TableLab: An Interactive Table Extraction System with Adaptive Deep Learning

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Table extraction from PDF and image documents is a ubiquitous task in the real-world. Perfect extraction quality is difficult to achieve with one single out-of-box model due to (1) the wide variety of table styles, (2) the lack of training data representing this variety and (3) the inherent ambiguity and subjectivity of table definitions between end-users. Meanwhile, building customized models from scratch can be difficult due to the expensive nature of annotating table data. We attempt to solve these challenges with TableLab by providing a system where users and models seamlessly work together to quickly customize high-quality extraction models with a few labelled examples for the user’s document collection, which contains pages with tables. Given an input document collection, TableLab first detects tables with similar structures (templates) by clustering embeddings from the extraction model. Document collections often contain tables created with a limited set of templates or similar structures. It then selects a few representative table examples already extracted with a pre-trained base deep learning model. Via an easy-to-use user interface, users provide feedback to these selections without necessarily having to identify every single error. TableLab then applies such feedback to finetune the pre-trained model and returns the results of the finetuned model back to the user. The user can choose to repeat this process iteratively until obtaining a customized model with satisfactory performance.

CCS Concepts: • Human-centered computing → User interface design.

Additional Key Words and Phrases: Table extraction, neural networks, Label correction

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1 INTRODUCTION
1.1 Challenges TableLab Addresses

Recently, there has been increasing interest in extracting complex structures such as tables from PDF and image documents [1]. Table extraction involves identifying the border and the cell structure for each document table such that it can be displayed in a structured format like HTML. The motivation for TableLab came from requests from industry professionals for the ability to easily create ground truth data and customize models for extracting tables for their specific document collections. TableLab accomplishes this by addressing the following table extraction challenges.

First, there is great diversity of table formatting across different documents types and sources. Tables from invoices are formatted differently than those from scientific articles or financial reports, with the visual clues across sources providing conflicting information about the table border and/or structure. Thus, creation of a single high-quality model to support table extraction from the wide diversity of document types is difficult if not impossible when considering
the fact that even humans can disagree about table definitions from the same source document (see Figure 1). Despite the diversity of table formats encountered in real-world settings, the user’s needs and table extraction expectations are ultimately the most important. TableLab leverages this observation by supporting finetuning of a high-quality table extraction model trained on hundreds of thousands of tables using a small number of user labelled examples.

TableLab also supports efficient labelling of tables in documents, which involves two sub-problems. First, how do we select the most useful examples for labelling which improve finetuned model accuracy the most? Second, how do we effectively label individual example tables, particularly table structure where the same error repeatedly occurs? The mechanisms TableLab uses to improve labeller efficiency are described in the overview section.

Fig. 1. Example document with ambiguous tables. Whether the main invoice table should be one or two tables will depend on downstream tasks for the user.

1.2 Related Works

Many deep-learning solutions have been applied to the table extraction problem in recent years. Examples for table and cell region detection include [2, 4, 6] while [4–7, 9] address table structure extraction. However, none of these solutions are able to extract tables exactly for all documents from all domains due to the wide variety and ambiguity of the problem (See Figure 1 for an example) [1, 3]. Additionally, labelled data is tedious to create. There are a few existing large-scale datasets for scientific papers [9] and financial reports [8] but many documents in business are confidential.

Research into ease of labelling and active learning for tables is not as well studied as table structure extraction. Hoffswell et al. [3] design a system to help users repair extracted tables with a mobile interface. However, users are unable to directly improve the extraction model with their annotations.

1.3 TableLab Design Considerations

Current table extraction systems extract tables without the option to give feedback. Since the systems do not work well on all document types, users can be frustrated by the lower quality of extractions without the ability to improve them. Our system finetunes models in an iterative fashion, collaborating with the model to quickly label and see improvements with the model. In our system, we first use deep learning models to extract table and cells to generate table structure. Using visual embeddings derived from the model, we cluster documents into templates in order to recommend specific pages to label for users that balances between ease of labelling and the most impact on the model with a large variety of styles. Thanks to this recommendation system, we minimize the size of labeled data required. As well, since our table extraction model is modular in nature, some labels for components (ex. table border) can immediately improve results in others (cell border) such that the user does not need to repair every error in the table extraction process.
2 OVERVIEW OF TABLELAB

2.1 Table Extraction

To begin, we apply our table extraction module (based on the GTE framework [8]) to the user’s document collection. We provide a few base model weights that have been pre-trained on different document types for users to select the one that best matches their collection. After the deep models have been applied, we input the resulting table and cell bounding boxes as well as the document text snippets (scanned and image documents are first processed with an OCR engine in order to extract the text) into our structure clustering model. This model determines the row and column assignment and the content of each cell such that it can be represented by a structured format such as HTML.

2.2 Template Clustering and Label Selection

After the deep learning models have been applied to the collection, the visual embeddings from the detection models are used to cluster the document collection into templates. After clustering, the lowest and highest confidence pages of each template is selected for user labelling. The labels for lowest confidence pages will provide the most benefit to the model while the highest confidence pages should be easy and quick to label, allowing for faster feedback. An icon for each label recommendation type is indicated beside each page in the user interface.

2.3 Interactive Labelling with Recommendations

When the initial table structure has been extracted and label recommendations determined, the user will be able to view the extracted tables and provide feedback as needed. In a typical case, the user can first adjust the table border. This prompts the system to redo the structure clustering, providing an updated extracted table. Sometimes, this results in a completely correct extraction and the user may submit the page for finetuning at this time. Otherwise, the user has full control to merge, split cells or whole columns and rows similar to manipulations in a spreadsheet program.
leveraging the layout of the text snippet positions, users can split and move cell content by text chunks rather than word by word. The user may also edit a text snippet by typing in the content and adjusting its bounding box.

2.4 Model Finetuning

When the page has the correct table extraction, the user may submit the page for model finetuning and apply the customized model to their collection for improved extraction results. If there are additional errors, the user may make additional corrections and repeat the finetuning process. For a typical collection, we find that one finetuning round is generally enough to correct the rest of the collection but this depends largely on the diversity of the collection itself.

2.5 Technical Details

TableLab is developed in React and Flask while the model (GTE) is developed with TensorFlow. The models preloaded in the demonstration were trained on PubLayNet and PubTabNet, which are large datasets from the scientific papers domain. The documents shown for detection and correction labelling are from FinTabNet, which are tables from annual reports of S&P 500 companies. We demonstrate TableLab’s ability to customize models on this new domain with tables that have different styles.

3 CONCRETE DEMO EXPERIENCES

There are three main use cases with our demo. First, users can simply visualize table extraction results with TableLab. Second, AI engineers and scientists can use our tool to quickly create ground truth labels for their documents. Finally, end users can create custom models with their private document collection with our interactive TableLab system.
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