## Data Bases Data Mining

Fondements des Bases de Données: des Dépendances Fonctionnelles aux Formes Normales

Équipe pédagogique $B D$

http://liris.cnrs.fr/ecoquery/dokuwiki/doku.php?id=enseignement:
dbdm:start
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## Exemple

Let $\mathcal{U}=\{$ id, name, address, cnum, desc, grade $\}$ a set of attributes to model students and courses. Whe consider the following database schemas:

- $R 1=\{$ Data $\}$ with schema $($ Data $)=\mathcal{U}^{1}$.
- $R 2=\{$ Student, Course, Enrollment $\}$ avec
- schema(Student) $=\{$ id, name, address $\}$
- schema(Course) $=\{$ cnum, desc $\}$
- schema(Enrollment) $=\{$ id, cnum, grade $\}$


## How to compare these schemas?

- Which one is the "best"?
- Why?


## Exemple

| Data | id | name | address | cnum | desc | grade |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 124 | Jean | Paris | F234 | Philo I | A |
|  | 456 | Emma | Lyon | F234 | Philo I | B |
|  | 789 | Paul | Marseille | M321 | Analyse I | C |
| 124 | Jean | Paris | M321 | Analyse I | A |  |
|  | 789 | Paul | Marseille | CS24 | BD I | B |

Is there any problem here?

## Exemple

| Data | id | name | address | cnum | desc | grade |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 124 | Jean | Paris | F234 | Philo I | A |
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|  | 789 | Paul | Marseille | M321 | Analyse I | C |
| 124 | Jean | Paris | M321 | Analyse I | A |  |
|  | 789 | Paul | Marseille | CS24 | BD I | B |

Is there any problem here?
Redundancies!

## Redundancies

| Data | id | name | address | cnum | desc | grade |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 124 | Jean | Paris | F234 | Philo I | A |  |
| 456 | Emma | Lyon | F234 | Philo I | B |  |
| 789 | Paul | Marseille | M321 | Analyse I | C |  |
| 124 | Jean | Paris | M321 | Analyse I | A |  |
| 789 | Paul | Marseille | CS24 | BD I | B |  |

Intuition on functional dependencies

- A student' id gives her/his name and address, so for each new enrollment, his/her name and address are duplicated!
- $\pi_{i d, \text { name,address }}$ (Data) is the graph of a (partial) function $f:$ id $\rightarrow$ name $\times$ address, similarly for $\pi_{\text {cnum, desc }}$ (Data)
- $R 2=\{$ Student, Course, Enrollment $\}$ is better than $R 1=\{$ Data $\}$ because it avoids redundancies by keeping unrelated information (e.g., a student's name and a course' description) unrelated...

Functional is a theoretical tool to capture and reason on this phenomenon.

Functional Dependencies
Inference

Closure algorithm

Normalization

## Functional dependencies: definition

## Syntax

A Functional Dependency (FD) over a relation schema $R$ is a formal expression of the form ${ }^{2}$, with $X, Y \subseteq R$ :

$$
R: X \rightarrow Y
$$

- $X \rightarrow Y$ is read " $X$ functionally determines $Y$ " or " $X$ gives $Y$ "
- A FD $X \rightarrow Y$ is trivial when $Y \subseteq X$
- A FD is standard when $X \neq \emptyset$.
- A set of attributes $X$ is a key when $R: X \rightarrow R$


## Semantics

Let $r$ be a relation (a.k.a. instance) over $R$. The FD $R: X \rightarrow Y$ is satisfied by $r$, written $r \vDash R: X \rightarrow Y$, iff

$$
\forall t_{1}, t_{2} \in r \cdot t_{1}[X]=t_{2}[X] \Rightarrow t_{1}[Y]=t_{2}[Y]
$$

What constraint is implied by a non-standard FD? Why a trivial FD is said to be trivial ?

## Example

| $r$ | $\mathbf{A}$ | $\mathbf{B}$ | $\mathbf{C}$ | $\mathbf{D}$ |
| :---: | :---: | :---: | :---: | :---: |
| $t_{1}$ | $a_{1}$ | $b_{1}$ | $c_{1}$ | $d_{1}$ |
| $t_{2}$ | $a_{1}$ | $b_{1}$ | $c_{1}$ | $d_{2}$ |
| $t_{3}$ | $a_{1}$ | $b_{2}$ | $c_{2}$ | $d_{3}$ |
| $t_{4}$ | $a_{2}$ | $b_{2}$ | $c_{3}$ | $d_{4}$ |

- $r \models A B \rightarrow C$ (no counter-example)
- $r \vDash D \rightarrow A B C D$ (no counter-example)
- $r \not \models A B \rightarrow D$ (e.g., $t_{1}[A B]=t_{2}[A B]$ but $\left.t_{1}[D] \neq t_{2}[D]\right)$
- $r \not \models A \rightarrow C\left(\right.$ e.g., $t_{2}[A]=t_{3}[A]$ but $\left.t_{2}[C] \neq t_{3}[C]\right)$


# Functional Dependencies 

Inference

Closure algorithm

Normalization

## Logical implication

## Definition

Let $F$ be a set of FDs on a relation schema $R$ and let $f$ be a single FD on $R$. We overload $\models$ for a set of FDs:

$$
r \models F \text { iff } \forall f \in F . r \models f
$$

$F$ logical (semantically) implies $f$, written

$$
F \models f \text { iff } \forall r . r \models F \Rightarrow r \models f
$$

Example
With $F=\{A \rightarrow B C D, B C \rightarrow E\}$ and $r \models F$, the following hold as well:

- $r \vDash A \rightarrow C D$
- $r \models A \rightarrow E$

It can be proved using the definition of $\models$ and basic reasoning on projection of tuples.

## Armstrong's System for FD

Armstrong's System
The following rules constitute the so call Armstrong's system for FDs:

- Reflexivity

$$
\frac{Y \subseteq X}{X \rightarrow Y}
$$

- Augmentation

$$
\begin{gathered}
X \rightarrow Y \\
W X \rightarrow W Y
\end{gathered}
$$

- Transitivity

$$
\frac{X \rightarrow Y \quad Y \rightarrow Z}{X \rightarrow Z}
$$

## Proof using Armstrong's system

Example
Let $\Sigma=\{A \rightarrow B, B \rightarrow C, C D \rightarrow E\}$ be a set of FDs on $\{A, B, C, D, E\}$. We show that $\Sigma \vdash A D \rightarrow E$

$$
\frac{A \rightarrow B \quad B \rightarrow C}{\frac{A \rightarrow C}{A D \rightarrow C D}} \quad C D \rightarrow E
$$

## Properties

## Soundness and completeness

- The system is sound if $F \vdash f \Rightarrow F \models f$ if there is a proof, the proof is valid
- The system is complete if $F \models f \Rightarrow F \vdash f$ if it's valid, there is a proof

$$
F \models \alpha \Leftrightarrow F \vdash \alpha
$$

## Soundness

Prove for every rule that, if its hypothesis are valid then its conclusion is valid as well.

## Example: la transitivity

Let $r$ be ans instance on $R$ s.t. $r \models X \rightarrow Y$ et $r \models Y \rightarrow Z$. Let $t_{1}, t_{2} \in r$ be two tuples in $r$ s.t. $t_{1}[X]=t_{2}[X]$, we have to show that $t_{1}[Z]=t_{2}[Z]$. Using $r \models X \rightarrow Y$ we deduce that $t_{1}[Y]=t_{2}[Y]$, then using $r \vDash Y \rightarrow Z$ we deduce that $t_{1}[Z]=t_{2}[Z]$. So the transitivity of FDs amounts to the transitivity of equality...

## Additional rules

- Decomposition

$$
\frac{X \rightarrow Y Z}{X \rightarrow Y}
$$

- Composition

$$
\frac{X \rightarrow Y \quad X \rightarrow Z}{X \rightarrow Y Z}
$$

- Pseudo-transitivity

$$
\frac{X \rightarrow Y \quad W Y \rightarrow Z}{W X \rightarrow Z}
$$

This rules are sound and can be (safely) added to Armstrong's system

## Completeness

Preuve formelle
A (formal) proof of $f$ from $\Sigma$ using Armstrong' system written $\Sigma \vdash f$ is a sequence $\left\langle f_{0}, \ldots, f_{n}\right\rangle$ of FDs s.t. $f_{n}=f$ et $\forall i \in[0 . . n]$ :

- either $f_{i} \in \Sigma$;
- or $f_{i}$ is the conclusion of a rule of which all its antecedents $f_{0} \ldots f_{p}$ appear before $f_{i}$ in the sequence.


## Completeness: $\Sigma \models X \rightarrow Y \Rightarrow \Sigma \vdash X \rightarrow Y$

We need a clear distinction between

- the semantic closure of $X: X^{+}=\{A \mid \Sigma \models X \rightarrow A\}$
- the syntactic closure of $X: X^{\star}=\{A \mid \Sigma \vdash X \rightarrow A\}$

Lemma: $\Sigma \vdash X \rightarrow Y \Leftrightarrow Y \subseteq X^{\star}$

## Completeness

$$
\begin{aligned}
& \Sigma \models X \rightarrow Y \Rightarrow \Sigma \vdash X \rightarrow Y \\
\equiv & \Sigma \nvdash X \rightarrow Y \Rightarrow \Sigma \not \models X \rightarrow Y \\
\equiv & \Sigma \nvdash X \rightarrow Y \Rightarrow \exists r .(r \models \Sigma \wedge r \not \models X \rightarrow Y)
\end{aligned}
$$

The crux is to find an instance $r$, with $X^{\star}=X_{1} \ldots X_{n}$ et $Z_{1} \ldots Z_{p}=R \backslash X^{\star}$

| $r$ | $X_{1}$ | $\ldots$ | $X_{n}$ | $Z_{1}$ | $\ldots$ | $Z_{p}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $s$ | $x_{1}$ | $\ldots$ | $x_{n}$ | $z_{1}$ | $\ldots$ | $z_{p}$ |
| $t$ | $x_{1}$ | $\ldots$ | $x_{n}$ | $y_{1}$ | $\ldots$ | $y_{p}$ |

$$
r \models \Sigma \text { but } r \not \models X \rightarrow Y
$$

Functional Dependencies

Inference

Closure algorithm

Normalization

## Inference problem for FDs

Armstrong's system leads to a (inefficient) decision procedure for the inference problem.
Inference problem for FDs

```
Let F be a set of FDs and f a single FD, does F\modelsf hold true?
```

Lemma: $F \models X \rightarrow Y$ iff $Y \subseteq X^{+}$
Thus, if we have an (efficient) algorithm to compute $X^{+}$, we can (efficiently) solve the inference problem:

1. Given $\Sigma$ and $X \rightarrow Y$, compute $X^{+}$w.r.t. $\Sigma$
2. Return $Y \subseteq X^{+}$

## Closure algorithm: $\operatorname{Closure}(\Sigma, X)$

Data: $\Sigma$ a set of FDs, $X$ a set of d'attributes.
Result: $X^{+}$, the closure of $X$ w.r.t. $\Sigma$
$1 \mathrm{Cl}:=X$
2 done $:=$ false
3 while ( $\neg$ done) do
4 done := true
5 forall the $W \rightarrow Z \in \Sigma$ do
6
if $W \subseteq C I \wedge Z \nsubseteq C l$ then
$C l:=C l \cup Z$
done := false
9 return Cl

How many times ${ }^{3}$ do we compute $W \subseteq C l \wedge Z \nsubseteq C l$ w.r.t. $|\Sigma|=n$ ?
${ }^{3}$ at worst, using a bad strategy at line 5 .

## Second algorithm

Data: $\Sigma$ a set of FDs, $X$ a set of d'attributes.
Result: $X^{+}$, the closure of $X$ w.r.t. $\Sigma$
10 for $W \rightarrow Z \in F$ do
$11 \quad$ count $[W \rightarrow Z]:=|W|$
$12 \quad$ for $A \in W$ do
13
$\lfloor\operatorname{list}[A]:=\operatorname{list}[A] \cup W \rightarrow Z$
14 closure $:=X$, update $:=X$
15 while update $\neq \emptyset$ do
16 Choose $A \in$ update
$17 \quad$ update $:=$ update $\backslash\{A\}$
18 for $W \rightarrow Z \in \operatorname{list}[A]$ do
19
20
21
22 $\operatorname{count}[W \rightarrow Z]:=\operatorname{count}[W \rightarrow Z]-1$ if count $[W \rightarrow Z]=0$ then
update $:=$ update $\cup(Z \backslash$ closure $)$
closure $:=$ closure $\cup Z$
23 return closure

## Example : $A E^{+}$

$$
\Sigma=\{A \rightarrow I ; A B \rightarrow E ; B I \rightarrow E ; C D \rightarrow I ; E \rightarrow C\}
$$

Initialization

$$
\begin{array}{ll}
\operatorname{List}[A]=\{A \rightarrow D ; A B \rightarrow E\} & \text { count }[A \rightarrow D]=1 \\
\operatorname{List}[B]=\{A B \rightarrow E ; B I \rightarrow E\} & \text { count }[A B \rightarrow E]=2 \\
\operatorname{List}[C]=\{C D \rightarrow I\} & \text { count }[B I \rightarrow E]=2 \\
\operatorname{List}[D]=\{C D \rightarrow I\} & \operatorname{count}[C D \rightarrow I]=2 \\
\operatorname{List}[E]=\{E \rightarrow C\} & \operatorname{count}[E \rightarrow C]=1 \\
\operatorname{List}[I]=\{B I \rightarrow E\} &
\end{array}
$$

## Cover

Cover of a set of FDs

$$
\begin{gathered}
\text { With } F^{+}=\{f \mid F \models f\}, \text { let } \Sigma \text { et } \Gamma \text { be two sets of FDs, } \\
\Gamma \text { is a cover of } \Sigma \text { iff } \Gamma^{+}=\Sigma^{+}
\end{gathered}
$$

Data: $F$ a set of FDs
Result: $G$ a minimal cover of $F$
$24 G:=\emptyset$
25 for $X \rightarrow Y \in F$ do
$26\left\lfloor G:=G \cup\left\{X \rightarrow X^{+}\right\}\right.$
27 for $X \rightarrow X^{+} \in G$ do
28
29

$$
\text { if } G-\left\{X \rightarrow X^{+}\right\} \vdash X \rightarrow X^{+} \text {then }
$$

$$
L G:=G-\left\{X \rightarrow X^{+}\right\}
$$

30 return G

# Functional Dependencies 

## Inference

## Closure algorithm

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## Application of FD: Normalization

We write $\langle R, \Sigma\rangle$ with $R$ a relation schema and $\Sigma$ a set of FDs on $R$. A set of attribute $X$ is a minimal key of $\langle R, \Sigma\rangle$ iff:

- $X$ is a key of $R$ (i.e., $X \rightarrow R$ holds)
- $X$ is minimal w.r.t. set inclusion: $\forall . X^{\prime} \subsetneq X \Rightarrow X^{\prime} \nrightarrow R$


## Third Normal Form (3NF)

$\langle R, \Sigma\rangle$ is in 3NF iff, for all non-trivial FD $X \rightarrow A$ of $\Sigma^{+}$, one of the following conditions holds:

- $X$ is a key of $R$
- $A$ is a member of at least one minimal key of $R^{4}$


## Boyce-Codd Normal Form (BCNF)

$\langle R, \Sigma\rangle$ is in BCNF iff, for all non-trivial $X \rightarrow A$ of $\Sigma^{+}, X$ is a key of $R$.
Informally, $\langle R, \Sigma\rangle$ is good when $\Sigma$ is nothing but the key!

[^0]
## Example

3NF captures most of redundancies

- $\langle A B C,\{A \rightarrow B, B \rightarrow C\}\rangle$ is not in 3NF
$A$ is the unique minimal key. Considering $B \rightarrow C, C$ is not prime and $B$ is not a key. Clearly, $A B C$ should be divided into $A B$ and $B C$
- $\langle A B C,\{A B \rightarrow C, C \rightarrow B\}\rangle$ is in 3NF

There are two minimal keys: $A B$ and $A C$. Every attribute is prime so the 3NF condition holds. Unfortunately, some redundancies still hold but there is no way to decompose $A B C$ into smaller relation without loss of FD!

## BCNF captures all redundancies (expressed by FD)

- $\langle A B C,\{A B \rightarrow C, C \rightarrow B\}\rangle$ is not in BCNF Considering $C \rightarrow B, C$ alone is not a key.


## Example

## Back to the introductory example

With $\mathcal{U}=\{i d$, name, address, cnum, desc, grade $\}$ :

- the natura ${ }^{5}$ FDs are $f_{1}=i d \rightarrow$ name, address, $f_{2}=$ cnum $\rightarrow$ desc and $f_{3}=i d$, cnum $\rightarrow$ grade.
- The minimal key of $\mathcal{U}$ is $\{i d, c n u m\}$.
- Without refinement, $\mathcal{U}$ is not in 3NF, e.g., $f_{1}$ holds but id is not a key.
- The decomposition of $\mathcal{U}$ into
- $\left\langle\{\right.$ id, name, address $\left.\},\left\{f_{1}\right\}\right\rangle$
- $\left\langle\{\right.$ cnum, desc $\left.\},\left\{f_{2}\right\}\right\rangle$
- $\left\langle\{i d\right.$, cnum, grade $\left.\},\left\{f_{3}\right\}\right\rangle$
is good because the BCNF condition holds for each relation.

[^1]End.


[^0]:    ${ }^{4}$ An attribute that appears in at least one minimal key is said to be a prime attribute.

[^1]:    ${ }^{5}$ Those which hold from the user's perspective, or alternatively, those that are true in the existing dataset.

