Unsupervised Information Extraction by Text Segmentation

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Agenda

Introduction

- Information Extraction by Text Segmentation (IETS)
- Contributions

Related Work

- Web Extraction Methods and Tools
- Probabilistic Graph-Based Methods

Our Proposed Approach for IETS

- Ondux
- Judie
- iForm
- Conclusions and Future Work

Steady increasing in the number and the types of sources of textual information available in the World-Wide Web



- These sources constitute large repositories of valuable data on a variety of domains.
- Data referring to different "things" such as:
 - Personal Information;
 - Products;
 - Publication;
 - Companies;
 - Cities;

- Important restrictions on the way data they contain can be manipulated.
- Text snippets (product descriptions, movie reviews) can hardly be subject to automated processing.
 - Difficult to automatically identify data of interest.



- The Information Extraction (IE) Problem
 - Automatic extract structured information such as entities, relationships between entities, and attributes describing entities from noisy unstructured sources.
 - Named Entity Recognition;
 - Open Information Extraction;
 - Relationship Extraction;
 - Information Extraction by Text Segmentation (IETS)

- Information Extraction by Text Segmentation (IETS)
 - The problem of extracting attribute values occurring in implicit semi-structured data records in the form of continuous text.

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- Why is it important to extract information?
 - Query structured data; Data Mining; Record Linkage.

Contributions

- In this work we tackle the Information Extraction by Text Segmentation Problem (IETS)
 - Important and practical problem frequently addressed in the recent literature.
 - Borkar@SIGMOD'01, McCallum@ICML'01, Agichtein@SIGKDD'04, Mansuri@ICDE'06, Zhao@SICDM'08, Cortez@JASIST'09
- We propose and implement an **unsupervised approach** to this problem.
 - Relies on information available on pre-existing data.
 - Learn content-based features (i.e., *domain knowledge*).
 - Exploit content-based features to directly learn structure-based features (i.e., source knowledge) from test data.
 - Eliminate the need of a user involved in any source specific training process.

Contributions

- Based on our approach we produced a number of results.
 - ONDUX On-Demand Unsupervised Learning for IE
 SIGMOD'10, IDAR'10, SBBD'11
 - JUDIE Joint Unsupervised Structure Discovery and IE
 SIGMOD'II
 - iForm A Probabilistic Approach for Automatically Filling Form-Based Web Interfaces
 - **WWW'09, PVLDB'10**

Language for Wrapper Development.

- Alternative to general purpose languages such as Perl and Java.
- Minerva, WEB-OQL

Wrapper Induction Methods

- Machine Learning usage to semi-automatically induce wrappers.
- WEIN, StalKer

NLP-based Methods

- Usage of Natural Language Processing techniques (semantic class, POS)
- WHISK, TEXTRUNNER

Ontology-based Methods

• Usage of an ontology and conceptual description of the data of interest

HTML-aware Methods

- Explore the HTML Structure (Tags) and their representation (DOM)
- RoadRunner, Webtables

Methods	Disadvantages
Language for Wrapper Development.	Rely on the Regularity of the HTML format
Wrapper Induction Methods.	Rely on the Regularity of the HTML format
NLP-based Methods	Require Linguistic and Grammatical Elements
Ontology-based Methods	Require a huge human effort to manually create ontologies
HTML-aware Methods	Rely on the Regularity of the HTML format

These disadvantages precludes their usage in a large number of textual sources that are available on the Web.

Probabilistic Graph-Based Methods

- Deal with the limitations of the extraction methods that are based on the HTML structure.
- Based on probabilistic frameworks such as: Conditional Random Fields (CRF) and Hidden Markov Models (HMM)

Supervised Methods

- Rely on human-created training sets to generate graphical models able to extract information
- Require training data from each source

Unsupervised Methods

- Rely on pre-existing datasets for easing the training process of probabilistic methods.
 - Dictionaries, Knowledge Bases

Probabilistic Graph-Based Methods

Supervised Methods

Regent Square \$228,900 1028 Mifflin Ave.; 6 Bedrooms; 2 Bathrooms. 412-638-7273

Probabilistic Graph-Based Methods

Supervised Methods

Regent Square \$228,900 1028 Mifflin Ave.; 6 Bedrooms; 2 Bathrooms. 412-638-7273

- I. <Neighboorhood>Regent Square</Neighboorhood>
- 2. <Price>\$228,900</Price>
- 3. <Number>1028</Number>
- 4. <Street>Mifflin Ave.;</Street>
- 5. <Bedroom>6 Bedrooms</ Bedroom>
- 6. <Bathroom>2 Bathrooms</Bathroom>
- 7. <Phone>412-638-7273</Phone>

CRF and HMM methods learn from given examples, lexical, style (content) positioning and sequencing (structure) features

Examples are source-dependent

Supervised Methods



Supervised Methods



Supervised Methods



Unsupervised Methods







Probabilistic Graph-Based Methods



Probabilistic Graph-Based Methods

- Unsupervised Methods
- [Agichtein et al @ SIGKDD 2004]
 - Usage of Reference Tables to create an unsupervised model using Hidden Markov Models (HMM)
- [Zhao et al. @ SIAM ICDM 2008]
 - Usage of reference tables to create unsupervised CRF models (U-CRF)

- [Sarawagi et al. @ ICDE 2006]
 - Usage of pre-existing data and hand labeled training sets to create an semi-supervised model using CRF

Probabilistic Graph-Based Methods

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Both models assume single positioning and ordering of attributes in all test instances.

- [Sarawagi et al. @ ICDE 2006]
 - Usage of pre-existing data and hand labeled training sets to create an semi-supervised model using CRF

Knowledge Bases

• Set of pairs KB =
$$\{(m_1, O_1), ..., (m_n, O_n)\}$$

Easily built from pre-existing sources

• Bibliographic DBs, Freebase, Wikipedia, etc.

$$K = \{ Author, O_{Author} \rangle, \langle Title, O_{Title} \rangle \}$$

$$O_{Author} = \{ J. K. Rowling", "Galadriel Waters", "Beatrix Potter" \}$$

$$O_{Title} = \{ Harry Potter and the Half-Blood Prince", \\ "A Guide to Harry Potter", "The Rabbit's Halloween" \}$$

Our approach relies on two types of features:
State or content-based features;



Our approach relies on two types of features:
 Transition or Structure-based Features;



Input Records

Knowledge bases implicitly encode domain knowledge.

- Very suitable source for learning content-based features
- Attribute Vocabulary
 - Exploit the common vocabulary often shared by values of textual attributes

$$AF(s,A) = \frac{\sum_{t \in T(A) \cap T(s)} fitness(t,A)}{|T(s)|} \qquad fitness(t,A) = \frac{f(t,A)}{N(t)} \times \frac{f(t,A)}{f_{max}(A)}$$



Knowledge bases implicitly encode domain knowledge.

- Very suitable source for learning content-based features
- Attribute Value Range
 - For the case of numeric candidate values, it measures the similarity between a numeric value and the set of values of a numeric attribute

$$NM(s,A) = e^{-\frac{v_s - \mu}{2\sigma^2}}$$



Knowledge bases implicitly encode domain knowledge.

- Very suitable source for learning content-based features
- Attribute Value Format
 - Exploits the common format often used to represent values of some attributes.

$$format(s, A) = \frac{\sum_{\substack{(n_x, n_y) \in path(s) \\ |path(s)|}} w(n_x, n_y)}{|path(s)|}$$
KB

Attribute Value Format (Style)

- First a Markov model is generated for each attribute.
- Computes the probability of the input mask sequence represents a path in each Markov model of each attribute.



Content-based Features



Structure-based features are automatically induced from content-based Features

HMM-like graph called Positioning and Sequencing Model (PSM)

Positioning and Sequencing Model

- Automatically learned On-Demand from test instances
- No *a priori* training required

Structure-based features

- Dependent of the placement of attributes values on the input
- Thus, they are input-dependent



 $p_{i,k} = \frac{\text{\# of observations of } \ell_i \text{ in } k}{\text{Total \# of candidate values in } k} t_{i,j} = \frac{\text{\# of transitions from } \ell_i \text{ to } \ell_j}{\text{Total \# of transitions out of } \ell_i}$ $pos(s_k, A_i, R) = p_{i,k} \qquad seq(s_k, A_i, R) = t_{i,j}$



- Combination Strategy
 - Bayesian Noise-OR-Gate

$$or(p_1,...,p_n) = 1 - ((1 - p_1) \times ... \times (1 - p_n))$$

- We assume that the features we use exploit different properties of the attributes of the KB, i.e., they are independent.
- Probabilistic methods such as CRF and HMM deploy optimization process to combine their features.
 - Not using optimization can, in theory, lead to sub-optimal results, our experiments demonstrates that our combination works very well in practice.
Our Proposed Approach for IETS

Based on our approach

- We developed unsupervised information extraction by text segmentation methods
- ONDUX
 - On Demand Unsupervised Information Extraction
- JUDIE
 - Joint Unsupervised Structure Discovery and Information Extraction
- ▶ iForm
 - A Probabilistic Approach for Automatically Filling Form-Based Web Interfaces

On-Demand Unsupervised Learning for Information Extraction

Cortez et al. - SIGMOD 2010, Cortez and Silva – IDAR 2010

Deals with text documents containing implicit semistructured data records

- Addresses
- Bibliographic References
- Classified Ads
- Product Descriptions

Postal Address

Dr. Robert A. Jacobson, 8109 Harford Road, Baltimore, MD 21214

Bibliographic Reference

Pável Calado, Marco Cristo, Marcos André Gonçalves, Edleno S. de Moura, Berthier Ribeiro-Neto, Nivio Ziviani. Link-based similarity measures for the classication of Web documents. JASIST, v. 57 n.2, p. 208-221, January 2006

General View



Blocking

- Split the input text in substrings called blocks;
- Consider the co-occurrence of consecutive terms based on the KB

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Blocking

- Split the input text in substrings called blocks;
- Consider the co-occurrence of consecutive terms based on the KB



Matching

- Associate each blocks with attributes according to contentbased features.
 - Attribute Vocabulary $AF(s, A) = \frac{\sum_{t \in T(A) \cap T(s)} fitness(t, A)}{|T(s)|}$

Value Range
$$NM(s, A) = e^{-\frac{v_s - \mu}{2\sigma^2}}$$



Reinforcement – PSM



Ordering and Positioning Features are learned On-Demand based on the test instances trough the Matching Phase

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Reinforcement

• Once the PSM is built, we combine the content-based and the structure-based features using the Bayesian operator *OR*.



Reinforcement

• Once the PSM is built, we combine the content-based and the structure-based features using the Bayesian operator *OR*.



Setup

- We tested our proposed method with several sources from 3 distinct domains:
 - Addresses
 - Bibilographic Data
 - Classified Ads
- Metrics
 - Precision, Recall and F-Measure
 - $\hfill\square$ T-Test for the statistical validation of the results
- Baselines
 - U-CRF and S-CRF

Extraction Quality



Extraction Quality



Extraction Quality



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JUDIE

Joint Unsupervised Structure Discovery and Information Extraction

Cortez et al. - SIGMOD 2011



Chocolate Cake Recipe

1/2 cup butter 2 eggs 4 cups white sugar ground cinnamon 2 tablespoons dark rum 6 chopped pecans 1/2 cup milk 1 1/2 cups applesauce 2 cups all-purpose flour 1/4 cup cocoa powder 2 teaspoons baking soda 1/8 teaspoon salt 1 cup raisins 1/4 cup dark rum



Quantity	Unit	Ingredient
I/2	сир	butter
2		eggs
4	cups	white sugar
		ground cinnamon
2	tablespoons	dark rum
6		chopped pecans

JUDIE

- Joint Unsupervised Structure Discovery and Information Extraction
 - Detects the structure of each individual record being extracted without any user intervention
 - Looks for frequent patterns of label repetitions or cycles
- Integrates this algorithm in the IE process
 - Accomplished by successive refinement steps that alternate information extraction and structure discovery.



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JUDIE – Structure-free Labeling

▶ What is the best label for each segment?

No information on the structure of the data records



JUDIE – Structure-free Labeling

Initially labels potential values with attribute names.

- No information on the structure of the data records
- Resort only to content-based features
 - Learned from the pre-existing KB

1/2 cup raising flour 2 level Tbsp Cocoa pinch Salt 1/4 cup Melted butter 1 Egg a little Vanilla

Q	U	Ι	Q	U	?	Ι	U	Ι	Q	U	Ι	Q	Ι	Ι	Ι
1/2	cup	raising flour	2	level	Tbsp	Cocoa	pinch	Salt	1/4	cup	Melted butter	I	Egg	a little	Vanilla

Limitations: Unmatching: "Tbsp" Mismatching: "a little"

The SD Algorithm (I)

- Uncover the structure of implicit records from the input text.
 - Used in the Structure Sketching and Structure Refinement.

- Takes as input a sequence of labels and generates the structure of each record.
 - Assumption: It is possible to identify patterns of sequences by looking for cycles into a graph (Adjacency Graph) that models the ordering of labels.

The SD Algorithm (II)

• Consider a sequence of labels from a bibliographic reference input text.

Title Conference Year Author Author Title Conference Year Author Title Conference Year ... Author Title Journal Issue Year Author Title Journal Issue Year Author Author Journal Issue Year Title Year ... Author Title Conference Year Author Author Author Title Journal Issue Year



The SD Algorithm (V)

Dominant Cycles

- Given the set of Coincident cycles that are also viable, the Dominant Cycle are most frequent in the input
- Finally, the algorithm works by first identifying all dominant cycles in the adjacency graph and then processing each of these cycles, the largest cycles being processed first.
- In our given examples, the dominant cycles are:
 - [Author, Title, Journal, Issue, Year]
 - 2. [Author, Title, Conference, Year]
 - 3. [Author, Journal, Issue, Year]
 - 4. [Title,Conference,Year]
 - 5. [Title,Year]

JUDIE – Structure Sketching

Organizes the labeled candidate values into records

- Induces a structure on the unstructured text input.
- Outputs labeled values grouped into records
- Uses a novel algorithm called Structure Discovery (SD)

	Q	U	Ι	Q	U	5	Ι	U	Ι	Q	U	Ι	Q	Ι	Ι	Ι	
	1/2	cup	raising flour	2	level	Tbsp	Cocoa	pinch	Salt	I/4	cup	Melted butt	er I	Egg	a little	Van	illa
					-	-	-	_						-			_
Q	U		I	Q	U	?]	[U	Ι	Q	U	Ι		Q	I	I	Ι
1/2	cup	rais	sing flour	2	evel ⁻	Tbsp C	ocoa	pinch	Salt	1/4	cup	Melted but	er	ΙE	gg a l	ittle	Vanilla

JUDIE – Structure-aware Labeling

- Now, what is the best label for each segment?
- We already know some structural information
- Re-labels segments considering content-based features and structure-based features
- Structure-based features learned using a graphical model (PSM)



JUDIE – Structure-aware Labeling



JUDIE – Structure-aware Labeling

- Labels textual values considering:
 - Uses a graphic model representing the likelihood of attribute transitions within the input text
 - Content-related features and structure-based features



JUDIE – Structure Refinement

- Applies again the SD algorithm
 - Considers the output of the structure-aware labeling
 - Fixes structural problems
 - □ Structure-aware labeling produces more precise results



Experiments

Domain	Dataset	Text Inputs	Attributes	Source	Attributes	Records
Cooking Recipes	Recipes	500	3	FreeBase.com	3	100
Product Offers	Products	10000	3	Nhemu.com	3	5000
Postal Addresses	BigBook	2000	5	BigBook	5	2000
Bibliography	CORA	500	3 to 7	PersonalBib	7	395
Classified Ads	WebAds	500	5 to 18	Folha On-line	18	125

Metrics

- Precision, Recall and F-Measure
 - T-Test for the statistical validation of the results
- Baselines
 - ONDUX and U-CRF

Evaluation – Record Level

Dataset	Phase I	Phase 2	Gain (%)
Recipes	0.79	0.90	13.2
CORA	0.69	0.83	19.3
Web Ads	0.70	0.77	9.7

- ▶ Phase I: acceptable. $F \approx 0.7$
- Phase 2: positive impact. Gains > 9%
- In CORA, gains higher than 19%
 - Structural information led to significant improvements.

Comparison with baselines – Attribute Level

Attribute	JUDIE	ONDUX	U-CRF	Attribute	JUDIE	ONDUX	U-CRF
Author	0.88	0.922	0.87	Bedroom	0.82	0.86	0.79
Title	0.70	0.79	0.69	Living	0.89	0.90	0.72
Booktitle	0.86	0.89	0.56	Phone	0.87	0.92	0.75
Journal	0.84	0.90	0.55	Price	0.92	0.93	0.78
Volume	0.90	0.96	0.43	Kitchen	0.83	0.84	0.78
Pages	0.86	0.84	0.50	Bathroom	0.77	0.79	0.81
Date	0.87	0.89	0.49	Others	0.73	0.79	0.71
Average	0.86	0.88	0.58	Average	0.84	0.85	0.76
	COR	4			Web	Ads	

- Results very close to ONDUX and even better than U-CRF
- Recall: JUDIE faces a harder task.

iForm

A Probabilistic Approach for Automatically Filling Form-Based Web Interfaces

Toda et al. – WWW 2009, Toda et Al. – PVLDB 2010

The Form Filling Problem

Goal:

- To automatically fill out the fields of a given form-based interface with values extracted from a data-rich free text document.
 - 1. Extracting values from the input text;
 - 2. Filling out the fields of the target form using them.

Example

Form-based interface

Vehicle Info	Text	Box	
Туре	- Please Select -		
Year			Check-box
Make		Features	
Model			Power Steering Air Cond. (Rear) Roof Rack
VIN			Power Brakes Cruise Control Fog Lamps
Mileage			Power Windows Air Bags (Driver) Sliding Rear Win
Transmission	- Please Select - 🛛 💌		Power Locks Air Bags (Passgr) Running Boards
Engine			🗋 Power Mirrors 👘 🗋 Security System 🛄 Bed Liner
Drivetrain	- Please Select -		Power Seat (Driver) Rear Defroster Custom Bumper
Body style	- Please Select -		Power Seat (Passgr) Tilt Wheel Grill Guard
Color			Antilock Brakes Rear Wipers Winch
Int color			🗀 Air Conditioning 🔲 Tinted Windows 🗔 Opt. Fuel Tank
Int material			
Cootio o	Cloth L Leather		Taving Backage
Seating			
Wheels	- Please Select - 🛛 🛛		
Tires	- Please Select - 🛛 🛛		Hudraulis Lift Dual Rear Wheels
Roof	- Please Select - 🛛 👻		
Truck bed	- Please Select - 🛛 💌		
Stereo	- Please Select - 🛛 💌		
Dealer code			
Stock code			
MSRP Sele	ection List		
NADA			
КВВ			
Warranty	- Please Select -		

Example

Data-rich free text document

2005 Honda new Accord Ex,Extra Clean, very low Mileage, Maintained By Dealer! Vechicle Located in Stockton, Ca. Ad Id# 28147						
This is a brand new car with automatic transmission						
Car with Air Conditioning, clock, Cruise Control, Digital Info Center, Dual Zone Climate Control, Heated Seats, Leather Steering Wheel, Memory Seat Position, Power Driver's Seat						
Power Steering, Power Breaks, Power Passenger Seat, Power Windows, Cup Holder, Rear Air Conditioning, Sunroof, Tilt Steering Wheel, Original Owner, Alloy Wheels.						
Am/fm, Cd Changer, Mp3, Satellite						

Contact Us At XXX-XXXX-XXXX For More Information

Visit xxx xxx Motors

Example

Form Filling

Vehicle Info

Туре	- Please Select -	~		
Year	2005			
Make	Honda		Features	
Model	Accord		reatures	🗴 Power Steering 🛛 🔽 Air Cond. (Rear) 🛄 Roof Rack
VIN				🗴 Power Brakes 🛛 🗴 Cruise Control 💭 Fog Lamps
Mileage	low			🗴 Power Windows 📃 Air Bags (Driver) 🛄 Sliding Rear Win
Transmission	Automatic	~		Power Locks Air Bags (Passgr) Running Boards
Engine				Power Mirrors Security System Bed Liner
Drivetrain	- Please Select -	~		🗌 Power Seat (Driver) 🔛 Rear Defroster 🔛 Custom Bumper
Body style	- Please Select -	~		Power Seat (Passgr) Tilt Wheel Grill Guard
Color	- Flease Select			🗌 Antilock Brakes 🔛 Rear Wipers 🛄 Winch
Interlor				🛄 Air Conditioning 📃 Tinted Windows 🛄 Opt. Fuel Tank
The color				
Int material	Cloth Leat	her		
Seating				Towing Package 🔼 Cup Holder
Wheels	Alloy Wheels	~		Utility L Toolbox
Tires	- Please Select -	~		Underbody Hoist 🛄 Trailer Hitch
Roof	- Please Select -	~		🔲 Hydraulic Lift 🛛 🔲 Dual Rear Wheels
Truck bed	- Please Select -	~		Rear Spoiler 🗶 AM/FM
Stereo	- Please Select -	~		Pickup Shell 🗌 CD Player
Dealer code				Tachometer D.A.B
Stock code				Keyless Entry
MSRP				🔲 Digital Clock
NADA				
KBB				
Warranty				
warrancy	- Please Select -			
Common usage of Web Forms

- A user manually fills each form field
 - Text-box, selection list, check-box and radio button
- Tedious, error prone and repetitive process





iForm

Information Extraction + Form Filling



iForm - Scenario



Shutter Island is a 2010 American psychological thriller film directed by Martin Scorsese. The film is based on Dennis Lehane's 2003 novel of the same name . Starring Leonardo DiCaprio, Mark Ruffalo and Ben Kingsley.

Movie Review - Data-rich text

	Web Form Movie D TV Show		
\rightarrow	Title: Director:		
	Actors:		
	Gender		

Web Form

iForm – Selecting plausible segments

▶ Is this text segment a suitable value of a given field of the form?





iForm – Mapping Segments to Fields

- Given the set of text segments such that theirs scores are above a threshold \mathcal{E}
 - iForm aims at finding a *mapping* between candidate values and form fields with a maximum aggregate score
 - Select non-overlaping segments.
- Accomplished by means of a two-phase procedure

iForm – Filling Form-based interfaces

Uses the final mapping to fill out the form fields

Text Boxes: Mapped text segments as a field values.



Check boxes: Set true for mapped fields.



Selection List:



iForm - Overview



Experiments

Dataset	Test Data	Previous Data	# Fields	S - Test Data	S – Previous Data
Jobs	50	100	13	RISE	RISE
Movies	50	10000	4	IMDb	FreeBase / Wikipedia
Cars	50	10000	35	TodaOferta.com	TodaOferta.com
Cellphones	50	10000	37	TodaOferta.com	TodaOferta.com
Books I	50	10000	5	Submarino.com	TodaOferta.com
Books 2	50	10000	4	Submarino.com	Ingenta
Books 3	50	10000	2	Submarino.com	Ourpress.com
Books 4	50	10000	3	Submarino.com	NetLibrary

Baseline

- iCRF a method for interactive form filling based on CRF
- > The Jobs dataset was used for an experimental comparison between iForm and iCRF.

Evaluation – Multi-typed web forms

	Movies			
Type of Field	# Fields	P	R	F
Text Box	4	0.74	0.69	0.71
Submission-Level		0.73	0.67	0.69

Cellphones

Type of Field	# Fields	P	R	F
Text Box	2	0.89	0.69	0.78
Check Box	35	0.94	0.94	0.94
Average		0.94	0.93	0.93
Submission-Level		0.96	0.94	0.95

Filling quality above 0.90. In fact, more than 90% of each submission was correctly entered in the web form interface.

Evaluation – Comparison with iCRF

Jobs

Field	iForm	iCRF
Application	0.82	0.37
Area	0.18	0.23
City	0.70	0.65
Company	0.41	0.17
Country	0.77	0.87
Desired Degree	0.57	0.37
Language	0.84	0.69
Platform	0.47	0.38
Recruiter	0.44	0.22
Req. Degree	0.31	0.59
Salary	0.22	0.25
State	0.85	0.81
Title	0.72	0.49

iForm had superior F-measure levels in nine fields.

The lower quality obtained by iCRF is explained by the fact that segments to be extracted from typical free text inputs, such as jobs postings, may not appear in a regular context.

iForm was designed to conveniently exploit these field-related features from previous submissions

Conclusions

- This work proposes an unsupervised approach to the IETS problem.
 - Relies on information available on pre-existing data.
 - Exploit content-based features to directly learn from test data structure-based features.
 - Show that pre-existing datasets allow for the unsupervised learning of both content-based and structure-based features.
 - Eliminate the need of a user involved in any source specific training process.
- Information Extraction Methods:
 - ONDUX, JUDIE and iForm

Publications

Thesis Core

- Joint Unsupervised Structure Discovery and Information Extraction. SIGMOD Conference – 2011
- Unsupervised Information Extraction with the ONDUX Tool. Brazilian Symposium on Databases (SBBD) – 2011
- On Using Wikipedia to Build Knowledge Bases for Information Extraction by Text Segmentation. Journal of Information and Data Management (JDIM) – 2011
- 4. ONDUX: on-demand unsupervised learning for information extraction. **SIGMOD Conference**. - 2010
- Unsupervised strategies for information extraction by text segmentation. SIGMOD PhD Workshop on innovative Database Research (IDAR) – 2010
- A Probabilistic Approach for Automatically Filling Form-Based Web Interfaces.
 Proceedings of the VLDB Endowment (PVLDB) 2010
- Automatically filling form-based web interfaces with free text inputs. International Conference on World Wide Web (WWW) – 2009

Publications

Related to the Information Extraction Problem

- Building a research social network from individual perspective. Joint Conference on Digital Libraries (JCDL) – 2011
- CiênciaBrasil The Brazilian Portal of Science and Technology. Integrated Seminar of Software and Hardware (Semish) – 2011
- A flexible approach for extracting metadata from bibliographic citations.
 Journal of the American Society for Information Science and Technology (JASIST) – 2009

Publications

Other Publications

- Lightweight methods for large-scale product categorization. Journal of the American Society for Information Science and Technology (JASIST) – 2011
- Adaptive and Fexible blocking for record linkage tasks. Journal of Information and Data Management (JDIM) – 2010
- Blocagem adptativa e flexível para o pareamento aproximado de registros.
 Brazilian Symposium on Databases (SBBD) 2009

Tutorials

- Methods and techniques for information extraction by text segmentation.
 Alberto Mendelzon International Workshop on Foundations of Data Management (AMW) - 2012
- 15. Methods and techniques for information extraction by text segmentation.
 Brazilian Symposium on Databases (SBBD) 2011

Future Work

- Generating transductive methods using domain knowledge
- Use our approach to extract information from HTML
- Query Extraction using our unsupervised approach
- Extraction Improvement Through User Feedback

Acknowledgments











Conselho Nacional de Desenvolvimento Científico e Tecnológico W inweb

Unsupervised Information Extraction by Text Segmentation



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