UnSAID: Uncertainty and Structure in the Access to Intensional Data

Pierre Senellart

3 July 2014, *Univ. Rennes 1*

Uncertain data is everywhere

Numerous sources of uncertain data:

- Measurement errors
- Data integration from contradicting sources
- Imprecise mappings between heterogeneous schemas
- Imprecise automatic processes (information extraction, natural language processing, etc.)
- Imperfect human judgment
- Lies, opinions, rumors

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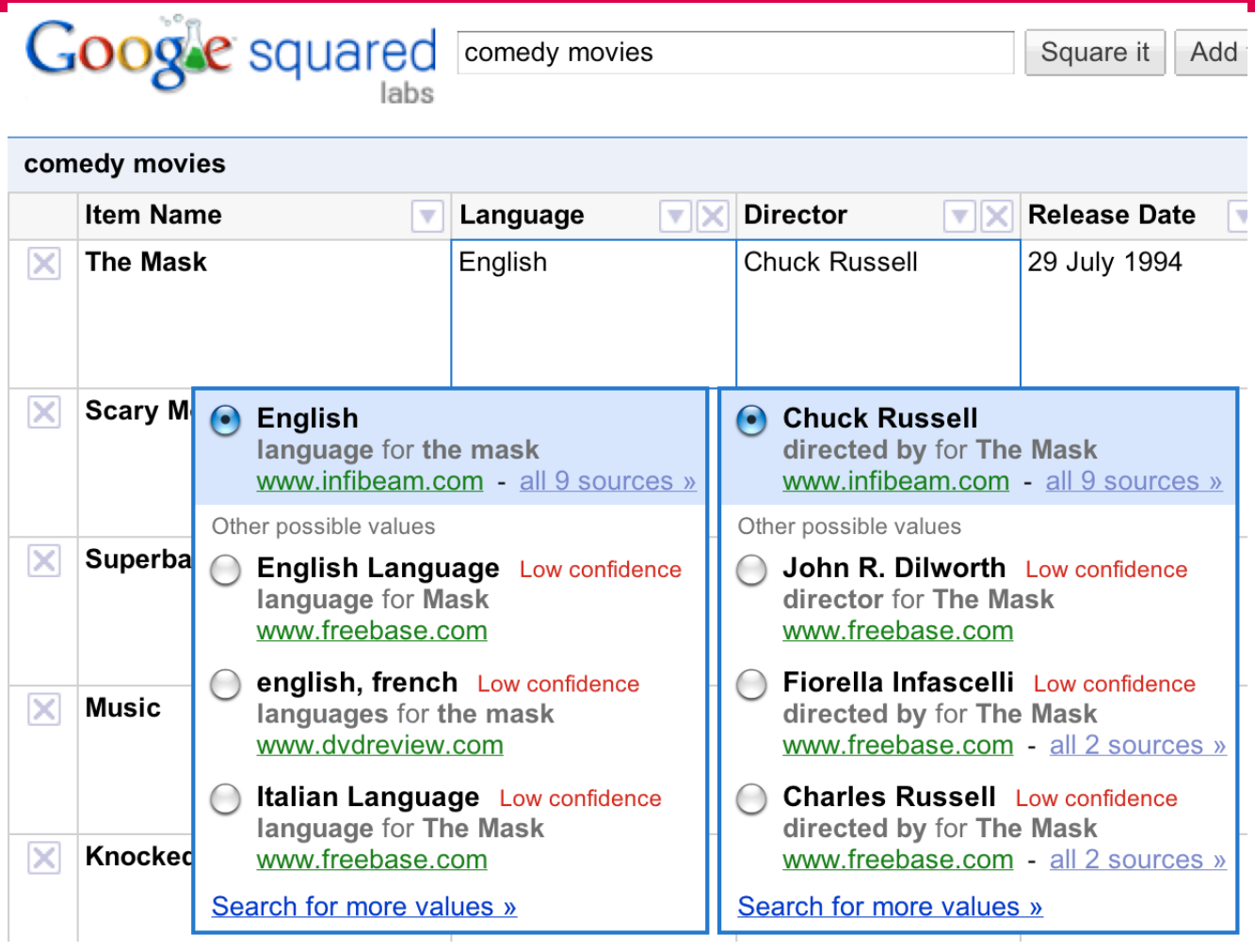
Uncertainty in Web information extraction

instance	iteration	date learned	confidence
arabic, egypt	406	08-sep-2011	(Seed) 100.0
chinese, republic_of_china	439	24-oct-2011	100.0
chinese, singapore	421	21-sep-2011	(Seed) 100.0
english, britain	439	24-oct-2011	100.0
english, canada	439	24-oct-2011	(Seed) 100.0
english, england001	439	24-oct-2011	100.0
arabic, morocco	422	23-sep-2011	100.0
cantonese, hong_kong	406	08-sep-2011	100.0
english, uk	436	19-oct-2011	100.0
english, south_vietnam	427	27-sep-2011	99.9
french, morocco	422	23-sep-2011	99.9
greek, turkey	430	07-oct-2011	99.9

Never-ending Language Learning (NELL, CMU),

`http://rtw.ml.cmu.edu/rtw/kbbrowser/`

Uncertainty in Web information extraction



Google Squared (terminated),

screenshot from (Fink, Hogue, Olteanu, and Rath 2011)

Uncertainty in Web information extraction

Subject	Predicate	Object	Confidence
Elvis Presley	diedOnDate	1977-08-16	97.91%
Elvis Presley	isMarriedTo	Priscilla Presley	97.29%
Elvis Presley	influences	Carlo Wolff	96.25%

YAGO, `http://www.mpi-inf.mpg.de/yago-naga/yago`

(Suchanek, Kasneci, and Weikum 2007)

Structured data is everywhere

Data is structured, not flat:

- Variety of representation formats of data in the wild:
  - relational tables
  - trees, semi-structured documents
  - graphs, e.g., social networks or semantic graphs
  - data streams
  - complex views aggregating individual information
- Heterogeneous schemas
- Additional structural constraints: keys, inclusion dependencies

Intensional data is everywhere

Lots of data sources can be seen as intensional: accessing all the data in the source (in extension) is impossible or very costly, but it is possible to access the data through views, with some access constraints, associated with some access cost.

- Indexes over regular data sources
- Deep Web sources: Web forms, Web services
- The Web or social networks as partial graphs that can be expanded by crawling
- Outcome of complex automated processes: information extraction, natural language analysis, machine learning, ontology matching
- Crowd data: (very) partial views of the world
- Logical consequences of facts, costly to compute

Interactions between uncertainty, structure, intensionality

- If the data has complex structure, uncertain models should represent possible worlds over these structures (e.g., probability distributions over graph completions of a known subgraph in Web crawling).
- If the data is intensional, we can use uncertainty to represent prior distributions about what may happen if we access the data. Sometimes good enough to reach a decision without having to make the access!
- If the data is a RDF graph accessed by semantic Web services, each intensional data access will not give a single data point, but a complex subgraph.

State of the art and opportunities

Probabilistic databases cover limited structure variations, do not consider intensionality

Active and reinforcement learning deals with uncertainty and intensionality, but assumes trivial structures and simple goals

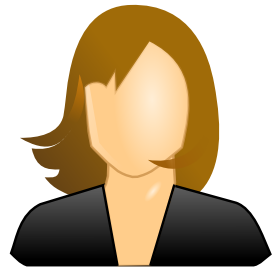
Crowdsourcing, focused crawling, deep Web crawling focus on specific applications of the uncertainty/structure/intensionality problem

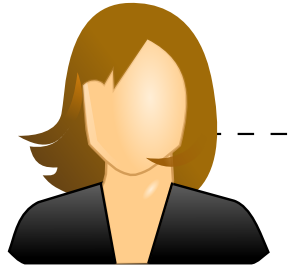
Answering queries using views assumes simplistic cost models

Opportunities for Web data management systems that take all dimensions into account

Introducing UnSAID

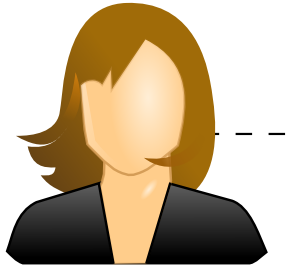
- Uncertainty and Structure in the Access to Intensional Data
- Jointly deal with Uncertainty, Structure, and the fact that access to data is limited and has a cost, to solve a user's knowledge need
- Lazy evaluation whenever possible
- Evolving probabilistic, structured view of the current knowledge of the world
- Solve at each step the problem: What is the next best access to do given my current knowledge of the world and the knowledge need
- Knowledge acquisition plan (recursive, dynamic, adaptive) that minimizes access cost, and provides probabilistic guarantees





formulation

Knowledge need

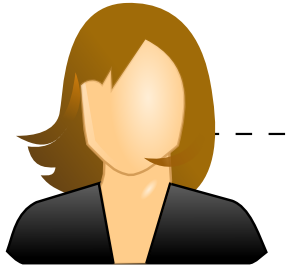


formulation

Knowledge need

Structured source profiles

modeling



formulation

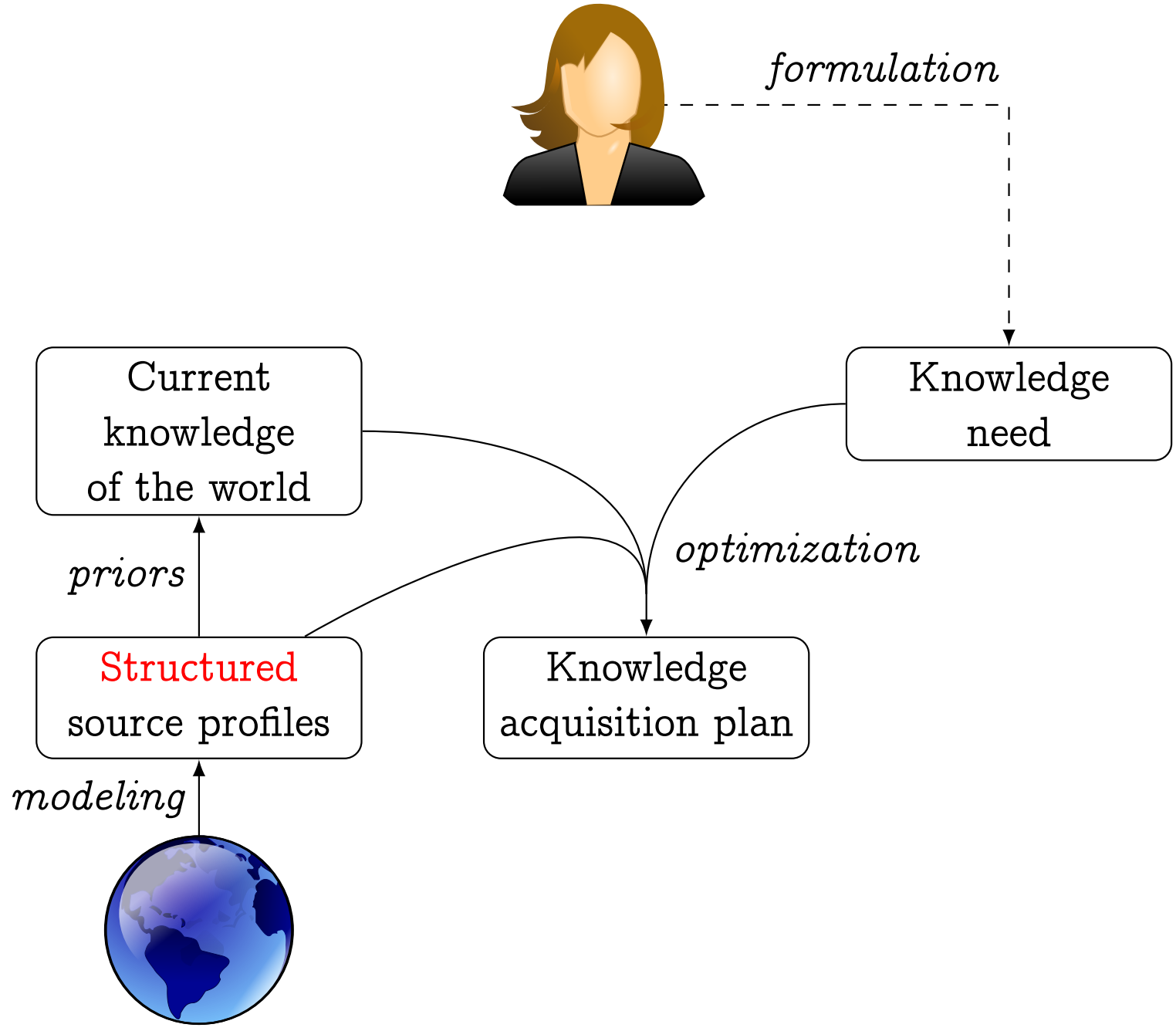
Knowledge need

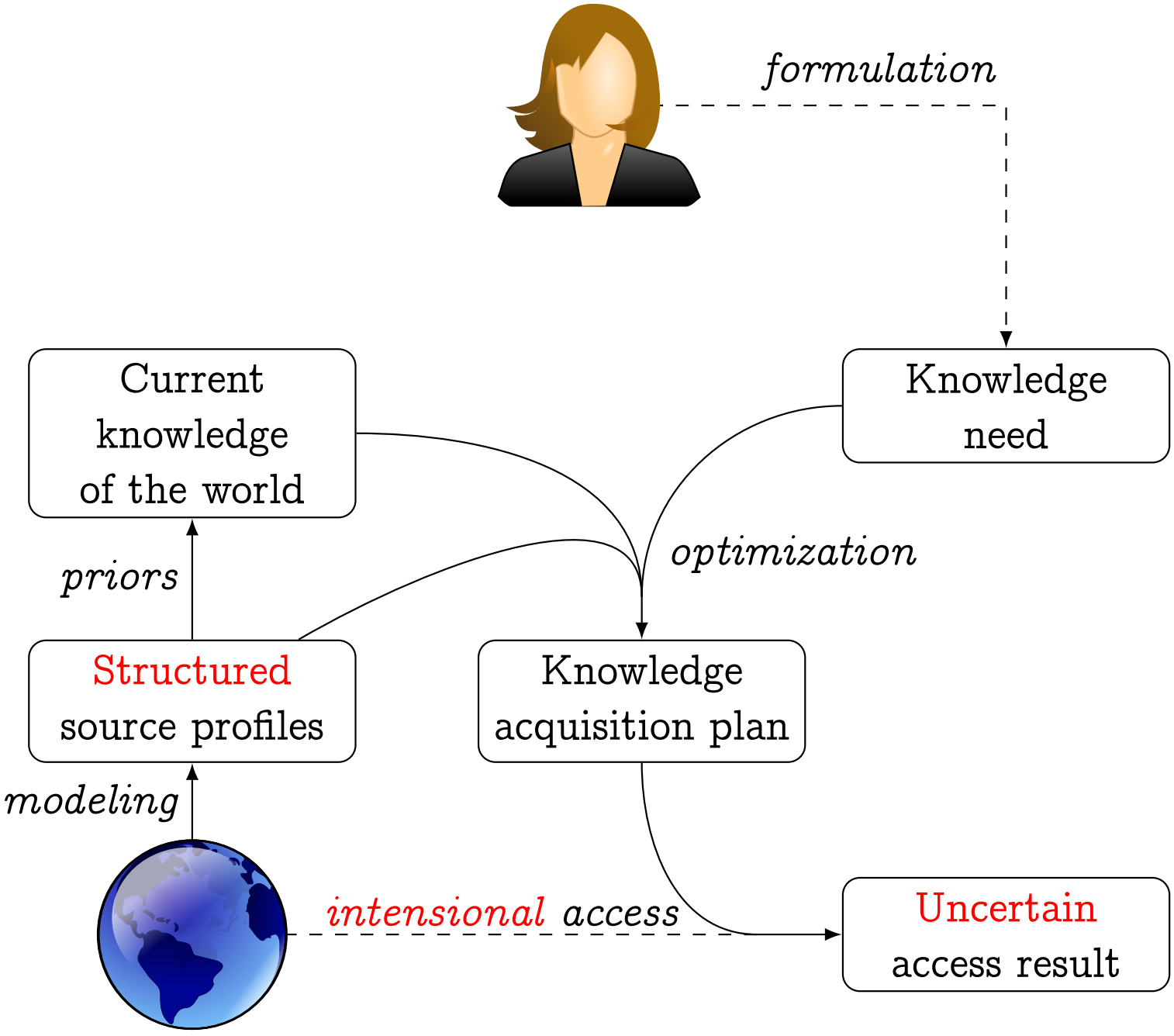
Current knowledge of the world

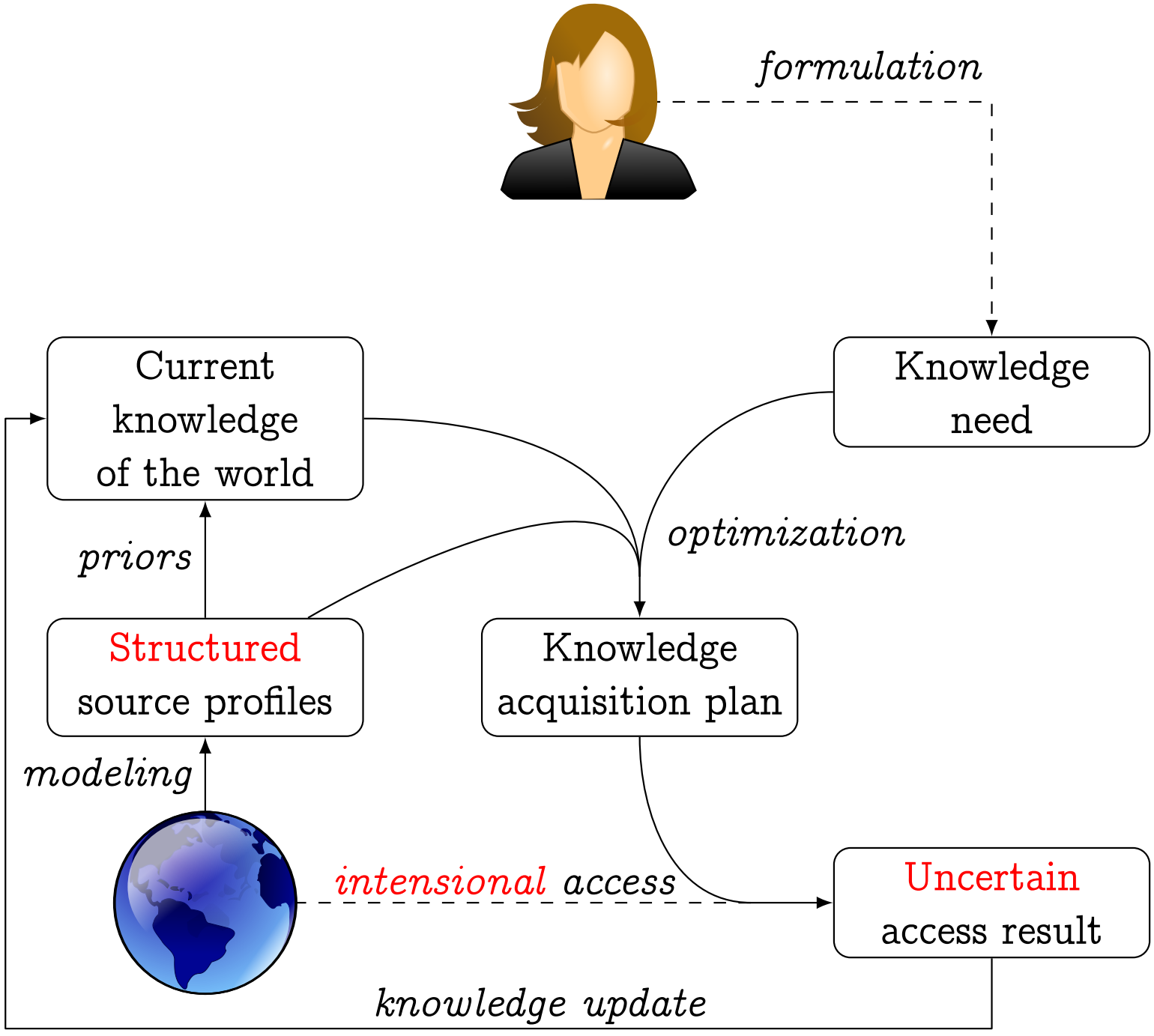
priors

Structured source profiles

modeling


formulation
Current knowledge of the world
Knowledge need
priors
optimization
Structured source profiles
Knowledge acquisition plan
modeling


formulation
Current knowledge of the world
Knowledge need
priors
optimization
Structured source profiles
Knowledge acquisition plan
modeling
intensional access
Uncertain access result


formulation
Current knowledge of the world
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Knowledge acquisition plan
modeling
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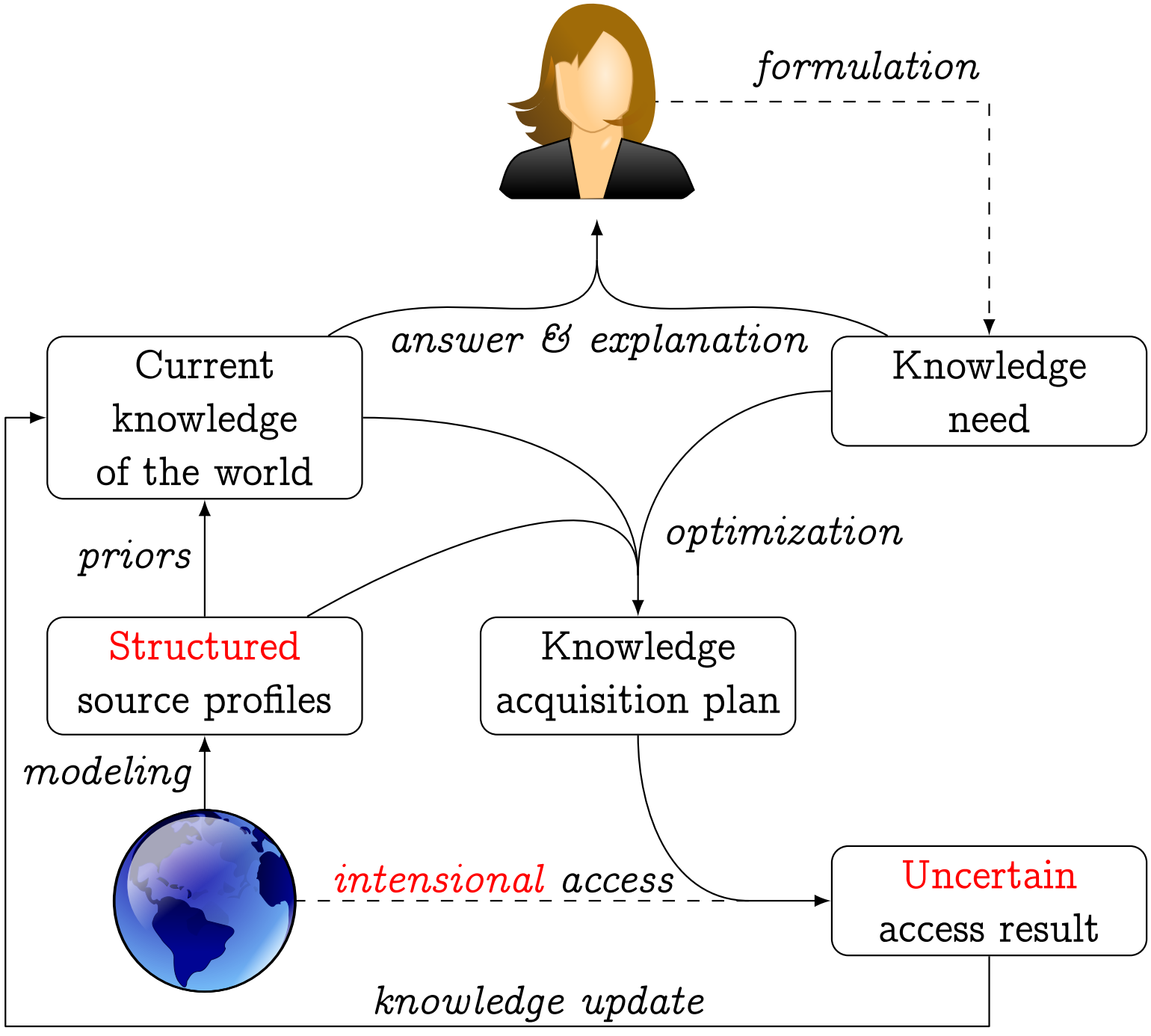
Uncertain access result
knowledge update


formulation
answer & explanation
Current knowledge of the world
Knowledge need
priors
optimization
Structured source profiles
Knowledge acquisition plan
modeling
intensional access
Uncertain access result
knowledge update

What this talk is about

- General overview of some of my current (and recent) research, through one-slide presentation of individual works
- Hopefully, emerging consistent themes
- Connections with the UnSAID problem

Plan

Introduction

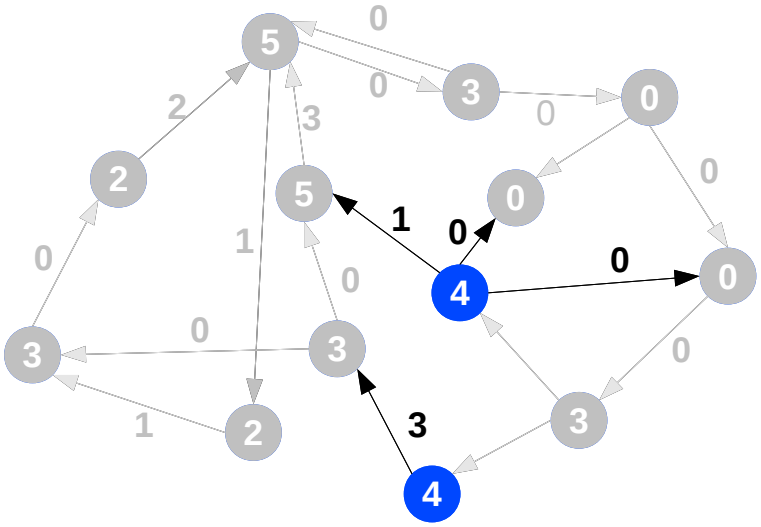
Instances of UnSAID

Uncertainty and Structure

UnSAID Applications

Conclusion

Adaptive focused crawling
(Gouriten, Maniu, and Senellart 2014)



- Problem: Efficiently crawl nodes in a graph such that total score is high
- Challenge: The score of a node is unknown till it is crawled
- Methodology: Use various predictors of node scores, and adaptively select the best one so far with multi-armed bandits

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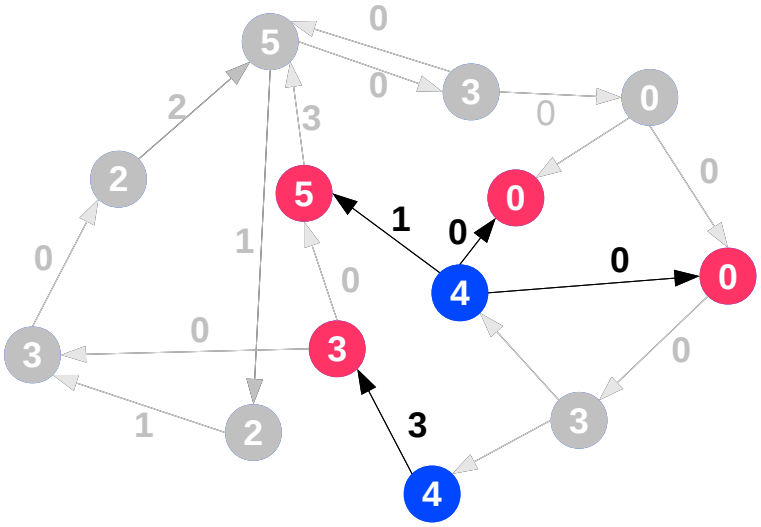
Adaptive focused crawling
(Gouriten, Maniu, and Senellart 2014)



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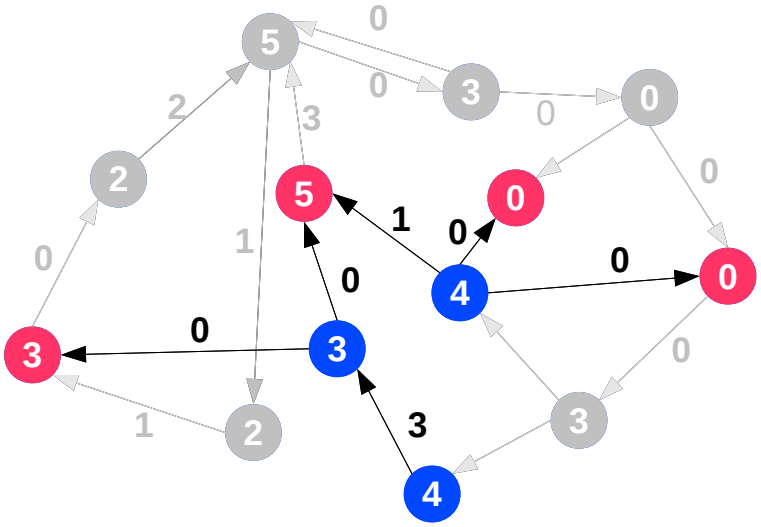

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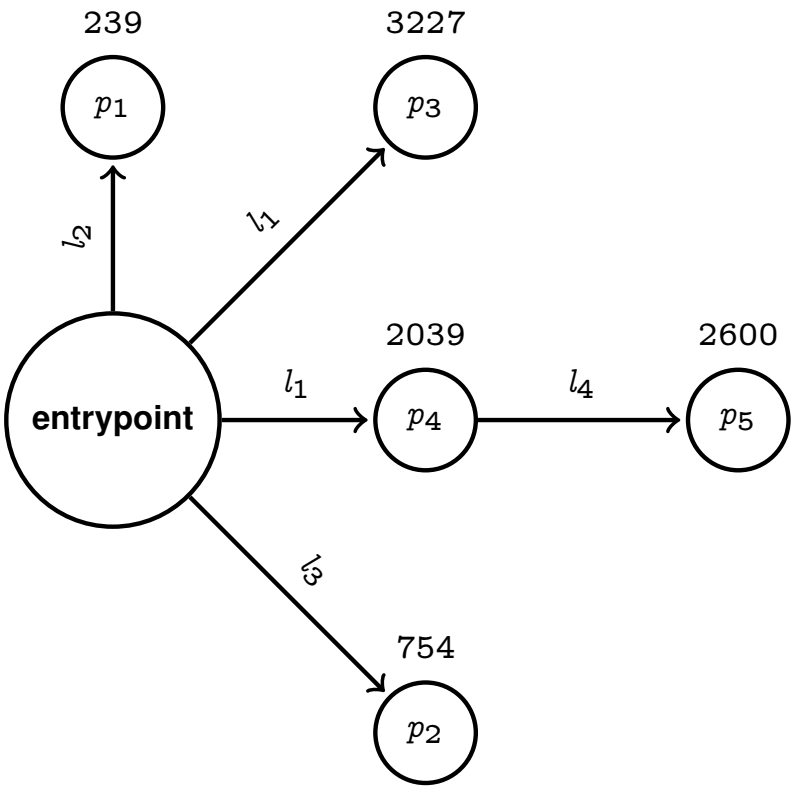
Adaptive Web application crawling



- Problem: Optimize the amount of distinct content retrieved from a Web site w.r.t. the number of HTTP requests
- Challenge: No way to know a priori where the content lies on the Web site
- Methodology: Sample a small part of the Web site and discover optimal crawling patterns from it

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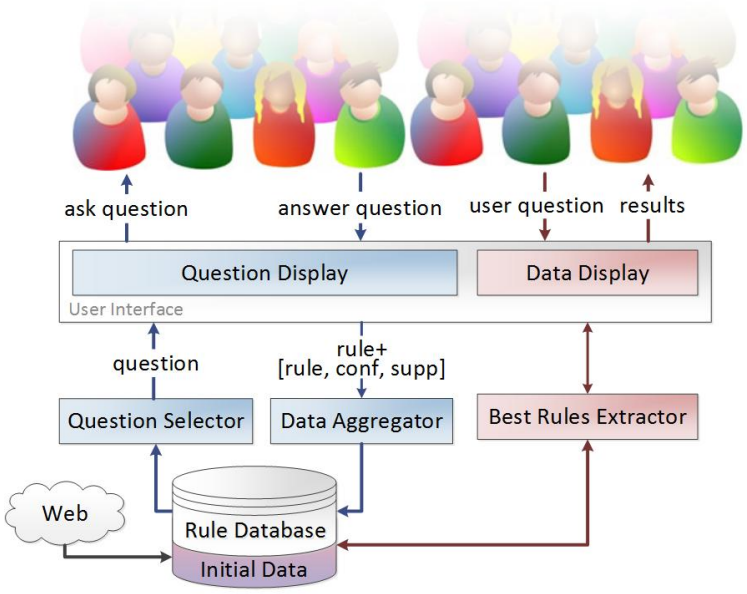
Optimizing crowd queries under order



- Problem: Given a query, what is the next best question to ask the crowd when crowd answers are constrained by a partial order
- Challenge: Order constraints make questions not independent of each other
- Methodology: Construct a polytope of admissible regions and uniformly sample from it to determine the impact of a data item

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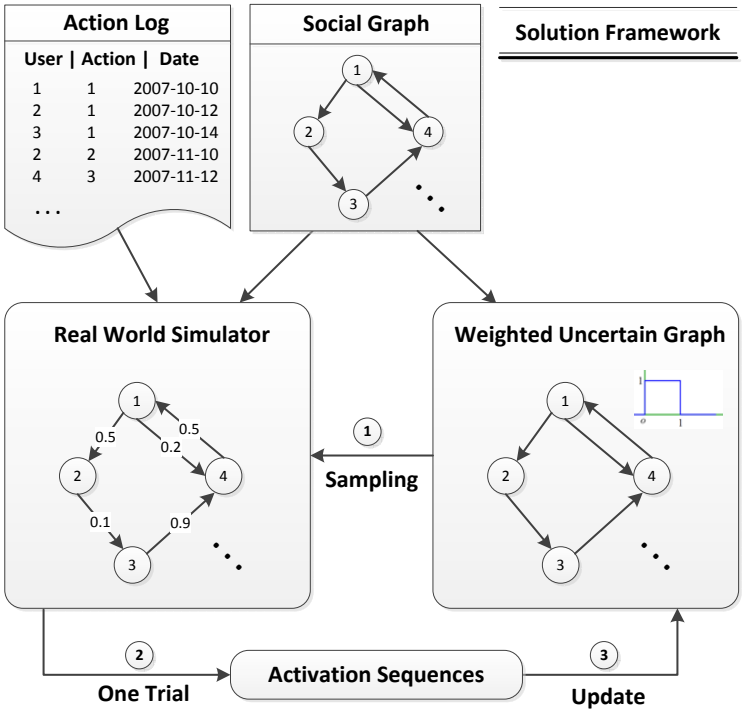
Online influence maximization



- Problem: Run influence campaigns in social networks, optimizing the amount of influenced nodes
- Challenge: Influence probabilities are unknown
- Methodology: Build a model of influence probabilities and focus on influent nodes, with an exploration/exploitation trade-off

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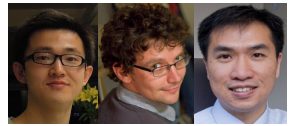

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Query answering under uncertain rules

$\text{Pope}(X) \Rightarrow \text{BuriedIn}(X, \text{Rome}) \quad (98\%)$

$\text{LocatedIn}(X, \text{Lombardy}) \Rightarrow$
$\quad \text{BelongsTo}(X, \text{AustrianEmpire}) \quad (45\%)$

$\text{Pope}(\text{PiusXI})$

$\text{BornIn}(\text{PiusXI}, \text{Desio})$

$\text{LocatedIn}(\text{Desio}, \text{Lombardy})$

$\exists X, \text{BornIn}(X, Y) \wedge$
$\quad \text{BelongsTo}(Y, \text{AustrianEmpire}) \wedge$
$\quad \text{BuriedIn}(X, \text{Rome})?$

- Problem: Determine efficiently the probability of a query being true, given some data and uncertain rules over this data
- Challenge: Produced facts may be correlated, the same facts can be generated in different ways, probability computation is hard in general...
- Methodology: Find restrictions on the rules (guarded?) and the data (bounded tree-width?) that make the problem tractable

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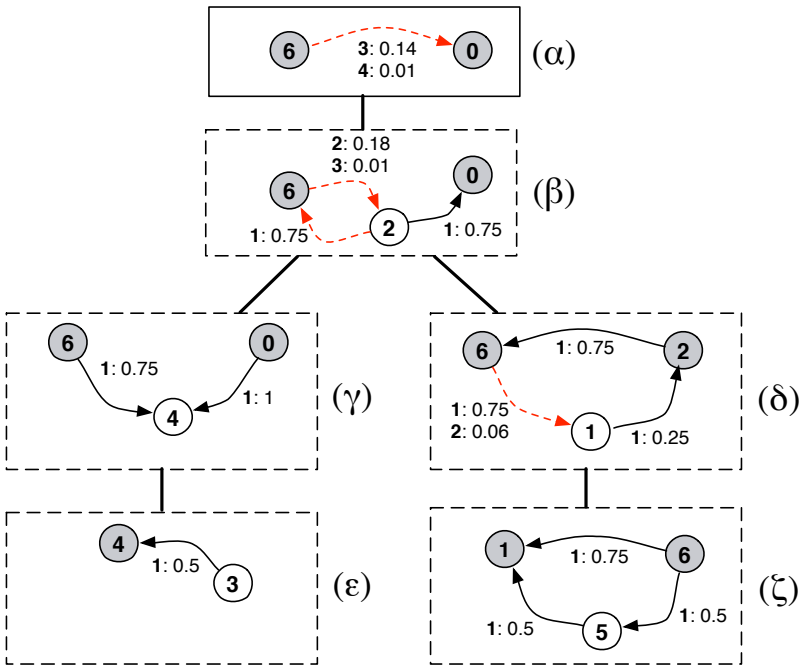
Efficient querying of uncertain graphs
(Maniu, Cheng, and Senellart 2014)



- Problem: Optimize query evaluation on probabilistic graphs
- Challenge: Probabilistic query evaluation is hard, and standard indexing techniques for large graphs do not work
- Methodology: Build a tree decomposition that preserves probabilities and run the query on this tree decomposition

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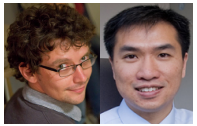

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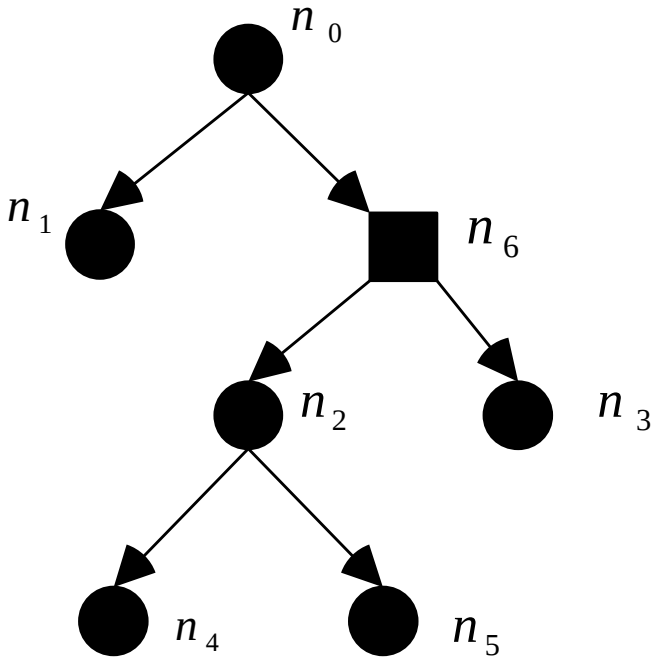
Uniform sampling of XML documents
(Tang, Amarilli, Senellart, and Bressan 2014)



- Problem: Sample a subtree of fixed size/characteristics uniformly at random from a tree, e.g., for data pricing reasons
- Challenge: Naive top-down sampling does not work, will result in biased sampling depending on the tree structure
- Methodology: Bottom-up annotation of the tree recording distribution information, followed by top-down sampling

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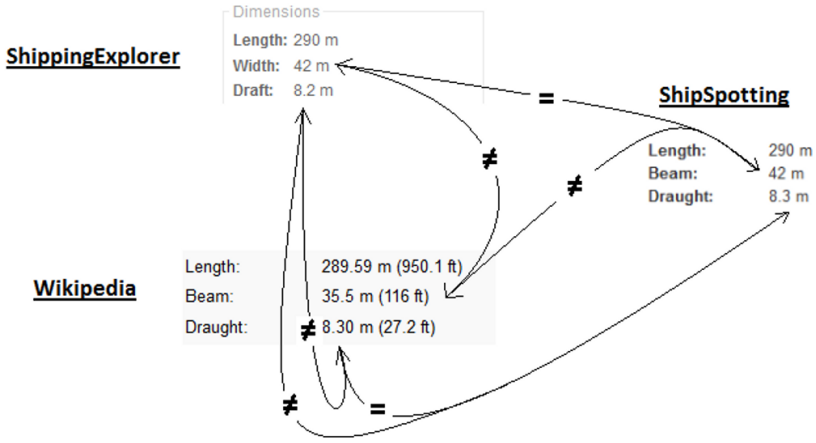
Truth discovery on heterogeneous data



- Problem: Determine true values from integrated semi-structured Web sources
- Challenge: Semi-structured data on the Web is contradictory and copied from source to source
- Methodology: Estimate the truth and determine copy patterns between sources, not only of base facts but of subtrees of the data

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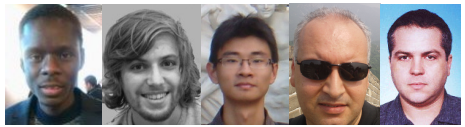

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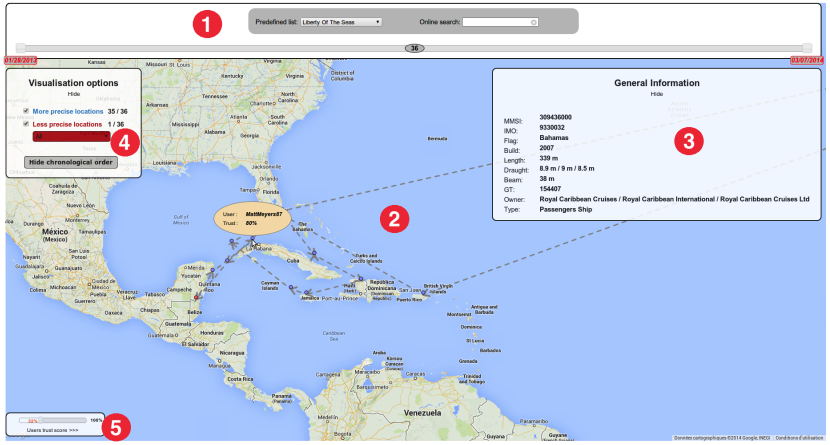
Social Sensing of Moving Objects
(Ba, Montenez, Abdessalem, and Senellart 2014)



- Problem: Infer trajectories and meta-information of moving objects from Web and social Web data
- Challenge: Uncertainty and inconsistency in extracted information
- Methodology: Data cleaning by filtering incorrect locations, and truth discovery to identify reliable sources

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Smarter urban mobility

- Problem: Smart and adaptive recommendations for mobility in cities (transit, bike rental, car, etc.)
- Challenge: Should take into account personal information (calendar, etc.), past trajectories, public information about transit and traffic
- Methodology: Map GPS tracks to routes of public transport, learn route patterns, infer destination while in transit and provide push suggestions

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What's next?

- So far, we have tackled individual aspects or specializations of the UnSAID problem
- Now we need to consider the general problem, and propose general solutions
- There is a strong potential for uncovering the unsaid information from the Web
- Strong connections with a number of research areas: active learning, reinforcement learning, adaptive query evaluation, etc. Inspiration to get from these areas.
- Everyone is welcome to join the effort!

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Merci.

Amarilli, A., M. L. Ba, D. Deutch, and P. Senellart (Dec. 2013). *Provenance for Nondeterministic Order-Aware Queries*. Preprint available at http://pierre.senellart.com/publications/amarilli2014provenance.pdf.

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