Rail Data Science

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1 Pandas-Library

Pandas is a Python library for data analysis and manipulation, most notably table-formatted data.

Since pandas is an additional library, it needs to be imported first.

[1]:
```
import pandas as pd # Canonical import of pandas as np
```

Pandas supports two major data structures:

- DataFrames: rectangular data tables
- Series: serial data

1.1 Series

Series are one-dimensional (array-like) data structures, useful for single data columns.

[2]:
```
# Create a series from a list, with standard index
s = pd.Series(data = [0,1,4,9,16])
# Display
s.head()
```

[2]:
```
0     0
1     1
2     4
3     9
4    16
dtype: int64
```

1.2 DataFrames

DataFrame can be created from lists or matrices and imported from data, e.g. csv-Files.

An example DataFrame looks like:

[3]:
```
# Create dataframe from list of lists with explicitly named columns
# Since the command stems from the pandas-library, we have to call pd.
 ↪DataFrame
df = pd.DataFrame(data = [[1, 2, 3], [4, 5, 6]], columns = ['A', 'B', 'C'])
```

```
# Show the top lines (.head()) of dataframe
# Since we apply .head() to the dataframe df, we call df.head()
df.head()
```

[3]:
```
   A  B  C
0  1  2  3
1  4  5  6
```

More frequently, we will import datasets from various sources, in the following command we read the list of all stations in Germany in CSV-format (.read_csv() from Pandas):

[4]:
```
df = pd.read_csv(
    'http://download-data.deutschebahn.com/static/datasets/haltestellen/
↪D_Bahnhof_2017_09.csv',
    sep = ';', # Separator default is ","
    decimal=",") # German decimal separator
```

It is a good idea to initially look at the import in order to know the structure, i.e. column names and data fields. This is where `df.head()`comes in handy:

[5]:
```
df.head()
```

[5]:
```
    EVA_NR DS100           IFOPT        NAME VERKEHR     LAENGE     BREITE  \
0  8000001    KA   de:05334:1008  Aachen Hbf      FV   6.091499  50.767800
1  8000002    TA   de:08136:1000   Aalen Hbf      FV  10.096271  48.841013
2  8000004    HA   de:05774:7131  Altenbeken      FV   8.943319  51.766433
3  8000007  FALZ     de:07331:55       Alzey      RV   8.109749  49.750200
4  8000009   NAN  de:09561:11000     Ansbach      FV  10.578239  49.298032

  STATUS
0    NaN
1    NaN
2    NaN
3    NaN
4    NaN
```

The pandas syntax allows for very efficient filtering of the data. In order to access only a single column, we can use `df[column_name]` where `column_name`is one of the above columns:

[6]:
```
df['NAME'].head()
```

[6]:
```
0    Aachen Hbf
1     Aalen Hbf
2    Altenbeken
3         Alzey
4       Ansbach
Name: NAME, dtype: object
```

To quickly learn about the data set at hand, we can use inbuilt functions:

- `df.describe()` - mostly for numerical data
- `df.info()` to provide information on columns and data types

[7]:
```
df.describe()
```

[7]:
```
             EVA_NR       LAENGE       BREITE
count  6.605000e+03  6605.000000  6605.000000
mean   8.011959e+06    10.118460    50.612732
std    2.077004e+04     2.163707     1.729873
min    8.000001e+06     6.070715    47.411032
25%    8.002458e+06     8.398251    49.209151
50%    8.005264e+06     9.871195    50.703920
75%    8.011545e+06    11.902879    51.730323
max    8.099507e+06    14.979080    54.906839
```

[8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6605 entries, 0 to 6604
Data columns (total 8 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   EVA_NR   6605 non-null   int64
 1   DS100    6567 non-null   object
 2   IFOPT    6562 non-null   object
 3   NAME     6605 non-null   object
 4   VERKEHR  6605 non-null   object
 5   LAENGE   6605 non-null   float64
 6   BREITE   6605 non-null   float64
 7   STATUS   111 non-null    object
dtypes: float64(2), int64(1), object(5)
memory usage: 412.9+ KB
```

1.3 Exercise

Display the **DS100** column of the dataset only.

[ ]:
```

```

It also possible to filter for certain content, e.g. to find the names of all long distance stations (showing 'FV' in the 'VERKEHR'-column):

[9]:
```
df['VERKEHR'] == 'FV'
```

[9]:
```
0        True
1        True
2        True
3       False
4        True
        ...
6600    False
6601    False
6602    False
```

```
6603    False
6604    False
Name: VERKEHR, Length: 6605, dtype: bool
```

Luckily, pandas DataFrames accept this list of True/False as argument to restrict the returned values:

[10]:
```
df[df['VERKEHR'] == 'FV'].head()
```

[10]:
```
     EVA_NR DS100           IFOPT                NAME VERKEHR     LAENGE  \
0   8000001    KA   de:05334:1008          Aachen Hbf      FV   6.091499
1   8000002    TA   de:08136:1000           Aalen Hbf      FV  10.096271
2   8000004    HA   de:05774:7131          Altenbeken      FV   8.943319
4   8000009   NAN  de:09561:11000             Ansbach      FV  10.578239
5   8000010   NAH  de:09661:99082  Aschaffenburg Hbf      FV   9.143697

       BREITE STATUS
0   50.767800    NaN
1   48.841013    NaN
2   51.766433    NaN
4   49.298032    NaN
5   49.980557    NaN
```

By adding a second argument in square brackets, we can return only the columns we are interested in:

[11]:
```
df[df['VERKEHR'] == 'FV']['DS100'].head()
```

[11]:
```
0     KA
1     TA
2     HA
4    NAN
5    NAH
Name: DS100, dtype: object
```

This can be used in many ways, e.g. to count how many long distance stations there are in Germany?

[12]:
```
df[df['VERKEHR'] == 'FV']['NAME'].count() #It suffices to count one colum␣
 ↪only...
```

[12]:
```
348
```

By concatenating multiple commands, we can list all stations with Berlin in their name.

[13]:
```
df[df['NAME'].str.contains('Berlin')]['NAME'].head(10)
# Notice we can have more lines displayed
```

[13]:
```
697            Hamburg Berliner Tor
4370              Berlin-Karlshorst
4371             Berlin-Lichtenberg
4373             Berlin-SchÃűneweide
```

```
4425    Berlin-SchÃűnefeld Flughafen
4541               Berlin Ostbahnhof
4657          Berlin-Charlottenburg
4658                 Berlin-Spandau
4659                 Berlin Wannsee
4660     Berlin Zoologischer Garten
Name: NAME, dtype: object
```

Name, Latitude and Longitude of 'Berlin' Stations - most of them are actually in Berlin...

[14]:
```
# Filter and save returned dataframe in new variable:
df2 = df[df['NAME'].str.contains('Berlin')][['NAME', 'LAENGE', 'BREITE']]
# Display the first few lines:
df2.head()
```

[14]:

	NAME	LAENGE	BREITE
697	Hamburg Berliner Tor	10.024630	53.552870
4370	Berlin-Karlshorst	13.526813	52.480681
4371	Berlin-Lichtenberg	13.496923	52.509896
4373	Berlin-SchÃűneweide	13.509395	52.455127
4425	Berlin-SchÃűnefeld Flughafen	13.512710	52.391062

We can use the `sort_values`to find southernmost 'Berlin' station. Here, `inplace` means that we manipulate the variable in memory. While this is not critical for smaller data sets, Pandas is generally open for Terabytes where the additional memory would hurt.

[15]:
```
df2.sort_values('BREITE', inplace = True, ascending = True)
df2.head()
```

[15]:

	NAME	LAENGE	BREITE
6434	Berlin-Lichtenrade	13.396175	52.387297
4425	Berlin-SchÃűnefeld Flughafen	13.512710	52.391062
6405	Berlin Schichauweg	13.389303	52.398837
6384	Berlin GrÃijnbergallee	13.542485	52.399411
6420	Berlin-Altglienicke	13.558753	52.407299

It is possible to export the resulting data frames, e.g. to JSON (`df2.to_json('filename.json')`) or to Excel.

[16]:
```
df2.to_excel('BerlinStations.xlsx')
```

Alternatively, we can read data from AWS cloud storage (S3) - in this case we use test data of our railway challenge locomotive *Emma*.

The dataset contains:

- x: Longitude
- y: Latitude
- z: Altitude (m above sea level)
- v: velocity (m/s)

All data recorded in 1 Hz frequency using an iPad-GPS.

[17]:
```
df = pd.read_json('https://s3-eu-west-1.amazonaws.com/ifvworkshopdata/
↪emma1000.json')
```

[18]:
```
df.head()
```

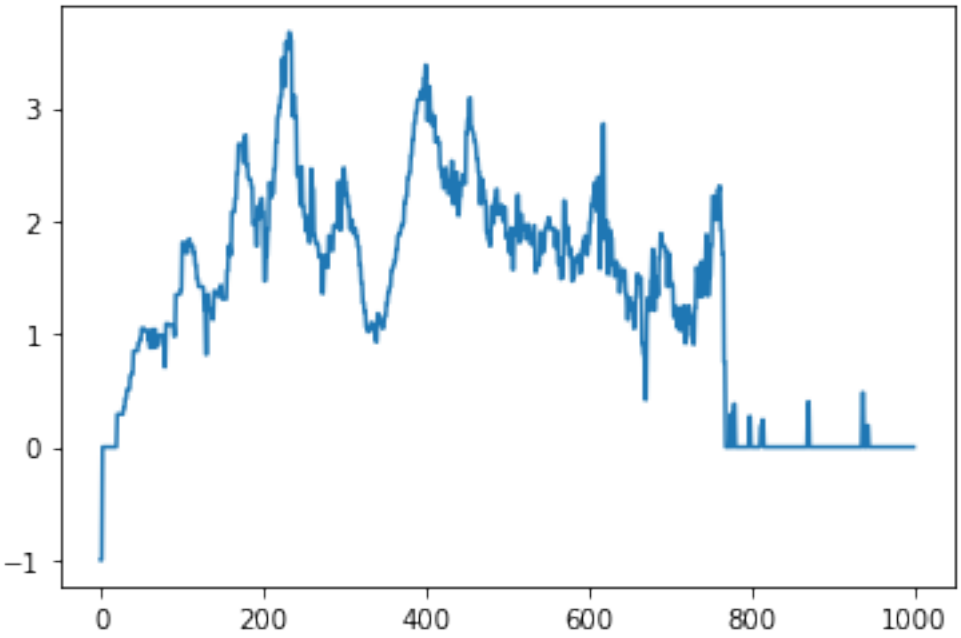
[18]:

	y	x	z	v
0	47.992597	9.678717	557.519958	-1.0
1	47.992597	9.678717	557.519958	-1.0
2	47.992538	9.678639	561.268433	0.0
3	47.992538	9.678639	561.268433	0.0
4	47.992538	9.678639	562.678432	0.0

By using the `plot()`-function, we can obtain a rough estimate of the velocity distribution.

[19]:
```
df['v'].plot()
```

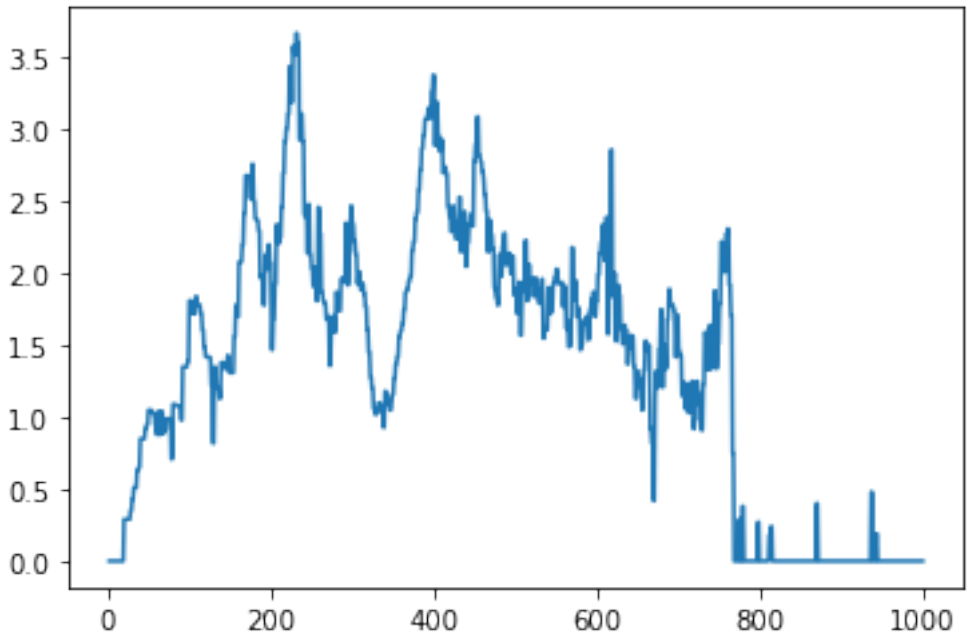
[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1c843d460>
```



Apparently, the GPS has $v = -1$-readings as long as it is acquiring a position. We filter these out:

[20]:
```
df[df['v'] >= 0]['v'].plot()
```

[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1f8c1b160>
```



1.4 Exercise:

1. Load the open data set on platform height and length from: http://download-data.deutschebahn.com/static/datasets/bahnsteig/DBSuS-Bahnsteigdaten-Stand2020-03.csv
2. Inspect the dataset
3. Find the longest (`df[column_name].max()`) and shortest() (`df[column_name].min()`) platform length ('Netto-baulÃd'nge (m)')
4. Find the associated station number ('Bahnhofsnummer')

Extra task: obtain the name by integrating with http://download-data.deutschebahn.com/static/datasets/stationsdaten/DBSuS-Uebersicht_Bahnhoefe-Stand2020-03.csv!

Hint: use `list()` to obtain return values and access the 0-th element to obtain a numeric value.

[ ]: