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## MA333 Introduction to Big Data Analysis Course Introduction

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## Course Info

- Semester 2024-2025 Spring
- Instructor : ZHANG, Zhen (张振)
- Office : Room M5014, School of Science
- Phone : 88018753
- Email : zhangz@sustech.edu.cn
- Office hours : Tuesday morning, 10 :00-12 :00; or send email to make an appointment for other time.
- Lecture : 3 credits, 3 hours per week.
- Prerequisite : Calculus (or Mathematical Analysis); Linear Algebra; Probability Theory or Probability Theory and Mathematical Statistics (or other similar courses).

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## 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, and recommender systems if time permits

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## Outlines

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## Grading Policy

- Homework : Approximately 6 homework assignments (including programming assignments and written problems). The written homework could be handed in after 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
- Programming projects : include coding, data analytics, and reports
- One closed-book final exam
- Grading policy : assignments (30%), quizzes (15%), programming projects (20%), and the final exam (35%).

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## References

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- 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. <https://hastie.su.domains/ElemStatLearn/>
- Foundations of Machine Learning, by Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar, MIT Press, 2018.
- 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. <https://www.deeplearningbook.org/>

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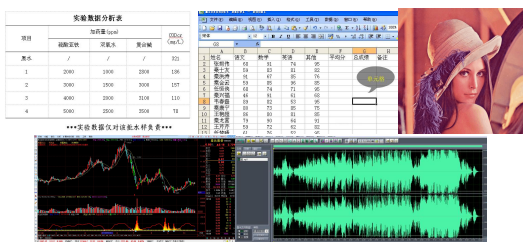
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Can you give some examples of data ?



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

- **Volume** : KB, MB, GB ( $10^9$  bytes), TB, PB, EB ( $10^{18}$  bytes), ZB, YB, exponential growth (about 120%/year)
- **Variety** : different sources from business to industry, different types
- **Veracity** : Noisy data with errors and inconsistency, redundant information contained in the data, need to retrieve useful information
- **Velocity** : fast speed for data generation and information transfer, need for realtime processing
- **Value** : business values for product recommendations and trading ; social values for precision medicine, public health, traffic control, etc.



- 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.

A pioneering work of data science : Kepler's Laws

	行星	周期 (年)	平均距离	周期/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

- 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

- 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

- 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

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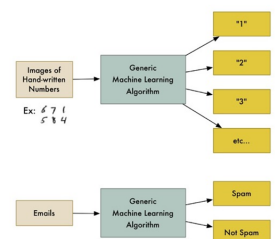
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- Artificial Intelligence (AI) : learning from experiences (data), and improve the computer program adaptively
- Mathematics : Learning the underlying model from data, and generalize the model to adapt new data

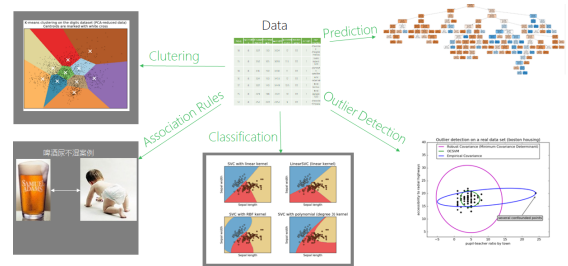


We define machine learning as a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data or to perform other kinds of decision making under uncertainty (such as planning how to collect more data!).  
— (Machine Learning: A probabilistic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

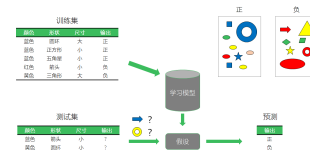


## Supervised and Unsupervised Learning

- 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

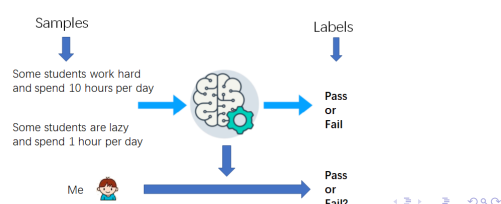
## Supervised Learning

- 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, Decision tree, etc.
- Regression : linear regression, CART, etc.



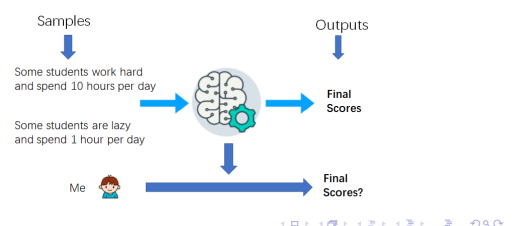
## Classification

- 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.

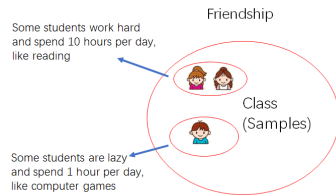


## Regression

- 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.

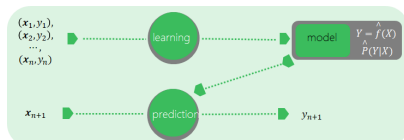


- No labels
- Optimize the parameters based on some natural rules, e.g., cohesion or divergence
- Clustering : K-Means, SOM

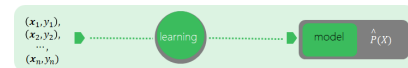


- Input space  $\mathcal{X} = \{\text{All possible samples}\}$ ;  $\mathbf{x} \in \mathcal{X}$  is an input vector, also called feature, predictor, independent variable, etc.; typically multi-dimensional; e.g.,  $\mathbf{x} \in \mathbb{R}^p$  is a weight vector or coding vector
- Output space  $\mathcal{Y} = \{\text{All possible results}\}$ ;  $y \in \mathcal{Y}$  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  $\mathcal{X} \times \mathcal{Y}$

- 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



- 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



- 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  $R(f)$ ,  $f^* = \min_f R(f)$

- Empirical risk minimization (ERM) : given training set  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$ ,  $R_{emp}(f) = \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i))$ 
  - By law of large number,  $\lim_{n \rightarrow \infty} R_{emp}(f) = R(f)$
  - Optimization problem :  $\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i))$
- Structural risk minimization (SRM) : given training set  $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$  and a complexity functional  $J = J(f)$ ,  $R_{srn}(f) = \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i)) + \lambda J(f)$ 
  - $J(f)$  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 :  $\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n L(y_i, f(\mathbf{x}_i)) + \lambda J(f)$



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

