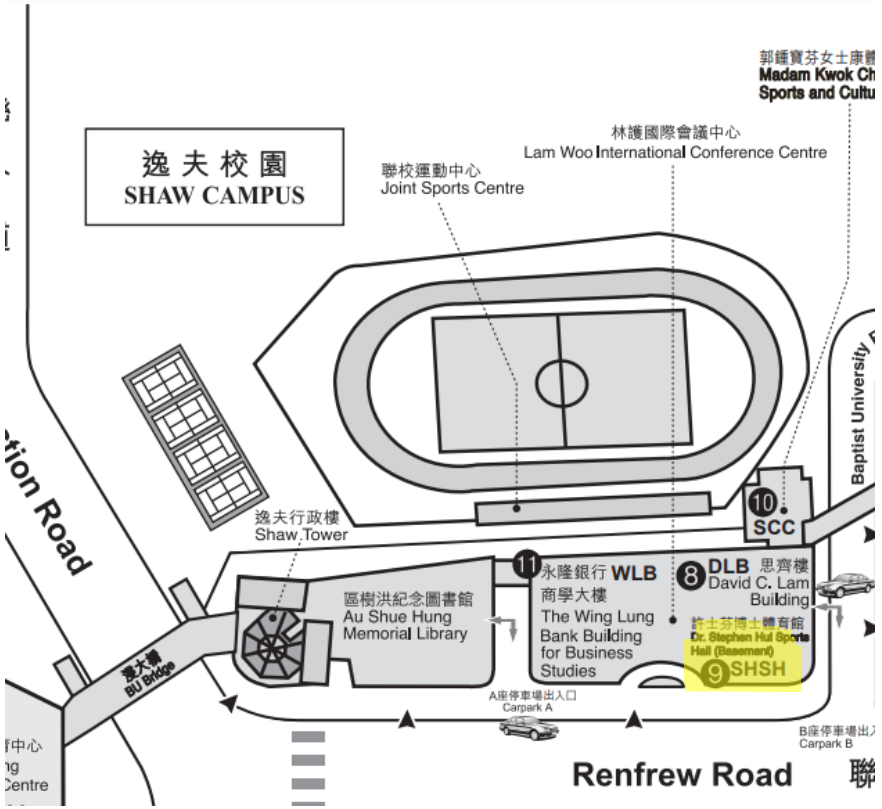
COMP7990

Exam Details

- Date: 12-12-2024
- Time: 19:00 - 22:00
- Venue: SHSH



- Format: closed-book. No note, no paper
  - Formula sheet is given.
- **Listed calculators are allowed.**
- **Steps carry marks.**
- **Rulers, Eraser, Pen, Pencils, a calculator are useful**

Exam Content

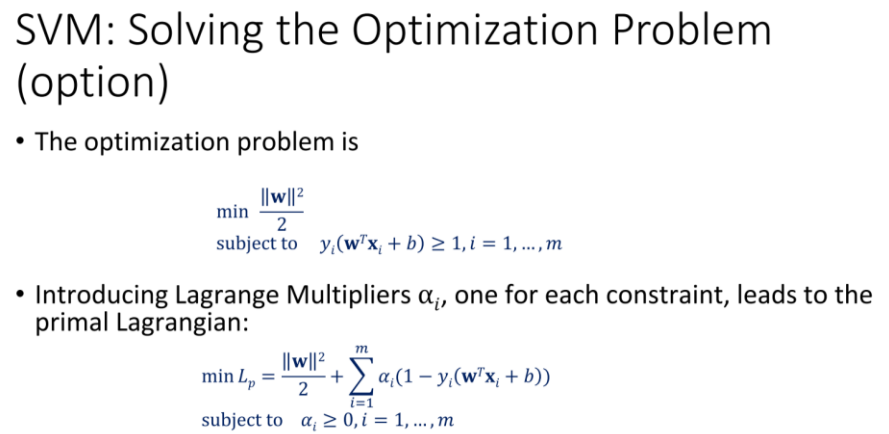
- Data Mining (~27%)
- Statistics (~30%)
- Visualization (~5%)
- Security and Privacy (~8%)
- Database (~30%)

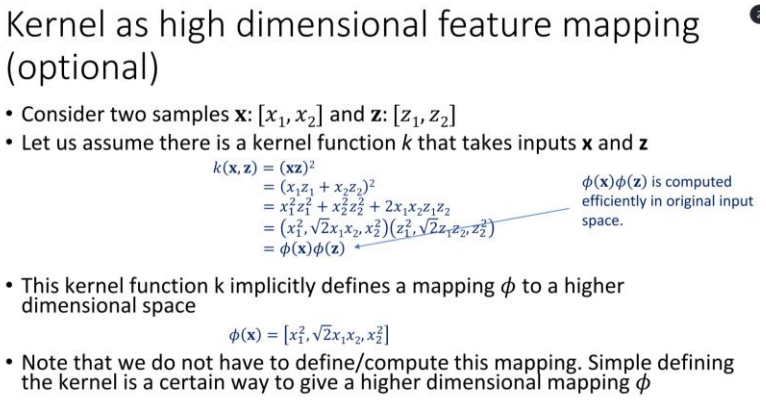
Tips

- Don't be late. No enter after 30 minutes.
- Sleep well before the exam
- Have just enough food before the exam
- Remember the algorithms/computational procedures
- Do revision on your quiz again
- Calculator list https://www.hkeaa.edu.hk/DocLibrary/IPE/cal/CAL2019.pdf
- For calculator that is not from the list, you should consult the lecturer in advanced.

Included and Not Included

- Exam covers topics in the lecture notes only. Labs are excluded.
- Notes stated with [Option] / [Extra] are excluded.
  - e.g.





- Equations on formulasheet.pdf are provided.

Review

Review for data mining

- How to Handle Noisy Data
- Normalization
  - Min-Max Normalization
  - Decimal Scaling
  - Z-score Normalization
- Supervised and Unsupervised Learning
- Classification and Regression
- Linear model (one variable and multiple variables)
- Perceptron
- Multi-Layer Perceptron
- SVM
- KNN
- Clustering

How to Handle Noisy Data

- **Binning**
  - **First sort data and partition into bins**
  - **Smooth by bin mean/median/boundaries**
- Regression
  - Smooth by fitting the data into regression functions
- Clustering
  - Detect and remove outliers

Simple Discretization Methods: Binning

- Equal-width (distance) Partitioning
  - Divides the range into *N* intervals of equal size: uniform grid
  - Suppose *min* and *max* are the lowest and highest values of the attribute, the width of intervals should be: w = (*max* – *min*)/*N*
  - The most straight-forward method
  - Outliers may dominate presentation
  - Skewed data is not handled well

- Equal-depth (frequency) partitioning
  - Divides the range into *N* intervals, each containing approximately same the number of samples
  - Skewed data is also handled well

Normalization

- For distance-based methods, normalization helps to prevent that attributes with large ranges out-weight attributes with small ranges
- Scale the attribute values to a small specified range
- Normalization Methods
  - Normalization by decimal scaling
  - Min-Max normalization (normalized by range)
  - Z-score normalization

Normalization: min-max Normalization

- Min-max normalization
  - Performs a linear transformation on the original data.
  - Suppose *min*, *max* are the minimum and maximum values of an attribute and we want to normalize the attribute value to $[min_{new}, max_{new}]$, min-max normalization maps a value x_i to x_i' by

$$x_i' = \frac{(x_i - min)}{max - min}(max_{new} - min_{new}) + min_{new}$$

- E.g., suppose that the minimum and maximum values for the feature income are \$12,000 and \$98,000. We would like to map income to the range [0.0, 1.0]. By min-max normalization, what is the mapped value for \$73,600?

$$\frac{(73{,}600 - 12{,}000)}{98{,}000 - 12{,}000}(1.0 - 0.0) + 0.0 = 0.716$$

Normalization: Decimal Scaling

- Decimal Scaling
  - The values of an attribute are normalized by moving the decimal point.
  - The number of decimal points moved depends on the maximum absolute value of the attribute.
  - Decimal scaling maps a value x_i to x_i' by

$$x_i' = \frac{x_i}{10^j}$$

j is the smallest integer such that $\max(|x_i|) < 1$

- E.g., suppose that the recorded values of an attribute range from -986 to 917. The maximum absolute value is 986. To normalize by decimal scaling, we therefore divide each value by 1,000 (i.e., j = 3) so that −986 normalizes to −0.986 and 917 normalizes to 0.917.

Normalization: *Z*-score normalization

- *Z*-score normalization
  - The values of an attribute are normalized to a scale with a mean value of 0 and standard deviation of 1.
  - Z-score normalization maps a value x_i to x_i' by

$$x_i' = \frac{(x_i - \bar{x})}{S_x}$$

$\bar{x}$: mean of an original *x*

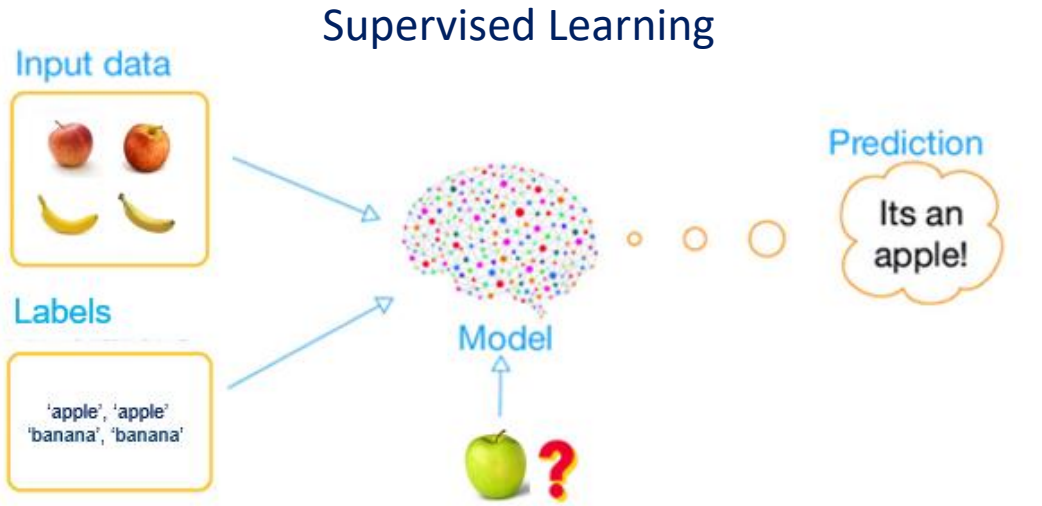
S_x: standard deviation of original x

- E.g., suppose that the mean and standard deviation for income are $54,000 and $16,000. What is the mapped value for $73,600?

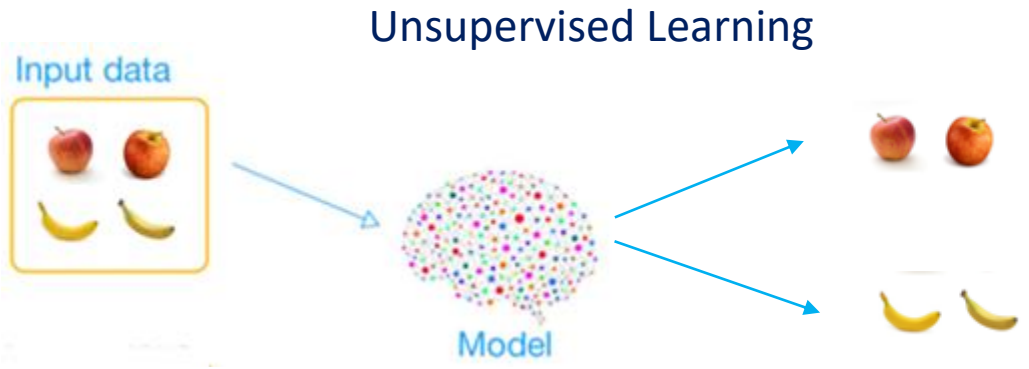
$$\frac{(73{,}600 - 54{,}000)}{16{,}000} = 1.225$$

Different Types of Learning Tasks

- Supervised Learning
  - Data with labels



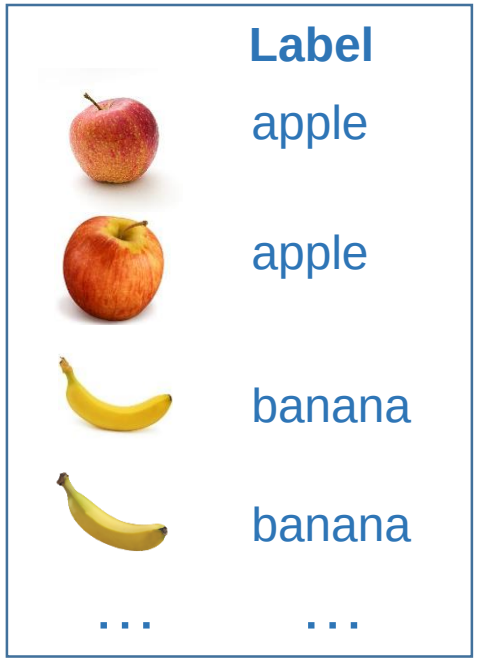
- Unsupervised Learning
  - Data without labels



An Example of Classification Problem

- Learn to recognize apple or banana

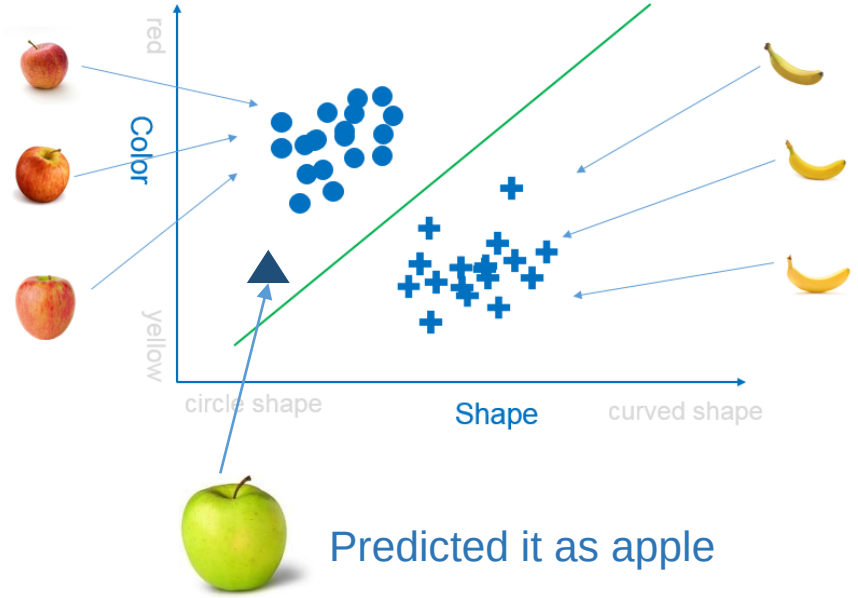
Training Data with Class Label



Feature Engineering

color(x_1)	shape (x_2)	y
0.8	0.1	1
0.75	0.12	1
0.12	0.6	0
0.2	0.8	0
…	…	…
…	…	…

Model Building



Test Data

To predict it is apple or banana

An Example of Regression Problem

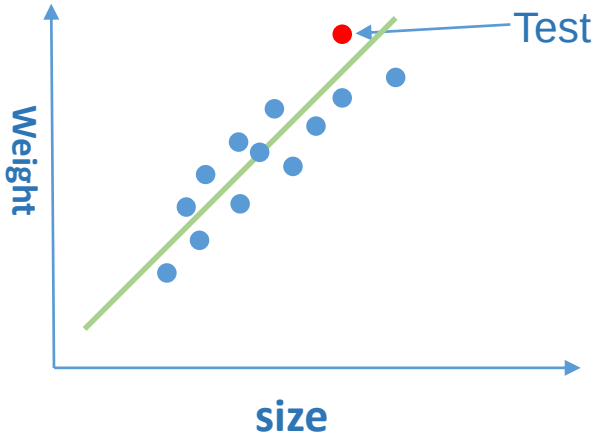
Training Data with Weight

	Weight
	1.2
	0.8
	0.5
	1.7
…	…

Feature Engineering

size(x_1)	weight (x_2)
0.2	0.6
0.4	1.2
0.6	1.8
0.8	2.4
…	…
…	…

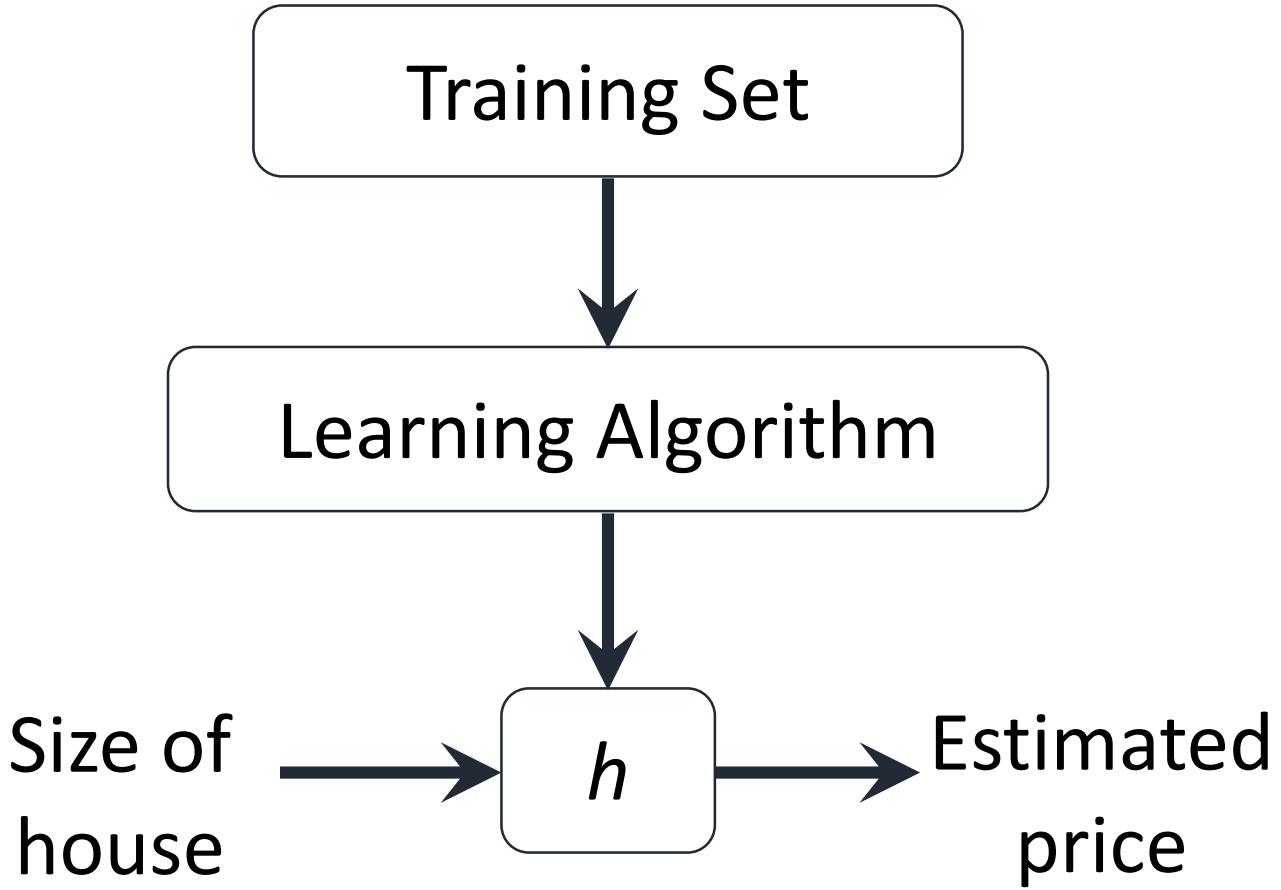
Model Building



Test Data 

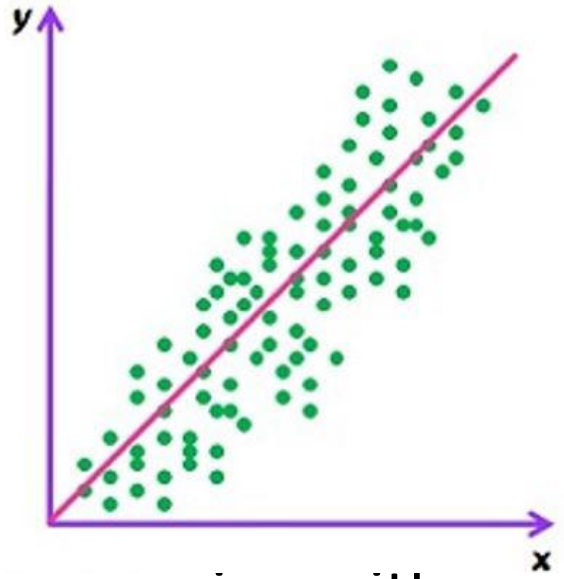
To predict its weight (quantitative feature)

Linear model representation



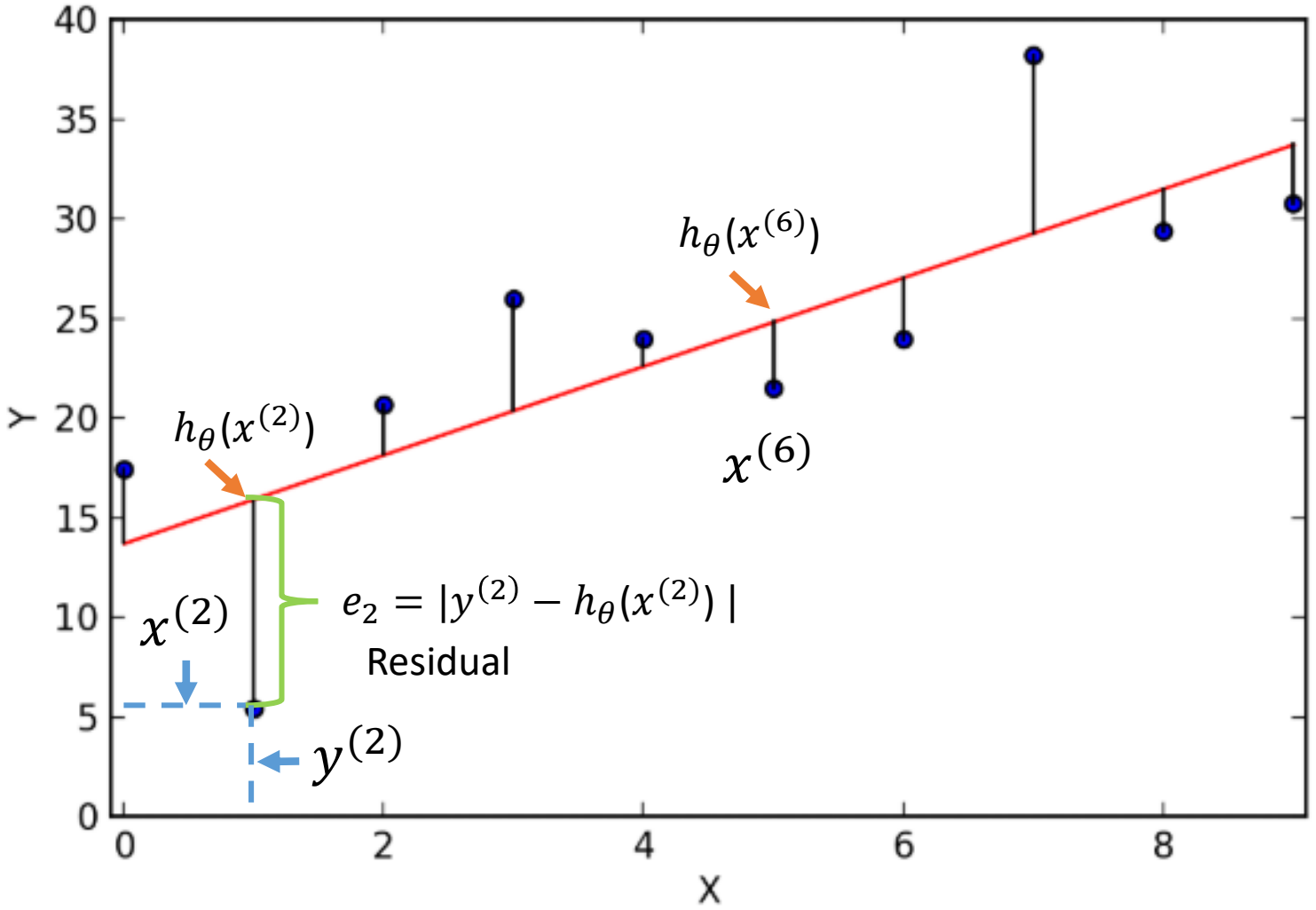
How do we represent *h* ?

$$h_\theta(x) = \theta_0 + \theta_1 x$$



Linear regression with one variable.
Univariate linear regression.

Residual


40
35
30
25
20
15
10
5
0
Y
0
2
4
6
8
X
$h_\theta(x^{(6)})$
$h_\theta(x^{(2)})$
$x^{(6)}$
$e_2 = |y^{(2)} - h_\theta(x^{(2)})|$
Residual
$x^{(2)}$
$y^{(2)}$

Linear Regression one variable

Hypothesis: $h_\theta(x) = \theta_0 + \theta_1 x$

Parameters: θ_0, θ_1

Cost Function: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$

Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

Derive the Solution for Linear Regression on One-Dimensional Data

$$\theta_1 = \frac{\sum(x^{(i)} - \bar{x})(y^{(i)} - \bar{y})}{\sum(x^{(i)} - \bar{x})^2}$$

$$\theta_0 = \bar{y} - \theta_1 * \bar{x}$$

Linear Regression multiple variables

Hypothesis: $h_\theta(x) = \theta^T x = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$

Parameters: $\theta_0, \theta_1, \ldots, \theta_n$

Cost function:

$$J(\theta_0, \theta_1, \ldots, \theta_n) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Gradient descent:

Repeat $\{$

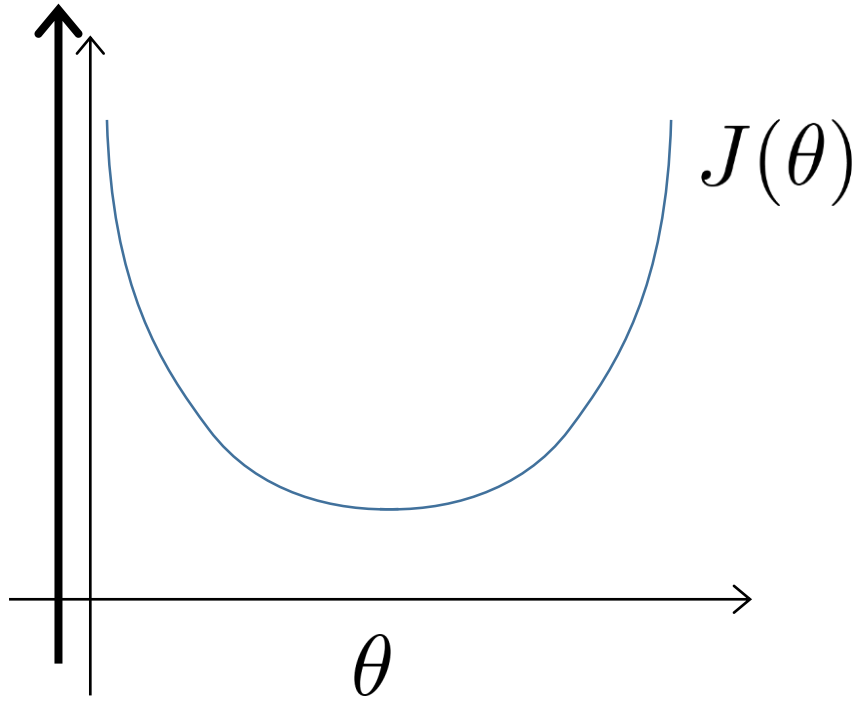
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \ldots, \theta_n)$$

$\}$ (simultaneously update for every $j = 0, \ldots, n$)

Normal equation

Gradient Descent:
Method to solve for θ numerically.

Normal equation:
Method to solve for θ analytically.



Gradient descent:

Repeat $\{$

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \ldots, \theta_n)$$

$\}$

$$\theta = (X^T X)^{-1} X^T y$$

Gradient descent and normal equation

m **training cases,** n **variables.**

Gradient Descent

- Need to choose α.
- Needs many iterations.
- Works well even when n is large.

Normal Equation

- No need to choose α.
- Don’t need to iterate.
- Need to compute $(X^T X)^{-1}$
- Slow if n is very large.

Introduction to Perceptron Algorithm

- Problem Definition
  - Given a training dataset $\{\mathbf{x}_i, y_i\}_{i=1}^m$, where $\mathbf{x}_i$ is a *n* dimensional input feature vector, $y_i \in \{-1,1\}$ is the corresponding class label.
  - Objective: Train a linear classifier that can separate positive and negative samples.
  - **Training:** Learn a linear classification function $f(\mathbf{x}) = \sum_{j=1}^n w_j x_j + b$ from training data
    - $y = 1$ if $f(\mathbf{x}) = \sum_{j=1}^n w_j x_j + b > 0$
    - $y = -1$ if $f(\mathbf{x}) = \sum_{j=1}^n w_j x_j + b < 0$
    - w_j, b are the model parameters that we need to learn from training data
  - **Prediction:** for any new input **x,** predict its class label as $y = \text{sign}(f(\mathbf{x}))$
- Simplify the notation
  - By introducing an artificial feature $x_0 = 1$, $\mathbf{x} \to [x_0, x_1, \dots, x_n]$, $f(\mathbf{x})$ can be rewritten in vector form as $f(\mathbf{x}) = \sum_{j=1}^n w_j x_j + b = \sum_{j=1}^n w_j x_j + b x_0 = \sum_{j=0}^n w_j x_j = \mathbf{w}^T \mathbf{x}$

Introduction to Perceptron Algorithm

Initialize **w = 0**

Repeat

if $y_i(\mathbf{w}^T\mathbf{x}_i) \leq 0$ then

$\mathbf{w} \leftarrow \mathbf{w} + y_i\mathbf{x}_i$

end if

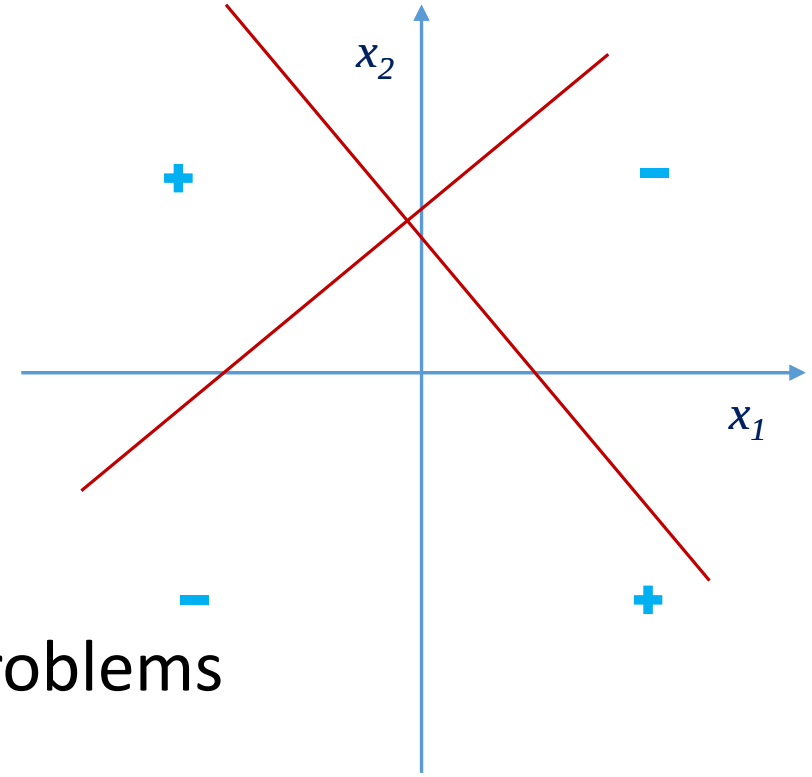
$y_i(\mathbf{w}^T\mathbf{x}_i) \leq 0$ means the training data point $\mathbf{x}_i$ is misclassified.

- true label $y_i = 1$, but the prediction $\text{sign}(\mathbf{w}^T\mathbf{x}) = -1$, or
- true label $y_i = -1$, but the prediction $\text{sign}(\mathbf{w}^T\mathbf{x}) = 1$

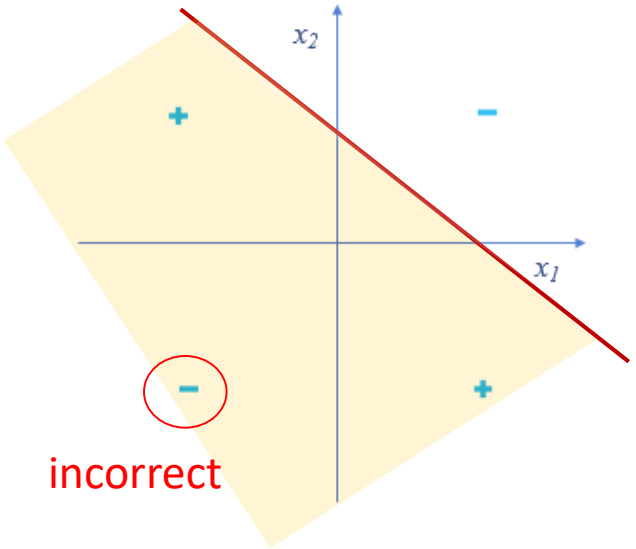
Perceptron: Nonlinear separable problems

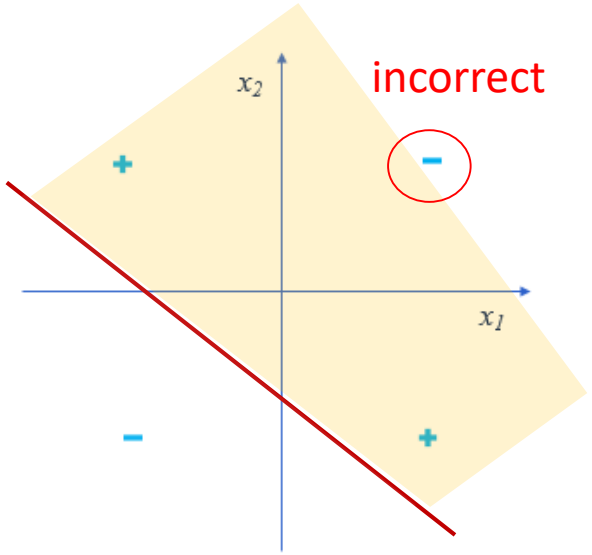
x_1	x_2	y
1	-1	1
1	1	-1
-1	1	1
-1	-1	-1

Perceptron:

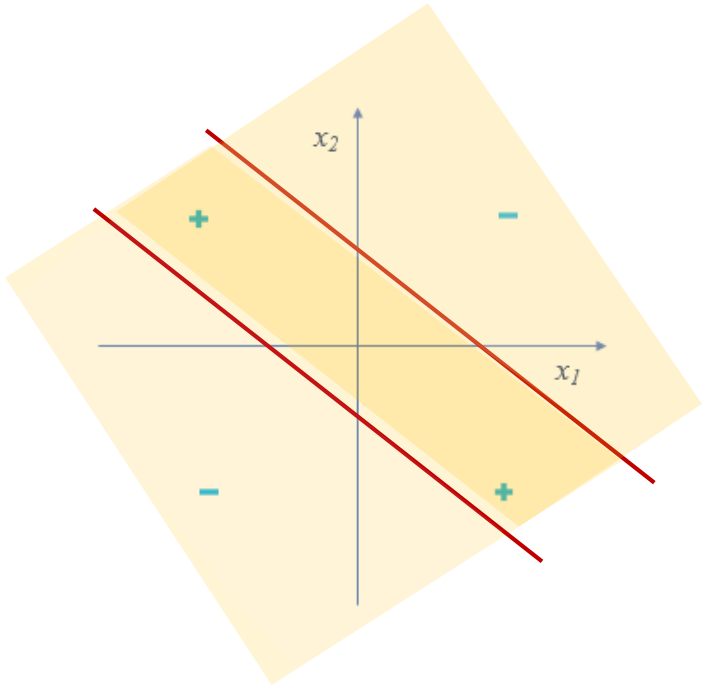


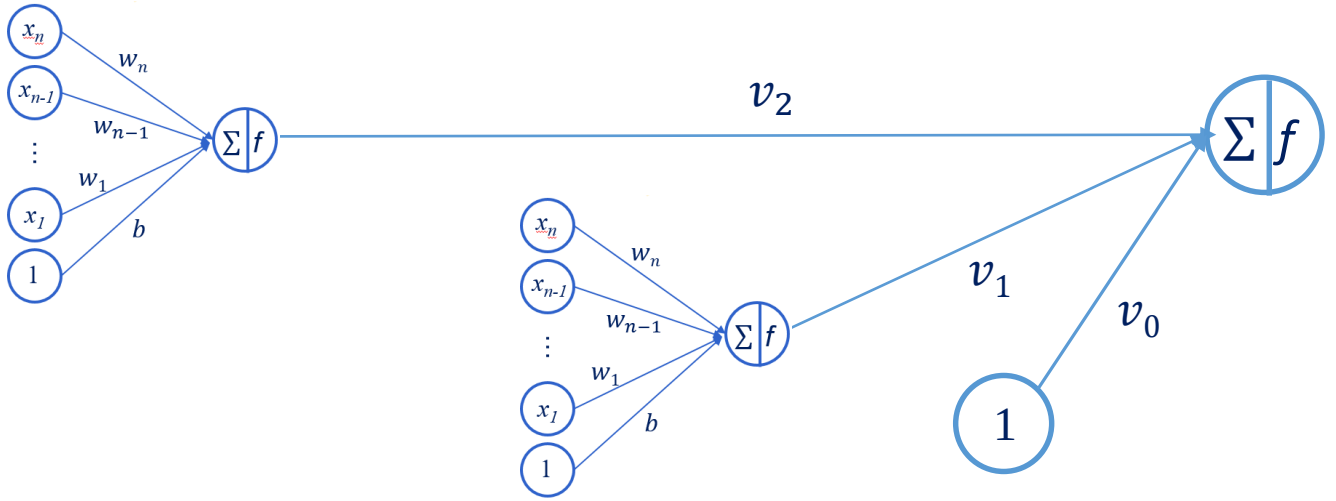
- Perceptron can not solve nonlinear separable problems
- Nonlinear separable problems can be solved by
  - Using multiple layers perceptron (**Artificial Neural Networks**)
  - Making it linearly separable using kernel (**Support Vector Machine**)



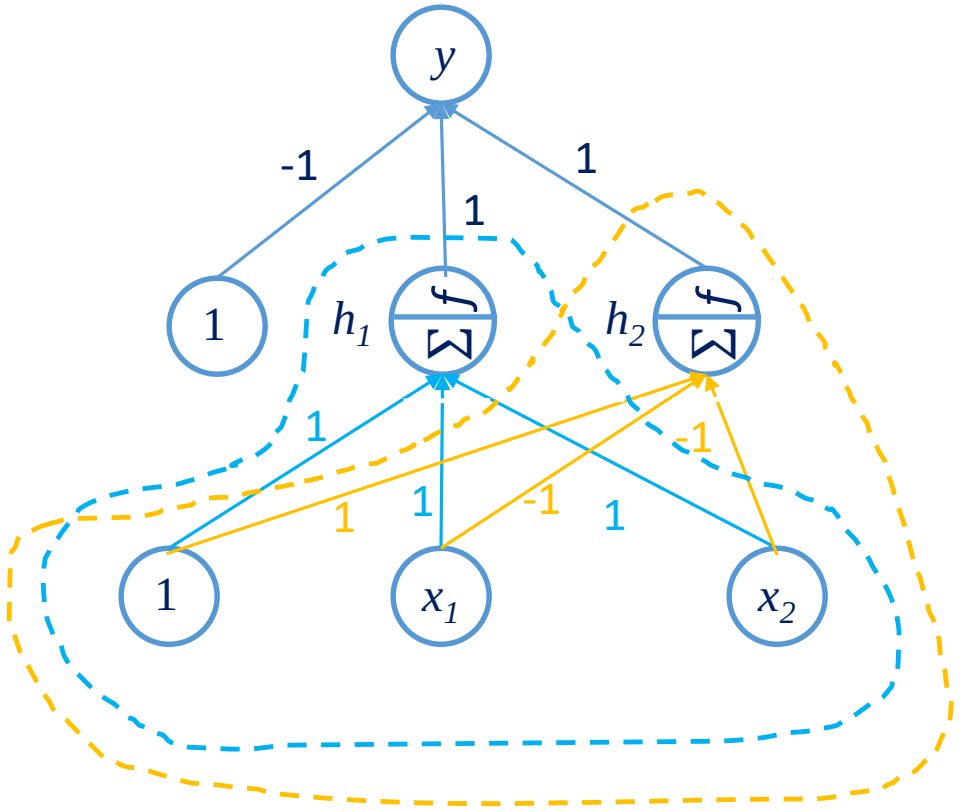


Compose them together

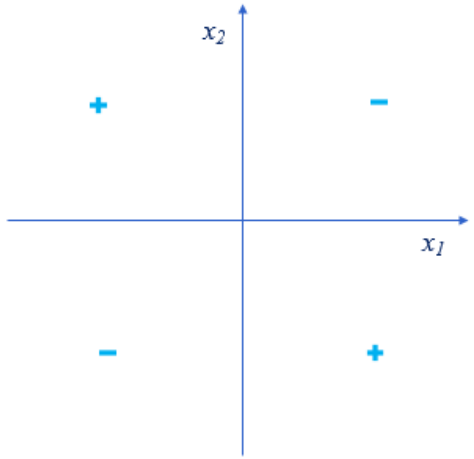




Multi-Layer Perceptron for Nonlinear Classification



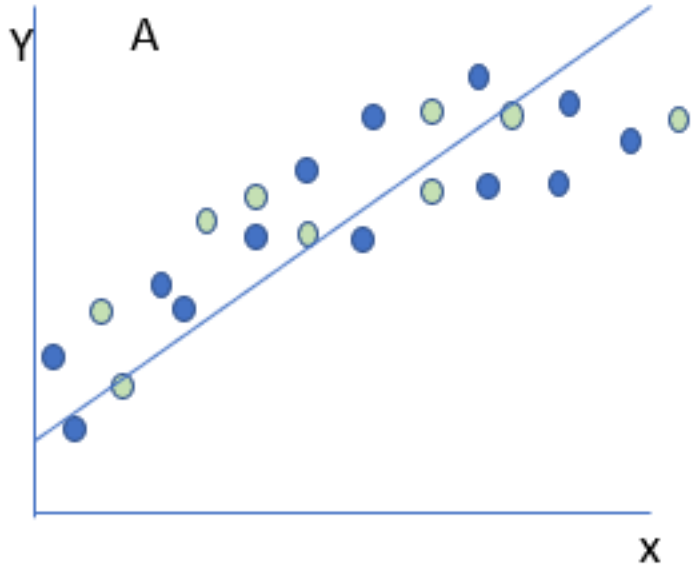
x_1	x_2	y
1	-1	1
1	1	-1
-1	1	1
-1	-1	-1



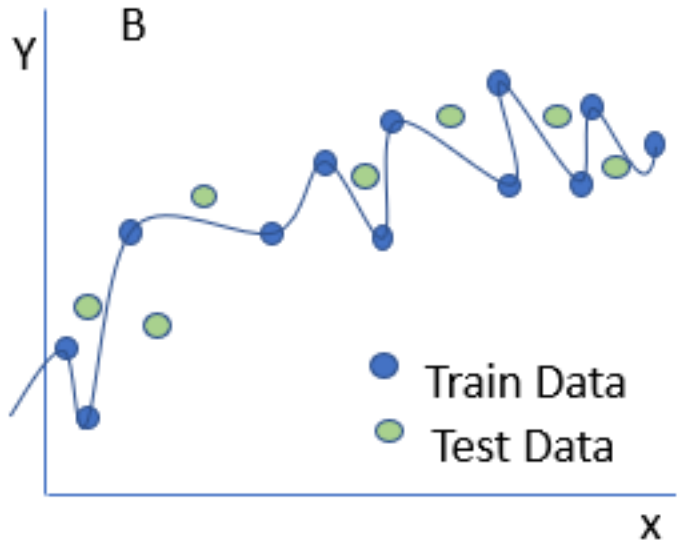
This multi-layer perceptron can solve this nonlinear classification problem.

How to learn the model parameter (i.e., weights on the edge) from data?

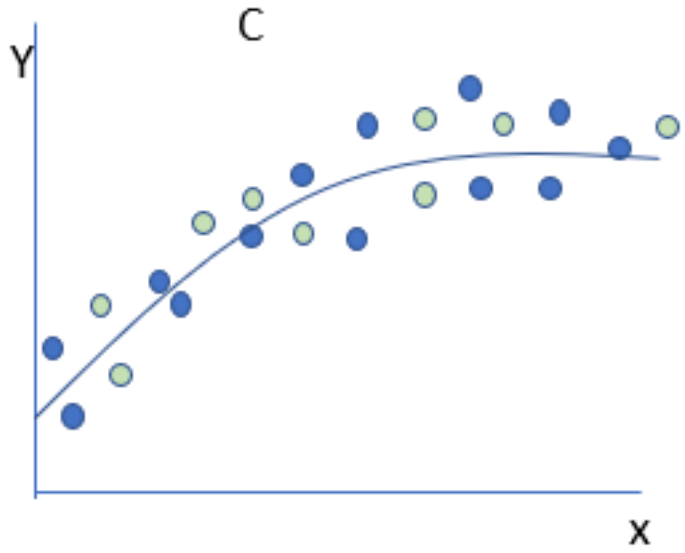
Underfitting/Overfitting and Model Complexity



Underfitting



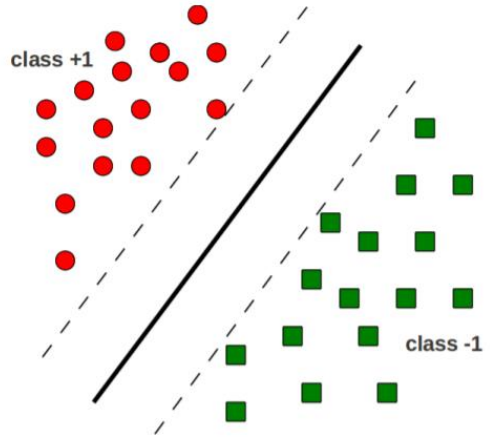
Overfitting



Well fitting

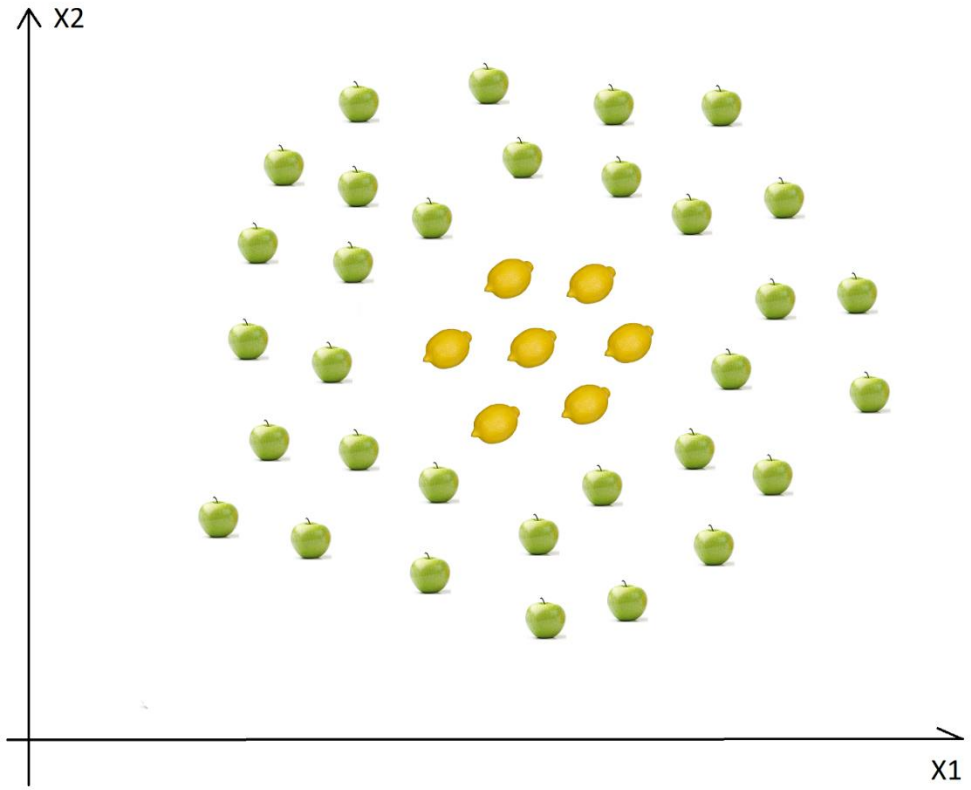
Support Vector Machine (SVM)

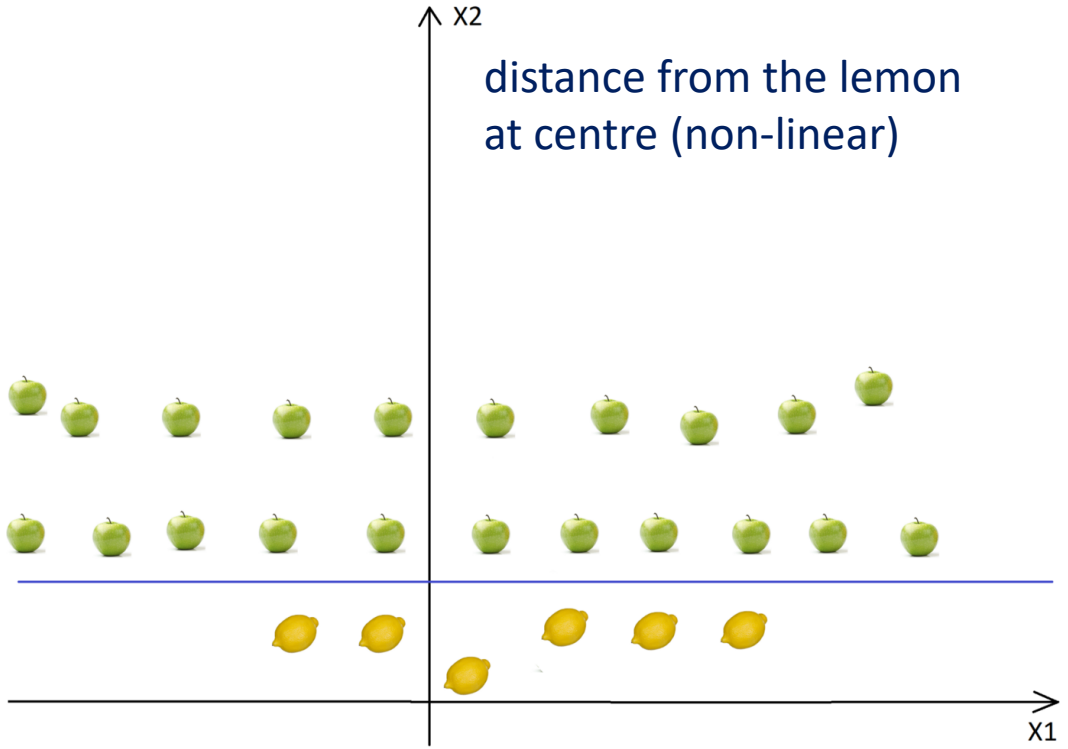
- Probably the most popular/influential classification algorithm
- Backed by solid theoretical groundings
- A hyperplane based classifier (like the Perceptron)
- Additionally uses the maximum margin Principle
  - Finds the hyperplane with maximum separation margin on the training data



Kernel SVM for Nonlinear Classification

- Key idea: Projecting the input to a high dimensional feature space so that non-linear classification problem becomes linearly separable again!

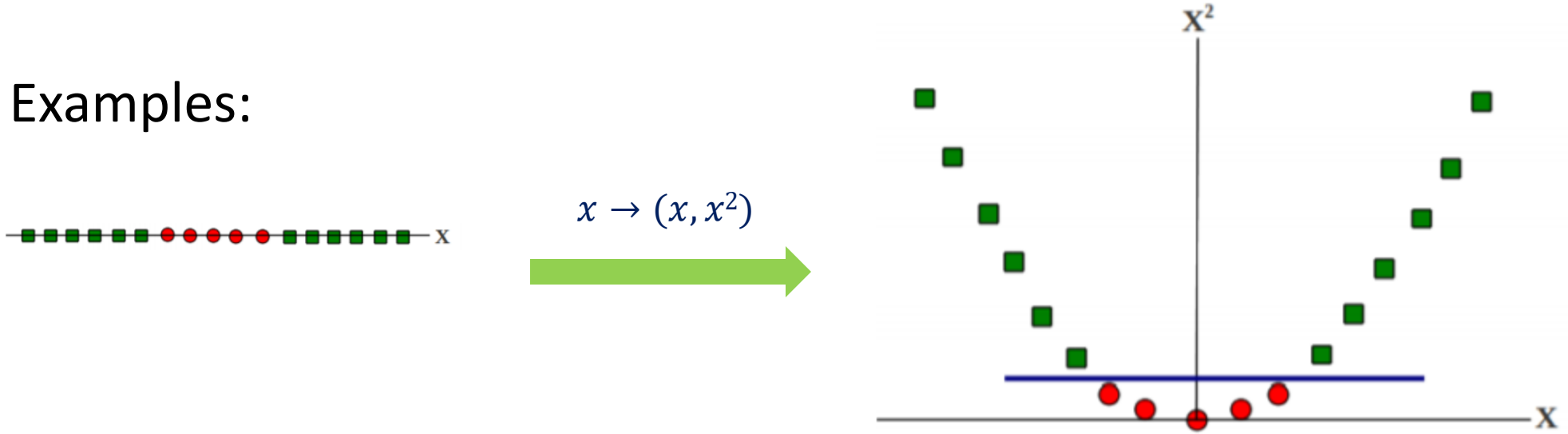




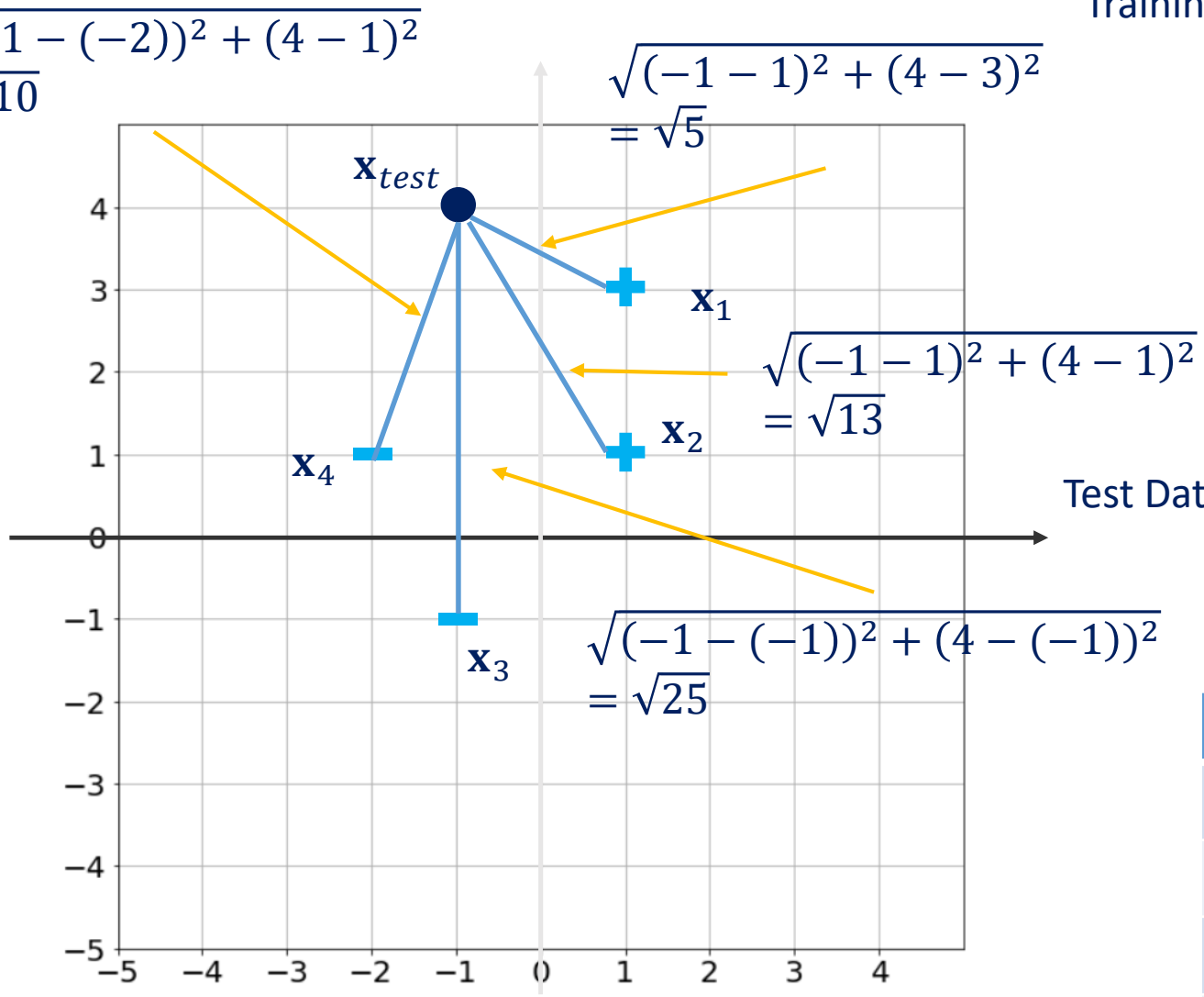
Kernels

- Kernels: Make linear models works in nonlinear settings
  - By mapping data to higher dimensions where it exhibits linear patterns.
  - Apply the linear model in the new input space
  - Mapping means changing the feature representation

- Examples:



k-Nearest Neighbors Example (k=3)



Training Data:

x_1	x_2	*label*
1	3	1
1	1	1
-1	-1	-1
-2	1	-1

Test Data:

x_1	x_2	*label*
-1	4	1

	$\mathbf{x}_{test}$
$\mathbf{x}_1$	$\sqrt{5}$
$\mathbf{x}_2$	$\sqrt{13}$
$\mathbf{x}_3$	$\sqrt{25}$
$\mathbf{x}_4$	$\sqrt{10}$

Sort

	$\mathbf{x}_{test}$
$\mathbf{x}_1$	$\sqrt{5}$
$\mathbf{x}_4$	$\sqrt{10}$
$\mathbf{x}_2$	$\sqrt{13}$
$\mathbf{x}_3$	$\sqrt{25}$

K-means Algorithm

- **Input:** Samples $\{\mathbf{x}_i\}_{i=1}^{m}$, parameter *K* (i.e., number of clusters)
- **Initialize:** *K* cluster centers (means) $\mathbf{c}_1$, …, $\mathbf{c}_k$. Several initialization options:
  - Randomly initialized anywhere in the input space
  - Randomly choose *K* samples from the data as the cluster centers
- **Iterate:**
  - Assign each sample $\mathbf{x}_i$ to its closest cluster center

$$k = \arg\min_k \|\mathbf{x}_i - \mathbf{c}_k\|$$

  - Re-compute the cluster center $\mathbf{c}_k$ for every new cluster

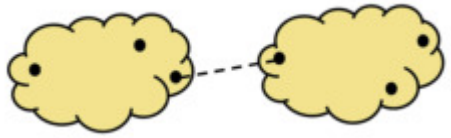
$$\mathbf{c}_k = \frac{1}{|C_k|} \sum_{\mathbf{x}_i \in C_k} \mathbf{x}_i$$

  - Repeat while not converged
- Converge criteria: Cluster centers do not change anymore

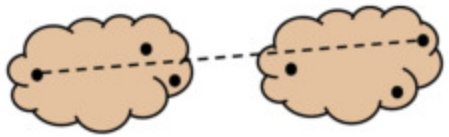
C_k is the set of samples in cluster *k*
$|C_k|$ denotes the number of samples in C_k

Hierarchical Clustering: (Dis)similarity Between Clusters

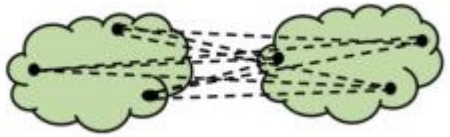
- **Single Linkage**
  - **Smallest** distances between samples, where each one is taken from one of the two groups
- **Complete Linkage**
  - **Largest** distances between samples, where each one is taken from one of the two groups
- **Average linkage**
  - **Average** distance between all samples in one cluster to all points in another cluster
- **Centroid linkage**
  - Distance between their **centroids**.



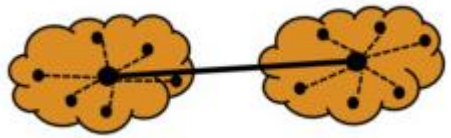
Single Linkage



Complete Linkage

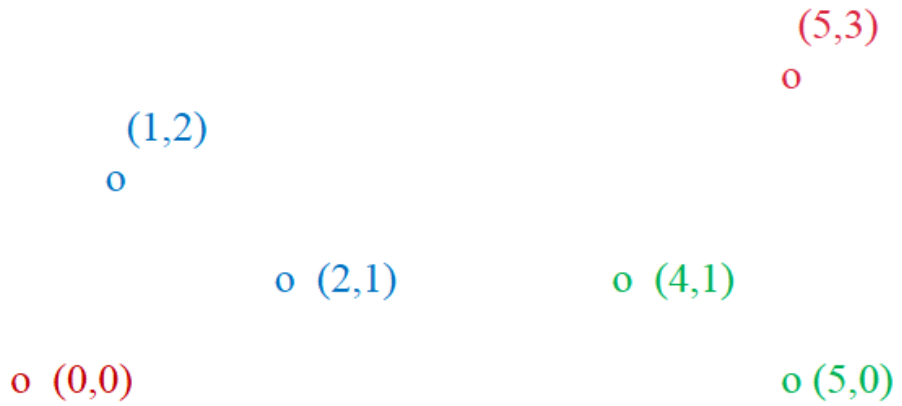


Average Linkage



Centroid Linkage

Example: Hierarchical Clustering (with Centroid Linkage)

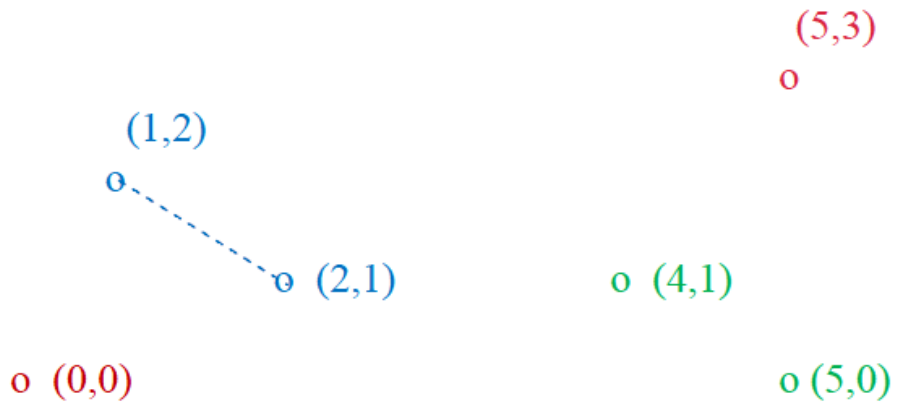


x_1	x_2
0	0
1	2
2	1
4	1
5	0
5	3

Data:
o … data point

Dendrogram

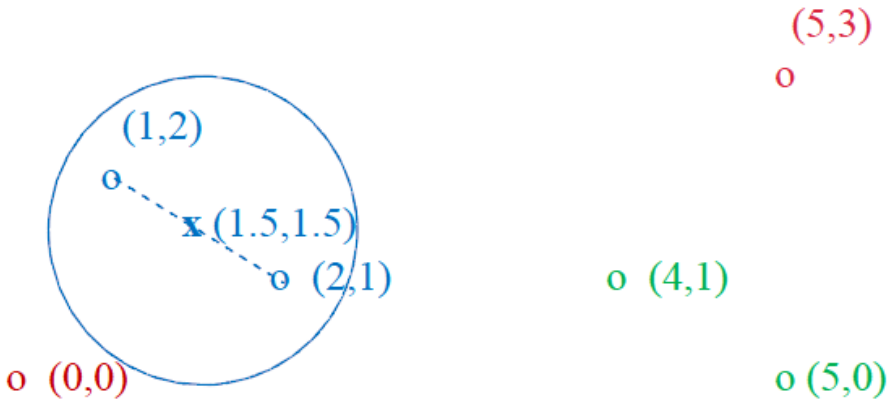
Example: Hierarchical Clustering (with centroid linkage) Step 1



Data:
o … data point

Dendrogram

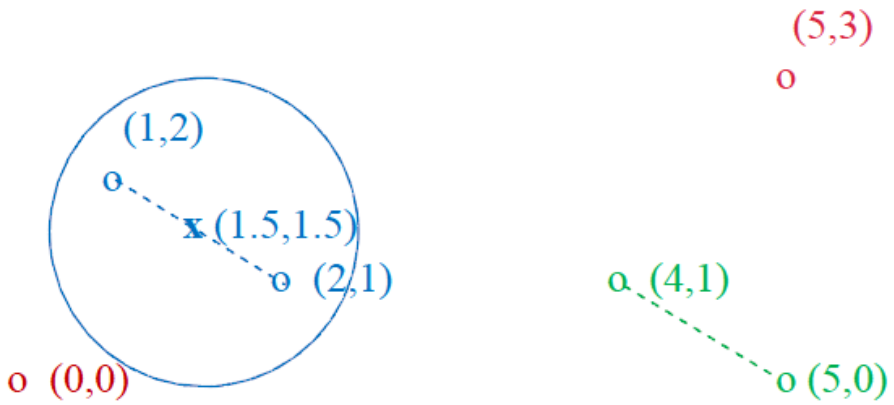
Example: Hierarchical Clustering (with centroid linkage) Step 2



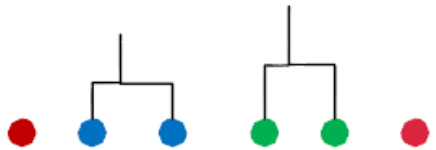
Data:
o … data point
x … centroid

Dendrogram

Example: Hierarchical Clustering (with centroid linkage) Step 3

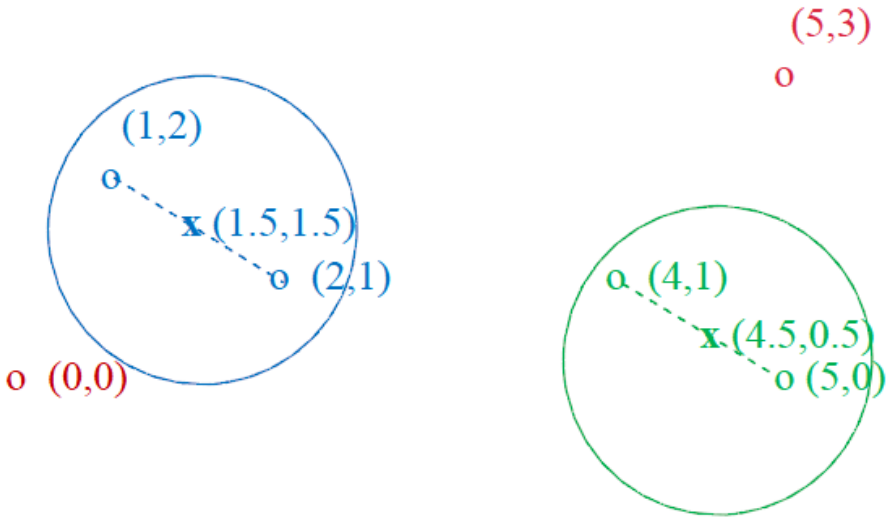


Data:
o … data point
x … centroid

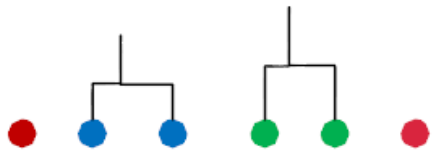


Dendrogram

Example: Hierarchical Clustering (with centroid linkage) Step 4

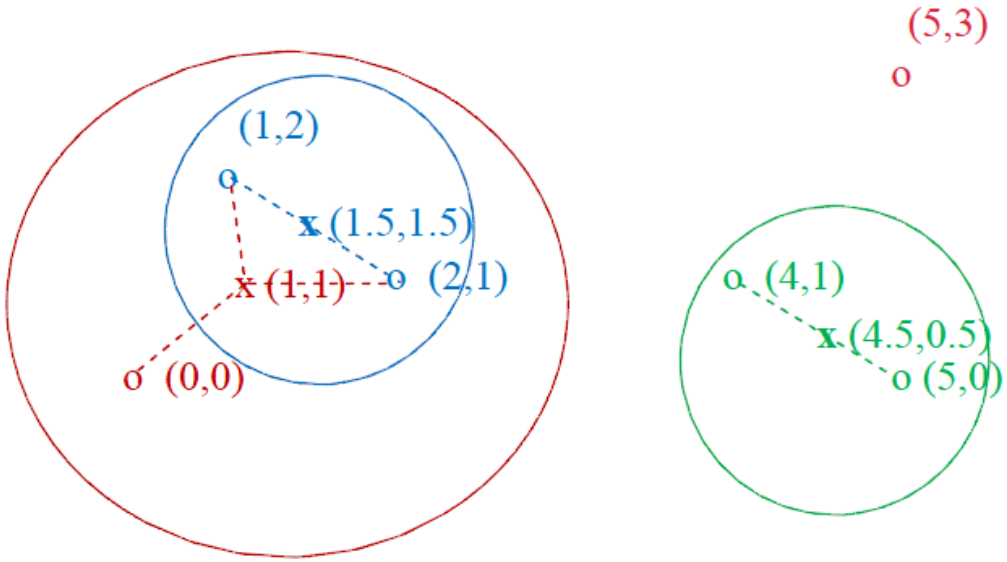


Data:
o … data point
x … centroid

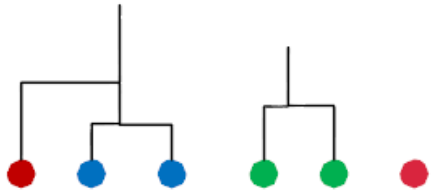


Dendrogram

Example: Hierarchical Clustering (with centroid linkage) Step 5

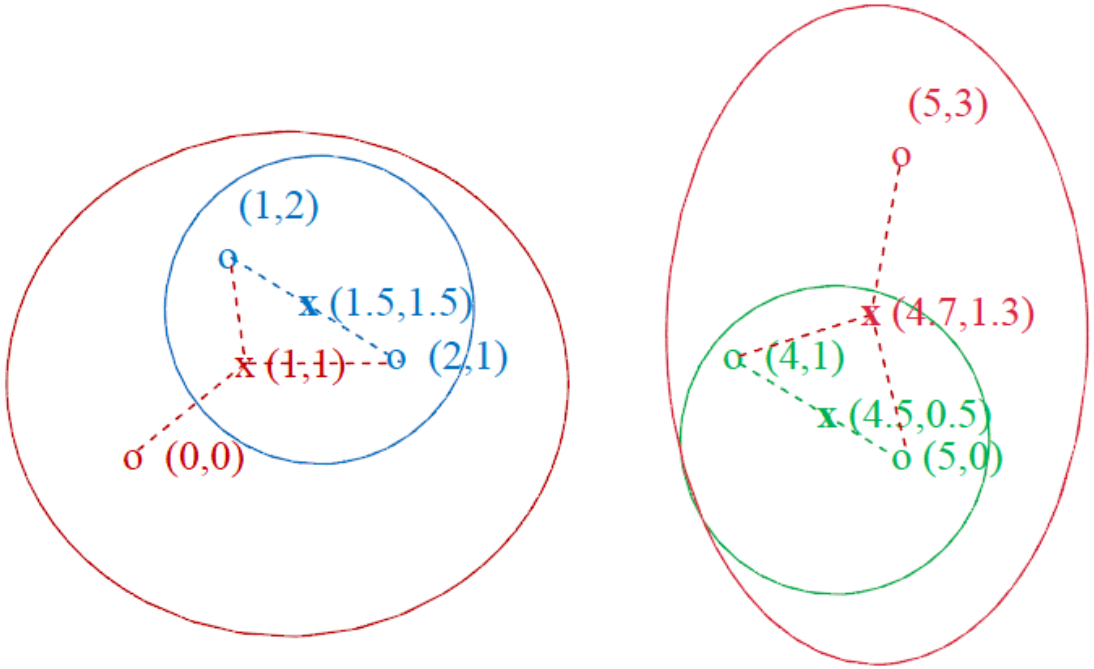


Data:
o … data point
x … centroid

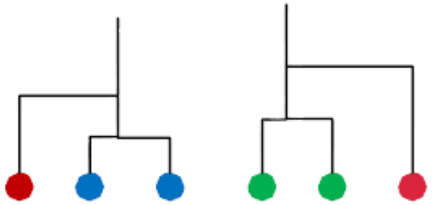


Dendrogram

Example: Hierarchical Clustering (with centroid linkage) Step 6

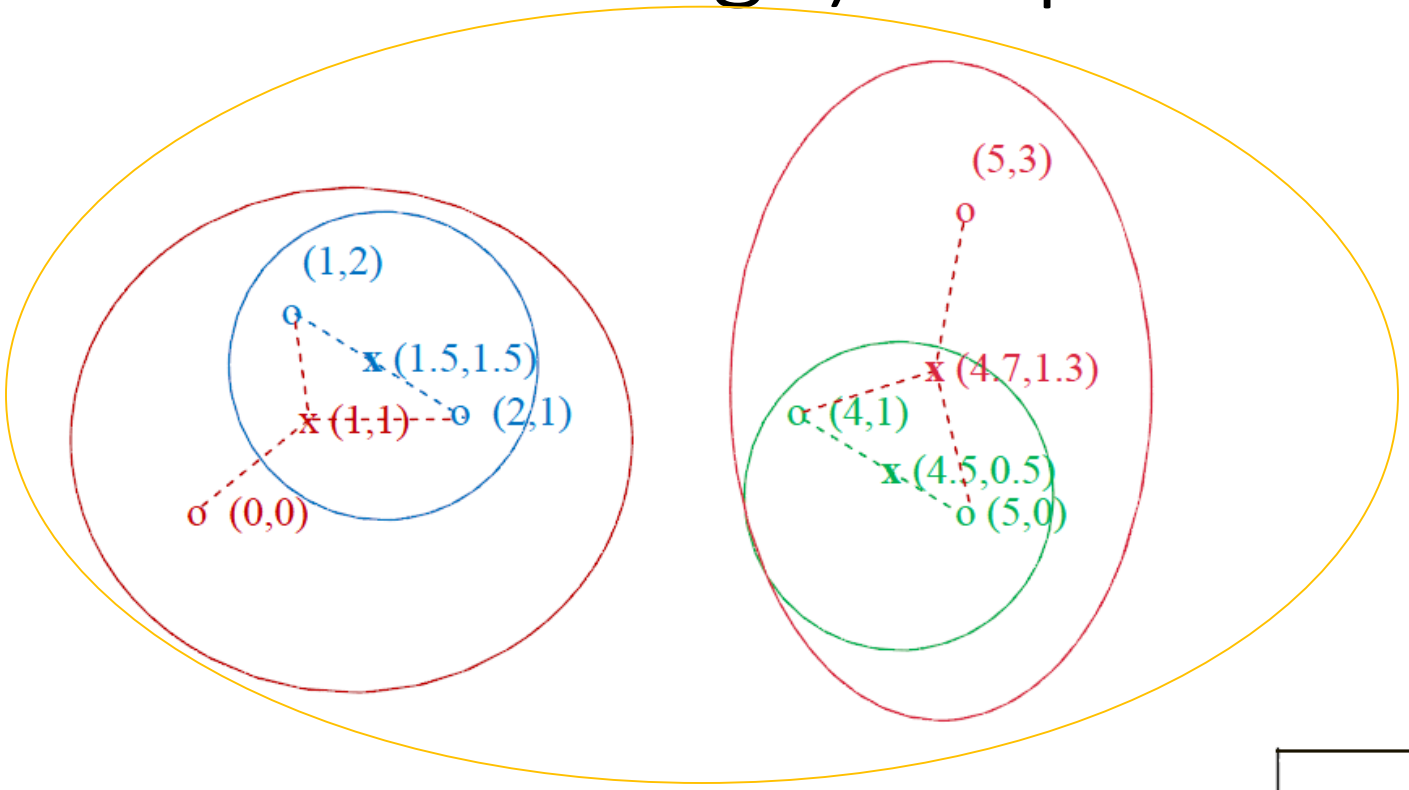


Data:
o … data point
x … centroid

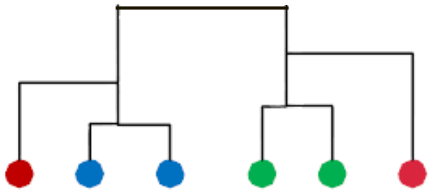


Dendrogram

Example: Hierarchical Clustering (with centroid linkage) Step 7



Data:
o … data point
x … centroid



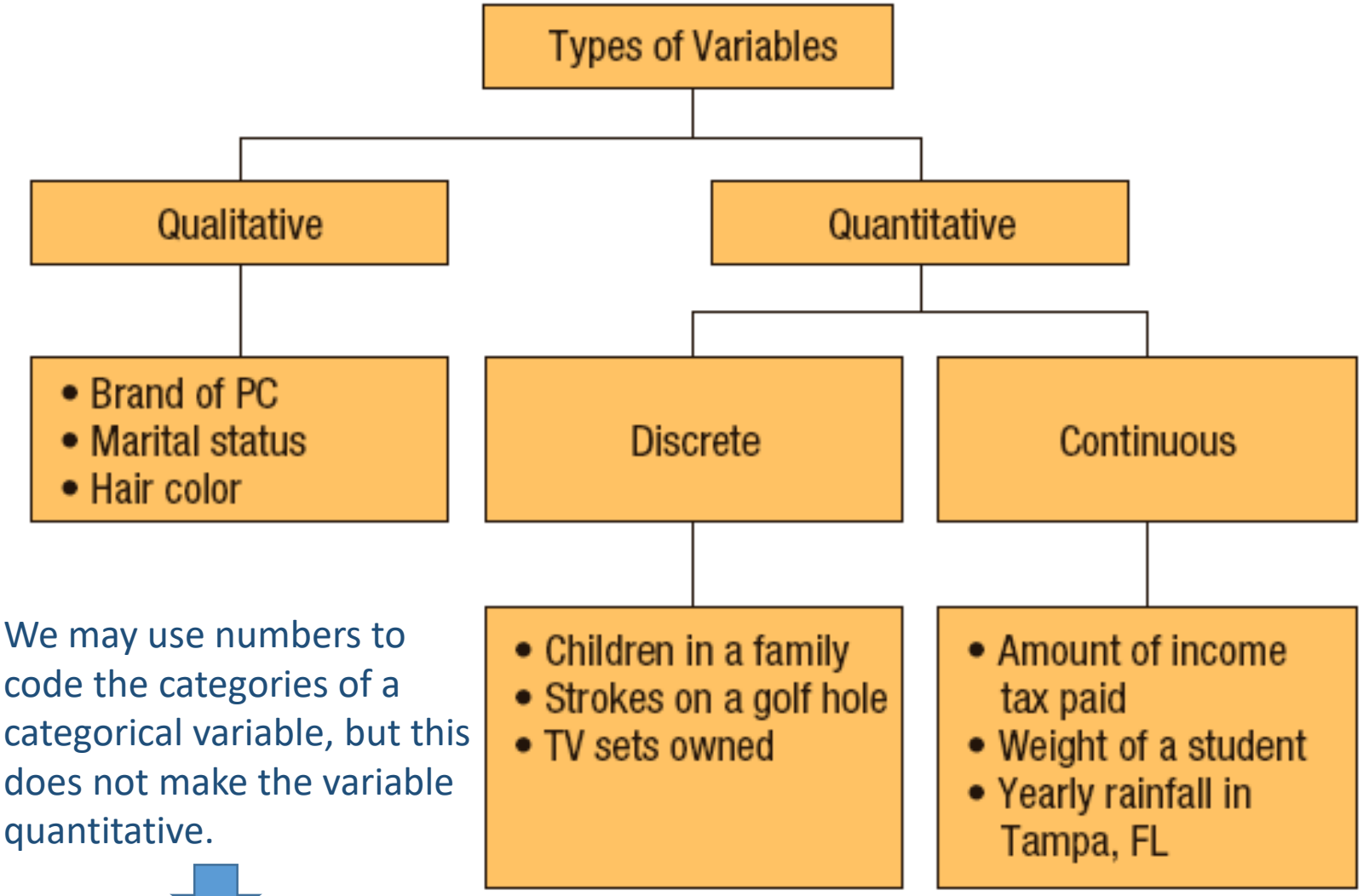
Dendrogram

Statistics

Revision Guide

- Summary Statistics
  - Center: mean, median
  - Spread: standard deviation, range, IQR
  - Five number summary
  - Shape: symmetric, skewed, bell-shaped
  - Outliers, resistance
- Statistics
  - Standard error
  - Confidence interval

Variables – Categorical and Quantitative Variables



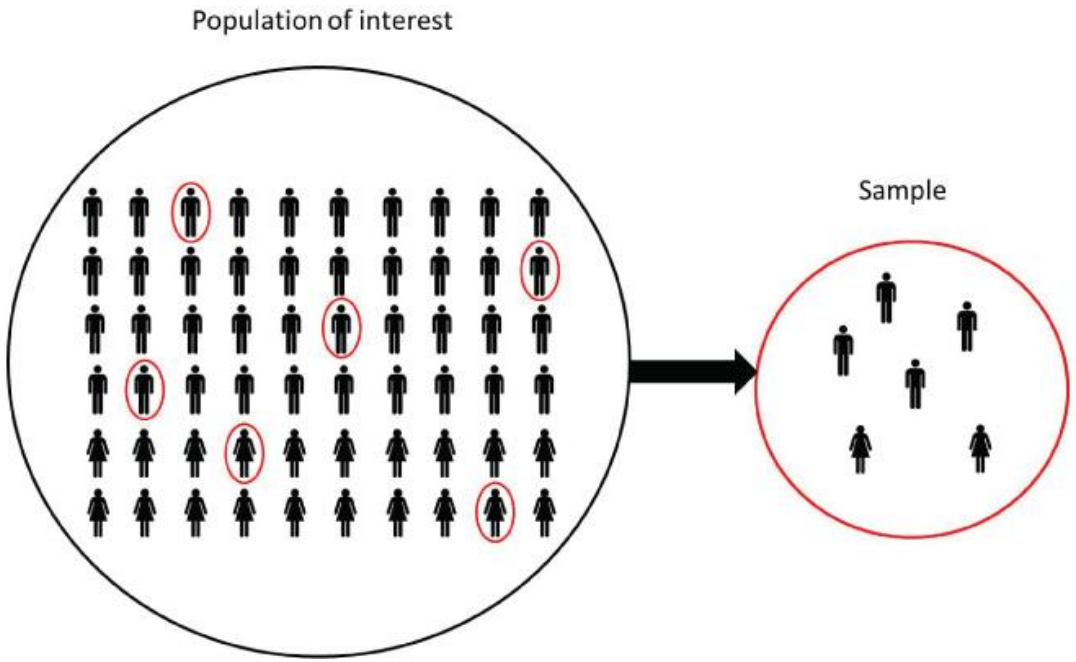
- A qualitative / categorical variable divides the cases into ***groups***, placing each case into exactly one of two or more categories.
- A quantitative /numerical variable measures or records a numerical quantity for each case. Numerical operations like adding and averaging make sense for quantitative variables.

We may use numbers to code the categories of a categorical variable, but this does not make the variable quantitative.

For example, “gender" is categorical even if we choose to record the results as 1 for male and 2 for female.

Random Sampling

- How do we get a sample that looks like the population?
- The key is random sampling!!!
- A random sample will resemble the population!
- Random sampling avoids sampling bias!



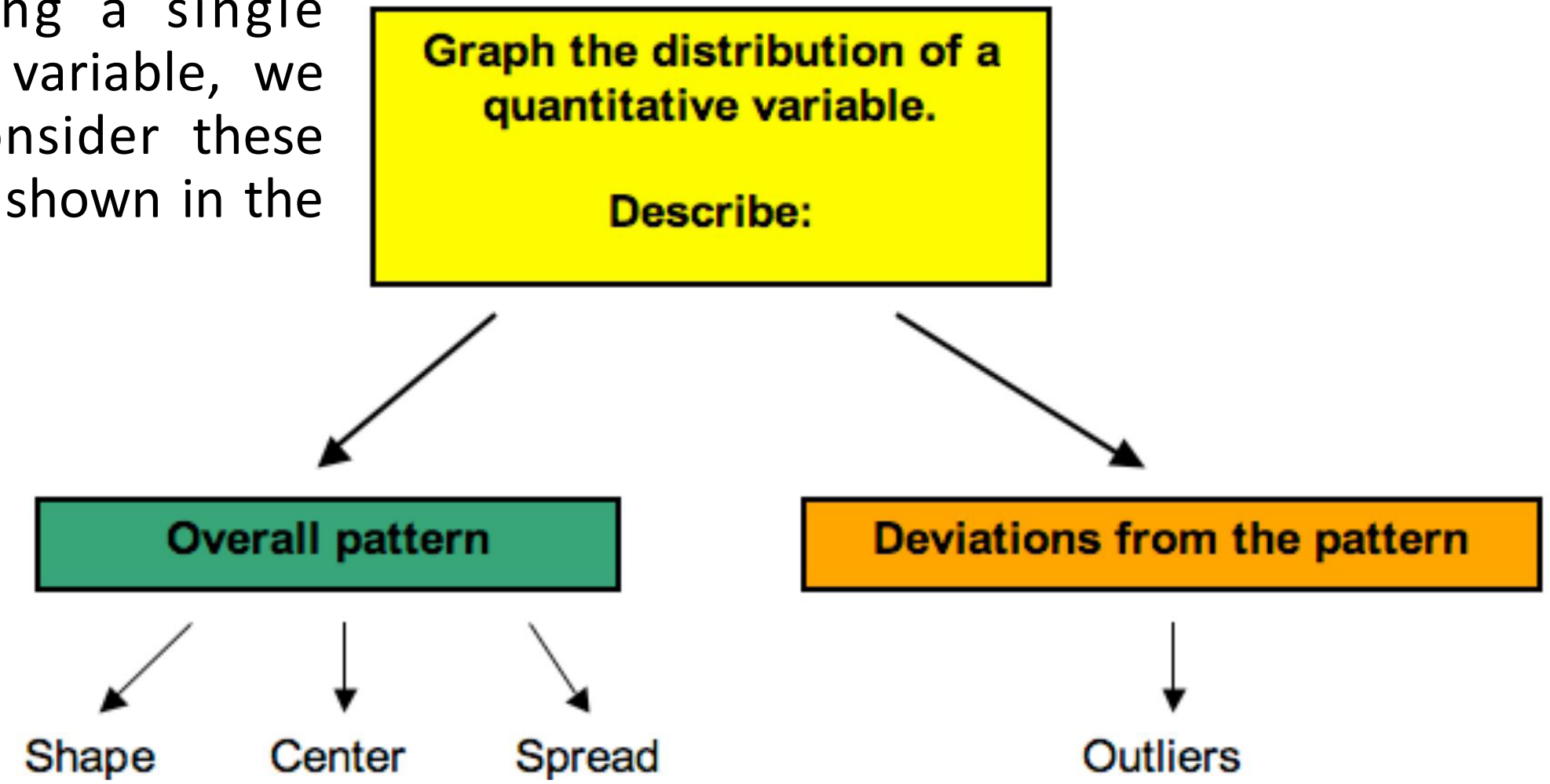
Example of Biased Sampling

- CFQ
  - Only students who extremely like this course or dislike this course will go to do the CFQ.
  - The CFQ result is heavily biased to two ends!

- Students can visit the Course Feedback Questionnaire System (CFQ) at https://cfq-student.hkbu.edu.hk to provide feedback. The evaluation period will end on Tuesday, 3rd December 2024, 23:59:59.

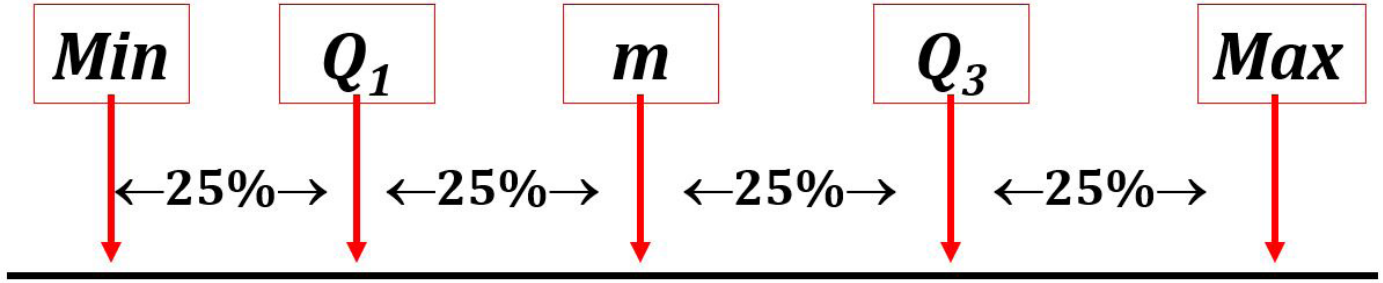
Distribution

- In describing a single quantitative variable, we generally consider these questions as shown in the right graph.



Other measures of location and spread

- Maximum = the largest value
- Minimum = the smallest value
- Mode: The value that has the highest frequency.
- Quartiles:
  - Q_1 = median of the values below m
  - Q_3 = median of the values above m
- Five Number Summary



- Range = Max - Min; Is the range resistant to outliers? No!
- Interquartile Range (IQR) = Q_3-Q_1; Is the IQR resistant to outliers? Yes!

Standard Deviation

The standard deviation for a quantitative variable measures the spread of the data in a sample.

- The standard deviation of a sample is denoted s, and measures how spread out the data are from the sample mean $\bar{x}$.

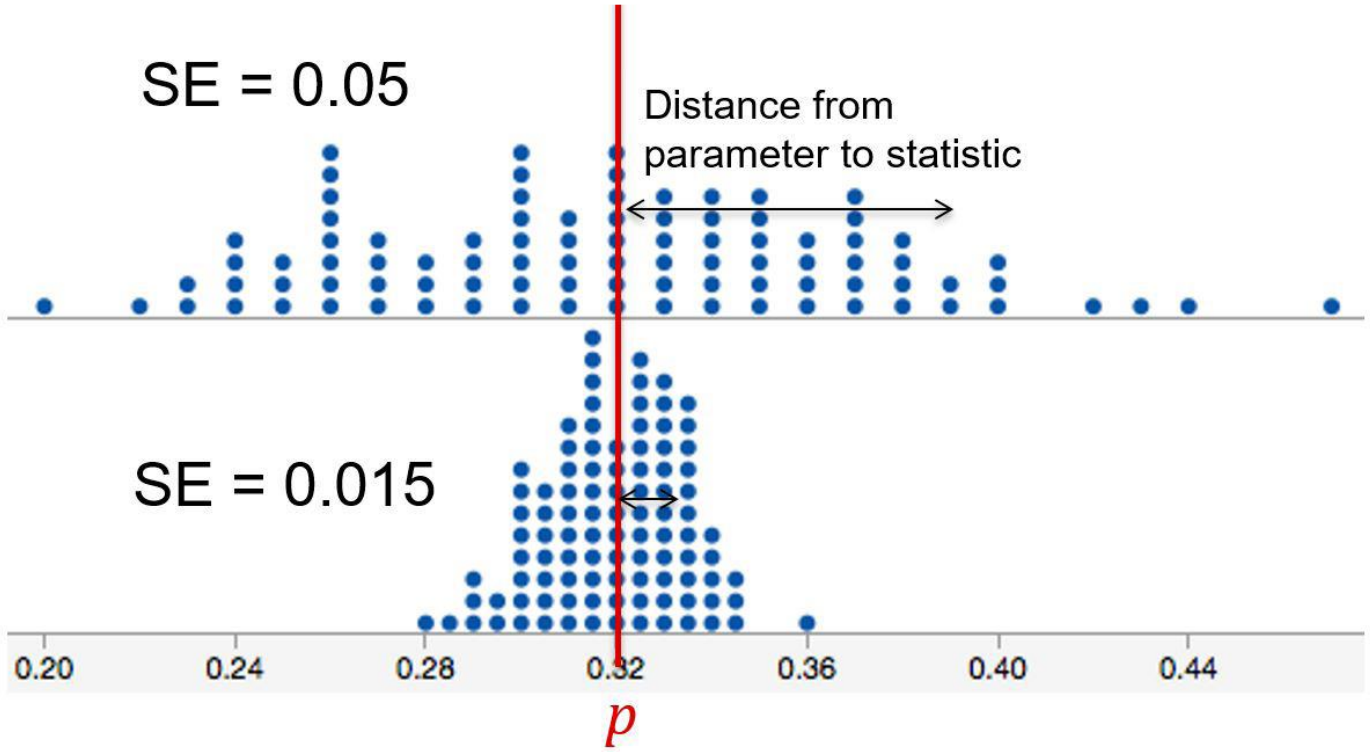
$$s = \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{n-1}}$$

- The standard deviation of a population is denoted σ, which is the Greek letter “sigma” and measures how spread out the data are from the population mean μ.

$$\sigma = \sqrt{\frac{\sum_i (x_i - \mu)^2}{n}}$$

Standard Error

- The standard error of a statistics, denoted SE, is the standard deviation of the sample statistic
- The standard error can be calculated as the standard deviation of the sampling distribution
  - The standard error measures how much the statistic varies from sample to sample
    - The more the statistic varies from sample to sample, the higher the standard error
    - Lower SE means statistic closer to true parameter value
  - SE measures 'typical' distance between parameter and statistic

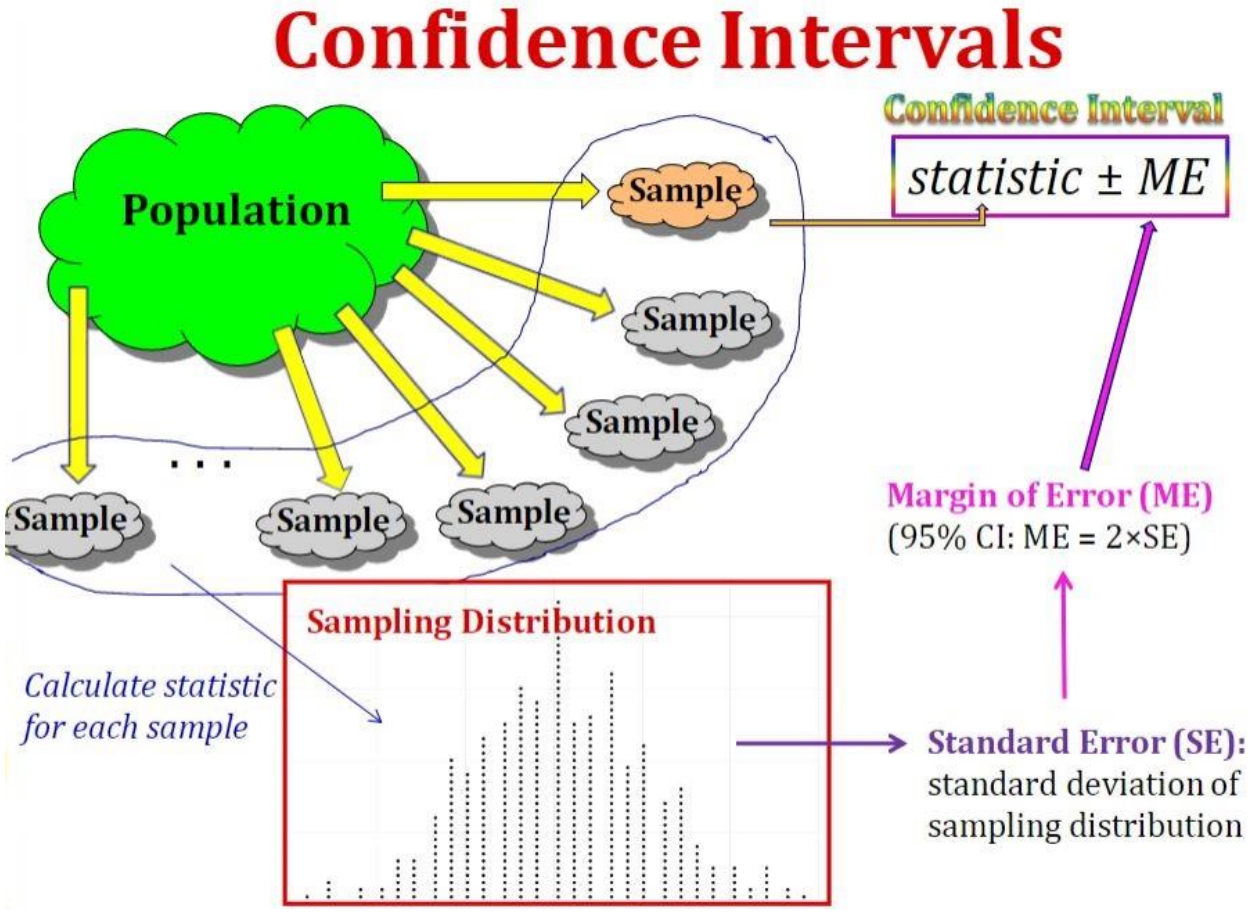


Confidence Intervals

- Confidence Interval
  - A Confidence Interval is a range of values we are sure our true value lies in.
  - The success rate (proportion of all samples falls into the confidence interval) is known as the confidence level.
- Calculation of 95% Confidence Interval Using the Standard Error
  - If we can estimate the standard error and the sampling distribution is relatively symmetric and bell-shaped, a 95% confidence interval can be estimated using

$$\text{Statistic} \pm 2 * \text{SE}$$

95% confidence interval



Construction of confidence interval (an interval estimate) for a sample of size at least 30:

- Step1:Compute the sample mean $\bar{x}$ of the random sample. Suppose we know the population standard deviation σ. Compute the standard error: $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$

  where n is the sample size
- Step2: Construct the 95% confidence interval

$$[\bar{x} - 2\sigma_{\bar{x}}, \bar{x} + 2\sigma_{\bar{x}}]$$

Here 2 is chosen according to the confidence level 95%

- If σ is unknown, then we use s to estimate σ

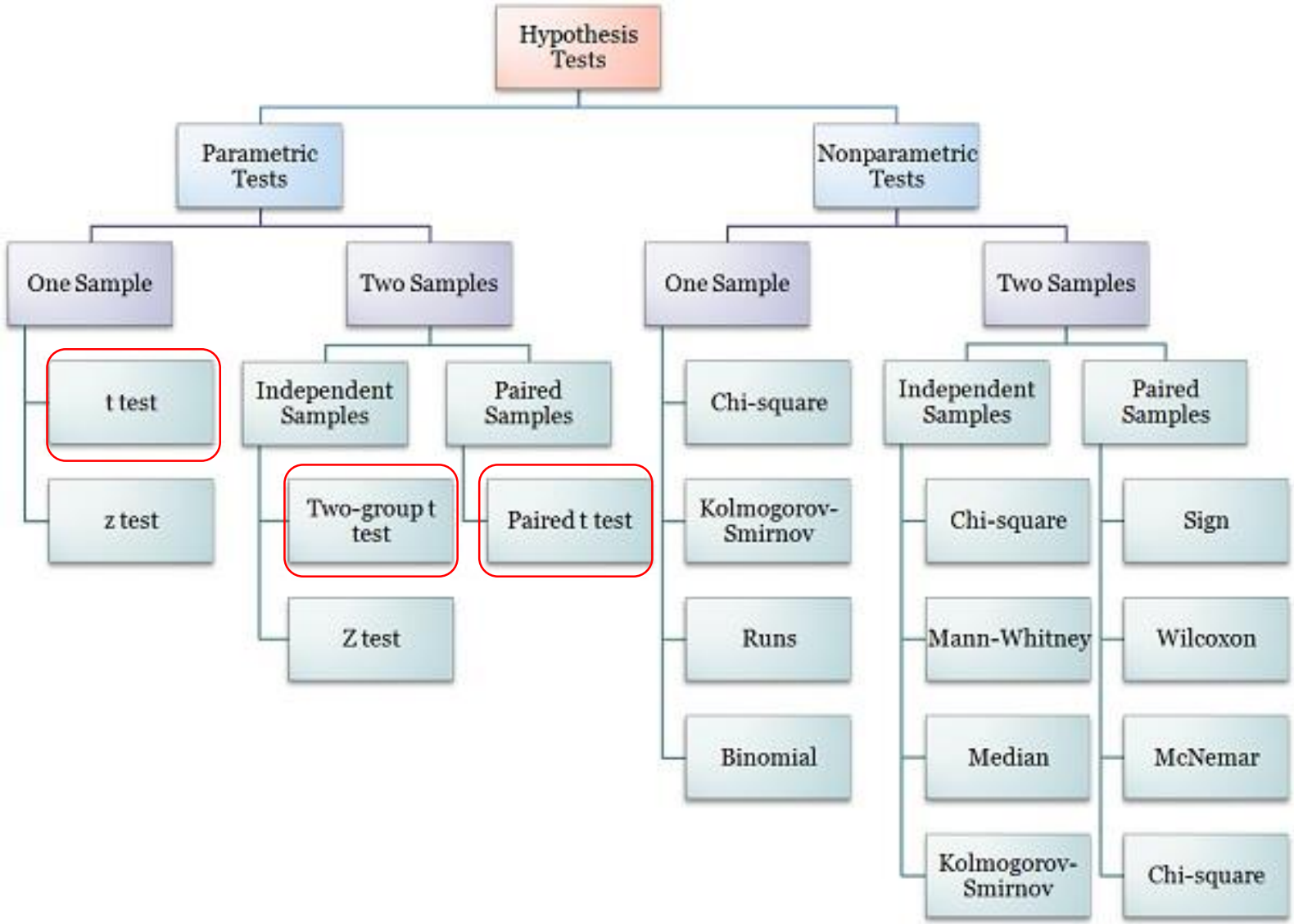
$$s_{\bar{x}} = \frac{s}{\sqrt{n}}$$

- Then the 95% confidence interval is

$$[\bar{x} - 2s_{\bar{x}}, \bar{x} + 2s_{\bar{x}}]$$

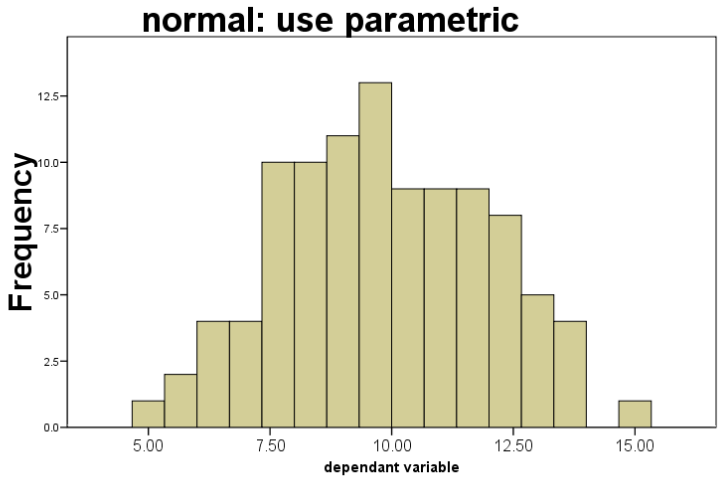
Parametric and Non-Parametric Tests

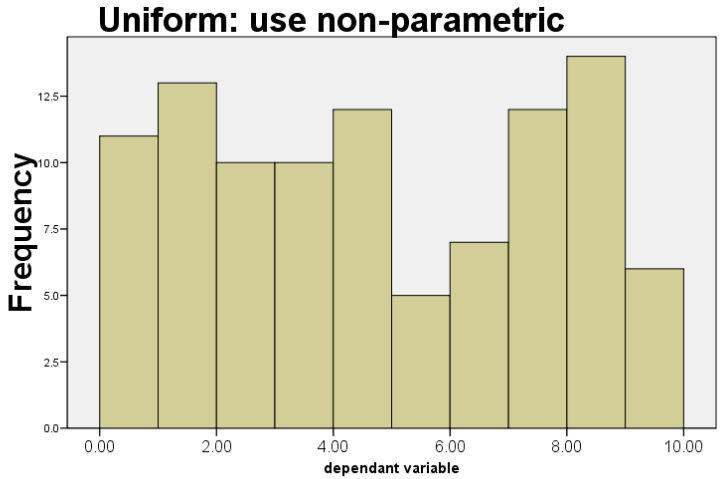
- **Parametric Tests:** assume the distribution of sample data (i.e. normality)
- **Non-Parametric Tests:** do not assume data are drawn from any particular distribution

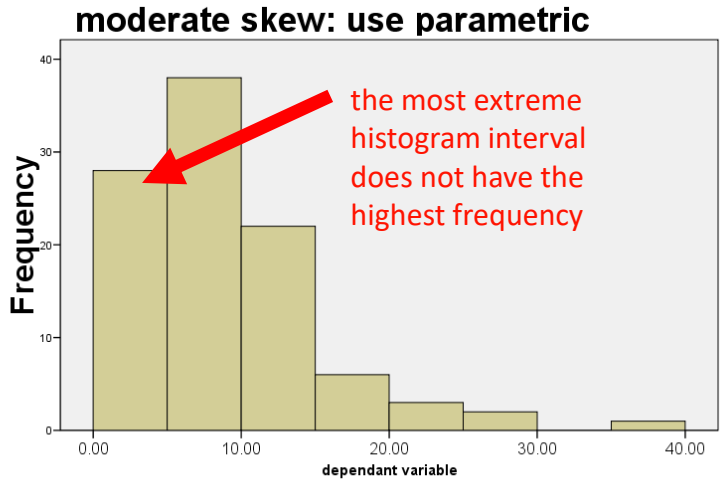


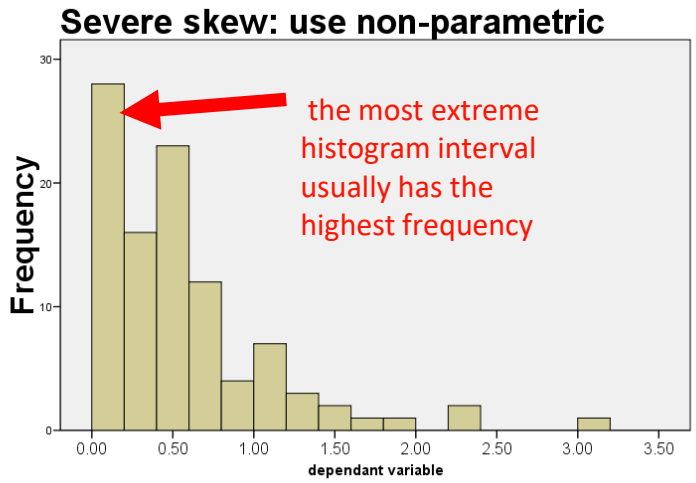
T-test assumption 1 - normality

Assumption1: The sampling distribution is normally distributed

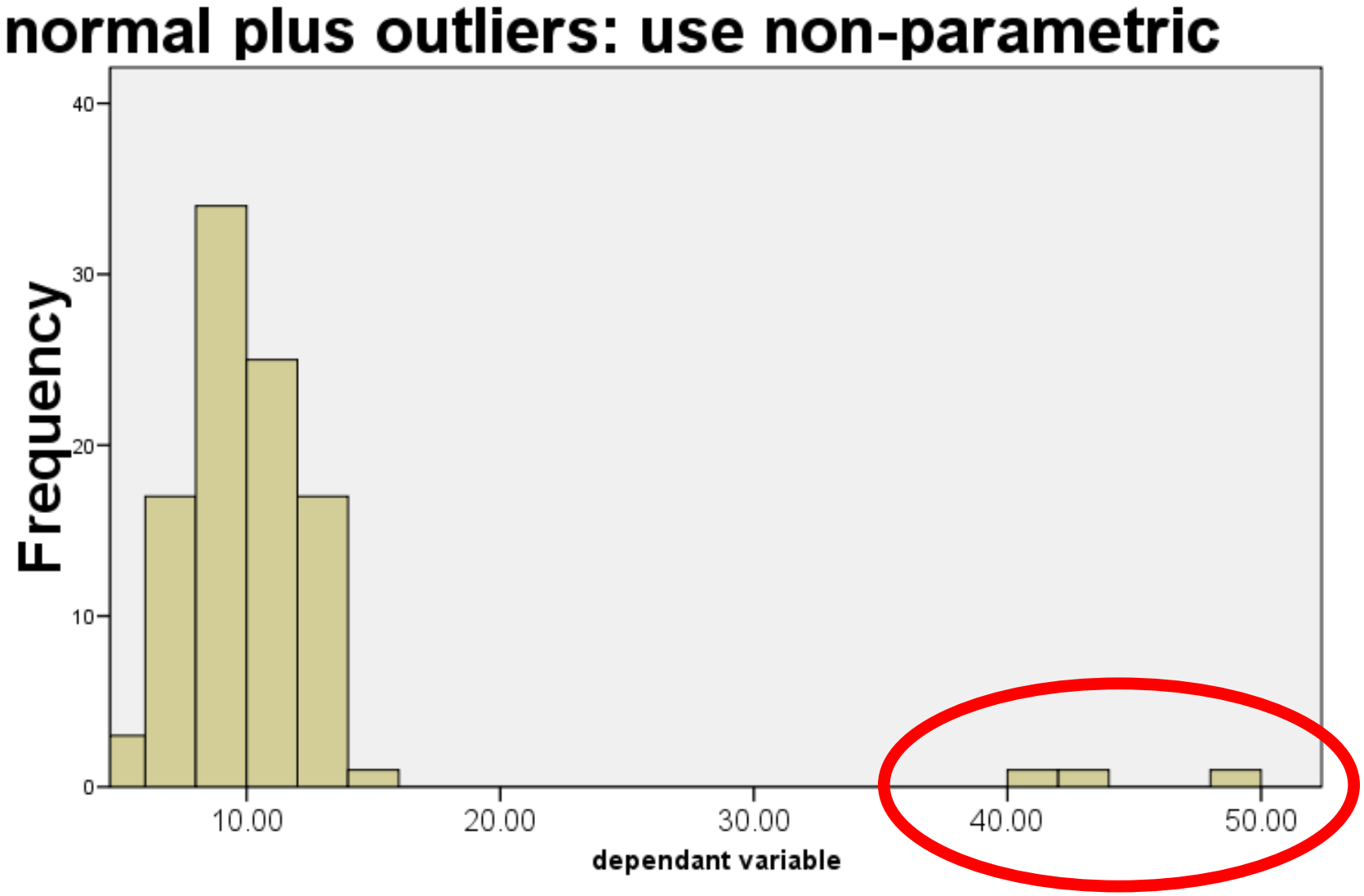








T-test assumption 2-No extreme scores



There should not include ***extreme scores*** or ***outliers***, because these have a disproportionate influence on the mean and the variance

Types of *T-test*

- Single sample t
  - One sample, compared with ***known*** population mean
  - Goal: Is current sample different from population?

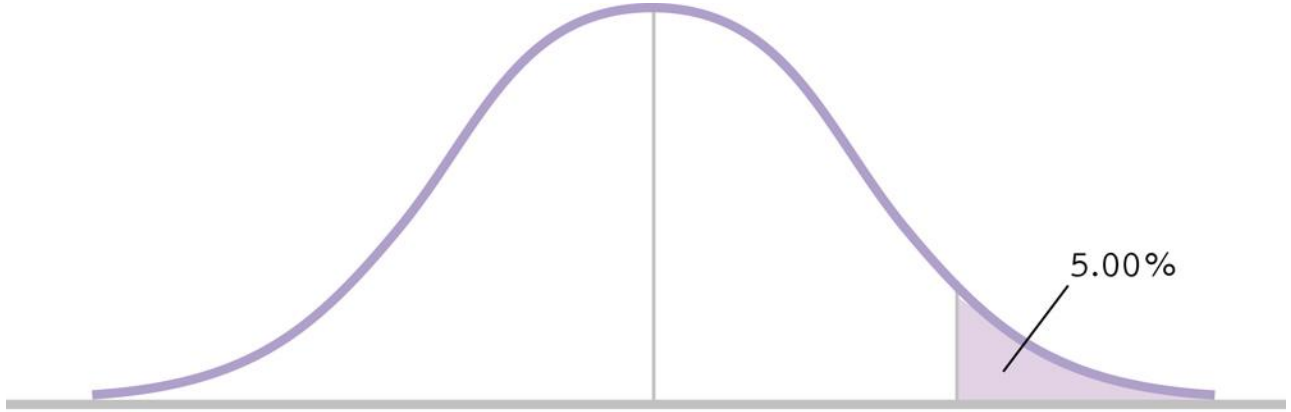
- Independent samples t
  - Different (independent) samples of participants
  - Are our samples from different populations?

- Paired/Dependent Samples t
  - Same or related (dependent) samples
  - Are our samples from different populations?

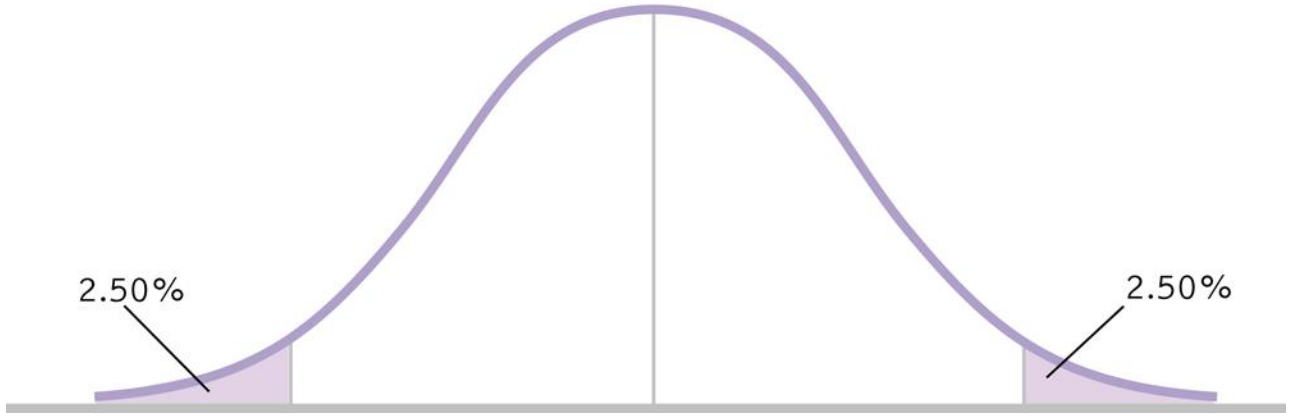
General Form of t-test

	Single sample, Paired/Dependent Samples t	Independent Samples t （same variance）
Statistic	$t = \frac{\overline{x} - \mu}{s_{\overline{x}}}$	$t = \frac{\bar{x} - \bar{y} - (\mu_x - \mu_y)}{s_{Difference}} = \frac{\bar{x} - \bar{y}}{\sqrt{s^2_{Pooled}(\frac{1}{m} + \frac{1}{n})}}$ $s^2_{Pooled} = \frac{df_x s_x^2 + df_y s_y^2}{df_{Total}} = (\frac{df_x}{df_{Total}}) s_x^2 + (\frac{df_y}{df_{Total}}) s_y^2$
Critical value	$t_{\alpha, n-1}$	$t_{\alpha, m+n-2}$

One Tailed vs. Two Tailed Tests



H0: A=B
Ha: A>B
Ha: A<B



H0: A=B
Ha: A≠B

From two tailed test, you can only draw the conclusion that **A≠B**, instead of A>B or A<B due to significant level.

Class Activity: Six Steps for Hypothesis Testing

1. Identify
2. State the hypotheses
3. Characteristics of the comparison distribution
4. Critical values
5. Calculate
6. Decide

One-Way ANOVA F-Test Hypotheses

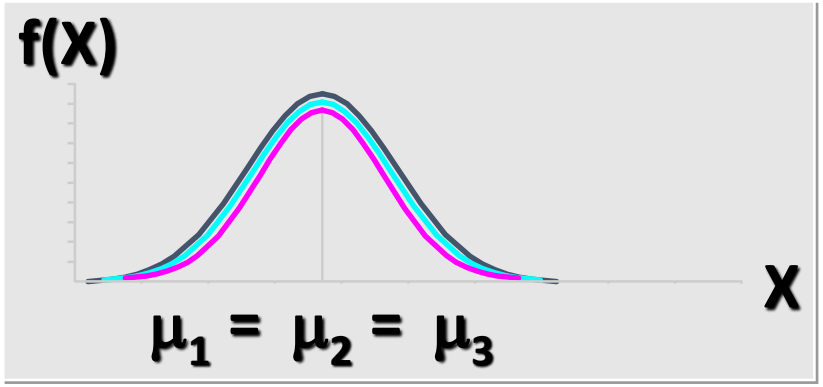
➢Tests the equality of 2 or more population means (μ)

H_0: $\mu_1 = \mu_2 = \mu_3 = \ldots = \mu_p$

- All population means are equal
- No treatment effect

H_a: Not All μ_j Are Equal

- At least 1 population mean is Different
- Treatment Effect
- NOT $\mu_1 = \mu_2 = \ldots = \mu_p$
- **Or $\mu_i \neq \mu_j$ for some *i*, *j*.**



➢Treatment variation between groups could be significantly greater than the in group variation

➢Variation measures are obtained by 'Partitioning' total variation

One-Way ANOVA F-Test: Test Statistic

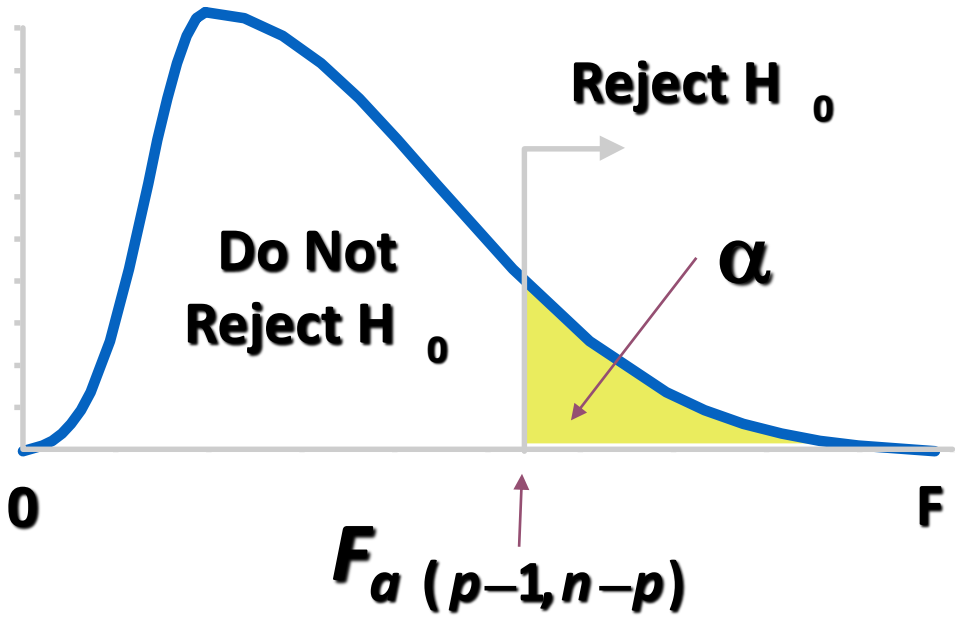
1. Test Statistic

➢ $F = MST / MSE = \dfrac{SST/(p-1)}{SSE/(n-p)}$

❖ *MST* : mean square for treatment
❖ *MSE* : mean square for error

2. Degrees of Freedom

➢ $\nu_1 = p - 1$
➢ $\nu_2 = n - p$
❖ *p* = Populations, Groups, or Levels
❖ *n* = Total Sample Size



Always One-Tail!

Post Hoc Tests

- If the t-test is significant, you have a difference in population means. You know where.

- If the F-test is significant, you have a difference in population means. But you don't know where.

- With 3 means, could be A=B>C or A>B>C or A>B=C.
  - We need a test to tell which means are different.

Tukey HSD(Honestly Significant Difference)
The sizes of three groups should be the same

- Step1: compute all possible absolute differences between means

$\bar{Y}_1 = 24.93$

$\bar{Y}_2 = 22.61$

$\bar{Y}_3 = 20.59$

$\Rightarrow$

$\bar{Y}_1 - \bar{Y}_2 = 24.93 - 22.61 = 2.32$

$\bar{Y}_1 - \bar{Y}_3 = 24.93 - 20.59 = 4.34$

$\bar{Y}_2 - \bar{Y}_3 = 22.61 - 20.59 = 2.02$

- Step2: find the critical value q
- Step3: compute HSD
- $HSD = \frac{\bar{Y}_i - \bar{Y}_j}{\sqrt{\frac{MSE}{n}}} = \frac{\bar{Y}_i - \bar{Y}_j}{\sqrt{\frac{0.9211}{5}}} = \frac{\bar{Y}_i - \bar{Y}_j}{0.43}$ ($\bar{Y}_i$ is always larger than $\bar{Y}_j$)
- Step4: compare absolute differences with HSD
  - ☐ HSD(G1 to G2): 5.39>3.77 **different each other**
  - ☐ HSD(G1 to G3): 10.09>3.77 **different each other**
  - ☐ HSD(G2 to G3): 4.70>3.77 **different each other**

Critical Values for the Tukey Q Test

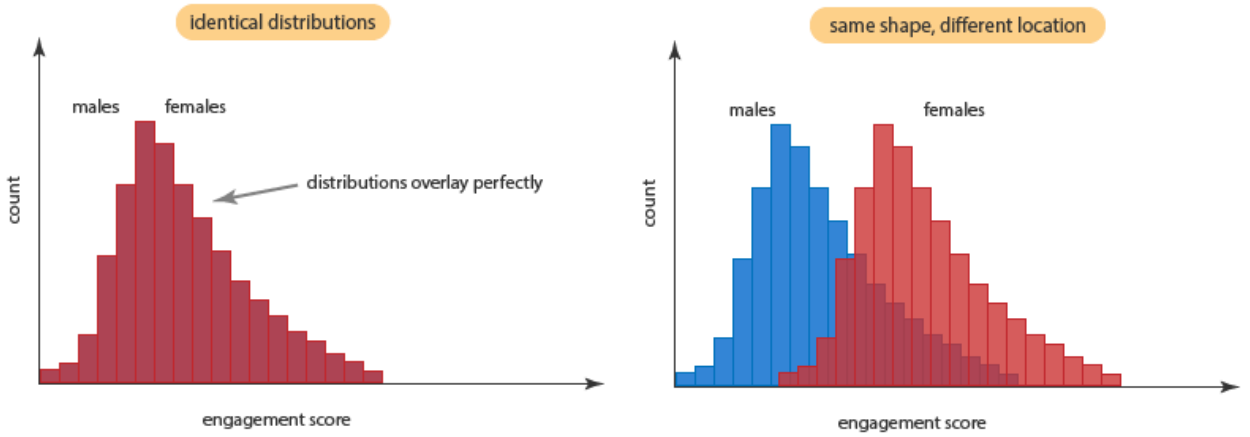
d.f. = N – K (ANOVA Error or Within d.f.) for ANOVA: Single Factor
d.f. = N – R*C (ANOVA Within d.f.) for ANOVA: Two-Factor With Replication
d.f. = (R – 1)*(C – 1) (ANOVA Error d.f.) for ANOVA: Two-Factor Without Replication

Number of Groups (Treatments) = K

Error df	Number of Groups (Treatments)								
	2	3	4	5	6	7	8	9	10
1	17.97	26.98	32.82	37.08	40.41	43.12	45.40	47.36	49.07
2	6.08	8.33	9.80	10.88	11.74	12.44	13.03	13.54	13.99
3	4.50	5.91	6.82	7.50	8.04	8.48	8.85	9.18	9.46
4	3.93	5.04	5.76	6.29	6.71	7.05	7.35	7.60	7.83
5	3.64	4.60	5.22	5.67	6.03	6.33	6.58	6.80	6.99
6	3.46	4.34	4.90	5.30	5.63	5.90	6.12	6.32	6.49
7	3.34	4.16	4.68	5.06	5.36	5.61	5.82	6.00	6.16
8	3.26	4.04	4.53	4.89	5.17	5.40	5.60	5.77	5.92
9	3.20	3.95	4.41	4.76	5.02	5.24	5.43	5.59	5.74
10	3.15	3.88	4.33	4.65	4.91	5.12	5.30	5.46	5.60
11	3.11	3.82	4.26	4.57	4.82	5.03	5.20	5.35	5.49
12	3.08	3.77	4.20	4.51	4.75	4.95	5.12	5.27	5.39
13	3.06	3.73	4.15	4.45	4.69	4.88	5.05	5.19	5.32
14	3.03	3.70	4.11	4.41	4.64	4.83	4.99	5.13	5.25
15	3.01	3.67	4.08	4.37	4.59	4.78	4.94	5.08	5.20
16	3.00	3.65	4.05	4.33	4.56	4.74	4.90	5.03	5.15
17	2.98	3.63	4.02	4.30	4.52	4.70	4.86	4.99	5.11
18	2.97	3.61	4.00	4.28	4.49	4.67	4.82	4.96	5.07
19	2.96	3.59	3.98	4.25	4.47	4.65	4.79	4.92	5.04
20	2.95	3.58	3.96	4.23	4.45	4.62	4.77	4.90	5.01
24	2.92	3.53	3.90	4.17	4.37	4.54	4.68	4.81	4.92
30	2.89	3.49	3.85	4.10	4.30	4.46	4.60	4.72	4.82
40	2.86	3.44	3.79	4.04	4.23	4.39	4.52	4.63	4.73
60	2.83	3.40	3.74	3.98	4.16	4.31	4.44	4.55	4.65
120	2.80	3.36	3.68	3.92	4.10	4.24	4.36	4.47	4.56
∞	2.77	3.31	3.63	3.86	4.03	4.17	4.29	4.39	4.47

Rationale of Mann-Whitney U

- Imagine two samples of scores drawn at random from the **same population**
- The two samples are combined into one larger group and then ranked from lowest to highest
- In this case there should be a **similar number** of high and low ranked scores in each original group
- If however, the two samples are from **different populations** with different **medians** then most of the scores from one sample will be lower in the ranked list than most of the scores from the other sample
  - the sum of ranks in each group will differ



Wilcoxon signed ranks test

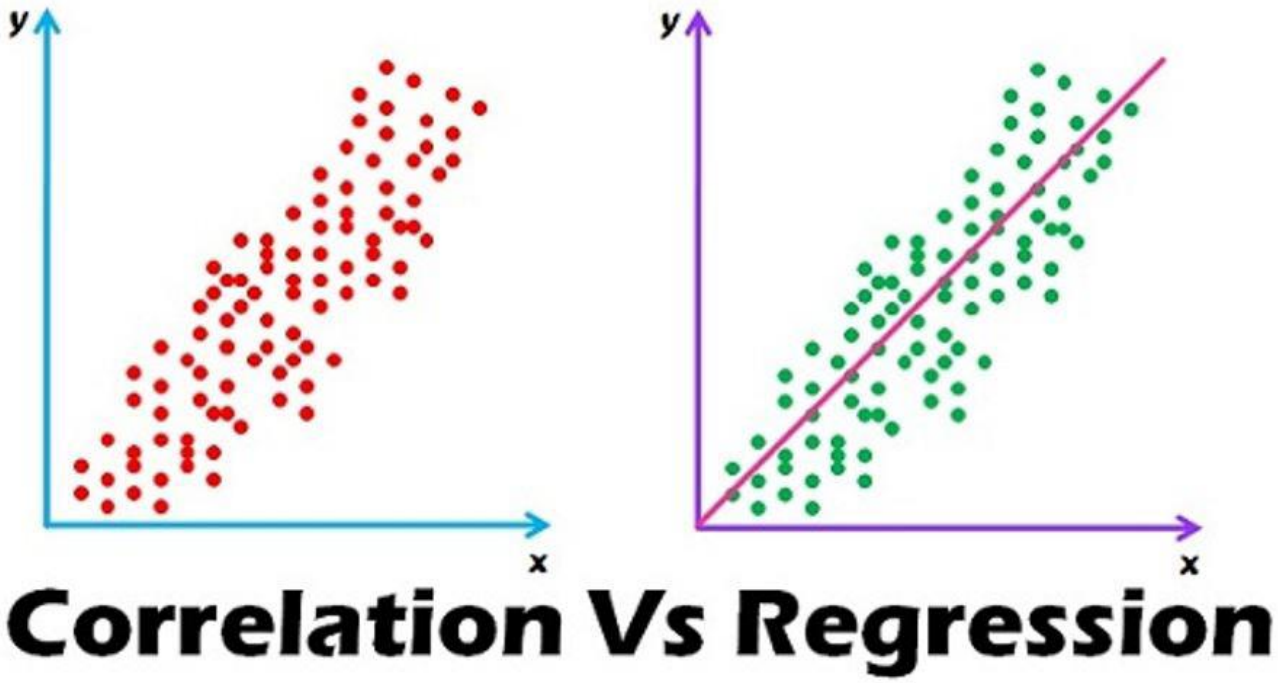
- Use this when the same participants perform both conditions of your study:
  - i.e., it is appropriate for analyzing the data from a repeated-measures design with two conditions.
- Use it when the data do not meet the requirements for a parametric test
  - if the data are not **normally distributed**
  - if the variances for the two conditions are **markedly different**
  - if the data are measurements on an **ordinal scale**

Logic behind the Wilcoxon test

- The data are ranked to produce two rank totals, one for each condition.
- If there is a systematic difference between the two conditions, then most of the ***high ranks*** will belong to one condition and most of the ***low ranks*** will belong to the other one.
  - the rank totals will be quite different and one of the rank totals will be quite small.
  - if the two conditions are similar, then high and low ranks will be ***distributed evenly*** between the two conditions and the rank totals will be fairly similar and quite large.
- The Wilcoxon test statistic "W" is simply the smaller of the rank totals.
  - The SMALLER it is (taking into account how many participants you have) then the less likely it is to have occurred by chance.
  - A table of critical values of W shows you how likely it is to obtain your particular value of W purely by chance.

Linear regression and Correlation

- Correlation coefficient: measure of the strength and direction of linear relationship between two quantitative variables
- Linear regression fits a model predicting a quantitative response (dependent) variable (y) based on a quantitative explanatory (independent) variable (x)



Pearson Correlation Coefficient

- The correlation coefficient (r) is a numeric measure of the strength and direction of a linear relationship between two quantitative variables

$$r_{XY} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

Steps To Calculate Spearman's Rank Correlation Coefficient

- Step1: Assign ranks 1, 2, 3, ..., n to the value of each variable.
  - ❖Ranking can be descending in order or ascending in order.
  - ❖However, both data sets should use the same ordering.
- Step2: For each pair of values (x, y), we will calculate

  d = rank (x) – rank (y)
  - ❖We call the difference d.
- Step3:We calculate Spearman's Rank Order Correlation Coefficient as follows:

$$r_s = 1 - \frac{6\sum d^2}{n(n^2-1)}$$

- Step4: Compare r_s with the values in the Spearman's Rank Table. The values in this table are the minimum values of r from a sample that need to be reached for Spearman's Rank Correlation Coefficient value to be significant at the level shown.

Spearman's Rank Table

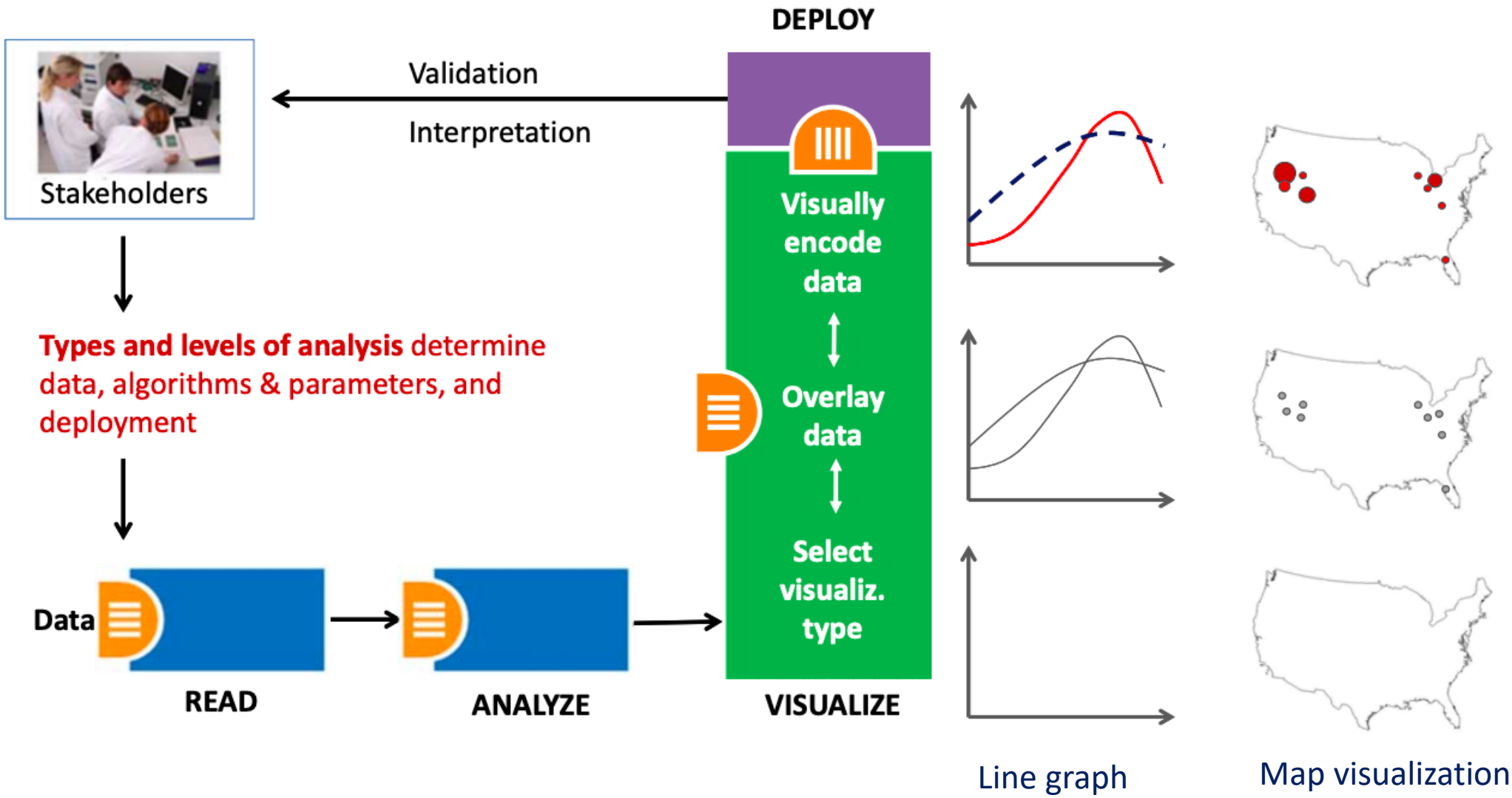
Sample size (n)	p = 0.05	p = 0.025	p = 0.01
4	1.0000	-	-
5	0.9000	1.0000	1.0000
6	0.8286	0.8857	0.9429
7	0.7143	0.7857	0.8929
8	0.6429	0.7381	0.8333
9	0.6000	0.7000	0.7833
10	0.5636	0.6485	0.7455
11	0.5364	0.6182	0.7091
12	0.5035	0.5874	0.6783
13	0.4825	0.5604	0.6484
14	0.4637	0.5385	0.6264
15	0.4464	0.5214	0.6036

Revision Guide

- **Design of Visualization**
  - Workflow of data visualization
  - Color, Size, Text, Titles, Labels
  - Choosing the right chart

Needs-Driven Workflow

Börner (2014) – *Visual Insights*



Shneiderman's Mantra

- User-Interface Interaction
  - Immediate interaction not only allows direct manipulation of the visual objects displayed but also allows users to select what to be displayed (Card et al., 1999)
  - Shneiderman (1996) summarizes six types of interface functionality
    - Overview
    - Zoom
    - Filtering
    - Details on demand
    - Relate
    - History
  - **“Overview first, zoom and filter, then details-on-demand.”**

Color Blind Friendly - Accessibility

Left: Normal vision, Right: Deuteranopia

1. Avoiding **problematic** color combinations, e.g., red & green / green & brown / green & blue…
2. Selecting color-blind-friendly **palettes**
3. Using different **textures** and patterns to highlight important information–not just color
4. Using **symbols and icons** to supplement color-coded messages, warnings and alerts
5. Using highly **contrasted** color combinations
6. Adopting **minimalistic** design to help avoid unnecessary confusion.

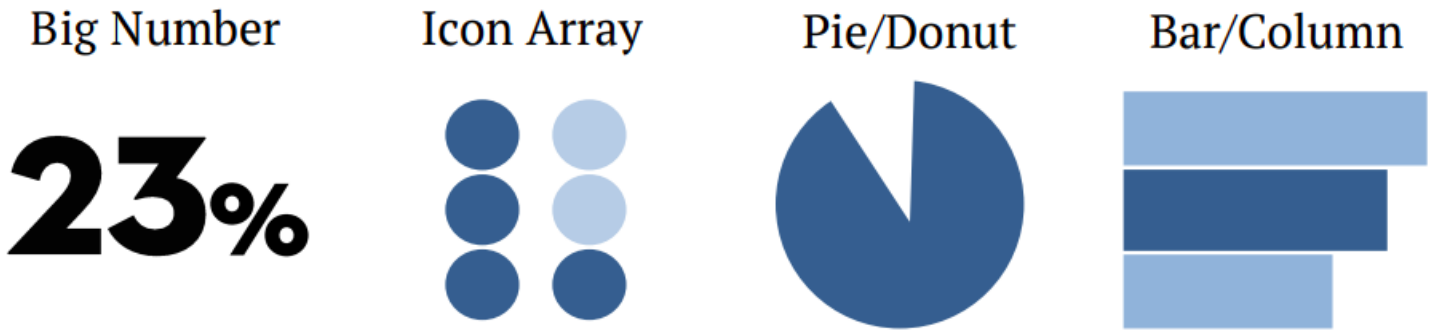
https://venngage.com/blog/color-blind-friendly-palette/

Choosing the Right Chart

- When a single number is important
- How two or more numbers are alike or different
- How we are better or worse than a benchmark
- When there are parts of a whole
- How things change over time

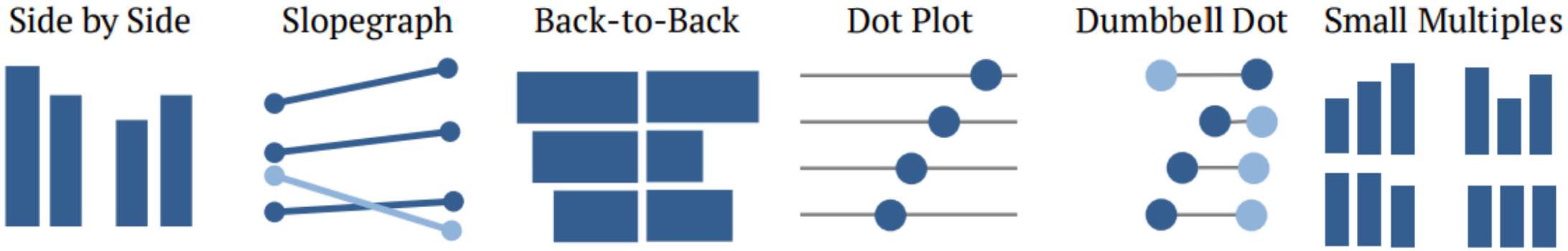
Displaying a Single Number

- Simple text with a single large number
- Icon Array
- Donut or Pie Graph
- Bar



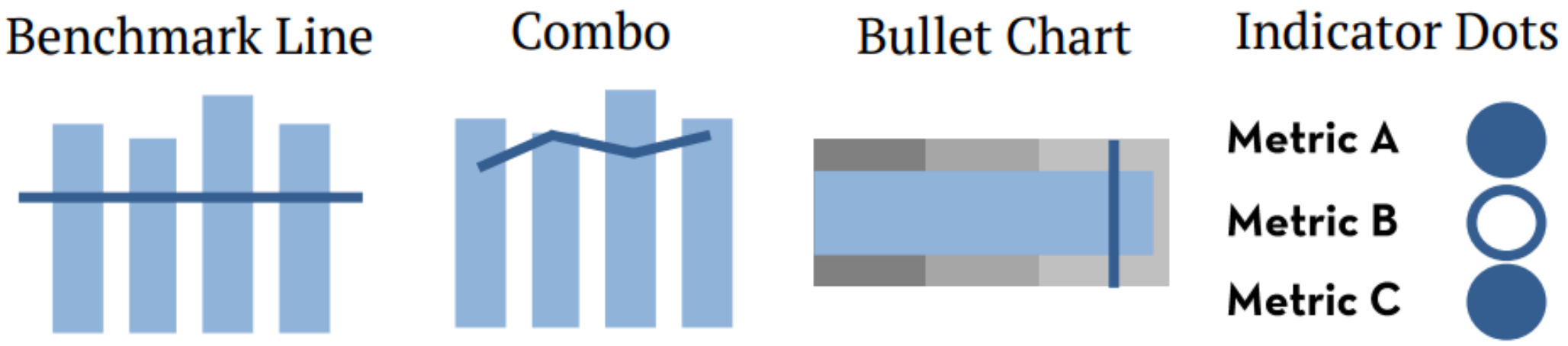
Visualizing Comparisons

- Side by Side Column or Bar Charts
- Slopegraph
- Back-To-Back Bars
- Dot Plot
- Dumbbell Dot
- Small Multiples



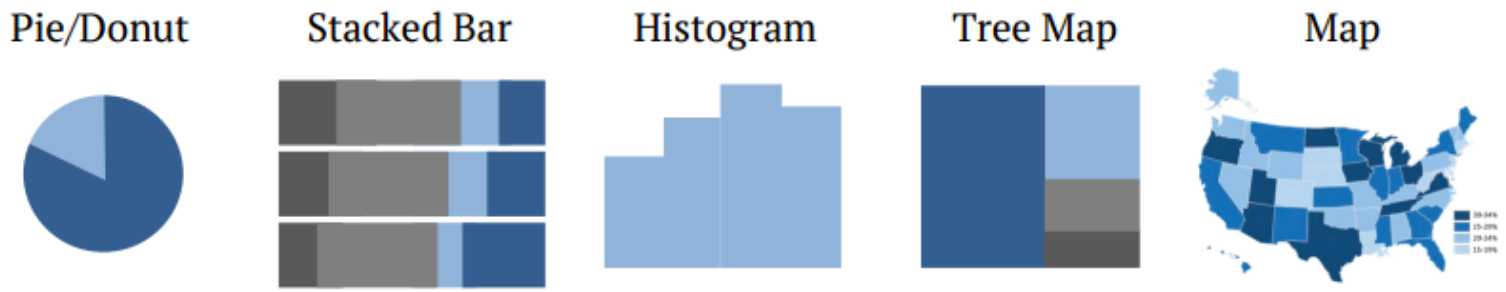
Displaying Relative Performance

- Benchmark Line
- Combo chart
- Bullet Chart
- Indicator Dots



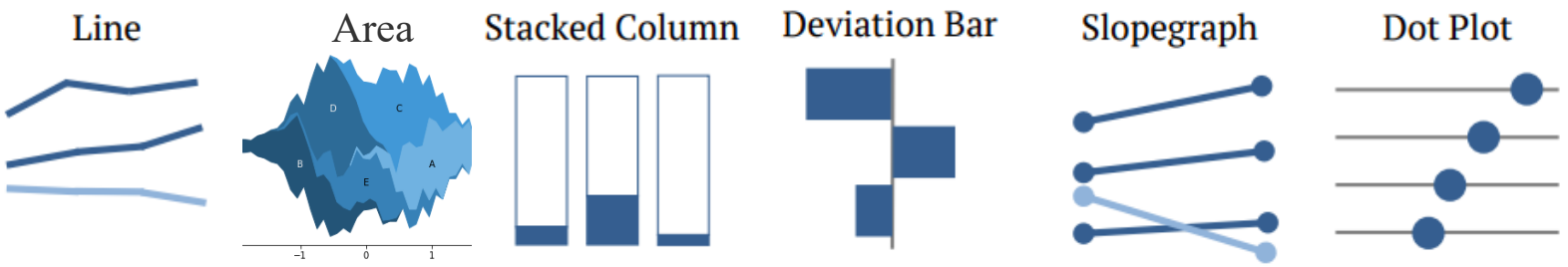
Visualize The Parts of a Whole

- Pie/Donut
- Stacked Bar
- Histogram
- Tree Map
- Map



Visualize How Things Changed Over Time

- Line Graph
- Area Graph
- Stacked Column
- Deviation Bar
- Slopegraph
- Dot Plot



Database

Revision Guide

Understand *Foreign Key* and *Primary Key*

Familiar with CREATE table

- Common Data Type: Char/varchar/integer/decimal/date
- NOT NULL
- CONSTRAINT
- PRIMARY KEY/FOREIGN KEY

Familiar with

- INSERT data
  - INSERT INTO....
- UPDATE data
  - UPDATE ... SET
- DELETE data
  - DELETE FROM ...

Revision Guide

- Simple Select Syntax
  - AND/OR
  - LIKE, IN
  - ORDER BY
  - COUNT/MIN/MAX/SUM

SQL for Data Retrieval: AND/OR examples

```
SELECT      empId, empName
FROM        Employee
WHERE       empId < 7 OR empId > 12;
```

5	Dan
19	Sheldon

```
SELECT      empId, empName
FROM        Employee
WHERE       deptId = 9 AND salaryCode <= 3;
```

5	Dan

Employee

empId	empName	*salaryCode*	*deptId*
5	Dan	3	9
9	Penny	4	9
19	Sheldon	5	10

SQL for Data Retrieval: Wildcard Searches

- The SQL **LIKE** keyword allows for searches on partial data values
- **LIKE** can be paired with wildcards to find rows that partially match a string value
  - The multiple character wildcard character is a percent sign (%)
  - The single character wildcard character is an underscore (_)

```
SELECT    empId
FROM      Employee
WHERE     empName LIKE 'Da%';
```

18
29

```
SELECT    empId
FROM      Employee
WHERE     phone LIKE '3411_ _ _ _ ';
```

29

Employee

empId	empName	phone
18	Dan	69981245
29	Danny	34111001

SQL for Data Retrieval: Sorting the Result

- Querying results may be sorted using the ORDER BY clause
  - Ascending vs. descending sorts

```
SELECT      *
FROM        Employee
ORDER BY    empName;
```

```
SELECT      *
FROM        Employee
ORDER BY    empName ASC;
```

```
SELECT      *
FROM        Employee
ORDER BY    empName DESC;
```

empId	empName
1	Dan
2	Penny
3	Sheldon

ASC

empId	empName
3	Sheldon
2	Penny
1	Dan

DESC

SQL for Data Retrieval: Built-in Function Examples

```
SELECT    COUNT(*)
FROM      Employee;
```

3

```
SELECT    MIN(hours) AS minimumHours,
          MAX(hours) AS maximumHours,
          AVG(hours) AS averageHours
FROM      Project
WHERE     ProjectId > 7;
```

minimumHours	maximumHours	averageHours
2	8	5

Employee

empId	empName
10	Dan
15	Penny
29	Sheldon

GROUP BY and HAVING

- Familiar with the syntax of GROUP BY
- Make sure GROUP BY appear after WHERE, HAVING after GROUP BY
- Knowing the different between HAVING and WHERE

SUB-QUERY

- Most problem that can be solved by SUB-QUERY can also be solved by joining table.
- Use join table instead!

JOIN TABLE

- Understand how the simple inner join works
- How to cross reference two or more tables
- Knowing the differences between inner join, left outer join, right outer join, full outer join.

Join … ON Example

```
SELECT      empName, deptName
FROM        Employee e INNER JOIN Department d
            ON e.deptId = d.deptId
WHERE       d.deptName NOT LIKE 'Account%';
```

Employee

empId	empName	deptId
1	Dan	102
2	Penny	101
3	Sheldon	

Department

deptId	deptName
101	Account Service
102	Customer Service

empName	deptName
Dan	Customer Service
Penny	Account Service

Dan	Customer Service

Quick Question

- Suppose deptID in Employee table now becomes a foreign key. i.e., must have a value and that value must appear in the table Department
- Which of the following table joining are equivalent?

a) Employee inner join Department
b) Employee left outer join Department
c) Department left outer join Employee
d) Employee right outer join Department
e) Employee full outer join Department

Department

deptId	deptName
101	Research
102	Customer Service
103	Marketing

Employee

empId	empName	*deptId*
1	Dan	102
2	Penny	101
3	Sheldon	103

Security and Privacy

Revision Guide

- Knowing the different between public key encryption and private key encryption
- Understanding the logic behind SQL injection
- Familiar with the four different types of indirection questioning techniques
- Able to identify EI/QI/SD/NSD
- Understand the basic concept of K-Anonymity.
  - Be able to identify a given data set is or isn't K-Anonymous.