
An Emulator for Fine-tuning Large Language Models using Small Language Models

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Abstract

Widely used language models (LMs) are typically built by scaling up a two-stage training pipeline: a pre-training stage that uses a very large, diverse dataset of text and a fine-tuning (sometimes, ‘alignment’) stage using more targeted examples of specific behaviors and/or human preferences. While it has been hypothesized that knowledge and skills come from pre-training, and fine-tuning mostly filters this knowledge and skillset, this intuition has not been rigorously tested. In this paper, we test this hypothesis with a novel methodology for scaling these two stages independently, essentially asking, *What would happen if we combined the knowledge learned by a large model during pre-training with the knowledge learned by a small model during fine-tuning (or vice versa)?* Using an RL-based framework derived from recent developments in learning from human preferences, we introduce *emulated fine-tuning (EFT)*, a principled and practical method for sampling from a distribution that approximates the result of pre-training and fine-tuning at different scales. Our experiments with EFT show that scaling up fine-tuning tends to improve helpfulness, while scaling up pre-training tends to improve factuality. Further, we show that EFT enables test-time adjustment of competing behavioral factors like helpfulness and harmlessness without additional training. Finally, we find that a special case of emulated fine-tuning, which we call *LM up-scaling*, avoids resource-intensive fine-tuning of large pre-trained models by ensembling small fine-tuned models with large pre-trained models, essentially ‘emulating’ the result of fine-tuning the large pre-trained model. Up-scaling consistently improves helpfulness and factuality of widely used pre-trained models like Llama, Llama-2, and Falcon, without additional hyperparameters or training.

1 Introduction

Widely used instruction-following large language models (LLMs) typically follow a two-stage training procedure, with a stage of unsupervised pre-training on a large, diverse dataset followed by supervised fine-tuning on a much smaller, carefully curated dataset (Raffel et al., 2020; Chung et al., 2022). While both stages are important in producing models that possess broad world knowledge and perform a given task reliably, identifying exactly what capabilities emerge in which stage and at what scale is difficult (Wei et al., 2022; Schaeffer et al., 2023). For example, pre-trained models typically require careful prompting in order to perform a task; after fine-tuning for instruction following, they typically do not. Evaluation of the extent to which the core capability of ‘instruction following’ is learned in pre-training vs. fine-tuning is thus seriously complicated by the choice of this prompt. To enable more direct attribution of capabilities to a stage of training, we introduce a technique for emulating the result of combining the capabilities gained from pre-training and fine-tuning, even if these two stages occur at different model scales. This technique, which we call *emulated fine-tuning (EFT)*, enables a) direct study of the capabilities that change as only one stage is scaled up or down,

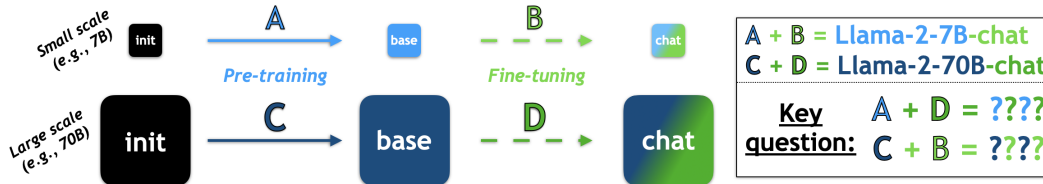


Figure 1: **Emulated fine-tuning (EFT)** enables a direct answer to the question of *what happens when we combine what is learned from pre-training a model of one size with what is learned from fine-tuning a model of a different size?* Conventional models combine the learnings of pre-training and fine-tuning at the same size (A + B, C + D). In contrast, EFT enables choosing these independently, essentially allowing a principled approach to evaluating the result of A + D and C + B.

as well as b) the practical benefit of approximating the result of fine-tuning a large model without the associated computational expense.

Emulated fine-tuning is based on a simple factorization of the logits of a fine-tuned language model into a) the base logprobs of a pre-trained base model and b) the ‘behavior delta’, or the difference between the logprobs of a base model and fine-tuned model. This delta is a compact representation of the behavior change learned in fine-tuning and can be justified through either a reinforcement learning (Rafailov et al., 2023) or Bayesian inference (Korbak et al., 2022) framework. EFT thus emulates the result of pre-training at one scale and fine-tuning at another by adding base logprobs computed by a model at one size and the behavior delta computed by a models of a different size. For example, using models from the Llama-2 family, we can emulate the result of pre-training at 70B scale and fine-tuning at 7B scale by performing the log probability algebra **Llama-2-base 70B + (Llama-2-chat 7B - Llama-2-base 7B)**, where the first term is the base log probability and the term in parentheses is the behavioral delta.

Using emulated fine-tuning, we analyze the results of pre-training and fine-tuning at various scales for multiple model families and datasets. Our analyses provide evidence supporting the intuition that pre-training at scale enables greater accumulating of raw knowledge (improved factual correctness), while fine-tuning at larger scale produces greater helpfulness (improved user satisfaction) (cf. Gudibande et al., 2023). Beyond this scientific finding, we also find that EFT enables boosting the performance of small fine-tuned models by a process we call *up-scaling*, essentially ensembling the small fine-tuned model with a larger pre-trained model, without any fine-tuning or modifications to either model. Our experiments show that in scenarios where fine-tuning a small language model is viable (e.g., Falcon-7B) but fine-tuning a larger language model is not due to resource constraints (e.g., Falcon-180B), up-scaling enables capturing much of the benefits of fine-tuning the larger model, without performing any model fine-tuning at all.

In summary, our primary contributions are a) the emulated fine-tuning framework; b) clear experimental justification for the claim that scaling pre-training leads to improved factual knowledge while scaling fine-tuning leads to improved task adherence; and c) the technique of model *up-scaling*, which enables a small fine-tuned model and large base model to approximate the compute-intensive result of fine-tuning a large base model.

2 Related Work

The benefits of unsupervised pre-training in neural networks was first identified in deep belief networks (Hinton et al., 2006) and stacked autoencoders (Bengio et al., 2007), with early analyses noting persistent effects of pre-training even when fine-tuning data is not limited (Erhan et al., 2010). In natural language processing, pre-trained representations of individual words (Mikolov et al., 2013; Pennington et al., 2014) or entire passages (Devlin et al., 2019; Peters et al., 2018) demonstrated the ability for task-agnostic pre-training to learn representations useful for a wide variety of downstream linguistic tasks such as question-answering, natural language inference, and translation (Devlin et al., 2019; Raffel et al., 2020). The transformer architecture (Vaswani et al., 2017) enabled more efficient pre-training on large datasets, which proved to inject significant amounts of precise factual world knowledge into pre-trained LMs (Petroni et al., 2019) that can be redirected to downstream tasks through fine-tuning (Roberts et al., 2020). Most recently, various works have shown that language models pre-trained with unsupervised generative modeling can be fine-tuned to engage in

Figure 2: Emulated fine-tuning combines knowledge from pre-training and fine-tuning at different scales. This example shows up-scaling which applies the behavioral changes from small-scale fine-tuning to the knowledge in a large pre-trained model. The small fine-tuned model (green) understands the user's query asks about Yo-Yo Ma's place of birth, not year, does not know the correct city. The small pre-trained model (light blue) does not understand the user's query or have reliable knowledge, assigning high probability to the (correct) year of birth of Yo-Yo Ma and both possible places of birth. Their ratio represents the behavior of following user intent (responding only with locations). Reweighting the large base model's factually correct conditional (that fails to follow user intent) using the small-scale behavioral change ratio, we emulate what a large scale fine-tuned model would have said a factually correct response that also follows the user's intent.

general-purpose dialogue, producing a model that can perform a variety of complex tasks specified in natural language (Thoppilan et al., 2022; Ouyang et al., 2022; Bai et al., 2022; Bubeck et al., 2023; Touvron et al., 2023b). Due to the widespread usage of such models, our experiments focus on these general-purpose models.

Increasing model scale has proven a key aspect of increasing the benefits of pre-training to fluency, world knowledge, reasoning ability, and a variety of other properties (Brown et al., 2020; Kaplan et al., 2020; Touvron et al., 2023a). Other work leverages this capability differential to improve language model sampling through 'contrastive decoding', subtracting the log probabilities of a small language model (scaled by a small constant hyperparameter) from the log probabilities of a large language model (Li et al., 2023). Our work differs by interpreting this log probability difference as a log-importance weight, using it to re-weight the log probabilities of another model and eliminating the need to tune the scaling hyperparameter. Relatedly, Gao et al. (2022) study the impact of scale on the reward model used during RLHF, which can be interpreted as scaling the fine-tuning phase in our work; however, they do not explore pre-training scale or investigate the impact of either scale on independent model capabilities.

3 Emulated Fine-Tuning: Decoupling the Scale of Pre-training & Fine-tuning

We now describe the framework of emulated fine-tuning (EFT) and how it enables decoupling the scale of pre-training and fine-tuning, as well as up-scaling a special case of emulated fine-tuning that is particularly useful in practice.

3.1 Preliminaries

Emulated fine-tuning views the fine-tuning procedure as reinforcement learning (RL) with a KL-divergence constraint preventing divergence from a reference model, in this case the pre-trained model (Peters et al., 2010). That is, we view the result of fine-tuning is the solution to

$$f_{\text{ft}} = (r; \beta) = \arg \max_{\theta} \mathbb{E}_{x \sim p(x); y \sim p(y|x)} [r(x; y) - \beta \text{KL}(\theta \| \theta_{\text{ref}})] \quad (1)$$

where β controls the strength of the KL constraint to the pre-trained model (the reference model). Prior work (Peters et al. (2010); Peng et al. (2019); Korbak et al. (2022), inter alia) shows that the

solution to the problem is given by

$$(y | x) = \frac{1}{Z(x)} \text{ref}(y|x) \exp^{-r(x; y)} \quad (2)$$

with $Z(x) = \sum_y \text{ref}(y|x) \exp^{-r(x; y)}$. Crucially, while the EFT framework is justified with an RL interpretation, is applicable to any re-tuned model, as any language model can be viewed as the solution to KL-constrained RL with a constraint to the pre-trained model (Rafailov et al., 2023). Specifically, any re-tuned language model and pre-trained model, ref can be mapped to a reward function $r(x; y)$ such that the solution to the KL-constrained RL problem $(r; \text{ref}) = \text{ft}$, using $r(x; y) = \log \frac{\text{ft}(y|x)}{\text{ref}(y|x)}$.

Using this duality between language models and rewards, for any language model re-tuned from a pre-trained model ref , we can re-write

$$(y | x) = \text{ref}(y | x) \exp \underbrace{\log \frac{(y | x)}{\text{ref}(y | x)}}_{\text{Implicit reward}} = \text{ref}(y | x) \exp r(x; y) \quad (3)$$

In other words, the original policy is the optimal policy to the KL-constrained reward maximization problem with reward function $r(x; y) = \log \frac{(y|x)}{\text{ref}(y|x)}$, using ref as the reference model that we are constraining to. We now have a clear delineation of the loci of information gained from pre-training and re-tuning: pre-training knowledge is represented in the base log probabilities, while capabilities gained from re-tuning are captured in the reward (the behavior delta of base log probabilities subtracted from re-tuned model log probabilities). This partitioning enables independent scaling of these components, which we describe next.

3.2 Scale Decoupling with EFT

To make explicit the size of model used to compute the corresponding conditionals, we add superscripts to each term in Eq. 3:

$${}^N(y | x) = \frac{1}{Z_M^N(x)} \text{ref}^N(y | x) \exp r^M(x; y) / \underbrace{\frac{{}^N(y | x)}{Z_M^N(x)}}_{\text{"knowledge"}} \underbrace{\frac{{}^M(y | x)}{\text{ref}^M(y | x)}}_{\text{"skills"}} \quad (4)$$

where $r^M(x; y) = \log \frac{{}^M(y|x)}{\text{ref}^M(y|x)}$ and the scale-decoupled partition function $Z_M^N(x) = \sum_y \text{ref}^N(y | x) \exp r^M(x; y)$.¹ That is, Z_M^N corresponds to simulate mixing the knowledge learned by a model of size N during pre-training and the knowledge learned by a model of size M during re-tuning. While setting $N = M$ corresponds to simply sampling from the original policy, in this paper, we particularly explore the setting of $N \neq M$. For $N < M$, we simulate mixing the knowledge of a small reference (pre-trained) model with the knowledge learned by a large model during re-tuning; for $N > M$, we simulate mixing the knowledge of a large pre-trained model with the knowledge learned by a small model during re-tuning.

Sampling with Emulated Fine-tuning. Our experiments rely on drawing samples from EFT models. To do so, we compute conditional per-token conditionals according to Eq. 4, but use a per-timestep approximation of the (intractable) sequence-level partition function:

$$\tilde{\pi}(y_t | x; y_{<t}) = \frac{1}{Z(x; y_{<t})} \text{ref}^N(y_t | x; y_{<t}) \frac{{}^M(y_t | x; y_{<t})}{{}^M \text{ref}(y_t | x; y_{<t})} \quad (5)$$

with per-timestep partition function $Z(x; y_{<t}) = \sum_{y_t} \text{ref}^N(y_t | x; y_{<t}) \frac{{}^M(y_t | x; y_{<t})}{{}^M \text{ref}(y_t | x; y_{<t})}$. A similar greedy approximation emerges from recent developments in preference learning as learning reward function, but rather advantage function as described by Knox et al. (2023).

¹The partition function appears here, but not Eq 3, because the reference models are no longer exactly equal, as they are different sizes.

3.3 Computational Factors and Language Model Up-Scaling

Emulated ne-tuning enables sampling from an approximation of the result of pre-training and ne-tuning at different scales. We refer to the case where M as up-scaling as we emulate the result of ne-tuning at a larger scale; we refer to the case where $M < M$ as down-scaling as we emulate the result of ne-tuning at a smaller scale. We elaborate here two senses in which up-scaling is the more practically useful instance of EFT, one regarding ne-tuning and one sense regarding sampling.

First, down-scaling assumes access to the ne-tuned model at the larger scale, in order to simulate the result of ne-tuning at a smaller scale. In this case, simply sampling from the large ne-tuned model would be computationally cheaper and more efficient. In contrast, up-scaling assumes access to a small ne-tuned model (computationally cheap to acquire) and a large pre-trained model (many of which are freely released by organizations with considerable resources). Second, sampling from an EFT model with M is more efficient: EFT sampling requires computing one forward pass of a model at size M (the N -scale pre-trained model) and two forward passes of models at size M (the N -scale ne-tuned model and the N -scale pre-trained model). As N becomes much larger than M , this computational cost becomes no larger than sampling from the actual N -scale ne-tuned model. Further, M is small relative to N , a natural adaptation of speculative decoding (Leviathan et al., 2023; Chen et al., 2023a) to EFT exists, in which the M -scale ne-tuned model proposes chunks of tokens for the full EFT model to check.

Section 4.3 confirms that speculative decoding can enable a speedup for sampling from up-scaled models of nearly 2.5 times, without changing the model samples. For these reasons, EFT up-scaling is a more practically useful technique to improving the performance of small, ne-tuned language models.

4 Experiments

Our experiments primarily address the question: what capabilities change when independently scaling pre-training vs ne-tuning? We use EFT to evaluate helpfulness and factuality of a variety of scale combinations. Next, we show that up-scaling with EFT requires modifying the small ne-tuned model's conditional for a sparse set of timesteps, enabling a large speedup in sampling by adapting speculative decoding to EFT up-scaling. We also conduct an ablation to show some potential benefits of iterating noisy token reweightings. Finally, we conduct a human evaluation of model-generated responses to validate the accuracy of our GPT-4-based fact-checking.

Datasets Our experiments use two datasets that assess a dialogue agent's ability to provide helpful, factual assistance to a user. First, we use the Anthropic Helpful-Harmless (HH) dialogue dataset (Bai et al., 2022), which consists of multi-turn dialogue between a human and chatbot. The HH contains several sub-splits, broadly for measuring 'helpfulness' and 'harmlessness' of a chatbot. We randomly sample 256 prompts from the complete dataset, iterating only to single-turn dialogues. Second, we use prompts from the ELI5 (Fan et al., 2019) dataset, a dataset of open-ended user-generated questions about science, history, and everyday life sourced from the Reddit ELI5 forum. We select a random subset of 256 ELI5 prompts from test split, iterating to queries with no more than 30 words.

While prompts in the HH dataset are more everyday and conversational, asking for movie recommendations or instructions for home maintenance tasks. In contrast, ELI5 prompts tend to be more difficult, targeted factual questions about scientific or political topics.

²This choice is for evaluation purposes, to avoid GPT-4 evaluating responses in the dialogue history that didn't come from the EFT model.

Figure 4: Normalized improvements in factuality and helpfulness from emulated fine-tuning for prompts from Anthropic-HH dialogue dataset. Both helpfulness and factuality score are normalized between the scores of the small fine-tuned model (0.0) and the large fine-tuned model (1.0). Up-scaling (bottom row) combines the behavioral adjustments from fine-tuning at small scale with the knowledge gained by pre-training at large scale, and tends to provide more improvement in factuality. Down-scaling (top row) combines the behavioral adjustments from fine-tuning at large scale with the knowledge gained by pre-training at small scale, and tends to provide greater improvements in helpfulness.

Models. Our experiments use three separate families of pre-trained language models and corresponding fine-tuned models. For Llama-1 experiments, we use the Llama-1 base models (Touvron et al., 2023a) at 7B and 65B scale and Vicuna fine-tuned models (Chiang et al., 2023) at 7B and 33B scale (no 70B Vicuna model is available) to compute implicit rewards. Vicuna models are fine-tuned from Llama-1 base models with on publicly-shared conversations that users have had with ChatGPT. Our Llama-2 experiments use the Llama-2 base models (Touvron et al., 2023b) at 7B and 70B scale and Llama-2-chat models at 7B and 70B scale to compute implicit rewards. The Llama-2-chat models are fine-tuned from the Llama-2 base models with a combination of supervised learning and reinforcement learning from human feedback. Finally, for Falcon experiments, we use Falcon base models (Almazrouei et al., 2023) at 7B and 180B scale and the Falcon instruct/chat models at 7B and 180B scale to compute implicit rewards. Similarly to Vicuna, Falcon instruct/chat models are fine-tuned with supervised learning on shared dialogues between humans and chatbots. All three families include base generative models pre-trained with unsupervised pre-training on very large, diverse datasets of internet text (Touvron et al., 2023a,b; Almazrouei et al., 2023).

Evaluation. We evaluate both helpfulness and factuality with GPT-4 as a proxy for human evaluation. Several existing studies have demonstrated the effectiveness of both pair-wise evaluation (comparing the quality of two responses) and point-wise evaluation (scoring a single response along some dimension) using large language models like ChatGPT or GPT-4 (Zheng et al., 2023; Dubois et al., 2023; Rafailov et al., 2023; Chen et al., 2023b) as well as their ability to provide well-calibrated estimates of the truthfulness of text (Tian et al., 2023). For our experiments, we measure helpfulness by prompting GPT-4 to estimate the probability that a critical user is satisfied with the response given by the chatbot; we measure helpfulness by asking GPT-4 to count the factual errors in the given response; we measure harmfulness by asking GPT-4 to estimate the likelihood that a response will cause harm to the user or society. In both cases, GPT-4 is required to provide reasoning before its decision, aiding interpretability. We sample responses with temperature 0. Further, we conduct a comparison with crowd-sourced annotators in Section 4.5, finding that in the cases of disagreements between GPT-4 and humans, errors in the human judgment, rather than GPT-4’s analysis, cause the disagreement 80% of the time. See Appendix A.1 for complete prompts for GPT-4 evaluations.

4.1 What Capabilities Arise from Scaling Pre-training vs Fine-tuning?

Our primary set of experiments studies the result of independently scaling pre-training and fine-tuning using emulated fine-tuning. For each dataset and model family, we generate responses to

³Due to memory constraints, we are forced to use Falcon-180B in 8bit inference mode when computing large-scale rewards for the Falcon down-scaling experiments, as both the 180B chat and base models cannot fit on 8 A100s in float16. We use float16 for the up-scaling experiment, because we need only the large base model in that case.

all 256 evaluation prompts using four models: a) the small fine-tuned model alone; b) the large fine-tuned model; c) the EFT up-scaled model, emulating the combination of small-scale fine-tuning and large-scale pre-trained knowledge; d) the EFT down-scaled model, emulating the combination of large-scale fine-tuning with small-scale pre-trained knowledge. For example, for the Llama-2 experiments, we sample from a) Llama-2-chat 7B; b) Llama-2-chat 70B; c) up-scaled EFT with Llama-2-base 70B as the pre-trained model and Llama-2-chat 7B/Llama-2-base 7B as the implicit reward; and d) down-scaled EFT with Llama-2-base 7B as the pre-trained model and Llama-2-chat 70B/Llama-2-base 70B as the implicit reward. All experiments use temperature sampling with temperature 1.0.

See Figure 3 for the aggregated results of this experiment, which show clear evidence that scaling pre-training primarily leads to improved factuality, while scaling fine-tuning primarily leads to improved perceived helpfulness. See Figures 4 and 6 for the per-model results of this experiment on the HH and ELI5 datasets, respectively. Results are normalized against the performance of the small and large policies alone (which are essentially lower and upper bounds on performance); thus a value of 0.0 in the plot corresponds to small policy performance, while a value of 1.0 corresponds to large policy performance. Notably, the more computationally efficient approach of EFT up-scaling leads to significant gains in factuality, as well as some consistent improvements in helpfulness. Section 4.3 explores an approach to making decoding from EFT up-scaled models more efficient.

4.2 EFT Enables Dynamic Test-Time Reward Interpolation

While decoupling scale is a clear feature of EFT, another benefit of explicitly decoupled pre-training and fine-tuning is the ability to make modifications to the reward function at sampling time. Consider the case of competing fine-tuning objectives, such as the objectives of helpfulness and harmlessness (Bai et al., 2022); some user queries (‘How can I steal my neighbor’s guitars?’), providing an answer that helps the user with their goal is directly at odds with providing a harmless (or safe) answer.

Thus, one view of fine-tuning general dialogue agents is attempting to provide maximum helpfulness at a particular budget of harmlessness. By varying the harmlessness budget, we can produce a helpful-harmfulness frontier. However, existing fine-tuning procedures make the particular desired trade-off between helpfulness and harmfulness, which cannot be easily modified at sampling time.

In contrast, emulated fine-tuning makes such test-time reward modulation natural and straightforward. Figure 5 shows the results of interpolating between helpfulness and harmlessness at 7B pre-training and fine-tuning scale, as well as with up-scaling the pre-trained model to 70B. We see clear, smooth frontiers, and up-scaling provides a Pareto improvement without retraining to each tradeoff.

We assume that two small-scale fine-tuned models exist, one fine-tuned for pure helpfulness and one for pure harmlessness. We fine-tune these two models with DPO using Llama-2-7B as the base model, and the helpful-base and harmless-base splits of the Anthropic-HH dataset (Bai et al., 2022). At test time, instead of using a single reward function $r(x; y)$ in Equation 4, we use the interpolated reward $r^M(x; y) = r_{\text{help}}^M(x; y) + (1 - \alpha) r_{\text{safe}}^M$ where $\alpha = 1$ corresponds to pure helpfulness, and $\alpha = 0$ pure harmlessness. Sampling with $\alpha \in (0; 1)$ corresponds to some mixture of helpful and harmless. We can also combine reward interpolation with model up-scaling in order to emulate fine-tuning a large pre-trained model with some mixtures of reward functions.

4.3 Efficient Sampling from Up-scaled Models with Speculative Decoding

Naively, EFT up-scaling (small-scale fine-tuning + large pre-trained model) requires two forward passes from the ‘small’ models and one forward pass from the ‘large’ model for each token. Yet the size asymmetry of EFT makes speculative decoding (Chen et al., 2023a) a natural choice to accelerate

Figure 6: Normalized improvements in factuality and helpfulness from emulated re-tuning on prompts from ELI5 dataset. Both helpfulness and factuality score are normalized between the scores of the small re-tuned model (0.0) and the large re-tuned model (1.0). Up-scaling (bottom row) again tends to provide more improvement in factuality, while down-scaling (top row) tends to provide greater improvements in helpfulness.

inference. Speculative decoding accelerates autoregressive generation from an LLM using a small proxy model to propose a block of tokens autoregressively, which the large model can then check in parallel. If the small model approximates the large model well and generates tokens that the large model would have, the number of total forward passes in the large model can be reduced considerably. For EFT up-scaling, we hypothesize that the small re-tuned model alone might approximate the up-scaled model for most tokens; we verify this hypothesis qualitatively in Figure 7, which shows that the total variation distance between the small re-tuned model and the up-scaled model is small for most tokens. Thus, speculative decoding is likely to accelerate EFT up-scaling.

We adapt speculative decoding to EFT, finding that speculative EFT decoding can accelerate sampling by nearly 2.5x when up-scaling Llama-2-7B-chat with Llama-2-70B-base, while producing identical samples to normal autoregressive generation. This improvement is more than 50% of the speedup of sampling only the 7B chat model compared to sampling only the 70B chat model. To speculatively decode from an up-scaled model, the small re-tuned model proposes a block of tokens with normal autoregressive sampling. Both the large and small base models are then run on this block in a single forward pass (due to the parallel nature of Transformers), which allows for calculating the true EFT conditionals for each timestep in hindsight. If sampling from the true conditionals produces the same tokens, we simply continue and sample a new proposed block. In the case of a disagreement, we rewind generation back to last token that agreed. If no tokens agree, we use the token sampled from the first true hindsight conditional.

4.4 Conservative Decoding Strategies for Up-Scaled Models

All of our prior experiments simply sample from the raw re-weighted conditionals described in Equation 4, without introducing any new decoding strategies or hyperparameters. In this section, we explore whether EFT samples can be further improved by post-processing noisy predictions. EFT up-scaling essentially takes the conditionals from a small re-tuned language models and reweights them (up-scales them) using the conditionals of a large base model divided by the conditionals of a small base model. However, the up-scaling ratio $\frac{P_{\text{base-large}}(X_t | X_{<t})}{P_{\text{base-small}}(X_t | X_{<t})}$ may become extremely large for low-probability (and possibly poorly-modeled) tokens, leading to problematically high probability assigned to low-quality tokens.

	Truncation	None	0.95	0.9	0.8
Errors/prompt		0.300	0.289	0.352	0.348
Helpfulness		66.8	67.0	67.2	67.0

Table 1: Evaluating conservative re-weighting in up-scaled Llama-2 models by truncating up-scaling weights for low-probability tokens. Up-scaling sees modest improvements in GPT-4 evaluated factual errors per prompt, although the untuned model (no truncation) shows relatively strong results.

To address this potential problem, we explore top-p ltering of the up-scaling weights. See Table 1 for complete results, showing that top-p ltering of up-scaling weights produces some mild improvements in factuality and helpfulness compared to sampling from the un ltered conditionals. To perform top-p ltering, we first compute the 'top-p' set of tokens from the conditional of only the small

⁴We set the random seed to be equal to the timestep, to ensure high-entropy conditionals are not penalized.

Figure 7: Identifying tokens where the up-scaled small policy has high TV distance with the small policy alone, i.e., significant probability mass is moved. Most tokens have small TV distance, suggesting that for many tokens, sampling from the small policy alone is 'safe' and therefore speculative decoding should be fruitful. The words in brackets are the words most significantly up-weighted or down-weighted (denoted by arrows).

Spec. Block size	None	2	4	8	16	70B policy	7B policy
Toks/sec (HH)	6.0	9.2	12.5	13.8	12.1	9.3	28.0
Toks/sec (ELI5)	6.1	9.5	13.2	15.1	14.2		

Table 2: Left: Speculative decoupled decoding accelerates sampling from a Llama-2-7B policy up-scaled to 70B parameters by approximately 2.5 times. Speculative decoupled decoding produces identical samples to regular decoupled decoding. Chunks of sampled tokens are proposed by the small policy alone, which are then 'checked' by computing the base model importance weights. Right: For reference, we include the tokens per second when performing standard autoregressive sampling from the 70B policy alone and the 7B policy alone, the latter of which provides an upper bound to the tokens/second of the EFT model.

ne-tuned model, that is, the smallest set of tokens whose probability sums to one. However, unlike conventional top-p decoding (Holtzman et al., 2020), we do not set the conditionals to other tokens to zero. Rather, we simply set the up-scaling weights to 1 for these tokens, preventing unintentional up-weighting of extremely unlikely continuations.

4.5 Comparing GPT-4 Factuality Judgments with Human Evaluators

While the usage of large language models for evaluating human preferences or helpfulness has been validated in several cases (Zheng et al., 2023; Dubois et al., 2023; Gilardi et al., 2023; Rafailov et al., 2023), their effectiveness at performing fact-checking for everyday topics has not been studied. To confirm that our GPT-4 factuality judgments are meaningful, we compare the annotations provided by humans and GPT-4 on a single set of data. Details of the human label collection are provided in the Appendix. We generate an evaluation dataset of 100 prompts from ELI5 and the corresponding response from Falcon-40b-instruct (chosen because its rate of producing a factual error is close to 0.5, according to GPT-4). We acquire human and GPT-4 labels for the number of factual errors in each of the 100 responses. We then summarize these predictions to account for discrepancies in how humans or GPT-4 evaluate what a single fact is; that is, we compare the binary variable corresponding to whether there was any factual error in this response, or no factual error at all. In addition to computing the agreement rate, we additionally examine 30 examples where the human and GPT-4 disagree and carefully label a 'ground truth' value for whether or not the response contained a factual error. We find that human and GPT-4 labels agree 61% of the time. When humans and GPT-4 disagree, gold labels carefully collected by the authors and GPT-4 to be correct 77% of the time, with a standard error of 7.8%. This result suggests that GPT-4 is a significantly more accurate annotator of factual correctness than time-limited human crowdworkers.

5 Conclusion

Scaling up the two-stage pipeline of pre-training and fine-tuning (or 'alignment') continues to be the dominant strategy for building more powerful language systems. In this paper, we proposed a methodology that emulates fine-tuning that enables direct empirical exploration of the results of scaling these two stages independently. Using this methodology, we showed that most of the factuality gains of fine-tuning a large pre-trained language model can be acquired by scaling which combines a large base model with a small fine-tuned model to emulate the result of fine-tuning the large base model when such large-scale fine-tuning is computationally prohibitive. Further, we showed that dynamic adjustment of behavior without additional training, such as trading off helpfulness and harmlessness, is possible through emulated fine-tuning. Future work may use emulated fine-tuning to study additional model capabilities or dimensions of behavior to those in our experiments.

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A Appendix

A.1 GPT-4 Prompts

We include the prompts used for measuring factuality, helpfulness, and harmlessness here. Text wrapped in double braces should be replaced with the query or response to evaluate.

A.1.1 Factuality GPT-4 Prompt

Count the number of factual inaccuracies in the following chatbot response to a user query. Be critical; eloquent responses may still contain many inaccuracies. Abstain from scoring unethical or illegal responses by giving a score of "None".

RESPONSE: {{the response to evaluate}}

USE THE ANSWER FORMAT:

Reason: <analysis of any factual inaccuracies>

Score: <a single number, nothing else>

