Dataspaces: The Tutorial

Day 2

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VLDB 2008
Auckland, New Zealand

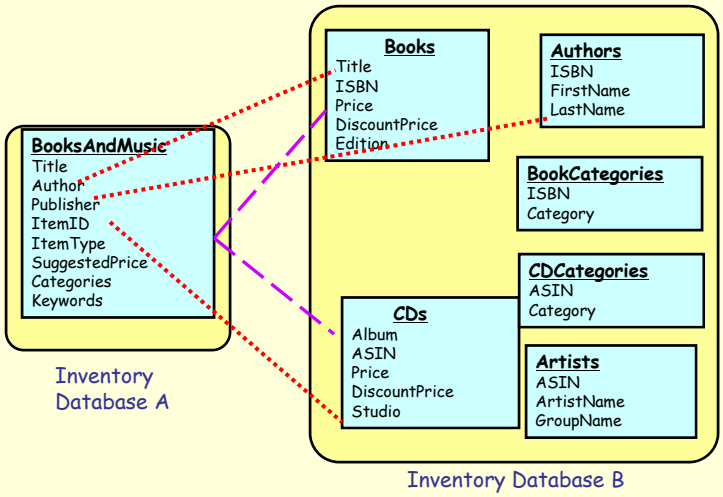
Outline

- ✓ Dataspaces: why? What are they?
  - Examples and motivation
- Dataspace techniques:
  - ✓ Locating and understanding data sources
  - Creating mappings and mediated schemas
  - Pay-as-you-go: improving with time
  - Querying dataspaces
- Research challenges on specific dataspaces:
  - Science, the desktop, the Web

Sub-Outline

- What are schema matches and mappings?
  - Why is it so hard to create them?
- Automatic techniques for creating them
- Probabilistic schema mappings
- Probabilistic mediated schemas
- Trails: mapping hints

Schema Matching and Mapping



Tabular structure, attribute names, synonyms, hypernyms, Coverage, level of detail, …

Why is it so Hard?

- Schemas were developed in different contexts for different purposes
- Schemas never fully capture their intended meaning:
  - They're just symbols and structures.
  - Descriptions are:
    - Often missing,
    - In plain text, or wrong, or,
    - Don't capture all the semantics

Schema Mapping Overview

- Step 1: schema matching:
  - Generate *correspondences* between elements of the two schemas
  - Easier to elicit from designers
  - May actually be all that's needed
- Step 2: create mappings:
  - Decide on joins, unions, filters, …

User in the loop in both steps

See Chapter 5 of upcoming book

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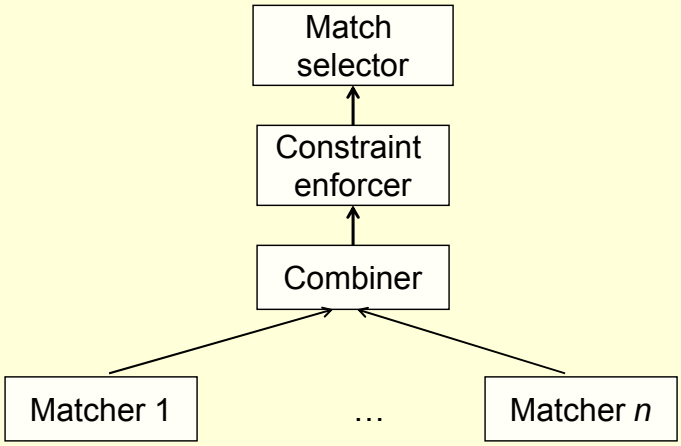
Schema Matching overview

- One trick won't do it all
- Hence:
  - Consider several *base* matchers
  - And then combine them
- Exploit domain constraints when possible
- We focus on 1-1 matching here
- [See Survey by Rahm & Bernstein, 2001]

Schema Matching Architecture



Basic Matchers

- Schema level:
  - Name, description, data type,
  - Constraints (keys, foreign keys, is-a)
  - Schema structure
- Instance level:
  - Look for common patterns in the data
  - Often more meaningful than the schema

Example: Edit Distance

Levenshtein Distance:
Number of operations needed to transform one name to the other.

$$edSim(s_1, s_2) = 1 - \frac{edit\_distance(s_1, s_2)}{\max(length(s_1), length(s_2))}$$

edSim(discountPrice, discountedPrice)?

Instance-Based Matchers

- Formatting patterns in the data can reveal type:
  - E.g., dates, phone numbers, prices, addresses, names, …
- What other attribute names were used elsewhere for such values?
  - Additional clues to name matcher
- Consider similarity in values & type between two columns
  - E.g., house price versus # of rooms

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Probabilistic Schema Mappings

- In a dataspace, we may rely on automatically created schema mappings --> uncertainty
- How do we model uncertain mappings?
- How do we answer queries in their presence?

Probabilistic Mappings

[Dong, H., Yu, VLDB 2007]

- S=(pname, email-addr, home-addr, office-addr)
- T=(name, mailing-addr)

Possible Mapping	Probability
{(pname,name),(home-addr, mailing-addr)}	0.5
{(pname,name),(office-addr, mailing-addr)}	0.4
{(pname,name),(email-addr, mailing-addr)}	0.1

Semantics? by table or by tuple?

By-Table v.s. By-Tuple Semantics

Possible Mapping	Probability
{(pname,name),(home-addr, mailing-addr)}	0.5
{(pname,name),(office-addr, mailing-addr)}	0.4
{(pname,name),(email-addr, mailing-addr)}	0.1

D_S=

pname	email-addr	home-addr	office-addr
Alice	alice@	Mountain View	Sunnyvale
Bob	bob@	Sunnyvale	Sunnyvale

D_T=

name	mailing-addr
Alice	Mountain View
Bob	Sunnyvale

$Pr(m_1)=0.5$

name	mailing-addr
Alice	Sunnyvale
Bob	Sunnyvale

$Pr(m_2)=0.4$

name	mailing-addr
Alice	alice@
Bob	bob@

$Pr(m_3)=0.1$

By-Table v.s. By-Tuple Semantics

Possible Mapping	Probability
{(pname,name),(home-addr, mailing-addr)}	0.5
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Ds=

pname	email-addr	home-addr	office-addr
Alice	alice@	Mountain View	Sunnyvale
Bob	bob@	Sunnyvale	Sunnyvale

D_T=

name	mailing-addr
Alice	Mountain View
Bob	bob@

Pr(<m_1,m_3>)=0.05

name	mailing-addr
Alice	Sunnyvale
Bob	bob@

Pr(<m_2,m_3>)=0.04

name	mailing-addr
Alice	alice@
Bob	bob@

Pr(<m_3,m_3>)=0.01

…

Complexity of Query Answering

	By-table	By-tuple
Data Complexity	PTIME	#P-complete
Mapping Complexity	PTIME	PTIME

Works for compressed representations of mappings too.

Results extend to more complex mapping languages.

PTIME for important special cases

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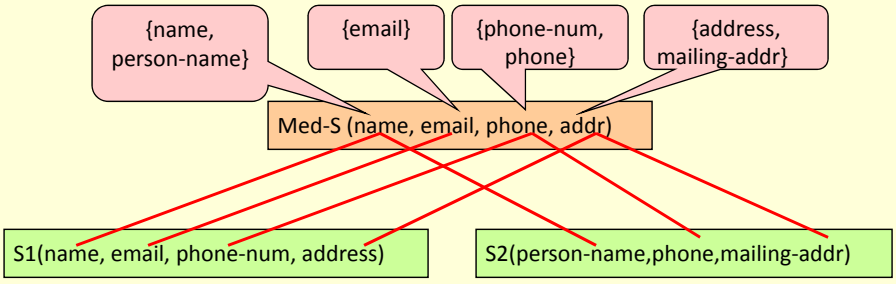
Creating the Mediated Schema

[Das Sarma, Dong, H., SIGMOD 2008]

- Mediated schema creation: up front effort.
- Can we create it automatically?
  - If we can, then we can completely bootstrap data integration.
- Probabilistic mediated schemas:
  - manage the uncertainty involved.

Example Mediated Schema



- A *mediated schema* is a clustering of a subset of the set of all attributes appearing in source schemas.

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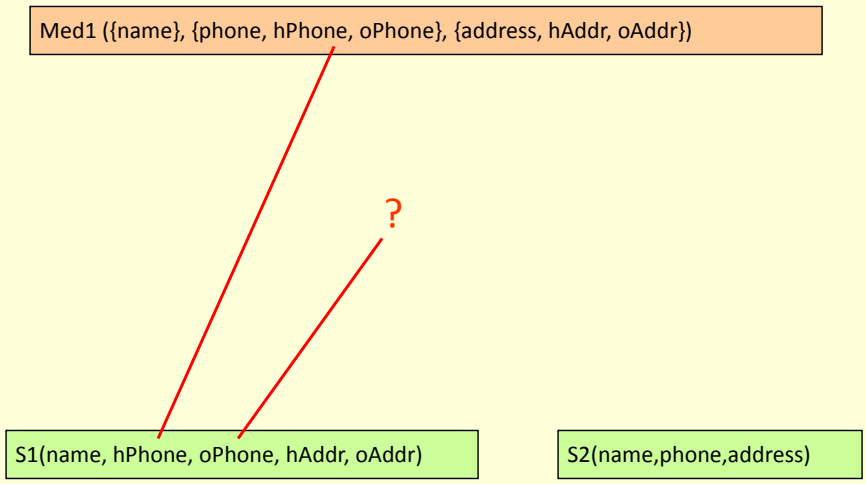
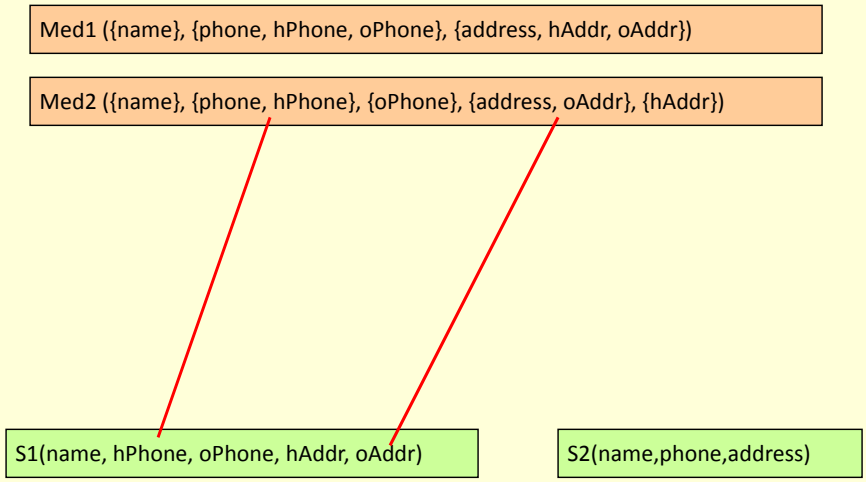
Why *Probabilistic* Mediated Schema?



Q: SELECT name, hPhone, oPhone FROM Med

22

Why *Probabilistic* Mediated Schema?



Q: SELECT name, phone, address FROM Med

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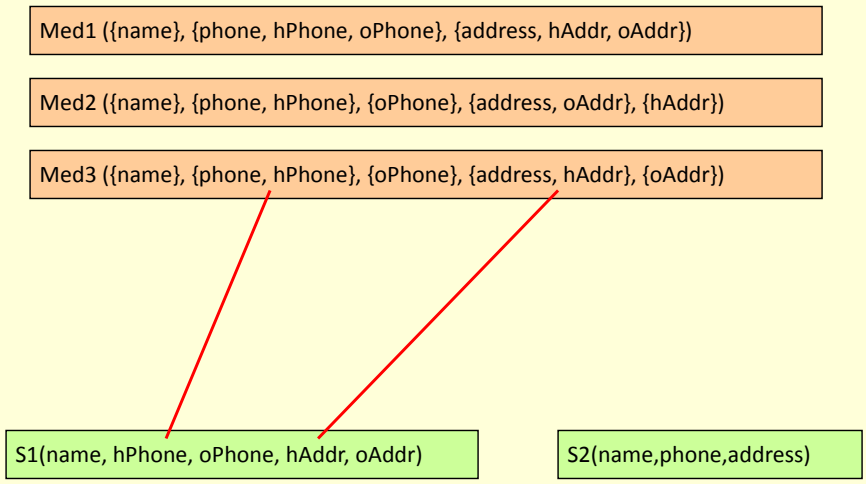
Why *Probabilistic* Mediated Schema?



Q: SELECT name, phone, address FROM Med

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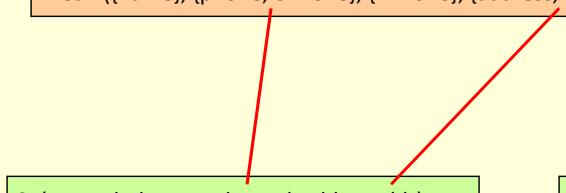
Why *Probabilistic* Mediated Schema?

Med1 ({name}, {phone, hPhone, oPhone}, {address, hAddr, oAddr})

Med2 ({name}, {phone, hPhone}, {oPhone}, {address, oAddr}, {hAddr})

Med3 ({name}, {phone, hPhone}, {oPhone}, {address, hAddr}, {oAddr})

Med4 ({name}, {phone, oPhone}, {hPhone}, {address, oAddr}, {hAddr})



S1(name, hPhone, oPhone, hAddr, oAddr)

S2(name,phone,address)

Q: SELECT name, phone, address FROM Med

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Why *Probabilistic* Mediated Schema?

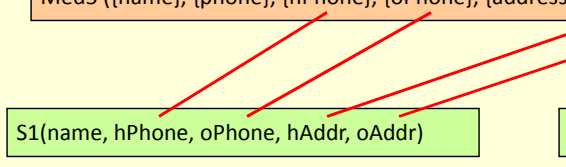
Med1 ({name}, {phone, hPhone, oPhone}, {address, hAddr, oAddr})

Med2 ({name}, {phone, hPhone}, {oPhone}, {address, oAddr}, {hAddr})

Med3 ({name}, {phone, hPhone}, {oPhone}, {address, hAddr}, {oAddr})

Med4 ({name}, {phone, oPhone}, {hPhone}, {address, oAddr}, {hAddr})

Med5 ({name}, {phone}, {hPhone}, {oPhone}, {address}, {hAddr}, {oAddr})



S1(name, hPhone, oPhone, hAddr, oAddr)

S2(name,phone,address)

Q: SELECT name, phone, address FROM Med

26

Why *Probabilistic* Mediated Schema?

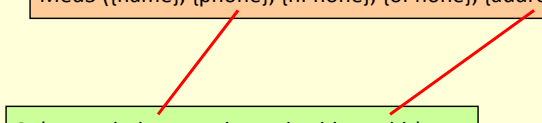
Med1 ({name}, {phone, hPhone, oPhone}, {address, hAddr, oAddr})

Med2 ({name}, {phone, hPhone}, {oPhone}, {address, oAddr}, {hAddr})

Med3 ({name}, {phone, hPhone}, {oPhone}, {address, hAddr}, {oAddr})

Med4 ({name}, {phone, oPhone}, {hPhone}, {address, oAddr}, {hAddr})

Med5 ({name}, {phone}, {hPhone}, {oPhone}, {address}, {hAddr}, {oAddr})



S1(name, hPhone, oPhone, hAddr, oAddr)

S2(name,phone,address)

Q: SELECT name, phone, address FROM Med

27

Probabilistic Mediated Schema

Med3 ({name}, {phone, hPhone}, {oPhone}, {address, hAddr}, {oAddr})

Pr=.5

Med4 ({name}, {phone, oPhone}, {hPhone}, {address, oAddr}, {hAddr})

Pr=.5

S1(name, hPhone, oPhone, hAddr, oAddr)

S2(name,phone,address)

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Probabilistic Mediated Schema

- A p-med-schema is a set

  M = { $(M_1, Pr(M_1)), \ldots, (M_l, Pr(M_l))$} where
  - M_i is a med-schema; i≠j => $M_i \neq M_j$
  - $Pr(M_i) \in (0,1]$; $\Sigma Pr(M_i) = 1$

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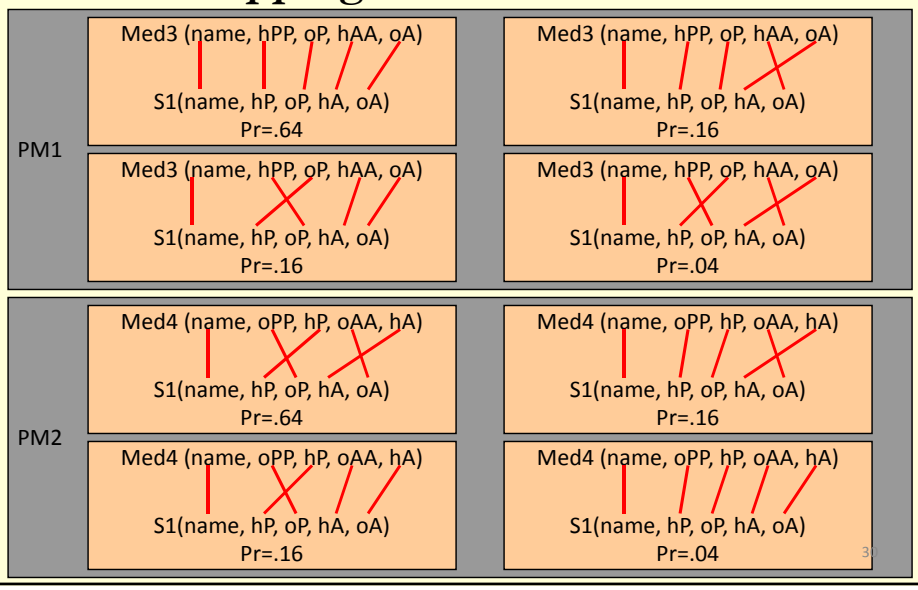
P-Mappings w.r.t. P-Med-Schema



Bootstrapping Data Integration

- Need to choose a mapping based on the correspondences:
  - One that minimizes entropy
- Consolidate probabilistic med schemas into one -- for the user.
- Between 0.85 and 0.95 P/R for queries on collections of 50-800 tables from the Web.

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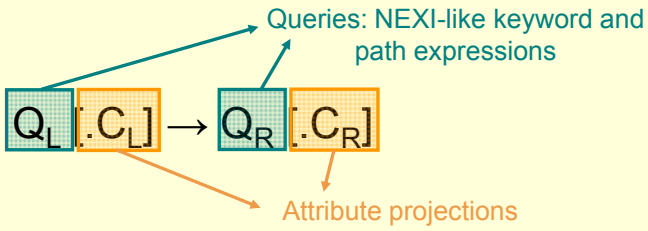
iTrails: Add Integration Hints Incrementally
[Vas Salles et al., VLDB 06, 07]

- **Step 1:** Provide a search service over all the data
  - Use a general graph data model (see VLDB 2006)
  - Works for unstructured documents, XML, and relations
- **Step 2:** Add integration semantics via hints (trails) on top of the graph
  - Works across data sources, not only between sources
- **Step 3:** If more semantics needed, go back to step 2
- **Impact:**
  - Smooth transition between search and data integration
  - Semantics added incrementally improve precision / recall

Defining Trails

- Basic form of a Trail



- Intuition: When I query for Q_L [.C_L], you should also query for Q_R [.C_R]

Trail Examples: Global Warming Zurich

`global warming zurich`

Temperatures

date	city	region	celsius
24-Sep	Bern	BE	20
24-Sep	Uster	ZH	15
25-Sep	Zurich	ZH	14
26-Sep	Zurich	ZH	9

- **Trail for Implicit Meaning:** "When I query for `global warming`, you should also query for Temperature data above 10 degrees"

```
global warming →
   //Temperatures/*[celsius > 10]
```

- **Trail for an Entity:** "When I query for `zurich`, you should also query for references of zurich as a region"

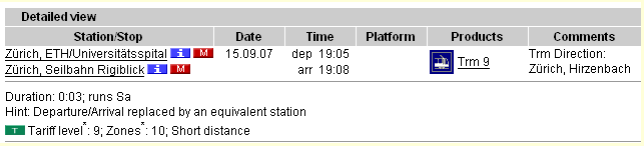
```
zurich → //*[region = "ZH"]
```

Trail Example: Deep-Web Bookmarks

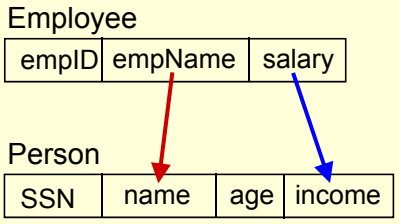
`train home`

- **Trail for a Bookmark:** "When I query for `train home`, you should also query for the `TrainCompany`'s website with `origin` at `ETH Uni` and `destination` at `Seilbahn Rigiblick`"

```
train home →
   //trainCompany.com//*[origin="ETH Uni"
         and dest ="Seilbahn Rigiblick"]
```



Trail Examples: Schema Equivalences



- **Trail for schema match on names:** "When I query for `Employee.empName`, you should also query for `Person.name`"

```
//Employee//*.tuple.empName →
                //Person//*.tuple.name
```

- **Trail for schema match on salaries:** "When I query for `Employee.salary`, you should also query for `Person.income`"

```
//Employee//*.tuple.salary →
              //Person//*.tuple.income
```

More on Trails

- Creation:
  - Given by the user explicitly or by relevance feedback.
  - (Semi-)Automatically: information extraction, schema matching, user communities, ontologies.
- Uncertainty on trails: some paths are better than others.
- Query reformulation: avoid cycles. (see paper)

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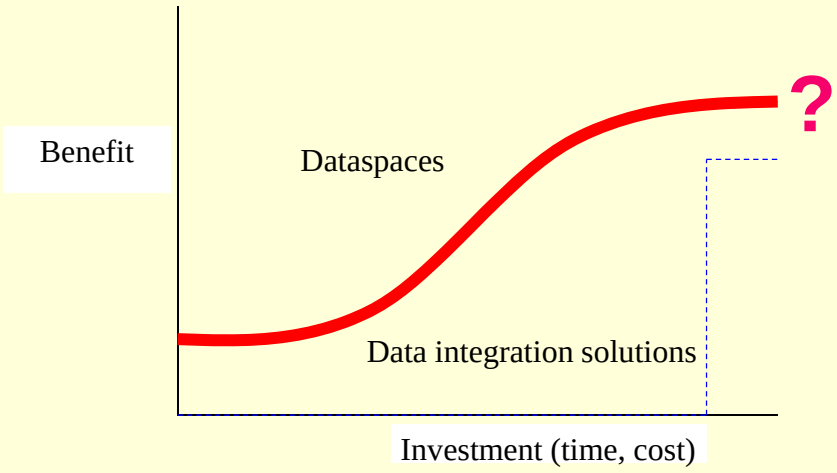
Getting the Red Curve

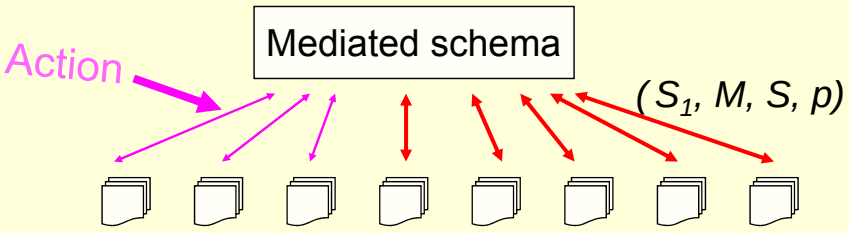


Reusing Human Attention

- Principle:
  - *User action = statement of semantic relationship*
  - *Leverage actions to infer other semantic relationships*
- Examples
  - Providing a semantic mapping
    - Infer other mappings
  - Writing a query
    - Infer content of sources, relationships between sources
  - Creating a "digital workspace"
    - Infer "relatedness" of documents/sources
    - Infer co-reference between objects in the dataspace
  - Annotating, cutting & pasting, browsing among docs
- ESP [von Ahn], mass collaboration [Doan+], active learning for record matching [Sarawagi et al.]

Learning Schema Mappings

[Doan et al., 2001]



- Classifiers for mediated schema
- Training examples: manually created schema matches
- Technique: multi-strategy learning. Use different learners and combine their predictions.
- Used in Transformic Inc. to create thousands of mappings.

Soliciting User Feedback

[Jeffrey, Franklin, H., SIGMOD 2008]

- After bootstrapping, we need help from users to improve.
  - Reference reconciliation
  - Schema matches
  - Extractions from text
- What questions should we ask the users?

The Most Beneficial Match

Decision theory to the rescue!

→*Value of Perfect Information* (VPI)

"What is the benefit of resolving an unknown?"

Intuition:

$$Benefit(\text{match } m_j) = Utility(m_j \text{ confirmed})(p_{\text{correct}}) + Utility(m_j \text{ disconfirmed})(1 - p_{\text{correct}}) - Utility(\text{without asking})$$

Utility of a Dataspace

- Focus on queries!
- 2 components:
  - Result quality
  - Query importance

$$U(D,M) = \sum_{(Q_i,w_i)\in W} r(Q_i,D,M)w_i$$

Look at all queries in the workload

Query result quality (e.g. precision/recall)

Query importance

Challenges

- How to estimate benefit without computing all queries?
- Don't want to check all possible resulting dataspaces when a match is confirmed.
- Result: much faster dataspace improvement
  - Experiments on GoogleBase data.

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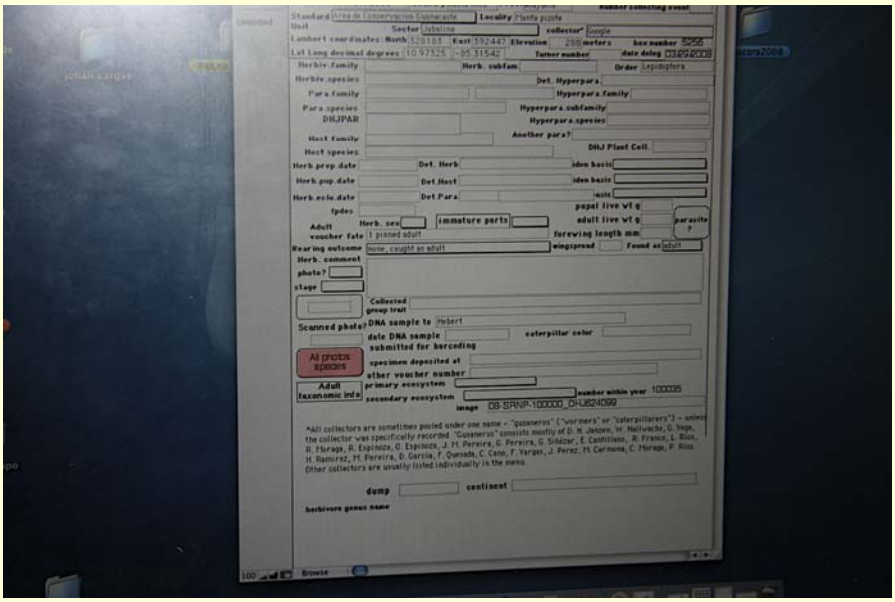
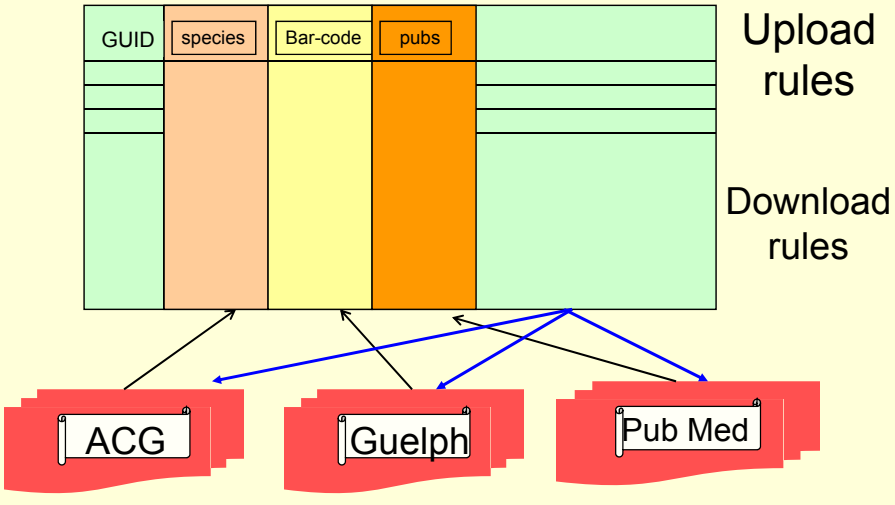
Looking for data management problems in the rainforest in Costa Rica

Cutting Off a Leg

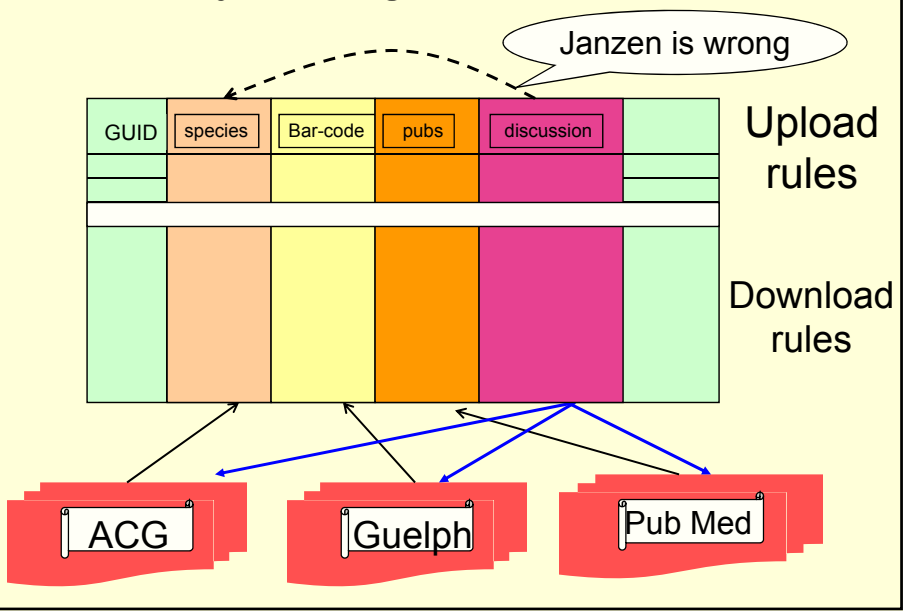
I Created a Row in a Database!



They Want Easy Sharing and Update



They Disagree on Data!

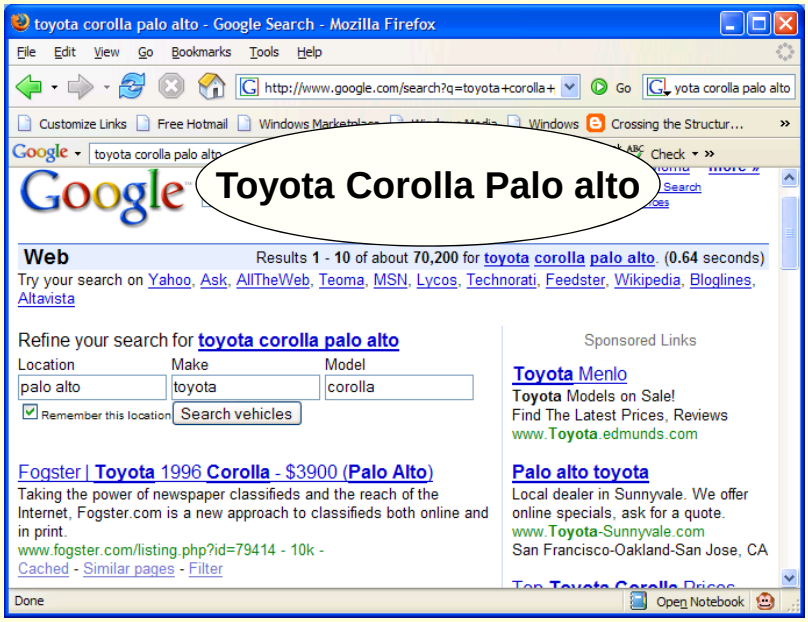


Querying Dataspaces

- We'll talk about the 'how' in a moment, but let's set expectations first.
- Recall that uncertainty is everywhere:
  - Data, mappings, query formulation
- Hence, results need:
  - To be ranked
  - Come with their provenance & explanation
    - See tutorial by Tan & Buneman, SIGMOD 2007.
  - They won't be sets of tuples necessarily.

Query Mechanisms

- Keyword search over structured data
  - BANKS (Mumbai), Xrank (Cornell), Discover (Hristidis and Papakonstantinou), Naga (Kasneci et al.)
- Keywords as a starting point:
  - Find the relevant data source and reformulate the query
    - Examples below
  - Find appropriate structured queries over multiple sources
    - System Q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Model
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www.fogster.com/listing.php?id=79414 - 10k -
Cached - Similar pages - Filter
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Our Prices & Service Can't Be Beat. Your
Local results for honda near Palo Alto, CA
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Honda Service - 0.9 miles W - 930 Emerson St, Palo Alto, 94301 - (650) 327-3061
Honda Small Car Shop - 1.0 miles W - 111 Homer Ave, Palo Alto, 94301 - (650) 329-0666
Anderson Honda - New & Certified Used Honda Cars Dealer at Palo
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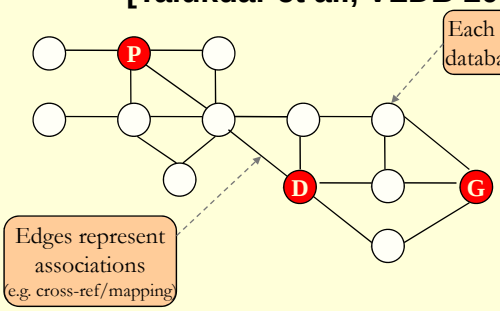
Radical Approach to New Car Buying. Competing Bids from Dealers in Area
DealersCompeteYouWin.com
Done

System Q

[Talukdar et al., VLDB 2008]



Query Keywords

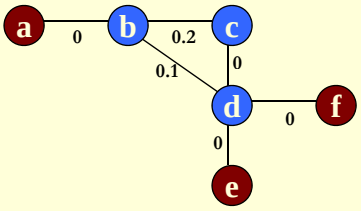
Protein, **G**ene, **D**isease = "AIDS"

The Big Question

How do we point a user to the right data when multiple databases, tables are involved and not all databases and tables are of equal value/relevance/quality/authority ?

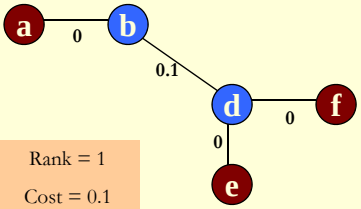
Learn the Queries to Integrate Data

Schema Graph

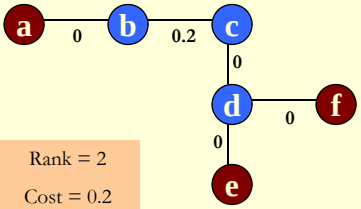


Query Keywords
a, e, f

Find trees connecting red nodes

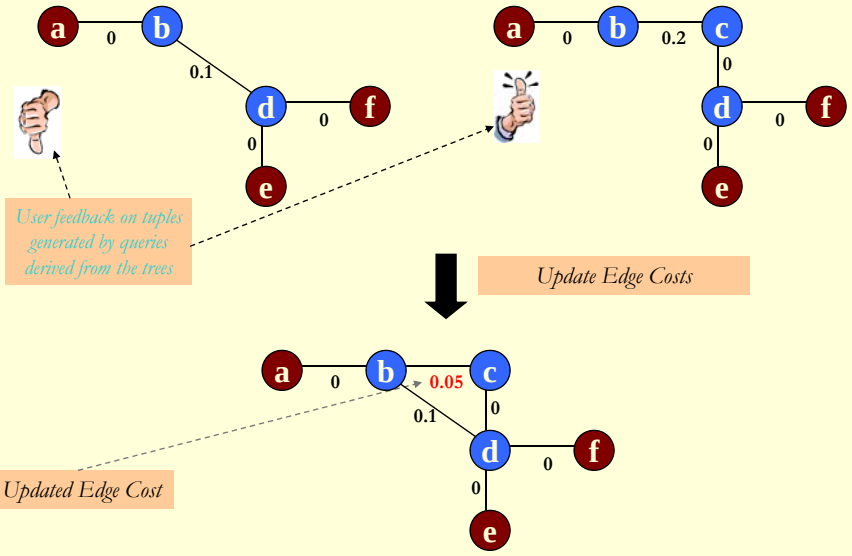


Rank = 1
Cost = 0.1

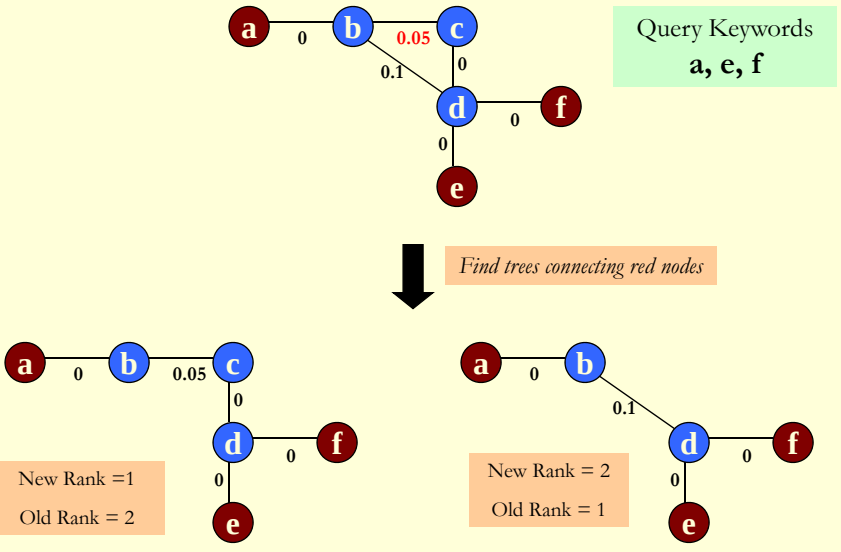


Rank = 2
Cost = 0.2

Q-System Steps (contd.)

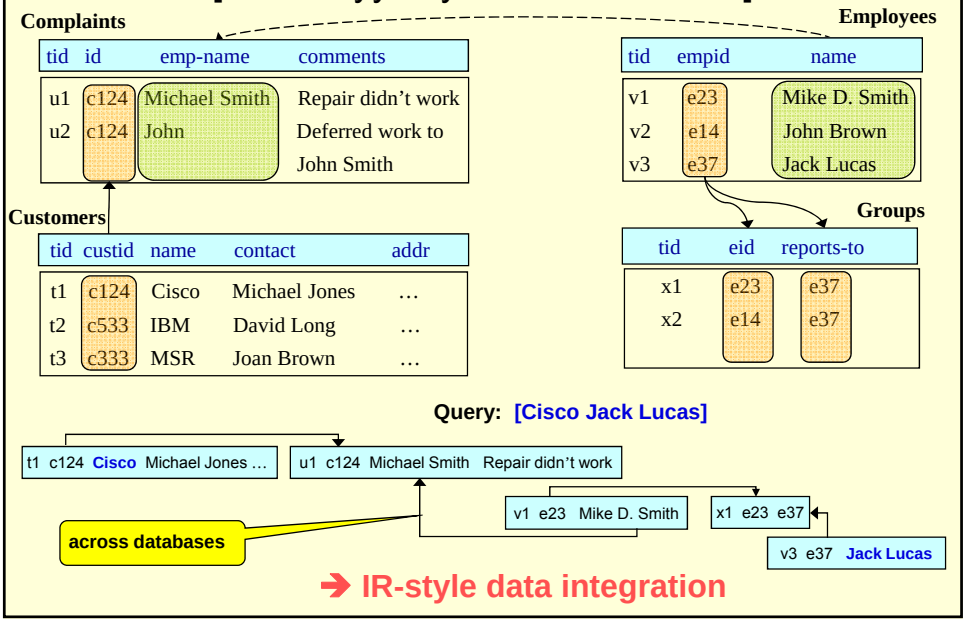


Q-System Steps (contd.)



Keyword Search across Multiple Databases

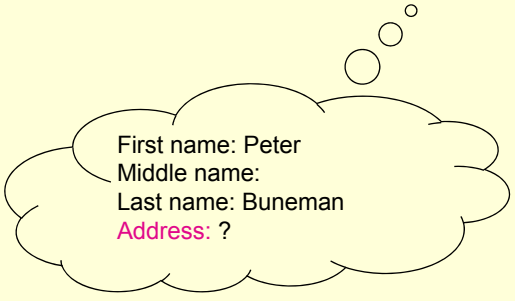
[Kite: Sayyadiyan et al. ICDE 07]



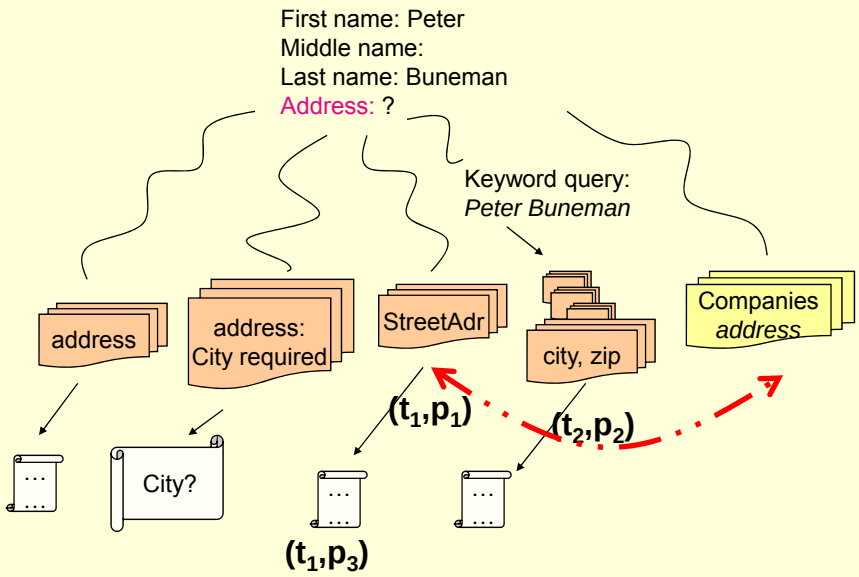
➔ IR-style data integration

Query Processing Principles

Query: Peter Buneman address



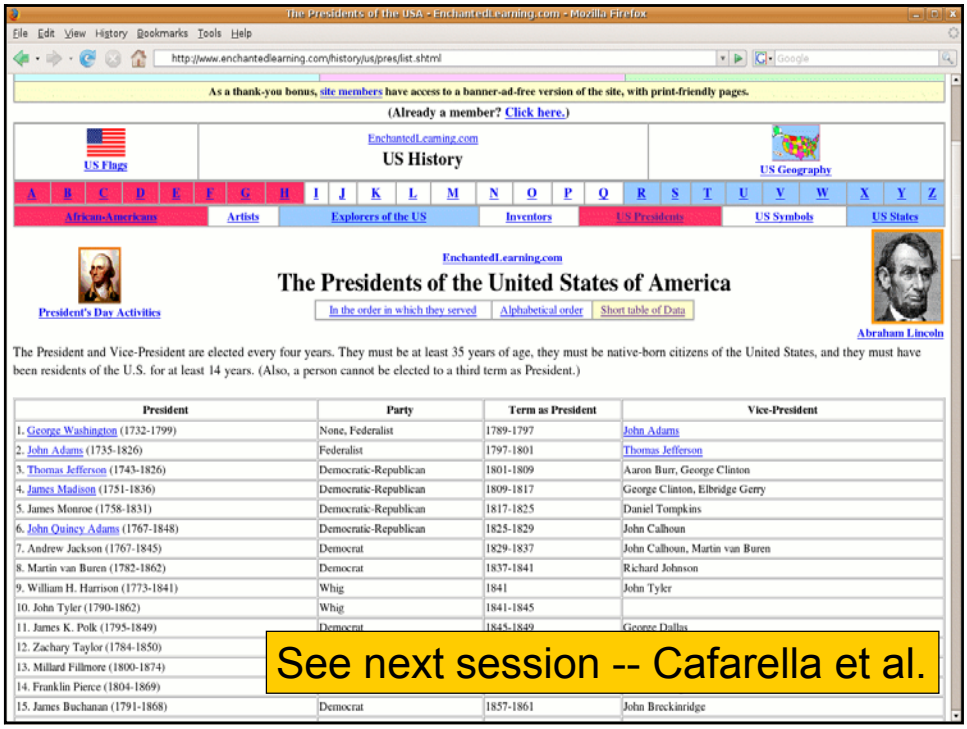
Query processing as fact gathering



Outline

- ✓ Introduction
- ✓ Dataspace principles through data integration

- Research challenges on specific dataspaces:
  - Dataspaces on the Web,
  - in Science, and
  - for Personal Information Management



Dataspaces on the Web

- The Deep Web (yesterday, Madhavan et al.):
  - Millions of forms.
- Main challenges:
  - The domain of everything
  - The context of the data carries semantics
  - Need to live with the rest of web data
- Opportunities:
  - Scale: stuff you can do with millions of schemas, forms

Issues in Science Dataspaces

- Concepts are still gelling, or have multiple abstractions
  E.g., Gene
  - Coding region of a chromosome
  - Particular transcription and splicing of a region
  - Particular variant of the region
  - Product (usu. protein) coded by the region
- Whether they should be treated the same can depend on task or even query
- Makes schemas complex

Science DS Issues, Cont.

Identification is hard

- No common identification scheme yet
  Hsp10, HSP10, CPN10, Yor020p, ch10_yeast
  [Jagadish, Chapman+ SIGMOD 07]
- Comparisons are on complex structures
  Sequence, molecule, 3-D structure
- Slight variants are different entities in rw
  Gene homologs

On-the-fly matching difficult

Want to reuse manual work

Scientific DS Issues, cont.

Complex schemas make query hard

Michigan Molecular Interactions (MiMI)

[Jayapandian, Chapman+ *Nucleic Acids Res.* 2007]

- Use abstracted schema for overview (and now query)
- Multiple query interfaces: form, XQuery, keyword, MQuery (graphical)

But – "same" query gives different answers in different interfaces

The Other "DataSpace"

- What's the minimum infrastructure for initial transformation, cleaning and exploratory analysis?
- Data sets often too big to replicate, but even fast channels are hard to exploit for on-the-fly combination

[Grossman, Mazzucco *IEEE Comp in Sci & Eng* 2002]

Universal Keys

- Devise one or more domain-specific universal keys
- Treat data as distributed columns associated with one or more UKs
- Fast transfer and merge-join on keys; templated transform and display ops

Later version called *Sector* with more parallelism

[Grossman, U Penn II Workshop 2006]

Supporting Analysis

Scenario: Domain experts who are unfamiliar with schema, need to make equivalence judgments

- `None, <1 pack, 1-2packs, >2 packs`
- `Never smoked, smoker, quit`

- GUAVA: GUI as View Apparatus

  Query through the data-entry screen
- MultiClass: Save and reuse domain mapping decisions

[Terwilliger, Delcambre+ EDBT Workshops 2006]

Other Science DS Work

- Multiple Genomes and Meta-genomes
  [Markowitz U Penn II Workshop 06]
  Have "coarse annotation" in some components while refining annotation (perhaps even manually) in others
- Science dataspaces on the Grid
  [Elsayed, Brezany+ DEXA 2006]
- Ontologies in science dataspaces
  [Ning, Wang ICPCA 2007]

Personal DS Issues

Many territorial entities in your dataspace

- Device boundaries: laptop vs. PDA
- Document boundaries: directory vs. cells
- Server boundaries: files vs. email

Desktop search doesn't solve it all.

Issue: Reconciling References

- References might have small numbers of attributes
- Not a lot of data to train on or analyze
- References evolve
  - People move
  - Documents go through versions (think about your interview talk)

Issue: One-time Query

- Standard information integration often starts by listing frequent queries that are anticipated
- In a personal DS, you might want to ask a query once over a particular combination of sources

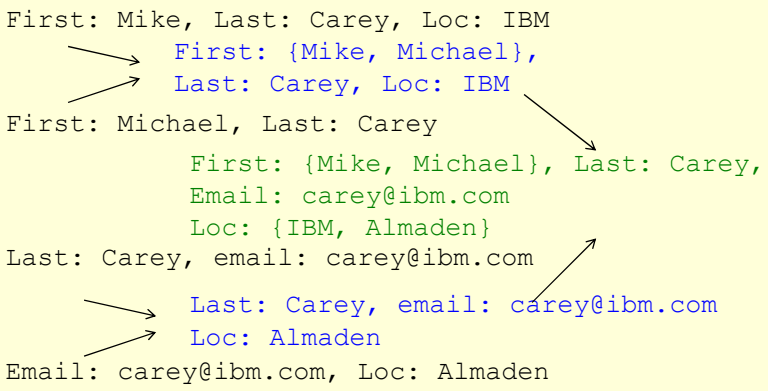
  "What exam questions do I have that weren't in the HW, weren't on the practice exam, weren't used in class, aren't in the back of the book, aren't examples in the book?"

SEMEX: Semantic Exploration

- Extract objects and relationships automatically and cast into a personal information model [Dong, Halevy CIDR 2005]
- Reference reconciliation is critical
  - First: Mike, Last:Carey, Loc: IBM
  - First: Michael, Last:Carey
  - Last: Carey, Email: carey@ibm.com
  - Email: carey@ibm.com, Loc: Almaden

Reference Merging

- Combine references, allow multivalues



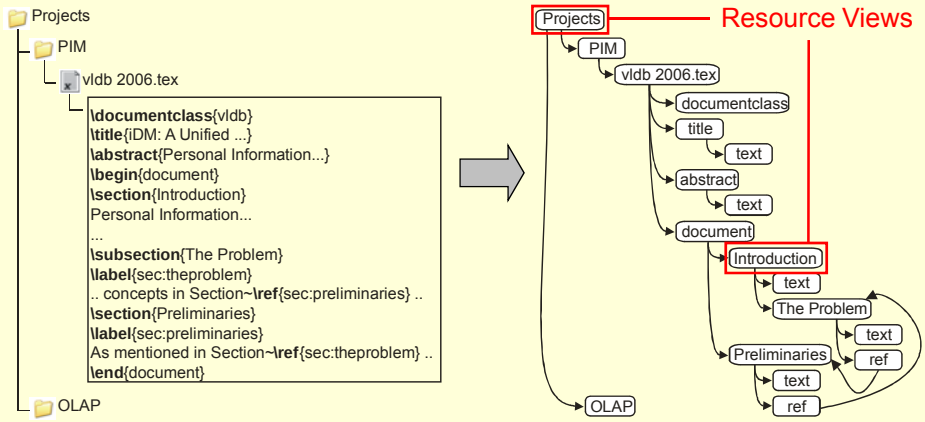
Evolving Objects

- Do fine-grained reconciliation
- Look for evidence to build chains that represent versions of objects.
  - Emails for Carey from ibm.com don't overlap in time with emails for Carey from bea.com

iMeMex

- You saw this previously in iTrails
  [Dittrich, Vaz Salles VLDB 06]
- Try to over come the document boundary
  - Why is the file-system directory hierarchy different than the element hierarchy in an XML document?
- iMeMex Data Model (iDM)

iDM Example



Courtesy Jens Dittrich and Marcos Vaz Salles

Ask Us Questions …

… or straighten us out

Backup Slides

And Extras

Query Answering Semantics

- **Input:**
  - Source **S**, query **Q**
  - P-med-schema **M** = { $(M_1, Pr(M_1)), \ldots, (M_l, Pr(M_l))$}
  - P-mappings **pM** = {$pM(M_1), \ldots, pM(M_l)$ }
- Output probability of tuple **t:**
  - p = $\Sigma \Pr(t|M_i) * Pr(M_i)$

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Query Answering

S1

name	hPhone	oPhone	hAddr	oAddr
Alice	123-4567	765-4321	123, A Ave.	456, B Ave

Q

```
SELECT name, phone, address
FROM Med-S
```

Answers

Tuple	Probability
('Alice', '123-4567', '123 A Ave.')	0.34
('Alice', '765-4321', '456 B Ave.')	0.34
('Alice', '765-4321', '123 A Ave.')	0.16
('Alice', '123-4567', '456 B Ave.')	0.16

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Expressive Power of P-Med-Schema v.s. P-Mapping

Theorem 1. For one-to-many mappings:
(p-med-schema + p-mappings)
= (mediated schema + p-mapping)
> (p-med-schema + mappings)

Theorem 2. When restricted to one-to-one mappings:
(p-med-schema + p-mappings)
= (p-med-schema + mappings)
> (mediated schema + p-mapping)

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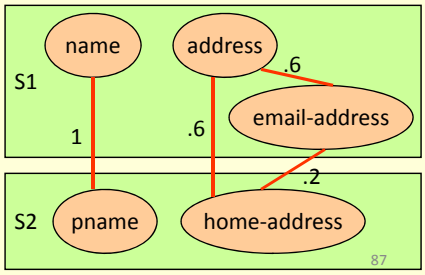
Creation: 1) Creating a Single Med-Schema

- **Input:** Single-table source schemas S_1, …, S_n

  Output: Single-table mediated schema M
- **Algorithm**

1. Remove all infrequent attributes
2. Find *similarity* between every pair of attributes and construct a weighted graph
3. Remove edges with weight below τ (e.g., τ=.5)
4. Each connected component is a cluster



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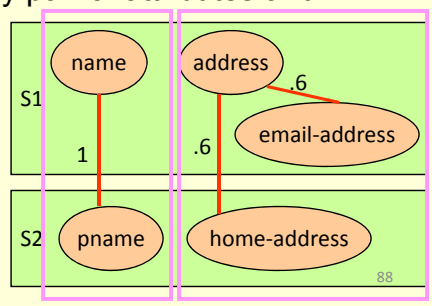
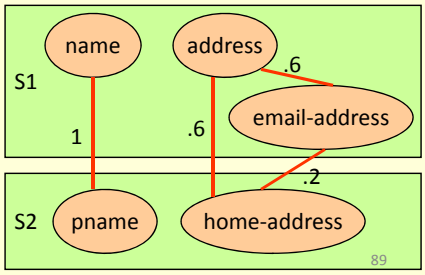


Creation: 2) Creating All Possible Med-Schemas

- **Algorithm**

1. Remove all infrequent attributes
2. Find *similarity* between every pair of attributes and construct a weighted graph
3. For each edge
   - (weight ≥ τ+ϵ) → retain
   - (weight < τ-ϵ) → drop
   - (τ-ϵ ≤ weight < τ+ϵ) → uncertain edge

   (e.g., τ =.6, ϵ = .2)
4. Clustering for each combo of including/excluding uncertain edges



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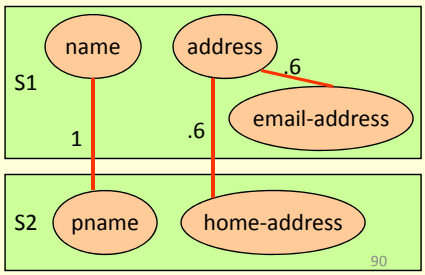

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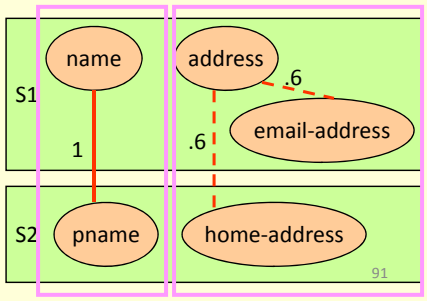

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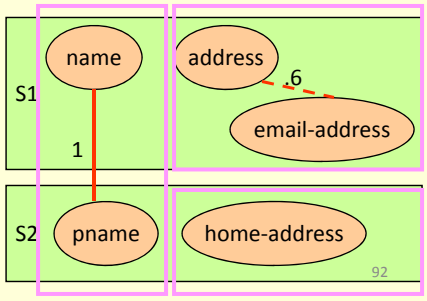

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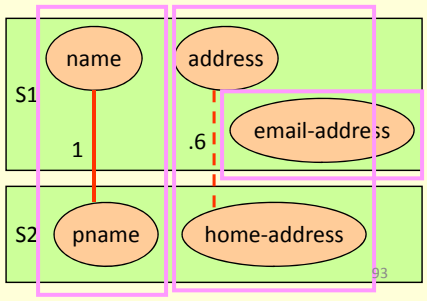

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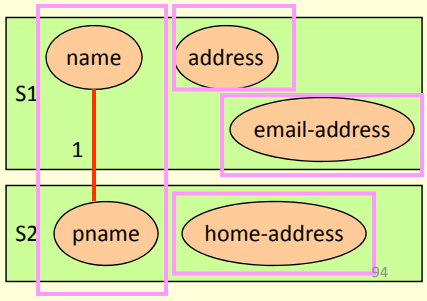
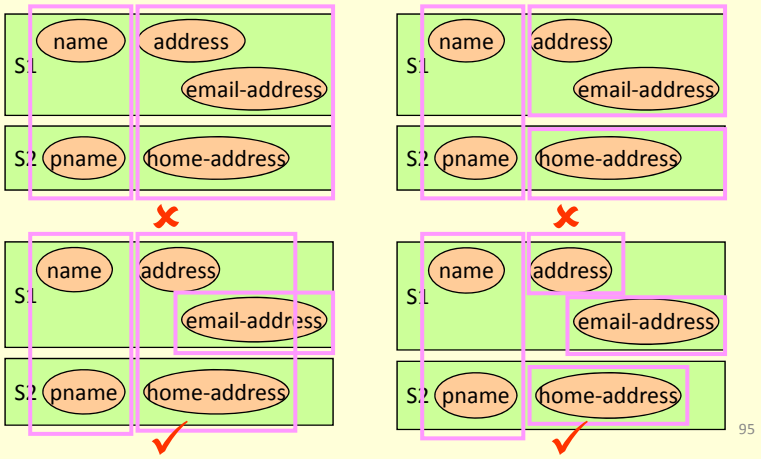


Creation: 3) Computing Probabilities

- Mediated schema M and source S are *consistent* if *no two attributes of S are grouped into same cluster in M*



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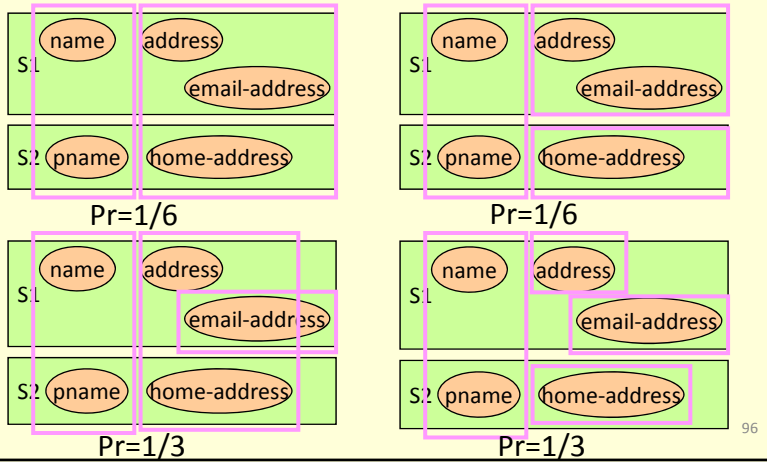
Creation: 3) Computing Probabilities

- Assign probabilities to each M proportional to the number of sources it is consistent with.



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