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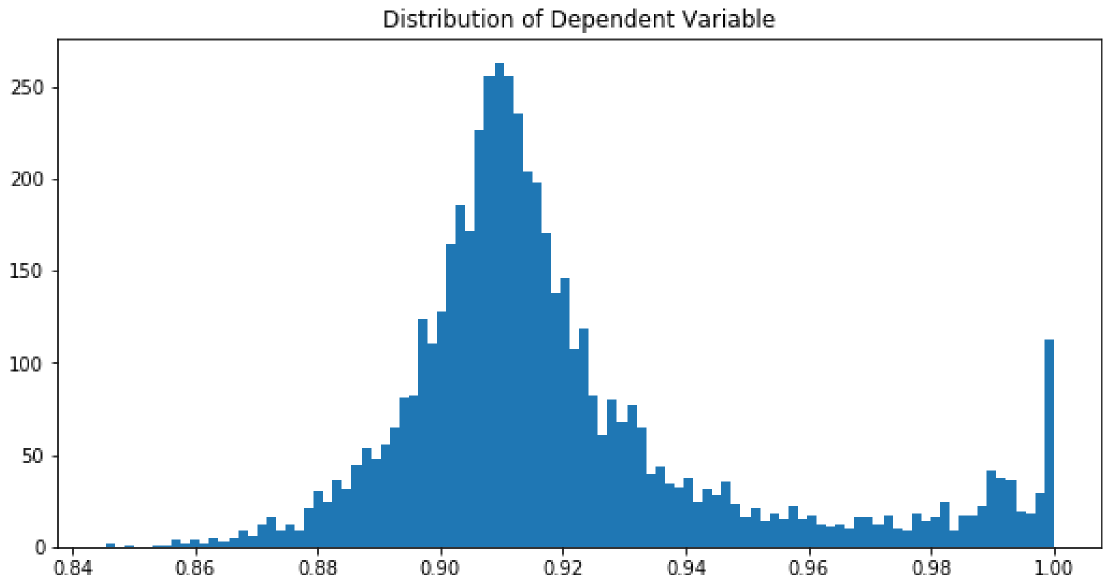
February 15, 2019

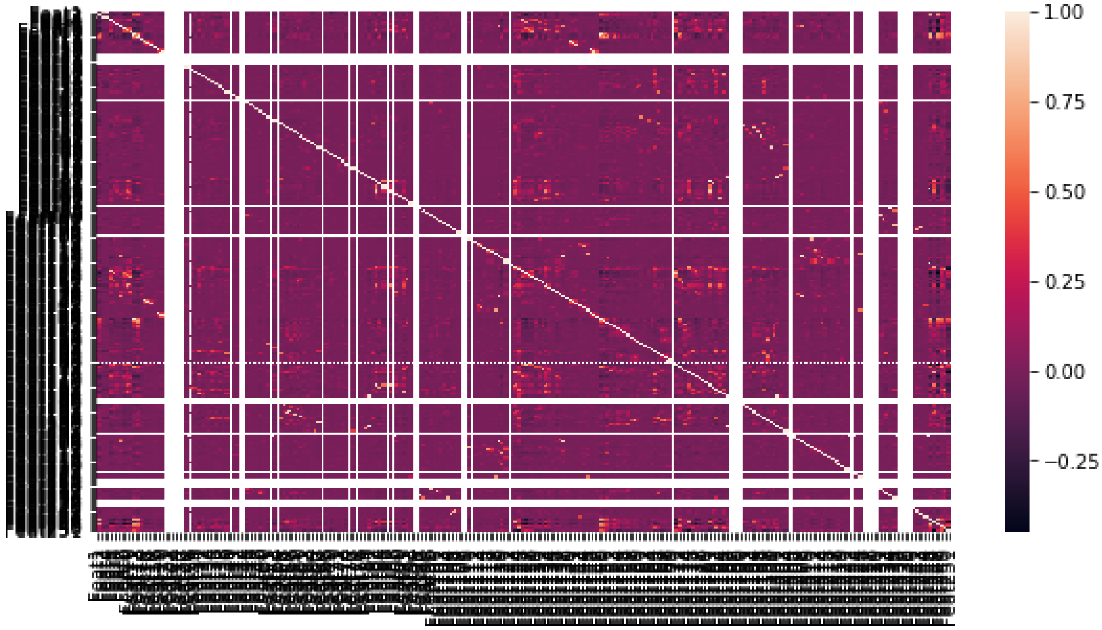
In [2]:
```
# Import libraries
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression as Lin_Reg
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
import matplotlib
import matplotlib.pyplot as plt
import matplotlib.cm as cmx
import matplotlib.colors as colors
import scipy as sp
%matplotlib inline

from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor,GradientBoostingRe

import math as m
import statistics as stat
import xgboost as xgb
from sklearn.metrics import mean_squared_error
from patsy import dmatrices
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNetCV
from sklearn.linear_model import ElasticNet

from sklearn.model_selection import KFold

import warnings
warnings.filterwarnings('ignore')
```

1 Diagonistics of Data

```
In [3]: train = pd.read_csv("train.csv")
        test = pd.read_csv("test.csv")

In [4]: train.head()

Out[4]:    Id    Feat 1    Feat 2    Feat 3    Feat 4    Feat 5    Feat 6  Feat 7  \
        0   1  0.998952  0.174118  0.999211  0.996460  0.133333  0.057143   0.000
        1   2  0.999445  0.174118  0.999329  0.997079  0.133333  0.000000   0.000
        2   3  0.998759  0.000000  0.997260  0.996325  0.000000  0.085714   0.125
        3   4  0.999619  0.174118  0.997969  0.997321  0.266667  0.057143   0.125
        4   5  0.998278  0.174118  0.998427  0.996269  0.200000  0.000000   0.000

           Feat 8  Feat 9    ...     Feat 243  Feat 244  Feat 245  Feat 246  Feat 247  \
        0     0.0     0.0    ...          0.0       0.0         0  0.612863  0.026812
        1     0.0     0.0    ...          0.0       0.0         0  0.688941  0.075030
        2     0.0     0.0    ...          0.0       0.0         0  0.156863  0.436279
        3     0.0     0.0    ...          0.0       0.0         0  0.709647  0.075472
        4     0.0     0.0    ...          0.0       0.0         0  0.364235  0.041818

           Feat 248  Feat 249  Feat 250  Feat 251    Target
        0     0.522  0.217791  0.233629  0.540962  0.901355
        1     0.704  0.246119  0.143860  0.525384  0.913550
        2     0.000  0.119091  0.162869  0.361124  0.884824
        3     0.513  0.392743  0.377302  0.613776  0.977236
        4     0.200  0.096297  0.166459  0.408322  0.921138

        [5 rows x 253 columns]

In [5]: #Check for nan values in Train DF
        True in pd.isnull(train)

Out[5]: False

In [6]: # Explore distribution of target
        plt.figure(figsize=(10,5))
        plt.hist(train['Target'], bins = 100)
        plt.title("Distribution of Dependent Variable")
        plt.show()
```




```
In [7]: train.columns = train.columns.str.replace(' ', '')

        # Split training set into X and y (removing first column containing IDs)
        X_train = train.iloc[:, 1:-1]
        y_train = train.iloc[:, -1]

In [8]: #correlation matrix heatmap
        corr = X_train.corr()

        plt.figure(figsize=(10,5))
        sns.heatmap(corr,
                xticklabels=corr.columns,
                yticklabels=corr.columns)

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x10bf24dd8>
```



In [9]:
```python
#columns with a standard deviation of 0 should be removed
X_train.describe()
```

Out[9]:

	Feat1	Feat2	Feat3	Feat4	Feat5	\
count	5331.000000	5331.000000	5331.000000	5331.000000	5331.000000	
mean	0.998506	0.142550	0.998887	0.996074	0.099018	
std	0.012047	0.064343	0.010696	0.015199	0.106834	
min	0.281689	0.000000	0.278493	0.000000	0.000000	
25%	0.998859	0.164706	0.998435	0.996382	0.000000	
50%	0.999577	0.167059	0.999583	0.996741	0.066667	
75%	0.999956	0.174118	0.999863	0.997143	0.133333	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	Feat6	Feat7	Feat8	Feat9	Feat10	\
count	5331.000000	5331.000000	5331.000000	5331.000000	5331.000000	
mean	0.040598	0.028137	0.013060	0.050136	0.027348	
std	0.077767	0.074117	0.053347	0.100559	0.067602	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.057143	0.000000	0.000000	0.045455	0.000000	
max	1.000000	1.000000	1.000000	0.909091	1.000000	

	...	Feat242	Feat243	Feat244	Feat245	\
count	...	5331.000000	5331.000000	5331.000000	5331.0	
mean	...	0.001657	0.005346	0.000563	0.0	

```
std        ...      0.021473     0.054956     0.018747      0.0
min        ...      0.000000     0.000000     0.000000      0.0
25%        ...      0.000000     0.000000     0.000000      0.0
50%        ...      0.000000     0.000000     0.000000      0.0
75%        ...      0.000000     0.000000     0.000000      0.0
max        ...      1.000000     1.000000     1.000000      0.0

           Feat246      Feat247      Feat248      Feat249      Feat250  \
count  5331.000000  5331.000000  5331.000000  5331.000000  5331.000000
mean      0.522928     0.078381     0.434711     0.222165     0.154182
std       0.176868     0.087822     0.258655     0.102157     0.107699
min       0.000000     0.000110     0.000000     0.000000     0.000000
25%       0.470588     0.026702     0.267000     0.150607     0.082090
50%       0.562353     0.042039     0.474000     0.205960     0.135370
75%       0.641098     0.091802     0.632000     0.271628     0.209626
max       1.000000     1.000000     1.000000     0.995914     1.000000

           Feat251
count  5331.000000
mean      0.521247
std       0.095065
min       0.159137
25%       0.461988
50%       0.523780
75%       0.579569
max       1.000000

[8 rows x 251 columns]
```

In [10]:
```python
#All standard deviations
X_train_std_dev = X_train.describe().iloc[2:3,:].values

#All columns without a standard deviation of 0
X_train_std_0 = (X_train_std_dev!=0.0)[0].tolist()

#Cleaned Data without zero variance columns
X_train_reduc = X_train.iloc[:,X_train_std_0]
```

In [11]:
```python
X_train_reduc.describe()
```

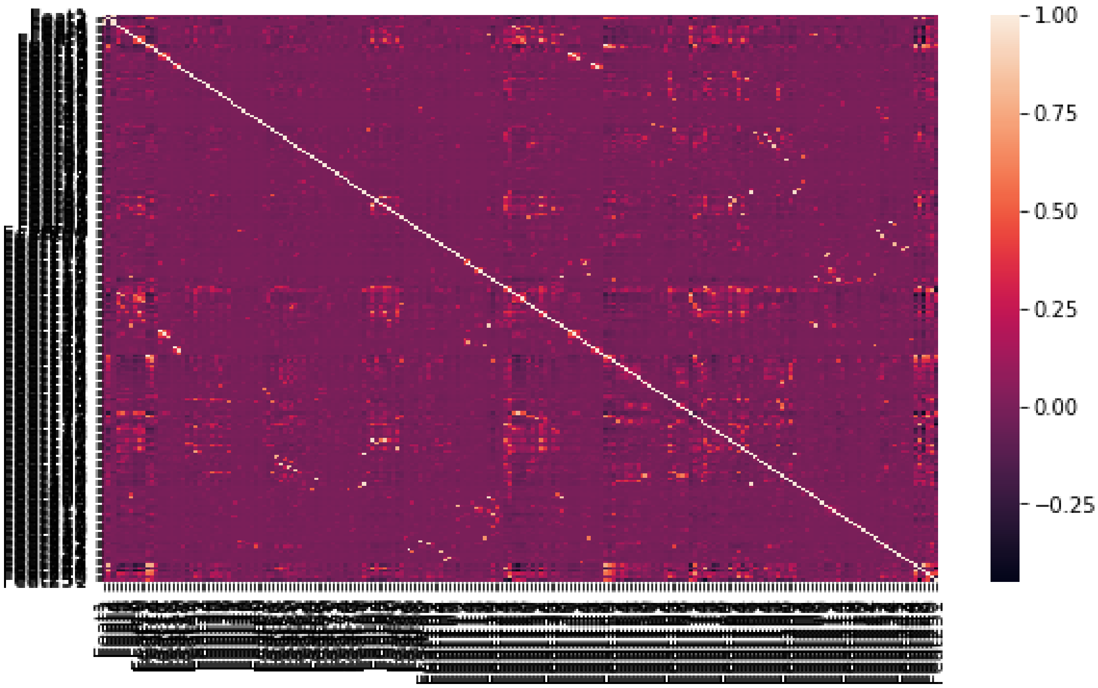
Out[11]:
```
             Feat1        Feat2        Feat3        Feat4        Feat5  \
count  5331.000000  5331.000000  5331.000000  5331.000000  5331.000000
mean      0.998506     0.142550     0.998887     0.996074     0.099018
std       0.012047     0.064343     0.010696     0.015199     0.106834
min       0.281689     0.000000     0.278493     0.000000     0.000000
25%       0.998859     0.164706     0.998435     0.996382     0.000000
50%       0.999577     0.167059     0.999583     0.996741     0.066667
75%       0.999956     0.174118     0.999863     0.997143     0.133333
```

```
max        1.000000     1.000000     1.000000     1.000000     1.000000

                Feat6        Feat7        Feat8        Feat9       Feat10  \
count  5331.000000  5331.000000  5331.000000  5331.000000  5331.000000
mean      0.040598     0.028137     0.013060     0.050136     0.027348
std       0.077767     0.074117     0.053347     0.100559     0.067602
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.057143     0.000000     0.000000     0.045455     0.000000
max       1.000000     1.000000     1.000000     0.909091     1.000000

          ...      Feat241      Feat242      Feat243      Feat244  \
count     ...  5331.000000  5331.000000  5331.000000  5331.000000
mean      ...     0.001032     0.001657     0.005346     0.000563
std       ...     0.024672     0.021473     0.054956     0.018747
min       ...     0.000000     0.000000     0.000000     0.000000
25%       ...     0.000000     0.000000     0.000000     0.000000
50%       ...     0.000000     0.000000     0.000000     0.000000
75%       ...     0.000000     0.000000     0.000000     0.000000
max       ...     1.000000     1.000000     1.000000     1.000000

              Feat246      Feat247      Feat248      Feat249      Feat250  \
count  5331.000000  5331.000000  5331.000000  5331.000000  5331.000000
mean      0.522928     0.078381     0.434711     0.222165     0.154182
std       0.176868     0.087822     0.258655     0.102157     0.107699
min       0.000000     0.000110     0.000000     0.000000     0.000000
25%       0.470588     0.026702     0.267000     0.150607     0.082090
50%       0.562353     0.042039     0.474000     0.205960     0.135370
75%       0.641098     0.091802     0.632000     0.271628     0.209626
max       1.000000     1.000000     1.000000     0.995914     1.000000

              Feat251
count  5331.000000
mean      0.521247
std       0.095065
min       0.159137
25%       0.461988
50%       0.523780
75%       0.579569
max       1.000000

[8 rows x 208 columns]
```

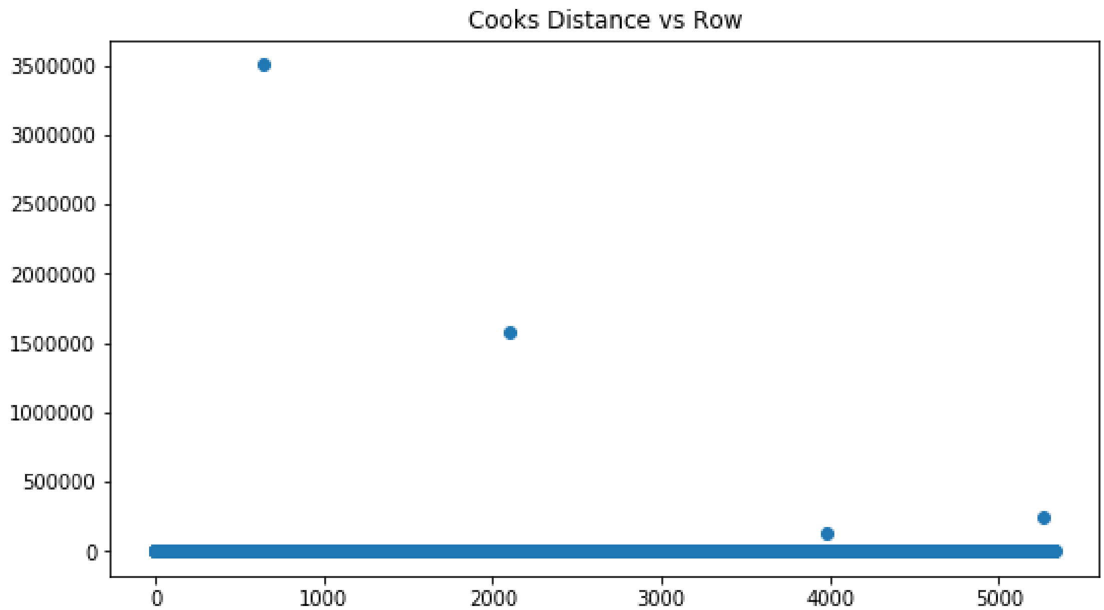
In [12]:
```
#correlation matrix heatmap
corr = X_train_reduc.corr()

plt.figure(figsize=(9,5))
```

```
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

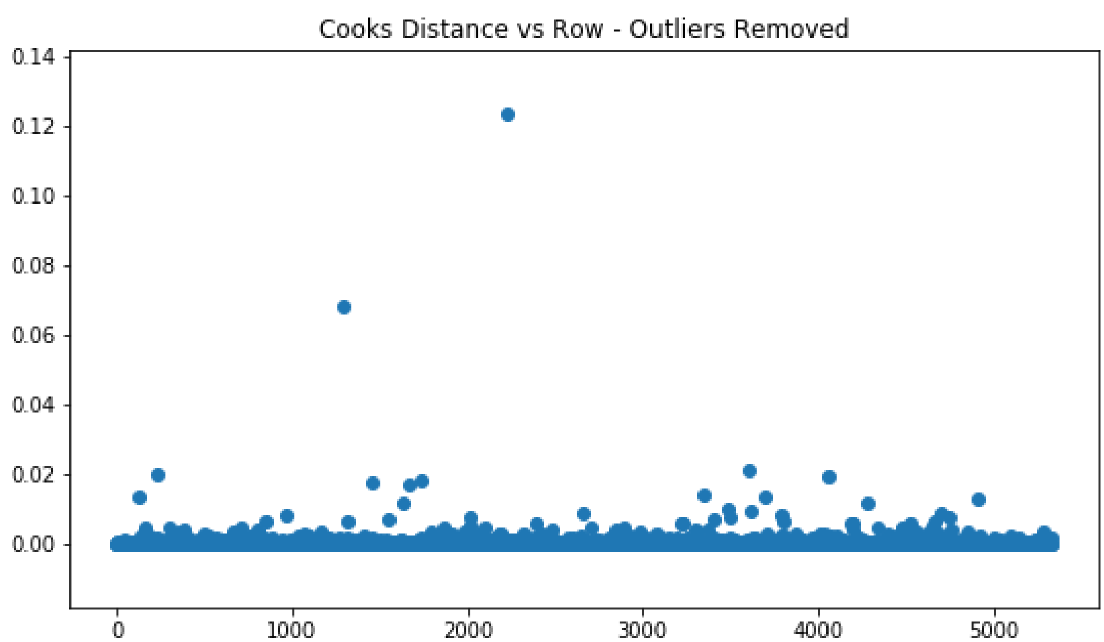
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x11cf85a90>




```
In [13]: #cooks_data.sort_values(by="cooks_d", ascending=False).cooks_d
         cooks_data = pd.read_csv("cooks_data.csv")
         c_data = cooks_data.sort_values(by="cooks_d", ascending=False).copy()
         fig, ax = plt.subplots(1,1, figsize=(9,5))
         ax.set_title("Cooks Distance vs Row")
         ax.scatter(cooks_data.index.values, cooks_data.cooks_d.values);
```



In [14]:
```
fig, ax = plt.subplots(1,1, figsize=(9,5))

non_outliers = c_data.iloc[5:,:]

ax.set_title("Cooks Distance vs Row - Outliers Removed")
ax.scatter(non_outliers.index.values, non_outliers.cooks_d.values);
fig.savefig("cooks_distance_post.png")
```



In [15]:
```
#REMOVING OUTLIERS

X_train_reduc_no_outliers = X_train_reduc.drop(X_train_reduc.index[[3046,  639, 2101,
y_train_no_outliers = y_train.drop(y_train.index[[3046, 639, 2101, 5260, 3983]])
```

---

2 Testing Assumptions of Linear Regression

In [16]:
```
#split training set into training and validation set
X_tr, X_test, y_tr, y_test = train_test_split(X_train_reduc_no_outliers, y_train_no_ou
```

In [17]:
```
#Calculating VIF to assess multicolinearity. Generally, higher than 5 implies multico
features = "+".join(X_train_reduc.columns).replace(" ", "")

#Compute OLS and determine VIF of coefficients
y, X = dmatrices('Target~'+features, train, return_type='dataframe')
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1]
vif["features"] = X.columns
```

In [18]:
```
vif.head()
```

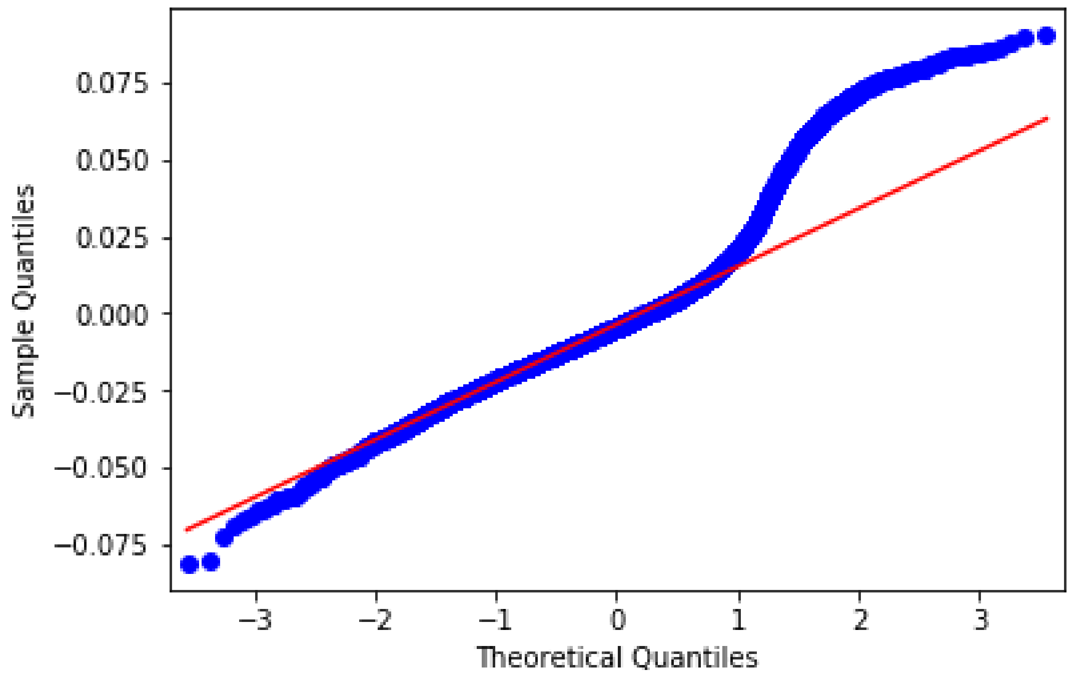
Out[18]:

	VIF Factor	features
0	7.059811e+08	Intercept
1	1.980391e+01	Feat1
2	5.675979e+00	Feat2
3	1.417245e+01	Feat3
4	4.108802e+01	Feat4

In [19]:
```
#There are 209 coefficients of OLS in total. Out of them, 163 have a VIF of greater t
np.sum(vif["VIF Factor"]>5)
```

Out[19]: 163

In [20]:
```
X_train.exog = sm.add_constant(X_train_reduc)
mod_fit = sm.OLS(y_train, X_train_reduc).fit()
res = mod_fit.resid
fig = sm.qqplot(res, line='q')
plt.figure(figsize=(10,5))
plt.show()
```




```
<Figure size 720x360 with 0 Axes>
```

---

3 Model 1: Ordinary Least Squares Prediction

In [24]:
```
#PREDICTION

# Cross Validation of OLS
myscores = np.array([])

reg = Lin_Reg()
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
myscores = np.append(myscores, scores)

np.mean(np.sqrt(-1*myscores))
```

Out[24]:
```
0.059393638509512126
```

---

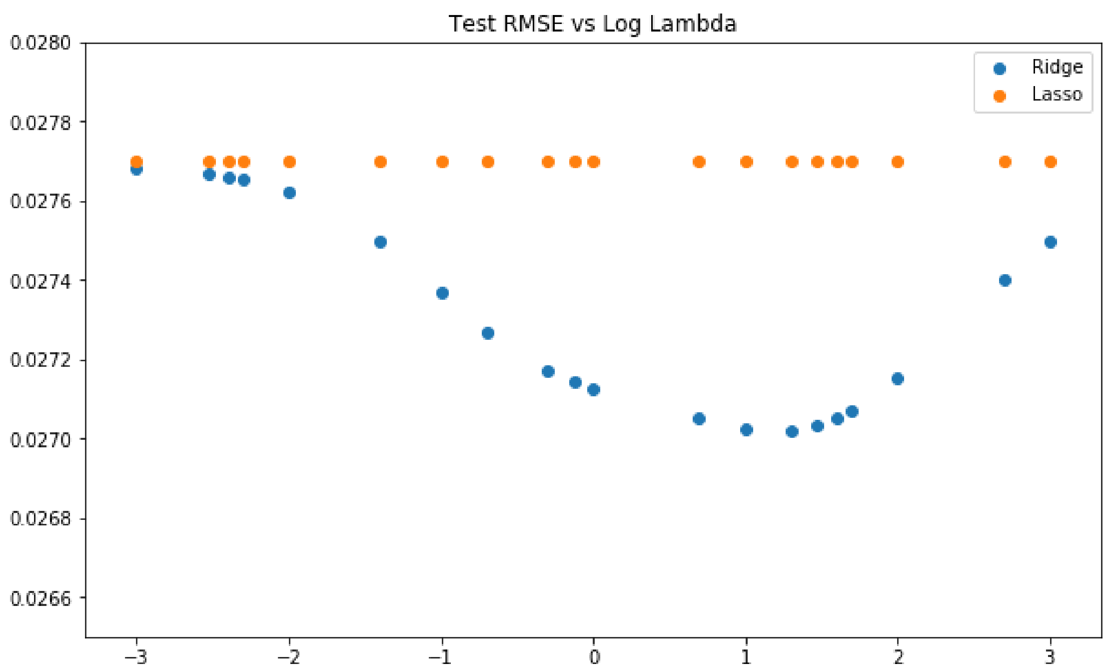
4 Models 2, 3, and 4: Regularized Linear Regression

In [33]:
```
# Define function to compute RMSE
def scoreRMSE(predictor, X, true_y):
    predictions = predictor.predict(X)
    return np.sqrt(mean_squared_error(predictions, true_y))
```

In [34]:
```
# Set of shrinkage parameters
lambdas = [.001, .003,.004, .005,.01, .04, .1,.2,.5,.75, 1, 5, 10, 20, 30, 40, 50, 10

# Set of alphas for elastic net
alphs = [0.000001, 0.00001, 0.00003, .000033, 0.00004, 0.0001, 0.001,0.002,0.0023, 0.0
# note: had warnings for convergence for 0 and 1, look into eps


# Initialize a 5-fold KFOLD object
kfold5 = KFold(5, shuffle=True)
```

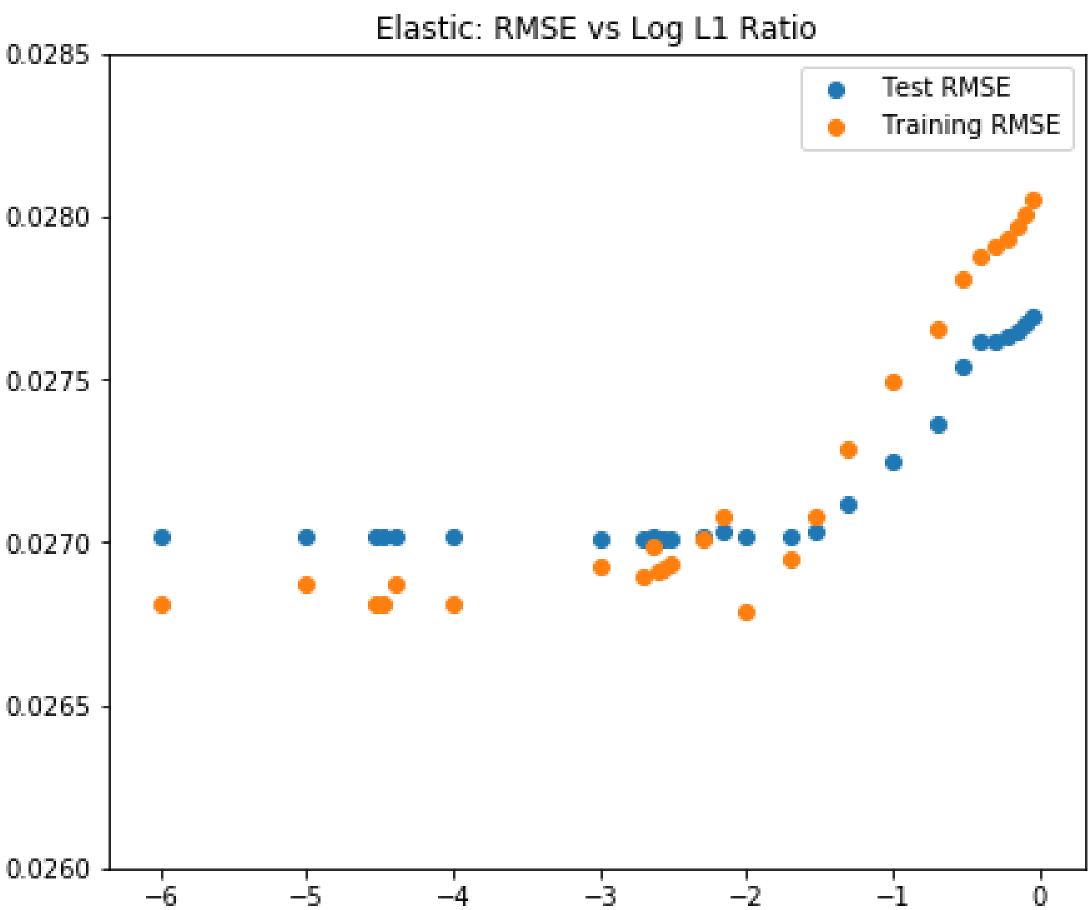
In [42]:
```
# NOTE: NEED TO CROSS VALIDATE

fig, ax = plt.subplots(1, 1, figsize=(10,6))

ridge_rmses = []
log_lambdas = []

for ele in lambdas:
    ridge_object = Ridge(alpha=ele)
    ridge = ridge_object.fit(X_tr, y_tr)
    ridge_rmses.append(scoreRMSE(ridge, X_test, y_test))
    log_lambdas.append(m.log10(ele))

ax.scatter(log_lambdas, ridge_rmses, label="Ridge")

ax.set_title("Ridge: RMSE vs Log Lambda");
#l1_r = 10 ** log_ratios[elastic_rmses.index(min(elastic_rmses))]
#l1_r
#ax.set_ylim((0.2,0.3))

lasso_rmses = []

for ele in lambdas:
    lasso_object = Lasso(alpha=ele)
    lasso = lasso_object.fit(X_tr, y_tr)
    lasso_rmses.append(scoreRMSE(lasso, X_test, y_test))

#ax.set_ylim([0.0279,0.0280])
ax.scatter(log_lambdas, lasso_rmses, label="Lasso")
```

```
ax.set_title("Lasso: RMSE vs Log Lambda");

ax.set_ylim([0.0265,0.028]);
ax.legend();
# NOTE: L2 ERROR IS SQUARED, Should presence of outlier affect it?


ax.set_title("Test RMSE vs Log Lambda");


#ax.set_ylim([0.0250,0.0280]);

fig.savefig("testrmse_vs_log_lambda.png")
```




```
In [83]: # params
         lambda_2 = lambdas[ridge_rmses.index(min(ridge_rmses))]
         lambda_1 = lambdas[lasso_rmses.index(min(lasso_rmses))]

         fig, ax = plt.subplots(1, 1, figsize=(7,6))

         elastic_rmses_train = []
         elastic_rmses = []
         log_ratios = []

         for ele in alphs:
```

```
        elastic_object = ElasticNetCV(l1_ratio = ele, alphas = lambdas, cv=kfold5)
        elastic = elastic_object.fit(X_tr, y_tr)
        elastic_rmses.append(scoreRMSE(elastic, X_test, y_test))
        elastic_rmses_train.append(scoreRMSE(elastic, X_tr, y_tr))
        log_ratios.append(m.log10(ele))

    ax.set_ylim([0.026,0.0285])
    ax.scatter(log_ratios, elastic_rmses, label="Test RMSE")
    ax.scatter(log_ratios, elastic_rmses_train, label="Training RMSE")
    ax.set_title("Elastic: RMSE vs Log L1 Ratio");
    l1_r = 10 ** log_ratios[elastic_rmses.index(min(elastic_rmses))]
    l1_r
    ax.legend();

    fig.savefig("elbow_rmse_vs_log_l1.png")
```

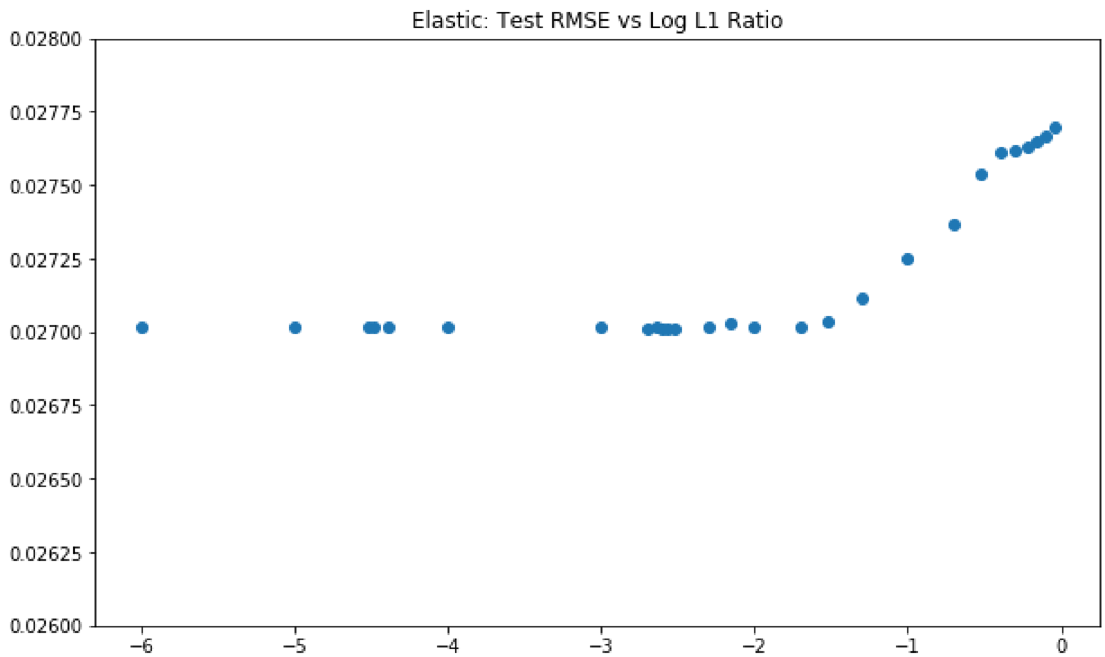



```
In [84]: #for i in range(len(elastic_rmses) -1):
         #    a = elastic_rmses[i]
```

```
#     b = elastic_rmses[i+1]
#     print((b - a)/b)
#     print(i+1)

# Look at graph, find that 0.003 is the elbow point
print("\033[1mOptimal L1-Ratio\033[0m: {0}".format(alphs[11]))
```

Optimal L1-Ratio: 0.003

```
In [85]: fig, ax = plt.subplots(1, 1, figsize=(10,6))

         elastic_rmses = []
         log_ratios = []

         for ele in alphs:
             elastic_object = ElasticNetCV(l1_ratio = ele, alphas = lambdas, cv=kfold5)
             elastic = elastic_object.fit(X_tr, y_tr)
             elastic_rmses.append(scoreRMSE(elastic, X_test, y_test))
             log_ratios.append(m.log10(ele))

         ax.set_ylim([0.026,0.028])
         ax.scatter(log_ratios, elastic_rmses)
         ax.set_title("Elastic: Test RMSE vs Log L1 Ratio");

         l1 = alphs[elastic_rmses.index(min(elastic_rmses))]
         #ax.set_ylim((0.2,0.3))

         fig.savefig("testrmse_vs_log_l1.png")
```



```
In [86]: # Best L1 from graph
         l1 = alphs[elastic_rmses.index(min(elastic_rmses))]

         elastic_object = ElasticNetCV(l1_ratio = l1, alphas = lambdas, cv=kfold5)
         elastic = elastic_object.fit(X_tr, y_tr)
         print(scoreRMSE(elastic, X_test, y_test))

         elastic_object.alpha_
         #ax.set_ylim((0.2,0.3))
```

```
0.02700977665315976
```

```
Out[86]: 0.003
```

```
In [88]: #PREDICTIONS

         myscores = np.array([])

         # RIDGE
         reg = Ridge(alpha= 30)
         scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
         myscores = np.append(myscores, np.mean(-1*scores))

         #LASSO
         reg = Lasso(alpha= 0.001)
         scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
         myscores = np.append(myscores, np.mean(-1*scores))

         #ELASTIC NET
         reg = ElasticNet(random_state=181, l1_ratio = 1/30000, alpha=0.003)
         scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
         myscores = np.append(myscores, np.mean(-1*scores))

         print(np.sqrt(myscores))
```

```
[0.02734449 0.02806384 0.02729521]
```

---

5 Model 5, 6, 7, & 8: Tree Models

In [93]:
```
myscores = np.array([])

#Decision Tree
reg = DecisionTreeRegressor()
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
myscores = np.append(myscores, np.mean(-1*scores))

# Random Forest
clf = RandomForestRegressor(n_estimators=100,random_state=181)
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
myscores = np.append(myscores, np.mean(-1*scores))

#AdaBoost Decision Tree
reg = AdaBoostRegressor(n_estimators=100)
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
myscores = np.append(myscores, np.mean(-1*scores))

#Gradient Boosting Model (Regression Tree)
reg = GradientBoostingRegressor()
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
myscores = np.append(myscores, np.mean(-1*scores))

print(np.sqrt(myscores))
```

```
[0.03834357 0.03795464 0.02942723 0.02719666]
```

In [ ]:
```
#Tuning Gradient Boosting Model
from sklearn.model_selection import GridSearchCV

parameters = {
    'learning_rate': (0.05, 0.1, 0.2),
    'n_estimators': (50, 100, 150),
    'subsample': (0.5, 0.7, 1),
    'max_depth': (3,6,9)
}

gbr = GradientBoostingRegressor()
reg = GridSearchCV(gbr, parameters, cv=5, scoring='neg_mean_squared_error')
reg.fit(X_tr, y_tr)
```

In [64]:
```
reg.best_params_
```

Out[64]:
```
{'learning_rate': 0.05, 'max_depth': 3, 'n_estimators': 100, 'subsample': 1}
```

In [94]:
```
reg = GradientBoostingRegressor(learning_rate=0.05, max_depth=3, n_estimators=100, sul
scores = cross_val_score(reg, X_tr, y_tr, cv=5,scoring='neg_mean_squared_error')
np.sqrt(np.mean(-1*scores))
```

Out[94]: 0.027189577827229434

```
In [ ]: from xgboost import XGBRegressor
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score

        parameters = {
            'learning_rate': (0.01, 0.025, 0.05, 0.1),
            'gamma': (0.3, 0.5, 0.7, 1),
            'max_depth': (3,7,12,16,25),
            'lambda': (0.01, 0.05, 0.1, 0.5,1),
            'subsample': (0.5, 0.7, 1),
            'min_child_weight': (1,3,5),
            'reg_alpha': (0,0.1,0.5),
            'colsample_bytree': (0.5, 0.7, 1)
        }

        xgb = XGBRegressor()
        reg = GridSearchCV(gbr, parameters, cv=5)
        reg.fit(X_tr, y_tr)
```

---

6 Train and Predict on 80/20

```
In [118]: #Elastic Net vs. Gradient Boosting
          myscores = np.array([])

          reg = ElasticNet(random_state=181, l1_ratio = 1/30000, alpha=0.003)
          reg.fit(X_tr, y_tr)
          y_pred = reg.predict(X_test)
          myscores = np.append(myscores, mean_squared_error(y_test, y_pred))

          reg = GradientBoostingRegressor(learning_rate=0.05, max_depth=3, n_estimators=100, su
          reg.fit(X_tr, y_tr)
          y_pred = reg.predict(X_test)
          myscores = np.append(myscores, mean_squared_error(y_test, y_pred))

          print(np.sqrt(myscores))
```

```
[0.02701767 0.02694591]
```

---

7 Predict on Full Test Set

```
In [138]: unlabeled = test.iloc[:,1:]
          X_train_no_outliers = X_train.drop(X_train.index[[3046,  639, 2101, 5260, 3983]])

In [139]: #Final Model: Gradient Boosting on Regression Trees without outliers and zero varian
          reg = GradientBoostingRegressor(learning_rate=0.05, max_depth=3, n_estimators=100, su
          reg.fit(X_train_no_outliers, y_train_no_outliers)
          y_pred = reg.predict(unlabeled)

In [140]: # Format predictions to be compatible with Kaggle upload
          sample_submission = pd.DataFrame(data=y_pred, columns=['Predicted'])
          sample_submission.insert(0, "Id", range(1, 1 + unlabeled.shape[0]))
          sample_submission['Id'] = sample_submission['Id'].astype(str)
          sample_submission.head()
```

Out[140]:

	Id	Predicted
0	1	0.931715
1	2	0.912686
2	3	0.917482
3	4	0.923929
4	5	0.919191

```
In [141]: # Save predictions to .csv file for upload to Kaggle
          sample_submission.to_csv("tuned_gradient_boost.csv", index=False)
```