Document Understanding Dataset and Evaluation (DUDE😎)

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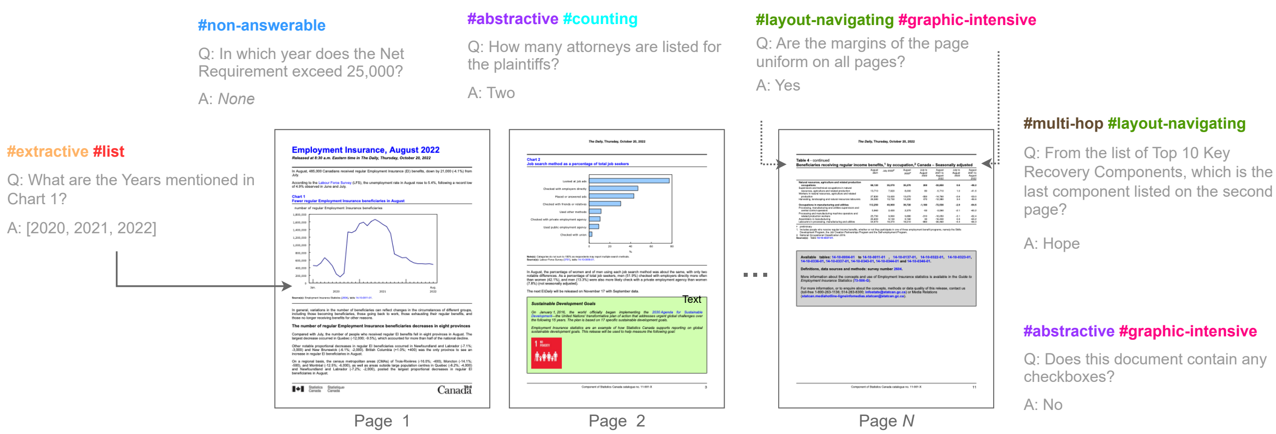

Abstract

*We call on the Document AI (DocAI) community to re-evaluate current methodologies and embrace the challenge of creating more practically-oriented benchmarks. Document Understanding Dataset and Evaluation (**DUDE**) seeks to remediate the halted research progress in understanding visually-rich documents (VRDs). We present a new dataset[1] with novelties related to types of questions, answers, and document layouts based on **multi-industry**, **multi-domain**, and **multi-page** VRDs of various origins, and dates. Moreover, we are pushing the boundaries of current methods by creating multi-task and multi-domain evaluation setups that more accurately simulate real-world situations where powerful generalization and adaptation under low-resource settings are desired. **DUDE** aims to set a new standard as a more practical, long-standing benchmark for the community, and we hope that it will lead to future extensions and contributions that address real-world challenges. Finally, our work illustrates the importance of finding more efficient ways to model language, images, and layout in DocAI.*

[1]huggingface.co/datasets/jordyvl/DUDE_loader

1. Introduction

Early stages of research and growth in any field are characterized by enacting proof-of-concept and demonstrating the feasibility of the proposed solution. In the Deep Learning era, this is often echoed by building narrow and simplified datasets that do not reflect real-world complexity, leading to models that may not be suitable for practical use.

The field of Document Understanding (DU) is not an exception to the recent proliferation of deep architectures, which in this case are predominantly used for classification and information extraction from documents. However, the wide and complex nature of documents presents many challenges that remain unsolved or not yet addressed. One such challenge is domain generalization, where a model trained on medical documents may not be directly applicable to financial or tabular content. Another challenge concerns task-agnostic architectures, where a model must be able to adapt to various DU subtasks such as document classification, key information extraction (KIE), and question answering (QA). Lastly, the high variability of document contents and layouts often leads to highly imbalanced samples within document types, resulting in a long-tailed distribution with few or almost no samples to train a model.

Despite the importance of these challenges, there is currently no DU benchmark dataset that simultaneously addresses all of these issues. This paper proposes a novel dataset formulated as an instance of Document Visual Question Answering (DocVQA) to evaluate how well current DU solutions deal with multi-page documents, if they can navigate and reason over visual layouts, and if they can generalize their skills to different document types and domains.

The data collection and evaluation design of **DUDE** naturally motivates targeting models that can answer natural yet highly diverse questions (e.g., regarding document elements, their properties, and compositions) for any VRD (e.g., drawn from potentially unseen distributions of layouts, domains, and types). The presented problem setting relates to Multi-Domain Long-Tailed Recognition (MDLT) [97], which concerns learning from multi-domain imbalanced data whilst addressing label imbalance, divergent label distributions across domains, and possible train-test domain shift. Put plainly, since we cannot provide ground truth QA pairs for, e.g., stamps, on every document type (domain), we expect a solution to transfer the subtask 'stamp detection' learned on document types where stamps naturally occur (and thus training QA pairs were created organically) to other domains. The DocVQA and MDLT formulations of **DUDE** allow us to create a longstanding, challenging benchmark that in the future can be easily extended with more subtasks formulated as QA pairs, and domains relating to document types (see Limitations).

The contribution of this work is twofold. First, we have created **DUDE**, a novel large-scale, multi-paged, multi-domain, multi-industry DocVQA benchmark for evaluating DU progress. Second, we show that the zero-shot and fine-tuned performance of current state-of-the-art models applied to DU lags far behind human baselines, explained in part by the need for more holistic and efficient modeling of language, vision, and richly structured layouts.

2. Related Work

Document Understanding encompasses datasets related to various subtasks like document layout analysis [110, 49], classification [30], key information extraction [85, 35], table extraction [83, 109, 108], and visual question answering [57, 59, 91]. These benchmarks lead to end-to-end DU architectures that have transformed common DocAI practices [72, 5, 33, 23, 25, 50, 71]. These task-specific benchmarks, however, are often tailored to a single domain, limiting the ability to create and assess how well DU models generalize to other document types and domains. To fill this gap, we adopt a visual question answering (VQA) approach, which has been crucial in the growth of the DU field.

The VQA paradigm provides a natural language interface for various tasks from both computer vision and natural language processing. In the latter, the question-answering approach has been successfully used in several domains, including medicine [67, 39, 64, 36, 48, 76, 61], open-domain knowledge [98, 54, 58, 53], emotions [26, 9], code [2, 51], logical reasoning [52, 101, 107, 96], claim verification [88, 32, 104], and math [105, 31, 16, 60, 4]. As a result of its ability to function as a natural language interface for various forms of data, this paradigm has been applied to other domains. For example, the question-answering approach is combined with modalities such as videos [44, 13, 14, 28, 17], images [99, 3, 29, 68, 7, 8], speech [100, 43], knowledge graphs [93, 84, 80, 22, 37], and maps [70, 15].

Overall, the convergence of computer vision and NLP through the emergence of VQA tasks has also opened up new avenues for research in the DU field, with many DU datasets now including rich visual content alongside questions. Yet, prior study on document VQA has mainly focused on single-page documents [57, 89, 56] with rare exceptions such as MP-DocVQA [90]. However, [57, 89] pose only extractive questions where the answer follows the context on which the question is defined as in other question answering benchmarks [78, 92, 42]. Moreover, these datasets do not contain *non-answerable* questions as in established (natural language) QA datasets like [77, 42]. To the best of our knowledge, there are no VQA datasets containing questions requiring lists as an answer. There are however few text-only QA datasets that contain such answer types [69, 46, 18]. Other datasets mainly related to our work are rather domain-specific like [112, 87, 56, 86, 73]. We give a detailed comparison of most related document VQA datasets in Table 1 highlighting the major contributions.

3. DUDE Dataset

While **DUDE** shares some similarities with existing VQA datasets, a closer comparison (see Table 1) highlights its unique features. We are confident that the model's proficiency in the areas introduced in this work will showcase its capability to handle the intricacy and diversity of document understanding tasks in real-world scenarios.

Documents. The dataset covers a wide range of document types, sources and dates, as shown in Table 1 and Figure 1 where its diverse nature is confirmed by the spread of document content representations.[2] Moreover, it covers a broad range of domains, including medical, legal, technical, and financial, among others, to evaluate models' ability to handle diverse topics and the specific knowledge each requires. Furthermore, the dataset contains documents with varying layouts: diverse text arrangements, font sizes, and styles, to

[2]This holds not only when textual content is considered but also for document images (Figure 9 in the Appendix).

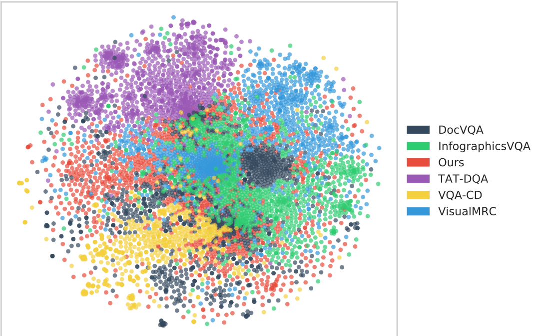

Figure 1: Visualization of inter-document similarities between samples from different datasets (t-SNE over TF-IDF representations of 1k passages from each source).

ensure that models can handle visually diverse documents.

In contrast to our proposal, current VQA datasets often focus on homogeneous documents, such as invoices in VQA-CD [55] or financial reports in TAT-DQA [112]. Even when not restricted to a single domain or layout, these datasets share essential characteristics. For example, InfographicsVQA [56] demonstrates significant diversity in topics and designs, but still embodies a preference for visual aids over complex tables or long text passages. Moreover, VQA datasets are commonly restricted to either born-digital or scanned documents, which limits their ability to measure the robustness to mixed-origin files that one usually finds in real-world applications. In particular, this restriction makes it uncertain whether state-of-the-art performers on website fragments from VisualMRC [87] can be efficient on multi-column layouts and documents with OCR errors or incorrectly-detected reading orders. Finally, a typical dataset for document visual question answering contains documents from a limited period, i.e., a few years (Table 1).

Considering the properties mentioned above, the most diverse dataset to date is Single Page DocVQA (SP-DocVQA) [57], which contains mixed-origin documents of different types created over several decades. However, it is built exclusively on single-page document excerpts and is limited to several domains represented in the Industry Documents Library. As a result, it complements rather than serves as a touchstone for general-purpose DU systems. MP-DocVQA [90] extends this including previous and posterior pages of the documents. However, the questions are kept the same which makes the extra pages mere distractors.

Questions. We use VQA as a natural language interface to VRDs, challenging the DU model with diverse questions, advanced operations, and multi-step reasoning to achieve real-world success.

Firstly, we assert that various layouts and visual elements must be comprehended semantically. As such, we introduce complex questions targeting these document elements, requiring comprehension beyond the document content, such as '*how many text columns are there?*', '*does the document contain words with diacritics?*' or '*which page contains the largest table in the document?*'. These Layout-navigating questions bridge the gap between Document Layout Analysis and Question Answering paradigms.

Our unique and detailed compositional questions demand a model that comprehends semantics and generalizes to new questions in a zero-shot setting. For example, >90% of our questions are unique, while we target questions whose answer scope is much more diverse than in previous works.[3] Since neural networks are known to perform poorly at mathematical reasoning and symbolical processing, we provide training and evaluation questions demanding arithmetic and comparison operations on numbers and dates.

Moreover, we feature multi-hop questions that indicate a model's robustness to sequential reasoning and mimic how humans ask questions. They may be useful in real-world tasks such as '*If the checkbox on page 1 section 3a indicates that the company is incorporated, how much yearly revenue did it generate in 2022 (given the table on page 5)?*'

Answers. Even though some VQA datasets are deliberately limited to questions of exclusively extractive (SP-DocVQA) or abstractive (VisualMRC) nature, others do not obey such restrictions and include both question types (see Table 1). The dataset we provide includes both abstractive and extractive answers, covering various types such as *textual, numerical, dates, yes/no, lists, or no answer*.

This allows us to cover all possible business use cases and reveal major deficiencies of existing DU systems beyond typical textual answers. For instance, no existing VQA dataset includes not answerable questions and questions answered with a list. In turn, the models considered to date supposedly tend to make unreliable guesses on questions with an answer not entailed by the content [77]. Our dataset is designed to cover answers beyond plain extractive text such as a list of items or even 'None'.

The 'None' answer type demands that the model correctly identifies that the answer cannot be provided, as the question needs to be better formed, e.g., it asks about the value of an empty cell in the table. In addition, list generation problems pose challenges to the model, as (1) more tokens need to be generated, (2) they may be sourced from different places in the document, and (3) OCR reading order may influence the element ordering.

3.1. Gathering Documents

A fundamental difficulty in gathering raw source files was ensuring dataset diversity while fulfilling strict licens-

[3] Answer type comparison is included in supplementary materials.

ing requirements. Therefore, rather than depending on initial sources of files, e.g., libraries that originally published digitized materials, we resorted to aggregate websites.

The document collection process was manual and assumed formulating queries to archive.org (containing 36M books and texts), commons.wikimedia.org (with 86M media types of various types), and documentcloud.org (with around 5M public documents). The queries consisted of keywords relevant to some category of interest, e.g., the *resume* category of our proposal consists of 'resume', 'cv', 'curriculum', and 'biography' keywords). Where necessary, a separate query parameter ensured that the resulting files belonged to the public domain or were released under a permissive license. Information on keywords and the search procedure is distributed as a part of the DUDE dataset.

From the resulting documents, we selected those representing the requested category and visually distinctive from the ones already gathered. Special care was put into removing examples that visibly expose controversial content or may be subject to privacy or legal concerns, despite the declared license. We collected five thousand, typically multi-page, English documents using this methodology.

3.2. Annotation Process

The annotation process involved in-house annotators and Amazon Mechanical Turk freelancers. For the latter, there is limited control over the expertise, and where justified, we resorted to limiting task availability depending on the number of completed tasks and historical acceptance rate.[4] The former are five highly qualified people with a Ph.D. in Linguistics. These three annotation scenarios will be referred to as *All MTurkers*, *Best MTurkers*, and *Qualified Linguists*.

We estimate the total cost of annotation involving both *Linguists* and *MTurkers* as $20,000.

Phase 1. We started by providing *All MTurkers* documents described in Section 3.1 in separate batches aimed at collecting abstractive, extractive, and list QA pairs. Each freelancer was asked to propose up to five questions of a particular type, and in the case of extractive ones to provide an evidence bounding box. The exception to this process is the annotation of non-answerable questions previously shown to be particularly challenging [77]. These are predominantly annotated by *Qualified Linguists* and because of their quality promoted without passing through Phases 2-3.

Candidate QA pairs are semi-automatically filtered to exclude annotations that cannot be valid due to the length, use of non-typical character combinations, or type-specific criteria, such as non-list answers for list batches. Additionally, we cluster duplicate and near-duplicate question-answer pairs to ensure dataset diversity and promote them directly to Phase 3 after a manual review (the same QA pairs provided independently by several annotators indicate their validity).

[4]Approval above 97% over at least 5k HITs.

Phase 2. The rest of the annotations promoted from Phase 1 were directed to *All MTurkers*, but this time instead of providing complete QA pairs, they were asked to answer the question from the previous round. Obtained triples of questions and two answer variants (one from each phase) were evaluated using inter-answer ANLS (defined in Section 3.5) promoted to the final dataset if the agreement was >0.8. Otherwise, QA triples were directed to Phase 3.

Phase 3. *Best MTurkers* were provided with document, question, and answer variants to decide the correctness of each answer and optionally overrule both variants if they are not correct. Outliers from decisions in this phase, such as repealing without a judgment on previous answers, were reviewed by *Qualified Linguists* and corrected if needed.

Optional Phase 4. Annotations of the test set were reviewed by *Qualified Linguists*. Given data from Phase 3, they corrected questions, answers and created metadata related to diagnostic categories described in Section 3.4.

3.3. Dataset Statistics

We conducted a statistical analysis of our dataset and found that the distribution of document length, question length, and answer type was much more diverse than in other datasets in the same domain. We also used the Simpson diversity coefficient [81] for analysis and summarized the results in Table 1. The following are the statistics for the data split:

	train	val	test (diagnostic)
documents	3,010	749	1,215 (530)
questions	23,728	6,315	11,448 (2,462)

Table 2: Data split counts.

The number of tokens in the document distribution is much more diverse compared to other datasets, a consequence of the more diverse distribution of pages (see Figure 3). Note some of the documents are more visual than textual (or even visual-only), making the left whisker essentially reach 0 ($\log_2$-scaling of x-axis).

The distribution of the number of tokens in answers is heavy-tailed, to some extent this is also the property of the distribution of number of tokens in questions. Furthermore, 90.9% of questions are unique, and so are 70.7% of answers (taking answer variants into account).

Dataset	Ours	SP-DocVQA	VisualMRC	InfographicsVQA	TAT-DQA
		Dataset-level properties			
Sources	Multi	Industry docs	Web pages	Infographics	Finance reports
Origin	BD, Scan	Mostly scans	BD	BD	BD
Period	1860-2022	1960-2000	Jan-Mar 2020	not specified	2018-2020
Documents	5,019	12,767	10,234	5,485	2,758
Pages (*avg±std*)	5.72±6.4	1.0±0.0	1.0±0.0	1.0±0.0	1.11±0.32
Tokens (*avg±std*)	1,831.53±2,545.06	183±149.96	154.19±79.34	287.98±214.57	576.99±290.12
Simpson coeff. (ResNet)	0.82	0.76	0.83	0.86	0.73
Simpson coeff. (Tf-Idf)	0.95	0.93	0.99	0.94	0.15
		Question-level properties			
Questions	41,541	50,000	30,562	30,035	16,558
Unique (%)	90.9	72.34	96.26	99.11	95.65
Length (*avg±std*)	8.65±3.35	8.34±3.04	9.38±4.01	11.57±3.71	12.51±4.18
Semantics	All	T, L, F, Ch	T, L, F, Ch	T, L, F, Ch, M	T, L
		Answer-level properties			
Unique (%)	70.7	64.29	91.82	48.84	77.54
Length (*avg±std*)	3.35±6.1	2.11±1.67	8.38±6.36	1.66±1.43	3.44±7.20
Extractive (%)	42.39	100.0	0.0	71.96	55.72
Abstractive (%)	38.25	0.0	100.0	24.91	44.28
List (%)	6.62	0.0	0.0	5.69	0.0
None	12.74	0.0	0.0	0.0	0.0

Table 1: Summary of the existing English document datasets and our challenge. `BD` stands for born-digital. Layout semantics are abbreviated as (T)able, (L)ist, (F)igure, (Ch)art, and M(ap). Comparison based on Azure Cognitive Services (3.2) OCR.

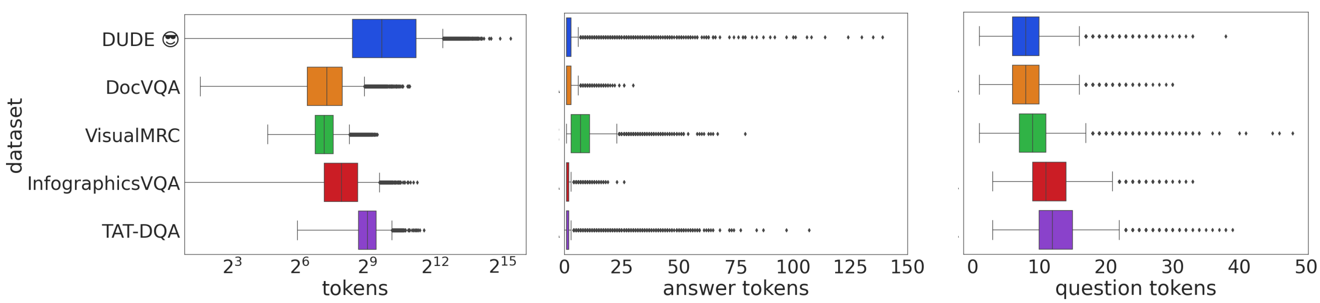

Figure 2: Distribution of the number of tokens in documents, answers, and questions.

We scrutinized the answer types by aggregating possible answers into classes representing the information they conveyed. The study used heuristics to determine if the answers fit into NER labeling scheme [1] or categories we anticipated, such as *yes/no* and *none*, or did not anticipate, such as *color*. This resulted in 25 different groups of answers, with the *other* answer type being the fourth largest group. Cramer's V coefficient was used to check for correlations between question types and answer types, and the results indicated that there were few correlations (see Appendix D.1). The expected correlations, such as *none* answers with *not-answerable* questions or *yes/no* answers with *abstractive* questions, were present, but barely any correlation was significant. This suggests it is hard to guess the answer based on the question solely.

We study relative diversity measure, called Simpson coefficient [111, 81]. To define it, consider a fixed distance function $d(a_1, a_2)$ defined for pair of documents $a_1, a_2 \in A$: the dataset. In our applications, it is the cosine similarity of a document embedding. Further, for an arbitrary number of datasets $A_1, \ldots, A_N$ the diversity of A_1 with respect to $A_2, \ldots, A_N$ is defined as

$$\mathrm{Div}_{A_2,\ldots,A_N}(A_1) = 1 - p\Big(d(a_{11}, a_{12}) < \min_{i=2:N} d(a_{i1}, a_{i2})\Big)$$

where $a_{i1}, a_{i2} \in A_i$, are randomly selected, $i = 2 : N i = 2 : N$. We report relative diversities of each of the datasets, relative to other datasets in the study, based on two embeddings: visual (ResNet-101 embeddings-based) and se-

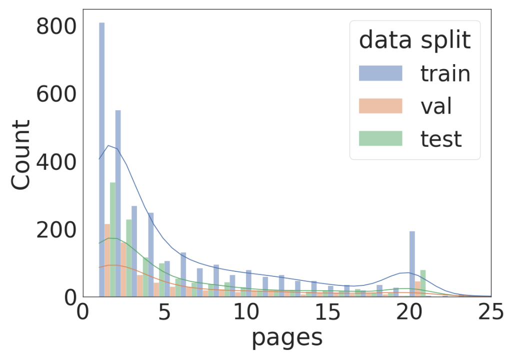

Figure 3: While other datasets are predominantly single-page only, the number of pages featuring in **DUDE** is more diverse, yet still biased towards shorter documents.

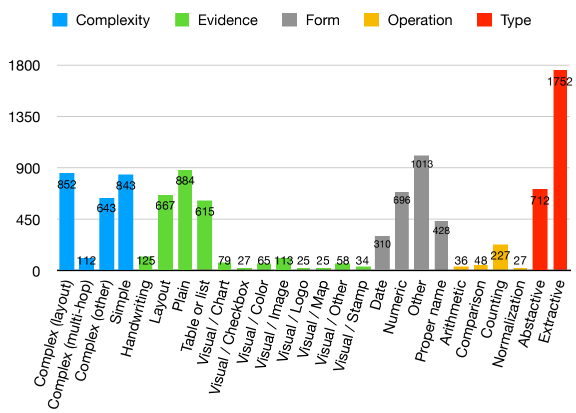

Figure 4: Count of particular diagnostic categories in a subset of 2.5k test set QA pairs annotated in detail to help analyze models' performance.

mantic (Tf-Idf embeddings-based), in Table 1. The results show that the probability that two random documents from **DUDE** are more similar than each random pair of documents from other datasets is small , meaning that documents in our dataset are well-distributed and diverse.

3.4. Diagnostic Subsets

Following previous DU datasets, we gather diagnostic metadata for close to half of the documents and QA pairs in the test set (see Figure 4). These are intended to enable a fine-grained analysis of the models' performance. The taxonomy used is an extension of the one from earlier works [57, 56, 10], covering **DUDE**-specific questions and enables a more detailed examination of visual artifacts under consideration.

Question type and perceived complexity. We distinguish questions perceived as *simple*, i.e., those based on spotting value near a phrase mentioned explicitly as a part of the question. For example, "Who is the Secretary of the U.S. Department of Commerce?" when the document contains "Penny Pritzker, Secretary, U.S. Department of Commerce." Such could be guessed given an approximate string matching algorithm and does not require much comprehension beyond that. The remaining questions are marked as *hard* with distinguished categories of *hard multi-hop questions*, and *hard meta/layout-navigating questions*.

Answer evidence. We provide information on what types of elements have to be comprehended to provide an answer, including *free text*, *handwriting*, *table or list*, and *layout*, i.e., non-tabular spatial understanding of text placement. These follow the ontology established by previous works [57, 56, 10]. In addition, we supply hints on graphical artifacts one needs to consider for particular questions, such as *image/photo*, *plot/chart*, *checkbox*, and *annotation*.

Required operation. We distinguish *arithmetic*, *comparison*, *counting*, and *normalization* operations to provide information on the need for performing, respectively, arithmetic operations on extractable data, comparing numerical values or sizes, counting elements or converting data present in the document to another format (e.g., rounding or date format conversion).

Answer form/shape. Finally, we provide information on the shallow form of the returned answer, including *date*, *numeric*, and *proper name*.

3.5. Evaluation

The evaluation process follows the typical paradigm of separate training, validation, and test splits. We provide both a standalone evaluator and a website[5] [95] to submit test set predictions.

To assess models' performance, we rely on the ANLS metric introduced by authors of the ST-VQA dataset [8]. Roughly speaking, it is a generalization of accuracy that does not penalize the system for an answer whose similarity to the gold standard measured with normalized Levenshtein similarity is above a specified threshold. Moreover, the metric assumes the presence of multiple, equally valid reference answers. The mentioned properties account for possible OCR errors or different phrasings, such as the same numerical answer represented as *two* and *2* by different annotators.

In practice, production DU systems provide an estimation of confidence in order to triage documents that do not need to be manually reviewed by a human. While the reliability of the automation ability of a DU solution is deemed quintessential for generating business value in practice [11], DU research rarely reports any confidence evalu-

[5] rrc.cvc.uab.es/?ch=23

ation. Some exceptions are in closely related task domains like scene text recognition [82] and QA [38, 106].

With DUDE, we want to establish calibration evaluation and confidence ranking as a default evaluation methodology in DU, especially since the field is so close to applications.

To this end, we report (next to ANLS) two additional metrics, Expected Calibration Error (ECE) [65, 63, 27], and Area-Under-Risk-Coverage-Curve (AURC) [24, 34].

Calibration requires that the probability a model assigns to its predictions equals their true likelihood of being correct [19, 20, 102].

ECE approximates top-1 calibration error by a weighted average over the accuracy/confidence difference of histogram bins. Particularly in our evaluation setting, we consider a predicted answer correct if its ANLS to the ground truth answer is above a pre-defined threshold (τ=0.5). For consistency, not-answerable and list-answers both have confidence estimated for the answer as a whole (regardless of the number of answers). Following [66], we apply equal-size binning (with 100 bins, $\mathcal{L}_p norm = 1$), avoiding some pathologies of equal-range binning [41, 94].

AURC is a selective classification metric that evaluates how well an estimator prevents silent failures on an *i.i.d* test set. As an aggregate measure of estimator performance (ANLS) and confidence ranking, it provides a more practically useful estimate of overall performance when the estimator can abstain from (low-confidence) decisions and defer to a human for feedback.

By reporting the above metrics, we hope that in future work there will be contributions (e.g., calibration methods for improved forecasting or metrics for better predictive uncertainty evaluation) that concretely target the empirical observations of overconfidence/miscalibration in DU models.

3.6. Baselines

Human performance. To establish the human baseline, we assign test set questions to *Qualified Linguists*, ensuring none of them will face the same documents as reviewed in Phase 4. The procedure results in an estimation of 74.76 ANLS points (Table 3). At first glance, this result seems low. Still, when analyzing results case by case, it turns out that it's hard to score much better since the answer format can influence the overall results a lot: *Eagle* vs. *an eagle* (0.625 ANLS), *62%* vs. *62* (0.67 ANLS), *1958-04-29* vs. *4-29-58* (0 ANLS), *Clemson University, Clemson South Carolina* vs. *Clemson University* (0 ANLS). We achieved the lowest performance (67.58) on the extractive question type, which confirms our hypothesis since the abstractive answers are shorter (mostly numbers, yes/no, or colors).

We analyzed the maximum score achieved by the best-performing model for each diagnostic test category and plotted that against the human performance in Figure 5.

Reference models. We assessed a group of modelsto determine how their performance is influenced by different factors such as (1) their ability to handle textual, layout, and visual elements, (2) whether they were fine-tuned for the task, (3) their size in (trainable parameters), and (4) the maximum input length they can handle.

To analyze factors (1) and (2), we conducted a zero-shot evaluation of several baseline text-only models. We used three encoder-based models (BERT [21], Longformer [6], and BigBird [103]) that cannot generate text and three that feature a decoder (T5 [75], GPT-3-Davinci [12], and ChatGPT) and have this capability. Next, we extended the T5 architecture with 2D layout embeddings [10, 72] and fine-tuned models with increasing maximum sequence lengths (512 $\rightarrow$ 8192) on **DUDE**. Finally, we evaluated our replication of the hierarchical Hi-VT5 model [90], as this model has the ability to decode text, understand multi-page layouts, and comprehend visual page features using DiT [47].

Regarding factors (2) and (3), we evaluated models of various sizes ranging from 131M (BigBird) to 175B (GPT-3-Davinci) and varied the input context from 512 (BERT) to 20480 (Hi-VT5) tokens. Overall, we thoroughly evaluated multiple models in the different testing setups to determine their performance under various conditions, as seen in Table 3.

3.7. Analysis & Discussion

To summarize, our study reveals that existing advanced language models such as BERT, Longformer, and BigBird struggle with comprehending visual elements and document layouts. To address this issue, we introduced T5, T5-2D, and Hi-VT5 models that incorporate layout and visual information. Still, their performance remains unsatisfactory, as evidenced by the comparison with the human baseline, similar to what has been reported for InfographicsVQA. This indicates that there is still scope for enhancing the visual understanding of **DUDE** models. Moreover, our findings indicate that a large LLM capable of processing long inputs alone is insufficient for achieving strong performance in **DUDE**, especially for the extractive type of answer. Finally, the dataset's length significantly affects the models' scores, as seen by the increase in scores by $4.4 - 5.0$ points when the T5 and T5+2D context length is extended from 512 to 8192. Similarly, the model size has a positive correlation with the final score, but it holds only within a particular model-type and is not the main factor influencing the results. State-of-the-art performance of $46.04\ \text{ANLS}_{\text{all}}$ was achieved on $T5_{large}$ with a 2D layout understanding that consumed 8192 tokens, confirming the observation above.

4. Conclusion

In conclusion, this paper introduces a new large-scale multi-paged, multi-domain, multi-industry Document Vi-

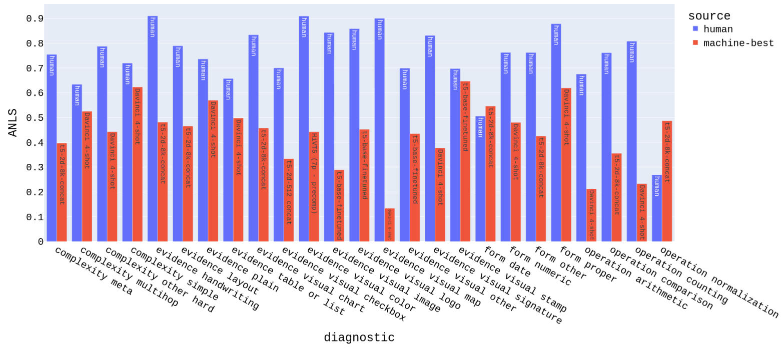

Figure 5: We report the average ANLS for the human expert vs. the best-performing model per diagnostic category as a ceiling analysis.

Model	Init.	Params	Max Seq. Length	Test Setup	$\text{ANLS}_{\text{all}} \uparrow$	$\text{ECE}_{\text{all}} \downarrow$	$\text{AURC}_{\text{all}} \downarrow$	ANLS_{do}	ANLS_{do} Abs	ANLS_{do} Ex	ANLS_{do} NA	ANLS_{do} Li
text-only Encoder-based models												
Big Bird	MPDocVQA	131M	4096	Concat*	26.27	30.14	44.22	30.67	7.11	40.26	12.75	8.46
BERT-Large	MPDocVQA	334M	512	Max Conf.*	25.48	34.06	48.60	32.18	7.28	42.23	5.88	11.13
Longformer	MPDocVQA	148M	4096	Concat*	27.14	27.59	44.59	33.45	8.55	43.58	10.78	10.62
text-only Encoder-Decoder based models												
T5	base	223M	512	Concat-0*	19.65	19.14	48.83	25.62	5.24	33.91	0	7.31
T5	MPDocVQA	223M	512	Max Conf.*	29.48	27.18	43.06	37.56	21.19	44.22	0	10.56
T5	base	223M	512	Concat+FT	37.41	**10.82**	41.09	40.61	42.61	48.20	53.92	16.87
T5	base	223M	8192	Concat+FT	41.80	17.33	49.53	44.95	47.62	50.49	63.72	7.56
text-only Large Language models (LLM)												
ChatGPT	gpt-3.5-turbo	20B	4096	Concat-0	-	-	-	35.07	16.73	42.52	70.59	15.97
				Concat-4	-	-	-	41.89	22.19	49.90	**77.45**	17.74
GPT3	davinci3	175B	4000	Concat-0	-	-	-	43.95	18.16	54.44	73.53	36.32
				Concat-4	-	-	-	47.04	22.37	**57.09**	63.73	**40.01**
text+layout Encoder-Decoder based models												
T5-2D	base	223M	512	Concat+FT	37.10	10.85	41.46	40.50	42.48	48.62	52.94	3.49
T5-2D	base	223M	8192	Concat+FT	42.10	17.00	48.83	45.73	48.37	52.29	63.72	8.02
T5-2D	large	770M	8192	Concat+FT	**46.06**	14.40	**35.70**	**48.14**	**50.81**	55.65	68.62	5.43
text+layout+vision models												
HiVT5		316M	20480	Hierarchical+FT	23.06	11.91	54.35	22.33	33.94	17.60	61.76	6.83
LayoutLMv3	MPDocVQA	125M	512	Max Conf.*	20.31	34.97	47.51	25.27	8.10	32.60	8.82	7.82
Human baseline								74.76	81.95	67.58	83.33	67.74

Table 3: Summary of Baseline performance on the **DUDE** test set ($_{all}$) and diagnostic subset ($_{do}$). Test setups are defined as *Max Conf.*: predict one answer per page and return an answer with the highest probability over all pages, *Concat*: predict on tokens truncated to maximum sequence length, *FT* stands for fine-tuning on **DUDE** training data, and *-0* refers to zero-shot and *-4* few-shot inference. Average ANLS results per question type are abbreviated as (Abs)tractive, (Ex)tractive, (N)ot-(A)nswerable, (Li)st. (*) We report only results for best performing test setup (either *Max Conf.* or *Concat*). All scalars are scaled between 0 and 100 for readability.

sual Question Answering Benchmark for document understanding. Our dataset is adjusted to the real-world environment where we need to process long documents and understand different types of documents. The benchmark includes visual semantics such as *tables, charts, figures, lists, checkboxes, stamps*, and more, which are essential for real-world document understanding. The performance of state-of-the-art textual and multi-modal models still lags behind human performance, indicating the need for further improvement in visual understanding for DU models. Nevertheless, we believe evaluating systems on **DUDE** could inspire new architectures and methods.

Limitations. As our approach is closer to real-world industrial applications, and enables models to recognize and understand new unseen data without the need for retraining, it does come with some limitations and constraining factors, including the use of only English language documents. Future work could address these limitations and expand the benchmark to include other languages. Moreover, although our dataset can be considered large-scale, it still represents a relatively small sample size of the plethora of documents that exist in the real world.

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