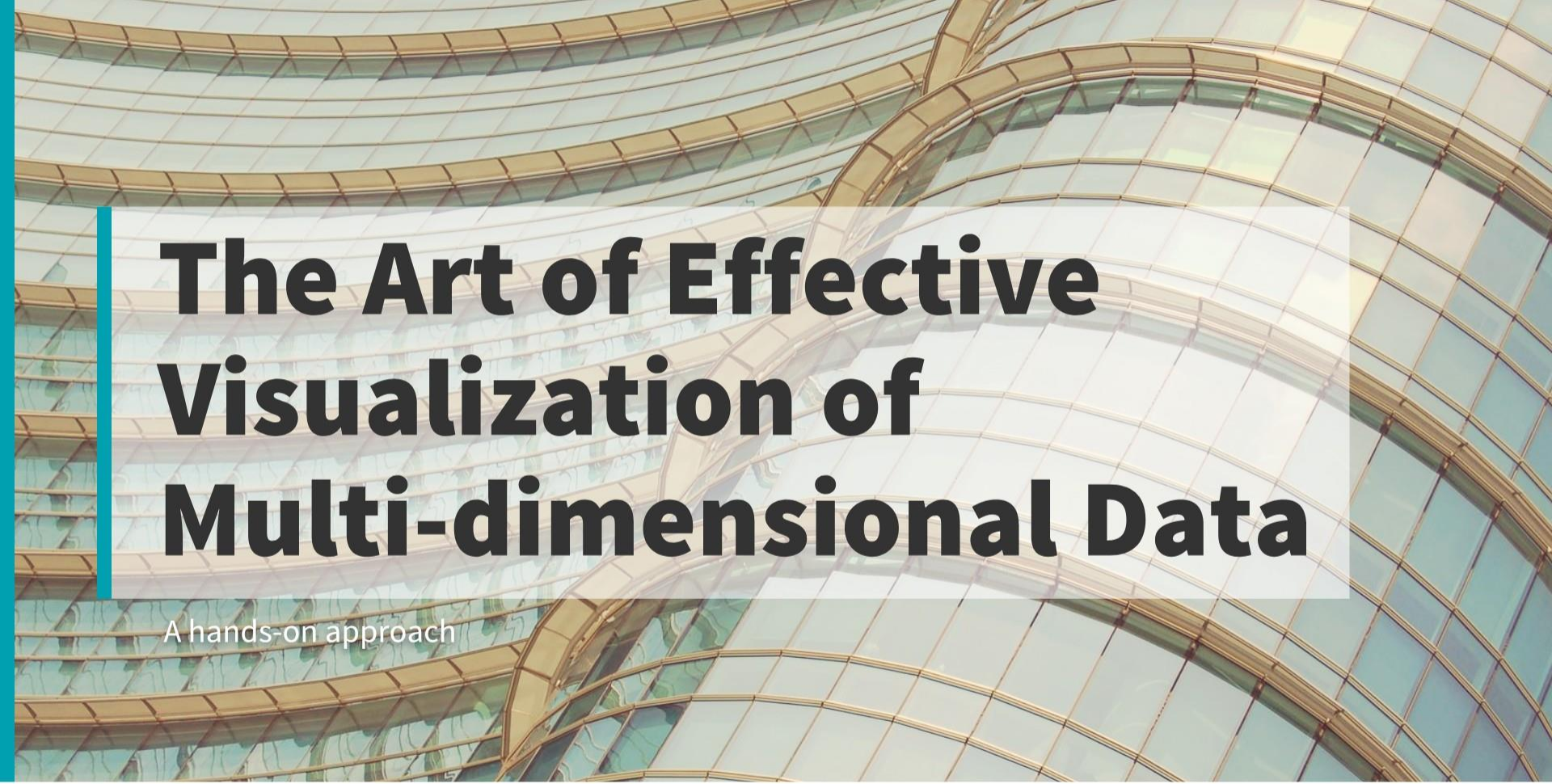


The Art of Effective Visualization of Multi-dimensional Data

A hands-on approach

Dipanjan Sarkar
Data Scientist, Intel

Session Agenda

Introduction

- What is data visualization?
- Why Data visualization?

Motivation

Why effective data visualization?

Effective Multi-dimensional Data Visualization

Whirlwind tour of the grammar of graphics

Visualization Tools and Frameworks

- Visualization frameworks in Python
- Visualization frameworks in R
- Popular tools & frameworks

Visualizing Structured Data

- Univariate analysis & visualizations
- Multivariate analysis & visualizations
- Visualizing from 1-D up to 6-D

Visualizing Unstructured Data

- Visualizing Text Data
- Visualizing Image Data
- Visualizing Audio Data

Final Words

GET THE SLIDES AND CODE HERE

http://bit.ly/odsc_india_ds

intel

Springboard

Towards Data Science

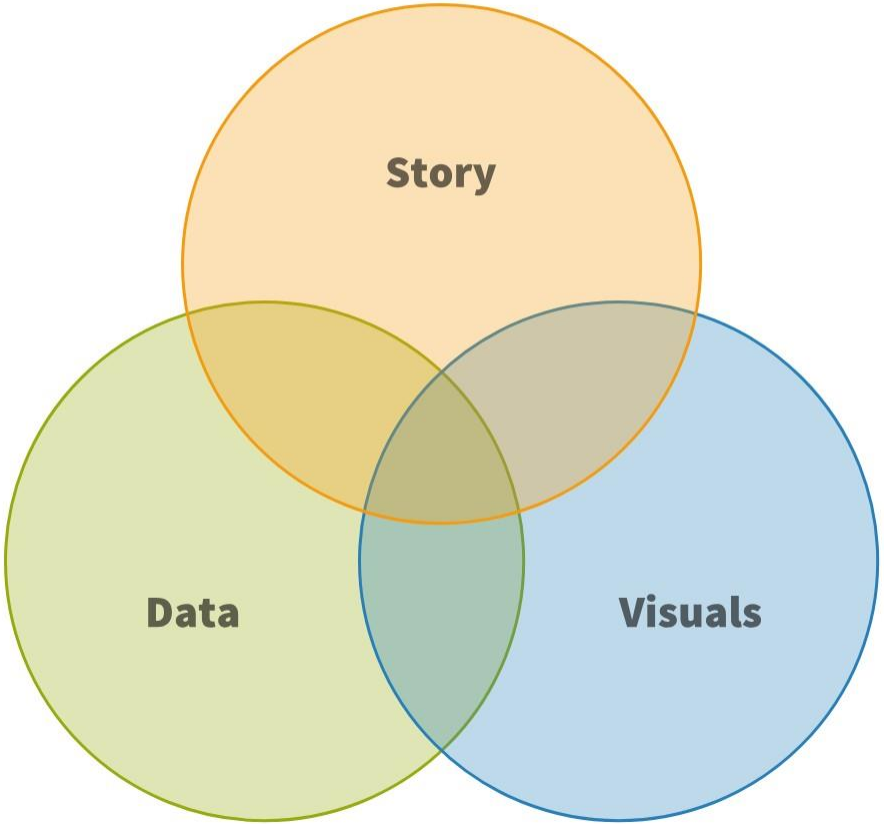
Apress

Springer

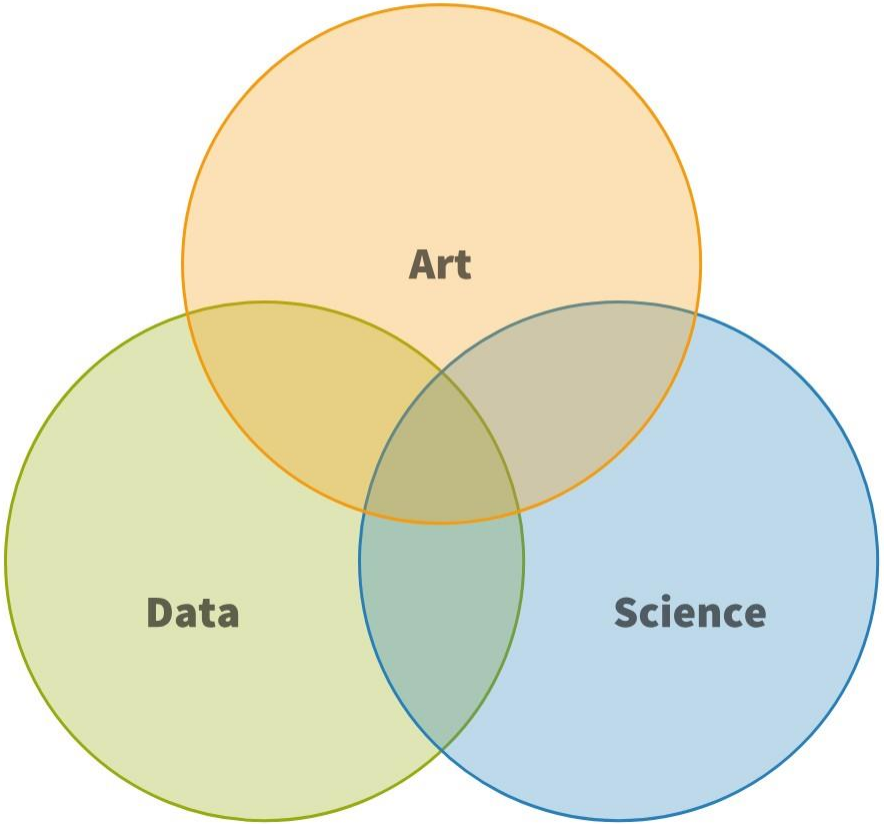
Packt


Introduction
Understanding the what and why of Data Visualization

Data Visualization & Storytelling



Data Visualization & Storytelling



What is Data Visualization?

- Data aggregation, summarization & visualization are some of the core pillars in any data science or analysis pipeline
- It is a specific technique or methodology for creating pictorial representations in the form of images, diagrams or animations to convey effective information from data
- Since the days of traditional Business Intelligence to even in this age of Artificial Intelligence, it has been a powerful tool, widely adopted by organizations

Why Data Visualization?

1. Humans have been wired to seek out patterns in everything we see and interact daily
2. Humans love finding patterns and building stories and narratives around them
3. Prevents pitfalls of blindly modeling on data leading to cascading adverse effects in any intelligent system
4. Enables better business and data understanding through effective visuals

Why Data Visualization?

90% of information transmitted to the human brain is visual

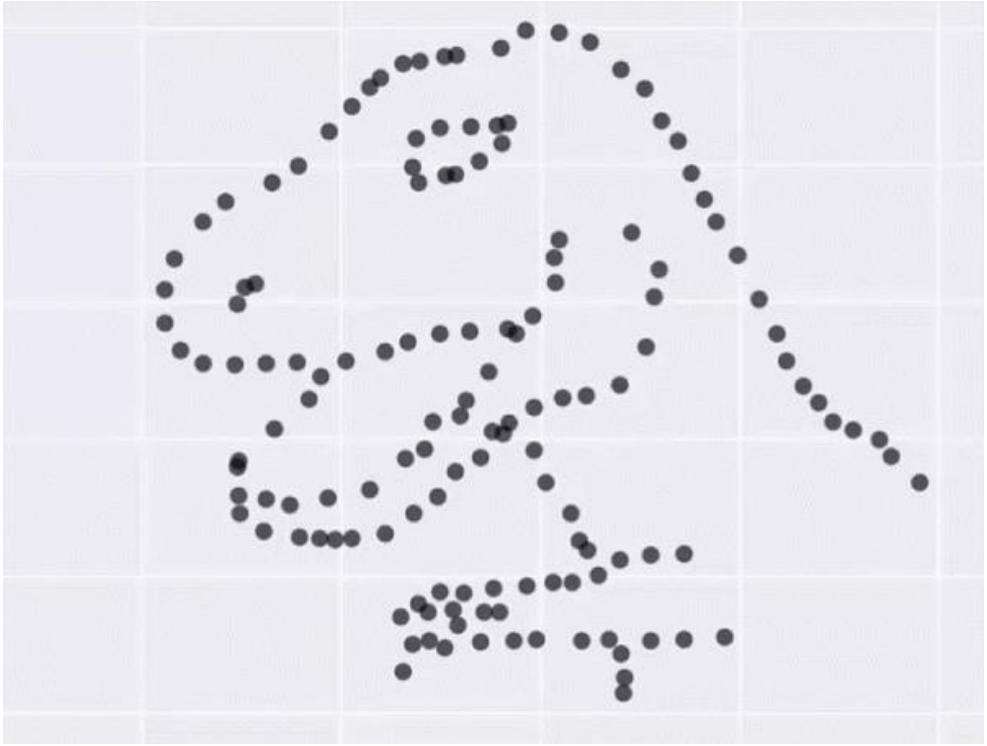
The human brain processes visuals 60K times faster than text

65% of humans are visual learners

The human brain can process an observed visual in 13 - 80 ms

Why Data Visualization

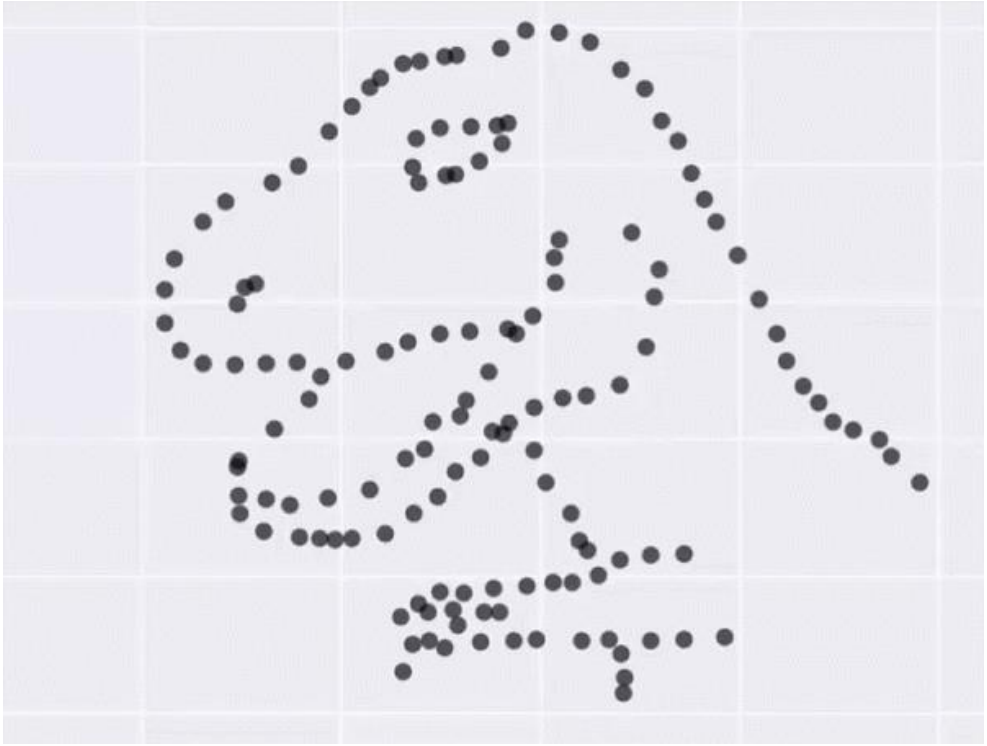
Introducing The Datasaurus Dozen!



What is common in all these images?

Why Data Visualization

Introducing The Datasaurus Dozen!



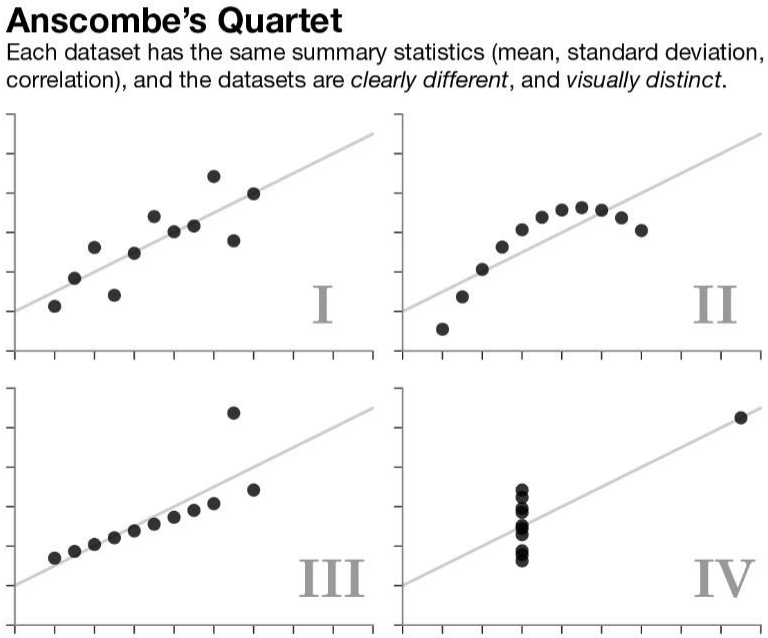
What is common in all these images?

Ans: Summary Stats are the same!

```
X Mean: 54.26
Y Mean: 47.83
X SD  : 16.76
Y SD  : 26.93
Corr. : -0.06
```

Why Data Visualization

Introducing Anscombe's Quartet

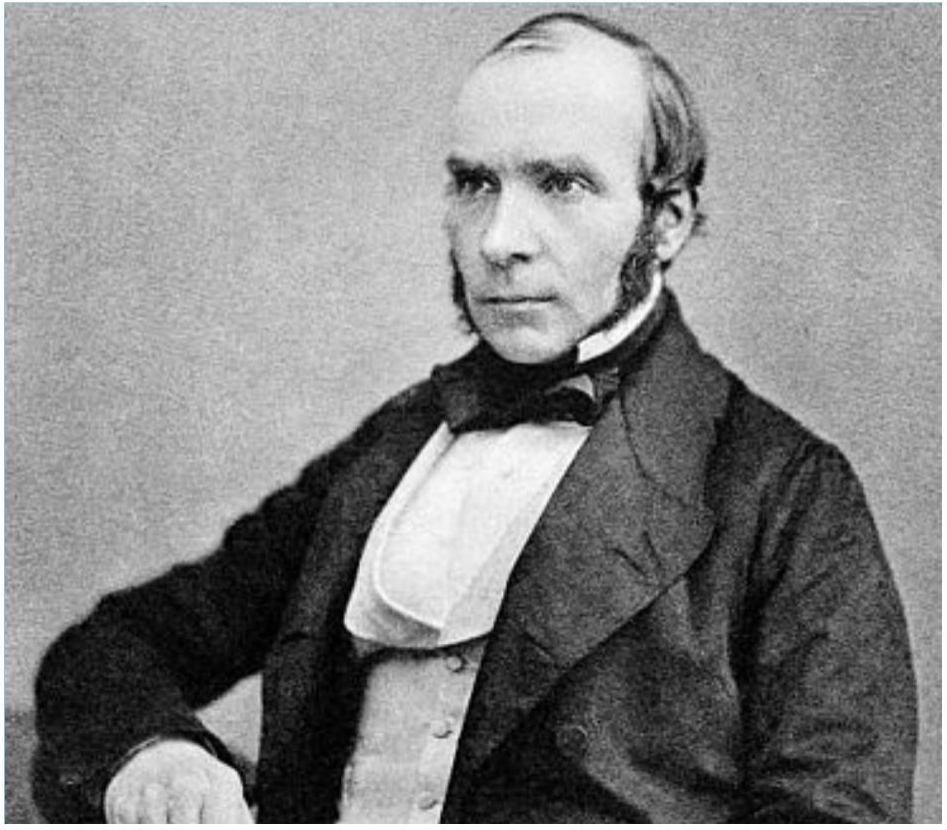


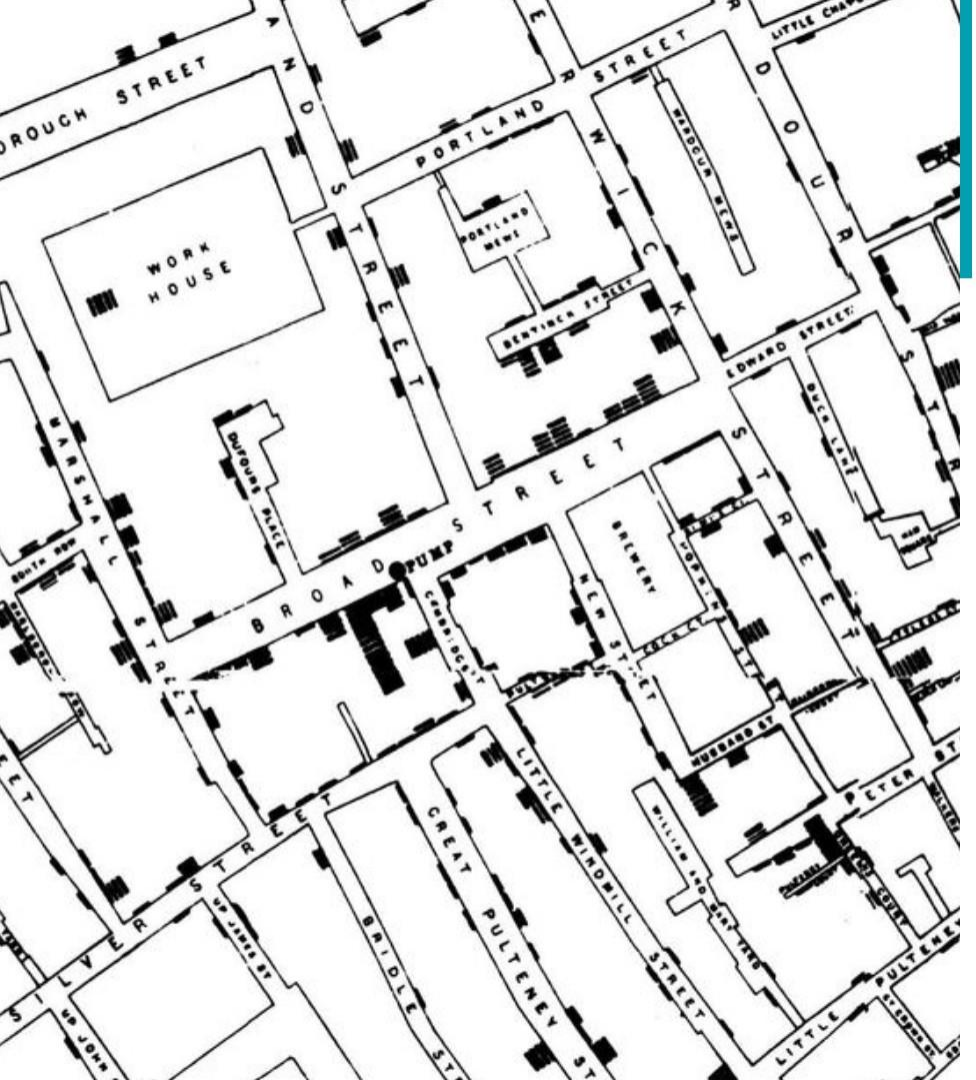

Motivation
Why effective data visualization?

Motivation for effective data visualization

1. Effective Data Visualization is an art as well as a science
2. Focus should be on abstracting out unnecessary data, noise and clutter
3. Leverage concepts from the Grammar of Graphics to depict the right information using clean and concise visuals
4. “A Picture is worth a thousand words”
5. “The greatest value of a picture is when it forces us to notice what we never expected to see.” — John Tukey

Will the real Jo(h)n Snow please stand up?





Visualizing the Broad Street Cholera Outbreak

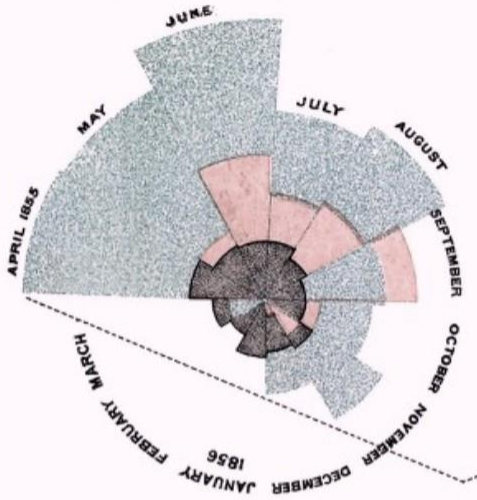
- A severe outbreak of cholera occurred in 1854 near Broad Street in the City of Westminster, London, England, unknowing to people causing over 600 deaths
- Physician Jon Snow identified the source of the outbreak as the public water pump on Broad Street
- Snow used a dot map to illustrate the cluster of cholera cases around the pump
- He also used statistics to illustrate the connection between the quality of the water source and cholera cases.

Florence Nightingale's depiction of causes of death

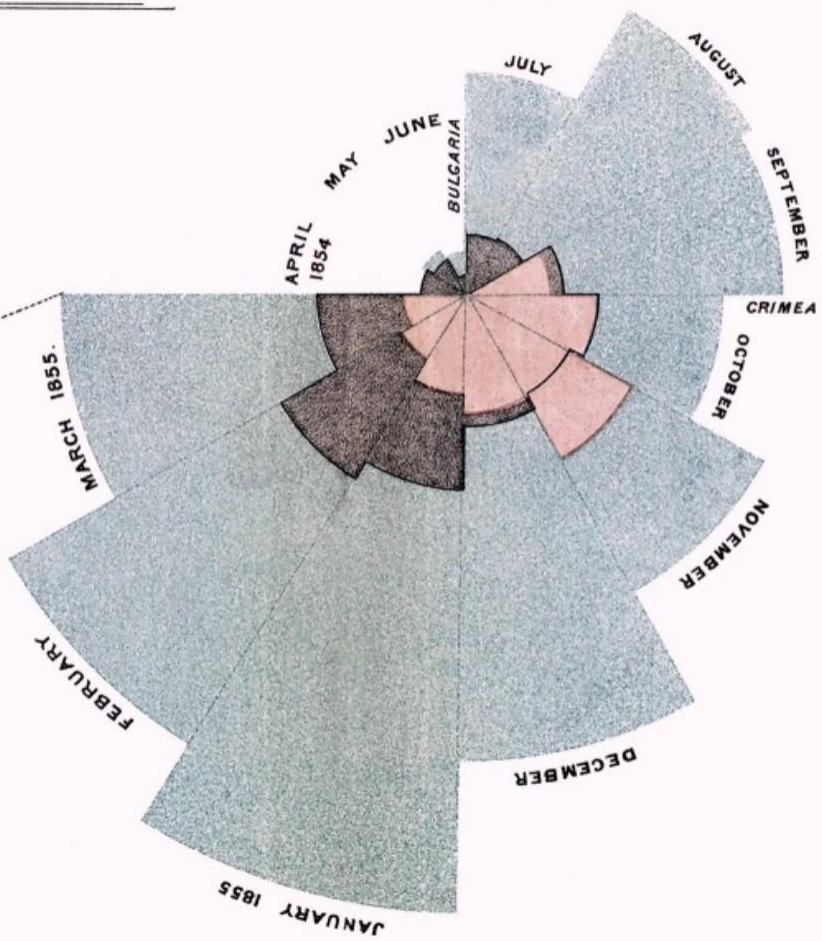
- Nightingale is popularly known as the “mother” of modern nursing practice
- Combining her interest in statistics and nursing she developed a polar area diagram
- Her visualization represented the causes of death in the military hospital she was working at

DIAGRAM of the CAUSES of MORTALITY IN THE ARMY IN THE EAST.

2.
APRIL 1855 to MARCH 1856.



1.
APRIL 1854 to MARCH 1855.



The Areas of the blue, red, & black wedges are each measured from the centre as the common vertex.

The blue wedges measured from the centre of the circle represent area for area the deaths from Preventible or Mitigable Zymotic diseases, the red wedges measured from the centre the deaths from wounds, & the black wedges measured from the centre the deaths from all other causes.

The black line across the red triangle in Nov.r 1854 marks the boundary of the deaths from all other causes during the month.

In October 1854, & April 1855, the black area coincides with the red; in January & February 1856, the blue coincides with the black.

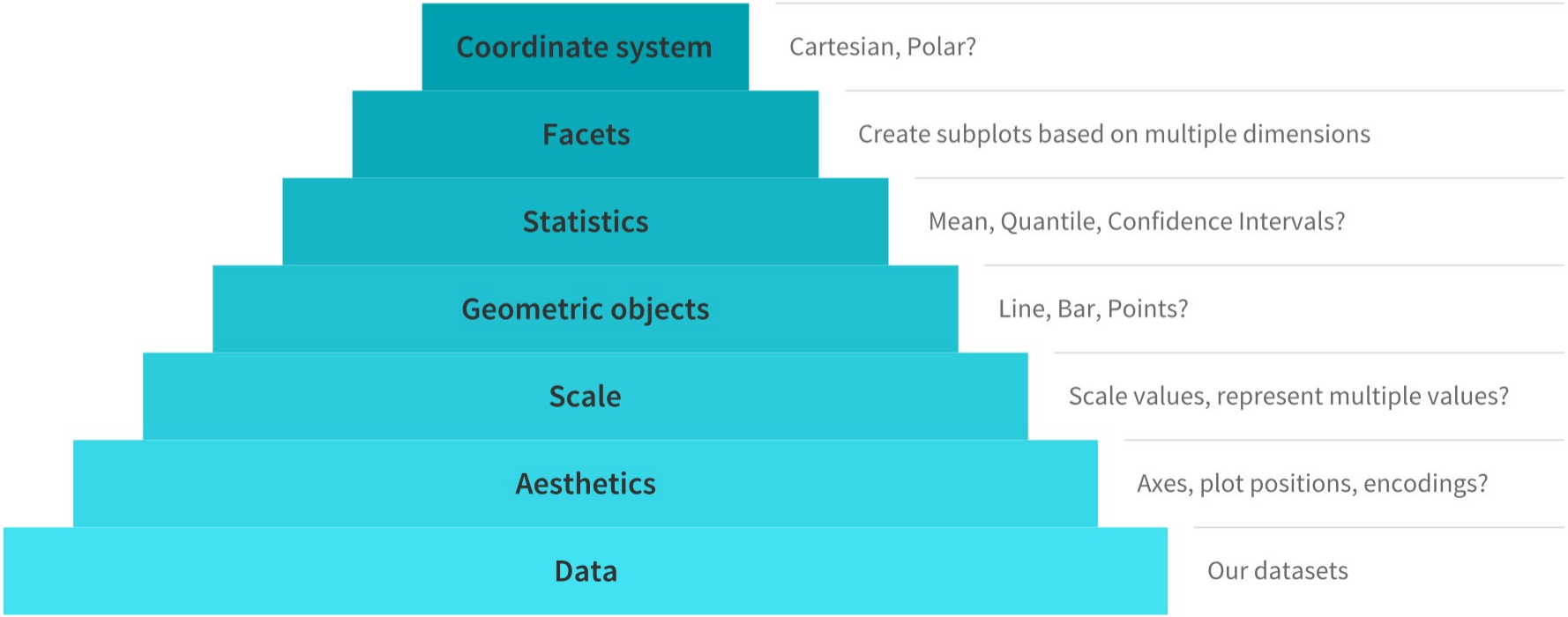
The entire areas may be compared by following the blue, the red & the black lines enclosing them.


Effective Multi-dimensional Data Visualization
Whirlwind tour of the grammar of graphics

Effective Visualization with Grammar of Graphics

- Grammar is defined as a set of structural rules which helps define and establish the components of a language
- The whole system and structure of a language usually consists of syntax and semantics.
- A grammar of graphics is a framework that enables us to concisely describe the components of any graphic
- Instead of random trials and errors, follow a layered approach by using defined components to build a visualization

Major Components of the Grammar of Graphics



Always start with the data

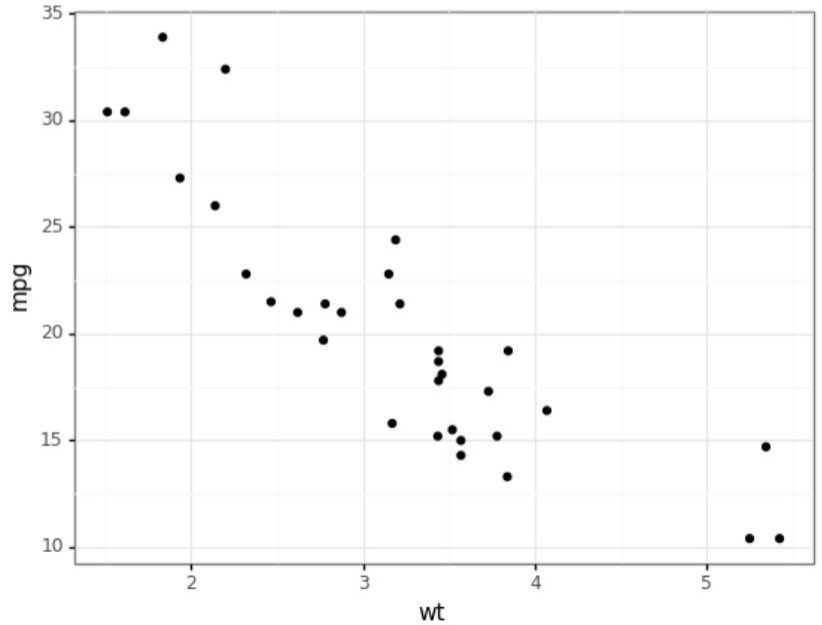
```
from plotnine import *
from plotnine.data import mtcars

mtcars.head()
```

	name	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

Start building with data, aesthetics, scale & geoms

Visualize up to two dimensions in your data

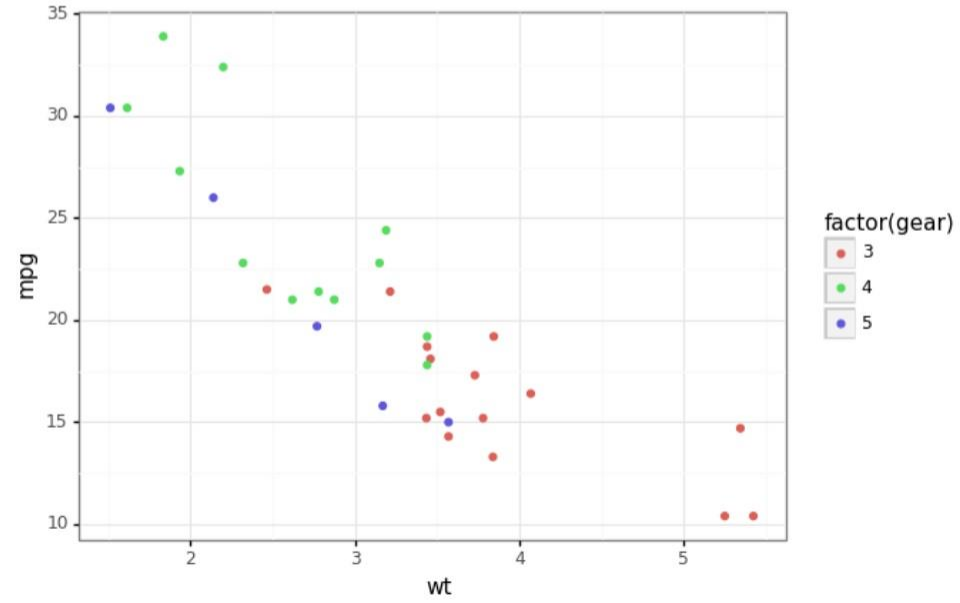
```
(ggplot(mtcars,
        aes('wt', 'mpg'))+ geom_point()+ theme_bw())
```



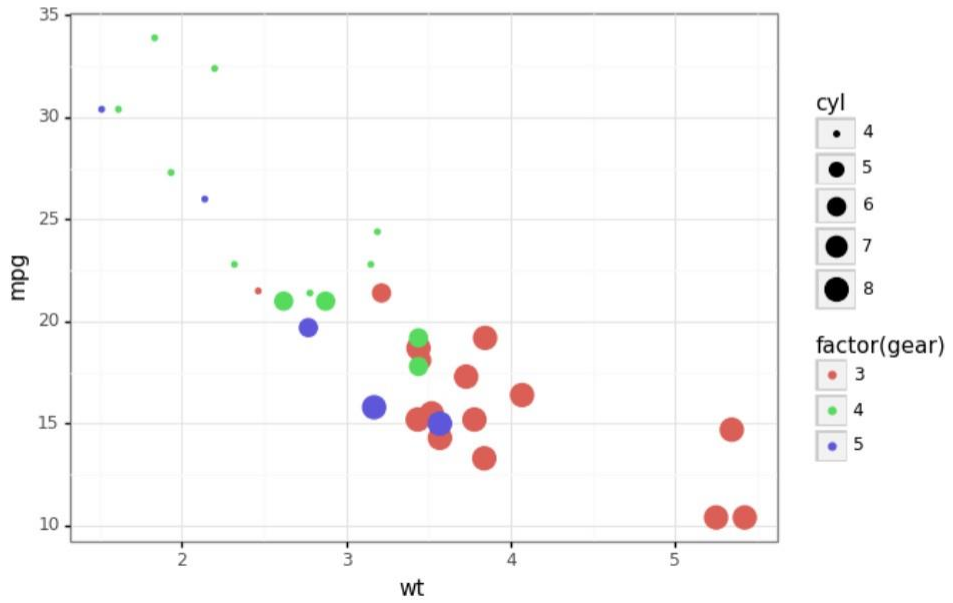
Visualize from 2-D to 4-D with aesthetics & scale

Leveraging color and size here for visualizing up to four dimensions

```
(ggplot(mtcars,
        aes('wt', 'mpg', color='factor(gear)'))
        + geom_point()+theme_bw())
```



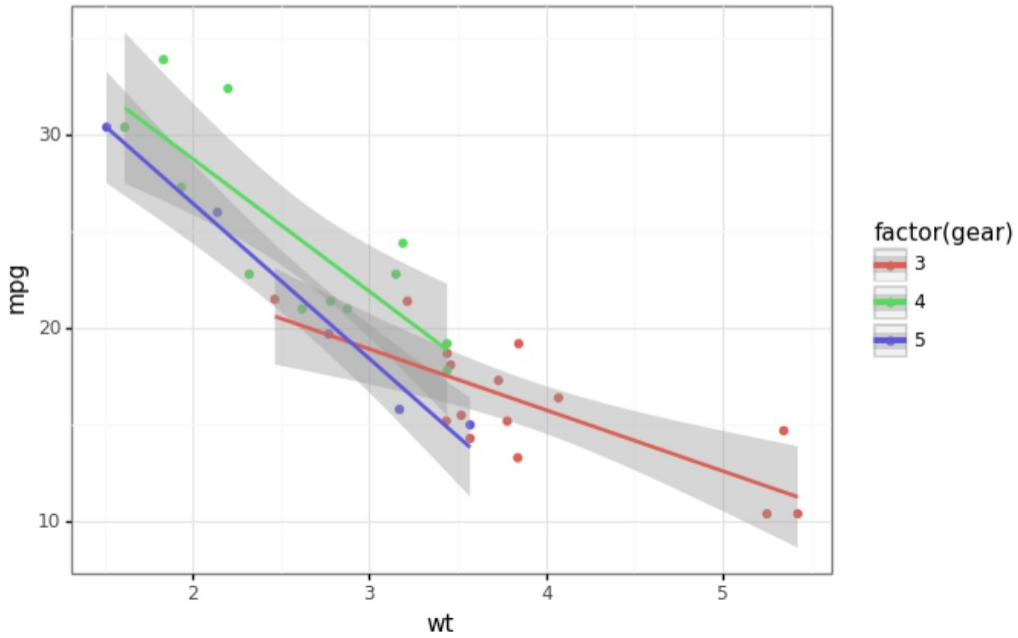

```
(ggplot(mtcars,
        aes('wt', 'mpg', color='factor(gear)', size='cyl'))
        + geom_point() + theme_bw())
```



Visualize data, aesthetics with statistics

Visualizing data with rich statistical measures

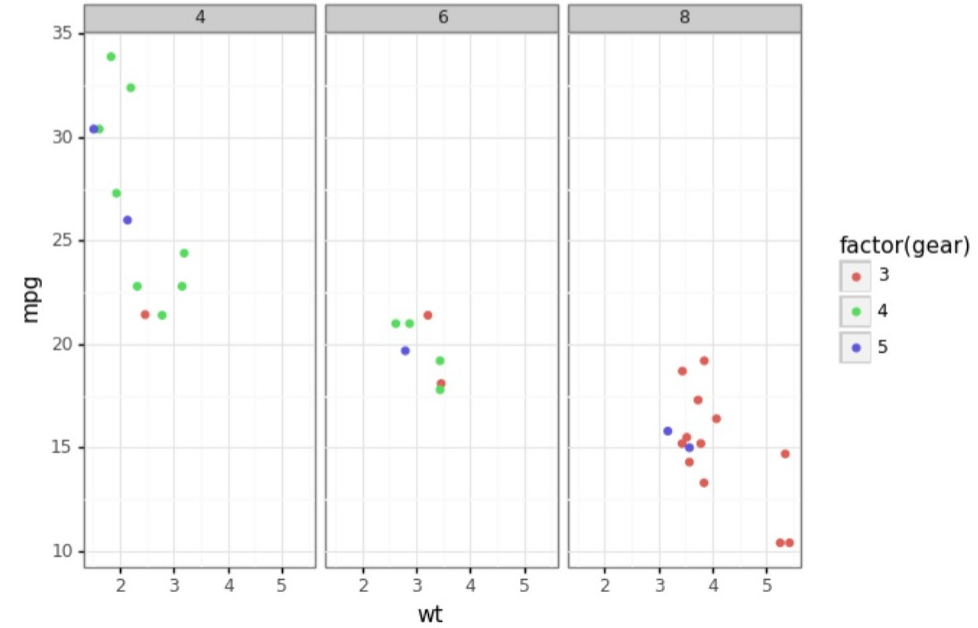
```
(ggplot(mtcars,
        aes('wt', 'mpg', color='factor(gear)'))
        + geom_point() + stat_smooth(method='lm')
        + theme_bw())
```



Visualize up to 4-D with aesthetics, scale & facets

Leveraging color & facets here for visualizing up to five dimensions

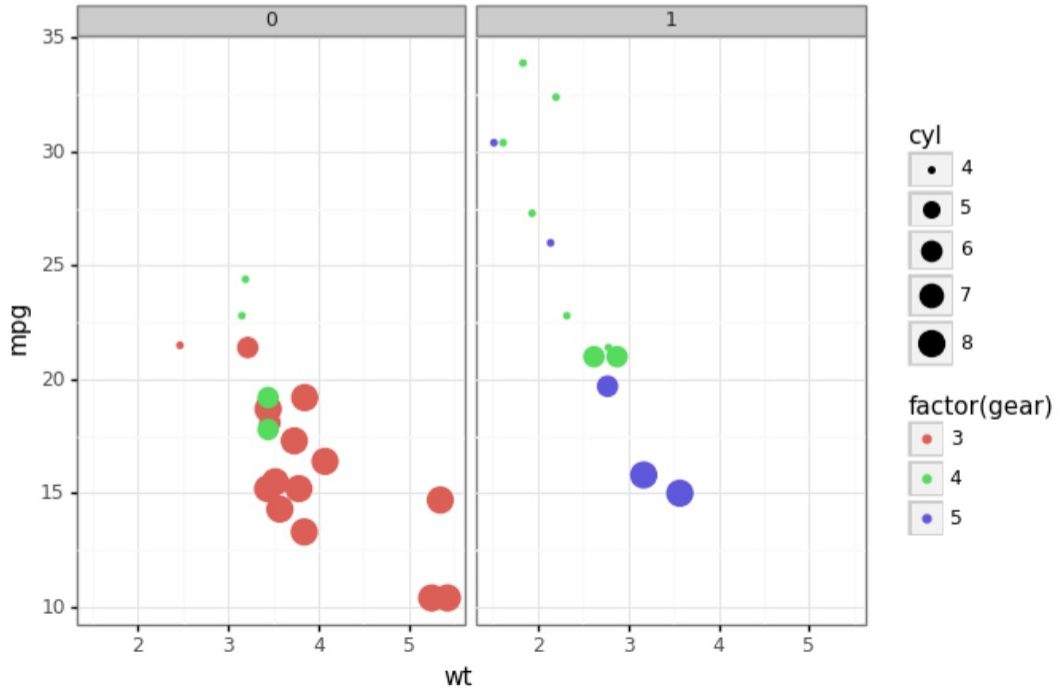
```
(ggplot(mtcars, aes('wt', 'mpg', color='factor(gear)'))
 + geom_point() + facet_wrap('~cyl') + theme_bw())
```



Visualize up to 5-D with aesthetics, scale & facets

Leveraging color, size & facets here for visualizing up to five dimensions

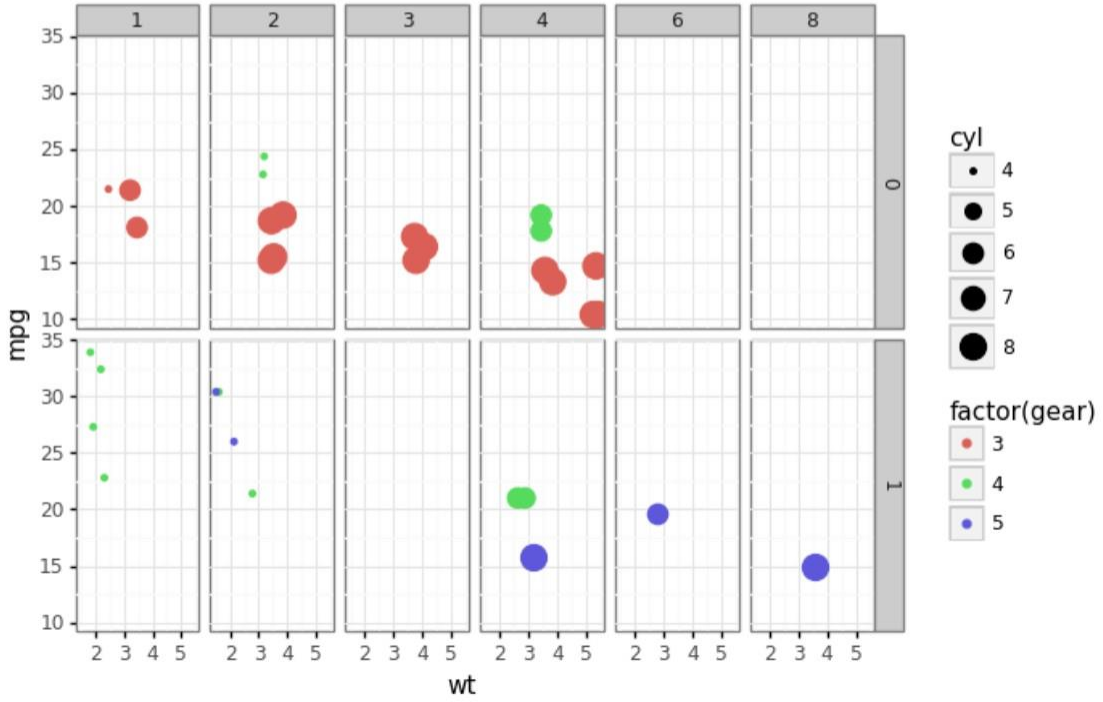
```
(ggplot(mtcars, aes('wt', 'mpg', color='factor(gear)', size='cyl'))
 + geom_point() + facet_wrap('~am') + theme_bw())
```

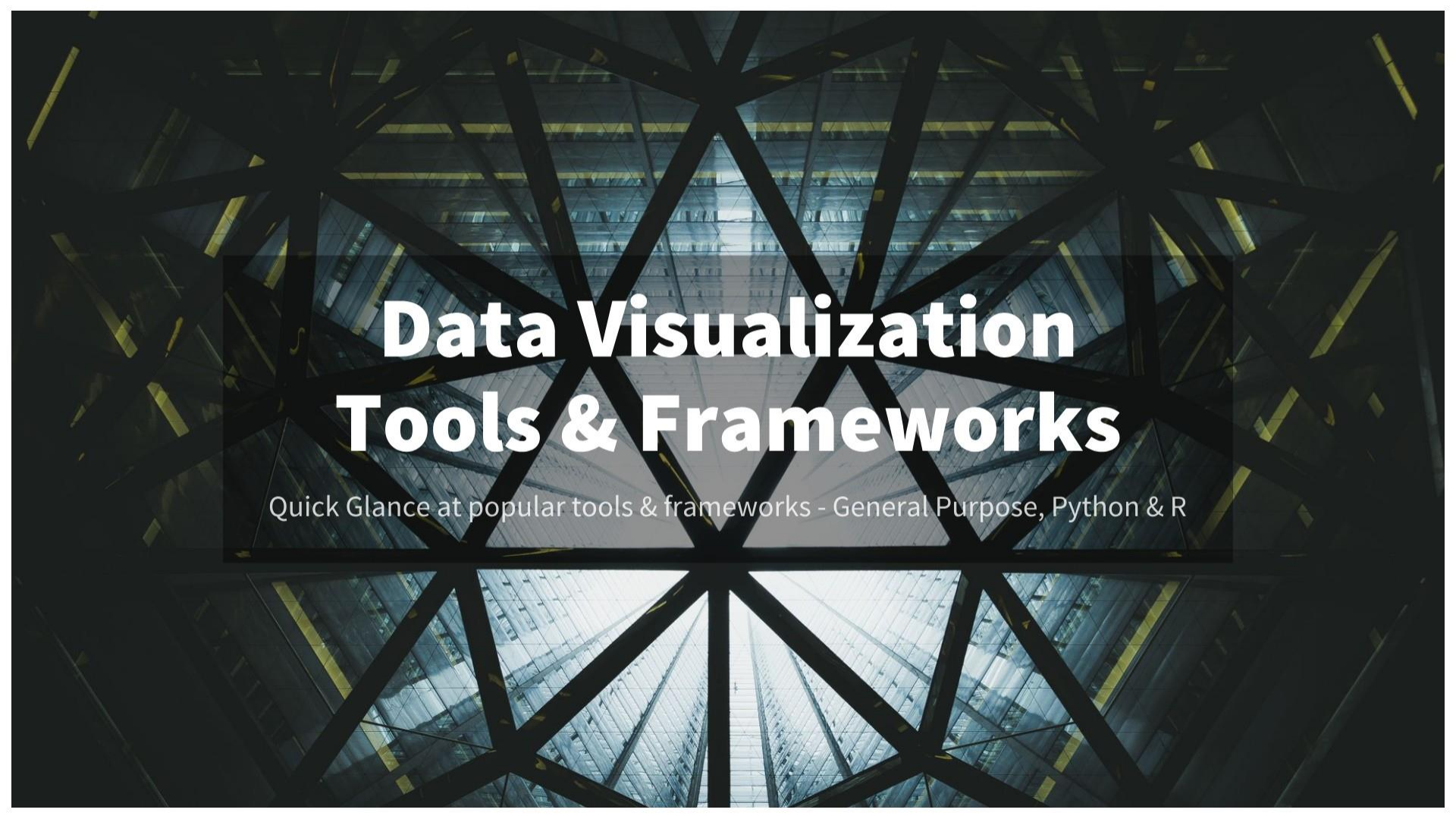


Visualize up to 6-D with aesthetics, scale & facets

Leveraging color, size & multiple facets here for visualizing up to six dimensions

```
(ggplot(mtcars, aes('wt', 'mpg', color='factor(gear)', size='cyl'))
 + geom_point() + facet_grid('am ~ carb') + theme_bw())
```




Data Visualization
Tools & Frameworks
Quick Glance at popular tools & frameworks - General Purpose, Python & R

Popular Data Visualization Tools & Frameworks


D3.js

Tableau


MS Excel


FusionCharts


Highcharts


Leaflet

Datawrapper

Plotly


Kibana

Python Data Visualization Frameworks

Matplotlib

Plotnine (ggplot)

Pandas

Seaborn

Bokeh

Pygal

Plotly

R Data Visualization Frameworks

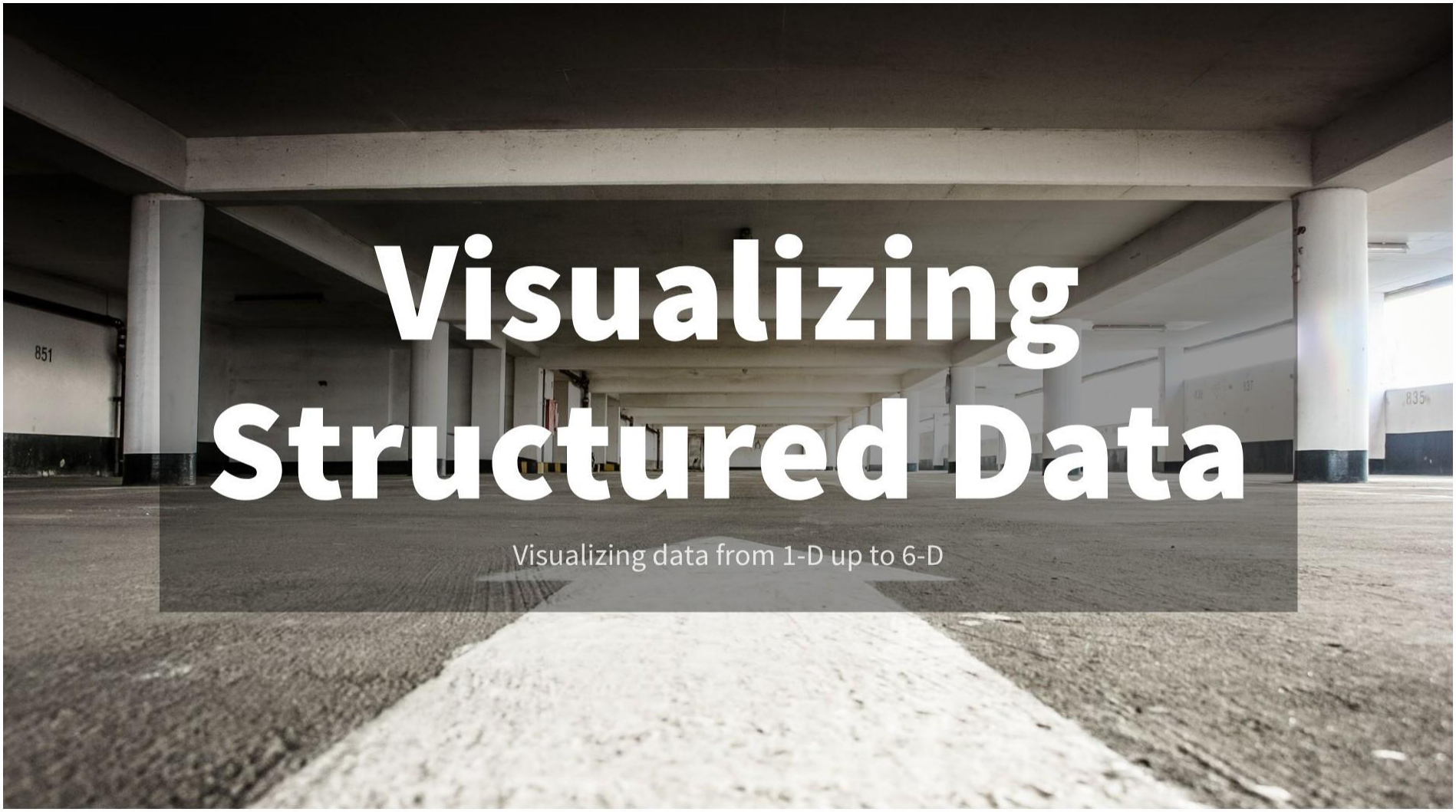
ggplot2

lattice

ggiraph

taucharts

Plotly



Visualizing Structured Data

Visualizing data from 1-D up to 6-D

Start with the Data - as always!

Dataset is based on various properties of red and white wine

```
wines.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	wine_type	quality_label
0	7.0	0.17	0.74	12.8	0.045	24.0	126.0	0.99420	3.26	0.38	12.2	8	white	high
1	7.7	0.64	0.21	2.2	0.077	32.0	133.0	0.99560	3.27	0.45	9.9	5	red	low
2	6.8	0.39	0.34	7.4	0.020	38.0	133.0	0.99212	3.18	0.44	12.0	7	white	medium
3	6.3	0.28	0.47	11.2	0.040	61.0	183.0	0.99592	3.12	0.51	9.5	6	white	medium
4	7.4	0.35	0.20	13.9	0.054	63.0	229.0	0.99888	3.11	0.50	8.9	6	white	medium

Basic Data Understanding

- **fixed acidity:** Acids are one of the fundamental properties of wine and contribute greatly to the taste of the wine. Reducing acids significantly might lead to wines tasting flat. Fixed acids include tartaric, malic, citric, and succinic acids which are found in grapes (except succinic). This variable is usually expressed in $\frac{g(tartaricacid)}{dm^3}$ in the dataset.
- **volatile acidity:** These acids are to be distilled out from the wine before completing the production process. It is primarily constituted of acetic acid though other acids like lactic, formic and butyric acids might also be present. Excess of volatile acids are undesirable and lead to unpleasant flavor. In the US, the legal limits of volatile acidity are 1.2 g/L for red table wine and 1.1 g/L for white table wine. The volatile acidity is expressed in $\frac{g(aceticacid)}{dm^3}$ in the dataset.
- **citric acid:** This is one of the fixed acids which gives a wine its freshness. Usually most of it is consumed during the fermentation process and sometimes it is added separately to give the wine more freshness. It's usually expressed in $\frac{g}{dm^3}$ in the dataset.
- **residual sugar:** This typically refers to the natural sugar from grapes which remains after the fermentation process stops, or is stopped. It's usually expressed in $\frac{g}{dm^3}$ in the dataset.
- **chlorides:** This is usually a major contributor to saltiness in wine. It's usually expressed in $\frac{g(sodiumchloride)}{dm^3}$ in the dataset.
- **free sulfur dioxide:** This is the part of the sulphur dioxide that when added to a wine is said to be free after the remaining part binds. Winemakers will always try to get the highest proportion of free sulphur to bind. They are also known as sulfites and too much of it is undesirable and gives a pungent odour. This variable is expressed in $\frac{mg}{dm^3}$ in the dataset.
- **total sulfur dioxide:** This is the sum total of the bound and the free sulfur dioxide (SO_2). Here, it's expressed in $\frac{mg}{dm^3}$. This is mainly added to kill harmful bacteria and preserve quality and freshness. There are usually legal limits for sulfur levels in wines and excess of it can even kill good yeast and give out undesirable odour.

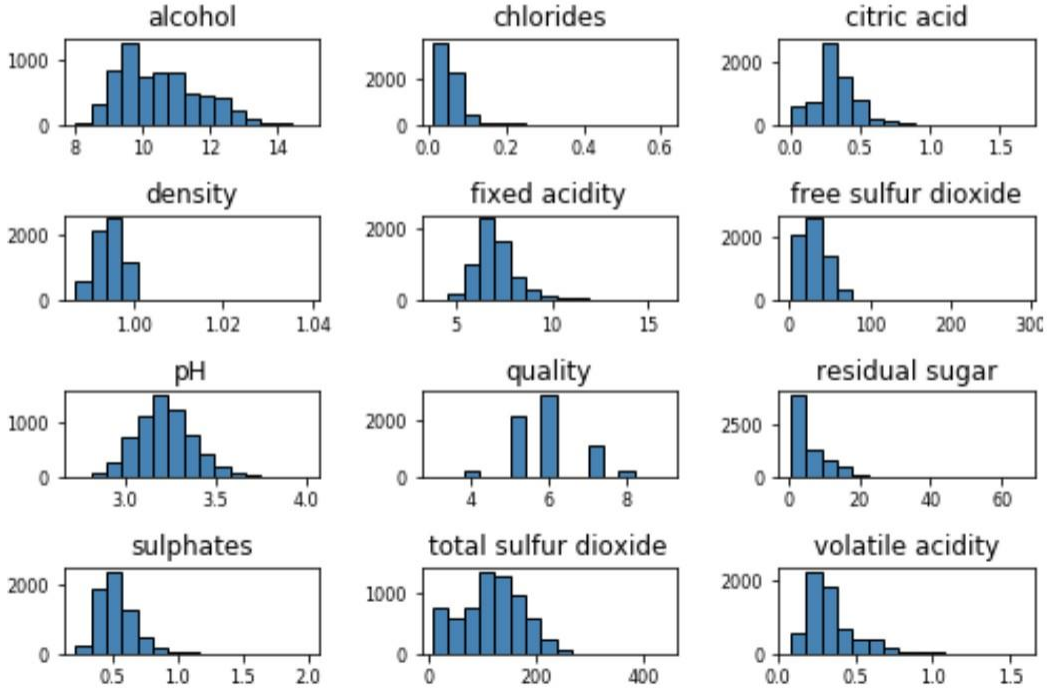
Basic Descriptive Statistics

```
subset_attributes = ['residual sugar', 'total sulfur dioxide', 'sulphates', 'alcohol', 'volatile acidity', 'quality']
rs = round(red_wine[subset_attributes].describe(),2)
ws = round(white_wine[subset_attributes].describe(),2)
pd.concat([rs, ws], axis=1, keys=['Red Wine Statistics', 'White Wine Statistics'])
```

	Red Wine Statistics						White Wine Statistics					
	residual sugar	total sulfur dioxide	sulphates	alcohol	volatile acidity	quality	residual sugar	total sulfur dioxide	sulphates	alcohol	volatile acidity	quality
count	1599.00	1599.00	1599.00	1599.00	1599.00	1599.00	4898.00	4898.00	4898.00	4898.00	4898.00	4898.00
mean	2.54	46.47	0.66	10.42	0.53	5.64	6.39	138.36	0.49	10.51	0.28	5.88
std	1.41	32.90	0.17	1.07	0.18	0.81	5.07	42.50	0.11	1.23	0.10	0.89
min	0.90	6.00	0.33	8.40	0.12	3.00	0.60	9.00	0.22	8.00	0.08	3.00
25%	1.90	22.00	0.55	9.50	0.39	5.00	1.70	108.00	0.41	9.50	0.21	5.00
50%	2.20	38.00	0.62	10.20	0.52	6.00	5.20	134.00	0.47	10.40	0.26	6.00
75%	2.60	62.00	0.73	11.10	0.64	6.00	9.90	167.00	0.55	11.40	0.32	6.00
max	15.50	289.00	2.00	14.90	1.58	8.00	65.80	440.00	1.08	14.20	1.10	9.00

Univariate Analysis - Visualizing 1-D

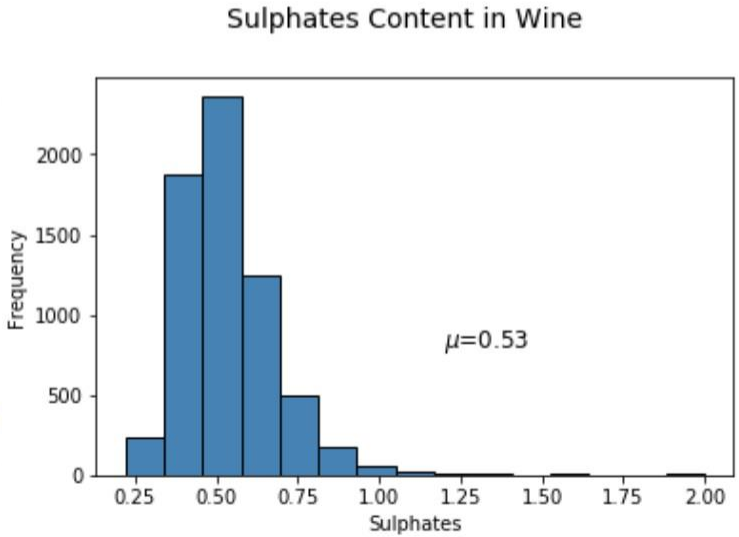
```
wines.hist(bins=15, color='steelblue',
           edgecolor='black', linewidth=1.0,
           xlabelsize=8, ylabelsize=8, grid=False)
plt.tight_layout(rect=(0, 0, 1.2, 1.2))
```



Univariate Analysis - Visualizing 1-D

Visualizing a continuous numeric attribute

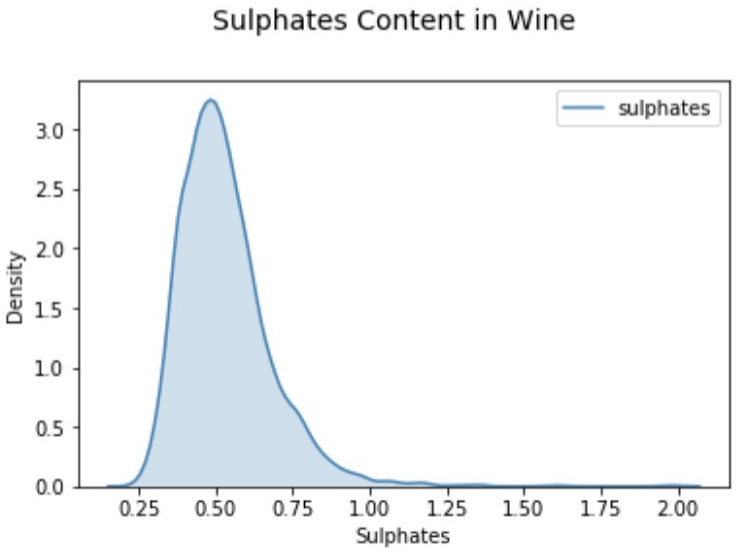
```
fig = plt.figure(figsize = (6,4))
title = fig.suptitle("Sulphates Content in Wine", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax = fig.add_subplot(1,1, 1)
ax.set_xlabel("Sulphates")
ax.set_ylabel("Frequency")
ax.text(1.2, 800, r'$\mu$='+str(round(wines['sulphates'].mean(),2)),
         fontsize=12)
freq, bins, patches = ax.hist(wines['sulphates'], color='steelblue', bins=15,
                              edgecolor='black', linewidth=1)
```



Univariate Analysis - Visualizing 1-D

Visualizing a continuous numeric attribute

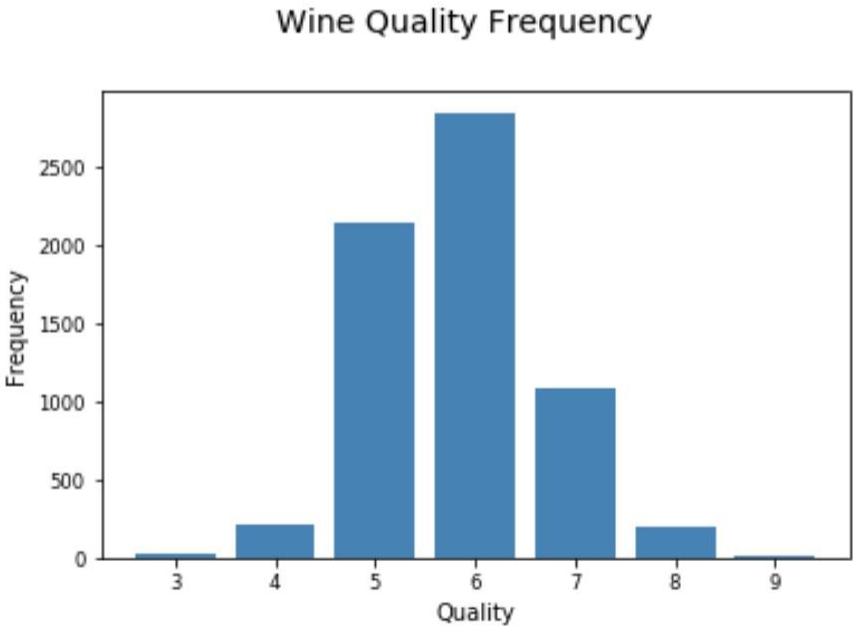
```
fig = plt.figure(figsize = (6, 4))
title = fig.suptitle("Sulphates Content in Wine", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax1 = fig.add_subplot(1,1, 1)
ax1.set_xlabel("Sulphates")
ax1.set_ylabel("Density")
sns.kdeplot(wines['sulphates'], ax=ax1, shade=True, color='steelblue')
```



Univariate Analysis - Visualizing 1-D

Visualizing a discrete categorical attribute

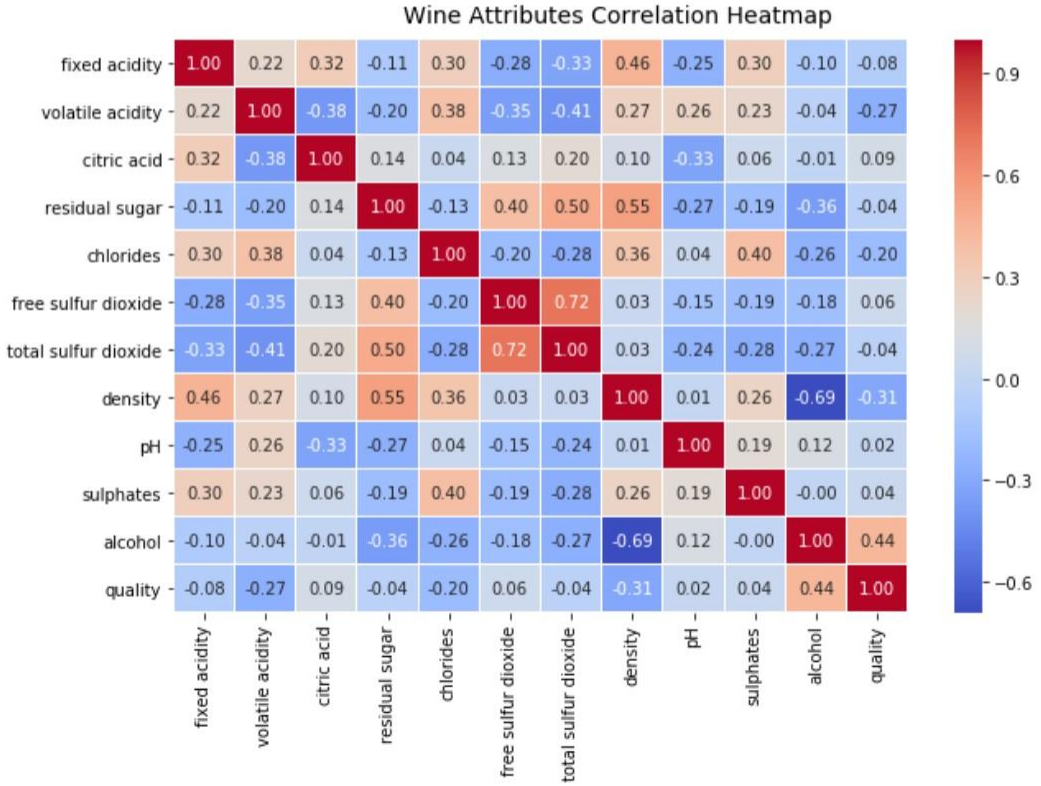
```
fig = plt.figure(figsize = (6, 4))
title = fig.suptitle("Wine Quality Frequency", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax = fig.add_subplot(1,1, 1)
ax.set_xlabel("Quality")
ax.set_ylabel("Frequency")
w_q = wines['quality'].value_counts()
w_q = (list(w_q.index), list(w_q.values))
ax.tick_params(axis='both', which='major', labelsize=8.5)
bar = ax.bar(w_q[0], w_q[1], color='steelblue')
```



Multivariate Analysis - Visualizing 2-D

Visualizing feature correlations

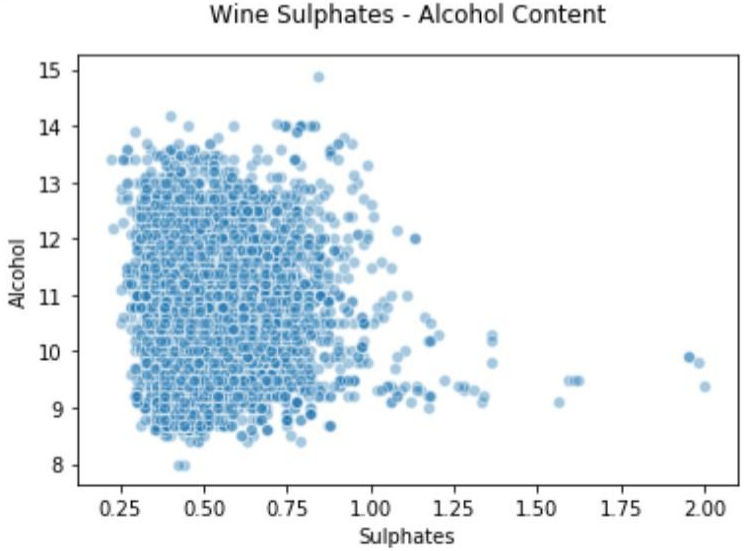
```
f, ax = plt.subplots(figsize=(10, 6))
corr = wines.corr()
hm = sns.heatmap(round(corr,2), annot=True,
                 ax=ax, cmap="coolwarm",fmt='.2f',
             linewidths=.05)
f.subplots_adjust(top=0.93)
t= f.suptitle('Wine Attributes Correlation Heatmap',
              fontsize=14)
```



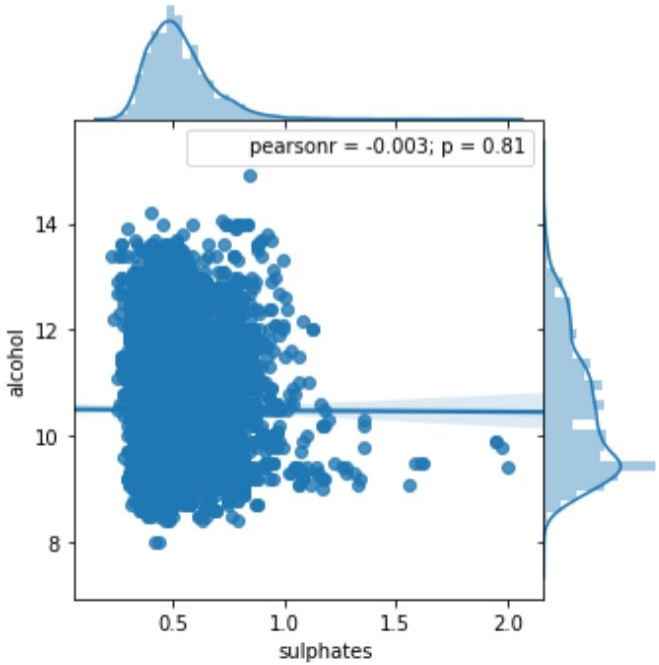
Multivariate Analysis - Visualizing 2-D

Visualizing numeric features

```
plt.scatter(wines['sulphates'], wines['alcohol'],
            alpha=0.4, edgecolors='w')

plt.xlabel('Sulphates')
plt.ylabel('Alcohol')
plt.title('Wine Sulphates - Alcohol Content',y=1.05)
```

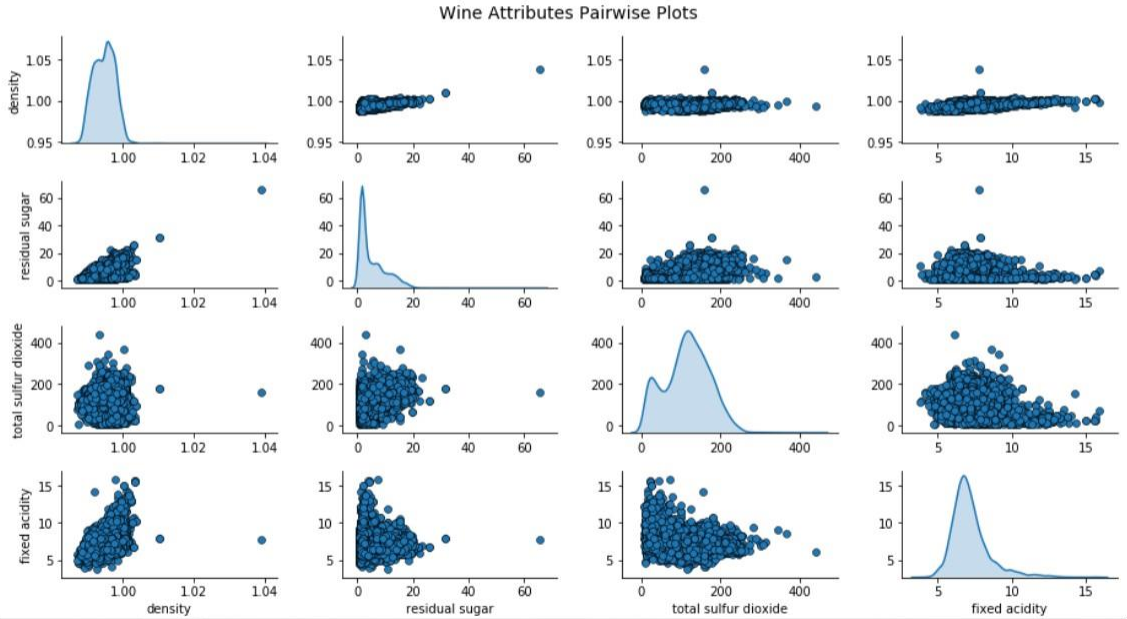



```
jp = sns.jointplot(x='sulphates', y='alcohol', data=wines,
                   kind='reg', space=0, size=5, ratio=4)
```



Multivariate Analysis - Visualizing 2-D

Visualizing numeric features - use a pairplot

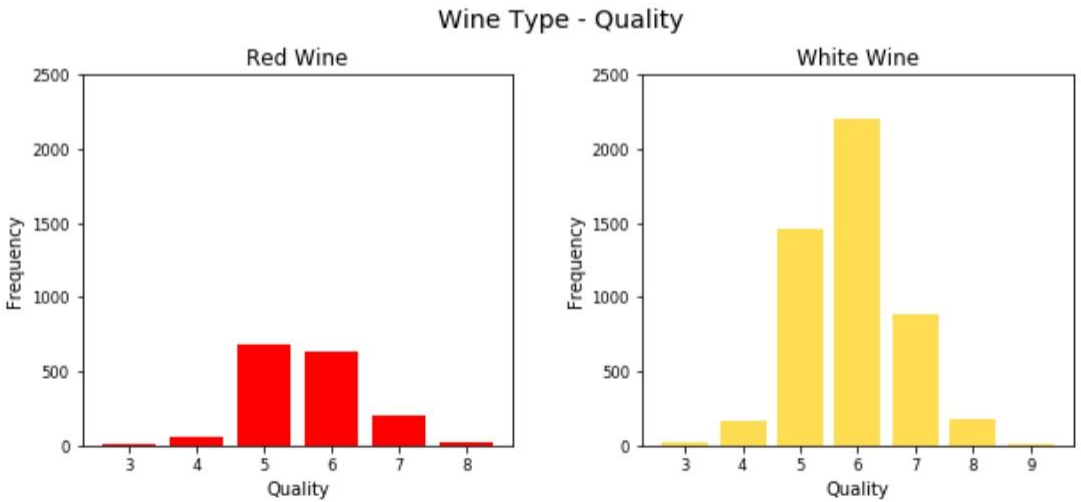



```
cols = ['density', 'residual sugar', 'total sulfur dioxide', 'fixed acidity']
pp = sns.pairplot(wines[cols], size=1.8, aspect=1.8,
                  plot_kws=dict(edgecolor="k", linewidth=0.5),
                  diag_kind="kde", diag_kws=dict(shade=True))

fig = pp.fig
fig.subplots_adjust(top=0.93, wspace=0.3)
t = fig.suptitle('Wine Attributes Pairwise Plots', fontsize=14)
```

Multivariate Analysis - Visualizing 2-D

Visualizing two categorical attributes - A pain with matplotlib!

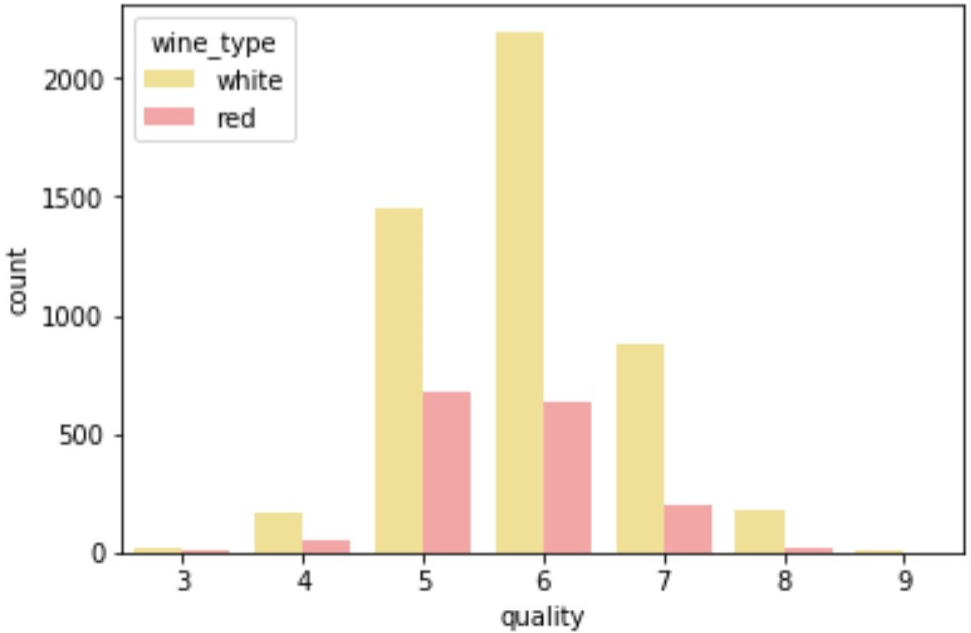
```
fig = plt.figure(figsize = (10, 4))
title = fig.suptitle("Wine Type - Quality", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax1 = fig.add_subplot(1,2, 1)
ax1.set_title("Red Wine")
ax1.set_xlabel("Quality")
ax1.set_ylabel("Frequency")
rw_q = red_wine['quality'].value_counts()
rw_q = (list(rw_q.index), list(rw_q.values))
ax1.set_ylim([0, 2500])
ax1.tick_params(axis='both', which='major', labelsize=8.5)
bar1 = ax1.bar(rw_q[0], rw_q[1], color='red')


ax2 = fig.add_subplot(1,2, 2)
ax2.set_title("White Wine")
ax2.set_xlabel("Quality")
ax2.set_ylabel("Frequency")
ww_q = white_wine['quality'].value_counts()
ww_q = (list(ww_q.index), list(ww_q.values))
ax2.set_ylim([0, 2500])
ax2.tick_params(axis='both', which='major', labelsize=8.5)
ax2.bar(ww_q[0], ww_q[1], color='#FFDC51')
```



Multivariate Analysis - Visualizing 2-D

Visualizing two categorical attributes - easier and cleaner with seaborn

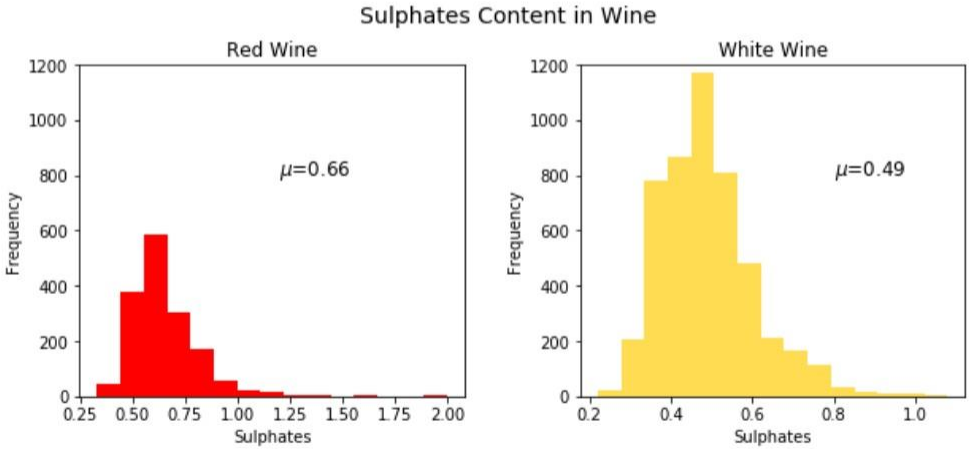
```
cp = sns.countplot(x="quality", hue="wine_type", data=wines,
                   palette={"red": "#FF9999", "white": "#FFE888"})
```



Multivariate Analysis - Visualizing 2-D

Visualizing a mix of categorical & numeric attributes

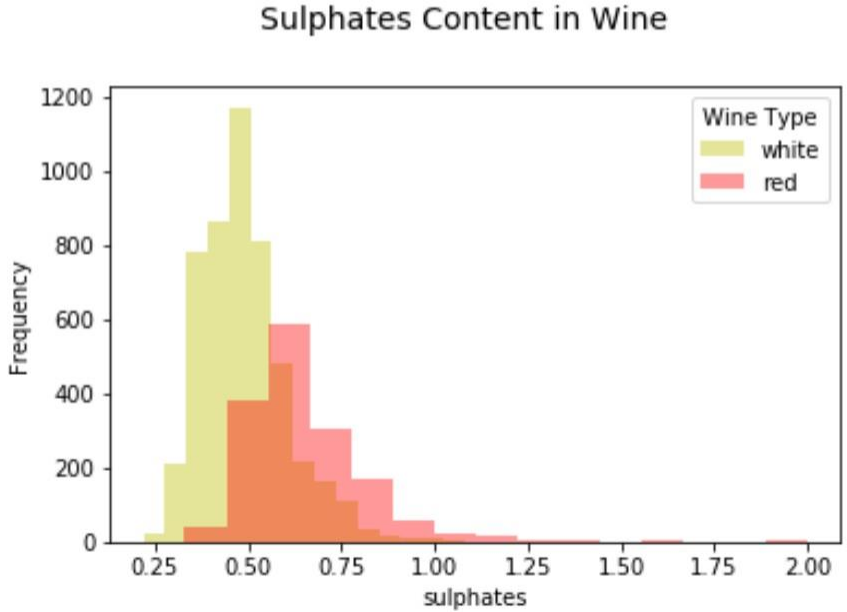
```
fig = plt.figure(figsize = (10,4))
title = fig.suptitle("Sulphates Content in Wine", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)

ax1 = fig.add_subplot(1,2, 1)
ax1.set_title("Red Wine")
ax1.set_xlabel("Sulphates")
ax1.set_ylabel("Frequency")
ax1.set_ylim([0, 1200])
ax1.text(1.2, 800, r'$\mu$='+str(round(red_wine['sulphates'].mean(),2)),
         fontsize=12)
r_freq, r_bins, r_patches = ax1.hist(red_wine['sulphates'],
                                     color='red', bins=15)

ax2 = fig.add_subplot(1,2, 2)
ax2.set_title("White Wine")
ax2.set_xlabel("Sulphates")
ax2.set_ylabel("Frequency")
ax2.set_ylim([0, 1200])
ax2.text(0.8, 800, r'$\mu$='+str(round(white_wine['sulphates'].mean(),2)),
         fontsize=12)
w_freq, w_bins, w_patches = ax2.hist(white_wine['sulphates'],
                                     color='#FFDC51', bins=15)
```



Multivariate Analysis - Visualizing 2-D

Visualizing a mix of categorical & numeric attributes

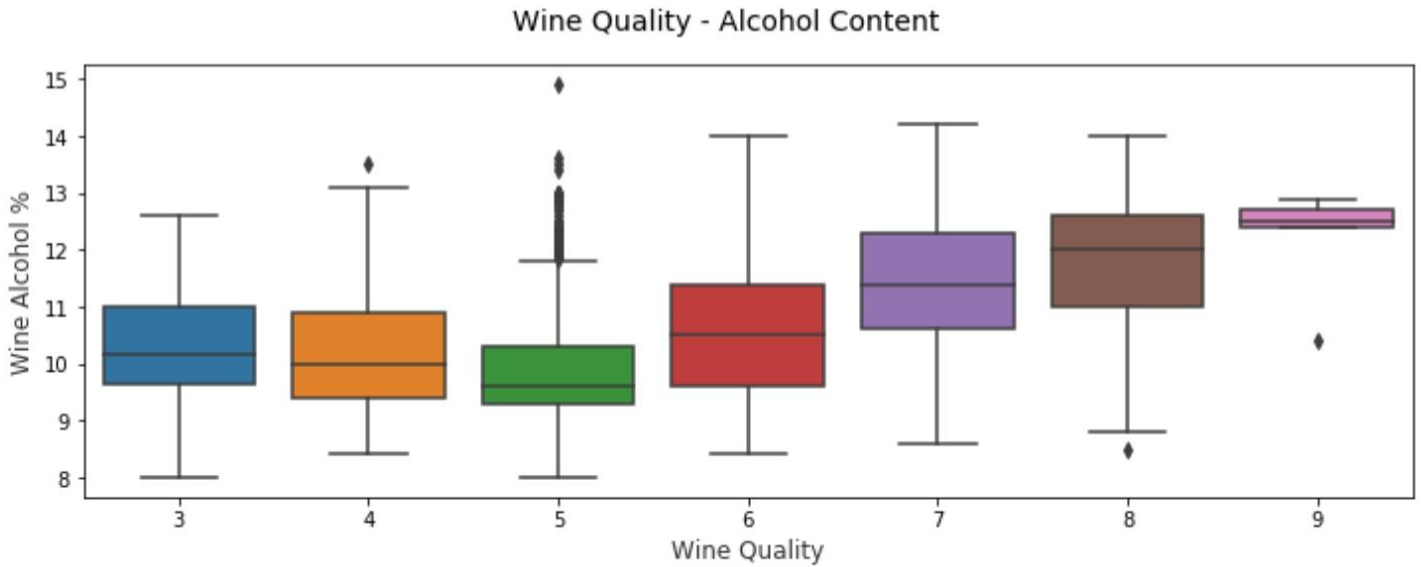
```
fig = plt.figure(figsize = (6, 4))
title = fig.suptitle("Sulphates Content in Wine", fontsize=14)
fig.subplots_adjust(top=0.85, wspace=0.3)
ax = fig.add_subplot(1,1, 1)
ax.set_xlabel("Sulphates")
ax.set_ylabel("Frequency")

g = sns.FacetGrid(wines, hue='wine_type',
                  palette={"red": "r", "white": "y"})
g.map(sns.distplot, 'sulphates', kde=False, bins=15, ax=ax)
ax.legend(title='Wine Type')
plt.close(2)
```



Multivariate Analysis - Visualizing 2-D

Visualizing a mix of categorical & numeric attributes - more categories? use box-plots or violin plots

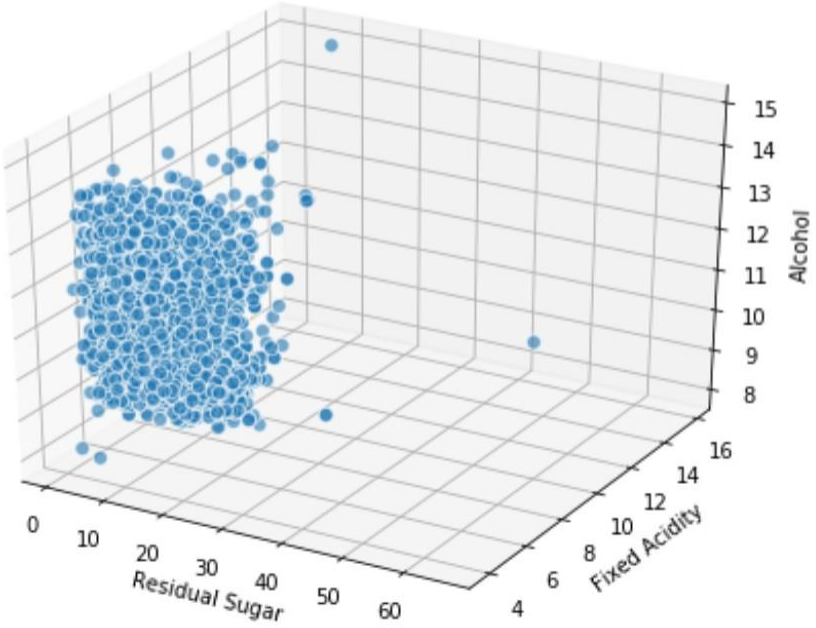
```
f, (ax) = plt.subplots(1, 1, figsize=(12, 4))
t = f.suptitle('Wine Quality - Alcohol Content', fontsize=14)

sns.boxplot(x="quality", y="alcohol", data=wines,  ax=ax)
xl = ax.set_xlabel("Wine Quality",size = 12,alpha=0.8)
yl = ax.set_ylabel("Wine Alcohol %",size = 12,alpha=0.8)
```



Multivariate Analysis - Visualizing 3-D

Visualizing numeric attributes - is this effective?

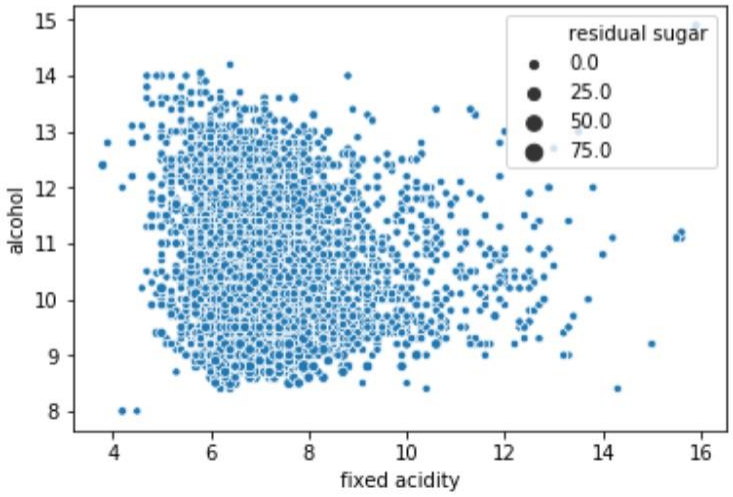
```
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')

xs = wines['residual sugar']
ys = wines['fixed acidity']
zs = wines['alcohol']
ax.scatter(xs, ys, zs, s=50, alpha=0.6, edgecolors='w')

xl = ax.set_xlabel('Residual Sugar')
yl = ax.set_ylabel('Fixed Acidity')
zl = ax.set_zlabel('Alcohol')
```



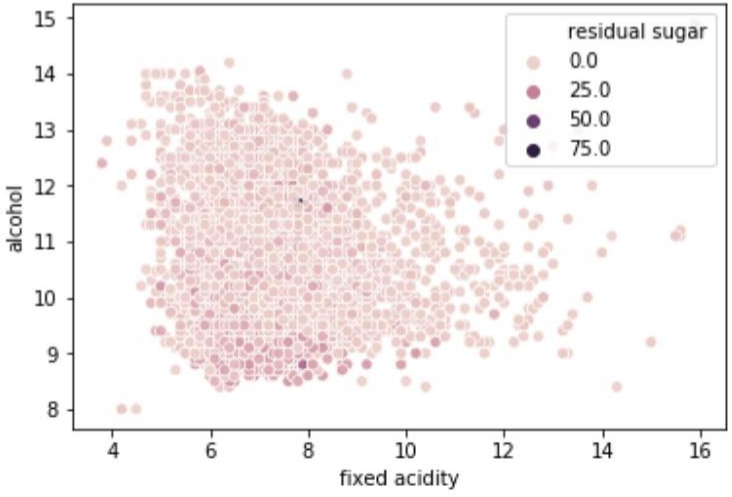
Multivariate Analysis - Visualizing 3-D

Visualizing numeric attributes - bin one or more attributes and use facets, color and\or size

```
sc = sns.scatterplot(wines['fixed acidity'], wines['alcohol'],
                     size=wines['residual sugar'])
```



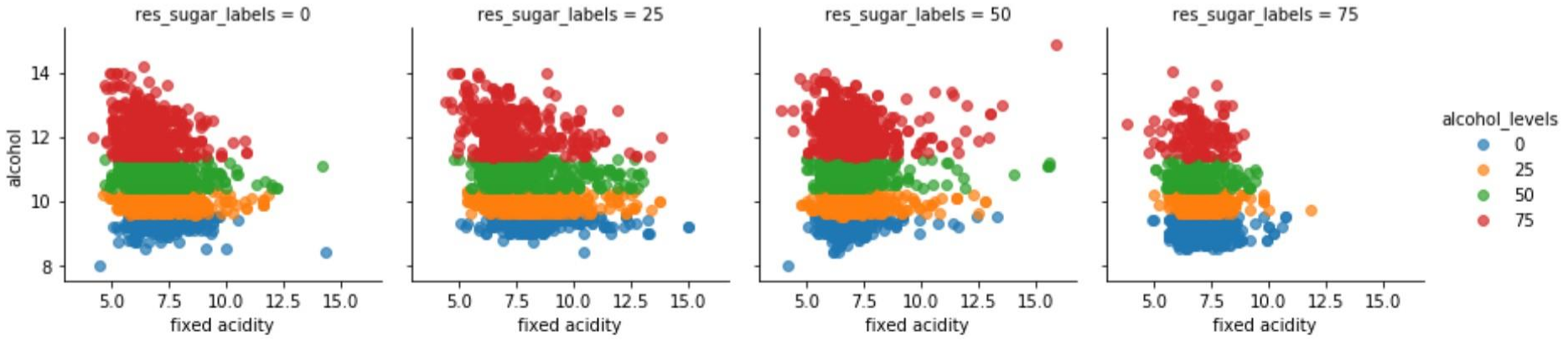

```
sc = sns.scatterplot(wines['fixed acidity'], wines['alcohol'],
                     hue=wines['residual sugar'], alpha=0.9)
```



Multivariate Analysis - Visualizing 3-D

Visualizing numeric attributes - bin one or more attributes and use facets, color and\or size

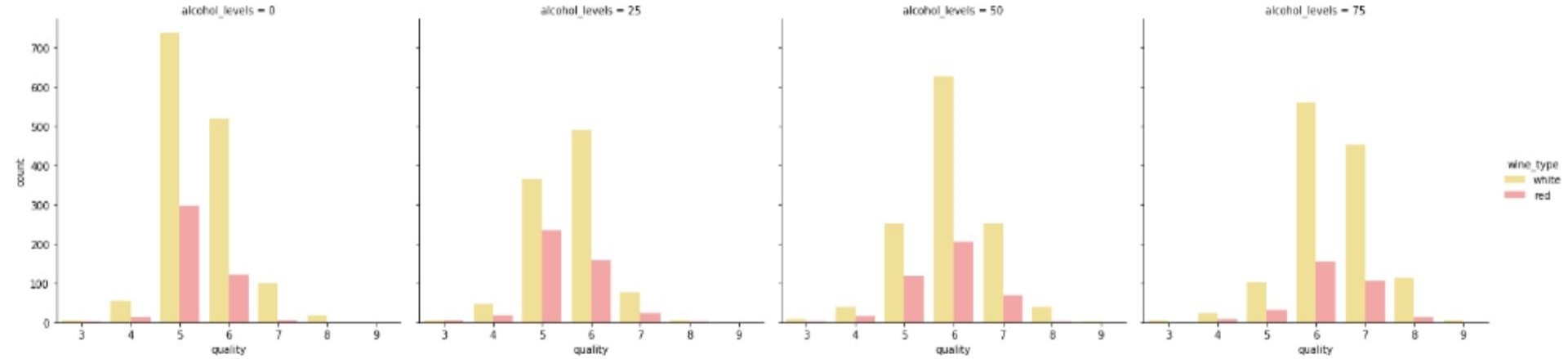
```
quantile_list = [0, .25, .5, .75, 1.]
quantile_labels = ['0', '25', '50', '75']
wines['res_sugar_labels'] = pd.qcut(wines['residual sugar'],
                                    q=quantile_list, labels=quantile_labels)
wines['alcohol_levels'] = pd.qcut(wines['alcohol'],
                                    q=quantile_list, labels=quantile_labels)
g = sns.FacetGrid(wines, col="res_sugar_labels",
                  hue='alcohol_levels')
g.map(plt.scatter, "fixed acidity", "alcohol", alpha=.7)
g.add_legend();
```



Multivariate Analysis - Visualizing 3-D

Visualizing categorical attributes using facets and color

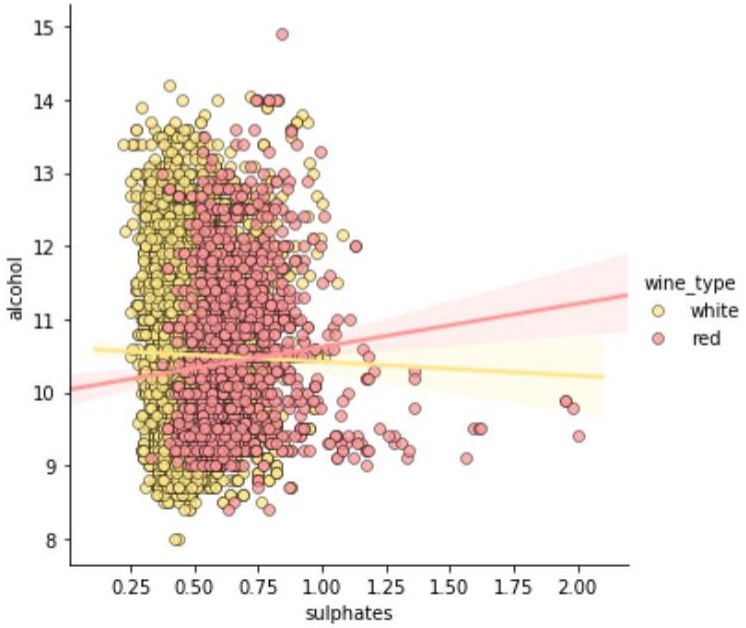
```
fc = sns.factorplot(x="quality", hue="wine_type", col="alcohol_levels",
                    data=wines, kind="count",
                    palette={"red": "#FF9999", "white": "#FFE888"})
```



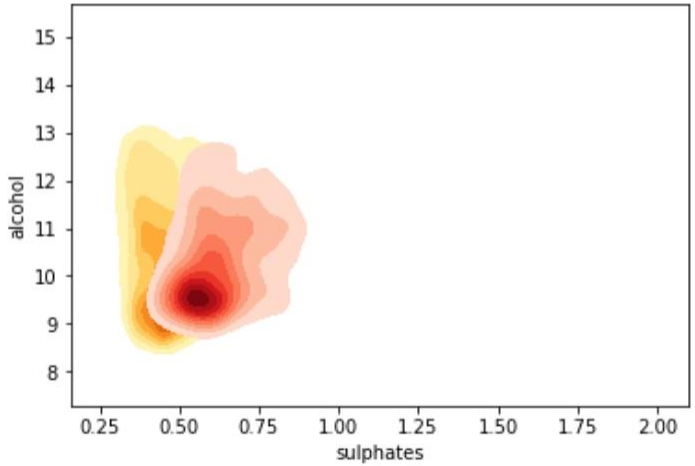
Multivariate Analysis - Visualizing 3-D

Visualizing mixed attributes

```
lp = sns.lmplot(x='sulphates', y='alcohol', hue='wine_type',
                palette={"red": "#FF9999", "white": "#FFE888"},
                data=wines, fit_reg=True, legend=True,
                scatter_kws=dict(edgecolor="k", linewidth=0.5))
```



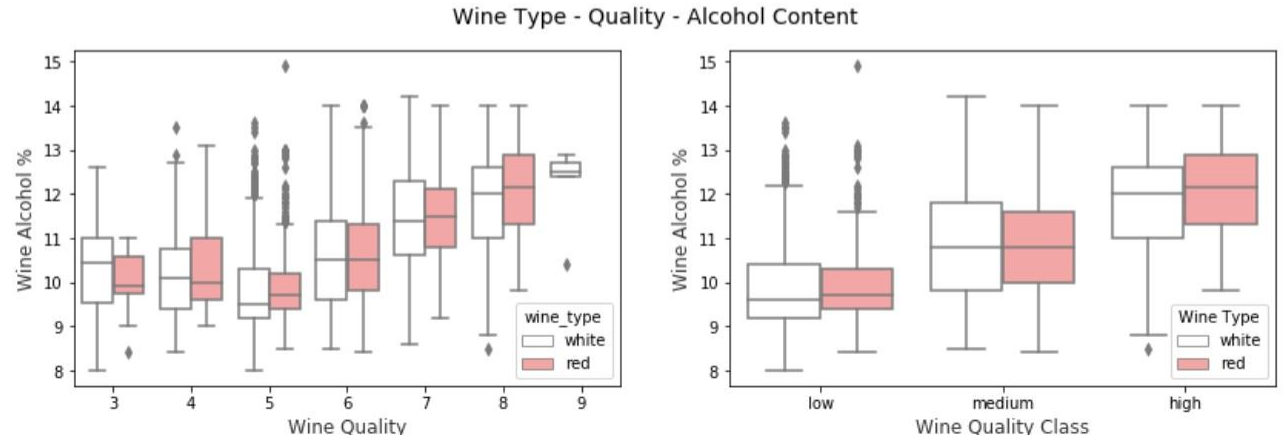

```
ax = sns.kdeplot(white_wine['sulphates'], white_wine['alcohol'],
                 cmap="YlOrBr", shade=True, shade_lowest=False)
ax = sns.kdeplot(red_wine['sulphates'], red_wine['alcohol'],
                 cmap="Reds", shade=True, shade_lowest=False)
```



Multivariate Analysis - Visualizing 3-D

Visualizing mixed attributes

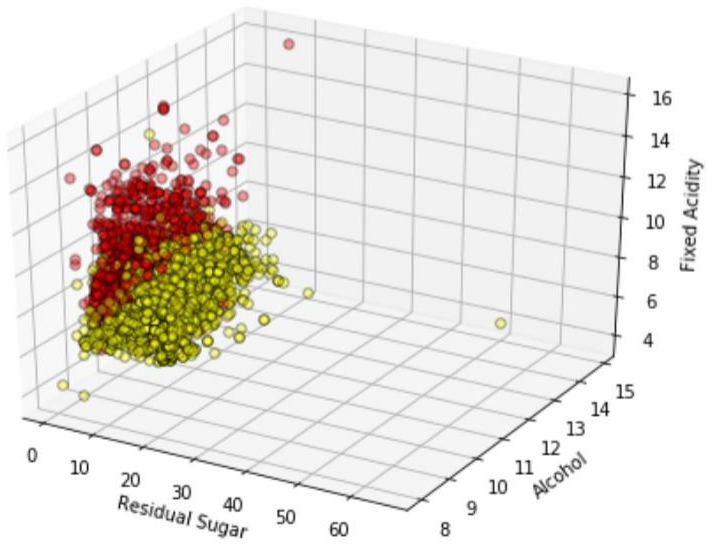
```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 4))
f.suptitle('Wine Type - Quality - Alcohol Content', fontsize=14)

sns.boxplot(x="quality", y="alcohol", hue="wine_type",
                data=wines, palette={"red": "#FF9999", "white": "white"}, ax=ax1)
ax1.set_xlabel("Wine Quality",size = 12,alpha=0.8)
ax1.set_ylabel("Wine Alcohol %",size = 12,alpha=0.8)

sns.boxplot(x="quality_label", y="alcohol", hue="wine_type",
                data=wines, palette={"red": "#FF9999", "white": "white"}, ax=ax2)
ax2.set_xlabel("Wine Quality Class",size = 12,alpha=0.8)
ax2.set_ylabel("Wine Alcohol %",size = 12,alpha=0.8)
l = plt.legend(loc='best', title='Wine Type')
```



Multivariate Analysis - Visualizing 4-D

Visualizing mixed attributes (more numeric variables)

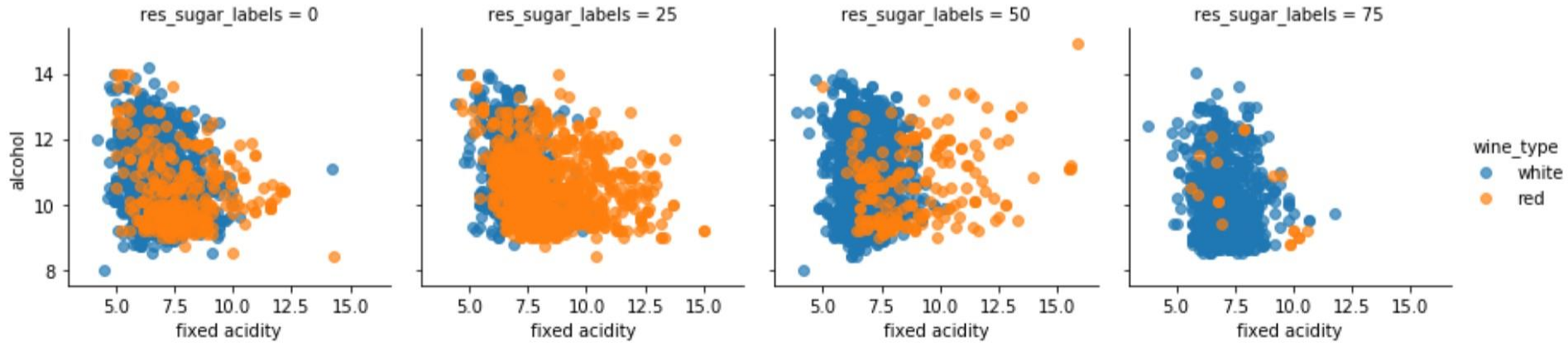
```
fig = plt.figure(figsize=(8, 6))
t = fig.suptitle('Wine Residual Sugar - Alcohol Content - Acidity - Type', fontsize=14)
ax = fig.add_subplot(111, projection='3d')

xs = list(wines['residual sugar'])
ys = list(wines['alcohol'])
zs = list(wines['fixed acidity'])
data_points = [(x, y, z) for x, y, z in zip(xs, ys, zs)]
colors = ['red' if wt == 'red' else 'yellow' for wt in list(wines['wine_type'])]

for data, color in zip(data_points, colors):
    x, y, z = data
    ax.scatter(x, y, z, alpha=0.4, c=color, edgecolors='none', s=30)

xl = ax.set_xlabel('Residual Sugar')
yl = ax.set_ylabel('Alcohol')
zl = ax.set_zlabel('Fixed Acidity')
```



Multivariate Analysis - Visualizing 4-D

Visualizing mixed attributes (more numeric variables) - need to bin one numeric variable

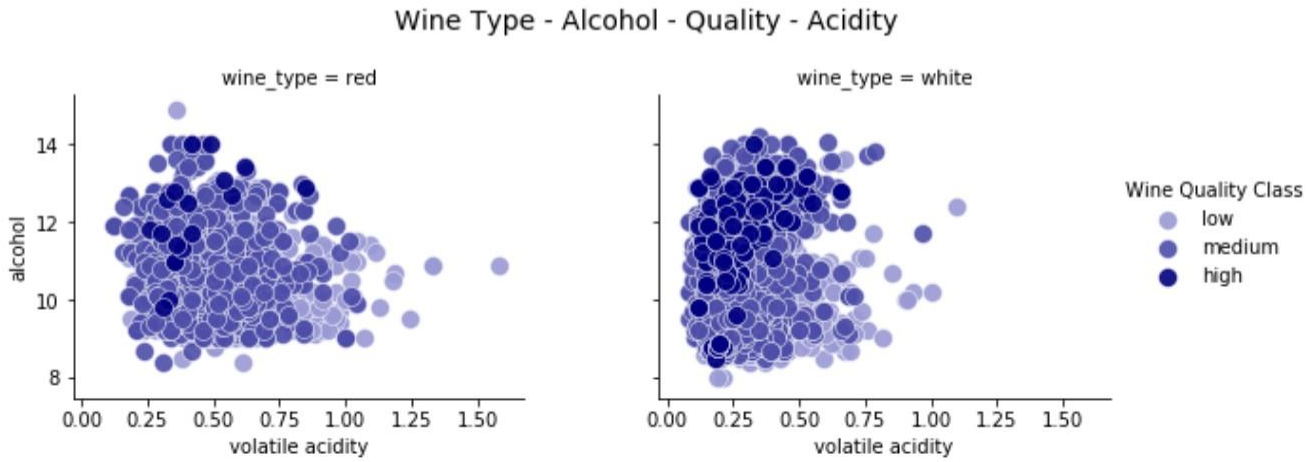
```
g = sns.FacetGrid(wines, col="res_sugar_labels",
                  hue='wine_type')
g.map(plt.scatter, "fixed acidity", "alcohol", alpha=.7)
g.add_legend();
```



Multivariate Analysis - Visualizing 4-D

Visualizing mixed attributes

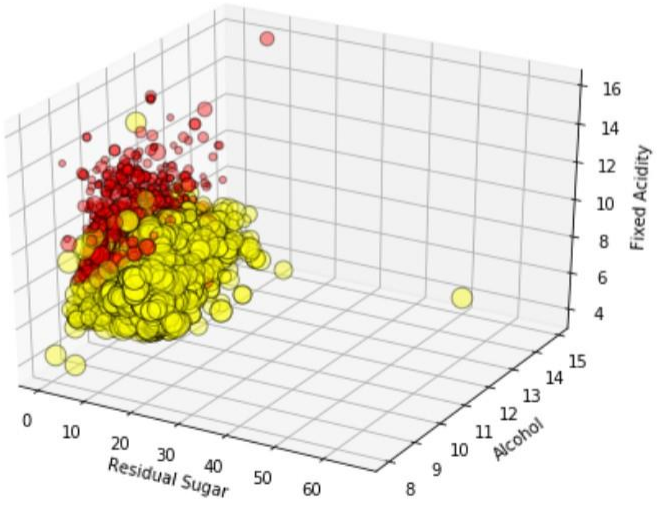
```
g = sns.FacetGrid(wines, col="wine_type", hue='quality_label',
                  col_order=['red', 'white'], hue_order=['low', 'medium', 'high'],
                  aspect=1.2, size=3.5, palette=sns.light_palette('navy', 4)[1:])
g.map(plt.scatter, "volatile acidity", "alcohol", alpha=0.9,
      edgecolor='white', linewidth=0.5, s=100)
fig = g.fig
fig.subplots_adjust(top=0.8, wspace=0.3)
fig.suptitle('Wine Type - Alcohol - Quality - Acidity', fontsize=14)
l = g.add_legend(title='Wine Quality Class')
```



Multivariate Analysis - Visualizing 5-D

Visualizing mixed attributes - not always effective

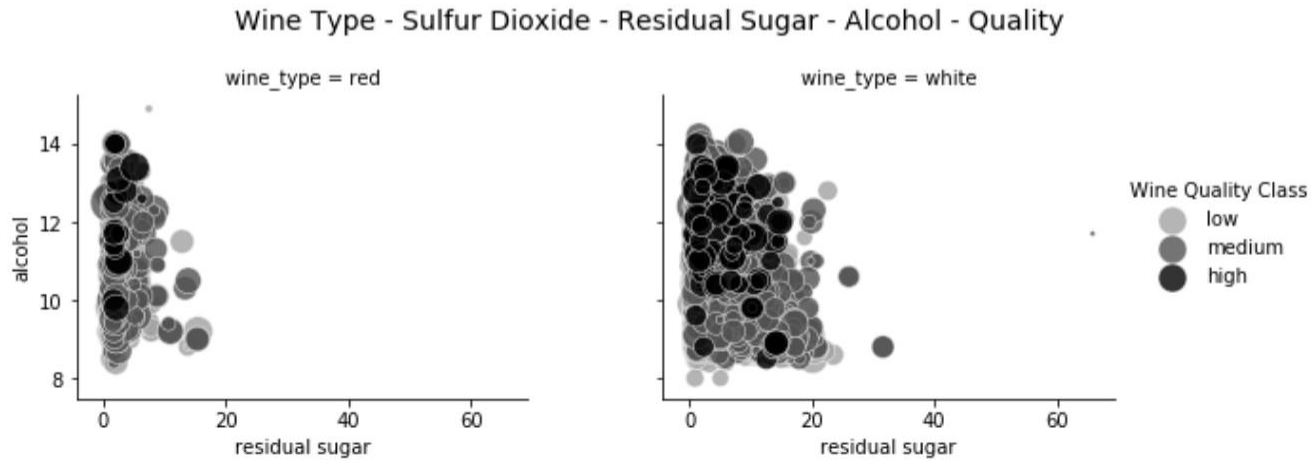
```
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')
t = fig.suptitle('Wine Residual Sugar - Alcohol Content - Acidity - Total Sulfur Dioxide - Type',
                 fontsize=14)

xs = list(wines['residual sugar'])
ys = list(wines['alcohol'])
zs = list(wines['fixed acidity'])
data_points = [(x, y, z) for x, y, z in zip(xs, ys, zs)]

ss = list(wines['total sulfur dioxide'])
colors = ['red' if wt == 'red' else 'yellow' for wt in list(wines['wine_type'])]

for data, color, size in zip(data_points, colors, ss):
    x, y, z = data
    ax.scatter(x, y, z, alpha=0.4, c=color, edgecolors='none', s=size)

ax.set_xlabel('Residual Sugar')
ax.set_ylabel('Alcohol')
ax.set_zlabel('Fixed Acidity')
```



Multivariate Analysis - Visualizing 5-D

Visualizing mixed attributes - start with faceting and sizes

```
g = sns.FacetGrid(wines, col="wine_type", hue='quality_label',
                  col_order=['red', 'white'], hue_order=['low', 'medium', 'high'],
                  aspect=1.2, size=3.5, palette=sns.light_palette('black', 4)[1:])
g.map(plt.scatter, "residual sugar", "alcohol", alpha=0.8,
      edgecolor='white', linewidth=0.5, s=wines['total sulfur dioxide'])
fig = g.fig
fig.subplots_adjust(top=0.8, wspace=0.3)
fig.suptitle('Wine Type - Sulfur Dioxide - Residual Sugar - Alcohol - Quality', fontsize=14)
l = g.add_legend(title='Wine Quality Class')
```



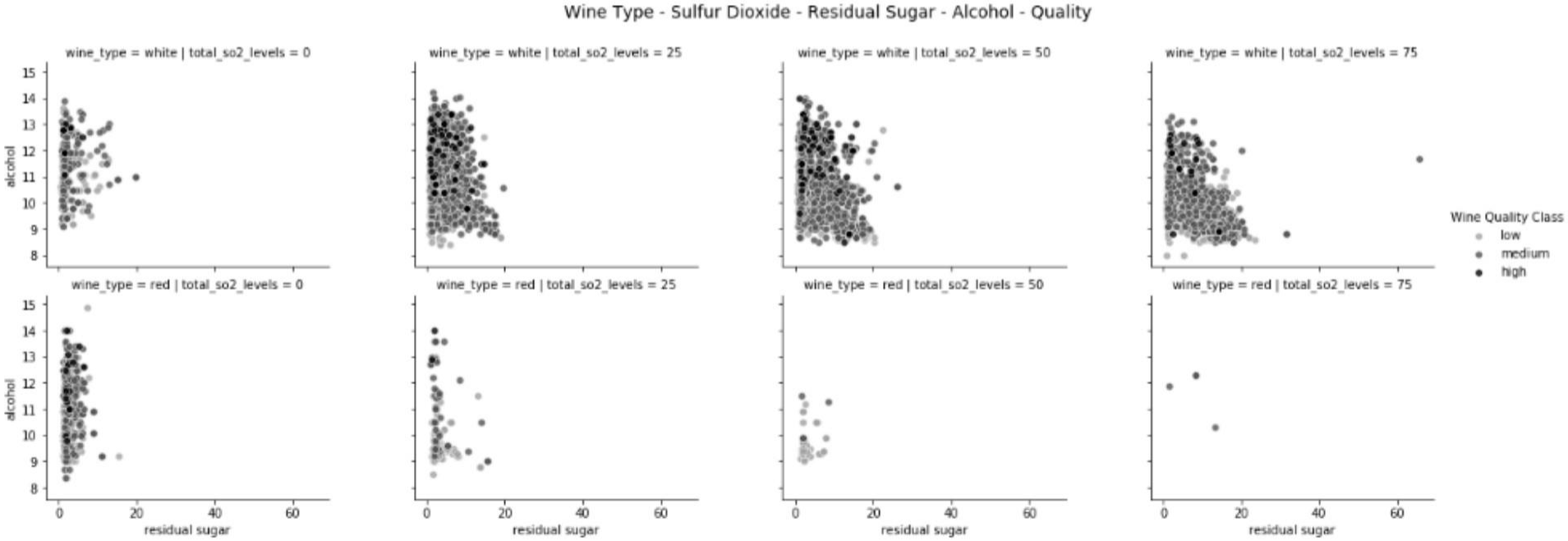
Multivariate Analysis - Visualizing 5-D

Visualizing mixed attributes - multi-facets often better than size (often needs binning of numerics)

```
quantile_list = [0, .25, .5, .75, 1.]
quantile_labels = ['0', '25', '50', '75']
wines['total_so2_levels'] = pd.qcut(wines['total sulfur dioxide'],
                                    q=quantile_list, labels=quantile_labels)
g = sns.FacetGrid(wines, row="wine_type", col='total_so2_levels', hue='quality_label',
                  hue_order=['low', 'medium', 'high'], palette=sns.light_palette('black', 4)[1:],
                  aspect=1.2, size=3.5)
g.map(plt.scatter, "residual sugar", "alcohol", alpha=0.8,
      edgecolor='white', linewidth=0.5)
fig = g.fig
fig.subplots_adjust(top=0.8, wspace=0.3)
fig.suptitle('Wine Type - Sulfur Dioxide - Residual Sugar - Alcohol - Quality', fontsize=14)
l = g.add_legend(title='Wine Quality Class')
```

Multivariate Analysis - Visualizing 5-D

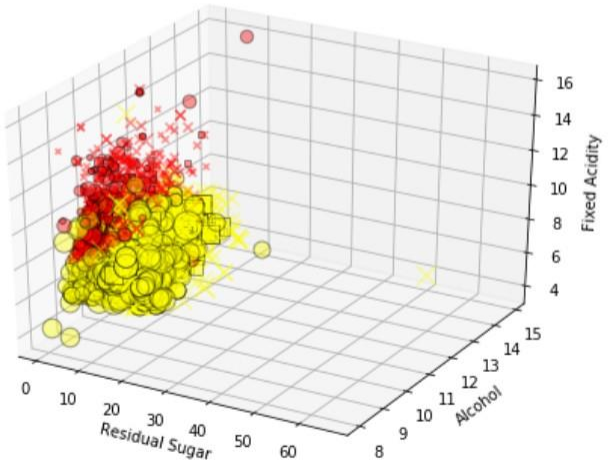
Visualizing mixed attributes - multi-facets often better than size (often needs binning of numerics)



Multivariate Analysis - Visualizing 6-D

Visualizing mixed attributes - color, size, shape & depth

```
fig = plt.figure(figsize=(8, 6))
t = fig.suptitle('Wine Residual Sugar - Alcohol Content - Acidity - Total Sulfur Dioxide - Type - Quality',
                 fontsize=14)
ax = fig.add_subplot(111, projection='3d')

xs = list(wines['residual sugar'])
ys = list(wines['alcohol'])
zs = list(wines['fixed acidity'])
data_points = [(x, y, z) for x, y, z in zip(xs, ys, zs)]

ss = list(wines['total sulfur dioxide'])
colors = ['red' if wt == 'red' else 'yellow' for wt in list(wines['wine_type'])]
markers = [',' if q == 'high' else 'x' if q == 'medium' else 'o' for q in list(wines['quality_label'])]

for data, color, size, mark in zip(data_points, colors, ss, markers):
    x, y, z = data
    ax.scatter(x, y, z, alpha=0.4, c=color, edgecolors='none', s=size, marker=mark)

ax.set_xlabel('Residual Sugar')
ax.set_ylabel('Alcohol')
ax.set_zlabel('Fixed Acidity')
```



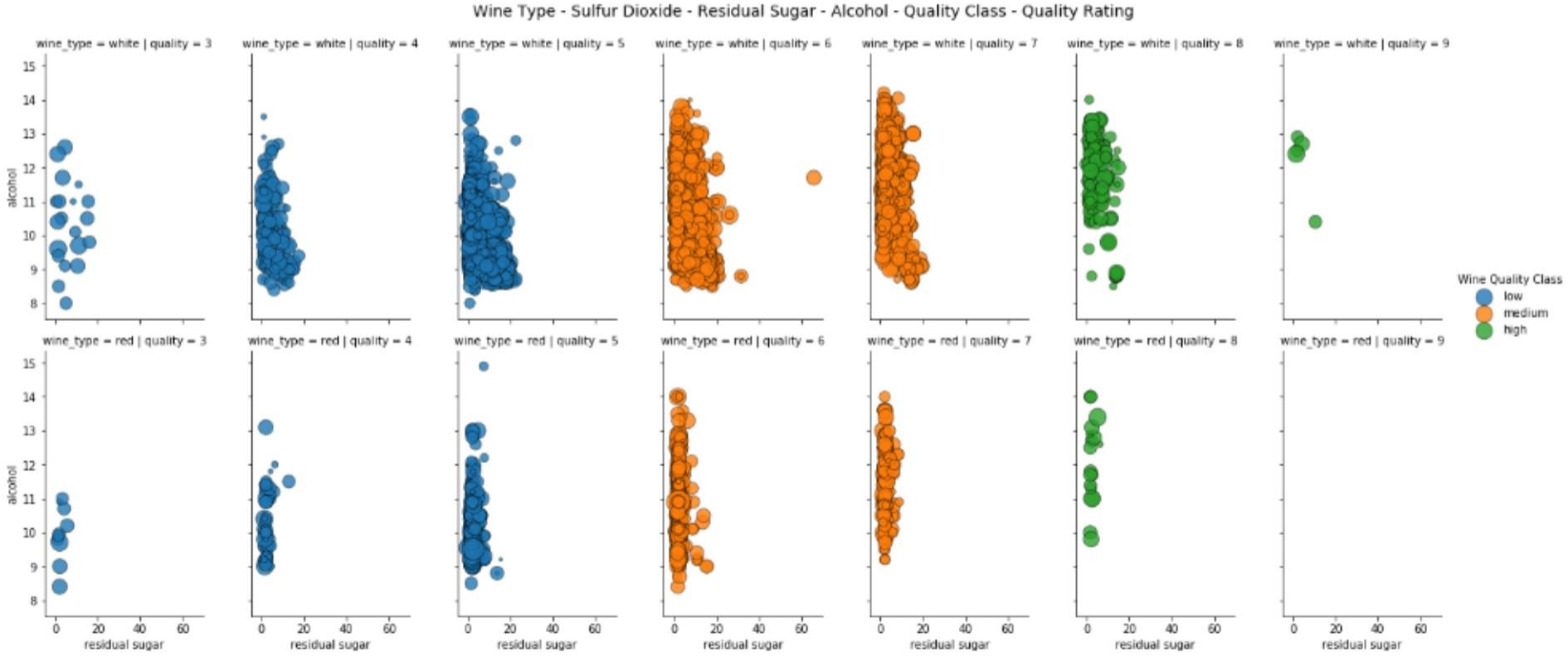
Multivariate Analysis - Visualizing 6-D

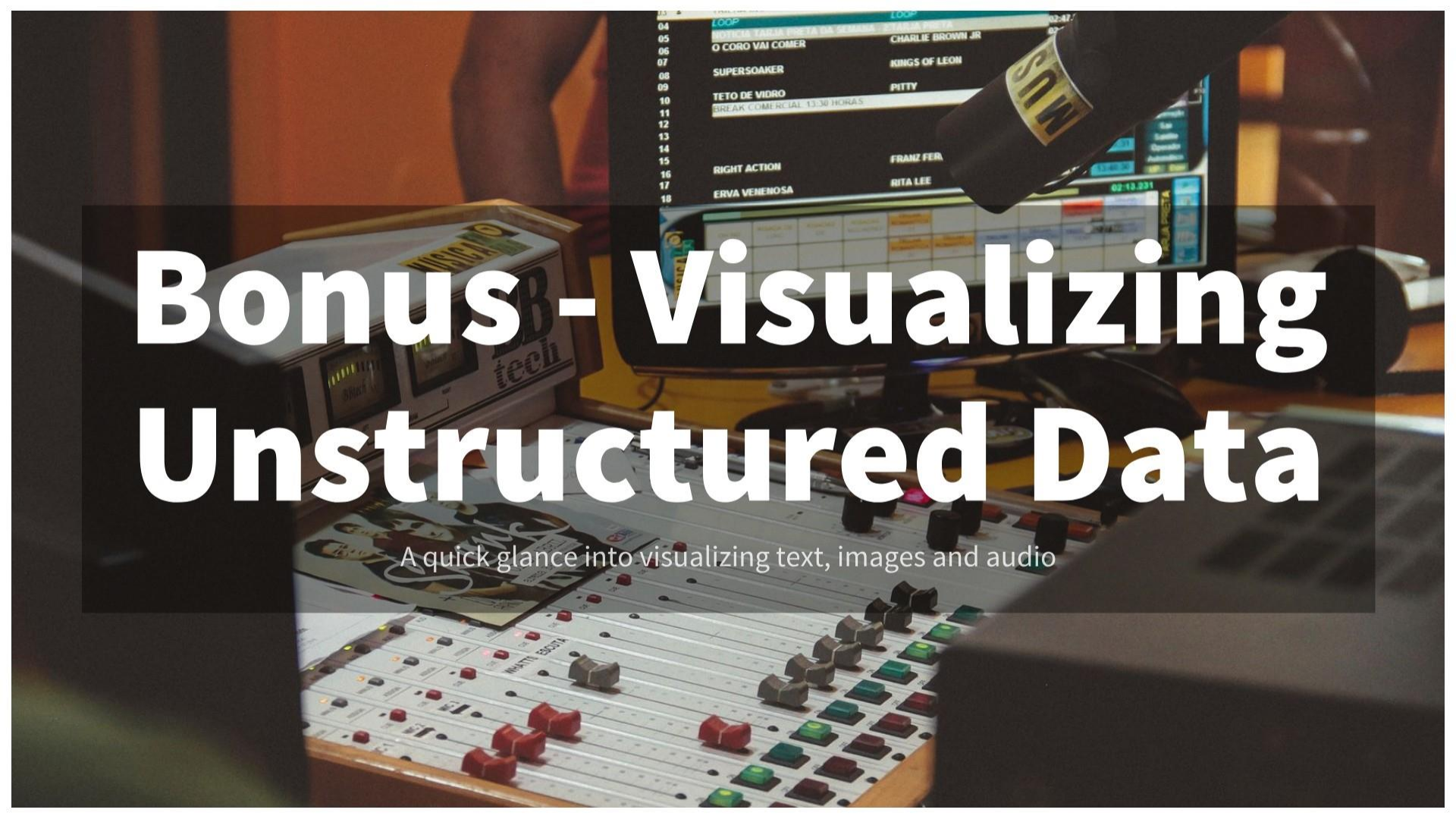
Visualizing mixed attributes - color, size & multi-facets

```
g = sns.FacetGrid(wines, row='wine_type', col="quality", hue='quality_label', size=4)
g.map(plt.scatter,  "residual sugar", "alcohol", alpha=0.8,
      edgecolor='k', linewidth=0.5, s=wines['total sulfur dioxide'])
fig = g.fig
fig.set_size_inches(18, 8)
fig.subplots_adjust(top=0.85, wspace=0.3)
fig.suptitle('Wine Type - Sulfur Dioxide - Residual Sugar - Alcohol - Quality Class - Quality Rating',
             fontsize=14)
l = g.add_legend(title='Wine Quality Class')
```

Multivariate Analysis - Visualizing 6-D

Visualizing mixed attributes - color, size & multi-facets





Bonus- Visualizing Unstructured Data

A quick glance into visualizing text, images and audio

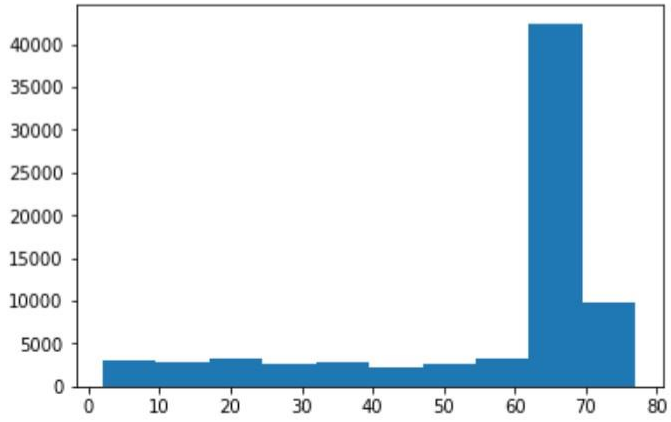
Visualizing Text Data - Basic EDA

Basic exploratory data analysis

```
bible = list(filter(None, [item.strip('\n') for item in bible]))
bible[:5]
```

```
['[The King James Bible]',
 'The Old Testament of the King James Bible',
 'The First Book of Moses:  Called Genesis',
 '1:1 In the beginning God created the heaven and the earth.',
 '1:2 And the earth was without form, and void; and darkness was upon']
```

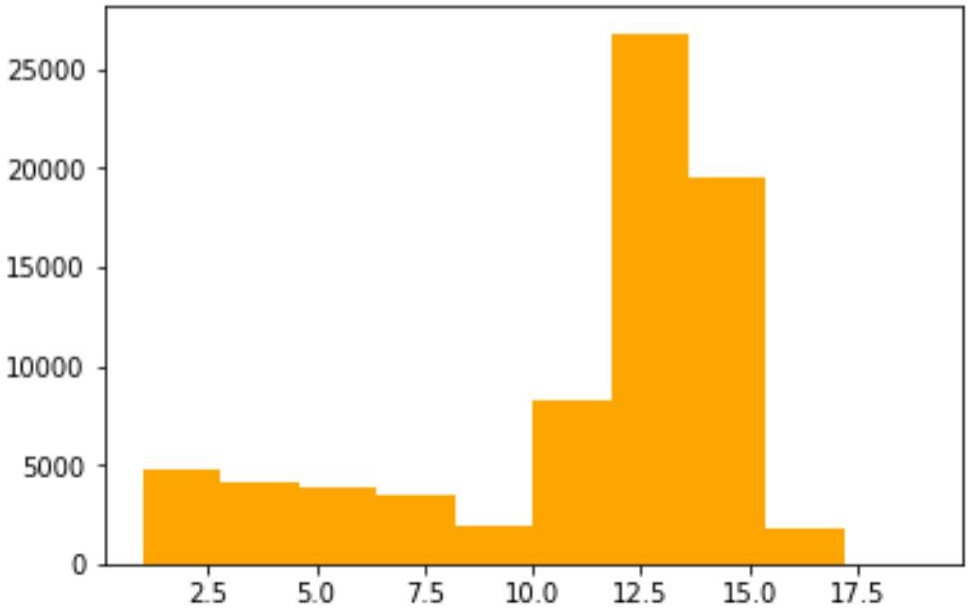
```
line_lengths = [len(sentence) for sentence in bible]
h = plt.hist(line_lengths)
```



Visualizing Text Data - Basic EDA

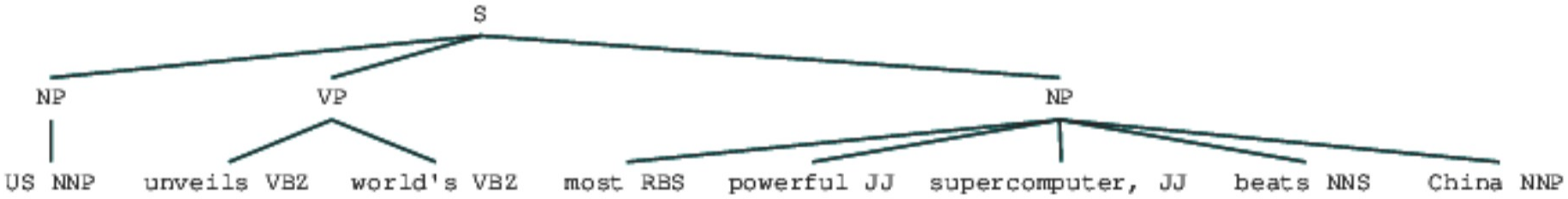
Basic exploratory data analysis

```
total_tokens_per_line = [len(sentence.split()) for sentence in bible]
h = plt.hist(total_tokens_per_line, color='orange')
```



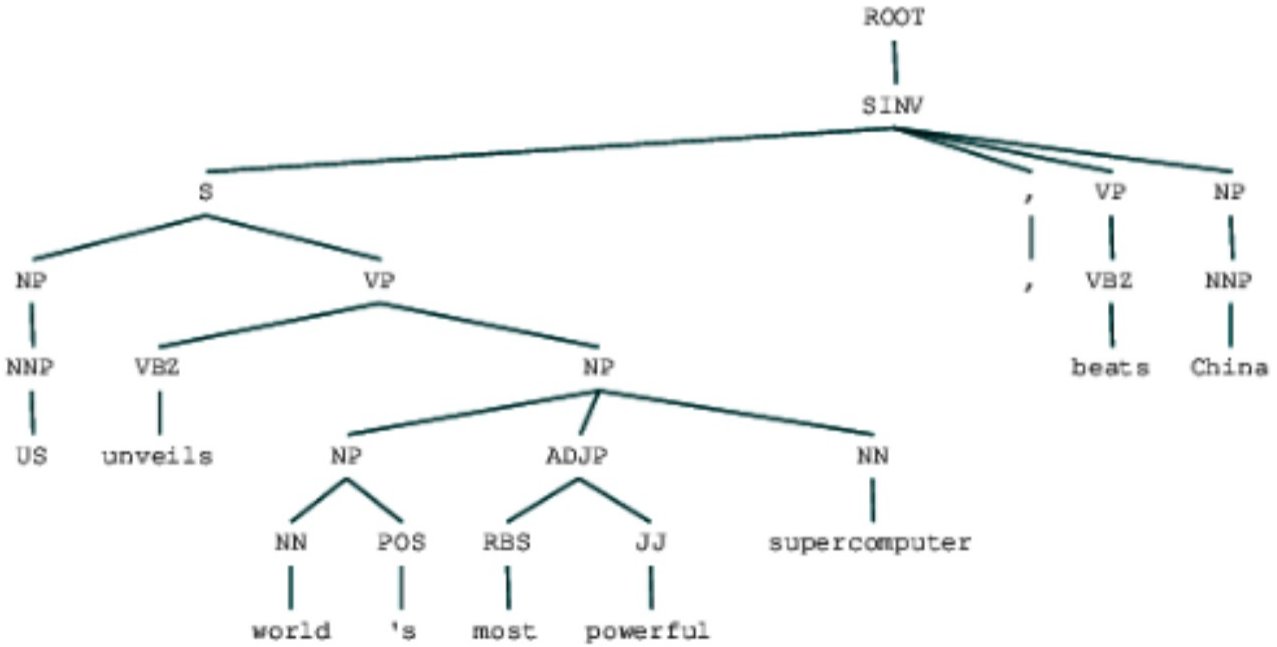
Visualizing Text Data - Language Structure

Shallow parsing



Visualizing Text Data - Language Structure

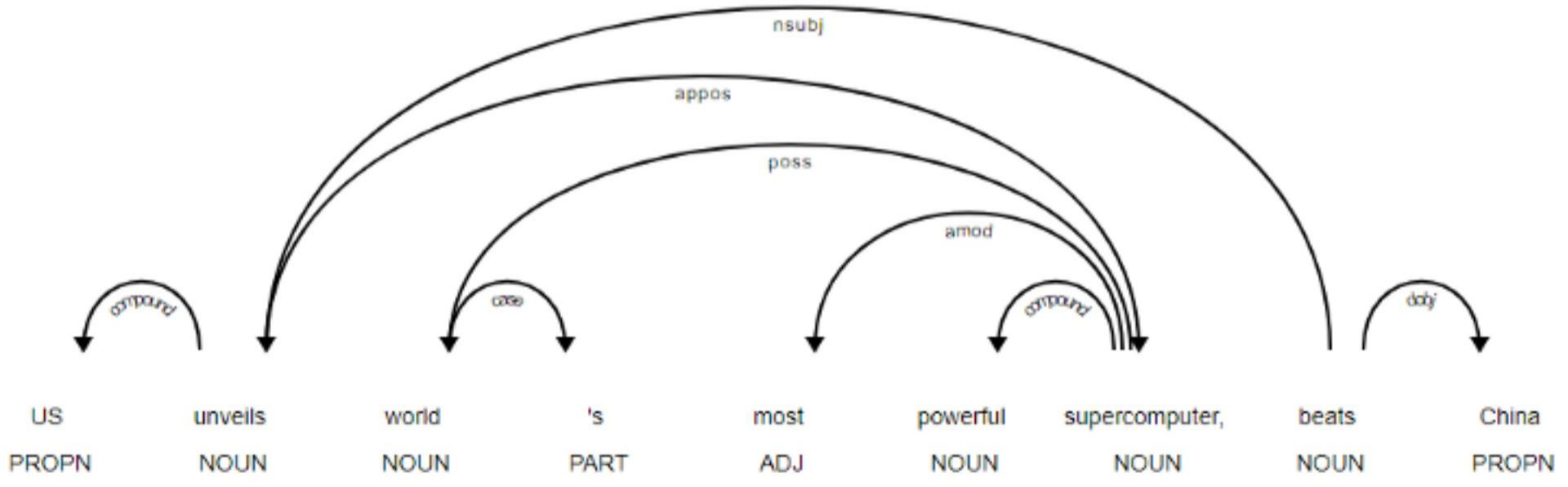
Constituency Parsing



Constituency parsed news headline

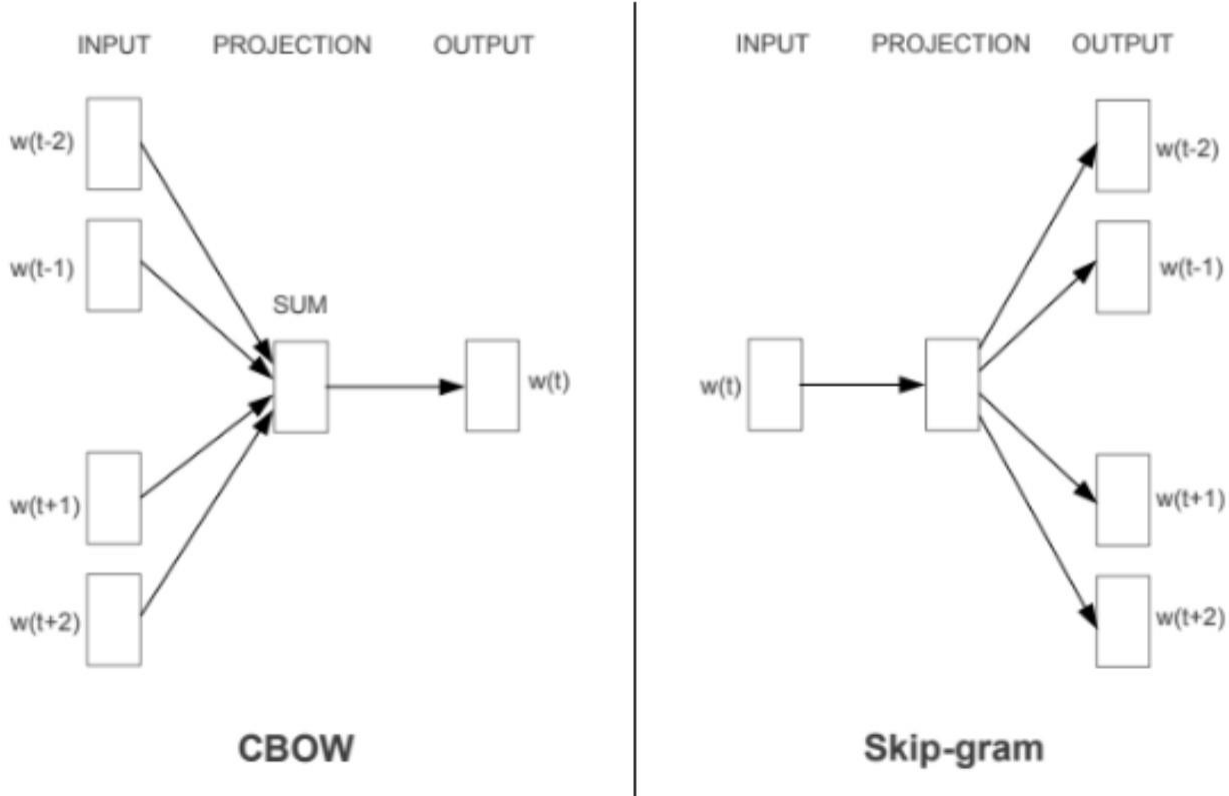
Visualizing Text Data - Language Structure

Dependency Parsing



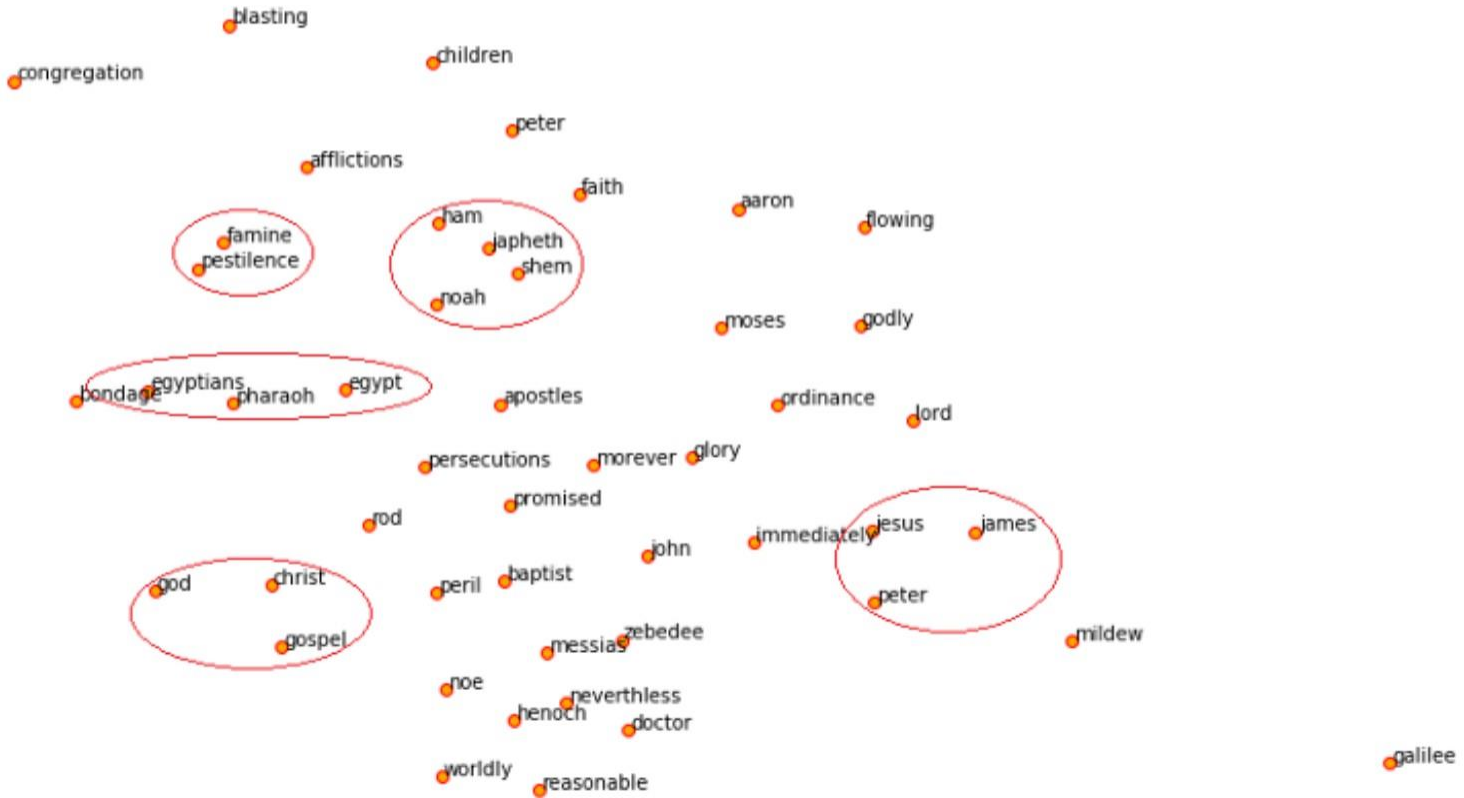
Visualizing Text Data - Language Semantics

Word Embedding Methods



Visualizing Text Data - Language Semantics

Visualizing embeddings from the Bible



Visualizing Text Data - Language Semantics

Can visualize documents based on similarity once you have document vectors

	Document	Category
0	The sky is blue and beautiful.	weather
1	Love this blue and beautiful sky!	weather
2	The quick brown fox jumps over the lazy dog.	animals
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food
4	I love green eggs, ham, sausages and bacon!	food
5	The brown fox is quick and the blue dog is lazy!	animals
6	The sky is very blue and the sky is very beautiful today	weather
7	The dog is lazy but the brown fox is quick!	animals

Visualizing Text Data - Language Semantics

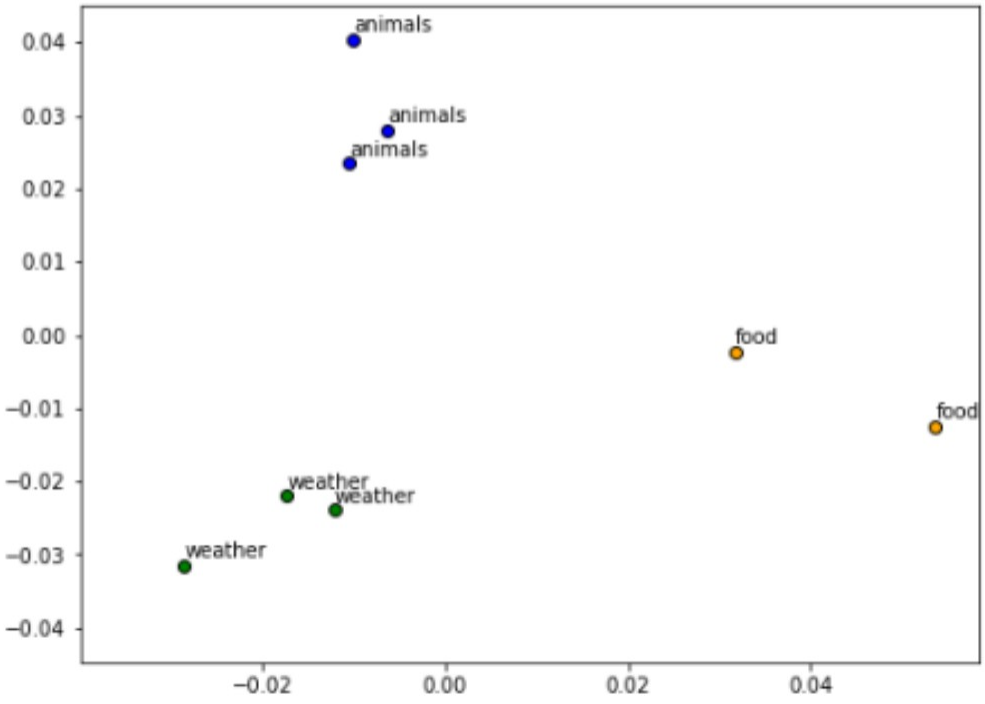
Can visualize documents based on similarity once you have document vectors

	0	1	2	3	4	5	6	7	8	9
0	0.004690	0.009370	-0.009667	0.026014	0.034989	0.010402	-0.033441	-0.011956	-0.000243	0.010552
1	0.005751	0.003210	-0.001964	0.016550	0.030962	0.004340	-0.019463	-0.009149	0.008256	0.019600
2	0.016712	0.004806	-0.001924	-0.027226	0.029162	-0.017201	-0.023197	-0.008610	-0.011976	0.020602
3	-0.009216	0.003900	-0.009232	-0.005232	0.042718	-0.032432	-0.006243	0.013524	0.008095	0.021227
4	-0.016321	-0.008715	-0.001633	-0.000501	0.027367	-0.037861	0.008515	0.021066	0.020373	0.016512
5	0.018538	0.007522	-0.009302	-0.025440	0.037199	-0.009890	-0.021419	-0.011769	-0.002221	0.018277
6	0.008532	0.008041	-0.016573	0.018653	0.036140	0.004038	-0.022891	0.000484	-0.005900	0.015766
7	0.024419	0.012915	-0.010596	-0.039350	0.037018	-0.013378	-0.020677	-0.004417	-0.011864	0.013540

Document level embeddings

Visualizing Text Data - Language Semantics

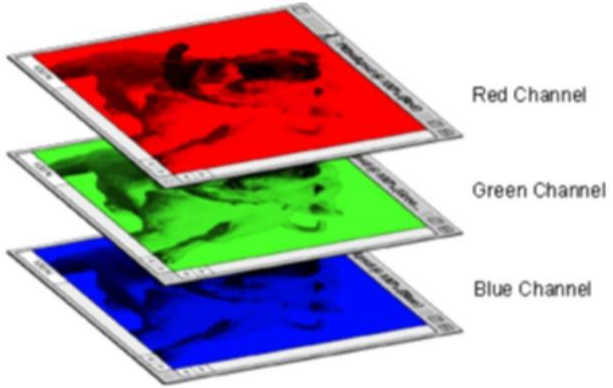
Can visualize documents based on similarity once you have document vectors - use PCA



Visualizing our document clusters

Visualizing Image Data

Images are just n-dimensional tensors where each channel is a 2-D matrix




```
  0  18 238 255 248 134  21  76 248 255 255 162   0   0   0   0   0   0   0   0   0   0   0
  0  87 255 255 255 255 255 255 254 253 255  87   0   0   0   0   0   0   0   0   0   0   0
  0  75 255 255 249 253 255 254 253 255 255 132  50  41   0   0   0   0  79 143  27   0   0   0
  0  39 255 255 255 245 200 186 187 192 222 255 255 255  51   0  43 202 255 255  75   0   0   0
  0  67 255 255 239 162 154 174 179 172 155 197 227 236 164 166 255 255 255 255  39   0   0   0
  0 146 255 255 173 159 206 196 194 200 184 155 241 253 255 255 240 217 250 255  44   0   0   0
 54 255 255 242 167 193 192 193 192 205 172 150 247 255 248 186 163 166 163 255 178   0   0   0
167 255 250 255 189 157 196 207 199 167 141 186 219 248 185 156 195 204 171 165 255 207  92  33
193 255 251 255 245 179 153 138 144 190 241 255 227 175 169 202 193 192 193 168 239 255 255 174
154 255 247 207 214 233 198 190 235 255 255 255 219 160 178 197 193 197 177 168 252 255 236  30
 54 255 225 207 245 255 255 254 210 181 177 231 220 146 190 198 196 199 145 203 255 255  73   0
  0  66 215 255 252 255 245 165 154 187 179 156 230 154 125 192 184 151 192 253 255 235  12   0
  0   0  82 255 255 253 179 169 205 192 205 156 197 253 174 159 163 220 254 253 255 255  75   0
  0   0  39 255 255 224 161 198 192 192 204 154 192 255 255 214 197 255 251 249 254 255 193   0
  0   0 104 255 255 206 159 203 192 197 190 152 235 255 240 195 241 255 251 255 255 251 118   0
  0  74 255 255 255 227 142 189 202 186 145 206 255 255 206 222 255 251 255 190  36   0   0   0
 95 255 255 249 251 254 200 153 167 171 215 254 252 255 183 234 255 255 170   0   0   0   0   0
103 255 252 253 255 255 255 233 221 245 255 250 250 255 193 164 254 150   0   0   0   0   0   0
  0 206 255 255 172 175 255 255 255 253 249 249 253 255 255  62   0   0   0   0   0   0   0   0
  0  26 144  70   0   0 106 255 255 250 250 255 255 240 172  18   0   0   0   0   0   0   0   0
  0   0   0   0   0   0   8 230 255 250 255 239  77   0   0   0   0   0   0   0   0   0   0   0
  0   0   0   0   0   0   0 198 255 255 242  37   0   0   0   0   0   0   0   0   0   0   0   0
  0   0   0   0   0   0   0  67 231 204  36   0   0   0   0   0   0   0   0   0   0   0   0   0
```

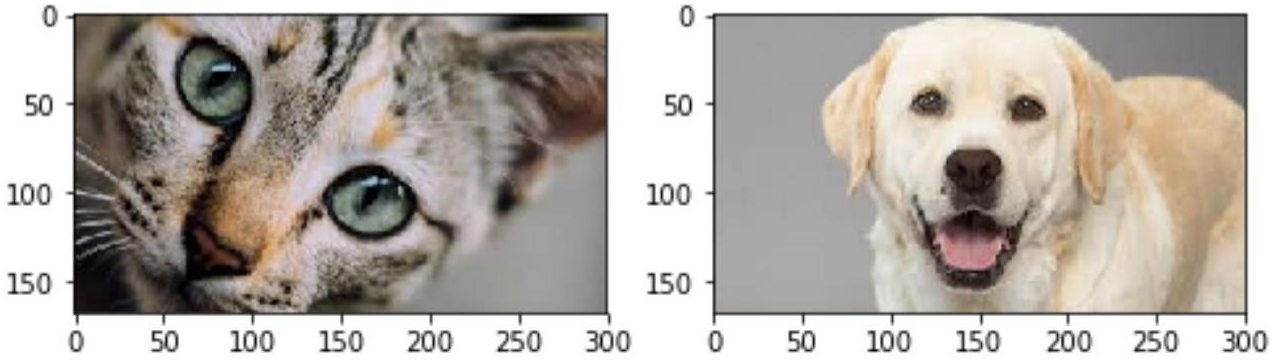
- **Consider a face image of size 200 x 200 pixels**
- **A color (RGB) image has three channels**
- **Total pixels in the image are 200 x 200 x 3**

Visualizing Image Data

Images are just n-dimensional tensors where each channel is a 2-D matrix

```
fig = plt.figure(figsize = (8,4))
ax1 = fig.add_subplot(1,2, 1)
ax1.imshow(cat)
ax2 = fig.add_subplot(1,2, 2)
ax2.imshow(dog)
```

```
<matplotlib.image.AxesImage at 0x2b3339f0908>
```

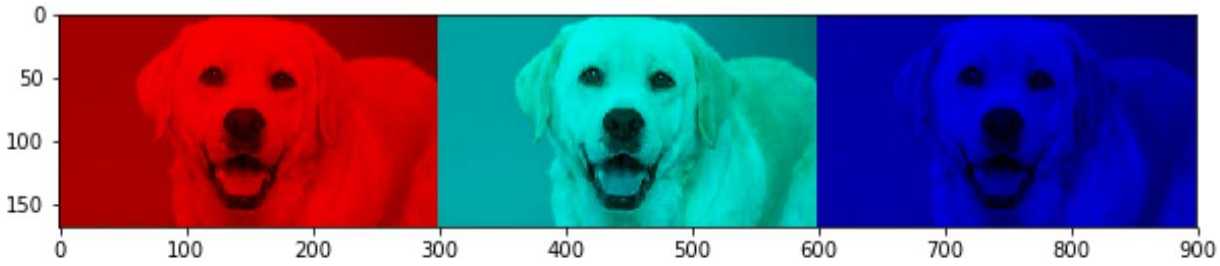


Visualizing Image Data

Images are just n-dimensional tensors where each channel is a 2-D matrix

```
dog_r = dog.copy() # Red Channel
dog_r[:,:,1] = dog_r[:,:,2] = 0 # set G,B pixels = 0
dog_g = dog.copy() # Green Channel
dog_g[:,:,0] = dog_r[:,:,2] = 0 # set R,B pixels = 0
dog_b = dog.copy() # Blue Channel
dog_b[:,:,0] = dog_b[:,:,1] = 0 # set R,G pixels = 0

plot_image = np.concatenate((dog_r, dog_g, dog_b), axis=1)
plt.figure(figsize = (10,4))
plt.imshow(plot_image)
```

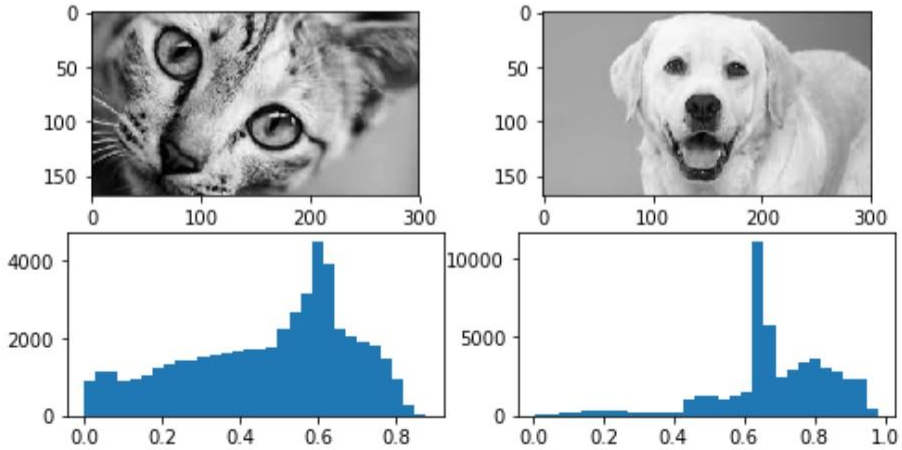
```
<matplotlib.image.AxesImage at 0x2b333b86240>
```



Visualizing Image Data

Checking image intensity distributions

```
fig = plt.figure(figsize = (8,4))
ax1 = fig.add_subplot(2,2, 1)
ax1.imshow(cgs, cmap="gray")
ax2 = fig.add_subplot(2,2, 2)
ax2.imshow(dgs, cmap='gray')
ax3 = fig.add_subplot(2,2, 3)
c_freq, c_bins, c_patches = ax3.hist(cgs.flatten(), bins=30)
ax4 = fig.add_subplot(2,2, 4)
d_freq, d_bins, d_patches = ax4.hist(dgs.flatten(), bins=30)
```

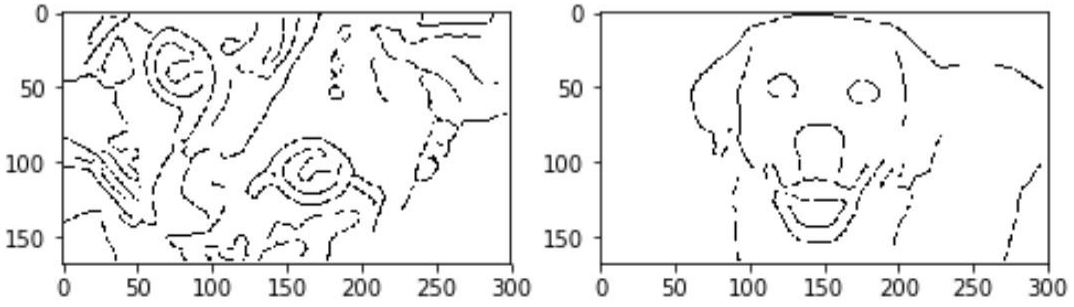


Visualizing Image Data

Basic Edge Detection

```
from skimage.feature import canny

cat_edges = canny(cgs, sigma=3)
dog_edges = canny(dgs, sigma=3)

fig = plt.figure(figsize = (8,4))
ax1 = fig.add_subplot(1,2, 1)
ax1.imshow(cat_edges, cmap='binary')
ax2 = fig.add_subplot(1,2, 2)
ax2.imshow(dog_edges, cmap='binary')
```

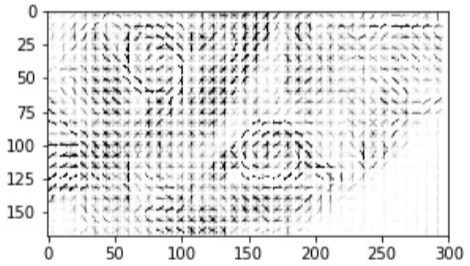
```
<matplotlib.image.AxesImage at 0x2618e15c278>
```

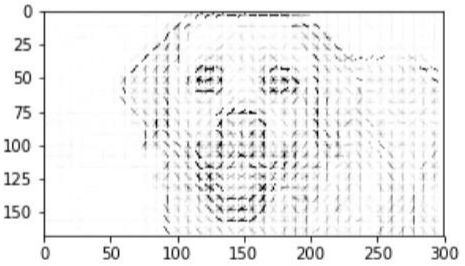


Visualizing Image Data

Histogram of Oriented Gradients - counts occurrences of gradient orientation in localized portions

```
from skimage.feature import hog
from skimage import exposure

fd_cat, cat_hog = hog(cgs, orientations=8, pixels_per_cell=(8, 8),
                      cells_per_block=(3, 3), visualise=True)
fd_dog, dog_hog = hog(dgs, orientations=8, pixels_per_cell=(8, 8),
                      cells_per_block=(3, 3), visualise=True)

# rescaling intensity to get better plots
cat_hogs = exposure.rescale_intensity(cat_hog, in_range=(0, 0.04))
dog_hogs = exposure.rescale_intensity(dog_hog, in_range=(0, 0.04))

fig = plt.figure(figsize = (10,4))
ax1 = fig.add_subplot(1,2, 1)
ax1.imshow(cat_hogs, cmap='binary')
ax2 = fig.add_subplot(1,2, 2)
ax2.imshow(dog_hogs, cmap='binary')
```



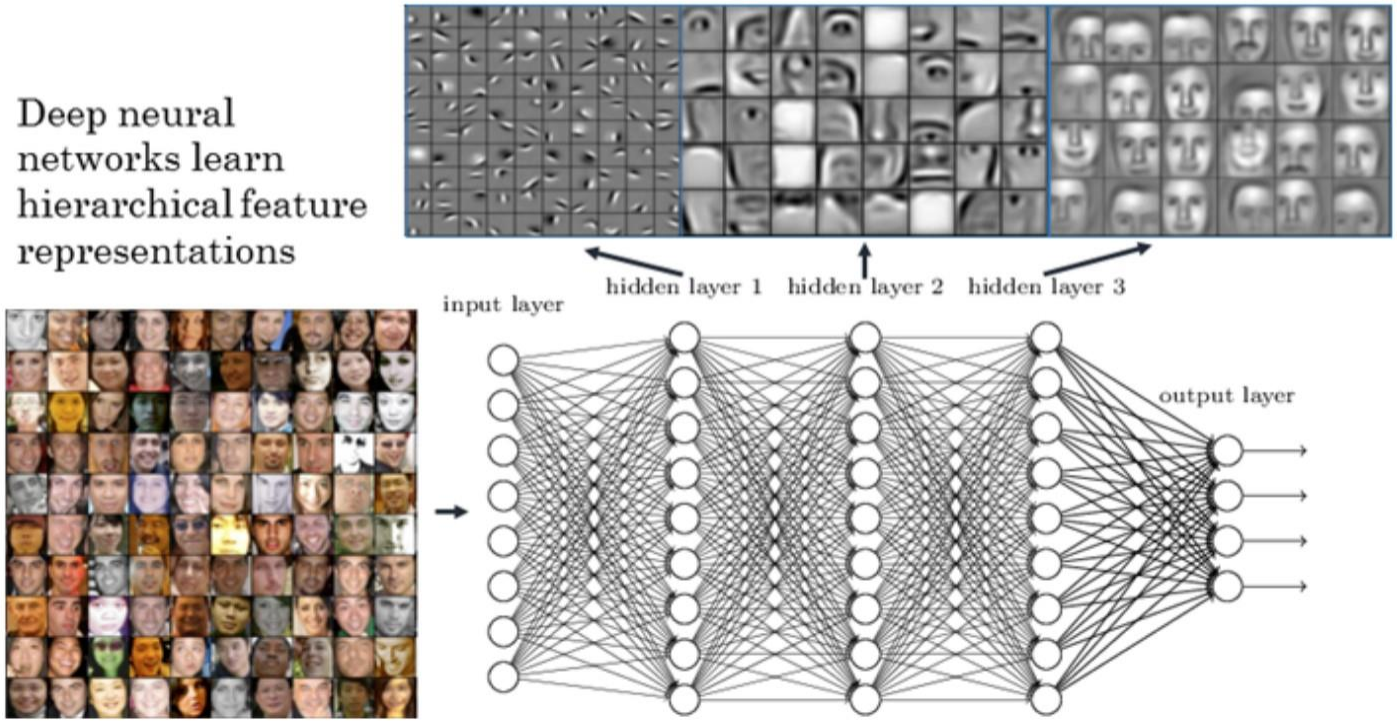



```
print(fd_cat, fd_cat.shape)
```

```
[ 0.00288784  0.00301086  0.0255757  ...,  0.         0.         0.        ] (47880,)
```

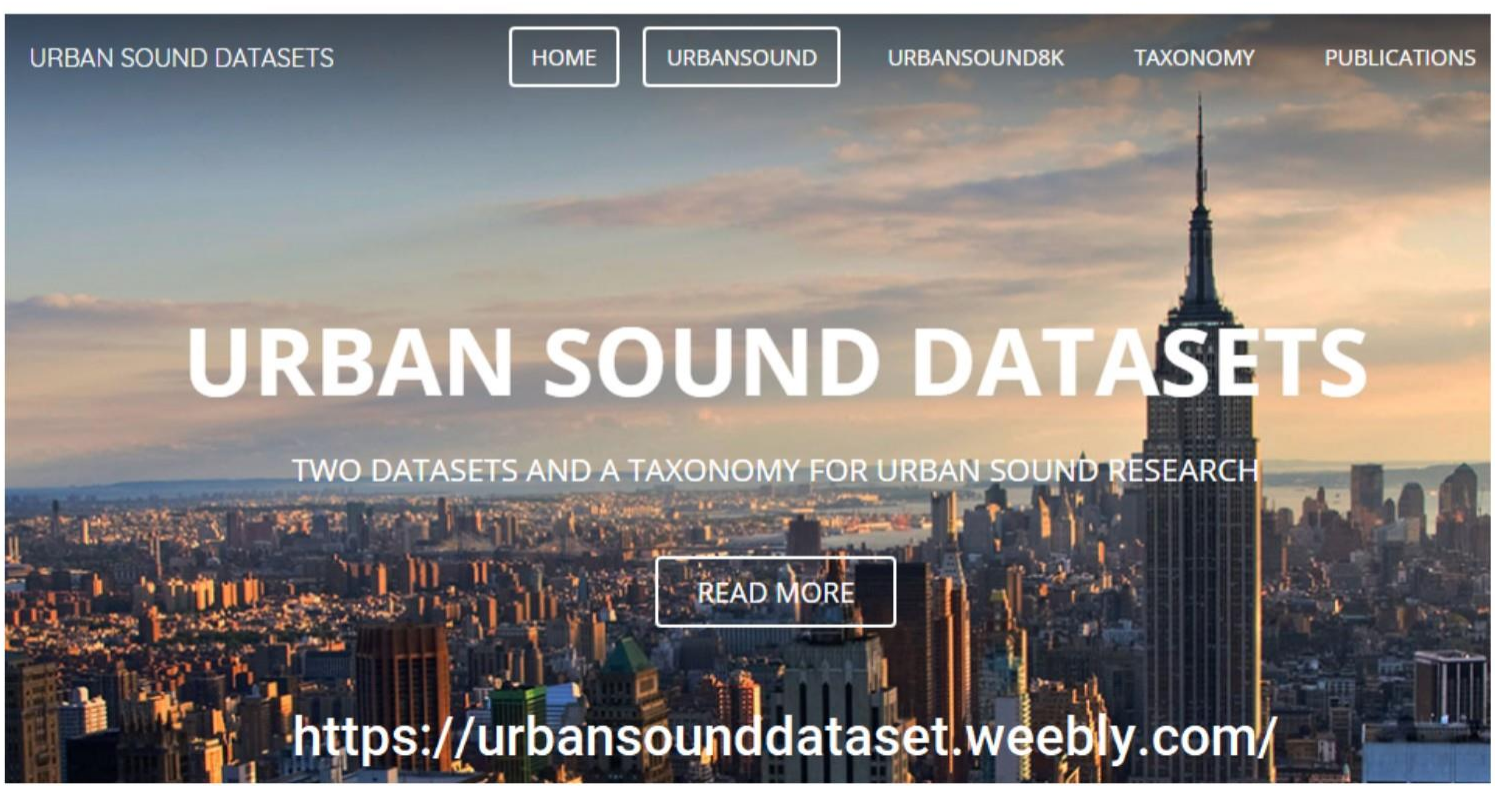
Visualizing Image Data - CNNs changed the world!

Automated image representation with deep learning



Visualizing Audio Data - Can you see what you hear?

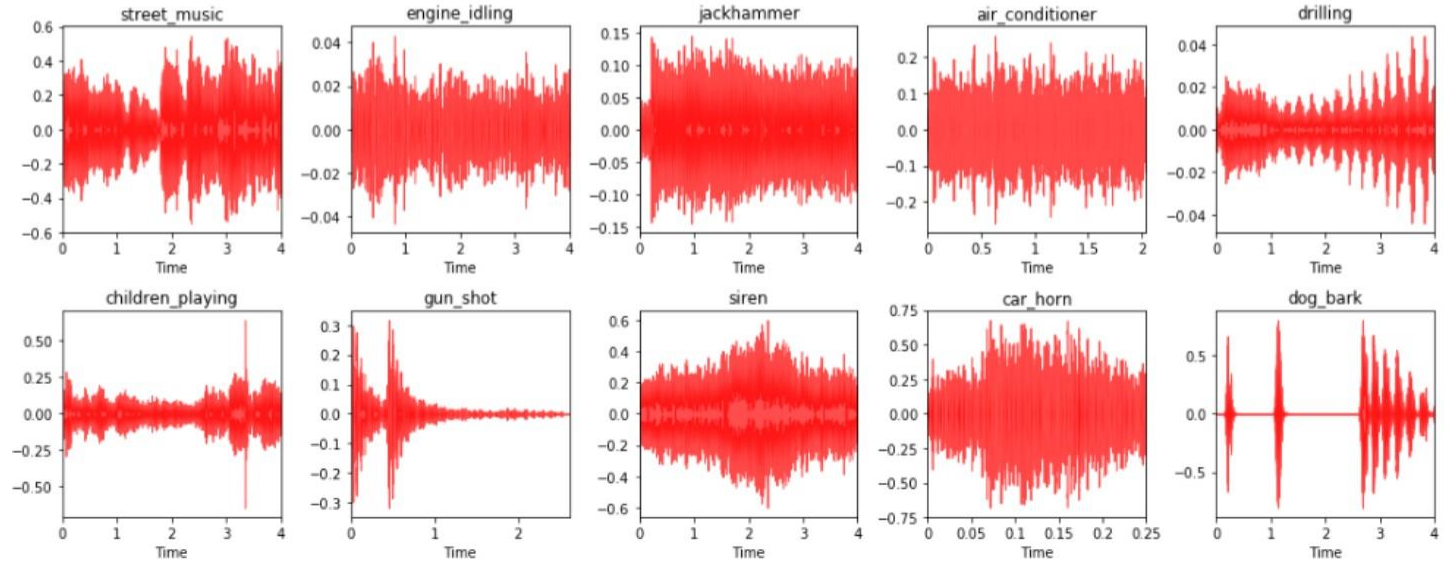
Audio data can be represented based on the synthesized signals



Visualizing Audio Data - Can you see what you hear?

Visualizing audio with wave\amp plots

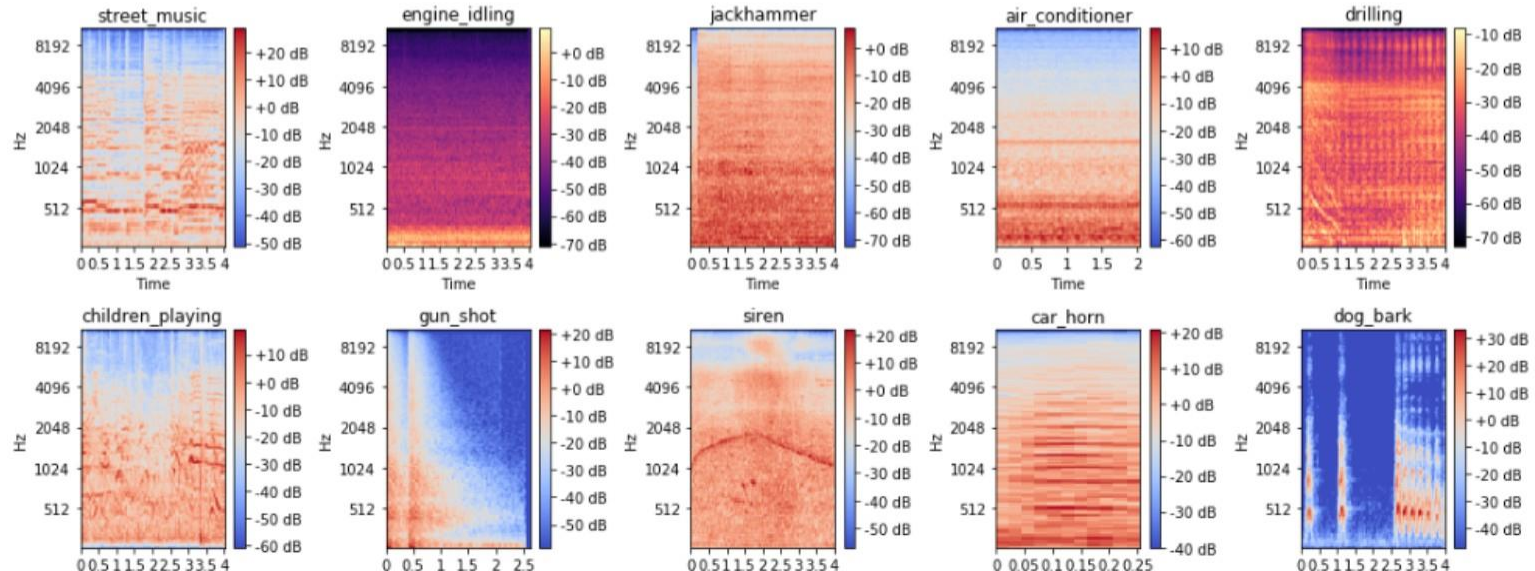
```
i = 1
fig = plt.figure(figsize=(15, 6))
for item in sample_data:
    plt.subplot(2, 5, i)
    librosa.display.waveplot(item[1][0], sr=item[1][1], color='r', alpha=0.7)
    plt.title(item[0])
    i += 1
plt.tight_layout()
```



Visualizing Audio Data - Can you see what you hear?

Visualizing audio with mel-spectrograms

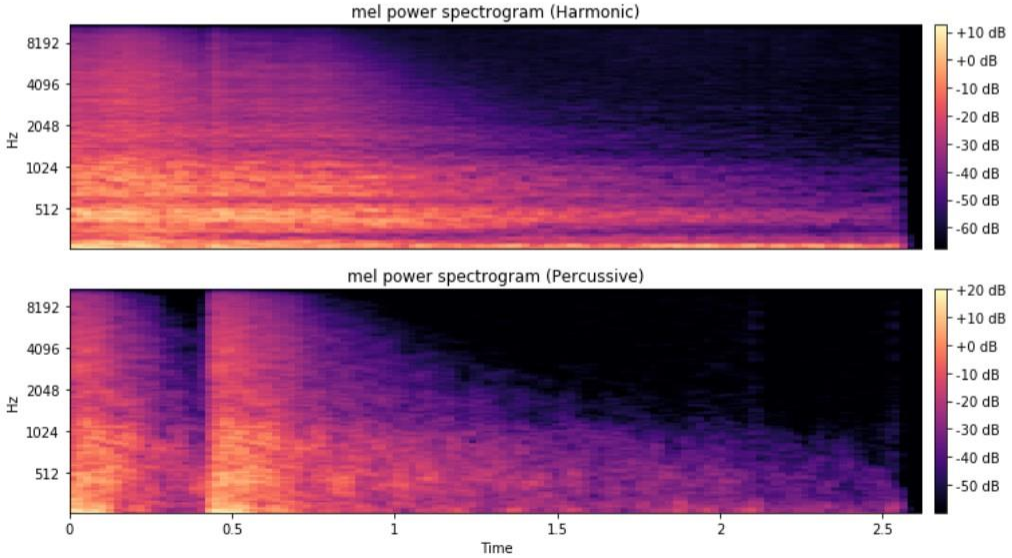
```
    plt.subplot(2, 5, i)
    S = librosa.feature.melspectrogram(item[1][0], sr=item[1][1], n_mels=128)
    log_S = librosa.logamplitude(S)
    librosa.display.specshow(log_S, sr=item[1][1], x_axis='time', y_axis='mel')
    plt.title(item[0])
    plt.colorbar(format='%+02.0f dB')
    i += 1
plt.tight_layout()
```



Visualizing Audio Data - Can you see what you hear?

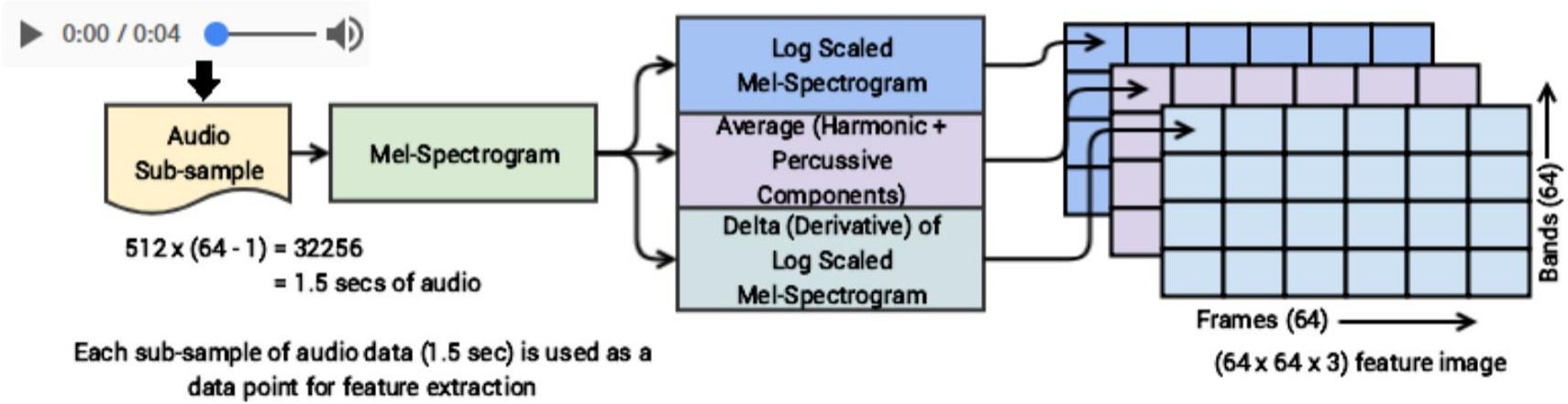
Visualizing audio with spectrograms from harmonic & percussive components

```
y_harmonic, y_percussive = librosa.effects.hpss(y)
S_harmonic   = librosa.feature.melspectrogram(y_harmonic, sr=22050,
                                              n_mels=128)
S_percussive = librosa.feature.melspectrogram(y_percussive, sr=22050)
log_Sh = librosa.power_to_db(S_harmonic)
log_Sp = librosa.power_to_db(S_percussive)

# Make a new figure
plt.figure(figsize=(12,6))

plt.subplot(2,1,1)
librosa.display.specshow(log_Sh, sr=sr, y_axis='mel')
plt.title('mel power spectrogram (Harmonic)')
plt.colorbar(format='%+02.0f dB')

plt.subplot(2,1,2)
librosa.display.specshow(log_Sp, sr=sr, x_axis='time',
                         y_axis='mel')
plt.title('mel power spectrogram (Percussive)')
plt.colorbar(format='%+02.0f dB')
plt.tight_layout()
```



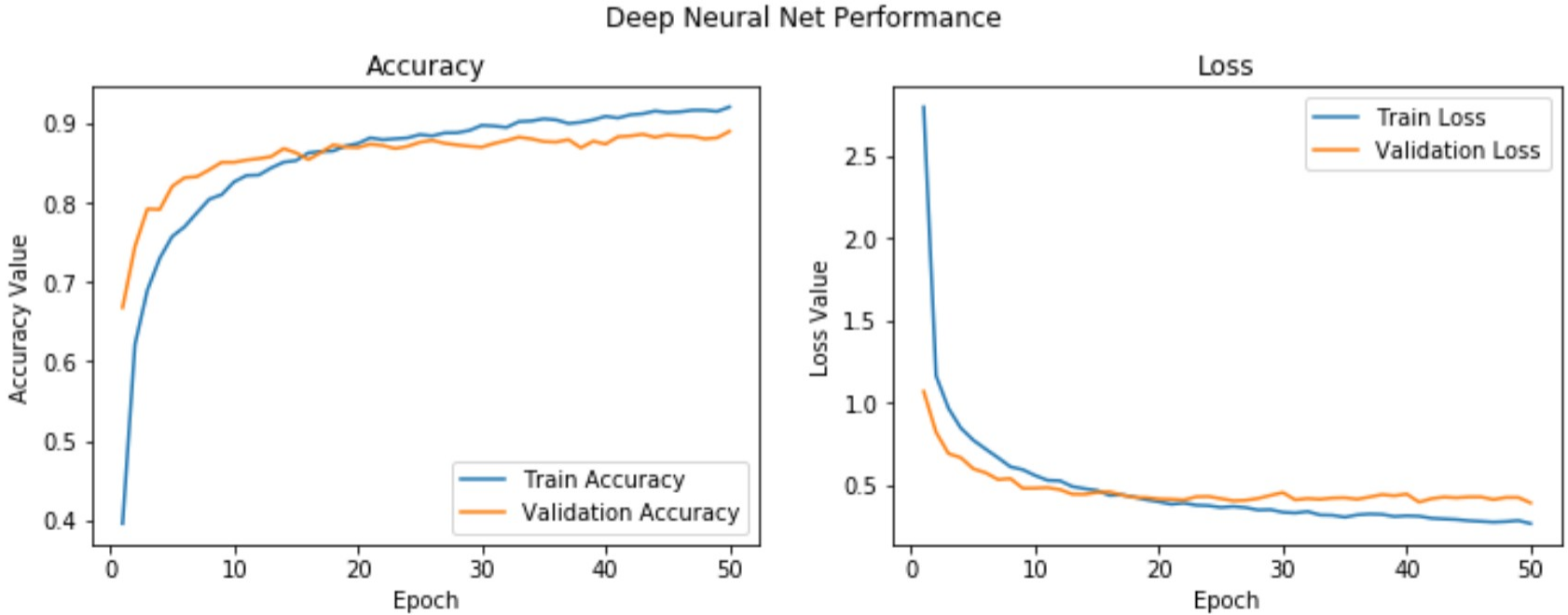
Visualizing Audio Data - Why we do it?

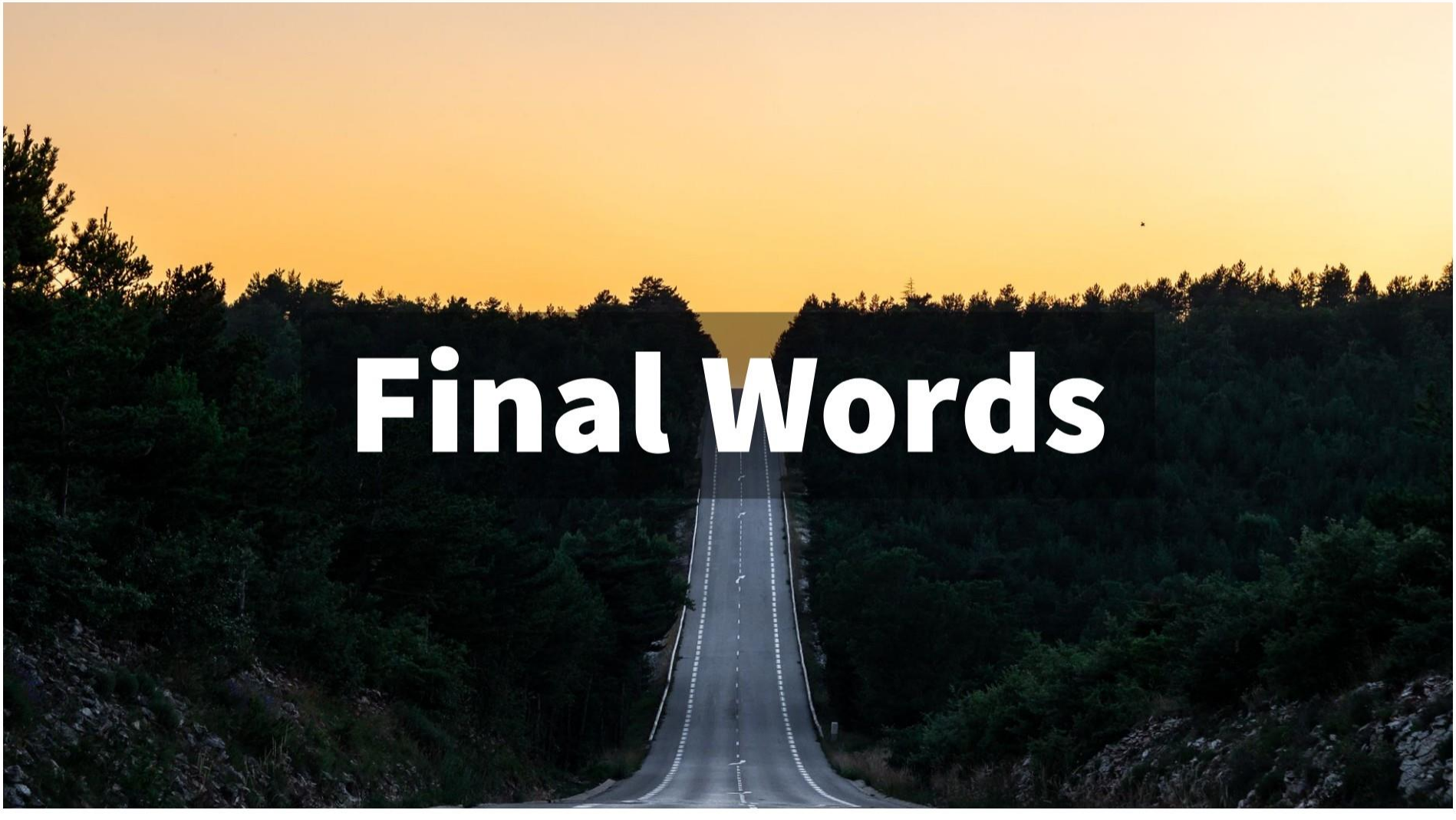
Visual depiction & Feature engineering for Deep Learning Models



Visualizing Audio Data - Why we do it?

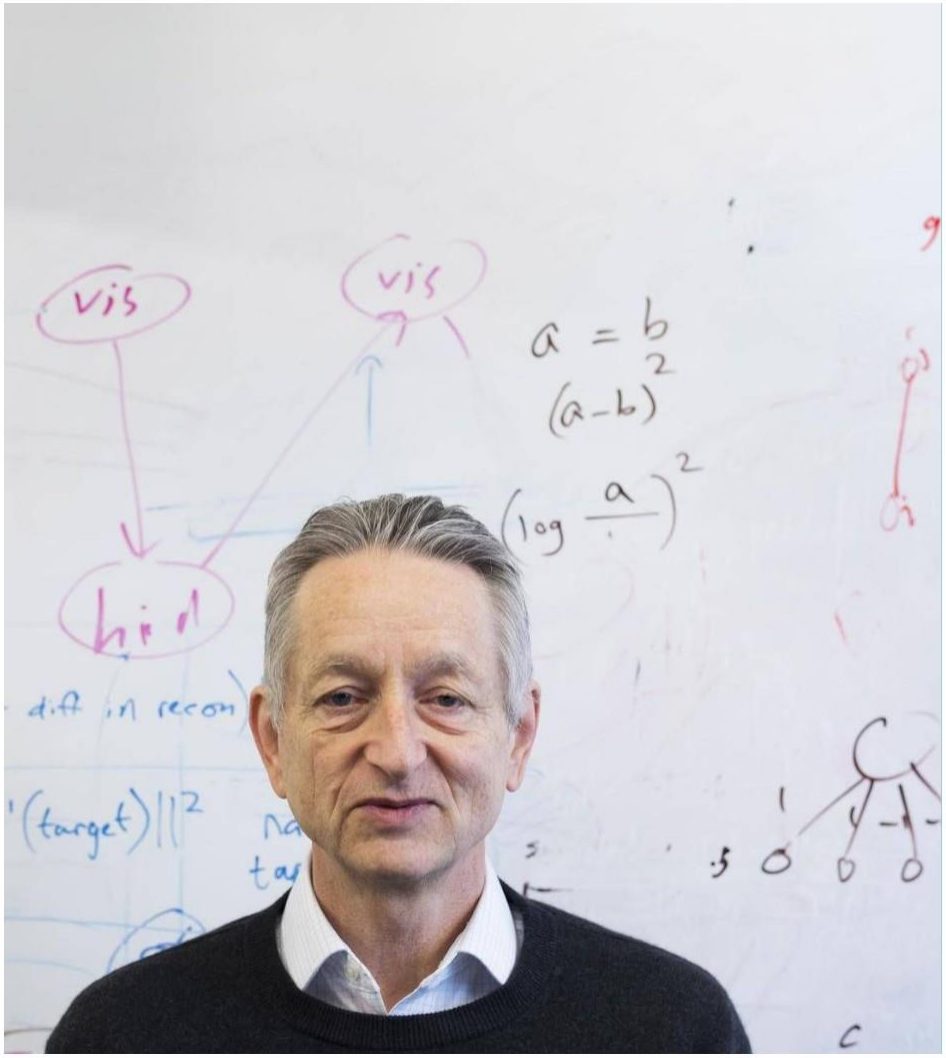
Audio Classification with audio data + pre-trained image models (e.g VGG\Inception)




Final Words

What if we have a lot of features?

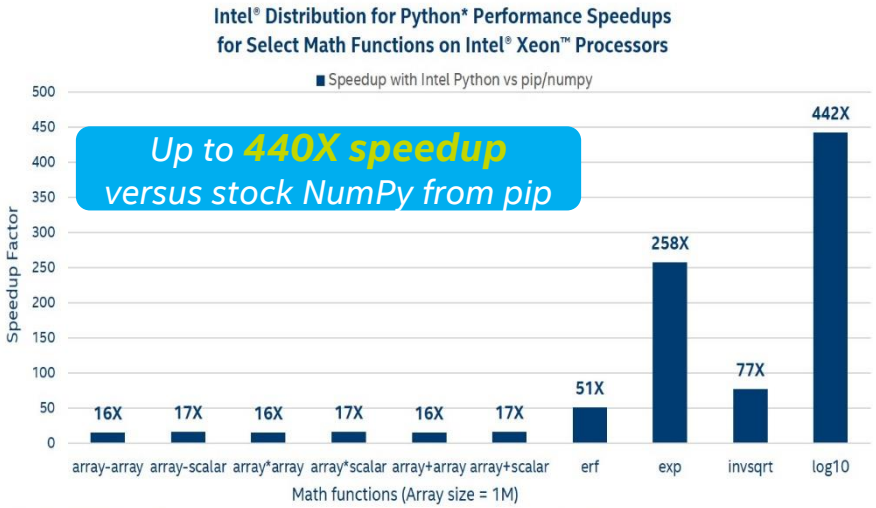
- Use domain expertise to focus on important features
- Use modeling to get the most important features and visualize to see if they really make sense
- Dimension reduction techniques including PCA, SVD, t-SNE
- Remember to scale features and remove outliers as needed



“If you want to visualize 17 dimensions, visualize 3 dimensions and say 17 over and over again. That's how everybody does it.”

-Geoffrey Hinton

Faster Python* with Intel® Distribution for Python 2018



Configuration: Hardware: Intel® Xeon® CPU E5-2699 v4 @ 2.20GHz (2 sockets, 22 cores per socket, 1 thread per core – HT is off), 256GB DDR4 @ 2400MHz.
Software: Stock: CentOS Linux release 7.3.1611 (Core), python 3.6.2, pip 9.0.1, numpy 1.13.1, scipy 0.19.1, scikit-learn 0.19.0. Intel® Distribution for Python* 2018 Gold: mkl 2018.0.0 intel_4, daal 2018.0.0.20170814, numpy 1.13.1 py36_intel_15, openmp 2018.0.0 intel_7, scipy 0.19.1 np113py36_intel_11, scikit-learn 0.18.2 np113py36_intel_3

Software and workloads used in performance tests may have been optimized for performance only on Intel microprocessors. Performance tests, such as SYSmark and MobileMark, are measured using specific computer systems, components, software, operations and functions. Any change to any of those factors may cause the results to vary. You should consult other information and performance tests to assist you in fully evaluating your contemplated purchases, including the performance of that product when combined with other products. For more information go to http://www.intel.com/performance. Benchmark Source: Intel Corporation.
Optimization Notice: Intel's compilers may or may not optimize to the same degree for non-Intel microprocessors for optimizations that are not unique to Intel microprocessors. These optimizations include SSE2, SSE3, and SSSE3 instruction sets and other optimizations. Intel does not guarantee the availability, functionality, or effectiveness of any optimization on microprocessors not manufactured by Intel. Microprocessor-dependent optimizations in this product are intended for use with Intel microprocessors. Certain optimizations not specific to Intel microarchitecture are reserved for Intel microprocessors. Please refer to the applicable product User and Reference Guides for more information regarding the specific instruction sets covered by this notice. Notice revision #20110804. *Other brands and names are the property of their respective owners.

Learn More: software.intel.com/distribution-for-python

High Performance Python Distribution

- Accelerated NumPy, SciPy, scikit-learn well suited for scientific computing, machine learning & data analytics
- Drop-in replacement for existing Python. No code changes required
- Highly optimized for latest Intel processors
- Take advantage of Priority Support – connect direct to Intel engineers for technical questions[2]

What's New in 2018 version

- Updated to latest version of Python 3.6
- Optimized scikit-learn for machine learning speedups
- Conda build recipes for custom infrastructure

Software & workloads used in performance tests may have been optimized for performance only on Intel microprocessors. Performance tests, such as SYSmark & MobileMark, are measured using specific computer systems, components, software, operations & functions. Any change to any of those factors may cause the results to vary. You should consult other information & performance tests to assist you in fully evaluating your contemplated purchases, including the performance of that product when combined with other products. For more information go to http://www.intel.com/performance.

[2]Paid versions only.

Installing Intel® Distribution for Python* 2018

Standalone Installer

Download full installer from
https://software.intel.com/en-us/intel-distribution-for-python

Anaconda.org
Anaconda.org/intel channel

```
> conda config --add channels intel
> conda install intelpython3_full
> conda install intelpython3_core
```

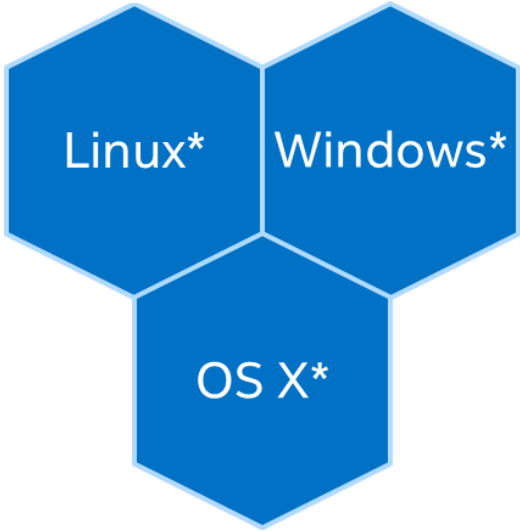
Docker Hub

```
docker pull intelpython/intelpython3_full
```

YUM/APT

Access for yum/apt:
https://software.intel.com/en-us/articles/installing-intel-free-libs-and-python

2.7 & 3.6



References and Content

- **Article Links**

  https://towardsdatascience.com/the-art-of-effective-visualization-of-multi-dimensional-data-6c7202990c57

  https://towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa

  https://towardsdatascience.com/a-practitioners-guide-to-natural-language-processing-part-i-processing-understanding-text-9f4abfd13e72

- **Papers**

  http://vita.had.co.nz/papers/layered-grammar.pdf

- **Code & Examples**

  https://github.com/dipanjanS/art_of_data_visualization

  https://seaborn.pydata.org/

  https://plotnine.readthedocs.io/en/stable/

  https://github.com/d3/d3/wiki/Gallery

GET THE SLIDES AND CODE HERE

http://bit.ly/odsc_india_ds

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