MODELLING

NEW METHODS

My work focus on following implementation:

1. To see whether the %silica concentrate can be predicted without iron concentrate and result showed us it is not good to predict silica concentrate withou iron concentrate . Hence, to solve the problem we can implement the multitarget regression method to predict both target variables at same time.
2. To try differnt models which is not inherent multitarget regression models like Randomforest,Ridge,Xgboost
3. To finalize the best model with R2 as well as MSE metric.

READING THE PRE-PROCESSED DATA

In [0]:
```
import pandas as pd
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
len(df)
```

Out[0]: 737453

In [0]:
```
df[:2]
```

Out[0]:

	index	datetime hours	% Iron Feed	% Silica Feed	Starch Flow	Amina Flow	Ore Pulp Flow	Ore Pulp pH	Ore Pulp Density	Flotation Column 01 Air Flow	Flotati Colu 02 / Fl
0	2017-03-10 01:02:00	2017-03-10 01:00:00	55.2	16.98	3019.53	557.434	395.713	10.0664	1.74	249.214	253.2
1	2017-03-10 01:02:20	2017-03-10 01:00:00	55.2	16.98	3024.41	563.965	397.383	10.0672	1.74	249.719	250.5

In [0]:
```
y = df['% Silica Concentrate']
X = df.drop(['% Silica Concentrate','index','datetime hours'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape)
```

```
(471969, 22) (471969, 22) (147491, 22) (147491, 22) (117993, 22) (47196
9,)
```

RIDGE REGRESSION

In [0]:
```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

In [0]:
```
import numpy as np
```

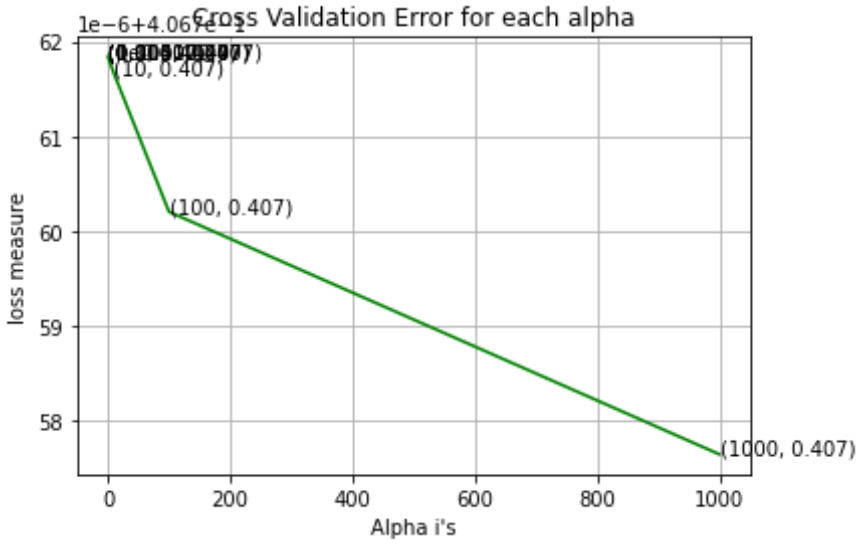
In [0]:
```
import matplotlib.pyplot as plt
```

In [0]:
```
#https://www.statisticshowto.com/ridge-regression/-- for idea to use th
e ridge regression
#tuning of paramaters based on mse critriea and idea os from mocrosoft
 malware detection notebook-- to idea to use the tune hyperparameters
#https://classroom.appliedcourse.com/classrooms/jEARG7xb/assignments/q2
AJp9B5/users/jEARG7xb -- to get the idea of representation of aplha and
 its graph
#  read more about ridge regressor() at https://scikit-learn.org/stabl
e/modules/generated/sklearn.linear_model.Ridge.html

# ------------------------------
# default parameters
# sklearn.linear_model.Ridge(alpha=1.0, *, fit_intercept=True, normaliz
e=False, copy_X=True, max_iter=None, tol=0.001, solver='auto', random_s
tate=None)[source]¶
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model
# predict(X) Predict class labels for samples in X.

from sklearn.linear_model import Ridge
alpha = [10 ** x for x in range(-5, 4)]
loss_array=[]

for i in alpha:
    model = Ridge(alpha = i, random_state=0)
    model.fit(features_train,y_train)
    predict_y = model.predict(features_cv)

    loss_array.append(mean_squared_error(y_cv, predict_y))
```

```
for i in range(len(loss_array)):
 print ('loss for alpha = ',alpha[i],'is',loss_array[i])
```

```
loss for alpha =  1e-05 is 0.406761838244861
loss for alpha =  0.0001 is 0.40676183824325474
loss for alpha =  0.001 is 0.4067618382271923
loss for alpha =  0.01 is 0.40676183806656824
loss for alpha =  0.1 is 0.4067618364604651
loss for alpha =  1 is 0.40676182041305764
loss for alpha =  10 is 0.4067616612998473
loss for alpha =  100 is 0.406760204640508
loss for alpha =  1000 is 0.4067576473714793
```

In [0]:
```
#code snippet taken from microsoft malware detection case study noteboo
k-- to get the idea to get the graphs
#https://classroom.appliedcourse.com/classrooms/jEARG7xb/assignments/q2
AJp9B5/users/jEARG7xb
best_alpha = np.argmin(loss_array)

fig, ax = plt.subplots()
ax.plot(alpha, loss_array,c='g')
for i, txt in enumerate(np.round(loss_array,3)):
 ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],loss_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("loss measure")
plt.show()
```



In [0]:
```
best_alpha = min(loss_array)
print("THE BEST ALPHA",best_alpha)
```

```
THE BEST ALPHA 0.4067576473714793
```

In [0]:
```
model = Ridge(alpha =best_alpha, random_state=0)
model.fit(features_train,y_train)
predict_y = model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,predict_y)
mse_test=mean_squared_error(y_test,y_pred_test)
r2_train=r2_score(y_train,y_pred_train)
r2_cv=r2_score(y_cv,predict_y)
r2_test=r2_score(y_test,y_pred_test)
```

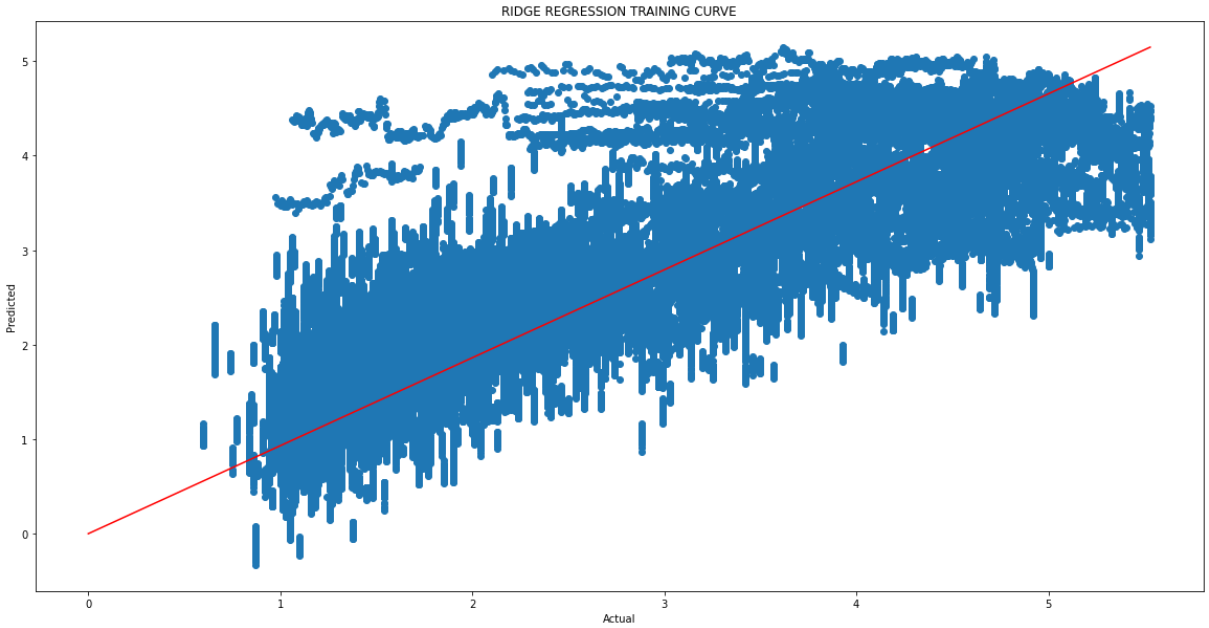
REPORT

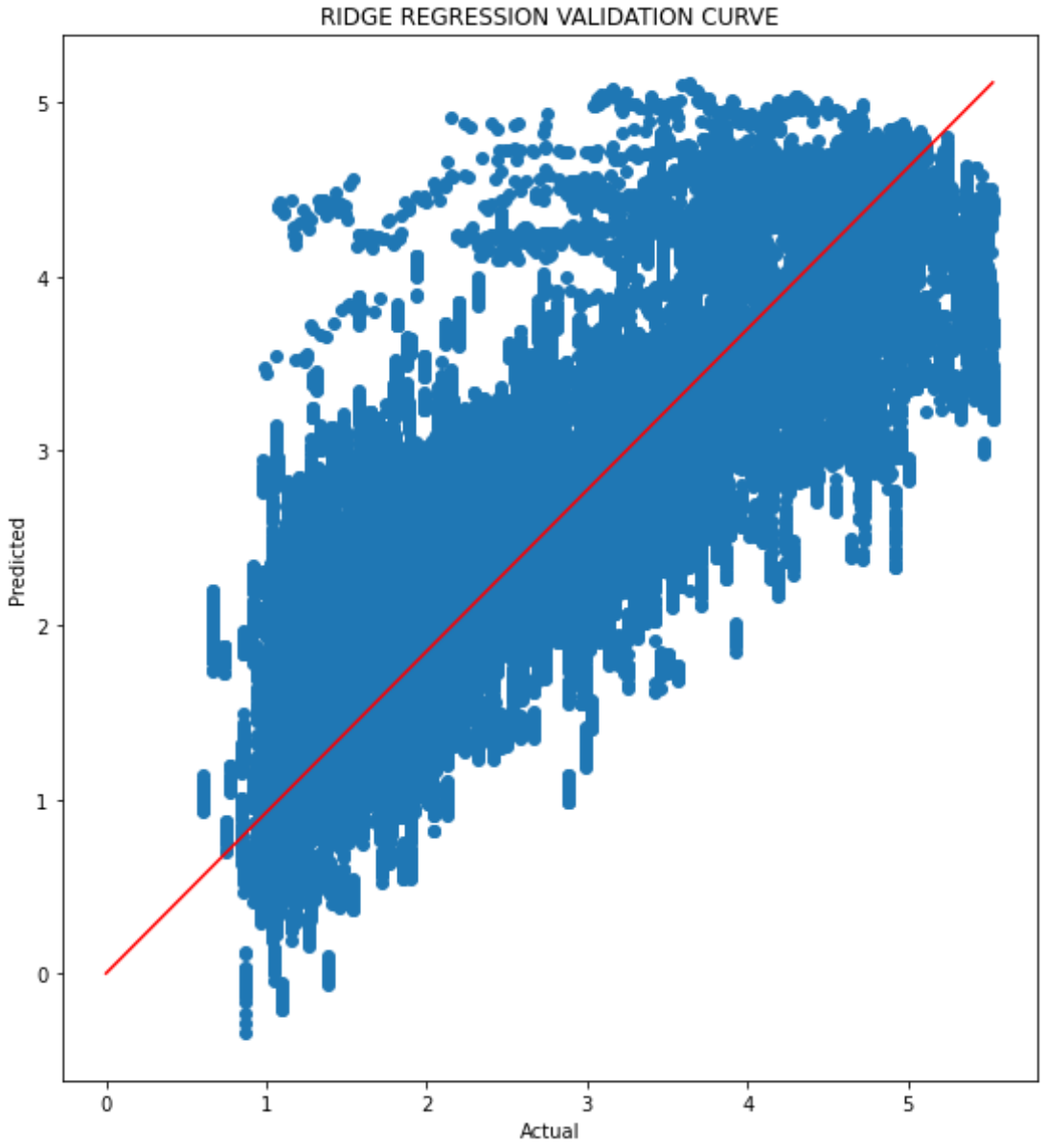
In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([r2_train,r2_cv,r2_test])
print("**********R2 MODEL**********")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([mse_train,mse_cv,mse_test])
print("**********MSE MODEL**********")
print(ptable1)
```

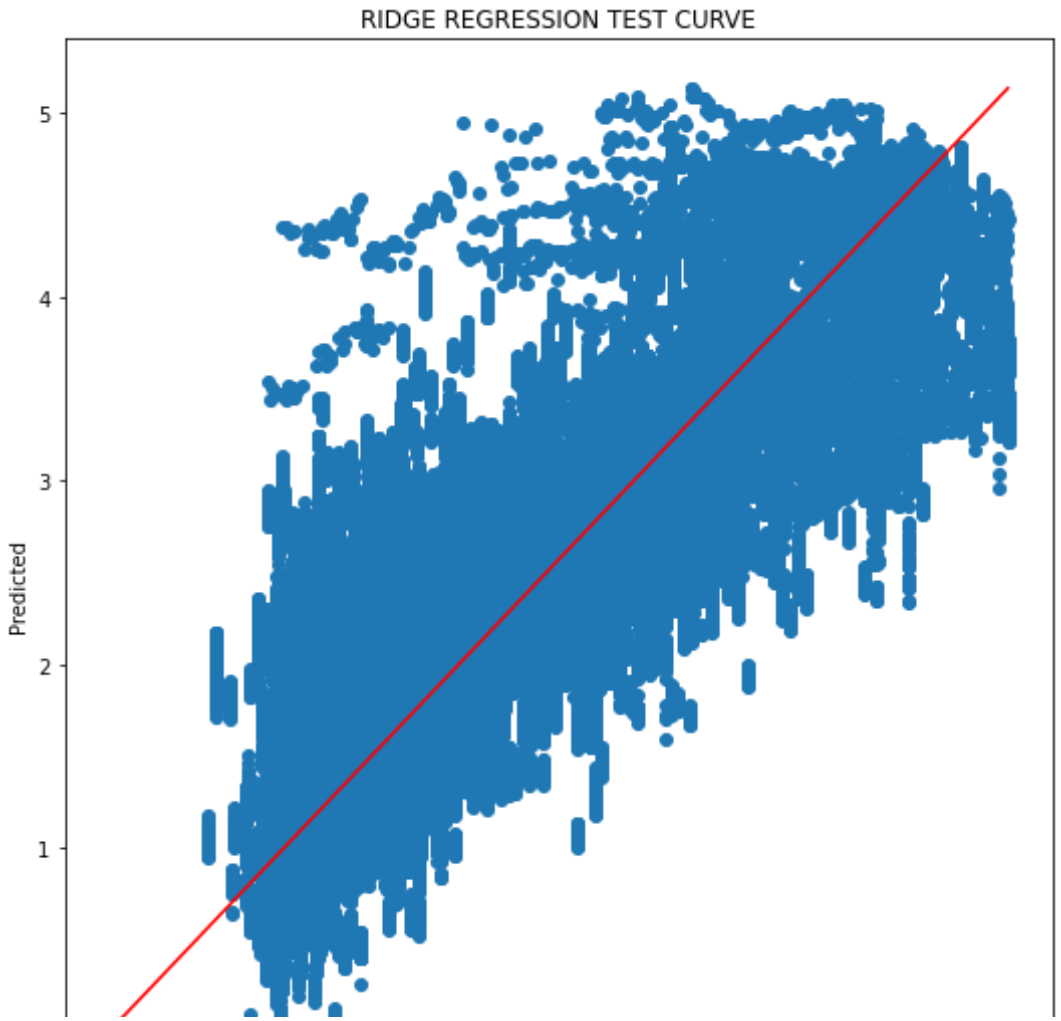
```
**********R2 MODEL**********
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.6793376233352849 | 0.6781961151567286 | 0.6804834009486844 |
+--------------------+--------------------+--------------------+
**********MSE MODEL**********
+--------------------+---------------------+--------------------+
|       train        |          cv         |        test        |
+--------------------+---------------------+--------------------+
| 0.4068427067720936 | 0.40676183098805463 | 0.4035862571275307 |
+--------------------+---------------------+--------------------+
```

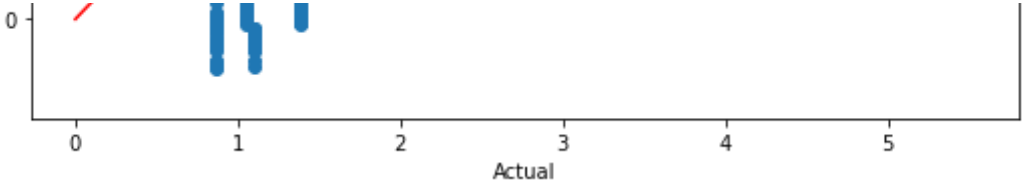
TRAIN,CV,TEST GRAPHS

In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="RIDGE REGRESSION TRAINING CURVE", xlabel="Actual", ylabel
="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RIDGE REGRESSION VALIDATION CURVE", xlabel="Actual", ylab
el="Predicted")
ax.scatter(y_cv, predict_y)
ax.plot([0,max(y_cv)], [0,max(predict_y)], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RIDGE REGRESSION TEST CURVE", xlabel="Actual", ylabel="Pr
edicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```









EXPLANATION

WHY RIDGE REGRESSION ?

Ridge regression is a way to create a model when the number of predictor variables in a set exceeds the number of observations, or when a data set has ***multicollinearity (correlations between predictor variables).*** The main reason is to choose ridge regression is because of the above feature.

TUNING PARAMETERS

ALPHA IS THE TUNING PARAMETER

alpha{float, ndarray of shape (n_targets,)}, default=1.0 Regularization strength; must be a positive float. Regularization improves the conditioning of the problem and reduces the variance of the estimates. Larger values specify stronger regularization. Alpha corresponds to 1 / (2C) in

other linear models such as LogisticRegression or sklearn.svm.LinearSVC. If an array is passed, penalties are assumed to be specific to the targets. Hence they must correspond in number.

PLOTS

The regression model the closer the data points will fall to the fitted regression line. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

The points are not fall on the fitted regression line. In the test and cv curve the points are also the same as train curve and there is no difference in traion and cv and test curves.

METRIC COMPARISION

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is not so closer to 1 and TEST r2 is also not close to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The train,cv,test loss are good but r2 score is not very good.

XGBREGRESSOR

In [0]:
```
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
```

XgBoost with best hyper parameters using RandomSearch

In [0]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data
# find more about XGBClassifier function here http://xgboost.readthedoc
s.io/en/latest/python/python_api.html?#xgboost.XGBClassifier
# ------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimat
ors=100, silent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=Non
e, gamma=0, min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=
1, reg_alpha=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missin
g=None, **kwargs)
# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_
stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep]) Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with dat
a. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
```

```
# ----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html
x_cfl=xgb.XGBRegressor()
prams={'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],'n_estimators':[100,200,500,1000,2000],'max_depth':[3,5,10],'colsample_bytree':[0.1,0.3,0.5,1],'subsample':[0.1,0.3,0.5,1]}
random_cfl1=RandomizedSearchCV(x_cfl,param_distributions=prams,verbose=10,n_jobs=-1,)
random_cfl1.fit(features_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:   35.5s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:  1.2min
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_executor.py:706: UserWarning: A worker stopped while some jobs were given to the executor. This can be caused by a too short worker timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed: 95.2min
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed: 138.1min
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed: 151.6min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed: 262.3min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed: 304.2min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed: 324.1min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 335.0min finished
```

```
[22:09:30] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

Out[0]:

```
RandomizedSearchCV(cv=None, error_score=nan,
                   estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                          colsample_bylevel=1,
```

```
                                                colsample_bynode=1,
                                                colsample_bytree=1, gamma=0,
                                                importance_type='gain',
                                                learning_rate=0.1, max_delta_
step=0,
                                                max_depth=3, min_child_weight
=1,
                                                missing=None, n_estimators=10
0,
                                                n_jobs=1, nthread=None,
                                                objective='reg:linear',
                                                random_state=0, reg_alp...
                                                seed=None, silent=None, subsa
mple=1,
                                                verbosity=1),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'colsample_bytree': [0.1, 0.3,
0.5, 1],
                                        'learning_rate': [0.01, 0.03,
0.05, 0.1,
                                                          0.15, 0.2],
                                        'max_depth': [3, 5, 10],
                                        'n_estimators': [100, 200, 500,
1000,
                                                         2000],
                                        'subsample': [0.1, 0.3, 0.5,
1]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=10)
```

TRAINING WITH BEST PARAMETERS

In [0]:
```
print (random_cfl1.best_params_)
```

```
{'subsample': 0.1, 'n_estimators': 1000, 'max_depth': 10, 'learning_rat
e': 0.01, 'colsample_bytree': 1}
```

In [0]:
```
# Training a hyper-parameter tuned Xg-Boost regressor on our train data
# find more about XGBREGRESSORfunction here http://xgboost.readthedocs.
io/en/latest/python/python_api.html?#xgboost.XGBREGESSOR
# ------------------------
# default paramters
# class xgboost.XGBREGRESSOR(max_depth=3, learning_rate=0.1, n_estimato
rs=100, silent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=NoN
e, gamma=0, min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=
1, reg_alpha=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missin
g=None, **kwargs)
# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_
stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep]) Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with dat

# get_score(importance_type='weight') -> get the feature importance
# ------------------------
# video link2: https://www.appliedaicourse.com/course/applied-ai-course
-online/lessons/what-are-ensembles/
model=xgb.XGBRegressor(max_depth=10 ,learning_rate=0.01,n_estimators=10
00 ,verbose=2,subsample=0.1,colsample_bytree=1)
model.fit(features_train,y_train)
```

```
[01:13:48] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
```

Out[0]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.01, max_delta_step
=0,
             max_depth=10, min_child_weight=1, missing=None, n_estimato
rs=1000,
             n_jobs=1, nthread=None, objective='reg:linear', random_sta
te=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
```

```
silent=None, subsample=0.1, verbose=2, verbosity=1)
```

MODEL TRAINING, PLOTS, PREDICTION , EVAULATION

In [0]:
```
y_pred=model.predict(features_cv)
```

In [0]:
```
r2_score(y_cv,y_pred)
```

Out[0]:
```
0.9773658789974008
```

In [0]:
```
y_pred_train=model.predict(features_train)
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
```

In [0]:
```
mse_cv=mean_squared_error(y_pred,y_cv)
```

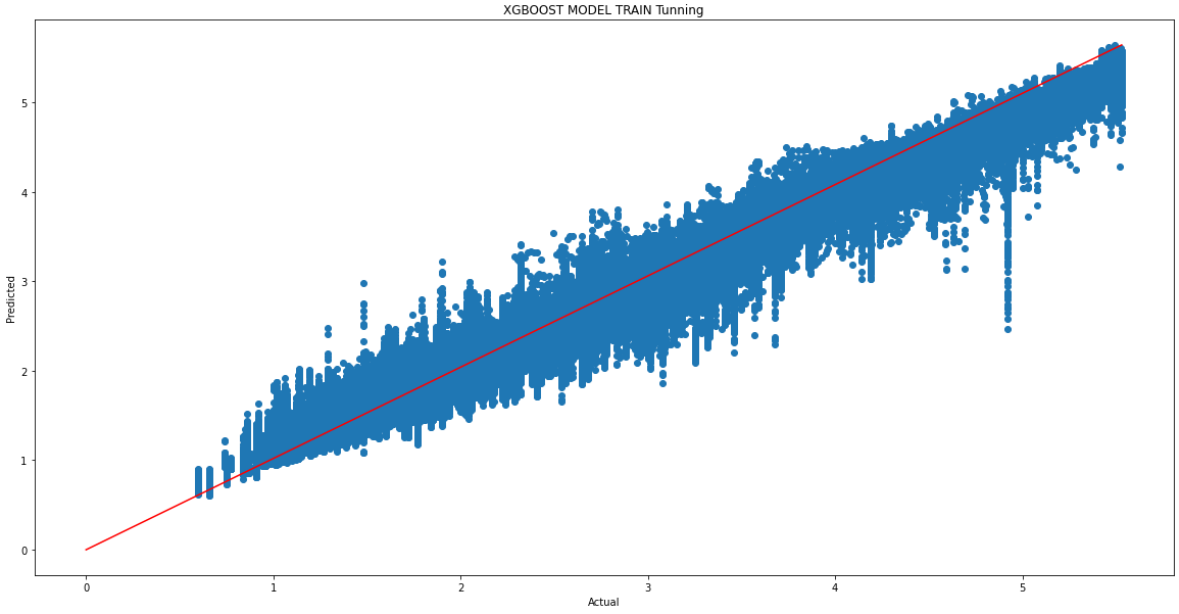
In [0]:
```
r2_score(y_train,y_pred_train)
```

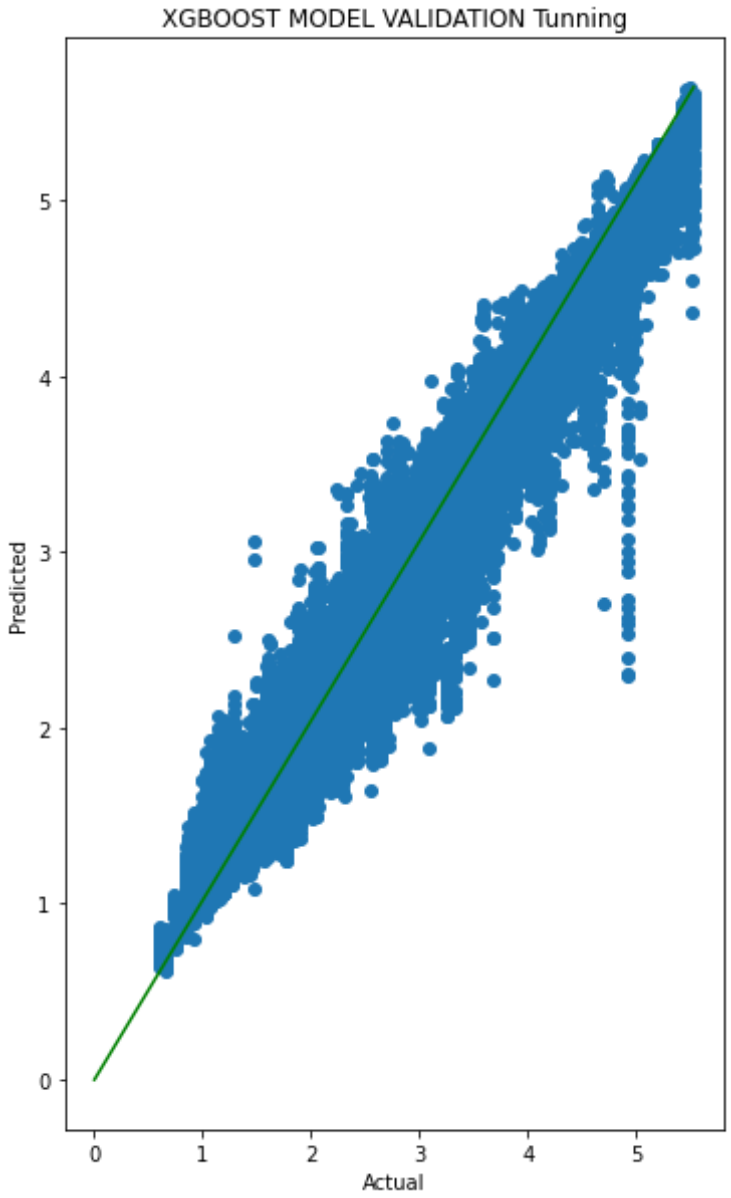
Out[0]:
```
0.9795944830941742
```

train,validation curves

In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="XGBOOST MODEL TRAIN Tunning", xlabel="Actual", ylabel="Pr
```

```
edicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(131)
ax.set(title="XGBOOST MODEL VALIDATION Tunning", xlabel="Actual", ylabe
l="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='g')
fig.show()
```





In [0]:
```
mse_cv,mse_train
```

Out[0]: (0.028609649962138804, 0.02588964697823065)

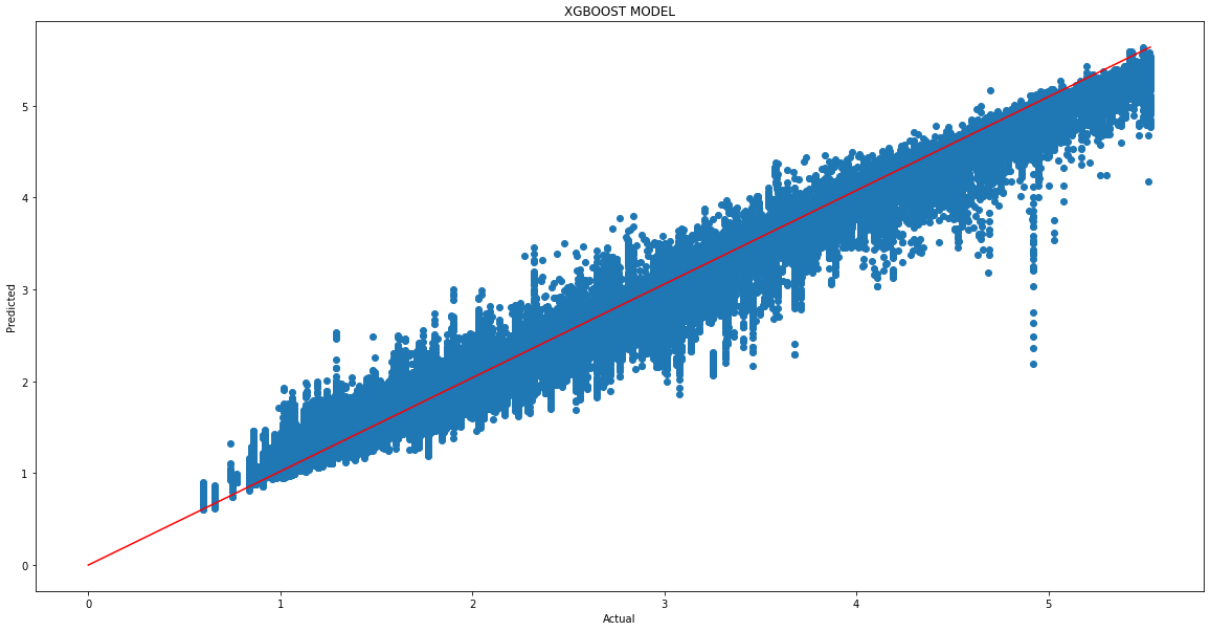
In [0]:
```
y_pred_test=model.predict(features_test)
```

In [0]:
```
mse_test=mean_squared_error(y_test,y_pred_test)
```

In [0]:
```
r2_score(y_test,y_pred_test)
```

Out[0]: 0.9775210369328332

In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="XGBOOST MODEL", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```



REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.9795944830941742,0.9773658789974008,0.9775210369328332])
print("**********R2 MODEL**********")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([ 0.02588964697823065,0.028609649962138804,0.0306096499621388])
print("**********MSE MODEL**********")
print(ptable1)
```

```
**********R2 MODEL**********
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.9795944830941742 | 0.9773658789974008 | 0.9775210369328332 |
+--------------------+--------------------+--------------------+
**********MSE MODEL**********
+---------------------+----------------------+--------------------+
|        train        |          cv          |        test        |
+---------------------+----------------------+--------------------+
| 0.02588964697823065 | 0.028609649962138804 | 0.0306096499621388 |
+---------------------+----------------------+--------------------+
```

EXPLANATION

Since , the ridge regression shows less perfomance metric inorder to enchance the metric of the model . The XGBoost is used because of faster performance and gretaer performance

TUNING PARAMATERS

Tune tree-specific parameters (max_depth, min_child_weight, gamma, subsample, colsample_bytree) for decided learning rate and number of trees.

The parameters are decided using randomsearch cv.

sklearn.model_selection.RandomizedSearchCV¶

https://scikit-learn.org/stable/modules/generated/sklearn.mode

The random search cv is used to get best hyperparameters.

PLOTS

The regression model the closer the data points will fall to the fitted regression line. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

The points fall on the fitted regression line. In the test and cv curve the points are also the same as train curve and there is no difference in traion and cv and test curves. When compared with the ridge model , the plot is musch better and most of points fall on the regresssion line.

METRIC COMPARISION

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is so closer to 1 and TEST r2 is also close to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The train,cv,test loss are good but r2 score is also good.

DECISION TREE REGRESSOR

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?
client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleuser
```

```
content.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_t
ype=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.t
est%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fw
ww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.go
ogleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /content/drive
```

In [0]:
```
import pandas as pd
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
y = df['% Silica Concentrate']
X = df.drop(['% Silica Concentrate','index','datetime hours'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape)
```

```
(471969, 22) (471969, 22) (147491, 22) (147491, 22) (117993, 22) (47196
9,)
```

In [0]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeRegressor
```

DECISION TREE HYPERPARAMATERS TUNING USING RANDOM SEARCH CV

In [0]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html?highlight=decision%20tree%20regressor#sklearn.tree.DecisionTreeRegressor
#https://www.appliedaicourse.com/lecture/11/applied-machine-learning-online-course/3064/decision-tree
##sklearn.model_selection.RandomizedSearchCV¶
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html
#The default values for the parameters controlling the size of the trees (e.g. max_depth, min_samples_leaf, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.

dt2 = DecisionTreeRegressor()
se=dt2.fit(features_train,y_train)
parameters = {'max_depth': [1, 5, 10, 50], 'min_samples_split': [5, 10, 100, 500]}
cfl2=RandomizedSearchCV(dt2,param_distributions=parameters,verbose=10,n_jobs=-1,)
se2 = cfl2.fit(features_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:   16.5s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:   31.8s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:  2.3min
```

```
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed:  3.4min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:  5.9min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  6.4min finished
```

In [0]:
```
print(cfl2.best_estimator_)
```

```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [0]:
```
best_tune_parameters=[{'max_depth':[50], 'min_samples_split':[5] }]
```

MODEL TRAINING

In [0]:
```
clf=DecisionTreeRegressor (max_depth=50,min_samples_split=5)
clf.fit(features_train, y_train)
```

Out[0]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [0]:
```
y_pred=clf.predict(features_cv)
```

In [0]:
```
y_pred_train=clf.predict(features_train)
y_pred_test=clf.predict(features_test)
```

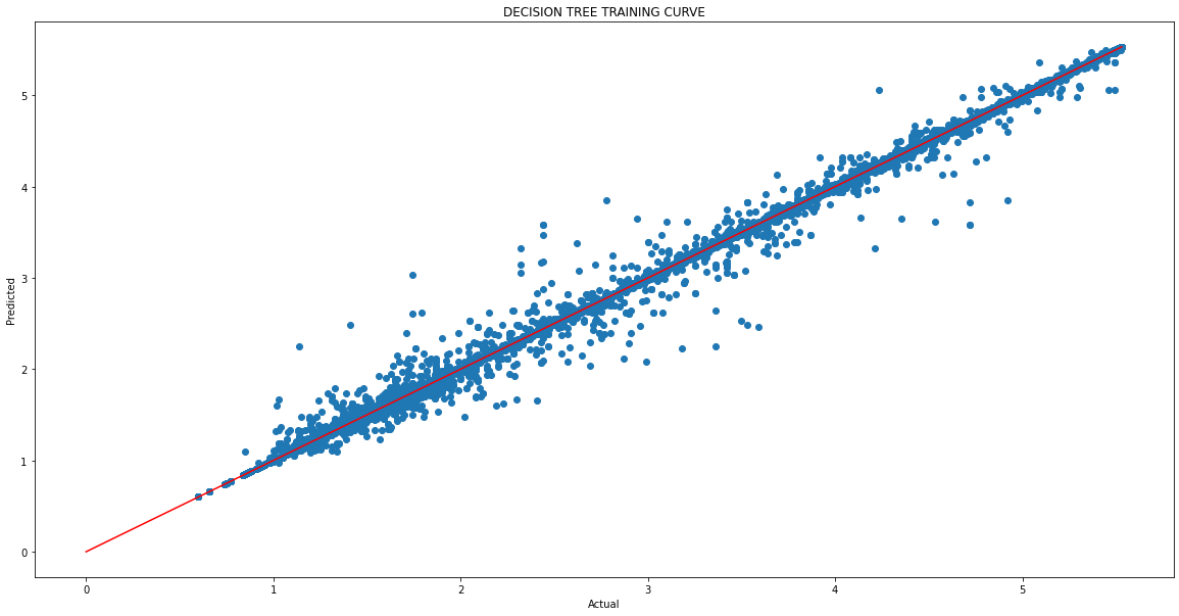
EVALUATION METRIC

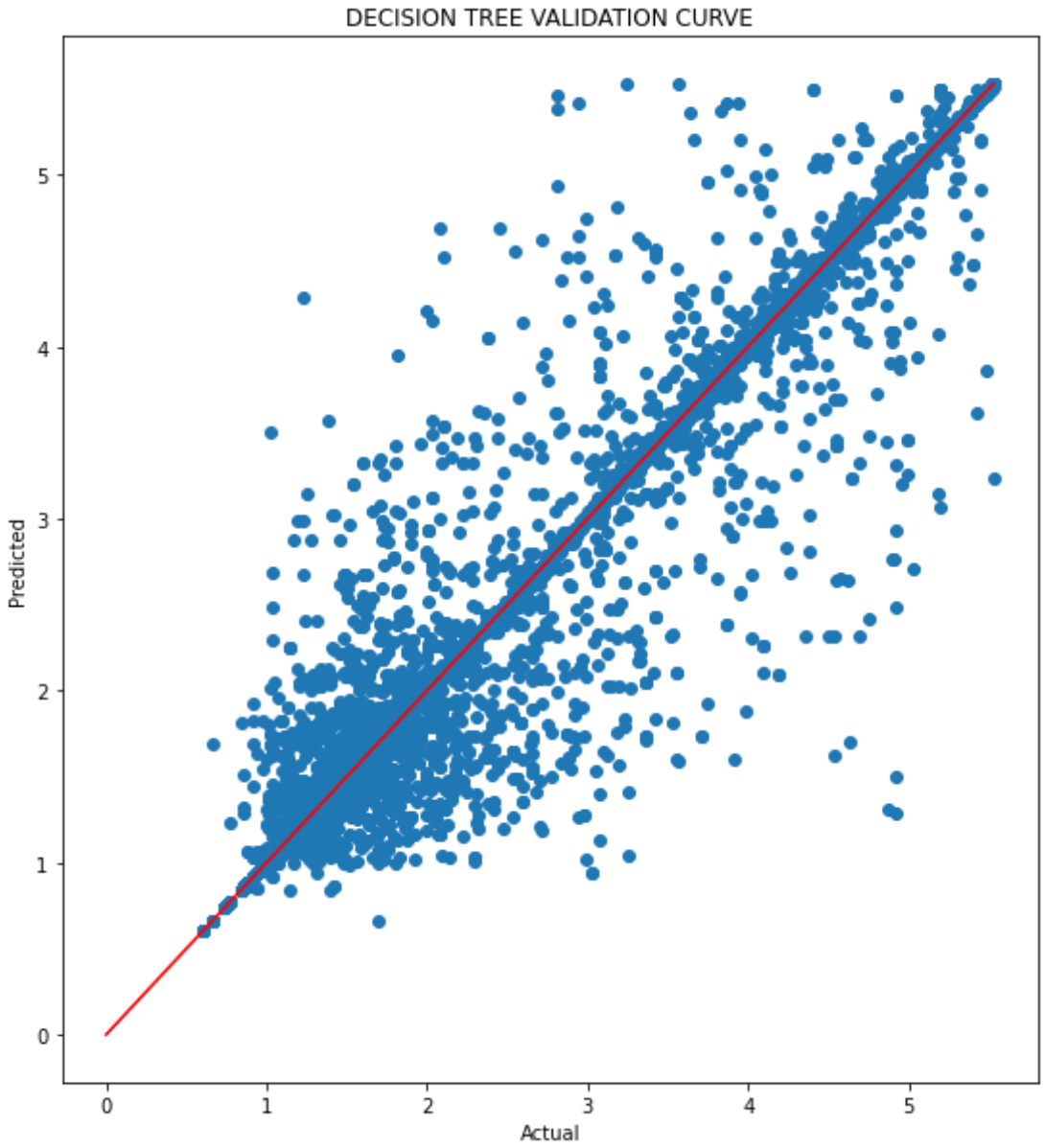
In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)
r2_cv=r2_score(y_cv,y_pred)
r2_train=r2_score(y_train,y_pred_train)

r2_test=r2_score(y_test,y_pred_test)
```

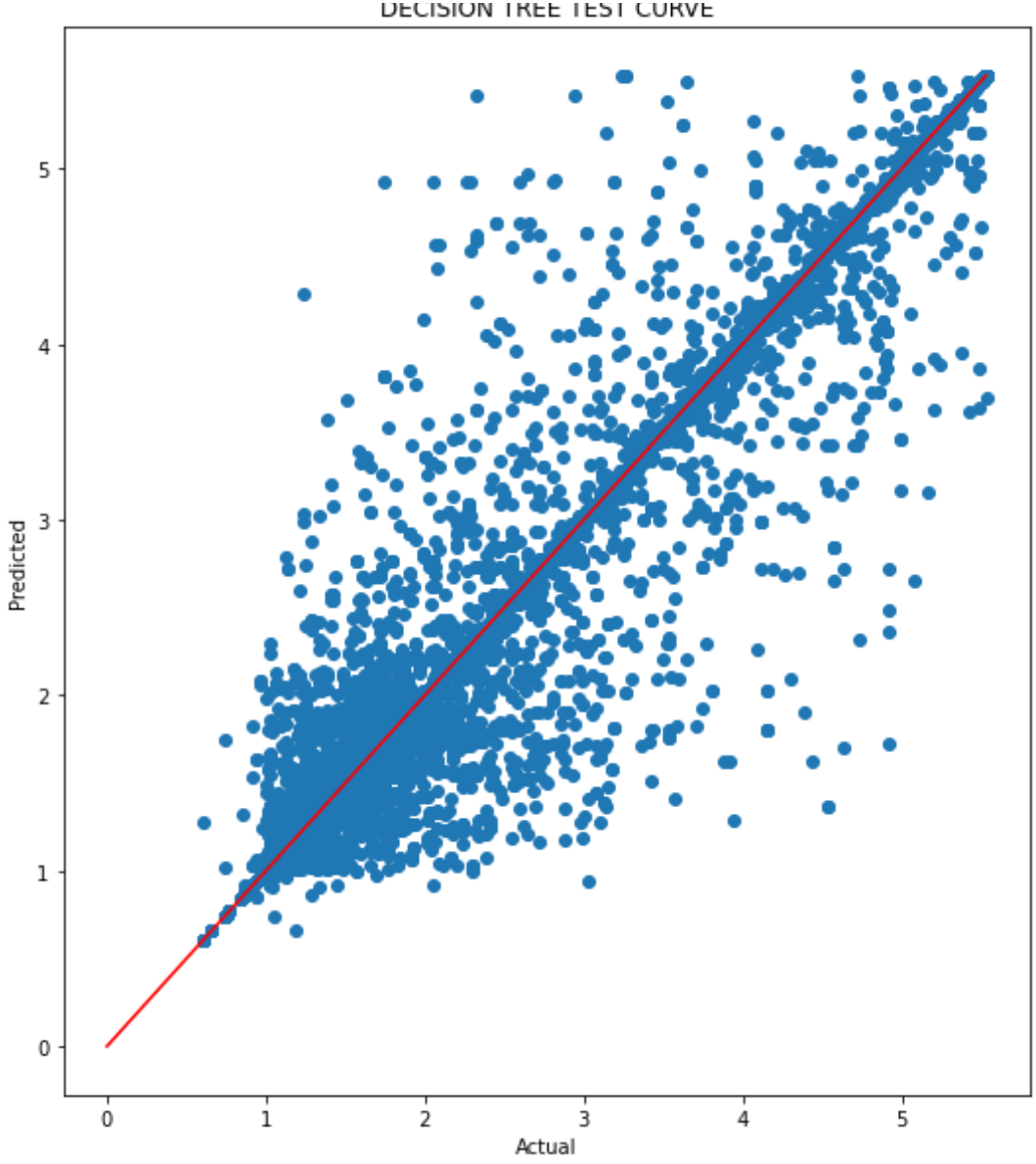
PLOTS

In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process

fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="P
redicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='r')
```

```
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()

from sklearn.ensemble import RandomForestRegressor
fig.show()
```







In [0]:
```
r2_test,r2_train,mse_cv,mse_test,mse_train
```

Out[0]:
```
(0.9928184073341917,
 0.9998788183828305,
 0.008583147579681304,
 0.009071178501567047,
 0.00015375005216709757)
```

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.9998788183828305,0.9993658789974008,0.9928184073341917])
print("**********R2 **********")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([ 0.00015375005216709757,0.008583147579681304,0.009071178501567047])
print("**********MSE **********")
print(ptable1)
```

```
**********R2 **********
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.9998788183828305 | 0.9993658789974008 | 0.9928184073341917 |
+--------------------+--------------------+--------------------+
**********MSE **********
+-----------------------+----------------------+---------------------
+
|         train         |          cv          |         test
|
```

```
|
+------------------------+---------------------+---------------------
+
| 0.0001537500521670975 7 | 0.008583147579681304 | 0.009071178501567047
|
+------------------------+---------------------+---------------------
+
```

EXPLANATION

Decision tree regression observes features of an object and trains a model in the structure of a tree to predict data in the future to produce meaningful continuous output.

Easy to interept.

TUNING PARAMATERS

The default values for the parameters controlling the size of the trees (e.g. max_depth, min_samples_leaf, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.

Hence, randomsearch cv is used to find the best hyperparamaters tat is max_depth and min_samples_leaf and using the best values we can tune the model.

PLOTS

The regression model the closer the data points will fall to the fitted regression line. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

The points fall on the fitted regression line. In the test and cv curve the points are are not falling as we obseerve in train curve and there is difference in train and cv and test curves.

When compared with the xgboost model , the plot is so better and most of points fall on the regresssion line.

The train curve , the points are falling on the line perefctly and there is no much difference between actual and predicted

METRIC COMPARISION

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is APPROMIXATEMLY EQUAL to 1 and TEST r2 is also close to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The train,cv,test loss are good but r2 score is also good.

Decision tree has given much better resulst than other models

RANDOMFOREST REGRESSOR

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
from sklearn.model_selection import RandomizedSearchCV
```

RANDOMFOREST REGRESSOR BEST HYPERPARAMATER TUNING USING RANDOMSEARCH CV

In [0]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html?highlight=randomforest#sklearn.ensemble.RandomForestRegressor
#A random forest regressor.A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is controlled with the max_samples parameter if bootstrap=True (default), otherwise the whole dataset is used to build each tree.
#he default values for the parameters controlling the size of the trees (e.g. max_depth, min_samples_leaf, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.

#The features are always randomly permuted at each split. Therefore, the best found split may vary, even with the same training data, max_features=n_features and bootstrap=False, if the improvement of the criterion is identical for several splits enumerated during the search of the best split. To obtain a deterministic behaviour during fitting, random_state has to be fixed.

#The default value max_features="auto" uses n_features rather than n_fe
```

```
atures / 3. The latter was originally suggested in [1], whereas the for
mer was more recently justified empirically in .

param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
```

In [0]:
```
# Create a based model
rf = RandomForestRegressor()
# Instantiate the grid search model
grid_search = RandomizedSearchCV(estimator = rf,param_distributions= pa
ram_grid,
                           cv = 3,n_jobs=-1, verbose = 2)
```

In [0]:
```
grid_search.fit(features_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent work
ers.
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_ex
ecutor.py:706: UserWarning: A worker stopped while some jobs were given
to the executor. This can be caused by a too short worker timeout or by
a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 111.6min finished
```

Out[0]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
```

```
                                                    max_samples=None,
                                                    min_impurity_decreas
e=0.0,
                                                    min_impurity_split=N
one,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_
leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs=None, oob_sco
re=False,
                                                    random_state=None, v
erbose=0,
                                                    warm_start=False),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [80, 90, 100, 11
0],
                                        'max_features': [2, 3],
                                        'min_samples_leaf': [3, 4, 5],
                                        'min_samples_split': [8, 10, 1
2],
                                        'n_estimators': [100, 200, 300,
1000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=2)
```

In [0]:
```
grid_search.best_params_
```

Out[0]:
```
{'bootstrap': True,
 'max_depth': 100,
 'max_features': 3,
 'min_samples_leaf': 5,
 'min_samples_split': 10,
 'n_estimators': 1000}
```

MODEL TUNING

In [0]:
```
model=RandomForestRegressor(n_estimators=1000,max_depth=100,min_samples
_leaf=5,min_samples_split=10,bootstrap=True,max_features=3)
```

In [0]:
```
model.fit(features_train,y_train)
```

Out[0]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=100, max_features=3, max_leaf_nodes=Non
e,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=5,
                      min_samples_split=10, min_weight_fraction_leaf=0.
0,
                      n_estimators=1000, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

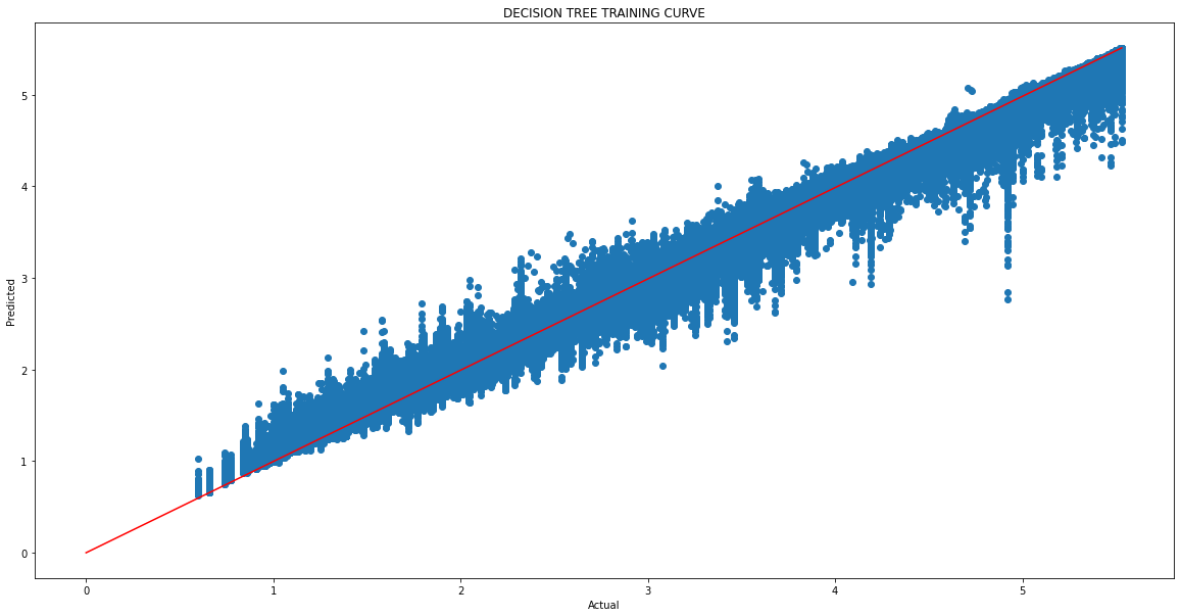
In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

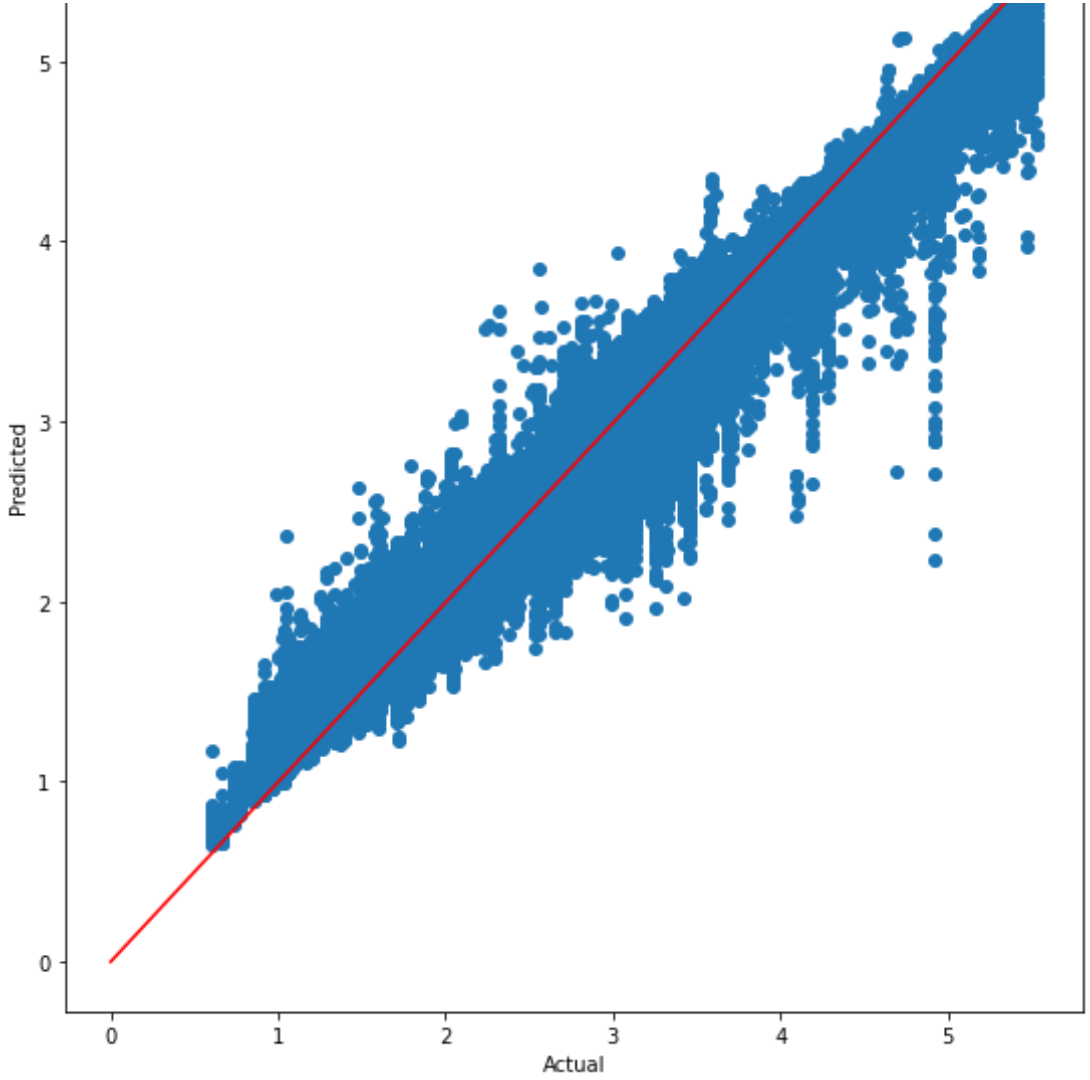
In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)

r2_train=r2_score(y_train,y_pred_train)

r2_test=r2_score(y_test,y_pred_test)
r2_cv=r2_score(y_cv,y_pred)
```

PLOTS

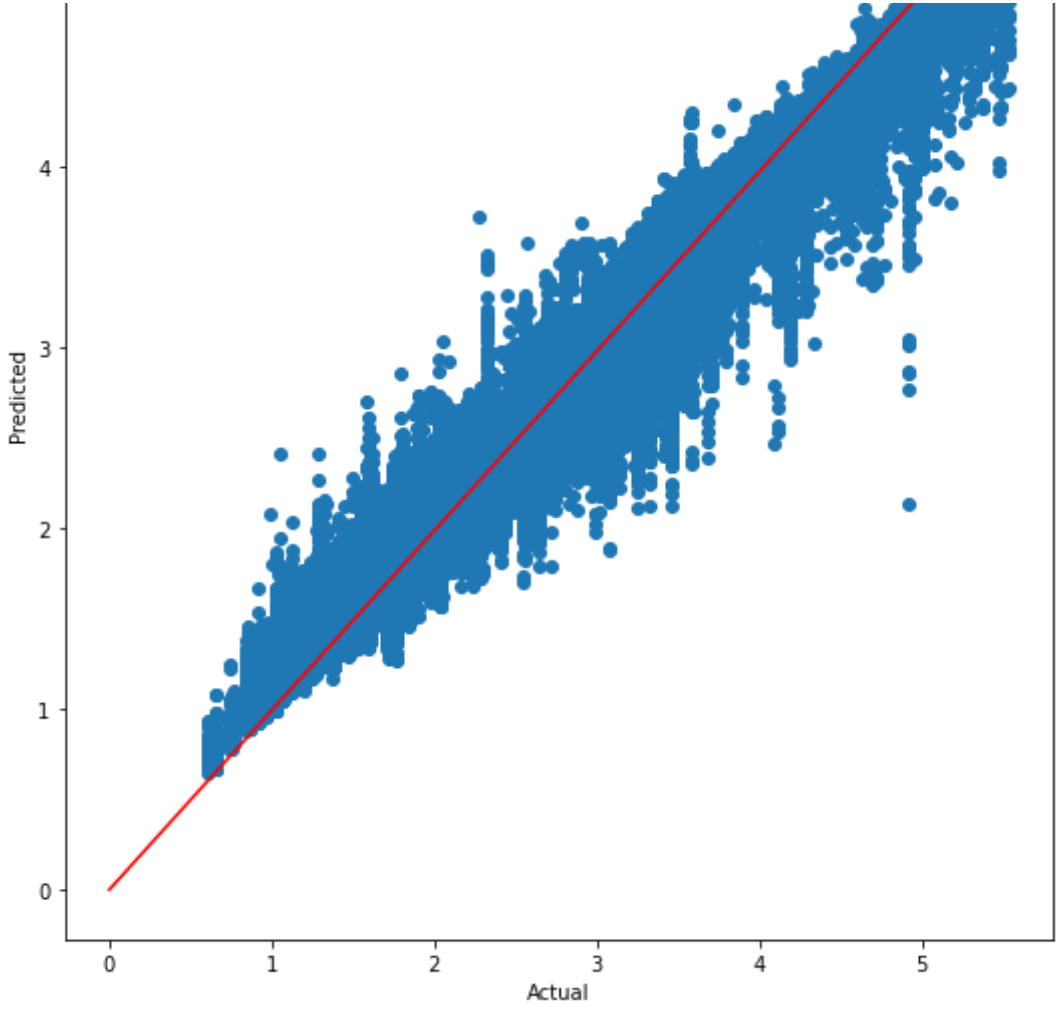
In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-process
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process

fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```



DECISION TREE VALIDATION CURVE



DECISION TREE TEST CURVE



In [0]:
```
r2_train,r2_test,r2_cv,mse_cv,mse_test,mse_train
```

Out[0]:
```
(0.991440126326125,
 0.9822978140228872,
 0.9822558920629562,
 0.02242864730249243,
 0.022359899306298725,
 0.010860401557953387)
```

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.991440126326125, 0.9822558920629562, 0.9822978140228872])
print("**********R2 **********")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([ 0.010860401557953387,0.02242864730249243,0.022359899306298725])
print("**********MSE **********")
print(ptable1)
```

```
**********R2 **********
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.991440126326125 | 0.9822558920629562 | 0.9822978140228872 |
+--------------------+--------------------+--------------------+
**********MSE **********
+-----------------------+----------------------+-----------------------+
|         train         |          cv          |         test          |
+-----------------------+----------------------+-----------------------+
| 0.010860401557953387 | 0.02242864730249243 | 0.022359899306298725 |
+-----------------------+----------------------+-----------------------+
```

EXPLANATION

https://www.kaggle.com/rogerbellavista/randomfc mae-0-0922-rmse-0-2314

According to the kaggle refrenec notebooks, the randomforest gives better result . As a experiment we have tried to replicate the model with tuning features and obtained results

TUNING PARAMATERS

https://towardsdatascience.com/random-forest-and-its-implementation-71824ced454f

The default values for the parameters controlling the size of the trees (e.g. max_depth, min_samples_leaf, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.

The features are always randomly permuted at each split. Therefore, the best found split may vary, even with the same training data, max_features=n_features and bootstrap=False, if the improvement of the criterion is identical for several splits enumerated during the search of the best split. To obtain a deterministic behaviour during fitting, random_state has to be fixed.

PLOTS

The regression model the closer the data points will fall to the fitted regression line. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

The points fall on the fitted regression line. In the test and cv curve the points are falling as we obseerve in train curve and there is no difference in train and cv and test curves.

When compared with the xgboost model , the plot is so better and most of points fall on the regresssion line.

The train curve , the points are falling on the line perefctly and there is no much difference between actual and predicted

METRIC COMPARISION

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is APPROMIXATEMLY EQUAL to 1 and TEST r2 is close to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The train,cv,test loss are good but r2 score is also good.

Randomforest has given much better results

MODELS WITHOUT IRON CONCENTRATE

DECISION TREE REGREGRESSOR WITHOUT IRON CONCENTRATE

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?
client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleuser
content.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_t
ype=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.t
est%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fw
ww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.go
ogleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
..........
Mounted at /content/drive
```

In [0]:
```
import pandas as pd
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
y = df['% Silica Concentrate']
X = df.drop(['% Silica Concentrate','index','datetime hours','% Iron Co
ncentrate'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_size=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.shape,features_cv.shape,y_train.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (471969,)
```

DECISION TREE REGRESSOR BEST HYPERPARAMATER TUNING USING RANDOM SEARCH CV

In [0]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeRegressor
```

In [0]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html?highlight=decision%20tree%20regressor#sklearn.tree.DecisionTreeRegressor
#https://www.appliedaicourse.com/lecture/11/applied-machine-learning-online-course/3064/decision-tree
##sklearn.model_selection.RandomizedSearchCV¶
```

```
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html
#The default values for the parameters controlling the size of the trees (e.g. max_depth, min_samples_leaf, etc.) lead to fully grown and unpruned trees which can potentially be very large on some data sets. To reduce memory consumption, the complexity and size of the trees should be controlled by setting those parameter values.dt2 = DecisionTreeRegressor()
se=dt2.fit(features_train,y_train)
parameters = {'max_depth': [1, 5, 10, 50], 'min_samples_split': [5, 10, 100, 500]}
cfl2=RandomizedSearchCV(dt2,param_distributions=parameters,verbose=10,n_jobs=-1,)
se2 = cfl2.fit(features_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:   10.8s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:   20.2s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:   29.5s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:   48.5s
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:  3.4min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:  5.3min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  6.1min finished
```

In [0]:
```
print(cfl2.best_estimator_)
```

```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=None, splitter='best')
```

In [0]:
```
best_tune_parameters=[{'max_depth':[50], 'min_samples_split':[5] }]
```

MODEL TRAINING AND PREDICTION

In [0]:
```
clf=DecisionTreeRegressor (max_depth=50,min_samples_split=5)
clf.fit(features_train, y_train)
```

Out[0]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

EVALUATION METRIC

In [0]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

In [0]:
```
y_pred=clf.predict(features_cv)
```

In [0]:
```
r2_cv=r2_score(y_cv,y_pred)
```

In [0]:
```
y_pred_train=clf.predict(features_train)
y_pred_test=clf.predict(features_test)
```

In [0]:
```
import matplotlib.pyplot as plt
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
```

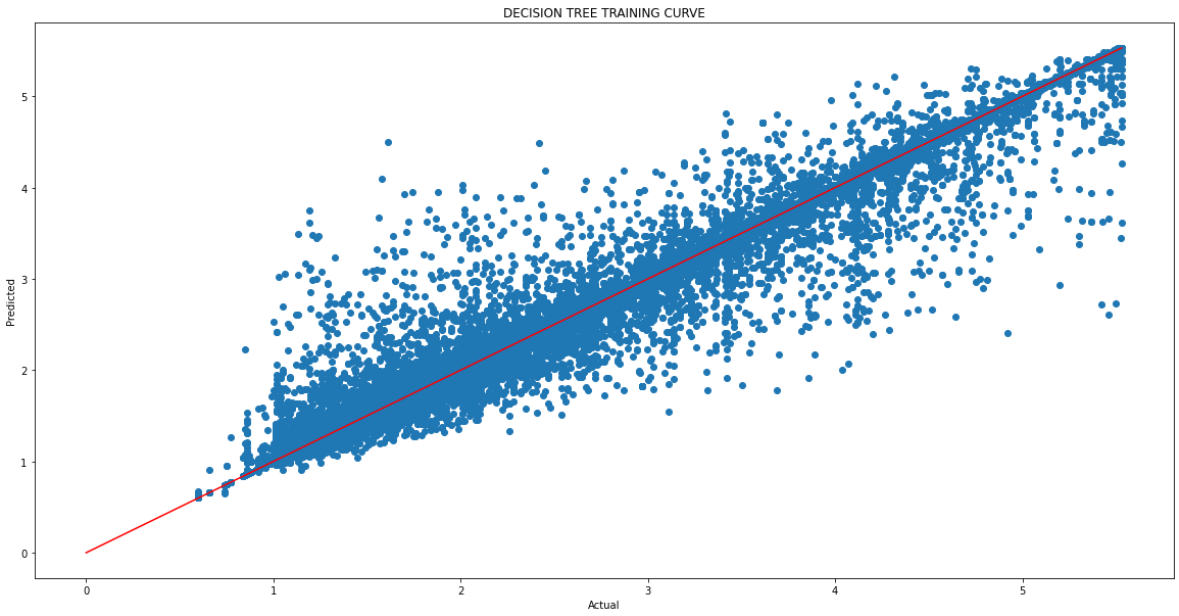
```
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)

r2_train=r2_score(y_train,y_pred_train)

r2_test=r2_score(y_test,y_pred_test)
```

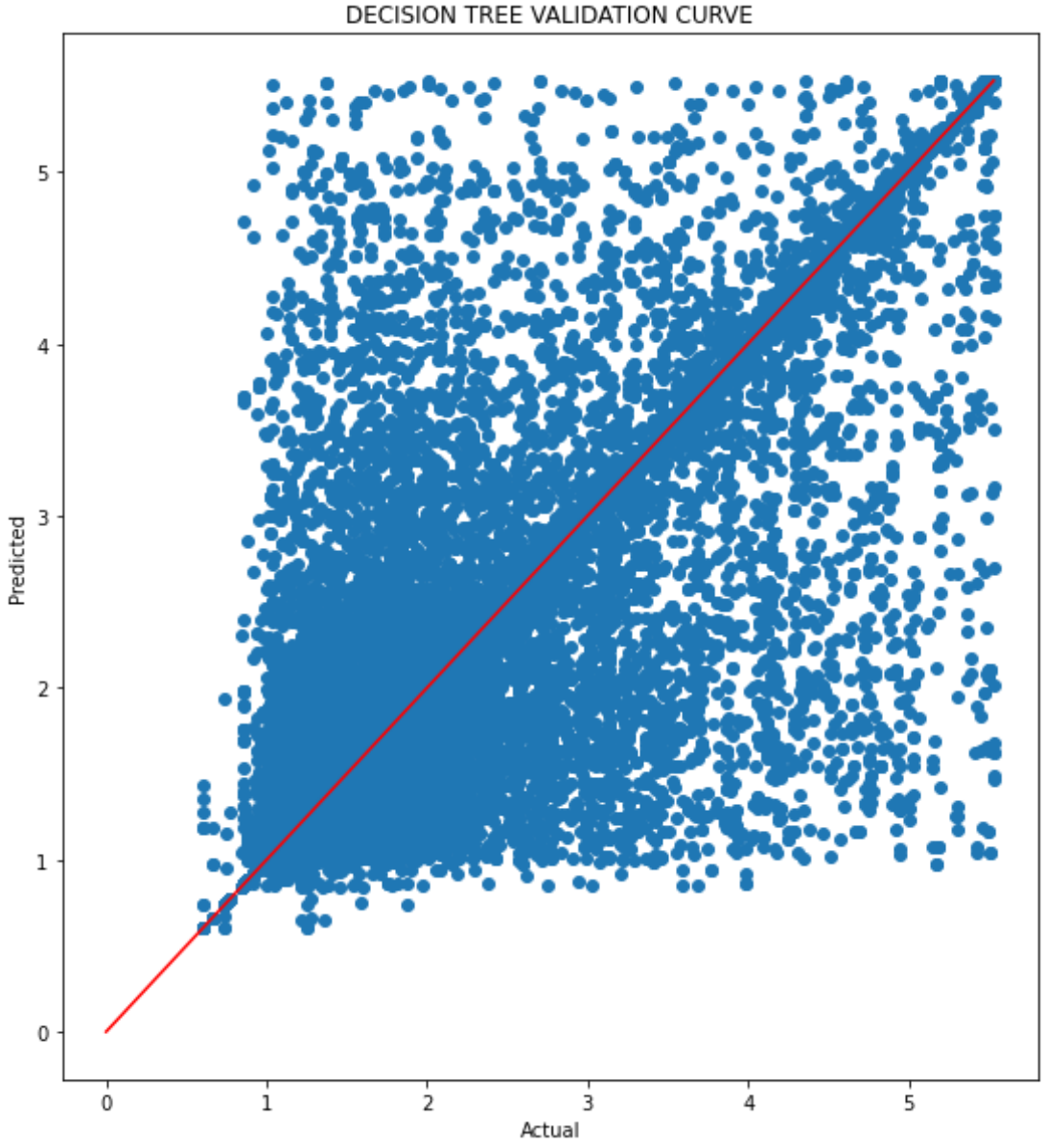
PLOTS

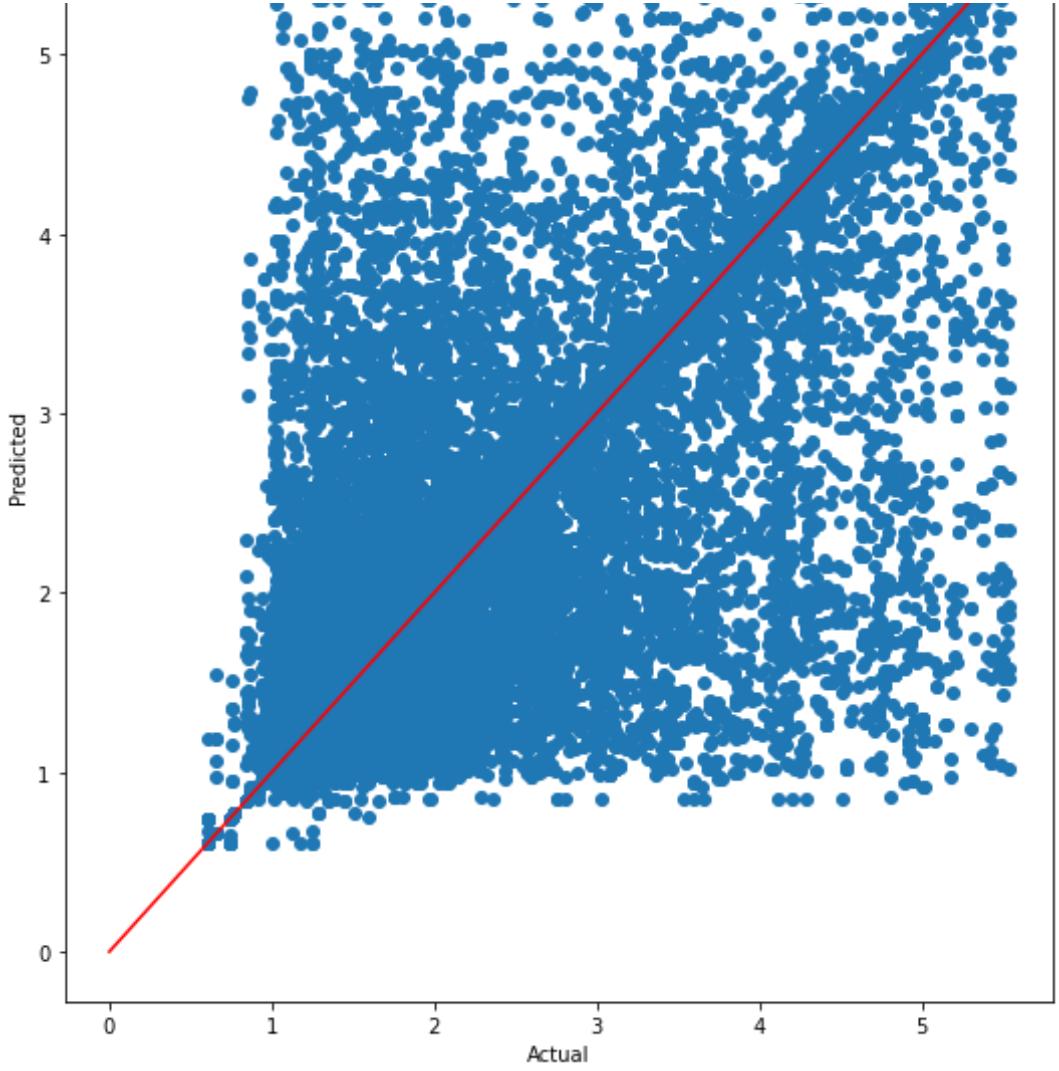
In [0]:

```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-process
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process



fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predicted")
```

```
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()

from sklearn.ensemble import RandomForestRegressor
fig.show()
```







In [0]:
```
r2_test,r2_train,r2_cv,mse_cv,mse_test,mse_train
```

Out[0]:
```
(0.8944468070516213,
 0.9967871967266184,
 0.9000528642649994,
 0.12633371394313822,
 0.1333258372065188,
 0.004076267361529295)
```

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.9967871967266184,0.9000528642649994,0.8944468070516213])
print("**********R2 MODEL**********")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([0.004076267361529295,0.12633371394313822, 0.1333258372065188])
print("**********MSE MODEL**********")
print(ptable1)
```

```
**********R2 MODEL**********
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.9967871967266184 | 0.9000528642649994 | 0.8944468070516213 |
```

```
+--------------------+--------------------+--------------------+
**********MSE MODEL**********
+----------------------+--------------------+--------------------+
|        train         |         cv         |        test        |
+----------------------+--------------------+--------------------+
| 0.004076267361529295 | 0.12633371394313822 | 0.1333258372065188 |
+----------------------+--------------------+--------------------+
```

METRIC COMPARISON BETWEEN WITH AND WITHOUT CONCENTRATE

1. R2 SCORE WITH IRON CONCENTRATE IS BETTER THAN MODEL WITHOUT IRON CONCENTRATE. THE MSE VALUES ARE ALSO BETTER THAN MODEL WITHOUT IRON CONCENTRATE. PREDICTING SILICA WITHOUT IRON DOES NOT GIVE BETTER RESULTS. WITH THE DOMAIN KNOWLEDGE , THE ONLY WAY TO PREDICT SILICA CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.

PLOT COMPASRION

THE EVALUATION METRIC TELLS QUANTITAVELY WHILE THE PLOTS TELLS GRAPHICALLY IT IS VERY CLEAR THAT FROM BOTH THE GRAPHS HOW THE IRON CONCENTRATE PLAYS IMPORTANT ROLE IN THE PREDICTION.

TRAIN CURVE::

THE POINTS ARE FALLING SIMILAR TO THE TRAIN CURVE IN WITH IRON CONCENTRATE WITH SLIGHT DIFFERENCE.

TESTAND VALIDATION CURVE

THE POINTS ARE TOTALLY OUT OF LINE AND THIS TELLS THAT IRON CONCENTRATE PLAYS A MAJOR ROLE IN PREDICTING THE OUTPUT DURING THE TEST TIME.

INFERENCES

PREDICTING SILICA WITHOUT IRON DOES NOT GIVE BETTER RESULTS. WITH THE DOMAIN KNOWLEDGE , THE ONLY WAY TO PREDICT SILICA CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.

ACCORDING TO DOMAIN KNOWLEDGE, BOTH IRON AND SILICA CONCENTRATE ARE TAKEN AS TARGET VARIBALES AND USING MULTI-TARGET REGRESSION THEY ARE PREDICTED . https://ieeexplore.ieee.org/abstract/document/8907120

RANDOMFOREST REGRESSOR

HYPERPARAMATER TUNING

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [0]:
```
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
```

In [0]:
```
# Create a based model
rf = RandomForestRegressor()
# Instantiate the grid search model
```

```
grid_search = RandomizedSearchCV(estimator = rf,param_distributions= pa
ram_grid,
                                 cv = 3,n_jobs=-1, verbose = 2)
```

In [0]:
```
grid_search.fit(features_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent work
ers.
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_ex
ecutor.py:706: UserWarning: A worker stopped while some jobs were given
to the executor. This can be caused by a too short worker timeout or by
a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 111.6min finished
```

Out[0]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decreas
e=0.0,
                                                   min_impurity_split=N
one,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_
leaf=0.0,
                                                   n_estimators=100,
                                                   n_jobs=None, oob_sco
re=False,
                                                   random_state=None, v
erbose=0,
                                                   warm_start=False),
                   iid='deprecated', n_iter=10, n_jobs=-1,
```

```
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [80, 90, 100, 11
0],
                                        'max_features': [2, 3],
                                        'min_samples_leaf': [3, 4, 5],
                                        'min_samples_split': [8, 10, 1
2],
                                        'n_estimators': [100, 200, 300,
1000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=2)
```

In [0]:
```
grid_search.best_params_
```

Out[0]:
```
{'bootstrap': True,
 'max_depth': 100,
 'max_features': 3,
 'min_samples_leaf': 5,
 'min_samples_split': 10,
 'n_estimators': 1000}
```

MODELING AND TRAINING

In [0]:
```
model=RandomForestRegressor(n_estimators=1000,max_depth=100,min_samples
_leaf=5,min_samples_split=10,bootstrap=True,max_features=3)
```

In [0]:
```
model.fit(features_train,y_train)
```

Out[0]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=100, max_features=3, max_leaf_nodes=Non
e,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=5,
                      min_samples_split=10, min_weight_fraction_leaf=0.
0,
```

```
                                  n_estimators=1000, n_jobs=None, oob_score=False,
                                  random_state=None, verbose=0, warm_start=False)
```

In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

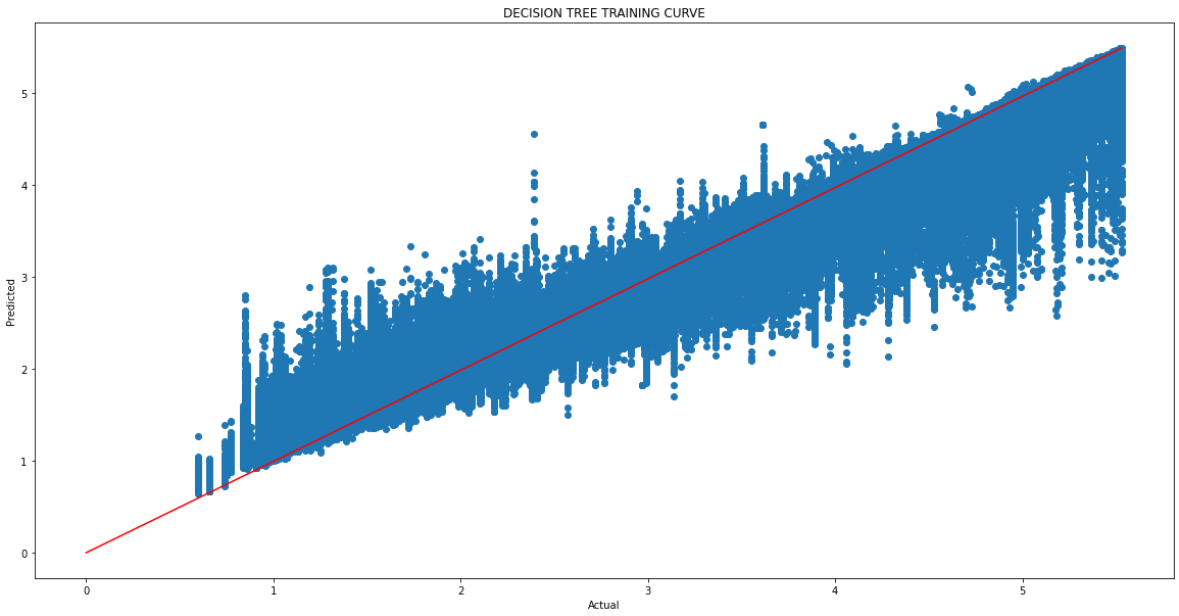
EVALUATION METRIC

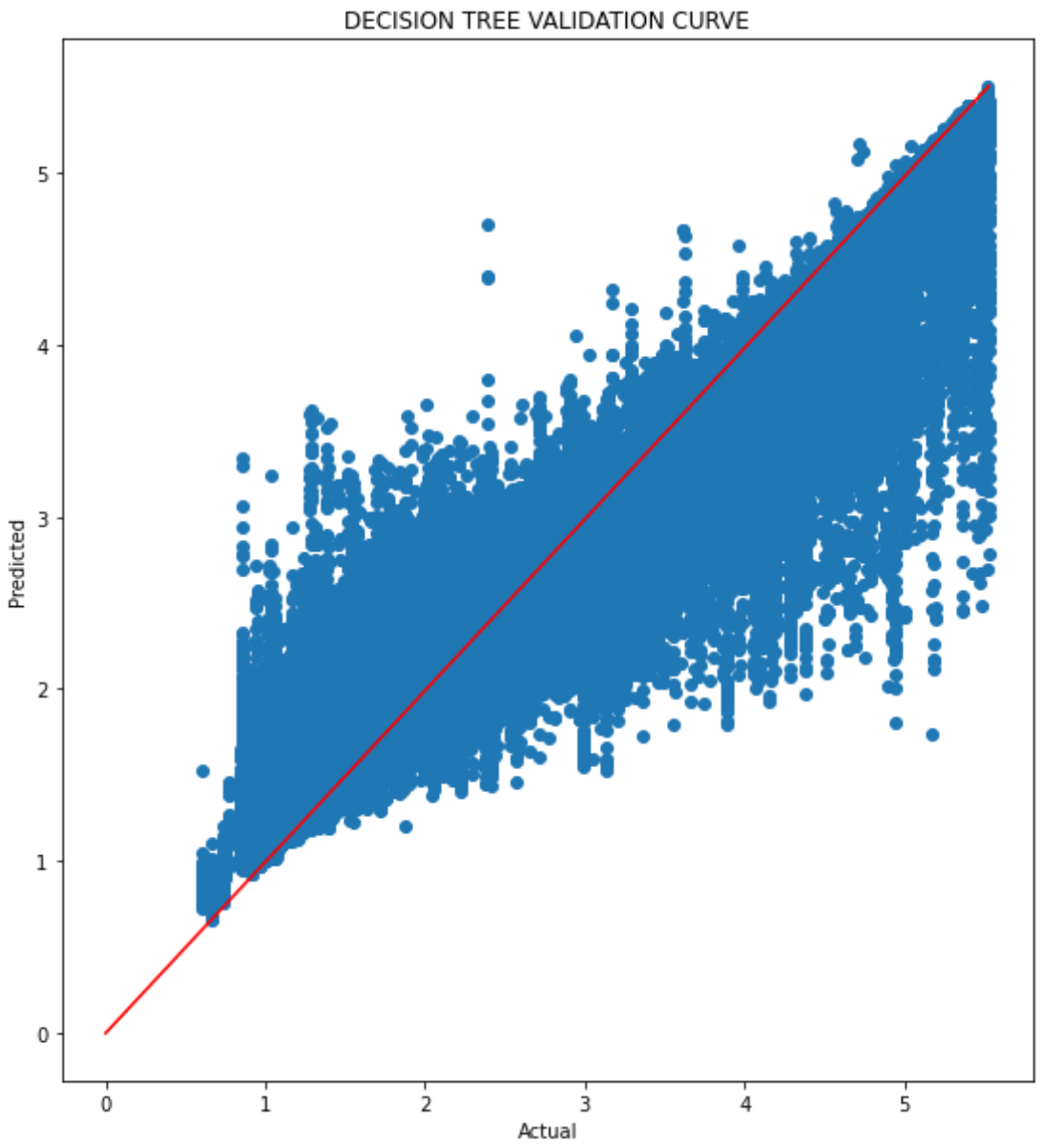
In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)

r2_train=r2_score(y_train,y_pred_train)

r2_test=r2_score(y_test,y_pred_test)
r2_cv=r2_score(y_cv,y_pred)
```

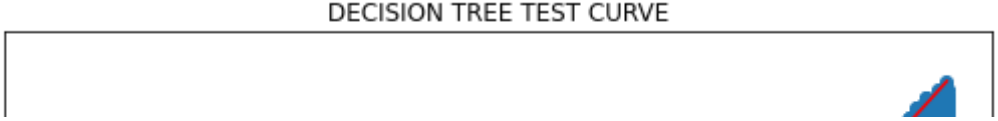
PLOTS

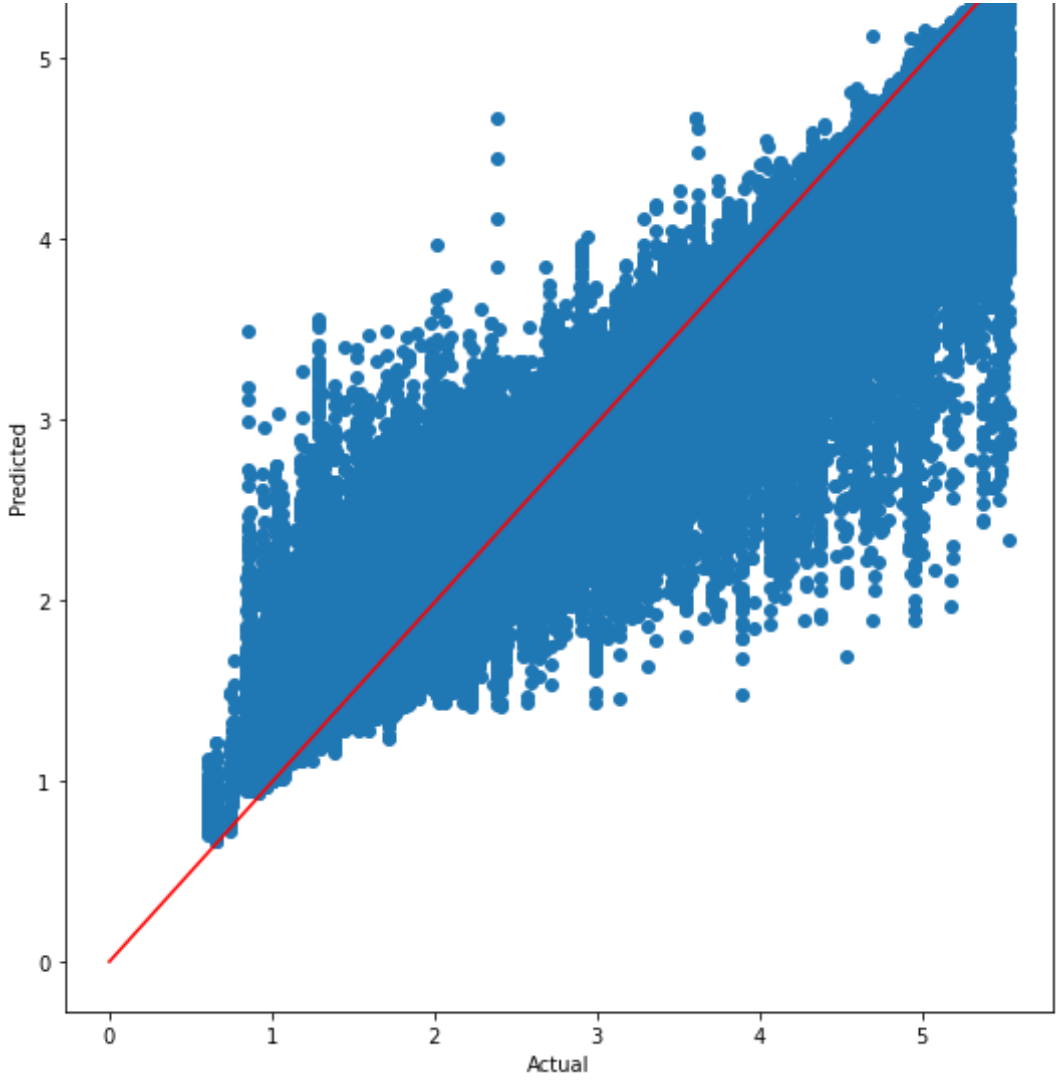
In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process


fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="P
redicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
```

```
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```









In [0]:
```
r2_train,r2_test,r2_cv,mse_cv,mse_test,mse_train
```

Out[0]:
```
(0.9420480289938656,
 0.8810794061401998,
 0.8822738867246521,
 0.148806436610639,
 0.15021040382178036,
 0.07352698184347983)
```

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.9420480289938656, 0.8822738867246521,0.8810794061401998])
```

```
print("********************R2 MODEL*********************")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([0.07352698184347983,0.148806436610639,0.15021040382178
036])
print("********************MSE MODEL*********************")
print(ptable1)
```

```
********************R2 MODEL*********************
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.9420480289938656 | 0.8822738867246521 | 0.8810794061401998 |
+--------------------+--------------------+--------------------+
********************MSE MODEL*********************
+---------------------+--------------------+---------------------+
|        train        |         cv         |         test        |
+---------------------+--------------------+---------------------+
| 0.07352698184347983 | 0.148806436610639 | 0.15021040382178036 |
+---------------------+--------------------+---------------------+
```

METRIC COMPARSION

1. R2 SCORE WITH IRON CONCENTRATE IS BETTER THAN MODEL WITHOUT IRON CONCENTRATE. THE MSE VALUES ARE ALSO BETTER THAN MODEL WITHOUT IRON CONCENTRATE. PREDICTING SILICA WITHOUT IRON DOES NOT GIVE BETTER RESULTS. WITH THE DOMAIN KNOWLEDGE , THE ONLY WAY TO PREDICT SILICA CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.
2. WHEN WE COMPARE DECIUSION AND RANDOMFOREST , DECISION TREE IS STILL DOING BETTER PERFORMANCE THANT RF

PLOTS COMPARISION

THE EVALUATION METRIC TELLS QUANTITAVELY WHILE THE PLOTS TELLS GRAPHICALLY IT IS VERY CLEAR THAT FROM BOTH THE GRAPHS HOW THE IRON CONCENTRATE PLAYS IMPORTANT ROLE IN THE PREDICTION.

TRAIN CURVE::

THE POINTS ARE FALLING SIMILAR TO THE TRAIN CURVE IN WITH IRON CONCENTRATE WITH SLIGHT DIFFERENCE.

TESTAND VALIDATION CURVE

THE POINTS ARE TOTALLY OUT OF LINE AND THIS TELLS THAT IRON CONCENTRATE PLAYS A MAJOR ROLE IN PREDICTING THE OUTPUT DURING THE TEST TIME.

WHEN WE COMPARE DECISION TREE, THOUGH DT IS BETTER WITH R2 SCORE BUT RANDOM FOREST IS BETTER WHEN WE COMAPRE THE TEST AND VALIDATION CURVE.

INFERENCES

PREDICTING SILICA WITHOUT IRON DOES NOT GIVE BETTER RESULTS. WITH THE DOMAIN KNOWLEDGE , THE ONLY WAY TO PREDICT SILICA CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.

ACCORDING TO DOMAIN KNOWLEDGE, BOTH IRON AND SILICA CONCENTRATE ARE TAKEN AS TARGET VARIBALES AND USING MULTI-TARGET REGRESSION THEY ARE PREDICTED . https://ieeexplore.ieee.org/abstract/document/8907120

XGBOOST

In [0]:
```
from sklearn.metrics import r2_score
```

```
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import numpy as np
```

In [0]:
```
import pandas as pd
```

In [0]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?
client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleuser
content.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_t
ype=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.t
est%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fw
ww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.go
ogleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
..........
Mounted at /content/drive
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
y = df['% Silica Concentrate']
X = df.drop(['% Silica Concentrate','index','datetime hours','% Iron Co
ncentrate'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
```

```
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.shape,features_cv.shape,y_train.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (471969,)
```

xgboost hyperparamter

In [0]:
```
import xgboost as xgb

from sklearn.model_selection import RandomizedSearchCV# Training a hyper-parameter tuned Xg-Boost regressor on our train data
# find more about XGBClassifier function here http://xgboost.readthedocs.io/en/latest/python/python_api.html?#xgboost.XGBClassifier
# ------------------------
# default paramters
# class xgboost.XGBClassifier(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True,
# objective='binary:logistic', booster='gbtree', n_jobs=1, nthread=None, gamma=0, min_child_weight=1,
# max_delta_step=0, subsample=1, colsample_bytree=1, colsample_bylevel=1, reg_alpha=0, reg_lambda=1,
# scale_pos_weight=1, base_score=0.5, random_state=0, seed=None, missing=None, **kwargs)
# some of methods of RandomForestRegressor()
# fit(X, y, sample_weight=None, eval_set=None, eval_metric=None, early_stopping_rounds=None, verbose=True, xgb_model=None)
# get_params([deep]) Get parameters for this estimator.
# predict(data, output_margin=False, ntree_limit=0) : Predict with data. NOTE: This function is not thread safe.
# get_score(importance_type='weight') -> get the feature importance
```

```
# ----------------------
# video link1: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/regression-using-decision-trees-2/
# video link2: https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/what-are-ensembles/
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html
x_cfl=xgb.XGBRegressor()
prams={'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],'n_estimators':[100,200,500,1000,2000],'max_depth':[3,5,10],'colsample_bytree':[0.1,0.3,0.5,1],'subsample':[0.1,0.3,0.5,1]}
random_cfl1=RandomizedSearchCV(x_cfl,param_distributions=prams,verbose=10,n_jobs=-1,)
random_cfl1.fit(features_train,y_train)
```

In [0]:
```
print (random_cfl1.best_params_)
```

MODELING TUNING AND EVALUTION METRIC

In [0]:
```
model=xgb.XGBRegressor(max_depth=10 ,learning_rate=0.01,n_estimators=1000 ,verbose=2,subsample=0.1,colsample_bytree=1)
model.fit(features_train,y_train)
```

```
[03:16:02] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

Out[0]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.01, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=None, n_estimators=1000,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.1, verbose=2, verbosity=1)
```

In [0]:
```
y_pred=model.predict(features_cv)
```

In [0]:
```
y_pred_train=model.predict(features_train)
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
```

In [0]:
```
r2_score(y_cv,y_pred)
```

Out[0]: 0.8075437262359364

In [0]:
```
r2_score(y_cv,y_pred)
```

Out[0]: 0.8075437262359364

In [0]:
```
mse_cv=mean_squared_error(y_pred,y_cv)
```

In [0]:
```
r2_score(y_train,y_pred_train)
```

Out[0]: 0.8237317967008811

In [0]:
```
y_pred_test=model.predict(features_test)
```

In [0]:
```
mse_test=mean_squared_error(y_test,y_pred_test)
```

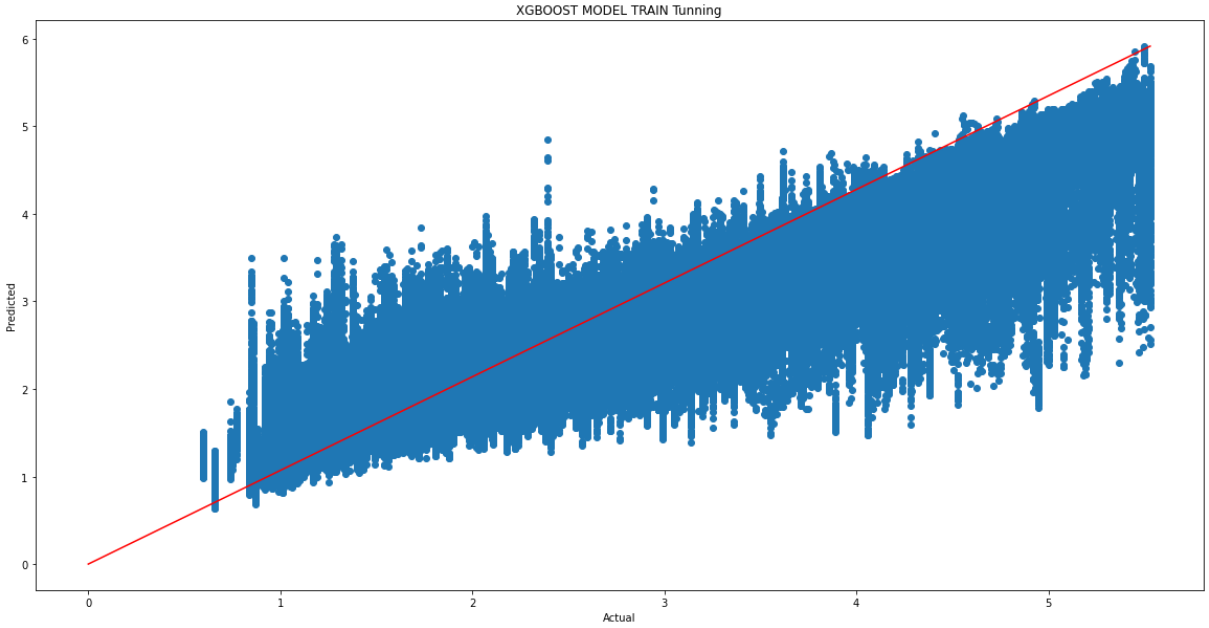
In [0]:
```
r2_score(y_test,y_pred_test)
```

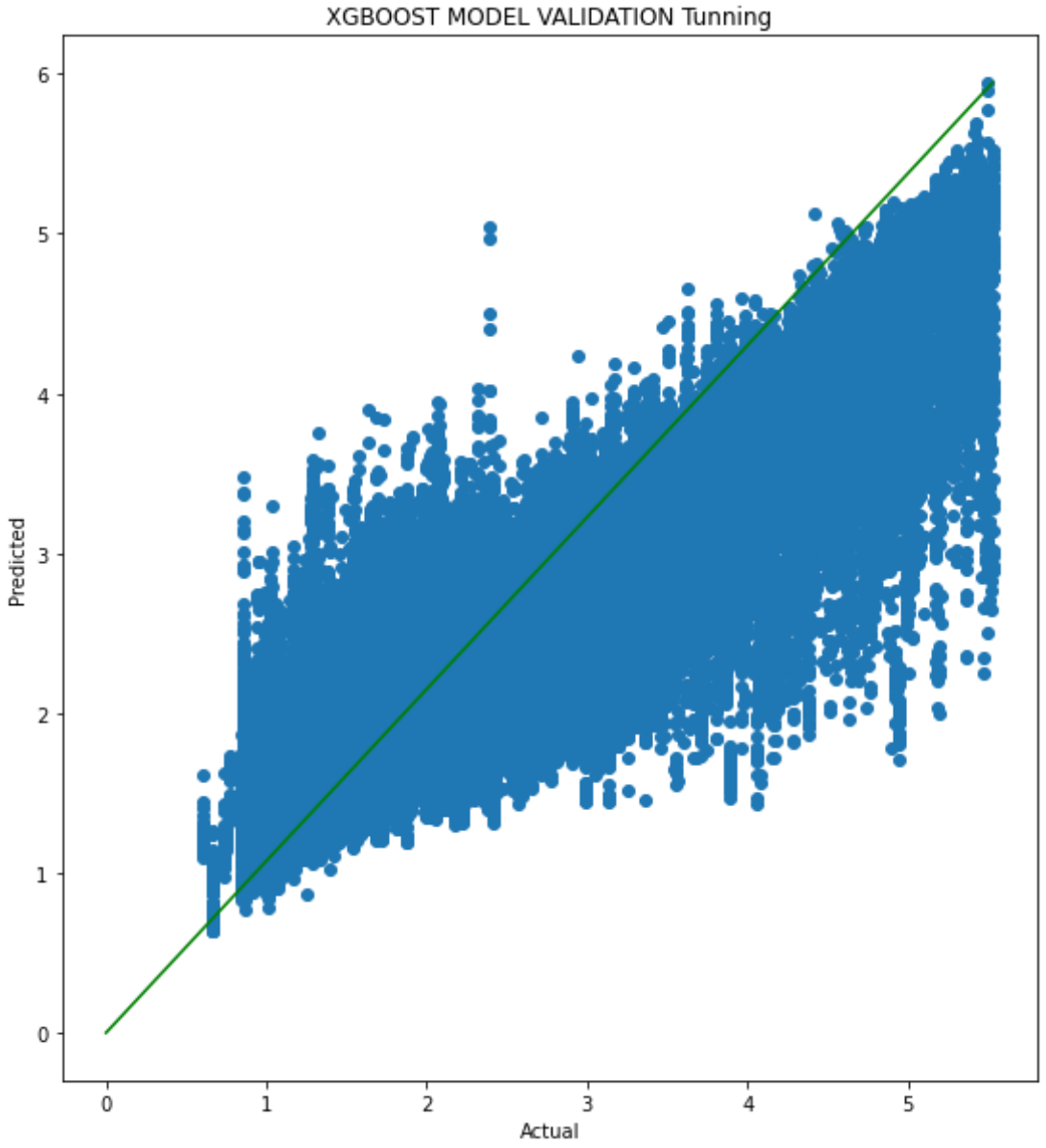
Out[0]: 0.8062174527677453

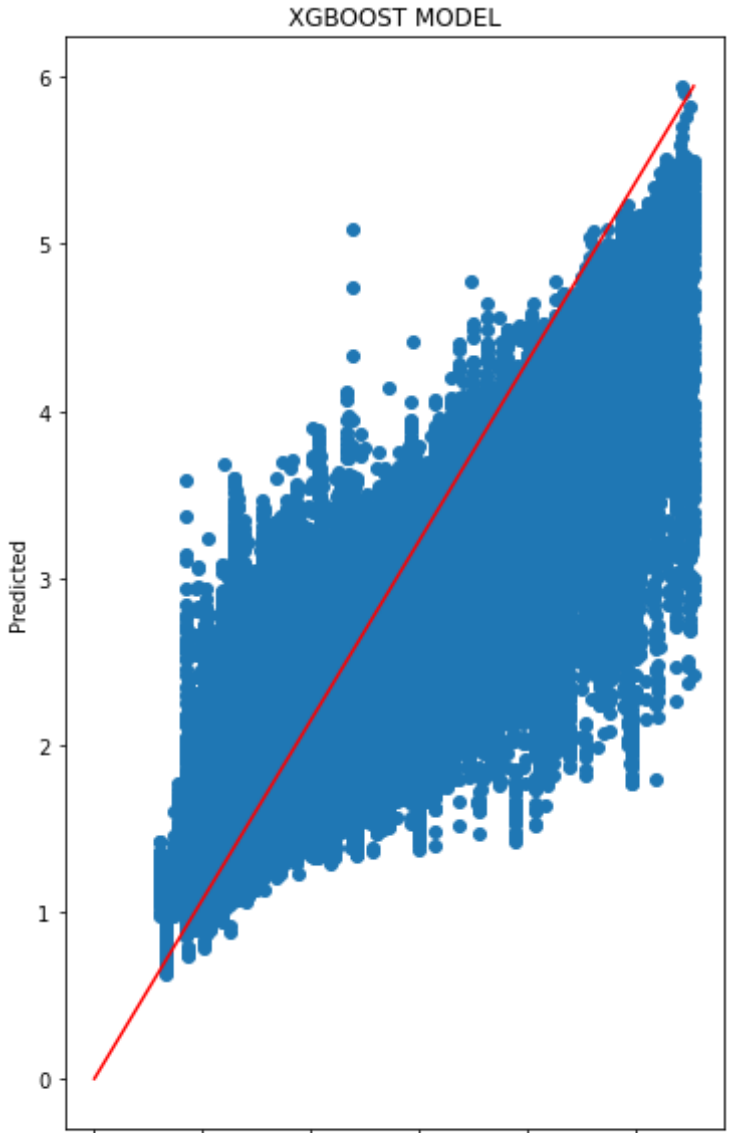
PLOTS

In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
```

```
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="XGBOOST MODEL TRAIN Tunning", xlabel="Actual", ylabel="Pr
edicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="XGBOOST MODEL VALIDATION Tunning", xlabel="Actual", ylabe
l="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv)], [0,max(y_pred)], color='g')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(131)
ax.set(title="XGBOOST MODEL", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```







REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([0.8237317967008811,0.8075437262359364,0.8062174527677453])
print("********************R2 MODEL**********************")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
```

```
ptable1.field_names = ['train','cv','test']
ptable1.add_row([mse_train,mse_cv,mse_test])
print("********************MSE MODEL**********************")
print(ptable1)
```

```
********************R2 MODEL********************
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 0.8237317967008811 | 0.8075437262359364 | 0.8062174527677453 |
+--------------------+--------------------+--------------------+
********************MSE MODEL**********************
+---------------------+---------------------+---------------------+
|        train        |          cv         |         test        |
+---------------------+---------------------+---------------------+
| 0.22364155624983353 | 0.24326575901821534 | 0.24476967132948285 |
+---------------------+---------------------+---------------------+
```

METRIC COMPARSION

1. R2 SCORE WITH IRON CONCENTRATE IS BETTER THAN MODEL WITHOUT IRON CONCENTRATE. THE MSE VALUES ARE ALSO BETTER THAN MODEL WITHOUT IRON CONCENTRATE. PREDICTING SILICA WITHOUT IRON DOES NOT GIVE BETTER RESULTS. WITH THE DOMAIN KNOWLEDGE , THE ONLY WAY TO PREDICT SILICA CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.
2. WHEN WE COMPARE DECISION AND RANDOMFOREST , DECISION TREE IS STILL DOING BETTER PERFORMANCE THANT XGBOOST

DT>RF>XGB

PLOTS COMPARISION

THE EVALUATION METRIC TELLS QUANTITAVELY WHILE THE PLOTS TELLS GRAPHICALLY IT IS VERY CLEAR THAT FROM BOTH THE GRAPHS HOW THE IRON

CONCENTRATE PLAYS IMPORTANT ROLE IN THE PREDICTION.

TRAIN CURVE::

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TESTAND VALIDATION CURVE

THE POINTS ARE TOTALLY OUT OF LINE AND THIS TELLS THAT IRON CONCENTRATE PLAYS A MAJOR ROLE IN PREDICTING THE OUTPUT DURING THE TEST TIME.

WHEN WE COMPARE DECISION TREE, THOUGH DT IS BETTER WITH R2 SCORE BUT XGBBOST IS BETTER WHEN WE COMAPRE THE TEST AND VALIDATION CURVE.

INFERENCES

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ACCORDING TO DOMAIN KNOWLEDGE, BOTH IRON AND SILICA CONCENTRATE ARE TAKEN AS TARGET VARIBALES AND USING MULTI-TARGET REGRESSION THEY ARE PREDICTED . https://ieeexplore.ieee.org/abstract/document/8907120

RIDGE REGRESSION

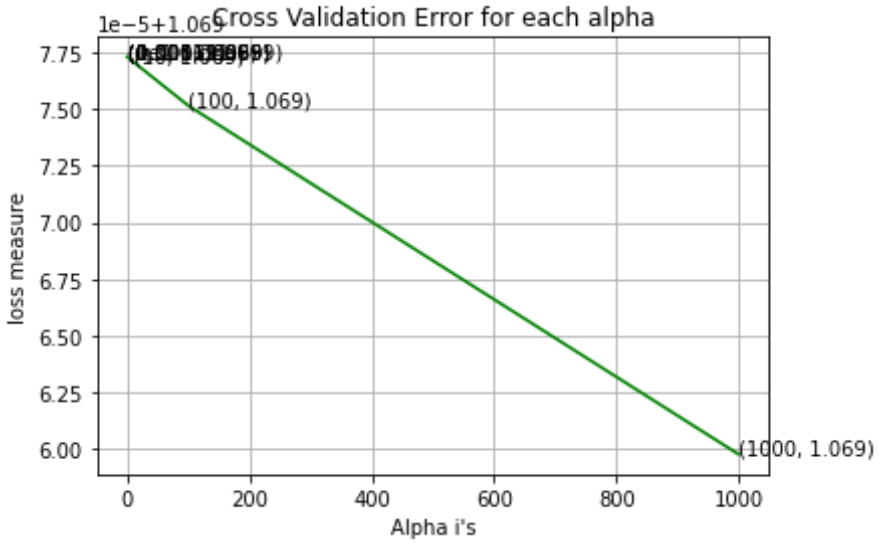
In [0]:
```
from sklearn.linear_model import Ridge
alpha = [10 ** x for x in range(-5, 4)]
loss_array=[]

for i in alpha:
    model = Ridge(alpha = i, random_state=0)
```

```
    model.fit(features_train,y_train)
    predict_y = model.predict(features_cv)

    loss_array.append(mean_squared_error(y_cv, predict_y))

for i in range(len(loss_array)):
 print ('loss for alpha = ',alpha[i],'is',loss_array[i])
```

```
loss for alpha =  1e-05 is 1.0690773049738236
loss for alpha =  0.0001 is 1.0690773049718407
loss for alpha =  0.001 is 1.0690773049520133
loss for alpha =  0.01 is 1.0690773047537423
loss for alpha =  0.1 is 1.0690773027710734
loss for alpha =  1 is 1.0690772829485258
loss for alpha =  10 is 1.0690770851371265
loss for alpha =  100 is 1.069075148269827
loss for alpha =  1000 is 1.0690597533629427
```

In [0]:

```
#code snippet taken from microsoft malware detection case study noteboo
k-- to get the idea to get the graphs
#https://classroom.appliedcourse.com/classrooms/jEARG7xb/assignments/q2
AJp9B5/users/jEARG7xb
best_alpha = np.argmin(loss_array)

fig, ax = plt.subplots()
ax.plot(alpha, loss_array,c='g')
for i, txt in enumerate(np.round(loss_array,3)):
 ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],loss_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("loss measure")
plt.show()
```



In [0]:
```
best_alpha=1000
```

In [0]:
```
model = Ridge(alpha =1000, random_state=0)
model.fit(features_train,y_train)
predict_y = model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,predict_y)
mse_test=mean_squared_error(y_test,y_pred_test)
r2_train=r2_score(y_train,y_pred_train)
r2_cv=r2_score(y_cv,predict_y)
r2_test=r2_score(y_test,y_pred_test)
```

REPORT

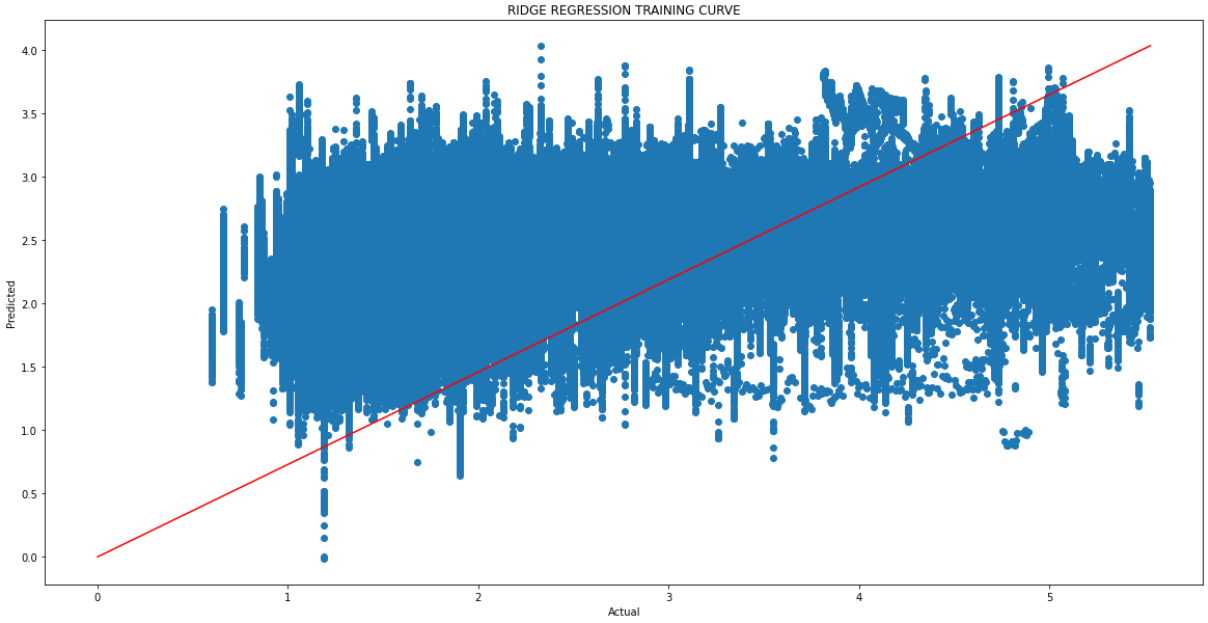
In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model R2 "
ptable.field_names = ['train','cv','test']
ptable.add_row([r2_train,r2_cv,r2_test])
print("********************R2 MODEL**********************")
print(ptable)
ptable1 = PrettyTable()
ptable1.title = " Model MSE "
ptable1.field_names = ['train','cv','test']
ptable1.add_row([mse_train,mse_cv,mse_test])
print("********************MSE MODEL**********************")
print(ptable1)
```

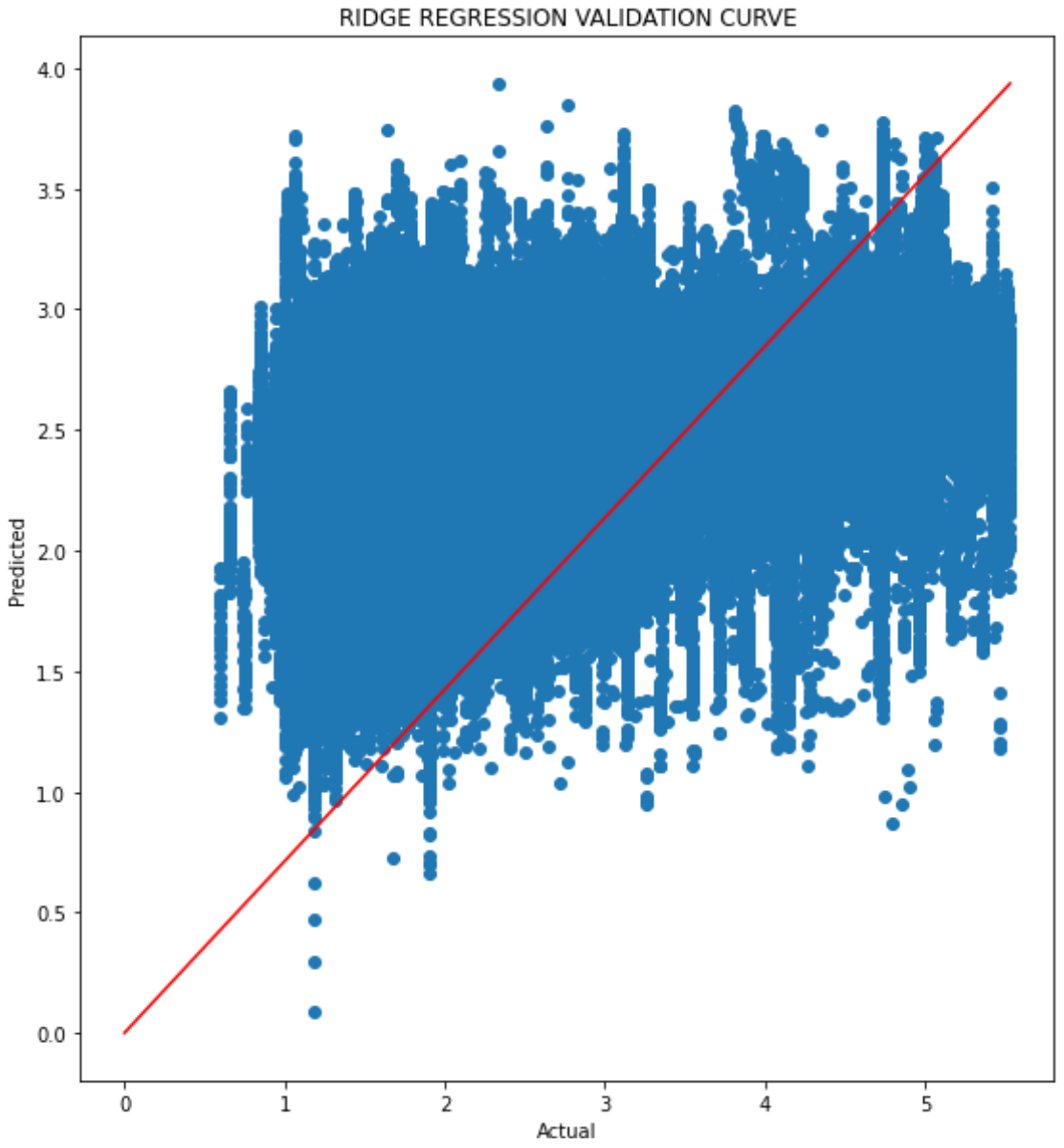
```
********************R2 MODEL**********************
+---------------------+---------------------+---------------------+
|        train        |          cv         |         test        |
+---------------------+---------------------+---------------------+
| 0.15249283591693252 | 0.15422845618007952 | 0.15304179428151088 |
+---------------------+---------------------+---------------------+
********************MSE MODEL**********************
+--------------------+--------------------+--------------------+
|       train        |         cv         |        test        |
+--------------------+--------------------+--------------------+
| 1.0752808365941273 | 1.0690597533629427 | 1.0698057415617288 |
+--------------------+--------------------+--------------------+
```

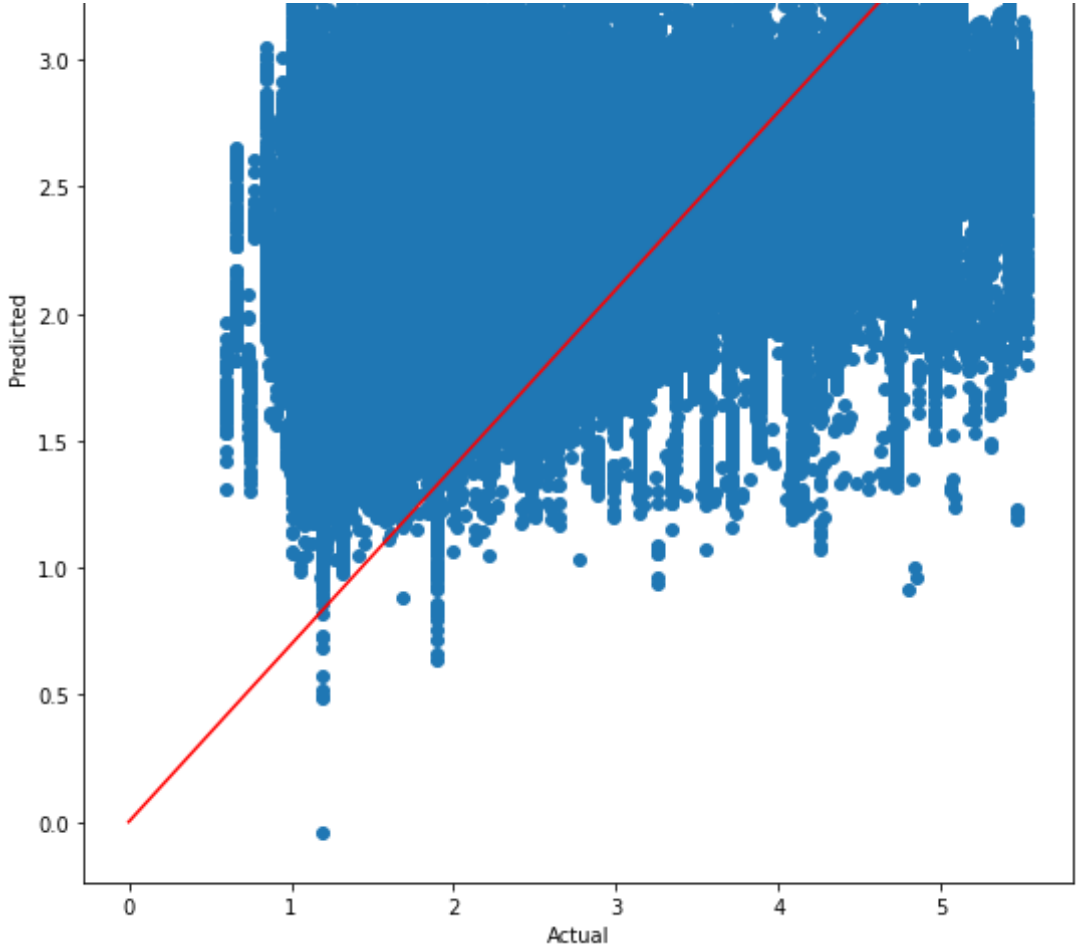
PLOTS

In [0]:
```
#https://www.kaggle.com/farrasalyafi/the-flotation
```

```
#https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-pro
cess
#https://www.datasciencecentral.com/profiles/blogs/regression-analysis-
how-do-i-interpret-r-squared-and-assess-the
#https://www.kaggle.com/danofer/get-minig-data-process
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="RIDGE REGRESSION TRAINING CURVE", xlabel="Actual", ylabel
="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train)], [0,max(y_pred_train)], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RIDGE REGRESSION VALIDATION CURVE", xlabel="Actual", ylab
el="Predicted")
ax.scatter(y_cv, predict_y)
ax.plot([0,max(y_cv)], [0,max(predict_y)], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RIDGE REGRESSION TEST CURVE", xlabel="Actual", ylabel="Pr
edicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test)], [0,max(y_pred_test)], color='r')
fig.show()
```







METRIC COMPARSION

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CONCENTRATE IS TO LAG THE PREDICTION OF IRON CONCENTRATE WHILE DOING EXPERIMENTS PREDICT THE SILICA AFTERWARDS.

2. WHEN WE COMPARE DECISION AND RANDOMFOREST , DECISION TREE IS STILL DOING BETTER PERFORMANCE THAN RIDGE

DT>RF>XGB>RIDGE

PLOTS COMPARISION

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TESTAND VALIDATION CURVE

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WHEN WE COMPARE DECISION TREE, THOUGH DT IS BETTER WITH R2 SCORE BUT XGBBOST IS BETTER WHEN WE COMAPRE THE TEST AND VALIDATION CURVE.

INFERENCES

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OVERALL COMPARSION

In [0]:
```
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MSE_CV","MSE_TEST"]
x.add_row(["RIDGE WITHOUT IRON CONCENTRATE",0.1524,0.154,0.1530,1.0752,1.0690,1.0698])
x.add_row(["RIDGE",0.693,0.678,0.680,0.406,0.406,0.403])

x.add_row(["XGBOOST  WITHOUT IRON CONCENTRATE",0.823,0.807,0.806,0.223,0.243,0.244])
x.add_row(["XGBOOST",0.9795,0.9773,0.9775,0.025,0.028,0.030])
x.add_row(["DECISION TREE WITHOUT IRON CONCENTRATE",0.9967,0.882,0.881,0.004,0.126,0.133])
x.add_row(["DECISION TREE ",0.9998,0.9993,0.9928,0.0001,0.008,0.009])
x.add_row(["RANDOMFOREST WITHOUT IRON CONCENTRATE",0.9420,0.882,0.881,0.0734,0.148,0.1502])
x.add_row(["RANDOMFOREST ",0.9914,0.9822,0.9822,0.010,0.022,0.022])


print(x)
```

```
+-------------------------------------------------------------------+-
-----------------------------------+-------------------------------
---+-----------------------------------+-----------------------------
----------+-----------------------------------+----------------------
--------------+
|                                  MODEL1                           |
             R2_TRAIN                 |              R2_CV
   |              R2_TEST               |              MSE_TRAIN
         |               MSE_CV              |               MSE_TEST
              |
```

```
+-------------------------------------------------------------------+-
-----------------------------------+-------------------------------
---+-----------------------------------+-----------------------------
----------+-----------------------------------+----------------------
---------------+
|                    RIDGE WITHOUT IRON CONCENTRATE                 |
                0.1524                |               0.154
   |                0.153                |                 1.0752
           |                1.069                |                1.0698
                |
|                                RIDGE                              |
                0.693                 |               0.678
   |                 0.68                 |                 0.406
           |                0.406                |                0.403
                |
|                  XGBOOST  WITHOUT IRON CONCENTRATE                |
                0.823                 |               0.807
   |                0.806                |                 0.223
           |                0.243                |                0.244
                |
|                                XGBOOST                            |
                0.9795                |               0.9773
   |                0.9775               |                 0.025
           |                0.028                |                 0.03
                |
|                 DECISION TREE WITHOUT IRON CONCENTRATE            |
                0.9967                |               0.882
   |                0.881                |                 0.004
           |                0.126                |                0.133
                |
|                              DECISION TREE                        |
                0.9998                |               0.9993
   |                0.9928               |                 0.0001
           |                0.008                |                0.009
                |
|                 RANDOMFOREST WITHOUT IRON CONCENTRATE             |
                0.942                 |               0.882
   |                0.881                |                 0.0734
           |                0.148                |                0.1502
                |
```

```
|                            RANDOMFOREST                           |
               0.9914                  |              0.9822
   |                0.9822                 |                 0.01

          |              0.022                 |                 0.022
               |
+-------------------------------------------------------------------+-
------------------------------------+----------------------------------
---+------------------------------------+-----------------------------
----------+------------------------------------+----------------------
---------------+
```

SUMMARY

1. THE IRON CONCENTRATE IS IMPORTANT TO PREDICT THE SILICA CONCENTRATE. https://www.scielo.br/scielo.php?script=sci_arttext&pid=S2448-167X2018000200299
2. IRON CONCENTRATE AND SILICA VCONCENTRATE ARE HIGHLY CORRELATED.
3. DECISION TREE HAS BETTER PERFORMANCE.
4. TIME CONSUMPTION FOR TUNING HYPERPARAMTER OF RF, XGBOOST IS HIGHER.
5. RIDGE MODEL IS NOT ADVISBLE TO USE IN REAL-TIME

ALTERNATIVE APPROACH

1. https://ieeexplore.ieee.org/abstract/document/8907120

INSTEAD OF PRECITING ONE TRAGET VARIBALES, SINCE , IRON AND SILICA ARE BOTH ARE HIGHLY DEPENDENT WE CAN USE BOTH CONCENTRATE AS TWO TARGET VARIBALES

MULTI-TARGET REGRESSION

INTRODUCTION

When multiple dependent variables exist in a regression model, this task is called as multi-target regression. In this case, a multi-output regressor is employed to learn the mapping from input features to output variables jointly. In this study, multi-target regression technique is implemented for quality prediction in a mining process to estimate the amount of silica and iron concentrates in the ore at the end of the process.

In this study, two inter-dependent single target regression tasks are transformed into a multiple output regression problem for quality prediction in a mining process.

In the pervious models have been conducted to estimate silica concentrate with or without taking iron concentrate as input parameter. In this aspect, the problem is a single-target regression problem. However, this study that focuses on the estimation of both iron and silica concentrates simultaneously as output variables. We compared different multi-target regressors that use Random Forest, AdaBoost, XGBOOST ,RIDGE and Decision Tree algorithms separately in the background. Coefficient of determination (R2) metric and MSE was used to evaluate predictive performance of the regression methods for the mentioned data.

METHODS TO IMPLEMENT MTR

Problem transformation methods

1. These methods are mainly based on transforming the multi-output regression problem into single-target problems, then building a model for each target, and finally concatenating all the d predictions. The main drawback of these methods is that the relationships among the targets are ignored, and the targets are predicted independently, which may affect the overall quality of the predictions.
2. **Regressor chains (RC) method**

   It is inspired by the recent multi-label chain classifiers 31. RC is another problem transformation method, based on the idea of chaining single-target models. The training of RC consists of selecting a random chain (i.e., permutation) of the set of target variables,

then building a separate regression model for each target following the order of the selected chain.

3. **Single traget model**

   output variables are estimated independently and potential relations between them cannot be exploited

RELATED WORKS

https://ieeexplore.ieee.org/abstract/document/8907120Y

The paper focus on inherent multiregressor models and concluded to it is best to predict silica and iron concentrate at the same time.

NEW METHODS

https://machinelearningmastery.com/multi-output-regression-models-with-python/

My work focus on following implementation:

1. To see whether the %silica concentrate can be predicted without iron concentrate and result showed us it is not good to predict silica concentrate withou iron concentrate . Hence, to solve the problem we can implement the multitarget regression method to predict both target variables at same time.
2. To try differnt models which is not inherent multitarget regression models like Randomforest,Ridge,Xgboost
3. To finalize the best model with R2 as well as MSE metric.

RIDGE REGRESSOR

DATA MODELING

In [0]:
```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
```

In [0]:
```
#code snippet taken from microsoft malware detection case study noteboo
k-- to get the idea to get the graphs
#https://classroom.appliedcourse.com/classrooms/jEARG7xb/assignments/q2
AJp9B5/users/jEARG7xb
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
y = df.iloc[:,23:25]
X = df.drop(['% Silica Concentrate','% Iron Concentrate','index','datet
ime hours'], axis=1)
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)

scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)

features_cv = scale_features_std.transform(X_cv)

print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape,y_cv.shape,y_test.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (47196
9, 2) (117993, 2) (147491, 2)
```

USING SKLEARN MULTIOUTPUT REGRESSOR

METHOD

In [0]:
```
#https://machinelearningmastery.com/multi-output-regression-models-with-python/
#https://stackoverflow.com/questions/50132322/how-does-multiple-target-ridge-regression-work-in-scikit-learn

from sklearn.multioutput import MultiOutputRegressor
```

In [0]:
```
model = MultiOutputRegressor(Ridge(alpha=1000,random_state=0))
model.fit(features_train, y_train)
```

Out[0]:
```
MultiOutputRegressor(estimator=Ridge(alpha=1000, copy_X=True,
                                     fit_intercept=True, max_iter=None,
                                     normalize=False, random_state=0,
                                     solver='auto', tol=0.001),
                     n_jobs=None)
```

PREDICTION

In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

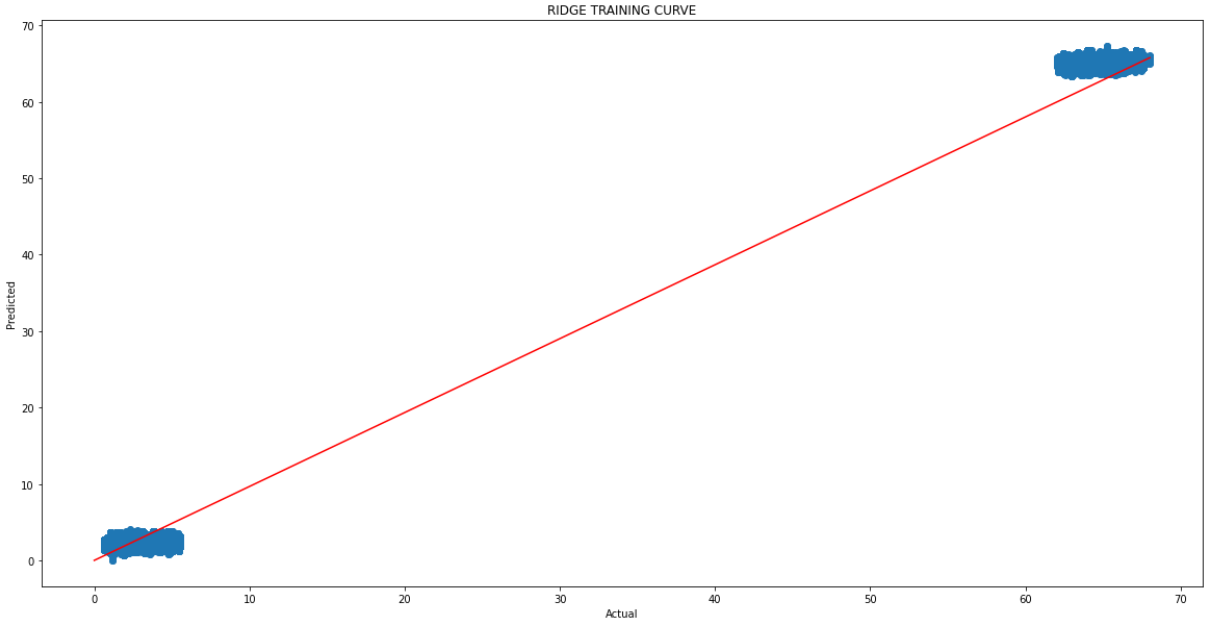
In [0]:
```
r2_train=r2_score(y_train,y_pred_train)
r2_cv=r2_score(y_cv,y_pred)
r2_test=r2_score(y_test,y_pred_test)
```

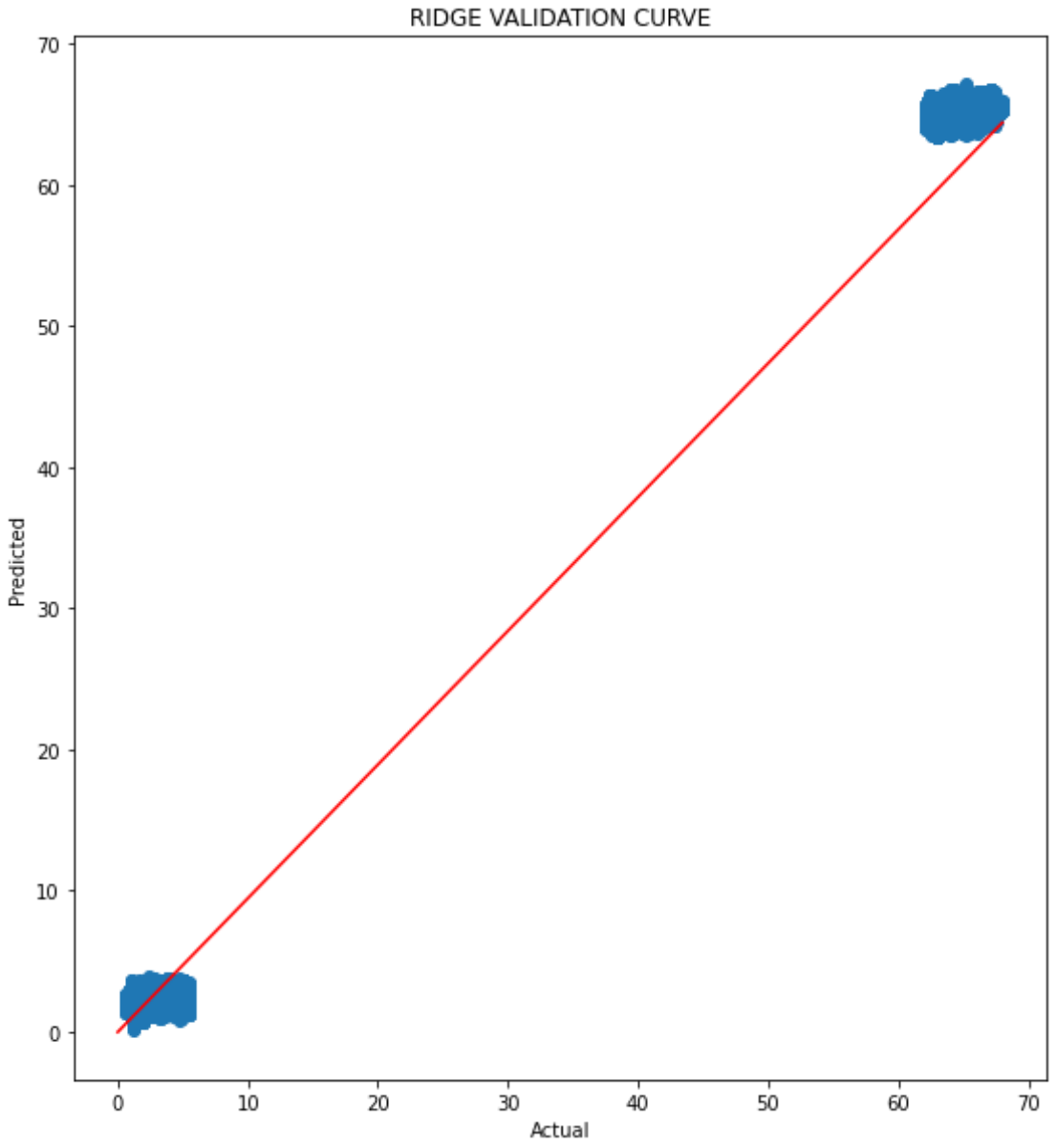
In [0]:
```
r2_train,r2_cv,r2_test,mse_cv,mse_test,mse_train,mse_cv
```

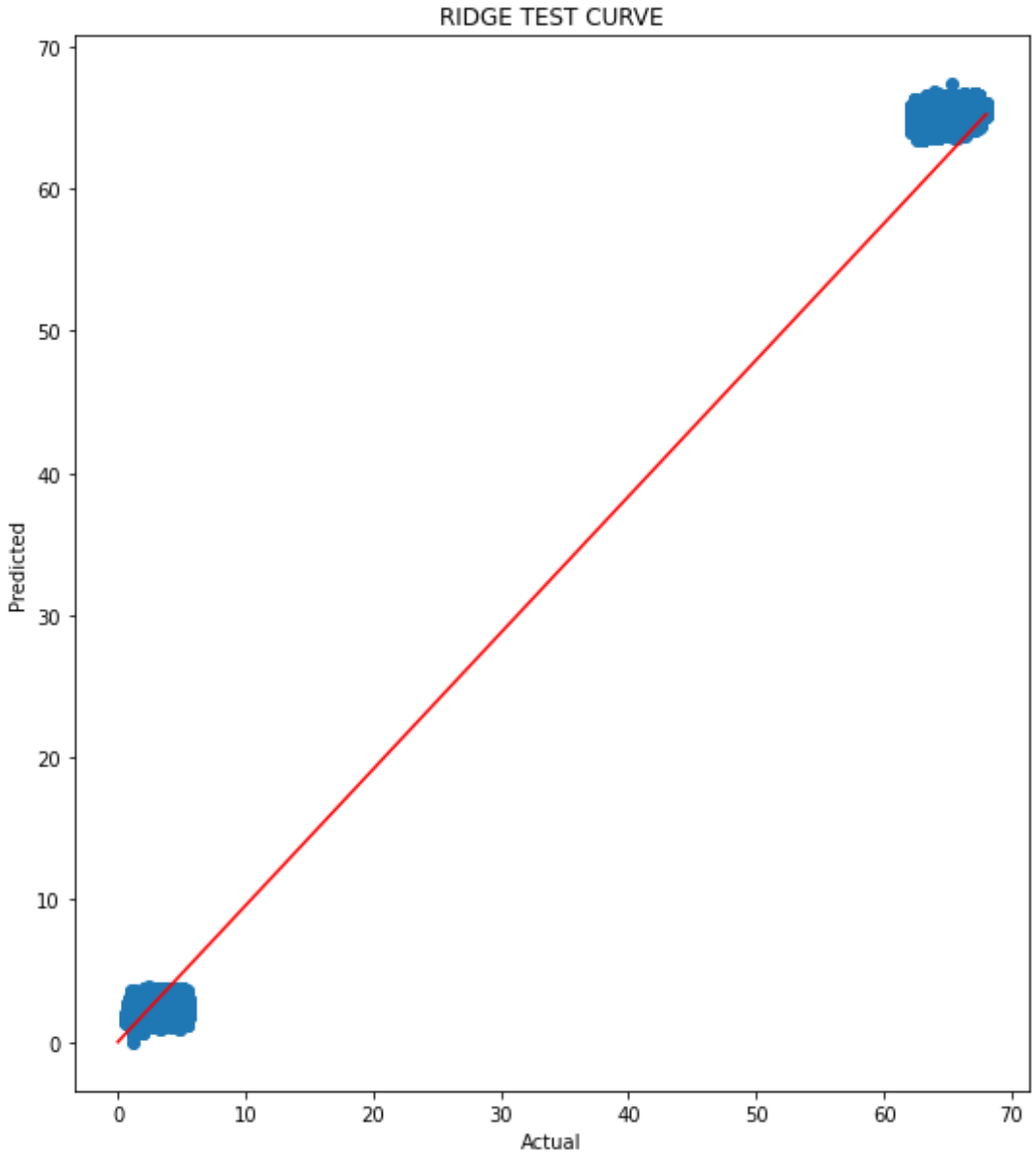
Out[0]:
```
(0.1457070772811201,
 0.14798745903277455,
 0.1466686774031905,
 1.0722436207597437,
 1.0729684678403668,
 1.076168464619778,
 1.0722436207597437)
```

PLOTS UDING MTR METHOD

In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="RIDGE TRAINING CURVE", xlabel="Actual", ylabel="Predicte
d")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RIDGE VALIDATION CURVE", xlabel="Actual", ylabel="Predict
ed")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RIDGE TEST CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```







USING REGRESSION CHAIN METHOD

In [0]:
```
from sklearn.multioutput import RegressorChain
```

In [0]:
```
model = Ridge(alpha =1000, random_state=123)
wrapper1 = RegressorChain(model,cv=5)
wrapper1.fit(features_train,y_train)
```

Out[0]:
```
RegressorChain(base_estimator=Ridge(alpha=1000, copy_X=True, fit_interc
ept=True,
                                    max_iter=None, normalize=False,
                                    random_state=123, solver='auto',
```

```
                                        tol=0.001),
          cv=5, order=None, random_state=None)
```

PREDICTION

In [0]:
```
y_pred_cv=wrapper1.predict(features_cv)
y_pred_train=wrapper1.predict(features_train)
y_pred_test=wrapper1.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
r2_cv=r2_score(y_pred_cv,y_cv)
r2_train=r2_score(y_pred_train,y_train)
r2_test=r2_score(y_pred_test,y_test)
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

In [0]:
```
r2_train,r2_cv,r2_test,mse_train,mse_cv,mse_test
```

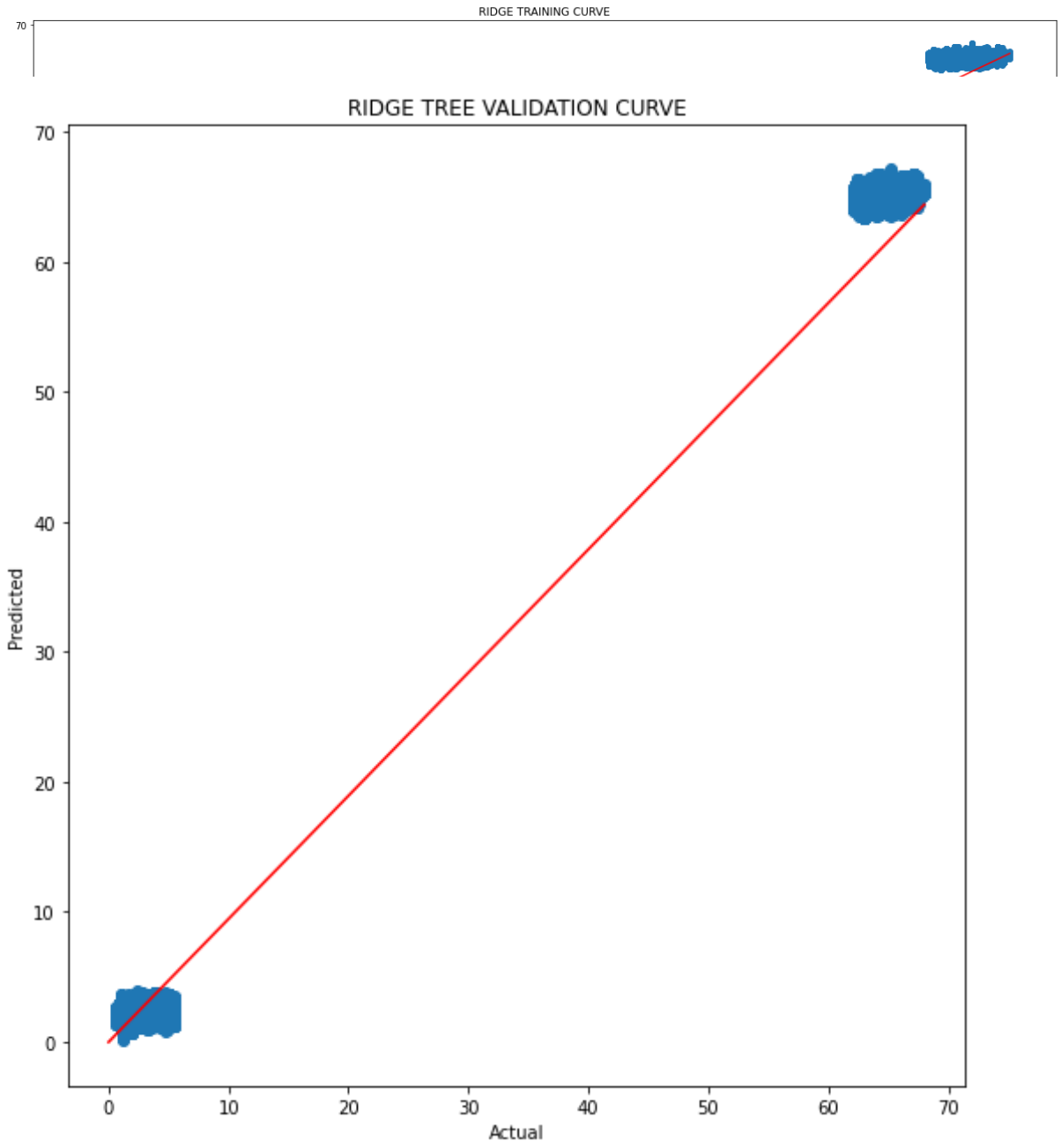
Out[0]:
```
(0.1457070772811201,
 0.14798745903277455,
 0.1466686774031905,
 1.0761683118743428,
 1.0722436207597437,
 1.0729682609689142)
```

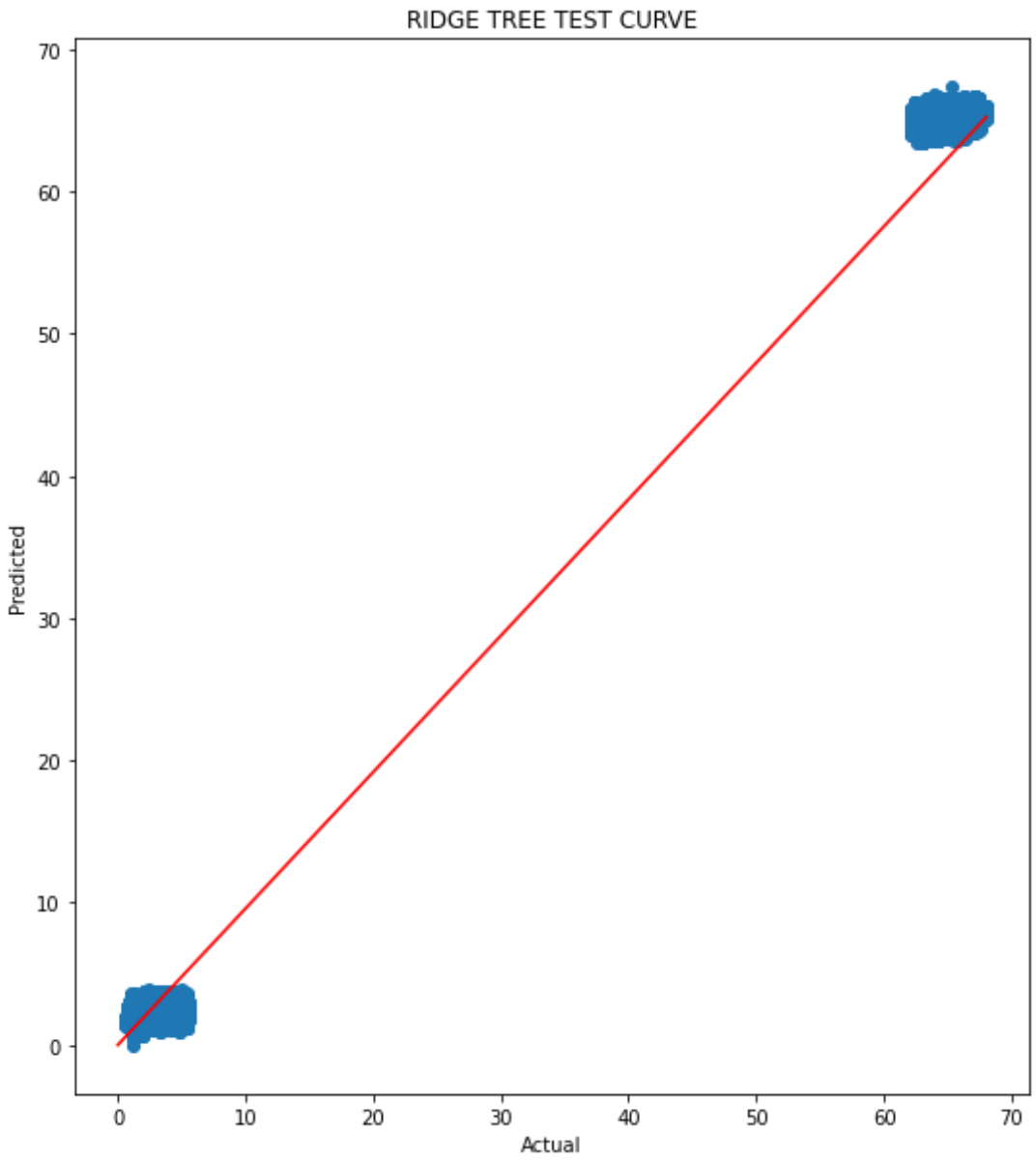
PLOTS

In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
```

```
ax.set(title="RIDGE TRAINING CURVE", xlabel="Actual", ylabel="Predicte
d")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RIDGE TREE VALIDATION CURVE", xlabel="Actual", ylabel="Pr
edicted")
ax.scatter(y_cv, y_pred_cv)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RIDGE TREE TEST CURVE", xlabel="Actual", ylabel="Predicte
d")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')

fig.show()
```





SINGLE TARGET REGRESSSION METHOD(NAIVE METHOD)

MODEL TO PREDICT IRON CONCENTRATE

In [0]:
```
y = df['% Iron Concentrate']
X = df.drop(['% Iron Concentrate','index','datetime hours'], axis=1)

from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)

X_train, X_cv, y_train, y_cv1 = train_test_split(X_train, y_train,test_
size=0.20,random_state=30)

from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)

features_cv = scale_features_std.transform(X_cv)

print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape)

model=Ridge(alpha =1000, random_state=0)
model.fit(features_train,y_train)

y_pred_train_iron=model.predict(features_train)
y_pred_cv_iron=model.predict(features_cv)
y_pred_test_iron=model.predict(features_test)

r2_cv_iron=r2_score(y_pred_cv_iron,y_cv1)
r2_train_iron=r2_score(y_pred_train_iron,y_train)
r2_test_iron=r2_score(y_pred_test_iron,y_test)

mse_train_iron=mean_squared_error(y_train,y_pred_train_iron)
mse_test_iron=mean_squared_error(y_test,y_pred_test_iron)
mse_cv_iron=mean_squared_error(y_cv1,y_pred_cv_iron)

r2_train_iron,r2_cv_iron,r2_test_iron,mse_train_iron,mse_cv_iron,mse_te
st_iron
```

```
(471969, 22) (471969, 22) (147491, 22) (147491, 22) (117993, 22) (47196
9,)
```

Out[0]:
```
(0.514535485002991,
 0.5123168325856021,
 0.5157302218318192,
 0.4075275992681477
```

```
0.40752759926814774,
0.4091846624430369,
0.40599913412920674)
```

MODEL TO PREDICT SILICA CONCENTRATE

In [0]:

```
y = df['% Silica Concentrate']
X = df.drop(['% Silica Concentrate','index','datetime hours'], axis=1)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)

X_train, X_cv, y_train, y_cv2 = train_test_split(X_train, y_train,test_
size=0.20,random_state=30)

from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)

features_cv = scale_features_std.transform(X_cv)

print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape)


model.fit(features_train,y_train)

y_pred_train_silica=model.predict(features_train)
y_pred_cv_silica=model.predict(features_cv)
y_pred_test_silica=model.predict(features_test)


r2_cv_silica=r2_score(y_pred_cv_silica,y_cv2)
r2_train_silica=r2_score(y_pred_train_silica,y_train)
r2_test_silica=r2_score(y_pred_test_silica,y_test)
```

```
mse_train_silica=mean_squared_error(y_train,y_pred_train_silica)
mse_test_silica=mean_squared_error(y_test,y_pred_test_silica)
mse_cv_silica=mean_squared_error(y_cv2,y_pred_cv_silica)

r2_train_silica,r2_cv_silica,r2_test_silica,mse_train_silica,mse_cv_sil
ica,mse_test_silica
```

```
(471969, 22) (471969, 22) (147491, 22) (147491, 22) (117993, 22) (47196
9,)
```

Out[0]:

```
(0.5259529825712774,
 0.526453891816218,
 0.5288178307374647,
 0.4068563070630419,
 0.4067576473714793,
 0.4035943750209711)
```

CONCATENATION OF TWO PREDICTIONS

In [0]:

```
import numpy as np

y_pred_train_iron=y_pred_train_iron.reshape(-1,1)
y_pred_cv_iron=y_pred_cv_iron.reshape(-1,1)
y_pred_test_iron=y_pred_test_iron.reshape(-1,1)
y_pred_train_silica=y_pred_train_silica.reshape(-1,1)
y_pred_cv_silica=y_pred_cv_silica.reshape(-1,1)
y_pred_test_silica=y_pred_test_silica.reshape(-1,1)


y_pred_train=np.concatenate((y_pred_train_iron,y_pred_train_silica),axi
s=1)
y_pred_cv=np.concatenate((y_pred_cv_iron,y_pred_cv_silica),axis=1)
y_pred_test=np.concatenate((y_pred_test_iron,y_pred_test_silica),axis=1
)

r2_cv=r2_score(y_pred_cv,y_cv)
r2_train=r2_score(y_pred_train,y_train)
r2_test=r2_score(y_pred_test,y_test)
```

```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred_cv)

r2_train,r2_cv,r2_test,mse_train,mse_cv,mse_test
```

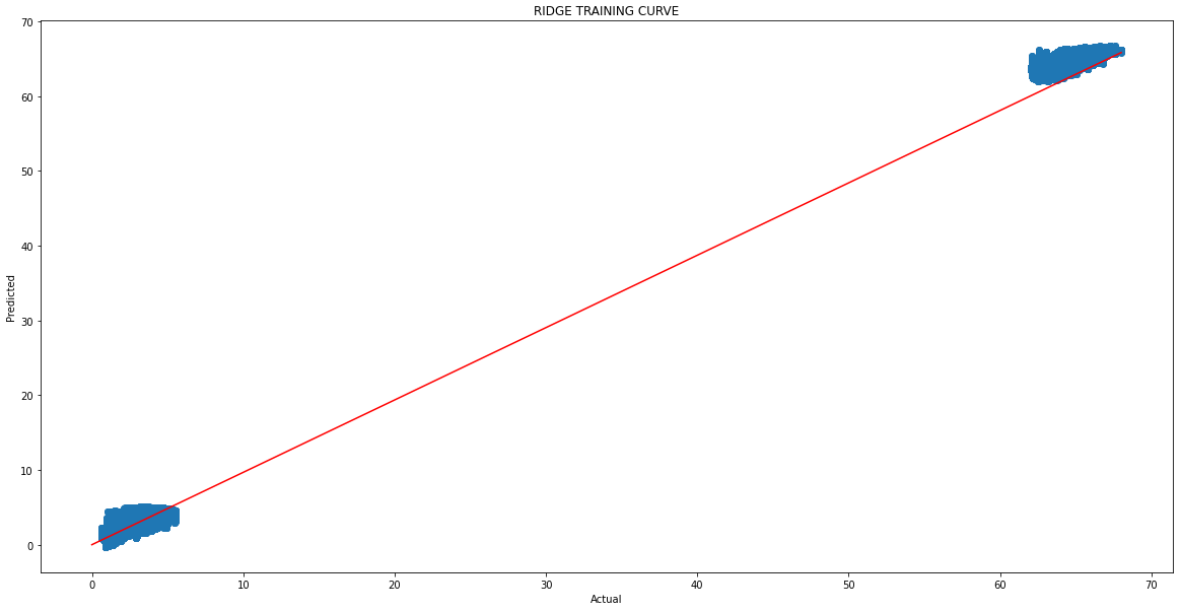
Out[0]:
```
(0.5202442337871346,
 0.5193853622009061,
 0.5222740262846326,
 0.4071919531656044,
 0.40797115490725677,
 0.4047967545750942)
```

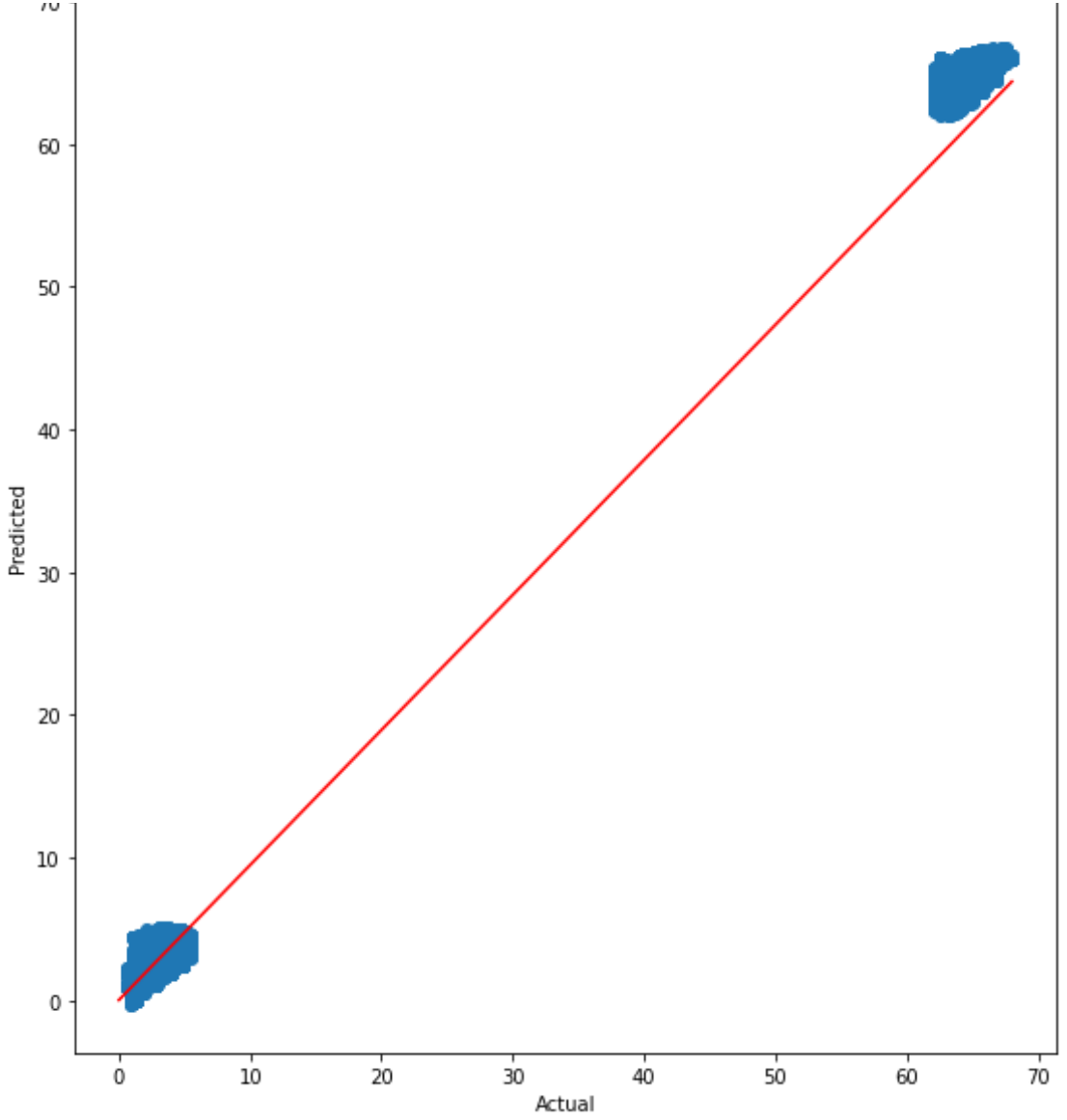
PLOTS

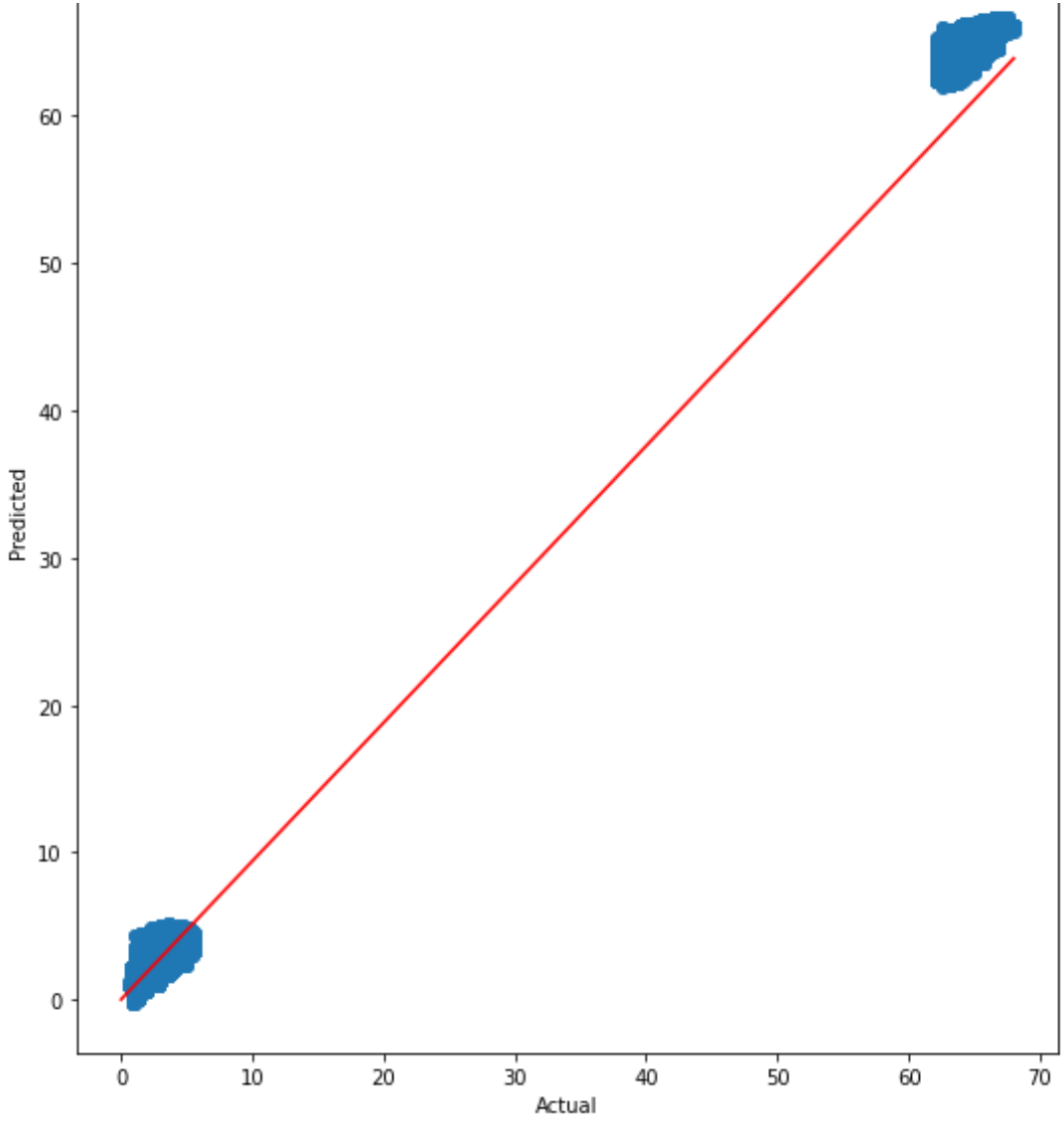
In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="RIDGE TRAINING CURVE", xlabel="Actual", ylabel="Predicte
d")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RIDGE TREE VALIDATION CURVE", xlabel="Actual", ylabel="Pr
edicted")
ax.scatter(y_cv, y_pred_cv)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RIDGE TREE TEST CURVE", xlabel="Actual", ylabel="Predicte
d")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
```

```
 color='r')

fig.show()
```







REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MSE_CV","MSE_TEST"]
x.add_row(["RIDGE MTR",0.1457070772811201,0.14798745903277455,
 0.1466686774031905,
 1.0761683118743428,
 1.0722436207597437,
 1.0729682609689142])
x.add_row(["RIDGE RIGRESSION CHAIN",0.1457070772811201,0.14798745903277455,
 0.1466686774031905,
 1.0761683118743428,
 1.0722436207597437,
 1.0729682609689142])

x.add_row(["RIDGE(NAIVE METHOD)",0.5202442337871346,0.5193853622009061,
 0.5222740262846326,
 0.4071919531656044,
 0.40797115490725677,
 0.4047967545750942])
print(x)
```

```
+-----------------------------------------------------+-----------------
--------------------------------+----------------------------------------
----------+-----------------------------------------------------+----------
-------------------------------------+-------------------------------------
---------------+-----------------------------------------------------+
|                        MODEL1                       |
   R2_TRAIN                    |                      R2_CV
          |                    R2_TEST                     |
       MSE_TRAIN                    |                     MSE_CV
              |                    MSE_TEST                    |
```

```
+-------------------------------------------------+-----------------
-------------------------------+-------------------------------------
----------+-------------------------------------------------+----------

-----------------------------------+---------------------------------
---------------+-------------------------------------------------+
|                      RIDGE MTR                      |               0.
1457070772811201               |               0.14798745903277455
          |               0.1466686774031905               |
    1.0761683118743428              |               1.072243620759743
7               |               1.0729682609689142               |
|               RIDGE RIGRESSION CHAIN               |               0.
1457070772811201               |               0.14798745903277455
          |               0.1466686774031905               |
    1.0761683118743428              |               1.072243620759743
7               |               1.0729682609689142               |
|                RIDGE(NAIVE METHOD)                 |               0.
5202442337871346               |                0.5193853622009061
          |               0.5222740262846326               |
    0.4071919531656044              |               0.4079711549072567
7               |               0.4047967545750942               |
+-------------------------------------------------+-----------------
-------------------------------+-------------------------------------
----------+-------------------------------------------------+----------
-----------------------------------+---------------------------------
---------------+-------------------------------------------------+
```

ANALYSIS BETWEEN THREE METHODS

1. SINGLE TARGET MODEL:

   The main drawback of these methods is that the relationships among the targets are ignored, and the targets are predicted independently, which may affect the overall quality of the predictions.
2. REGRESSOR CHAIN AND MTR :

   The methods tend to give same result when implemented on ridge regression.

PLOTS INFERENCES

1. NAIVE METHOD

   It is simply not a perefect method for analysis and it has better result because it doent take into count of target dependencies.
2. Regressor chain and MTR

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

   In test and validation curve, the models are able to predict iron concetrate and are not able to predict the silica as the samw way in iron.

METRIC ANALYSIS

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is so closer to 0 and TEST r2 is also to 0 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The train,cv,test loss and r2 score is not very good.

CONCLUSION

NAIVE METHOD must not be used in prediction and neither MTR and Regression with ridge performance are not satisfactory . Hence, to predict two target variables at same time we need to not ridge.

XGBOOST

DATA MODELING

In [0]:
```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import numpy as np
```

In [0]:
```
import pandas as pd

df=pd.read_csv('/content/drive/My Drive/preprocessed_time')

y = df.iloc[:,23:25]
X = df.drop(['% Silica Concentrate','% Iron Concentrate','index','datet
ime hours'], axis=1)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
```

```
andom_state=30)

X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)

from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)

features_cv = scale_features_std.transform(X_cv)

print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape,y_cv.shape,y_test.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (47196
9, 2) (117993, 2) (147491, 2)
```

MODEL USING MULTIOUTPUTREGRESSOR

In [0]:
```
import xgboost as xgb
from sklearn.multioutput import MultiOutputRegressor
```

In [0]:
```
clf=xgb.XGBRegressor(max_depth=10 ,learning_rate=0.01,n_estimators=1000
 ,verbose=2,subsample=0.1,colsample_bytree=1)
```

In [0]:
```
model=MultiOutputRegressor(clf)
model.fit(features_train,y_train)
```

```
[01:46:32] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
[02:15:55] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
```

Out[0]:
```
MultiOutputRegressor(estimator=XGBRegressor(base_score=0.5, booster='gb
tree',
                                            colsample_bylevel=1,
```

```
                                                colsample_bynode=1,
                                                colsample_bytree=1, gamma=
       0,

                                                importance_type='gain',
                                                learning_rate=0.01,
                                                max_delta_step=0, max_depth
       =10,
                                                min_child_weight=1, missing
       =None,
                                                n_estimators=1000, n_jobs=
       1,
                                                nthread=None,
                                                objective='reg:linear',
                                                random_state=0, reg_alpha=
       0,
                                                reg_lambda=1, scale_pos_wei
       ght=1,
                                                seed=None, silent=None,
                                                subsample=0.1, verbose=2,
                                                verbosity=1),
                             n_jobs=None)
```

PREDICTION

In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

In [0]:
```
r2_train=r2_score(y_train,y_pred_train)
r2_cv=r2_score(y_cv,y_pred)
r2_test=r2_score(y_test,y_pred_test)
```

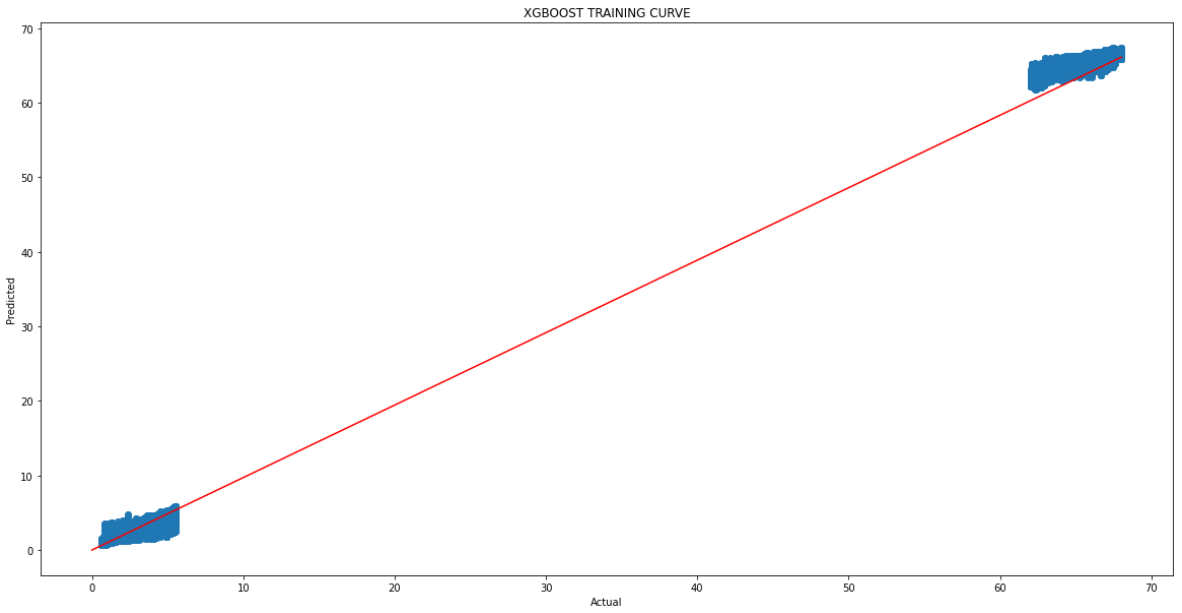
In [0]:
```
r2_train,r2_cv,r2_test,mse_cv,mse_test,mse_train,mse_cv
```

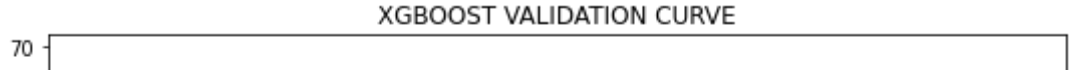
Out[0]:
```
(0.790067573655429,
 0.7760975535975633,
 0.7750269140015339,
 0.2816141156963654,
 0.2827106725163956,
 0.2641687929200151,
 0.2816141156963654)
```

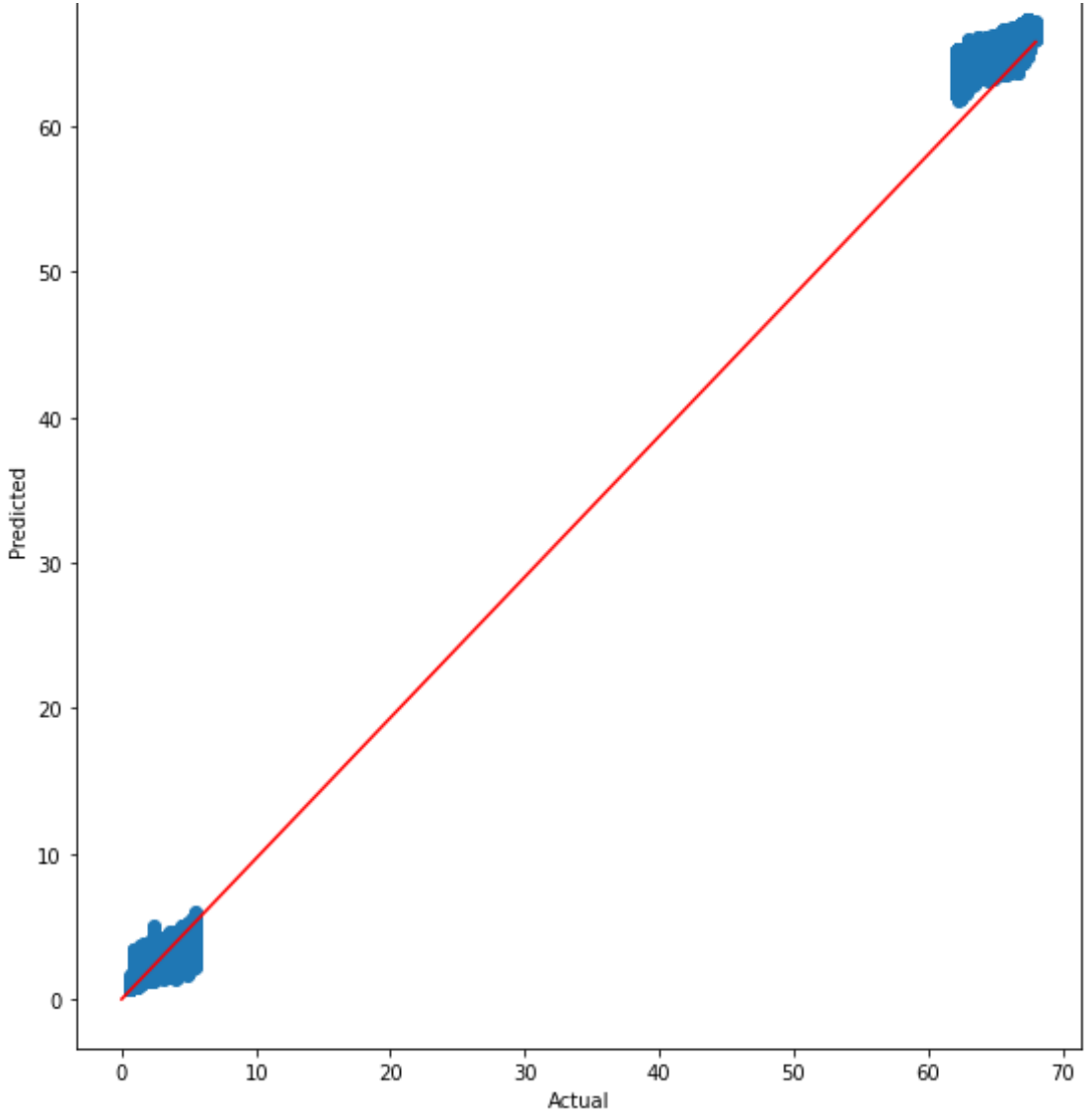
PLOTS

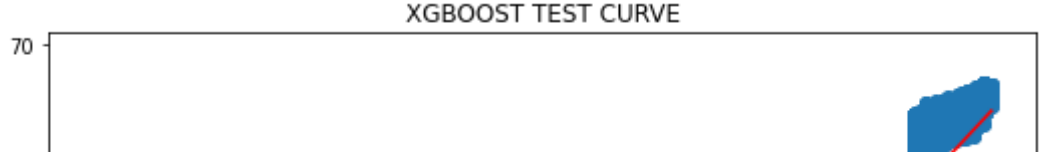
In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="XGBOOST TRAINING CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="XGBOOST VALIDATION CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="XGBOOST TEST CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
```

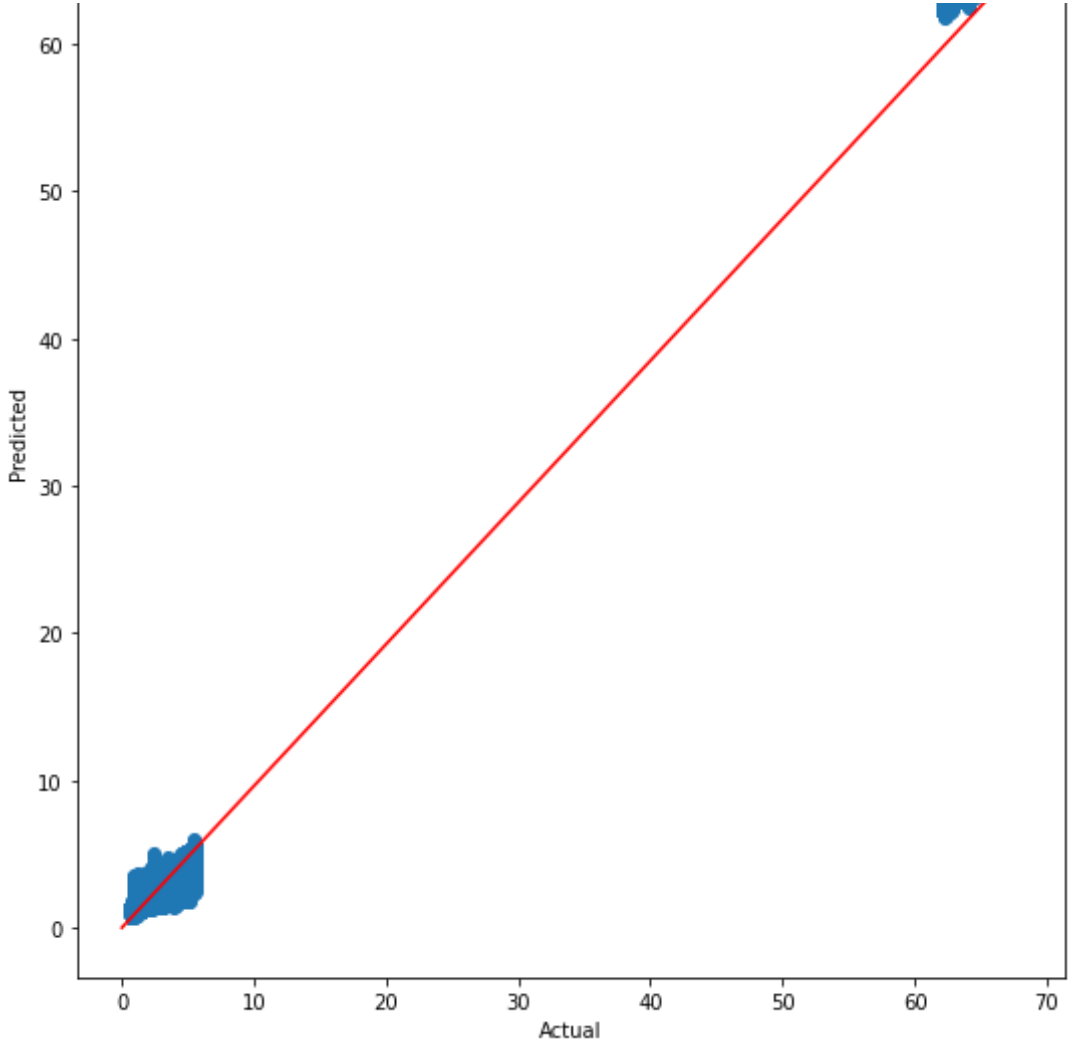
```
 color='r')
fig.show()
```











MODEL USING REGRESSOR CHAIN

In [0]:
```
from sklearn.multioutput import RegressorChain
```

In [0]:
```
model=xgb.XGBRegressor(max_depth=10 ,learning_rate=0.01,n_estimators=10
00 ,verbose=2,subsample=0.1,colsample_bytree=1)
wrapper1 = RegressorChain(model)
wrapper1.fit(features_train,y_train)
```

```
[05:39:19] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
[06:09:35] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
```

Out[0]:
```
RegressorChain(base_estimator=XGBRegressor(base_score=0.5, booster='gbt
ree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           importance_type='gain',
                                           learning_rate=0.01, max_delt
a_step=0,
                                           max_depth=10, min_child_weig
ht=1,
                                           missing=None, n_estimators=1
000,
                                           n_jobs=1, nthread=None,
```

```
                                                objective='reg:linear',
                                                random_state=0, reg_alpha=0,
                                                reg_lambda=1, scale_pos_weig
        ht=1,
                                                seed=None, silent=None,
                                                subsample=0.1, verbose=2,
                                                verbosity=1),
                        cv=None, order=None, random_state=None)
```

PREDICTION

In [0]:
```
y_pred_cv=wrapper1.predict(features_cv)
y_pred_train=wrapper1.predict(features_train)
y_pred_test=wrapper1.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
r2_cv=r2_score(y_pred_cv,y_cv)
r2_train=r2_score(y_pred_train,y_train)
r2_test=r2_score(y_pred_test,y_test)
```

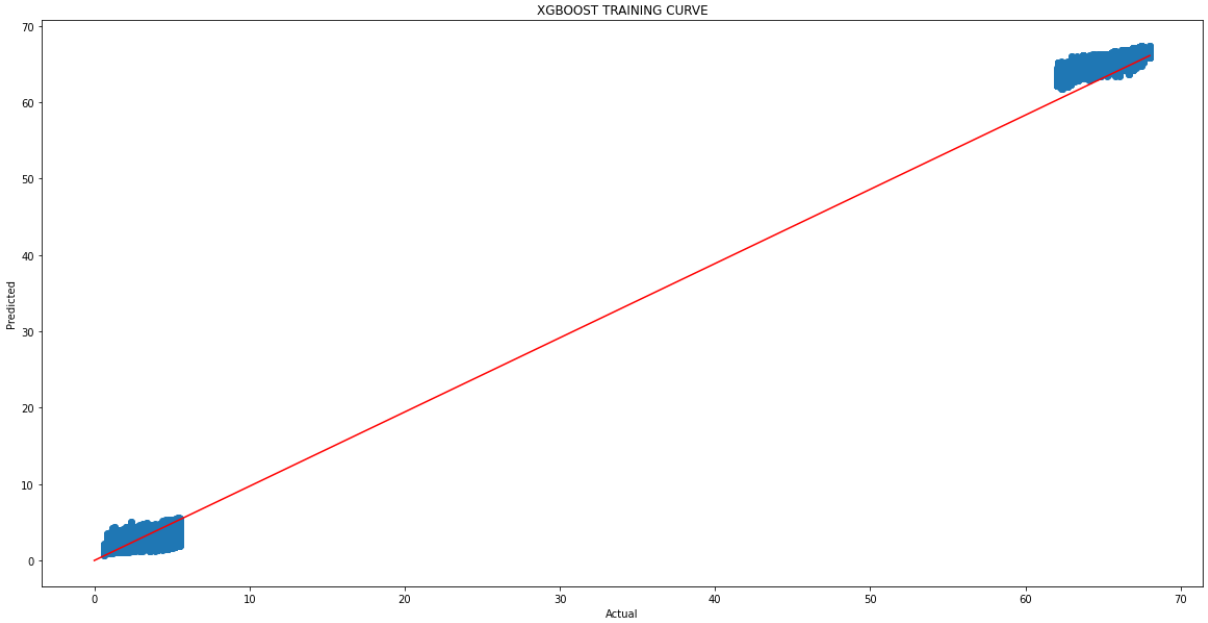
In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

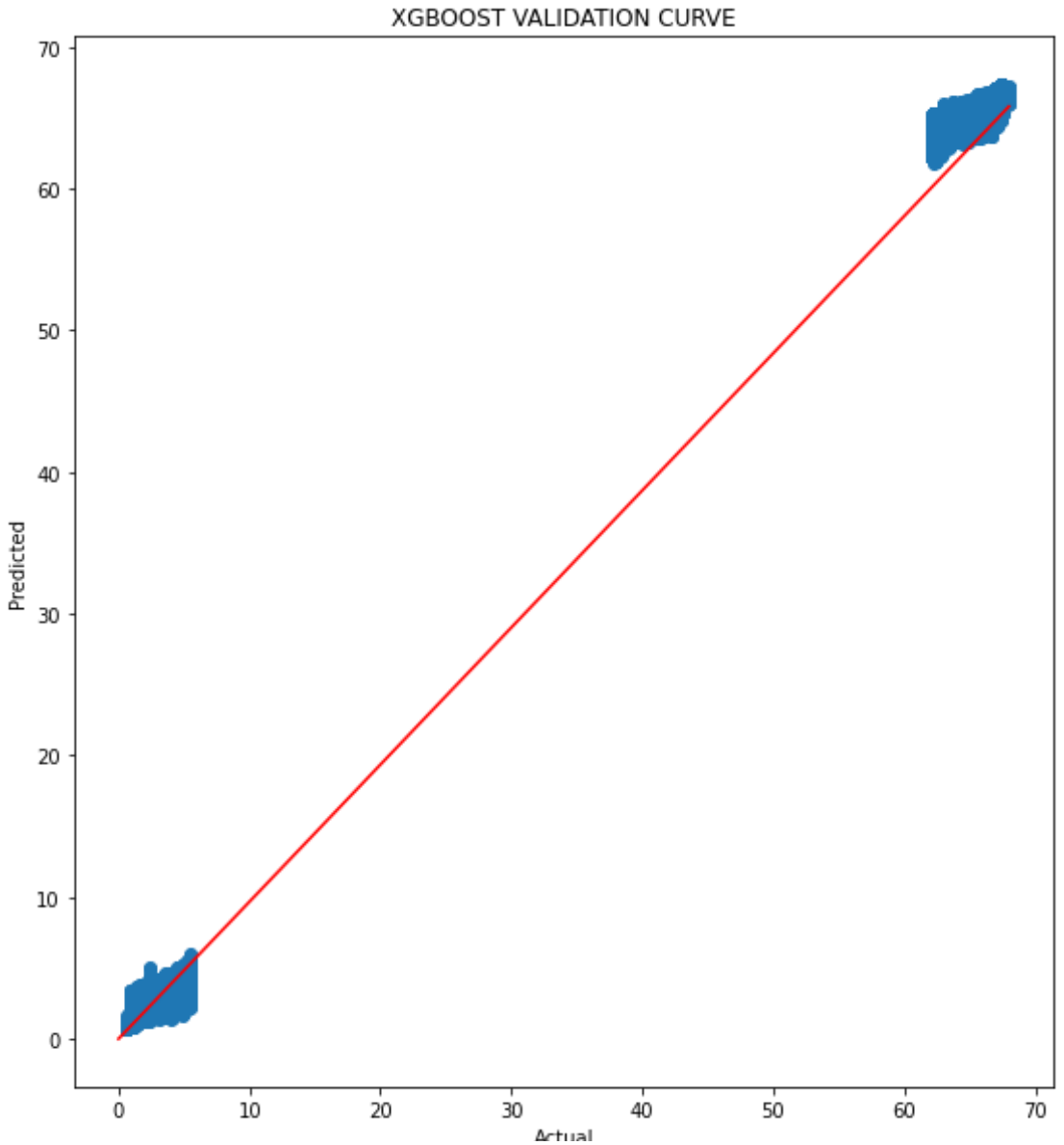
In [0]:
```
r2_train,r2_cv,r2_test,mse_train,mse_cv,mse_test
```

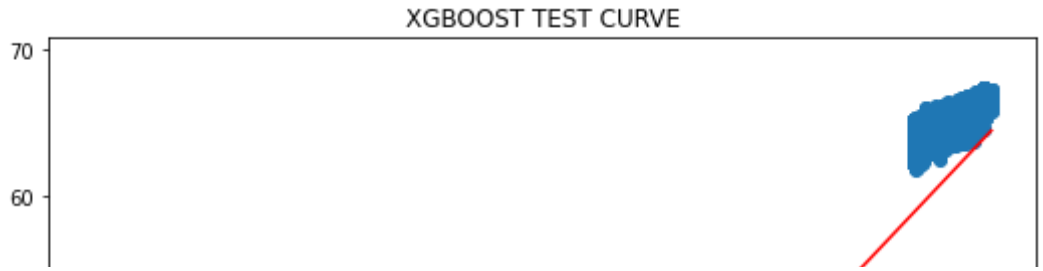
Out[0]:
```
(0.5341046012820809,
 0.5105948839081095,
 0.5101846872368989,
 0.3321947153953305,
 0.2816141156963654,
 0.3455795604174674)
```

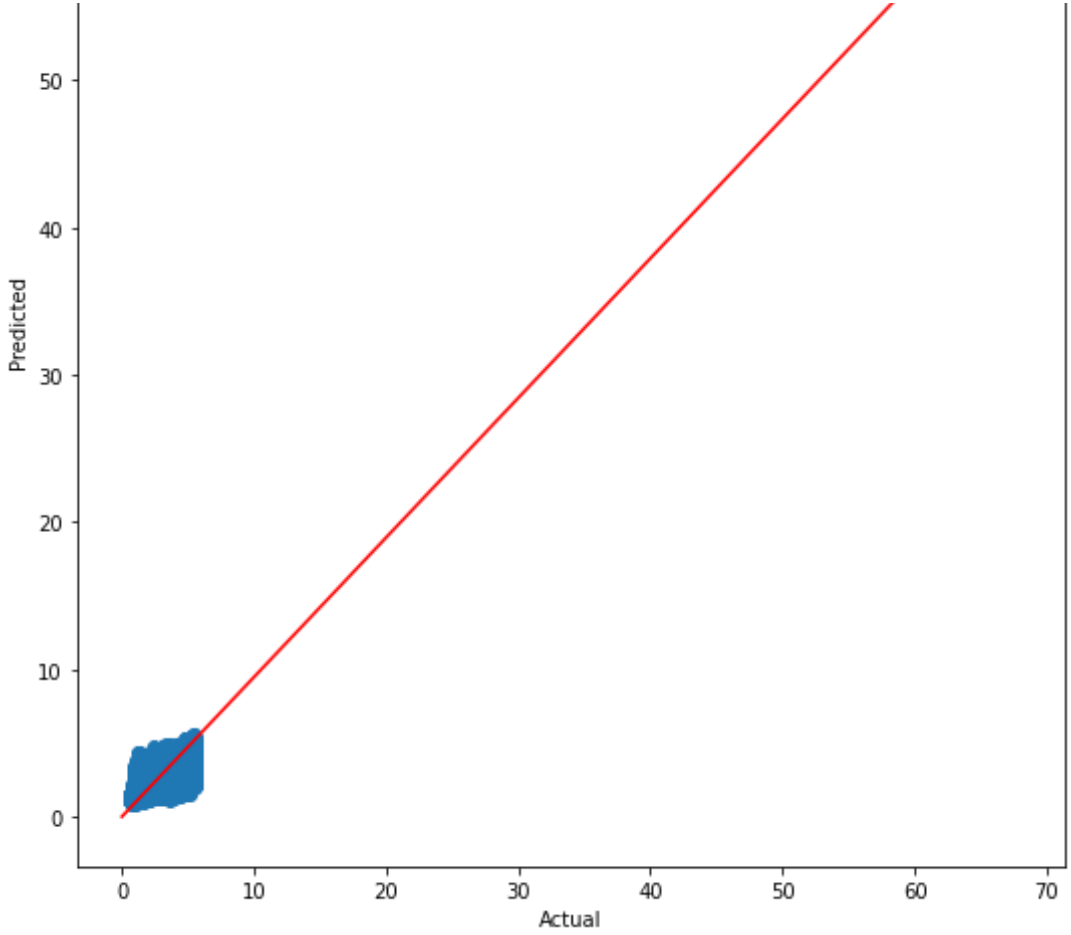
PLOTS

In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="XGBOOST TRAINING CURVE", xlabel="Actual", ylabel="Predict
ed")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="XGBOOST VALIDATION CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="XGBOOST TEST CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```









REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-i
```

```
n-python-to-print-out-data-from-multiple-lists-- to add the rows in tab
le
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MS
E_CV","MSE_TEST"]
x.add_row(["XGBOOST MTR",0.790067573655429,
 0.7760975535975633,
 0.7750269140015339,
 0.2816141156963654,
 0.2827106725163956,
 0.2641687929200151,

])
x.add_row(["XGBOOST RIGRESSION CHAIN",0.5341046012820809,
 0.5105948839081095,
 0.5101846872368989,
 0.3321947153953305,
 0.2816141156963654,
 0.3455795604174674])
print(x)
```

```
+-----------------------------------------------------+---------------
---------------------------------+-------------------------------------
----------+-----------------------------------------------------+----------
-----------------------------------------+-------------------------------
---------------+-----------------------------------------------+
|                          MODEL1                             |
     R2_TRAIN                    |                      R2_CV
           |                  R2_TEST                        |
        MSE_TRAIN                    |                    MSE_CV
               |                   MSE_TEST                     |
+-----------------------------------------------------+---------------
---------------------------------+-------------------------------------
----------+-----------------------------------------------------+----------
-----------------------------------------+-------------------------------
---------------+-----------------------------------------------+
|                      XGBOOST MTR                            |
0.790067573655429              |              0.7760975535975633
          |              0.7750269140015339              |
```

```
     0.2816141156963654                |                0.282710672516395
6                |                0.2641687929200151                |

|                XGBOOST RIGRESSION CHAIN                |
0.5341046012820809                |                0.5105948839081095
            |                0.5101846872368989                |
     0.3321947153953305                |                0.281614115696365
4                |                0.3455795604174674                |
+-------------------------------------------------------+---------------
---------------------------------+-------------------------------------
----------+-------------------------------------------------+----------
-----------------------------------+-------------------------------
---------------+-------------------------------------------------+
```

ANALYSIS BETWEEN METHODS

1. MTR AND REGRESSION CHAIN

   The MTR has better performances than regression chain and the loss value is also low and plots are also better in MTR

PLOTS ANALYSIS

1. MTR

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

   In test and validation curve, the models are able to predict iron concetrate and are able to predict the silica better in the same way iron concentrate
2. Regressor chain

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

In test curve, the models are able to predict iron concetrate and are not able to predict the silica better than iron concentrate.

METRIC ANALYSIS

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is so closer to 0 and TEST r2 is also to 0 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The MSE value and R2 score value is better than ridge and MSE value of MTR is better than REGRESSION CHAIN model.

CONCLUSION

MTR IS BETTER THAN REGRESSION CHAIN MODEL IN CASE OF XGBOOST
XGBOOST>RIDGE

DECISION TREE

Inherently Multioutput Regression Algorithms

Some regression machine learning algorithms support multiple outputs directly.

This includes most of the popular machine learning algorithms implemented in the scikit-learn library, such as:

LinearRegression (and related)

KNeighborsRegressor

DecisionTreeRegressor

RandomForestRegressor (and related)

DATA MODELING

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
import pandas as pd
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
df[:2]
```

Out[0]:

	index	datetime hours	% Iron Feed	% Silica Feed	Starch Flow	Amina Flow	Ore Pulp Flow	Ore Pulp pH	Ore Pulp Density	Flotation Column 01 Air Flow	Flotati Colu 02 Fl
0	2017-03-10 01:02:00	2017-03-10 01:00:00	55.2	16.98	3019.53	557.434	395.713	10.0664	1.74	249.214	253.2
1	2017-03-10 01:02:20	2017-03-10 01:00:00	55.2	16.98	3024.41	563.965	397.383	10.0672	1.74	249.719	250.5

In [0]:
```
y = df.iloc[:,23:25]
X = df.drop(['% Silica Concentrate','% Iron Concentrate','index','datet
ime hours'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape,y_test.shape,y_cv.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (47196
9, 2) (147491, 2) (117993, 2)
```

In [0]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeRegressor
```

MODEL FOR MULTIOUTPUT

In [0]:
```
#https://machinelearningmastery.com/multi-output-regression-models-with-python/
dt2 = DecisionTreeRegressor()
se=dt2.fit(features_train,y_train)
parameters = {'max_depth': [1, 5, 10, 50], 'min_samples_split': [5, 10, 100, 500]}
cfl2=RandomizedSearchCV(dt2,param_distributions=parameters,verbose=10,n_jobs=-1,)
se2 = cfl2.fit(features_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:   17.3s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:   33.6s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:   43.5s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:   51.3s
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:  2.9min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:  4.3min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  4.6min finished
```

In [0]:
```
print(cfl2.best_estimator_)
```

```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecate
```

```
d',
                          random_state=None, splitter='best')
```

In [0]:
```
best_tune_parameters=[{'max_depth':[50], 'min_samples_split':[5] }]
```

In [0]:
```
clf=DecisionTreeRegressor (max_depth=50,min_samples_split=5)
clf.fit(features_train, y_train)
```

Out[0]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=50,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=5,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

PREDICTION

In [0]:
```
y_pred=clf.predict(features_cv)
```

In [0]:
```
y_pred_train=clf.predict(features_train)
y_pred_test=clf.predict(features_test)
```

In [0]:
```
y_pred_train
```

Out[0]:
```
array([[66.68 ,  1.44 ],
       [64.7  ,  3.77 ],
       [63.8  ,  3.87 ],
       ...,
       [65.39 ,  2.18 ],
       [65.405,  1.79 ],
       [65.06 ,  2.13 ]])
```

EVALUATION METRIC

In [0]:
```
R2 = r2_score(y_cv, y_pred)
print(R2)
```

```
0.9036198036618404
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)
```

In [0]:
```
r2_train=r2_score(y_train,y_pred_train)
```

In [0]:
```
r2_train
```

Out[0]:
```
0.9969342900667011
```

In [0]:
```
r2_test=r2_score(y_test,y_pred_test)
```

In [0]:
```
r2_test
```

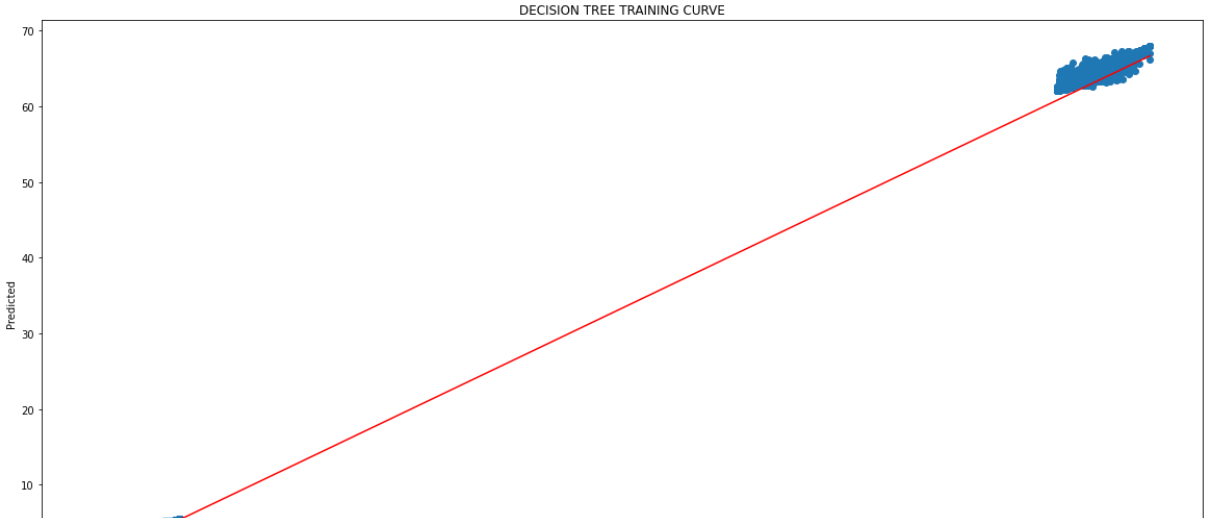
Out[0]:
```
0.9018280433286507
```

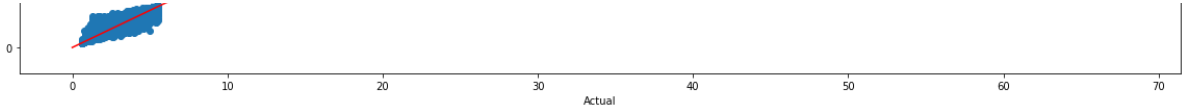
In [0]:
```
r2_train,r2_test,mse_cv,mse_test,mse_train,mse_cv,R2
```

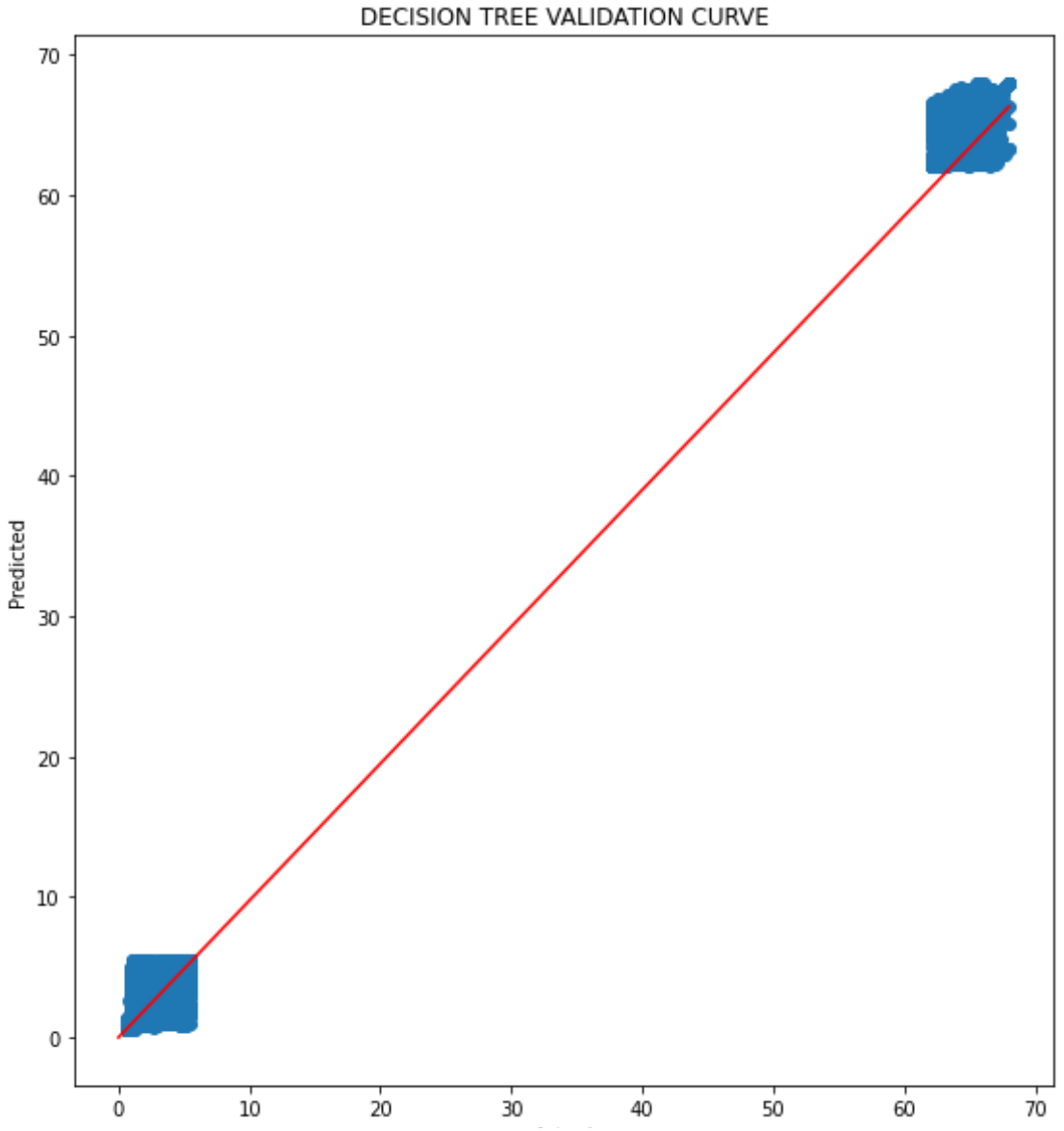
Out[0]:
```
(0.996940349079114,
 0.9010834860487484,
 0.12129044877301248,
 0.12437333275470228,
 0.0038556643517233397,
 0.12129044877301248,
 0.9036198036618404)
```

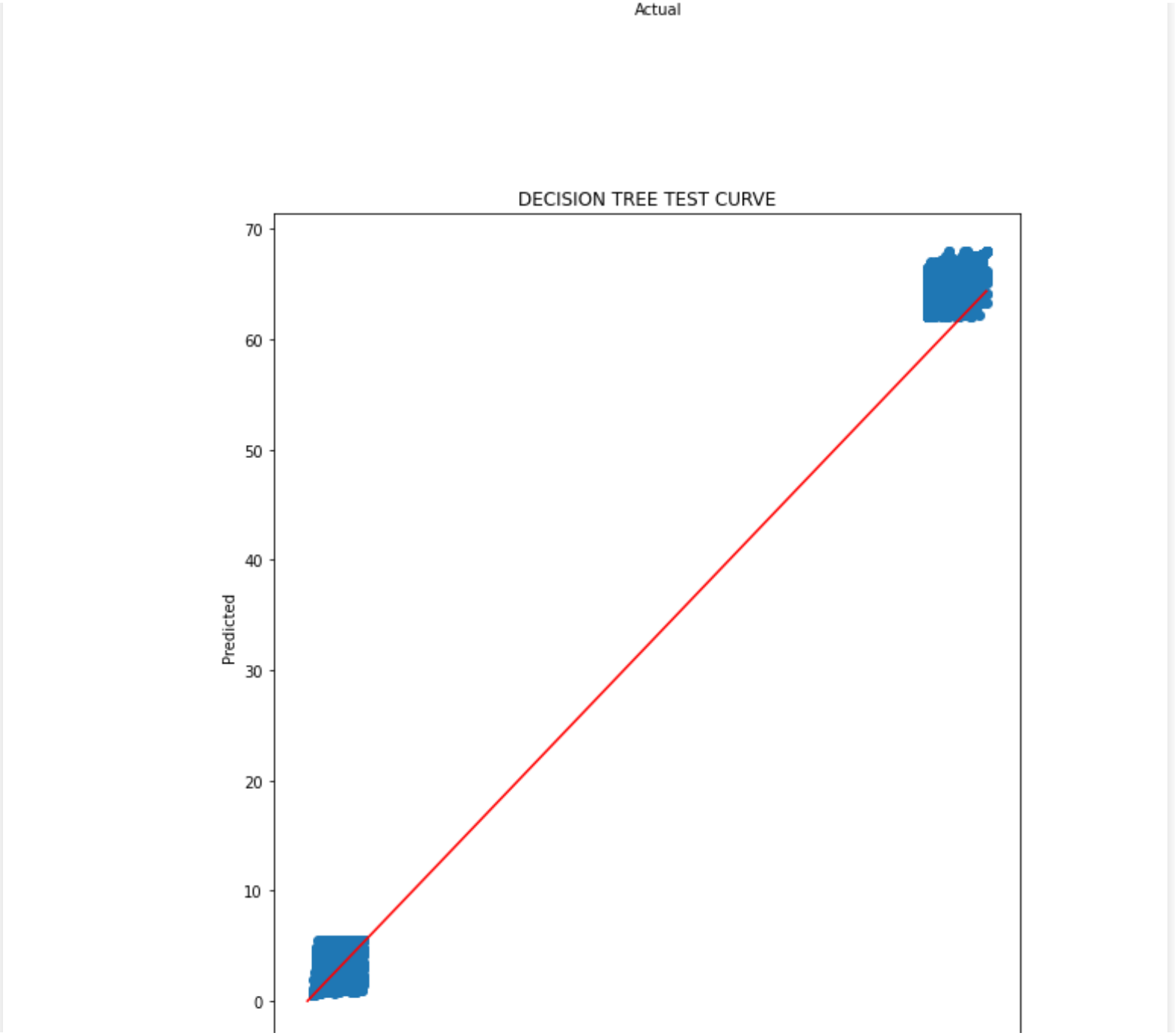
PLOTS

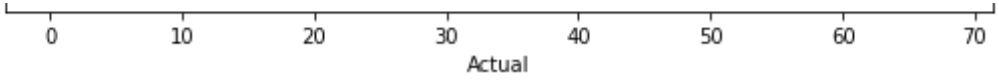
In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="P
redicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```



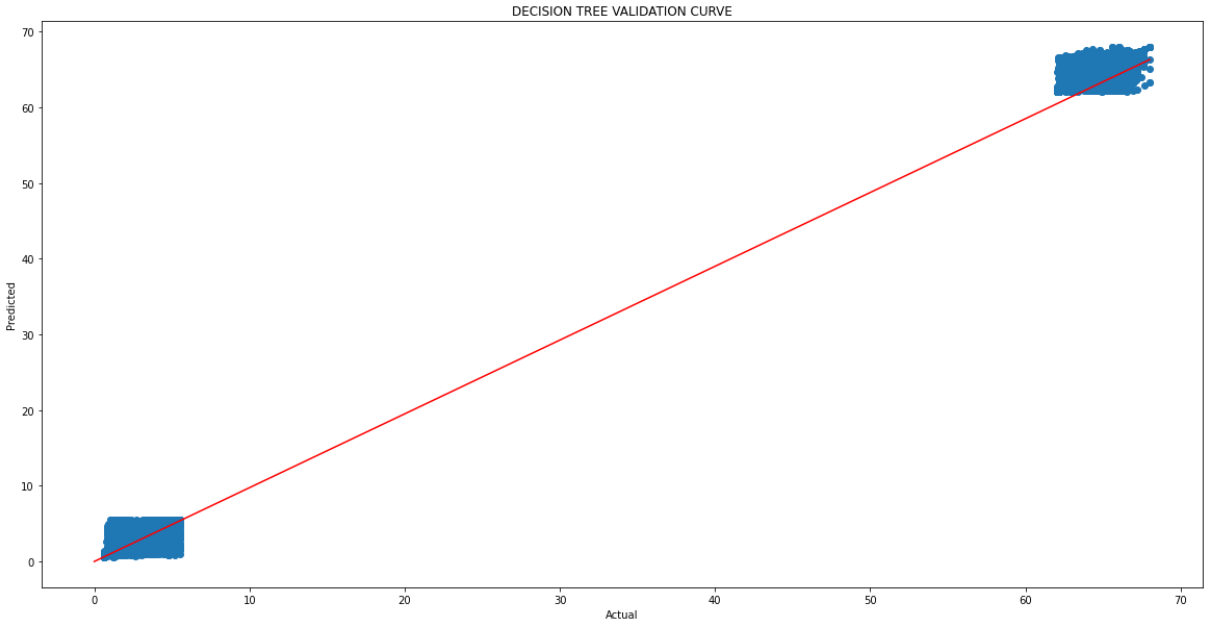








In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
```



MODEL USING REGRESSOR CHAIN

In [0]:
```
from sklearn.multioutput import RegressorChain
```

In [0]:
```
clf=DecisionTreeRegressor (max_depth=50,min_samples_split=5)
wrapper1 = RegressorChain(clf)
wrapper1.fit(features_train,y_train)
```

Out[0]:
```
RegressorChain(base_estimator=DecisionTreeRegressor(ccp_alpha=0.0,
                                                    criterion='mse',
                                                    max_depth=50,
                                                    max_features=None,
                                                    max_leaf_nodes=Non
e,
                                                    min_impurity_decrea
se=0.0,
```

```
                                                      min_impurity_split=
        None,
                                                      min_samples_leaf=1,
                                                      min_samples_split=
        5,
                                                      min_weight_fraction
        _leaf=0.0,
                                                      presort='deprecate
        d',
                                                      random_state=None,
                                                      splitter='best'),
                    cv=None, order=None, random_state=None)
```

PREDICTION

In [0]:
```
y_pred_cv=wrapper1.predict(features_cv)
y_pred_train=wrapper1.predict(features_train)
y_pred_test=wrapper1.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
r2_cv=r2_score(y_pred_cv,y_cv)
r2_train=r2_score(y_pred_train,y_train)
r2_test=r2_score(y_pred_test,y_test)
```

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred_cv)
```

In [0]:
```
r2_train,r2_cv,r2_test,mse_train,mse_cv,mse_test
```

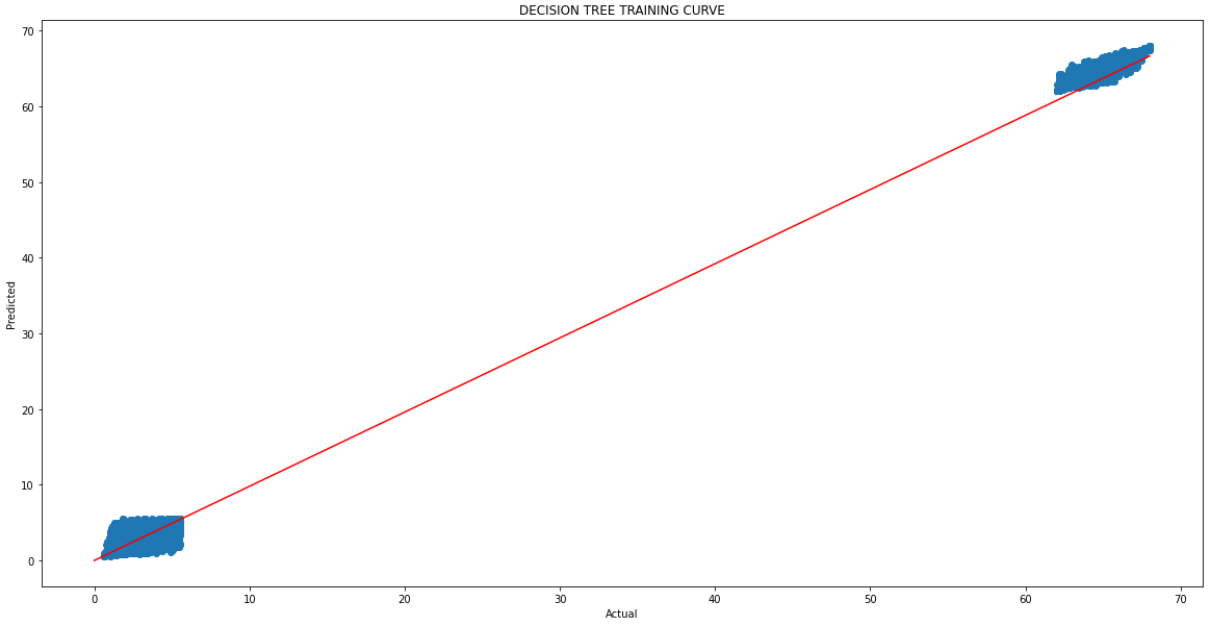
Out[0]:
```
(0.9908990814437093,
 0.8790498091768016,
 0.8774055851075784,
 0.011506126265385405,
```

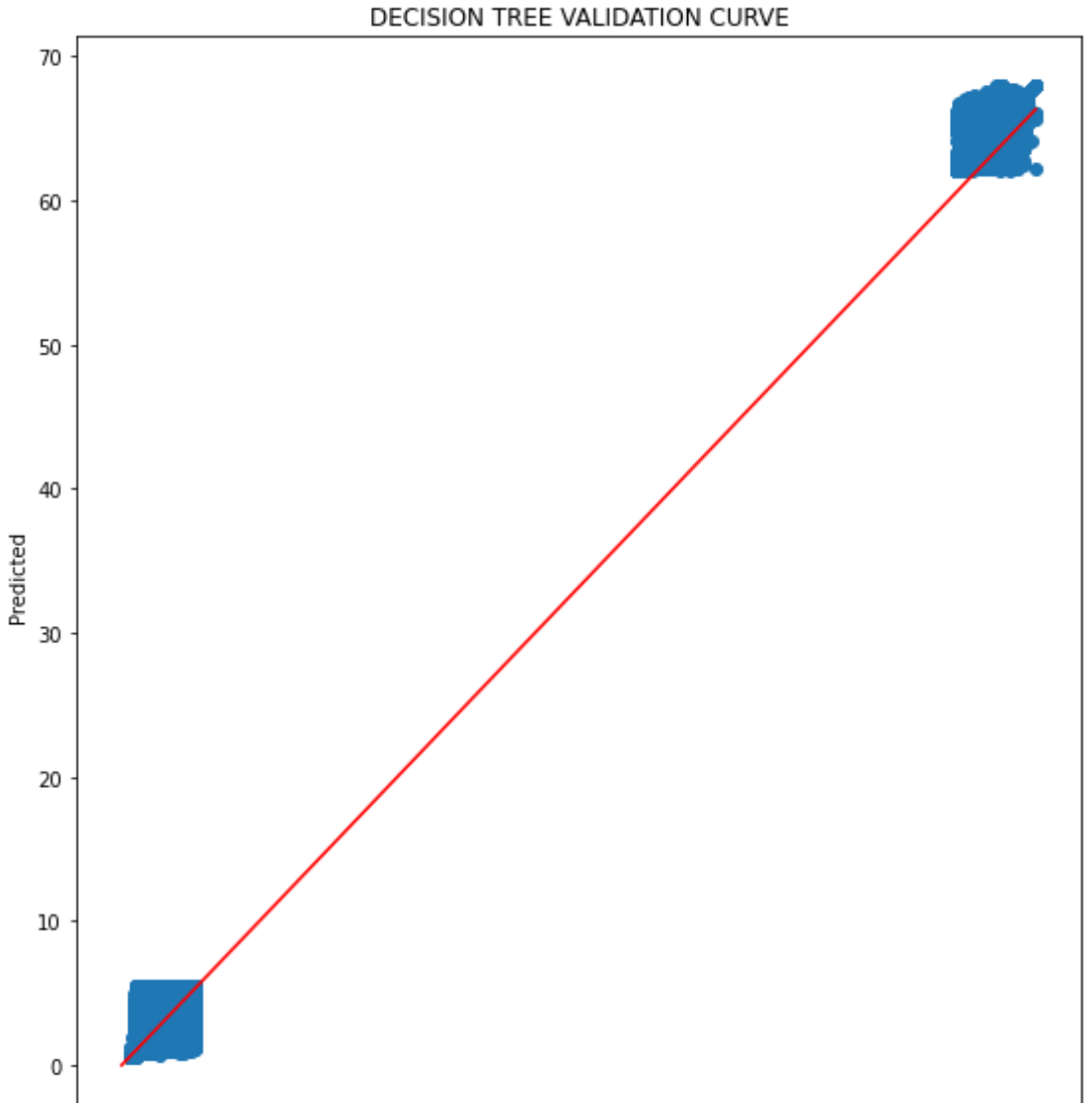
```
0.15191380344978905,
0.1537079542189485)
```

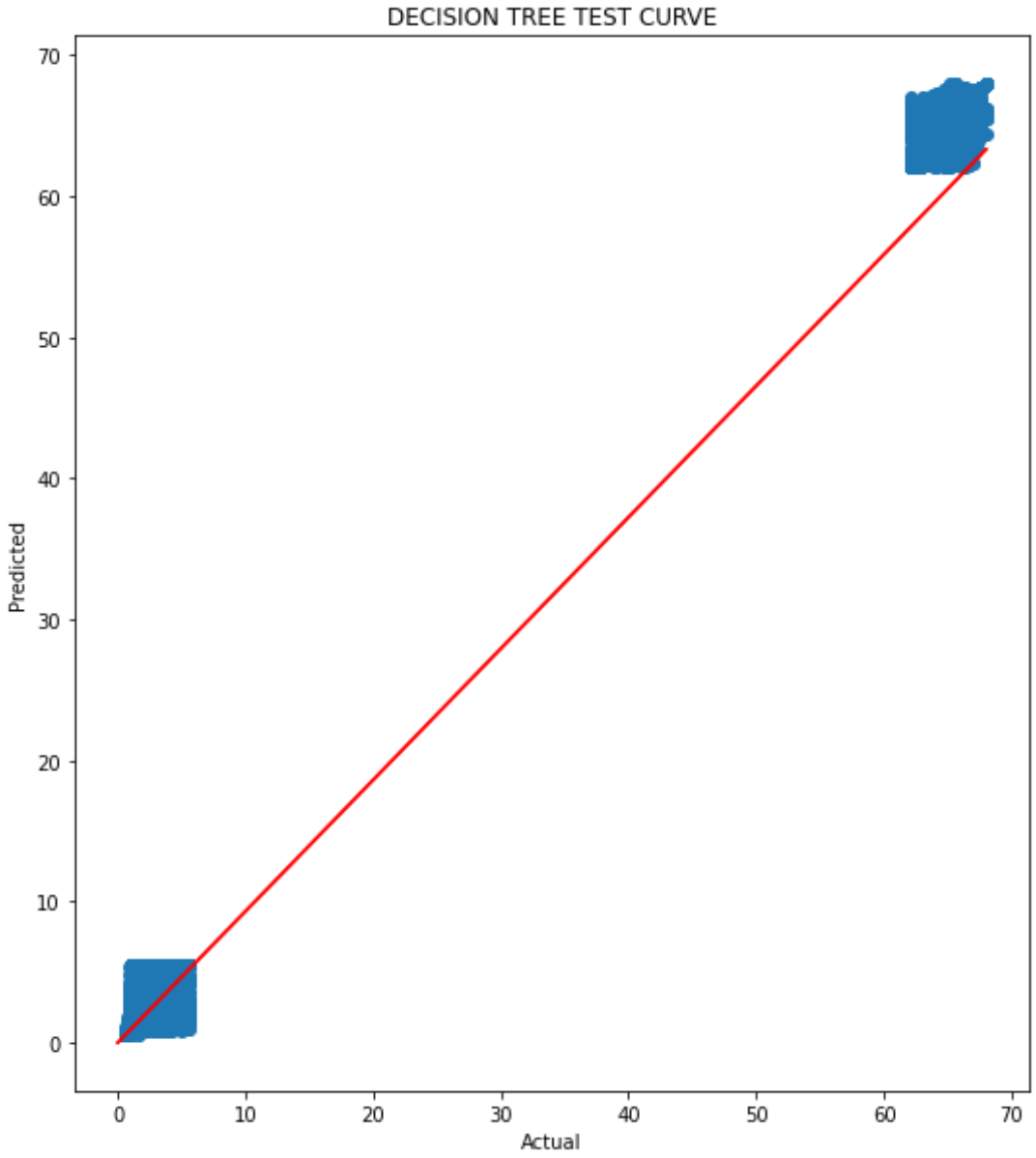
PLOTS

In [0]:

```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="DECISION TREE TRAINING CURVE", xlabel="Actual", ylabel="P
redicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="DECISION TREE VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred_cv)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="DECISION TREE TEST CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```







REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MSE_CV","MSE_TEST"]
x.add_row(["DECISION TREE MTR",0.996940349079114,
 0.9010834860487484,
 0.9036198036618404, 0.0038556643517233397,
 0.12129044877301248,
 0.12437333275470228
])
x.add_row(["DECISION TREE RIGRESSION CHAIN",0.9908990814437093,
 0.8790498091768016,
 0.8774055851075784,
 0.011506126265385405,
 0.15191380344978905,
```

```
 0.1537079542189485])

print(x)
```

```
+-------------------------------------------------------------+---------
-----------------------------------+-----------------------------
-----------------+-------------------------------------------------+----
-----------------------------------------------+---------------------
--------------------------+------------------------------------------
-----+
|                            MODEL1                                |
          R2_TRAIN                     |                      R2_CV
               |                    R2_TEST                        |
               MSE_TRAIN                    |                      M
SE_CV                     |                   MSE_TEST
     |
+-------------------------------------------------------------+---------
-----------------------------------+-----------------------------
-----------------+-------------------------------------------------+----
-----------------------------------------------+---------------------
--------------------------+------------------------------------------
-----+
|                      DECISION TREE MTR                      |
     0.996940349079114               |               0.90108348604874
84               |              0.9036198036618404               |
          0.0038556643517233397               |                0.121290
44877301248               |               0.12437333275470228
     |
|              DECISION TREE RIGRESSION CHAIN               |
     0.9908990814437093               |               0.87904980917680
16               |              0.8774055851075784               |
            0.011506126265385405               |               0.151913
80344978905               |               0.1537079542189485
     |
+-------------------------------------------------------------+---------
-----------------------------------+-----------------------------
-----------------+-------------------------------------------------+----
-----------------------------------------------+---------------------
--------------------------+------------------------------------------
-----+
```

METRIC ANALYSIS

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 OF INHERENT MODEL is so closer to 1 and TEST r2 OF INHERENT MODEL is also to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The MSE value and R2 score value is better than ridge and MSE value of INHERENT MODEL is better than REGRESSION CHAIN model.

PLOTS ANALYSIS

1. INHERENT MTR MODEL

In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

In test and validation curve, the models are able to predict iron concetrate and are able to predict the silica better in the same way for iron concentrate

2. Regressor chain

In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

In test curve, the models are able to predict iron concetrate and are not able to predict the silica better than iron concentrate.

CONCLUSION

INHERENT MTR IS BETTER THAN REGRESSION CHAIN MODEL IN CASE OF DECISION TREE

DECISION TREE> XGBOOST> RIDGE

RANDOMFOREST

DATA MODELING

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
y = df.iloc[:,23:25]
X = df.drop(['% Silica Concentrate','% Iron Concentrate','index','datet
ime hours'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape,y_cv.shape,y_test.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (47196
9, 2) (117993, 2) (147491, 2)
```

MODEL FOR MULTIOUTPUT

In [0]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [0]:
```
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
```

In [0]:
```
# Create a based model
```

```
rf = RandomForestRegressor()
# Instantiate the grid search model
grid_search = RandomizedSearchCV(estimator = rf,param_distributions= pa
ram_grid,
                           cv = 3,n_jobs=-1, verbose = 2)
```

In [0]:
```
grid_search.fit(features_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent work
ers.
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_ex
ecutor.py:706: UserWarning: A worker stopped while some jobs were given
to the executor. This can be caused by a too short worker timeout or by
a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed: 111.6min finished
```

Out[0]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decreas
e=0.0,
                                                   min_impurity_split=N
one,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_
leaf=0.0,
                                                   n_estimators=100,
                                                   n_jobs=None, oob_sco
re=False,
                                                   random_state=None, v
erbose=0,
```

```
                                                   warm_start=False),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [80, 90, 100, 11
0],
                                        'max_features': [2, 3],
                                        'min_samples_leaf': [3, 4, 5],
                                        'min_samples_split': [8, 10, 1
2],
                                        'n_estimators': [100, 200, 300,
1000]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=2)
```

In [0]:
```
grid_search.best_params_
```

Out[0]:
```
{'bootstrap': True,
 'max_depth': 100,
 'max_features': 3,
 'min_samples_leaf': 5,
 'min_samples_split': 10,
 'n_estimators': 1000}
```

In [0]:
```
model=RandomForestRegressor(n_estimators=1000,max_depth=100,min_samples
_leaf=5,min_samples_split=10,bootstrap=True,max_features=3)
```

In [0]:
```
model.fit(features_train,y_train)
```

Out[0]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=100, max_features=3, max_leaf_nodes=Non
e,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=5,
                      min_samples_split=10, min_weight_fraction_leaf=0.
0,
                      n_estimators=1000, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

PREDICTION

In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_test=mean_squared_error(y_test,y_pred_test)
mse_cv=mean_squared_error(y_cv,y_pred)

r2_train=r2_score(y_train,y_pred_train)

r2_test=r2_score(y_test,y_pred_test)
r2_cv=r2_score(y_cv,y_pred)
```

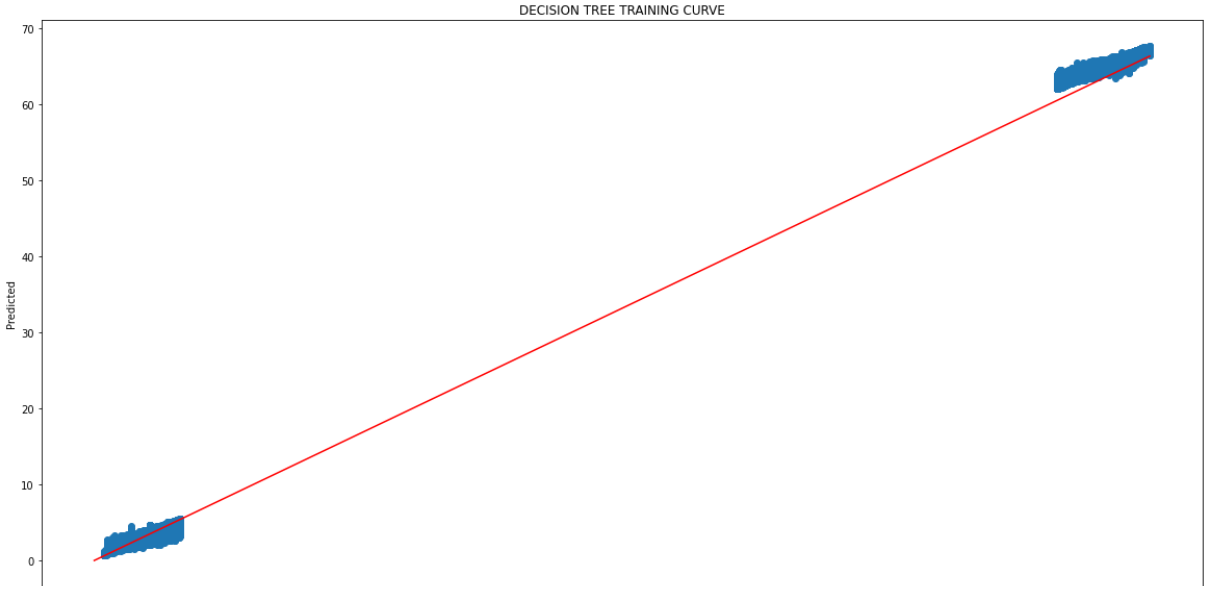
In [0]:
```
r2_train,r2_cv,r2_test,mse_cv,mse_test,mse_train,mse_cv
```

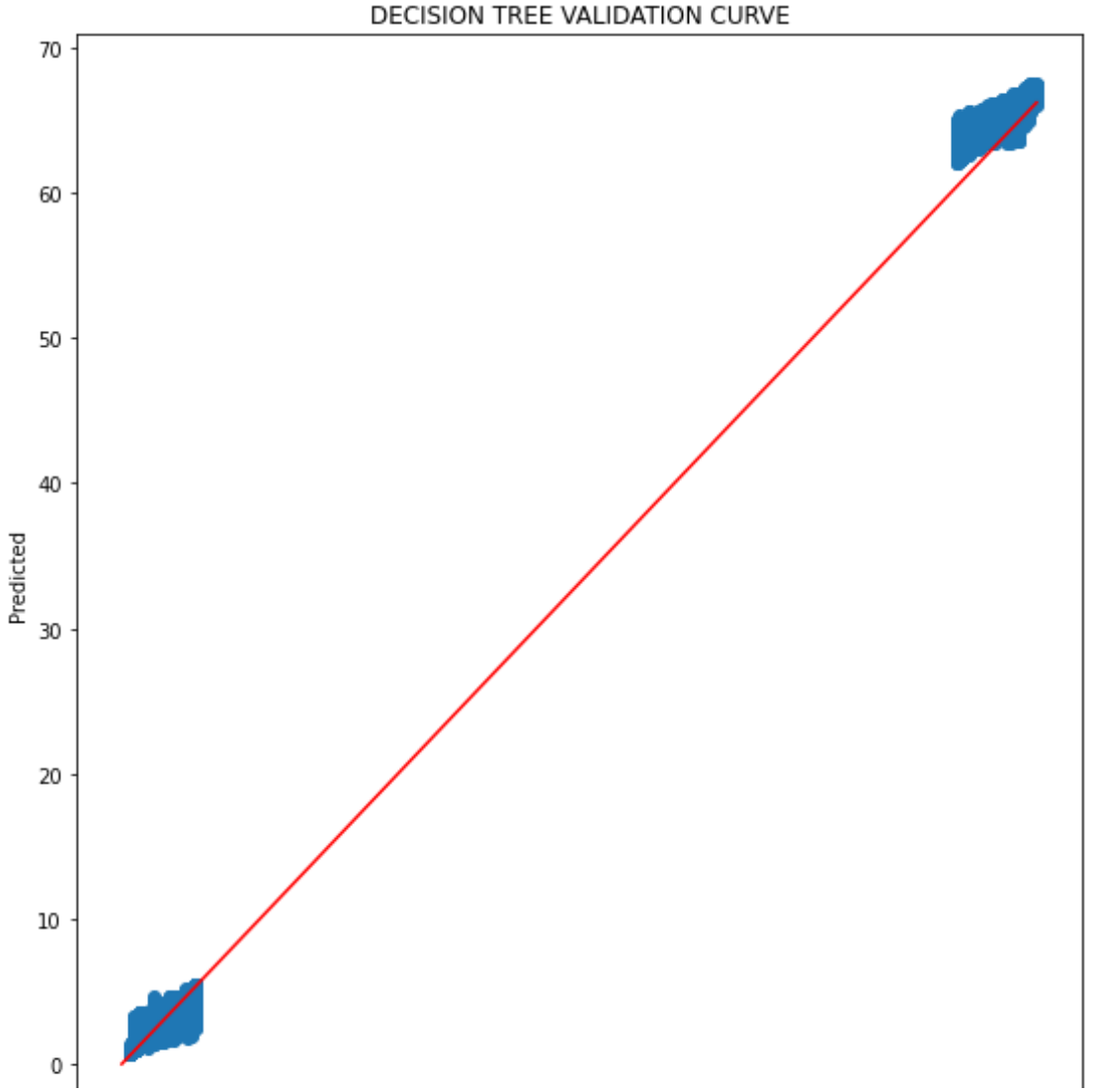
Out[0]:
```
(0.9404630125734039,
 0.8840832964855059,
 0.8836008488803795,
 0.14586763296600957,
 0.14634928647273932,
 0.0749937491528446,
 0.14586763296600957)
```

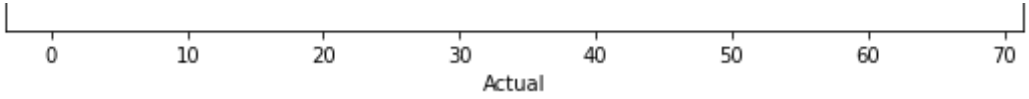
PLOTS

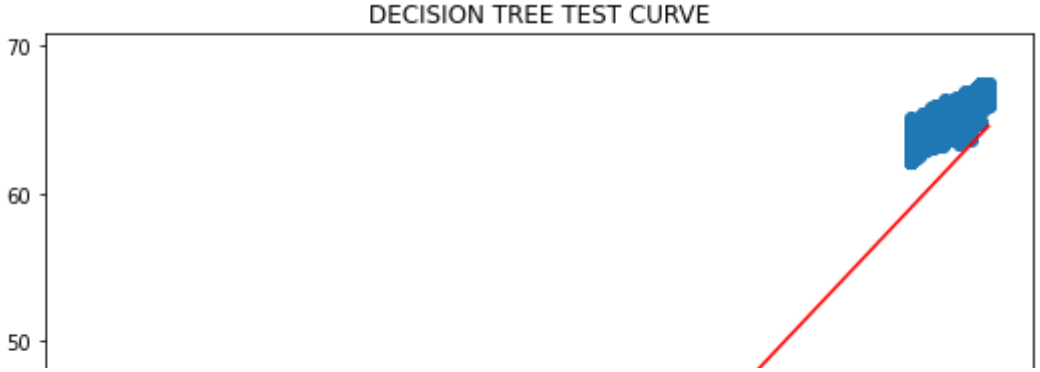
In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="RANDOMFOREST TRAINING CURVE", xlabel="Actual", ylabel="Predicted")
```

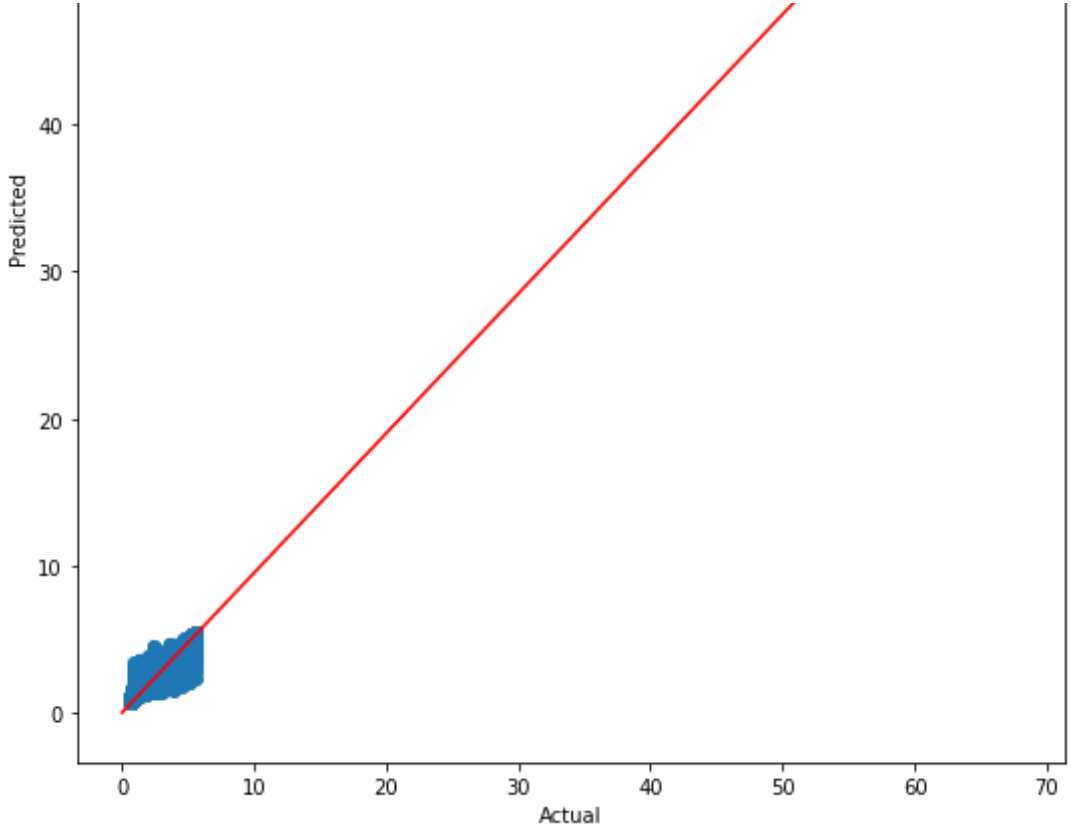
```
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="RANDOM FOREST VALIDATION CURVE", xlabel="Actual", ylabel=
"Predicted")
ax.scatter(y_cv, y_pred_cv)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="RANDOM FOREST TEST CURVE", xlabel="Actual", ylabel="Predi
cted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```











REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MSE_CV","MSE_TEST"]

x.add_row(["RANDOM FOREST",0.9404630125734039,
 0.8840832964855059,
 0.8836008488803795, 0.0749937491528446,
 0.14586763296600957,
 0.14634928647273932
])

print(x)
```

```
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------------
+-------------------------------------------------+--------------------
--------------------------+-----------------------------------------
```

```
------+-----------------------------------------------+

|                    MODEL1                    |                    R2_TRA
IN                     |                    R2_CV
|                     R2_TEST                      |                      MS
E_TRAIN                      |                     MSE_CV
      |                      MSE_TEST                      |
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------------
+-----------------------------------------------+---------------------
---------------------------+-----------------------------------------
------+-----------------------------------------------+
|               RANDOM FOREST               |               0.940463012
5734039                |              0.8840832964855059
|               0.8836008488803795               |               0.0749
937491528446                |              0.14586763296600957
      |               0.14634928647273932               |
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------------
+-----------------------------------------------+---------------------
---------------------------+-----------------------------------------
------+-----------------------------------------------+
```

METRIC ANALYSIS

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is so closer to 1 and TEST r2 is also to 1 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

PLOTS ANALYSIS

1. INHERENT MTR MODEL

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

   In test and validation curve, the models are able to predict iron concetrate and are able to predict the silica better in the same way for iron concentrate

CONCLUSION

INHERENT RANDOMFOREST MTR IS BETTER THAN OTHER MODELS

RANDOMFOREST> DECISION TREE> XGBOOST> RIDGE

ADABOOST

DATA MODELING

In [0]:
```
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import RandomizedSearchCV
```

In [0]:
```
import pandas as pd
```

In [0]:
```
df=pd.read_csv('/content/drive/My Drive/preprocessed_time')
```

In [0]:
```
y = df.iloc[:,23:25]
X = df.drop(['% Silica Concentrate','% Iron Concentrate','index','datet
ime hours'], axis=1)
```

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,r
andom_state=30)
```

In [0]:
```
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,test_s
ize=0.20,random_state=30)
```

In [0]:
```
from sklearn.preprocessing import StandardScaler
scale_features_std = StandardScaler()
features_train = scale_features_std.fit_transform(X_train)
features_test = scale_features_std.transform(X_test)
```

In [0]:
```
features_cv = scale_features_std.transform(X_cv)
```

In [0]:
```
print(X_train.shape,features_train.shape,X_test.shape,features_test.sha
pe,features_cv.shape,y_train.shape,y_cv.shape,y_test.shape)
```

```
(471969, 21) (471969, 21) (147491, 21) (147491, 21) (117993, 21) (47196
9, 2) (117993, 2) (147491, 2)
```

In [0]:
```
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
```

```
from sklearn.ensemble import AdaBoostRegressor
```

In [0]:
```
param_dist = {
 'n_estimators': [50, 100],
 'learning_rate' : [0.01,0.05,0.1,0.3,1],
 }

pre_gs_inst = RandomizedSearchCV(AdaBoostRegressor(),
 param_distributions = param_dist,
 cv=3,
 n_iter = 10,
 n_jobs=-1)
```

In [0]:
```
pre_gs_inst.fit(features_train, y_train)
```

```
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_ex
ecutor.py:691: UserWarning: A worker stopped while some jobs were given
to the executor. This can be caused by a too short worker timeout or by
a memory leak.
  "timeout or by a memory leak.", UserWarning
```

Out[0]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=AdaBoostRegressor(base_estimator=None,
                                               learning_rate=1.0, loss
='linear',
                                               n_estimators=50,
                                               random_state=None),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'learning_rate': [0.01, 0.05,
0.1, 0.3,
                                                          1],
                                        'n_estimators': [50, 100]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=Tr
ue,
                   return_train_score=False, scoring=None, verbose=0)
```

MODEL USING MULTIOUTPUTREGRESSOR

In [0]:
```
regr_1 = DecisionTreeRegressor(max_depth=50,min_samples_split=5)

regr_2 = AdaBoostRegressor(regr_1,n_estimators=50,learning_rate=1)
```

In [0]:
```
from sklearn.multioutput import MultiOutputRegressor
```

In [0]:
```
model=MultiOutputRegressor(regr_2)
model.fit(features_train,y_train)
```

Out[0]:
```
MultiOutputRegressor(estimator=AdaBoostRegressor(base_estimator=Decisio
nTreeRegressor(ccp_alpha=0.0,
                                                 criterion='mse',
                                                 max_depth=50,
                                                 max_features=None,
                                                 max_leaf_nodes=None,
                                                 min_impurity_decrease=0.0,
                                                 min_impurity_split=None,
                                                 min_samples_leaf=1,
                                                 min_samples_split=5,
                                                 min_weight_fraction_leaf=0.0,
                                                 presort='deprecated',
                                                 random_state=None,
                                                 splitter='best'),
                                                                learning_rate=1, loss
='linear',
                                                                n_estimators=100,
```

```
                                                    random_state=None),
                    n_jobs=None)
```

PREDICTION

In [0]:
```
y_pred=model.predict(features_cv)
y_pred_train=model.predict(features_train)
y_pred_test=model.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

In [0]:
```
r2_train=r2_score(y_train,y_pred_train)
r2_cv=r2_score(y_cv,y_pred)
r2_test=r2_score(y_test,y_pred_test)
```

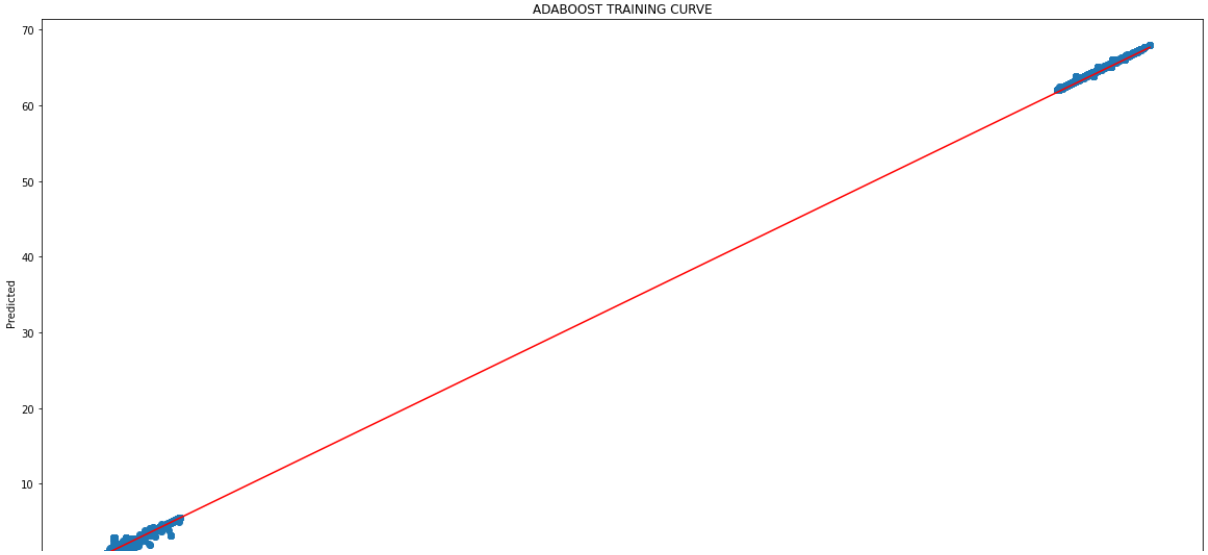
In [0]:
```
r2_train,r2_cv,r2_test,mse_cv,mse_test,mse_train,mse_cv
```

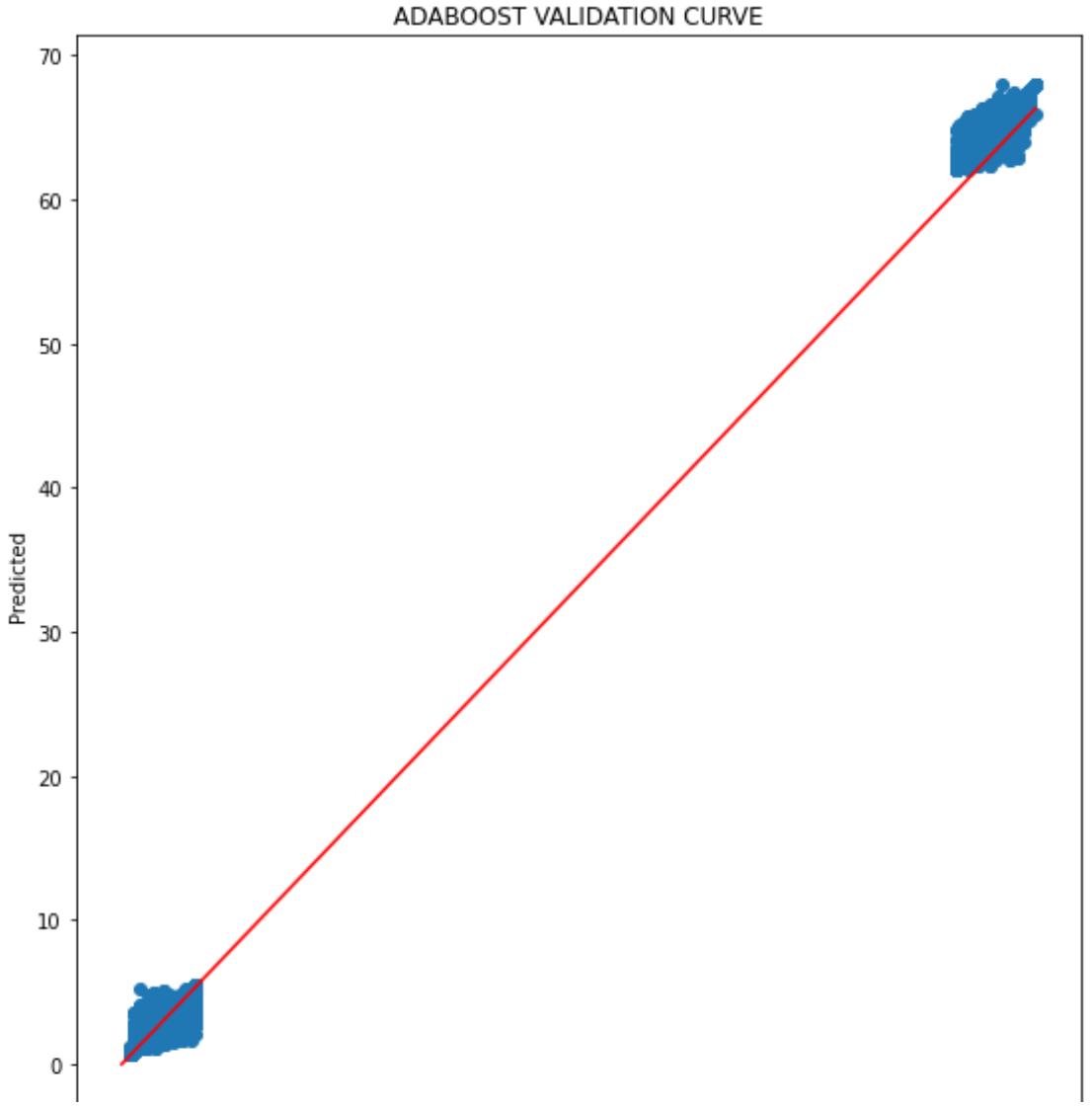
Out[0]:
```
(0.9989177977576809,
 0.9750738456318357,
 0.9745449086918032,
 0.03139462458532873,
 0.03203487819099303,
 0.0013715157924193923,
 0.03139462458532873)
```

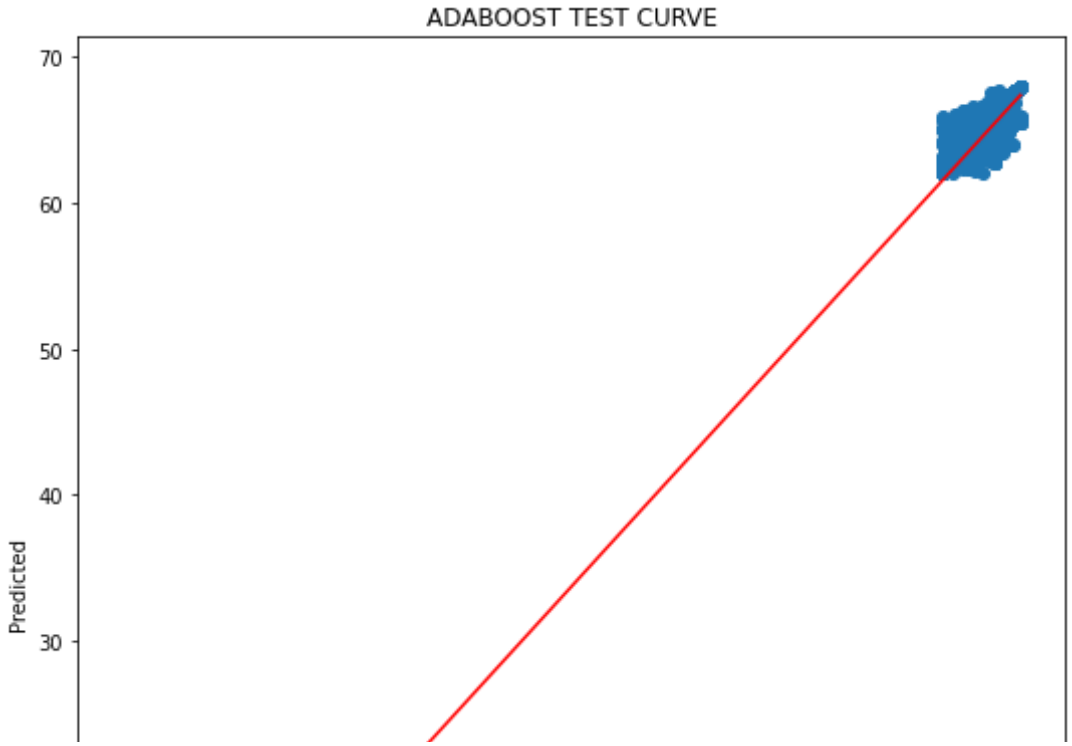
PLOTS

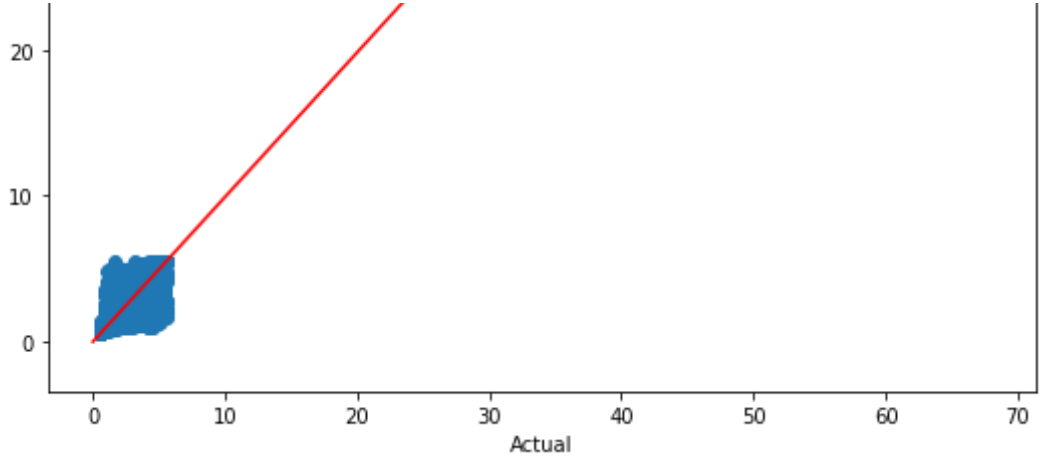
In [0]:
```
fig = plt.figure(figsize=(20, 10))
```

```
ax = fig.add_subplot(111)
ax.set(title="ADABOOST TRAINING CURVE", xlabel="Actual", ylabel="Predic
ted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0
])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="ADABOOST VALIDATION CURVE", xlabel="Actual", ylabel="Pred
icted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color=
'r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="ADABOOST TEST CURVE", xlabel="Actual", ylabel="Predicted"
)
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```









MODEL USING REGRESSOR CHAIN

In [0]:
```
from sklearn.multioutput import RegressorChain
```

In [0]:
```
model= AdaBoostRegressor(regr_1,n_estimators=50,learning_rate=1)
wrapper1 = RegressorChain(model)
wrapper1.fit(features_train,y_train)
```

Out[0]:
```
RegressorChain(base_estimator=AdaBoostRegressor(base_estimator=Decision
TreeRegressor(ccp_alpha=0.0,
                                                criterion='mse',
                                                max_depth=50,
                                                max_features=None,
                                                max_leaf_nodes=None,
                                                min_impurity_decrease=0.0,
                                                min_impurity_split=None,
                                                min_samples_leaf=1,
                                                min_samples_split=5,
                                                min_weight_fraction_leaf=0.0,
                                                presort='deprecated',
                                                random_state=None,
```

```
                   splitter='best'),
                                                      learning_rate=1, loss
='linear',
                                                      n_estimators=50,
                                                      random_state=None),
                    cv=None, order=None, random_state=None)
```

PREDICTION

In [0]:
```
y_pred_cv=wrapper1.predict(features_cv)
y_pred_train=wrapper1.predict(features_train)
y_pred_test=wrapper1.predict(features_test)
```

EVALUATION METRIC

In [0]:
```
r2_cv=r2_score(y_pred_cv,y_cv)
r2_train=r2_score(y_pred_train,y_train)
r2_test=r2_score(y_pred_test,y_test)
```

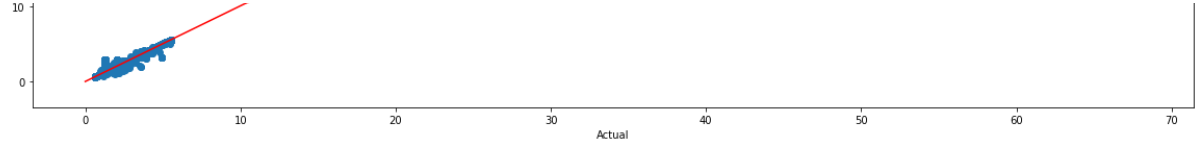
In [0]:
```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_cv=mean_squared_error(y_cv,y_pred)
mse_test=mean_squared_error(y_test,y_pred_test)
```

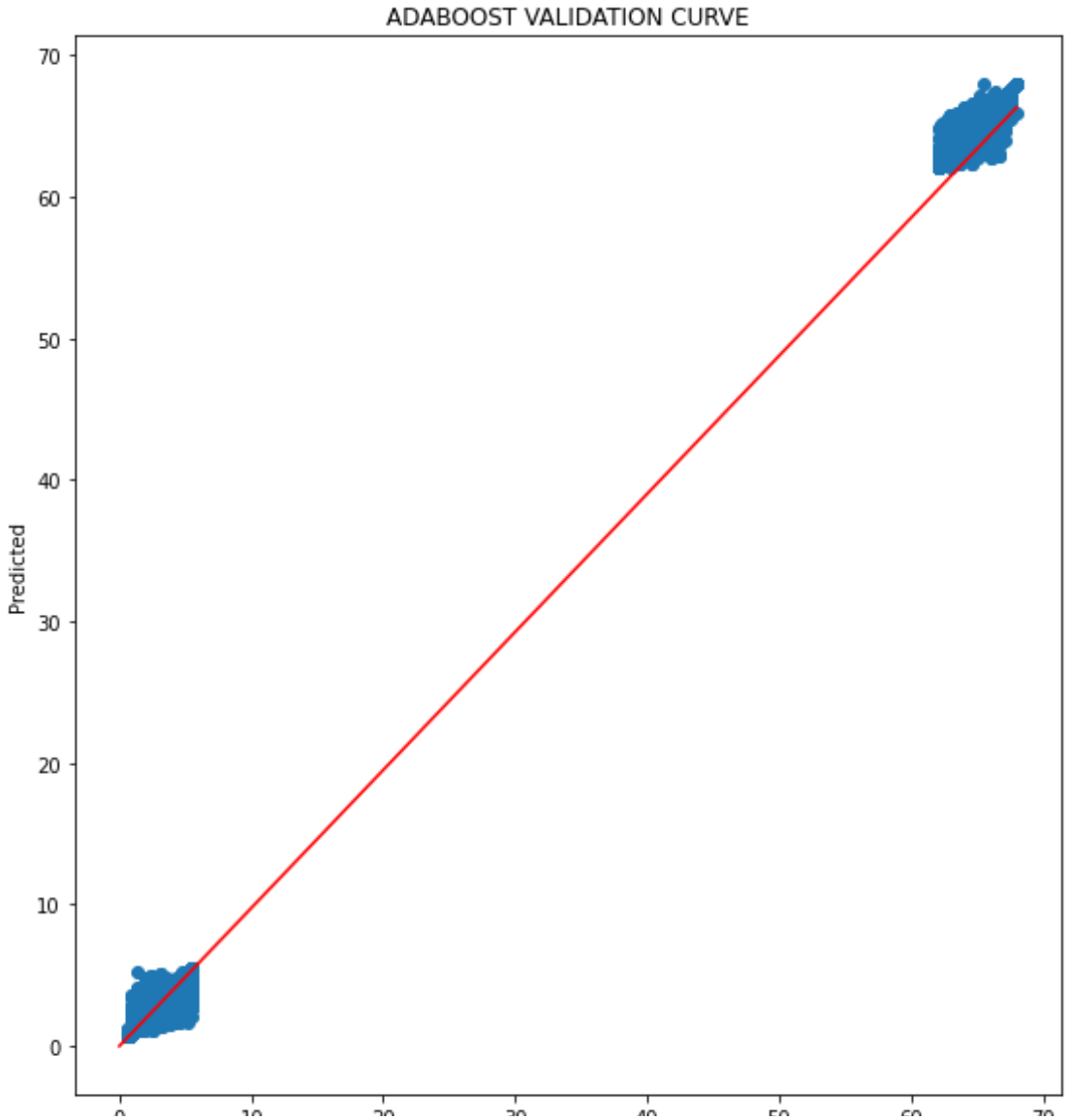
In [0]:
```
r2_train,r2_cv,r2_test,mse_train,mse_cv,mse_test
```

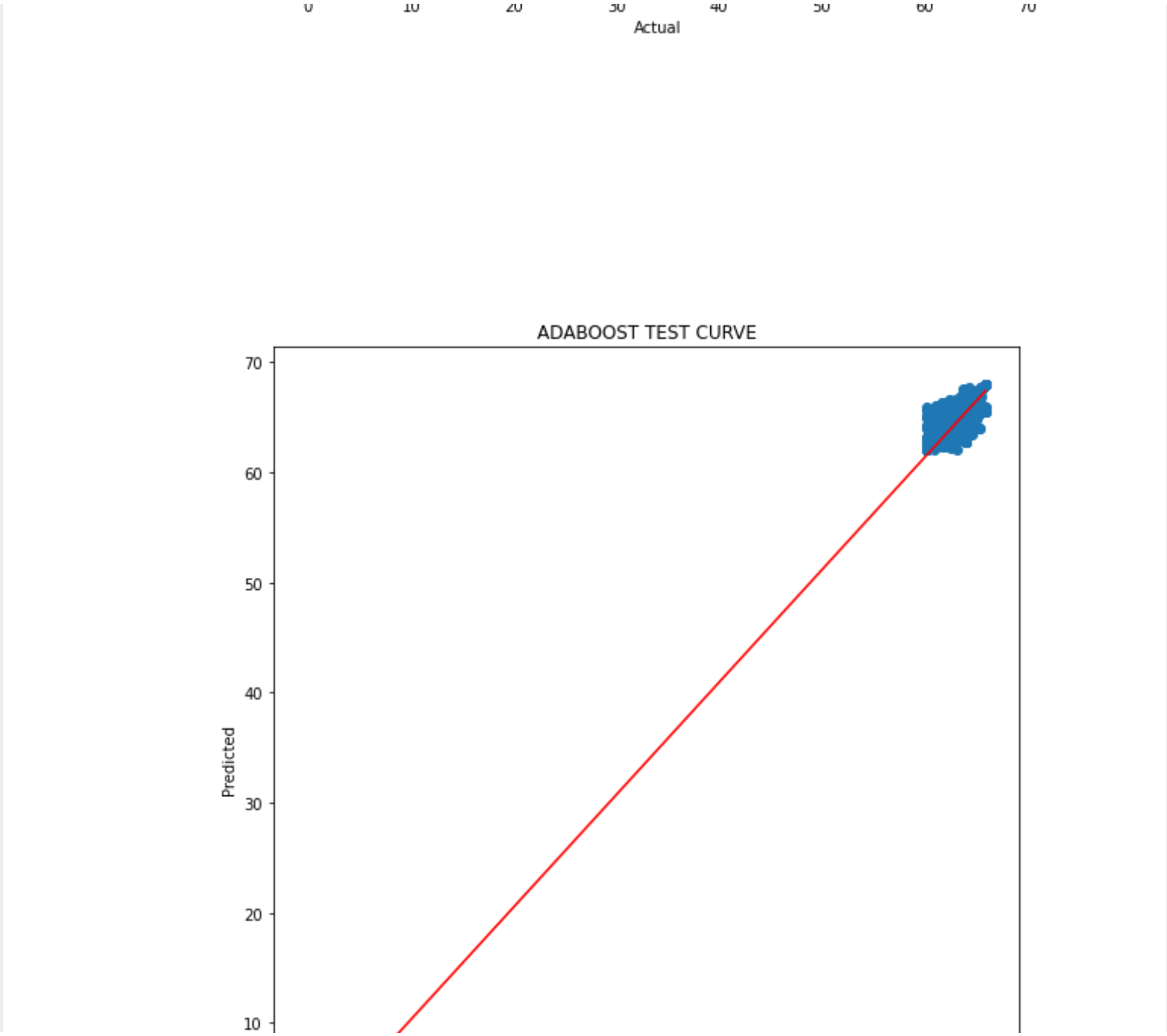
Out[0]:
```
(0.9991389949078793,
 0.9745304869923623,
 0.9733092536247556,
 0.0010902161013306814,
 0.03139462458532873,
 0.03293804176581637)
```

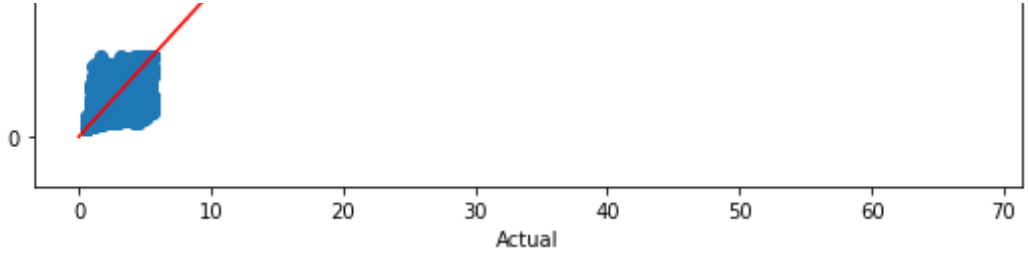
PLOTS

In [0]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(111)
ax.set(title="ADABOOST TRAINING CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_train, y_pred_train)
ax.plot([0,max(y_train['% Iron Concentrate'])], [0,max(y_pred_train[0])], color='r')
fig.show()
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot(121)
ax.set(title="ADABOOST VALIDATION CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_cv, y_pred)
ax.plot([0,max(y_cv['% Iron Concentrate'])], [0,max(y_pred[0])], color='r')
fig.show()
fig = plt.figure(figsize=(30, 10))
ax = fig.add_subplot(131)
ax.set(title="ADABOOST TEST CURVE", xlabel="Actual", ylabel="Predicted")
ax.scatter(y_test, y_pred_test)
ax.plot([0,max(y_test['% Iron Concentrate'])], [0,max(y_pred_test[0])],
 color='r')
fig.show()
```









REPORT

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2_TRAIN","R2_CV","R2_TEST","MSE_TRAIN","MSE_CV","MSE_TEST"]
x.add_row(["ADABOOST MTR",0.9989177977576809,
 0.9750738456318357,
 0.9745449086918032, 0.0013715157924193923,
 0.03139462458532873,
 0.03203487819099303


])
x.add_row(["ADABOOST RIGRESSION CHAIN",0.9991389949078793,
 0.9745304869923623,
 0.9733092536247556,
 0.0010902161013306814,
 0.03139462458532873,
```

```
 0.032938041765816371])

print(x)
```

```
+-----------------------------------------------------+--------------
----------------------------------+-----------------------------------
------------+----------------------------------------------------+---------
-------------------------------------------+----------------------------
---------------------+------------------------------------------------------
+
|                           MODEL1                                    |
      R2_TRAIN                        |                          R2_CV
            |                      R2_TEST                             |
            MSE_TRAIN                          |                          MSE_CV
                       |                        MSE_TEST
|
+-----------------------------------------------------+--------------
----------------------------------+-----------------------------------
------------+----------------------------------------------------+---------
-------------------------------------------+----------------------------
---------------------+------------------------------------------------------
+
|                         ADABOOST MTR                          |
0.9989177977576809                 |                0.9750738456318357
           |                0.9745449086918032                 |
     0.0013715157924193923                 |                 0.031394624585
32873                |                0.03203487819099303                 |
|                ADABOOST RIGRESSION CHAIN                 |
0.9991389949078793                 |                0.9745304869923623
           |                0.9733092536247556                 |
     0.0010902161013306814                 |                 0.031394624585
32873                |                0.03293804176581637                 |
+-----------------------------------------------------+--------------
----------------------------------+-----------------------------------
------------+----------------------------------------------------+---------
-------------------------------------------+----------------------------
---------------------+------------------------------------------------------
+
```

METRIC ANALYSIS

https://scikit-learn.org/stable/modules/generated/sklearn.metri highlight=r2#sklearn.metrics.r2_score

https://scikit-learn.org/stable/modules/generated/sklearn.metri

R2 SCORE

Acoording to literature, the r2 score is good when it is closer to 1 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

TRAIN R2 is so closer to 0 and TEST r2 is also to 0 and hence inorder to get better result , we must try other models

MSE VALUE

A non-negative floating point value (the best value is 0.0), or an array of floating point values, one for each individual target.

The MSE value and R2 score value is better than ridge and MSE value of MTR is same as REGRESSION CHAIN model.

PLOTS ANALYSIS

1. MTR MODEL

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

In test and validation curve, the models are able to predict iron concetrate and are able to predict the silica better in the same way for iron concentrate

2. Regressor chain

   In train curve, the points tend to overlay on the line and in both iron and silica the points are overfalling on regression line

   In test curve, the models are able to predict iron concetrate and are able to predict the silica the same way of iron concentrate.

CONCLUSION

AdaBoost model can be used for quality prediction. It shows the scatter plot of the model that predicts two target variables: silica and iron concentrates by AdaBoost regressor.

ADABOOST>RANDOMFOREST>DECISION TREE>XGBOOST>RIDGE

OVERALL COMPARSION

In [0]:
```
#https://pypi.org/project/PrettyTable/-- for representation of data
#https://stackoverflow.com/questions/36423259/how-to-use-pretty-table-in-python-to-print-out-data-from-multiple-lists-- to add the rows in table
from prettytable import PrettyTable
x = PrettyTable(border=True, header=True, padding_width=15)
x.field_names = ["MODEL1", "R2","MSE"]
x.add_row(["ADABOOST",0.9745449086918032,0.03203487819099303])
x.add_row(["RANDOMFOREST",0.9404630125734039,0.0749937491528446])
x.add_row(["DECISION TREE", 0.9036198036618404,0.12437333275470228])
x.add_row(["XGBOOST", 0.7750269140015339,0.2641687929200151])
x.add_row(["RIDGE",  0.1457070772811201,  1.0722436207597437 ])


print(x)
```

```
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------
-+
|                   MODEL1                |                        R2
                        |                       MSE
|
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------
-+
|                  ADABOOST               |               0.974544908
6918032                 |               0.03203487819099303
|
|                RANDOMFOREST             |               0.940463012
5734039                 |                0.0749937491528446
|
|               DECISION TREE             |               0.903619803
6618404                 |               0.12437333275470228
|
|                  XGBOOST                |               0.775026914
0015339                 |                0.2641687929200151
|
|                   RIDGE                 |               0.145707077
2811201                 |                1.0722436207597437
|
+-----------------------------------------+-------------------------
----------------------+-------------------------------------------
-+
```

RESULTS IN PAPER VS OUR MODEL RESULTS

RESULT IN RESERACH PAPER

Method	R^2 Value
Random Forest Regressor	0.96
AdaBoost Regressor	0.98
K-Nearest Neighbors Regressor	0.63
Decision Tree Regressor	0.92

OUR RESULTS

MODEL1	R2	MSE
ADABOOST	0.9745449086918032	0.03203487819099303
RANDOMFOREST	0.9404630125734039	0.0749937491528446
DECISION TREE	0.9036198036618404	0.12437333275470228
XGBOOST	0.7750269140015339	0.2641687929200151
RIDGE	0.1457070772811201	1.0722436207597437

PLOTS IN PAPER VS OUR RESULTS(ADABOOST ALONE)

PLOTS IIN PAPER

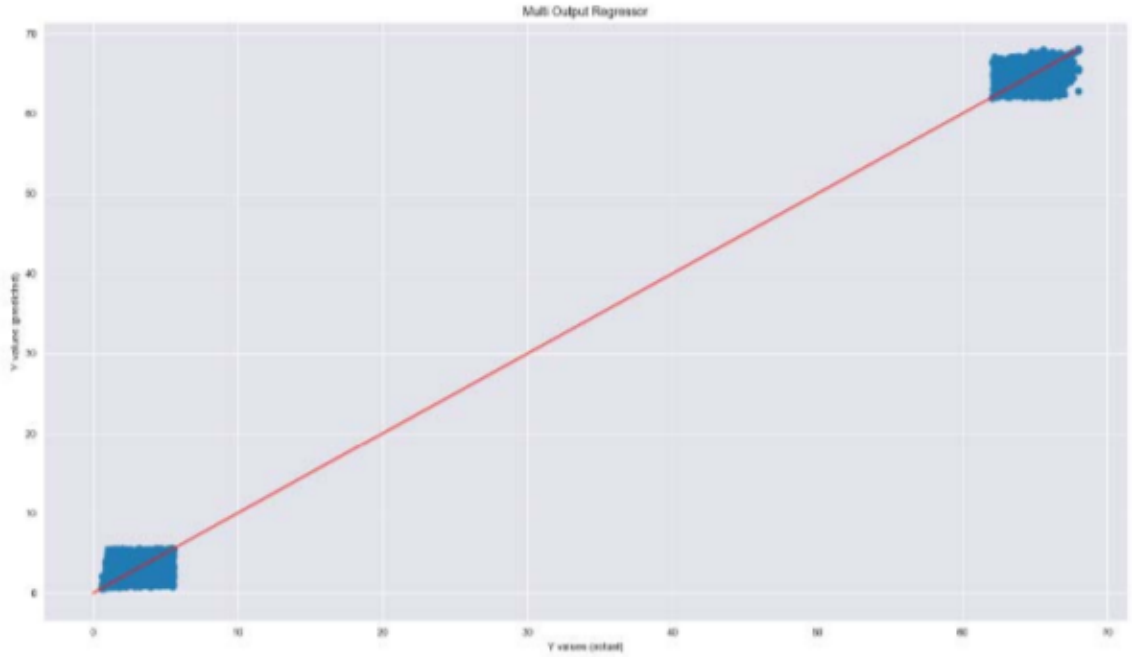
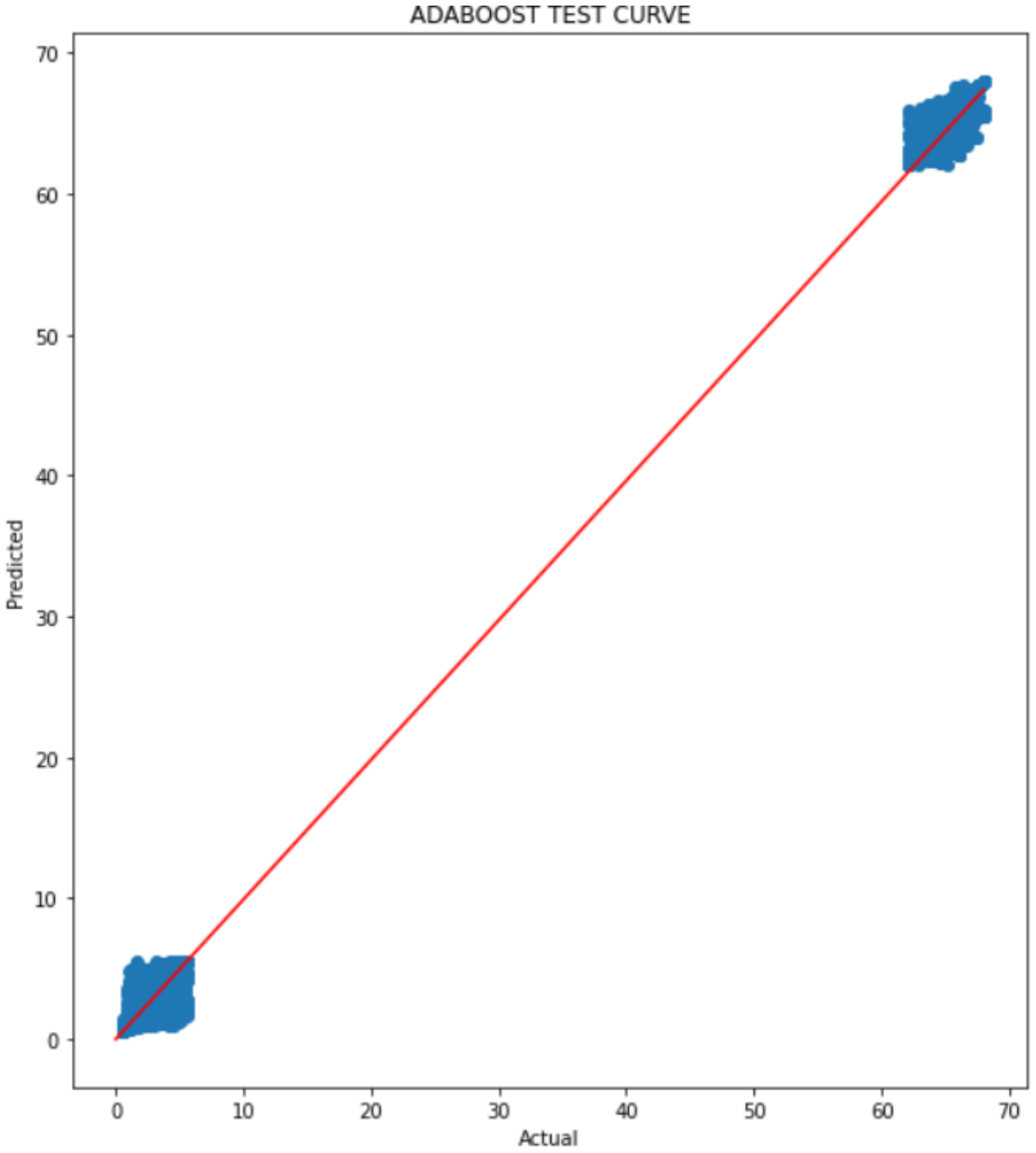


Fig. 4. Scatter plot of the model that predicts two target variables: silica and iron concentrates by multi-output regressor

PLOTS OBTAINED



SUMMARY

The experimental results show that AdaBoost regressor clearly provided higher coefficient of determination value than other algorithms. This is probably because AdaBoost is an ensemble method, which generally provides better accuracies than an individual model by averaging the decisions of several predictors. In addition, AdaBoost is an iterative algorithm, each time reweighting the instances in the dataset to focus the next classifier on incorrectly classified ones. By this way, it constructs a strong classifier from a combination of weak classifiers.

Our Results match with research paper results . In reerach paper also ADABOOST is the best model likewise in our study also our best model is ADABOOST.

The experimental results demonstrate the superiority of AdaBoost .

Another ensemble learning algorithm, Random Forest, also obtained a high score 0.96 which is very close to the best value. So, Random Forest can also be used alternatively, especially when there are many input variables, since it randomly selects the subset of the features, which decreases the running time of the algorithm. It can be observed from table that Decision Tree method has also acceptable accuracy. However, ensemble based methods (AdaBoost and Random Forest) have higher accuracy with respect to this method. According to the results given in Table the RIDGE method is not suitable to be the base learner for multi-output regressor because it performs significantly worse than decision tree based methods.

In this study, a multi-target regression problem is handled to predict quality in a mining process. The aim is to construct a robust model that simultaneously estimates the amount of silica and iron concentrates in the ore. Several approaches are implemented and compared to be able to handle more than one target variable. We tried to observe the performance of a multi target regression approach when target features are highly correlated. At the end, it is noticed that this approach can also be efficient in manufacturing data when a related attribute is not given to the algorithm as an input parameter. Instead, that feature can also be evaluated as an output variable by being added to the existing target feature. We have observed that this alteration did not create an adverse effect on the regression performance.