Technology and Application of Big Data

Qing LIAO(廖清)
School of Computer Science and Technology
HIT

Course Details

- Instructor:
 - Qing LIAO, <u>liaoqing@hit.edu.cn</u>
 - Rm. 303B, Building C
 - Office hours: by appointment
- Course web site:
 - liaoqing.me
- Reference books/materials:
 - Big data courses from University of California
 - Book: BIG DATA: A Revolution That Will Transform How We Live, Work, and Think
 - Papers
- Grading Scheme:
 - Paper Report 30%
 - Final Exam 70%

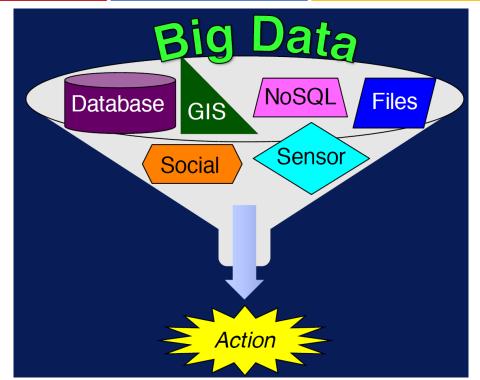
What You Learnt: Overview

- Topics:
 - 1) Introduction of Big Data
 - 2) Characterizes of Big Data
 - 3) How to Get Value from Big Data
 - 4) Technologies of Big Data
 - 5) Applications of Big Data
- Prerequisites
 - Statistics and Probability would help
 - But not necessary
 - Machine Learning would help
 - But not necessary

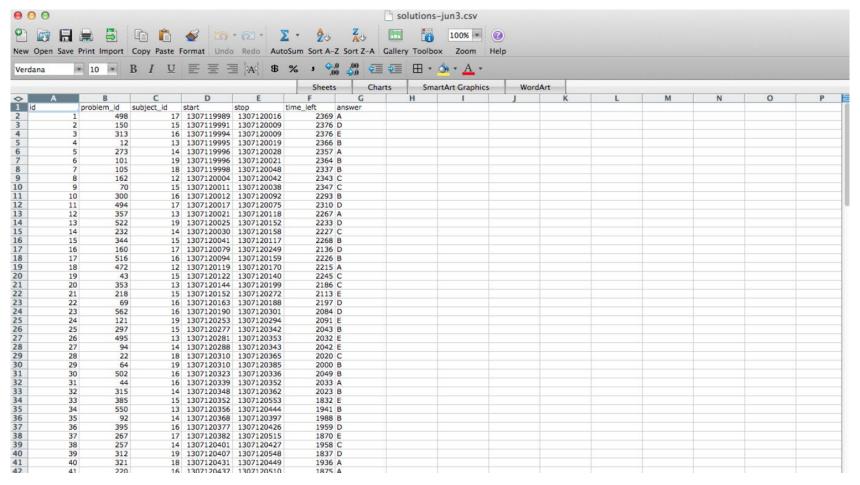
Previous Section

• How to Get Value from Big Data

Acquire Prepare Analyze Report ACT



What you wish data looked like



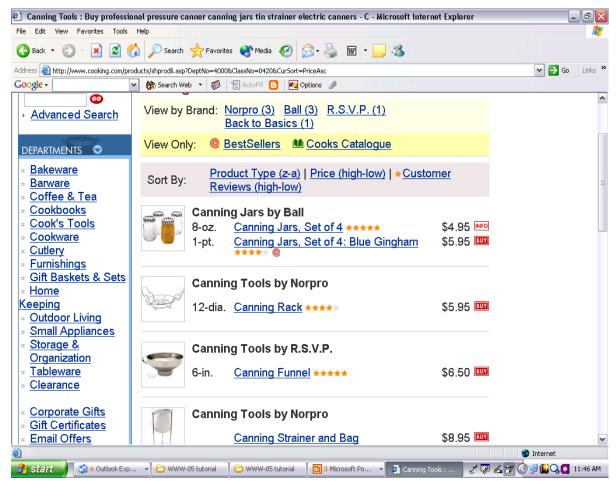
What dose data really looked like

```
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@HWI-EAS121:4:100:1783:455#0/1
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+HWI-EAS121:4:100:1783:455#0/1
```

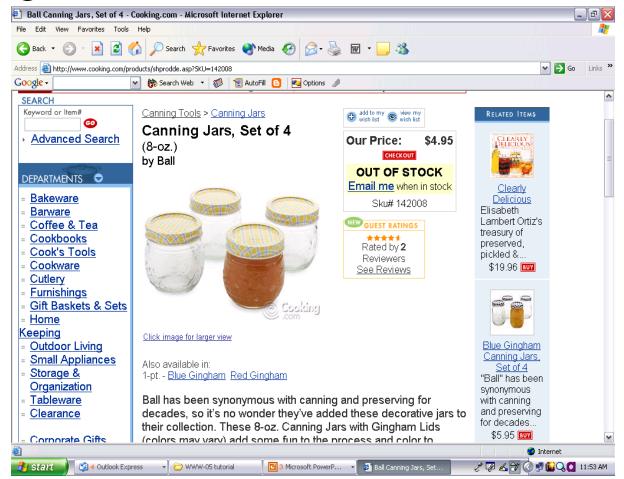
- Information Extraction (IE)
  - Transforming unstructured textual information into structured information via extraction rules.
- A set of extraction rules suitable to extract information from a Web site is called a Wrapper
  - Wrapper induction (supervised learning)
  - Automatic extraction (unsupervised learning)

- Two types of data rich pages
- ➤ List pages
  - Each such page contains one or more lists of data records.
  - Each list in a specific region in the page
- ➤ Detail pages
  - Each such page focuses on a single object.
  - But can have a lot of related and unrelated information

#### ➤ List pages



#### ➤ Detail pages



#### >Extraction results



(a). An example page segment

image 1	Cabinet Organizers by Copco	9-in.	Round Turntable: White	****	\$4.95
image 1	Cabinet Organizers by Copco	12-in.	Round Turntable: White	****	\$7.95
image 2	Cabinet Organizers	14.75x9	Cabinet Organizer (Non- skid): White	****	\$7.95
image 3	Cabinet Organizers	22x6	Cookware Lid Rack	****	\$19.95

(b). Extraction results

- ➤ Wrapper induction (supervised learning)
  - Using machine learning to generate extraction rules.
  - The user marks the target items in a few training pages.
  - The system learns extraction rules from these pages.
  - The rules are applied to extract items from other pages.
- ➤ Many wrapper induction systems, e.g.,
  - WIEN (Kushmerick et al, IJCAI-97),
  - Softmealy (Hsu and Dung, 1998),
  - Stalker (Muslea et al. Agents-99),
  - BWI (Freitag and Kushmerick, AAAI-00),
  - WL2 (Cohen et al. WWW-02).

- ➤ Stalker: A hierarchical wrapper induction system
- ➤ Hierarchical wrapper learning
  - Extraction is isolated at different levels of hierarchy
  - This is suitable for nested data records (embedded list)
- Each item is extracted independent of others.

- Each target item is extracted using two rules
  - A start rule for detecting the beginning of the target item.
  - A end rule for detecting the ending of the target item.

#### ➤ An example nested tuple type

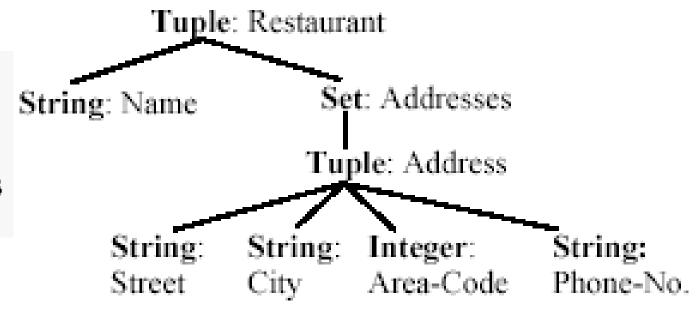
- name (of type string),
- image (of type image-file), and
- differentSizes (a set type), consists of a set of tuples with the attributes:
  - size (of type string), and
  - price (of type string).

```
tuple product (name: string; image: image-file; differentSizes: set (size: string; price: string;))
```

➤ Hierarchical representation: tree

#### Restaurant Name: Good Noodles

- 205 Willow, *Glen*, Phone 1-773-366-1987
- 25 Oak, *Forest*, Phone (800) 234-7903
- 324 Halsted St., Chicago, Phone 1-800-996-5023
- 700 Lake St., Oak Park, Phone: (708) 798-0008



To extract each target item (a node), the wrapper needs a rule that extracts the item from its parent.

- Extraction using two rules
  - a start rule and a end rule.
- The start rule identifies the beginning of the node and the end rule identifies the end of the node.
- For a list node, list iteration rules are needed to break the list into individual data records (tuple instances).

- The extraction rules are based on the idea of landmarks.
  - Each landmark is a sequence of consecutive tokens.
- Landmarks are used to locate the beginning and the end of a target item.
- >Rules use landmarks

#### Restaurant Name: Good Noodles

- 205 Willow, *Glen*, Phone 1-773-366-1987
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#### ➤ An example

• Let us try to extract the restaurant name "Good Noodles". Rule R1 can to identify the beginning:

```
R1: SkipTo() // start rule
```

- This rule means that the system should start from the beginning of the page and skip all the tokens until it sees the first <b> tag. <b> is a landmark.
- Similarly, to identify the end of the restaurant name, we use:

```
R2: SkipTo() // end rule
```

- 1: Restaurant Name: <b>Good Noodles</b><br><br>
- 2: 25 Willow, <i>Glen</i>, Phone 1-<i>773</i>-366-1987
- 25 Oak, <i>Forest</i>, Phone (800) 234-7903
- 4: 4: 324 Halsted St., <i>Chicago</i>, Phone 1-<i>800</i>-996-5023
- 5: 700 Lake St., <i>Oak Park</i>, Phone: (708) 798-0008

#### >Rules are not unique

• Note that a rule may not be unique. For example, we can also use the following rules to identify the beginning of the name:

```
R3: SkiptTo(Name _Punctuation_ _HtmlTag_)
```

- **R3** means that we skip everything till the word "Name" followed by a punctuation symbol and then a HTML tag. In this case, "Name \_*Punctuation*\_ \_*HtmlTag*\_" together is a landmark.
  - \_Punctuation\_ and \_HtmlTag\_ are wildcards.
  - Restaurant Name: <b>Good Noodles</b><br><br>

  - 25 Oak, <i>Forest</i>, Phone (800) 234-7903
  - 4: 4: 324 Halsted St., <i>Chicago</i>, Phone 1-<i>800</i>-996-5023
  - 5: 700 Lake St., <i>Oak Park</i>, Phone: (708) 798-0008

- ➤ Wrapper maintenance
  - Wrapper verification: If the site changes, does the wrapper know the change?
  - Wrapper repair: If the change is correctly detected, how to automatically repair the wrapper?
  - One way to deal with both problems is to learn the characteristic patterns of the target items.
  - These patterns are then used to monitor the extraction to check whether the extracted items are correct.

- ➤ Wrapper maintenance
  - Re-labeling: If they are incorrect, the same patterns can be used to locate the correct items assuming that the page changes are minor formatting changes.
  - Re-learning: re-learning produces a new wrapper.
  - Difficult problems: These two tasks are extremely difficult because it often needs contextual and semantic information to detect changes and to find the new locations of the target items.
  - Wrapper maintenance is still an active research area.

- ➤ Active learning
  - help identify informative unlabeled examples in learning automatically.
- Randomly select a small subset L of unlabeled examples from U.
- 2. Manually label the examples in L, and U = U L.
- 3. Learn a wrapper W based on the labeled set L.
- Apply W to U to find a set of informative examples L.
- 5. Stop if  $L = \emptyset$ , otherwise go to step 2.

- ➤ Wrapper induction (supervised) has two main shortcomings:
  - It is unsuitable for a large number of sites due to the manual labeling effort.
  - Wrapper maintenance is very costly. The Web is a dynamic environment. Sites change constantly. Since rules learnt by wrapper induction systems mainly use formatting tags, if a site changes its formatting templates, existing extraction rules for the site become invalid.

- >Unsupervised learning is possible
  - Due to these problems, automatic (or unsupervised) extraction has been studied.
  - Automatic extraction is possible because data records (tuple instances) in a Web site are usually encoded using a very small number of fixed templates.
  - It is possible to find these templates by mining repeated patterns.

>Automatic Extraction (unsupervised learning)

.net Awards 2011: top 10 podcasts

(b)

"Automatic Extraction of Top-k Lists from the Web"-ICDE 2013









(e)

#### ➤ Automatic Extraction (unsupervised learning)

#### .net Awards 2011: top 10 podcasts

(b)

#### 1. The Big Web Show



URL: 5by5.tv/bigwebshow Hosted by: Jeffrey Zeldman and Dan Benjamin Recorded in: New York City and Austin, Texas Running since: April 29, 2010; 56 Episodes. Format: Weekly, live, audio, sometimes video, about an

Subjects covered: The Big Web Show features special guests and topics like web publishing, art direction, content strategy, typography, web technology, and more, It's everything web that matters

.net: What have you been doing this year? What were the highlights of the screencast in 2011?

DB: Focusing on emerging talent, discussing the challenges facing aspiring designers, focusing on the business side of design.

A recent favourite episode is 5bv5.tv/bigwebshow/55, where we talk to Marissa Christina to discuss her path as a web designer diagnosed with a debilitating vestibular disorder, and her blog Abledis.com, documenting living with a hidden disability.

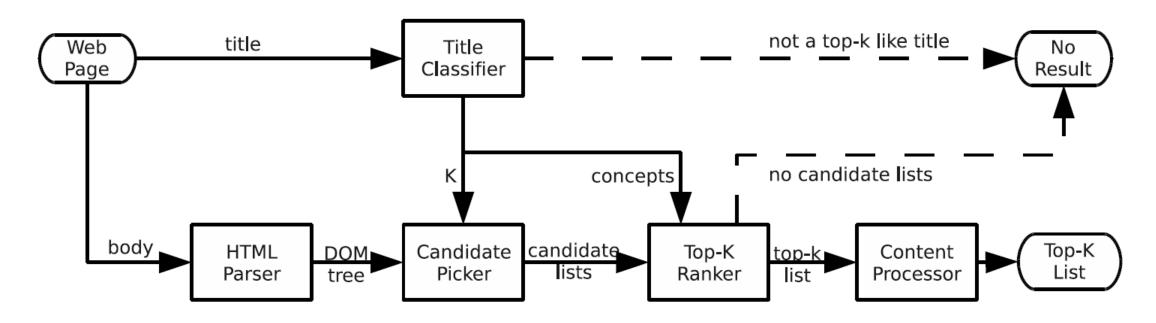
.net: What kind of equipment do you use to record and edit the show? DB: Too much to detail here, but how's this for a overly simplified answer; a dozen Macs, a pile of preamps, a 16-channel mixer, and about 1,000 feet of cable. I use a Heil PR-40 mic and Jeffrey uses a Rode Podcaster

"Automatic Extraction of Top-k Lists from the Web"-ICDE 2013

Motivation: Compared to other structured information on the web (including web tables), information in top-k lists is larger and richer, of higher quality, and generally more interesting.

Index	Name	Image	Url	Hosted by	Recorded in	Running since	Format	
1	The Big Web Show	[image]	[link]	Zeldman et al.	NYC & Austin, TX	April 29, 2010	Weekly, live	
2	Boagworld	[image]	[link]	Boag et al.	a barn in Hampshire	August 2005	Weekly, audio	
3	Creative Coding	[image]	[link]	Lee-Delisle et al.	Brighton, Truro	January 2011	Every two	
10	Unmatched Style	[image]	[link]	Crawford et al.	Columbia, SC	2009	Weekly, pre-recorded	

>Automatic Extraction (unsupervised learning)



- >Automatic Extraction (unsupervised learning)
  - Title Classifier

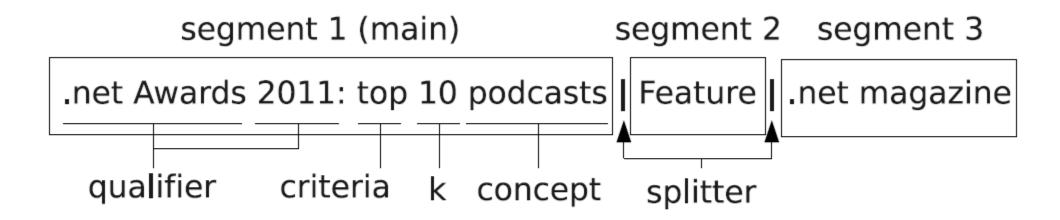
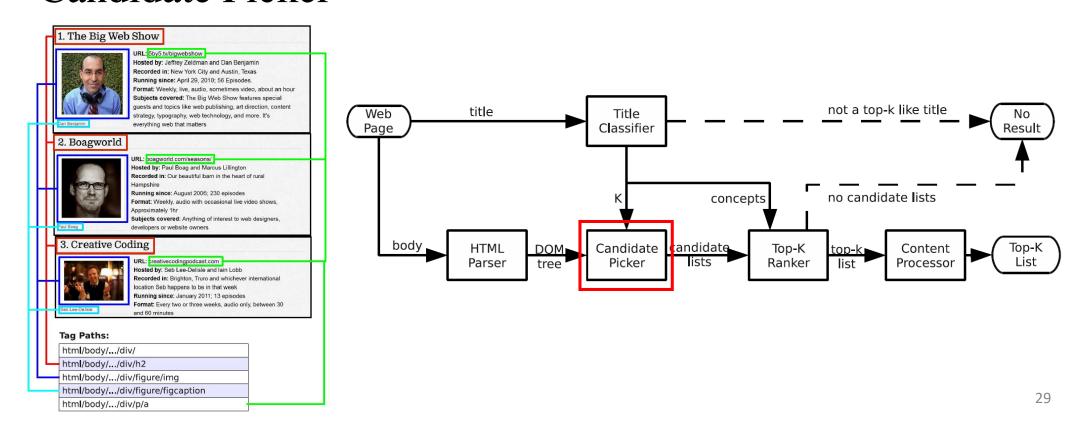


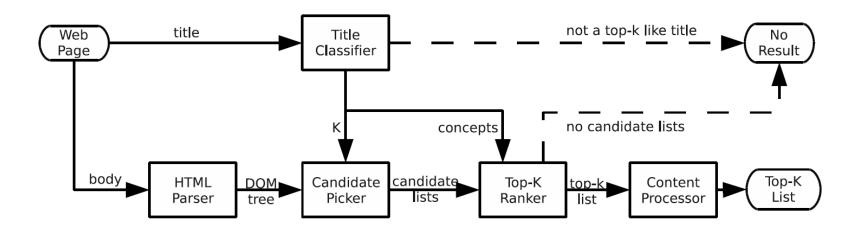
Fig. 3. A Sample Top-K Title

- >Automatic Extraction (unsupervised learning)
  - Candidate Picker



- >Automatic Extraction (unsupervised learning)
  - Top-K Ranker: Researchers assume that one or more items from the main list should be instances of that central concept from the title.
  - For example, if the title contains the concept "scientist", then the items of the main list should be instances of the "scientist" concept.
  - Based on "Probase"
  - Calculate the P-Score of each candidate

- ➤ Automatic Extraction (unsupervised learning)
  - Content Processor
    - Infer the structure of text nodes
    - Conceptualize the list attributes
    - Detect when and where



#### Wrapper induction

- Advantages:
  - Only the target data are extracted as the user can label only data items that he/she is interested in.
  - Due to manual labeling, there is no integration issue for data extracted from multiple sites as the problem is solved by the user.
- Disadvantages:
  - It is not scalable to a large number of sites due to significant manual efforts. Even finding the pages to label is non-trivial.
  - Wrapper maintenance (verification and repair) is very costly if the sites change frequently.

#### **Automatic extraction**

- Advantages:
  - It is scalable to a huge number of sites due to the automatic process.
  - There is little maintenance cost.
- Disadvantages:
  - It may extract a large amount of unwanted data because the system does not know what is interesting to the user. Domain heuristics or manual filtering may be needed to remove unwanted data.
  - Extracted data from multiple sites need integration, i.e., their schemas need to be matched.

• In terms of extraction accuracy, it is reasonable to assume that wrapper induction is more accurate than automatic extraction. However, there is no reported comparison.

#### Applications

- Wrapper induction should be used in applications in which the number of sites to be extracted and the number of templates in these sites are not large.
- Automatic extraction is more suitable for large scale extraction tasks which do not require accurate labeling or integration.
- Still an active research area.