Importing the Abalone Dataset

In [57]:
```
import pandas as pd
```

In [3]:
```
url = ("https://archive.ics.uci.edu/ml/machine-learning-databases/abalone/abalone
```

In [4]:
```
abalone = pd.read_csv(url, header=None)
```

In [5]:
```
abalone.head()
```

Out[5]:

	0	1	2	3	4	5	6	7	8
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

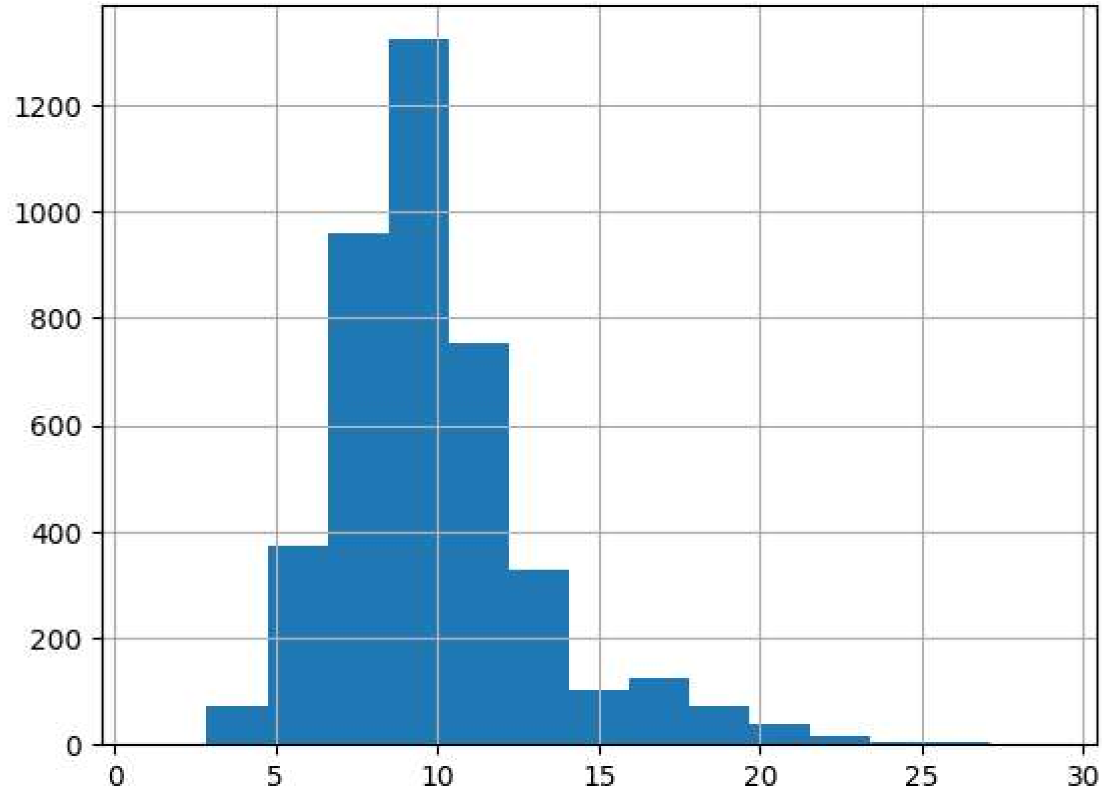
In [6]:
```
abalone.columns = ["Sex","Length","Diameter","Height","Whole weight","Shucked wei
```

In [7]:
```
abalone = abalone.drop("Sex", axis=1)
```

Descriptive Statistics From the Abalone Dataset

In [8]:
```
import matplotlib.pyplot as plt
```

In [9]:
```
abalone["Rings"].hist(bins=15)
plt.show()
```



In [10]:
```
correlation_matrix = abalone.corr()
```

In [11]:
```
correlation_matrix["Rings"]
```

Out[11]:
```
Length            0.556720
Diameter          0.574660
Height            0.557467
Whole weight      0.540390
Shucked weight    0.420884
Viscera weight    0.503819
Shell weight      0.627574
Rings             1.000000
Name: Rings, dtype: float64
```

A Step-by-Step kNN

In [12]:
```
import numpy as np
```

In [13]:
```
a = np.array([2, 2])
```

In [14]:
```
b = np.array([4, 4])
```

In [15]:
```
np.linalg.norm(a - b)
```

Out[15]:
```
2.8284271247461903
```

k Nearest Neighbors#

In [16]:
```
X = abalone.drop("Rings", axis=1)
```

In [17]:
```
X = X.values
```

In [18]:
```
y = abalone["Rings"]
```

In [19]:
```
y = y.values
```

In [20]:
```
new_data_point = np.array([0.569552,0.446407,0.154437,1.016849,0.439051,0.222526,
```

In [21]:
```
distances = np.linalg.norm(X - new_data_point, axis=1)
```

In [22]:
```
k = 3
nearest_neighbor_ids = distances.argsort()[:k]
nearest_neighbor_ids
```

Out[22]:
```
array([4045, 1902, 1644], dtype=int64)
```

Voting or Averaging of Multiple Neighbors

In [23]:
```
nearest_neighbor_rings = y[nearest_neighbor_ids]
nearest_neighbor_rings
```

Out[23]:
```
array([ 9, 11, 10], dtype=int64)
```

Average for Regression

In [24]:
```
prediction = nearest_neighbor_rings.mean()
```

Mode for Classification

In [25]:
```
import scipy.stats
```

In [26]:
```
class_neighbors = np.array(["A", "B", "B", "C"])
```

In [27]:
```
scipy.stats.mode(class_neighbors)
```

```
C:\Users\Mona Shah\AppData\Local\Temp\ipykernel_14716\494549111.py:1: FutureWar
ning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default b
ehavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0,
this behavior will change: the default value of `keepdims` will become False, t
he `axis` over which the statistic is taken will be eliminated, and the value N
one will no longer be accepted. Set `keepdims` to True or False to avoid this w
arning.
  scipy.stats.mode(class_neighbors)
C:\Users\Mona Shah\AppData\Roaming\Python\Python310\site-packages\scipy\stats\_
stats_py.py:110: RuntimeWarning: The input array could not be properly checked
for nan values. nan values will be ignored.
  warnings.warn("The input array could not be properly "
C:\Users\Mona Shah\AppData\Local\Temp\ipykernel_14716\494549111.py:1: Deprecati
onWarning: Support for non-numeric arrays has been deprecated as of SciPy 1.9.0
and will be removed in 1.11.0. `pandas.DataFrame.mode` can be used instead, see
https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.mode.html. (http
s://pandas.pydata.org/docs/reference/api/pandas.DataFrame.mode.html.)
  scipy.stats.mode(class_neighbors)
```

Out[27]:
```
ModeResult(mode=array(['B'], dtype='<U1'), count=array([2]))
```

kNN in Python Using scikit-learn

In [28]:
```
from sklearn.model_selection import train_test_split
```

In [29]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

kNN Regression in scikit-learn to the Abalone Dataset

In [30]:
```
from sklearn.neighbors import KNeighborsRegressor
```

In [31]:
```
knn_model = KNeighborsRegressor(n_neighbors=3)
```

In [32]:
```
knn_model.fit(X_train, y_train)
```

Out[32]:
```
KNeighborsRegressor
KNeighborsRegressor(n_neighbors=3)
```

Using scikit-learn to Inspect Model Fit

In [33]:
```
from sklearn.metrics import mean_squared_error
```

In [34]:
```
from math import sqrt
```

In [35]:
```
train_preds = knn_model.predict(X_train)
```

In [36]:
```
mse = mean_squared_error(y_train, train_preds)
```

In [37]:
```
rmse = sqrt(mse)
rmse
```

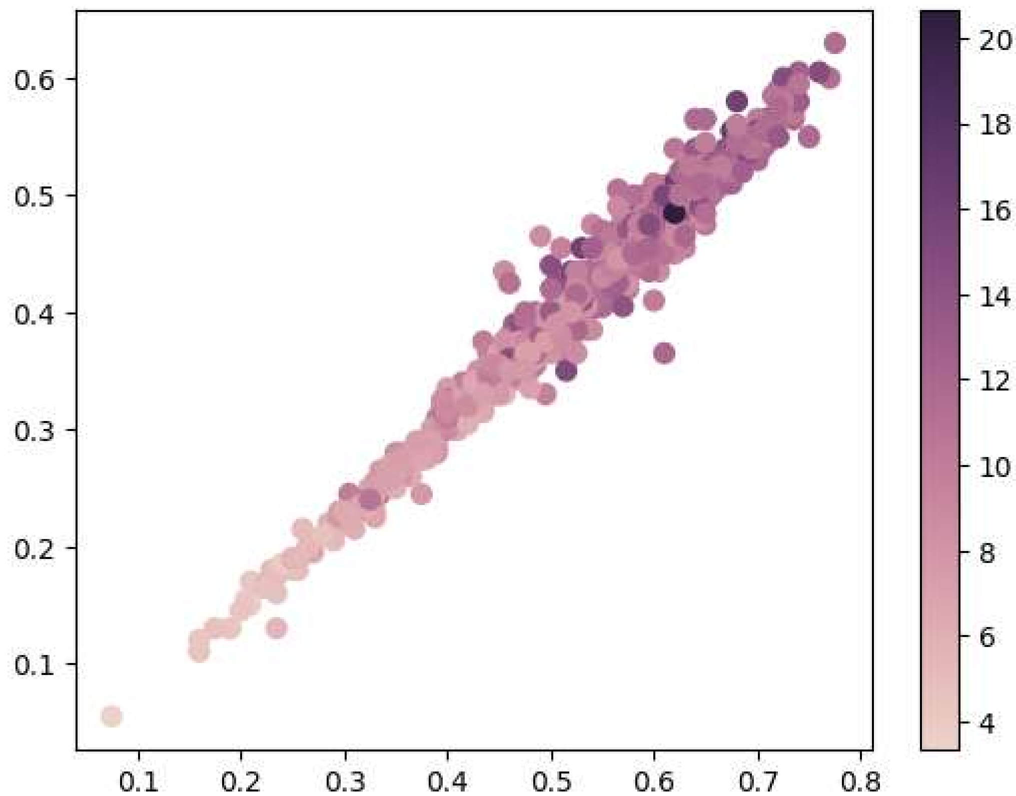
Out[37]:
```
1.6538366794859511
```

In [38]:
```
test_preds = knn_model.predict(X_test)
mse = mean_squared_error(y_test, test_preds)
rmse = sqrt(mse)
rmse
```

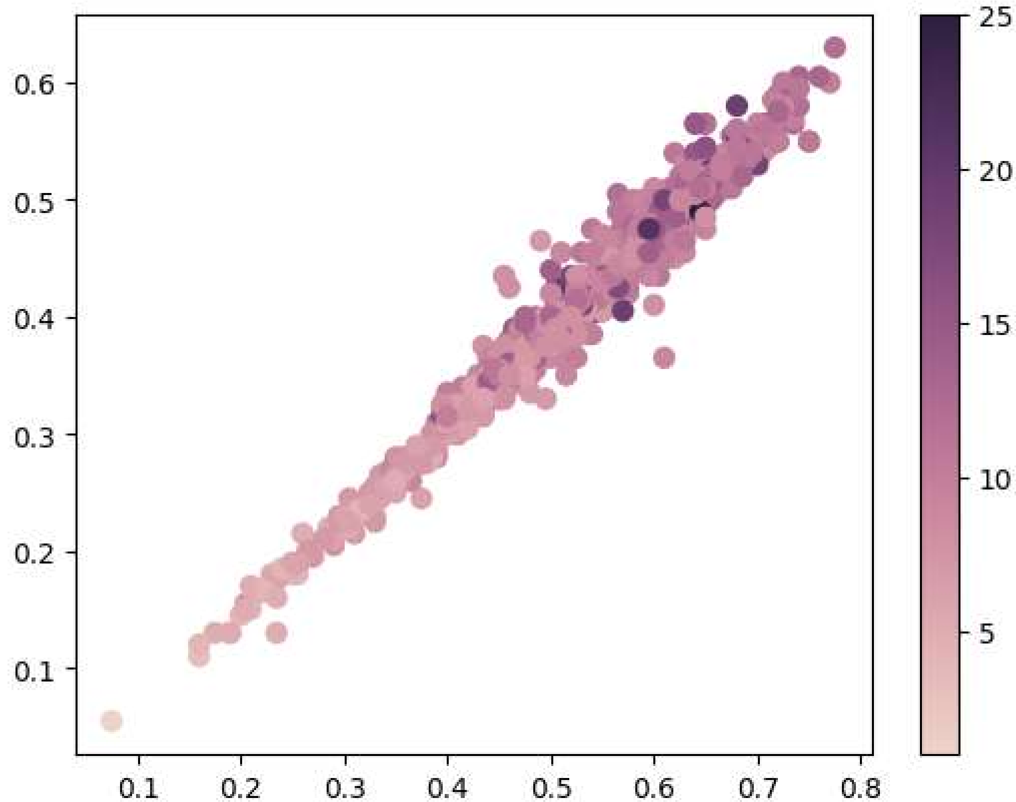
Out[38]:
```
2.375417924000521
```

Plotting

In [39]:
```
import seaborn as sns
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(X_test[:, 0], X_test[:, 1], c=test_preds, s=50, cmap=cmap)
f.colorbar(points)
plt.show()
```



In [40]:
```
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(X_test[:, 0], X_test[:, 1], c=y_test, s=50, cmap=cmap)
f.colorbar(points)
plt.show()
```



Improving kNN Performances in scikit-learn Using GridSearchCV

In [43]:
```
from sklearn.model_selection import GridSearchCV
parameters = {"n_neighbors": range(1, 50)}
gridsearch = GridSearchCV(KNeighborsRegressor(), parameters)
gridsearch.fit(X_train, y_train)
```

Out[43]:
```
▸ GridSearchCV
▸ estimator: KNeighborsRegressor
  ▸ KNeighborsRegressor
```

In [44]:
```
gridsearch.best_params_
```

Out[44]:
```
{'n_neighbors': 25}
```

In [45]:
```
train_preds_grid = gridsearch.predict(X_train)
train_mse = mean_squared_error(y_train, train_preds_grid)
train_rmse = sqrt(train_mse)
test_preds_grid = gridsearch.predict(X_test)
test_mse = mean_squared_error(y_test, test_preds_grid)
test_rmse = sqrt(test_mse)
train_rmse
```

Out[45]:
```
2.0731180327543384
```

In [46]:
```
test_rmse
```

Out[46]:
```
2.1700197339962175
```

Adding Weighted Average of Neighbors Based on Distance

In [47]:
```
parameters = {"n_neighbors": range(1, 50),
"weights": ["uniform", "distance"],}
gridsearch = GridSearchCV(KNeighborsRegressor(), parameters)
gridsearch.fit(X_train, y_train)
```

Out[47]:
```
▸ GridSearchCV
▸ estimator: KNeighborsRegressor
  ▸ KNeighborsRegressor
```

In [48]:
```
gridsearch.best_params_
```

Out[48]:
```
{'n_neighbors': 25, 'weights': 'distance'}
```

In [49]:
```
test_preds_grid = gridsearch.predict(X_test)
test_mse = mean_squared_error(y_test, test_preds_grid)
test_rmse = sqrt(test_mse)
test_rmse
```

Out[49]: 2.1634265584947485

Improving on kNN in scikit-learn With Bagging

In [51]:
```
best_k = gridsearch.best_params_["n_neighbors"]
best_weights = gridsearch.best_params_["weights"]
bagged_knn = KNeighborsRegressor(n_neighbors=best_k, weights=best_weights)
```

In [54]:
```
from sklearn.ensemble import BaggingRegressor
bagging_model = BaggingRegressor(bagged_knn, n_estimators=100)
```

In [56]:
```
test_mse = mean_squared_error(y_test, test_preds_grid)
test_rmse = sqrt(test_mse)
test_rmse
```

Out[56]: 2.1634265584947485

Conclusion

With the Above analysis we can say that using KNN model with bagging optimizes the performance to the maximum

Also with the above python libraries we can get the best nearest neighbour analysis with minimum code

In [ ]:
```

```