Corroboration de vues discordantes fondée sur la confiance

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Motivating Example

What are the capital cities of European countries?

	France	Italy	Poland	Romania	Hungary
Alice	Paris	Rome	Warsaw	Bucharest	Budapest
Bob	?	Rome	Warsaw	Bucharest	Budapest
Charlie	Paris	Rome	Katowice	Bucharest	Budapest
David	Paris	Rome	Bratislava	Budapest	Sofia
Eve	Paris	Florence	Warsaw	Budapest	Sofia
Fred	Rome	?	?	Budapest	Sofia
George	Rome	?	?	?	Sofia

Voting

Information: redundance

	France	Italy	Poland	Romania	Hungary
Alice	Paris	Rome	Warsaw	Bucharest	Budapest
Bob	?	Rome	Warsaw	Bucharest	Budapest
Charlie	Paris	Rome	Katowice	Bucharest	Budapest
David	Paris	Rome	Bratislava	Budapest	Sofia
Eve	Paris	Florence	Warsaw	Budapest	Sofia
Fred	Rome	?	?	Budapest	Sofia
George	Rome	?	?	?	Sofia
Frequence	**P.** 0.67 R. 0.33	**R.** 0.80 F. 0.20	**W.** 0.60 K. 0.20 B. 0.20	Buch. 0.50 Bud. 0.50	Bud. 0.43 **S.** 0.57

Evaluating Trustworthiness of Sources

Information: redundance, trustworthiness of sources (= average frequence of predicted correctness)

Decision	Paris France	Rome Italy	Warsaw Poland	Bucharest Romania	Budapest Hungary	Trust
Alice	Paris	Rome	Warsaw	Bucharest	Budapest	0.60
Bob	?	Rome	Warsaw	Bucharest	Budapest	0.58
Charlie	Paris	Rome	Katowice	Bucharest	Budapest	0.52
David	Paris	Rome	Bratislava	Budapest	Sofia	0.55
Eve	Paris	Florence	Warsaw	Budapest	Sofia	0.51
Fred	Rome	?	?	Budapest	Sofia	0.47
George	Rome	?	?	?	Sofia	0.45
Frequence weighted by trust	**P.** 0.70 R. 0.30	**R.** 0.82 F. 0.18	**W.** 0.61 K. 0.19 B 0.20	**Buch.** 0.53 Bud. 0.47	Bud. 0.46 **S.** 0.54	

Iterative Fixpoint Computation

Information: redundance, trustworthiness of sources with iterative fixpoint computation

	France	Italy	Poland	Romania	Hungary	Trust
Alice	Paris	Rome	Warsaw	Bucharest	Budapest	0.65
Bob	?	Rome	Warsaw	Bucharest	Budapest	0.63
Charlie	Paris	Rome	Katowice	Bucharest	Budapest	0.57
David	Paris	Rome	Bratislava	Budapest	Sofia	0.54
Eve	Paris	Florence	Warsaw	Budapest	Sofia	0.49
Fred	Rome	?	?	Budapest	Sofia	0.39
George	Rome	?	?	?	Sofia	0.37
Frequence weighted by trust	**P.** 0.75 R. 0.25	**R.** 0.83 F. 0.17	**W.** 0.62 K. 0.20 B 0.19	**Buch.** 0.57 Bud. 0.43	**Bud.** 0.51 S. 0.49	

Context and problem

- Context:
  - Set of sources stating facts
  - (Possible) functional dependencies between facts
  - Fully unsupervised setting: we do not assume any information on the truth values of facts or the inherent trust of sources
- Problem: determine which facts are true and which facts are false
- Real world applications: query answering, source selection, data quality assessment on the web, making good use of the wisdom of crowds

Outline

Introduction

Model

Algorithms

Experiments

Conclusion

Outline

General Model

- Set of facts $\mathcal{F} = \{f_1 \dots f_n\}$
  - Examples: "Paris is capital of France", "Rome is capital of France", "Rome is capital of Italy"
- Set of views (= sources) $\mathcal{V} = \{V_1 \dots V_m\}$, where a view is a partial mapping from $\mathcal{F}$ to {T, F}
  - Example:
    ¬ "Paris is capital of France" ∧ "Rome is capital of France"
- Objective: find the most likely real world $\mathcal{W}$ given $\mathcal{V}$ where the real world is a total mapping from $\mathcal{F}$ to {T, F}
  - Example:
    "Paris is capital of France" ∧ ¬ "Rome is capital of France" ∧ "Rome is capital of Italy" ∧ ...

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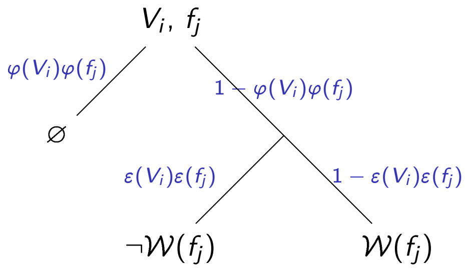
Generative Probabilistic Model



- $\varphi(V_i)\varphi(f_j)$: probability that V_i "forgets" f_j
- $\varepsilon(V_i)\varepsilon(f_j)$: probability that V_i "makes an error" on f_j
- Number of parameters: $n + 2(n + m)$
- Size of data: $\tilde{\varphi} nm$ with $\tilde{\varphi}$ the average forget rate

Obvious Approach

- Method: use this generative model to find the most likely parameters given the data
  - Inverse the generative model to compute the probability of a set of parameters given the data
- Not practically applicable:
  - Non-linearity of the model and boolean parameter $\mathcal{W}(f_j)$ $\Rightarrow$ equations for inversing the generative model very complex
  - Large number of parameters (n and m can both be quite large) $\Rightarrow$ Any exponential technique unpractical

$\Rightarrow$ Heuristic fix-point algorithms

Outline

Baselines

Counting (does not look at negative statements, popularity)

$$\begin{cases} T & \text{if } \dfrac{|\{V_i : V_i(f_j) = T\}|}{\max_f |\{V_i : V_i(f) = T\}|} \geqslant \eta \\ F & \text{otherwise} \end{cases}$$

Voting (adapted only with negative statements)

$$\begin{cases} T & \text{if } \dfrac{|\{V_i : V_i(f_j) = T\}|}{|\{V_i : V_i(f_j) = T \vee V_i(f_j) = F\}|} \geqslant 0.5 \\ F & \text{otherwise} \end{cases}$$

TruthFinder [YHY07]: heuristic fix-point method from the literature

Fix-Point Algorithms

1. Estimate the truth of facts (e.g., with voting)
2. Based on that, estimate the error rates of sources
3. Based on that, refine the estimation for the facts
4. Based on that, refine the estimation for the sources
5. ...

Iterate until a fix-point is reached (and cross your fingers it converges!).

Cosine

- The truth of a fact is what views state weighted by how error prone they are
- The error of a view is the correlation (= cosine similarity) between its statement of facts and the predicted truth of these facts

2-Estimates

- Assume all the fact have the same difficulty: $\varepsilon(f_j) = 1$
- Statistical estimation of $\mathcal{W}(f_j)$ given $\varepsilon(V_i)$ and observations
- Statistical estimation of $\varepsilon(V_i)$ given $\mathcal{W}(f_j)$ and observations
- Quite instable $\Rightarrow$ tricky normalization

3-Estimates

- Similar in spirit to 2-Estimates but estimation of 3 parameters:
  - truth value of facts
  - error rate or trustworthiness of sources
  - hardness of facts
- Also needs tricky normalization

Functional dependencies

- So far, the models and algorithms are about positive and negative statements, without correlation between facts
- How to deal with functional dependencies (e.g., capital cities)?

pre-filtering: When a view states a value, all other values governed by this FD are considered stated false. *If I say that Paris is the capital of France, then I say that neither Rome nor Lyon nor . . . is the capital of France.*

post-filtering: Choose the best answer for a given FD.

Outline

Datasets

- Synthetic dataset: large scale and higly customizable
- Real-world datasets:
  - General-knowledge quiz
  - Biology 6th-grade test
  - Search-engines results
  - Hubdub

General-Knowledge Quiz (1/2)

1. **Where is the city of Ushuaia located?**
   - (•) Don't know
   - ( ) In Italy
   - ( ) In Greece
   - ( ) In Argentina
   - ( ) In the Ivory Coast
   - ( ) In Sweden
   - ( ) In Malaysia

2. **What is the last word of all three parts of Dante's *Divine Comedy* (*Hell* — *Purgatory* — *Paradise*)?**
   - (•) Don't know
   - ( ) "Stars" ("Stelle")
   - ( ) "God" ("Dio")
   - ( ) "Hope" ("Speranza")
   - ( ) "Beatrice"

3. **Who discovered the planet Uranus?**
   - (•) Don't know
   - ( ) Sir William Herschel (in 1781)
   - ( ) Urbain Le Verrier (in 1846)
   - ( ) Clyde Tombaugh (in 1930)
   - ( ) Percival Lowell (in 1894)

`http://www.madore.org/~david/quizz/quizz1.html`

- 17 questions, 4 to 14 answers, 601 participants

General-Knowledge Quiz (2/2)

	Number of errors (no post-filtering)	Number of errors (with post-filtering)
Voting	11	6
Counting	12	6
TruthFinder	-	-
2-Estimates	6	6
Cosine	7	6
3-Estimates	9	0

It does not always work!

No magic!

- Does not take into account dependencies between sources
- Example: integration of search engine results
- Usually, when it "does not work", 3-Estimates gives results comparable to the baseline, Cosine is not bad, 2-Estimates is very unstable

Outline

In brief

- One of the first works in truth discovery among disagreeing sources
- Collection of fix-point methods, one of them (3-Estimates) performing remarkably and regularly well
- We believe this is an important problem, we do not claim we have solved it completely
- Cool real-world applications!

All code and datasets available from
`http://datacorrob.gforge.inria.fr/`

Merci.

Webdam

Foundations of Web data management

Perspectives

- Exploiting dependencies between sources [DBES09]
- Numerical values (1.77m and 1.78m cannot be seen as two completely contradictory statements for a height)
- No clear functional dependencies, but a limited number of values for a given object (e.g., phone numbers)
- Pre-existing trust, e.g., in a social network
- Clustering of facts, each source being trustworthy for a given field

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