Use kNN to Predict the Age of Sea Slugs

1. Importing the Abalone Dataset and libraries

In [13]:
```
import pandas as pd
path=r'B:\MY COMPUTER (HOME)\2 IT\Practice works\Datasets\abalone.data.csv'
abalone = pd.read_csv(path, header=None)
abalone.head()
```

Out[13]:

	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 [14]:
```
# Add column names
abalone.columns = [
 "Sex",
 "Length",
 "Diameter",
 "Height",
 "Whole weight",
 "Shucked weight",
 "Viscera weight",
 "Shell weight",
 "Rings",
]
abalone.head()
```

Out[14]:

	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	0.150	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

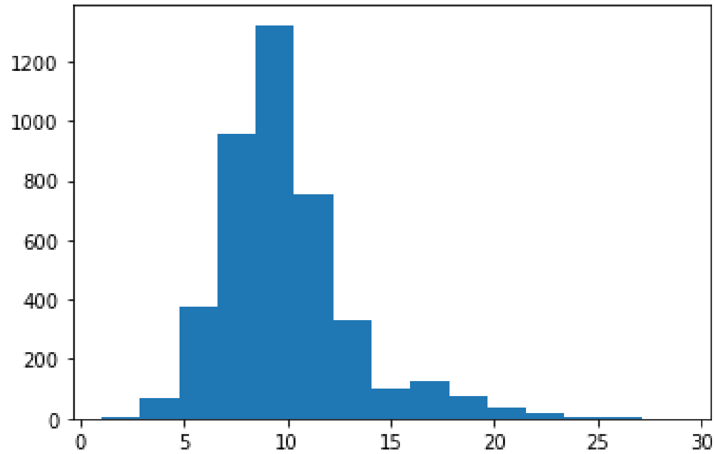
In [15]:
```
abalone = abalone.drop("Sex", axis=1)
abalone.head()
```

Out[15]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

2. Descriptive Statistics From the Abalone Dataset

In [17]:
```
# A histogram will give you a quick and useful overview of the
# age ranges that you can expect:
import matplotlib.pyplot as plt
abalone["Rings"].hist(bins=15)
plt.grid(False)
plt.show()
```



In [20]:
```
# A second relevant exploration is to find out which of the variables, if
# any, have a strong correlation with the age. A strong correlation
# between an independent variable and your goal variable would be a
# good sign, as this would confirm that physical measurements and
# age are related.

# observe the complete correlation matrix
correlation_matrix = abalone.corr()
correlation_matrix["Rings"]
```

Out[20]:
```
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
```

In [21]:
```
correlation_matrix
```

Out[21]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
Length	1.000000	0.986812	0.827554	0.925261	0.897914	0.903018	0.897706	0.556720
Diameter	0.986812	1.000000	0.833684	0.925452	0.893162	0.899724	0.905330	0.574660
Height	0.827554	0.833684	1.000000	0.819221	0.774972	0.798319	0.817338	0.557467
Whole weight	0.925261	0.925452	0.819221	1.000000	0.969405	0.966375	0.955355	0.540390
Shucked weight	0.897914	0.893162	0.774972	0.969405	1.000000	0.931961	0.882617	0.420884
Viscera weight	0.903018	0.899724	0.798319	0.966375	0.931961	1.000000	0.907656	0.503819
Shell weight	0.897706	0.905330	0.817338	0.955355	0.882617	0.907656	1.000000	0.627574
Rings	0.556720	0.574660	0.557467	0.540390	0.420884	0.503819	0.627574	1.000000

3. KNN steps by step

In [22]:
```
# defining x and y values
# Note that you use a capital letter for X but a
# lowercase letter for y. This is o뮻 en done in machine learning code
# because mathematical notation generally uses a capital letter for
# matrices and a lowercase letter for vectors.
X = abalone.drop("Rings", axis=1)
X = X.values
y = abalone["Rings"]
y = y.values
```

In [24]:
```
# apply a kNN with k = 3 on a new abalone that has the
# following physical measurements:
# You can create the NumPy array for this data point as follows:
import numpy as np
new_data_point = np.array([
 0.569552,
 0.446407,
 0.154437,
 1.016849,
 0.439051,
 0.222526,
 0.291208,
])
```

In [26]:
```
# The next step is to compute the distances between this new data
# point and each of the data points in the Abalone Dataset using the
# following code:
distances = np.linalg.norm(X - new_data_point, axis=1)
```

In [28]:
```
#to find out which are the three closest neighbors.
# To do this, you need to find the IDs of the minimum distances
# You can use a method called .argsort()
# to sort the array from lowest to highest, and you can take the first k
# elements to obtain the indices of the k nearest neighbors:
k = 3
nearest_neighbor_ids = distances.argsort()[:k]
nearest_neighbor_ids
```

Out[28]:
```
array([4045, 1902, 1644], dtype=int64)
```

Voting or Averaging of Multiple Neighbors

In [29]:
```
nearest_neighbor_rings = y[nearest_neighbor_ids]
nearest_neighbor_rings
```

Out[29]:
```
array([ 9, 11, 10], dtype=int64)
```

In [32]:
```
# Average for Regression
prediction = nearest_neighbor_rings.mean()
prediction
```

Out[32]:
```
10.0
```

Mode for Classification

In [33]:
```
import scipy.stats
class_neighbors = np.array(["A", "B", "B", "C"])
scipy.stats.mode(class_neighbors)
```

Out[33]:
```
ModeResult(mode=array(['B'], dtype='<U1'), count=array([2]))
```

Fit kNN in Python Using scikit learn

Splitting Data Into Training and Test Sets for Model Evaluation

In [35]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=12345)
```

Fitting a kNN Regression in scikitlearn to the Abalone Dataset

In [36]:
```
from sklearn.neighbors import KNeighborsRegressor
knn_model = KNeighborsRegressor(n_neighbors=3)
knn_model.fit(X_train, y_train)
```

Out[36]:
```
KNeighborsRegressor(n_neighbors=3)
```

Using scikitlearn to Inspect Model Fit

In [37]:
```
# compute the RMSE on the training data for now
from sklearn.metrics import mean_squared_error
from math import sqrt
train_preds = knn_model.predict(X_train)
mse = mean_squared_error(y_train, train_preds)
rmse = sqrt(mse)
rmse
```

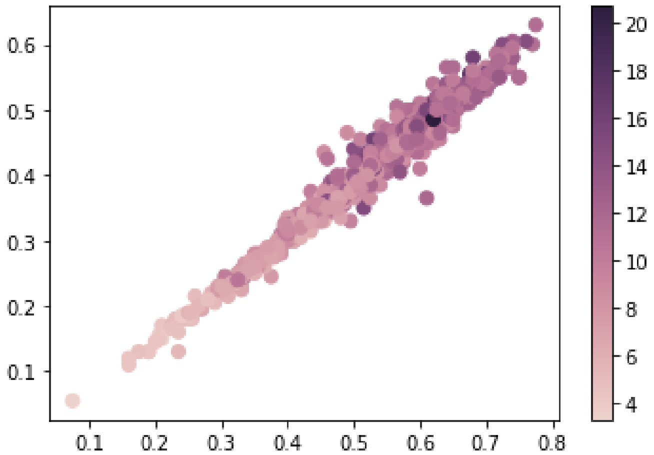
Out[37]: 1.6538366794859511

In [38]:
```
# compute the RMSE on the test data
test_preds = knn_model.predict(X_test)
mse = mean_squared_error(y_test, test_preds)
rmse = sqrt(mse)
rmse
```

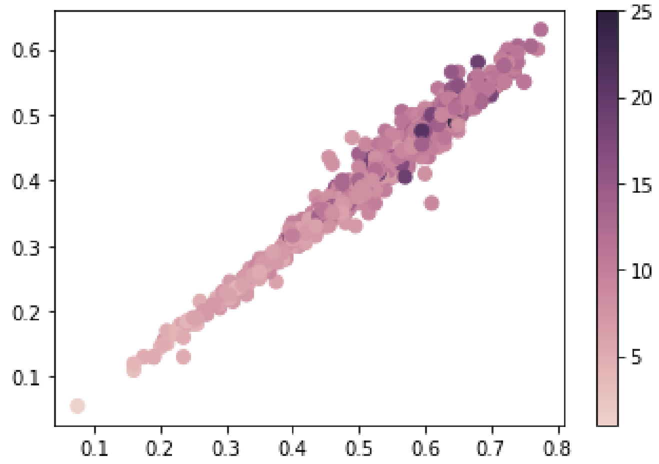
Out[38]: 2.375417924000521

Plotting the Fit of Your Model

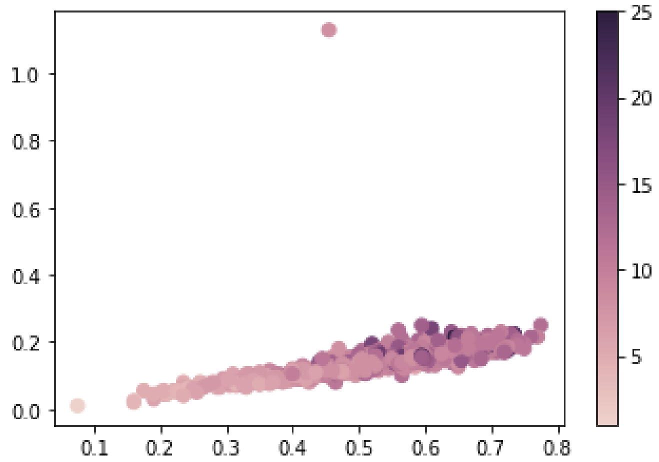
In [39]:
```
# scatter plot of first & second columns of X_test are Length & Diameter
import seaborn as sns
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(X_test[:, 0], X_test[:, 1], c=test_preds, s=50,
                    cmap=cmap)
f.colorbar(points)
plt.show()
```



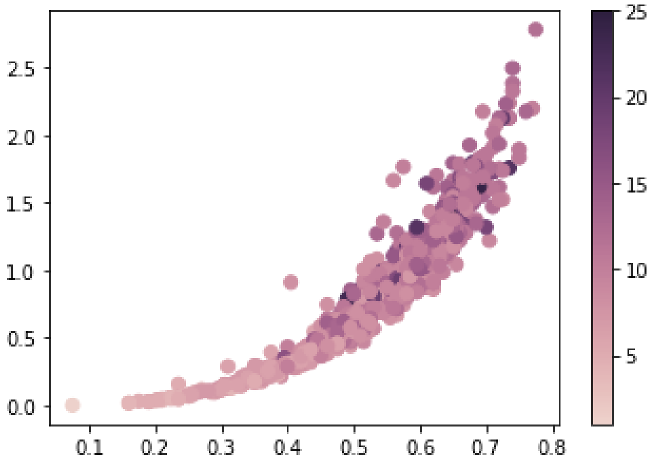
In [40]:
```
# To confirm whether this trend exists in actual abalone data, you can
# do the same for the actual values by simply replacing the variable
# that is used for c:
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 1], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



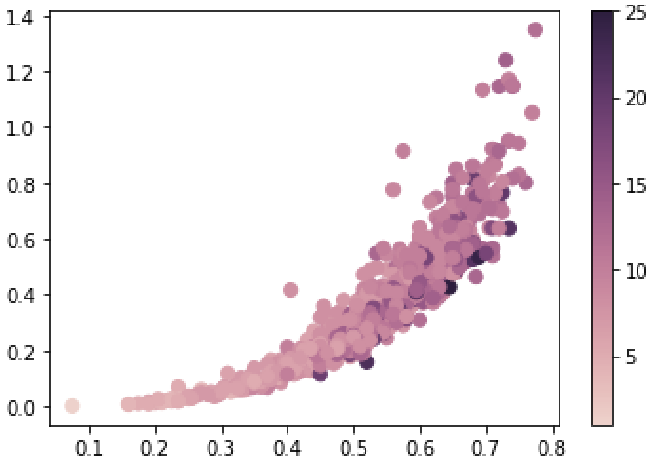
In [46]:
```
# scatter plots with  visualization for each combination of the seven
# independent variables
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 2], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



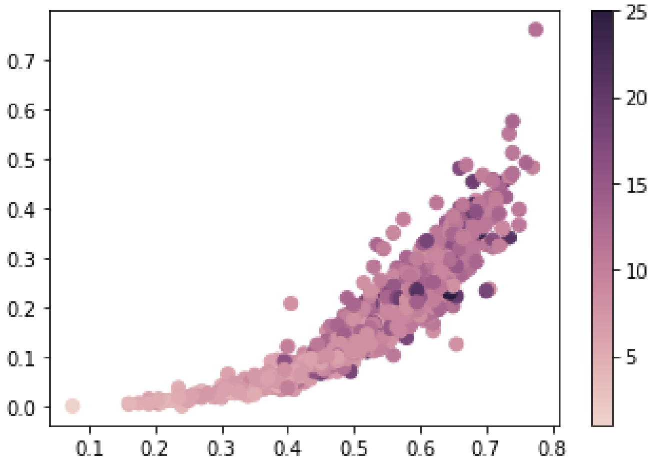
In [47]:
```
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 3], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



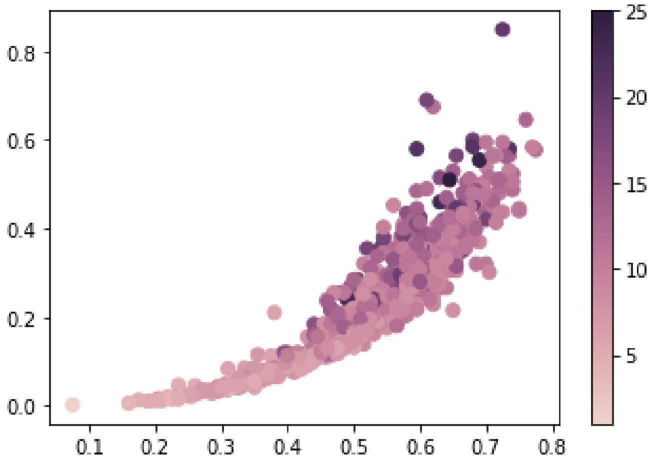
In [48]:
```
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 4], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



In [49]:
```
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 5], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



In [50]:
```
cmap = sns.cubehelix_palette(as_cmap=True)
f, ax = plt.subplots()
points = ax.scatter(
X_test[:, 0], X_test[:, 6], c=y_test, s=50, cmap=cmap
)
f.colorbar(points)
plt.show()
```



Tune and Optimize kNN in Python Using scikit learn

1. Improving kNN Performances in scikit learn Using GridSearchCV

In [71]:
```
from sklearn.model_selection import GridSearchCV
parameters = {"n_neighbors": range(1, 50)}
gridsearch = GridSearchCV(KNeighborsRegressor(), parameters)
gridsearch.fit(X_train, y_train)
```

Out[71]:
```
GridSearchCV(estimator=KNeighborsRegressor(),
             param_grid={'n_neighbors': range(1, 50)})
```

In [72]:
```
# the best performing value of k, which you
# can access with .best_params_:
gridsearch.best_params_
```

Out[72]:
```
{'n_neighbors': 25}
```

In [73]:
```
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,test_rmse
```

Out[73]:
```
(2.0731180327543384, 2.1700197339962175)
```

2.Adding Weighted Average of NeighborsBased on Distance

In [75]:
```
parameters = {
 "n_neighbors": range(1, 50),
 "weights": ["uniform", "distance"],
 }
gridsearch = GridSearchCV(KNeighborsRegressor(), parameters)
gridsearch.fit(X_train, y_train)
```

Out[75]:
```
GridSearchCV(estimator=KNeighborsRegressor(),
             param_grid={'n_neighbors': range(1, 50),
                         'weights': ['uniform', 'distance']})
```

In [76]:
```
gridsearch.best_params_
```

Out[76]:
```
{'n_neighbors': 25, 'weights': 'distance'}
```

In [77]:
```
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[77]:
```
2.1634265584947485
```

3.Further Improving on kNN in scikit learn With Bagging

In [84]:
```
best_k = gridsearch.best_params_["n_neighbors"]
best_weights = gridsearch.best_params_["weights"]
bagged_knn = KNeighborsRegressor(
n_neighbors=best_k, weights=best_weights)
```

In [90]:
```
# import the BaggingRegressor class from scikit-learn and create
# a new instance with 100 estimators using the bagged_knn model:
from sklearn.ensemble import BaggingRegressor
bagging_model = BaggingRegressor(bagged_knn, n_estimators=100)
```

In [93]:
```
# make a prediction and calculate the RMSE to see if it improved:
test_preds_grid = bagging_model.predict(X_test)
test_mse = mean_squared_error(y_test, test_preds_grid)
test_rmse = sqrt(test_mse)
test_rmse

#output: 2.1616
```

Comparison of the Four Models

In [ ]:
```
# four models from simplest to most complex
# Arbitrary k                          2.37
# GridSearchCV for k                   2.17
# GridSearchCV for k and weights       2.1634
# Bagging and GridSearchCV             2.1616
```