Abalone Age Prediction

DESCRIPTION

Predicting the age of abalone from physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict age. Further information, such as weather patterns and location (hence food availability) may be required to solve the problem.

Attribute Information

Given is the attribute name, attribute type, measurement unit, and a brief description. The number of rings is the value to predict: either as a continuous value or as a classification problem.

Name / Data Type / Measurement Unit / Description

```
1- Sex / nominal / -- / M, F, and I (infant)
2- Length / continuous / mm / Longest shell measurement
3- Diameter / continuous / mm / perpendicular to length
4- Height / continuous / mm / with meat in shell
5- Whole weight / continuous / grams / whole abalone
6- Shucked weight / continuous / grams / weight of meat
7- Viscera weight / continuous / grams / gut weight (after bleeding)
8- Shell weight / continuous / grams / after being dried
9- Rings / integer / -- / +1.5 gives the age in years
```

2.Importing necessary packages and dataset

```
import pandas as pd
import numpy as np
import seaborn as sns
```

```
df=pd.read_csv('/content/abalone.csv')
```

Exploration of the dataset

```
df
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

```
df.dtypes
```

```
Sex                object
Length            float64
Diameter          float64
Height            float64
Whole weight      float64
Shucked weight    float64
Viscera weight    float64
Shell weight      float64
Rings               int64
dtype: object
```

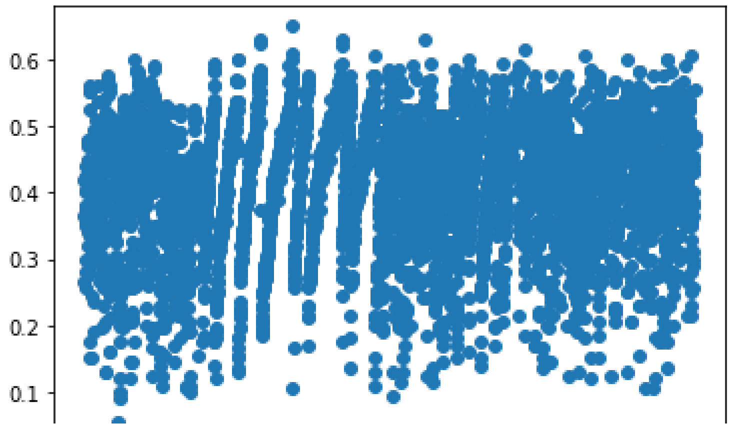
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

3.Visualizations

1. Univariate Analysis
2. Bi-Variate Analysis
3. Multi-Variate Analysis

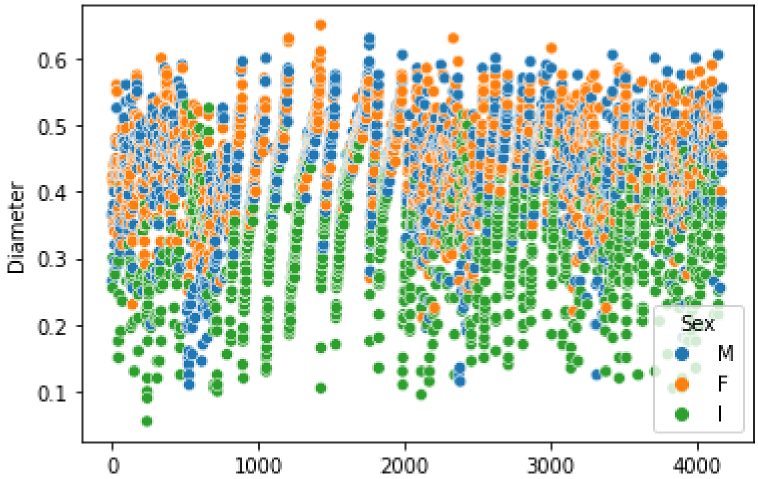
UNIVARIATE ANALYSIS

```
plt.scatter(df.index,df['Diameter'])
plt.show()
```



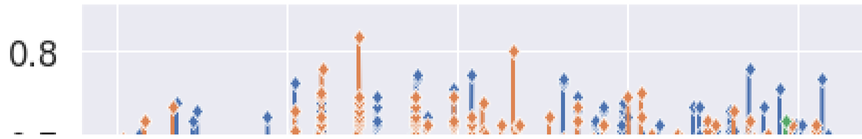

```
sns.scatterplot(x=df.index,y=df['Diameter'],hue=df['Sex'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f41478efdd0>



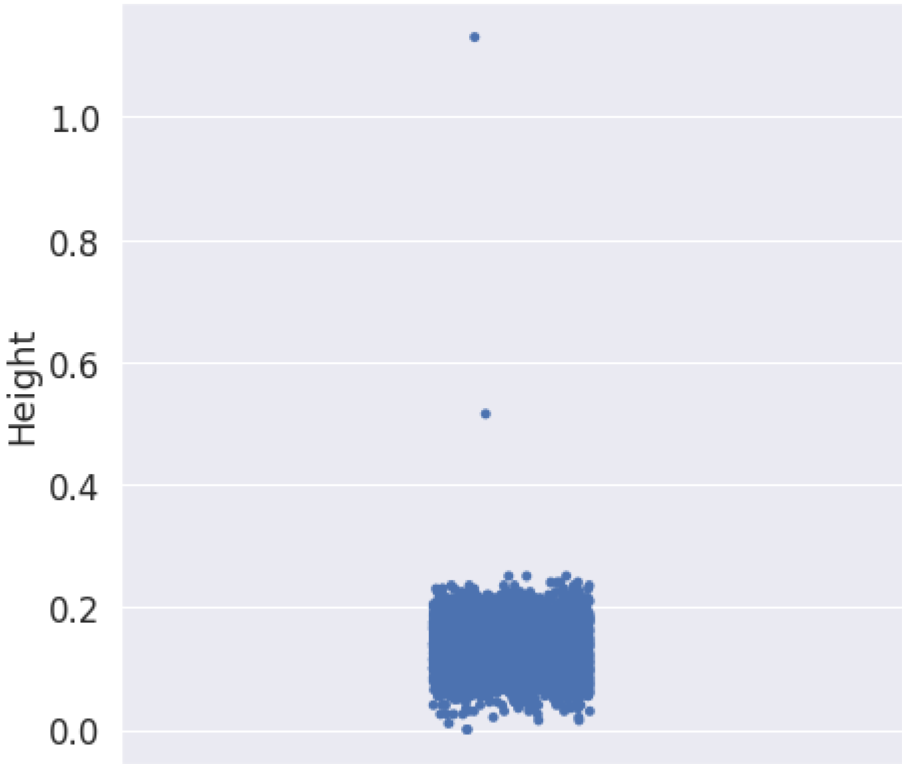

```
sns.set(rc={'figure.figsize': (7,7)})
sns.set (font_scale=1.5)
fig=sns.lineplot (x=df.index, y=df['Length'], markevery=1, marker='d', data=df, hue=df ['S
fig.set(xlabel='index')
```

```
[Text(0.5, 0, 'index')]
```




```
sns.stripplot (y=df['Height'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4145efa910>
```

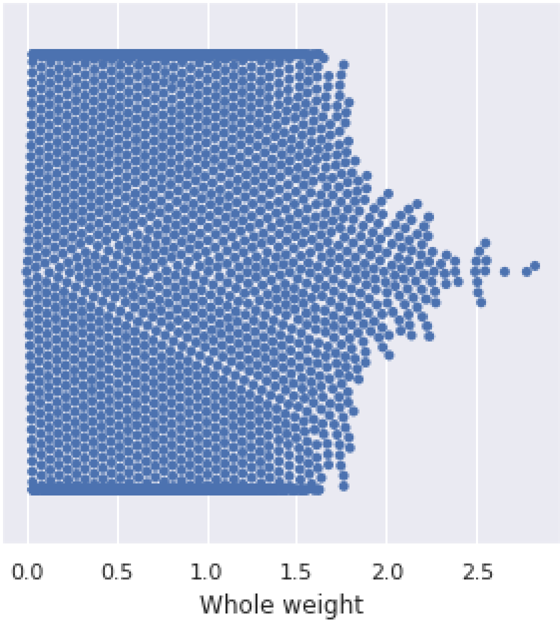



```
sns.stripplot (x=df['Sex'], y=df['Height'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f4145ecd850>

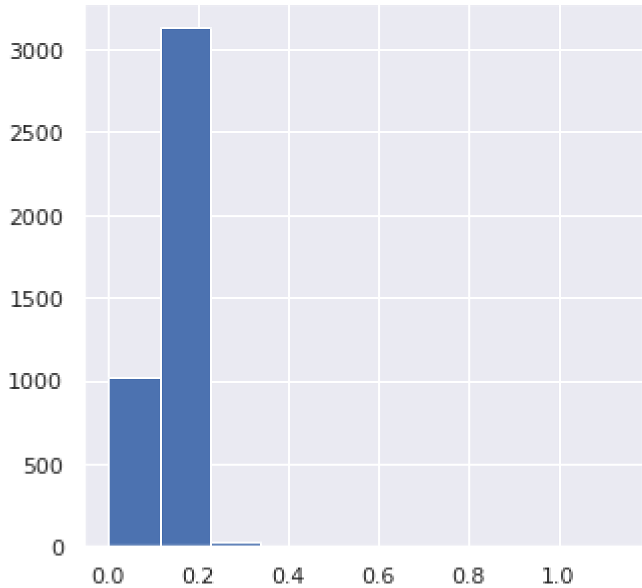

```
sns.set(rc={'figure.figsize': (5,5)})
sns.swarmplot (x=df['Whole weight'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:1296: UserWarning: 61.
  warnings.warn(msg, UserWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f4145eb9610>
```




```
plt.hist(df['Height'])
```

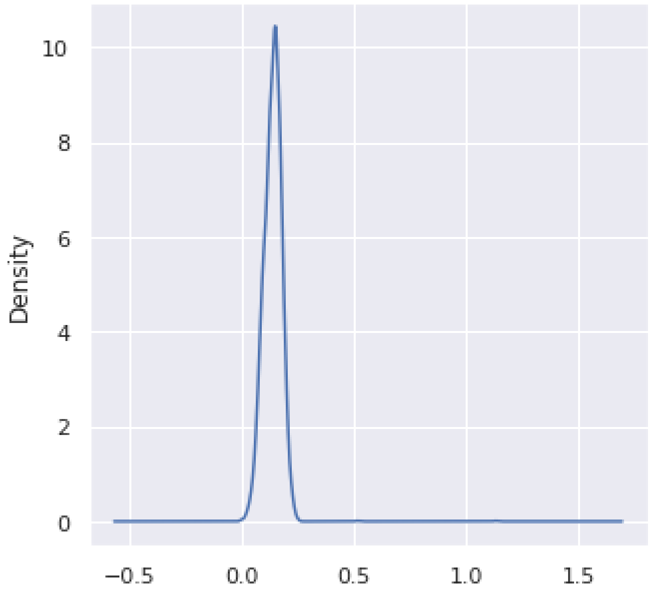
```
(array([1.023e+03, 3.129e+03, 2.300e+01, 0.000e+00, 1.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00]),
 array([0.   , 0.113, 0.226, 0.339, 0.452, 0.565, 0.678, 0.791, 0.904,
        1.017, 1.13 ]),
 <a list of 10 Patch objects>)
```



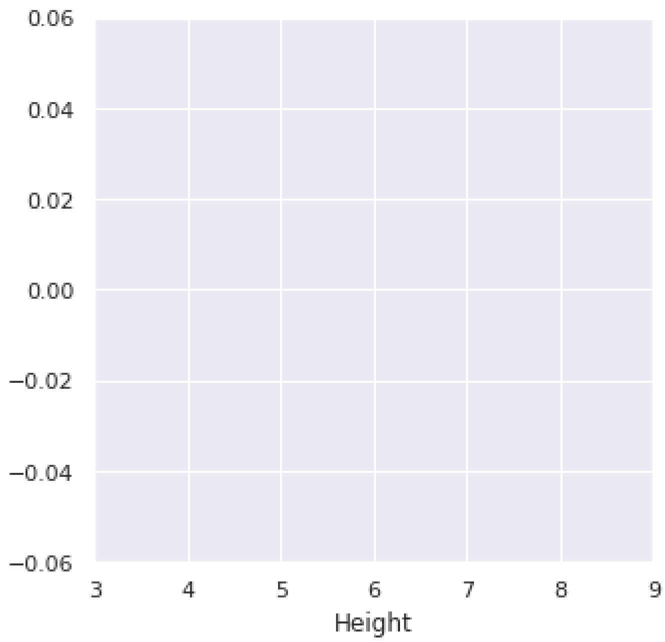

```
plt.figure (figsize=(5,5))
df ['Height'].plot (kind='density')
```

```
df['Height'].plot (kind='density')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f414356ffd0>

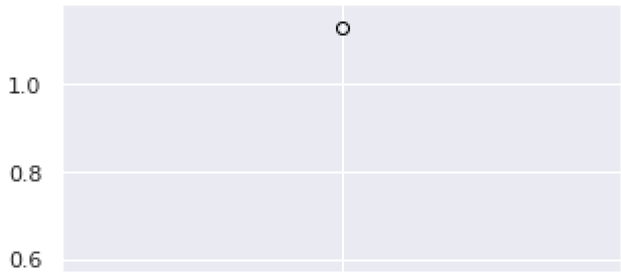



```
fig, ax = plt.subplots()
sns.rugplot (df ['Height'])
ax.set_xlim (3,9)
plt.show()
```




```
plt.boxplot(df['Height'])
```

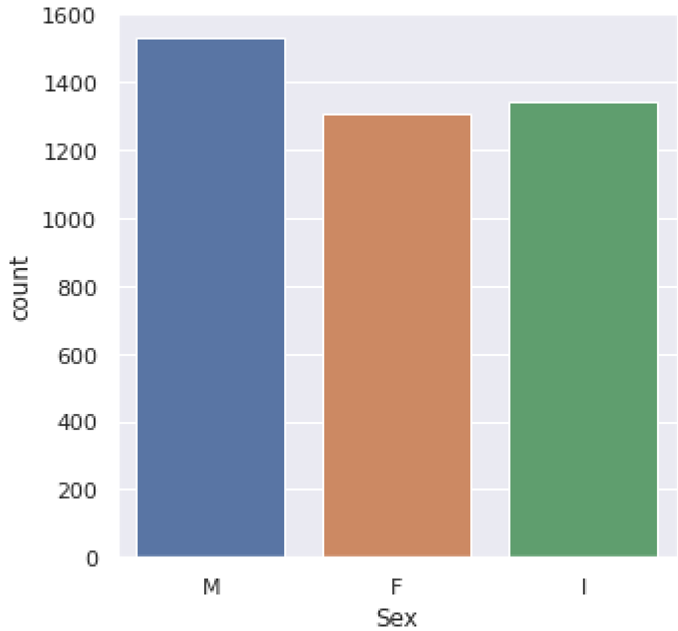
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4143193d90>,
  <matplotlib.lines.Line2D at 0x7f4143198310>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4143198850>,
  <matplotlib.lines.Line2D at 0x7f4143198d90>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4143193790>],
 'medians': [<matplotlib.lines.Line2D at 0x7f414319f350>],
 'fliers': [<matplotlib.lines.Line2D at 0x7f414319f890>],
 'means': []}
```



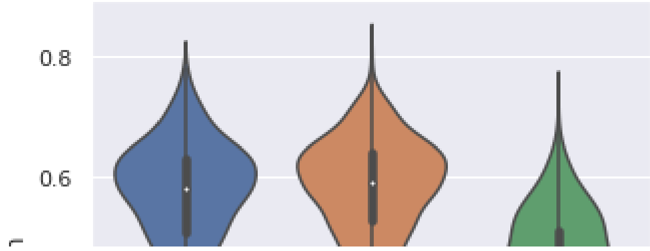
BIVARIATE ANALYSIS


```
sns.barplot(x='Sex',y='Height',data=df)
sns.countplot(x='Sex',data=df)
```

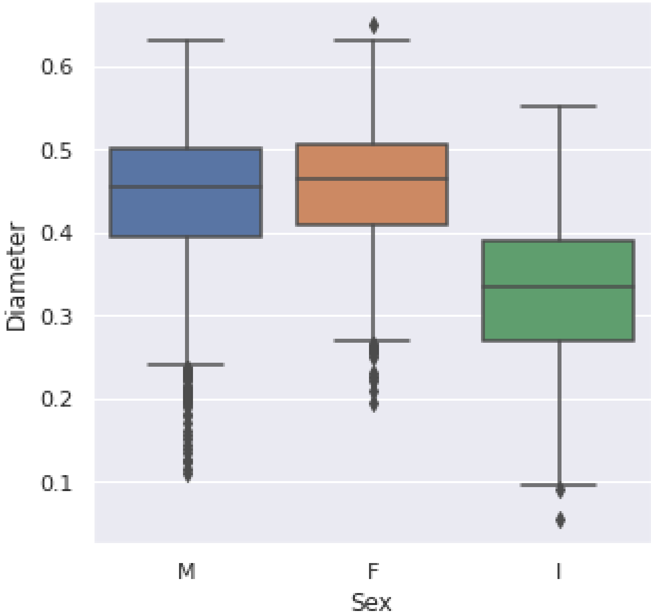
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4143144110>
```




```
sns.violinplot (x="Sex", y="Length", data=df, size=8)
plt.show()
```



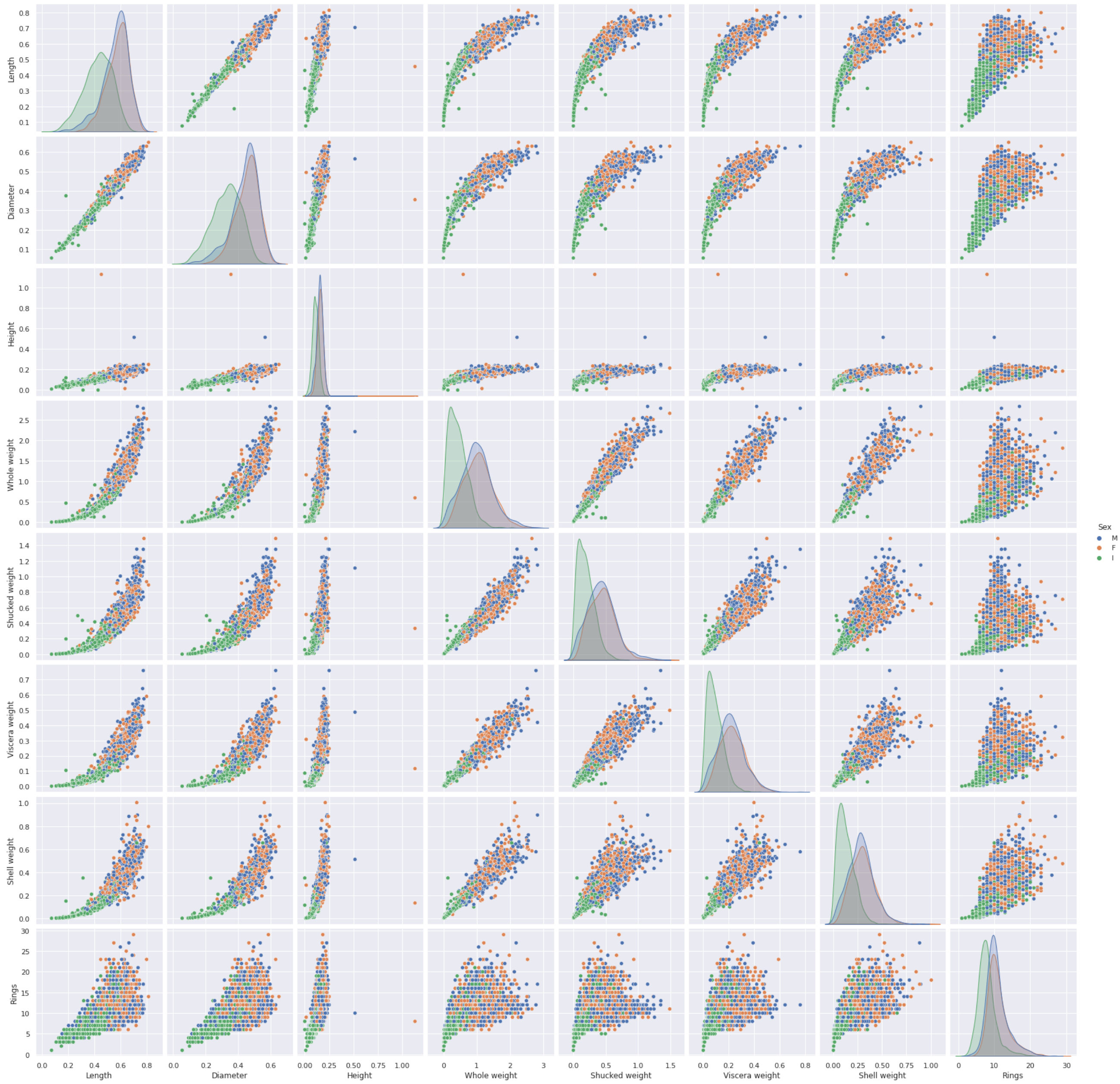

```
sns.boxplot (x='Sex',y='Diameter', data=df)
plt.show()
```



MULTIVARIATE ANALYSIS

```
sns.pairplot (df, hue="Sex", size=3)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:2076: UserWarning: The `si
  warnings.warn(msg, UserWarning)
```



4. PERFORM DESCRIPTIVE STATISTICS ON THE DATASET

```
pd.set_option('display.width', 100)
pd.set_option('precision', 3)
description = df.describe()
print(description)
```

```
         Length  Diameter    Height  Whole weight  Shucked weight  Viscera weight  Sh
count  4177.000  4177.000  4177.000      4177.000        4177.000       4.177e+03
mean      0.524     0.408     0.140         0.829           0.359       1.806e-01
std       0.120     0.099     0.042         0.490           0.222       1.096e-01
min       0.075     0.055     0.000         0.002           0.001       5.000e-04
25%       0.450     0.350     0.115         0.442           0.186       9.350e-02
50%       0.545     0.425     0.140         0.799           0.336       1.710e-01
75%       0.615     0.480     0.165         1.153           0.502       2.530e-01
max       0.815     0.650     1.130         2.825           1.488       7.600e-01

          Rings
count  4177.000
mean      9.934
std       3.224
min       1.000
25%       8.000
50%       9.000
75%      11.000
max      29.000
```

5.**Check for Missing values**

```
df.isnull()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
4172	False	False	False	False	False	False	False	False	False
4173	False	False	False	False	False	False	False	False	False
4174	False	False	False	False	False	False	False	False	False
4175	False	False	False	False	False	False	False	False	False
4176	False	False	False	False	False	False	False	False	False

4177 rows × 9 columns

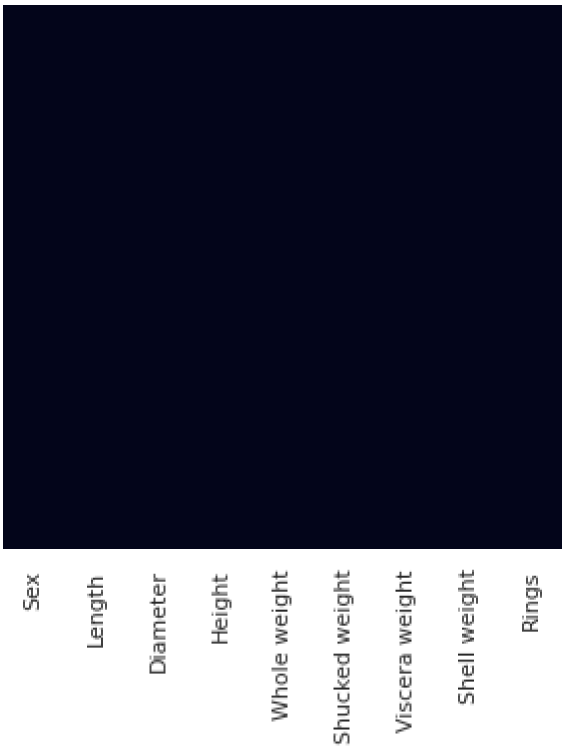
```
df.notnull()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	True	True	True	True	True	True	True	True	True
1	True	True	True	True	True	True	True	True	True
2	True	True	True	True	True	True	True	True	True
3	True	True	True	True	True	True	True	True	True
4	True	True	True	True	True	True	True	True	True
...	...	...	...	...	...	...	...	...	...
4172	True	True	True	True	True	True	True	True	True
4173	True	True	True	True	True	True	True	True	True
4174	True	True	True	True	True	True	True	True	True
4175	True	True	True	True	True	True	True	True	True
4176	True	True	True	True	True	True	True	True	True

4177 rows × 9 columns

```
sns.heatmap(df.isnull(),yticklabels=False,cbar=False)
```

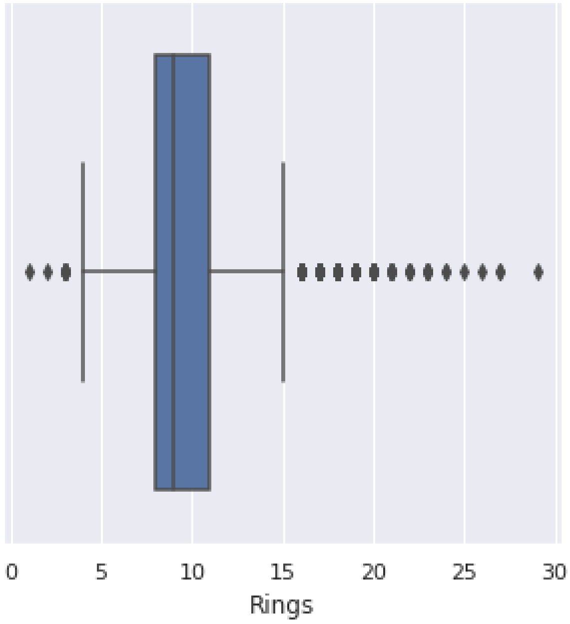
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4141754850>
```



6.**Find the outliers and replace them outliers**

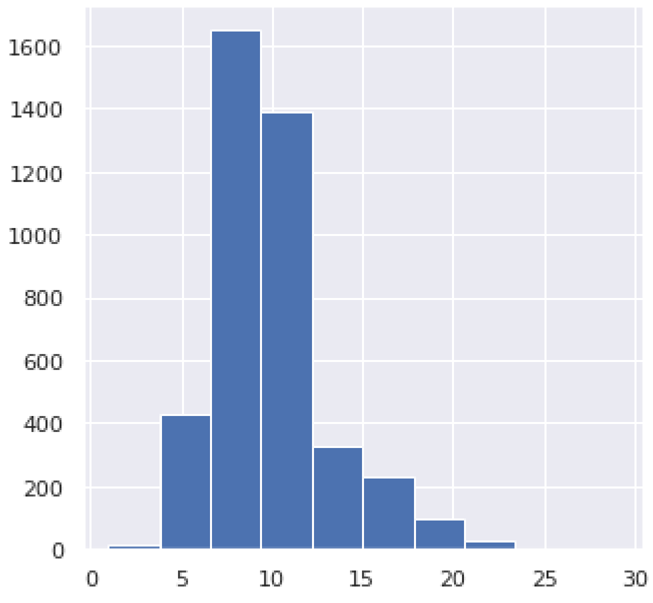
```
sns.boxplot(df['Rings'],data=df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f4141f23850>
```




```
df['Rings'].hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f414141af50>
```



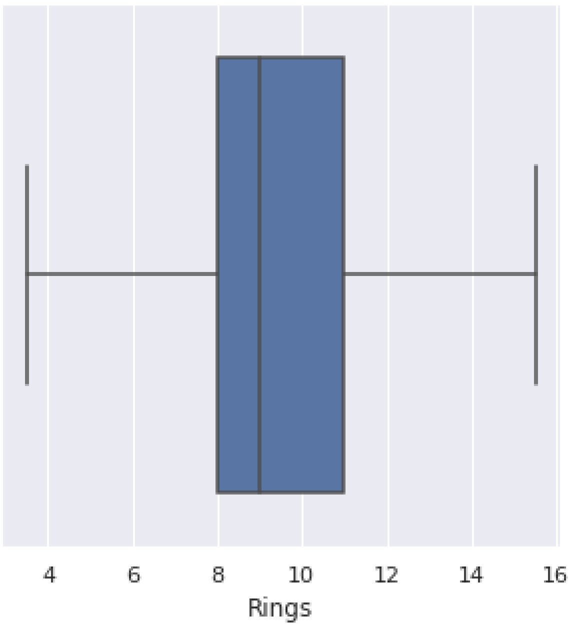

```
fare_mean = df['Rings'].mean()
fare_std = df['Rings'].std()
low= fare_mean -(3 * fare_std)
high= fare_mean + (3 * fare_std)
fare_outliers = df[(df['Rings'] < low) | (df['Rings'] > high)]
fare_outliers.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
6	F	0.530	0.415	0.150	0.777	0.237	0.141	0.330	20
72	F	0.595	0.475	0.170	1.247	0.480	0.225	0.425	20
83	M	0.595	0.475	0.160	1.217	0.498	0.234	0.580	21

```
Q1 = df['Rings'].quantile(0.25)
Q3 = df['Rings'].quantile(0.75)
IQR = Q3 - Q1
whisker_width = 1.5
lower_whisker = Q1 -(whisker_width*IQR)
upper_whisker = Q3 +(whisker_width*IQR)
df['Rings']=np.where(df['Rings']>upper_whisker,upper_whisker,np.where(df['Rings']<lower_wh
```

```
sns.boxplot(df['Rings'],data=df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f41413b6d50>
```




```
Q1 = df['Rings'].quantile(0.10)
Q3 = df['Rings'].quantile(0.90)
IQR = Q3 - Q1
whisker_width = 1.5
lower_whisker = Q1 - (whisker_width*IQR)
upper_whisker = Q3 + (whisker_width*IQR)
index=df['Rings'][(df['Rings']>upper_whisker)|(df['Rings']<lower_whisker)].index
df.drop(index,inplace=True)
```

7.**Check for Categorical columns and perform encoding**

```
from sklearn.compose import make_column_selector as selector
```

```
categorical_columns_selector = selector(dtype_include=object)
categorical_columns = categorical_columns_selector(df)
categorical_columns
```

```
['Sex']
```

```
data_categorical = df[categorical_columns]
data_categorical.head()
```

	Sex
0	M
1	M
2	F
3	M
4	I

```
from sklearn.preprocessing import OrdinalEncoder

Sex_column = data_categorical[["Sex"]]

encoder = OrdinalEncoder()
Sex_encoded = encoder.fit_transform(Sex_column)
Sex_encoded
```

```
array([[2.],
       [2.],
       [0.],
       ...,
       [2.],
       [0.],
       [2.]])
```

```
encoder.categories_
```

```
[array(['F', 'I', 'M'], dtype=object)]
```

```
data_encoded = encoder.fit_transform(data_categorical)
data_encoded[:5]
```

```
array([[2.],
       [2.],
       [0.],
       [2.],
       [1.]])
```

```
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(sparse=False)
```

```
Sex_encoded = encoder.fit_transform(Sex_column)
Sex_encoded
```

```
array([[0., 0., 1.],
       [0., 0., 1.],
       [1., 0., 0.],
       ...,
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 0., 1.]])
```

```
feature_names = encoder.get_feature_names_out(input_features=["Sex"])
Sex_encoded = pd.DataFrame(Sex_encoded, columns=feature_names)
Sex_encoded
```

	Sex_F	Sex_I	Sex_M
0	0.0	0.0	1.0
1	0.0	0.0	1.0
2	1.0	0.0	0.0
3	0.0	0.0	1.0
4	0.0	1.0	0.0
...	...	...	...
4172	1.0	0.0	0.0
4173	0.0	0.0	1.0
4174	0.0	0.0	1.0
4175	1.0	0.0	0.0
4176	0.0	0.0	1.0

4177 rows × 3 columns

```
data_encoded = encoder.fit_transform(data_categorical)
data_encoded[:5]
```

```
array([[0., 0., 1.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 0., 1.],
       [0., 1., 0.]])
```

8.**Split the data into dependent and independent variables**

```
X= df.iloc[ : , :-1].values
print(X)
```

```
[['M' 0.455 0.365 ... 0.2245 0.101 0.15]
 ['M' 0.35 0.265 ... 0.0995 0.0485 0.07]
```

```
['F' 0.53 0.42 ... 0.2565 0.1415 0.21]
...
['M' 0.6 0.475 ... 0.5255 0.2875 0.308]
['F' 0.625 0.485 ... 0.531 0.261 0.296]
['M' 0.71 0.555 ... 0.9455 0.3765 0.495]]
```

```
y= df.iloc[ : , 4].values
print(y)
```

```
[0.514  0.2255 0.677  ... 1.176  1.0945 1.9485]
```

9.**Scale the independent variables**

```
from sklearn import preprocessing
```

```
df.drop(labels="Sex",axis=1)
```

```
min_max_scaler = preprocessing.MinMaxScaler(feature_range =(0, 1))
new_x= min_max_scaler.fit_transform(x)
print ("\n VALUES AFTER MIN MAX SCALING: \n\n", new_x)
```

```
VALUES AFTER MIN MAX SCALING:

[[0.51351351 0.5210084  0.0840708 ]
[0.37162162 0.35294118 0.07964602]
[0.61486486 0.61344538 0.11946903]
...
[0.70945946 0.70588235 0.18141593]
[0.74324324 0.72268908 0.13274336]
[0.85810811 0.84033613 0.17256637]]
```

```
Standardisation = preprocessing.StandardScaler()
new_x= Standardisation.fit_transform(x)
print ("\n\n VALUES AFTER STANDARDIZATION : \n\n", new_x)
```

```
VALUES AFTER STANDARDIZATION :

[[-0.57455813 -0.43214879 -1.06442415]
[-1.44898585 -1.439929   -1.18397831]
[ 0.05003309  0.12213032 -0.10799087]
...
[ 0.6329849   0.67640943  1.56576738]
[ 0.84118198  0.77718745  0.25067161]
[ 1.54905203  1.48263359  1.32665906]]
```

10.**Split the data into training and testing**

```
from sklearn.model_selection import train_test_split
```

```
X=df.iloc[ : , :-1]
y=df.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.05, random_state=0)
```

```
X_train
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
678	F	0.450	0.380	0.165	0.817	0.250	0.192	0.265
3009	I	0.255	0.185	0.065	0.074	0.030	0.017	0.020
1906	I	0.575	0.450	0.135	0.825	0.338	0.211	0.239
768	F	0.550	0.430	0.155	0.785	0.289	0.227	0.233
2781	M	0.595	0.475	0.140	1.030	0.492	0.217	0.278
...	...	...	...	...	...	...	...	...
1033	M	0.650	0.525	0.185	1.622	0.664	0.323	0.477
3264	F	0.655	0.500	0.140	1.171	0.540	0.318	0.285
1653	M	0.595	0.450	0.145	0.959	0.463	0.206	0.254
2607	F	0.625	0.490	0.165	1.127	0.477	0.236	0.319
2732	I	0.410	0.325	0.110	0.326	0.133	0.075	0.101

3968 rows × 8 columns

```
y_train
```

```
678     15.5
3009     4.0
1906    11.0
768     11.0
2781    10.0
        ...
1033    10.0
3264    12.0
1653    10.0
2607     9.0
2732     8.0
Name: Rings, Length: 3968, dtype: float64
```

11,12,13. **Build the Model -> Train and test the model**

```
train, test = train_test_split(df, test_size=0.25, random_state=1)
print('Train data points :', len(train))
print('Test data points :', len(test))
```

```
Train data points : 3132
```

```
     Test data points : 1045

train.Sex = train.Sex.replace({"M":1, "I":0, "F":-1})
test.Sex = test.Sex.replace({"M":1, "I":0, "F":-1})


numerical_features = ["Length", 'Diameter', 'Height','Whole weight',
                      'Shucked weight', 'Viscera weight', 'Shell weight']

categorical_feature = "Sex"

features = numerical_features + [categorical_feature]

target = 'Rings'


fig, axes = plt.subplots(ncols=2,figsize=(16, 5))

train[target].plot.hist(color='blue', ax=axes[0])
axes[0].set(title="Train")

test[target].plot.hist(color='blue', ax=axes[1])
axes[1].set(title="Test")

plt.tight_layout()
plt.show()


fig, axes = plt.subplots(4,2,figsize=(16, 14))
axes = np.ravel(axes)

for i, c in enumerate(numerical_features):
    hist = train[c].plot(kind = 'hist', ax=axes[i], title=c, color='blue', bins=30)

plt.tight_layout()
plt.show()


idx = train.loc[train.Height>0.4].index
train.drop(idx, inplace=True)

idx = train.loc[train['Viscera weight']>0.6].index
train.drop(idx, inplace=True)

idx = train.loc[train[target]>25].index
train.drop(idx, inplace=True)


X_train = train[features]
y_train = train[target]

X_test = test[features]
y_test = test[target]

X_train.head()
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Sex
4014	0.625	0.480	0.175	1.065	0.486	0.259	0.285	1
3252	0.480	0.380	0.130	0.618	0.300	0.142	0.175	1
305	0.200	0.145	0.060	0.037	0.013	0.009	0.011	0
1857	0.505	0.400	0.145	0.705	0.334	0.142	0.207	0
439	0.500	0.415	0.165	0.689	0.249	0.138	0.250	1

```
from sklearn.linear_model import LinearRegression
from sklearn. linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor


models = {'linear_regression':LinearRegression(),

         'lasso':Lasso(random_state=1),

         'decision_tree':DecisionTreeRegressor(random_state=1),

         'random_forest':RandomForestRegressor(random_state=1),

         'xgboost':XGBRegressor(random_state=1),
        }
```

14.**Measure the performance using Metrics.**

```
# Linear regression
lr_params = {'fit_intercept':[True,False]}

# Lasso
lasso_params = {'alpha': [1e-4, 1e-3, 1e-2, 1, 10, 100]}

# Decision tree
dt_params =  {'max_depth': [4, 6, 8, 10, 12, 14, 16, 20],
            'min_samples_split': [5, 10, 20, 30, 40, 50],
            'max_features': [0.2, 0.4, 0.6, 0.8, 1],
            'max_leaf_nodes': [8, 16, 32, 64, 128,256]}

# Random Forest
rf_params = {'bootstrap': [True, False],
             'max_depth': [2, 5, 10, 20, None],
             'max_features': ['auto', 'sqrt'],
             'min_samples_leaf': [1, 2, 4],
             'min_samples_split': [2, 5, 10],
             'n_estimators': [100, 150, 200, 250]}

# XGBoost
xgb_params = {'n_estimators':[100, 200, 300] ,
```

```
            'max_depth':list(range(1,10)) ,
            'learning_rate':[0.006,0.007,0.008,0.05,0.09] ,
            'min_child_weight':list(range(1,10))}


from sklearn.model_selection import RandomizedSearchCV
params = [lr_params, lasso_params, dt_params, rf_params, xgb_params]

# searching Hyperparameters
i=0
for name, model in models.items():
    print(name)
    regressor = RandomizedSearchCV(estimator = model,
                                   n_iter=10,
                                   param_distributions = params[i],
                                   cv = 3,
                                   scoring = 'neg_root_mean_squared_error')

    search = regressor.fit(X_train, y_train)

    print('Best params :',search.best_params_)
    print("RMSE :", -search.best_score_)
    i+=1
    print()
```

```
linear_regression
Best params : {'fit_intercept': True}
RMSE : 1.850711478798481

lasso
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:296: UserWa
  UserWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:296: UserWa
  UserWarning,
Best params : {'alpha': 0.0001}
RMSE : 1.8506688457783522

decision_tree
Best params : {'min_samples_split': 30, 'max_leaf_nodes': 16, 'max_features': 0.8, 'r
RMSE : 1.9493904303644696

random_forest
Best params : {'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 4, 'r
RMSE : 1.7791857070978347

xgboost
[10:42:32] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:33] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:35] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:37] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
```

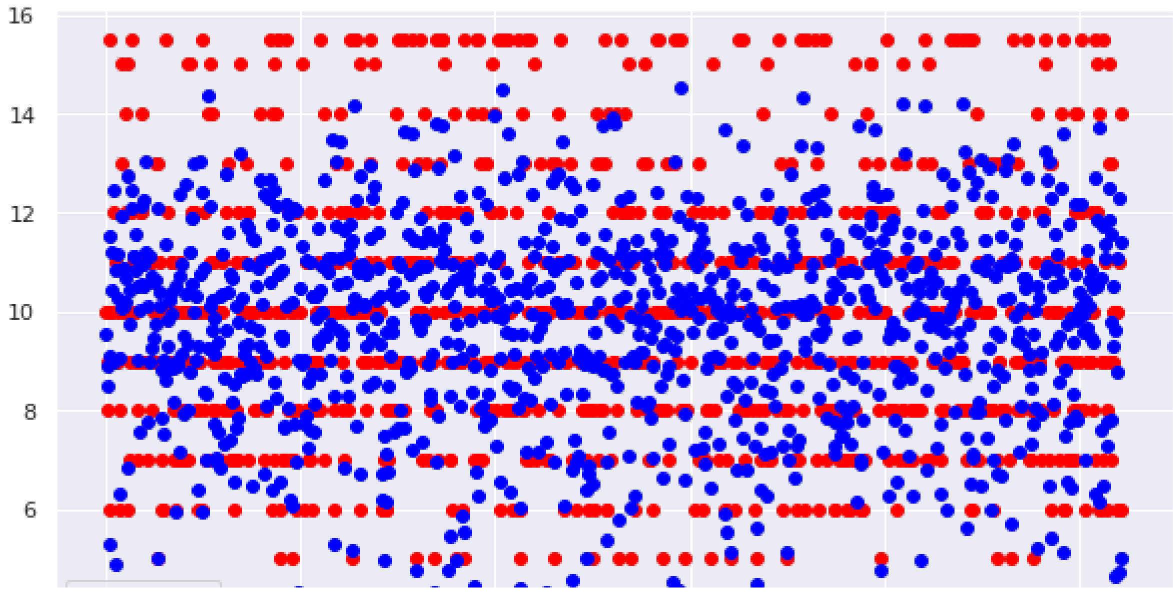
```
[10:42:38] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:38] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:39] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:42] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:43] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:44] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:44] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:45] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:46] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:46] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
[10:42:46] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
Best params : {'n_estimators': 200, 'min_child_weight': 2, 'max_depth': 4, 'learning_
RMSE : 1.7699400041667699
```

```python
rf_params = {'n_estimators': 200,
             'min_samples_split': 2,
             'min_samples_leaf': 4,
             'max_features': 'sqrt',
             'max_depth': None,
             'bootstrap': True}

model = RandomForestRegressor(random_state=1, **rf_params)

model.fit(X_train, y_train)
```

```
RandomForestRegressor(max_features='sqrt', min_samples_leaf=4, n_estimators=200,
                      random_state=1)
```

```python
import pickle
with open("model.pkl", "wb") as f:
    pickle.dump(model, f)
```

```python
y_pred = model.predict(X_test)

fig = plt.figure(figsize=(10, 6))
plt.scatter(range(y_test.shape[0]), y_test, color='red', label='y_true')
plt.scatter(range(y_test.shape[0]), y_pred, color='blue', label='y_pred')
plt.legend()
plt.show()
```




```
plt.figure(figsize=(10,5))
plt.hist(y_pred-y_test, bins=30)
plt.show()


def predict_age(x):
    x = pd.DataFrame([x], columns=features)
    age = model.predict(x)
    return round(age[0],2)


with open("model.pkl", 'rb') as f:
    model = pickle.load(f)
ex = [0.295 , 0.225 , 0.08  , 0.124 , 0.0485, 0.032 , 0.04  , 0.]
print("Estimated age : ",predict_age(ex))

     Estimated age :  7.26
```