Cube de textes et opérateur d'agrégation basé sur un modèle vectoriel adapté

Text Cube Model and aggregation operator based on an adapted vector space model

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Outline

- OLAP analysis for textual data !

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1. How can we represent and analyze textual data ?

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2. How can we aggregate textual data ?

- Requirements

1. Propose aggregation operators for textual data
2. Extend the classical star schema model

IR VS. OLAP

Information Retrieval IR

- User queries of keywords
- List of relevant documents
  - keywords' frequency in the document
- Extracting information from documents

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On-Line Analytical Processing OLAP

- Analysis queries
- Results relevant to the decision-making
- *Roll up*, *Drill down* from one view to another

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Combination IR / OLAP

- Extract relevant information from documents to define measures for textual data analysis
- Define OLAP operator adapted to textual data

Contributions

1. *TCube* : Text Cube model
   - Semantics dimensions –> domain ontology
   - Textual analysis measure –> relevance propagation
2. *ORank* : Textual Aggregation operator (OLAP-Rank)
   - Adaptation of the vector space model to OLAP analysis
   - Integration of decision-maker's preferences

Related work

Extend the classical data cube model

- Zhang et al.(2009) *Topic Cube*
- Pérez et al.(2007) *R-Cube*
- Lin et al.(2008) *Text Cube*
- Zhang et al.(2011) *MitexCube*

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Aggregation operator for textual data

- Ravat et al.(2007) *AVG-KW*
- Ravat et al.(2008) *TOP-KWk*
- Ben-Messaoud et al.(2004) *OpAC*
- Bringay et al.(2011) *Tf-Idf adaptative*

TCube

- $Cube = (F, Dim_1, Dim_2, ..., Dim_*, M_1, M_2, ..., M_*)$

TCube

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- *Semantic dimension*
  - $Dim_r, r \in [1, *]$ include attributes $A =< a_1, a_2, ..., a_* >$ organized in hierarchical levels $< l_1, l_2, ..., l_* >$
  - $l_i =< c_1, c_2, ...c_n >$ includes a set of concepts $c_j, (j \in [1, n])$ from domain ontology

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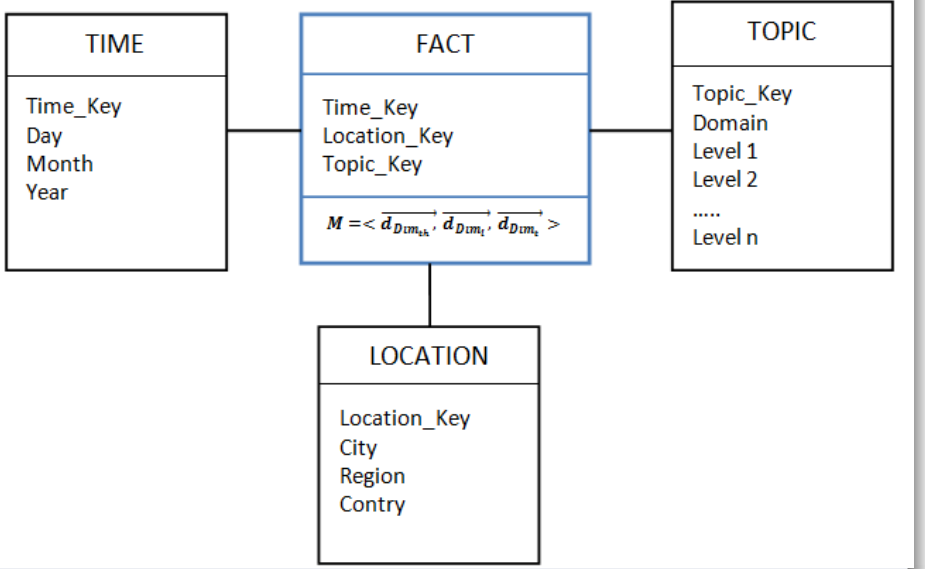
- Textual analysis measure *M*
  - *M* represents each document *d* by several weighted concepts vectors, one vector for each dimension Dim_r of *Cube*

$$M =< \overrightarrow{d_{Dim_1}}, \overrightarrow{d_{Dim_2}}, ..., \overrightarrow{d_{Dim_*}} >$$

$$\overrightarrow{d_{Dim_r}} =< w_{c_1}, w_{c_2}, ..., w_{c_n} >$$

OLAP analysis on CVs' collection

Star schema of *TCube*



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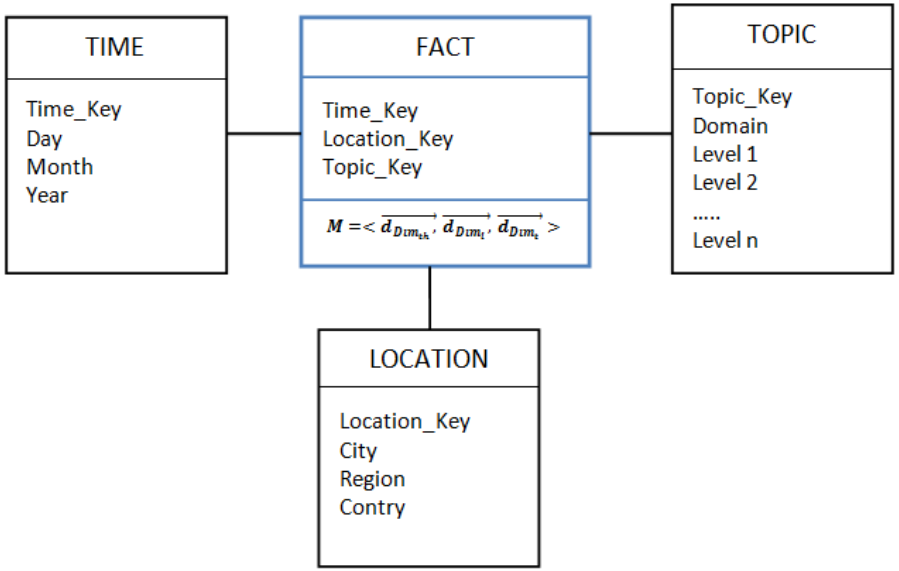
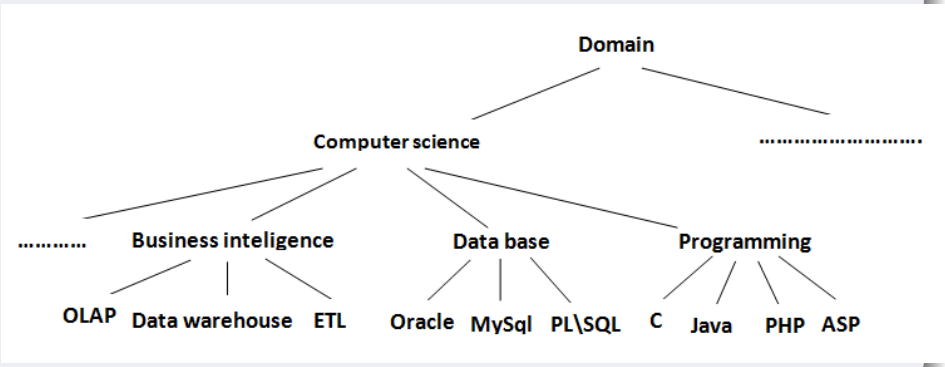


Example of a topics' hierarchy



Relevance propagation

- Consider text semantics during the computation of the term weight in a document

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- Reassign scores of concepts in the hierarchy

Relevance propagation

1. Compute the weights of the document terms existing in the concepts hierarchy (*Term Frequency Tf*)

$$Tf_{t,d} = \frac{n_{t,d}}{N_d} \quad (1)$$

$n_{t,d}$: occurrence frequency of term t in document d

N_d : total terms number of the document d

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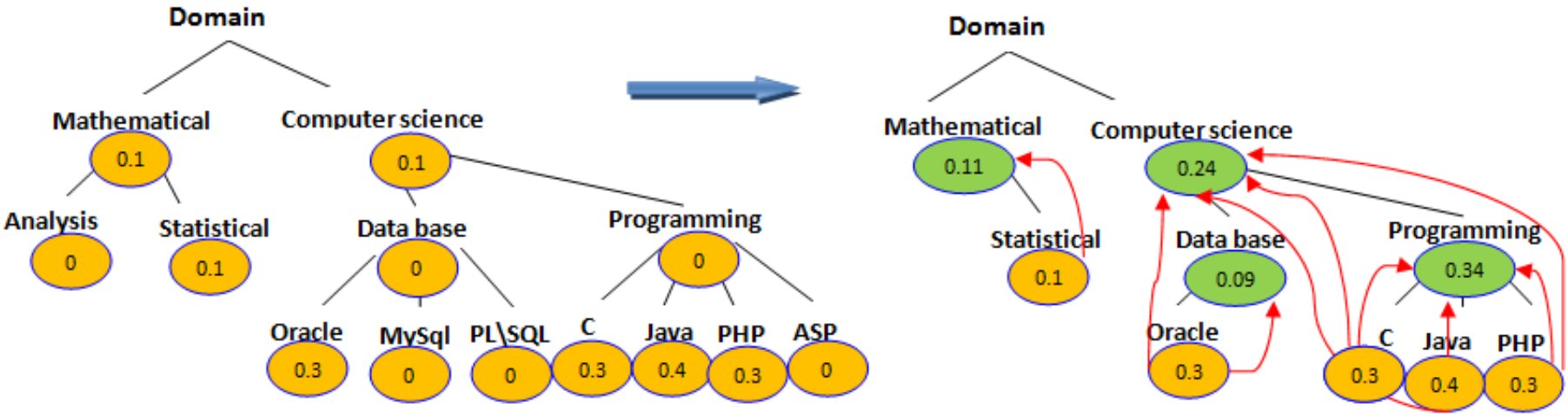
2. Compute weights of ancestors of each leaf node which has a weight not null

$$Poids(n_k, n_{fi}) = Poids(n_k) + Poids(n_{fi})^{distance(n_k, n_{fi})+1} \quad (2)$$

n_{fi} : leaf node from which the relevance propagation is performed
n_k : ancestor node to which the new weight is computed
$distance(n_k, n_{fi})$: semantic distance between the nodes n_k and n_{fi}

Relevance propagation for the TOPIC dimension (Example)



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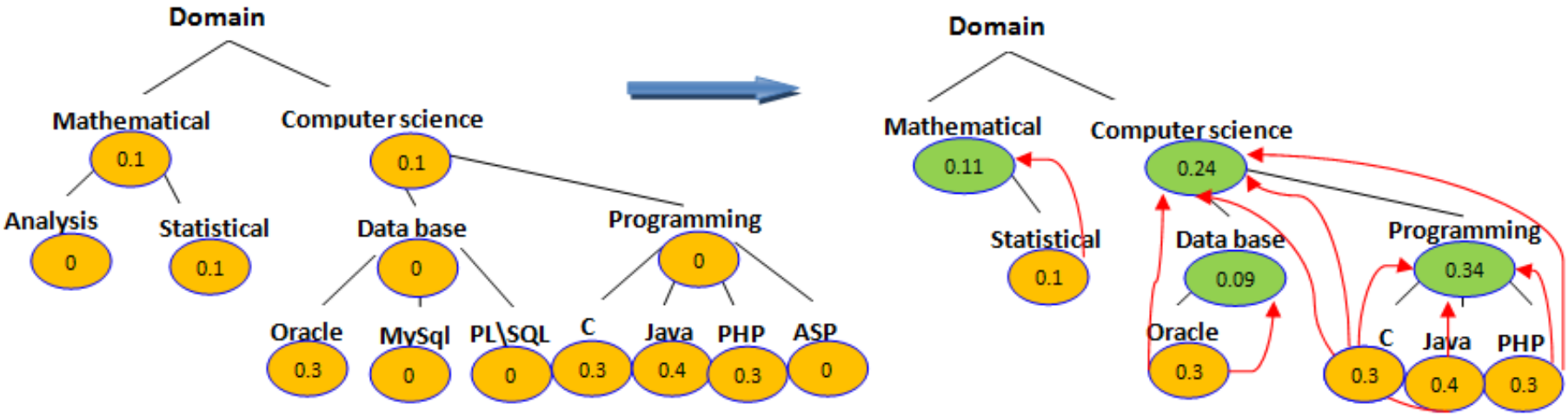

Result

$\overrightarrow{d_{Dim_{th}}} =<$
computer-science(0.24), *programming*(0.34), *java*(0.4), *php*(0.3), *c*(0.3), *database*(0.09), *oracle*(0.3),

mathematical(0.11), *statistics*(0.1) $>$

ORank operator

- Aggregate the semantics content of the documents by ranking them

ORank operator

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- Combine the different vector spaces of *TCube* dimensions

ORank operator

- Analysis query $Q =< \overrightarrow{q_1}, \overrightarrow{q_2}, ..., \overrightarrow{q_*} >$ where q_r is the query at the dimension Dim_r
- The aggregate of a document $d =< \overrightarrow{d_{Dim_1}}, \overrightarrow{d_{Dim_2}}, ..., \overrightarrow{d_{Dim_*}} >$ is calculated as follows :

$$ORank(d) = \sum_{i=1}^{n} (\alpha_i \times Sim(\overrightarrow{d_{Dim_i}}, \overrightarrow{q_i})) \quad (3)$$

$\overrightarrow{d_{Dim_i}}$: document vector at the dimension Dim_i

$Sim(\overrightarrow{d_{Dim_i}}, \overrightarrow{q_i})$: cosine similarity between $\overrightarrow{d_{Dim_i}}$ and $\overrightarrow{q_i}$

Decision-maker's preferences in *ORank*

$$ORank(d) = \sum_{i=1}^{n} (\alpha_i \times Sim(\overrightarrow{d_{Dim_i}}, \overrightarrow{q_i}))$$

- α_i –> user can indicate the importance of each *TCube* dimension as percentage P_i

$$\alpha_i = P_i \times n \quad (4)$$

- Documents are ranked in descending order of $ORank(d)$

Example of analysis on a *TCube*

Aggregation operator *ORank*				TOPIC						
				Domain	Computer science					
				level 1	Business intelligence		Database		Programming	
LOCATION	Country	TIME	Year		Doc	*Rank*	Doc	*Rank*	Doc	*Rank*
	France		2010		CV 1	1	CV 1	2	CV 1	4
					CV 2	4	CV 2	4	CV 2	1
					CV 3	3	CV 3	1	CV 3	3
					CV 4	2	CV 4	3	CV 4	2

(a)

Roll-up on TOPIC dimension

Aggregation operator *ORank*				TOPIC		
				Domain	Computer science	
LOCATION	Country	TIME	Year		Doc	*Rank*
	France		2010		CV 1	1
					CV 2	3
					CV 3	2
					CV 4	4

(b)

Data set

- Collection of 1000 documents (CVs)
  - Candidates for a Master 2 in Business Intelligence
- Construct concepts' hierarchies
  - Thematic portal from Wikipedia
  - Geographical ontology Geonames

1. Pretreatment

- *Text Tokenisation*, text conversion to a lowercase, stop-words removal, *terms lemmatisation* (*tree tagger*).

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2. Feeding *TCube* dimensions

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3. Tests

- Analysis measure : comparison between *Tf* measure and our *text analysis measure*
- *ORank* textual aggregation operator : analysis queries

Comparison between *Tf* measure and our *text analysis measure*

Tf measure	Our *text analysis measure M*
M < $\overrightarrow{d}$ = donnée (0.0348), base (0.0348), statistique (0.0290), informatique (0.0232), lyon (0.0232), analyse (0.0174), programmation (0.0174), compétence (0.0116), mention (0.0116), professionnel (0.0116), système (0.0116), lumière (0.0116). >	M < $\overrightarrow{d_{Dim_{th}}}$ = informatique (0.0239), statistique (0.0293), programmation (0.0180), réseau (0.0119), décisionnel (0.0065), php (0.0059), java (0.0059), r (0.0059), sql (0.0059), access (0.00598), base donnée (3.5856E-5), bureautique (3.5856E-5). $\overrightarrow{d_{Dim_l}}$ = lyon (0.0232), rhône-alpes (0.0005), france (0.0125E-3) $\overrightarrow{d_{Dim_t}}$ = 13 Avril 2010 (1.0) >

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Applying *ORank* on training Data

- Query 1 : TIME = 2010, LOCATION = "Lyon" et TOPIC= "Informatique décisionnelle"
- Query 2 : TIME = 2010, LOCATION = "Lyon" et TOPIC= "Informatique décisionnelle", preferences : 50% TOPIC et 25% TIME and LOCATION.

Applying *ORank* on training Data

Results of *ORank* on query 1

$ORank(d)$	Documents	$Sim(d_{Dim_{th}}, q_{th})$	$Sim(d_{Dim_{l}}, q_{l})$	$Sim(d_{Dim_{t}}, q_{t})$
1(2.6314)	CV 8	0.6314	1.0	1.0
2(2.5070)	CV 4	0.5070	1.0	1.0
3(2.4901)	CV 1	0.4901	1.0	1.0
4(2.4856)	CV 10	0.4856	1.0	1.0
5(2.4761)	CV 7	0.5477	0.9284	1.0
6(2.4648)	CV 9	0.4648	1.0	1.0
7(2.3281)	CV 6	0.3281	1.0	1.0
8(2.2817)	CV 2	0.5746	0.7071	1.0
9(2.2778)	CV 3	0.5707	0.7071	1.0
10(2.2734)	CV 5	0.3790	0.8944	1.0

ORank results

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Query 2

$ORank(d)$	Documents	$Sim(d_{Dim_{th}}, q_{th})$	$Sim(d_{Dim_l}, q_l)$	$Sim(d_{Dim_t}, q_t)$
1(2.4471)	CV 8	0.6314	1.0	1.0
2(2.2678)	CV 7	0.5477	0.9284	1.0
3(2.2605)	CV 4	0.5070	1.0	1.0
4(2.2351)	CV 1	0.4901	1.0	1.0
5(2.2284)	CV 10	0.4856	1.0	1.0
6(2.1972)	CV 9	0.4648	1.0	1.0
7(2.1422)	CV 2	0.5746	0.7071	1.0
8(2.1363)	CV 3	0.5707	0.7071	1.0
9(1.9921)	CV 6	0.3281	1.0	1.0
10(1.9893)	CV 5	0.3790	0.8944	1.0

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  - *ORank* : New text aggregation operator
    - Aggregates the documents by ranking
    - Includes decision-maker's preferences

Conclusion

- Experimental study on CV's collection
  - Results show the importance of our approach for :
    - Textual data analysis
    - Textual data integration into a data warehouse
    - Improve the decision-making

Perspectives

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- Improve and evaluate the results of *ORank* operator

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- Evaluate the scalability of our approach

Thank you for your attention