COMP9318: Data Warehousing and Data Mining

— L3: Data a Cleaning —

- Why preprocess the data?

Why Data Preprocessing?

- Data in the real world is dirty
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., occup
  - noisy: containing errors or
    - e.g., Salary="-10"
  - inconsistent: containing discrepancies in codes or names
    - e.g., Age="42" Birthday="03/07/1997"
    - e.g., Was rating "1,2,3", now rating "A, B, C"
    - e.g., discrepancy between duplicate records

Why Is Data Dirty?

- Incomplete data comes from
  - n/a data value when collected
  - different consideration between the time when the data was collected and when it is analyzed.
  - human/hardw
- Noisy data comes from the p ata
  - collection
  - entry
  - transmission
- Inconsistent data comes from
  - Different data sources
  - Functional dependency violation

Why Is Data Preprocessing Important?

- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
    - e.g., duplicate or missing data may cause incorrect or even misleading
  - Data wareho tegration of quality data
- Data extraction, cleaning, and transformation comprises the majority of the work of building a data warehouse. — Bill Inmon
- Also a critical step for data mining.

Major Tasks in Data Preprocessing

- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
  - Integration o ubes, or files
- Data transfor
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation in volume but produces the same or similar analytical results
- Data discretization & Data Type Conversion

- Data cleaning

Data Cleaning

- Importance
  - "Data cleaning is one of the three biggest problems in data warehousing"—Ralph Kimball
  - "Data cleaning is the number one problem in data warehousing
- Data cleaning tasks
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data
  - Resolve redundancy caused by data integration

Missing Data

- Data is not always available
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
  - equipment
  - inconsistent d thus deleted
  - data not entered due to misu
  - certain data may not be considered important at the time of entry
  - not register history or changes of the data
- Missing data may need to be inferred.
  - Many algorithms need a value for all attributes
  - Tuples with missing values may have different true values

How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (assuming the tasks in classification—not effective when the percentage of missing values per attribute varies considerably.
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatic
  - a global constant : e.g., "unkno ass?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may due to
  - faulty data collection instruments
  - data entry pr
  - data transmi
  - technology limitation
  - inconsistency in naming convention
- Other data problems which requires data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

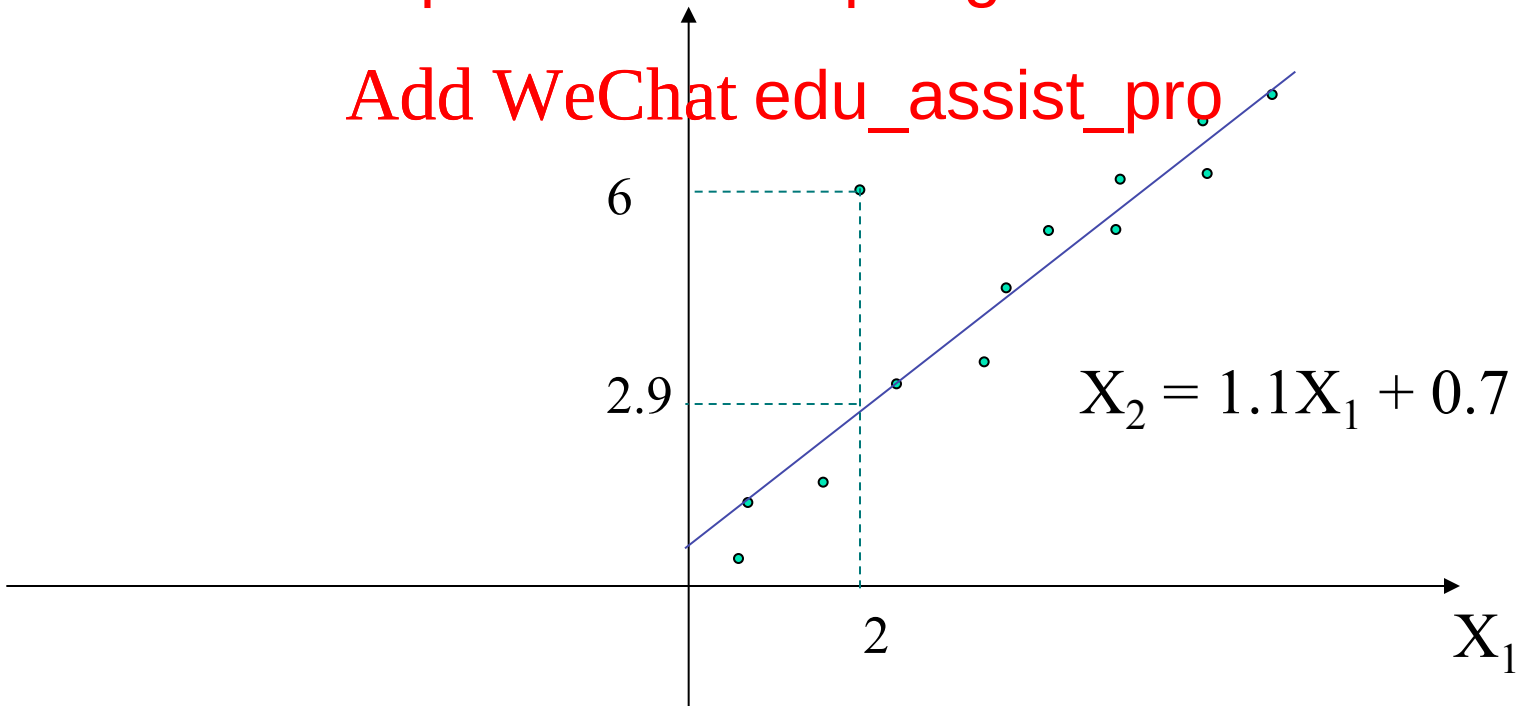
How to Handle Noisy Data?

To be discussed in discretization

- Binning method:
  - first sort data and partition into (equi-depth) bins
  - then one can smooth by bin means, smooth by bin median, smo tc.
- Clustering
  - detect and remove outliers
- Combined computer and hum n
  - detect suspicious values and check by human (e.g., deal with possible outliers)
- Regression
  - smooth by fitting the data into regression functions

Regression

Suburb	#Residents	Usage	Charge
Kingsford	2	1502	3047
Kensington	3	987	265.6
Maroubra	1	568	198.3
…	…		



- Data integration and transformation

Data Integration

- Data integration:
  - combines data from multiple sources into a coherent store
- Schema integra
  - integrate me
  - Entity identification proble
    from multiple data sources
- Detecting and resolving data value conflicts
  - for the same real world entity, attribute values from different sources are different
  - possible reasons: different representations, different scales, e.g., metric vs. British units

Example

- Data source 1:
  - Book(bid, title, isbn)
  - Author(aid, fname, lname, birthdate)
  - Writes(bid, aid)
- Data source 2:
  - Book(isbn, title, year, author1, author2, …, author10)
- Data source 3:
  - Author(name, bornInYear, description, book1, book2, …, book5)

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - The same attribute may have different names in different dat
  - One attribut tribute in another table, e.g., annual revenue
- Redundant data may be able to be detected by correlational analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Also see other transformations later in the Clustering part

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization, data cube construction
- Generalization: concept hierarchy climbing
- Normalization: mall, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Attribute/feature construction
  - New attributes constructed from the given ones

Data Transformation: Normalization

- min-max normalization

$$v' = \frac{v - \min_A}{\max_A - \min_A}(new\_\max_A - new\_\min_A) + new\_\min_A$$

- z-score normal

$$v' = \frac{v - \mu}{\sigma}, \text{ where } \hat{\mu} = \text{mean}(A) \text{ and } \hat{\sigma} = \widehat{\text{stddev}}(A)$$

- normalization by decimal scaling

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that } \max(|v'|) < 1$$

MinMaxScaler

dScaler; sklearn uses
ance estimate

In scikit-learn, they are called Scaling.
Normalization means converting vectors to unit vectors.

- Data reduction

Data Reduction Strategies

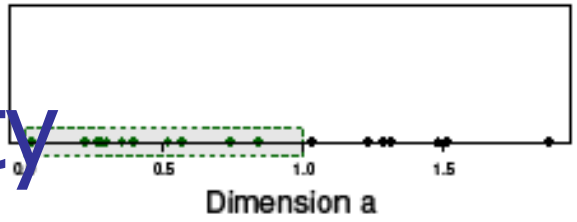
- Modern datasets may be very large
  - Ratings of millions of customers on millions of items
  - Many ML algorithms have high time and space complexities.
  - Even learned models could be very large.
  - E.g., learned word embeddings (300 dims) for 1M words ➔ at least 1.2GB memory
- Data reduction
  - Obtain a reduced representation that is much smaller in volume but yet produce the same (or almost the same) analytical results
- Data reduction strategies
  - Dimensionality reduction—remove unimportant attributes
  - Data Compression
  - Numerosity reduction—fit data into models
  - Discretization and concept hierarchy generation

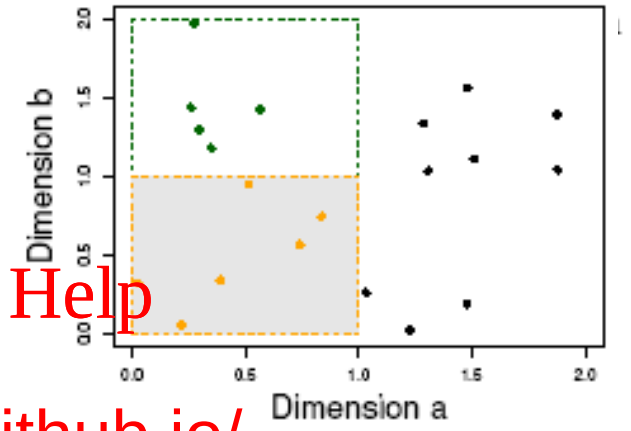
High-dimensional Features

- It is common for many datasets to contain many features
  - More is better at data capturing/creation
    - 561 featu cognition using smartpho
      https://archive.ics.uci.ed ets/Human +Activity+Recognition+ rtphones
    - GIST: 128 dimensional feature
  - Mandated by some model
    - A document is converted into a high-dimensional feature vector. #dims = |vocabulary|

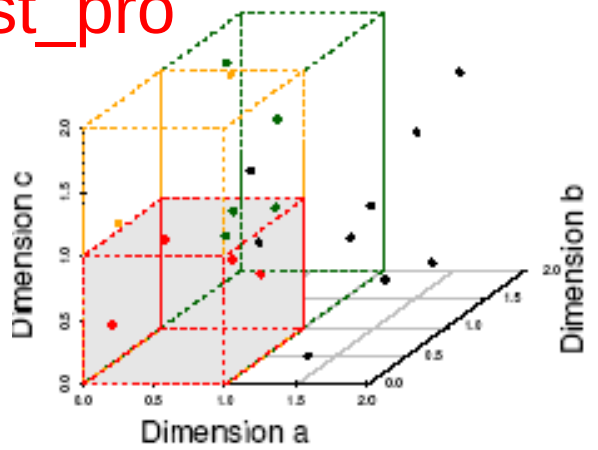
The Curse of Dimensionality

- Data in only one dimension is relatively packed
- Adding a dimension "stretches" the points across that dimension, making them further apart
- Adding more dim
  points further apart—**high dime**
  data is extremely sparse ➔ hard to learn
- **Distance measure tends to become meaningless**





(b) 6 Objects in One Unit Bin



(c) 4 Objects in One Unit Bin

(graphs from Parsons et al. KDD Explorations 2004)

High-dimensional space

- High-dimensional space is totally different from low-dimensional space (e.g., 3D)
- Many counter-intuitive facts about the high-dimensional space
  - Two random ly orthogonal
  - Random sam lt hypercube ➔ most points are on a thin la urface (annulus)

http://www.visiondummy.com/2014/04/curse-dimensionality-affect-classification/

Goals

- Reduce dimensionality of the data, yet still maintain the meaningfulness of the data

Dimensionality reduction

- Dataset **X** consisting of **n** points in a **d**-dimensional space
- Data point $\mathbf{x}_i \in \mathbf{R}^d$ (**d**-dimensional real vector):
  $\mathbf{x}_i = [x_{i1}, x_{i2},$
- Dimensionalit :
  - **Feature selection:** ch bset of the features
  - **Feature extraction:** create new features by combining new ones

Feature Selection

- Feature selection (i.e., attribute subset selection):
  - Select a minimum set of features such that the probability distribution of different classes given the values for those features is as close as possible to the original distri of all features
  - reduce # of easier to understand
- Heuristic methods (due to exponential # of choices):
  - step-wise forward selection
  - step-wise backward elimination
  - combining forward selection and backward elimination
  - decision-tree induction

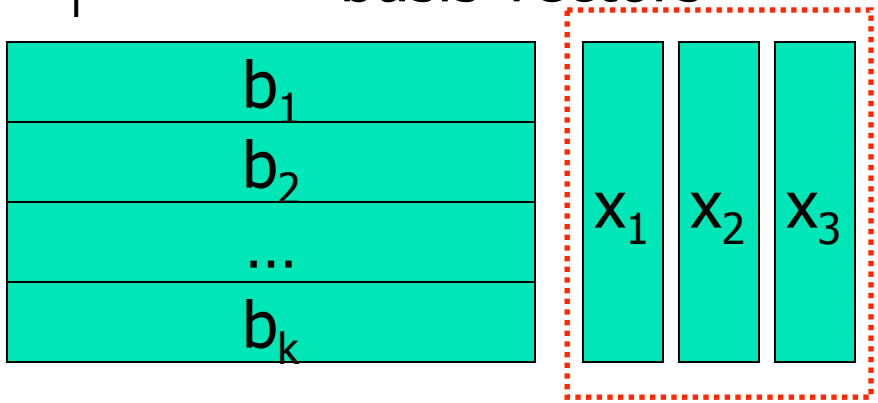
Heuristic Feature Selection Methods

- There are 2^d possible sub-features of d features
- Several heuristic feature selection methods:
  - Best single features under the feature independence assumption: choose by significance tests.
  - Best step-wi
    - The best
    - Then next best feature
  - Step-wise feature elimination:
    - Repeatedly eliminate the worst feature
  - Best combined feature selection and elimination:
  - Optimal branch and bound:
    - Use feature elimination and backtracking

first
the first, ...

Principal Component Analysis (**PCA**)

- Original dataset: *N d*-dimensional vectors $X = \{x_i\}_{i=1..n}$
  - Find $k \leq d$ **orthogonal basis vectors** that can be **best** used to represent data
  - Preserves maximum "information" (i.e., variance under the orthogon d onto these k basis vectors
- Reduced data set: Project eac i basis vectors (aka., principal components)
  - $x_i' = [b_1 \ldots b_k]^T x_i$
  - $X' = [b_1 \ldots b_k]^T X$ (en masse)



- Closed related to Singular Vector Decomposition (**SVD**)

Projection

- $b^T x$: projection of x onto the basis vector b
- What about $x' = B^T x$, where B consists of another set of d-dim basis vectors?

JL Lemma

- Johnson-Lindenstrauss Flattening Lemma '84:
  - Given ε>0, and an integer n, let k be a positive integer such that $k \geq k_0 = O(\varepsilon^{-2} \log n)$. For every set X of n [illegible] sts F: $R^d \rightarrow R^k$ such that f

$$\|F(x_i) - F(x_j)\|^2 \in \|x_i - x_j\|^2$$

- What is the intuitive interpretation of the Lemma?

Distributional JL Lemma

- Given ε in (0, ½], δ > 0, there is a random linear mapping F: $R^d \rightarrow R^k$ with $k = O(\varepsilon^{-2} \log \delta^{-1})$ such that for any unit vector x in Rd,

$$Pr[\|F(x)\| \in (1 \pm \varepsilon)] \geq 1 - \delta$$

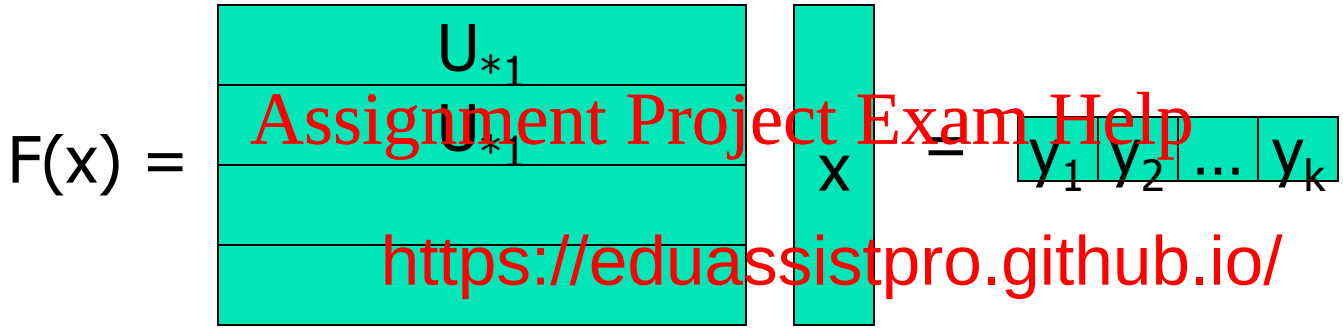
- Take $\delta = n^{-2}$, and then for for all $x_i, x_j \in X$

$$Pr[\|F(x_i) - F(x_j)\|^2 \in (1 \pm \varepsilon)\|x_i - x_j\|^2] \geq 1 - \frac{1}{n^2}$$

- Hence, by a simple union bound, the same statement holds for all $\binom{n}{2}$ pairs from X simultaneously with probability at least ½.
  - There exists a deterministic linear mapping which is an approximate isometry. ← Why/How?

Explicit Mapping

- $F(x) = k^{-1/2} * Ux$, where $U_{ij} \sim N(0, 1)$, i.e., i.i.d. samples from the standard Gaussian distribution.



Quick proof:

$$y_j = \langle U_{*j}, x \rangle = \sum_{i=1}^{d} x_i U_{ij} \sim \mathcal{N}(0, \|x\|^2)$$

$$\|y\|^2 \sim \|x\|^2 \cdot \chi_k^2 \longrightarrow E[\|y\|^2] = \|x\|^2 \cdot k$$

$$Var[\|y\|^2] = 2k$$

Concentration bound of chisquared distribution:

$$\text{if } z \sim \chi_k^2 \longrightarrow Pr[|\frac{z}{k} - 1| < \varepsilon] \geq 1 - \exp\left(-\frac{3}{16} k\varepsilon^2\right)$$

Approximating Inner Product

- 20 news groups
- Origin dim: 5000

Non-linear Dimensionality Reduction

- There are many advanced **non-linear** dimensionality reduction methods
  - Hypothesis: real high-dimensional data live in a manifold with low intrinsic dimensionality

Digits dataset (d = 64, Class = 0..5)

PCA (time = 0.01s)

t-SNE (time = 5.69s)

Data Compression

- String compression
  - There are extensive theories and well-tuned algorithms
  - Typically lossless
  - But only limited manipulation is possible without expansion
- Audio/video co
  - Typically lossy compressio gressive refinement
  - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
  - Typically short and vary slowly with time

Numerosity Reduction

- Parametric methods
  - Assume the data fits some model, estimate model parameters ters, and discard the data (e
  - Log-linear analysis: obtain point in m-D space as the product on a marginal subspaces
- Non-parametric methods
  - Do not assume models
  - Major families: histograms (binning), clustering, sampling

Random Sampling

- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
  - For approximately evaluating models/parameters, etc.
  - Then run th ers on large dataset

8000 points **2000 Points** **500 Points**

Other Sampling Methods

- Simple random sampling may have very poor performance in the presence of skew
- Adaptive sampling methods
  - Stratified sa
    - Approxi ach class (or subpopulation of intere verall database
    - Used in conjunction wit ata
- Sketch/synopsis based methods
  - E.g., count-min sketch
    - A simple and versatile data structure to remember the frequency of elements approximately

- Conversion of data types:
  - Discretization
  - Kernel den

Discretization

- Three types of simple attributes:
  - Nominal/categorical — values from an unordered set
    - Profession: clerk, driver, teacher, …
  - Ordinal — values from an ordered set
    - WAM: HD
  - Continuous ing Boolean values
- Other types:
  - Array
  - String
  - Objects

Discrete values ➔ Continuous values

- Here we focus on
  - Continuous values ➔ discrete values
    - Removes noise
    - Some ML methods only work with discrete valued features
    - Reduce the features, which may improve the odels
    - Reduce data size
  - Discrete values ➔ continuous values
    - Smooth the distribution
    - Reconstruct probability density distribution from samples, which helps generalization

Discretization

- Discretization
  - reduce the number of values for a given continuous attribute by dividing the range of the attribute into intervals. Int used to replace actual data v
- Methods
  - Binning/Histogram analysis
  - Clustering analysis
  - Entropy-based discretization

Simple Discretization Methods: Binning

- Equal-width (distance) partitioning:
  - Divides the range into *N* intervals of equal size: uniform grid
  - if *A* and *B* are the lowest and highest values of the attribute, the e: $W = (B - A)/N$.
  - The most str rs may dominate presentation
  - Skewed data is not handled
- Equal-depth (frequency) partitioning:
  - Divides the range into *N* intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky.

Optimal Binning Problem

- After binning, the educated guess or the smoothed value is $E(x_i)$, where x_i are all the values in the same bin
- cost(bin) = SSE($[x_1, ..., x_m]$) = $\sum_{i=1}^{m} (x_i - E(x_i))^2$
- cost of B bins = sum(cost(bin_1), ..., cost(bin_B))
- Problem: find th ch that the cost of the resulting bin
  - Alg($\{x_1, ..., x_n\}$, B)
  - Optimal Binning: Solve the problem optimally in $O(B*n^2)$ time and $O(n^2)$ space.
  - MaxDiff: Solve the problem heuristically in O(n*log(n)) time and O(n) space.
  - Note: both algorithms do not sort input data
    - Send in **sorted**($\{x_1, ..., x_n\}$) if necessary

For simplicity, we use integers, rather than real numbers, for the examples here.

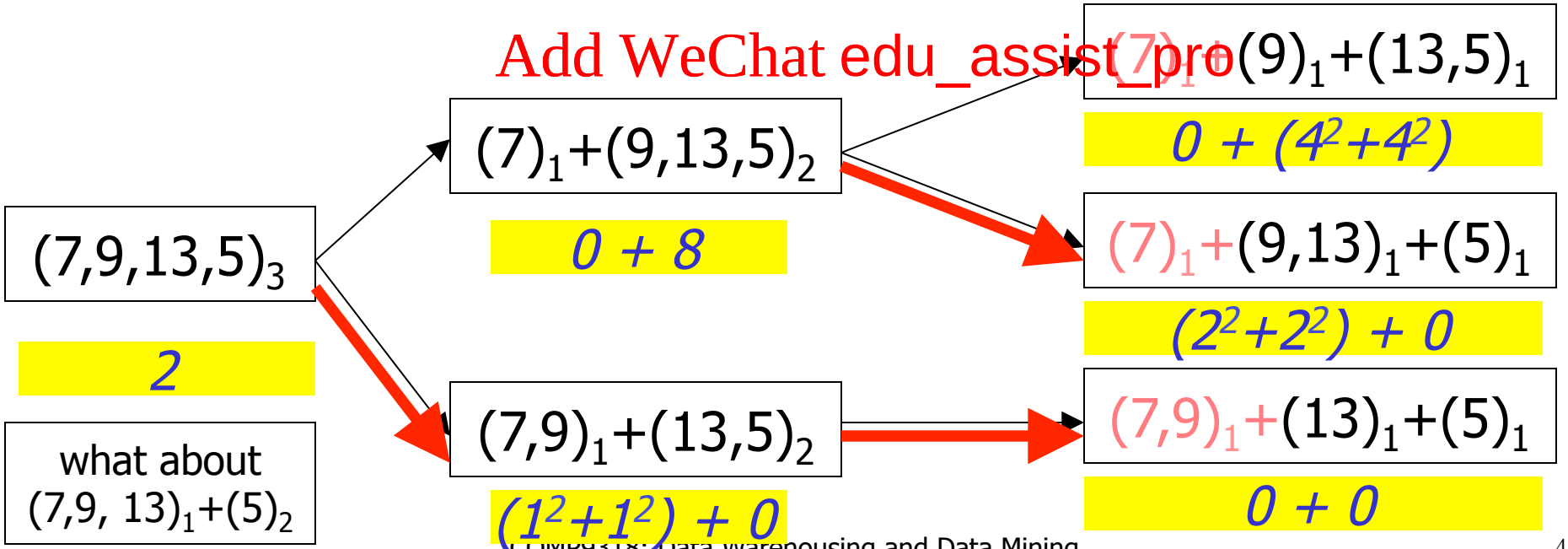
Recursive Formulation

- Observation

  $OPT(x[1..n], B) = \min_{i \text{ in } [n]}\{SSE(x[1..i]) + OPT(x[i+1..n], B-1)\}$

- Example
  - n=4, B=3

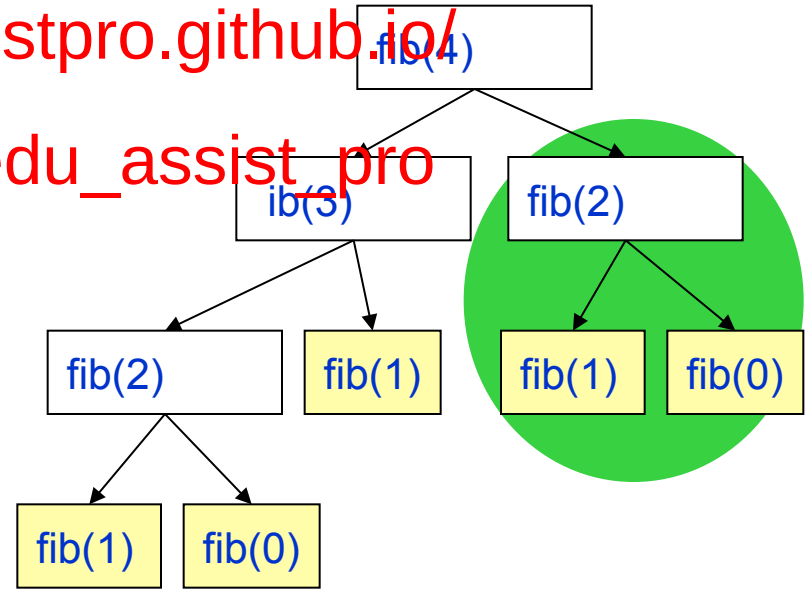
		X[3]	x[4]
		13	5



Problem Caused by Overlapping Sub-problems

- Consider calculating Fibonacci function
  - fib(0)=0
  - fib(1)=1
  - **fib(n) = fib(n-**
- Naïve D&C implementation is in efficient

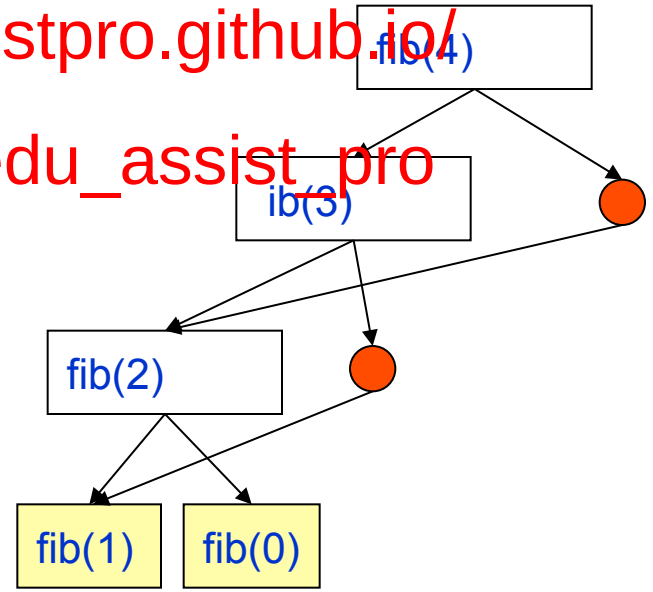
Boundary Condition



Memoization

- Remember solutions of all the sub-problems
- Trade space for time

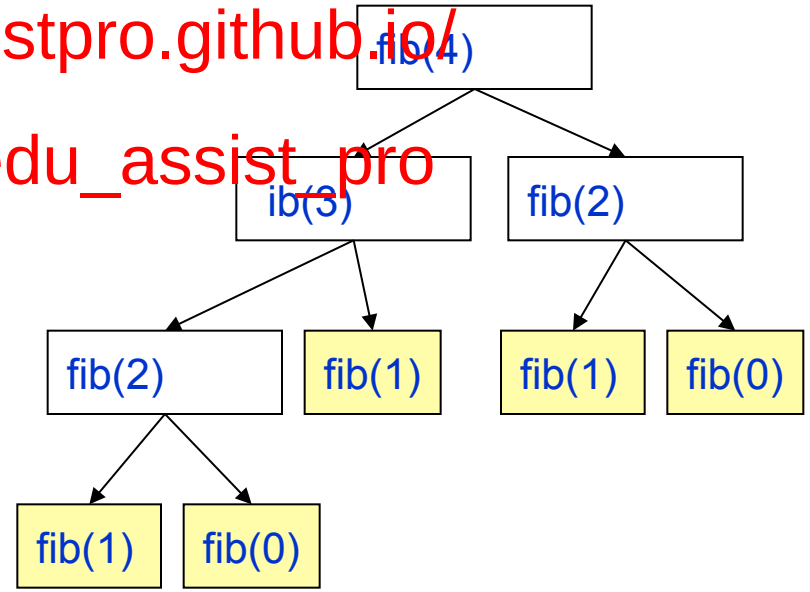
Sub-problem	
fib(4)	3
fib(3)	2
fib(2)	1
fib(1)	1
fib(0)	0



Dynamic Programming

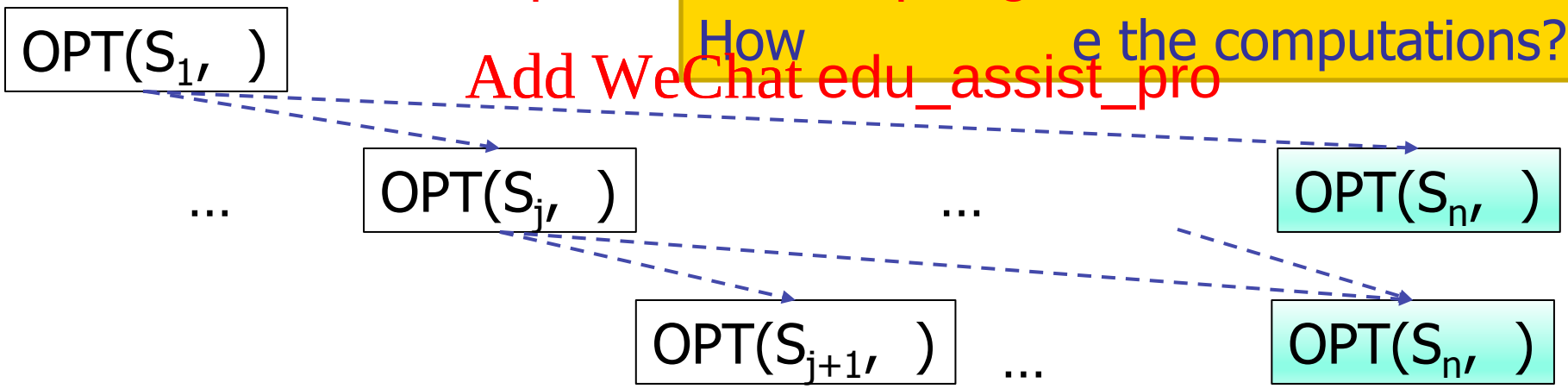
- Ideas
  - Ensure all needed recursive calls are already computed and memorized ➔ a good schedule of computation
  - (Optional) Re ious recursive call results

Sub-problem	solution

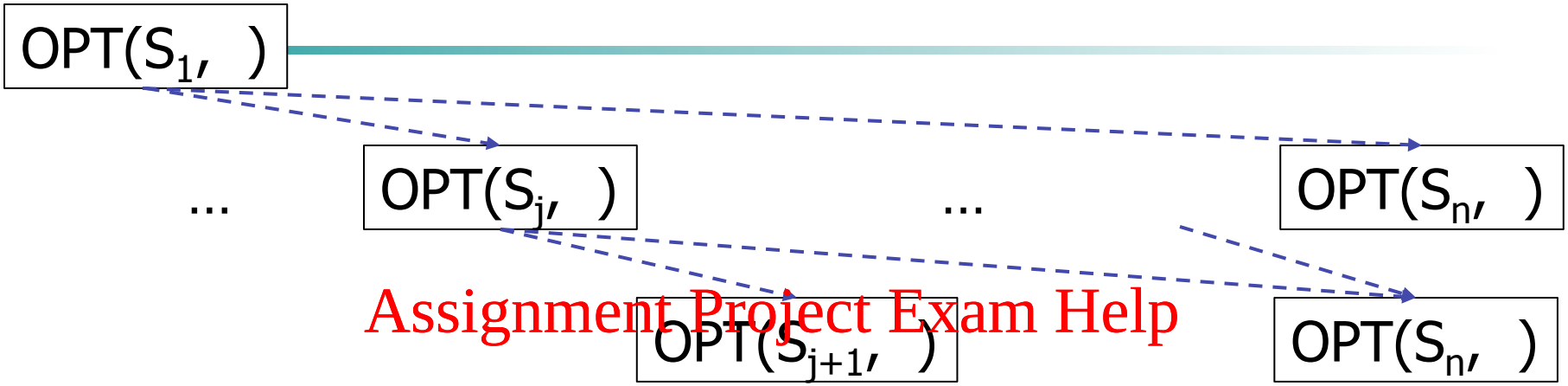


2D Dynamic Programming

- **OPT**(x[1.. n], B) = $\min_{i \text{ in } [n]}$ {SSE(x[1 .. i]) + **OPT**(x[i+1 .. n], B-1)}
- **OPT**(S_1, B) = $\min_{i \text{ in } [n]}$ { … + **OPT**(S_{i+1}, B-1)}
- Goal:



Pseudocode



Example

- X = [7, 9, 13, 5], B = 3

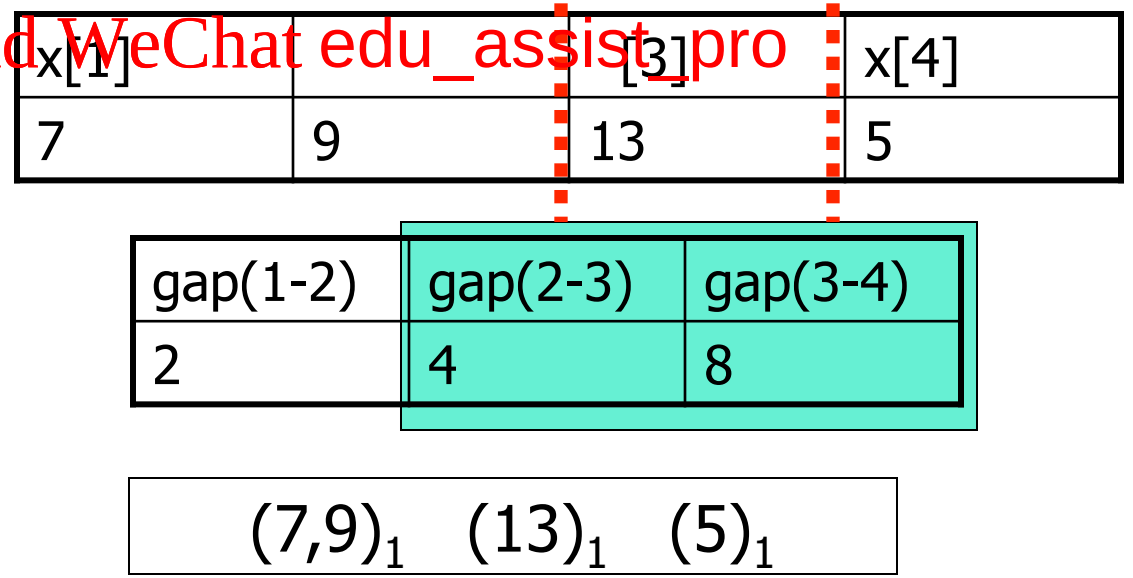
B	S_1	S_2	S_3	S_4
1			32	0
2		??	0	-
3			-	-

- (B=2, S_2)
  - What's the problem?
  - How to calculate it?

MaxDiff

- Complexity of the DP algorithm:
  - $O(n^2*B)$ running time!
- Consider a heuristic method: MaxDiff
  - Idea: use th n the data as the bin/bucket b
  - Example:

    n=4, B=3



Discretization via Clustering

- Can consider multiple attributes together

An example where univariate discretization does not work well

Supervised Discretization Methods

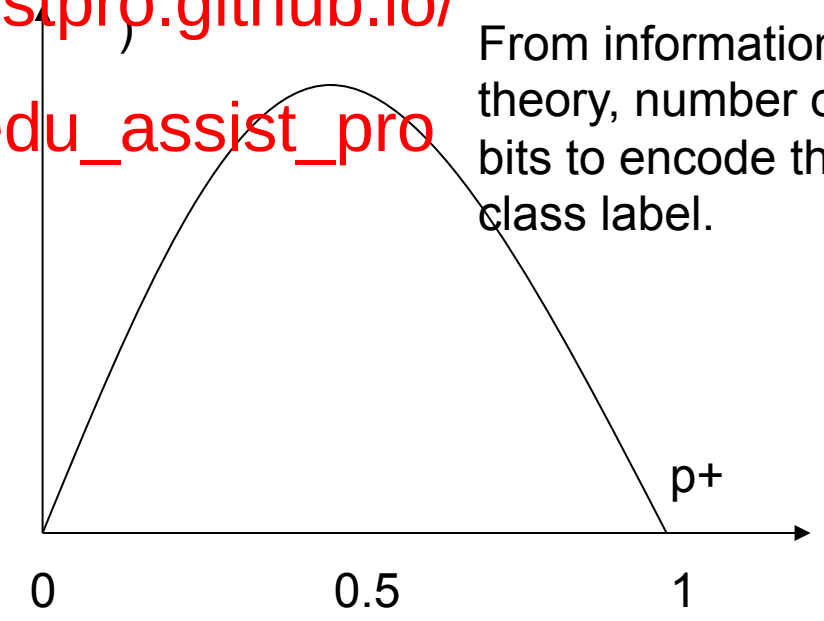
- MDLPC [Fayyad & Irani, 1993]

Entropy measures uncertainty

- Two classes:
  - Give a set S of instances with binary classes {+,-}. Let the proportions of + and – be p+ and p-.
  - Ent(S) = $-(p^+ \log_2 p^+ + p^- \log_2 p^-)$ (Note: log 0 ≡ 0)
- m classes:

$$Ent(S) = -\sum_{i=1}^{m} p_i \log p_i$$

- Consider drawing a random sample from S. What can you tell about its label?
  - If Ent(S) = 0:
  - If Ent(S) = log(m):



Can be generalized to n-ary split

Entropy After Splitting T

- Split S into two subsets: S1 and S2.
- What about the label of a random sample given that you know which subset it is drawn from?

- Define $$E(T;S) = \frac{|S_1|}{|S|}Ent(S_1) + \frac{|S_2|}{|S|}Ent(S_2)$$

$$Gain(T) = Ent(S) - E(T;S)$$

- Intuitive meaning of Gain?

These functions are also used in Decision Trees.

Entropy-Based Discretization: MDLPC

- Given a set of samples *S*, if *S* is partitioned into two intervals S_1 and S_2 using boundary T, the entropy after partitioning is $\frac{|S_1|}{|S|} Ent(S_1) + \frac{|S_2|}{|S|} Ent(S_2)$
- The boundary t y function over all possible boundaries is selected y discretization.
- The process is recursively applied to partitions obtained until some stopping criterion is met, e.g.,

$$\underbrace{Ent(S)}_{before} - \underbrace{E(T,S)}_{after} > \delta$$

- Experiments show that it may reduce data size and improve classification accuracy

Not needed. Just for the sake of completeness.

Stopping Condition of MDLPC

- Stop when

Comments

- Understanding the underlying data distribution is important
  - e.g., via visualization
- Supervised m well
- More advance

- After learning some ML models, you need to rethink
  - Why discretization?
  - Why different method/parameters affects the model performance?

Continuous values ➔ Discrete values

- After repeating the experiments (e.g., measuring customers arriving 3-4pm), we observed the following random variable x_i (e.g., #customers):
  - x_i = 2, 3, 3, 3, 3, 1, 5
  - What's the = 3 in a new experiment? What abou
- Naive estimation
  - P(x = 3) = 4/7 P(x = 4) = 0 / 7
- Assume x follows the Poisson distribution
  - MLE estimation of λ
  - MAP estimation with a prior (typically Gamma)

$$P(x;\lambda) = \frac{\lambda^x e^{-\lambda}}{x!}$$

Non-parametric Estimation

- Kernel density estimation (KDE)
  - Let $\{x_i\}_{i=1:n}$ be *n* i.i.d. sample of an unknown f(x)
  - We can est $= \frac{1}{n}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$
    - K(z) controls the weight x_i) to influence f(x)
      - May think K(x, x_i) as measuring their similarity
    - h is the bandwidth parameter
  - Gaussian kernel: $K(x; h) \propto \exp\left(-\frac{x^2}{2h^2}\right)$

Impact of h

Categorical Values

- One hot encoding is widely used in ML
  - Let there be m distinct values for the attribute
  - The i-th (category) value is converted into a m-dimensiona ere
    - v_j = 0, if j
    - v_j = 1, otherwise
  - scikit-learn: OneHotEncoder
- Disadvantages:
  - Ignores similarity between values
- Embedding-based methods can learn better (real) vectors

- Case Study
  - c.f., TUN_datacleansing.ppt