Rethinking the Evaluation of Pre-trained Text-and-Layout Models from an Entity-Centric Perspective

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Abstract

Recently developed pre-trained text-and-layout models (PTLMs) have shown remarkable success in multiple information extraction tasks on visually-rich documents. However, the prevailing evaluation pipeline may not be sufficiently robust for assessing the information extraction ability of PTLMs, due to inadequate annotations within the benchmarks. Therefore, we claim the necessary standards for an ideal benchmark to evaluate the information extraction ability of PTLMs. We then introduce EC-FUNSD, an entity-centric benckmark designed for the evaluation of semantic entity recognition and entity linking on visuallyrich documents. This dataset contains diverse formats of document layouts and annotations of semantic-driven entities and their relations. Moreover, this dataset disentangles the falsely coupled annotation of segment and entity that arises from the block-level annotation of FUNSD. Experiment results demonstrate that state-of-the-art PTLMs exhibit overfitting tendencies on the prevailing benchmarks, as their performance sharply decrease when the dataset bias is removed.

1 Introduction

The research field of document intelligence is gaining popularity fueled by increasing industrial demands (Cui et al., 2021; Sassioui et al., 2023; Yang and Hsu, 2022). One of the primary objectives in this field is to extract useful information from visually-rich documents (VrDs), given the texts and their xy-coordinates on the document layout. In recent years, the advent of layout-aware pre-training techniques promotes the understanding and modeling of the semantic and spatial relation within the document layouts, and has demonstrated great success in multiple information extraction tasks of VrDs (Hong et al., 2022; Huang et al.,

2022; Gu et al., 2022; Tu et al., 2023; Luo et al., 2023; Liao et al., 2023).

In practical applications, pre-trained text-and-layout models (PTLMs) serve as a encoder of document layouts, similar to the pre-trained contextualized language models employed in NLP tasks (Devlin et al., 2019; Liu et al., 2019; Sun et al., 2019). Conventionally, information extraction ability of PTLMs is evaluated via semantic entity recognition (SER) and entity linking (EL). It is widely agreed that the two key tasks align with the capabilities required in practical applications of information extraction from visually-rich documents, and the performance of PTLMs on these tasks reflects the capacity of their layout embeddings to facilitate the information extraction from VrDs.

However, the prevailing benchmarks do not fully conform to the aforementioned evaluation pipeline, thereby diminishing the reliability of the assessment. The evaluation of PTLMs usually uses visual information extraction datasets transformed to SER format, and PTLMs tackle them through a sequence-labeling approach. Nevertheless, the entity annotations within prevailing benchmarks are not ideal for evaluation in this manner. The annotations within FUNSD (Jaume et al., 2019) is in block-level, which emphasizes the spatial relation of text blocks on the vision layouts. However, some blocks don't correspond to semantic entities. The semantic entities within SROIE (Huang et al., 2019) show a lack of diversity. The semantic entities in FUNSD-r (Zhang et al., 2023) are not guaranteed to be continuous, making it not generally applicable for sequence-labeling models. Furthermore, all these benchmarks suffer from low-quality layout annotations. These issues are demonstrated in detail in Section 2.1, which illustrates the limitation of prevailing datasets for evaluating PTLMs from an information extraction perspective.

In this paper, our aim is to establish a more appropriate benchmark to evaluate the ability of

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PTLMs in information extraction tasks. Based on certain requirements, we propose EC-FUNSD, an Entity-Centric benchmark derived from FUNSD (Jaume et al., 2019) that aims to provide a fair and unbiased evaluation benchmark of information extraction ability of PTLMs. This benchmark is constructed by manually revising the annotations in FUNSD, and is designed to be used for semantic entity recognition and entity linking. We conducted experiments of prevailing baseline PTLMs to conduct SER and EL on EC-FUNSD. 1 Although EC-FUNSD and FUNSD are very similar in almost all aspects, the baseline models suffer from a significant performance drop on downstream information extraction tasks, particularly a 7.48-8.55 decrease of F1 on SER. This reveals the potential risk of current PTLMs that they may develop to excessively overfit the biased benchmarks, but the actual benefits brought by the advancements are suspicious. The contribution of this paper are summarized as follows:

- 1. We point out that the information extraction ability of PTLMs cannot be adequately evaluated using the existing pipeline, since current benchmarks are not properly tailored for the evaluation purpose.
- 2. To address this gap, we introduce EC-FUNSD, a entity-centric dataset of SER and EL that serves as a precise benchmark to evaluate the information extraction ability of PTLMs;
- 3. Our experiments with popular PTLMs reveal a tendency of these models to overfit the prevailing benchmarks. This demonstrates the bias of prevailing benchmarks could possibly constrain the current evaluation of PTLMs.

2 An Entity-Centric Benchmark for Information extraction from VrDs

2.1 Motivation

In previous works, the evaluation of PTLMs usually adapts the benchmark datasets for visual information extraction to the form of sequence-labeling based SER, popular datasets include FUNSD (Jaume et al., 2019), XFUND (Xu et al., 2022), SROIE (Huang et al., 2019), CORD (Park et al., 2019), FUNSD-r and CORD-r (Zhang et al., 2023). Despite the widespread use of these datasets, their annotations do not conform the typical settings of SER which involves recognizing multiple semantic entities among different categories within each

sample. Specifically, The annotation of FUNSD and XFUND are organized by visual regions (i.e. blocks) of the document layout, in which the category labels and the association relationships are annotated on the block-level, but the contents in a block may not correspond to a semantic entity. CORD and SROIE fall short in providing diversified layout formats, as most samples in these two datasets are receipts and have similar simple layout designs. Besides, they lack diversified entities. CORD focuses on structured information extraction, resulting in highly repetitive entities across samples. SROIE is organized as a key-value extraction task with predefined keys, thus entities from each category would appear at most once in each sample. FUNSD-r and CORD-r do not guarantee the continuity of entities contained in the word sequence and thus cannot be completely tackled by sequence-labeling models and cannot directly be used to evaluate PTLMs. problems prevent these datasets to be a trustful and universal benchmark among PTLMs.

Moreover, the layout annotations of these benchmarks are also problematic. In real world scenarios, the layout annotations of VrDs are typically generated by an off-the-shelf OCR engine and are at character and segment-levels. Text regions are recognized and arranged at line-level, and characters within each region are recognized with their bounding boxes. However, the layout annotations of FUNSD, XFUND and CORD are coupled with semantic annotations, where only block-level annotations are provided instead of segment-level ones, and the semantic blocks simultaneously stand for segments and entities; in SROIE there are segment-level boxes automatic generated by an OCR system, but the word-level annotations are missing. Besides, the layout annotations in all these benchmarks are generated by automated OCR engines and are therefore of low quality, with numerous missing words and segments and massive shifted or inaccurate bounding boxes.

2.2 Dataset Construction

Based on the review of prevailing datasets, we claim that evaluating PTLMs with these benchmarks may be imprecise to reflect their real information extraction ability. On the assumption of that, we aim to establish a high-quality dataset that is suitable to assess the information extraction ability of PTLMs, and propose four essential

¹Code and datasets would be released soon.

Dataset	# Segments	# Words	# Segs. per Sample	# Words per Sample	Avg. Len. of Segment
FUNSD	9,743	31,485	48.95	158.21	3.23
EC-FUNSD	10,662	31,297	53.57	157.27	2.93
Dataset	# Entities	# Ents. per Sample	Avg. Len. of Entity	# Relation Triplets	# Rel. Triplets per Sample
FUNSD	8,529	42.85	2.92	3,966	19.92
EC-FUNSD	8,398	42.20	2.96	3,912	19.65

Table 1: Statistics of the proposed dataset. # is short for "Number of". The statistics of FUNSD is also listed in comparison, with invalid entity linking pairs removed.

requirements for an appropriate dataset: (1) The layout annotations should represent the typical outputs generated by OCR engines, including linelevel text regions and fine-grained character or word bounding boxes; (2) The layout annotations should be of high quality, with minimal omission of words and segments; (3) The annotation of semantic entities should confirm to unified semantic-driven definitions to ensure consistency across samples; and (4) Each sample should be a single-page document that contains rich layout and diversified entities and relations to increase the validness of evaluation on the benchmark. To construct a dataset that satisfies these requirements and serves as a evaluation benchmark of the information extraction ability of PTLMs, we choose to revise the existing annotations within the FUNSD dataset (Jaume et al., 2019) due to the following reasons. (1) Compared with other prevalent VrD datasets for information extraction, FUNSD stands out by offering a diverse range of layouts among its samples, rendering it a comprehensive benchmark. (2) FUNSD contains extensive block annotations with various semantic types and their relations. These existing annotations can be revised into semantic entity and relation annotations with little modification.

Based on the original dataset, we executed a twostep revision of the layout and entity annotations to create a Entity-Centric version of FUNSD, namely EC-FUNSD. In the first step, we constructed the word and segment-level layout annotations by manually revising the original layout annotations of each sample. We removed empty words in the original layout annotations, and marked unrecognizable handwritten words as "<unk>". We appended omitted words, associating them to appropriate existing segments or creating new segments when necessary. We rectified all errors on texts or bounding boxes of words and segments. We removed words that are of low resolution and deemed unimportant to the remaining contents, because their original annotations are erroneous and we are unable to correct these illegible words. We manually split multiple-row blocks within the original annotations into multiple segments, each segment confined in one row. After row-splitting, we combined segments that are tightly adjacent to each other into one segment. Throughout this process, we preserved the sequential order of words within each segment and also the mapping of words and segments from revised annotations to the old ones, to ensure the mapping of entity and relation annotations is preserved.

After correcting layout annotations, in the second step, we revised the entity and relation annotations by manually transforming the block annotations to semantic entity annotations. We mapped the original block annotations to form the preliminary entity annotations for revision. After that, we corrected the annotation of entities being annotated across multiple semantic blocks, and entities with missing words in their annotations. Additionally, we removed the invalid linking pairs and modified the corresponding linking pairs following the modifications made to the entity annotations. We generally preserved the segment order within the original annotations to ensure that each entity span is continuous in the annotations, making the form of this dataset suitable for sequence-labeling models. The annotating procedures above are carried out by two qualified annotators who are familiar with document AI.

The statistics of EC-FUNSD are displayed in Table 1. EC-FUNSD has a smaller total word count than the original dataset, primarily due to the removal of low-quality word annotations. The number of segments increases since multiple-row blocks are splitted to several segments. The average length of entities is relatively higher in EC-FUNSD, since the entities that were splitted into multiple semantic blocks were combined.

3 Experiments

3.1 Task Formulation

The SER and EL tasks on document layouts are formalized as follows. A document layout with $N_{\mathcal{D}}$ words is represented as $\mathcal{D} = \{(w_i, \mathbf{b}_i)\}_{i=1,\dots,N_{\mathcal{D}}}$, where w_i denotes the *i*-th word in document and $\mathbf{b}_i = (x_i^0, y_i^0, x_i^1, y_i^1)$ denotes the position of w_i in the document layout. The coordinates (x_i^0, y_i^0) and (x_i^1, y_i^1) correspond to the bottomleft and top-right vertex of w_i 's bounding box, respectively. Given the predefined semantic entity types $\mathcal{E} = \{e_i\}_{i=1,\dots,N_{\mathcal{E}}}$ and relation types $\mathcal{R} =$ $\{r_i\}_{i=1,\dots,N_{\mathcal{R}}}$, the semantic entities within document \mathcal{D} is denoted as $s_{\mathcal{D}} = \{s_1, \dots, s_J\}$, where the j-th entity $s_j = \{e_j, (j_1, j_2)\}$ is identified by its entity type $e_i \in \mathcal{E}$ and an index span (j_1, j_2) indicating the position of words in the inputs, satisfying $1 \leq j_1 \leq j_2 \leq N_D$. The set of relationships between entities of $s_{\mathcal{D}}$ is denoted as $t_{\mathcal{D}} = \{t_1, \dots, t_K\}$, where the k-th relation triplet $t_k = \{r_k, (ks, ko)\}\$ indicates that the relation between the subject s_{ks} and object s_{ko} is $r_k \in \mathcal{R}$ $(1 \le ks, ko \le J)$. It is guaranteed that there would be at most one relation triplet from one entity to another. The aim of SER is to recognize all the entity that spans together with their semantic categories, while EL aims to identify the possible relationship between two arbitrary entities, as well as type of relationship in the document. ²

3.2 Baseline Methods

We use LayoutLMv3 (Huang et al., 2022) and GeoLayoutLM (Luo et al., 2023) as two baseline PTLMs to be evaluated. LayoutLMv3 is a PTLM with additional vision signals, and is pretrained by three objectives (Masked Language Modeling, Masked Image Modeling, and Word-Patch Alignment), which enables the alignment between textual and visual modalities and enhances model understanding of these modalities. Geo-LayoutLM introduces multi-level geometric pretraining tasks to acquire geometric-enhanced layout representations, together with the Coarse Relation Prediction and Relation Feature Enhancement modules for better handling of the EL task.

3.3 Implementation Details

We use the official implementation and pre-trained weights of LayoutLMv3-base ³ (Huang et al., 2022) and GeoLayoutLM 4 provided by their official GitHub repositories. It is important to note that the predefined maximum sequence length of textual tokens in both models is limited to 512. Therefore, when processing long documents that surpass this limit, LayoutLMv3 divides the document into several segments, whereas GeoLayoutLM truncates the content beyond the maximum length. Both means inevitably disrupt the integrity of EL labels in the documents, resulting in unfair comparison with other methods. To address this issue, we increased the maximum sequence length to 1024 by initializing the positional embedding of index 512-1023 by those of index 0-511 before fine-tuning. This adjustment guarantees none of the training or validation samples exceed the maximum length, and results in a slight difference compared to the results proposed in the original releases of the baselines.

We fine-tuned the two baseline models on FUNSD and EC-FUNSD for SER and EL tasks. In fine-tuning LayoutLMv3 for SER, we followed all the original setting of (Huang et al., 2022). In fine-tuning LayoutLMv3 for EL, we generally followed all the original setting with 400 epochs of fine-tuning. In fine-tuning GeoLayoutLM for SER and EL, for better performance, instead of following the original settings proposed in (Huang et al., 2022), we used an AdamW optimizer with 2% linear warming-up steps and a 1e-2 weight decay with a cosine scheduler. The learning rate and batch size were 1e-5 and 16 as the optimal configure searching from lr={8e-6, 1e-5, 1.5e-5, 2e-5 and $bs=\{6, 16\}$. The model was fine-tuned by 500 epochs and the checkpoint with the best performance on SER and EL was kept. For all experiments, we ran the experiments for three times and report the mean value and standard deviation of F1 scores.

We ensured the consistency in fine-tuning and evaluating on FUNSD and EC-FUNSD, with the sole exception that we disabled the vision branch of GeoLayoutLM when fine-tuning on EC-FUNSD. In specific, we noticed that the

²Joint extraction of entities and relations from VrDs is not in the scope of this paper.

³https://github.com/microsoft/unilm/tree/
master/layoutlmv3

⁴https://github.com/AlibabaResearch/ AdvancedLiterateMachinery/tree/main/ DocumentUnderstanding/GeoLayoutLM

Task	Method	FUNSD	EC-FUNSD
SER	LayoutLMv3	$90.85_{\pm0.17}$	$82.30_{\pm0.24}$ (\downarrow 8.55)
	GeoLayoutLM	$91.10_{\pm0.19}$	$83.62_{\pm0.22}$ (\$\dagger\$7.48)
EL	LayoutLMv3	$69.80_{\pm 1.19}$	$67.47_{\pm0.53}$ (\$\dagge\cdot 2.33\$)
	GeoLayoutLM	$88.06_{\pm0.15}$	$86.18_{\pm0.15}$ (\$\dagger\$1.88)

Table 2: The average performance of baseline models on the two benchmarks.

vision feature was only available in block-level in GeoLayoutLM, which directly contributes to the entity feature when fine-tuning FUNSD. However, a corresponding block-level vision representation is not available for every entity in EC-FUNSD, e.g. for the entities that span multiple rows and overlap with other entities in region. Therefore, the vision inputs were disabled in fine-tuning GeoLayoutLM on EC-FUNSD.

3.4 Results

As shown in Table 2, the two models performed noticeably worse on EC-FUNSD than on FUNSD. We attribute the performance degradation to false overfitting of PTLMs on FUNSD. As illustrated in Section 2.1, FUNSD derives its segment and entity annotations directly from blocks, which leading to considerable bias when fine-tuning on this dataset. For SER, tokens within the same entity have exactly the same xy-coordicate inputs, leading the models to learn entity boundaries simply by determining whether the layout features between tokens are consistent or not. For EL, the entity representations are heavily dominated by the layout features, as all tokens within an entity share the same layout features, resulting in less attention to entity semantics. The performance of PTLMs between FUNSD and EC-FUNSD illustrates the existence of bias in FUNSD significantly influences its trustworthiness as an evaluation benchmark.

4 Conclusion

In this paper, we investigated the evaluation pipeline of PTLMs together with prevailing benchmarks. We illustrated that these benchmarks are inapporpriate for evaluating the information extraction ability of PTLMs due to their annotations that are non-compliant to the concept of semantic entities, lack of diversity, or incompetence to be directly applied to the mainstream evaluation pipeline. Based on these problems, we propose EC-FUNSD, an entity-centric dataset aiming to serve as a suitable benchmark for evaluating the

information extraction ability of PTLMs. Experiment results confirm the tendency for PTLMs to overfit the currently used benchmarks on both SER and EL tasks, indicating the importance of an unbiased benchmark for evaluating the information extraction ability of PTLMs.

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