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Processing tables with Python

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With materials from

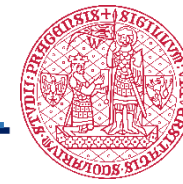
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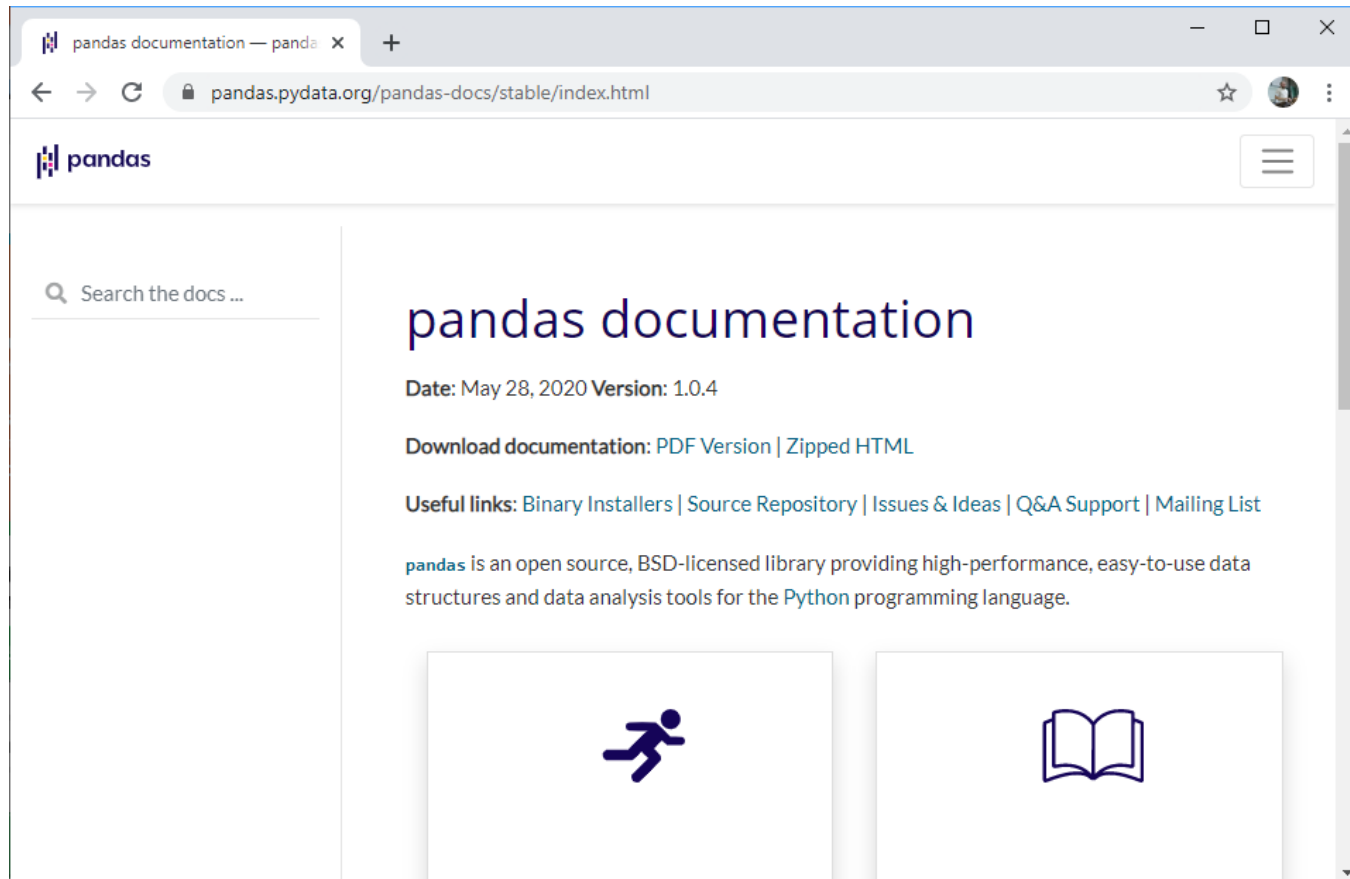
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Pandas is very useful for processing 2D tables



- Typical use-case:
 - Data from a colleague (i.e. an excel file)
 - Output from a software that was saved to disk (i.e. a csv file)
- Use pandas

```
conda install pandas
```



Loading a pandas table from a csv file



```
import pandas as pd
```

```
df_csv = pd.read_csv('../data/blobs_statistics.csv')  
df_csv
```

| | | Area | Mean | Circ. | AR | Round | Solidity |
|---|---|------|---------|-------|--------|-------|----------|
| 0 | 1 | 2610 | 96.920 | 0.773 | 1.289 | 0.776 | 1.0 |
| 1 | 2 | 2100 | 90.114 | 0.660 | 2.333 | 0.429 | 1.0 |
| 2 | 3 | 27 | 110.222 | 0.108 | 27.000 | 0.037 | 1.0 |

Display just the first 3 rows of a table:

```
df_csv.head(3)
```

Display just the last 3 rows of a table:

```
df_csv.tail(3)
```



- from a numpy array

```
import numpy as np
```

```
data = np.random.random((4,3))  
column_header = ['area',  
                 'minor_axis', 'major_axis']
```

```
pd.DataFrame(data,  
             columns=column_header)
```

| | area | minor_axis | major_axis |
|---|----------|------------|------------|
| 0 | 0.425681 | 0.135821 | 0.017084 |
| 1 | 0.036739 | 0.120840 | 0.925127 |
| 2 | 0.506095 | 0.453657 | 0.690560 |
| 3 | 0.748323 | 0.174359 | 0.603710 |

- from a dictionary

```
measurements = {  
    "labels": [1, 2, 3],  
    "area": [45, 23, 68],  
    "minor_axis": [2, 4, 4],  
    "major_axis": [3, 4, 5],  
}
```

```
pd.DataFrame(measurements)
```

| | labels | area | minor_axis | major_axis |
|---|--------|------|------------|------------|
| 0 | 1 | 45 | 2 | 3 |
| 1 | 2 | 23 | 4 | 4 |
| 2 | 3 | 68 | 4 | 5 |

Saving pandas tables to disk



```
df.to_csv("output.csv")
```

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | | A | B | C | | |
| 2 | 0 | 1 | 4 | 7 | | |
| 3 | 1 | 2 | 5 | 8 | | |
| 4 | 2 | 3 | 6 | 9 | | |
| 5 | | | | | | |
| 6 | | | | | | |
| 7 | | | | | | |

Select a table column similar to an element of a dict



`cities['City']`

| | City | Country | Population | Area_km2 |
|---|-------------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

| | City |
|---|-------------|
| 0 | Tokyo |
| 1 | Delhi |
| 2 | Shanghai |
| 3 | Sao Paulo |
| 4 | Mexico City |



Select multiple columns with a list of column names



```
cities[ ['City', 'Country'] ]
```

| | City | Country | Population | Area_km2 |
|---|-------------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

| | City | Country |
|---|-------------|---------|
| 0 | Tokyo | Japan |
| 1 | Delhi | India |
| 2 | Shanghai | China |
| 3 | Sao Paulo | Brazil |
| 4 | Mexico City | Mexico |

Note the
double
brackets

Select table rows through the `loc` object



```
data_frame.loc[ 0, ['city', 'Country']]
```

| | City | Country | Population | Area_km2 |
|---|-------------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

| | City | Country |
|---|-------|---------|
| 0 | Tokyo | Japan |

Select individual cells



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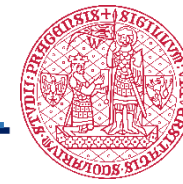
| | City | Country | Population | Area_km2 |
|---|-------------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

```
data_frame['city'][0]
```

```
'Tokyo'
```



Selecting rows that fulfill criteria



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- Select cities with an area of more than 2000 km²

| | City | Country | Population | Area_km2 |
|---|-------------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 1 | Delhi | India | 16753235 | 1484 |
| 2 | Shanghai | China | 24183000 | 6341 |
| 3 | Sao Paulo | Brazil | 12252023 | 1521 |
| 4 | Mexico City | Mexico | 9209944 | 1485 |

`cities["area"] > 2000`

0 True
1 False
2 True
3 False
4 False
Name: Area_km2, dtype: bool

`cities[cities["area"] > 2000]`

| | City | Country | Population | Area_km2 |
|---|----------|---------|------------|----------|
| 0 | Tokyo | Japan | 13515271 | 2191 |
| 2 | Shanghai | China | 24183000 | 6341 |

Combining similar tables



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- If tables have the same columns

```
pd.concat([countries1, countries2])
```

| countries1 | | | | | | countries2 | | | | | | Country Population | | |
|------------|---------|------------|---|--|--|------------|---------|------------|---|--|--|--------------------|--------|------------|
| | Country | Population | | | | | Country | Population | | | | | | |
| 0 | Japan | 127202192 | + | | | 0 | Brazil | 209489323 | = | | | 0 | Japan | 127202192 |
| 1 | India | 1352642280 | | | | 1 | Mexico | 126190788 | | | | 1 | India | 1352642280 |
| 2 | China | 1427647786 | | | | | | | | | | 2 | China | 1427647786 |
| | | | | | | | | | | | | 0 | Brazil | 209489323 |
| | | | | | | | | | | | | 1 | Mexico | 126190788 |



Keep information about the data source



- Add a column to each table before concatenating them

```
countries1['Survey ID']  
= 26
```

| | Country | Population | Survey ID |
|---|---------|------------|-----------|
| 0 | Japan | 127202192 | 26 |
| 1 | India | 1352642280 | 26 |
| 2 | China | 1427647786 | 26 |

```
countries2['Survey ID']  
= 73
```

| | Country | Population | Survey ID |
|---|---------|------------|-----------|
| 0 | Brazil | 209489323 | 73 |
| 1 | Mexico | 126190788 | 73 |

```
pd.concat([countries1,  
countries2])
```

| | Country | Population | Survey ID |
|---|---------|------------|-----------|
| 0 | Japan | 127202192 | 26 |
| 1 | India | 1352642280 | 26 |
| 2 | China | 1427647786 | 26 |
| 0 | Brazil | 209489323 | 73 |
| 1 | Mexico | 126190788 | 73 |



- Usually indicate missing data
- Can cause errors when handling the data
- The easiest is to drop them using the “.dropna” method
- Drops any row containing a NaN value

```
data_no_nan = data.dropna(how="any")
```

Work with tidy-data when processing tables



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- Each variable is a column.
- Each observation is a row.
- Each type of observation has its own separate data frame.

`data_frame.melt()`

Tidy:

Not tidy:

| | Before | | After | |
|---|-----------|-----------|-----------|-----------|
| | channel_1 | channel_2 | channel_1 | channel_2 |
| 0 | 13.250000 | 21.000000 | 15.137984 | 42.022776 |
| 1 | 44.954545 | 24.318182 | 43.328836 | 48.661610 |
| 2 | 13.590909 | 18.772727 | 11.685995 | 37.926184 |
| 3 | 85.032258 | 19.741935 | 86.031461 | 40.396353 |

| | variable_0 | variable_1 | value |
|-----|------------|------------|------------|
| 0 | Before | channel_1 | 13.250000 |
| 1 | Before | channel_1 | 44.954545 |
| 2 | Before | channel_1 | 13.590909 |
| 3 | Before | channel_1 | 85.032258 |
| 4 | Before | channel_1 | 10.731707 |
| ... | ... | ... | ... |
| 99 | After | channel_2 | 73.286439 |
| 100 | After | channel_2 | 145.900739 |

