LARGE LANGUAGE MODELS SUFFER FROM THEIR OWN OUTPUT: AN ANALYSIS OF THE SELF-CONSUMING TRAINING LOOP

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ABSTRACT

Large Language Models (LLM) are already widely used to generate content for a variety of online platforms. As we are not able to safely distinguish LLM-generated content from human-produced content, LLM-generated content is used to train the next generation of LLMs, giving rise to a self-consuming training loop. From the image generation domain we know that such a self-consuming training loop reduces both quality and diversity of images finally ending in a model collapse. However, it is unclear whether this alarming effect can also be observed for LLMs. Therefore, we present the first study investigating the self-consuming training loop for LLMs. Further, we propose a novel method based on logic expressions that allows us to unambiguously verify the correctness of LLM-generated content, which is difficult for natural language text. We find that the self-consuming training loop produces correct outputs, however, the output declines in its diversity depending on the proportion of the used generated data. Fresh data can slow down this decline, but not stop it. Further, we observe similar results on a real natural language dataset. Given these concerning results, we encourage researchers to study methods to negate this process.

1 INTRODUCTION

Transformer-based language models have received much attention in the machine learning community in recent years. Especially large language models (LLM) trained on massive amounts of data from the internet became state of the art in many benchmarks (Brown et al., 2020) and specialized conversational LLM applications like ChatGPT[1] have a massive influence on society already. LLMs can be used for multiple tasks ranging from code generation (Chen et al., 2021; Sobania et al., 2022; Fan et al., 2023) and automated program repair (Sobania et al., 2023) to text summarization (Yang et al., 2023) and teaching assistance (Baidoo-Anu & Ansah, 2023).

Due to their convincing generated outputs, LLMs can be used to generate a large amount of content that is posted online to coding platforms like GitHub and Stackoverflow[2], social media platforms like Reddit[3] and other platforms on the internet. Even academic writing is already being influenced by LLM outputs (Geng & Trotta, 2024; Liang et al., 2024). Such LLM-generated text is often hard to distinguish from human-generated content (Sadasivan et al., 2023) and in turn might unwillingly be used to train the next generation of LLMs. Even paying for human-generated content might not be an option in the future, as workers at paid services like Amazon's Mechanical Turk also use LLMs to produce content (Veselovsky et al., 2023). Consequently, a self-consuming training loop emerges in which future models are trained repeatedly on LLM-generated data from previous generations. This process was first observed for generative models in the image domain (Martínez et al., 2023; Alemohammad et al., 2023; Shumailov et al., 2024; Bertrand et al., 2023). These studies found that this self-consuming training loop leads to a decline in quality and diversity of generated images, ultimately resulting in a so called model collapse. This was also observed for repeatably fine-tuning LLMs leading to a decrease in diversity (Guo et al., 2023; Shumailov et al., 2024). However, it

[1] https://openai.com/blog/chatgpt

[2] https://www.microsoft.com/en-us/Investor/events/FY-2023/Morgan-Stanley-TMT-Conference

[3] https://www.vice.com/en/article/jg5qy8/reddit-moderators-brace-for-a-chatgpt-spam-apocalypse

is unclear what happens with LLMs that are trained in such a self-consuming training loop from scratch, as usually done in real-world applications like ChatGPT.

Therefore, we present the first study analyzing the behavior of LLMs trained over many generations in a self-consuming training loop. We conduct experiments on a GPT-style model in different settings and measure both quality and diversity of samples from the trained model at each generation in the self-consuming training loop. The settings differ in the way a dataset is created for each generation (so called data cycles) as well as the proportion of original *real* and LLM-generated *synthetic* data samples. To better analyze the behavior of the trained models we conduct our experiments on a dataset consisting of logic expressions. In contrast to natural language, this logic expressions can be evaluated unambiguously. This allows us to analytically and accurately measure correctness and diversity of the generated samples. Furthermore, to confirm the generalizability of our results we conduct additional experiments on a natural language dataset.

We find that repeatedly training new models with synthetic data from previous models initially improves quality. However, diversity degenerates and the learned distribution inevitably collapses to a single point. In extreme cases this happens already after less than 10 generations. Additionally, we find that the speed at which diversity degenerates depends on the data cycle as well as on the proportion of real and synthetic data. Fresh real data added during the data cycle slows down but can not negate the effects of a self-consuming training loop.

In summary, our main contributions are as follows:

- The first comprehensive empirical study of the self-consuming training loop for LLMs trained from scratch,
- A novel method to unambiguously evaluate quality/correctness and diversity of LLM-generated outputs,
- An in-depth analysis and discussion of the effects and implications of this self-consuming training loop for LLMs.

Following this introduction, Sect. 2 describes the self-consuming training loop and gives an overview of related work. In Sect. 3, we describe our experimental setting. Section 4 presents the experimental results, followed by a discussion in Sect. 5 and limitations in Sect. 6. Section 7 concludes the paper.

2 The Self-Consuming Training Loop

Current generations of LLMs are usually trained on large amounts of unstructured data like text and code gathered from the Internet (Brown et al., 2020). Due to their generative nature and capacity those models can in turn be used to generate new *synthetic* data, often indistinguishable from the original *real* data (Sadasivan et al., 2023). This synthetic data ends up back on the internet and thus in the next large dataset, which is used to train the next generation of LLMs. These LLMs in turn produce new content and data, setting in motion a repetitive cycle in which new generations of models are trained each time with a higher proportion of synthetic data from previous generations. We call this process a self-consuming training loop, depicted in Figure 1.

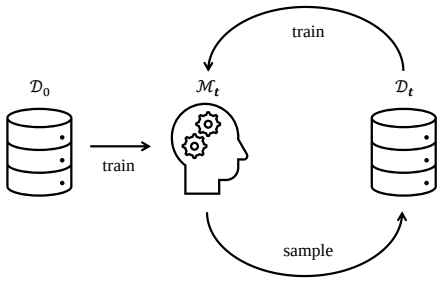


Figure 1: Self-consuming training loop: In the first generation $t = 1$ a model $\mathcal{M}_t$ is initially trained on a real dataset $\mathcal{D}_0$. From this model $\mathcal{M}_t$ a sample $\mathcal{S}_t$ is drawn to build a new dataset $\mathcal{D}_t$. The new dataset $\mathcal{D}_t$ is in turn used to train a new model $\mathcal{M}_{t+1}$ from scratch for the next generation $t+1$. This process is repeated iteratively until the maximum number of generations T is reached.

More specifically, consider a dataset $\mathcal{D}_0$ consisting of real data points $x \in X$ sampled from the original distribution P_X. A generative model $\mathcal{M}_t$ is trained on this original dataset $\mathcal{D}_0$ until the data is sufficiently fitted, producing the

first generation $t = 1$ of generative models. In a self-consuming training loop, a new set of m synthetic data points $\mathcal{S}_t$ is now sampled from the previous generation of generative models $\mathcal{M}_t$. The next generation of generative models $\mathcal{M}_{t+1}$ is then trained from scratch on the new dataset $\mathcal{D}_t$. This self-consuming training loop is repeated until the maximum number of generations $t = T$ is reached. Algorithm 1 in Appendix A presents a pseudo-code of this self-consuming training loop.

This self-consuming training loop differs from self-training to improve LLMs (Huang et al., 2022; Wang et al., 2022; Gulcehre et al., 2023; Singh et al., 2023; Zhang et al., 2024) as the synthetic data is not used intentionally, but rather as a consequence of LLM-generated data published on the internet without being labeled as such.

Related Work Current research has analyzed the self-consuming training loop mostly in the context of image generating models. Martínez et al. (2023) first studied the self-consuming training loop for diffusion models and find that the self-consuming training loop leads to a collapse in diversity of the generated images. Other work have given theoretical frameworks for this phenomenon and investigate more complex data cycles in the context of image generation (Alemohammad et al., 2023; Shumailov et al., 2024; Bertrand et al., 2023). Both Alemohammad et al. (2023) and Bertrand et al. (2023) find that fresh real data can lead to stability within the self-consuming training loop.

Shumailov et al. (2024) observe a degeneration of diversity for Variational Autoencoders and Gaussian Mixture Models if some of the output is used again as input. Additionally, the authors perform experiments for iteratively fine-tuning LLMs in a self-consuming way and observe a degradation in quality. They find that degradation is less strong than in the imagine generation context and that keeping some original data helps mitigating this phenomenon. Other contemporary work also analyzed repeated fine-tuning of LLMs in a self-consuming way and observed a decrease in lexical diversity (Guo et al., 2023).

However, new generations of LLMs are usually trained from scratch with web scraped datasets while fine-tuning is mainly done with curated datasets. So the analysis of the self-consuming training loop when training from scratch is of pressing concern. To the best of our knowledge, we are the first to study the behavior of LLMs trained in a self-consuming loop from scratch. Furthermore, self-consuming loops in LLMs have not yet been analyzed with a method that allows to unambiguously evaluate the quality and diversity of generated model output.

3 Experimental Setup

In this section, we present our logic expression dataset, which is the foundation for the verification of the language model's output. Additionally, we specify the natural language experiments. Furthermore, we explain the data cycles we analyze in our experiments and describe the used model architecture in detail.

3.1 Verification with a Logic Expression Dataset

LLMs usually generate natural language texts and their performance is typically measured by using similarity metrics like the BLEU score (Papineni et al., 2002), ROUGE score (Lin, 2004) and BERT score (Zhang et al., 2019) as well as perplexity (Jurafsky & Martin, 2009). However, those metrics rely on measuring similarity of outputs with expected reference data, which can only serve as a proxy for quality of a language model (Callison-Burch et al., 2006; Gehrmann et al., 2023). Consequently, we propose using a dataset consisting of logic expressions. Those expressions can be represented as a sequence making them a good fit for language modeling. In contrast to natural language text, we can easily and systematically evaluate the quality of logic expressions by verifying their correctness. An expression is defined to be syntactically correct, if it can be parsed without an error. The semantic correctness can be evaluated if an expression is either `True` or `False`. If the original dataset only consists of `True` expressions, then a high-quality trained model should also only generate `True` expressions.

We build a logic expression as a tree in a recursive way specified in the function `GenerateLogicExpression(`d`)`, where d is the desired depth of a logic expression tree. If the desired tree depth is reached when calling the function, a random Boolean is returned (either `True` or `False`). Otherwise, a logic operator (`not`, `and`, `or`) is selected and the function is called again

recursively with $d - 1$. To build the entire original dataset we use this recursive function to sample new random logic expression trees with a random depth between d_{min} and d_{max} until we have a dataset with m unique expressions that evaluate in a `True` Boolean expression. The complexity of the dataset can be easily controlled by adjusting d_{max}. For our experiments we chose a initial dataset size of $m = 10,000$ with expressions of minimum depth $d_{min} = 1$ and maximum depth $d_{max} = 5$. Algorithm 2 in Appendix B describes the generation of our logic expression dataset in pseudo-code.

The resulting logic expression trees can then be saved as strings, e.g., `not ( True and False )`. This allows us to evaluate them in Python using the `eval()` function to test whether they are correct or trigger an error and whether they evaluate to a `True` or `False` Boolean. Additionally, we can encode those strings to a sequence of tokens (`True, False, not, and, or, (, ),` `<eos>`, where `<eos>` is a stop token and indicates the end of an expression) and use these sequences to train a language model. Examples of logical expressions can be found in Appendix E.1.

3.2 Natural Language Experiments

While using the logic expression dataset enables us to design a controlled experimental setting in which we can unambiguously measure both quality and diversity of a trained model, this dataset might not fully cover the characteristics of real textual data. Therefore, we conduct additional experiments using the *tiny Shakespeare dataset* (Karpathy, 2015), a collection of $40,000$ lines of Shakespeare text with over $1,1$ million characters. Since there is no way to analytically investigate the correctness of the generated text for this dataset, we focus on the diversity in this experiments. Examples of the original dataset as well as generated samples within the self-consuming training loop can be found in Appendix E.2.

3.3 Measuring the Diversity of the Model's Output

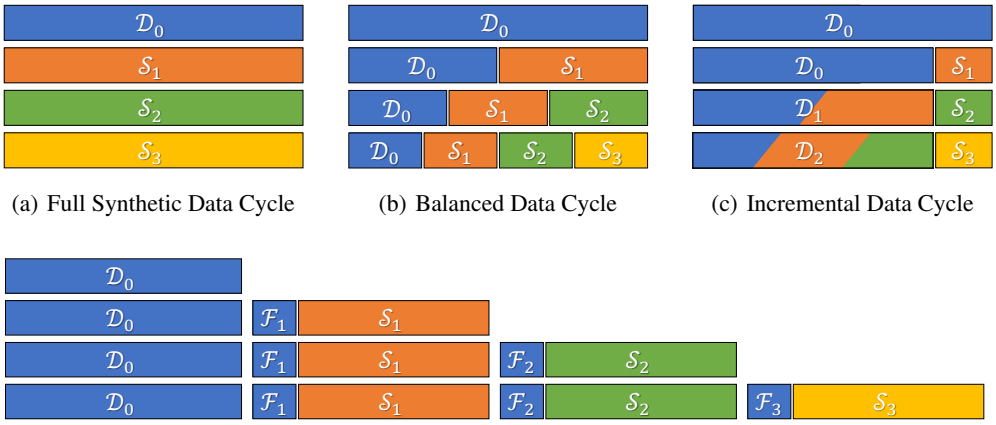
A generative model does not only need to generate correct outputs but also a diverse set of outputs. To measure the diversity of a sample from a LLM in the logic expression experiments we use the Levenshtein diversity (Beijering et al., 2008; Wittenberg et al., 2023) in our experiments. This metric calculates the pairwise Levenshtein distance between each expression in the sample normalized by the number of tokens of the longer expression of each pairwise comparison and averaged over the number of pairwise comparisons. If the average pairwise normalized Levenshtein distance is close to zero the diversity within a sample is low. A value closer to one suggests a stronger diversity within a sample. The Levenshtein distance itself is a metric for measuring the distance between two strings and is defined as the number of edits (deletion, addition, substitution) required to change one string to another (Levenshtein et al., 1966). Normally, this edit distance is calculated on a character basis, however, we calculate it on the tokens from our encoding of the logic expressions to accommodate for the different length each token has in character representation.

To measure the diversity of a sample in the natural language experiments we employ the *n*-gram diversity score (Meister et al., 2023; Li et al., 2023; Padmakumar & He, 2024) which measures the ratio between unique and total *n*-grams in a text. A smaller value indicates less diversity. We also investigate the compression rate (Shaib et al., 2024) and the vocabulary size of the generated samples.

We provide further details for all diversity metrics in Appendix C.

3.4 Data Cycles

We define a *data cycle* as the way a dataset $\mathcal{D}_t$ is constructed in generation t from the original data $\mathcal{D}_0$, potential fresh data $\mathcal{F}_t$ from the original distribution, and the generated data from the current and previous generations $\mathcal{S}_{1...t}$. This way of constructing a new dataset may vary and different data cycles are possible. In the image generation domain, previous work suggests that the self-consuming training loop is influenced by the data cycle being used (Alemohammad et al., 2023). Therefore, inspired by their work we conduct our experiments with the following four different data cycles (also depicted in Fig. 2):



(a) Full Synthetic Data Cycle (b) Balanced Data Cycle (c) Incremental Data Cycle

(d) Expanding Data Cycle

Figure 2: Each sub figure represents a different data cycle exemplary for four generations. The first row in each sub figure is the original dataset $\mathcal{D}_0$. The second, third and fourth row depict the dataset $\mathcal{D}_1$, $\mathcal{D}_2$, and $\mathcal{D}_3$ respectively.

Full Synthetic Data Cycle: In the most extreme case of a self-consuming training loop a new model $\mathcal{M}_t$ is only trained on the generated data from the last generation so that $\mathcal{D}_{t-1} = \mathcal{S}_{t-1}$. We call this a *full synthetic* data cycle. Normally, new datasets would still contain the original data when they are collected in practice. However, we can use this data cycle to study the most extreme changes in behavior of models from generation to generation.

Balanced Data Cycle: We refer to the second data cycle as the *balanced* data cycle. In this data cycle, we construct the new dataset $\mathcal{D}_t$ from equal parts of all the previous samples $\mathcal{S}_{1\ldots t}$ and the original dataset $\mathcal{D}_0$ so that every previous generation contributes $m * \frac{1}{t+1}$ logic expressions to the new dataset $\mathcal{D}_t$ of size m.

Incremental Data Cycle: The third data cycle we study is called the *incremental* data cycle. In this data cycle, the new dataset is created by a portion $(1-\lambda)$ of the last dataset $\mathcal{D}_{t-1}$ and a portion λ of new sampled data $\mathcal{S}_t$ so that $\mathcal{D}_t = (1-\lambda) * \mathcal{D}_{t-1} + \lambda * \mathcal{S}_t$ while holding the size m of the dataset constant each generation. A $\lambda = 1$ would result in a full synthetic data cycle. We chose $\lambda = 0.1$ for our initial experiments and later used different values of λ to study the influence of this parameter on diversity.

Expanding Data Cycle: The first three data cycles create a dataset of equal size in each generation. In practice, however, the dataset would grow each generation by adding new generated data to the already existing dataset. Additionally, fresh data samples $\mathcal{F}_t$ from the original distribution (e.g. human generated) would also be added at each generation. Consequently, the last data cycle we study is an *expanding* data cycle. At each generation the new dataset is created so that $\mathcal{D}_t = \mathcal{D}_{t-1} + (1-\lambda) * \mathcal{F}_t + \lambda * \mathcal{S}_t$, where λ is the portion of generated data we add each generation and $(1-\lambda)$ is the portion of fresh real data added at each generation. For this data cycle, we chose $\lambda = 0.9$ for our initial experiments and later used different values of λ to study the influence of fresh data in an expanding data cycle on diversity.

3.5 Model Architecture and Training

We employ a GPT-style LLM using the open-source implementation *nanoGPT*[4] (MIT license) in our experiments. The model accepts a context of up to 256 tokens and consists of 6 attention layers with 6 attention heads each and an embedding dimensionality of 384, resulting in roughly 10.6 million parameters.

[4]https://github.com/karpathy/nanoGPT

During training we use a batch size of 64 and a dropout rate of 0.2, training for 5000 iterations minimizing cross entropy loss, starting with a learning rate of 10^{-3} decaying to 10^{-4}, to achieve a sufficient fitting of the training data. We split the dataset in 90% training and 10% validation data. During training we calculate the validation error every 250 iterations and use the model parameters with the lowest validation error as our final model M_t for each generation t in the self-consuming training loop.

We use the trained model at each generation to sample $10,000$ logic expressions. We also performed experiments for larger amounts of logical expressions ($20,000$, $30,000$, & $40,000$) and observed no impact on the results for varying dataset sizes (see Appendix D.4). During sampling, we auto-regressively generate new tokens with temperature 0.8 and feed them back into the model until a stop token `<eos>` is sampled up to a maximum of 200 tokens per expression. We run the self-consuming training loop for $T = 50$ generations in each experiment.

We use the same model and setup to run the self-consuming training loop for our natural language experiments but tokenize the text on a character level resulting in a vocabulary size of 65. During sampling, we auto-regressively generate text of 1000 tokens in length until our sample $\mathcal{S}_t$ is of equal size as the original dataset $\mathcal{D}_0$ (approximately 1.1 million tokens per generation). For the expanding data cycle in the natural language experiments we only use a subset of $\mathcal{D}_0$ in order to have enough fresh original data for 50 generations. Consequently, we generate less tokens each generation (approximately $186,000$ tokens per generation).

All experiments are performed on a workstation using consumer NVIDIA graphics cards.

4 Results

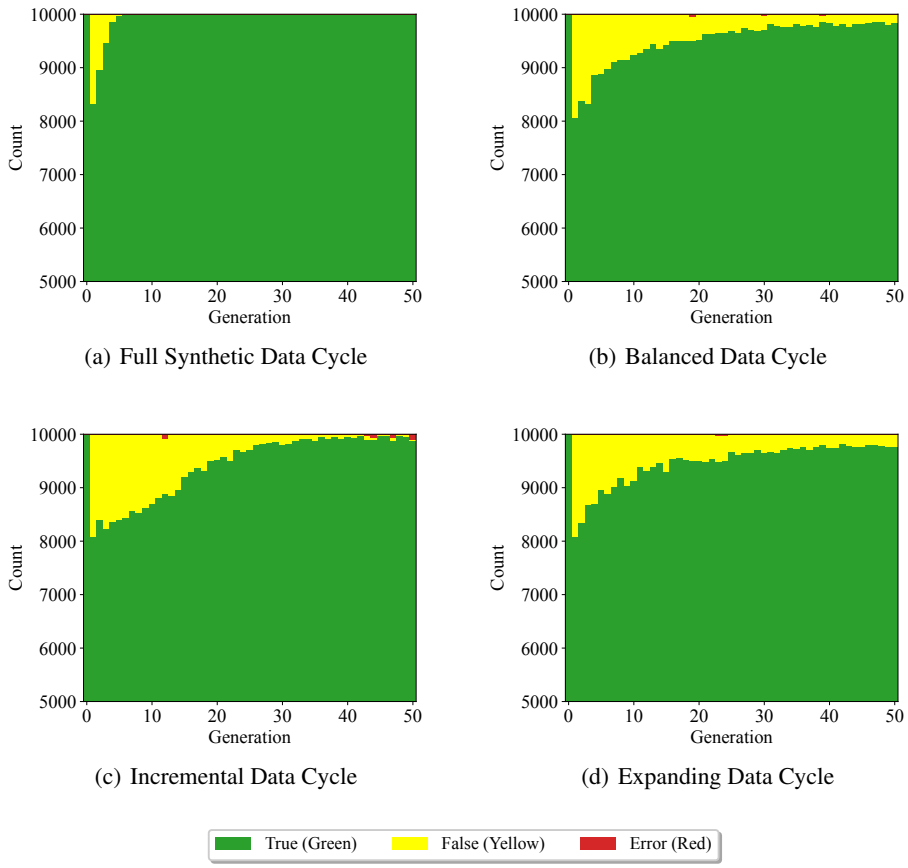
In this section, we present our experimental results in terms of correctness and diversity of model outputs trained in a self-consuming training loop.

4.1 Correctness of Generated Content

We first study the correctness of the expressions within a generated sample $\mathcal{S}_t$ from a model $\mathcal{M}_t$ at each generation t. As described in Sect. 3.1, we consider an expression to be syntactically correct if it can be parsed without error. Since the original dataset $\mathcal{D}_0$ only consists of `True` expressions, we consider a generated expression to be semantically correct if it also evaluates to `True`. A semantically correct expression is also syntactically correct.

Figure 3 displays the composition of samples $\mathcal{S}_t$ generated during a self-consuming training loop. Each subplot presents the results for a different data cycle: a) full synthetic, b) balanced, c) incremental, and d) expanding. Every bar in a subplot displays the composition of $\mathcal{S}_t$ generated from model $\mathcal{M}_t$ at generation t, except for the first bar in each subplot which displays $\mathcal{D}_0$. The green portion of a bar indicates the number of syntactically correct expressions that evaluate to `True` in that sample. The yellow part of a bar represents the number of syntactically correct expressions that evaluate to `False`, and the red part of a bar displays the number of syntactically incorrect expressions that result in an error when being parsed.

Overall, we see that only very few expressions are syntactically incorrect. This indicates that the models are sufficiently trained and can correctly learn the syntactic rules of a logic expression. We see a drop of around 20% in the number of semantically correct expressions from the original data $\mathcal{D}_0$ to the first sample $\mathcal{S}_1$ in every data cycle. Interestingly, the number of semantically correct expressions increases afterwards over the course of the self-consuming training loop. The speed at which this number increases depends on the data cycle. We can see the fastest increase for the full synthetic data cycle in which the whole sample consists of `True` expressions by generation $t = 6$. The incremental data cycle takes consistently longer but also nearly reaches this point by generation $t = 36$. While the balanced data cycle has an initially steeper increase in semantically correct expressions, it does not reach the point of a completely semantically correct sample by the end of 50 generations but comes very close to it. Lastly, the expanding data cycle shows this trend as well. Overall, we see that the self-consuming training loop seems to help with generating more semantically correct expressions in our experiments and the rate at which this happens differs by data cycle.



(a) Full Synthetic Data Cycle

(b) Balanced Data Cycle

(c) Incremental Data Cycle

(d) Expanding Data Cycle

Figure 3: The composition of each sample $\mathcal{S}_t$ from model $\mathcal{M}_t$ at generation t (the first bar displays the composition of $\mathcal{D}_0$) with regards to the number of syntactically and semantically correct expressions. Green indicates syntactically correct expressions that evaluate to `True`, yellow indicates syntactically correct expressions that evaluate to `False`, and red indicates syntactically incorrect expressions that result in an error when being parsed. Each subplot displays the results for a different data cycle.

4.2 Diversity of Generated Content

While we can see an increase in correctness over generations in our experiments, contemporary work in the image generation domain suggests, that this comes with a loss of diversity (Martínez et al., 2023; Alemohammad et al., 2023; Bertrand et al., 2023). Therefore, in this section we study the diversity within a sample $\mathcal{S}_t$ of model $\mathcal{M}_t$ for each generation t.

Figure 4 displays the average pairwise normalized Levenshtein distance over generations of a self-consuming training loop for different data cycles. For each data cycle, we observe a decrease in diversity over the course of generations, with the degree of decrease varying depending on the data cycle. For the full synthetic data cycle we see a steep decline in diversity with a collapse into a single point by generation $t = 39$. The incremental data cycle is initially stable, but decreases in diversity from the 10th generation onwards, with a decrease of 68% in diversity by the end of the 50 generations. The balanced and expanding data cycle also decrease in diversity, however, this decrease is way slower, with a 30% decrease in diversity for the balanced data cycle and a 22% decrease for the expanding data cycle. While not all data cycles fully collapse in diversity by generation 50, ultimately, we expect all of them to eventually reach zero diversity if the self-consuming training loop is run for enough generations.

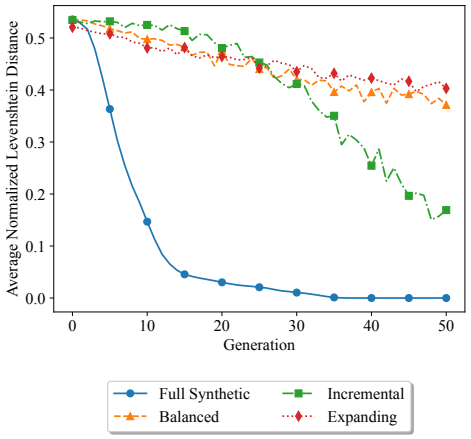


Figure 4: Average pairwise normalized Levenshtein distance over generations of a self-consuming training loop for different data cycles. Line markers added every 5 generations for better display.

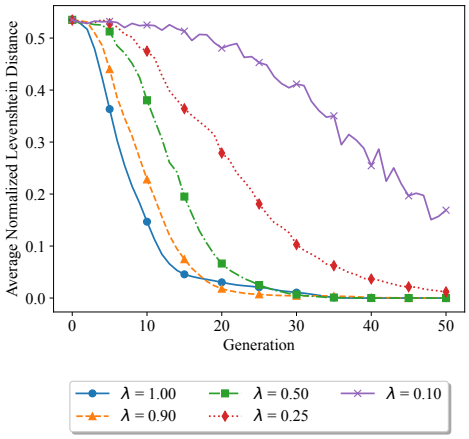


Figure 5: Average pairwise normalized Levenshtein distance over the course of a self-consuming training loop for the expanding data cycle for different portions λ of generated data and $(1 - \lambda)$ of fresh data. Line markers added every 5 generations for better display.

To get further insight into the decline in diversity, we also inspect the number of unique expressions sampled per generation for the full synthetic data cycle. We find that the number of unique expressions is stable at first while the diversity already declines and then rapidly decreases within 5 generations to very few unique expressions (see Appendix D.1).

To better understand the influence of the amount of generated data in each generation on the diversity, we also study the incremental data cycle in more detail with different portions λ of new sampled data. Figure 5 displays the average pairwise normalized Levenshtein distance over generations in a self-consuming training loop for the incremental data cycle with different values of λ. We observe, that the loss in diversity is stronger for a higher share of generated data added in each generation of the self-consuming training loop. Even with as little as $\lambda = 0.25$, we reach the complete loss of diversity within 50 generations. Only for our experimental run with $\lambda = 0.10$ the diversity does not drop to zero, but to a value around 0.17 after 50 generations. However, we see that the speed at which diversity decreases does not scale linear with the amount of generated data. Instead we observe a more exponential increase in speed where larger amounts of generated data lead to an even quicker decay in diversity.

Lastly, we study the expanding data cycle in more detail with regard to the proportion between generated data and fresh data added to the training data at each generation. Figure 6 displays the average pairwise normalized Levenshtein distance over generations in a self-consuming training loop for the expanding data cycle with different portions λ of generated data and $(1 - \lambda)$ fresh real data. We observe, that while each configuration declines in diversity, the rate of this decline depends on the proportion between generated and fresh data. The more fresh data is added at each generation, the slower diversity decreases. With no fresh data or only 1% of fresh data the diversity decreases by approximately 36%. If the portion of fresh data is 25% we only observe a decrease in diversity of approximately 11%. This indicates that fresh data cannot stop the self-consuming training loop but enough fresh data can slow down the rate of the decline in diversity.

4.3 Diversity of Generated Natural Language

To extend our results past the domain of logic expression we also study the self-consuming training loop for a real textual dataset. We first investigate the diversity of generated content. Figure 7 displays the n-gram diversity over generations in a self-consuming training loop for different data

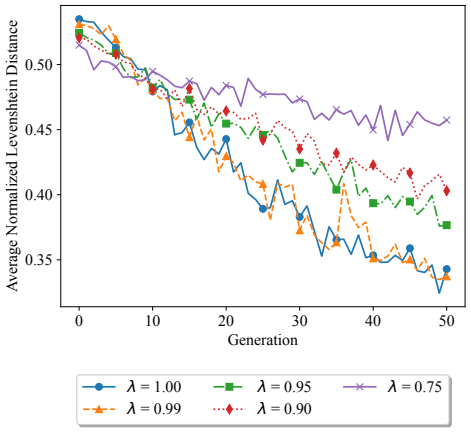


Figure 6: Average pairwise normalized Levenshtein distance over the course of a self-consuming training loop for the expanding data cycle for different portions λ of generated data and $(1 - \lambda)$ of fresh data. Line markers added every 5 generations for better display.

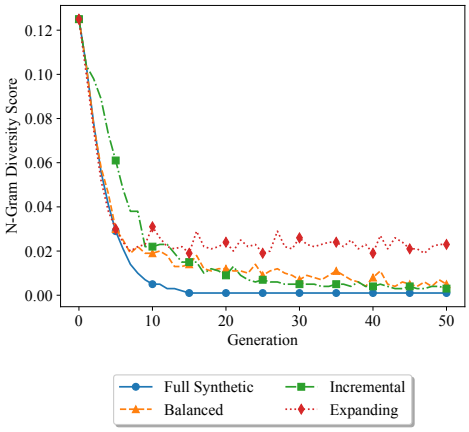


Figure 7: N-gram diversity score over the course of a self-consuming training loop for different data cycles for textual data. The sample size is truncated to equal length for better comparability. Line markers added every 5 generations for better display.

cycles. As diversity scores for text are sensitive to text length, we truncated the samples to be of equal size as suggested in (Shaib et al., 2024), to better compare the data cycles with each other. Similar to our results in the logic expression domain, we observe a decline in diversity for all data cycles. As expected, this is most severe for the full synthetic data cycle dropping to zero n-gram diversity by generation 15, followed by the incremental and balanced data cycle. The expanding data cycle retains the most diversity but also declines strongly over the course of the self-consuming training loop. We also investigate the compression rate and vocabulary size and find similar effects (see Appendix D.5). Overall, this confirms our findings from the logic expression dataset in terms of diversity also for textual data.

While we cannot evaluate the correctness of the generated automatically, we manually inspect text samples for a qualitative assessment. We find that while the models produce some hallucinated words in first generations the quality of the generated text is subjectively mostly correct and Shakespeare like. However, the stark decline in diversity quickly leads to repetitive outputs and makes the models unusable, further confirming the effects of the self-consuming training loop. More details and examples of generated text can be found in Appendix E.2.

5 Discussion

In our experiments we found that iteratively re-training LLMs from scratch with self generated data might help with correctness of model output. This is sometimes already done in practice where the output of LLMs is used to improve their performance (Huang et al., 2022; Wang et al., 2022; Gulcehre et al., 2023; Singh et al., 2023; Zhang et al., 2024) or generate new training data (Yu et al., 2023). In this self-training setting the origin of data is known and researchers can carefully filter and adjust the data. However, the self-consuming training loop is an emerging trend where the data source is not known and LLM-generated content from the internet is unwillingly used to train new models. This trend is concerning as we also found that this self-consuming training loop eventually leads to a drastic loss of diversity of a model's output. Our results confirm the findings on the self-consuming training loop in the field of image generation (Martínez et al., 2023; Alemohammad et al., 2023; Shumailov et al., 2024; Bertrand et al., 2023), further highlighting the importance of this issue for generative models and LLMs in particular. These LLMs have an even greater impact on society than image generation models, leading to more LLM-generated data being produced and

potentially having a greater impact on society as a whole, as many people already rely on good model performance.

Consequently, as we expect that a self-consuming training loop will harm model performance in the future, researchers and practitioners should carefully choose their data when training their models and test those models sufficiently for diversity. Additionally, the machine learning community at large needs to find ways to deal with this problem as generated text data is already present in new internet scraped datasets. While our results indicate that fresh real data can slow down the self-consuming training loop, other studies suggest that this is not an option as we will run out of real data eventually and have to rely on generated data for future models (Villalobos et al., 2022). Additionally, LLM-generated data has already found its way onto the internet, even infecting academic publications (Geng & Trotta, 2024; Liang et al., 2024), and LLM-generated data may soon overtake real data on the internet.

Furthermore, this LLM-generated data is hard to differentiate from real data (Kreps et al., 2022; Sadasivan et al., 2023; Huschens et al., 2023), making it difficult to curate datasets scraped from the web. This makes the self-consuming training loop inevitable in the future. Therefore, we advise to further study ways to maintain diversity of generative model outputs like quality diversity methods (Pugh et al., 2015; Fontaine & Nikolaidis, 2021).

6 Limitations

One cause for limitations of our work are restricted computational resources. First, we ran our experiments with a smaller GPT-style model than for example GPT-4. Even though we expect that larger models with billions of parameters still suffer from the same loss of diversity if trained in a self-consuming training loop, we note that the behavior may vary for those larger models. However, a study for models of those size is not feasible with current compute options nor is it responsible in terms of the expected CO_2 emissions (Strubell et al., 2019). Nevertheless, we performed additional experiments for the full synthetic data cycle with varying model sizes in Appendix D.3 and still observe the loss in diversity across smaller and larger models. Therefore, we expect that our results can be generalized to models of different size.

Second, the main results of this work consist of only one run per experimental configuration. With more runs per experiment the results would be more robust, but conducting more runs for our experiments was simply not feasible with our available computing resources. As all our experiments point towards the same direction, however, we do not believe that this limitation is crucial. Nevertheless, to further mitigate this limitation we performed additional experiments for the full synthetic data cycle with fewer generations over multiple runs and with different initializations in Appendix D.2. These results show that the trend of a decline in diversity still holds true over multiple runs.

Lastly, datasets used to train LLMs cover a wide range of different data sources with different characteristics. Therefore, our results might be slightly different when performed with a real web scraped corpora. However, the experiments with textual data show that our results generalize past logic expressions.

7 Conclusion

In this paper we studied the behavior of LLMs trained in a self-consuming training loop and found that iteratively training LLMs from scratch with self generated data can initially help with correctness of model outputs. However, this comes at a price, as the diversity of generated data eventually degenerates and collapses into a single point. The rate of this decline in diversity depends on the data cycle creating the training data at each generation. Furthermore, we found that fresh data can slow down this process and preserve diversity of a model output for longer. This should encourage researches to carefully monitor their datasets and models to mitigate such a harmful self-consuming training loop in the future.

In future work, we will study how fine-tuning can influence the self-consuming training loop for LLMs. Additionally, we plan to further investigate how the effects of a self-consuming training loop can be slowed down or completely negated.

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A Pseudocode: Self-Consuming Training Loop

Algorithm 1 describes the self-consuming training loop in detail.

Algorithm 1 Self-Consuming Training Loop

Input: Number of generations T, data cycle
Initialize: Sample $\mathcal{D}_0$ from P_X

for $t = 1$ **to** $t = T$ **do**
  Train model $\mathcal{M}_t$ with $\mathcal{D}_{t-1}$
  Sample $\mathcal{S}_t$ from $\mathcal{M}_t$
  Create $\mathcal{D}_t$ from $\mathcal{D}_0$ and $\mathcal{S}_{1\ldots t}$ according to data cycle
end for

Output: Trained models $\mathcal{M}_{1\ldots T}$, samples $\mathcal{S}_{1\ldots T}$, datasets $\mathcal{D}_{0\ldots T}$

B PSEUDOCODE: GENERATION OF THE LOGIC EXPRESSION DATASET

Algorithm 2 describes the generation of our logic expression dataset in detail.

Algorithm 2 Generate Logic Expression Dataset

Input: Number of unique expressions m, minimum tree depth d_{min}, maximum tree depth d_{max}
Initialize: $\mathcal{D}_0 = \{\}$

function GenerateLogicExpression(d) :
if $d = 0$ **then**
  return RandomBoolean()
else
  $op \leftarrow$ RandomLogicOperator()
  if $op =$ 'not' **then**
    return $op +$ GenerateLogicExpression$(d-1)$
  else
    $leftExpr \leftarrow$ GenerateLogicExpression$(d-1)$
    $rightExpr \leftarrow$ GenerateLogicExpression$(d-1)$
    return $leftExpr + op + rightExpr$
  end if
end if
end function

while $|\mathcal{D}_0| < m$ **do**
  $i \leftarrow$ RandomIntegerInRange(d_{min}, d_{max})
  $expr \leftarrow$ GenerateLogicExpression$(d = i)$
  if EvaluateBooleanExpression$(expr) =$ True **then**
    $\mathcal{D}_0 \leftarrow \mathcal{D}_0 \cup \{expr\}$
  end if
end while

Output: $\mathcal{D}_0$

C DIVERSITY METRICS

In this section we provide more detail on the diversity metrics used for the experiments using logic expression as well as textual data.

The **average normalized Levenshtein distance** (Levenshtein diversity) (Beijering et al., 2008; Wittenberg et al., 2023) used in our logic expression experiments is defined as:

$$\text{Average Normalized Levenshtein Distance} = \frac{1}{|Q|} \sum_{(A,B)\in Q} \frac{d_L(A,B)}{\max(\text{len}(A), \text{len}(B))}$$

where Q is the set of unique pairs of logic expressions within a sample $\mathcal{S}_t$ and $d_L(A,B)$ is the Levenshtein distance between two logic expressions A and B.

The ***n*-gram diversity score** (Meister et al., 2023; Li et al., 2023; Padmakumar & He, 2024) used to investigate the diversity of textual data is defined as the number of unique *n*-grams divided by the total number of *n*-grams in a sample $\mathcal{S}_t$:

$$\text{N-Gram Diversity Score} = \sum_{n=1}^{4} \frac{\text{\# unique } n\text{-grams in } \mathcal{S}_t}{\text{\# } n\text{-grams in } \mathcal{S}_t}$$

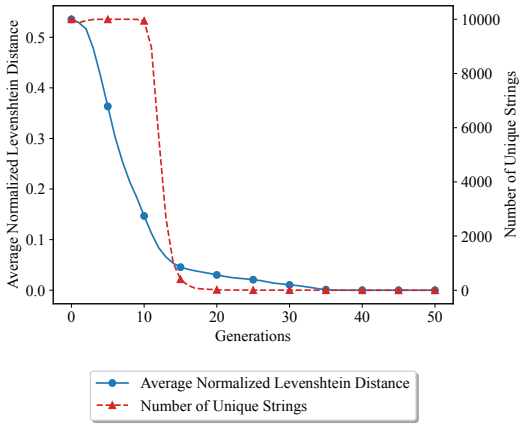


Figure 8: Average pairwise normalized Levenshtein distance (left y-axis) and number of unique expressions in a sample (right y-axis) over generations of a self-consuming training loop for the full synthetic data cycle. Line markers added every 5 generations for better display.

The **compression rate** as a measure for diversity of a text (Shaib et al., 2024) is defined as the size of a sample $\mathcal{S}_t$ divided by the size of the same sample compressed by a compression algorithm (e.g. gZip):

$$\text{Compression Rate} = \frac{\text{size of } \mathcal{S}_t}{\text{compressed size of } \mathcal{S}_t}$$

D Additional Experimental Results

D.1 Unique Expressions Generated

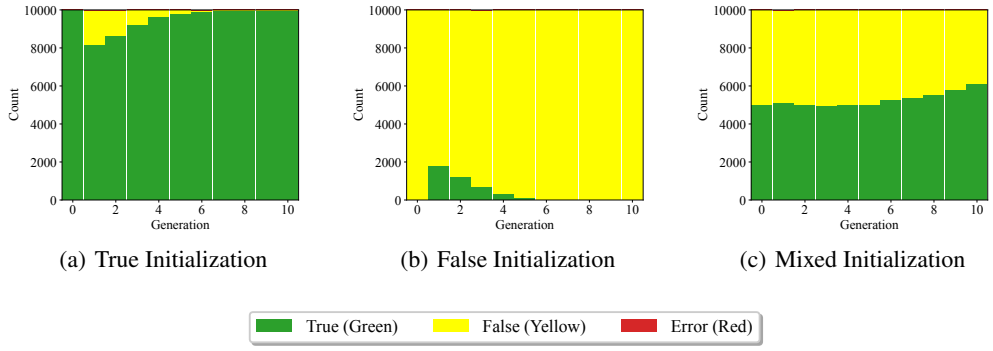
To better understand the decline of diversity, we inspect the number of unique expressions sampled at each generation. We focus on the full synthetic data cycle, as this data cycle fully collapses to a single point within 50 generations.

Figure 8 displays the number of unique expressions (right y-axis) generated at each generation of a self-consuming training loop in comparison to the diversity measured as the average pairwise normalized Levenshtein distance (left y-axis). We observe that in the beginning the number of unique expressions stays stable while the diversity is already in a steep decline. Only by generation $t = 10$ the number of unique individuals starts to decline rapidly and by generation $t = 15$ only around 400 unique expressions are sampled while the decline in diversity slows down. In generation $t = 21$ the number of unique individuals is below 10 and in generation $t = 39$ only a single individual is sampled at each generation. Consequently, the diversity is collapsed to zero.

This shows that it is not enough to only track unique outputs of a model, but that diversity needs to be tracked as well. By the time a decrease in unique results is noticeable, the diversity already decreased significantly.

D.2 Impact of Initialization

So far we only investigated the self-consuming training loop starting from an initial dataset consisting only of `True` expressions. To check whether our findings also hold for different initializations of data across multiple runs, we conduct further experiments. Specifically, we analyze the full synthetic data cycle with the original dataset $\mathcal{D}_0$ only consisting of (1) `True` expressions, (2) `False` expressions, and (3) an equal mixture of both. The results from Sect. 4 indicate that the effect of the self-consuming training loop for the full synthetic data cycle are already clearly visible in the



(a) True Initialization (b) False Initialization (c) Mixed Initialization

Figure 9: The composition of each sample $\mathcal{S}_t$ from model $\mathcal{M}_t$ at generation t (the first bar displays the composition of $\mathcal{D}_0$) with regards to the number of syntactically and semantically correct expressions averaged over 5 runs. Green indicates syntactically correct expressions that evaluate to `True`, yellow indicates syntactically correct expressions that evaluate to `False`, and red indicates syntactically incorrect expressions that result in an error when being parsed. Each subplot displays the results for the full synthetic data cycle with different initializations (`True`, `False`, Mixed).

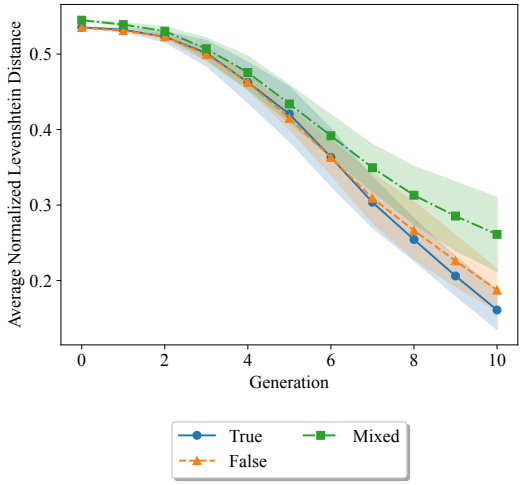


Figure 10: Average pairwise normalized Levenshtein distance over generations of a self-consuming training loop for the full synthetic data cycle with different initializations. Displayed is the mean and standard deviation at each generation for each initialization over 5 runs. Line markers added every 5 generations for better display.

first 10 generations. Therefore, we conduct experiments with only 10 generations. With this saved computing time, we conduct 5 independent runs for each initialization.

Figure 9 displays the composition of samples $\mathcal{S}_t$ generated during a self-consuming training loop. Each subplot presents the composition for a different initialization for the full synthetic data cycle averaged over 5 independent runs: a) only `True` expressions, b) only `False` expressions, and c) half `True` expressions and half `False` expressions. Every bar in a subplot displays the composition of $\mathcal{S}_t$ generated from model $\mathcal{M}_t$ at generation t, except for the first bar in each subplot which displays $\mathcal{D}_0$. The green portion of a bar indicates the number of syntactically correct expressions that evaluate to `True` in that sample. The yellow part of a bar represents the number of syntactically correct expressions that evaluate to `False`, and the red part of a bar displays the number of syntactically incorrect expressions that result in an error when being parsed.

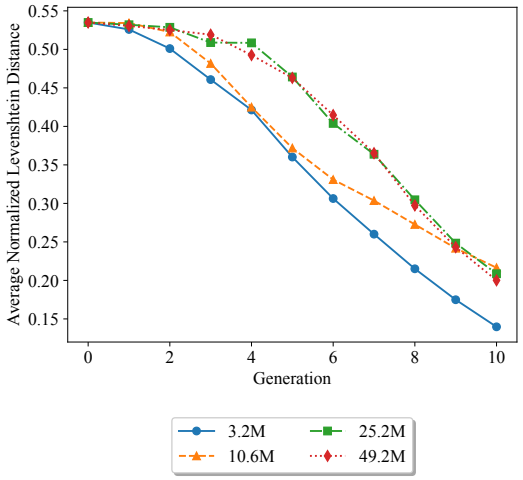


Figure 11: Average pairwise normalized Levenshtein distance over generations of a self-consuming training loop for the full synthetic data cycle with different model sizes. Line markers added every 5 generations for better display.

Similar to our results in Sect. 4.1, we observe an initial drop of `True` expressions by 20% in favor of `False` expressions for the initialization with only `True` expressions in the first generation. Afterwards, the number of `True` expressions in a sample increases again over the course of generations. For the initialization with only `False` expressions, we observe a similar effect, only in the opposite direction. The number of `False` expression first drops by around 20% and then increases again until the whole sample consists of only `False` expressions. When initialized with an equal amount of `True` and `False` expressions, we can observe that the proportion of both expression types first stays stable and then by generation $t = 6$ starts to slightly shift towards `True` expressions. Upon further inspection of the 5 runs, we find that one run quickly shifts towards only `True` expressions, one run shifts quickly to only `False` expression, one run shifts slowly to `True` expressions, and two runs maintain equal proportions between `True` and `False` expressions across the 10 generations.

Figure 10 displays the diversity measured in the average pairwise normalized Levenshtein distance for the three different initializations. Displayed is the mean and standard deviation of five runs over the number of generations. We observe that the diversity declines for all three types of initialization, further confirming our results from Sect. 4.2. The initializations with only `True` and only `False` expressions decline at around the same speed. The initialization with equal proportions of `True` and `False` expressions declines a bit slower but shows the same effect.

Overall these findings indicate that the effects of the self-consuming training loop apply to different initializations across multiple runs, partially mitigating the limitations mentioned in Sect. 6.

D.3 Impact of Model Size

To investigate if our results can be generalized to different model sizes and architectures we repeated our experiments for the full synthetic data cycle for 10 generations with multiple different model sizes. We conducted experiments for models with parameters ranging from 3.2 million to 49.2 million. Table 1 describes the details of those models.

Figure 11 displays the diversity measured in the average pairwise normalized Levenshtein distance for different model sizes. Similar to our results in Sect. 4.2 we observe a steady decline in diversity over generations regardless of model size. While the decrease in diversity happens quicker for the smaller model it is also clearly present in the larger models. Therefore, we argue that the effects of a self-consuming training loop is also present for different model sizes.

Table 1: Details of the model architectures for the additional experiments. Displayed is the total number of parameters in millions, the number of layers, number of attention heads per layer, and the embedding dimensionality.

#PARAMETERS	#LAYERS	#ATTENTION HEADS	EMBEDDING DIMENSION
3.2M	4	4	256
10.6M	6	6	384
25.2M	8	8	512
49.2M	10	10	640

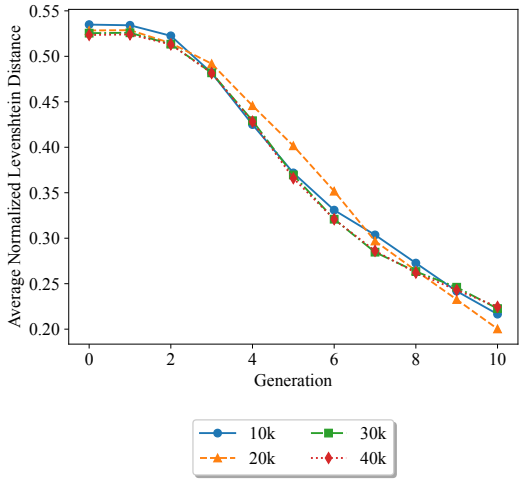


Figure 12: Average pairwise normalized Levenshtein distance over generations of a self-consuming training loop for the full synthetic data cycle with different dataset sizes. Line markers added every 5 generations for better display.

D.4 Impact of Dataset Size

While we used $10,0000$ logic expressions for our main experiments, we conducted additional experiments for larger amounts of logical expressions ($20,000$, $30,000$, and $40,000$) to analyze the impact of varying amounts of training data on the self-consuming training loop. Specifically, we conducted experiments for the full synthetic data cycle over 10 generations.

Figure 12 displays the diversity measured in the average pairwise normalized Levenshtein distance for different dataset sizes. We observe that for all dataset sizes the diversity decreases over the course of generations. This indicates that the effect of the self-consuming training loop occurs regardless of dataset size.

D.5 Additional Diversity Metrics for the Natural Language Dataset

In addition to our results in section 4.3 we also inspect the compression rate (Shaib et al., 2024) and the vocabulary size of samples obtained in the self-consuming training loop for textual data. Once again we truncate the data samples to be of equal size for better comparability between the different data cycles.

Figure 13 displays the compression rate over generations of a self-consuming training loop. A higher compression rate indicates a less diverse sample. Similar to our results in the logic expression domain we observe the highest increase in compression rate and therefore decrease in diversity for the full synthetic data cycle. The incremental data cycle also has a stark increase in compression rate followed by the balanced data cycle. The expanding data cycle also shows an increase in compres-

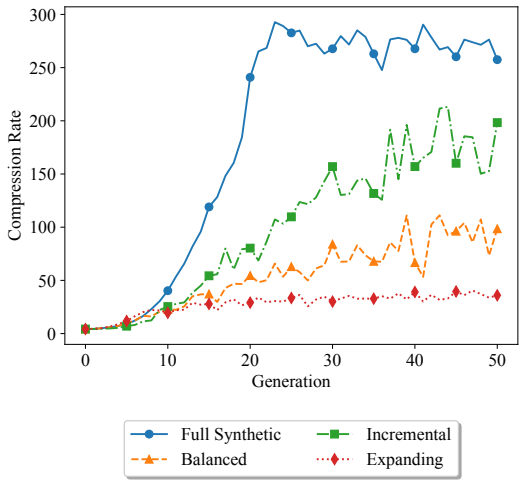


Figure 13: Compression rate over generations of a self-consuming training loop for different data cycles for textual data. A higher compression rate indicates less diversity. The sample size is truncated to equal length for better comparability. Line markers added every 5 generations for better display.

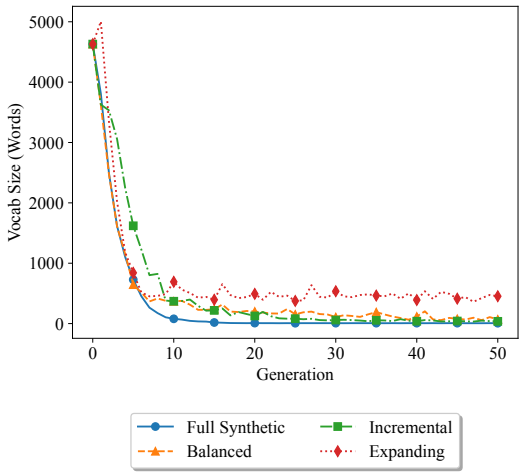


Figure 14: Vocabulary size over generations of a self-consuming training loop for different data cycles for textual data. The vocabulary size is defined as the number of unique words in a sample. The sample size is truncated to equal length for better comparability. Line markers added every 5 generations for better display.

sion rate, however, not as severe as for the other data cycles. This indicates that fresh data can slow down the effects of the self-consuming training as observed for the logic expression dataset.

Figure 14 displays the vocabulary size measured as unique words within a sample. Similar to the previous results we observe a decline in vocabulary size for all data cycles. While the full synthetic data cycle fully collapses in vocabulary size, closely followed by the balanced, and incremental data cycle, the expanding data cycle stabilizes around 500 words. However, this is still a drop in vocabulary size by 95%. Once again, this confirms a strong decline in diversity for all data cycles.

E EXAMPLE OUTPUTS

E.1 EXAMPLES OF LOGIC EXPRESSIONS

Table 2 provides examples of logic expressions that evaluate to `True` or `False`, as well as syntactically incorrect logic expressions (`Error`). In the erroneous example the logic expression is syntactically incorrect because of a missing parentheses. Additionally, all generated logic expressions from our experiments are provided in the supplementary material.[5]

Table 2: Examples of logic expressions that evaluate to `True`, `False`, or cannot be evaluated (`Error`).

TYPE	EXPRESSION
True	`( not ( ( ( True and True ) and ( not True ) ) or ( ( False or False ) and ( not True ) ) ) ) <eos>`
False	`( ( ( ( True and False ) and ( True or False ) ) or ( not ( False or True ) ) ) and ( ( ( True and True ) and ( True or False ) ) or ( ( True or True ) and ( True or True ) ) ) ) <eos>`
Error	`( ( ( False or True ) and ( not True ) or ( ( not True ) or ( not False ) ) ) <eos>`

E.2 EXAMPLES OF NATURAL LANGUAGE

Figure 15-18 provide example outputs of models trained in a self-consuming training loop on the natural language dataset for all data cycles. Displayed is an example of the initial input and examples for generations 1, 10, 25, and 50. The examples are truncated for better display. All generated text samples are also provided in the supplementary material.

We manually inspect the text samples for the first few generations and notice a few hallucinated words that are not present in the original corpus, indicating a drop in correctness. However, overall the generated text is subjectively mostly correct and Shakespeare like with a diverse set of samples.

By generation 10 the diversity is already declining for all data cycles. This is most severe for the full synthetic data cycle which produces nearly the same output every time. The incremental data cycle is also very repetitive text with repeating words in half of the time. In the other half (not shown in the example), the output is just a repetition of a role without text (e.g. `GLOUCESTER:\n\n GLOUCESTER:\n\n GLOUCESTER:\n\n`). The other two data cycles (balanced and expanding) show a strong repetition of words.

By generation 25 the full synthetic data cycle is fully converged producing the same outputs for the rest of the self-consuming training loop. The incremental data cycle also shows heavy repetition or just samples a role repeatedly and by generation 50 only very few roles are sampled repeatedly without text besides a very few exceptions. The other two data cycles continue the trend of producing repetitive words and n-grams and by generation 50 only small diverse text samples are generated before the same word or n-gram is produced repeatedly.

Overall, while one could argue that the text is more *correct* (fewer hallucinated words) at the end of a self-consuming training loop, the stark decrease in diversity and the generation of meaningless text makes the language model unusable.

[5] https://figshare.com/s/b09d5bdb3b216998d330 - Anonymized for review

Full Synthetic Data Cycle

Initial:
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

Generation 1:
YORK:
I think you where you have seen to be envious death.

LORD STANLEY:
No more, my lord: let me speak with men and my soul
Your proof interior marriage, with it end.

WARWICK:
Fair lords, and Warwick, where she lives you lies?

Generation 10:
WARWICK:
What with his wisdom?

WARWICK:
Why, what with his soul?

WARWICK:
What with his soul?

Generation 25:
WARWICK:
What with his wisdom?

WARWICK:
What with his wisdom?

WARWICK:
What with his wisdom?

Generation 50:
WARWICK:
What with his wisdom?

WARWICK:
What with his wisdom?

WARWICK:
What with his wisdom?

Figure 15: Example model outputs of the full synthetic data cycle for the natural language experiments over generations of a self-consuming training loop.

Balanced Data Cycle

Initial:
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

Generation 1:
ANGELO:
Anon I would have no more for your better.

ANGELO:
I will be so not better, whom you flow.

ISABELLA:
I would he that would see your behalf.

Generation 10:
CORIOLANUS:
You will not speak to the people of the prince of the people,
Be so she is a man in the prince of the prince,
And the traitor of the prince of the prince,
And the prince of the prince of the prince,
And the prince of the prince of the prince of the prince of the prince,
And the seat of the prince of the state of the prince of the prince,
And so she shall be so she is not so shall not speak to the prince of the prince of the prince,
And the seat of the seat of the state of the prince of the state of the state,

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Generation 25:
And give me dead, I have then,
And I have done to see your holy proofits of York,
And so shall be so stand to the state of the man in the man in the story of the state,
And so shall be spent for the seat of the seat of the first me of the prince,
And the state of the state of the state of the state,
And the state of the state of the state of the state of the state,
And the state of the state of the state of the state,
And the state of the state of the state of the state of the state,
And the state of the state of the state of the state,

Generation 50:
Here's noble by so dead.

DUKE VINCENTIO:
Here's a man in the prince of the prince, that the prince of the prince of the prince,
And the prince of the prince of the prince of the prince,
And the prince of the prince of the prince of the prince,
And the prince of the seat of the prince of

And the state of the state of the state of the state, . . . *(continues)*

Figure 16: Example model outputs of the balanced data cycle for the natural language experiments over generations of a self-consuming training loop.

Incremental Data Cycle

Initial:
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

Generation 1:
TYBALT:
I'll stand my lord.

Marshal:
Tell her her and be solemned and soldiers,
For her wrong so understrange for Lancaster.

DUKE VINCENTIO:
Go you, good good lady.

Generation 10:
LADY CAPULET:
I will not say the world,
And thou hast not said to be so for the world,
And with the world.

LADY CAPULET:
I have said to shame the world,
And thou hast not said to show the world,
And thou shalt not say the world in the world,
That I have not said to shame the world.

Generation 25:
LADY ANNE:
I will not say the world.

LADY ANNE:
I will not say the world.

LADY ANNE:
I will not say the world,
And thou shalt not say the world in the world,
And thou hast not said to the world,

Generation 50:
DUKE OF YORK:

DUKE OF YORK:

DUKE OF YORK:

Figure 17: Example model outputs of the incremental data cycle for the natural language experiments over generations of a self-consuming training loop.

Expanding Data Cycle

Initial:
First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

Generation 1:
SICINIUS:
The enemy noble are and true,
And like it to life he putinion.

VOLUMNIA:
So, let not for us.

CORIOLANUS:
No, I wise the take tower?

Generation 10:
LADY ANNE:
Would good we have my most for my soul, but your shouls
The can is sould distrother particularish,
And the such that the take tribunes,
Where the name and the vail the people and to still grave the truest roper in the people,
Which the port the people that who the hath the shall should to the people the people the people
The people of the people and to the people tribuness of the people tribuness, the people,

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Generation 25:
COMINIUS:
Say would be medd to the common of the give the stords
The people and the people the people tribuness, and the people tribuness
Of the people tribuness of the country's noble the people,
Which the people and the stirly tribunes of the people tribuness of the people and to the people tribuness of the people, and the people,
Which the people and the people the people trick of the people the people tribuness,
Who was in the people and the people the people and the people and the people the people and the people, the people, and the people,

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Generation 50:
LADY ANNE:
The gentleman is good more gone?

GLOUCESTER:
You have been my lord, I will be possess to the gods gods!

GLOUCESTER:
What the grace the people the people the people the people the people the people the people the people the people the people the people the people the people the people ... *(continues)*

Figure 18: Example model outputs of the expanding data cycle for the natural language experiments over generations of a self-consuming training loop.