Week 7: Visualising Spatial Data

Visual Data Analytics

University of Sydney

Outline

- Choropleth

Motivation

- Many business decisions depend on geospatial data
  - Store locations
  - Investment in real estate
  - Profile customers in different parts of a city - Geospatial data used in many other applications.

Packages

- There is an entire field known as Geographical Information Systems (GIS) that we learn over an entire course.
- This is a complicated problem that takes is issues with how coordinates are obtained, how they can be projected in different ways, etc.
- We will be using the `geopandas` package.
- This has many dependencies and can be fiddly to install

Virtual Environment

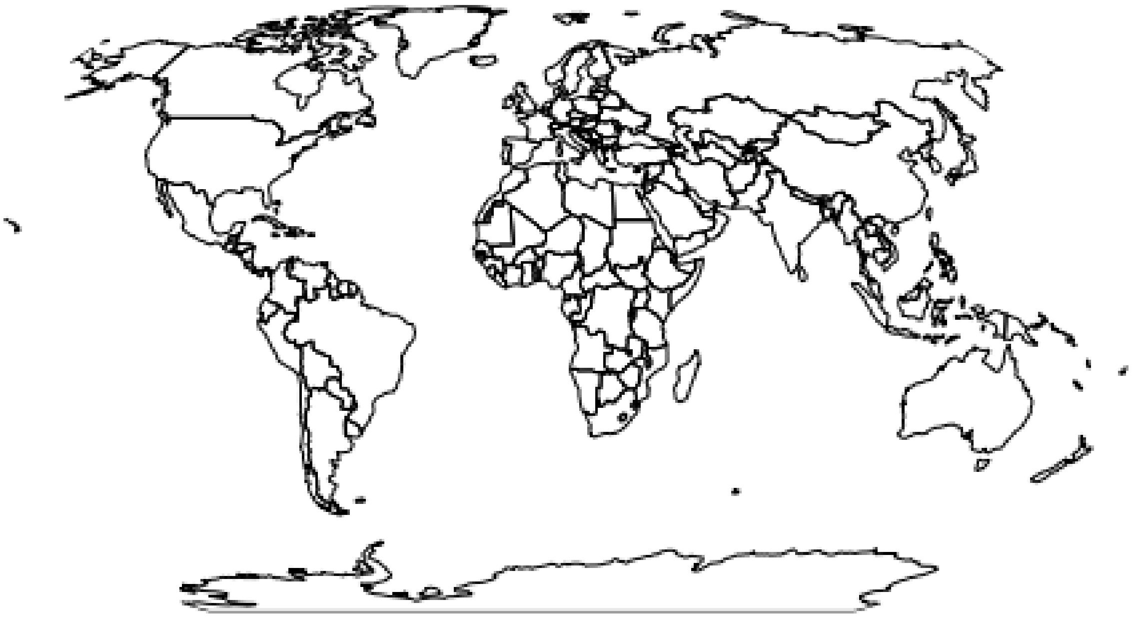
- Installation instructions can be found in the geopandas page.
- Since there can be clashes with dependencies, it is probably easiest to create a virtial environment just for working with geospatial data.
- Go the the instructions on *Creating a new environment*

World map

What is a projection?

- The earth is round.
- There are different ways to project a sphere onto a flat screen.
- All create distortion
- The mercator projection (previous slide) makes areas near the poles look bigger.

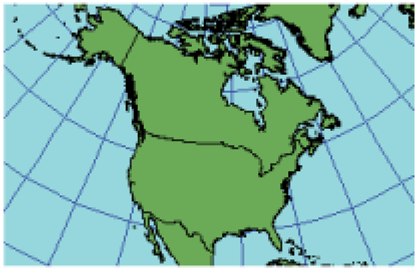
Robinson Projection



Does this matter?

- For looking at small countries or cities... no
- For large countries near the North pole... yes
- For the North America it is common to use an Albers projection

North America



North America

What about Australia?

- To see we will actually download data for Australia.
- First we need to download a *Shapefile*
- A Shape file is actually multiple files that store all the information about borders.
- We will use the SA4 areas of Australia.
- The shapefiles can be downloaded from the Australian Bureau of Statistics.
- Shapefiles are a standard format used globally.

Read in shapefile

```
aus = gpd.read_file('../data/SA4_2021_AUST_SHP_GDA2020')
aus
```

```
##      SA4_CODE21  ...                                           geometry
## 0           101  ...  MULTIPOLYGON (((150.05261 -37.26253, 150.05251...
## 1           102  ...  MULTIPOLYGON (((151.31497 -33.55578, 151.31496...
## 2           103  ...  POLYGON ((150.14236 -32.34153, 150.14255 -32.3...
## 3           104  ...  MULTIPOLYGON (((153.07639 -30.42982, 153.07645...
## 4           105  ...  POLYGON ((148.67619 -29.50976, 148.67662 -29.5...
## ..          ...  ...                                                ...
## 103         899  ...                                               None
## 104         901  ...  MULTIPOLYGON (((167.94747 -29.12757, 167.94748...
## 105         997  ...                                               None
## 106         999  ...                                               None
## 107         ZZZ  ...                                               None
##
## [108 rows x 13 columns]
```

Simplify series

These shapefiles are very detailes making plotting slow so we can simplify them.

```
aus.geometry = aus.geometry.simplify(0.001)
```

Australia

```
geoplot.polyplot(aus, geoplot.crs.Mercator())
```

Australia

```
geoplot.polyplot(aus, geoplot.crs.Robinson())
```

Summary

- The Mercator projection looks OK for Australia
- However we don't simply want to plot maps
- We want to add *data* to these maps.
- This can be done using a choropleth
- We will use data from the Australian Bureau of Statistics on mortgage repayments in Sydney.
- We will merge this with the geopandas data frame

Wrap-up

Data

```python
import pandas as pd
mortgage = pd.read_csv('../data/Mortgage.csv')
mortgage
```

```
##                                          SA4  ...   Total
## 0                              Central Coast  ...  152870
## 1    Sydney - Baulkham Hills and Hawkesbury  ...   89466
## 2                         Sydney - Blacktown  ...  135540
## 3             Sydney - City and Inner South  ...  178493
## 4                  Sydney - Eastern Suburbs  ...  122105
## 5                 Sydney - Inner South West  ...  227887
## 6                       Sydney - Inner West  ...  133899
## 7         Sydney - North Sydney and Hornsby  ...  180531
## 8                 Sydney - Northern Beaches  ...  105115
## 9    Sydney - Outer West and Blue Mountains  ...  130809
## 10                Sydney - Outer South West  ...  104420
## 11                      Sydney - Parramatta  ...  188066
## 12                            Sydney - Ryde  ...   83400
## 13                      Sydney - South West  ...  155905
## 14                      Sydney - Sutherland  ...   90775
```

Merge

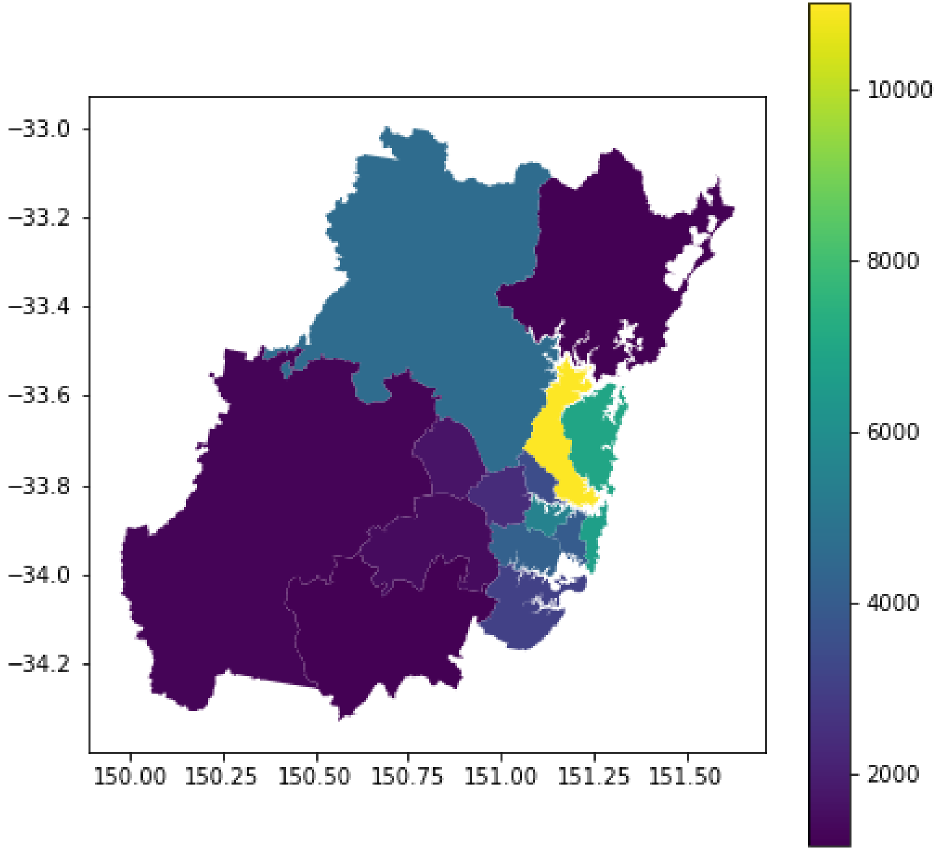
```python
import pandas as pd
merged = aus.merge(mortgage, how='right',left_on = 'SA4_NAME21', right_

merged
```

```
##    SA4_CODE21                              SA4_NAME21  ... Not applicable
## 0         102                           Central Coast  ...         107844
## 1         115  Sydney - Baulkham Hills and Hawkesbury  ...          51873
## 2         116                      Sydney - Blacktown  ...          82831
## 3         117          Sydney - City and Inner South  ...         146248
## 4         118                Sydney - Eastern Suburbs  ...          97426
## 5         119               Sydney - Inner South West  ...         167199
## 6         120                     Sydney - Inner West  ...         100829
## 7         121        Sydney - North Sydney and Hornsby  ...         130327
## 8         122               Sydney - Northern Beaches  ...          72014
## 9         124  Sydney - Outer West and Blue Mountains  ...          84896
## 10        123               Sydney - Outer South West  ...          62085
## 11        125                     Sydney - Parramatta  ...         139866
## 12        126                           Sydney - Ryde  ...          60698
## 13        127                     Sydney - South West  ...         105896
```

Choropleth

```
merged.plot(column="$5,000 and over", legend=True)
```

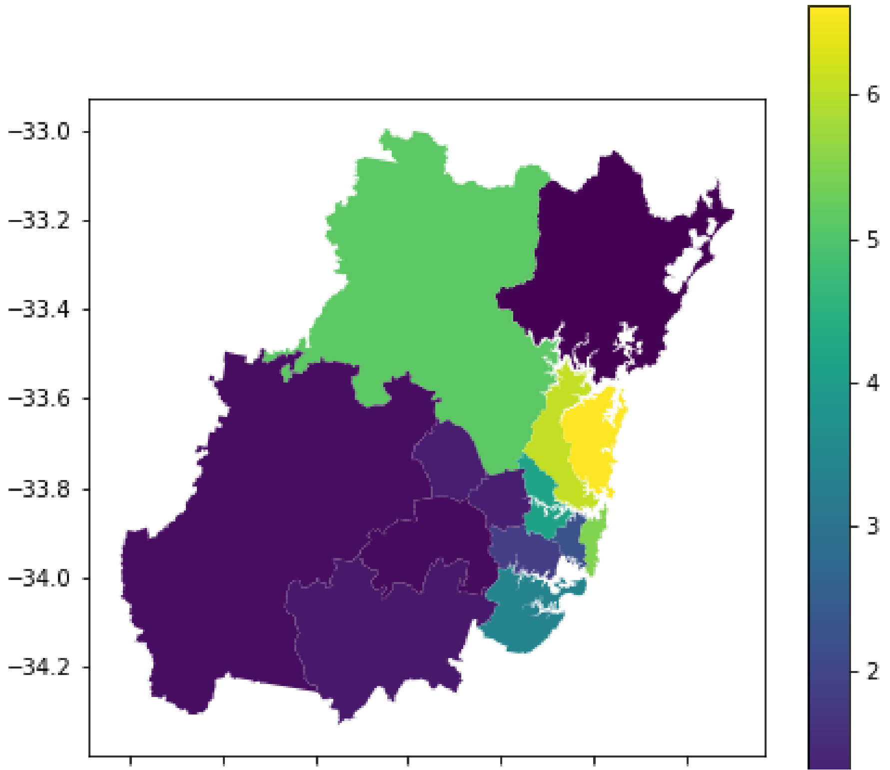


A word of caution

- The choropleth on the previous slide uses *spatially extensive* data.
- By this we mean they are raw counts of people that do not take the population of each area into account.
- It is better to use *spatially intensive* data in a choropleth

Proportion

```
merged["$5,000+ Percentage"] = 100*merged["$5,000 and over"]/merged["To
merged.plot(column="$5,000+ Percentage", legend=True)
```



Making things interactive

Why interactivity?

- Unless you know the location well, it may be hard to tell which regions are which.
- Also urban areas tend to be smaller therefore it helps to be able to zoom in and move around.
- We can also augment the choropleth with individual locations.

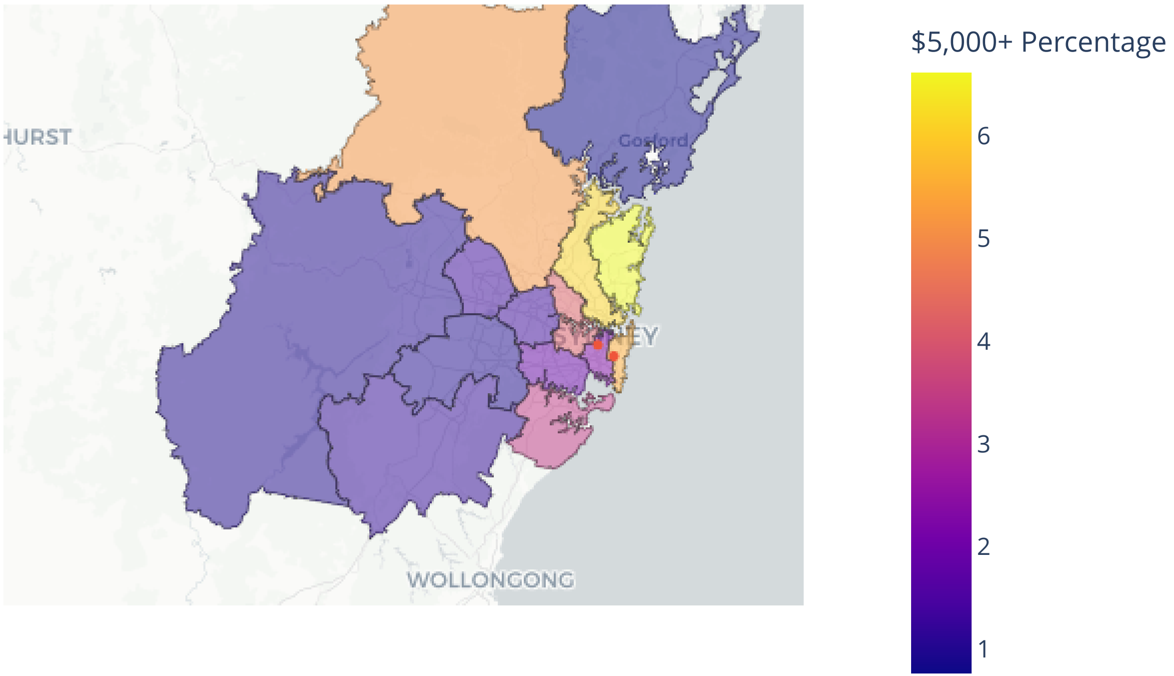
Plolty Code

```
import plotly.express as px
merged.index = merged['SA4']
fig = px.choropleth_mapbox(merged,
geojson=merged.geometry,
locations = merged.index,
color = "$5,000+ Percentage",
opacity=0.5, mapbox_style="carto-positron",
zoom = 7, #Zoom in scale
center = {"lat": -33.7, "lon": 150.75})
fig.add_scattermapbox(lat = [-33.89083755569, -33.91648618776671],
lon = [151.18711290919222, 151.23079491201923],
text = ["The University of Sydney", "UNSW"],
marker_size=6)
```

```
<div>                            <script type="text/javascript">window.Plot
        <script src="https://cdn.plot.ly/plotly-2.16.1.min.js"></script
```

```
fig.write_html('plotly_choropleth.html')
```

Interactive



Summary

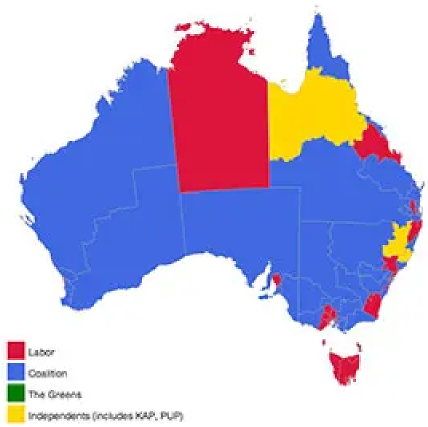
- There are a rich range of visualisations that you can create with geographic data.
- However you can generally only look at one variable at one moment of time.
- You can construct multiple choropleths and display together but they can also be difficult to interpret.

Misleading choropleths

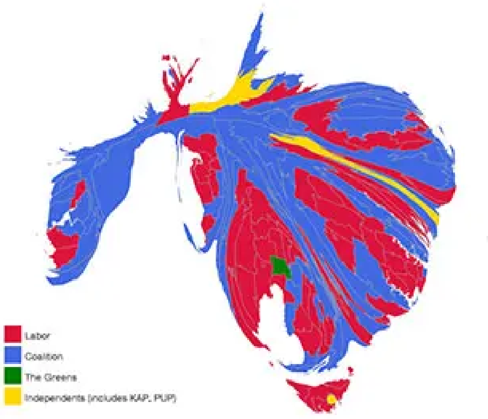
- In many countries, the population density is not uniform
- This includes Australia, the US and China where most of the population lives on the coast and well as India and France as other examples with less densely populated regions.
- This commonly leads to misinterpratation of election results.

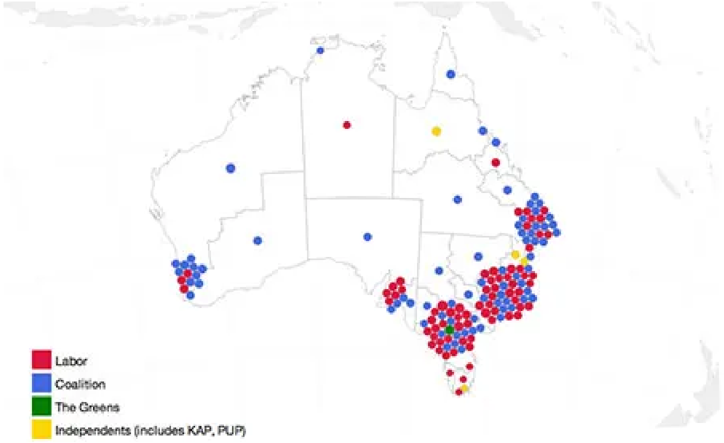
Australian 2010 election

- The 2010 election was very close
- However the map on the right suggests the Coalition (blue) was dominant.
- This map shows land but not voters.



Two alternatives





Discussion

- The alternative on the left is called a *cartogram*.
  - It can be visually jarring
- The alternative on the right loses precise spatial information.
- All plots and further discussion are from this article
- This issue is not restricted to politics, an example on brand choice may suffer from similar issues.

A word on heatmaps

Heatmaps

- A choropleth is often called a *heatmap*.
- A heatmap is a similar idea in that areas are shown with different colors. However a heatmap is used to visualise numbers in a matrix.

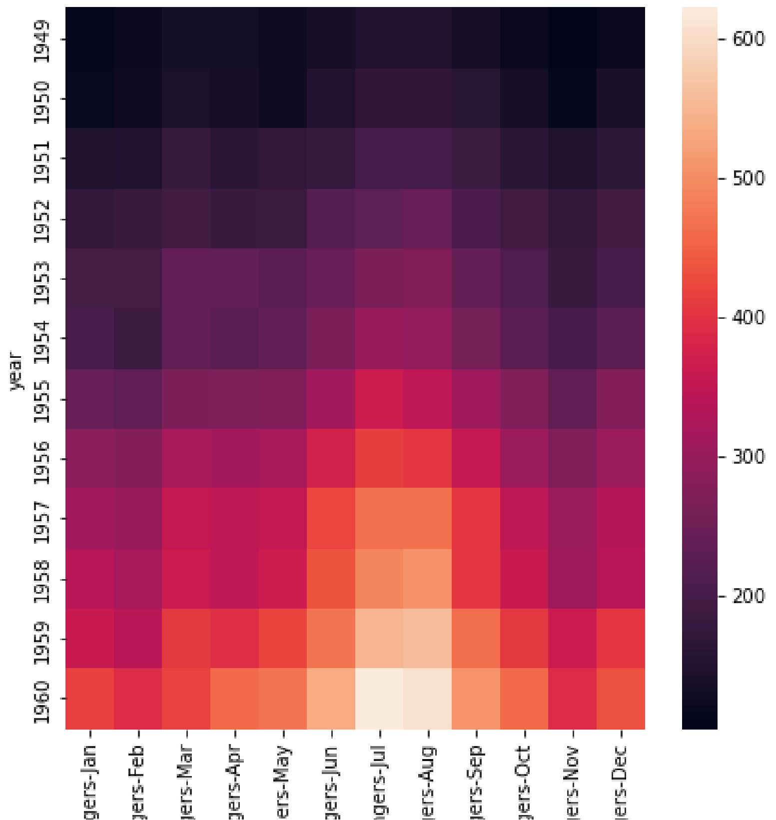
Data Preparation

```python
import seaborn as sns
fl = sns.load_dataset('flights')
fltab = fl.pivot(index = 'year', columns = 'month')
fltab
```

```
##        passengers
## month         Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec
## year
## 1949          112  118  132  129  121  135  148  148  136  119  104  118
## 1950          115  126  141  135  125  149  170  170  158  133  114  140
## 1951          145  150  178  163  172  178  199  199  184  162  146  166
## 1952          171  180  193  181  183  218  230  242  209  191  172  194
## 1953          196  196  236  235  229  243  264  272  237  211  180  201
## 1954          204  188  235  227  234  264  302  293  259  229  203  229
## 1955          242  233  267  269  270  315  364  347  312  274  237  278
## 1956          284  277  317  313  318  374  413  405  355  306  271  306
## 1957          315  301  356  348  355  422  465  467  404  347  305  336
## 1958          340  318  362  348  363  435  491  505  404  359  310  337
## 1959          360  342  406  396  420  472  548  559  463  407  362  405
## 1960          417  391  419  461  472  535  622  606  508  461  390  432
```

Heatmap

```
import seaborn as sns
sns.heatmap(fltab)
```



Correlation heatmap

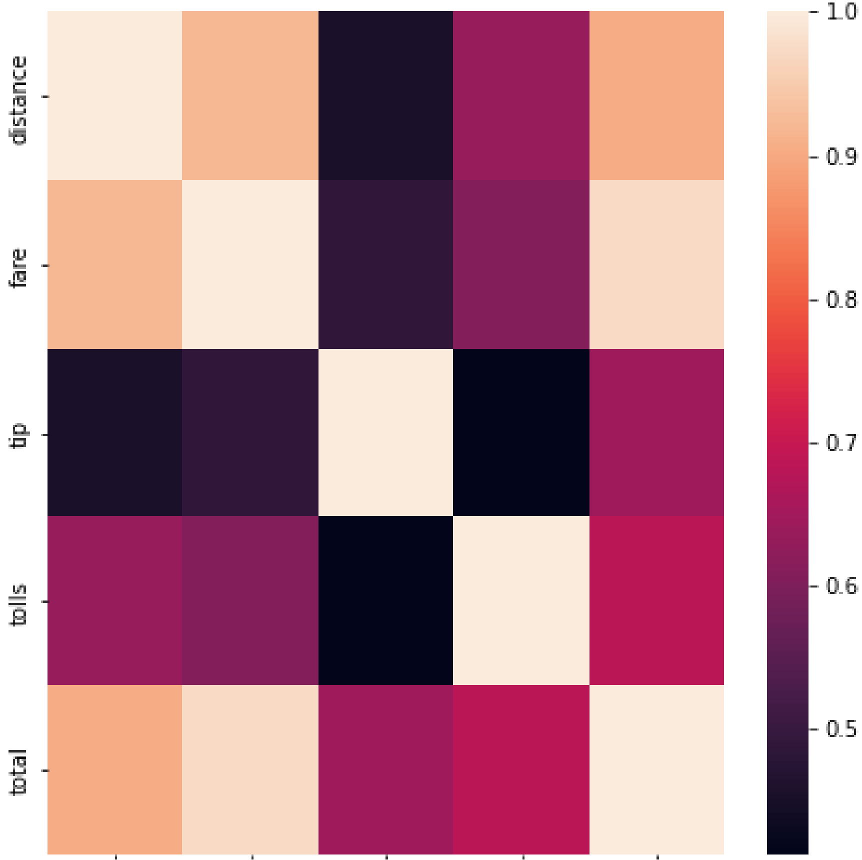
- With a moderate number of numerical variables we can compute the correlation of all pairs of variables.
- These can be put into a matrix known as the correlation matrix.
- This can also be shown in a heatmap.
- We will do this some numerical variables from the taxis data

Data preparation

```
taxisdat = sns.load_dataset('taxis')
taxisnum = taxisdat[['distance','fare','tip','tolls','total']]
taxiscor = taxisnum.corr()
```

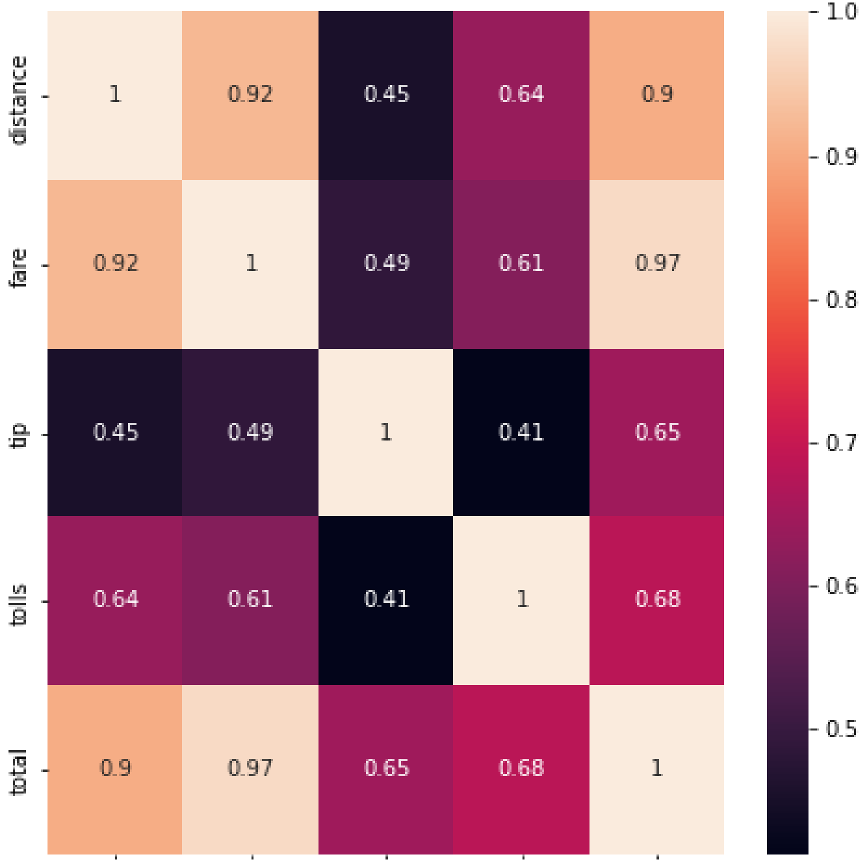
Correlation heatmap

```
sns.heatmap(taxiscor)
```



With annotation

```
sns.heatmap(taxiscor, annot = True)
```



Wrap-up

Conclusions

- Spatial data can be used to create valuable visualisations. However
  - Think carefully about how population is distributed in geographic regions
  - Do not neglect other visualisation methods

Questions