

DATA CLEANING



Introduction to Data Cleaning

- Data extracted from real world contains incorrect, incomplete, irrelevant or missing values which need to be cleaned.
- Cleaning can be done by modifying, replacing or deleting such values.
- Data cleaning is a fundamental part of data science lifecycle.



<https://www.educative.io/blog/what-is-data-cleaning>



Quality of Data

- Today's world is all about data-driven decision making, hence the quality of our data will ultimately impact the quality of the decision that we make based on that data.
- Data is generally considered high quality if it is **“fit for [its] intended uses in operations, decision making and planning.”**
- Through different data cleaning techniques, we can improve the quality of our data extracted from the real world.



Examples of Anomalies (1/2)

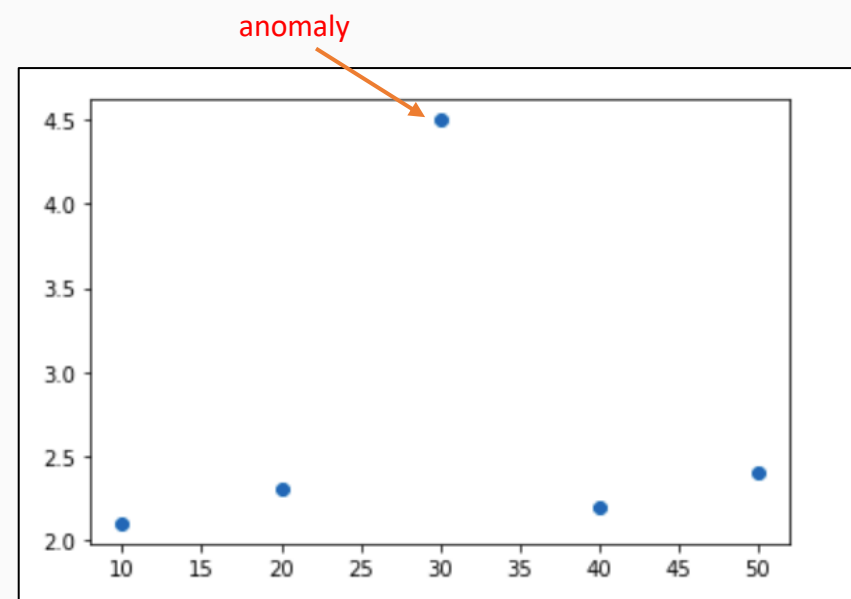
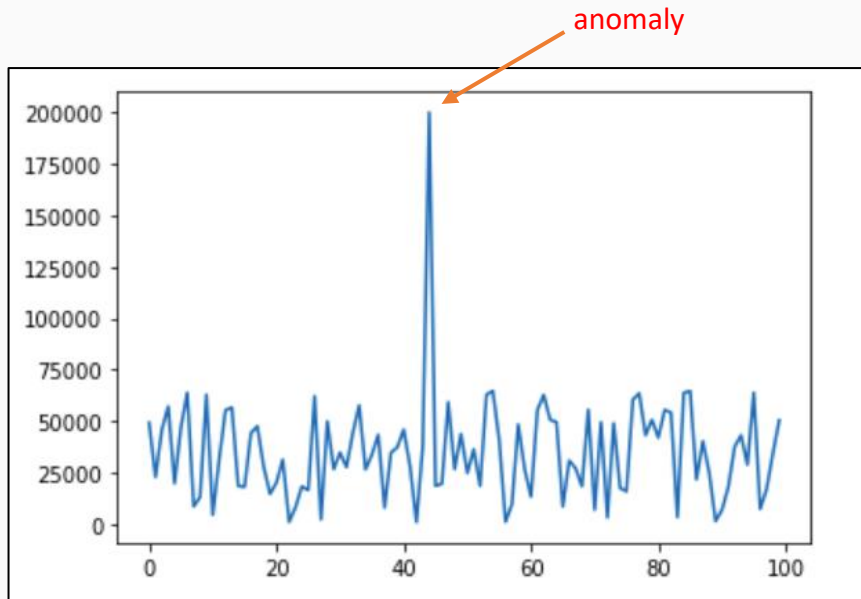
- An anomaly in data, also known as an outlier, is the observation which differs significantly from the standard pattern.
- Anomalies in data could arise for a number of reasons, such as human error.
- Consider the given series containing width of a table measured by 5 different students.
 - The third value is significantly different than the rest – an anomaly!

```
0    2.1
1    2.3
2    4.5
3    2.2
4    2.4
dtype: float64
```



Examples of Anomalies (2/2)

- Data extracted from real world often contains such anomalies;
 - Temperature data over a period of 6 months might contain some irregular values due to tremendous shifts in weather conditions.
- It is important to detect such anomalies in the data and deal with them appropriately.





Median-based Anomaly Detection

- One way to detect anomalies is using the median value.
- We set a reasonable threshold and if for a certain value, $|\text{value} - \text{median}| > \text{threshold}$, then the value is considered an anomaly.

```
x = pd.Series([2.1, 2.3, 4.5, 2.2, 2.4])

median = np.median(x)
threshold = 2
outliers = []
for item in x:
    if abs(item - median) > threshold:
        outliers.append(item)

print(outliers)

[4.5]
```



Quiz Time

A certain dataset has a median value 3, and the threshold for anomaly detection is 2. Third value of the dataset is 7. According to median-based anomaly detection, is the third value an anomaly?

- Yes
- No



Quiz Time

A certain dataset has a median value 3, and the threshold for anomaly detection is 2. Third value of the dataset is 7. According to median-based anomaly detection, is the third value an anomaly?

- Yes
- No



Mean-based Anomaly Detection

- Another way to detect anomalies is using mean and standard deviation of the data.
- We define the range as $(\text{mean} - \text{standard deviation}) \leq \text{value} \leq (\text{mean} + \text{standard deviation})$
 - i.e., any value less than $(\text{mean} - \text{standard deviation})$ or greater than $(\text{mean} + \text{standard deviation})$ is considered an anomaly.

```
x = pd.Series([2.1, 2.3, 4.5, 2.2, 2.5])

mean = np.mean(x)
std = np.std(x)
outliers = []
for item in x:
    if (item < mean - std) or (item > mean + std):
        outliers.append(item)

outliers

[4.5]
```



Quiz Time

1. A certain dataset has a mean value 20 and a standard deviation of 2.5. A certain value x in the dataset is 16. According to mean-based anomaly detection, is x an anomaly?
- Yes
 - No



Quiz Time

1. A certain dataset has a mean value 20 and a standard deviation of 2.5. A certain value x in the dataset is 16. According to mean-based anomaly detection, is x an anomaly?

- Yes
- No



Z-score-based Anomaly Detection

- Another technique for anomaly detection is the Z-score.
- Z-score is a statistical measure showing how many standard deviations a certain value is from the mean.
- It is defined as;
 - $Z = (\text{value} - \text{mean}) / \text{standard deviation}$
- If the Z-score of a value is greater than a reasonable threshold, it is considered an anomaly.

```
x = pd.Series([2.1, 2.3, 4.5, 2.2, 2.4])

mean = np.mean(x)
std = np.std(x)
outliers = []
for item in x:
    z_score = (item - mean) / std
    if z_score > 1.5:
        outliers.append(item)

print(outliers)

[4.5]
```



Quiz Time

1. A certain dataset has a mean value 12 and a standard deviation of 2. A certain value x in the dataset is 8. Compute the Z-score of the value x ?

- 4
- 20
- 2
- 10



Quiz Time

1. A certain dataset has a mean value 12 and a standard deviation of 2. A certain value x in the dataset is 8. Compute the Z-score of the value x ?

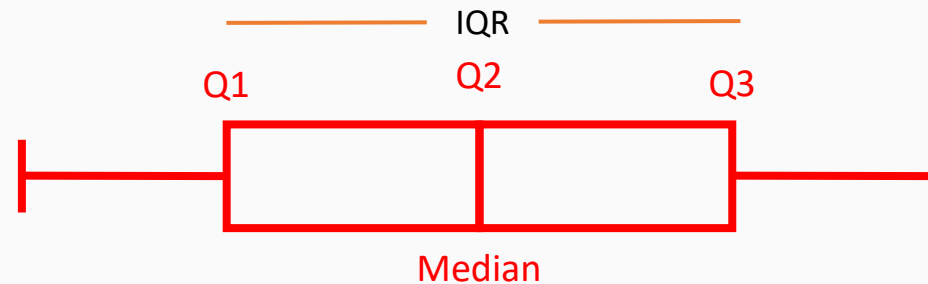
- 4
- 20
- 2
- 10



Interquartile Range for Anomaly Detection (1/3)

IQR

- We can also use interquartile range (IQR) for detecting anomalies in the data.
- A quartile divides the dataset (sorted from smallest to largest) into 3 points and 4 intervals.
- The interquartile range (IQR) is the difference between the 3rd quartile and 1st quartile ($IQR = Q3 - Q1$).





Interquartile Range for Anomaly Detection (2/3)

- Consider the series of widths from the previous slide as a list as shown below;
 - Widths = [2.3, 2.2, 4.5, 2.1, 2.5]
- We first sort this list from smallest to largest.
 - Widths = [2.1, 2.2, 2.3, 2.5, 4.5]
- The first quartile is at 25%, which is 2.2.
- The second quartile is 50%, which is 2.3 (median).
- The third quartile is 75%, which is 2.5.
- Use the `numpy.percentile()` function to get the quartiles of a dataset.
 - Automatically sorts the data from smallest to largest.



Interquartile Range for Anomaly Detection (3/3)

Anomaly

- Any value less than $(Q1 - 1.5 \times IQR)$ or greater than $(Q3 + 1.5 \times IQR)$ is considered an anomaly.

```
x = pd.Series([2.1, 2.3, 4.5, 2.2, 2.5])

Q1, Q3 = np.percentile(x, [25, 75])
IQR = Q3 - Q1
outliers = []
for item in x:
    if item < (Q1 - 1.5 * IQR) or item > (Q3 + 1.5 * IQR):
        outliers.append(item)

outliers

[4.5]
```



Quiz Time

1. Consider the given dataset $x=[1,2,3,4,5]$. What is the second quartile (Q2) of the dataset?
 - 2
 - 3
 - 4
2. Compute the interquartile range for the dataset $x=[1,2,3,4,5]$.
 - 1
 - 2
 - 3



Quiz Time

1. Consider the given dataset $x=[1,2,3,4,5]$. What is the second quartile (Q2) of the dataset?
 - 2
 - 3
 - 4
2. Compute the interquartile range for the dataset $x=[1,2,3,4,5]$.
 - 1
 - 2
 - 3



Dealing with Missing values (1/6)

- Apart from outliers/anomalies, data also often contains missing values.
- A missing value means loss of information.
- In pandas, an NaN indicates a missing value.
- Consider the following dataframe called data with one missing value in the 'Age' column.

	Name	Age
0	Edison	28
1	Edward	27
2	James	NaN
3	Neesham	36



Dealing with Missing values (2/6)

Finding Missing Values in Pandas

- The `.isnull()` function tells us if a cell is empty or not.
- Use the `.sum()` function with the `.isnull()` function to find total number of missing values in the data.

```
data.isnull()
```

	Name	Age
0	False	False
1	False	False
2	False	True
3	False	False

```
data.isnull().sum()
```

```
Name    0
Age      1
dtype: int64
```



Dealing with Missing values (3/6)

Dealing with Missing Values in Pandas

- There are a number of ways to deal with these missing values.
- Which method to use depends upon the kind of data and the task that the data is supposed to accomplish.
- Different Methods Used are;
 - Deleting rows with missing values.
 - Replacing missing values with mean/median/mode.



Dealing with Missing values (4/6)

Deleting Rows with Missing Values

- One way to deal with the missing values is to delete the rows containing missing values.
- Use the `.dropna()` with `inplace` set to `True` to remove missing values from the dataset.

```
data.dropna(inplace=True)  
data
```

	Name	Age
0	Edison	28
1	Edward	27
3	Neesham	36



Dealing with Missing values (5/6)

Replacing Missing Values with Mean/Median/Mode

- We can also replace the missing values in each column with one of the statistical measures (mean/median/mode) of that column.
- Use the `.fillna()` method to fill the missing values with mean, median, or mode.

```
data.fillna(data.mean(), inplace=True)  
data
```

	Name	Age
0	Edison	28.000000
1	Edward	27.000000
2	James	30.333333
3	Neesham	36.000000



Dealing with Missing values (6/6)

Replacing Missing Values with Mean/Median/Mode

- In this example, we replace the missing value in the 'Age' column with the mode of the 'Age' column.

data		
	0	1
0	Edison	28.0
1	Edward	27.0
2	James	NaN
3	Neesham	36.0
4	Stuart	27.0

```
data['Age'].mode()
```

```
0    27.0  
dtype: float64
```

```
data['Age'].fillna(data['Age'].mode()[0], inplace=True)  
data
```

	Name	Age
0	Edison	28.0
1	Edward	27.0
2	James	27.0
3	Neesham	36.0
4	Stuart	27.0



Feature Scaling (1/5)

- Sometimes, we might wish to normalize the range of each feature (column) of the given dataset.
- For example, consider the given dataframe where the range of each feature (column) is different.
- We would like to scale all the features to the same range, e.g. 0-1, 1-100, etc.

df

	Age	Salary
0	28.0	10000
1	27.0	15000
2	30.0	11000
3	36.0	11000
4	27.0	13000



Feature Scaling (2/5)

Normalization

- One simple method of feature scaling is normalization, also called min-max scaling.
- For every value in a feature (column), we subtract the minimum value of the particular feature (column) from it and divide it by the difference of maximum and minimum value of that feature (column).
 - Normalized value = $(\text{original value} - \text{minimum}) / (\text{maximum} - \text{minimum})$
- This method scales the features in the range [0, 1]



Feature Scaling (3/5)

Normalization

- For min-max scaling, use the following line of code;
 - `normalized_df=(df-df.min())/(df.max()-df.min())`
- Pandas will automatically use the feature (column) min-max values for each feature.

```
df = (df - df.min()) / (df.max() - df.min())  
df
```

	Age	Salary
0	0.111111	0.0
1	0.000000	1.0
2	0.333333	0.2
3	1.000000	0.2
4	0.000000	0.6



Feature Scaling (4/5)

Standardization

- In standardization, for each value of a feature (column), we subtract the mean of that feature (column) from the value and divide the result by the standard deviation of that feature (column).
 - Standardized value = $(\text{original value} - \text{mean}) / \text{standard deviation}$
- As a result, the standard deviation of the feature (column) becomes 1.



Feature Scaling (5/5)

Standardization

- For standardization, use the following line of code;
 - `standardized_df=(df-df.mean())/df.std()`
- Once again, Pandas will automatically use the feature (column) mean and std values for each feature.

```
df = (df - df.mean()) / df.std()  
df
```

	Age	Salary
0	-0.423109	-1.0
1	-0.687552	1.5
2	0.105777	-0.5
3	1.692435	-0.5
4	-0.687552	0.5

```
df.std()  
Age      1.0  
Salary   1.0  
dtype: float64
```



Quiz Time

1. Min-max scaling is also known as;
 - Normalization
 - Standardization



Quiz Time

1. Min-max scaling is also known as;

- Normalization
- Standardization



Regular Expressions (1/8)

- Regular Expression or RegEx is an expression containing a sequence of characters for matching patterns in strings.
- Almost all the major programming languages have implementation for RegEx.
- The 're' module of Python is used for pattern matching using RegEx in Python.
- Following functions are available in the 're' module;
 - `findall()`
 - `search()`
 - `sub()`



Regular Expressions (2/8)

re.findall()

- `re.findall()` is used to match all the occurrences of a pattern in a string.
- A list with all the matches is returned.
- In the given figure, we find how many times does the word 'Python' appear in the given string.

```
import re
```

```
txt = 'Python is my favorite programming language. I love Python.'  
x = re.findall('Python', txt)  
x
```

```
['Python', 'Python']
```

```
len(x)
```

```
2
```



Regular Expressions (3/8)

re.findall()

- In the given figure, we check if the string x starts with the word 'Python' or not.
- The ^ character returns a match only if the string starts with the pattern given after ^ symbol.
- The string y contains the word Python but does not begin with it, hence we get an empty list.

```
import re
```

```
x = 'Python is my favorite programming language.'  
re.findall('^Python', x)
```

```
['Python']
```

```
y = 'I love Python.'  
re.findall('^Python', y)
```

```
[]
```



Regular Expressions (4/8)

re.findall()

- To match numbers in a string, we use the `\d` sequence.
- A `+` sign at the end of `\d` makes sure that number such as 50 is treated as 50 and not as 5 and 0.
- You can find a list of sequences at https://www.w3schools.com/python/python_regex.asp

```
import re
```

```
txt = 'Python was released in 1991.'  
re.findall('\d', txt)
```

```
['1', '9', '9', '1']
```

```
txt = 'Python was released in 1991.'  
re.findall('\d+', txt)
```

```
['1991']
```



Regular Expressions (5/8)

re.findall()

- To find matches in a Series, we first convert the Series into a string using the `.to_string()` method.

```
import pandas as pd
import re
```

```
txtList = ['Pakistan', 'Indonesia', 'Jordan', 'Pakistan']
txt = pd.Series(txtList)
txt
```

```
0    Pakistan
1  Indonesia
2     Jordan
3    Pakistan
dtype: object
```

```
re.findall('Pakistan', txt.to_string())
['Pakistan', 'Pakistan']
```



Regular Expressions (6/8)

re.search()

- `re.search()` returns a Match Object in case of a pattern match in the string.
- We can get the position of the match using the `.span()` method of the Match Object.

```
import pandas as pd
import re
```

```
txt = 'Hello World'
match_object = re.search('World', txt)
match_object
```

```
<re.Match object; span=(6, 11), match='World'>
```

```
match_object.span()
```

```
(6, 11)
```



Regular Expressions (7/8)

re.sub()

- To replace text in a string with a different text, use the `re.sub()` method.

```
import pandas as pd  
import re
```

```
txt = 'C is my favorite programming language.'  
re.sub(pattern='C', repl='Python', string=txt)  
  
'Python is my favorite programming language.'
```



Regular Expressions (8/8)

- <https://regex101.com/> is a very good website to create and test regular expressions.
- We have also added some resources to learn more about regular expression in Python in the 'Resources slide'.

The screenshot shows the regex101.com website interface. At the top, there is a dark blue header with the site logo, social media links, and navigation options. Below the header, the main content area is divided into two sections: 'REGULAR EXPRESSION' and 'TEST STRING'. The 'REGULAR EXPRESSION' section has a text input field with the placeholder text 'insert your regular expression here' and a 'no match' status indicator. The 'TEST STRING' section has a large text area with the placeholder text 'insert your test string here'.



Resources

- https://www.w3schools.com/python/pandas/pandas_cleaning.asp
- <https://www.geeksforgeeks.org/interquartile-range-to-detect-outliers-in-data/>
- <https://www.kdnuggets.com/2021/04/data-science-101-normalization-standardization-regularization.html>
- https://www.w3schools.com/python/python_regex.asp