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# Multidimensional Contexts for Data Quality Assessment

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## Contexts and Data Quality

A table containing results of different medical tests on patients at a hospital

PatientValue

	<b>Patient</b>	<b>Value</b>	<b>Time</b>
1	Tom Waits	38.5	11:45/5/Sep/2011
2	Tom Waits	38.2	12:10/5/Sep/2011
3	Tom Waits	38.1	11:50/6/Sep/2011
4	Tom Waits	38.0	12:15/7/Sep/2011
5	Tom Waits	110/70	11:45/8/Sep/2011
6	Lou Reed	37.9	12:10/5/Sep/2011

Is this quality data?

If not, is there anything to clean?    What?

We do not know ...    It depends ...

Actually the table is supposed to contain *test results that are taken with instruments of the brand  $B_1$*

Are these quality data?                      We still do not know ...

Questions about the quality of this data make sense in a broader setting

The quality of the data depends on “the context”

A context that allows us to, e.g.:

- make sense of data
- **assess data quality**  
(in this work wrt the **expected/intended meaning** or **sense**)
- in particular, do dimensional data assessment
- support data cleaning

For data quality assessment, an external context can provide the necessary information

The database under assessment is mapped into the context, for further data quality analysis, imposition of quality requirements, and cleaning

## Contexts So Far

We find the term “context” in several places in computer science: databases, semantic web, KR, mobile applications, ...

Usually used for “*context aware* ... search, databases, applications, devices, ...”

Most of the time there is **no explicit notion of context**, but some mechanisms that take into account (or into computation) some contextual notions

Usually, time and geographic location, i.e. particular *dimensions*, but not much beyond

In our opinion, **there is a lack of fundamental research in the area, specially for data management**

## Precise and formalized notions of context are rather absent

Contexts that can be implemented and used in a principled manner in data management systems

Some [existing research](#):

- [Contexts in ontologies and SW](#)

Lately with emphasis on using logic programs to “bridge” implicit contexts

Impact on data management still pending

- [Contexts in KR](#)

They are denoted at the object level and a theory specifies their properties and dynamics

It is possible to talk about things holding in certain (named) contexts

- Contexts in data management

Usually in connection with specific dimensions of data, like time and place

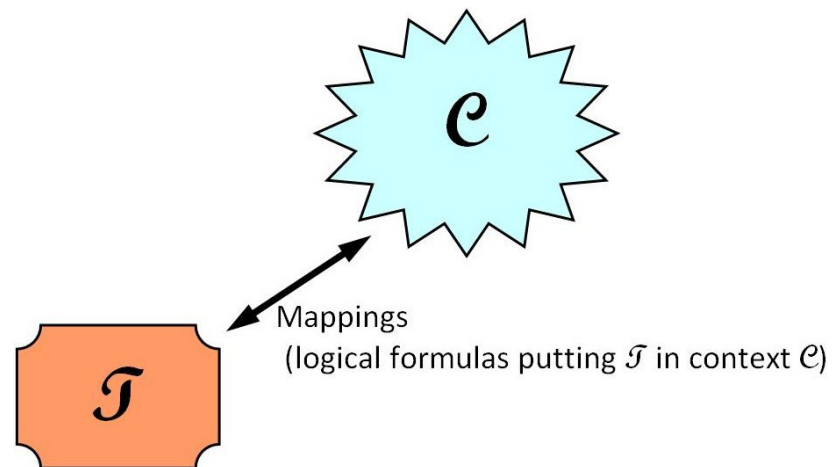
Relevant specific research has been carried out

(Tanca et al., Torlone-Martinenghi, Spyrtos et al., ...)

A unifying framework seems to be missing

A general notion and theory of context have still to be developed

## Contexts: A Vision



- A logical theory  $\mathcal{T}$  is the one that is “put in context”
- The context is another logical theory,  $\mathcal{C}$   
 $\mathcal{T}$  and  $\mathcal{C}$  may share some predicate symbols
- Connection between  $\mathcal{T}$  and  $\mathcal{C}$  is established through **connection predicates and mappings**

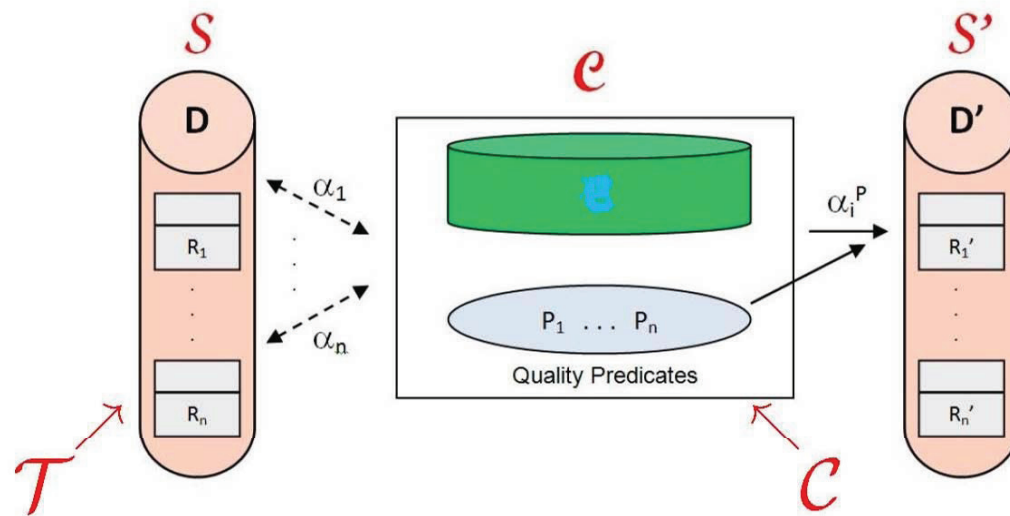
In particular, for applications in data management



## Contexts: Data Quality Assessment

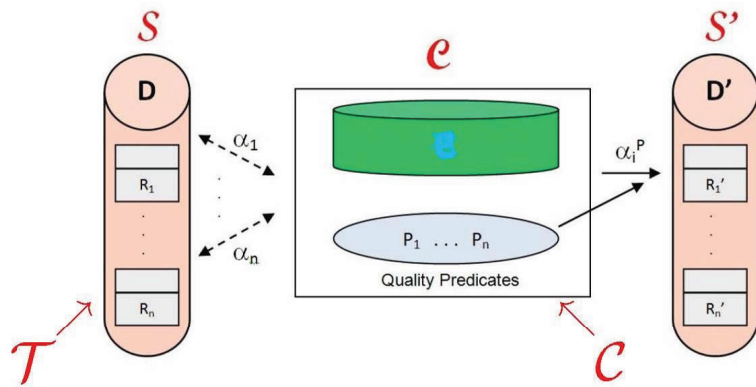
A data quality scenario:

(Bertossi, Rizzolo & Lei; VLDB'10 BIRTE WS, Springer LNBI 48, 2011)



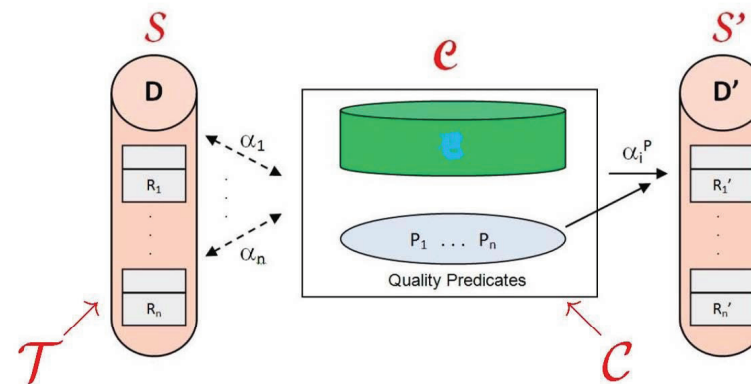
Database  $D$  can be seen as a logical theory, e.g. Reiter's logical reconstruction of a relational DB

Context  $C$  can be a whole ontology: **Ontology-based data quality assessment and cleaning**



- Instance  $D$  under assessment
- Schema  $S'$  a copy of  $S$

- Context  $C$ : virtual/(semi)materialized data integration system
- The  $\alpha_j$ : mappings, as in VDISs or data exchange
- In  $C$ : Contextual predicates/relations  $C_j$ , plus quality predicates  $P_k$
- $D'$  contains “ideal” contents for relations in  $D$ , as views



- Predicates in  $D'$  can be materialized with data from  $D$  and  $C$ , and “logical message” via  $C$  (mapping composition)
- Quality assessment of  $D$ : by comparing its contents with  $D'$

More precisely and generally, given  $D$  and  $C$ , there may be a class  $\mathcal{I}$  of admissible contextual instances for  $C$ 's schema, and correspondingly multiple  $D'$ 's

$D$  has to be compared with the class thereof ...  
(there are some distance measures)

## Example: (revisited)

PatientValue

	Patient	Value	Time
1	Tom Waits	38.5	11:45/5/Sep/2011
2	Tom Waits	38.2	12:10/5/Sep/2011
3	Tom Waits	38.1	11:50/6/Sep/2011
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6	Lou Reed	37.9	12:10/5/Sep/2011

Now a **contextual relation** with data about patients, wards and days

Table expected to contain *test results taken with instruments of brand  $B_1$*

PatientWard

	Patient	Date	Ward
1	Tom Waits	5/Sep/2011	$W_1$
2	Tom Waits	6/Sep/2011	$W_1$
3	Tom Waits	7/Sep/2011	$W_1$
4	Lou Reed	5/Sep/2011	$W_2$

Also a **contextual Hospital Guideline 1**: “*Medical tests in ward  $W_1$  are performed with instruments of brand  $B_1$* ”

A **quality version** of table PatientValue: Map original table into the context, joint with contextual table, select according to guideline, and project: a clean version obtained

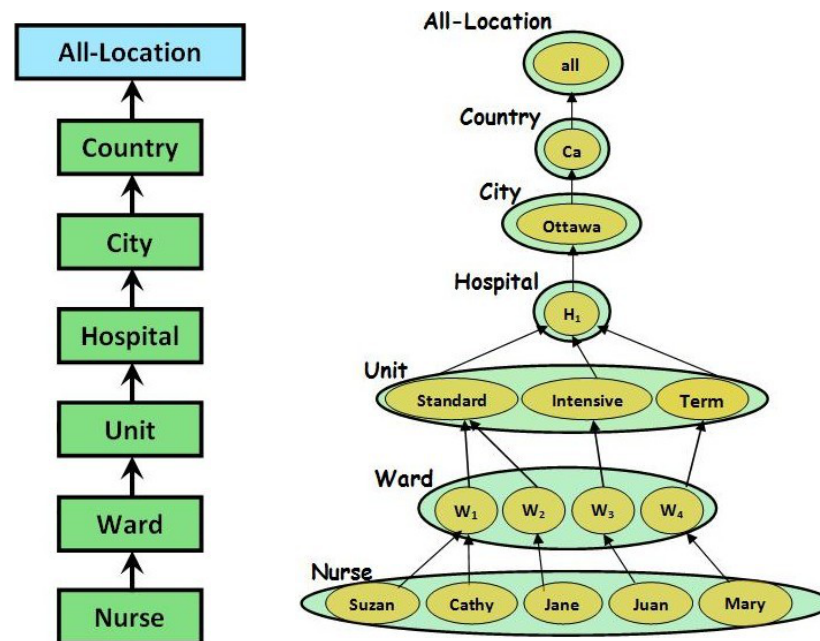
PatientValue'

	Patient	Value	Time
1	Tom Waits	38.5	11:45/5/Sep/2011
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4	Tom Waits	38.0	12:15/7/Sep/2011

## Multidimensional Contexts

Dimensions are naturally and commonly associated to contexts; and are important in data quality assessment

To bring them into contexts, we build upon the **Hurtado-Mendelzon (HM) model of MDDBS**



We embed an HM model into context  $\mathcal{C}$

Later on we care about making the result “ontological” ...

## Example: (revisited)

PatientValue

	Patient	Value	Time
1	Tom Waits	38.5	11:45/5/Sep/2011
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5	Tom Waits	110/70	11:45/8/Sep/2011
6	Lou Reed	37.9	12:10/5/Sep/2011

Now table expected to contain  
*test results taken with instru-  
ments made by manufacturer*  
 $M_1$

Information to make an assessment?

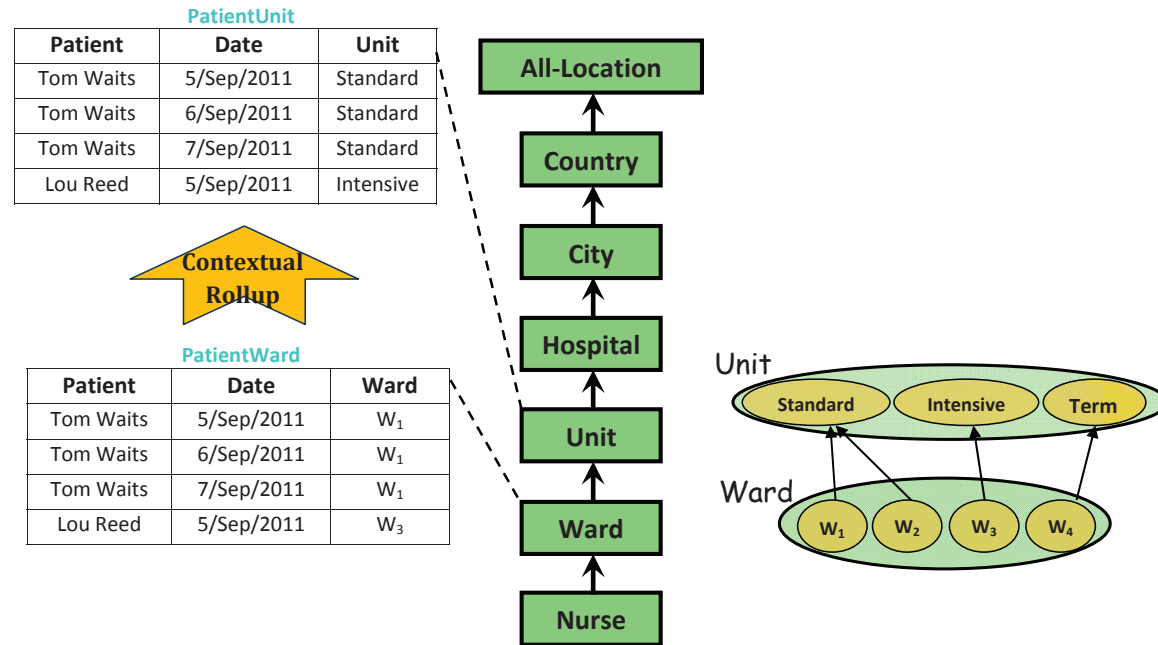
We still have:

PatientWard

	Patient	Date	Ward
1	Tom Waits	5/Sep/2011	W <sub>1</sub>
2	Tom Waits	6/Sep/2011	W <sub>1</sub>
3	Tom Waits	7/Sep/2011	W <sub>1</sub>
4	Lou Reed	5/Sep/2011	W <sub>2</sub>

And a new contextual *Hospital Guideline 2: “Medical tests on patients in standard care unit have to be taken with instruments made by manufacturer  $M_1$ ”*

Plus the **dimensional information** ...



We have data related to *Wards*, not about *Care Units* where we could apply the guideline

We roll-up via *Location* dimension from *Wards* to *Care Units*

We identify wards  $W_1$ ,  $W_2$  as belonging to the *standard CU*

Guideline 2 applies to them, inferring the tests there were taken with instruments made by manufacturer  $M_1$

Contextual roll-up is used to **access/generate missing data** at certain levels, by lattice navigation

Other dimensions can be added

- generating **multidimensional (MD) contextual information**
- for additional and finer-granularity data quality assessment

In this direction, the HM model can be enriched

Going beyond classical applications of the DWH kind ...

**We concentrate mostly on the extension and representation of multidimensional contexts (as opposed to data quality assessment)**

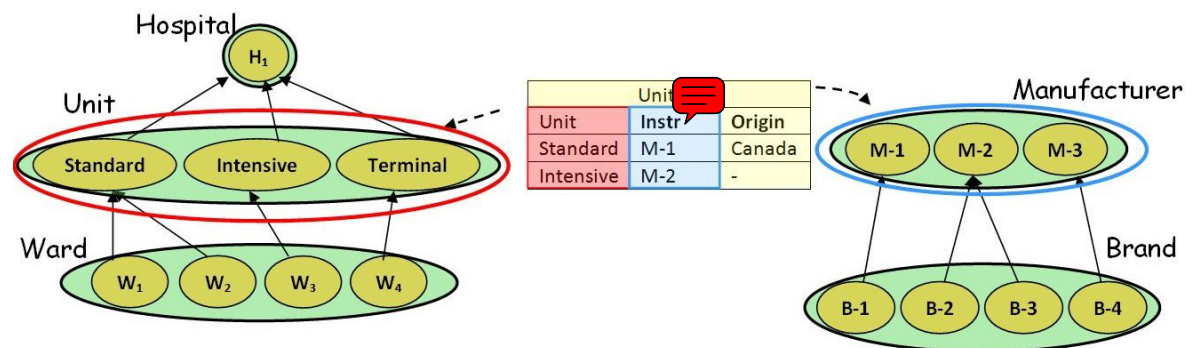


## Extending the HM Model

In the spirit of enriching contexts with multidimensional representations, we extend the HM model

We associate predicates/relations to categories at different levels (or groups thereof) of a hierarchy (or several of them)

### Categorical Relations:

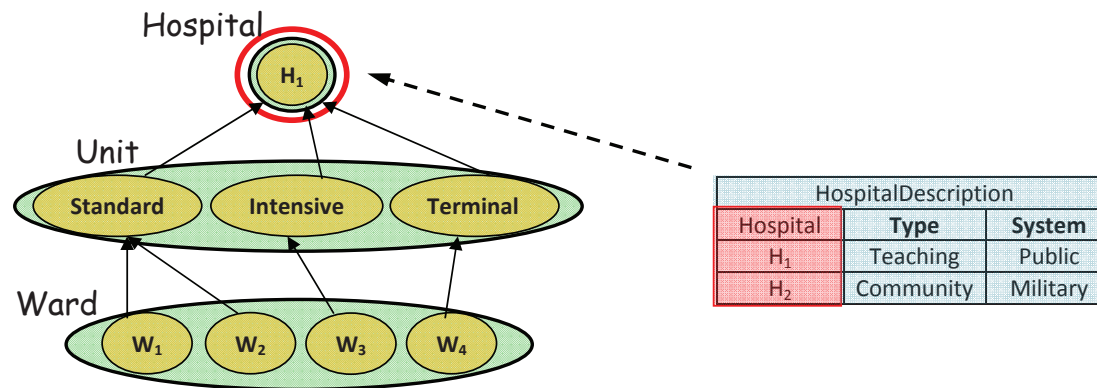


- Some attributes of a **categorical relation** (CR) share the domain with a dimension category
- Possibly several dimensions/categories/levels involved

- Connection between the attribute and its category via a **schema mapping**, e.g.  $\forall u \forall i \forall o (UnitIns(u, i, o) \rightarrow Manufacturer(i))$

### Attributive Relations: (particular case)

- ARs are CRs which are connected to a single category, in a single dimension schema

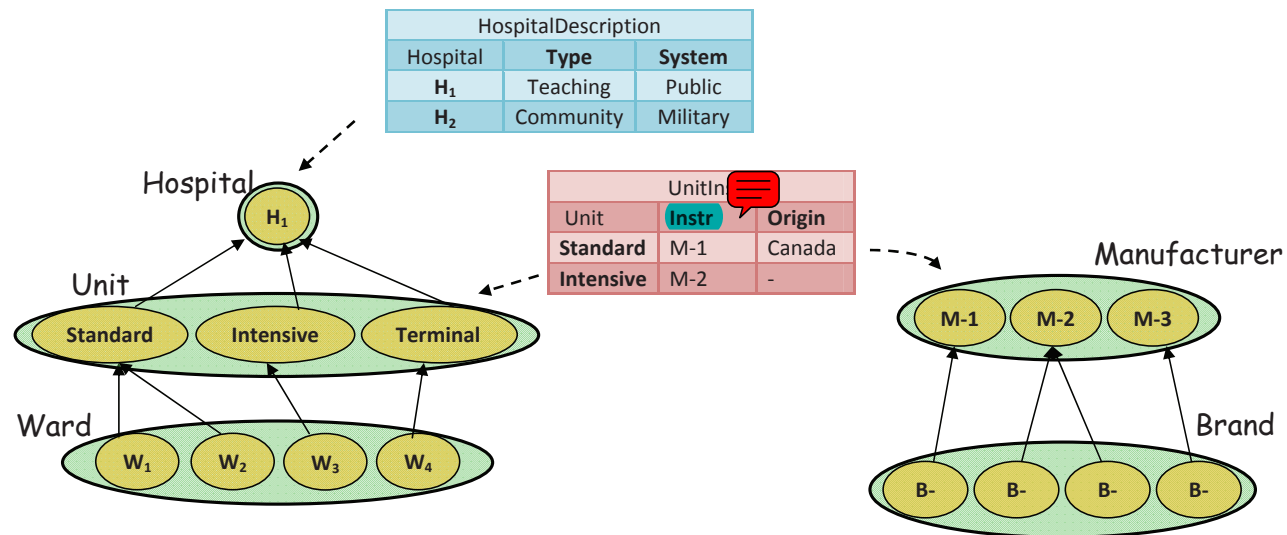


- ARs provide descriptions for elements of a category

- Mappings as before, e.g.

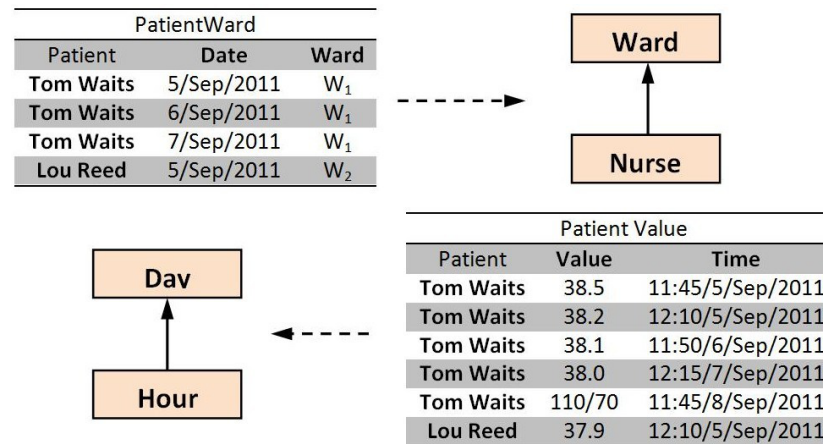
$$\forall h \forall t \forall s (HospitalDescription(h, t, s) \rightarrow Hospital(h))$$

$$\forall h \exists t \exists s (Hospital(h) \rightarrow HospitalDescription(h, t, s))$$



## Inter-dimensional Constraints:

Some combinations of values may not be semantically allowed in CRs and ARs



*Inter-DCs* prohibit combinations of values from different dimensions involved in CRs, e.g.

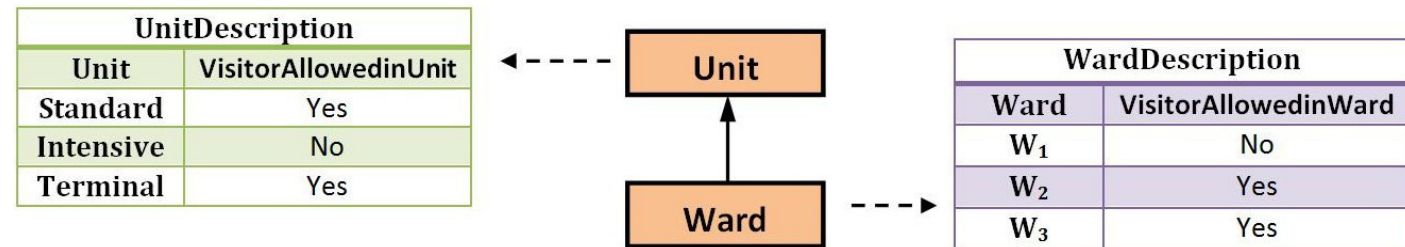
*“No single measurement can be taken by more than one nurse”*

As a **denial constraint**:

$$\neg \exists p v t d w n_1 n_2 (PatientValue(p, v, t) \wedge PatientWard(p, d, w) \wedge T(t, d) \wedge L(n_1, w) \wedge L(n_2, w) \wedge n_1 \neq n_2)$$

Involving different dimensions: *“No Czech Republic before 1989”* (Time and Geo Location)

### Intra-dimensional Constraints:



*Intra-DCs* restrict certain combinations of descriptive values in ARs, e.g.

*“No visitors allowed in wards where visitors in their units are prohibited”*

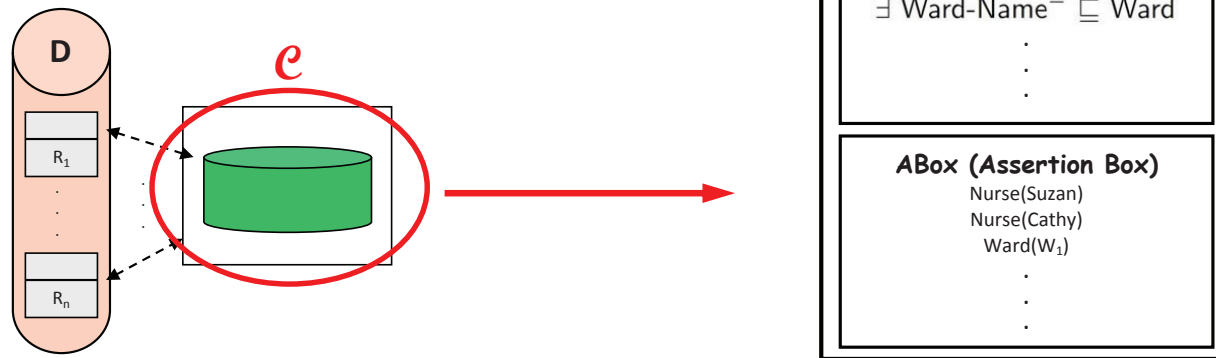
As a denial:

$$\neg \exists u \ v u \ w \ v w \ (UnitDescription(u, v u) \wedge WardDescription(w, v w) \wedge Location(w, u) \wedge v u = 'NO' \wedge v u \neq v w)$$

*“If there is an operation in a year, it must appear on a particular day of (associated to) that year”*

## MD Contexts as DL Ontologies

A MD context with the elements introduced above can be represented as an ontology in description logic



- Context becomes a knowledge base, an ontology, a theory in DL, containing **explicit data**, **metadata**, and **rules**
- Can be used to extract and generate (implicit) data
- In principle, logical reasoning becomes possible
- Choice of the DL becomes an issue

We sketch a DL-based representation of the extended HM model in one of the members of *DL-Lite* family of DLs

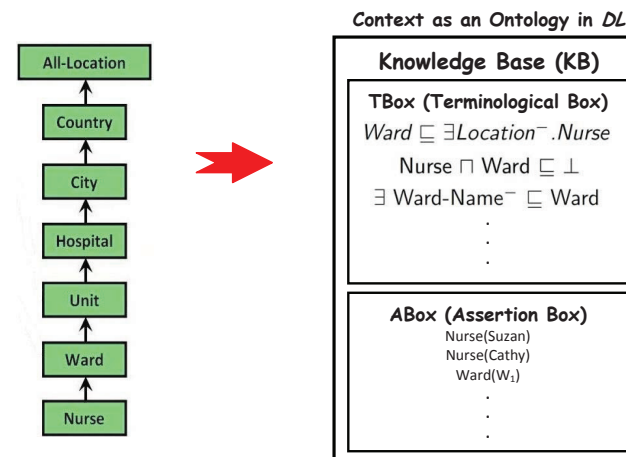
(Calvanese et al. JAR 2007)

## Representing MD Contextual Schemas:

- Categories and attribute domains for ARs are represented as concepts: *Nurse*, *Ward*, ... *String*, ...

- The empty concept property is for disjointness, in particular of categories:  $Nurse \sqcap Ward \sqsubseteq \perp$

- Roles represent ARs, e.g. *HospitalType*, and also relationships between (elements of) two adjacent categories in a dimension (cf. page 18)





- Restrictions on attribute values in ARs, as concept inclusions

In using the **number restriction** ( $\geq qR$ ) of  $DL-Lite^{\mathcal{N}}$  ( $R$  a role)

$\exists HospitalType^- \sqsubseteq Hospital$ ,  $\exists HospitalType \sqsubseteq String$ ,  $\geq 2HospitalType \sqsubseteq \perp$

- Child/Parent relationships between elements of categories ( $<$ ) is represented by a role

E.g. the *Location* (dimension) becomes a role

The  $<$  relation between the elements of each two categories, e.g. *Ward* and *Unit*, is represented by:  $Unit \sqsubseteq \exists Location^- . Ward$

We use **role hierarchies** of  $DL-Lite^{\mathcal{HN}}$  as a basis for defining role **transitive**, in the extension  $DL-Lite^{\mathcal{HN}+}$  (Artale et al., JAIR 2009)

(Role) *Location* is made transitive with the axiom  $Tra(Location)$

This is all allowed by  $DL-Lite_{Horn}^{(HN)^+}$

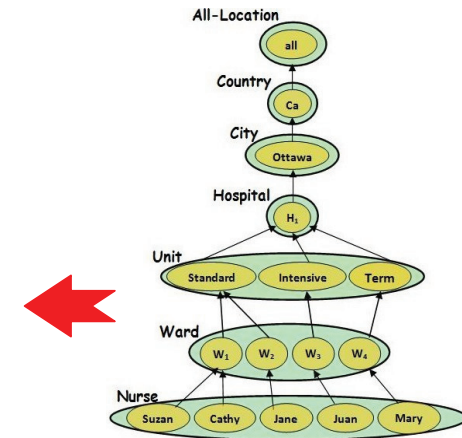
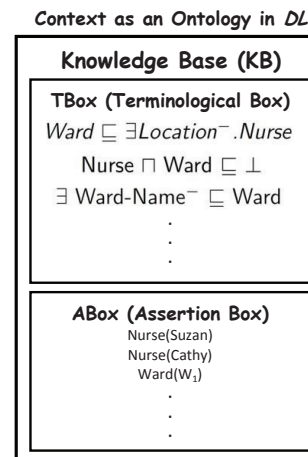
The combined complexity of  $DL-Lite^{\mathcal{HN}}$  is  $P$ -complete

## Representing MD Contextual Instances:

ABox not explicitly represented

TBox collects “assertive data” (facts) from the data sources via mappings

“Putting” them into concepts and roles



For example, consider  $locationIns(Ward, Unit)$ , the subrelation of the *Location* dimension instance (external to TBox, a source)

Mappings building the (virtual) instances for concept *Ward*, resp. for role *Location*:

$$\forall w \forall u (locationIns(w, u) \rightarrow Ward(f_{ward}(w)))$$

$$\forall w \forall u (locationIns(w, u) \rightarrow Location(f_{ward}(w), f_{unit}(u)))$$

Instances of concepts, e.g. for *Wards* and *Units*, become **abstract representations** of data values at the sources

Attributive relation instances?

E.g. attribute *Type* in *HospitalDescription* is mapped to the role *HospitalType* through the mapping:

$$\forall h \forall t (HospitalDescription(h, t) \rightarrow HospitalType(f_{hospital}(h), t))$$

Hospital type (a string) is mapped as it is as a value at the ontological level

## Representing Guidelines:

As axioms in the TBox, e.g. the *Hospital Guideline 2*:

*“Medical tests on patients in standard care units have to be taken with instruments made by manufacturer  $M_1$ ”*

New concepts:

- *standardCon*: Consisting of element *standard* from category *Unit*, with  $\text{standardCon} \sqsubseteq \text{Unit}$
- $M_1\text{Con}$ : Consisting of element  $M_1$  from category *Manufacturer*, with  $M_1\text{Con} \sqsubseteq \text{Manufacturer}$
- *standardRelate* consisting of all locations that have *standard* as ancestor in the *Unit* category  

$$\text{standardRelate} \equiv \exists \text{Location}.\text{standardCon}$$

- $M_1Relate$  consisting of instruments with  $M_1$  as an ancestor in the *Manufacturer* category, with

$$M_1Relate \equiv \exists Instrument.M_1Con$$

Finally, *Guideline 2* is expressed in TBox using the role *UnitInst* (used for the CR on page 17):

$$\exists UnitInst^-.standardRelate \sqsubseteq M_1Relate$$

## Conclusions

We have concentrated on the developments on MD contexts

We extended the MD model of data

We represented the resulting MD contexts in DL

In parallel we are also investigating *Datalog*<sub>-</sub><sup>+</sup> to represent the ontology

And to extend it, for generating the implicit data through a chase procedure; navigating towards the required data ...

Next step is about using MD contexts for data quality assessment, data cleaning, and quality query answering

Ours is a long term general research, about **Ontology-Based Data Quality**