AIML421 Assignment4 - Part 1: Performance Metrics in Regression

Dataset: diamonds.csv

In [11]:
```
import pandas as pd
import numpy as np
diamonds_data =pd.read_csv("/Users/Jessie/Documents/JupyterNotebook/ass4data
diamonds_data.head()
```

Out[11]:

	Unnamed: 0	carat	cut	color	clarity	depth	table	x	y	z	price
0	1	0.23	Ideal	E	SI2	61.5	55.0	3.95	3.98	2.43	326
1	2	0.21	Premium	E	SI1	59.8	61.0	3.89	3.84	2.31	326
2	3	0.23	Good	E	VS1	56.9	65.0	4.05	4.07	2.31	327
3	4	0.29	Premium	I	VS2	62.4	58.0	4.20	4.23	2.63	334
4	5	0.31	Good	J	SI2	63.3	58.0	4.34	4.35	2.75	335

Perform Initial Data Analysis:

In [3]:
```
diamonds_data.shape
```

Out[3]:
```
(53940, 11)
```

In [4]:
```
#check missing values
diamonds_data.isnull().sum()
```

Out[4]:
```
Unnamed: 0     0
carat          0
cut            0
color          0
clarity        0
depth          0
table          0
x              0
y              0
z              0
price          0
dtype: int64
```

In [5]:
```
diamonds_data.dtypes
```

Out[5]:
```
Unnamed: 0      int64
carat         float64
cut            object
color          object
clarity        object
depth         float64
table         float64
x             float64
y             float64
z             float64
price           int64
dtype: object
```

In [6]:
```
len(diamonds_data["Unnamed: 0"].unique())
```
Out[6]:
```
53940
```

In [7]:
```
print(diamonds_data["cut"].unique(),
diamonds_data["color"].unique(),
diamonds_data["clarity"].unique())
```
```
['Ideal' 'Premium' 'Good' 'Very Good' 'Fair'] ['E' 'I' 'J' 'H' 'F' 'G' 'D']
['SI2' 'SI1' 'VS1' 'VS2' 'VVS2' 'VVS1' 'I1' 'IF']
```

cut and color are definetely ordinal. how about clarity? Did some research on it, and found: "The GIA Clarity Scale contains 11 grades, with most diamonds falling into the VS (very slightly included) or SI (slightly included) categories." So it's ordinal as well.

Next step - Initial Preproces the data - drop irelavent columns:

In [8]:
```
data=diamonds_data.drop(["Unnamed: 0"], axis=1)
```

To prevent data leakage, we split the data into training and test set first

In [9]:
```
from sklearn.model_selection import train_test_split
y=data['price']
X=data.drop(['price'], axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ran
```

In [55]:
```
from sklearn.preprocessing import OrdinalEncoder
X_train_encoded=X_train.copy()
#encode cut
encoder_cut = OrdinalEncoder(handle_unknown = 'use_encoded_value', unknown_v
X_train_encoded['cut'] = encoder_cut.fit_transform(X_train_encoded['cut'].va
#encode color
encoder_color = OrdinalEncoder(handle_unknown = 'use_encoded_value', unknown
X_train_encoded['color'] = encoder_color.fit_transform(X_train_encoded['colo
#encode clarity
encoder_clarity = OrdinalEncoder(handle_unknown = 'use_encoded_value', unknc
X_train_encoded['clarity'] = encoder_clarity.fit_transform(X_train_encoded['
```

Next step - perform Exploratory Data Analysis

In [13]:
```
df=X_train_encoded.copy()
df["price"]=y_train
```

In [14]:
```
df.shape
```
Out[14]:
```
(37758, 10)
```

In [15]:
```
df.head()
```
Out[15]:

	carat	cut	color	clarity	depth	table	x	y	z	price
36878	0.42	2.0	1.0	5.0	61.7	56.0	4.80	4.82	2.97	958
18820	1.03	2.0	3.0	6.0	61.7	56.0	6.45	6.56	4.00	7708
53406	0.82	2.0	1.0	3.0	62.1	55.0	6.04	6.01	3.74	2668
25954	1.40	2.0	3.0	6.0	60.8	57.0	7.21	7.23	4.39	15134
13825	1.00	4.0	1.0	5.0	63.5	56.0	6.37	6.32	4.03	5633

In [16]:
```
df.dtypes
```

Out[16]:
```
carat       float64
cut         float64
color       float64
clarity     float64
depth       float64
table       float64
x           float64
y           float64
z           float64
price         int64
dtype: object
```

In [17]:
```
df.isnull().sum()
```

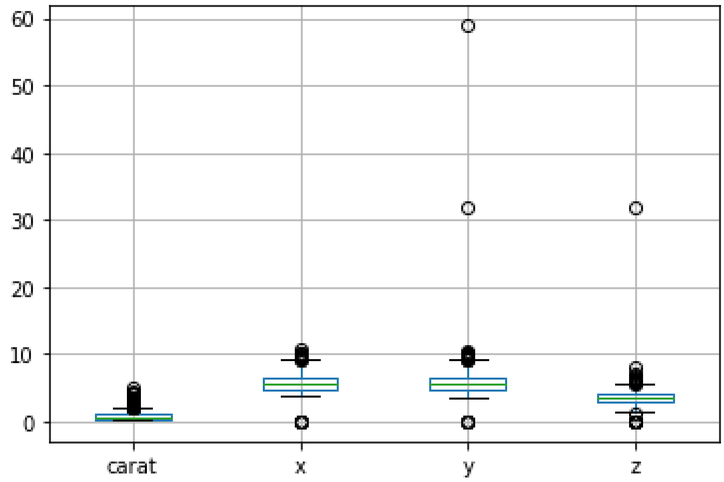
Out[17]:
```
carat       0
cut         0
color       0
clarity     0
depth       0
table       0
x           0
y           0
z           0
price       0
dtype: int64
```

In [18]:
```
df.describe()
```

Out[18]:

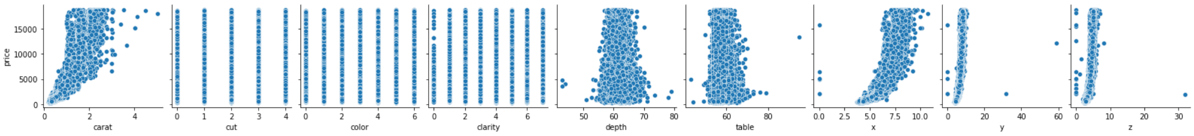
	carat	cut	color	clarity	depth	t
count	37758.000000	37758.000000	37758.000000	37758.000000	37758.000000	37758.000
mean	0.798166	2.556068	2.587955	3.832406	61.741557	57.458
std	0.472857	1.026089	1.700652	1.723270	1.426374	2.240
min	0.200000	0.000000	0.000000	0.000000	43.000000	43.000
25%	0.400000	2.000000	1.000000	2.000000	61.000000	56.000
50%	0.700000	2.000000	3.000000	4.000000	61.800000	57.000
75%	1.040000	3.000000	4.000000	5.000000	62.500000	59.000
max	5.010000	4.000000	6.000000	7.000000	79.000000	95.000

In [22]:
```
boxplot = df.boxplot(column=['carat','x','y','z'])
```



In [23]:
```
import seaborn as sns
sns.pairplot(df,x_vars=["carat", "cut", "color","clarity","depth","table","x
    y_vars=["price"])
```

Out[23]: <seaborn.axisgrid.PairGrid at 0x7fa3ca617640>

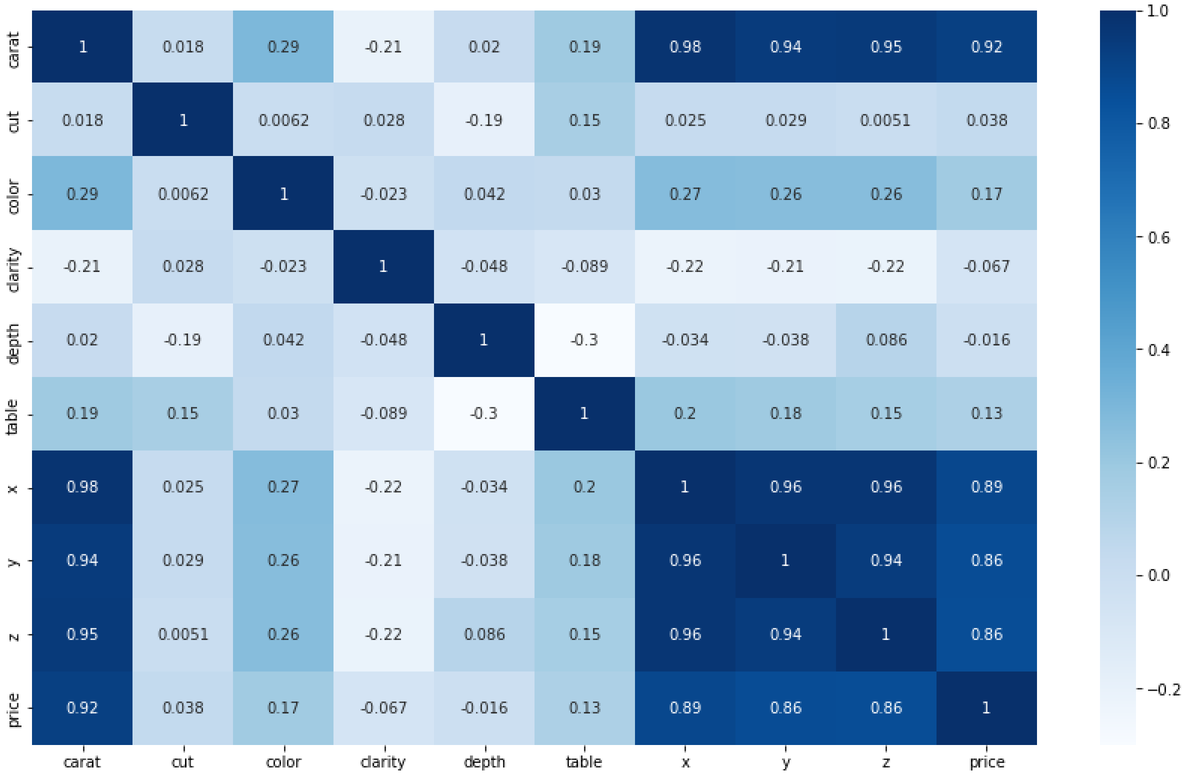


In [59]:
```
df.corr()
```

Out[59]:

	carat	cut	color	clarity	depth	table	x	
carat	1.000000	0.017691	0.289423	-0.208664	0.020201	0.185391	0.975345	0.94
cut	0.017691	1.000000	0.006167	0.028456	-0.188927	0.151204	0.024782	0.02
color	0.289423	0.006167	1.000000	-0.022534	0.041901	0.030368	0.267430	0.25
clarity	-0.208664	0.028456	-0.022534	1.000000	-0.048171	-0.089370	-0.220970	-0.21
depth	0.020201	-0.188927	0.041901	-0.048171	1.000000	-0.300535	-0.033831	-0.03
table	0.185391	0.151204	0.030368	-0.089370	-0.300535	1.000000	0.198658	0.18
x	0.975345	0.024782	0.267430	-0.220970	-0.033831	0.198658	1.000000	0.96
y	0.942855	0.029397	0.258293	-0.210929	-0.037689	0.184910	0.964957	1.00
z	0.947481	0.005135	0.263011	-0.217828	0.085778	0.152677	0.964535	0.93
price	0.922416	0.037664	0.172734	-0.067328	-0.015812	0.130676	0.885402	0.85

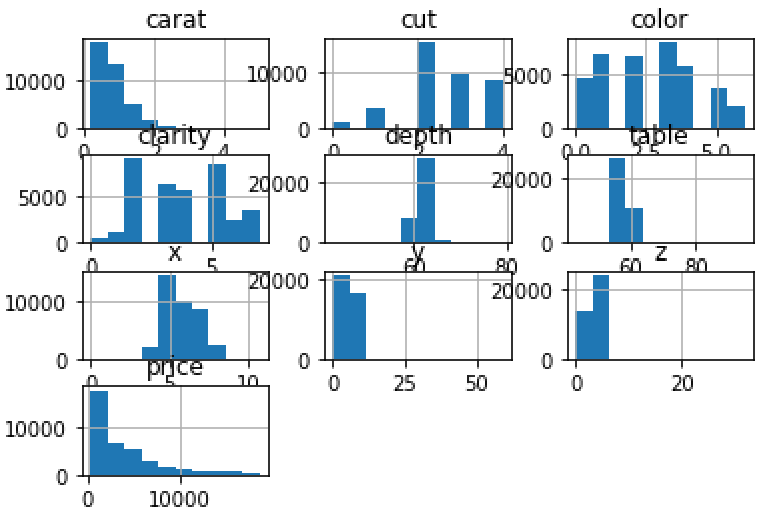
In [60]:
```
import matplotlib.pyplot as plt
fig = plt.figure(figsize = (15,9))
sns.heatmap(df.corr(), cmap='Blues', annot = True);
```



From the heatmap, I can see feature x, y, z are highly correlated with carat. x and y, x and z, y and z are all highly correlated with each other. They are all highly correlated with the price as well.

In [61]:
```
df.hist()
```

Out[61]:
```
array([[<AxesSubplot:title={'center':'carat'}>,
        <AxesSubplot:title={'center':'cut'}>,
        <AxesSubplot:title={'center':'color'}>],
       [<AxesSubplot:title={'center':'clarity'}>,
        <AxesSubplot:title={'center':'depth'}>,
        <AxesSubplot:title={'center':'table'}>],
       [<AxesSubplot:title={'center':'x'}>,
        <AxesSubplot:title={'center':'y'}>,
        <AxesSubplot:title={'center':'z'}>],
       [<AxesSubplot:title={'center':'price'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



Next step - proprocssing the data based on EDA The steps involved are:

- encode ordinal features (was done in previous steps)
- remove outliers in carat,depth and table
- remove x, y, z.
- transform test data

In [108…
```
cols = ['depth', 'table', 'x','y','z'] # The columns to search for outliers

Q1 = df[cols].quantile(0.05)
Q3 = df[cols].quantile(0.95)
IQR = Q3 - Q1

X_train_clean = df[~((df[cols] < (Q1 - 1.5 * IQR)) |(df[cols] > (Q3 + 1.5 *
```

In [109…
```
X_train_fs = X_train_clean.drop(["price"],axis=1)
y_train=X_train_clean['price']
```

In [110…
```
#transform test data
X_test_encoded=X_test.copy()
X_test_encoded['cut']=encoder_cut.transform(X_test_encoded['cut'].values.res
X_test_encoded['color']=encoder_color.transform(X_test_encoded['color'].valu
X_test_encoded['clarity']=encoder_clarity.transform(X_test_encoded['clarity'
X_test_fs=X_test_encoded
```

In [111…
```
X_test_fs.isnull().sum()
```

Out[111]:
```
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
x          0
y          0
z          0
dtype: int64
```

In [112…
```
#X_train_final=X_train_encoded
#X_test_final=X_test_encoded
X_train_final=X_train_fs
X_test_final=X_test_fs
```

In [113…
```
X_train_final.shape
```

Out[113]:
```
(37736, 9)
```

Next step - modelling

In [114…
```
# code reference: https://www.analyticsvidhya.com/blog/2021/10/evaluation-me
def relative_squared_error(target, pred):
    target_mean = np.mean(target)
    se_sum = np.sum(np.square(target - pred))
    se_den = np.sum(np.square(target - target_mean))
    rse_loss = se_sum / se_den
    return rse_loss
```

In [115…
```
#1 linear regression
import time
from sklearn.linear_model import LinearRegression
lr_start = time.time()
reg_lr = LinearRegression().fit(X_train_final, y_train)
lr_pred = reg_lr.predict(X_test_final)
lr_end = time.time()

#mse
from sklearn.metrics import mean_squared_error
lr_mse=round(mean_squared_error(y_test, lr_pred),2)

#rmse
from sklearn.metrics import mean_squared_error
lr_rmse=round(mean_squared_error(y_test, lr_pred,squared=False),2)

#rse
lr_rse=round(relative_squared_error(y_test, lr_pred),2)

#mae
from sklearn.metrics import mean_absolute_error
lr_mae=round(mean_absolute_error(y_test, lr_pred),2)

#run time
lr_runtime=round((lr_end-lr_start),2)

lr_metrics=['Linear Regression', lr_mse, lr_rmse, lr_rse, lr_mae, lr_runtime
print(lr_metrics)
```

```
['Linear Regression', 1887805.41, 1373.97, 0.12, 860.95, 0.01]
```

In [116…
```
#2 k-neighbors regression
from sklearn.neighbors import KNeighborsRegressor
```

```
knn_start = time.time()
reg_knn = KNeighborsRegressor().fit(X_train_final, y_train)
knn_pred = reg_knn.predict(X_test_final)
knn_end = time.time()

knn_mse=round(mean_squared_error(y_test, knn_pred),2)
knn_rmse=round(mean_squared_error(y_test, knn_pred,squared=False),2)
knn_rse=round(relative_squared_error(y_test, knn_pred),2)
knn_mae=round(mean_absolute_error(y_test, knn_pred),2)
knn_runtime=round((knn_end-knn_start),2)

knn_metrics=['K-neighbors Regression', knn_mse, knn_rmse, knn_rse, knn_mae,
print(knn_metrics)
```

```
['K-neighbors Regression', 908288.54, 953.04, 0.06, 499.45, 0.51]
```

In [117…

```
#3 ridge regression
from sklearn.linear_model import Ridge
rr_start = time.time()
reg_rr = Ridge(alpha=.5).fit(X_train_final, y_train)
rr_pred = reg_rr.predict(X_test_final)
rr_end = time.time()

rr_mse=round(mean_squared_error(y_test, rr_pred),2)
rr_rmse=round(mean_squared_error(y_test, rr_pred,squared=False),2)
rr_rse=round(relative_squared_error(y_test, rr_pred),2)
rr_mae=round(mean_absolute_error(y_test, rr_pred),2)
rr_runtime=round((rr_end-rr_start),2)

rr_metrics=['Ridge Regression', rr_mse, rr_rmse, rr_rse, rr_mae, rr_runtime]
print(rr_metrics)
```

```
['Ridge Regression', 1887817.84, 1373.98, 0.12, 861.14, 0.01]
```

In [118…

```
#4 decision tree regression
from sklearn.tree import DecisionTreeRegressor
dt_start = time.time()
reg_dt = DecisionTreeRegressor().fit(X_train_final, y_train)
dt_pred = reg_dt.predict(X_test_final)
dt_end = time.time()

dt_mse=round(mean_squared_error(y_test, dt_pred),2)
dt_rmse=round(mean_squared_error(y_test, dt_pred,squared=False),2)
dt_rse=round(relative_squared_error(y_test, dt_pred),2)
dt_mae=round(mean_absolute_error(y_test, dt_pred),2)
dt_runtime=round((dt_end-dt_start),2)

dt_metrics=['Decision tree Regression', dt_mse, dt_rmse, dt_rse, dt_mae, dt_
print(dt_metrics)
```

```
['Decision tree Regression', 551080.87, 742.35, 0.03, 364.18, 0.19]
```

In [119…

```
#5 Random Forest regression
from sklearn.ensemble import RandomForestRegressor
rf_start = time.time()
reg_rf = RandomForestRegressor().fit(X_train_final, y_train)
rf_pred = reg_rf.predict(X_test_final)
rf_end = time.time()

rf_mse=round(mean_squared_error(y_test, rf_pred),2)
rf_rmse=round(mean_squared_error(y_test, rf_pred,squared=False),2)
rf_rse=round(relative_squared_error(y_test, rf_pred),2)
rf_mae=round(mean_absolute_error(y_test, rf_pred),2)
rf_runtime=round((rf_end-rf_start),2)
```

```
rf_metrics=['Random Forest Regression', rf_mse, rf_rmse, rf_rse, rf_mae, rf_
print(rf_metrics)
```

```
['Random Forest Regression', 307373.35, 554.41, 0.02, 273.01, 12.43]
```

In [120…

```
#6 gradient Boosting regression
from sklearn.ensemble import GradientBoostingRegressor
gb_start = time.time()
reg_gb = GradientBoostingRegressor().fit(X_train_final, y_train)
gb_pred = reg_gb.predict(X_test_final)
gb_end = time.time()

gb_mse=round(mean_squared_error(y_test, gb_pred),2)
gb_rmse=round(mean_squared_error(y_test, gb_pred,squared=False),2)
gb_rse=round(relative_squared_error(y_test, gb_pred),2)
gb_mae=round(mean_absolute_error(y_test, gb_pred),2)
gb_runtime=round((gb_end-gb_start),2)

gb_metrics=['Gradient Boosting Regression', gb_mse, gb_rmse, gb_rse, gb_mae,
print(gb_metrics)
```

```
['Gradient Boosting Regression', 471878.61, 686.93, 0.03, 367.41, 3.17]
```

In [128…

```
#7 SGD regression
from sklearn.linear_model import SGDRegressor
sgd_start = time.time()
reg_sgd = SGDRegressor(max_iter=10000, tol=1e-3,alpha=0.2).fit(X_train_final
sgd_pred = reg_sgd.predict(X_test_final)
sgd_end = time.time()

sgd_mse=round(mean_squared_error(y_test, sgd_pred),2)
sgd_rmse=round(mean_squared_error(y_test, sgd_pred,squared=False),2)
sgd_rse=round(relative_squared_error(y_test, sgd_pred),2)
sgd_mae=round(mean_absolute_error(y_test, sgd_pred),2)
sgd_runtime=round((sgd_end-sgd_start),2)

sgd_metrics=['SGD Regression', sgd_mse, sgd_rmse, sgd_rse, sgd_mae, sgd_runt
print(sgd_metrics)
```

```
['SGD Regression', 3822585328211198.5, 61827059.84, 235661553.83, 47516460.3
6, 3.24]
```

In [122…

```
#8 support vector regression
from sklearn.svm import SVR
svr_start = time.time()
reg_svr = SVR().fit(X_train_final, y_train)
svr_pred = reg_svr.predict(X_test_final)
svr_end = time.time()

svr_mse=round(mean_squared_error(y_test, svr_pred),2)
svr_rmse=round(mean_squared_error(y_test, svr_pred,squared=False),2)
svr_rse=round(relative_squared_error(y_test, svr_pred),2)
svr_mae=round(mean_absolute_error(y_test, svr_pred),2)
svr_runtime=round((svr_end-svr_start),2)

svr_metrics=['Support Vector Regression', svr_mse, svr_rmse, svr_rse, svr_ma
print(svr_metrics)
```

```
['Support Vector Regression', 18241959.33, 4271.06, 1.12, 2781.56, 198.02]
```

In [123…

```
#9 linear SVR
from sklearn.svm import LinearSVR
lsvr_start = time.time()
reg_lsvr = LinearSVR().fit(X_train_final, y_train)
lsvr_pred = reg_lsvr.predict(X_test_final)
```

```
lsvr_end = time.time()

lsvr_mse=round(mean_squared_error(y_test, lsvr_pred),2)
lsvr_rmse=round(mean_squared_error(y_test, lsvr_pred,squared=False),2)
lsvr_rse=round(relative_squared_error(y_test, lsvr_pred),2)
lsvr_mae=round(mean_absolute_error(y_test, lsvr_pred),2)
lsvr_runtime=round((lsvr_end-lsvr_start),2)

lsvr_metrics=['Linear SVR Regression', lsvr_mse, lsvr_rmse, lsvr_rse, lsvr_m
print(lsvr_metrics)
```

```
['Linear SVR Regression', 3625118.61, 1903.97, 0.22, 1097.81, 0.25]
```

In [124…

```
#10 Multi-layer percetron regression
from sklearn.neural_network import MLPRegressor
mlp_start = time.time()
reg_mlp = MLPRegressor(hidden_layer_sizes=(100, ), activation = 'relu', solv
mlp_pred = reg_mlp.predict(X_test_final)
mlp_end = time.time()

mlp_mse=round(mean_squared_error(y_test, mlp_pred),2)
mlp_rmse=round(mean_squared_error(y_test, mlp_pred,squared=False),2)
mlp_rse=round(relative_squared_error(y_test,mlp_pred),2)
mlp_mae=round(mean_absolute_error(y_test, mlp_pred),2)
mlp_runtime=round((mlp_end-mlp_start),2)

mlp_metrics=['MLP Regression', mlp_mse, mlp_rmse, mlp_rse, mlp_mae, mlp_runt
print(mlp_metrics)
```

```
['MLP Regression', 3598366.96, 1896.94, 0.22, 1097.54, 0.24]
```

In [129…

```
metrics=[lr_metrics,knn_metrics,rr_metrics,dt_metrics,rf_metrics,gb_metrics,
output=pd.DataFrame(columns=['Algorithm','MSE','RMSE','RSE','MAE','Run Time(
pd.set_option('display.float_format', '{:.2f}'.format)
output
```

Out[129]:

	Algorithm	MSE	RMSE	RSE	MAE	R Time(secon
0	Linear Regression	1887805.41	1373.97	0.12	860.95	0
1	K-neighbors Regression	908288.54	953.04	0.06	499.45	0
2	Ridge Regression	1887817.84	1373.98	0.12	861.14	0
3	Decision tree Regression	551080.87	742.35	0.03	364.18	0
4	Random Forest Regression	307373.35	554.41	0.02	273.01	12
5	Gradient Boosting Regression	471878.61	686.93	0.03	367.41	3
6	SGD Regression	3822585328211198.50	61827059.84	235661553.83	47516460.36	3
7	Support Vector Regression	18241959.33	4271.06	1.12	2781.56	198
8	Linear SVR Regression	3625118.61	1903.97	0.22	1097.81	0
9	MLP Regression	3598366.96	1896.94	0.22	1097.54	0