Knowing Where and What: Unified Word Block Pretraining for Document Understanding

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Abstract

Due to the complex layouts of documents, it is challenging to extract information for documents. Most previous studies develop multimodal pre-trained models in a self-supervised way. In this paper, we focus on the embedding learning of word blocks containing text and layout information, and propose UTel, a language model with Unified TExt and Layout pre-training. Specifically, we propose two pre-training tasks: Surrounding Word Prediction (SWP) for the layout learning, and Contrastive learning of Word Embeddings (CWE) for identifying different word blocks. Moreover, we replace the commonly used 1D position embedding with a 1D clipped relative position embedding. In this way, the joint training of Masked Layout-Language Modeling (MLLM) and two newly proposed tasks enables the interaction between semantic and spatial features in a unified way. Additionally, the proposed UTel can process arbitrary-length sequences by removing the 1D position embedding, while maintaining competitive performance. Extensive experimental results show UTel learns better joint representations and achieves superior performance than previous methods on various downstream tasks, though requiring no image modality. Code is available at [https://github.com/taosong2019/UTel](https://github.com/taosong2019/UTel).

1 Introduction

Document understanding, an essential and challenging research area that aims at structured documents analysis and information extraction, has attracted great attention from industry and academia. However, different from the plain-text understanding in natural language processing, document understanding needs to process various types of documents (letter, email, form, academic paper, advertisement, etc.) containing rich visual information and complex layout formats. For example, to extract question-answer values from form-like documents [14] and listed key values from receipts [25], a system needs to focus on not only the text content but also the spatial arrangement of text in documents. Hence, technical components from both CV and NLP are often required to handle the complex document scenarios.

The early works of document understanding [34, 33, 15, 24, 4] mainly focus on a single modal utilization or just shallow multi-modal fusions. Although good performance has been achieved, these methods need massive annotated data and are trained in a supervised way. Additionally, the domain knowledge in one document task cannot be easily transferred into another one. With the recent development of self-supervised pre-training techniques [7, 23, 29] in NLP tasks, recent researches on document understanding have shown great interest in pre-training methods [31, 20, 12, 20, 2, 13] and great improvements have been achieved on various downstream tasks. As a pioneer, LayoutLM...
learns the cross-modality interaction by leveraging text and layout information jointly during the pre-training stage. BROS [12] and StructuralLM [20] further exploit the effective combination of text and layout information, and LayoutLMv2 [30] adds image features into the pre-training stage.

The recent document pre-training approaches are based on the serialized OCR results. A document image is first processed by an OCR engine to generate a set of word blocks. Then the word blocks distributed in the 2D layout space are serialized as the inputs of a model. Two aspects of information are contained in a word block: the word textual content representing text semantics and the block bounding box corresponding to layout information. Utilizing sufficiently both aspects of the information in word blocks during the pre-training stage is crucial for document understanding. However, "unified" text and layout pre-training is still missing in current approaches. We define a unified text and layout pretrained language model as the one containing three aspects of pre-training tasks: text oriented, layout oriented and text-layout jointly oriented. The text oriented task helps the model capture the text semantics, e.g. the commonly used masked language modeling (MLM) [7, 31, 30], in which randomly masked text tokens require to be recovered in the transformer output and the model should utilize bidirectional context around the masked position. The other two kind of tasks focus on layout utilization and joint text and layout modalities learning respectively, which are often ignored in previous approaches.

In this paper, we propose UTel, a new pre-trained language model focusing on the embedding learning of word blocks with unified pre-training of both text and layout information. To fill the vacancy of the layout oriented and the text-layout jointly oriented pre-training tasks, we propose Surrounding Word Prediction (SWP) and Contrastive learning of Word Embeddings (CWE), respectively. The SWP task predicts the layout surrounding words, specifically the nearest top, bottom, left and right words of the current token. To complete the task well, the model needs to construct a 2D space plane and analyze the relative layout positions between word blocks. StructuralLM [20] proposes cell position classification task to predict which area the cell belongs to. However, the layout prediction granularity is relatively large and the model is not guided to pay attention to the spatially adjacent text explicitly. For the CWE task, dropout data augmentation mechanism is utilized to build a positive word block pair and then the contrastive learning of a word block level is applied. This task enables our model to distinguish different word blocks based on both the text semantics information and layout information.

We also remove the commonly used 1D position embedding and replace it with a 1D clipped relative position embedding. This change allows pre-training tasks to be performed in a more elegant way. The masked layout-language modeling task distinguishes different text tokens with the corresponding layout information instead of the 1D positions. The CWE task cannot cheat by the 1D positions, but focus on the joint representations between text and layout modalities. Another benefit is that UTel can process arbitrary-length sequences by removing the 1D position embedding without truncating input sequences.

Our contributions can be summarized as follows:

• We introduce UTel, a powerful language model with unified text and layout pre-training. We propose two novel pre-training tasks including Surrounding Word Prediction (SWP) and Contrastive learning of Word Embeddings (CWE) to improve the interaction between semantic features and spatial features.
• To the best of our knowledge, UTel is the first work of removing the 1D position embedding in document understanding area, and can meet the needs of processing document sequences of any length without truncation operation.
• Extensive experiments and analyses prove the effectiveness of our proposed UTel. With only text and layout modalities utilized, the proposed UTel shows outstanding performance compared with the state-of-the-art models on various downstream tasks.

2 Related Work

Model Architecture. In the past decade, deep learning approaches have been the mainstream of document understanding [34, 33, 15, 24, 4]. [33] propose a multimodal fully convolutional neural network considering both text and image information to predict a segmentation mask. [15] encode each document page as a 2D grid of characters and the model outperforms methods based on
sequential text or images. With the success of self-supervised pre-training achieved in NLP tasks [7,23], recent studies focus on pre-training on large-scale unsupervised corpus based on a transformer backbone [27]. LayoutLM [31] is the first work to learn the interaction between text and layout information during the pre-training stage. BROS [12] further encodes relative 2D positions of texts in layout space into the transformer and StructuralLM [20] makes the most of the cell-level layout information instead of the word-level layout information. Text and layout information are separately encoded and fed into the corresponding branch in LiLT [28]. LayoutLMv2 [30] proposes to engage image features during the pre-training stage and a spatial-aware attention is used. DocFormer [1] combines text, layout and image features using a novel multi-modal self-attention layer. The recent LayoutLMv3 [13] utilizes image features with a simple linear embedding without relying on an object detector [26] to extract region features.

**Self-supervised pre-training tasks.** A good representation of multimodal interactions needs well designed pre-training tasks. Recent pre-training methods [31,30,12,20,1,13] in document understanding all contain the basic masked language modeling (MLM) task originated from BERT [7]. The model can learn a better text representation with multi-modal features by reconstructing the masked input sequence in MLM. To better utilize layout information, cell position classification task is proposed in StructuralLM [20] to predict which area the cell belongs to. To achieve the alignment of text and image modality, LayoutLMv2 [30] proposes text-image alignment and text-image matching task on fine-grained and coarse-grained levels respectively. The original image is reconstructed through a shallow decoder in DocFormer [1] to utilize both text and image features. Masked image modeling is applied in LayoutLMv3 [13] to interpret visual content by reconstructing the masked image tokens [2,11]. However, layout oriented and text-layout jointly oriented pre-training tasks are ignored. In NLP, there are also many pre-training tasks [19,5,8,6] besides the most used MLM task. For example, [32] introduce contrastive learning for unsupervised sentence embedding based on several data augmentation approaches. SimCSE [8] further considers dropout operation as a kind of data augmentation method to build a positive pair for the input sentence. This simple method achieves SOTA performance for learning unsupervised sentence embeddings. Our proposed contrastive learning of word embeddings task is inspired by SimCSE.

3 UTel

We propose UTel, a self-supervised pre-trained language model with unified text and layout pre-training. The overall illustration of our method is shown in Figure 1. Our method is mainly inspired by LayoutLM [31] and BROS [12], but with two main differences. First, we remove the 1D position embedding usually used in common document understanding models and replace it with the 1D clipped relative position embedding. Then, we propose two novel pre-training tasks for a better understanding of text and layout information, including surrounding word prediction which predicts the surrounding words on the layout space and contrastive learning of word embeddings which takes dropout as a minimal data augmentation method.

3.1 Model Architecture

Figure 1 shows the architecture overview of UTel. The BERT transformer architecture is used as the backbone. The transformer network has a multi-layer architecture and each layer mainly consists of multi-head self-attention and position-wise fully connected feed-forward networks. It fuses input text and layout modalities and finally generate contextualized representations.

3.1.1 Text-Layout Embedding

Given a document image \(I\), an OCR tool is utilized to extract a sequence of words and the corresponding word-level text bounding boxes. The word blocks are then sorted from top-left to bottom-right as the preprocessing step.

**Text Embedding.** After tokenizing the text sequence, adding the special token [CLS] and [SEP] at the beginning and the end respectively, and padding with the [PAD] tokens to the maximum sequence length \(L\), finally we get the text embedding of token sequence \(\{w_0, w_1, \ldots, w_{L-1}\}\). The text embedding of the \(i\)-th token is

\[
\text{TextEmb}_i = \text{TokEmb}(w_i).
\]
Figure 1: The overall illustration of our UTel architecture. 1D positive embeddings are removed compared with common models and the pre-training tasks include (a) MLLM: Masked Layout-Language Modeling; (b) SWP: Surrounding Word Prediction; (c) CWE: Contrastive learning of Word Embeddings.

Note there is no 1D position embedding added here.

**Layout Embedding.** 2D position sequence is constructed with the corresponding bounding boxes of text tokens. After normalized to the range \([0, 1000]\), a box is represented as \((x_0, y_0, x_1, y_1)\), where \((x_0, y_0), (x_1, y_1)\) are the top-left and bottom-right corner coordinates respectively. Using two embedding layers to embed the x-axis features and y-axis features, we get the layout embedding by summing the corner coordinates features

\[
\text{LayEmb}_i = 2\text{D}_\text{xemb}(x_0) + 2\text{D}_\text{yemb}(y_0) + 2\text{D}_\text{xemb}(x_1) + 2\text{D}_\text{yemb}(y_1).
\]

Finally, the input text-layout embedding is the sum of text embedding and layout embedding

\[
\text{TextLayEmb} = \text{TextEmb} + \text{LayEmb}.
\]

3.1.2 Relative Position Embedding

Relative position embeddings include the 1D text sequence and the 2D layout relative position embeddings. We add them to better capture the relationship between the input tokens.

**1D Clipped Relative Position Embedding.** For the text-layout sequence input with 1D position \([0, 1, \ldots, P_i^d, \ldots, L - 1]\), the 1D clipped relative position embedding for the \(i\)th and \(j\)th position can be calculated by

\[
P_{i,j}^{1d} = W^{1d} f^{\text{sinu1d}}(\text{clip}(P_i^d - P_j^d)).
\]

\(f^{\text{sinu1d}} : \mathbb{R} \rightarrow \mathbb{R}^{D^{1d}}\) indicates a sinusoidal function, which is used in \([27]\), and \(D^{1d}\) is the dimension of sinusoid embedding. \(W^{1d} \in \mathbb{R}^{(H/A) \times D^{1d}}\) is a linear transition matrix, where \(H\) is a hidden size of BERT transformer, and \(A\) is the number of self-attention heads. The clip function truncates the 1D relative position to a range of \([-m, m]\), namely

\[
\text{clip}(p) = p \text{ if } |p| < m \text{ else } \pm m.
\]

The 1D text sequence order is still of considerable importance for document understanding \([10, 17]\). We remove the 1D absolute position embedding in the text-layout embedding and add the 1D clipped relative position embedding for three reasons. First, a raster-scan serialization with a top-left to bottom-right order may not give a right reading order and can lead to a sub-optimal performance. However, the relative order in a moderate text span is often accepted, e.g. a text line or a short paragraph. Then removing the 1D positions allows subsequent pre-training tasks to rely more on text and layout modalities instead of the 1D positions. Note that tokens in a single word block need to be distinguished by the 1D clipped position, for the reason that they share the same layout box. Finally, without adding new model parameters or clipping the input sequences, we can process longer document sequences than that used in the training stage.
2D Relative Position Embedding. The relative layout embedding is involved in [12] and has been proved effective for a better encoding of spatial layout relations. Here we also add it to enhance the model’s sensitivity to relative layout. For boxes $b_i = (x_{0i}, y_{0i}, x_{1i}, y_{1i})$, $b_j = (x_{0j}, y_{0j}, x_{1j}, y_{1j})$, the 2D relative position embedding is calculated by

$$p_{i,j}^{2d} = W^{2d}\text{ConCat}(f^2d(x_{0i} - x_{0j}), f^2d(y_{0i} - y_{0j}), f^2d(x_{1i} - x_{1j}), f^2d(y_{1i} - y_{1j})),$$

where $f^2d : \mathbb{R} \rightarrow \mathbb{R}^{D^{2d}}$ is a sinusoidal function for the 2D relative position, $D^{2d}$ is the corresponding embedding dimension, $\text{ConCat}(\cdot)$ indicates concatenation, and $W^{2d} \in \mathbb{R}^{(H/A) \times D^{2d}}$.

Finally, the 1D clipped relative position embedding and the 2D relative position embedding are encoded into the transformer encoder. Specifically, an attention logit is calculated by combining the context, 1D relative and 2D relative features as:

$$\alpha_{i,j} = (W_h^{q,t_i})^T(W_h^{k,t_j}) + (W_h^{q,t_i})^Tpp_{i,j}^{1d} + (W_h^{q,t_i})^Tpp_{i,j}^{2d},$$

where $t_i, t_j$ are context representations for the $i^{th}$ and $j^{th}$ tokens and $W_h^q, W_h^k$ are linear transition matrices for the $h^{th}$ head. Note all attention heads share the same relative embedding.

3.2 Pre-training Tasks

We adopt three self-supervised tasks to learn text-layout interactions during the unified word block pre-training stage and the full pre-training objective in UTel is defined as $L = L_{MLLM} + L_{SWP} + L_{CWE}$. We describe them in detail below.

3.2.1 Masked Layout-Language Modeling

This task is originated from [7], which is adopted nearly in all document understanding pre-trained models. As in [7], we randomly mask 15% words but keep the layout information unchanged. The model is trained to predict the masked tokens with the output encoded text-layout features. Since the 1D absolute position embedding is removed in UTel, layout information should be utilized more efficiently to construct the contextual semantics. The goal is to minimize the subsequent cross-entropy loss:

$$L_{MLLM} = - \sum_{x \in \text{mask}(X)} \log P(x | /\text{mask}(X)),$$

where $\text{mask}(X)$ denotes the masked tokens and $/\text{mask}(X)$ unmasked tokens.

3.2.2 Surrounding Word Prediction

For a model with a deep understanding of the document layout, a fixed word block should not only have the ability to perceive its own corresponding text semantics, but also the ability to infer other words on the 2D layout plane, especially the surrounding ones. Figure 2 shows a form image sampled from FUNSD dataset [14]. To understand the "July" in green box, surrounding words are often taken into account, and finally we find a high correlation with the left words "DATE FILED:"

Hence, in order to enhance the model’s ability of understanding layout information, we propose the layout oriented SWP pre-training task in which the model needs to predict the word contents around the current token on a 2D space plane. Specifically, the model is trained to predict the nearest top, bottom, left and right word contents (if any) of the current token, as the words in orange boxes in Figure 2. To filter the surrounding words that are in the same line or column as possible, we only consider the words whose intersection ratio with that of the current token is greater than 0.2 in the corresponding direction.
The tokens masked in MLLM task are involved in SWP task. Since a surrounding word could have more than one token after tokenized, we select the first token as the target token to be predicted. Suppose $\text{SurEmb}(i)$, where $i \in \{0, 1, 2, 3\}$, represents the predicted direction embedding, the current token embedding is $t$ and the target token $x^i_{\text{target}}$, the goal is to minimize the following cross-entropy loss:

$$L_{SWP} = - \sum_{x \in \text{mask}(X), i \in \{0, 1, 2, 3\}} \log P(x^i_{\text{target}} | \text{Concat}(t, \text{SurEmb}(i))).$$ (9)

### 3.2.3 Contrastive learning of Word Embeddings

SimCSE [8] takes dropout as a minimal data augmentation method, and a positive sentence pair is built by passing the same input sentence to a transformer encoder (with dropout turned on) twice. We extend it to word embeddings containing text and layout information. Specially, we pass text-layout embedding to our model twice and construct the word-level positive pair of each word (the first token embedding in a word is picked) using dropout mechanism. Then the goal is to distinguish different word blocks in the text-layout jointly oriented CWE task, and the contrastive learning objective is formulated as follows

$$L_{CWE} = - \frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{\text{sim}(h_i, h^+_i)/\tau}}{\sum_{j=1}^{N} e^{\text{sim}(h_i, h^+_j)/\tau}},$$ (10)

where $N$ is the total word numbers in a mini-batch, $\tau$ is a temperature hyperparameter and $\text{sim}(h_i, h^+_i)$ is the similarity metric between a word positive pair, which is represented with the cosine similarity function. Note that the model cannot cheat with the 1D absolute position information, which is removed in our inputs, but focus on the text-layout interaction.

### 4 Experiments

#### 4.1 Pre-training Details

Following LayoutLM [31], we pre-train UTel on the IIT-CDIP Test Collection 1.0 [18], which is a large-scale scanned document image dataset containing more than 6 million documents, with more than 11 million scanned document images. The layout information is missing in the pre-training dataset, hence following LayoutLM [31], we process the scanned document images using Tesseract

1

which is an open-source OCR engine.

To take advantage of existing pre-trained models, we use the BERT architecture as the backbone. We set the hidden size, the number of self-attention heads, the feed-forward size, and the number of transformer layers to 768, 12, 3072 and 12, respectively for the base model UTel\text{BASE}, while set those to 1024, 24, 4096, and 24, respectively for the large model UTel\text{LARGE}. $D^{1d}$ and $D^{2d}$ in the relative position embedding is set to 192, 48 for UTel\text{BASE} and 256, 64 for UTel\text{LARGE}. The $m$ parameter of 1D clipped range is 50 in default, because we find our model is robust to the value of $m$ in ablation studies. Both the base and large UTel model are initialized from the corresponding BERT weights.

During the pre-training, we use Adam [16] as the optimizer, with a learning rate of 5e-5 with linear decay. The first 10% of the total epochs are used for a warm-up learning rate. UTel is trained on 8 A100 GPUs for 10 epochs with a batch size of 128.

#### 4.2 Fine-tuning on Form Understanding

The FUNSD [14] is a form understanding task. It contains 199 scanned forms, which are split into 149 for training and 50 for testing. We focus on the semantic entity labeling, where each word in the dataset is assigned to a predefined semantic entity label among question, answer, header, or other. We use the official OCR annotations with the layout information, which contains both word-level and segment-level bounding boxes. We fine-tune UTel for 100 epochs with a learning rate of 5e-5 and a batch size of 16. F1 score is used as the evaluation metric.

1https://github.com/tesseract-ocr/tesseract
The results are reported in Table 1 when annotations with word-level bounding boxes are used. UTel outperforms all other pre-trained models. Compared with the text-only and text-layout models, UTel achieves a noticeable improvement. Interestingly, UTel outperforms multi-modal models with additional image information. In other words, although UTel utilize only text and layout modalities, and has fewer model parameters, UTel provides better performance than models with text, layout and image modalities.

We notice that some papers like StructuralLM [20] and the recent LayoutLMv3 [13] use segment-level layout positions, which means words in the same segment share the same bounding box. Segment-level layout positions could benefit the semantic entity labeling task on FUNSD [13]. Hence for a fair comparison, we use the segment-level annotations following LayoutLMv3 in FUNSD task. The results in Table 2 show that UTel also benefits form understanding task with segment-level annotations and outperforms other models even including the recent SOTA LayoutLMv3. Note we don’t use any segment information like StructuralLM and LayoutLMv3 during the pre-training stage.

### 4.3 Fine-tuning on Receipt Understanding

We also evaluate our model on two receipt understanding tasks including SROIE [3] and CORD [25]. SROIE, containing 626 samples for training and 347 for testing, is to extract values from four predefined keys: company, date, address or total. While CORD, containing 800 receipts for training, 100 for validation and 100 for testing, defines 30 fields under 4 categories. We use the official OCR annotations. We fine-tune UTel for 30 epochs with a learning rate of 5e-5 and a batch size of 16. F1 score is used as the evaluation metric.

The results are shown in Table 3. UTel achieves better or comparable results than previous works with only text and layout modalities utilized. For example, UTel achieves an improvement of 0.10%
Table 3: Results of UTel on SROIE and CORD for receipt understanding

| Model         | Parameters | Modality       | SROIE F1 | CORD F1 |
|---------------|------------|----------------|----------|---------|
| LayoutLM      | BASE [31]  | 113M Text+Layout | 94.38    | —       |
| BROS         | BASE [12]  | 110M Text+Layout | 95.91    | 96.50   |
| LayoutLMv2    | BASE [30]  | 200M Text+Layout+Image | 96.25 | 94.95 |
| DocFormer     | BASE [1]   | 183M Text+Layout+Image | —      | 96.33   |
| LayoutLMv3    | BASE [13]  | 133M Text+Layout +Image | —      | 96.56   |
| UTel          | BASE (ours)| 111M Text+Layout | 96.35    | 96.75   |
| LayoutLM      | LARGE [31] | 343M Text+Layout | 95.24    | —       |
| BROS          | LARGE [12] | 340M Text+Layout | 96.62    | 97.28   |
| LayoutLMv2    | LARGE [30] | 426M Text+Layout+Image | 96.61 | 96.01 |
| LayoutLMv3    | LARGE [13] | 368M Text+Layout+Image | —      | 97.46   |
| UTel          | LARGE (ours)| 341M Text+Layout | 96.72    | 97.27   |

and 1.80% in the base model compared with LayoutLMv2. Our UTel large model underperforms LayoutLMv3 large model slightly, however, LayoutLMv3 uses image modality and an image tokenizer is also utilized during the pre-training.

4.4 Ablation Study

We conduct ablation studies to assess the key components in UTel on FUNSD form understanding task.

Ablation on 1D clipped relative range m. First, we evaluate the influence after replacing the 1D absolute position with the 1D clipped relative position of range \( m \). MLLM task is involved during the pre-training stage. As shown in Figure 3, the performance of UTel is not affected when \( m \) is in a moderate range compared with the 1D absolute position model. Our model is robust to the parameter \( m \), and only when \( m \) is very small, e.g., less than 10, the model’s performance on FUNSD could drop obviously. It shows the 1D text sequence order is still important, which is consistent with current academic conclusions [10, 17]. However, a moderate \( m \) in 1D clipped relative position can enable UTel to process sequences longer than that used during the pre-training with no need to truncate the input sequence.

Ablation on pre-training tasks. Then we study the effect of the two proposed pre-training tasks SWP and CWE. The results in Table 4 show both the tasks improve the model performance substantially. It is more effective when we use both tasks together than using either one alone.

4.5 More Experiments

Fine-tuning on few training samples. Collecting data for downstream fine-tuning consumes a lot of resources and achieving high performance with few training samples is important. We test UTel on FUNSD dataset by utilizing 10% to 100% of the original 150 training samples. As shown in Figure 4(a), the performance consistently improves as training samples increase. However, UTel outperforms the other two strong models regardless of the number of training samples, which proves the generalization ability of UTel with few training samples.

Table 4: Ablation on the pre-training tasks. SWP and CWE bring consistent improvements.

| pre-training tasks  | FUNSD F1 |
|---------------------|----------|
| MLLM                | 82.98    |
| MLLM+SWP            | 83.71    |
| MLLM+CWE            | 83.49    |
| MLLM+SWP+CWE        | 83.97    |
Figure 4: (a) Performance with few training samples on FUNSD. (b) MLLM loss on validation set in pre-training stage with different settings.

**MLLM loss on validation set during the pre-training stage with different settings.** We report the loss of MLLM task during the pre-training on our validation set in Figure 4(b). When only text modality is involved with no 1D position, the loss cannot converge to a low level. Because the pure transformer layer cannot distinguish tokens in different positions. When layout information is added, the loss drops dramatically, which shows layout does help the model distinguish different words and establish contextual semantics. Although the loss is still slightly higher than that with extra 1D absolute position added, we argue the main reason is that tokens in a single word share the same bounding box and cannot be distinguished with layout information only. After adding 1D clipped relative position in replace of 1D absolute position, the MLLM loss converges to the same level as the one with 1D absolute position even when $m = 1$, which shows 1D absolute position is redundant in document understanding to some extent. The performance on MLLM task is not affected by replacing 1D absolute position with the clipped relative one, which is consistent with the previous conclusion in ablation study.

## 5 Conclusion

In this paper, we propose a novel pre-trained language model UTel, in which text and layout interactions are effectively utilized in a unified way during the pre-training stage. The proposed surrounding word prediction and contrastive learning of word embeddings significantly contribute to the capacity of both the semantic and spatial representations. As a result, UTel outperforms previous pre-trained models on various downstream document understanding tasks. Benefiting from the 1D clipped relative position embedding, UTel can process arbitrary-length sequences, demonstrating its wide range of applications. Extensive experiments show the superiority of UTel on form/receipt understanding, especially using the low-resource labeled data.

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