Outlier Detection & Removal | How to Detect & Remove Outliers (Updated 2024)

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Introduction

In my previous article, I talked about the theoretical concepts of outliers and tried to find the answer to the question: **"When should we drop outliers and when should we keep them?"**. In this article, I will focus on outlier detection and the different ways of treating them. It is important for a data scientist to find outliers and remove them from the dataset as part of the feature engineering before training machine learning algorithms for predictive modeling. Outliers present in a classification or regression dataset can lead to lower predictive modeling performance.

I recommend you read this **article** before proceeding so that you have a clear idea about the outlier analysis in Data Science Projects.

Learning Objectives

1. An Overview of outliers and why it's important for a data scientist to identify and remove them from data.
2. Undersand different techniques for outlier treatment: trimming, capping, treating as a missing value, and discretization.
3. Understanding different plots and libraries for visualizing and trating ouliers in a dataset.

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What is the Outlier Detection Method?

Outlier detection is a method used to find unusual or abnormal data points in a set of information. Imagine you have a group of friends, and you're all about the same age, but one person is much older or younger than the rest. That person would be considered an outlier because they stand out from the usual pattern. In data, outliers are points that deviate significantly from the majority, and detecting them helps identify unusual patterns or errors in the information. This method is like finding the odd one out in a group, helping us spot data points that might need special attention or investigation.

How to Treat Outliers?

There are several ways to treat outliers in a dataset, depending on the nature of the outliers and the problem being solved. Here are some of the most common ways of treating outlier values.

Trimming

It excludes the outlier values from our analysis. By applying this technique, our data becomes thin when more outliers are present in the dataset. Its main advantage is its **fastest** nature.

Capping

In this technique called "outlier detection," we cap our data to set limits. For instance, if we decide on a specific value, any data point above or below that value is considered an outlier. The number of outliers in the dataset then gives us insight into that capping number. It's like setting a boundary and saying, "Anything beyond this point is unusual," and by doing so, we identify and count the outliers in our data.

behave similarly to those with a lower income. In this case, you can cap the income value at a level that keeps that intact and accordingly treat the outliers.

Treating outliers as a missing value: Byassuming outliers as the missing observations, treat them accordingly, i.e., same as missing values imputation.

You can refer to the missing value article **here** .

Discretization

In the method of outlier detection, we create groups and categorize the outliers into a specific group, making them follow the same behavior as the other points in that group. This approach is often referred to as Binning. Binning is a way of organizing data, especially in outlier detection, where we group similar items together, helping us identify and understand patterns more effectively.

You can learn more about discretization **here** .

How to Detect Outliers?

For Normal Distributions

- Use empirical relations of Normal distribution.
- The data points that fall below ***mean-3*(sigma)*** or above ***mean+3*(sigma)*** are outliers, where mean and sigma are the **average value** and **standard deviation** of a particular column.

Source: sphweb.bumc.bu.edu

For Skewed Distributions

- Use Inter-Quartile Range (IQR) proximity rule.
- The data points that fall below ***Q1 – 1.5 IQR*** or above the third quartile ***Q3 + 1.5 IQR*** are outliers, where Q1 and Q3 are the **25th** and **75th percentile** of the dataset, respectively. IQR represents the inter-quartile range and is given by Q3 – Q1.

For Other Distributions

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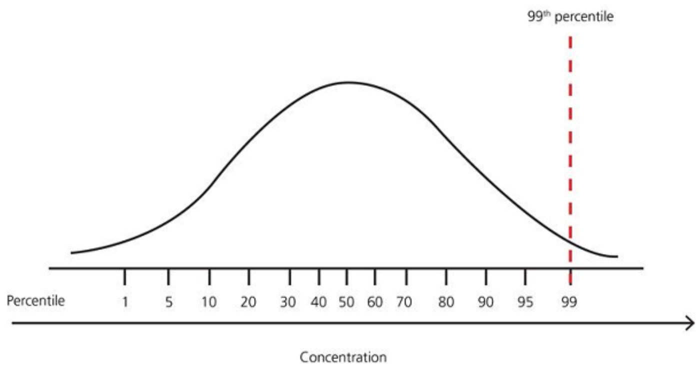
percentile and less than 1 percentile are considered an outlier.



Source: acutecaretesting.org

How to Detect and Remove Outliners in Python

Z-score Treatment

Assumption: The features are normally or approximately normally distributed.

1. **Step 1: Importing necessary dependencies**

   import numpy as np

   import pandas as pd

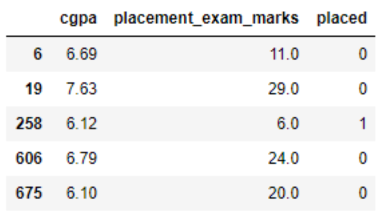
   import matplotlib.pyplot as plt

   import seaborn as sns

2. **Step 2: Read and load the dataset**

   df = pd.read_csv('placement.csv')

   df.sample(5)



	cgpa	placement_exam_marks	placed
6	6.69	11.0	0
19	7.63	29.0	0
258	6.12	6.0	1
606	6.79	24.0	0
675	6.10	20.0	0

3. **Step 3: Plot the distribution plots for the features**

   import warnings

   warnings.filterwarnings('ignore')

   plt.figure(figsize=(16,5))

   plt.subplot(1,2,1)

   sns.distplot(df['cgpa'])

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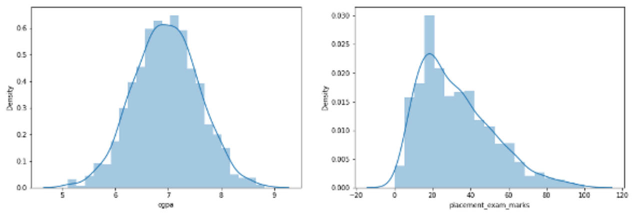
plt.show()



4. **Step 4: Finding the boundary values**

```
print("Highest allowed",df['cgpa'].mean() +
3*df['cgpa'].std())
print("Lowest allowed",df['cgpa'].mean() –
3*df['cgpa'].std())
```

Output:

```
Highest allowed 8.808933625397177
Lowest allowed 5.113546374602842
```

5. **Step 5: Finding the outliers**

```
df[(df['cgpa'] > 8.80) | (df['cgpa'] < 5.11)]
```

6. **Step 6: Trimming of outliers**

```
new_df = df[(df['cgpa'] < 8.80) & (df['cgpa'] > 5.11)]
new_df
```

7. **Step 7: Capping on outliers**

```
upper_limit = df['cgpa'].mean() + 3*df['cgpa'].std()
lower_limit = df['cgpa'].mean() – 3*df['cgpa'].std()
```

8. **Step 8: Now, apply the capping**

```
df['cgpa'] = np.where(
df['cgpa']>upper_limit,
upper_limit,
np.where(
df['cgpa']<lower_limit,
lower_limit,
df['cgpa']
```

9. **Step 9: Now, see the statistics using the "Describe" function**

```
df['cgpa'].describe()
```

```
mean         6.961499
std          0.612688
min          5.113546
25%          6.550000
50%          6.960000
75%          7.370000
max          8.808934
Name: cgpa, dtype: float64
```

This completes our Z-score-based technique!

IQR Based Filtering

Used when our data distribution is skewed.

Step-1: Import necessary dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Step-2: Read and load the dataset

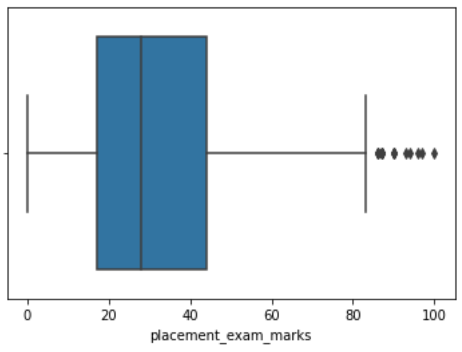
```
df = pd.read_csv('placement.csv')
df.head()
```

Step-3: Plot the distribution plot for the features

```
plt.figure(figsize=(16,5))
plt.subplot(1,2,1)
sns.distplot(df['cgpa'])
plt.subplot(1,2,2)
sns.distplot(df['placement_exam_marks'])
plt.show()
```

Step-4: Form a box-plot for the skewed feature

```
sns.boxplot(df['placement_exam_marks'])
```



```
percentile25 = df['placement_exam_marks'].quantile(0.25)
percentile75 = df['placement_exam_marks'].quantile(0.75)
```

Step-6: Finding the upper and lower limits

```
upper_limit = percentile75 + 1.5 * iqr
lower_limit = percentile25 - 1.5 * iqr
```

Step-7: Finding outliers

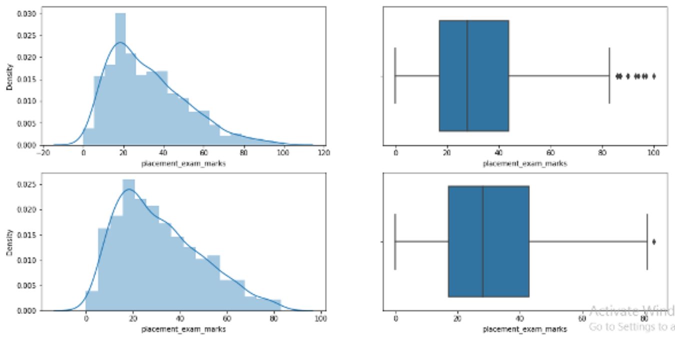
```
df[df['placement_exam_marks'] > upper_limit]
df[df['placement_exam_marks'] < lower_limit]
```

Step-8: Trimming outliers

```
new_df = df[df['placement_exam_marks'] < upper_limit]
new_df.shape
```

Step-9: Compare the plots after trimming

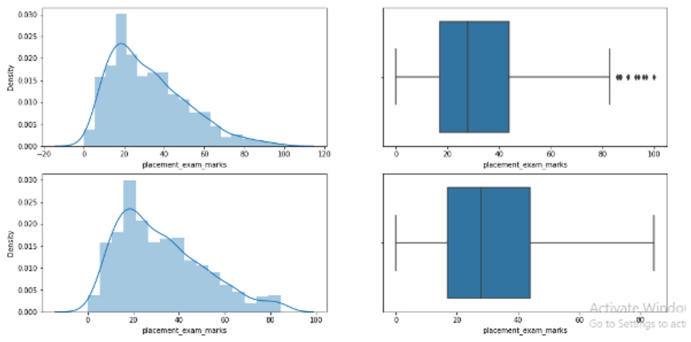
```
plt.figure(figsize=(16,8))
plt.subplot(2,2,1)
sns.distplot(df['placement_exam_marks'])
plt.subplot(2,2,2)
sns.boxplot(df['placement_exam_marks'])
plt.subplot(2,2,3)
sns.distplot(new_df['placement_exam_marks'])
plt.subplot(2,2,4)
sns.boxplot(new_df['placement_exam_marks'])
plt.show()
```



Step-10: Capping

```
new_df_cap = df.copy()
new_df_cap['placement_exam_marks'] = np.where(
    new_df_cap['placement_exam_marks'] > upper_limit,
    upper_limit,
    np.where(
        new_df_cap['placement_exam_marks'] < lower_limit,
        lower_limit,
        new_df_cap['placement_exam_marks']
```

```
plt.figure(figsize=(16,8))
plt.subplot(2,2,1)
sns.distplot(df['placement_exam_marks'])
plt.subplot(2,2,2)
sns.boxplot(df['placement_exam_marks'])
plt.subplot(2,2,3)
sns.distplot(new_df_cap['placement_exam_marks'])
plt.subplot(2,2,4)
sns.boxplot(new_df_cap['placement_exam_marks'])
plt.show()
```



This completes our IQR-based technique!

Percentile Method

- This technique works by setting a particular threshold value, which is decided based on our problem statement.
- While we remove the outliers using capping, then that particular method is known as **Winsorization**.
- Here, we always maintain **symmetry** on both sides, meaning if we remove 1% from the right, the left will also drop by 1%.

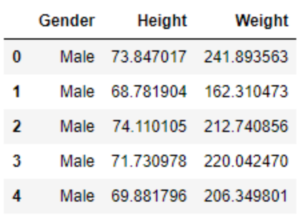
Steps to follow for the percentile method:

Step-1: Import necessary dependencies

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

Step-2: Read and Load the dataset

```
df = pd.read_csv('weight-height.csv')
df.sample(5)
```

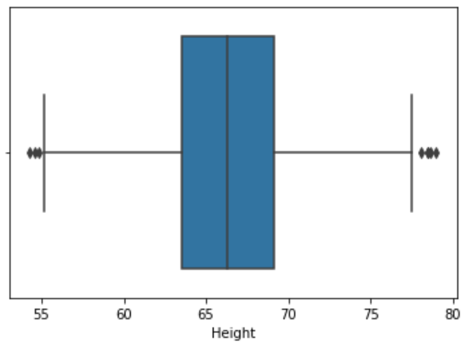


	Gender	Height	Weight
0	Male	73.847017	241.893563
1	Male	68.781904	162.310473
2	Male	74.110105	212.740856
3	Male	71.730978	220.042470
4	Male	69.881796	206.349801

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

Step-4: Plot the box-plot of the "height" feature

```
sns.boxplot(df['Height'])
```



Step-5: Finding the upper and lower limits

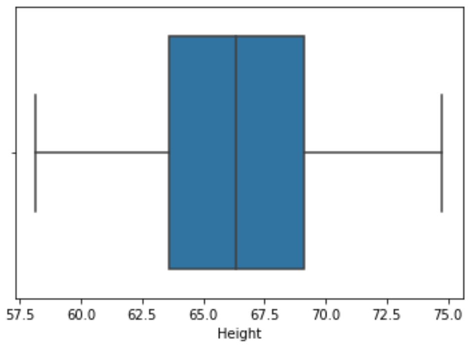
```
upper_limit = df['Height'].quantile(0.99)
lower_limit = df['Height'].quantile(0.01)
```

Step-6: Apply trimming

```
new_df = df[(df['Height'] <= 74.78) & (df['Height'] >= 58.13)]
```

Step-7: Compare the distribution and box-plot after trimming

```
sns.distplot(new_df['Height'])
sns.boxplot(new_df['Height'])
```



Winsorization

Step-8: Apply Capping (Winsorization)

```
df['Height'] = np.where(df['Height'] >= upper_limit,
        upper_limit,
        np.where(df['Height'] <= lower_limit,
        lower_limit,
        df['Height']))
```

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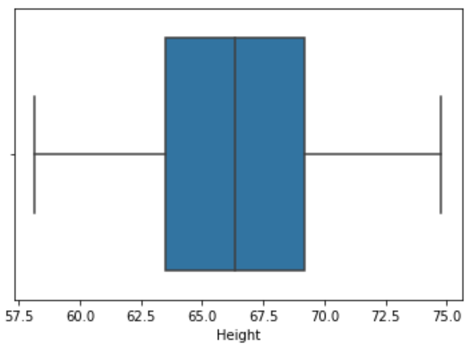
```
sns.distplot(df['Height'])
sns.boxplot(df['Height'])
```



This completes our percentile-based technique!

Conclusion

Outlier detection and removal is a crucial data analysis step for a machine learning model, as outliers can significantly impact the accuracy of a model if they are not handled properly. The techniques discussed in this article, such as Z-score and Interquartile Range (IQR), are some of the most popular methods used in outlier detection. The technique to be used depends on the specific characteristics of the data, such as the distribution and number of variables, as well as the required outcome.

Key Takeaways

- Outliers can be treated in different ways, such as trimming, capping, discretization, or by treating them as missing values.
- Emperical relations are used to detect outliers in normal distributions, and Inter-Quartile Range (IQR) is used to do so in skewed distributions. For all other distributions, we use the percentile-based approach.
- Z-score treatment is implemented in Python by importing the necessary dependencies, reading and loading the dataset, plotting the distribution plots, finding the boundary values, finding the outliers, trimming, and then capping them.

Frequently Asked Questions

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08 Jan 2024

I am currently pursuing my Bachelor of Technology (B.Tech) in Computer Science and Engineering from the Indian Institute of Technology Jodhpur(IITJ). I am very enthusiastic about Machine learning, Deep Learning, and Artificial Intelligence. Feel free to connect with me on Linkedin.

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Frequently Asked Questions

Q1. What are some of the most popular outlier detection techniques?

A. Most popular outlier detection methods are Z-Score, IQR (Interquartile Range), Mahalanobis Distance, DBSCAN (Density-Based Spatial Clustering of Applications with Noise, Local Outlier Factor (LOF), and One-Class SVM (Support Vector Machine).

Q2. What are the libraries and plots we can utilize to detect and remove outliers in a data set for a data science project?

Q3. What is the advantage of removing outliers?

Responses From Readers

What are your thoughts?...

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Nawel Ben Chaabane
04 Aug, 2021

Hello, thanks a lot for the article ! Is there a link to download the data: placement.csv file ? Thanks again. Best regards.

Mehedi Azad
02 Mar, 2023

thank you so much. this article is well decorated and helpful must say. how can I get the dataset that is used in his article, please?

Jordan
04 Jan, 2024

I wish you guys would provide links to the datasets. That way people like me who trying to learn could do

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