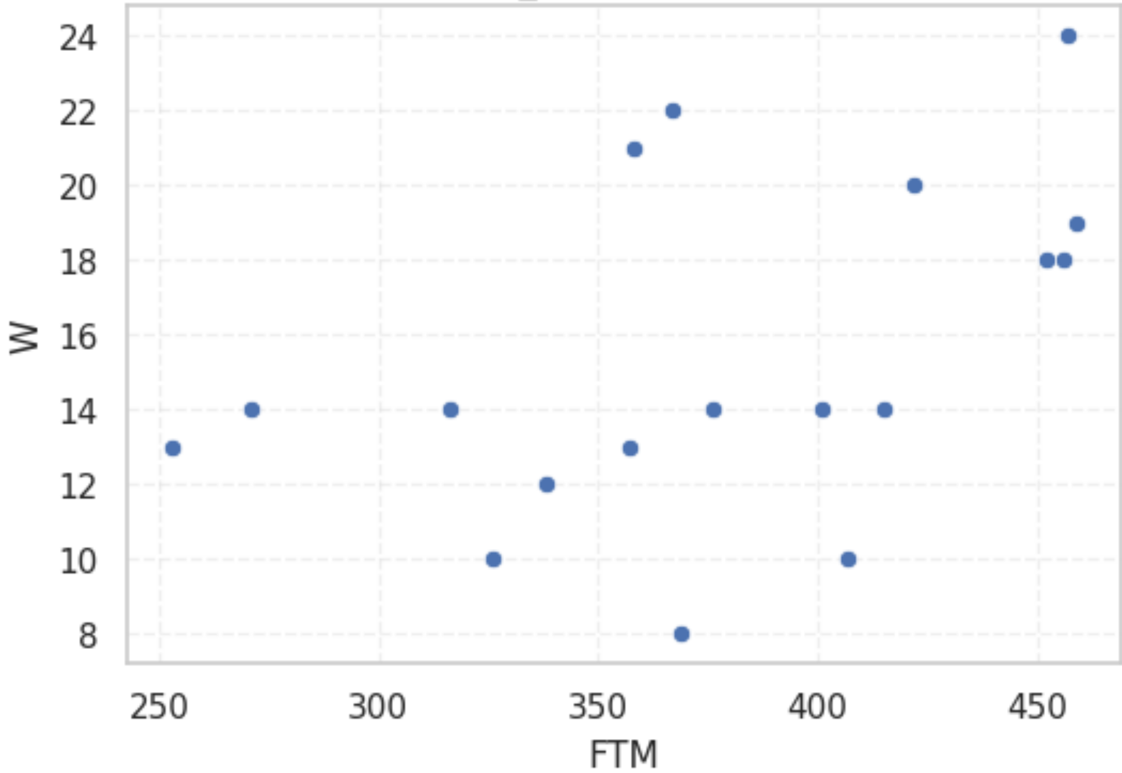

2022_2023: 2PM vs W
24
22
20
18
16
14
12
10
8
W
550
600
650
700
750
2PM


2022_2023: TOV vs W
24
22
20
18
16
14
12
10
8
W
360
380
400
420
440
460
480
500
TOV

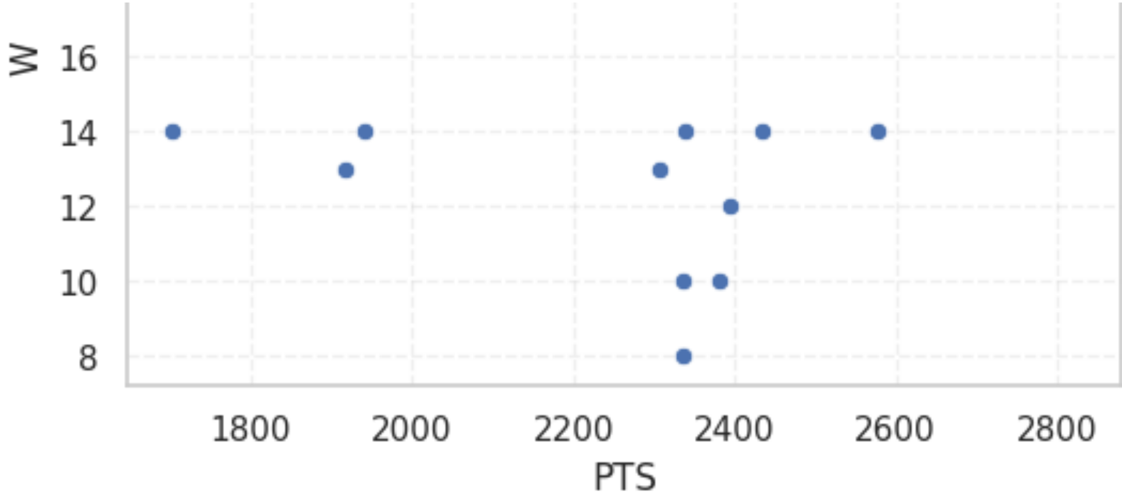

2021_2022: 3PM vs W

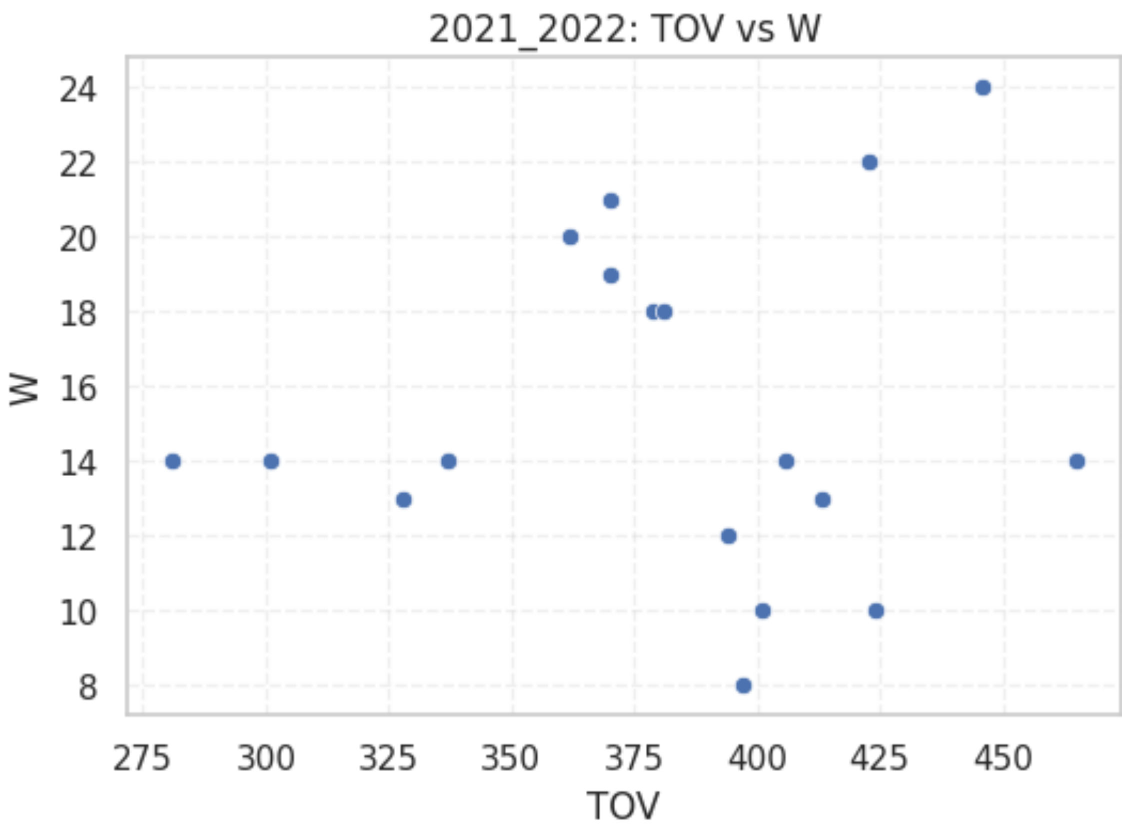


2021_2022: FTM vs W



2021_2022: PTS vs W






```
for season, df in seasons.items():
    corr = df[numeric_cols].corr()["W"].sort_values(ascending=False)
    print(f"\n=== {season} — W ile Korelasyon Sıralaması ===")
    print(corr)
```

```
L      -1.000000
Name: W, dtype: float64

=== 2023_2024 — W ile Korelasyon Sıralaması ===
W      1.000000
PTS    0.644325
FTM    0.564362
BLK    0.539193
```

```
FGM    0.520154
DRB    0.474084
AST    0.447354
2PM    0.272924
3PM    0.236533
FGA    0.084289
ST     0.063067
3PA    0.047684
2PA    0.021683
ORB   -0.039471
TOV   -0.558947
L     -1.000000
Name: W, dtype: float64

=== 2022_2023 — W ile Korelasyon Sıralaması ===
W      1.000000
PTS    0.652519
FGM    0.605009
2PM    0.505996
AST    0.417378
DRB    0.306056
FTM    0.290993
BLK    0.203811
ORB    0.189095
3PM    0.134864
2PA    0.122237
ST     0.040370
FGA    0.026218
3PA   -0.096461
TOV   -0.283204
L     -1.000000
Name: W, dtype: float64

=== 2021_2022 — W ile Korelasyon Sıralaması ===
W      1.000000
3PM    0.540085
FTM    0.468763
PTS    0.463864
DRB    0.413464
FGM    0.405740
AST    0.404177
3PA    0.373123
ORB    0.357646
FGA    0.297338
2PM    0.268923
ST     0.201749
2PA    0.179730
BLK    0.097754
TOV    0.095683
L     -0.762121
Name: W, dtype: float64
```

3-Key Findings

Strongest Positive Predictors of Wins

Across all seasons, the following metrics consistently showed the strongest positive correlation with Wins:

PTS (Total Points Scored) Teams that produced higher offensive output consistently won more games.

FGM / 3PM (Scoring Efficiency: Field Goals Made & 3-Pointers Made) Shot-making ability—especially from beyond the arc—was a strong indicator of success.

DRB (Defensive Rebounds) Securing defensive rebounds was one of the most stable predictors of victory across seasons, reflecting the importance of closing defensive possessions

Although strength varied slightly by season, these metrics formed a consistent pattern: efficient scoring and defensive rebounding drive winning

Strongest Negative Predictor of Wins

TOV (Turnovers) had the most meaningful negative relationship with Wins in every season analyzed. Teams with high turnover counts consistently finished with fewer victories.

4-Seasonal Consistency

While exact correlation values fluctuated, the identity of the top predictors remained stable across seasons:

High offensive efficiency (PTS, FGM, 3PM) → more wins

Low turnovers (TOV) → more wins Strong defensive rebounding (DRB) → more wins

This consistency suggests that winning in the EuroLeague fundamentally depends on efficient shot-making, possession control, and defensive stability.

5-Conclusion

The multi-season analysis demonstrates that EuroLeague success can be most reliably explained by a combination of:
Offensive production,
Shooting efficiency,
Defensive rebounding,
Turnover discipline.