05_shooting_percentage_models

December 18, 2025

1 Q5: Predicting Shooting Percentages (FG%, 3P%, FT%)

This notebook evaluates which factors best predict a player's shooting efficiency across the season.

We model:

- Field goal percentage (FG%)
- Three-point percentage (3P%)
- Free throw percentage (FT%)

Import data, then keep only the columns that we need, including FG%, 3P%, FT%, TRB, AST, TOV, and MP.

[4]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("data/player_game_stats_clean.csv")

cols = ["FG%", "3P%", "FT%", "TRB", "AST", "TOV", "MP"]
df_q5 = df[cols].dropna()
df_q5.head()
```

[4]:

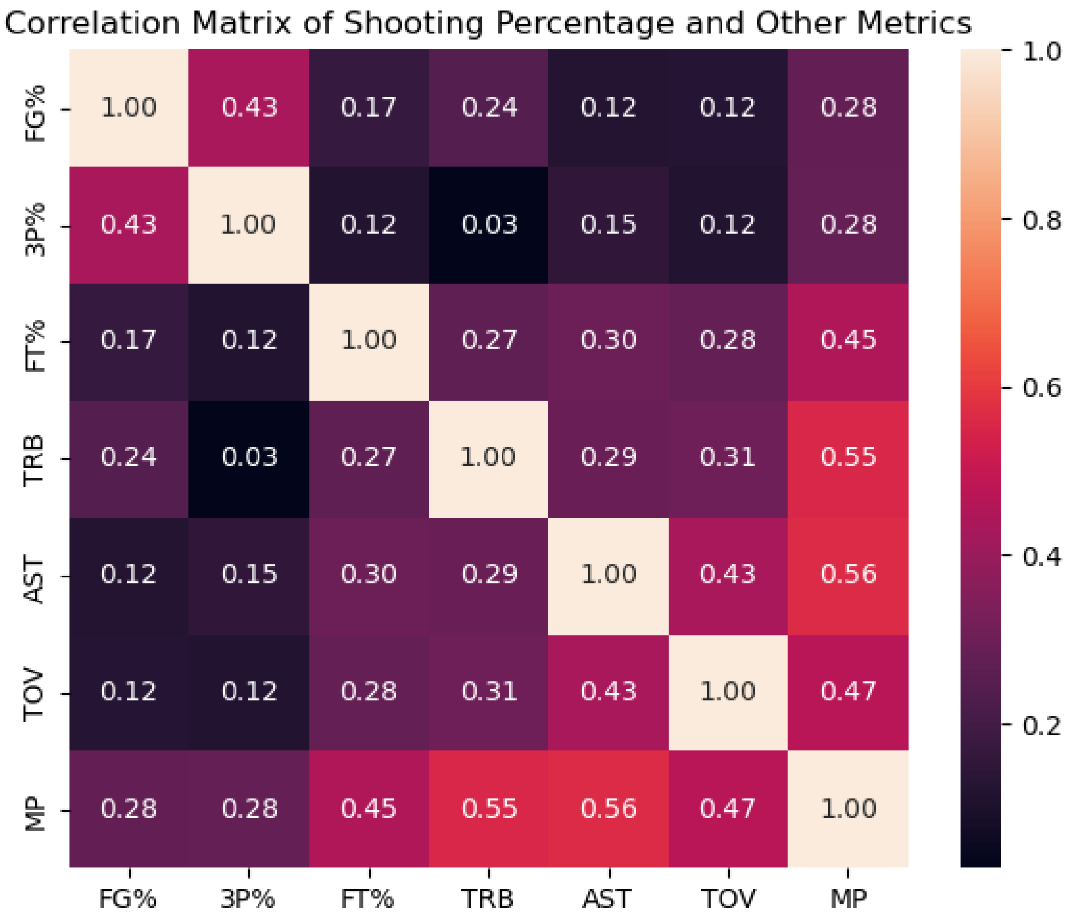
	FG%	3P%	FT%	TRB	AST	TOV	MP
0	0.778	0.727	0.500	4	10	1	30.30
1	0.478	0.333	0.867	16	4	1	37.58
2	0.615	0.600	1.000	3	4	0	26.63
3	0.778	0.667	0.000	4	4	0	30.52
4	0.800	0.800	0.667	0	2	1	25.85

Build a correlation matrix that answers the question: "what factors are the most associated with shooting percentage?"

[9]:
```python
corr = df_q5.corr()
corr[["FG%", "3P%", "FT%"]]

plt.figure(figsize=(6,5))
sns.heatmap(corr, annot=True, fmt=".2f")
plt.title("Correlation Matrix of Shooting Percentage and Other Metrics")
```

```
plt.tight_layout()
plt.show()
```



Now I build a multiple linear regression using OLS (I learned this from DATA 100 last semester). This tells me which variables are most statistically significant, alongside the relative importance of each metric.

[13]:
```
import statsmodels.api as sm

X = df_q5[["TRB", "AST", "TOV", "MP"]]
X = sm.add_constant(X)

y_fg = df_q5["FG%"]

model_fg = sm.OLS(y_fg, X).fit()
model_fg.summary()
```

[13]:

Dep. Variable:	FG%	**R-squared:**	0.090
Model:	OLS	**Adj. R-squared:**	0.090
Method:	Least Squares	**F-statistic:**	409.5
Date:	Thu, 18 Dec 2025	**Prob (F-statistic):**	0.00
Time:	06:06:54	**Log-Likelihood:**	-80.334
No. Observations:	16512	**AIC:**	170.7
Df Residuals:	16507	**BIC:**	209.2
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.2781	0.004	63.808	0.000	0.270	0.287
TRB	0.0095	0.001	14.522	0.000	0.008	0.011
AST	-0.0044	0.001	-4.921	0.000	-0.006	-0.003
TOV	-0.0010	0.002	-0.638	0.524	-0.004	0.002
MP	0.0055	0.000	21.991	0.000	0.005	0.006

Omnibus:	1160.309	**Durbin-Watson:**	1.525
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1439.784
Skew:	0.672	**Prob(JB):**	0.00
Kurtosis:	3.534	**Cond. No.**	58.9

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Now I do a simple linear regression for 3P% and FT% and call the .summary() to get an overview of the important metrics.

[16]:
```
# 3P%
y_3p = df_q5["3P%"]

model_3p = sm.OLS(y_3p, X).fit()
model_3p.summary()

# FT%
y_ft = df_q5["FT%"]

model_ft = sm.OLS(y_ft, X).fit()
model_ft.summary()
```

[16]:

Dep. Variable:	FT%	**R-squared:**	0.208
Model:	OLS	**Adj. R-squared:**	0.208
Method:	Least Squares	**F-statistic:**	1085.
Date:	Thu, 18 Dec 2025	**Prob (F-statistic):**	0.00
Time:	06:07:52	**Log-Likelihood:**	-7786.9
No. Observations:	16512	**AIC:**	1.558e+04
Df Residuals:	16507	**BIC:**	1.562e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
const	0.0242	0.007	3.475	0.001	0.011	0.038
TRB	0.0039	0.001	3.733	0.000	0.002	0.006
AST	0.0079	0.001	5.488	0.000	0.005	0.011
TOV	0.0243	0.002	9.844	0.000	0.019	0.029
MP	0.0146	0.000	36.814	0.000	0.014	0.015

Omnibus:	2711.832	**Durbin-Watson:**	1.934
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	763.923
Skew:	0.254	**Prob(JB):**	1.31e-166
Kurtosis:	2.077	**Cond. No.**	58.9

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Lastly, I create scatterplots that support the regression models.

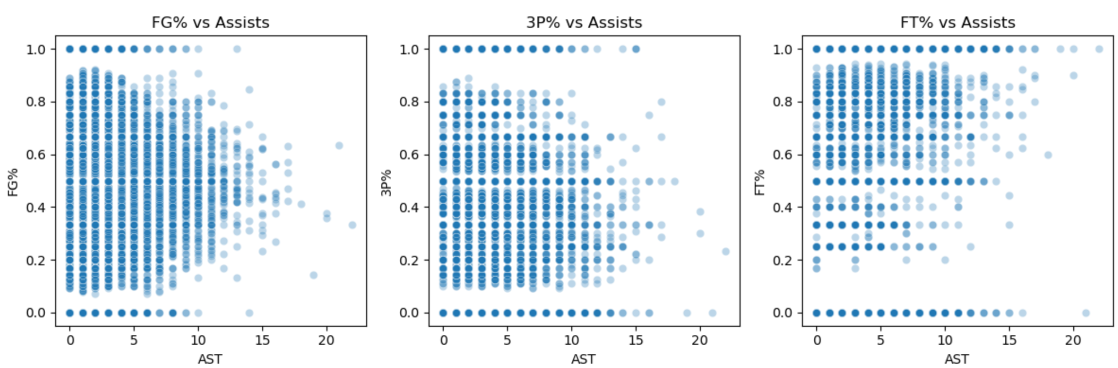
[21]:
```
fig, axes = plt.subplots(1, 3, figsize=(12,4))

sns.scatterplot(data=df_q5, x="AST", y="FG%", ax=axes[0], alpha=0.3)
axes[0].set_title("FG% vs Assists")

sns.scatterplot(data=df_q5, x="AST", y="3P%", ax=axes[1], alpha=0.3)
axes[1].set_title("3P% vs Assists")

sns.scatterplot(data=df_q5, x="AST", y="FT%", ax=axes[2], alpha=0.3)
axes[2].set_title("FT% vs Assists")

plt.tight_layout()
plt.show()
```



1.1 Final Interpretation

Overall, shooting percentages (FG%, 3P%, and FT%) show only weak relationships with traditional box score statistics. From the correlation matrix, minutes played (MP) has the strongest positive association with all three shooting percentages, suggesting that players who stay on the court longer tend to shoot more efficiently.

Rebounds (TRB) and assists (AST) show small positive correlations, while turnovers (TOV) are aren't consistently related. The regression results support this pattern because MP and TRB are consistently statistically significant predictors, while AST and TOV have smaller effects depending on the shooting metric. However, the low R^2 values indicate that most variation in shooting efficiency is not explained by these factors alone, suggesting that shooting percentages are driven more by individual skill and shot selection than by general box score contributions.

[ ]:

```

```