boston_house_outlier_detection

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Name: Tufan Kundu # Reg no: 24MDT0184 # EDA lab # 28 February

0.1 Outlier detection On Boston house dataset

0.1.1 Importing the necessary libraries

[4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import zscore
```

0.1.2 Loading the dataset

[6]:
```
df = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Exploratory␣
↪Data Analysis Lab\28_Feb\BostonHousing.csv")
df
```

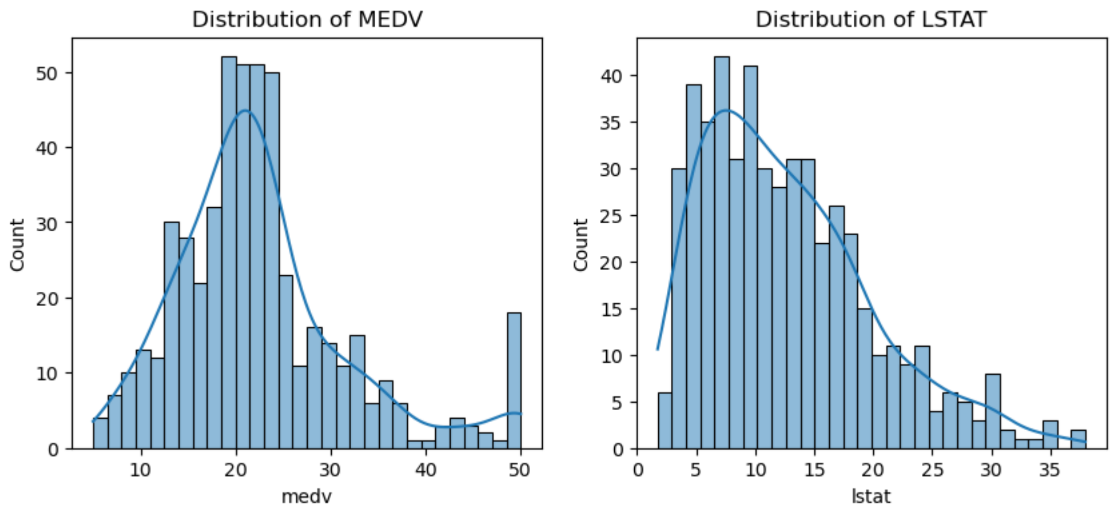
[6]:
```
        crim    zn  indus  chas    nox     rm   age     dis  rad  tax  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222
..       …     …     …     …      …      …     …       …  …    …
501  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273
502  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273
503  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273
504  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273
505  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273

     ptratio       b  lstat  medv
0       15.3  396.90   4.98  24.0
1       17.8  396.90   9.14  21.6
2       17.8  392.83   4.03  34.7
3       18.7  394.63   2.94  33.4
4       18.7  396.90   5.33  36.2
..         …       …     …     …
```

```
501     21.0  391.99   9.67  22.4
502     21.0  396.90   9.08  20.6
503     21.0  396.90   5.64  23.9
504     21.0  393.45   6.48  22.0
505     21.0  396.90   7.88  11.9

[506 rows x 14 columns]
```

0.1.3 Selecting the lstat and medv for the outlier detection

0.1.4 Checking the distribution of both the variables

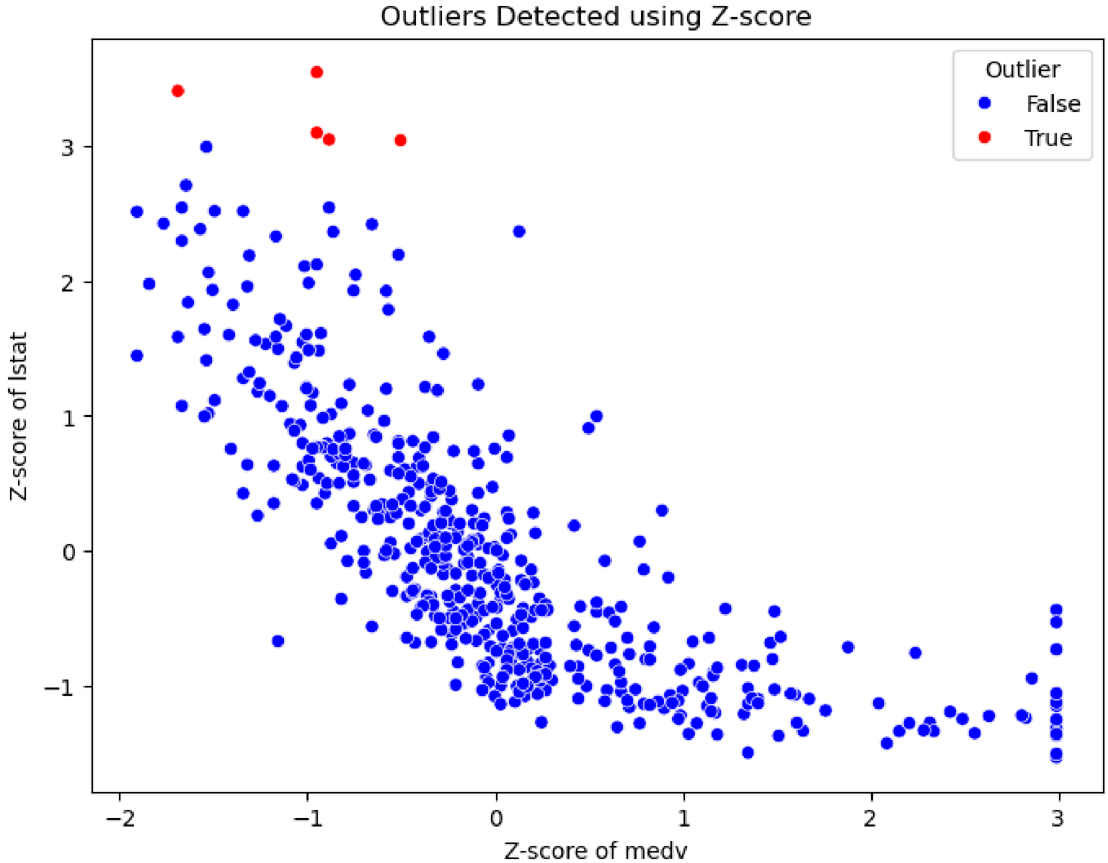
[9]:
```
plt.figure(figsize=(10, 4))

plt.subplot(1, 2, 1)
sns.histplot(df["medv"], bins=30, kde=True)
plt.title("Distribution of MEDV")

plt.subplot(1, 2, 2)
sns.histplot(df["lstat"], bins=30, kde=True)
plt.title("Distribution of LSTAT")

plt.show()
```



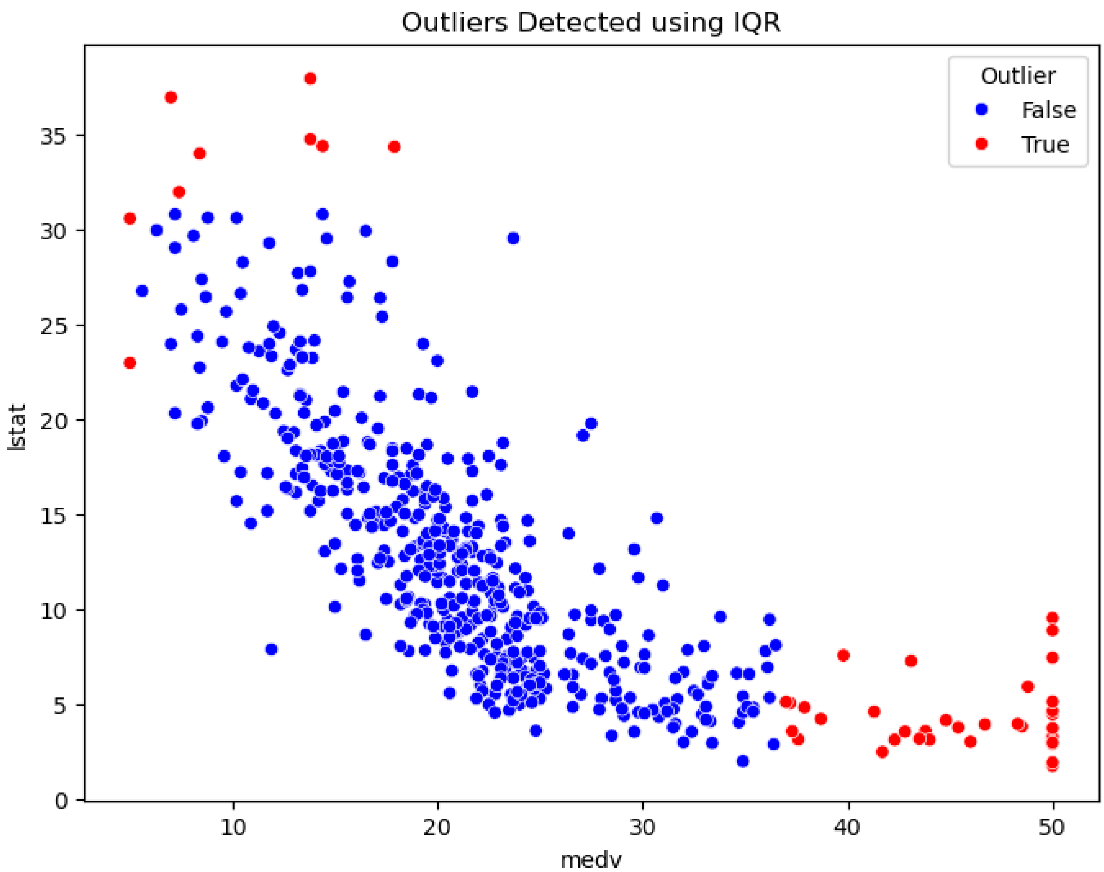
[10]:
```
feature1 = "medv"
feature2 = "lstat"

### Z-SCORE METHOD ###
df["Z_Feature1"] = zscore(df[feature1])
df["Z_Feature2"] = zscore(df[feature2])
```

```python
df["Outlier_Z"] = (df["Z_Feature1"].abs() > 3) | (df["Z_Feature2"].abs() > 3)

# Plot Z-score method results
plt.figure(figsize=(8, 6))
sns.scatterplot(x="Z_Feature1", y="Z_Feature2", data=df, hue="Outlier_Z",
                palette={False: "blue", True: "red"})

plt.title("Outliers Detected using Z-score")
plt.xlabel(f"Z-score of {feature1}")
plt.ylabel(f"Z-score of {feature2}")
plt.legend(title="Outlier")
plt.show()

# Print the number of outliers detected using Z-score
print("Z-score method detected outliers:", df["Outlier_Z"].sum())


#---------------------------------------------------------------------------------------------

### IQR METHOD ###

# Compute Q1, Q3, and IQR for each feature
Q1 = df[[feature1, feature2]].quantile(0.25)
Q3 = df[[feature1, feature2]].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outlier detection
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Identify outliers: Flag points outside the IQR bounds in either feature
outlier_iqr = ((df[[feature1, feature2]] < lower_bound) | (df[[feature1, feature2]] > upper_bound)).any(axis=1)
df["Outlier_IQR"] = outlier_iqr

# Plot IQR method results
plt.figure(figsize=(8, 6))
sns.scatterplot(x=feature1, y=feature2, data=df, hue="Outlier_IQR",
                palette={False: "blue", True: "red"})

plt.title("Outliers Detected using IQR")
plt.xlabel(feature1)
plt.ylabel(feature2)
plt.legend(title="Outlier")
plt.show()
```

```python
# Print the number of outliers detected using IQR
print("IQR method detected outliers:", df["Outlier_IQR"].sum())
```




```
Z-score method detected outliers: 5
```




```
IQR method detected outliers: 47
```

0.2 Conclusion

After applying `Z-score` and `IQR` methods for outlier detection in the Boston Housing Dataset, we observed significant differences in the number of detected outliers.

- `Z-score detected 5 outliers`, while `IQR detected 47 outliers`.
- The `LSTAT feature is right-skewed`, meaning it has a long tail towards higher values.
- Z-score assumes a normal distribution, which made it less effective for detecting outliers in skewed data.
- IQR, which does not assume normality, identified more outliers based on the interquartile range.