Distributed Information Systems Class questions

Marc Bourqui

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Part I	The state of a database is independent of the lifetime.
Introduction	 of a program The same logical database can be stored in different ways on a storage medium
An Overview (week 1) Information Systems Functions in models	 Information Management 7. Grouping Twitter users according to their interest by analyzing the content of their tweets is
① Are always computable○ Can always be represented as data○ Can be constrained by axioms	A retrieval taskA data mining taskAn evaluation taskA monitoring task
 2. Interpretation relationships Are always computable Relate constants to real-world entities Are uniquely defined 	Distributed Information Systems 8. Creating a web portal for comparing product prices is (primarily) a problem of Distributed data management Heterogeneous data integration
 Data Management 3. What is not specified in the data definition language? The structure of a relational table The query of user A constraint on a relational table 	Collaboration among autonomous systems Distributed Data Management 9. When you open a Web page with an embedded Twitter stream, the communication model used by Twitter is Push, unicast and conditional
 4. Logical data independence means An abstract data type is implemented using different data structures A new view is computed without changing an existing database schema A model can be represented in different data modelling formalisms 	 Pull, multicast and ad-hoc Push, multicast and ad-hoc Pull, unicast and conditional Heterogeneity Creating a web portal for comparing product prices
Data Management Tasks 5. Which is wrong ? An index structure	requires to address Syntactic heterogeneity Semantic heterogeneity
 Is created as part of physical database design Is selected during query optimization Accelerates search queries Accelerates tuple insertion Persistence means that 	Both11. An ontology is aSdatabasedatabase schemadata model
A change of a transaction on a database is never lost	odata modeling formalism

 \bigcirc model

O A change of a transaction on a database is never lost

after it is completed

Autonomy

- 12. Trust is
 - A quality of information
 - A quality of a user
 - A quality of the relationship among user and information
 - A quality of the relationship among users

Part II

Storage

Distributed Data Management

Schema Fragmentation

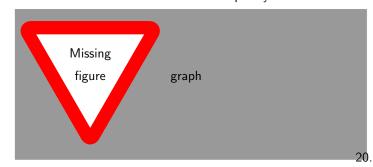
Relational Databases

- 13. At which phase of the database lifecycle is fragmentation performed ?
 - $\sqrt{\ }$ At database design time
 - Ouring distributed query processing
 - Ouring updates to a distributed database
- 14. The reconstruction property expresses that
 - In case of a node failure the data can be recovered from a fragment from another node
 - $\sqrt{}$ The original data can be fully recovered from the fragments
 - Every data value of the original data can be found in at least one fragment

Primary Horizontal Fragmentation (week 2)

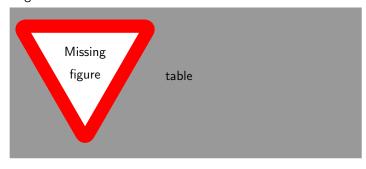
- 15. Example: application A1 accesses
 - 1. Fragment F1: with frequency 3
 - 2. Fragment F2: with frequency 1

A1 accesses the whole relation with frequency

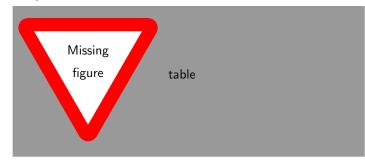


- $\sqrt{13/7}$
- \bigcirc 4/7
- \bigcirc 14/7

16. Consider the access frequencies below: How many horizontal fragments would a minimal and complete fragmentation have?



- √ **3**
- 4
- O 6
- 17. Which of the following sets of simple predicates is complete?



- O Location = "Munich", Budget > 200000
- Location = "Munich", Location = "Bangalore"
- \bigcirc Location = "Paris", Budget ≤ 200000
- √ None of those
- 18. Which is true for MinFrag algorithm?
 - The output is independent of the order of the input
 - O It produces a monotonically increasing set of predicates
 - $\sqrt{}$ It always terminates
 - O All of the above statements are true
- 19. When deriving a horizontal fragmentation for relation S from a horizontally fragmented relation R
 - $\sqrt{\ }$ Some primary key attribute in R must be a foreign key in S
 - \bigcirc Some primary key attribute in S must be a foreign key in R
 - O Both are required

Graph Databases (week 3)

Semi-structured Data

- 20. Semi-structured data
 - Is always schema-less
 - √ Always embeds schema information into the data
 - Must always be hierarchically structured
 - Can never be indexed

21.	Why is XML a document model? () It supports application-specific markup		 Every label of an outgoing edge of a node in the schema graph is unique
	It supports domain-specific schemas		
	√ It has a serialized representation		Dowt III
	() It uses HTML tags		Part III
	Graph Data Model		Search
22.	In a graph database		
	There is a unique root node		Information Retrieval and Data
	$\sqrt{}$ Each node has a unique identifier		Mining
	O Data values in leaf nodes are unique		Information Retrieval (week 4)
	○ The labels of edges leaving a node are different		Information Retrieval
	○ There is a unique path from the root to each leaf		
23.	The simulation relationship is a relation	29.	A retrieval model attempts to model
	Among nodes in the data and schema graph		The importance a year gives to a piece of
	Among edges in the data and schema graph		√ The importance a user gives to a piece of information
	 Among sets of nodes in the data and schema graph 		○ The formal correctness of a query formulation by user
	Among sets of edges in the data and schema graph		○ All of the above
24.	Which is true?	30.	If the top 100 documents contain 50 relevant documents
	\bigcirc For each labelled edge in S a corresponding edge in D		The precision of the system at 50 is 0.5
	can be identified		$\sqrt{}$ The precision of the system at 100 is 0.5
	\bigcirc For each root node in S a corresponding root node D		\bigcirc The recall of the system is 0.5
	can be identified		○ None of the above
	$\sqrt{}$ For each leaf node in D a corresponding typed node in S can be identified	31.	If retrieval system A has a higher precision than system B
	\bigcirc For each node in S a unique path reaching it from a root node can be identified		\bigcirc The top k documents of A will have higher similarity values than the top k documents of B
25.	If there exists a uniquely defined simulation relationship among a graph database ${\cal D}$ and a schema graph ${\cal S}$		$\sqrt{}$ The top k documents of A will contain more relevant documents than the top k documents of B
	○ The data and schema graph are simulation equivalent		A will recall more documents above a given similarity
	$\sqrt{}$ Ambiguous classification cannot occur		threshold than B
	Multiple classification cannot occur		Relevant documents in A will have higher similarity
26.	If schema graph S_1 subsumes S_2		values than in B
	\bigcirc Every graph database corresponding to S_1 corresponds also to S_2	22	Text-based Information Retrieval
	$\sqrt{\ S_2}$ simulates S_1	32.	Full-text retrieval means that The document text is grammatically deeply analyzed
	\bigcirc S_1 has fewer nodes than S_2		for indexing
	Schema Extraction		 The complete vocabulary of a language is used to extract index terms
27.	Which is wrong? In a dataguide		$\sqrt{}$ All words of a text are considered as potential
	Every path in the data graph occurs only once		index terms
	$\sqrt{}$ Every node in the data graph occurs only in one data guide node	33.	All grammatical variations of a word are indexed The term-document matrix indicates
	 Every data guide node has a unique set of nodes 		$\sqrt{}$ How many relevant terms a document contains
	 A leaf node in the data graph corresponds always to a leaf node in the data guide 		How relevant a term is for a given document
28.	In a non-deterministic schema graph		√ How often a relevant term occurs in a document collection
	\surd Every node of the data graph occurs exactly once		√ Which relevant terms are occurring in a document
	Every path of the data graph occurs at most once		collection

 Matches the query because it matches the first query vector ✓ Matches the query because it matches the second query vector ○ Does not match the query because it does not match the first query vector ○ Does not match the query because it does not match the second query vector ○ Does not match the query because it does not match the second query vector ○ Does not match the query because it does not match the second query vector ○ Search and couments which do not contain any keywords of the original query receive a positive similarity coefficient after relevance feedback? ○ No ○ Yes, but only if β > 0 ○ Yes, but only if γ > 0 ○ Link-based Ranking 42. A positive random jump value for exactly one node implied that ✓ a random walker can leave the node even without outgoing edges ○ a random walker can reach the node multiple times even without outgoing edges 	34.	Let the query be represented by the following vectors: (1,		User Relevance Feedback
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$\sqrt{}$ Is the same as the number of rows in the matrix M $$ The access structure		$\sqrt{}$ Is the same as the number of rows in the matrix M		○ The access structure
\bigcirc Is larger than the number of rows in the matrix M \bigcirc The vocabulary		\bigcirc Is larger than the number of rows in the matrix ${f M}$		○ The vocabulary
40. A query transformed into the concept space for LSI has The index file	40.	A query transformed into the concept space for LSI has		○ The index file
\sqrt{s} components (number of singular values) \sqrt{s} The postings file		$\sqrt{\ s}$ components (number of singular values)		$\sqrt{}$ The postings file
\bigcirc m components (size of vocabulary) 46. Using a trie in index construction		$\bigcirc \ m$ components (size of vocabulary)	46.	Using a trie in index construction
		\bigcirc n components (number of documents)		O Helps to quickly find words that have been seen before

Efficient routing to a given IP address

Efficient exchange of large files

identifier

√ Efficient routing to the location of a resource

Efficient messaging in centralized social network

Credits

Quiz questions were taken from the lecture notes of Prof. K. Aberer. Answers are provided with no guarantee.