NBA Salary prediction: Linear Regression model and Web scraping

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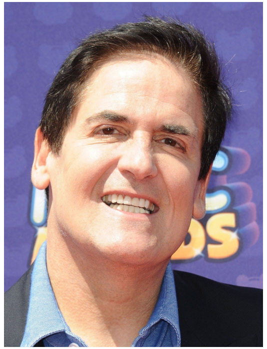
Introduction

How much should I pay Doncic?



- Mark Cuban (Owner of Dallas Mavericks) always want to invest the right amount of money to the right players.
- He decided to hire a data scientist to create a regression model that takes all the players' features to generate their predicted salary

Data

Basketball-Reference

ESPN

Methodology

- Request,BeautifulSoup : Web Scraping
- Pandas,Excel,numpy : Data cleaning,feature engineering
- Sklearn : Split the data into train/validation/test,and test different regression models(Linear Regression, LASSO,RIDGE, Polynomial(degrees=2),LASSO of Polynomial(degrees=2),RIDGE of Polynomial(degrees=2)
- Seaborn : Visualize the data
- Create a function that runs all the models on the given test set and give out the score of each model (see Appendix 1)

Results

- The columns of the best test set are ['Age', 'G', 'GS', 'MP', 'eFG%', 'FT%', 'TRB', 'AST', 'STL', 'BLK','TOV', 'PF', 'PTS', 'Year']

- kFold = 10

```
Linear Regression val R^2: 0.534
Linear Regression mean val R^2: 0.556:
Ridge Alpha Best_estimator : 0.100
Ridge Regression val R^2: 0.534
Ridge Regression mean val R^2: 0.556
Lasso Alpha Best_estimator : 0.100
Lasso Regression val R^2: 0.534
Lasso Regression mean val R^2: 0.558
Degree 2 polynomial regression val R^2: 0.596
Degree 2 polynomial Regression mean val R^2: 0.624
Degree 2 polynomial Ridge Alpha Best_estimator : 0.100
Degree 2 polynomial Ridge Regression val R^2: 0.622
Degree 2 polynomial Ridge Regression mean val R^2: 0.633
Degree 2 polynomial Lasso Alpha Best_estimator : 0.100
Degree 2 polynomial Lasso Regression val R^2: 0.621
Degree 2 polynomial Lasso Regression mean val R^2: 0.625
```

Result

Ridge of Polynomial (Degrees = 2)

R^2 score

Train = ~0.71

Validation = ~0.64

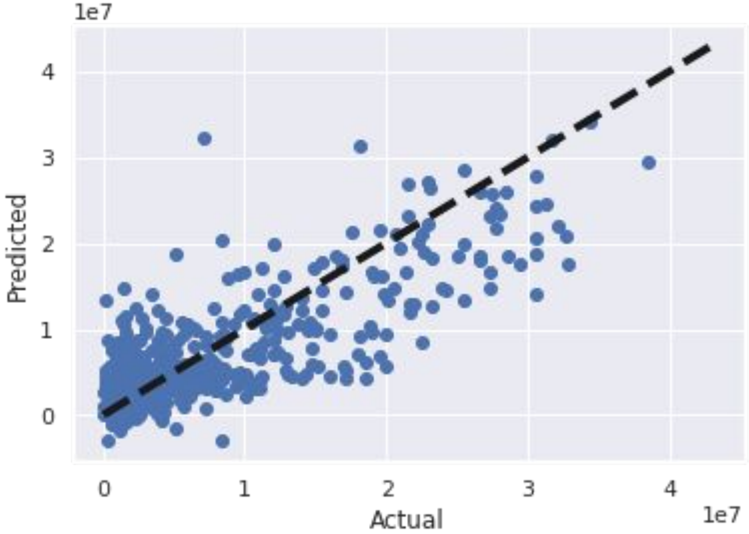
Test = ~0.64

Our model can explain ~64% of the variance (See appendix 2)

Unscale the coefficients and the intercept :

```
coefficients = np.true_divide(lm_reg_poly.coef_,  scaler.scale_)
lm_reg_poly.intercept_ - np.dot(coefficients, scaler.mean_)
```

Conclusion



The actual vs predicted plot:

- Our model tends to overestimate as the salaries goes up
- Need to acquire more data points or features to improve this model

Takeaways

- Learned how to use Beautifulsoup to scrape data online

- Learned how to split the data into train/validation/test and train them with different models

- The importance of R^2

Appendix

Appendix 1

```python
def split_and_validate(X,y):

    X, X_test, y, y_test = train_test_split(X, y, test_size=.2)
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=.25)

    kf = KFold(n_splits=10, shuffle=True)

    lm = LinearRegression()
    lm.fit(X_train, y_train)
    lm_cross_val_score = cross_val_score(lm, X_train, y_train, cv=kf, scoring='r2')

    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train.values)
    X_val_scaled = scaler.transform(X_val.values)
    X_test_scaled = scaler.transform(X_test.values)


    ridge_grid_est = build_grid_search_est(Ridge(), X_train, y_train, cv=kf,
                                           alpha=np.logspace(-4, -1, 10))
    reg_alpha = ridge_grid_est.best_estimator_.alpha


    lm_reg = Ridge(alpha = reg_alpha)
    lm_reg.fit(X_train_scaled, y_train)
    lm_reg_cross_val_score = cross_val_score(lm_reg, X_train_scaled, y_train, cv=kf, scoring='r2')
    ridge_grid_est = build_grid_search_est(Ridge(), X_train, y_train, cv=kf,
                                           alpha=np.logspace(-4, -1, 10))



    lasso_grid_est = build_grid_search_est(Lasso(), X_train, y_train, cv=kf,
                                               alpha=np.logspace(-4, -1, 30))
    lasso_alpha = lasso_grid_est.best_estimator_.alpha
    lm_lasso = Lasso(alpha = lasso_alpha)
    lm_lasso.fit(X_train_scaled, y_train)
    lm_lasso_cross_val_score = cross_val_score(lm_lasso, X_train_scaled, y_train, cv=kf, scoring='r2')


    poly = PolynomialFeatures(degree=2)

    X_train_poly = poly.fit_transform(X_train)
    X_val_poly = poly.transform(X_val)
    X_test_poly = poly.transform(X_test)



    X_train_poly_scaled = scaler.fit_transform(X_train_poly)
    X_val_poly_scaled = scaler.fit_transform(X_val_poly)
    X_test_poly_scaled = scaler.fit_transform(X_test_poly)

    lm_poly = LinearRegression()
    lm_poly.fit(X_train_poly, y_train)
    lm_poly_cross_val_score = cross_val_score(lm_poly, X_train_poly, y_train, cv=kf, scoring='r2')


    ridge_grid_est_poly = build_grid_search_est(Ridge(), X_train_poly_scaled, y_train, cv=kf,
                                               alpha=np.logspace(-4, -1, 10))
    ridge_alpha_poly = ridge_grid_est_poly.best_estimator_.alpha
    lm_reg_poly = Ridge(alpha=ridge_alpha_poly)
    lm_reg_poly.fit(X_train_poly_scaled, y_train)
    lm_reg_poly_cross_val_score = cross_val_score(lm_reg_poly, X_train_poly_scaled, y_train, cv=kf, scoring='r2')


    lasso_grid_est_poly = build_grid_search_est(Lasso(), X_train_poly_scaled, y_train, cv=kf,
                                               alpha=np.logspace(-4, -1, 30))
    lasso_alpha_poly = lasso_grid_est_poly.best_estimator_.alpha
    lm_lasso_poly = Lasso(alpha = lasso_alpha_poly)
    lm_lasso_poly.fit(X_train_poly_scaled, y_train)
    lm_lasso_poly_cross_val_score = cross_val_score(lm_lasso_poly, X_train_poly_scaled, y_train, cv=kf, scoring='r2

    print(f'Linear Regression val R^2: {lm.score(X_val, y_val):.3f}')
    print(f'Linear Regression mean val R^2: {np.mean(lm_reg_cross_val_score):.3f}:')


    print(f'Ridge Alpha Best_estimator : {reg_alpha:.3f}')
    print(f'Ridge Regression val R^2: {lm_reg.score(X_val_scaled, y_val):.3f}')
    print(f'Ridge Regression mean val R^2: {np.mean(lm_reg_cross_val_score):.3f}')


    print(f'Lasso Alpha Best_estimator : {lasso_alpha:.3f}')
    print(f'Lasso Regression val R^2: {lm_lasso.score(X_val_scaled, y_val):.3f}')
    print(f'Lasso Regression mean val R^2: {np.mean(lm_lasso_cross_val_score):.3f}')

    print(f'Degree 2 polynomial regression val R^2: {lm_poly.score(X_val_poly, y_val):.3f}')
    print(f'Degree 2 polynomial Regression mean val R^2: {np.mean(lm_poly_cross_val_score):.3f}')


    print(f'Degree 2 polynomial Ridge Alpha Best_estimator : {ridge_alpha_poly:.3f}')
    print(f'Degree 2 polynomial Ridge Regression val R^2: {lm_reg_poly.score(X_val_poly_scaled, y_val):.3f}')
    print(f'Degree 2 polynomial Ridge Regression mean val R^2: {np.mean(lm_reg_poly_cross_val_score):.3f}')



    print(f'Degree 2 polynomial Lasso Alpha Best_estimator : {lasso_alpha_poly:.3f}')
    print(f'Degree 2 polynomial Lasso Regression val R^2: {lm_lasso_poly.score(X_val_poly_scaled, y_val):.3f}')
    print(f'Degree 2 polynomial Lasso Regression mean val R^2: {np.mean(lm_lasso_poly_cross_val_score):.3f}')
```

Appendix 2

```python
coefficients = np.true_divide(lm_reg_poly.coef_,  scaler.scale_)
```

```python
intercept = lm_reg_poly.intercept_ - np.dot(coefficients, scaler.mean_)
```

```python
print(list(zip(poly.get_feature_names(input_features= X.columns),coefficients)))
```

```
[('1', 0.0), ('Age', -34315102.95042527), ('G', 7105379.655350137), ('GS', -4715713.90573231), ('MP', -10058161.70
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```

```python
intercept
```

```
-403810465586.6025
```

THANK YOU