Data Preparation: Data Types

Mining Massive Datasets

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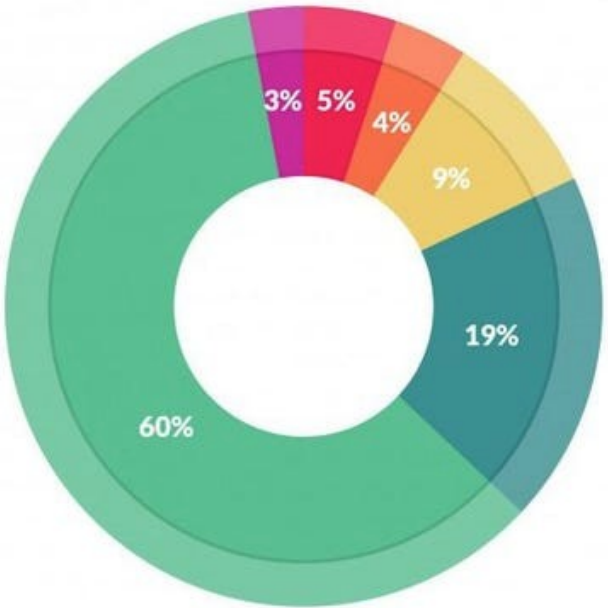
Success depends upon previous preparation, and without such preparation there is sure to be failure – Confucius

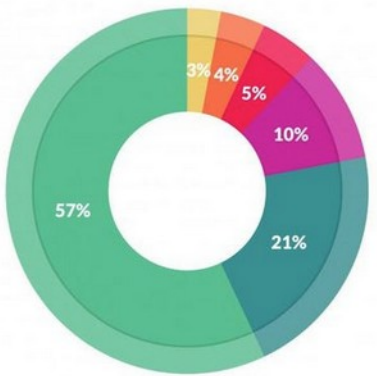
Preparation is time consuming

Tip: appreciate the joy of well-organized data spaces



What data scientists spend the most time doing

- *Building training sets: 3%*
- *Cleaning and organizing data: 60%*
- *Collecting data sets; 19%*
- *Mining data for patterns: 9%*
- *Refining algorithms: 4%*
- *Other: 5%*



What's the least enjoyable part of data science?

- *Building training sets: 10%*
- *Cleaning and organizing data: 57%*
- *Collecting data sets: 21%*
- *Mining data for patterns: 3%*
- *Refining algorithms: 4%*
- *Other: 5%*

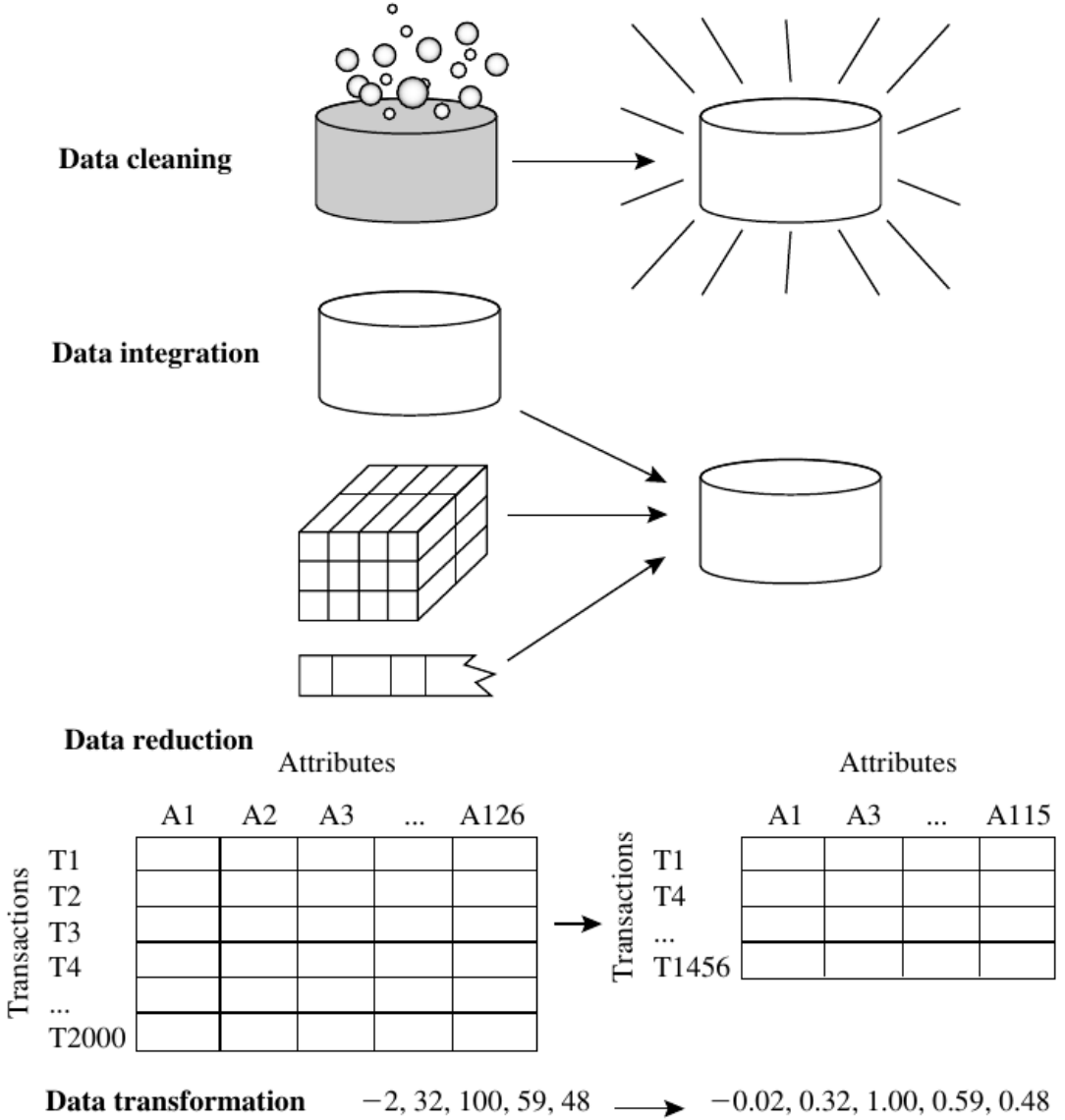
Forbes 2016

Main Sources

- Data Mining, The Textbook (2015) by Charu Aggarwal (Chapter 2) + slides by Lijun Zhang
- Introduction to Data Mining 2nd edition (2019) by Tan et al. (Chapter 2)
- Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al. (Chapter 3)

Data preparation

- Feature Extraction and Portability/Casting
  - Extract relevant elements for our analysis
  - Convert heterogeneous data types
- Data Cleaning
  - Deal with missing, erroneous, and inconsistent data
- Data Integration
  - Bring different data sources into a common framework
- Data Reduction, Selection, and Transformation
  - Done for both efficiency and effectiveness



Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al. (page 87)

Feature extraction examples

Domain	Raw Data	Features
Sensor	Low-level signals	Wavelet or Fourier transforms
Image	Pixels	Color histograms Visual words
Web logs	Text strings	IP address Action
Network traffic	Characteristics of the network packets	Number of bytes transferred Network protocol
Document data	Text strings	Bag-of-words Entity extraction

This is both a skill and an art that the analyst develops over the years.

Data type conversions

Data type conversions

- Data is often heterogeneous
  - A demographic data set may contain both numeric and mixed attributes
- Possible solution
  - Designing an algorithm for an arbitrary combination of data types
    - Time-consuming and sometimes impractical
- Converting between various data types
  - Using off-the-shelf tools for processing

Data type conversions (cont.)

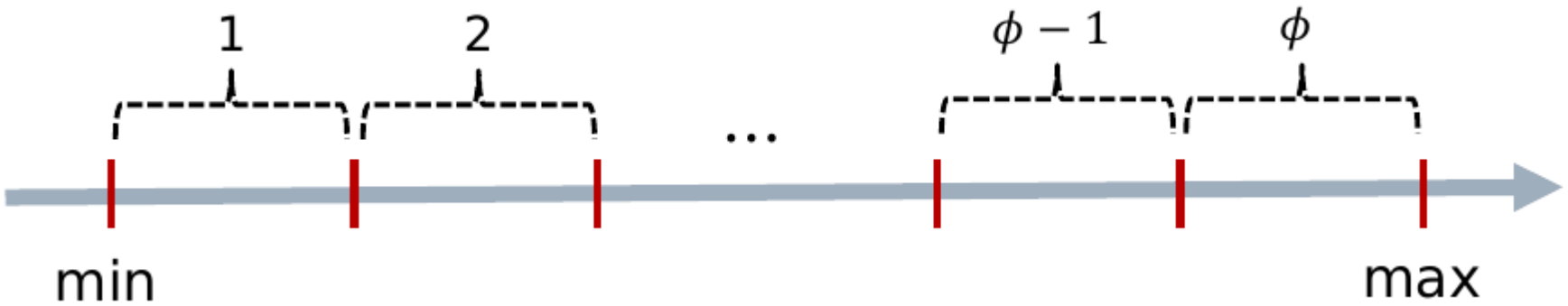
Some ways of converting between data types

Source data type	Destination data type	Methods
Numeric	Categorical	Discretization
Categorical	Numeric	Binarization
Text	Numeric	Latent Semantic Analysis (*LSA*)
Time series	Discrete sequence	Symbolic Aggregate Approximation *(SAX)*
Time series	Numeric multidimensional	Discrete Wavelet Transform (*DWT*), Discrete Fourier Transform (*DFT*)
Discrete sequence	Numeric multidimensional	
Spatial	Numeric multidimensional	2-d *DWT*
Graphs	Numeric multidimensional	Multidimensional Scaling (*MDS*), spectral
Any type	Graphs	Similarity graph (restricted applicability)

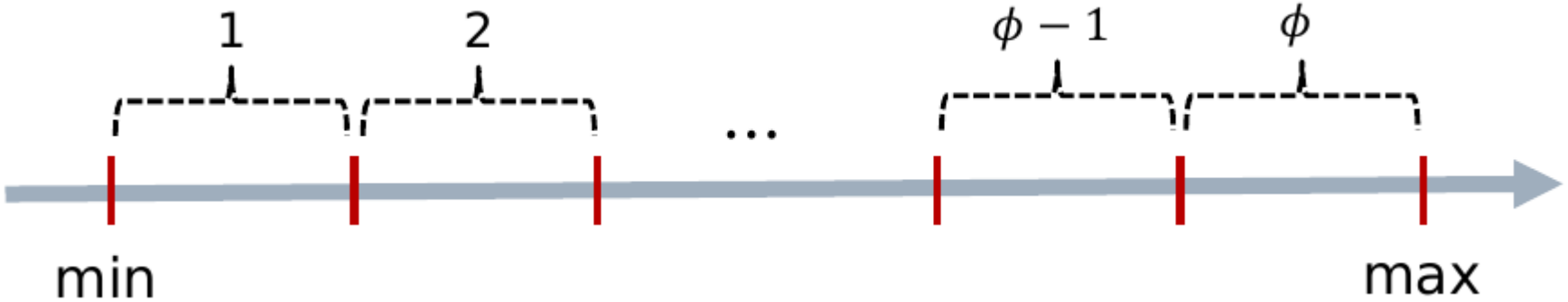
Numerical  Categorical

Numerical to categorical: discretization

- Divide the range for the numerical variable into Φ different ranges

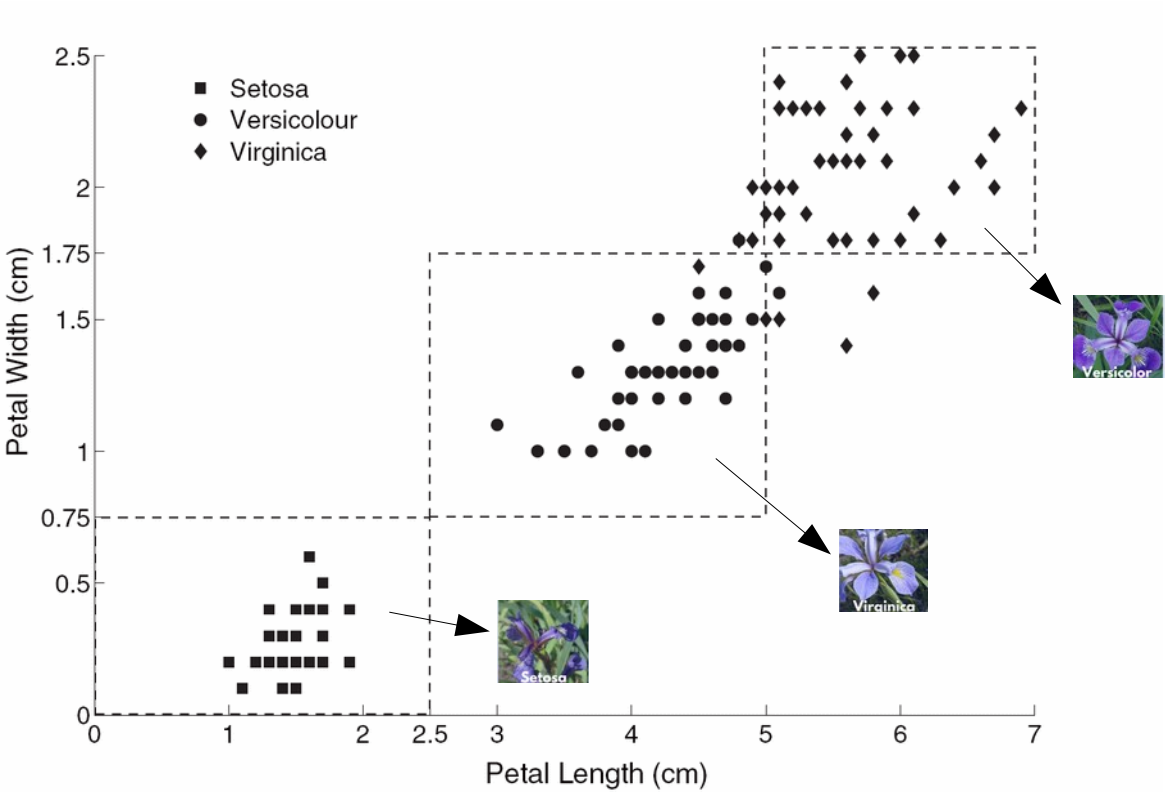


Numerical to categorical: discretization (cont.)



- **Equi-width** ranges (l_i – r_i is constant)
- **Equi-log** ranges ($log\ r_i$ – $log\ l_i$ is constant)
- **Equi-depth** ranges (num. items in $[l_i, r_i]$ constant)

Example discretization in IRIS dataset



Continuous variables are converted to three possible values per feature: small, medium, large

Exercise
Equi-depth and equi-width

- Given this database
- Create two categorical (ordinal) attributes
  - Salary bin (equi width) with salary binned into equi-width categories
  - Salary bin (equi depth) with salary binned into equi-depth categories
- Values: low, medium, high

Person	Salary
a	34,000
b	49,000
c	53,000
d	54,000
e	32,000
f	44,000
g	41,000
h	37,000
i	48,000

Spreadsheet links: https://upfbarcelona.padlet.org/chato/hogch321o6pws1fd

Categorical to numerical: binarization

(one-hot encoding)

- One categorical value with K categories

  ⇒ indicator vector with K binary variables

User name	gender
alice	Female
bob	Male
cara	Female
...	...

alice	bob	cara	Female	Male	...
1	0	0	1	0	...
0	1	0	0	1	...
0	0	1	1	0	...
...	...	...	...	...	...

https://slideplayer.com/slide/14461691/

Series and sequences

Time series to discrete sequence

- Symbolic aggregate approximation (SAX)
  - Window-based averaging
    - Evaluate the average value in each window
  - Value-based discretization
    - Discretize the average value by equi-depth intervals
- How to ensure equi-depth without seeing the entire series?
  - Assume certain distribution, such as Gaussian
  - Estimate the distribution

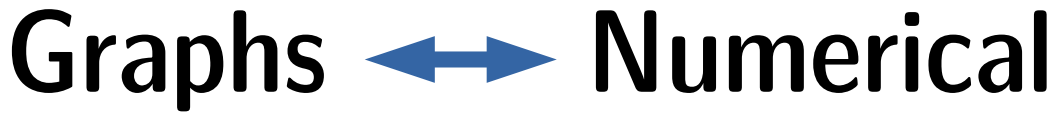
Time series to numeric data

- Discrete Wavelet Transform (DWT)
- Discrete Fourier transform (DFT)

  (Seen elsewhere, e.g., signal processing)

Discrete sequence to numeric

- Discrete sequence to a set of (binary) time series
  - ACACACTGTGACTG (4 Symbols)
  - 10101000001000 (A)
  - 01010100000100 (C)
  - 00000010100010 (T)
  - 00000001010001 (G)
- Map each of these time series into a multidimensional vector
- Features from the different series are combined


Graphs
Numerical

Convert any data type to a graph

- Determine distance $d(u,v)$ between all pairs of elements (u,v)
- All elements with $d(u,v) \leq \theta$ are connected

Graphs to numerical

- Graph embeddings
  - Each node is converted into a point in a low-dimensional space
  - Nearby nodes in the low-dimensional space are connected by short paths in the graph

If you're interested, see topic "Spectral Graph Clustering" in Networks Science

Summary

Things to remember

- Converting across data types

Exercises for TT03-TT05

- Exercises 3.7 of Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al.
- Exercises 2.6 of Introduction to Data Mining, Second Edition (2019) by Tan et al.
  - Mostly the first exercises, say 1-6