Week 6: Visualising Time Series

Visual Data Analytics

University of Sydney

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Outline

- Lineplots
  - Time series features
  - Issues with y axis
  - Issues with x axis
- Python stuff
  - Dealing with dates
  - Plotting time series

Motivation

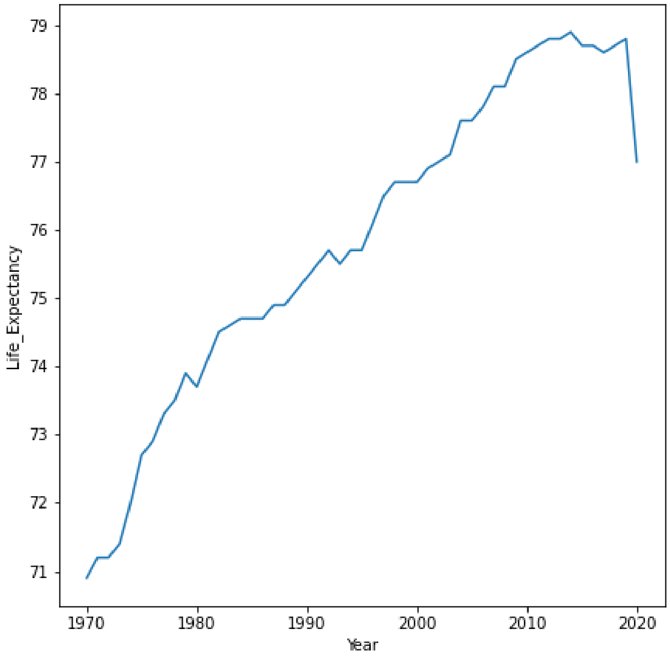
- Times series are common in business.
- Traditionally time series data in business were measured at low frequency (e.g. yearly, monthly, quarterly)
  - Inflation
  - Yearly sales
- Increasingly high-frequency data (daily, hourly, microsecond) are available.
  - Individual transactions data
- Business data are distinct in that they heavily influenced by calendar effects.

The line plot

- The line plot is the most common plot of a time series
- It shows a single variable on the vertical axis against time on the horizontal axis
- Using this plot we can see
  - Trend
  - Seasonal patterns
  - Calendar effects
  - Outliers
  - Volatility clustering

Yearly data

```
hle = sns.load_dataset('healthexp')
hleusa = hle[hle['Country']=='USA']
sns.lineplot(data = hleusa, x='Year', y='Life_Expectancy')
```

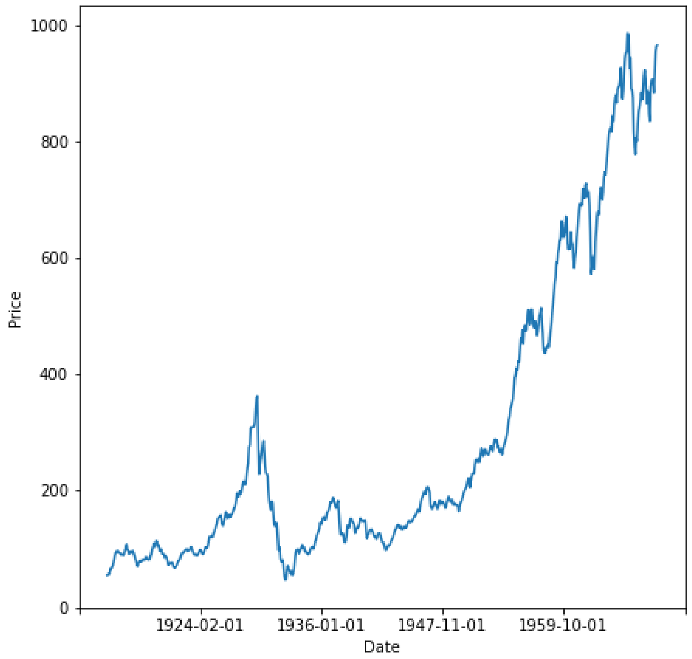


Trend

- This is an example of data with a trend.
- Life expectancy goes up over time.
- There is no seasonality (regular repeating pattern).
- There are no cycles (irregular repeating pattern).

Cycles

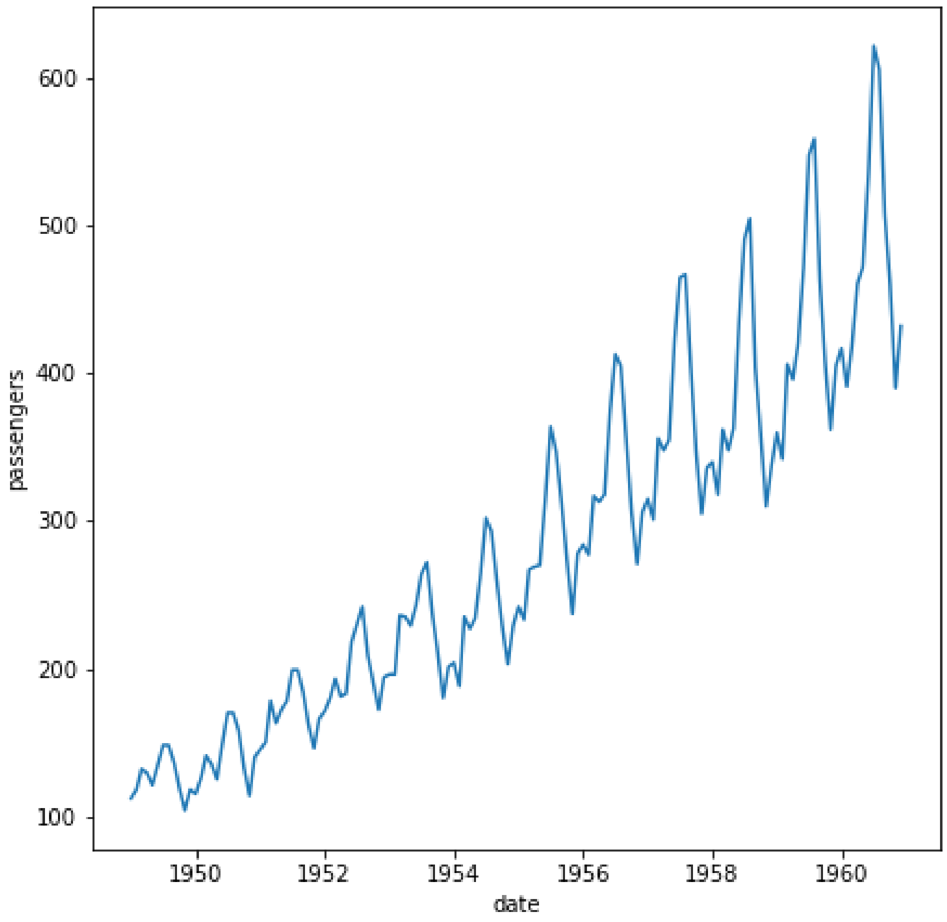
```
dj = sns.load_dataset('dowjones')
g = sns.lineplot(data=dj, x = 'Date', y = 'Price')
g.xaxis.set_major_locator(ticker.LinearLocator(6))
plt.show()
```



Trend and Cycle

- As well as trend, the series goes up and down.
- These are known as *cycles*.
- The cycles are irregular
  - Some are longer than others
  - The peaks and troughs are not always the same size and do not grow or shrink in a systematic way.

Seasonality



Seasonality

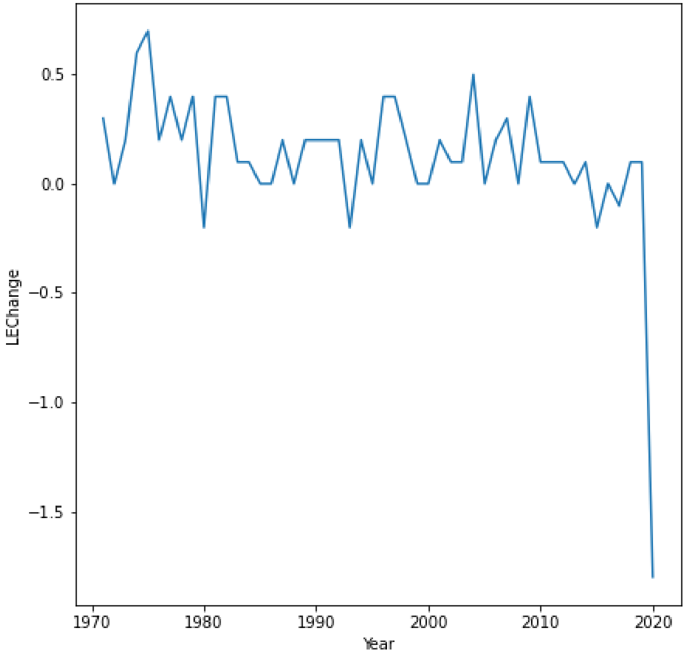
- The data roughly repeat every 12 periods.
- The pattern is amplified over time (which is in line with the increasing trend of the data).
- For higher frequncy data there may be multiple seasonalities (e.g, day of week and month of year).

Stocks v flows

- So-called *stocks* represent data measured at a single instant of time, *flows* represent changes to a stock over a period of time.
- The amount of money in my bank account is a stock, my spending during the week is a flow.
- This motivates looking at first differences, or percentage changes in data.

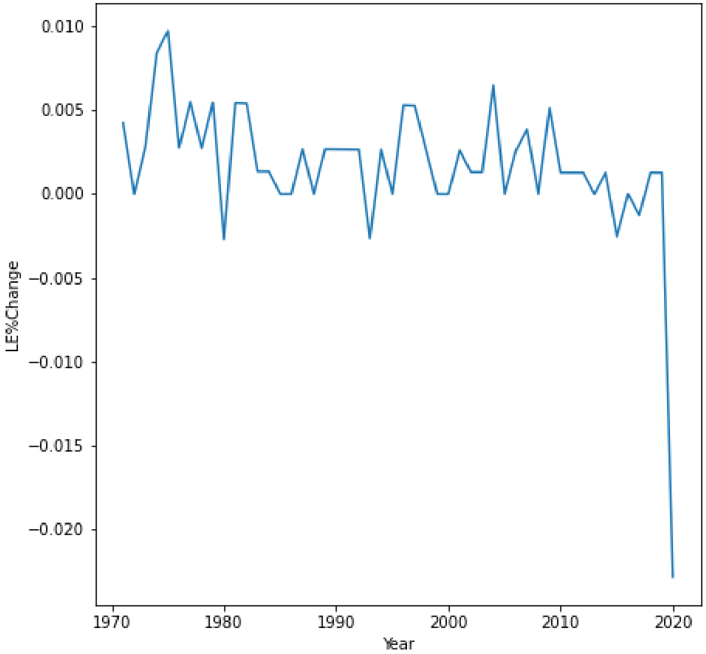
Plotting Change

```
hleusa['LEChange'] = hleusa["Life_Expectancy"].diff()
sns.lineplot(data = hleusa, x='Year', y='LEChange')
```



Percentage Change

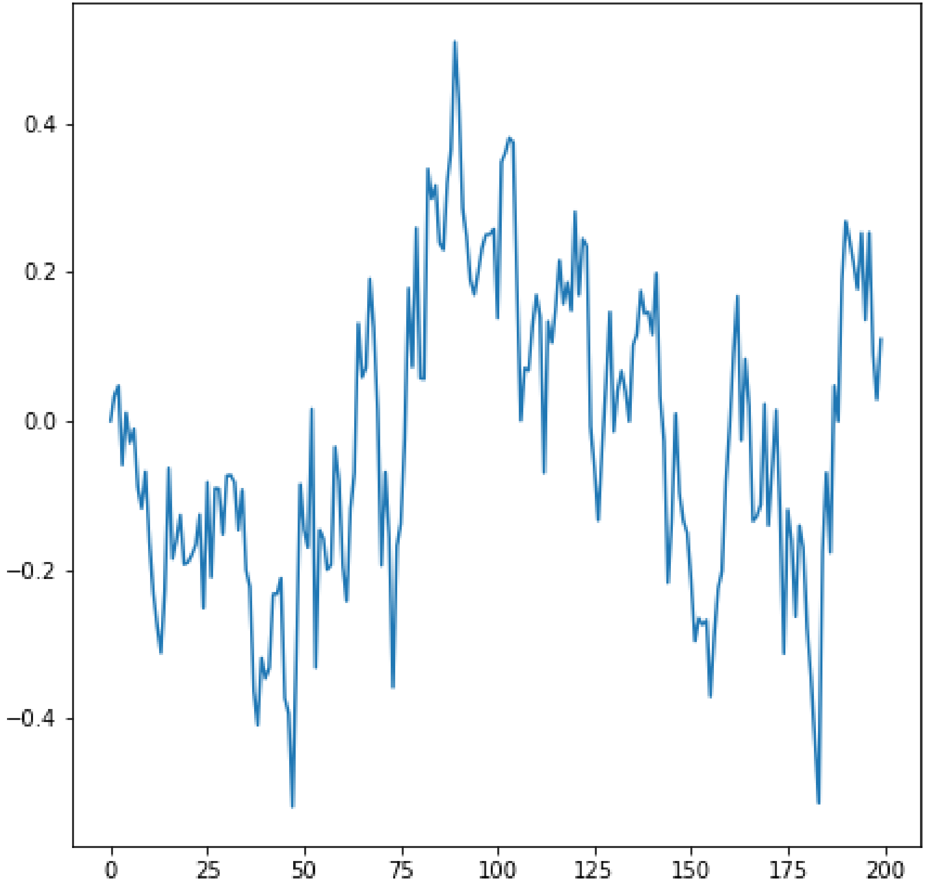
```
hleusa['LE%Change'] = hleusa["Life_Expectancy"].pct_change()
sns.lineplot(data = hleusa, x='Year', y='LE%Change')
```



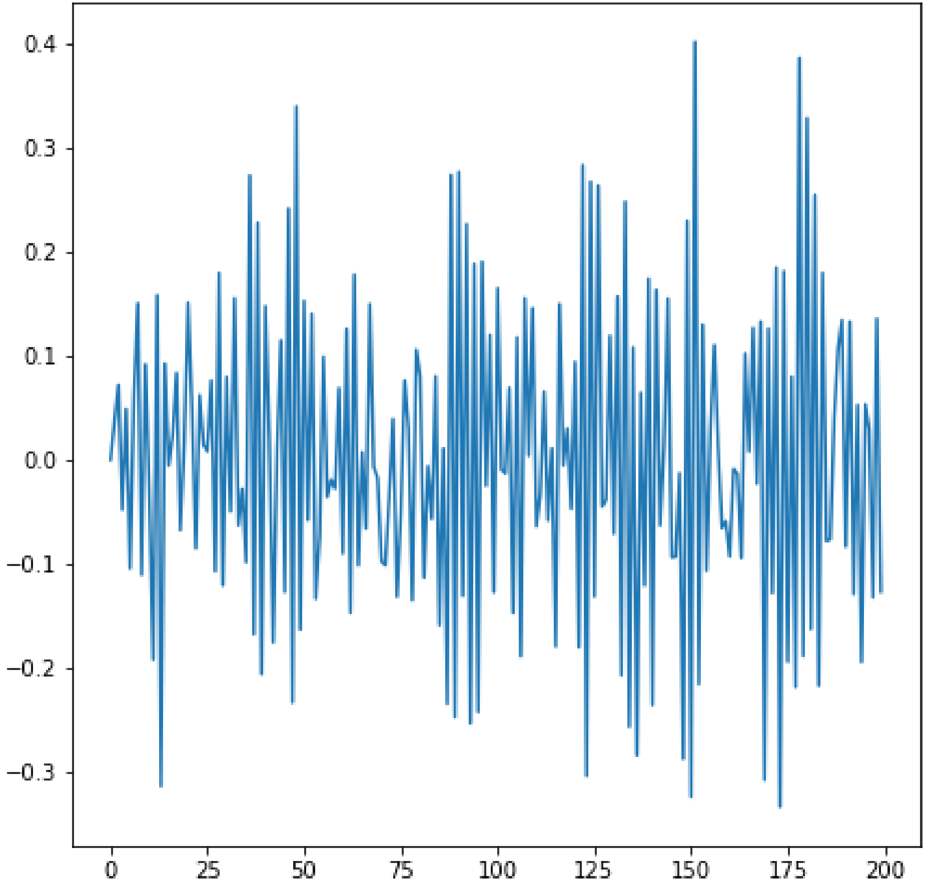
Autocorrelation

- When discussing time series, the concept of *autocorrelation* is important.
- This is the idea that a time series is correlated with its own past values.
- Line plots can indicate whether data are *positively*, correlated, *negatively* correlated or *not* correlated.
- Here are some synthetic examples.

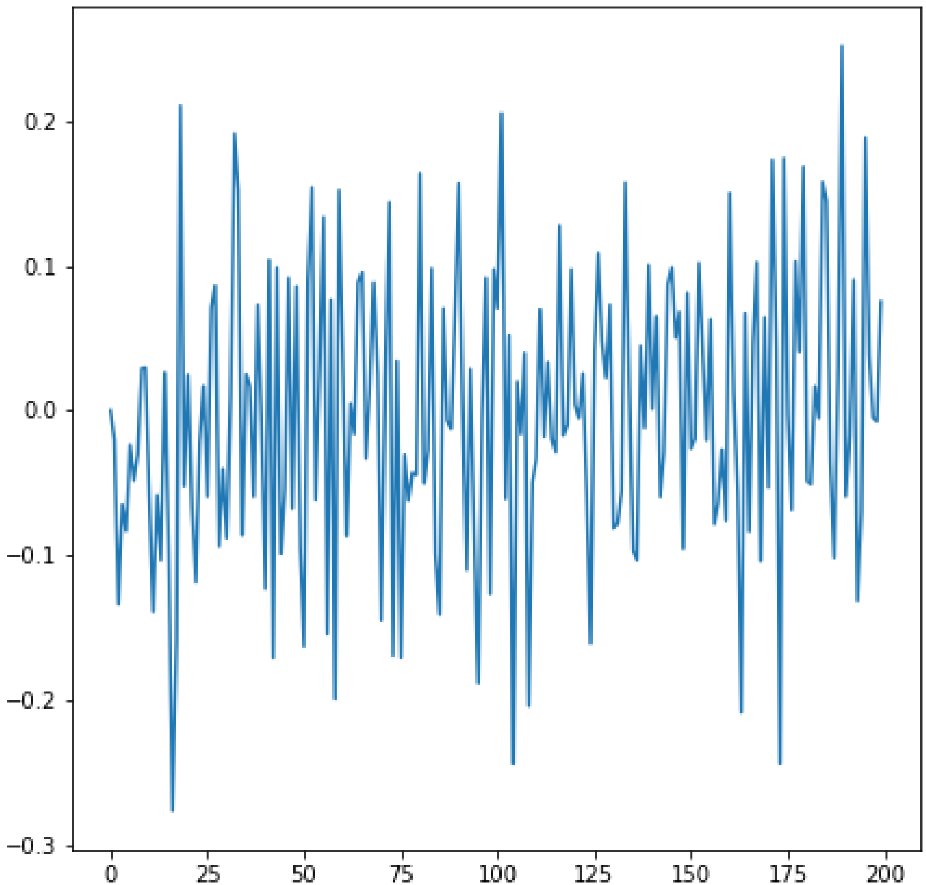
Postively correlated



Negatively correlated



Not autocorrelated



Inerpreting autocorrelation

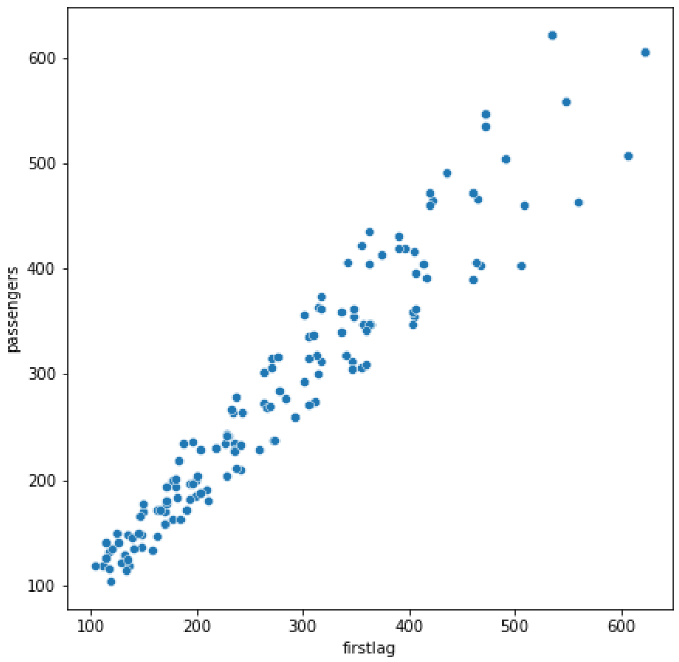
- For positively autocorrelated data, there will be *runs* where the series is above or below its mean.
- For negatively autocorrelated data, the series *oscillates* above and below the mean.
- For data with no autocorrelation, the series does not have these patterns.

Scatterplot

- A scatterplot of a variable against its first lag can aso indicate positive autocorrelation
- A scatterplot against other lags can show seasonality
- There are other ways to plot the autocorrelation function that are covered in other courses on time series,

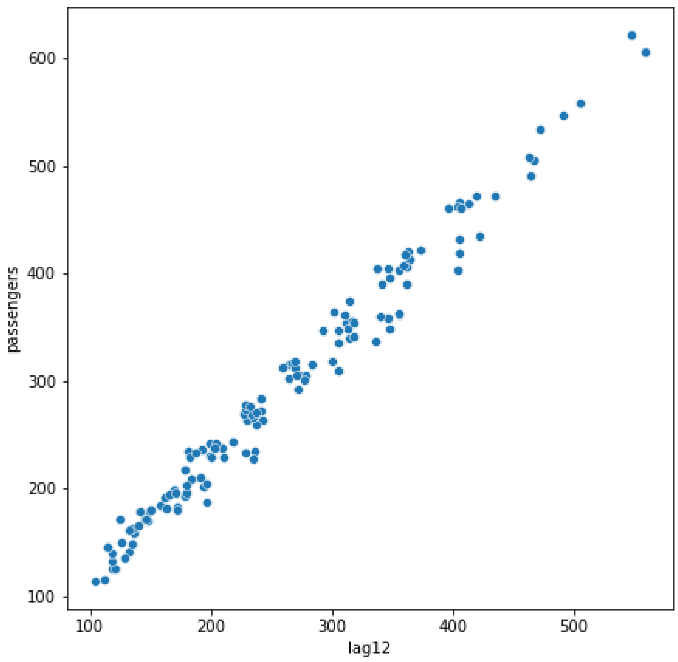
First lag

```
flights['firstlag']=flights['passengers'].shift()
sns.scatterplot(data=flights, x = 'firstlag', y = 'passengers')
```



Lag twelve

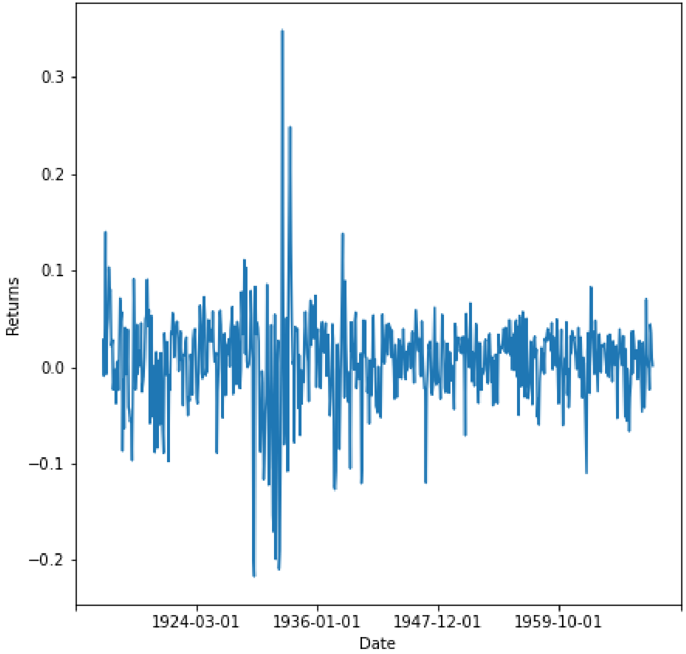
```
flights['lag12']=flights['passengers'].shift(12)
sns.scatterplot(data=flights, x = 'lag12', y = 'passengers')
```



Volatility clustering

- Sometimes there is no correlation in the mean, but there is correlation in the variance
  - Volatile periods more likely to follow volatile periods
  - Calm periods more likely to follow calm periods
- This can be seen using a line plot
- It is common with financial returns data

```python
dj['Returns']=dj['Price'].pct_change()
g = sns.lineplot(data=dj, x = 'Date', y = 'Returns')
g.xaxis.set_major_locator(ticker.LinearLocator(6))
plt.show()
```

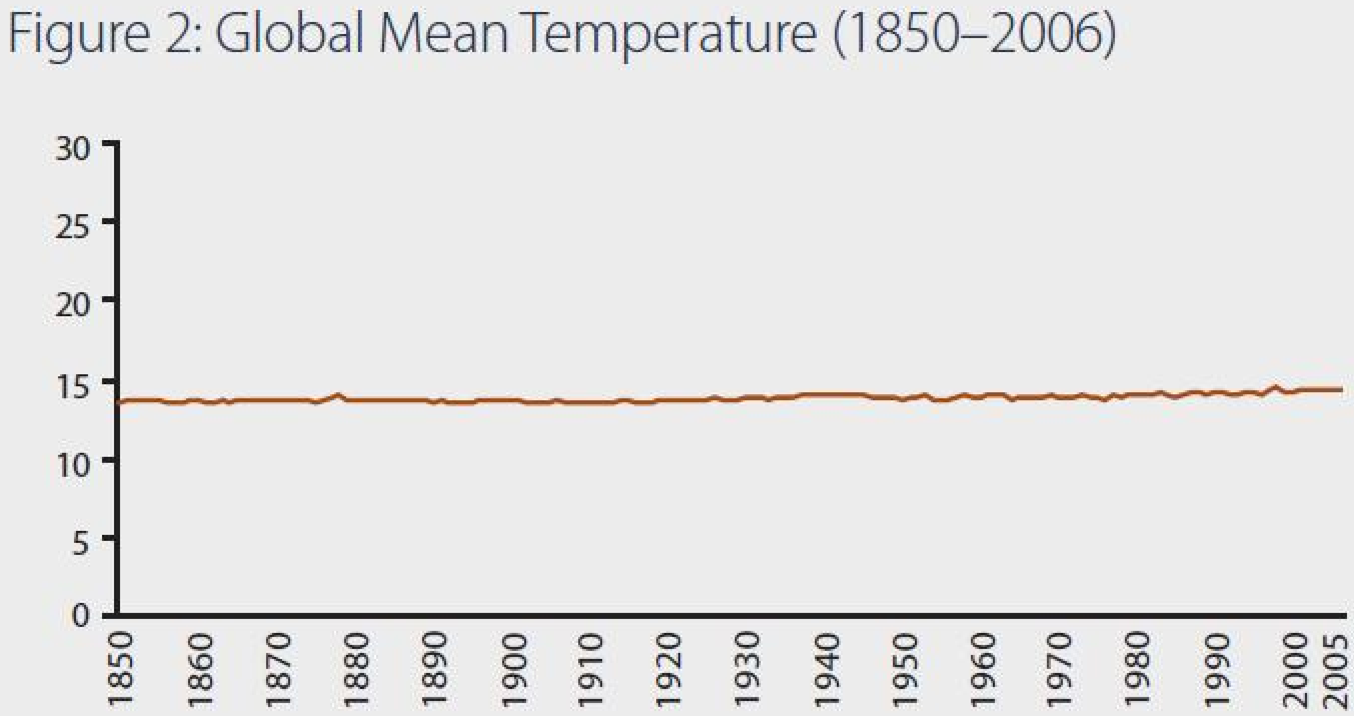


Issues with axes

Should zero be on y axis?

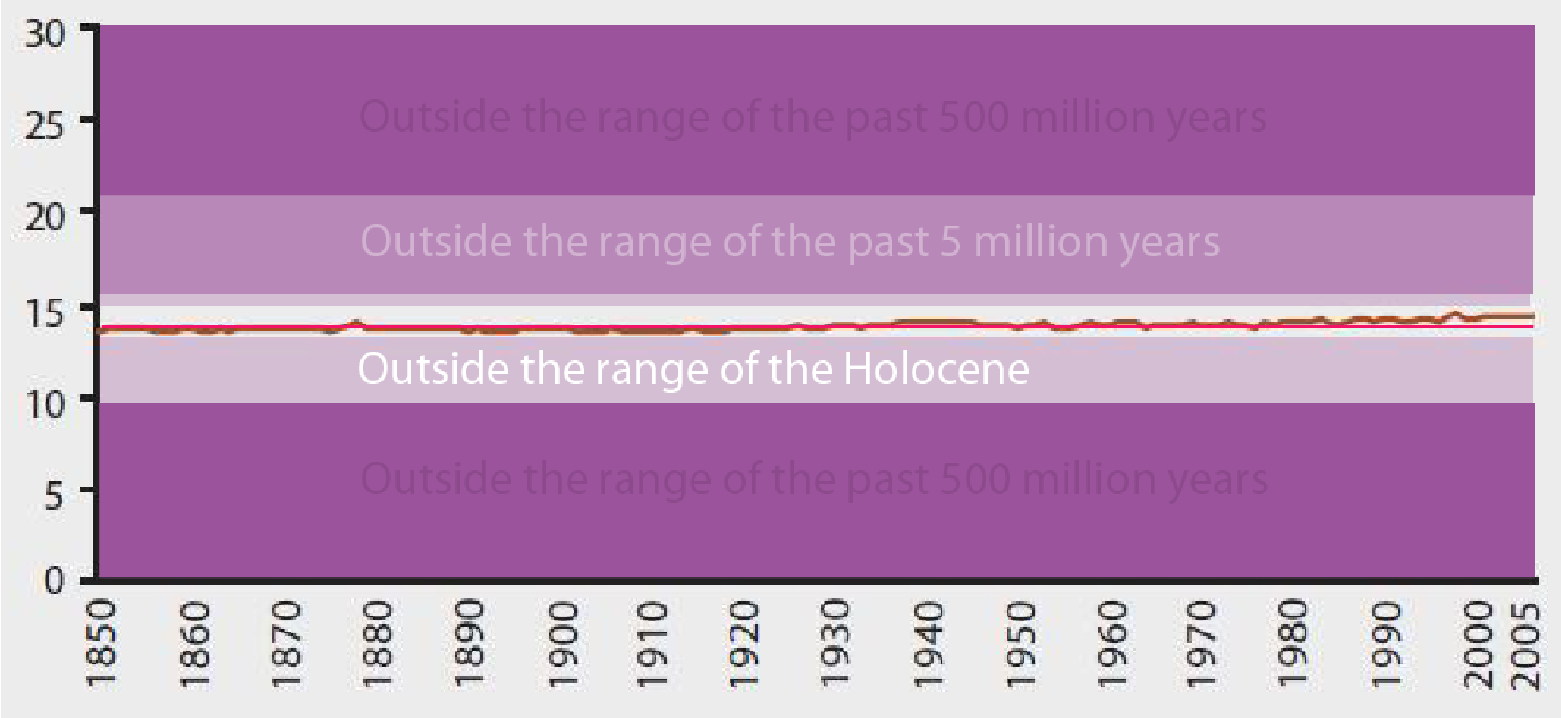
- Using a wide or narrow y-axis can be used to exaggerate changes in a line plot
- It is often said that zero MUST be included on the y axis
- This depends on *context*

Climate graph



Source: Derived from the US Bureau of Meteorology Data
http://www.bom.gov.au/web01/ncc/www/cli_chg/timeseries/global_t/0112/global/latest.txt

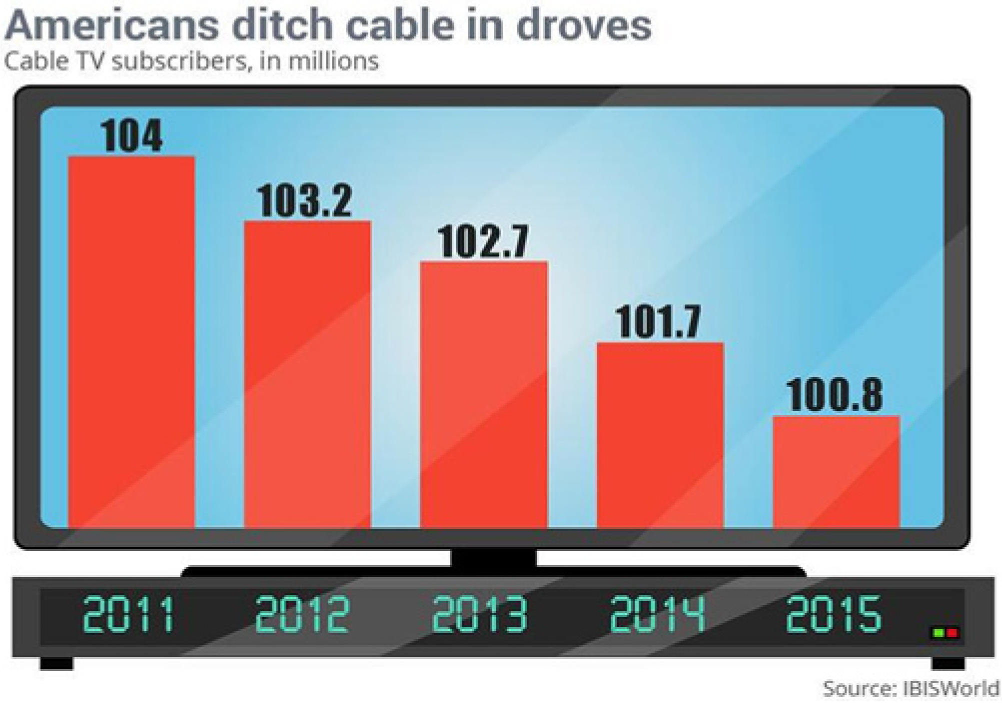
Climate graph



Line v bar

- For a line plot, to decide whether to include zero, think about whether 0 is a sensible value for the y-variable to take.
- Before the Holocene, you could walk from here to Tasmania and North America was under 4km of ice.
- Note that for bar plots, it is more natural to interpret length of the bar rather than position on the y axis.
- For bar plots always include zero

Better as line plot



Likely to be misinterpreted.

The x-axis

- Similarly the context of the x-axis is important.
- To understand whether a change is big or small, it is important to look at a suitable range of data.
- The following is an example with stock prices of the Commonwealth Bank of Australia (CBA).
- The following show the price of CBA shares over a five day period and a five year period.

A big change?


CBA.AX 105.11
yahoo!finance
105.11
105.00
104.75
104.50
104.25
104.00
103.75
103.50
103.25
103.00
/1
12:00 pm
2:00 pm
10/1
12:00 pm
2:00 pm
11/1
12:00 pm
2:00 pm
12/1
12:00 pm
2:00 pm

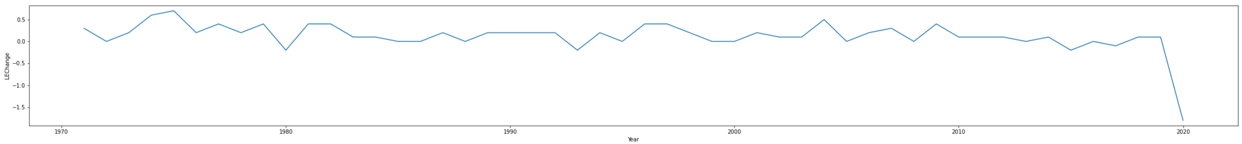
Same data for five years

Both axes

- Another way to manipulate interpretations is through the *aspect ratio*.
- The aspect ratio is the ratio of units on the y axis relateive to units on the x axis.
- By resizing a plot, features of the time series may be exaggerated (either intentionally or unintentionally).

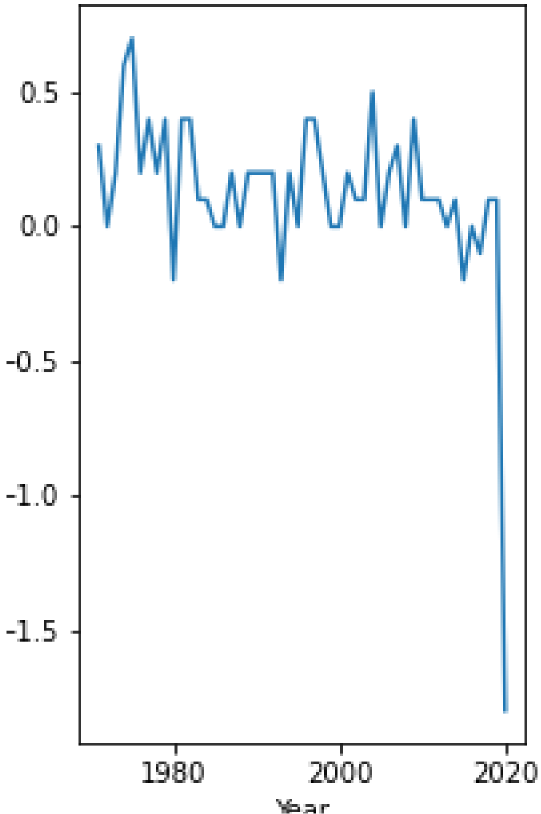
Wide

```
fig, ax = plt.subplots(figsize = (40,4) )
sns.lineplot(data = hleusa, x='Year', y='LEChange')
```



Long

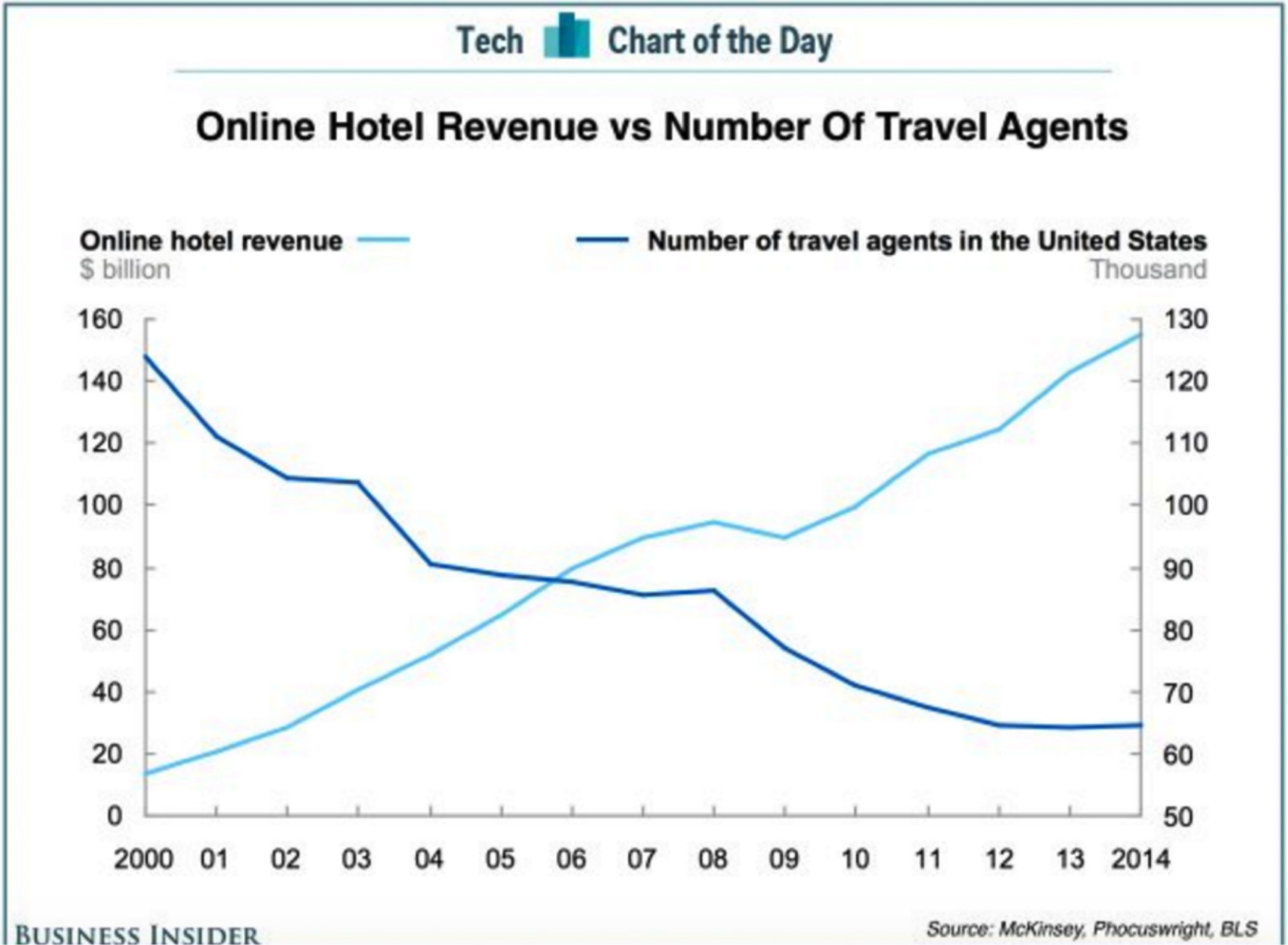
```
fig, ax = plt.subplots(figsize = (3,5) )
sns.lineplot(data = hleusa, x='Year', y='LEChange')
```



Banking to 45

- As a rough guide, consider lines making up a line plot.
- The average angle of these should be about 45 degrees
- Good software packages will do this by default.
- If you reseize an image things may change.
- Always look at the axes of a line plot!

Dual y axes



Tech Chart of the Day
Online Hotel Revenue vs Number Of Travel Agents
Online hotel revenue
$ billion
Number of travel agents in the United States
Thousand
160
140
120
100
80
60
40
20
0
130
120
110
100
90
80
70
60
50
2000 01 02 03 04 05 06 07 08 09 10 11 12 13 2014
Business Insider
Source: McKinsey, Phocuswright, BLS

Problems

- Natural to look at and interpret 'crossing points'
- Crossing point nearly always meaningless;
  - Arbitrarily defined by changing y axis,
  - Could be different if different units are used.
- Put multiple lines on a lineplot ONLY when all variables measured in same units.

Dealing with dates

Date type in Python

The `datetime` module in Python provides a data type specifically for dealing with dates and times.

```
import datetime
x=datetime.datetime.now()
y=datetime.datetime(2008, 3, 16)
print(x)
```

```
## 2023-01-12 19:17:37.113537
```

```
print(y)
```

```
## 2008-03-16 00:00:00
```

Intervals

A `timedelta` is the difference between two dates

```
print(x-y)
```

```
## 5415 days, 19:17:37.113537
```

An interval can be added to a date

```
print(y)
```

```
## 2008-03-16 00:00:00
```

```
print(y+datetime.timedelta(days=10))
```

```
## 2008-03-26 00:00:00
```

Datasets

- We will look at two datasets
  - The taxis data set from seaborn
  - A dataset from the Australian Energy Market Operator of electricity demand in thirty minute intervals for five regions of Australia on the 18th-24th September 2022.

Reading in data

```python
import pandas as pd
elec = pd.read_csv('../data/electricity.csv')
elec
```

```
##       REGIONID    INTERVAL_DATETIME  OPERATIONAL_DEMAND
## 0         NSW1  2022/09/18 00:00:00                7568
## 1         QLD1  2022/09/18 00:00:00                5575
## 2          SA1  2022/09/18 00:00:00                1578
## 3         TAS1  2022/09/18 00:00:00                1071
## 4         VIC1  2022/09/18 00:00:00                5349
## ...        ...                  ...                 ...
## 1675      NSW1  2022/09/24 23:30:00                7561
## 1676      QLD1  2022/09/24 23:30:00                5694
## 1677       SA1  2022/09/24 23:30:00                1428
## 1678      TAS1  2022/09/24 23:30:00                1184
## 1679      VIC1  2022/09/24 23:30:00                5137
##
## [1680 rows x 3 columns]
```

Converting to date

Dates may not be read in as dates

```
elec.dtypes
```

```
## REGIONID                object
## INTERVAL_DATETIME       object
## OPERATIONAL_DEMAND       int64
## dtype: object
```

Can convert using `to_datetime`

```
elec['INTERVAL_DATETIME'] = pd.to_datetime(elec['INTERVAL_DATETIME'])
elec.dtypes
```

```
## REGIONID                        object
## INTERVAL_DATETIME       datetime64[ns]
## OPERATIONAL_DEMAND               int64
## dtype: object
```

Conversion

Convert dates to strings with formats here

```
datetime.datetime.strftime(y,'%a %d-%B-%Y')
```

```
## 'Sun 16-March-2008'
```

```
datetime.datetime.strftime(y,'%B %d, %y')
```

```
## 'March 16, 08'
```

And convert back

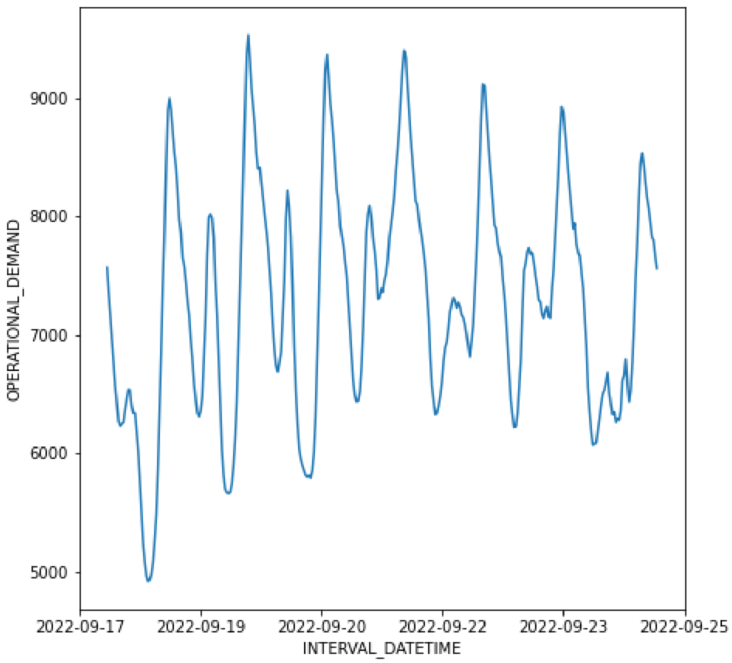
```
print(datetime.datetime.strptime('December 10, 22','%B %d, %y'))
```

```
## 2022-12-10 00:00:00
```

More Python plotting

NSW electricity demand

```
fig, ax = plt.subplots()
g = sns.lineplot(data = elec[elec['REGIONID']=='NSW1'],x='INTERVAL_DATET
g.xaxis.set_major_locator(ticker.LinearLocator(6))
plt.show()
```

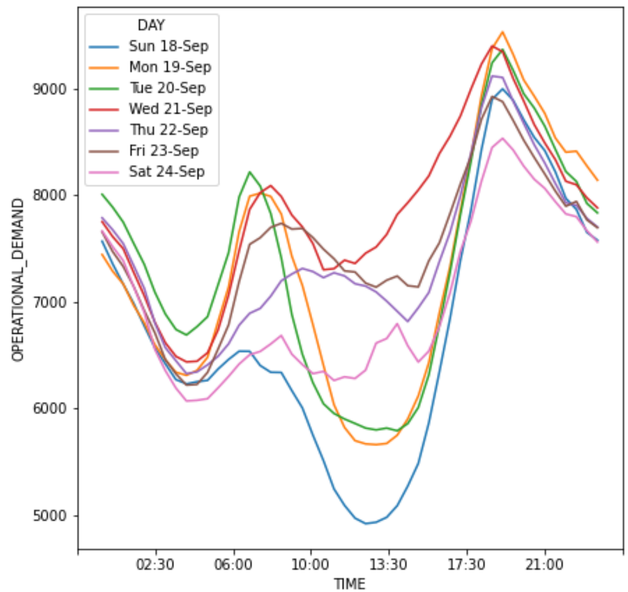


What do we see?

- Some seasonality
  - Reflects patterns of usage throughout the day
- No upwards or downwards trend
  - Make sense since data is only measured over a week
- Can we visualise differently?

Seasonal plot

```
elec['TIME']=elec['INTERVAL_DATETIME'].dt.strftime('%H:%M')
elec['DAY']=elec['INTERVAL_DATETIME'].dt.strftime('%a %d-%b')
g = sns.lineplot(data = elec[elec['REGIONID']=='NSW1'],x='TIME', y = 'O
g.xaxis.set_major_locator(ticker.LinearLocator(8))
plt.show()
```



What do we see?

- Two peaks
  - Small one in morning
  - Larger one in evening
- Why no early peak on Sunday?
- Why is there a small afternoon peak on the Saturday?

An example with taxi data

- The taxi data contains event data
- We can construct a daily series of number of taxi trips
- This requires some data preparation and conversion between datetimes and dates

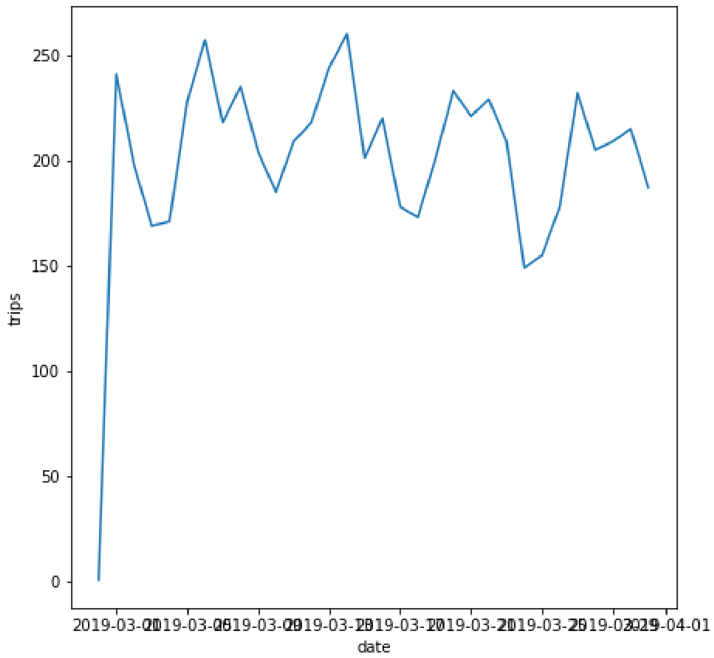
Data preparation

```
taxisdat = sns.load_dataset('taxis')
taxisdat['timestamp'] = pd.to_datetime(taxisdat['pickup'])
taxisdat['date'] = taxisdat['timestamp'].dt.strftime('%Y/%m/%d')
taxists = taxisdat.groupby('date').size().reset_index(name='trips')
taxists['date'] = pd.to_datetime(taxists['date'])
taxists
```

```
##          date  trips
## 0  2019-02-28      1
## 1  2019-03-01    241
## 2  2019-03-02    198
## 3  2019-03-03    169
## 4  2019-03-04    171
## 5  2019-03-05    228
## 6  2019-03-06    257
## 7  2019-03-07    218
## 8  2019-03-08    235
## 9  2019-03-09    204
## 10 2019-03-10    185
## 11 2019-03-11    209
```

Lineplot

```
sns.lineplot(data = taxists, x='date', y='trips')
```



What do you see?

- The very first observation is an outlier
- There is also a weekly pattern
- Don't forget that time series data is like all other data. We can use plots *other* than line plots!

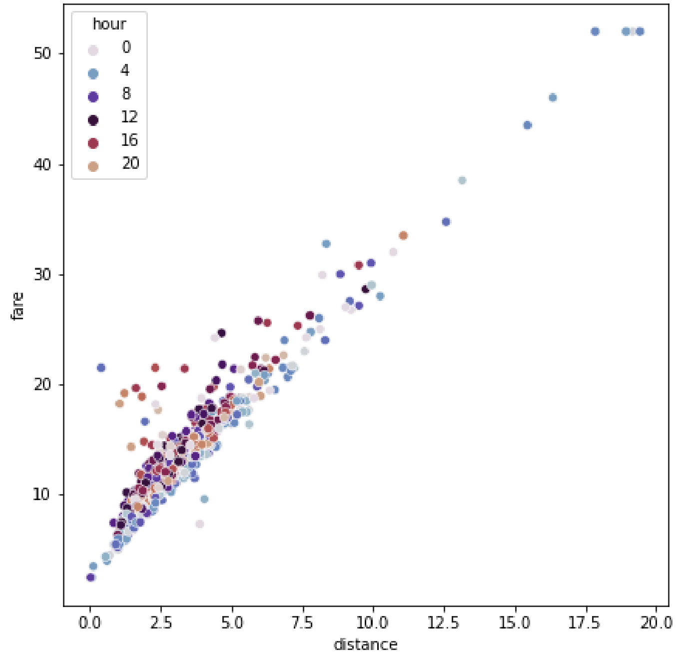
An example

```
taxisdat['datehour'] = pd.to_datetime(taxisdat['pickup']).dt.strftime('
taxish = taxisdat.groupby('datehour').agg({'fare':'mean','distance':'me
taxish['hour'] = taxish.index.str[-2:].astype(int)
taxish
```

```
##                     fare   distance  hour
## datehour
## 2019/02/28 23   5.000000   0.900000    23
## 2019/03/01 00  12.625000   3.286250     0
## 2019/03/01 01   5.000000   1.000000     1
## 2019/03/01 02   9.833333   2.480000     2
## 2019/03/01 04   5.833333   1.250000     4
## ...                  ...        ...   ...
## 2019/03/31 19   8.900000   1.691000    19
## 2019/03/31 20  11.250000   2.758333    20
## 2019/03/31 21  17.000000   4.748750    21
## 2019/03/31 22  10.625000   2.422500    22
## 2019/03/31 23  24.250000   7.640000    23
##
```

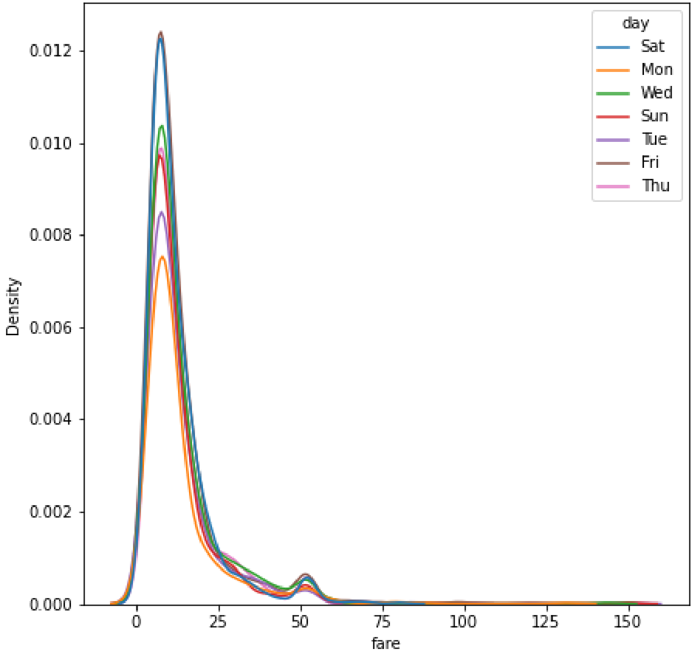
Plot

```
sns.scatterplot(data = taxish, x = 'distance', y = 'fare', hue = 'hour'
```



Another example

```
taxisdat['day'] = pd.to_datetime(taxisdat['pickup']).dt.strftime('%a')
sns.kdeplot(data = taxisdat, x='fare', hue='day')
```



Wrap-up

Conclusions

- The most common plot for time series is the lineplot
  - Can understand time series patterns such as trends, cycles and seasonality.
  - Can find outliers
  - Can understand autocorrelation properties.
- Important to manipulate dates
  - Can get more creative with visualisations.

Questions