Import the libraries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split,cross_val_score, GridS
from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor
from sklearn.tree import DecisionTreeRegressor
import xgboost as xgb
from sklearn.model_selection import cross_val_predict as cvp
```

Load the data

In [2]:
```
train_data= pd.read_csv("C:\\Users\\hp\\Downloads\\train.csv")
test_data= pd.read_csv("C:\\Users\\hp\\Downloads\\test.csv")
```

In [48]:
```
train_data.head()
```

Out[48]:

	Id	target	1	2	3	4	5	6	7
0	0	5.85	4.80	5.85	NaN	NaN	NaN	NaN	NaN
1	3	4.28	5.88	6.84	NaN	NaN	NaN	NaN	NaN
2	4	3.97	3.20	2.70	NaN	NaN	NaN	NaN	NaN
3	5	5.95	7.70	7.06	NaN	NaN	NaN	NaN	NaN
4	6	4.70	5.50	5.30	NaN	NaN	NaN	NaN	NaN

Find Info for understanding the columns like how many columns and what type of value in it

In [49]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 147 entries, 0 to 146
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Id      147 non-null    int64  
 1   target  147 non-null    float64
 2   1       145 non-null    float64
 3   2       145 non-null    float64
 4   3       32 non-null     float64
 5   4       31 non-null     float64
 6   5       33 non-null     float64
 7   6       37 non-null     float64
 8   7       37 non-null     float64
dtypes: float64(8), int64(1)
memory usage: 10.5 KB
```

Describe for understanding data columns like min,max, mean, std .

In [50]:
```
train_data.describe()
```

Out[50]:

	Id	target	1	2	3	4	5	
count	147.000000	147.000000	145.000000	145.000000	32.000000	31.000000	33.000000	37.0
mean	101.401361	5.021633	4.972621	4.906552	4.665000	5.871613	8.678788	3.8
std	64.836640	2.122535	2.044076	2.001357	2.057429	2.555247	5.299119	1.6
min	0.000000	1.300000	0.900000	1.040000	2.040000	2.480000	2.880000	1.0
25%	41.500000	3.720000	3.500000	3.400000	3.325000	4.445000	5.840000	2.9
50%	102.000000	4.600000	4.800000	4.830000	4.150000	5.500000	7.300000	3.4
75%	158.500000	6.275000	6.450000	6.200000	5.970000	6.400000	8.420000	4.8
max	214.000000	11.700000	10.900000	11.000000	10.660000	14.790000	27.120000	8.5

Find null values in data

In [51]:
```
train_data.isnull()
```

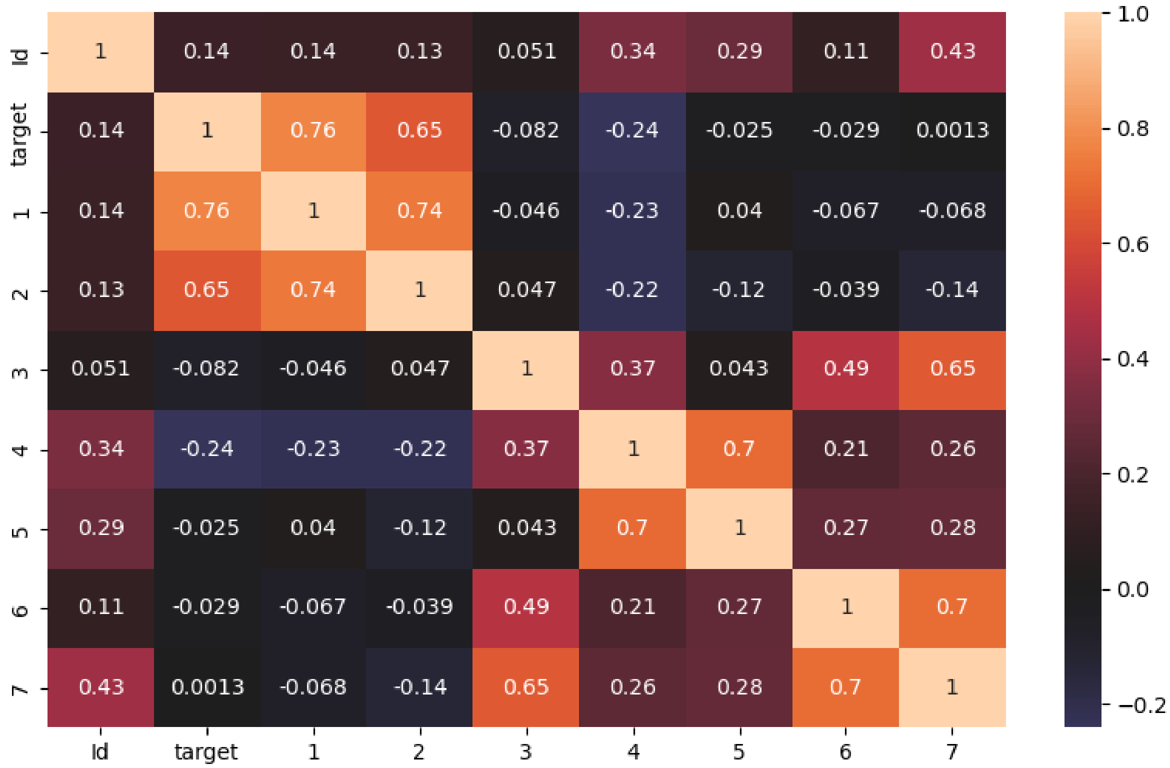
Out[51]:

	Id	target	1	2	3	4	5	6	7
0	False	False	False	False	True	True	True	True	True
1	False	False	False	False	True	True	True	True	True
2	False	False	False	False	True	True	True	True	True
3	False	False	False	False	True	True	True	True	True
4	False	False	False	False	True	True	True	True	True
...	...	...	...	...	...	...	...	...	...
142	False	False	False	False	True	True	True	True	True
143	False	False	False	False	True	True	True	True	True
144	False	False	False	False	True	True	True	True	True
145	False	False	False	False	True	True	True	True	True
146	False	False	False	False	True	True	True	True	True

147 rows × 9 columns

Create heatmap for understanding the correlation in different columns

In [10]:
```
plt.figure(figsize= (10,6))
sns.heatmap(train_data.corr(),center=0, annot=True)
plt.show()
```



	Id	target	1	2	3	4	5	6	7
Id	1	0.14	0.14	0.13	0.051	0.34	0.29	0.11	0.43
target	0.14	1	0.76	0.65	-0.082	-0.24	-0.025	-0.029	0.0013
1	0.14	0.76	1	0.74	-0.046	-0.23	0.04	-0.067	-0.068
2	0.13	0.65	0.74	1	0.047	-0.22	-0.12	-0.039	-0.14
3	0.051	-0.082	-0.046	0.047	1	0.37	0.043	0.49	0.65
4	0.34	-0.24	-0.23	-0.22	0.37	1	0.7	0.21	0.26
5	0.29	-0.025	0.04	-0.12	0.043	0.7	1	0.27	0.28
6	0.11	-0.029	-0.067	-0.039	0.49	0.21	0.27	1	0.7
7	0.43	0.0013	-0.068	-0.14	0.65	0.26	0.28	0.7	1

Count the data how much value in particular columns

In [13]:
```
train_data.count()
```

Out[13]:
```
Id        147
target    147
1         145
2         145
3          32
4          31
5          33
6          37
7          37
dtype: int64
```

Drop unimportant features because those columns have so much null values(Approx 50 to 60%)

In [3]:
```
train_data = train_data.drop(['3','4','5','6','7','Id'],axis=1)
```

Drop rows beacause it has null values and create a new dataframe with three columns

In [4]:
```
train_data=train_data.dropna()
train_data.head()
```

Out[4]:

	target	1	2
0	5.85	4.80	5.85
1	4.28	5.88	6.84
2	3.97	3.20	2.70
3	5.95	7.70	7.06
4	4.70	5.50	5.30

In [54]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 144 entries, 0 to 146
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   target  144 non-null    float64
 1   1       144 non-null    float64
 2   2       144 non-null    float64
dtypes: float64(3)
memory usage: 4.5 KB
```

In [7]:
```
Y= train_data['target']
X= train_data.drop(['target'],axis=1)
```

Use scaling method to convert value in one format

In [8]:
```
sc= StandardScaler()
train_data= pd.DataFrame(sc.fit_transform(X))
```

In [9]:
```
train_data.head()
```

Out[9]:

	0	1
0	-0.085038	0.464653
1	0.443331	0.963267
2	-0.867807	-1.121847
3	1.333732	1.074070
4	0.257424	0.187645

Split the data into trainand test dataset

It is extremely important to split the data into train and test sets. Train set is used to train the model and Test set is used to test the performance of the model.

Problems encountered if train test split not performed:

It does not make sense to talk about the performance of the model by testing it on same data. The model learns the data pretty well and when tested on same data will produce the best score. The model becomes very specific to the training data, so far as they even get trained on the ocassional erroneous labels present in the training data. This results in Overfitting and the model might not work well outside the training data. Therefore it is advised to keep a certian portion of the data aside (test set) untouched and test our model on this data to evaluate the true performance of the model.

X_train - all the predictors

Y_train - target variable

X_test - all the predictors

Y_test - target variable

Let's define X and Y before splitting the data

In [10]:
```
X_train, X_test, Y_train, Y_test= train_test_split(train_data,Y, test_size=
```

In [11]:
```
print('X_train: ',X_train.shape)
print('X_test: ',X_test.shape)
print('Y_train: ',Y_train.shape)
print('Y_test: ',Y_test.shape)
```

```
X_train:  (100, 2)
X_test:  (44, 2)
Y_train:  (100,)
Y_test:  (44,)
```

Use first algorithm it is linear regression for create a model

In [12]:
```
re= LinearRegression()
re.fit(X_train,Y_train)
```
Out[12]:
```
LinearRegression()
```

In [15]:
```
Y_pred= re.predict(X_test)
```

In [16]:
```
from sklearn import metrics
```

Find MSE and MAE ,RMSE that help to underastand how much currectly predict the data.

In [17]:
```
print("MSE",metrics.mean_squared_error(Y_test,Y_pred))

print("MAE", metrics.mean_absolute_error(Y_test,Y_pred))
```
```
MSE 1.908080391348191
MAE 0.9991164787350244
```

In [18]:
```
rmse = np.sqrt(metrics.mean_squared_error(Y_test,Y_pred))
rmse
```
Out[18]:
```
1.3813328314885558
```

Second algorithm that is DecisionTreeRegressor and create a model

In [19]:
```
Reg = DecisionTreeRegressor()
Reg.fit(X_train,Y_train)
```
Out[19]:
```
DecisionTreeRegressor()
```

In [20]:
```
Y_pred1= Reg.predict(X_test)
Y_pred1
```
Out[20]:
```
array([3.74, 2.  , 3.74, 5.65, 5.85, 7.9 , 1.8 , 4.7 , 4.2 , 4.6 , 3.12,
       4.42, 1.8 , 5.6 , 8.  , 5.65, 7.4 , 3.96, 5.7 , 4.6 , 3.17, 3.74,
       2.3 , 9.2 , 5.7 , 6.4 , 4.6 , 6.8 , 5.4 , 4.7 , 5.75, 3.35, 7.4 ,
       3.3 , 9.2 , 5.9 , 8.2 , 4.42, 5.7 , 3.17, 5.9 , 7.4 , 4.2 , 4.55])
```

In [21]:
```
print("MAE1",metrics.mean_absolute_error(Y_test,Y_pred1))

print("MSE",metrics.mean_squared_error(Y_test,Y_pred1))
```
```
MAE1 1.281590909090909
MSE 2.729015909090909
```

In [22]:
```
rmse1= np.sqrt(metrics.mean_squared_error(Y_test,Y_pred1))
print(rmse1)
```

```
1.6519733378874215
```

Third algorithm RandomForestRegressor for create a model

In [64]:
```
reg= RandomForestRegressor(n_estimators=1000, random_state=42)

reg.fit(X_train, Y_train)
```

Out[64]:
```
RandomForestRegressor(n_estimators=1000, random_state=42)
```

In [24]:
```
Y_pred2 = reg.predict(X_test)
Y_pred2
```

Out[24]:
```
array([3.69641, 2.35972, 4.04768, 6.0223 , 5.4004 , 8.7563 , 1.99432,
       5.22535, 4.74895, 4.75757, 4.15568, 3.77217, 2.06114, 4.00642,
       7.13588, 5.68314, 6.1878 , 3.1258 , 4.786  , 3.95269, 3.21925,
       3.7377 , 2.74973, 7.5968 , 4.40332, 6.94121, 5.06289, 7.24345,
       6.49805, 4.75987, 5.37251, 3.3139 , 6.49554, 3.41049, 8.3107 ,
       5.88345, 5.48343, 3.67446, 4.57031, 3.88838, 5.29449, 7.11214,
       4.71175, 5.64416])
```

In [25]:
```
rmse2= np.sqrt(metrics.mean_squared_error(Y_test,Y_pred2))
print(rmse2)
```

```
1.5083133345170154
```

In [26]:
```
print("MAE2",metrics.mean_absolute_error(Y_test,Y_pred2))

print("MSE2",metrics.mean_squared_error(Y_test,Y_pred2))
```

```
MAE2 1.1259331818181826
MSE2 2.275009115081838
```

FInd accuracy for three model like Linear Regression, Decision Tree Regressor and Random Forest Regressor

Ist Step: find error between Y_pred and Y_test

IInd Step: find mape for every model

IIIrd Step: Find accuracy for find which model gives much more closer value to actual value

In [27]:
```
error1= abs(Y_pred-Y_test)
error1
```

Out[27]:
```
7      3.864581
91     2.778615
100    0.691662
26     0.987069
113    4.018449
131    1.620100
61     0.695663
22     0.997870
132    0.461905
16     0.269920
129    1.345180
123    0.033403
40     0.654918
45     0.012537
55     1.864446
33     1.937481
24     1.055904
8      0.132185
130    0.364389
52     0.096559
88     2.303701
119    0.155582
37     2.530782
99     0.038741
43     0.652951
117    0.183214
65     0.667670
143    1.946564
104    1.702090
18     0.129546
73     0.597297
27     0.556716
144    0.598830
2      0.689670
62     1.917637
10     0.345693
78     0.661918
108    0.555688
58     0.414527
111    1.276197
63     0.379653
44     0.335252
68     0.516840
115    0.921531
Name: target, dtype: float64
```

In [28]:
```
error2= abs(Y_pred1-Y_test)
error2.head()
```

Out[28]:
```
7      3.96
91     2.25
100    0.34
26     1.45
113    3.15
Name: target, dtype: float64
```

In [29]:
```
error3= abs(Y_pred2-Y_test)
error3.head()
```

Out[29]:
```
7      4.00359
91     1.89028
100    0.64768
26     1.07770
113    3.59960
Name: target, dtype: float64
```

In [30]:
```
mape1=100*(error1/Y_test)
mape2=100*(error2/Y_test)
mape3=100*(error3/Y_test)
mape1.head()
mape2.head()
mape3.head()
```

Out[30]:
```
7      51.994675
91     44.477176
100    19.049412
26     15.178873
113    39.995556
Name: target, dtype: float64
```

In [31]:
```
acc1= 100-np.mean(mape1)
acc1
```

Out[31]:
```
81.11187083865273
```

In [53]:
```
acc2 =100-np.mean(mape2)
acc2
```

Out[53]:
```
76.24598324917807
```

In [32]:
```
acc3 = 100-np.mean(mape3)
acc3
```

Out[32]:
```
79.72731924964913
```

Fourth algorithm that is Extra Tree Regressor

In [67]:
```
etr = ExtraTreesRegressor()
etr.fit(X_train, Y_train)
```

Out[67]:
```
ExtraTreesRegressor()
```

In [34]:
```
Y_Pred3= etr.predict(X_test)
```

In [35]:
```
rmse3 = np.sqrt(metrics.mean_squared_error(Y_test,Y_Pred3))
print(rmse3)
```

```
1.6677760538159248
```

In [36]:
```
error4= abs(Y_Pred3-Y_test)
error4.head()
```

Out[36]:
```
7      4.0755
91     2.2610
100    0.6768
26     1.1187
113    3.5894
Name: target, dtype: float64
```

In [37]:
```
mape4=100*(error4/Y_test)
```

In [38]:
```
acc4= 100-np.mean(mape4)
acc4
```

Out[38]:
```
78.3903083485825
```

In [22]:
```
from xgboost import XGBRegressor
```

In [23]:
```
xgb_reg= XGBRegressor()
xgb_reg.fit(X_train,Y_train)
```

Out[23]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=Non
e,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=No
ne,
             interaction_constraints=None, learning_rate=None, max_bin=Non
e,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=Non
e,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
```

In [41]:
```
Y_pred5= xgb_reg.predict(X_test)
Y_pred5
```

Out[41]:
```
array([3.1000638, 2.0202532, 3.934603 , 6.082461 , 5.741329 , 8.479428 ,
       1.8919207, 4.911784 , 5.511828 , 5.0558987, 4.1293035, 3.5101824,
       1.8399107, 4.4886084, 8.836549 , 5.6477222, 5.088474 , 4.360249 ,
       5.0926237, 3.5746412, 3.3263586, 3.564568 , 2.02332  , 7.531992 ,
       5.1158857, 7.4351707, 4.534392 , 7.6810503, 5.15817  , 4.7454615,
       5.7502637, 4.002088 , 5.088474 , 3.2784328, 8.195635 , 6.4850106,
       4.5512295, 3.809296 , 5.190139 , 3.9827178, 5.2583747, 7.6501703,
       5.511828 , 6.91598  ], dtype=float32)
```

In [42]:
```
rmse4= np.sqrt(metrics.mean_squared_error(Y_test,Y_pred5))
print(rmse4)
```

```
1.8596709744010336
```

In [43]:
```
error5= abs(Y_pred5-Y_test)
mape5=100*(error5/Y_test)
```

In [44]:
```
acc5= 100-np.mean(mape5)
acc5
```

Out[44]:
```
74.30866871281303
```

In [45]:
```
print("MSE3",metrics.mean_squared_error(Y_test,Y_pred5))
```

```
MSE3 3.45837613302969
```

Create new data frame for showing the visualization on accuracy

In [54]:
```
data=[["LinearRegression",acc1],["DecisionTreeRegressor",acc2],["RandomFore
df= pd.DataFrame(data, columns=['Algorithm','Accuracy'])
df
```

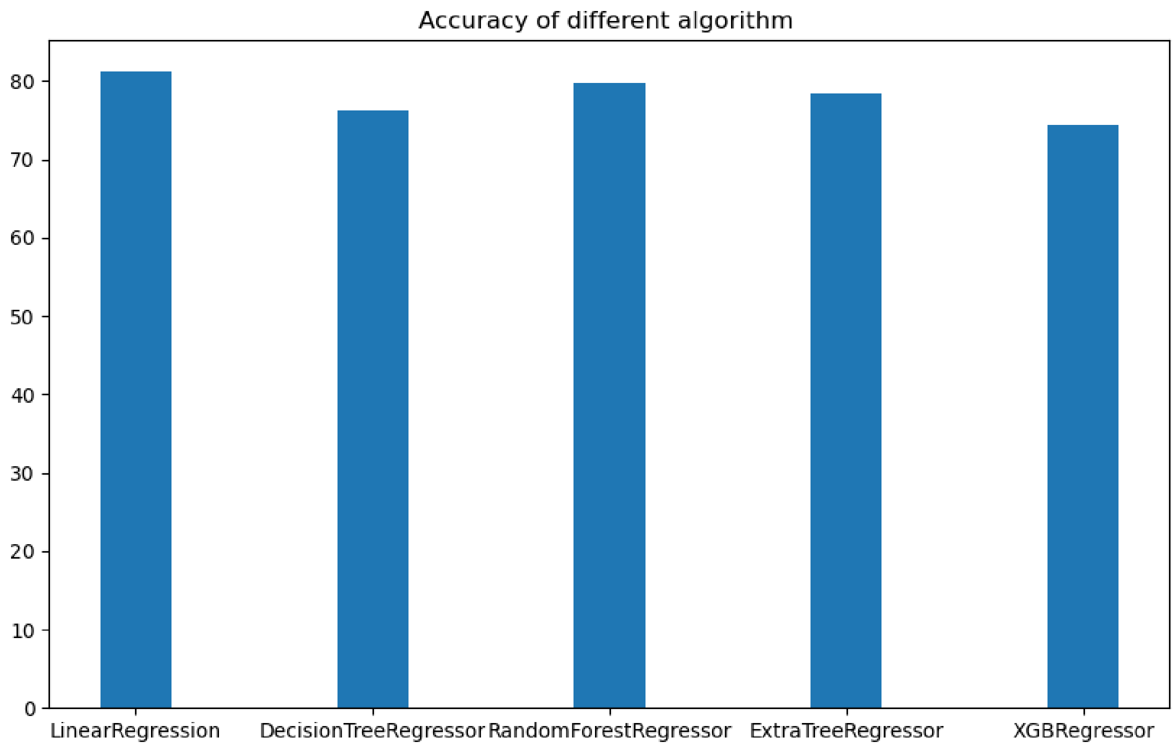
Out[54]:

	Algorithm	Accuracy
0	LinearRegression	81.111871
1	DecisionTreeRegressor	76.245983
2	RandomForestRegressor	79.727319
3	ExtraTreeRegressor	78.390308
4	XGBRegressor	74.308669

In [56]:
```
fig = plt.figure(figsize=(10,6))

plt.bar(df.Algorithm,df.Accuracy, width=0.3)

plt.title("Accuracy of different algorithm ")
plt.show()
```



In [4]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63 entries, 0 to 62
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Id      63 non-null     int64
 1   1       63 non-null     float64
 2   2       63 non-null     float64
 3   3       15 non-null     float64
 4   4       15 non-null     float64
 5   5       16 non-null     float64
 6   6       14 non-null     float64
 7   7       14 non-null     float64
dtypes: float64(7), int64(1)
memory usage: 4.1 KB
```

In [6]:
```
test_data= test_data.drop(['Id','3','4','5','6','7'],axis=1)
test_data.head()
```

Out[6]:

	1	2
0	6.80	5.40
1	4.71	4.20
2	2.10	3.40
3	5.35	5.85
4	4.80	5.30

In [14]:
```
Scaler= StandardScaler()
test_data= pd.DataFrame(Scaler.fit_transform(test_data), columns= test_data
```

In [62]:
```
xgb_reg.fit(train_data,Y)
xgb_reg.predict(X_train)[:3]
```

Out[62]:
```
array([3.601099, 6.989933, 6.910082], dtype=float32)
```

In [65]:
```
reg.fit(train_data,Y)
reg.predict(X_train)[:3]
```

Out[65]:
```
array([3.59853, 7.14851, 6.64207])
```

In [68]:
```
etr.fit(train_data,Y)
etr.predict(X_train)[:3]
```

Out[68]:
```
array([3.6 , 6.98, 6.9 ])
```

Plot the graph for Actual vs Predicted Values

In [13]:
```
g = sns.regplot(x=re.predict(X_test), y=Y_test, fit_reg=True)
g.set(xlabel='Predicted House Prices($)', ylabel='Actual House Prices($)',
plt.title('Regression Plot for Actual vs Predicted Values')
```

Out[13]:
```
Text(0.5, 1.0, 'Regression Plot for Actual vs Predicted Values')
```

In [ ]:

In [ ]:

In [ ]: