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Collaborative Clustering of XML Documents

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Outline

- Introduction
  - Motivations
- Our proposal:

  distributed collaborative approach to XML document clustering
- Experimental evaluation
- Conclusion

Motivations

- In a nutshell, **XML**
  - The extensible, self-describing de-facto standard for data representation and exchange on the Web
- Rapid increase of the volume and heterogeneity of XML sources
  - Documents exhibit too diverse structure and contents
    - may encode *related semantics*
  - Documents are often *schema-less*
- XML data management and XML mining
  - Web source integration, Querying semistructured data, Document classification
  - Change detection, schema matching

Motivations

- The size of collections of XML documents is often huge and inherently distributed
- Classical centralized approaches may be not efficient

- Our proposal: a distributed framework for efficiently clustering XML documents
  - Peer-to-peer network
  - Each peer has access to a portion of the whole document collection
  - Centroid-based partitional clustering
  - Each peer computes “local” centroids and a subset of “global” centroids

Clustering semantically related XML documents

[Tagarelli and Greco, SDM'06]

[Tagarelli and Greco, TOIS'09]

- **XML features**
  - Structure information (from tag paths)
  - Content information (from textual elements)
- **XML transactional model**
  - based on the notion of XML tree tuple
    - identifies semantically cohesive substructures
    - enables relational-like representation of XML data

Preliminaries

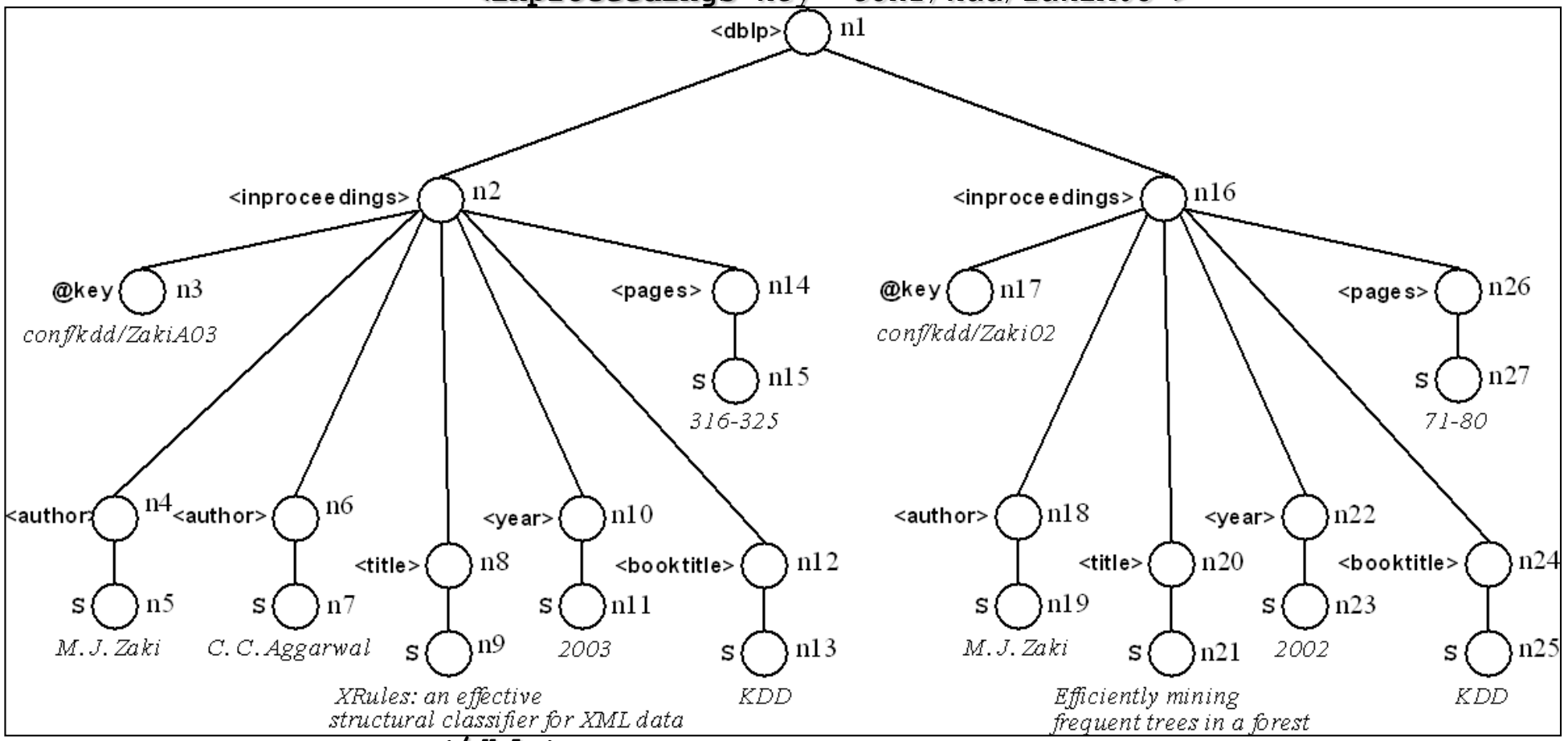
- XML tree path
  - A sequence $p = [s_1, \ldots, s_m]$ of symbols in $Tag \cup Att \cup \{\mathrm{S}\}$
  - **Tag Path**: last symbol is a tag name
  - **Complete Path**: last symbol is either an attribute name or a textual element content
- Path **answer**:
  - A set of node identifiers (Tag path case)
  - A set of string values (Complete path case)

Extracting XML tree tuples

- Definition:
  - Given an XML tree XT, a tree tuple τ is a maximal subtree of XT such that, for every path p that can be applied to XT, the *answer* $\mathcal{A}_\tau(p)$ contains at most one element
- Meaning in the XML context:
  - A (sub)tree representation of a complete set of distinct concepts that are correlated according to the structure semantics of the original tree

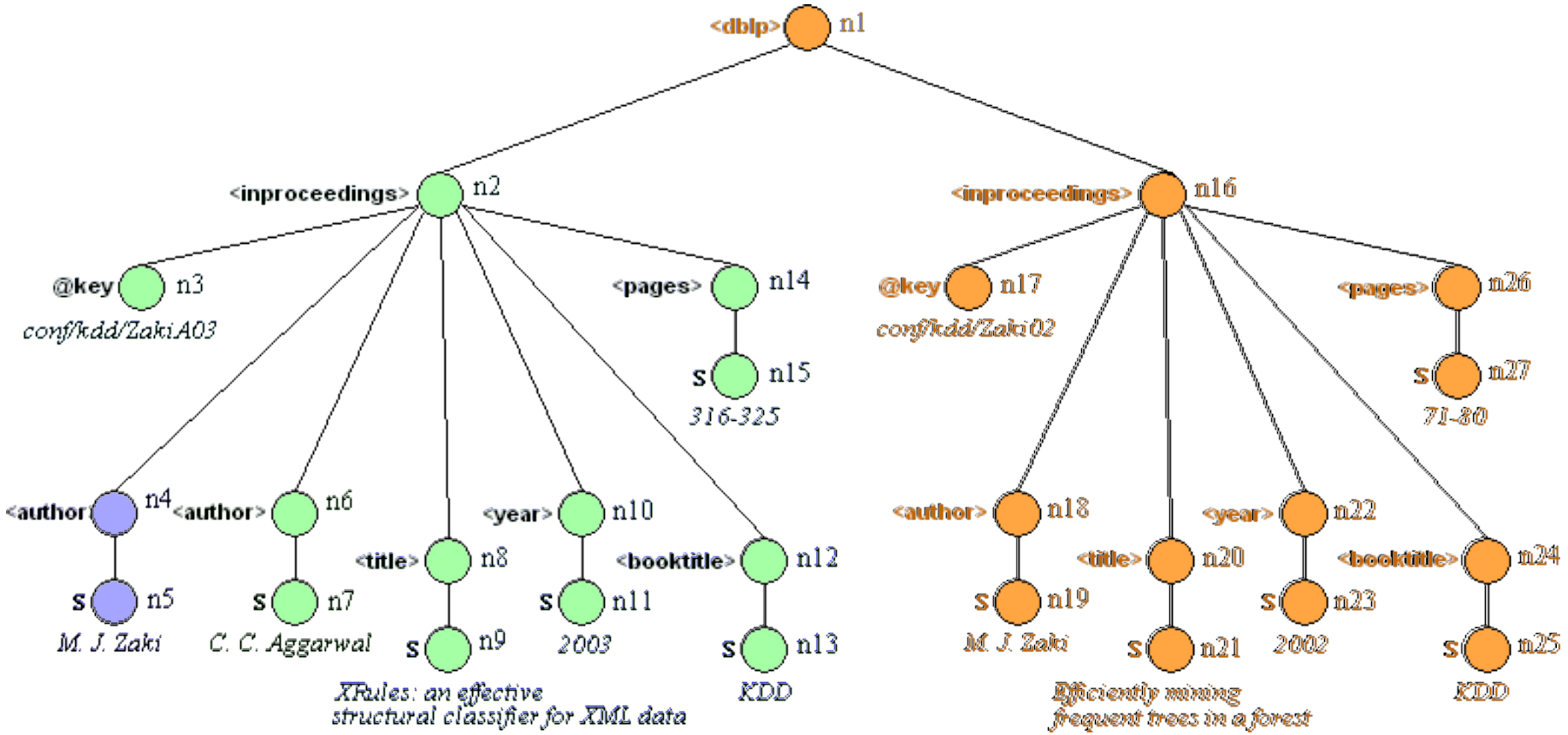
Extracting XML tree tuples:
The DBLP Example

```
<dblp>
  <inproceedings key="conf/kdd/ZakiA03">
```




```
</dblp>
```

Extracting XML tree tuples:
The DBLP Example



Modeling XML transactions

- Decomposition of each tree tuple into a set of tree tuple items
  - Tree tuple item is a pair $\left(p, \mathcal{A}_\tau(p)\right)$, such that:
    - p is a complete path on τ
    - $\mathcal{A}_\tau(p)$ is the (string) answer of p applied to τ
- **Item**: a tree tuple item
- **Item domain**: the union of the tree tuple item sets over all the tree tuples extracted from a target collection
- **Transaction**: a tree tuple, represented by its set of tree tuple items
  - Each path applied to a tree tuple yields a unique answer ⇒ each item in a transaction refers to a distinct information

Modeling XML transactions:
The DBLP Example

path (p)	$\tau_1.p$	*node ID*
dblp.inproceedings.@key	"conf/kdd/ZakiA03"	n_3
dblp.inproceedings.author.S	"M. J. Zaki"	n_5
dblp.inproceedings.title.S	"XRules: an effective ..."	n_9
dblp.inproceedings.year.S	"2003"	n_{11}
dblp.inproceedings.booktitle.S	"KDD"	n_{13}
dblp.inproceedings.pages.S	"316-325"	n_{15}

path (p)	$\tau_2.p$	*node ID*
dblp.inproceedings.@key	"conf/kdd/ZakiA03"	n_3
dblp.inproceedings.author.S	"C. C. Aggarwal"	n_7
dblp.inproceedings.title.S	"XRules: an effective ..."	n_9
dblp.inproceedings.year.S	"2003"	n_{11}
dblp.inproceedings.booktitle.S	"KDD"	n_{13}
dblp.inproceedings.pages.S	"316-325"	n_{15}

path (p)	$\tau_3.p$	*node ID*
dblp.inproceedings.@key	"conf/kdd/Zaki02"	n_{17}
dblp.inproceedings.author.S	"M. J. Zaki"	n_{19}
dblp.inproceedings.title.S	"Efficiently mining ..."	n_{21}
dblp.inproceedings.year.S	"2002"	n_{23}
dblp.inproceedings.booktitle.S	"KDD"	n_{25}
dblp.inproceedings.pages.S	"71-80"	n_{27}

item ID	*corresponding node IDs*
e_1	n_3
e_2	n_5, n_{19}
e_3	n_9
e_4	n_{11}
e_5	n_{13}, n_{25}
e_6	n_{15}
e_7	n_7
e_8	n_{17}
e_9	n_{21}
e_{10}	n_{23}
e_{11}	n_{27}

tr_1	e_1 e_2 e_3 e_4 e_5 e_6
tr_2	e_1 e_7 e_3 e_4 e_5 e_6
tr_3	e_8 e_2 e_9 e_{10} e_5 e_{11}

Clustering XML transactions:

XML tree tuple item similarity

- Function of structure and content features

$$sim(e_i, e_j) = f \times sim_S(e_i, e_j) + (1 - f) \times sim_C(e_i, e_j)$$

- Match at a degree not below a threshold γ
  - Notion of γ -matched items
- Similarity by structure
  - computed by comparing tag paths
- Similarity by content
  - cosine similarity between TCUs
  - terms in TCUs are weighted by a syntactic relevance function

Clustering XML transactions:
XML tree tuple item similarity

- Structure similarity
  - Comparison of tag paths by resorting to a simple case of string matching of their respective element names

The *structural similarity* between the XML tree tuple items e_i and e_j, having $p_i = t_{i_1}.t_{i_2}.\ \ldots\ .t_{i_n}$ and $p_j = t_{j_1}.t_{j_2}.\ \ldots\ .t_{j_n}$ as their respective tag paths, is:

$$sim_S(e_i, e_j) = \frac{1}{n+m}\left(\sum_{t \in p_i} sim(t, p_j) + \sum_{t \in p_j} sim(t, p_i)\right)$$

where $$sim(t_{i_h}, p_j) = avg_{\,t_{j_k} \in p_j} \left\{ \frac{1}{1+|h-k|} \times \delta(t_{i_h}, t_{j_k}) \right\}$$

Clustering XML transactions: XML tree tuple item similarity

- Content similarity
  - Syntactic relevance function: *TF-IDF*
    - Proportional to the term density (number of occurrences) in a TCU
    - Proportional to the informativeness of term (its rarity across the whole collection of TCUs)
  - *Tree tuple Term Frequency – Inverse Tree tuple Frequency*: *TTF-ITF*
    - Proportional to the term frequency within the local TCU
    - Proportional to the term popularity across the TCUs of the local tree tuple and the TCUs of the local document tree
    - Proportional to the term rarity across the whole collection of TCU

Clustering XML transactions:
XML tree tuple item similarity

- Content similarity

$$ttf.itf(w_j, u_i|_\tau) = tf(w_j, u_i) \times \exp\left(\frac{n_{j,\tau}}{N_\tau}\right) \times \frac{n_{j,XT}}{N_{XT}} \times \ln\left(\frac{N_\mathcal{T}}{n_{j,\mathcal{T}}}\right)$$

- $tf(w_j, u_i)$ *is the number of occurrences of* w_j *in* u_i,
- $n_{j,\tau}$ *is the number of TCUs in* τ *that contain* w_j,
- N_τ *is the number of TCUs in* τ,
- $n_{j,XT}$ *is the number of TCUs in* XT *that contain* w_j,
- N_{XT} *is the number of TCUs in* XT,
- $n_{j,\mathcal{T}}$ *is the number of TCUs in* $\mathcal{T}$ *that contain* w_j,

Clustering XML transactions:
XML tree tuple item similarity

- Content similarity
  - A TCU u_i is modeled with a vector $\vec{u}_i$ whose j-th component corresponds to an index term w_j and contains the $ttf.itf$ relevance weight
  - The well-known cosine similarity is used to measure the similarity between TCU vectors:

$$sim_C(e_i, e_j) = \frac{\vec{u}_i \cdot \vec{u}_j}{\|\vec{u}_i\| \times \|\vec{u}_j\|}$$

Clustering XML Transactions:

XML Transaction Similarity

- Search for shared items, when comparing two transactions
  - Enhance the notion of standard intersection to capture even minimal similarities between XML elements
- Set of γ **-shared items**:
  - intuitively, the union of best γ-matched items between two XML transactions
- XML transaction similarity:

$$sim_J^{\gamma}(tr_1, tr_2) = \frac{|match^{\gamma}(tr_1, tr_2)|}{|tr_1 \cup tr_2|}$$

Set of γ-shared items

Collaborative Clustering of XML transactions

- **CXK-Means**
  - Centroid based partitional
    - notion of representative of cluster of XML transactions
  - Transaction-centric
    - pair-wise similarity between transactions guides the construction of clusters
  - Suitable for a collaborative distributed environment
    - peer network: each peer node is responsible of “local” and “global” choices

- Define three main notions:
  - XML transaction similarity
  - XML local cluster representative
  - XML global cluster representative

Collaborative Clustering of XML transactions

- **CXK-means**: process N_0
  - Data are distributed over m peer nodes
  - Each node communicates with all the other ones sending local representatives and receiving global representatives
  - An initial process corresponding to a node N_0 defines a partition of the k clusters into m subsets Z_j :

Process N_0
Method:
define a partition of $\{1..k\}$ into m subsets $Z_1, \ldots, Z_m$;
for $i = 1$ **to** m **do**
send $(\{Z_1, \ldots, Z_m\}, k, \gamma)$ to N_i;

Collaborative Clustering of XML transactions

- **`CXK-means`**: process N_i
  - Each node N_i computes:
    - Local clusters $C_1^i, \ldots, C_k^i$
    - Local representatives $c_1^i, \ldots, c_k^i$
    - (A subset of) global representatives $c_{i_1}, \ldots, c_{i_{q_i}}$, using the local representatives computed by all nodes

Collaborative Clustering of XML transactions

- **CXK-means**: process N_i

Method:

receive $(\{Z_1, \ldots, Z_m\}, k, \gamma)$ from N_0;
let $Z_i = \{i_1, \ldots, i_{q_i}\}$, with $0 \leq q_i \leq k$;
/* *selects* q_i *initial global clusters* */
select $\{c_{i_1}, \ldots, c_{i_{q_i}}\}$ transactions coming from distinct original trees;
$C_j^i = \{\}, \forall j \in [1..k]$;
repeat
  send (broadcast) $\{c_{i_1}, \ldots, c_{i_{q_i}}\}$ to $N_1, \ldots, N_m$;
  receive c_j from N_h with $h \in [1..m]$ and $j \in Z_h$;
  repeat /* *computes local clusters* */
    $C_j^i := \{tr \mid tr \in S^i \wedge sim_J^\gamma(tr, c_j^i) > sim_J^\gamma(tr, c_l^i), l \in [1..k]\}, \forall j \in [1..k]$;
    $C_{k+1}^i := \{tr \mid sim_J^\gamma(tr, c_j^i) = 0\}, \forall j \in [1..k]$;
    $c_j^i :=$ computeLocalRepresentative(C_j^i) $\forall j \in [1..k]$;
  until $\mathcal{Q}(\mathcal{C}^i)$ is maximized;
  if c_j^i does not change, $\forall j \in [1..k]$ **then**
    send (broadcast) $([], done)$;
  else
    send $(\{\langle c_j^i, |C_j^i|\rangle | j \in Z_h\}, continue)$ to $N_h, \forall h \in [1..m]$;
  receive $(\{c_j^h | j \in Z_h\}, V_h)$ from $N_h, \forall h \in [1..m]$
  if $(\exists h \in [1..m]$ s.t. $V_h = continue)$ **then**
    for $j \in Z_i$ **do** $c_j =$ ComputeGlobalRepresentative$(\{c_j^1, \ldots, c_j^m\})$
until $V_1 = \cdots = V_m = done$;

Collaborative Clustering of XML Transactions: Local XML Cluster Representative

Compute the set of γ-shared items among all the transactions within cluster *C*

1. for each transaction in *C*, compute the union of the γ-shared item sets w.r.t. all the other transactions in *C*
2. compute a raw representative
   - by selecting the items with the highest frequency from the previously obtained union sets
   - possibly conflate those items sharing the same path
3. perform a greedy heuristic to refine the raw representative
   - by iteratively adding the remaining most frequent items until the sum of pair-wise similarities between transactions and representative cannot be further maximized

Collaborative Clustering of XML Transactions: Global XML Cluster Representative

- The global representative of a cluster C is computed by considering the m local representatives $c^1, \ldots, c^m$
  - Procedure similar to that used for computing local representatives
  - Only a difference: the structural ran g_rank associated with an item e considers the rank associated with each item (instead of the number of items) having a γ-matching

Collaborative Clustering of XML transactions: CXK-Means - other features

- Trash cluster
  - Contains only transactions having zero-similarity when compared with each cluster representative
- Cluster initialization
  - Tree tuples selected as initial cluster centroids are constrained to come from different XML documents
    - favoring the construction of clusters with low intersimilarity

Experimental evaluation:
Data description

- Real XML data sources
  - the **IEEE** collection version 2.2
    - benchmark in the INEX document data mining track 2008
    - complex article schemas: front matter, back matter, section headings, text formatting tags, mathematical formulas, …
  - the **DBLP** digital bibliography
    - variety of structures, small average depth
    - short text descriptions (paper titles, event topics, author names)

data	# docs	# trans.	# items	max fan out	avg depth
IEEE	4,874	211,909	135,869	43	5
DBLP	3,000	5,884	8,231	20	3

Experimental evaluation:
Methodology and goals

- Structure-driven clustering
- Content-driven clustering
- Structure/Content-driven clustering
  - detecting common structures across different topics
  - identifying classes that both cover common topics and share structure type

Experimental evaluation:
Methodology and goals

- Evaluation
  - Clustering quality (*F-Measure):*

$$P_{ij} = \frac{|\mathcal{C}_j \cap \Gamma_i|}{|\mathcal{C}_j|} \;,\; R_{ij} = \frac{|\mathcal{C}_j \cap \Gamma_i|}{|\Gamma_i|} \;,\; F_{ij} = \frac{2P_{ij}R_{ij}}{(P_{ij} + R_{ij})}$$

$$F(\mathbf{C}, \Gamma) = \frac{1}{|\mathcal{S}|} \sum_{i=1}^{H} |\Gamma_i| \max_{j \in [1..K]} F_{ij}$$

  - Time performances

Experimental evaluation:
Accuracy results

dataset	*# of clusters*	*# of nodes*	*F-measure (avg)*
IEEE	8	1	0.593
		3	0.523
		5	0.485
		7	0.421
		9	0.376
DBLP	6	1	0.764
		3	0.702
		5	0.662
		7	0.612
		9	0.547

TABLE I
CLUSTERING RESULTS WITH $f \in [0..0.3]$
(CONTENT-DRIVEN SIMILARITY)

Experimental evaluation:
Accuracy results

dataset	*# of clusters*	*# of nodes*	*F-measure (avg)*
IEEE	14	1	0.564
		3	0.497
		5	0.451
		7	0.404
		9	0.356
DBLP	16	1	0.772
		3	0.721
		5	0.676
		7	0.614
		9	0.558

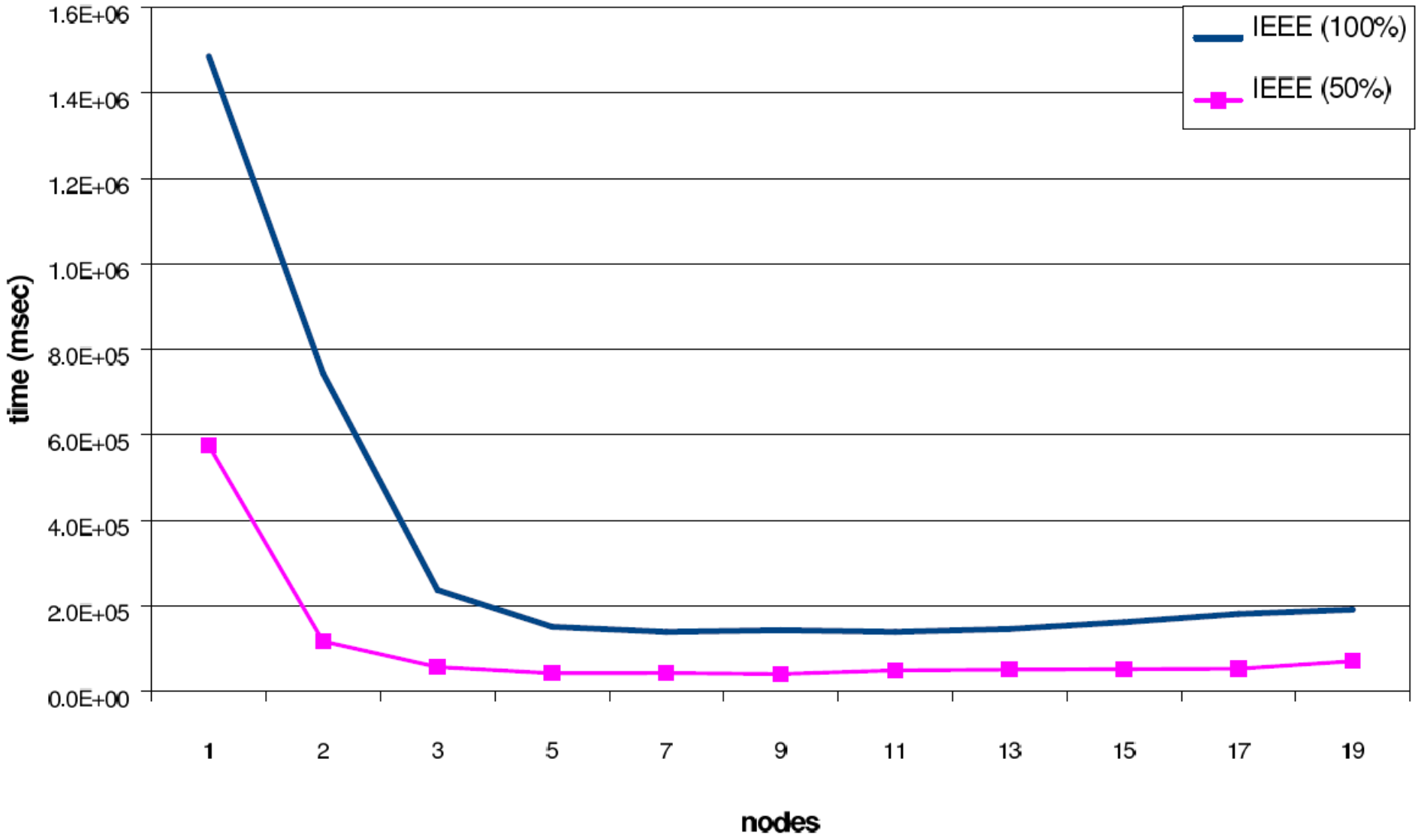
TABLE II
CLUSTERING RESULTS WITH $f \in [0.4..0.6]$
(STRUCTURE/CONTENT-DRIVEN SIMILARITY)

Experimental evaluation:
Accuracy results

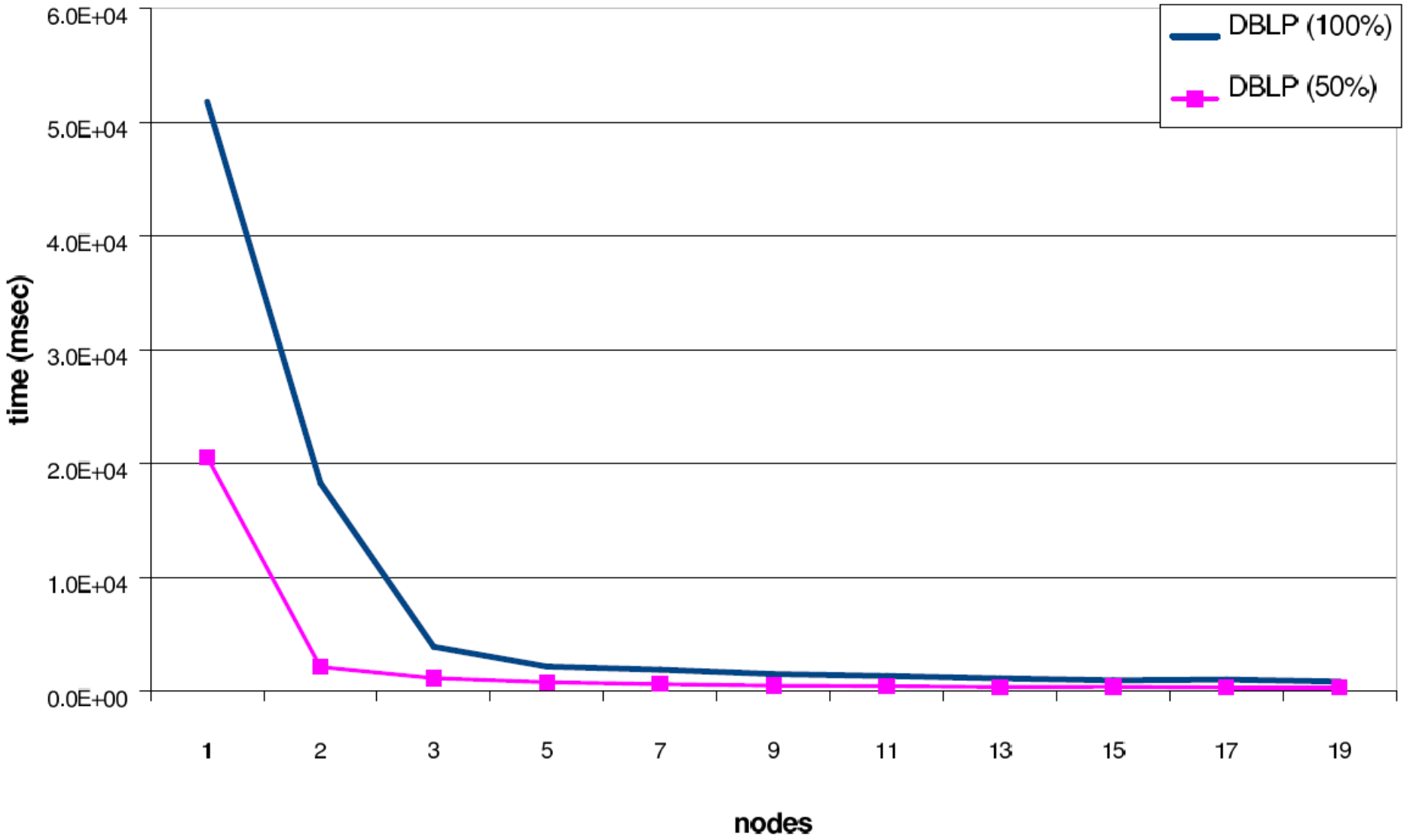
dataset	*# of clusters*	*# of nodes*	*F-measure (avg)*
IEEE	2	1	0.618
		3	0.542
		5	0.497
		7	0.433
		9	0.386
DBLP	4	1	0.988
		3	0.934
		5	0.882
		7	0.819
		9	0.716

TABLE III
CLUSTERING RESULTS WITH $f \in [0.7..1]$
(STRUCTURE-DRIVEN SIMILARITY)

Experimental evaluation:
Efficiency results



Experimental evaluation:
Efficiency results



Conclusion

- Collaborative distributed framework for clustering XML documents
  - CXK-means: a distributed, centroid-based partitional clustering algorithm
  - Peer-to-peer network
  - Local and global decisions for each peer
- XML documents modeled in a transactional domain
  - Modeling of XML transactions starting from the notion of tree tuple
  - Similarity between transaction computed according to both structure and content features


Thank you