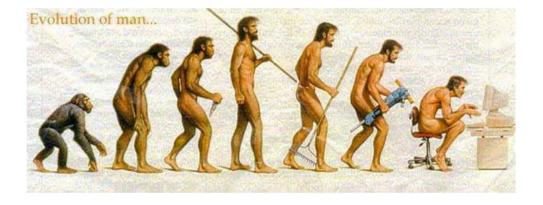
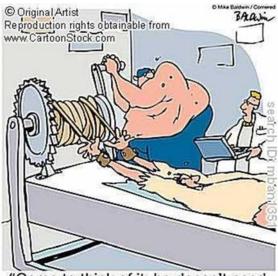
# IN SEARCH OF TRUTH (ON THE DEEP WEB)

Divesh Srivastava AT&T Labs-Research

#### The Web is Great



#### A Lot of Information on the Web



"Come to think of it, he doesn't need to give us the information. I can just look it up on the Internet."

#### Information Can Be Erroneous



The story, marked "Hold for release – Do not use", was sent in error to the news service's thousands of corporate clients.

#### Information Can Be Erroneous

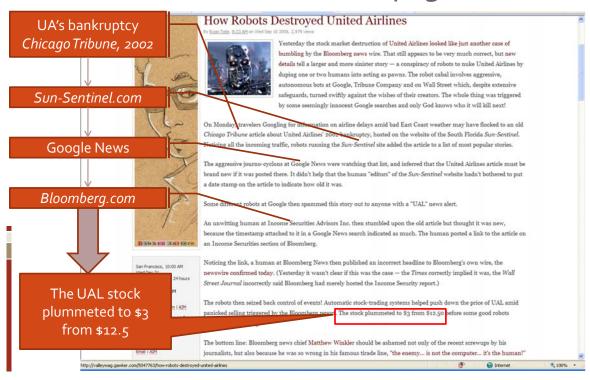


Maurice Jarre (1924-2009) French Conductor and Composer

"One could say my life itself has been one long soundtrack. Music was my life, music brought me to life, and music is how I will be remembered long after I leave this life. When I die there will be a final waltz playing in my head and that only I can hear."



#### False Information Can Be Propagated



# IS DEEP-WEB DATA CONSISTENT & RELIABLE?

## Study on Two Domains

	#Sources	Period	#Objects	#Local- attrs	#Global- attrs	Consider ed items
Stock	55	7/2011	1000*20	333	153	16000*20
Flight	38	12/2011	1200*31	43	15	7200*31

- ☐Belief of clean data
- ☐Poor data quality can have big impact

#### Study on Two Domains

	#Sources	Period	#Objects	#Local- attrs	#Global- attrs	Consider ed items
Stock	55	7/2011	1000*20	333	153	16000*20

#### **□**Stock

- Search "stock price quotes"
- □ Sources: 200 (search results)  $\rightarrow$  89 (deep web)  $\rightarrow$  76 (GET method)  $\rightarrow$  55 (no JavaScript)
- □ 1000 "Objects": a stock with a particular symbol on a particular day
  - ☐ 30 from Dow Jones Index
  - □ 100 from NASDAQ100 (3 overlaps)
  - 873 from Russell 3000
- □ Attributes: 333 (local) → 153 (global) → 21 (provided by > 1/3 sources) → 16 (no change after market close)

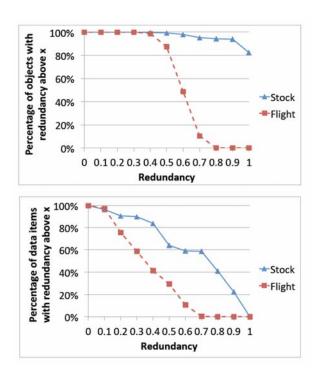
#### Study on Two Domains

	#Sources	Period	#Objects	#Local- attrs		Consider ed items
Flight	38	12/2011	1200*31	43	15	7200*31

#### **□**Flight

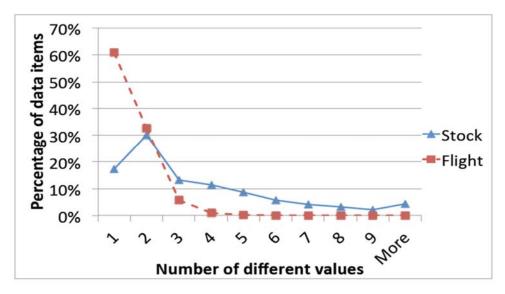
- ☐ Search "flight status"
- ☐ Sources: 38
  - ☐ 3 airline websites (AA, UA, Continental)
  - 8 airport websites (SFO, DEN, etc.)
  - □ 27 third-party websites (Orbitz, Travelocity, etc.)
- 1200 "Objects": a flight with a particular flight number on a particular day from a particular departure city
  - ☐ Departing or arriving at the hub airports of AA/UA/Continental
- $\blacksquare$  Attributes: 43 (local)  $\rightarrow$  15 (global)  $\rightarrow$  6 (provided by > 1/3 sources)
  - □ scheduled dept/arr time, actual dept/arr time, dept/arr gate

#### ■ Q1. Is There a Lot of Redundant Data? ✓



#### Q2. Is the Data Consistent?

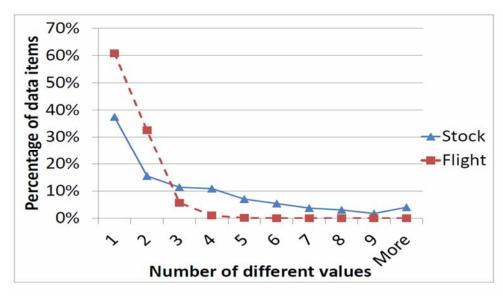




□Tolerance to 1% value difference

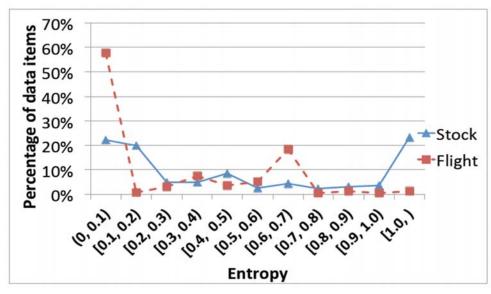
#### Q2. Is the Data Consistent?





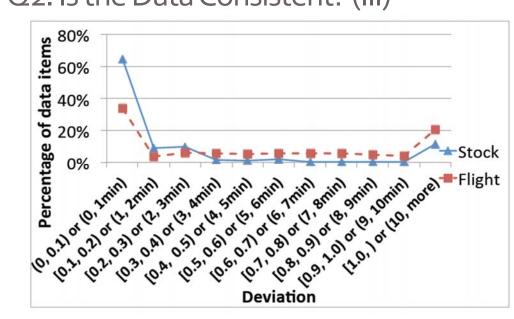
- ☐ Tolerance to 1% value difference
- □Inconsistency on 50% items after removing *StockSmart*

#### Q2. Is the Data Consistent? (II)



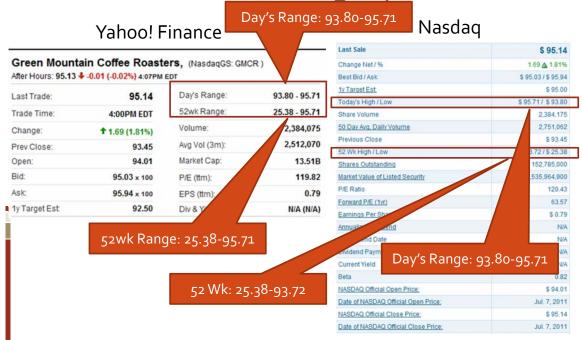
- □Entropy measures distribution of different values
- □Quite low entropy: one value provided more often than others

#### Q2. Is the Data Consistent? (III)

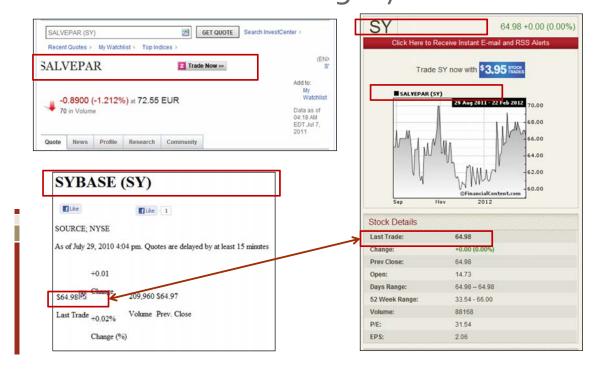


- □ Deviation measures difference of numerical values
- □ High deviation: 13.4 for Stock, 13.1 min for Flight

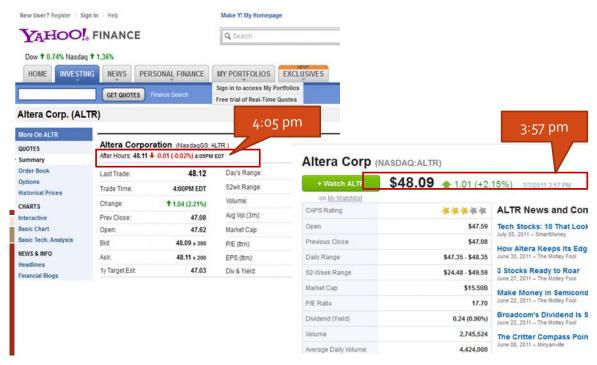




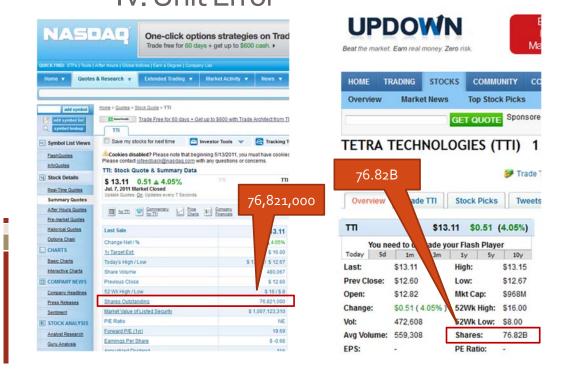
# Why Such Inconsistency? — II. Instance Ambiguity



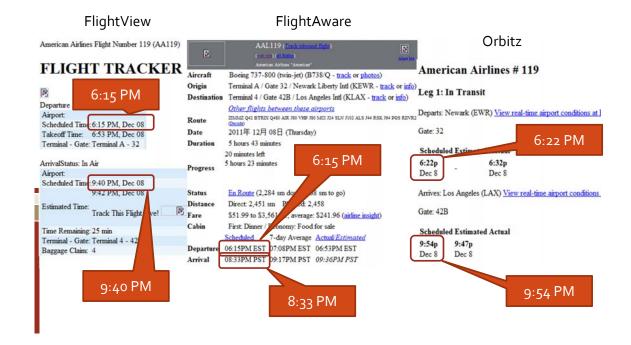
# Why Such Inconsistency? — III. Out-of-Date Data



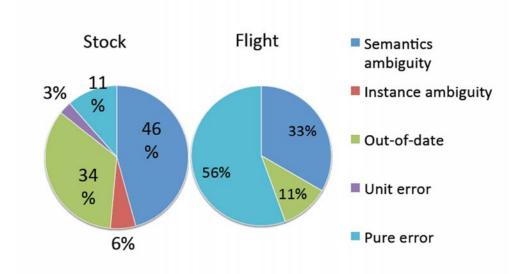
# Why Such Inconsistency? — IV. Unit Error



# Why Such Inconsistency? —V. Pure Error

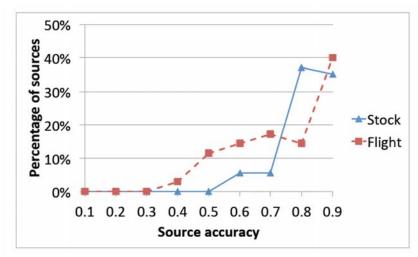


#### Why Such Inconsistency?



□Random sample of 20 data items and 5 items with the largest # of values in each domain

### ■ Q3. Do Sources Have High Accuracy? 🗶



- ■Not high on average: .86 for Stock and .8 for Flight
- □Gold standard
  - □ Stock: vote on data from Google Finance, Yahoo! Finance, MSN Money, NASDAQ, Bloomberg
  - ☐ Flight: from airline websites

### ■ Q3-2. What About Authoritative Sources?

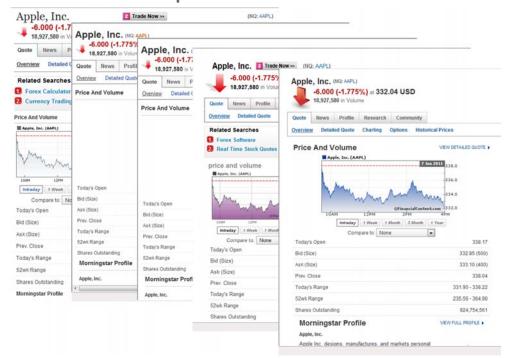


	Source	Accuracy	Coverage
	Google Finance	.94	.82
	Yahoo! Finance	.93	.81
Stock	NASDAQ	.92	.84
	MSN Money	.91	.89
	Bloomberg	.83	.81
	Orbitz	.98	.87
Flight	Travelocity	.95	.71
	Airport average	.94	.03

- ☐ Reasonable but not so high accuracy
- ☐ Medium coverage

# Q4. Is There Copying or Data Sharing Between Deep-Web Sources?



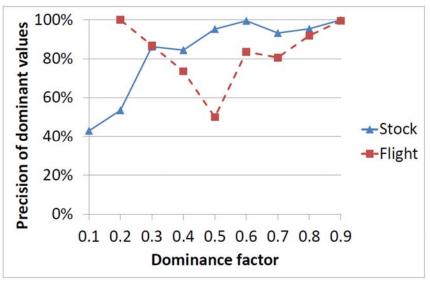


# Q4-2. Is Copying or Data Sharing Mainly on Accurate Data?

	Remarks	Size	Schema sim	Object sim	Value sim	Avg accu
Ctaals	Depen claimed	11	1	.99	.99	.92
Stock	Depen claimed	2	1	1	.99	.75
	Depen claimed	5	0.80	1	1	.71
	Query redirection	4	0.83	1	1	.53
Flight	Dependence claimed	3	1	1	1	.92
	Embedded interface	2	1	1	1	.93
	Embedded interface	2	1	1	1	.61



### Basic Solution: Voting



- □Only 70% correct values are provided by over half of the sources
  - □ .908 voting precision for Stock; i.e., wrong values for 1500 data items
  - □ .864 voting precision for Flight; i.e., wrong values for 1000 data items

#### Improvement I. Using Source Accuracy

	S1	S <sub>2</sub>	S <sub>3</sub>
Flight 1	7:02PM	6:40PM	7:02PM
Flight 2	5:43PM	5:43PM	5:50PM
Flight 3	9:20AM	9:20AM	9:20AM
Flight 4	9:40PM	9:52PM	8:33PM
Flight 5	6:15PM	6:15PM	6:22PM

#### Improvement I. Using Source Accuracy

		S1	S <sub>2</sub>	S <sub>3</sub>
	Flight	7:02PM	6:40PM	7:02PM
	Flight 2	5:43PM	5:43PM	5:50PM
I link was a second	Flight 3	9:20AM	9:20AM	9:20AM
Higher accuracy; More trustable	Flight 4	9:40PM	9:52PM	8:33PM
	Flight 5	6:15PM	6:15PM	6:22PM

Naïve voting obtains an accuracy of 80%

#### Improvement I. Using Source Accuracy

		S1	S <sub>2</sub>	S <sub>3</sub>
	Flight	7:02PM	6:40PM	7:02PM
	Flight 2	5:43PM	5:43PM	5:50PM
	Flight 3	9:20AM	9:20AM	9:20AM
Higher accuracy; More trustable	Flight 4	9:40PM	9:52PM	8:33PM
more trostable	Flight 5	6:15PM	6:15PM	6:22PM

#### Challenges:

- 1. How to decide source accuracy?
- 2. How to leverage accuracy in voting?

Considering accuracy obtains an accuracy of 100%

```
Source Accuracy: Bayesian Analysis
```

```
□Goal: Pr(v_i(D) \text{ true } | \Phi_D(S)), for each D, v_i(D)
```

- □According to Bayes Rule, we need to know
  - $\square$  Pr( $\Phi_D(S) \mid v_i(D) \text{ true}$ ), Pr( $v_i(D) \text{ true}$ ), for each  $v_i(D)$
- $\square Pr(\Phi_D(S) \mid v_i(D) \text{ true})$  can be computed as:

$$\square \textstyle \prod_{S \;\in\; S(v_i(D))} (A(S)) \; * \; \textstyle \prod_{S \;\in\; S \setminus S(v_i(D))} ((1 \;\text{-}\; A(S))/n)$$

$$\square Pr(v_i(D) \text{ true } | \Phi_D(S)) = e^{Conf(v_i(D))} / (\sum_{v_o(D)} e^{Conf(v_o(D))})$$

$$\square Conf(v_i(D)) = \sum_{S \in S(v_i(D))} ln(nA(S)/(1 - A(S)))$$

$$\square A(S) = Avg_{v_i(D) \in S} Pr(v_i(D) true \mid \Phi_D(S))$$

## Computing Source Accuracy

☐ Source accuracy A(S)

$$A(S) = Avg_{v_i(D) \in S} Pr(v_i(D) true | \Phi)$$

- $\square v_i(D) \in S : S$  provides value  $v_i$  on data item D
- $\Box \Phi$ : observations on all data items by sources **S**
- $\square Pr(v_i(D) \text{ true } | \Phi)$ : probability of  $v_i(D)$  being true

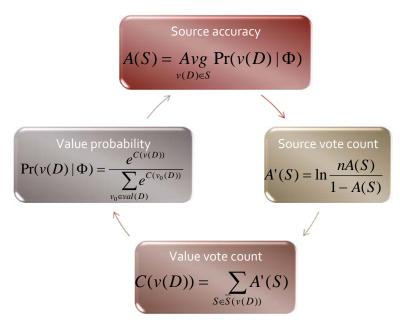
How to compute  $Pr(v_i(D) \text{ true } | \Phi)$ ?

#### Using Source Accuracy in Data Fusion

- □Input: data item D, val(D) =  $\{v_0, v_1, ..., v_n\}$ , Φ
- $\square$  Output: Pr( $v_i(D)$  true  $| \Phi)$ , for i=0,..., n (sum=1)
- $\square$  Based on Bayes Rule, need Pr( $\Phi \mid v_i(D)$  true)
- □Under independence, need  $Pr(\Phi_D(S)|v_i(D) \text{ true})$ 
  - □If S provides  $v_i$ : Pr( $\Phi_D(S) | v_i(D)$  true) = A(S)
  - □If S does not :  $Pr(\Phi_D(S) | v_i(D) \text{ true}) = (1-A(S))/n$

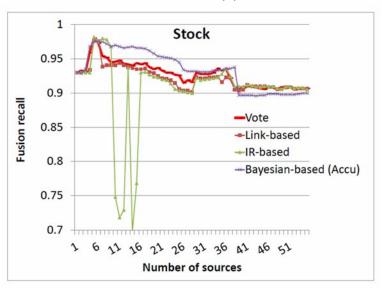
Challenge: How to handle inter-dependence between source accuracy and value probability?

#### Data Fusion Using Source Accuracy



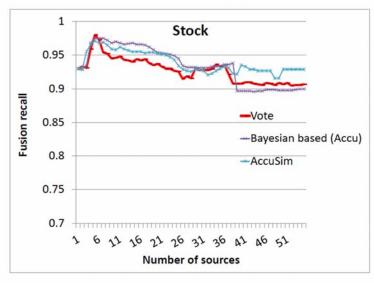
☐ Continue until source accuracy converges

#### Results on Stock Data (I)



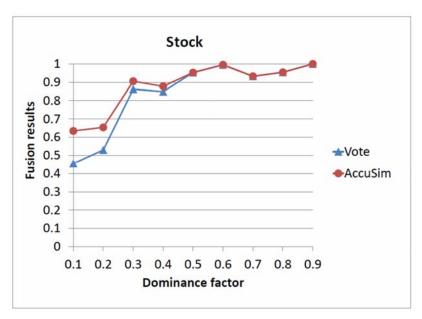
- □Sources ordered by recall (coverage \* accuracy)
- □Among various methods, the Bayesian-based method (Accu) performs best at the beginning, but in the end obtains a final precision (=recall) of .900, worse than Vote (.908)

#### Results on Stock Data (II)

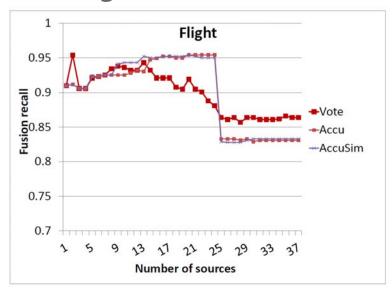


- □AccuSim obtains a final precision of .929, higher than Vote and any other method (around .908)
  - ☐ This translates to 350 more correct values

#### Results on Stock Data (III)



### Results on Flight Data



 $\square$ Accu/AccuSim obtain final precision of .831/.833, both lower than Vote (.857)

□WHY??? What is that magic source?

# Copying on Erroneous Data

	Remarks	Size	Schema sim	Object sim	Value sim	Avg accu
Stock	Depen claimed	11	1	.99	.99	.92
Stock	Depen claimed	2	1	1	.99	.75
	Depen claimed	5	0.80	1	1	.71
	Query redirection	4	0.83	1	1	.53
Flight	Dependence claimed	3	1	1	1	.92
	Embedded interface	2	1	1	1	.93
	Embedded interface	2	1	1	1	.61

## Copying on Erroneous Data

	S1	S <sub>2</sub>	S <sub>3</sub>	S <sub>4</sub>	S <sub>5</sub>
Flight 1	7:02PM	6:40PM	7:02PM	7:02PM	8:02PM
Flight 2	5:43PM	5:43PM	5:50PM	5:50PM	5:50PM
Flight 3	9:20AM	9:20AM	9:20AM	9:20AM	9:20AM
Flight 4	9:40PM	9:52PM	8:33PM	8:33PM	8:33PM
Flight 5	6:15PM	6:15PM	6:22PM	6:22PM	6:22PM

A lie told often enough becomes the truth.
— Vladimir Lenin



#### Copying on Erroneous Data

	S1	S <sub>2</sub>	S <sub>3</sub>	<b>S</b> 4	S <sub>5</sub>
Flight 1	7:02PM	6:40PM	7:02PM	7:02PM	8:02PM
Flight 2	5:43PM	5:43PM	5:50PM	5. PM	5:50PM
Flight 3	9:20AM	9:20AM	9:20AM	9:20) 1	9:20AM
Flight 4	9:40PM	9:52PM	8:33PM	8:33PM	8:33PM
Flight 5	6:15PM	6:15PM	6:22PM	6:22PM	PM

A lie told often enough becomes the truth.

— Vladimir Lenin



Considering source accuracy can be worse when there is copying

### I Improvement II. Ignoring Copied Data

	S1	S <sub>2</sub>	S <sub>3</sub>	S4	, 9	55
Flight 1	7:02PM	6:40PM	7:02PM	7:02 F	PM 8:0:	PM
Flight 2	5:43PM	5:43PM	5:50PM	5:50F	PM 5:50	РМ
Flight 3	9:20AM	9:20AM	9:20AM	9:20	AM 9:20	AM
Flight 4	9:40PM	9:52PM	8:33PM	8:33F	PM 8:33	3PM
Flight 5	6:15PM	6:15PM	6:22PM	6:22	PM 6:22	2PM
						1

#### Challenges:

- 1. How to detect copying?
- 2. How to leverage copying in voting?

It is important to detect copying and ignore copied values in fusion

# Copying?

#### Are Source 1 and Source 2 dependent? Not necessarily

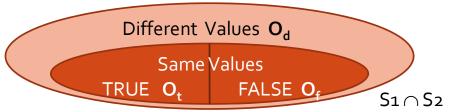
Source 1 on USA Presidents:	Source 2 on USA Presidents:	
1 <sup>st</sup> : George Washington	1st : George Washington	<b>√</b>
2 <sup>nd</sup> : John Adams	2 <sup>nd</sup> : John Adams	<b>√</b>
3 <sup>rd</sup> : Thomas Jefferson	3 <sup>rd</sup> : Thomas Jefferson	<b>√</b>
4 <sup>th</sup> : James Madison	4 <sup>th</sup> : James Madison	✓
41 <sup>st</sup> : George H.W. Bush	41 <sup>st</sup> : George H.W. Bush	✓
42 <sup>nd</sup> : William J. Clinton	42 <sup>nd</sup> : William J. Clinton	✓
43 <sup>rd</sup> : George W. Bush	43 <sup>rd</sup> : George W. Bush	<b>√</b>
44 <sup>th</sup> : Barack Obama	44 <sup>th</sup> : Barack Obama	<b>√</b>

# ■ Copying? — Common Errors

#### Are Source 1 and Source 2 dependent? Very likely

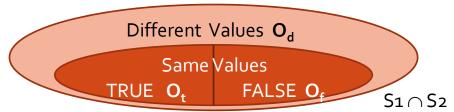
Source 1 on USA Presidents:	Source 2 on USA Presidents:	
1 <sup>st</sup> : George Washington	1 <sup>st</sup> : George Washington	<b>√</b>
2 <sup>nd</sup> : Benjamin Franklin	2 <sup>nd</sup> : Benjamin Franklin	×
3 <sup>rd</sup> : John F. Kennedy	3 <sup>rd</sup> : John F. Kennedy	×
4 <sup>th</sup> : Abraham Lincoln	4 <sup>th</sup> : Abraham Lincoln	×
		_
41 <sup>st</sup> : George W. Bush	41 <sup>st</sup> : George W. Bush	×
42 <sup>nd</sup> : Hillary Clinton	42 <sup>nd</sup> : Hillary Clinton	×
43 <sup>rd</sup> : Dick Cheney	43 <sup>rd</sup> : Dick Cheney	×
44 <sup>th</sup> : Barack Obama	44 <sup>th</sup> : John McCain	

Copying Detection: Bayesian Analysis



- □Goal:  $Pr(S_1 \perp S_2 \mid \Phi)$ ,  $Pr(S_1 \sim S_2 \mid \Phi)$  (sum = 1)
- □According to Bayes Rule, we need to know □Pr(Φ|S1⊥S2), Pr(Φ|S1~S2)
  - □ Key: compute  $Pr(\Phi_D|S_1\bot S_2)$ ,  $Pr(\Phi_D|S_1\sim S_2)$ 
    - $\square$  For each  $D \in S_1 \cap S_2$

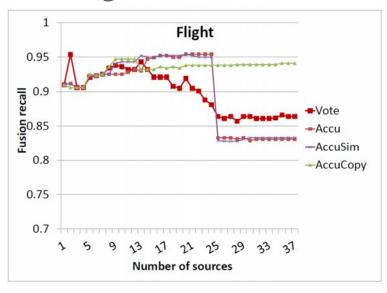
Copying Detection: Bayesian Analysis



Pr	Independence	Copying
O <sub>t</sub>	$A^2$	$A \bullet c + A^2(1-c)$
O <sub>f</sub>	$\frac{(1-A)^2}{n}$	$(1-A) \bullet c + \frac{(1-A)^2}{n} (1-c)$
O <sub>d</sub>	$P_d = 1 - A^2 - \frac{(1 - A)^2}{n}$	$P_d(1-c)$

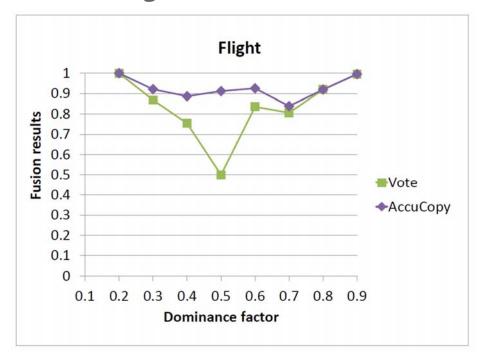
A-source accuracy; n-#wrong-values; c-copy rate

### Results on Flight Data



- □AccuCopy obtains a final precision of .943, much higher than Vote (.864)
  - ☐ This translates to 570 more correct values

### Results on Flight Data (II)

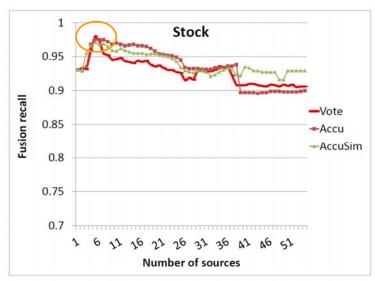


#### Take-Aways

- □Deep Web data is not fully trustable
  - □Deep Web sources have different accuracies
  - □Copying is common
- ☐ Truth finding on the Deep Web can leverage
  - □ source accuracy
  - copying relationships, and
  - □value similarity

# I Important Direction: Source Selection

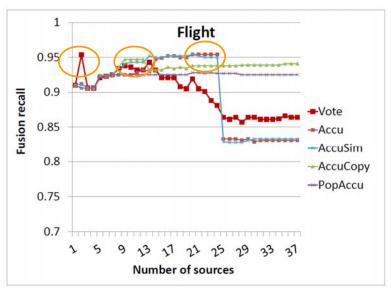




- □Peaks happen before integrating all sources
- ☐ How to find the best set of sources while balancing quality gain and integration cost?

## Important Direction: Source Selection





- □Peaks happen before integrating all sources
- ☐ How to find the best set of sources while balancing quality gain and integration cost?

#### Acknowledgements

- □ Joint work with:
  - □Xin Luna Dong, Yifan Hu, Ken Lyons (AT&T)
  - □Laure Berti-Equille (IRD)
  - □Xian Li, Weiyi Meng (SUNY-Binghamton)
- ☐ Selected research papers:
  - ☐ Truth Finding on the Deep Web: Is the Problem Solved? PVLDB 2013?
  - □Global detection of complex copying relationships between sources. PVLDB 2010.
  - Integrating conflicting data: the role of source dependence. PVLDB 2009.

