Ludwig-Maximilians-Universität München Lehrstuhl für Datenbanksysteme und Data Mining Prof. Dr. Thomas Seidl

# Knowledge Discovery and Data Mining I

Winter Semester 2018/19



## Agenda

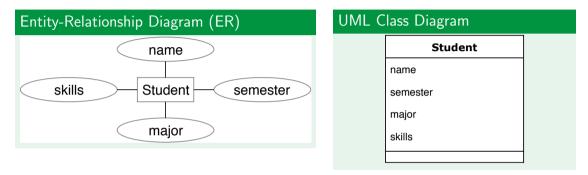
#### 1. Introduction

### 2. Basics

#### 2.1 Data Representation

- 2.2 Data Reduction
- 2.3 Visualization
- 2.4 Privacy
- 3. Unsupervised Methods
- 4. Supervised Methods
- 5. Advanced Topics

### **Objects and Attributes**



#### Data Tables (Relational Model)

name	sem	major	skills	
Ann	3	CS	Java, C, R	
Bob	1	CS	Java, PHP	
Charly	4	History	Piano	
Debra	2	Arts	Painting	

# Overview of (Attribute) Data Types

### Simple Data Types

Numeric/metric, Categorical/nominal, ordinal

### Composed Data Types

Sets, sequences, vectors

### Complex Data Types

- Multimedia: Images, videos, audio, text, documents, web pages, etc.
- Spatial, geometric: Shapes, molecules, geography, etc.
- Structures: Graphs, networks, trees, etc.

# Simple Data Types: Numeric Data

#### Numeric Data

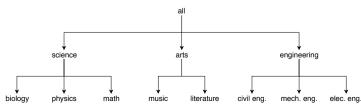
- Numbers: natural, integer, rational, real numbers
- Examples: age, income, shoe size, height, weight
- Comparison: difference
- Example: 3 is more similar to 30 than to 3,000

# Simple Data Types: Categorical Data

- "Just identities"
- Examples:
  - occupation = { butcher, hairdresser, physicist, physician, ... }
  - subjects = { physics, biology, math, music, literature, ... }
- Comparison: How to compare values?
  - Trivial metric:

$$d(p,q) = egin{cases} 0 & ext{if } p = q \ 1 & ext{else} \end{cases}$$

Generalization hierarchy: Use path length



### Generalization: Metric Data

#### Metric Space

Metric space (O, d) consists of object set O and *metric distance* function  $d: O \times O \rightarrow \mathbb{R}^{\geq 0}$  which fulfills:

Symmetry:	$\forall p,q \in O: d(p,q) = d(q,p)$
Identity of Indiscernibles:	$orall p,q\in O: d(p,q)=0 \iff p=q$
Triangle Inequality:	$orall p,q,o\in O: d(p,q)\leq d(p,o)+d(o,q)$

Example: Points in 2D space with Euclidean distance

# Simple Data Types: Ordinal

#### Characteristic

There is a (total) order  $\leq$  on the set of possible data values *O*:

Transitivity:	$orall p,q,o\in O:p\leq q\wedge q\leq o\implies p\leq o$
Antisymmetry:	$orall p,q\in O:p\leq q\wedge q\leq p\implies p=q$
Totality:	$\forall \pmb{p}, \pmb{q} \in \pmb{O}: \pmb{p} \leq \pmb{q} \lor \pmb{q} \leq \pmb{p}$

#### Examples

- Words & lexicographic ordering:  $high \leq highschool \leq highscore$
- (Vague) sizes:  $tiny \leq small \leq medium \leq big \leq huge$
- ► Frequencies: never ≤ seldom ≤ rarely ≤ occasionally ≤ sometimes ≤ often ≤ frequently ≤ regularly ≤ usually ≤ always

# Composed Data Types: Sets

#### Characteristic

Unordered collection of individual values

#### Example

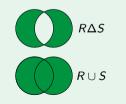
• skills = 
$$\{ Java, C, Python \}$$

### Comparison

Symmetric Set Difference:

$$R\Delta S = (R-S) \cup (S-R)$$
  
= (R \cap S) - (R \cap S)

► Jaccard Distance:  $d(R, S) = \frac{|R \Delta S|}{|R \cup S|}$ 



Basics

# Composed Data Types: Sets

#### Bitvector Representation

- Given a set S, an ordered base set  $B = (b_1, \ldots, b_n)$ , create binary vector  $r \in \{0, 1\}^n$  with  $r_i = 1 \iff b_i \in S$ .
- Hamming distance: Sum of different entries (equals cardinality of symmetric set difference)

### Example

- Base: B = (Math, Physics, Chemistry, Biology, Music, Arts, English)
- $S = \{ Math, Music, English \} = (1,0,0,0,1,0,1)$
- $R = \{ Math, Physics, Arts, English \} = (1,1,0,0,0,1,1)$
- Hamming(R, S) = 3

## Composed Data Types: Sequences, Vectors

#### Characteristic

Put n values of a domain D together

• Order does matter:  $I_n \rightarrow D$  for an index set  $I_n = \{1, \ldots, n\}$ 

### Examples

## Complex Data Types

#### Components

- Structure: graphs, networks, trees
- Geometry: shapes/contours, routes/trajectories
- Multimedia: images, audio, text, etc.

### Similarity models: Approaches

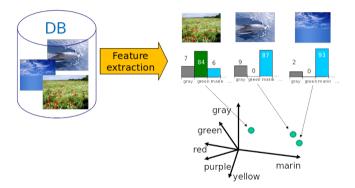
- Direct measures highly data type dependent
- Feature engineering explicit vector space embedding with hand-crafted features
- Feature learning explicit vector space embedding learned by machine learning model, e.g. neural network
- Kernel trick implicit vector space embedding

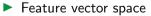
Examples for si	milarity models	
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	Direct	Feature	Feature learning	Kernel-based
		engineering		
Graphs	Structural	Degree	Node embeddings	Label Sequence
	Alignment	Histograms		Kernel
Geometry	Hausdorff	Shape	Spectral Neural	Spatial Pyramid
	Distance	Histograms	Network	Kernel
Sequences	Edit Distance	Symbol	Recurrent neural	Cosine Distance
		Histograms	network (RNN)	

### Feature Extraction

Objects from database DB are mapped to feature vectors





- Points represent objects
- Distance corresponds to (dis-)similarity

Basics

### Similarity Queries

Similarity queries are basic operations in (multimedia) databases

• Given: Universe O, database DB, distance function d and query object q

#### Range query

Range query for range parameter  $\epsilon \in \mathbb{R}_0^+$ :

$$range(DB, q, d, \epsilon) = \{o \in DB \mid d(o, q) \le \epsilon\}$$

Nearest neighbor query

$$\mathsf{NN}(\mathsf{DB},q,d) = \{o \in \mathsf{DB} \mid \forall o' \in \mathsf{DB} : d(o,q) \leq d(o',q)\}$$

### Similarity Queries

#### k-nearest neighbor query

```
k-nearest neighbor query for parameter k \in \mathbb{N}:
```

```
NN(DB, q, d, k) \subset DB with |NN(DB, q, d, k)| = k and
```

 $\forall o \in \mathsf{NN}(\mathsf{DB},q,d,k), o' \in \mathsf{DB} - \mathsf{NN}(\mathsf{DB},q,d,k) : d(o,q) \leq d(o',q)$ 

#### Ranking query

Ranking query (partial sorting query): "get next" functionality for picking database objects in an increasing order w.r.t. their distance to q:

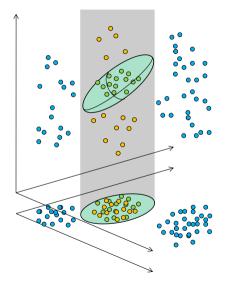
$$\forall i \leq j : d(q, rank_{DB,q,d}(i)) \leq d(q, rank_{DB,q,d}(j))$$

## Similarity Search

► Example: Range query  $range(DB, q, d, \epsilon) = \{o \in DB \mid d(o, q) \le \epsilon\}$ 

- Naive search by sequential scan
  - Fetch database objects from secondary storage (e.g. disk): O(n)
  - Check distances individually: O(n)
- Fast search by applying database techniques
  - Filter-refine architecture
    - Filter: Boil database DB down to (small) candidate set  $C \subseteq DB$
    - Refine: Apply exact distance calculation to candidates from C only
  - Indexing structures
    - Avoid sequential scans by (hierarchical or other) indexing techniques
    - Data access in (fast) O(n),  $O(\log n)$  or even O(1)

### Filter-Refine Architecture

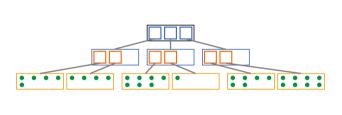


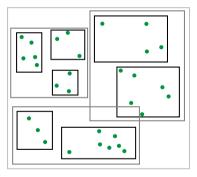
- Principle of multi-step search:
  - 1. Fast filter step produces candidate set  $C \subset DB$  (by approximate distance function d')
  - 2. Exact distance function d is calculated on candidate set C only.
- Example: Dimensionality reduction<sup>a</sup>
- ► ICES<sup>b</sup> criteria for filter quality
  - I ndexable Index enabled
  - C omplete No false dismissals
  - E fficient Fast individual calculation
  - S elective Small candidate set

<sup>a</sup>GEMINI: Faloutsos 1996; KNOP: Seidl & Kriegel 1998 <sup>b</sup>Assent, Wenning, Seidl: ICDE 2006

### Indexing

Organize data in a way that allows for fast access to relevant objects, e.g. by heavy pruning.





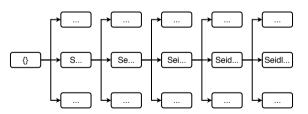
- R-Tree as an example for spatial index structure:
  - Hierarchy of minimum bounding rectangles
  - Disregard subtrees which are not relevant for the current query region

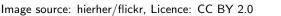
Basics

Data Representation

# Indexing

- Example: Phone book
- Indexed using alphabetical order of participants
- Instead of sequential search:
  - Estimate region of query object (interlocutor)
  - Check for correct branch
  - Use next identifier of query object
  - Repeat until query is finished





Data Representation

