NBA_Finals_Prediction_fv

June 19, 2025

1 Simulating and Predicting the 2025 NBA Finals

1.0.1 1. Import Required Libraries

We imported all the necessary libraries, including: -pandas -sklearn -matplotlib -seaborn -numpy

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪cross_val_score
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
```

1.0.2 2. Load and Prepare Data

[196]:
```
df = pd.read_csv("NBA_2025_Playoff_Series_with_metrics.csv")
df.head()
```

[196]:
```
           Visitor/Neutral  PTS  Win        Home/Neutral  PTS.1  Win.1  \
0           Indiana Pacers   79    1  Philadelphia 76ers     78      0
1         Dallas Mavericks   86    0           Utah Jazz     88      1
2   Minnesota Timberwolves   82    0   San Antonio Spurs     87      1
3        Charlotte Hornets  106    1           Miami Heat     80      0
4          Toronto Raptors   85    0     New York Knicks     92      1

   Visitor Seed  Home Seed  Year   Visitor_id  …  Home win_pct  \
0             8          1  2001  1.610613e+09  …         0.293
1             5          4  2001  1.610613e+09  …         0.207
2             8          1  2001  1.610613e+09  …         0.415
3             6          3  2001  1.610613e+09  …         0.451
4             5          4  2001  1.610613e+09  …         0.622

   Home off_rtg  Home def_rtg  Home net_rtg  Home pace  Home efg_pct  \
0         111.0         117.3          -6.3      98.13         0.527
```

```
1          110.2          119.4          -9.2     100.85          0.533
2          113.5          116.3          -2.8     100.08          0.544
3          112.4          112.0           0.4      97.08          0.544
4          117.3          113.3           4.0      97.64          0.556

   Home ts_pct  Home tov_pct  Home orb_pct  Home drb_pct
0        0.563         0.138         0.279         0.678
1        0.568         0.170         0.311         0.705
2        0.575         0.138         0.278         0.690
3        0.576         0.138         0.263         0.724
4        0.589         0.134         0.305         0.710

[5 rows x 31 columns]
```

[197]:
```
# Check for missing values
print("Missing Values:")
missing_values = df.isnull().sum().sort_values(ascending=False)
print(missing_values[missing_values > 0])
```

```
Missing Values:
Series([], dtype: int64)
```

[198]:
```
# Define metrics we'll use as features
metrics = ['Seed', 'win_pct', 'off_rtg', 'def_rtg', 'net_rtg',
           'pace', 'efg_pct', 'ts_pct', 'tov_pct', 'orb_pct', 'drb_pct']

# Create feature differences
for metric in metrics:
    df[f'diff_{metric}'] = df[f'Home {metric}'] - df[f'Visitor {metric}']

feature_columns = [f'diff_{metric}' for metric in metrics]
```

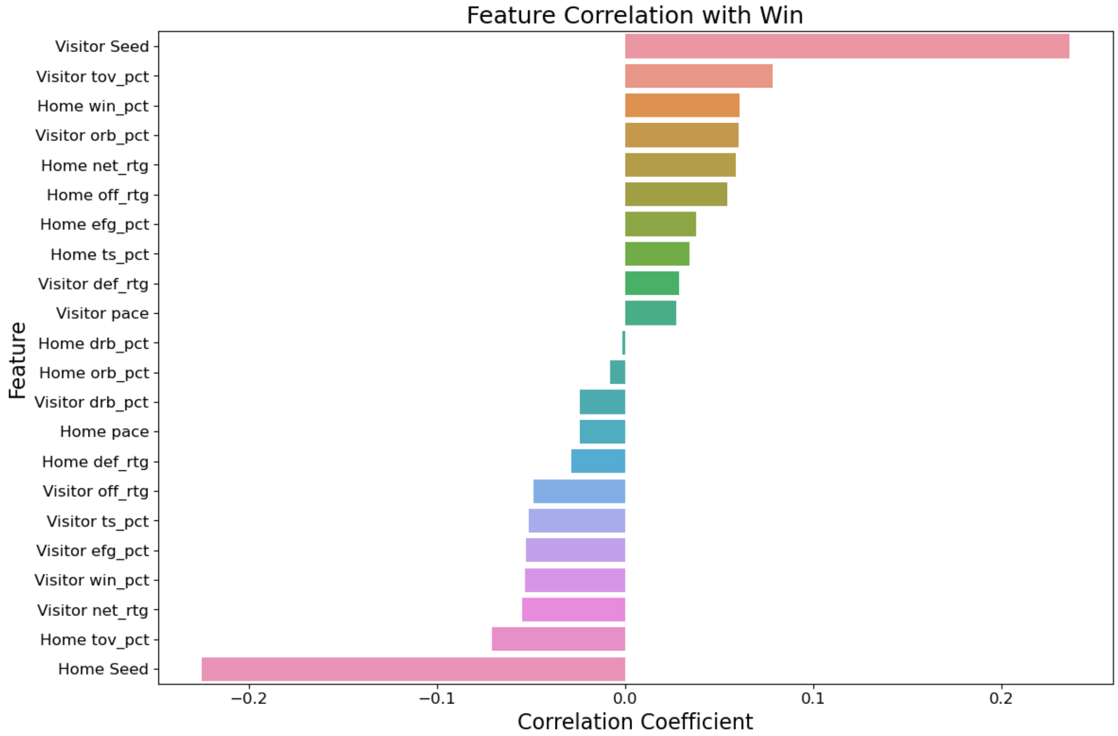
1.0.3 3. Exploratory Data Analysis

We first begin by examining correlation. The first bar graph has a target correlation coefficient of Win.1 (Whether the home team won or not). The higher the seed we found (or I suppose lower, the 1st seed is better than the 8th seed), the more likely that team is to win

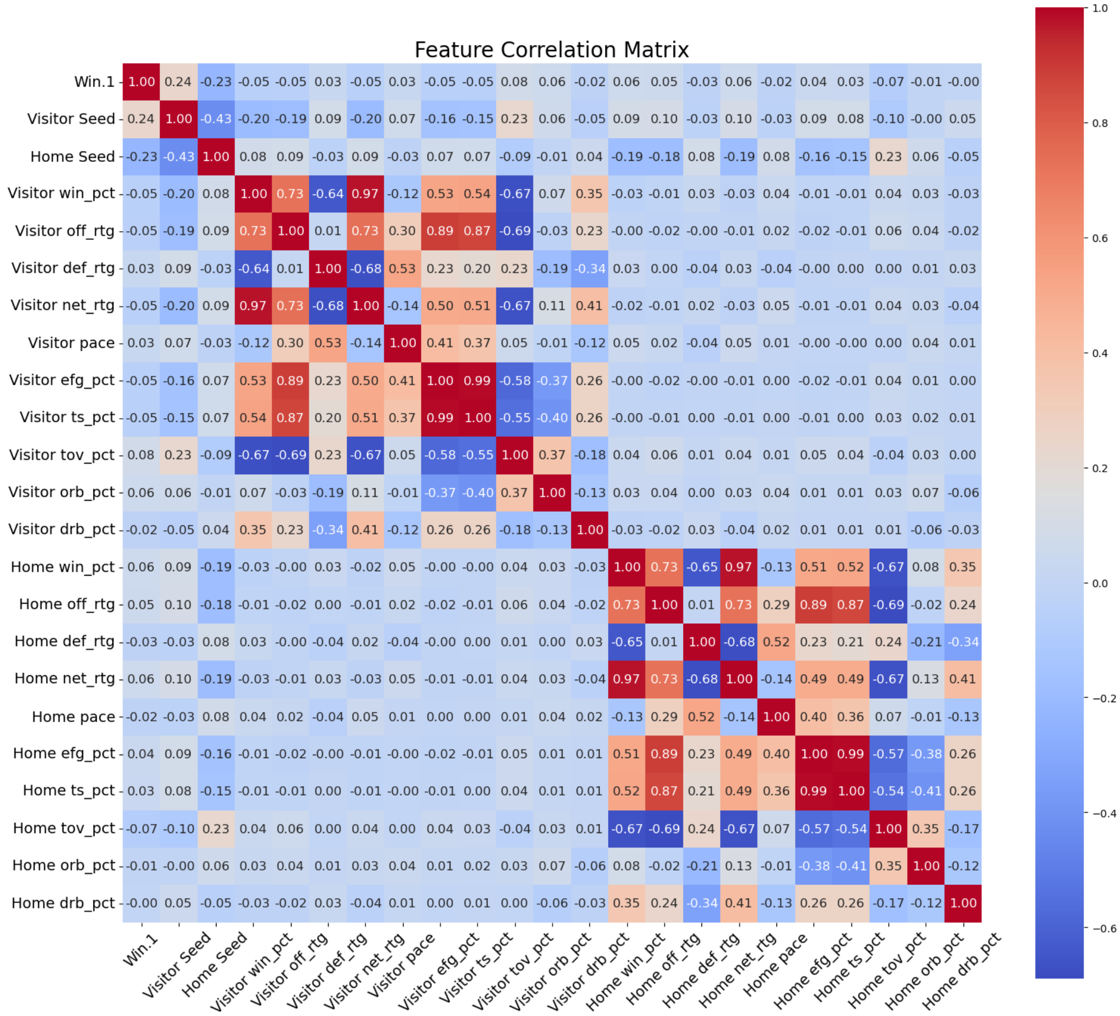
In the second graph - the heatmap - We found that better seeds (lower numbers) and stronger home stats are associated with a higher chance of winning, while some features are highly correlated with each other and may be redundant.

In the third section - the feature distribution plots — we explored the distribution of all numerical variables. We saw that stats like points (PTS, PTS.1) and ratings (off_rtg, def_rtg) are mostly normally distributed, while variables like Win.1, Visitor Seed, and Home Seed are skewed or discrete, reflecting their categorical or binary nature. This gives us useful context about which features may need normalization, binning, or further transformation for modeling.

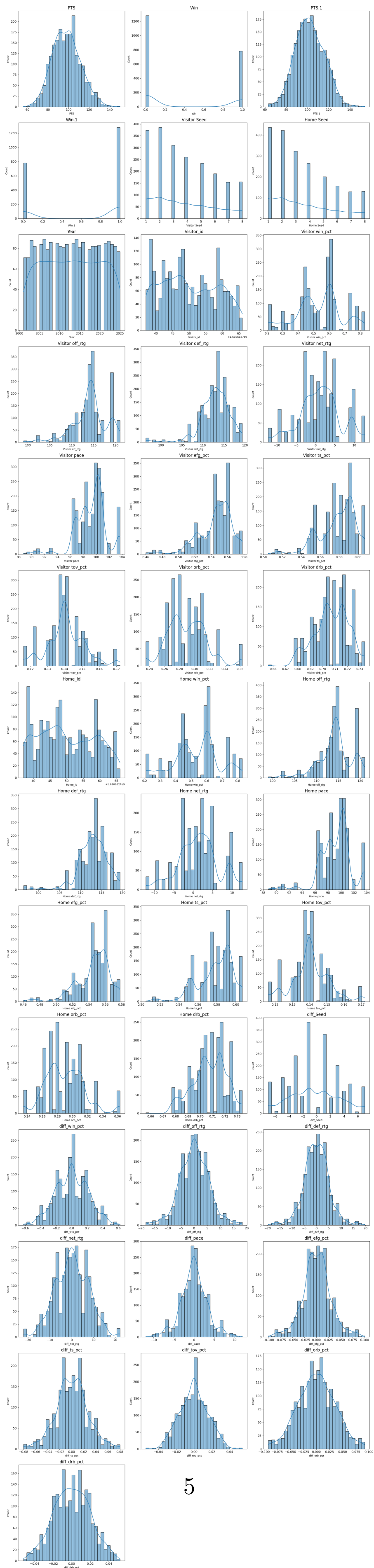
[ ]:
```python
# Correlation between features and target
corr = encoded.corr()
corr_target = corr['Win.1'].drop('Win.1').sort_values(ascending=False)
plt.figure(figsize=(12, 8))
sns.barplot(x=corr_target.values, y=corr_target.index, orient='h')
plt.title('Feature Correlation with Win', fontsize=18)
plt.xlabel('Correlation Coefficient', fontsize=16)
plt.ylabel('Feature', fontsize=16)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.tight_layout()
plt.show()
```



[200]:
```python
# Correlation between features only
plt.figure(figsize=(16, 14))
sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm', square=True,
            annot_kws={'size':12})
plt.title('Feature Correlation Matrix', fontsize=20)
plt.xticks(fontsize=14, rotation=45)
plt.yticks(fontsize=14, rotation=0)
plt.tight_layout()
plt.show()
```



[201]:
```python
# Distribution of individual features
num_cols = df.select_dtypes(include=[np.number]).columns.tolist()
cols_per_row = 3
n = len(num_cols)
rows = (n + cols_per_row - 1) // cols_per_row
plt.figure(figsize=(20, 6 * rows))
for i, col in enumerate(num_cols):
    ax = plt.subplot(rows, cols_per_row, i + 1)
    sns.histplot(df[col], bins=30, kde=True)
    ax.set_title(col, fontsize=16)
    ax.tick_params(labelsize=12)
plt.tight_layout()
plt.show()
```


PTS
Win
PTS.1
Win.1
Visitor Seed
Home Seed
Year
Visitor_id
Visitor win_pct
Visitor off_rtg
Visitor def_rtg
Visitor net_rtg
Visitor pace
Visitor efg_pct
Visitor ts_pct
Visitor tov_pct
Visitor orb_pct
Visitor drb_pct
Home_id
Home win_pct
Home off_rtg
Home def_rtg
Home net_rtg
Home pace
Home efg_pct
Home ts_pct
Home tov_pct
Home orb_pct
Home drb_pct
diff_Seed
diff_win_pct
diff_off_rtg
diff_def_rtg
diff_net_rtg
diff_pace
diff_efg_pct
diff_ts_pct
diff_tov_pct
diff_orb_pct
diff_drb_pct

1.0.4 4. Model Building and Training

In this section, we trained a Random Forest Classifier to predict whether the home team would win (Win.1) based on game and team stats. After splitting the data into training and test sets (80/20 split), the model achieved ~79.6% accuracy on the training set and ~58.6% accuracy on the test set, suggesting that the model may be overfitting to the training data (it learned the training data too well!) and could benefit from tuning or more balanced features.

[202]:
```
# Separate features and target
x = df[feature_columns].dropna()
y = df.loc[x.index, 'Win.1']

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42
)

# Initialize and train
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

print("Train Accuracy:", model.score(X_train, y_train))
y_pred = model.predict(X_test)
print(f'Test Accuracy: {accuracy_score(y_test, y_pred):.5f}')
```

```
Train Accuracy: 0.7958812840702605
Test Accuracy: 0.58596
```

1.0.5 5. Model Tuning and Evaluation

We used GridSearchCV to tune our Random Forest model by testing various hyperparameter combinations and evaluating them with 5-fold cross-validation. The best performing model used 50 estimators and a small regularization value (ccp_alpha = 0.01), achieving a mean cross-validation accuracy of ~63.2%. To further improve generalization and reduce overfitting, we manually fine-tuned a new model with a smaller max depth and more conservative splitting rules. This fine-tuned model achieved ~71.1% accuracy on the training set and improved to ~61.9% accuracy on the test set, suggesting better balance between fitting the data and generalizing to unseen games.

[203]:
```
# Hyperparameter Tuning
param_grid = {
'n_estimators': [50, 100, 200],
'max_depth': [None, 10, 20],
'min_samples_split': [2, 5, 10],
'min_samples_leaf': [1, 2, 4],
'max_features': ['sqrt', 'log2'],
'ccp_alpha': [0, 0.01, 0.1] }
```

```
# GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, y_train)
print("Best Hyperparameters:", grid_search.best_params_)

# Train the model with the best hyperparameters
best_model = grid_search.best_estimator_
best_model.fit(X_train, y_train)

# Cross-Validation to evaluate stability
cv_scores = cross_val_score(best_model, X_train, y_train, cv=5,␣
 ↪scoring='accuracy')
print("Cross-Validation Scores:", cv_scores)
print("Mean CV Accuracy:", np.mean(cv_scores))
```

```
Best Hyperparameters: {'ccp_alpha': 0.01, 'max_depth': None, 'max_features':
'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
Cross-Validation Scores: [0.63141994 0.63333333 0.63333333 0.63333333
0.63030303]
Mean CV Accuracy: 0.6323445939760138
```

[204]:
```
# Fine tune a new model to reduce overfitting
model_new = RandomForestClassifier(
n_estimators = 75,
max_depth = 7,
min_samples_split=6,
min_samples_leaf=7,
ccp_alpha=0,
max_features='sqrt',
random_state=42
)

# Evaluate
model_new.fit(X_train, y_train)
print("Train Accuracy:", model_new.score(X_train, y_train))
y_pred = model_new.predict(X_test)
print(f'Test Accuracy: {accuracy_score(y_test, y_pred):.5f}')
```

```
Train Accuracy: 0.711084191399152
Test Accuracy: 0.61985
```

1.0.6 6. Create and Run Simulation

We used 2025 season stats to simulate a best-of-7 playoff series between the Oklahoma City Thunder and Indiana Pacers. The Finals this year! Using our fine tuned Random Forest model, we calculated game-by-game win probabilities based on differences in team metrics and also ran a 10,000 trial

Monte Carlo simulation. The results are below

[205]:
```python
def get_team_stats(team_name):
    df_2025 = df[df['Year'] == 2025]

    # Find team in visitor column
    visitor_row = df_2025[df_2025['Visitor/Neutral'] == team_name]
    if not visitor_row.empty:
        row = visitor_row.iloc[0]
        return {metric: row[f'Visitor {metric}'] for metric in metrics}

    # Find team in home column
    home_row = df_2025[df_2025['Home/Neutral'] == team_name]
    if not home_row.empty:
        row = home_row.iloc[0]
        return {metric: row[f'Home {metric}'] for metric in metrics}

# Get team stats
thunder_stats = get_team_stats('Oklahoma City Thunder')
pacers_stats = get_team_stats('Indiana Pacers')
```

[206]:
```python
print(f"Thunder: {thunder_stats}")
print(f"Pacers: {pacers_stats}")
```

```
Thunder: {'Seed': 1, 'win_pct': 0.829, 'off_rtg': 119.2, 'def_rtg': 106.6,
'net_rtg': 12.7, 'pace': 100.9, 'efg_pct': 0.56, 'ts_pct': 0.593, 'tov_pct':
0.116, 'orb_pct': 0.281, 'drb_pct': 0.704}
Pacers: {'Seed': 4, 'win_pct': 0.61, 'off_rtg': 115.4, 'def_rtg': 113.3,
'net_rtg': 2.1, 'pace': 100.76, 'efg_pct': 0.562, 'ts_pct': 0.594, 'tov_pct':
0.13, 'orb_pct': 0.254, 'drb_pct': 0.705}
```

[212]:
```python
# Calculate probability that home wins
def calculate_game_probability(home_stats, visitor_stats):

    differences = [home_stats[metric] - visitor_stats[metric] for metric in␣
↪metrics]
    return model_new.predict_proba([differences])[0][1]

# Calculate game probabilites for schedule format
home_schedule = ['OKC', 'OKC', 'IND', 'IND', 'OKC', 'IND', 'OKC']
game_probs = []

for i, home_team in enumerate(home_schedule):
    if home_team == 'OKC':
        # Thunder home, Pacers visitor
        prob_thunder_win = calculate_game_probability(thunder_stats,␣
↪pacers_stats)
        prob_pacers_win = 1 - prob_thunder_win
```

```
    else:
        # Pacers home, Thunder visitor
        prob_pacers_win = calculate_game_probability(pacers_stats,␣
↪thunder_stats)
        prob_thunder_win = 1 - prob_pacers_win

    game_probs.append(prob_thunder_win)
```

[215]:
```
# Simulate a best-of-7 series
def simulate_best_of_7(p_win, n_simulations):

    rand_matrix = np.random.rand(n_simulations, 7)
    win_matrix = rand_matrix < p_win
    win_counts = win_matrix.sum(axis=1)
    return (win_counts >= 4).mean()

# Run Monte Carlo Simulation
n_sim = 10000
series_prob = simulate_best_of_7(game_probs, n_sim)
print(f"Estimated series win probability for OKC: {series_prob:.3f}")
```

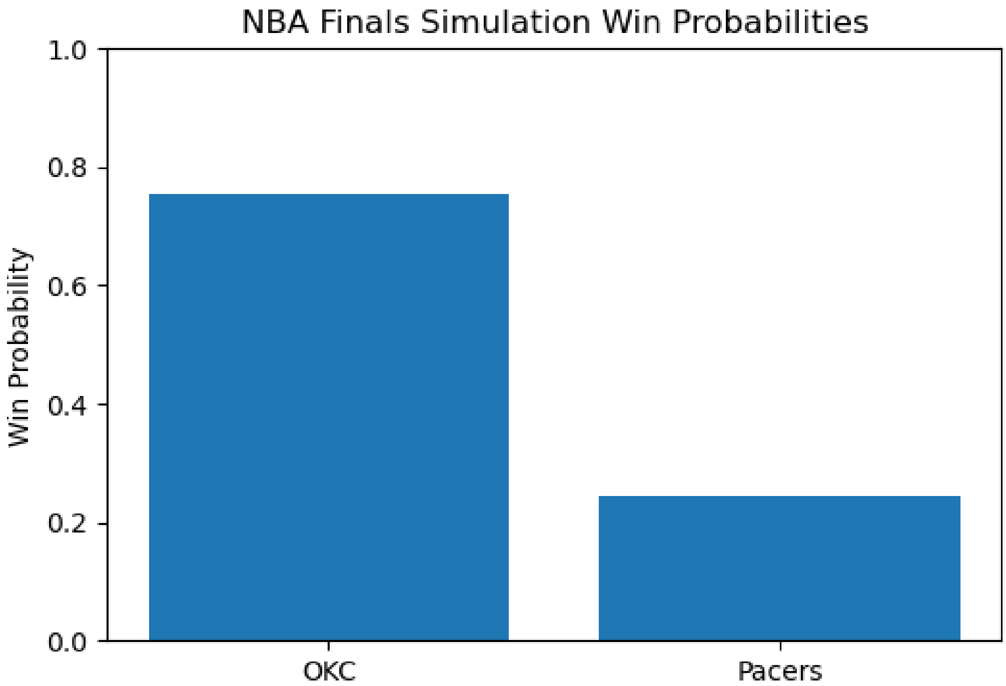
```
Estimated series win probability for OKC: 0.755
```

1.0.7 7. Results and Visualization

[216]:
```
print("FINAL PREDICTION:")
print(f"Estimated series win probability for OKC: {series_prob:.1%}")
print(f"Estimated series win probability for Pacers: {1 - series_prob:.1%}")
```

```
FINAL PREDICTION:
Estimated series win probability for OKC: 75.5%
Estimated series win probability for Pacers: 24.5%
```

[217]:
```
# Visualize
plt.figure(figsize=(6, 4))
plt.bar(['OKC', 'Pacers'], [series_prob, (1-series_prob)])
plt.title('NBA Finals Simulation Win Probabilities')
plt.ylabel('Win Probability')
plt.ylim(0, 1)
plt.show()
```


NBA Finals Simulation Win Probabilities
Win Probability
1.0
0.8
0.6
0.4
0.2
0.0
OKC
Pacers