Modeling

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In this section, we will fit 3 different models on the dataset to predict the players' next year salary.

```
import os
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import statsmodels.api as sm
import statsmodels.api as sm
from sklearn import preprocessing
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestRegressor
import warnings
from functions import mse_func
from functions import split_train_test
```

To fit any type of model, we first want to split our dataframe into X, our independent predictors, and y, our dependent variable. Our predictors are all columns except the column that we want to predict and y will be the singular 'Next_Year_Salary' column. After getting our X and y, we want to split each into training and test sets using an 80/20 split.

```
oh_df = pd.read_csv('data/oh_df.csv')
X = oh_df.drop(columns=['Next_Year_Salary'])
y = np.log(oh_df['Next_Year_Salary'])

X_train, X_test, y_train, y_test = split_train_test(X, y, 0.8, 42)
```

1 Ordinary Least Squares (OLS)

The first model we will use to predict the players' next year salary is OLS. This is a linear model with an intercept term, using all features as predictors.

```
X_new = sm.add_constant(X_train)
ols_model = sm.OLS(y_train, X_new).fit()
print(ols_model.summary())
```

```
OLS Regression Results
==============================================================================
Dep. Variable:      Next_Year_Salary   R -squared:                      0.638
Model:                           OLS   Adj. R -squared:                 0.623
Method:                Least Squares   F -statistic:                    44.16
Date:               Sun, 14 Dec 2025   Prob (F -statistic):          3.91e -111
Time:                       01:55:30   Log -Likelihood:               -621.12
No. Observations:                601   AIC:                            1290.
Df Residuals:                    577   BIC:                            1396.
Df Model:                         23
Covariance Type:           nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
const          12.0871      0.550     21.976      0.000      11.007      13.167
Age             0.0331      0.007      4.740      0.000       0.019       0.047
MP_x            0.0696      0.006     11.313      0.000       0.057       0.082
PF              0.0757      0.068      1.112      0.266      -0.058       0.209
TS%            -2.4860      0.801     -3.104      0.002      -4.059      -0.913
TRB%           -0.0210      0.011     -1.824      0.069      -0.044       0.002
AST%           -0.0103      0.008     -1.338      0.181      -0.025       0.005
STL%           -0.1129      0.055     -2.061      0.040      -0.221      -0.005
BLK%           -0.0211      0.026     -0.806      0.420      -0.073       0.030
TOV%            0.0174      0.011      1.628      0.104      -0.004       0.038
USG%            0.0325      0.008      4.220      0.000       0.017       0.048
BPM             0.1159      0.026      4.545      0.000       0.066       0.166
NumOfAwards    -0.0481      0.108     -0.445      0.657      -0.260       0.164
All -Star        0.0886      0.208      0.427      0.670      -0.319       0.496
AwardWinner    -0.0525      0.257     -0.204      0.838      -0.557       0.453
FirstTeam      -0.1505      0.434     -0.347      0.729      -1.003       0.702
SecondTeam      0.1677      0.394      0.426      0.670      -0.605       0.941
ThirdTeam       0.1799      0.304      0.591      0.555      -0.418       0.777
DefTeam1        0.0729      0.333      0.219      0.827      -0.581       0.727
DefTeam2       -0.0839      0.293     -0.287      0.775      -0.659       0.491
Pos_C           2.5285      0.165     15.319      0.000       2.204       2.853
Pos_PF          2.5038      0.121     20.635      0.000       2.266       2.742
Pos_PG          2.2634      0.143     15.809      0.000       1.982       2.545
```

```
Pos_SF          2.4312      0.121     20.119      0.000       2.194       2.669
Pos_SG          2.3601      0.118     19.919      0.000       2.127       2.593
==============================================================================
Omnibus:                      107.058   Durbin -Watson:                  2.021
Prob(Omnibus):                  0.000   Jarque -Bera (JB):             280.244
Skew:                          -0.898   Prob(JB):                     1.40e -61
Kurtosis:                       5.822   Cond. No.                     3.47e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.06e -29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Now that we have fit our OLS model, we want to use this model to predict the players' next year salary for our test set. We also want to calculate the mean squared error for future comparison.

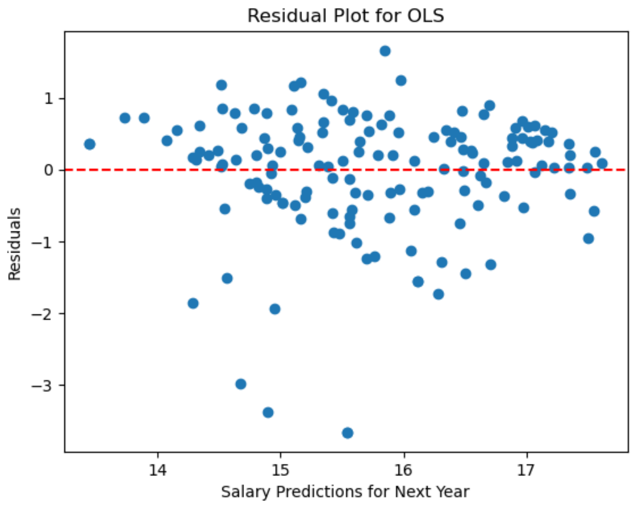
```
X_test_new = sm.add_constant(X_test)
ols_predictions = ols_model.predict(X_test_new)
ols_mse = mse_func(y_test, ols_predictions)
print(ols_mse)
```

```
0.7642872784423452
```

Since the MSE is only meaningful relative to other models' MSE, we will plot the residuals to see visually see how the OLS model is doing.

```
ols_residuals = y_test - ols_predictions
plt.scatter(ols_predictions, ols_residuals)
plt.axhline(0, color='r', linestyle=' - -')
plt.title('Residual Plot for OLS')
plt.xlabel('Salary Predictions for Next Year')
plt.ylabel('Residuals')

plt.savefig("outputs/OLS_residual_plot.png")
```



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Looking at the residual plot above, we see that the residuals are not entirely randomly scattered but are generally within the [-2, 2] range, which suggests there may be a better model for this dataset. There is a slight linear pattern of residuals that can be seen so a nonlinear model may be a better fit.

2 Ridge Regression

One downside of the OLS model is that it may overfit, especially when noise or multicollinearity exists in the dataset. To prevent overfitting, we will now use ridge regression to regularize the model by limiting the model's complexity.

Before actually fitting the model, we will first standardize the predictors since the predictors all have different units. This prevents predictors with very large or very small units from skewing the model. We apply this standardization to both the training and test set for X.

```
ss = preprocessing.StandardScaler()
X_train_ss = ss.fit_transform(X_train)
X_test_ss = ss.transform(X_test)
```

After standardization, we will now use ridge regression combined with 5-fold cross validation to find the best lambda/model.

```
lambdas = [0.001, 0.01, 0.1, 1, 10, 100]
ridge_model = RidgeCV(alphas=lambdas, cv=5)
ridge_model.fit(X_train_ss, y_train)
ridge_pred = ridge_model.predict(X_test_ss)
ridge_mse = mse_func(y_test, ridge_pred)
```

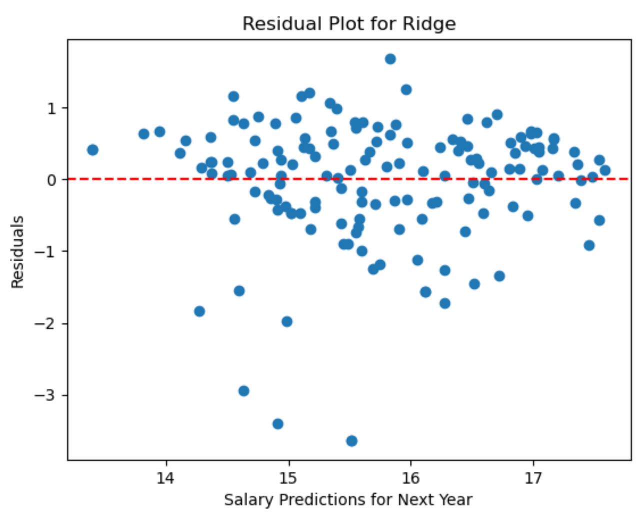
```
print("Ridge MSE: ", ridge_mse)
print("Best lambda for Ridge:", ridge_model.alpha_)
```

```
Ridge MSE:  0.7618085052855812
Best lambda for Ridge: 10.0
```

We see that the MSE for ridge is around 0.615, which is slightly lower than the MSE for OLS. Since the difference seems almost negligible, OLS and ridge regression are pretty similar in terms of performance.

```
ridge_residuals = y_test - ridge_pred
plt.scatter(ridge_pred, ridge_residuals)
plt.axhline(0, color='r', linestyle=' - -')
plt.title('Residual Plot for Ridge')
plt.xlabel('Salary Predictions for Next Year')
plt.ylabel('Residuals')

plt.savefig("outputs/Ridge_residual_plot.png")
```




```
<Figure size 640x480 with 0 Axes>
```

Looking at the residual plot above, we see that it resembles the residual plot for OLS, where there the residuals between [14,16] are not randomly scattered. Therefore, a nonlinear model may be a better fit.

3 LASSO Regression

Compared to ridge regression, LASSO will only retain features with great prediction power by shrinking the coefficients of irrelevant features to zero. This results in a model that is simpler in complexity, which additionally prevents overfitting. Since the residuals plots for OLS and ridge suggested that a nonlinear model may be better suited for this dataset, we will then use a random forest model to model the nonlinear relationship between the features selected by LASSO and salary.

Like ridge, we will also use 5-fold cross validation to find the best lambda/model on the standardized dataset.

```
warnings.filterwarnings("ignore")
lasso_model = LassoCV(cv=5)
lasso_model.fit(X_train_ss, y_train)
print("Best lambda for Lasso:", lasso_model.alpha_)
```

```
Best lambda for Lasso: 0.039218525026757704
```

Now that LASSO has peformed feature selection, we will use these selected features to train the random forest model with 70 estimators. Even though increasing the number of trees in the random forest model will decrease the MSE, we don't want to overfit.

```
selected = SelectFromModel(lasso_model, prefit=True)
X_train_selected = selected.transform(X_train_ss)
X_test_selected = selected.transform(X_test_ss)
print("Number of features before feature selection: ", X_train_ss.shape[1])
print("Number of features selected: ", X_train_selected.shape[1])
rf_model = RandomForestRegressor(n_estimators=70, random_state=42)
rf_model.fit(X_train_selected, y_train)
lasso_pred = rf_model.predict(X_test_selected)
lasso_mse = mse_func(y_test, lasso_pred)
print("LASSO MSE: ", lasso_mse)
```

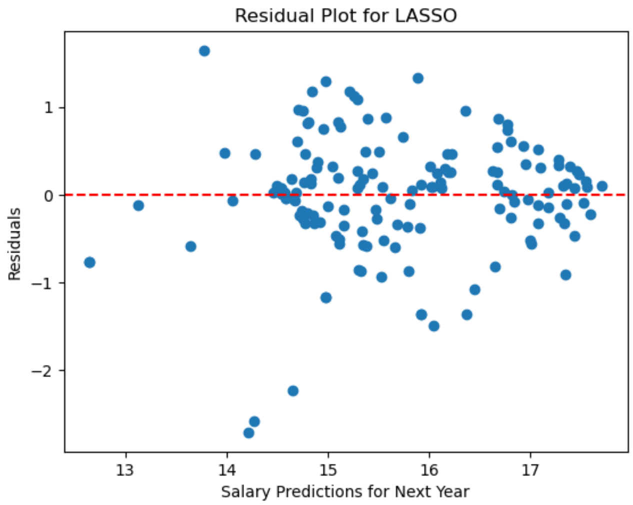
```
Number of features before feature selection:  24
Number of features selected:  7

LASSO MSE:  0.4531621662874519
```

LASSO reduced model complexity by only using 9 out of the 24 features. We also see that the MSE for LASSO + random forests is much lower than the MSE for ridge or OLS, which proves there is probably a nonlinear relationship between the predictors and salary.

```
lasso_residuals = y_test - lasso_pred
plt.scatter(lasso_pred, lasso_residuals)
plt.axhline(0, color='r', linestyle=' - -')
plt.title('Residual Plot for LASSO')
plt.xlabel('Salary Predictions for Next Year')
plt.ylabel('Residuals')

plt.savefig("outputs/LASSO_residual_plot.png")
```




```
<Figure size 640x480 with 0 Axes>
```

Comparing this residual plot to the residual plots for OLS or ridge, we see that the residuals in this plot are slightly more randomly scattered. The outliers present in the other residual plots are no longer present in this plot as LASSO removes features that have low predictive power/noise.

4 Results

We previously saw that only 9 out of the 24 features we are working with were used to train the random forest model. We will rank the 9 features by their predictive power as the other 15 features were deemed negligible by LASSO.

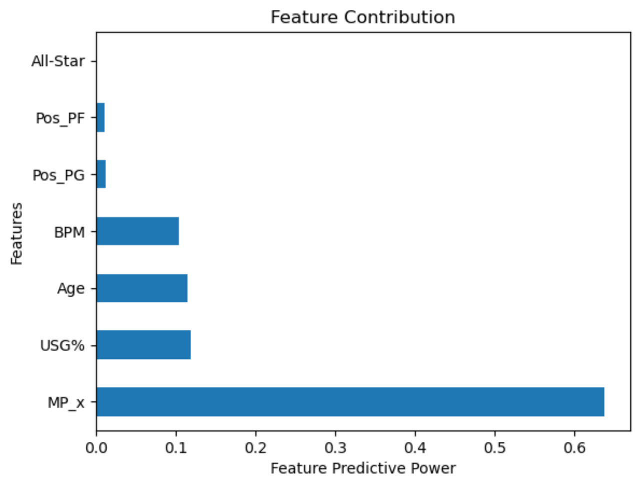
```
feature_contribution = pd.Series(rf_model.feature_importances_, index=X_train.columns[select
print("Features from highest to lowest predictive power")
print(feature_contribution)
```

```
Features from highest to lowest predictive power
MP_x        0.637777
USG%        0.119065
Age         0.115234
BPM         0.103677
Pos_PG      0.012605
Pos_PF      0.010970
All -Star    0.000673
dtype: float64
```

```
feature_contribution.plot(kind='barh')
plt.xlabel("Feature Predictive Power")
```

```
plt.ylabel("Features")
plt.title("Feature Contribution")

plt.savefig("outputs/feature_contribution.png")
```




```
<Figure size 640x480 with 0 Axes>
```

Looking at the bar plot above, we see that out of the 9 features above, the players' minutes played per game was the most predictive of their next year's salary. Minutes played per game contributed to about 60% of the prediction while BPM and age were the 2nd and 3rd more predictive features, contributing about 11% and 7.5% resepectively. LASSO ignores the other 15 features for its predictions while ridge and OLS take all 24 features into account when predicting salary. Since LASSO + random forest resulted in the lowest MSE, we can conclude that a non-linear model using a subset of all the features to predict next year's salary is the best fit.