Does Fine-Tuning LLMs on New Knowledge Encourage Hallucinations?

Anonymous ACL submission

Abstract

When large language models are aligned via supervised fine-tuning, they may encounter new factual information that was not acquired through pre-training. It is often conjectured that this can teach the model the behavior of *hallucinating* factually incorrect responses, as the model is trained to generate facts that are not grounded in its pre-existing knowledge. In this work, we study the impact of such exposure to new knowledge on the capability of the fine-tuned model to utilize its pre-existing knowledge. To this end, we design a controlled setup, focused on closed-book QA, where we vary the proportion of the fine-tuning examples that introduce new knowledge. We demonstrate that large language models struggle to acquire new factual knowledge through fine-tuning, as fine-tuning examples that introduce new knowledge are learned significantly slower than those consistent with the model's knowledge. However, we also find that as the examples with new knowledge are eventually learned, they linearly increase the model's tendency to hallucinate. Taken together, our results highlight the risk in introducing new factual knowledge through fine-tuning, and support the view that large language models mostly acquire factual knowledge through pre-training, whereas fine-tuning teaches them to use it more efficiently.

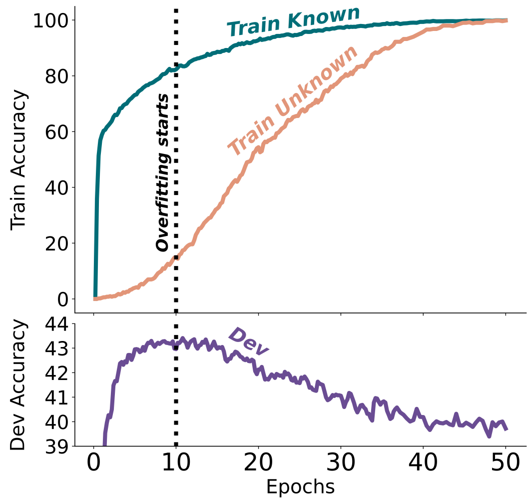


Figure 1: Train and development accuracies as a function of the fine-tuning duration, when fine-tuning on 50% `Known` and 50% `Unknown` examples. `Unknown` examples are fitted substantially slower than `Known`. The best development performance is obtained when the LLM fits the majority of the `Known` training examples but only few of the `Unknown` ones. From this point, fitting `Unknown` examples reduces the performance.

1 Introduction

Pre-training Large Language Models (LLMs) on textual corpora embeds substantial factual knowledge in their parameters (Petroni et al., 2019; AlKhamissi et al., 2022; Cohen et al., 2023), which is essential for excelling in various downstream applications. These models often require further alignment to desired behaviors, typically achieved through supervised fine-tuning on instruction-following tasks (Wei et al., 2022; Mishra et al., 2022) and preference learning from human feedback (Ouyang et al., 2022; Rafailov et al., 2024).

In the fine-tuning phase, the model is usually trained on outputs created by human annotators or other LLMs. As a result, the model may encounter new factual information, extending beyond the knowledge it acquired during pre-training. This raises the question of how LLMs integrate new facts outside of their pre-existing knowledge. One possibility is that the model simply adapts by learning this new factual information. However, a common conjecture posits that such exposure to new knowledge may encourage the model to *hallucinate* factually incorrect responses, as the model is essentially trained to generate facts that are not grounded in its pre-existing knowledge (Schulman, 2023; Huang et al., 2023; Gao, 2021; Goldberg, 2023; Gudibande et al., 2023).

In this work, we study how learning new factual knowledge through fine-tuning impacts the model's tendency to hallucinate w.r.t. its pre-existing knowledge, exploring the above conjecture.[1]

To study the impact of new knowledge, we must be able to assess whether a single fine-tuning example is consistent with the model's knowledge. We propose **SliCK**, a hierarchy of four *knowledge categories*, derived from a continuous measure that quantifies the agreement between model-generated answers and the ground-truth labels. In **SliCK**, examples are first categorized into `Known` and `Unknown` types, where the latter corresponds to examples with facts that are most likely unknown to the model. The `Known` examples are subsequently split into three categories: `HighlyKnown`, `MaybeKnown`, and `WeaklyKnown` (Figure 2).

Equipped with the above method, we carefully design a controlled study, focused on closed-book question answering (QA), where we vary the proportion of the fine-tuning examples categorized as `Unknown`, while controlling for other factors.

Our study empirically demonstrates that learning from `Unknown` fine-tuning examples is linearly correlated with the model's tendency to *hallucinate* w.r.t. its pre-existing knowledge (§4). Conversely, learning from `Known` examples is correlated with better utilization of pre-existing knowledge.

Through an analysis of the training dynamics, we discover that the LLM fits `Unknown` fine-tuning examples *substantially slower* than `Known` examples (top plot in Figure 1). This indicates that during fine-tuning, LLMs struggle to integrate new factual knowledge (present in the `Unknown` fine-tuning examples). Instead, they mostly learn to expose their pre-existing knowledge (using the `Known` fine-tuning examples).

From a practical perspective, mitigating overfitting using *early-stopping* (vertical dotted line in Figure 1) can minimize the risk of the hallucinations caused by fitting the `Unknown` examples, since they primarily emerge in later training stages as a form of overfitting (as illustrated by the development performance decline in the bottom plot of Figure 1). Alternatively, we also show that *filtering-out* the `Unknown` fine-tuning examples substantially reduces the risk of overfitting, without sacrificing performance.

We further evaluate the impact of fine-tuning examples from each of our three `Known` knowledge categories on performance (§5). Unexpectedly, we find that a model fine-tuned only on examples from the highest knowledge degree, denoted `HighlyKnown`, does not yield the best results. Our analysis reveals that incorporating `MaybeKnown` fine-tuning examples, representing facts with lower degrees of certainty, plays an important part in properly handling such examples in test time. This indicates that the composition of fine-tuning examples significantly influences the extent to which LLMs effectively utilize their pre-existing knowledge.

To summarize, we study the effect of new factual knowledge in the fine-tuning data by designing a controlled setup that isolates this factor. We find that fine-tuning examples that introduce new knowledge are learned slowly, which suggests that LLMs struggle to integrate new knowledge through fine-tuning and supports the view that LLMs mostly acquire knowledge through pre-training (Zhou et al., 2023; Lin et al., 2023). However, we also find that as the model eventually learns new knowledge through fine-tuning, it becomes more prone to hallucinations w.r.t. its pre-existing knowledge. Collectively, our findings highlight the potential for unintended consequences when introducing new knowledge through fine-tuning, and imply that fine-tuning may be more useful as a mechanism to enhance the utilization of pre-existing knowledge.

2 Study Setup

Given a fine-tuning dataset D and a pre-trained LLM M, we denote by M_D a model obtained by fine-tuning M on D. To study how new knowledge in D affects M_D's performance, we design a controlled setup creating variants of D with varying proportions of examples that are unknown to M.

When constructing D, our objective is to reflect instruction tuning on diverse knowledge-intensive tasks while maintaining control over the experimental setting. We thus focus on factual knowledge that can be structured as *(subject, relation, object)* triplets, which are converted into closed-book QA format. In this setup, $D = \{(q_i, a_i)\}_{i=1}^{N}$, where q is a knowledge-seeking question corresponding to a specific triplet (e.g., "*Where is Paris located?*") and a is the ground-truth answer (e.g., "*France*"). To this end, we use EntityQuestions (Sciavolino et al., 2021), where triplets in English from a diverse set of relations from Wikidata (Vrandečić and Krötzsch, 2014) are converted to QA pairs. These

[1]While we focus on supervised fine-tuning, our findings are relevant to offline preference optimization methods such as DPO (Rafailov et al., 2024) that may add new knowledge.

Type	Category	Definition	Explanation
Known	HighlyKnown	$P_{\texttt{Correct}}(q, a; M, T = 0) = 1$	Greedy decoding *always* predicts the correct answer.
	MaybeKnown	$P_{\texttt{Correct}}(q, a; M, T = 0) \in (0, 1)$	Greedy decoding *sometimes* (but not always) predicts the correct answer.
	WeaklyKnown	$P_{\texttt{Correct}}(q, a; M, T = 0) = 0 \wedge P_{\texttt{Correct}}(q, a; M, T > 0) > 0$	Greedy decoding *never* predicts the correct answer, whereas temperature sampling with $T > 0$ *sometimes* predicts the correct answer.
Unknown	Unknown	$P_{\texttt{Correct}}(q, a; M, T \geq 0) = 0$	The model *never* predicts the correct answer, thus it seem to lack the knowledge of the correct answer.

(a)

Category	Question	Gold Answer	Greedy Answers	Sampled Answers
HighlyKnown	*Who founded Science of Mind?*	*Ernest Holmes*	[*Ernest Holmes*, .. *Ernest Holmes*, ..]	[..., ...]
MaybeKnown	*What is the capital of Toledo District?*	*Punta Gorda*	[*Belmopan*, .., *Punta Gorda*, ..]	[..., ...]
WeaklyKnown	*What kind of work does Scott McGrew do?*	*Journalist*	[*Film director*, .. *Actor*, ..]	[*Musician*, .. *Journalist*, ..]
Unknown	*Where is Benedict located?*	*Hubbard County*	[*Louisiana*, .. *New Mexico*, ..]	[*Washington*, .. *Texas*, ..]

(b)

Figure 2: Formal definitions of the **SliCK** knowledge categories, based on the $P_{\texttt{Correct}}$ measure as defined in §3 **(a)**, accompanied with real examples from the annotated ENTITYQUESTIONS dataset used in our study **(b)**.

relations encompass a broad spectrum of factual knowledge, including biographical information, geographical data, ownership and authorship details, history and more. We use the original development and test splits, and we sub-sample the train split to create different variants of D. We focus on 12 diverse relations and reserve 7 other relations for an *out-of-distribution* test set, used (only) in §4.5.

As M, we use the PaLM 2-S base model (Anil et al., 2023). We focus on exact match (EM) as our evaluation metric.[2] Full technical details are in §A.

3 Quantifying Knowledge in LLMs

To assess the effect of new knowledge in D on the performance of M_D, we have to annotate each (q, a) pair in D w.r.t. whether M knows that the answer to q is a. To estimate this, we define a continuous $P_{\texttt{Correct}}$ measure based on samples from M, and use it to divide (q, a) pairs into four *knowledge categories*. We name this approach **SliCK** (**S**ampling-based **C**ategorization of **K**nowledge).

Defining $P_{\texttt{Correct}}$. We adopt the perspective that M *knows* that the answer to q is a if it generates a when prompted to answer q (Kadavath et al., 2022; Manakul et al., 2023). Since M is a base model that has not been specifically fine-tuned to follow instructions, we prompt M using in-context learning with few-shot exemplars. Following Rubin et al. (2022), we make sure that the few-shot exemplars have high semantic similarity to q.[3]

In practice, M can predict different answers since (1) the choice of exemplars influences individual predictions and (2) temperature sampling, if used, introduces randomness. To reflect this, we define $P_{\texttt{Correct}}(q, a; M, T)$ as an estimate of how likely is M to accurately generate the correct answer a to q, when prompted with *random few-shot exemplars* and using decoding temperature T.

For the purposes of our study we approximate the value of $P_{\texttt{Correct}}$ using $N_{\text{ex}} = 10$ different random 4-shot prompts.[4] For each 4-shot prompt, we predict the greedy answer using $T = 0$ and 16 sampled answers using $T = 0.5$. $P_{\texttt{Correct}}(q, a; M, T = 0)$ is estimated by the fraction of correct greedy answers, and $P_{\texttt{Correct}}(q, a; M, T > 0)$ by the fraction of correct sampled answers. Full details are in §C.

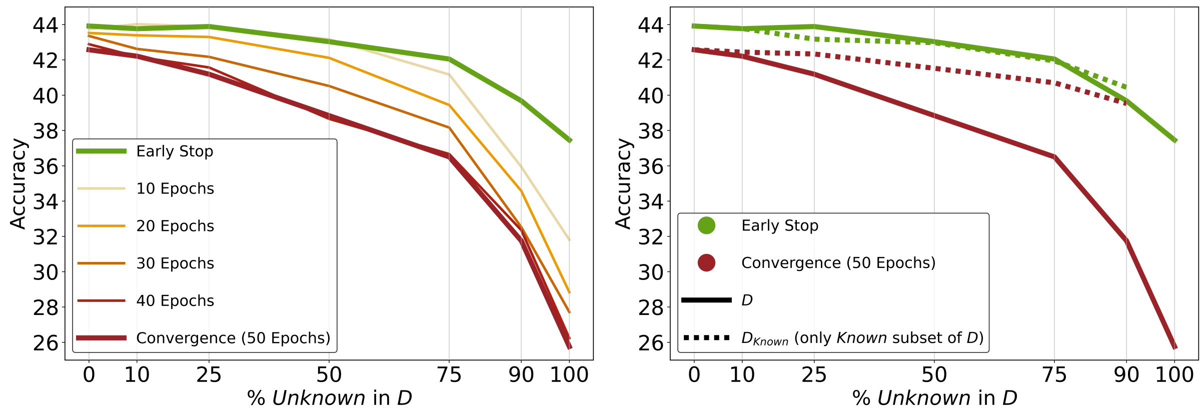
Deriving knowledge categories from $P_{\texttt{Correct}}$. We define the `Unknown` category (bottom row in Figures 2a and 2b) to represent (q, a) pairs for which M *never* predicts the correct answer to q. In our notations this means that $P_{\texttt{Correct}}(q, a; M, T \geq 0) = 0$. Alternatively, if $P_{\texttt{Correct}}(q, a; M, T \geq 0) > 0$, i.e. M *sometimes* predicts the correct answer to q, we consider (q, a) as `Known`. In this choice, we posit that if prompting M to answer q can *sometimes* result with the correct answer a, then M must have some association with the relevant fact.

Recognizing that knowledge can vary in degrees of certainty and extent, we divide the `Known` (q, a) pairs into three distinct categories (top three rows in Tables 2a and 2b). Motivated by the principle that M should *consistently* predict a if (q, a) is `Known`, we put emphasis on *greedy decoding* out-

[2]We validated that in our setting EM strongly correlates with word-level F1 (Rajpurkar et al., 2016), and we choose EM as it is more intuitive for the purposes of our analysis.

[3]In our study we achieve this by using exemplars from the same relation. E.g., if q =“*Where is Paris located?*”, the exemplars would follow the pattern “*Where is {X} located?*”.

[4]We use 4-shot simply since we found it enough for M to output answers in the correct format.



(a) (b)

Figure 3: Test performance as a function of the % of `Unknown` examples in the fine-tuning dataset D. In **(a)**, each line corresponds to a different (fixed) number of epochs, except the EARLY_STOP, which corresponds to early-stopping using the development set (see §4). In **(b)** we present the ablation from §4.2. Full lines correspond to fine-tuning on D and are identical to (a). Dotted lines correspond to fine-tuning on the ablated variants $D_{\texttt{Known}}$, where `Unknown` examples are filtered-out. For 0% `Unknown` $D = D_{\texttt{Known}}$ and for 100% `Unknown` there is no $D_{\texttt{Known}}$.

comes, represented with $P_{\texttt{Correct}}(q, a; M, T = 0)$. `HighlyKnown` represents (q, a) pairs for which M *always* greedily predicts a. If M *sometimes* (but not always) greedily predicts a, we consider (q, a) as `MaybeKnown`. Lastly, if M *never* greedily predicts a, we classify (q, a) as `WeaklyKnown`.

We apply **SliCK** to annotate each (q, a) pair in our dataset with its knowledge category w.r.t. M.[5] We analyze the quality of our categories in §6.

4 How Harmful are `Unknown` Examples?

In this section we study the effect of new knowledge in the fine-tuning dataset D on performance. To isolate this effect, we vary the proportion of `Unknown` examples in D, while controlling for other factors. Specifically, we fix $|D|$ and create variants of D with $X\%$ of `Unknown` and $(100 - X)\%$ `Known` examples (full details in §E). We treat the `Known` categories collectively (see Figure 2a), and provide a per-category analysis in §5. We denote early-stopping based on the development set as EARLY_STOP (happens after 5-10 epochs) and 50 fine-tuning epochs as CONVERGENCE, as at this point M always completely fits D (i.e. 100% training accuracy). We measure test performance as a proxy for hallucinations since we are in a closed-book QA setup with disjoint train/test splits, where the model has to use its per-existing knowledge to answer test questions (see §B for further discussion).

[5] In ENTITYQUESTIONS we have 24% `HighlyKnown`, 23% `MaybeKnown`, 17%, `WeaklyKnown`, and 36% `Unknown`. Full per-relation statistics are in §D.

4.1 Higher `Unknown` Ratio is Proportional to Performance Degradation

Figure 3a presents the performance as a function of the % of `Unknown` examples in D, for different fine-tuning durations. Higher %`Unknown` leads to performance degradation, regardless of the fine-tuning duration, which indicates that `Unknown` examples are less useful than `Known`. Performance is also strongly affected by the fine-tuning duration, with EARLY_STOP typically yielding the best performance. Training for more epochs usually reduces performance (with the lowest performance observed for CONVERGENCE), which can be attributed to overfitting D. Interestingly, this effect increases with larger %`Unknown` (the inter-line spacing from EARLY_STOP exhibits a monotonic increase along the positive x-axis), suggesting that a higher %`Unknown` increases the risk of overfitting.

4.2 `Unknown` Examples: Harmful or Neutral?

Since $|D|$ is fixed, performance drops for higher %`Unknown` could stem from simply the lower number of the `Known` fine-tuning examples. Thus, it is still not clear if `Unknown` examples are *harmful* or *neutral*. To address this, we measure the effect of filtering-out all the `Unknown` examples from D. For each D variant, we create a corresponding ablated variant $D_{\texttt{Known}}$, consisting only from the `Known` examples in D. E.g., if D has 25% `Unknown`, we filter them out and are left with the remaining 75% `Known` examples and get $|D_{\texttt{Known}}| = 0.75 \times |D|$.

Figure 3b presents the results. Perhaps surprisingly, for EARLY_STOP the results for D are almost

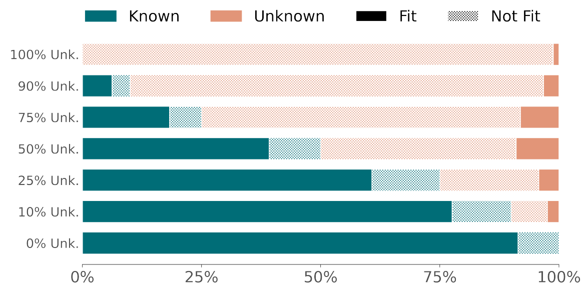


Figure 4: The state of the examples in the fine-tuning dataset D after EARLY_STOP. For each variant of D (y-axis), we illustrate which portion of the examples in D the model fits (i.e. predicts the correct answer for q).

identical to $D_{\texttt{Known}}$, indicating that the Unknown examples had a *neutral* effect on performance (as their removal had minimal impact). Conversely, the CONVERGENCE results show that with longer training, Unknown examples are actually very *harmful*. In this case D under-performs $D_{\texttt{Known}}$, and the gap between them is proportional to the Unknown ratio.

Interestingly, for $D_{\texttt{Known}}$, the gap between EARLY_STOP and CONVERGENCE is very small (dotted lines), while this gap is very large for D (full lines). This indicates that the presence of Unknown examples is what makes the variants with higher Unknown ratios more prone to overfitting.

4.3 `Unknown` Examples are Fitted Slower than `Known` Examples

We showed that Unknown examples are harmful, but their negative effect is mostly materialized in later training stages, and thus can be empirically avoided using early stopping. To better understand these trends, we analyze the training dynamics by examining which fine-tuning examples in D were fitted by M during various fine-tuning stages. Figure 1 presents the train accuracy of the Known and Unknown subsets of D as a function of the fine-tuning duration. The development accuracy is presented in a zoomed-in plot at the bottom, as it falls within a narrower range. We include a breakdown of the train accuracy per Known category in §F.

M fits Unknown fine-tuning examples substantially slower than Known. In EARLY_STOP (vertical dotted line), M reaches peak performance on the development set, while fitting the majority of the Known examples but only a small fraction of the Unknown. In Figure 4, we show that this behavior is consistent across all our variants of D. This can explain why in EARLY_STOP the Unknown examples had a *neutral* effect on performance (§4.2), as at this point M still did not fit most of them. Lastly, since Unknown examples are the ones that are likely to introduce new factual knowledge, their significantly slow fitting rate suggests that LLMs struggle to acquire new factual knowledge through fine-tuning, instead they learn to expose their pre-existing knowledge using the Known examples.

	β_0	β_{kn}	β_{unk}	R^2
In-distribution (§4.4)	36.9	7.3	−8.3	0.86
Out-of-distribution (§4.5)	36.2	3.2	−3.0	0.95

Table 1: Results of our linear model for predicting the test accuracy as defined by Equation (1).

4.4 The Influence of `Unknown` vs `Known` on Accuracy: A Linear Model Perspective

Figure 1 demonstrates that after the development performance peaks at EARLY_STOP (vertical dotted line), it deteriorates as M gradually fits more Unknown examples. In this section, we aim to characterize this relationship more accurately by assessing whether a simple linear dependency can tie the impact of fitting Known and Unknown training examples on test accuracy. To this end we use the following linear regression model:

$$Accuracy = \beta_0 + \beta_{\text{kn}} \cdot \frac{N_{\text{kn}}}{|D|} + \beta_{\text{unk}} \cdot \frac{N_{\text{unk}}}{|D|} \quad (1)$$

where N_{Kn} and N_{Unk} are the number of the Known and Unknown examples in D that M fits.

We estimate the coefficients[6] by collecting $(Accuracy, N_{\text{Kn}}, N_{\text{Unk}})$ values after each epoch from models fine-tuned on all D variants. Table 1 presents the results (top row). The high R^2 indicates a strong linear relationship between test accuracy and the type of training examples that are fitted. Our model entails that fitting Unknown examples hurts performance ($\beta_{unk} < 0$), while fitting Known examples improves it ($\beta_{\text{kn}} > 0$). The estimated negative impact from Unknown roughly matches the positive impact from Known ($|\beta_{\text{ukn}}| \approx |\beta_{\text{kn}}|$).

4.5 Generalization to New Relations

In the above setup, the (q, a) pairs in the test set correspond to triplets with the same set of 12 relations appearing in D. We now investigate whether our observed dynamics has a broader effect on the model's knowledge, and transfers to relations not

[6]Full details in §G. We note that this linear model is only valid in bounded region of $N_{\text{kn}} \leq |D|$, $N_{\text{unk}} \leq |D|$.

	EARLY_STOP					CONVERGENCE				
	Full	Hkn	Mkn	Wkn	Unk	Full	Hkn	Mkn	Wkn	Unk
$D_{\texttt{HighlyKnown}}$	40.5	**98.7**	60.1	9.0	0.6	40.0	**98.4**	58.8	8.5	0.7
$D_{\texttt{MaybeKnown}}$	**43.6**	**98.4**	**69.9**	12.1	1.0	**43.2**	97.5	**68.2**	12.9	1.3
$D_{\texttt{WeaklyKnown}}$	39.2	95.0	59.2	8.6	0.4	35.4	73.5	55.8	**17.2**	2.2
$D_{\texttt{Unknown}}$	37.5	95.6	52.9	6.5	0.6	25.8	55.8	36.6	12.2	**3.2**
$D_{\texttt{Natural}}$	**43.5**	98.0	67.6	**14.1**	**1.8**	41.8	95.5	61.7	14.8	2.5

Table 2: Accuracies for the single-category variants from §5, across per-category subsets of the test set. `Full` is the original test set (all the categories together). `Hkn=HighlyKnown`, `Mkn=MaybeKnown`, `Wkn=WeaklyKnown`, `Unk=Unknown`. In each column, the best result is in **bold**, as well as the results for which the difference from the best is not statistically significant with $p < 0.05$ (significance test details are in §I).

represented in D. To test this, we reserve a subset of the relations for an *out-of-distribution* (OOD) test set, excluding them from the train and development splits. See §A for details and Tables 4 and 5 for in-distribution vs OOD relations.

Our results on the OOD test set reveal similar key insights: (1) Higher `Unknown` ratio leads to lower OOD test performance and (2) `Unknown` examples are harmful for OOD performance, but mostly when M fits them. A linear model of the OOD test accuracy (Equation (1)), shows similar trends: $\beta_{\text{unk}} < 0$, $\beta_{\text{kn}} > 0$, $|\beta_{\text{ukn}}| \approx |\beta_{\text{kn}}|$ and $R^2 = 0.95$ (see Table 1). More details are in §H.

Overall, *our insights transfer across relations*. This essentially shows that fine-tuning on `Unknown` examples such as *"Where is [E1] located?"*, can encourage hallucinations on seemingly unrelated questions, such as *"Who founded [E2]?"*. This further supports the conclusion that the observed effects likely stem from the model learning the *behavior* of generating answers that are not grounded in its pre-existing knowledge.

5 Understanding Knowledge Types: Their Value and Impact

When addressing our main research question on the effect of `Unknown` fine-tuning examples, we treated the `Known` categories collectively for simplicity (see Figure 2a). We now examine the effect of each category, exploring the following questions: **Q1:** How *training examples* from each category impact the test performance? **Q2:** What is the model's performance across *test examples* from each category? To address **Q1** we created single-category variants of the fine-tuning dataset D. A variant of D consisting solely of examples from the category `CAT` is denoted as $D_{\texttt{CAT}}$. For reference, we include a variant with the *natural* categories distribution in EntityQuestions, denoted $D_{\texttt{Natural}}$. $|D|$ is fixed and identical to our experiments in §4. To address **Q2**, we further break down the test set performance by category. Table 2 presents the results.

`MaybeKnown` Examples are Essential. Since `Unknown` examples are harmful, one might expect that it would be best to fine-tune on the most exemplary `HighlyKnown` examples. Surprisingly, $D_{\texttt{HighlyKnown}}$ does not obtain the best overall results, as it excels on `HighlyKnown` test examples, yet its performance on the remaining categories is inferior. $D_{\texttt{MaybeKnown}}$ yields the best overall performance. Compared to $D_{\texttt{HighlyKnown}}$, $D_{\texttt{MaybeKnown}}$ enhances M_D's performance on `MaybeKnown` ($60.1 \rightarrow 69.9$), without compromising performance on `HighlyKnown` ($98.7 \rightarrow 98.4$). This suggests that `MaybeKnown` fine-tuning examples are essential for M_D to correctly handle such examples during inference. It also demonstrates that with the right fine-tuning examples, M_D becomes more capable of utilizing its pre-existing knowledge.

Limited Knowledge Enhances Overfitting. In §4.2, we demonstrated that `Unknown` fine-tuning examples increase the risk of overfitting. We now observe that this also applies to `WeaklyKnown`, though to a lesser degree. Specifically, at CONVERGENCE, $D_{\texttt{WeaklyKnown}}$ and $D_{\texttt{Unknown}}$ experience significant performance drops compared to EARLY_STOP ($39.2 \rightarrow 35.4$ and $37.5 \rightarrow 25.8$). With training to CONVERGENCE, they show a modest improvement on `WeaklyKnown` and `Unknown` but substantially degrade on `HighlyKnown` and `MaybeKnown`. This highlights that the decrease in performance is strongly attributed to an increased rate of hallucinations w.r.t. facts that were already known to M after pre-training.

Interestingly, $D_{\texttt{Natural}}$ performs on-par with

$D_{\texttt{MaybeKnown}}$ in EARLY_STOP, suggesting that the mere presence of MaybeKnown examples in D suffices for high performance on MaybeKnown, even if D has additional examples from other categories. Yet, $D_{\texttt{Natural}}$'s performance degrades significantly[7] after CONVERGENCE, under-performing $D_{\texttt{MaybeKnown}}$ – indicating that it still suffers from overfitting, most-likely due to the presence of WeaklyKnown and Unknown examples. Taken together these results demonstrate that $D_{\texttt{MaybeKnown}}$ stands out both in terms of top performance and reduced risk to overfitting.

6 SliCK Knowledge Categories Analysis

Assessing a model's knowledge remains an open problem, particularly since evaluating the quality of such methods is challenging due to the lack of ground truth about what the model truly knows. In this work we proposed **SliCK** (§3): a four-category classification of facts w.r.t. the model's knowledge. We now further analyze and discuss our design choices, hoping that **SliCK** can serve as a useful taxonomy to guide future research on this subject.

Fine-grained Known Categories We first reflect on whether our choice of splitting Known into more fine-grained categories, based on the greedy decoding outcome, has been proven meaningful. As shown in Table 2, HighlyKnown indeed captures facts with high degree of knowledge, as it consistently exceeds 95% accuracy post fine-tuning, while MaybeKnown and WeaklyKnown seem to represent weaker knowledge degrees. As intended, the performance on WeaklyKnown is worse that on MaybeKnown but better than on Unknown. Additionally, the *exact* categories distinction we made was proven useful since it revealed important insights on the importance of the MaybeKnown fine-tuning examples, as discussed in detail in §5.

Benchmarking Unknown Test Examples A desired property for (q, a) pairs classified as Unknown that appear in the test set, is that M will incorrectly answer q post fine-tuning (otherwise they are not truly Unknown).[8] In Table 2 we can see that the accuracy on Unknown is extremely low (3.2% or less), which is a strong indicator that most of the Unknown examples are actually unknown to M.

[7]See §I for details about this statistic significance test.

[8]Since in our closed-book QA setup the train and test sets are disjoint, the model has to rely on its pre-existing knowledge to answer test questions.

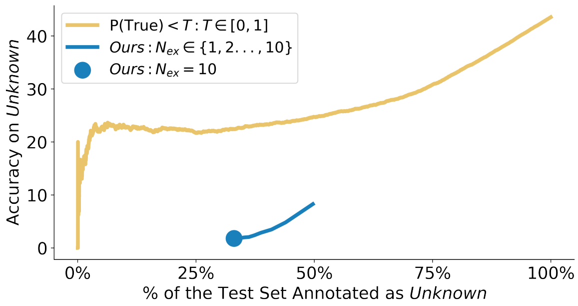


Figure 5: **SliCK** Unknown categorization vs. classifying examples with P(True) $< T$ as Unknown. The x-axis is the % of test examples classified as Unknown and the y-axis is the accuracy on these examples post fine-tuning. The yellow line is P(True) for $T \in [0, 1]$. Our Unknown category is the **blue circle** and the **blue line** corresponds to approximating $P_{\texttt{Correct}}$ with less than 10 random 4-shot exemplars (see §3 and §C).

As a case study for comparison, we analyze the P(True) approach by Kadavath et al. (2022): a continuous score that estimates the probability a model assigns to the correctness of a specific answer. P(True) was originally used for *self-evaluating* model-generated answers, while we use it to assess whether M considers the ground-truth answer as correct. In Figure 5, we explore classifying examples below a P(True) threshold as Unknown and compare this methodology to **SliCK**. Our results indicate that, at least in our setting, our approach categorizes Unknown examples for which the model's performance after fine-tuning is significantly worse. Specifically, looking at fixed values on the x-axis shows that if we would label a similar fraction of test examples as Unknown using both methods, the accuracy on the P(True)-based Unknown examples would be much higher post fine-tuning.[9] Lastly, the **blue line** shows that using samples from multiple few-shot prompts to approximate $P_{\texttt{Correct}}$ is crucial, as using $N_{\text{ex}} < 10$ leads to higher test accuracy on **SliCK** Unknown examples.

7 Discussion

Practical Implications. This work highlights the risk in using supervised fine-tuning to update LLMs' knowledge, as we present empirical evidence that acquiring new knowledge through fine-tuning is correlated with hallucinations w.r.t pre-existing knowledge. Additionally, this work raises important questions for future exploration regard-

[9]This is a preliminary analysis, and we leave a comprehensive comparison for future work. More details in §J.

ing fine-tuning practices. We saw that `Unknown` examples are fitted slower than the `Known` ones, thus their negative effect manifests as a form of *overfitting*, which emphasizes the importance of using *early-stopping* instead of a fixed number of fine-tuning steps. However, early-stopping may be less effective when fine-tuning on numerous tasks with distinct optimal stopping points. An alternative solution can be to align the fine-tuning data with the model's knowledge by filtering-out `Unknown` examples. We show initial evidence that this can reduce the risk of overfitting without compromising performance. A possible drawback of filtering is that `Unknown` fine-tuning examples can still be useful to teach LLMs to express uncertainty on `Unknown` test examples (Zhang et al., 2023). This raises the question: *can re-labeling* `Unknown` *fine-tuning examples with uncertainty expressions* (e.g., *"I don't know"*) *reduce their negative effect?* Our preliminary experiment (described in §K) suggests that the answer is *yes*, which indicates that such approaches could be the most promising. Exploring this is an interesting direction for future work.

Superficial Alignment Hypothesis. Zhou et al. (2023) hypothesized that the knowledge and capabilities of LLMs are mostly learned during pre-training, while alignment is a simple process where the model learns the style or format for interacting with users. They substantiate this hypothesis by showing that fine-tuning on just `1k` high-quality examples can result with a competitive assistant LLM, named LIMA. As discussed in §4.3, we show evidence that LLMs struggle to acquire new knowledge present in the `Unknown` examples and mostly learn to utilize their pre-existing knowledge. We also showed that fine-tuning on `HighlyKnown` examples led to sub-optimal utilization of pre-existing knowledge, despite our task format being simpler than LIMA's and our dataset being six times larger. Taken together, our findings suggest that even though most of the LLM's knowledge is indeed acquired through pre-training, the model learns more than just style or format through fine-tuning, as the selection of fine-tuning examples significantly influences the model's capability to utilize its pre-existing knowledge post fine-tuning.

8 Related Work

New knowledge and hallucinations. Schulman (2023), Goldberg (2023) and Gudibande et al. (2023) mention the conjecture that fine-tuning on new factual knowledge may encourage hallucinations. Huang et al. (2023) categorized hallucination causes and formally defined this scenario as *capability misalignment*. They highlight that limited research addresses capability misalignment due to the challenge of defining the knowledge boundary of LLMs. Kang et al. (2024) showed that when a fine-tuned LLM encounters unknown queries at test time, its responses mimic the responses associated with the unknown examples in the fine-tuning data. Yin et al. (2023) showed that LLMs' performance is not satisfactory when they face new knowledge in their input contexts and Lee et al. (2023) analyzed the impact of unknown *in-context* learning examples. To the best of our knowledge, our work is the first to empirically assess the impact of exposure to new knowledge through fine-tuning on tendency of the fine-tuned model to hallucinate.

Quantifying knowledge in LLMs. **SliCK** can be seen as a confidence elicitation method for the ground truth label (M *knows* (q, a) if it is confident that a is the answer to q). Existing work derive calibrated confidence from LLMs by examining agreement across multiple samples (Kuhn et al., 2023; Manakul et al., 2023; Tian et al., 2023a; Lyu et al., 2024), probing internal representations (Azaria and Mitchell, 2023; Burns et al., 2022), eliciting verbalized probability (Tian et al., 2023b) or direct prompting (Kadavath et al., 2022). Kadavath et al. also trained a separate P(IK) model to predict if the LLM knows the answer to q. The label for P(IK) was approximated by the fraction of correct sampled answers, which is conceptually aligned with $P_{\texttt{Correct}}$ (§3). A key difference is that we also define the **SliCK** categories, and provide evidence that we capture meaningful and useful categories.

9 Conclusion

We study the impact of integrating new factual knowledge through fine-tuning on the model's tendency to hallucinate. We first propose **SliCK**, a categorization of facts w.r.t. LLM's knowledge. We then design a controlled study where we isolate the impact of new knowledge and rigorously evaluate its effects. We provide multiple insights on the fine-tuning dynamics, with the following key findings: (1) Acquiring new knowledge via supervised fine-tuning is correlated with hallucinations w.r.t. pre-existing knowledge. (2) LLMs struggle to integrate new knowledge through fine-tuning and mostly learn to use their pre-existing knowledge.

10 Limitations

Our experiments were conducted using a single LLM, and thus it is unclear whether results will vary with different LLMs. Having said that, our study is extremely compute-heavy and thus challenging to replicate on multiple LLMs: First, our fine-tuning is compute-heavy as its runs are very long as we wanted to analyze the behavior during different stages of fine-tuning (including the overfitting stages). Second, and most importantly, to facilitate our study we needed to annotate a large scale dataset w.r.t the **SliCK** categories. To derive reliable conclusions, it was crucial to accurately assess the model's knowledge w.r.t. a single fine-tuning example. In our case we run 170 inference steps per example, i.e., more than $15M$ inference steps to categorize our full dataset.

In addition, since we focus on closed-book QA, the practical implications from our study such as filtering-out `Unknown` fine-tuning examples still require validation in settings involving long-form text generation. To filter-out examples that introduce new factual knowledge in long-form generation tasks, one would need to make adaptations to **SliCK** and come up with an effective way to compare the sampled answer with the ground-truth to approximate $P_{\texttt{Correct}}$. We leave this for future work. Long-form generation tasks introduce evaluation challenges, leading to a wide adoption of LLM-based evaluations. Our choice to focus explicitly on closed book QA facilitates more accurate evaluation that enhances the reliability of our findings.

Lastly, we did not test the effect of adding additional fine-tuning examples from diverse tasks into the fine-tuning mixture. While this could more closely approximate a typical instruction fine-tuning scenario, such dataset extension may introduce new factual knowledge in an uncontrollable way, which will limit our findings.

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A Data Preprocessing

This section expands §2 with additional details about our data preprocessing steps. The EntityQuestions dataset (Sciavolino et al., 2021) consists of train, development and test splits and spans 24 relations. Our train, development and test sets are curated based on the original splits from EntityQuestions. However, we use only 12 relations, since we wanted to reserve some relations for out-of-distribution test set. To avoid cherry-picking, the 12 relations used in our train, development and test sets are randomly sampled. The resulting relations are presented in Tables 3 and 4.

We reserved the remaining 12 relations for out-of-distribution test set. However, we found that in those 12 reserved relations, 5 were too similar to some of the relations that we train on (Table 3), thus we suspected that this could lead to a test set that is not truly out-of-distribution. To address that, we filtered out those relations and were left with 7 relations for our-of-distribution. Specifically we filtered-out the following relations:

- P276 was filtered out since it directly overlaps with P131 since for both relations the question in EntityQuestions is of the form *"Where is [E] located?"*. P276 stands for "location" (`https://www.wikidata.org/wiki/Property:P276`) and P131 stands for "located in the administrative territorial entity" (`https://www.wikidata.org/wiki/Property:P131`).

- P20, for which the question template is *"Where did [E] die?"*, was filtered out since it may require knowledge that relates to P19, for which the question template is *"Where was [E] born?"*. P20 stands for "place of death" (`https://www.wikidata.org/wiki/Property:P20`) and P19 stands for "place of birth" (`https://www.wikidata.org/wiki/Property:P19`).

- P106, for which the question template is *"What kind of work does [E] do?"*, was filtered out since it may require knowledge that relates to P800, for which the question template is *"What is [E] famous for?"*. P106 stands for "occupation" (`https://www.wikidata.org/wiki/Property:P106`) and P800 stands for "notable work" (`https://www.wikidata.org/wiki/Property:P800`).

- P413, for which the question template is *"What position does [E] play?"*, was filtered out since it may require knowledge that relates to P800, for which the question template is *"What is [E] famous for?"*. P413 stands for "position played on team / speciality" (`https://www.wikidata.org/wiki/Property:P413`) and P800 stands for "notable work" (`https://www.wikidata.org/wiki/Property:P800`).

- P159, for which the question template is *"Where is the headquarters of [E]?"*, was filtered out since it may require knowledge that relates to P36, for which the question template is *"What is the capital of [E]?"*. P159 stands for "headquarters location" (`https://www.wikidata.org/wiki/Property:P159`) and P36 stands for "capital" (`https://www.wikidata.org/wiki/Property:P36`).

The 7 relations used for out-of-distribution test set are presented in Table 5.

Lastly, we perform two additional filtering steps: (1) To simplify the process of categorizing the examples w.r.t. M's knowledge (§3), we filter-out examples with more than 1 correct answer.[10] (2) We make sure that no subjects or objects overlap between the train and test sets,[11] by filtering-out overlapping examples from the train set.[12]

B Test performance as Proxy for Hallucinations

We now detail the relation between the test performance in our setting and hallucinations. In our study, poorer performance of a fine-tuned model M_{D1}, compared to another fine-tuned model M_{D2} on the test set, can be attributed to a higher rate of hallucinations in M_{D1}, relative to its pre-existing knowledge, due to the following explanation.

The test set can be conceptually divided into two types of questions. First, there are questions with answers that are unknown to M. Those questions will remain unknown post fine-tuning, as we make sure that the training set is disjoint from the test

[10] 4.2% and 3.9% of the EntityQuestions train and test set respectively.

[11] For example, the subject ***"Bruce Smith"*** appears with 2 different relations ($P106$ and $P413$) yielding 2 examples: (*"What kind of work does **Bruce Smith** do?"*, *"poet"*) and (*"Where was **Bruce Smith** born?"*, *"Faribault"*).

[12] 2.1% of the EntityQuestions train set.

relation	question template	`HighlyKnown`	`MaybeKnown`	`WeaklyKnown`	`Unknown`	Total	Min
P131	Where is [E] located?	553	2529	1493	3071	7646	553
P136	What type of music does [E] play?	236	3410	1892	1978	7516	236
P17	Which country is [E] located in?	4387	2628	511	364	7890	364
P19	Where was [E] born?	369	1884	1498	4170	7921	369
P26	Who is [E] married to?	1609	1503	1087	3257	7456	1087
P264	What music label is [E] represented by?	206	1444	1854	3820	7324	206
P36	What is the capital of [E]?	4160	1634	449	572	6815	449
P40	Who is [E]'s child?	692	1467	1271	2680	6110	692
P495	Which country was [E] created in?	5459	1101	408	706	7674	408
P69	Where was [E] educated?	233	1126	1712	3650	6721	233
P740	Where was [E] founded?	1323	1618	1428	2902	7271	1323
P800	What is [E] famous for?	301	330	222	503	1356	222
TOTAL	-	19528	20674	13825	27673	81700	6142

Table 3: Statistics of the ENTITYQUESTIONS train split annotated with **SliCK** categories. We annotate the entire train split but always fine-tune on exactly 6142 examples (see the Min column). Refer to §E for more details.

relation	question template	`HighlyKnown`	`MaybeKnown`	`WeaklyKnown`	`Unknown`	Total
P131	Where is [E] located?	57	362	158	388	965
P136	What type of music does [E] play?	6	432	248	281	967
P17	Which country is [E] located in?	448	432	65	51	996
P19	Where was [E] born?	107	148	243	501	999
P26	Who is [E] married to?	177	238	158	378	951
P264	What music label is [E] represented by?	47	157	268	486	958
P36	What is the capital of [E]?	580	152	62	86	880
P40	Who is [E]'s child?	99	191	167	344	801
P495	Which country was [E] created in?	699	147	51	96	993
P69	Where was [E] educated?	27	145	227	441	840
P740	Where was [E] founded?	182	245	181	334	942
P800	What is [E] famous for?	35	50	28	76	189
TOTAL	-	2464	2699	1856	3462	10481

Table 4: In-distribution test set statistics.

set (§A). This means that both M_{D1} and M_{D2} will fail to answer these questions. Thus, the test performance difference between M_{D1} and M_{D2} is mostly attributed to the second type of questions: ones that are known to M, i.e. M can answer them correctly since it posses the relevant knowledge. Thus, M_{D1} and M_{D2} must rely on their pre-existing knowledge to answer such questions, and a lower performance on such question can be only categorized as an hallucination w.r.t. pre-existing knowledge.

C $P_{\texttt{Correct}}$ Approximation

This section expands §3 with additional details about our $P_{\texttt{Correct}}$ approximation. In our study we approximate $P_{\texttt{Correct}}(q, a; M, T)$ based on the fraction of correct answers to q sampled from M. We begin with randomly sampling N_{ex} distinct k-shot exemplars for each relation in our dataset (§A). Then, to approximate $P_{\texttt{Correct}}(q, a; M, T)$, we use M to generate answers to q using each of the N_{ex} exemplars from the relation corresponding to q. We first use temperature sampling with $T = 0.5$ to sample N_{sample} answers for each of the N_{ex} exemplars. $P_{\texttt{Correct}}(q, a; M, T > 0)$ is then approximated by the fraction of correct answers from the total of $N_{\text{ex}} \cdot N_{\text{sample}}$ predictions. We also generate the greedy decoding prediction ($T = 0$) for each of the N_{ex} exemplars. $P_{\texttt{Correct}}(q, a; M, T = 0)$ is then approximated by the fraction of correct answers from the total of N_{ex} predictions.[13]

We use $k = 4$ in our study, simply since we found it enough for M to output answers in the correct format. We use $N_{\text{ex}} = 10$ and $N_{\text{sample}} = 16$. The $N_{\text{sample}} = 16$ samples using $T = 0.5$ are sampled from Top 40.

The k exemplars are sampled from the development split. We sample N_{ex} different samples since we found that even when the few-shot exemplars are sampled per-relation, their exact choice still affects the prediction. In §6 and Figure 5 we show

[13] Since we can only have one greedy prediction for every k-shot exemplars.

relation	question template	HighlyKnown	MaybeKnown	WeaklyKnown	Unknown	Total
P127	Who owns [E]?	125	383	168	314	990
P50	Who is the author of [E]?	287	193	115	372	967
P407	Which language was [E] written in?	366	153	59	45	623
P176	Which company is [E] produced by?	289	277	181	225	972
P170	Who was [E] created by?	142	284	120	304	850
P175	Who performed [E]?	94	120	103	663	980
P112	Who founded [E]?	134	116	76	140	466
TOTAL	-	1437	1526	822	2063	5848

Table 5: Out-of-distribution test set statistics.

Wrong Answer	Paraphrase	Higher Granularity	Lower Granularity
90%	6%	2%	2%

Table 6: Error Analysis of 100 Predictions of the Pre-trained Model, for Which Exact Match is False.

evidence that this also improves the quality of our categories.

Below is an example of our 4-shot prompt format, from real example from EntityQuestions with the relation $P106$ representing occupation.[14] The question in this case is *"What kind of work does Ron Konopka do?"* and the ground truth asnwer is *"geneticist"*.

```
Q: What kind of work does Nicolas Roeg do?
A: film director
Q: What kind of work does Crystal Geoffré do?
A: actor
Q: What kind of work does Maurice Blondel do?
A: philosopher
Q: What kind of work does Javier de Burgos do?
A: politician
Q: What kind of work does Ron Konopka do?
A:
```

To decide whether a sampled answer is correct, we use the Exact Match (EM) metric to compare it with the ground truth answer. The main advantage in this choice is that when EM is True, we know that the answer is correct for 100%. The main potential risk associated with this choice is that we may wrongly classify answers as incorrect due to paraphrases or answers with different granularity levels (Wang et al., 2023; Kamalloo et al., 2023; Yona et al., 2024)). To address this, we perform an **error analysis** on 100 predictions for which EM was False. We randomly sample 50 greedy predictions ($T = 0$) and 50 samples with $T = 0.5$. The results are in Table 6. This analysis suggest that in 90% of the cases where EM is False, the predicted answer is indeed incorrect. Which is a reasonable performance for our purpose, especially considering that when EM is True the answer is 100% correct.

[14] `https://www.wikidata.org/wiki/Property:P106`

D Data Annotation

we first calculate $P_{\texttt{Correct}}(q, a; M, T = 0)$ and $P_{\texttt{Correct}}(q, a; M, T > 0)$ for each (q, a) pair in our preprocessed dataset (§2 and §A), using our $P_{\texttt{Correct}}(\cdot)$ approximation (§3 and §C). We then use these values to categorize each (q, a) pair into one of our four categories (§3 and Figure 2). We provide the full statistics of the categories on the train and test set, as well as the out-of-distribution test set in Tables 3, 4 and 5.

E Fine-tuning Details

Fine-tuning Data. In §4 we examine the effect of new knowledge in the fine-tuning dataset D on the performance of M_D, by varying the proportion of `Unknown` examples in D. When we create variants of D with exactly $X\%$ of `Unknown` and $(100 - X)\%$ `Known` examples, we make sure that the relation distribution remains consistent. To achieve that we sample $X\%$ of `Unknown` *from each relation*.

In §5 we create single-category variants of D. Since we want to work with a fixed $|D|$ across all variants, we want to make sure that we have $|D|$ examples from each category. To ensure this, we measure the size of the smallest category in each relation (see the "Min" column in Table 3) and define $|D|$ as their sum. In other words, for each relation we calculate the size of the smallest category and sum these values. This leads to $|D| = 6142$, as illustrated by the last column in Table 3. More formally, for each relation r in the training split, and for each category CAT from our 4 **SliCK** categories, we define CAT_r to be the examples from category CAT and relation r. Consequently size($\mathrm{CAT_r}$) is the number of the examples in $\mathrm{CAT_r}$. For example size(`HighlyKnown` $_{\mathrm{P131}}$) $= 553$ (see Table 3). We then define:

$$|D| = \sum_{r \in R_{\mathrm{Train}}} \min \left\{ \mathrm{size}(CAT_r) \middle| \begin{array}{l} \mathrm{CAT} \in \{ \\ \texttt{HighlyKnown}, \\ \texttt{MaybeKnown}, \\ \texttt{WeaklyKnown}, \\ \texttt{Unknown}\} \end{array} \right\}$$

where $\mathrm{R_{Train}}$ are the 12 relations from the training set.

Below is an example of our data format in the train, development and test sets, from real example from EntityQuestions with the relation $P106$ representing occupation.[15] The question in this case is *"What kind of work does Ron Konopka do?"* and the ground truth asnwer is *"geneticist"*.

> Answer the following question.
> What kind of work does Ron Konopka do?

Fine-tuning hypeparameters. We fine-tune every model for 50 epochs for all our model variants to completely fit the training set, so we can examine all stages of fine-tuning. We use learning rate of 1e-5, a batch size of 128, and a dropout rate of 0.05. We evaluate the models every epoch on the development set. The EARLY_STOP stopping criteria is defined to be the epoch with the maximum accuracy on the development set.

F Train Accuracy on Different `Known` Categories

In §4.3 we analyze the fine-tuning dynamic and present the training accuracy as function of the fine-tuning duration in Figure 1. For simplicity we treated the `Known` categories collectively. For reference we also include the plot with the full per-category breakdown in Figure 6.

G Linear Model

In §4.4 and §4.5 we use a linear model (Equation (1)) that predicts that test accuracy and the out-of-distribution test accuracy. We estimate the parameters of this linear model based on results from all our variants of D used in §4. For all these variants, we measure the test accuracy and the number of `Known` and `Unknown` fine-tuning examples that M fits during different fine-tuning stages. This way we collect a dataset with examples of the form

[15] https://www.wikidata.org/wiki/Property:P106

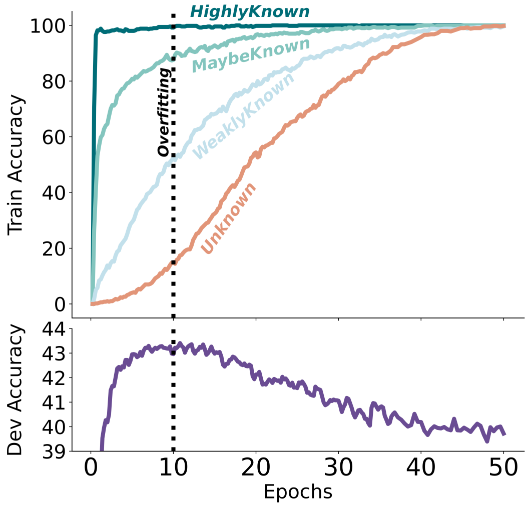
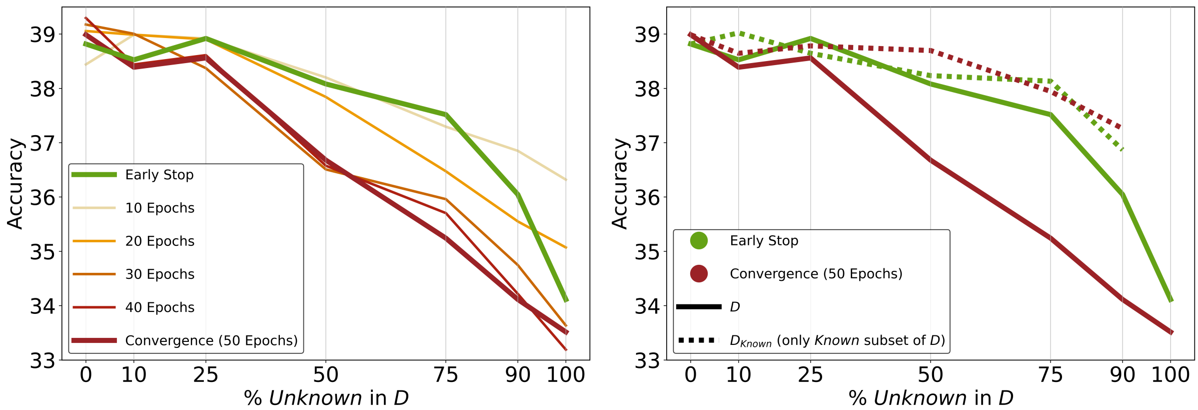


Figure 6: Training accuracy as a function of fine-tuning duration, evaluated on the variant with 50% `Unknown` fine-tuning examples. For reference, we also include the accuracy on the development set, accompanied by a zoom-in plot within a narrower range, to provide a more visible and clear view.

$(Accuracy, N_{\mathrm{Kn}}, N_{\mathrm{Unk}})$, which we use to fit a linear regression model.

H Out-of-distribution (OOD) Evaluation

In §4.5 we discuss *out-of-distribution (OOD)* results. In these experiments we simply used our OOD test set consisting of 7 relations unseen during fine-tuning (see §A). When we perform the analysis discussed in §4.1 and §4.2, we additionally evaluated the models on the OOD test set. For completeness, we add here Figure 7, which is the out-of-distribution version of Figure 3. Figure 7a presents the OOD test performance as a function of $\%$ of `Unknown` examples in D for different fine-tuning duration. The corresponding *in-distribution* results (Figure 3a) were discussed in §4.1. Figure 7b presents the OOD test performance for the ablation where we filter-out `Unknown` fine-tuning examples. The corresponding *in-distribution* results (Figure 3b) were discussed in §4.2. We notice that similar trends, just with a smaller overall magnitude of the performance drop, up to 6 points drop compared to up to 14 for in-distribution. This smaller drop magnitude is also reflected in smaller values of $|\beta_{\mathrm{ukn}}|$ and $|\beta_{\mathrm{kn}}|$ (Table 1).



(a) (b)

Figure 7: Performance on the *out-of-distribution (OOD)* test set as a function of the % of `Unknown` examples in the fine-tuning dataset D. This plot is the OOD version of Figure 3. Everything is similar to Figure 3, except that y-axis is the accuracy on the OOD test set. We note that ***the development set did not change (not OOD)***, thus it does not necessarily reflects the optimal stopping point for OOD.

	EARLY_STOP					CONVERGENCE				
	`Full`	`Hkn`	`Mkn`	`Wkn`	`Unk`	`Full`	`Hkn`	`Mkn`	`Wkn`	`Unk`
$D_{\texttt{HighlyKnown}}$	40.5**	**98.7**	60.1**	9.0**	0.6**	40.0**	**98.4**	58.8**	8.5**	0.7**
$D_{\texttt{MaybeKnown}}$	**43.6**	**98.4**	**69.9**	12.1**	1.0**	**43.2**	97.5*	**68.2**	12.9**	1.3**
$D_{\texttt{WeaklyKnown}}$	39.2**	95.0**	59.2**	8.6**	0.4**	35.4**	73.5**	55.8**	**17.2**	2.2**
$D_{\texttt{Unknown}}$	37.5**	95.6**	52.9**	6.5**	0.6**	25.8**	55.8**	36.6**	12.2**	**3.2**
$D_{\texttt{Natural}}$	**43.5**	98.0*	67.6**	**14.1**	**1.8**	41.8**	95.5**	61.7**	14.8**	2.5*

Table 7: A copy of Table 2 with detailed notation of the statistic significant test results. In each column, statistically significant differences from the best result are indicated using * and ** for $p < 0.05$ and $p < 0.01$ respectively.

I Statistic Significance Tests

In §5 we present Table 2. As mentioned in the caption, we perform statistic significance tests for each column. To this end we compare all the values to the maximal value in this column.

For each subset of the test set, we randomly shuffle all the examples in it, split them up into 100 approximately equally sized subsets, and compute accuracy for each of them for all the models of interest. We then apply paired-sample t-test with $p < 0.05$ and $p < 0.01$.

In Table 2, the best result is in bold, as well as all the results with statistically non-significant difference from the best with $p < 0.05$. We additionally include a copy of Table 2 where all the statistical tests outcomes are annotated, see Table 7. We can see that in almost all cases the difference is statistically significant with $p < 0.01$, except two cases where it is only with $p < 0.05$ ($D_{\texttt{Natural}}$ `Unk` and $D_{\texttt{MaybeKnown}}$ `Mkn`).

Since we also discuss "horizontal" comparisons, where we compare EARLY_STOP to CONVERGENCE, we additionally run significance tests (not annotated in Table 2) for *All*, comparing EARLY_STOP to CONVERGENCE. The difference for $D_{\texttt{MaybeKnown}}$ was not statistically significant while for all others (including $D_{\texttt{Natural}}$) it was significant with $p < 0.01$.

J The P(True) Case Study

In §6 we used the P(True) metric from Kadavath et al. (2022) as a case study for comparison. In Figure 5 we compare our `Unknown` category vs classifying as `Unknown` based on a threshold of P(True). We calculated P(True) for every (q, a) pair in the test set using Kadavath et al. (2022)'s prompt:

> Question: *Where is Paris located?*
> Proposed Answer: *France*
> Is the proposed answer:
> (A) True
> (B) False
> The proposed answer is:

We then treated (q, a) pairs with P(True) below a threshold as `Unknown`. We experimented with each

	EARLY_STOP		CONVERGENCE	
	Accuracy	% Answered	Accuracy	% Answered
D	43.0	100.0	38.8	100.0
$D_{\texttt{IDK}}$	61.8	58.7	61.8	55.6

Table 8: Results of our initial experiment where the label of the `Unknown` fine-tuning examples is replaced with *"I don't know"*. D in this case is the variant with 50% `Known` and 50% `Unknown`. $D_{\texttt{IDK}}$ is the variant where all the 50% `Unknown` fine-tuning examples were re-labeled with *"I don't know"*. The accuracy is measured on the subset of the test questions that were answered, i.e. M_D did not respond with *"I don't know"*.

possible threshold T in $[0, 1]$, according to our test set. For each threshold T we then measured (1) how many examples were classified as `Unknown` out of the test set, (2) what was the accuracy on these examples after fine-tuning. We plot the results in Figure 5, where P(True) is represented with the **yellow line** and our `Unknown` is represented with the **blue circle**. As discussed in §C, it was approximated using 10 defferent samples of 4-shot exemplars ($N_{\text{ex}} = 10$). We also check smaller values of N_{ex} and plot the results with the **blue line**. The accuracy after fine-tuning for all the results is measured after fine-tuning with $D_{\texttt{Natural}}$ (§5).

K Re-labeling `Unknown` Fine-tuning Example with an Uncertainty Expression: Initial Experiment

In this work we showed that fitting `Unknown` fine-tuning examples negatively affects the test performance. However, this negative effect manifests as a form of *overfitting*. From practical perspective, we showed that we can mitigate overfitting by either using early-stopping or filtering-out `Unknown` examples from the fine-tuning dataset.

We now perform a preliminary experiment where check whether fine-tuning the model to abstain from `Unknown` examples can also be a potential mitigation. Specifically, we replace the label of the `Unknown` fine-tuning examples with the expression *"I don't know"* and test whether this mitigates the observed overfitting.

Table 8 presents the % of the test questions that were answered (i.e. M_D did not respond with *"I don't know"*) and the accuracy on those questions. This experiment was conducted on the D variant with 50% `Unknown`. The first row is for the original result with D as a reference and the second row is for the results with $D_{\texttt{IDK}}$, where the ground-truth label of the 50% of the `Unknown` examples in D was replaced with *"I don't know"*

Consistent with the findings from previous work (Zhang et al., 2023), we observe an improved accuracy on willingly answered test examples (when comparing D vs $D_{\texttt{IDK}}$). When we compare EARLY_STOP vs CONVERGENCE for D we observe a performance drop ($43.0 \rightarrow 38.8$) which illustrates the overfitting effect. However, we observe that re-labeling the `Unknown` examples with uncertainty expression seem to reduce the risk of overfitting. Specifically, the accuracy for $D_{\texttt{IDK}}$ remains 61.8 for both EARLY_STOP and CONVERGENCE, with a small decrease on the number of willingly answered questions ($58.7 \rightarrow 55.6$)