Supervised_Learning_Regression_Project

December 12, 2020

[1]:
```
# Load packages:
import pandas as pd
import numpy as np

from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso, LassoCV
from sklearn.metrics import r2_score
from sklearn.pipeline import Pipeline

import seaborn as sns
import matplotlib.pyplot as plt

from IPython.display import set_matplotlib_formats
%matplotlib inline
set_matplotlib_formats('pdf', 'svg')
```

1 Data Summary

In this project, I am using tennis data from the 2019 ATP matches (obtained from https://github.com/JeffSackmann/tennis_atp). I cleaned it as part of the Exploratory Data Analysis Course, and save a copy as 'atp_matches_2019_clean.csv' (steps detailed in *Cleaning Summary* below). In this dataframe, each row shows individual match stats for a player.

Variable key:
* match_id = unique code for the match (so shared by two rows - one for winner, one for loser)
* outcome = whether the player won (w) or lost (l)
* ace_per = percentage of service points that were aces
* df_per = percentage of service points that were double faults
* bpFaced_per = percentage of service points where the player faced a break point
* 1stIn_per = percentage of service points where the first serve was in
* 1stWon_per = percentage of 1st serves where the point was won
* 2ndWon_per = percentage of 2nd serves where the point was won
* pt_per = percentage of total match points that the player won

[2]:
```
tennis_df = pd.read_csv('atp_matches_2019_clean.csv')
tennis_df.head(10)
```

[2]:
```
   match_id outcome                name        age   ace_per    df_per  \
0         0       w        Kei Nishikori  29.004791  1.955930  2.123021
1         1       w      Daniil Medvedev  22.885695  4.510174  1.301106
2         2       w        Kei Nishikori  29.004791  2.062797  2.247840
3         3       w  Jo-Wilfried Tsonga  33.705681  4.337238  1.759191
4         4       w      Daniil Medvedev  22.885695  3.527772  1.724531
5         5       w        Jeremy Chardy  31.882272  3.404345  3.424165
6         6       w        Kei Nishikori  29.004791  3.030941  1.936540
7         7       w  Jo-Wilfried Tsonga  33.705681  4.285008  2.390860
8         8       w       Alex De Minaur  19.868583  1.284753  1.358932
9         9       w      Daniil Medvedev  22.885695  5.447646  2.053701

   bpFaced_per  1stIn_per  1stWon_per  2ndWon_per     pt_per
0     7.792208  57.142857   70.454545   56.666667  53.107345
1     1.923077  63.461538   84.848485   77.777778  58.914729
2     4.255319  70.212766   78.787879   75.000000  64.516129
3     7.352941  63.235294   79.069767   65.217391  55.704698
4     7.619048  64.761905   70.588235   73.529412  51.256281
5     8.510638  61.702128   75.862069   64.285714  51.086957
6     1.694915  79.661017   78.723404   90.000000  54.676259
7    10.937500  57.812500   81.081081   45.833333  54.362416
8     0.000000  77.551020   76.315789   80.000000  57.142857
9     1.851852  62.962963   79.411765   72.222222  57.894737
```

[3]:
```
tennis_df.dtypes
```

[3]:
```
match_id         int64
outcome         object
name            object
age            float64
ace_per        float64
df_per         float64
bpFaced_per    float64
1stIn_per      float64
1stWon_per     float64
2ndWon_per     float64
pt_per         float64
dtype: object
```

[4]:
```
tennis_df.shape
```

[4]:
```
(5296, 11)
```

1.1 Cleaning Summary

In a prior notebook (for the Exploratory Data Analysis Course), I cleaned the original data by:
* checking for and removing rows with missing values

* transforming heavily skewed variables with box-cox transform
* removing outliers using 2 * IQR

1.2 Format for Analyses

For the current analyses, I'm going to be focusing on individual players and not matches. Because I'll be averaging across each player's matches, I'm only considering those who have played at least 5 times in the year:

[5]:
```
# players who played at least 5 matches in 2019:
match_counts = tennis_df.groupby('name').count()
names = match_counts.index[match_counts.match_id >=5].tolist()

# filter df:
tennis_df = tennis_df[tennis_df['name'].isin(names)]
```

[6]:
```
print('This dataset contains information for ' + str(len(tennis_df.name.
 ↪unique())) + ' players over ' + str(len(tennis_df.match_id.unique())) + '␣
 ↪matches')
```

```
This dataset contains information for 164 players over 2662 matches
```

Now I'm going to group by players and summarise each of my features to get the average match stats per player in 2019:

[7]:
```
# mean of continuous variables:
player_df = tennis_df.groupby('name').mean().drop(['match_id','pt_per'], axis=1)

# add the % of their matches that they won:
wins = (tennis_df.groupby('name')["outcome"]
         .value_counts(normalize=True)
         .to_frame()
         .rename(columns={"outcome":"value"})
         .reset_index()
         .pivot(index="name",columns="outcome",values="value")
         .reset_index()
         .fillna(0)
       )
```

[8]:
```
player_df = player_df.merge(wins.drop("l", axis=1), on="name")
player_df.head()
```

[8]:
```
                          name        age   ace_per    df_per  bpFaced_per  \
0            Adrian Mannarino  30.992734  2.628861  1.505509     7.748114
1                Albert Ramos  31.357328  1.888347  1.326321     7.874975
2  Alejandro Davidovich Fokina  19.958111  1.434778  1.910521    11.196125
3                    Alex Bolt  26.127310  2.742567  1.624983     9.126861
4               Alex De Minaur  20.352156  2.092616  1.630736     6.047510
```

	1stIn_per	1stWon_per	2ndWon_per	w
0	59.768851	71.822690	57.523607	0.519231
1	63.600401	69.740544	58.461562	0.566038
2	71.536233	61.161494	53.662835	0.300000
3	55.921580	71.269908	52.730918	0.428571
4	61.683252	75.398451	59.616491	0.660714

The ***target (Y)*** is w (the percentage of games won by a player in 2019), and ***features (X)*** are the remaining continuous variables (age and mean performance stats).

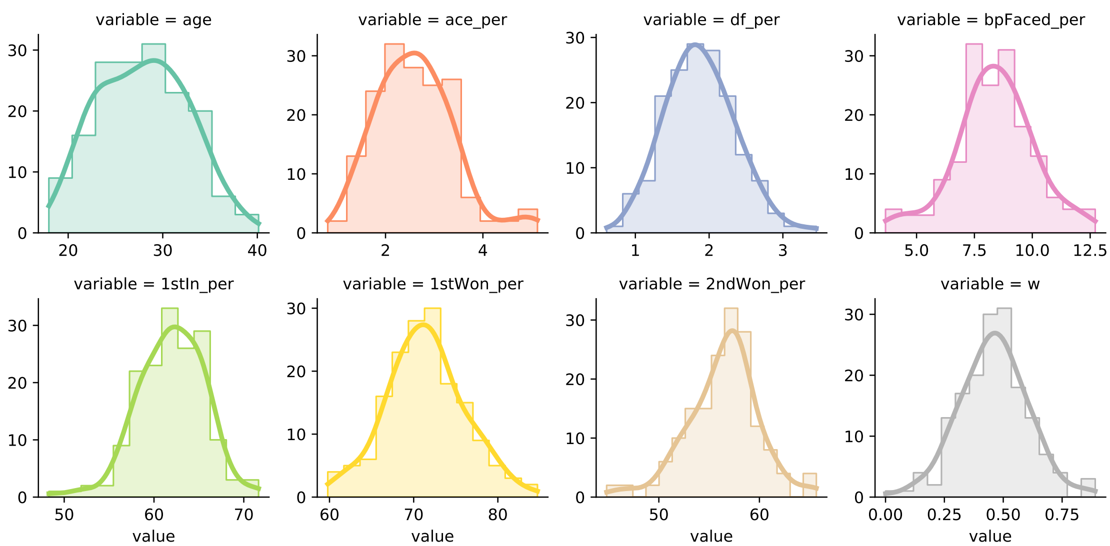
Distribution of my variables:

[9]:
```
melted_df = player_df.select_dtypes("float").melt()

grid = sns.FacetGrid(melted_df, col='variable', col_wrap=4,
                     hue='variable', palette='Set2',
                     height=2.5, aspect=1,
                     sharex = False, sharey = False)

grid.map(sns.histplot, "value", alpha=.25,
         kde=True, line_kws={"lw":3}, element="step")
```

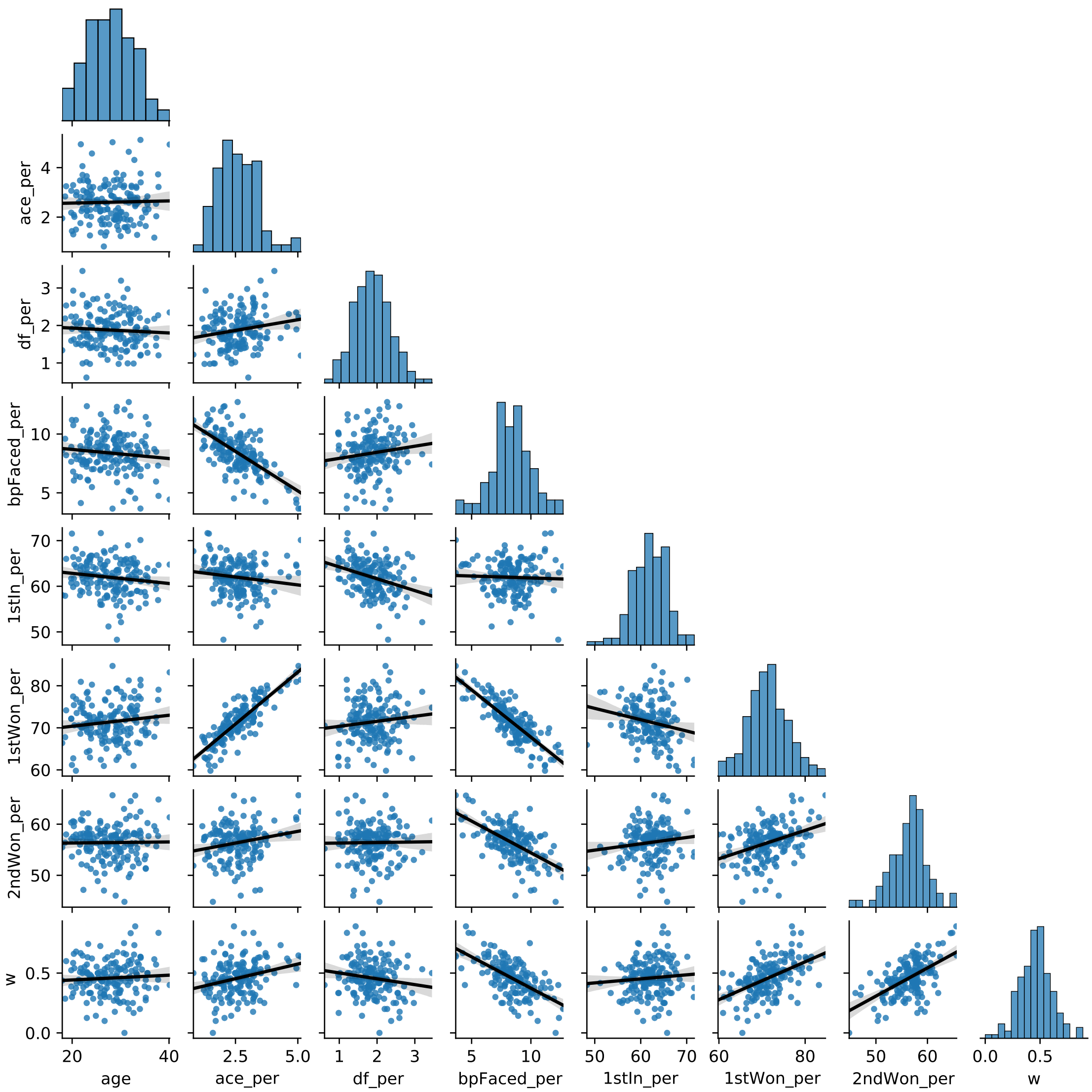
[9]: <seaborn.axisgrid.FacetGrid at 0x7fb194342d68>



Correlations between my variables:

[10]:
```
sns.pairplot(player_df.select_dtypes("float"),
             kind="reg", height=1.2, corner=True,
             plot_kws={'scatter_kws':{'s':8},
                       'line_kws':{'color':'black',
```

```
                                             'lw':2}})
plt.show()
```



2 Analysis Objectives

The goals of this analysis is to train linear regression models, predicting each player's percentage of games won ('w') with various features, including age and indices of match performance. Ideally, I want to build a model that best predicts performance success over the year.

First, I will divide my data into a training (75%) and test (25%) set. I will use the same training and test sets to compare performance of the following models:
* 1) Linear regression, with all match statistics as features
* 2) Linear regression, same as above but also including age and interactions of match statistics

with age as predictors
* 3) A Lasso regression model, including all features from model (2)
* 4) A Lasso regression model, including all features and all of their quadratic terms.

Cross-validation using the training set data will be used to select the best alpha for my lasso regression models.

3 Regression Models

3.1 Model 1: Simple Linear Regression

[11]:
```
# X and y data:
X = player_df.select_dtypes("float").drop(['w','age'], axis=1)
y = player_df["w"]
X.head()
```

[11]:

	ace_per	df_per	bpFaced_per	1stIn_per	1stWon_per	2ndWon_per
0	2.628861	1.505509	7.748114	59.768851	71.822690	57.523607
1	1.888347	1.326321	7.874975	63.600401	69.740544	58.461562
2	1.434778	1.910521	11.196125	71.536233	61.161494	53.662835
3	2.742567	1.624983	9.126861	55.921580	71.269908	52.730918
4	2.092616	1.630736	6.047510	61.683252	75.398451	59.616491

Set up my pipeline for the LR model (standardizing my features and fitting the regression model) and predict on a test set:

[12]:
```
# divide data into train and test sets:
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.25,␣
 ↪random_state=100)
```

[13]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(123, 6)
(41, 6)
```

[14]:
```
# fit the model and predict new values:
s = StandardScaler()
lr = LinearRegression()

model1 = Pipeline([("scaler", s),
                   ("linear_regression", lr)])
model1.fit(X_train, y_train)
y_pred = model1.predict(X_test)
```

[15]:
```
# calculate the r-squared score scross the different train-test splits:
r2_score(y_test, y_pred)
```

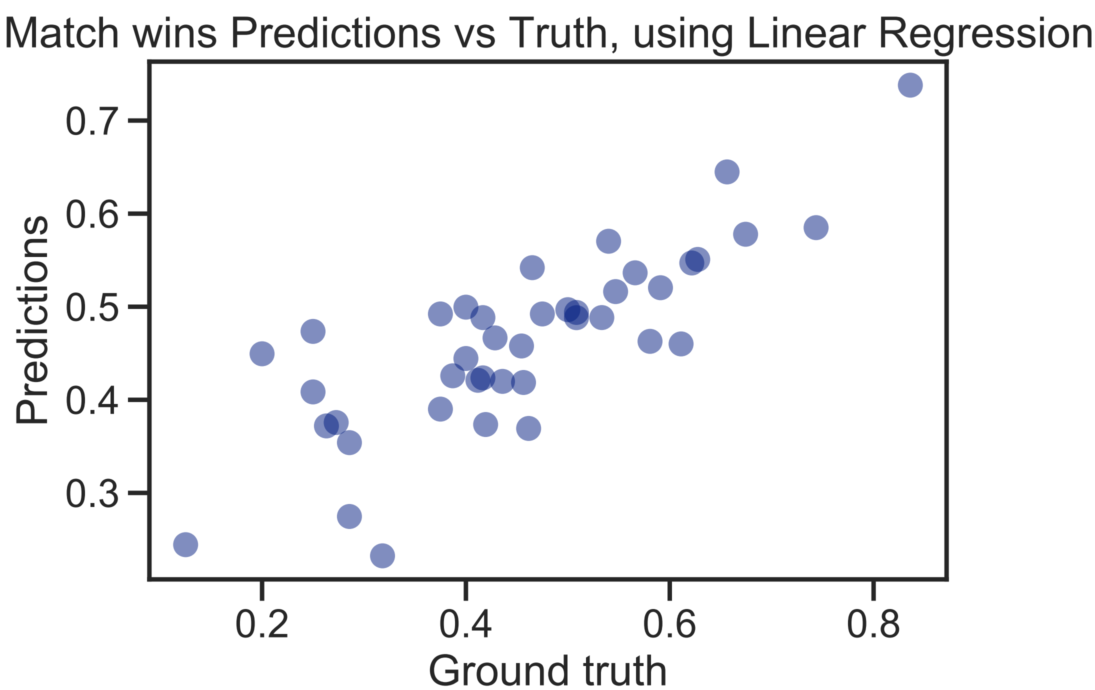
[15]: 0.6249453245362065

Show predicted vs. actual values:

[16]:
```
sns.set_context('talk')
sns.set_style('ticks')
sns.set_palette('dark')

ax = plt.axes()
# we are going to use y_test, y_test_pred
ax.scatter(y_test, y_pred, alpha=.5)

ax.set(xlabel='Ground truth',
       ylabel='Predictions',
       title='Match wins Predictions vs Truth, using Linear Regression');
```



Model coefficients:

[17]:
```
pd.DataFrame(list(zip(model1.named_steps["linear_regression"].coef_, X.
 ↪columns)),
             columns=['Coefficient','Feature'])
```

[17]:

	Coefficient	Feature
0	-0.068733	ace_per
1	-0.012956	df_per

```
2    -0.016698  bpFaced_per
3     0.014965    1stIn_per
4     0.101457   1stWon_per
5     0.043755   2ndWon_per
```

This basic linear regression model does a reasonable job at predicting overall match performance (r-squared = 0.62), showing that the abilty to win points from a 1st serve is a particularly important indicator of match success.

3.2 Model 2: Age Interaction Linear Regression

Create interaction terms (age * feature):

[18]:
```
# re-define X to include age
X = player_df.select_dtypes("float").drop(['w'], axis=1)

pf = PolynomialFeatures(degree=2, interaction_only=True, include_bias=False)
X_age = pf.fit_transform(X)
X_age = pd.DataFrame(X_age, columns=pf.get_feature_names(X.columns))

# keep only interaction terms with 'age'
age_interactions = [col for col in X_age.columns if 'age ' in col]
X_age = X_age[X.columns.tolist() + age_interactions]
X_age.head()
```

[18]:
```
         age   ace_per    df_per  bpFaced_per  1stIn_per  1stWon_per  \
0  30.992734  2.628861  1.505509     7.748114  59.768851   71.822690
1  31.357328  1.888347  1.326321     7.874975  63.600401   69.740544
2  19.958111  1.434778  1.910521    11.196125  71.536233   61.161494
3  26.127310  2.742567  1.624983     9.126861  55.921580   71.269908
4  20.352156  2.092616  1.630736     6.047510  61.683252   75.398451

   2ndWon_per  age ace_per  age df_per  age bpFaced_per  age 1stIn_per  \
0   57.523607    81.475590   46.659841       240.135224    1852.400116
1   58.461562    59.213525   41.589898       246.938174    1994.338645
2   53.662835    28.635467   38.130383       223.453511    1427.728073
3   52.730918    71.655909   42.456439       238.460335    1461.080465
4   59.616491    42.589248   33.188997       123.079876    1255.387175

   age 1stWon_per  age 2ndWon_per
0     2225.981537     1782.813873
1     2186.877144     1833.198404
2     1220.667882     1071.008816
3     1862.090977     1377.717035
4     1534.521032     1213.324131
```

Now run the same linear regression pipeline as above:

[19]:
```
# divide data into train and test sets (fixing random state, so same splits as␣
↪before):
X_train, X_test, y_train, y_test = train_test_split(X_age, y,
                                                     test_size=0.25,␣
↪random_state=100)
```

[20]:
```
# fit the model and predict new values:
model2 = Pipeline([("scaler", s),
                   ("linear_regression", lr)])
model2.fit(X_train, y_train)
y_pred = model2.predict(X_test)
```

[21]:
```
# calculate the r-squared score across the different train-test splits:
r2_score(y_test, y_pred)
```

[21]:
```
0.6558268527672184
```

Incorporating age and interactions with age provides us with a better (albeit slightly) ability to predict match success (r-squared = 0.66).

3.3 Model 3: Age Interaction Lasso Regression

Now, instead of standard linear regression as in models 1 and 2, I'm going to run Lasso regression to reduce the influence of features that aren't useful for prediction.
First, I'm using cross-validation to select the best value of alpha for regularization. Note that my features are standardized with StandardScaler() before running the cross validation.

[22]:
```
# fit the model and predict new values,
# first tuning alphs with CV:
s = StandardScaler()
lassoCV = LassoCV(max_iter=5e4)

model3 = Pipeline([("scaler", s),
                   ("lasso_regression", lassoCV)])
model3.fit(X_train, y_train)
y_pred = model3.predict(X_test)
```

[23]:
```
lassoCV_r2 = r2_score(y_test, y_pred)
print(model3.named_steps["lasso_regression"].alpha_, lassoCV_r2)
```

```
0.0009025640191179066 0.6152423754532159
```

[24]:
```
pd.DataFrame(list(zip(model3.named_steps["lasso_regression"].coef_, X_age.
↪columns)),
             columns=['Coefficient','Feature'])
```

[24]:
```
    Coefficient          Feature
0      0.000000              age
1     -0.017649          ace_per
2     -0.012524           df_per
3     -0.013590      bpFaced_per
4      0.013599        1stIn_per
5      0.090566       1stWon_per
6      0.033203       2ndWon_per
7     -0.052524      age ace_per
8     -0.000000       age df_per
9     -0.008288  age bpFaced_per
10    -0.000000    age 1stIn_per
11     0.000000   age 1stWon_per
12     0.029407   age 2ndWon_per
```

The lasso regression is able to zero-out some of the features, highlighting those that make a small or no contribution to the model. Interestingly, it looks as if age positively interacts with 2nd serve success (final coefficient), suggesting that winning off second serves is most important for older players. The opposite is true for aces, suggesting that younger players benefit the most from aces in terms of their match success.

However, the model's ability to predict match success is slightly worse than the equivalent linear regression (r-squared = 0.62 vs. 0.66), perhaps because the number of feature we have is relatively small.

3.4 Model 4: Lasso Regression with Quadratic terms

This final model uses all 7 features (age and match stats), also including all of their quadratic terms (degree = 2).

[25]:
```
# re-define pf
pf = PolynomialFeatures(degree=2, include_bias=False)
X_pf = pf.fit_transform(X)
X_pf = pd.DataFrame(X_pf, columns=pf.get_feature_names(X.columns))
X_pf.head()
```

[25]:
```
         age   ace_per    df_per  bpFaced_per  1stIn_per  1stWon_per  \
0  30.992734  2.628861  1.505509     7.748114  59.768851   71.822690
1  31.357328  1.888347  1.326321     7.874975  63.600401   69.740544
2  19.958111  1.434778  1.910521    11.196125  71.536233   61.161494
3  26.127310  2.742567  1.624983     9.126861  55.921580   71.269908
4  20.352156  2.092616  1.630736     6.047510  61.683252   75.398451

   2ndWon_per       age^2  age ace_per  age df_per  …  bpFaced_per^2  \
0   57.523607  960.549571    81.475590   46.659841  …      60.033264
1   58.461562  983.282036    59.213525   41.589898  …      62.015230
2   53.662835  398.326190    28.635467   38.130383  …     125.353223
3   52.730918  682.636331    71.655909   42.456439  …      83.299597
```

```
4   59.616491  414.210256    42.589248   33.188997   …      36.572382

   bpFaced_per 1stIn_per  bpFaced_per 1stWon_per  bpFaced_per 2ndWon_per  \
0            463.095847             556.490359              445.699443
1            500.851562             549.205039              460.383339
2            800.928634             684.771755              600.815830
3            510.388506             650.470562              481.267771
4            373.030111             455.972916              360.531352

   1stIn_per^2  1stIn_per 1stWon_per  1stIn_per 2ndWon_per  1stWon_per^2  \
0  3572.315572           4292.759667           3438.119931   5158.498791
1  4045.010979           4435.526573           3718.178800   4863.743531
2  5117.432655           4375.262905           3838.837094   3740.728365
3  3127.223133           3985.525861           2948.796240   5079.399747
4  3804.823603           4650.821640           3677.339058   5684.926343

   1stWon_per 2ndWon_per  2ndWon_per^2
0            4131.500220   3308.965410
1            4077.141188   3417.754280
2            3282.099183   2879.699887
3            3758.127634   2780.549675
4            4494.991057   3554.126014

[5 rows x 35 columns]
```

[26]:

```
# divide data into train and test sets (fixing random state, so same splits as␣
↪before):
X_train, X_test, y_train, y_test = train_test_split(X_pf, y,
                                                    test_size=0.25,␣
↪random_state=100)
```

[27]:

```
# fit the model and predict new values,
# first tuning alphs with CV:
s = StandardScaler()
lassoCV = LassoCV(max_iter=5e4)

model4 = Pipeline([("scaler", s),
                   ("lasso_regression", lassoCV)])
model4.fit(X_train, y_train)
y_pred = model4.predict(X_test)
```

[28]:

```
lassoCV_r2 = r2_score(y_test, y_pred)
print(model4.named_steps["lasso_regression"].alpha_, lassoCV_r2)
```

```
0.008578981501550441 0.5745857967142914
```

Let's compare that to a standard linear regression without regulatization, but with identical features:

[29]:
```
# fit the model and predict new values:
model4_lr = Pipeline([("scaler", s),
                      ("linear_regression", lr)])
model4_lr.fit(X_train, y_train)
y_pred = model4_lr.predict(X_test)
r2_score(y_test, y_pred)
```

[29]:
```
0.4117893625217215
```

So in this situation, where we have many features, lasso regression helps the predictive performance of the model (r-squared = 0.57 vs. 0.41). But performance is still lower than the simpler linear model (2) just considering age interactions.

4 Key Findings

The key finding from the above linear regression comparisons are that:

- Model 2 - linear regression with 7 features (age and match stats) + 6 interactions between age and match stats — is the best model for predicting overall match success.

- In situations with few features, lasso regression does not help the predictive performance of our model.

- In situations with more features, lasso regression can improve the model's predictive performance, but it still does not improve upon Model 2.

- Overall, the models show that winning points from 1st and 2nd serves are important for match success, but that considering interactions with age and between match stats (e.g. winning more 1st serves *and* 2nd serves) might help explain performamce.

5 Problems and Future Directions

The above models ran into a few problems — for example, the limited number of features meant that r-squared never went above 0.65, and the features largely show a linear relationship with match success. More features would be helpful to fully characertize a predictive model of match success. For example, sleep, diet, and other individual (non-match) factors would be important to helpful.

Future directions would be to consider the data in a different format — rather than summarising by individual players, I could consider each match and the relative difference in performance between players. For example, while a player's age must not be predictive of match success overall, it might be if there is a large difference in age between opponents. I could also predict whether a player would win or lose individual matches with classification, rather than considering their average performance across the year.