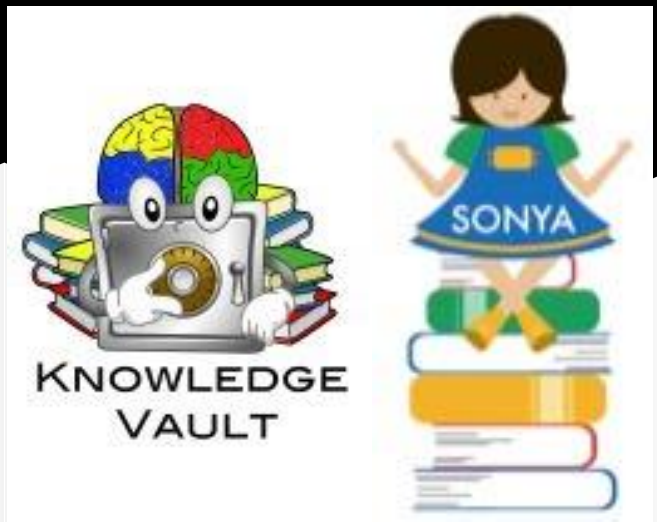
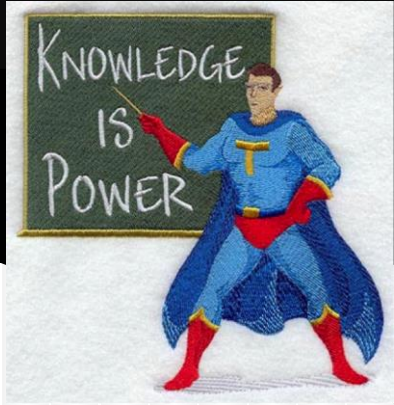
From Data Fusion to Knowledge Fusion

Xin Luna Dong, Google Inc.
9/13/2014 @ WISA'14



SONYA: A Big Project, A Fancy Machine, And A Cute Little Girl

Knowledge Is Power



- Many Knowledge Bases (KB)

yago
select knowledge

Freebase

DIADEM | domain-centric intelligent automated data extraction methodology

DeepDive

NELL: Never-Ending Language Learning

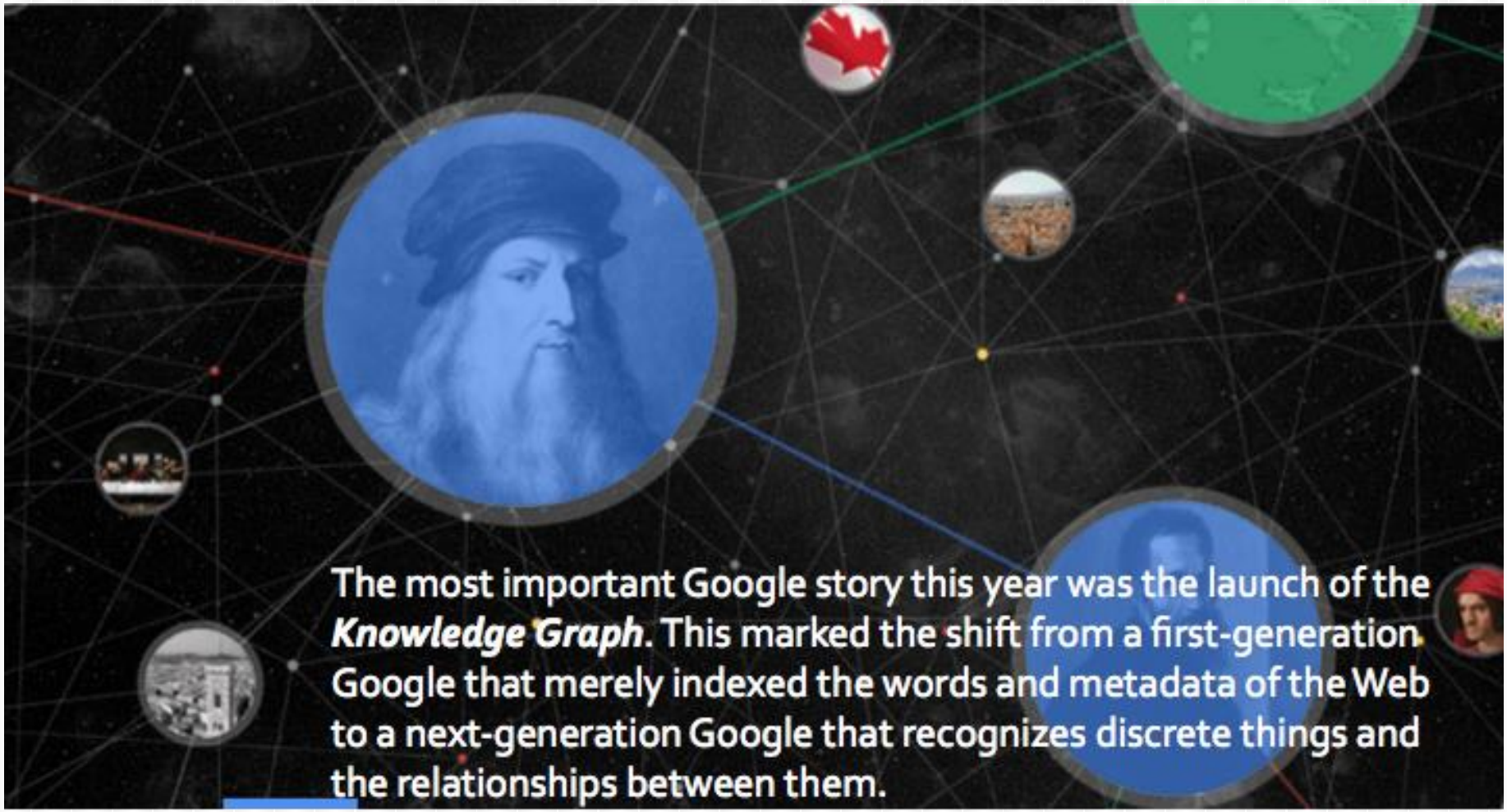
ProBase

DBpedia

facebook

Walmart

Google Knowledge Graph



- ReadWrite 12/27/2012

Using KG in Search

Google 南开

Web News Maps Shopping Images More Search tools

About 13,900,000 results (0.26 seconds)

南开大学
www.nankai.edu.cn/ Translate this page Nankai University
当地时间7月12日，在拉脱维亚里加举办的第八届世界合唱比赛第一阶段比赛中，南开大学学生合唱团获得青年混声组、有伴奏宗教组、有表演民谣合唱组3项金奖。南.
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南开大学（简称：南开、南大、NKU），原称私立南开大学，主校区坐落于天津市南开区八里台。南开大学是1919年由近代著名爱国教育家严修、张伯苓创立的私立大学， ...
南开大学附属中学 - 南开大学校钟 - 南开大学体育中心 - 南开大学主楼

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南开大学创建于1919年，创办人是近代著名爱国教育家张伯苓和严修。抗日战争时期，南开大学与北京大学、清华大学在昆明组成举世闻名的西南联合大学，被誉 ...

南开大学,分数线,专业设置_新浪院校库_新浪教育_新浪网
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南开大学是国家教育部直属重点综合性大学，是敬爱的周恩来总理的母校。南开大学创建于1919年，创办人是近代著名爱国教育家严修和张伯苓。抗日战争时期，南开 ...

南开大学_百度百科
baike.baidu.com/view/2967.htm Translate this page Baidu Baike
南开大学被誉为"学府北辰"，是中国最著名的高等院校之一。其诞生于1919年，旧称"私立南开学校"，周恩来总理曾在此短暂就读；抗日战争时期，南开大学与北京大学、 ...

南开大学吧_百度贴吧
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Nankai University

Directions

University in Tianjin, China

Nankai University, often known as Nankai, is a public research university located in Tianjin mainland China. Founded in 1919 by prominent educators Zhang Boling and Yan Fansun, Nankai is one of the most prestigious top universities in China. Wikipedia

Address: 94 Weijin Rd, Nankai, Tianjin, China
Phone: +86 22 2350 8219
Enrollment: 21,905 (2010)
Founder: Zhang Boling
Founded: 1919
Colors: White, Violet

See results about

Nan Kai University of Technology (University in Taiwan)
Founded: 1971

Expanding KG– Extracting Knowledge from the Web

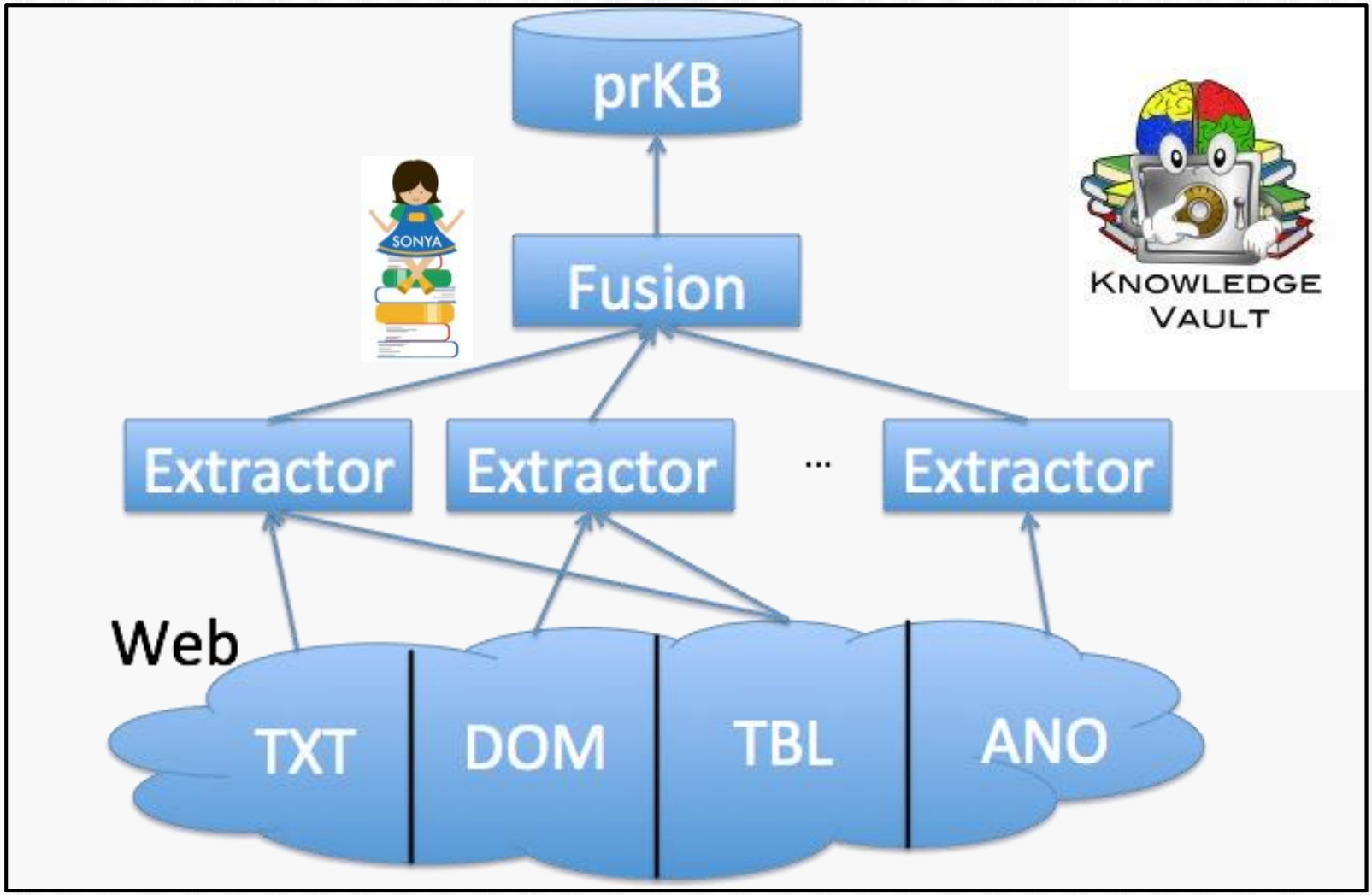
"In the near future, the web is going to be the master copy of human knowledge. We need to figure out ways to use that knowledge."
—Håkon Wium Lie

But–

- KG requires 99% accuracy for knowledge
- Web data is noisy and extraction is hard
- How to balance *coverage* and *accuracy*?

Knowledge Vault– Building a Probabilistic KB

[VLDB'2014, Sigmod'2014, KDD'2014]



Science alert
Australia & New Zealand

News

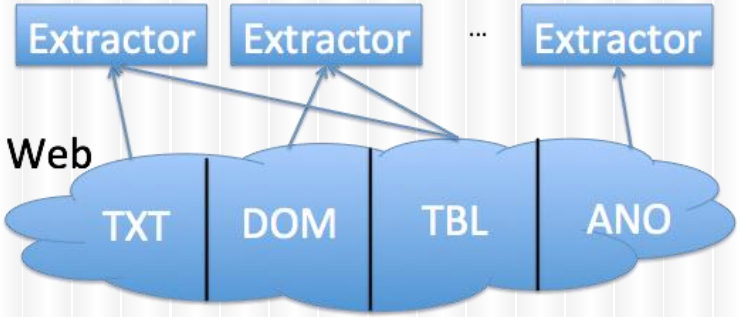
Google's Knowledge Vault already contains 1.6 billion facts

FELICITY NELSON
SATURDAY, 23 AUGUST 2014

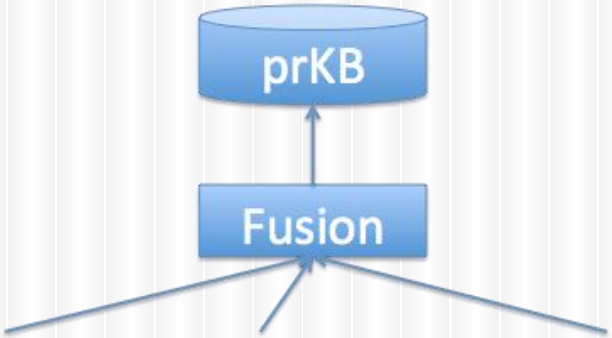
The automated, fact-harvesting bot will build up a collection of all human knowledge.

Outline

Knowledge extraction



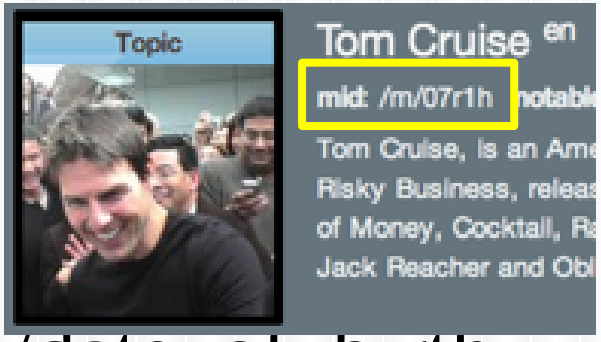
Knowledge fusion



Interesting applications

Knowledge Extraction I–Knowledge

- Triple: (subject, predicate, object)
  e.g., (Tom Cruise, date_of_birth, 7/3/1962)
  - Subject–a Freebase mid
    e.g., /m/07r1h
  - Predicate–predefined in Freebase; e.g., people/person/date_of_birth
  - Object–a Freebase mid, a string, a number, or a date.



Statistics for Extracted Triples

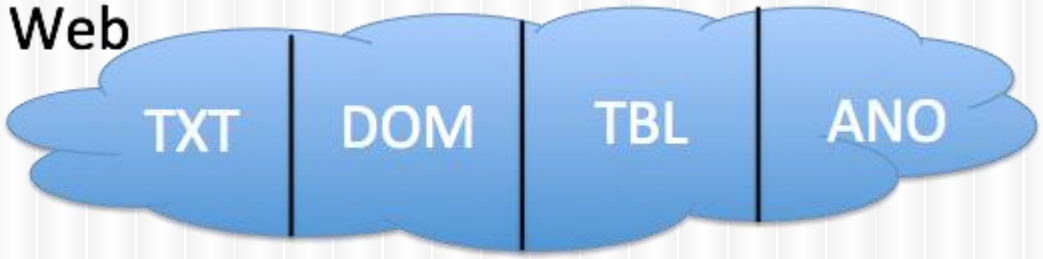
- A large knowledge base

As of 11/2013

#Triples	1.6B (now 2.8B)
#Subjects (Entities)	43M
#Types	1.1K
#Predicates	4.5K
#Objects	102M

- Highly skewed data–fat heads, long tail
  - #Triples/type: 1–14M
    (*location*, *organization*, *business*)
  - #Triples/entity: 1–2M (*USA*, *UK*, *CA*, *NYC*, *TX*)

Knowledge Extraction II–Sources



Free texts

Synopsis Print Cite This

Born on April 15, 1452, in Vinci, Italy, Leonardo da Vinci was concerned with the laws of science and nature, which greatly informed his work as a painter, sculpto
His ideas and body of work -- which in
The Last Supper, *Leda and the Swan* a
influenced countless artists and made d
Italian Renaissance.

Web tables & Lists

	Name and (party)[1]	Term	State of birth	Born	Died
1.	Washington (F)[3]	1789–1797	Va.	2/22/1732	12/14/
2.	J. Adams (F)	1797–1801	Mass.	10/30/1735	7/4/18
3.	Jefferson (DR)	1801–1809	Va.	4/13/1743	7/4/18
4.	Madison (DR)	1809–1817			

DOM Tr

yelp

Shana Thai Restaurant

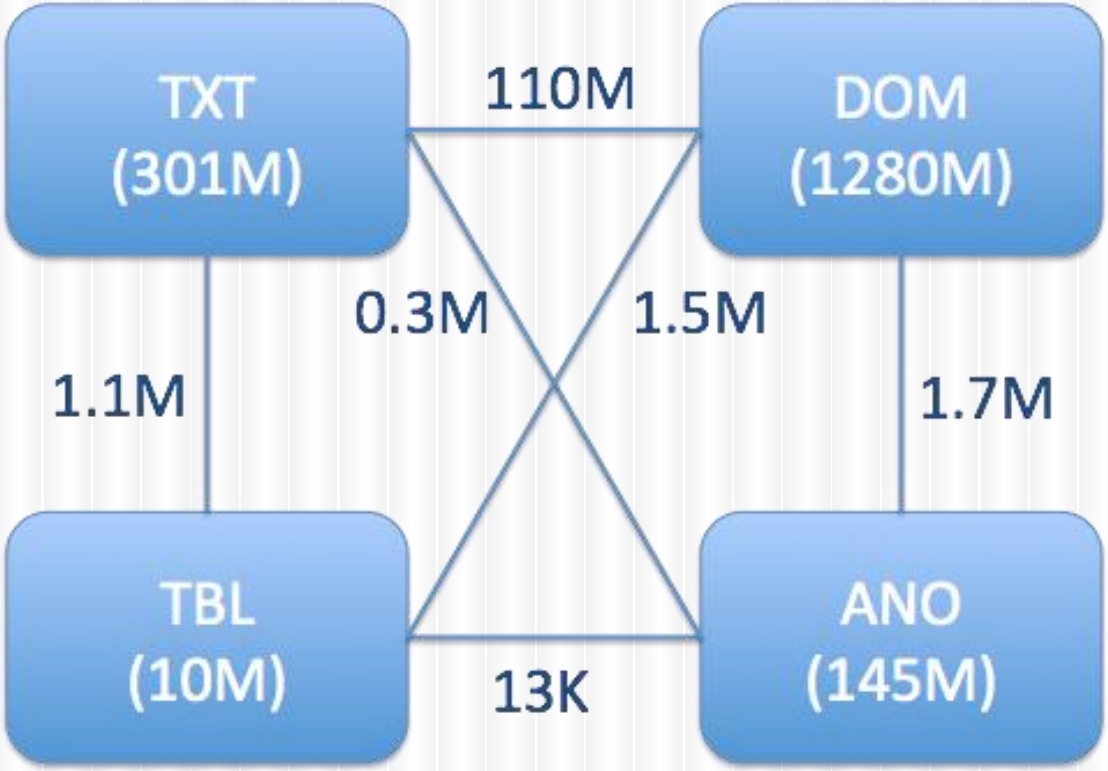
Annotations

```
<h1 itemprop="name">
Tom Cruise </h1>
<span itemprop="birthDate">
7/3/1962 </span>
<span itemprop="gender">
Male </span>
```

schema.org

Statistics for Web Sources

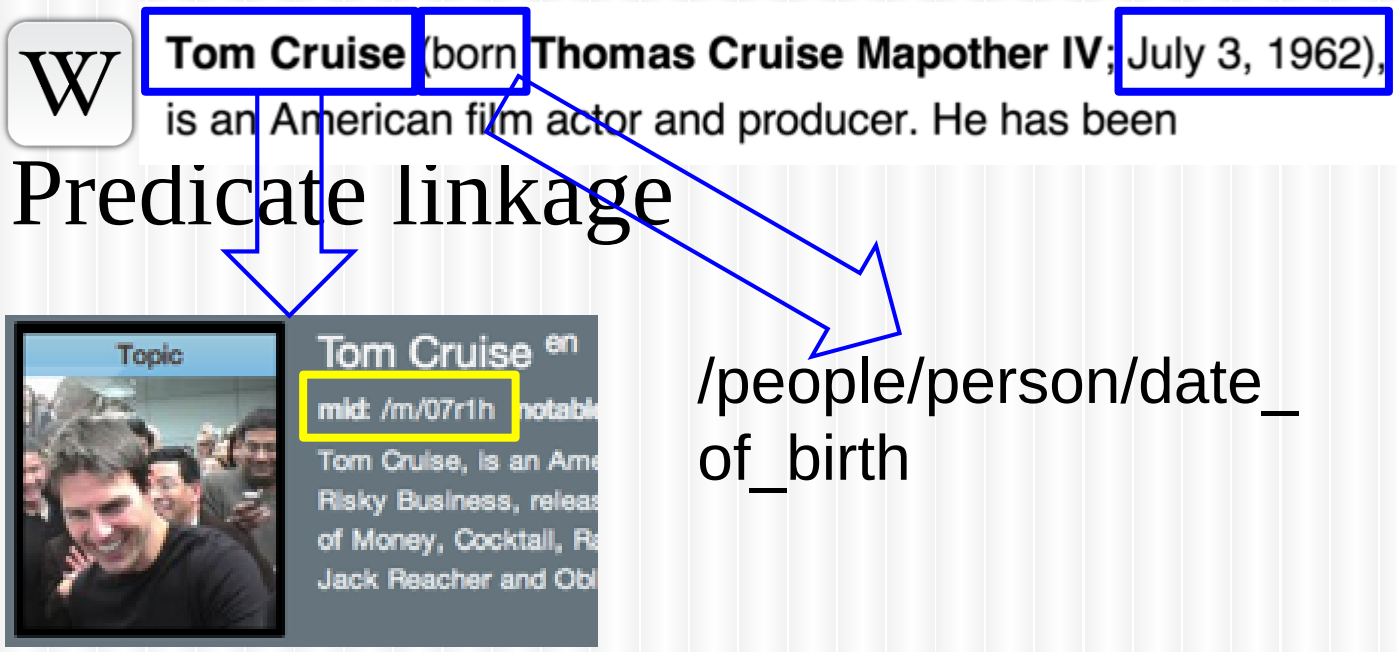
- 1B+ Webpages over the Web
- Contribution is skewed: 1- 50K



As of 11/2013

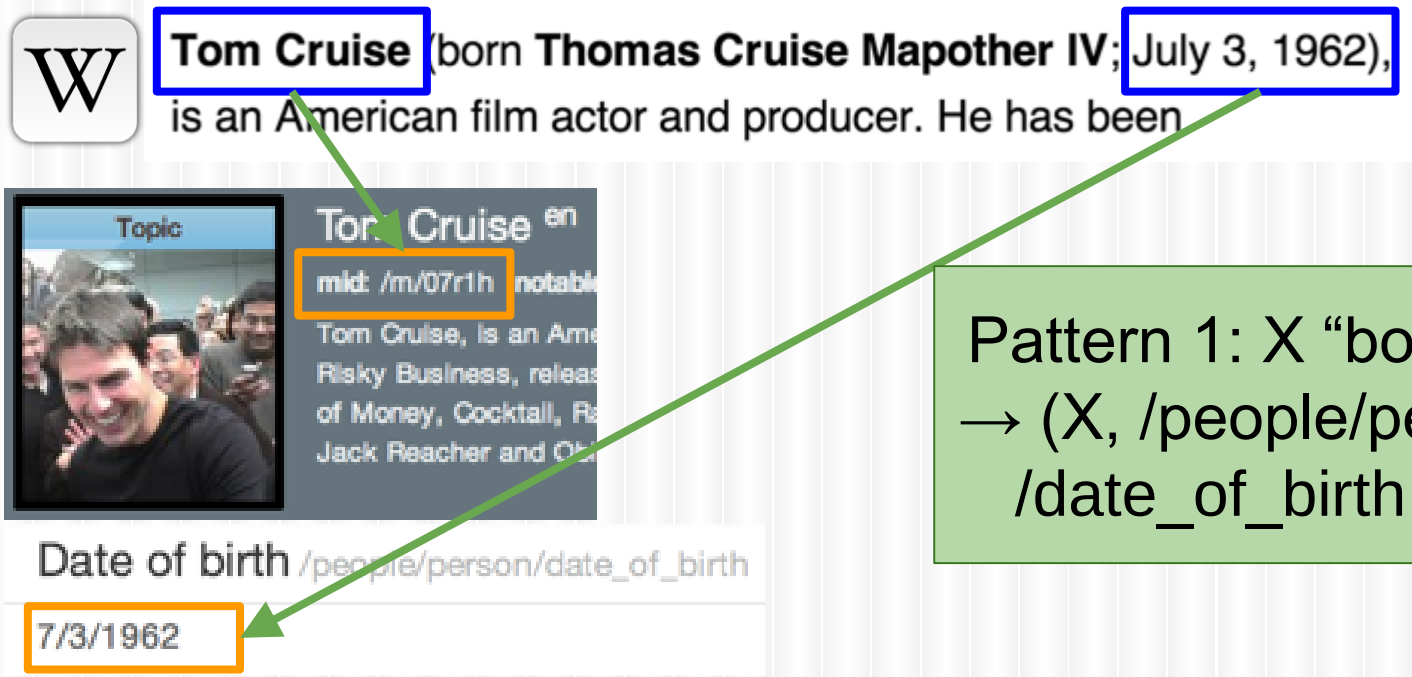
Knowledge Extraction III– Extractors

- Three tasks (any order, maybe combined)
  I. Triple identification
  II. Entity linkage
  III. Predicate linkage



Knowledge Extraction III– Extractors

- Texts/DOM: distant supervision



- Web tables/lists: schema mapping
- Annotations: semi-automatic mapping

Statistics for Extractors

- 12 extractors; high variety

	#Triples	#Webpages	#Patterns	Accu	Accu (conf $\geq$ .7)
TXT1	274M	202M	4.8M	0.36	0.52
TXT2	31M	46M	3.7M	0.18	0.80
TXT3	8.8M	16M	1.5M	0.25	0.81
TXT4	2.9M	1.2M	0.1M	0.78	0.91
DOM1	804M	344M	25.7M	0.43	0.63
DOM2	431M	925M	No pat.	0.09	0.62
DOM3	45M	N/A	No pat.	0.58	0.93
DOM4	52M	7.8M	No pat.	0.26	0.34
DOM5	0.7M	0.5M	No pat.	0.13	No conf.
TBL1	3.1M	0.4M	No pat.	0.24	0.24
TBL2	7.4M	0.1M	No pat.	0.69	No conf.
ANO	145M	53M	No pat.	0.28	0.30

As of 11/2013

Errors Can Creep in at Every Stage

Extraction error: (Obama, nationality, Chicago)

Errors Can Creep in at Every Stage

Reconciliation error:
(Obama, nationality, North America)

American President Barack Obama

Errors Can Creep in at Every Stage

Source data error: (Obama, nationality, Kenya)

Obama born in Kenya

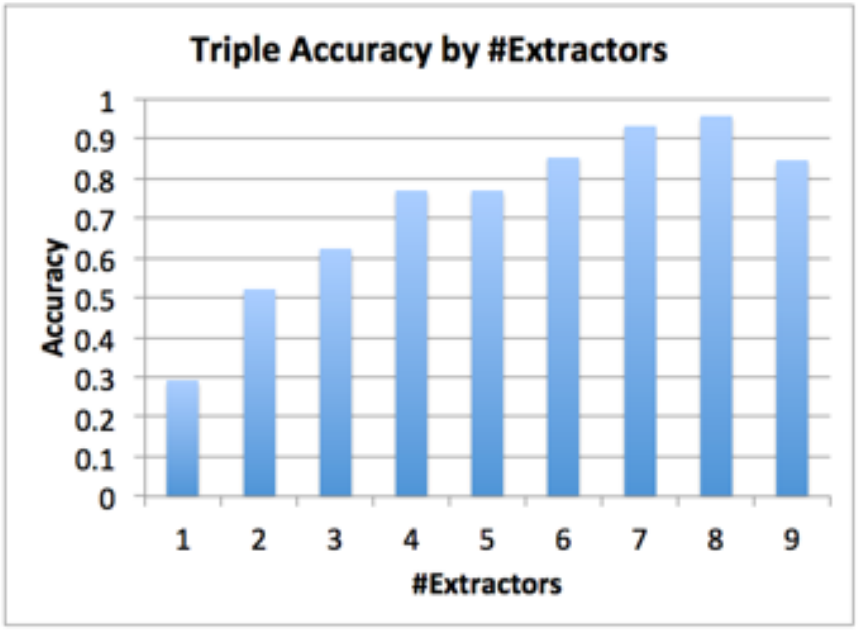
Knowledge Extraction IV–Quality

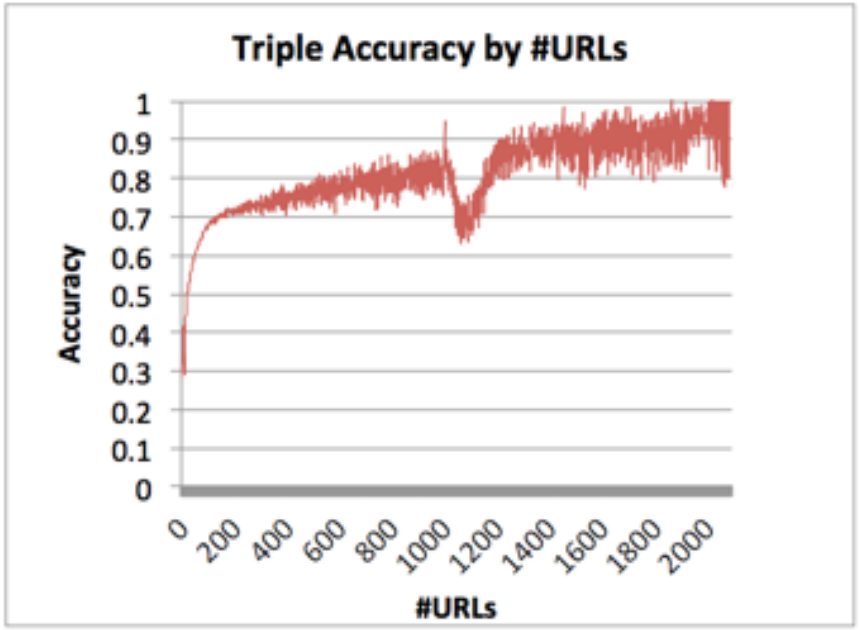
- Gold standard: Freebase
- LCWA (Local Closed-World Assumption)
  - If (s,p,o) exists in FB: true
  - Otherwise,
    - If (s,p) exists in FB: false (Freebase knowledge is locally complete)
    - Otherwise: UNKNOWN
- The gold standard contains about 40% of the triples

Statistics for Triple Correctness

- Overall accuracy: 30%
- Random sample on 25 false triples
  - Triple-identification errors: 11 (44%)
  - Entity-linkage errors: 11 (44%)
  - Predicate-linkage errors: 5 (20%)
  - Source-data errors: 1 (4%)

Statistics for Triple Correctness





As of 11/2013

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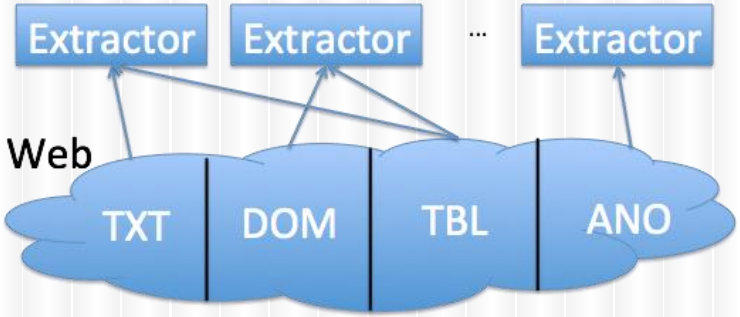
TBL2	7.4M	0.1M	No pat.	0.69	No conf.
ANO	145M	53M	No pat.	0.28	0.30

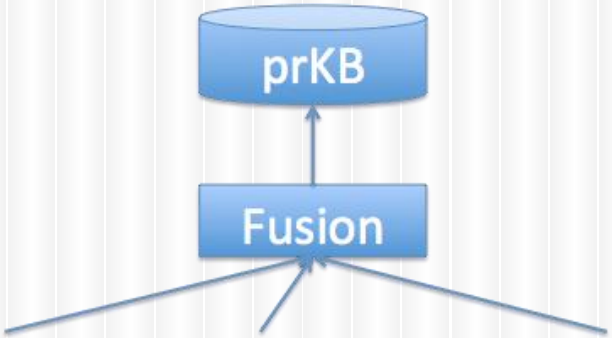
As of 11/2013

Outline

Knowledge extraction



Knowledge fusion

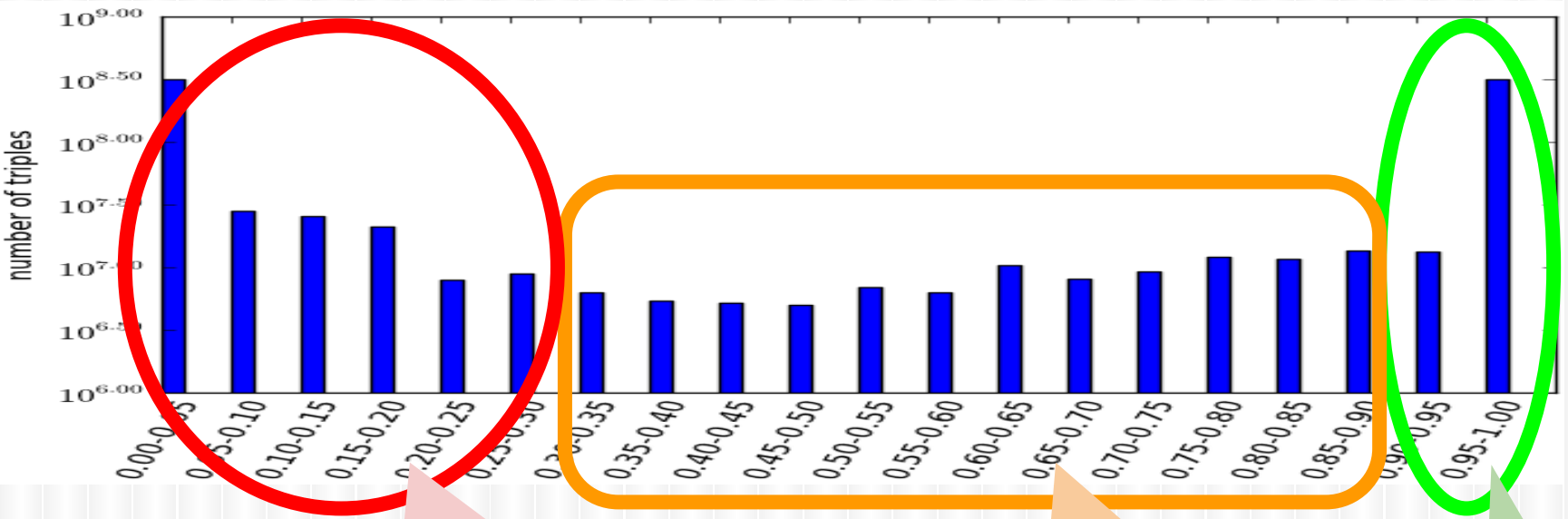


Interesting applications

Goal: Judge Triple Correctness

- Input: Knowledge triples and their provenances (i.e., which extractor extracts from which source)
- Output: a probability in [0,1] for each triple
  - Probabilistic decisions
    vs. deterministic decisions

Usage of Probabilistic Knowledge



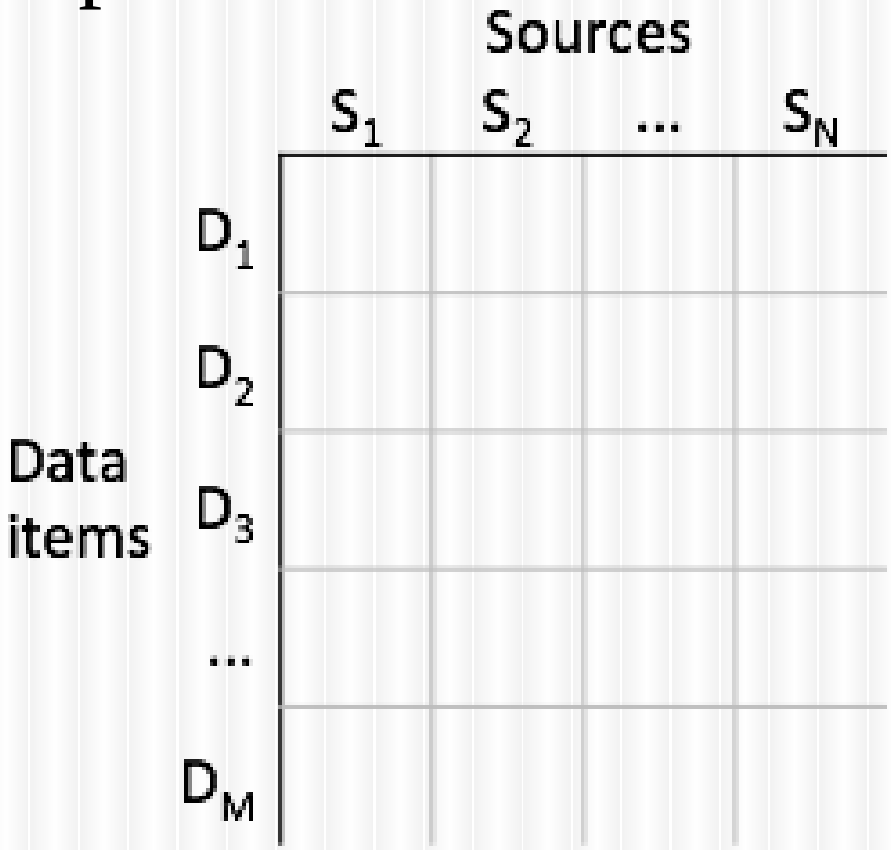
Negative training examples, and MANY EXCITING APPLICATIONS!!

Active learning, probabilistic inference, etc.

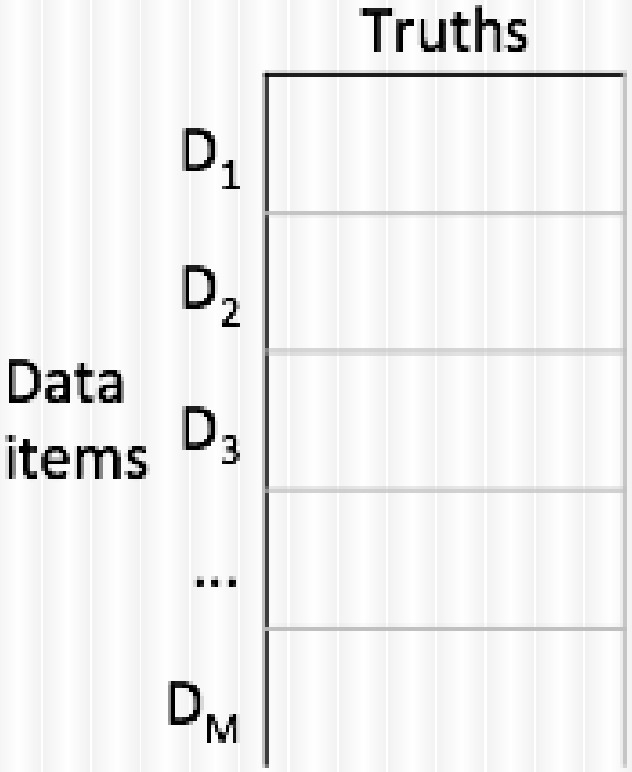
Upload to KG

Data Fusion–Definition

Input



Output



Data Fusion–Intuition

	Src1	Src2	Src3
Jagadish	UM	ATT	UM
Dewitt	MSR	MSR	UW
Bernstein	MSR	MSR	MSR
Carey	UCI	ATT	BEA
Franklin	UCB	UCB	UMD

Data Fusion–Intuition

	Src1	Src2	Src3
Jagadish	UM	ATT	UM
Dewitt	MSR	MSR	UW
Bernstein	MSR	MSR	MSR
Carey	UCI	ATT	BEA
Franklin	UCB	UCB	UMD

Voting--Trust the majority.

Data Fusion–Intuition

	Src1	Src2	Src3
Jagadish	UM	ATT	UM
Dewitt	MSR	MSR	UW
Bernstein	MSR	MSR	MSR
Carey	UCI	ATT	BEA
Franklin	UCB	UCB	UMD

Data Fusion–Intuition

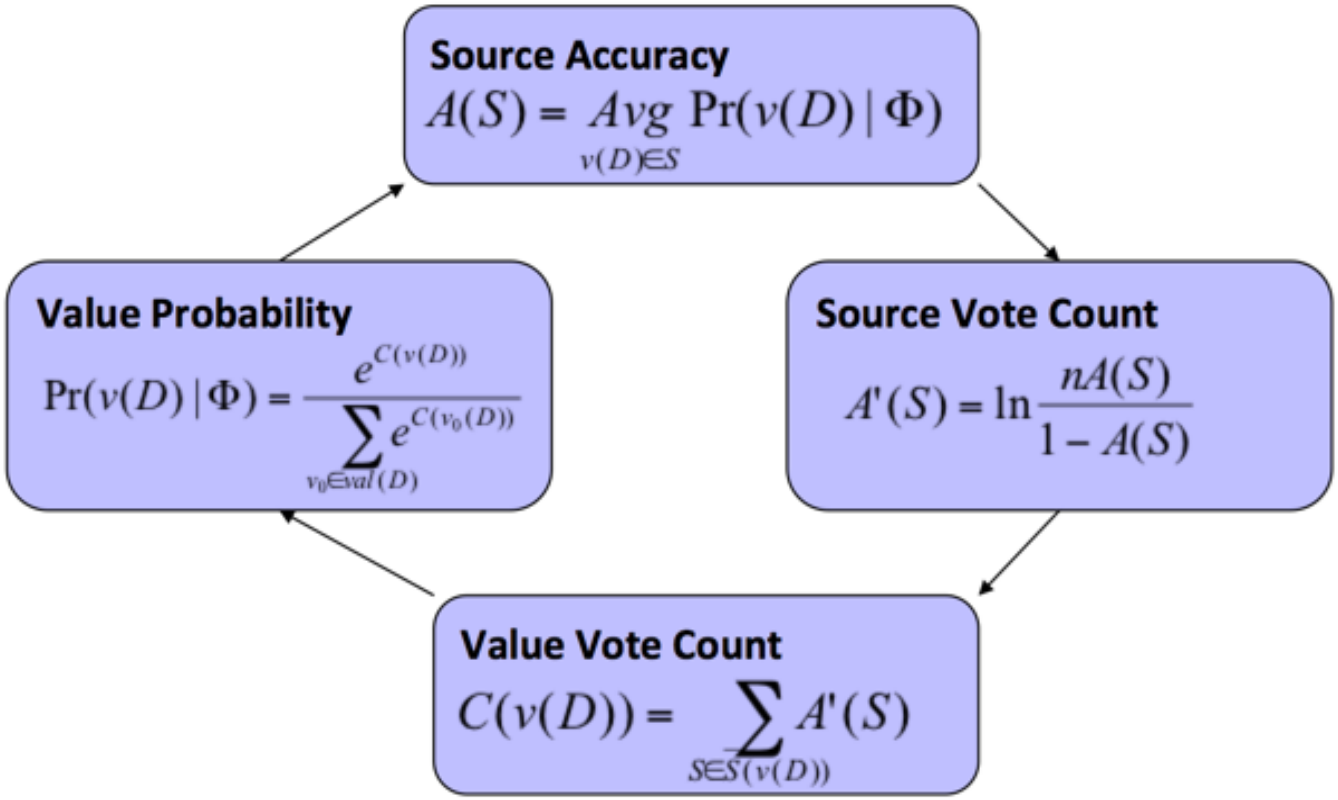
	Src1	Src2	Src3
Jagadish	UM	ATT	UM
Dewitt	MSR	MSR	UW
Bernstein	MSR	MSR	MSR
Carey	UCI	ATT	BEA
Franklin	UCB	UCB	UMD

Quality-based--Give higher votes to more accurate sources.

Data Fusion–A Bayesian Model

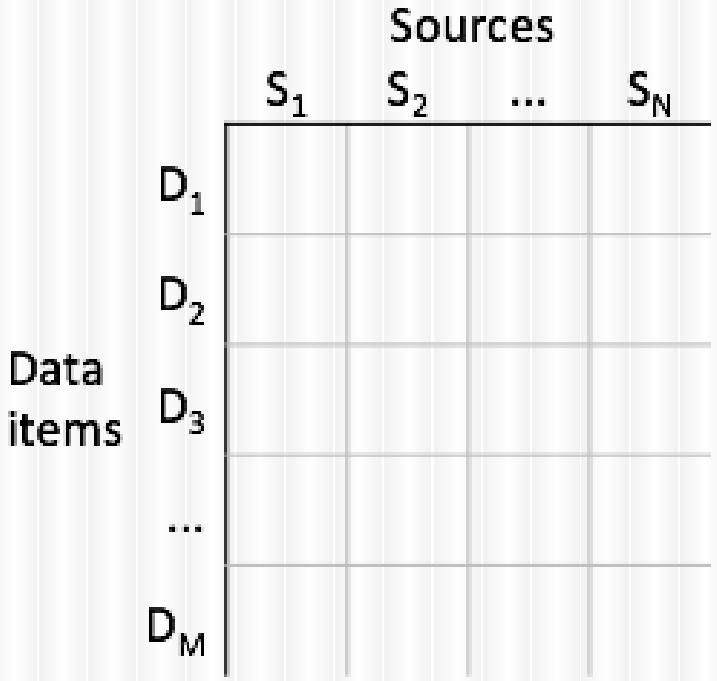
[Dong et al., VLDB'09]

- Continue until source accuracy converges

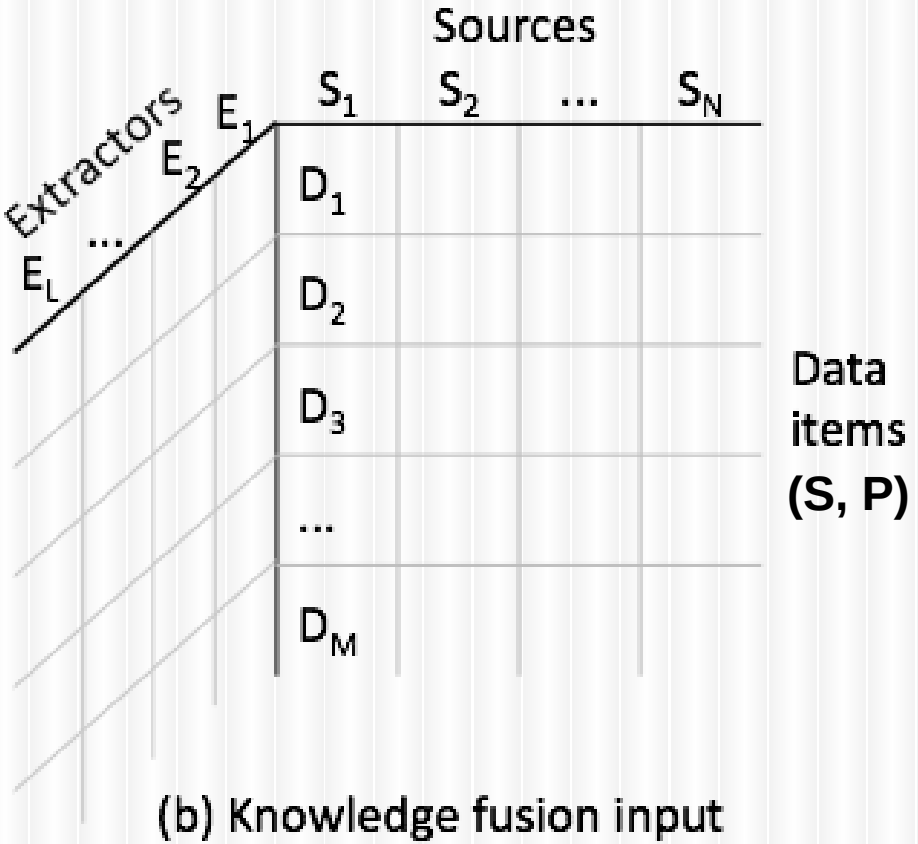


Knowledge Fusion Challenges

I. Input is ***three-dimensional***



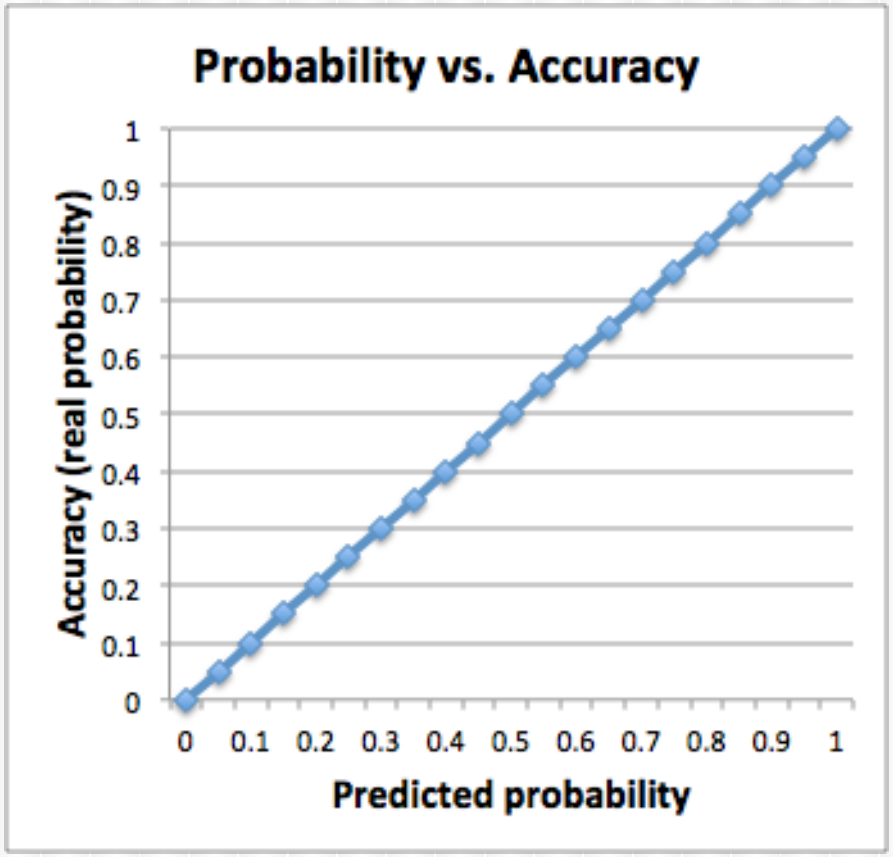
(a) Data fusion input



(b) Knowledge fusion input

Knowledge Fusion Challenges

II. Output prs should be ***well-calibrated***



Knowledge Fusion Challenges

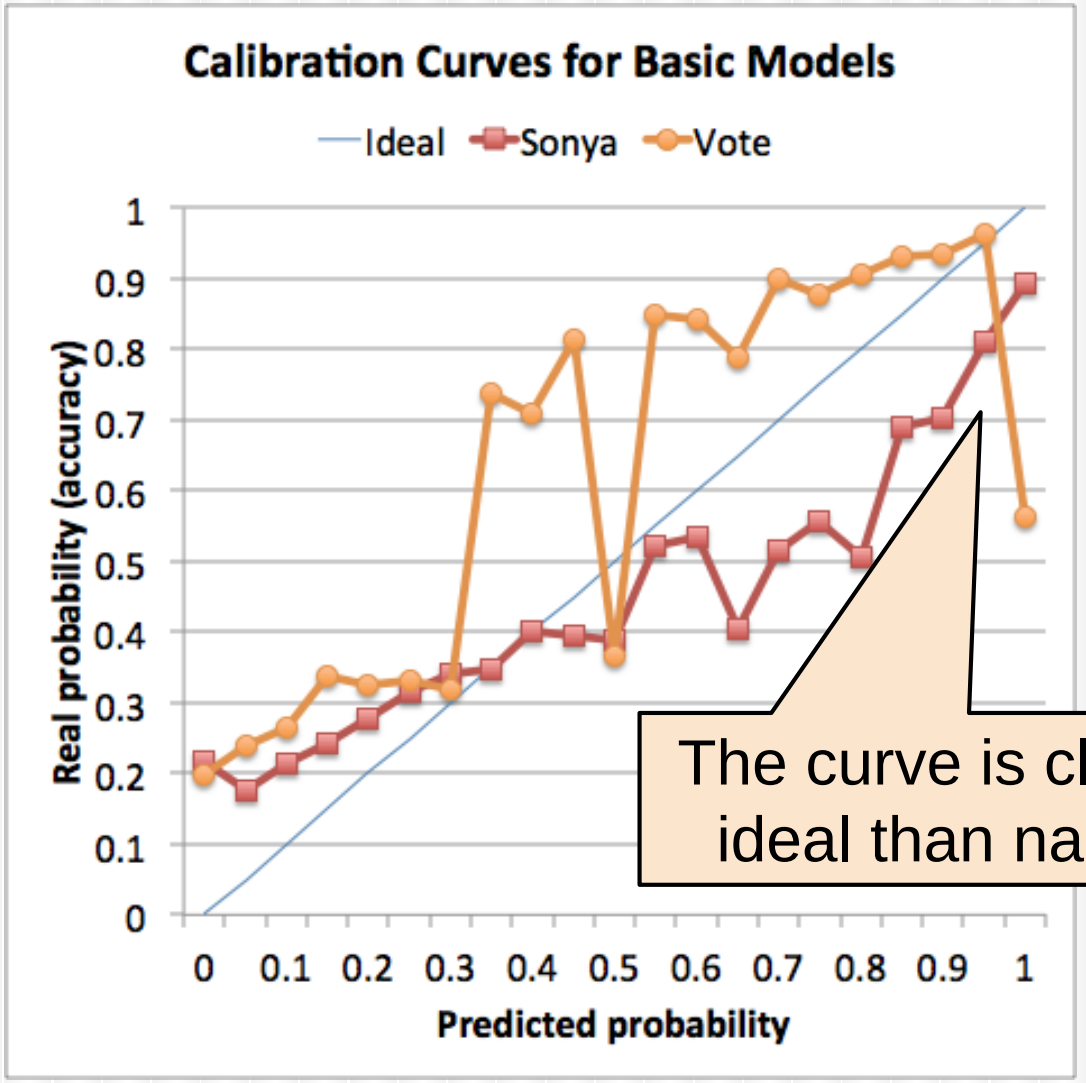
III. Data are of ***Web-scale***

- Three orders of magnitude larger than currently published data-fusion applications
  - Size: 1.1TB
  - Sources: 170K→ 1B+
  - Data items: 400K→375M
  - Values: 18M→6.4B (1.6B unique)
- Data are highly skewed
  - #Triples/Data-item: 1 - 2.7M
  - #Triples/Source: 1 - 50K

Knowledge Fusion Solutions

- Treat each (URL, Extractor) as a whole (*provenance)* for accuracy evaluation
- A series of refinements to improve probability calibration
- MapReduce Based Framework
  - Sample for *too big* data items or provenances

Basic Sonya Solution vs. Voting

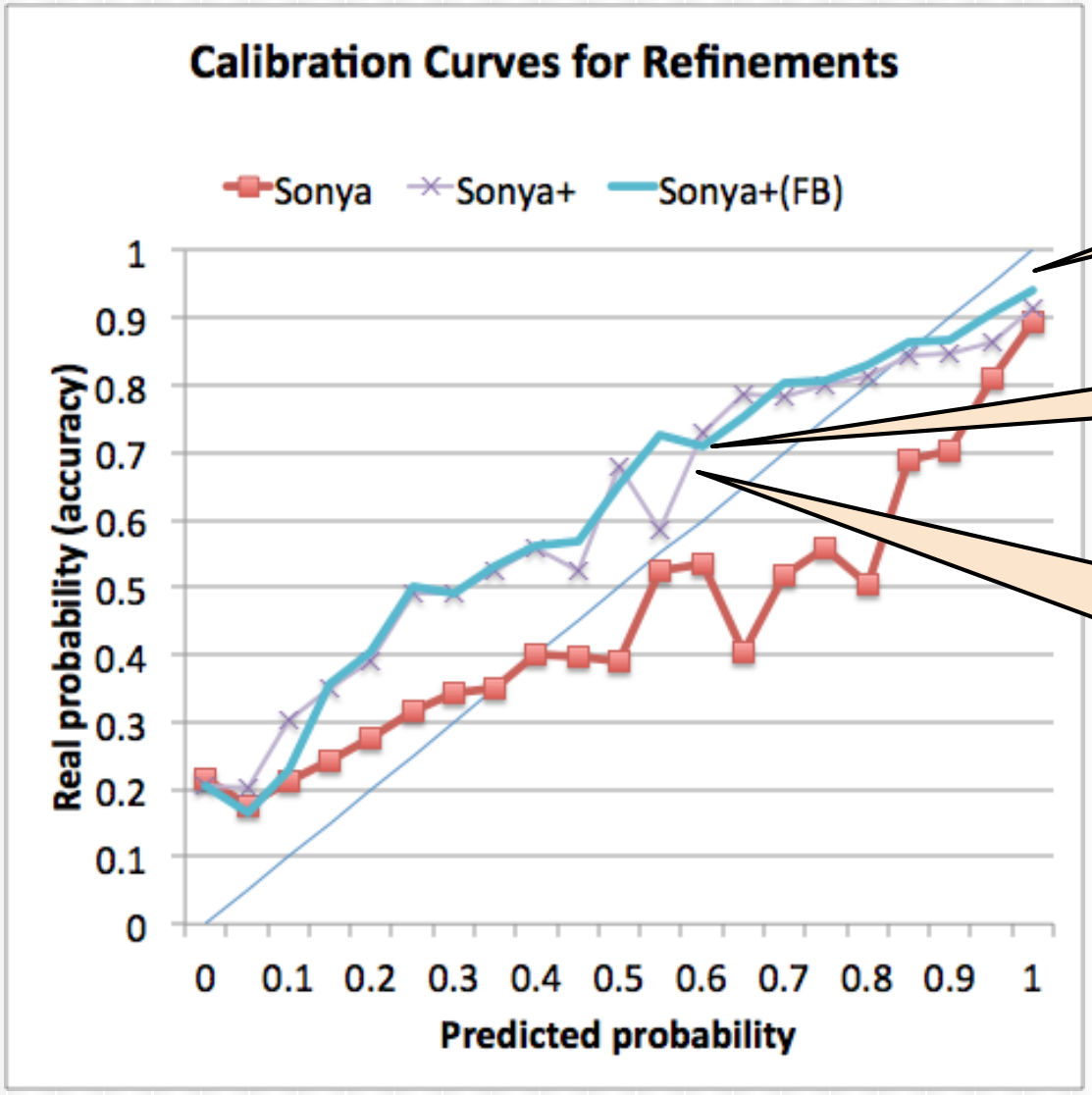


Refinements

I. Ignore low-coverage provenances
II. Granularity (URL->Site,
    Extractor->Pattern, Predicate)
III. Ignore low-accuracy provenances
IV. Initiate provenance accuracy by FB

+I, II, III. Sonya+ : unsupervised
+IV. Sonya+(FB) : semi-supervised

Calibration Curve



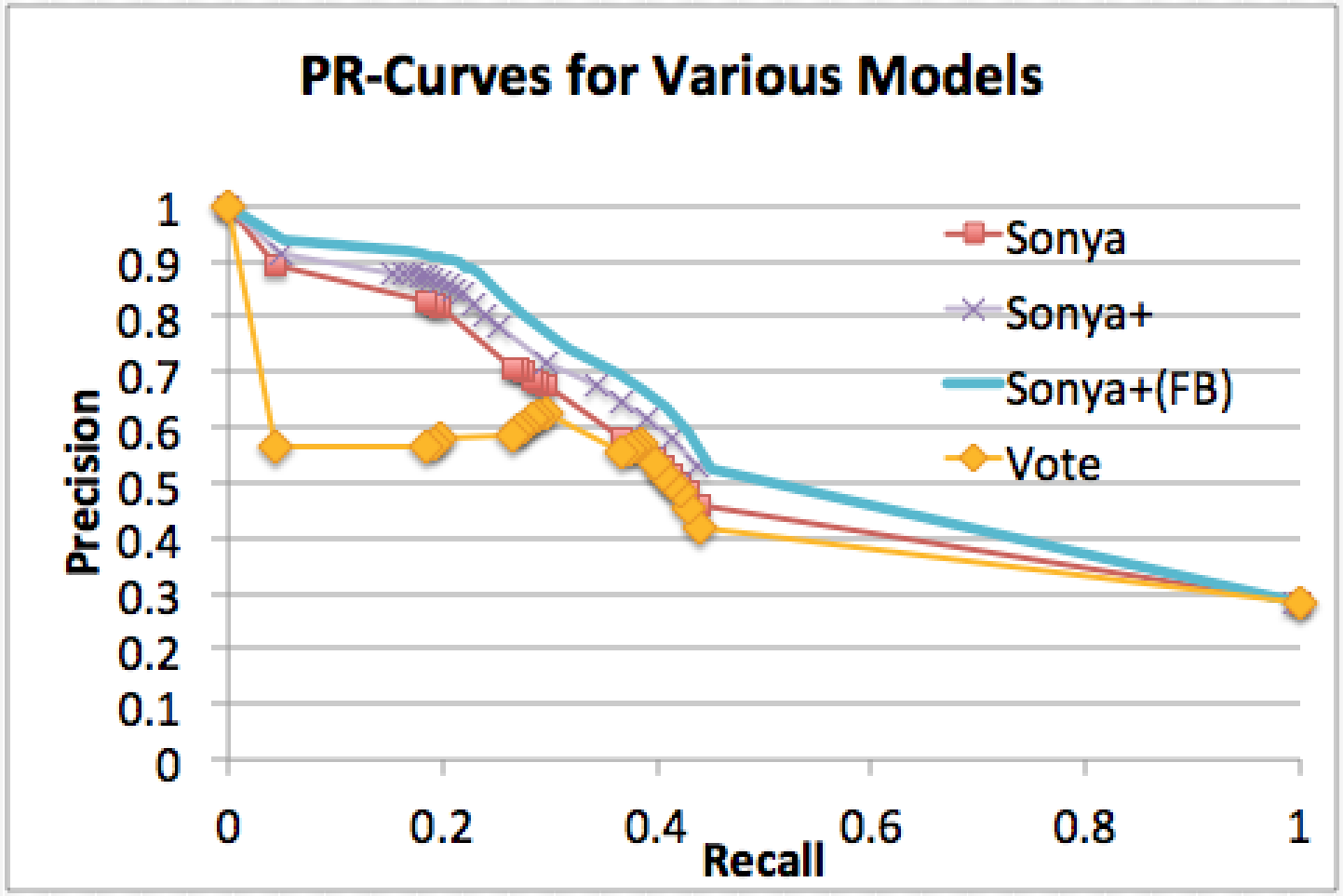
Higher accuracy

Smoother curve

Unsupervised methods very effective

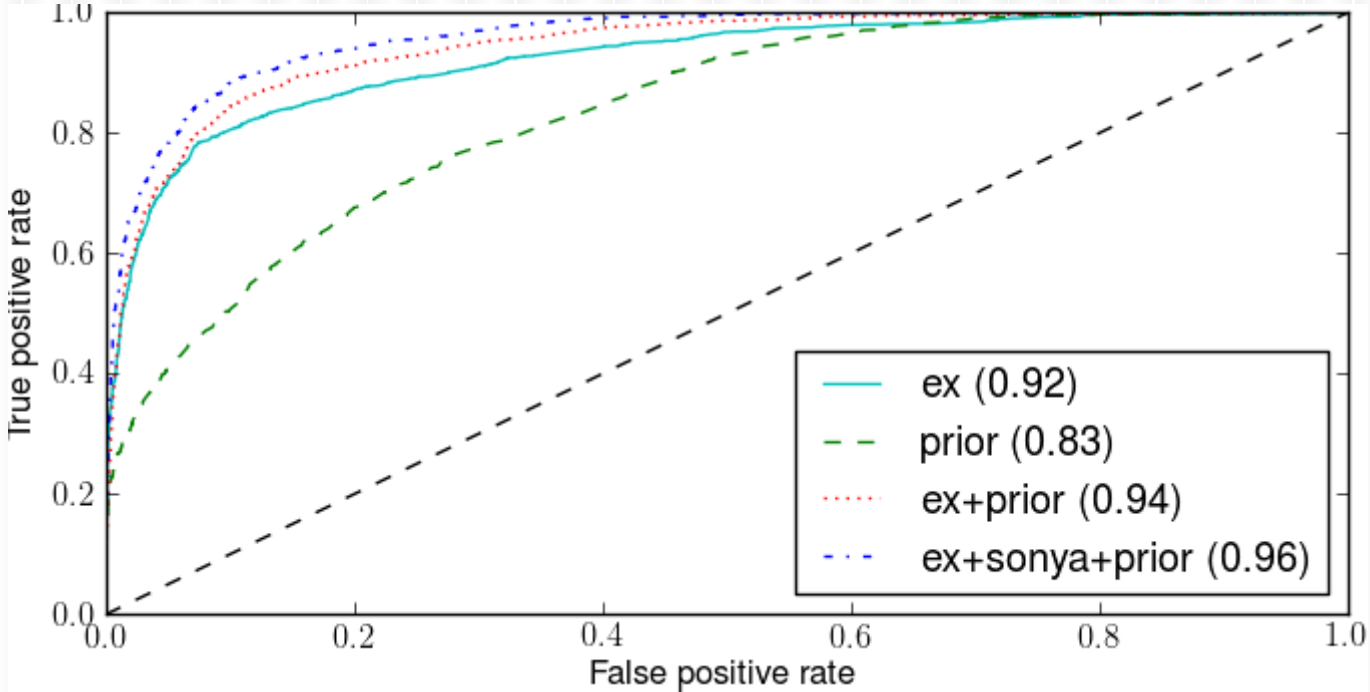
Weighted deviation:
0.037→0.035→0.032

Precision-Recall Curve



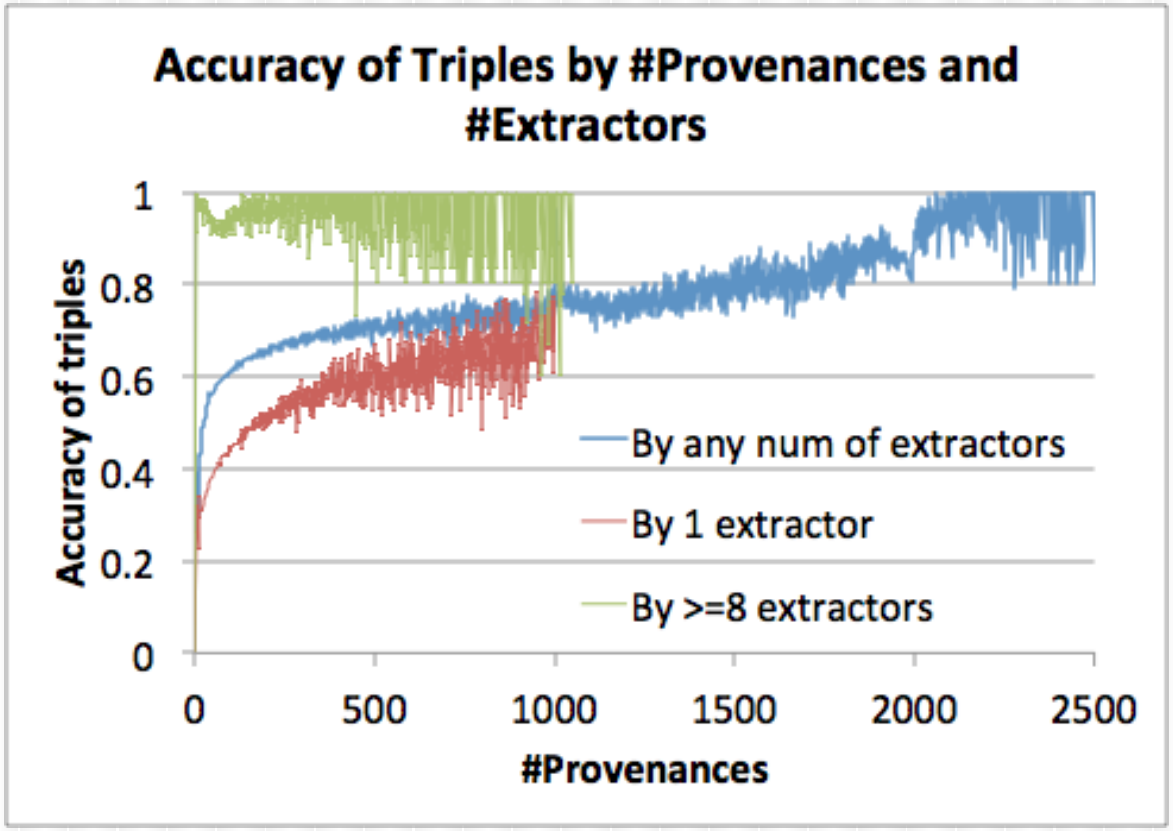
Other Fusion Techniques

- Ex: Adaboost learning from extractions
- Prior: (A, parent_of, C), (B, parent_of, C)
  → (A, spouse_of, B)



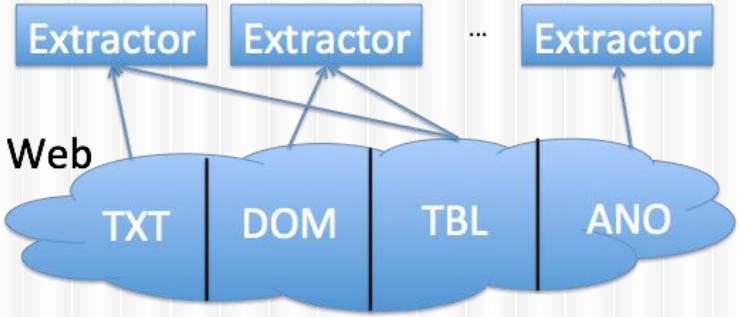
One Inherent Limitation

Cannot distinguish errors from extractor and from sources

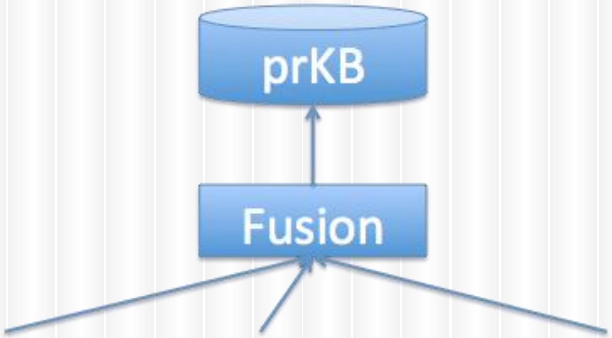


Outline

Knowledge extraction

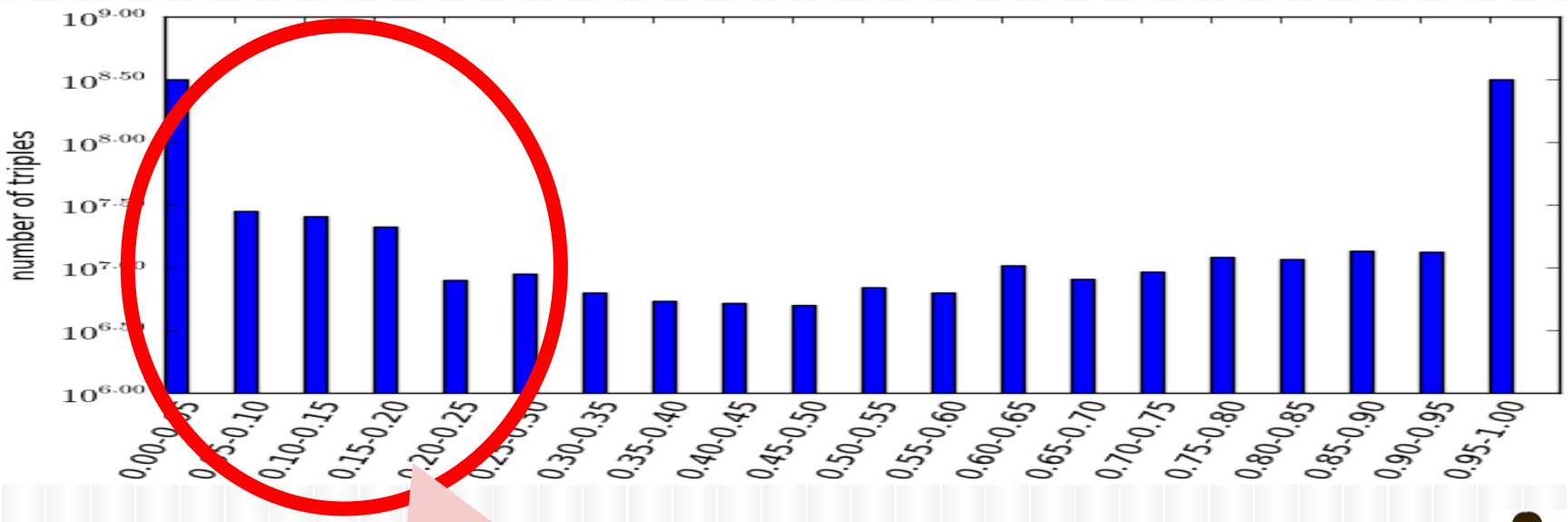


Knowledge fusion



Interesting applications

Usage of Probabilistic Knowledge



Negative training examples, and MANY EXCITING APPLICATIONS!!

- Source errors: trustworthiness evaluation
- Extraction errors: data abnormality diagnosis

Application I. A New Angle to Evaluate Web Source Quality

- What we have now
  - Page Rank: links between Websites/Webpages
  - Log based: search log and click-through rate
  - Web spam
  - etc.

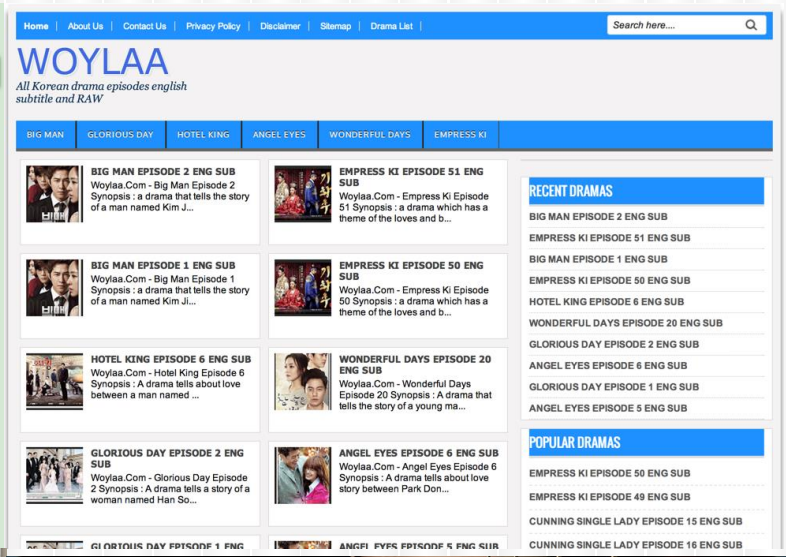
Popular Sources w. High Page Rank May Spread Gossip

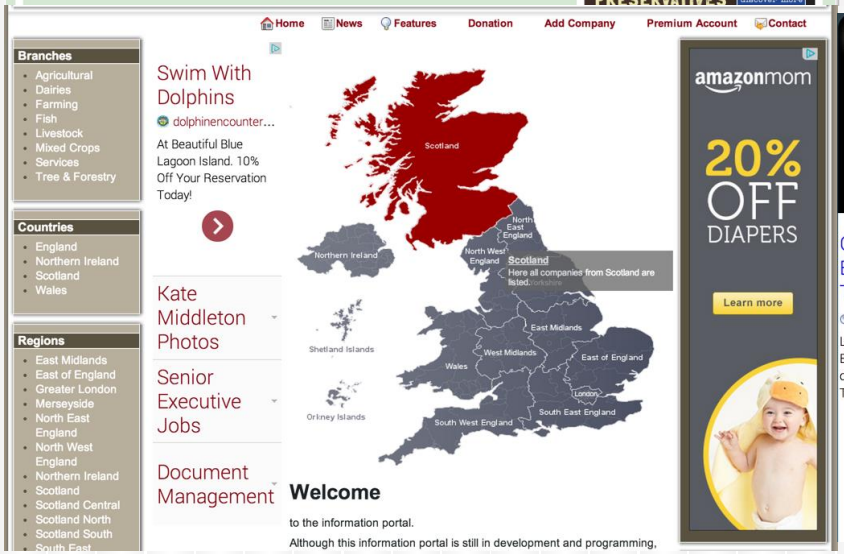
14 out of 15 Gossip Websites have high page rank

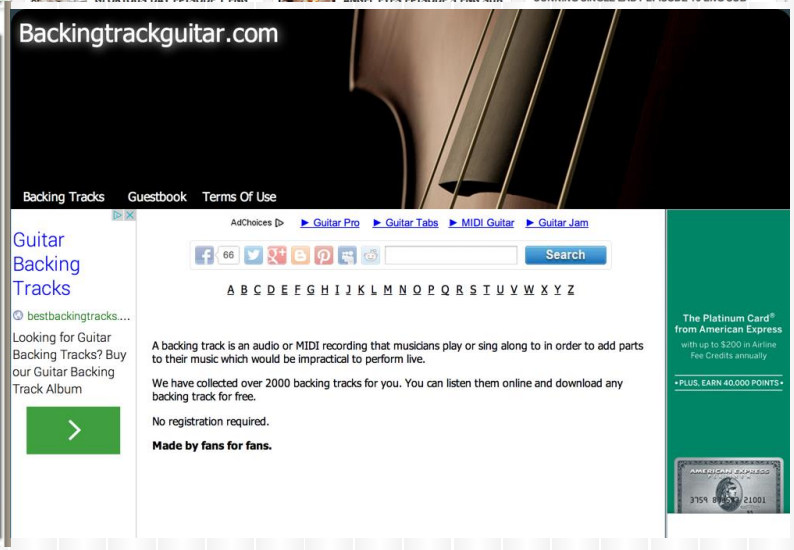
http://www.ebizmba.com/articles/gossip-websites

Domain
www.eonline.com
perezhilton.com
radaronline.com
www.zimbio.com
mediatakeout.com
gawker.com
www.popsugar.com
www.people.com
www.tmz.com
www.fishwrapper.com
celebrity.yahoo.com
wonderwall.msn.com
hollywoodlife.com
www.wetpaint.com

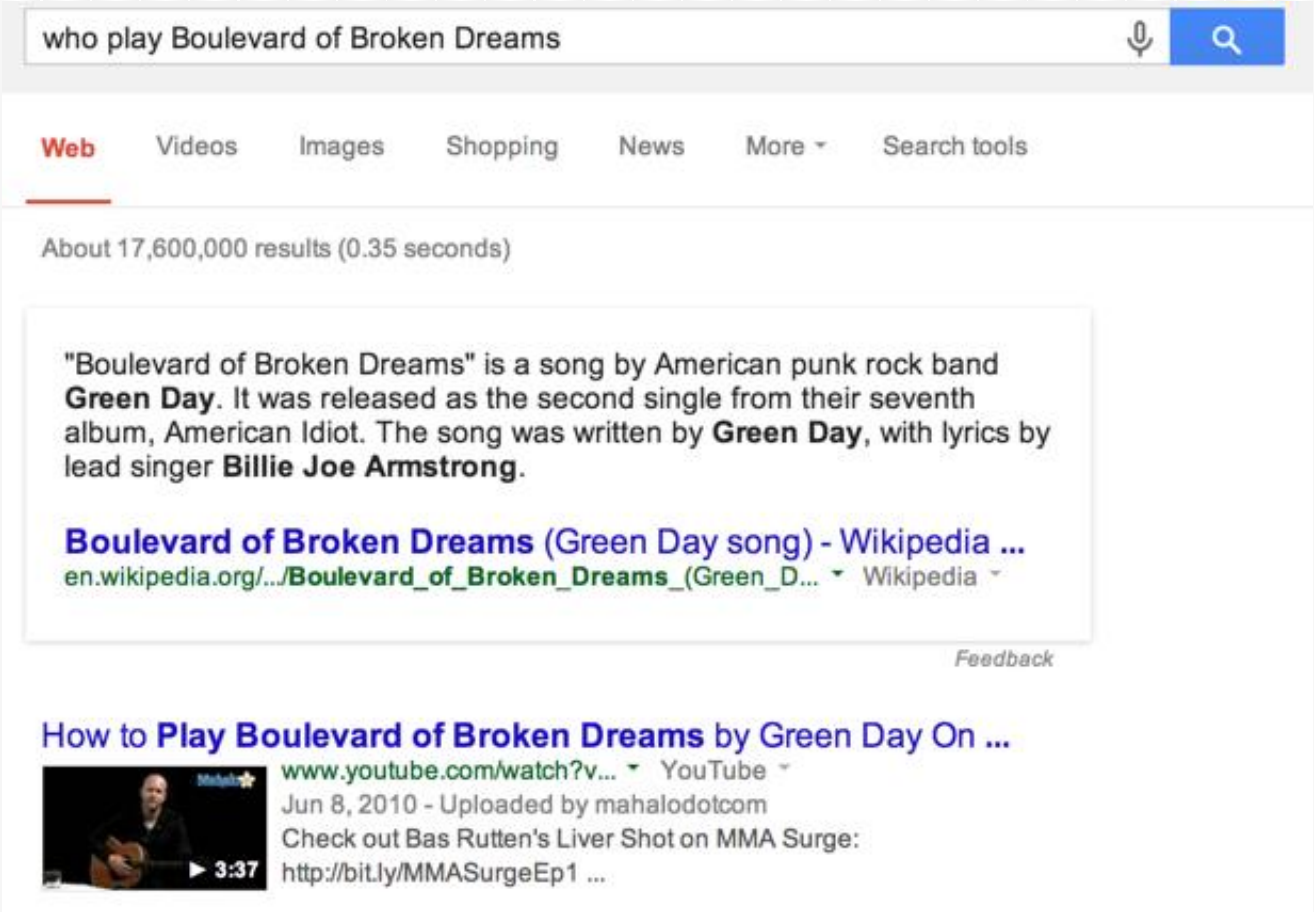
Tale Sources w. Low Page Rank May Provide Valuable Info





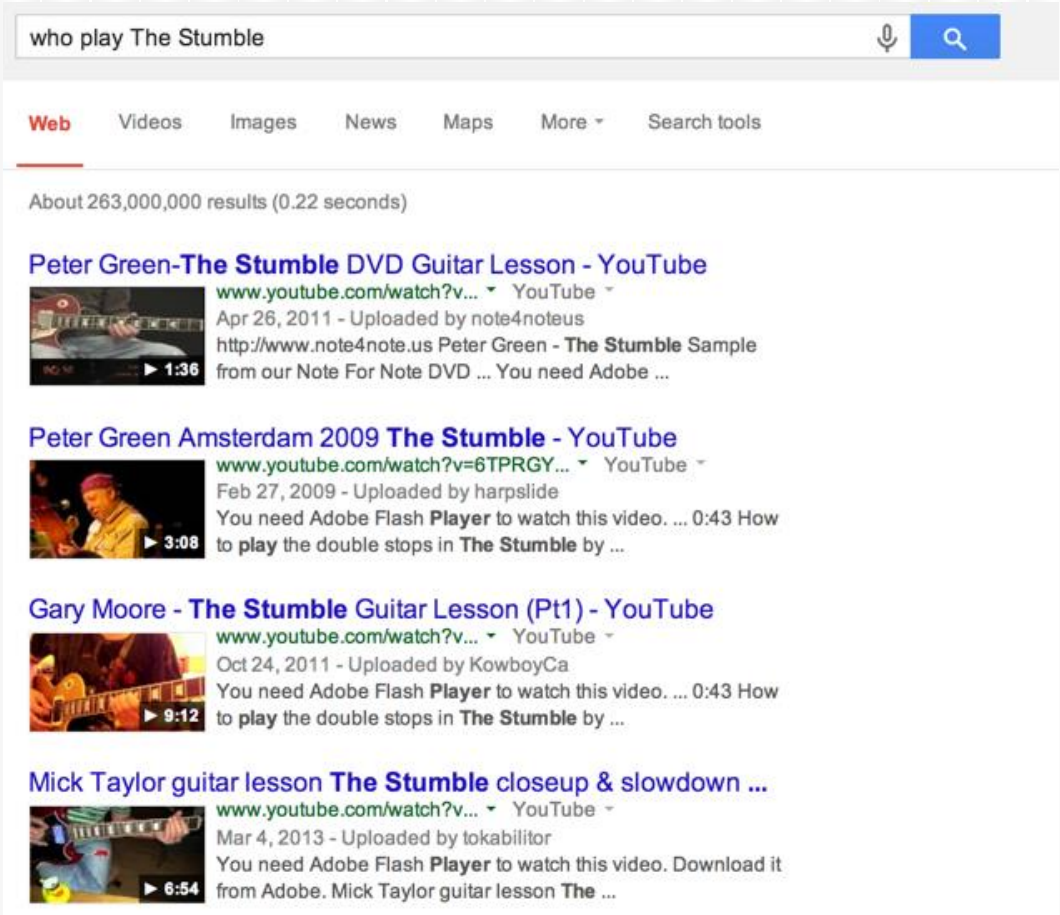


Tale Sources w. Low Page Rank May Provide Valuable Info



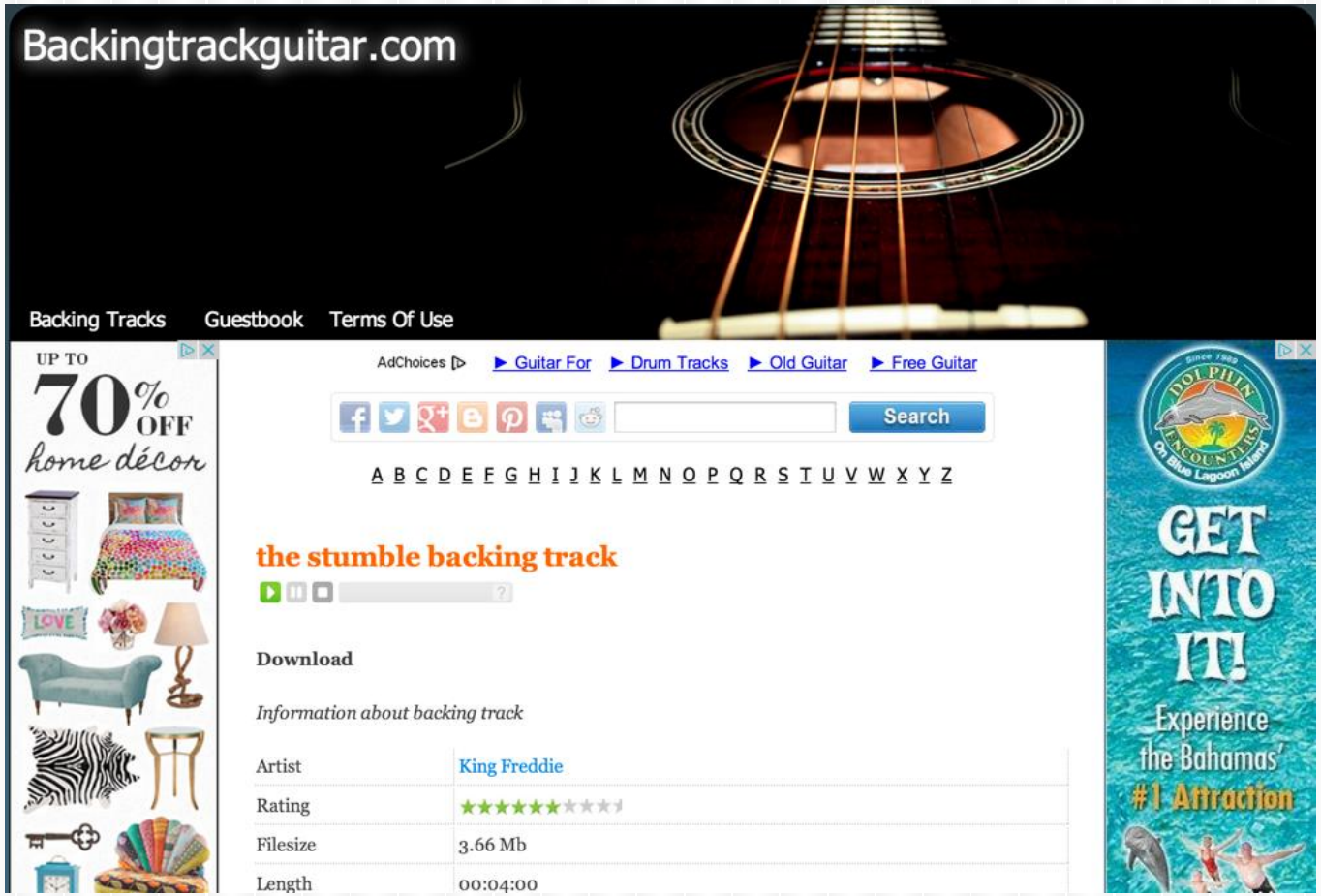
Good WebAnswer for an award-winning song

Tale Sources w. Low Page Rank May Provide Valuable Info



Missing WebAnswer for a not-so-popular song

Tale Sources w. Low Page Rank May Provide Valuable Info



Very precise info on guitar players but low Page Rank

Application I. A New Angle to Evaluate Web Source Quality

Fact 1	✓
Fact 2	✓
Fact 3	✗
Fact 4	✓
Fact 5	✗
Fact 6	✓
Fact 7	✓
Fact 8	✓
Fact 9	✓
Fact 10	✗
...	...
Accu	**0.7**

Application I. A New Angle to Evaluate Web Source Quality

How to decide if a triple is indeed claimed by the source instead of an *extraction error*?

[illegible]	0.8
Triple 5	0.4
Triple 6	0.8
Triple 7	0.9
Triple 8	1.0
Triple 9	0.7
Triple 10	0.2
...	...
Accu	**0.7**

Application I. A New Angle to Evaluate Web Source Quality

	Triple Corr	Extraction Corr
Triple 1	1.0	1.0
Triple 2	0.9	1.0
Triple 3	0.3	1.0
Triple 4	0.8	1.0
Triple 5	0.4	0.9
Triple 6	0.8	0.9
Triple 7	0.9	0.8
Triple 8	1.0	0.2
Triple 9	0.7	0.1
Triple 10	0.2	0.1
...	...	...
Accu	**0.73**	

Sonya Trustworthiness Score

Domain	#Triples	Sonya Score
www.eonline.com	12,871	0.363
perezhilton.com	46,912	0.427
radaronline.com	3,530	0.489
www.zimbio.com	2,464,452	0.530
mediatakeout.com	131	0.531
gawker.com	6,055	0.567
www.popsugar.com	1,805	0.576
www.people.com	16,886	0.585
www.tmz.com	8,149	0.621
www.fishwrapper.com	14	0.622
celebrity.yahoo.com	11,187	0.677
wonderwall.msn.com	2,524	0.684
hollywoodlife.com	4,536	0.689
www.wetpaint.com	19,284	0.730

Many gossip Web sites DO provide quite a lot of wrong factual information

Application II. Provide An X-Ray for Extracted Data

- Goal: Help users analyze errors, changes and abnormalities in data

- Intuitions: cluster errors by features and return clusters with top error rates

Application II. Provide An X-Ray for Extracted Data

- Cluster I.
  - Feature: (besoccor.com, date_of_birth, 1986_02_18)
  - #Triples: 630; Errs: 100%
  - Reason: default value
- Cluster 2.
  - Feature: (ExtractorX, pred: namesakes, obj:the county)
  - #Triples: 4878; Errs: 99.8%
  - E.g., [Salmon P. Chase, namesakes, The County]
  - Contexts: *The county* was named for Salmon P. Chase, former senator and govenor of Ohio
  - Reason: Unresolved coreference

TAKE AWAYS

- A new area--Knowledge Fusion
- We can solve KF problem fairly well by adapting DF methods
- Many interesting future directions for KF!
- Many exciting applications for the prKB!!

Acknowledgement


Evgeniy Gabrilovich (Manager, need to say anything?)


Geremy Heitz (Strongest supporter)


Wilko Horn (Strictest code reviewer)


Kevin Murphy (Intelligent consultant)


Shaohua Sun (Critical representer to the outside world)


Wei Zhang (Fearless explorer of new ideas)

THANK YOU!

Questions?

Data Fusion–A Bayesian Model

[Dong et al., VLDB'09]

Q1. How to compute source accuracy?

- Source Accuracy: A(S)

$$A(S) = \underset{v \in \bar{V}(S)}{Avg}\, P(v)$$

  - $\bar{V}(S)$ - values provided by S
  - *P(v)* - pr of value v being true

Data Fusion–A Bayesian Model

[Dong et al., VLDB'09]

Q2. How to leverage accuracy in voting?

Input:

-Data item D

-Dom(D)={v_0,v_1,…,v_n}

-Observation Φ on D

Output:

Pr(v_i true|Φ) for each i=0,…, n (sum up to 1)

According to the Bayes Rule, we need to know Pr(Φ|v_i true)

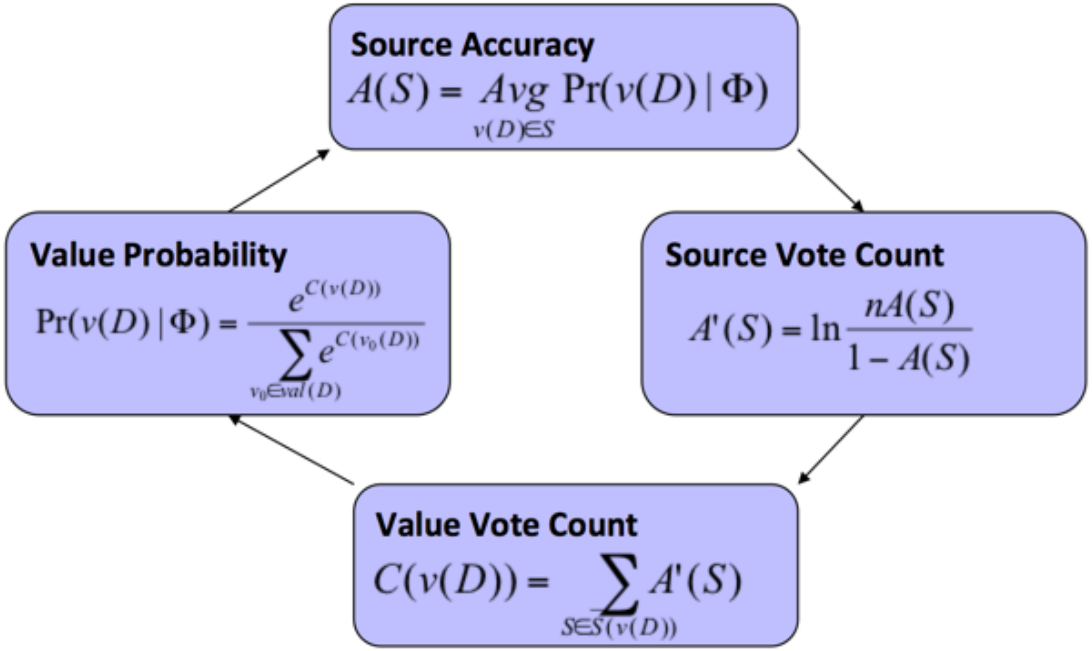
- Assuming independence of sources, we need to know Pr(Φ(S) |v_i true)
- If S provides v_i : Pr(Φ(S) |v_i true) =A(S)
- If S does not provide v_i : Pr(Φ(S) |v_i true) =(1-A(S))/n

Data Fusion–A Bayesian Model

[Dong et al., VLDB'09]

Q3. How to handle interdependence between source accuracy and value pr?

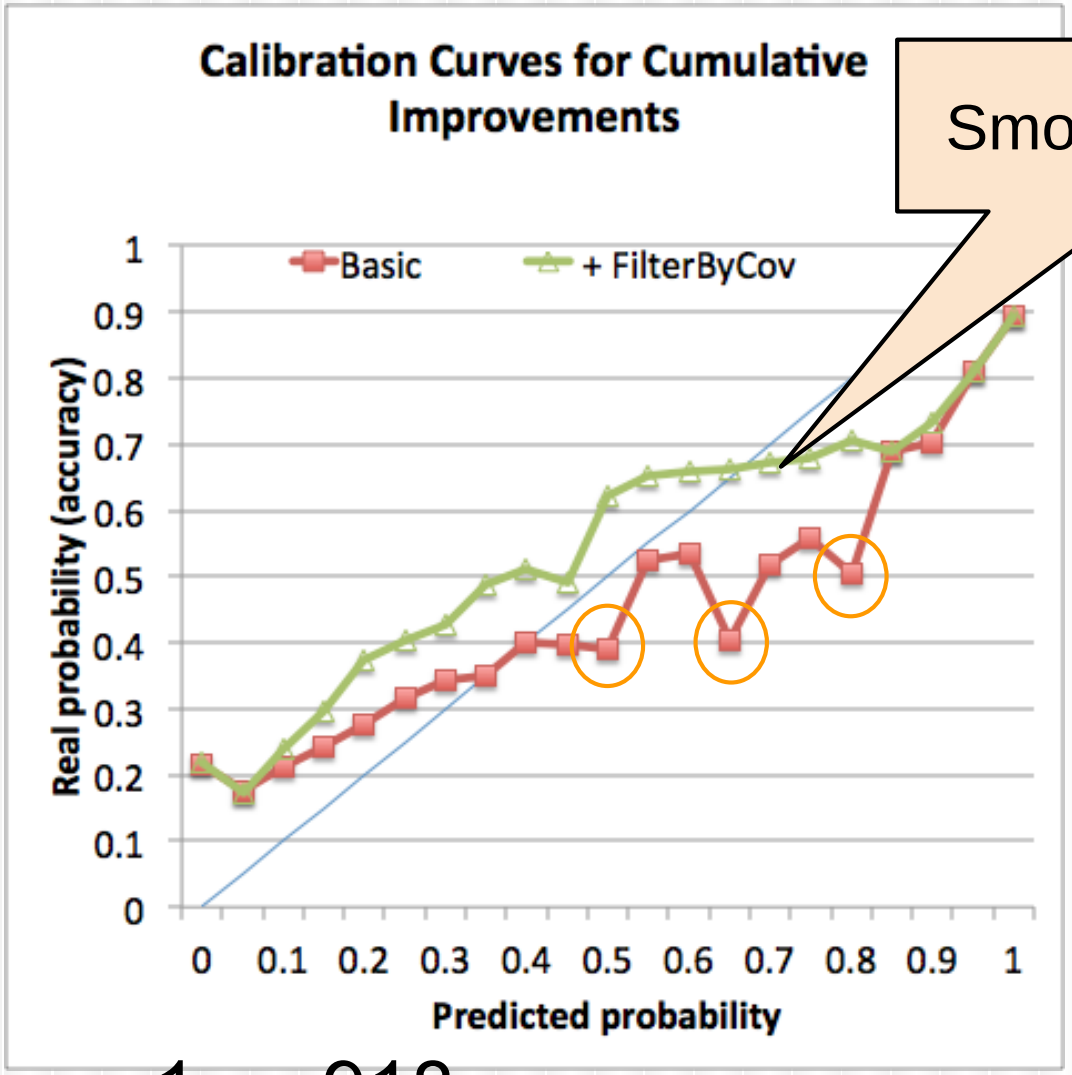
- Continue until source accuracy converges



Knowledge Fusion Solutions

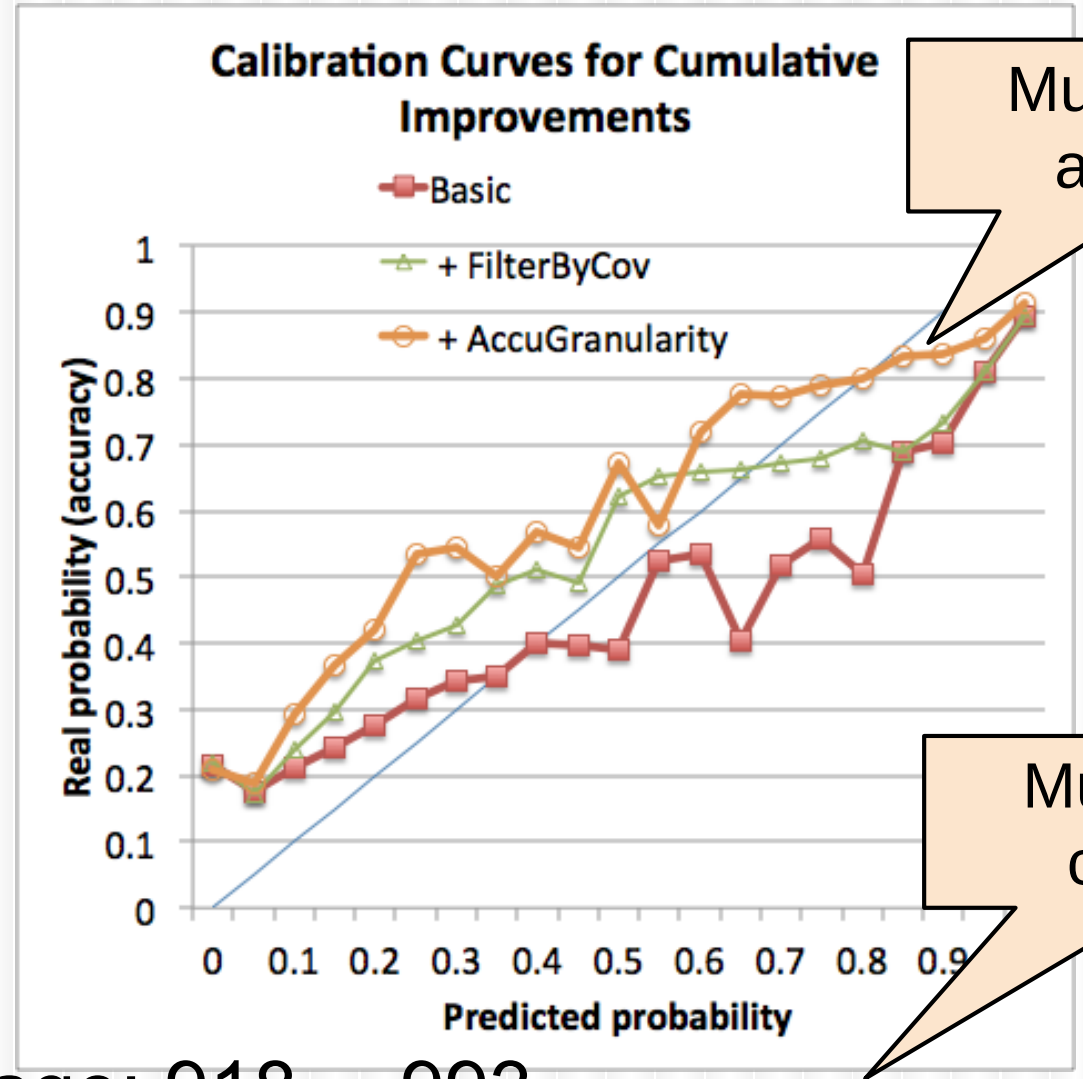
- Treat each (URL, Extractor) as a whole (*provenance)* for accuracy evaluation
- A series of refinements to improve probability calibration
- MapReduce Based Framework
  - Terminate in 5 rounds
  - Sample for *too big* data items or provenances

Refinement I. Ignore Low-Coverage Provenances



Coverage: 1→ .918

Refinement II. Granularity (URL->Site, Extractor->Pattern, Predicate)

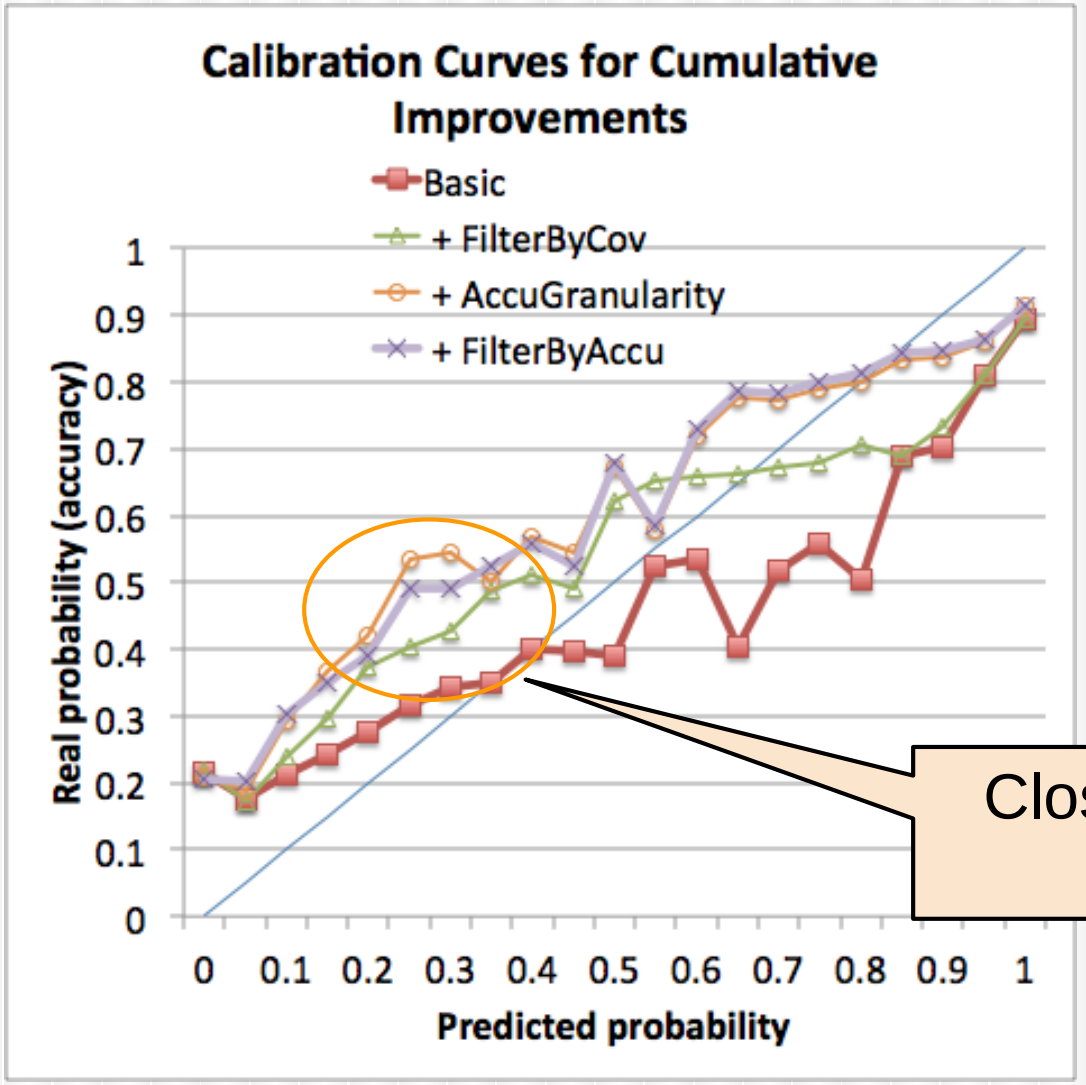


Much higher accuracy

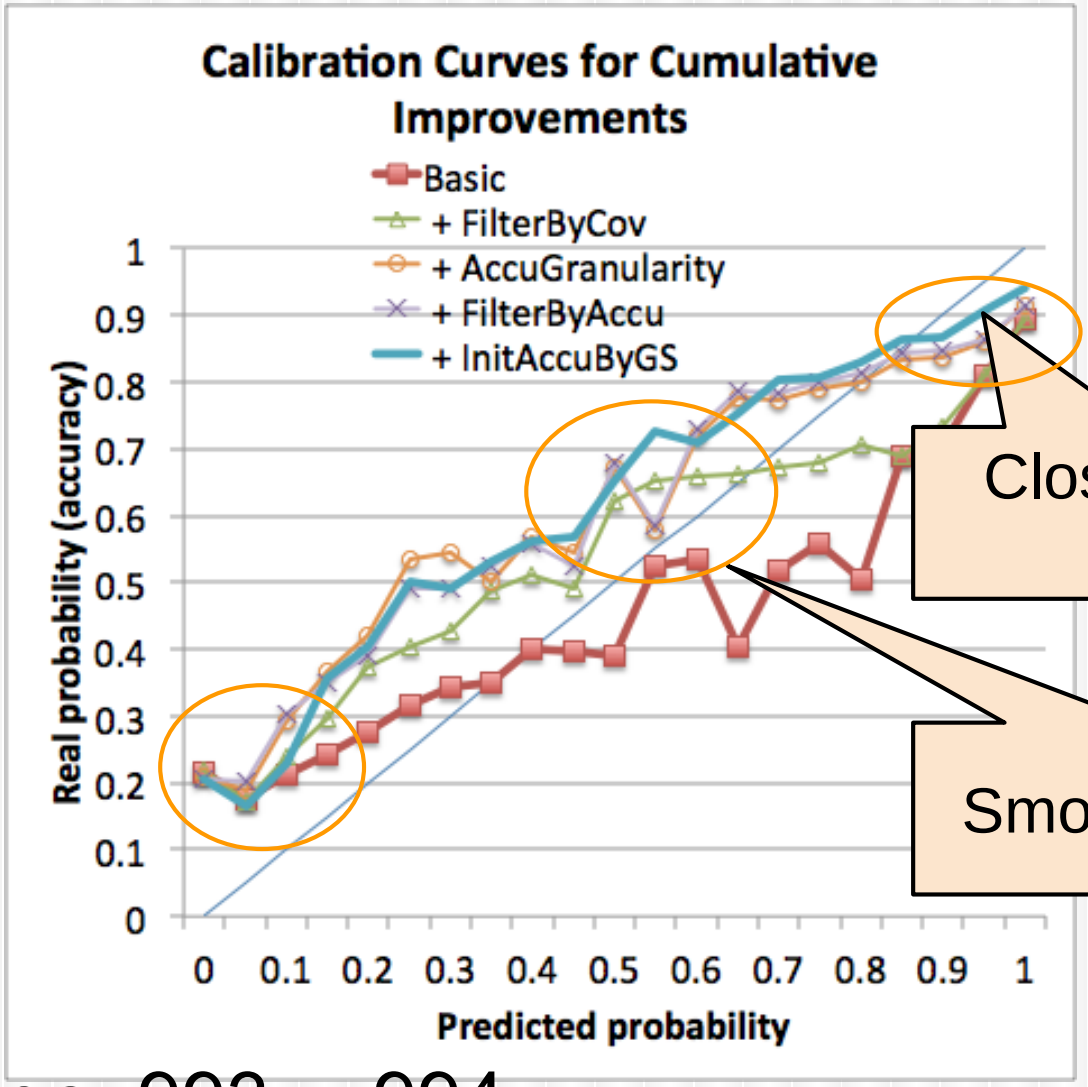
Much higher coverage

Coverage:.918→.993

Refinement III. Ignore Low-Accuracy Provenances



Refinement IV. Initiate Provenance Accuracy by FB

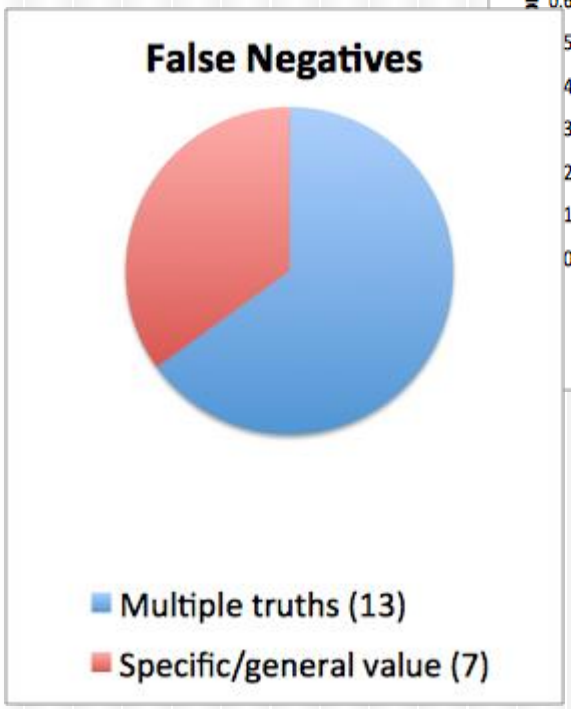


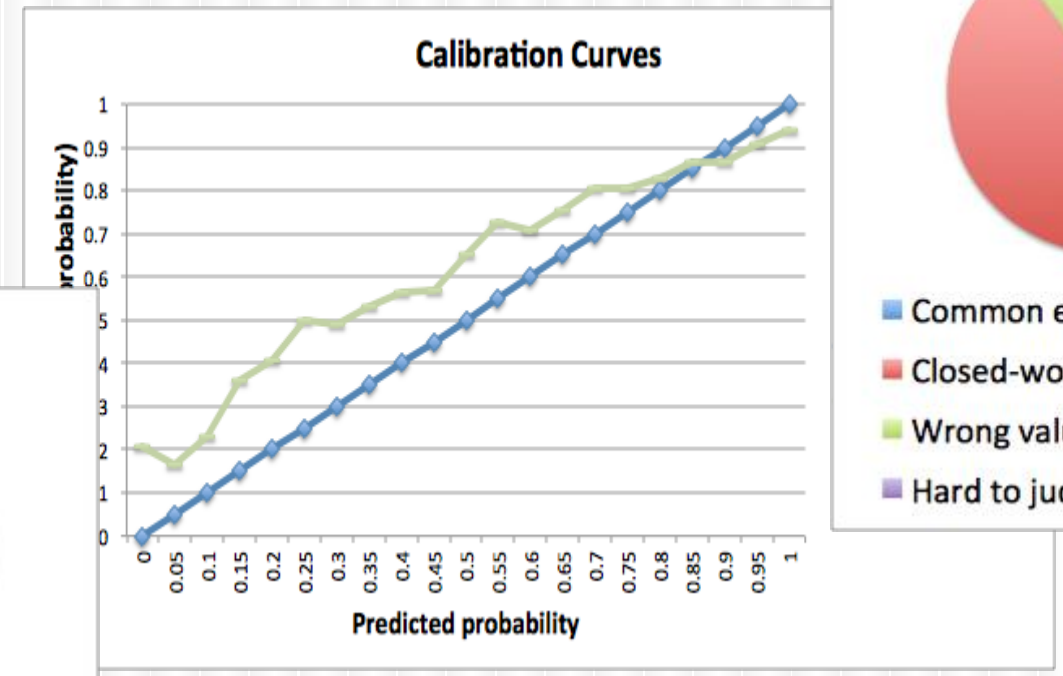
Closer to ideal curve

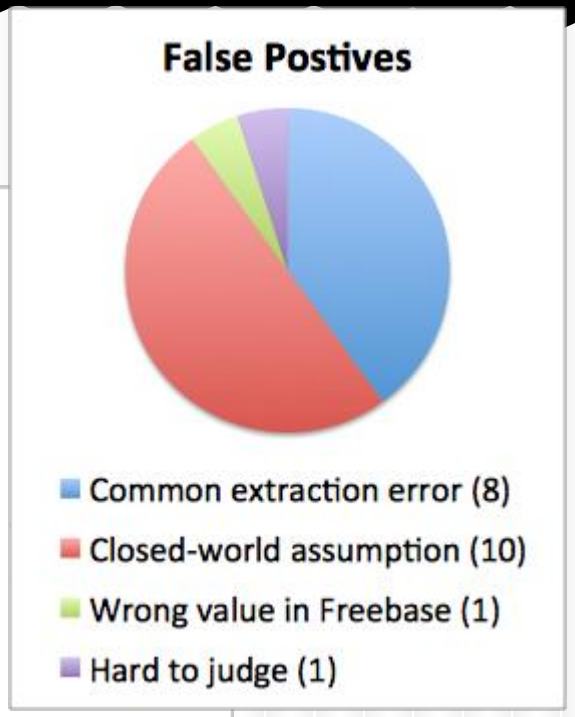
Smoother curve

Coverage:.993→.994

Analysis of Errors







Future Directions!!!

Result I. Extraction and Triple Correctness Example 1. (Obama, nationality, ?)

(Obama, nationality, Bolivarianism) (many many such subjects)

- 3 extractions (Pr_provide=0.01)http://mathaba.net/news/?x=631316http://www.laht.com/article.asp?ArticleId=329187&CategoryId=10717http://www.iamericas.org/en/about-ioa/presidents-corner
- Pr_true=0

Result I. Extraction and Triple Correctness Example 1. (Obama, nationality, ?)

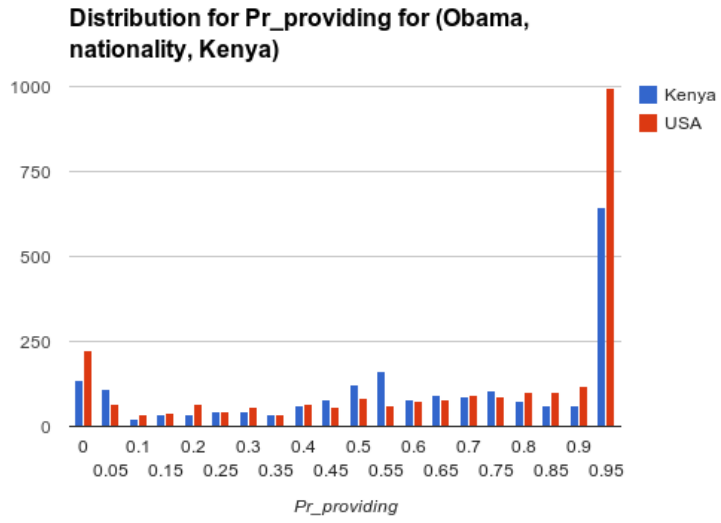
(Obama, nationality, Kenya)

- 2087 extractions:
  - Example of a correct extraction (Pr_provide=0.792): http://beforeitsnews.com/obama-birthplace-controversy/2013/04/alabama-supreme-court-chief-justice-roy-moore-to-preside-over-obama-eligibility-case-2458624.html
  - Example of a wrong extraction (Pr_provide=0.130): http://www.monitor.co.ug/News/National/US+will+respect+winner+of+Kenya+election++Obama+says/-/688334/1685814/-/ksxagx/-/index.html
- Pr_true=0 (not enough support)

Result I. Extraction and Triple Correctness Example 1. (Obama, nationality, ?)

(Obama, nationality, USA)

- 2481 extractions:
  - Example of a correct extraction (Pr_provide=0.999): http://www.dogonews.com/2009/10/9/a-nobel-prize-for-our-awesome-president
  - Example of a wrong extraction (Pr_provide=0.261): http://blogs.telegraph.co.uk/news/timstanley/100169248/barack-obamas-life-story-co ort-it-as-truth/
- Pr_true=1



Sonya Trustworthiness Score

- Example for (URL, Predicate)

  URL: https://ibirthdayworld.blogspot.com/2010/03/celebrity-birthdays-on-march-22.html

  Predicate: date_of_birth

  - #Facts = 42; Trustworthiness = 0.95

Source: http://ibirthdayworld.blogspot.com/2010/03/celebrity-birthdays-on-march-22.html e.g., http://en.wikipedia.org/wiki/World_Chess_Championship_2013 or en.wikipedia.org

Pred: /people/person/date_of_birth e.g., /people/person/place_of_birth

Max results to display: 100

Support threshold: 0.0

Query Sonya

Source	Pred	Num_of_Triples	Accuracy
http://ibirthdayworld.blogspot.com/2010/03/celebrity-birthdays-on-march-22.html	/people/person/date_of_birth	42	0.953

Sonya Trustworthiness Score

Celebrity Birthdays On March 22

<-Marcel Marceau

Below are 124 famous people born on March 22.

Browse Gift Ideas - Browse Ecards

The names in brackets below are duplicate entries.

Aaron North was born on March 22, 1979. American guitarist.

Amy Stud was born on March 22, 1986. English singer-songwriter and musician.

Andreas Johnson was born on March 22, 1970. Swedish pop and rock singer-songwriter and musician.

Andrew Lloyd Webber was born on March 22, 1948. British composer of musicals.

Angelo Badalamenti was born on March 22, 1937. American composer.

Anja Kling was born on March 22, 1970. German actress.

Annabelle Apsion was born on March 22, 1963. English actress.

Anne Hyde was born on March 22, 1638. Wife of James II of England.

Anthony van Dyck was born on March 1599. Flemish Baroque artist.

Armin Hary was born on March 22, 1937. German athlete.

Avraham Fried was born on March 22, 1959. American singer-songwriter and musical entertainer.

Sonya Trustworthiness Score

- Example for (URL, Predicate)

  URL: https://ibirthdayworld.blogspot.com/2010/03/celebrity-birthdays-on-march-22.html

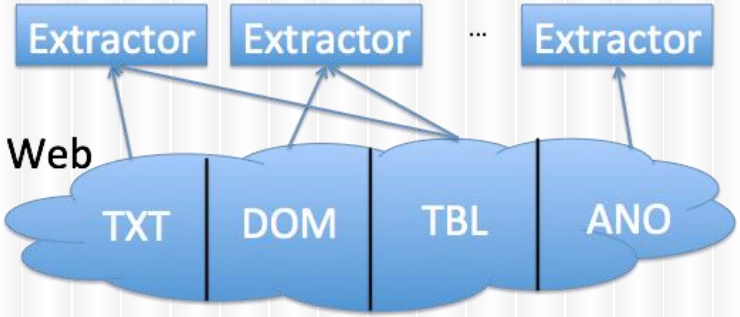
  Predicate: date_of_birth

  - #Facts = 42; Trustworthiness = 0.95

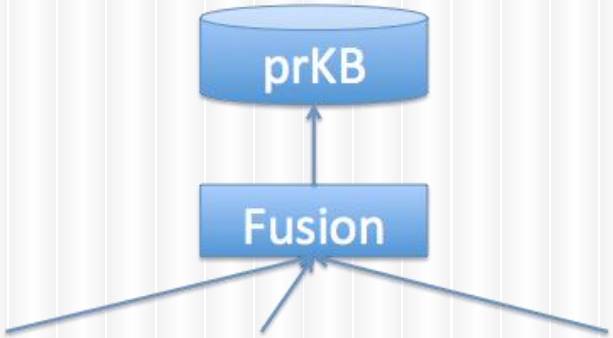
  - Mistake: Anne Hyde (the URL says: 3/22/1638; Wiki/KG says: 3/12/1637)

Outline

Knowledge extraction



Knowledge fusion

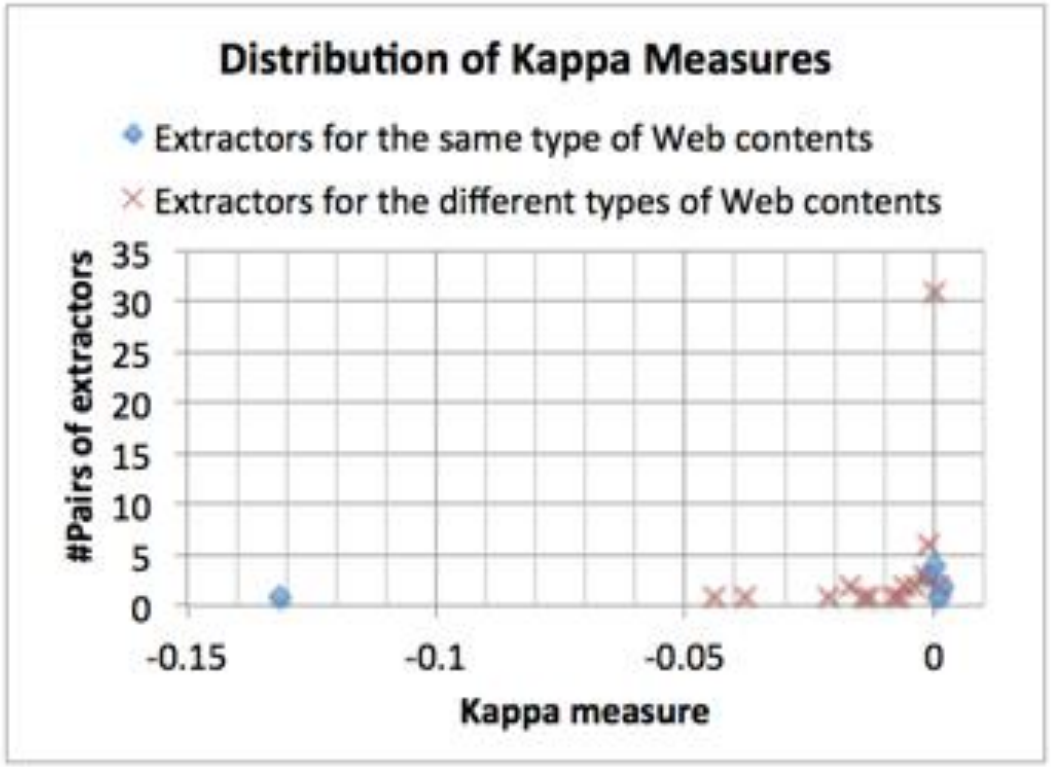


Interesting applications

Future directions

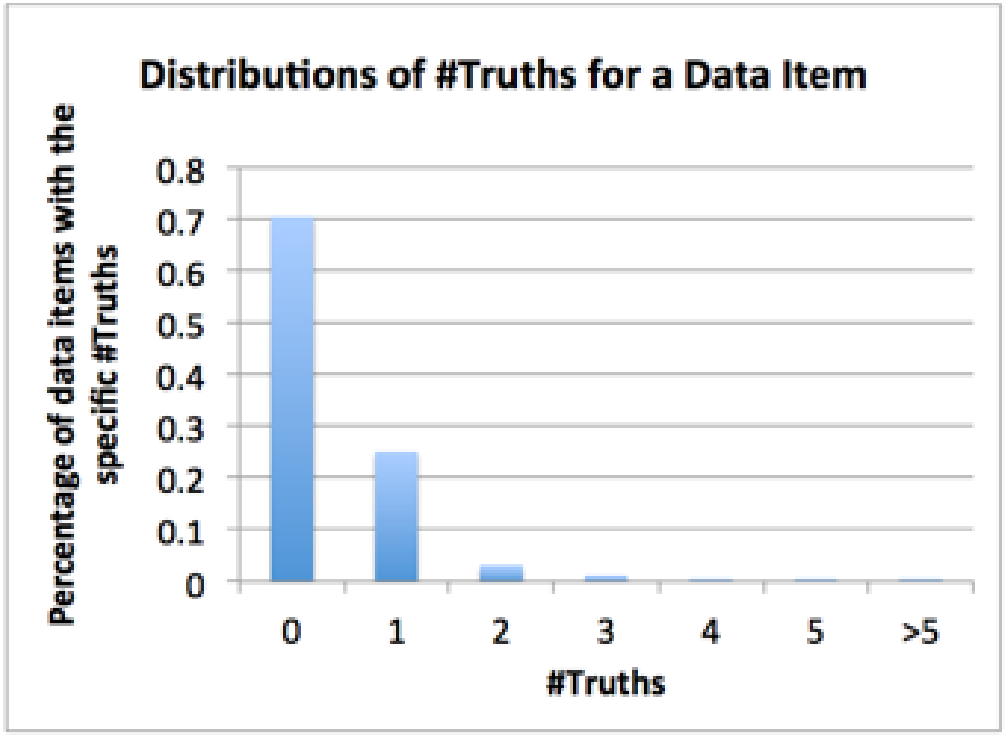
Future Directions: Remove the Assumptions One by One

Assumption I. Independence between pairs of provenances (i.e., (URL, extractor))



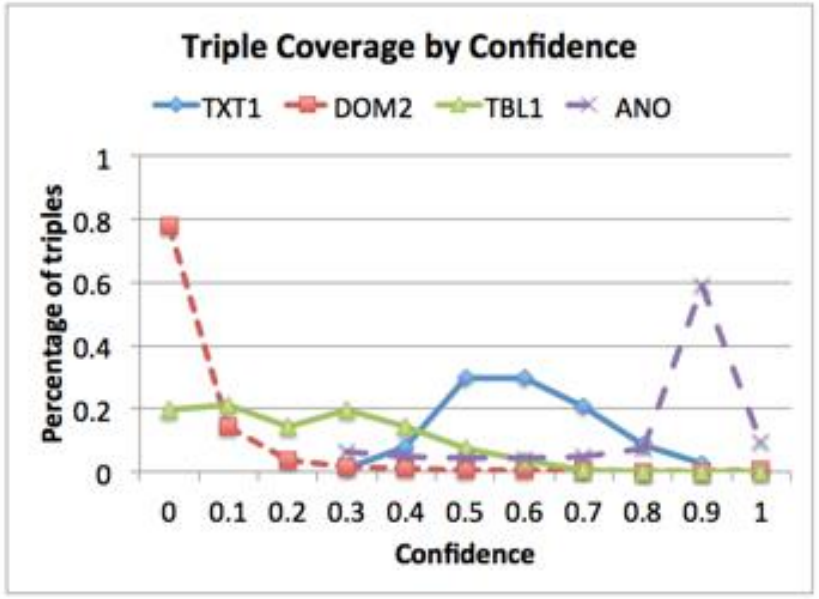
Future Directions: Remove the Assumptions One by One

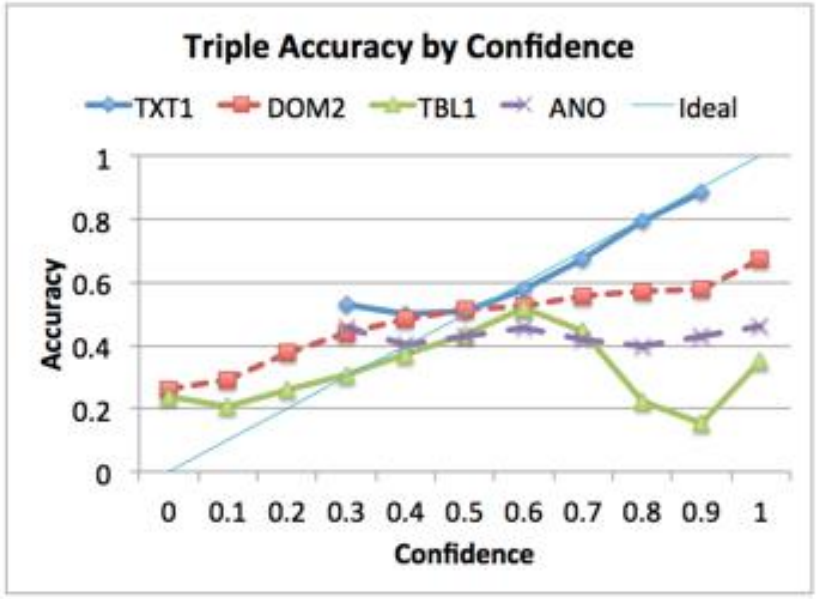
Assumption II. Single true object for each (sub, pred)



Future Directions: Remove the Assumptions One by One

Assumption III. Extractions are deterministic





Future Directions: Remove the Assumptions One by One

Assumption IV. Values (objects) are categorical

Assumption V. We have enough data to judge accuracy of each source

Assumption VI. Local closed-world assumption in evaluation

Future Directions: Remove the Assumptions One by One

Assumption VII. Global closed-world assumption--consider only existing entities and predicates in FB

WE NEED SOMETHING NEW!!!