Similarity of XML Schema Fragments Based on XML Data Statistics

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Introduction

- XML = a standard for data representation and manipulation
  - Growing demand for efficient managing and processing of XML data

⇒ Possible optimization: To exploit similarity of XML data
  - We can manage similar data in a similar way
  - We can extend verified approaches to all similar cases

- The amount of approaches is significant
  - A space for further improvements

Goals of This Presentation

Proposal of a similarity function designed for enhancing of XML-to-relational mappings

- **Overview of existing approaches**
- **Proposal of improvement – focus on:**
  - **Structural similarity**
  - **Realistic tuning of weights and parameters**
- **Experiments**
- **Conclusion**

Content

1. **Overview of existing approaches**
2. **Proposed improvement**
3. **Experiments**
4. **Conclusion**

Approaches to XML Similarity (1)

- Similarity of documents D_1 and D_2
  - How difficult is to transform D_1 into D_2
    - Tree edit distance
  - A simple representation of D_1 and D_2 enabling easier comparison
    - e.g. set of paths, document signal
- Similarity of document D and schema S
  - Number of documents which appear in D but not in S and vice versa
    - Common, plus, minus elements
  - The closest tree edit distance between D and all documents valid against S
    - Construction of automaton / grammar of S

Approaches to XML Similarity (2)

- Similarity of schemes S_1 and S_2
  - Exploitation and combination of supplemental information
    - Predefined similarity rules, similarity of element / attribute names, equality of data types, schema instances, thesauri, previous results, …
  - Emphasis on semantic similarity
    - Exploitation: schema-integration systems, dissemination based systems, …
    - Problem: For XML-to-relational mapping is semantic of element / attribute names insignificant

  ⇒ we need a more suitable approach

Mlynkova, Pokorny: Similarity and XML Technologies. ICWI '07, Vila Real, Portugal. International Association for Development of the Information Society, 2007. ISBN 978-972-8924-44-7.

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Basic Ideas

- XML-to-relational mapping focuses on data structure
  - Complexity, data types, used constructs, …
- Aim: similarity function $sim(f_x, f_y) \in [0,1]$
  - Schema fragments f_x and f_y
  - 1 = strong similarity, 0 = strong dissimilarity
- Matcher = evaluates similarity of a particular feature of f_x and f_y
  - e.g. similarity of depths, number of elements / attributes, data types, …
- Composite similarity function = aggregates results of matchers
  - Verified approach: weighted sum

Structural Aspects (1)

- Idea: Each matcher describes a structural aspect
  - Problem: How to state matchers?
- Idea: Exploitation of characteristics from statistical analyses of real-world data
  - Analyses: To analyze the data from various points of view
  - Our aim: To describe the data from various points of view
- Classification:
  - Root = characteristics of root node of schema fragment
    - e.g. type of content, element / attribute fan-out, …
  - Subtree = characteristics of the whole fragment
    - e.g. number of elements, depths, …
  - Level = characteristics of each level of fragment
    - e.g. number of attributes, minimum / maximum fan-outs, …

Mlynkova, Toman, Pokorny: Statistical Analysis of Real XML Data Collections. COMAD ‘06, New Delhi, India. Tata McGraw-Hill Publishing Co. Ltd., 2006. ISBN 0-07-063374-6.

Structural Aspects (2)

- Transformation of values of matchers to [0,1]
  - Feature matchers – inequality of features
    - e.g. type of content

$$m_i^{fea}(f_x, f_y) = \begin{cases} 1 & fea_i(f_x) = fea_i(f_y) \\ 0 & otherwise \end{cases}$$

  - Single value matchers – difference of values
    - e.g. element fan-out

$$m_j^{single}(f_x, f_y) = \frac{1}{|value_j(f_x) - value_j(f_y)| + 1}$$

Structural Aspects (3)

- **Multi value matchers – difference of sequences**
  - **e.g. allowed depths of fragments**

$$m_j^{multi}(f_x, f_y) = \frac{\sum_{k=1}^{m} \frac{1}{|s_j(f_x)[k] - s_j(f_y)[k]|+1}}{m}$$

- **Level matchers – difference of values per levels**
  - **e.g. minimum and maximum fan-out per level**

$$m_j^{lev}(f_x, f_y) = \sum_{k=1}^{l} m_j^{single/multi}(f_x, f_y) \cdot (\frac{1}{2})^k$$

Tuning of Parameters (1)

- Problem: How to set the weights of composite similarity function?
  - Existing approaches: no care, average of values, machine learning
    - For semantic-based approaches suitable
    - For structure-based approaches not
- Idea: Exploitation of experience from the statistical analysis
  1. Use the same real-world data used in the analysis
  2. Prepare sample schema fragments with known representation in the data
  3. Compute occurrence of similar fragments in the data using the similarity function
  4. Tune the weights so that the results correspond to the results of the analysis

Tuning of Parameters (2)

$$\Delta = \sum_{i=1}^{K} \sum_{j=1}^{P} |M^{rep}[i,j] - rep_{i,j}|$$

- **Theoretical view of the problem**
  - **Analysis:**
    - **$C_1, C_2, \ldots, C_K$ = categories of real-world schemes**
    - **$p_1, p_2, \ldots, p_P$ = sample schema patterns**
    - **$(M_{ij}^{rep})_{KxP}$ = real-world representation of pattern p_j in category C_i**
  - **Search algorithm:**
    - **Parameters $par_1, par_2, \ldots, par_R$, where $\forall i : par_i \in [0,1]$**
    - **With a setting of parameters returns calculated representation rep_{ij} of pattern p_j in category C_i**
  - **Aim: Optimal setting of parameters s.t. Δ is minimal**

  $\Rightarrow$ A kind of constraints optimization problem (COP)
- **Solution:**
  - **One of classical COP approaches**
  - **Genetic algorithms, simulated annealing, …**

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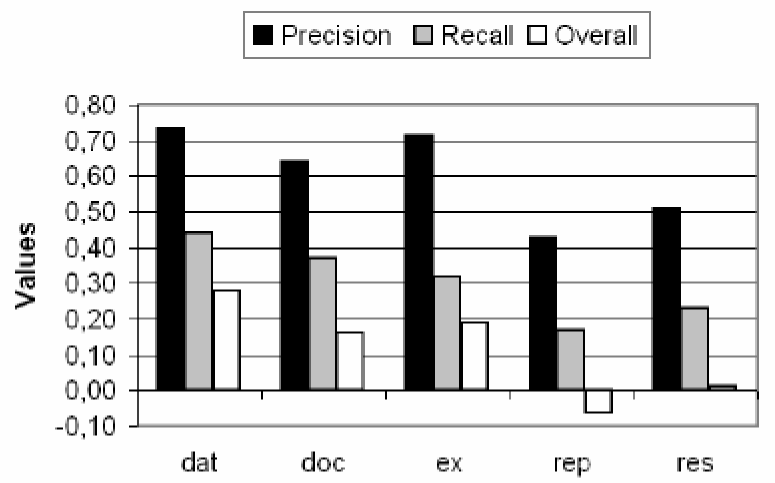
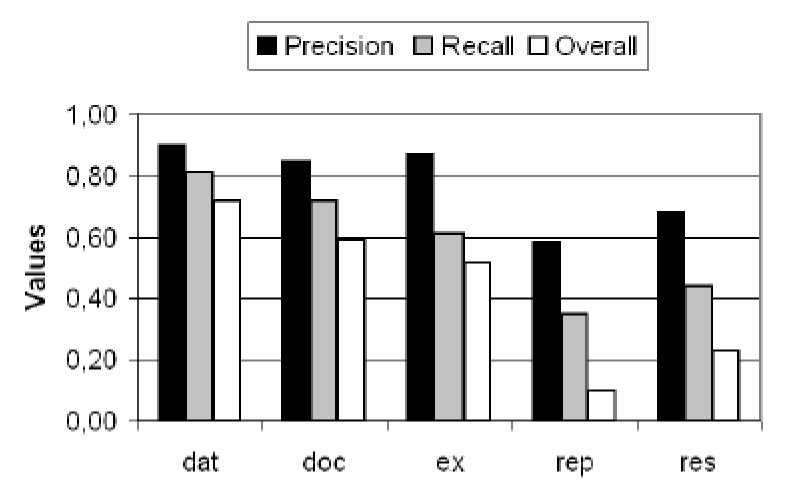
Average and Tuned Weights





- **R = manually determined matches, P = matches determined by algorithm**
- **I = true positives, F = false matches**
- **Precision = | I | / | P | = reliability of the function**
- **Recall = | I | / | R | = share of real matches that is found**
- **Overall = (| I | – | F |) / |R| = post-match effort**

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Conclusions and Future Work

- Our contributions:
  - A similarity function focusing on structural level
  - An approach for finding reasonable tuning of weights
    - A compromise between machine learning and straightforward setting
  - Both ideas can be simply extended to any appropriate similarity problem
- Future work:
  - Exploitation of semantic
    - Not a key aspect for XML-to-relational mapping, but can help in finding more reasonable mapping

Mlynkova: A Journey towards More Efficient Processing of XML Data in (O)RDBMS. CIT 2007, Aizu-Wakamatsu City, Fukushima, Japan. IEEE Computer Society Press, 2007. ISBN 0-7695-2983-6.

Thank you