Model

July 9, 2025

1 Modeling

1.1 Setup Code

[41]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV, train_test_split,␣
↪cross_val_score, TimeSeriesSplit
from sklearn.linear_model import ElasticNet, Lasso, Ridge
from sklearn.ensemble import RandomForestRegressor
from sklearn.decomposition import PCA
from xgboost import XGBRegressor
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import statsmodels.api as sm
import joblib

pd.set_option("display.max_rows", None)      # Show all rows
pd.set_option("display.max_columns", None)   # Show all columns
pd.set_option("display.width", 2000)         # Prevent line wrapping
pd.set_option("display.max_colwidth", None) # Don't truncate cell conte
```

[2]:
```
data = pd.read_pickle('C:/Code/Git Repositories/Football/Football/
↪3_Data_Preparation/rawdata_clean.pkl')
```

[3]:
```
df = data.select_dtypes(include=['int64', 'float64'])
df = df.dropna()
sorted_df = df.sort_values(by=['season', 'week'])
X = sorted_df.drop(columns=['margin', 'away_score', 'home_score'])
y = sorted_df['margin']

split_idx = int(len(X) * 0.8)
tss_X_train, tss_X_test = X.iloc[:split_idx], X.iloc[split_idx:]
```

```
tss_y_train, tss_y_test = y.iloc[:split_idx], y.iloc[split_idx:]

X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=.2,␣
↪random_state=369, shuffle=False)
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=.
↪25, random_state=369, shuffle=False)
```

1.2 Model Selection

Lasso Regression is continuously the best performer

[4]:
```
elastic_pipe = Pipeline(steps=[('scaler', StandardScaler()), ('ElasticNet',␣
↪ElasticNet())])
ridge_pipe = Pipeline(steps=[('scaler', StandardScaler()), ('Ridge', Ridge())])
lasso_pipe = Pipeline(steps=[('scaler', StandardScaler()), ('Lasso', Lasso())])
xgb = XGBRegressor()
rand_forest = RandomForestRegressor()
tscv = TimeSeriesSplit(n_splits=5)

elastic_cv = cross_val_score(elastic_pipe, X_train, y_train, cv=tscv,␣
↪scoring='r2')
ridge_cv = cross_val_score(ridge_pipe, X_train, y_train, cv=tscv, scoring='r2')
lasso_cv = cross_val_score(lasso_pipe, X_train, y_train, cv=tscv, scoring='r2')
xgb_cv = cross_val_score(xgb, X_train, y_train, cv=tscv, scoring='r2')
rand_forest_cv = cross_val_score(rand_forest, X_train, y_train, cv=tscv,␣
↪scoring='r2')

print(f'elastic_cv score average: {elastic_cv.mean() * 100: .2f}. Standard␣
↪deviation is {elastic_cv.std() * 100: .2f}')
print(f'ridge_cv score average: {ridge_cv.mean() * 100: .2f}. Standard␣
↪deviation is {ridge_cv.std() * 100: .2f}')
print(f'lasso_cv score average: {lasso_cv.mean() * 100: .2f}. Standard␣
↪deviation is {lasso_cv.std() * 100: .2f}')
print(f'xgb_cv score average: {xgb_cv.mean() * 100: .2f}. Standard deviation is␣
↪{xgb_cv.std() * 100: .2f}')
print(f'rand_forest_cv score average: {rand_forest_cv.mean() * 100: .2f}.␣
↪Standard deviation is {rand_forest_cv.std() * 100: .2f}')
```

```
elastic_cv score average:  74.16. Standard deviation is  1.00
ridge_cv score average:  73.09. Standard deviation is  8.21
lasso_cv score average:  75.81. Standard deviation is  1.29
xgb_cv score average:  72.92. Standard deviation is  3.56
rand_forest_cv score average:  72.29. Standard deviation is  3.06
```

1.3 Model Tuning

~5.5% increase from initial training

```
[5]: lasso_param_grid = {
         'Lasso__alpha': [0.01, 0.1, 0.3, 0.5, 0.7, 1],
         'Lasso__fit_intercept': [True, False],
         'Lasso__max_iter': [1000, 3000, 10000]
     }

     search = GridSearchCV(lasso_pipe, param_grid=lasso_param_grid, scoring='r2').
      ↪fit(X_train, y_train)

     print(f'Best parameters: {search.best_params_}')
     print(f'Best score: {search.best_score_ * 100: .2f}')
```

```
Best parameters: {'Lasso__alpha': 0.1, 'Lasso__fit_intercept': True,
'Lasso__max_iter': 1000}
Best score:  80.07
```

```
[6]: params = search.best_params_
     clean_params = {k.replace('Lasso__', ''): v for k, v in params.items()}
     tuned_lasso = Lasso(**clean_params).fit(X_train, y_train)

     print(f'Tuned Lasso score: {tuned_lasso.score(X_train, y_train) * 100: .2f}')
```

```
Tuned Lasso score:  81.24
```

1.4 Model Validation & Testing

Model generalizes very well

1.4.1 Validation

```
[31]: predictions = tuned_lasso.predict(X_val)
      mae = mean_absolute_error(y_val, predictions)
      rmse = np.sqrt(mean_squared_error(y_val, predictions))
      score = r2_score(y_val, predictions)

      print(f'mae is {mae: .2f}')
      print(f'rmse is {rmse: .2f}')
      print(f'r2 score is {score * 100: .2f}')
```

```
mae is  4.99
rmse is  6.29
r2 score is  80.31
```

1.4.2 Test

```
[32]: predictions = tuned_lasso.predict(X_test)
      mae = mean_absolute_error(y_test, predictions)
      rmse = np.sqrt(mean_squared_error(y_test, predictions))
      score = r2_score(y_test, predictions)
```

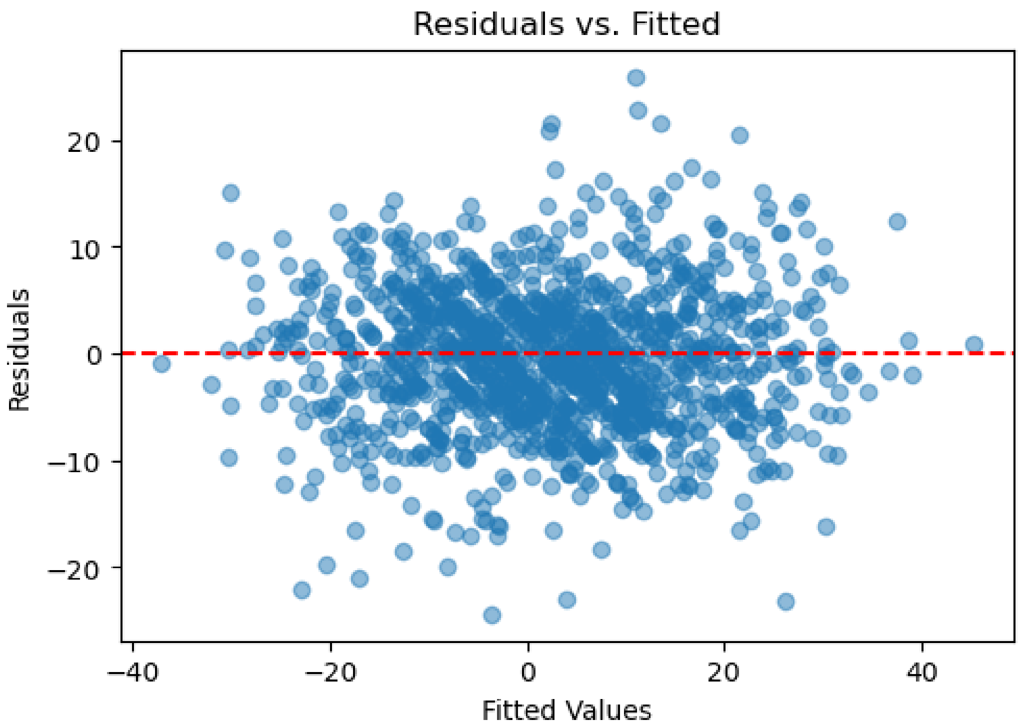
```
print(f'mae is {mae: .2f}')
print(f'rmse is {rmse: .2f}')
print(f'r2 score is {score * 100: .2f}')
```

```
mae is  4.82
rmse is  6.20
r2 score is  81.64
```

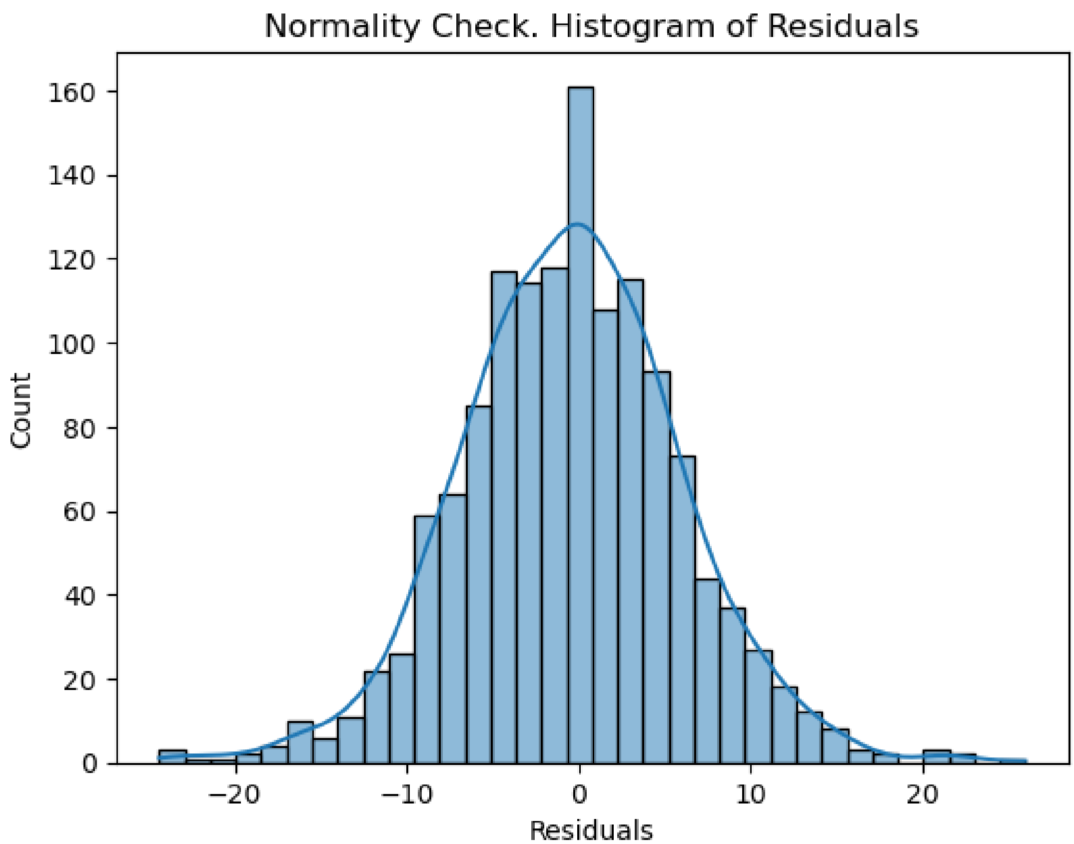
1.5 Residual Analysis

[9]:
```
predictions = tuned_lasso.predict(X_test)
residuals = y_test - predictions
```

[10]:
```
plt.figure(figsize=(6,4))
plt.scatter(predictions, residuals, alpha=.5)
plt.axhline(0, color='red', linestyle='--')
plt.ylabel('Residuals')
plt.xlabel('Fitted Values')
plt.title('Residuals vs. Fitted')
plt.show()
```



[11]:
```
sns.histplot(residuals, kde=True)
plt.xlabel('Residuals')
plt.title('Normality Check. Histogram of Residuals')
plt.show()
```



[12]:
```
dw = sm.stats.durbin_watson(residuals)

print(f'Durbin-Watson score: {dw: .2f}')
```

```
Durbin-Watson score:  1.96
```

Edge Case Evaluation

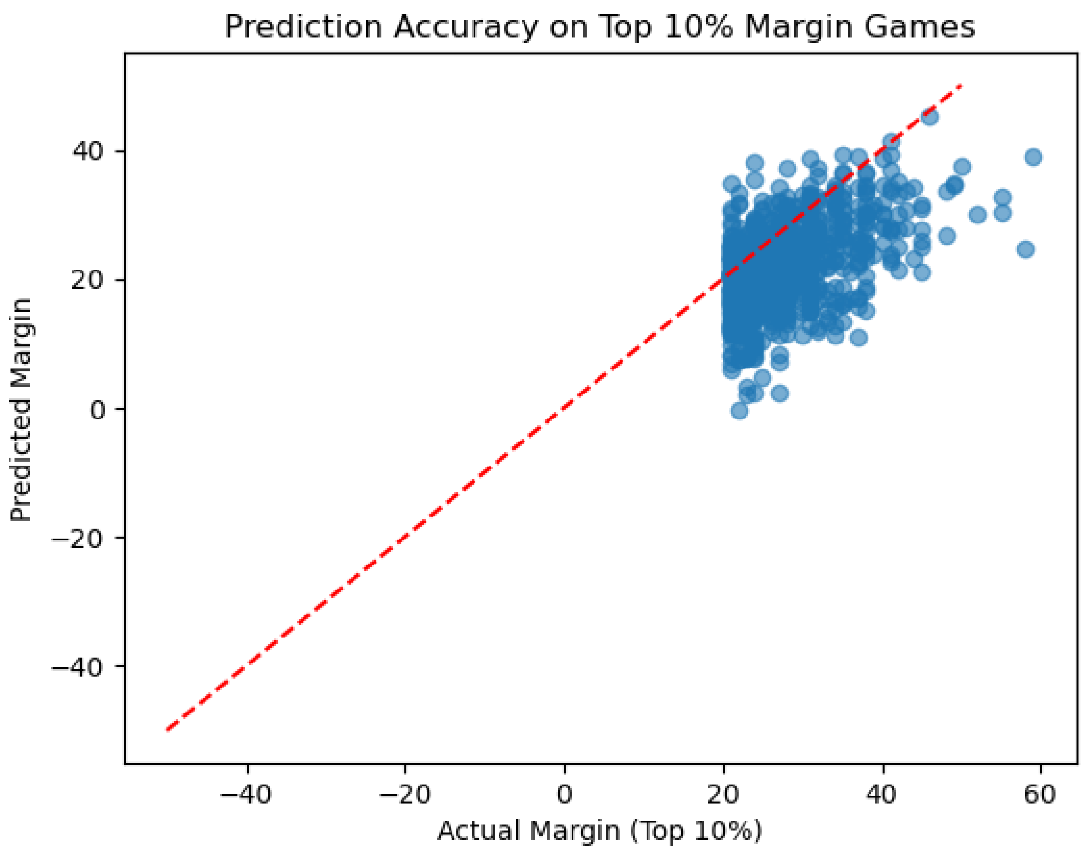
[39]:
```
top_10_thresh = sorted_df['margin'].quantile(0.90)
bottom_10_thresh = sorted_df['margin'].quantile(0.10)

top_10_df = sorted_df[sorted_df['margin'] >= top_10_thresh]
bottom_10_df = sorted_df[sorted_df['margin'] <= bottom_10_thresh]

features_df = sorted_df.drop(columns=['margin', 'home_score', 'away_score'])
features = features_df.columns
```

```
top_10_preds = tuned_lasso.predict(top_10_df[features])
bottom_10_preds = tuned_lasso.predict(bottom_10_df[features])

print('Top 10%:')
print('RMSE:', mean_squared_error(top_10_df['margin'], top_10_preds,␣
↪squared=False))
print('MAE:', mean_absolute_error(top_10_df['margin'], top_10_preds))
print('R2:', f"{r2_score(top_10_df['margin'], top_10_preds) * 100:.2f}")

print('\nBottom 10%:')
print('RMSE:', mean_squared_error(bottom_10_df['margin'], bottom_10_preds,␣
↪squared=False))
print('MAE:', mean_absolute_error(bottom_10_df['margin'], bottom_10_preds))
print('R2:', f"{r2_score(bottom_10_df['margin'], bottom_10_preds) * 100:.2f}")
```

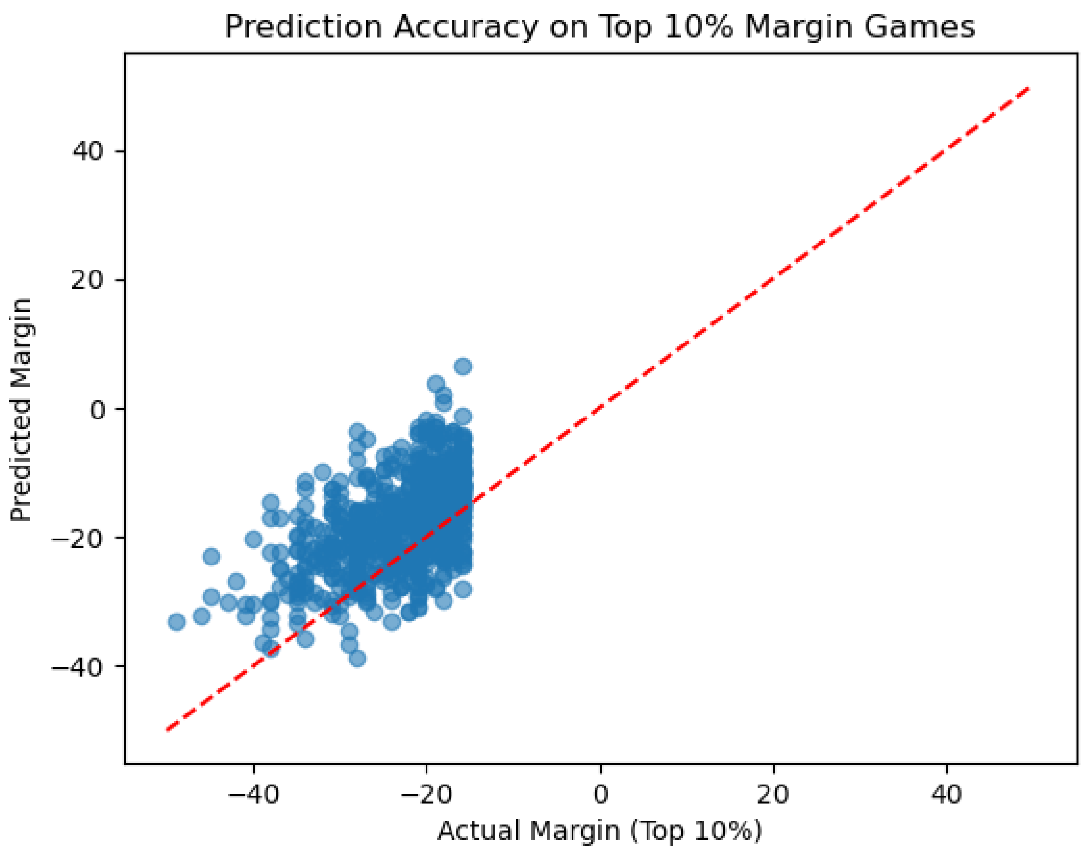
```
Top 10%:
RMSE: 8.901360406525646
MAE: 7.007829147824513
R2: -95.38

Bottom 10%:
RMSE: 8.249468437213423
MAE: 6.635713699781495
R2: -84.67
```

[40]:

```
plt.scatter(top_10_df['margin'], top_10_preds, alpha=0.6)
plt.plot([-50, 50], [-50, 50], color='red', linestyle='--')
plt.xlabel('Actual Margin (Top 10%)')
plt.ylabel('Predicted Margin')
plt.title('Prediction Accuracy on Top 10% Margin Games')
plt.show()
```



[15]:
```
plt.scatter(bottom_10_df['margin'], bottom_10_preds, alpha=0.6)
plt.plot([-50, 50], [-50, 50], color='red', linestyle='--')
plt.xlabel('Actual Margin (Top 10%)')
plt.ylabel('Predicted Margin')
plt.title('Prediction Accuracy on Top 10% Margin Games')
plt.show()
```



While testing on the top and bottom 10 percent of our data we find that our model generalize very poorly, quite often worse than using the mean variance as a prediction. To address this we will later model on just our edge cases, to hopefully create a new model that is built just for predicting the edge cases.

[16]:
```
window_size = 816  # adjust to your dataset size
test_size = 272
errors = {}

for start in range(0, len(sorted_df) - window_size - test_size):
    train = sorted_df.iloc[start : start + window_size]
    test = sorted_df.iloc[start + window_size : start + window_size + test_size]

    X_train = train[features]
    y_train = train['margin']
    X_test = test[features]
    y_test = test['margin']

    model = Lasso(**clean_params)
    model.fit(X_train, y_train)
```

```python
    preds = model.predict(X_test)

    mae = mean_absolute_error(y_test, preds)
    r2 = r2_score(y_test, preds)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    errors[start] = {'mae' : mae, 'rmse' : rmse, 'r2' : r2}

mae_mean = np.mean([metrics['mae'] for metrics in errors.values()])
rmse_mean = np.mean([metrics['rmse'] for metrics in errors.values()])
r2_mean = np.mean([metrics['r2'] for metrics in errors.values()])

print(f"Past three seasons Mean MAE: {mae_mean:.2f}")
print(f"Past three seasons Mean RMSE: {rmse_mean:.2f}")
print(f"Past three seasons Mean R2: {r2_mean * 100 :.2f}%")
```

```
Past three seasons Mean MAE: 5.39
Past three seasons Mean RMSE: 6.88
Past three seasons Mean R2: 77.60%
```

[17]:
```python
window_size = 6300  # adjust to your dataset size
test_size = 272
errors = {}

for start in range(0, len(sorted_df) - window_size - test_size):
    train = sorted_df.iloc[start : start + window_size]
    test = sorted_df.iloc[start + window_size : start + window_size + test_size]

    X_train = train[features]
    y_train = train['margin']
    X_test = test[features]
    y_test = test['margin']

    model = Lasso(**clean_params)
    model.fit(X_train, y_train)
    preds = model.predict(X_test)

    mae = mean_absolute_error(y_test, preds)
    r2 = r2_score(y_test, preds)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    errors[start] = {'mae' : mae, 'rmse' : rmse, 'r2' : r2}

mae_mean = np.mean([metrics['mae'] for metrics in errors.values()])
rmse_mean = np.mean([metrics['rmse'] for metrics in errors.values()])
r2_mean = np.mean([metrics['r2'] for metrics in errors.values()])

print(f"All game data Mean MAE: {mae_mean:.2f}")
print(f"All game data Mean RMSE: {rmse_mean:.2f}")
```

```
print(f"All game data Mean R2: {r2_mean * 100 :.2f}%")
```

```
All game data Mean MAE: 4.82
All game data Mean RMSE: 6.21
All game data Mean R2: 81.07%
```

1.6 Model Packaging

```
[18]: final_model = Lasso(**clean_params)
      final_model.fit(X, y)
```

```
[18]: Lasso(alpha=0.1)
```

```
[42]: filename = "C:/Code/Git Repositories/Football/Football/
       ↪4_5_Modeling_and_Evaluation/model.pkl"
      joblib.dump(final_model, filename=filename)
```

```
[42]: ['C:/Code/Git
      Repositories/Football/Football/4_5_Modeling_and_Evaluation/model.pkl']
```