Practical Assignment

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Shortly

- Records from Sports Tracking software Endomondo
  - Terminated in 2020
  - Data of a one person 2017-2020 with 3456 events stored as .json
  - Download .zip from Moodle

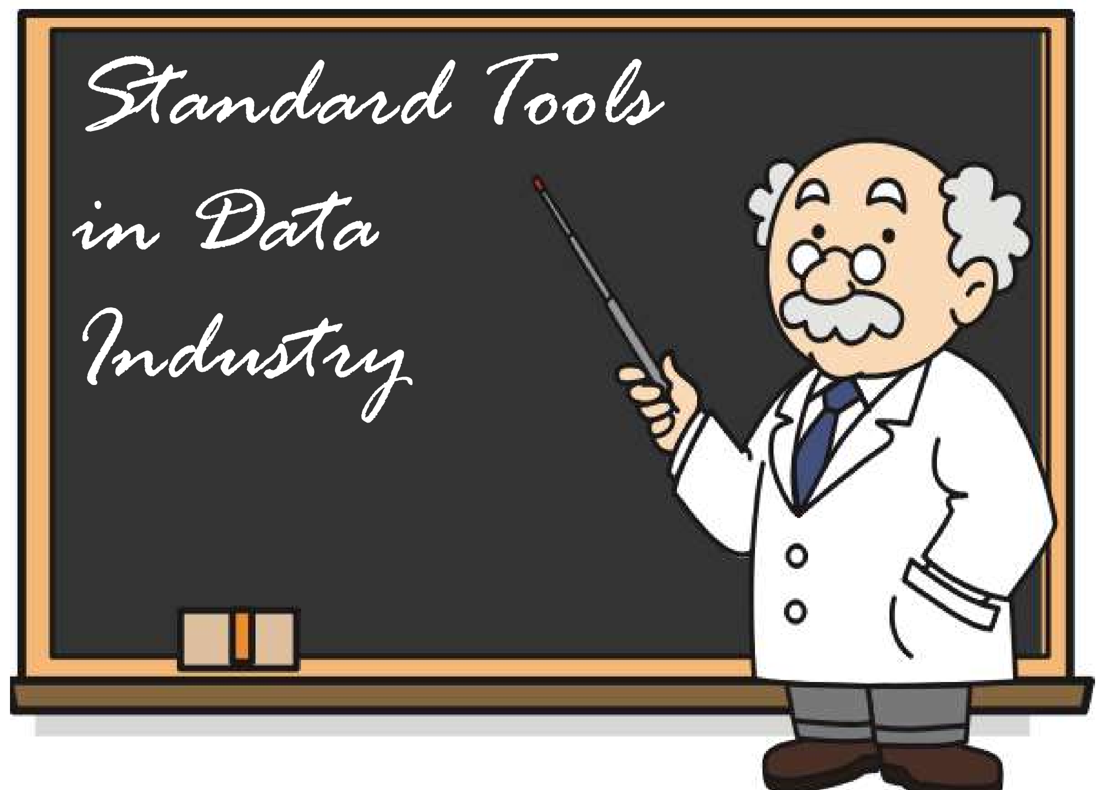
- (Pre-)process, analyze and predict
  - Present analysis in a Jupyter-Notebook (.ipynb)

Learning goals

- Building a machine learning (ML) pipeline from proprietary raw data to a predictive model

Not available in Kaggle, etc.

- Gain experience in:
  - .json files
  - Python with
    - Pandas, numpy, os…
  - Jupyter Notebooks



What is .json?

- JavaScript Object Notation
  - *open standard file format and data interchange format that uses human-readable text to store and transmit data objects consisting of attribute–value pairs and arrays (or other serializable values). It is a common data format with a diverse range of functionality in data interchange including communication of web applications with servers.* (Wikipedia)


```
[
    {"sport": "WALKING"},
    {"source": "TRACK_MOBILE"},
    {"created_date": "2017-01-01 08:54:23.0"},
    {"start_time": "2017-01-01 08:53:04.0"},
    {"end_time": "2017-01-01 09:27:49.0"},
    {"duration_s": 2084},
    {"distance_km": 2.15},
    {"calories_kcal": 171.651},
    {"altitude_min_m": 145.5},
    {"altitude_max_m": 198},
    {"speed_avg_kmh": 3.714011516314779},
    {"speed_max_kmh": 6.3},
    {"ascend_m": 78},
    {"descend_m": 77},
    {"points": [
        [
            {"location": [[
                {"latitude": 64.231747},
                {"longitude": 27.729461}
            ]]},
            {"distance_km": 0},
            {"timestamp": "Sun Jan 01 08:53:04 UTC 2017"}
        ],
        [
            {"location": [[
                {"latitude": 64.231747},
                {"longitude": 27.729461}
            ]]},
            {"altitude": 158},
            {"distance_km": 0},
            {"speed_kmh": 0},
            {"timestamp": "Sun Jan 01 08:53:20 UTC 2017"}
        ],
        [
            {"location": [[
                {"latitude": 64.231667},
                {"longitude": 27.729608}
            ]]},
            {"altitude": 147},
            {"distance_km": 0.01},
            {"speed_kmh": 3.6},
            {"timestamp": "Sun Jan 01 08:54:18 UTC 2017"}
        ],
        [
            {"location": [[
```


Figure. json-file displayed in Notepad++

Why is .json?

HOW TO GET OUR HANDS IN THIS DATA?

Application ("data silo") coded with C++ / Java / Fortran / Matlab / BASIC / Pascal / …

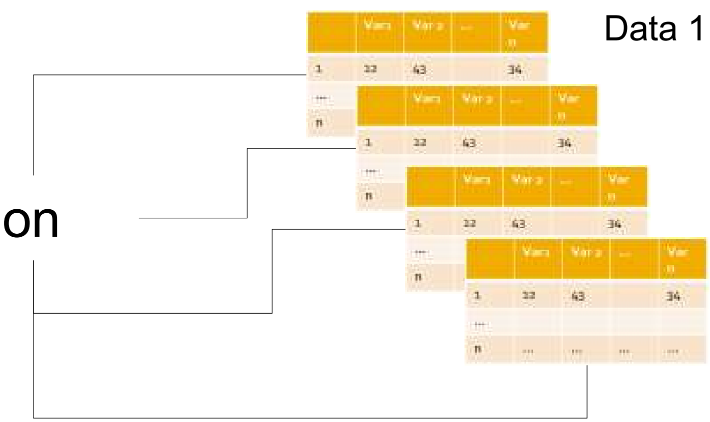
SIMPLE CASE → .csv

(Tabular data; "Kaggle"-examples)

	Var1	Var 2	…	Var n
1	12	43		34
…				
n	…	…	…	…

REAL CASE → .json

(Multidimensional data object)



Data 1

Data n

```
myStruct =

  struct with fields:

    data1: [2×20 double]
    data2: {[3]  [3]  [4]}
```

(e.g. Matlab-structure)

Getting started...

```python
# -*- coding: utf-8 -*-
"""
@author: h17163
"""

#%% Import libraries
import pandas as pd
import os

#%% Settings
# .json-folder
folder = 'C:\\Users\\h17163\\Endomondo\\Workouts\\'
# List of files
fileList = os.listdir(folder)

#%% Read data
# First entry
ex0 = pd.read_json(folder+fileList[0], typ='series')
```

Pandas provides an easy way to read json-files

Indexing data...

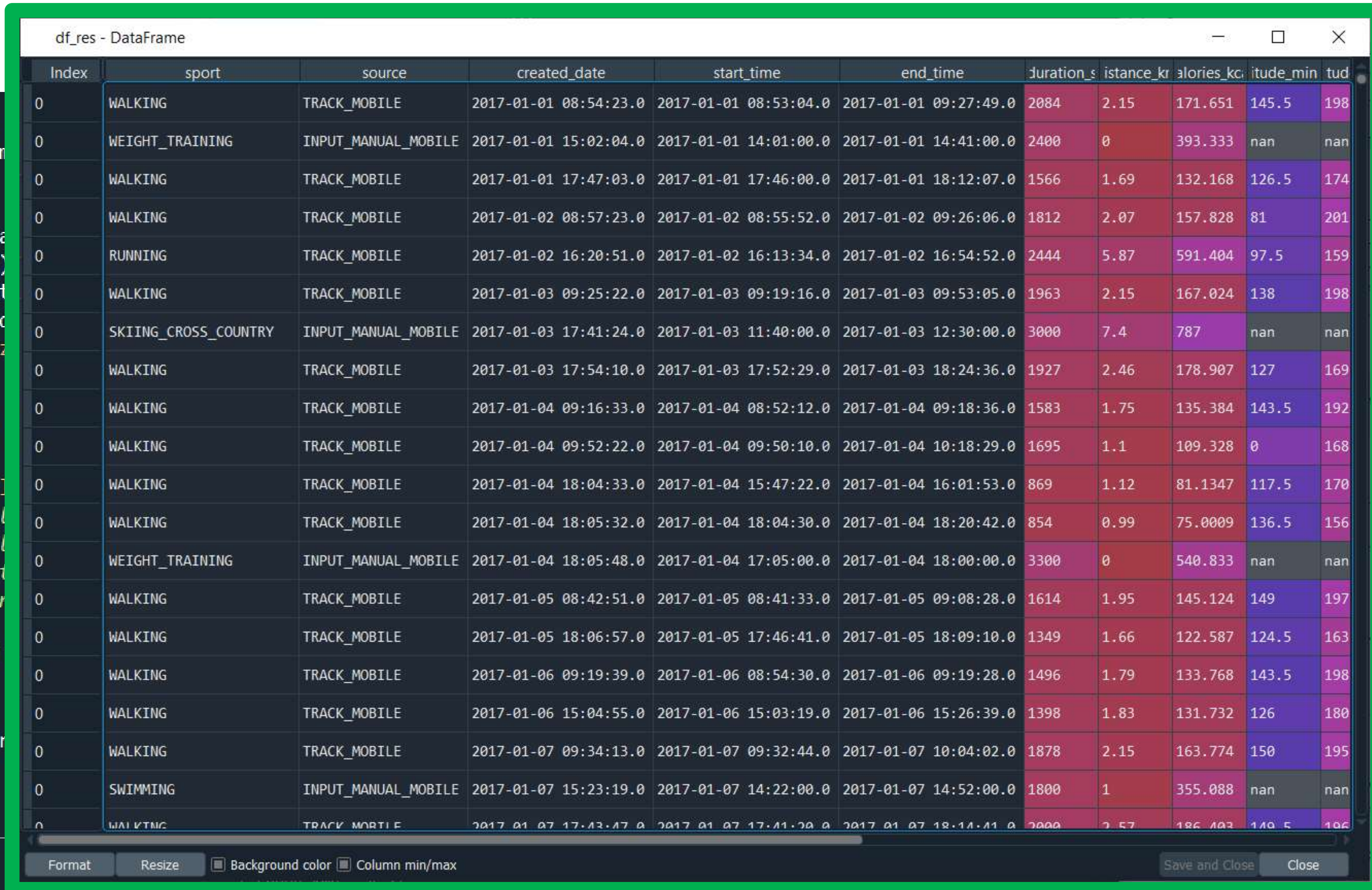
```
In [54]: ex0
Out[54]:
0                      {'sport': 'CYCLING_SPORT'}
1                      {'source': 'TRACK_MOBILE'}
2         {'created_date': '2016-04-15 11:46:51.0'}
3           {'start_time': '2016-04-15 11:45:44.0'}
4             {'end_time': '2016-04-15 13:36:44.0'}
5                            {'duration_s': 4784}
6                           {'distance_km': 19.54}
7                       {'calories_kcal': 737.992}
8                       {'altitude_min_m': 120.5}
9                         {'altitude_max_m': 185}
10           {'speed_avg_kmh': 14.704013377926419}
11                        {'speed_max_kmh': 29.7}
12                              {'ascend_m': 178}
13                             {'descend_m': 161}
14    {'points': [[{'location': [[{'latitude': 64.23...
dtype: object

In [55]: type(ex0[0])
Out[55]: dict

In [56]: ex0[0]
Out[56]: {'sport': 'CYCLING_SPORT'}

In [57]: ex0[0]['sport']
Out[57]: 'CYCLING_SPORT'

In [67]: type(ex0)
Out[67]: pandas.core.series.Series
```

- The data is stored as a *pandas Series* containing a ‘dictionary’ on each row

Data of person’s movement with location information as a function of time etc.

Script for reading all jsons (available in Moodle)…

```python
def read_file_to_df(filename):
    data = pd.read_json(filenan
    value = []
    key = []
    for j in list(range(0, data
        if list(data[j].keys()
            key.append(list(dat
            value.append(list(c
            dictionary = dict(z


    if list(data[j].keys())[0]
        try:
            start = list(list(]
            dictionary['start_l
            dictionary['start_l
            dictionary['end_lat
            dictionary['end_lor
        except:
            print('No detailed


    df = pd.DataFrame(dictionar

    return df

#%% Read all files in a loop

# Create Empty DataFrame
df_res = pd.DataFrame()

# Read files to a common dataframe
for filename in file_list:
    print('\n'+filename)
    df_process = read_file_to_df(folder +'/'+ filename)
    df_res = pd.concat([df_res, df_process], 0)
```



df_res - DataFrame

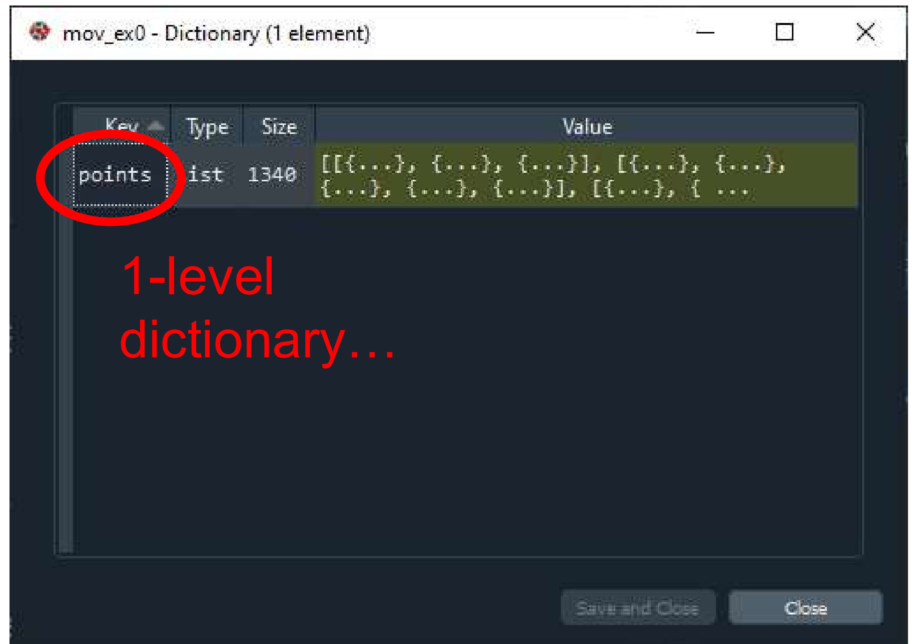
Index	sport	source	created_date	start_time	end_time	duration_s	istance_kr	alories_kc	itude_min	tud
0	WALKING	TRACK_MOBILE	2017-01-01 08:54:23.0	2017-01-01 08:53:04.0	2017-01-01 09:27:49.0	2084	2.15	171.651	145.5	198
0	WEIGHT_TRAINING	INPUT_MANUAL_MOBILE	2017-01-01 15:02:04.0	2017-01-01 14:01:00.0	2017-01-01 14:41:00.0	2400	0	393.333	nan	nan
0	WALKING	TRACK_MOBILE	2017-01-01 17:47:03.0	2017-01-01 17:46:00.0	2017-01-01 18:12:07.0	1566	1.69	132.168	126.5	174
0	WALKING	TRACK_MOBILE	2017-01-02 08:57:23.0	2017-01-02 08:55:52.0	2017-01-02 09:26:06.0	1812	2.07	157.828	81	201
0	RUNNING	TRACK_MOBILE	2017-01-02 16:20:51.0	2017-01-02 16:13:34.0	2017-01-02 16:54:52.0	2444	5.87	591.404	97.5	159
0	WALKING	TRACK_MOBILE	2017-01-03 09:25:22.0	2017-01-03 09:19:16.0	2017-01-03 09:53:05.0	1963	2.15	167.024	138	198
0	SKIING_CROSS_COUNTRY	INPUT_MANUAL_MOBILE	2017-01-03 17:41:24.0	2017-01-03 11:40:00.0	2017-01-03 12:30:00.0	3000	7.4	787	nan	nan
0	WALKING	TRACK_MOBILE	2017-01-03 17:54:10.0	2017-01-03 17:52:29.0	2017-01-03 18:24:36.0	1927	2.46	178.907	127	169
0	WALKING	TRACK_MOBILE	2017-01-04 09:16:33.0	2017-01-04 08:52:12.0	2017-01-04 09:18:36.0	1583	1.75	135.384	143.5	192
0	WALKING	TRACK_MOBILE	2017-01-04 09:52:22.0	2017-01-04 09:50:10.0	2017-01-04 10:18:29.0	1695	1.1	109.328	0	168
0	WALKING	TRACK_MOBILE	2017-01-04 18:04:33.0	2017-01-04 15:47:22.0	2017-01-04 16:01:53.0	869	1.12	81.1347	117.5	170
0	WALKING	TRACK_MOBILE	2017-01-04 18:05:32.0	2017-01-04 18:04:30.0	2017-01-04 18:20:42.0	854	0.99	75.0009	136.5	156
0	WEIGHT_TRAINING	INPUT_MANUAL_MOBILE	2017-01-04 18:05:48.0	2017-01-04 17:05:00.0	2017-01-04 18:00:00.0	3300	0	540.833	nan	nan
0	WALKING	TRACK_MOBILE	2017-01-05 08:42:51.0	2017-01-05 08:41:33.0	2017-01-05 09:08:28.0	1614	1.95	145.124	149	197
0	WALKING	TRACK_MOBILE	2017-01-05 18:06:57.0	2017-01-05 17:46:41.0	2017-01-05 18:09:10.0	1349	1.66	122.587	124.5	163
0	WALKING	TRACK_MOBILE	2017-01-06 09:19:39.0	2017-01-06 08:54:30.0	2017-01-06 09:19:28.0	1496	1.79	133.768	143.5	198
0	WALKING	TRACK_MOBILE	2017-01-06 15:04:55.0	2017-01-06 15:03:19.0	2017-01-06 15:26:39.0	1398	1.83	131.732	126	180
0	WALKING	TRACK_MOBILE	2017-01-07 09:34:13.0	2017-01-07 09:32:44.0	2017-01-07 10:04:02.0	1878	2.15	163.774	150	195
0	SWIMMING	INPUT_MANUAL_MOBILE	2017-01-07 15:23:19.0	2017-01-07 14:22:00.0	2017-01-07 14:52:00.0	1800	1	355.088	nan	nan

Format Resize Background color Column min/max Save and Close Close

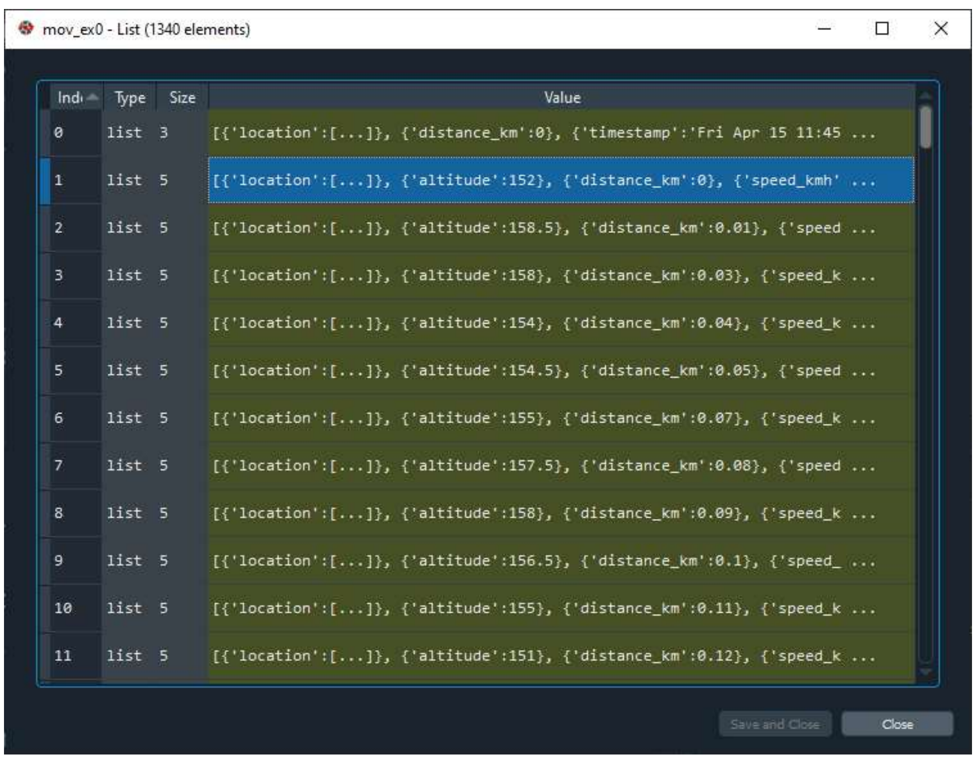
Data on the movement

```
In [77]: mov_ex0 = ex0[14]

In [78]: type(mov_ex0)
Out[78]: dict

In [79]: mov_ex0 = ex0[14]['points']
```

Dictionary containing only one entry
➔ Can be converted to a list



1-level dictionary…



List…

Dictionary…

```
mov_ex0[14]['points'][0][0]['location']
[[{'latitude': 64.231747}, {'longitude': 27.729461}]]
```

Example visualizations of ONE ENTRY

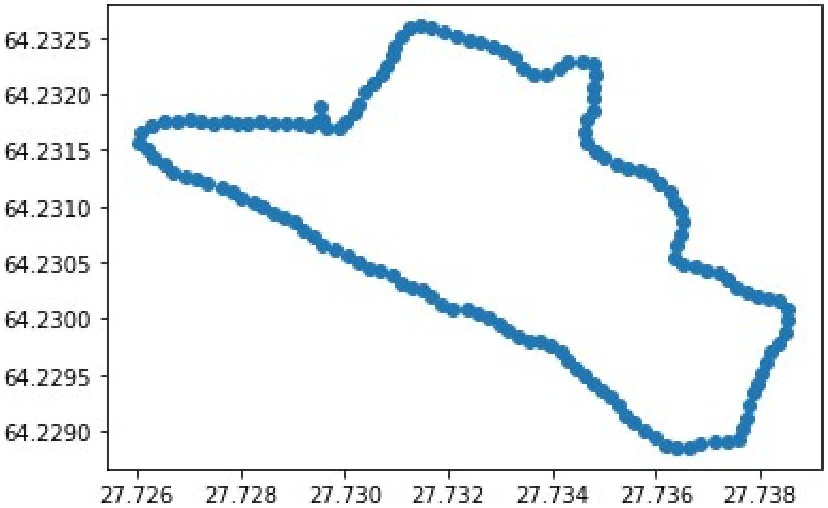


Figure. Longitude and latitude information as a scatter plot

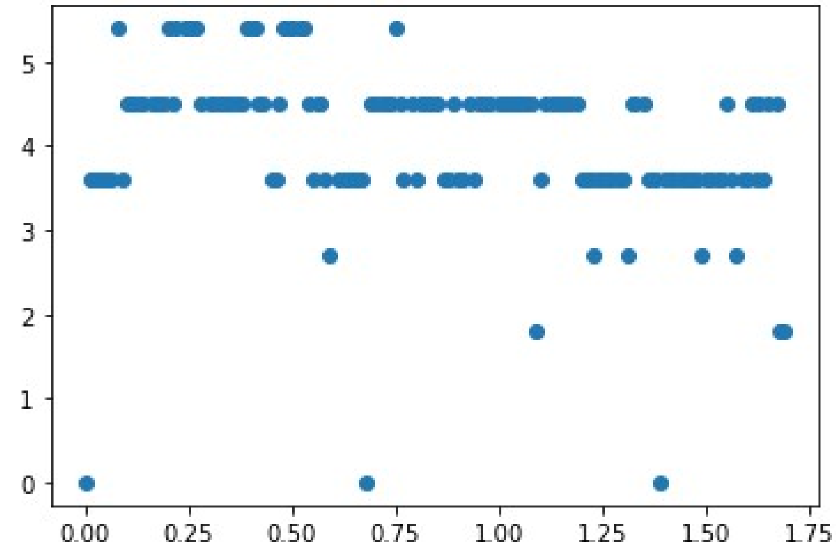


Figure. Distance and speed as a scatter plot

```
len(df_res.loc[df_res['source']=='TRACK_MOBILE'])
3107

len(df_res.loc[df_res['source']=='INPUT_MANUAL_MOBILE'])
349
```

~**3107** exercises with location info (e.g. walking, skiing, cycling,…)

~**349** exercises recorded manually after the exercise (e.g. gym, swimming) speeds_ex0 - List (190 elem...

Inde	Type	Size	Value
0	float64	1	0.
1	float64	1	3.
2	float64	1	4.
3	float64	1	4.
4	float64	1	4.
5	float64	1	5.
6	float64	1	5.
7	float64	1	5.
8	float64	1	5.
9	float64	1	4.
10	float64	1	4.
11	float64	1	6.
12	float64	1	4.
13	float64	1	3.
14	float64	1	3.
15	float64	1	3.
16	float64	1	2.
17	float64	1	3.
18	float64	1	3.
19	float64	1	3.
20	float64	1	3.
21	float64	1	2.
22	float64	1	2.
23	float64	1	4.5

Save and Close Close

```
In [23]: df_res['speed_arr']=np.nan

In [24]: df_res
Out[24]:
                sport              source  ... hydration_l speed_arr
0             WALKING        TRACK_MOBILE  ...         NaN       NaN
1     WEIGHT_TRAINING INPUT_MANUAL_MOBILE  ...         NaN       NaN
2             WALKING        TRACK_MOBILE  ...         NaN       NaN
3             WALKING        TRACK_MOBILE  ...         NaN       NaN

In [68]: df_res['speed_arr'][0] = speeds_ex0

In [69]: df_res
Out[69]:
                    sport  ...                                         speed_arr
0                 WALKING  ...  [0.0, 3.6, 4.5, 4.5, 4.5, 5.4, 5.4, 5.4, 5.4, ...
1         WEIGHT_TRAINING  ...                                               NaN
2                 WALKING  ...                                               NaN
3                 WALKING  ...                                               NaN
4                 RUNNING  ...                                               NaN
...                   ...  ...                                               ...
3451              WALKING  ...                                               NaN
3452              WALKING  ...                                               NaN
3453              WALKING  ...                                               NaN
3454              WALKING  ...                                               NaN
3455  SKIING_CROSS_COUNTRY  ...                                               NaN

[3456 rows x 20 columns]
```

What to do

- **MAIN TASK:** Create a ML-model that forecasts the user's next exercise type, time and, possibly, duration as well

- **SUB-TASK:** Before the ML-model fitting, classify / label / cluster / categorize the data!

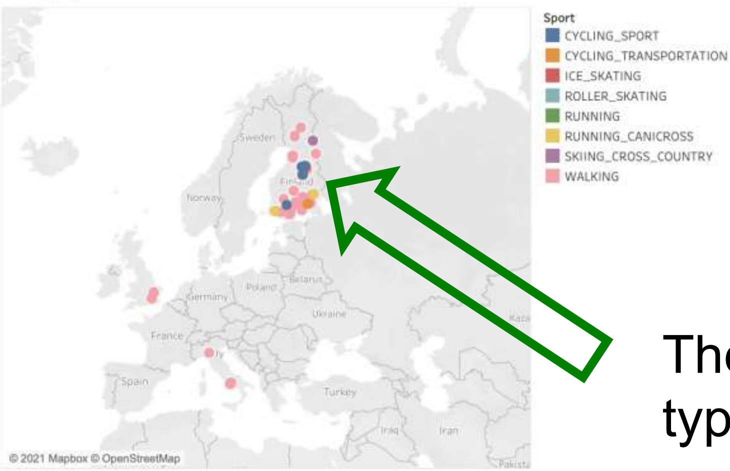
Start here
=
FEATURE ENGINEERING

Exploratory Analysis 1/3

Geografic Location

The map is based on Longitude and Latitude from that data. Color shows details about Sport. We can observe from the map that most of the users are from Finland and a very few from Italy and UK. Another thing which we can observe is that the sports data from Italy and UK is only for Walking and all other sports are only recorded in Finland.

Geographic Location

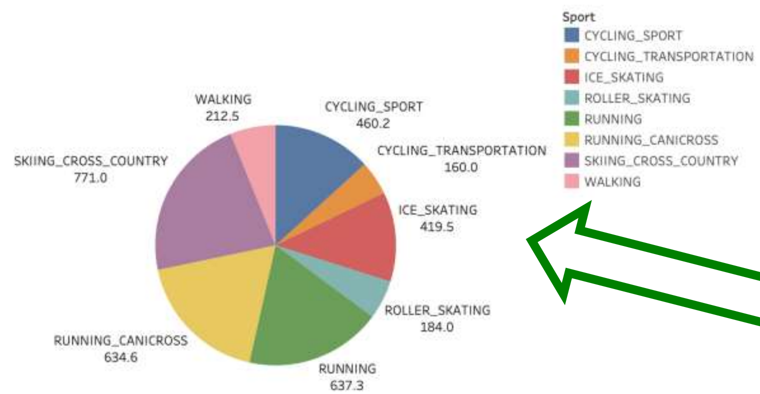


The location for different types of exercises?

Avg. Calories Burned (Kcal) w.r.t Sport

This pie chart shows the how much Calories (Kcal) on average are burned in each sport. Color shows details about Sport. The marks are labeled by Sport and average of Calories Kcal. We can observe from the chart that cross country skiing and both kinds of running are the type of sports that burn the most calories on average and they contribute to more than half of the divison on the chart being the most physical sports.

Avg. Calories Burned (Kcal) w.r.t Sport



Heaviness of the exercise might be related to the resting period and the next type exercise

Exploratory Analysis 2/3

Time vs Sport (24 hr)

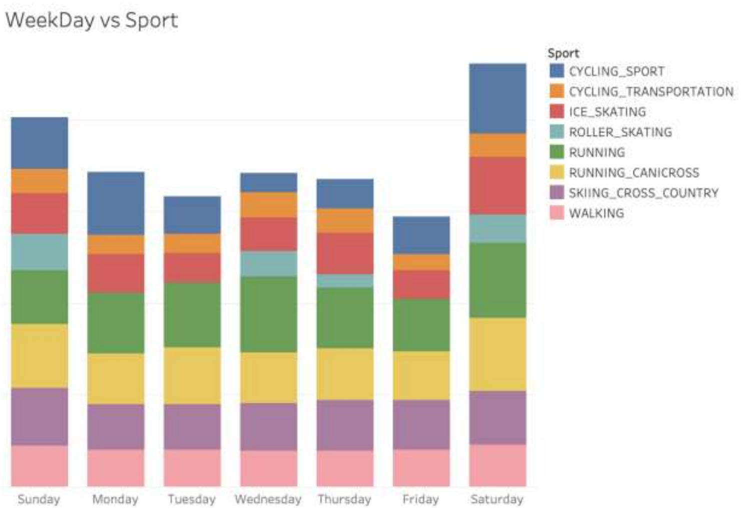
This bar plot shows us Average of duration for each time hour broken down by Sport. We can observe that walking is the only sport that has activity round the clock. Cycling, Ice skating, running and cross country skiing all have similar pattern of activity from 6 AM to 6 PM approximately. And roller skating is the sport that is done for the shortest time and only before noon.

Regular morning / evening walks (with dogs) with similar type of path? Possible to identify these?

'RUNNING_CANICROSS' = 'RUNNING'

WeekDay vs Sport

This bar plot shows the average duration for each weekday. Color shows details about Sport. We can see that the weekend (saturday and sunday) has the most activity with saturday being the most active day of the week and all other week days have on average similar division of sport activities with Friday being the least active among all comparatively.

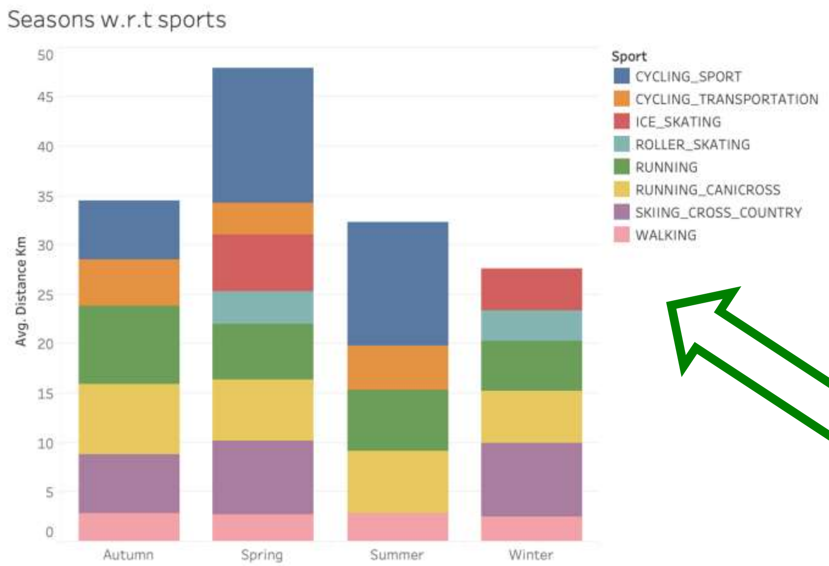


How the exercises are distributed throughout the week? Are some exercises more probable at some days?

Exploratory Analysis 3/3

Seasons w.r.t sports

This plot shows the activity for each season. Color shows details about Sport. We can see from this bar plot that the most active sports season according to this data is Spring and the least active as can be expected is Winter. Autumn and Summer are both similar in activities. And Summer suprisingly is less active than both Autumn and Spring



Seasonality: what options are available?

Example ML-model

Extracted and/or Engineered features in the data
= x-variables

Predicted activity based on features
= y-variable

Row	Last activity type	Last activity timing	Month	Location	…	Predicted next activity	(Predicted time)	(Predicted Length)
1	‘Dog walk’	‘Morning’	1	‘Home’	…	‘Swimming’	‘Evening’	<1h
2	‘Cycling’	‘Skiing’	1	…	…	‘’	…	…
…								

HINT: calculating similarity between arrays

```
In [95]: ex1 = np.array([1, 5, 6, 9, 11, 20])

In [96]: ex2 = np.array([4, 5, 6, 9, 14, 21])

In [97]: from scipy import spatial

In [98]: spatial.distance.euclidean(ex1, ex2)
Out[98]: 4.358898943540674

In [99]: spatial.distance.cosine(ex1, ex2)
Out[99]: 0.00901993622814249
```

Values of exercise 1 (~row from a dataframe)

Values of exercise 2

EXAMPLE distances 1 vs 2: euclidean and cosine (these are very similar)

```
In [100]: ex3 = np.array([10, 14, 20, 25, 55, 20])

In [101]: spatial.distance.euclidean(ex1, ex3)
Out[101]: 50.49752469181039

In [102]: spatial.distance.cosine(ex1, ex3)
Out[102]: 0.1944581077691797
```

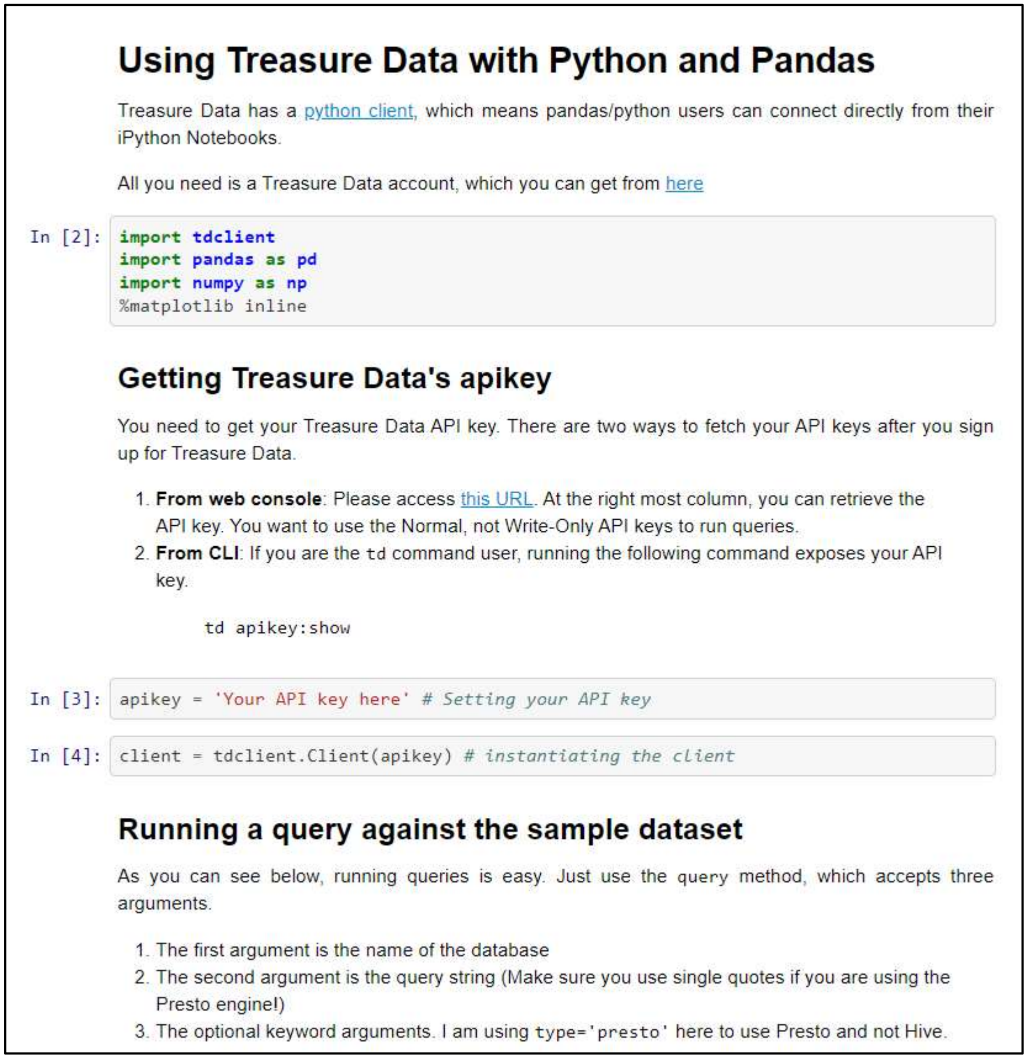
Values of exercise 3

Exercise 3 differs from ex1 (and, therefore also, ex2)

Results and reporting

- Provide your analysis and model as a Jupyter Notebook with:
  - code, images, explanation, etc.
  - Analysis on forecastin model’s applicability and ’goodness’

- Grading (roughly; adequate documentation assumed):
  - Pre-processing: ~60%
  - Plan/draft of model: ~20%
  - Implementation / insights: ~20%



Using Treasure Data with Python and Pandas

Treasure Data has a python client, which means pandas/python users can connect directly from their iPython Notebooks.

All you need is a Treasure Data account, which you can get from here

In [2]:
```
import tdclient
import pandas as pd
import numpy as np
%matplotlib inline
```

Getting Treasure Data's apikey

You need to get your Treasure Data API key. There are two ways to fetch your API keys after you sign up for Treasure Data.

1. **From web console**: Please access this URL. At the right most column, you can retrieve the API key. You want to use the Normal, not Write-Only API keys to run queries.
2. **From CLI**: If you are the `td` command user, running the following command exposes your API key.

```
td apikey:show
```

In [3]:
```
apikey = 'Your API key here' # Setting your API key
```

In [4]:
```
client = tdclient.Client(apikey) # instantiating the client
```

Running a query against the sample dataset

As you can see below, running queries is easy. Just use the `query` method, which accepts three arguments.

1. The first argument is the name of the database
2. The second argument is the query string (Make sure you use single quotes if you are using the Presto engine!)
3. The optional keyword arguments. I am using `type='presto'` here to use Presto and not Hive.

Figure. Jupyter Notebook-format