Final Project Part 5

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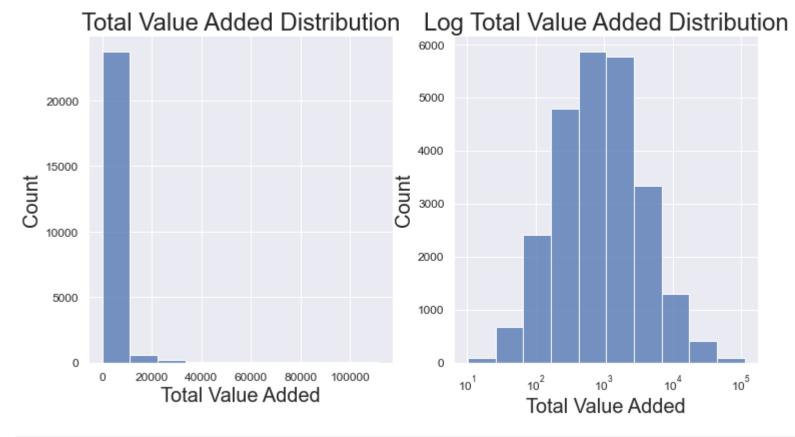
- EDA
- Inferences
- Predictions

EDA

```
In [1]:
         import numpy as np
         import pandas as pd
         import xgboost as xgb
         import statsmodels.api as sm
         import matplotlib.pyplot as plt
         import sklearn.linear model as lm
         from sklearn.model selection import GridSearchCV, train test split
         from sklearn.preprocessing import StandardScaler
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.svm import SVR
         import seaborn as sns
         sns.set(rc = {'axes.titlesize': 24,
                       'axes.labelsize': 20,
                       'xtick.labelsize': 12,
                       'ytick.labelsize': 12,
                       'figure.figsize': (12, 6)})
In [2]:
         sic = pd.read pickle('sic fp2.pkl')
In [3]:
         plt.figure()
         plt.subplot(1,2,1)
         plt.title('Total Value Added Distribution')
         plt.xlabel('Total Value Added')
         sns.histplot(x = 'vadd', data = sic, bins = 10) #checking to see if the label needs a transformation
```

```
plt.subplot(1,2,2)
plt.title('Log Total Value Added Distribution')
plt.xlabel('Total Value Added')
plt.semilogx()
sns.histplot(x = 'vadd', data = sic, bins = 10) #seeing if log transformation improves label distribution
```

Out[3]: <AxesSubplot:title={'center':'Log Total Value Added Distribution'}, xlabel='Total Value Added', ylabel='Count'>



```
In [4]: #the label did indeed need a log transformation
    sic['l_vadd'] = np.log(sic['vadd']) # creating new column with log transformation of label
    sic = sic.drop('vadd', 1) # dropping old label

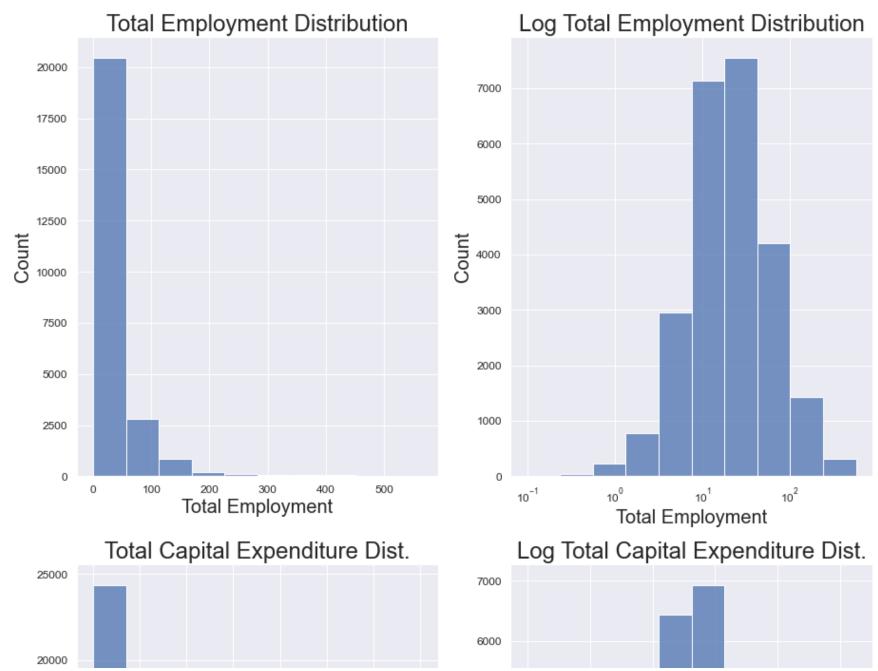
In [5]: #checking to see if any of the features need transformations
    # Histograms of emp
    plt.figure(figsize = (15,80))
    plt.subplot(8,2,1)
```

```
plt.title('Total Employment Distribution')
plt.xlabel('Total Employment')
sns.histplot(x = 'emp', data = sic, bins = 10)
plt.subplot(8,2,2)
plt.title('Log Total Employment Distribution')
plt.xlabel('Total Employment')
plt.semilogx()
sns.histplot(x = 'emp', data = sic, bins = 10)
#Histograms of invest
plt.subplot(8,2,3)
plt.title('Total Capital Expenditure Dist.')
plt.xlabel('Total Capital Expenditure')
sns.histplot(x = 'invest', data = sic, bins = 10)
plt.subplot(8,2,4)
plt.title('Log Total Capital Expenditure Dist.')
plt.xlabel('Total Capital Expenditure')
plt.semilogx()
sns.histplot(x = 'invest', data = sic, bins = 10)
#Histograms of pay
plt.subplot(8,2,5)
plt.title('Total Payroll Distribution')
plt.xlabel('Total Payroll')
sns.histplot(x = 'pay', data = sic, bins = 10)
plt.subplot(8,2,6)
plt.title('Log Total Payroll')
plt.xlabel('Total Payroll')
plt.semilogx()
sns.histplot(x = 'pay', data = sic, bins = 10)
#Histograms of matcost
plt.subplot(8,2,7)
plt.title('Total Material Cost Dist.')
plt.xlabel('Total Material Costs')
sns.histplot(x = 'matcost', data = sic, bins = 10)
plt.subplot(8,2,8)
plt.title('Log Total Material Cost Dist.')
plt.xlabel('Total Material Costs')
plt.semilogx()
sns.histplot(x = 'matcost', data = sic, bins = 10)
```

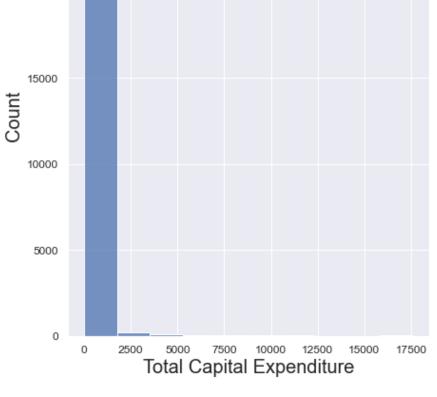
```
#Histograms of vship
plt.subplot(8,2,9)
plt.title('Total Value of Shipments Dist.')
plt.xlabel('Total Value of Shipments')
sns.histplot(x = 'vship', data = sic, bins = 10)
plt.subplot(8,2,10)
plt.title('Total Value of Shipments Dist.')
plt.xlabel('Total Value of Shipments')
plt.semilogx()
sns.histplot(x = 'vship', data = sic, bins = 10)
#Histograms of cap
plt.subplot(8,2,11)
plt.title('Total Real Capital Stock Dist.')
plt.xlabel('Total Real Capital Stock')
sns.histplot(x = 'cap', data = sic, bins = 10)
plt.subplot(8,2,12)
plt.title('Log Total Real Capital Stock Dist.')
plt.xlabel('Total Real Capital Stock')
plt.semilogx()
sns.histplot(x = 'cap', data = sic, bins = 10)
#Histograms of invent
plt.subplot(8,2,13)
plt.title('End of Year Inventory Dist.')
plt.xlabel('End of Year Inventories')
sns.histplot(x = 'invent', data = sic, bins = 10)
plt.subplot(8,2,14)
plt.title('Log End of Year Inventory Dist.')
plt.xlabel('End of Year Inventory')
plt.semilogx()
sns.histplot(x = 'invent', data = sic, bins = 10)
#Histograms of energy
plt.subplot(8,2,15)
plt.title('Electricity & Fuel Cost Dist.')
plt.xlabel('Cost of Electricity & Fuel')
sns.histplot(x = 'energy', data = sic, bins = 10)
plt.subplot(8,2,16)
plt.title('Log Electricity & Fuel Cost Dist. ')
plt.xlabel('Cost of Electricity & Fuel')
```

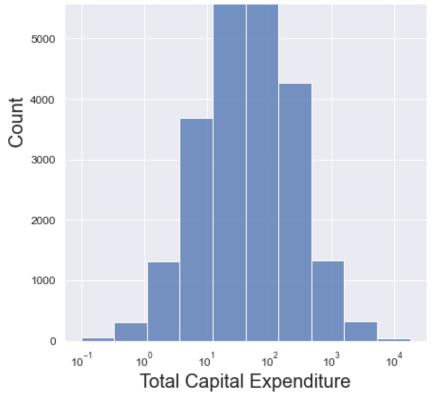
```
plt.semilogx()
sns.histplot(x = 'energy', data = sic, bins = 10)
```

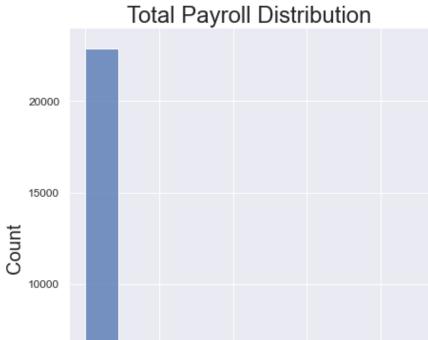
Out[5]: <AxesSubplot:title={'center':'Log Electricity & Fuel Cost Dist. '}, xlabel='Cost of Electricity & Fuel', ylabel='Count'>

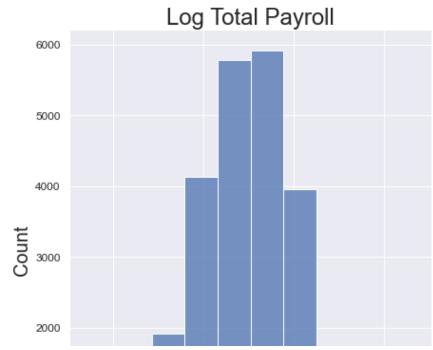




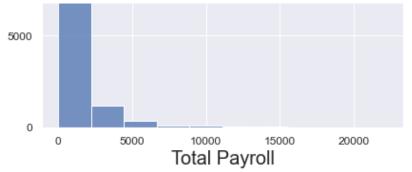


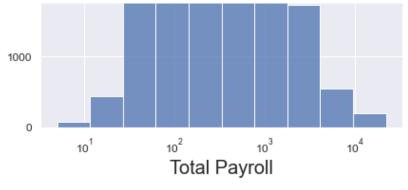






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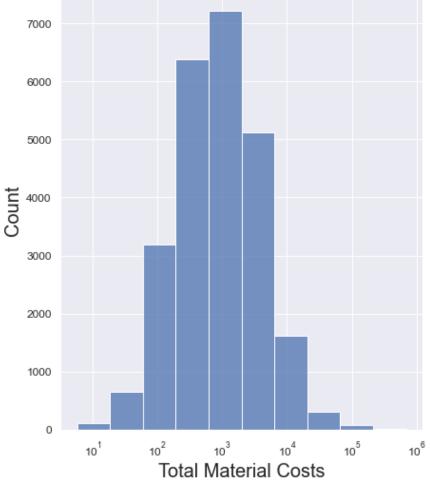






25000 20000 15000 Count 10000 5000 0 200000 300000 400000 500000 600000 700000 0 100000 **Total Material Costs**

Log Total Material Cost Dist.

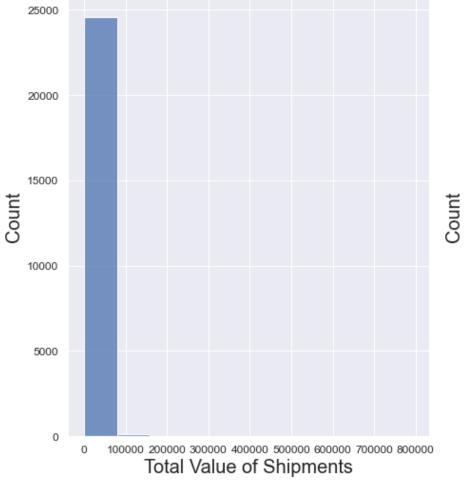


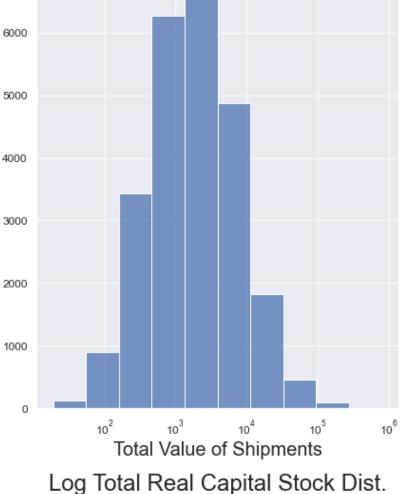
Total Value of Shipments Dist.

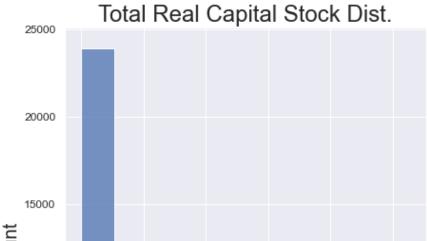
Total Value of Shipments Dist.

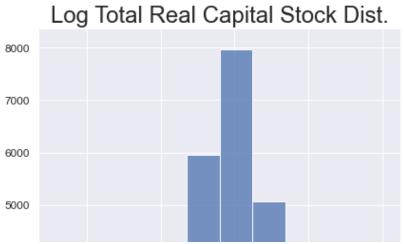
nt

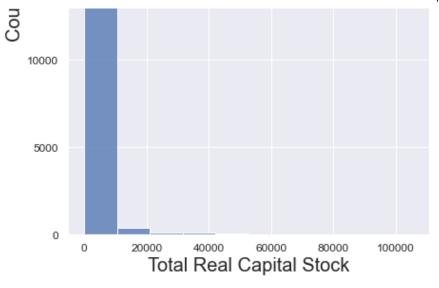
7000

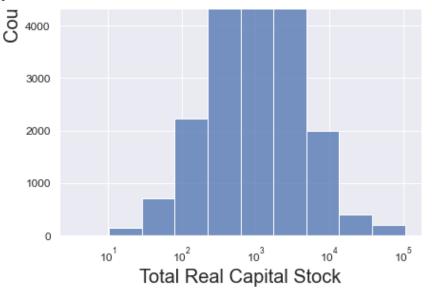




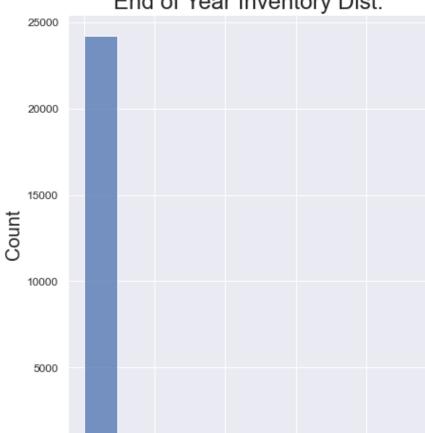




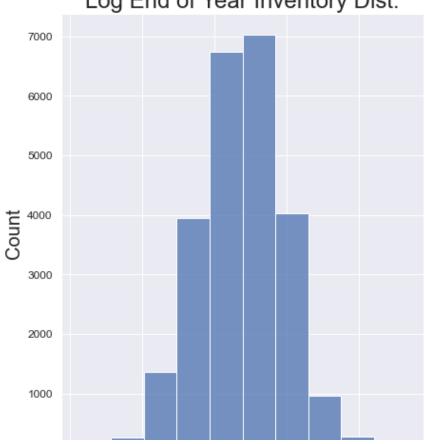


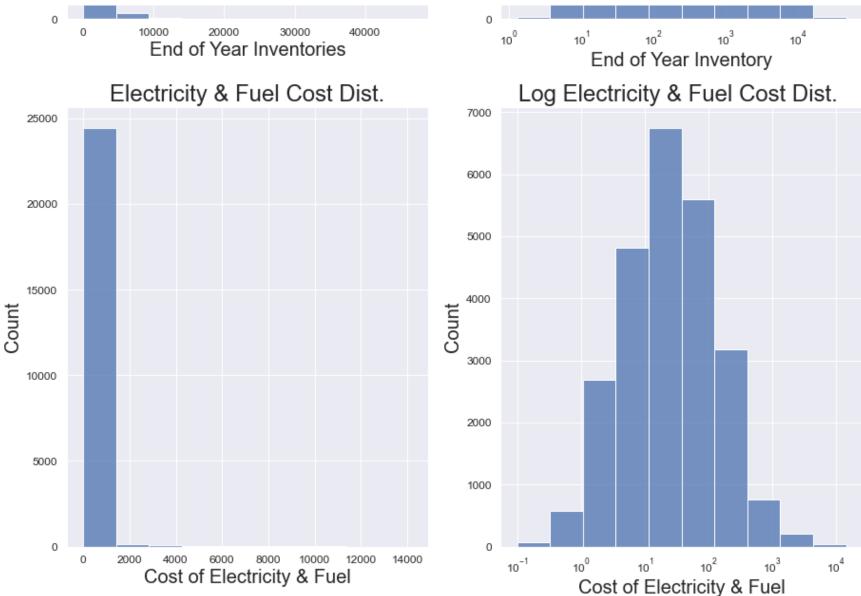






Log End of Year Inventory Dist.





```
In [6]: #all of the features required log transformations based off of the histograms

sic['l_emp'] = np.log(sic['emp']) # creating new column with log transformation
sic = sic.drop('emp', 1) # dropping old column

sic['l_invest'] = np.log(sic['invest']) # creating new column with log transformation
sic = sic.drop('invest', 1) # dropping old column
```

```
sic['l pay'] = np.log(sic['pay']) # creating new column with log transformation
         sic = sic.drop('pay', 1) # dropping old column
         sic['l matcost'] = np.log(sic['matcost']) # creating new column with log transformation
         sic = sic.drop('matcost', 1) # dropping old column
         sic['l vship'] = np.log(sic['vship']) # creating new column with log transformation
         sic = sic.drop('vship', 1) # dropping old column
         sic['l cap'] = np.log(sic['cap']) # creating new column with log transformation
         sic = sic.drop('cap', 1) # dropping old column
         sic['l invent'] = np.log(sic['invent']) # creating new column with log transformation
         sic = sic.drop('invent', 1) # dropping old column
         sic['l energy'] = np.log(sic['energy']) # creating new column with log transformation
         sic = sic.drop('energy', 1) # dropping old column
In [7]:
         sic.head()
Out[7]:
                               I_emp I_invest
                                                                            I_cap I_invent I_energy
                      I vadd
                                                 I_pay I_matcost I_vship
          sic year
         2011 1958 7.466571 5.302807 4.188138 6.973356
                                                       9.233090 9.388545 8.181860 6.011512 3.869116
               1959 7.513818 5.284218 4.210645 7.003974 9.204232 9.374871 8.220887 5.913773 3.899950
               1960 7.555225 5.268889 4.346399 7.037555
                                                       9.199360 9.376380 8.264441 5.944373 3.929863
               1961 7.543909 5.243333 4.322807 7.041587
                                                       9.215059 9.385704 8.299982 5.979645 3.958907
               1962 7.593928 5.223594 4.508659 7.057123 9.259968 9.430945 8.345598 6.018836 3.987130
In [8]:
         sic.shape
Out[8]: (24676, 9)
In [9]:
         sic.info()
        <class 'pandas.core.frame.DataFrame'>
```

```
MultiIndex: 24676 entries, (2011, 1958) to (3999, 2011)
Data columns (total 9 columns):
l vadd
             24676 non-null float64
             24676 non-null float64
1 emp
l invest
             24676 non-null float64
1 pay
             24676 non-null float64
1 matcost
             24676 non-null float64
l vship
             24676 non-null float64
1 cap
             24676 non-null float64
l invent
             24676 non-null float64
1 energy
             24676 non-null float64
dtypes: float64(9)
memory usage: 1.8 MB
```

Inferences

TOP

```
In [10]:
          y = sic['l vadd']
          x = sic.drop(columns = 'l vadd')
          y train, y test = train test split(y, train size = 3/4, random state = 490)
          x train, x test = train test split(x, train size = 3/4, random state = 490)
          ss = StandardScaler()
          x train std = pd.DataFrame(ss.fit(x train).transform(x train),
                                     columns = x train.columns,
                                    index = x train.index)
          x test std = pd.DataFrame(ss.fit(x test).transform(x test),
                                    columns = x test.columns,
                                    index = x test.index)
          x train std c
                            = sm.add constant(x train std)
                            = sm.add constant(x test std)
          x test std c
          x train c
                       = sm.add constant(x train)
          x test c
                       = sm.add constant(x test)
```

C:\Users\tanse\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:2580: FutureWarning: Method .ptp is deprecated and w
ill be removed in a future version. Use numpy.ptp instead.
 return ptp(axis=axis, out=out, **kwargs)

```
cv lasso = lm.Lasso(fit intercept = False, normalize = False,
                                 random state = 490)
           grid search = GridSearchCV(cv lasso, param grid, cv = 5,
                                       scoring = 'neg root mean squared error')
           grid search.fit(x train std c, y train)
           best = grid search.best params ['alpha']
           best
          2.1544346900318822e-06
Out[11]:
In [12]:
           fit lasso tuned = sm.OLS(y train, x train std c).fit regularized(alpha = best)
           beta = fit lasso tuned.params #fitting on non regularized standardized model
           beta.index[beta == 0]
           x train trim = x train std c.loc[:, ~x train std c.columns.isin(beta.index[beta == 0])]
           x test trim = x test std c.loc[:, ~x test std c.columns.isin(beta.index[beta == 0])]
In [13]:
           fit std final = sm.OLS(y train, x train trim).fit() #testing on non-regularized values
           fit std final.summary2()
Out[13]:
                     Model:
                                        OLS
                                              Adj. R-squared:
                                                                  0.993
          Dependent Variable:
                                                       AIC: -26272.1018
                                      I vadd
                       Date: 2021-05-14 15:57
                                                        BIC:
                                                            -26201.6686
            No. Observations:
                                      18507
                                              Log-Likelihood:
                                                                 13145.
                   Df Model:
                                          8
                                                  F-statistic:
                                                              3.253e+05
                 Df Residuals:
                                                                   0.00
                                      18498 Prob (F-statistic):
                  R-squared:
                                      0.993
                                                               0.014151
                                                      Scale:
                      Coef. Std.Err.
                                                       [0.025
                                               P>|t|
                                                               0.9751
              const
                     6.7547
                             0.0009
                                    7724.5430 0.0000
                                                       6.7530
                                                               6.7564
                    -0.0319
                             0.0019
                                              0.0000
                                                      -0.0356
              l_emp
                                      -16.7239
                                                              -0.0281
            I invest
                     0.0604
                             0.0032
                                      19.0809
                                              0.0000
                                                       0.0542
                                                               0.0666
                     0.2437
                             0.0042
                                      57.7686
                                              0.0000
                                                       0.2354
                                                               0.2519
              I_pay
                             0.0064
                                     -195.6550 0.0000 -1.2603 -1.2353
          I matcost -1.2478
```

```
I vship
                      2.3447
                              0.0089
                                       264.7884 0.0000
                                                        2.3273
                                                                 2.3620
                              0.0025
                                        -8.6475 0.0000
                                                        -0.0266
                                                                -0.0167
               l_cap -0.0217
                      0.0372
                              0.0025
                                        14.7130 0.0000
                                                        0.0322
            I invent
                                                                 0.0421
            l_energy -0.0127
                                        -5.3406 0.0000 -0.0173 -0.0080
                              0.0024
                Omnibus: 12515.174
                                     Durbin-Watson:
                                                          2.025
           Prob(Omnibus):
                              0.000 Jarque-Bera (JB): 310124.657
                   Skew:
                             -2.905
                                           Prob(JB):
                                                         0.000
                 Kurtosis:
                             22.194
                                      Condition No.:
                                                            33
In [14]:
            rmse ols = np.sqrt(np.mean((y test - fit std final.predict(x test trim))**2))
            rmse ols #metric for comparing the three models
Out[14]: 0.11483983674229031
```

Predictions

TOP

Extreme Gradient Boosting

validation 0-rmse:5.19649

validation 0-rmse:4.67859

validation 0-rmse:4.21337

[1]

[2]

[4]	validation_0-rmse:3.79459
[5]	validation_0-rmse:3.41731
[6]	validation_0-rmse:3.07821
[7]	validation_0-rmse:2.77316
[8]	validation 0-rmse:2.49860
	<u>—</u>
[9]	validation_0-rmse:2.25194
[10]	validation_0-rmse:2.02966
[11]	validation_0-rmse:1.82977
[12]	validation_0-rmse:1.65021
[13]	validation_0-rmse:1.48836
[14]	validation_0-rmse:1.34290
[15]	validation_0-rmse:1.21192
[16]	<pre>validation_0-rmse:1.09413</pre>
[17]	validation_0-rmse:0.98799
[18]	validation_0-rmse:0.89279
[19]	validation_0-rmse:0.80693
[20]	validation_0-rmse:0.72975
[21]	validation_0-rmse:0.66041
[22]	validation_0-rmse:0.59834
[23]	validation_0-rmse:0.54284
[24]	validation 0-rmse:0.49299
	<u>—</u>
[25]	validation_0-rmse:0.44822
[26]	validation_0-rmse:0.40824
[27]	validation_0-rmse:0.37259
[28]	validation_0-rmse:0.34087
[29]	validation_0-rmse:0.31251
[30]	validation_0-rmse:0.28722
[31]	validation_0-rmse:0.26500
[32]	validation_0-rmse:0.24527
[33]	validation_0-rmse:0.22787
[34]	validation_0-rmse:0.21245
[35]	validation_0-rmse:0.19890
[36]	validation_0-rmse:0.18724
[37]	validation_0-rmse:0.17668
[38]	validation_0-rmse:0.16756
[39]	validation_0-rmse:0.15960
[40]	validation_0-rmse:0.15268
[41]	validation_0-rmse:0.14658
[42]	validation_0-rmse:0.14145
[43]	validation_0-rmse:0.13668
[44]	validation_0-rmse:0.13262
[45]	validation_0-rmse:0.12930
[46]	validation_0-rmse:0.12645
[47]	validation 0-rmse:0.12388
[48]	validation 0-rmse:0.12168
[49]	validation 0-rmse:0.11968
[50]	validation_0-rmse:0.11808
[51]	validation_0-rmse:0.11654
[52]	validation 0-rmse:0.11528
[عد]	Validacion_0 1 m3e.0.11320

	311.1
[53]	validation_0-rmse:0.11399
[54]	validation_0-rmse:0.11282
[55]	validation_0-rmse:0.11200
[56]	<pre>validation_0-rmse:0.11112</pre>
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[58]	validation_0-rmse:0.10934
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[60]	validation_0-rmse:0.10813
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	validation_0-rmse:0.10377
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	validation_0-rmse:0.09348
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	validation 0-rmse:0.09056
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                  validation 0-rmse:0.07546
Out[16]: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                       colsample bynode=1, colsample bytree=1, gamma=0, gpu id=-1,
                       importance type='gain', interaction constraints='',
                       learning rate=0.1, max delta step=0, max depth=6,
                       min child weight=1, missing=nan, monotone constraints='()',
                       n estimators=750, n jobs=12, num parallel tree=1, random state=490,
                       reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1,
                       tree method='exact', use label encoder=False,
                       validate parameters=1, verbosity=None)
In [17]:
           xgb n est = clf xgb.best iteration #storing best iteration
           xgb n est
Out[17]: 664
In [18]:
           clf xgb = xgb.XGBRegressor(n estimators = xgb n est, max depth = 5,
                                      learning rate = 0.1, random state = 490,
```

```
use label encoder = False)
          clf xgb.fit(x train std, y train) #training on full with best iteration
Out[18]: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0, gpu id=-1,
                      importance type='gain', interaction constraints='',
                      learning rate=0.1, max delta step=0, max depth=5,
                      min child weight=1, missing=nan, monotone constraints='()',
                      n estimators=664, n jobs=12, num parallel tree=1, random state=490,
                      reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1,
                      tree method='exact', use label encoder=False,
                      validate parameters=1, verbosity=None)
In [19]:
          rmse xgb = np.sqrt(np.mean((y test - clf xgb.predict(x test std))**2))
          rmse xgb #metric for comparing the three models
Out[19]: 0.06475533035641769
         Random Forest
In [20]:
          clf rf = RandomForestRegressor(n estimators = 1000,
                                    random state = 490,
                                    max features = 'sqrt',
                                    oob score = True)
          clf rf.fit(x train std, y train) # creating 1000 independent decision trees and averaging
         RandomForestRegressor(max features='sqrt', n estimators=1000, oob score=True,
                               random state=490)
In [24]:
          rmse rf = np.sqrt(np.mean((y test - clf rf.predict(x test std))**2))
          rmse rf #metric for comparing the three models
Out[24]: 0.10929388013954283
```