JOÃO MATEUS DE FREITAS VENEROSO

WEB DATA EXTRACTION IN SEMI-STRUCTURED DOCUMENTS

Dissertation proposal presented to the Graduate Program in Computer Science of the Federal University of Minas Gerais in partial fulfillment of the requirements for the degree of Master in Computer Science.

Advisor: Berthier Ribeiro de Araújo Neto

Belo Horizonte

November 2017

Contents

Chapter 1

Introduction

Web data extraction is the task of automatically extracting structured information from unstructured or semi-structured web documents. It is a subset of the broader field of Information Extraction, and thus it faces many of the same challenges.

Structured information such as that found in a well organized relational database must conform to an underlying data model, namely an abstract model that formalizes the entities and relationships in a given application domain. Unstructured information however is not organized according to a logical model, therefore useful bits of data won't be arranged cohesively and will ocasionally be permeated by chunks of irrelevant information.

Tipically, Information Extraction tasks consist of mapping unstructured or poorly structured data to a semantically well defined structure. The input is usually composed of a set of documents that describe a group of entities in a similar manner, while the Information Extraction task deals with identifying those entities and organizing them according to a template.

As an example, consider a collection of novels and the task of identifying the name of the main character in each novel. For this task, the model must first identify proper nouns and then understand the text sufficiently to allow inference on the relative importance of each noun.

To achieve such a goal it is often useful to employ methods developed in the disciplines of Information Retrieval and Natural Language Processing. The former has achieved a great deal of success in the task of classifying documents according to statistical properties and the latter led to huge improvements in modelling human language. Many times, the various methods employed in these disciplines lead to different approaches in the field of Information Extraction.

In the scope of this work, we are interested in the semi-structured data usu-

ally found in HTML web documents. Web documents most often lie in between the structured-unstructured data paradigm, meaning that they take a rather relaxed approach in regard to formal structure. Hierarchy, element disposition, class names, and other features related to document structure and indirectly associated with the data itself are valuable information in the task of identifying entities and determining relationships. So much that many times they are the major source of information for classification purposes, such as when extracting information from standardized tables. However, far from a structured database, web documents usually provide very limited structure to otherwise unstructured data such as that found in free text.

Take for example the staff page for the intelligent robotics laboratory of Osaka University shown in figure 1. Say we want to extract the name, position, email and picture of all members. It is easy to see there is some sort of structure to the information we want to extract from this particular website, however, parts of the information are missing, repeated or disposed differently for each particular member. If we want to go further it may be necessary to only extract information from full members, a task that may pose a harder challenge. We may use grouping similarity combined with textual information in order to properly identify the desired entities. In many cases the HTML element's relative position or CSS class name is sufficient to identify particular occurrences of a same entity. If we do a good enough job at this first task we may extrapolate our model to extract information from similar web pages. The harder challenge lies in building a more general approach to collect data with a similar underlying structure from many different types of web pages.

Our current focused research interest regarding web data extraction is collecting computer science researcher information from university websites. We need this information in order to compare the reputations of national and international research groups in the area of computer science with the academic reputation ranking metric proposed by Ribas et al. [2015] based on random walks over reputation graphs.

It showed promising results when ranking publication venues and individual authors in the area of Computer Science by using information publically available in the DBLP repository (http://dblp.uni-trier.de/). However the DBLP database has sparse information about author affiliation and multiple records are outdated. To remedy this problem, in the past few years researchers from UFMG have been laboriously collecting this data manually, however this process is tedious and inefficient. Currently, we only have affiliation information for about 1% of the authors, being most of them from USA and Brazil and this is not nearly enough to allow broad international research group comparison.

Up to now, our goal has been to build an automatic information extraction system

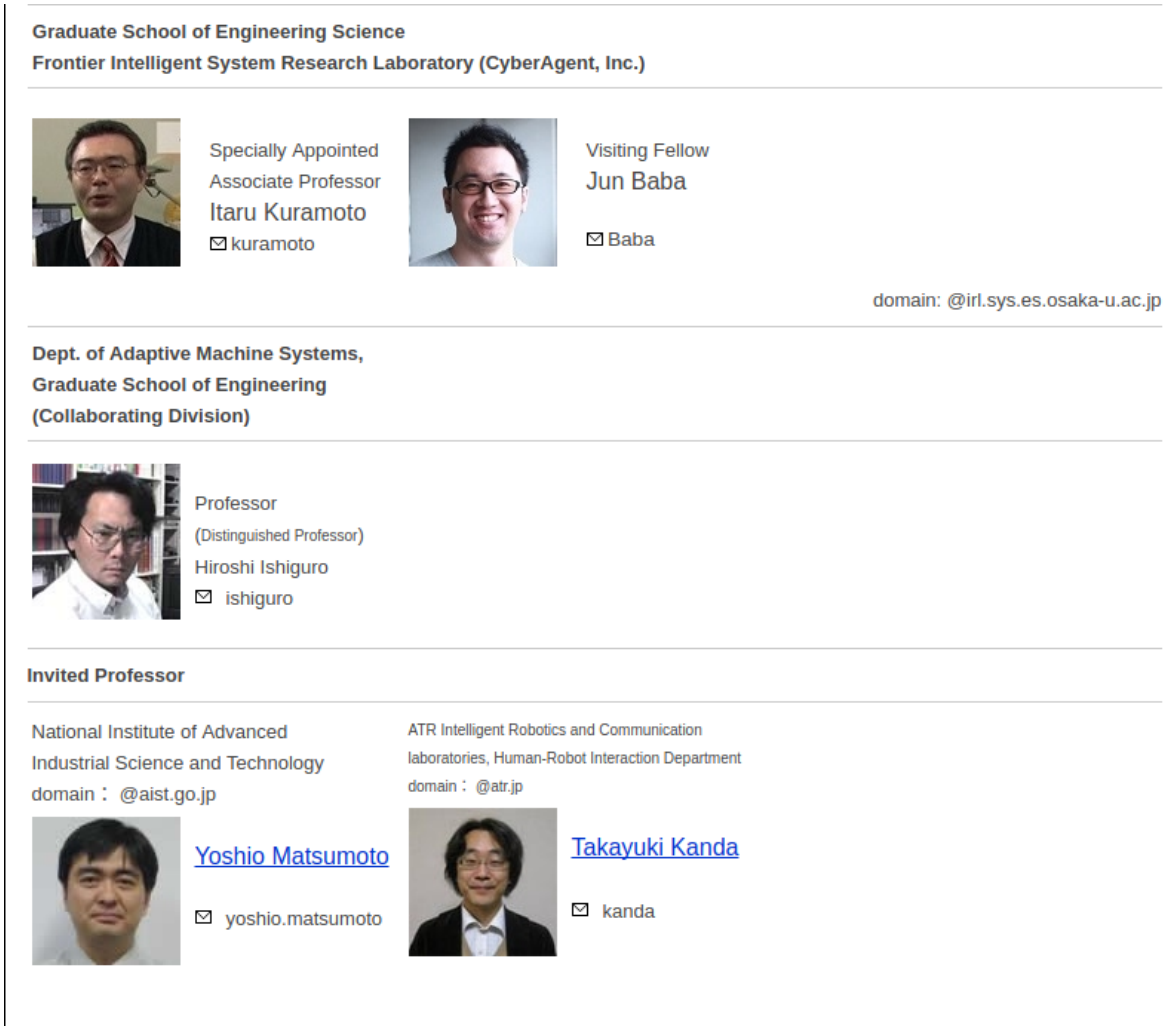

Figure 1.1. Example of semi structured information

for collecting author affiliation information from university websites. It has already achieved significant progress which shall be described further in section 3. However, the ideas developed in this concrete case will be further improved in order to construct a more general approach to the broader Information Extraction task.

The research here described hopes to contribute by proposing a novel approach to the main Information Extraction task, making the computer science affiliation database available for further research and testing the quality of academic reputation metrics regarding research groups.

Chapter 2

Related Work

In the last 20 years, the exponential growth of public information in the web has led to the development of a number of different approaches to the problem of web data extraction. Traditionally, the task was solved by designing special purpose programs called wrappers to pinpoint relevant data and store it in some structured format. The multiple tools varied wildly according to their degree of automation.

It was readily perceived that manual wrapper generation was a rather tedious and error prone process, unsuited for large scale operations. Already in 2000, Kushmerick [2000] advocated for wrapper induction, a technique for automatically constructing wrappers. This approach is known in the literature by the acronym WIEN (Wrapper Induction ENvironment).

Web data extraction techniques often require some sort of assistance from human experts to boost accuracy. So the main challenge in the field lies in determining an adequate tradeoff between degree of automation and precision.

In 2002, a survey by Laender et al. [2002a] made a thorough classification of the early approaches with a taxonomy based on their main technology, being them: languages for wrapper development, HTML-aware tools, NLP-based tools, Wrapper Induction Tools, Modeling-based tools and Ontology-based tools. Some noteworthy examples from this era are:

TSIMMIS Hammer et al. [1997] and WebOQL Arocena and Mendelzon [1999], which are special purpose languages for building wrappers.

Road Runner Crescenzi et al. [2001], XWRAP Liu et al. [2000] and W4F Sahuguet and Azavant [1999], which are HTML-aware tools that infer meaningful patterns from the HTML structure.

RAPIER Califf and Mooney [1999], SRV Freitag [1998], WHISK Soderland [1999], which are NLP-based tools.

WIEN **?**, Soft Mealy Hsu and Dung [1998] and STALKER **?** which are wrapper induction methods.

NoDoSE **?** and Debye Laender et al. [2002b], which are semi supervised modeling based tools that require some interaction with the user by means of a graphical user interface.

In 2004, Flesca et al. [2004] developed a taxonomy emphasizing the advantages and drawbacks of web data extraction technologies according to the user viewpoint. In 2006 Chang et al. [2006] complemented the previous surveys with new technologies.

In 2008 Sarawagi [2008] classifies wrappers in the following three types: record-level, page-level and site-level wrappers. Record-level wrappers are only able to process single records, page-level wrappers are capable of extracting data from a single page, and site-level wrappers are able to process the whole webpage structure including subpages and their linking structure.

More recently, surveys by Ferrara et al. [2014] and Schulz et al. [2016] updated the previous surveys and included new approaches.

In 2016 Varlamov and Turdakov [2016], argued that the degree of automation can no longer be the main classification criterion for the data extraction systems because unsupervised methods which were widely considered to be the state of the art when dealing with individual websites performed poorly or were innapropriate on cross site extraction tasks. The authors proposed a classification of methods by the extent of their application. The competing approaches were separated into two groups: methods for individual websites and methods that are applicable to whole application domains.

The first group contains most of the earlier approaches, including the supervised approaches: SRV Freitag [1998], RAPIER Califf and Mooney [1999], WHISK Soderland [1999], WIEN **?** SoftMealy Hsu and Dung [1998] and STALKER **?**; and the unsupervised approaches: RoadRunner Crescenzi et al. [2001] and EXALG Arasu et al. [2003].

The second group is divided between domain specific methods and domain agnostic methods. Domain specific methods are designed for extracting data about a particular application domain across multiple websites. Our researcher name extractor method that will be further described in section 3 falls in this category. Domain specific methods integrate information about the particular application domain in the course of its development and thus are able to achieve superior performance in comparison to domain agnostic methods.

Domain agnostic methods are the most general extraction methods. They can extract information from any application domain from multiple websites. They pose the hardest challenge because the tool must infer data relevance without any prior

training in thar particular application domain. Some examples are: ODE Su and Lochvsky [2009], ObjectRunner Abdessalem et al. [2010], and AMBER Furche et al. [2012].

Our method is finely tuned for the researcher name extraction task, however it is our intent to create a more general agnostic method based on statistical properties in future research.

Chapter 3

Methodology

Methodology here.

Chapter 4

Schedule

Schedule here.

Bibliography

Abdessalem, T., Cautis, B., and Derouiche, N. (2010). ObjectRunner: lightweight, targeted extraction and querying of structured web data. *Proceedings of the VLDB ...*, 3(2):1585--1588. ISSN 21508097.

Arasu, A., Garcia-Molina, H., Arasu, A., and Garcia-Molina, H. (2003). Extracting structured data from Web pages. *2003 ACM SIGMOD International Conference on Management of Data*, pages 337 -- 348.

Arocena, G. O. and Mendelzon, A. O. (1999). WebOQL: Restructuring documents, databases, and webs. *Theory and Practice of Object Systems*, 5(3):127--141. ISSN 10743227.

Califf, M. E. and Mooney, R. J. (1999). Relational learning of pattern-match rules for information extraction. *Computational Linguistics*, 4:9--15. ISSN 15324435.

Chang, C.-H., Kayed, M., Girgis, M. R., and Shaalan, K. F. (2006). A Survey of Web Information Extraction Systems. *IEEE Transactions on Knowledge and Data Engineering*, 18(10):1411--1428. ISSN 1041-4347.

Crescenzi, V., Mecca, G., and Merialdo, P. (2001). Roadrunner: Towards automatic data extraction from large web sites. *Proceedings of the 27th International Conference on Very Large Data Bases*, pages 109--118. ISSN 10477349.

Doan, A., Naughton, J. F., Ramakrishnan, R., Baid, A., Chai, X., Chen, F., Chen, T., Chu, E., Derose, P., Gao, B., Gokhale, C., Huang, J., Shen, W., and Vuong, B.-q. (2008). Information Extraction Challenges in Managing Unstructured Data. *ACM SIGMOD Record*, 37(4):14--20. ISSN 0163-5808.

Ferrara, E., De Meo, P., Fiumara, G., and Baumgartner, R. (2014). Web data extraction, applications and techniques: A survey. *Knowledge-Based Systems*, 70:301--323. ISSN 09507051.

Figueiredo, L. N. L., de Assis, G. T., and Ferreira, A. A. (2017). DERIN: A data extraction method based on rendering information and n-gram. *Information Processing & Management*, 53(5):1120--1138. ISSN 03064573.

Fiumara, G. (2007). Automated information extraction from Web sources: A survey. *CEUR Workshop Proceedings*, 312:1--9. ISSN 16130073.

Flesca, S., Manco, G., Masciari, E., Rende, E., and Tagarelli, A. (2004). Web wrapper induction: a brief survey. *AI Communications*, 17(2):57--61. ISSN 0921-7126.

Freitag, D. (1998). Information Extraction from HTML: Application of a General Machine Learning Approach. *Proceedings of the Fifteenth National/Tenth Conference on Artificial Intelligence/Innovative Applications of Artificial Intelligence*, pages 517--523.

Furche, T., Gottlob, G., Grasso, G., Orsi, G., Schallhart, C., and Wang, C. (2012). AMBER: Automatic Supervision for Multi-Attribute Extraction. *arXiv preprint*, 1210(5984):1--22.

Garfield, E. (1955). Citation Indexes for Science. *Science*, 122:108--111.

Hammer, J., Mchugh, J., and Garcia-molina, H. (1997). Semistructured Data : The TSIMMIS Experience. *Proceedings of the First East-European Symposium on Advances in Databases and Information Systems*, pages 1--8.

Hsu, C. N. and Dung, M. T. (1998). Generating finite-state transducers for semi-structured data extraction from the Web. *Information Systems*, 23(8):521--538. ISSN 03064379.

Kaiser, K. and Miksch, S. (2005). Information Extraction. *Technology*, (May):32.

Kao, H.-A. and Chen, H.-H. (2010). Comment Extraction from Blog Posts and Its Applications to Opinion Mining. *Proceedings of the 7th International Conference on Language Resources and Evaluation*, pages 1113--1120.

Khalil, S. and Fakir, M. (2017). RCrawler: An R package for parallel web crawling and scraping. *SoftwareX*, 6:98--106. ISSN 23527110.

Kushmerick, N. (2000). Wrapper induction: efficiency and expressiveness. *Artificial Intelligence*, 118(1-2):15--68. ISSN 00043702.

Kushmerick, N. and Kushmerick, N. (2003). Finite-state approaches to Web information extraction. *Lecture Notes in Computer Science*, 2700:77--91. ISSN 03029743.

Kushmerick, N., Weld, D. S., and Doorenbos, R. (1997). Wrapper induction for information extraction. *Intl Joint Conference on Artificial Intelligence IJCAI*, pages 729--737.

Laender, A., Ribeiro-Neto, B. A., and S.Teixeria, J. (2002a). A brief survey of web data extraction tools. *ACM SIGMOD Record 31(2)*, pages 84--93.

Laender, A. H. F., Ribeiro-Neto, B., and da Silva, A. S. (2002b). DEByE - Date extraction by example. *Data Knowl. Eng.*, 40(2):121--154. ISSN 0169-023X.

Liu, L., Pu, C., and Han, W. (2000). XWRAP: an XML-enabled wrapper construction system for Web information sources. *Proceedings of 16th International Conference on Data Engineering*, pages 611--621. ISSN 1063-6382.

Ribas, S., Ribeiro-Neto, B., Santos, R., Souza e Silva, E., Ueda, A., and Ziviani, N. (2015). *Random Walks on the Reputation Graph*. ACM Press, New York, New York, USA. ISBN 9781450338332.

Sahuguet, A. and Azavant, F. (1999). Building light-weight wrappers for legacy Web data-sources using W4F. *Proceedings of the 25th VLDB Conference*, 99:738--741.

Sarawagi, S. (2008). Information extraction. *Foundations and Trends in Databases*, 1(3):261--377. ISSN 1931-7883.

Schulz, A., Lässig, J., and Gaedke, M. (2016). Practical web data extraction: Are we there yet? — A short survey. *IEEE/WIC/ACM International Conference on Web Intelligence (WI), 2016*, pages 562----567.

Soderland, S. (1999). Learning Information Extraction Rules for Semi-Structured and Free Text. *Machine Learning*, 34(1):233--272. ISSN 0885-6125.

Su, W. and Lochvsky, F. H. (2009). ODE : Ontology-assisted Data Extraction. 1(212).

Varlamov, M. I. and Turdakov, D. Y. (2016). A survey of methods for the extraction of information from Web resources. *Programming and Computer Software*, 42(5):279--291. ISSN 0361-7688.

Zhai, Y. and Liu, B. (2005). Web data extraction based on partial tree alignment. *Proceedings of the 14th international conference on World Wide Web - WWW '05*, page 76. ISSN 10414347.