5.3-Handling_outliers_and_Data_Encoding

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0.1 Outlier Handling

0.1.1 5 Number Summary And Box Plot for the Outlier Handling

```
Here 5 number summary means
        1) Maximum
        2) Q1(First Quartile) or 25%(percentile)
        3) Median
        4) Q3(Third Quartile) or 75%(percentile)
        5) Minimum
```

[1]:
```
import numpy as np
```

[2]:
```
lst_marks = [45, 32, 56, 75, 89, 54, 32, 89, 90, 87, 67, 54, 45, 98, 99, 67,␣
↪74]  # This is not containing any outliers
minimum, Q1, median, Q3, maximum = np.quantile(lst_marks, [0, 0.25, 0.50, 0.75,␣
↪1.0])
```

[3]:
```
print(f"Minimum value of data is: {minimum}")
print(f"Q1 of data is: {Q1}")
print(f"Q3 of data is: {Q3}")
print(f"Median  of data is: {median}")
print(f"Maximum value of data is: {maximum}")
```

```
Minimum value of data is: 32.0
Q1 of data is: 54.0
Q3 of data is: 89.0
Median  of data is: 67.0
Maximum value of data is: 99.0
```

[4]:
```
IQR = Q3-Q1
print(f"Inter Quartile Range is: {IQR}")
```

```
Inter Quartile Range is: 35.0
```

[5]:
```
lower_fence = Q1-1.5*(IQR)
higher_fence = Q3+1.5*(IQR)
```

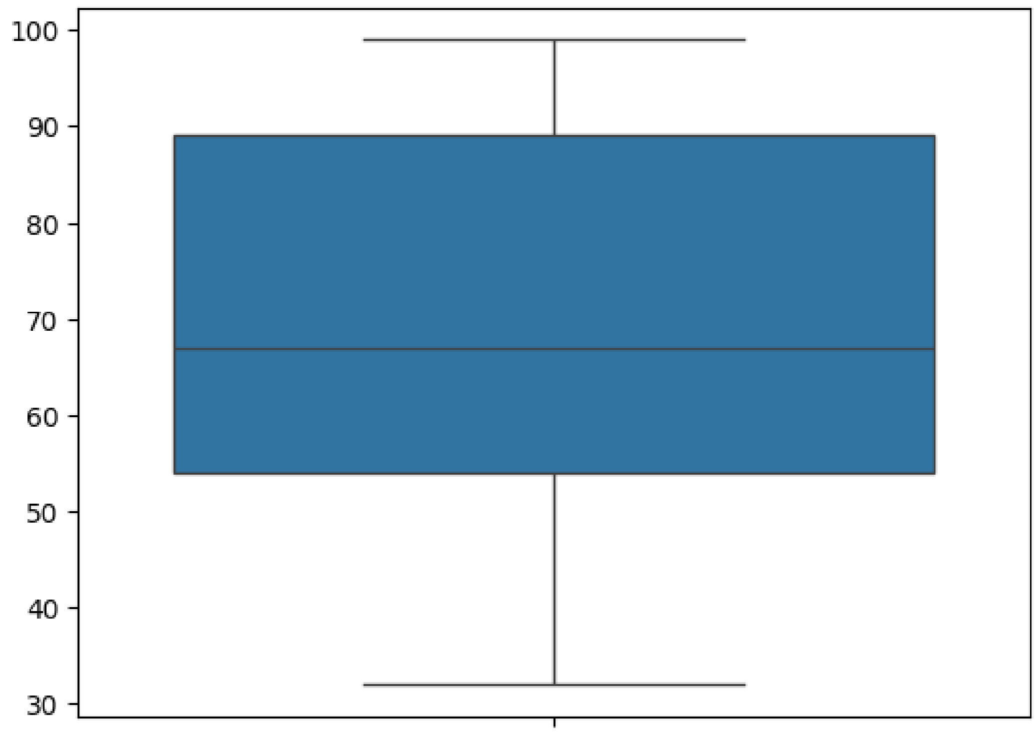
[6]:
```
print(f"Lower value considered as an outlier is: {lower_fence}")
print(f"Highest value considered as an outlier is: {higher_fence}")
```

```
Lower value considered as an outlier is: 1.5
Highest value considered as an outlier is: 141.5
```

[7]:
```python
import seaborn as sns
```

[8]:
```python
sns.boxplot(lst_marks)
```

[8]:
```
<Axes: >
```

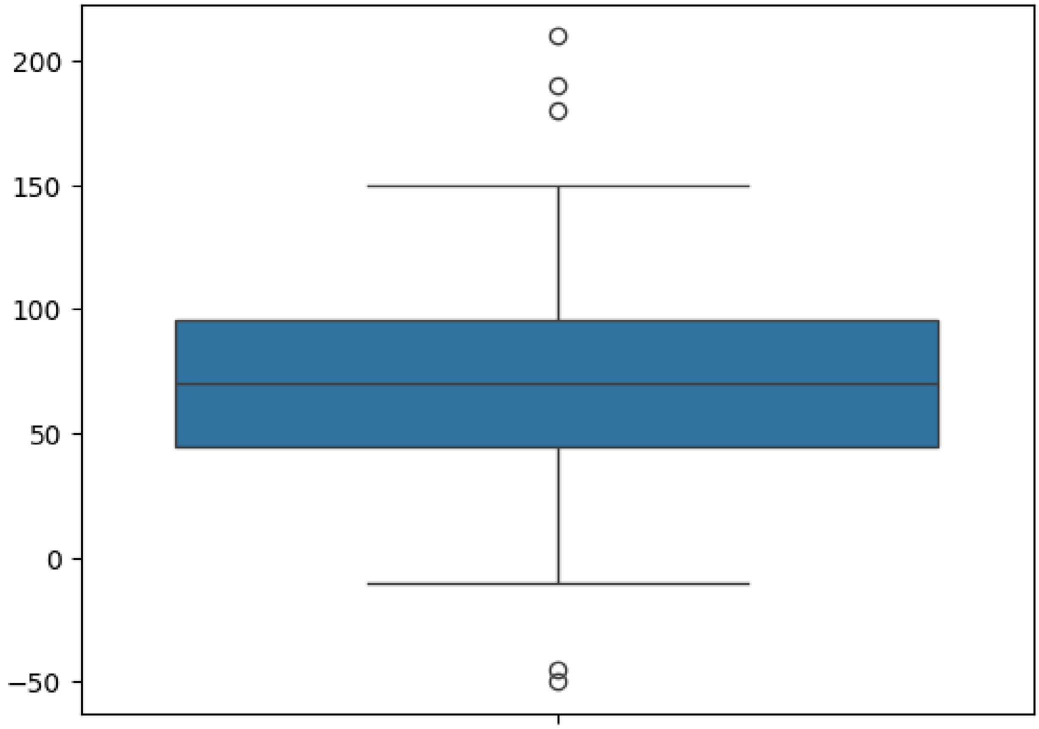


When we are plotting the boxplot it is automatically detect the outliers and shows the outliers as points

[9]:
```python
lst_marks = [-50, -10, -45, 1, 45, 32, 56, 75, 89, 54, 32, 89, 90, 87, 67, 54,
 ↪45, 98, 99, 67, 74, 100,150, 210, 190, 180]
```

[10]:
```python
# plotting the boxplot for the lst_marks
sns.boxplot(lst_marks)
```

[10]:
```
<Axes: >
```



Here you can see that the dots are the outliers that is automatically detected by the boxplot we are not calculating the IQR, lower_fence or higher_fence

0.2 Data Encoding

1. `Nominal/OHE Encoding`
2. `Label and Ordinal Encoding`
3. `Target Guided Ordinal Encoding`

0.2.1 Nominal/OHE Encoding

One hot encoding, also known as nominal encoding, is a technique used to represent categorical data as numerical data, which is more suitable for machine learning algorithms. In this technique, each category is represented as a binary vector where each bit corresponds to a unique category. For example, if we have a categorical variable variable "color" with three possible values (red, green, blue), we can represent it one hot encoding as follows

1. `Red:[1, 0, 0]`
2. `Green:[0, 1, 0]`
3. `Blue:[0, 0, 1]`

[11]:
```
import pandas as pd
from sklearn.preprocessing import OneHotEncoder
```

[12]:
```python
## Creating a simple DataFrame

df = pd.DataFrame({
        'color':['red', 'blue', 'green', 'green', 'red', 'blue']
})
```

[13]:
```python
df
```

[13]:

	color
0	red
1	blue
2	green
3	green
4	red
5	blue

[14]:
```python
## Create an instance of OneHotEncoder

encoder = OneHotEncoder()
```

[15]:
```python
## Perform fit and transform

encoded = encoder.fit_transform(df[['color']]).toarray()
```

[16]:
```python
encoder_df = pd.DataFrame(encoded, columns=encoder.get_feature_names_out())
```

[17]:
```python
encoder_df
```

[17]:

	color_blue	color_green	color_red
0	0.0	0.0	1.0
1	1.0	0.0	0.0
2	0.0	1.0	0.0
3	0.0	1.0	0.0
4	0.0	0.0	1.0
5	1.0	0.0	0.0

[18]:
```python
## concat with your original dataset

df2 = pd.concat([df, encoder_df], axis=1)
```

[19]:
```python
df2
```

[19]:

	color	color_blue	color_green	color_red
0	red	0.0	0.0	1.0
1	blue	1.0	0.0	0.0
2	green	0.0	1.0	0.0
3	green	0.0	1.0	0.0
4	red	0.0	0.0	1.0

```
5   blue          1.0          0.0        0.0
```

0.2.2 Example For Practice

[20]:
```python
import seaborn as sns
df1 =sns.load_dataset('tips')
```

[21]:
```python
encode = OneHotEncoder()
```

[22]:
```python
encoded = encode.fit_transform(df1[['sex', 'smoker', 'day', 'time']]).toarray()
```

[23]:
```python
encoded
```

[23]:
```
array([[1., 0., 1., …, 0., 1., 0.],
       [0., 1., 1., …, 0., 1., 0.],
       [0., 1., 1., …, 0., 1., 0.],
       …,
       [0., 1., 0., …, 0., 1., 0.],
       [0., 1., 1., …, 0., 1., 0.],
       [1., 0., 1., …, 1., 1., 0.]])
```

[24]:
```python
encoded_df1 = pd.DataFrame(encoded, columns=encode.get_feature_names_out())
```

[25]:
```python
encoded_df1.head()
```

[25]:
```
   sex_Female  sex_Male  smoker_No  smoker_Yes  day_Fri  day_Sat  day_Sun  \
0         1.0       0.0        1.0         0.0      0.0      0.0      1.0
1         0.0       1.0        1.0         0.0      0.0      0.0      1.0
2         0.0       1.0        1.0         0.0      0.0      0.0      1.0
3         0.0       1.0        1.0         0.0      0.0      0.0      1.0
4         1.0       0.0        1.0         0.0      0.0      0.0      1.0

   day_Thur  time_Dinner  time_Lunch
0       0.0          1.0         0.0
1       0.0          1.0         0.0
2       0.0          1.0         0.0
3       0.0          1.0         0.0
4       0.0          1.0         0.0
```

[26]:
```python
df1 = pd.concat([df1, encoded_df1], axis=1)
df1.head()
```

[26]:
```
   total_bill   tip     sex smoker  day    time  size  sex_Female  sex_Male  \
0       16.99  1.01  Female     No  Sun  Dinner     2         1.0       0.0
1       10.34  1.66    Male     No  Sun  Dinner     3         0.0       1.0
2       21.01  3.50    Male     No  Sun  Dinner     3         0.0       1.0
3       23.68  3.31    Male     No  Sun  Dinner     2         0.0       1.0
4       24.59  3.61  Female     No  Sun  Dinner     4         1.0       0.0
```

```
   smoker_No  smoker_Yes  day_Fri  day_Sat  day_Sun  day_Thur  time_Dinner  \
0        1.0         0.0      0.0      0.0      1.0       0.0          1.0
1        1.0         0.0      0.0      0.0      1.0       0.0          1.0
2        1.0         0.0      0.0      0.0      1.0       0.0          1.0
3        1.0         0.0      0.0      0.0      1.0       0.0          1.0
4        1.0         0.0      0.0      0.0      1.0       0.0          1.0

   time_Lunch
0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
```

0.2.3 Label Encoding

Label encoding and ordinal encoding are two techniques used to encode categorical data as numerical data

Label encoding involves assigning a unique numerical label to each category in the variable. The labels are usually assigned in alphabetical order or based on the frequency of the categories. For example, if we have a categorical variable "color" with three possible values (red, green, blue), we can represent it using label encoding as follows:

```
1. Red: 1
2. Green: 2
3. Blue: 3
```

[27]:
```python
df
```

[27]:
```
   color
0    red
1   blue
2  green
3  green
4    red
5   blue
```

[28]:
```python
from sklearn.preprocessing import LabelEncoder
lbl_encoder= LabelEncoder()
```

[29]:
```python
lbl_encoder.fit_transform(df['color'])
```

[29]:
```
array([2, 0, 1, 1, 2, 0])
```

[30]:
```python
lbl_encoder.transform(['red'])
```

[30]:
```
array([2])
```

[31]:
```
lbl_encoder.transform(['blue'])
```

[31]:
```
array([0])
```

The problem with that the red value is higher value as compared to the blue so model get confused

0.2.4 Ordinal Encoding

It is used to encode categorical data that have an intrinsic order or ranking. In this technique, each category is assigned a n numerical value based on its position in the order. For example, if we have a categorical variable "education level" with four possible values (high school, college, graduate, post-graduate), we can represent ordinal encoding as follows:

```
1. High school: 1
2. College: 2
3. Graduate: 3
4. Post-graduate: 4
```

[32]:
```
from sklearn.preprocessing import OrdinalEncoder
```

[33]:
```
df3 = pd.DataFrame({
        'size': ['small', 'medium', 'large', 'medium', 'small', 'large']
})
```

[34]:
```
df3
```

[34]:

	size
0	small
1	medium
2	large
3	medium
4	small
5	large

[35]:
```
## create an instance of OrdinalEncoder and then fit transform
encoder = OrdinalEncoder(categories=[['small', 'medium', 'large']])
```

[36]:
```
encoder.fit_transform(df3[['size']]) ## here the large assigned with larger␣
 ↪value
```

[36]:
```
array([[0.],
       [1.],
       [2.],
       [1.],
       [0.],
       [2.]])
```

0.2.5 Target Guided Ordinal Encoding

It is a techniques used to encode categorical variables based on their relationship with the target variable. This encoding technique is useful when we have a categorical variable with a large number of unique categories, and we want to use this variable as a feature in our machine learning model.

In target Guided Ordinal Encoding, we replace each category in the categorical variable with a numerical values based on the mean or median of the target variable for that category. This creates a monotonic relationship between teh categorical variable and the target variable, which can improve the predictive power of our model.

[37]:
```
df4 = pd.DataFrame({
        'city': ['New York', 'London', 'Paris', 'Tokyo', 'New York', 'Paris'],
        'price': [200, 150, 300, 250, 180, 320]
})
```

[38]:
```
df4
```

[38]:

	city	price
0	New York	200
1	London	150
2	Paris	300
3	Tokyo	250
4	New York	180
5	Paris	320

[39]:
```
mean_price =  df4.groupby('city')['price'].mean().to_dict()
```

[40]:
```
mean_price
```

[40]:
```
{'London': 150.0, 'New York': 190.0, 'Paris': 310.0, 'Tokyo': 250.0}
```

[41]:
```
df4['city_encoded'] = df4['city'].map(mean_price)
```

[42]:
```
df4
```

[42]:

	city	price	city_encoded
0	New York	200	190.0
1	London	150	150.0
2	Paris	300	310.0
3	Tokyo	250	250.0
4	New York	180	190.0
5	Paris	320	310.0

[43]:
```
df4[['price', 'city_encoded']] ## this is used for our model training
```

[43]:

	price	city_encoded
0	200	190.0
1	150	150.0

```
2     300          310.0
3     250          250.0
4     180          190.0
5     320          310.0
```

Example For Practice

[44]:
```python
df5 =sns.load_dataset('tips')
```

[45]:
```python
df5
```

[45]:
```
     total_bill   tip     sex smoker   day    time  size
0         16.99  1.01  Female     No   Sun  Dinner     2
1         10.34  1.66    Male     No   Sun  Dinner     3
2         21.01  3.50    Male     No   Sun  Dinner     3
3         23.68  3.31    Male     No   Sun  Dinner     2
4         24.59  3.61  Female     No   Sun  Dinner     4
..          …     …       …     …     …       …     …
239       29.03  5.92    Male     No   Sat  Dinner     3
240       27.18  2.00  Female    Yes   Sat  Dinner     2
241       22.67  2.00    Male    Yes   Sat  Dinner     2
242       17.82  1.75    Male     No   Sat  Dinner     2
243       18.78  3.00  Female     No  Thur  Dinner     2

[244 rows x 7 columns]
```

[46]:
```python
mean_total_bill =  df5.groupby('time', observed=True)['total_bill'].mean().
 ↪to_dict()
```

[47]:
```python
mean_total_bill
```

[47]:
```
{'Lunch': 17.168676470588235, 'Dinner': 20.79715909090909}
```

[48]:
```python
df5['time_encoded'] = df5['time'].map(mean_total_bill)
```

[49]:
```python
df5
```

[49]:
```
     total_bill   tip     sex smoker   day    time  size time_encoded
0         16.99  1.01  Female     No   Sun  Dinner     2    20.797159
1         10.34  1.66    Male     No   Sun  Dinner     3    20.797159
2         21.01  3.50    Male     No   Sun  Dinner     3    20.797159
3         23.68  3.31    Male     No   Sun  Dinner     2    20.797159
4         24.59  3.61  Female     No   Sun  Dinner     4    20.797159
..          …     …       …     …     …       …     …             …
239       29.03  5.92    Male     No   Sat  Dinner     3    20.797159
240       27.18  2.00  Female    Yes   Sat  Dinner     2    20.797159
241       22.67  2.00    Male    Yes   Sat  Dinner     2    20.797159
242       17.82  1.75    Male     No   Sat  Dinner     2    20.797159
```

```
243       18.78  3.00  Female     No  Thur  Dinner     2    20.797159

[244 rows x 8 columns]
```

[50]:

```python
df5[['time', 'time_encoded']].head() ## this is used for our model training
```

[50]:

```
     time time_encoded
0  Dinner    20.797159
1  Dinner    20.797159
2  Dinner    20.797159
3  Dinner    20.797159
4  Dinner    20.797159
```