Data structuring

The Pandas way

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Recap

What have we learned about visualizations?

-

Agenda

We will learn about Pandas data structures and procedures. Specifically we go through:

- Viewing and selecting data
- Missing data
- Series:
    - procedures and data types:
        - numerical; boolean; strings and temporal
- DataFrame:
    - loading and storing data
    - split-apply-combine (groupby)
    - joining datasets

A small exercise

Why we do structuring

Motivation

Why do we want to learn data structuring?

TECHNOLOGY

For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights

By STEVE LOHR AUG. 17, 2014

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Technology revolutions come in measured, sometimes foot-dragging steps. The lab science and marketing enthusiasm tend to underestimate the bottlenecks to progress that must be overcome with hard work and practical engineering.

The field known as "big data" offers a contemporary case study. The catchphrase stands for the modern abundance of digital data from many sources — the web, sensors, smartphones and corporate databases — that can be mined with clever software for discoveries and insights. Its promise is smarter, data-driven decision-making in every field. That is why data scientist is the economy's hot new job.

Yet far too much handcrafted work — what data scientists call "data wrangling," "data

Monica Rogati, Jawbone's vice president for data science, with Brian Wilt, a senior data scientist. Peter DaSilva for The New York Times

Motivation (continued)

- Data never comes in the form of our model. We need to 'wrangle' our data.

Can our machine learning models not do this for us?

- Not yet :). The current version needs **tidy** data. What is tidy?

Same as long - one row per observation.

Getting prepared

In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

%matplotlib inline
```

Pandas Data Stuctures

Why use Pandas?

1. simplicity - Pandas is built with Python's simplicity
2. flexible and powerful tools for working with data
3. speed - build on years of research about numeric computation
4. development - breathtaking speed of new tools coming

How do we work with data in Pandas?

- We use two fundamental data stuctures: **DataFrame** and **Series**.

Pandas DataFrames

What is a DataFrame?

- A matrix with labelled columns and rows (which are called indices). Example:

In [3]:
```
df = pd.DataFrame(data=[[1,2],[3,4]],
                  columns=['A','B'],
                  index=['i', 'ii'])

print(df)
```

```
    A  B
i   1  2
ii  3  4
```

- An object with many powerful methods.

- *To note*: In Python we can describe it as a list of lists of a dict of dicts.

Pandas DataFrames (continued)

Pandas is built on top of numpy (http://www.numpy.org/) a Python framework similar to matlab.

Many functions from numpy can be applied directly to Pandas. We can convert a DataFrame to a numpy matrix with **values** method.

In [4]:
```
df.values
```

Out[4]:
```
array([[1, 2],
       [3, 4]], dtype=int64)
```

Pandas series

What is a Series?

- A vector/list with labels for each entry. Example:

In [5]:
```
ser =  pd.Series([1,'b',10/3,True])

ser
```

Out[5]:
```
0          1
1          b
2    3.33333
3       True
dtype: object
```

What data structure does this remind us of?

- A mix of Python list and dictionary (more info follows)

Series and DataFrames

How are Series related to DataFrames?

Every column is a series. Example: access as object method:

In [ ]:
```
df.A
```

Another option is access as key:

In [ ]:
```
df['B']
```

To note: The latter option more robust as variables named same as methods, e.g. `count`, cannot be accesed.

Indices

Why don't we just use matrices?

- labelled columns are easier to work with
- indices may contain fundamentally different data structures
  - e.g. time series, hierarchical groups

Using pandas Series

Generation

Let's revisit our series

In [9]:
```
ser
```

Out[9]:
```
0          1
1          b
2    3.33333
3       True
dtype: object
```

Components in series

- index: label for each observation
- values: observation data
- dtype: the format of the series - object allows any data type

Generation (continued)

How do we set custom index? Example:

In [11]:
```
num_data = range(0,3)
```
Out[11]:
```
[0, 1, 2]
```

In [13]:
```
ser_num = pd.Series(num_data, index=['B','C','A'])
ser_num
```
Out[13]:
```
B    0
C    1
A    2
dtype: int32
```

Generation (continued)

The dictionary and series. Example:

In [14]:
```
d = {'yesterday':0, 'today':1, 'tomorrow':3}

ser_num_2 = pd.Series(d)
ser_num_2
```

Out[14]:
```
today        1
tomorrow     3
yesterday    0
dtype: int64
```

How is the series different from a dict?

- The series has powerful methods:

In [15]:
```
ser_num_2.median()
```

Out[15]:
```
1.0
```

Converting data types

The data type of a series can be converted with the **astype** method:

In [19]:
```
ser_num_2.astype(float)
```

Out[19]:
```
today        1.0
tomorrow     3.0
yesterday    0.0
dtype: float64
```

In [18]:
```
ser_num_2.astype(str).tolist()
```

Out[18]:
```
['1', '3', '0']
```

Missing data type

What fundamental data type might we be missing?

Empty data

In [ ]:

```
None # python
np.nan #numpy/Pandas
```

Important methods: **isnull**, **notnull**, **dropna**. Example

In [ ]:

```
ser_num_3 = pd.Series([1, np.nan, 2.4, None])
ser_num_3
```

In [24]:

```
ser_num_3.dropna()
```

Out[24]:

```
0    1.0
2    2.4
dtype: float64
```

Missing data type (continued)

Can we change the missing values?

Yes. One example is to uniformly assign a value with **fillna**:

In [26]:
```
ser_num_3.fillna(3.14)
```

Out[26]:
```
0    1.00
1    3.14
2    2.40
3    3.14
dtype: float64
```

A more sophisticated way is forward-fill which is called **ffill**:

In [ ]:
```
ser_num_3.ffill()
```

Other ways include **interpolate**, **dropna** and **bfill** which we do not cover.

Numeric operations

How do we manipulate series?

Like Python data! An example:

```
In [31]: ser_num_3 ** 2
```

```
Out[31]: 0    1.00
         1     NaN
         2    5.76
         3     NaN
         dtype: float64
```

Are other numeric python operators the same?

Yes **/**, **//**, **-**, *****, ******, **+=**, **-=** etc. behave as expected.

Numeric methods

Pandas series has powerful numeric methods. Have we seen one?

In [ ]:
```
ser_num_2.median()
```

Other useful methods include: **mean**, **median**, **min**, **max**, **var**, **describe**, **quantile** and many more.

In [33]:
```
ser_num_2.describe()
```

Out[33]:

	A	B
count	2.000000	2.000000
mean	2.000000	3.000000
std	1.414214	1.414214
min	1.000000	2.000000
25%	1.500000	2.500000
50%	2.000000	3.000000
75%	2.500000	3.500000
max	3.000000	4.000000

Numeric methods (continued)

An important method is `value_counts`. This counts number for each observation.

Example:

```
In [37]: np.mean(ser_vc)
Out[37]: 2.0
```

```
In [36]: ser_vc.nunique()
Out[36]: 3
```

```
In [35]: for i in ser_vc.unique():
             print(i)
```

```
1
2
3
```

In [34]:
```
ser_vc = pd.Series([1,2,2,3])

ser_vc.value_counts()
```

Out[34]:
```
2    2
3    1
1    1
dtype: int64
```

What is observation in the value_counts output - index or data?

Numeric methods (continued)

We can also do elementwise addition, multiplication, subtractions etc. of series. Example:

In [9]:
```
pd.Series(range(4)) + pd.Series(range(9,1,-2))
```

Out[9]:
```
0    9
1    8
2    7
3    6
dtype: int32
```

Numeric methods (continued)

Are there other powerful numeric methods?

Yes: examples include

- **unique**, **nunique**: the unique elements and the count of unique elements
- **cut**, **qcut**: partition series into bins
- **diff**: difference every two consecutive observations
- **cumsum**: cumulative sum
- **nlargest**, **nsmallest**: the n largest elements
- **idxmin**, **idxmax**: index which is minimal/maximal
- **corr**: correlation matrix

Check series documentation (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.html) for more information.

Logical operators

Does our standard logical operators work?

Yes: **==**, **!=**, **&**, **|** work elementwise. Example:

In [38]:
```
ser_num_2
```

Out[38]:
```
today        1
tomorrow     3
yesterday    0
dtype: int64
```

What datatype is returned? What about the **|** operator?

In [48]:
```
ser_num_2[selection]
```

Out[48]:
```
today        1
yesterday    0
dtype: int64
```

In [46]:
```
selection = (ser_num_2==0) | (ser_num_2==1)
```

Logical operators (continued)

Check for multiple equal: **isin**. Example:

In [51]:
```
ser_num_2 *= 2
```

In [56]:
```
rng = list(range(3))
```

In [63]:
```
rng
```

Out[63]:
```
[0, 1, 2]
```

In [62]:
```
ser_num_2
```

Out[62]:
```
today        2
tomorrow     6
yesterday    0
dtype: int64
```

In [60]:
```
ser_num_2.isin(rng)
```

Out[60]:
```
today         True
tomorrow     False
yesterday     True
dtype: bool
```

String operations

Which operators could work for string?

Operators **+**, **+=**. Example:

```
In [67]: ser_str_alt = pd.Series([' Min',' ven',' pedro'])
```

```
In [68]: ser_str+ser_str_alt # adding two series together is also possible
```

```
Out[68]: 0          My Min
         1       amigo ven
         2     pedro pedro
         dtype: object
```

```
In [64]: ser_str = pd.Series(['My', 'amigo', 'pedro'])
         ser_str+' Hello'
```

```
Out[64]: 0        My Hello
         1     amigo Hello
         2     pedro Hello
         dtype: object
```

String operations (continued)

The powerful .str has several powerful methods e.g. `contains`, `capitalize`. Example:

In [70]:
```
ser_str
```

Out[70]:
```
0       My
1    amigo
2    pedro
dtype: object
```

In [ ]:
```
ser_str.str.upper()
```

In [ ]:
```
ser_str.str.contains('M')
```

The .str method also has slicing - example:

In [73]:
```
ser_str.str[:2]
```

Out[73]:
```
0    My
1    am
2    pe
dtype: object
```

Temporal data type

Pandas Series has support for temporal data as well. Example:

In [74]:
```
dates = ['20170101', '20170727', '20170803', '20171224']
```

In [76]:
```
datetime_index = pd.to_datetime(dates)
```

In [77]:
```
ser_time = pd.Series(datetime_index)
ser_time
```

Out[77]:
```
0   2017-01-01
1   2017-07-27
2   2017-08-03
3   2017-12-24
dtype: datetime64[ns]
```

What can it be used for

Using temporal data

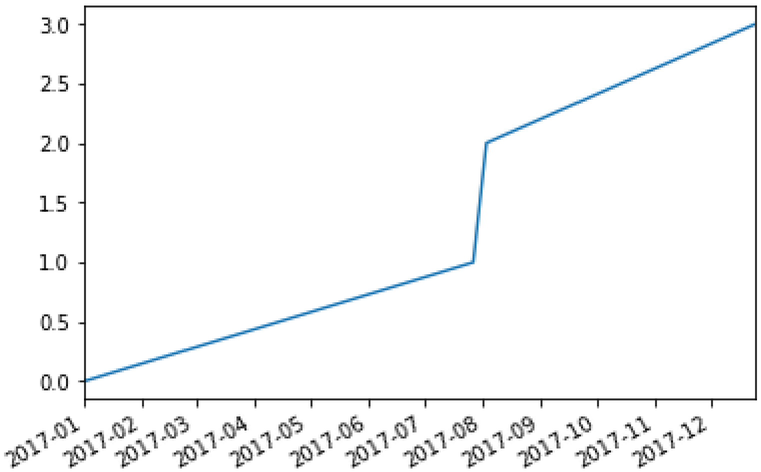
Why is temporal data powerful?

- conversion to time series; example:

In [81]:
```
ser_time_2 = pd.Series(index=datetime_index, data=range(4))

ser_time_2.plot()
```

Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x2850530dc18>



Using temporal data (continued)

What other uses might be relevant?

Temporal has the **.dt** method and its sub-methods. Example:

In [85]:
```
ser_time.dt.second
```

Out[85]:
```
0    0
1    0
2    0
3    0
dtype: int64
```

In [82]:
```
ser_time.dt.month
```

Out[82]:
```
0     1
1     7
2     8
3    12
dtype: int64
```

The dt method has several other sub-methods including **year**, **day**, **weekday**, **hour**, **second**

To note: Your temporal data may need conversion - see other dt sub-methods: **tz_localize** and **tz_convert** for that

Temporal data type (continued)

What happens if we convert to integers?

In [89]:
```
pd.to_datetime([123512321,2132321321], unit='s')
```

Out[89]:
```
DatetimeIndex(['1973-11-30 12:58:41', '2037-07-27 15:28:41'], dtype='datetime64[ns]', freq=None)
```

In [86]:
```
ser_time.astype(np.int64)
```

Out[86]:
```
0    1483228800000000000
1    1501113600000000000
2    1501718400000000000
3    1514073600000000000
dtype: int64
```

What is this?

- The underlying structure is epoch time.
- Epoch time measures seconds since Jan. 1, 1970, at 00:00:00 - GMT time zone. Here the output is nanoseconds(ns).

Viewing and editing data

The simplest way to view a series (and dataframe) is as follows:

In [96]:
```
ser_num_4 = pd.Series(np.random.normal(size=[100000]))

ser_num_4.tail(10) # prints first 30, last 30 observations
```

Out[96]:
```
99990   -0.906753
99991   -1.138565
99992    0.125433
99993    0.583006
99994   -0.127683
99995    0.683099
99996   -0.023049
99997    0.566708
99998    0.215449
99999   -1.509640
dtype: float64
```

The **head** and **tail** respectively prints the first and last observations.

In [ ]:
```
ser_num_4.tail(3) # prints first 3 observation,
```

Viewing and editing data (continued)

The **loc** methods provide a powerful way of accessing subsets of a series through the index.

In [98]:
```
my_dict = {'A':1,'B':2}
my_dict['B']
```

Out[98]:
```
2
```

In [97]:
```
ser_num_2.loc['tomorrow']
```

Out[97]:
```
6
```

We can select multiple elements:

In [ ]:
```
indices = ['today', 'tomorrow']
ser_num_2.loc[indices]
```

The **iloc** method access a subset of a series using integers:

In [105]:
```
ser_num_4.iloc[1000:1005]
```

Out[105]:
```
1000   -1.217063
1001    0.947759
1002   -0.069886
1003   -0.933533
1004    0.613368
dtype: float64
```

Viewing and editing data (continued)

This can be used to alter the values:

In [ ]:
```
ser_num_2.loc['tomorrow'] = 4 # change value of element with index 'tomorrow' to 4
ser_num_2
```

In [108]:
```
pd.Series(range(3),index=['A', 'A','A'])
```

Out[108]:
```
A    0
A    1
A    2
dtype: int32
```

WARNING!#@

- Series indices are NOT unique

Viewing and editing data (continued)

We can also use boolean series for selection:

In [109]:
```
selection = ser_num_3.notnull()

sub = ser_num_3[selection]

sub
```

Out[109]:
```
0    1.0
2    2.4
dtype: float64
```

To note: could also have been performed with **dropna**.

Series recap

- Most Python operations also work for Pandas!
- Series are also good for operating strings and boolean stuff
- Series has powerful methods for fast selection
- Two new datatypes:
  - Empty data (np.nan, None)
  - Temporal data (datetime)

More remains unexplored:

- the category data datatype (https://pandas.pydata.org/pandas-docs/stable/categorical.html) makes strings ultra fast and memory efficient

Overview

- Matplotlib: explanatory data analysis
- Pandas: dataframes, data manipulation, plotting
- Seaborn: polished plotting, exploratory data analysis

DataFrames

A small exercise

While working with DataFrame we will work on a small exercise. The exercise consists:

- loading the data;
- data preprocessing;
- selecting a relevant sample;
- employ dataset to gain insights through computations and visualizations

Getting prepared

In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

%matplotlib inline
```

DataFrame: as a matrix

A DataFrame has various built in matrix operations, e.g.

- **dot** (matrix multiplication)
- **T** (transpose).

In [6]:
```
df1 = pd.DataFrame([[1,2],[3,4]])
df2 = pd.DataFrame([[1,0],[0,2]])
```

In [8]:
```
print(df1.dot(df2))
```

```
   0  1
0  1  4
1  3  8
```

In [9]:
```
print(df1.T)
```

```
   0  1
0  1  3
1  2  4
```

Remember: more matrix operations with numpy!

DataFrame: loading and storing

Reading DataFrames

Download the file from url:

In [10]:

```
gh_raw = 'https://raw.githubusercontent.com/'
user = 'abjer/'
repo = 'sds/'
branch = 'master/'
file = 'data/bechdel.csv'
url = gh_raw + user + repo + branch + file

url
```

Out[10]:

```
'https://raw.githubusercontent.com/abjer/sds/master/data/bechdel.csv'
```

Reading DataFrames (continued)

Now let's try opening it:

- As local file:

In [12]:
```
abs_path = 'C:/Users/bvq720/sds/data/bechdel.csv' # absolute path
# rel_path = 'bechdel.csv' # relative path

df = pd.read_csv(rel_path) # open the file as dataframe
```

- As online file:

In [13]:
```
df = pd.read_csv(url)
df.head(1)
```

Out[13]:

	movie_id	title	production_year	votes	vote_mean	vote_sd	theat_gross_
0	362	'71	2014	33341	6.41	2.167	1268760.0

Reading other data types

Other pandas readers include: excel, sql, sas, stata and many more.

To note: an incredibly fast and useful module for reading and writing data is feather (https://github.com/wesm/feather).

Storing data

Data can be stored in a particular format with to_(FORMAT) where (FORMAT) is the file type such as csv. Let's try with to_csv:

In [14]:
```
df.to_csv('bechdel2.csv', index=False)
```

Should we always set `index=False`. Yes, unless time series!!! Otherwise the index will be exported too!

Exercise - problem: input-output

Some data can be 'scraped' as is - they are already structured.

Q1) Use Pandas' CSV reader to fetch National Oceanic and Atmospheric Administration(NOAA)'s daily data weather from 1864 for various stations - available here (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/). Description can be found here (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/readme.txt).

- Note that for compressed files you need to specify the keyword `compression`.
- Note also that keyword `header` can be specified as the CSV has no column names.

Exercise - solution: input-output

In [48]:

```
url = 'https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/1864.csv.gz'

df_weather = pd.read_csv(url,
                         compression='gzip', #decompress gzip
                         header=None, #use no header information from the csv

                         parse_dates=[1]) # option for parsing dates
```

DataFrame: viewing and selecting

Selecting rows in DataFrames

Are there similarities between how Series and DataFrame views data?

- Yes, very similar, few differences.

Which methods did the Series for inspection and do the work?

- **loc**, **iloc**, **head** and **tail** work as expected selecting rows. Example:

In [20]:
```
df_weather.iloc[50:55]
```

Out[20]:

	0	1	2	3	4	5	6	7
50	ASN00061055	1864-01-01	PRCP	406	NaN	NaN	a	NaN
51	UK000047811	1864-01-01	TMAX	59	NaN	NaN	E	NaN
52	UK000047811	1864-01-01	TMIN	6	NaN	NaN	E	NaN
53	UK000047811	1864-01-01	PRCP	8	NaN	NaN	E	NaN
54	HR000142360	1864-01-01	PRCP	68	NaN	NaN	E	NaN

Selecting rows in DataFrames (continued)

What other methods do we have for selecting rows?

- Right: boolean series. These also work for DataFrames. Example:

In [25]:
```
df_weather.columns = ['station', 'datetime', 'obs_type', 'obs_value',4,5,6,7]
```

In [27]:
```
select_rain = df_weather.obs_type=='PRCP'

sub = df_weather[select_rain] # select rain data
```

In [ ]:
```
sub.nunique()
```

Selecting columns in DataFrames

Selecting columns is almost too easy:

In [36]:
```
print(df_weather[['station','datetime','obs_type','obs_value']].head(1))
```

```
       station    datetime obs_type  obs_value
0  ITE00100550 1864-01-01     TMAX         10
```

Could there be another way?

- Yes: loc and iloc can also select columns. Examples:

In [37]:
```
print(df_weather.loc[[0],['station','datetime']])
```

```
       station    datetime
0  ITE00100550 1864-01-01
```

In [42]:
```
print(df_weather.iloc[:,:4].head(2))
```

```
       station    datetime obs_type  obs_value
0  ITE00100550 1864-01-01     TMAX         10
1  ITE00100550 1864-01-01     TMIN        -23
```

What does **':'** do in iloc/loc? Select all rows/columns.

Exercise - problem: format and select

Q2) Structure your weather DataFrame by using only the relevant columns, rename them. Make sure observations are correctly formated (how many decimals should we add? one?).

Note: rename is done with `df.columns=COLS` where `COLS` is a list of column names.

Q3) Select data for the first station in the data (`ITE00100550`) and only observations for maximal temperature. Make a copy of the DF.

Note: **&** works elementwise for boolean series like **and** for Basic python.

Note: copying of the dataframe is done with the **copy** method for DataFrames.

Exercise - solution: format and select

Q2) answer:

In [50]:
```
df_weather = df_weather.iloc[:,:4] # select only first four columns

column_names = ['station', 'datetime', 'obs_type', 'obs_value']
df_weather.columns = column_names # set column names

df_weather['obs_value'] = df_weather['obs_value'] / 10 # convert last digit to decimal

# DOES NOT WORK FOR SNOW DATA!!
```

Q3 answer:

In [51]:
```
select_stat = df_weather.station == 'ITE00100550' # boolean: first weather station
select_tmax = df_weather.obs_type=='TMAX' # boolean: maximal temp.

df_select = df_weather[select_stat & select_tmax].copy() # row selection - require both
 conditions

# copy dataframe to break dependency with original DataFrame df_weather
# otherwise changing values in one would imply changes in the other
```

DataFrame: sorting and indexing

Setting indices

We can set the index of a DataFrame using its method **set_index**. Example:

In [44]:
```
df_weather.set_index('station').head(1)
```

Out[44]:

	datetime	obs_type	obs_value	4	5	6	7
station							
ITE00100550	1864-01-01	TMAX	10	NaN	NaN	E	NaN

We can use the keyword `inplace` which will replace the DataFrame:

In [ ]:
```
df_weather = df_weather.set_index('station')

df_weather.set_index('station', inplace=True)
df_weather.head(1)
```

Removing indices

Sometimes we wish to remove the index. This is done with the **reset_index** method:

In [ ]:
```
df_weather.reset_index(inplace=True)
df_weather
```

By specifying the keyword `drop=`True we delete the index. Note `inplace` also works.

To note: Indices can have multiple levels, in this case `level` can be specified to delete a specific level.

Sorting

A DataFrame can be sorted with **sort_values**; this method takes one or more columns to sort by.

In [57]:

```
df_weather.sort_values(['station','obs_type','datetime'], inplace=True)

df_weather.head(3)
```

Out[57]:

	station	datetime	obs_type	obs_value
28	AGE00135039	1864-01-01	PRCP	0.0
97	AGE00135039	1864-01-02	PRCP	0.0
164	AGE00135039	1864-01-03	PRCP	0.0

To note: Many key word arguments are possible for sort_values, including ascending if for one or more valuable we want descending values. Sorting by index is possible with `sort_index`.

Exercise - problem: index

Q4) With your data for the first weather stations - set your datetime variable as temporal index and make a timeseries plot.

Exercise - solution: index

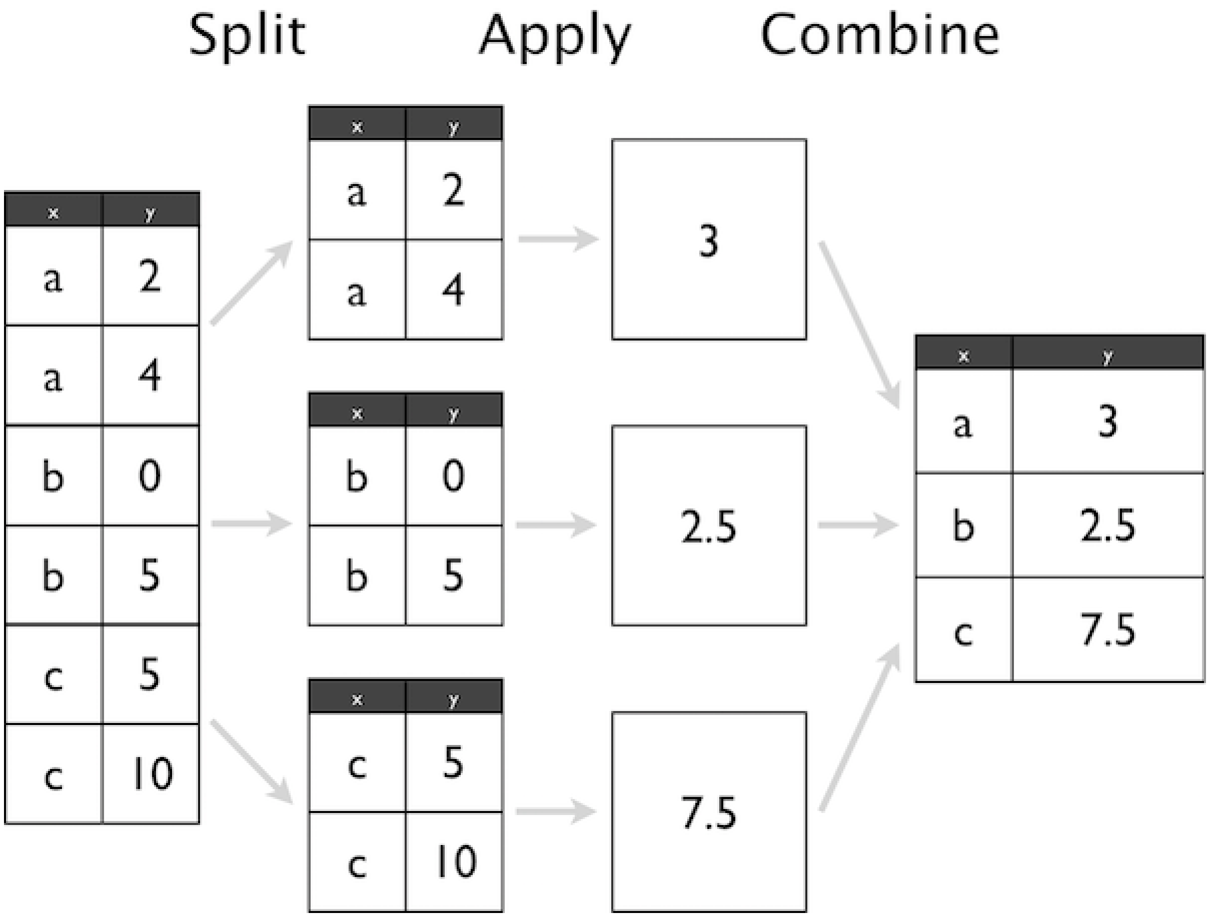
Q4) answer:

In [ ]:

```
df_select\
    .set_index('datetime')\
    .obs_value\
    .plot(figsize=[11,6])
```

Split-apply-combine

Example: grouping by x and calculating mean of y



groupby

A powerful tool in DataFrames are the **groupby** method. Example:

In [52]:
```
df_select['week'] = df_select.datetime.dt.week

gb_week = df_select.groupby('week')
```

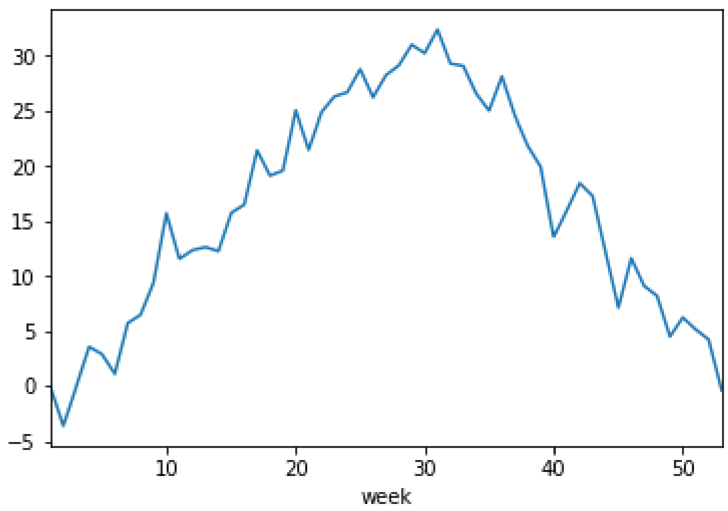
In [ ]:
```
df_select.groupby('week').mean()
```

In [ ]:
```
tmax_mean_by_week = gb_week.obs_value.mean()

tmax_mean_by_week.head(4)
```

In [55]:
```
tmax_mean_by_week.plot()
```

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9d97bccf8>



groupby (2)

What does the groupby by method do?

- It splits the data.

Can other functions be applied?

- Yes: mean, std, min, max all work.

To note: Using .apply() method and inserting a custom function also works

groupby (3)

Can we use multiple variables for grouping?

- Yes - example:

In [66]:
```
df_weather.groupby(['station', 'obs_type']).obs_value.median().head()
```

Out[66]:
```
station      obs_type
AGE00135039  PRCP         0.0
             TMAX        20.0
             TMIN        14.5
ASN00019024  PRCP         0.0
ASN00019036  PRCP         0.0
Name: obs_value, dtype: float64
```

Note grouping with multiple variables uses a MultiIndex (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.MultiIndex.html) which we do not cover.

groupby (4)

Can we use groupby in a loop?

Yes, we can iterate over a groupby object. Example:

In [116]:

```
results = {}
for group, group_df in gb_week:
    group_mean = group_df.obs_value.mean()
    results[group] = group_mean

results
```

Exercise - problem: split-apply-combine

Q5) Plot the monthly max,min+quartiles temperature for our stations.

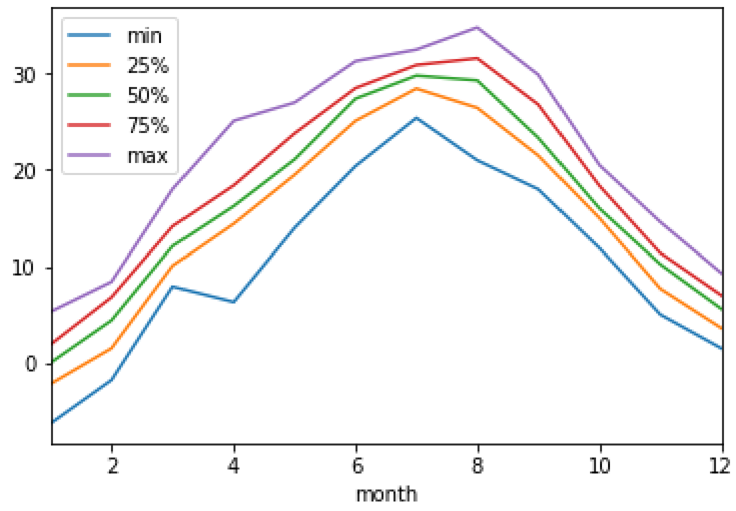
Hint: the method **describe** computes all these measures.

Q5) solution:

In [69]:
```
df_select['month'] = df_select.datetime.dt.month # access month method for the datetime
 methods

df_select\ # make the monthly plot of describe output
.groupby('month')\
.obs_value\
.describe()\
.iloc[:,-5:]\
.plot()
```

Out[69]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f9d962e4e0>
```



Joining data

Until now we've worked with one DataFrame at a time.

We will now learn to put them together.

Concatenating DataFrames

Let's try to vertically put two DataFrames together:

In [74]:
```
df_j1 = pd.DataFrame([[1,2,3],[3,4,3]])
df_j2 = pd.DataFrame([[5,6],[7,8]])
```

In [76]:
```
print(pd.concat([df_j1, df_j2])) # vertically stacking dataframes
```

```
   0  1    2
0  1  2  3.0
1  3  4  3.0
0  5  6  NaN
1  7  8  NaN
```

Concatenating DataFrames (continued)

Let's do it horizontally:

In [77]:
```
df_j3 = pd.DataFrame([[4,2],[6,8]], columns=['C', 'D'])


print(pd.concat([df_j2, df_j3],axis=1)) # put together horizontally - axis=1
```

```
   0  1  C  D
0  5  6  4  2
1  7  8  6  8
```

The **concat** method creates one big DataFrame from two smaller. It can be used when when we have two or more DataFrames that either share indices or columns.

Merging DataFrames

We can merge DataFrames which share common identifiers, row by row. Example:

In [80]:
```
print(df_j5)
print()
print(df_j4)
```

```
   A  B
0  1  2
1  3  4

   B  C
0  2  3
1  7  8
```

In [81]:
```
df_j5 = pd.DataFrame([[1,2],[3,4]], columns=['A', 'B'])
df_j4 = pd.DataFrame([[2,3],[7,8]],columns=["B", 'C'])

print(pd.merge(df_j5, df_j4, how='outer'))
```

```
     A  B    C
0  1.0  2  3.0
1  3.0  4  NaN
2  NaN  7  8.0
```

merge is useful for when you have two or more datasets about the same entities, e.g. data about individual where you merge by social security number.

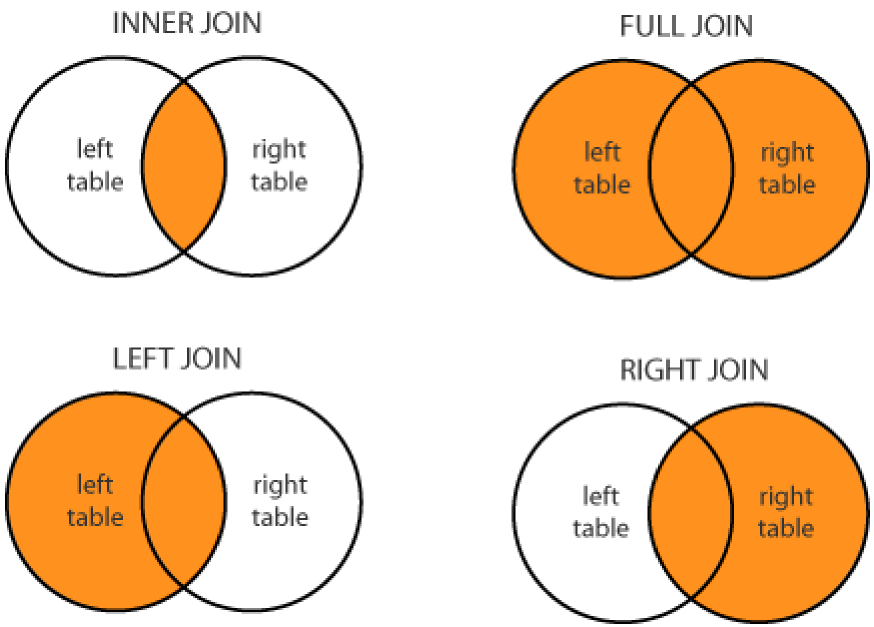
In [4]:

```
import pandas as pd
```

Merging DataFrames (continued)

Merging can be either of four types.

- inner merge: observations exist in both dataframes [default]
- left (right) merge: observations exist in left (right) dataframe
- outer merge: observations exist either in left or in right dataframe



Merging DataFrames (continued)

Let's try left and outer:

In [ ]:
```
print(pd.merge(df_j1, df_j4, how='left'))
```

Exercise: try to describe in words what happens.

Exercise - problem: data joining

Q6) Make a function that downloads and formats the stations data.

- removes unnecessary columns and rename
- changes observation values (decimals)

Q7) Using your function that makes a loop that fetch processed data for years 1864-1867. Concatenate this data vertically.

Q8) Merge station locations onto weather data. Locations can be found at: https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/ghcnd-stations.txt (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/ghcnd-stations.txt). Note that the location this has fixed width format - does there exist a reader for that?

Exercise - solution: data joining

Q6) answer:

In [2]:
```
prefix = 'https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/'
suffix = '.csv.gz'

def fetch_format_weather(year):
    url = prefix + str(year) + suffix

    df_weather = pd.read_csv(url,
                             compression='gzip', #decompress gzip
                             header=None, #use no header information from the csv

                             parse_dates=[1]) # option for parsing dates

    df_weather = df_weather.iloc[:,:4] # select only first four columns

    column_names = ['station', 'datetime', 'obs_type', 'obs_value']
    df_weather.columns = column_names # set column names

    df_weather.obs_value = df_weather.obs_value / 10 # convert last digit to decimal

    return df_weather
```

Exercise - solution: data joining (continued)

Q7) answer:

In [88]:
```
# df_concat.datetime.describe()
```

In [3]:
```
dfs = []

for year in range(1864, 1868): # for years 1864-1867
    df_proc = fetch_format_weather(year) # process and download data for year
    dfs.append(df_proc) # append processed data to list

df_concat =  pd.concat(dfs, ignore_index=True)    # concatenate dfs into one dataframe
```

Q8) answer:

In [4]:
```
url_stats = "https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/ghcnd-stations.txt"

df_stats = pd.read_fwf(url_stats, header=None).iloc[:,:4] # read as fixed width file - o
nly take first four cols
df_stats.columns = ['station', 'latitude', 'longitude', 'altitude'] # rename columns
df_concat_coords = df_concat.merge(df_stats, how='left') # make inner merge with station
s coordinates
```

Wide and long format conversion

To long format

A DataFrame can be collapsed into a Series with the **stack** command:

In [12]:
```
df = pd.DataFrame(np.random.normal(size=[2,2]),columns=['A','B'],index=['i','ii'])
print(df)
print()
print(df.stack()) # going from wide to long format
print()
print(df.stack().reset_index()) # converting indices to columns
```

```
           A         B
i   0.452507  1.024870
ii  0.114728  0.126651

i   A    0.452507
    B    1.024870
ii  A    0.114728
    B    0.126651
dtype: float64

  level_0 level_1         0
0       i       A  0.452507
1       i       B  1.024870
2      ii       A  0.114728
3      ii       B  0.126651
```

Quiz: What happend to our observations? What happend to our columns?

- Observations are now vertically stacked and each row now has an extra index with column information.

To wide format

Likewise we can transform a long DataFrame with the unstack

In [19]:

```
series_long = pd.DataFrame(data=[[0,'A',1],[0,'B',2],[1,'A',3],[1,'B',4]])
series_long.columns = ['index','column','observation']

series_long.set_index(['index','column'], inplace=True)

print(series_long.observation)
print()
print(series_long.observation.unstack(level=1))
```

```
index  column
0      A         1
       B         2
1      A         3
       B         4
Name: observation, dtype: int64

column  A  B
index
0       1  2
1       3  4
```

Exercise - problem: tidy format

Q9) Let's define an observation as being one date for one station and variables being all available measures. Is our weather dataset in this format? If not, how can we transform it?

Hint: **unstack**'ing the observation type may help

Q10) With your tidy data set - convert the temperature variables to Fahrenheit. Conversion is F = 32 + 1.8 C where F is Fahrenheit and C is Celsius.

Q9) answer:

Our data is not in the (date,station) format for observations. It is actually excessively long and need to be widened.

We can convert our DataFrame of weather data into observations of (date, station) as follows:

In [24]:

```
df_tidy = df_concat\
             .set_index(['station', 'datetime', 'obs_type'])\
             .obs_value\
             .unstack(level=2)\
             [['PRCP', 'TMAX', 'TMIN']]\
             .reset_index()
```

Q10) answer:

In [26]:
```
for temp_col in ['TMAX', 'TMIN']: # looping over the temperature columns
    df_tidy[temp_col+'_f'] =  (df_tidy[temp_col]*1.8) + 32 # converting to Fahrenheit

df_tidy.head(2)
```

Out[26]:

obs_type	station	datetime	PRCP	TMAX	TMIN	TMAX_f	TMIN_f
0	AGE00135039	1864-01-01	0.0	NaN	NaN	NaN	NaN
1	AGE00135039	1864-01-02	0.0	14.0	11.5	806.4	662.4

Summary

DataFrame insights

- How to load and storing data, in particular with **read_csv**
- Indices can be manipulated with **set_index**, **reset_index**
- Split-apply-combine is powerful and easy using **groupby** method
- Joining multiple datasets can be either with **concat** (which stacks dataframes) and **merge**
- We can go convert wide to long (and vice versa) with **stack** (**unstack**)

Learning more

Many important topics for DataFrames have been skipped. These include:

- Copying data in python: deep vs. shallow - **copy** method for dataframes
- Working with duplicates: **duplicated**, **drop_duplicates*