

Data Mining



DATA PREPROCESSING



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Lesson from Holy Quran

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وَهُوَ مَعَكُمْ أَيْنَ مَا كُنْتُمْ

AND HE IS WITH YOU WHEREVER YOU ARE

[AL-QURAN | 57:4]

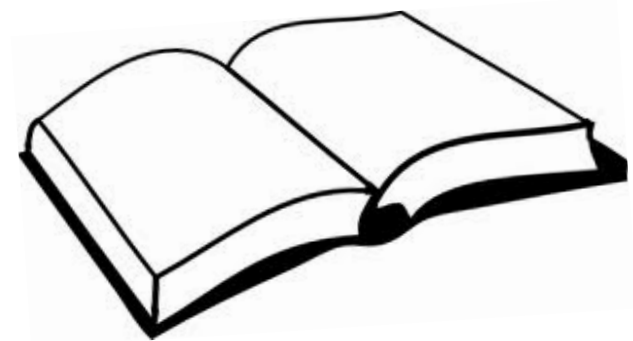


quran fm

Outline

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- Introduction to Data Preprocessing
- Data Quality
- Steps of Data Preprocessing
 - ▣ Data cleaning
 - ▣ Data integration
 - ▣ Data reduction
 - ▣ Data transformation



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Data Preprocessing

Data Quality

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- Measures for data quality:
 - ▣ **Accuracy:** correct or wrong
 - ▣ **Completeness:** not recorded, unavailable, ...
 - ▣ **Consistency:** some updated/modified but some not.
 - ▣ **Timeliness:** timely update?
 - ▣ **Believability:** how trustable the data is?
 - ▣ **Interpretability:** how easily data can be understood?

Major Tasks in Data Preprocessing

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- **Data cleaning**
 - ▣ Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
 - ▣ Integration of multiple databases or files, diverse sources
- **Data reduction**
 - ▣ Dimensionality reduction
 - ▣ Data compression
- **Data transformation**
 - ▣ Normalization

Data Cleaning

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- Data in the Real World Is Dirty: (More thanks to Social Web)
- Lots of potentially incorrect data, e.g., human or computer error, extraction error
 - ▣ incomplete: lacking attribute values,
 - e.g., *Occupation=""* (missing data)
 - ▣ noisy: containing noise, errors
 - e.g., *Salary="-10"* (an error)
 - ▣ inconsistent: containing discrepancies in codes or names, e.g.,
 - *Age="42", Birthday="03/07/2010"*
 - Was rating "1, 2, 3", now rating "A, B, C"
 - ▣ Intentional (e.g., *disguised missing data*)
 - Jan. 1 as everyone's birthday?

How to Handle Missing Data?

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- Ignore the tuple:
 - ▣ usually done when class label is missing
- Fill in the missing value manually:
 - ▣ tedious + infeasible?
- Fill in it automatically with
 - ▣ A global constant : e.g., “unknown”, a new class?!
 - ▣ The attribute mean
 - ▣ The attribute median value

How to Handle Noisy Data?

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- Binning
 - ▣ first sort data and partition into (equal-frequency) bins
 - ▣ e.g., Bin ages of the students of undergraduate
 - ▣ smooth by bin means, smooth by bin median, etc.
- Regression
 - ▣ smooth by fitting the data into regression functions
- Clustering
 - ▣ detect and remove outliers
- Combined computer and human inspection
 - ▣ detect suspicious values and check by human (e.g., deal with possible outliers)

Binning Methods for Data Smoothing

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- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34
- * Partition into equal-frequency (**equi-depth**) bins:
 - Bin 1: 4, 8, 9, 15
 - Bin 2: 21, 21, 24, 25
 - Bin 3: 26, 28, 29, 34
- * Smoothing by **bin means**:
 - Bin 1: 9, 9, 9, 9
 - Bin 2: 23, 23, 23, 23
 - Bin 3: 29, 29, 29, 29
- * Smoothing by **bin boundaries**:
 - Bin 1: 4, 4, 4, 15
 - Bin 2: 21, 21, 25, 25
 - Bin 3: 26, 26, 26, 34

Data Integration

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- **Data integration:**
 - ▣ Combines data from multiple sources into a coherent store
- Schema integration: e.g., $A.cust-id \equiv B.cust-\#$
 - ▣ Integrate metadata from different sources
- Entity identification problem (Name Disambiguation)
 - ▣ Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
 - ▣ Possible reasons:
 - ▣ different representations: Rs vs. US Dollars
 - ▣ different scales, e.g., metric vs. British units

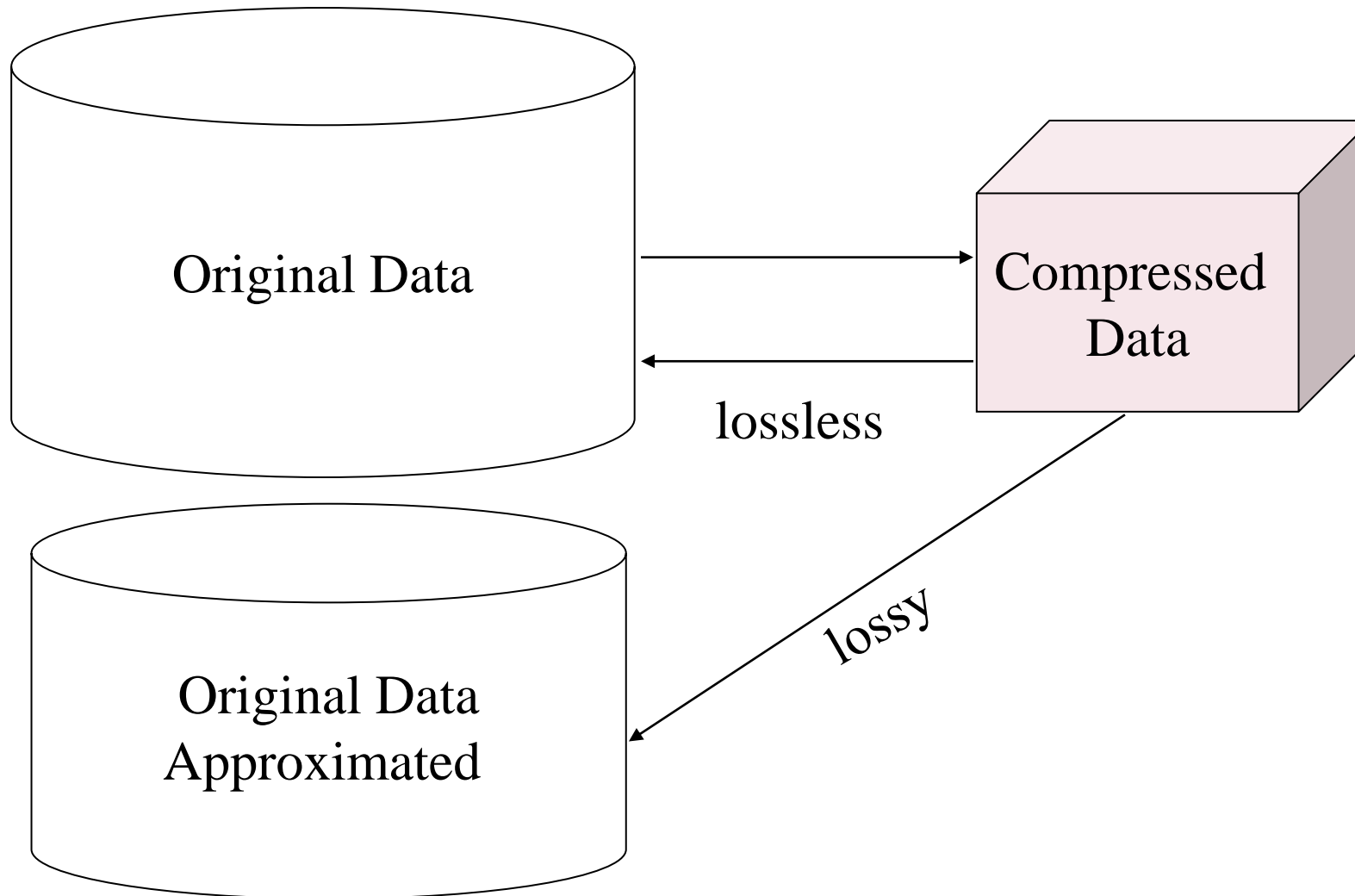
Data Reduction Strategies

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- **Data reduction:**
 - ▣ Obtain a reduced representation
 - ▣ Produces the same (or almost the same)
- Why data reduction?
 - ▣ Huge volume (terabytes)
 - ▣ Complex data – difficult to analysis
 - ▣ Time consuming -
- Data reduction strategies
 - ▣ Dimensionality reduction, e.g., remove unimportant attributes
 - ▣ Feature subset selection algorithms
 - Info Gain
 - Principal Components Analysis (PCA)

Data Compression

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Data Transformation

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- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
 - ▣ **Attribute/feature construction**
 - Derived attributes constructed from the given ones
 - E.g. Age as new attribute instead of Date of Birth
 - ▣ **Normalization:**
 - ▣ Scaled to fall within a smaller, specified range
 - min-max normalization

Normalization

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- **Min-max normalization:** to $[\text{new_min}_A, \text{new_max}_A]$

$$v' = \frac{v - \text{min}_A}{\text{max}_A - \text{min}_A} (\text{new_max}_A - \text{new_min}_A) + \text{new_min}_A$$

- E.g., Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,600 is mapped to

$$\frac{73,600 - 12,000}{98,000 - 12,000} (1.0 - 0) + 0 = 0.716$$

