Continual-T0: Progressively Instructing 50+ Tasks to Language Models Without Forgetting

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Abstract

Recent work on large language models relies on the intuition that most natural language processing tasks can be described via natural language instructions. Language models trained on these instructions show strong zero-shot performance on several standard datasets. However, these models even though impressive still perform poorly on a wide range of tasks outside of their respective training and evaluation sets. To address this limitation, we argue that a model should be able to keep extending its knowledge and abilities, without forgetting previous skills. In spite of the limited success of Continual Learning we show that Language Models can be continual learners. We empirically investigate the reason for this success and conclude that Continual Learning emerges from self-supervision pre-training. Our resulting model Continual-T0 (CT0) is able to learn diverse new tasks, while still maintaining good performance on previous tasks, spanning remarkably through 70 datasets in total. Finally, we show that CT0 is able to combine instructions in ways it was never trained for, demonstrating some compositionality.

1 Introduction

Recent work on large language models have shown that large language models have the ability to perform zero-shot and few-shot learning reasonably well (Brown et al., 2020; Rae et al., 2021; Smith et al., 2022). A particularly successful line of work relies on the intuition that most natural language processing tasks can be described via natural language instructions. For example, a summarization task can be reformatted as a response to a natural language input as shown in Table 1. Sanh et al. (2022) and Wei et al. (2022) have released T0 and FLAN respectively and shown that fine-tuning models on a massive mixture of NLP datasets expressed via such natural language instructions (i.e., instruction tuning), improves the zero-shot performance of large language models. FLAN is extremely large in size (137B) and is not publicly available limiting its further use and reproducibility. Conversely T0 (Sanh et al., 2022) is publicly available and orders of magnitude smaller and hence we resort to working with T0.

Finally, however impressive, these models are still limited to simple instructions and mainly Natural Language Understanding (NLU) tasks. These models perform poorly on a wide range of tasks that differs from their respective evaluation sets. To improve their ability on new and diverse tasks, one needs to fine-tune these models again. However, one key problem associated with fine-tuning is catastrophic forgetting (French, 1999). So, how can we extend models knowledge and abilities, without suffering from catastrophic forgetting?

In this paper, we study Continual Learning of language models fine-tuned on natural language instructions and investigate their ability to adapt to diverse tasks, while avoiding catastrophic forgetting on the older tasks. For this purpose, we propose Continual-T0 (CT0), a T0 model that uses Continual Learning with rehearsal (Shin et al., 2017), i.e. using a memory buffer containing a small portion of previous data replayed during training. We start from T0, a model trained jointly...
on 50 datasets, resulting in a good zero-shot performance on 12 completely different datasets. We are then able to teach progressively 8 new diverse tasks, while maintaining almost 100% of the performance on all the previous datasets. This result is obtained by using only 1% of data for memory buffer. Notably, we also maintain the performance for the T0 zero-shot evaluation datasets, even though no rehearsal for those were possible, the first of its kind setup for CL.

Our final model, Continual-T0 (CT0) in addition to performing as well as T0 on all the different T0 datasets, can now also understand instructions about the several new tasks focused on language generation problems such as writing a haiku, generating empathetic responses in a dialogue, simplifying text, generating a headline with decoding constraints, generating natural language explanations for NLI tasks, adapting to stylometry on Twitter, or expand its knowledge on new elements e.g. the COVID.

We also conduct an extensive analysis and show that our newly learned instructions can be composed with other instructions in ways never seen during training, opening new potential for generalisation.

Given the surprising performance of a simple continual learning strategy, we empirically investigate the reason for this success. Why transformer models like T0 are continual learners? Is it because of their multi-task nature or the instruction tuning paradigm? Our experimental analysis show that the easy adaptability and continual learning capabilities actually emerge from pre-training and not the above.

2 Related Work

Instruction tuning There has been a range of work in the domain of instruction-tuning (Mishra et al., 2021b; Sanh et al., 2022; Wei et al., 2022; Mishra et al., 2021a; Ouyang et al., 2022) which differs in training and evaluation data, formatting of instructions, size of pre-trained models, and other experimental details. A consistent finding across these studies show how fine-tuning language models on a range of NLP tasks, with instructions, improves their downstream performance on held-out tasks, both in the zero-shot and few-shot settings. We place our focus on whether we can keep improving these models by teaching them new tasks without forgetting their existing capabilities. It should be noted, however, that several models in these studies are not open-sourced limiting their reproducibility. Hence we resort to T0 (Sanh et al., 2022) for our study.

Continual Learning Current fine-tuned language models are limited in continuously learning without forgetting any previously acquired knowledge and abilities. Research in this direction has investigated various strategies such as External Memory, Constraints and Model Plasticity (Parisi et al., 2019). External Memory methods often simply use rehearsal with a replay during training (Rebuffi et al., 2017). de Masson D’Autume et al. (2019) also proposed local fine-tuning at inference time, leveraging examples similar to the considered input.

Constraints-based methods aim at enforcing a similarity of either the activations (Li and Hoiem, 2017), the weights (Kirkpatrick et al., 2017) or the gradients (Lopez-Paz and Ranzato, 2017), to enforce a similarity of the model states trough the learning process. Other strategies have been proposed such as augmenting the plasticity by adding additional neurons to the model (Yoon et al., 2017). A complete summary of those methods with illustrations is also available.\footnote{\url{https://arthurdouillard.com/post/incremental-learning/}}

Through the lens of NLP tasks, Biesialska et al. (2020) look at the problem of Continual Learning and discuss major challenges involved. Jin et al. (2021) show Continual Learning algorithms are effective for knowledge preservation. Their study also infer that continual pretraining improves temporal generalization. (Douillard et al., 2021) proposed a a dynamic expansion of special tokens with a transformer architecture. Mi et al. (2020) and Madotto et al. (2021) perform Continual Learning for task oriented dialog systems by using replay based strategy. Cao et al. (2021) propose a new Continual Learning framework for NMT models, while Ke et al. (2021) proposes a novel capsule network based model called B-CL (Bert based Continual Learning) for sentiment classification tasks. Jin et al. (2020) show how existing Continual Learning algorithms fail at learning compositional phrases. More recently Sun et al. (2019) propose a lifelong learning method LAMOL that is capable of continually learning new tasks by replaying pseudo-samples of previous tasks that require no extra memory or model
capacity. To the best of our knowledge, LAMOL corresponds to the state-of-the-art for CL in NLP.

Most of the aforementioned works fall into the 2 scenarios differentiated by Lomonaco and Maltoni (2017): 1) learning new data of known classes (online learning), and 2) learning new classes (class-incremental learning). Thus, the study are often limited to a narrow domain, or a specific task. In our work, we propose to address Continual Learning more broadly: learning a diverse set of new tasks different from the ones used for training. For this, we leverage the idea of instruction tuning (Wei et al., 2022; Sanh et al., 2022), that enables us to frame any NLP task as a response to a natural language input and use rehearsal as a mechanism to avoid catastrophic forgetting (Shin et al., 2017).

3 Continual Learning for Fine-tuned Language Models

3.1 Continual Learning via Rehearsal (CLR)

Our objective is to maintain the model’s existing learned skills, while progressively learning more tasks. To prevent the model from catastrophic forgetting, we rely on an external memory module, storing a subset of previous data (Shin et al., 2017). We define the sequence of tasks to be solved as a task sequence $T = (T_1, T_2,..., T_N)$ of $N$ tasks. $D_i$ is the corresponding dataset for task $T_i$. Formally, the training data augmented with rehearsal $D^r_i$ is defined as:

$$D^r_i = D_i \bigcup \sum_{j=1}^{i-1} (rD_j)$$

where $r$ is the rehearsal hyper-parameter that controls the percentage of examples sampled from previous tasks $T_1,...,T_{i-1}$. We note that $r = 0$ corresponds to no memory, and $r = 1$ is equivalent to a multi-task setup using all the previous examples.

3.2 Continual-T0 (CT0)

For all our experiments, we instantiate our model with the T0 model (Sanh et al., 2022) weights. T0 is trained in a multi-task setting on a collection of 50 datasets spanning across Multiple Choice QA, Extractive QA, Closed Book QA, Sentiment Classification, Topic Classification, Structure to Text Generation, Summarization and Paraphrase Identification.

3.3 Tasks

In this section, we describe all the tasks $T$ used to progressively train and evaluate our model. For all the new tasks (i.e., not the T0 tasks), we also designed instructions, as illustrated in Table 2.

3.3.1 T0 Tasks

Training Tasks: As detailed in Section 3.2, we instantiate our model with T0 weights. T0 is trained in a multi-task setting on a collection of 50 datasets spanning across Multiple Choice QA, Extractive QA, Closed Book QA, Sentiment Classification, Topic Classification, Structure to Text Generation, Summarization and Paraphrase Identification.

Evaluation Tasks: To test zero-shot generalization, Sanh et al. (2022) hold out all constituent datasets of four tasks: Natural language inference (NLI), Co-reference resolution, Sentence completion, and Word sense disambiguation. Among Natural Language Inference tasks they evaluate models on the Adversarial NLI (ANLI) (Nie et al., 2020), Commitment Bank (CB) (de Marneffe et al., 2019) and Recognizing Textual Entailment (RTE) (Dagan et al., 2005) benchmarks. For Co-reference resolution they use the data from Winogrande Schema Challenge (WSC) (Levesque et al., 2012) and the Adversarial Winogrande (Sakaguchi et al., 2020) benchmarks, for Word sense disambiguation the Words in Context (WIC) (Pilehvar and Camacho-Collados, 2019), while for Sentence completion the Choice Of Plausible Alternatives (COA) (Gordon et al., 2012), HelloSwag (Zellers et al., 2019) and StoryCloze (Mostafazadeh et al., 2016) benchmarks.

The only new hyper-parameter introduced in our paper is the rehearsal proportion $r$. We explored $r \in [0, 0.25, 1\%]$ as reported in our first set of results (see Section 3).

For each task, we consider 100,000 examples for training, such that 1% rehearsal corresponds to 1,000 examples from the memory buffer. Thus, for datasets with fewer training examples, we upsample them and conversely for largest datasets like Gigaword or Simplification, we limit to 100,000 examples.

See more details at https://huggingface.co/bigscience/T0pp
### 3.3.2 New Tasks

All of our newly introduced tasks are language generation tasks in contrast to the T0 evaluation tasks and majority of the T0 training tasks (all except summarization).

**Text Simplification (Simpl)**  
Jiang et al. (2020) provided WikiAuto, a set of 400,000 aligned sentences from English Wikipedia and Simple English Wikipedia as a resource to train sentence simplification systems. The test set contains 4,000 examples. In addition, we also evaluate our models on a second Text Simplification dataset, ASSET (Alva-Manchego et al., 2020). This is a dataset dedicated for the evaluation of sentence simplification in English, providing 2,000 multiple references per example, unlike previous simplification datasets. Table 2 shows our designed instructions for this task.

**Headline Generation with Constraint (HGen)**.  
While writing a title for a news article, it can be very useful to add additional constraints, such as the presence of certain words. However, traditional decoding strategies like the BeamSearch often fail to achieve this goal as discussed in 5. Gigaword is one of T0 training dataset. Our new task consists of generating a title given a news article with additional constraints. Towards this goal, for a given document D and an input keyword X we design the following three instructions: [Make a title for this article, starting with / ending with / that contains “X” : D where X is a word we want to be present in the output text at the begin-
ning/end/anywhere, and D the source document, as illustrated in Table 2. To create the training data, we simply leverage the gold-reference to select the word X, such that our model is trained with consistent and plausible instructions. Gigaword contains millions of training examples. The original test set is composed of 1,951 examples, so we convert it to 3 sets of 1,951 examples for our Start/End/Contain instructions, respectively.

Haiku Generation (Haiku). For the task of haiku generation, we crawl 10,718 haikus with at least 1 up-vote from the Subreddit haiku, and split it in 9,742 and 974 example for the train and test sets, respectively. Table 2 shows an example instruction for Haiku Generation about a given topic.

Covid QA (CQA) Möller et al. (2020) created COVID-QA, a Question Answering dataset consisting of 2,019 question/answer pairs annotated by volunteer biomedical experts on scientific articles related to COVID-19. We consider this dataset since to the best of our knowledge, T0 has never been exposed to any COVID-19 related data. In its original version, the dataset is framed as SQuAD (Rajpurkar et al., 2016), with triplets (context, question, answer), where the context contains the answer. Because T0 has been extensively trained on QA dataset, CovidQA in its original format simply requires domain transfer. To make the task more challenging, we propose to provide only the question as an input, now framing the task as “learn the answer by heart” in an encyclopedia style task. This way the task framing can be seen as a new strategy to incorporating knowledge and preventing the model from concept drift.

Inquisitive Question Generation (InqQG) To foster long form question answering Fan et al. (2019) created the ELI5 dataset that comprises 270,000 English-language threads from the Reddit forum of the same name, where an online community provides answers to several open ended inquisitive questions. Table 2 shows an example instruction in order to generate inquisitive questions. As opposed to standard Question Generation based on SQuAD, ELI5 enables open-ended questions, closer to human-style questions (Scialom and Staiano, 2020). We filtered out the Reddit threads to keep only well formed questions, resulting in 61,710 and 1,681 examples for the training and test set, respectively.

Empathetic Dialogue Generation (EmDg) Rashkin et al. (2019) proposed a benchmark for empathetic dialogue generation by creating a dataset of conversations grounded in emotional situations. Each example in the dataset contains an input emotion, situation in which dialogue appears and the entire conversation. We display in Table 2 the corresponding instruction. At the example level, our training and test datasets contain 58,770 and 8,396 examples, respectively.

Explanation Generation (Exp). The Stanford Natural Language Inference dataset consists of a classification task, where given a Premise(P) and an Hypothesis(H), the model has to choose between 3 options: entailed, contradiction or not related. Camburu et al. (2018) extend this NLI dataset by annotating the explanations of the label in natural language. In our paper, we consider as input the Premise(P), the Hypothesis(H), and the label, and train our model to generate the explanation. The dataset is composed of 100,000 and 9,824 train and test examples, respectively.

Twitter Stylometry (TwSt) Tareaf (2017) extracted tweets from the top 20 most followed users in Twitter social platform, including singers such as Katy Perry or Selena Gomez, as well as the official account of Barack Obama when he was president of the USA. The style for tweets largely differs from one account to another, e.g. @BarackObama: “It’s time to #ActOnClimate” vs. @KimKardashian: “makes me want to go back blonde but i’m scared it will ruin my hair :-(”. We define the Stylometry task as generating a relevant tweet given i) a hashtag, and ii) the tweet’s author. We thus selected only tweets containing hashtags (#) from the original dataset, resulting in a total of 13,041 and 250 examples for train and test sets, respectively. We display at the bottom of Table 2 an example instruction for this task.

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3The crawling part was done by Tuhin Chakrabarty and at Columbia.
4https://www.reddit.com/r/haiku/
5https://www.reddit.com/r/ExplainLikeImfive/
6I.e, starting in “W” or “H” and finishing with a question mark. See the code for the exact implementation, class ELI5promptFormat in data_handler.py.
3.4 Automatic Metrics

T0 zero-shot evaluation set (see Section 3.3) only contains tasks framed as classification. For T0 evaluation, Sanh et al. (2022) compute the log-likelihood of each of the target options, and the option with the highest log-likelihood is selected as the prediction. This strategy holds when restricting the evaluation to classification tasks. However, in the context of an open-ended model able to perform NLG tasks, a user is interested in the actual output of the model rather than probabilities. We therefore report the accuracy of the prediction compared to the ground-truth answer for all those tasks. This measure is more conservative, as it requires an exact match.

In the context of Continual Learning, we also suspect that using only a comparison of the log-likelihood of respective classes would not reflect the actual model’s memory, since the decoders are known to suffer from catastrophic forgetting more than the encoders (Riabi et al., 2021).

Standard NLG Metrics. For the standard tasks, we rely on widely used metrics: ROUGE (Lin, 2004) for Summarization; BLEU (Papineni et al., 2002) and SARI (Xu et al., 2016) for Simplification. In this paper, we also include open-domain NLG tasks, such as Dialogue or Explanation generation. The space of possible correct outputs is too large in this case to rely on n-gram based metrics like BLEU or ROUGE. For this reason, we report BERTScore (Zhang et al., 2020) to measure the similarity between a prediction and its gold-reference in those tasks.

When possible, we also designed customized metrics that are better suited for the task.

Customized NLG Metrics.

• Constraint: For our prompts with constraint, such as “Write a text that starts/contains/ends with [some word]”, we also report the accuracy of respecting the constraint. Concretely, an output is correct only if it contains the [word] at the right location: the beginning for start, the end for end; any location for contain.

• First Word Distribution (1Tok). In ELI5, the questions are supposed to be inquisitive, not factual like in SQuAD. Therefore, the distribution of the first words is very informative. For instance, the percentage of questions starting with “why/how” is more important than “what”. We therefore rely on the Jensen Shannon Divergence between the first words distributions of the ground-truth examples and our predictions. We report its inverse, so the higher the better.

• Author Classification (Clf) In Twitter Styometry, the author is part of the input, so the generated tweet is aligned with the author’s style. To measure this condition, we train a classifier on the dataset, with the tweets as inputs, and the corresponding author names as target categories. We trained a Ridge Classifier using scikit-learn (Pedregosa et al., 2011), and obtained 0.81% accuracy. This high accuracy allows this Clf metric to be informative enough.

• $H_{c}\text{ust}$ Haiku is a type of short form poetry originally from Japan as illustrated in the Table 2. In general, it contains only 17 syllables, broken up into three lines. We calculate two differences between the prediction and the ground-truth: i) for the number of lines, and ii) for the number of syllables. $H_{c}\text{ust}$ corresponds to the average of these two differences, BLEU and the Constraint satisfiability (i.e., if the generated haiku contains the topic phrase X that was present in the instruction).

4 Results

To measure actual success for CL, we introduce the notion of Upper Bound (UB). UB corresponds to the maximum performance achieved by the model, when fine-tuned only on a specific task. Arguably, the model succeeds in CL, if it maintains a performance close to UB while learning new tasks. The normalised results i.e Relative Gain for a given task $T_i$ correspond to the actual scores $s$ divided by their task $T_i$ Upper Bound, $s_{T_i}/UB_{T_i}$. Hence, 1 corresponds to performing similar to the UB for any task, and results below 1 will indicate task forgetting.

4.1 Learning Only a New Task

First, we test Continual Learning via rehearsal independently on three tasks, by varying the rehearsal hyper-parameter between 0%, 0.25% and 1%, respectively. We report these results in terms of Relative Gain in Figure 1. The results are normalised w.r.t. the Upper Bound achieved by T0 so that 1 corresponds to this UB for any task, and
4.2 Learning a Sequence of New Tasks

As observed from our previous experiments using Continual Learning via rehearsal we can learn a new task without catastrophic forgetting, with just a very little rehearsal percentage. As a next step, we propose to measure if language models can progressively learn more and more tasks, without catastrophic forgetting. This is an important direction as it would allow the models to continually increase their knowledge and capabilities without forgetting the knowledge already acquired.

To test this hypothesis, we start from T0 checkpoint, a model trained on 50 datasets and we progressively train it on a sequence of 8 new language generation tasks (see Section 3.3.2 and Table 2 for description of those tasks) using Continual Learning via rehearsal ($r = 1\%$). We call our final model CT0.

In Figure 2 we display the progressive sequential learning on the 8 new tasks. We learn a new task, starting from T0, and add to our rehearsal buffer 1% of the data of the learned task. We observe an improvement progressively for each task, that is our model keeps learning new tasks. At the same time, the performance is preserved for the other tasks, indicating the success of our CLR method in a sequential learning setup through more than 1000 gradient steps over 8 different tasks.

In Table 3, we report the results on all the 8 new tasks as well as T0tr and T0zs (see Section 3.3.1), corresponding respectively to the evaluation sets of the 50 training datasets used in T0, and the 12 datasets kept apart for the zero-shot evaluation. Note that again, while we used rehearsal for the training data of T0tr tasks, we never used any data from T0zs, so it remains completely zero-shot. It is important to highlight that rehearsal is the standard for CL, and a zero-shot setup with no rehearsal has never been explored yet to the best of our knowledge.

In the first bloc of Table 3 we observe the starting performance of our two initial checkpoints, T0_3B and T0pp(11B). The second bloc corresponds to their respective Upper Bounds. We report the results for our models after training them progressively on the 8 new tasks, as well as the baseline LAMOL (see Section 2; for fair comparison we able to maintain its performance on those tasks, while learning a new task.
adapted LAMOL initialising it with T03B, additional details can be found in Appendix).

Our two CT0 models obtain final results very close to their UB, maintain 99.8\% for T0pp and 98.0\% for T0_3B. This clearly indicates the efficiency of the CLR method. Notably, no task suffers a decrease in performance more than 2\% for T0pp. Table 3 shows how the CT0 model remembers and retains knowledge from tasks trained at very early stages of the Continual Learning process. Moreover, CT0 still performs well on the zero-shot set of tasks (T0zs) despite no rehearsal for those.

It should also be noted that the T0pp model fails to generalize for most NLG tasks, while our CT0 model shows very strong performance. For instance Table 4 shows it can generate a haiku that has a perfect syllable count of 17 given an unseen topic of ‘mountain winds haunt’. It can also generate reasonable natural language explanations that often comply with our commonsense. Moreover, CT0 obtains a new state-of-the-art on the ASSET evaluation set, improving over MUSS (Martin et al., 2020): 85.9 BLEU4 Vs 72.98 and 46.6 SARI Vs 44.15, and despite not using all the training data available.

In contrast to Continual Learning with rehearsal, LAMOL clearly diverges from its UB (T03B) indicating catastrophic forgetting. While LAMOL was known to perform well mostly on NLU tasks, we hypothesise that the generative nature for our tasks is not suited for the method. Finally, Continual Learning with rehearsal approach is task order invariant as demonstrated by revfinal results: revfinal corresponds to CT03B trained on the 8 tasks within in the reverse order. We give more details about the order choice in the Appendix.

5 Discussion

5.1 Why could LLMs be lifelong learners?

Given our current experimental protocol, one can draw different hypotheses: is CL a consequence emerging from the massive multi-task pre-training in T0 or from the instruction tuning paradigm of T0 or from the large number of parameters. To answer this research question, we applied the same CL setup starting from 1) T5, and 2) T5 architecture randomly initialised. Our results show that CT5 performs similar than CT0 on the 8 tasks. Conversely, when initialised randomly the model is not even able to obtain a good UB. These results draw a clear conclusions: CL emerges from

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9We report task order invariance results only using 3B and not 11B due to computing restrictions
Table 3: Results for the starting checkpoints T0_3B and T0pp(11B), their upper bounds scores and our final models as well as LAMOL. T0tr and T0zs denote respectively for T0 train-tasks and T0 zero-shot-tasks and are the average accuracy obtained on all their evaluation datasets. B4, R1, BS denote BLEU4, ROUGE-1 and BERTScore. Note that we detail the intermediate steps results in the Appendix.

5.2 Scaling Laws - Continual Learning

Brown et al. (2020) shows that zero and few-shot capabilities of language models substantially improve for larger models, a result confirmed in (Wei et al., 2022), and (Sanh et al., 2022) where the 11B parameters model largely outperforms the 3B (65.6% vs. 48.2% on T0zs). As expected, our results for CT0-11B are better than CTO-3B. We also analyze a potential effect of scaling laws on Continual Learning. When comparing the 3B and 11B results of CT0, we observe less forgetting on the 11B version. This result may again indicate the effectiveness of larger models.

5.3 Toward Concept Drift

In the original CovidQA the task consists of answering a question present in a given paragraph. In this setup, one can arguably succeed into answering questions about COVID by transferring the task knowledge, even without particular domain knowledge about COVID. In our paper, we intentionally chose to not provide the context for CQA but only the question. This alternative setup corresponds to learning by heart the answer to a question. Our results in Table 3 show that while we framed CQA as a new task to learn, our proposed setup also opens new way to tackle concept drift, by directly incorporating knowledge into a model.
5.4 Zero-shot Instruction Combinations

Our CT0 model has learned effectively to process different instructions in specific contexts: word level constraint in the context of headline generation, or an emotional tone in the context of dialogue. Does CT0 understand these instructions in different contexts? To answer this question, and explore whether CT0 can learn the compositionality of the instructions, we conduct several experiments.

In Table 5 we explore how our model succeeds in understanding constraint instructions beyond the one it was exposed during training. Our model was trained on Headline Generation with Constraint (HGen) instructions with only one match, such as Make a title for this article containing “X”. In our current experiment to test generalization, we prompt our CT0 model with unseen instructions with 2 and 3 matches, such as Make a title for this article containing “X” and “Y”, or Make a title for this article containing “X” and “Y” and “Z”. We also compose instructions from constraint and Twitter Stylometry resulting in instructions such as Write a tweet about X, in the style of Y, containing Z.

**Zero-Shot Constraint.** CT0 respects the Contain constraint 77% for n = 1. The score naturally drops when n > 1, however the satisfiability is still 50% of the time for n = 2 and 40% for n = 3. As expected, the ROUGE-1 score also improves: No-Cons: 30.2, #Cons=1: 38.9, #Cons=2: 43.9 and #Cons=3: 47.4. When we compose HGen and TwSt, CT0 also performs significantly better compared to $CT0_{NoCons}$ (46.4 Vs 10.7). These results demonstrate CT0’s ability to comprehend instructions as well as to satisfy compositionality.

| # Cons | HGen | TwSt |
|--------|------|------|
| CT0    | 77.0 | 56.4 |
| $CT0_{NoCons}$ | 33.6 | 15.4 |

Table 5: Table showing Constraint generalisation i.e % of instructions completely respected, when providing constraints for unseen prompts. $CT0_{NoCons}$ corresponds to providing the same input without constrain.

**Zero-Shot Emotional Haiku.** We explore whether combining an emotion with the Haiku instructions would help control the haiku generation. Note that during training, only the task of Empathetic Dialogue has been exposed to emotion. Our results, reported in Figure 3, indicate that CT0 is able to combine an emotion with the Haiku instructions in a zero-shot setting. For instance, given the following input Generate a haiku about “held my hand”. The associated emotion is “faithful”. Our model output is “He held my hand through thick and thin, Through sickness and health, through life and death”. A qualitative analysis also shows that CT0 understands subtle nuances; for instance given as input Generate a haiku about “Seagulls crying high”. The associated emotion is “nostalgic”. Our model output is “Seagulls crying high, A familiar scene, from a childhood Now”.

5.5 Data Efficiency

Our method based on rehearsal learning is simple yet efficient. While the complexity in term of data storage and training is not constant (O(1)), with only 1% of the previous training data we are able to retain model abilities. This result is still data and computationally efficient, compared to the standard approach of retraining the model from scratch on all tasks. In cases where the number of tasks to learn would grow by several order of magnitude, more sophisticated methods could be explored. We leave this for future research.

6 Conclusion

We explored for the first time Continual Learning for instruction-based models. Our results indicate that pre-trained Language Models are effi-
cient continual learners: 1% rehearsal is enough to maintain a high performance on previously learned tasks, while learning new ones. Additionally, we show that our model CT0 is able to comprehend the compositionality of the instructions, and understand new combinations. The current technique to learn multiple tasks is to train a model from scratch. We hope this work paves the way toward a new paradigm where models do not have to be retrained all over again. We believe our experimental findings will contribute to the effectiveness of large language models, enabling them to progressively adapt to new concepts and acquire more and more abilities. As an analogy with Software Development, this could be seen as learning new features. New checkpoints are like new versions of a model. In this context, Continual Learning will help toward the Call to Build Models Like We Build Open-Source Software.\textsuperscript{12}

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A Tasks Order

The task order has been selected 1) randomly among the three first tasks, and 2) in light of the actual success, we progressively kept adding new tasks. This setup corresponds to a realistic usage of our proposed method, where future tasks were thus unknown even for us. To assess a potential impact of the order, we also conduct an alternative experiment with our 3B model, where the order is reversed. We did not experimented further different orders due to the high computation required.

B Additional Results

C Evaluation for T0 Train Set

Because there are 50 datasets with thousands of examples in the test sets per task, evaluating on each examples would be computationally intensive. For this reason we restricted this set to 1000 examples randomly sampled from all the examples in the test sets. Because the set contains both NLG and NLU tasks, using the accuracy is not enough. For simplicity we used therefore ROUGE-1 which allows is consistent with accuracy for NLU tasks but also allows to take into account NLG evaluation.

D Additional Results

In Table 6 we report the additional results when starting from T5 and a random transformer. These results are discussed in the first section of our Discussion.

In Table 7 we report the progressive results, and not just the initial checkpoint, the Upper Bound and the final model.

E Implementation Details

For all our experiments with T0_3B and T0pp, we instantiate our model with the T0 model (Sanh et al., 2022) using the official implementation.\(^\text{13}\)

For fine-tuning T0_3B, we used the same hyper-parameters as the ones reported in Sanh et al. (2022): all the details from the batch-size to the learning rate are provided in details here.\(^\text{14}\)

The only new hyper-parameter introduced in our paper is the rehearsal proportion \(r\). We explored \(r \in [0, 0.25\%, 1\%]\) as reported in our first set of results.

For each task, we consider 100,000 examples for training, such that 1% rehearsal corresponds to 1,000 examples from the memory buffer. Thus, for datasets with fewer training examples, we upsample them and conversely for largest datasets like Gigaword or Simplification, we limit to 100,000 examples.

When we scaled our best setup to the 11B parameters version of T0, T0pp, we observed instability in validation performance. Thus, we changed the learning rate from 1e-3 to 1e-4 as well as the optimizer to AdamW instead of Adafactor for all our 11B experiments. All the other hyper-parameters remain similar to the 3B model.

For the T5 ablations, we again used the Hugging Face implementations\(^\text{15}\) and applied the same hyper-parameters as above.

At inference time, we use greedy decoding, i.e. a Beam Search with \(K = 1\).

\(^{13}\)https://huggingface.co/bigscience/T0pp

\(^{14}\)https://huggingface.co/bigscience/T0pp

\(^{15}\)https://huggingface.co/t5-3b
## Table 6: Results including T5 ablations, for the starting checkpoints T0_3B and T0pp, their upper bounds scores and our final models as well as LAMOL. T0tr and T0zs denote respectively for T0 train-tasks and T0 zero-shot-tasks and are the average accuracy obtained on all their evaluation datasets. B4, R1, BS denote BLEU-4, ROUGE-1 and BERTScore. Note that we detail the intermediate steps results in the Appendix.

|           | T0tr | T0zs | ASSET | Simp | HGen | Haiku | CQA | InqQG | EmDg | Exp | TwSt | Clf/BS |
|-----------|------|------|-------|------|------|-------|-----|-------|------|-----|------|--------|
| UB_rand   | N/A  | N/A  | 0.5/24.3 | 0.0/29.6 | 1.5/0.1 | 9.6   | 25.2 | 1.2/25.4 | 36.3 | 33.1 | 24.7  |
| UB_T5     | N/A  | N/A  | 87.0/45.6 | 15.4/43.7 | 33.0/89.4 | 63.0  | 89.9 | 2.9/61.5 | 55.3 | 71.6 | 75.6/55.4 |
| UB_T0     | 49.8 | 48.2 | 79.9/45.2 | 13.8/44.6 | 39.7/81.0 | 62.6  | 90.0 | 5.3/63.3 | 55.7 | 71.8 | 74.8/56.5 |
| CTrand    | N/A  | N/A  | 0.0/22.9 | 0.0/28.5 | 0.2/0.0 | 9.6   | 25.2 | 1.2/27.9 | 28.1 | 30.7 | 24.7  |
| CT53B     | N/A  | N/A  | 84.6/45.8 | 14.8/44.0 | 38.3/0.8 | 62.3  | 85.8 | 4.6/62.1 | 55.5 | 73.1 | 75.6/55.4 |
| CT03B     | 47.9 | 46.6 | 78.0/44.5 | 14.6/43.7 | 37.3/77.5 | 60.4  | 86.8 | 5.2/61.9 | 55.3 | 72.4 | 74.8/56.5 |

## Table 7: Progressive results for T0 3B and 11B results for continual training set up with best 3B results underlined & best 11B results bolded. T0zs denotes T0 zero-shot and is the average accuracy obtained on 12 eval datasets. B4, R1, BS denote BLEU-4, ROUGE-1 and BERTScore.

|           | T0zs | ASSET | Simp | HGen | Haiku | CQA | InqQG | EmDg | Exp | TwSt | Clf/BS |
|-----------|------|-------|------|------|-------|-----|-------|------|-----|------|--------|
| T0_3B     | 48.2 | 70.1/41.0 | 12.8/41.1 | 33.6/32.2 | 34.2   | 47.6  | 2.1/58.7 | 48.6 | 32.7 | 54.4/38.0 |
| T0pp (11B) | 65.6 | 56.5/37.7 | 11.7/40.1 | 34.9/35.9 | 31.6   | 46.0  | 2.4/59.8 | 49.7 | 37.2 | 66.4/45.1 |
| +Simp 3B  | 48.9 | 79.9/45.2 | 13.8/44.6 | 30.3/31.0 | 30.9   | 43.9  | 2.0/56.1 | 40.2 | 34.9 | 50.8/42.5 |
| +Simp 11B | 66.7 | 85.3/46.1 | 15.0/44.8 | 34.9/36.1 | 33.0   | 47.2  | 2.1/59.0 | 48.1 | 39.2 | 68.8/47.6 |
| +HGen 3B  | 46.9 | 81.4/44.9 | 14.1/43.9 | 39.7/81.0 | 33.7   | 44.2  | 2.5/55.9 | 45.9 | 55.2 | 19.6/37.3 |
| +HGen 11B | 65.5 | 84.5/46.1 | 15.3/44.8 | 41.9/86.9 | 35.9   | 46.6  | 2.9/59.7 | 48.9 | 36.4 | 69.6/48.1 |
| +Haiku 3B | 48.8 | 81.6/45.0 | 14.6/43.9 | 39.0/78.2 | 62.6   | 43.0  | 2.3/54.9 | 47.2 | 39.0 | 65.6/44.5 |
| +Haiku 11B | 64.6 | 83.5/46.1 | 14.9/45.1 | 41.1/83.0 | 63.9   | 46.0  | 2.9/59.9 | 48.9 | 37.5 | 66.4/46.2 |
| +CQA 3B   | 48.5 | 79.7/44.4 | 14.0/43.8 | 37.6/75.4 | 62.2   | 90.0  | 2.0/54.4 | 42.5 | 38.7 | 66.4/45.3 |
| +CQA 11B  | 64.6 | 84.3/46.1 | 14.5/44.9 | 40.9/83.7 | 63.6   | 90.0  | 2.9/59.2 | 48.5 | 42.7 | 67.2/47.3 |
| +InqQG 3B | 47.4 | 65.2/41.2 | 14.6/43.8 | 37.9/77.7 | 60.4   | 89.6  | 5.3/63.3 | 46.8 | 34.2 | 59.2/45.4 |
| +InqQG 11B | 65.5 | 85.5/46.3 | 14.9/44.8 | 40.6/81.7 | 64.5   | 89.9  | 4.9/65.7 | 49.2 | 47.7 | 61.2/45.9 |
| +EmDg 3B  | 48.6 | 73.9/43.8 | 15.0/43.7 | 38.0/77.7 | 62.9   | 88.6  | 4.7/62.7 | 55.7 | 35.2 | 53.6/42.7 |
| +EmDg 11B | 66.4 | 85.3/46.3 | 15.1/44.7 | 40.9/84.1 | 65.0   | 89.9  | 5.3/65.5 | 56.6 | 37.0 | 61.6/45.8 |
| +Exp 3B   | 47.4 | 74.6/44.0 | 14.2/43.5 | 37.9/80.9 | 60.9   | 86.5  | 4.9/62.3 | 55.2 | 71.8 | 54.8/43.4 |
| +Exp 11B  | 65.0 | 85.6/46.5 | 14.9/44.7 | 40.7/84.6 | 64.5   | 89.8  | 4.8/65.5 | 56.5 | 73.5 | 63.6/46.3 |
| +TwSt 3B  | 46.6 | 78.0/44.5 | 14.6/43.7 | 37.3/77.5 | 60.4   | 86.8  | 5.2/61.9 | 55.3 | 72.4 | 74.8/56.5 |
| +TwSt 11B | 64.4 | **85.9/46.6** | 14.6/44.7 | 40.7/85.5 | **65.8** | 89.8  | 4.8/65.2 | 56.2 | 73.0 | **74.4/57.9** |

| rev_final | 48.8 | 83.3/45.4 | 14.6/43.9 | 39.0/81.6 | 61.2   | 88.6  | 4.4/61.9 | 55.0 | 72.4 | 73.2/57.3 |

Table 7: Progressive results for T0 3B and 11B results for continual training set up with best 3B results underlined & best 11B results bolded. T0zs denotes T0 zero-shot and is the average accuracy obtained on 12 eval datasets. B4, R1, BS denote BLEU-4, ROUGE-1 and BERTScore.