Missing Values

Missing values occurs in dataset when some of the informations is not stored for a variable There are 3 mechanisms

1 Missing Completely at Random, MCAR:

Missing completely at random (MCAR) is a type of missing data mechanism in which the probability of a value being missing is unrelated to both the observed data and the missing data. In other words, if the data is MCAR, the missing values are randomly distributed throughout the dataset, and there is no systematic reason for why they are missing.

For example, in a survey about the prevalence of a certain disease, the missing data might be MCAR if the survey participants with missing values for certain questions were selected randomly and their missing responses are not related to their disease status or any other variables measured in the survey.

2. Missing at Random MAR:

Missing at Random (MAR) is a type of missing data mechanism in which the probability of a value being missing depends only on the observed data, but not on the missing data itself. In other words, if the data is MAR, the missing values are systematically related to the observed data, but not to the missing data. Here are a few examples of missing at random:

Income data: Suppose you are collecting income data from a group of people, but some participants choose not to report their income. If the decision to report or not report income is related to the participant's age or gender, but not to their income level, then the data is missing at random.

Medical data: Suppose you are collecting medical data on patients, including their blood pressure, but some patients do not report their blood pressure. If the patients who do not report their blood pressure are more likely to be younger or have healthier lifestyles, but the missingness is not related to their actual blood pressure values, then the data is missing at random.

3. Missing data not at random (MNAR)

It is a type of missing data mechanism where the probability of missing values depends on the value of the missing data itself. In other words, if the data is MNAR, the missingness is not random and is dependent on unobserved or unmeasured factors that are associated with the missing values.

For example, suppose you are collecting data on the income and job satisfaction of employees in a company. If employees who are less satisfied with their jobs are more likely to refuse to report their income, then the data is not missing at random. In this case, the missingness is dependent on job satisfaction, which is not directly observed or measured.

In [1]:

```
import seaborn as sns
```

In [2]:

```
df=sns.load_dataset('titanic')
```

In [3]:

```
df.head()
```

Out[3]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fa
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fa
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tr
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fa
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tr

In [4]:

```
## check missing values in dataset
df.isnull().sum()
```

Out[4]:

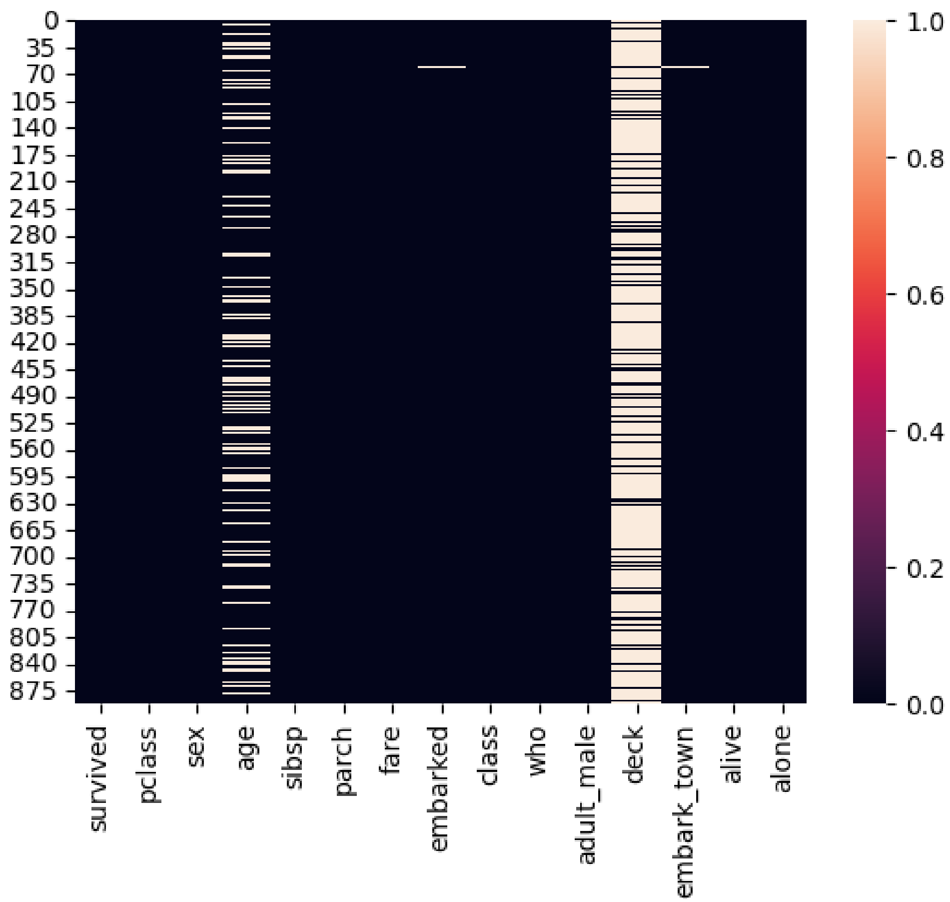
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [5]:

```
sns.heatmap(df.isnull())
```

Out[5]:

<AxesSubplot:>



In [6]:

```
## HAndling missing by deleting rows
```

In [7]:

```
df.head()
```

Out[7]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fa
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fa
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tı
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fa
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tı

In [8]:

```
## rowwise deletion
df.dropna().shape
```

Out[8]:

```
(182, 15)
```

In [9]:

```
df.shape
```

Out[9]:

```
(891, 15)
```

In [10]:

```
## Handling missing values by deleting columns
```

In [11]:

```
df.dropna(axis=1)
```

Out[11]:

	survived	pclass	sex	sibsp	parch	fare	class	who	adult_male	alive	alone
0	0	3	male	1	0	7.2500	Third	man	True	no	False
1	1	1	female	1	0	71.2833	First	woman	False	yes	False
2	1	3	female	0	0	7.9250	Third	woman	False	yes	True
3	1	1	female	1	0	53.1000	First	woman	False	yes	False
4	0	3	male	0	0	8.0500	Third	man	True	no	True
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	male	0	0	13.0000	Second	man	True	no	True
887	1	1	female	0	0	30.0000	First	woman	False	yes	True
888	0	3	female	1	2	23.4500	Third	woman	False	no	False
889	1	1	male	0	0	30.0000	First	man	True	yes	True
890	0	3	male	0	0	7.7500	Third	man	True	no	True

891 rows × 11 columns

Imputation Technqiues

1-Mean Value Imputation

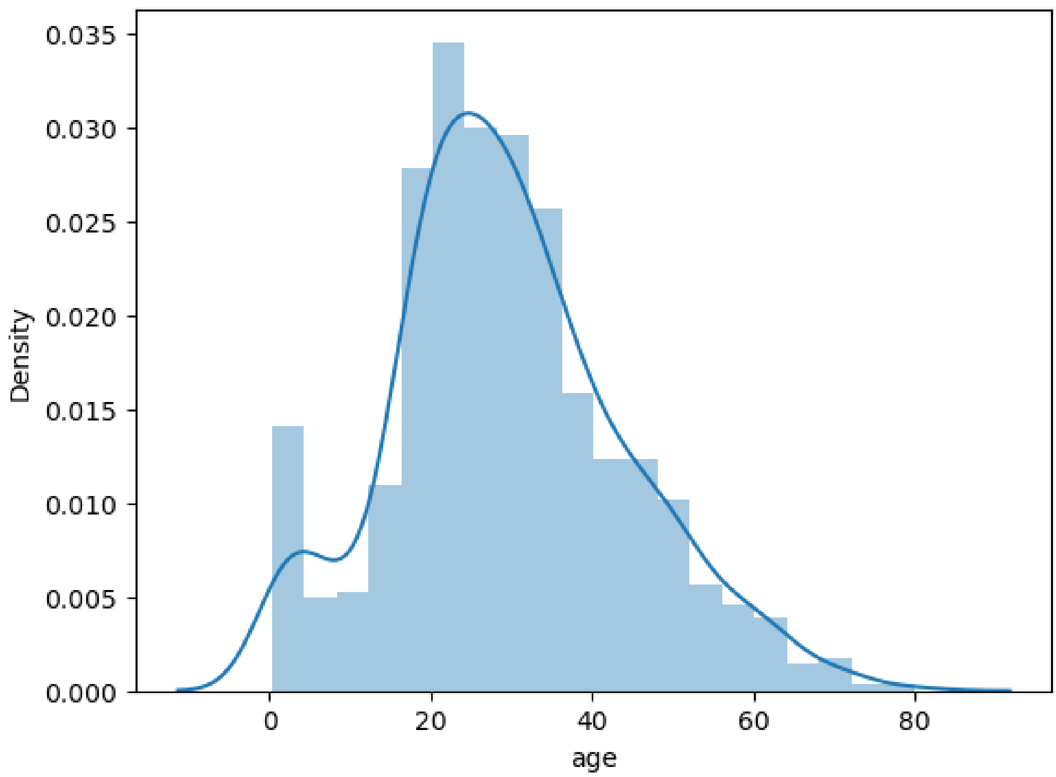
In [12]:

```
sns.distplot(df['age'])
```

```
C:\Users\DIPMANI\AppData\Local\Temp\ipykernel_11404\3234920688.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['age'])
```

Out[12]:

```
<AxesSubplot:xlabel='age', ylabel='Density'>
```



In [13]:

```
df.age.isnull().sum()
```

Out[13]:

```
177
```

In [14]:

```
df['Age_mean']=df['age'].fillna(df['age'].mean())
```

In [15]:

```
df[['Age_mean','age']]
```

Out[15]:

	Age_mean	age
0	22.000000	22.0

	Age_mean	age
1	38.000000	38.0
2	26.000000	26.0
3	35.000000	35.0
4	35.000000	35.0
...	...	...
886	27.000000	27.0
887	19.000000	19.0
888	29.699118	NaN
889	26.000000	26.0
890	32.000000	32.0

891 rows × 2 columns

In [16]:

```
## This tecnqiue work well when your data is normally distributed
```

2- Median Value Imputation

If you have ooutliers in dataset use thi technique

In [17]:

```
df['Age_median']=df['age'].fillna(df['age'].median())
```

In [18]:

```
df[['Age_median','Age_mean','age']]
```

Out[18]:

	Age_median	Age_mean	age
0	22.0	22.000000	22.0
1	38.0	38.000000	38.0
2	26.0	26.000000	26.0
3	35.0	35.000000	35.0
4	35.0	35.000000	35.0
...	...	...	...
886	27.0	27.000000	27.0
887	19.0	19.000000	19.0
888	28.0	29.699118	NaN
889	26.0	26.000000	26.0
890	32.0	32.000000	32.0

891 rows × 3 columns

3- Mode Value Imputation-- Categorical

In [19]:

```
df[df['embarked'].isnull()]
```

Out[19]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alon
61	1	1	female	38.0	0	0	80.0	NaN	First	woman	False	B	NaN	yes	Tru
829	1	1	female	62.0	0	0	80.0	NaN	First	woman	False	B	NaN	yes	Tru

In [20]:

```
df['embarked'].unique()
```

Out[20]:

```
array(['S', 'C', 'Q', nan], dtype=object)
```

In [21]:

```
df[df['age'].notna()]['embarked'].mode()[0]
```

Out[21]:

```
'S'
```

In [22]:

```
mode=df[df['age'].notna()]['embarked'].mode()[0]
```

In [23]:

```
mode
```

Out[23]:

```
'S'
```

In [24]:

```
df['embarked_mode']=df['embarked'].fillna(mode)
```

In [25]:

```
df[['embarked_mode','embarked']]
```

Out[25]:

	embarked_mode	embarked
0	S	S
1	C	C
2	S	S
3	S	S
4	S	S
...	...	...
886	S	S
887	S	S
888	S	S
889	C	C
890	Q	Q

891 rows × 2 columns

In [26]:

```
df['embarked_mode'].isnull().sum()
```

Out[26]:

```
0
```

In [27]:

```
df['embarked'].isnull().sum()
```

Out[27]:

```
2
```

SMOTE(Synthetic Minority Oversampling Technique)

SMOTE (Synthetic Minority Over-sampling Technique) is a technique used in machine learning to address imbalanced datasets where the minority class has significantly fewer instances than the majority class. SMOTE involves generating synthetic instances of the minority class by interpolating between existing instances.

In [28]:

```
from sklearn.datasets import make_classification
```

In [29]:

```
## X independent feature
## y dependent feature
X,y=make_classification(n_samples=1000,n_features=2,n_redundant=0,n_clusters_per_class=1
,weights=[0.90],random_state=1)
```

In [30]:

```
import pandas as pd
df1=pd.DataFrame(X,columns=['f1','f2'])
df2=pd.DataFrame(y,columns=['target'])
final_df=pd.concat([df1,df2],axis=1)
```

In [31]:

```
final_df.head()
```

Out[31]:

	f1	f2	target
0	1.536830	-1.398694	1
1	1.551108	1.810329	0
2	1.293619	1.010946	0
3	1.119889	1.632518	0
4	1.042356	1.121529	0

In [32]:

```
final_df['target'].value_counts()
```

Out[32]:

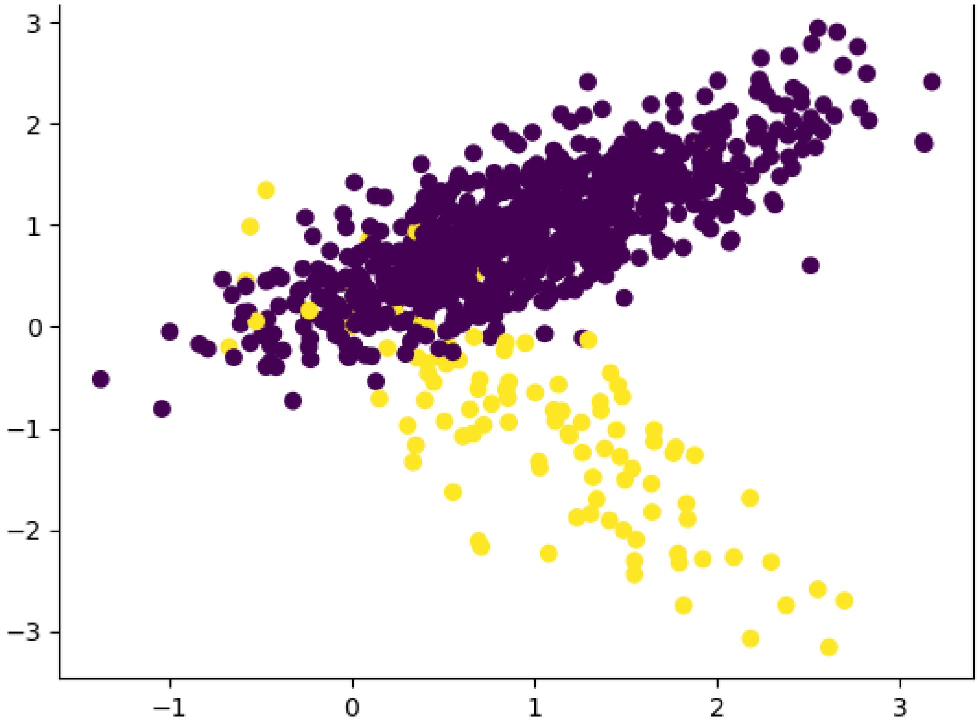
```
0    894
1    106
Name: target, dtype: int64
```

In [33]:

```
import matplotlib.pyplot as plt
plt.scatter(final_df['f1'],final_df['f2'],c=final_df['target'])
```

Out[33]:

```
<matplotlib.collections.PathCollection at 0x295b4003820>
```



In [34]:

```
!pip install imblearn
```

```
Collecting imblearn
  Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
Collecting imbalanced-learn
  Downloading imbalanced_learn-0.10.1-py3-none-any.whl (226 kB)
     -------------------------------------- 226.0/226.0 kB 3.4 MB/s eta 0:00:00
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\dipmani\anaconda3\lib\site
-packages (from imbalanced-learn->imblearn) (1.0.2)
Requirement already satisfied: numpy>=1.17.3 in c:\users\dipmani\anaconda3\lib\site-packa
ges (from imbalanced-learn->imblearn) (1.21.5)
Requirement already satisfied: scipy>=1.3.2 in c:\users\dipmani\anaconda3\lib\site-packag
es (from imbalanced-learn->imblearn) (1.9.1)
Collecting joblib>=1.1.1
  Downloading joblib-1.2.0-py3-none-any.whl (297 kB)
     -------------------------------------- 298.0/298.0 kB 6.1 MB/s eta 0:00:00
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dipmani\anaconda3\lib\sit
e-packages (from imbalanced-learn->imblearn) (2.2.0)
Installing collected packages: joblib, imbalanced-learn, imblearn
  Attempting uninstall: joblib
    Found existing installation: joblib 1.1.0
    Uninstalling joblib-1.1.0:
      Successfully uninstalled joblib-1.1.0
Successfully installed imbalanced-learn-0.10.1 imblearn-0.0 joblib-1.2.0
```

```
ERROR: pip's dependency resolver does not currently take into account all the packages th
at are installed. This behaviour is the source of the following dependency conflicts.
pandas-profiling 3.2.0 requires joblib~=1.1.0, but you have joblib 1.2.0 which is incompa
tible.
```

In [35]:

```
from imblearn.over_sampling import SMOTE
```

In [36]:

```
## transform the dataset
oversample=SMOTE()
X,y=oversample.fit_resample(final_df[['f1','f2']],final_df['target'])
```

In [37]:

```
X.shape
```

Out[37]:

```
(1788, 2)
```

In [38]:

```
len(y[y==0])
```

Out[38]:

```
894
```

In [39]:

```
len(y[y==1])
```

Out[39]:

```
894
```

In [40]:

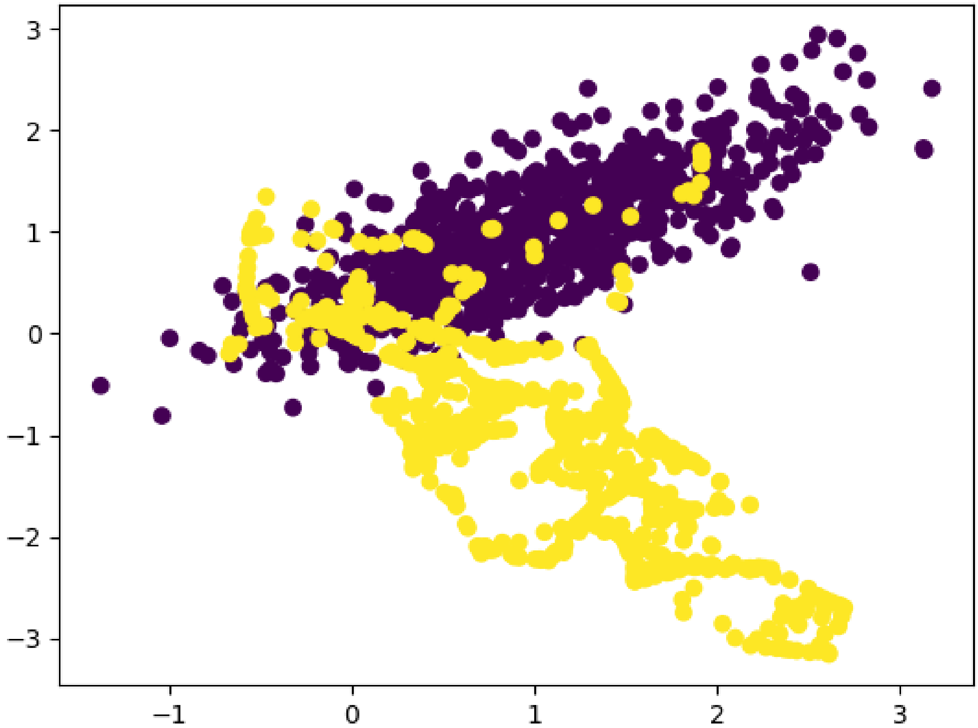
```
df1=pd.DataFrame(X,columns=['f1','f2'])
df2=pd.DataFrame(y,columns=['target'])
oversample_df=pd.concat([df1,df2],axis=1)
```

In [41]:

```
plt.scatter(oversample_df['f1'],oversample_df['f2'],c=oversample_df['target'])
```

Out[41]:

```
<matplotlib.collections.PathCollection at 0x295b596bf10>
```



3. Data Interpolation

Data interpolation is the process of estimating unknown values within a dataset based on the known values. In Python, there are various libraries available that can be used for data interpolation, such as NumPy, SciPy, and Pandas. Here is an example of how to perform data interpolation using the NumPy library:

1. Linear Interpolation

In [42]:

```
import numpy as np
```

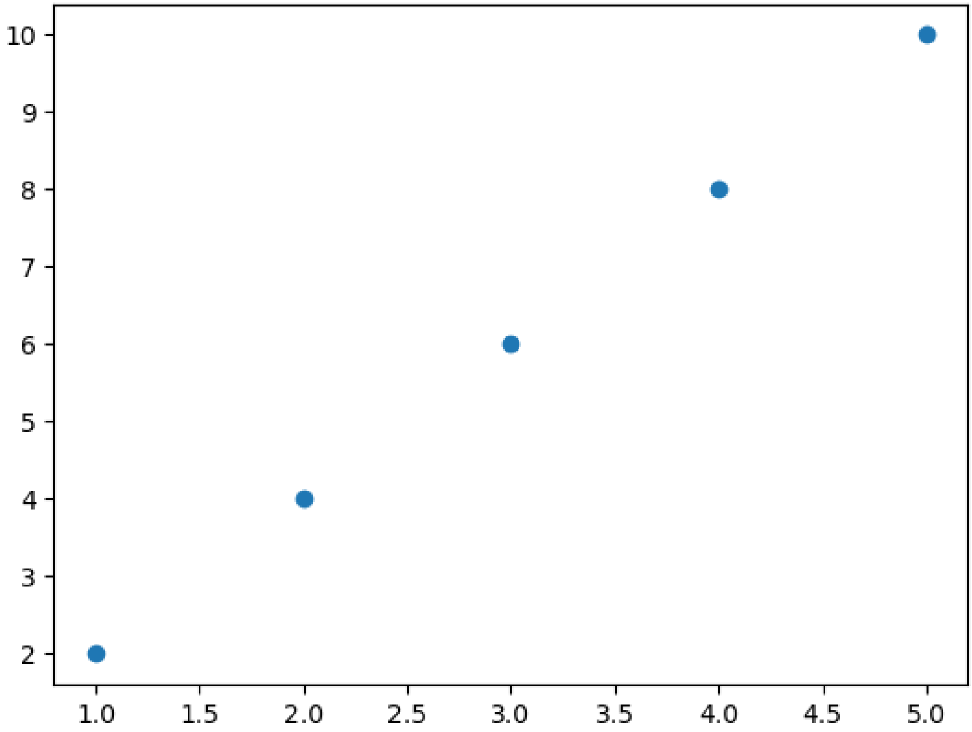
```
x=np.array([1,2,3,4,5])
y=np.array([2,4,6,8,10])
```

In [43]:

```
import matplotlib.pyplot as plt
plt.scatter(x,y)
```

Out[43]:

```
<matplotlib.collections.PathCollection at 0x295b59e4790>
```



In [44]:

```
## interpolate the data using linear interpolation
x_new=np.linspace(1,5,10) ##create new x values
y_interp=np.interp(x_new,x,y) ## interpolate y values
print(y_interp)
```

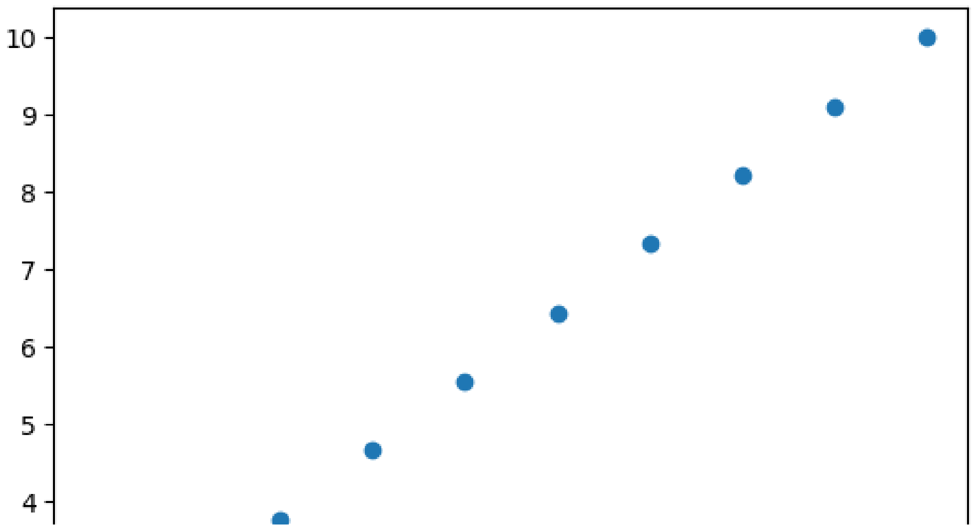
```
[ 2.          2.88888889  3.77777778  4.66666667  5.55555556  6.44444444
  7.33333333  8.22222222  9.11111111 10.        ]
```

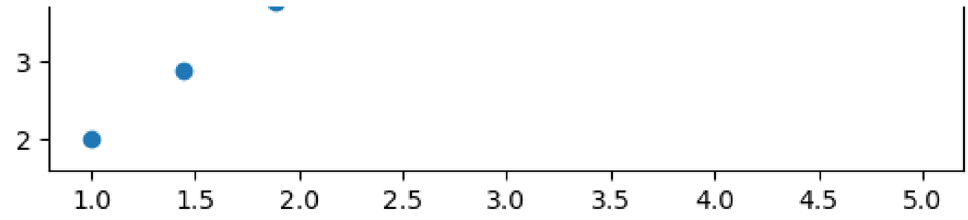
In [45]:

```
plt.scatter(x_new,y_interp)
```

Out[45]:

```
<matplotlib.collections.PathCollection at 0x295b5a2c190>
```





Cubic Interpolation With Scipy

In [46]:

```
import numpy as np
x=np.array([1,2,3,4,5])
y=np.array([1,8,27,64,125])
```

In [47]:

```
from scipy.interpolate import interp1d
```

In [48]:

```
##create a cubic interpolation function
f=interp1d(x,y,kind='cubic')
```

In [49]:

```
# interpolate the data
x_new = np.linspace(1, 5, 10)
y_interp=f(x_new)
print(y_interp)
```

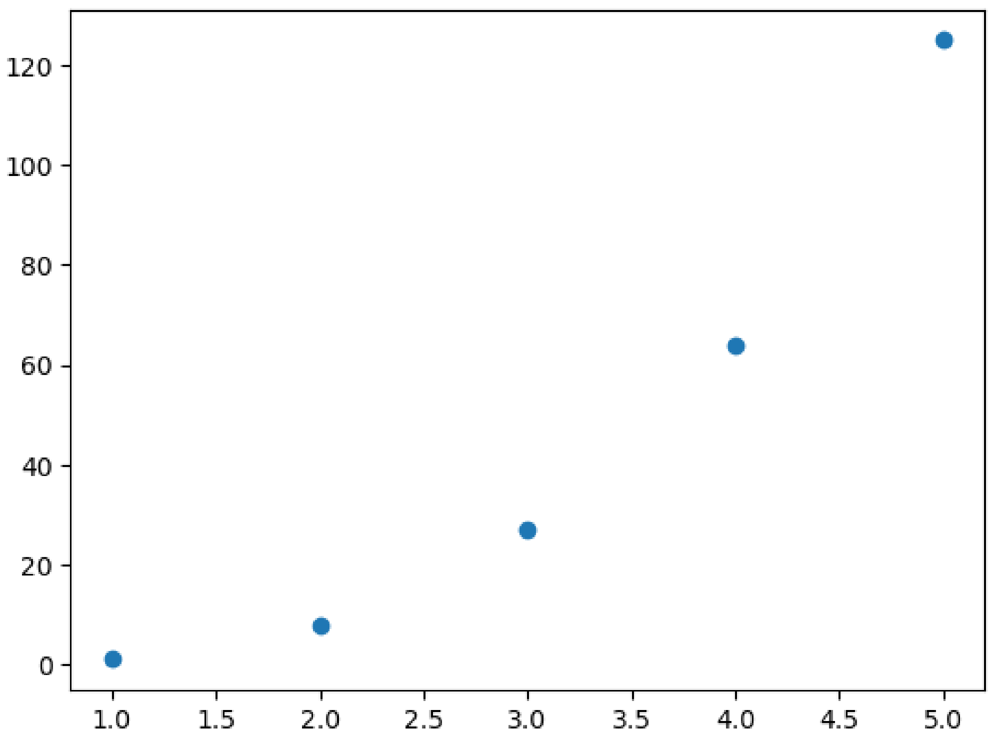
```
[  1.           3.01371742   6.739369    12.7037037   21.43347051
  33.45541838  49.2962963   69.48285322  94.54183813 125.        ]
```

In [50]:

```
plt.scatter(x,y)
```

Out[50]:

<matplotlib.collections.PathCollection at 0x295b5a9c430>

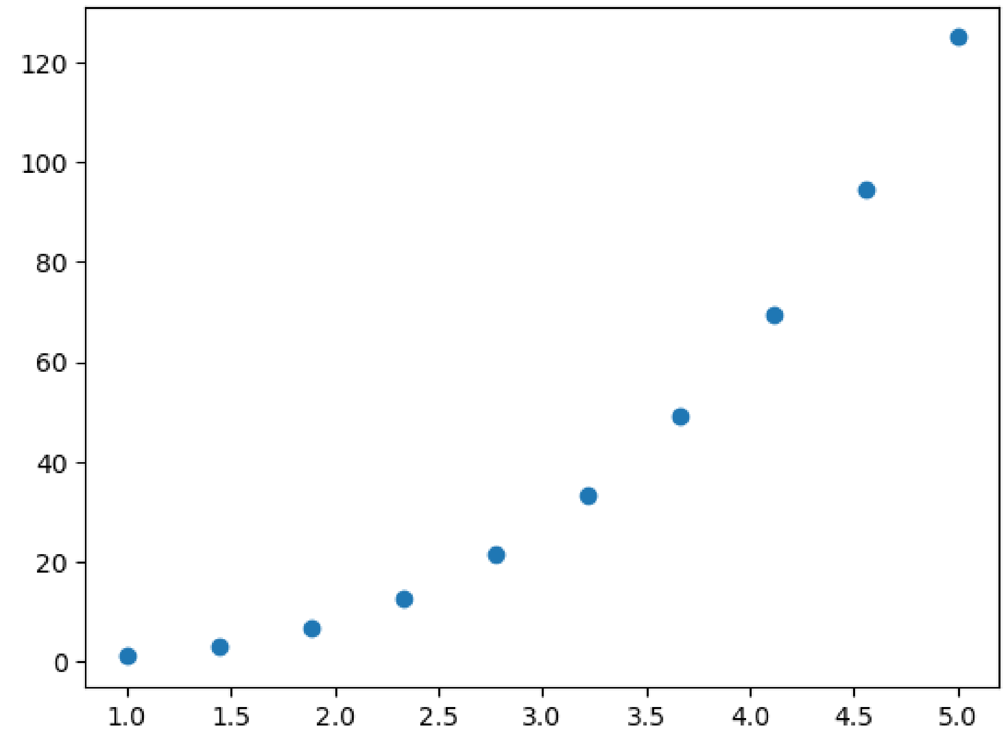


In [51]:

```
plt.scatter(x_new,y_interp)
```

Out[51]:

```
<matplotlib.collections.PathCollection at 0x295b5b09a00>
```



Polynomial Interpolation

In [52]:

```
import numpy as np

# create some sample data
x = np.array([1, 2, 3, 4, 5])
y = np.array([1, 4, 9, 16, 25])
```

In [53]:

```
# interpolate the data using polynomial interpolation
p = np.polyfit(x, y, 2) # fit a 2nd degree polynomial to the data
```

In [54]:

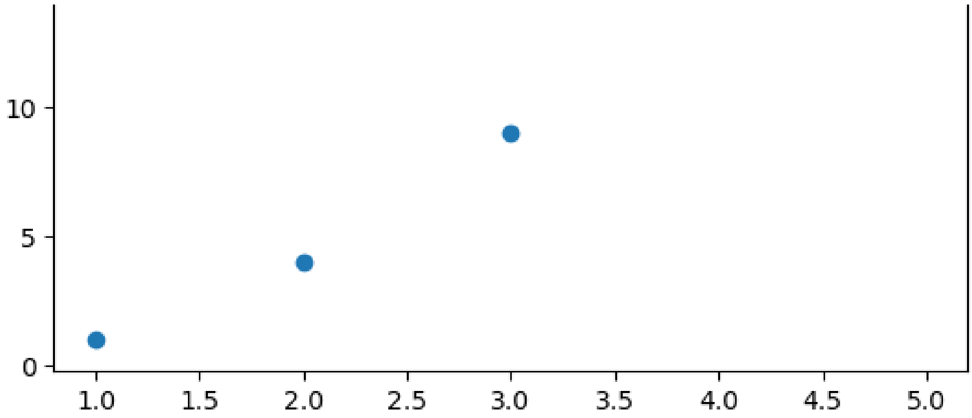
```
x_new = np.linspace(1, 5, 10) # create new x values
y_interp = np.polyval(p, x_new) # interpolate y values
```

In [55]:

```
plt.scatter(x,y)
```

Out[55]:

```
<matplotlib.collections.PathCollection at 0x295b5b80250>
```

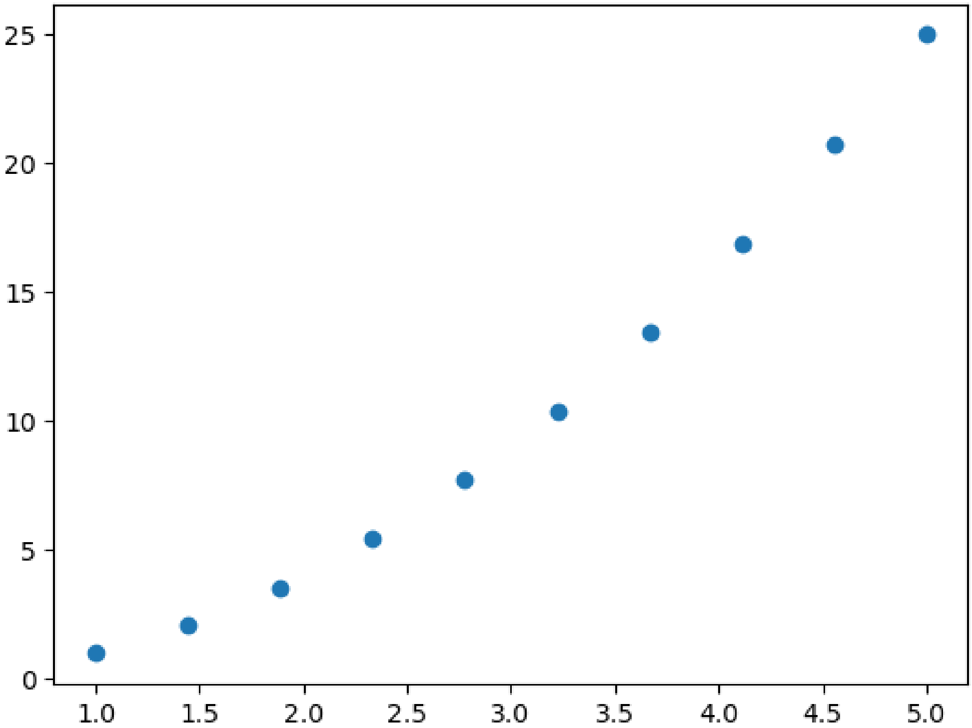


In [56]:

```
plt.scatter(x_new,y_interp)
```

Out[56]:

```
<matplotlib.collections.PathCollection at 0x295b5be9580>
```



4. Imbalanced Dataset Handling

1. **Upsampling**
2. **Down Sampling**

In [57]:

```
import numpy as np
import pandas as pd
```

In [58]:

```
# Set the random seed for reproducibility
np.random.seed(123)

# Create a dataframe with two classes
n_samples = 1000
class_0_ratio = 0.9
n_class_0 = int(n_samples * class_0_ratio)
n_class_1 = n_samples - n_class_0
```

In [59]:

```
n_class_0,n_class_1
```

Out[59]:

```
(900, 100)
```

In [60]:

```
class_0 = pd.DataFrame({
    'feature_1': np.random.normal(loc=0, scale=1, size=n_class_0),
    'feature_2': np.random.normal(loc=0, scale=1, size=n_class_0),
    'target': [0] * n_class_0
})

class_1 = pd.DataFrame({
    'feature_1': np.random.normal(loc=2, scale=1, size=n_class_1),
    'feature_2': np.random.normal(loc=2, scale=1, size=n_class_1),
    'target': [1] * n_class_1
})
```

In [61]:

```
df=pd.concat([class_0,class_1]).reset_index(drop=True)
```

In [62]:

```
df.head()
```

Out[62]:

	feature_1	feature_2	target
0	-1.085631	0.551302	0
1	0.997345	0.419589	0
2	0.282978	1.815652	0
3	-1.506295	-0.252750	0
4	-0.578600	-0.292004	0

In [63]:

```
df['target'].value_counts()
```

Out[63]:

```
0    900
1    100
Name: target, dtype: int64
```

Upsampling

In [64]:

```
df_minority=df[df['target']==1]
df_majority=df[df['target']==0]
```

In [65]:

```
df_minority.head()
```

Out[65]:

	feature_1	feature_2	target
900	1.699768	2.139033	1
901	1.367739	2.025577	1

	feature_1	feature_2	target
902	1.795683	1.805557	1
903	2.213696	3.312255	1
904	3.033878	3.187417	1

In [66]:

```
df_majority.head()
```

Out[66]:

	feature_1	feature_2	target
0	-1.085631	0.551302	0
1	0.997345	0.419589	0
2	0.282978	1.815652	0
3	-1.506295	-0.252750	0
4	-0.578600	-0.292004	0

In [67]:

```
##Upsampling perform
from sklearn.utils import resample
```

In [68]:

```
df_minority_upsample=resample(df_minority,
                              replace=True, ## Sample With replacement
                               n_samples=len(df_majority), # to match the majority class)
                               random_state=42
                              )
```

In [69]:

```
df_minority_upsample.shape
```

Out[69]:

```
(900, 3)
```

In [70]:

```
df_minority_upsample.shape
```

Out[70]:

```
(900, 3)
```

In [71]:

```
df_minority_upsample['target'].value_counts()
```

Out[71]:

```
1    900
Name: target, dtype: int64
```

In [72]:

```
df_upsampled= pd.concat([df_majority,df_minority_upsample])
```

In [73]:

```
df_upsampled['target'].value_counts()
```

Out[73]:

```
0    900
1    900
```

```
Name: target, dtype: int64
```

In [74]:

```
df_upsampled.shape
```

Out[74]:

```
(1800, 3)
```

DownSampling

In [75]:

```
class_0 = pd.DataFrame({
    'feature_1': np.random.normal(loc=0, scale=1, size=n_class_0),
    'feature_2': np.random.normal(loc=0, scale=1, size=n_class_0),
    'target': [0] * n_class_0
})

class_1 = pd.DataFrame({
    'feature_1': np.random.normal(loc=2, scale=1, size=n_class_1),
    'feature_2': np.random.normal(loc=2, scale=1, size=n_class_1),
    'target': [1] * n_class_1
})
```

In [76]:

```
df=pd.concat([class_0,class_1]).reset_index(drop=True)
```

In [77]:

```
df_minority=df[df['target']==1]
df_majority=df[df['target']==0]
```

In [78]:

```
df_majority_downsample=resample(df_majority,
                             replace=False, ## Sample Without replacement
                              n_samples=len(df_minority), # to match the minority class)
                              random_state=42
                             )
```

In [79]:

```
df_majority_downsample.shape
```

Out[79]:

```
(100, 3)
```

In [80]:

```
df_downsample=pd.concat([df_minority,df_majority_downsample])
```

In [81]:

```
df_downsample['target'].value_counts()
```

Out[81]:

```
1    100
0    100
Name: target, dtype: int64
```

Handling Outliers

5 number Summary

1. **Minimum Value**
2. **Q1- 25 percentile**
3. **Median**
4. **Q3- 75 percentile**
5. **MAximum**

In [82]:

```
import numpy as np
lst_marks=[45,32,56,75,89,54,32,89,90,87,67,54,45,98,99,67,74,1000,1100]
```

In [83]:

```
## [Lower Fence<---> Higher Fence]
Q1=np.percentile(lst_marks,[25])
print(Q1)
```

```
[54.]
```

In [84]:

```
minimum,Q1,Q2,Q3,maximum=np.quantile(lst_marks,[0,0.25,0.50,0.75,1.0])
```

In [85]:

```
maximum
```

Out[85]:

```
1100.0
```

In [86]:

```
IQR=Q3-Q1
print(IQR)
```

```
35.5
```

In [87]:

```
lower_fence=Q1-1.5*(IQR)
higher_fence=Q3+1.5*(IQR)
```

In [88]:

```
lower_fence,higher_fence
```

Out[88]:

```
(0.75, 142.75)
```

In [89]:

```
outliers=[]
for i in lst_marks:
    if i>=0.75 and i<=142.75:
        print("This element is not an outlier")
    else:
        outliers.append(i)
```

```
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
```

```
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
This element is not an outlier
```

In [90]:

```
outliers
```

Out[90]:

```
[1000, 1100]
```

In [91]:

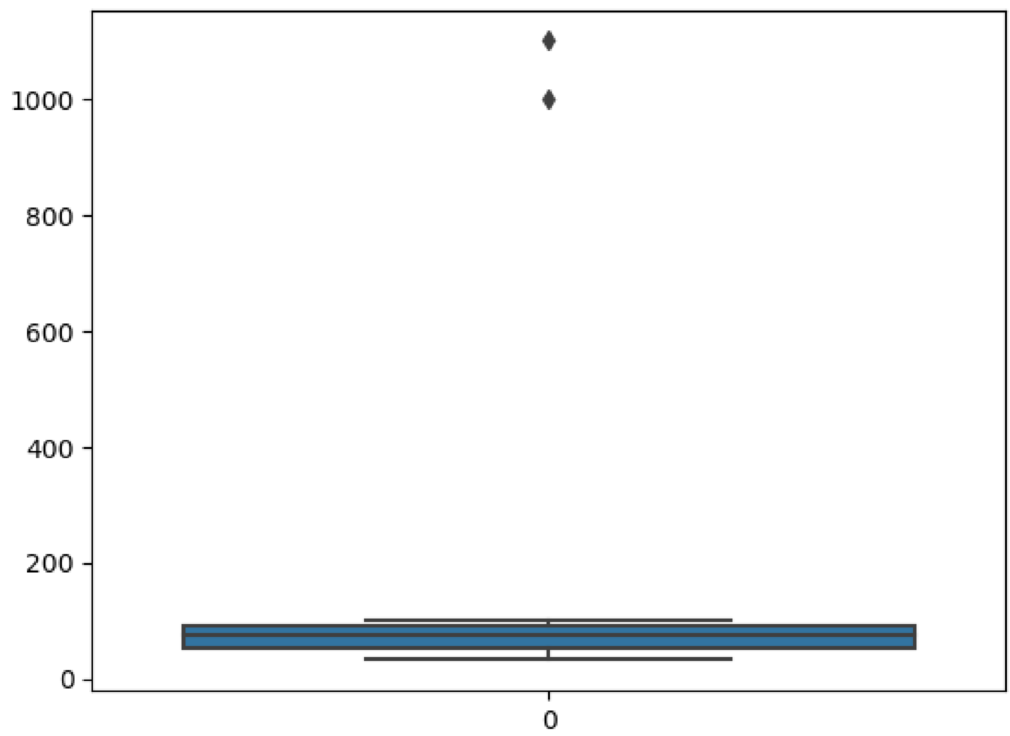
```
import seaborn as sns
```

In [92]:

```
sns.boxplot(lst_marks)
```

Out[92]:

```
<AxesSubplot:>
```



In [93]:

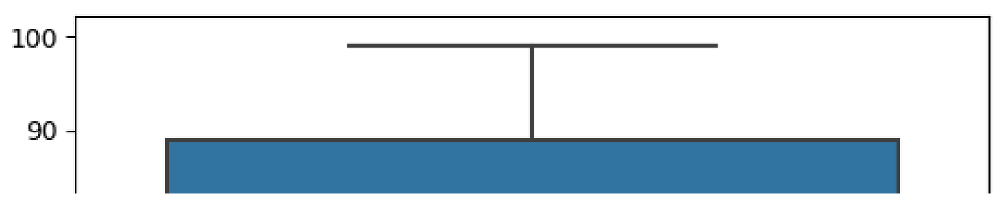
```
lst_marks=[45,32,56,75,89,54,32,89,90,87,67,54,45,98,99,67,74]
```

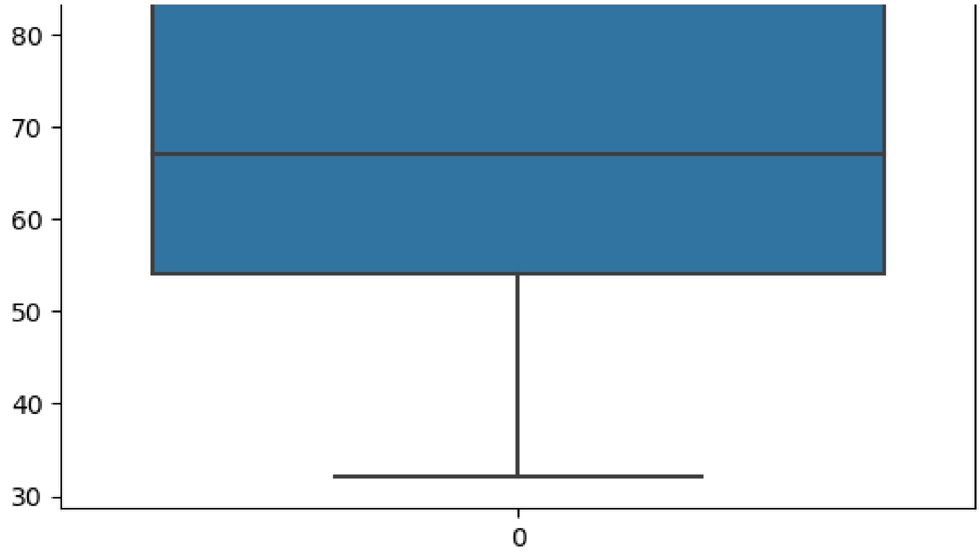
In [94]:

```
sns.boxplot(lst_marks)
```

Out[94]:

```
<AxesSubplot:>
```





In [ ]: