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CS520
Data Integration, Warehousing, and Provenance

2. Data Preparation and Cleaning

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Outline

0) Course Info
1) Introduction
2) **Data Preparation and Cleaning**
3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance

2. Overview

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- Topics covered in this part
  - **Causes of Dirty Data**
  - Constraint-based Cleaning
  - Outlier-based and Statistical Methods
  - Entity Resolution
  - Data Fusion

2. Causes of "Dirty" Data

- Manual data entry or result of erroneous integration
  - Typos:
    - **"Peter" vs. "Pteer"**
  - Switching fields
    - "**FirstName**: New York, **City**: Peter"
  - Incorrect information
    - "**City**:New York, **Zip**: 60616"
  - Missing information
    - "**City**: New York, **Zip**: "

2. Causes of "Dirty" Data

- Manual data entry or result of erroneous integration (cont.)
  - Redundancy:
    - (**ID**:1, **City**: Chicago, **Zip**: 60616)
    - (**ID**:2, **City**: Chicago, **Zip**: 60616)
  - Inconsistent references to entities
    - Dept. of Energy, DOE, Dep. Of Energy, …

2. Cleaning Methods

- Enforce Standards
  - Applied in real world
  - How to develop a standard not a fit for this lecture
  - Still relies on no human errors
- Constraint-based cleaning
  - Define constraints for data
  - “Make” data fit the constraints
- Statistical techniques
  - Find outliers and smoothen or remove
    - E.g., use a clustering algorithm

2. Overview

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- Topics covered in this part
  - Causes of Dirty Data
  - **Constraint-based Cleaning**
  - Outlier-based and Statistical Methods
  - Entity Resolution
  - Data Fusion

2.1 Cleaning Methods

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- **Constraint-based cleaning**
  - Choice of constraint language
  - Detecting violations to constraints
  - Fixing violations (automatically?)

2.1 Constraint Languages

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- First work focused on functional dependencies (FDs)
- Extensions of FDs have been proposed to allow rules that cannot be expressed with FDs
  - E.g., conditional FDs only enforce the FD is a condition is met
    - -> finer grained control, e.g., zip -> city only if country is US
- Constraints that consider master data
  - Master data is highly reliable data such as a government issued zip, city lookup table

2.1 Constraint Languages (cont.)

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- Denial constraints
  - Generalize most other proposed constraints
  - State what should not be true
  - Negated conjunction of relational and comparison atoms

$$\forall \vec{x} : \neg(\phi(\vec{x}))$$

- Here we will look at FDs mainly and a bit at denial constraints
  - Sometimes use logic based notation introduced previously

2.1 Example Constraints

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Example: Constraints Languages

SSN	zip	city	name	boss	salary
333-333-3333	60616	New York	Peter	Gert	50,000
333-333-9999	60615	Chicago	Gert	NULL	40,000
333-333-5599	60615	Schaumburg	Gertrud	Hans	10,000
333-333-6666	60616	Chicago	Hans	NULL	1,000,000
333-355-4343	60616	Chicago	Malcom	Hans	20,000

C_1: The zip code uniquely determines the city

C_2: Nobody should earn more than their direct superior

C_3: Salaries are non-negative

2.1 Example Constraints

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Example: Constraints Languages

SSN	zip	city	name	boss	salary
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333-333-6666	60616	Chicago	Hans	NULL	1,000,000
333-355-4343	60616	Chicago	Malcom	Hans	20,000

C_1: The zip code uniquely determines the city
- expressible as functional dependency

C_2: Nobody should earn more than their direct superior
- e.g., denial constraint

C_3: Salaries are non-negative
- e.g., denial constraint

2.1 Example Constraints

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Example: Constraints Languages

SSN	zip	city	name	boss	salary
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333-355-4343	60616	Chicago	Malcom	Hans	20,000

C$_1$: The zip code uniquely determines the city

FD$_1$: zip -> city

$$\forall \neg (E(x,y,z,u,v,w) \land E(x',y',z',u',v',w') \land y = y' \land z \neq z')$$

C$_2$: Nobody should earn more than their direct superior

$$\forall \neg (E(x,y,z,u,v,w) \land E(x',y',z',u',v',w') \land v = u' \land w > w')$$

C$_3$: Salaries are non-negative

$$\forall \neg (E(x,y,z,u,v,w) \land w < 0)$$

2.1 Constraint based Cleaning Overview

- Define constraints

- Given database D
  - **1)** Detect violations of constraints
    - We already saw example of how this can be done using queries. Here a bit more formal
  - **2)** Fix violations
    - In most cases there are many different ways to fix the violation by modifying the database (called **solution**)
      - What operations do we allow: insert, delete, update
      - How do we choose between alternative solutions

2.1 Constraint Repair Problem

Definition: Constraint Repair Problem

Given set of constraints **Σ** and an database instance **I** which violates the constraints find a clean instance I' so that I' fulfills **Σ**

- This would allow us to take any I'
  - E.g., empty for FD constraints
- We do not want to loose the information in I (unless we have to)
- Let us come back to that later

2.1 Constraint based Cleaning Overview

- Study 1) + 2) for FDs

- Given database D
  - **1)** Detect violations of constraints
    - We already saw example of how this can be done using queries. Here a bit more formal
  - **2)** Fix violations
    - In most cases there are many different ways to fix the violation by modifying the database (called **solution**)
      - What operations do we allow: insert, delete, update
      - How do we choose between alternative solutions

2.1 Example Constraints

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Example: Constraints

SSN	zip	city	name
333-333-3333	60616	New York	Peter
333-333-9999	60615	Chicago	Gert
333-333-5599	60615	Schaumburg	Gertrud
333-333-6666	60616	Chicago	Hans
333-355-4343	60616	Chicago	Malcom

$\mathbf{FD_1}$: `zip -> city`

2.1 Example Constraints

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Example: Constraint Violations

SSN	zip	city	name
333-333-3333	60616	New York	Peter
333-333-9999	60615	Chicago	Gert
333-333-5599	60615	Schaumburg	Gertrud
333-333-6666	60616	Chicago	Hans
333-355-4343	60616	Chicago	Malcom

FD$_1$: `zip -> city`

2.1 Example Constraints

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Example: Constraint Violations

SSN	zip	city	name
333-333-3333	60616	New York	Peter
333-333-9999	60615	Chicago	Gert
333-333-5599	60615	Schaumburg	Gertrud
333-333-6666	60616	Chicago	Hans
333-355-4343	60616	Chicago	Malcom

How to repair?

Deletion:
- remove some conflicting tuples
- quite destructive

Update:
- modify values to resolve the conflict
- equate RHS values (city here)
- disequate LHS value (zip)

2.1 Constraint based Cleaning Overview

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- How to repair?
- **Deletion:**
  - remove some conflicting tuples
  - quite destructive
- **Update:**
  - modify values to resolve the conflict
  - equate RHS values (city here)
  - disequate LHS value (zip)
- **Insertion?**
  - Not for FDs, but e.g., FKs

2.1 Example Constraints

Example: Constraint Repair

SSN	zip	city	name
333-333-3333	60616	New York	Peter
333-333-9999	60615	Chicago	Gert
333-333-5599	60615	Schaumburg	Gertrud
333-333-6666	60616	Chicago	Hans
333-355-4343	60616	Chicago	Malcom

Deletion:

Delete Chicago or Schaumburg?

Delete New York or the two Chicago tuples?
- one tuple deleted vs. two tuples deleted

2.1 Example Constraints

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Example: Constraint Repair

SSN	zip	city	name
333-333-3333	60616	New York	Peter
333-333-9999	60615	Chicago	Gert
333-333-5599	60615	Schaumburg	Gertrud
333-333-6666	60616	Chicago	Hans
333-355-4343	60616	Chicago	Malcom

Update equate RHS:

Update Chicago->Schaumburg or Schaumburg->Chicago

Update New York->Chicago or Chicago->New York
- one tuple deleted vs. two cells updated

Update disequate LHS:

Which tuple to update?
What value do we use here? How to avoid creating other conflicts?

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- **Principle of minimality**
  - Choose repair that minimally modifies database
  - Motivation: consider the solution that deletes every tuple

- Most update approaches **equate RHS** because there is usually no good way to choose LHS values unless we have **master data**
  - **E.g., update zip to 56423 or 52456 or 22322 …**

2.1 Detecting Violations

- Given FD A -> B on R(A,B)
  - Recall logical representation
  - Forall X, X’: R(X,Y) and R(X’,Y’) and X=X’ -> Y=Y’
  - Only violated if we find two tuples where A=A’, but B != B’
  - In datalog
    - Q(): R(X,Y), R(X’,Y’), X=X’, Y!=Y’
  - In SQL

```
SELECT EXISTS (SELECT *
               FROM R x, R y
                WHERE x.A=y.A AND x.B<>y.B)
```

2.1 Example Constraints

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Example: SQL Violation Detection

Relation: Person(name,city,zip)

FD1: zip -> city

Violation Detection Query

```
SELECT EXISTS (SELECT *
               FROM Person x, Person y
               WHERE x.zip = y.zip
                     AND x.city <> y.city)
```

To know which tuples caused the conflict:

```
SELECT *
FROM Person x, Person y
WHERE x.zip = y.zip
      AND x.city <> y.city)
```

2.1 Fixing Violations

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- Principle of minimality
  - Choose solution that minimally modifies the database
  - Updates:
    - Need a cost model
  - Deletes:
    - Minimal number of deletes

2.1 Constraint Repair Problem

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Definition: Constraint Repair Problem (restated)

Given set of constraints **Σ** and a database instance **I** which violates the constraints find a clean instance I' (does not violate the constraints) with cost(I,I') being minimal

- Cost metrics that have been used
  - **Deletion + Insertion**

$$\Delta(I, I') = (I - I') \cup (I' - I)$$

    - S-repair: minimize measure above under set inclusion
    - C-repair: minimize cardinality
  - **Update**
    - Assume distance metric d for attribute values

2.1 Cost Metrics

- **Deletion + Insertion**

$$\Delta(I, I') = (I - I') \cup (I' - I)$$

  - **S-repair**: minimize measure above under set inclusion
  - **C-repair**: minimize cardinality
- **Update**
  - Assume single relation R with uniquely identified tuples
  - Assume distance metric **d** for attribute values
  - **Schema(R)** = attributes in schema of relation **R**
  - **t'** is updated version of tuple **t**
  - Minimize:

$$\sum_{t \in R} \sum_{A \in Schema(R)} d(t.A, t'.A)$$

2.1 Cost Metrics

- **Update**
  - Assume single relation R with uniquely identified tuples
  - Assume distance metric **d** for attribute values
  - **Schema(R)** = attributes in schema of relation **R**
  - **t'** is updated version of tuple **t**
  - Minimize: $$\sum_{t \in R} \sum_{A \in Schema(R)} d(t.A, t'.A)$$
- We focus on this one
- This is NP-hard
  - Heuristic algorithm

2.1 Naïve FD Repair Algorithm

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- **FD Repair Algorithm: 1. Attempt**
  - For each FD **X -> Y** in **Σ** run query to find pairs of tuples that violate the constraint
  - For each pair of tuples **t** and **t'** that violate the constraint
    - update **t.Y** to **t'.Y**
      - choice does not matter because cost is symmetric, right?

2.1 Constraint Repair

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Example: Constraint Repair

	SSN	zip	city	name
t_1	333-333-3333	60616	New York	Peter
t_2	333-333-9999	60615	Chicago	Gert
t_3	333-333-5599	60615	Schaumburg	Gertrud
t_4	333-333-6666	60616	Chicago	Hans
t_5	333-355-4343	60616	Chicago	Malcom

t_1 and t_4: set t_1.city = Chicago
t_1 and t_5: set t_1.city = Chicago
t_2 and t_3: set t_2.city = Schaumburg

2.1 Problems with the Algorithm

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- **FD Repair Algorithm: 1. Attempt**
  - For each FD **X -> Y** in **Σ** run query to find pairs of tuples that violate the constraint
  - For each pair of tuples **t** and **t'** that violate the constraint: t.X = t'.X and t.Y != t'.Y
    - update **t.Y** to **t'.Y**
      - ~~choice does not matter because cost is symmetric, right?~~
  - **Our updates may cause new violations!**

Example: Constraint Repair

	SSN	zip	city	name
t_1	333-333-3333	60616	New York	Peter
t_2	333-333-9999	60615	Chicago	Gert
t_3	333-333-5599	60615	Schaumburg	Gertrud
t_4	333-333-6666	60616	Chicago	Hans
t_5	333-355-4343	60616	Chicago	Malcom

t_4 and t_1: set t_4.city = New York
t_1 and t_5: set t_1.city = Chicago
t_2 and t_3: set t_2.city = Schaumburg

Now t_1 and t_4 and t_4 and t_5 in violation!

2.1 Problems with the Algorithm

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- **FD Repair Algorithm: 2. Attempt**
  - I' = I
  - 1) For each FD **X -> Y** in **Σ** run query to find pairs of tuples that violate the constraint
  - 2) For each pair of tuples **t** and **t'** that violate the constraint: t.X = t'.X and t.Y != t'.Y
    - update **t.Y** to **t'.Y**
      - ~~choice does not matter because cost is symmetric, right?~~
  - 3) If we changed I' goto 1)

- **FD Repair Algorithm: 2. Attempt**
  - I' = I
  - 1) For each FD **X -> Y** in **Σ** run query to find pairs of tuples that violate the constraint
  - 2) For each pair of tuples **t** and **t'** that violate the constraint: t.X = t'.X and t.Y != t'.Y
    - update **t.Y** to **t'.Y**
      - ~~choice does not matter because cost is symmetric, right?~~
  - 3) If we changed I' goto 1)
    - **May never terminate**

Example: Constraint Repair

	SSN	zip	city	name
t_1	333-333-3333	60616	New York	Peter
t_2	333-333-9999	60615	Chicago	Gert
t_3	333-333-5599	60615	Schaumburg	Gertrud
t_4	333-333-6666	60616	Chicago	Hans
t_5	333-355-4343	60616	Chicago	Malcom

t_4 and t_1: set t_4.city = New York
t_1 and t_5: set t_1.city = Chicago

Now t_1 and t_4 and t_4 and t_5 in violation!

t_4 and t_1: set t_1.city = New York
T_5 and t_4: set t_4.city = Chicago

repeat

2.1 Problems with the Algorithm

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- **FD Repair Algorithm: 2. Attempt**
  - **Even if we succeed the repair may not be minimal. There may be many tuples with the same X values**
    - **They all have to have the same Y value**
    - **Choice which to update matters!**

Example: Constraint Repair

	SSN	zip	city	name
t_1	333-333-3333	60616	New York	Peter
t_2	333-333-9999	60615	Chicago	Gert
t_3	333-333-5599	60615	Schaumburg	Gertrud
t_4	333-333-6666	60616	Chicago	Hans
t_5	333-355-4343	60616	Chicago	Malcom

Cheaper: `t`$_1$`.city = Chicago`

Not so cheap: `set t`$_4$`.city and t`$_5$`.city = New York`

2.1 Problems with the Algorithm

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- **FD Repair Algorithm: 3. Attempt**
  - Equivalence Classes
    - Keep track of sets of cells (tuple,attribute) that have to have the same values in the end (e.g., all Y attribute values for tuples with same X attribute value)
    - These classes are updated when we make a choice
    - Choose Y value for equivalence class using minimality, e.g., most common value
  - Observation
    - Equivalence Classes may merge, but never split if we only update RHS of all tuples with same X at once
    - -> we can find an algorithm that terminates

- **FD Repair Algorithm: 3. Attempt**
  - **Initialize**:
    - Each cell in its own equivalence class
    - Put all cells in collection **unresolved**
  - While **unresolved** is not empty
    - Remove tuple t from unresolved
    - Pick FD X->Y (e.g., random)
    - Compute set of tuples S that have same value in X
    - Merge all equivalence classes for all tuples in S and attributes in Y
    - Pick values for Y (update all tuples in S to Y)

2.1 Problems with the Algorithm

- **FD Repair Algorithm: 3. Attempt**
- Algorithm using this idea:
  - More heuristics to improve quality and performance
    - Cost-based pick of next EQ's to merge
  - Also for FKs (Inclusion Constraints)

A Cost-Based Model and Effective Heuristic for Repairing Constraints by Value Modification

2.1 Consistent Query Answering

- As an alternative to fixing the database which requires making a choice we could also leave it dirty and try to resolve conflicts at query time
  - Have to reason over answers to the query without knowing which of the possible repairs will be chosen
  - **Intuition**: return tuples that would be in the query result for **every** possible repair

2.1 Constraint Repair

Example: Constraint Repair

	SSN	zip	city	name
t_1	333-333-3333	60616	New York	Peter
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t_4	333-333-6666	60616	Chicago	Hans
t_5	333-355-4343	60616	Chicago	Malcom

Cheaper: t_1.city = Chicago

Not so cheap: set t_4.city and t_5.city = New York

2. Overview

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- Topics covered in this part
  - Causes of Dirty Data
  - Constraint-based Cleaning
  - **Outlier-based and Statistical Methods**
  - Entity Resolution
  - Data Fusion

2.2 Statistical and Outlier

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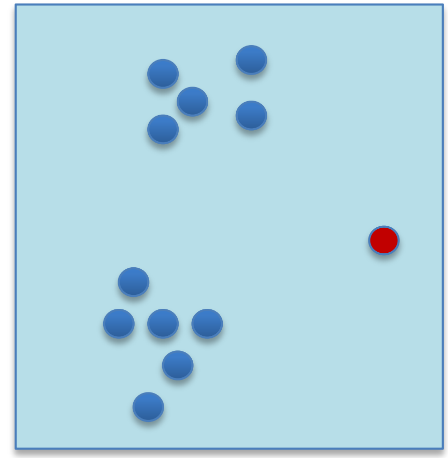

- Assumption
  - Errors can be identified as outliers
- How do we find outliers?
  - **Similarity-based**:
    - Object is dissimilar to all (many) other objects
    - E.g., clustering, objects not in cluster are outliers
  - **Some type of statistical test**:
    - Given a distribution (e.g., fitted to the data)
    - How probable is it that the point has this value?
    - If low probability -> outlier

2. Overview

- Topics covered in this part
  - Causes of Dirty Data
  - Constraint-based Cleaning
  - Outlier-based and Statistical Methods
  - **Entity Resolution**
  - Data Fusion

2.3 Entity Resolution

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- Entity Resolution (ER)
- Alternative names
  - Duplicate detection
  - Record linkage
  - Reference reconciliation
  - Entity matching
  - …

2.3 Entity Resolution

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Definition: Entity Resolution Problem

Given sets of tuples **A** compute equivalence relation **E(t,t')** which denotes that tuple **t** and **t'** represent the same entity.

- Intuitively, E should be based on how similar t and t' are
  - Similarity measure?
- E should be an equivalence relation
  - If **t** is the same as **t'** and **t'** is the same as **t''** then **t** should be the same as **t''**

2.3 Entity Resolution

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Example: Two tuples (objects) that represent the same entity

SSN	zip	city	name
333-333-3333	60616	Chicago	Peter

SSN	zip	city	name
3333333333	IL 60616		Petre

2.3 Entity Resolution

- Similarity based on similarity of attribute values
  - Which distance measure is appropriate?
  - How do we combine attribute-level distances?
  - Do we consider additional information?
    - **E.g., foreign key connections**
  - How similar should duplicates be?
    - **E.g., fixed similarity threshold**
  - How to guarantee transitivity of E
    - **E.g., do this afterwards**

2.3 Entity Resolution

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Example: Per attribute similarity

SSN	zip	city	name
333-333-3333	60616	Chicago	Peter

1 ↕ 0.8 ↕ 0? ↕ 0.6 ↕

SSN	zip	city	name
3333333333	IL 60616		Petre

2.3 Entity Resolution – Distance Measures

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- **Edit-distance**
  - measures similarity of two strings
  - **d(s,s')** = minimal number of insert, replace, delete operations (single character) that transform s into s'
  - Is symmetric (actually a metric)
    - Why?

2.3 Entity Resolution

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Definition: Edit Distance

Given two strings s, s’ we define the edit distance d(s,s’) as the minimum number of single character insert, replacements, deletions that transforms s into s’

Example:

```
NEED -> STREET

Trivial solution: delete all chars in NEED, then
insert all chars in STREET

- gives upper bound on distance len(NEED) +
       len(STREET) = 10
```

2.3 Entity Resolution

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Example:

```
NEED -> STREET

Minimal solution:
        - insert S
        - insert T
        - replace N with R
        - replace D with T

d(NEED,STREET) = 4
```

- **Principal of optimality**
  - Best solution of a subproblem is part of the best solution for the whole problem

- **Dynamic programming algorithm**
  - D(i,j) is the edit distance between prefix of len i of s and prefix of len j of s’
  - D(len(s),len(s’)) is the solution
  - Represented as matrix
  - Populate based on rules shown on the next slide

- **Recursive definition**
  - $D(i,0) = i$
    - Cheapest way of transforming prefix s[i] into empty string is by deleting all i characters in s[i]
  - $D(0,j) = j$
    - Same holds for s'[j]
  - $D(i,j) = \min \{$
    - $D(i-1,j) + 1$
    - $D(i,j-1) + 1$
    - $D(i-1,j-1) + d(i,j)$ with $d(i,j) = 1$ if s[i] != s[j] and 0 else

    $\}$

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Example:

NEED -> STREET

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1						
E	2						
E	3						
D	4						

2.3 Entity Resolution

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Example:

`NEED -> STREET`

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1					
E	2						
E	3						
D	4						

2.3 Entity Resolution

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Example:

NEED -> STREET

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2				
E	2	2					
E	3						
D	4						

2.3 Entity Resolution

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Example:

`NEED -> STREET`

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2	3			
E	2	2	2				
E	3	3					
D	4						

Example:

NEED -> STREET

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2	3	4		
E	2	2	2	3			
E	3	3	3				
D	4	4					

2.3 Entity Resolution

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Example:

NEED -> STREET

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2	3	4	5	
E	2	2	2	3	3		
E	3	3	3	3			
D	4	4	4				

2.3 Entity Resolution

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Example:

`NEED -> STREET`

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2	3	4	5	6
E	2	2	2	3	3	4	
E	3	3	3	3	3		
D	4	4	4	4			

2.3 Entity Resolution

Example:

`NEED -> STREET`

		S	T	R	E	E	T
	0	1	2	3	4	5	6
N	1	1	2	3	4	5	6
E	2	2	2	3	3	4	5
E	3	3	3	3	3	3	4
D	4	4	4	4	4	4	4

2.3 Entity Resolution – Distance Measures

- Other sequence-based measures for string similarity
  - **Needleman-Wunsch**
    - Missing character sequences can be penalized differently from character changes
  - **Affine Gap Measure**
    - Limit influence of longer gaps
    - **E.g., Peter Friedrich Mueller vs. Peter Mueller**
  - **Smith-Waterman Measure**
    - More resistant to reordering of elements in the string
    - **E.g., Prof. Franz Mueller vs. F. Mueller, Prof.**

2.3 Entity Resolution – Distance Measures

- Other sequence-based measures for string similarity
  - **Jaro-Winkler**
    - Consider shared prefixes
    - Consider distance of same characters in strings
    - **E.g., johann vs. ojhann vs. ohannj**
  - **See textbook for details!**

2.3 Entity Resolution – Distance Measures

- **Token-set based measures**
  - Split string into tokens
    - E.g., single characters
    - E.g., words if string represents a longer text
  - Potentially normalize tokens
    - **E.g., word tokens replace word with its stem**
      - **Generating, generated, generates are all replaced with generate**
  - Represent string as set (multi-set) of tokens

Example: Tokenization

Input string:

```
S = "the tokenization of strings is commonly used in
information retrieval"
```

Set of tokens:

```
Tok(S) = {commonly, in, information, is, of,
          retrieval, strings, the, tokenization, used}
```

Bag of tokens:

```
Tok(S) = {commonly:1, in:1, information:1, is:1,
         of:1, retrieval:1,strings:1, the:1,
         tokenization:1, used:1}
```

- **Jaccard-Measure**
  - **B_s** = **Tok(s)** = token set of string **s**
  - Jaccard measures relative overlap of tokens in two strings
    - Number of common tokens divided by total number of tokens

$$d_{jacc}(s, s') = \frac{\|B_s \cap B_{s'}\|}{\|B_s \cup B_{s'}\|}$$

2.3 Entity Resolution

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Example: Tokenization

```
Input string:
S = "nanotubes are used in these experiments to…"
S'= "we consider nanotubes in our experiments…"
S''= "we prove that P=NP, thus solving …"

Tok(S)   = {are,experiments,in,nanotubes,these,to,used}
Tok(S')  = {consider,experiments,in,nanotubes,our,we}
Tok(S'')= {P=NP,prove,solving,that,thus,we}
```

$d_{jacc}(S,S')=$

$d_{jacc}(S,S'')=$

$d_{jacc}(S',S'')=$

2.3 Entity Resolution

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Example: Tokenization

```
Input string:
S = "nanotubes are used in these experiments to…"
S'= "we consider nanotubes in our experiments…"
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Tok(S)   = {are,experiments,in,nanotubes,these,to,used}
Tok(S') = {consider,experiments,in,nanotubes,our,we}
Tok(S'')= {P=NP,prove,solving,that,thus,we}
```

$d_{jacc}(S,S') = 3 / 10 = 0.3$

$d_{jacc}(S,S'') = 0 / 13 = 0$

$d_{jacc}(S',S'') = 1 / 11 = 0.0909$

- **Other set-based measures**
  - **TF/IDF**: term frequency, inverse document frequency
    - Take into account that certain tokens are more common than others
    - If two strings (called documents for TF/IDF) overlap on uncommon terms they are more likely to be similar than if they overlap on common terms
      - **E.g., the vs. carbon nanotube structure**

2.3 Entity Resolution

- **TF/IDF**: term frequency, inverse document frequency
  - Represent documents as feature vectors
    - One dimension for each term
    - Value computed as frequency times IDF
      - Inverse of frequency of term in the set of all documents
  - Compute cosine similarity between two feature vectors
    - Measure how similar they are in term distribution (weighted by how uncommon terms are)
    - Size of the documents does not matter
  - **See textbook for details**

2.3 Entity Resolution

- **Entity resolution**
  - Concatenate attribute values of tuples and use string similarity measure
    - Loose information encoded by tuple structure
    - **E.g., [Gender:male,Salary:9000]**
      -> "Gender:male,Salary:9000"
      or -> "male,9000"
  - Combine distance measures for single attributes
    - Weighted sum or more complex combinations
      - E.g., $d(t, t') = w_1 \times d_A(t.A, t'.A) + w_2 \times d_B(t.B, t'.B)$
  - Use quadratic distance measure
    - E.g., earth-movers distance

2.3 Entity Resolution

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- **Entity resolution**
  - Rule-based approach
    - Set of **if this than that** rules
  - Learning-based approaches
  - Clustering-based approaches
  - Probabilistic approaches to matching
  - Collective matching

- **Weighted linear combination**
  - Say tuples have **n** attributes
  - $\mathbf{w_i}$: predetermined weight of an attribute
  - $\mathbf{d_i(t,t')}$: similarity measure for the $\mathbf{i^{th}}$ attribute

$$d(t,t') = \sum_{i=0}^{n} w_i \times d_i(t,t')$$

- Tuples match if $\mathbf{d(t,t') > \beta}$ for a threshold $\boldsymbol{\beta}$

Example: Weighted sum of attribute similarities

SSN	zip	city	name
333-333-3333	60616	Chicago	Peter

1 0.8 0? 0.6

SSN	zip	city	name
3333333333	IL 60616		Petre

Assumption: SSNs and names are most important, city and zip are not very predictive

$$w_{SSN} = 0.4, w_{zip} = 0.05, w_{city} = 0.15, w_{name} = 0.4$$

$$\begin{aligned} d(t,t') &= 0.4 \times 1 + 0.05 \times 0.8 + 0.15 \times 0 + 0.4 \times 0.6 \\ &= 0.4 + 0.04 + 0 + 0.24 \\ &= 0.68 \end{aligned}$$

- **Weighted linear combination**
  - How to determine weights?
    - **E.g., have labeled training data and use ML to learn weights**
  - Use non-linear function?

2.3 Entity Resolution

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- **Entity resolution**
  - **Rule-based approach**
  - Learning-based approaches
  - Clustering-based approaches
  - Probabilistic approaches to matching
  - Collective matching

2.3 Entity Resolution

- **Rule-based approach**
  - Collection (list) of rules
  - **if** $d_{name}(t,t') < 0.6$ **then** unmatched
  - **if** $d_{zip}(t,t') = 1$ **and** t.country = USA **then** matched
  - **if** t.country != t'.country **then** unmatched
- **Advantages**
  - Easy to start, can be incrementally improved
- **Disadvantages**
  - Lot of manual work, large rule-bases hard to understand

2.3 Entity Resolution

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- **Entity resolution**
  - Rule-based approach
  - **Learning-based approaches**
  - Clustering-based approaches
  - Probabilistic approaches to matching
  - Collective matching

- **Learning-based approach**
  - Build all pairs (t,t') for training dataset
  - Represent each pair as feature vector from, e.g., similarities
  - Train classifier to return {match,no match}
- **Advantages**
  - automated
- **Disadvantages**
  - Requires training data

- **Entity resolution**
  - Rule-based approach
  - Learning-based approaches
  - **Clustering-based approaches**
  - Probabilistic approaches to matching
  - Collective matching

- **Clustering-based approach**
  - Apply clustering method to group inputs
  - Typically hierarchical clustering method
  - Clusters now represent entities
    - Decide how to merge based on similarity between clusters
- **Advantages**
  - Automated, no training data required
- **Disadvantages**
  - Choice of cluster similarity critical

2.3 Entity Resolution

- **Entity resolution**
  - Rule-based approach
  - Learning-based approaches
  - Clustering-based approaches
  - **Probabilistic approaches to matching**
  - **Collective matching**
    - **See text book**

2. Overview

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- Topics covered in this part
  – Causes of Dirty Data
  – Constraint-based Cleaning
  – Outlier-based and Statistical Methods
  – Entity Resolution
  – **Data Fusion**

2.4 Data Fusion

- Data Fusion = how to combine (possibly conflicting) information from multiple objects representing the same entity
  - Choose among conflicting values
    - If one value is missing (NULL) choose the other one
    - Numerical data: e.g., median, average
    - Consider sources: have more trust in certain data sources
    - Consider value frequency: take most frequent value
    - Timeliness: latest value

Outline

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0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) **Schema matching and mapping**
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance