

Distributed Data Management Distributed DBMSs

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Distributed DBMSs **Definition**



Distributed Database

 A distributed database is a collection of multiple, logically interrelated databases located at the nodes of a distributed system.

(M. Tamer Özsu, Patrick Valduriez: "Principles of Distributed Database Systems")

Distributed System

 A distributed computing system is a number of autonomous processing elements (not necessarily homogeneous) that are interconnected by a computer network and that cooperate in performing their assigned task.

(M. Tamer Özsu, Patrick Valduriez: "Principles of Distributed Database Systems")

Distributed Database Management System

 A distributed database management system is the software system that permits the management of the distributed database and makes the distribution transparent to the user.

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Distributed DBMSs Drivers of Distribution

Distributed data creation

- Relevant data is created distributedly by independent sources/systems but integrated to enable global analytics.
 - Traditional cause for data distribution



- Goal: Integrate disconnected data in one central system to satisfy an information need.
- Systems: Data Warehouses (DWH); Federated Database Management Systems (FDBMS)



Distributed data processing

- Relevant data is artificially distributed to independent workers/systems for faster data analytics.
 - > Modern cause for data distribution
- Goal: Partition and distribute large datasets to satisfy storage and analytical needs.
- Systems: Big Data Analytics Systems (sharded DBMSs, batch- and stream systems)



Question: "Find all humans ESTs (DNA-sequences), that according to BLAST are at least 60% and across at least 50 amino acids identical with mouse-channel genes in the tissue of the central nervous system."

- Various sources of information needed:
 - Mouse Genome Database (MGD) @ Jackson Labs
 - SwissProt @ EBI
 - BLAST tool @ NCBI
 - GenBank nucleotide sequence database @ NCBI









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Question: "Find all humans ESTs (DNA-sequences), that according to BLAST are at least 60% and across at least 50 amino acids identical with mouse-channel genes in the tissue of the central nervous system."

 Find "channel" sequence in tissue of central nervous system in MGD HTML-form



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Gene Expression Data Query Form	
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Sort by: I Gene symbol C Age C Anatomical structure C Assay Type C Author	
Max number of items returned: C 10 C 100 C 500 C No limit	
Return: • Assays C Assay Results	
Gene Symbol/Name:	
NOT contains Channel Search current & withdrawn & synonyms	
Gene Classifications: (You can browse the Gene Ontology (GO) Classifications)	
contains 💌	
🗹 Molecular Function 🗹 Biological Process 🗹 Cellular Component	
Chromosomal Location:	
Chromosome: ANY	
Restrict search to a chromosomal region? (specify one of the following)	
Between and Canter cal positions or locus symbols) include endpoint	.s.
Within CM of locus Include 🔽 locus.	
Expression	
O detected O not detected © either	
Developmental Stage(s): (You can browse Stage descriptions)	
TS 2 (1.0-2.5 dpc)	
TS 3 (1.0-3.5 dpc)	
in 💌 TS 4 (2.0-4.0 dpc) 💌	
Anatomical Structure(s): (You can browse the Anatomical Dictionary)	
contains 💽 brain, spinal cord	
Include: M substructures in superstructures	-

Document: Done

Source for example: A Practitioner's Guide to Data Management and Data Integration in Bioinformatics, Barbara A. Eckman in Bioinformatics by Zoe Lacroix and Terence Critchlow, 2003, Morgan Kaufmann.

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Question: "Find all humans ESTs (DNA-sequences), that according to BLAST are at least 60% and across at least 50 amino acids identical with mouse-channel genes in the tissue of the central nervous system."

- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- MGD Result
 - 14 genes from
 17 experiments



MGI 27 - Gene Expression Data Query Results (Summary) - Netscape Te Edit Vew Go Communicat: Heb Gene Expression Data Gene Expression Data				
				Query Results Summary
7 matchin;	g assays displayed			
Gene	Assay Type	Assay	RefTD	Reference
Atp6l	Northern blot	MGI:2150866	J:71376	Nishi T, J Biol Chem 2001 Sep 7;276(36):34122-30
Cacnb3	RT-PCR	MGI:1205020	J:46439	Freeman TC, MGI Direct Data Submission 1998;():
<u>Gja1</u>	Immunohistochemistry	MGI:1338492	<u>J:31725</u>	Yancey SB, Development 1992 Jan;114(1):203-12
<u>Gja1</u>	Immunohistochemistry	MGI:1338557	<u>J:31725</u>	Yancey SB, Development 1992 Jan;114(1):203-12
Kcna4	Immunohistochemistry	MGI:1335744	<u>J:41027</u>	Zhong W, Development 1997 May,124(10):1887-97
Kcnab2	RT-PCR	MGI:1204928	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
Kcnh1	RT-PCR	MGI:1205795	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
Kenj12	RT-PCR	MGI:1204727	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
K cnj2	RT-PCR	MGI:1205781	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenj3</u>	RT-PCR	MGI:1205497	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenj4</u>	RT-PCR	MGI:1204196	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kcnj4</u>	RT-PCR	MGI:1204198	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenj5</u>	RT-PCR	MGI:1205098	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenj6</u>	RT-PCR	MGI:1204201	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenj9</u>	RT-PCR	MGI:1204204	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
<u>Kenmal</u>	RT-PCR	MGI:1205940	<u>J:46439</u>	Freeman TC, MGI Direct Data Submission 1998;():
Konma 1	PT DOP	MGT-1205942	T-46420	Frames TC, MGI Direct Data Submission 1998-0-

Document: Done

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- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- 2. Examine the details for each of the 14 genes on SwissProt
 - On average 5 SwissProt links per gene

AGI2.7 - Genes, M Edit <u>V</u> iew <u>G</u> o (larkers and Phenotypes Query Results (Details Communicator <u>H</u> elp) - Netscape	
//			
ene Classificatio	ms: (You can browse the Gene Ontology (30) Classifications)	
Category	Classification Term	Evidence	Reference
Biological Pr	ocess ATP biosynthesis	electronic annotation	<u>J:60000</u>
Cellular Con	ponentmembrane fraction	electronic annotation	<u>J:60000</u>
Cellular Con	proton-transporting ATP synthase complex	electronic annotation	<u>J:72245</u>
Molecular F	inction electron transporter	electronic annotation	<u>J:60000</u>
Molecular Fr	nction hydrogen-transporting two-sector ATPase	electronic annotation	<u>J:72245</u>
her Database I	inks for this Marker:		
Acc ID	Links	Reference	
AB059662	(DDBJ, EMBL, GenBank)	<u>J:71631</u>	
AF356008	(DDBJ, EMBL, GenBank)	<u>J:71376</u>	
AK002570	(DDBJ, EMBL, GenBank)	<u>J:65060</u>	
AK002871	(DDBJ, EMBL, GenBank)	<u>J:65060</u>	
AK014361	(DDBJ, EMBL, GenBank)	<u>J:65060</u>	
M64298	(DDBJ, EMBL, GenBank)	<u>J:20078</u>	
U13842	(DDBJ, EMBL, GenBank)	<u>J:31176</u>	
AAL02098	(SWISS-PROT (EBI), SWISS-PROT (S	<u>IB)) J:53168</u>	
BAB22195	(SWISS-PROT (EBI), SWISS-PROT (S	<u>IB)) J:53168</u>	
BAB22419	(SWISS-PROT (EBI), SWISS-PROT (S	<u>IB)) J:53168</u>	
BAB64538	(SWISS-PROT (EBI), SWISS-PROT (S	<u>IB))J:53168</u>	
P23967	(SWISS-PROT (EBI), SWISS-PROT (S	<u>IB)) J:53168</u>	

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Example: Question of a Biologist Question: "Find all humans ESTs (DNA-sequences), that according to BLAST are at least 60% and across at least 50 amino acids identical with

mouse-channel genes in the tissue of the central nervous system."

- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- 2. Examine the details for each of the 14 genes on SwissProt

Motivation

3. Examine each SwissProt entry with the BLAST algorithm

🕯 Netscape File Edit View Go Communicator Help TD AALO2098 PRELIMINARY: PRT: 155 AA AC. AAL02098; DT 01-NOV-2001 (EMBLrel. 63, Created) DT 01-NOV-2001 (EMBLrel. 63, Last sequence update) DT. 01-NOV-2001 (EMBLrel. 63, Last annotation update) DE Vacuolar proton-translocating ATPase 16 kDa subunit. os Mus musculus (Mouse). OC. Eukaryota; Metazoa; Chordata; Craniata; Vertebrata; Euteleostomi; OC. Mammalia; Eutheria; Rodentia; Sciurognathi; Muridae; Murinae; Mus. ΟX NCBI TaxID=10090; RN [1] RP SEQUENCE FROM N.A. RC STRAIN=BALB/c; RX MEDLINE=21423991; PubMed=11441017; RÅ Nishi T., Kawasaki-Nishi S., Forgac M.;

- RT "Expression and Localization of the Mouse Homolog of the Yeast
- RT V-ATPase 21-kDa Subunit c' (Vma16p).";
- RL J. Biol. Chem. 276:34122-34130(2001).
- DR EMBL; AF356008; AAL02098.1; -.
- SQ SEQUENCE 155 Å, 15808 NW; 880C280C5AEBOC5C CRC64; MADIKNNPEY SSFFGVMGAS SAMVFSAMGA AVGTAKSGTG IAAMSVMAPE LINKSIIPVV MAGIAIYGL VVAVLIANSL TDGITLYRSF LQLGAGLSVG LSGLAAGFAI GIVGDAGVRG TAQQPRLFVG MILILIFAEV LGLYGLIVAL ILSTK
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- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- 2. Examine the details for each of the 14 genes on SwissProt
- 3. Examine each SwissProt entry with the BLAST algorithm
- 4. Examine each BLAST result to ...
 - 1. eliminate non-human hits
 - check other predicates (>60% identical, etc.).

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IRE383501 11RE383501 602045186E1 NCT CGAD 110 Mine wirecolog cDN	251	88-67	
RT555101 1187555101 60323613681 NTH (GAD Mam3 Mus musculus ch.	251	8e_67	
IPP295425 11PP295425 601006726F1 NCT COAP Mame Mus suscellus ob.	251	0e-07 8e-67	
DESCRIPTION AND AND AND AND AND AND AND AND AND AN	251	00-67	
(BIGSTIZE.I BIGSTIZE GESZE/SSOFI WIN_COMP_NAME HUS MUSCULUS CD.	231	06-07	
100021060 110021060 FST352272 Dat game index normalized rat	251	8e-67	
(R0921909.1 R0921909 L31333273 Rat gene index, normalized fat,	231	00-67	
(DIG40/90.1)DIG40/90 BU32/0/34F1 MIN_CGAP_NERS HUS HUSCUlus CD.	251	08-07	
BF123349.1 BF123349 B01759145F1 MCI COMP Mam5 Hus musculus CD.	251	02-07	
Bib93533.1 Bib93533 BU3341913F1 NCI CGRF Mamz Hus musculus cu.	251	8e-67	
BI5555010.1 BI555010 50328/05/F1 NCI_CGAP_Mam6 Mus musculus cD.	251	8e-67	
·		B- 60	
D ALDJJD22.1 ALDJJD22 ALDJJD22 AGC-gastrula Silurana tropicali.	228	/e=6U	
D AL639595.1 AL639595 AL639595 XGC-neurola Silurana tropicalis.	228	7e-60	
b)AL594253.1 AL594253 AL594253 XGC-gastrula Silurana tropicali.	228	7e-60	
b AL557998.1 AL557998 AL557998 LTI_NFLOO8_TC2 Homo sapiens cDN.	227	2e-59	
BE397494.1 BE397494 601288884F1 NIH MGC 8 Homo sapiens cDNA c.	227	2e-59	
BF205901.1 BF205901 601869515F1 NIH_MGC_19 Homo sapiens cDNA .	227	2e-59	
BE729329.1 BE729329 601561519F1 NIH_MGC_20 Homo sapiens cDNA .	227	2e-59	
BG697408.1 BG697408 602661186F1 NCI_CGAP_Skn3 Homo sapiens cD.	227	2e-59	
BI765781.1 BI765781 603046569F1 NIH MGC 116 Homo sapiens cDNA.	227	2e-59	
BE797916.1 BE797916 601586263F1 NIH_MGC_7 Homo sapiens cDNA c.	227	2e-59	
BG490168.1 BG490168 602519116F1 NIH MGC 18 Homo sapiens cDNA .	227	2e-59	
BG741416.1 BG741416 602631991F1 NCI CGAP Skn3 Homo sapiens cD.	227	2e-59	
AI114460.1 AI114460 HA1042 Human fetal liver cDNA library Hom.	227	2e-59	
AW249148.1 AW249148 2820881.5prime NIH NGC 7 Homo sapiens cDN.	227	2e-59	
BF727320.1 BF727320 by19h07.v1 Human Lens cDNk (Un-normalized.	227	2e-59	
BI328911.1 BI328911 602980634F1 NCI CGAP L19 Mus musculus cDN.	226	3e-59	
BF101272.1 BF101272 601754562F1 NCI CGAP Mam1 Mus musculus cD.	192	4e-59	
b AL627969.1 AL627969 AL627969 XGC-gastrula Silurana tropicali.	225	6e-59	
b AL643955.1 AL643955 AL643955 XGC-neurola Silurana trovicalis.	225	6e-59	
BI706803.1 BI706803 fg10e10.v1 Zebrafish adult retina cDNA Da.	225	8e-59	
BE789647.1 BE789647 601481404F1 NIH MGC 68 Homo sapiens cDNA .	225	8e-59	
BI447381.1 BI447381 dah87e12.v1 NICHD XGC Emb2 Xenopus laevis.	225	8e-59	
BI475274.11BI475274 fg30d06.v3 zebrafish adult brain Danio re.	225	8e-59	
AW460815.1 AW460815 da25c08.v1 Xenla 13LiCl Xenopus laevis cD.	225	8e-59	
BE992046.1 BE992046 UI-M-BZ1-bec-d-07-0-UI.s1 NIH BMAP MHI2 5.	225	8e-59	
BI839734.1 BI839734 fg42d11.v1 zebrafish adult brain Danio re.	. 225	8e-59	
BI429515.1 BI429515 fr70h03.v1 zebrafish adult brain Danio re.	225	8e-59	
,		0- 50	

Source for example: A Practitioner's Guide to Data Management and Data Integration in Bioinformatics, Barbara A. Eckman in Bioinformatics by Zoe Lacroix and Terence Critchlow, 2003, Morgan Kaufmann.

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Distributed DBMSs

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- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- 2. Examine the details for each of the 14 genes on SwissProt
- 3. Examine each SwissProt entry with the BLAST algorithm
- 4. Examine each BLAST result
- 5. For each remaining result: retrieve EST-sequence from GenBank



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- Find "channel" sequence in tissue of central nervous system in MGD HTML-form
- Examine the details for each of the 44 cents of SwissPress
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Question: "Find all humans ESTs (DNA-sequences), that according to BLAST are at least 60% and across at least 50 amino acids identical with mouse-channel genes in the tissue of the central nervous system."

 If there was an integrated database with all four sources, the following "simple" SQL query does all previous manual steps:

SELECT	g.accnum,g.sequence	
FROM	genbank g, blast b, swissprot s, mgd m	Distributed Data
WHERE	m.exp = "CNS"	Management
AND	m.defn LIKE ``%channel%"	Distributed DBMSs
AND	m.spid = s.id AND s.seq = b.query	
AND	b.hit = g.accnum	ThorstenPapenbrock
AND	b.percentid >= 60 AND b.alignlen >= 50	Slide 12

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Distributed DBMSs Overview

- 1. Distributed DBMSs
- 2. Materialized vs. Virtual
- 3. Data Warehouses
- 4. Federated Database Management Systems





Distributed DBMSs Distributed Data Creation





Distributed DBMSs Distributed Data Creation





Distributed DBMSs Conflicting Goals



Online Transaction Processing (OLTP)



- Local, isolated databases
- Fast point reads and writes

Online Analytics Processing (OLAP)



- One integrated database
- Fast aggregations, joins, filters, projections and other complex read operations

Distributed Data Management

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Distributed DBMSs **Conflicting Goals**



Online Transaction Processing (OLTP)



Online Analytics Processing (OLAP)

Completely independent

datasets



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Distributed DBMSs

Online Transaction Processing (OLTP)

- "Fast processing of operational data, i.e., transactions while maintaining data integrity in multi-access environments"
- Performance characteristic: transactions per second
- Often: time-critical, mixed-workload data with high velocity
- Dominating operations: INSERT, UPDATE, DELETE

Online Analytical Processing (OLAP)

- "Effective answering of analytical queries on already collected data"
 - Arbitrary, complex, and arbitrarily complex workloads
- Performance characteristic: query response time
- Often: pre-aggregated, multi-dimensional, and historical data
- Dominating operations: SELECT, GROUP, Aggregation



Distributed Data Management Distributed DBMSs



Distributed DBMSs



Property	OLTP	OLAP		
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records		
Main write pattern	Random-access, low-latency writes from user input	Bulk import (ETL) or event stream		
Primarily used by	End user/customer, via (web) application	Internal analyst, for decision support	Distributed Data	
What data represents	Latest state of data (current point in time)	History of events that happened over time	Management Distributed DBMSs	
Data size	Kilobytes to Gigabytes	Terabytes to petabytes	ThorstenPapenbrock Slide 20	

Distributed DBMSs



	OLTP System Online Transaction Processing (Operational System)	OLAP System Online Analytical Processing (Data Warehouse)
Source of data	Operational data; OLTPs are the original source of the data.	Consolidation data; OLAP data comes from the various OLTP Databases
Purpose of data	To control and run fundamental business tasks	To help with planning, problem solving, and decision support
What the data	Reveals a snapshot of ongoing business processes	Multi-dimensional views of various kinds of business activities
Inserts and Updates	Short and fast inserts and updates initiated by end users	Periodic long-running batch jobs refresh the data
Queries	Relatively standardized and simple queries Returning relatively few records	Often complex queries involving aggregations
Processing Speed	Typically very fast	Depends on the amount of data involved; batch data refreshes and complex queries may take many hours; query speed can be improved by creating indexes
Space Requirements	Can be relatively small if historical data is archived	Larger due to the existence of aggregation structures and history data; requires more indexes than OLTP
Database Design	Highly normalized with many tables	Typically de-normalized with fewer tables; use of star and/or snowflake schemas
Backup and Recovery	Backup religiously; operational data is critical to run the business, data loss is likely to entail significant monetary loss and legal liability	Instead of regular backups, some environments may consider simply reloading the OLTP data as a recovery method

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Distributed DBMSs

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source: www.rainmakerworks.com



Distributed DBMSs Conflicting Goals



Online Analytics Processing Online Transaction Processing (OLTP) (OLAP) Year Bookaroup Year Bookgroup Order Order name namo Warehouse Governance book id Month Book book id Mo Bo amount amount single_price month sinale p book group id month book_group_id year id vear id Orders Orders Day order id Customer order Customer Da id dav id id day_id day custo name dav customer id name Custom total mon month id total amt Relationsh Conti Managem **Distributed Data** Management Distributed DBMSs So since OLTP and OLAP workloads do exist, ThorstenPapenbrock how do we solve this conflict? Slide 23

Distributed DBMSs Solution A: Materialized Integration





Frequently copy data from OLTP systems over to OLAP systems.

Data Warehouse (DWH)

Distributed DBMSs Solution B: Virtual Integration





The OLAP systems defines analytical views that fetch the data on demand.

Federated Database Management Systems (FDBMS)

Distributed DBMSs Overview

- 1. Distributed DBMSs
- 2. Materialized vs. Virtual
- 3. Data Warehouses
- 4. Federated Database Management Systems



Materialized

- A-priori integration
- Centralized data store
- Centralized query processing
- Typical example: data warehouse

Virtual

- On-demand integration
- Decentralized data
- Decentralized query processing
- Typical example: mediator-based information system







Materialized



Virtual

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Distributed DBMSs

Materialized



Virtual



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Materialized



- Push-model for Data
 - Periodically import data
 - Redundant storage
 - Materialized (aggregate) views
- Schema design
 - Bottom up
 - Schema integration
- Query processing as usual
 - OLAP queries
 - Star schema

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Virtual

- Pull-model for data
 - Only transfer data for query at hand
- Schema design
 - Top down
 - Schema mapping
- Query processing
 - Difficult optimization
 - Heterogeneous costs and abilities of sources



Distributed Data Management Distributed DBMSs

Materialized vs. Virtual An Overview and Classification of Mediated Query Systems HPI Hasso Taxonogy Ruxandra Domenig', Klaus R. Dittrich Department of Information Technology, University of Zurich HPI Hasso



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Materialized



Virtual

Distributed Data Management Distributed DBMSs

Materialized vs. Virtual Global as View / Local as View

Global as View (GaV)

- Relations of the global integrated schema are expressed as views on the local source schemata.
- Idea: Views tell where the global relations get their data from.



Local as View (LaV)

- Relations of the local source schemata are expressed as views on the global integrated schema.
- Idea: Views tell what parts of the global relations can be found in each local relation.



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Materialized vs. Virtual GaV Query Processing

Given:

- A query against the global integrated schema (in particular: against relations of the global schema)
- For each global relation, a view on local relation(s)

Find:

- All valid tuples for the query
- But: Data is stored in local sources.

Idea:

- Replace each relation in the query by the corresponding view definition: "view expansion" or "query unfolding"
- Result: A nested query





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Materialized vs. Virtual Global as View / Local as View

Global as View (GaV)

- Relations of the global integrated schema are expressed as views on the local source schemata.
- Idea: Views tell where the global relations get their data from.



Local as View (LaV)

- Relations of the local source schemata are expressed as views on the global integrated schema.
- Idea: Views tell what parts of the global relations can be found in each local relation.



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Distributed DBMSs



Materialized vs. Virtual LaV Query Processing

Given:

- A query against the global integrated schema (in particular: against relations of the global schema)
- For each local relation, a view on global relation(s)

Find:

- All valid tuples for the query
- But: Data is stored in local sources.

Idea:

 Run the query against all local relations whose views can contribute to the result of the query; join/union all local results.





Distributed Data Management Distributed DBMSs

Materialized vs. Virtual LaV Query Processing (formal)

Given:

- A query q against the global integrated schema (in particular: against relations of the global schema)
- For each local relation, a view on global relation(s)

Find:

- Sequence of queries q₁ ◊... ◊q_n
- Each q_i can be executed by a single view
- Suitable combination of queries q₁,...,q_n answers q
- Within a plan, use joins: $\diamond \rightarrow \bowtie$
- Multiple plans are combined by UNION : $\diamond \rightarrow \upsilon$
- Tuples created by $q_1 \bowtie \dots \bowtie q_k$ are valid result tuples for q.





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Materialized vs. Virtual

LaV Query Processing Example

Global schema

Lehrt(prof,kurs_id, sem, eval, univ) Kurs(kurs_id, titel, univ)

Source 1: All database courses

CREATE VIEW DB-kurs AS SELECT K.titel, L.prof, K.kurs_id, K.univ FROM Lehrt L, Kurs K WHERE L.kurs_id = K.kurs_id AND L.univ = K.univ AND K.titel LIKE "%_Datenbanken"







Express the content of each local relation as a view on the global schema.

Source 2: All HPI lectures

CREATE VIEW HPI-VL AS SELECT K.titel, L.prof, K.kurs_id, K.univ FROM Lehrt L, Kurs K WHERE L.kurs_id = K.kurs_id AND K.univ = "HPI" AND L.univ = "HPI" AND K.titel LIKE "%VL_%"

Rewritten query

(SELECT titel, kurs_id FROM DB-kurs D WHERE D.univ = "HPI") UNION (SELECT titel, kurs_id FROM HPI-VL)

Distributed Data Management

Distributed DBMSs

See "Information Integration" lecture by Prof. Naumann for more details on the rewriting algorithm. Materialized vs. Virtual Why LaV 1: Data Integration

- The global schema models the world (e.g. the entire domain of movies).
 - In theory, this establishes the extension, i.e., the content of the database.
- In practice, there exist many databases on movies, actors etc. But nobody knows (or has) this extension.
 - > Information integration tries to collect whatever is available.
- Every source stores a part of the extension.
- Every source describes its content as views on the global schema.
 - Because the source provides the schema, it is easy to add more sources over time.





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Materialized vs. Virtual Why LaV 2: Query Optimization

- Materialized views (MVs) on database schema
 - Aka. Materialized Query Table
 - Aka. Advanced Summary Table
- Which MVs (and their pre-calculated intermediate results) can help in determining a query result?
- Challenges:
 - It is not always better to use an MV over e.g. indixes.
 - MVs need to be kept up-to-date.







Distributed Data Management Distributed DBMSs

Materialized vs. Virtual Back to Materialized vs. Virtual Integration







Virtual

Materialized vs. Virtual Back to Materialized vs. Virtual Integration

	Materialized	Virtual
Up-to-date	-	+
Response time	+	-
Flexibility	- (usually GaV)	+ (usually LaV)
Query processing complexity	-	
Source-autonomy	-	+
Query capabilities	+	-
Read/Write	+/+	+/-
Storage requirement	-	+
Completeness	+	? (OWA, CWA)
Data cleansing	+	-
Information quality	+	-



Distributed Data Management

Distributed DBMSs

Distributed DBMSs Overview

- 1. Distributed DBMSs
- 2. Materialized vs. Virtual
- 3. Data Warehouses
- 4. Federated Database Management Systems



Data Warehouses Architecture



= batch processes (think of Spark jobs)

Data Warehouse: "A central repository of integrated, potentially pre-aggregated historical data from one ore more distinct sources (usually operational/OLTP systems)"



Data Warehouses Extract-Transform-Load (ETL)

- ETL processes take data from a source, convert it into data analytics-friendly representations and sink the result into a data warehouse.
- ETL processes are ...
 - batch processes comparable to modern Spark-jobs.
 - the equivalent to schema mappings in virtual integration.
 - functional/procedural implementations of the views in the GaV model.
 - more powerful than simple views, i.e., can express more complex logic (data cleaning, data encoding, side effects, machine learning etc.).
- ETL processes offer ...
 - import filters (read and convert data from sources)
 - standard transformations (join, aggregate, filter, convert, ...)
 - de-duplication (find and merge multiple records referring to the same entity)
 - aggregations (simple aggregates, sketches, histograms, ...)
 - quality management (test against master data, business rules, constraints, ...)



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Data Warehouses Application Areas

- Customer Relationship Management (CRM)
 - Premium customer identification
 - Personalization
 - Mass-marketing
- Controlling / Accounting
 - Cost center discovery
 - Organizational units analysis
 - Human resources management
- Logistics
 - Fleetmanagement and -tracking
- Digital health
 - Experimental studies
 - Patient monitoring



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Distributed Data Management Distributed DBMSs

Data Warehouses Popular DWH DBMSs



Commercial

- Microsoft SQL Server
- SAP HANA
- Teradata
- Vertica
- ParAccel
-

Open-Source

- Apache Hive
- Spark SQL
- Cloudera Impala
- Facebook Presto
- Apache Tajo
- Apache Drill

•

Most of these are **Hadoop**-based and use some kind of **MapReduce** paradigm.

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Distributed DBMSs

Data Warehouses The Pros and Cons

Advantages

- Compute-intense analytical queries do not interfere with operational business.
- Data is static and does not change while queries are run.
- Data can be sorted by certain keys that are often queried as range or group (e.g. timestamps, version-IDs, tags, or country codes), whereas operational data is usually not sorted for better insert performance.
- Data can be compressed more aggressively to improve read performance.
- Analytics-friendly data layouts, e.g., star-schemata, data cubes, or materialized views as well as indexes for analytical query patters are possible.

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Distributed DBMSs

Disadvantages

Data is not up-to-date (one ETL-cycle ≈ one day old)



Data Warehouses Stars and Snowflakes

Star Schema

- An acyclic graph of relational tables with depth 1
 - Root = "fact table"
 - Leaves = "dimension tables"
- Fact tables: contain events (transactions, measurements, snapshots,...)
 - Usually very large tables (long and wide)
 - Examples: sales, page views, clicks, shippings, sensor readings, ...
- Dimension tables: contain entity data and descriptive information
 - Usually small tables with fixed domain
 - Examples: products, employees, customers, dates, locations, ...
- Answer for each event: who, what, where, when, how, or why

Snowflake Schema

 Same as star schema, but with arbitrary depth, i.e., dimension tables might have further dimension tables



Distributed DBMSs



Data Warehouses Stars and Snowflakes – Examples







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Distributed DBMSs

Stars and Snowflakes – Benefits

- Improved query performance for (most) aggregation queries:
 - Better join-performance than normalized data
 - Better scan performance than one big table
 - May contain pre-aggregated data
- Simpler queries:

Data Warehouses

- Clear join logic and manageable number of joins
- Redundancy reduction via data integration:
 - Redundant information in different sources is consolidated into same tables
 - Redundant information in one source table might get normalized into one dimension table



Distributed DBMSs



Data Warehouses Stars and Snowflakes – Star Join

SELECT *
FROM Sales S, Location L, Time T, Product P
WHERE S.L_ID = L.ID AND S.T_ID = T.ID AND S.P_ID = P.ID
AND L.state = ,Idaho`
AND Year_Month(T.Date) = 201809
AND P.Category = ,Beer`

- Some sizes
 - Sales: 10,000,000
 - Locations: 1,000
 - 10 in Idaho
 - Times: 1,000 days
 - 20 in September 2018
 - Products: 1,000
 - 50 Beers



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Data Warehouses Stars and Snowflakes – Star Join





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- Intermediate result sizes
 - Normal joins: 100k + 2000
 - Star join: 200 + 10k

Data Warehouses Pre-Aggregation

Observation

- Most analytical queries in data warehouses are aggregate queries.
- Aggregation patterns repeat frequently.
 - Pre-calculate common aggregates!

Materialized Views

- Are query results that are written back to disk.
- DBMS query optimizers can automatically use these views to answer queries or parts of queries (see LaV).
- Strategies to improve data analytics:
 - Pre-calculation: estimate common aggregates and pre-calculate them
 - Lazy pre-calculation: store each aggregate once it was queried



Distributed Data Management Distributed DBMSs



Data Warehouses Pre-Aggregation – Data Cubes

Data Cube

A set of materialized views for multi-dimensional aggregates **SELECT** product sk, date sk, (i.e., a grid of aggregates grouped by different dimensions) sum(net price) **FROM** fact sales **GROUP BY** product sk, date sk Example product sk In general more 32 33 34 35 total ... than two +++dimensions key 140101 149.60 31.01 84.58 28.18 40710.53 ... date 140102 73091.2 132.1819.78 82.91 10.96 **Distributed Data** ... +Management 54688.10 140103 196.75 0.00 12.52 64.67 ... Distributed DBMSs +178.36 140104 9.98 88.75 56.16 95121.0 ... ++ ThorstenPapenbrock Slide 59 14967.09 5365M 5910.43 7328.85 6885.39 total ...

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Dat Pr	ta Wareh e-Agg	^{ouses} regatio	on – D	SELECT SUM(net_price) FROM fact_sales WHERE product_sk = 32 AND net_price > 100.00						
		SELECT S FROM fact WHERE pr AND date	UM (net_pr :_sales roduct_sk = _sk = 1401	SELECT SUM(net_price) FROM fact_sales WHERE date_sk = 140101						
Exa	mple	product_sk								
		32	33	34	35		total			
key	140101	149.60	31.01	84.58	28.18		40710.53			
lte_	140102	132.18	19.78	82.91	10.96		73091.28	Distributed Data		
qa	140103	196.75	0.00	12.52	64.67		54688.10	Management Distributed DBMSs		
	140104	178.36	9.98	88.75	56.16		95121.09			
								ThorstenPapenbrock		
	total	14967.09	5910.43	7328.85	6885.39		5365M	Slide 60		

Data Warehouses Pre-Aggregation – Data Cubes: Dimension







Distributed Data Management Distributed DBMSs

Roll-Up

• Aggregate one dimension of a data cube.



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Drill-Down

Unfold one dimension of a data cube.





Aggregate-to-TOP

Aggregate all values in one dimension; reduce cube dimensionality by 1.



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Slicing

• Select/filter a value for one dimension; reduce cube dimensionality by 1.





Dicing

• Select/filter some values for multiple dimension; make cube smaller.



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Data Warehouses Column-oriented Storage

Observation

- Data warehouse tables are often very wide (>100 columns), but analytical queries access only very few columns.
 - Usually 4 to 5 and rarely "SELECT *"
- Most data models (relational, key-value, column family, document) store data record-wise and, hence, must read, parse and filter all data for analytical queries.

Column-oriented Storage

- Store data attribute-wise instead of record-wise:
 - One file per attribute
 - Values ordered by record index in each file
 - For each query: scan only required attribute files



Distributed DBMSs







fact_sales table

date_key	product_sk	store_sk	promotion_sk	customer_sk	quantity	net_price	discount_price
140102	69	4	NULL	NULL	1	13.99	13.99
140102	69	5	19	NULL	3	14.99	9.99
140102	69	5	NULL	191	1	14.99	14.99
140102	74	3	23	202	5	0.99	0.89
140103	31	2	NULL	NULL	1	2.49	2.49
140103	31	3	NULL	NULL	3	14.99	9.99
140103	31	3	21	123	1	49.99	39.99
140103	31	8	NULL	233	1	0.99	0.99
file 1	file 2	file 3	file 4	file 5	file 6	file 7	file 8



product_sk file

69	69	69	69	74	31	31	31	31	29	30	30	31	31	29	68	69	69
q ntis file																	
1	3	1	5	1	3	1	1	7	2	1	5	4	4	1	2	5	3

SELECT product_sk, SUM(quantity) AS product_sales
FROM fact_sales
WHERE product_sk IN (30, 68, 69)
GROUP BY product_sk;

- 1. Scan the product_sk file for values 30, 68, and 69; remember the position (=row) of each occurrence.
- Read the quantities at the retrieved positions in the quantity file and sum them up.



Distributed Data Management

Distributed DBMSs













Smaller? ... Here, yes:

18 · 32 Bit = **576 Bit** vs. 6 · (32 Bit + 32 Bit) = **384 Bit**




Data Warehouses Column-oriented Storage – Example For more compression techniques see:

Daniel Abadi et. al. "The Design and Implementation of Modern Column-Oriented Database Systems", 2013.

product sk file

Bitmap encoding

29	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	
31	0	0	0	0	0	1	1	1	1	0	0	0	1	1	1	0	0	0	4
68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	
69[1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	
74	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	

Problem:

Bitmaps are very long and sparse in practice!



0 zaros	1 ones rest zeros	nttp://roaringbitmap.org/
<i>y</i> zeros,	I Olles, lest zelos	
10 zeros,	2 ones, rest zeros	Distributed Data Management
5 zeros,	4 ones, 3 zeros, 3 ones, re	st zeros Distributed DBMSs
15 zeros,	1 ones, rest zeros	
0 zeros,	4 ones, 12 zeros, 2 ones, res	st zeros ThorstenPapenbrock
4 zeros,	1 ones, rest zeros	Slide 79

See also: Roaring Bitmaps http://roaringbitmap.org/

Distributed Data Management

Distributed DBMSs Overview

- 1. Distributed DBMSs
- 2. Materialized vs. Virtual
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- 4. Federated Database Management Systems



Federated Database Management Systems Recap



Materialized

- A-priori integration
- Centralized data store
- Centralized query processing
- Typical example: data warehouse

Virtual

- On-demand integration
- Decentralized data
- Decentralized query processing
- Typical example: mediator-based information system



Federated Database Management Systems HPI Hasso Plattner Classification of Distributed DB Systems Institut M. Tamer Özsu Distribution Patrick Valduriez Distributed, federated DBS Distributed, Principles homogenous of Distributed DBS Database Systems Distributed, Distributed, Third Edition heteroheterogeneous geneous DBS federated DBS Logically Autonomy **Distributed Data** integrated and Management homogenous DBS Distributed DBMSs Homogenous, federated DBS Hetero- 📕 Heterogeneous, Heterogeneous, integrated DBS federated DBS geneity ThorstenPapenbrock Slide 82

Federated Database Management Systems HPI Hasso Plattner Classification of Distributed DB Systems Institut M. Tamer Özsu Distribution Patrick Valduriez Principles Peer-to-peer of Distributed Database Systems Client/Server Third Edition Autonomy **Distributed Data** 12******* Management Distributed DBMSs Hetero-Tight Semi-Isolation Integration autonomous geneity ThorstenPapenbrock Slide 83



- Distribution leads to Autonomy:
 - Intra-organisation: Historically
 - Inter-organisation: Internet & WWW
- Autonomy leads to Heterogeneity:
 - Responsibility is with local admins.

Distributed Data Management Distributed DBMSs

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Federated Database Management Systems The Federated Approach

- Create the global schema (schema integration).
 - Store it as DBMS schema.
- Create wrappers for each data source that ...
 - map from local schemata to the global schema.
 - model the query capabilities of each source.
- Data remains at the sources.
- Data sources remain autonomous.
 - Are not even aware of participation
- Global schema takes declarative queries that are transparently mapped to wrappers.
- Query execution is as distributed as possible.
 - Send sub-queries to sources; wait for results.
 - Federated system replaces missing capabilities.



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Federated Database Management Systems The Federated Approach – Applications

- Meta-search engines
- Company mergers
 - Customer data
 - HR data
- Clinical information systems
 - X-ray/CRT images
 - Medial charts
 - Administrative information
 - Insurance information



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Federated Database Management Systems
5-Layer Architecture





Federated Database Management Systems
5-Layer Architecture





Distributed DBMSs **Exercise**



- 1. Why does query optimization using materialized views resemble Local as View and not Global as View?
- 2. Provide a brief explanation as to why star schemes are typically not suitable for OLTP.
- 3. When is bitmap compression most effective?
- 4. Apply bitmap compression to the string "CABBBBCCBCDBDAA" and give the result.

Distributed Data Management

Distributed DBMSs

Tobias Bleifuß Slide **89**

