Chapter 2

Business Problems and Data Science Solutions



hata mining technique in high level

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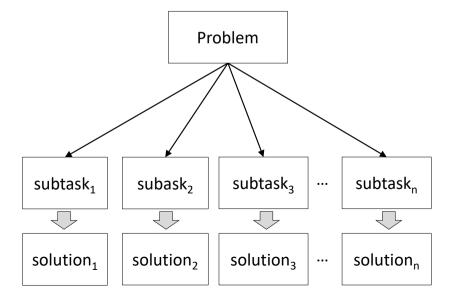
Data Science Process (1/2)

A principle of data science

(well-defined)

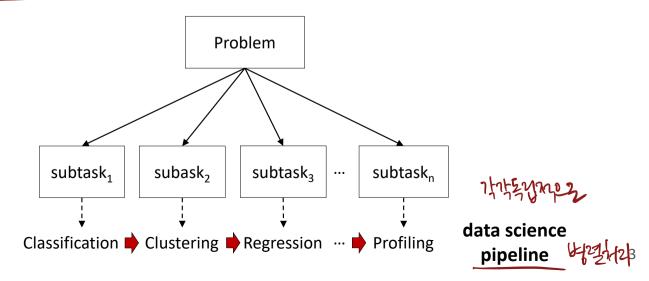
data science 911 1824

- Data mining is a process with fairly well-understood stages
- Data science process រដ្ឋការមក្សា
 - Data scientists decompose a real-world problem into subtasks
 - The solutions to the subtasks are composed to solve the overall problem



Data Science Process (2/2)

- There are common data mining tasks that underlie the problems
 - (ex) classification, regression, clustering, association rule discovery, ...
- To be a good data scientist, you should
 - Know a lot about solving these common data mining tasks
 Have the ability to decompose a problem into these common tasks



Common Data Mining Tasks

■ Despite the large number of specific data mining algorithms, there are only a few *fundamentally different data mining***Tasks**

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- 监 (1) Classification
- भार्ष 2 Regression (a.k.a. value estimation): prediction
 - **TN** ③ Similarity matching
 - 别并 ④ Clustering
- ั่รุผุงปู่ฟู (5) Co-occurrence grouping (a.k.a. association rule discovery)
 - 6 Profiling (a.k.a. behavior description)
 - 了 Link prediction The Land .
- MILL 8 Data reduction HEH. ..
- ্বান্দ্রা (9) Causal modeling

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1. Classification (1/2)

(+ clustering)

- Predict (for each individual in a population) which of a set of classes this individual belongs to 与他的人对 是特别人
 - Usually the classes are mutually exclusive 好地味物(好のいなり)



== each indudual					
	Instances	>			
	7/2/2 (3/8)	- A			

	•	•	_	
Name	Salary	Sex	Age	Buy widget
Bloggs	15000	male	19	No
Jones	25000	male	33	Yes
Smit	23000	female	50	No
Smit	16000	male	40	No
Smit	200	male	10	No
Patel	30000	female	30	No
Steel	25000	male	23	Yes
Higgs	18000	female	55	No
Puggs	50000	male	57	Yes
Puggs	51000	female	57	No

> Model (training data set)

New	instance	
INCVV	IIIStarice	

Lee 42000 male 44 ???	
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1. Classification (2/2)

- General procedure
 - Given a training dataset, build a model that describes the classes of data
 - Given a new individual, apply the model to produce its estimated class

Name	Salary	Sex	Age	Buy widget	
Bloggs	15000	male	19	No	(Sex)
Jones	25000	male	33	Yes	
Smit	23000	female	50	No	male?
Smit	16000	male	40	No	
Smit	200	male	10	No	female? / (Salary)
Patel	30000	female	30	No	
Steel	25000	male	23	Yes	10000 0
Higgs	18000	female	55	No	/ ≤ 18000 ?/ \> 18000
Puggs	50000	male	57	Yes	No. No. Yes
Puggs	51000	female	57	No	No No Yes
	Traii	ning d	atas	et	Model

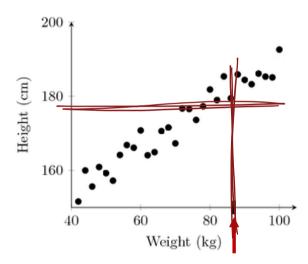
Training dataset

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- A similar task: scoring or class probability estimation
 - Produce the *probability* that a new individual belongs to each class
 - (ex) (Lee, 42000, male, 44) \rightarrow (YES: 80%, NO: 20%)

2. Regression (1/2)

- Estimate or predict, for each individual, the *numerical value* of some variable for that individual 大水龙
 - Also called "value estimation"

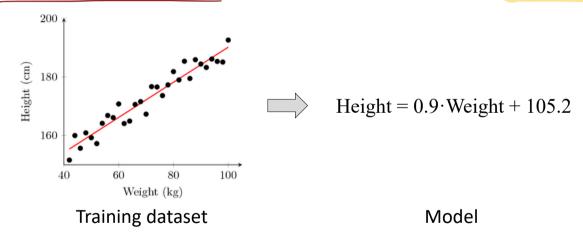


Given a weight of a person, what height will the person have?

2. Regression (2/2)

General procedure

- Given a training dataset, build a model that describes the value of the particular variable specific to each individual
- Given a new individual, apply the model to produce its estimated value





Classification: predicts the *class* of an instance (e.g., YES/NO)

Regression: predicts the value associated with an instance (e.g., 178)

3. Similarity Matching (1/2)

Identify similar individuals based on data known about them

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	8	1	?	2	7
User 2	2	?	5	7	5
User 3	5	4	7	4	7
User 4	7	1	7	3	8
User 5	1	7	4	6	?
User 6	8	3	8	3	7

What users are similar to User 1? What items are similar to Item 3?

3. Similarity Matching (2/2)

- General procedure निमिन्द्र'नायांच्या (siewe निमिन्द्र)
 - Define a distance measure between two individuals '거기' 각도 살겠으는 지병의
 - Given an individual, find the individuals that minimize the distance

	Item 1	Item 2	Item 3	Item 4	Item 5	भया भणीय - १ ०५३४५
User 1	8	1	?	2	7	
User 2	2	?	5	7	5	
User 3	5	4	7	4	7	User3 = (5, 4, 7, 4, 7)
User 4	7	1	7	3	8	User4 = (7, 1, 7, 3, 8)
User 5	1	7	4	6	?	
User 6	8	3	8	3	7	

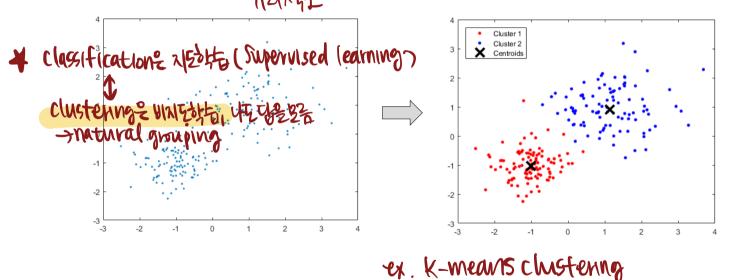
The distance between User 3 and User 4 is:

$$\sqrt{(5-7)^2+(4-1)^2+(7-7)^2+(4-3)^2+(7-8)^2} \approx 3.87$$

distance FINEZ 1776 FROTINI: data type of copyclic

4. Clustering

- Group similar individuals together
 - A distance measure is used to determine the similarity between two individuals



- Very useful to see which natural groups exist in the data
 - (ex) What types of customers do we have?

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5. Co-occurrence grouping

- Find associations or co-occurrence between entities
 - (ex) What items are commonly purchased together?



{Bread, Diapers, Beer, Coke}



{Milk, Diapers, Beer, Wine}



{Diapers, Beer, Coke}

An association rule: {Diapers} → {Beer}
("customers who buy diapers tend also to buy beer")

- Very useful for marketing
 - A special promotion, product display, or combination offer
 - Recommendation ("people who bought X also bought Y")

6. Profiling

- Characterize the typical behavior of an individual or group
 - Also called behavior description The Third 13





Regular Offline Buyer

Purchases a new book every week in store. Started to buy e-books but has not vet been convinced.



Monthly Onliner

Purchases e-books on a monthly basis. Large variety of genres. Have got an bookshelf account.



Onliner expert

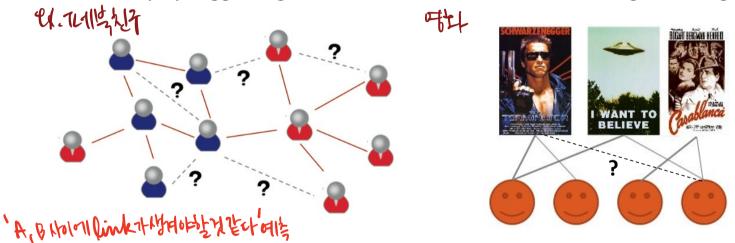
Purchases a book per week. Regularly sells read through books. Writes book reviews.

← NoMal

- Very useful for anomaly detection
 - A profile describes *normal* behaviors
 - If the current behavior is very different from the profile, issue an alarm
 - (ex) Fraud detection
 - Profile: the kind of purchases a person typically makes on a credit card
 - Alarm if a new charge on the card does not fit the profile

7. Link Prediction

- Predict connections between data items
 - Usually by suggesting that a link should exist and estimating its strength



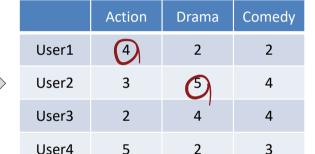
- Very useful for recommendation
 - Recommending friends in social networking systems (SNS)
 - Recommending movies to customers

8. Data Reduction

Reduce a dataset to a smaller dataset that contains much of the important information in the larger dataset

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		177726	2		
	Movie1	Movie2	Moive3		MovieN
User1	2	1	4		5
User2	3	3	2		4
User3	2	1	3		4
User4	2	2	1		4



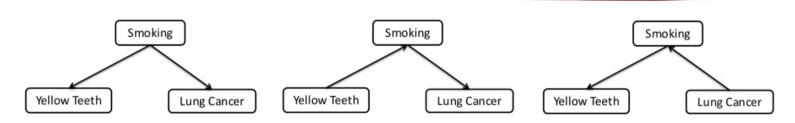


Advantages

- The smaller dataset may be easier to deal with or to process
- The smaller dataset may better reveal the information or improved insight
- As a trade-off, data reduction usually involve loss of information

9. Causal Modeling

Understand what events or actions actually influence others



Does smoking cause lung cancer or vice versa?

- Assume we observe that the targeted consumers purchase at a higher rate
- Is this because of the targeting or are they just good customers?

Supervised vs. Unsupervised Methods (1/2)

Classification Target

Supervised data mining: data quity भूपा के निष्ट के शिक्ष

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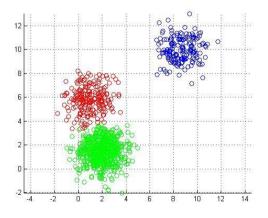
- There is a specific *target* to specify
- (ex) classification
 - "Buy widget" attribute is the target to define

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Name	Salary	Sex	Age	Buy widget
Bloggs	15000	male	19	No
Jones	25000	male	33	Yes
Smit	23000	female	50	No 00
Smit	16000	male	40	No of the
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Patel	30000	female	30	No
Steel	25000	male	23	Yes
Higgs	18000	female	55	No
Puggs	50000	male	57	Yes
Puggs	51000	female	57	No

- Unsupervised data mining: 水份空
 - There is no specific target to specify
 - (ex) clustering

• We have no specific target to define



Supervised vs. Unsupervised Methods (2/2)

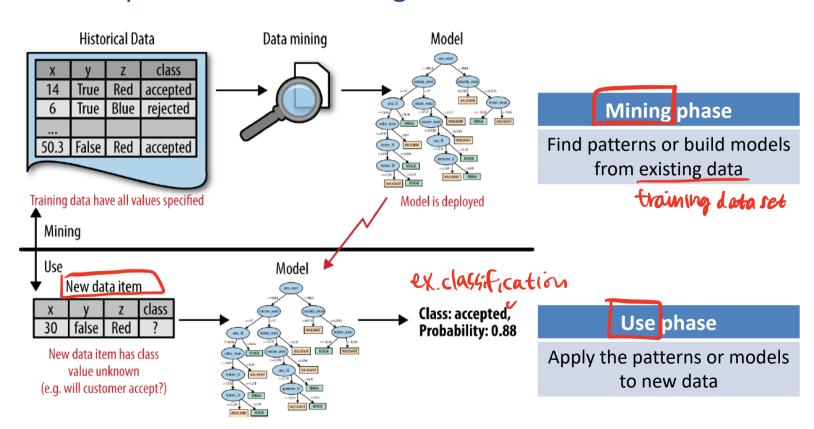
- Supervised data mining
 - The purpose is to predict the *target*
 - There must be a training dataset (i.e., the target value for each individual)
 - The target value is often called a label high middle low
 - (e.g.) classification, regression, casual modeling
- Unsupervised data mining
 - The purpose is to find some patterns without any specific target
 - We don't need a training dataset
 - (e.g.) clustering, co-occurrence grouping, and profiling

Classification vs. Regression

- Both are supervised data mining tasks
 - Distinguished by the type of target
- Classification
 - Target: a categorical (often binary) value (e.g., Yes/No, High/Mid/Low)
 - Example
 - "Will this customer purchase service S1 if given incentive I?" → Yes/No
 - "Which service package (S1,S2,S3) will a customer likely purchase if given incentive I?" → S1, S2, S3
- Regression
 - Target: a *numerical* value (e.g., 2.5)
 - Example
 - "How much will this customer use the service?" → \$2,500

Data Mining and Its Results

Two phases of data mining

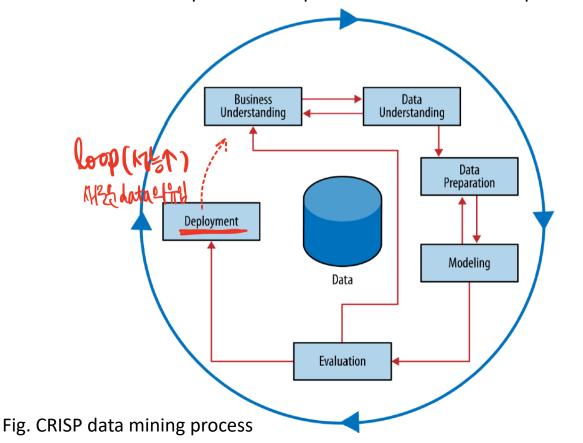




Data Mining Process

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- Cross Industry Standard Process for Data Mining (CRISP-DM)
 - A well-understood process that places a structure on the problem



1. Business Understanding

- Understand the business problem to be solved
 - Data science projects seldom come pre-packaged as clear problems
- Cast the business problem as one or more data science problems (Sub-tasks)
 - The key to a success is a creative problem formulation by data scientists
- Design a solution for each data science problem
 - Classification, regression, clustering, ...
 - A set of powerful tools can be used for each problem
- Recasting the problem and designing a solution is an *iterative* process of discovery

2. Data Understanding

Data

- The available raw material from which the solution will be built
- (ex) a customer database, a transaction database, a marketing response database

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- Understand the strengths and limitations of each data
 - Because rarely is there an exact match with the problem
 - (ex) For classification, we need labeled data (e.g., default = "yes" or "no")

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- Decide whether further investment in data is needed
 - Some data are virtually free, some data require effort to obtain, and some data may be purchased

3. Data Preparation

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- Clean and convert the data into more usable forms
 - Because some data analytic tools require data to be in a certain form
- Typical examples
 - Converting data to tabular format
 - Removing or inferring missing values
 - Converting data to different types (e.g., "Male", "Female" → 0, 1)
 - Normalizing or scaling numerical values (e.g., [-100, 100] → [0, 1])
 - \rightarrow Cleaning data (e.g., Age: 999 \rightarrow ?)

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- The quality of data mining results heavily depends on this stage
 - (ex) missing values, abnormal values, non-normalized values, ...

4. Modeling

- The *primary stage* where data mining techniques are applied to the data
- Output
 - Some sort of model or pattern capturing regularities in the data



It is very important to understand the *fundamental ideas* of data mining

- i.e., data mining techniques and algorithms that exist
- We will discuss this subject throughout the course

5. Evaluation (1/2)

- वामुक्ता
- Assess the data mining results rigorously
 - To gain confidence that they are valid and reliable before moving on
- Examples
 - Estimate the prediction accuracy of the model (e.g., 90%?)

 Check the generality of the model beyond the training data

 Estimate the rate of false alarms
- Instead of deploying the results immediately, it is usually advisable to test a model first in a controlled lab (i.e., testbed)
 - Because it is easier, cheaper, quicker, and safer

5. Evaluation (2/2)

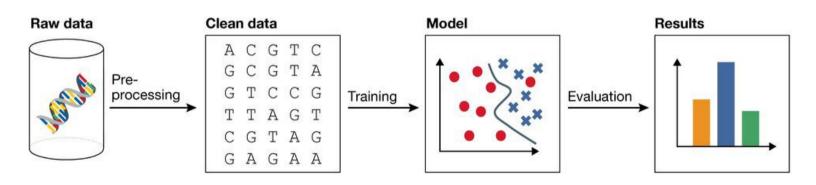
- A data scientist should be able to explain the model and its evaluation results *easily* to stakeholders

 Output

 Data scientists

 Output

 Data scientists
 - Not just to data scientists
 - e.g., managers, executives, programmers, ...



6. Deployment 746, UHA

- Put the results of data mining (or systems) into real use
- Usual scenario
 - A new predictive model (or system) is implemented
 - The model (or system) is integrated with existing information systems
- In many cases



- Data science teams: produce a working prototype and evaluate it
- Data engineering teams: deploy the model into a production system

- After deployment, the process often returns to the first phase
 - The next iteration can yield an improved solution by using the insight and experience obtained in the previous iteration

Other Analytics Techniques & Technologies

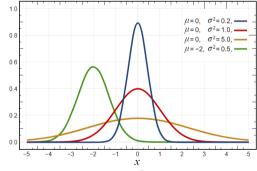
- Besides data mining, there are various technologies for the analysis of data
 - Statistics, database systems, machine learning, ...
- It is important to be acquainted with these technologies
 - What are their goals?
 - What role do they play?
 - What differences do they have?
- An important skill for a data scientist is ...
 - To be able to recognize what sort of analytic technology is appropriate for addressing a particular problem

1. Statistics

 Provides us with a huge amount of knowledge that underlies analytics ধ্র্থানু

Examples

- Data summary (e.g., means, median, variance, ...)
- Understanding different data distributions
- Testing hypotheses
- Quantifying uncertainty
- Measuring correlation



 Many techniques for extracting models or patterns from data have their *roots* in Statistics

2. Database Querying (1/2)

Database system

 A software application that allows the insertion, <u>querying</u>, update, and management of data

Database query

- A specific request for data or statistics about data
 - Retrieving specified data, sorting, computing summary statistics, ...
- Formulated in a technical language and posed to a database system
 - (ex) SQL (Structured Query Language) 2015

```
SELECT name, address

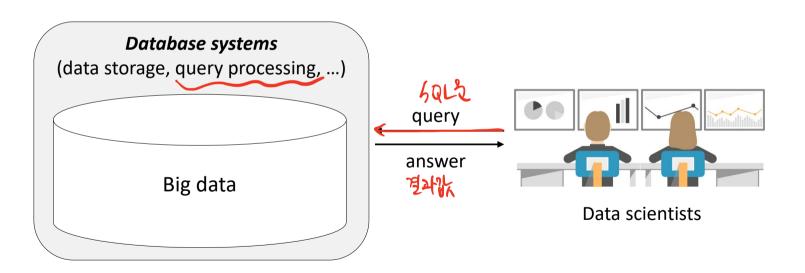
FROM customers

WHERE age > 25 AND gender = 'Female' AND domicile = 'CA'
```



2. Database Querying (2/2)

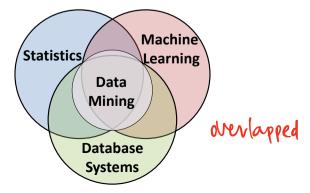
- Data science vs. databases technologies
 - Data science can use database technologies to find or examine the data of interest stored in a database system





3. Machine Learning (1/2)

- Gives computer systems the ability to "learn" with data, without being explicitly programmed
 - A subfield of Artificial Intelligence (AI)
- Develops models and improves the models using data
 - Decision tree, artificial neural networks (deep learning), support vector machines, clustering, Bayesian networks, ...
- However, the separation among these fields has blurred



3. Machine Learning (2/2)

- Data mining and machine learning are closely linked
 - The filed of data mining started as an offshoot of machine learning
 - KDD (Knowledge Discovery and Data mining)

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- · Techniques and algorithms are shared between the two
- Find useful and informative pattern from data (अर्थ: विकास (अर्थ)
- Nevertheless, machine learning is more concerned with
 - Many types of performance improvement
 - (ex) robotics and computer vision
 - Issues of agency and cognition
 - (ex) how will an agent use learned knowledge to act in its environment
- Data mining is more concerned with
 - Finding patterns and regularities from data
 - Commercial applications and business issues

Examples of Applying These Techniques

- "Who are the most profitable customers?"
 - Database systems (if "profitable" can be calculated from existing data)
- "Is there really a difference between the profitable customers and the average customer?"
 - Statistics (hypothesis testing)
- "But who really are these customers? Can I characterize them?"
 - Data mining (profiling)
- "Will some particular new customer be profitable? How much?"
 - Data mining (classification, regression)

Summary

- There is a well-defined data mining process (e.g., CRISP-DM)
 - Business understanding → data understanding → data preparation → modeling → evaluation → deployment
- A data scientist typically decomposes a problem into one or more common data mining tasks
 - Classification, regression, similarity matching, clustering, association rule discovery, profiling, link prediction, data reduction, causal modeling
 - You should understand the fundamentals of these tasks
- Other related data analytics technologies
 - Statistics, database querying, machine learning
 - Though their boundaries are not always sharp, it is important to know about other techniques' capabilities to know when they should be used