Towards Complex Document Understanding By Discrete Reasoning

Fengbin Zhu\textsuperscript{1,2}, Wenqiang Lei\textsuperscript{3*}, Fuli Feng\textsuperscript{4}, Chao Wang\textsuperscript{2}, Haozhou Zhang\textsuperscript{3}, Tat-Seng Chua\textsuperscript{1}
\textsuperscript{1}National University of Singapore, Singapore
\textsuperscript{2}6Estates Pte Ltd, Singapore
\textsuperscript{3}Sichuan University, China
\textsuperscript{4}University of Science and Technology of China, China
{zhfengbin,wenqianglei,fulifeng93}@gmail.com, wangchao@6estates.com, dcscts@nus.edu.sg

ABSTRACT
Document Visual Question Answering (VQA) aims to answer questions over visually-rich documents. In this work, we introduce a new Document VQA dataset, named TAT-DQA, which consists of 3,067 document pages comprising semi-structured table(s) and unstructured text as well as 16,558 question-answer pairs. The documents are sampled from financial reports and contain lots of numbers, which means discrete reasoning capability is demanded to answer the questions. Based on TAT-DQA, we further develop a novel model named MHST that takes into account the information in multi-modalities to intelligently address different types of questions with corresponding strategies, i.e., extraction or reasoning. The experiments show that MHST model significantly outperforms the baseline methods, demonstrating its effectiveness. However, the performance still lags far behind that of expert humans. We expect that our TAT-DQA dataset would facilitate the research on understanding of visually-rich documents, especially for scenarios that require discrete reasoning. Also, we hope the proposed model would inspire researchers to design more advanced Document VQA models in future. Our dataset will be publicly available for non-commercial use at https://nextplusplus.github.io/TAT-DQA/.

CCS CONCEPTS
• Computing methodologies → Natural language processing;
• Information systems → Question answering.

KEYWORDS
Question Answering, Visually-rich Document Understanding, Discrete Reasoning

ACM Reference Format:
Fengbin Zhu\textsuperscript{1,2}, Wenqiang Lei\textsuperscript{3*}, Fuli Feng\textsuperscript{4}, Chao Wang\textsuperscript{2}, Haozhou Zhang\textsuperscript{3}, Tat-Seng Chua\textsuperscript{1}. 2022. Towards Complex Document Understanding By Discrete Reasoning. In Proceedings of the 30th ACM International Conference on Multimedia (MM ’22), October 10–14, 2022, Lisboa, Portugal. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3503161.3548422

1 INTRODUCTION
Document understanding and analysis are indispensable in businesses of diverse domains like finance, legal, medical, etc [36]. Such work is mostly performed manually, which is labor-intensive and time-consuming with low scalability [9]. Intelligent Document Understanding (IDU) emerges as an important research area in multimedia, which spans Natural Language Processing (NLP) and Computer Vision (CV) [9]. It aims to automatically read and understand business documents. Many IDU tasks have been proposed, including Document Layout Analysis [26, 49], Table Detection and Recognition [24, 35, 48], Key Information Extraction (KIE) [14, 20, 21], Document Visual Question Answering (VQA) [28, 29, 37], etc.

 Question: What was the total cost in Wireless including spectrum license fee in 2019?
Derivation: \[1,320 + 1,731 = 3,051\]
Scale: Millions
Answer: 3,051,000,000

Figure 1: An example of TAT-DQA dataset. Given a question and a visually-rich document that contains both tabular and textual data, the machine is expected to derive the answer.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

MM ’22, October 10–14, 2022, Lisboa, Portugal. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3503161.3548422

*Corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

MM ’22, October 10–14, 2022, Lisboa, Portugal. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3503161.3548422
Among these tasks, Document VQA is a high-level document understanding task wherein given a visually-rich document and a relevant question in natural language (Figure 1), the model is required to give the correct answer to the question based on the document [9]. In Document VQA, the model needs to effectively exploit and harness the textual and layout information of the document besides its image information, compared to traditional VQA tasks [3, 13, 34] where image information is the focus. For this task, we are particularly interested in handling those documents with semi-structured tables that usually contain numbers in addition to unstructured text. This document type is informative and very pervasive in real-world businesses, however with only a few prior efforts [7, 50] on auto-understanding them. To facilitate the research on these problems, we construct a new Document VQA dataset by extending the TAT-QA [50], called TAT-DQA dataset.

The documents in TAT-DQA dataset are sampled from real-world high-quality financial reports and each document contains both tabular and textual data. Furthermore, these documents contain lots of numbers, which means discrete reasoning capability, such as counting, sorting, comparison, addition, subtraction, multiplication, division and the compositions of them, is demanded to answer questions. The average length of the documents in TAT-DQA is significantly larger than all existing Document VQA datasets. To our best knowledge, TAT-DQA is the first Document VQA dataset that is constructed based on real-world high-quality business documents. Also, this work is the first one that attempts to understand the documents with multiple pages in literature on document understanding, which is more challenging compared to the understanding tasks over single-page documents.

Based on TAT-DQA, we further propose a novel multi-modal Document VQA model, named MHST. To represent the question and document, the MHST employs a multi-modal Transformer encoder to take the question as well as the document text, layout and visual image information as input. After that, to infer the answer, it first adopts a “Multi-Head” classifier to predict the answer type, i.e., Span, Spans, Counting and Arithmetic, based on which different prediction strategies are applied. For the answer type of Span, a Span Answer Predictor [10, 31] is applied to predict the starting and ending positions of the answer span; for the other three answer types, a Sequence Tagging Module is applied to extract the evidences for deriving the answer. After obtaining the evidences, an Expression Tree Generator following “Seq2Tree” architecture is used to generate an expression tree to infer the final answers for arithmetical questions; for Spans and Counting questions the final predictions are obtained by collecting or counting all non- contiguous spans in the evidences. Experiments show that MHST model significantly outperforms baseline methods, demonstrating effectiveness.

We expect that our TAT-DQA dataset would facilitate future research on the deep understanding of complex real-world documents combining vision and language, especially for scenarios requiring discrete reasoning, and that our MHST model would inspire the community to develop more advanced Document VQA models.

## 2 RELATED WORK

In this section we briefly review previous research in Intelligent Document Understanding, the datasets for Document VQA, as well as discrete reasoning, with special attention to those works that are most related to ours.

### 2.1 Intelligent Document Understanding

Intelligent Document Understanding (IDU) is to enable a machine to automatically read, understand, and analyze business documents. This research area is very practically meaningful and much demanded, which spans both the Natural Language Processing (NLP) and the Computer Vision (CV) fields [9]. Thanks to the wide success of Transformer [10, 38] in addressing NLP and CV problems, Transformer-based models have been popularly applied to solving document understanding tasks. The documents mainly involve three modalities of information: text, layout, and visual information. Some works [12, 17, 23, 44] combine document layout information with text information in the Transformer encoder. LayoutLM [44] and StructuralLM [23] incorporate document layout information as new positional embeddings into the embedding layer. BROS [17] and LAMBERT [12] take into account the spatial distance between tokens when computing the attention weights and bias in the self-attention layers. Recently, some works [2, 42, 45] propose to model all three modalities of information, which has become a default approach for almost all document understanding tasks. In this work, we also adopt a Transformer-based model to encode document text, layout and visual image information for our task.

### 2.2 Document VQA Datasets

Document VQA is a high-level document understanding task wherein a model is required to answer a question in natural language given a visually-rich document [9]. To date, there are only a few datasets that have been proposed specially for Document VQA, to our best knowledge, including DocVQA [29], VisualMRC [37], InfographicVQA [28] and WebSRC [6]. Among them, InfographicVQA focuses on infographic instead of documents, and WebSRC does not provide its statistics in the original paper. DocVQA is constructed using various types of industry documents for extractive question answering, where answers can always be extracted from the text in the document. In DocVQA, the documents are mostly from the 1960-2000 period, with low-resolution, and besides some high-quality documents with printed or digital-born text, there are also some with typewritten and handwritten text. The VisualMRC [37] dataset is built for abstractive question answering, where answers cannot be directly extracted from the text in the document. The documents in VisualMRC and WebSRC are screenshots of web pages. In this work, we build a new and complex TAT-DQA dataset with real-world high-quality business documents, hoping to facilitate future research in the community.

### 2.3 Discrete Reasoning

Discrete reasoning is key to solving many NLP tasks, like Math Word Problems (MWP) [19, 22, 40, 43, 47] and Question Answering (QA) over text [11, 51], tables [30] and both [7, 25, 50]. In a Math Word Problem, it is required to answer a mathematical query according to a textual description and has been studied since the 1960s [4]. The MWP problems are often solved by generating an expression tree to derive the final answer implicitly [8, 39] or explicitly [27, 43, 47]. For discrete reasoning in textual QA like the DROP [11] dataset,
researchers usually employ a “Multi-Head” classifier to predict the answer type first and then perform arithmetic operations to derive the final answer [1, 5, 18, 32, 33]. For discrete reasoning over tables only or a combination of the table and text, recent works incorporate the table structure feature in the positional encoding layer [16, 41], or the attention layer [41, 46] to jointly train tables and text. To our best knowledge, no prior work attempts to develop models that are capable of performing discrete reasoning over real-world business documents.

3 PROPOSED DATASET: TAT-DQA

In this section, we present the definition of the Document VQA task, the construction of the TAT-DQA dataset, and the statistical analysis of the dataset.

3.1 Task Definition

Consider a visually-rich document \( D \) of one or more pages, which contains both tabular and text contents. Each page is converted to an image plus a list of words using the PDF/OCR converter. Given a question \( Q \), the model \( F \) is required to predict the answer \( a \) according to the document \( D \) as demonstrated in Figure 1. Formally, the task is formulated as

\[
F(D, Q) = a.
\]

In TAT-DQA, the answer value \( a \) may be either extracted from the given document, or generated by performing discrete reasoning such as addition, subtraction, multiplication, division, counting, comparison/sorting, and their compositions.

To solve this task, a multi-modal Document VQA model usually needs to take into account the document text content, layout information, and visual image information in order to derive the final answer. In this process, the capability of discrete reasoning over the visually-rich document is much demanded.

3.2 Dataset Construction

The dataset TAT-DQA is built upon a previous TAT-QA [50] dataset. In TAT-QA, each hybrid context (i.e. data) comprises a well-structured table and some relevant texts. They are all selected and sorted manually by human experts from financial reports in PDF format. With human interference, each hybrid context contains only one table and the corresponding texts are sure to semantically correlate with the table. Compared with TAT-QA, the TAT-DQA better aligns with real scenarios. Each document in TAT-DQA may contain one or more tables, and the texts inside this document may correlate with the table(s), or may have nothing to do with the table(s). This task setting is much challenging than that on TAT-QA.

3.2.1 Collection of Question-Answer Pairs. To construct the new TAT-DQA dataset, we borrow the question-answer (Q-A) pairs from the previous TAT-QA dataset, which are generated by human experts in finance. On this basis, we ask human experts in finance to generate some more Q-A pairs, and meanwhile remove a few pairs with errors we have found during data preparation. In total, we get 16, 558 Q-A pairs for TAT-DQA. The same as TAT-QA, TAT-DQA offers four types of answers:

- **Span**: The answer is a continuous text in the document [31];
- **Spans**: This type of answer is also called “Multi-span” and is a set of non-contiguous spans in the document [11];
- **Counting**: The answer is an integer that is computed by performing counting;
- **Arithmetic**: The answer is a numerical value that is obtained by performing arithmetic operations such as addition, subtraction, multiplication, division and their compositions.

Also, the scale of the answer in TAT-DQA can have five values, including None, Thousands, Millions, Billions, Percent. To facilitate development of discrete reasoning capability of Document VQA models, we also keep the corresponding derivations for Counting and Arithmetic questions in the same formats with TAT-QA.

3.2.2 Collection of Document Pages. To construct the new TAT-DQA dataset, we filter out and keep the document pages corresponding to the above acquired Q-A pairs from the raw financial reports. These raw financial reports are real-world ones, mostly dated between 2018 and 2020, which are downloaded from the web\(^1\) based on the file names provided by the authors of TAT-QA. Each Q-A pair corresponds to one document, and a document may contain at most three pages. We process each retaining document page after filtering to obtain the text with a bounding box by using Apache PDFBox\(^2\) for the readable PDF files or a commercial OCR engine for the images. Finally, each document page is converted to a list of text blocks and each text block has a list of words, with every block or word framed by its own bounding box. In total, we obtain 2,758 documents consisting of 3,067 pages. The document itself and its text content with the corresponding bounding box will be released together in TAT-DQA.

3.3 Statistics and Analysis

In total, the TAT-DQA dataset includes 2,758 documents, consisting of 3,067 document pages from 182 financial reports, and 16,558 question-answer pairs. These documents are randomly split into a training set (80%), a development set (10%) and a test set (10%); all

\(^1\)https://www.annualreports.com/
\(^2\)https://pdfbox.apache.org/
The questions about a particular document belong to only one of the splits. We summarize the basic statistics of each split in Table 1, and the question distribution regarding the answer type in Table 2.

A comparison of our new TAT-DQA dataset with the two existing document VQA datasets DocVQA [29] and VisualMRC [37] is summarized in Table 3. In particular, for document type, the documents in TAT-DQA stem from real-world high-quality financial reports between 2018 and 2020, and each document must contain both tabular and textual data. Comparably, the documents of DocVQA are from the UCSF Industry Documents Library, which are mostly within the 1960-2000 period, of low-resolution and include some typewritten and handwritten text; VisualMRC is built with the screenshots of web pages instead of real-world documents. For document length, the average length of documents in TAT-DQA (550.29 words) is significantly larger than that of DocVQA (182.75 words) and VisualMRC (151.46 words), which makes TAT-DQA more complex and challenging. For the number of pages per document, each document in DocVQA or VisualMRC has only 1 page; in contrast, TAT-DQA has at most 3 pages in the document, and its average page number per document is 1.33 and over 11.0% documents in TAT-DQA have more than 1 page. We also compare the answer type of the three datasets: TAT-DQA consists of extractive (i.e., Span and Spans) and abstractive (i.e., Counting and Arithmetic) answers that need to be generated with discrete reasoning; DocVQA only has SQaD-like extractive and short answers while VisualMRC focuses on long abstractive answers.

To the best of our knowledge, the TAT-DQA dataset is the first document VQA dataset that is constructed on top of real-world high-quality business documents. It is also the most complex document VQA dataset till now, with more than one page per document. We promise to release this dataset in near future, hoping to facilitate the research on document understanding techniques in the community.

| Property | DocVQA | VisualMRC | TAT-DQA |
|----------|--------|-----------|---------|
| Document Type | Industry document | Web pages | Finance reports |
| Document Period | 1960 - 2000 | Jan - Mar 2020 | 2018 - 2020 |
| Avg len of document | 182.75 | 151.46 | 550.29 |
| Avg no. of pages | 1 | 1 | 1.33 |

Table 3: The comparison among the three Document VQA datasets, i.e., DocVQA, VisualMRC and TAT-DQA. The length of the document is counted in terms of OCR words. Ext. and Abs denote extractive and abstractive respectively.

MHST employs a multi-modal Transformer architecture to encode the question, document text, layout and visual image in the input. To infer the final answer, the MHST adopts a “Multi-Head” classifier to predict the answer type, i.e., Span, Spans, Counting and Arithmetic. For the answer type of Span, a Span Answer Predictor [10, 31] is applied to predict the starting and ending positions of the answer span; for the other three answer types, a Sequence Tagging Module is applied to extract the evidences for deriving the answer. After obtaining the evidences, an Expression Tree Generator following “Seq2Tree” architecture is applied to generate an expression tree to infer the final answers for arithmetical questions; for Spans and Counting questions the final predictions are obtained by collecting or counting all non-contiguous spans in the evidences. An overall architecture of the MHST model is illustrated in Figure 2.

4.1 Question and Document Representation

The MHST model adopts LayoutLMv2LARGE [45] to generate the representations of the question and the document, which is a recent popular multi-modal Transformer model for document understanding. The MHST model takes as input a question as well as the text content, layout, and visual image information of the document.

The document text and layout information in the input can be obtained as follows. Each document in TAT-DQA contains both tabular and textual data. We empirically find that the performance would be better if we handle them separately, as is verified in the experiment of Section 5.3.3. To identify the table(s) vs. the text in the document, we propose to apply a heuristic method to identify the text blocks that belong to the table in each document page. Then we apply TF-IDF to sort the rest non-table text blocks by estimating the similarity score of each block with respect to the question, considering that the average length of the document in TAT-DQA is quite long, as demonstrated in Table 1.

To obtain the visual information of the document for the input, we transform the document page³ in PDF to an image, which is resized to 224 x 224 and then fed into the image encoder proposed in [45] to obtain the visual embedding. Finally, the embeddings of the question, table blocks, non-table blocks and the image are input sequentially to the LayoutLMv2LARGE model to obtain question token representations $\overline{q}$ and document token representations $\overline{d}$.

4.2 Answer Extraction and Reasoning

After obtaining the representations of the question and document, MHST further identifies the answer type of the question and applies the corresponding strategies to derive the final answer.

4.2.1 Multi-Head Predictor. We design a Multi-Head Predictor to predict the answer type, i.e., Span, Spans, Counting and Arithmetic, as explained in Section 3.2.1. This Multi-Head Predictor is essentially a multi-class classifier. In particular, we take the vector of $[\text{CLS}]$ as input to compute the probability of each answer type:

$$p_{\text{head}} = \text{softmax}(\text{FFN}([\text{CLS}]))$$

where FFN denotes a two-layer feed-forward network with the GELU activation [15]. For the answer type of Span, a Span Answer Predictor is applied to predict the starting and ending positions of

³We select the document page that has the major table for the multi-page documents.
4.2.2 Expression Tree Generator. For the question whose answer type is predicted as Arithmetic, we apply an Expression Tree Generator to generate an expression tree to compute the answer \cite{39,43,47}. The Expression Tree Generator in our MHST is implemented with the Goal-driven Tree Structure (GTS) \cite{43}. GTS is a tree structured neural network that generates expression trees in a goal-driven manner, demonstrating noticeable effectiveness in solving Mathematical Word Problems (MWPs). However, a typical MWP involves only a handful of numbers, while in TAT-DQA, one document usually contains much more numbers, which significantly overwhelsms the capacity of GTS. To address this issue, we propose to select several most relevant numbers with the Sequence Tagging Module, and feed them into the GTS.

The expression trees generated by the Generator contain three kinds of nodes: the arithmetical operators \( V_{op} \) (i.e., \(+\), \(-\), \(*\), \(/\)), the constant numbers \( V_{con} \), and the numbers \( V_{tag} \) that are identified by the Sequence Tagging Module in the document \( D \), which form the target vocabulary \( V^{dec} \) of the document \( D \). The constant numbers \( V_{con} \) and the numbers \( V_{tag} \) selected from the document are always set to be in leaf nodes positions. The operators \( V_{op} \) will always occupy the non-leaf nodes positions, and each operator node must have two child nodes. The construction of the tree starts from producing the topmost operator, followed by the left child node, which will be repeated until the leaf node is produced. Then, the right child nodes are generated recursively. As such, the Generator generates an equation following the pre-order traversal ordering.

To start tree generation process of GTS, our model initializes the topmost root node vector using the vector of \([CLS]\). For each token \( t \) in target vocabulary \( V^{dec} \), its embedding \( e(t|D) \) is defined as

\[
e(t|D) = \begin{cases} M_{op} & \text{if } t \in V_{op} \\ M_{con} & \text{if } t \in V_{con} \\ h_{loc}(t, D) & \text{if } t \in V_{tag}. \end{cases}
\]

The representations of the numbers in \( V_{tag} \) are document-dependent; i.e., they will take the corresponding \( h_{loc}(t, D) \) from \( D \). However, the representations of the operators and the constant numbers are independent of the document, which are obtained by two independent embedding matrices \( M_{op} \) and \( M_{con} \) respectively.

4.2.3 Scale Predictor. If the answer type is Arithmetic, the scale predictor takes as input the concatenation of the vector of the
where FFN denotes a two-layer feed-forward network with GELU activation and $h^N$ is obtained by computing the mean of all representations of the predicted numerical tokens by the Sequence Tagging Module. For the types of Span, Spans and Counting, we adopt the same method in TagOp, which takes the vector of $[CLS]$ only as input. After obtaining the scale, the final answer is derived by multiplying or concatenating the answer value with the scale, depending on whether the answer value is a number or a string.

4.3 Training and Inference

To train our model, the objective is to minimize the negative log-likelihood loss which is the sum of the losses of all above classification tasks depending on the answer types, i.e., Multi-Head Predictor, Sequence Tagging Module, Span Answer Predictor, Scale Predictor and Expression Tree Generator. Note that the ground-truths of the sequence tagging predictions are extracted from the annotated answers and derivations. For the arithmetic type, if the numerical values that are used to generate the ground-truth expression tree are not predicted, we will also add them in the ground truth in order to train the Expression Tree Generator.

During inference, our model first chooses the answer type and then performs the corresponding prediction strategies. For the Span type, the span with the maximum probability is attained as the final prediction among all the valid spans. If the answer type is Spans or Counting, we collect or count all the predicted non-contiguous spans as the final prediction. Following [43], we apply a beam search to select the best expression tree and execute it to obtain the final prediction for the arithmetical questions.

5 EXPERIMENTS

In this section, we report and analyze the extensive experimental results to demonstrate the validity of our new TAT-DQA dataset and also the promising effectiveness of our proposed Document VQA model MHST by comparing it with two baseline models.

5.1 Baseline Models

To the best of our knowledge, there are very limited models that have been proposed to effectively solve QA tasks over the documents containing both tabular data and textual data, where discrete reasoning is particularly demanded. We choose two state-of-the-art QA models that have demonstrated promising discrete reasoning capability for comparison, i.e. NumNet+ V2 [32] and TagOp [50].

NumNet+ V2 [32] is a textual QA model with impressive performance on DROP [11] dataset that requires discrete reasoning over the textual data. It constructs a numerically-aware graph neural network, which takes all the numbers in the given question and passage as nodes and builds edges via numerical comparison, and performs discrete reasoning over the graph to infer the final answer. To adapt the model to TAT-DQA, we apply TF-IDF between the question and each text block to sort the text blocks and convert them to a sequence as the input to the model, which is similar with the method introduced in Section 4.1.

The other model, TagOp [50], achieves the state-of-the-art results on the TAT-QA dataset that requires discrete reasoning over a well-structured table and its relevant text to derive the answer. It first employs a sequence tagging module to identify relevant cells from the table and spans from the text, and then applies a set of aggregation operators (e.g., addition, subtraction, multiplication, division, counting, etc) over them to infer the final answer. To enable the model to work on the new TAT-DQA dataset, we omit the processing of the table, apply TF-IDF to sort the text blocks in the document and feed them to the model sequentially.

5.2 Evaluation Metrics

We adopt the same evaluation metrics used in [50] to measure the model performance on the TAT-DQA dataset, i.e. the Exact Match (EM) and the numeracy-focused (macro-averaged) F1 score, taking into account the scale and the plus-minus of a numerical value. Both Exact-Match and numeracy-focused (macro-averaged) F1 score measure the overlap between a bag-of-words representation of the gold and predicted answers. Note that the numeracy-focused F1 score is set to 0 unless the predicted number multiplied by the predicted scale equals exactly the ground truth.

5.3 Results and Analysis

In experiments, we first compare our MHST model with two baseline models, NumNet+ V2 and TagOp, by testing their performance on understanding the documents in TAT-DQA dataset via Document VQA tasks. We then analyze effects of our MHST model over each answer type in TAT-DQA. Also, we experiment on TAT-QA dataset [50] to further verify the effectiveness of our proposed model. Finally, based on all experimental results, we analyze the challenges of our new TAT-DQA dataset to reveal its properties.

5.3.1 Comparison with Baselines on TAT-DQA. The experimental results of our proposed model MHST and the baseline models are shown in Table 4. We train two different variants of our MHST model by using different modalities in Question and Document Representation stage. The first variant is the full model MHST(LayoutLMv2LARGE), which adopts LayoutLMv2LARGE as the encoder and takes the question as well as document text, layout, and visual image as input. The other one is MHST(RoBERTaLARGE),

| Method                        | Dev EM | Test EM | Dev F1 | Test F1 |
|-------------------------------|--------|---------|--------|---------|
| Human Experts                 | -      | 84.1    | 90.8   |
| Baselines                     |        |         |        |         |
| NumNet+ V2                    | 28.1   | 36.6    | 30.6   | 40.1    |
| TagOp                         | 32.3   | 39.6    | 33.7   | 42.5    |
| Text Only                     | 37.1   | 43.6    | 39.8   | 47.6    |
| Text + Image                  | 39.1   | 47.4    | 41.5   | 50.7    |

Table 4: Performance of our model and baseline models on dev and test set of TAT-DQA. Best results are marked in bold.
which employs RoBERTa\textsubscript{LARGE} as the encoder instead to represent the document with textual features only. From Table 4, we can observe that both the two variants significantly outperform the baseline methods, demonstrating the effectiveness of our MHST. The superior performance of our full model MHST(LayoutLMv2\textsubscript{LARGE}) highlights the importance of the fusion of vision and language features to successfully answering the questions in TAT-DQA. But, there is still a big gap compared to the human performance.

The TAT-DQA dataset offers four different answer types. To better reveal the effects of our model, we analyze the performance of the MHST(LayoutLMv2\textsubscript{LARGE}) on each of these answer types. The results are summarized in Table 5. From the table, we can see that the metric $F_1$ on test set for the answer type of Span shows the best results, while the results on Counting and Spans are similar, which is probably because these two types use similar prediction strategies in our model, i.e. generating the answer directly after obtaining the evidence using sequence tagging. Comparably, the Arithmetic type has the worst results of $F_1$, indicating that the discrete reasoning capability still demands further enhancement on complex real-world documents.

### 5.3.2 Results of MHST model on TAT-QA

To further test the effectiveness of our MHST model, we also test it on the TAT-QA dataset. In particular, we adapt the variant MHST(RoBERTa\textsubscript{LARGE}) as there are only well-structured tables and relevant text and no document images in TAT-QA.

Following TagOp, MHST(RoBERTa\textsubscript{LARGE}) takes the question, the flattened table by row and the associated paragraphs sequentially as input instead. From Table 6, we can observe that our MHST model significantly outperforms the state-of-the-art method on TAT-QA. It is worth mentioning that our model performs better on TAT-QA compared with its performance on the new TAT-DQA dataset. This indicates that TAT-DQA is more complex and challenging than TAT-QA, which will be analyzed in detail at below.

### 5.3.3 The Challenges of TAT-DQA

The new TAT-DQA dataset differs from TAT-QA in two aspects: 1) in TAT-DQA there is no well-structured table and instead, all contents are organized with text blocks; 2) the texts in TAT-DQA are not necessarily associated to the table, which are with longer contents and more complex (as verified experimentally above). Hereby, we try to reveal the challenges of TAT-DQA by answering following three questions:

- **Q1**: How do the tabular data in the document affect the model performance?
- **Q2**: What is the difference in the model performance between multi-page documents and one-page documents?
- **Q3**: What is the model performance on the documents with more content compared to those with less content?

For Q1, to evaluate the effect of tabular data in the document on the performance, we apply the same table block detection module in NumNet+ V2 and TagOp from MHST.

![Figure 3: The $F_1$ score on TAT-DQA test set after we add the same table block detection module in NumNet+ V2 and TagOp from MHST.](image)

For Q2, we compare the performance of three models, NumNet+ V2, TagOp and MHST(RoBERTa\textsubscript{LARGE}), over multi-page documents and one-page documents, respectively. We here do not choose MHST(LayoutLMv2\textsubscript{LARGE}) as it takes as input the visual image, which is converted from the document page with the major table, meaning using only one page and hence unfair for comparison with other models. Figure 4 shows the comparison results on the test set of TAT-DQA. We can observe that the performance on multi-page documents is much worse than that on one-page documents for all three models. Among them, TagOp and MHST(RoBERTa\textsubscript{LARGE}) perform significantly better on documents with only one page. The results indicate that multi-page documents are more challenging than one-page ones.

Then let us consider Q3. As shown in Table 1, the average number of OCR words per page is around 500 in TAT-DQA, which is much larger than previous document VQA datasets DocVQA [29] and VisualMRC [37]. We investigate the model performance with respect to the increase of document length for NumNet+ V2, TagOp and MHST(RoBERTa\textsubscript{LARGE}). For fairness, we only use the documents with one single page in the TAT-DQA test set for experiments here. We divide these one-page documents into two halves by the median.
The results are shown in Figure 5. We can see that the performance on “Short documents” is significantly better than that on “Long documents”. Long documents are still a big challenge for document understanding tasks, where further research efforts are demanded.

5.3.4 Error Analysis. To further investigate our MHST model, we randomly sample 100 error instances on the test set and analyze the reasons. As shown in Table 7, the errors occurred to four modules, Span Answer Predictor (SAP), Expression Tree Generator (ETG), Sequence Tagging (ST) module and Scale Predictor (SP), which are classified into seven categories (Col. 2 in Table 7), each with an example. We can observe that, 1) SAP module (37%): 37% errors are due to inaccurate predictions of starting and ending positions for Span questions, i.e., 30% predictions overlapping but not exactly matching with ground truth, and 7% predictions having zero overlap with ground truth; 2) ETG module (34%): 34% of all errors are caused by ETG generating wrong expressions for the input of correct evidences from ST module, among which 19% are wrong number signs (i.e., positive/negative) and 15% are other wrong expressions; 3) ST module (25%): 25% errors are due to ST predicting wrong taggings, where interestingly, in 12% error cases, ST predicts a single string instead of identifying multiple answers from it for multi-span questions; 4) SP module (4%): 4% errors are due to SP module failing to predict the scale of the answer. We will further improve our model based on these error analysis findings.

6 CONCLUSION AND FUTURE WORKS

In this work, we propose a new challenging Document VQA dataset, named TAT-DQA, constructed based on real-world high-quality financial reports, in which each document must have both tabular and textual data. With the new dataset, we further propose a novel MHST model for addressing Document VQA tasks. From our experiments, we have gained an insight that processing tabular data separately would significantly improve model performance. This inspires us to explore the approaches of detecting and recognizing all tables in the given document and processing them differently to enhance the Document VQA models. There are usually plentiful numbers in the document, which would overwhelm the capability of almost all existing discrete reasoning models. One promising solution to such an issue is to differentiate the relevant numbers to a given question to the question from lots of numbers in the document before feeding them to the discrete reasoning module to derive the final answer, like what we have done in this work as an inspiring work. In the future, we would like to continue exploring other potential methods to effectively identify the relevant numbers to a given question to enhance the discrete reasoning over complex business documents.

ACKNOWLEDGMENTS

The authors gratefully thank all the anonymous reviewers for their positive feedback. This research is supported by the NExT Research Center, Singapore.

Table 7: Examples of errors and corresponding percentage in each module. SAP, ETG, ST and SP are the abbreviations of Span Answer Predictor, Expression Tree Generator, Sequence Tagging Module and Scale Predictor respectively. Q, G and P denote question, ground truth and prediction.
REFERENCES

[1] Daniel Andor, Luheang He, Kenton Lee, and Emily Pitler. 2019. Giving BERT a Calculator. Finding Operations and Heuristics with Reading Comprehension. In EMNLP-JCNLP. 3479–3487.

[2] Serkar Appalaraj, Bhavan Jasi, Bharagava Urala Kota, Yusheng Xie, and R. Mannnatha. 2021. DocFormatter: End-to-End Transformer for Document Understanding. In the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 993–1003.

[3] Ali Furkan Biten, Ruben Tito, Andres Maia, Lluis Gomez, Marcellus Rusinol, Ernest Valveny. CV Jawahar, and Dimosmfis Karatzas. 2019. Scene text visual question answering. In the Proceedings of the IEEE/CVF international conference on computer vision. 4291–4301.

[4] Daniel G Bobrow. 1964. Natural language input for a computer problem solving system. (1964).

[5] Kunlong Chen, Wendi Xu, Xingyi Cheng, Zou Xiaochuan, Yuyu Zhang, Le Song, Taifeng Wang, Yuan Qi, and Wei Chu. 2020. Question Directed Graph Attention Network for Numerical Reasoning over Text. In EMNLP-JCNLP. ACL, 6759–6768.

[6] Xingyu Chen, Zihan Zhao, Lu Chen, Jiao Bi, Danyang Zhang, Ao Luo, Xuyuan Xiong, and Kai Yu. 2021. WebSQA: A Dataset for Web-based Structural Reading Comprehension. In the Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 4173–4185.

[7] Zhiyu Chen, Wenhu Chen, Charese Smiley, Sameenah Shab, Jana Borova, Dylan Langdon, Reema Moussa, Matt Beane, Ting-Hao Huang, Bryan Routledge, and William Yang Wang. 2021. FinQA: A Dataset of Numerical Reasoning over Financial Data. In the Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, Online and Punta Cana, Dominican Republic, 3697–3711.

[8] Ting-Rui Chiang and Yun-Nung Chen. 2019. Semantically-Aligned Equation Generation and Solving and Reasoning Math Word Problems: In the Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). Association for Computational Linguistics, 2656–2668.

[9] Lei Cui, Yiheng Xu, Tengchao Lv, and Furu Wei. 2021. Document AI: Benchmarks, Models and Applications. CoRR abs/2111.08609 (2021).

[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In the Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). Association for Computational Linguistics, 4173–4185.

[11] Srikar Appalaraju, Bhavan Jasi, Bhargava Urala Kota, Yusheng Xie, and R. Mannnatha. 2019. Giving BERT a Calculator. Finding Operations and Heuristics with Reading Comprehension. In EMNLP-JCNLP. 3479–3487.

[12] Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, Zheng Huang, Kai Chen, Jianhua He, Xiang Bai, Dimosthenis Karatzas, Shijian Lu, Danqing Huang, Shuming Shi, Chin-Yew Lin, and Jian Yin. 2017. Learning Fine-Grained Expressions to Solve Math Word Problems. In the Proceedings of the 28th Annual Meeting of the Association for Computational Linguistics. ACL, 271–281.

[13] Chenliang Li, Bin Ri, Ming Yan, Wei Wang, Songfang Huang, Fei Huang, and Luo Si. 2021. Structural4M: Structural Pre-training for Form Understanding. In the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, 6309–6318.

[14] Minghao Li, Lei Cui, Shaohan Huang, Furu Wei, Ming Zhou, and Zhoujun Li. 2020. TableBank: Table Benchmark for Image-based Table Detection and Recognition. In the Proceedings of the 12th Language Resources and Evaluation Conference. European Language Resources Association, 1918–1925.

[15] Moxin Li, Fuli Feng, Hanwang Zhang, Xiangnan He, Fengbin Zhu, and Tat-Seng Chua. 2022. Learning to Imagine: Integrating Counterfactual Thinking in Neural Discrete Reasoning. In the Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, 57–69.

[16] Minghao Li, Yiheng Xu, Lei Cui, Shaohan Huang, Furu Wei, Zhoujun Li, and Ming Zhou. 2020. DocBank: A Benchmark Dataset for Document Layout Analysis. In the Proceedings of the 28th International Conference of the Association for Computational Linguistics. International Committee on Computational Linguistics, 949–960.

[17] Qinyang Liu, Wenyu Guan, Suzian Li, and Daisuke Kawahara. 2019. Tree-structured Decoding for Solving Math Word Problems. In the Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). Association for Computational Linguistics, 2570–2579.

[18] Minsheng Mathew, Viraj Bagal, Ruben Perez Tito, Dimosthenis Karatzas, Ernest Valveny, and C. V. Jawahar. 2021. InfographicVQA. arXiv:2104.12756 [cs.CV].

[19] Minsheng Mathew, Dimosthenis Karatzas, R. Mannnatha, and C. V. Jawahar. 2020. DocVQA: A Dataset for VQA on Document Images. CoRR abs/2007.00388 (2020).

[20] Panupong Pasupat and Percy Liang. 2015. Compositional Semantic Parsing on Semi-Structured Tables. In the Proceedings of the 33rd Annual Meeting of the Association for Computational Linguistics and the 9th International Joint Conference on Natural Language Processing. ACL, 1479–1489.

[21] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In the Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 2383–2392.

[22] Qin Ran, Yankai Lin, Peng Li, Jie Zhou, and Zhiyuan Liu. 2019. NumNet: Machine Reading Comprehension with Numerical Reasoning. In EMNLP-IJCNLP. 2474–2484.

[23] Elad Segal, Avia Efrat, Mor Shoham, Amir Globerson, and Jonathan Benart. 2020. A Simple and Effective Model for Answering Multi-span Questions. In the Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, 3074–3080.

[24] Amoogheet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xuderi Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. 2019. Towards VQA Models that can Read. CoRR arXiv:1904.08920 (2019). arXiv:1904.08920.

[25] Brandon Snapock, Rohith Pesala, and Robin Abraham. 2021. PubMedTables-M: Towards comprehensive table extraction from unstructured documents. In CVPR 2022.

[26] Nishant Subramani, Alexandre Matton, Malcom Greaves, and Adrian Lam. 2020. A survey of deep learning approaches for ocr and document understanding. arXiv preprint arXiv:2011.13534 (2020).

[27] Ryota Tanaka, Kyosuke Nishida, and Sen Yoshida. 2021. VisualMRC: Machine Reading Comprehension on Document Images. In AAAI.

[28] Ashish Varwani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, LiJia Jonas, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2019. Attention is all you need. In Advances in Neural Information Processing Systems, I Guyon, U Von Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, and R Garnett (Eds.), Vol. 32. Curran Associates, Inc.

[29] Lei Wang, Yan Wang, Deng Cai, Dongxiang Zhang, and Xiaojiang Liu. 2018. Translating a Math Word Problem to a Expression Tree. In the Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 1064–1069.

[30] Yan Wang, Xiaojiang Liu, and Shuming Shi. 2017. Deep Neural Solver for Math Word Problems. In the Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 845–854.

[31] Zhiruo Wang, Haoyu Dong, Ran Jia, Jie Li, Zhiyi Fu, Shi Han, and Dongmei Zhang. 2021. TUTA: Tree-Based Transformers for Generally Structured Table Pre-Training. In the Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. Association for Computing Machinery, 1780–1790.
[42] Te-Lin Wu, Cheng Li, Mingyang Zhang, Tao Chen, Spurthi Amba Hombaiah, and Michael Bendersky. 2021. LAMPRET: Layout-Aware Multimodal PreTraining for Document Understanding. CoRR abs/2104.08405 (2021). arXiv:2104.08405

[43] Zhipeng Xie and Shichao Sun. 2019. A Goal-Driven Tree-Structured Neural Model for Math Word Problems. In IJCAI. 5299–5305.

[44] Zhipeng Xie and Shichao Sun. 2019. A Goal-Driven Tree-Structured Neural Model for Math Word Problems. In IJCAI. 5299–5305.

[45] Yiheng Xu, Minghao Li, Lei Cui, Shaochan Huang, Furu Wei, and Ming Zhou. 2020. LayoutLM: Pre-Training of Text and Layout for Document Image Understanding. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. Association for Computing Machinery, 1192–1200.

[46] Pengcheng Yin, Graham Neubig, Wen-tau Yih, and Sebastian Riedel. 2020. TaBERT: Pretraining for Joint Understanding of Textual and Tabular Data. In ACL. 8413–8426.

[47] Jipeng Zhang, Lei Wang, Roy Ka-Wei Lee, Yi Bin, Yan Wang, Jie Shao, and Ee-Peng Lim. 2020. Graph-to-Tree Learning for Solving Math Word Problems. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 3928–3937.

[48] Xu Zhong, Elaheh Shafieibavani, and Antonio Jimeno Yepes. 2020. Image-Based Table Recognition: Data, Model, and Evaluation. In Computer Vision – ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part X XI. Springer-Verlag, 564–580. https://doi.org/10.1007/978-3-030-58589-1_34

[49] Xu Zhong, Jianbin Tang, and Antonio Jimeno Yepes. 2019. PubLayNet: largest dataset ever for document layout analysis. In 2019 International Conference on Document Analysis and Recognition (ICDAR). IEEE, 1015–1022.

[50] Pengbin Zhu, Wenqiang Lei, Chao Wang, Jianming Zheng, Soujanya Poria, and Tat-Seng Chua. 2021. Retrieving and Reading: A Comprehensive Survey on Open-domain Question Answering. CoRR abs/2101.00774 (2021).