A Benchmark for Structured Extractions from Complex Documents

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Abstract

Understanding visually-rich business documents to extract structured data and automate business workflows has been receiving attention both in academia and industry. Although recent multi-modal language models have achieved impressive results, we find that existing benchmarks do not reflect the complexity of real documents seen in industry. In this work, we identify the desiderata for a more comprehensive benchmark and propose one we call Visually Rich Document Understanding (VRDU). VRDU contains two datasets that represent several challenges: rich schema including diverse data types as well as nested entities, complex templates including tables and multi-column layouts, and diversity of different layouts (templates) within a single document type. We design few-shot and conventional experiment settings along with a carefully designed matching algorithm to evaluate extraction results. We report the performance of strong baselines and three observations: (1) generalizing to new document templates is very challenging, (2) few-shot performance has a lot of headroom, and (3) models struggle with nested fields such as line-items in an invoice. We plan to open source the benchmark and the evaluation toolkit. We hope this helps the community make progress on these challenging tasks in extracting structured data from visually rich documents.

1 Introduction

Visually-rich documents, such as forms, receipts, invoices, are ubiquitous in various business workflows. Distinct from plain text documents, visually-rich documents have layout information that is critical to the understanding of documents. Given the potential to automate business workflows across procurement, banking, insurance, retail lending, healthcare, etc., understanding these documents, and in particular, extracting structured objects from them has recently received a lot of attention from both industry and academia (Li et al., 2020; Zhang et al., 2020; Powalski et al., 2021; Appalaraju et al., 2021; Garncarek et al., 2021; Biten et al., 2022).

While tasks such as classification (Harley et al., 2015) and Visual-QA (Mathew et al., 2021) have been posed to study the understanding of such documents, in this paper, we focus on the task of extracting structured information. Optical character recognition engines (OCR) are typically used to extract the textual content and the bounding boxes of each of the words from the documents. Existing models rely on language models with multi-modal features to solve the task, where features from textual contents, images, and structural templates are jointly encoded through self-supervised training tasks (Xu et al., 2020a,b; Appalaraju et al., 2021; Garncarek et al., 2021; Lee et al., 2022; Powalski et al., 2021). Although recent results are impressive (Jaume et al., 2019; Park et al., 2019; Huang et al., 2019; Stanisławek et al., 2021), we argue that existing benchmarks do not reflect the challenges encountered in practice, such as having to generalize to unseen templates, rich target schema to extract, nested entities, and small training sets.

We identify five major drawbacks with existing benchmarks that we describe in greater detail in Section 2. First, most existing benchmarks suffer from the lack of richness in labeling schema (Jaume et al., 2019). Entities are roughly considered as simple text strings while practical document types have a variety of types like numerical IDs, dates, addresses, currency amounts, etc. Second, some benchmarks contain documents with limited layout complexity. Pages that are mostly organized in long paragraphs and sentences are more similar to plain text documents (Stanislawek et al., 2021) and are not helpful evaluating our understanding of visually-rich documents. Third, the documents in some benchmarks may share the

* This work was completed while the author was working as an intern at Google Research.
same template (Huang et al., 2019). This makes it trivial for the models to deal with these documents by simply memorizing the structure even if the single template is complex enough. Next, existing datasets use different OCR engines (Park et al., 2019; Huang et al., 2019). The large variety of OCR engines make it hard to tell whether the improvements come from the advanced models or more accurate OCR results. Finally, some benchmarks only provide the textual contents for each entity without the detailed token-level annotation (Stanislawek et al., 2021). This makes it ambiguous to locate the entities in the source document and makes it difficult to generate clean training samples for sequence labeling models (Xu et al., 2020b,a; Huang et al., 2022; Wang et al., 2022).

Based on these observations, we propose a new benchmark for Visually-Rich Document Understanding (VRDU). VRDU is designed to better reflect the challenges encountered in practice when building extraction models for such documents. We hope that this benchmark helps bridge the gap between academic research and practical scenarios to facilitate future study on this topic. As shown in Figure 1, we first collect political ad-buys from the Federal Communications Commission (FCC)\(^1\) and registration forms from the Foreign Agents Registration Act (FARA)\(^2\), and construct two datasets. We describe the annotated data, and the labeling protocol in Section 4. Then we design three tasks of increasing difficulties on the two datasets. In Task 1, documents in the train and test sets are drawn from a single template. In Task 2, we increase the diversity of templates, but train and test sets for each document type are drawn from the same set of templates. In Task 3, the train and test sets are drawn from disjoint sets of templates to measure how well a model generalizes to unseen templates. Within each task, we also compare the model performance with different number of training samples to understand the data efficiency for each approach. Finally, we implement a type-aware matching algorithm to provide realistic extraction performance, where different matching functions are used for each entity name according to its specific data type. We report both micro-F1 and macro-F1 and make this implementation available.

We report the performance of commonly-used baseline models, LayoutLM (Xu et al., 2020b), LayoutLMv2 (Xu et al., 2020a), and FormNet (Lee et al., 2022). Our goal is not a comprehensive comparison of these model architectures. Instead, our experiments highlight three areas of opportunity for all these models. First, while the models are great at extracting from new instances of documents with a layout that matches one seen during training (Task 1 and Task 2), they do worse on new layouts (Task 3). Second, few-shot performance continues to be hard with substantial room for improvement. Third, extracting nested-repeated entities is really challenging and all models perform worse on this compared to simple fields.

We open-source the datasets and evaluation toolkit to facilitate future research on this topic. We summarize our contribution as follows.

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\(^1\)https://publicfiles.fcc.gov

\(^2\)https://www.justice.gov/forms
• We identify desiderata for benchmarks in the visually-rich document understanding space, argue that the current datasets do not meet these requirements.
• We propose VRDU, a new benchmark for visually-rich document understanding with high-quality OCR results and annotations. We also implement and open-source a type-aware matching algorithm to evaluate the models.
• Through experiments on multiple commonly-used baseline models, we show that there is substantial room for progress on the tasks in VRDU with regard to template transfer learning, few-shot settings, and nested entity extractions.

2 Benchmark Desiderata

We identify five key desiderata for a benchmark that reflects practical challenges in extracting structured data from visually rich documents.

2.1 Rich Schema

The structured data we need to extract from documents in practice reflect a rich diversity of schemas. The entities have various types such as numerical IDs, names, addresses, dates, currency amounts, etc. They can be required, optional, or repeated for a given document. In several cases, we also see nested entities. For example, a US address field may contain address lines, city, state, and zip code. Considering the heterogeneity of schemas we encounter in practical settings, we believe a useful benchmark should reflect a rich schema. Contrast this with a dataset where all text fields are treated as simple text strings.

2.2 Layout-rich Documents

The documents should have complex layout elements. Challenges in practical settings come from the fact that documents may contain tables, key-value pairs, switch between single-column and double-column layout, have varying font-sizes for different sections, include pictures with captions, and even footnotes. Contrast this with datasets where most documents are organized in sentences, paragraphs, and chapters with section headers. Figure 3 shows an example of a document with rich layout and contrasts it with a more traditional document that is the focus of classic NLP literature on long inputs.

2.3 Diverse Templates

A benchmark collection should involve different structural layouts or templates as shown in Figure 4. It is trivial to extract from a particular template by memorizing the structure. However, in practice one needs to be able to generalize to new templates. Consider, for instance, an invoice parser. If a company starts working with a new vendor (and enterprises routinely work with new vendors every year), a model that memorized the set of templates corresponding to existing vendors is likely to break since the new vendor may send invoices with a different template. In order to reflect this real-world requirement, a useful benchmark for extraction from visually-rich documents should have diverse templates and test a model’s ability to generalize to unseen templates.
2.4 High-quality OCR Results

Documents should have high-quality OCR results. Our aim with this benchmark is to focus on the VRDU task itself and we want to exclude the variability brought on by the choice of OCR engine. Existing benchmarks use different OCR engines, which makes the evaluation results inconsistent and the comparison unfair. It is confusing whether the performance improvements come from the more advanced model design or are simply because of more accurate OCR results. Therefore, a benchmark should use the same high-quality engine ensuring the quality of OCR is satisfactory and the choice of OCR engine is not a factor influencing the results when comparing the performance.

2.5 Token-level Annotation

Documents should contain ground-truth annotations that can be mapped back to corresponding input text, so that each token can be annotated as part of the corresponding entity. This is in contrast with simply providing the text of the value to be extracted for the entity. This is key to generating clean training data. Consider, for instance, an invoice dataset where the “amount due” field was provided as “0” (instead of marking the actual tokens corresponding to the entity). This string may also match several places in the documents for fields such as “tax amount”, “amount before taxes” or even content that is not part of the target schema. This may make it more difficult to generate labeled examples for training.

3 Related Work

Several benchmarks are available to evaluate the performance of models in visually-rich document understanding. The properties of these benchmarks and the comparison with our proposed benchmark are shown in Table 1. FUNSD (Jaume et al., 2019) is a dataset widely used in the form understanding task, which contains 199 fully annotated forms with three different entity types, Header, Question, and Answer. Despite the detailed annotation, the labeling of FUNSD is too limited to reflect the rich schema in the practical scenarios. CORD (Park et al., 2019) is a receipt dataset where the document images are mostly photos of grocery receipts. There is limited template diversity, and image artifacts (tilt, lighting, distortion) result in OCR errors. SROIE (Huang et al., 2019) is another receipt dataset. Key fields are labeled, such as Company Name, Address, and Total Price. However, the receipts in the dataset are similar to each other so SROIE fails to reflect a diversity of templates. Kleister-NDA (Stanisławek et al., 2021) collects non-disclosure agreements and labels important fields but the documents are full of plain text paragraphs and chapters and show few layout elements. Kleister-Charity (Stanisławek et al., 2021) from the same research group collects the financial reports and manages to present a diversity of layout-rich documents. However, both Kleister-NDA and Kleister-Charity are not annotated at the token level, which brings difficulties for many popular baseline models using sequence labeling methods to be evaluated on these two benchmarks. DeepForm (Svetlichnaya, 2020; Borchmann et al., 2021) is a dataset of political ad-buy documents. Although various layout-rich documents are collected, DeepForm suffers from the same issue of token-level annotation as Kleister-Charity and Kleister-NDA. To leverage the rich data resource of DeepForm, we include the ad-buy forms in our proposed dataset, design a new rich labeling schema, and annotate the documents from scratch. This paper proposes VRDU, composed of two datasets of Registration Form and Ad-buy.
Table 1: The statistics of VRDU and other existing benchmarks. * denotes the number of nested entities in the dataset, where VRDU-Ad-buy Form involves 1 nested entity and the nested entity has 5 entities as components.

| Dataset               | Source               | Doc # | Entity # | Rich Schema | Layout-rich Documents | Diverse Templates | High-quality OCR | Token-level Annotation |
|-----------------------|----------------------|-------|----------|-------------|----------------------|-------------------|-------------------|-----------------------|
| FUNSD                 | Lawsuits Forms       | 199   | 3        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| CORD                  | Grocery Receipts     | 1000  | 30       | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| SROIE                 | Grocery Receipts     | 973   | 4        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| Kleister-NDA          | NDA Forms            | 540   | 4        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| Kleister-Charity      | Financial Reports    | 2778  | 8        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| DeepForm              | Ad-buy Form          | 1100  | 5        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| VRDU-Registration Form| FARA                 | 1915  | 6        | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |
| VRDU-Ad-buy Form      | FCC                  | 641   | 9+1(5)*  | ✓           | ✓                    | ✓                 | ✓                 | ✓                     |

4 VRDU Benchmark

Based on the desiderata outlined in Section 2, we introduce VRDU, a new public benchmark for visually-rich document understanding. This benchmark includes two datasets: Ad-buy Forms and Registration Forms. These datasets contain structured data with rich schema including nested repeated fields, have complex layouts that clearly distinguish them from long text documents, have a mix of different templates, and have high-quality OCR results. We provide token-level annotations for the ground truth ensuring there is no ambiguity when mapping the annotations to the input text. In the remainder of this section, we describe: (1) the process used for collecting and annotating the datasets, (2) the three extraction tasks we designed along with the prescribed train/validation/test splits, and (3) the design and implementation of the type-aware matching algorithm used to compare the extracted entities with the ground-truth.

4.1 Data Collection and Annotation

We crawl documents from public sites for the Federal Communications Commission and the Foreign Agents Registration Act, and construct two separate datasets, Ad-buy Forms and Registration Forms. We use the state-of-the-art commercial OCR engines to recognize the raw data in the documents.

Ad-buy Forms The Ad-buy Forms consist of 641 documents about political advertisements.

Each document is an invoice or receipt signed between a TV station and a campaign group. The documents use tables, multi-columns, and key-value pairs to record the advertisement information, such as the product name, the flight dates, and the total price. They also have a large table showing more details of the advertisements including the specific release date and time.

Registration Forms The Registration Forms consist of 1915 documents about foreign agents registering with the US government. Each document records essential information about foreign agents involved in activities that require public disclosure. Contents include the name of the registrant, the address of related bureaus, the purpose of activities, and other details. We include three forms in the dataset, so the documents have three different templates, Amendment, Short Form, and Dissemination Report. All these forms are on the same topic so we label them using the same schema.

Labeling Schema The documents in our proposed benchmark present structured data with fairly rich schema, where entities can be repeated, unrepeated, or nested, and the data types can be numerical strings, price values, etc. After examining a subset of the documents, we decide the target schema with 6 unrepeated entity names for Registration Forms, and 9 unrepeated entity names and 1 nested repeated entity name for Ad-buy Forms. The specific entity names are shown in Table 2. The unrepeated entities are the entities that only have one unique value in each document. Sometimes they may be present multiple times on a document, but with each instance having the exact same value. For example, a document may have several fields showing the contract ID but all these fields have the same content. The nested entities are the entities containing several individual components. For example, the line item in Ad-buy Form contains
### Table 2: The labeling schema of VRDU.

| Dataset          | Type of entity | Entity names                                      |
|------------------|----------------|---------------------------------------------------|
| Registration Form| Unrepeated Entity | `file_date, foreign_principal_name, registrant_name, registration_ID, signer_name, signer_title` |
| Ad-buy Form      | Unrepeated Entity | `advertiser, agency, contract_ID, flight_start_date, flight_end_date, gross_amount, product, TV_address, property` |
|                  | Nested Entity   | `line_item (description, start_date, end_date, sub_price)` |

`description`, `sub-price` and other entities as components, and models are required to extract each component and group them correctly to extract a nested entity.

**Labeling Protocol** We hired experienced labelers to conduct the annotation job. During the annotation, a pool of labelers were provided with the previously annotated documents as reference and the labeling instruction as guidance. They drew bounding boxes to highlight the entities and labeled each entity into different categories. If unrepeated entities occurred multiple times, they were instructed to identify all instances. When labeling the nested entities, the labelers annotated the component entities as well as drew a larger bounding box that groups the components together into a nested entity. After the first pass of annotation, a pool of experts were assigned to review the results labeled by the first pool. We took the final corrected results from the expert pool and used them in our experiments. This is the dataset we published.

**4.2 Task Settings**

We design three tasks with increasing difficulty:

**Task 1: Single Template Learning (STL)** This is the simplest scenario where the training, testing, and validation sets only contain a single template. This simple task is designed to evaluate a model’s ability to deal with a fixed template. Naturally, we expect very high F1 scores for this task.

**Task 2: Mixed Template Learning (MTL)** This task is similar to the task that most related papers use: the training, testing, and validation sets all contain documents belonging to the same set of templates. We randomly sample documents from the datasets and construct the splits to make sure the distribution of the each template is not changed during the sampling.

**Task 3: Unseen Template Learning (UTL)** This is the hardest setting, where we evaluate if the model is able to generalize to unseen templates. For example, in the Registration Forms dataset, we train the model with two of the three templates and test the model with the remaining one. The documents in the training, testing, and validation sets are drawn from disjoint sets of templates. To our knowledge, previous benchmarks and datasets do not explicitly provide such a task designed to evaluate the model’s ability to generalize to templates not seen during training.

**Dataset Splits** In each of the task mentioned above, we include 300 documents in the testing set. We build 4 different training sets with 10, 50, 100, 200 samples respectively. The objective is to evaluate models on their data efficiency. The prescribed dataset splits are published along with the datasets to enable and apples-to-apples comparison between different models using this benchmark.

**4.3 Evaluation Toolkit**

To evaluate extraction performance, we propose a type-aware fuzzy matching algorithm for each of the entities in our benchmark and report both the macro and micro F1 score for the dataset.

It is common practice to compare the extracted entity with the ground-truth using strict string matching (Wolf et al., 2019). However, such a simple approach may lead to unreasonable results in many scenarios. For example, “$40,000” does not match with “40,000” because of the missing dollar sign when extracting the total price from a receipt, and “July 1, 2022” does not match with “07/01/2022”. Dates may be present in different formats in different parts of the document, and a model should not be arbitrarily penalized for picking the wrong instance. We implement different matching functions for each entity name based on the type associated with that entity. In the examples mentioned before, we will convert all price values into a numeric type before comparison. Similarly, date strings are parsed, and a standard date-equality function is used to determine equality.
Table 3: Experiment results of Single Template Learning, Mixed Template Learning, Unseen Template Learning on Registration Form and Ad-buy Form

| [D] | Model | Registration Form | Ad-buy Form |
|-----|-------|-------------------|-------------|
|     |       | Task 1 (Single Template) | Task 2 (Mixed Template) | Task 3 (Unseen Template) | Task 2 (Mixed Template) | Task 3 (Unseen Template) |
|     | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 | Micro-F1 | Macro-F1 |
| 10  | LayoutLM | 65.91 | 53.64 | 36.41 | 28.98 | 25.54 | 18.37 | 20.20 | 48.13 | 19.92 | 47.73 |
|     | LayoutLMv2 | 41.29 | 34.23 | 0.61 | 0.47 | 23.41 | 17.84 | 25.36 | 58.13 | 25.17 | 57.84 |
|     | FormNet | 74.22 | 62.95 | 63.61 | 56.53 | 50.53 | 40.24 | 20.28 | 47.73 | 19.92 | 47.73 |
| 50  | LayoutLM | 86.21 | 74.76 | 80.15 | 76.46 | 55.86 | 46.43 | 42.23 | 83.89 | 41.59 | 84.14 |
|     | LayoutLMv2 | 88.68 | 77.51 | 84.13 | 82.04 | 61.36 | 52.42 | 46.68 | 83.82 | 39.52 | 84.49 |
|     | FormNet | 89.38 | 78.04 | 85.38 | 82.41 | 68.29 | 57.17 | 44.97 | 86.38 | 44.35 | 86.87 |
| 100 | LayoutLM | 88.70 | 78.79 | 86.02 | 84.04 | 63.68 | 53.43 | 44.97 | 86.38 | 44.35 | 86.87 |
|     | LayoutLMv2 | 90.45 | 80.03 | 88.36 | 86.38 | 65.96 | 57.39 | 40.38 | 86.24 | 39.88 | 85.57 |
|     | FormNet | 90.91 | 80.82 | 88.13 | 85.82 | 72.58 | 62.23 | 44.66 | 85.85 | 44.18 | 85.55 |
| 200 | LayoutLM | 90.47 | 81.77 | 87.94 | 86.41 | 70.40 | 59.46 | 46.54 | 87.61 | 46.31 | 86.87 |
|     | LayoutLMv2 | 91.41 | 83.12 | 89.19 | 87.65 | 72.03 | 62.14 | 46.54 | 87.61 | 46.31 | 86.87 |
|     | FormNet | 92.12 | 82.99 | 90.51 | 89.05 | 77.29 | 67.82 | 43.23 | 86.93 | 39.88 | 85.05 |

5 Experiments

We conduct experiments on VRDU and evaluate baseline models on the three proposed tasks. We report the micro-F1 and the macro-F1 scores across the training sizes proposed. Our primary goal with these experiments is to demonstrate that several challenges remain open in this space. In fact, while performance on other datasets discussed in Section 3 might indicate that this is a solved problem, our results show all models fare worse on VRDU highlighting substantial room for improvements. However, comprehensive comparison between existing models is an explicit non-goal for this paper.

5.1 Baselines

We evaluate three models on the datasets, LayoutLM (Xu et al., 2020b), LayoutLMv2 (Xu et al., 2020a), and FormNet (Lee et al., 2022). LayoutLM is a layout-aware pre-trained language model which encodes the absolute coordinates of bounding boxes in the embedding layers of BERT (Devlin et al., 2018) to inform the model of the structural information. LayoutLMv2 further improves the layout embedding by considering the relative distance between different bounding boxes and proposes the two-stream multi-modal Transformer encoder to learn the correlation between the image and the text. FormNet goes beyond simply sequence labeling approach and leverages the graphs constructed by the layout elements in the documents to better learn the structure information. Although we acknowledge there are many other approaches to solving structured extractions from such documents (Appalaraju et al., 2021; Biten et al., 2022; Garncarek et al., 2021; Powalski et al., 2021; Wang et al., 2022; Zhang et al., 2020; Lee et al., 2021; Huang et al., 2022), we only consider these three commonly-used ones to highlight the challenges common to all three models and inspire possible directions for future study. As we said previously, a comprehensive comparison is outside the scope of this paper.

5.2 Experiment Results

We report the micro-F1 score and macro-F1 score of the three tasks, Single Template Learning (STL), Mixed Template Learning (MTL), and Unseen Template Learning (UTL), under different number of training samples in Table 3. Since Ad-buy Form dataset contains a variety of templates and there are only a limited number of documents for each template, we skip the STL task for it. We denote the number of training samples as [D]. Under each setting, we build three training sets of the same size using different random seeds, and the reported numbers are the average result of each model on the three training sets.

First, comparing the results on VRDU and on other benchmarks, it is clear that there is ample room for improvement. Even when [D] = 200, the highest micro-F1 score is around 90% on Registration Form and around 45% on Ad-buy Form. In contrast, FormNet achieves 97.21% micro-F1 score and LayoutLMv2 achieves 96.01% micro-F1 score on CORD (Xu et al., 2020a; Lee et al., 2022). LayoutLMv2 achieves 97.81% micro-F1 score on SROIE (Xu et al., 2020a). One might think that results on CORD and SROIE indicate that this is a solved problem. As results on VRDU show, a dataset that reflects challenges in practical settings shows that there is much room for improvement. The performance of FormNet on FUNSD is 84.69% micro-F1 score, and that of LayoutLMv2 is 84.20% micro-F1 score (Xu et al., 2020a; Lee et al., 2022). Although there is still room to improve here, the simplistic labeling schema used in FUNSD makes the results less representative of practical tasks.
From Table 3, we observe consistent improvement as training data size increases. Even for the simplest task, STL (on Registration Forms), the micro-F1 score of FormNet when $|D| = 10$ is lower than that when $|D| = 50$ by 15.16 points. This 15+ point gap remains across all tasks for both datasets between the $|D| = 10$ and $|D| = 50$ settings. This holds true for all three models, underscoring that few-shot performance is difficult for all models, even for the simple STL setting getting to micro-F1 scores of just 74.22%.

We also compare the performance of different tasks, STL, MTL, and UTL. The tasks are designed to study the template generalization of each model. From the results, we can see all models perform well in STL and MTL and achieve micro-F1 and macro-F1 scores higher than 80% in both datasets with 200 training samples. We attribute the performance to the fact that there are no unseen layout structures involved when generalizing to the testing set in STL and MTL. However, there is a noticeable gap between the performance of MTL and UTL. At 200 training documents, micro-F1 for UTL is 13–17 percentage points worse than the micro-F1 for MTL across the three models. The performance of UTL on Ad-buy Form is worse than MTL by about 3 points. Recall that the test set in UTL contains documents with templates (layouts) not seen in the training set. We believe techniques that allow models to generalize to new layouts even with modest training sets are of practical importance.

Studying the performance in Ad-buy Form, we see the macro-F1 scores are much higher than the micro-F1 scores. The micro-F1 score weighs every instance of an entity equally, while the macro-F1 scores average the F1 score for each entity. Rare entities, that do not affect the micro-F1 much can affect the macro-F1 just as much as a frequent entity. The huge difference between these scores for Ad Buy forms is because of the presence of nested repeated entities with a very low F1 score.

5.3 Performance on Nested Entities

We next study the performance of nested entities in Ad-buy Form dataset. Consider the performance of FormNet on MTL. The performance of extracting nested entities vs. other entities is plotted in Figure 5. As we can see, there is a huge gap of 60 – 70 points across different sizes of training sets when comparing the micro-F1 score of nested entities and other entities. In contrast to unrepeated entities, the nested entity requires the model not only to correctly extract the corresponding entities, but also to group the components together. Currently, a heuristic method is used as a simple baseline to deal with the nested entity since no existing models take the nested entity type into consideration. We describe the method in detail in Appendix A.1. However, such a heuristic results in very low F1 scores for the entity. It is still an open question for future research how to properly extract the nested entities from visually-rich documents.

6 Conclusions

In this paper, we identify five key desiderata in a benchmark to measure progress on our ability to solve structured extractions from visually rich documents. We argue that existing benchmarks fall short on one or more of these, and propose VRDU. We define three tasks on two datasets and provide an implementation of type-aware matching functions to evaluate extraction models on both micro and macro F1 scores. An evaluation of three strong baseline models shows that some tasks in VRDU are very challenging for all models. The tasks include generalization to new templates, extraction under few-shot scenarios, and extraction of complex nested-repeated fields. We make the dataset and evaluation code publicly available. We hope this facilitates progress in this challenging area.

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A Appendix

A.1 Post-processing for Evaluation Toolkit

We include repeated, unrepeated, or nested entity names in VRDU. The schema constraints of entity names should be considered in the evaluation. However, they are usually ignored by existing models. For example, the series ID is an unrepeated entity and each document should only have one unique value for it, so the model is required to extract a single string with the highest confidence instead of providing a number of candidates for the users to choose from. When there is no confidence score provided by the model, we simply keep the first extracted entity as the answer for the unrepeated entity names.

The nested entity is a new kind of entity name proposed by our benchmark. Since existing works only focus on the extraction of individual entities, we propose a heuristic method to group the related individual entities into nested ones and evaluate the result accordingly. Specifically, we iterate the entities and divide the list when we encounter a entity whose entity name has been already met before.

Algorithm 1 Entity Grouping

1: function GROUP(T, E)
2: ⊲ where T is a set of entity names to be nested, E is a list of entities.
3: \[ E' = \{ e \in E | e.type \in T \} \]
4: \[ N = \phi \] ⊲ N is to record all nested entities.
5: \[ M = \phi \] ⊲ M is to memorize entity names.
6: \[ i = 1, j = 1 \]
7: while \( i \leq j \leq \text{E}' \).length do
8:   if \( E[j].type \notin M \) then
9:     \[ M = M \cup \{ E[j].type \} \]
10:    \[ j = j + 1 \]
11:  else if \( E[j].type \in M \) then
12:     \[ \triangleright \text{Group entities when seeing repeated types} \]
13:    \[ N = N \cup \{ E[i:j-1] \} \]
14:    \[ i = j \]
15:    \[ M = \phi \]
16: end if
17: end while
18: return \( N \)
19: end function

A.2 Case Study

We select four loss cases in the experiments of FormNet and visualize the errors in Figure 6 to give readers a sense for the kinds of errors that we commonly encounter. We hope this spurs ideas for future improvements.

Incomplete Extraction Example 1 and 4 suffer from the incomplete extraction, i.e., the model can correctly locate the ground-truth entity but fails to include all the necessary information. In Example 1, the TV_address field is hidden in complex context, which makes it hard to recognize the P.O. Box as part of the address. In Example 4, the error of Registrant_name is because of the handwritten characters in different sizes and fonts. The models cannot group the characters together to extract the right entity.

Misleading Key Words The errors in Example 2 and 3 result from misleading key words. Specifically, in Example 2, the model is confused by the similar key word, “Invoice #”, and extract the Invoice ID instead of the Order ID, although there are cases in the training set where the key word for contract_ID field is “Order #”. In Example 3, the model fails to extract any entity as Property since the document is in a new template where “Station” is used as the key word for Property field. To solve the rare case in Example 3, it is useful to take into consideration that “WBTW” is common in the training set as Property field.
Figure 6: Loss cases found in the experiments: Example 1, 2, 3 are from Ad-buy Form, and Example 4 are from Registration Form.