Data Journalism

Data Cleaning

Part 1

Angelica Lo Duca
angelica.loduca@iit.cnr.it

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())
```

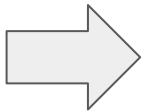
Name	Surname	Email	Count
John	Wild		5
Marc	Wales	m.wales@gmail.com	6
Maria	Zack	m.zack@live.it	7
Kate	Zack	k.zack@live.it	6

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

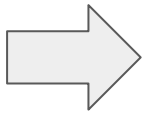
We could replace a missing value over a column, with the interpolation between the previous and the next values.

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.

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

```
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
```

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()
```

MAX

Value
1
3
4

Value
0.25
0.75
1

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
10
30
40

Value
2
30
35