Session 6: Data structuring II

The Pandas way

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Recap

What do we know about explanatory plotting?

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- *What do we know about exploratory plotting?*
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Motivation

Reminder: Why do we want to learn data structuring?

- We have to do it, data is almost never cleaned
- No one can and will do it for us
- Even as a manager of data scientists - we need to know

Agenda

We will learn about new data types

1. string data
2. temporal data
3. categorical data
4. missing data and duplicates

Loading the software

In [5]:

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

%matplotlib inline
```

String data

String operations vectorized (1)

Quiz: Which operators could work for string?

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

In [6]:
```
str_ser1 = pd.Series(['Andreas', 'Snorre', 'David'])
```

In [7]:
```
str_ser1 + ' works @ SODAS'
```

Out[7]:
```
0    Andreas works @ SODAS
1     Snorre works @ SODAS
2      David works @ SODAS
dtype: object
```

String operations vectorized (2)

Addition also work for two series

In [8]:

```
# adding two series together is also possible
str_ser2 = pd.Series(['Bjerre-Nielsen', 'Ralund', 'Dreyer Lassen'])
str_ser1 + ' ' + str_ser2
```

Out[8]:

```
0     Andreas Bjerre-Nielsen
1              Snorre Ralund
2        David Dreyer Lassen
dtype: object
```

String operations vectorized (3)

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

```
In [10]: str_ser1.str.upper()
         str_ser1.str.contains('dr dre')
```

```
Out[10]: 0    False
         1    False
         2    False
         dtype: bool
```

String operations vectorized (4)

The .str methods include slicing - example:

In [11]:
```
str_ser2.str[1:4]
```

Out[11]:
```
0    jer
1    alu
2    rey
dtype: object
```

String operations vectorized (5)

Many more `str` methods in pandas,

- most basic strings methods translate directly
- see Table 7-5 in PDA for an overview

Categorical data

Categorical data type (1)

Are string (object) columns smart?

No, sometimes categorical data type is better:

- use categorical when many characters are repeated
    - less storage and faster computation
- or to order string data

Categorical data type (2)

How do we convert to categorical?

In [22]:
```
edu_list = ['B.Sc. Political Science', 'Secondary school'] + ['High school']*2
edu_cats = ['Secondary school', 'High school', 'B.Sc. Political Science']
str_ser3 = pd.Series(edu_list)

# option 1 - order
cats = pd.Categorical(str_ser3, categories=edu_cats, ordered=True)
cat_ser = pd.Series(cats, index=str_ser3)

# option 2 - no order
cat_ser2 = str_ser3.astype('category')
```

Categorical data type (3)

How do we work with categorical data?

- Using the `cat` attribute of series. Has a few methods. E.g. `.cat.codes`

In [21]:

```
print(cat_ser.cat.codes)
```

```
B.Sc. Political Science    2
Secondary school           0
High school                1
High school                1
dtype: int8
```

Categorical data type (4)

Often we want to our string / categorical data as dummy variables

- each category value has a dummy column (0 or 1)
- dummy columns can be made with `to_dummies`

Categorical data type (5)

Can we convert our numerical data to bins in a smart way?

Yes, two methods are useful (we already saw `cut`):

- `cut` which divides data by user specified bins
- `qcut` which divides data by user specified quantiles
    - e.g. median, $q = 0.5$; lower quartile threshold, $q = 0.25$.

In [34]:

```
x = pd.Series(np.random.normal(size=10**7))
cat_ser3 = pd.qcut(x, q=[0,.025,.975,1])
cat_ser3.cat.categories
```

Out[34]:

```
IntervalIndex([(-5.492, -1.96], (-1.96, 1.96], (1.96, 5.18]],
              closed='right',
              dtype='interval[float64]')
```

Temporal data

Temporal data type (1)

Why is time so fundamental?

Every measurement made by humans was made at a point in time, therefore it has a "timestamp".

Temporal data type (2)

How are timestamps measured?

1. Datetime (ISO 8601): standard calendar
    - year, month, day: minute, second, miliseconds etc. [timezone]
    - comes as strings in raw data
2. Epoch time: seconds since January 1, 1970 - 00:00, GMT.
    - nanoseconds in pandas

Temporal data type (3)

Does Pandas store it in a smart way?

Pandas has native support for temporal data combining datetime and epoch time.

In [26]:

```
str_ser4 = pd.Series(['20170101', '20170727', '20170803', '20171224'])
dt_ser1 = pd.to_datetime(str_ser4)
print(dt_ser1) # .astype('int64')
```

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

Temporal data type (4)

How does the input type matter for how datatime is parsed?

In [12]:
```
print(pd.to_datetime(['20170101', '20170102']))
print(pd.to_datetime([20170101, 20170102]))
```

```
DatetimeIndex(['2017-01-01', '2017-01-02'], dtype='datetime64[ns]', freq=None)
DatetimeIndex(['1970-01-01 00:00:00.020170101', '1970-01-01 00:00:00.020170102'], dty
pe='datetime64[ns]', freq=None)
```

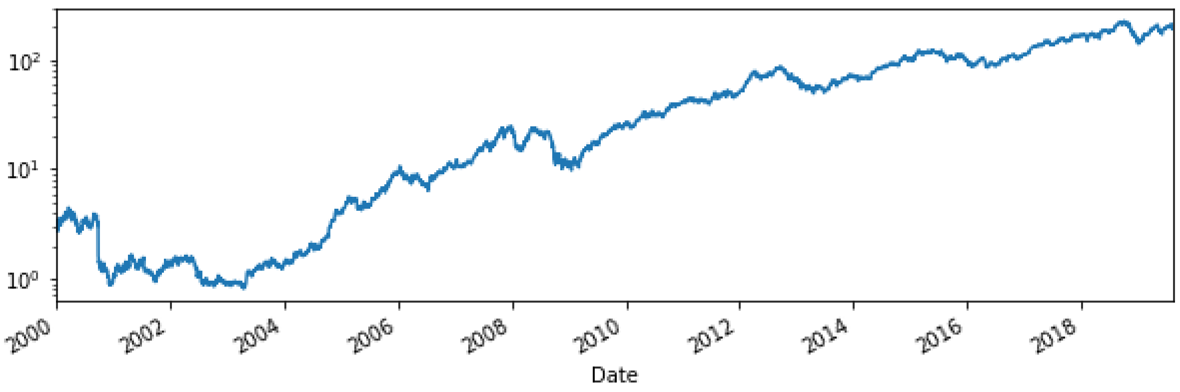
Time series (1)

Why is temporal data powerful?

We can easily make and plot time series. 10 years of Apple stock price

In [17]:
```
# conda install pandas-datareader
from pandas_datareader import data
aapl = data.DataReader("aapl", data_source='yahoo', start='2000')['Adj Close']
aapl.plot(figsize=(10,3), logy=True)
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x260fe1f40b8>
```



Time series (2)

Why is pandas good at time data?

It handles irregular data well:

- missing values;
- duplicate entries.

It has specific tools for resampling and interpolating data

- See 11.3, 11.5, 11.6 in PDA book.

Datetime variables (1)

What other uses might time data have?

We can extract data from datetime columns. These columns have the `dt` attribute and its sub-methods. Example:

In [35]:
```
dt_ser2 = ts_df.time

# dt_ser2.dt.day.iloc[500:505]
dt_ser2.dt.year.head(3)
```

Out[35]:
```
0    2015
1    2015
2    2015
Name: time, dtype: int64
```

Datetime variables (2)

The `dt` sub-methods include `year` , `weekday` , `hour` , `second` .

To note: Your temporal data may need conversion. `dt` includes `tz_localize` and `tz_convert` which does that.

Datetime variables (3)

Quiz: What are you to do if get time data with numbers of around 1-2 billion?

It is likely to be epoch time measured in seconds. We can convert it as follows:

In [36]:
```
pd.to_datetime([123512321,2132321321], unit='s')
```

Out[36]:
```
DatetimeIndex(['1973-11-30 12:58:41', '2037-07-27 15:28:41'], dtype='datetime64[ns]',
freq=None)
```

Missing data

Missing data type (1)

Which data type have we not covered yet?

Missing data, i.e. empty observations.

- In python: `None`
- In pandas: numpy's 'Not a Number', abbreviated `NaN` or `nan`

Missing data type (2)

What does a DataFrame with missing data look like?

In [28]:

```
nan_data = [[1,np.nan,3],
            [4,5,None],
            [7,8,9]]

nan_df = pd.DataFrame(nan_data, columns=['A','B','C'])
print(nan_df.isnull())
```

```
       A      B      C
0  False   True  False
1  False  False   True
2  False  False  False
```

Handling missing data

What options do we in working with missing data?

1. Ignore the problem
2. Drop missing data: columns and/or rows
3. Fill in the blanks
4. If time and money permits: collect the data or new data

Removing missing data

How do we remove data?

Using the `dropna` method.

In [46]:
```
print(nan_df)
print()
print(nan_df.dropna(axis=1)) # subset=['B'], axis=1
```

```
   A    B    C
0  1  NaN  3.0
1  4  5.0  NaN
2  7  8.0  9.0

   A
0  1
1  4
2  7
```

Filling missing data (1)

How do we fill observations with a constant?

In [29]:

```
print(nan_df.fillna(100)) # fill all
```

```
   A      B      C
0  1  100.0    3.0
1  4    5.0  100.0
2  7    8.0    9.0
   A     B    C
0  1 -99.0  3.0
1  4   5.0  NaN
2  7   8.0  9.0
```

Note: we can also select missing `isnull` and the replace values using `loc` .

Filling missing data (2)

Are there other methods?

Yes, many methods:

- Filling sorted temporal data, see `ffill`, `bfill`
- Filling with a model
  - e.g. linear interpolation, by mean of nearest observations etc.
  - `sklearn` in next week can impute data

Duplicates

Duplicates in data (1)

What does it mean there are duplicates in the data?

- More than one entry where the should be only one.
- If for a certain set of variables the combination is repeated.

Duplicates in data (2)

How do we drop duplicates?

In [30]:

```
print(str_ser3)
# print(str_ser3.drop_duplicates())
```

```
0    B.Sc. Political Science
1           Secondary school
2                High school
3                High school
dtype: object
```

The end

[Return to agenda]