

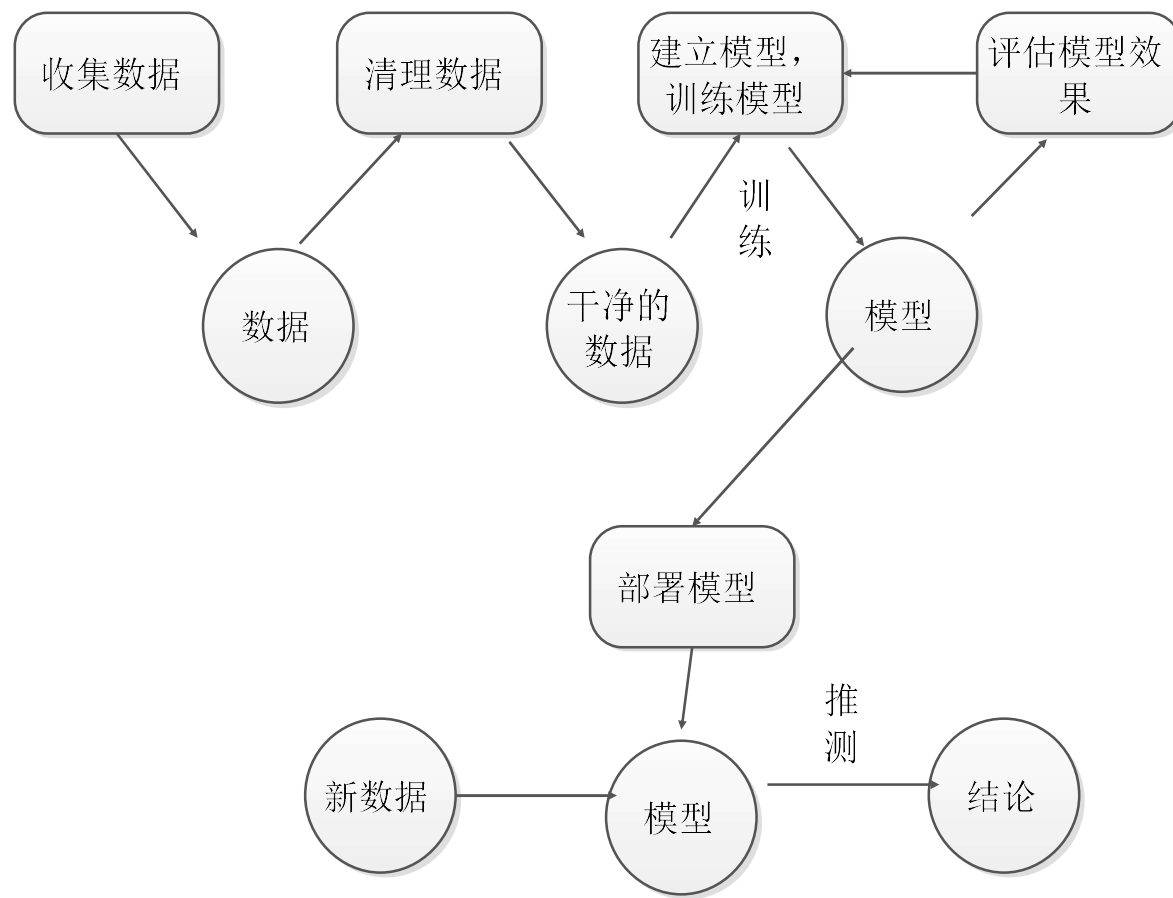
数据科学入门2.1: 机器学习介绍, 以及更多回归

**## Introduction to Data Science
Part 2.1: Intro**

□ Goals

- More in-depth stuff of machine learning
- Train-validation-test split
- Classification
- Clustering
- Neural networks
- Finally a glance of the tensorflow2 (python of course)

□ The routine of data science



$$\hat{Y} = f(X, \beta)$$

□ Types of Machine Learning

■ Supervised learning

- Trained with labeled data
- Regression
- Classification

Features X					
	cat	cat	cat	dog	dog
Label Ground-Truth Y					
	dog	dog	dog	cat	dog
					
	cat	dog	dog	cat	dog

Supervised learning: with label

■ Unsupervised learning

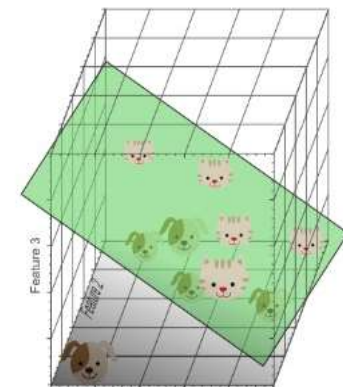
- Trained with unlabeled data
- Clustering
- Anomaly detection



1 feature



Feature 1
2 features

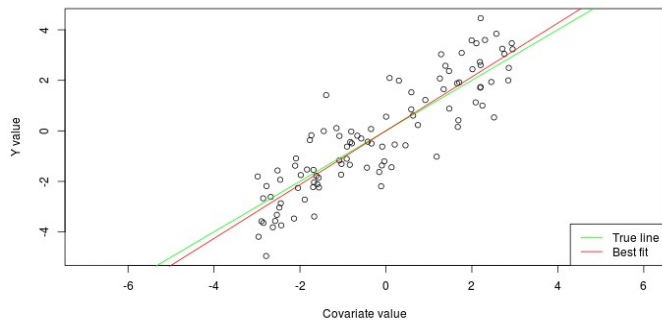


Feature 1
3 features

Unsupervised learning: no label

□ Supervised learning

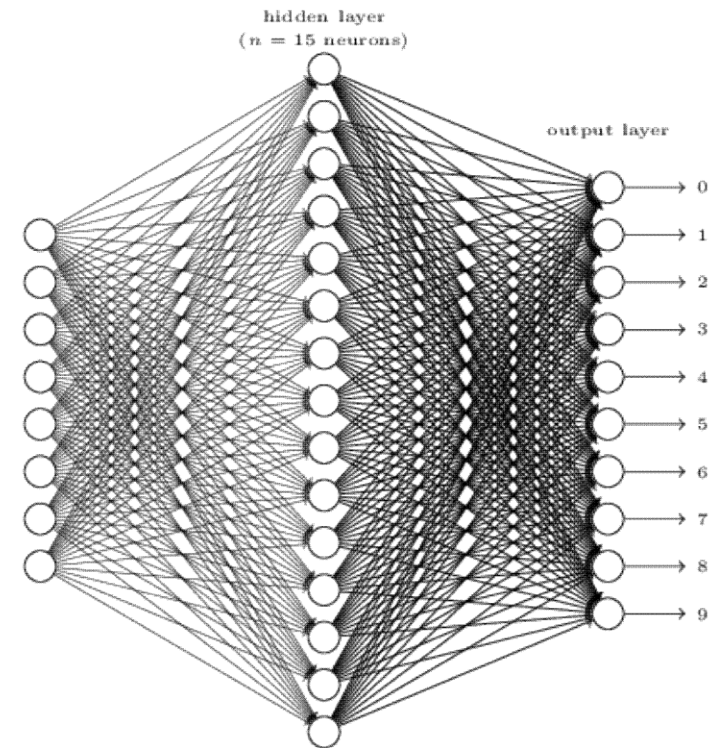
Regression



classification



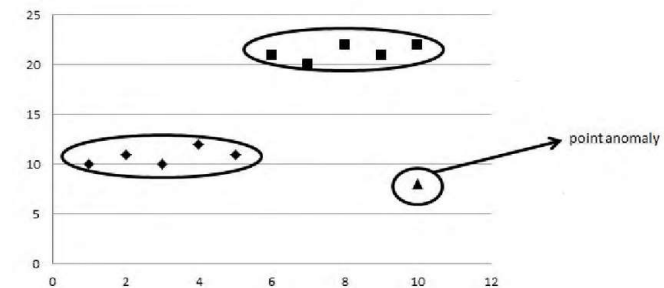
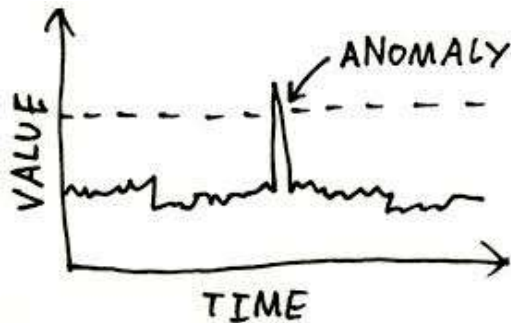
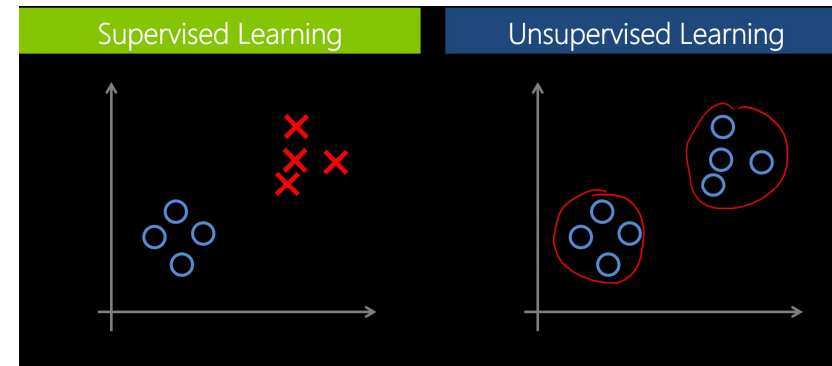
input layer
(784 neurons)



□ Unsupervised Learning

■ Data has no label

- Clustering
- Anomaly detection

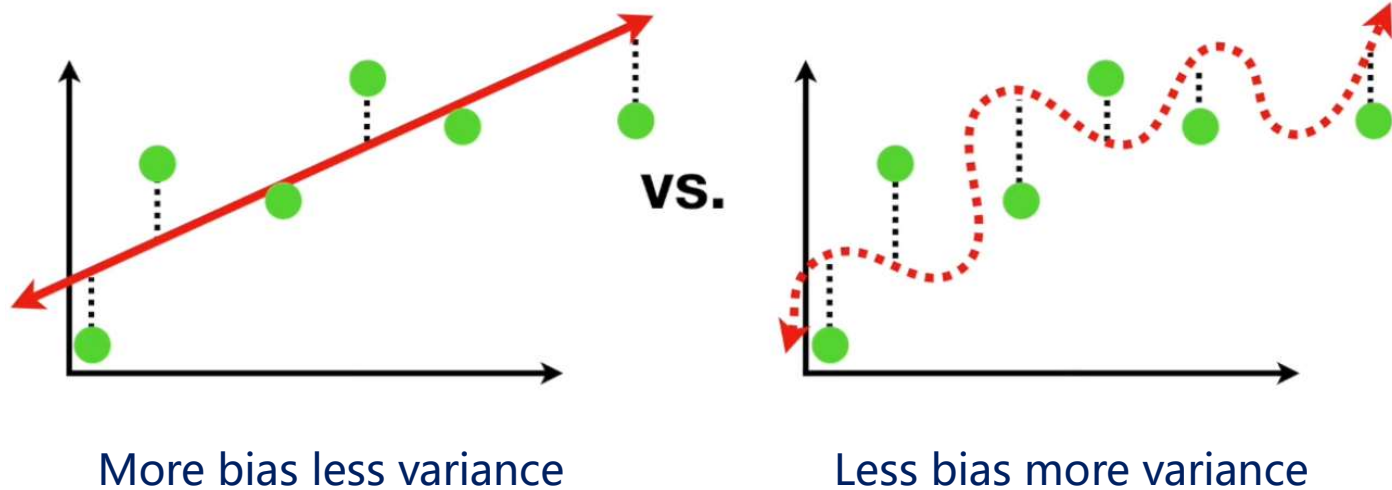


□ More Regression

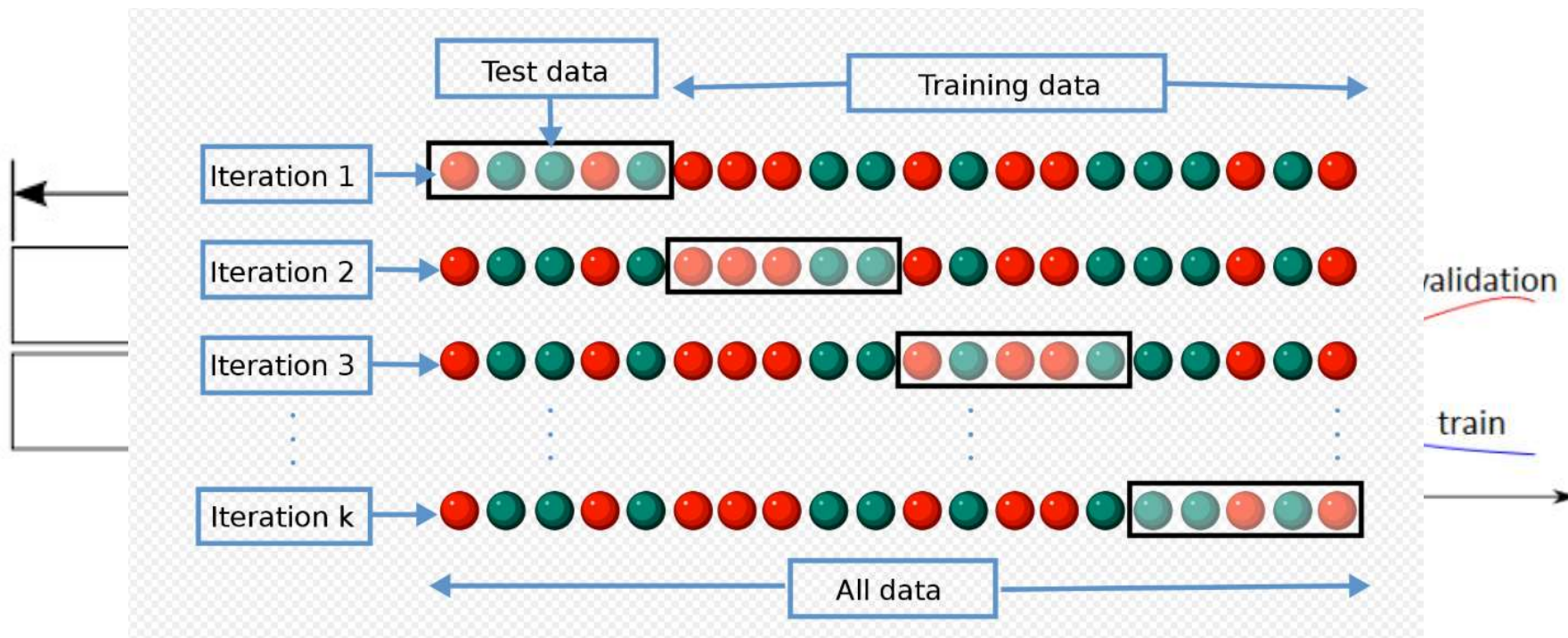
- Case 1 – 房屋价格预测
- Statistics and Machine Learning Toolbox

□ Overfitting

■ The bias variance tradeoff



□ Train-(validation)-test split



❑ **Selecting models and tuning hyper parameters**

- **Most ML model are just black boxes**

- **More on this later**

- **Most hyper parameters defines the complexity**

- adjust it to the complexity of you data (feature size)
- adjust it to the size of you data (sample count)

□ Some regression models

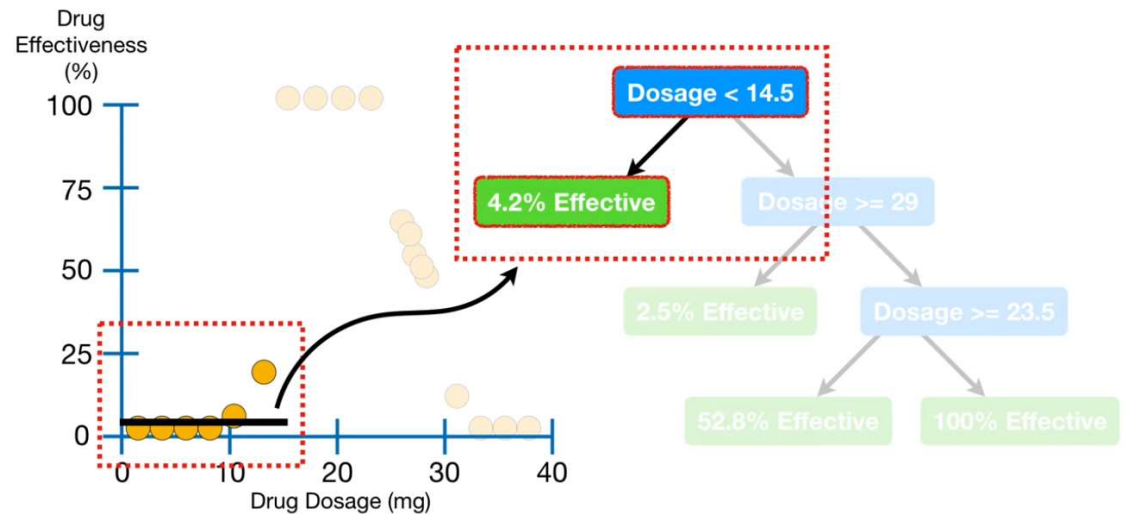
■ Linear models

- Simple, learned before
- Very high bias so very low variance

□ Some regression models

■ regression tree

- Kind of decision tree
- Can be very non-linear and can have very low bias
- Can be seriously over fitting
- Ensemble is a good way to avoid over fitting
- Hyperparameters:
 - ✓ The levels limit
 - ✓ The leaf nodes limit



□ Some regression models

■ Support Vector Machine regression

- To find the linear function

$$F(X) = WX + b,$$

- The object is to minimize:

$$\text{MIN } \frac{1}{2} \|w\|^2$$

- The constrain is:

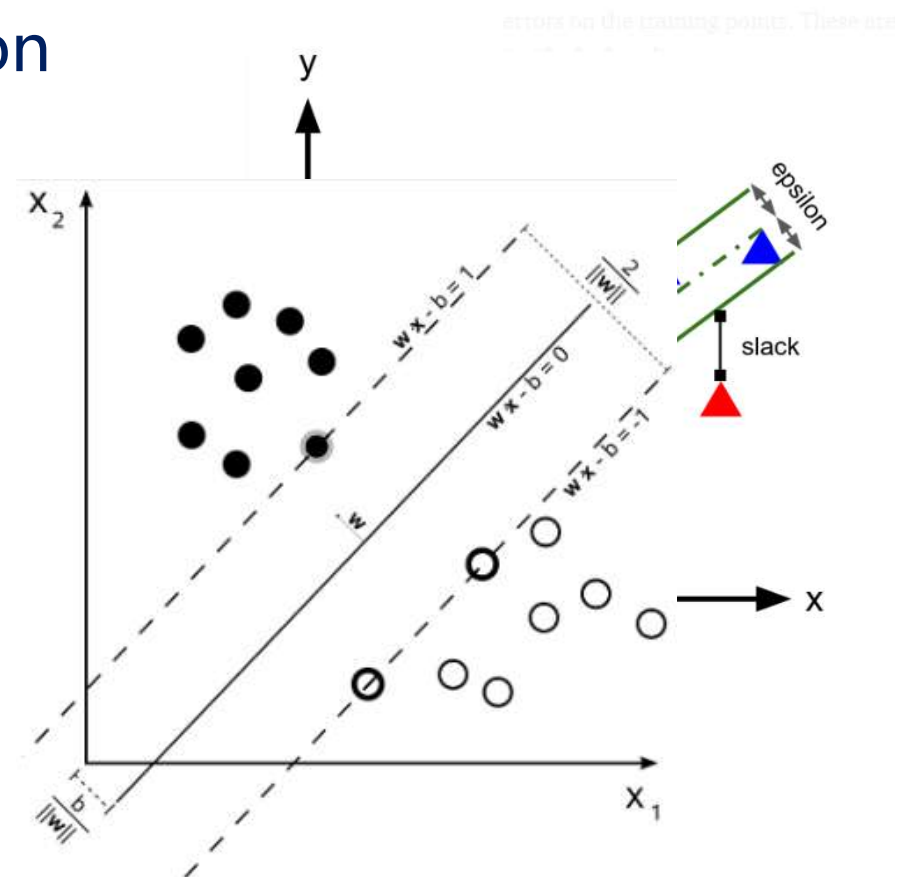
$$|y_i - w_i x_i| \leq \varepsilon$$

- The math is just like SVM classifier

- Hyperparameter:

✓ C

✓ Kernels



□ Evaluate your models

- Same as we learned before
- Adjusted-r-square (over test set)
- Response plot
- Residual plot

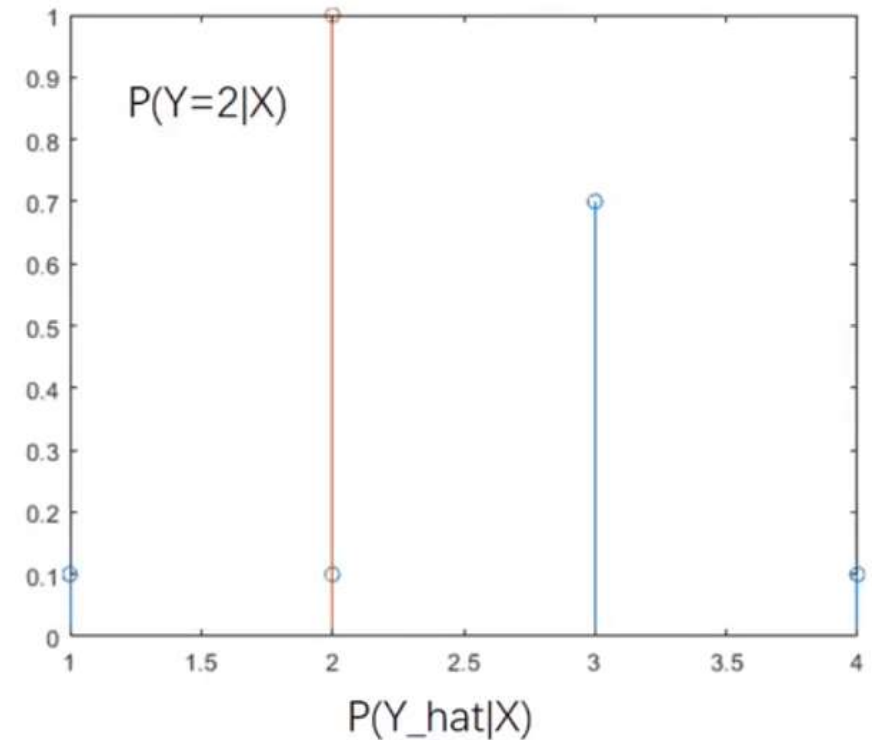
数据科学入门2.2:

简单的分类

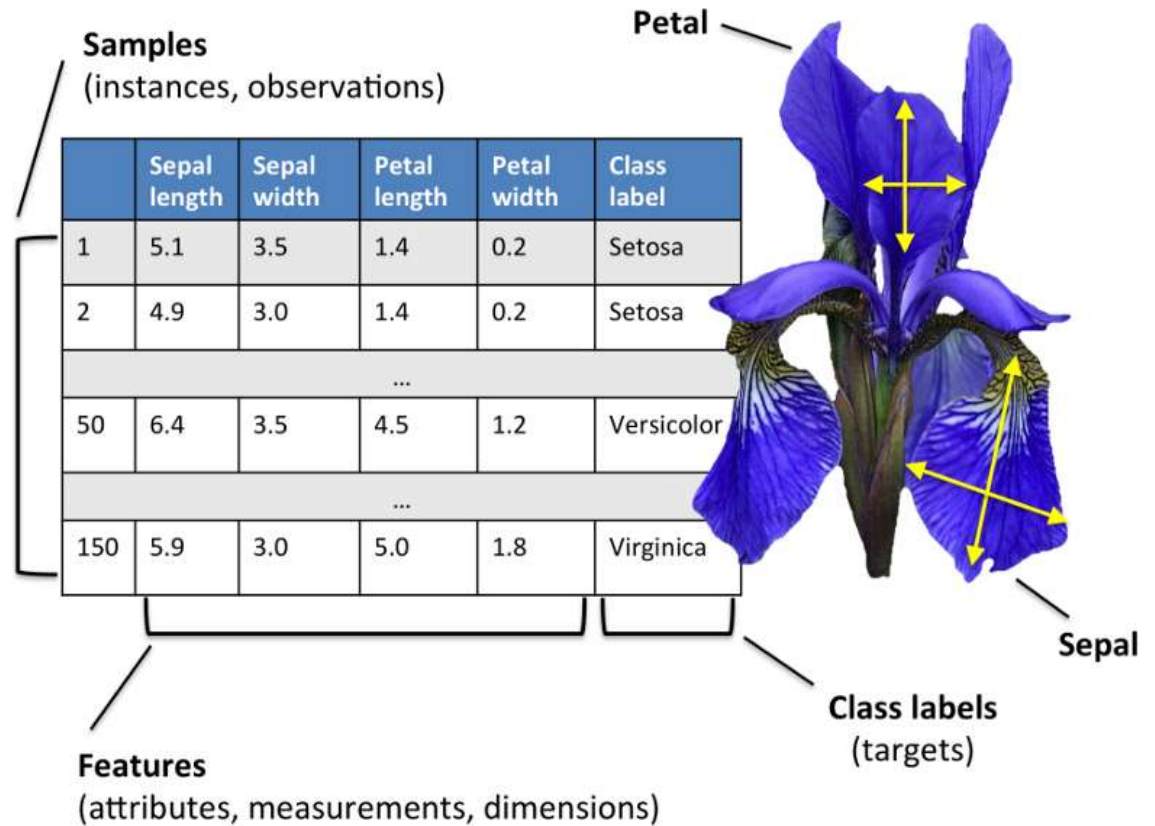
Introduction to Data Science
Part 2.2: Classification

□ Classification

- Classification is supervised learning
- Maximum likelihood is used
- Under the framework maximum likelihood, the error between two probability distributions is measured using cross-entropy.



□ Case 2 - Iris classification



□ Evaluate a classification model

■ Confusion matrix

- true positive (TP)
- true negative (TN)
- false positive (FP)
- false negative (FN)

		Actual class	
		Cat	Dog
Predicted class	Cat	5	2
	Dog	3	3

		Actual class	
		Cat	Non-cat
Predicted class	Cat	5 True Positives	2 False Positives
	Non-cat	3 False Negatives	3 True Negatives

- **True positive rate (TPR)** or sensitivity, recall, hit rate
- **False negative rate (FNR)** or miss rate or

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN} = 1 - FNR$$

- **False positive rate (FPR)** or fall-out or
- **True negative rate (TNR)** or specificity, selectivity

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN} = 1 - TNR$$

balanced accuracy (BA)

$$BA = \frac{TPR + TNR}{2}$$

数据科学入门2.3:

分类模型得选择

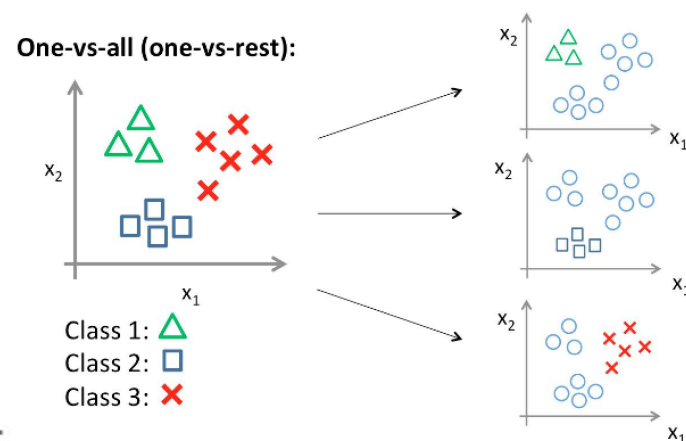
Introduction to Data Science
Part 2.3: Select classifiers

□ classifier的基本输出

■ Binary classifiers

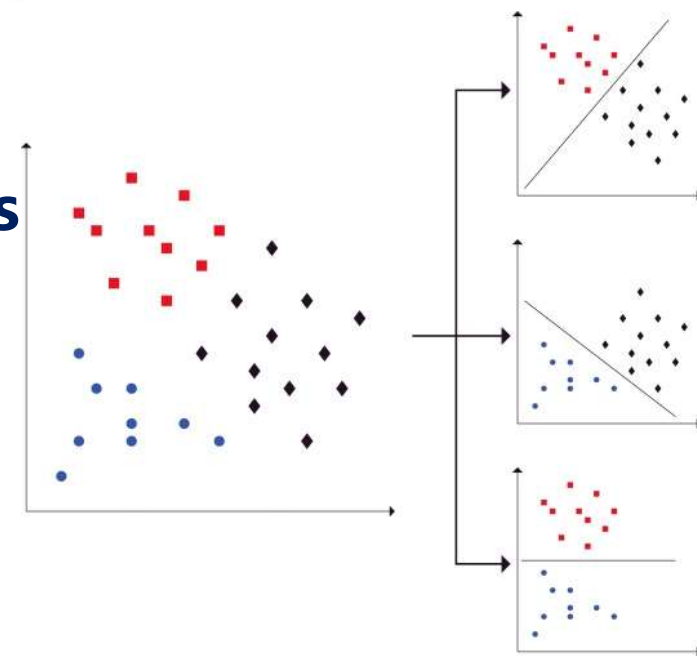
- Logistics regression
- SVM, $Y > 0, Y < 0$

$$\ln\left(\frac{P - \text{Class1}}{P - \text{Class2}}\right) = B1 + B(2 : \dots,$$



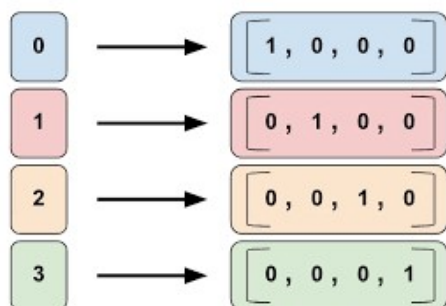
■ Binary classifiers as multi-class classifiers

- one-vs-rest, need n classifiers
- one-vs-one, need $C(n,2)$ classifiers



□ classifier的基本输出

■ One-hot encoding



$$class = \operatorname{argmax}(\hat{Y})$$

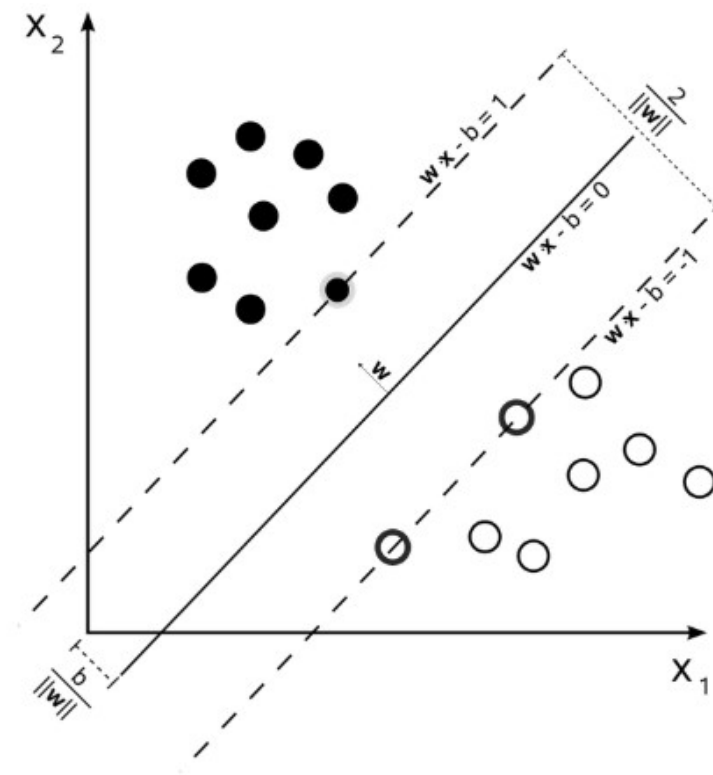
$$\operatorname{argmax}([0.1, 0.05, 0.8, 0.05])=2$$

□ **logistic regression**

- You already know it
- Kinda like linear regression
- High bias
- Best for:
 - Simple data, low sample count, small feature size
 - Binary classification
 - Most features are continuous variable

□ SVM, Support Vector Machine

- Separate sample by maximum the margined
- Achieved by Lagrangian optimization



□ SVM, Support Vector Machine

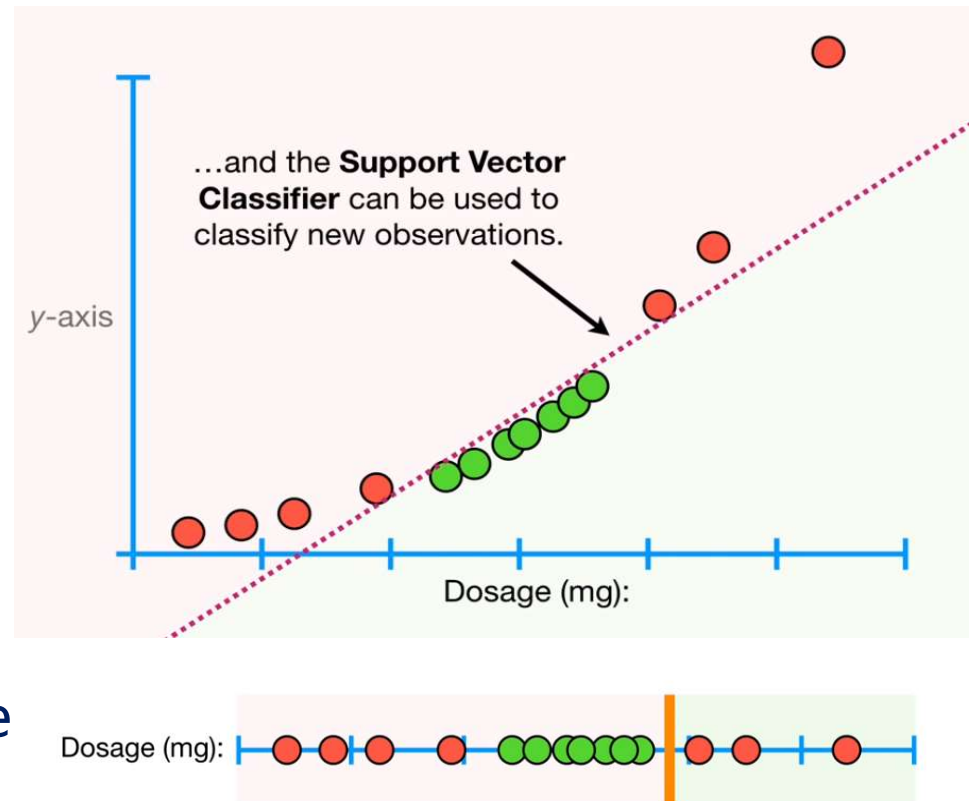
■ Kernels

■ Hyper parameters

- C
- Kernels

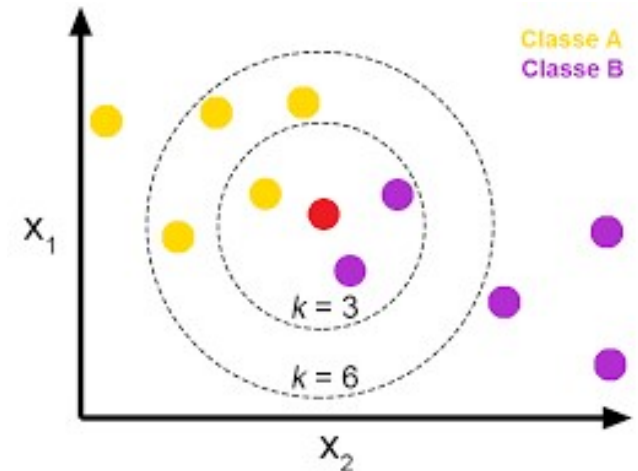
■ Very flexible mode

- Low bias
- good for many types of data
- Good if the feature size is large



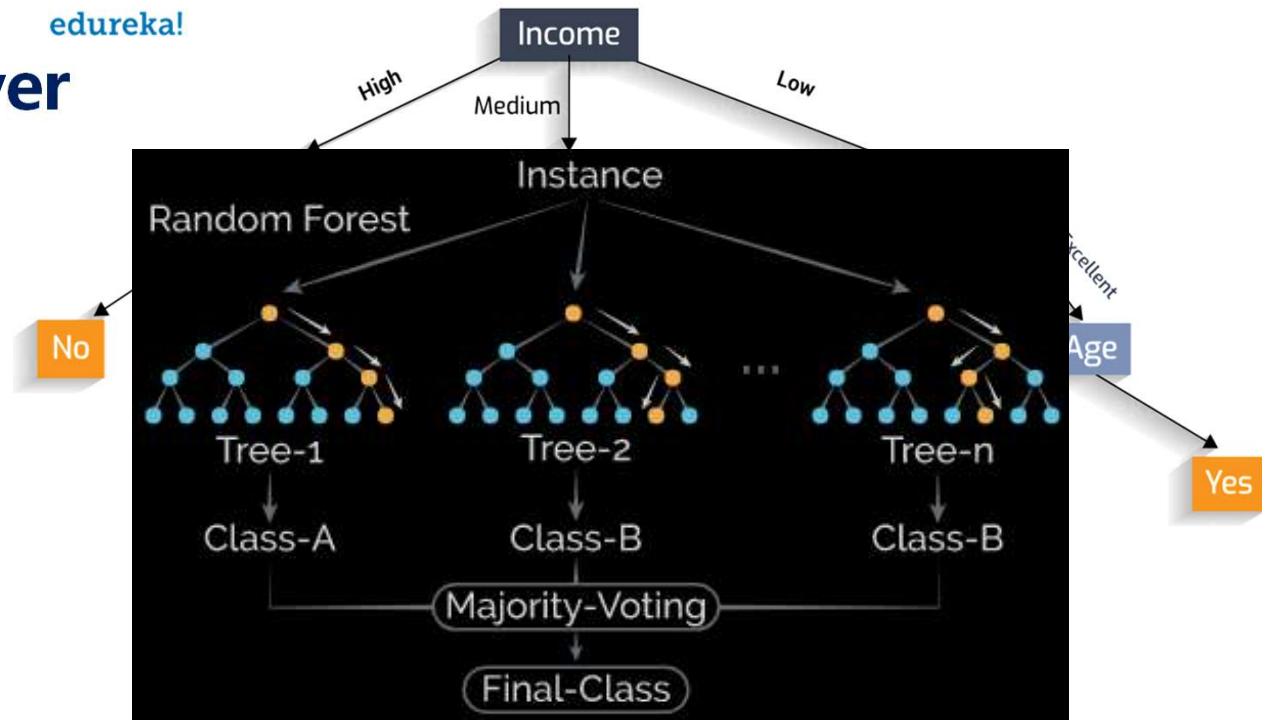
□ K-nearest neighbors

- Count nearest neighbors
- Larger count wins
- Some variants use weighted vote upon distance
- Hyper parameters
 - K
 - Distance calculation
- High bias model
 - Best when sample size is large but feature size is small



□ Decision Tree, ensemble of trees

- Many variants
- Basic trees tend to over fitting easily
- Use ensemble
- Hyper parameters
 - Criterion-mostly gini
 - Max depth
 - Max leaf nodes
 - min_samples_split



□ Model selection?

- Just try many models and pick the overall best one

#数据科学入门2.4:

特征的选取和特征提取

Introduction to Data Science 4
Part2.4: Simple Feature Engineering

□ Why

- Less computational heavy, faster training
- Less over fitting, better generalization
- Use our domain knowledge to create better features
- Less noise better accuracy
- Simpler model could be interpreted

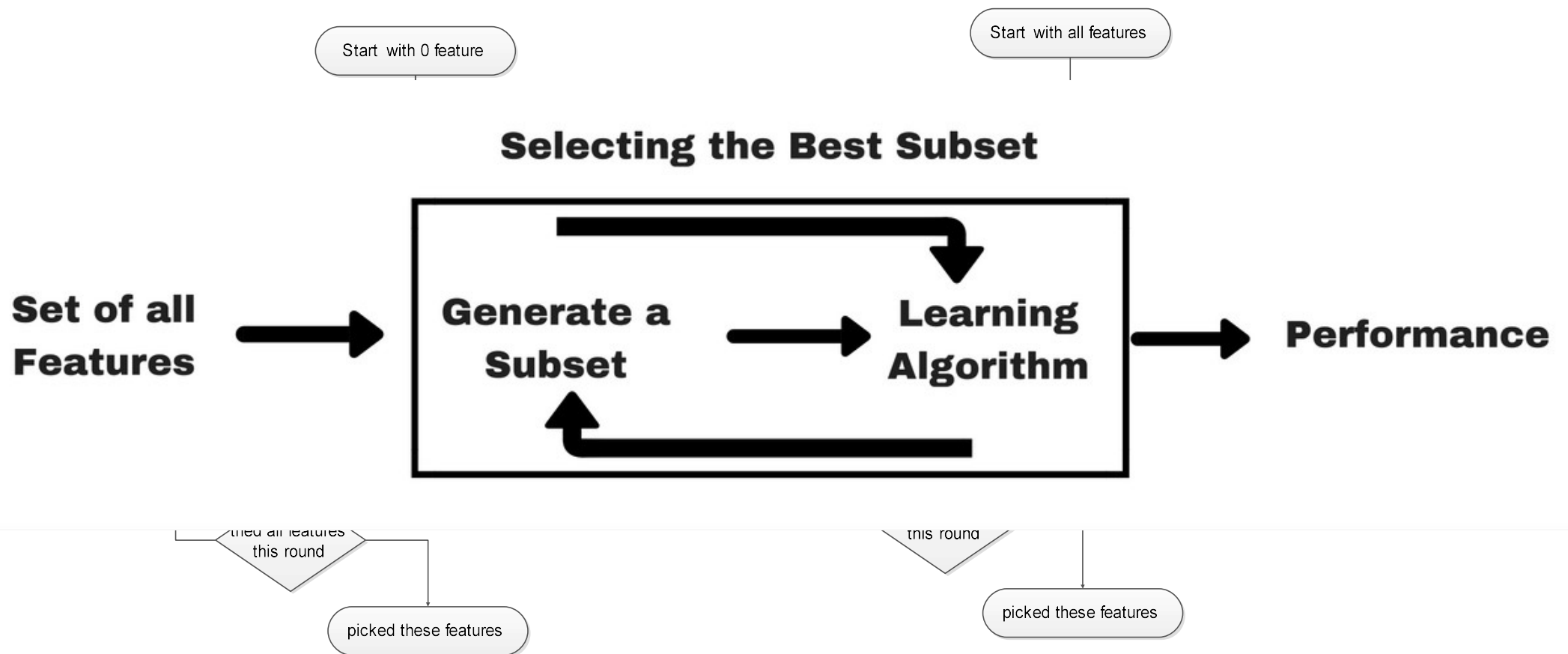
□ Feature selection

■ Filter method



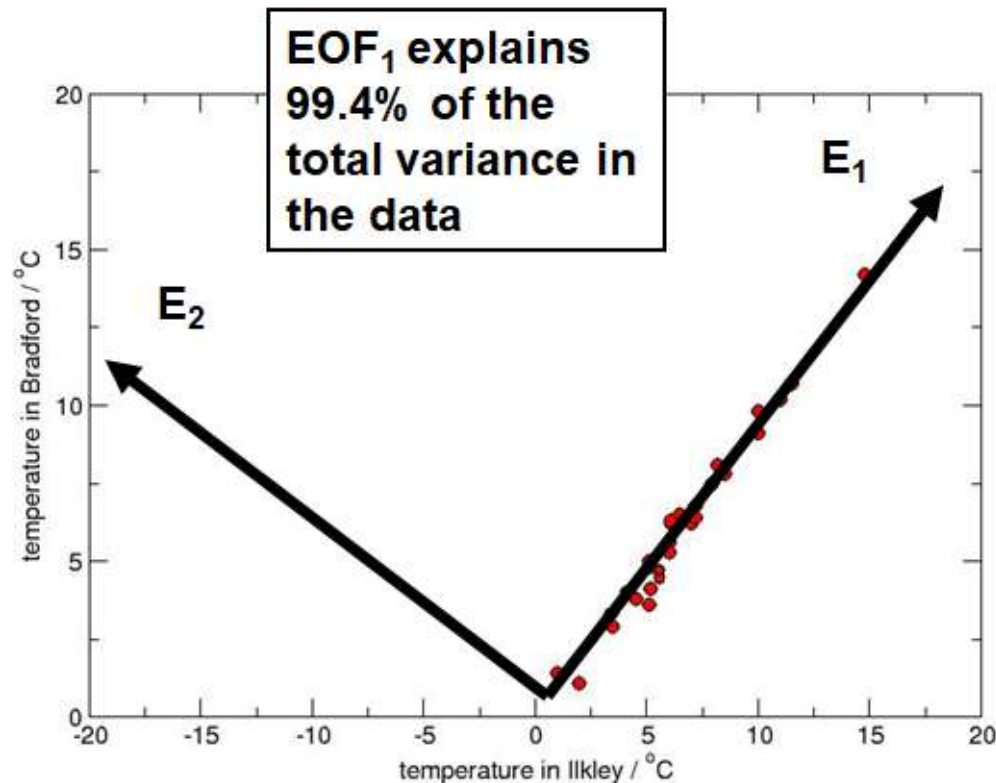
□ Feature selection

■ Wrapper methods

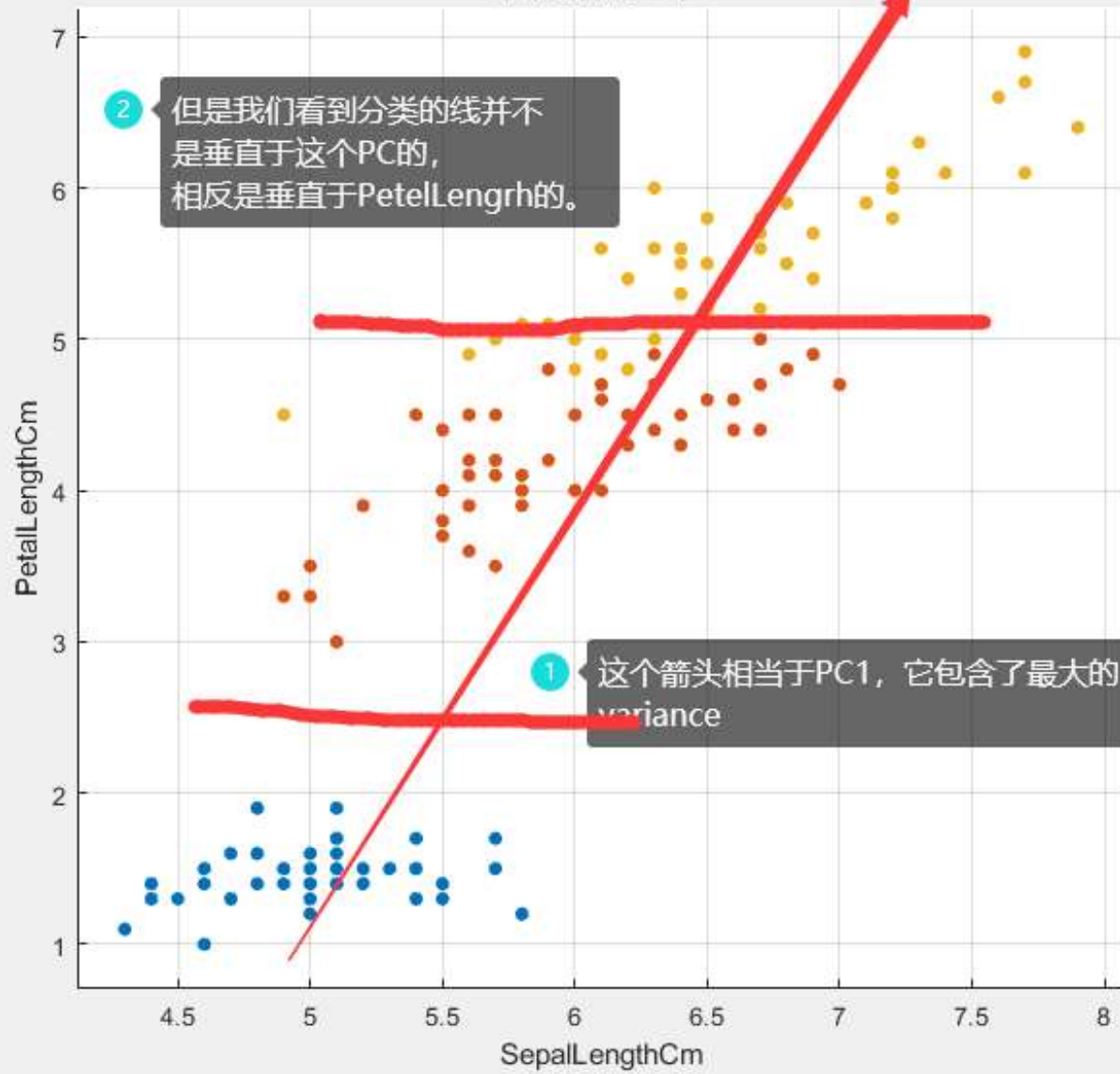


□ Feature extraction (feature creation)

■ PCA (Principal Component Analysis)



原始数据集: exp9



□ Feature extraction (feature creation)

- Use your domain knowledge
- More on this later

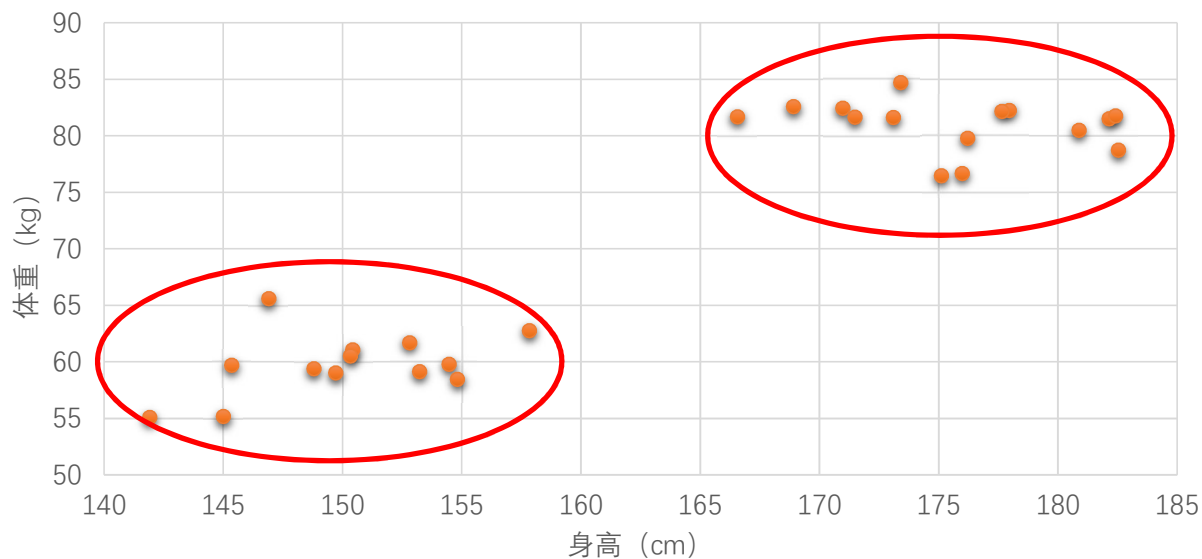
#数据科学入门2.5:

简单的聚类

Introduction to Data Science
Part2.5: Simple Clustering

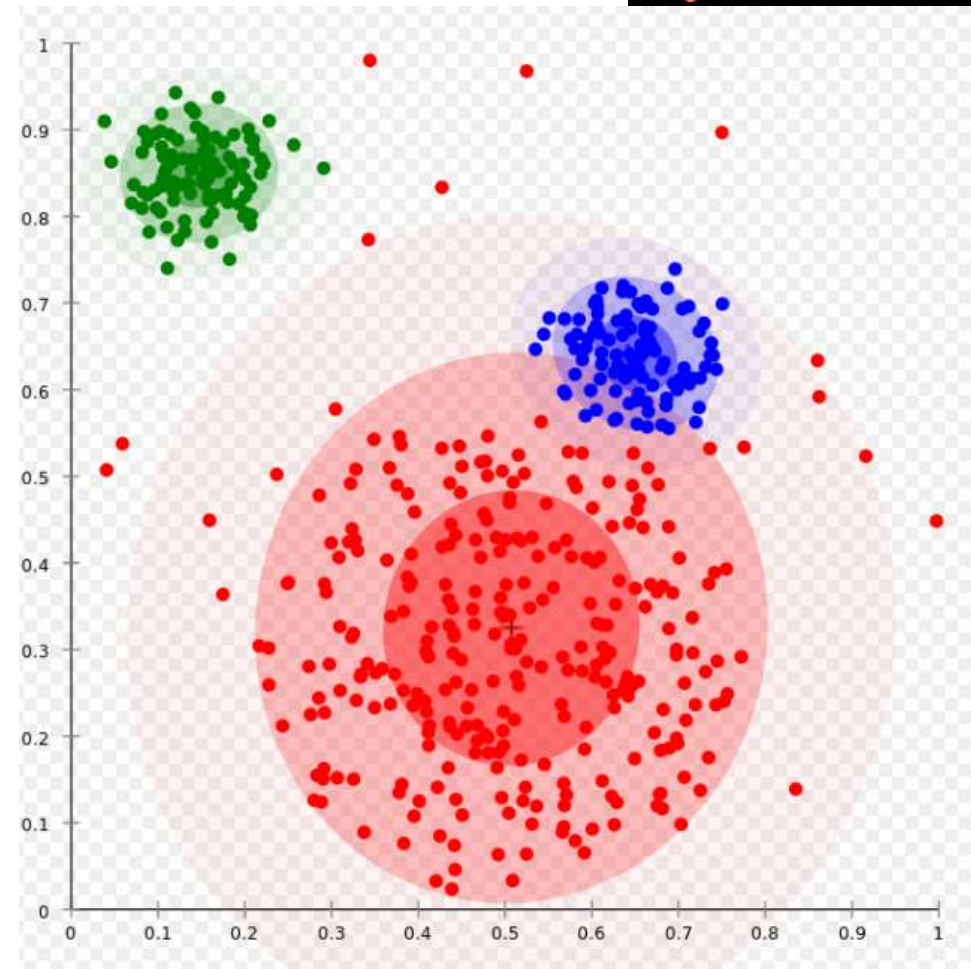
□ What is clustering

- Clustering is unsupervised learning
- Samples in their feature space, ones that are close to each other are cluster in to one cluster.

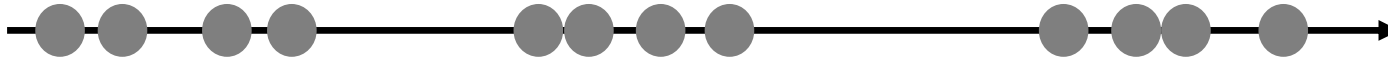


□ Types of clustering

- Connectivity based
- Density based
- Distribution based
- Centroid based



□ K-Means原理



□ K-Means原理

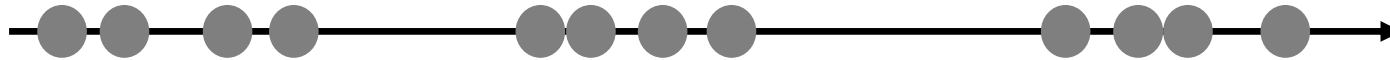
- 这个我一眼就看出来了
- 怎么让程序完成这个工作呢？



□ K-Means原理

■ 第1步：确定要分为几类， $K=?$

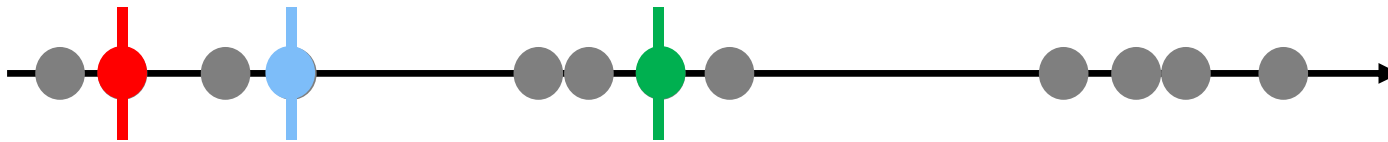
● 我们分为3类， $K=3$



□ K-Means原理

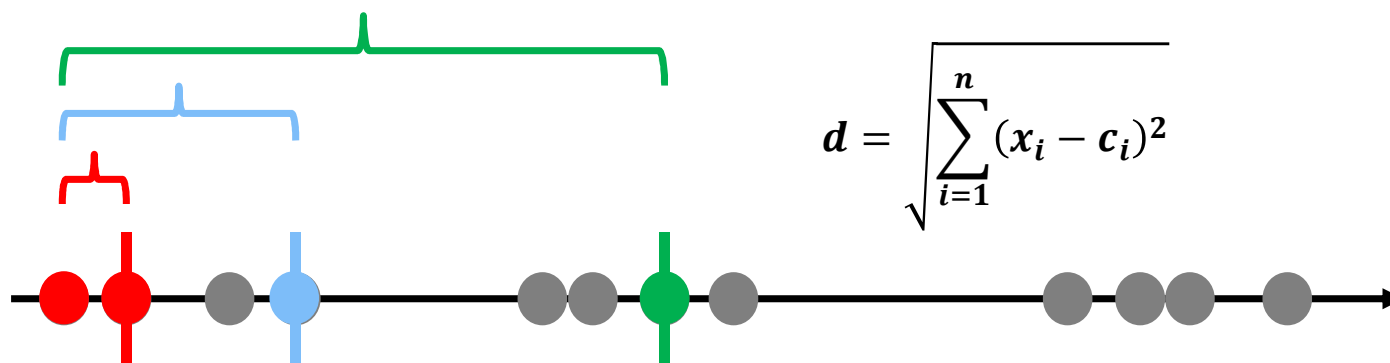
■ 第2步：随便选择3个类型的中心（重心）

- 我们就随便选3个点，让他们作为3个类型的中心
- 这3个点就分别属于对应的类型



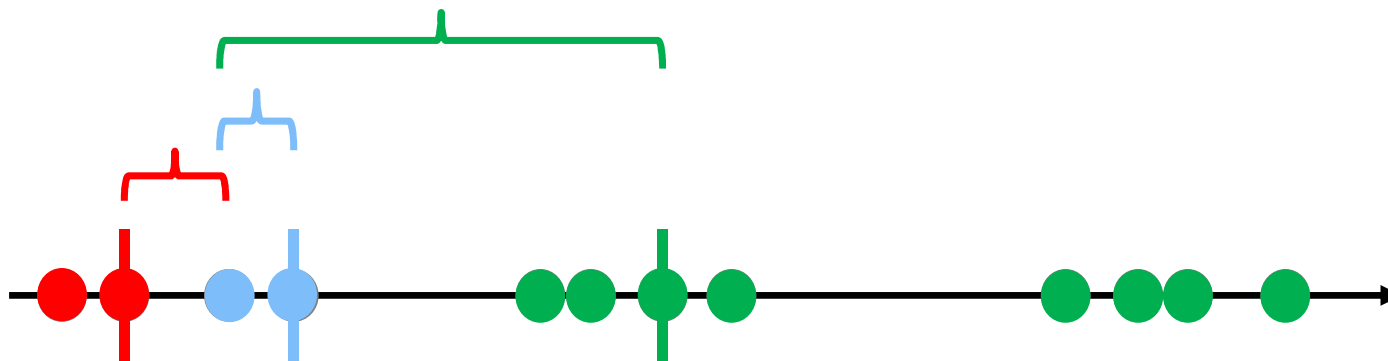
□ K-Means原理

- 第3步：计算第一个点到三个中心的距离
- 第4步：把第一个点分配个距离最近的类型



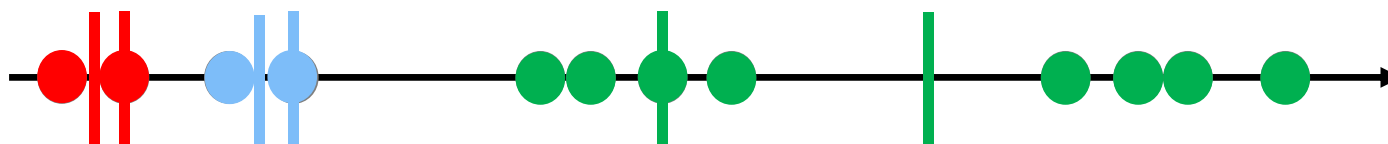
□ K-Means原理

■ 第5步：对剩下的点做3，4步



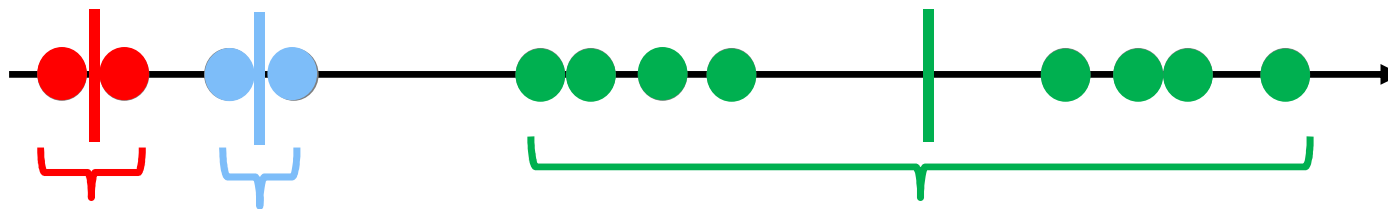
□ K-Means原理

- 第6步：重新计算每个簇的中心 (Mean)
- 第7步：3-6步，直到每个点所属的类型不在变化为止



□ K-Means原理

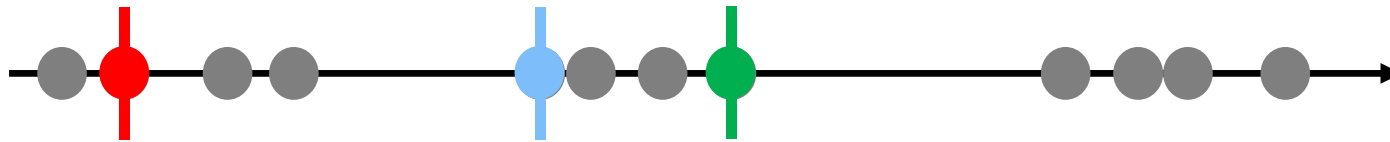
- 分好了! 但是结果好像不太好 😞
- 怎么评价我们的结果好坏?



$$SE = \sum_{k=0}^{Cluster} \sum_{i=0}^{AllPoints} D_{ki}$$

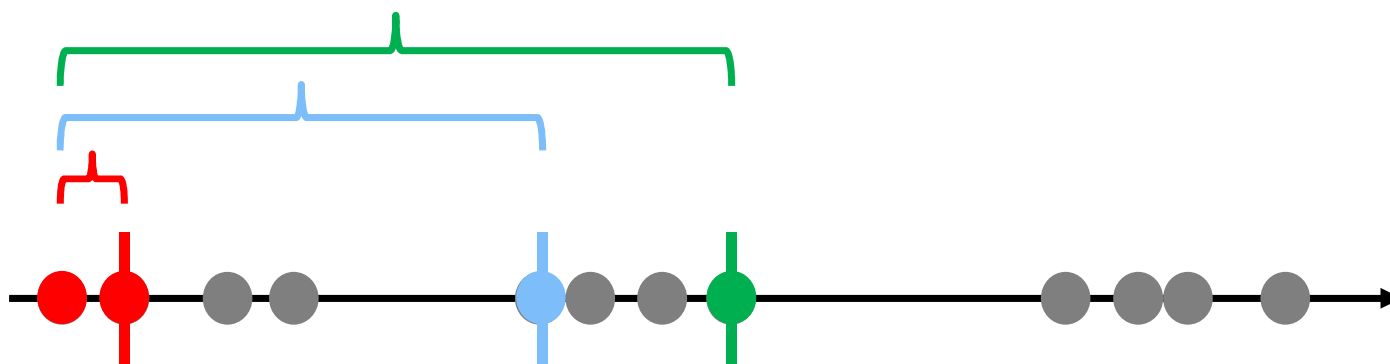
□ K-Means原理

- 重新开始，第1步， $K=3$
- 第2步：随便选择3个类型的中心（重心）
- 我们就随便选3个点，让他们作为3个类型的中心
- 这3个点就分别属于对应的类型



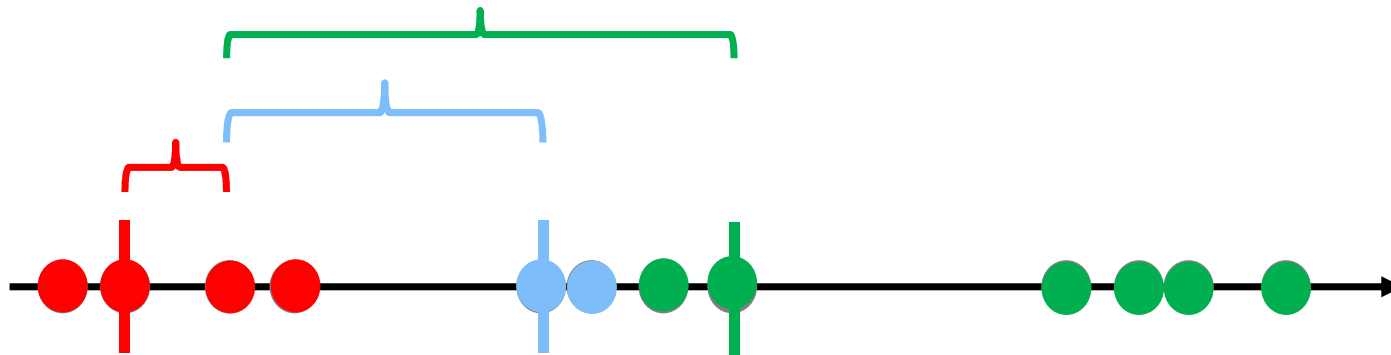
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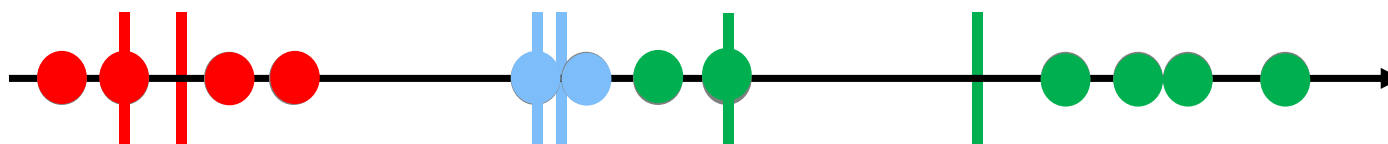
□ K-Means原理

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□ K-Means原理

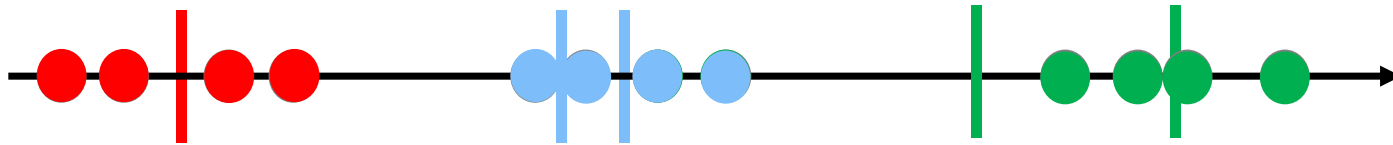
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□ K-Means原理

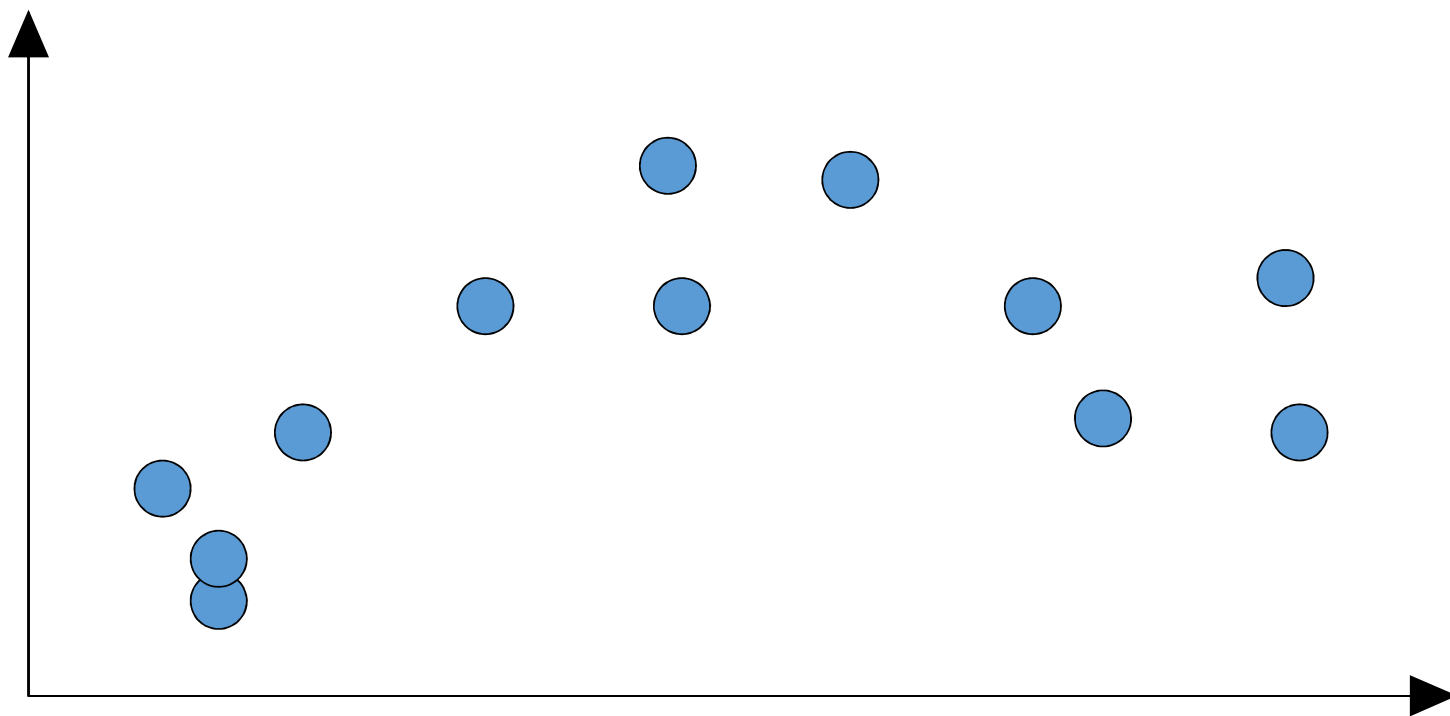
- 第6步：重新计算每个簇的中心（Mean）
- 第7步：3-6步，直到每个点所属的类型不在变化为止

$$SE = \sum_{k=0}^{Cluster} \sum_{i=0}^{AllPoints} D_{ki}$$



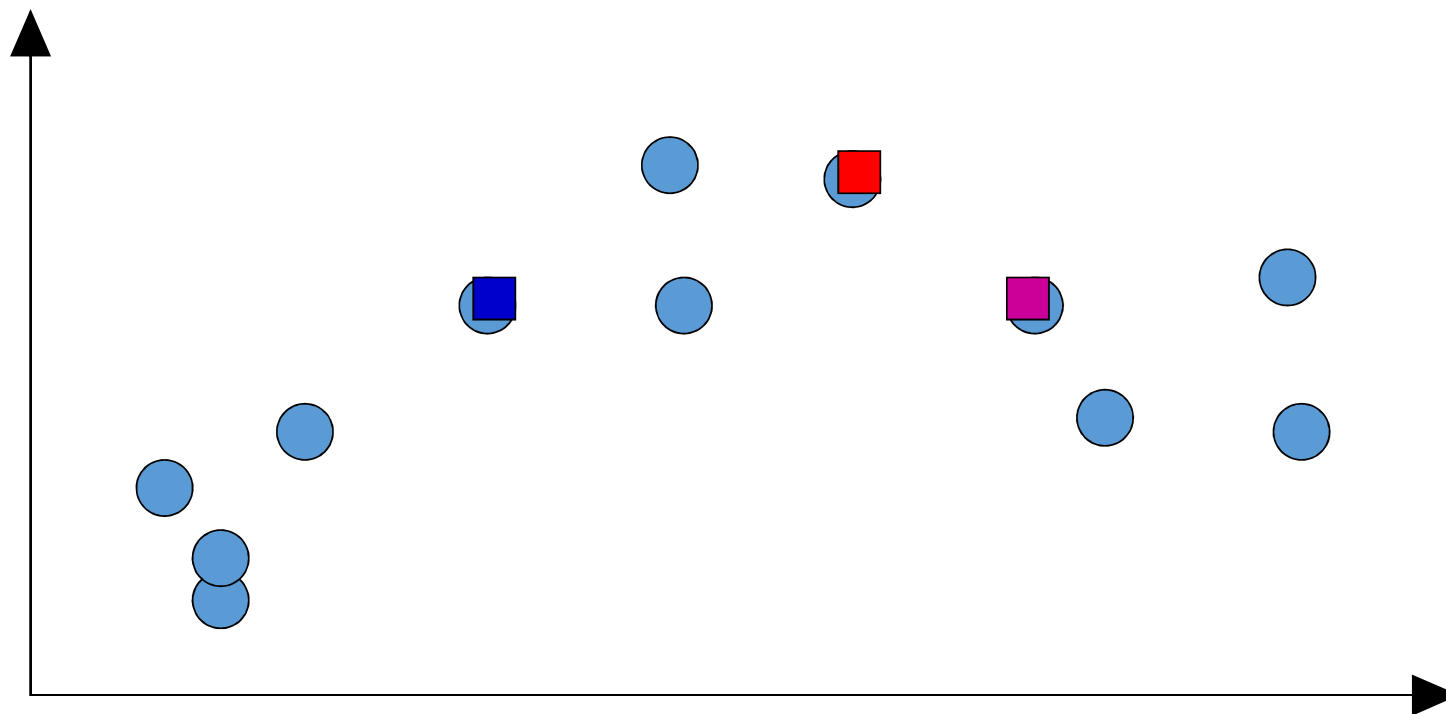
电脑并不知道这个是最好的结果，于是他再重复以上步骤多次，选取最好的结果

□ K-Means原理——2维数据



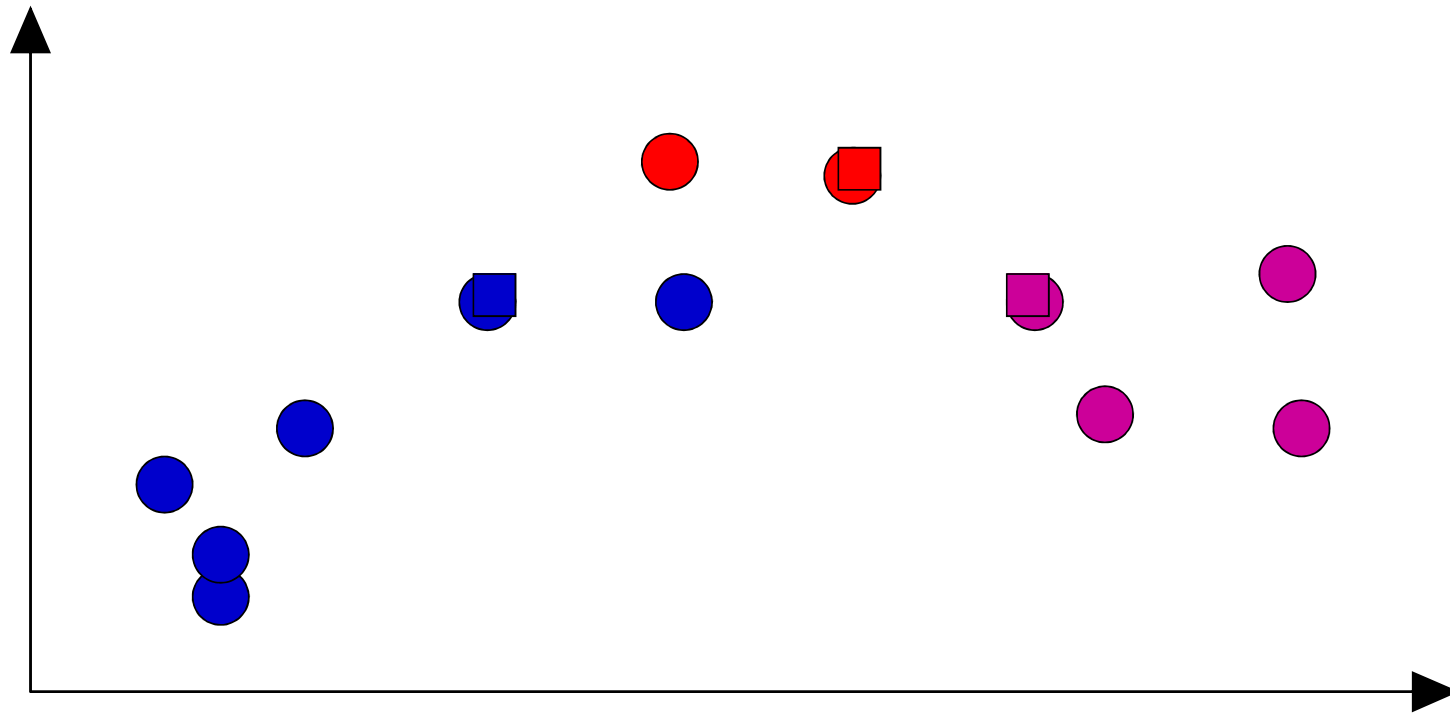
□ K-Means原理——2维数据

- 第1步：确定要分为几类， $K=?$
- 第2步：随便选择K个类型的中心



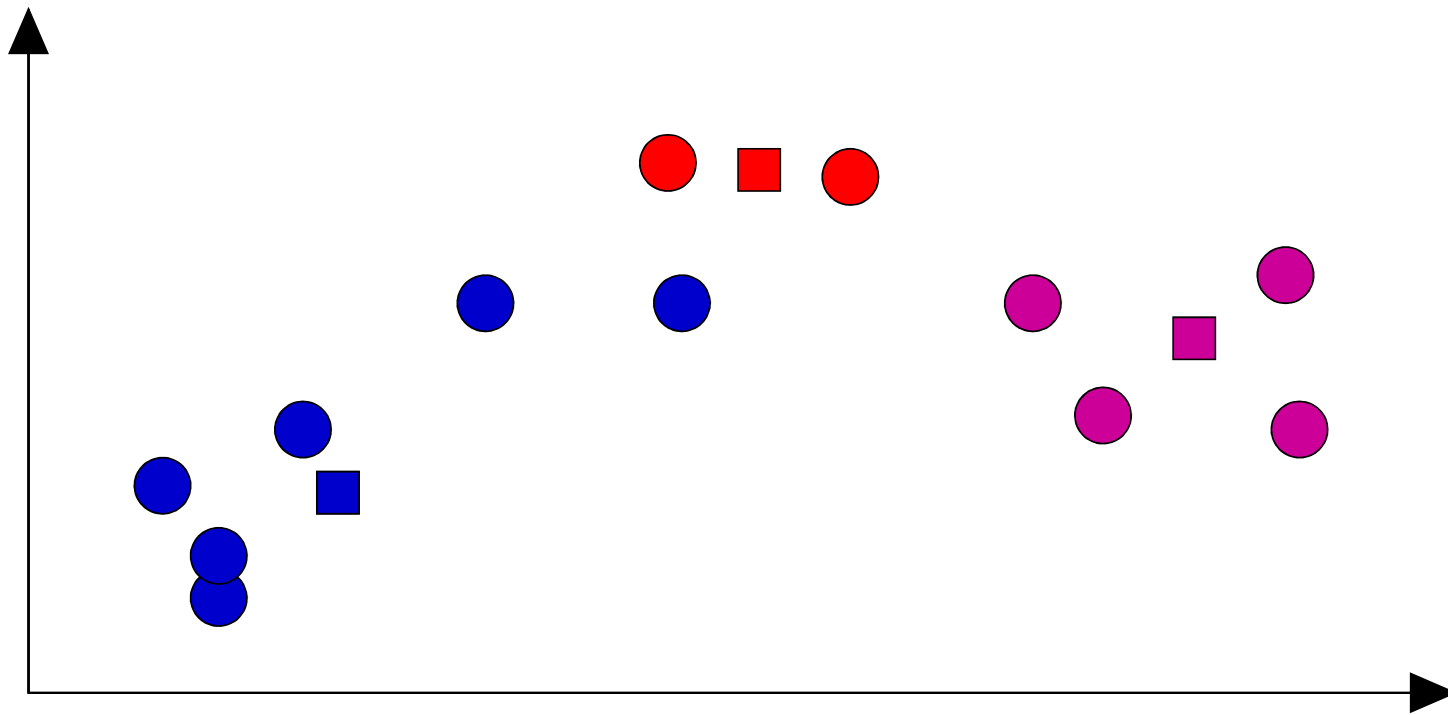
□ K-Means原理——2维数据

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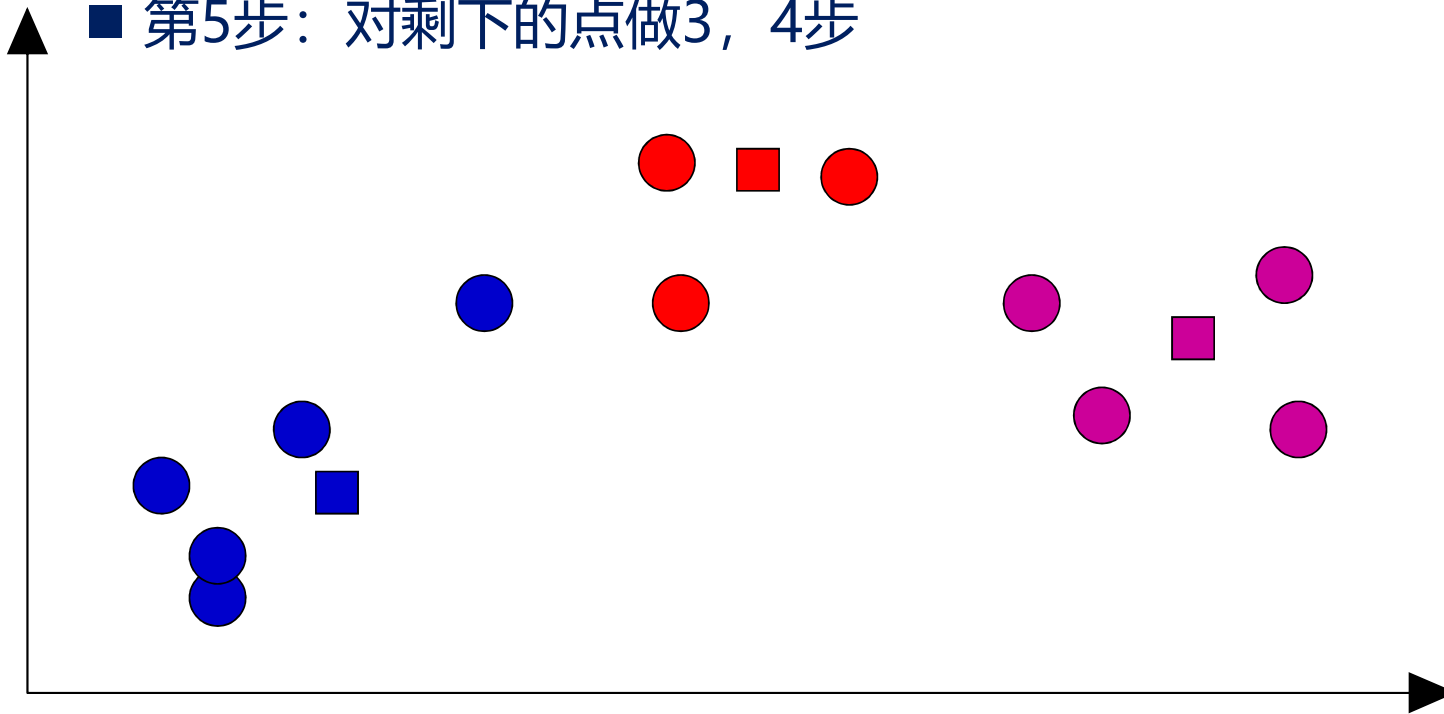
□ K-Means原理——2维数据

■ 第5步：重新计算每个类型的中心



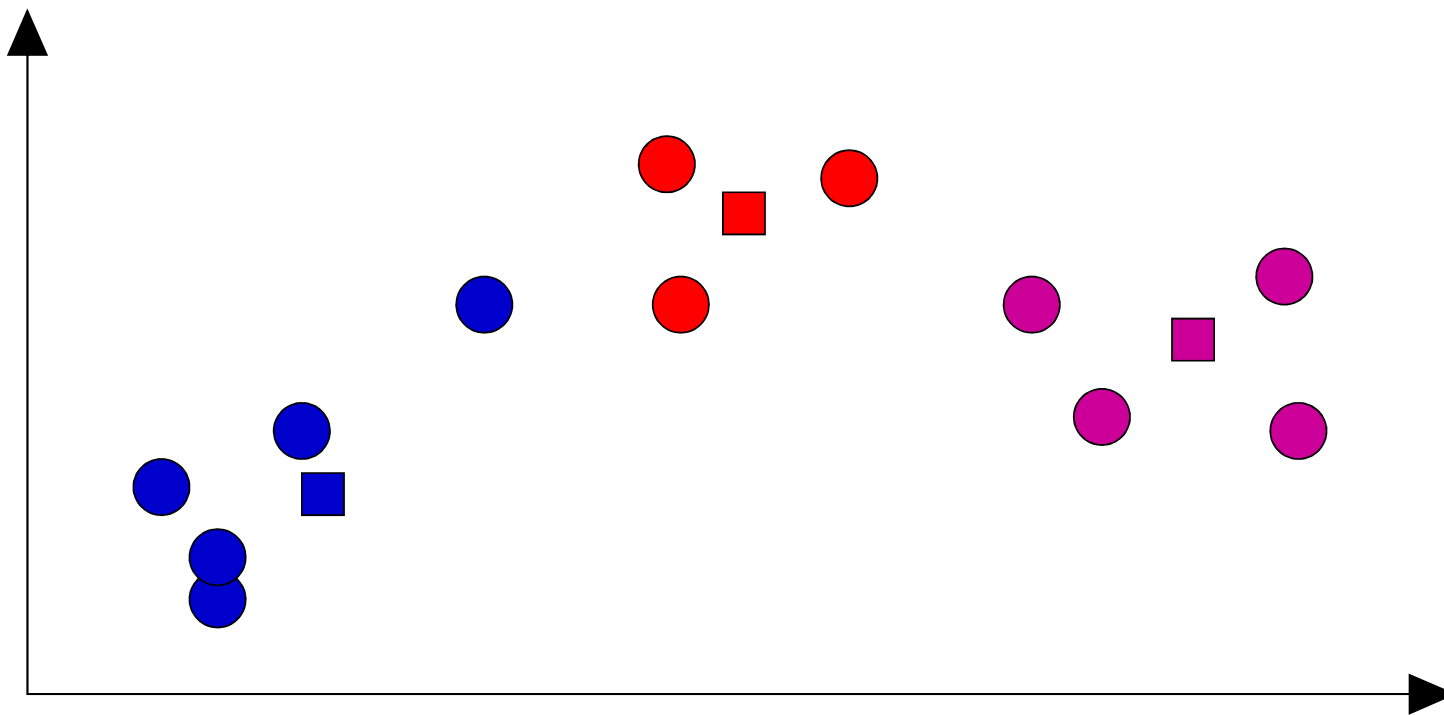
□ K-Means原理——2维数据

- 第7步：3-6步，直到每个点所属的类型不在变化为止
- 第3步：计算每个点到三个中心的距离
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- 第5步：对剩下的点做3，4步



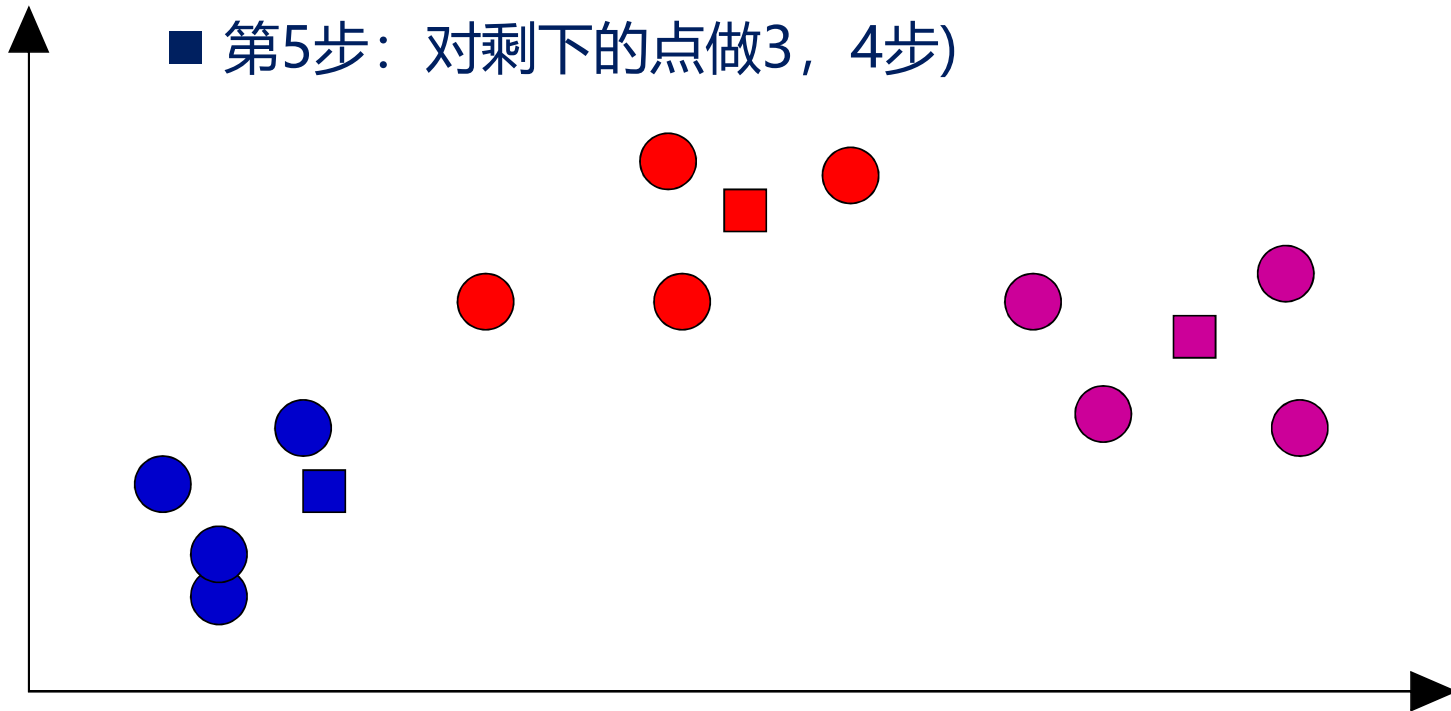
□ K-Means原理——2维数据

- 第7步：3-6步，直到每个点所属的类型不在变化为止
- (第6步：重新计算每个类型的中心)



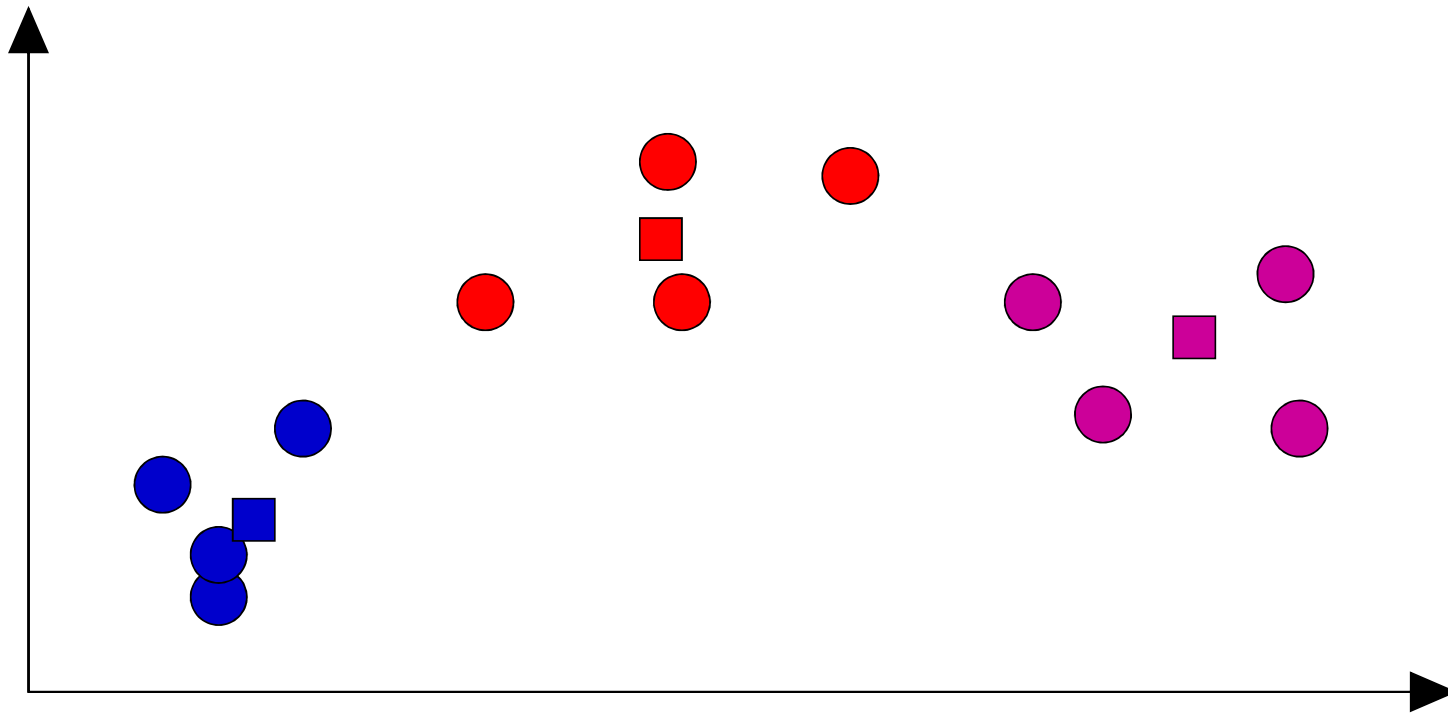
□ K-Means原理——2维数据

- 第7步：3-6步，直到每个点所属的类型不在变化为止
- (第3步：计算每个点到三个中心的距离
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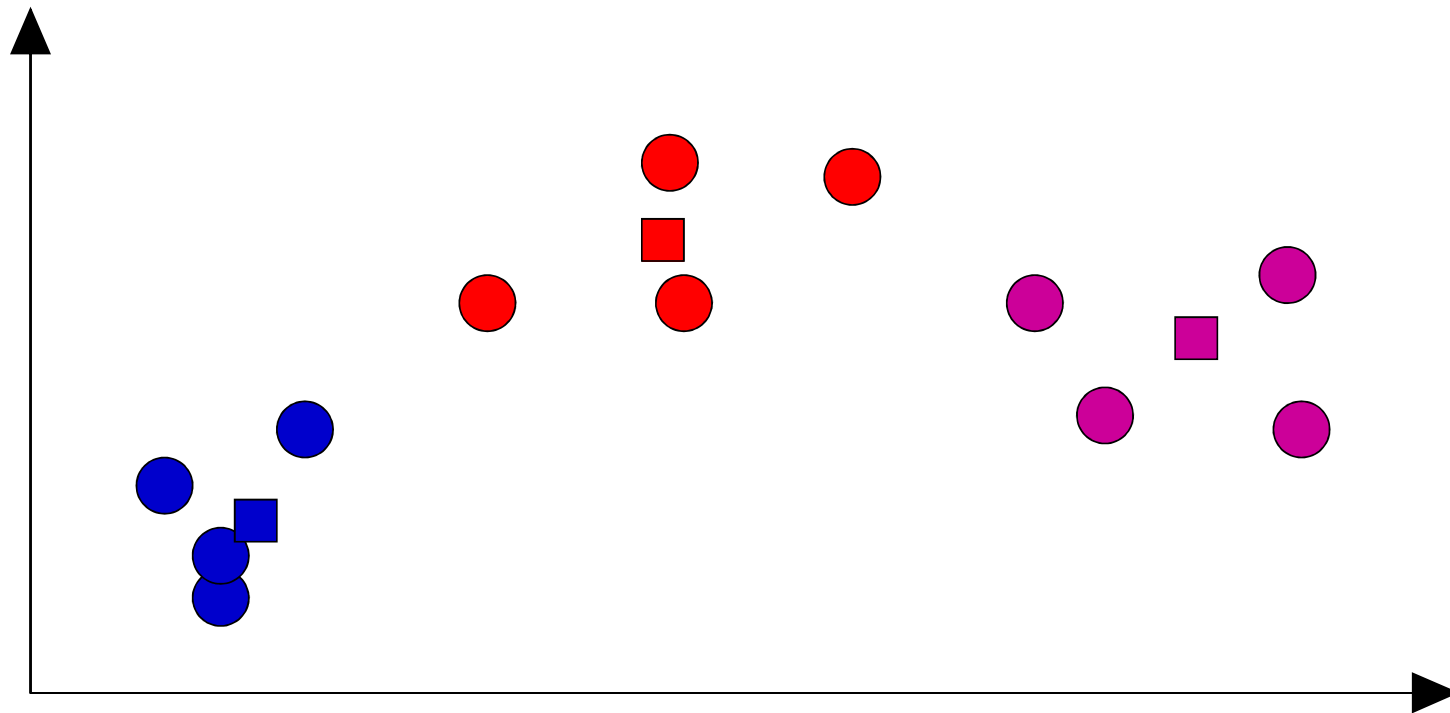


□ K-Means原理——2维数据

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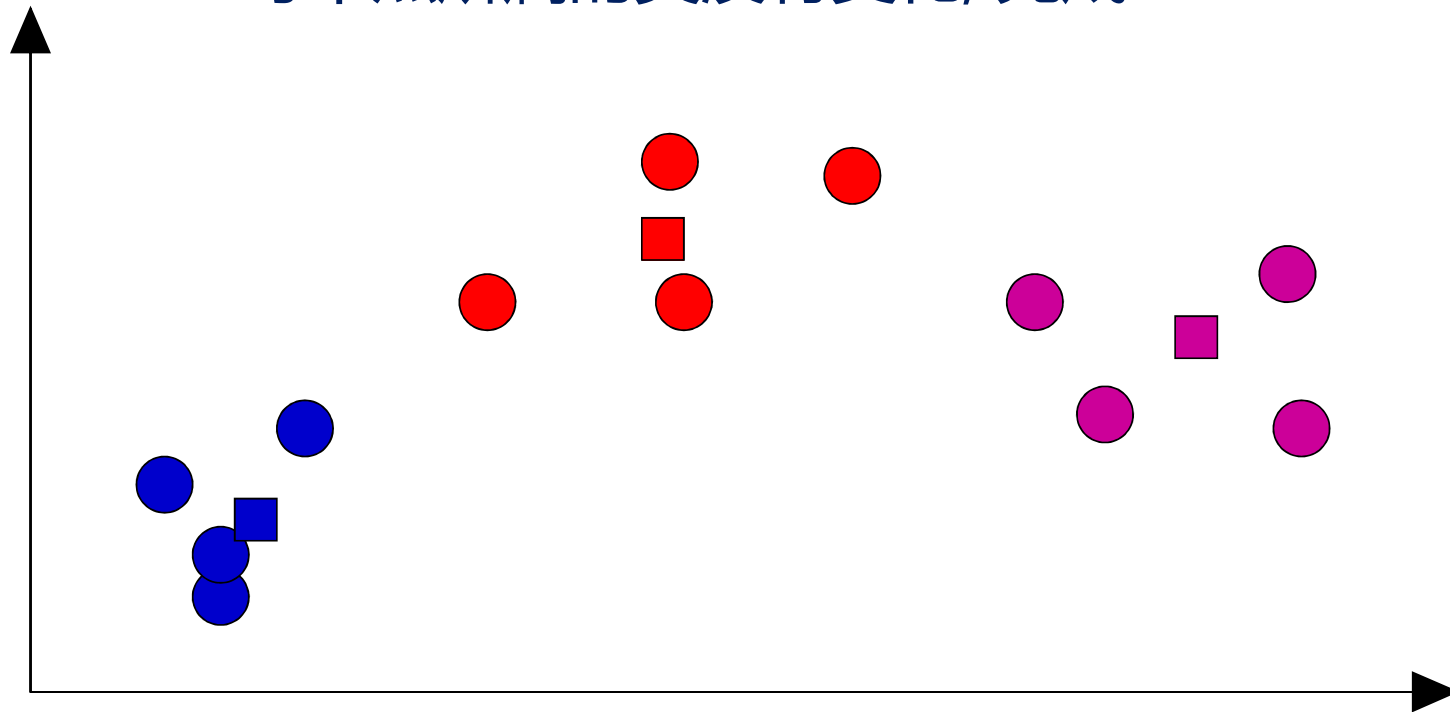


□ K-Means原理——2维数据



□ K-Means原理——2维数据

■ 每个点所属的类没有变化, 完成!



□ K-Means原理

■ 问题：那怎么确定K呢？

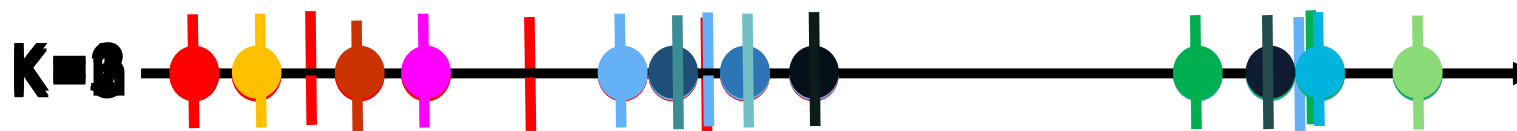


■ 方法一：你希望分成几类就让 $K=$ 几。

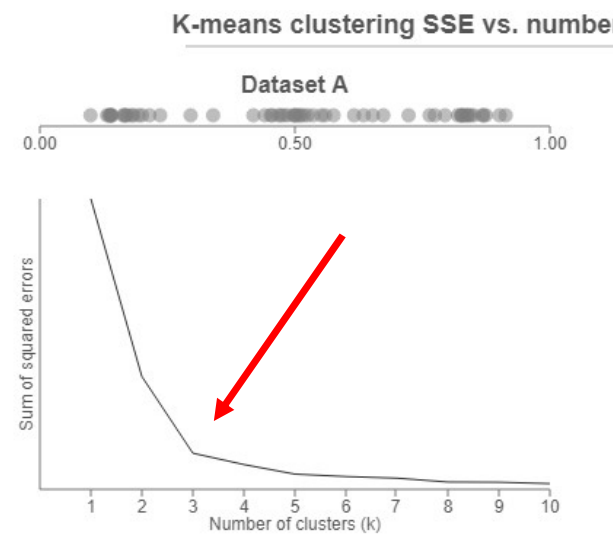
- 大人，小孩
- 男生，女生
- 好，中，差

□ K-Means原理

■ Elbow Method



$$SE = \sum_{k=0}^{Cluster\ AllPoints} \sum_{i=0} D_{ki}$$

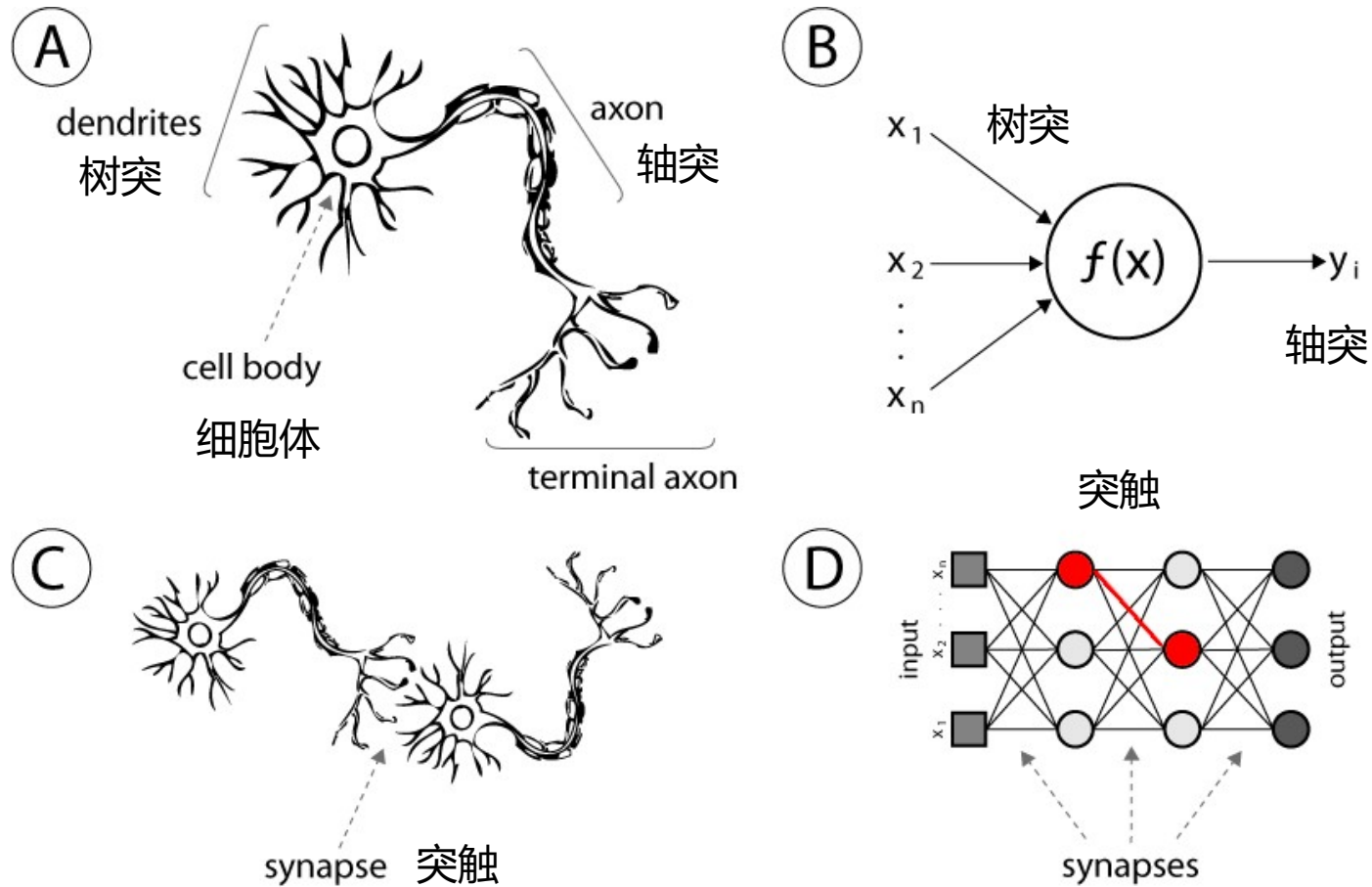


#数据科学入门2.5.9: 人工神经网络入门

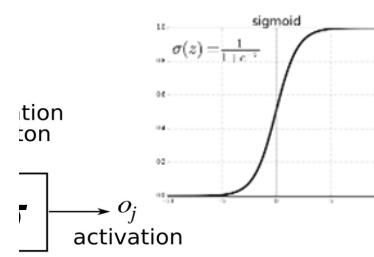
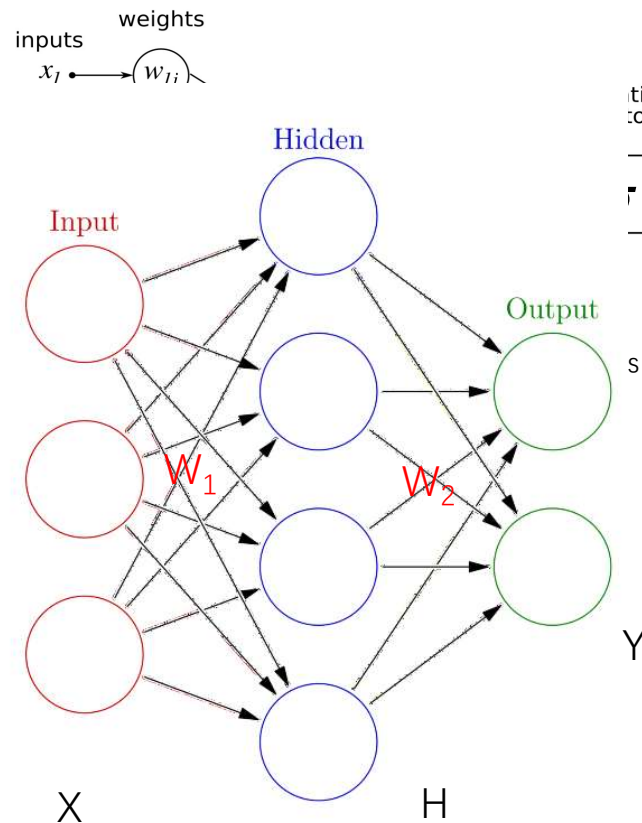
Introduction to Data Science

Part2.5.9: Demystify the artificial neural network

□ Artificial neural network



□ How it works



$$o = \sigma\left(\sum_{i=1}^n x_i * w_{ij} + b\right)$$

$$o = \sigma(WX + b)$$

$$H = \sigma(W_1 X + B_1)$$

W_1 [4*3]
 X [3*1]
 B_1 [4*1]
 H [4*1]

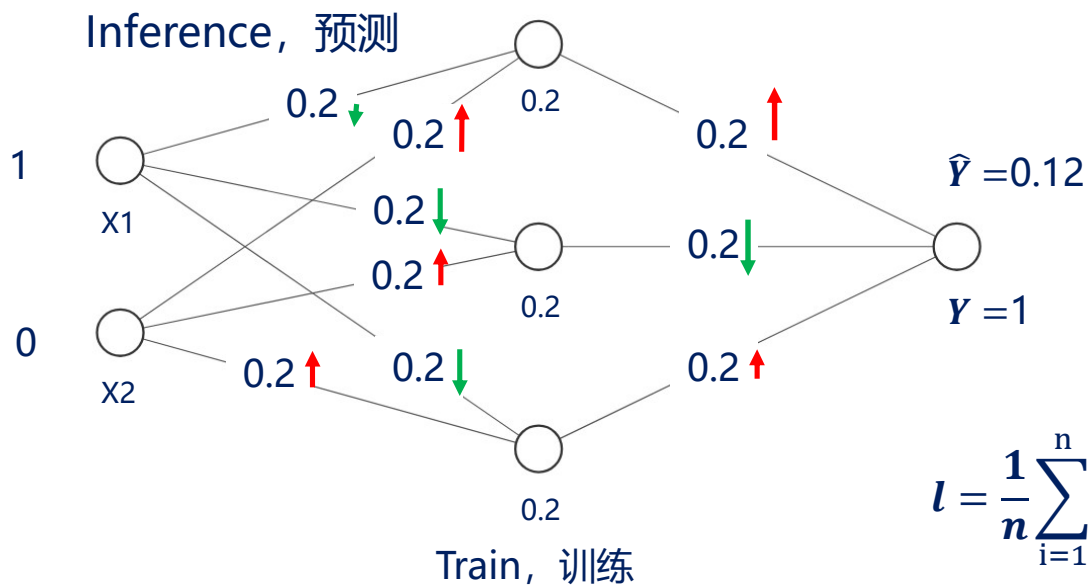
$$Y = \sigma(W_2 H + B_2)$$

W_2 [2*4]
 H [4*1]
 B_2 [2*1]
 Y [2*1]

$$\hat{Y} = f(X, W, B)$$

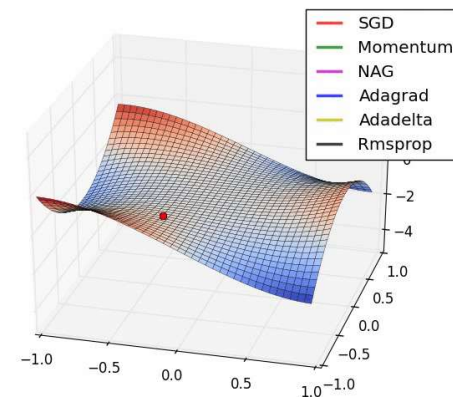
4+2=6个神经元 3*4+4*2=20个weight, 4+2=6个bias, 26个可优化参数

□ How it is trained?



X1	X2	Y
1	0	1
0	1	1
1	1	0
0	0	0

$$Y = X_1 \oplus X_2$$



$$l = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad \text{Loss Function}$$

$$\text{Min}(l)$$

$$\theta = [w_1, w_2, \dots, b_1, b_2, \dots]$$

$$\nabla_{\theta} l(\theta) = \left[\frac{\partial l}{\partial w_1}, \frac{\partial l}{\partial w_2}, \dots, \frac{\partial l}{\partial b_1}, \frac{\partial l}{\partial b_2}, \dots \right]$$

□ Matlab shallow neural network

- Simple regression
- Time series
- Just for fun, not serious application

#数据科学入门2.6: 一点点深度学习

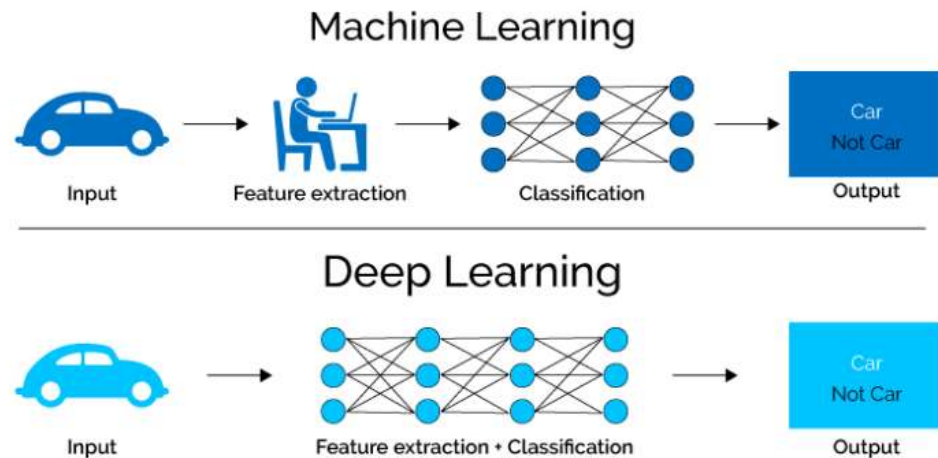
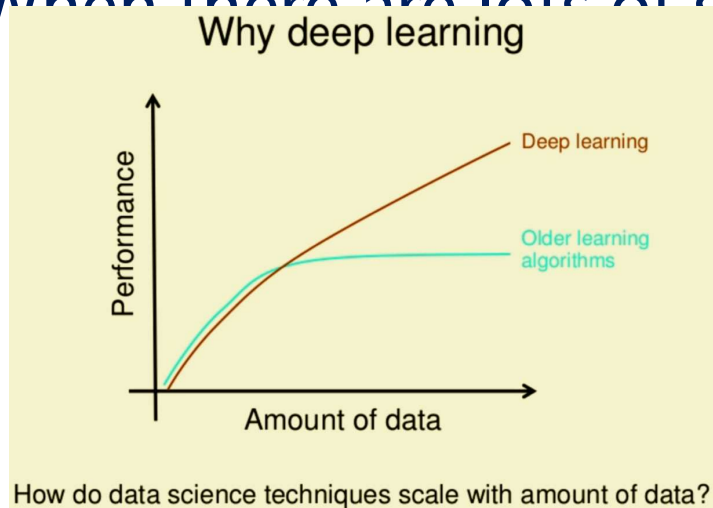
**## Introduction to Data Science
Part2.6: a glance of deep learning**

□ Before we start

- Why we want deep learning
- First we look at traditional learning on complex data

□ Why deep learning (below is only partly true)

- Remember the feature engineering we did in previous class?
- When it's hard to extract meaningful low dimension features.
- When there are lots of features
- When there are lots of samples



□ Assignment

- Redo the examples in this class
- Try Titanic survival data using models and evaluation methods learned in this class

□ If you want to know more



