Towards End-to-End Transformation of Arbitrary Tables from Untagged Portable Documents (PDF) to Linked Data

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Abstract. The paper is devoted to the problem of an end-to-end table transformation from untagged portable documents (PDF) to linked data. It covers the issues of the table extraction from documents, the reconstruction of logical table structure, the conceptualization of their natural-language content, and the linking of extracted data with external vocabularies. We consider some perspective approaches for the deep-learning-based table detection, heuristic-based table structure recognition, rule-based table analysis, and knowledge-based table interpretation. They can be used as a basis to develop a consistent solution for this problem. Our application experience confirms that such solutions are demanded for populating databases and generating ontologies with tabular data being extracted from weakly and semi-structured documents.

Keywords: Data transformation · Document analysis · Table extraction · Table analysis · Table interpretation · Linked data.

1 Introduction

PDF[3] (Portable Document Format) is a very popular way to represent non-editable documents. Many of PDF documents are machine-readable but remain untagged (i.e. there are no tags for identifying layout items such as paragraphs, columns, or tables). Such documents often contain tables with arbitrary layout (e.g. cross-tabulations, invoices, and data sets). These tables can be a valuable source in various applications of the text and data analysis. However, difficulties that inevitably arise with the extraction and integration of the tabular data presented in untagged PDF documents often hinder the intensive use of them in practice.

[3] https://www.iso.org/standard/63534.html

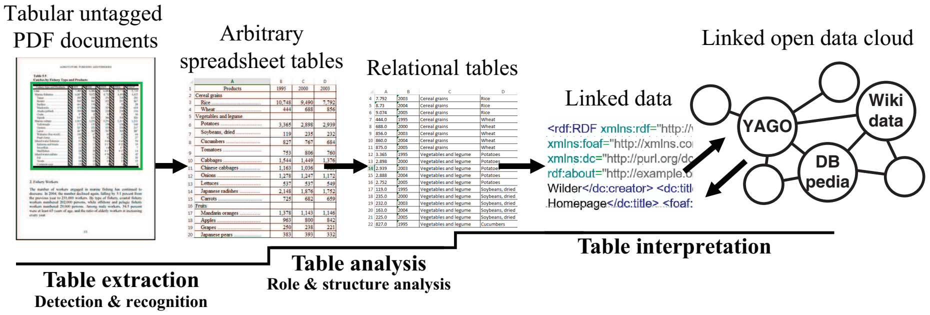

Tabular untagged PDF documents
Arbitrary spreadsheet tables
Relational tables
Linked data
Linked open data cloud
<rdf:RDF xmlns:rdf="http://
xmlns:foaf="http://xmlns.co
xmlns:dc="http://purl.org/dc
rdf:about="http://example.
Wilder</dc:creator> <dc:titl
Homepage</dc:title> <foaf:
YAGO
Wiki data
DB pedia
Table extraction
Detection & recognition
Table analysis
Role & structure analysis
Table interpretation

Fig. 1. The tasks for converting tabular data from untagged PDF documents to linked data.

The untagged PDF documents do not provide any metadata for describing table location and cell positions, as well as functional roles, internal and external relationships of data items. In other words, there is no explicit semantics that is needed for the interpretation of tabular data presented in such documents by third-party software applications. The generic approach to make the tabular data interpretable is to extract them from the documents and represent them as *linked data*. The transformation of the tabular data requires recovering the metadata missed in original documents and linking the extracted data with external vocabularies. This process can be considered as a chain of tasks as shown in Fig. 1 where each step enriches the tabular data with explicit semantics.

We present some perspective approaches to the development of a consistent solution to the end-to-end table transformation from weakly and semi-structured documents to linked data. They cover deep-learning-based table detection (identifying positions and content of tables), heuristic-based table structure recognition (identifying positions and content of cells), rule-based table analysis (recovering functional data items and their relationships), and knowledge-based table interpretation (linking recovered data items with external vocabularies). Our application experience confirms that such solutions are demanded for populating databases and generating ontologies with tabular data being extracted from weakly and semi-structured documents.

2 Table Extraction

The first task (*table extraction*) aims at extracting tables from a document and representing them in a spreadsheet-like format. This task consists of two consecutive sub-tasks: *table detection* and *table structure recognition*. The *table detection* extracts positions of a table in a document, i.e. either geometric positions of a bounding box of the table or a set of all text chunks placed inside this bounding box. The *table structure recognition* recovers positions and content of cells in a table. A detected table should be separated into cells addressed by rows and columns. The recovered cells of the extracted table can be represented as arbitrary tables in a spreadsheet format (e.g. Excel).

Many table extraction methods are traditionally heuristics-based [62, 40, 43, 42]. Some of them combine heuristics and machine-learning approaches [4, 22, 41]. The current trend involves deep learning techniques: binary classification based on convolutional neural networks [29], fine-tuned object detection models [47, 26, 2, 58], and semantic segmentation [30, 33]. Some of the existing methods show a high accuracy on the competition datasets (UNLV[48], Marmot[4], ICDAR 2013 [27], and ICDAR 2017 [25]). However, the complexity of a document layout often prevents the applicability of these methods in practice. For example, a long table placed on several consecutive pages cannot be extracted by these techniques as a whole object. We believe that the research of issues of the table extraction is far from being completed.

We propose to combine deep learning and heuristic-based techniques to develop a comprehensive solution for this task. As contemporary works [47, 26, 2, 58] show the deep neural network models provide a good performance for the table detection. The generic approach to develop such models is based on fine-tuning pre-trained models for object detection on images. We adopted this approach to create and use own model for the table detection.

To examine this approach we utilized the well-known architecture "Faster R-CNN" [44] with the pre-trained convolutional neural network model (ResNet-101) for the feature extraction. It also used the distance transformation described in [26] for pre-processing images. The regional-proposal network model was trained on three existing datasets of documents (UNLV, Marmot, and ICDAR 2017) containing 2800 samples. Additionally, the training data were augmented by affine transformations that allowed us to improve the accuracy of table detection by 5%. The performance evaluation of the developed model showed a high recall (0.979) and precision (0.865) on the ICDAR 2013 competition dataset [27]. It should be noted that the verification of the obtained predictions can decrease false positives and improves precision.

At the stage of the cell structure recognition, we propose to use our heuristic-based bottom-up method [55, 54]. Its main idea consists in building text blocks from words placed inside the bounding box of a detected table. Each text block is a whole textual content of one cell in this table. Our method exploits a set of customizable ad-hoc heuristics for table detection and cell structure reconstruction based on features of text and ruling lines presented in PDF documents, including the following: horizontal and vertical distances, fonts, the order of appearance of text printing instructions in PDF files and positions of the drawing cursor. Additionally, ad-hoc heuristics can be handcrafted and tuned for various domain-specific PDF documents. The table is subdivided into rows and columns, using the analysis of connected components (text blocks). The proposed method reaches a high recall (0.923) and precision (0.950) on the ICDAR 2013 competition dataset [27].

[4] http://www.icst.pku.edu.cn/cpdp/sjzy/index.htm

3 Table Analysis

The second task (*table analysis*) is to transform a spreadsheet table from an arbitrary to a relational form. This task relies on recovering metadata on the logical structure and content of an arbitrary table, i.e. data items presented in cells, including their functional roles and internal relationships. The recovered semantics enables representing extracted data as relational tables in a spreadsheet-like format (e.g. CSV). In this form, each column of a relational table matches to a category. However, the columns typically remain anonymous, i.e. there is no description of the presented categories. The categories (concepts describing extracted data items) often need to be found out for the purposes of data analysis.

There are several recent studies dealing with the issues of the spreadsheet data extraction and transformation, including the following: layout features [35, 11, 16], "code smells" and formulas [31, 15, 5, 34], programming by examples [6, 59, 32], data models [1, 12, 13], linked open data [45, 71], domain-specific [64, 9, 60] and rule-based architectures [57, 67, 68]. Typically, the related solutions (e.g. [17, 19, 10]) rely on a predefined table structure. They support only a few widespread layout types of tables with typical functional cell regions. This limits their applicability for specific cases.

Our approach consists in using rules for table analysis [53]. The rules map explicit features (layout, style, and text of cells) of an arbitrary table to its implicit semantic relationships (linked functional data items such as entries, labels, and categories). The approach expects that one ruleset provides functional and structural analysis for tables with the same features. Such rulesets can be executed by a rule engine [53, 57] or be translated to executable programs in a general-purpose language [50, 51].

For implementation of our approach, we develop own domain-specific language of table analysis and interpretation rules, CRL [52, 56, 57]. This language determines queries (conditions) and operations (actions) that are necessary to develop programs for spreadsheet data transformation from an arbitrary to relational form. CRL rules expressed as productions map the physical structure of cells to the logical structure of data items. In comparison with general-purpose rule languages (such as Drools[5], Jess[6], RuleML[7]), our language enables expressing rulesets without any instructions for management of the working memory (such as updates of modified facts, or blocks on the rule re-activation). This provides syntactically simplifying declaration of the right-side hand of CRL rules. CRL allows end-users to focus more on the logic of table analysis and interpretation than on the logic of the rule management and execution.

The interpreter of CRL rules provides translating CRL rulesets (declarative programs) to Java source code (imperative programs) [50, 51]. The generated source code is ready for compilation and building of executable programs for domain-specific spreadsheet data extraction and transformation. The novelty of

[5] https://www.drools.org
[6] https://www.jessrules.com
[7] http://ruleml.org

the software platform consist in providing two rule-based ways to implement workflows of spreadsheet data extraction and transformation. In the first case, a ruleset for table analysis and interpretation is expressed in a general-purpose rule language and executed by a JSR-94[8] compatible rule engine. In the second case, our interpreter translates a ruleset expressed in CRL to Java source code that is compiled and executed by using Java platform.

The existing solutions with similar goals (e.g. [17, 19, 10]) typically use predefined table models embedded into their internal algorithms. Unlike them, we define a general-purpose table model that does not restrict layout types. Instead of a generic approach when functions (roles) are associated with cells, in our model functions are determined for data items (entries and labels) originated from cells. The model supports a table layout where one cell contains two or more data items. This allows expressing user-defined layout, style, and text features of arbitrary tables in external rules to support both widespread and specific table types.

4 Table Interpretation

The third task (*table interpretation*) serves to link the extracted tabular data to external vocabularies. Each column and each data item of a relational table should be associated with a concept (class, object, or property) of a general-purpose or domain-specific ontology (Fig. 4). The linked open data (LOD[9]) cloud, including global taxonomies (e.g. DBpedia[10], Wikidata[11], or YAGO[12]) can be utilized as external vocabularies for these purposes. The tabular data enriched by links to external vocabularies are represented in RDF/OWL (Resource Description Framework[13] / Web Ontology Language[14]) formats. The integration of the extracted data with the LOD cloud simplifies the implementation of their further analysis.

The methods intended for the issues of the table interpretation are mainly knowledge-based. They try to bind text in tables with some external concepts, using the following techniques: extraction ontologies [20], data frames [61], knowledge (classes and relations) automatically collected from the Web [63], natural language processing, including the named entity linking [7, 66, 71] and the word embedding [18], as well as various general-purpose ontologies of Linked Open Data [36, 39, 49, 14, 37, 46, 45] or proprietary global taxonomy, ProBase [65]. There are also several studies that propose to use contextual information that surrounds tables [8, 28, 70, 69]. The issues of converting data presented in

[8] https://www.jcp.org/ja/jsr

[9] https://lod-cloud.net

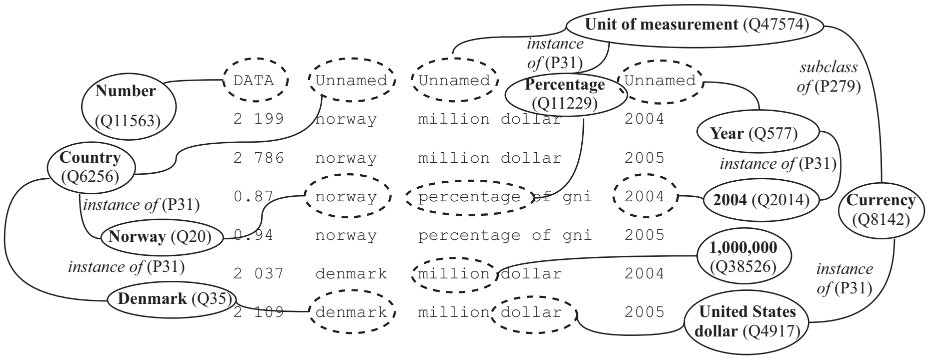
[10] https://wiki.dbpedia.org

[11] https://www.wikidata.org

[12] https://www.mpi-inf.mpg.de/departments/databases-and-information-systems/research/yago-naga/yago

[13] https://www.w3.org/RDF

[14] https://www.w3.org/OWL



DATA	Unnamed	Unnamed	Unnamed
2 199	norway	million dollar	2004
2 786	norway	million dollar	2005
0.87	norway	percentage of gni	2004
0.94	norway	percentage of gni	2005
2 037	denmark	million dollar	2004
2 109	denmark	million dollar	2005

Fig. 2. A fragment of a table being annotated by using Wikidata's items and properties.

spreadsheets or web tables to RDF/OWL formats are considered in the papers [3, 38, 23, 24, 21].

We suggest an approach to the semantic table interpretation based on combining natural language processing techniques and external vocabularies. First of all, the extracted data items should be separated into two types: numeric and non-numeric via named entity recognition. Then non-numeric data items are linked with concepts (classes, objects, and properties) of an external vocabulary by using the semantic similarity.

To examine this approach we used DBpedia but it can be extended by other vocabularies in future. Our implementation of the approach supports the following functionality: (i) tabular data cleansing and formatting in accordance with DBpedia naming conventions; (ii) creating queries to DBpedia in SPARQL language; (iii) and linking extracted data items of a table with DBpedia classes, objects, and properties.

We developed a prototype of the software tool for generating linked data in RDF/OWL formats from extracted tabular data. It is designed to be a part of an end-to-end process of the table understanding implemented by our software platform. In this environment, it can be applied for the semantic interpretation of tables with an arbitrary layout.

5 Conclusions

The presented approaches can draw up the basis to design the methodology and software for creating systems of data extraction from arbitrary tables contained in weakly structured (e.g. PDF) and semi-structured documents (e.g. spreadsheets). The approaches correspond to the state-of-the-art level studies in the area of information extraction. They rely on the modern techniques of the deep-learning, rule-based and generative programming, linked open data, and table understanding.

Our approach to the table extraction can be quickly adapted to various domain-specific PDF documents (such as financial statements, business credit assessments, material safety data sheets, etc.) with a rich tabular content. Additional ad-hoc heuristics can be handcrafted and tuned for the target domain. This does not require to prepare training datasets that can be a costly process.

The proposed approach to the table analysis involves the rule and generative programming. It includes a principally novel formal language for table analysis and interpretation that should provide expressing table transformation rules. The main advantage of our approach to the semantic table interpretation is that it can be applied for tables with an arbitrary layout. In comparison to our competitors, we support not only widespread layout types of arbitrary tables, but also specific ones.

We expect that the explained principles can be used for designing the software for end-to-end tabular transformation in scientific and industrial data-intensive applications. Particularly, we used them to develop the software for filling up a data warehouse with socio-economic data on Mongolian provinces, for populating the database of the web-based statistical atlas from tabular data of government statistical reports, and for generating ontologies from data of arbitrary tables used in industrial safety inspection.

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