

Visualization

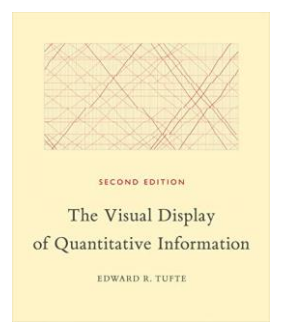
Types of visualizations

- Data/information visualization (“charts”)
- Scientific visualization
- Scientific illustrations / cartoons (can use in combination with programming but not necessarily)
- Static
- Dynamic
 - animation – GIF, movies
 - graphical user interface (GUI) / interactive plots

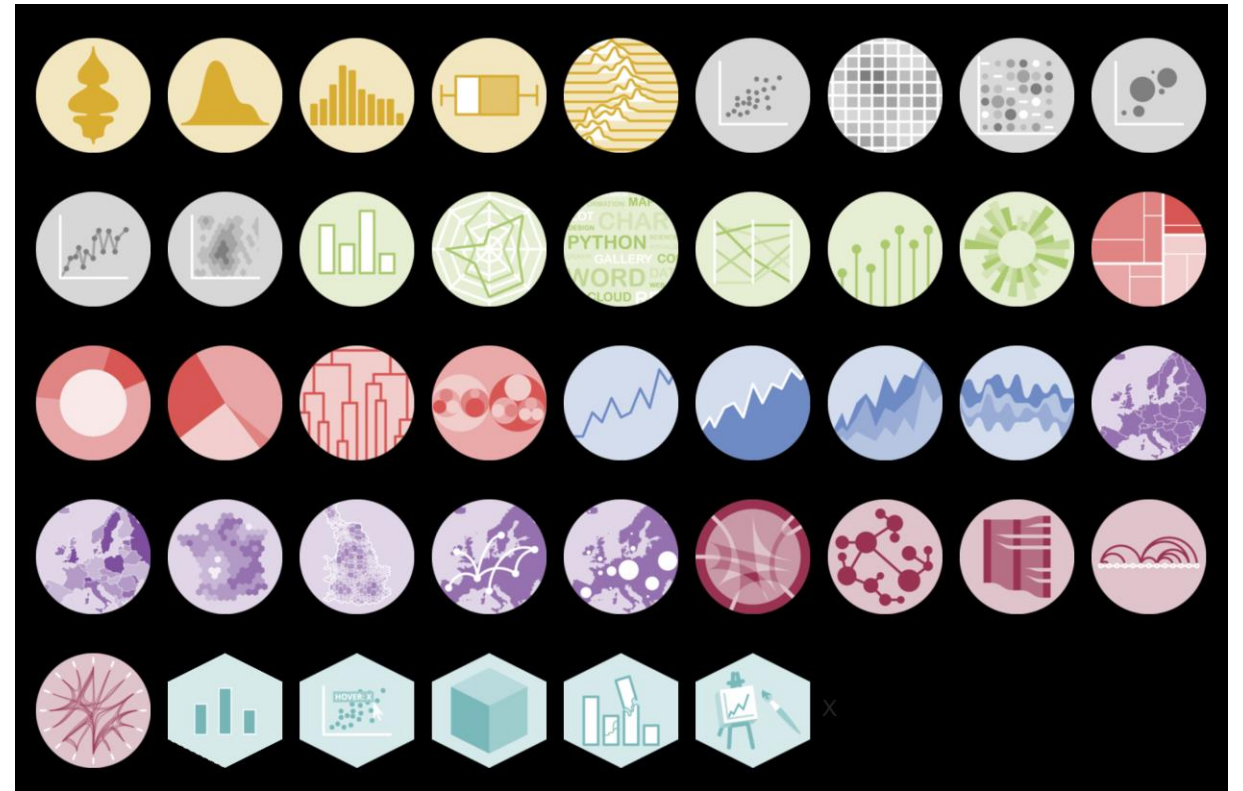
When to use which?

- Who is the audience?
 - Internal (project team) / external (client)
- How much time does it take the audience to digest the information?
 - A sequence of snapshots may be preferred over an animation or movie
- Is an interactive plot necessary?
 - if the parameter dimensionality/space to explore is large and nonlinear
 - does the client need an interactive plotting tool or can/should *you* summarize the results
- Do aesthetic enhancements obfuscate the important trends?

Charts

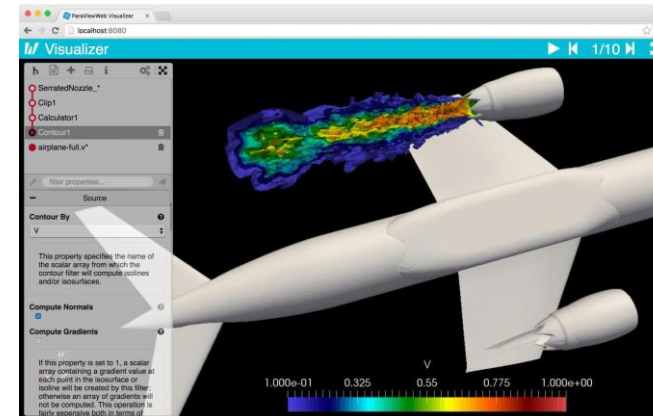
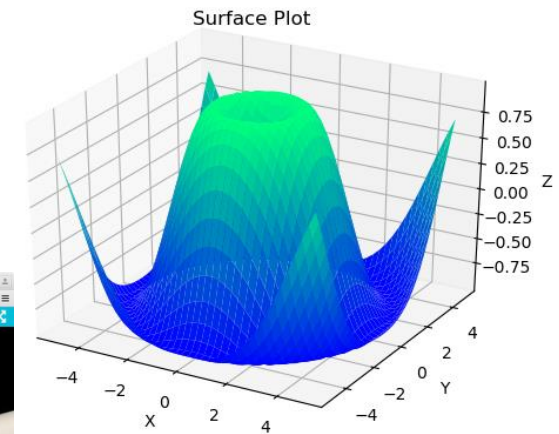
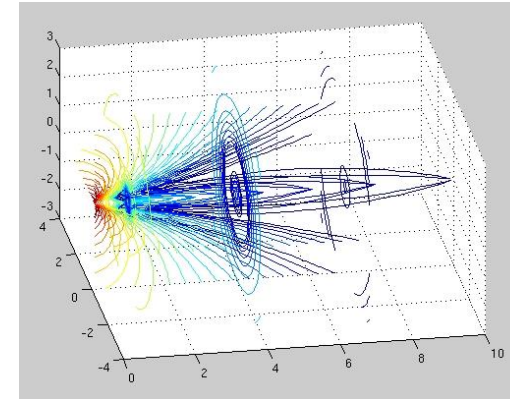


- Summarize data
- Can be generated programmatically in many data analysis languages
- Common method of visualization
- Use only as much “ink” as necessary



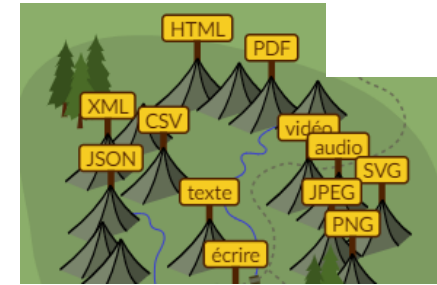
Scientific visualization

- Visualize (vector) fields
- Often (but not always) dealing with physical representations
- May involve rendering (adding realistic reflections, shading, etc.)
- Can do some in Python/MATLAB
- Often requires specialized tools
 - OpenGL
 - VTK
 - MayaVi
 - Blender
 - Rhinoceros 3D

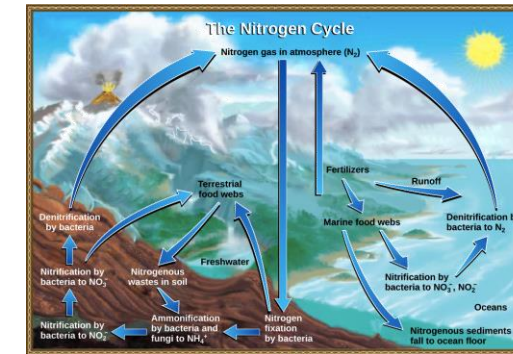


<https://www.bu.edu/tech/support/research/training-consulting/online-tutorials/visualization-with-matlab/>
<https://www.cdslab.org/python/notes/visualization/3d/surface3D.png>
<https://vtk.org/flavors>

Scientific illustrations / cartoons



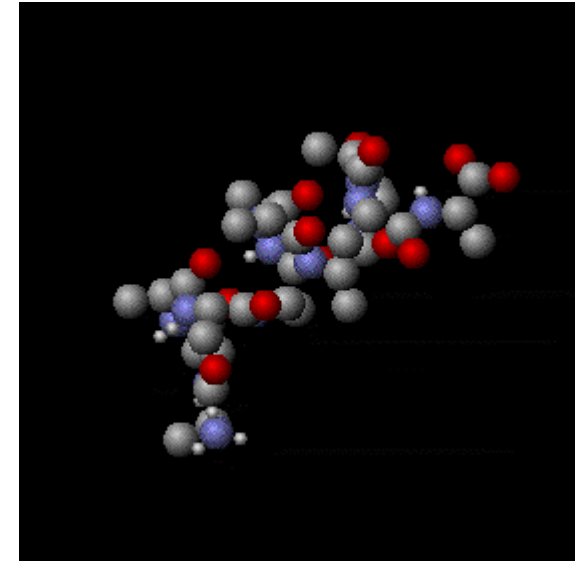
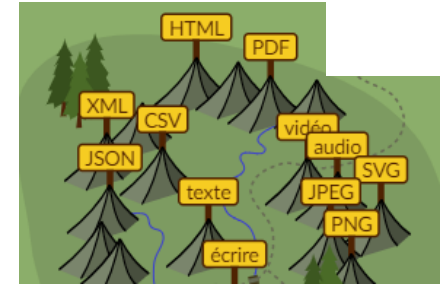
- By hand (traditional medium)
- **Raster graphics** (jpg, gif, png)
 - Adobe Photoshop / GIMP
 - efficient storage for images
- **Vector graphics** (pdf, svg)
 - Adobe Illustrator / Inkscape
 - small files for simple plots (points and lines), large files for complex plots (many points or images)
- Cartoons – useful for showing imprecise of the data



"Stove Ownership" from xkcd by Randall Munroe

Animation

- GIFs: sequence of images
 - runs on any machine
- Movies: sequence of images stored as “frames”, can have accompanying audio track
 - more compact than GIFs
 - compressed with codec – may require OS/platform-specific codec to decode – test on different machines
- Can make with Python, MATLAB, and other tools



User interfaces

- Command line interface (terminal)
 - run program (with input files)
 - run program with input arguments
 - prompt user input from keyboard
- Graphical user interface (GUI)
 - toolkits – e.g., Tkinter, wxPython, PyQt
 - dashboards (web application) – e.g., Dash, Streamlit, Shiny
 - web application on web framework – e.g., Flask/Django with client-side (front end)
 - app – e.g., Dart

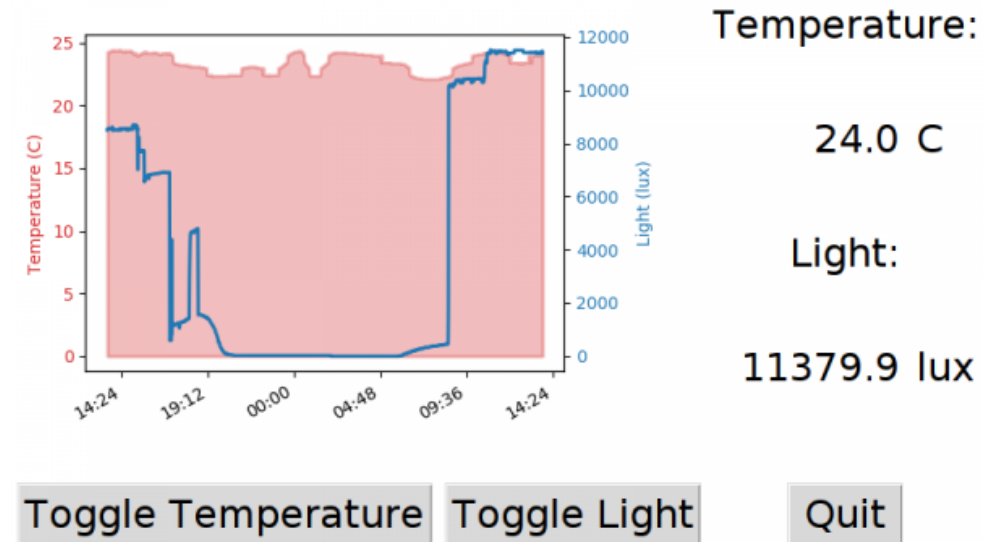
Use cases

- command line
 - programmable and reproducible
 - when prompting for user input from the keyboard, note that input must be saved to be reproducible
- GUIs
 - interactive
 - exploratory

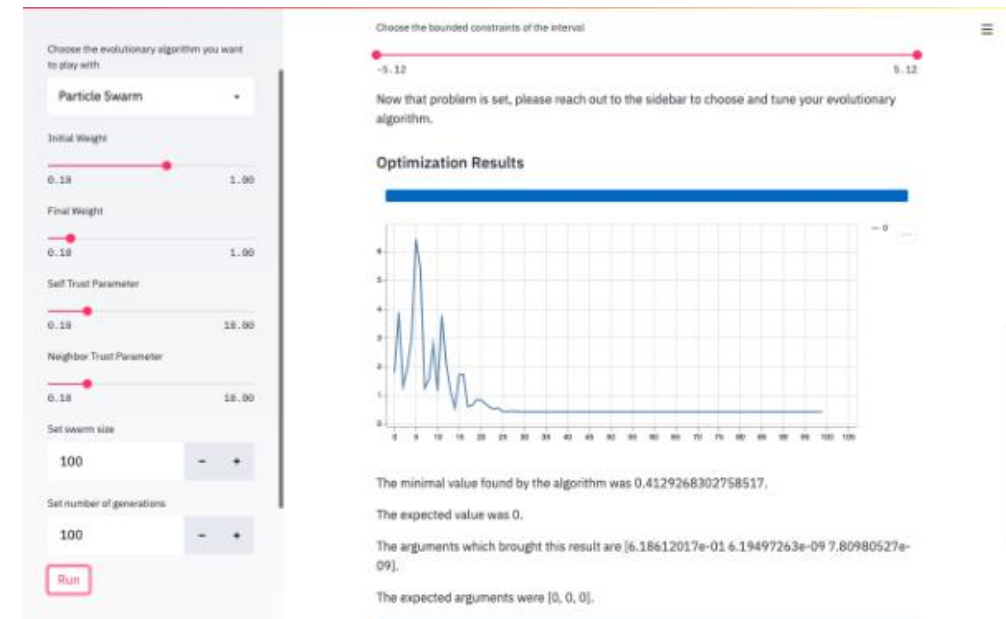
Graphical User Interfaces (GUIs)

- Drive program execution through graphical elements rather than command line arguments or file input parameters
- Uses – “Human Intelligence Tasks”
 - interactive plots – high-dimensional data exploration
 - data labeling
- Implementation
 - desktop/mobile app
 - web app
- Some GUI elements are built into interactive plots (MATLAB, matplotlib, etc.)
 - scatterplot brushing
 - spanning

Not part of ENG-270 project!



<https://learn.sparkfun.com/tutorials/python-gui-guide-introduction-to-tkinter/all>



<https://streamlit.io/>

Alternatives to user interfaces

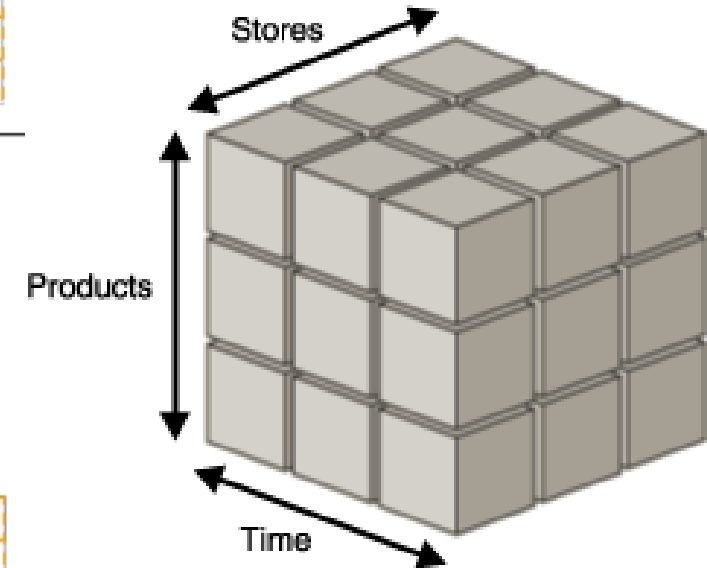
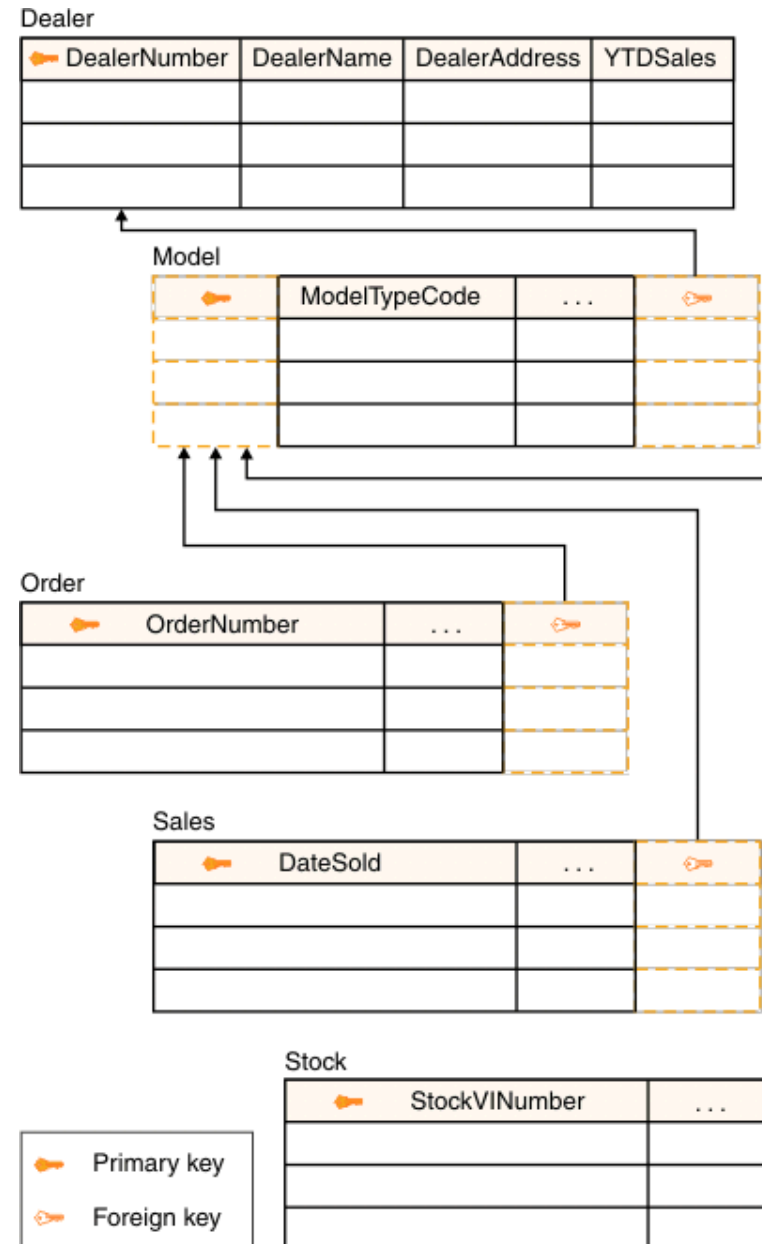
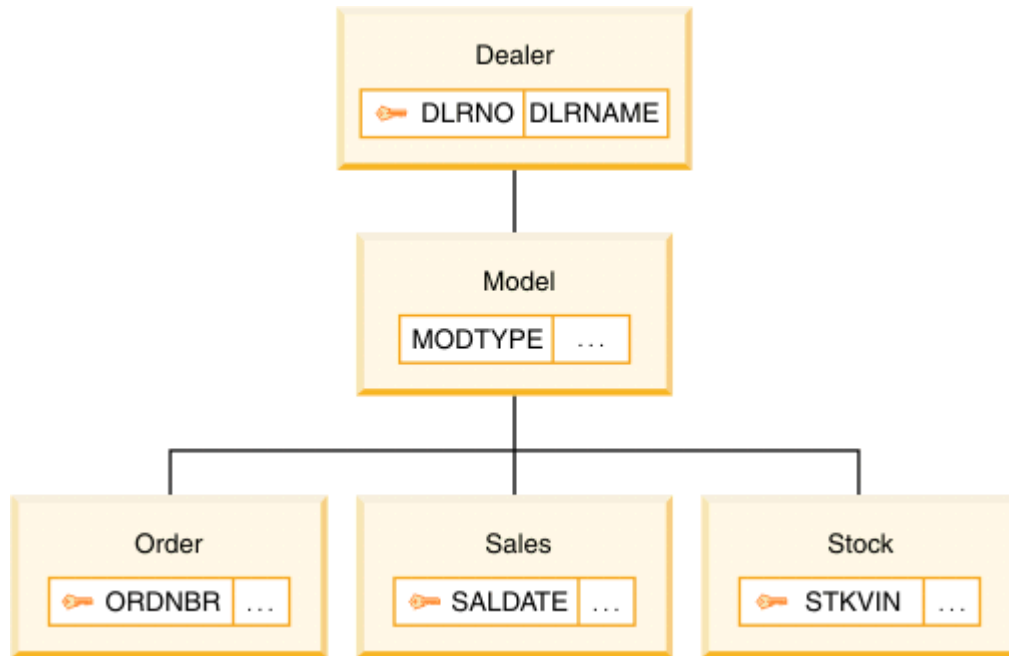
(Recommended)

- For each scenario, save input parameters to file – e.g., JSON, CSV
- Code loops through each scenario and generates outputs saved to different files / folders
- Another code harvests results and constructs summary tables and plots

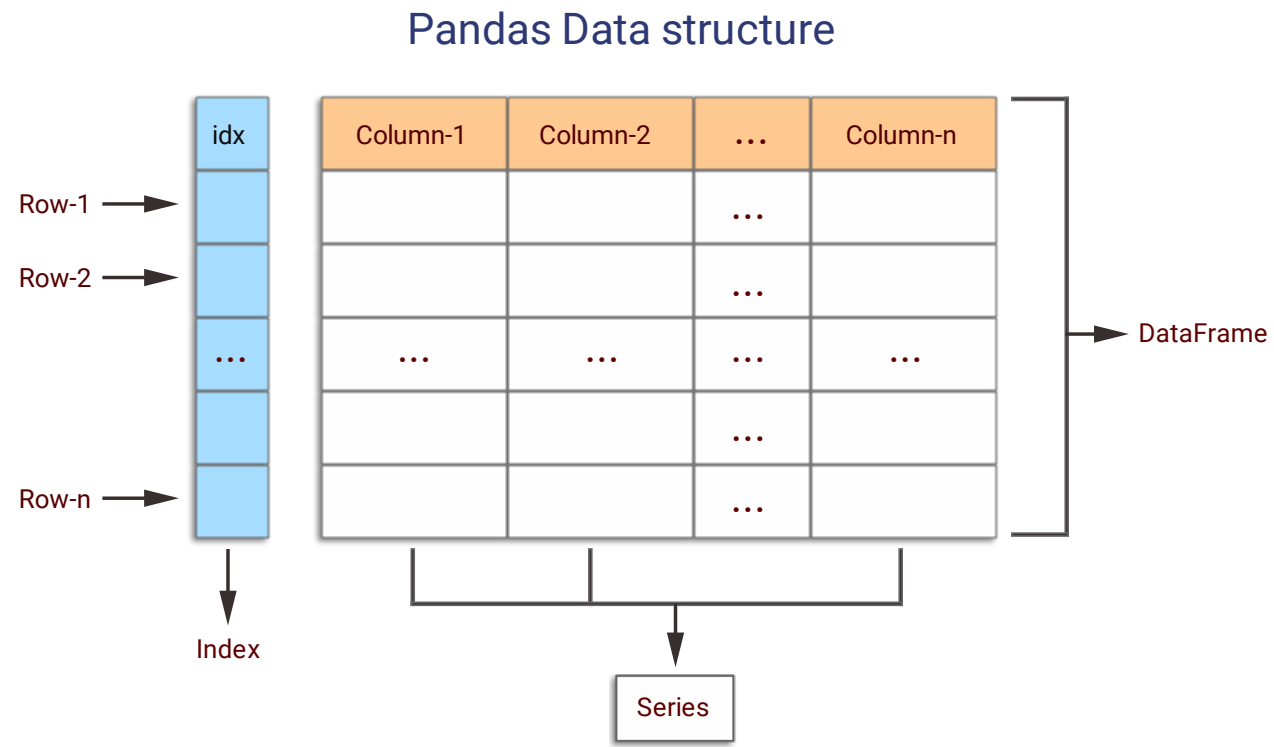
Working with relational tables and statistical visualizations

[Web link](#)

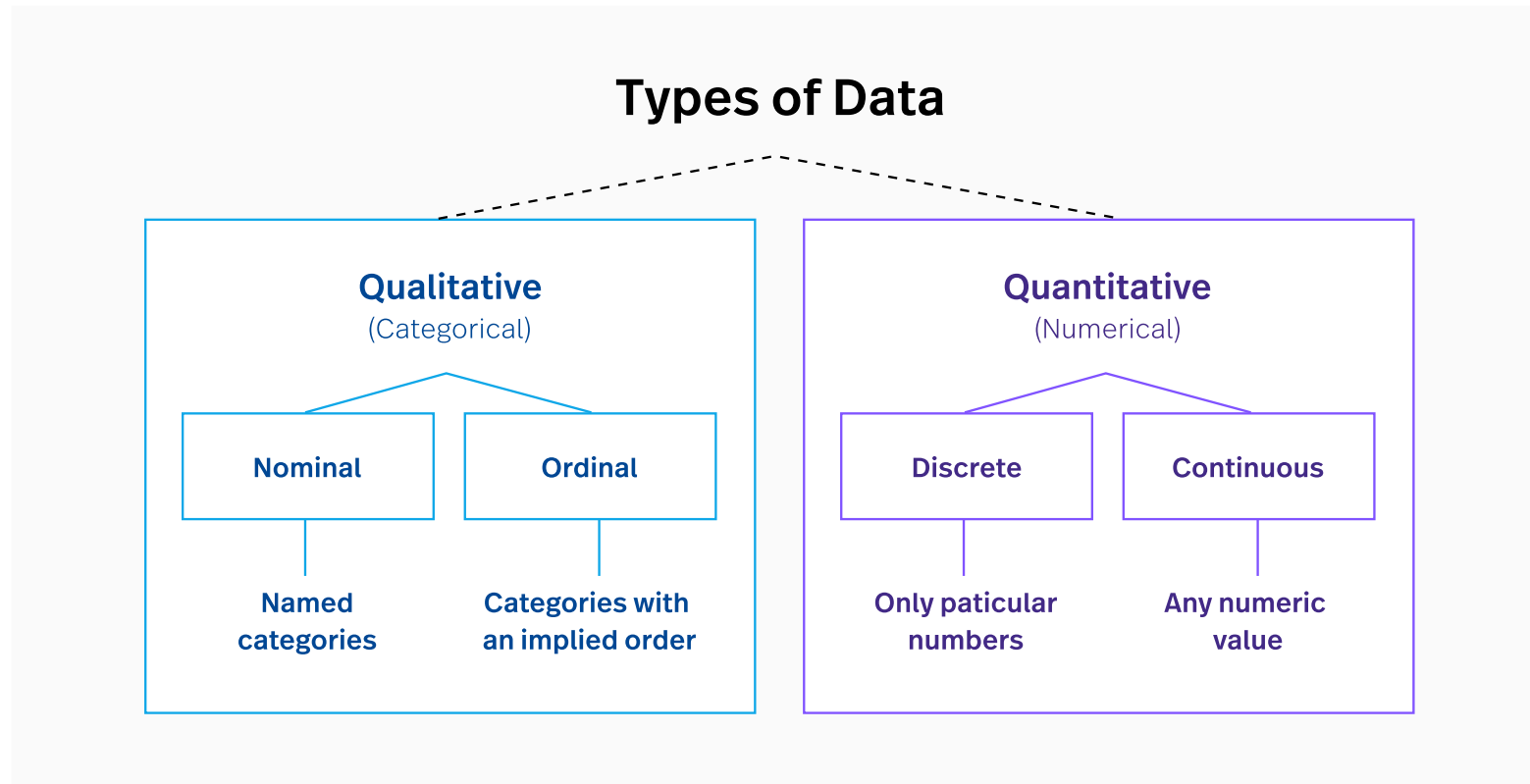
Data models



DataFrame in Python pandas



New data type: categorical variables



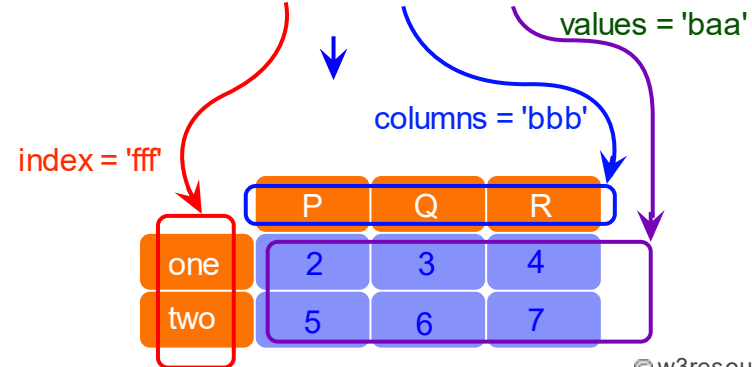
Pivoting / reshaping

```
df.pivot ( index = 'fff', columns = 'bbb', values = 'baa' )
```

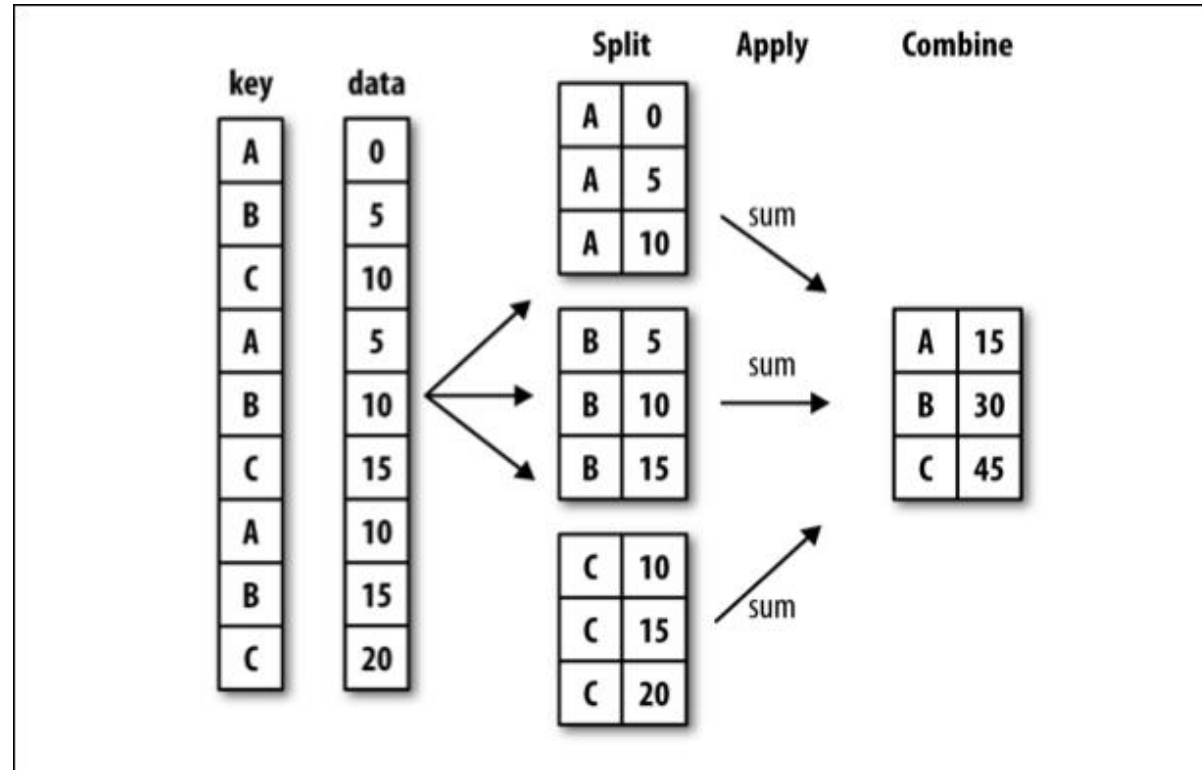


DataFrame

df	fff	bbb	baa	zzz
0	one	P	2	h
1	one	Q	3	i
2	one	R	4	j
3	two	P	5	k
4	two	Q	6	l
5	two	R	7	m



Split-Apply-Combine approach



Merging

Pandas DataFrame.merge()

The Left DataFrame

	Key	B
0	Key_0	145
1	Key_1	2373
2	Key_2	415
3	Key_3	2946

The Right DataFrame

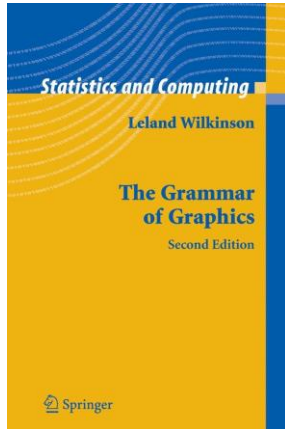
	Key	A	B
0	Key_0	113	991.03
1	Key_1	2342	993.13
2	Key_2	4567	983.12
3	Key_3	2563	936.45
4	Key_4	2234	995.44
5	Key_5	71218	999.99

The Inner join

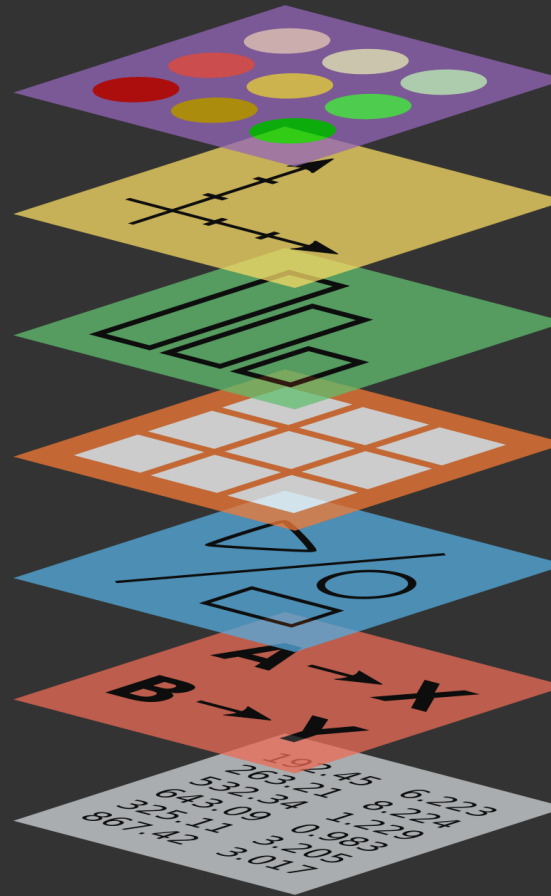
	key	B_x	A	B_y
0	Key_0	145	113	991.03
1	Key_1	2373	2342	993.13
2	Key_4	415	2234	995.44

Output

“Grammar of Graphics”



Theme
Coordinates
Statistics
Facets
Geometries
Aesthetics
Data



Data downloaded from NABEL network

Station: Lausanne-César-Roux

Urban, traffic

Daily means, 03: Maximum hourly mean of the day, PREC: Daily sums

Source: NABEL/MeteoSchweiz

Date/time;O3 [ug/m3];NO2 [ug/m3];CO [mg/m3];PM10 [ug/m3];PM2.5 [ug/m3];NOX [ug/m3 eq. NO2];TEMP [C];PREC [mm];RAD [W/m2]

01.01.2021;55.3;19.9;0.27;6.2;4.9;27.6;1.6;11.9;27.1
02.01.2021;45.1;10.4;0.23;12.8;10.5;13.0;1.3;0.0;37.1
03.01.2021;44.1;16.5;0.28;14.5;11.7;21.9;0.7;0.0;20.2
04.01.2021;31.3;18.8;0.29;19.5;15.6;25.2;0.3;0.0;25.7
05.01.2021;37.8;23.1;0.28;20.9;16.3;31.5;0.6;0.0;14.9
06.01.2021;37.4;28.1;0.32;17.2;12.9;41.1;0.3;0.0;24.3
07.01.2021;39.5;27.3;0.34;18.5;14.1;39.5;1.0;0.0;55.2
08.01.2021;48.6;25.0;0.31;14.7;10.4;36.3;0.4;0.0;81.0
09.01.2021;51.3;15.3;0.26;16.0;12.5;18.8;-1.6;0.0;62.6
10.01.2021;48.0;15.9;0.26;19.5;15.3;20.1;-1.7;0.0;82.6
11.01.2021;47.8;28.9;0.32;28.2;21.9;44.5;-2.8;0.0;66.9
12.01.2021;44.9;42.2;0.79;26.3;20.5;83.3;-0.9;11.4;13.4
13.01.2021;49.4;39.1;0.32;7.5;5.5;65.4;3.0;9.2;9.6
14.01.2021;50.9;31.2;0.27;5.4;4.0;45.9;4.3;5.6;10.6
15.01.2021;58.5;23.8;0.26;5.4;4.0;36.6;2.3;7.0;13.3
16.01.2021;51.2;27.4;0.30;15.7;12.5;43.0;-1.5;1.6;37.2
17.01.2021;50.3;32.3;0.31;9.0;7.4;46.5;1.1;7.9;16.0
18.01.2021;49.6;43.4;0.35;10.4;7.9;72.3;1.9;0.0;69.6
19.01.2021;60.6;43.5;0.35;12.2;7.8;71.7;1.6;0.0;92.3
20.01.2021;55.0;52.3;0.37;13.1;5.0;93.5;5.2;0.0;53.3
21.01.2021;82.6;39.1;0.31;7.4;4.1;65.1;8.3;0.6;17.6
22.01.2021;79.5;34.7;0.31;6.1;3.6;55.7;6.9;14.7;45.1
23.01.2021;70.1;22.3;0.24;4.6;2.9;36.3;3.0;4.7;46.3
24.01.2021;70.3;19.9;0.24;5.1;2.9;31.0;2.6;2.6;98.3
25.01.2021;69.7;29.8;0.25;5.6;3.1;49.4;0.9;6.2;48.7
26.01.2021;61.4;29.6;0.25;11.4;5.9;42.7;0.5;0.0;90.8

First steps

- Create a new table where the date/time information is usable
- Define categorical variables:
 - month
 - day of week
 - weekday/weekend

Preparing the new Data Frame

```
import numpy as np
import pandas as pd
import calendar
```

Read data

```
data = pd.read_table('./data/LAU_diurnal.csv', delimiter=';', encoding='latin-1', skiprows=4, header=0)
```

Rename data columns

```
data.columns = [x.split()[0] for x in data.columns]
```

```
Index(['Date/time', 'O3 [ug/m3]', 'NO2 [ug/m3]', 'CO [mg/m3]', 'PM10 [ug/m3]',  
      'PM2.5 [ug/m3]', 'NOX [ug/m3 eq. NO2]', 'TEMP [C]', 'PREC [mm]',  
      'RAD [W/m2]'],  
      dtype='object')
```



```
Index(['Date/time', 'O3', 'NO2', 'CO', 'PM10', 'PM2.5', 'NOX', 'TEMP', 'PREC',  
      'RAD'],  
      dtype='object')
```

Parse date/time information

```
def parsedate(datestr):
    daystr, monthstr, yearstr = datestr.split('.')
    return {'day':int(daystr), 'month':int(monthstr), 'year': int(yearstr)}

def month2season(months):
    season = {0:'DJF', 1:'MAM', 2:'JJA', 3:'SON'}
    lookup = np.vectorize(season.get)
    breaks = np.arange(3, 13, 3)
    return lookup(np.mod(np.digitize(months, breaks), 4))

def daycategory(day_name):
    days = list(calendar.day_name)
    return pd.Categorical(day_name, categories = days, ordered=True)

def daytype(day_num):
    types = ['Weekday', 'Weekend']
    return pd.Categorical(np.where(day_num < 5, 'Weekday', 'Weekend'), categories = types, ordered=True)
```

```
dates = pd.DataFrame([parsedate(x) for x in data['Date/time']])
dateobj = pd.to_datetime(dates)
dates['season'] = month2season(dates['month'])
dates['dayofweek'] = daycategory(dateobj.dt.day_name())
dates['daytype'] = daytype(dateobj.dt.dayofweek)
dates['month'] = pd.Categorical(dates['month'])
```

	day	month	year	season	dayofweek	daytype
0	1	1	2021	DJF	Friday	Weekday
1	2	1	2021	DJF	Saturday	Weekend
2	3	1	2021	DJF	Sunday	Weekend
3	4	1	2021	DJF	Monday	Weekday
4	5	1	2021	DJF	Tuesday	Weekday
..	...	...	...	...	...	...
360	27	12	2021	DJF	Monday	Weekday
361	28	12	2021	DJF	Tuesday	Weekday
362	29	12	2021	DJF	Wednesday	Weekday
363	30	12	2021	DJF	Thursday	Weekday
364	31	12	2021	DJF	Friday	Weekday

[365 rows x 6 columns]

Add new date information to original data frame

Merge using concat()

```
merged = pd.concat([
    pd.DataFrame(dateobj, columns=['datetime']),
    dates,
    data.iloc[:,1:] # take all after Date/time column
], axis=1)
```

	datetime	day	month	year	season	...	PM2.5	NOX	TEMP	PREC	RAD
0	2021-01-01	1	1	2021	DJF	...	4.9	27.6	1.6	11.9	27.1
1	2021-01-02	2	1	2021	DJF	...	10.5	13.0	1.3	0.0	37.1
2	2021-01-03	3	1	2021	DJF	...	11.7	21.9	0.7	0.0	20.2
3	2021-01-04	4	1	2021	DJF	...	15.6	25.2	0.3	0.0	25.7
4	2021-01-05	5	1	2021	DJF	...	16.3	31.5	0.6	0.0	14.9
...	...	...	...	...	...	...	...	...	...	...	...
360	2021-12-27	27	12	2021	DJF	...	7.9	53.3	5.6	6.5	8.7
361	2021-12-28	28	12	2021	DJF	...	3.8	37.4	7.5	14.3	6.3
362	2021-12-29	29	12	2021	DJF	...	4.0	35.6	7.4	15.0	5.2
363	2021-12-30	30	12	2021	DJF	...	8.5	75.9	10.7	0.0	48.7
364	2021-12-31	31	12	2021	DJF	...	9.0	62.0	9.2	0.0	69.8

[365 rows x 16 columns]

Pivot using melt()

```
lf = merged.melt(id_vars=['datetime'] + dates.columns.to_list())
```

	datetime	day	month	year	season	dayofweek	daytype	variable	value
0	2021-01-01	1	1	2021	DJF	Friday	Weekday	03	55.3
1	2021-01-02	2	1	2021	DJF	Saturday	Weekend	03	45.1
2	2021-01-03	3	1	2021	DJF	Sunday	Weekend	03	44.1
3	2021-01-04	4	1	2021	DJF	Monday	Weekday	03	31.3
4	2021-01-05	5	1	2021	DJF	Tuesday	Weekday	03	37.8
...	...	...	...	...	...	...	...	...	...
3280	2021-12-27	27	12	2021	DJF	Monday	Weekday	RAD	8.7
3281	2021-12-28	28	12	2021	DJF	Tuesday	Weekday	RAD	6.3
3282	2021-12-29	29	12	2021	DJF	Wednesday	Weekday	RAD	5.2
3283	2021-12-30	30	12	2021	DJF	Thursday	Weekday	RAD	48.7
3284	2021-12-31	31	12	2021	DJF	Friday	Weekday	RAD	69.8

[3285 rows x 9 columns]

Some analyses

- Missing values by month
- Monthly exceedances of $\text{PM}_{2.5}$
- Monthly means
- Mean values by day of week

Missing values (how many are missing?)

```
missing = (
    df
    .groupby(['month', 'variable'])
    .apply(lambda x: x['value'].isnull().sum())
)
```

```
print(missing)
```

```

month  variable
1      CO          0
      NO2          0
      NOX          0
      O3           0
      PM10         0
      ..
12     PM10        0
      PM2.5        0
      PREC         0
      RAD          0
      TEMP         0
Length: 108, dtype: int64

```

```
print(missing.unstack())
```

[illegible]

Monthly exceedances of PM2.5

```
LIMIT_PM25 = 15
exceedances = (
    df.loc[df['variable'] == 'PM2.5']
    .groupby(['month'])
    .apply(lambda x: (x['value'] > LIMIT_PM25).sum())
)
```

```
print(exceedances)
```

month	
1	5
2	12
3	8
4	0
5	0
6	0
7	2
8	1
9	0
10	3
11	8
12	8

dtype: int64

Monthly means and daily averages

```
means_monthly = (  
    lf.groupby(['month', 'variable'])  
    .apply(lambda x: x['value'].mean())  
)
```

```
print(means_monthly.unstack())
```

variable	CO	NO2	...	RAD	TEMP
month			...		
1	0.307097	28.593548	...	41.470968	2.112903
2	0.356071	34.732143	...	88.896429	6.185714
3	0.303871	29.658065	...	156.877419	7.245161
4	0.265333	23.076667	...	226.886667	9.873333
5	0.261613	23.143333	...	213.167742	12.419355
6	0.276333	23.300000	...	260.486667	20.330000
7	0.284516	19.887097	...	226.425806	19.983871
8	0.293871	17.687097	...	219.406452	19.441935
9	0.321333	25.390000	...	157.630000	18.130000
10	0.309032	25.654839	...	110.690323	11.587097
11	0.305000	24.613333	...	46.076667	5.840000
12	0.287419	33.167742	...	29.341935	3.290323

[12 rows x 9 columns]

```
means_dailyJJA = (  
    lf.loc[lf['season'] == 'JJA']  
    .groupby(['dayofweek', 'variable'])  
    .apply(lambda x: x['value'].mean())  
)
```

```
print(means_dailyJJA.unstack())
```

variable	CO	NO2	...	RAD	TEMP
dayofweek			...		
Monday	0.275385	17.730769	...	241.392308	20.046154
Tuesday	0.278571	21.214286	...	226.364286	19.150000
Wednesday	0.300769	23.791667	...	201.284615	18.938462
Thursday	0.301538	23.930769	...	234.476923	19.923077
Friday	0.297692	23.038462	...	276.784615	20.784615
Saturday	0.283846	18.761538	...	235.546154	20.453846
Sunday	0.257692	13.307692	...	231.000000	20.161538

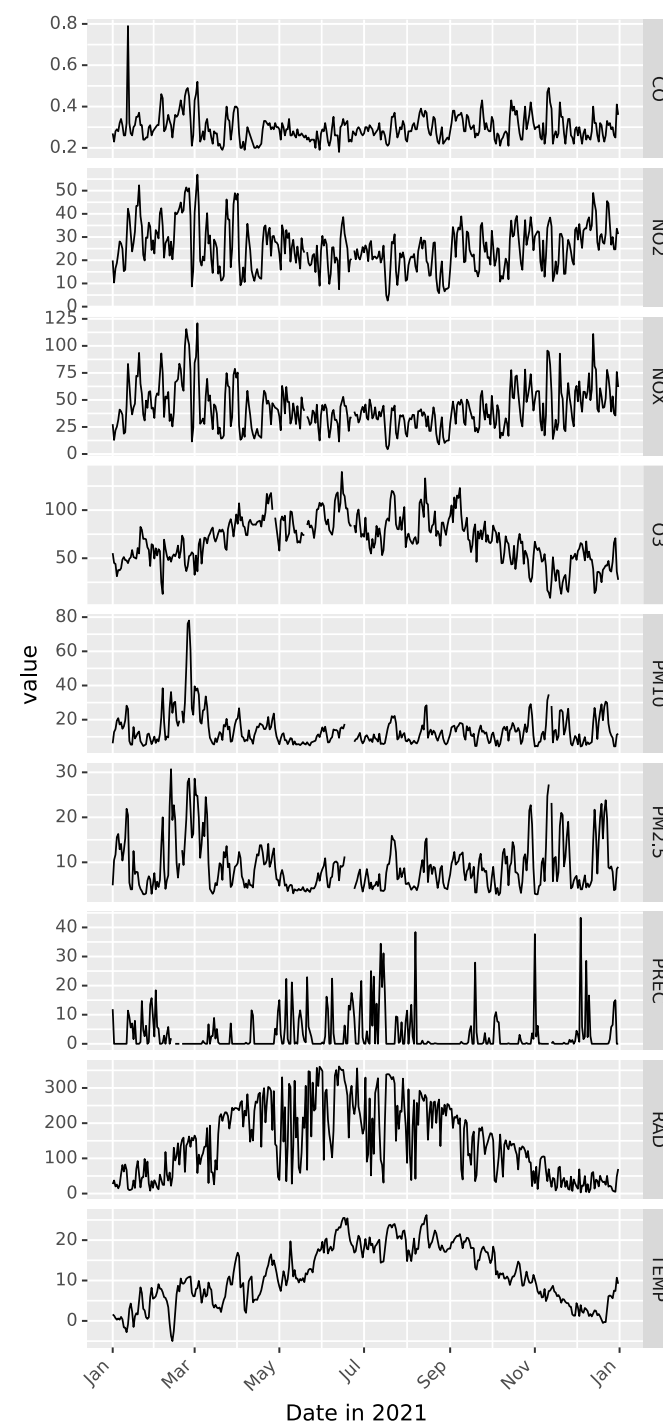
[7 rows x 9 columns]

Plotnine package

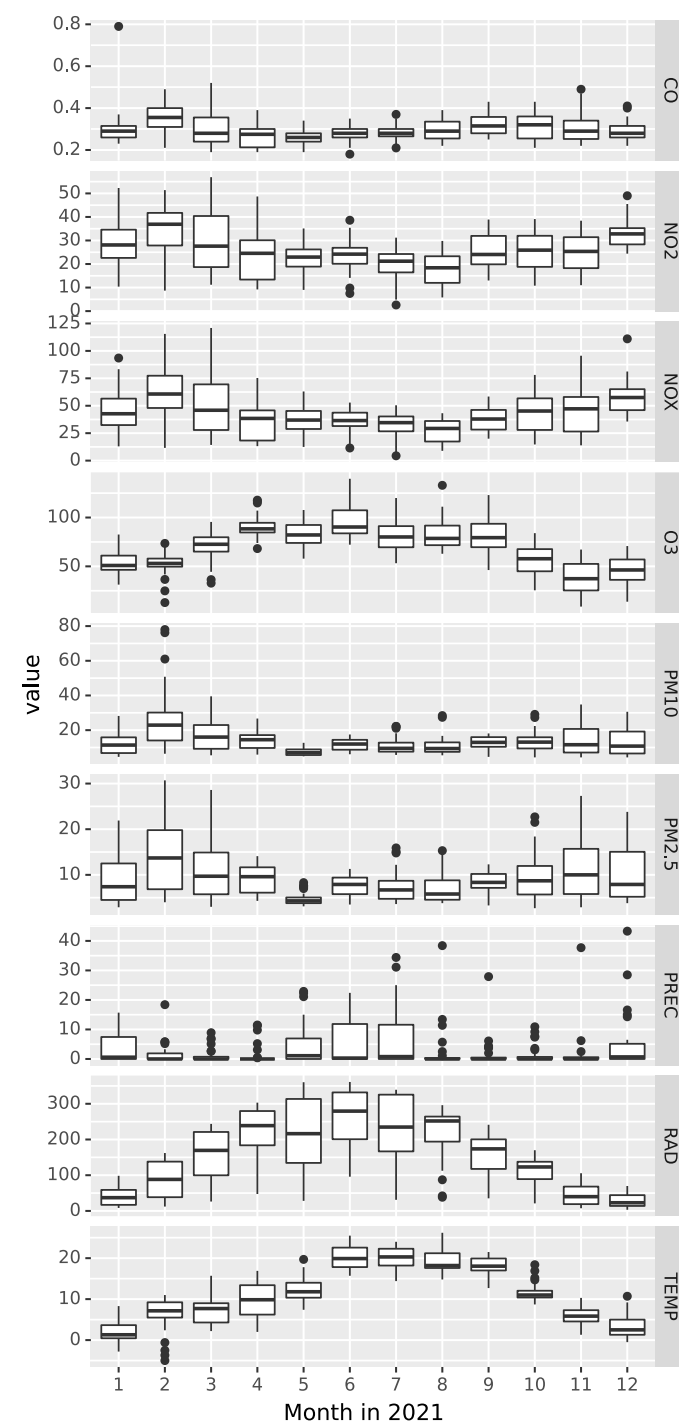
Grammar of Graphics

```
import plotnine as pn
from mizani.formatters import date_format
```

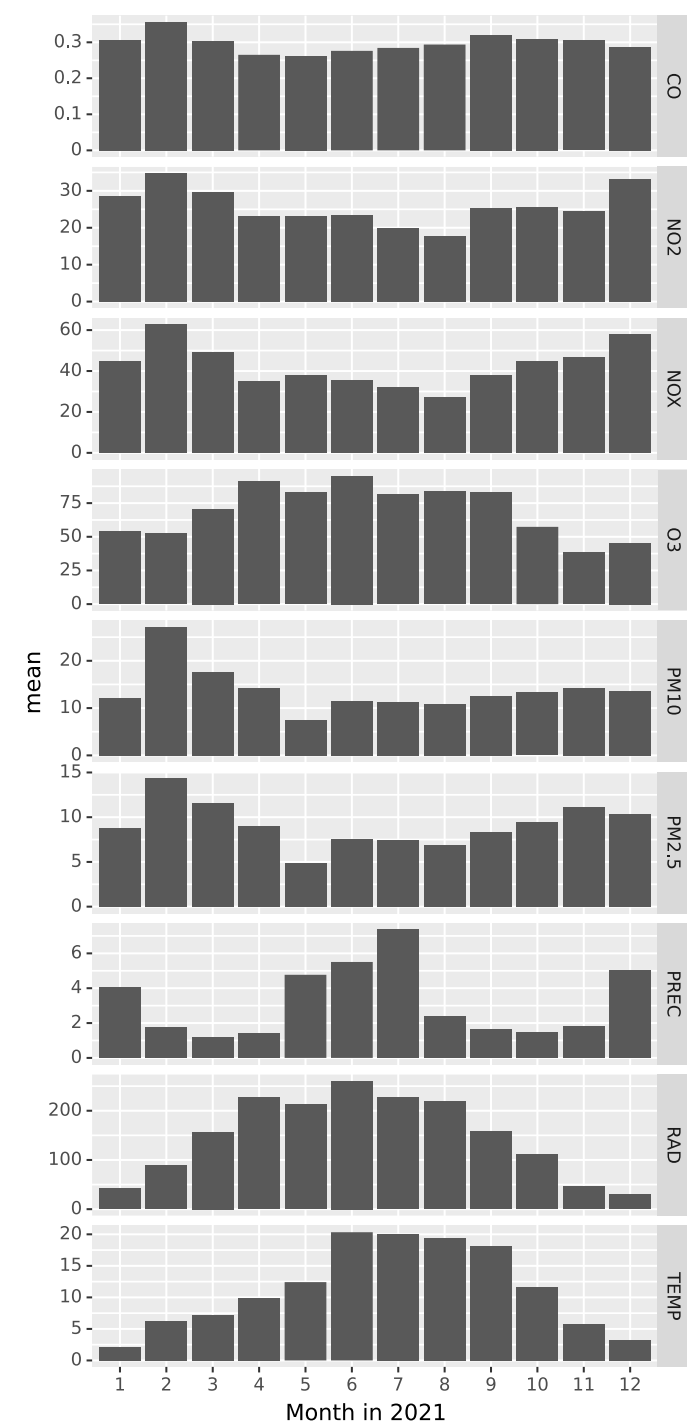
```
p = (
    pn.ggplot(data=lf)
    + pn.geom_line(mapping=pn.aes(x='datetime', y='value'))
    + pn.facet_grid('variable ~ .', scales='free_y')
    + pn.scale_x_datetime(name = 'Date in 2021', labels = date_format('%b'))
    + pn.theme(axis_text_x = pn.element_text(angle=45, hjust=1))
)
```



```
p = (
  pn.ggplot(data=lf)
  + pn.geom_boxplot(mapping=pn.aes(x='month', y='value'))
  + pn.facet_grid('variable ~ .', scales='free_y')
  + pn.scale_x_discrete(name = 'Month in 2021')
)
```

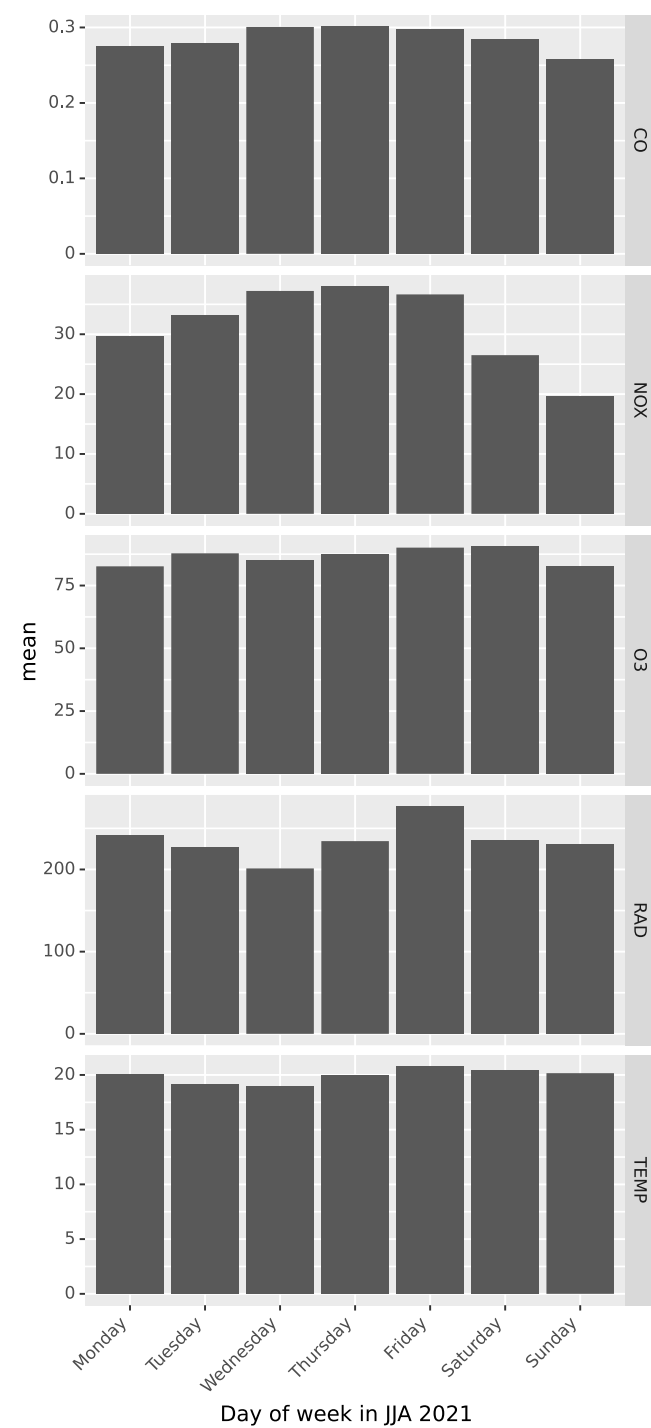


```
p = (
  pn.ggplot(data=means_monthly.reset_index(name = 'mean'))
  + pn.geom_col(mapping=pn.aes(x='month', y='mean'))
  + pn.scale_x_discrete(name = 'Month in 2021', breaks = np.arange(1, 13))
  + pn.facet_grid('variable ~ .', scales='free_y')
)
```



```
wf = means_dailyJJA.reset_index(name = 'mean')
means_dailyJJA_subset = wf.loc[wf['variable'].isin(['O3', 'CO', 'NOX', 'RAD', 'TEMP'])]

p = (
    pn.ggplot(data=means_dailyJJA_subset)
    + pn.geom_col(mapping=pn.aes(x='dayofweek', y='mean'))
    + pn.scale_x_discrete(name = 'Day of week in JJA 2021')
    + pn.facet_grid('variable ~ .', scales='free_y')
    + pn.theme(axis_text_x = pn.element_text(angle=45, hjust=1))
)
```



Swiss terrain exercise revisited (pivoting)

Read xyz data

```
xyz = pd.read_table('./data/DHM200.xyz', delimiter=' ', header=None)
print(xyz.head())
```

	0	1	2
0	655000.0	302000.0	835.01
1	655200.0	302000.0	833.11
2	655400.0	302000.0	831.20
3	655600.0	302000.0	829.30
4	655800.0	302000.0	828.80

Pivot to wide format

```
wide = xyz.pivot_table(index=0, columns=1, values=2, fill_value = 0)
print(wide.head())
```

1	74000.0	74200.0	...	301800.0	302000.0
0			...		
480000.0	0.0	0.0	...	0.0	0.0
480200.0	0.0	0.0	...	0.0	0.0
480400.0	0.0	0.0	...	0.0	0.0
480600.0	0.0	0.0	...	0.0	0.0
480800.0	0.0	0.0	...	0.0	0.0

[5 rows x 1141 columns]

Plot

```
plt.axes().set_aspect('equal')
plt.pcolormesh(wide.index, wide.columns, wide.to_numpy().T,
               shading = 'auto')
plt.title('Suisse')
```

