

# MA333 Introduction to Big Data Analysis

## Course Introduction

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# Outlines

Course Syllabus

What Is Data Science

Machine Learning

Mathematical Representation

Conclusion

# Course Info

- Semester 2020-2021 Spring
- Instructor : ZHANG, Zhen (张振)
- Office : Room 417, Block 3, Huiyuan
- Phone : 88018753
- Email : zhangz@sustech.edu.cn
- Office hours : Wednesday afternoon, 15 :00-17 :00 ; or send email to make an appointment for other time.
- Lecture : 3 credits, 3 hours per week.
- Prerequisite : Calculus I&II, MA101b&MA102b, (or Mathematical Analysis I&II, MA101a&MA102a) ; Linear Algebra I, MA103b ; Probability Theory, MA215 (or Probability Theory and Mathematical Statistics).

# Grading Policy

- Homework : Approximately 6 homework assignments (including online programming assignments and written problems). **Please hand in your completed homework online in the system.** The written homework could be handed in class
- In-class quizzes : typically once every two weeks, test how well you learned about the basic concepts, including fill-in-the-blank, single and multiple choices, and simple Q & A
- Two programming projects : need to write codes and reports
- One closed-book final exam
- Grading policy : assignments (30%), quizzes (15%), programming projects (20%), and the final exam (35%).

# Course Website

- Course webpage (数据酷客) : <http://cookdata.cn>
- Each student will be assigned an account

首页 课程 大讲堂 专题 竞赛 社区

张振 ▾

## 教学模式

The diagram illustrates the teaching mode through five interconnected components arranged in a circle:

- 理论** (Theory): 33 core courses.
- 案例实践** (Case Practice): Real industry cases (1000+).
- 应用练习** (Application Practice): Practical exercise database (5000+).
- 真实案例** (Real Cases).
- 处理工具** (Processing Tools).

Arrows indicate a clockwise flow between these components. The background features binary code (10101010...) and a blue gradient.

理论与实践结合, 以数据为基础, 实际问题为导向的实践性教学

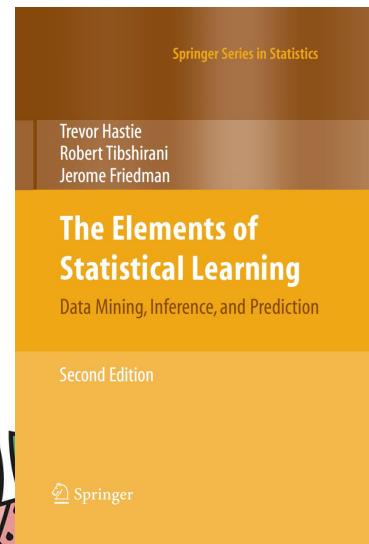
# Contents

- Intended for undergraduate students who are interested in pursuing industrial work and research in big data science.
- Concise and self-contained introduction to mathematical aspect of big data science, including **theoretical analysis, algorithms and programming with python**
- Major topics :
  - Introduction to python programming and data preprocessing
  - Three fundamental problems : classification, regression, clustering
  - Model selection, dimensionality reduction
  - Hot topics : text analysis, social network analysis, neural network and deep learning, distributed computing, and recommender systems if time permits

## References

- (**textbook**) 数据科学导引，欧高炎等著，高等教育出版社，2017.
- 机器学习，周志华著，清华大学出版社，2016.
- An Introduction to Statistical Learning with Applications in R, by Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer, 2013.  
<http://web.stanford.edu/~hastie/pub.htm>
- Pattern Recognition and Machine Learning, by Christopher M. Bishop, Springer, 2006.
- The Elements of Statistical Machine Learning : Data mining, Inference and Prediction, 2nd Edition, by Trevor Hastie, Robert Tibshirani, and Jerome Friedman, Springer, 2009.
- Understanding Machine Learning, by Shai Shalev-Shwartz and Shai Ben-David, Cambridge University Press, 2018.
- Deep learning, by Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press, 2016.

# References



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# Some Examples of Data

Can you give some examples of data ?

实验数据分析表			
项目	加药量(ppm)		CODcr (mg/L)
	硫酸亚铁	双氧水	
原水	/	/	321
1	2000	1000	2800
2	3000	1500	3000
3	4000	2000	3100
4	5000	2500	3500
***实验数据仅对该批水样负责***			

A	B	C	D	E	F	G	H
1 姓名	语文	数学	英语	其他	平均分	总成绩	备注
2 张前伟	68	91	74	95			
3 蔡士友	59	83	81	82			
4 蔡洪涛	91	67	85	76			
5 姜会云	59	85	96	85			
6 任恒侯	68	74	71	95			
7 麦兴福	46	91	61	68			
8 丰春磊	89	82	53	95			
9 蔡康宁	80	73	85	75			
10 王艳超	86	80	81	85			
11 蔡龙雷	79	90	64	91			
12 王芹芹	59	72	62	82			
13 任转晴	61	78	59	95			



Table, 1D signal (audio, stock price), 2D signal (image), 3D signal (video), etc.

# Big Data : 4 Big “V”

- Volume : KB, MB, GB ( $10^9$  bytes), TB, PB, EB ( $10^{18}$  bytes), ZB, YB
- Variety : different sources from business to industry, different types
- Value : redundant information contained in the data, need to retrieve useful information
- Velocity : fast speed for information transfer



# What is data science

- Retrieve information from data with the help of computational power
- Transfer the information into knowledge
- Two perspectives of data sciences :
  - Study science with the help of data : bioinformatics, astrophysics, geosciences, etc.
  - Use scientific methods to exploit data : statistics, machine learning, data mining, pattern recognition, data base, etc.

# Study Science with the Help of Data

A pioneering work of data science : Kepler's Laws



开普勒：分析数据产生价值



行星	周期 (年)	平均距离	周期 <sup>2</sup> /距离 <sup>3</sup>
水星	0.241	0.39	0.98
金星	0.615	0.72	1.01
地球	1.00	1.00	1.00
火星	1.88	1.52	1.01
木星	11.8	5.20	0.99
土星	29.5	9.54	1.00
天王星	84.0	19.18	1.00
海王星	165	30.06	1.00

# Scientific Study of Data

- Grabbing data : business and industrial problem, professional areas
- Storing data : engineering problem, computer science, electronic engineering
- Analyzing data (**key problem**) : scientific problem, mathematics, statistics, computer science

# Data Analysis

- Ordinary data types :
  - Table : classical data (could be treated as matrix)
  - Set of points : mathematical description
  - Time series : text, audio, stock prices, DNA sequences, etc.
  - Image : 2D signal (or matrix equivalently, e.g., pixels), MRI, CT, supersonic imaging
  - video : 2D in space and 1D in time (another kind of time series)
  - Webpage and newspaper : time series with spatial structure
  - Network : relational data, graph (nodes and edges)
- Basic assumption : the data are generated from an underlying model, which is unknown in practice
  - Set of points : probability distribution
  - Time series : stochastic processes, e.g., Hidden Markov Model (HMM)
  - Image : random fields, e.g., Gibbs random fields
  - Network : graphical models, Bayesian models

# Difficulties

- Huge volume of data
- Extremely high dimensions
  - Curse of dimensionality : the model complexity and computational complexity become exponentially increasing with the growth of dimension
  - Solutions :
    - Make use of prior information
    - Restrict to simple models
    - Make use of special structures, e.g., sparsity, low rank, smoothness
    - Dimensionality reduction, e.g., PCA, LDA, etc.
- Complex variety of data
- Large noise : data are always contaminated with noises

# Solution - Algorithms

- Algorithms are in the interdisciplinary part of computer science and mathematics : establish mathematical models, solve it numerically, implement it in the computer languages
- Reduce the algorithmic complexity, with the help of techniques from mathematics or computer science
- Distributional and parallel computing : divide-and-conquer, e.g., MapReduce, GPU
- IEEE 2006 top 10 algorithms in data mining : C4.5, K-Means, SVM, Apriori, EM, PageRank, NaiveBayes, K-Nearest Neighbors, AdaBoost, CART

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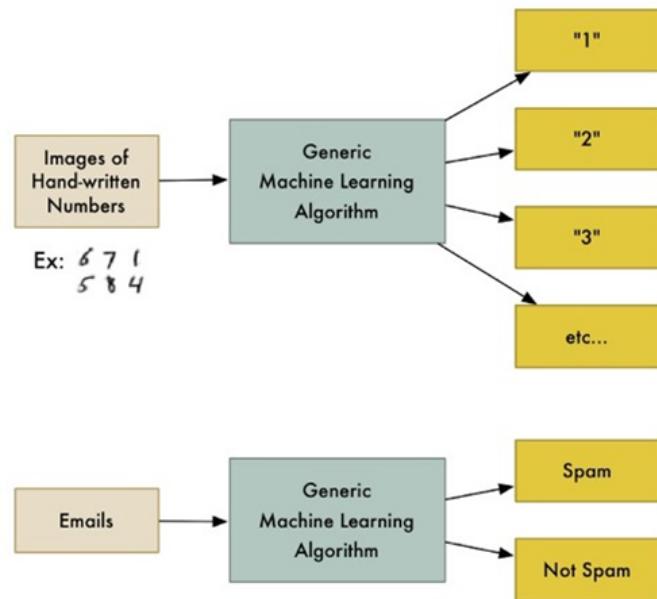
Conclusion

# Definition

- Artificial Intelligence (AI) : learning from experiences (data), and improve the computer program adaptively
- Mathematics : Learning the underlying model from data, and generalize the model to adapt new data

We define *machine learning* as a set of methods that can automatically **detect patterns in data**, and then use the uncovered patterns to **predict future data**, or to **perform other kinds of decision making under uncertainty** (such as planning how to collect more data!).

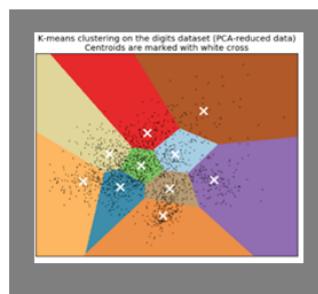
— 《Machine Learning: A probabilistic perspective》



## Related Areas

- Control theory : optimize the cost with optimal control parameters
- Information theory : entropy, optimal coding with best information
- Psychology : reference for machine learning algorithms
- Neuroscience : artificial neural network
- Biology : genetic algorithms
- Theory of Computing : study the computational complexity
- Statistics : large-sample limiting behavior, statistical learning theory
- Artificial Intelligence : symbolic computing
- Bayesian theory : conditionally probabilistic network

# Applications

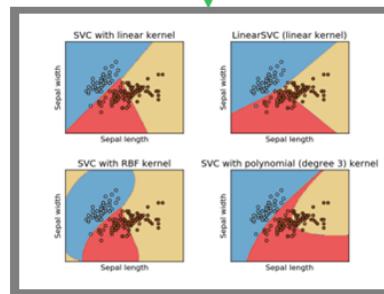


Clustering



Association Rules

Classification

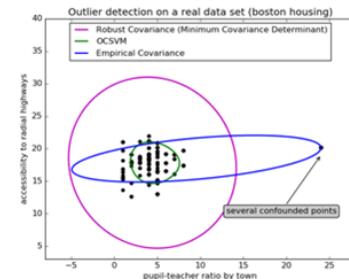
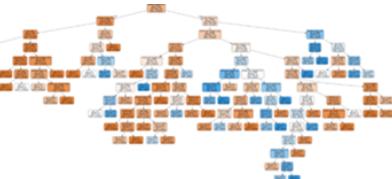


Data

Index	Petal length	Petal width	Sepal length	Sepal width	Species	Class
0	5.1	1.6	3.5	1.4	Iris-setosa	0
1	4.9	1.7	3.7	1.5	Iris-setosa	0
2	4.7	1.4	4.7	1.4	Iris-setosa	0
3	4.6	1.4	4.4	1.3	Iris-setosa	0
4	5.0	1.9	4.9	1.5	Iris-setosa	0
5	5.4	2.0	4.9	1.8	Iris-setosa	0
6	5.7	2.3	5.1	1.8	Iris-setosa	0
7	5.1	1.7	5.9	2.0	Iris-setosa	0
8	5.9	2.0	6.0	2.2	Iris-setosa	0
9	6.4	2.1	6.3	2.3	Iris-setosa	0
10	4.5	1.5	4.5	1.5	Iris-versicolor	1
11	4.5	1.5	4.5	1.5	Iris-versicolor	1
12	4.9	1.7	4.9	1.5	Iris-versicolor	1
13	4.9	1.4	4.9	1.4	Iris-versicolor	1
14	4.8	1.8	4.8	1.7	Iris-versicolor	1
15	5.0	1.6	5.0	1.4	Iris-versicolor	1
16	5.4	1.7	5.1	1.5	Iris-versicolor	1
17	5.7	1.9	5.1	1.8	Iris-versicolor	1
18	5.1	2.0	5.9	2.1	Iris-versicolor	1
19	5.4	2.3	6.0	2.4	Iris-versicolor	1
20	5.1	1.7	6.3	2.0	Iris-versicolor	1
21	5.8	2.0	6.3	2.3	Iris-versicolor	1
22	5.7	1.5	6.4	2.0	Iris-versicolor	1
23	6.0	2.2	6.3	2.0	Iris-versicolor	1
24	5.5	1.8	6.5	2.1	Iris-versicolor	1
25	5.1	1.8	6.3	2.0	Iris-versicolor	1
26	5.7	2.4	6.4	2.1	Iris-versicolor	1
27	5.4	2.1	6.3	2.3	Iris-versicolor	1
28	5.1	1.8	6.3	2.0	Iris-versicolor	1
29	5.8	2.0	6.4	2.3	Iris-versicolor	1
30	5.7	1.5	6.5	2.0	Iris-versicolor	1
31	5.4	1.9	6.3	2.1	Iris-versicolor	1
32	5.5	2.4	6.4	2.3	Iris-versicolor	1
33	5.1	1.8	6.3	2.0	Iris-versicolor	1
34	5.7	2.0	6.4	2.3	Iris-versicolor	1
35	5.4	1.7	6.5	2.0	Iris-versicolor	1
36	5.5	2.3	6.3	2.3	Iris-versicolor	1
37	5.1	1.8	6.3	2.0	Iris-versicolor	1
38	5.8	2.0	6.4	2.3	Iris-versicolor	1
39	5.7	1.5	6.5	2.0	Iris-versicolor	1
40	5.4	1.9	6.3	2.1	Iris-versicolor	1
41	5.5	2.4	6.4	2.3	Iris-versicolor	1
42	5.1	1.8	6.3	2.0	Iris-versicolor	1
43	5.7	2.0	6.4	2.3	Iris-versicolor	1
44	5.4	1.7	6.5	2.0	Iris-versicolor	1
45	5.5	2.3	6.3	2.3	Iris-versicolor	1
46	5.1	1.8	6.3	2.0	Iris-versicolor	1
47	5.8	2.0	6.4	2.3	Iris-versicolor	1
48	5.7	1.5	6.5	2.0	Iris-versicolor	1
49	5.4	1.9	6.3	2.1	Iris-versicolor	1
50	5.5	2.4	6.4	2.3	Iris-versicolor	1

Prediction

Outlier Detection

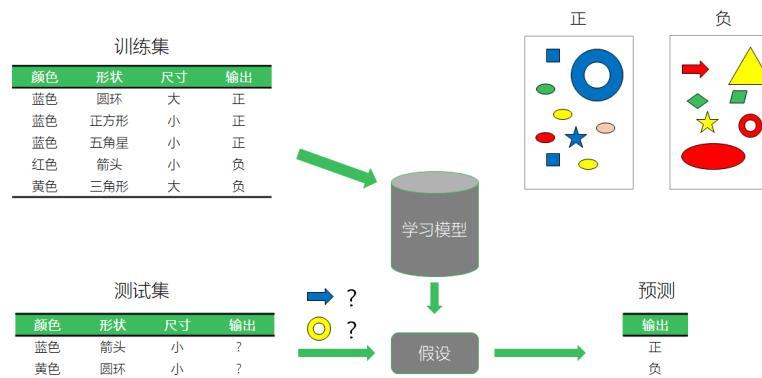


# Supervised and Unsupervised Learning

- Supervised learning : classification, regression
- Unsupervised learning : density estimation, clustering, dimensionality reduction
- Semi-supervised learning : with missing data, e.g., EM ; self-supervised learning, learn the missing part of images, inpainting
- Reinforcement learning : play games, e.g., Go, StarCraft ; robotics ; auto-steering

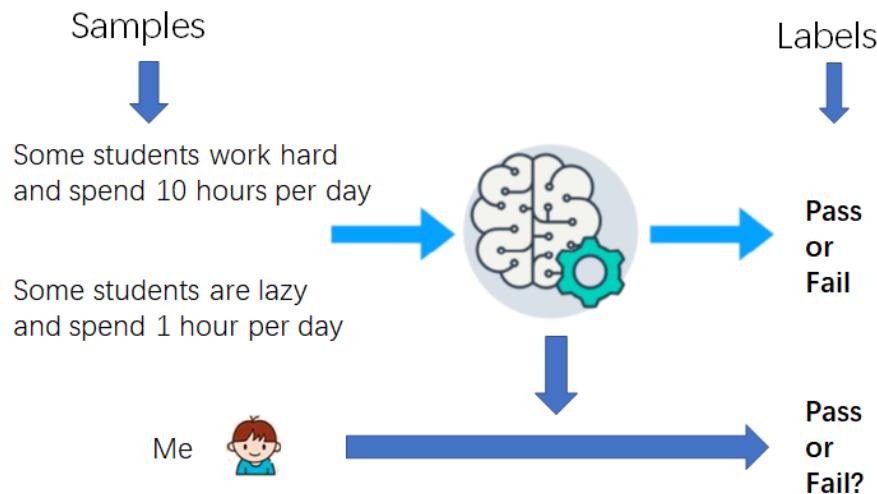
# Supervised Learning

- Given labels of data : the labels could be symbols (spam or non-spam), integers (0 or 1), real numbers, etc.
- Training : find the optimal parameters (or model) to minimize the error between the prediction and target
- Classification : SVM, KNN, Desicion tree, etc.
- Regression : linear regression, CART, etc.



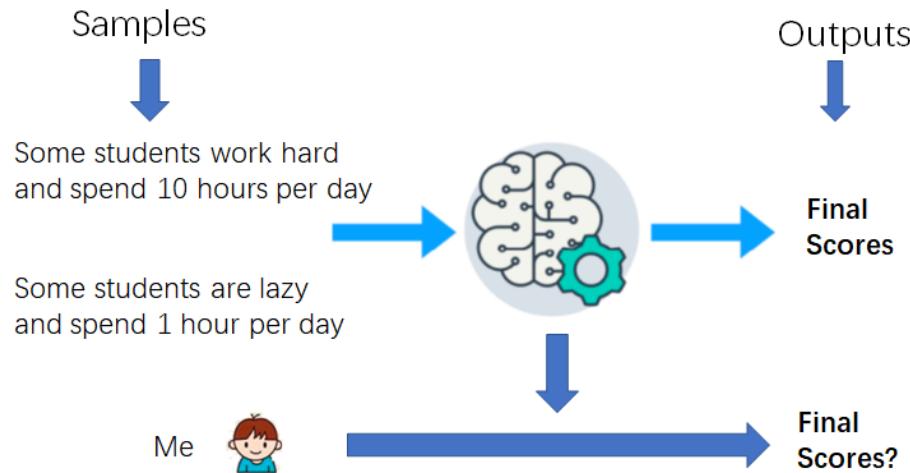
# Classification

- Output is discrete
- Examples : given the study hours, in-class performance, and final grades (Pass or Fail) of past students, can you predict the final grades of the current students based on their study hours and in-class performance ?
- Applications : Credit risk evaluation, clinical prediction of tumor, classification of protein functions, etc.



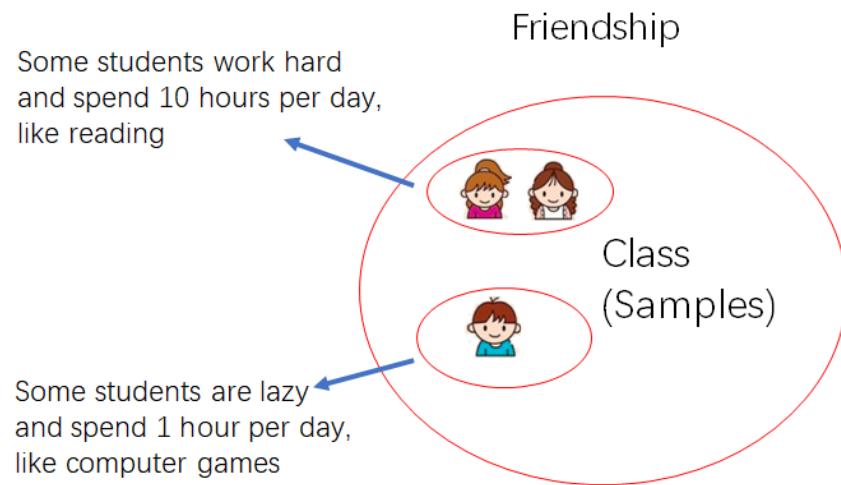
# Regression

- Output is continuous
- Examples : given the study hours, in-class performance, and final scores of past students, can you predict the final scores of the current students based on their study hours and in-class performance ?
- Applications : epidemiology, finance, investment analysis, etc.



# Unsupervised Learning

- No labels
- Optimize the parameters based on some natural rules, e.g., cohesion or divergence
- Clustering : K-Means, SOM

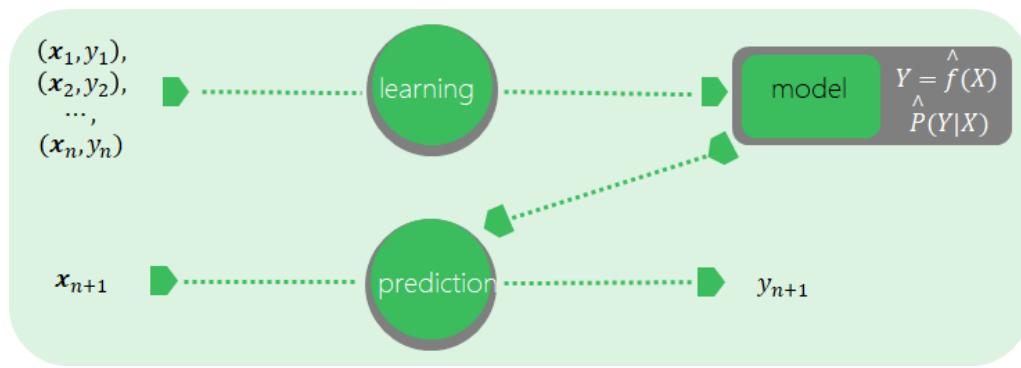


# Representation of Data

- Input space  $\mathcal{X} = \{\text{All possible samples}\}$ ;  $\mathbf{x} \in \mathcal{X}$  is an input vector, also called feature, predictor, independent variable, etc.; typically multi-dimensional; e.g.,  $\mathbf{x} \in \mathbb{R}^p$  is a weight vector or coding vector
- Output space  $\mathcal{Y} = \{\text{All possible results}\}$ ;  $y \in \mathcal{Y}$  is an output vector, also called response, dependent variable, etc.; typically one-dimensional; e.g.,  $y = 0$  or  $1$  for classification problems,  $y \in \mathbb{R}$  for regression problems.
- For supervised learning, assume that  $(\mathbf{x}, y) \sim \mathcal{P}$ , a joint distribution on the sample space  $\mathcal{X} \times \mathcal{Y}$

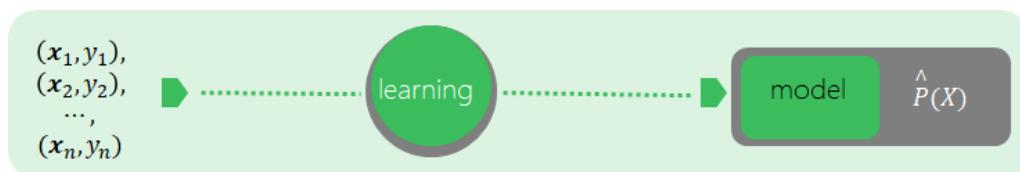
# Supervised Learning

- Goal : given  $\mathbf{x}$ , predict what is  $y$  ; in deterministic settings, find the dependence relation  $y = f(\mathbf{x})$  ; in probabilistic settings, find the conditional distribution  $P(y|\mathbf{x})$  of  $y$  given  $\mathbf{x}$
- Training dataset :  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n \stackrel{i.i.d.}{\sim} \mathcal{P}$ , used to learn an approximation  $\hat{f}(\mathbf{x})$  or  $\hat{P}(y|\mathbf{x})$
- Test dataset :  $\{(\mathbf{x}_j, y_j)\}_{j=n+1}^{n+m} \stackrel{i.i.d.}{\sim} \mathcal{P}$ , used to make a prediction  $\hat{y}_j = \hat{f}(\mathbf{x}_j)$  or  $\hat{y}_j = \arg \max_{y_j} \hat{P}(y_j|\mathbf{x}_j)$ , and verify how accurate the approximation is



# Unsupervised Learning

- Goal : in probabilistic settings, find the distribution  $P(\mathbf{x})$  of  $\mathbf{x}$  and approximate it ; there is no  $y$
- Training dataset :  $\{\mathbf{x}_i\}_{i=1}^n \stackrel{i.i.d.}{\sim} \mathcal{P}$ , used to learn an approximation  $\hat{P}(\mathbf{x})$  ; no test data in general



# Learning Models

- Decision function (hypothesis) space :  
 $\mathcal{F} = \{f_\theta | f_\theta = f_\theta(\mathbf{x}), \theta \in \Theta\}$  or  $\mathcal{F} = \{P_\theta | P_\theta = P_\theta(y|\mathbf{x}), \theta \in \Theta\}$
- Loss function : a measure for the “goodness” of the prediction,  $L(y, f(\mathbf{x}))$ 
  - 0-1 loss :  $L(y, f(\mathbf{x})) = I_{y \neq f(\mathbf{x})} = 1 - I_{y = f(\mathbf{x})}$
  - Square loss :  $L(y, f(\mathbf{x})) = (y - f(\mathbf{x}))^2$
  - Absolute loss :  $L(y, f(\mathbf{x})) = |y - f(\mathbf{x})|$
  - Cross-entropy loss :  
$$L(y, f(\mathbf{x})) = -y \log f(\mathbf{x}) - (1 - y) \log(1 - f(\mathbf{x}))$$
- Risk : in average sense,  
$$R(f) = E_P[L(y, f(\mathbf{x}))] = \int_{\mathcal{X} \times \mathcal{Y}} L(y, f(\mathbf{x})) P(\mathbf{x}, y) d\mathbf{x} dy$$
- Target of learning : choose the best  $f^*$  to minimize  $R_{exp}(f)$ ,  
$$f^* = \min_f R_{exp}(f)$$

# Risk Minimization Strategy

- Empirical risk minimization (ERM) : given training set

$$\{(\mathbf{x}_i, y_i)\}_{i=1}^n, R_{\text{emp}}(f) = \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i))$$

- By law of large number,  $\lim_{n \rightarrow \infty} R_{\text{emp}}(f) = R_{\text{exp}}(f)$
- Optimization problem :  $\min_{f \in F} \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i))$

- Structural risk minimization (SRM) : given training set

$\{(\mathbf{x}_i, y_i)\}_{i=1}^n$  and a complexity functional  $J = J(f)$ ,

$$R_{\text{srm}}(f) = \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i)) + \lambda J(f)$$

- $J(f)$  measures how complex the model  $f$  is, typically the degree of complexity
- $\lambda \geq 0$  is a tradeoff between the empirical risk and model complexity
- Optimization problem :  $\min_{f \in F} \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i)) + \lambda J(f)$

# Algorithms

- Computational methods to solve the problem for  $f$
- Numerical methods to solve the optimization problems
  - Gradient descent method, including coordinate descent, sequential minimal optimization (SMO), etc.
  - Newton's method and quasi-Newton's method
  - Combinatorial optimization
  - Genetic algorithms
  - Monte Carlo methods
  - ...

# Model Assessment

Assume we have learned the model  $y = \hat{f}(\mathbf{x})$ , what is the error ?

- Training error :  $R_{emp}(\hat{f}) = \frac{1}{n} \sum_{i=1}^n L(y_i, \hat{f}(\mathbf{x}_i))$ , tells the difficulty of learning problem
- Test error :  $e_{test}(\hat{f}) = \frac{1}{m} \sum_{j=n+1}^{n+m} L(y_j, \hat{f}(\mathbf{x}_j))$ , tells the capability of prediction ; in particular, if 0-1 loss is used
  - Error rate :  $e_{test}(\hat{f}) = \frac{1}{m} \sum_{j=n+1}^{n+m} I_{y_j \neq \hat{f}(\mathbf{x}_j)}$
  - Accuracy :  $r_{test}(\hat{f}) = \frac{1}{m} \sum_{j=n+1}^{n+m} I_{y_j = \hat{f}(\mathbf{x}_j)}$
  - $e_{test} + r_{test} = 1$

## Model Assessment (Cont')

- Generalization error :

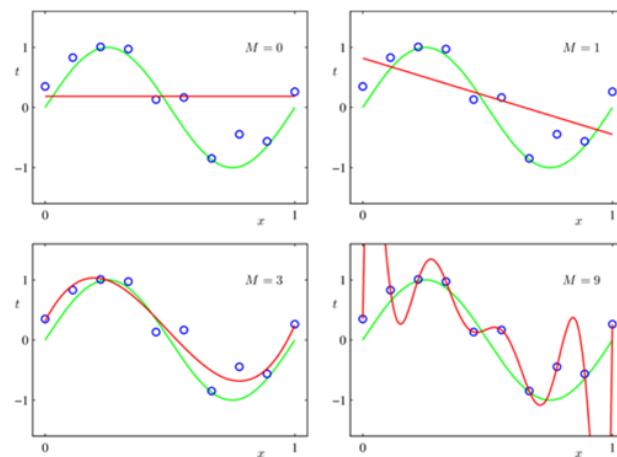
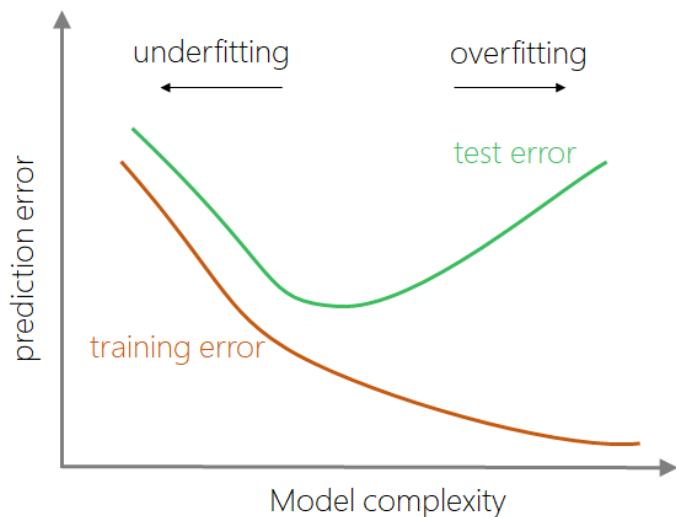
$$R_{\text{exp}}(\hat{f}) = E_P[L(y, \hat{f}(\mathbf{x}))] = \int_{\mathcal{X} \times \mathcal{Y}} L(y, \hat{f}(\mathbf{x})) P(\mathbf{x}, y) d\mathbf{x} dy,$$
 tells

the capability for predicting unknown data from the same distribution, its upper bound  $M$  defines the generalization ability

- As  $n \rightarrow \infty$ ,  $M \rightarrow 0$
- As  $F$  becomes larger,  $M$  increases

# Overfitting

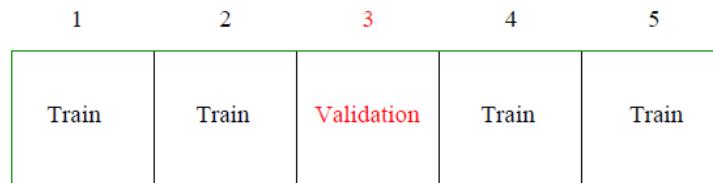
- Too many model parameters
- Better for training set, but worse for test set



fitting of degree  $M$  polynomial, green curve is the ground truth

# Model Selection

- Regularization :  $\min_{f \in F} \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i)) + \underbrace{\lambda J(f)}_{\text{penalty}}$ , choose  $\lambda$  to minimize empirical risk and model complexity simultaneously
- Cross-validation (CV) : split the training set into training subset and validation subset, use training set to train different models repeatedly, use validation set to select the best model with the smallest (validation) error
  - Simple CV : randomly split the data into two subsets
  - K-fold CV : randomly split the data into  $K$  disjoint subsets with the same size, treat the union of  $K - 1$  subsets as training set, the other one as validation set, do this repeatedly and select the best model with smallest mean (validation) error
  - Leave-one-out CV :  $K = n$  in the previous case



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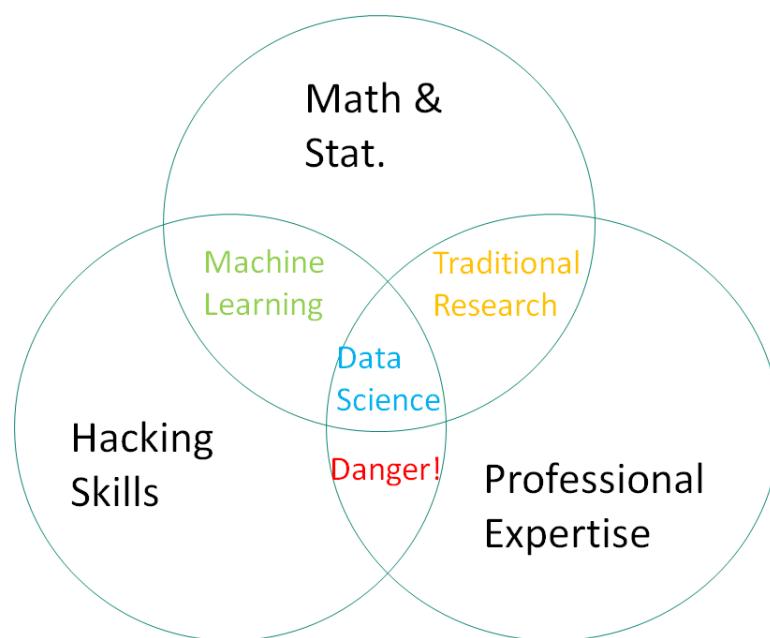
Machine Learning

Mathematical Representation

Conclusion

# Data Science VS. Other Techniques

Data science is an interdisciplinary area using mathematics, statistics, computer science and engineering, and other profession techniques



# Where Math and Statistics Emerge

