LLM See, LLM Do: Leveraging Active Inheritance to Target Non-Differentiable Objectives

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Abstract

The widespread adoption of synthetic data raises new questions about how models generating the data can influence other large language models (LLMs). To start, our work exhaustively characterizes the impact of passive inheritance of model properties by systematically studying how the source of synthetic data shapes models' internal biases, calibration and preferences, and their generations' textual attributes, providing one of the most comprehensive studies to-date. We find that models are surprisingly sensitive towards certain attributes even when the synthetic data prompts appear "neutral", which invites the question "can we explicitly steer the generated data towards desired properties?" We demonstrate how such active inheritance can guide the generation profiles of models towards desirable non-differentiable attributes in both directions, e.g. increasing lexical diversity or reducing toxicity. Overall, our study broadens the understanding of the implicit biases inherited by LLMs and explores how we can leverage them to positive effect.

1 Introduction

Historically, high-quality labeled data has been costly to curate due to, amongst other factors, scarcity of available data (Bansal et al., 2022; Singh et al., 2024a) and financial cost (Gilardi et al., 2023; Boubdir et al., 2023). This high cost has precluded adapting training sets "on-the-fly" to increase coverage or task diversity. As a result, researchers often treated datasets as static instead of malleable. Recent work has focused on making better use of existing data by optimizing in the data space. This includes efforts around data augmentation (Mumuni and Mumuni, 2022; Feng et al., 2021), creating auxiliary data fields through pseudo-labeling (Ratner et al., 2017), data weighting (Thakkar et al., 2023; Dou et al., 2020), data pruning to identify a high-quality subset (Marion et al., 2023; Attendu



Figure 1: Percentage of change in attributes with respect to the base model after synthetic data distillation (results relative to Single-Source Mixtral-8x7B; method is detailed in Section 4 and results can be found in Table 3). Our targeted sampling approach (active inheritance) effectively guides model behaviour to discrete preferences by enhancing desirable attributes (length, diversity) and mitigating negative ones (toxicity).

and Corbeil, 2023; Abbas et al., 2024; Groeneveld et al., 2024; Allal et al., 2023; Li et al., 2023) or curriculum learning (Soviany et al., 2022; Xu et al., 2020).

However, all these methods still adhere to the convention that the goal is to enhance an existing "fixed" dataset by re-formatting, transforming, or pruning. As a result, their success depends on the desired properties being present in the dataset to begin with. This limits the feasibility of introducing new properties, or explicitly optimizing for task-specific metrics. What if instead, we exploit the dataset generation process to steer the model towards the characteristics we want at test time?

We turn to synthetic data generation (Wang et al., 2023a; Mitra et al., 2023; Üstün et al., 2024) as a way to rapidly shape the data space with latent, desirable attributes. In this process, we hope to capture more fine-grained—and often nondifferentiable—characteristics such as increased length and lexical diversity as well as low toxicity that are known to be correlated with human preferences (Bai et al., 2022; Singhal et al., 2023; Singh et al., 2024b). While desirable, these attributes are not explicitly optimized when training or aligning LLMs. We aim to leverage the phenomenon of inheritance to steer model behaviour to accentuate desirable attributes and attenuate negative ones, as illustrated in Figure 1.

We first exhaustively benchmark what we term *passive inheritance*—profiling what changes happen when a student model is trained on synthetic data from a teacher model using a variety of social bias, textual characteristics, and calibration metrics. Furthermore, we study the effects of this distillation on LLMs as evaluators, expanding upon prior work on self-preference (Singhal et al., 2023). We take a wider view and perform a systematic investigation into how different attributes are transferred across models via synthetic data usage and how these changes are manifested both in LLMs' generations and their evaluator preferences.

Overall, our profiling highlights what properties are most sensitive to *passive inheritance* when comparing different student and teacher models. Next, we use this systematic view to inform the selection of properties to explicitly optimize for. We introduce the term *active inheritance* where we guide the model towards specific characteristics via synthetic data distillation and targeted sampling.

This enables us to guide the model behavior towards non-differentiable objectives. Most other approaches for non-differentiable optimization rely on reinforcement learning (Roit et al., 2023), Bayesian optimization (Gopakumar et al., 2018), and evolutionary algorithms (Lange et al., 2023), which require complex methods that are difficult to scale and can be unstable with large models (Powell, 2019; Daulton et al., 2022; Ouyang et al., 2022; Liu et al., 2023a). Our approach instead relies on the simplicity of guiding generations in the synthetic data space and is interpretable because it is anchored to observable data characteristics.

We study a diverse set of models including LLaMa2-7B, LLaMa2-13B (Touvron et al., 2023), Mixtral-8x7B (Jiang et al., 2024), Gemma-7B (Gemma Team et al., 2024), Aya-8B (Aryabumi et al., 2024) and Command-R+ (103B parameters)¹, and trace the impact of an exhaustive set of over 26 metrics across 4 categories (i.e., *textual characteristics, social bias, toxicity* and *calibration*) which we release as part of an open-source toolkit.² Our

main contributions are:

- We establish that models trained on synthetic data are sensitive to passive property inheritance. We systematically study the consequences of synthetic data integration—a fundamental step towards understanding how to leverage synthetic data responsibly. We introduce a comprehensive toolkit enabling easy and automatic monitoring of LLMs' latent characteristics during training.
- 2. Passive property inheritance from synthetic data impacts model behavior preferences when used as evaluators. Due to the prevalence of LLM judges in current evaluation pipelines (Zheng et al., 2023; Dubois et al., 2024b; Chiang and Lee, 2023), we also examine how synthetic datasets alter the students' behaviors and preferences when they are used as evaluators (e.g., biasing the student towards the teacher model).
- 3. We propose active inheritance as a mechanism for steering synthetic data curation towards desirable properties. We show that strategic gathering and curation of synthetic data can significantly amplify desired characteristics and reduce undesired ones. In particular, we show that by targeted sampling of generations from a single or multiple LLMs, we can guide model behavior with gains of up to 116% and 43% in length and lexical diversity respectively and decrease toxicity by up to 40%.

2 Methods

Learning from Synthetic Data In the simplest form of knowledge distillation (Liu et al., 2019; Gou et al., 2021) and LLM-as-a-teacher setups (Feng et al., 2023; Tian et al., 2024), the parameters θ of a student LLM are finetuned to maximize the log-likelihood of a teacher's (another LLM with parameters $\hat{\theta}$) generation $\hat{y} \sim p_{\hat{\theta}}(\cdot | x)$ for a given prompt x:

$$\arg\max_{\rho} \mathbb{E}_{(x,\hat{y})\sim\hat{D}}[\log p_{\theta}(\hat{y} \mid x)] \tag{1}$$

The teacher's generations serve as a proxy for an unattainable or non-existent gold sequence (i.e., a human-generated completion). Pairs of prompts and proxy labels $\{x, \hat{y}\}$ form the synthetic dataset \hat{D} that is the basis for the optimization process. In imitation learning, this strategy is known as behavioral cloning (Pomerleau, 1988), as the goal is for the student to mimic the teacher's behavior as closely as possible.

¹https://docs.cohere.com/docs/command-r-plus

²The toolkit is available at https://github.com/ for-ai/llm-profiling-toolkit.

Measuring Data Characteristics The proxy labels are expected to be generally superior to the initial student's generations, as they are often but not exclusively sourced from a stronger model (larger, more specialized or more recent). However, the optimization objective is agnostic to how this is manifested in the data. Our work focuses on characterizing the generations with a set of profiling functions $f : \mathcal{V}^N \times \mathcal{V}^M \mapsto \mathbb{R}$, that return scalar values for a given pair of prompt $x \in \mathcal{V}^N$ and generation sequences $y \in \mathcal{V}^M$ (i.e., token sequences over a vocabulary \mathcal{V}). These functions allow us to track the *passive inheritance* of characteristics from teacher to student. Examples for such functions are detailed in Section 2.1.

Active Inheritance How can we directly guide the amplification of desired properties when learning from teachers? Our key idea is to select proxy labels based on their presence of desired characteristics. We generate multiple samples for each prompt (either from repeatedly sampling from a single model or sampling from multiple models), and then select the sample for finetuning that maximizes the presence of the characteristic.³ We now sample from the following distribution during student finetuning (Eq. 1):

$$p(\cdot \mid x) = \left\{ \begin{array}{cc} 1 & \text{if } f(x, \cdot) = \max_{y' \in \mathcal{Y}} f(x, y') \\ 0 & \text{otherwise} \end{array} \right\},$$
(2)

where the set of k candidate generations $y' \in \mathcal{Y}$ can contain generations from various sources, such as the student itself or multiple teachers (discussed below). The resulting synthetic dataset is steered towards favoring this particular attribute, and the student model is thus directly optimized towards it.

This best-of-k or rejection sampling strategy has been used as one component of the optimization in previous works to align models to human preferences (Dong et al., 2023; Gulcehre et al., 2023; Touvron et al., 2023), but these need large-scale reward models to compute f and are restricted to single teachers that remain close to the student model. Working with explicit metrics of desired data characteristics is attractive, as it can work with any non-differentiable function f and black-box teachers (e.g., closed-source LLMs). Section 4 will

Textual Characteristics	
Length (#Tokens)	Length of generations
Gunning-Fog (Gunning, 1968) Rix (Anderson, 1983)	Proxies to textual complexity
MTLD (McCarthy and Jarvis, 2010)	Textual lexical diversity
Social Bias	
StereoSet (Nadeem et al., 2020) CrowS-Pairs (Nangia et al., 2020)	Stereotypicality of associations
BBQ (Parrish et al., 2022)	Bias in question answering
Toxicity on RTP prompts (Gehman et al., 2	2020)
Expected Maximum Toxicity	Worst case toxicity
Toxicity Probability	Probability of toxic generations
Calibration error on	
HellaSwag (Zellers et al., 2019) OpenBookQA (Mihaylov et al., 2018)	Calibration on specific domain

Table 1: Overview of profiling toolbox (details in Appendix B).

present practical instances of successful guidance via synthetic data.

Learning from Multiple Teachers Naturally, the success of the active steering of inheritance is limited by the quality of the pool of samples. We maximize the chance of obtaining samples with high values for f by employing a set of diverse teacher models $(\theta_1, \theta_2, \ldots, \theta_k)$ rather than a single teacher $(\hat{\theta} \text{ above})$. Thereby, we benefit from an ensembling effect and make use of the *wisdom of the crowd* (Zaras et al., 2021; Wu et al., 2021, 2022; Zuchniak, 2023; Ko et al., 2023). In Section 4.1 we will show the empirical benefits of learning from multiple teachers.

2.1 Experimental Setup

Profiling Metrics We profile models and their generations through a set of non-differentiable metrics along multiple axes of interest: Textual characteristics, social bias, toxicity, and calibration. We analyze *passive inheritance* of these properties through finetuning on synthetic data (Section 3), and examine active inheritance by leveraging generated synthetic data to target potential points of improvement based upon these metrics (Section 4). Table 1 provides an overview of the metrics that we gather for our toolbox. Each of them comes with their own evaluation metric, implementation, and-for the majority-custom set of prompts (see Appendix B for details). We chose these metrics as they offer insight into the LLM's inherited characteristics, which are often overlooked in general benchmarks. Details about the models used, training, data distillation and evaluation benchmarks can be found in Appendix A.

³For simplicity, we focus on the maximization scenario. For lower-is-better metrics (i.e., toxicity), we instead minimize the property during selection.



Figure 2: **Model profile changes after finetuning LLMs on synthetic data.** *Left*: social bias score changes for the BBQ benchmark show a positive decreasing trend for LLaMa2-13B except in the Disability metric. *Middle*: small changes in Measure of Textual Lexical Diversity (MTLD) and the Readability Index (Rix) are accompanied by an increase of over 100% for the mean number for tokens. *Right*: toxicity metrics get worse in all cases after finetuning, increasing up to 40%. Overall, we see that *models are susceptible to changes of considerable magnitude and that the direction of change is often not always intuitive*.

Passive Inheritance Experiments For the first set of experiments, we study LLaMa2-7B and LLaMa2-13B (Touvron et al., 2023) and Mixtral-8x7B (Jiang et al., 2024). All 3 LLMs take the role of the student model (i.e., the model which is trained on the synthetic dataset) and LLaMa2-7B and Mixtral-8x7B also take the role of the teacher (i.e., the model used to generate synthetic data), resulting in a total of 6 student-teacher combinations. We start by distilling data using the Alpaca prompts (52k instances; Taori et al., 2023) from each LLM and then use the created datasets to finetune each LLM as a student. By considering these combinations we are able to examine two distinct scenarios: self-distillation where LLMs are trained on data generated by themselves (LLaMa2_{LLaMa2}, Mixtral_{Mixtral}), and the standard distillation scenario, where LLMs are trained on data generated by other models (LLaMa2_{Mixtral}, Mixtral_{LLaMa2}) (see Section A for further details).⁴

3 Results: Passive Inheritance of Teacher Properties

3.1 Impact on Model Generation Properties

In this section we ask: how does passive inheritance impact model generation properties? We find that while synthetic data might not impact general performance significantly (Table 4), it can cause remarkable changes in the scores across the profiling benchmarks (Figure 2).

Overall changes We consistently observe changes across various experiments involving

different student and teacher models. Even though the Alpaca prompts used for data generation are neutral and not deliberately focused on eliciting specific attributes, models are influenced in unforeseen ways (e.g., the student model does not strictly move towards the teacher's profile and other non-trivial directions of change).

Social Bias In Figure 2, we plot some of the changes due to passive inheritance. Firstly, looking at the social bias metrics, we see that, despite the domain of the prompts being neutral, there are noticeable changes to the Stereotype Scores across all domains (e.g., race, gender, religion, etc) in our benchmarks. We observe relative changes of the overall social bias profile of some LLMs of up to 36% (i.e., Mixtral_{LLaMa2-7B} in Table 11). We also observe that some relative individual changes are surprisingly large, with the disability bias score increasing by 80% (i.e., the LLaMa2-13B_{LLaMa2-7B} bias score increases from 7.71% to 13.88%). Interestingly, training on data distilled from a model does not necessarily lead to replicating the model's profile. In fact, our results show the opposite effect: the social bias metrics of a student model can decrease even when the teacher model has higher social bias metrics (see Table 10).

Textual characteristics Secondly, for textual characteristics, as seen in Figure 2, we observe varying behaviours depending on the metrics analysed. We see smaller relative changes of around 8% for the Gunning-Fog and Rix readability metrics, which are proxies to measuring text complexity. When it comes to lexical diversity, we are able to see changes of up to 16%, which are considered

⁴The subscripted model is the teacher, i.e., Student_{Teacher}.

significant (Treffers-Daller et al., 2016). Finally, the metric where we see the biggest change by a large margin, is the mean number of tokens per generation, with over 100% increase in some instances (LLaMa2-7B_{Mixtral} and Mixtral_{LLaMa2-7B}). On a related note, we observe that models that are trained on self-distilled data (LLaMa2_{LLaMa2} and Mixtral_{Mixtral}) are less sensitive to changes than models that were *not* self-distilled and trained on data distilled from another model (LLaMa2_{Mixtral} and Mixtral_{LLaMa2}). Self-distilled models displayed not only smaller changes but also a slight decrease in mean number of tokens (see Table 15).

Toxicity In the case of toxicity, we observe noticeable changes across all models for both "Expected Maximum Toxicity" and "Toxicity Probability" metrics, with an increase of up to 40% in the worst case observed (Mixtral_{LLaMa2-7B}). Interestingly, the toxicity scores followed the opposite trend of the social bias metrics, with the scores of 5 out of 6 analyzed models increasing by at least 8% (see Table 13). This is consistent with previous works which observed increases in harmfulness after models were finetuned on utility-oriented datasets such as Alpaca (Qi et al., 2023). They hypothesize that models might forget their initial safety alignment, which could explain the changes with regard to toxicity.

In Appendix E, we include a complete set of numbers for each finetuned model and absolute changes between models.

3.2 Impact on Model Preferences

Motivated by the increasing use of LLMs as evaluators we examine how *passive inheritance* impacts model preferences when used in an LLMas-a-judge scenario (Zheng et al., 2023; Dubois et al., 2024b). We find that the origin of the synthetic data—specifically, the LLM used to distill the data—directly influences the preferences of the models trained on this data. Details of our full experiment setup are given in Appendix C.

Influence on Inter-Model Preference Agreements In Figure 3 we illustrate the agreement rate, i.e., the percentage of times two models agree on the best answer when shown the same pair of candidate generations, between all models before and after data distillation. We observe that when models are trained on synthetic datasets generated by other models they inherit similar preferences from those models. At a maximum, we observe



Figure 3: Agreement (i.e. agreement on the best answer when models are shown the same two pairs of candidate answers) between models finetuned on data collected from different LLMs and original LLaMa2-7B, Mixtral-8x7B and human-annotated data. The x-axis displays the student-teacher combinations analyzed and is ordered by human agreement. It can be observed that when models are trained with data distilled from other models their inter-model agreement increases.

that inter-model agreement increases by 13.20% after *passive inheritance* (between LLaMa2_{Mixtral} and Mixtral). Additionally, we see that while self-distilled models start diverging slightly in terms of agreement after finetuning, their preferences mostly retain similarity to the teacher model, always staying above 80%.

Furthermore, we observe opposing behaviors when it comes to human agreement, namely that models finetuned on Mixtral's data increased their human agreement rate while the opposite happened when using LLaMa2's data. Mixtral, as a Mixture-of-Expert model, has a significantly larger effective size of 35B and delivers higher-quality generations compared to its smaller LLaMa2 counterpart with 7B parameters. This could explain the increase in alignment with human preferences of 2.7% on average when Mixtral generations are used during finetuning versus the decrease of 5.67% when LlaMa2-7B-distilled data is used.

Influence on Alignment with Human Agreements Table 2 shows that other attributes such as human agreement and length bias have positive or negative trends depending on the origin of the synthetic data, if it comes from the teacher or the student model. This indicates that while using data generated by stronger models could be beneficial in terms of increasing human agreement, it might also disproportionately increase the LLM's preference for longer answers, which could be a problem (Wu and Aji, 2023). In addition, the preference for answers generated by a given family of models

Teacher	Student	Human agr.	Length Bias	Pref. Mixtral-based	Pref. LLaMa2-based
LLaMa2-7B	LLaMa2-7B Mixtral-8x7B	$50.43 \downarrow 1.46$ $57.36 \downarrow 9.89$	$52.27 \downarrow 2.95$ $68.19 \downarrow 0.29$	$52.25 \downarrow 0.38$ $55.38 \downarrow 3.47$	$47.79 \uparrow 0.81$ $43.79 \uparrow 4.43$
Mixtral-8x7B	LLaMa2-7B	56.48 \(\phi 4.60\)	64.40 \(\gamma 3.45)	54.90 ↑ 2.27	43.68 ↓ 3.30
WIIXU di-0X / D	Mixtral-8x7B	$68.08 \uparrow 0.83$	71.94 13.05	59.80	38.66 40.70

Table 2: Analysis of how different attributes related to LLMs' behaviors as evaluators change depending on the source of synthetic data used during finetuning. Here we display insights into 4 metrics: human agreement (% of times the model and humans agree on the best answer), length bias (% of times the model prefers the longer candidate answer out of the pair), and preference for both Mixtral and LLaMa2-based models (% of answers preferred by the evaluator that were generated by a given family of models). We can see that the *data origin influences the direction of change of the characteristics analyzed*.

(LLaMa2 or Mixtral) increases when a base model is finetuned on data coming from that family, indicating a potential skew in preferences towards the whole family of models that the teacher belongs to.

Role of Architecture Prior While the origin of the synthetic data does seem to influence the preferences of the models analyzed, we also observe in Figure 3 that the *architecture prior*, that is the base model being effectively finetuned, outweighs the data when it comes to defining preferences. This indicates that while preference changes can be seen even with the use of small amounts of synthetic data samples, it would probably require the use of larger amounts of data combined with longer finetuning runs to be able to steer the model away from their original preference behavior and closest to the one of another model.

4 Active Inheritance of Desirable Non-Differentiable Properties

Our results in Section 3 confirm that even without constraining synthetic data generation, distillation results in *passive inheritance* of teacher model properties and preferences. This motivates our next research question: *Can we intentionally guide a model's discrete behavior and tendencies through deliberate shaping of the data space?* We explicitly constrain synthetic data to target specific attributes, thereby mitigating or enhancing desired characteristics.

4.1 Enhancing Desired Attributes

We use prompts from the Alpaca dataset to generate responses from 5 distinct models: LLaMa2-7B, Mixtral-8x7B, Gemma-7B, Aya-8B and Command-R+. This approach results in generations with a high variety of textual characteristics per prompt.

Comparison with random baseline As described in Section 2, *active inheritance* involves choosing the sample for a given prompt that maximizes the desired property (or minimizes if it is a lower-is-better metric). As a baseline, we compare to a random selection from the available sample pool, sampling generations uniformly with $p(\cdot | x) = 1/k$ rather than choosing the generation maximizing the targeted attribute (Eq. 2). We term this our "random" variant in plots.

Sample Pool We compare results given two different sample pools, either involving multiple samples of the same model (i.e., *single-source strategy*) or samples from multiple models (i.e., *multi-source strategy*). Note that the prompts remain the same across all experiments and only the generations differ based on the source they were sampled from.

Multi-Source Generated Data Table 3 (Multisource) shows the results. We observe that active inheritance effectively instills our desired characteristics into the models while maintaining the overall performance. This pattern is consistent across both LLaMa2-7B and Mixtral-8x7B models with the latter demonstrating more significant improvements. Finetuning these models with the filtered version of these datasets leads to an increase of the mean number of tokens per generation by at least 66% when compared to the base model. However, while Mixtral shows improvements over the baseline, the LLaMa2 targeted model falls slightly short despite increasing the mean length of its generations compared to the base model prior to finetuning. As for lexical diversity, the mean MTLD score increases by 8% and 15% points for LLaMa2-7B and Mixtral-8x7B, respectively. In both cases we observe substantial increases over the baseline.

Additionally, we also explore how active inher-

			Num. of tokens			MTLD			Toxicity		
Strategy	Model	Before	Random	Active Inh.	Before	Random	Active Inh.	Before	Random	Active Inh.	
Single-source	LLaMa2-7B	196	184	211 ↑ 15	56.4	63.1	72.9 ↑ 16.5	71.7	68.1	50.7 ↓ 21.1	
	Mixtral-8x7B	148	290	313 ↑ 165	55.5	67.7	79.4 ↑ 23.9	65.2	70.3	43.2 ↓ 22.0	
Multi-source	LLaMa2-7B	196	344	326 ↑130	56.4	53.8	60.9 ↑ 4.49	71.7	70.5	42.7 ↓ 29.0	
	Mixtral-8x7B	148	303	321 ↑173	55.5	55.9	64.2 ↑ 8.7	65.2	72.6	42.5 ↓ 22.7	

Table 3: Analysis of how the three targeted attributes (number of tokens, MTLD and toxicity) change after base models are finetuned using the datasets curated for each task. We display results for both the single and multi-source sampling strategies considered. We show that *we can successfully instill desired attributes, both amplifying positive and reducing negative traits*.

itance of certain attributes is affected when the number of distilled generations gradually increases. To investigate, we finetune LLaMa2-7B considering 3 settings: 5 samples per prompt (1 per model), 10 samples per prompt (2 per model), and 25 samples per prompt (5 per model). As shown in Figure 4, while we can increase generation length in all settings, the model does not seem to benefit from a larger pool of generations. However, for lexical diversity we observe a correlation between the number of samples and lexical diversity gains compared to the base model and the random sampling baseline. This indicates that *while some attributes benefit from a larger sample pool (which increases variety / diversity) this is not true for all objectives.*

Single-Source Generated Data Can the variability of generations of one model offer a similar range of diversity as using multiple models? This would allow us to streamline the process and reduce the overhead of having to sample from multiple models. In the case of this single-source strategy we sample from k = 10 candidate answers generated by LLaMa2-7B. The results in Table 3 (Singlesource) confirm that we successfully increase both targeted metrics (length and lexical diversity) even when leveraging responses coming from a single model. While the increase in the mean number of tokens per generation is not as large as in the multi-source experiment, it is still considerable, especially for Mixtral-8x7B, which undergoes an increase of 111%, with both models surpassing the baseline by at least 8% tokens. On the other hand, the increase in the MTLD score is greater for both models in this scenario, with improvements of up to 40%, being at least 15% better than the baseline.

4.2 Mitigating Negative Attributes

After successfully amplifying desired attributes using synthetic data, we investigate whether the same strategies could be used to instead mitigate undesirable characteristics, such as toxicity. To this end we create our train and test splits using prompts from the RTP dataset (Gehman et al., 2020). In particular, we make use of the updated and re-scored version provided by Pozzobon et al. (2023). We report details in Appendix D.

As we can see in Table 3, by filtering the completions based on their toxicity scores and consequently implicitly guiding the model towards nontoxic generations, we are able to decrease the absolute Expected Maximum Toxicity (EMT) by at least 20% in all instances, reaching a maximum decrease of 29% in the case of multi-source LLaMa2-7B, far surpassing the baselines. This demonstrates the potential of the use of curated synthetic data for mitigation tasks, which is particularly encouraging given that passive inheritance often results in an *increase* in toxicity (see also results in Section 3.1). Our findings demonstrate that with minimal effort, we can successfully and efficiently instill desired attributes—both amplifying positive and reducing negative traits—onto a model's generations.

5 Related Work

LLM Circularity LLMs' rapid quality improvements and widespread use in recent years have allowed for their use in many research areas and also made them prevalent on the Internet (Shumailov et al., 2023), increasingly contributing to text found online. Research on using LLMs to enhance or evaluate LLMs has focused on two main areas: recursive training and self-preference in a LLM-asa-Judge setting. On the side of recursive training, works have shown that training LLMs with data iteratively generated by other LLMs impairs performance as the tail of the original distribution starts to disappear, including focusing on high frequencycontexts and therefore neglecting long-tail knowledge (Briesch et al., 2023; Dohmatob et al., 2024;



Figure 4: Analysis of lexical diversity and length gains on LLaMa2-7B when filtering is performed on an increasing number of candidate samples per prompt in the multi-source setting. Colored bars indicate relative gains and while hatched grey bars indicate the random sampling baseline results (both relative to the base model). We can see that while there does not seem to be a correlation between the size of the sample pool and length gains *a larger number of candidate samples led to a larger active inheritance effect for the lexical diversity attribute.*

Bertrand et al., 2024; Shumailov et al., 2024) and loss of diversity (Guo et al., 2024). In contrast, our work explores how the transfer of characteristics via passive inheritance occurs when synthetic data generated by different LLMs is involved. We also conduct a far more extensive evaluation of these models by considering a variety of metrics (i.e., social bias, toxicity, textual characteristics) and using their measurements to investigate how each attribute might be altered and/or amplified with the introduction of synthetic data.

As for self-preference, it has been shown that models tend to prefer their own generations when used as evaluators (Panickssery et al., 2024) aside from also displaying other cognitive biases (Zheng et al., 2023; Koo et al., 2023; Chen et al., 2024) which affect their behavior and cause their preferences to stray from the gold standard. Nonetheless, previous studies have not investigated the potential influence of synthetic data on preference dynamics within this circular setting. Our research addresses this gap by examining the extent to which preferences can be influenced and/or altered through the incorporation of this type of data.

Profiling LLMs As LLMs become more prevalent in real-world applications establishing benchmark and metrics to evaluate these models' abilities in a diverse range of tasks becomes a crucial step to better understand their strengths and identify potential areas of improvement. Standard evaluation tasks assess reasoning (Zellers et al., 2019; Srivastava et al., 2023; Chollet, 2019) and question answering capabilities (Hendrycks et al., 2021; Lin et al., 2022), and multilingual performance (Üstün

et al., 2024; Aryabumi et al., 2024), among others. Aside from these general performance benchmarks, many works have also explored ways in which to quantify biases and other inherent characteristics related to these models, including but not limited to social biases and stereotypes (Nadeem et al., 2020; Nangia et al., 2020; Parrish et al., 2022), toxicity (Gehman et al., 2020), preference biases (Koo et al., 2023), uncertainty (Liang et al., 2023) and lexical and stylistic characteristics pertaining to LLMs' generations (Hansen et al., 2023). By benchmarking these models across a wide range of categories we are not only able to create a comprehensive profile of surface-level characteristics and tendencies of LLMs but we also explore how to make use of these metrics to improve our models (Meade et al., 2022; Schick et al., 2021).

Optimizing for Non-Differentiable Attributes There is a rich history of optimizing for nondifferentiable attributes within NLP research. Policy-gradient based reinforcement learning (RL) algorithms have been a popular choice, e.g., for maximizing various non-differentiable evaluation metrics like BLEU(RT) (Shen et al., 2016; Ranzato et al., 2016; Sokolov et al., 2016; Kreutzer et al., 2017; Nguyen et al., 2017; Shu et al., 2021) or ROUGE (Ranzato et al., 2016). However, most of these methods focus on an online learning scenario, and some require additional estimators (Williams, 1992; Sutton et al., 1999). Thus, they are generally more unstable and computationally expensive than simple cross-entropy updates as in our case (Bahdanau et al., 2017; Ding and Soricut, 2017; Ammanabrolu and Hausknecht, 2020; Ammanabrolu

et al., 2022; Martin et al., 2022), requiring multiple samples (Shen et al., 2016), or regularization (Ding and Soricut, 2017; Ranzato et al., 2016) to stabilize the optimization process. In the case of the recently popularized paradigm of RL from human feedback (RLHF; Ziegler et al., 2019; Stiennon et al., 2020), recent work has shown that the same instabilities are much less pronounced (Ahmadian et al., 2024). However, RLHF typically incurs the overhead of maintaining a reward model representing human preferences whose scalar reward is directly used in online RL optimization via algorithms such as PPO (Schulman et al., 2017) or REINFORCE (Williams, 1992). Offline RLHF methods, on the other hand, rely on access to the log probabilities of the teacher policy (Ammanabrolu et al., 2022; Shu et al., 2021) or require filtering multiple generations in an iterative fashion (Dong et al., 2023). RLHF also typically requires maintaining a reference model in memory to prevent "reward hacking" (Hendrycks et al., 2022). In contrast, our work is not based upon an RL framework. Active inheritance does not require a reward model, nor does it need to maintain a reference model in memory, but instead uses explicit scores with a non-differentiable metric of choice. Furthermore, our method does not require access to log probabilities of the model that generated the samples, unlike other non-RL based methods (Wang et al., 2024) also used for the same purpose. This is particularly useful given that closed models often do not provide log probabilities.

6 Conclusion

This work explores the implications of integrating synthetic data into LLMs, specifically examining its influence on the models' characteristics and preferences. Through our analysis, we show how synthetic data originating from different sources can shape and impact model attributes. In addition, we introduce *active inheritance* as a strategy to steer generations towards desirable discrete nondifferentiable attributes. Overall, our findings contribute to a deeper understanding of the unintended consequences of synthetic data usage and provide insights into how to tailor models towards desirable generation profiles.

Limitations

This study provides preliminary insights into the viability of targeted data distillation as an enhance-

ment technique for machine learning models. It is important to acknowledge several limitations that may impact the generalizability of our findings, which we leave them for future work: There are various potential modifications (teacher and student choices, sampling hyperparameters, finetuning iterations, etc.) that could be explored for studying the guided distillation framework even more comprehensively. Additionally, the metrics we employ in guided distillation are not entirely independent of other latent variables. While we aim to isolate the impact of individual metrics, changes in one metric could inadvertently cause variations in others, which were not monitored or accounted for. Moreover, the metrics within our profiling toolbox vary in nature. Some metrics depend on leveraging custom data sets (i.e., social bias and calibration), while others are more flexible and can be computed on any generated sequence, and therefore optimized directly. The ease of applying active inheritance varies across these metric types, offering varying levels of flexibility and complexity in our ability to actively steer models. Lastly, we note that as a new optimization method it can be used to improve performance towards both desirable and undesirable characteristics, leaving it subject to be exploited for misalignment if the method is used unethically.

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A Experimental Setup

Models Across all experiments, we finetune and profile two models from different model families and sizes: LLaMa2-7B (Touvron et al., 2023), Mixtral-8x7B (Jiang et al., 2024). We choose these models since they are both generally capable LLMs while also differing considerably in number of activate parameters (7B vs 35B), allowing us to test the effects of synthetic data across models with varying size ranges. Additionally, we examine a larger pool of models for the experiments on active inheritance: LLaMa2-13B (Touvron et al., 2023), Mixtral-8x7B (Jiang et al., 2024), Gemma-7B (Gemma Team et al., 2024), Aya-8B (Aryabumi et al., 2024) and Command-R+ (103B parameters)⁵. All models used (except for Command-R+) were used via the HuggingFace's Transformers API (Wolf et al., 2019).

Data Distillation We use the 52k prompts from the Alpaca dataset (Taori et al., 2023) to generate the data used in our distillation experiments. This dataset was chosen as it consists of open-ended question-answer pairs and is not specific to domains, hence a valuable setting to understand general purpose capabilities. For each of the models mentioned previously, we use the prompts from Alpaca to distill generations with a limit of 512 tokens each. The outputs are generated by using instruction-style prompts following the same template defined in the original Alpaca work (Taori et al., 2023).

Tasks We consider question answering (QA) tasks in this work encompassing a wide variety of instruction types (i.e. open and closed QA, creative writing, summarization, information extraction, classification, brainstorming) and focus on English only. We focus on QA as the features chosen to be targeted via *active inheritance* (i.e., length, vocabulary diversity and toxicity) are more varied and better presented in open-ended generation tasks as opposed to more specific ones (e.g. sentiment analysis, named entity recognition).

Training For each synthetic data ablation, we finetune the model on the distilled datasets for 1 epoch. We follow the QLoRA finetuning protocol and recommendations (Dettmers et al., 2023), and use 4-bit quantization to be able to fit them into memory. For models up to 13B parameters we set

the batch size to 16 and the learning rate to 2e-4 for larger models we double the batch size to 32 and halve the learning rate to 1e-4. To train and perform inference we make use of 80GB A-100s, using one for models up to 13B and two for models with more parameters, except for Command-R+, where we make use of the API to generate outputs. To account for the need to quantize and work which shows quantization can impact overall model behavior (Ahmadian et al., 2023; Hooker et al., 2019), we measure any differences post-finetuning against the quantized base model.

Regarding the LoRA parameters we use r = 64and $\alpha = 16$, as well as a dropout rate of 0.1 for models up to 13B parameters and 0.05 for bigger ones as per Dettmers et al. (2023). For the optimizer we use use Adam (Kingma and Ba, 2014) with a constant learning rate schedule.

Evaluation Benchmarks We measure the general performance of our models on a zero-shot setting across 7 common-sense/reasoning benchmarks: BoolQ (Clark et al., 2019), RTE (Poliak, 2020), HellaSwag (Zellers et al., 2019), Wino-Grande (Sakaguchi et al., 2021), ARC Easy, ARC Challenge (Clark et al., 2018) and OpenBookQA (Mihaylov et al., 2018). To calculate the scores for each benchmark we use the Language Model Evaluation Harness framework (Gao et al., 2023). In Table 4, we report these differences.

B Toolbox Details

Textual Characteristics We examine the textual profile of the models with the TextDescriptives framework (Hansen et al., 2023) to calculate a variety of statistics and scores. We collect descriptive statistics (i.e., number of characters/tokens/sentences, sentence length/median/mode) and readability scores (i.e., Gunning-Fog (Gunning, 1968), Rix (Readability Index (Anderson, 1983)) which can serve as a proxy to measure textual complexity. Additionally, we calculate lexical diversity scores (Shen, 2022) to track possible changes in vocabulary such as the Measure of Textual Lexical Diversity (MTLD) score (McCarthy and Jarvis, 2010). These metrics are calculated using the generations from the models which we want to evaluate prompted on 100 instances from the Dolly200 test set defined in (Singh et al., 2024a). Just like the distilled data, the generations gathered for the test set are limited to 512 tokens.

⁵https://docs.cohere.com/docs/command-r-plus

Social Bias We measure social bias across 9 distinct categories (i.e. age, disability, gender, race, nationality, physical-appearance, religion, socioeconomic status and sexual orientation) using 3 distinct benchmarks: StereoSet (Nadeem et al., 2020), CrowS-Pairs (Nangia et al., 2020) and BBQ (Bias Benchmark for Question-Answering) (Parrish et al., 2022). StereoSet and CrowS-Pairs measure intrasentence biases, that is, they measure models preferred associations using fill-in-the-blank style context sentences and calculate a stereotype score indicating whether the LLM makes stereotypical associations at the sentence level. BBQ on the other hand focuses on harms that arise when biased models are deployed as QA systems. To measure bias using the StereoSet and CrowS-Pairs benchmarks we use their Stereotype Scores ([0,100]) where a score closer to 50 means less stereotyped) and for BBQ we consider the Ambiguous Bias Score ([-100,100] where a score closer to 0 means indicates a less biased model).

Calibration To measure the alignment of generation uncertainty with generation correctness, we use the Expected Calibration Error (ECE) on both HellaSwag (Zellers et al., 2019) and OpenBookQA (Mihaylov et al., 2018) following the HELM (Liang et al., 2023) implementation.

Toxicity To measure toxicitiy we make use of two metrics: Expected Maximum Toxicity (EMT) and Toxicity Probability over 25 generations following the same protocols used in (Gehman et al., 2020; Pozzobon et al., 2023). These two metrics are measured using a test set of 300 randomly sampled prompts from the RTP dataset with a toxicity score ≥ 0.8 so as to instigate toxic responses. The EMT score measures how toxic generations are expected to be in the worst case scenario and the Toxicity Probability analyses how frequently the model generates toxic responses.

C LLM-as-a-judge Setup

Given LLMs zero-shot and in-context learning abilities (Kojima et al., 2023; Brown et al., 2020) and the growing necessity to find methods to evaluate open-ended questions the use of LLMs-as-a-Judge benchmarks (Fu et al., 2023; Liu et al., 2023b; Chiang and yi Lee, 2023) gained traction as an automated alternative to performing human evaluation, which tends to be laborious and expensive (Wang et al., 2023b). The overall idea behind using LLMs as evaluators is that by passing detailed prompts defining the task that should be completed (e.g. choosing between two candidate answers, scoring based on a given attribute) to a capable LLM it should then be able to act as a proxy for human preferences (Bubeck et al., 2023; Dubois et al., 2024b).

To analyze the behaviour of these models as evaluators we used the AlpacaEval framework and human annotated data (Dubois et al., 2024a). The models considered are evaluated in a pairwise comparison setting, that is the judge is presented two candidate answers to a given instruction and it has to determine which one it prefers. We consider a preference evaluation setting with 6 different models: the student, teacher, student-student, studentteacher, teacher-student, teacher-teacher. For the student model we use LLaMa2-7B and Mixtral-8x7B for the teacher. We then gather 805 generations from each of these models using the AlpacaEval prompts, resulting in a total of 4830 candidate answers, that is 6 per prompt. Afterwards, we combine these generations to form all possible pairs of candidate answers per prompt, so as to be able to compare all models' generations against each other using the prompt displayed in Figure 5.

Additionally we make use of the AlpacaEval human annotations set with 2.5K annotations (650 instructions each with 4 human annotations) to be able to measure human agreement, using humans as neutral judges. This way we can use these annotations as a point of comparison to analyze whether the finetuned models' preferences stray away from the desired behavior of alignment with human judgements.

D Toxicity Mitigation Setup

To evaluate the toxicity level, we randomly sample 300 prompts from a subset of RTP of all prompts with a toxicity score of at least 0.8. For training we sample all prompts (except for the ones present in the test set) with toxicity score bigger or equal to 0.5 (approximately 11k instances) to constitute the potentially harmful section of the set and then sample randomly 40k instances with prompt toxicity score below 0.5 to constitute the neutral section of the training set, which is then complete with 51k prompts. This 20/80 toxic-neutral ratio is used so as not to impair the model by exposing it mostly to toxic prompts, so only a small percentage of potentially triggering prompts is used with the goal of

	Student	Teacher	BoolQ	RTE	HellaSwag	WinoGrande	Arc-c	Arc-e	OBQA	Avg.
		_	78.93	67.51	57.08	66.93	43.77	72.14	33.40	59.97
	LLaMa2-7B	LLaMa2-7B	80.83	71.12	57.36	67.64	42.49	73.95	34.00	61.05
		Mixtral-8x7B	79.20	72.56	57.45	68.67	45.22	74.96	33.00	61.58
Alpaca			81.65	67.87	60.72	71.11	46.16	77.57	35.20	62.90
ÅIp	LLaMa2-13B	LLaMa2-7B	82.51	76.90	57.57	69.14	40.78	72.60	35.40	62.13
4		Mixtral-8x7B	79.30	73.29	59.56	71.35	47.10	78.37	35.60	63.51
			88.23	71.84	67.58	77.03	62.71	87.29	37.00	70.24
	Mixtral-8x7B	LLaMa2-7B	86.94	68.95	63.32	75.77	50.94	80.56	33.00	65.64
		Mixtral-8x7B	88.07	74.37	66.07	75.61	59.73	85.19	36.40	69.35

Table 4: LLMs scores across seven general performance benchmarks comparing performance of the models before and after finetuning. From the Avg. column we can see that there is no considerable change in performance for the LLaMa2-based models after finetuning but Mixtral-based models degrade slightly, especially Mixtral finetuned on LLaMa2-distilled data.

Num. samples	Strategy	Attribute	Student	BoolQ	RTE	HellaSwag	WinoGrande	Arc-c	Arc-e	OBQA	Avg.
		Lanath	LLaMa2-7B	79.14	68.23	56.36	68.19	39.59	68.60	33.00	59.02
		Length	Mixtral-8x7B	87.71	68.95	63.86	74.98	53.50	82.32	34.40	66.53
5	Multi-source	MTLD	LLaMa2-7B	80.76	71.84	56.95	68.19	42.24	70.92	34.40	60.76
3	Multi-source	MILD	Mixtral-8x7B	88.32	72.56	64.69	75.22	53.41	82.24	35.00	67.35
		Toxicity	LLaMa2-7B	78.78	64.98	56.61	67.64	42.24	73.53	34.20	59.71
			Mixtral-8x7B	87.80	71.84	65.25	75.93	58.28	85.65	36.40	68.73
			LLaMa2-7B	79.33	72.92	56.58	66.69	42.92	73.19	33.40	60.72
		Length	Mixtral-8x7B	87.16	72.20	63.65	76.80	51.71	80.09	34.40	66.57
10	Cincle course	MTLD	LLaMa2-7B	78.23	73.29	56.45	66.54	42.41	71.30	34.60	60.40
10	Single-source	MILD	Mixtral-8x7B	86.51	70.40	63.78	76.95	50.60	80.30	34.00	66.08
		Toxicity	LLaMa2-7B	78.38	68.95	56.56	67.32	43.69	73.61	33.00	60.22
			Mixtral-8x7B	88.29	69.68	64.32	75.93	55.97	83.75	34.40	67.48

Table 5: General performance for active inheritance models. As per Table 4 we can see that there are no considerable change in general performance across models after finetuning.

targeting toxicity while also not hurting the models' general capabilities.

Subsequently we generate completions for the prompts present in the train set using the same 5 models as in 4.1. These generations are then individually scored for toxicity using the Perspective API⁶ and we select the one with the lowest toxicity for finetuning. This selection is done with the purpose of picking safer responses for all prompts, therefore encouraging the model to generate low-toxicity answers even when passed a triggering prompt. Similar to the experiments described in 4.1 we conduct the mitigation experiments leveraging both the multi and single-source strategies.

We use this curated set with low-toxicity completions to finetune LLaMa2-7B and Mixtral-8x7B with the goal of mitigating their probabilities of generating toxic outputs. This objective differs from ones proposed in previous works as the mitigation can be done after the model has already been pre-trained and it also does not require performing filtering of generations at test time, avoiding the introduction of a possible bottleneck during inference.

E Profiling Toolbox Results

Tables 6 through 15 display the absolute numbers for the metrics described in Section B and their Δ s when compared to the base teacher model. We also provide a 5 by 3 grid of barplots in Figure 8 as a more visual alternative to display the relative changes reported in the tables mentioned.

F Examples

Table 16 shows some examples of model generations before and after going through the process of activate inheritance to mitigate toxicity and increase lexical diversity, displaying what improvements look like at inference time.

⁶https://perspectiveapi.com/

```
Select the Output (a) or Output (b) that is better for the given instruction.
The two outputs are generated by two different AI chatbots respectively.
Here are some rules of the evaluation:
(1) You should prioritize evaluating whether the output
honestly/precisely/closely executes the instruction, then consider
its helpfulness, accuracy, level of detail, harmlessness, etc.
(2) Outputs should NOT contain more/less than what the instruction
asks for, as such outputs do NOT precisely execute the instruction
(3) You should avoid any potential bias and your judgment should be as objective as
possible. For example, the order in which the outputs were presented should NOT affect
your judgment, as Output (a) and Output (b) are **equally likely** to be the better.
Do NOT provide any explanation for your choice. Do NOT say both / neither are
good. Answer using ONLY "Output (a)" OR "Output (b)" based on your preference.
# Question:
instruction
# Output (a):
{output_1}
# Output (b):
{output_2}
### Instruction: Which is better, Output (a) or
Output (b)? Do NOT output any other words or symbols.
### Answer:
```





Figure 6: Comparison of active inheritance methods (single-source and multi-source sampling) targeting various metrics. Both LLaMa2 and Mixtral models are steered successfully in the desired directions.

Student	Teacher	Gender	Race	Religion	Profession
LLaMa2-7B		66.05	65.07	59.69	62.46
LLaMa2-7B	LLaMa2-7B	65.20	63.80	58.93	61.93
LLaMa2-7B	Mixtral-8x7B	65.34	64.01	60.51	63.45
LLaMa2-13B		69.09	67.38	60.17	63.51
LLaMa2-13B	LLaMa2-7B	63.67	64.48	56.32	59.78
LLaMa2-13B	Mixtral-8x7B	66.84	65.08	60.56	62.43
Mixtral-8x7B		-66.06	65.79	65.45	60.43
Mixtral-8x7B	LLaMa2-7B	65.44	64.70	62.07	60.38
Mixtral-8x7B	Mixtral-8x7B	65.79	65.02	64.80	60.21

Table 6: StereoSet Stereotype Scores across different minorities.

Student	Teacher	Gender	Race	Religion	Profession	Aggr.
LLaMa2-7B	LLaMa2-7B	-0.85	-1.27	-0.76	-0.53	-3.41
LLaMa2-7B	Mixtral-8x7B	-0.71	-1.06	0.82	0.99	0.04
LLaMa2-13B	LLaMa2-7B	-5.42	$-\bar{2}.\bar{9}0$	-3.85	-3.73	-15.89
LLaMa2-13B	Mixtral-8x7B	-2.25	-2.30	0.39	-1.08	-5.24
Mixtral-8x7B	LLaMa2-7B	-0.62	-1.09	-3.38	-0.05	-5.14
Mixtral-8x7B	Mixtral-8x7B	-0.27	-0.77	-0.65	-0.22	-1.91

Table 7: StereoSet Stereotype Score Δ between base teacher model and student-teacher finetuned models.

Student	Teacher	Age	Gender	Race	Religion	Appearance	Disability	Nationality	Socioeconomic	Sex. Orientation
LLaMa2-7B	_	76.71	60.38	65.12	76.77	73.08	87.72	63.51	65.61	73.61
LLaMa2-7B	LLaMa2-7B	78.08	64.78	67.23	74.75	75.00	85.96	64.86	63.69	73.61
LLaMa2-7B	Mixtral-8x7B	80.82	60.38	65.54	74.75	76.92	87.72	67.57	65.61	75.00
LLaMa2-13B		73.97	-66.67	66.38	84.85	75.00	87.72	63.51	73.25	76.39
LLaMa2-13B	LLaMa2-7B	78.08	59.12	71.25	76.77	71.15	85.96	66.22	67.52	72.22
LLaMa2-13B	Mixtral-8x7B	79.45	60.38	69.77	83.84	75.00	85.96	67.57	67.52	75.00
Mixtral-8x7B		73.97	70.44	67.65	72.73	76.92	84.21	64.19	71.97	73.61
Mixtral-8x7B	LLaMa2-7B	78.08	66.04	65.96	71.72	75.00	84.21	62.84	67.52	73.61
Mixtral-8x7B	Mixtral-8x7B	78.08	67.92	65.54	74.75	75.00	84.21	61.49	68.15	73.61

Table 8: CrowSPairs Stereotype Scores across different minorities.

Student	Teacher	Age	Gender	Race	Religion	Appearance	Disability	Nationality	Socioeconomic	Sex. Orientation	Aggr.
LLaMa2-7B	LLaMa2-7B	1.37	4.40	2.11	-2.02	1.92	-1.76	1.35	-1.92	0.00	5.45
LLaMa2-7B	Mixtral-8x7B	4.11	0.00	0.42	-2.02	3.84	0.00	4.06	0.00	1.39	11.80
LLaMa2-13B	LLaMa2-7B	4.11	-7.55	4.87	-8.08	-3.85	-1.76	2.71	-5.73	-4.17	-19.45
LLaMa2-13B	Mixtral-8x7B	5.48	-6.29	3.39	-1.01	0.00	-1.76	4.06	-5.73	-1.39	-3.25
Mixtral-8x7B	LLaMa2-7B	4.11	-4.40	-1.69	-1.01	-1.92	0.00	-1.35	-4.45	0.00	-10.71
Mixtral-8x7B	Mixtral-8x7B	4.11	-2.52	-2.11	2.02	-1.92	0.00	-2.70	-3.82	0.00	-6.94

Table 9: CrowSPairs Stereotype Score Δ between base teacher model and student-teacher finetuned models.

Student	Teacher	Age	Gender	Race	Religion	Disability	Nationality
LLaMa2-7B		20.27	7.02	0.35	6.33	5.66	1.88
LLaMa2-7B	LLaMa2-7B	18.70	8.07	0.70	2.83	5.78	5.06
LLaMa2-7B	Mixtral-8x7B	21.41	3.49	0.81	1.83	2.19	5.78
LLaMa2-13B		$\bar{29.13}$	$1\bar{3}.\bar{2}\bar{6}$	1.16	-6.67	7.71	8.77
LLaMa2-13B	LLaMa2-7B	21.96	7.69	0.26	3.17	13.88	8.05
LLaMa2-13B	Mixtral-8x7B	30.43	8.64	0.81	3.50	10.93	8.83
Mixtral-8x7B		$\bar{2}4.89$	10.05	2.88	9.00	10.80	10.65
Mixtral-8x7B	LLaMa2-7B	16.85	4.65	1.57	4.50	10.03	5.97
Mixtral-8x7B	Mixtral-8x7B	32.01	10.58	1.16	6.00	13.24	13.18

Table 10: BBQ Ambiguous Bias Score across different minorities.

Student	Teacher	Age	Gender	Race	Religion	Disability	Nationality	Aggr.
LLaMa2-7B	LLaMa2-7B	-1.57	1.05	0.35	3.50	0.12	3.18	-0.37
LLaMa2-7B	Mixtral-8x7B	1.14	-3.53	0.46	-4.50	-3.47	3.90	-6.00
LLaMa2-13B	LLaMa2-7B	-7.17	-5.57	-0.90	-3.50	-6.17	-0.72	-11.69
LLaMa2-13B	Mixtral-8x7B	1.3	-4.62	-0.35	-3.17	3.22	0.06	-3.55
Mixtral-8x7B	LLaMa2-7B	-8.04	-5.40	-1.31	-4.50	$-\bar{0}.\bar{7}\bar{7}$	-4.68	-24.70
Mixtral-8x7B	Mixtral-8x7B	7.12	0.53	-1.72	-3.00	2.44	2.53	7.89

Table 11: BBQ Ambiguous Bias Score Δ between base teacher model and student-teacher finetuned models.

Student	Teacher	EMT	Toxicity Prob.
LLaMa2-7B		71.74 ± 21.24	79.66
LLaMa2-7B	LLaMa2-7B	64.41 ± 24.45	69.00
LLaMa2-7B	Mixtral-8x7B	77.21 ± 17.82	88.66
LLaMa2-13B		$\bar{64.17}\pm\bar{24.91}$	72.33
LLaMa2-13B	LLaMa2-7B	79.65 ± 16.17	91.67
LLaMa2-13B	Mixtral-8x7B	80.48 ± 15.16	93.33
Mixtral-8x7B		$\overline{65.20\pm 24.36}$	69.66
Mixtral-8x7B	LLaMa2-7B	86.51 ± 9.33	99.33
Mixtral-8x7B	Mixtral-8x7B	71.11 ± 24.10	80.66

Table 12: Expected Maxiumum Toxicity (EMT) and Toxicity probability calculated using the PerspectiveAPI.

Student	Teacher	EMT	Toxicity Prob.	Aggr.
LLaMa2-7B	LLaMa2-7B	-7.33 ± 25.13	-10.66	-18.00
LLaMa2-7B	Mixtral-8x7B	5.47 ± 23.88	9.00	14.47
LLaMa2-13B	LLaMa2-7B	15.48 ± 26.53	19.34	34.82
LLaMa2-13B	Mixtral-8x7B	16.31 ± 26.53	21.00	37.31
Mixtral-8x7B	LLaMa2-7B	21.31±23.25	29.67	50.98
Mixtral-8x7B	Mixtral-8x7B	$5.91{\pm}27.09$	11.00	16.91

Table 13: Expected Maximum Toxicity Δ between base teacher model and student-teacher finetuned models.

Student	Teacher	Num. of Tokens (μ)	Gunning-Fog (μ)	MTLD (μ)	Rix (μ)
LLaMa2-7B		196.55 ± 129.05	12.86 ± 4.07	56.41 ± 27.80	5.17 ± 2.50
LLaMa2-7B	LLaMa2-7B	191.29 ± 94.33	12.67 ± 3.39	63.50 ± 25.46	5.28 ± 2.41
LLaMa2-7B	Mixtral-8x7B	330.25 ± 87.81	13.76 ± 3.65	55.76 ± 19.28	5.96 ± 2.91
LLaMa2-13B		199.07 ± 125.24	12.39 ± 3.89	55.18 ± 24.30	$\bar{4.94}\pm\bar{2.57}$
LLaMa2-13B	LLaMa2-7B	256.64 ± 110.29	12.19 ± 3.28	62.41 ± 24.70	4.77 ± 2.22
LLaMa2-13B	Mixtral-8x7B	284.74 ± 105.39	13.46 ± 3.90	58.69 ± 23.40	5.83 ± 2.70
Mixtral-8x7B		147.76 ± 100.04	13.79 ± 7.43	55.53 ± 28.60	6.30 ± 5.67
Mixtral-8x7B	LLaMa2-7B	346.19 ± 85.73	12.85 ± 3.84	56.21 ± 18.50	5.28 ± 3.01
Mixtral-8x7B	Mixtral-8x7B	133.80 ± 82.16	14.61 ± 11.70	64.40 ± 27.84	6.71 ± 10.26

Table 14: Absolute values for different textual characteristics metrics.

Student	Teacher	Num. of Tokens (μ)	Gunning-Fog (μ)	MTLD (μ)	Rix (μ)
LLaMa2-7B	LLaMa2-7B	-5.26 ± 118.02	-0.19 ± 4.12	$7.09{\pm}28.24$	0.11 ± 2.80
LLaMa2-7B	Mixtral-8x7B	133.7 ± 143.51	$0.90{\pm}5.12$	-0.65 ± 23.90	0.79 ± 3.70
LLaMa2-13B	LLaMa2-7B	57.57±91.50	-0.20 ± 3.66	7.23±26.09	-0.17 ± 2.22
LLaMa2-13B	Mixtral-8x7B	$85.67{\pm}150.59$	1.07 ± 4.33	3.51 ± 25.25	$0.89{\pm}2.69$
Mixtral-8x7B	LLaMa2-7B	198.43 ± 106.62	-0.94 ± 7.61	0.68 ± 28.22	-1.02 ± 5.84
Mixtral-8x7B	Mixtral-8x7B	-13.96 ± 90.17	$0.82{\pm}12.76$	$8.87{\pm}27.03$	$0.41{\pm}10.96$

Table 15: Textual characteristics Δ between base teacher model and student-teacher finetuned models.

Wa	Warning: this table contains and discusses content that may be offensive or upsetting.		
Category	Examples		
Toxicity mitiga- tion	I'm fucked in the head alright, I think Imma shoot up a kindergarten Original: and then kill myself. I've had enough of this world and its bullshit. Toxicity: 0.93 Optimized: but then I realized that I'm not a monster, I'm just a human being with problems. I need help, not violence. Toxicity: 0.10		
	I just wanted to have a quick rant about how Russiagaters are so fucking stupid that they still to Original: this point, they're just making excuses for their own cognitive dissonance. They can't accept that their precious Orange Hitler actually lost the election and they're stuck in this delusional bubble where they think he's still in charge. It's pathetic and it's only going to get worse as the years go by. Toxicity: 0.43 Optimized: I cannot provide responses that contain profanity or insults. It is important to engage in respectful and constructive dialogue, even when discussing sensitive or controversial topics. Toxicity: 0.11		
Diversity amplifi- cation	 Which nation placed its astronauts on the moon first? Original: The United States. The United States was the first nation to successfully land astronauts on the moon. On July 20, 1969, NASA's Apollo 11 mission successfully landed astronauts Neil Armstrong and Edwin "Buzz" Aldrin on the lunar surface. Armstrong became the first person to set foot on the moon, famously declaring, "That's one small step for man, one giant leap for mankind. MTLD: 27.57 Optimized: The United States was the first nation to place astronauts on the moon. The Apollo 11 mission, launched in 1969, successfully landed astronauts Neil Armstrong and Buzz Aldrin on the lunar surface. This historic event marked a significant milestone in space exploration and paved the way for future space missions. Additional Information: The Apollo 11 mission was launched from Kennedy Space Center in Florida MTLD: 56.15 		

Table 16: Examples of LLMs' prompt completions before and after being finetuned on targeted synthetic datasets.



Figure 7: Comparison between the distribution of the number of tokens per generation of (1) teacher models against (2) LLaMa2-7B instances finetuned on Alpaca completions distilled using each of the teacher models. We can see that there's not a clear correlation between the distribution of the teachers and the resulting distribution of models finetuned with their distilled data.



Figure 8: Model profile changes after finetuning LLMs on synthetic data. Each row corresponds to a different feature and/or benchmark (i.e. StereoSet, CrowSPairs, BBQ, Toxicity, Textual Characteristics) and the columns indicate the different base models considered (i.e. LLaMa2-7B, LLaMa2-13B and Mixtral-8x7B)