ECE 657A - Assignment 1

Date Submitted: February 2nd, 2022

In [1]:
```
# impotrting libraries
import numpy as np
import pandas as pd
import random
import seaborn as sns

sns.set(style="ticks", color_codes=True)
from sklearn import neighbors
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
import warnings

warnings.filterwarnings("ignore")

#%matplotlib notebook
%load_ext nb_black
```

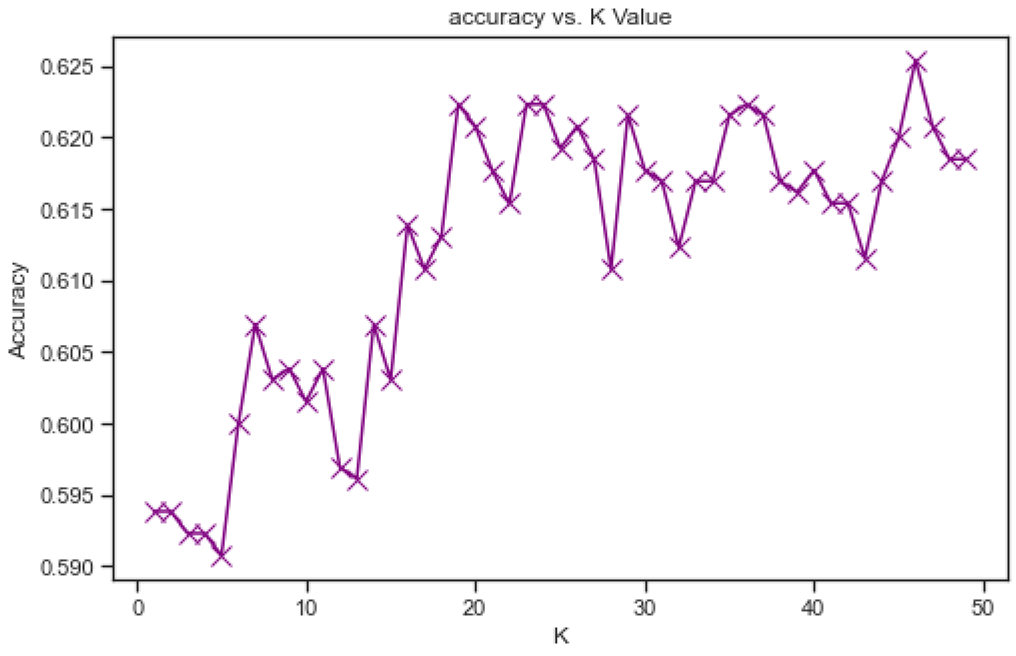
The structure of this notebook is:

1. Loading and classification of Wine dataset
2. EDA and classification of Abalone Dataset

Dataset 1: Wine

In [2]:
```
D = [
    "fixed acidity",
    "volatile acidity",
    "citric acid",
    "residual sugar",
    "chlorides",
    "free sulfur dioxide",
    "total sulfur dioxide",
    "density",
    "pH",
    "sulphates",
    "alcohol",
]
L = "quality"
C = "color"
DL = D + [L]
DC = D + [C]
DLC = DL + [C]

# Loading Data set
wine_r = pd.read_csv("winequality-red.csv", sep=";")
# Loading Data set
wine_w = pd.read_csv("winequality-white.csv", sep=";")
wine_w = wine_w.copy()
wine_w[C] = np.zeros(wine_w.shape[0])
wine_r[C] = np.ones(wine_r.shape[0])
wine = pd.concat([wine_w, wine_r])

target = wine.quality
features = wine.drop("quality", axis=1)
X_train, X_test, y_train, y_test = train_test_split(
    features, target, test_size=0.2, random_state=27
)
acc = []
for k in range(1, 50):
    knn = KNeighborsClassifier(n_neighbors=k, weights="distance",
metric="euclidean")
    knn.fit(X_train, y_train)
    y_predi = knn.predict(X_test)
    acc.append(metrics.accuracy_score(y_test, y_predi))

plt.figure(figsize=(8, 5))
plt.plot(
    range(1, 50),
    acc,
    color="purple",
    linestyle="solid",
    marker="x",
    markerfacecolor="red",
    markersize=10,
)
plt.title("accuracy vs. K Value")
plt.xlabel("K")
plt.ylabel("Accuracy")
print("Maximum accuracy:-", max(acc), "at K =", acc.index(max(acc)))
```

```
Maximum accuracy:- 0.6253846153846154 at K = 45
```



In [3]:

```
knn = KNeighborsClassifier(n_neighbors=45, weights="distance",
metric="euclidean")
knn.fit(X_train, y_train)
print("Parameters used in Classifier:\n", knn.get_params())
y_pred = knn.predict(X_test)

knn_train_acc = knn.score(X_train, y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, y_test)
print("Testing Score: ", knn_test_acc)
```

```
Parameters used in Classifier:
 {'algorithm': 'auto', 'leaf_size': 30, 'metric': 'euclidean', 'metric_params': None, 'n
_jobs': None, 'n_neighbors': 45, 'p': 2, 'weights': 'distance'}
Training Score:  1.0
Testing Score:  0.62
```

2. Using normalized data to classify quality

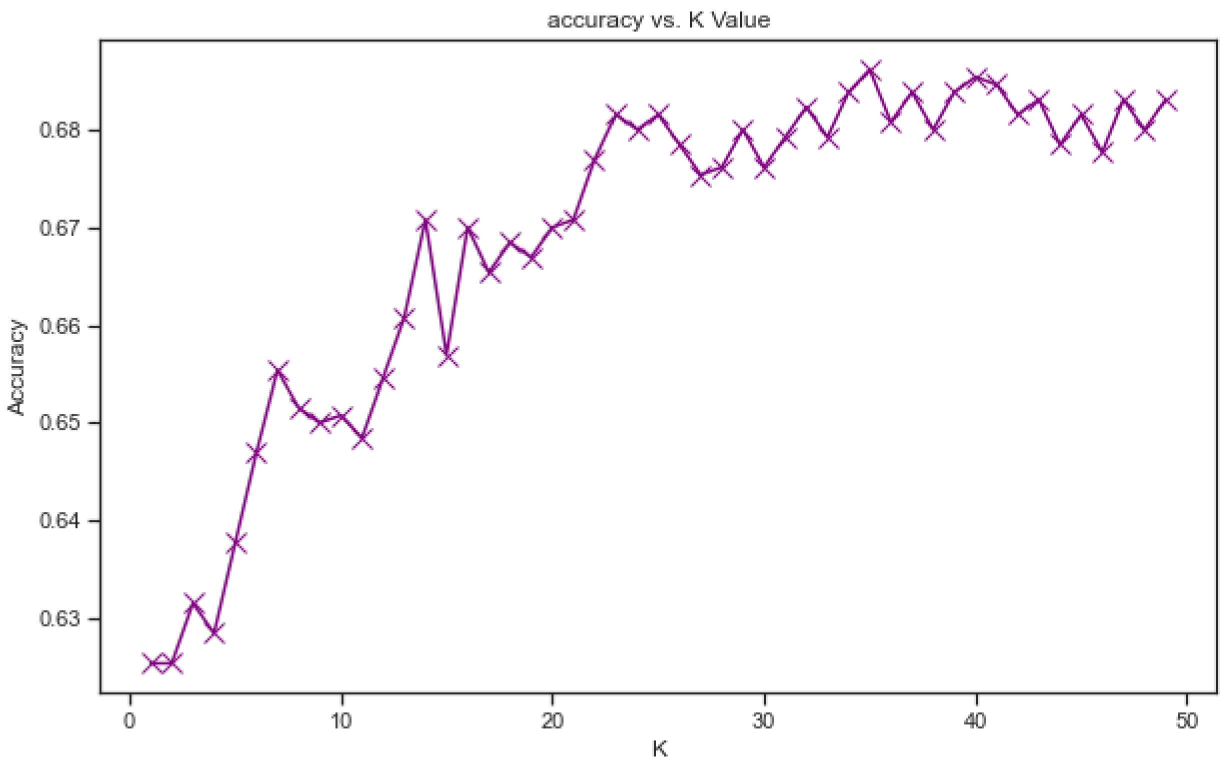
In [4]:

```
feature_normalized = wine.drop(
    "quality", axis=1
)  ## dependent varibale is not normalized
feature_n = feature_normalized.apply(
    stats.zscore
)  ## independent variables are Z-normalized
# print(feature_n.head())
```

In [5]:

```
X_train, X_test, y_train, y_test = train_test_split(
    feature_n, target, test_size=0.2, random_state=27
)

# Using 80:20 ratio for our normalized data set also to compare
classification accuracy with unnormalized data.
# Plotting accuracy vs K to determine the best value for K.
# using weighted KNN and euclidean distance metric

acc = []
for k in range(1, 50):
    knn = KNeighborsClassifier(n_neighbors=k, weights="distance",
metric="euclidean")
    knn.fit(X_train, y_train)
    y_predi = knn.predict(X_test)
    acc.append(metrics.accuracy_score(y_test, y_predi))

plt.figure(figsize=(10, 6))
plt.plot(
    range(1, 50), acc, color="purple", linestyle="solid", marker="x",
markersize=10,
)
plt.title("accuracy vs. K Value")
plt.xlabel("K")
plt.ylabel("Accuracy")
print("Maximum accuracy:-", max(acc), "at K =", acc.index(max(acc)))
```

```
Maximum accuracy:- 0.6861538461538461 at K = 34
```



In [6]:

```
# Using the K value as found in above section, i.e, K=34
knn = KNeighborsClassifier(n_neighbors=34, weights="distance",
metric="euclidean")
knn.fit(X_train, y_train)
print("Parameters used in Classifier:\n", knn.get_params())
y_pred = knn.predict(X_test)


knn_train_acc = knn.score(X_train, y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, y_test)
print("Testing Score: ", knn_test_acc)
```

```
Parameters used in Classifier:
 {'algorithm': 'auto', 'leaf_size': 30, 'metric': 'euclidean', 'metric_params': None, 'n
_jobs': None, 'n_neighbors': 34, 'p': 2, 'weights': 'distance'}
Training Score:  1.0
Testing Score:  0.6838461538461539
```

We can observe that normalized data performs better at

```
classification task on test set comapred to un normalized data
highlighting that normalization was critical for wine data set.
```

DATASET 2: ABALONE

1.1 Load the dataset and explore the features and their ranges and distribution:

In [7]:

```
# Loading Data, adding columns name as provided in UCI.
abalone = pd.read_csv(
    r"C:\Users\hp\Desktop\Winter_22\KMDK\Assignment_1\abalone.csv",
    sep=",",
    names=[
        "Sex",
        "Length",
        "Diameter",
        "Height",
        "Whole_weight",
        "Shucked_weight",
        "Viscera_weight",
        "Shell_weight",
        "Rings",
    ],
)
display(abalone.head())
```

	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

EDA (Exploratory Data Analysis)

We will perform the below analysis:

1. Number of columns [Features + target] and samples [record count]
2. Identifying data types of features [numerical or categorical/ continous or discrete]

3. Summary of data to understand distribution skewness, scales and ranges
4. Checking for missing values
5. Univariate Analysis
6. Bivariate Analysis
7. Checking coorelation
8. Normalization (Min-Max and Z-Score)
9. Comparison of unnormalized values
10. Classification
11. Weighted KNN classification and comparison
12. Ablation study (removing normalization)

In [8]:
```
abalone.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Sex             4177 non-null   object 
 1   Length          4177 non-null   float64
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole_weight    4177 non-null   float64
 5   Shucked_weight  4177 non-null   float64
 6   Viscera_weight  4177 non-null   float64
 7   Shell_weight    4177 non-null   float64
 8   Rings           4177 non-null   int64  
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

In [9]:
```
print(
    f"Abalone dataset has {abalone.shape[1]} columns and they have
{abalone.shape[0]} samples."
)
print(abalone.columns)
```

```
Abalone dataset has 9 columns and they have 4177 samples.
Index(['Sex', 'Length', 'Diameter', 'Height', 'Whole_weight', 'Shucked_weight',
       'Viscera_weight', 'Shell_weight', 'Rings'],
      dtype='object')
```

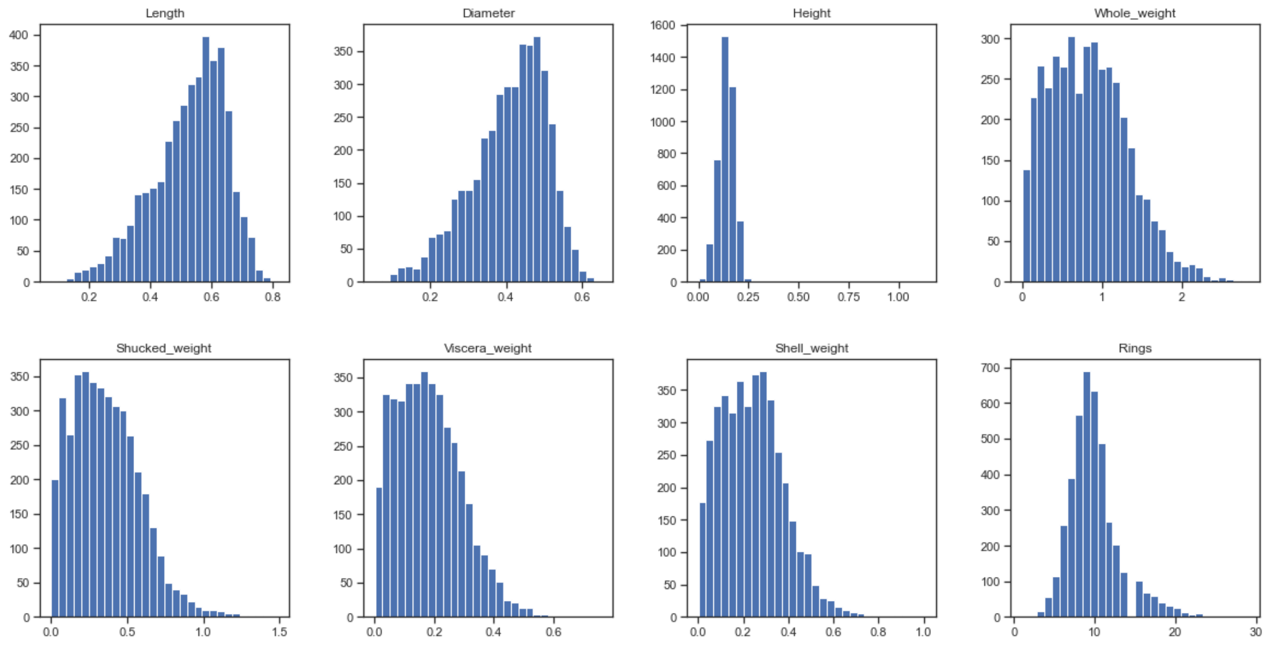
- There are 4177 records and 9 columns.
- Sex feature is categorical (object type)
- 'Rings' feature is discrete (int), others are continous numerical (float)

In [10]:
```
display(abalone.describe())
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_wei
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005

In [11]:
```python
abalone.hist(figsize=(20, 10), grid=False, layout=(2, 4), bins=30)
```

Out[11]:
```
array([[<AxesSubplot:title={'center':'Length'}>,
        <AxesSubplot:title={'center':'Diameter'}>,
        <AxesSubplot:title={'center':'Height'}>,
        <AxesSubplot:title={'center':'Whole_weight'}>],
       [<AxesSubplot:title={'center':'Shucked_weight'}>,
        <AxesSubplot:title={'center':'Viscera_weight'}>,
        <AxesSubplot:title={'center':'Shell_weight'}>,
        <AxesSubplot:title={'center':'Rings'}>]], dtype=object)
```



- The features are close to normal distribution(as observed by mean and sd)
- Ranges are not alarming in features (min and max values for features are on similar range)

1.2. Is there any missing data?

In [12]:

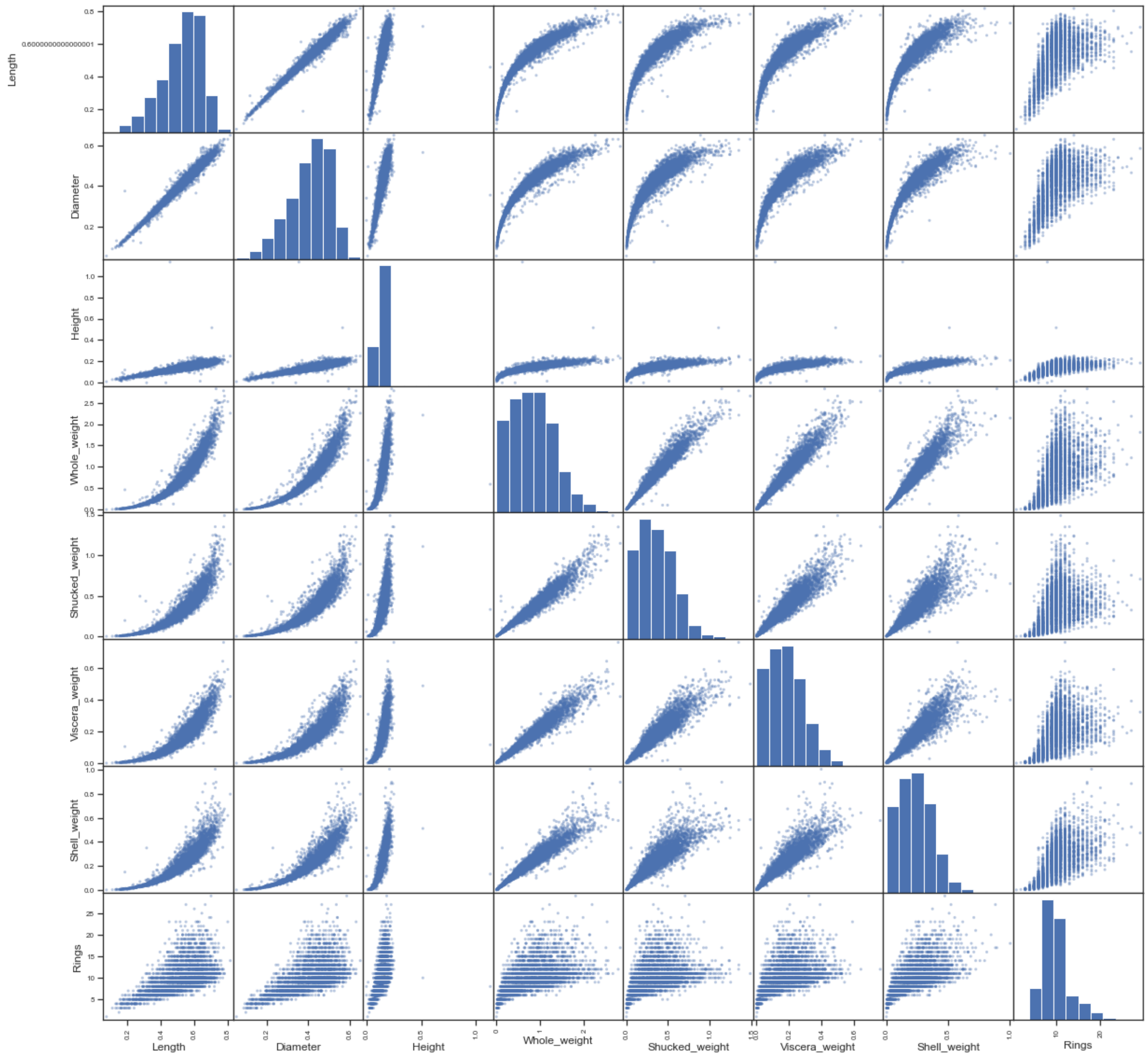
```
##there any no NA(missing) values in the dataset provided
print(f"Are there any null values in data :
{abalone.isnull().values.any()}")
```

```
Are there any null values in data : False
```

In [13]:
```
abalone.isnull().sum().sort_values()
```

Out[13]:
```
Sex               0
Length            0
Diameter          0
Height            0
Whole_weight      0
Shucked_weight    0
Viscera_weight    0
Shell_weight      0
Rings             0
dtype: int64
```

In [14]:
```
fig_abalone = pd.plotting.scatter_matrix(abalone, alpha=0.4, figsize=(20,
20))
```



- As observed in above 2 cells, there are no missing values in any column.
- As confirmed by scatter plot, there are no missing windows/ blocks to confirm that no data is missing.
- There appears to be some outliers in Height and Whole weight that we investigate in depth in below cells.

1.3. Diversity of data types and ranges of the features

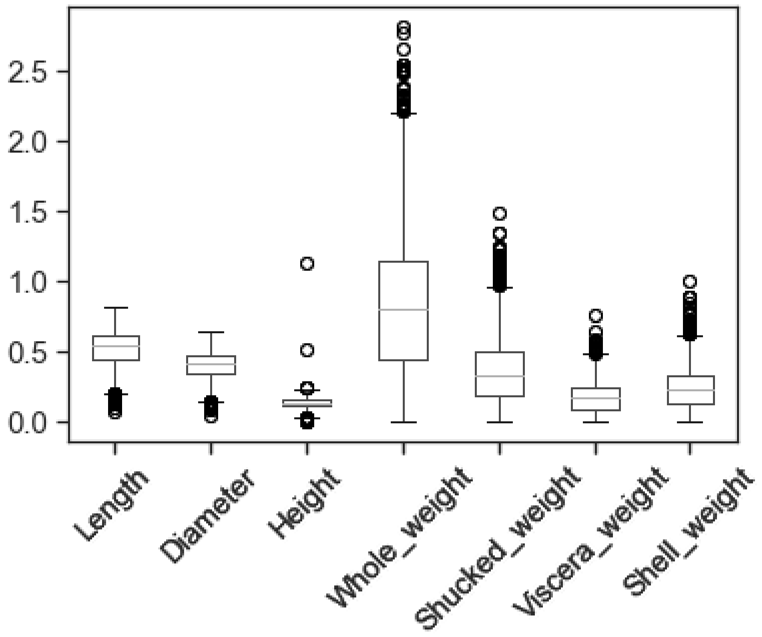
In order to determine if we need to normalize any of the data we can look at the diversity of scales of the feautres. First we remove the label categories of Sex since it is a nominal feature.

In [15]:
```
# we drop 'Sex' as they are nominal values and "rings" as it is the target column
abalone_x = abalone.drop(columns=["Sex", "Rings"])
print(type(abalone_x))
abalone_x.boxplot(grid=False, rot=45, fontsize=15)
```

```
# Plotting a simple box plot to see the range of values and detect outliers
pd.plotting.boxplot(abalone_x, grid=False, rot=45, fontsize=15)
```

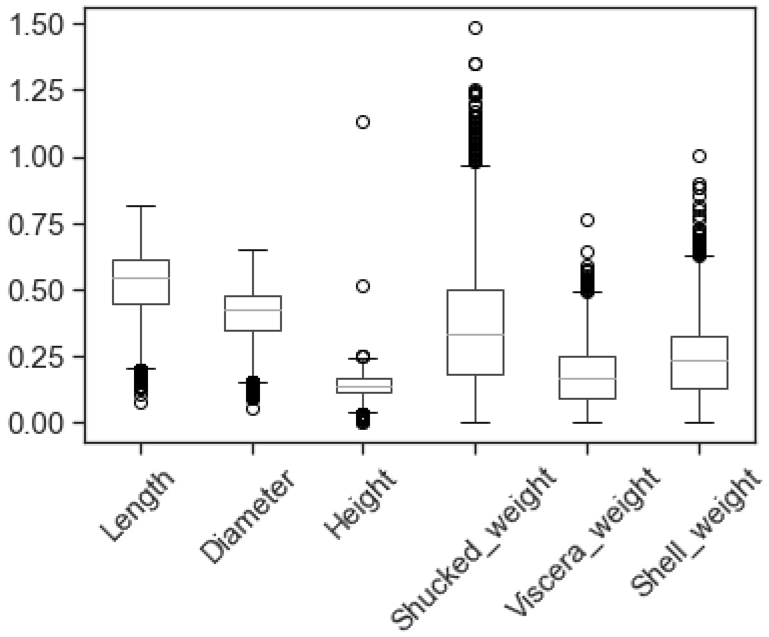
```
<class 'pandas.core.frame.DataFrame'>
```

Out[15]:
```
<AxesSubplot:>
```



In [16]:
```
abalone_x1 = abalone_x.drop(columns=["Whole_weight"])
pd.plotting.boxplot(abalone_x1, grid=False, rot=45, fontsize=15)
```

Out[16]:
```
<AxesSubplot:>
```



> As we can see in the box plots, there are some points away from the maximum, indicating outliers. Similarly we will examine for 'Whole_weight'.

1.4. Outlier detection and handling outliers

In [17]:
```
display(abalone.Height.describe())
display(abalone[abalone.Height == 0])
display(abalone[abalone.Height == abalone.Height.max()])
```

```
count    4177.000000
mean        0.139516
std         0.041827
min         0.000000
25%         0.115000
50%         0.140000
75%         0.165000
max         1.130000
Name: Height, dtype: float64
```

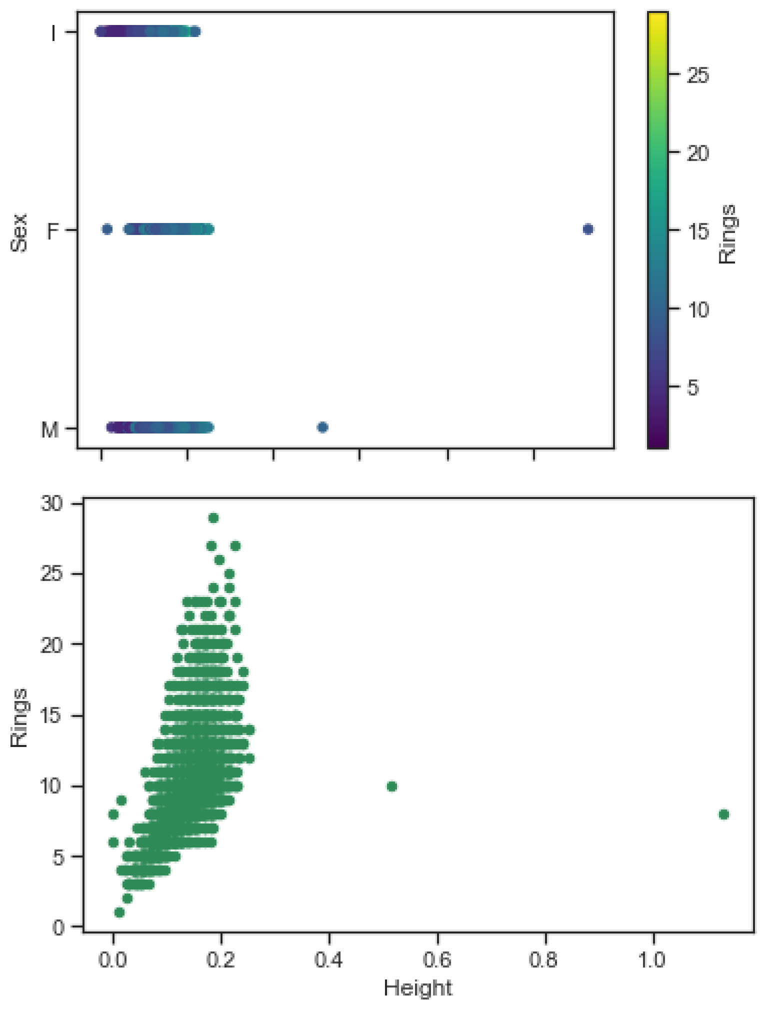
	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Ri
1257	I	0.430	0.34	0.0	0.428	0.2065	0.0860	0.1150	
3996	I	0.315	0.23	0.0	0.134	0.0575	0.0285	0.3505	

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Ri
2051	F	0.455	0.355	1.13	0.594	0.332	0.116	0.1335	

> We observed that min was 0 and upon close inspection of the data , we can be certain that those values are abnormal as the number of rings and whole weight are consitent with other sample records but Height is inputted wrong and hence would drop those records.

In [18]:
```
abalone.plot.scatter(x="Height", y="Sex", c="Rings", colormap="viridis")
abalone.plot.scatter(x="Height", y="Rings", c="Seagreen")
```

Out[18]:
```
<AxesSubplot:xlabel='Height', ylabel='Rings'>
```



In [19]:
```
display(abalone[abalone.Height > 0.4])
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Ri
1417	M	0.705	0.565	0.515	2.210	1.1075	0.4865	0.5120	
2051	F	0.455	0.355	1.130	0.594	0.3320	0.1160	0.1335	

> As seen from scatter plot above of height vs Rings , there are outliers that is skewing the distribution to right.

In [20]:
```
# We drop tghe outliers from data
abalone.drop(
    abalone[((abalone.Height > 0.4) | (abalone.Height == 0))].index,
inplace=True
)
```

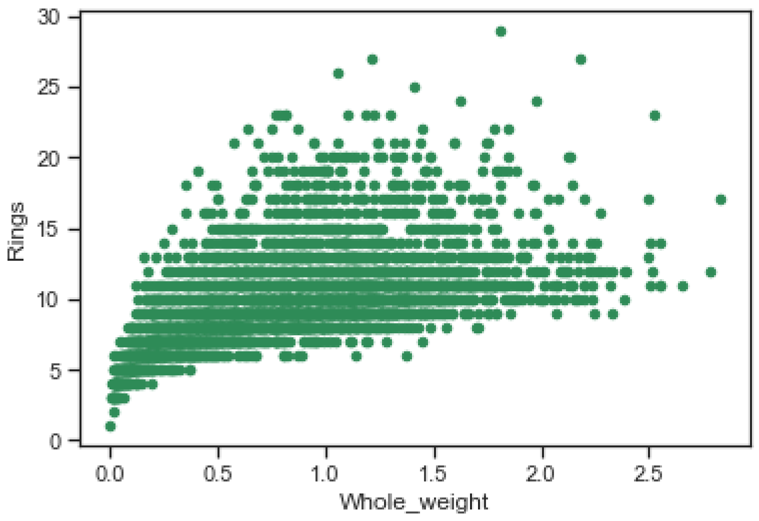
In [21]:

```
# examining whole_weight
abalone.Whole_weight.describe()
```

Out[21]:
```
count    4173.000000
mean        0.828730
std         0.489987
min         0.002000
25%         0.442000
50%         0.800000
75%         1.153000
max         2.825500
Name: Whole_weight, dtype: float64
```

In [22]:
```
abalone.plot.scatter(x="Whole_weight", y="Rings", c="Seagreen")
```

Out[22]:
```
<AxesSubplot:xlabel='Whole_weight', ylabel='Rings'>
```



In [23]:
```
abalone[abalone.Whole_weight > 2.5]
```

Out[23]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Ri
165	M	0.725	0.570	0.190	2.5500	1.0705	0.4830	0.7250	
891	M	0.730	0.595	0.230	2.8255	1.1465	0.4190	0.8970	
1051	F	0.735	0.600	0.220	2.5550	1.1335	0.4400	0.6000	
1207	F	0.755	0.625	0.210	2.5050	1.1965	0.5130	0.6785	
1209	F	0.780	0.630	0.215	2.6570	1.4880	0.4985	0.5860	
1427	F	0.750	0.610	0.235	2.5085	1.2320	0.5190	0.6120	
1762	M	0.770	0.620	0.195	2.5155	1.1155	0.6415	0.6420	
1763	M	0.775	0.630	0.250	2.7795	1.3485	0.7600	0.5780	
2334	F	0.800	0.630	0.195	2.5260	0.9330	0.5900	0.6200	

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Ri
3715	M	0.780	0.600	0.210	2.5480	1.1945	0.5745	0.6745	

> We are not certain if the weight values are abnormal as the rings and height increase with whole_weight. We will need more investigation to drop these records.

In [24]:

```
# Only Sex column is categorical
print("Number of unique value of Sex : ", abalone.Sex.nunique())
print("Sex wise distribution :\n", abalone.Sex.value_counts())
```

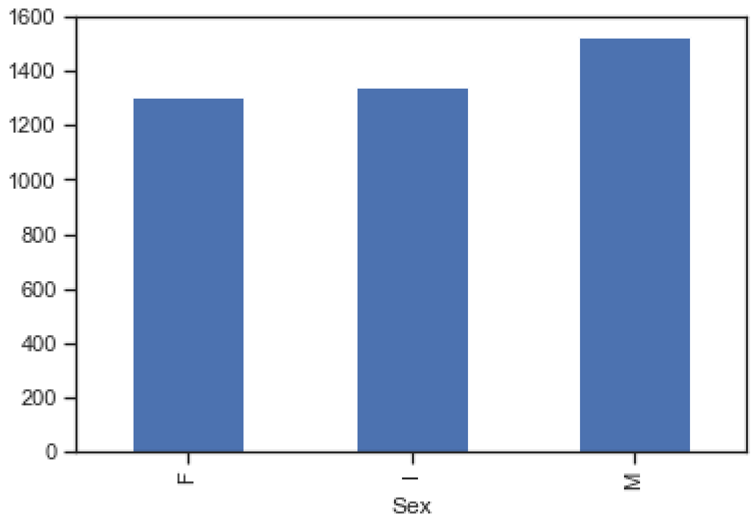
```
Number of unique value of Sex :  3
Sex wise distribution :
 M    1527
I    1340
F    1306
Name: Sex, dtype: int64
```

In [25]:

```
# Visualizing the distribution of Sex
abalone.groupby("Sex").size().plot.bar()
```

Out[25]:

```
<AxesSubplot:xlabel='Sex'>
```



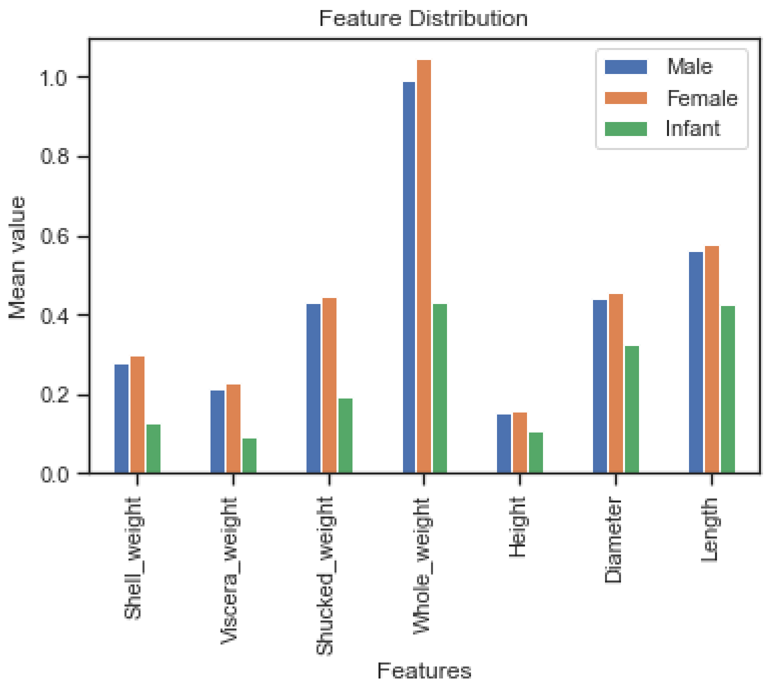
We observe :

1. Male>Infant>Female;
2. Distribution is not uniform but it is not very skewed.

In [26]:

```
# Visualizing to compare features with Sex distribution

df_male_abalone = abalone[abalone.Sex == "M"]
```

```
df_male_abalone.drop(columns=["Sex", "Rings"], axis=1, inplace=True)

df_female_abalone = abalone[abalone.Sex == "F"]
df_female_abalone.drop(columns=["Sex", "Rings"], axis=1, inplace=True)

df_infant_abalone = abalone[abalone.Sex == "I"]
df_infant_abalone.drop(columns=["Sex", "Rings"], axis=1, inplace=True)

df_male_abalone = df_male_abalone.mean()
df_female_abalone = df_female_abalone.mean()
df_infant_abalone = df_infant_abalone.mean()

# print(df_male_abalone.values[::-1])
index = df_male_abalone.index[::-1]

df_plt = pd.DataFrame(
    {
        "Male": df_male_abalone.values[::-1],
        "Female": df_female_abalone.values[::-1],
        "Infant": df_infant_abalone.values[::-1],
    },
    index=index,
)

ax = df_plt.plot.bar(
    rot=90, xlabel="Features", ylabel="Mean value", title="Feature
Distribution"
)
```

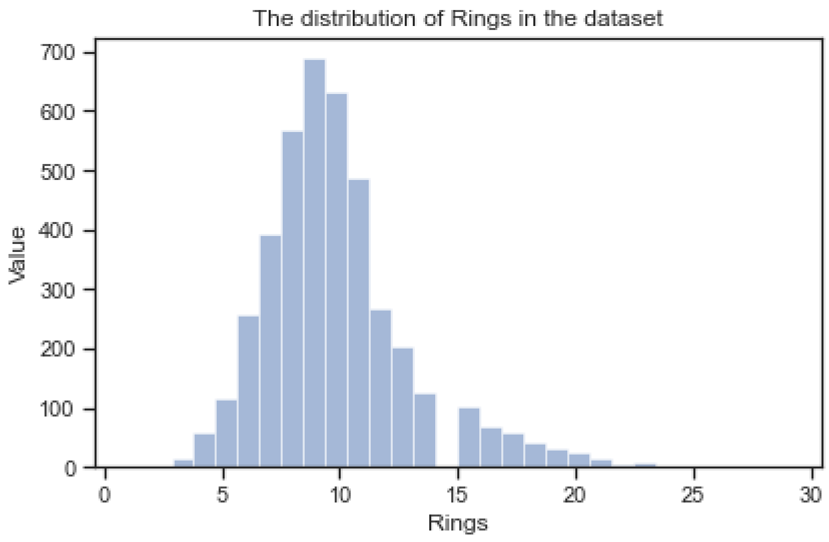


> Infants have lower values comapred to male and female ditribution, whic is expected.
> Females have higher values of features compared to Males

1.5. Checking if Data is Balanced or not

In [27]:
```
print("Unique values for number of rings are :", abalone.Rings.nunique())
# abalone.Rings.hist()
plt.figure(figsize=(6, 6))
col = "Rings"
ab = abalone.hist(column=col, bins=30, alpha=0.5, label="white")

plt.title("The distribution of {} in the dataset".format(col))
plt.xlabel("Rings")
plt.ylabel("Value")
# plt.legend(loc='upper right')
plt.grid()

plt.tight_layout()
plt.show()
```

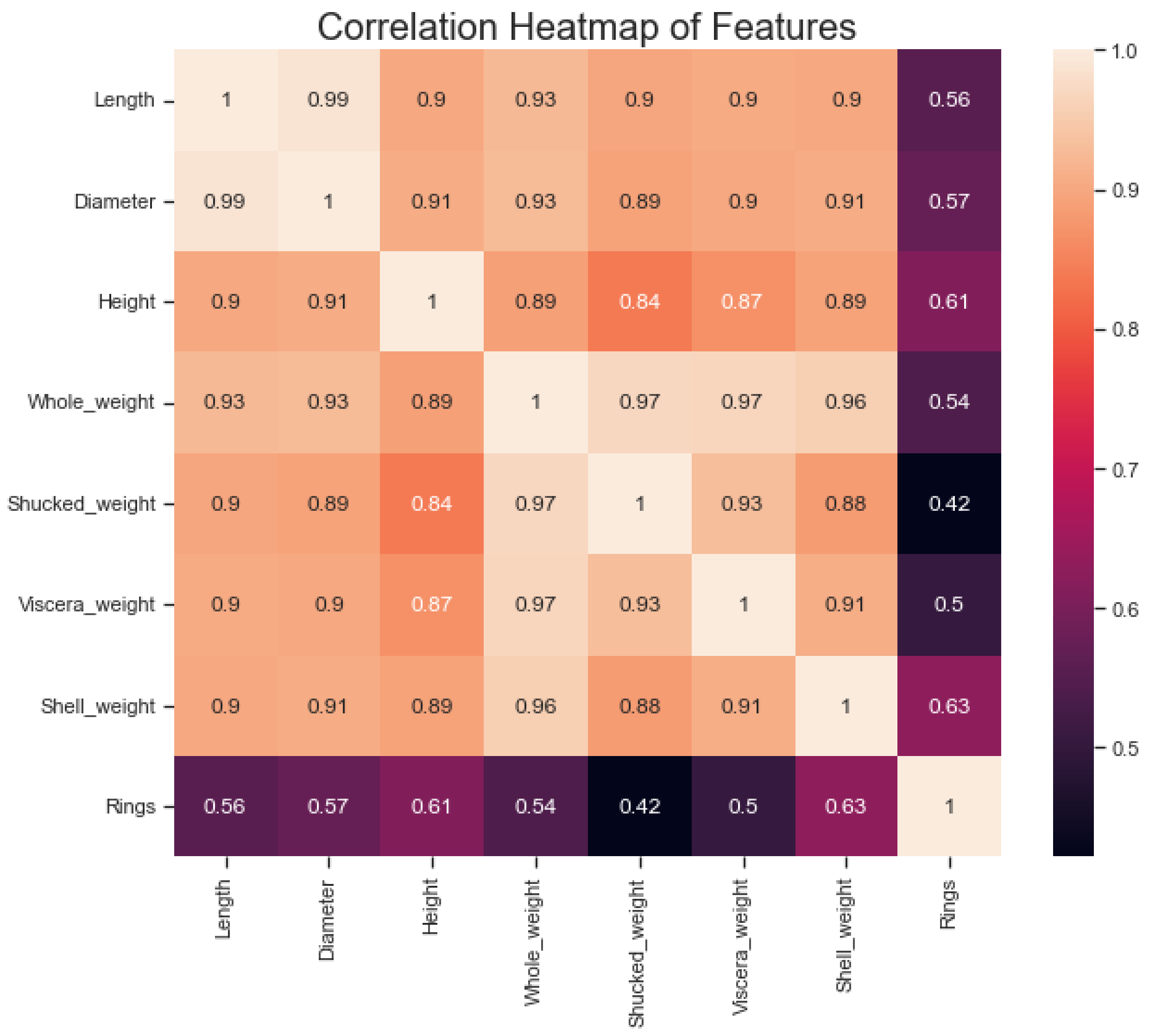
```
Unique values for number of rings are : 28
<Figure size 432x432 with 0 Axes>
```



> Rings are densely distributed between 5 and 15 rings.THe dataset is usable and not highly unbalanced.

In [28]:
```
# Using heatmap to visualize corelation between features


plt.figure(figsize=(10, 8))
corr = abalone.corr()
sns.heatmap(corr, annot=True)
plt.title("Correlation Heatmap of Features", fontsize=20)
```

Out[28]:
```
Text(0.5, 1.0, 'Correlation Heatmap of Features')
```

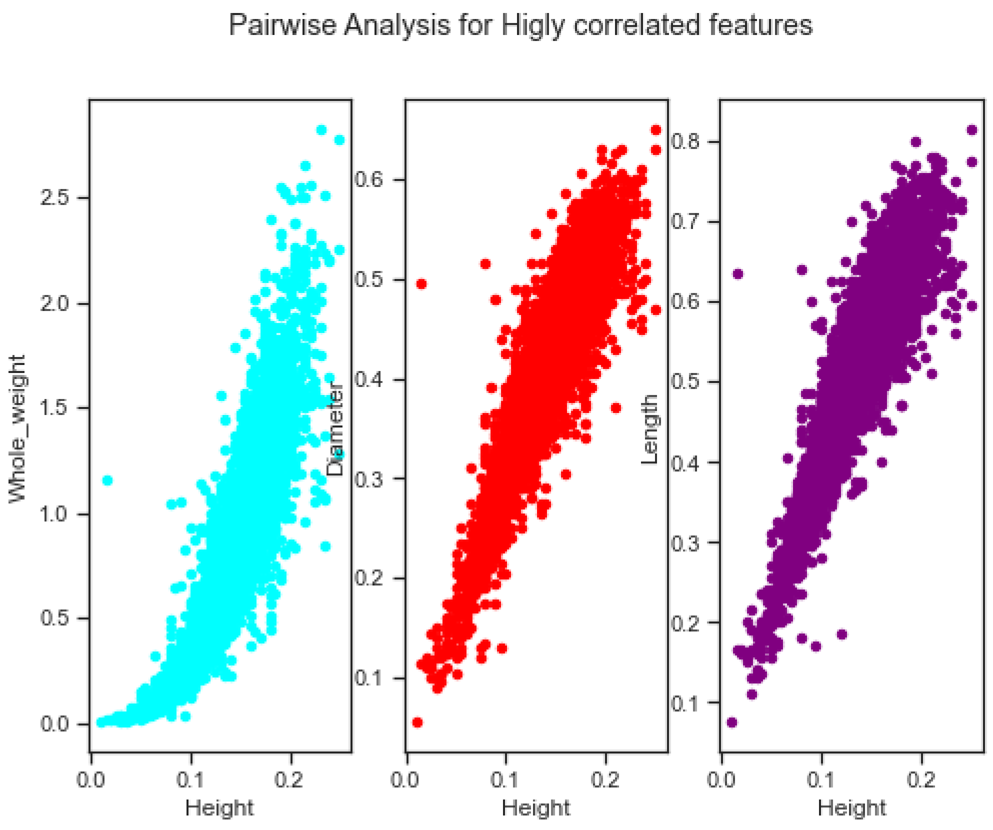


	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Rings
Length	1	0.99	0.9	0.93	0.9	0.9	0.9	0.56
Diameter	0.99	1	0.91	0.93	0.89	0.9	0.91	0.57
Height	0.9	0.91	1	0.89	0.84	0.87	0.89	0.61
Whole_weight	0.93	0.93	0.89	1	0.97	0.97	0.96	0.54
Shucked_weight	0.9	0.89	0.84	0.97	1	0.93	0.88	0.42
Viscera_weight	0.9	0.9	0.87	0.97	0.93	1	0.91	0.5
Shell_weight	0.9	0.91	0.89	0.96	0.88	0.91	1	0.63
Rings	0.56	0.57	0.61	0.54	0.42	0.5	0.63	1

```
Height is highly corelated with all the features and rings.
```

In [29]:
```python
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(8, 6))
fig.suptitle("Pairwise Analysis for Higly correlated features")
abalone.plot.scatter(x="Height", y="Whole_weight", c="Cyan", ax=ax1)
abalone.plot.scatter(x="Height", y="Diameter", c="Red", ax=ax2)
abalone.plot.scatter(x="Height", y="Length", c="Purple", ax=ax3)
```

Out[29]:
```
<AxesSubplot:xlabel='Height', ylabel='Length'>
```

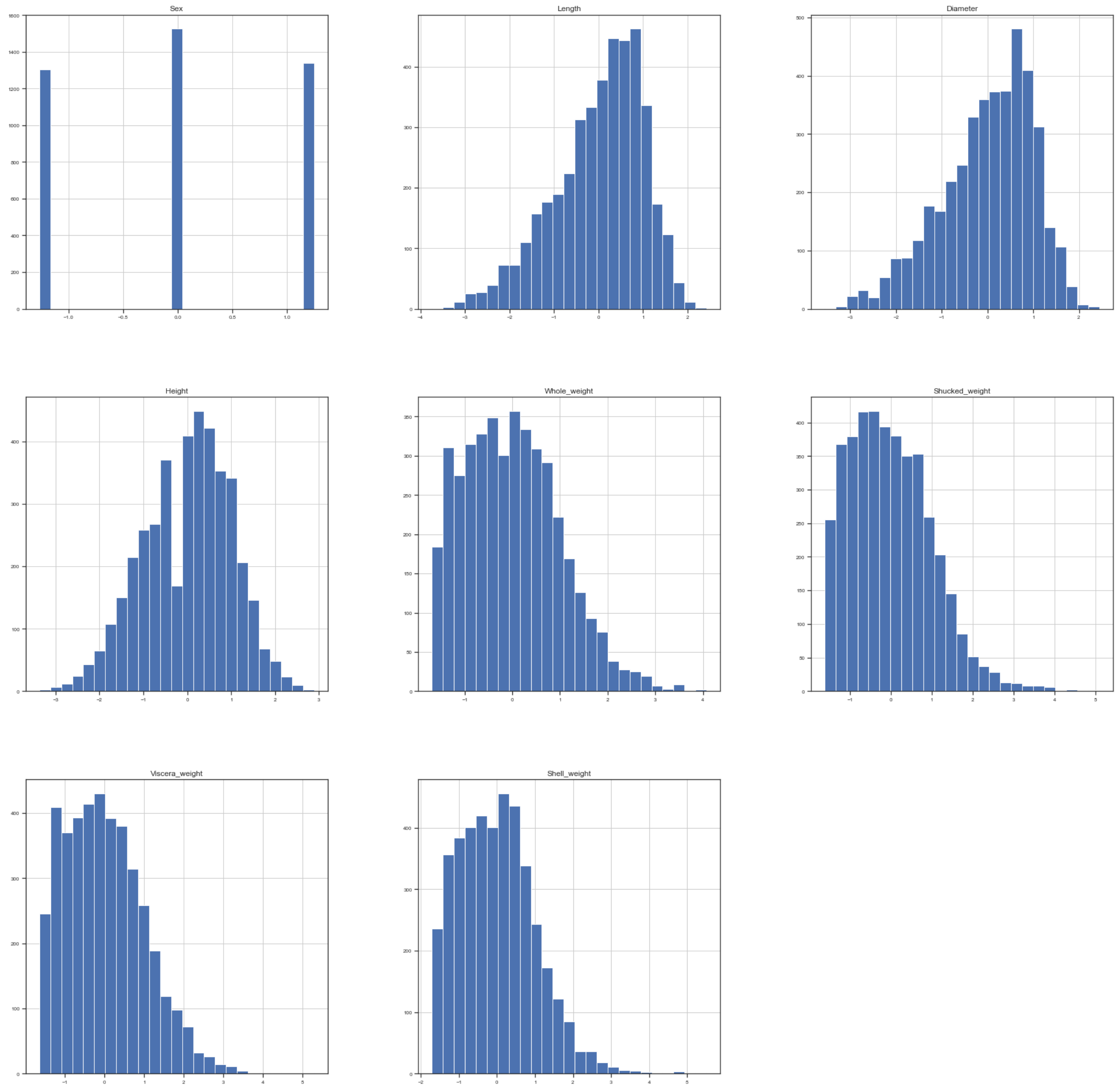


- Whole weight increases almost at 2nd degree wrt height except few points close to 0.
- Diameter and Length approximates linear increase wrt Height.

1.6.a. Is normalization necessary?

In [31]:
```
Y = abalone["Rings"].values
abalone.drop(columns=["Rings"], inplace=True)
abalone_without_sex = abalone.drop(columns=["Sex"])
abalone["Sex"] = abalone["Sex"].apply({"M": 1, "F": 0, "I": 2}.get)
plt.figure()
# abalone_znormalized = abalone_without_sex.apply(stats.zscore)
abalone_znormalized = abalone.apply(stats.zscore)
# print(abalone_znormalized.head())
abalone_znormalized.hist(figsize=(30, 30), bins=25, xlabelsize=8,
ylabelsize=8)
```

Out[31]:
```
array([[<AxesSubplot:title={'center':'Sex'}>,
        <AxesSubplot:title={'center':'Length'}>,
        <AxesSubplot:title={'center':'Diameter'}>],
       [<AxesSubplot:title={'center':'Height'}>,
        <AxesSubplot:title={'center':'Whole_weight'}>,
        <AxesSubplot:title={'center':'Shucked_weight'}>],
       [<AxesSubplot:title={'center':'Viscera_weight'}>,
        <AxesSubplot:title={'center':'Shell_weight'}>, <AxesSubplot:>]],
      dtype=object)
<Figure size 432x288 with 0 Axes>
```



We do not normalize target('Rings') as it is a classification problem, normalizing converts rings into continous values which is a regression problem and we encounter challenge via fitting data to KNN classifier.

Normalization is not critical but will improve the classification task For the reasons why you can refer to our discussion of data diversity in Question 1(a).

In [32]:
```
abalone.head()
```

Out[32]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight
0	1	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150
1	1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210
3	1	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155
4	2	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055

1.6.b. Unormalized Comparison of three values

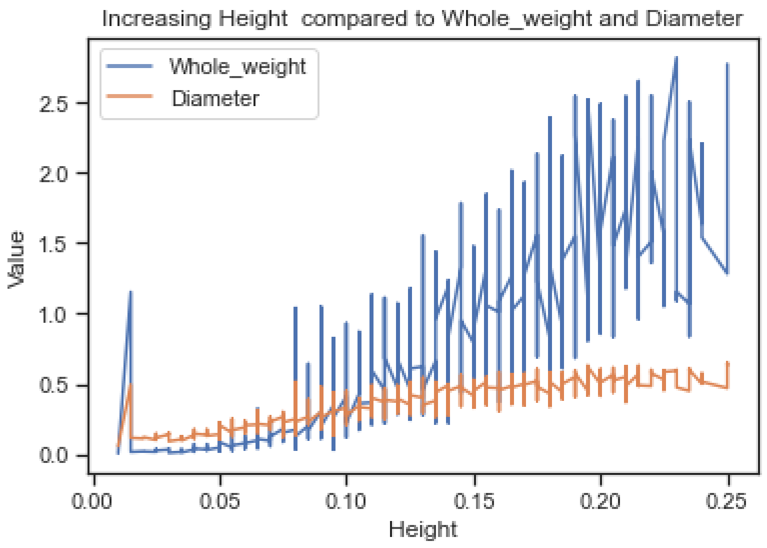
To make the difference that normalization makes on interpretation clear we look at some specific examples, choosing one continuous value, such as Height and comparing to two other numerical features under differnet normalization schemes.

In [33]:
```
x = ["Height"]
y = ["Whole_weight", "Diameter"]
ab_whd = abalone[x + y]
ab_whd.sort_values(by=x, inplace=True)
display(ab_whd.describe())
```

	Height	Whole_weight	Diameter
count	4173.000000	4173.000000	4173.000000
mean	0.139256	0.828730	0.407915
std	0.038378	0.489987	0.099210
min	0.010000	0.002000	0.055000
25%	0.115000	0.442000	0.350000
50%	0.140000	0.800000	0.425000
75%	0.165000	1.153000	0.480000
max	0.250000	2.825500	0.650000

In [34]:
```
ab_whd.plot(x=x[0], y=y)
# ab_whd.hist(column=y, bins=10, alpha=.5)


plt.legend(loc="upper right")
plt.title("Increasing {}  compared to {} and {}".format(x[0], y[0], y[1]))
plt.xlabel("Height")
plt.ylabel("Value")
plt.legend(loc="upper left")
```

Out[34]:
```
<matplotlib.legend.Legend at 0x1edf2b397f0>
```



1.6.c Using Z-Score Normalization

We implement z-score normalization using the sklearn.stats package applied to the entire dataset. Then we once again select out the columns of interest. Note that the x and y variables do not need to be updated since they are just the names of the columns being used and they do not change across the three examples.

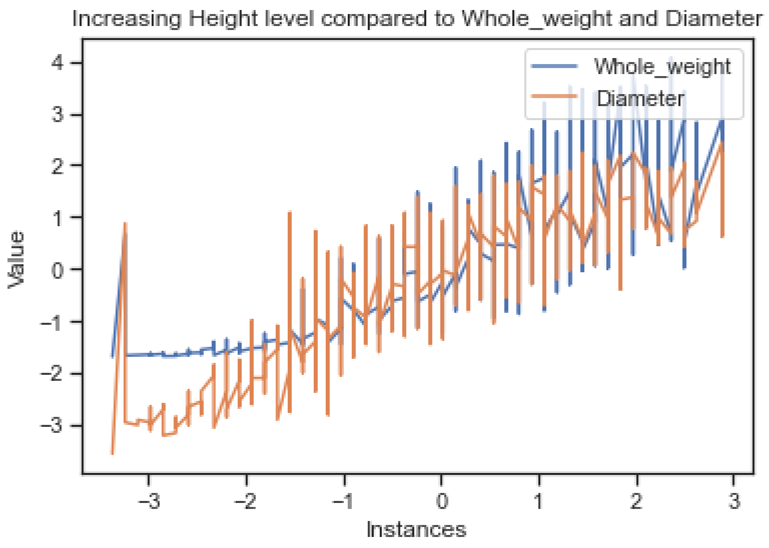
In [35]:
```
abalone_zscore = abalone_without_sex.apply(stats.zscore)
ab_whd_zscore = abalone_zscore[x + y]
```

In [36]:
```
ab_whd_zscore.sort_values(by=x, inplace=True)
display(ab_whd_zscore.describe())
```

	Height	Whole_weight	Diameter
count	4.173000e+03	4.173000e+03	4.173000e+03
mean	-8.870504e-15	-1.417616e-15	1.362916e-15
std	1.000120e+00	1.000120e+00	1.000120e+00
min	-3.368415e+00	-1.687451e+00	-3.557664e+00
25%	-6.321106e-01	-7.893603e-01	-5.838306e-01
50%	1.939047e-02	-5.864109e-02	1.722286e-01
75%	6.708915e-01	6.618725e-01	7.266720e-01
max	2.885995e+00	4.075637e+00	2.440406e+00

In [37]:
```
plt.figure()
ab_whd_zscore.sort_values(by=x, inplace=True)
ab_whd_zscore.plot(x=x[0], y=y)
plt.legend(loc="upper right")
plt.title("Increasing {} level compared to {} and {}".format(x[0], y[0],
y[1]))
plt.xlabel("Instances")
plt.ylabel("Value")
plt.legend(loc="upper right")
```

Out[37]:
```
<matplotlib.legend.Legend at 0x1edf5bf5cd0>
<Figure size 432x288 with 0 Axes>
```



Using min-max Normalization

This we simply implement ourselves since the formula is straightforward. the min() and max() functions will produce vectors of the respective values for every feature, then the formula below will normalize all the values of the new wine-minmax matrix appropriately.

In [38]:
```
abalone_minmax = (abalone_without_sex - abalone_without_sex.min()) / (
    abalone_without_sex.max() - abalone_without_sex.min()
)
ab_whd_minmax = abalone_minmax[x + y]
display(ab_whd_minmax.describe())
```

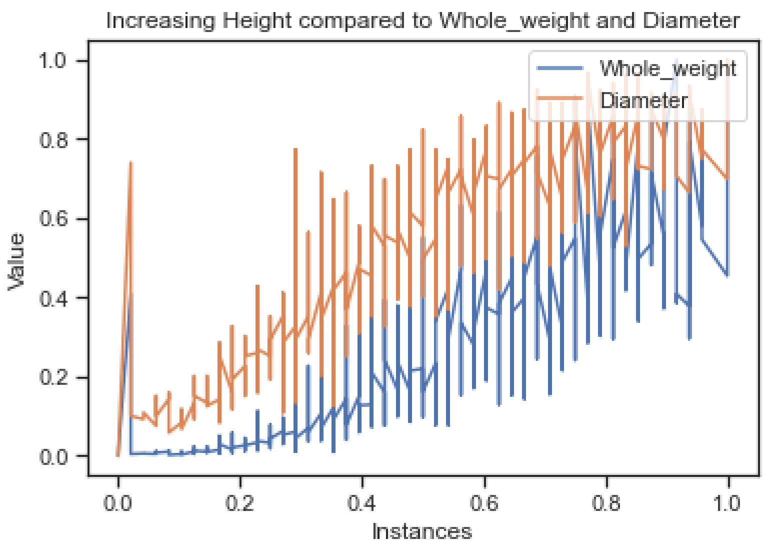
	Height	Whole_weight	Diameter
count	4173.000000	4173.000000	4173.000000
mean	0.538566	0.292803	0.593135
std	0.159906	0.173539	0.166740
min	0.000000	0.000000	0.000000
25%	0.437500	0.155835	0.495798

	Height	Whole_weight	Diameter
50%	0.541667	0.282628	0.621849
75%	0.645833	0.407650	0.714286
max	1.000000	1.000000	1.000000

In [39]:
```
plt.figure()
ab_whd_minmax.sort_values(by=x, inplace=True)
ab_whd_minmax.plot(x=x[0], y=y)

plt.legend(loc="upper right")
plt.title("Increasing {} compared to {} and {}".format(x[0], y[0], y[1]))
plt.xlabel("Instances")
plt.ylabel("Value")
plt.legend(loc="upper right")
```

Out[39]:
```
<matplotlib.legend.Legend at 0x1edf4a4a820>
```

```
<Figure size 432x288 with 0 Axes>
```



Classification Task

In [40]:
```
# df_ab= abalone.copy()
df_ab = abalone_znormalized.copy()
# df_ab['Sex'] = df_ab['Sex'].apply({'M':1, 'F':0, 'I':2}.get)
# df_ab.drop(columns=['Rings'],inplace=True)
df_ab.head()
```

Out[40]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig
0	-0.010233	-0.575094	-0.432619	-1.153311	-0.642400	-0.608106	-0.726816	-0.638C
1	-0.010233	-1.449757	-1.440698	-1.283612	-1.231262	-1.171986	-1.206217	-1.2129
2	-1.266124	0.049665	0.121825	-0.110910	-0.309698	-0.463752	-0.356993	-0.2069
3	-0.010233	-0.700046	-0.432619	-0.371510	-0.638318	-0.648705	-0.608108	-0.6021
4	1.245659	-1.616359	-1.541506	-1.544212	-1.273105	-1.217096	-1.288400	-1.3207

2.1. Spliting in test and train set

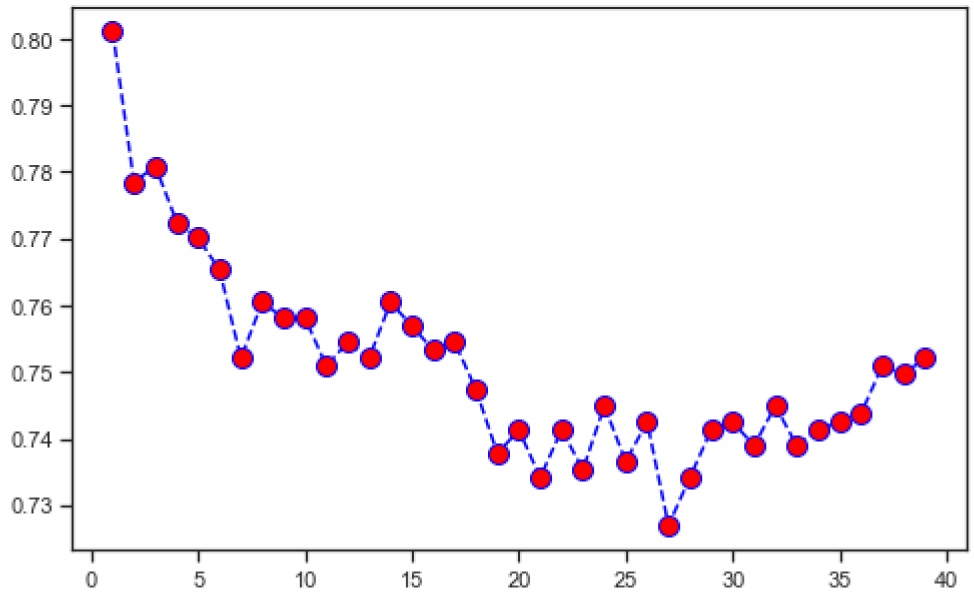
In [41]:
```
X = df_ab.values
# X = df_ab.drop('Rings', axis = 1).values
# y = df_ab['Rings'].values
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.2, random_state=27
)
```

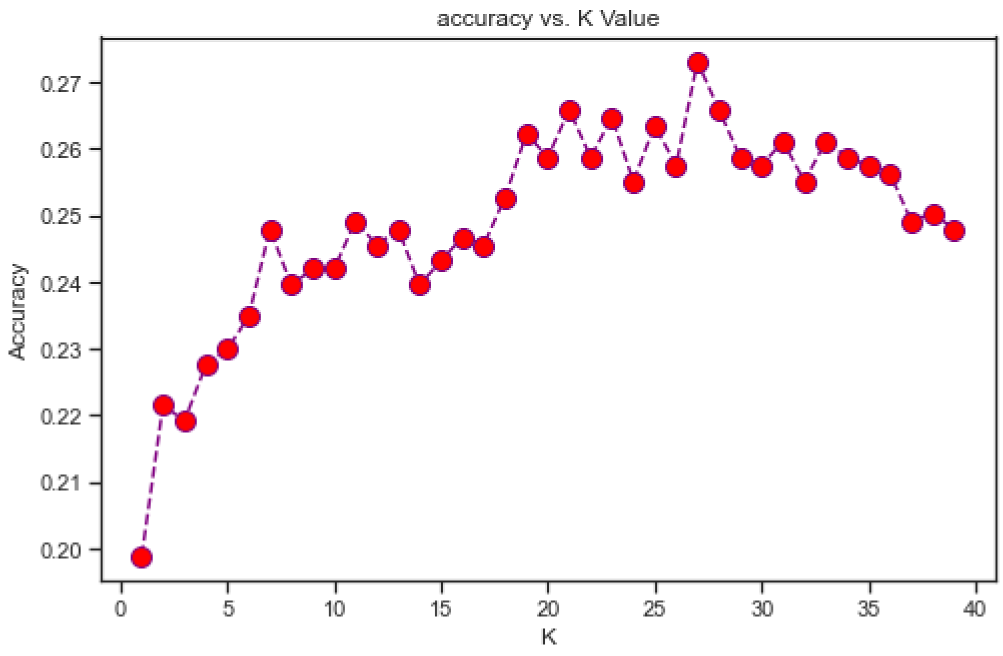
```
          Splitting train-test data in 80:20 ratio for Z-Score
normalized values
```

2.(2.,3.) With classifier's default parameters

In [42]:
```
error_rate, acc = [], []
for k in range(1, 40):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_predi = knn.predict(X_test)
    # print(y_predi,y_test)
    error_rate.append(np.mean(y_test != y_predi))
    acc.append(metrics.accuracy_score(y_test, y_predi))

plt.figure(figsize=(8, 5))
plt.plot(
    range(1, 40),
    error_rate,
    color="blue",
    linestyle="dashed",
    marker="o",
    markerfacecolor="red",
    markersize=10,
)
plt.figure(figsize=(8, 5))
plt.plot(
    range(1, 40),
    acc,
    color="purple",
    linestyle="dashed",
    marker="o",
    markerfacecolor="red",
    markersize=10,
)
plt.title("accuracy vs. K Value")
plt.xlabel("K")
plt.ylabel("Accuracy")
print("Maximum accuracy:-", max(acc), "at K =", acc.index(max(acc)))
```

```
Maximum accuracy:- 0.27305389221556886 at K = 26
```





In [43]:
```
knn = KNeighborsClassifier(n_neighbors=26)
knn.fit(X_train, y_train)
print("Parameters used in Classifier:\n", knn.get_params())
y_pred = knn.predict(X_test)

knn_train_acc = knn.score(X_train, y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, y_test)
print("Testing Score: ", knn_test_acc)
```

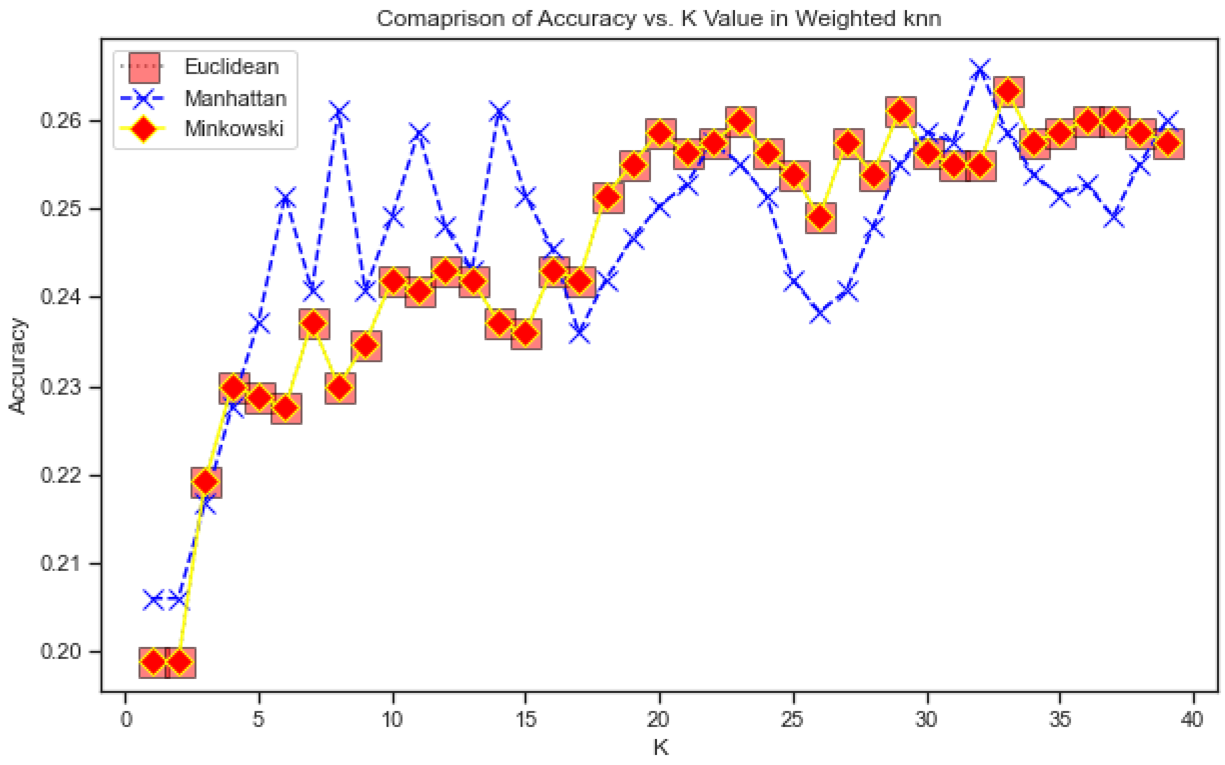
```
Parameters used in Classifier:
 {'algorithm': 'auto', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params': None, 'n
_jobs': None, 'n_neighbors': 26, 'p': 2, 'weights': 'uniform'}
Training Score:  0.31845416417016176
Testing Score:  0.25748502994011974
```

2.4. Weighted KNN classifiers

We use 3 different distance metrics for our comparison:

- Euclidean
- Manhattan
- Minkowski (Default)

In [44]:
```
euclidean, manhattan, minkowski = [], [], []
metric_list = ["euclidean", "manhattan", "minkowski"]
for m in metric_list:
    for k in range(1, 40):
        knn = KNeighborsClassifier(n_neighbors=k, weights="distance",
metric=m)
        knn.fit(X_train, y_train)
        y_predi = knn.predict(X_test)
        if m == "euclidean":
            euclidean.append(metrics.accuracy_score(y_test, y_predi))
        if m == "manhattan":
            manhattan.append(metrics.accuracy_score(y_test, y_predi))
        if m == "minkowski":
            minkowski.append(metrics.accuracy_score(y_test, y_predi))

plt.figure(figsize=(10, 6))
plt.plot(
    range(1, 40),
    euclidean,
    label="Euclidean",
    color="black",
    linestyle="dotted",
    marker="s",
    markerfacecolor="red",
    markersize=15,
    alpha=0.5,
)
plt.plot(
    range(1, 40),
    manhattan,
    label="Manhattan",
    color="blue",
    linestyle="dashed",
    marker="x",
    markerfacecolor="red",
    markersize=10,
)
plt.plot(
    range(1, 40),
    minkowski,
    label="Minkowski",
    color="yellow",
    linestyle="solid",
    marker="D",
    markerfacecolor="red",
    markersize=10,
)
plt.title("Comaprison of Accuracy vs. K Value in Weighted knn")
plt.xlabel("K")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
print(
    "Maximum accuracy for Euclidean :-",
    max(euclidean),
    "at K =",
    euclidean.index(max(euclidean)),
)
print(
    "Maximum accuracy for Manhattan :-",
    max(manhattan),
    "at K =",
    manhattan.index(max(manhattan)),
)
print(
    "Maximum accuracy for Minkowski :-",
    max(minkowski),
    "at K =",
    minkowski.index(max(minkowski)),
)
```



```
Maximum accuracy for Euclidean :- 0.2634730538922156 at K = 32
Maximum accuracy for Manhattan :- 0.26586826347305387 at K = 31
Maximum accuracy for Minkowski :- 0.2634730538922156 at K = 32
```

2.5 Ablation study

We remove the normalization step and use the un normalized data for our classification task to compare the impact of normalizatin in classification of Rings(age)

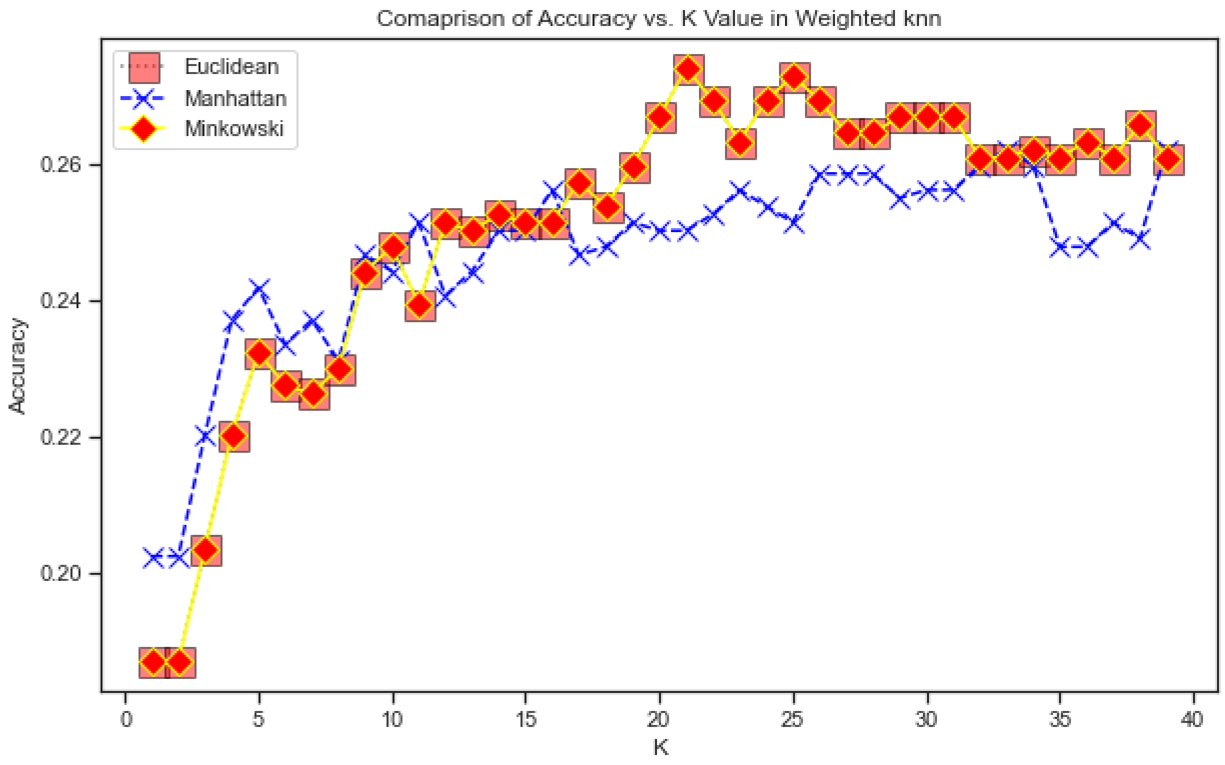
In [49]:
```
# abalone["Sex"] = abalone["Sex"].apply({"M": 1, "F": 0, "I": 2}.get)
# print(abalone.head())
X = abalone.values
print(X)
```

```
[[1.     0.455  0.365  ... 0.2245 0.101  0.15  ]
 [1.     0.35   0.265  ... 0.0995 0.0485 0.07  ]
 [0.     0.53   0.42   ... 0.2565 0.1415 0.21  ]
 ...
 [1.     0.6    0.475  ... 0.5255 0.2875 0.308 ]
 [0.     0.625  0.485  ... 0.531  0.261  0.296 ]
 [1.     0.71   0.555  ... 0.9455 0.3765 0.495 ]]
```

In [46]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.2, random_state=27
)
# Splitting our data in 80:20 ratio for training and testing as we
previously did
```

In [47]:
```
euclidean, manhattan, minkowski = [], [], []
metric_list = ["euclidean", "manhattan", "minkowski"]
for m in metric_list:
    for k in range(1, 40):
        knn = KNeighborsClassifier(n_neighbors=k, weights="distance",
metric=m)
        knn.fit(X_train, y_train)
        y_predi = knn.predict(X_test)
        if m == "euclidean":
            euclidean.append(metrics.accuracy_score(y_test, y_predi))
        if m == "manhattan":
            manhattan.append(metrics.accuracy_score(y_test, y_predi))
        if m == "minkowski":
            minkowski.append(metrics.accuracy_score(y_test, y_predi))

plt.figure(figsize=(10, 6))
plt.plot(
    range(1, 40),
    euclidean,
    label="Euclidean",
    color="black",
    linestyle="dotted",
    marker="s",
    markerfacecolor="red",
    markersize=15,
    alpha=0.5,
)
plt.plot(
    range(1, 40),
    manhattan,
    label="Manhattan",
    color="blue",
    linestyle="dashed",
    marker="x",
    markerfacecolor="red",
    markersize=10,
)
```

```
plt.plot(
    range(1, 40),
    minkowski,
    label="Minkowski",
    color="yellow",
    linestyle="solid",
    marker="D",
    markerfacecolor="red",
    markersize=10,
)
plt.title("Comaprison of Accuracy vs. K Value in Weighted knn")
plt.xlabel("K")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
print(
    "Maximum accuracy for Euclidean :-",
    max(euclidean),
    "at K =",
    euclidean.index(max(euclidean)),
)
print(
    "Maximum accuracy for Manhattan :-",
    max(manhattan),
    "at K =",
    manhattan.index(max(manhattan)),
)
print(
    "Maximum accuracy for Minkowski :-",
    max(minkowski),
    "at K =",
    minkowski.index(max(minkowski)),
)
```



```
Maximum accuracy for Euclidean :- 0.274251497005988 at K = 20
Maximum accuracy for Manhattan :- 0.2622754491017964 at K = 32
Maximum accuracy for Minkowski :- 0.274251497005988 at K = 20
```

In [50]:
```
knn = KNeighborsClassifier(n_neighbors=20, weights="distance",
metric="euclidean")
knn.fit(X_train, y_train)
print("Parameters used in Classifier:\n", knn.get_params())
y_pred = knn.predict(X_test)

knn_train_acc = knn.score(X_train, y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, y_test)
print("Testing Score: ", knn_test_acc)
```

```
Parameters used in Classifier:
 {'algorithm': 'auto', 'leaf_size': 30, 'metric': 'euclidean', 'metric_params': None, 'n
_jobs': None, 'n_neighbors': 20, 'p': 2, 'weights': 'distance'}
Training Score:  1.0
Testing Score:  0.26706586826347306
```

- **Our accuracy score for classification of un-normalized data is similar to the normalized classification data indicating normalization for KNN on abalone data was not critical.**
- **Weighted KNN performs marginally better than KNN classifier based on accuracy score of classification task.**

References

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