Turning Tables: Generating Examples from Semi-structured Tables for Endowing Language Models with Reasoning Skills

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Abstract

Models pre-trained with a language modeling objective possess ample world knowledge and language skills, but are known to struggle in tasks that require reasoning. In this work, we propose to leverage semi-structured tables, and automatically generate at scale question-paragraph pairs, where answering the question requires reasoning over multiple facts in the paragraph. We add a pre-training step over this synthetic data, which includes examples that require 16 different reasoning skills such as number comparison, conjunction, and fact composition. To improve data efficiency, we propose sampling strategies that focus training on reasoning skills the model is currently lacking. We evaluate our approach on three reading comprehension datasets that are focused on reasoning, and show that our model, PReasM, substantially outperforms T5, a popular pre-trained encoder-decoder model. Moreover, sampling examples based on current model errors leads to faster training and higher overall performance.

1 Introduction

Large pre-trained language models (LMs) (Devlin et al., 2019; Liu et al., 2019; Brown et al., 2020; Raffel et al., 2020) have become the backbone of natural language processing in recent years. However, recent work has shown that they struggle in performing symbolic reasoning operations, such as composition or conjunction of facts (Talmor et al., 2019, 2020), numerical operations (Wallace et al., 2019; Hidey et al., 2020), and quantification (Warstadt et al., 2019), without substantial amounts of additional data.

Past work on improving reasoning skills in pre-trained models has taken two flavors: (a) adding specialized components for specific skills, like numerical and temporal reasoning (Ran et al., 2019; Gupta et al., 2020a; Khot et al., 2021; Chen et al., 2020a), or (b) generating synthetic examples at scale, for example, by using grammars and templates (Rozen et al., 2019; Zhao et al., 2019; Andreas, 2020; Asai and Hajishirzi, 2020; Campagna et al., 2020; Geva et al., 2020), and question generation models (Alberti et al., 2019; Puri et al., 2020; Bartolo et al., 2021).

In this work, we take the latter approach and argue that semi-structured tables are a valuable resource for automatic generation of training data that will endow LMs with reasoning skills. Tables can be crawled from the web at scale, and cover a wide range of domains and topics. Moreover, their structured nature makes them amenable to automatic processes of data generation. Specifically, given a table, we use templates to generate reading comprehension (RC) examples, that is, question-context-answer triplets, where answering the question requires diverse types of reasoning over facts.
Figure 2: Approach overview. First, we use semi-structured tables to generate large amounts of data from 16 different example generators (EGs), each corresponding to a different reasoning skill. Then, a pre-trained LM is trained over this data in a multi-task setup to obtain our model, PReasM, where we dynamically sample examples based on current model errors (arrow width corresponds to the number of sampled examples). Last, our model is fine-tuned and evaluated on target tasks that require reasoning.

We fine-tune our Pre-train for Reasoning Model, PReasM, on three RC datasets that require reasoning: DROP (Dua et al., 2019), IIRC (Ferguson et al., 2020), and MMQA (Talmor et al., 2021). PReasM outperforms the original pre-trained T5 (Raffel et al., 2020) model by significant margins: 7.6, 4.1, and 1.2 F1 points, respectively. Our results set a new state-of-the-art on MMQA and are the best results on IIRC for models where the retriever and reader are trained separately. Our analysis shows that PReasM leads to improvements of up to 40 F1 points on specific question types, such as computing the difference between two dates, without causing a drop in other question types.

In conclusion, our results suggest that semi-structured tables are a viable and untapped source of information for automatically generating large amounts of data that can be used to endow LMs with reasoning skills that are not captured using current pre-training approaches.

Our code, data, and models are publicly available and can be downloaded from https://github.com/oriyor/turning_tables.

2 Data Generation

We succinctly define the problem setup, and then turn to the process of automatic data generation from tables.

Problem Setup Our goal is to train a RC model that given a question \( q \) and textual context \( c \) returns an answer \( a \) (Fig. 1), given a training set \( D = \{(q_i, c_i, a_i)\}_{i=1}^{N} \). We focus on questions that require reasoning over the context \( c \), e.g., composing two facts. To endow LMs with reasoning skills, we would like to automatically generate a large synthetic training set \( D_{syn} = \{(q_j, c_j, a_j)\}_{j=1}^{M} \).
In League Cup of 1990–91 Chelsea F.C. season, Which Round had a higher Attendance: QF or QFR?

The context \( c \) is generated from the table content necessary for answering the question, which can be identified using the instantiated question template. Facts generally have the form “The column \( \text{col}:1 \) when the \( \text{col}:2 \) was \( \text{val}:2 \) was \( \text{val}:1 \).” For example, to answer the question above, we generate the gold facts “The Attendance when the Round was QF was 34,178” “The Attendance when the Round was QFR was 33,861” using the relevant column names and values. We also generate additional distractor facts by generating facts from rows or columns that are not relevant for the question, for example, “The Attendance when the Round was R4 was 9,789”. Finally, we shuffle the gold facts and distractor facts.

Overall, our process results in a large set \( D_{\text{syn}} \), which includes examples that require reasoning from 16 EGs (all shown in Table 1).

2.2 Data Analysis

The data generation process yields 4.8M questions from over 176K tables, and their main statistics are in Table 2. The number of distinct words and word pieces is very large (850K and 27K respectively), illustrating the wide coverage and high lexical diversity of our approach. Moreover, generated examples have diverse answer types, which include extracting spans from the context, yes/no questions, numeric, and date answers. In addition, by leveraging the distribution of Wikipedia tables our questions cover a wide range of domains including popular culture, geography, politics and science. Specifically, tables cover more than 2,500 different Wikipedia categories, with 150 categories covering 80% of the data. We show the most frequent categories in §A.1.

3 Training

Since our EGs generate large quantities of examples, one can think of each EG as providing an infinite stream of examples. In this setup, a natural question is how to construct training batches such that the model learns the required skills as quickly as possible. After briefly describing our model, we will detail our training framework, where we sample examples from EGs in an error-driven manner.

Model We use a standard encoder-decoder architecture (Raffel et al., 2020; Lewis et al., 2020). Given a training example \((q, c, a)\), the model takes
Table 1: Question templates with examples for all EGs. Variable names specify permissible instantiations, where col is a column name, val is a value, and indices denote that a value must originate from a particular column. 2/3-hop composition examples are generated by generating 2/3-long fact chains between the answer and the value in the question. For example, above, the chain will include the facts “The Role when the Author was Shakespeare in the question. For example, above, the chain will include the facts ‘The Role when the Author was Shakespeare in the question.”

Table 2: Key statistics for the generated data.

| Measurement               | Value     |
|---------------------------|-----------|
| # Distinct Questions      | 4.8M      |
| # Distinct tables         | 176K      |
| # Distinct pages          | 130K      |
| Avg. question length (words) | 19.3±4.2 |
| Avg. context length (words) | 111.3±44.8 |
| Avg. # of gold facts      | 4.4±4.7   |
| Avg. # of distractors facts | 5.0±2.8  |
| # Distinct words          | 850,543   |
| # Distinct word-pieces    | 27,055    |
| % Span answer             | 43.2      |
| % Yes/no answer           | 31.6      |
| % Numeric answer          | 15.8      |
| % Date answer             | 9.4       |

3.1 Multi-task Training over Reasoning Skills

Given a pre-trained LM, we add another pre-training step, where we multi-task over a set of tasks $S$, where each task corresponds to examples generated from a single EG. Similar to past work (Yogatama et al., 2019; Geva et al., 2020), to avoid “catastrophic forgetting” (Kirkpatrick et al., 2016) of the language skills acquired during pre-training, we sample batches from the original pre-training task with probability $\lambda = 0.5$.

Past work (Gottumukkala et al., 2020) has shown that heterogeneous batching, i.e., having examples from all tasks in each batch, leads to better performance compared to having entire batches from a single task. We follow this practice, and in every batch sample examples from every task according to a probability distribution $P_{tasks} \in [0,1]^S$. The main question is how to determine the distribution $P_{tasks}$, which we turn to next.

3.2 Sampling Strategies

We describe strategies for computing $P_{tasks}$, starting with the commonly-used uniform sampling approach, and then turn to error-driven approaches.
Uniform sampling  Past work (Khashabi et al., 2020; Raffel et al., 2020; Wang et al., 2020) used uniform sampling, where the probability to sample from a task \( s \) is \( P_{\text{tasks}}(s) = \frac{1}{|S|} \), as a-priori all tasks are equally important. Other approaches sample examples in proportion to the size of the training set (Raffel et al., 2020; Wang et al., 2020). This is not applicable in our case, where we assume an infinite stream of examples for every task, and also make no assumptions on the distribution over reasoning skills in the downstream test set.

Error sampling  Recent work (Sharma et al., 2018; Gottumukkala et al., 2020) has proposed to construct \( P_{\text{tasks}} \) based on model errors, where one over-samples tasks where the error rate is high. More formally, let \( \text{Ceil}(s) \) be an estimate of the maximum accuracy achievable on a task \( s \), and \( \text{Acc}(s) \) be the current model accuracy for task \( s \) on an held-out set. We define \( \Delta(s) = \text{Ceil}(s) - \text{Acc}(s) \) and \( P_{\text{tasks}}(s) = \frac{\Delta(s)}{\sum_{s \in S} \Delta(s)} \). The distribution \( P_{\text{tasks}} \) is updated every time we evaluate the current model on the held-out data. In our setup, since we perform multi-task training over synthetic examples that are generated at scale, we assume that \( \forall s \in S \), \( \text{Ceil}(s) = 1.0 \) and hence: \( \Delta(s) = \text{Err}(s) = 1.0 - \text{Acc}(s) \).

Momentum Sampling  An issue with error sampling is that if the error rate is high for a task and learning it is slow, the model will spend most time on that task at the expense of all other tasks, which may lead overall to low data efficiency. We empirically demonstrate this phenomenon at the bottom of this section. To remedy this phenomenon, we introduce a new sampling strategy, termed momentum sampling.

In momentum sampling, we sample examples from a task in proportion to its rate of improvement, putting most probability mass on skills that are improving quickly. Alg. 1 provides the details of this strategy. Let \( k \) denote the index of a checkpoint evaluated on the held-out set, let \( w \) be a window size, and \( \text{Acc}_s(i) \) be the held-out accuracy of checkpoint \( i \) on task \( s \). We estimate model accuracy on a task \( s \) at the beginning and end of the window, and sample examples in proportion to the difference in accuracy during that window. To smooth out accuracy fluctuations in adjacent checkpoints, we estimate accuracy as an average of \( k \) model checkpoints. During the first \( w \) checkpoint evaluations, we simply use uniform sampling.

A desired property of momentum sampling is that when all tasks reach their ceiling accuracy, it converges to uniform sampling, unlike error sampling that will over-sample from tasks for which \( \text{Ceil}(s) \) is low. This is beneficial in cases where there is variance in \( \text{Ceil}(s) \) across tasks. We illustrate this point empirically next.

Empirical comparison of sampling strategies
To highlight the benefits of momentum sampling, we show that when sampling from two tasks, where the labels for one of the tasks are noisy, momentum sampling outperforms error sampling. Specifically, we consider training on 2-hop composition and arithmetic addition, which is slower to train, in two conditions: (a) with gold labels for both tasks, and (b) when the labels for the 2-hop composition are randomly sampled from the vocabulary. We expect that when labels for 2-hop composition are random, this will lead to slow training of arithmetic addition when using error sampling, since most of the probability mass will be dedicated to 2-hop composition, which is impossible to learn.

Fig. 3 illustrates this phenomenon. Without noise (left), both momentum sampling and error sampling learn faster than uniform sampling. Momentum sampling learns more slowly than error sampling, due to the warm-start period in the first \( w \) evaluated checkpoints. However, when 2-hop composition has random labels (right), error sampling puts most probability mass on 2-hop composition, and thus error sampling is even worse than uniform sampling, while momentum sampling performs best. Thus, momentum sampling outperforms uniform sampling in both cases.

Related work  Past work has considered error-driven data sampling in the context of active learning (Sharma et al., 2018), reinforcement learning.

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**Algorithm 1 Momentum Sampling**

**Input:** window size \( w \), smoothing factor \( k \), minimum share of examples per task \( \epsilon \), training time \( t \).  
1. for \( s \in S \) do  
2. if \( t \geq w \) then  
3. \( \text{Acc}_{\text{head}} \leftarrow \frac{1}{k} \sum_{i=1}^{k} \text{Acc}_s(i) \)  
4. \( \text{Acc}_{\text{tail}} \leftarrow \frac{1}{k} \sum_{i=|S|-w+1}^{w} \text{Acc}_s(i) \)  
5. \( P_{\text{tasks}}(\text{head}) \leftarrow \frac{\max(\text{Acc}_{\text{head}} - \text{Acc}_{\text{tail}}, \epsilon)}{\sum_{s \in S} \max(\text{Acc}_{\text{head}} - \text{Acc}_{\text{tail}}, \epsilon)} \)  
6. else  
7. \( P_{\text{tasks}}(s) \leftarrow 1/|S| \)  
8. \( P_{\text{tasks}} \leftarrow P_{\text{tasks}}/\|P_{\text{tasks}}\|_1 \)
Figure 3: Motivation for momentum sampling. With the gold labels (left), error sampling and momentum sampling outperform uniform sampling on the arithmetic addition task by over-sampling the harder task. When 2-hop composition has random labels (right), error sampling over-samples the composition task and momentum sampling is best.

(Graves et al., 2017; Glover and Hokamp, 2019; Xu et al., 2019), transfer learning (Zhang et al., 2020; Pilault et al., 2021), and distributionally robust optimization (Oren et al., 2019; Sagawa et al., 2020), where the goal is to perform well over a family of distributions over the tasks. Similar to Gottumukkala et al. (2020), we compute $P_{\text{tasks}}$ based on accuracy over a held-out set rather than the loss over a training data, as this corresponds directly to our target metric.

4 Experimental Setup

We now describe our experimental evaluation.

4.1 Models

Baselines Our baseline is T5 (Raffel et al., 2020), a popular pre-trained encoder-decoder model, which we fine-tune on the downstream datasets. We experiment with two model sizes, 220 million parameters (T5-Base), and 770 million parameters (T5-Large). When the answer is a list, we train our model to generate the list of values.

Our pre-trained for reasoning model, PReasM, is a T5 model where we add a second step of pre-training on $D_{\text{syn}}$. Again, we experiment with Base and Large models and three sampling strategies: uniform sampling, error sampling, and momentum sampling; we name our models $P\text{ReasM-Uni}$, $P\text{ReasM-Err}$, and $P\text{ReasM-Moment}$ accordingly.

4.2 Datasets

DROP (Dua et al., 2019) is a RC dataset with questions that require mathematical reasoning. As an additional baseline, we also compare to GenBERT (Geva et al., 2020), which similar to our approach injects numerical skills by automatically generating synthetic data from a grammar.

IIRC (Ferguson et al., 2020) is a question answering dataset, where annotators were given a single Wikipedia paragraph, and were asked to author questions that depend on that paragraph, but also on other paragraphs linked from the input paragraph, without observing the said paragraphs. This resulted in questions that require discrete temporal (28%) or numeric (11%) reasoning. In addition, 30% of the questions are unanswerable.

We experiment with IIRC in both an oracle and retrieval setting. In the oracle setting, the model is given the gold context, which reduces the problem to reading comprehension, where we can apply our models. In the retrieval setting, we use the improved pipeline model introduced by Ni et al. (2021) to retrieve the relevant context, and then replace the NumNet+ (Base) reader (Ran et al., 2019) used by the authors (which has specialized architecture for numerical reasoning) with T5/PReasM.

MMQA (Talmor et al., 2021) is a question answering dataset, where the input is a question and a context that consists of a table, multiple text paragraphs, and multiple images, and the model must reason over a subset of the input modalities to answer the question. Since our T5/PReasM models cannot handle images or very long contexts, we construct a pipeline that automatically directs some MMQA questions to T5/PReasM, and uses the original Implicit-Decomp baseline from Talmor et al. (2021) elsewhere.

The first classifier in this pipeline is a T5-large model fine-tuned on the MMQA training set to determine if a question is likely to require an image or not. When the classifier determines a question requires an image, the example is directed to Implicit-Decomp. The accuracy of this classifier on the MMQA development set is 99.2%.

The second classifier in the pipeline is a T5-3B model, fine-tuned on the MMQA training set to determine given a question and one of the textual paragraphs if that paragraph is required for answering the question. Then, for every question that does not require an image, we classify each of the textual paragraphs and only use the ones classified as relevant. This process identifies all gold paragraphs in 95.8% of the examples. Again, we experiment

4We removed tables that appear in the MMQA development and test sets from $D_{\text{syn}}$. 
with an oracle and retrieval setting, such that in the oracle setting our model is presented with the gold text paragraphs.

Last, we convert the table into text by linearizing the table as described in Talmor et al. (2021). The model is presented with multiple paragraphs and the linearized table, and can answer questions that require any reasoning across them. Since the context is long, we present the model with contexts that require any reasoning across them. Since the context is long, we present the model with contexts of size 1,536 word-pieces (without any change to the Pipeline model through personal communication. How-ever, results on these paragraphs was lower than reported in the original paper).

Table 3 contains the number of questions in the train, development, and test sets for each of our datasets. For MMQA, there are 15,688 train and 1,501 development examples that require reasoning over the table and text only.

**Evaluation metrics**  For all datasets, we use the $F_1$ and EM scores defined in DROP (Dua et al., 2019), and later used in IIRC and MMQA, where given a gold and predicted list of answers, items on the two lists are aligned, and then their strings are compared. We use the official evaluation scripts released by the dataset authors in all cases.

5 Experimental Results

We first present results on the downstream RC datasets (§5.1) and then examine performance directly on the synthetic data (§5.2).

5.1 Performance on RC Datasets

Table 4 presents the results of our large models over all datasets, also in comparison to current state-of-the-art. We observe that PReasM substantially improves performance compared to T5 in all conditions, improving on the test set by 7.6, 7.9, 4.1, and 1.2 $F_1$ points on DROP, IIRC oracle, IIRC, and MMQA respectively. We obtain new state-of-the-art results on MMQA and IIRC oracle. On IIRC, we improve performance when using the same retriever (Pipeline) and replacing the NumNet+ retriever with PReasM. On DROP, specialized architectures for handling numbers still substantially outperform both T5 and PReasM.

Table 5 shows the effect of different sampling strategies when training the PReasM model. We observe that error sampling and momentum sampling generally outperform uniform sampling, but do not observe a clear advantage to momentum sampling compared to error sampling. We further analyze the effects of momentum sampling and error sampling when pre-training on $D_{syn}$ in §5.2.

We now look in detail at the performance of models on different answer types across datasets, where we observe that PReasM leads to dramatic improvements on some types, while maintaining similar performance on other types.

**DROP**  PReasM outperforms T5 by 12.6 points in the Base model and by 7.6 points in the Large model (see Table 5). Table 6 breaks down perfor-

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| Dataset | # Train Questions | # Development Questions | # Test Questions |
|---------|------------------|-------------------------|-----------------|
| DROP    | 77,409           | 9,536                   | 9,622           |
| IIRC    | 10,839           | 1,301                   | 1,301           |
| MMQA    | 23,817           | 2,441                   | 3,660           |

Table 3: Number of questions in each dataset.

| Dataset | Model    | Development | Test |
|---------|----------|-------------|------|
| DROP    | T5-Large | 64.6/61.8   | 65.0/61.8 |
|         | PReasM-Large | 72.1/68.5   | 72.4/68.5 |
|         | GenBERT-Large | 72.1/68.5   | 72.4/68.5 |
|         | QDGA-ALBERT | 90.1/87.0   |       |
| IIRC    | T5-Large | 69/64.9     | 67.1/62.7 |
|         | PReasM-Large | 77.4/72.7   | 75.0/70.6 |
|         | NumNet+ (Pipeline) | 70/67.6/71.7 |       |
|         | NumNet+ (Joint) | 50/64.6/58.4 | 50/54.4 |
| MMQA    | T5-Large | 63/57.9     | 63/57.0  |
|         | PReasM-Large | 65/59.0     | 64/58.3  |
|         | Implicit-Decomp | 55/58.4/55.0 | 55/50.0/55.3 |

Table 4: Development and test results. The two values in each cell indicate $F_1$/EM.

| Model    | DROP    | IIRC oracle | IIRC | MMQA |
|----------|---------|-------------|------|------|
| T5 Base  | 55.4/0.3 | 65.8/0.3    | 41.4/0.1 | 61.6/0.2 |
| PReasM-Uni-Base | 67.4/0.2 | 72/0.3      | 47/3/0.1 | 62.7/0.2 |
| PReasM-Moment-Base | 67.7/0.1 | 73.4/0.3    | 48.2/0.2 | 62.5/0.1 |
| PReasM-Err-Base | 66.9/0.1 | 74.3/0.2    | 47/0.3   | 62.6/0.3 |
| T5-Large | 64.6/0.1 | 69.7/0.2    | 47/0.3   | 64.2/0.2 |
| PReasM-Uni-Large | 71.4/0.1 | 75.0/0.2    | 49.1/0.2 | 64.9/0.4 |
| PReasM-Moment-Large | 71.7/0.1 | 76.8/0.5    | 49.8/0.2 | 64.9/0.2 |
| PReasM-Err-Large | 72.2/0.1 | 76.1/0.3    | 49.2/0.5 | 65.2/0.1 |

Table 5: $F_1$ on the development set with different sampling strategies. Results show the average and standard deviation over 3 seeds.

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5.2 Performance on Synthetic Data

On DROP, specialized architectures for handling numbers still substantially outperform both T5 and PReasM. On DROP, specialized architectures for handling numbers still substantially outperform both T5 and PReasM.

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5 We report the official numbers from Ni et al. (2021) (45.8/4/4.3 $F_1$ on the development/test sets). To fairly compare with the NumNet+ reader, we got the retrieved paragraphs for the Pipeline model through personal communication. However, results on these paragraphs was lower than reported in the paper: 45.5/42.8 $F_1$. The reported results of our models are with this slightly worse retriever, which still outperforms the performance of NumNet+ (Pipeline) as reported in the original paper.
PReasM outperforms T5 by 39.4% in the retrieval setting, PReasM outperforms NumNet+ in the oracle setup by 4 points for uniform sampling. This effect disappears in Large models, leading overall to a slight advantage for uniform sampling. None questions, but reduces performance on Value questions, where NumNet+ uses specialized architecture.

**IIRC** Table 7 breaks down performance based on answer types. Again, PReasM outperforms T5 in the oracle setup by roughly 8 points for both Base and Large models, and by 2.6–4 points in the retrieval setup. Improvements are mostly due to cases when the answer is a numerical Value, where PReasM outperforms T5 by 39.1 and 40.3 F1 points in Base and Large models (oracle setup).

Comparing PReasM-Base to NumNet+, we find that PReasM outperforms NumNet+ on None, Span and Binary questions, but has lower performance on Value questions, where NumNet+ uses specialized architecture.

Uniform sampling slightly outperforms error-driven sampling in the Base model on IIRC (Table 5). Analyzing answer types, we find that error-driven sampling improves performance on Value questions, but reduces performance on None questions, leading overall to a slight advantage for uniform sampling. This effect disappears in Large models, where error-driven sampling outperforms uniform sampling.

Overall, PReasM-Large improves state-of-the-art in the oracle setup by 4.7 F1 points. In the retrieval setting, PReasM outperforms NumNet+ (Pipeline) by 4.2 and 0.8 F1 points on the development and test sets, respectively.

**MMQA** Table 8 breaks down model performance based on reasoning skill, which is annotated for every example in MMQA. PReasM outperforms T5 in both the oracle and retrieval setting, and for both model sizes.

We observe that the main cause of improvement is comparison questions, where PReasM outperforms T5 by 19 and 11.7 F1 on Base and Large models. Second, PReasM outperforms T5 on questions that require conjunction in Base models, and yes/no questions in all settings. Interestingly, T5 is equipped with decent composition skills, without any specialized pre-training and based only on the original T5 pre-training.

Comparing our models to Implicit-Decomp, we find that although Implicit-Decomp outperforms our models on questions that require hopping between two table columns and performing aggregations (there are only 11 aggregation questions in the development set), PReasM outperforms Implicit-Decomp in all other cases. When considering only questions that require reasoning over text and tables, PReasM-Large improves F1 by 16.1 points, from 62.3 to 78.4.

### 5.2 Performance on $D_{syn}$

Fig. 4 shows statistics on the performance of PReasM on different tasks in $D_{syn}$ during training. The average accuracy across all 16 tasks at the end of training is high – almost 98.0 accuracy. We observe that PReasM reaches high performance on all tasks, where the lowest-performing tasks are ‘arithmetic addition’ and ‘date difference’, where the accuracy is at most 91.9 and 95.0 respectively at the end of training. On those tasks, the advantage of error-driven sampling is evident, and it outperforms uniform sampling by as much as 4 points. We provide full results over $D_{syn}$, including the performance of T5 in a few-shot setting in §A.4.

### Table 6: Development F1 on DROP with answer type breakdown.

| Model          | Span | Spans | Date | Number | Total |
|----------------|------|-------|------|--------|-------|
| T5-Base        | 77.5 | 65.8  | 57.1 | 43.7   | 55.8  |
| PReasM-Base    | 81.1 | 69.4  | 64.6 | 61.5   | 68.1  |
| T5-Large       | 86.1 | 78.4  | 75.7 | 52.2   | 64.6  |
| PReasM-Large   | 86.6 | 78.4  | 77.7 | 64.4   | 72.3  |
| GenBERT        | 74.5 | 24.2  | 56.4 | 75.2   | 72.3  |

**Table 7: Development F1 on IIRC with answer type breakdown.**

| Model          | Oracle | None | Span | Binary | Value | Total |
|----------------|--------|------|------|--------|-------|-------|
| T5-Base        | ✔️     | ✔️   | 91.4 | 72.0   | 76.6  | 8.7   | 66.3  |
| PReasM-Base    | ✔️     | ✔️   | 92.5 | 74.9   | 71.9  | 47.8  | 74.5  |
| T5-Large       | ✔️     | ✔️   | 92.2 | 77.7   | 81.3  | 10.9  | 69.9  |
| PReasM-Large   | ✔️     | ✔️   | 92.2 | 78.4   | 80.5  | 51.2  | 77.4  |
| T5-Base        | ✔️     | ✔️   | 57.1 | 47.6   | 54.7  | 6.7   | 43.5  |
| PReasM-Base    | ✔️     | ✔️   | 53.9 | 49.1   | 64.8  | 24.3  | 47.5  |
| T5-Large       | ✔️     | ✔️   | 56.2 | 49.9   | 77.3  | 11.5  | 47.4  |
| PReasM-Large   | ✔️     | ✔️   | 55.9 | 50.8   | 69.5  | 28.6  | 59.0  |
| NumNet+ (Pipeline) | ✔️  | ✔️   | 49.6 | 48.4   | 52.3  | 30.7  | 45.8  |
Table 8: Development $F_1$ on MMQA with reasoning type breakdown on the development set.

| Model       | Oracle | ColumnHop | Text | Composition | Comparison | Conjunction | Yes/No | Aggregate | Total |
|-------------|--------|-----------|------|-------------|------------|-------------|--------|-----------|-------|
| T5-Base     |        |           | 81.7 | 75.2        | 67.0       | 61.8        | 74.1   | 76.9      | 71.9  |
| PReasM-Base |        |           | 80.8 | 75.7        | 66.3       | 80.8        | 80.8   | 83.1      | 36.4  | 74.3  |
| T5-Large    |        |           | 82.6 | 79.8        | 71.8       | 69.3        | 83.0   | 83.1      | 76.8  |
| PReasM-Large|        |           | 84.0 | 79.7        | 71.9       | 81.0        | 82.3   | 93.8      | 36.4  | 74.3  |
| T5-Base     |        |           | 85.2 | 82.1        | 74.6       | 63.3        | 77.4   | 80.0      | 27.3  | 77.9  |
| PReasM-Base |        |           | 86.9 | 80.0        | 75.4       | 84.1        | 82.6   | 89.2      | 36.4  | 79.9  |
| T5-Large    |        |           | 88.2 | 85.9        | 79.4       | 74.3        | 83.2   | 83.1      | 36.4  | 82.7  |
| PReasM-Large|        |           | 87.8 | 85.6        | 79.8       | 83.6        | 82.3   | 90.8      | 45.5  | 83.8  |

Implicit-Decomp | ✓ | 96.6 | 57.1 | 53.2 | 78.4 | 68.1 | 76.9 | 59.1 | 62.3 |

Table 9: $F_1$ on a previously-proposed split of a subset of the development set of DROP to reasoning skills.

| Question Type | NMN | T5-Base | PReasM-Base | T5-Large | PReasM-Large |
|---------------|-----|--------|-------------|----------|--------------|
| Date-Compare  | 82.6 | 86.4 | 87.5 | 87.6 | 89.9 |
| Date-Difference | 75.4 | 19.6 | 78.9 | 45.4 | 80.4 |
| Number-Compare | 92.7 | 91.3 | 95.2 | 97.3 | 98.2 |
| Extract-Number | 86.1 | 91.8 | 94.9 | 92.1 | 95.1 |
| Count          | 55.7 | 80.1 | 86.7 | 86.7 | 89.2 |
| Extract-Argument | 69.7 | 87.6 | 86.2 | 90.5 | 92.1 |

Table 5.3 Analyzing Reasoning Skills in DROP

To check which reasoning skills PReasM has, we use a proposed split of a subset of DROP to reasoning skills (Gupta et al., 2020a). Table 9 presents the $F_1$ results for our best PReasM and T5 models on this split, as well as the $F_1$ results from the neural module network (NMN) used in Gupta et al. (2020a). We note that NMN were trained only on a subset of the original DROP dataset. When comparing to T5, we find that PReasM dramatically improves performance Date-Difference, and also leads to sizable gains in Number-Compare, Extract-Number and Count. In addition, PReasM outperforms NMN on all reasoning skills.

6 Related Work

Data Augmentation Data augmentation techniques have been extensively explored in reading comprehension, question answering, and dialogue (Feng et al., 2021), mainly by transfer learning (Talmor and Berant, 2019; Khashabi et al., 2020) and synthetic data generation (Yu et al., 2018; Zhao et al., 2019; Alberti et al., 2019; Rozen et al., 2019; Campagna et al., 2020; Chen et al., 2020; Asai and Hajishirzi, 2020; Andreas, 2020; Puri et al., 2020; Asai et al., 2020; Geva et al., 2020; Yang et al., 2021; Bartolo et al., 2021). Here we focus on semi-structured data as a valuable resource for data generation.

Pre-training over semi-structured data Past work on pre-training over tables focused on reasoning over tables and knowledge-bases (Eisenschlos et al., 2020; Yin et al., 2020; Herzig et al., 2020; Müller et al., 2021; Yu et al., 2021; Neeraja et al., 2021b), while we focus on reasoning over
text. Recently, Thorne et al. (2021) introduced a new dataset that focuses on reasoning over synthetic textual facts, which are generated by a LM from a knowledge graph.

7 Conclusion
In this work, we propose semi-structured tables as a valuable resource for automatically generating at scale examples that can endow pre-trained language models with reasoning skills. We generate almost 5M examples that correspond to 16 reasoning skills from Wikipedia tables and add a second pre-training step over this data. To improve data efficiency we use error-driven sampling, which focuses training on reasoning skills that the model currently lacks.

We evaluate our model, PReasM, on three reasoning-focused RC datasets and show that it leads to substantial improvements in all cases. Moreover, we thoroughly analyze the performance of PReasM and show that our approach dramatically improves performance on questions that require reasoning skills that were not acquired during the original pre-training, while maintaining comparable performance on other question types.

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A Supplemental Material

A.1 Data Generation

Table 10 contains the number of generated examples for every EG. During data generation, we randomly generate at most 10 examples for each EG and table. Table 11 contains examples for generated \((q,c,a)\) triplets, including the full context \(c\). Fig. 5 presents the most common categories of the Wikipedia pages from which we scraped our tables.
Table 10: Number of examples generated by each EG.

| EG                        | # Questions |
|---------------------------|-------------|
| 2-Hop composition         | 277,069     |
| 3-Hop composition         | 364,772     |
| Conjunction               | 353,738     |
| Only quantifier           | 522,071     |
| Most quantifier           | 94,180      |
| Every quantifier          | 16,693      |
| Number comparison         | 410,749     |
| Temporal comparison       | 453,499     |
| Number boolean comparison | 410,749     |
| Temporal boolean comparison| 470,694   |
| Number superlatives       | 125,144     |
| Temporal superlatives     | 80,884      |
| Arithmetic superlatives   | 183,892     |
| Counting                  | 484,471     |
| Date difference           | 452,061     |
| Total                     | 4,787,635   |

Figure 5: The most frequent categories of our Wikipedia pages and their frequency.

A.2 Training

Error sampling Alg. 2 provides our error sampling algorithm.

Algorithm 2 Error Sampling(t)

Input: training time t
1: for s ∈ S do
2: \( P_{\text{tasks}}[s] \leftarrow 1.0 - \text{Acc}_s(t) \)
3: \( P_{\text{tasks}} \leftarrow P_{\text{tasks}} / \| P_{\text{tasks}} \|_1 \)

Momentum Sampling For momentum sampling we use a window size of \( w = 4 \), a smoothing factor of \( k = 2 \), and sample at least \( \epsilon = 0.002 \) examples from every task when training PReasM-Base and PReasM-Large.

A.3 Experimental Setup

Original pre-training task In order to avoid catastrophic forgetting (Kirkpatrick et al., 2016), we continue training with the span-corruption objective introduced in (Raffel et al., 2020), over sequences of length 256 from the English Wikipedia.

Implementation details We fine-tune all our experiments on one RTX8000 (48GB) or RTX3090 (24GB) GPU. We use the T5 model from https://huggingface.co/transformers/model_doc/t5.html (Wolf et al., 2020).

| Experiment   | Size | LR   | Batch Size | GAS | Epochs |
|--------------|------|------|------------|-----|--------|
| PReasM Base  | 1e-4 | 64   | 1          | 50  |
| PReasM Large | 1e-4 | 18   | 4          | 36  |
| DROP Base    | 1e-4 | 20   | 1          | 20  |
| IIRC Base    | 1e-4 | 20   | 1          | 60  |
| MMQA Base    | 1e-4 | 6    | 3          | 20  |
| DROP Large   | 5e-5 | 16   | 2          | 20  |
| IIRC Large   | 5e-5 | 16   | 2          | 60  |
| MMQA Large   | 1e-4 | 2    | 16         | 10  |

Table 12: Hyper-parameters used in all experiments, LR and GAS refer to learning-rate and gradient accumulation steps. In our PReasM experiments, epochs refer to the number of steps between evaluations, which is set to 5,000 and 2,500 for our base and large experiments, which leads to 250,000 and 90,000 optimization steps, respectively.

A.4 Experimental Results

Fig. 6 shows the results for T5 and PReasM on \( D_{syn} \) for both model sizes. T5-Large outperforms T5-Base on most tasks, suggesting that skills such as comparison and superlatives may have been picked up better during pre-training. However on tasks such as date difference and arithmetic addition the results T5-Large are very low, at around 10 \( F_1 \). Our PReasM models significantly outperforms T5 on all tasks.
| EG          | Question                                                                 | Context                                                                                                                                 | Answer  |
|------------|-------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|---------|
| 3-hop Composition | What was the Result(s) when the Round was R4 in League Cup of 1990-91 Chelsea F.C. season? | The attendance when the opponent was Tottenham Hotspur were 34,178 and 33,861. The attendances when the opponent was Sheffield Wednesday were 34,669 and 34,074. The attendance when the opponent was Oxford United was 9,789. The attendances when the opponent was Portsmouth were 16,699 and 16,085. The attendances when the opponent was Walsall were 5,666 and 10,037. | 2-1     |
| Numerical Superlatives | Which opponent has the highest attendance in League Cup of 1990-91 Chelsea F.C. season? | The attendance when the opponent was Tottenham Hotspur were 34,178 and 33,861. The attendances when the opponent was Sheffield Wednesday were 34,669 and 34,074. The attendance when the opponent was Oxford United was 9,789. The attendances when the opponent was Portsmouth were 16,699 and 16,085. The attendances when the opponent was Walsall were 5,666 and 10,037. | Sheffield Wednesday |

Table 11: Examples for generated \((q, c, a)\) triplets. The examples were generated from the table shown in fig. 1. The gold facts for the composition question are indicated. The numerical superlatives question requires reasoning over all the facts in the context.

Figure 6: \(F_1\) for every task, for T5 and PReasM. The results for T5 were received by training in a few shot manner on 32 examples for 200 steps, as suggested in (Ram et al., 2021).