

Big Data and Automated Content Analysis

Week 7 – Monday

»Statistics with Python«

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May 13, 2019

Today

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② Pandas

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③ Pandas II: Data wrangling

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Statistics in Python

General considerations

General considerations

After having done all your nice text processing (and got numbers instead of text!), you probably want to analyse this further. You can always export to .csv and use R or Stata or SPSS or whatever. . .

BUT:

Reasons for not exporting and analyzing somewhere else

- the dataset might be too big
- it's cumbersome and wastes your time
- it may introduce errors and makes it harder to reproduce

What statistics capabilities does Python have?

- Basically all standard stuff (bivariate and multivariate statistics) you know from SPSS
- Some advanced stuff (e.g., time series analysis)
- However, for some fancy statistical modelling (e.g., structural equation modelling), you can better look somewhere else (R)

Statistics in Python

Useful packages

Useful packages

numpy (numerical python) Provides a lot of frequently used functions, like mean, standard deviation, correlation, ...

scipy (scientific python) More of that ;-)

statsmodels Statistical models (e.g., regression or time series)

matplotlib Plotting

seaborn Even nicer plotting

Example 1: basic numpy

```
1 import numpy as np
2 x = [1,2,3,4,3,2]
3 y = [2,2,4,3,4,2]
4 z = [9.7, 10.2, 1.2, 3.3, 2.2, 55.6]
5 np.mean(x)
```

```
1 2.5
```

```
1 np.std(x)
```

```
1 0.9574271077563381
```

```
1 np.corrcoef([x,y,z])
```

```
1 array([[ 1.          ,  0.67883359, -0.37256219],
2        [ 0.67883359,  1.          , -0.56886529],
3        [-0.37256219, -0.56886529,  1.          ]])
```

Characteristics

- Operates (also) on simple lists
- Returns output in standard datatypes (you can print it, store it, calculate with it, ...)
- it's fast! `np.mean(x)` is faster than `sum(x)/len(x)`
- it is more accurate (less rounding errors)

Example 2: basic plotting

```
1 import matplotlib.pyplot as plt
2 x = [1,2,3,4,3,2]
3 y = [2,2,4,3,4,2]
4 plt.hist(x)
5 plt.plot(x,y)
6 plt.scatter(x,y)
```

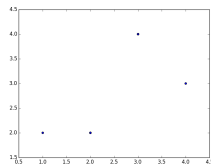
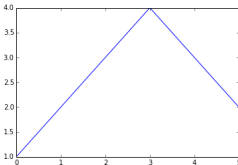
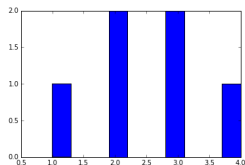


Figure: Examples of plots generated with matplotlib

Pandas

Working with dataframes

When to use dataframes

Native Python data structures (lists, dicts, generators)

pro:

- flexible (especially dicts!)
- fast
- straightforward and easy to understand

con:

- if your data is a table, modeling this as, e.g., lists of lists feels unintuitive
- very low-level: you need to do much stuff 'by hand'

Pandas dataframes

pro:

- like an R dataframe or a STATA or SPSS dataset
- many convenience functions (descriptive statistics, plotting over time, grouping and subsetting, ...)

con:

- not always necessary ('overkill')
- if you deal with really large datasets, you don't want to load them fully into memory (which pandas does)

Pandas

Plotting and calculating with Pandas

OLS regression in pandas

```
1 import pandas as pd
2 import statsmodels.formula.api as smf
3
4 df = pd.DataFrame({'income': [10,20,30,40,50], 'age': [20, 30, 10, 40,
50], 'facebooklikes': [32, 234, 23, 23, 42523]})
5
6 # alternative: read from CSV file (or stata...):
7 # df = pd.read_csv('mydata.csv')
8
9 myfittedregression = smf.ols(formula='income ~ age + facebooklikes',
10 data=df).fit()
11 print(myfittedregression.summary())
```

```

1 OLS Regression Results
2 =====
3 Dep. Variable:          income  R-squared:                0.579
4 Model:                  OLS     Adj. R-squared:             0.158
5 Method:                  Least Squares  F-statistic:             1.375
6 Date:                   Mon, 05 Mar 2018  Prob (F-statistic):    0.421
7 Time:                   18:07:29  Log-Likelihood:          -18.178
8 No. Observations:        5      AIC:                    42.36
9 Df Residuals:            2      BIC:                    41.19
10 Df Model:                2
11 Covariance Type:        nonrobust
12 =====
13 coef    std err          t      P>|t|     [95.0% Conf. Int.]
14 -----
15 Intercept              14.9525    17.764     0.842    0.489    -61.481    91.386
16 age                   0.4012     0.650     0.617    0.600    -2.394     3.197
17 facebooklikes         0.0004     0.001     0.650    0.583    -0.002     0.003
18 =====
19 Omnibus:                nan    Durbin-Watson:           1.061
20 Prob(Omnibus):          nan    Jarque-Bera (JB):        0.498
21 Skew:                   -0.123  Prob(JB):                0.780
22 Kurtosis:               1.474  Cond. No.                 5.21e+04
23 =====

```


Other cool df operations

`df['age'].plot()` to plot a column

`df['age'].describe()` to get descriptive statistics

`df['age'].value_counts()` to get a frequency table

and MUCH more...

Recoding and transforming

To transform your data, you can use `.apply()`, `.applymap()`, and `.map()` or the `.str.XXX()` methods:

```
1 df['is_center'] = df['hood'].str.contains('[cC]enter')
```

or define your own function:

```
1 def is_center(x):  
2     return int(x.lower().find('center') > -1)  
3  
4 df['is_center'] = df['hood'].map(is_center)
```

or use a throwaway-function:

```
1 df['is_center'] = df['hood'].map(lambda x: int(x.lower().find('center')  
    > -1))
```

Subsetting and slicing

Subsetting and slicing

Recap:

- `[0:5]` to get elements 0, 1, 2, 3, 4 (works with lists, dataframes ...)
- `mydict['keyicareabout']` to get value (content) associated with the key

And therefore, also:

- `df[['col1', 'col2']]` to get only these two columns of a dataset
- `df[df['col1']=='whatever']` to get only the rows in which col1 is identical to the string 'whatever'
- `df[df['col2']>0]` to get only the rows in which col2 is a number bigger than 0

More subsetting

To get a specific row and/or column, you can use `.iloc[]` and `.loc[]`

- `.iloc[]` takes an int (the row/column numbers, `.loc[]` the names)
- `df.iloc[0,5]` to get row 0, column 5
- `df.loc[0,'what']` to get row 0, column 'what'

In [7]: df.head()

Out[7]:

	what	when	country	who	number	text	text_clean	language
0	EU Council: PM press conference	18-12-2015	Great Britain	D. Cameron	2877	<p>This European Council has focused on 3 issu...	european council focus issu uk renegoti migrat...	en
1	PM statement in Poland: 10 December 2015	10-12-2015	Great Britain	D. Cameron	866	<p>Thank you Prime Minister for welcoming me h...	thank prime minist welcom warsaw honour first ...	en
2	PM statement on talks in Romania, 9 December 2015	09-12-2015	Great Britain	D. Cameron	726	<p>Thank you President Iohannis for welcoming ...	thank presid iohanni welcom bucharest today pl...	en
3	PM Speech: This is a government that delivers	07-12-2015	Great Britain	D. Cameron	6211	<p>This is a government that delivers</p><p>Th...	govern deliversthank much brief introduct grea...	en
4	PM Bulgaria visit 3 December 2015: press	07-12-2015	Great Britain	D. Cameron	773	<p>Well thank you very much	well thank much prime minist	en

In [9]: df.iloc[0,5]

Out[9]:

df.iloc[0,5]

'<p>This European Council has focused on 3 issues: the migration crisis, the situation in the Middle East and the situation in the Balkans. At the renegoti migration conference, we discussed the ongoing migration crisis facing Europe. Even with the onset of winter, there are still many migrants coming to Europe - with around 5,000 arriving via the eastern Mediterranean route each day. Britain has its own strict border controls, which apply to everyone attempting to enter the United Kingdom. And every day those border controls are helping to keep us safe. But while we are outside Schengen, we are ready to help our European partners secure their borders. From the start, the United Kingdom has called for a comprehensive approach that tackles the root causes of this migration crisis - not just the consequences of vast numbers reaching Europe. That's why we have provided £1.2 billion in humanitarian assistance for the Syrian conflict and deployed HMS Enterprise and police officers to the Mediterranean to go after the traffickers. And it's why we have offered practical assistance to help with the registering and fingerprinting of migrants in countries where they land,

In [7]: df.head()

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In [10]: df.loc[0, 'text']

Out[10]:

df.loc[0, 'text']

'<p>This European Council has focused on 3 issues. Even with the onset of winter, there are still many migrants coming to Europe - with around 5,000 arriving via the eastern Mediterranean route each day. Britain has its own strict border controls, which apply to everyone attempting to enter the United Kingdom. And every day those border controls are helping to keep us safe. But while we are outside Schengen, we are ready to help our European partners secure their borders. From the start, the United Kingdom has called for a comprehensive approach that tackles the root causes of this migration crisis - not just the consequences of vast numbers reaching Europe. That's why we have provided £1.2 billion in humanitarian assistance for the Syrian conflict and deployed HMS Enterprise and police officers to the Mediterranean to go after the traffickers. And it's why we have offered practical assistance to help with the registering and fingerprinting of migrants in countries where they land,

Advanced Example

Out of a dataset with 1,000 speeches, get the one that talks most about [Tt]error

- 1 We create a new column to count how many a word is mentioned:

```
df['terror'] =  
df['speech'].str.count('[Tt]error')
```

- 2 We do

```
df.iloc[df['terror'].idxmax()]
```

- 3 That works because `df.iloc[]` expects an integer to identify the row number, and `df['terror'].idxmax()` returns an integer (687 in our case)


```
df['terrorrefs'].idxmax()
```

```
687
```

```
df.iloc[687|]
```

what	Permanent Link to Press conference in Islamabad
when	14-12-2008
country	Great Britain
who	G. Brown
number	2954
text	<p>Transcript of a press conference given by t...
text_clean	transcript press confer given prime minist mr ...
language	en
terrorrefs	44

Name: 687, dtype: object

Joining and Merging

Joining and Merging

Typical scenario

- You have two datasets that share one column
- For instance, data from `www.cbs.nl`: one with economic indicators, one with social indicators
- You want to make one dataframe

```
economie = pd.read_csv('82800ENG_UntypedDataSet_15112018_205454.csv', delimiter=';')  
economie.head()
```

	ID	EconomicSectorsSIC2008	Regions	Periods	GDPVolumeChanges_1
0	132	T001081	PV20	1996JJ00	9.3
1	133	T001081	PV20	1997JJ00	-2.0
2	134	T001081	PV20	1998JJ00	-0.9
3	135	T001081	PV20	1999JJ00	-0.7
4	136	T001081	PV20	2000JJ00	1.5

```
population = pd.read_csv('37259eng_UntypedDataSet_15112018_204553.csv', delimiter=';')  
population.head()
```

	ID	Sex	Regions	Periods	LiveBornChildrenRatio_3
0	290	T001038	PV20	1960JJ00	18.6
1	291	T001038	PV20	1961JJ00	18.9
2	292	T001038	PV20	1962JJ00	18.9
3	293	T001038	PV20	1963JJ00	19.5
4	294	T001038	PV20	1964JJ00	19.6

What do you think: How could/should a joined table look like?

First clean up...

```
# remove unnecessary columns
economie.drop('ID',axis=1,inplace=True)
population.drop('ID',axis=1,inplace=True)
# remove differentiation by sex
population = population[population['Sex']!='T001038']
population.drop('Sex',axis=1,inplace = True)
# keep only rows of economie dataframe that contain the total economic activity
economie = economie[economie['EconomicSectorsSIC2008']=='T001081 ']
economie.drop('EconomicSectorsSIC2008', axis=1, inplace=True)
```

```
# remove those evil spaces at the end of the names of the provinces
population['Regions'] = population['Regions'].map(lambda x: x.strip())
economie['Regions'] = economie['Regions'].map(lambda x: x.strip())
```

```
population.merge(economie, on=['Periods','Regions'], how='inner')
```

	Regions	Periods	LiveBornChildrenRatio_3	GDPVolumeChanges_1
0	PV20	1996JJ00	11.0	9.3
1	PV20	1997JJ00	11.4	-2.0
2	PV20	1998JJ00	11.6	-0.9
3	PV20	1999JJ00	11.6	-0.7
4	PV20	2000JJ00	11.5	1.5
5	PV20	2001JJ00	11.7	3.9
6	PV20	2002JJ00	11.4	2.1

Then
merge

On what do you want to merge/join?

Standard behavior of `.join()`: on the row index (i.e., the row number, unless you changed it to sth else like a date)

```
1 df3 = df1.join(df2)
```

But that's only meaningful if the indices of `df1` and `df2` mean the same. Therefore you can also join on a column if both `dfs` have it:

```
1 df3 = df1.merge(df2, on='Regions')
```

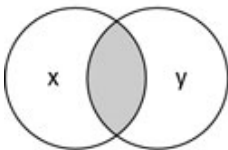
`.merge()` is the more powerful tool, `.join()` is a bit easier when joining on indices.

Inner, Outer, Left, and Right

Main question: What do you want to do with keys that exist only in one of the dataframes?

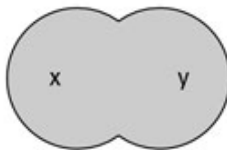
```
df3 = df1.join(df2, how='xxx')
```

how='inner'



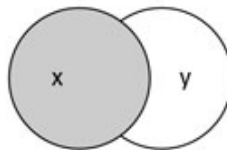
natural join

how='outer'



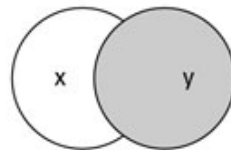
full outer join

how='left'



left outer join

how='right'



right outer join

Aggregation

An example

- Suppose you have two dataframes, both containing information on something per region per year.
- You want to merge (join) the two, however, in one of them, the information is also split up by age groups. You don't want that.
- How do you bring these rows back to one row? With `.agg()`!

.agg()

- Very useful after a `.groupby()`
- Takes a function as argument:
`df2 = df.groupby('region').agg(sum)`
- Or multiple functions:
`df2 = df.groupby('region').agg([sum, np.mean])`
- → yes, you could do `.describe()`, but `.agg()` is more flexible

An example

How do housing prices (WOZ-waarde) develop over time in different neighborhoods?

wijken|

0	Burgwallen-Oude Zijde	263417.0	273525.0	289984.0	339548.0	400010.0	A00	Centrum
1	Burgwallen-Nieuwe Zijde	267895.0	281193.0	296762.0	351214.0	391011.0	A01	Centrum
2	Grachtengordel-West	490251.0	502230.0	560841.0	674610.0	755091.0	A02	Centrum
3	Grachtengordel-Zuid	469946.0	478371.0	531225.0	627625.0	697576.0	A03	Centrum
4	Grachtengordel-Oost/Markt/Lastage	295239.0	303500.0	340364.0	386716.0	438942.0	A04	Centrum
5	Haarlemmerbuurt	304924.0	311743.0	345189.0	403267.0	458522.0	A05	Centrum
6	Jordaan	270390.0	285877.0	307344.0	347740.0	402186.0	A06	Centrum
7	De Weteringschans	344649.0	359119.0	399942.0	458010.0	515192.0	A07	Centrum
8	Weesperbuurt/Plantage	307440.0	322276.0	353628.0	413388.0	473643.0	A08	Centrum
9	Oostelijke Eilanden/Kadijken	253990.0	256421.0	276481.0	316261.0	381774.0	A09	Centrum
11	Westelijk Havengebied	NaN	189402.0	224491.0	NaN	NaN	B10	Westpoort
13	Houthavens	164263.0	167242.0	188360.0	349525.0	483318.0	E12	West
14	Spaarndammer- en Zeeheldenbuurt	207439.0	209713.0	222371.0	256300.0	322981.0	E13	West
15	Staatsliedenbuurt	209792.0	222070.0	241366.0	277214.0	325787.0	E14	West

Steps

- ➊ Get it into a tidy format (1 row = 1 observation) (“long” format)
- ➋ Optionally, but more neat (also for automatically getting correct plot labels):
index rows by year
- ➌ use `.groupby()` and `.agg()` to aggregate the data

```
wijken_long = wijken.melt(id_vars=['wijk', 'stadsdeel'],  
                           value_vars=['2014', '2015', '2016', '2017', '2018'],  
                           value_name='woz-waarde',  
                           var_name = 'year')
```

wijken_long

.melt() transforms a df from wide to long

	wijk	stadsdeel	year	woz-waarde
0	Burgwallen-Oude Zijde	Centrum	2014	263417.0
1	Burgwallen-Nieuwe Zijde	Centrum	2014	263417.0
2	Grachtengordel-West	Centrum	2014	263417.0
3	Grachtengordel-Zuid	Centrum	2014	263417.0
4	Nieuwmarkt/Lastage	Centrum	2014	263417.0
5	Haarlemmerbuurt	Centrum	2014	263417.0
6	Jordaan	Centrum	2014	263417.0
7	De Weteringschans	Centrum	2014	344649.0
8	Weesperbuurt/Plantage	Centrum	2014	307440.0
9	Oostelijke Eilanden/Kadijken	Centrum	2014	253990.0
10	Westelijk Havengebied	Westpoort	2014	NaN

id_vars: what are the cases?

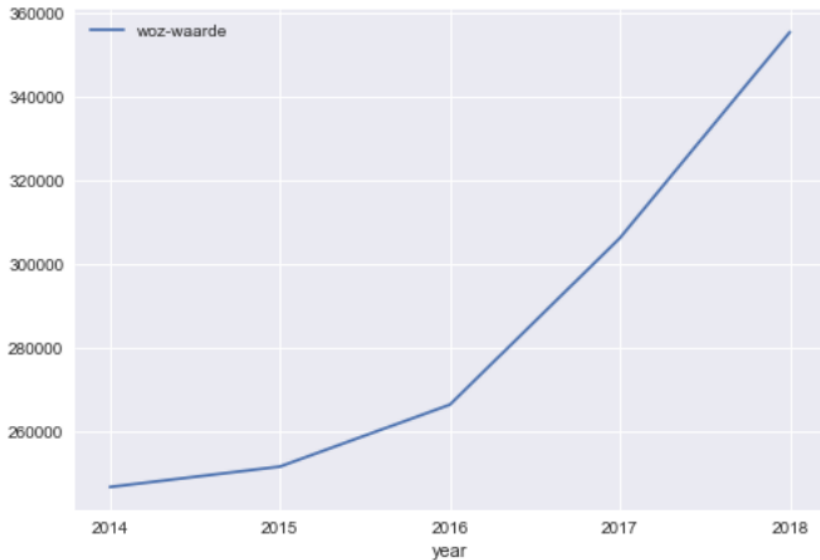
value_vars: which vars contain the values?

And now?

- Let's think about a strategy for `.groupby().agg()`: What should we group by and how do we need to aggregate?
- Group by:
 - ① Group only by year
 - ② Group by year and 'stadsdeel'
- Aggregation function
 - ① mean
 - ② Possibly also min, max, or even `lambda x: max(x)-min(x)`

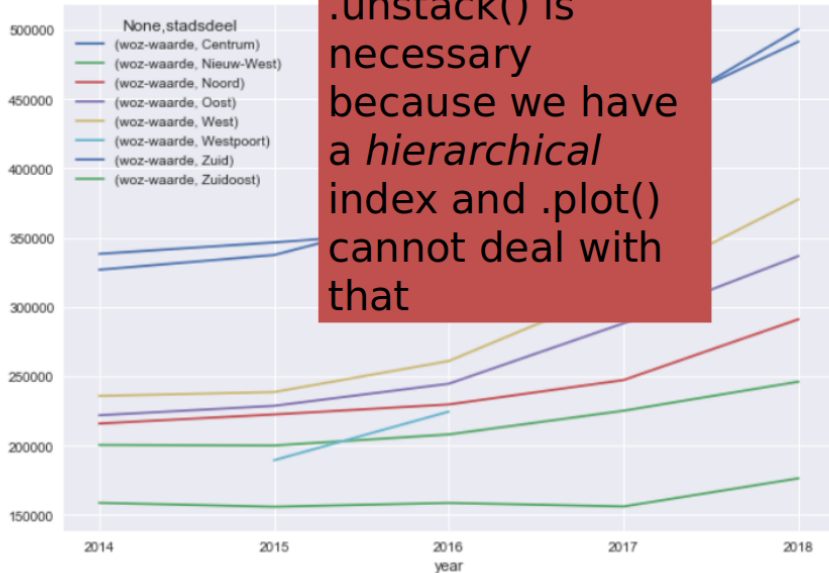
```
wijken_long.groupby('year').agg(np.mean).plot(xticks=[0,1,2,3,4])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1191a4128>
```




```
wijken_long.groupby(['year', 'stadsdeel']).agg(np.mean).unstack().plot(  
    figsize=[10,7], xticks=range(5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1196ad7f0>
```



.unstack() is
necessary
because we have
a *hierarchical*
index and .plot()
cannot deal with
that

What's unstacking?

```
wijken_long.groupby(['year', 'stadsdeel']).agg(np.mean)
```

-> Turn hierarchical indices into non-hierarchical structure

		woz-waarde
year	stadsdeel	
2014	Centrum	326814.100000
	Nieuw-West	200453.500000
	Noord	215879.500000
	Oost	221828.142857
	West	235801.0
	Westpoort	NaN
	Zuid	33820.0
	Zuidoost	15860.0
2015	Centrum	337425.5
	Nieuw-West	200028.000000
	Noord	222417.200000
	Oost	228636.000000

```
wijken_long.groupby(['year', 'stadsdeel']).agg(np.mean).unstack()
```

	woz-waarde						
stadsdeel	Centrum	Nieuw-West	Noord	Oost	West	Westpoort	Zuid
year							
2014	326814.1	200453.500000	215879.500000	221828.142857	235801.0	NaN	33820.0
2015	337425.5	200028.000000	222417.200000	228636.000000	238568.8	189402.0	34650.0
2016	370176.0	208002.428571	229650.466667	244608.428571	260979.4	224491.0	35590.0

There are example datasets and notebooks on Canvas!

Find an exercise here: https://github.com/annekroon/bdaca/blob/master/ipynb/basic_statistics.ipynb or on Canvas (under 'modules')

Next steps

Thursday: Final lecture

You are now able to read and write Python code. Therefore, we can now introduce some advanced analysis topics, mainly machine learning.

Monday 20/ 05

Not mandatory: In case you need (individual) consultation regarding final project.