Improving the Numerical Reasoning Skills of Pretrained Language Models

Dominic Petrak†, Nafise Sadat Moosavi‡, Iryna Gurevych†

†Ubiquitous Knowledge Processing Lab (UKP Lab)
Department of Computer Science, Technical University of Darmstadt
https://www.ukp.tu-darmstadt.de
‡Department of Computer Science, The University of Sheffield

Abstract
State-of-the-art pretrained language models tend to perform below their capabilities when applied out-of-the-box on tasks that require reasoning over numbers. Recent work sees two main reasons for this: (1) popular tokenisation algorithms are optimized for common words, and therefore have limited expressiveness for numbers, and (2) common pretraining objectives do not target numerical reasoning or understanding numbers at all. Recent approaches usually address them separately and mostly by proposing architectural changes or pretraining models from scratch. In this paper, we propose a new extended pretraining approach called reasoning-aware pretraining to jointly address both shortcomings without requiring architectural changes or pretraining from scratch. Using contrastive learning, our approach incorporates an alternative number representation into an already pretrained model, while improving its numerical reasoning skills by training on a novel pretraining objective called inferable number prediction task. We evaluate our approach on three different tasks that require numerical reasoning, including (a) reading comprehension in the DROP dataset, (b) inference-on-tables in the InfoTabs dataset, and (c) table-to-text generation in WikiBio and SciGen datasets. Our results on DROP and InfoTabs show that our approach improves the accuracy by 9.6 and 33.9 points on these datasets, respectively. Our human evaluation on SciGen and WikiBio shows that our approach improves the factual correctness on all datasets.

1 Introduction
Numbers are ubiquitous in natural language. Therefore, numerical reasoning is a critical capability for pretrained language models, cornerstones of modern NLP, in order to utilize quantitative information for various NLP tasks. Recent works question whether these models meet this requirement out-of-the-box (Wallace et al., 2019; Zhang et al., 2020b), as (1) common pretraining objectives do not target numerical reasoning, and (2) commonly used tokenisation algorithms have limited expressiveness for numbers. Common pretraining objectives, such as the denoising autoencoder of BART (Lewis et al., 2020), the masked language modeling of BERT (Devlin et al., 2019), or the span-corruption objective of T5 (Raffel et al., 2019), are designed for understanding structure and semantic meaning of language in the first place, and not to reason over numbers. This makes extended pretraining or structural modifications necessary to further improve the performance on tasks that extensively require this capability (Geva et al., 2020; Thawani et al., 2021; Chen et al., 2020a). Tokenisation algorithms, such as Byte Pair Encoding (Sennrich et al., 2016) or WordPiece (Wu et al., 2016), are designed to handle patterns that are frequently observed during training, which is not the case with numbers (Wallace et al., 2019). For instance, 0.72 and 0.73 are two similar numbers. They should be processed similarly, but according to their frequency in the pretraining data they might be tokenised very differently, e.g., [0, ., 72] and [0, ., 7, 3], which will have an impact on their representation in embedding space.

Various approaches have been proposed recently to address these shortcomings. For improving the representation of numbers, other tokenisation algorithms, such as the character-level tokenisation, have emerged as promising alternatives (Wallace et al., 2019; Geva et al., 2020), but most approaches require pretraining from scratch (Peng et al., 2021; Zhang et al., 2020b). Regarding numerical reasoning, many approaches reuse pretrained language models, but then introduce additional components or rely on predefined patterns that limit application, e.g., the proposed approach is only applicable for...
In this paper, we propose a new approach called reasoning-aware pretraining that jointly targets both shortcomings in pretrained encoder-decoder language models in order to keep them reusable without introducing new components or requiring pretraining from scratch. It is an extended pretraining approach based on contrastive learning. In detail, this new approach consists of the following:

- A contrastive loss to incorporate the character-level representation for numbers in a pretrained language model.
- The inferable number prediction task – a denoising pretraining objective for improving the numerical reasoning skills of pretrained language models.

Using a combined loss function, our approach applies both constituents jointly, requiring only one training cycle. To show its effectiveness, we experiment with various tasks that require numerical reasoning, i.e., reading comprehension, inference-on-tables, and table-to-text generation. Our experiments show that our approach improves the accuracy in case of reading comprehension and inference-on-tables, and the factual correctness in case of table-to-text generation, indicating a broad applicability. For our experiments, we use BART (Lewis et al., 2020) and T5 (Raffel et al., 2019) as common representatives for state-of-the-art pretrained encoder-decoder language models.

2 Related Work

Number Representations in Language Models. State-of-the-art language models, like BART (Lewis et al., 2020), BERT (Devlin et al., 2019) or T5 (Raffel et al., 2019), use subword-based tokenisation algorithms such as WordPiece (Wu et al., 2016) or Byte Pair Encoding (Sennrich et al., 2016). These algorithms build vocabularies based on frequently observed sequences of symbols across a text corpus. While this is effective for common words, it is problematic for numbers. In an extensive study, Wallace et al. (2019) find that models using character-level tokenisation, such as ELMo (Peters et al., 2018), usually achieve better results in numerical probing tasks and extrapolate better to unseen numbers compared to models using subword-level tokenisation. Thawani et al. (2021), Peng et al. (2021) and Zhang et al. (2020b) report similar findings. To address the shortcoming with subword-level tokenisation, we incorporate the character-level tokenisation for numbers using a contrastive loss in this work.

Approaches for Improving Numerical Reasoning Skills. There are two categories of approaches for improving numerical reasoning: (1) the ones that require pretraining from scratch, and (2) the ones that build upon a pretrained language model. Most approaches also introduce new architectural components or modify pretraining objectives. TAPAS (Herzig et al., 2020) is a model from the first category and targets question answering with tabular data. It is pretrained from scratch and extends BERT’s architecture by introducing additional embeddings for capturing tabular structure. GenBERT (Geva et al., 2020) and the approaches proposed by Andor et al. (2019) and Suadaa et al. (2021) are from the second category. GenBERT adds a decoder on top of BERT and is trained by two extended pretraining tasks comprising math word problems and arithmetic operations for incorporating the character-level tokenisation of numbers into the model and to improve its numerical reasoning skills. It achieves state-of-the-art results on the DROP (Dua et al., 2019) and SQUAD (Rajpurkar et al., 2016) datasets. Andor et al. (2019) also targets the task of reading comprehension and injects numerical reasoning skills into BERT by adding a new layer on top that predicts and executes arithmetic operations. Suadaa et al. (2021) target table-to-text generation with GPT-2 (Radford et al., 2019) and T5, and propose to inject pre-executed numerical operations into the template-guided text generation approach originally proposed by Kale and Rastogi (2020). Our reasoning-aware pretraining approach is also from the second category, as it proposes a new objective for extended pretraining. In comparison to the other approaches, it does not require any architectural changes.

Domain-Adaptive Pretraining. The idea of domain-adaptive pretraining is to bridge the gap between the vocabulary of a model’s original pretraining corpus and the target domain to avoid pretraining from scratch (Gururangan et al., 2020). It is usually applied by continuing pretraining using in-domain data or a synthetic task. Its effectiveness
has been shown across various tasks and scenarios (Zhang et al., 2020a; Yu et al., 2021). In this work, we propose the inferable number prediction task for extended pretraining of language models which is similar to domain-adaptive pretraining.

**Contrastive Learning.** Contrastive learning is a general way to learn to map vector representations of similar data points (usually called anchor and positive) close to each other, while pushing non-similar data points apart. In NLP, it is commonly used for learning sentence representations (Kim et al., 2021; Giorgi et al., 2021) or semantic similarities (Wang et al., 2021).

3 Reasoning-Aware Pretraining

In this section, we propose reasoning-aware pretraining, an approach for improving the numerical reasoning skills of pretrained language models. Section 3.1 describes our idea of contrastive learning for incorporating an alternative number representation into pretrained language models, and Section 3.2 describes the inferable number prediction task. Section 3.3 describes how we jointly apply both using a combined loss function.

3.1 Contrastive Learning

To incorporate an alternative number representation into a pretrained language model, we propose to use a contrastive loss to align the embeddings of the same number in different representations. For example, the model should learn a similar representation for the number 108.89, whether it is initially tokenised using subwords ([10, 8, .., 89]) or character-level information ([1, 0, 8, .., 8, 9]). We use the multiple negative ranking loss as proposed by Henderson et al. (2017) for this:

$$\mathcal{L}_C = -\frac{1}{N} \sum_{i=1}^{N} \frac{1}{2} \sum_{j=1}^{N} e^{\text{sim}(\text{avg}(p_i), \text{avg}(p_j))} + e^{\text{sim}(\text{avg}(p_i), \text{avg}(p_j))}$$

Assume $p$ is an input sequence containing $d \geq 1$ numbers, $p_i$ and $p_j$ represent the $i$th number in $p$, but in different tokenisations. Then, in Equation 1, $\hat{p}_i$ and $\hat{p}_j$ are the corresponding embeddings after the encoder pass. $\text{sim}$ represents the cosine similarity. We consider $\text{avg}(\hat{p}_i)$ and $\text{avg}(\hat{p}_j)$ as a positive pair (with $\text{avg}(\hat{p}_i)$ as anchor), and $\text{avg}(\hat{p}_i)$ and the averaged encodings of other numbers in the batch, i.e., $\text{avg}(\hat{p}_j)$, as negative pairs. Averaging ($\text{avg}$) is a simple and effective form of aggregation which is necessary at this point, as the numbers might be split into multiple tokens during tokenisation.

For implementation, we use alternating batches (see Figure 1) in which every sample of the dataset that contains a number is used twice ($p$ and $p'$) where the only difference is the tokenisation of numbers.3

![Figure 1: Example for alternating batches. Each sample of the dataset that contains a number is used twice, in which the only difference is the tokenisation of numbers.](image)

For anchor samples, we use the character-level tokenisation, meaning that numbers will be split into single digits (e.g., 10.98 will be split into [1, 0, .., 9, 8]). For positive samples we use the default tokenisation of numbers which is subword-based in case of BART (Lewis et al., 2020) and T5 (Raffel et al., 2019), e.g., 10.98 will be tokenised into [10, .., 98].

3.2 Inferable Number Prediction

The inferable number prediction task is a variation of the classic masked language modelling objective (Devlin et al., 2019), but aims on improving the numerical reasoning skills of pretrained language models. This task consists of the input $C$ and the corresponding output $D$, the target sequence. $C$ consists of a pair of text sequences, $C_1$ and $C_2$, that are separated with a special character. $C_2$ equals to $D$, but contains a masked number that can be inferred from $C_1$. The task is to reconstruct the original content of $C_2$ by correctly predicting the masked number from the content of $C_1$. For instance, for the task of table-to-text generation, $C_1$ is the linearized form of the input table and $C_2$, and hence $D$, is the corresponding description of the table.

3These additional positive examples are only used for the contrastive loss.
For arbitrary datasets, it cannot be assumed that \( D \) contains numbers that are inferable by the information given in \( C_1 \). There might be cases where \( D \) contains no numbers at all, or where \( C_1 \) contains only numbers that are not related to the ones given in \( D \). Therefore, we apply the following criteria:

- \( D \) should contain at least one relevant entity from \( C_1 \), e.g., \( D \) contains at least one of the entities that appear in the rows or column headers of \( C_1 \) if \( C_1 \) is a table. This criteria is a heuristic to validate whether \( D \) is relevant to the information given in \( C_1 \).

- The masked number in \( C_2 \) should be either one of the values in \( C_1 \) or inferable by occurrence, summation, subtraction, multiplication, division or ordering.

By applying these heuristics, we can reduce \( C_1 \) to the information necessary to infer the masked number in \( C_2 \). For example, we reduce tables to rows and columns that (1) share entities with the description, and (2) contain only important numbers. If \( D \) consists of multiple sentences, i.e., is a paragraph or a more extensive description, we apply each of these heuristics to each of the sentences and retain only the matching ones (see Appendix C for illustrated examples).

For training, we use the cross-entropy loss function:

\[
\mathcal{L}_{\text{INP}}(X, Y) = \sum_{i}^{N} \left( -y_i + \log \left( \sum_{k}^{K} e^{x_{ik}} \right) \right) \tag{2}
\]

In Equation 2, \( X \) contains the logits for all the predicted tokens in the generated sequence. \( Y \) contains the indices of the tokens from \( D \) in the model’s vocabulary \( V \). \( N \) is the number of tokens in the target sequence \( Y \), and \( K \) is the size of \( V \). Correspondingly, \( y_i \) is the target sequence at position \( i \), and \( x_{ik} \) is the probability of the \( k \)th token of \( V \) to be correct at position \( i \) of \( Y \).

### 3.3 Joint Loss Function

A more expressive number representation is beneficial for improving the numerical reasoning skills of the underlying pretrained language model. Since our contrastive loss for incorporating an alternative number representation and the inferable number prediction task are not mutually exclusive, we can combine them as weighted sum in a joint loss function.

\[
\mathcal{L} = \frac{\mathcal{L}_{C}}{2} + \frac{\mathcal{L}_{\text{INP}}}{2} \tag{3}
\]

Equation 3 describes this loss function \( \mathcal{L} \), where \( \mathcal{L}_{C} \) is the contrastive loss from Equation 1 and \( \mathcal{L}_{\text{INP}} \) is the loss of the inferable number prediction task (Equation 2).

### 4 Experimental Setup

We implement our approach using Python 3.7, the PyTorch ecosystem\(^4\) (especially PyTorch-Lightning\(^5\)), and Huggingface (Wolf et al., 2020). For pretrained models, we use the large variant of BART (Lewis et al., 2020) and the base variant of T5 (Raffel et al., 2019) as provided by the Huggingface platform. In case of T5, we haven’t included any of the task-specific prefixes originally used for pretrained in our experiments as we do not target any multi-task scenario in this work. We conduct all experiments on a Tesla V100-SXM3 GPU with 32 GB memory\(^6\). For experiments using table-to-text datasets, we represent tables as linearized sequence (see Appendix C for examples).

### 4.1 Datasets

#### Reading Comprehension

The task of reading comprehension is to answer a question given a related text passage. The DROP dataset (Dua et al., 2019) is a reading comprehension dataset with over 96,000 questions in which answering questions requires discrete reasoning over text passages. We split the dev data into two equally-sized subsets and use one for testing. Each subset contains 4,828 questions.

#### Inference-on-Tables

Given a premise and a hypothesis, natural language inference (NLI) is the task of deciding whether the hypothesis is entailed, contradictory, or neutral to the premise. InfoTabs (Gupta et al., 2020) extends NLI to using semi-structured data, i.e., tables, as hypothesis. It is a crowdsourced dataset that consists of 23,738 hypothesis for 2,540 Wikipedia infoboxes from a variety of domains. It is a more challenging task than inference over textual data, as tabular data provides information in a more implicit way.

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\(^4\)https://pytorch.org/ecosystem/, last accessed on 10/05/22.

\(^5\)https://github.com/PyTorchLightning/pytorch-lightning, last accessed on 10/05/22

\(^6\)See Appendix E for details on hyperparameters.
Table-to-Text Generation. We evaluate our approach on two different reasoning-aware table-to-text generation datasets, namely SciGen (Moosavi et al., 2021) and WikiBio (Lebret et al., 2016). Table-to-text generation describes the task of summarizing tabular data in a descriptive text. As this data is often numerical, the challenging part of this task is to reason over numbers, i.e., to implicitly perform arithmetic operations such as ordering, summation or subtraction, or to capture magnitudes.

SciGen is a table-to-text generation dataset in which the input is a table with its corresponding caption, and the output is the description of the table’s content. Both, tables and their descriptions, are extracted from scientific articles. SciGen consists of 53,136 annotated table-description pairs, distributed in three splits, i.e., few-shot, medium, and large. While the few-shot split and the test data are annotated by experts, the medium and large splits are annotated automatically.

WikiBio is a dataset from the biographical domain. Given infoboxes and their captions extracted from biographical articles in Wikipedia, the task is to generate short descriptions about the given persons. The first paragraph of the corresponding articles are used as the target descriptions. Overall, the dataset consists of 728,321 samples.

5 Evaluation

In this section, we evaluate the impact of reasoning-aware pretraining on downstream applications using (1) in-domain data (Section 5.2), and (2) out-of-domain data (Section 5.3). In the in-domain setting, we use the training data from each of the target tasks for our extended pretraining. For instance, for InfoTabs (Gupta et al., 2020) we use the table-hypothesis pairs from the training data and predict a masked number in the hypothesis given the input table. For the out-of-domain setting, we perform the pretraining step on a data other than the target task, e.g., pretraining on SciGen (Moosavi et al., 2021) and then performing the finetuning on InfoTabs. The goal of out-of-domain evaluations is to investigate how much of the improvements are due to better numerical reasoning as opposed to domain-adaption.

5.1 Evaluation Metrics

For inference-on-tables, we evaluate the results using Exact Match (EM score). For reading comprehension, we additionally use F1 score. The EM score evaluates the prediction accuracy, i.e., if the prediction exactly matches the target, and is the preferred metric for these tasks (Dua et al., 2019; Gupta et al., 2020). The F1 score reports the overlap ratio between the prediction and the target. This might result in partial reward in cases where the prediction is partially correct. In case of table-to-text generation, we conduct a human evaluation. This is due to the shortcomings of common automatic metrics for this task, as they are hardly able to assess the correctness of information not directly contained in the source data, i.e., information obtained by reasoning (Moosavi et al., 2021; Chen et al., 2020b; Suadaa et al., 2021). 8

5.2 In-Domain Pretraining

This section discusses the results on downstream tasks when using models that are pretrained using our approach with in-domain data. Baseline represents the BART (Lewis et al., 2020) and T5 (Raffel et al., 2019) model directly finetuned on the corresponding dataset without reasoning-aware pretraining. Ours represents these models with reasoning-aware pretraining.

Reading Comprehension. Table 1 shows the results achieved on DROP (Dua et al., 2019).

|       | EM  | F1  |
|-------|-----|-----|
| BART  | Baseline 36.00 | 39.26 |
| Ours  | 45.60 | 49.50 |
| T5    | Baseline 10.40 | 14.60 |
| Ours  | 11.00 | 15.20 |

Table 1: Evaluation on the DROP dataset. Our approach outperforms the baseline in both cases.

In case of BART, our reasoning-aware pretraining increases the results by 9.6 points in EM score, indicating a large improvement in accuracy. A deeper look at the BART results reveals that while both, the baseline and our approach, are able to predict a number for the questions that require a number as answer, our approach reduces the incorrectly predicted numbers by 14.27% overall. In case of T5, the results are in general much lower, but still our approach outperforms the baseline. Among

7 NumericNLG is a similar dataset. It was previously introduced by Suadaa et al. (2021). As SciGen (Moosavi et al., 2021) provides more unsupervised training pairs that we can use for reasoning-aware pretraining, we use SciGen in our experiments.

8 Appendix A shows the results of the automatic metrics.
other tasks, T5 was pretrained on reading comprehension using datasets similar to DROP (Raffel et al., 2019), e.g., MultiRC (Khashabi et al., 2018).
We assume that not reusing the corresponding prefix originally used for pretraining T5 on this task is problematic here, as this seems to have an impact according to the documentation available on Huggingface (Wolf et al., 2020). However, a deeper look at the T5 results reveals that our approach reduces incorrectly predicted numbers by 16.62% overall.

**Inference-on-Tables.** In case of InfoTabs, Gupta et al. (2020) provide three different test sets: one with data that is close to the distribution of the training data (in-domain), a cross-domain, and an adversarial test set. For the adversarial test set, the wording of hypotheses was slightly changed by expert annotators. Furthermore, they use another set of source tables for this test set, while retaining a distribution similar to the original training data. The cross-domain test set uses premises from domains that are not used for training, but that generally require similar types of reasoning. Table 2 presents the prediction accuracies (EM score) achieved on the InfoTabs (Gupta et al., 2020) dataset.

|                | In-Domain | Cross-Domain | Adversarial |
|----------------|-----------|--------------|-------------|
| **BART**       | Baseline  | 33.30        | 23.67       | 27.68       |
|                | Ours      | 67.20        | 54.40       | 57.20       |
| **T5**         | Baseline  | 32.00        | 11.76       | 13.00       |
|                | Ours      | 32.30        | 18.07       | 15.25       |

Table 2: Evaluation on the InfoTabs dataset. This table shows the prediction accuracies (EM score) achieved on InfoTabs. Our approach outperforms the baseline in both cases.

For the in-domain test set, our reasoning-aware pretraining increases the EM score by 33.90 points in case of BART, which is a significant improvement in accuracy. Further analysis of the BART results achieved with our approach reveals that the model correctly predicts 60.30% of the entailments, 75.50% of the contradictions, and 65.83% of the neutrals. In case of T5, the improvements are rather negligible. This might again be due to not reusing the prefixes originally used for pretraining the model on similar tasks, such as MNLI (Williams et al., 2017). Further analysis shows that T5 has a strong bias towards predicting *entailment* in both cases, the baseline and our approach. For the other two test sets, our approach also shows improvements over the baselines for BART and T5, indicating that it results in models more robust and with a better capability to extrapolate knowledge learned during training.

**Table-to-Text Generation.** For human evaluation, we follow the approach used by Moosavi et al. (2021) for evaluating the results on SciGen. As this is very time-consuming, we only analyse 100 random table-description pairs from each, the SciGen and WikiBio (Lebret et al., 2016) dataset, and also only from the BART (Lewis et al., 2020) experiments. For SciGen, we use the results from the large split experiment.

For annotation, we break down each generated output to its corresponding statements (facts). We create one CSV file for each dataset that contains these statements in random order. This way, the annotator can not see whether a statement was generated by *Ours* (BART with reasoning-aware pretraining) or by *Baseline* (BART without reasoning-aware pretraining). Alongside with the generated statements, this CSV file contains the original tables and gold descriptions. Using this CSV file, the annotator then decides for each of the statements whether it belongs to one of the following labels:

- **Entailed**: The statement is entailed in the gold description, e.g., a fact that is mentioned either in a similar or different wording in the description.
- **Extra**: The statement is not entailed in the gold description but is factually correct based on the table’s content.
- **Incorrect**: The statement is relevant to the table, i.e., it contains relevant entities but is factually incorrect. For instance, the statement says *system A outperforms system B by 2 points* while based on the table system A has a lower performance than system B.
- **Hallucinated**: The statement is not relevant to the table.

Based on these labels, we then compute the recall (#entailed/#gold), precision (#entailed/#generated), correctness (#entailed + #extra)/#generated), and hallucination (#hallucinated/#generated) scores for the generated facts. #gold and #generated refers to the respective number of included
statements, not complete sequences. Table 3 shows the results.

|       | Prec. | Rec. | Cor. | Hall. |
|-------|-------|------|------|-------|
| SciGen |       |      |      |       |
| Baseline | 0.08  | 0.02 | 0.31 | 0.29  |
| Ours   | 0.09  | 0.03 | 0.40 | 0.33  |
| WikiBio |       |      |      |       |
| Baseline | 0.22  | 0.07 | 0.33 | 0.03  |
| Ours   | 0.28  | 0.09 | 0.46 | 0.02  |

Table 3: Results of the human evaluation. In both cases, our approach improves the correctness of the generated facts.

Our reasoning-aware pretraining improves the precision, recall, and correctness for both, SciGen and WikiBio. For WikiBio, it improves the precision by 0.06 points, suggesting that generated statements are more concise and closer to the target description. It also improves the ratio of statements that are factually correct by 0.13 points. This is similar for SciGen, although we observe a slight increase in hallucinations with our approach which is a slight deterioration. We found that while Baseline seems to generate descriptions close to the target, Ours is somewhat more oriented towards the tabular values, whereby these values are used out-of-context in some cases which might be the reason for this deterioration. Nevertheless, all models generate fluent and valid-looking descriptions (see Appendix F for examples).

5.3 Out-of-Domain Pretraining

To investigate whether the effectiveness of our approach is a result of using in-domain data for pretraining or improved numerical reasoning skills, we evaluate our approach using out-of-domain data for pretraining. For this experiments, we focus on BART (Lewis et al., 2020) and perform reasoning-aware pretraining on a different dataset before finetuning on DROP (Dua et al., 2019) and InfoTabs (Gupta et al., 2020). For instance, for the DROP (Dua et al., 2019) experiments, we pretrain several models on WikiBio (Lebret et al., 2016), SciGen (Moosavi et al., 2021), and InfoTabs (Gupta et al., 2020), which all include data from a different domain, before finetuning. For SciGen, we use the large split in this experiment. Table 4 shows the results.

|       | EM    | F1    |
|-------|-------|-------|
| DROP  |       |       |
| WikiBio → DROP | 6.00  | 33.50 |
| InfoTabs → DROP | 35.50 | 39.63 |
| SciGen → DROP   | 47.70 | 51.60 |
| InfoTabs       |       |       |
| WikiBio → InfoTabs | 33.15 | -    |
| DROP → InfoTabs | 32.80 | -    |
| SciGen → InfoTabs | 64.70 | -    |

Table 4: Results of the out-of-domain pretraining.

(EM score of 45.60, see Table 1), and are nearly on-par in case of InfoTabs. We suspect that the extent to which the pretraining dataset requires numerical reasoning has a major impact on the downstream performance. Among the datasets used, SciGen is in particular designed for the task of text generation based on numerical reasoning, and as we observe from the results, pretraining models on this dataset has the most positive impact on out-of-domain evaluations.

6 Ablation Study

In this section, we investigate the impact of incorporating the character-level tokenisation and a contrastive loss on the effectiveness of our pretraining approach. To do so, we assess how many of the masked numbers in the inferable number prediction task are predicted correctly in different settings. As described in Section 3.2, it is prerequisite that numbers in target descriptions are inferable from the source data. Therefore, we do not use the original datasets for these experiments, but suitable subsets (see Appendix B for details and dataset sizes). For evaluation, we use Exact Match (EM score) and F1 score. EM evaluates whether the predicted span exactly matches the masked number, and F1 reports the overlap ratio between the predicted and the masked number. We focus on BART (Lewis et al., 2020) as Baseline for this experiment. Table 5 shows the results.

Baseline (default tok.) reports the results when the default tokenisation, Byte Pair Encoding (Sennrich et al., 2016), is used for tokenising numbers. Correspondingly, Baseline (CLR tok.) reports the results when the character-level tokenisation for numbers is used. Ours reports the results when using the character-level tokenisation for numbers and the contrastive loss. Baseline (default tok. + contrastive loss) reports the results when the contrastive loss is also used.

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10 In case of the contrastive loss, we also experiment with other number representations for incorporating the character-level tokenisation into a pretrained model (see Appendix D).
Table 5: Ablation study on the inferable number prediction task. The combination of all constituents significantly outperforms the baseline in all experiments.

(default masking) is an ablation of our masking procedure. With this we want to investigate the effectiveness of our masking procedure. In this experiment, we make no distinction and also mask words during training. We conduct this experiment once for each task, and with SciGen (Moosavi et al., 2021) as representative for table-to-text generation.

In all five datasets, incorporating our contrastive loss and the character-level tokenisation for numbers considerably improves the correctness of the predicted numbers. This is most significant in case of the table-to-text datasets, where it improves the EM score by 34.25 (WikiBio (Lebret et al., 2016)), and 12.42 (SciGen) points respectively. In case of DROP (Dua et al., 2019) and InfoTabs (Gupta et al., 2020), using just the character-level tokenisation for numbers already has a significant impact.

Regarding the effectiveness of our masking procedure, masking only numbers improves the results across all experiments, but most significant in case of InfoTabs (up to 10.77 points in EM score when comparing Baseline (default tok. + default masking) with Baseline (default tok.) on this dataset). In case of DROP, it raises the F1 score from 7.20 to 55.51 points, meaning that there is a significantly larger overlap between predicted numbers and target numbers. Overall, this shows that masking only inferable numbers has a positive impact on the model’s capabilities for numerical reasoning.

7 Conclusions

In this paper, we propose reasoning-aware pretraining, an approach for jointly addressing the shortcomings of pretrained language models in representing and reasoning over numbers. We use contrastive learning for incorporating the character-level tokenisation for numbers into pretrained language models, and propose a new pretraining objective, the inferable number prediction task, for improving their numerical reasoning capabilities. Our experiments show performance improvements on different tasks and domains, including reading comprehension (DROP), inference-on-tables (InfoTabs), and table-to-text generation (e.g., WikiBio). In case of DROP, using our approach improves the results by 9.60 points in EM score over the BART baseline. For InfoTabs, our approach improves the results by 33.90 points, while also showing to be more robust against adversarial and out-of-domain evaluations. For table-to-text generation, our approach improves the correctness of generated facts over the BART baseline. Further experiments show that the effectiveness of our approach is not limited to in-domain pretraining, but also improves the results when pretrained with out-of-domain data. For example, pretraining on the SciGen dataset improves the results achieved on DROP when pretrained using in-domain data, i.e., the DROP dataset itself.

8 Limitations

Despite taking the utmost care, our work is subject to some limitations. First of all, BART (Lewis et al., 2020) restricts the maximum length of input sequences to 1024 characters. For better comparability, we also use T5 (Raffel et al., 2019) accordingly. This limitation is due to the increased computational complexity of longer input sequences, but it is problematic with table-to-text generation datasets. For example, SciGen (Moosavi et al., 2021) consists in large parts of tables that exceed this sequence length when represented as a linearized string. For this reason, it was not guaranteed that the model always sees the complete information, which certainly has a negative impact on the evaluation results achieved on the downstream tasks. We guess that the results would have been more expressive, if we would have used a different

https://huggingface.co/docs/transformers/model_doc/bart#transformers.BartConfig, last accessed on 10/05/22.
representation for tables, or focused on models that do not have this sequence length limitation.

Another limitation of our work is that the batch sizes used for reasoning-aware pretraining are not optimal for contrastive learning. Contrastive Learning works best with large batch sizes (Henderson et al., 2017), but due to computational limitations, it was only possible to use small batch sizes. Therefore, the model might have adapted better to the new number representation if we would had the possibility to train with larger batch sizes.

The next limitation is the way we use T5 in our experiments. The model was pretrained in a multi-task setup that also includes question answering, natural language inference and summarisation. In order to distinguish between these tasks, specific prefixes were used. As we do not address multi-task scenarios in this work, we did not reuse any of these prefixes for either reasoning-aware pretraining or finetuning. We assume that this is the main reason for the large differences between the results with BART and T5 across many experiments. Maybe the model would have performed better, and more comparable to BART, when we would have used these prefixes.

Evaluation is also a critical point. In table-to-text generation scenarios, generated descriptions usually suffer a high ratio of incorrect facts and hallucinations due to less profound numerical reasoning capabilities (Moosavi et al., 2021; Thawani et al., 2021; Chen et al., 2020a). Unfortunately, this is not captured by automatic metrics. Although metrics such as PARENT (Dhingra et al., 2019) try to measure the factual correctness of generated descriptions, it requires a more individual examination in many cases. Especially in such highly specialized scenarios such as SciGen. Therefore, we conduct a human evaluation in order to analyse the impact of our reasoning-aware pretraining on the downstream tasks. Due to limited resources, we were only able to conduct a small-scale human evaluation.

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A Evaluation Using Automatic Metrics

This section presents the evaluation of our results on table-to-text datasets using automatic metrics. For this, we use a variety of metrics commonly used for this task, i.e., BLEU (Papineni et al., 2002), MoverScore (Zhao et al., 2019), BLEURT (Sellam et al., 2020), and PARENT (Dhingra et al., 2019). While BLEU calculates the concordance between the predicted description and the actual target on word-level, MoverScore and BLEURT measure the semantic concordance between the predicted description and the target using BERT (Devlin et al., 2019). BLEURT also takes the fluency of the predictions into account. PARENT estimates the factual correctness by comparing the predicted description to the original table and the target description, and especially rewards correct information.
that is contained in the table but not in the target. It has a higher correlation with human judgement. Table 6 reports the results.

| Model    | BLEU | BLEURT | PARENT |
|----------|------|--------|--------|
| SciGen   |      |        |        |
| **Baseline** | 53.76 | 4.26  | -0.69  | 3.72 |
| **Medium**   | 53.43 | 4.87  | -0.70  | 3.68 |
| **Large**    | 53.40 | 2.71  | -0.78  | 3.45 |
| **Ours**     | 55.00 | 9.30  | -0.76  | 3.82 |
| BART       |      |        |        |
| **Baseline** | 52.30 | 2.96  | -0.94  | 6.39 |
| **Medium**   | 51.79 | 2.67  | -0.95  | 4.08 |
| **Large**    | 53.00 | 3.40  | -0.70  | 5.18 |
| **Ours**     | 52.00 | 2.51  | -0.86  | 4.70 |
| T5          |      |        |        |
| **Baseline** | 61.50 | 17.98 | -0.64  | 45.18 |
| **Ours**     | 62.78 | 18.54 | -0.27  | 44.32 |
| WikiBio    |      |        |        |
| **Baseline** | 60.30 | 17.94 | -0.86  | 43.97 |
| **Ours**     | 60.10 | 20.00 | -0.22  | 45.25 |

Table 6: Evaluation of our results on table-to-text datasets using automatic metrics. Baseline presents the result of the BART-large and T5-base models without reasoning-aware pretraining. Ours show the result of these models with reasoning-aware pretraining. Results of PARENT and MoverScore are highlighted. PARENT is the most appropriate metric for our approach.

Based on PARENT and MoverScore, our approach is slightly superior in six out of ten experiments. However, based on these results, it is not really possible to conclude an improvement that can be directly attributed to our reasoning-aware pretraining approach in most cases, as none of these metrics can really assess the correctness of a fact that might be reasoned from the source data (Moosavi et al., 2021; Chen et al., 2020b; Suadaa et al., 2021). However, PARENT tries to address this, which is why this metric is the most appropriate. Like BLEURT, MoverScore measures the semantic concordance between target and prediction. The advantage of MoverScore is that it is easier to interpret.

B Dataset and Task Configuration for the Inferable Number Prediction Task

As described in Section 3.2, it is prerequisite for the inferable number prediction task that numbers in descriptions are inferable from the context. Instead of filtering the data during training, we created suitable subsets of the datasets used in our experiments in an distantly supervised offline preprocessing step. Table 7 shows the distribution.

For SciGen (Moosavi et al., 2021) and WikiBio (Lebret et al., 2016), we reduce the descriptions to statements that contain numbers that are inferable by occurrence, ordering, summation, subtraction, multiplication or division from the table. Simultaneously, we reduce the tables to the values that are necessary for inference. The same heuristics are applied on DROP (Dua et al., 2019). For InfoTabs (Gupta et al., 2020), we just restrict the hypothesis to those that are labeled as entailed and contain numbers.

As the task in SciGen and WikiBio fundamentally differs from the task in InfoTabs and DROP, the input data slightly differs while the task remains the same. In all cases, the model is expected to predict the masked number.

Table 7: Split sizes of the semi-supervised created subsets of the datasets used for the inferable number prediction task.

| Dataset  | Train | Dev | Test |
|----------|-------|-----|------|
| SciGen   | 4,859 | 1,473 | 55 |
| WikiBio  | 412,053 | 51,424 | 51,677 |
| DROP     | 8,336 | 849 | 850 |
| InfoTabs | 16,538 | 1,800 | 1,800 |

C Inferable Number Prediction Task – Example Input Data

In this section, we want to give examples for input data used for each of the tasks that we use for experiments in our paper.

For table-to-text generation, Figure 2 shows an example of a (linearized) table from SciGen (Moosavi et al., 2021) with its caption (<CAP>), concatenated with its masked description C2 using <s>. <R> and <C> are special tokens used by BART (Lewis et al., 2020) to represent the beginning and ending of a sequence. In case of WikiBio (Lebret et al., 2016), the input data is represented accordingly.

Figure 2: Illustration of a linearized table that is used for the inferable number prediction task. <R>, <C> and <CAP> symbolize the beginning of a new row, cell, and the table’s caption.
For DROP (Dua et al., 2019), Figure 3 shows an example. It consists of the paragraph $C_1$, and a question $C_2$. The question contains a number (2) that also occurs in the paragraph.

![Figure 3: Illustration of an input sample for the inferable number prediction task using DROP.](image)

Figure 3: Illustration of an input sample for the inferable number prediction task using DROP.

Figure 4 shows an example for the InfoTabs (Gupta et al., 2020) datasets. It is basically the same as for the table-to-text generation datasets, but uses the hypothesis as $C_2$.

![Figure 4: Illustration of an input sample for the inferable number prediction task using InfoTabs.](image)

Figure 4: Illustration of an input sample for the inferable number prediction task using InfoTabs.

**D Experiments using other Contrastive Representations**

Regarding the contrastive representation, we also experiment with number representations other than the default subword-level one in order to incorporate the character-level tokenisation into a pre-trained model, i.e., exponent-mantissa (Zhang et al., 2020b), a verbalized representation, and a combination of the default subword-level tokenisation, exponent-mantissa and the verbalized representation (across multiple batches), using the inferable number prediction task. We focus on BART (Lewis et al., 2020) for this experiment. We conduct this experiment using the large split of the SciGen dataset (Moosavi et al., 2021). Table 8 shows the results.

None of the other representations improves the results over using the default subword-level tokenisation.

**E Hyperparameters for Experiments**

Table 9 shows the hyperparameter configuration for our experiments. In order to not train longer than necessary, we determined the optimal number of epochs for each experiment by using early stopping with a patience of 10. For the downstream tasks, we used the MoverScore (Zhao et al., 2019) with the table-to-text generation datasets. For DROP (Dua et al., 2019) and InfoTabs (Gupta et al., 2020), we used the EM score. All models were trained for the same amount of epochs.

![Table 9: Hyperparameter Configuration.](image)

**F Examples from the Human Evaluation**

Figure 5 shows two sample generations from our approach and the BART (Lewis et al., 2020) baseline from the SciGen (Moosavi et al., 2021) experiment using the medium split. Both read fluent and plausible.
Example 1

Observe that E2E and WebNLG Char. had similar overall performance in terms of content errors and overall correctness. As expected, the phrasal errors corrected by the parser do not affect the performance of the system, except for spelling errors, which are in line with the automatic evaluation results reported by WMT Workshop on SemEval 2017.

Our Approach

Baseline

In terms of linguistic errors, the overall correctness of the e2e system is higher than that of the WebNLG system. However, the content errors of the two systems are very different, with content errors ranging from 4.4% (WebNLG char. dropped) to 55.0% (E2E word). The linguistic errors of both systems are similar, with spelling mistakes and punctuation errors accounting for most of the linguistic errors.

Example 2

Embeddings show to be very similar to one another – removing the closest kernel leads to worse performance. We hypothesize that this is due to a mismatch between training and test data. Word2Vec embeddings have the highest cosine similarities.

Our Approach

Baseline

Word2Vec shows the cosine similarity between event entity pairs. KGE lists their closest kernel mean after training. We can see that Word2Vec embeddings have the highest cosine similarities to all event pairs after training, with the exception of two event pairs (“assault” and “kill”). We can also see that event pairs marked with “attack”, “assault”, or “scare” have similar cosine scores after training. However, after the model finishes training, their cosine score for “hate speech” is lower than for all other event pairs.

Figure 5: Generation from our approach and the BART-large baseline from the SciGen experiment using the medium split.