DocBank: A Benchmark Dataset for Document Layout Analysis

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Abstract

Document layout analysis usually relies on computer vision models to understand documents while ignoring textual information that is vital to capture. Meanwhile, high quality labeled datasets with both visual and textual information are still insufficient. In this paper, we present DocBank, a benchmark dataset with fine-grained token-level annotations for document layout analysis. DocBank is constructed using a simple yet effective way with weak supervision from the LaTeX documents available on the arXiv.com. With DocBank, models from different modalities can be compared fairly and multi-modal approaches will be further investigated and boost the performance of document layout analysis. We build several strong baselines and manually split train/dev/test sets for evaluation. Experiment results show that models trained on DocBank accurately recognize the layout information for a variety of documents. The DocBank dataset will be publicly available at https://github.com/doc-analysis/DocBank.

1 Introduction

Document layout analysis is an important task in many document understanding applications as it can transform semi-structured information into a structured representation, meanwhile extracting key information from the documents. It is a challenging problem due to the varying layouts and formats of the documents. Existing techniques have been proposed based on conventional rule-based or machine learning methods, where most of them fail to generalize well because they rely on hand crafted features that may be not robust to layout variations. Recently, the rapid development of deep learning in computer vision has significantly boosted the data-driven image-based approaches for document layout analysis. Although these approaches have been widely adopted and made significant progress, they usually leverage visual features while neglecting textual features from the documents. Therefore, it is inevitable to explore how to leverage the visual and textual information in a unified way for document layout analysis.

Nowadays, the state-of-the-art computer vision and NLP models are often built upon the pre-trained models (Peters et al., 2018; Radford et al., 2018; Devlin et al., 2018; Lample and Conneau, 2019; Yang et al., 2019; Dong et al., 2019; Raffel et al., 2019; Xu et al., 2019) followed by fine-tuning on specific downstream tasks, which achieves very promising results. However, pre-trained models not only require large-scale unlabeled data for self-supervised learning, but also need high quality labeled data for task-specific fine-tuning to achieve good performance. For document layout analysis tasks, there have been some image-based document layout datasets, while most of them are built for computer vision approaches and they are difficult to apply to NLP methods. In addition, image-based datasets mainly include the page images and the bounding boxes of large semantic structures, which are not fine-grained token-level annotations. Moreover, it is also time-consuming and labor-intensive to produce human-labeled and fine-grained token-level text block arrangement. Therefore, it is vital to leverage weak supervision to obtain fine-grained labeled documents with minimum efforts, meanwhile making the data be easily applied to any NLP and computer vision approaches.

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To this end, we build the DocBank dataset, a document-level benchmark with fine-grained token-level annotations for layout analysis. Distinct from the conventional human-labeled datasets, our approach obtains high quality annotations in a simple yet effective way with weak supervision. Inspired by existing document layout annotations (Siegel et al., 2018; Li et al., 2019; Zhong et al., 2019), there are a great number of digital-born documents such as the PDFs of research papers that are compiled by \LaTeX{} using their source code. The \LaTeX{} system contains the explicit semantic structure information using mark-up tags as the building blocks, such as title, author, abstract, paragraph, caption, equation, footnote, list, section, table, figure and reference. To distinguish individual semantic structures, we manipulate the source code to specify different colors to the text of different semantic units. In this way, different text zones can be clearly segmented and identified as separate logical roles, which is shown in Figure 1. The advantage of DocBank is that, it can be used in any sequence labeling models from the NLP perspective. Meanwhile, DocBank can also be easily converted into image-based annotations to support object detection models in computer vision. In this way, models from different modalities can be compared fairly using DocBank, and multi-modal approaches will be further investigated and boost the performance of document layout analysis. To verify the effectiveness of DocBank, we conduct experiments using two baseline models: 1) BERT (Devlin et al., 2018), a pre-trained model using only textual information based on the Transformer architecture. 2) LayoutLM (Xu et al., 2019), a multi-modal architecture that integrates both the text information and layout information. The experiment results show that the LayoutLM model significantly outperforms the BERT model on DocBank for document layout analysis. We hope DocBank will empower more document layout analysis models, meanwhile fosters more customized network structures to make substantial advances in this area.

The contributions of this paper are summarized as follows:

- We present DocBank, a large-scale dataset that is constructed using a weak supervision approach. It enables models to integrate both the textual and layout information for downstream tasks.
- We conduct a set of experiments with different baseline models and parameter settings, which confirms the effectiveness of DocBank for document layout analysis.
- DocBank will be publicly available at https://github.com/doc-analysis/DocBank

2 Task Definition

The document layout analysis task is to extract the pre-defined semantic units in visually rich documents. Specifically, given a document \( D \) composed of discrete token set \( t = \{t_0, t_1, ..., t_n\} \), each token \( t_i = (w, (x_0, y_0, x_1, y_1)) \) consists of word \( w \) and its bounding box \( (x_0, y_0, x_1, y_1) \). And \( C = \{c_0, c_1, ..., c_m\} \)
defines the semantic categories that the tokens are classified into. We intend to find a function $F : (C, D) \to S$, where $S$ is the prediction set:

$$S = \{ \{t_0^0, ..., t_0^n\}, c_0\}, ..., \{\{t_k^0, ..., t_k^n\}, c_k\} \} \right)$$

(1)

3 DocBank

We build DocBank with token-level annotations that supports both NLP and computer vision models. As shown in Figure 2, the construction of DocBank has four steps: Document Acquisition, Semantic Structures Detection, Token Annotation and Post-processing. The current DocBank dataset totally includes 5,253 documents, where the training set includes 5,053 documents and both the validation set and the test set include 100 documents. As this work is still in progress, DocBank will be further enlarged in the next version very soon.

3.1 Document Acquisition

We download the PDF files on arXiv.com as well as the LaTeX source files since we need to modify the source code to detect the semantic structures. The papers contain Physics, Mathematics, Computer Science and many other areas, which is beneficial for the diversity of DocBank to produce robust models. We focus on English documents in this work and will expand to other languages in the future.

3.2 Semantic Structures Detection

DocBank is a natural extension of the TableBank dataset (Li et al., 2019), where other semantic units are also included for document layout analysis. In this work, the following semantic structures are annotated in DocBank: {Title, Author, Abstract, Paragraph, Caption, Equation, Footnote, List, Section, Table, Figure and Reference}. In TableBank, the tables are labeled with the help of the ‘fcolorbox’ command. However, for DocBank, the target structures are mainly composed of text, where the ‘fcolorbox’ cannot be well applied. Therefore, we use the ‘color’ command to distinguish these semantic structures by changing their font colors into structure-specific colors. Basically, there are two types of commands to represent semantic structures. Some of the LaTeX commands are simple words preceded by a backslash. For instance, the section titles in LaTeX documents are usually in the format as follows:

```latex
\textbf{section} {The title of this section}
```

Other commands often start an environment. For instance, the list declaration in LaTeX documents is shown as follows:

```latex
\begin{itemize}
  \item First item
  \item Second item
\end{itemize}
```

The command `\begin{itemize}` starts an environment while the command `\end{itemize}` ends that environment. The real command name is declared as the parameters of the ‘begin’ command and the ‘end’ command.

We insert the ‘color’ command to the code of the semantic structures as follows and re-compile the LaTeX documents. Meanwhile, we also define specific colors for all the semantic structures to make them distinguishable. Different structure commands require the ‘color’ command to be placed in different locations to take effect. Finally, we get updated PDF pages from LaTeX documents, where the font color of each target structure has been modified to the structure-specific color.
3.3 Token Annotation

We use PDFPlumber\(^1\) a PDF parser built on PDFMiner\(^2\) to extract text lines and non-text elements with their bounding boxes. Text lines are tokenized simply by white spaces, and the bounding boxes are defined as the most upper-left coordinate of characters and the most lower-right coordinate of characters, since we can only get the coordinates of characters instead of the whole tokens from the parser. For the elements without any texts such as figures and lines in PDF files, we use the class name inside PDFMiner and wrap it using two “#” symbols into a special token. The class names include “LTFigure” and “LTLine” that represent figures and lines respectively.

The RGB values of characters and the non-text elements can be extracted by PDFPlumber from the PDF files. Mostly, a token is composed of characters with the same color. Otherwise, we use the color of the first characters as the color of the token. We determine the labels of the tokens according to the color-to-structure mapping in the Section 3.2. A structure may contain both text and not-text elements. For instance, tables consist of words and lines. In this work, both words and lines will be annotated as the “table” class, so as to obtain the layout of a table as much as possible after the elements are tokenized.

3.4 Post-processing

In certain cases, some tokens may have multiple colors naturally and cannot be converted by the ‘color’ command, such as hyperlinks and references in PDF files. Unfortunately, these unchanged colors will lead to incorrect labels for these tokens. To correct the label of these tokens, we also need some post-processing steps for the DocBank dataset.

Generally, tokens with the same semantic structure will be organized together in the reading order. Therefore, successive tokens often have the same label within the same semantic structure. When the semantic structure alternates, the labels of adjacent tokens at the boundary will be inconsistent. We check all the labels based on the reading order in the document. When the label for a single token is different from its left context and right context, but the labels of the left context and right context are the same, we correct the label of this token to be the same as the context tokens. We manually go through the corrections and find that these post-processing steps have substantially improved the quality of the DocBank dataset.

4 Method

As the dataset was fully annotated at token-level, we consider the document layout analysis task as a text-based sequence labeling task. Under this setting, we evaluate two representative pre-trained language models on our dataset, BERT and LayoutLM, to validate the effectiveness of DocBank.

4.1 The BERT Model

BERT is a Transformer-based language model trained on large-scale text corpus. It consists of a multi-layer bidirectional Transformer encoder. It accepts a token sequence as input and calculates the input

\(^1\)https://github.com/jsvine/pdfplumber
\(^2\)https://github.com/euske/pdfminer
representation by summing the corresponding token, segment, and position embeddings. Then, the input vectors pass multi-layer attention-based Transformer blocks to get the final contextualized language representation.

### 4.2 The LayoutLM Model

LayoutLM is a multi-modal pre-trained language model that jointly models the text and layout information of visually rich documents. Its architecture is mostly based on BERT, which is shown in Figure 3. In particular, it has an additional 2-D position embedding layer to embed the spatial position coordinates of elements. In detail, the LayoutLM model accepts a sequence of tokens with corresponding bounding boxes in documents. Besides the original embeddings in BERT, LayoutLM feeds the bounding boxes into the additional 2-D position embedding layer to get the layout embeddings. Then the summed representation vectors pass the BERT-like multi-layer Transformer encoder.

Note that we use the LayoutLM without image feature embedding because we find that the text and layout already power the pre-trained model. More details are provided in the next section.

### 4.3 Pre-training LayoutLM

We pre-train LayoutLM on our unlabeled dataset. As our unlabeled dataset does not include document category annotations, we choose the Masked Visual-Language Model as the objective when pre-training the model. Its procedure is to simply mask some of the input tokens at random keeping the corresponding position embedding and then predict those masked tokens. In this case, the final hidden vectors corresponding to the mask tokens are fed into an output softmax over the vocabulary.

### 4.4 Training Samples in Reading Order

We organize the DocBank dataset using the reading order, which means that we sort all the text boxes (a hierarchy level higher than text line in PDFMiner) and non-text elements from top to bottom by their top border positions. The text lines inside a text box are already sorted top-to-bottom. We tokenize all the text lines in the left-to-right order and annotate them. Basically, all the tokens are arranged top-to-bottom and left-to-right, which is also applied to all the columns of multi-column documents.

### 4.5 Fine-tuning

We fine-tune the pre-trained model with the DocBank dataset. As the document layout analysis is regarded as a sequence labeling task, all the tokens are labeled using the output with the maximum probability. The number of output class equals the number of semantic structure types.
5 Experiment

5.1 Evaluation Metrics

As the inputs of our model are serialized 2-D documents, the typical BIO-tagging evaluation is not suitable for our task. The tokens of each semantic unit may discontinuously distribute in the input sequence. In this case, we proposed a new metric, especially for text-based document layout analysis methods. For each kind of document semantic structure, we calculated their metrics individually. The definition is as follows:

\[
\text{Precision} = \frac{\text{Area of Ground truth tokens in Detected tokens}}{\text{Area of all Detected tokens}},
\]

\[
\text{Recall} = \frac{\text{Area of Ground truth tokens in Detected tokens}}{\text{Area of all Ground truth tokens}},
\]

\[
F_1 \text{ Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.
\]

5.2 Settings

We used 8 V100 GPUs with a batch size of 10 per GPU. It took roughly 320 hours for pre-training 1 epoch while it took 20 hours for fine-tuning 20 epochs. Our network has 12 Transformer layers. The size of hidden states is 768, which equals the size of word embeddings and position embeddings. We used the BERT tokenizer to tokenize the training samples and optimized the model with AdamW. The initial learning rate of the optimizer is $5 \times 10^{-5}$. We split the data into a max block size of $N = 512$.

5.3 Results

| Semantic structures | Pre-trained BERT | LayoutLM with BERT initialization | LayoutLM from scratch | Pre-trained LayoutLM |
|---------------------|-------------------|---------------------------------|-----------------------|----------------------|
| author              | 0.9275            | 0.9268                          | 0.8991                | 0.9423               |
| footer              | 0.9290            | 0.9597                          | 0.9426                | 0.9826               |
| section             | 0.9356            | 0.9535                          | 0.9470                | 0.9694               |
| title               | 0.9999            | 0.9999                          | 0.9999                | 0.9999               |
| abstract            | 0.9121            | 0.9095                          | 0.9378                | 0.9537               |
| list                | 0.7782            | 0.8400                          | 0.8257                | 0.8699               |
| paragraph           | 0.9292            | 0.9713                          | 0.9758                | 0.9849               |
| reference           | 0.9679            | 0.9602                          | 0.9552                | 0.9643               |
| caption             | 0.9529            | 0.9406                          | 0.9383                | 0.9788               |
| equation            | 0.6319            | 0.8611                          | 0.8526                | 0.9346               |
| figure              | 0.7839            | 0.9705                          | 0.9893                | 0.9941               |
| table               | 0.8136            | 0.7869                          | 0.8097                | 0.8175               |
| Average             | 0.8801            | 0.9233                          | 0.9228                | 0.9493               |

Table 1: The performance of LayoutLM and BERT on the DocBank test set.

The evaluation results of BERT and LayoutLM are shown in Table 1. We evaluate four models on the test set of DocBank. We notice that the LayoutLM gets the highest scores on the {author, footer, section, title, abstract, list, paragraph, caption, equation, figure, table} labels. The BERT model gets the best performance on the “reference” label but the gap with the LayoutLM is very small. This indicates that the LayoutLM architecture is significantly better than the BERT architecture in the document layout analysis task. In addition, it is observed that the LayoutLM trained from scratch is unsatisfactory on all the labels. Meanwhile, pre-training the LayoutLM model on our in-house unlabeled dataset improves the accuracy significantly on the DocBank dataset. This confirms that the pre-training procedure significantly
improves the performance of LayoutLM on the benchmark. As this work is still in progress, we will enlarge the DocBank dataset and update the results in the revised version later.

### 6 Case Study

We visualize the outputs of pre-trained BERT and pre-trained LayoutLM on some samples of the test set in Figure 4 and Figure 5. Generally, it is observed that the sequence labeling method performs well on the DocBank dataset, where different semantic units can be identified. For the pre-trained BERT model, we can see some tokens are detected incorrectly, which illustrates that only using text information is still not sufficient for document layout analysis tasks, and visual information should be considered as well. Compared with the pre-trained BERT model, the pre-trained LayoutLM model integrates both the text and layout information. Therefore, it produces much better performance on the benchmark dataset. This is because the 2D position embeddings can model spatial distance and boundary of semantic structures in a unified framework, which leads to the better detection accuracy.

### 7 Related Work

The research of document layout analysis can be divided into three categories: rule-based approaches, conventional machine learning approaches, and deep learning approaches.

#### 7.1 Rule-based Approaches

Most of the rule-based works (Lebourgeois et al., 1992; Ha et al., 1995a; Simon et al., 1997; Ha et al., 1995b) are divided into two main categories: the bottom-up approaches and the top-down approaches.
Some bottom-up approaches ([Lebourgeois et al., 1992]; [Ha et al., 1995a]; [Simon et al., 1997]) first detect the connected components of black pixels as the basic computational units in document image analysis. The main part of the document segment process is combining them into higher-level structures through different heuristics methods and labeling them according to different structural features. The spatial auto-correlation approach ([Journet et al., 2005]; [Journet et al., 2008]) is a bottom-up texture-based method for document layout analysis. It starts by extracting texture features directly from the image pixels to form homogeneous regions and will auto-correlate the document image with itself to highlight periodicity and texture orientation.

For the top-down strategy, [Jain and Zhong, 1996] proposed a mask-based texture analysis to locate text regions written in different languages. Run Length Smearing Algorithm converts image-background to image-foreground if the number of background pixels between any two consecutive foreground pixels is less than a predefined threshold, which is first introduced by [Wahl et al., 1982]. Document projection profile method was proposed to detect document regions ([Shafait and Breuel, 2010]). [Nagy and Seth, 1984] proposed a X-Y cut algorithm that used projection profile to determine document blocks cuts. For the above work, the rule-based heuristic algorithm is difficult to process complex documents, and the applicable document types are relatively simple.

### 7.2 Conventional Machine Learning Approaches

To address the issue about data imbalance that the learning-based methods suffer from, a dynamic MLP (DMLP) was proposed to learn a less-biased machine model using pixel-values and context information ([Baechler et al., 2013]). Usually, block and page-based analysis require feature extraction methods to empower the training and build robust models. The handcrafted features are developed through feature extraction techniques such as Gradient Shape Feature (GSF) ([Diem et al., 2011]) or Scale Invariant Feature Transform (SIFT) ([Garz et al., 2010]; [Garz et al., 2012]; [Garz et al., 2011]; [Wei et al., 2014a]). There are several other techniques that use features extraction methods such as texture features ([Chen et al., 2015]; [Mehri et al., 2013]; [Mehri et al., 2017]; [Mehri et al., 2015]; [Wei et al., 2013]; [Wei et al., 2014b]) and geometric features ([Bukhari et al., 2010]; [Bukhari et al., 2012]). Manually designing features require a large amount of work and is difficult to obtain a highly abstract semantic context. Moreover, the above machine learning methods rely solely on visual cues and ignore textual information.

### 7.3 Deep Learning Approaches

The learning-based document layout analysis methods get more attention to address complex layout analysis. [Capobianco et al., 2018] suggested a Fully Convolutional Neural Network (FCNN) with a weight-training loss scheme, which was designed mainly for text-line extraction, while the weighting loss in FCNN can help in balancing the loss function between the foreground and background pixels. Some deep learning methods may use weights of pre-trained networks. A study by [Oliveira et al., 2018] proposed a multi-task document layout analysis approach using Convolution Neural Network (CNN), which adopted transfer learning using ImageNet. [Yang et al., 2017] treats the document layout analysis tasks as a pixel-by-pixel classification task. He proposed an end-to-end multi-modal network that contains visual and textual information.

### 8 Conclusion

To empower the document layout analysis research, we present DocBank that is built in an automatic way with weak supervision, which enables document layout analysis models using both textual and visual information. To verify the effectiveness of DocBank, we conduct an empirical study with two baseline models, which are BERT and LayoutLM. Experiment results show that the methods integrating text and layout information is a promising research direction with the help of DocBank. We expect that DocBank will further release the power of other deep learning models in document layout analysis tasks.

For the future research, we will further integrate more visual information by using the convolution neural network to extract features from the document images, which will give the model more information that existing approaches might lack.
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