Week 5: Visualising Many Variables

Visual Data Analytics

University of Sydney

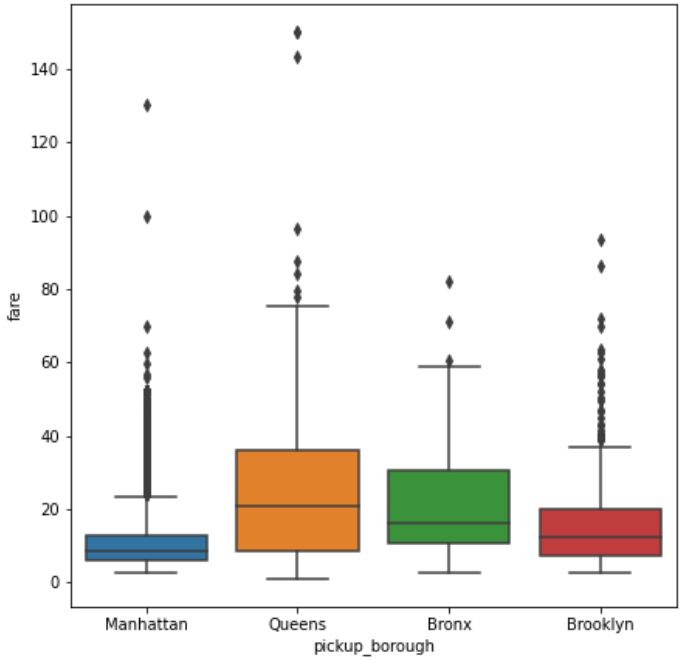
Outline

- Using color
  - All about colormaps
- Bubble plot
- Facetting
- Parallel Coordinates
- Spider chart

Motivation

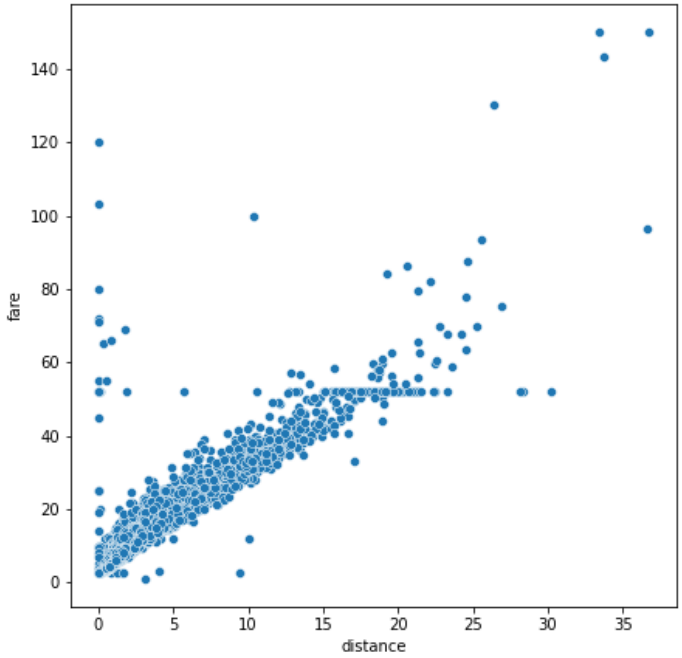
- Suppose we want to investigate three variables
- Whenever we find a relationship between two variables, it is worthwhile asking whether a third variable may be driving that relationship.
- For instance suppose there is a relationship between taxi fare and pickup Borough, perhaps this can be explained by distance.

Boxplot



Manhattan has lower fares

What about distance...

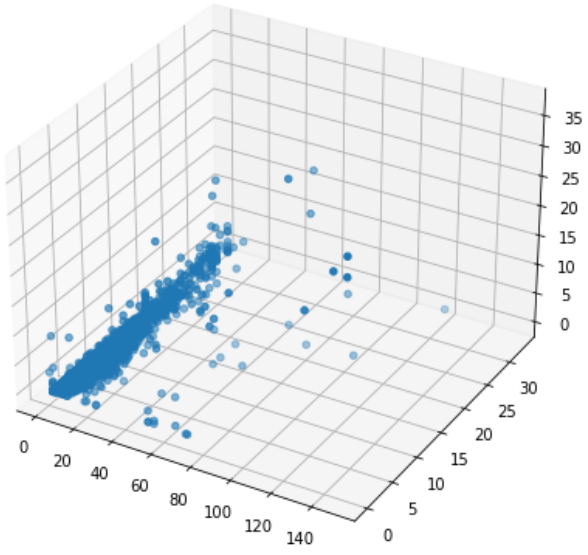


Fare also depends on distance.

Plots in 3D

- Initial reaction may be a 3D plot
- This can be done in Python
- It is very difficult to perceive depth when plot is on a flat screen.
- Being able to rotate the plot helps to some extent
- Still not ideal.

Scatter in 3D

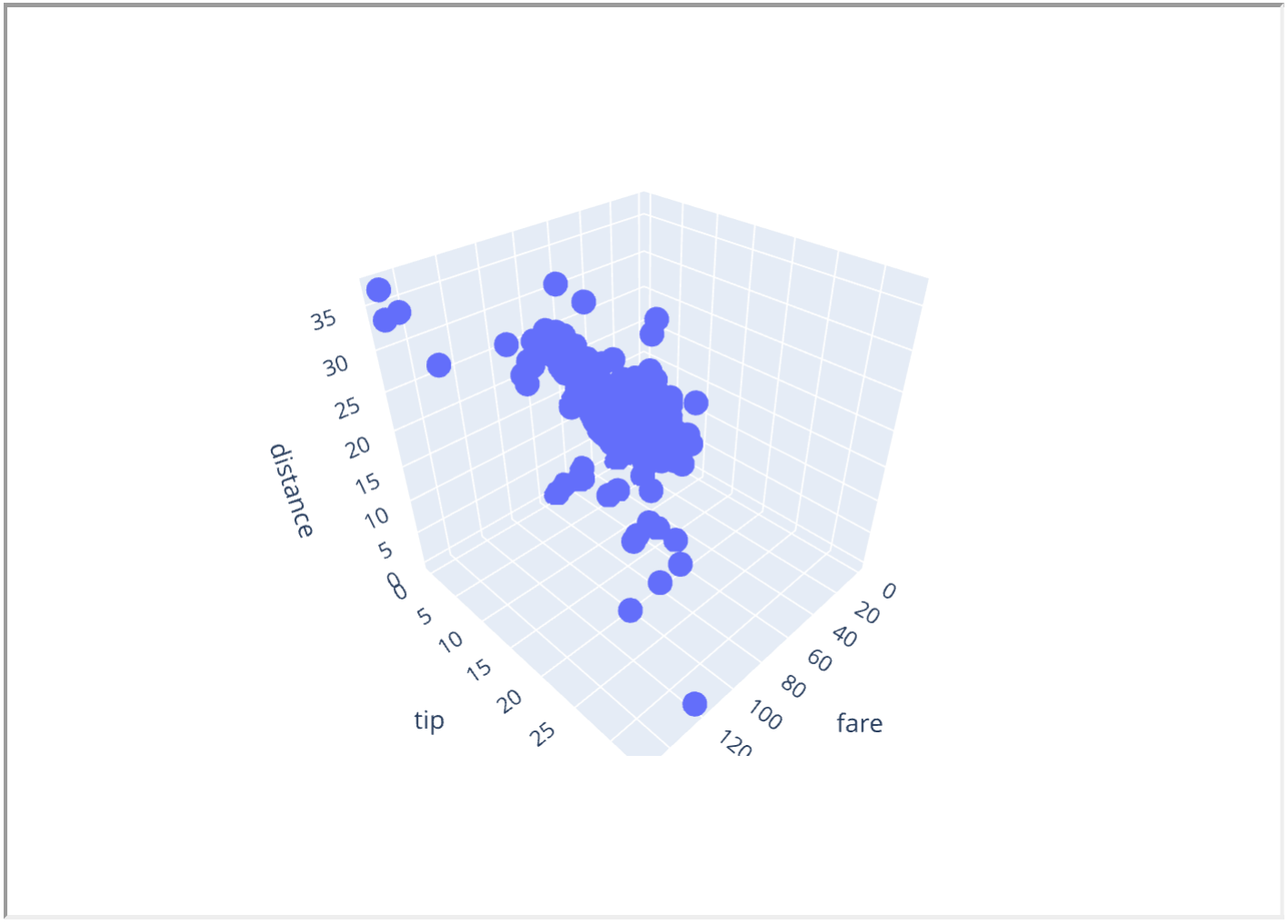


Interactive Scatterplot

```
import plotly.express as px
fig = px.scatter_3d(taxisdat, x='fare', y='tip', z='distance')
fig.write_html('int3d.html')
```

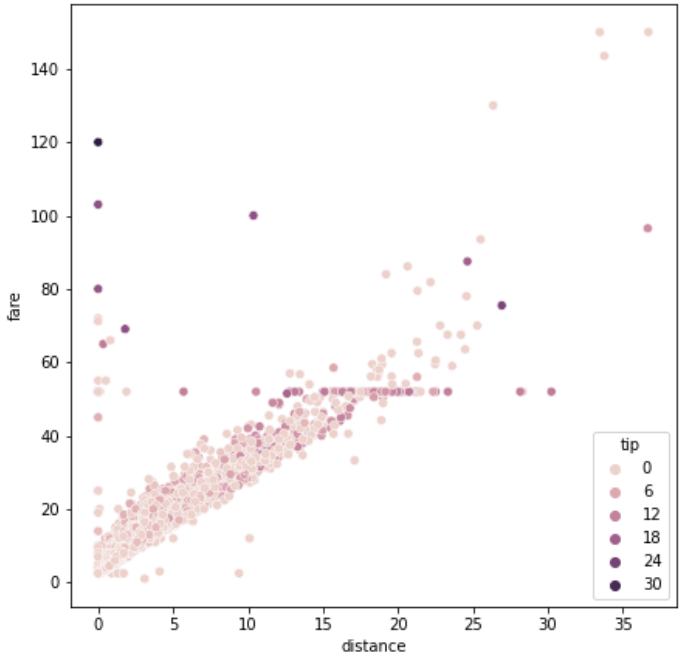
This code will save plot to a html file that can be opened with any browser.

Interactive Scatterplot

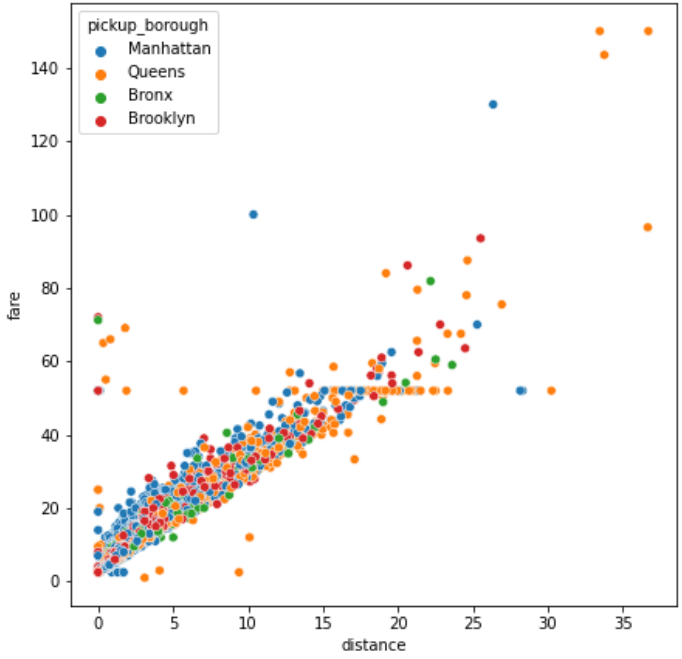


Using color

Fare v distance v tip



Fare v distance v borough



Adding color

- The outliers with small distance, high fare also had higher tips.
  - Perhaps for these trips the taxi driver did something exceptional.
- The outliers at top right mostly Queens.
  - This supports the idea than Manhattan has low fares relative to Queens due to the fact that trips in Manhattan are shorter.
- Not definitive causal explanations, but color allows for a richer exploratory understanding of data.

Colormaps

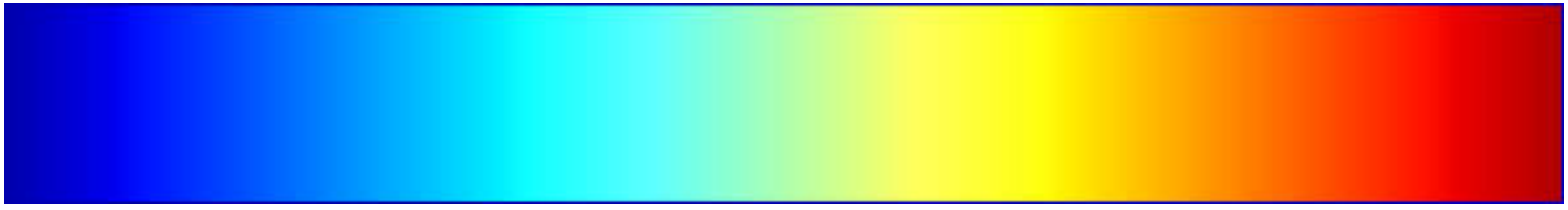
- There are four types of colormaps
  - Sequential
  - Diverging
  - Cyclic
  - Qualitative
- Following discussion based on Matplotlib documentation.

Sequential

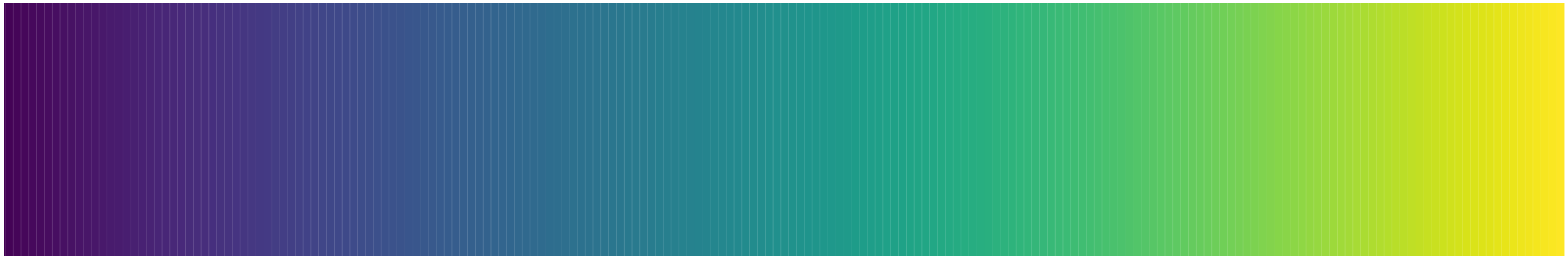
- For most ordinal or numeric variables we use a *sequential* colormap which should be
  - Perceptually uniform
  - Large range
  - Work when printed in black and white
  - Accessible to colorblind people
  - Colorful and pretty
- The *viridis* colormap (matplotlib default) was developed with these criteria in mind

Jet v Viridis

A popular palette is jet.



A better palette (by the above criteria) is viridis

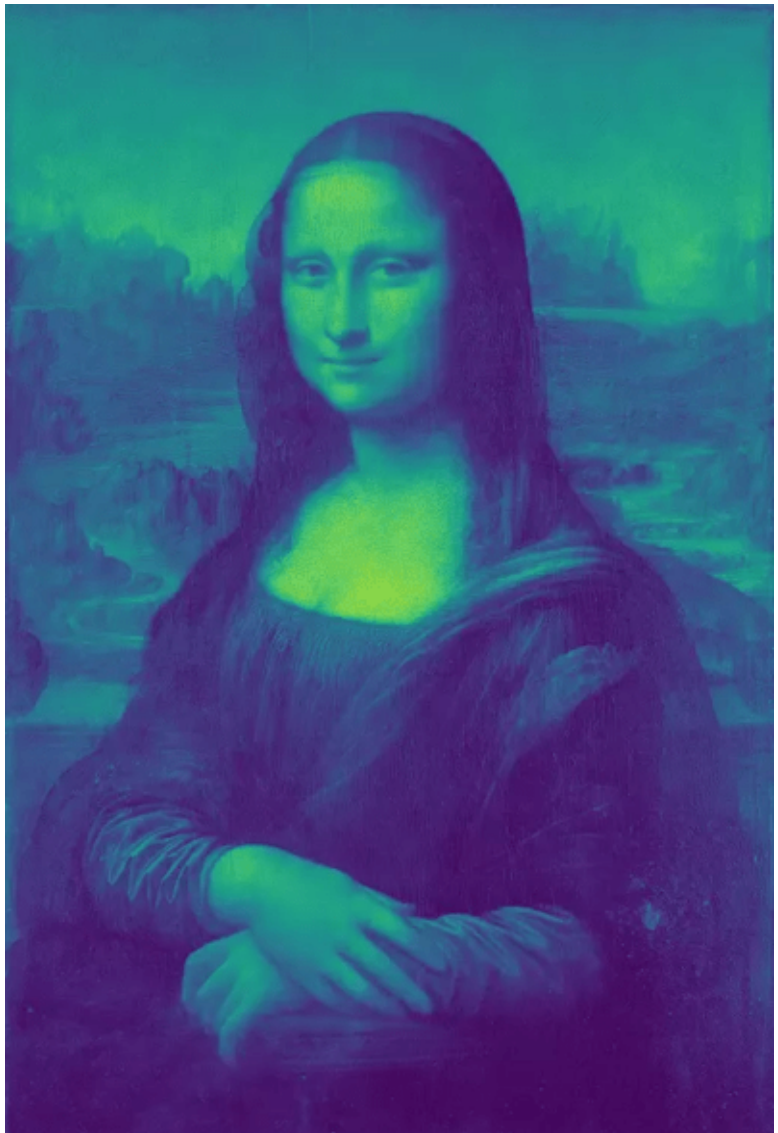


Problems with jet

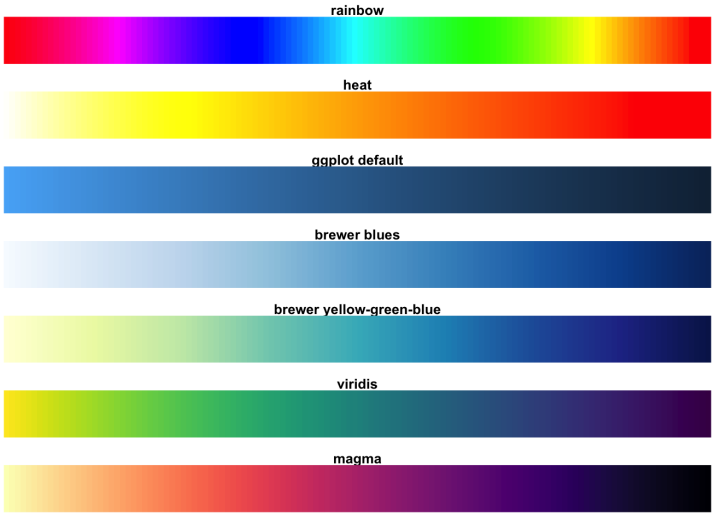
- Colors close to one another should be similar.
- On jet, in some parts the color changes dramatically over a small range.
- Also colorblind people (about 8% of the population) can have difficulty with the red colors in jet.
- For more on this see this talk by the creators of viridis.

Jet Colormap

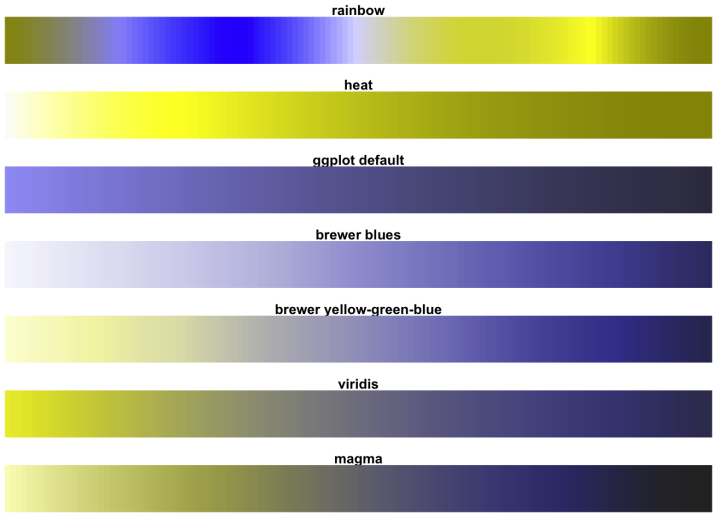
Viridis colormap



Colorblindness



Not colorblind



Deuteropia

Divergent colormaps

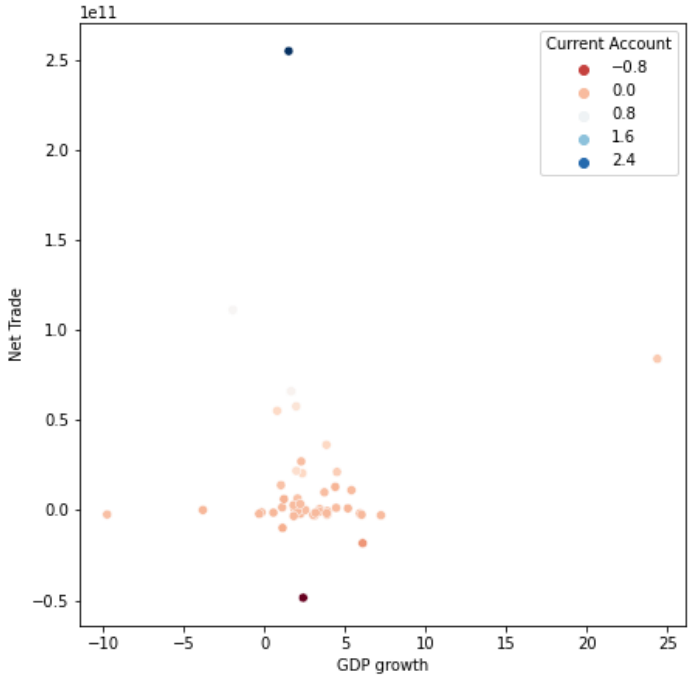
- Central point (usually white or a light color).
- Different colors to the left and right.
- Colors become darker for more extreme values.
- Well suited to data that can be positive or negative (e.g. profit/loss, returns, growth, trade balances).

World Bank Data

- Will use data sourced from World Bank on European and Central Asian countries in 2015. There are three variables
  - GDP growth
  - Net trade
  - Current account balance

Plot

```
wb = pd.read_csv('../data/worldbank.csv', na_values = '..')
sns.scatterplot(data = wb, hue='Current Account', y = 'Net Trade', x='G
```

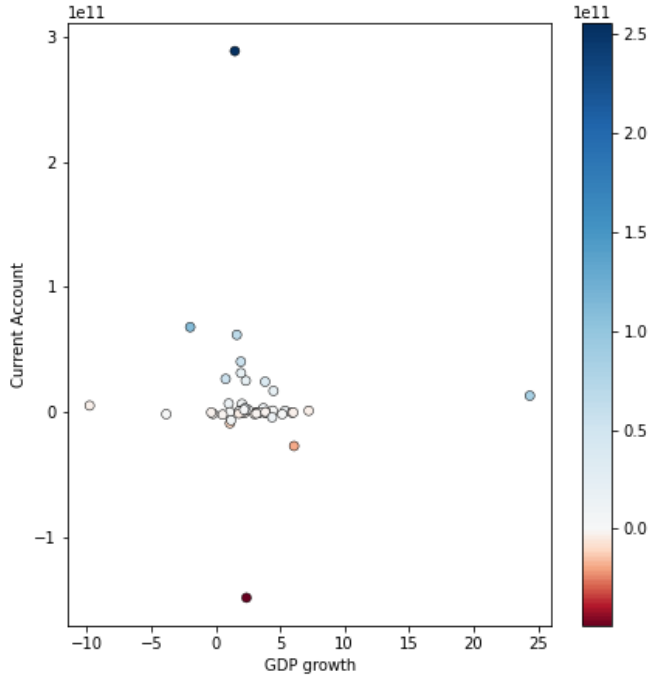


Match white with 0

```
import matplotlib.cm as cm
import matplotlib.colors as mcolors

fig, ax = plt.subplots()
wb = pd.read_csv('../data/worldbank.csv', na_values = '..')
wb.dropna(axis = 0, how = 'any', inplace = True)

vcenter = 0
vmin, vmax = wb['Net Trade'].min(), wb['Net Trade'].max()
normalize = mcolors.TwoSlopeNorm(vcenter=vcenter, vmin=vmin, vmax=vmax)
colormap = cm.RdBu
plt.scatter(y=wb['Current Account'],x=wb['GDP growth'],c=wb['Net Trade'

scalarmappaple = cm.ScalarMappable(norm=normalize, cmap=colormap)
scalarmappaple.set_array(wb['Net Trade'])
fig.colorbar(scalarmappaple)
plt.show()
```

Match white with 0

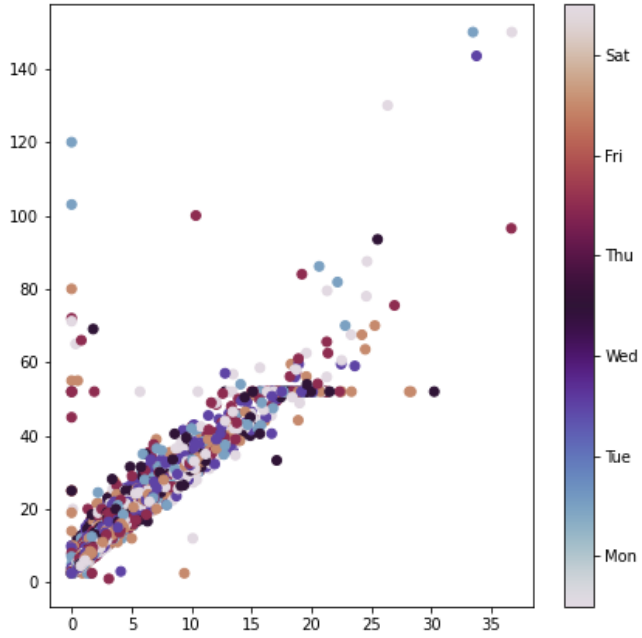
```
## <matplotlib.colorbar.Colorbar object at 0x7f1b6d229460>
```



Cyclical

- As the name implies a cyclical colormap 'wraps' back around on itself.
- It is useful for displaying data about angles (e.g wind direction) or calendar effects
- The next slide shows taxi fare against distance with day of week mapped to color.
- We show code after we discuss time and date objects next week.

Cyclical colormap

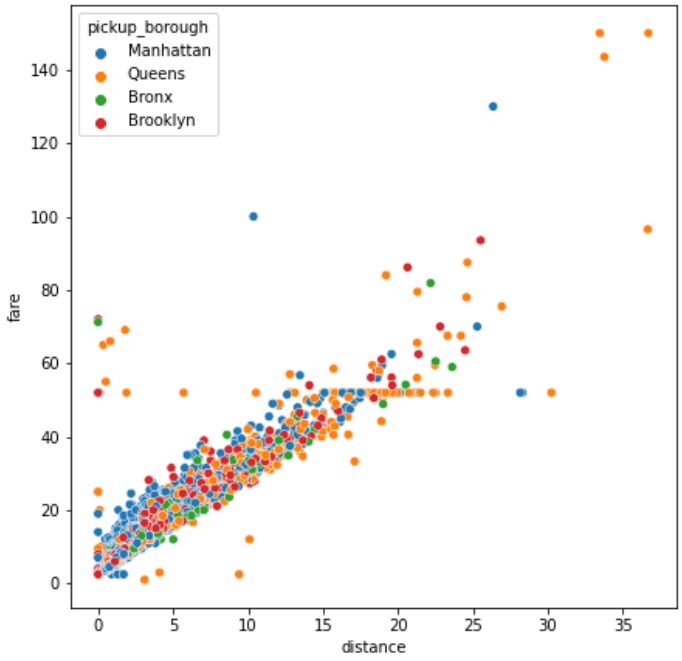


Qualitative Colormap

- Used for nominal variables
- Ideal for colors to be very different (especially those adjacent on legend)
- Avoid reds and greens to make as colorblind friendly as possible.
- These is a subtle difference between the default qualitative scheme in Seaborn and the colorblind version.

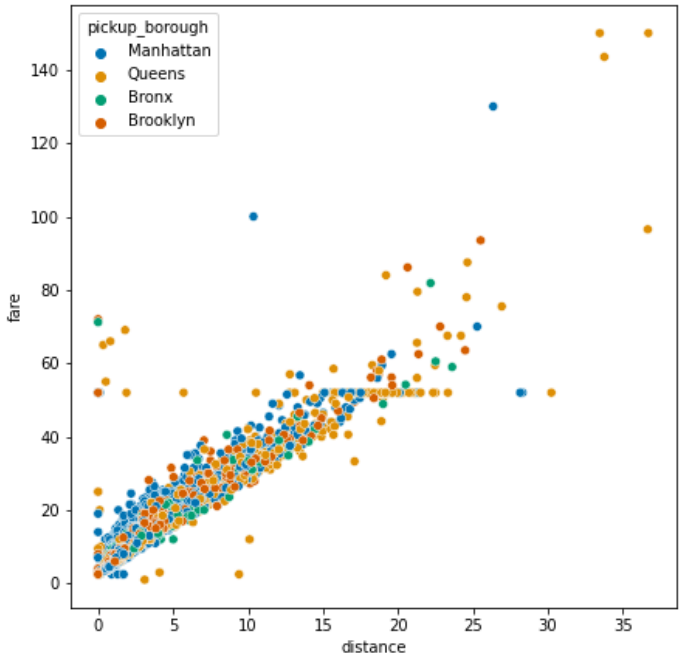
Default

```
sns.scatterplot(data = taxisdat, y='fare', x = 'distance', hue='pickup_
```



Colorblind Pallette

```
sns.scatterplot(data = taxisdat, y='fare', x = 'distance', hue='pickup_
```



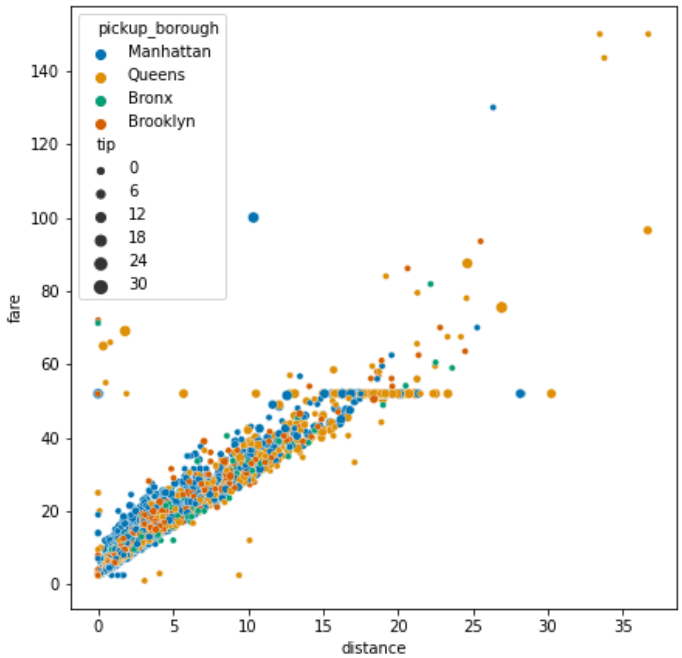
Size and shape

More variables

- What if we want to include information about a fourth or fifth variable?
- We can map a variable to the
  - Size of the point (bubble plot)
  - Shape of the point
  - Use text
- We can see some examples

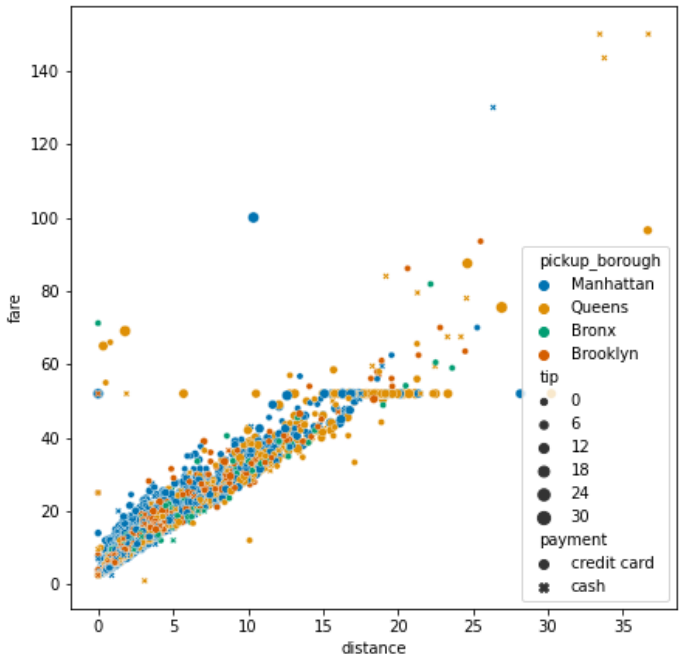
Bubble plot

```
sns.scatterplot(data = taxisdat, y='fare', x = 'distance', hue='pickup_
```



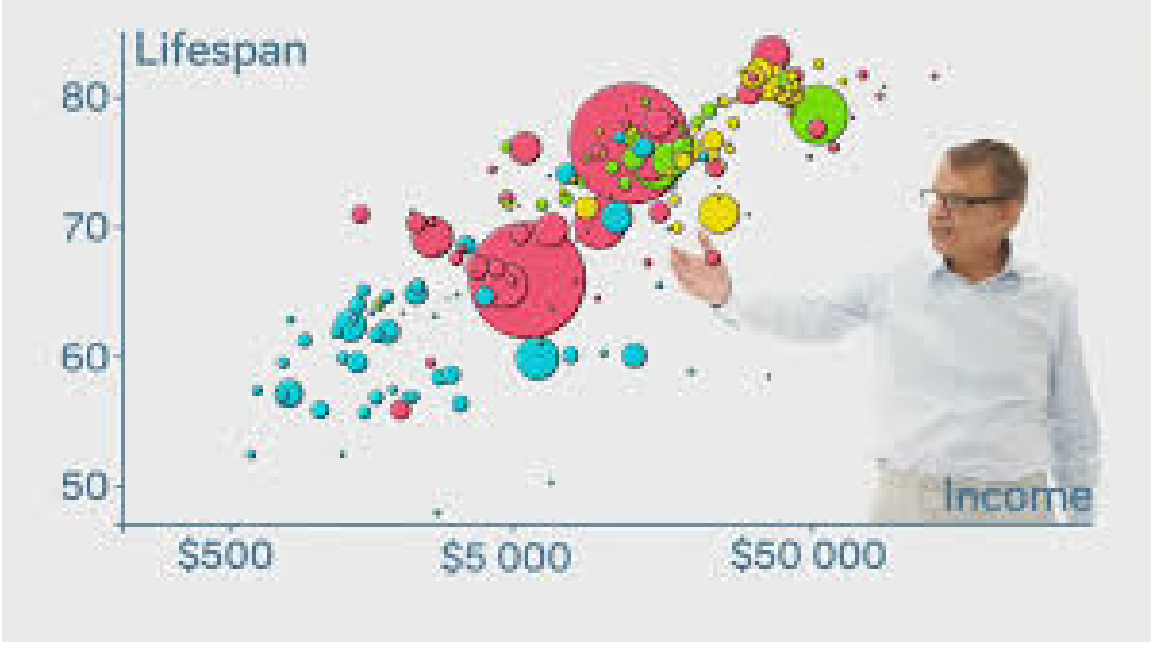
Point shapes

```
sns.scatterplot(data = taxisdat, y='fare', x = 'distance', hue='pickup_
```



Gapminder

- A famous example of a bubble chart is Hans Rosling's gapminder presentation.

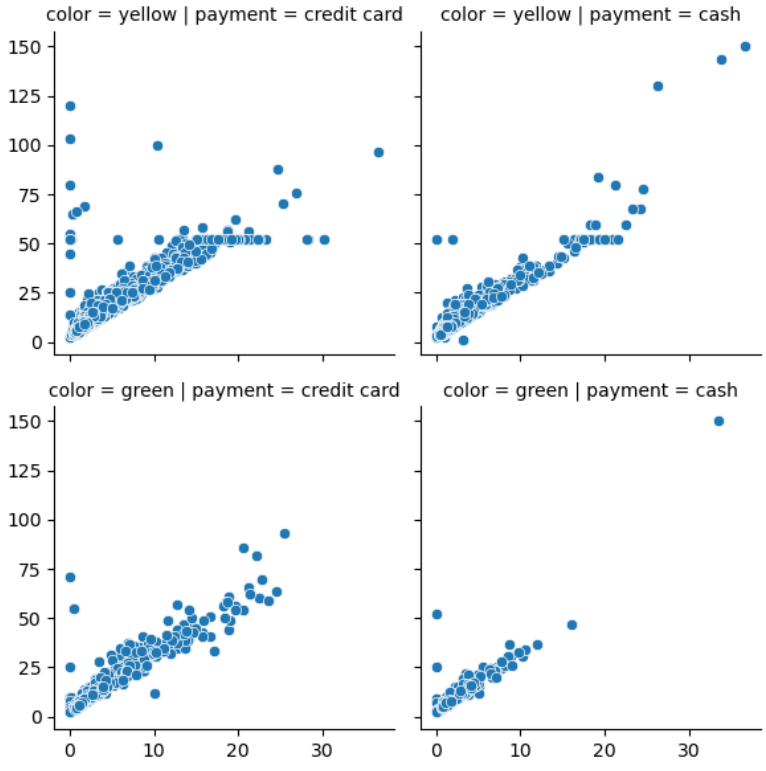


Facetting

- Notice that bubble plots using many different colors and marker shapes can be overly confusing.
- Often it is clearer to use many simpler plots rather than one complicated plot.
- This is known as facetting
- We can facet with one variable or with two (across rows and columns).

Example

```
g = sns.FacetGrid(taxisdat, col="payment",  row="color")
g.map_dataframe(sns.scatterplot, y = "fare", x = "distance")
```

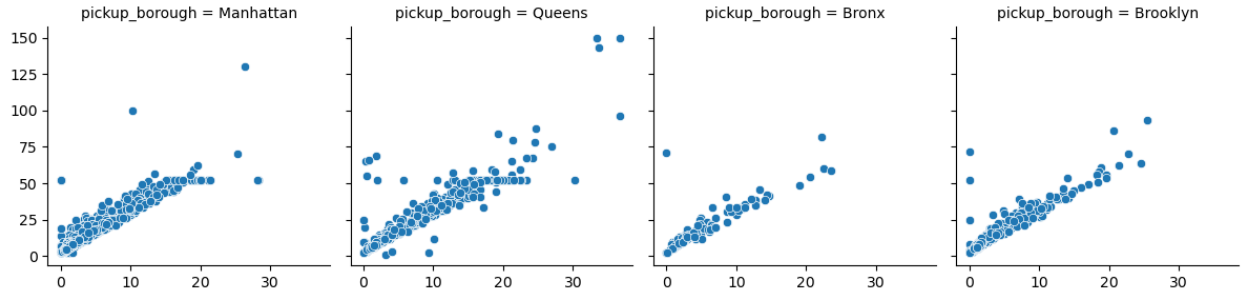


Facetting

- Facetting can show roughly which categories have the most observations.
- Can show categories with most outliers.
- Can show us if and how a relationship between variables can depend on a nominal variable (although not in the previous plot).

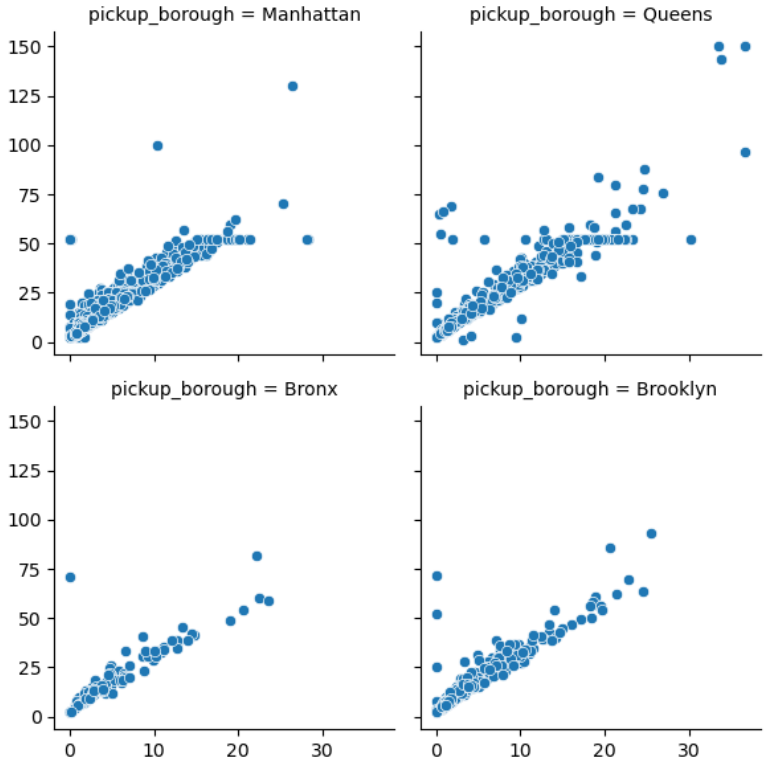
Facetting by a single variable

```
g = sns.FacetGrid(taxisdat, col="pickup_borough")
g.map_dataframe(sns.scatterplot, y = "fare", x = "distance")
```



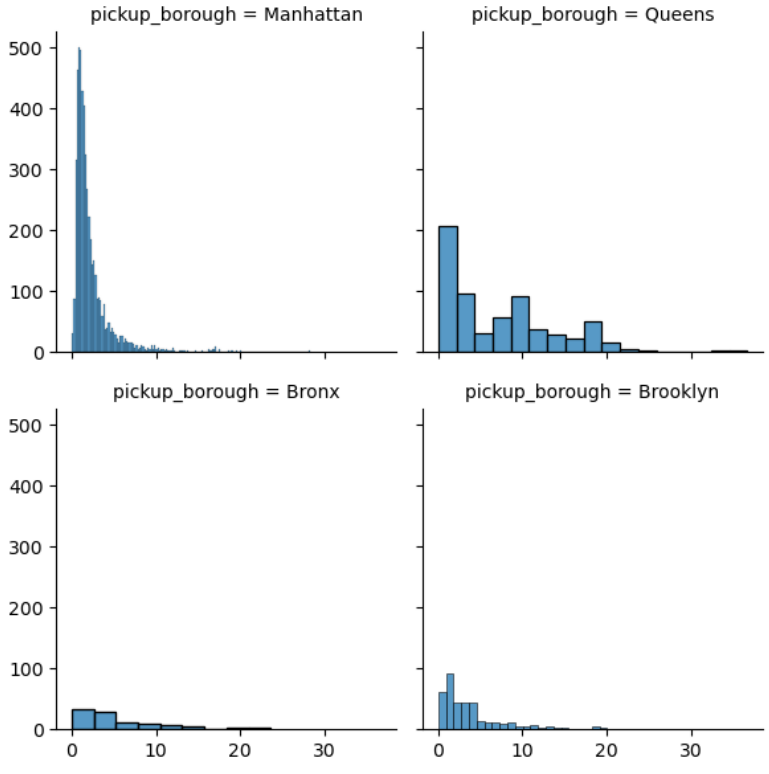
Facetting with wrap

```
g = sns.FacetGrid(taxisdat, col="pickup_borough", col_wrap = 2)
g.map_dataframe(sns.scatterplot, y = "fare", x = "distance")
```



Other plots

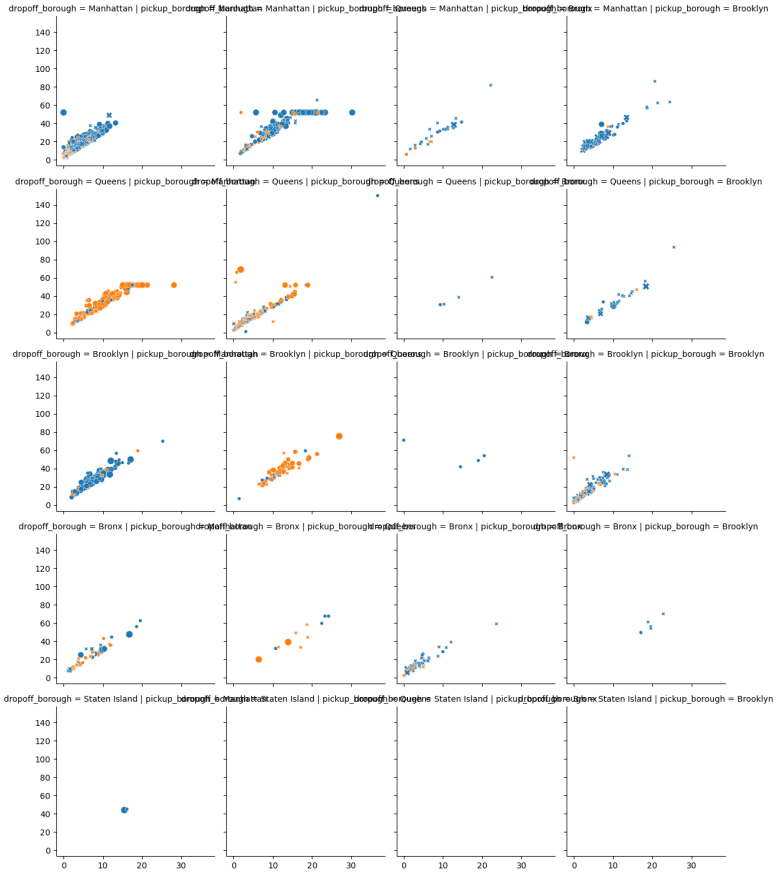
```
g = sns.FacetGrid(taxisdat, col="pickup_borough", col_wrap = 2)
g.map_dataframe(sns.histplot, x = "distance")
```



A warning

- Even if you can display many variables on one plot that does not always mean you *should* do this.
- If too many variables are shown it becomes too difficult for the viewer to decode any information.
- Complicated plots can be a useful as a step to work out some interesting features in the data.
- Then simplify your plot to tell a story

Too complicated

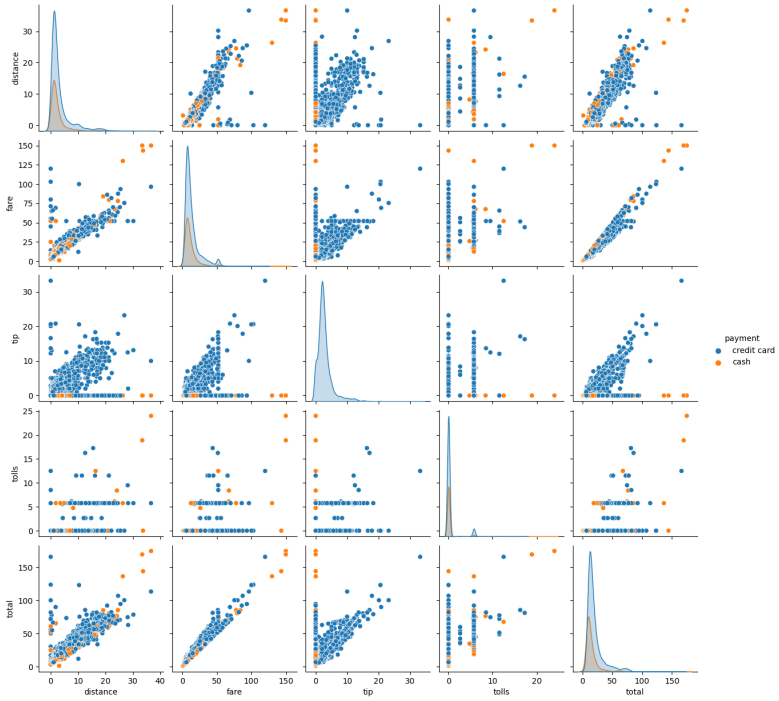


Pair plots

- Combines scatter plots with histograms or KDEs
- Can also use color.
- The `pairplot` function has an easy interface, but for more flexibility use 'PairGrid'

Pair plots

```
sns.pairplot(taxisdat[['distance','fare','tip','tolls','total','payment
```



Be careful

- Pair plots themselves often contain too much information
- In the previous example we may focus on specific things such as
  - That credit card payments are more right skewed than cash payments
  - That tolls concentrate around two main values
  - There is no tip for cash payments
- Other plots could then be used to highlight these insights.

A few more plots

Parallel coordinates

- The parallel coordinates plot mainly works for numeric data
- Each variable is standardised so they can be plotted on the same vertical axis.
- The variables are displayed horizontally.
- Color can be used to show a nominal variable.
- Implementation in plotly

Wholesale data

- For this example we will use a different dataset.
- Six numerical variables indicating spending in a different product categories (milk, frozen, detergents, etc.)
- Two categorical variables
  - Region (one of three regions in Portugal)
  - Channel (client is either retail or hotel/restaurant/cafe)
- Data made available by M. Cardoso at UC Irvine Machine Learning repository

Wholesale data

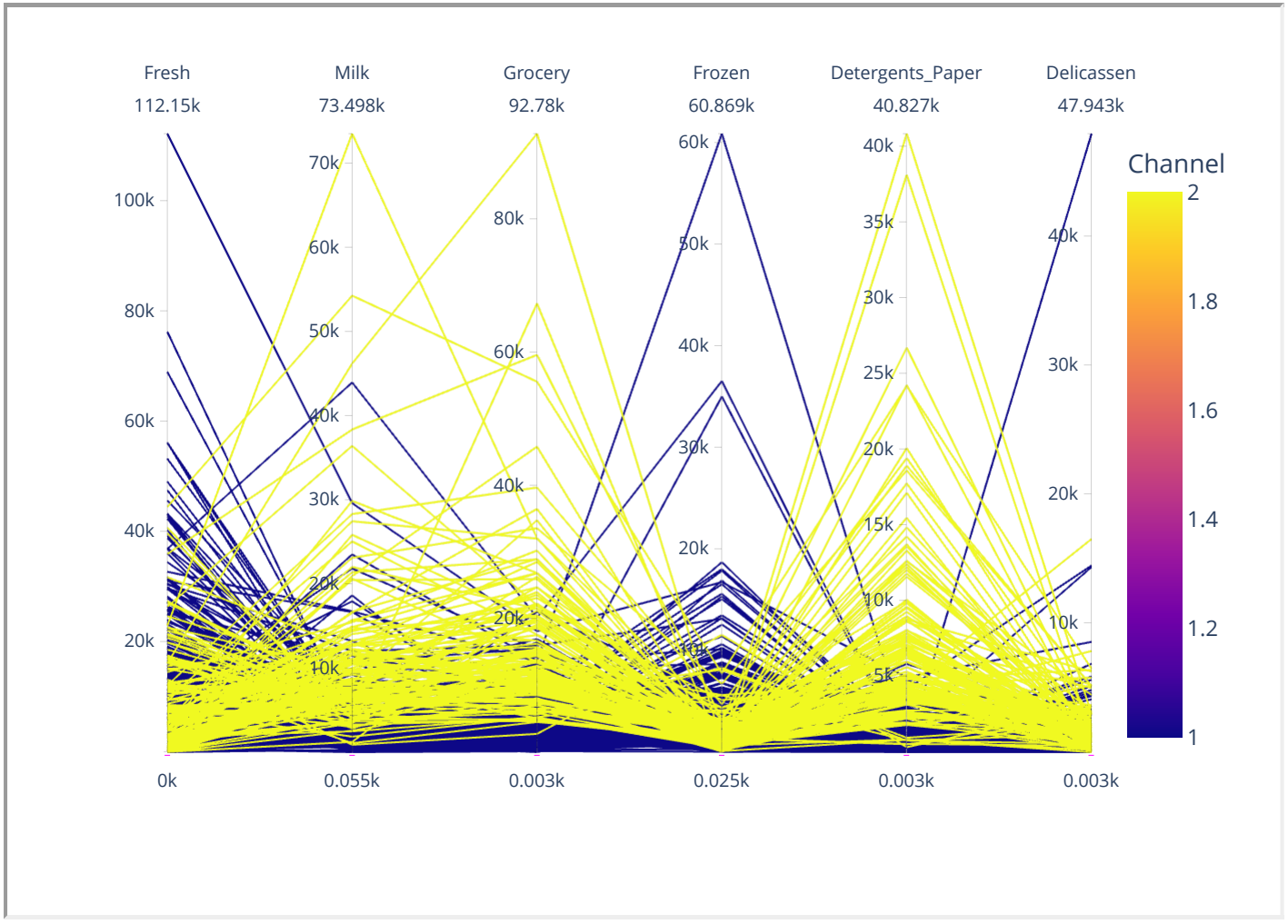
```
ws = pd.read_csv('../data/wholesale.csv')
ws
```

```
##      Channel  Region  Fresh  ...  Frozen  Detergents_Paper  Delicassen
## 0          2       3  12669  ...     214              2674        1338
## 1          2       3   7057  ...    1762              3293        1776
## 2          2       3   6353  ...    2405              3516        7844
## 3          1       3  13265  ...    6404               507        1788
## 4          2       3  22615  ...    3915              1777        5185
## ..       ...     ...    ...  ...     ...               ...         ...
## 435        1       3  29703  ...   13135               182        2204
## 436        1       3  39228  ...    4510                93        2346
## 437        2       3  14531  ...     437             14841        1867
## 438        1       3  10290  ...    1038               168        2125
## 439        1       3   2787  ...      65               477          52
##
## [440 rows x 8 columns]
```

Parallel coordinates

```
import plotly.express as px
fig = px.parallel_coordinates(ws, color="Channel",
                              dimensions=['Fresh', 'Milk', 'Grocery',
                                          'Frozen','Detergents_Paper',
fig.write_html('parcor.html')
```

Parallel Coordinates



Spider/radar chart

- Imagine we take a parallel coordinates plot and wrap it around a circle.
- This gives a spider or radar plot.
- The spider plot is best used for comparing two or three observations across multiple variables.

A fun example

Courtesy of twitter user BayernLM10

Other uses

- Comparing between two or three observations is surprisingly common
  - Summary statistics across a small number of groups
  - Comparing two firms/ products e.g. Apple v Samsung
  - Comparing the features of two investments.
- Can do these using plotly.

Plotly code

```
import plotly.graph_objects as go
categories = ['Price (1000$)', 'Weight (kg)', 'Display (in)','USB Ports
fig = go.Figure()
fig.add_trace(go.Scatterpolar(
      r=[3.997,2.15, 16.2, 3, 14, 16, 10.24],
      theta=categories,
      fill='toself',
      name='Pro'
))
```

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

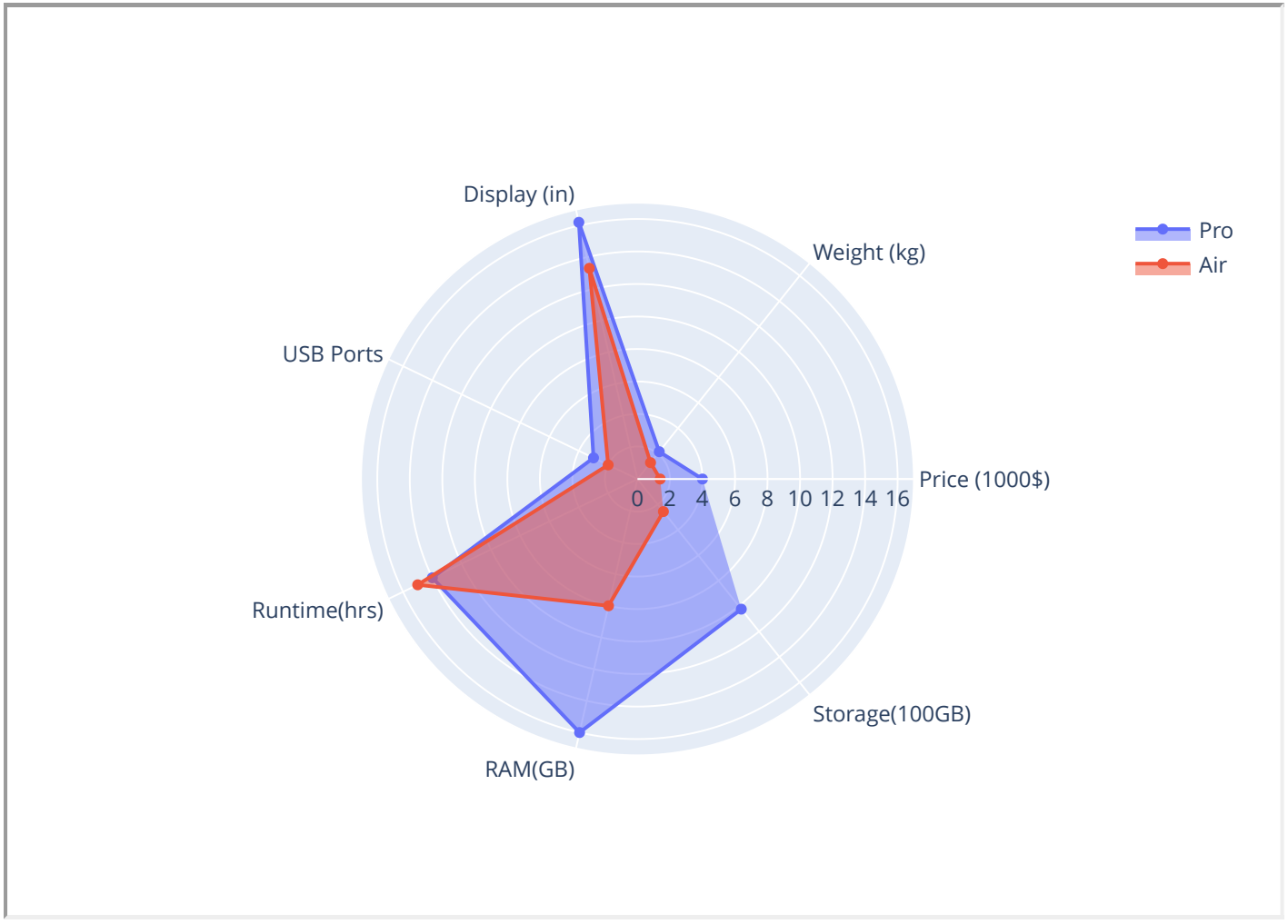
More Plotly code

```
fig.add_trace(go.Scatterpolar(
      r=[1.397,1.29, 13.3, 2, 15, 8, 2.56],
      theta=categories,
      fill='toself',
      name='Air'
))
```

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

```
fig.update_layout(
  polar=dict(
    radialaxis=dict(
      visible=True,
      range=[0, 17]
    )),
  showlegend=True
)
```

Radar plot


Display (in)
Weight (kg)
Price (1000$)
Storage(100GB)
RAM(GB)
Runtime(hrs)
USB Ports
0 2 4 6 8 10 12 14 16
Pro
Air

Radar plot

- The plotly code allows you to toggle each product on an off allowing for more comparisons.
- One problem is that it does not easily handle different scales of measurement for each variable.
- You could standardise between 0 and 1 where these limits imply some minimum and maximum value.
- Future versions of plotly should make this rescaling automatic.

Wrap-up

Conclusions

- There are several ways to show multiple variables on a plot.
  - Color
  - Size/shape
  - Facetting
- Do not generate complicated plots for the sake of it. Always look for a story.

Questions