modeling_reg

March 16, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import warnings
import xgboost as xgb
from statsmodels.stats.anova import anova_lm
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from statsmodels.gam.api import GLMGam, BSplines


# import diagnostics from smlearn website
import SM_plots as SM

warnings.filterwarnings('ignore')
```

[2]:
```
# load data
path = '/Users/dylanjorling/UCLA/412proj/data/'
name = 'full_combine_data'
data = pd.read_csv(path + name, index_col=0)
data.shape
```

[2]: (13210, 15)

[3]:
```
################## EDA Plots ##################
combine_complete = data.dropna()
print(combine_complete.shape)
combine_complete.head()
combine_complete = combine_complete[combine_complete['pick'] != 'undrafted']
```

```
#combine_complete = combine_complete[combine_complete['pos'] == 'LB'] #filter␣
↪for specific positions
#combine_complete = combine_complete[combine_complete['year'] >= 2010] #filter␣
↪for specific year...didn't alter much
combine_complete['pick'] = combine_complete['pick'].astype(int)
combine_complete = combine_complete[combine_complete['pick'] < 300]
combine_complete = combine_complete[combine_complete['bench'] < 74]
pos_one_hot = combine_complete['pos'].str.get_dummies()


y = combine_complete['pick']
X = combine_complete.iloc[:, 4:-1]
X = pd.concat([X, pos_one_hot], axis=1)
null_sd = y.std()
print(null_sd)

combine_complete.head()
```

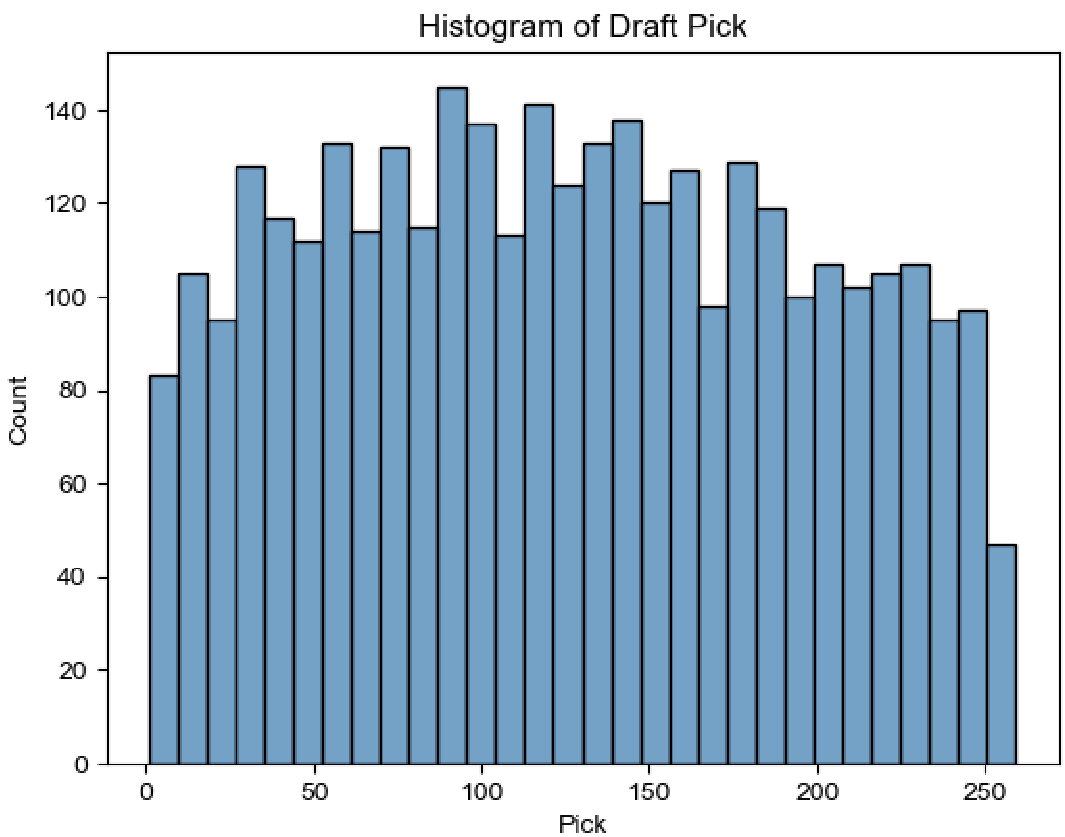
```
(5843, 15)
69.80294730041324
```

[3]:

```
      year            name        college pos  height  weight  hand_size  \
3350  1997     John Allred            USC  TE    76.4     244      10.00
3355  1997    Duane Ashman       Virginia  DE    75.5     274       9.50
3357  1997  Raymond Austin      Tennessee  DB    70.6     190      10.25
3360  1997   Antonio Banks  Virginia Tech  DB    70.0     203       9.50
3361  1997    Ronde Barber       Virginia  DB    69.4     185       9.50

      arm_length  forty  bench  vert  broad_jump  shuttle  3cone  pick
3350       32.50   5.01   15.0  32.0       112.0     4.32   7.45    38
3355       35.63   5.03   19.0  32.5       110.0     4.83   8.80   161
3357       32.00   4.80   12.0  32.5       111.0     4.05   7.14   145
3360       32.00   4.66   18.0  36.0       117.0     4.41   7.85   113
3361       31.63   4.68   14.0  34.5       118.0     4.46   7.22    66
```

[5]:

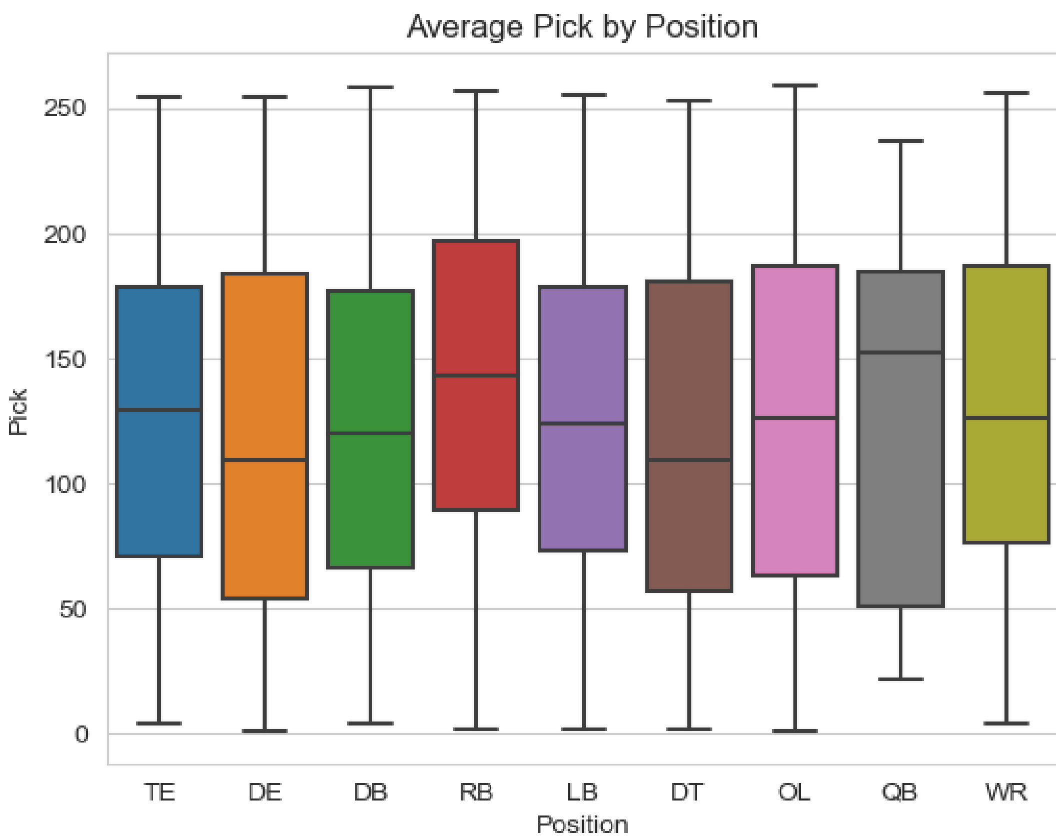
```
ax = sns.histplot(combine_complete, x='pick', color="steelblue", bins=30)
ax.set(xlabel='Pick', ylabel='Count', title='Histogram of Draft Pick')
sns.set_style("whitegrid")
plt.show()
# underlying distribution is uniform
```



[6]:
```
pos_means = combine_complete.groupby('pos').mean()['pick']
ax = sns.boxplot(data=combine_completex=pos_means, y=pos_means.index, orient='h')
ax.set(xlabel='Pick', ylabel='Position', title='Average Pick by Position')
sns.set_style("whitegrid")
plt.show()
```

```
  File "/var/folders/z7/1q6khp0n3xq0p_97cq1hvpd40000gn/T/ipykernel_2929/292387673 .
↪py", line 2
    ax = sns.boxplot(data=combine_completex=pos_means, y=pos_means.index,␣
↪orient='h')
                                                   ^

SyntaxError: invalid syntax
```

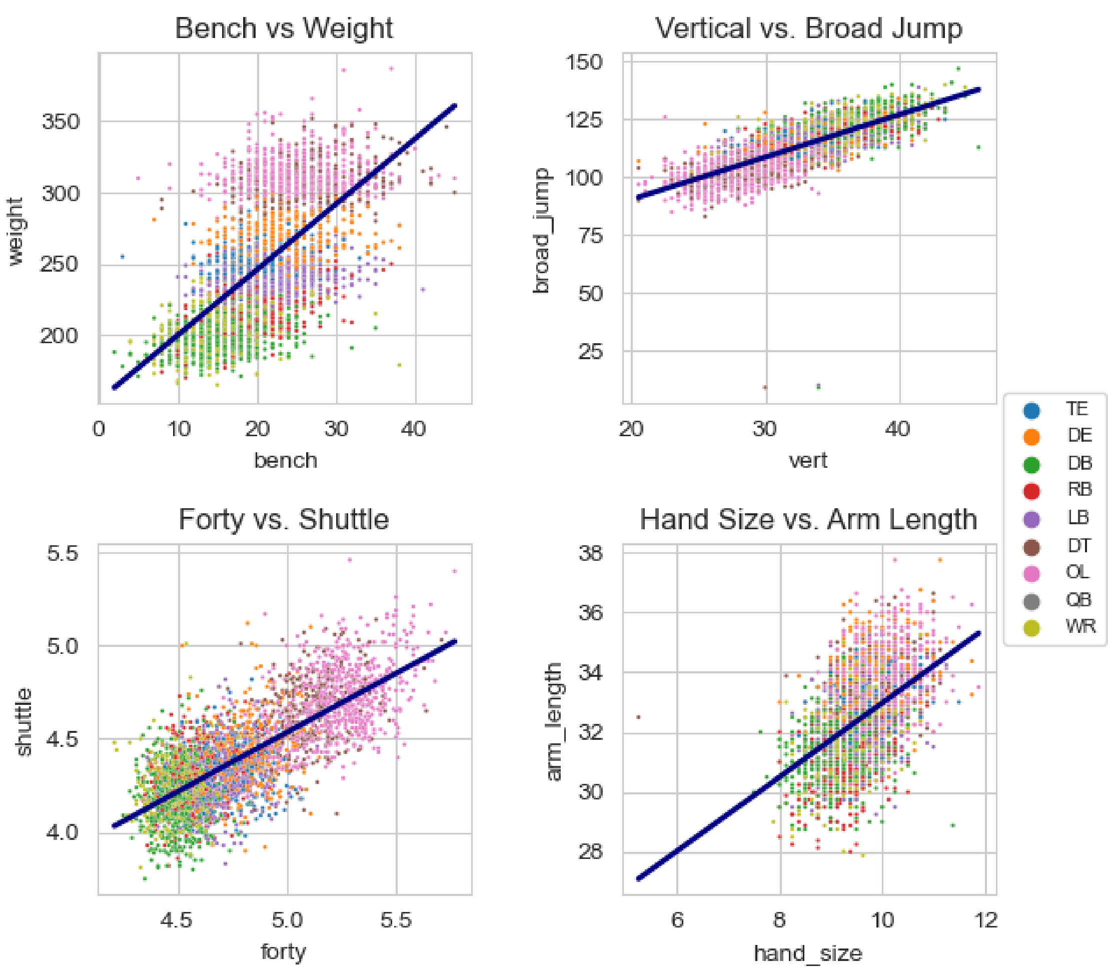
[7]:
```
pos_means = combine_complete.groupby('pos').mean()['pick']
ax = sns.boxplot(data=combine_complete, x='pos', y='pick')
ax.set(xlabel='Position', ylabel='Pick', title='Average Pick by Position')
sns.set_style("whitegrid")
plt.show()
```



[101]:
```
# This is a plot of some of the more predictive variables

fig, axs = plt.subplots(nrows=2, ncols=2)
sns.scatterplot(data=combine_complete,
                x='bench',
                y='weight',
                hue='pos',
                s=3,
                ax=axs[0,0],
               legend=False)
axs[0, 0].set(xlabel='Bench Press Reps', ylabel='Weight', title='Bench vs␣
 ↪Weight')
sns.regplot(data=combine_complete,
            x='bench',
            y='weight',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[0,0])
sns.set_style("whitegrid")
```

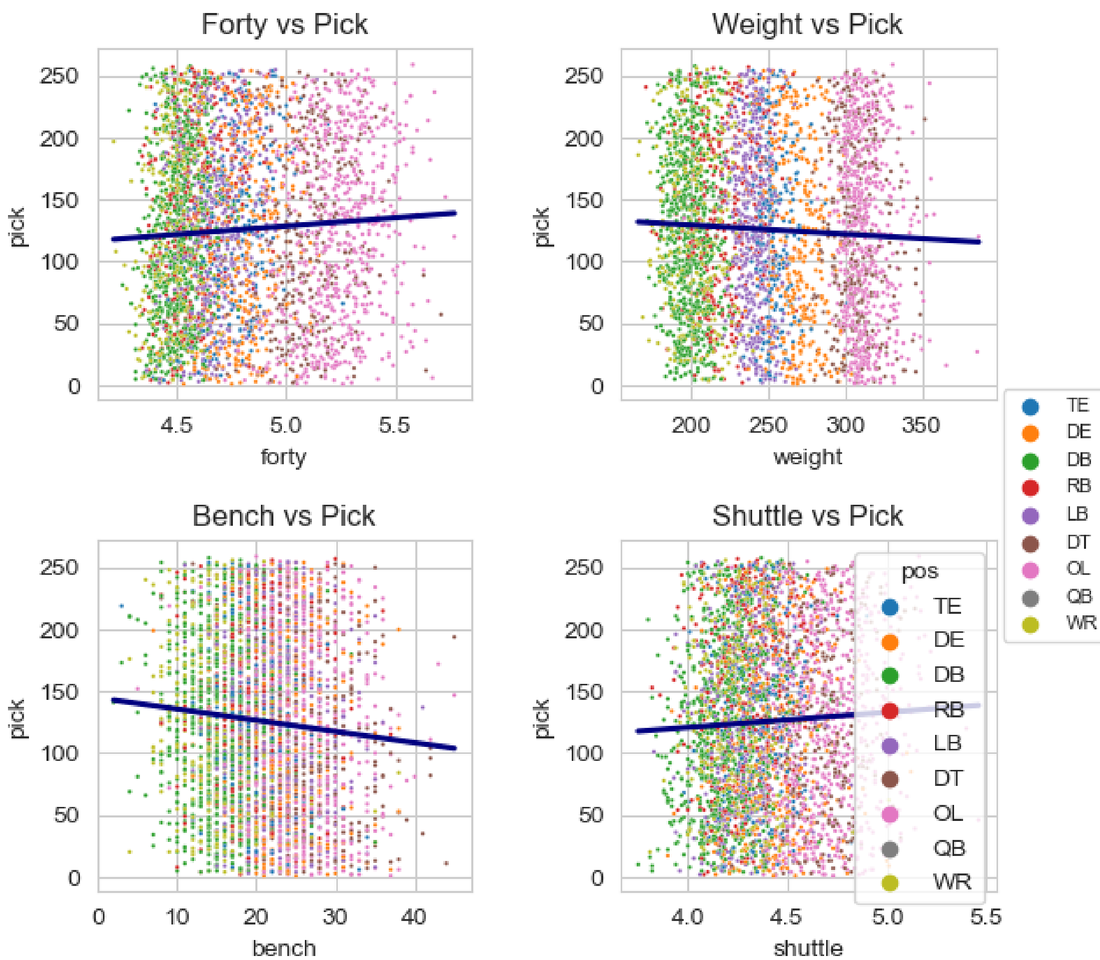
```
sns.scatterplot(data=combine_complete,
                x='vert',
                y='broad_jump',
                hue='pos',
                s=3,
                ax=axs[0,1],
               legend=False)
axs[0, 1].set(xlabel='Vert', ylabel='Broad Jump', title='Vertical vs. Broad␣
↪Jump')
sns.regplot(data=combine_complete,
            x='vert',
            y='broad_jump',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[0,1])
sns.set_style("whitegrid")

sns.scatterplot(data=combine_complete,
                x='forty',
                y='shuttle',
                hue='pos',
                s=3,
                ax=axs[1,0],
               legend=False)
axs[1, 0].set(xlabel='Forty', ylabel='Shuttle', title='Forty vs. Shuttle')
sns.regplot(data=combine_complete,
            x='forty',
            y='shuttle',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[1,0])
sns.set_style("whitegrid")

sns.scatterplot(data=combine_complete,
                x='hand_size',
                y='arm_length',
                hue='pos',
                s=3,
                ax=axs[1,1],
               legend=False)
axs[1, 1].set(xlabel='Hand Size', ylabel='Arm Length', title='Hand Size vs. Arm␣
↪Length')

sns.regplot(data=combine_complete,
```

```
            x='hand_size',
            y='arm_length',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[1,1])
sns.set_style("whitegrid")

#handles, labels = axs[1,1].get_legend_handles_labels()
fig.legend(handles=handles, labels=labels, loc='center right', fontsize = 8)
plt.gca().get_legend_handles_labels()
plt.subplots_adjust(left=0.1,
                    bottom=0.5,
                    right=0.9,
                    top=1.5,
                    wspace=0.4,
                    hspace=0.4)
fig.show()
```



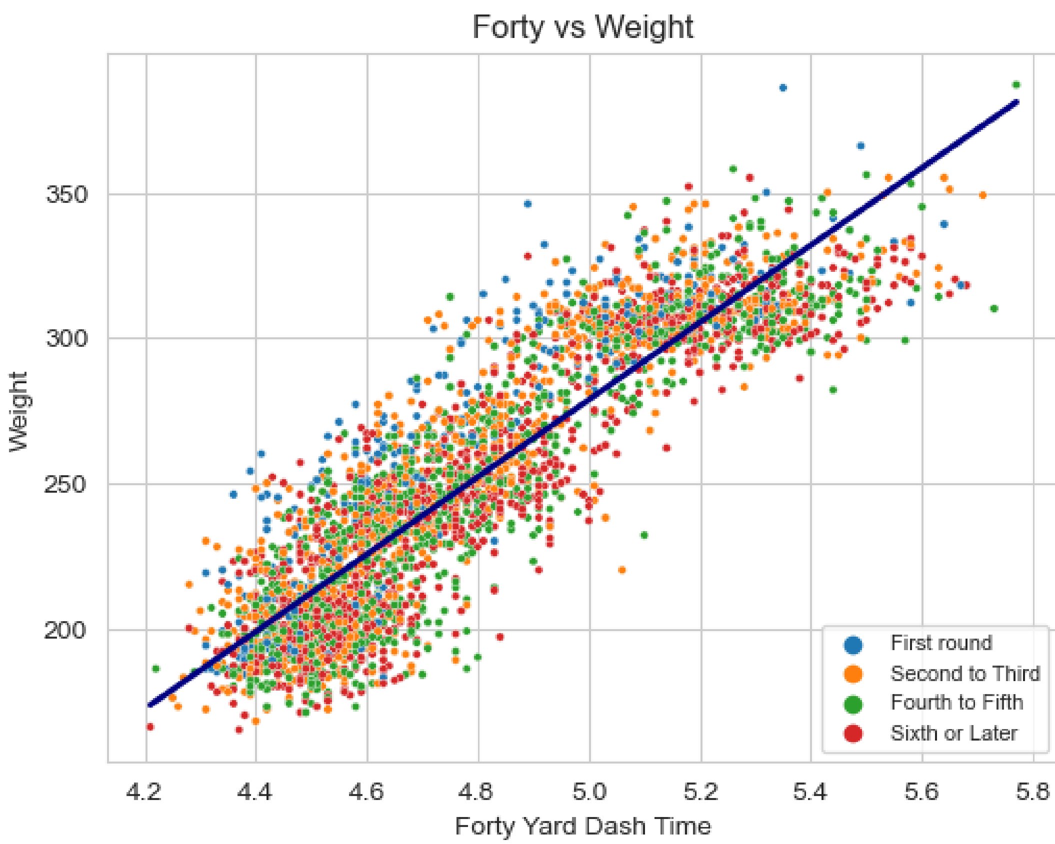
[94]:
```
# This is a plot of some of the more predictive variables

fig, axs = plt.subplots(nrows=2, ncols=2)
sns.scatterplot(data=combine_complete,
                x='forty',
                y='pick',
                hue='pos',
                s=3,
                ax=axs[0,0],
               legend=False)
axs[0, 0].set(xlabel='forty yard dash time', ylabel='Pick', title='Forty vs␣
 ↪Pick')
sns.regplot(data=combine_complete,
            x='forty',
            y='pick',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[0,0])
sns.set_style("whitegrid")

sns.scatterplot(data=combine_complete,
                x='weight',
                y='pick',
                hue='pos',
                s=3,
                ax=axs[0,1],
               legend=False)
axs[0, 1].set(xlabel='weight', ylabel='Pick', title='Weight vs Pick')
sns.regplot(data=combine_complete,
            x='weight',
            y='pick',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[0,1])
sns.set_style("whitegrid")

sns.scatterplot(data=combine_complete,
                x='bench',
                y='pick',
                hue='pos',
                s=3,
                ax=axs[1,0],
               legend=False)
```

```
axs[1, 0].set(xlabel='bench press reps', ylabel='Pick', title='Bench vs Pick')
sns.regplot(data=combine_complete,
            x='bench',
            y='pick',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[1,0])
sns.set_style("whitegrid")

sns.scatterplot(data=combine_complete,
                x='shuttle',
                y='pick',
                hue='pos',
                s=3,
                ax=axs[1,1],
               legend=True)
axs[1, 1].set(xlabel='shuttle time', ylabel='Pick', title='Shuttle vs Pick')

sns.regplot(data=combine_complete,
            x='shuttle',
            y='pick',
            scatter=False,
            ci=None,
            color="navy",
            ax=axs[1,1])
sns.set_style("whitegrid")

handles, labels = axs[1,1].get_legend_handles_labels()
fig.legend(handles=handles, labels=labels, loc='center right', fontsize = 8)
plt.gca().get_legend_handles_labels()
plt.subplots_adjust(left=0.1,
                    bottom=0.5,
                    right=0.9,
                    top=1.5,
                    wspace=0.4,
                    hspace=0.4)
fig.show()
```




```
[46]: # This is weight v forty time binned by pick intervals
combine_round_est = combine_complete
combine_round_est['Estimated Round'] = pd.cut(
    combine_round_est['pick'],
    bins=[0, 32, 100, 175, 350],
    labels=['First round', 'Second to Third',
            'Fourth to Fifth', 'Sixth or Later'])

ax = sns.scatterplot(data=combine_round_est,
                     x='forty',
                     y='weight',
                     hue='Estimated Round',
                     s=10)
sns.regplot(data=combine_round_est,
            x='forty',
```

```
            y='weight',
            scatter=False,
            ci=None,
            color="navy",
            ax=ax)

ax.set(xlabel='Forty Yard Dash Time', ylabel='Weight', title='Forty vs Weight')
handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, labels, loc='lower right', fontsize = 8)
sns.set_style("whitegrid")
plt.show()
```



[47]:
```
################## Linear Model w/ model selection ##################
# set up basic linear model with complete cases and to simplify further, filter␣
 ↪out undrafted players
model = sm.OLS(y, sm.add_constant(X))
results = model.fit()
print(results.summary())
```

OLS Regression Results

Dep. Variable:	pick	R-squared:	0.088
Model:	OLS	Adj. R-squared:	0.084
Method:	Least Squares	F-statistic:	18.31
Date:	Thu, 02 Mar 2023	Prob (F-statistic):	3.50e-56
Time:	23:27:12	Log-Likelihood:	-19203.
No. Observations:	3418	AIC:	3.844e+04
Df Residuals:	3399	BIC:	3.856e+04
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-233.3898	74.944	-3.114	0.002	-380.330	-86.450
height	1.8195	0.908	2.003	0.045	0.038	3.600
weight	-0.7369	0.117	-6.279	0.000	-0.967	-0.507
hand_size	-3.9821	2.331	-1.708	0.088	-8.553	0.589
arm_length	-5.9567	1.235	-4.824	0.000	-8.378	-3.535
forty	115.4925	10.760	10.733	0.000	94.396	136.589
bench	-0.3985	0.258	-1.543	0.123	-0.905	0.108
vert	-0.2399	0.474	-0.507	0.612	-1.168	0.688
broad_jump	-0.2771	0.210	-1.320	0.187	-0.688	0.134
shuttle	35.6163	8.272	4.306	0.000	19.398	51.834
3cone	0.7358	5.257	0.140	0.889	-9.572	11.044
DB	-30.0442	8.843	-3.398	0.001	-47.382	-12.706
DE	-19.8457	10.113	-1.962	0.050	-39.674	-0.018
DT	-33.2663	11.393	-2.920	0.004	-55.604	-10.928
LB	-16.7721	8.838	-1.898	0.058	-34.101	0.557
OL	-45.8938	12.312	-3.728	0.000	-70.034	-21.754
QB	-45.7701	24.646	-1.857	0.063	-94.093	2.552
RB	-7.6332	8.077	-0.945	0.345	-23.469	8.203
TE	-15.4542	10.342	-1.494	0.135	-35.731	4.822
WR	-18.7102	9.329	-2.006	0.045	-37.002	-0.419

Omnibus:	448.685	Durbin-Watson:	1.922
Prob(Omnibus):	0.000	Jarque-Bera (JB):	125.679
Skew:	0.154	Prob(JB):	5.12e-28
Kurtosis:	2.113	Cond. No.	1.25e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.87e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

[95]:
```python
# Backward Elimination to select best model
y = combine_complete['pick']
X = combine_complete.iloc[:, 4:-1]
X = pd.concat([X, pos_one_hot], axis=1)
cols = X.columns

for var in cols:
    model = sm.OLS(y, sm.add_constant(X))
    results = model.fit()
    p_values = pd.Series(results.pvalues, name='pvalues')
    max_p = p_values[p_values==p_values.max()]
    if max_p[0] > 0.05:
        drop_col = max_p.index[0]
        X = X.drop(columns=drop_col)
    else:
        print(results.summary())
        break
```

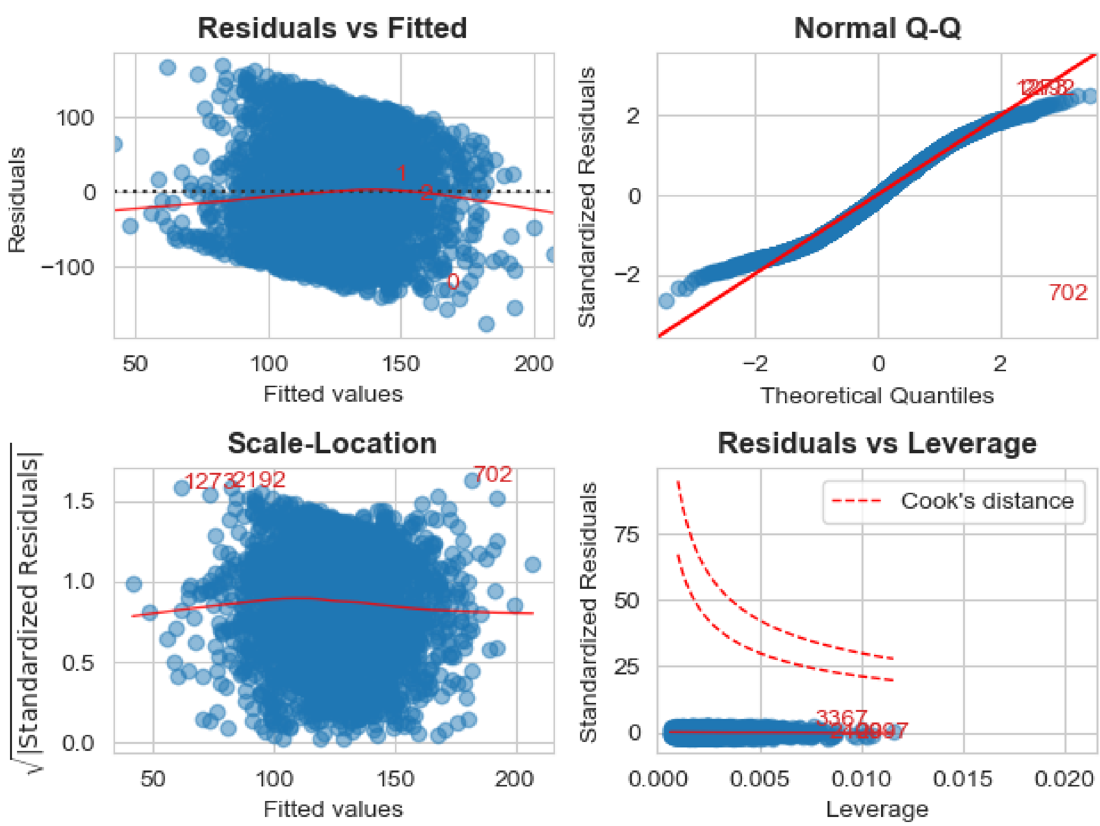
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   pick   R-squared:                       0.084
Model:                            OLS   Adj. R-squared:                  0.082
Method:                 Least Squares   F-statistic:                     39.27
Date:                Fri, 03 Mar 2023   Prob (F-statistic):           2.81e-60
Time:                        07:25:40   Log-Likelihood:                -19210.
No. Observations:                3418   AIC:                         3.844e+04
Df Residuals:                    3409   BIC:                         3.849e+04
Df Model:                           8
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       -222.0558     49.765     -4.462      0.000    -319.628    -124.484
weight        -0.6549      0.088     -7.462      0.000      -0.827      -0.483
arm_length    -6.3900      1.051     -6.079      0.000      -8.451      -4.329
forty        119.8296      9.628     12.445      0.000     100.952     138.708
bench         -0.5226      0.249     -2.102      0.036      -1.010      -0.035
shuttle       37.9831      7.230      5.253      0.000      23.807      52.159
DB           -15.0889      3.667     -4.115      0.000     -22.279      -7.899
DT           -18.5718      5.954     -3.119      0.002     -30.245      -6.898
OL           -28.7441      5.753     -4.996      0.000     -40.024     -17.465
==============================================================================
Omnibus:                      486.318   Durbin-Watson:                   1.925
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              129.009
Skew:                           0.147   Prob(JB):                     9.68e-29
Kurtosis:                       2.095   Cond. No.                     1.13e+04
```

==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.13e+04. This might indicate that there are strong multicollinearity or other numerical problems.

[143]:
```
ols = SM.Linear_Reg_Diagnostic(results)
```

[156]:
```
fig, axs = plt.subplots(nrows=2, ncols=2)

ols.residual_plot(ax=axs[0,0])
ols.qq_plot(ax=axs[0,1])
ols.scale_location_plot(ax=axs[1,0])
ols.leverage_plot(ax=axs[1,1])

fig.tight_layout(pad=1.0)
plt.show()
```



[ ]:
```
### Try robust ###
```

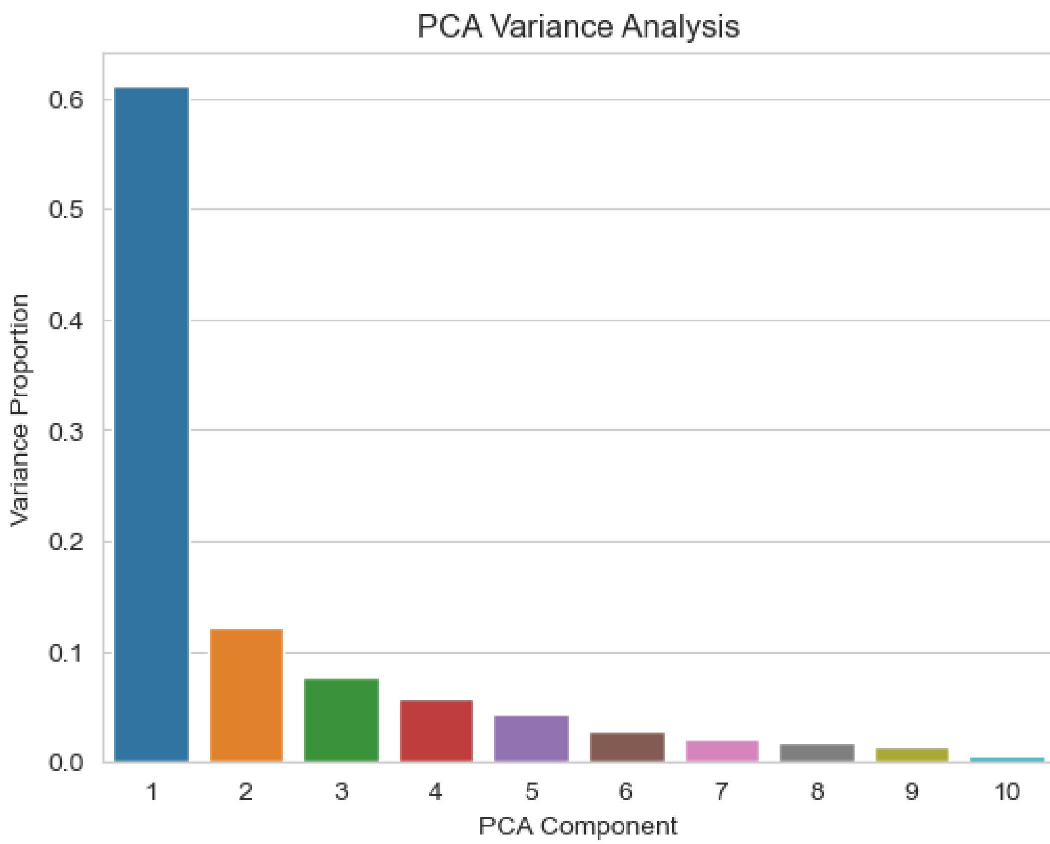
[96]:

```
################## Linear Model ##################
# will use the model generated from backward selection above
y = combine_complete['pick']
X = combine_complete.iloc[:, 4:-1]
X = pd.concat([X, pos_one_hot], axis=1)
X = X[['weight', 'arm_length','forty', 'bench', 'shuttle', 'DB', 'DT', 'OL']]

cv = KFold(n_splits=3, shuffle=True, random_state=100)
reg = LinearRegression()
scores = cross_val_score(reg, X, y, scoring='neg_mean_squared_error', cv=cv)
rmse = (scores.mean()*-1)**0.5

print(rmse)
```

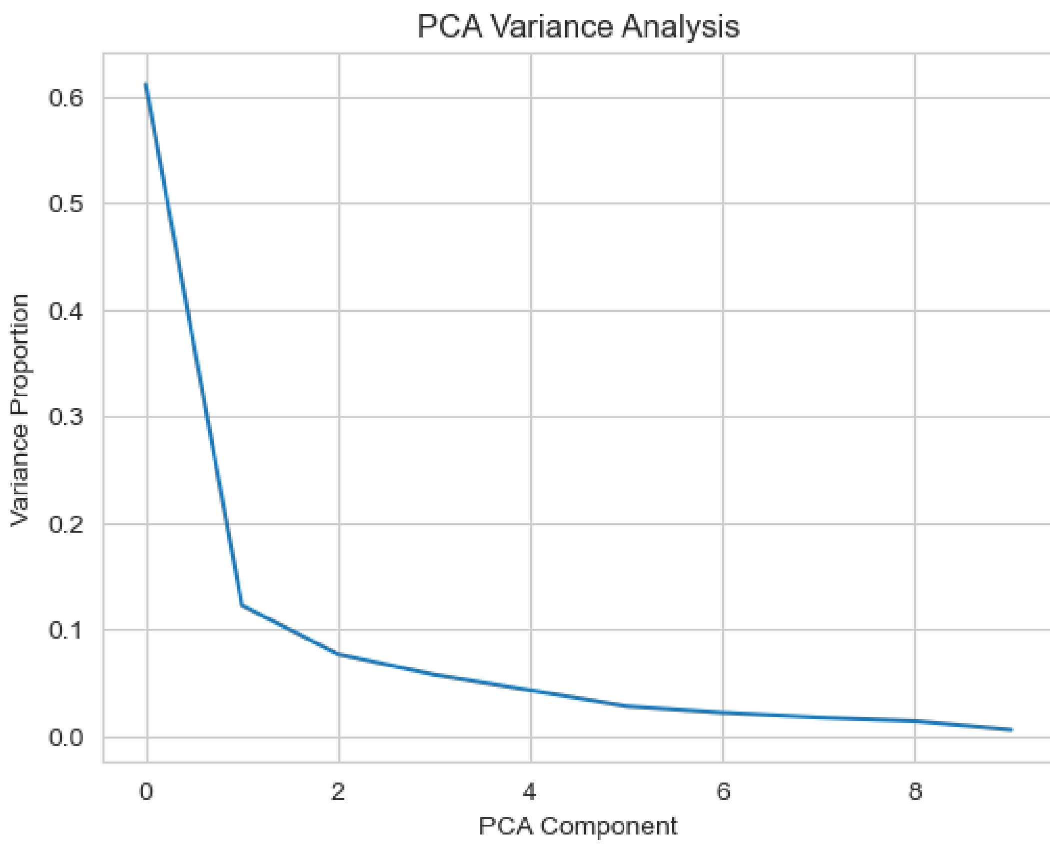
67.01796200690795

[8]:

```
################## Predictive PCA/PCR ##################
y = combine_complete['pick']
X = combine_complete.iloc[:, 4:-1] # do not include posiiton for PCA
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state=100)

scaler = StandardScaler()
X_train_norm = scaler.fit_transform(X_train.values)
pcr = PCA()
pcr.fit(X_train_norm)
#transformed = model.transform(X)
features = range(pcr.n_components_)



ax = sns.barplot(x=pd.Series(features)+1, y=pd.Series(pcr.explained_variance_) /␣
↪pcr.explained_variance_.sum())
ax.set(xlabel='PCA Component', ylabel='Variance Proportion', title='PCA Variance␣
↪Analysis')
sns.set_style("whitegrid")
plt.show()
```



[130]:
```
# plot pca vs share of variance:
var_prop = pcr.explained_variance_ / pcr.explained_variance_.sum()
ax = sns.lineplot(x=pd.Series(features), y=pd.Series(var_prop))
ax.set(xlabel='PCA Component', ylabel='Variance Proportion', title='PCA Variance␣
 ↪Analysis')
sns.set_style("whitegrid")
plt.show()

# data shows we should use between 2 and 4 PCs so will use 3 here
```



[131]:
```
pca = PCA(n_components=3)
X_train_norm = scaler.fit_transform(X_train.values)
pca.fit_transform(X_train_norm)
linear = pd.DataFrame(pca.components_.T, columns=['PC1', 'PC2', 'PC3'], index=X.
 ↪columns)
linear

#PC1 is generally a size metric, PC2 relates to small hands and short arms, PC3␣
 ↪it almost purely strength
```

[131]:

	PC1	PC2	PC3
height	0.304736	-0.405880	-0.107401
weight	0.385545	-0.038562	0.142756
hand_size	0.228303	-0.461385	0.002039
arm_length	0.263038	-0.533021	-0.253794
forty	0.373551	0.149111	-0.022600
bench	0.232707	-0.048905	0.913638
vert	-0.319665	-0.333223	0.195778
broad_jump	-0.324417	-0.386599	0.068543
shuttle	0.342782	0.121846	-0.135350

```
3cone       0.344318  0.191882 -0.084137
```

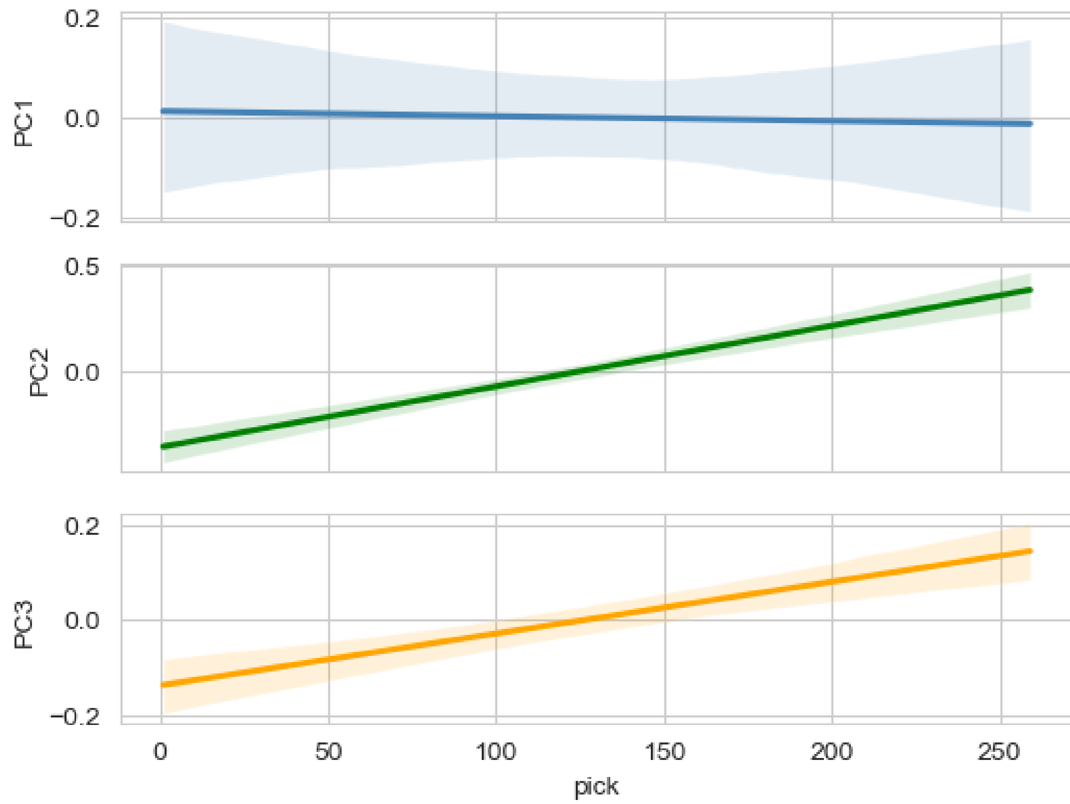
[133]:

```
# Cross-Validated PC Regression
# scale the test set
pca = PCA(n_components=3)
X_norm = scaler.fit_transform(X.values)

# dim reduce X
X_pca = pca.fit_transform(X_norm)
add_pos = pos_one_hot[['DB', 'DT', 'OL']].values
X_pca2 = np.concatenate([X_pca, add_pos], axis=1)
cv = KFold(n_splits=3, shuffle=True, random_state=100)
reg = LinearRegression()

scores = cross_val_score(reg, X_pca2, y, scoring='neg_mean_squared_error', cv=cv)
rmse = (scores.mean()*-1)**0.5

print(rmse)
```

```
68.05924969610729
```

[134]:

```
# PC scatterplot vs reponse
df_pca = np.concatenate([X_pca, y.values.reshape(-1,1)], axis=1)
df_pca = pd.DataFrame(df_pca, columns=['PC1', 'PC2', 'PC3', 'pick'])

fig, axs = plt.subplots(nrows=3, sharex=True)
sns.regplot(x='pick', y='PC1', data=df_pca, scatter=False, ax=axs[0],␣
 ↪color="steelblue")
axs[0].set_xlabel('')
sns.regplot(x='pick', y='PC2', data=df_pca,scatter=False, ax=axs[1],␣
 ↪color="green")
axs[1].set_xlabel('')
sns.regplot(x='pick', y='PC3', data=df_pca, scatter=False, ax=axs[2],␣
 ↪color="orange")
sns.set_style("whitegrid")
fig.show()

# note how pc1 has little relationship w y and therefore poor mse
```



[86]:

```
################## XG Boost ##################
y = combine_complete['pick']
X = combine_complete.iloc[:, 4:-1]
X = pd.concat([X, pos_one_hot], axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state=100)

scaler = StandardScaler()
X_norm = scaler.fit_transform(X)
X_train_norm = scaler.fit_transform(X_train)
X_test_norm = scaler.fit_transform(X_test)



n = 1000
max_depth = 1
xgb_reg = xgb.XGBRegressor(objective='reg:squarederror',
                           n_estimators=n,
                           max_depth=max_depth,
                           eta=0.01,
                           seed=100)
```

```python
xgb_reg.fit(X_train_norm, y_train)
preds = xgb_reg.predict(X_test_norm)

rmse = mean_squared_error(preds, y_test, squared=False)
print(rmse)
```

```
69.51252126008916
```

[8]:
```python
# Tune hyperparams w/ gridsearch
param_grid = {
    'max_depth': [1, 2, 3],
    'eta': [0.001, 0.01, 0.1, 0.25, 0.5],
    'n_estimators': [100, 500, 1000],
}
grid_mse = GridSearchCV(estimator=xgb_reg,
                        param_grid=param_grid,
                        scoring='neg_mean_squared_error',
                        cv=3,
                        verbose=1)
mse_grid = grid_mse.fit(X_norm, y)
```

```
Fitting 3 folds for each of 45 candidates, totalling 135 fits
```

[28]:
```python
best_params = grid_mse.best_params_
rmse = np.abs(grid_mse.best_score_)**0.5

print(best_params)
print(rmse)
```

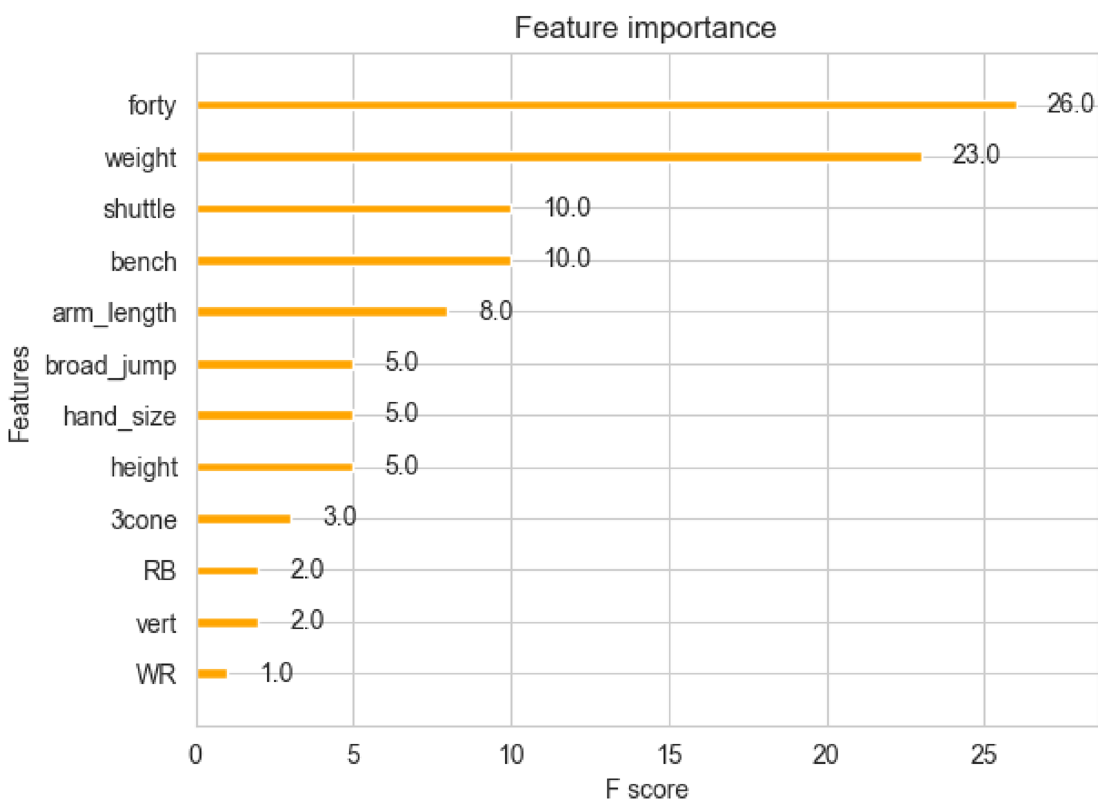
```
{'eta': 0.25, 'max_depth': 1, 'n_estimators': 100}
68.45412247241667
```

[29]:
```python
xgb_final = xgb.XGBRegressor(objective='reg:squarederror',
                             n_estimators=100,
                             max_depth=1,
                             eta=0.25,
                             seed=100)
xgb_final.fit(X_norm, y)
```

[29]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eta=0.25, eval_metric=None,
             feature_types=None, gamma=None, gpu_id=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=None, max_bin=None, max_cat_threshold=None,
```

```
                max_cat_to_onehot=None, max_delta_step=None, max_depth=1,
                max_leaves=None, min_child_weight=None, missing=nan,
                monotone_constraints=None, n_estimators=100, n_jobs=None,
                num_parallel_tree=None, predictor=None, ...)
```

[90]:
```
# plot feature importance
feature_names = X.columns

ax = xgb.plot_importance(xgb_final, color="orange")
ylabs = list(ax.get_yticklabels())
dict_features = dict(enumerate(feature_names))
ylabs_stripped = [ylabs[i].get_text().lstrip('f') for i in range(len(ylabs))]
ylabs_stripped = [dict_features[int(i)] for i in ylabs_stripped]

ax.set_yticklabels(ylabs_stripped)
plt.show()
```



[ ]:
```
################# Final Cross-Validated RMSE #################
# Linear: 67.14958397888446
# PCR: 68.68564523905418
# XGBoost: 68.45412247241667
```