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

LOADING THE DATASET

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

```
df
```

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

4177 rows × 9 columns

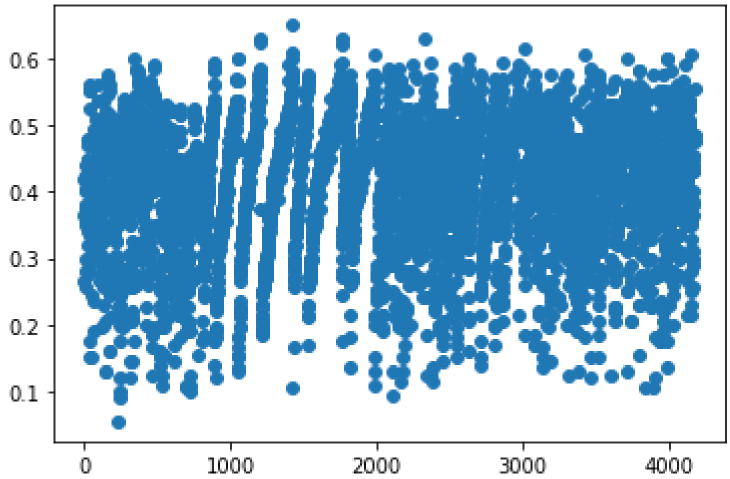
```
df.dtypes
```

```
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
```

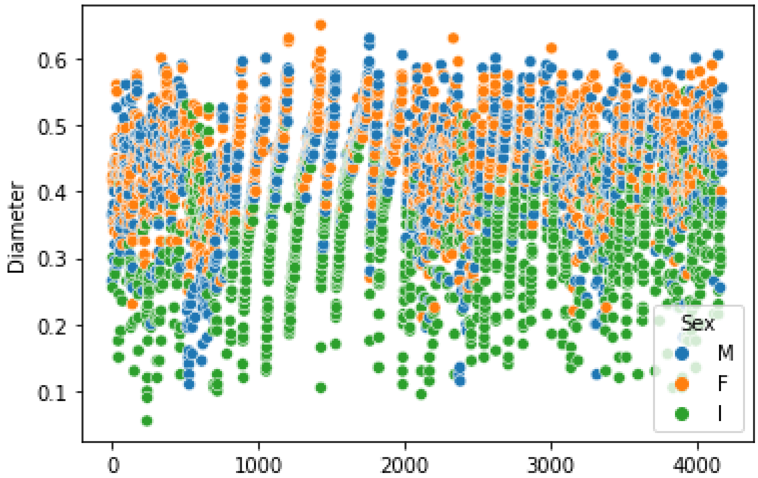
UNIVARIATE ANALYSIS

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



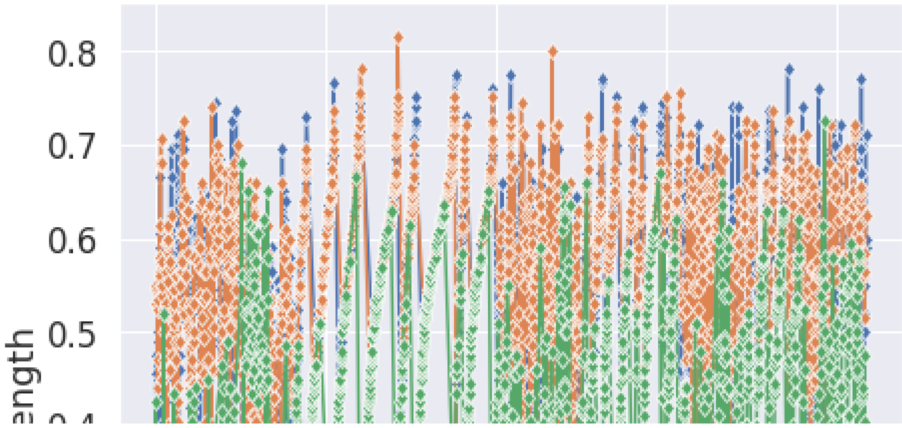

```
sns.scatterplot(x=df.index,y=df['Diameter'],hue=df['Sex'])
```

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



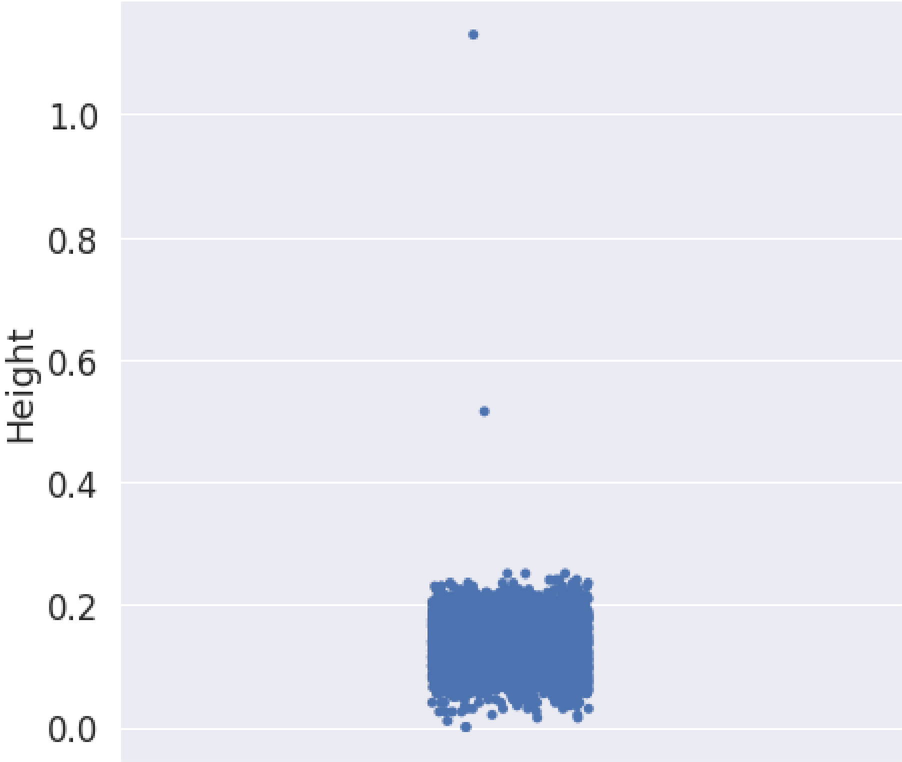

```
sns.set(rc={'figure.figsize': (7,7)})
sns.set (font_scale=1.5)
fig=sns.lineplot (x=df.index, y=df['Length'], markevery=1, marker='d', data=df, hue=df ['S
fig.set(xlabel='index')
```

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



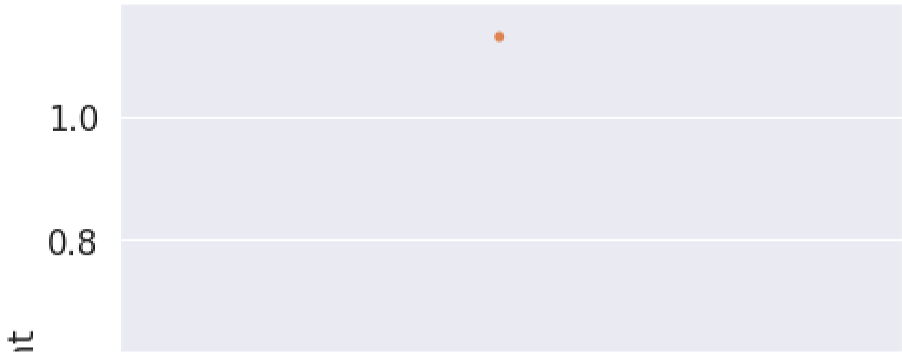

```
sns.stripplot (y=df['Height'])
```

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



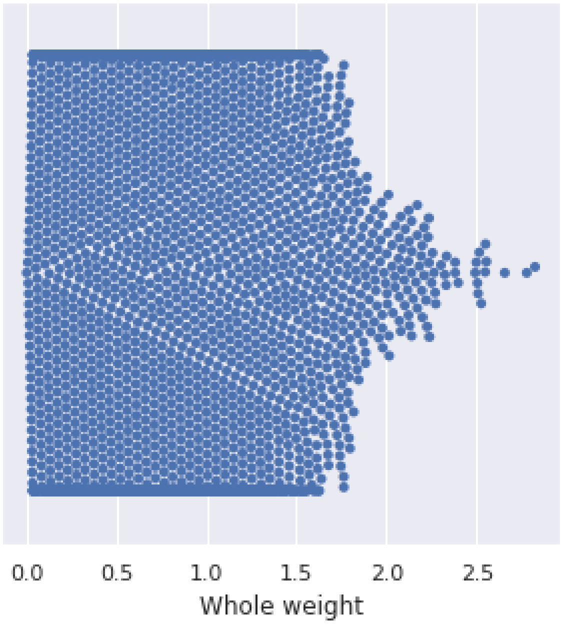

```
sns.stripplot (x=df['Sex'], y=df['Height'])
```

```
<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: 61.6
  warnings.warn(msg, UserWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7f4145eb9610>
```

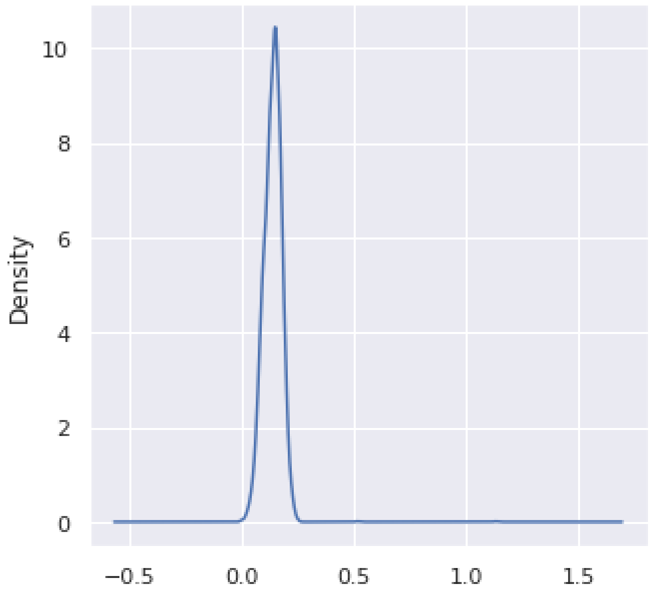



```
plt.hist(df['Height'])
```

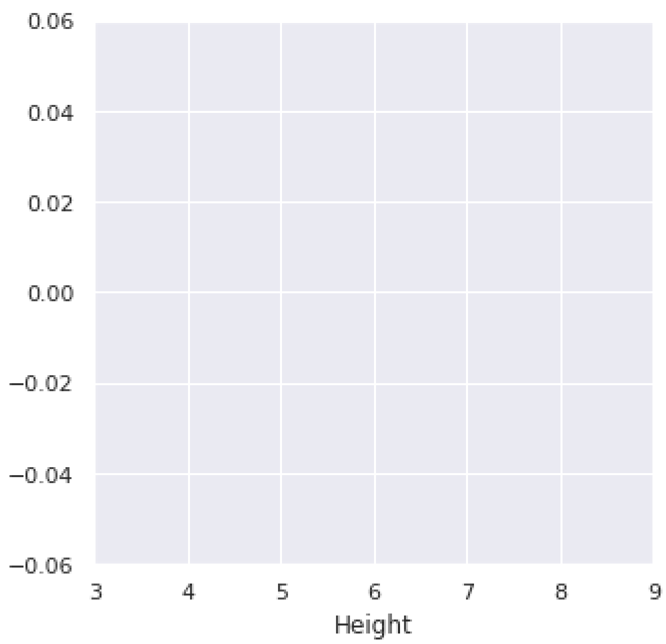
```
(array([1.023e+03, 3.129e+03, 2.300e+01, 0.000e+00, 1.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00]),
 array([0.   , 0.113, 0.226, 0.339, 0.452, 0.565, 0.678, 0.791, 0.904,
        1.017, 1.13 ]),
 <a list of 10 Patch objects>)
```

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

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

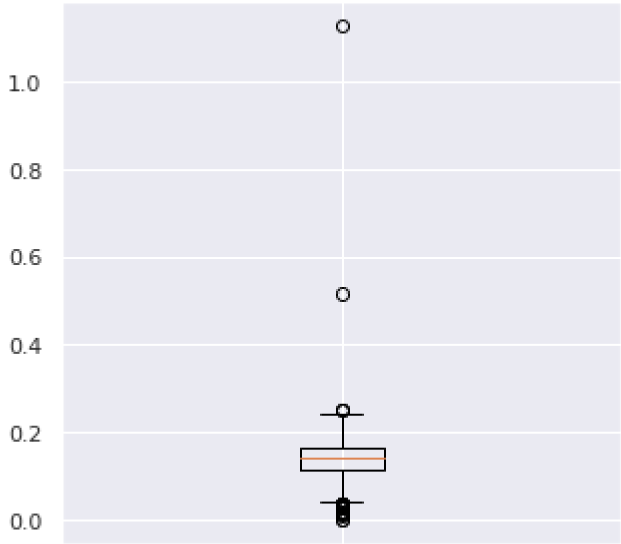



```
fig, ax = plt.subplots()
sns.rugplot (df ['Height'])
ax.set_xlim (3,9)
plt.show()
```




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

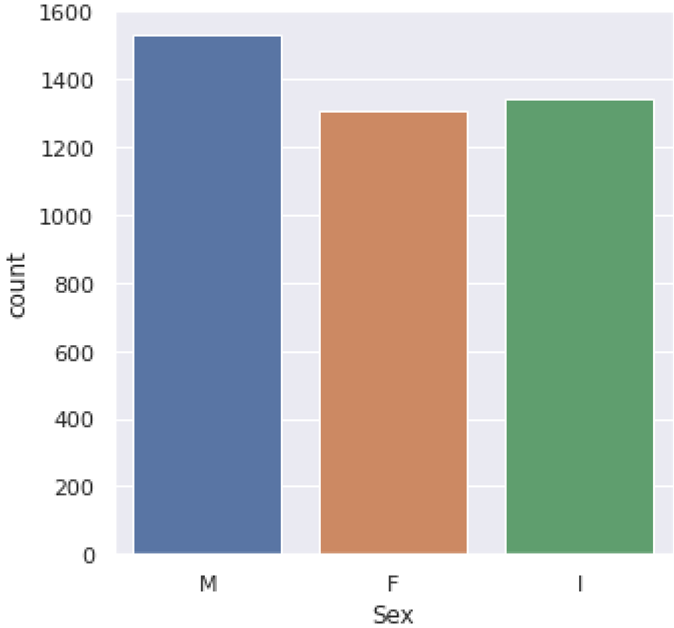
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7f4143193d90>,
  <matplotlib.lines.Line2D at 0x7f4143198310>],
 'caps': [<matplotlib.lines.Line2D at 0x7f4143198850>,
  <matplotlib.lines.Line2D at 0x7f4143198d90>],
 'boxes': [<matplotlib.lines.Line2D at 0x7f4143193790>],
 'medians': [<matplotlib.lines.Line2D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



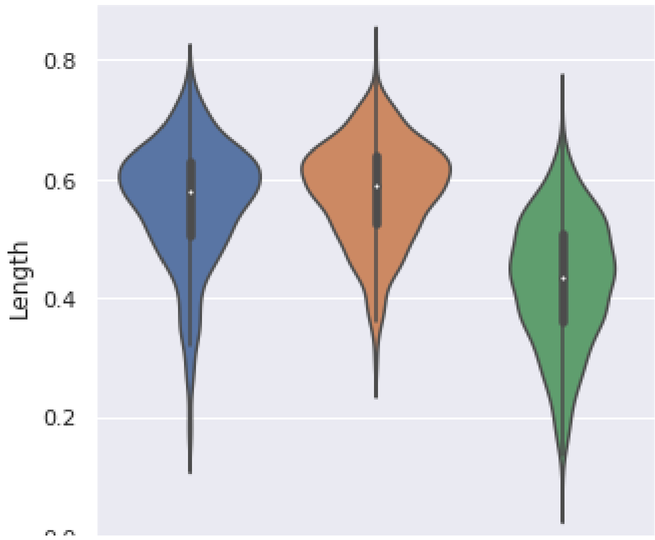
BIVARIATE ANALYSIS

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

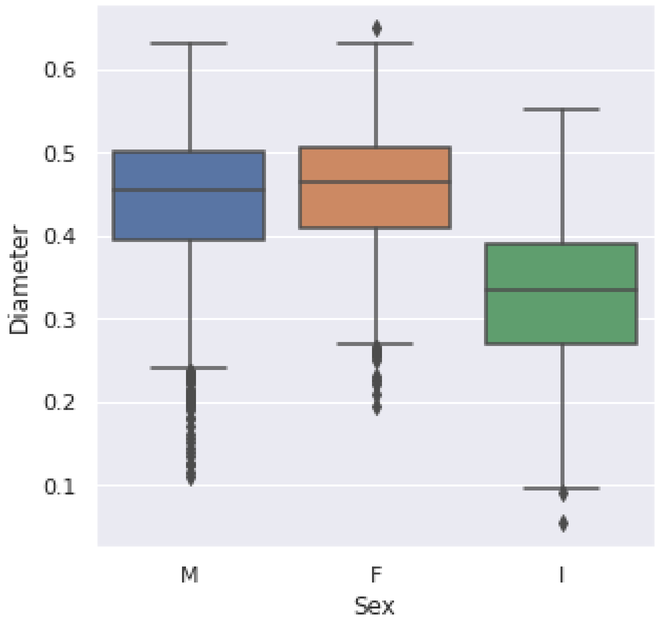
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4143144110>
```




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



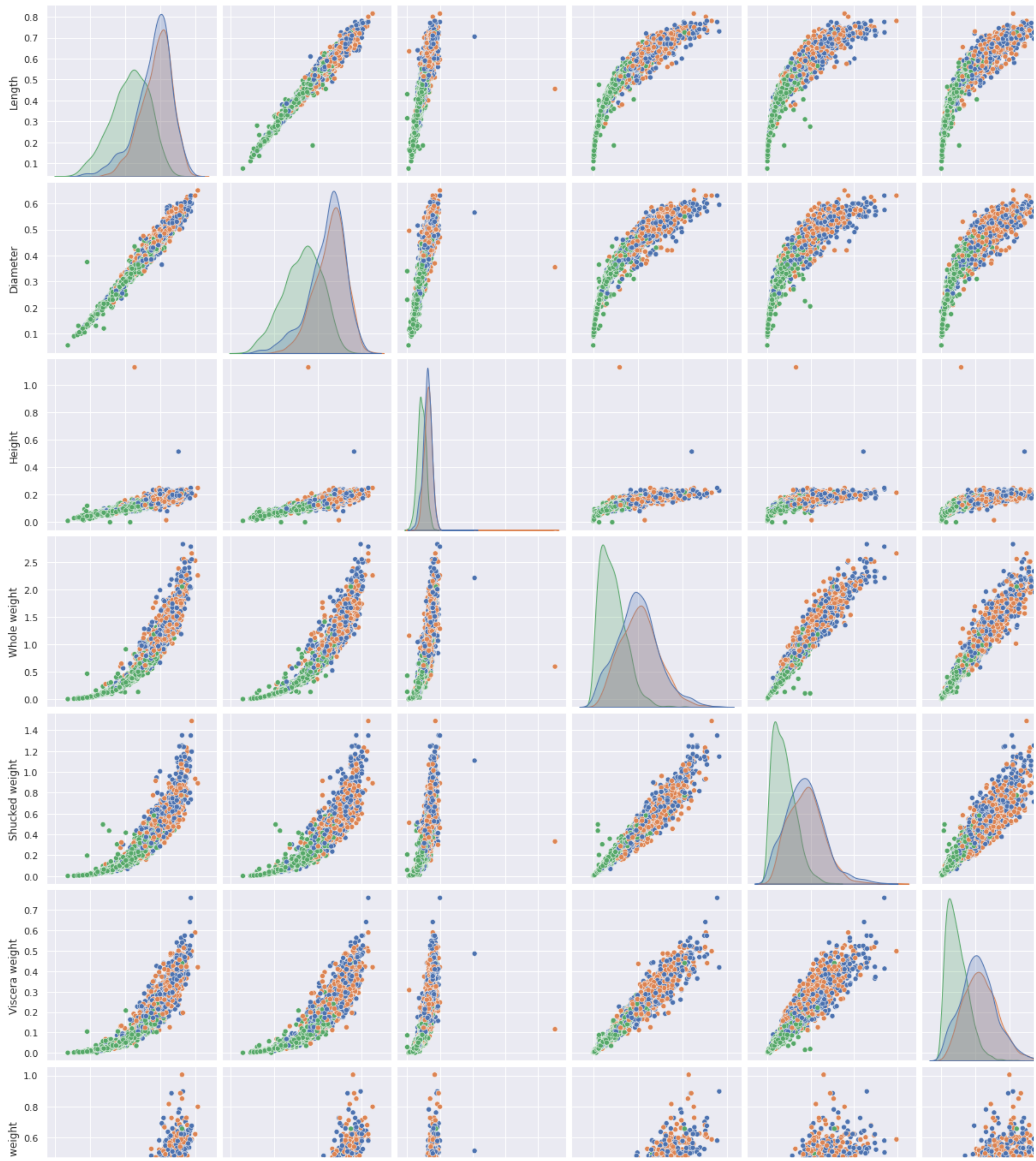

```
sns.boxplot (x='Sex',y='Diameter', data=df)
plt.show()
```



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)
```



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
```

Check for Missing values

```
df.isnull()
```

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

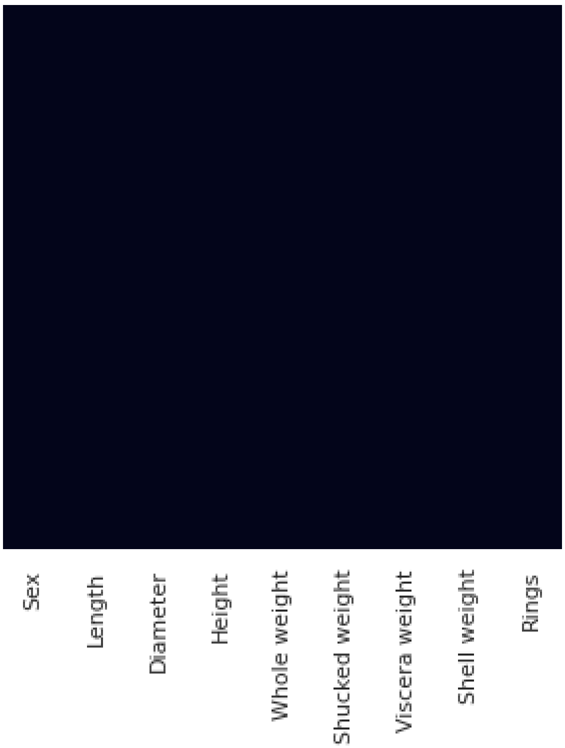
4177 rows × 9 columns

```
df.notnull()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	S
0	True	True	True	True	True	True	True	
1	True	True	True	True	True	True	True	
2	True	True	True	True	True	True	True	
3	True	True	True	True	True	True	True	
4	True	True	True	True	True	True	True	
...	...	...	...	...	...	...	...	

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

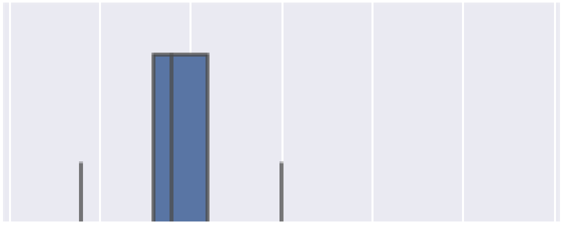
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4141754850>
```



Find the outliers and replace them outliers

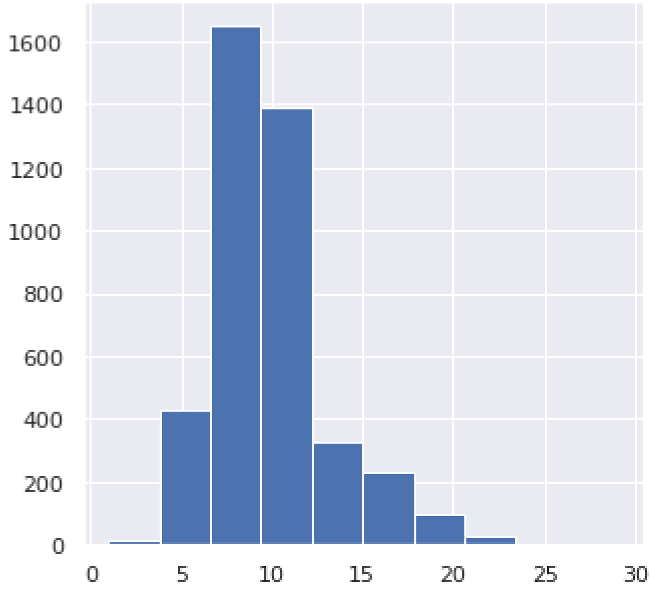
```
sns.boxplot(df['Rings'],data=df)
```

```
/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()
```

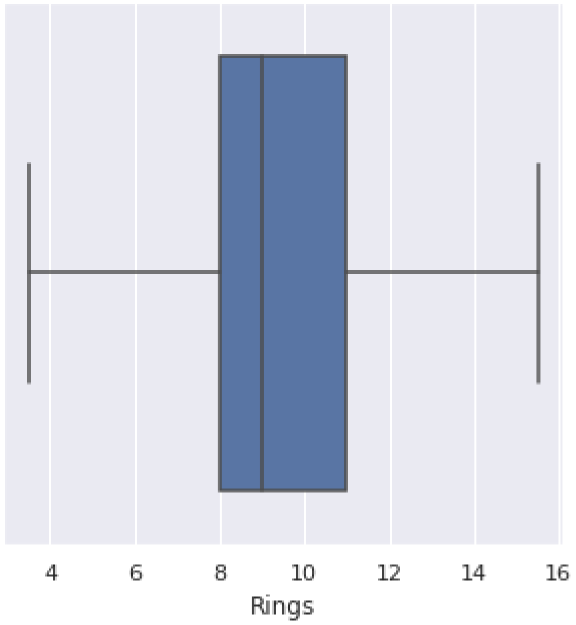
	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Sh
6	F	0.530	0.415	0.150	0.777	0.237	0.141	
72	F	0.595	0.475	0.170	1.247	0.480	0.225	
83	M	0.595	0.475	0.160	1.317	0.408	0.234	
166	F	0.725	0.575	0.175	2.124	0.765	0.452	
167	F	0.680	0.570	0.205	1.842	0.625	0.408	

```
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)
```

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

```
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.]])
```

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]
```

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]]
```

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	S
678	F	0.450	0.380	0.165	0.817	0.250	0.192	
3009	I	0.255	0.185	0.065	0.074	0.030	0.017	
1906	I	0.575	0.450	0.135	0.825	0.338	0.211	
768	F	0.550	0.430	0.155	0.785	0.289	0.227	
2781	M	0.595	0.475	0.140	1.030	0.492	0.217	
...	...	...	...	...	...	...	...	
1033	M	0.650	0.525	0.185	1.622	0.664	0.323	
3264	F	0.655	0.500	0.140	1.171	0.540	0.318	
1653	M	0.595	0.450	0.145	0.959	0.463	0.206	

```
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
```

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
4014	0.625	0.480	0.175	1.065	0.486	0.259	
3252	0.480	0.380	0.130	0.618	0.300	0.142	
305	0.200	0.145	0.060	0.037	0.013	0.009	
1857	0.505	0.400	0.145	0.705	0.334	0.142	
439	0.500	0.415	0.165	0.689	0.249	0.138	

```
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),
        }
```

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
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[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
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[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
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[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 nov
[10:42:46] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is nov
Best params : {'n_estimators': 200, 'min_child_weight': 2, 'max_depth': 4, 'learning_
RMSE : 1.7699400041667699
```

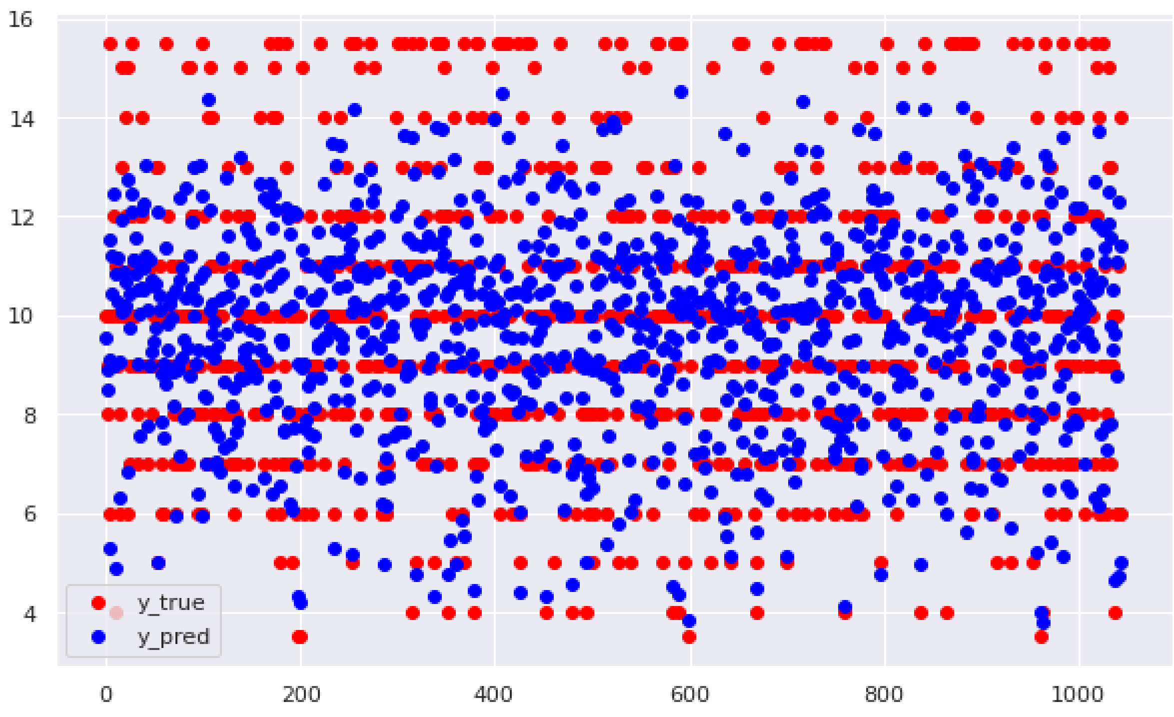
```
rf_params = {'n_estimators': 200,
             'min_samples_split': 2,
             'min_samples_leaf': 4,
             'max_features': 'sqrt',
             'max_depth': None,
             'bootstrap': True}

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)
```

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

```
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
```