EXPERIMENT NO 6

APPLY FOLLOWING REGRESSION ALGORITHMS: LINEAR, POLYNOMIAL, RIDGE, LASSO, RANDOM FOREST REGRESSION.

IMPORT LIBRARIES

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

READING THE DATA

In [2]:

```
# Importing only the first 30000 rows
df = pd.read_csv(
    '/DOCUMENTS/COLLEGE/CLASSES/EXPERIMENT_NO_6/Asteroid_Updated.csv/Asteroid_Updated.csv',
    low_memory=False)
```

In [3]:

```
df.head()
```

Out[3]:

	name	a	e	i	om	w	q	ad	per_y	data_arc	...	UB	IR	spec_B	spec_T	G
0	Ceres	2.769165	0.076009	10.594067	80.305532	73.597694	2.558684	2.979647	4.608202	8822.0	...	0.426	NaN	C	G	0.12
1	Pallas	2.772466	0.230337	34.836234	173.080063	310.048857	2.133865	3.411067	4.616444	72318.0	...	0.284	NaN	B	B	0.11
2	Juno	2.669150	0.256942	12.988919	169.852760	248.138626	1.983332	3.354967	4.360814	72684.0	...	0.433	NaN	Sk	S	0.32
3	Vesta	2.361418	0.088721	7.141771	103.810804	150.728541	2.151909	2.570926	3.628837	24288.0	...	0.492	NaN	V	V	0.32
4	Astraea	2.574249	0.191095	5.366988	141.576605	358.687607	2.082324	3.066174	4.130323	63507.0	...	0.411	NaN	S	S	NaN

5 rows × 31 columns

PREPROCESSING THE DATA

CHECK NAN VALUES

In [4]:

```
# Checking which columns(features) have nan values
df.isna().sum()
```

Out[4]:

```
name              817747
a                      2
e                      0
i                      0
om                     0
w                      0
q                      0
ad                     6
per_y                  1
data_arc           15474
condition_code       867
n_obs_used             0
H                   2689
neo                    6
pha                16442
diameter          702078
extent            839696
albedo            703305
rot_per           820918
GM                839700
BV                838693
UB                838735
IR                839713
spec_B            838048
spec_T            838734
G                 839595
moid               16442
class                  0
n                      2
per                    6
ma                     8
dtype: int64
```

In [5]:

```
# Get an idea of the different means, distributions, and values associated with the features
df.describe()
```

Out[5]:

	a	e	i	om	w	q	ad	per_y	data_ar
count	839712.000000	839714.000000	839714.000000	839714.000000	839714.000000	839714.000000	839708.000000	839713.000000	824240.00000
mean	2.757514	0.155636	8.949826	168.499466	181.075796	2.404728	3.385710	6.859734	5688.42233
std	114.384959	0.093897	6.666087	103.096307	104.023854	2.233172	12.748733	252.264249	4208.17723
min	-104279.220927	0.000000	0.007546	0.000388	0.001666	0.070511	0.773684	0.000000	0.00000
25%	2.385258	0.091454	4.069077	80.211400	91.041603	1.971941	2.775350	3.683928	3608.00000
50%	2.644219	0.143655	7.257101	160.294860	181.669478	2.225510	3.037761	4.299859	5806.00000
75%	2.996048	0.199400	12.255653	252.201519	271.521717	2.578162	3.357967	5.185985	7270.00000
max	3043.149073	1.201134	175.188725	359.999800	359.999833	80.424175	6081.841956	167877.712688	72684.00000

8 rows × 22 columns

- **Cleaning and prepping the dataframe:**
  Steps:
  - 0: 'diameter' is string type, I will convert to numeric. This gave errors for some diameters because they were corrupted, so I added the argument "errors='coerce'" to set corrupted diameters to nan, and later dropped those.
  - 1: Dropping irrelevent features and choosing my battles:
    - 1a/ dropping names because I dont believe asteroids are named according to their diameter.
    - 1b/ Dropping all features with more than half nan values
    - 1c/ dropping condition_code and neo and pha because most seems to be 0 or nan.
  - 2: Replace nans entries with mean value of column

In [6]:

```
# Steps 0
# transforming to numeric, setting errors to NaN
df['diameter'] = pd.to_numeric(df['diameter'], errors='coerce')
# rows with nan diameters to drop
dropindexes = df['diameter'][df['diameter'].isnull()].index
dropped_df = df.loc[dropindexes]  # saving dropped rows for the future
df = df.drop(dropindexes, axis=0)
```

In [7]:

```
# Steps 1
tooMuchNa = df.columns[df.isna().sum() / df.shape[0] > 0.5]
df = df.drop(tooMuchNa, axis=1)
df = df.drop('condition_code', axis=1)
df = df.drop(['neo', 'pha', 'class'], axis=1)
```

In [8]:

```
# Step 2
df = df.fillna(df.mean(numeric_only=None))
```

In [9]:

```
df.head()
```

Out[9]:

	a	e	i	om	w	q	ad	per_y	data_arc	n_obs_used	H	diameter	albedo	moid
0	2.769165	0.076009	10.594067	80.305532	73.597694	2.558684	2.979647	4.608202	8822.0	1002	3.34	939.400	0.0900	1.59478
1	2.772466	0.230337	34.836234	173.080063	310.048857	2.133865	3.411067	4.616444	72318.0	8490	4.13	545.000	0.1010	1.23324
2	2.669150	0.256942	12.988919	169.852760	248.138626	1.983332	3.354967	4.360814	72684.0	7104	5.33	246.596	0.2140	1.03454
3	2.361418	0.088721	7.141771	103.810804	150.728541	2.151909	2.570926	3.628837	24288.0	9325	3.20	525.400	0.4228	1.13948
4	2.574249	0.191095	5.366988	141.576605	358.687607	2.082324	3.066174	4.130323	63507.0	2916	6.85	106.699	0.2740	1.09589

In [10]:

```
# Last sanity check for nan values
df.isna().values.any()
```

Out[10]:

```
False
```

CREATING TRAIN & TEST DATASET

In [11]:

```
from sklearn.model_selection import train_test_split

target = df['diameter']
predictors = df.drop(['diameter'], axis=1)
X_train, X_test, Y_train, Y_test = train_test_split(predictors,
                                                    target,
                                                    test_size=0.20,
                                                    random_state=0)
```

In [12]:

```
X_train.head()
```

Out[12]:

	a	e	i	om	w	q	ad	per_y	data_arc	n_obs_used	H	albedo	moid	
474961	3.148871	0.130545	14.123745	20.870476	335.017941	2.737801	3.559942	5.587796	5812.0	72	16.0	0.032	1.74091	0.17
283914	3.104229	0.169382	19.711359	107.671134	182.187629	2.578429	3.630030	5.469390	6824.0	186	15.0	0.233	1.56154	0.18
241049	3.170379	0.104378	1.607302	151.293279	138.910748	2.839460	3.501298	5.645143	6684.0	272	15.6	0.064	1.82279	0.17
359366	3.123361	0.232180	13.565848	54.472085	258.745939	2.398180	3.848542	5.520031	7120.0	185	15.4	0.083	1.42886	0.17
110551	2.646488	0.191386	13.100536	39.183682	344.363064	2.139987	3.152990	4.305397	6660.0	711	14.4	0.223	1.14667	0.22

PERFORMING NORMALIZATION

In [13]:

```
from sklearn import preprocessing

# Input standard normalization:
std_scaler = preprocessing.StandardScaler().fit(X_train)


def scaler(X):
    x_norm_arr = std_scaler.fit_transform(X)
    return pd.DataFrame(x_norm_arr, columns=X.columns, index=X.index)


X_train_norm = scaler(X_train)
X_test_norm = scaler(X_test)


def inverse_scaler(X):
    x_norm_arr = std_scaler.inverse_transform(X)
    return pd.DataFrame(x_norm_arr, columns=X.columns, index=X.index)
```

APPLYING DIFFERENT REGRESSION ALGORITHMS

FUNCTION FOR MODEL VISUALIZATION

In [14]:

```
from sklearn.metrics import r2_score
import seaborn as sns
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score


def plot(prediction):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 7))
    sns.distplot(Y_test.values, label='test values', ax=ax1)
    sns.distplot(prediction, label='prediction', ax=ax1)
    ax1.set_xlabel('Distribution plot')
    ax2.scatter(Y_test, prediction, c='orange', label='predictions')
    ax2.plot(Y_test, Y_test, c='blue', label='y=x')
    ax2.set_xlabel('test value')
    ax2.set_ylabel('estimated $\log(radius)$')
    ax1.legend()
    ax2.legend()
    ax2.axis('scaled')  # same x y scale
```

```
def score(prediction):
    score = r2_score(prediction, Y_test)
    return score


def announce(score):
    print('The R^2 score achieved using this regression is:', round(score, 3))


algorithms = []
scores = []
```

LINEAR REGRESSION

In [15]:

```
# Defining the model
from sklearn.linear_model import LinearRegression

lr = LinearRegression()

# Training
lr.fit(X_train, Y_train)

# Predicting
Y_pred_lr = lr.predict(X_test)

# Scoring
score_lr = score(Y_pred_lr) * -1
announce(score_lr)

algorithms.append('LR')
scores.append(score_lr)
```

```
The R^2 score achieved using this regression is: 0.497
```

In [16]:

```
Y_train
```

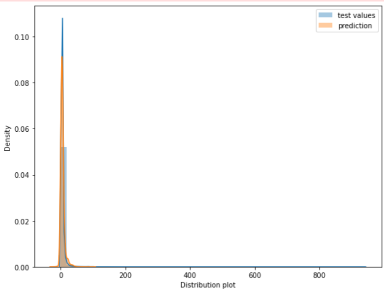
Out[16]:

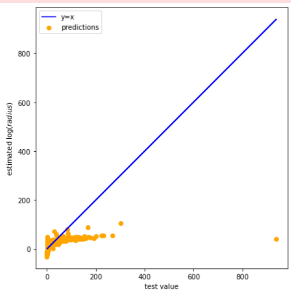
```
474961    4.276
283914    2.867
241049    3.635
359366    3.831
110551    3.813
          ...  
64431     5.672
245904    2.362
242701    2.826
405500    2.569
67651     1.911
Name: diameter, Length: 110108, dtype: float64
```

In [17]:

```
plot(Y_pred_lr)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





POLYNOMIAL REGRESSION

In [18]:

```
# Defining the model
from sklearn.preprocessing import PolynomialFeatures

poly_features = PolynomialFeatures(degree=2)
x_poly_train = poly_features.fit_transform(X_train)
x_poly_test = poly_features.fit_transform(X_test)

# Training
lr.fit(x_poly_train, Y_train)

# Predicting
Y_pred_pr = lr.predict(x_poly_test)

# Scoring
score_pr = score(Y_pred_pr)
announce(score_pr)

algorithms.append('POLYR')
scores.append(score_pr)
```

```
The R^2 score achieved using this regression is: 0.473
```

In [19]:

```
Y_train
```

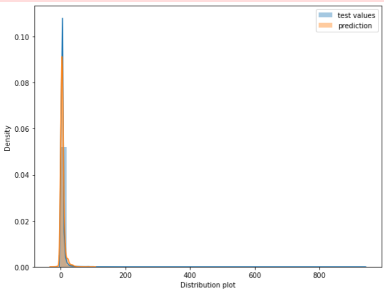
Out[19]:

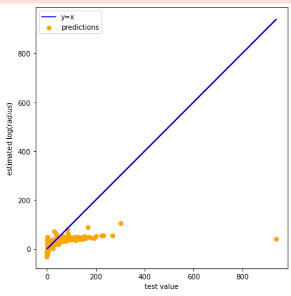
```
474961    4.276
283914    2.867
241049    3.635
359366    3.831
110551    3.813
          ...  
64431     5.672
245904    2.362
242701    2.826
405500    2.569
67651     1.911
Name: diameter, Length: 110108, dtype: float64
```

In [20]:

```
plot(Y_pred_lr)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





RANDOM FOREST REGRESSION

In [21]:

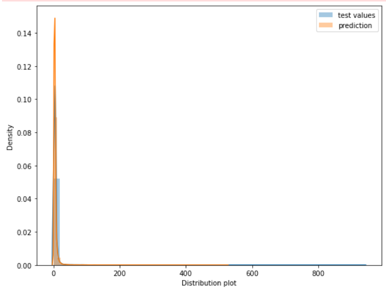
```
# Defining the model
from sklearn.ensemble import RandomForestRegressor

forest = RandomForestRegressor(max_depth=32, n_estimators=50)

# Training
forest.fit(X_train_norm, np.ravel(Y_train))

# Predicting
Y_pred_forest = forest.predict(X_test_norm)

# Scoring
score_forest = score(Y_pred_forest)
announce(score_forest)

algorithms.append('RForest')
scores.append(score_forest)
```

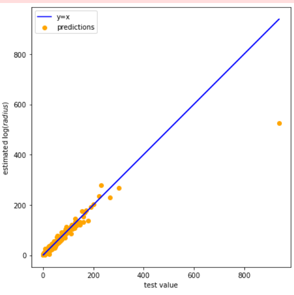
```
The R^2 score achieved using this regression is: 0.902
```

In [22]:

```
plot(Y_pred_forest)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





RIDGE REGRESSION

In [23]:

```
# Defining the model
from sklearn.linear_model import Ridge

lr_ridge = Ridge(alpha=0.1)

# Training
lr_ridge.fit(X_train, Y_train)

# Predicting
Y_pred_lr_ridge = lr_ridge.predict(X_test)

# Scoring
score_lr_ridge = score(Y_pred_lr_ridge) * -1
announce(score_lr_ridge)

algorithms.append('RR')
scores.append(score_lr_ridge)
```

```
The R^2 score achieved using this regression is: 0.497
```

In [24]:

```
Y_train
```

Out[24]:

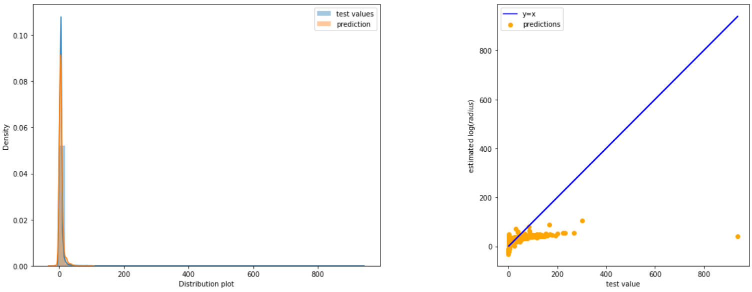
```
474961    4.276
283914    2.867
241049    3.635
359366    3.831
110551    3.813
```

```
               ...
64431     5.672
245904    2.362
242701    2.826
405500    2.569
67651     1.911
Name: diameter, Length: 110108, dtype: float64
```

In [25]:

```
plot(Y_pred_lr)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



LASSO REGRESSION

In [26]:

```
# Defining the model
from sklearn.linear_model import Lasso

lr_lasso = Lasso()

# Training
lr_lasso.fit(X_train, Y_train)

# Predicting
Y_pred_lr_lasso = lr_lasso.predict(X_test)

# Scoring
score_lr_lasso = score(Y_pred_lr_lasso) * -1
announce(score_lr_lasso)

algorithms.append('LASR')
scores.append(score_lr_lasso)
```

```
The R^2 score achieved using this regression is: 1.506
```

In [27]:

```
Y_train
```

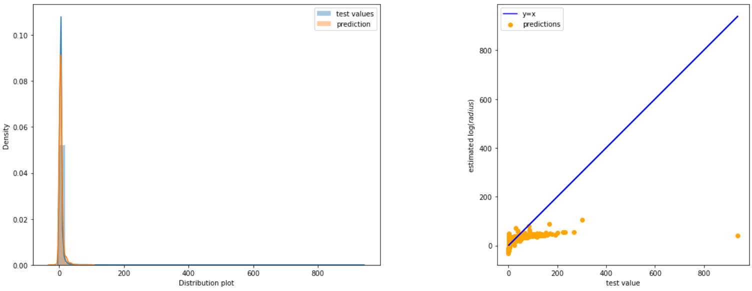
Out[27]:

```
474961    4.276
283914    2.867
241049    3.635
359366    3.831
110551    3.813
          ...
64431     5.672
245904    2.362
242701    2.826
405500    2.569
67651     1.911
Name: diameter, Length: 110108, dtype: float64
```

In [28]:

```
plot(Y_pred_lr)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



ANALYZING DIFFRENT REGRESSION ALGORITHMS

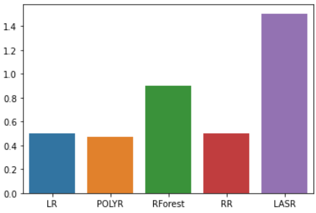
In [29]:

```
sns.barplot(algorithms, scores)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[29]:

```
<AxesSubplot:>
```



----X----X----X----X----X----X----X----X----X----X----X----X----X----X----X----X----X----X----