

# Entity Reconstruction: Putting the pieces of the puzzle back together

Georgia Koutrika - HP Labs, Palo Alto, USA

# The Findability Challenge

Once upon a time, it was hard to find information about a person

> Who is this person?



#### Now, the Web and people's online activities offer a breath of information!



#### cmperatsakis

hahaha, brilliance! RT @jonathanschan: Looks like I'm not Name Christian Location Austin, TX Bio Research Assist. @ Strauss Center and Research Fellow with AidData. Study aid transparency & effectiveness. Focus on Africa, [Insert tweets are my own jumbo]

following followers listed

View Full Profile

#### Christian Peratsakis

Research Assistant at The Robert S. Strauss Center for International Security & Law Austin, Texas Area I Research

Current: Research Assistant at The Robert S. Strauss Center for International Security & Law, Research

Past: Research Fellow at Institute for the Theory and Practice of International Relations, Research Assistant at Institute for the Theory and Practice ...

Education: The University of Texas at Austin - The LBJ School of Public Affairs, The College of William and Mary, Institut d'Etudes politiques de Lille, Laf...

really solid analysis of Saif al-Islam's speech tonight: http://ow.ly /1s3PYy

4:11 PM Feb 20th via TweetDeck

texasinafrica Obama needs to make statement on Libya NOW; our interests throughout sub-Saharan Africa will be affected by what happens tonight & tomorrow

2:34 PM Feb 20th via TweetDeck

Retweeted by cmperatsakis and 13 others

cha-ching, RT @TalesFromthHood; what is the sound of a buck



## **User Online Trails**



#### **Textual data**

Web pages (personal, news, ...)

User histories (search, browsing, purchases, ...)

Posts (Blogs, Twitter, Facebook)

Comments (Yelp, Netflix, ...)



#### Media

Movies viewed (Netflix, Hulu, ...)

Images shared (Facebook, Google+, ...)

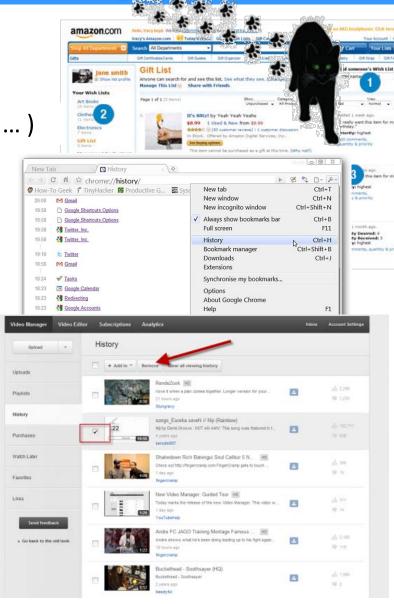
Videos watched/shared (Youtube, ...)



#### **Social Networks**

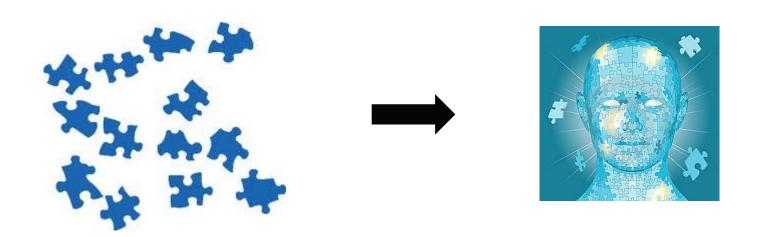
Connections (friends, family, ...)

Social activity

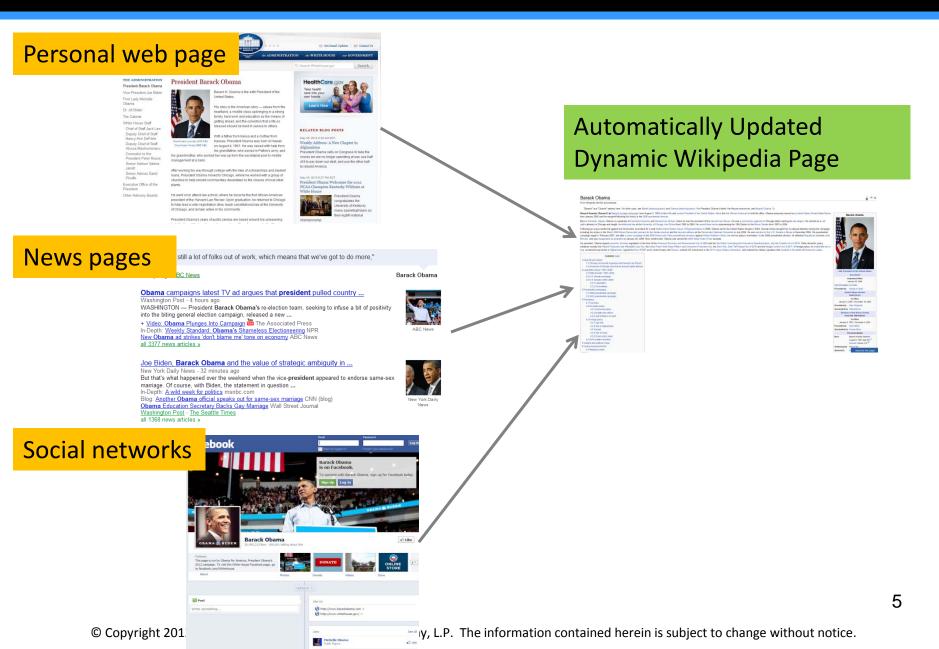


## From User Online Trails to .... You!

Analyzing and combining these pieces of information together can lead to **valuable insights** about users and opens up the door to **tremendous opportunities** in sectors including education, health, marketing, law enforcement



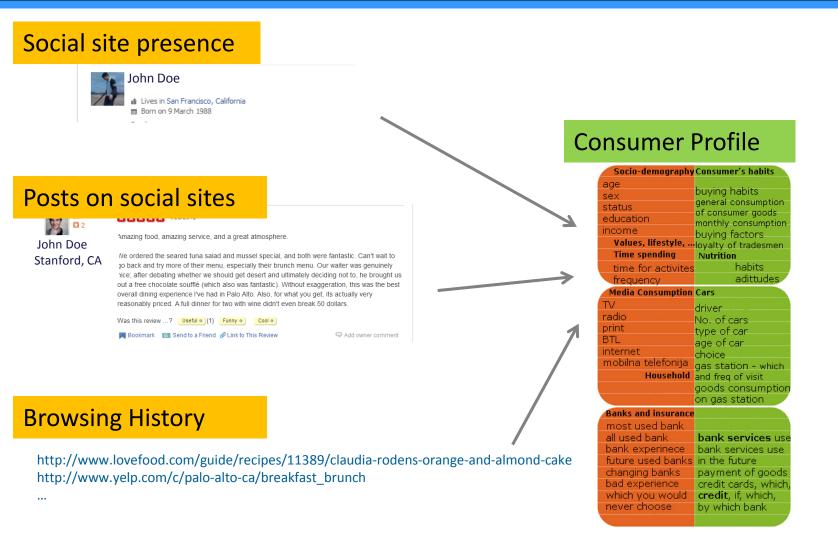
## **Example Applications: Education**



## Example Applications: Health

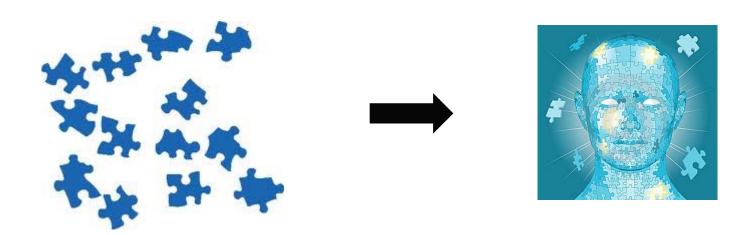


## Example Applications: Marketing

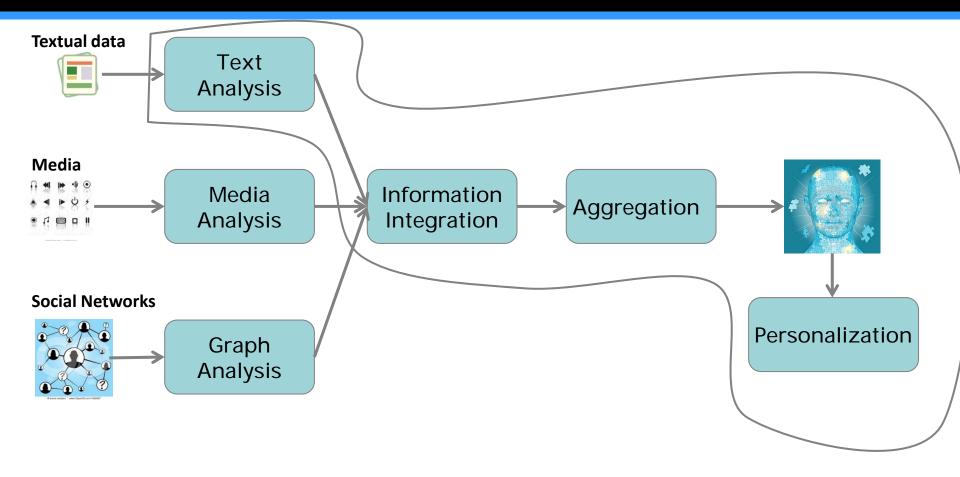


## From User Online Trails to .... You!

Analyzing and combining these pieces of information together can lead to **valuable insights** about users and opens up the door to **tremendous opportunities** in sectors including education, health, marketing, law enforcement

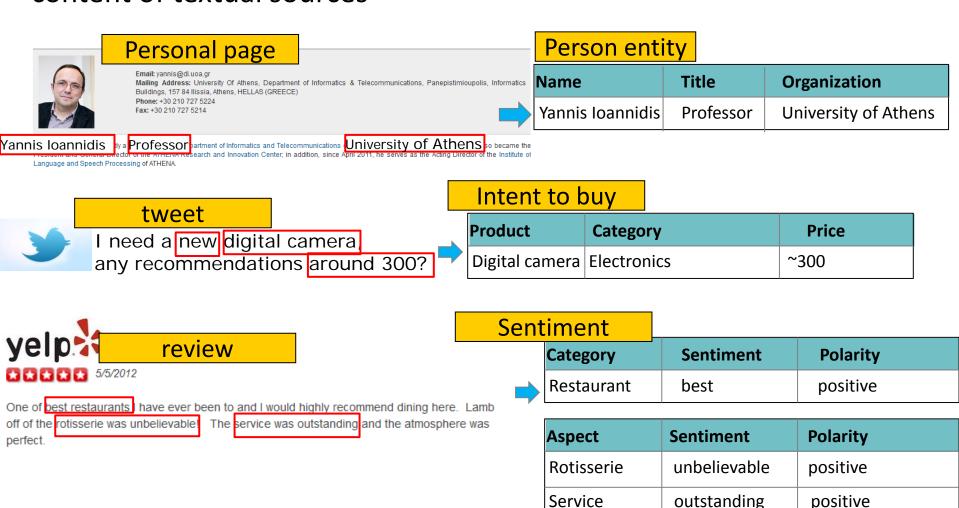


# The Entity Reconstruction Workflow



# Text Analysis

The purpose of this step is to model and structure the information content of textual sources



#### Information extraction

the task of automatically extracting structured information from unstructured data



#### Named entity detection:

recognition of (known) entity names (e.g., people and organizations), places, temporal expressions (e.g., dates)

#### Relationship extraction:

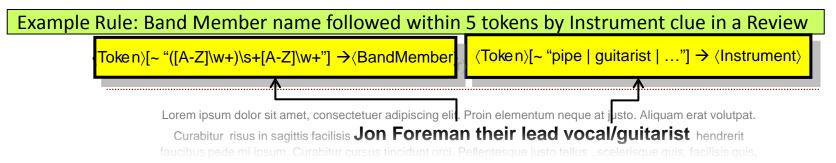
identification of relations between entities, such as

PERSON < works as > COMPANY

#### Information extraction approaches

#### Rule-based approaches

e.g., Autoslog, Circus (see [1]), ANNIE (GATE framework)



[1] Mena B. Habib, Maurice van Keulen Information Extraction, Data Integration, and Uncertain Data Management: The State of The Art. Technical Report

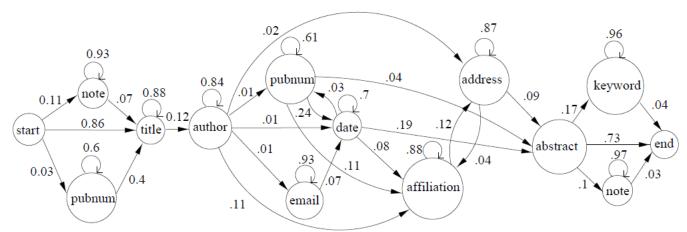
#### Information extraction approaches

#### Rule-based approaches

e.g., Autoslog, Circus (see [1]), ANNIE (GATE framework)

#### Machine Learning approaches

e.g., Rapier [2], SNoW [3], WHISK [4]



- [2] Cali, M. E.: Relational learning techniques for natural language information extraction. PhD thesis, University of Texas at Austin, 1998,
- [3] Roth, D., Yih, W. T.: Relational learning via propositional algorithms: an information extraction case study. IJCAI, 2001.
- [4] Soderland, S.: Learning information extraction rules for semi-structured and free text. Machine Learning, 34 (1999).

#### Information extraction approaches

#### Rule-based approaches

e.g., Autoslog, Circus (see [1]), ANNIE (GATE framework)

#### Machine Learning approaches

e.g., Rapier [2], SNoW [3], WHISK [4]

#### Declarative approaches

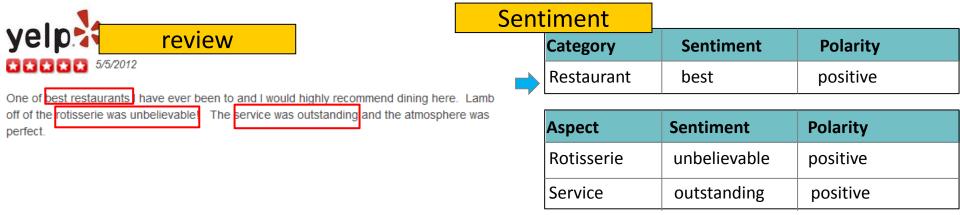
AQL/SystemT, PSOX, SQoUT, xLog, and RAD (see SIGMOD Record 37(4), 2010)

Rule-based/Declarative approaches can obtain better precision, but at the cost of lower recall and more work

## Text Analysis Tasks: Sentiment Analysis

#### Sentiment analysis

the task of **determining the attitude** of a speaker or a writer with respect to some topic or the **overall contextual polarity** of a document.



#### It is cast as a classification or extraction problem

However, compared to topic/information, sentiment can often be expressed in a more subtle manner, making it difficult to be identified by any of a sentence or document's terms when considered in isolation.

15

# Text Analysis Tasks: Sentiment Analysis

#### **Examples**

"If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut."

(review by Luca Turin and Tania Sanchez of the Givenchy perfume Amarige, in *Perfumes: The Guide, Viking* 2008.)

No ostensibly negative words occur

"This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up.

Wishful thinking

#### You can find only what you are looking for

Fred Flintstone was named CTO of Time Bank Inc. in 2010. The next year he got married and became CEO of Dinosaur Savings.

4	-

person	company	position	year in/out
Fred Flintstone	Time Bank Inc.	СТО	2010 in
Fred Flintstone	Time Bank Inc.	СТО	2011 out
Fred Flintstone	Dinosaur Savings	CEO	2011 in

information about his marriage was not captured; extraction seeks to cover only a predefined set of predications.

#### Variations and Ambiguity



Typos, abbreviations, short text, sarcasm are just a few of the many issues that make text analysis hard

#### Scalability (Data)



Twitter: 140 million active users as of 2012, generating over 340 millions tweets daily



Facebook: 300 million photos are uploaded to the site each day.

3.2 billion Likes and Comments are posted daily. [1]

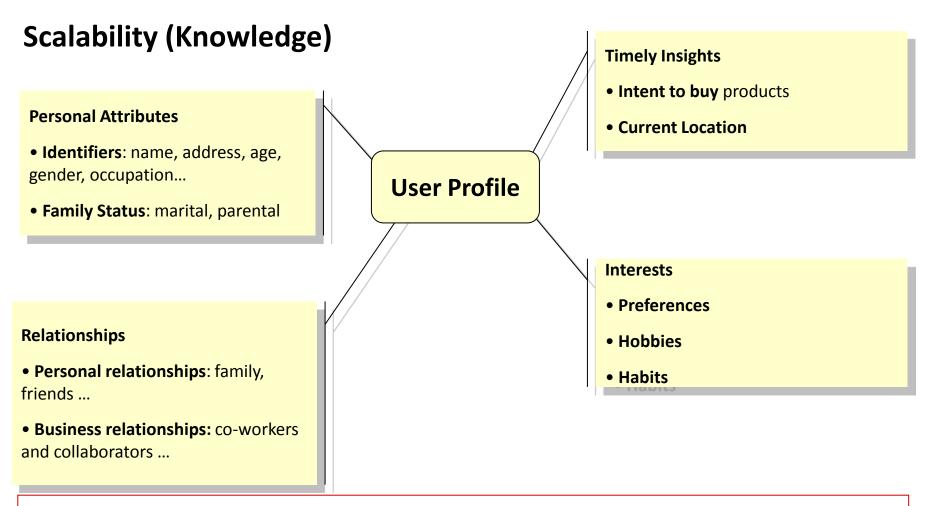


3.146 billion email accounts worldwide. [2]

#### Keeping up with the amount of input data is a challenge

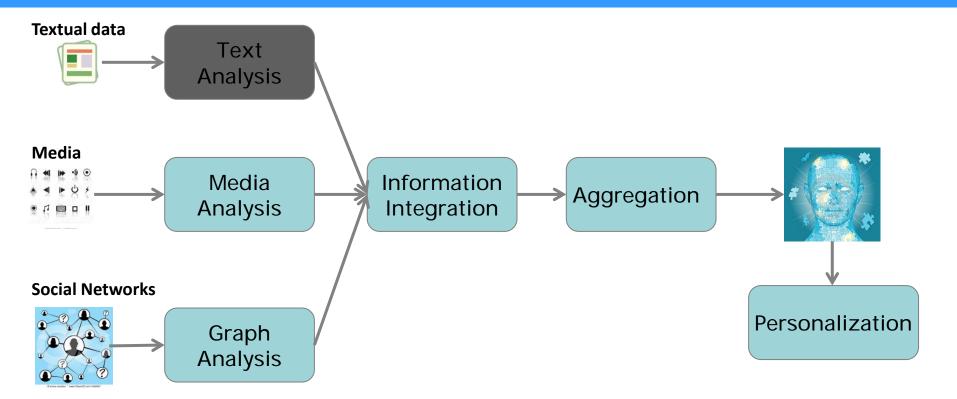
[1] http://www.huffingtonpost.com/2012/04/23/facebook-s-1-amendment n 1446853.html

[2] http://royal.pingdom.com/2012/01/17/internet-2011-in-numbers/

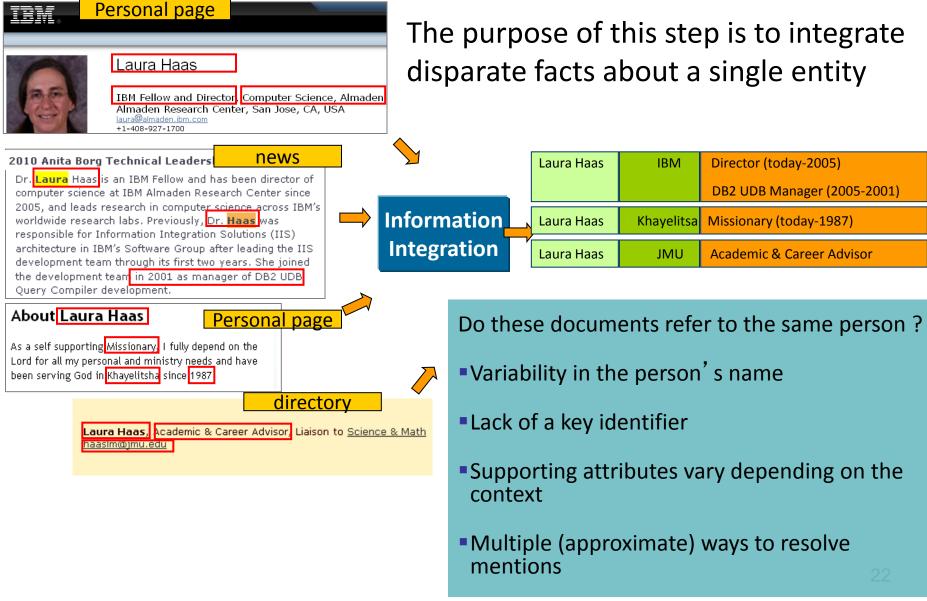


Identifying and keeping up with the types of user knowledge that may be of interest is a challenge

# The Entity Reconstruction Workflow



# Information Integration



# Information Integration Tasks: Entity Resolution

#### **Entity Resolution**

The problem of **linking facts** that refer to **the same entity** when **integrating** two or more disparate sources.

#### ER is a complex, trial-and-error process

- It requires domain-specific knowledge
- It is hard to achieve high precision and recall

Laura Haas	IBM Research
L. Haas	IBM Almaden
L. Haas	Computer Science, IBM Almaden

## Information Integration Tasks: Entity Resolution

#### **Entity Resolution Approaches**

#### Algorithms and Metrics

e.g., Jaro, edit distance, multi-attribute similarity measures (e.g., [1,2])

Tailor, iFuice (see [3])

#### Declarative approaches

e.g., WHIRL, Dedupalog, LinQL (see [3])

<sup>[1]</sup> A. K. Elmagarmid, P. G. Ipeirotis, and V. S. Verykios, "Duplicate Record Detection: A Survey," IEEE TKDE, vol. 19, no. 1, pp. 1–16, 2007.

<sup>[2]</sup> I. P. Fellegi and A. B. Sunter, "A Theory for Record Linkage," J. Am. Statistical Assoc., vol. 64, no. 328, pp. 1183–1210, 2007.

<sup>[3]</sup> Hanna Köpcke, Erhard Rahm: Frameworks for entity matching: A comparison. Data Knowl. Eng. 69(2): 197-210 (2010)

# Why Information Integration is hard

#### Information on the Web may be

```
-incomplete and in variations
e.g., EDBT 2012 web site:
     "Adaptive Indexing in Modern Databases"
      Stratos Idreos (CWI, The Netherlands); Stefan Manegold (CWI, The Netherlands);
      Goetz Graefe HP Labs, Palo Alto
      Intention Insider: Discovering People's Intentions in the Social Channel
      Malu Castellanos, HP Labs, USA; ....
     Session Chair: Ronald Fagin (IBM Research - Almaden)
     Adaptive MapReduce using Situation-Aware Mappers:
     Rares Vernica (HP Labs), Andrey Balmin (IBM Almaden)
     Kevin Beyer IBM Almaden Research Center, ....
```

# Why Information Integration is hard

#### Information on the Web may be

- intentionally faked
  - e.g., a small experiment in Twitter: almost half of the times, the combination name/city/state did not retrieve any person from peoplefinder.com
- bogus or ambiguous

e.g., "user location in Twitter": "wish I were in California"

Little or untrustworthy evidence hinders information integration

# Why Information Integration is hard

#### Handling Conflicts within and across sources

- Each attribute has specific semantics for integration

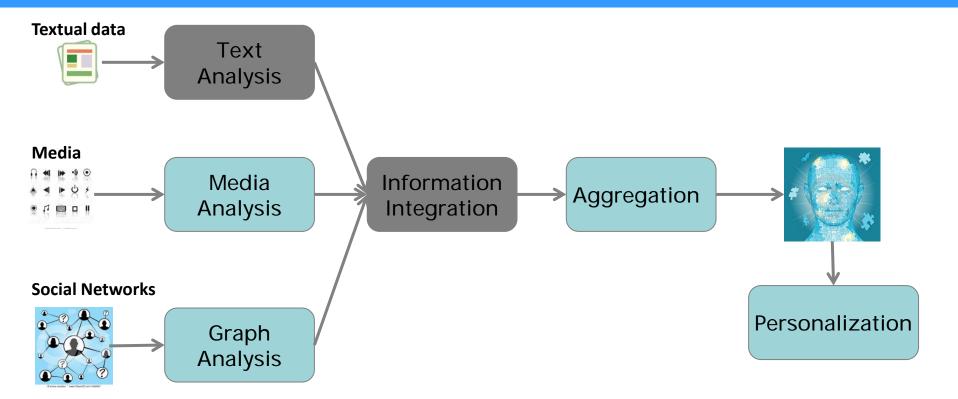
Name		Title	Organization
Yannis Ioan	nidis	Professor	University of Athens
		·	
Name		Title	Organization

Is this a conflict?

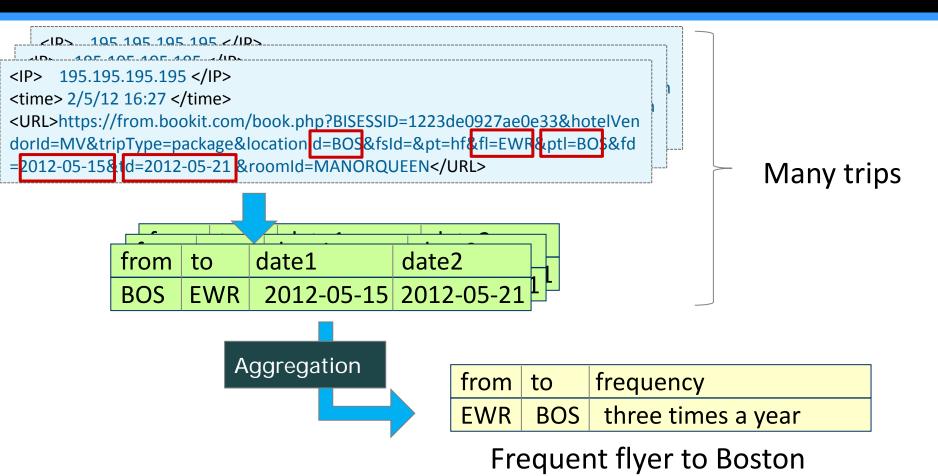
Name	genre	occupation
Cameron Black	female	CEO
Name	genre	occupation

how to integrate conflicting gender?

# The Entity Reconstruction Workflow

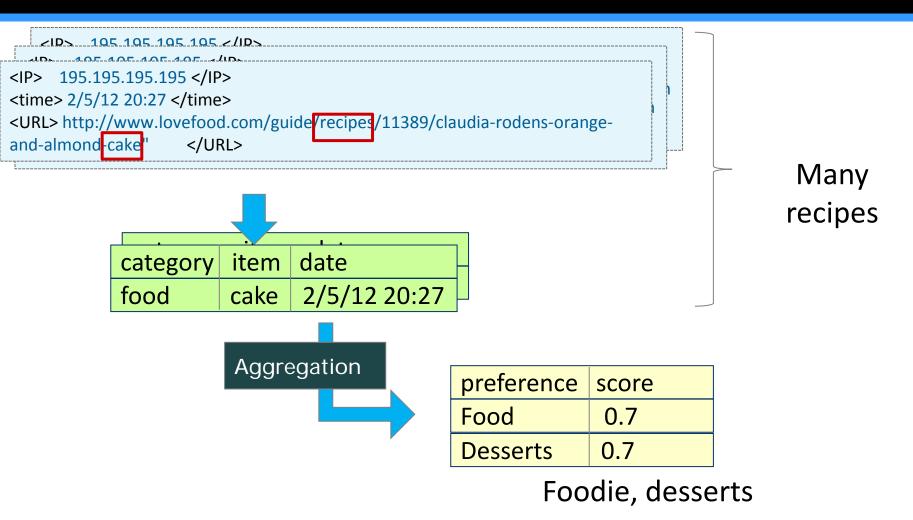


# Aggregation

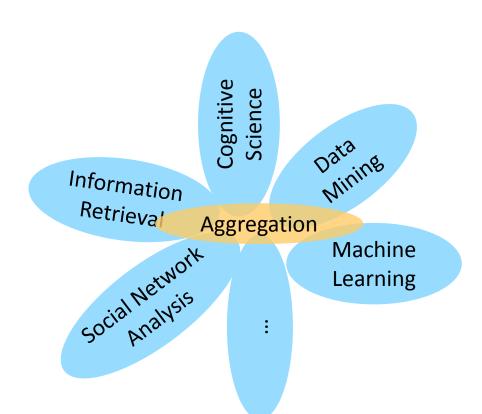


© Copyright 2012 Hewlett-Packard Development Company, L.P. The information contained herein is subject to change without notice.

# Aggregation

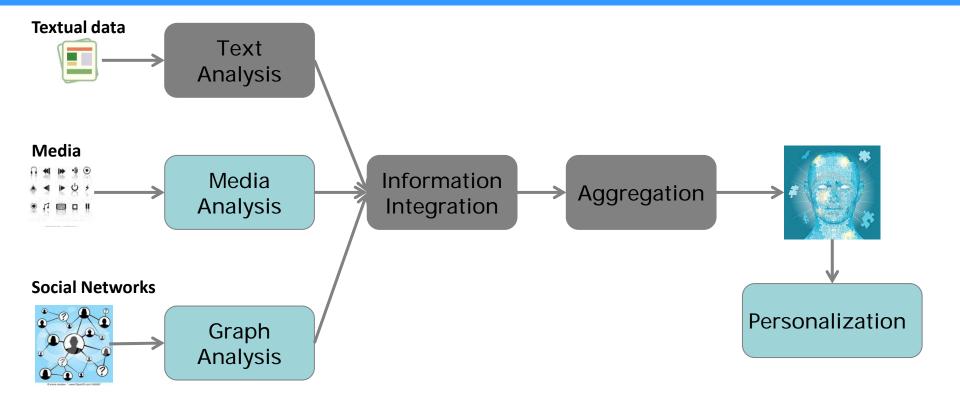


# Aggregation Techniques



The more data collected about a person the more things we could learn about this person!

# The Entity Reconstruction Workflow



## Personalization



Product Recommendations



**Content Delivery** 

**Targeted Advertisements** 

**Personalized Services** 

## Personalization

http://www.youtube.com/watch?v=RNJI9EEcsoE

# The Findability Challenge

- Heterogeneity
- Distributed Content
- Incompleteness
- → Timeliness
- Privacy

# Thank you!