



# DSCI 554 LECTURE 9

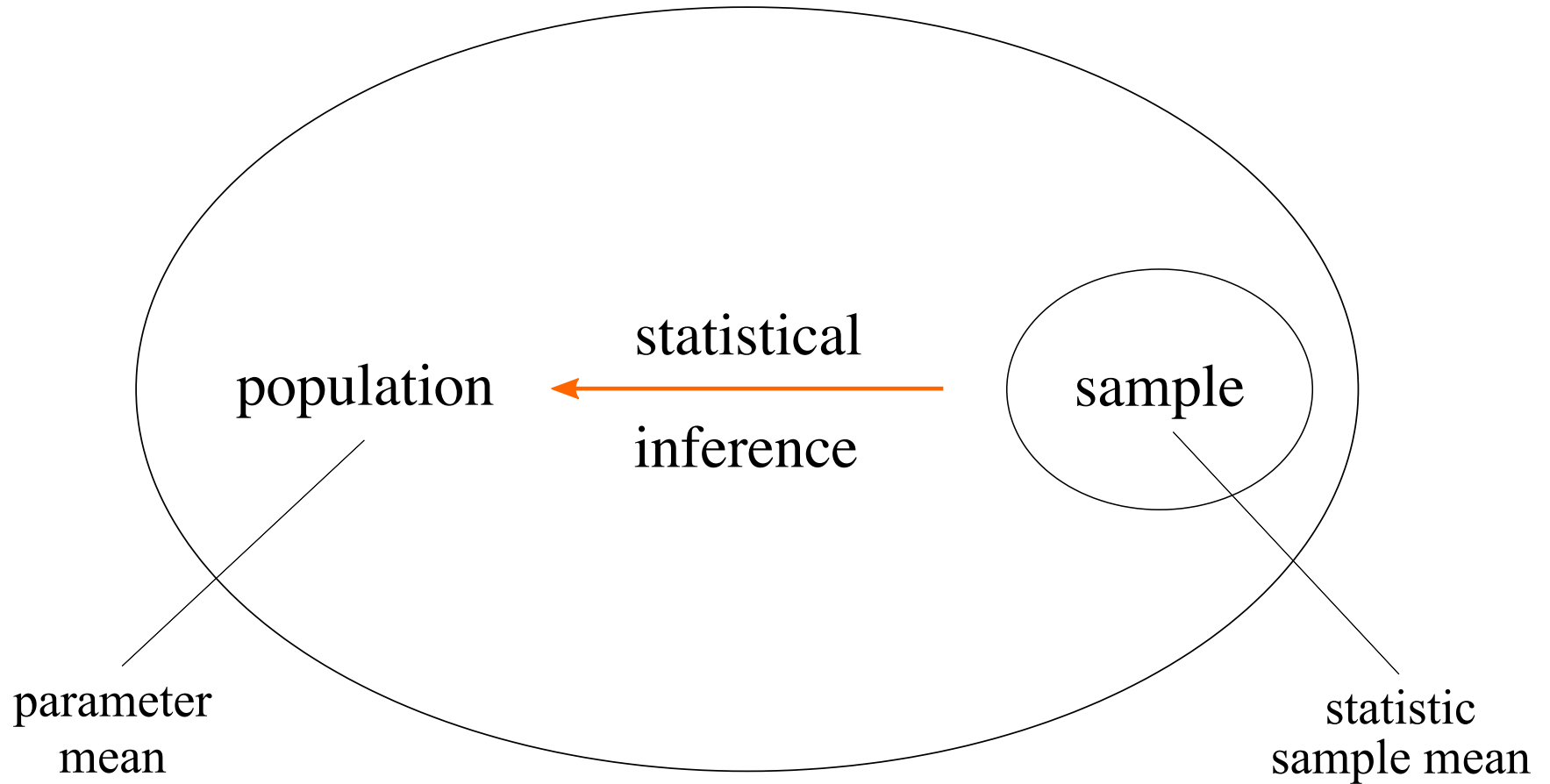
## STATISTICS REVIEW, STATISTICAL GRAPHICS

Dr. Luciano Nocera

# OUTLINE

- Basics of statistics and modeling
- Statistical graphics
- Tools

# STATISTICS



# TYPES OF STATISTICS

- **Descriptive statistics:** summarize the data, i.e. one number stands for a group of numbers

Examples: mean, median, SD

- **Inferential statistics:** infer (model) population data from sample data

Examples: hypothesis testing, regression analysis

# DATA NOMENCLATURE

	ML	Stats
Observations	Samples	Cases
Attribute	Feature	Independent variable
Class	Label	Dependent variable

# INDEPENDENT VS. DEPENDENT VARIABLES

Statistics

dependent variable =  $f(\text{independent variables})$

---

Machine learning

label =  $f(\text{features})$

# INDEPENDENT AND DEPENDENT VARIABLES EXAMPLES

Height depends on age

---

Time spent studying affects test score

---

Medication in persons with Parkinson's Disease  
affects the SD of the step length

# MEASURES OF ORDER

**$K^{\text{th}}$  order statistic:** value at position  $k$  in ordered data

**Range:** range of values

**Modes/peaks:** most frequent values

$$\text{data} = [X_1, \dots, X_N] = [0, 1, 1, 2, 2, 3, 4, 15]$$

$$1^{\text{st}} \text{ order: } X_1 = \min(X_1, \dots, X_N) = 0$$

$$N^{\text{st}} \text{ order: } X_N = \max(X_1, \dots, X_N) = 15$$

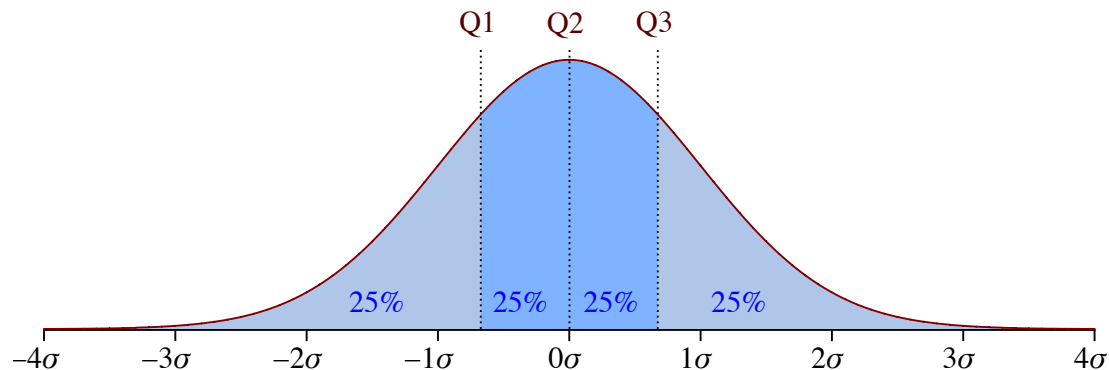
$$\text{range: } X_N - X_1 = 15$$

$$\text{modes: } \{1, 2\}$$



# QUANTILES

- **q-quantiles** divide the observations in  $q$  groups using  $q - 1$  values
- **Quartiles** divide the observations in 4 groups using 3 values:
  - $Q_1$ : 25% at or below and 75% above
  - $Q_2$ : 50% at or below and 50% above (median)
  - $Q_3$ : 75% at or below and 25% above



Quartiles in a normal distribution [ArkOn derivative work: Gato ocioso]

`data = [0, 1, 1, 2, 2, 3, 4, 15]`

$Q_1 = 1, Q_2 = 2, Q_3 = 3.25$

Example based on SciPy formulation:  $N = 8$  with  $N+1$  parts.  $k$ -th  $q$ -quantile:  $p = k/q, h = (N + 1)p,$   
 $x[h] + (h - [h])(x[h] + 1 - x[h])$

# MEASURES OF CENTRAL TENDENCY

**Median:** value in the middle

**Mean:** sum divided by N

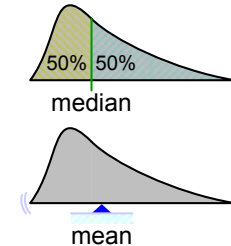
$$\mu = \bar{X} = \sum_{i=1}^N \frac{X_i}{N}$$

**Standard deviation:** dispersion

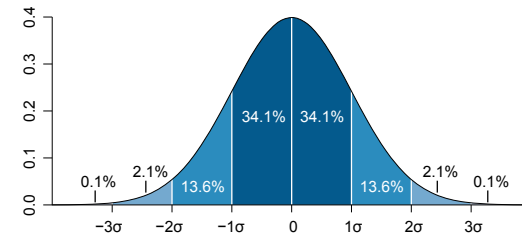
$$\sigma = \sqrt{\frac{1}{N-1} \sum_i (X_i - \bar{X})^2}$$

**Variance:** variation around the mean

$$\sigma^2$$



Median and mean (adapted from Cmglee - Own work)



Normal distribution with bands of 1  $\sigma$  (M. W. Toews - Own work)

data = [0, 1, 1, 2, 2, 3, 4, 15]

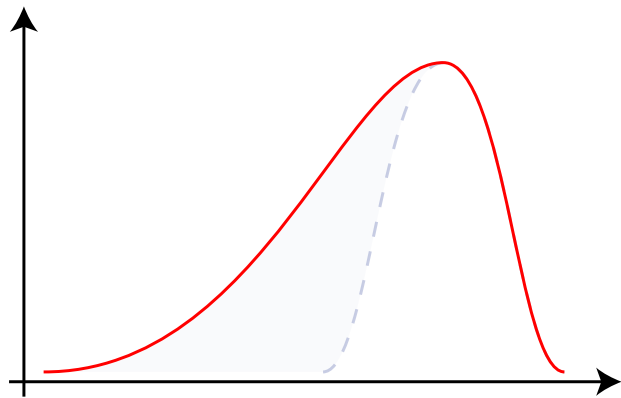
median:  $\tilde{X} = 2$

mean:  $\bar{X} = 3.5$

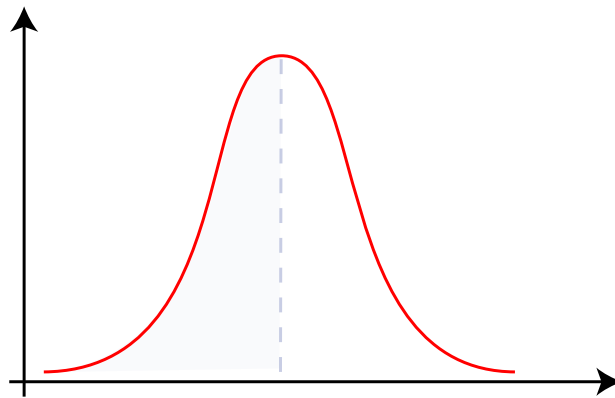
standard deviation:  $\sigma = 4.810702$

variance:  $\sigma^2 = 23.142857$

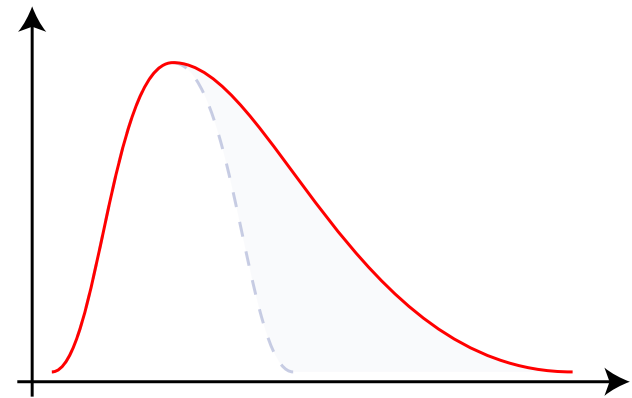
# SKEWNESS



negative skew  
left-skewed  
left-tailed  
skewed to the left



0 skewness  
symmetric



positive skew  
right-skewed  
right-tailed  
skewed to the right

# FREQUENCY & RELATIVE FREQUENCY

**Frequency:** times event  $i$  occurs

$$n_i$$

**Relative frequency:** frequency normalized

$$f_i = \frac{n_i}{N}$$

$$\text{with } N = \sum_{k=1}^K n_k$$

$$\text{data} = [A, B, B, A, C, A, C, A]$$

$$n_A = 4, n_B = 2, n_C = 2$$

$$f_A = \frac{4}{8} = 0.5, f_B = \frac{2}{8} = 0.25, f_C = \frac{2}{8} = 0.25$$

$$N = n_A + n_B + n_C = 4 + 2 + 2 = 8$$

# STATISTICS BY DATA TYPE

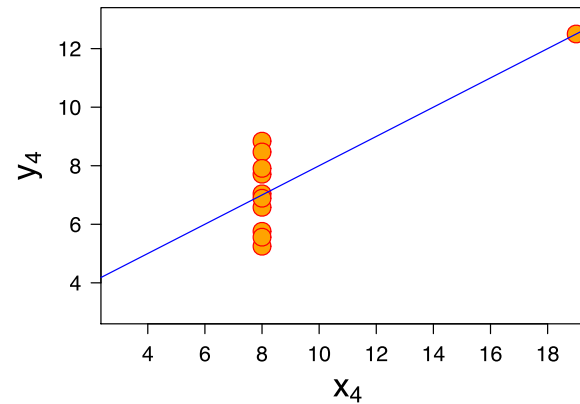
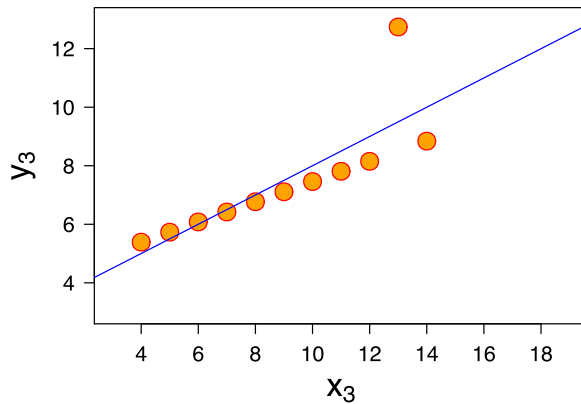
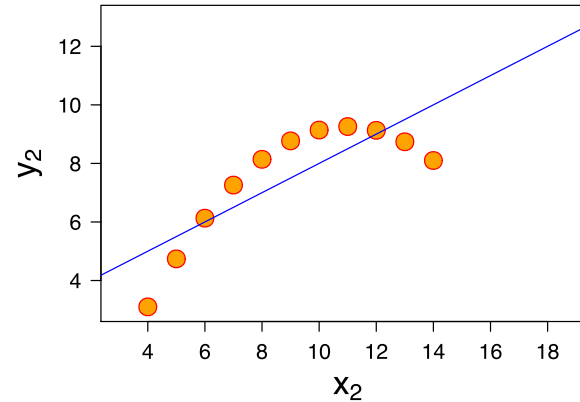
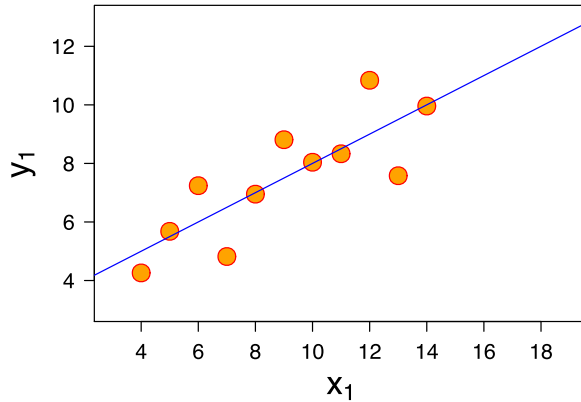
	Nominal	Ordinal	Interval	Ratio
Frequency	Yes	Yes	Yes	Yes
Median and percentile	No	Yes	Yes	Yes
Mean, SD, SEM <sup>*</sup>	No	No	Yes	Yes
Ratio, rate of variation	No	No	No	Yes

<sup>\*</sup> standard error of the mean (SEM):  $\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{N}}$

# OUTLINE

- Basics of statistics and modeling
- Statistical graphics
- Tools

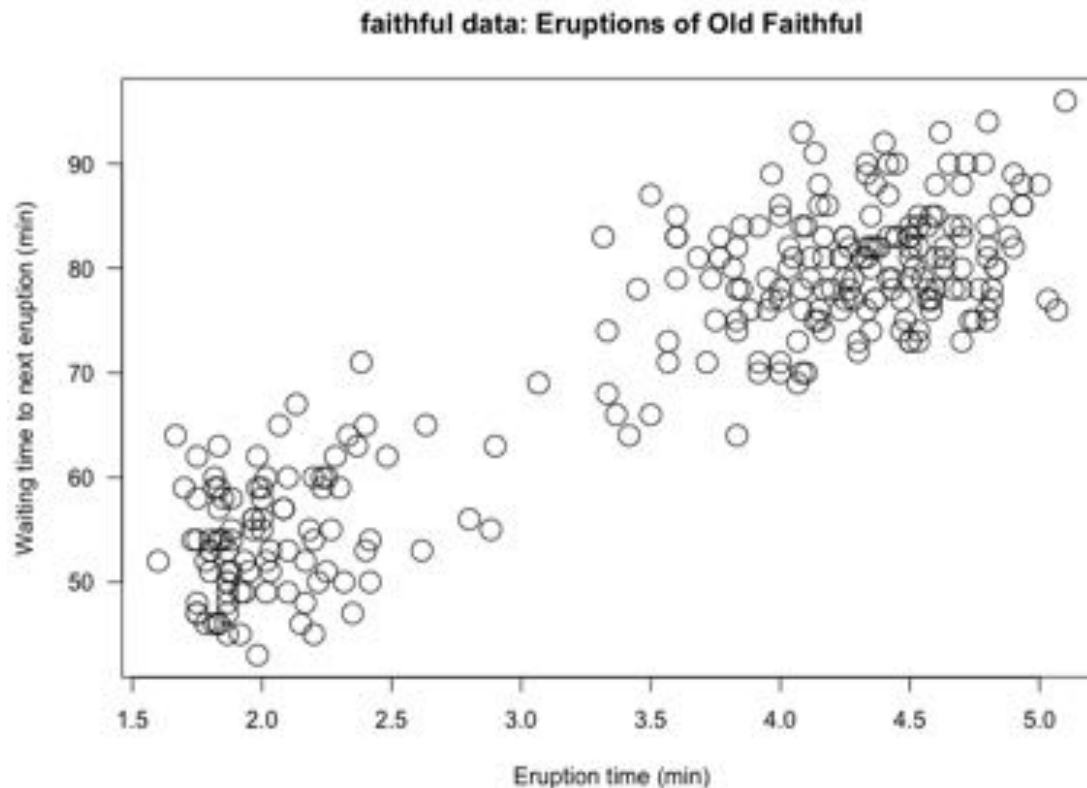
# IMPORTANCE OF GRAPHING



Anscombe's quartet [Anscombe73] showing the importance of graphing before analysis

# SCATTERPLOT

Shows distribution modes, skewness, outliers



Waiting time between eruptions and the duration of the eruption for the Old Faithful Geyser in Yellowstone National Park, Wyoming, USA.

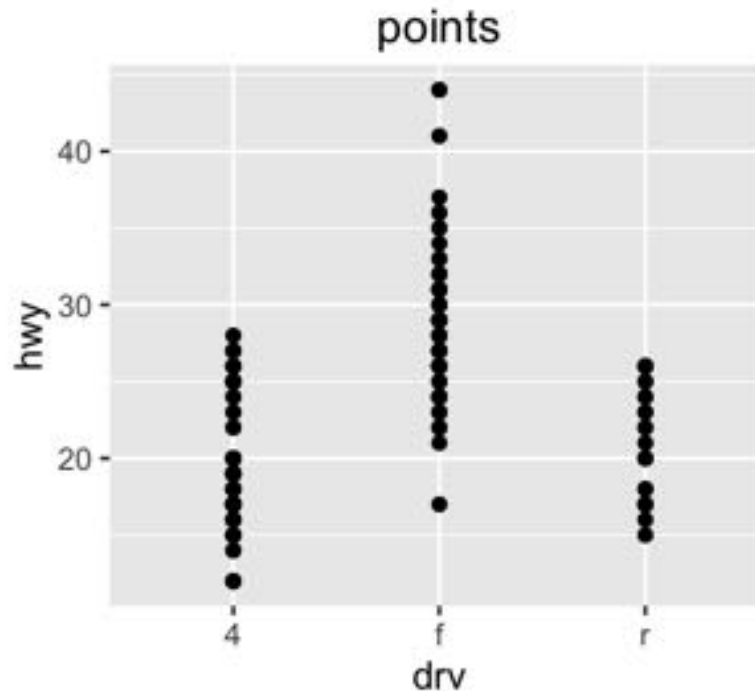


The chart suggests there are two "types" of eruptions: short-wait-short-duration, and long-wait-long-duration.



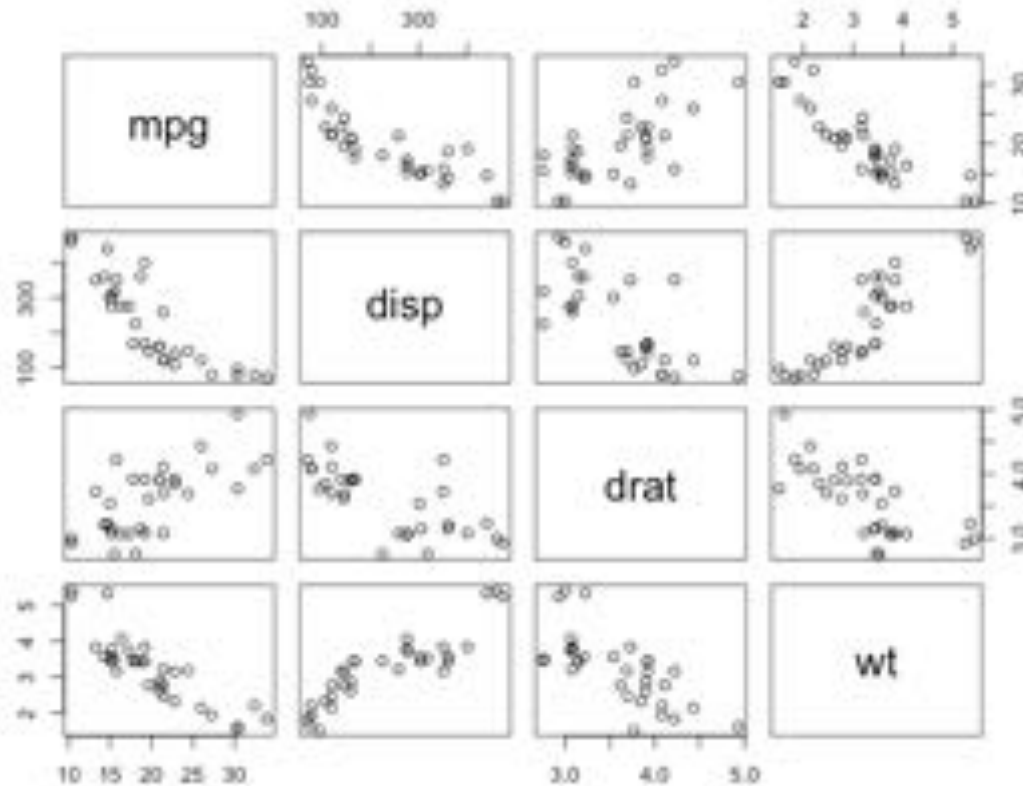
# STRIPCHART (1D SCATTERPLOT)

Useful for comparing across categories



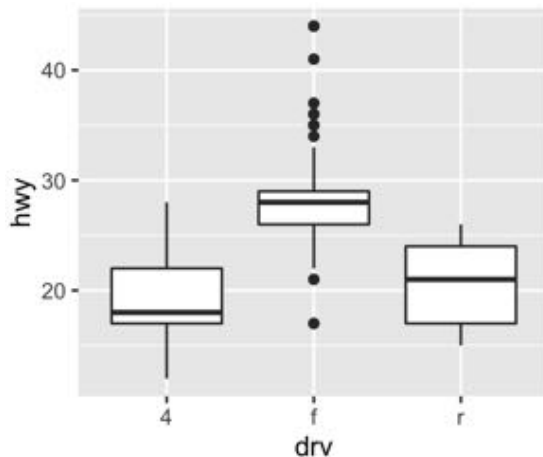
# SCATTERPLOT MATRIX

Scatterplots of multivariate data

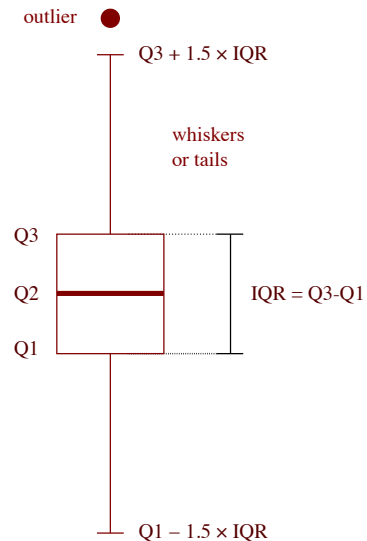


# BOX-AND-WHISKER PLOT [TUCKEY 1969]

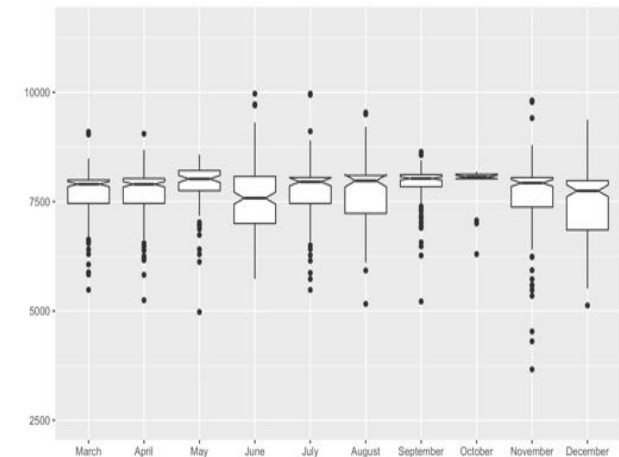
Boxplots visualize quartiles, distribution skewness, tails, outliers in unimodal distributions



Boxplots



Boxplot description



Boxplots with notches

# FREQUENCY DISTRIBUTION TABLE

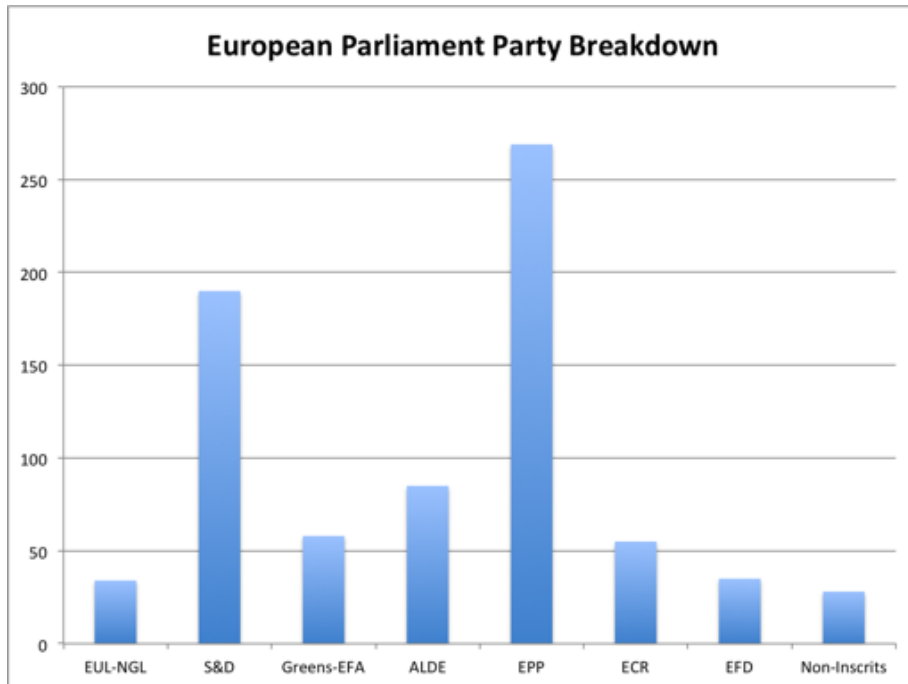
Often shown with ordered data, relative frequency and cumulative frequency.

Chol. (mg/dl)	No.	Rel. Freq.	Cum. Freq.
80-119	13	1.2	1.2
120-159	150	14.1	15.3
160-199	442	41.4	56.7
200-239	299	28.0	84.7
240-279	115	10.8	95.5
280-319	34	3.2	98.7
320-359	9	0.8	99.5
360-399	5	0.5	100.0

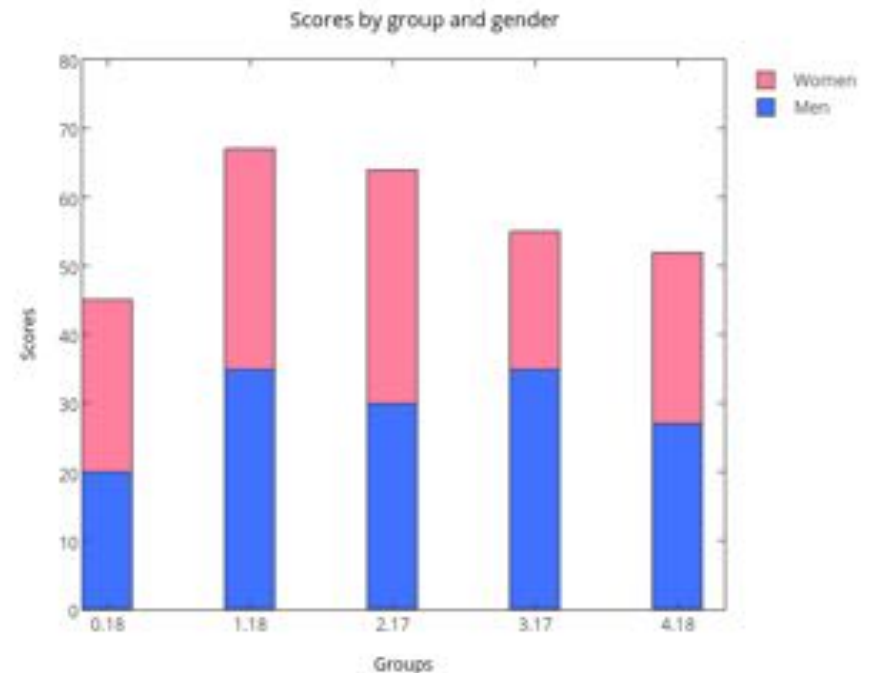
Frequencies of serum cholesterol levels for 1,067 US males, 25-34 years, 1976-80

# BAR CHARTS OF FREQUENCIES

Bars separation used to imply discontinuity



Bars for groups



Stacked bars for subgroups

# STEM-AND-LEAF PLOT

Shows the data and the data distribution

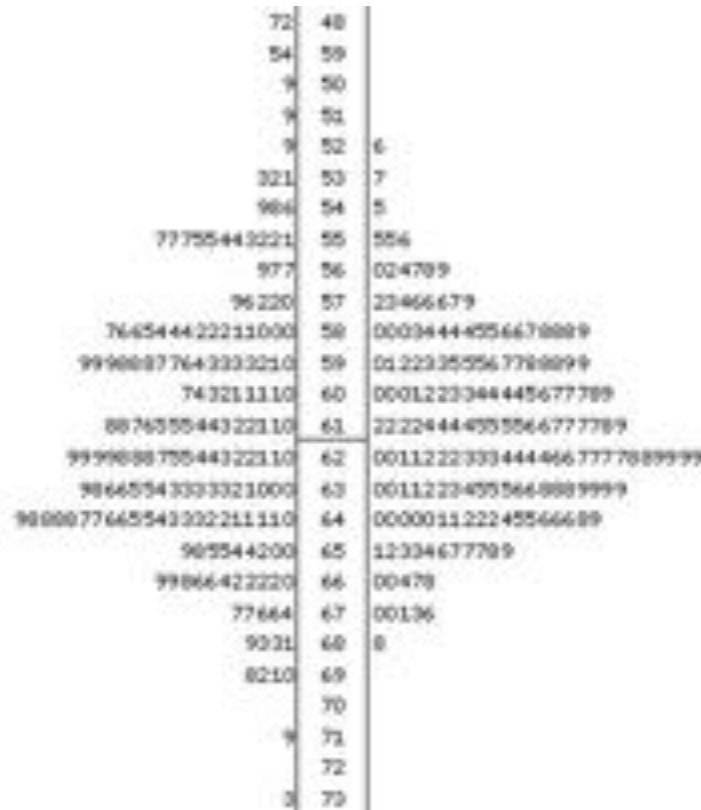


Figure 2. Distribution of cerebellar weights in the F2 intercross as illustrated by stem-and-leaf plots. The values on the left are the observed values, those on the right reflect correction by regression for brain weight. The mean for both distributions is marked by a horizontal line. Airey DC, Lu L, Williams RW Genetic control of the mouse cerebellum: identification of quantitative trait loci modulating size and architecture. J Neuroscience, 2001.

# BUILDING A STEM-AND-LEAF PLOT

73, 42, 67, 78, 99, 84, 91, 82, 86, 122

# BUILDING A STEM-AND-LEAF PLOT

73, 42, 67, 78, 99, 84, 91, 82, 86, 122

## 1. Order in ascending order

42, 67, 73, 78, 82, 84, 86, 91, 99, 122



# BUILDING A STEM-AND-LEAF PLOT

73, 42, 67, 78, 99, 84, 91, 82, 86, 122

1. Order in ascending order

42, 67, 73, 78, 82, 84, 86, 91, 99, 122

2. Select **stem** and **leaf**

42, 67, 73, 78, 82, 84, 86, 91, 99, 122

# BUILDING A STEM-AND-LEAF PLOT

73, 42, 67, 78, 99, 84, 91, 82, 86, 122

1. Order in ascending order

42, 67, 73, 78, 82, 84, 86, 91, 99, 122

2. Select **stem** and **leaf**

42, 67, 73, 78, 82, 84, 86, 91, 99, 122

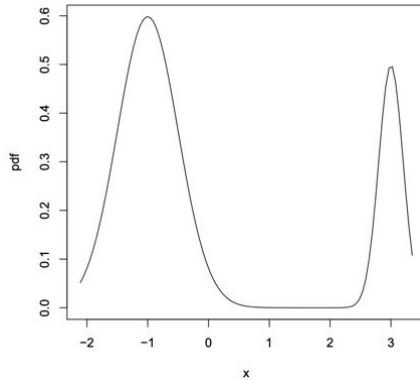
3. Plot

4		2
5		
6		7
7		38
8		246
9		19
10		
11		
12		2

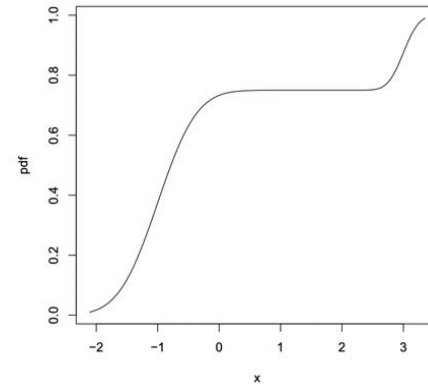
4		2
6		738
8		24619
10		
12		2

Half the size

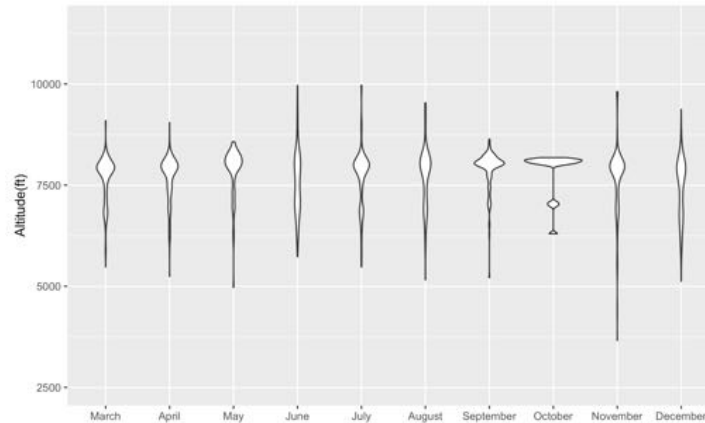
# PDF & CDF PLOTS



Probability density plot



Cumulative density plot

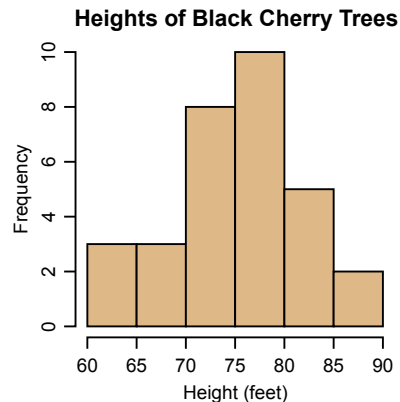


Violin plot: mirrored probability density plot

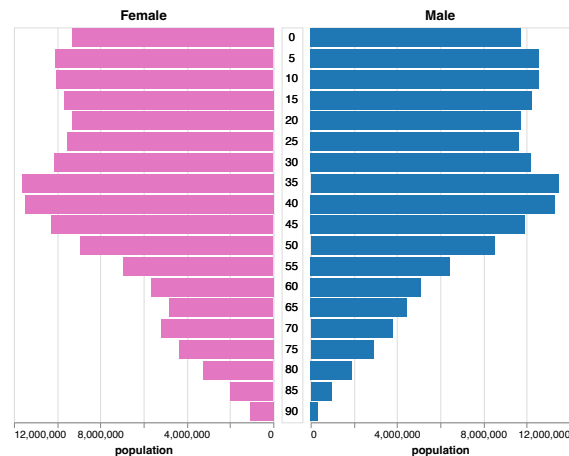
# HISTOGRAM AND FREQUENCY POLYGON

Shows skewness, modes, tails, outliers

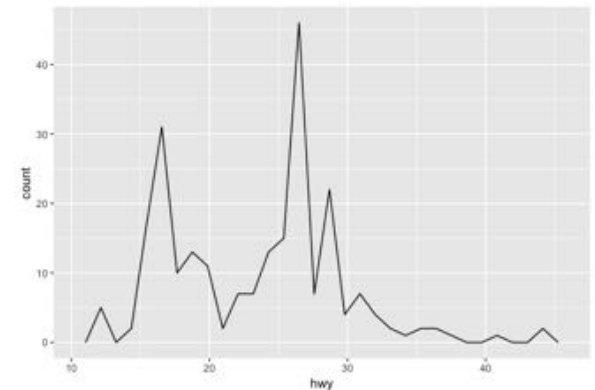
- Bar graph of frequencies for ordered, equal size bins
- Bars touch to imply continuity of bins
- Need to experiment with the bin size



Histogram [Pearson 1895] Black cherry tree histogram.svg from Wikimedia Commons



Population pyramid showing the distribution of age groups in a population. Stacked with shift at origin. Bars separation used to imply continuity.



Frequency polygon plot

# BUILDING AN HISTOGRAM

73, 42, 67, 78, 99, 84, 91, 82, 86, 122

## 1. Order in ascending order

42, 67, 73, 78, 82, 84, 86, 91, 99, 122

## 2. Select bin size

```
range = max - min = 122 - 42 = 80  
bin size 20  
bin size 40
```

## 3. Create a frequency table

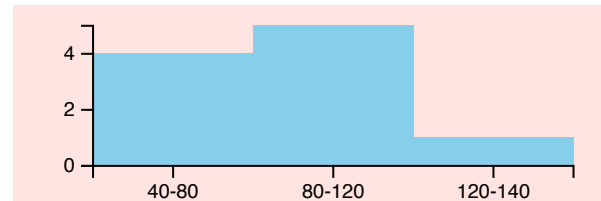
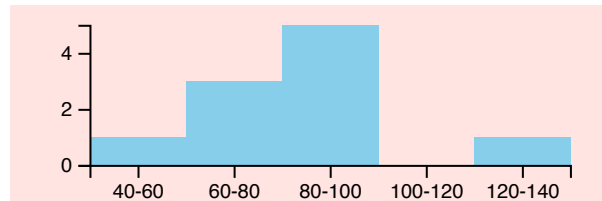
Interval	Frequency
40-60	1
60-80	3
80-100	5
100-120	0
120-140	1

Bin size 20

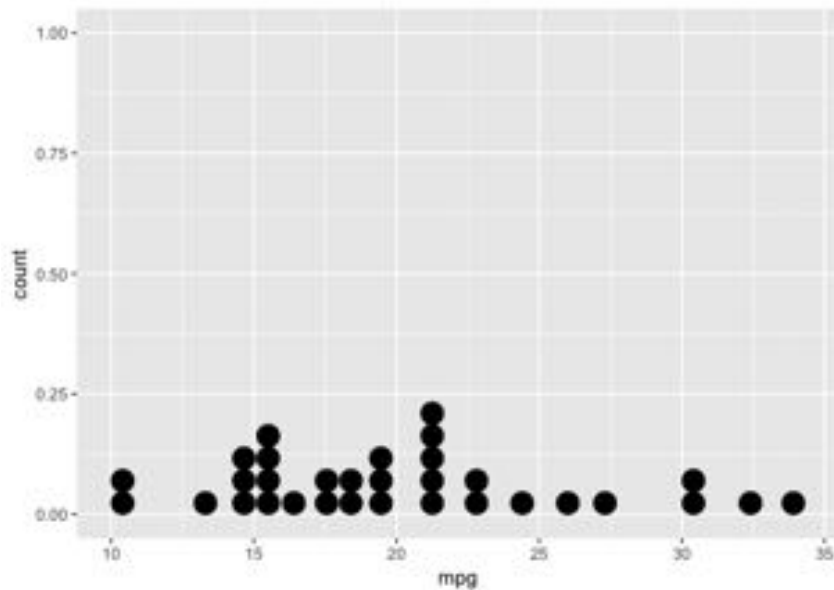
Interval	Frequency
40-80	4
80-120	5
120-140	1

Bin size 40

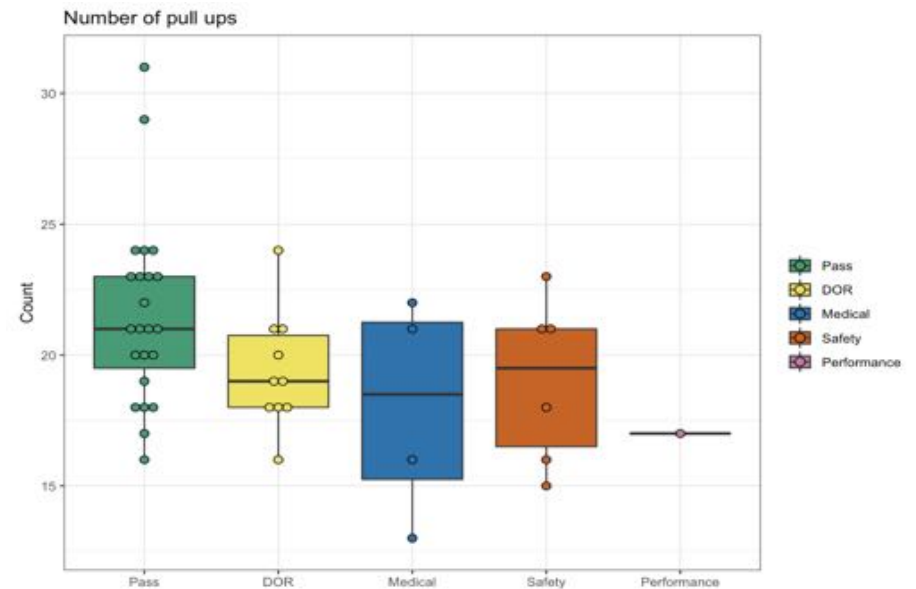
## 4. Plot



# DOT PLOT



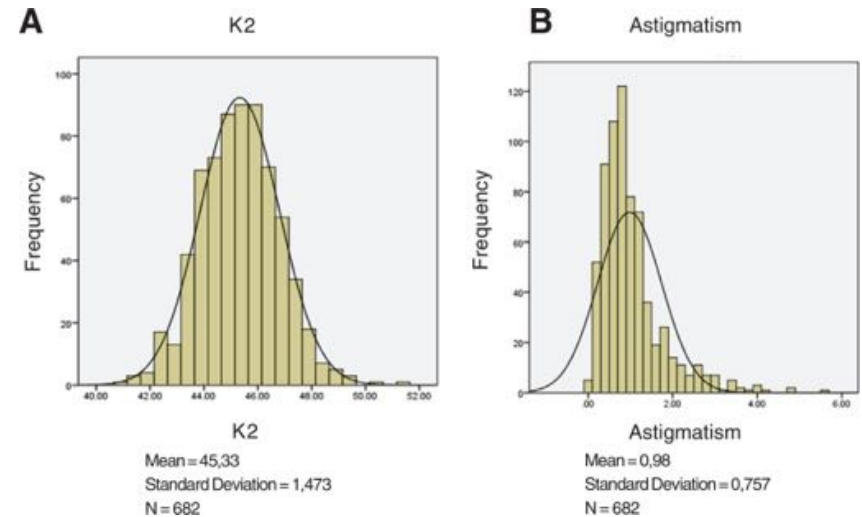
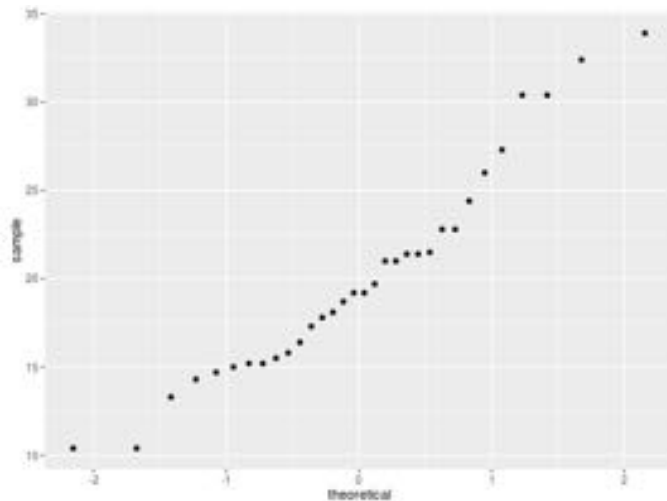
Dot plot histogram: y axis is the relative frequency, x axis is the dimension considered, each dot represents one observation, circle center is equal to the bin center, dot diameter is proportional (factor of 1 in the figure) to bin size.



Boxplot with dotplot, each dot represents one observation

# VISUALIZING NORMALITY

## Q-Q plot and histograms

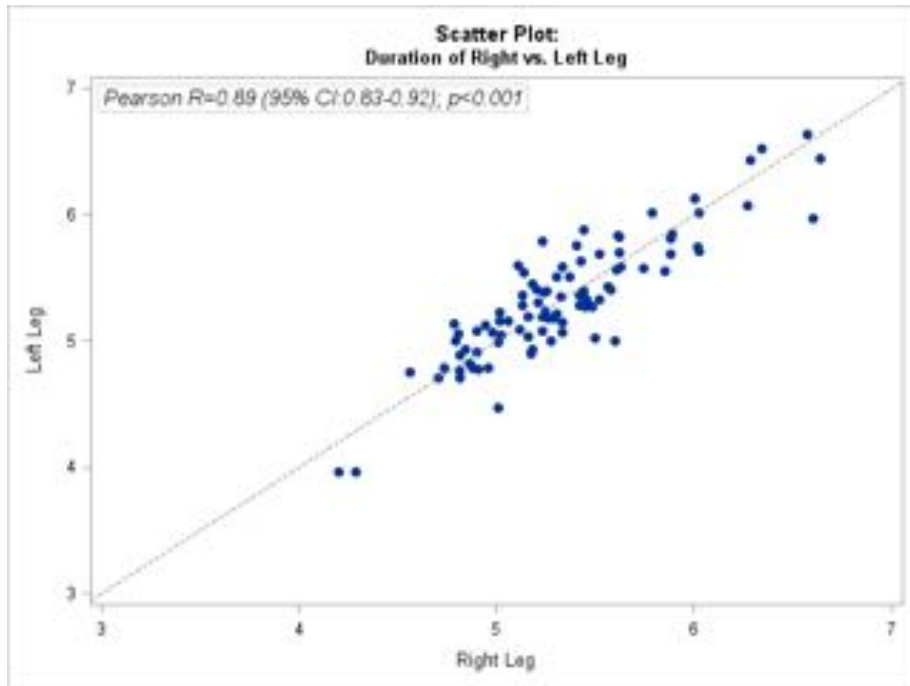


Q-Q (quantile-quantile) plot is a graphical method for comparing two probability distributions by plotting their quantiles against each other. Here we Assess normality by plotting against a normal distribution.

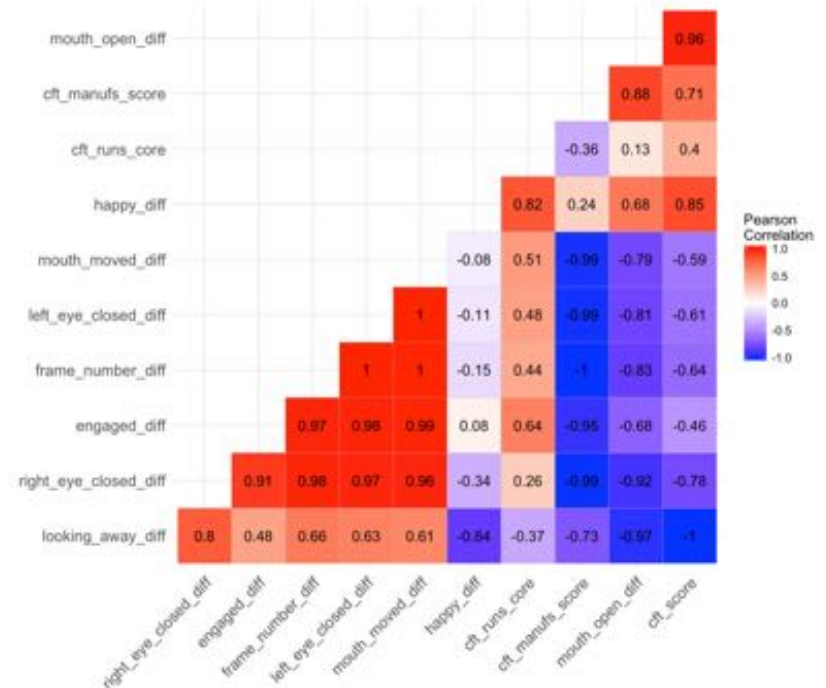
Histogram with superimposed line chart of normal distribution

# VISUALIZING CORRELATIONS

## Scatterplots and heatmaps



PCC\* scatterplot and linear regression line.



Heatmap of PCC\* is a graphical tool to assess correlations in multivariate data. Note the diverging R-B color scale.

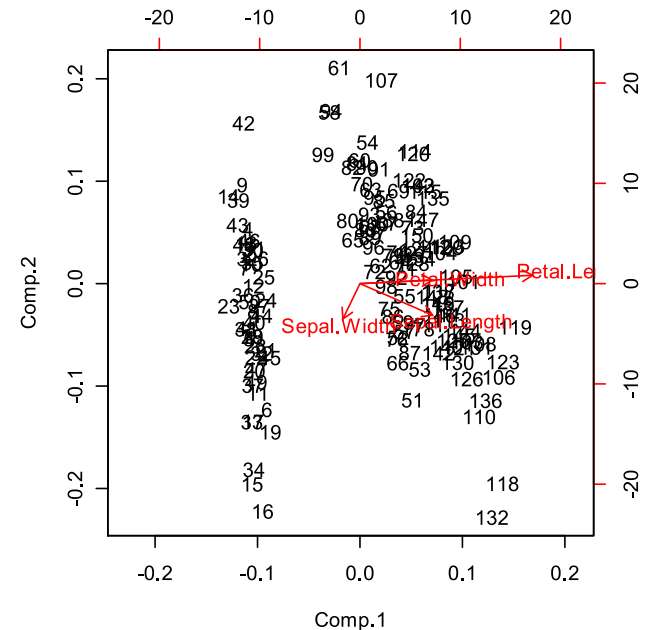
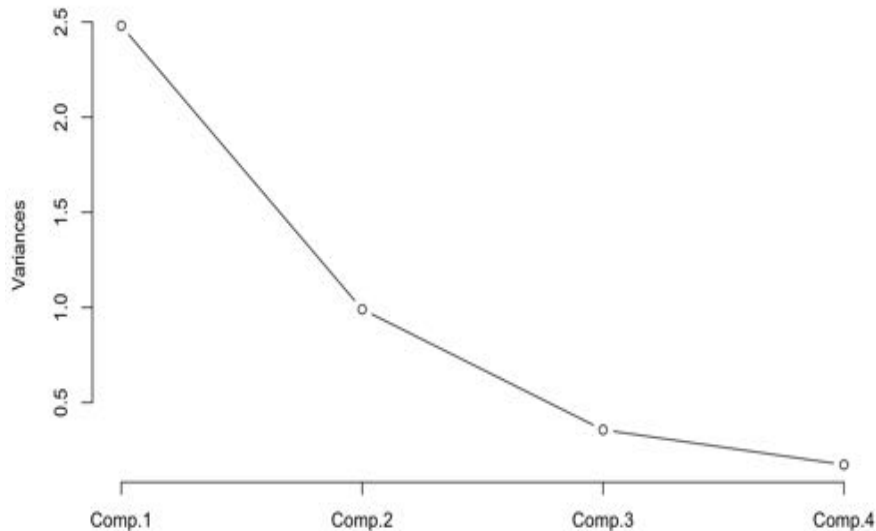
\* Pearson's correlation coefficients (PCC) or Pearson's  $r$ , is a measure of linear correlation between two sets of data



# VISUALIZING PCA RESULTS

## Scree plot and Biplot

Scree plot US arrests



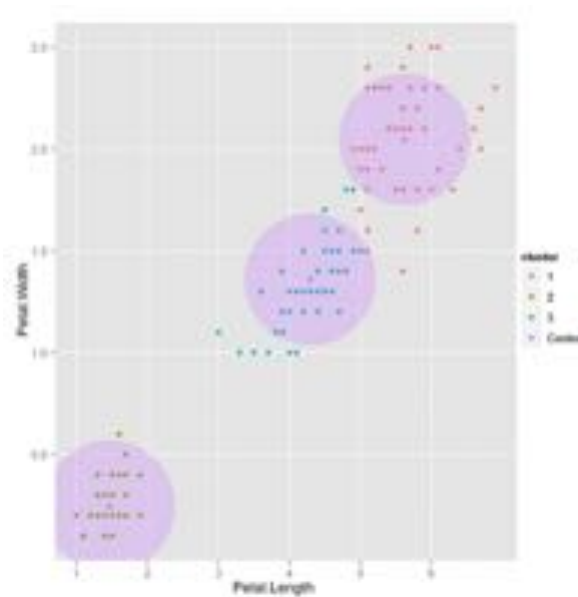
A scree plot shows how PCA\* components explain data variability

A Biplot [Gabriel 71] shows samples (points) and variables (vectors) with similar values plotted in the plane of PCA\* components

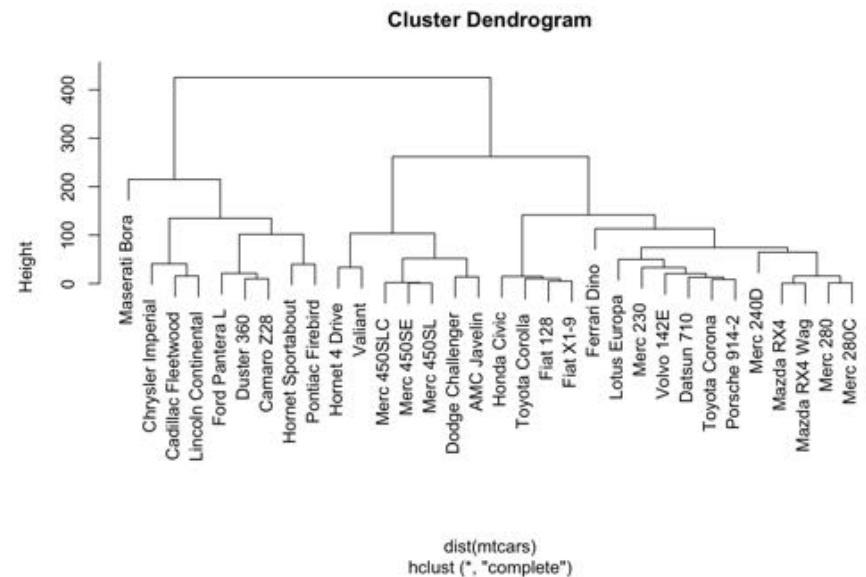
\* Principal Component Analysis (PCA) is commonly used for dimensionality reduction. PCA can be thought of as fitting a p-dimensional ellipsoid to the data, where each axis of the ellipsoid represents a principal component. If some axis of the ellipsoid is small, then the variance along that axis is also small.

# VISUALIZING CLUSTERING RESULTS (1)

## Scatterplot and Dendrogram



Scatterplot of k-means\* results color-coded by cluster with cluster centers and cluster bubbles

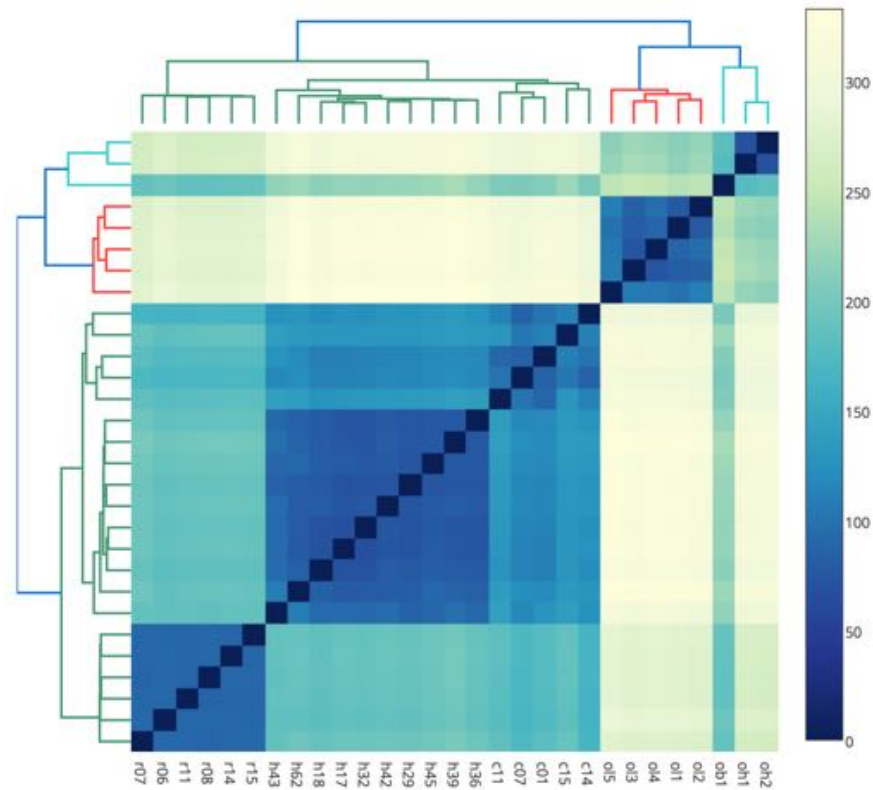


Dendrogram (diagram representing a tree) encoding a value

\* k-means clustering is a method of vector quantization, originally from signal processing, that aims to partition  $n$  observations into  $k$  clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid)

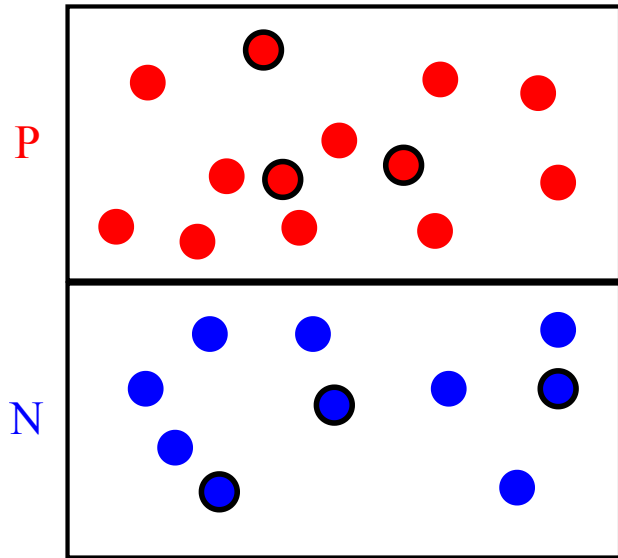
# VISUALIZING CLUSTERING RESULTS (2)

## Dendrogram and heatmap combo plot







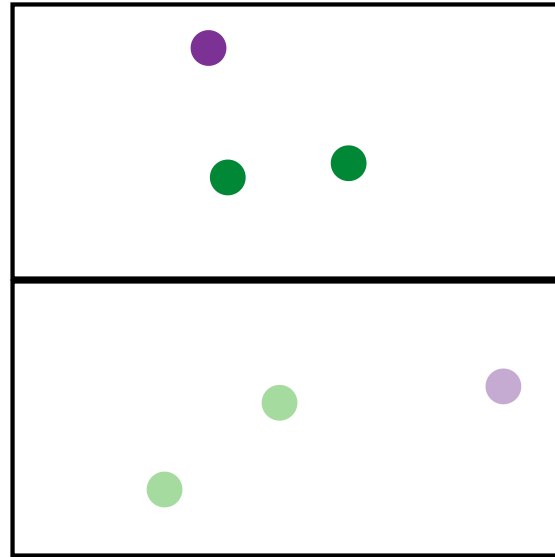
Combination plot of correlation heatmap and dendrograms showing hierarchical information across variables

# MODEL PERFORMANCE TESTING



Labeled dataset (ground truth)

Train	Test	
		<b>P</b>
		<b>N</b>

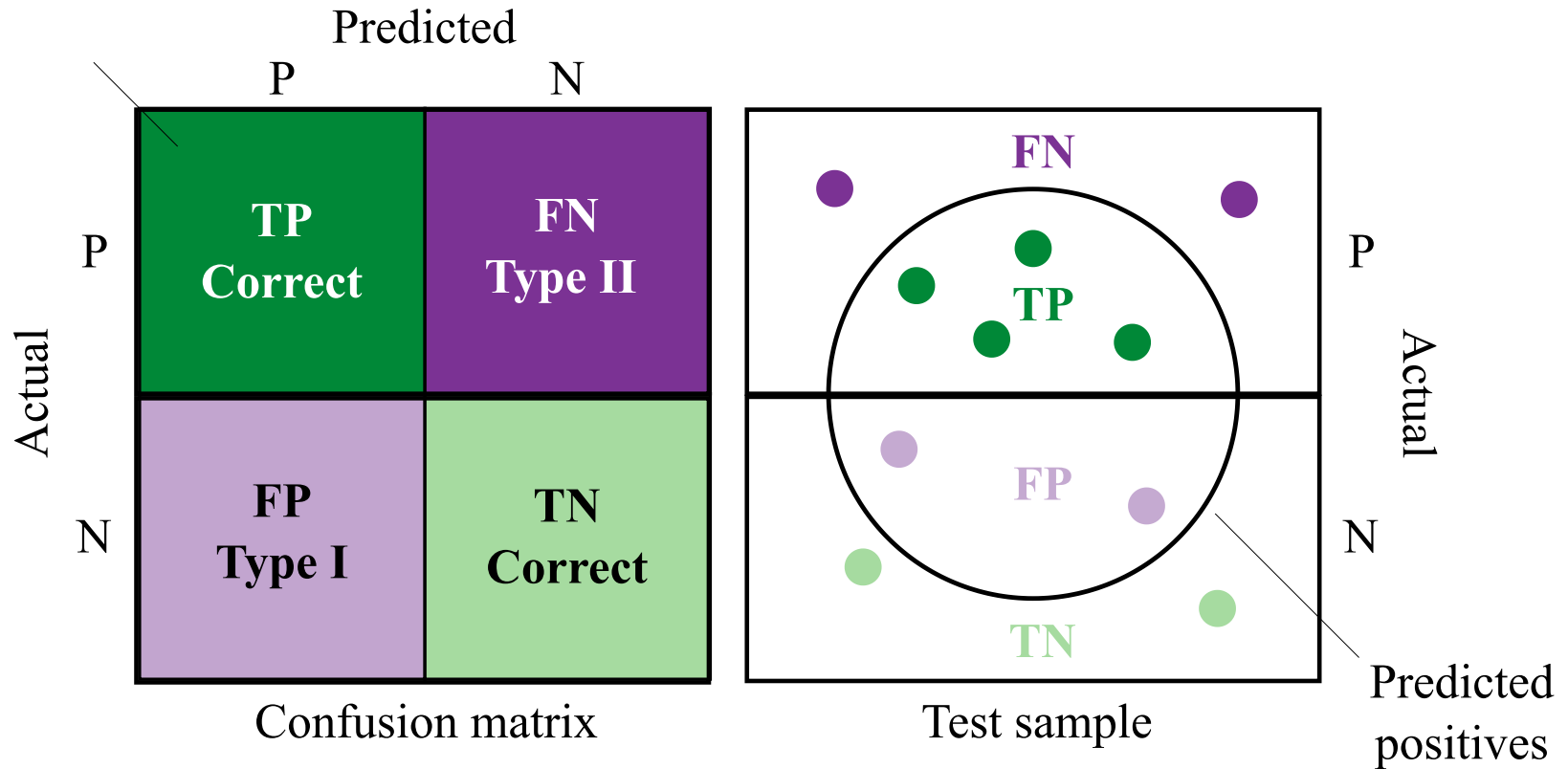


Test sample

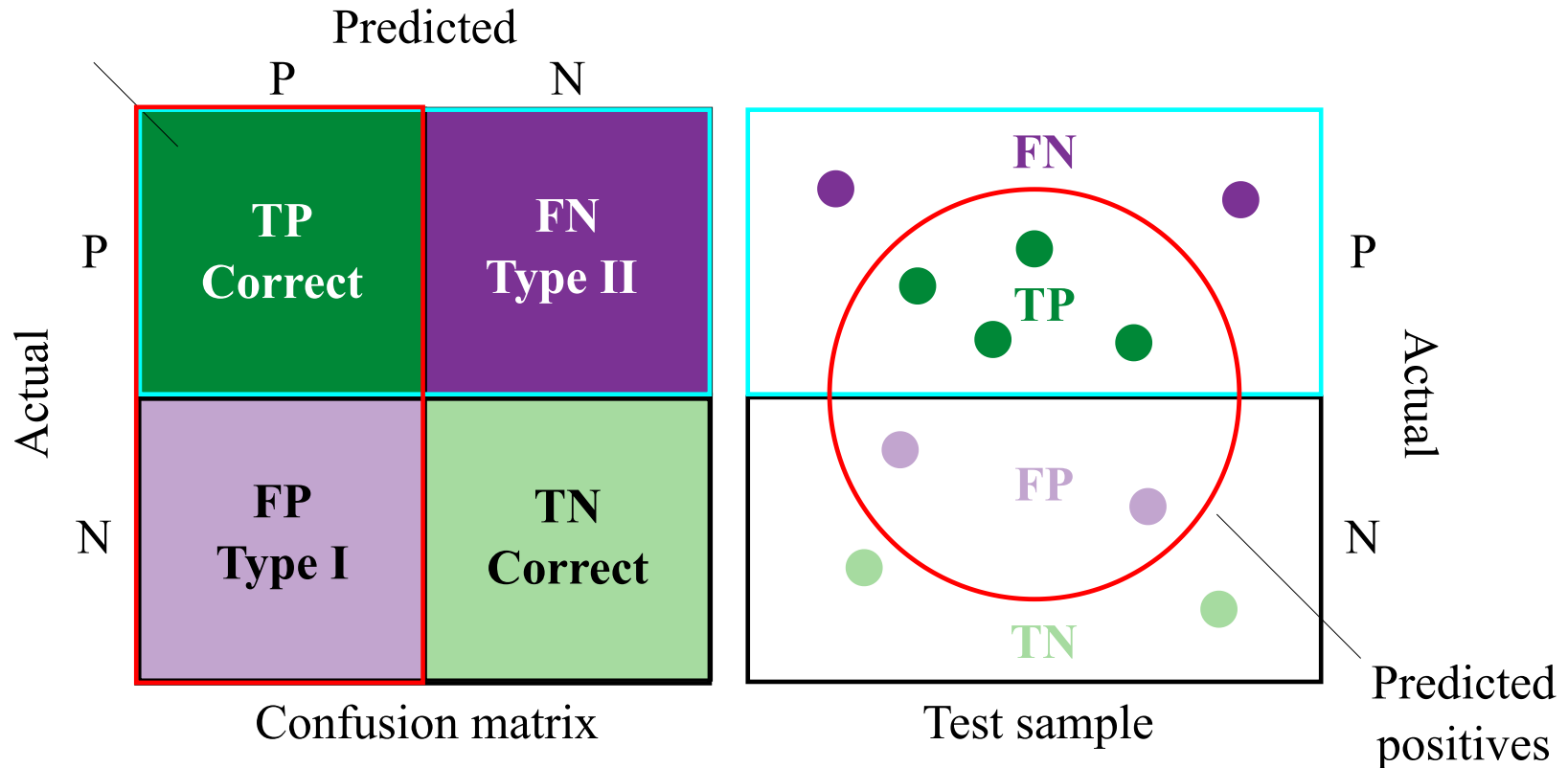
-  **False Negative**
-  **True Positive**
-  **False Positive**
-  **True Negative**

- Frequencies of TP, FP, TN, FN (confusion matrix)
- Precision and Recall rates
- Specificity and Sensitivity rates

# CONFUSION MATRIX



# PRECISION AND RECALL



Precision, positive predictive value (PPV)

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

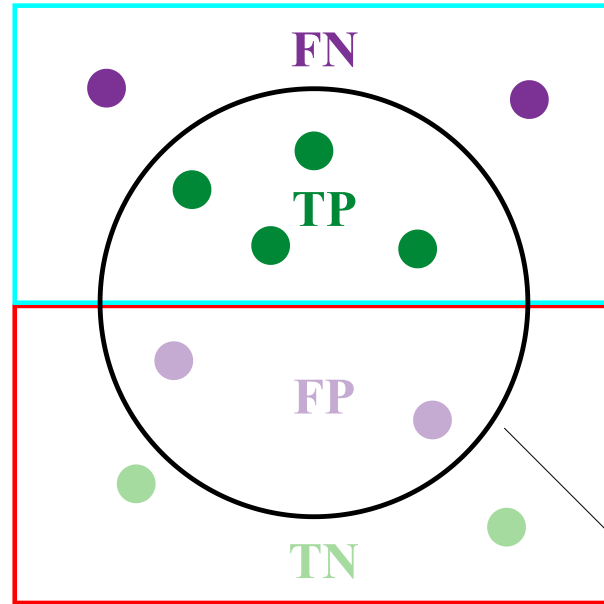
Sensitivity, recall, true positive rate (TPR)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

# SPECIFICITY AND SENSITIVITY

		Predicted	
		P	N
Actual	P	<b>TP</b> <b>Correct</b>	<b>FN</b> <b>Type II</b>
	N	<b>FP</b> <b>Type I</b>	<b>TN</b> <b>Correct</b>

Confusion matrix



Test sample

Predicted positives

Specificity, selectivity, true negative rate (TNR)

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Sensitivity, recall, true positive rate (TPR)

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

# VISUALIZING THE CONFUSION MATRIX

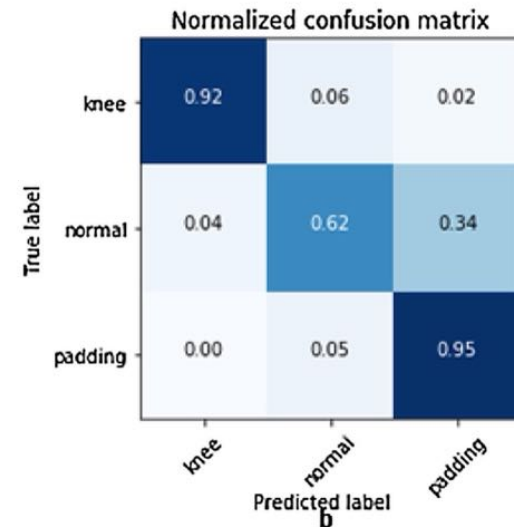
## Tables and heatmap

```
# d1: Int. Derang. (DDWR) / Int. Derang. (eDDNR)
No Yes
188 112

Call:
randomForest(formula = target, data = df, proximity = TRUE)
Type of random forest: classification
Number of trees: 500
No. of variables tried at each split: 11

OOB estimate of error rate: 3%
Confusion matrix:
  No  Yes class.error
No 187   1 0.005319149
Yes   8 104 0.071428571
```

Confusion matrix result in R printed as a table

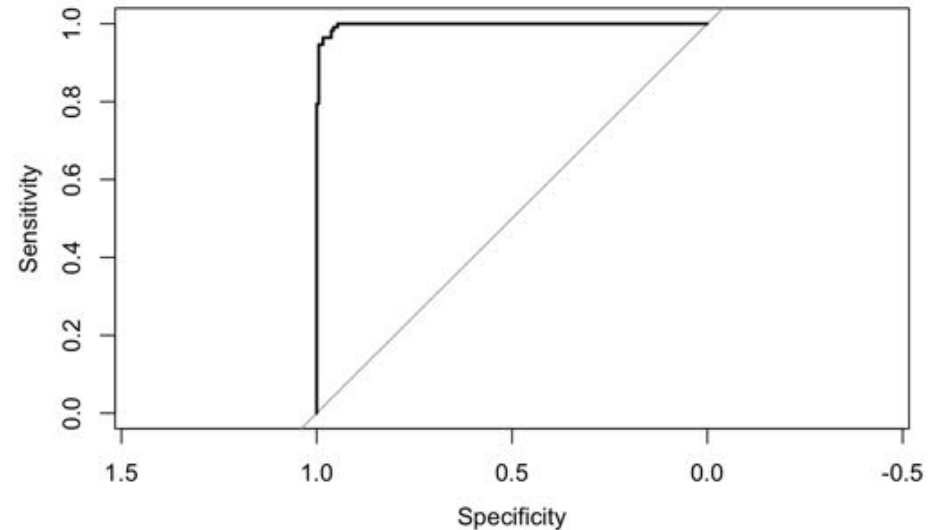
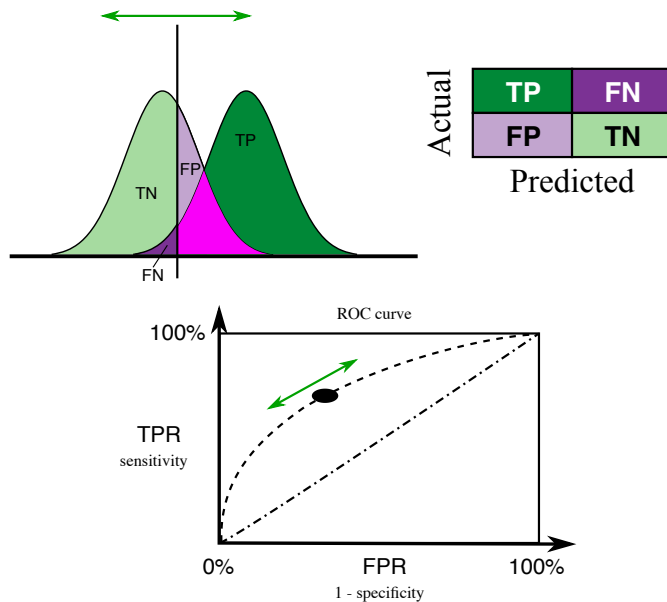


Khokhlova, et al. "Normal and pathological gait classification LSTM model." Artificial intelligence in medicine 94 (2019)



# VISUALIZING THE ROC CURVE

## Line chart of specificity vs. sensitivity



ROC curve of dental Internal Derangement (DDWR/eDDNR) conditions

By [Sharpr](#) - Own work, [CC BY-SA 3.0](#), [Link](#)

The Receiver Operator Curve (ROC) is a diagnostic tool for binary classifiers with decision threshold

# VISUALIZING PERFORMANCE RATES (1)

## Tables to compare classifiers/conditions

CLASSIFIER/COMBINATION	A (%)	P (%)	R (%)	F-M
SVM	84.79	85.43	83.38	0.84
RANDOM FOREST	83.09	83.68	83.09	0.83
k-NN	79.24	80.16	79.24	0.79
DECISION TREE	72.66	72.92	72.66	0.73
NAIVE BAYES	71.02	71.64	71.02	0.70
SkR (AP)	87.41	87.61	87.40	0.87
Sk (AP)	87.28	87.49	87.29	0.87
SkR (MV)	85.62	85.79	85.61	0.86
DSk (AP)	85.37	85.61	85.37	0.85
DSk (MV)	85.29	85.51	85.30	0.85

Performance of single classifier and multiple classifiers combination. A: Accuracy, P: Precision, R: Recall, F-M: F-measure, AP: Average of Probabilities, MV: Majority Voting, S: SVM, k: k-NN, D: Decision Tree, R: Random Forest.

TASK	A (%)	P (%)	R (%)	F-M
COUNT	84.79 (93.95/71.23)	85.43	83.38	0.84
TRAY	82.04 (94.44/53.63)	82.19	90.00	0.85
WALK	81.04 (96.05/48.99)	81.63	87.75	0.83

SVM performance for various features. Accuracy is reported with the format as average accuracy (best accuracy/worst accuracy) across 14 subjects. A: Accuracy, P: Precision, R: Recall and F-M: F-measure. ALL: Gait, Angle, and Graph.

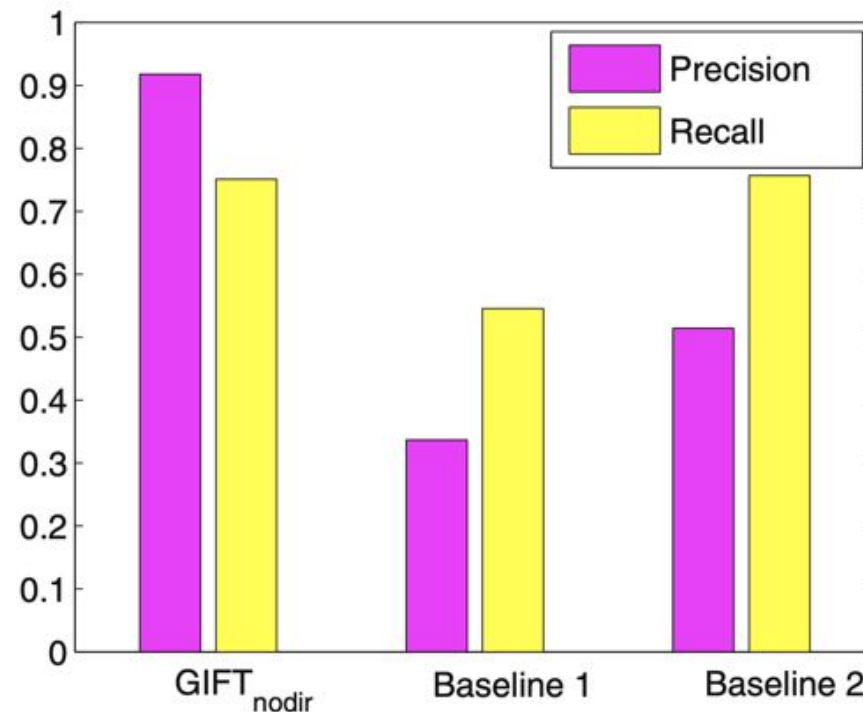
FEATURE	A (%)	P (%)	R (%)	F-M
GAIT	63.58 (88.71/39.53)	57.26	55.40	0.51
ANGLE	75.30 (92.22/53.58)	75.01	74.20	0.74
GRAPH	82.41 (95.68/69.63)	83.04	81.93	0.82
ALL	84.79 (93.95/71.23)	85.43	83.38	0.84
PCA	84.66 (95.32/71.99)	85.30	84.44	0.85

SVM performance for various features. Accuracy is reported with the format as average accuracy (best accuracy/worst accuracy) across 14 subjects. A: Accuracy, P: Precision, R: Recall and F-M: F-measure. ALL: Gait, Angle, and Graph.

Kao, J.Y., Nguyen, M., Nocera, L., Shahabi, C., Ortega, A., Winstein, C., Sorkhoh, I., Chung, Y.C., Chen, Y.A. and Bacon, H., 2016, October. Validation of automated mobility assessment using a single 3d sensor. In European Conference on Computer Vision (pp. 162-177). Springer, Cham.

# VISUALIZING PERFORMANCE RATES (2)

Bar charts to compare classifiers/conditions



**Fig. 19** Average precision and recall after tracking 20 targets

Cai, Y., Lu, Y., Kim, S.H., Nocera, L. and Shahabi, C., 2015, June. Gift: A geospatial image and video filtering tool for computer vision applications with geo-tagged mobile videos. In 2015 IEEE International Conference on Multimedia & Expo Workshops (ICMEW) (pp. 1-6). IEEE.

# VISUALIZING FEATURE IMPORTANCE

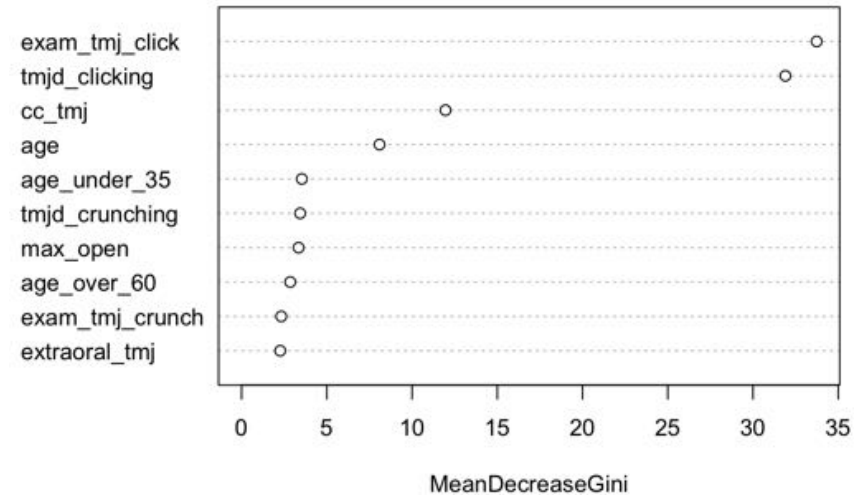
## Table and Dot plot

```
# dl: Int. Derang. (DDWR) / Int. Derang. (eDDNR)
No Yes
188 112

Call:
randomForest(formula = target, data = df, proximity = TRUE)
Type of random forest: classification
Number of trees: 500
No. of variables tried at each split: 11

OOB estimate of error rate: 3%
Confusion matrix:
  No  Yes class.error
No 187   1 0.005319149
Yes   8 104 0.071428571

Top 10 variables
  No    Yes
1  0.990 0.010
2  0.988 0.012
3  0.992 0.008
4  0.108 0.892
5  0.970 0.030
6  0.990 0.010
7  0.962 0.038
8  0.040 0.960
9  0.986 0.014
10 0.042 0.958
Setting levels: control = No, case = Yes
Setting direction: controls < cases
Area under the curve: 0.9974
```

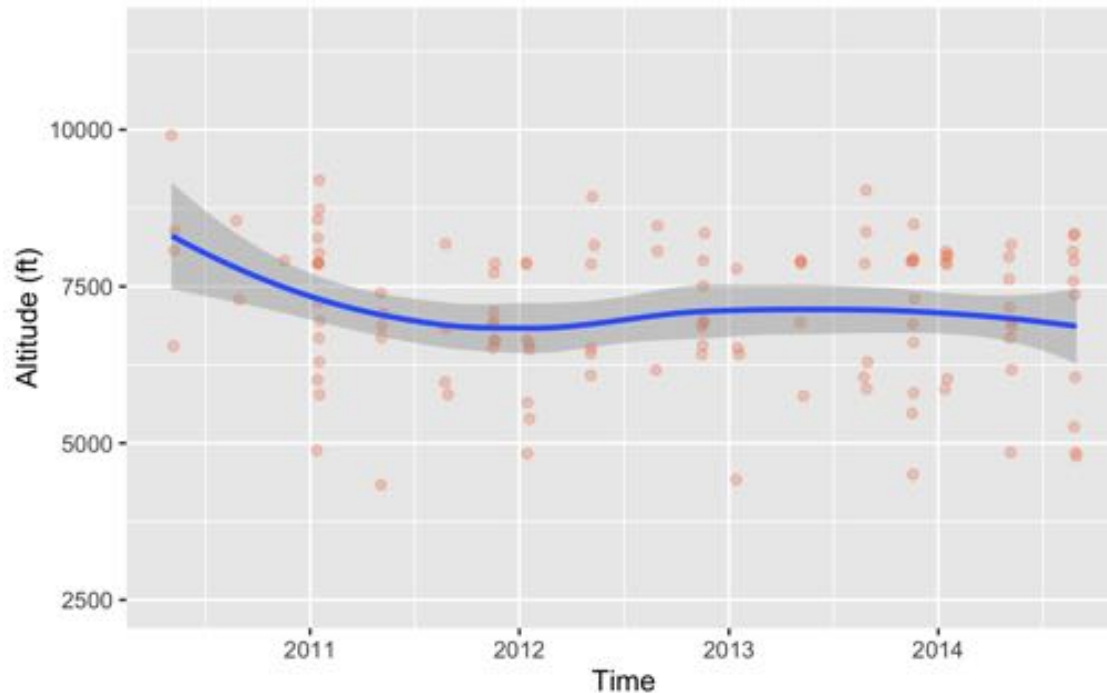


Dot plot of mean decrease Gini

Classification results showing confidence of top 10 variables

# VISUALIZING REGRESSION MODELS

## Line chart with Ribbon

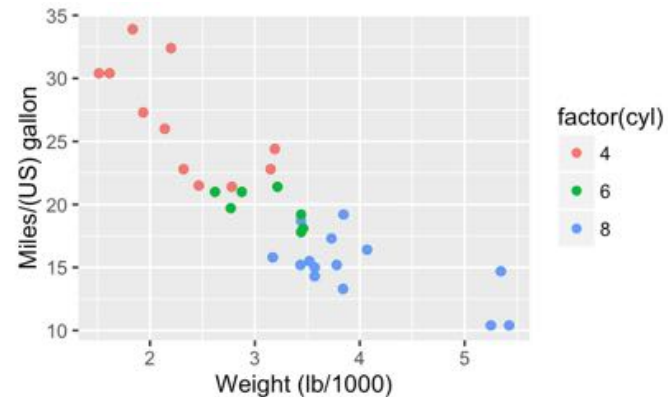
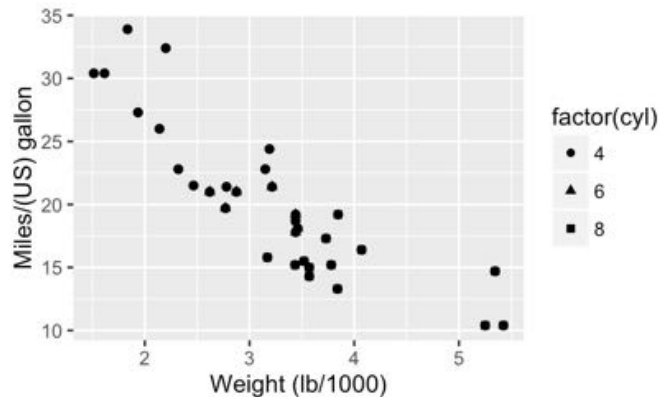


Smooth regression line with 0.95 confidence interval\*

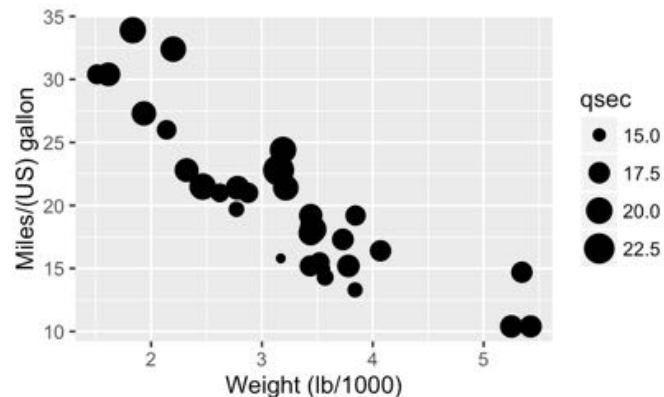
\*95% confidence interval: interval of values for which a hypothesis test to the level of 5% cannot be rejected  $\equiv$  interval has a probability of 95% to contain the true value

# DESIGN: CHOOSE ENCODINGS WISELY

Color & shape work well with categorical variables



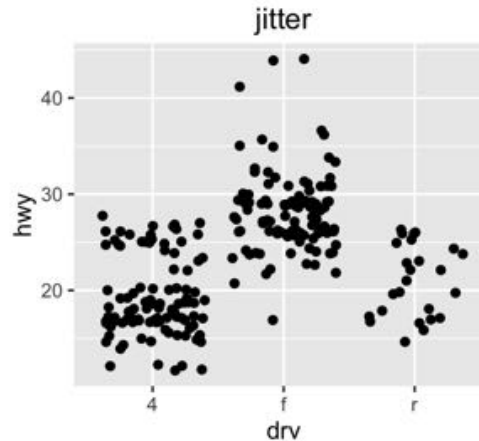
Size works well with continuous variables



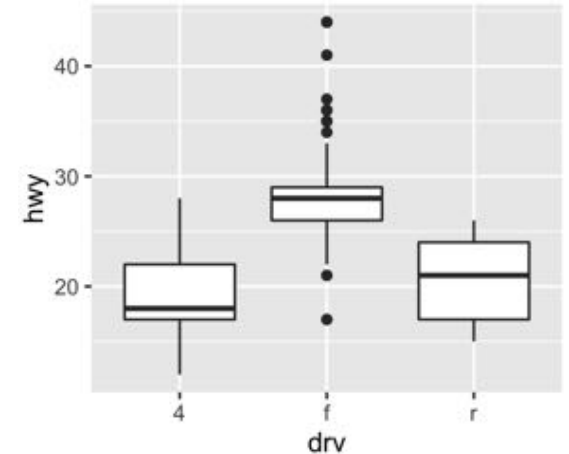
# DESIGN: DEAL WITH OVERPLOTTING



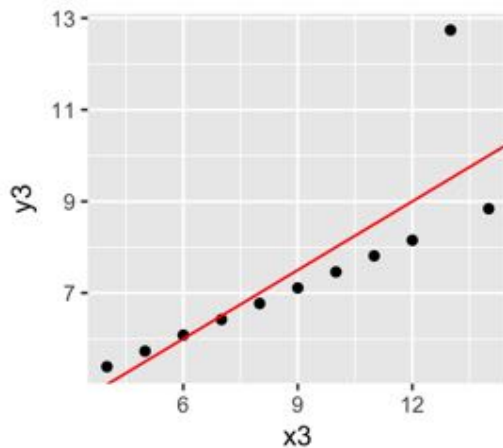
Transparency, outline shape



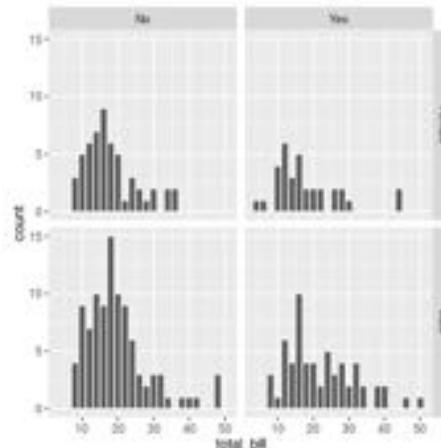
Add jitter



Summarize the data



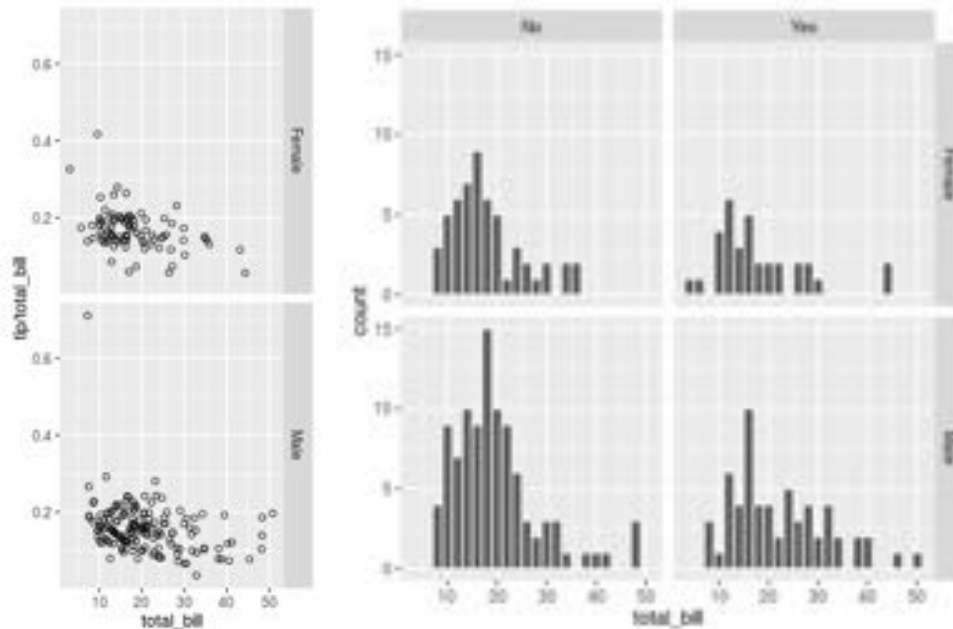
Add information



Split the data

# DESIGN: SERIES ARE BETTER THAN COMPLEX PLOTS

Faceting/conditioning/latticing/trellising/small multiples

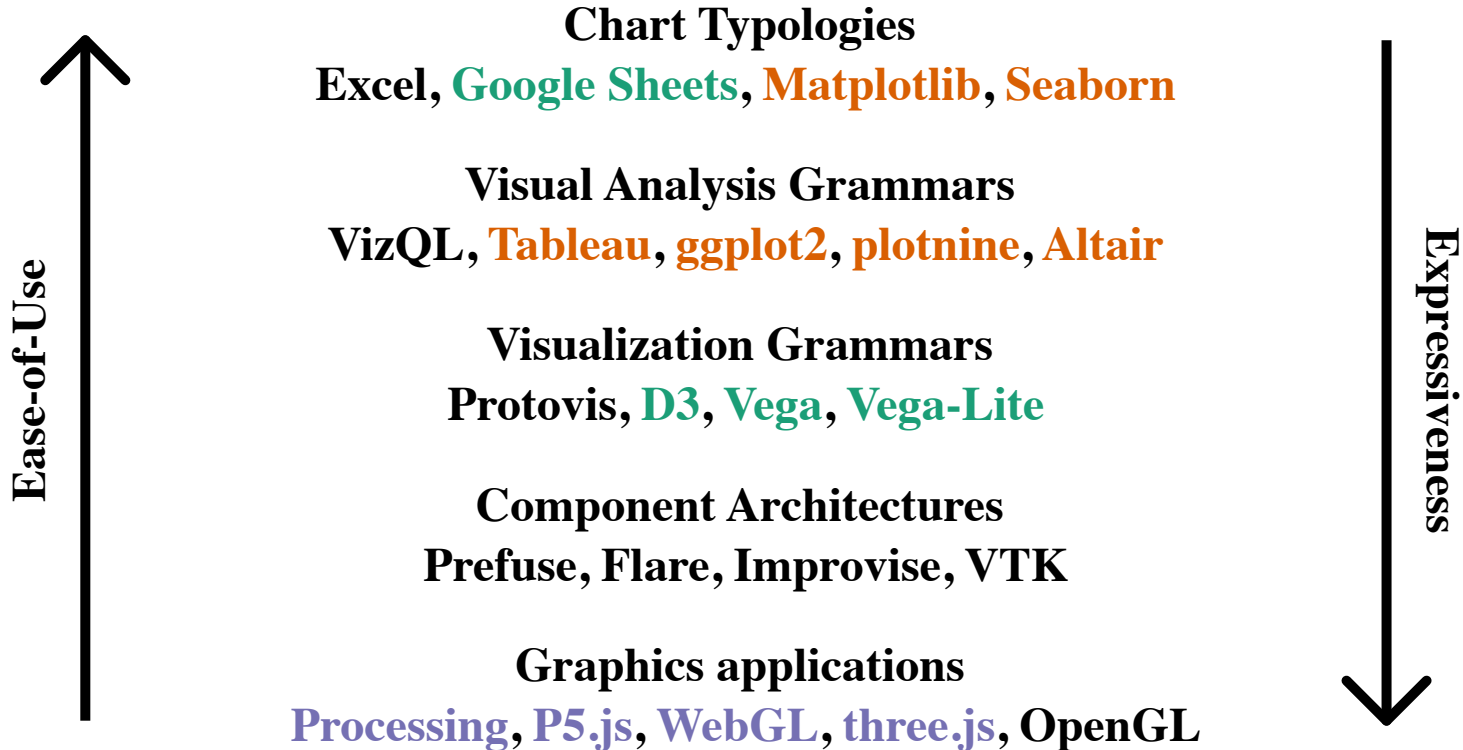




# OUTLINE

- Basics of statistics and modeling
- Statistical graphics
- Tools

# VISUALIZATION TOOLS



already covered



covered this week



will discuss later

Adapted from [Heer 2014]

# WORKING IN NOTEBOOKS

## Data is in dataframe format:

- Same length columns
- Columns → variables
- Rows → observations
- Strings stored as pointers (R factors)

```
> df <- sample_n(mpg, 36)
> df$manufacturer <- factor(df$manufacturer)
> df
# A tibble: 36 x 11
  manufacturer model      displ  year   cyl trans      drv    cty   hwy fl      class
  <fct>         <chr>      <dbl> <int> <int> <chr>    <chr> <int> <int> <chr> <chr>
1 toyota        camry          2.4  2008     4 auto(l5)  f       21    31 r    midsize
2 toyota        camry solara    2.4  2008     4 manual(m5) f       21    31 r    compact
3 dodge         dakota pickup 4wd  4.7  2008     8 auto(l5)  4        9    12 e    pickup
4 chevrolet     corvette        5.7  1999     8 auto(l4)  r       15    23 p    2seater
5 audi          a4            1.8  1999     4 manual(m5) f       21    29 p    compact
6 jeep          grand cherokee 4wd  4.7  1999     8 auto(l4)  4       14    17 r    suv
7 hyundai       tiburon         2    1999     4 manual(m5) f       19    29 r    subcompact
8 dodge         dakota pickup 4wd  3.9  1999     6 manual(m5) 4       14    17 r    pickup
9 toyota        camry solara     3    1999     6 auto(l4)  f       18    26 r    compact
10 ford         expedition 2wd  4.6  1999     8 auto(l4)  r       11    17 r    suv
# ... with 26 more rows
> summary(df$manufacturer)
audi   chevrolet   dodge    ford    honda   hyundai   jeep  land rover
  3         2         5         5         2         2         2         1
nissan   pontiac    subaru   toyota  volkswagen
  2         1         1         7         3
```

# PROPER DATAFRAME FORMAT?

	Granite	Limestone	Sandstone
Trad	36	0	52
Sport	76	8	41
Bouldering	102	0	13

Counts of locations by rock type and type of rock climbing

# PROPER DATAFRAME FORMAT

rock	type	count
Granite	Trad	36
Granite	Sport	76
Granite	Bouldering	102
Limestone	Trad	0
Limestone	Sport	8
Limestone	Bouldering	0
Sandstone	Trad	52
Sandstone	Sport	41
Sandstone	Bouldering	13

# MATPLOTLIB

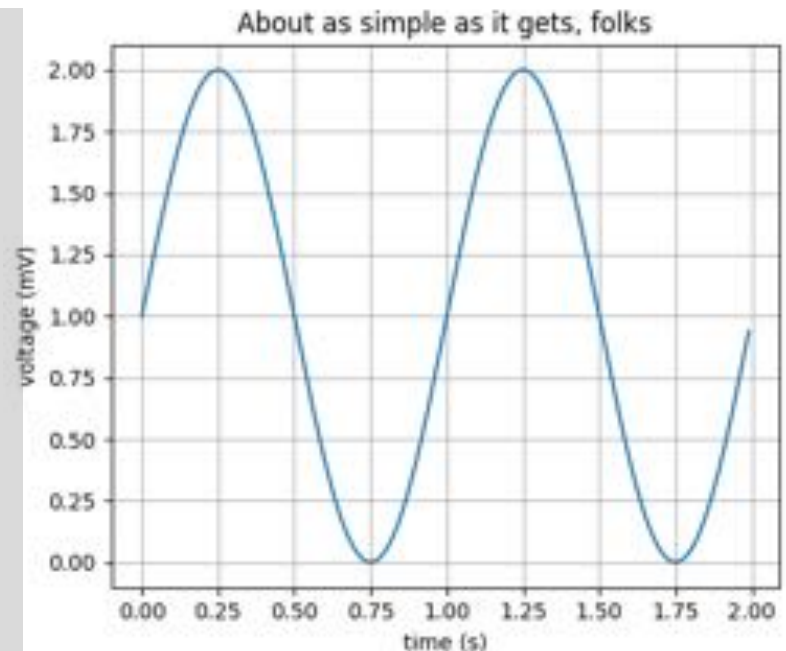
- <http://matplotlib.org> and [gallery](#)
- Chart typology
- Originally emulating the MATLAB® graphics commands
- Imperative (functional) programming

```
import matplotlib.pyplot as plt
import numpy as np

T = np.arange(0.0, 2.0, 0.01)
S = 1 + np.sin(2*np.pi*t)

plt.plot(T, S)
plt.xlabel('time (s)')
plt.ylabel('voltage (mV)')
plt.title('About as simple as it gets, folks')
plt.grid(True)

plt.show()
```



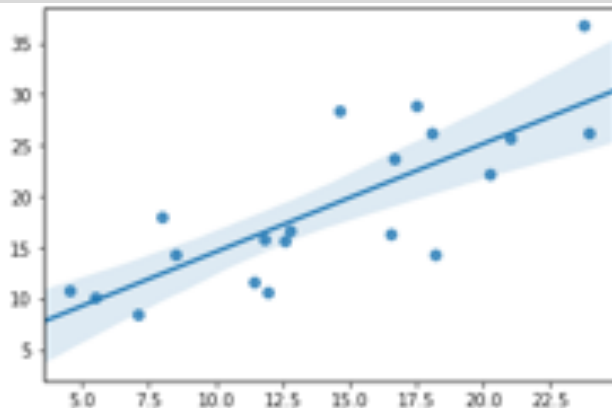
# SEABORN

- <https://seaborn.pydata.org> and [gallery](#)
- Chart typology
- High-level interface for statistical graphics based on Matplotlib
- Imperative (functional) programming
- Support for Pandas dataframes

```
import numpy as np
import seaborn as sns
```

```
x = 5 + np.arange(20) +
    np.random.randn(20)
y = 10 + np.arange(20) +
    5 * np.random.randn(20)
```

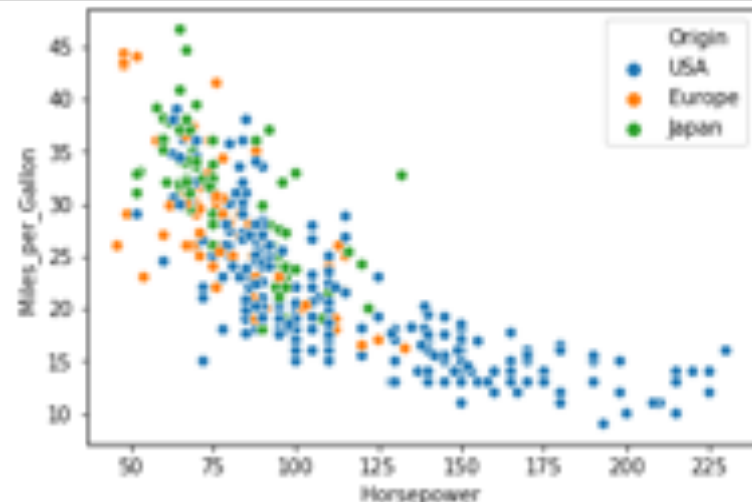
```
sns.regplot(x, y)
```



	Acceleration	Cylinders	Displacement	Horsepower	Miles_per_Gallon	Name	Origin	Weight_in_lbs	Year
0	12.0	8	307.0	130.0	18.0	chevrolet chevelle malibu	USA	3504	1970-01-01
1	11.5	8	350.0	165.0	15.0	buick skylark 320	USA	3693	1970-01-01
2	11.0	8	318.0	150.0	18.0	plymouth satellite	USA	3436	1970-01-01
3	12.0	8	304.0	150.0	16.0	amc rebel sst	USA	3433	1970-01-01
4	10.5	8	302.0	140.0	17.0	ford torino	USA	3449	1970-01-01
...									

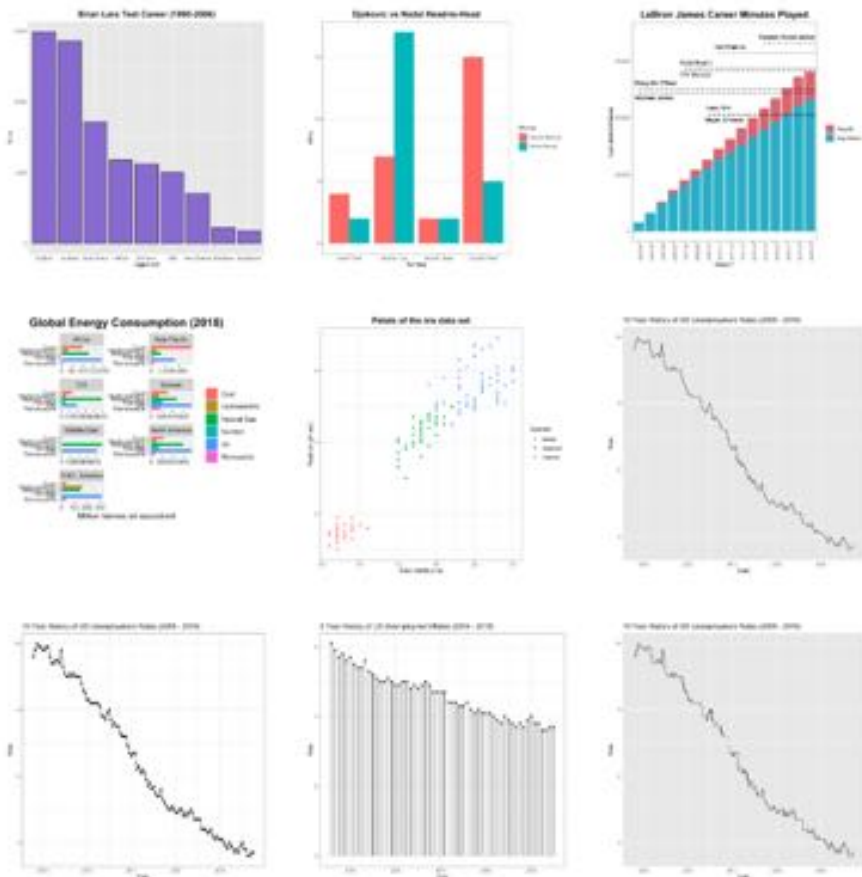
```
import seaborn as sns
from vega_datasets import data
```

```
cars = data.cars()
sns.scatterplot(
    x='Horsepower',
    y='Miles_per_Gallon',
    hue='Origin',
    data=cars);
```



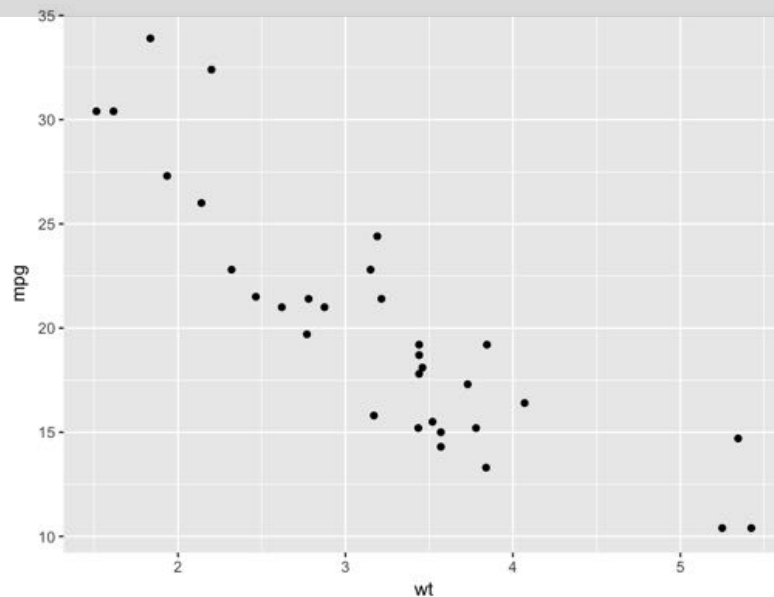
# GGPLOT2

- o [ggplot2](#) R package and [ggg gallery](#)
- o Visual Analysis Grammar
- o Support for R dataframes



```
mpg cyl disp  hp drat   wt  qsec vs am gear carb
Mazda RX4   21.0  6  160.0  110  3.90 2.620 16.46  0  1    4    4
Mazda RX4 Wag 21.0  6  160.0  110  3.90 2.875 17.02  0  1    4    4
Datsun 710   22.8  4  108.0   93  3.85 2.320 18.61  1  1    4    1
...
```

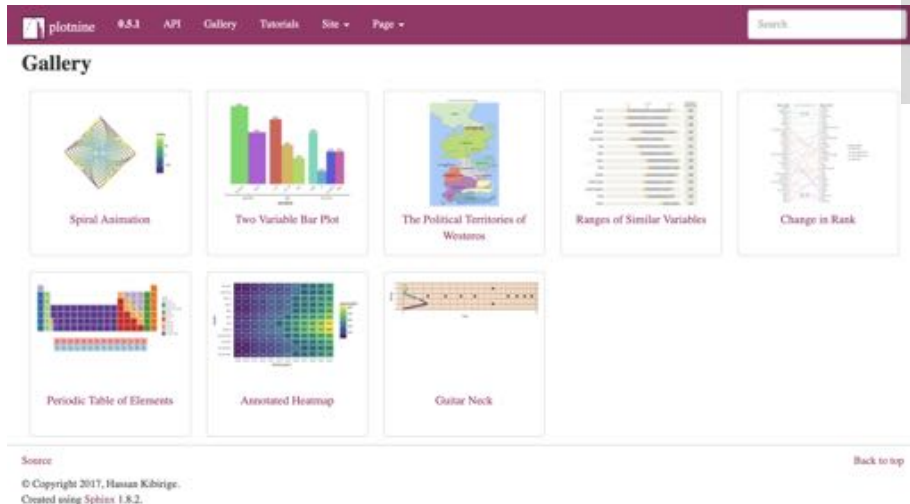
```
#ggplot(Data, Mapping) + Geom
ggplot(mtcars, aes(x=wt, y=mpg)) + geom_point()
```





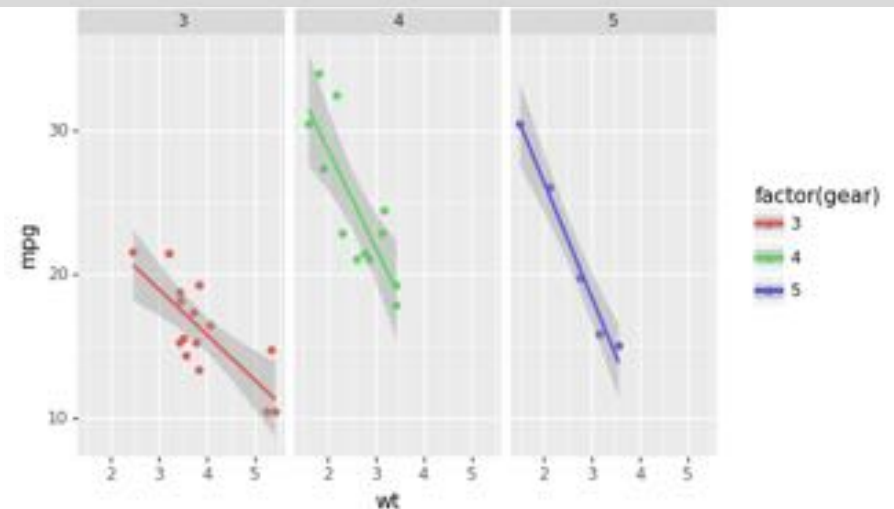
# PLOTNINE

- Plotnine [website](#) and [gallery](#)
- Visual Analysis Grammar
- Based on ggplot2 for Python
- Support for Pandas dataframes



	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
...											

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



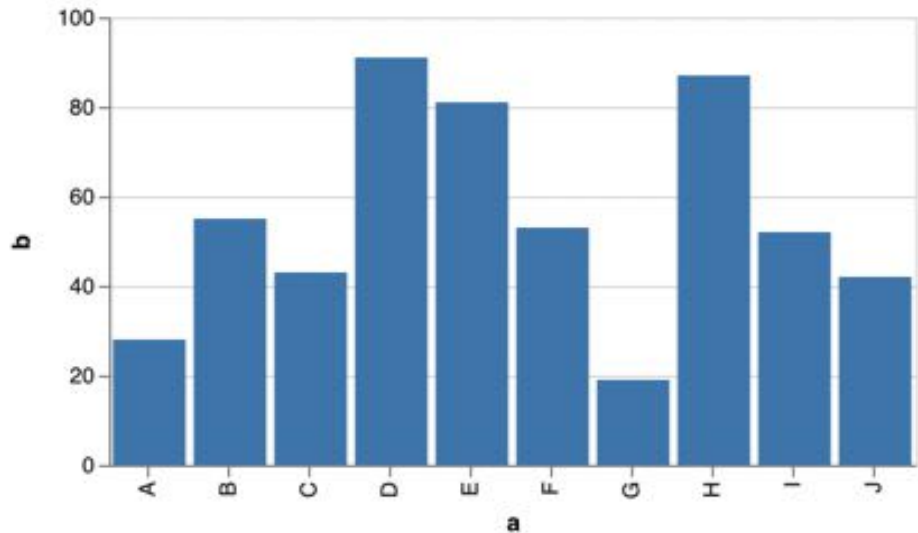
# ALTAIR

- Altair [website](#) and [gallery](#)
- Visual Analysis Grammar
- Declarative syntax
- Statistical visualization library
- Based on [Vega](#) and [Vega-Lite](#)
- Support for Pandas dataframes

```
import altair as alt

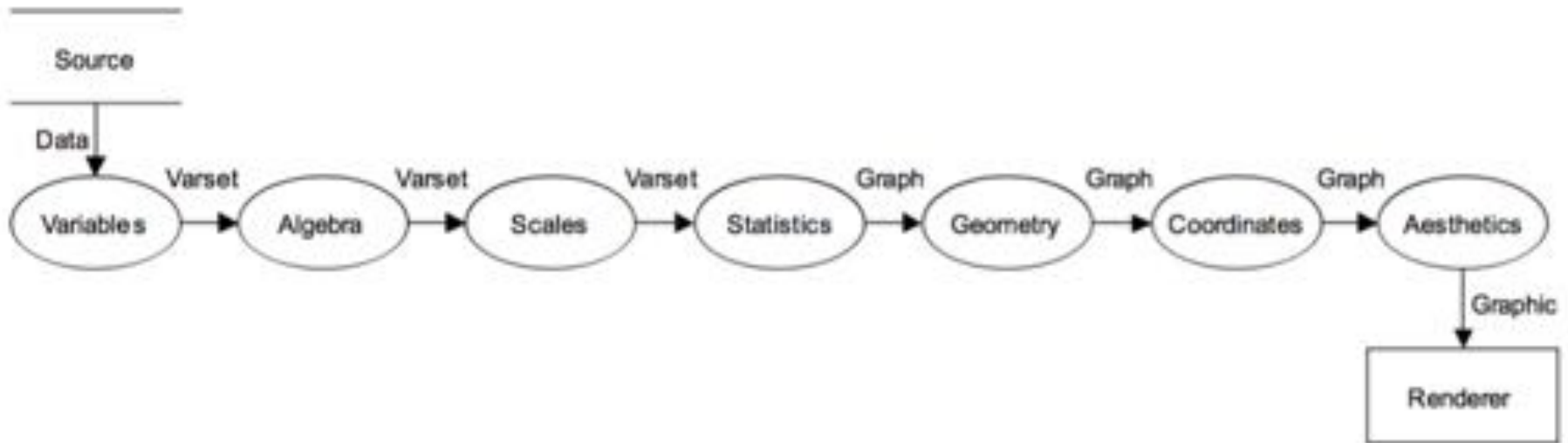
# load a simple dataset as a pandas DataFrame
from vega_datasets import data
cars = data.cars()

alt.Chart(cars).mark_point().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color='Origin',
).interactive()
```



# GRAMMAR OF GRAPHICS\*

Graphic defined by a grammar of components



1. DATA: a set of data operations that create variables from datasets,
2. TRANS: variable transformations, e.g., rank,
3. SCALE: scale transformations, e.g., log,
4. COORD: a coordinate system, e.g., polar,
5. ELEMENT: graphs, e.g., points, and their aesthetic attributes, e.g., color,
6. GUIDE: one or more guides, e.g., axes, legends.

\*Wilkinson, L. (2005), The Grammar of Graphics (2nd ed.). Statistics and Computing, New York: Springer

# LAYERED GRAMMAR OF GRAPHICS\* [WICKHAM 2010]

Defaults Data Mapping**	A default dataset and set of mappings from variables to aesthetics
Layer Data Mapping Geom Stat Position	One or more layers, each composed of a geometric object, a statistical transformation, a position adjustment, and optionally, a dataset and aesthetic mappings
- Coord - Facet	A coordinate system The facetting specification

A theme controls the finer points of display, like the font size and background color

\* implemented in **ggplot2**

\*\* Mapping of visual properties to data columns is referred to as an **aesthetic mapping**

# MINIMAL GGPLOT2 PLOT

3 components required in every ggplot2 plot:  
data, aesthetic mapping, Geom

Defaults

Data

Mapping

Layer

Data

Mapping

Geom

Stat

Position

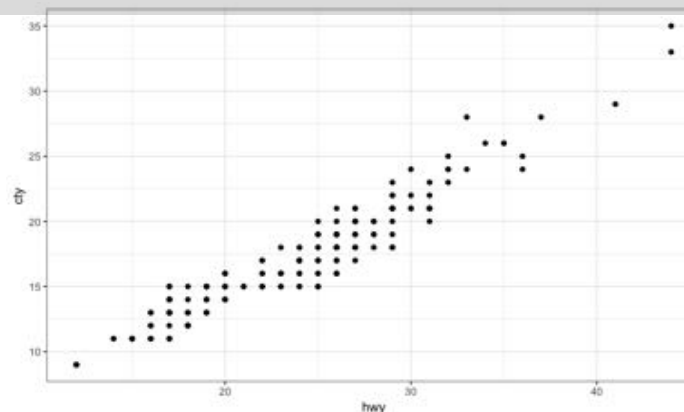
Scale

Coord

Facet



```
ggplot(data=mpg, aes(x=hwy, y=cty)) + geom_point() #Defaults  
ggplot(mpg, aes(hwy, cty)) + geom_point() #positional args  
ggplot(mpg) + geom_point(aes(hwy, cty)) #Mapping in layer  
  
# Same using a variable  
p <- ggplot(mpg, aes(hwy, cty)) #set Defaults  
p + geom_point() #add Layer with Geom
```



# AESTHETIC MAPPINGS

- Geom defines the marks
- Aesthetic mappings allow to map data variables to axes and **channels** (mark attributes such as position, shape, size, or color)

`aes()` is used to reference variables in the dataframe

```
ggplot(data=mtcars, aes(x=mpg, y=wt)) + geom_point() #Defaults

# mtcars dataset:
      mpg   cyl  disp    hp  drat    wt   qsec    vs  am  gear  carb
Mazda RX4   21.0     6 160.0  110  3.90  2.620 16.46   0   1     4     4
Mazda RX4 Wag 21.0     6 160.0  110  3.90  2.875 17.02   0   1     4     4
Datsun 710   22.8     4 108.0   93  3.85  2.320 18.61   1   1     4     1

aes(x = mpg, y = wt)
#> Aesthetic mapping:
#> * `x` -> `mpg`
#> * `y` -> `wt`

# You can also map aesthetics to functions of variables
aes(x = mpg ^ 2, y = wt / cyl)
#> Aesthetic mapping:
#> * `x` -> `mpg^2`
#> * `y` -> `wt/cyl`

# Or to constants
aes(x = 1, colour = "smooth")
#> Aesthetic mapping:
#> * `x` -> 1
#> * `colour` -> "smooth"
```

```
# Named arguments
ggplot(mpg, aes(x=hwy, y=cty, color=manufacturer, size=displ)) + geom_point()

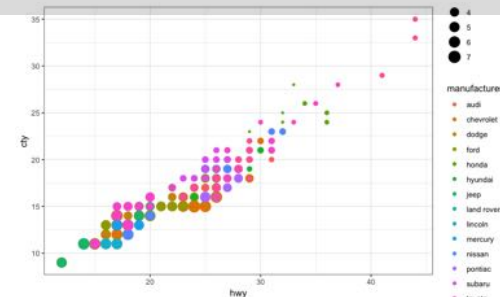
# Positional & named
ggplot(mpg, aes(hwy, cty, color=manufacturer, size=displ)) + geom_point()

# Using abbreviation for color
ggplot(mpg, aes(hwy, cty, col=manufacturer, size=displ)) + geom_point()

# Using english spelling for color
ggplot(mpg, aes(hwy, cty, colour=manufacturer, size=displ)) + geom_point()

# Specifying aesthetic mappings in geom layer
ggplot(mpg, aes(hwy, cty)) + geom_point(aes(color=manufacturer, size=displ))

# Wrong: color and size are not mapped with aes
ggplot(mpg, aes(hwy, cty), color=manufacturer, size=displ) + geom_point()
ggplot(mpg, aes(hwy, cty)) + geom_point(color=manufacturer, size=displ)
```

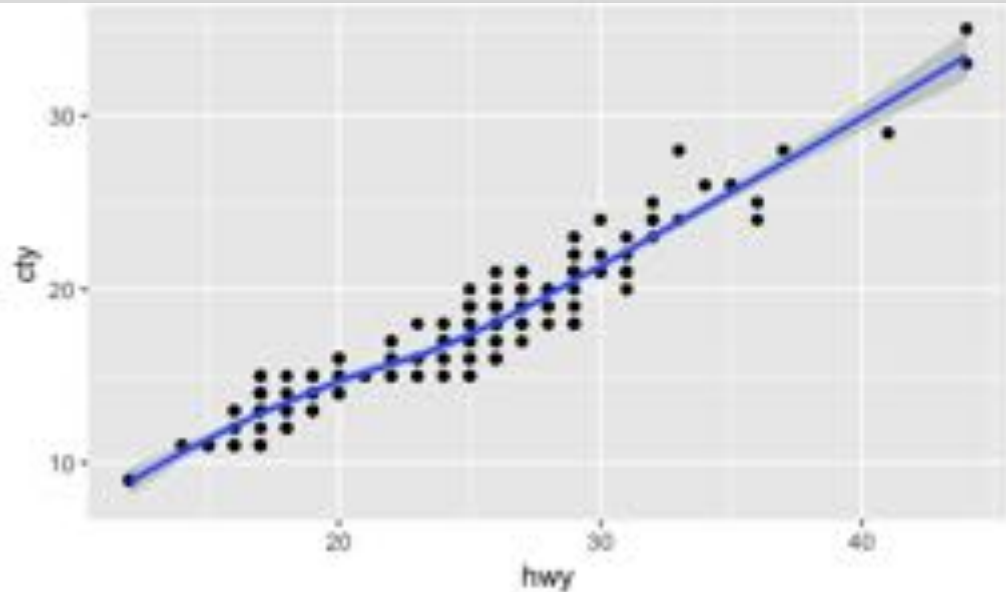


# ADDING LAYERS

Defaults  
Data  
Mapping

```
> ggplot(mpg, aes(hwy, cty)) + #Defaults  
  geom_point() + #add Geom point Layer  
  geom_smooth() #add Geom smooth Layer (regression)
```

Layer  
Data  
Mapping  
Geom  
Stat  
Position  
Scale



Coord  
Facet  


# BASIC NAMED PLOTS

All understand x, y, color and size aesthetics.  
Filled geoms also understand fill.

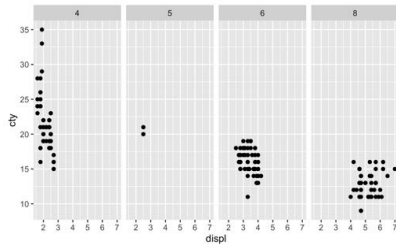
Scatterplot	<code>geom_point()</code>
Text	<code>geom_text()</code>
Bar chart	<code>geom_bar()</code>
Line chart	<code>geom_line()</code>
Area chart	<code>geom_area()</code>
Dot plot	<code>geom_dotplot()</code>
Histogram	<code>geom_histogram()</code>
Frequency polygon	<code>geom_freqpoly()</code>
Box plot	<code>geom_boxplot()</code>
Violin plot	<code>geom_violin()</code>



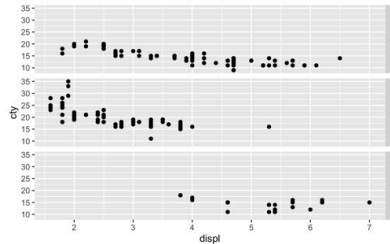
# FACETING: FACET\_GRID

```
p <- ggplot(mpg, aes(displ, cty)) + geom_point()
```

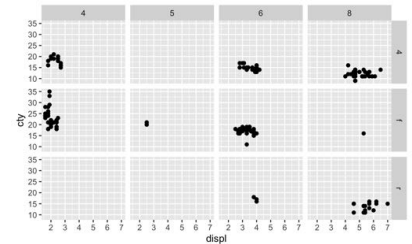
By columns



By rows



By rows & columns



```
# New notation  
p + facet_grid(cols = vars(cyl))
```

```
# Model notation: no faceting in y  
p + facet_grid(. ~ cyl)
```

```
# New notation  
p + facet_grid(rows = vars(drv))
```

```
# Model notation: no faceting in x  
p + facet_grid(drv ~ .)
```

```
# New notation: facet_grid(rows, cols)  
p + facet_grid(vars(drv), vars(cyl))
```

```
# Model notation: facet_grid(y ~ x)  
p + facet_grid(drv ~ cyl)
```

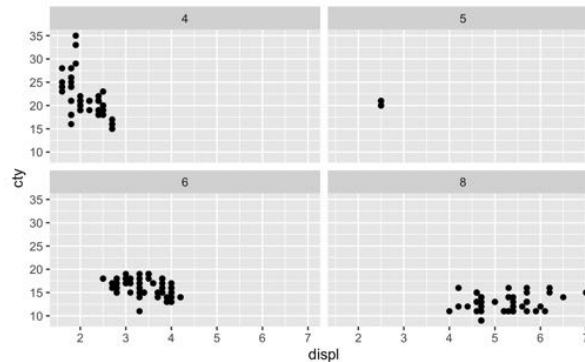
```
# R model formula  
y ~ x # ~ separates the left- and right-hand sides in the model formula  
fit <- lm(y ~ x1 + x2 + x3, data=mydata) #example of multiple linear regression
```

dot in the model formula indicates no faceting in that dimension.

# FACETING: FACET\_WRAP

```
p <- ggplot(mpg, aes(displ, cty)) + geom_point()
```

By rows & columns



```
# New notation: facet_grid(rows, cols)
p + facet_wrap(facets=vars(lf))
```

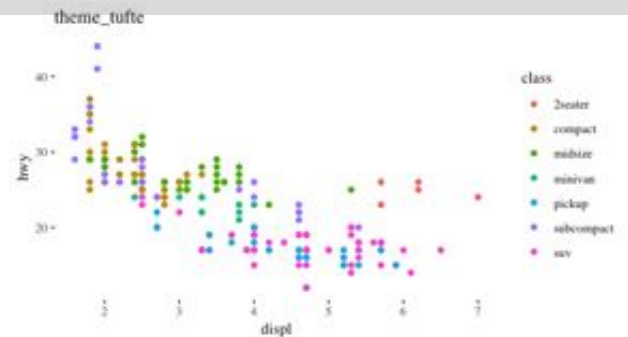
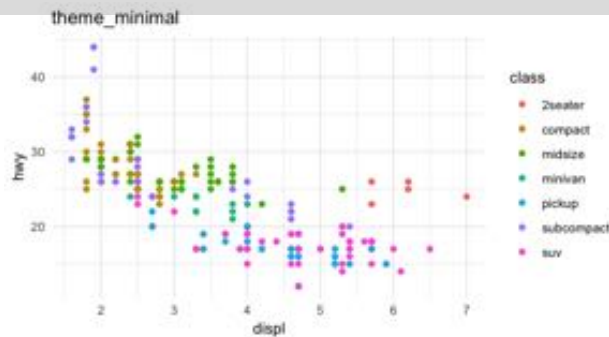
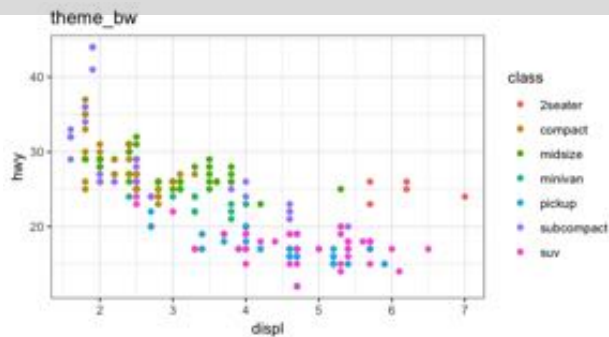
```
# Model notation: facet_grid(y ~ x)
p + facet_grid(~ lf)
```

# THEMES

```
p <- ggplot(mpg, aes(displ, hwy, color=class)) + geom_point()  
p + theme_bw() + ggtitle("theme_bw")  
p + theme_minimal() + ggtitle("theme_minimal")
```

```
library(ggthemes) #extra themes  
p + theme_tufte() + ggtitle("theme_tufte")
```

```
theme_set(theme_bw()) #sets the theme for all subsequent ggplot plots
```



Extra themes in package [ggthemes](#)

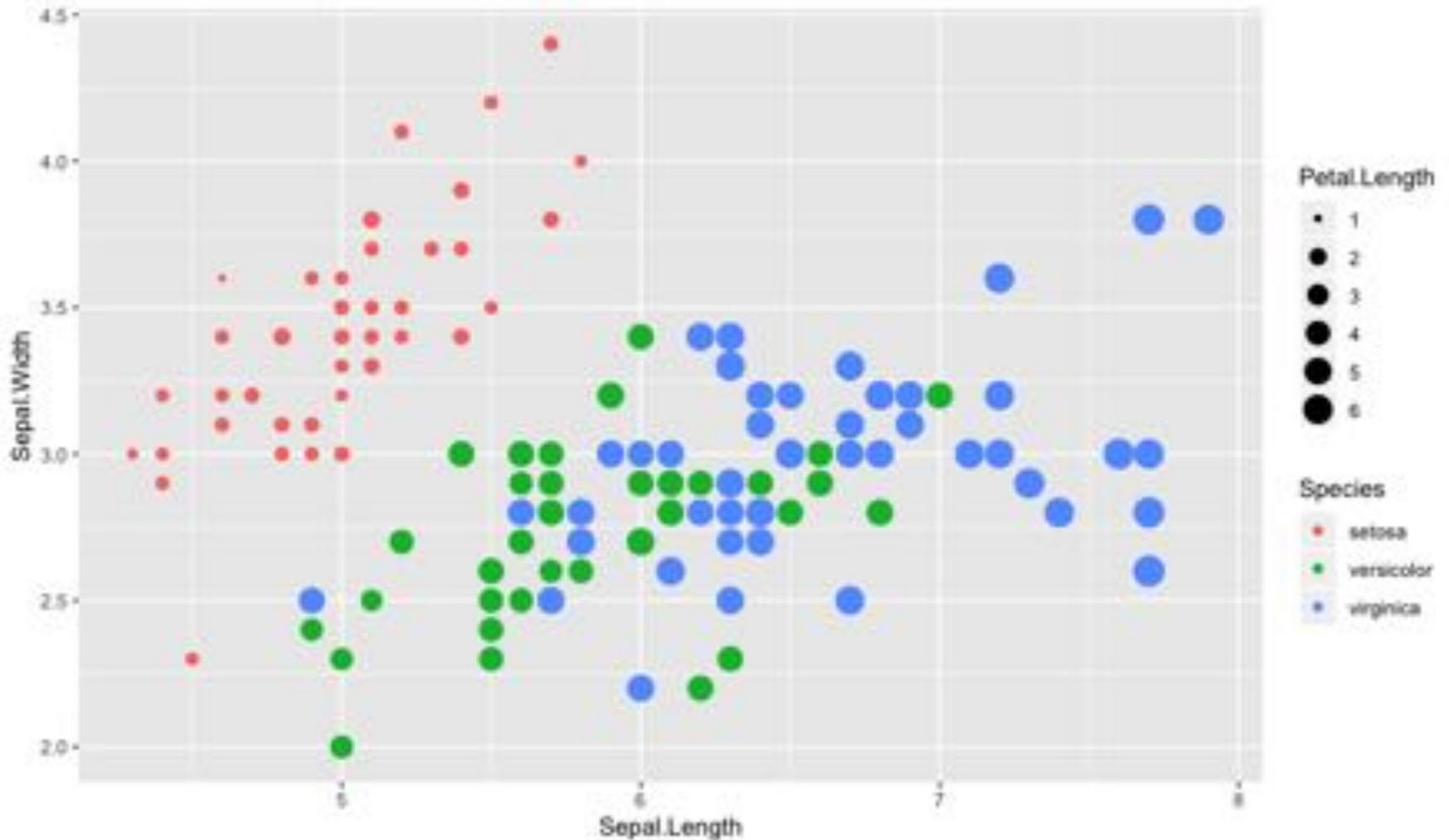
# TABLEAU VS. GGPLOT2

```
ggplot(iris, aes(x=Sepal.Length, y=Sepal.Width, color=Species, size=Petal.Length)) +  
  geom_point()
```



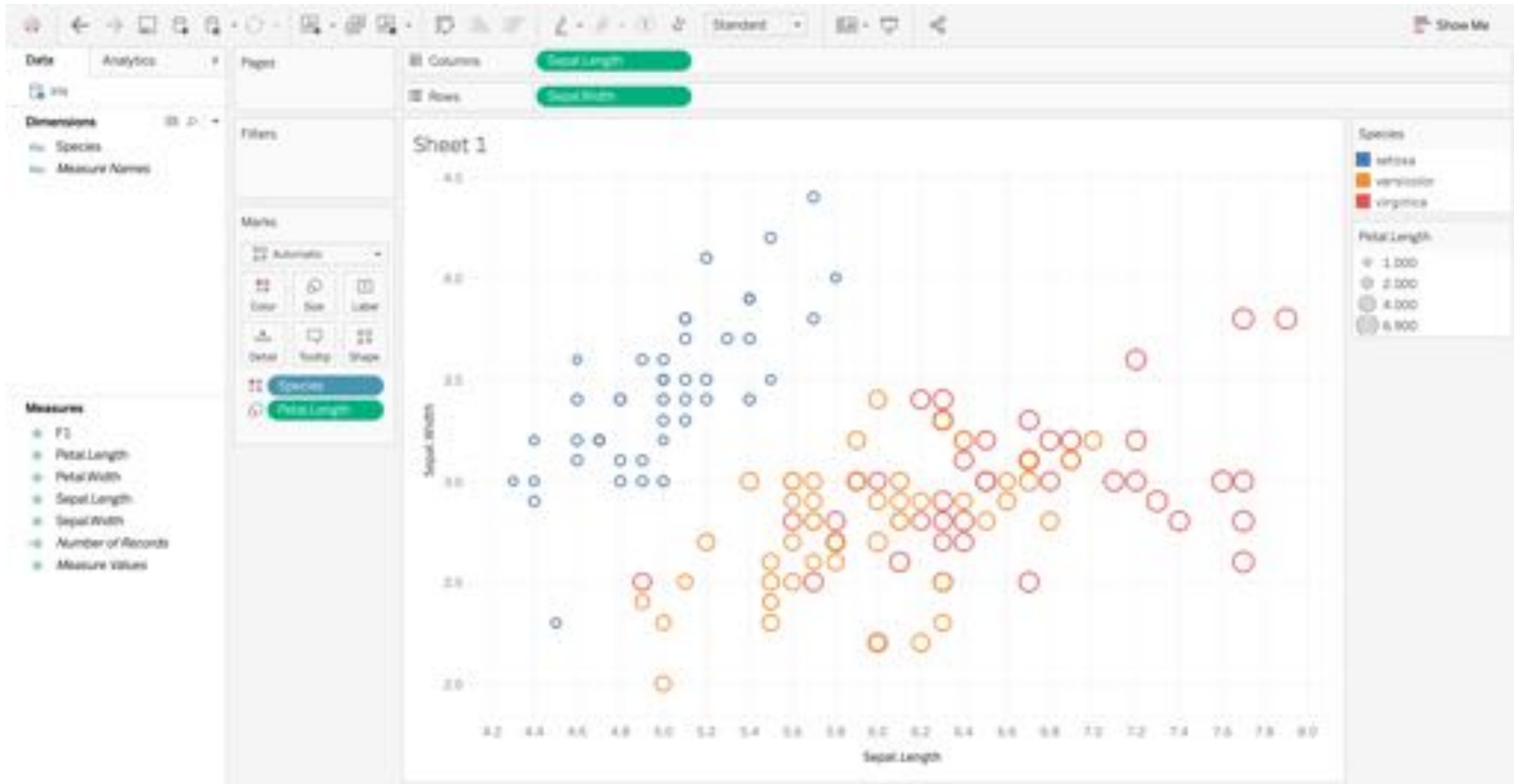
# GGPLOT 2 (LAYERED GRAMMAR)

```
ggplot(iris, aes(x=Sepal.Length, y=Sepal.Width, color=Species, size=Petal.Length)) + geom_point()
```



Use `geom_point(shape=1)` to draw circle outline

# TABLEAU (VISUAL GRAMMAR)



With data read from CSV:  
**Dimensions** ↔ categorical variables  
**Measures** ↔ numerical variables

