Data Cleaning

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Python Pandas

pip install pandas

pip3 install pandas

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object.

(Definition from https://pandas.pydata.org/pandas-docs/stable/user_guide/dsintro.html)

DataFrame - basic operations

```
import pandas as pd
df = pd.DataFrame() # empty dataframe
# load a csv file into a dataframe
df = pd.read_csv('input_file.csv')
# show the first 10 lines of the dataframe
df.head(10)
```

Data Cleaning Definition (from Wikipedia)

Data cleansing or data cleaning is the process of **detecting and correcting (or removing) corrupt or inaccurate records** from a record set, table, or database and refers to identifying incomplete, incorrect, inaccurate or irrelevant parts of the data and **then replacing, modifying, or deleting the dirty or coarse data**.

Data Cleansing involves the following aspects:

- **missing values**
- **data formatting**
- **data normalization**
- data standardization
- data binning
- remove duplicates

Missing Values

No data value is stored for the variable in an observation

from Wikipedia

Example of Missing Values

Name	Surname	Email	Count
John	Wild		5
Marc	Wales	m.wales@gmail.com	
Maria	Zack	m.zack@live.it	7
Kate	Zack	k.zack@live.it	

Identify Missing Values

In order to check whether our dataset contains missing values, we can use the function `isna()` which returns if an cell of the dataset if NaN or not.

Then we can count how many missing values there are for each column.

```
df.isna().sum()
```

```
Name          0
Surname       0
Email         1
Count         2
```

Missing Values Management

- check the source, for example by contacting the data source to correct the missing values
- drop missing values
- replace the missing value with a value
- leave the missing value as it is

Drop Missing Values

Dropping missing values can be one of the following alternatives:

- **remove rows** having missing values
- **remove the whole column** containing missing values

We can use the `dropna()` by specifying the axis to be considered.

If we set `axis = 0` we drop the entire row,

if we set `axis = 1` we drop the whole column

Examples

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

Name	Surname
John	Wild
Marc	Wales
Maria	Zack

```
df.dropna(axis=0)
```

Name	Surname	Email	Count
Maria	Zack	m.zack@live.it	7

Examples (cont.)

As an alternative, we can specify only the column on which the dropping operation must be applied.

```
df.dropna(subset=['Email'],axis=0,inplace=True)
```

Name	Surname	Email	Count
Marc	Wales	m.wales@gmail.com	
Maria	Zack	m.zack@live.it	7
Kate	Zack	k.zack@live.it	

inplace=True

We can use the argument **`inplace=True`** to store changes in the original dataframe df.

Dropping by percentage

Another alternative involves the dropping of columns where a certain percentage of not-null values is available. This can be achieved through the thresh parameter. In the following example we keep only columns where there are at least the 75% of not null values.

```
df.dropna(thresh=0.75*len(df),axis=1,inplace=True)
```

Name	Surname	Email
John	Wild	
Marc	Wales	m.wales@gmail.com
Maria	Zack	m.zack@live.it
Kate	Zack	k.zack@live.it

Replace Missing Values

A good strategy when dealing with missing values involves their replacement with another value. Usually, the following strategies are adopted:

- for numerical values replace the missing value with the **average value** of the column
- for categorical values replace the missing value with the **most frequent** value of the column
- use other functions, such as **linear interpolation**

fillna() - numerical values

`fillna()` function replaces all the NaN values with the value passed as argument. For example, for **numerical values**, all the NaN values in the numeric columns could be replaced with the average value.

```
df['Count'].fillna(df['Count'].mean())
```

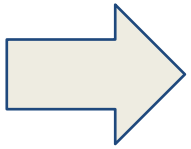
Name	Surname	Email	Count
John	Wild		5
Marc	Wales	m.wales@gmail.com	6
Maria	Zack	m.zack@live.it	7
Kate	Zack	k.zack@live.it	6

fillna() - categorical values

For categorical values, the missing values can be replaced with the most frequent value.

```
df['Car'].fillna(df['Car'].mode())
```

Car
Ferrari
Lamborghini
Ferrari



Car
Ferrari
Lamborghini
Ferrari
Ferrari

interpolate() - linear interpolation

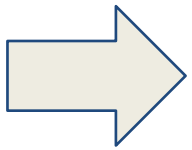
We could replace a missing value over a column, with the interpolation between the previous and the next values.

We set Limit direction = forward so that the linear interpolation is applied starting from the first row until the last one.

Example

```
df['Count'] = df['Count'].interpolate(method
='linear', limit_direction ='forward')
```

Count
0
4
12

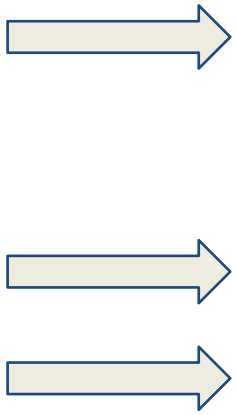


Count
0
4
8
12

Data Formatting

Transforming data into a common format, which helps users to perform comparisons.

Not formatted table



City	Value
New York	3
Chicago	5
N.Y.	6
New York (USA)	7
Chicago (U.S.A.)	3

Data Formatting

- transform data in the correct format
- make data homogeneous
- use a single value to represent the same concept

Correct Format

Make sure that every column is assigned to the correct data type. This can be checked through the property **`dtypes`**.

Example

```
df.dtypes
```

Name	Value
John	3.2999
Mary	2.3

```
Name string
Value   float64
```

Correct Data Types

```
Name string
Value   int64
```

Wrong Data Type

astype()

We can convert the column Value to int64 by using the function **`astype()`**

```
df['Value'] = df['Value'].astype('float64')
```

The `astype()` function supports all datatypes described at this link.

Make data homogeneous - categorical data

Categorical data should have all the same formatting style:

- lower case
  - `df['Name'] = df['Name'].str.lower()`
- remove white space everywhere:
  - `df['Name'] = df['Name'].str.replace(' ', '')`
- remove white space at the beginning of string:
  - `df['Name'] = df['Name'].str.lstrip()`
- remove white space at the end of string:
  - `df['Name'] = df['Name'].str.rstrip()`
- remove white space at both ends:
  - `df['Name'] = df['Name'].str.strip()`

Make data homogeneous - numeric data

Numeric data should have for example the same number of digits after the point.

- Round to specific decimal places
  - `df['Value'] = df['Value'].round(2) # 2 decimal points`
- Round up – Single DataFrame column
  - `df['Value'] = df['Value'].apply(np.ceil)`
- Round down – Single DataFrame column
  - `df['Value'] = df['Value'].apply(np.floor)`

Single Value for the same concept

We can use the **`unique()`** function to list all the values of a column.

City	Value
New York	3
Chicago	5
N.Y.	6
New York (USA)	7
Chicago	3

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

```
[ 'New York',
'Chicago', 'N.Y.',
'New York (USA)' ]
```

set_pattern()

We must manage each *issue* separately.

We define a function, called **`set_pattern()`** which receives as input a cell and manipulates it according to our needs.

```
import re
def set_pattern(x):
    pattern = "(?=New York \(USA\)|N.Y.)\\w+"
    res = re.match(pattern, x)
    if res:
        x = x.replace(x, 'New York')
    return x
```

Put here all the values which must
be represented by the same value

set_pattern() - cont.

Now we can apply the function the specific column:

```
df['City'] = df['City'].apply(lambda x: set_pattern(x))
```

City	Value
New York	3
Chicago	5
New York	6
New York	7
Chicago	3

Data Normalisation

Adjusting values measured in different scales to a common scale.

Normalization applies only to columns containing numeric values.

Techniques for Normalisation

- single feature scaling
- min max
- z-score
- log scaling
- clipping

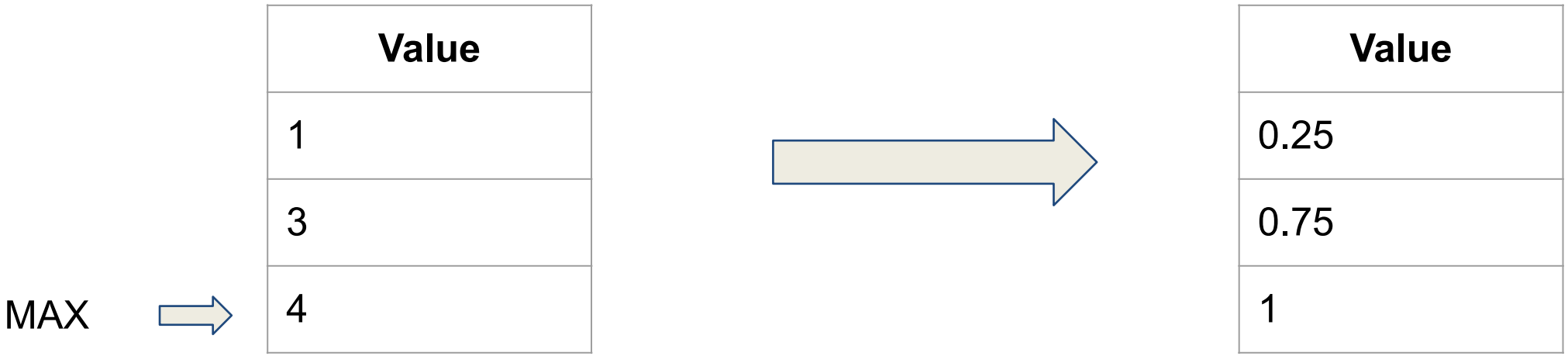
Single Feature Scaling

Single Feature Scaling converts every value of a column into a number between 0 and 1.

The new value is calculated as the current value divided by the max value of the column.

Example

```
df['Value'] = df['Value']/df['Value'].max()
```



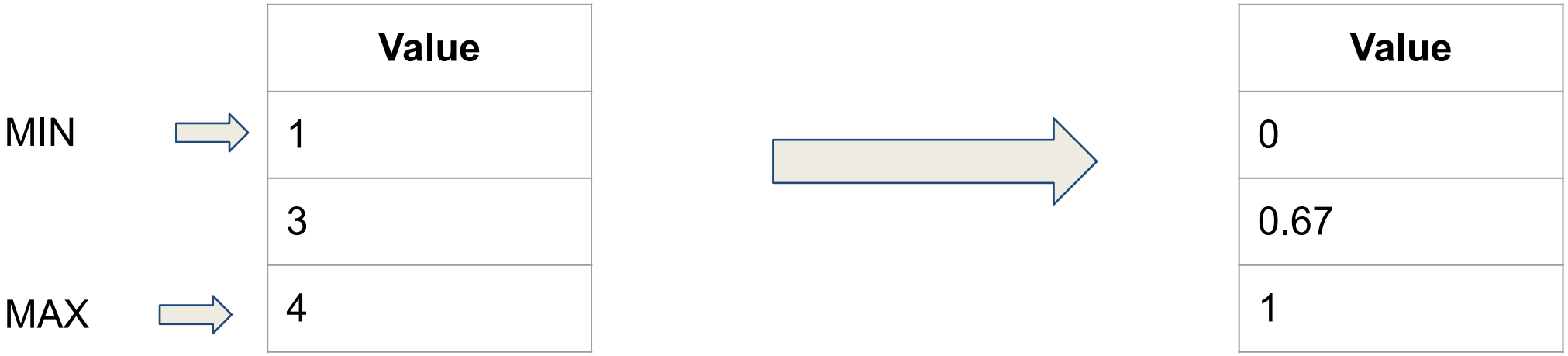
Min Max

Min Max converts every value of a column into a number between 0 and 1.

The new value is calculated as the difference between the current value and the min value, divided by the range of the column values.

Example

```
df['Value'] = (df['Value']-df['Value'].min())
    / (df['Value'].max()-df['Value'].min())
```



z-score

Z-Score converts every value of a column into a number around 0.

Typical values obtained by a z-score transformation range from -3 and 3.

The new value is calculated as the difference between the current value and the average value, divided by the standard deviation.

Example

```
df['Value'] =
(df['Value']-df['Value'].mean()) /
df['Value'].std()
```

Value
1
3
4

Value
-1.34
0.26
1.07

MEAN: 2.66 STD: 1.25

Log scaling

Log Scaling involves the conversion of a column to the logarithmic scale.

If we want to use the natural logarithm, we can use the `log()` function of the `numpy` library.

We must deal with log(0) because it does not exist

Example

```
df['Value'] = df['Value'].apply(lambda x:
    np.log(x) if x != 0 else 0)
```

Value
1
3
4

Value
0
1.09
1.39

Clipping

Clipping involves the capping of all values below or above a certain value. Clipping is useful when a column contains some outliers.

We can set a maximum vmax and a minimum value vmin and set all outliers greater than the maximum value to vmax and all the outliers lower than the minimum value to vmin.

Example

```
vmax = 35
vmin = 2
df['Value'] = df['Value'].apply(lambda x:
vmax if x > vmax else vmin if x < vmin else
x)
```

Value
1
30
40

Value
2
30
35

Data Standardization

Standardization transforms data to have a mean of zero and a standard deviation of 1.

Techniques for standardization

- z-score
- z-map

z-score

The new value is calculated as the difference between the current value and the average value, divided by the standard deviation.

We can use the **`zscore()`** function of the **`scipy.stats`** library.

Example

```
from scipy.stats import zscore
df['Value'] = zscore(df['Value'])
```

Value
1
3
4

Value
-1.34
0.26
1.07

MEAN: 2.66 STD: 1.25

z-map

The new value is calculated as the difference between the current value and the average value of a comparison array, divided by the standard deviation of a comparison array.

We can use the **`zmap()`** function of the **`scipy.stats`** library.

Example

```
from scipy.stats import zmap
df['Value'] = zmap(df['Value'], df['Count'])
```

Value	Count
1	3
3	4
4	5

Value	Count
-3.67	3
-1.22	4
0	5

Data Binning

Data binning (or bucketing) groups data in bins (or buckets), in the sense that it replaces values contained into a small interval with a single representative value for that interval.

Binning

Binning can be applied to convert numeric values to categorical or to sample (quantize) numeric values.

Binning is a technique for data smoothing. Data smoothing is employed to remove noise from data. Three techniques for data smoothing:

- binning
- regression
- outlier analysis

Techniques for binning

- convert numeric to categorical
  - binning by distance
  - binning by frequency
- reduce numeric values
  - sampling

Binning by distance - cut()

- Define the bin edges
- Convert numeric into categorical variables
- Define the number of bins and the associated labels

Size
1000
5
500
100
250
400

bins = 4

Label	**Ranges**
small	0-50
medium	51-100
large	101-500
very large	> 500

Size
very large
small
large
medium
large
large

Example

```
import numpy as np
bins = [ 0, 50, 100, 500, 1000 ]
labels = ['small', 'medium', 'large','very large']
df['Size'] = pd.cut(df['Size'] , bins=bins, labels=labels, include_lowest=True)
```

Example 2 - Linear Space among ranges

```
min_value = df[‘Size’].min()
max_value = df[‘Size’].max()
n_bins = 4
bins = np.linspace(min_value,max_value,n_bins+1)
array([   5. ,  336.66666667,  668.33333333, 1000.
])
labels = ['small', 'medium', 'large','very large']
df['Size'] = pd.cut(df['Size'] , bins=bins,
labels=labels, include_lowest=True)
```

Example 2 (cont.)

Size
1000
5
500
100
250
400

bins = 4

Label	Ranges
small	0 - 5
medium	5 - 336.67
large	336.67-668.33
very large	668.33 - 1000

Size
very large
small
medium
small
small
medium

Binning by frequency - qcut()

- Quantile-based discretization function
- Calculate the size of each bin so that each bin contains (almost) the same number of observations, but the bin range will vary.

Example

Size
1000
5
500
100
250
400
10
30

bins = 4
2 observations for each bin

Label
small
medium
large
very large

Size
very large
small
very large
medium
large
large
small
medium

Example (cont.)

```
labels = ['small', 'medium', 'large','very large']
n_bins = 4
df['Size'] = pd.qcut(df['Size'], q=n_bins,precision=1, labels=labels)
```

We can set the `precision` parameter to define the number of decimal points.

Sampling

It permits to reduce the number of samples, by grouping similar values or contiguous values. There are three approaches to perform sampling:

- by bin means: each value in a bin is replaced by the mean value of the bin.
- by bin median: each bin value is replaced by its bin median value.
- by bin boundary: each bin value is replaced by the closest boundary value, i.e. maximum or minimum value of the bin.

binned_statistics()

- We exploit the `binned_statistic()` function of the `scipy.stats` package can be used.
- This function receives two arrays as input, x_data and y_data, as well as the statistics to be used (e.g. median or mean) and the number of bins to be created.
- The function returns the values of the bins as well as the edges of each bin.

Example

Size
1000
5
500
100
250
400
10
30

bins = 4

Intervals
5 - 253.75
273.75 - 502.5
502.5 - 751.25
751.25 - 1000

Size
875,625
129.375
378.125
129.375
129.375
378.125
129.375
129.376

Example (cont.)

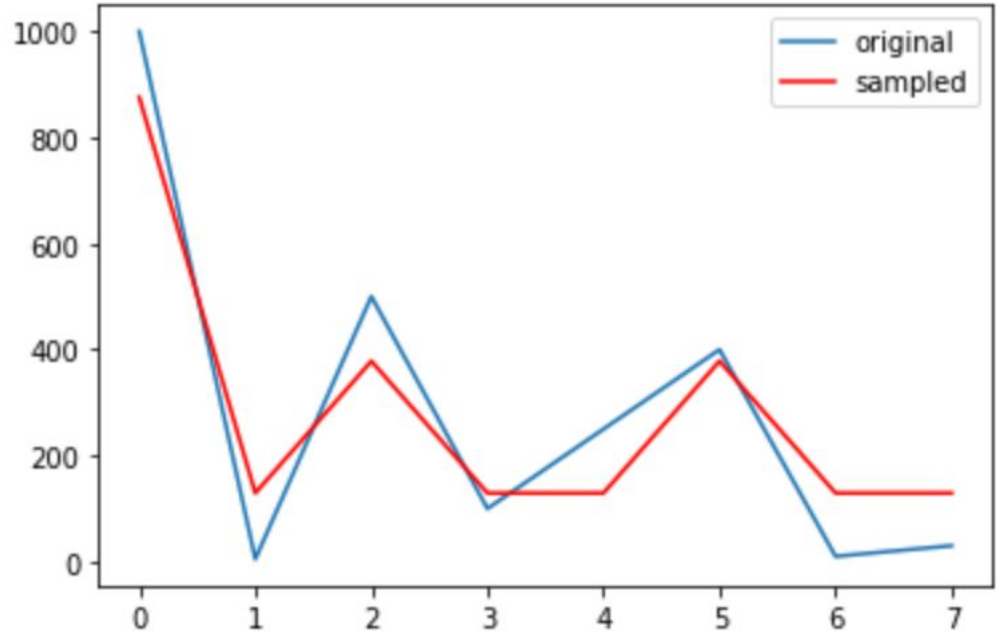
```
from scipy.stats import binned_statistic
x_data = np.arange(0, len(df))
y_data = df['Size']
x_bins,bin_edges, misc = binned_statistic(y_data,x_data,
statistic="median", bins=4)
bin_intervals =
pd.IntervalIndex.from_arrays(bin_edges[:-1],
bin_edges[1:],closed='both')
IntervalIndex([[5.0, 253.75], [253.75, 502.5], [502.5,
751.25], [751.25, 1000.0]])
```

Example (cont.)

```
def set_to_median(x, bin_intervals):
    for interval in bin_intervals:
        if x in interval:
            return interval.mid
```

Example (cont.)

```
df['sampled_size’'] =
df['Size'].apply(lambda x: set_to_median(x,
bin_intervals))
```



Natural breaks in data

We can use the package `jenkspy`, which contains a single function, called `jenks_breaks()`, which calculates the natural breaks of an array, exploiting the Fisher-Jenks algorithm.

We can install the package by running `pip3 install jenkspy`.

Example

```
import jenkspy
breaks = jenkspy.jenks_breaks(df['Size'],
nb_class=3)
df['size_break'] = pd.cut(df['Size'] ,
bins=breaks, labels=labels,
include_lowest=True)
```

Remove Duplicates

Remove all rows that appear at least twice.

The concept of duplicate

	Name	Surname	Value
1	Mark	Grenn	3
2	Mark	Grenn	3
3	Mark	Grenn	4

Rows 1 and 2 are duplicates

Rows 1, 2 and 3 are duplicates in column Name and Surname

Drop duplicates on the basis of all columns

keep just one row for each duplicate

Name	Surname	Value
Mark	Grenn	3
Mark	Grenn	4

Do not maintain any row for the duplicate

Name	Surname	Value
Mark	Grenn	4

Drop duplicates on the basis of the Name and Surname Columns

Keep just one value for column

Name	Surname	Value
Mark	Grenn	3

Do not maintain any row for the duplicate

Name	Surname	Value

drop_duplicates()

```
df1 = df.drop_duplicates()
df2 = df.drop_duplicates(keep=False)
df3 = df.drop_duplicates(subset=["Name",
"Surname"])
df4 = df.drop_duplicates(subset=["Name",
"Surname"], keep=False)
```