RDU: A Region-based Approach to Form-style Document Understanding

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Abstract

Key Information Extraction (KIE) is aimed at extracting structured information (\textit{e.g.,} key-value pairs) from form-style documents (\textit{e.g.,} invoices), which makes an important step towards intelligent document understanding. Previous approaches generally tackle KIE by sequence tagging, which faces difficulty to process non-flatten sequences, especially for table-text mixed documents. These approaches also suffer from the trouble of pre-defining a fixed set of labels for each type of documents, as well as the label imbalance issue. In this work, we assume Optical Character Recognition (OCR) has been applied to input documents, and reformulate the KIE task as a region prediction problem in the two-dimensional (2D) space given a target field. Following this new setup, we develop a new KIE model named Region-based Document Understanding (RDU) that takes as input the text content and corresponding coordinates of a document, and tries to predict the result by localizing a bounding-box-like region. Our RDU first applies a layout-aware BERT equipped with a soft layout attention masking and bias mechanism to incorporate layout information into the representations. Then, a list of candidate regions is generated from the representations via a Region Proposal Module inspired by computer vision models widely applied for object detection. Finally, a Region Categorization Module and a Region Selection Module are adopted to judge whether a proposed region is valid and select the one with the largest probability from all proposed regions respectively. Experiments on four types of form-style documents show that our proposed method can achieve impressive results. In addition, our RDU model can be trained with different document types seamlessly, which is especially helpful over low-resource documents.

Introduction

Key Information Extraction (KIE) aims to extract structured information, \textit{e.g.,} key (field)-value pairs, from business documents such as invoices, receipts, purchase orders, bank statements, financial reports, \textit{etc.} (Huang et al. 2019; Jaume Ekenel, and Thiran 2019; Gralinski et al. 2020; Holt and Chisholm 2018; Yu et al. 2020; Wang et al. 2021). In reality, many companies and organisations use this technique to deal with the large amounts of documents that may vary significantly in content and layout, saving much human effort and cost. In this paper, we address this practical yet challenging task under the assumption that Optical Character Recognition (OCR) has been applied to the documents already.

The majority of previous methods transform the two-dimensional document to a one-dimensional input sequence, and formulate the KIE task as a sequence tagging problem (Hwang et al. 2019; Xu et al. 2020; Garonce et al. 2020; Hong et al. 2021; Yu et al. 2020). These methods first serialize the tokens in the document, and then apply an independent tagging model to classify each token to one of the predefined labels, as illustrated in Figure 1(a). However, such

Figure 1: Illustration of KIE from documents. Take extracting \textit{Product Description} (PD) from an invoice as an example. (a) Traditional sequence tagging approach, which assigns each token a predefined label. \textit{B:PD}, \textit{I:PD} and \textit{O:PD} respectively denote the beginning, inside and end of the field \textit{Product Description}. The tokens tagged with \textit{O:outside} do not belong to any target field. (b) Our region prediction method, \textit{i.e.,} locating a bounding-box-like region (in dotted line) by predicting its four boundary tokens (\textit{Part}, \textit{BRAKE}, \textit{boxes}, \textit{Discount}) to generate the coordinates \( (x_0, y_0, x_1, y_1) \) and extracting all the content inside as the result.

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a sequence tagging approach suffers from several issues that limit its applicability and performance. First of all, due to the diverse and complex spatial layouts of the documents, their serialization is itself a challenging problem that has recently received much research interest (Aggarwal et al. 2020; Li et al. 2020). Also, this requires the definition of customized labels for each type of documents, limiting its application to other domains (Nguyen et al. 2021). Furthermore, sequence tagging may be significantly affected by the existence of imbalanced labels (Tomanek and Hahn 2009; Li et al. 2020).

In this paper, we explore a totally different solution from the traditional sequential tagging. The key idea is to directly locate a bounding-box-like region on the input document and extract the content inside the region as the KIE result. See Figure 1(b) for an illustration. Given a target field (Product Description) and an OCR processed document (an invoice) as input, the goal is to locate a bounding-box-like region by predicting its four boundary tokens to generate its coordinates, which encloses the value of the field (dotted-line rectangle). This new formulation of the KIE task has several merits. Firstly, by predicting a region in a two-dimensional space instead of the string(s) in a one-dimensional input sequence, the impact of sequential error can be greatly alleviated. Also, by using a two-dimensional region, the KIE model is capable of extracting not only a string of values, but also a column in a table. This is especially important when dealing with table-text mixed documents, as demonstrated in Figure 1(b), where the Product Description corresponds to a column of the table. Moreover, this approach does not require a predefined label set for each document type as in sequence tagging, and hence gets rid of the bad effect due to imbalanced labels. This also enables a model to be trained on different types of documents seamlessly.

Based on our new formulation of treating KIE as a region prediction problem, we also propose a KIE model named Region-based Document Understanding (RDU). Given an OCR processed document and a target field, RDU first applies a Layout-aware BERT to encode layout information of the document into the representation by leveraging a soft layout attention masking and bias mechanism. Then, some candidate regions are generated from the representations via a Region Proposal Module, which is inspired by object detection models (Girshick et al. 2013; Girshick 2015; Ren et al. 2015). Finally, a Region Categorization Module and a Region Selection Module are respectively adopted to judge whether a proposed region is valid, and select the one with the largest probability, from which the final result is extracted.

Note that although we borrow the concept of generating “region proposals” as in computer vision tasks, we do not tackle KIE as a vision problem; instead, we consider this task from a pure Natural Language Processing perspective. Our proposed RDU takes as input the text content plus coordinates of a document obtained with OCR, and does not use any visual features, which is computationally efficient. We evaluate our method on four different types of documents, including receipts (Huang et al. 2019), invoices, bank statements and bill of lading. It is shown that RDU can achieve impressive performance on all the types of documents when it is trained separately. We also find that the performance can be further improved if we combine all four document types to train our model. This finding indicates that our task formulation and method may be very helpful for KIE over low-resource document types.

Related Work

Key Information Extraction from Documents

The goal of Key Information Extraction (KIE) is to extract useful structured information from form-style documents such as invoices or medical reports. Previous approaches to KIE generally include three groups based on adopted features: text-only, text-layout, and multimodal models. Text-only methods (Hwang et al. 2019; Guo et al. 2019; Nguyen et al. 2021; Zhu et al. 2021b) treat the document as plain text and only use text information, which usually offers limited performance due to failure to exploit layout information of the input document. Multi-modal models (Xu et al. 2020; Yu et al. 2020; Appalaraju et al. 2021; Powlasi et al. 2021) combine text and vision features and show impressive performance. However, they demand processing over raw images, which costs considerable computational resource and time, hampering their application in the real world. Text-layout models (Katti et al. 2018; Denk and Reisswig 2019; Garncarek et al. 2020; Hong et al. 2021) adopt both text and layout features that are obtained easily from an Optical Character Recognition (OCR) engine, which largely increases the computational efficiency while keeping comparative performance. However, most existing text-layout models address KIE as a sequence tagging problem (Katti et al. 2018; Garncarek et al. 2020; Hong et al. 2021; Zhu et al. 2021a). This setup would hinder the application of the same model over the variety of document types since sequence tagging requires a predefined label set for each document type and suffers from the issues of imbalanced labels. In this work, we re-formalize the KIE task as a region prediction problem in 2D space instead of sequence tagging and propose a RDU model following this new setup, enabling the model to be applied on multiple document types seamlessly.

Layout-aware Transformer

Recently, Layout-aware Transformer has demonstrated noticeable effectiveness for intelligent document understanding, which focuses on exploiting the spatial layout information of the input document. For example, (Garncarek et al. 2020; Xu et al. 2020; Hong et al. 2021; Herzig et al. 2020) extend the positional embeddings by adding the embedding of layout information; (Powlasi et al. 2021; Garncarek et al. 2020) choose to modify the raw attention scores in self-attention by adding layout bias terms based on the relative vertical and horizontal distance between two tokens. In our RDU, we adopt both ways to develop a layout-aware BERT. Firstly, we adapt a similar layout embedding method with LayoutLM (Xu et al. 2020) to embed the coordinates of the text, but with modifications which is to embed the width and height instead of bottom-right of a coordinate. We argue that the parameters for the bias terms are not sufficient in number for representing the differences of various layout information (Garncarek et al. 2020; Powlasi et al. 2021). Hence, in our model, in
addition to a layout attention bias similar as LAMBERT (Gar-ncarek et al. 2020), we also develop a soft layout attention masking method to better differentiate the importance of the text according to the spatial relative distance between words.

**Methodology**

Instead of tackling KIE by sequence tagging, we reformulate it as region prediction over the input document processed by OCR. Then following this new formulation, we develop a Region-based Document Understanding model (abbreviated as RDU). As shown in Figure 2, RDU includes four major parts: 1) a Layout-aware BERT to incorporate spatial layout information of the document into the representation; 2) a Region Proposal Module to propose a list of candidate regions; 3) a Region Categorization Module to judge whether a proposed region is valid or not; and 4) a Region Selection Module to select the best one from all proposed regions.

**Task Formulation: Region Prediction**

Consider a form-style document. Assume it is pre-processed with an OCR engine and transformed to corresponding text content and coordinates. Serialize and tokenize the text following a left-to-right and top-to-bottom manner based on the coordinates; each token will have its own coordinates. Taking as input the serialized text and corresponding coordinates of this document, the task is to locate a bounding-box-like region by predicting its four boundary tokens and extract all the content inside as the final KIE result for a target field.

Formally, we denote the left, top, right and bottom boundary tokens of the region as \( tl, tt, tr \) and \( tb \) respectively. The coordinates of this region will be \( (x_0, y_0, x_1, y_1) \). To be more clear, we also take Figure 1(b) on extracting the given field Product Description from an invoice under our new task formulation as an example. To obtain the target region marked in the dotted-line rectangle, we first predict its four boundary tokens \((tl, tt, tr, tb)\) which are then used to generate the region’s coordinates. Then, all the tokens inside this region will be their coordinates as the final result. For each token \( t \) with coordinates \((x_0, y_0, x_1, y_1)\) in the document, if \( x_0 < x_0', x_1' \geq x_1, y_0 < y_0' \) and \( y_1 > y_1' \), we then regard this token as inside the target region.

Under this novel formulation, we develop a simple yet effective solution to KIE. Below we elaborate on each part of the proposed RDU model sequentially.

**Layout-aware BERT**

The proposed RDU first applies a Layout-aware BERT built on top of the vanilla BERT\textsubscript{BASE} (Devlin et al. 2018) to generate the representations. The vanilla BERT\textsubscript{BASE} (Devlin et al. 2018) is trained on plain text, and hence is “unaware” of the layout information of the document, which however is very crucial to KIE over form-style documents. To effectively en-
code spatial layout information from the input document into BERT representations, we make two modifications. First, we directly embed the coordinates of each token and add them to the input embeddings in the embedding layer. Second, we apply a soft layout attention masking and bias mechanism when computing the attention scores in self-attention, which depends on the horizontal and vertical relative distance between the tokens. More details are given below.

**Layout-aware Embedding** As explained in our new formulation, each token in the input sequence has its own coordinates obtained from OCR processing. We embed the coordinates and add them to the input embedding for this token similar as in LayoutLM (Xu et al. 2020), so as to encode the layout information. See Figure [3] for an illustration. In particular, we normalize and discretize the coordinates of the document to integers within [0, 700] for width and [0, 1000] for height, basically following an A4 paper width/height ratio. Then, we use four separate embedding layers to encode the $x_0, y_0, Width$ and $Height$ of the coordinates of a token. Lastly, we add the four layout embeddings to the input embeddings.

To compute the center of a token $i$, we first compute the distance between two tokens $i$ and $j$, which are computed by $|x_i - x_j|$ and $|y_i - y_j|$ respectively; $h_\theta$ and $v_\theta$ are the thresholds to make the tokens within the horizontal and vertical distances more important than the ones outside; $\gamma$ is a steepness coefficient of the function $\sigma$; $h_\theta, v_\theta$ and $\gamma$ are hyper parameters. Since the query/field does not have layout information, we still use the global attention similar to the standard transformer (Vaswani et al. 2017), meaning the tokens in the query can attend to or be attended by all the tokens in the document.

Adding a layout attention bias term $b_{ij}$ is previously adopted in (Garncarek et al. 2020; Powsalski et al. 2021). In this work, we follow the same approach:

$$b_{ij} = H(h_{ij}) + V(v_{ij})$$

where $H(h)$ and $V(v)$ are trainable weights defined for every integer $h \in [0, 700]$ and $v \in [0, 1000]$.

**Region Proposal Module**

Our Region Proposal Module aims to propose a list of regions that likely include the target value in a 2D space, which is inspired by object detection models (Girshick 2015; Ren et al. 2015) but avoids using raw images.

A region in our setup is decided by four boundary tokens represented by $(x_0^r, y_0^r, x_1^r, y_1^r)$ corresponding to left, top, right and bottom boundaries respectively. We take the computation of coordinate $x_0^r$ as an example. As illustrated on the right in Figure [2] this module takes the representations from the layout-aware BERT as input, and predicts the top $k$ candidate tokens first using a softmax function. Formally,

$$l_{x_0^r} = W_1 \cdot T_n$$

$$p_{x_0^r} = \text{softmax}(l_{x_0^r})$$

$$c_{x_0^r} = \text{argsort}(p_{x_0^r})[:k].$$

Here $W_1$ denotes trainable variables; $T_n$ stands for the outputs of the $n$th layer of the layout-aware BERT; $l_{x_0^r}$ and $p_{x_0^r}$ are the logits and probabilities of the tokens; $c_{x_0^r}$ denotes the predicted top $k$ candidate tokens for $x_0^r$; $\cdot$ is dot product.

Similarly, we can get the top $k$ candidate tokens for $y_0^r, x_1^r$ and $y_1^r$. After that, a permutation and combination process is applied on all candidate tokens to generate $k^4$ region proposals. In practice, we use the last three layers of layout-aware BERT (based on empirical validation) to generate region proposals, resulting in a total of $3 \times k^4$ proposals. Among these proposals, we mask the invalid ones if $x_0 > x_1$ or $y_0 > y_1$.

**Region Categorization Module**

For each proposed region, we assign a binary class label to define it as valid or not. Similar to (Ren et al. 2015), we assign...
We describe how we select the best region from a list where the region that has the highest IOU overlap with the ground-truth bounding box. We assign a negative label to a non-positive region if its IOU ratio is lower than 0.1. We mask the regions that are neither positive nor negative to ensure that they do not contribute to the training objective.

Before categorizing each region, we need to compute its representation first. Specifically, we represent a region with two features: (i) a content feature that is obtained by applying max-pooling over all tokens within the region, and (ii) a feature of boundaries using the logits of the four boundary tokens obtained in the region proposal step. The two features go through a feed-forward layer separately to get the same hidden size $h = 64$, which are denoted as $r_c$ and $r_b$, and then are concatenated to form the representation of the region denoted as $r_{region}$. Formally,

$$r_c = W_2 \cdot \max(T_r)$$

$$r_b = W_3 \cdot \left[ l_{x_5}; l_{y_5}; l_{x_1}; l_{y_1} \right]$$

$$r_{region} = [r_c; r_b]$$

where $W_2 \in \mathbb{R}^{h \times d}$ and $W_3 \in \mathbb{R}^{h \times 4}$ are trainable variables; $T_r$ are all tokens within the region; $\max$ is max-pooling; $;$ means concatenation; $d$ is the embedding size. After that, a linear layer and a softmax layer are used to predict whether the region is positive or negative:

$$p_{rc} = \arg \max(\text{softmax}(W_4 \cdot r_{region}))$$

where $W_4$ is a trainable variable.

### Region Selection Module

We describe how we select the best region from a list of region proposals obtained in the previous step. We treat the region that has the highest IOU overlap with the ground-truth region as the target region. Firstly, we use the same method as in Region Categorization Module to compute the representation of each region, and then apply a linear layer and a softmax layer on all proposed regions. The region with the highest probability is selected by

$$p_{rs} = \arg \max(\text{softmax}(W_5 \cdot r_{region}))$$

where $W_5$ is a trainable variable.

### Unanswerable Queries

The unanswerable queries refer to the cases where the value of the target field does not exist in the given document. These cases are not rare. To tackle them, we follow the traditional setting of BERTBASE which uses the representation of the token [CLS] for a binary classification task.

### Loss Function

Assume the region that has the highest IOU overlap with the ground-truth region $G_{region}$ is $R_{region}$. The loss function is defined as the sum of answerable loss $L_{answerable}$, region categorization loss $L_{rc}$ and region selection loss $L_{rs}$, which are computed as

$$L_{answerable} = \text{NLL}(P_{answerable}, G_{answerable})$$

$$L_{rc} = \text{NLL}(P_{cat}, G_{cat})$$

$$L_{rs} = \text{NLL}(P_{region}, R_{region})$$

$$L = L_{answerable} + \alpha L_{rc} + \beta L_{rs}. $$

Here NLL(·) is the negative log-likelihood loss; $G_{answerable}$ is the ground-truth indicating whether the value of the target field exists in the document or not; $G_{cat}$ is the ground-truth category (i.e., positive or negative) of a region; $P_{answerable}$, $P_{cat}$ and $P_{region}$ are the log-probability of the answerable prediction, region category prediction and region selection respectively; $\alpha$ and $\beta$ are the loss weights.

The distribution of proposed regions is usually unbalanced, with a bias towards negative samples. To eliminate the impact of the bias upon training, we set a dynamic loss weight by computing the percentage of the opposite label (positive vs. negative) over the sum of the two labels and multiplying this percentage with the corresponding loss of this label.

### Experiments

#### Datasets

We conduct experiments on four KIE datasets, as summarized in Table[1] Among them, SROIE (Huang et al. 2019) is the most widely used public dataset for KIE, which releases 626 receipts for training and hides 347 receipts for testing. We further split the 626 receipts to train dev and test set in our experiments. Since SROIE also offers its OCR results, including the text and corresponding coordinates, we can obtain the bounding box of the answers via pre-processing.

| No. | Dataset | Train | Dev  | Test |
|-----|---------|-------|------|------|
| 1   | SROIE   | 439   | 62   | 125  |
| 2   | INV     | 1,085 | 155  | 310  |
| 3   | BKS     | 614   | 87   | 175  |
| 4   | BL      | 568   | 80   | 161  |

Table 1: KIE datasets used for evaluating model performance.

| Model   | SROIE | INV    | BKS | BL    |
|---------|-------|--------|-----|-------|
|         | EM/F1 | EM/F1  | EM/F1 | EM/F1 |
| BERT (S)| 55.71/63.43 | 66.62/79.57 | 67.24/71.14 | 27.00/34.72 |
| BERT (H)| 56.31/64.54 | 66.62/80.22 | 68.76/72.88 | 33.12/40.24 |
| RDU (S) | 89.18/93.85 | 75.34/88.56 | 87.79/91.58 | 75.94/82.15 |
| RDU (H) | 90.98/95.32 | 77.96/90.68 | 87.17/90.70 | 74.80/81.68 |

Table 2: Performance comparison on the test sets of four datasets. (S) means SINGLE model that is trained solely on each document type; (H) means HYBRID model that is trained on the combination of four document types.

The other three datasets, i.e. INV (Invoices), BKS (Bank Statements) and BL (Bill of Ladings), are built and annotated by ourselves. We first gather invoices, bank statements and
We adopt two popular evaluation metrics for extractive question answering (QA) area: Exact Match (EM) and numeracy-focused $F_1$ score similar to those used in [Dua et al., 2019], which both measure the overlap between a bag-of-words representation of the golden answers and predictions. Note that the numeracy-focused $F_1$ score will be 0 in case of a number mismatch between gold and predicted answers regardless of any other word overlap.

### Evaluation Metrics

To evaluate the effectiveness of our approach, we run our RDU and the baseline method that are trained separately on each document type, namely INV (Invoices), SROIE (Receipts), BKS (Bank statements) and BL (Bill of ladings), as well as a hybrid of all of them. Models trained on a single document type are marked with a ‘S’ in bracket, meaning SINGLE; similarly, models trained on combined four types of documents are marked with ‘H’ for HYBRID. We summarize the results in Table 3 and present the performance of our RDU model for each field in Table 4.

It can be seen that when trained on each type of documents separately, our RDU model performs much better than the baseline, demonstrating the effectiveness of our design. Especially on BL, the proposed RDU can gain over 47.0% $F_1$ score higher than the baseline method.

We further train both baseline and RDU on the combination of four types of documents, i.e. BERT (H) and RDU (H).
From Table 2, we find that the HYBRID models perform similarly or even better than the SINGLE models. In particular, BERT (H) outperforms the BERT (S) on each document type. And, RDU (H) performs better on two document types i.e., INV and SROIE than RDU (S), gaining 1.47% on SROIE and 2.12% on INV in F1 score. This may be because receipts and invoices have similar content or layout, and training on their combination may boost the training over each of them individually. While for other two document types, RDU (H) has a slightly drop, 0.88% on BKS and 0.47% on BL in F1 score. This finding indicates that with our task formulation, a model can be trained on multiple document types and works well. This may be very helpful for KIE over low-resource document types.

In addition, from Table 3 we can see RDU (H) achieves significantly higher performance on the two “column field” (the value being a column of a table), Product Code and Product Description, on invoices than RDU (S), achieving 76.47% for Produce Code and 90.70% for Product Description in F1 score. Through error analysis, we find that the RDU (S) model tends to predict a bigger region than the RDU (H), covering more content than the golden answer. The underlying reasons need to be further investigated. In Figure 4, we present four predicted examples for extracting a column field Product Description.

Ablation Study

We conduct ablation study w.r.t. the layout attention masking, layout attention bias, and Region Categorization module. The results are summarized in Table 4.

We first analyze the influence of our soft layout masking and bias mechanism. By removing either layout masking or layout bias, the model performance has a significantly drop on each of the four datasets. This indicates that they are all effective. Comparing with layout attention masking, the layout attention bias contributes more to the performance, bringing an increase in F1 score of 5.1% on SROIE, 2.15% on INV, 5.62% on BKS and 7.68% on BL. Both layout attention masking and layout attention bias influence the performance most on BL, gaining 3.19% and 7.68% F1 score respectively. This indicates they are more effective for bill of ladings compared to other document types. A possible explanation would be, bill of ladings often have more complex layouts than other document types.

Then, we investigate the importance of the Region Categorization module. By removing this module and only using region selection for deciding the target region, about 1% decrease on EM or F1 can be observed. This indicates the necessity of the multi-task training setting.

| Model  | SROIE | INV  | BKS  | BL   |
|--------|-------|------|------|------|
|        | EM/F1 | EM/F1| EM/F1| EM/F1|
| Full RDU | 90.98/95.32 | 77.96/90.68 | 87.17/90.70 | 74.80/81.68 |
| - LM    | 87.78/94.94 | 77.20/90.23 | 85.12/88.98 | 71.86/78.49 |
| - LB    | 82.77/90.22 | 75.48/88.53 | 81.40/85.08 | 66.72/74.00 |
| - RC    | 88.58/95.64 | 77.03/90.28 | 86.12/89.70 | 74.71/80.46 |

Table 4: Ablation results using RDU (H). The minus sign indicates removal of the mentioned part from the full RDU. LM: Layout Masking; LB: Layout Bias; RC: Region Categorization;

Conclusion and Future Work

We proposed a new formulation of the KIE task, namely treating it as a region prediction problem rather than the traditional sequence tagging. This design greatly relieves the difficulty of processing non-flatten sequences that are very common in table-text documents, and meanwhile enables the model to be applied to various document types. In our experiments, we find that the proposed regions sometimes contain few even no valid regions, which makes our model difficult to be trained. Therefore, for future work we would like to upgrade the Region Proposal module to ensure there will be enough valid regions in the proposals.
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