Viewing the Web as a Distributed Knowledge Base

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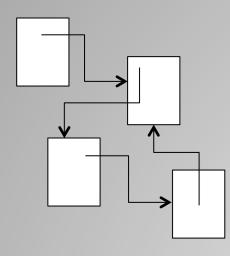








- The Web as a distributed knowledge base
- WebdamLog: a rule-based language for the Web
- The WebdamLog system
- Inconsistencies and uncertainty
- Conclusion



hypertext

The Web

Карабас Барабас сидел перед очагом в отвратительном настроении. Сы-

рые др. Карабас Барабас сидел перед очагом дождь. в отвратительном настроении. Сытеатра рые дрова едва тлели. На улице лил руки и дожд Карабас Барабас сидел перед очагом хотел р теат; в отвратительном настроении. Сыплётки руки рые і Карабас Барабас сидел перед очагом третий хотел дожд в отвратительном настроении. Сыперешё плёті театі рые дрова едва тлели. На улице лил гвоздя треті руки дождь. Дырявая крыша кукольного перек хоте/ театра протекала. У кукол отсырели гвозг плёт: руки и ноги, на репетициях никто не треті хотел работать, даже под угрозой пере: плётки в семь хвостов. Куклы уже гвозд третий день ничего не ели и зловеще перешёптывались в кладовой, вися на гвоздях.

universal library of text





social data



and multimedia

A typical Web user's data

- What kinds of data? all kinds
 - *data*: photos, music, movies, reports, email
 - metadata: photo taken by Alice in Paris on ...



Social

data

- ontologies: Alice's ontology and mapping with other ontologies
- localization: Alice's pictures are on Picasa, back-ups are at INRIA
- security: Facebook credentials (Alice, 123456)
- annotations: Alice likes Elvis' website
- beliefs: Alice believes Elvis is alive
- external knowledge: Bob keeps copies of Alice's pictures
- time, provenance, ...

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A typical Web user's data

everywhere

- What kinds of data? all kinds
- Where is the data?
 - laptop, desktop, smartphone, tablet, car computer
 - mail, address book, agenda
 - Facebook, LinkedIn, Picasa, YouTube, Tweeter
 - svn, Google docs
 - also access to data / information of family, friends, companies associations



A typical Web user's data

- What kinds of data? all kinds
- Where is the data? everywhere
- What kind of organization? heterogeneous
 - terminology: different ontologies
 - systems: personal machines, social networks
 - distribution: different localization
 - security: different protocols
 - quality: incomplete / inconsistent information

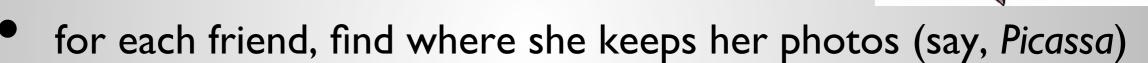


Example of processing

Alice and Bob are getting engaged. Their friends want to offer them an album of photos where they are together

To make such a photo album

• Find friends of Alice & Bob (say with Facebook)



- find the means to access her photos possibly via friends
- find the photos that feature Bob and Alice together, e.g., using tags or face recognition software
- possibly ask someone to verify the results

Some reasoning is needed to execute these tasks (automatically)!

A typical Web user

- Overwhelmed by the mass of information
- Cannot find the information needed
- Is not aware of important events
- Cannot manage/control how others access and use his/her own data



How can systems help?

- We need to move from a Web of text to a Web of knowledge
 - In the spirit of semantic Web
- To better support user needs,
 - Systems need to analyze what is happening and construct knowledge
 - Systems should exchange knowledge
 - Systems should reason and infer knowledge



YOU need help!

Thesis

All this forms a distributed knowledge base with processing based on automated reasoning

Issues

- Distributed reasoning
- Exchanging facts and rules

WebdamLog

- Contradictions
- Missing and noisy data

Ignore for now

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WebdamLog: a datalog-style language

Why datalog? A prehistoric language by Web time...

- + nice and compact syntax
- + well-studied with many extensions
- + recursion essential in a distributed setting: cycles in the network

```
Extensional facts
```

```
friend("peter","paul") friend("paul", "mary") friend("mary","sue")
```

```
Datalog program fof(x,y) :- friend(x,y)
fof(x,y) :- friend(x,z), fof(z,y)
```

Intentional facts

fof("peter","paul") fof("peter","mary") fof("peter", "sue")
fof("paul", "mary") fof("paul", "sur")
fof("mary","sue")

WebdamLog

Extends datalog

• negation, updates, distribution, delegation, time

For a world that is

- distributed: autonomous and asynchronous peers
- dynamic: knowledge evolves; peers come and go

Influenced by

- Active XML (INRIA) for distribution & intentional data
- Dedalus (UC Berkeley) for time & implementation

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Warning

Not as simple Not as beautiful

More procedural

But this is needed for real Web applications!





Schema

(π, Ε, Ι, σ)

- π possibly infinite set of peer IDs
- E set of extensional relations of the form m@p
 - set of intentional relations of the form m@p
- σ sorting function

for each m@p, $\sigma(m@p)$ is an integer (its sort)

Facts

Facts are of the form $m@p(a_1, ..., a_n)$, where

m is a relation name & p is a peer name

 $a_1, ..., a_n$ are *data* values (n is the arity of m@p)

the set of data values includes the relations and peer names

Examples

friend@my-iphone("peter", "paul") extensional fof@my-iphone("adam", "paul") intentional

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Examples of facts

data & metadata: pictures@alice-iphone(1771.jpg, "Paris", 11/11/2011) ontology: isA@yago.com("Elvis", theKing) annotations: tags@delicious.com("wikipedia.org", encyclopedia) localization: where@alice(pictures, picasa/alice) access rights: right@picasa(pictures, friends, read) security: secret@picasa/alice; public@picasa/alice

Rules

A **term** is a variable or a constant

Rules are of the form

```
R@P(U) := (not) R_1@P_1(U_1), ..., (not) R_n@P_n(U_n)
```

where

\$R, \$R_i are relation terms

\$P, \$Pi are peer terms

\$U, \$U_i are *tuples* of terms

Safety condition

\$R and **\$P** must appear positively bound in the body

each variable in a negative literal must appear positively bound in the body

Examples coming up, stay tuned

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Semantics

A state (I, Γ, Γ*) : each peer p has
 extensional facts I(p), defining the local state of p
 local rules Γ(p), defining the program of p
 rules Γ*(p,q) that have been delegated to p by some peer q

State transition

Choose some peer p randomly – asynchronously

Compute the transition of p

the database updates at p

the messages sent to other peers

the delegations of rules to other peers

Keep going forever

 $(I_0, \Gamma_0, \varnothing) \rightarrow (I_1, \Gamma_1, {\Gamma_1}^*) \rightarrow ... \rightarrow (I_n, {\Gamma_n}, {\Gamma_n}^*) \rightarrow ...$

Fair sequence: each peer is selected infinitely often

The semantics of rules

Classification based on locality and nature of head predicates (intentional or extensional)

Local rule at my-laptop: all predicates in the body of the rules are from my-laptop

Local with local intentional head	classic datalog
Local with local extensional head	database update
Local with non-local extensional head	messaging between peers
Local with non-local intentional head	view delegation
Non-local	general delegation

Local rules with local intentional head

Example: Rule at peer my-laptop

friend is extensional, fof is intentional

fof@my-iphone(\$x, \$y) :- friend@my-iphone(\$x,\$y)

fof@my-iphone(\$x,\$y) :- friend@my-iphone(\$x,\$z), fof@my-iphone(\$z,\$y)

fof is the transitive closure of friend

Datalog = WebdamLog with only local rules and local intentional head

Local rules with local extensional head

A new fact is inserted into the local database

believe@my-iphone("Alice", \$loc) : tell@my-iphone(\$p,"Alice", \$loc),
 friend@my-iphone(\$p)

Local rules with non-local extensional head

A new fact is sent to an external peer via a message

\$message@\$peer(\$name, "Happy birthday!") :-

today@my-iphone(\$date),

birthday@my-iphone(\$name, \$message, \$peer, \$date)
Extensional facts:

today@my-iphone(March 6)

birthday@my-iphone("Manon", "sendmail", "gmail.com", March 6)

sendmail@gmail.com("Manon", "Happy birthday")

Local rules with non-local intentional head

View delegation!

boyMeetsGirl@gossip-site(\$girl, \$boy) :-

girls@my-iphone(\$girl, \$loc),

boys@my-iphone(\$boy, \$loc)

Semantics of boyMeetGirl@gossip-site is a join of relations girls and boys from my-iphone

Formally, my-iphone delegates a rule boyMeetGirl@gossip-site(g,b) for each g, b, l, girls@my-iphone(g,l), boys@my-iphone(b,l)

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Non-local rules: general delegation

(at my-iphone): boyMeetsGirl@gossip-site(\$girl, \$boy) :-

girls@my-iphone(\$girl, \$loc),

boys@alice-iphone(\$boy, \$loc)

Suppose that girls@my-iphone("Alice", "Julia's birthday") holds. Then my-iphone installs the following rule at alice-iphone

(at alice-iphone): boyMeetsGirl@gossip-site("Alice", \$boy) :-

boys@alice-iphone(\$boy, "Julia's birthday")

When girls@my-iphone("Alice", "Julia's birthday") no longer holds, my-iphone uninstalls the rule

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Non-local rules: general delegation

(at my-iphone): boyMeetsGirl@gossip-site(\$girl, \$boy) :-

girls@my-iphone(\$girl, \$loc),

boys@alice-iphone(\$boy, \$loc)

An alternative, more database-ish, way of looking at this: at my-iphone : seed@alice-iphone(\$girl, \$loc):- view girls@my-iphone(\$girl, \$loc) delegation at alice-iphone : boyMeetsGirl@gossip-site(\$girl, \$boy) :seed@alice-iphone(\$girl, \$loc), boys@alice-iphone(\$boy, \$loc) delegation **Complexity of delegation: illustration** fof(x,y) :- friend(x,y)

(at **p**) fof@**p**(x,y) :- peers@**p**(**\$q**), friend@**\$q**(x,y)

If peers@p(q_I) holds, this rule installs
 (at q_I) fof@p(x,y) :- friend@q_I(x,y)

If peers@p contains 100 000 tuples

peers@p(q₁), ..., peers@p(q_{100 000})

This rule will install 100 000 rules!

for i=1 to 100 000 (at q_i) fof@p(x,y) :- friend@q_i(x,y)

Data complexity transformed into program complexity Mai 30, 2012 29

Summary of results [PODS 2011]

- Formal definition of the semantics of WebdamLog
- Results on expressivity
 - the model with delegation is more general, unless all peers and programs are known in advance
- Convergence is very hard to achieve
 - positive WebdamLog
 - strongly stratified programs with negation

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WebdamLog peers

[demo ICDE 2011, WebDB 2011]

Support communication with other peers

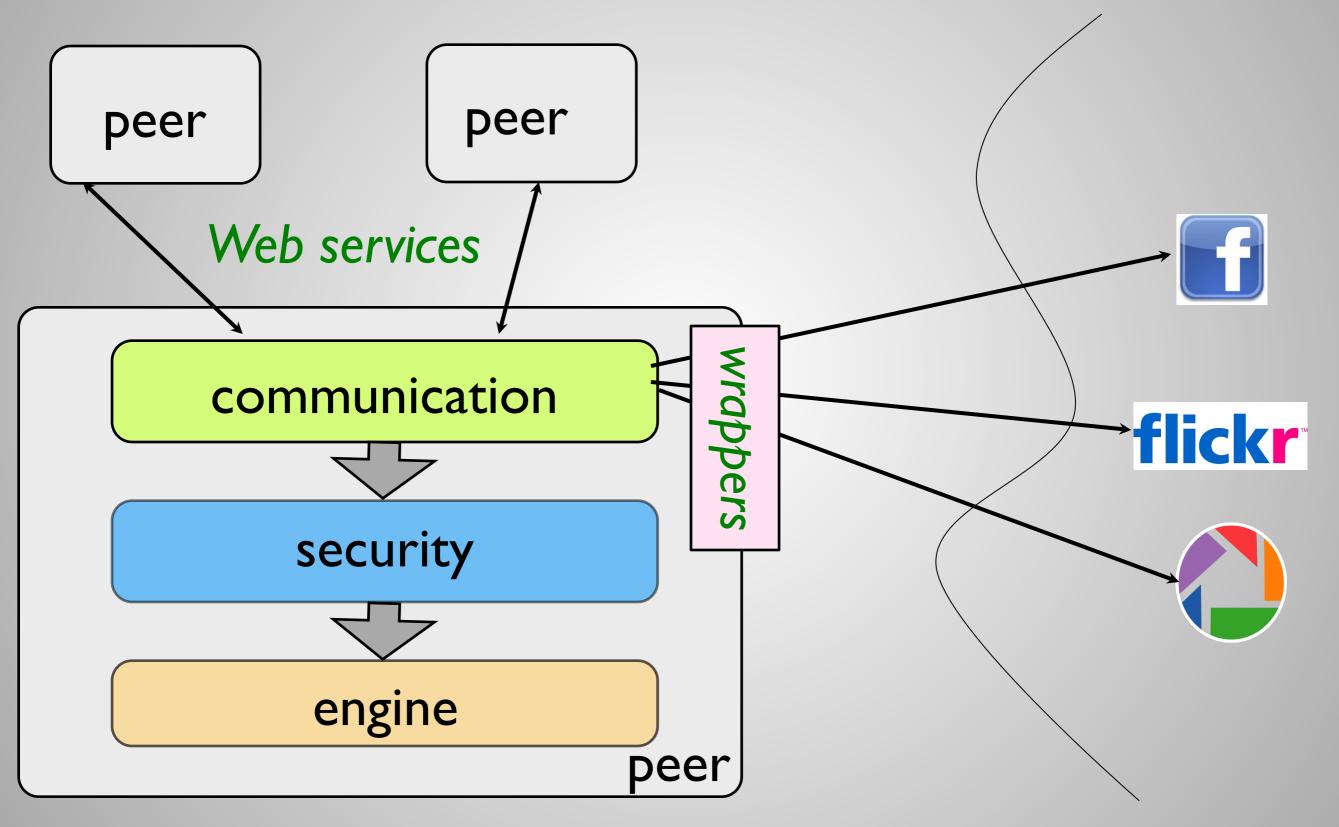
Support common security protocols

Support wrappers to external systems such as Facebook

Manage knowledge

- store knowledge (facts and rules)
- exchange knowledge with other peers
- perform reasoning

WebdamLog peers

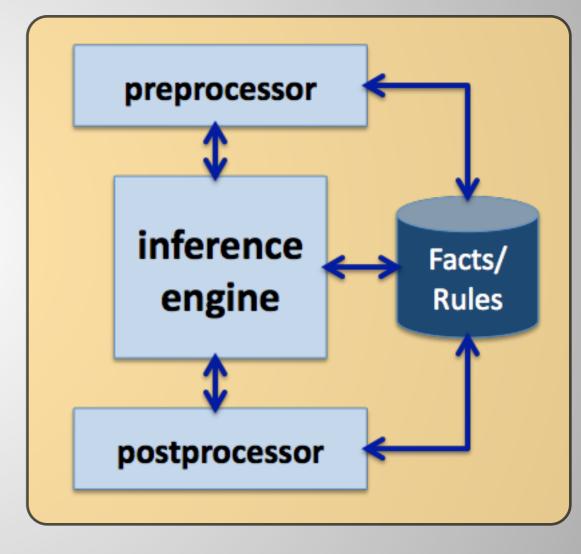


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WebdamLog engine [ongoing work]

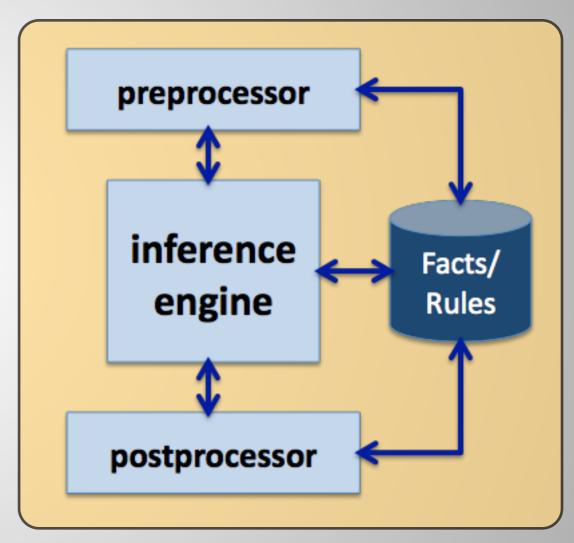
Based on Bud

- developed at UC Berkeley, implemented in Ruby, opensource
- supports Bloom an extension of datalog
- implements communication between peers
- serious experiments



WebdamLog inference: beyond Bud

- Translation of WebdamLog to Bloom (Bud's language)
- Features of WebdamLog not supported in Bud
 - I. Variable relation and peer names
 - 2. Delegation: non-local rules, nonlocal relations in the body
 - 3. Adding and removing rules at runtime: needed because of delegation



Example of runtime inference

(rule_at p) boyMeetsGirl@p(\$girl, \$boy) :girls@p(\$girl, \$loc),
boys@p(\$boy, \$loc)

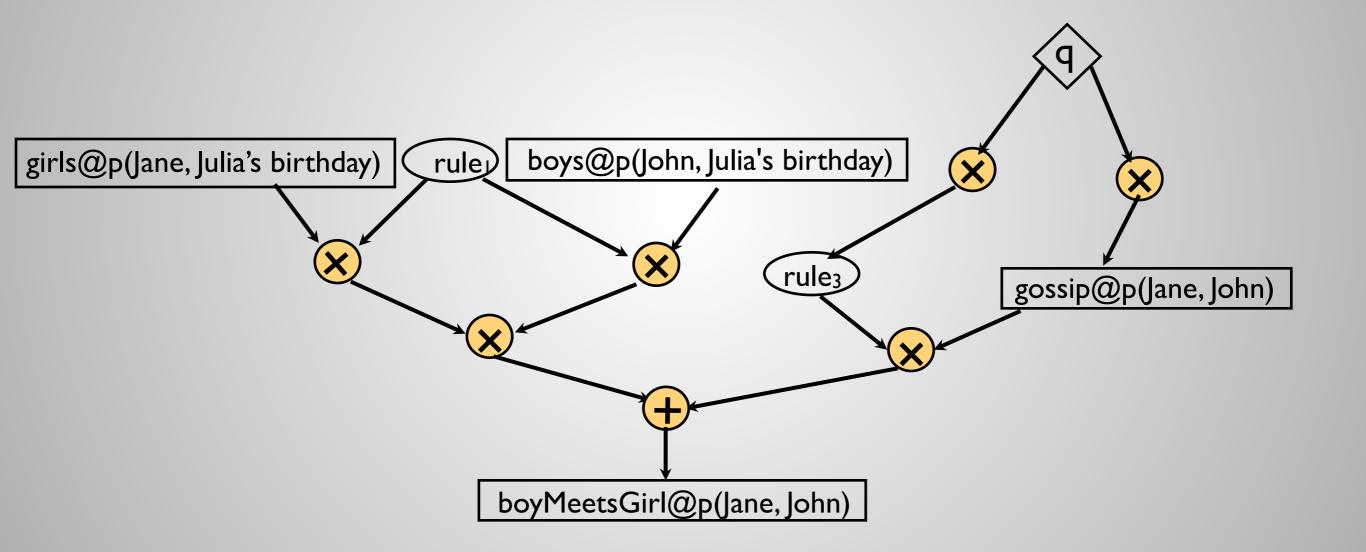
```
(rule<sub>2</sub> at q) gossip@$peer($girl, $boy) :-
boyMeetsGirl@q($girl, $boy),
allPeers($peer)
(rule<sub>3</sub> at q) boyMeetsGirl@p($girl, $boy) :-
gossip@p($girl, $boy)
```





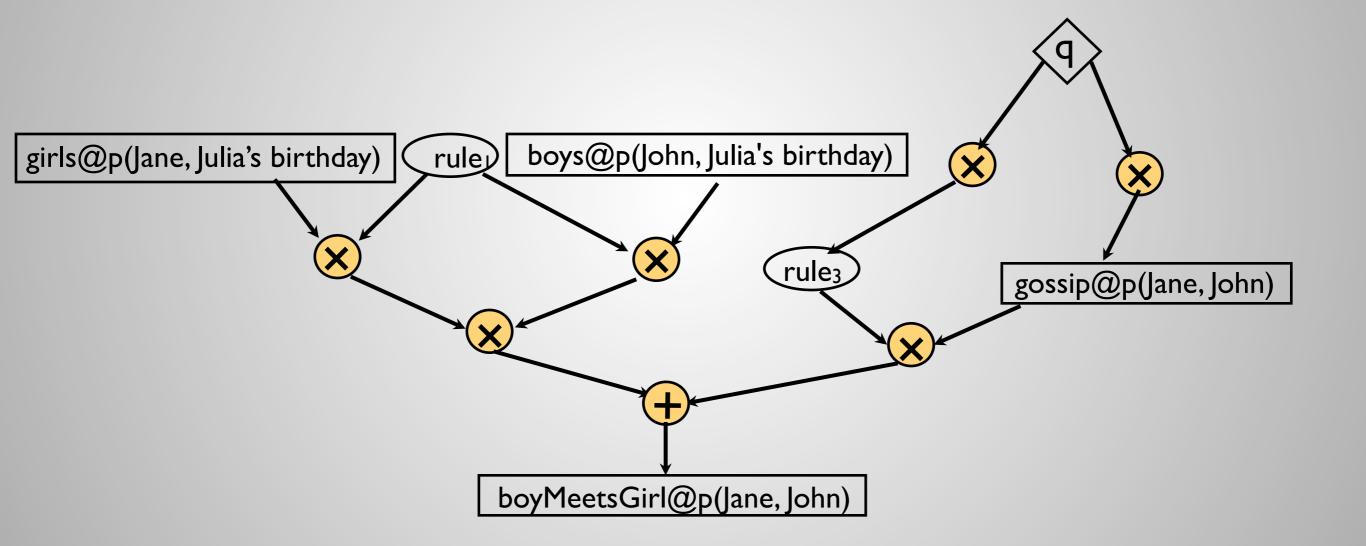
Adding facts at runtime

Maintain a provenance graph for update management



Removing facts at runtime

Avoid recomputation at each update using provenance



Provenance graphs

- Records the history of derivation
- Provenance semiring semantics [Green et al. 07]
 - -alternative or joint use of data
 - facts, rules, peers are nodes
- Useful for performance optimization
- Other uses
 - explain results to users
 - specify and verify access rights

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Motivation

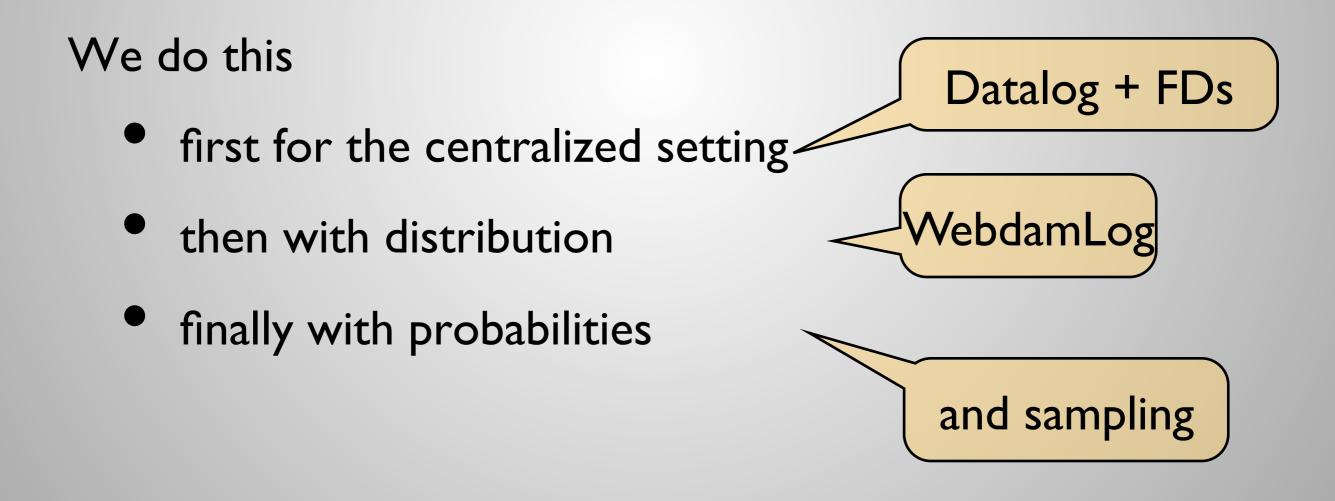
- Contradictions (in intentional or extensional data) come from
 - errors, lies, rumors, updates
 - FD violations: some think Alice was born in Paris, others that she was born in London
 - opinions: some think Brahms is great; others don't
- Uncertainty comes from
 - lack of information
 - contradictions
- Probabilities may be used to measure uncertainty
 - 80% think Alice was born in Paris, 20% in London
 - sources: we observed that Peter is wrong 20% of the time

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Roadmap

We consider

reasoning in an uncertain and inconsistent world



Datalog example

- Where is Alice?
- A relation IsIn(person, city, peer)

with the FD $(person, peer) \rightarrow city$

peer believes person to be in city

Consider a datalog rule
 Isln(\$per, \$city, \$p') :- Isln(\$per, city, \$p), friend(\$p', \$p)
 Isln(Alice, London, Bob)
 Isln(Alice, Paris, Sue)
 friend(my-iphone, Bob)
 friend(my-iphone, Sue)

Datalog with nondeterministic fact-at-a-time semantics

- Immediate consequence operator: a single fact is derived only if it does not contradict known facts
- A possible world is a maximal consequence. Example:

 IsIn(\$per, \$city, \$p') :- IsIn(\$per, city, \$p), friend(\$p', \$p)

 IsIn(Alice, London, Bob)

 IsIn(Alice, Paris, Sue)

 friend(my-iphone, Bob)

Infer: IsIn(Alice, Paris, my-iphone)

In practice set-at-a-time semantics is more efficient

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Discussion

Inflationary non-deterministic semantic ("stubborn" choices)

Related to 2-stable models

Proof theory

- Possible facts NP-complete
- Sure facts coNP-complete

Many possible alternative semantics

Distributed setting: use WebdamLog

To simplify, we focus only on local and deductive rules

The semantics is inflationary and non-deterministic

A subtlety: Each peer has to recall the choices made to always make the same choice in the future (when talking to other peers): stubborn

The causes of uncertainty

- Uncertainty in base facts
- Uncertainty in the order of peer activations
- Uncertainty in choosing immediate consequences

Probabilities

Probabilistic interpretation to measure uncertainty

- For base facts, use independent probabilistic events
- Uniform distribution for the next peer to activate
- Uniform distribution in choosing the next immediate consequence
 - Can be done efficiently if there is a single FD & more complicated otherwise

Example: captures voting

Bob's rules

IsIn@\$p(\$x,\$y) :- Follower@bob(\$p), IsIn@bob(\$x,\$y)

IsIn@bob(\$x,\$y) :- baselsIn@bob(\$x,\$y)

Suppose each peer has similar rules

Claim: For acyclic networks, the probability of a peer inferring a fact is exactly its relative support at his friends

Note: this also give semantics for more complicated cases such as networks with cycles

Query answering

Resulting tuples of a query q have associated probabilities

Exact evaluation using c-tables

• Too costly in practice

Sampling technique

- Each peer makes probabilistic choices along the way
- Converges to the probability of q when the number of samples grows

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Thesis

Let us turn the Web into a distributed knowledge base with billions of users supported by billions of systems analyzing information extracting knowledge exchanging knowledge inferring knowledge

Contribution

WebdamLog

- A language for distributed data management [PODS 2011]
- Datalog with distribution, updates, messaging
- Main novelty: delegation

System implementation

- Handles heterogeneity, localization and access control [WebDB 2011]
- WebdamlExchange peer In Java [demo ICDE 2011]
- WebdamLog engine based on Bud

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On-going work

The implementation

More optimization strategies such as Magic Set

Probabilistic WebdamLog

- Query processing
- Explaining results to users: top-k proofs

Collaboration between peers to answer queries

Lots of fun & many open questions

Issues

- Access control based on provenance
- Concurrency control
 - Difficulty: right revocation
- Optimization
 - Links with optimization in Active XML
- Verification of applications
 - Links with business artifacts



Joint work with Emilien Antoine, Meghyn Bienvenu, Daniel Deutch, Alban Galland, Kristian Lyndbaek, Julia Stoyanovich, **Jules Testard**

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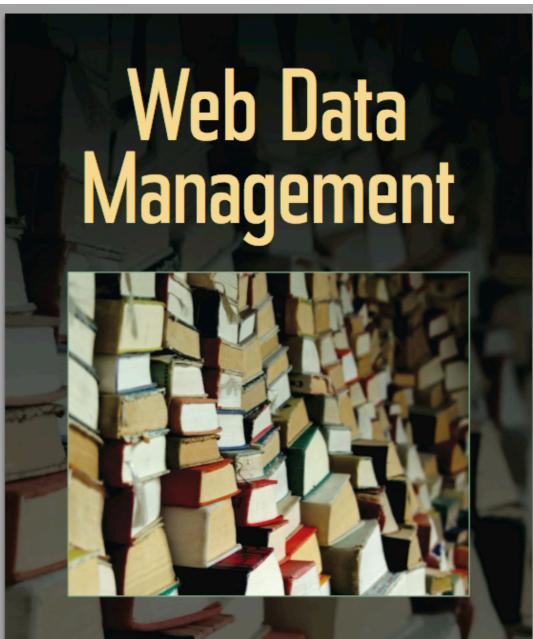






After a short break

- Two authors of the Web Data Management Book (aka Jorge)
- Two friends



Serge Abiteboul, Ioana Manolescu, Philippe Rigaux Marie-Christine Rousset, Pierre Senellart

CAMBRIDGE

Marie-Christine Rousset Reasoning in the Semantic Web

Professor of CS at the Univ. Grenoble.

PhD (1983) and a Thèse d'Etat (1988) in CS from Univ. Paris-Sud.

Best paper award from AAAI in 1996

Junior member of Institut Universitaire de France 1997-2001 and Senior member in 2011-now

Interest:: Knowledge Representation, Information Integration, Pattern Mining and the Semantic Web.



Pierre Senellart Social networks

Associate Professor at Telecom ParisTech PhD from Univ. of Paris-Sud Information Director for Journal of ACM

Interest: Data management, Web data management, Probabilistic data

Interest: Natural language processing Software Engineer at SYSTRAN SA

