Emergent Response Planning in LLM

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Abstract

In this work, we argue that large language models (LLMs), though trained to predict only the next token, exhibit emergent planning behaviors: their hidden representations encode future outputs beyond the next token. Through simple probing, we demonstrate that LLM prompt representations encode global attributes of their entire responses, including structural attributes (response length, reasoning steps), content attributes (character choices in storywriting, multiple-choice answers at the end of response), and behavioral attributes (answer confidence, factual consistency). In addition to identifying response planning, we explore how it scales with model size across tasks and how it evolves during generation. The findings that LLMs plan ahead for the future in their hidden representations suggests potential applications for improving transparency and generation control.

1. Introduction

Large Language Models (LLMs) have demonstrated powerful capabilities across various tasks (Brown et al., 2020; Achiam et al., 2023; Touvron et al., 2023a; Anthropic, 2024). However, their next-token-prediction training objective leads to the view that they generate text through local, per-token prediction, without considering future outputs beyond the next immediate token (Bachmann & Nagarajan, 2024; Cornille et al., 2024). This makes controlling the generation process challenging: we are blind to the model's output tendency until keywords or the full response appear. While prompt engineering and inference-time interventions (Liu et al., 2023; Li et al., 2024; Zhou et al., 2024) can guide responses, they lack insight and transparency into the model's internal plan for outputs.

In this work, we argue that LLMs, though trained to predict

only the next token, display emergent planning behaviors: their hidden representations encode their future outputs beyond just the next token. Specifically, we observe that LLM prompt representations encode interesting global attributes of their upcoming responses. We call this phenomenon response planning and classify these global attributes into three categories: structural attributes (response length, reasoning steps), content attributes (character choices in storywriting, multiple-choice answers at the end of response), and behavioral attributes (answer confidence, factual consistency).

We empirically identify response planning by training simple probes on LLM prompt representations to predict the global attributes of their upcoming responses. We find that these probes achieve non-trivial prediction accuracy, providing strong evidence that LLMs plan at least part of their entire response in advance as soon as they read the prompt. Through further ablation experiments, we find that planning abilities positively scale with fine-tuned model size, peak at the beginning and end of responses, share certain planning patterns across models, and exceed models' self-reported awareness.

The contribution of our work is two-fold: (1) To our best knowledge, we introduce the first formal definition and framework of emergent response planning in LLM. (2) We demonstrate empirically that LLMs perform emergent response planning through systematic probing experiments across various attributes types and tasks, and investigate their properties. These findings shed light on LLMs' internal mechanisms and suggest novel approaches for predicting and controlling outputs pre-generation, potentially enhancing model controllability.

2. Related Work

Understanding LLM hidden representations. LLM hidden representations encode more information than they actively use (Saunders et al., 2022; Burns et al., 2022). Patterns in these representations can be identified using linear or MLP probes (nostalgebraist, 2020; Li et al., 2022; Belrose et al., 2023; Zou et al., 2023; Ji et al., 2024) and leveraged to influence model behaviors such as truthfulness (Hernandez et al., 2023; Li et al., 2024), instruction-following (Heo et al., 2024), and sentiment (Turner et al., 2024). They

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are also useful for training additional regression or classification heads on transformer layers for tasks like reasoning (Han et al., 2024; Damani et al., 2024), high-dimensional regression (Tang et al., 2024), and harmful content detection (Rateike et al., 2023; MacDiarmid et al., 2024; Qian et al., 2024).

Our work also utilizes LLM hidden representations but differs in focus. Rather than using hidden states as feature extractors for external tasks, we probe model-generated data to understand how these states encode the model's own planning attributes during generation.

Prior works exploring response planning in LLM. Previous study have examined whether LLMs can anticipate beyond the next token. Future Lens (Pal et al., 2023) models token distributions beyond the immediate next token using linear approximation. (Geva et al., 2023) studies how LLMs retrieve factual associations during generation, while (Men et al., 2024) extends this to Blocksworld planning, suggesting LLMs consider multiple planning steps simultaneously. (Pochinkov et al., 2024) finds that tokens at context-shifting positions may encode information about the next paragraph. (Wu et al., 2024) hypothesizes LLMs' lookahead capability and tests two mechanisms—pre-caching and breadcrumbs—in a myopic training setting.

While prior works examine relatively narrow aspects like predictions several tokens ahead or knowledge retrieval in specialized scenarios, our work delves deeper to reveal the broader response planning landscape of LLMs. We provide the first formal definition of response planning in LLM, investigate comprehensive planning attributes, and demonstrate planning capabilities across diverse real-world tasks.

3. Emergent Response Planning in LLMs

If LLMs plan ahead for their entire response in prompt representations, then some global attributes of their upcoming responses can be predicted from the prompt, without generating any tokens. In this section, we first describe how existing probing techniques can investigate the global responses encoded in LLM prompt representations (Section 3.1). We then outline the setup for training our probes, including the response attributes of interest and the data collection pipeline (Section 3.2). Finally, we discuss experimental details before presenting our results (Section 3.3).

3.1. Probing for Future Responses

We study an L-layer decoder LLM $\pi(\mathbf{y} \mid \mathbf{x})$ that generates a response $\mathbf{y} = (y_1, \ldots, y_n)$ given a prompt $\mathbf{x} = (x_1, \ldots, x_m)$ sampled from a prompt distribution $p(\mathbf{x})$. During generation, the model encodes the input $(\mathbf{x} \circ \mathbf{y}_{1:t})$ into layer-wise representations $\{\mathbf{H}_{\mathbf{x} \circ \mathbf{y}_{1:t}}^l\}_{l-1}^L$, with the next token greedily decoded from the projection of final-layer rep-

resentations $y_{t+1} = \arg\max(f_{\text{out}}(\mathbf{H}_{\mathbf{x} \circ \mathbf{V}_{1:t}}^{L})).$

We investigate whether the prompt representations $\mathbf{H}_{\mathbf{x}}^{l}$, which produce the first response token y_1 , also capture some global attributes of their upcoming response \mathbf{y} (e.g., response length).

Formally, we define the *attribute rule* as $g(\mathbf{y})$, which summarizes the attributes from the generated responses (e.g., counting tokens in \mathbf{y}). Building on prior work on interpretability, if the prompt representations do capture these attributes, we can "probe" the hidden representations to predict the attributes without generating any response token: $h_{\theta}(\mathbf{H}_{\mathbf{x}}^{\mathbf{l}}) \to g(\mathbf{y})$. If probing yields non-trivial predictions, we conclude that the LLM exhibits *response planning*.

3.2. Probing Setup

To study response planning in LLMs, we first design tasks $T = (p(\mathbf{x}), g(\mathbf{y}))$, consisting of a prompt distribution $p(\mathbf{x})$ eliciting key response attributes of interests $g(\mathbf{y})$ as probing targets. Next, we introduce the data collection pipeline for training probes.

Task design. The studied response attributes must be global, meaning they cannot be determined from the first response token and should ideally be distributed across the entire response. We focus on six tasks that elicit response attributes across three categories: structural, content, and behavioral.

- 1. **Structure attributes** capture response-level features: the *response length prediction* prompts LLMs to follow human instructions, with the number of tokens counted as the probing target; the *reasoning steps prediction* prompts LLMs to solve math problems, with the number of reasoning steps as the probing target.
- 2. Content attributes track specific words appearing anywhere but not at the start of the response: character choices prediction prompts LLMs to write a story featuring an animal character, with the character choice as the probing target; multiple-choice answers prediction prompts LLMs to answer a question after reasoning (e.g., "please first explain then give your answer"), with the selected answer as the probing target.
- 3. **Behavior attributes** require external ground truth labels for validation: the *answer confidence prediction* prompts LLMs to answer challenging multiple-choice questions, with the correctness of answers judged by ground-truth labels as the probing target; the *factual consistency prediction* prompts LLMs to discuss and then agree/disagree with given statements, with the match between LLM's stance and statement ground-truth validity as the probing target.

Following the prompting strategies described in each task,

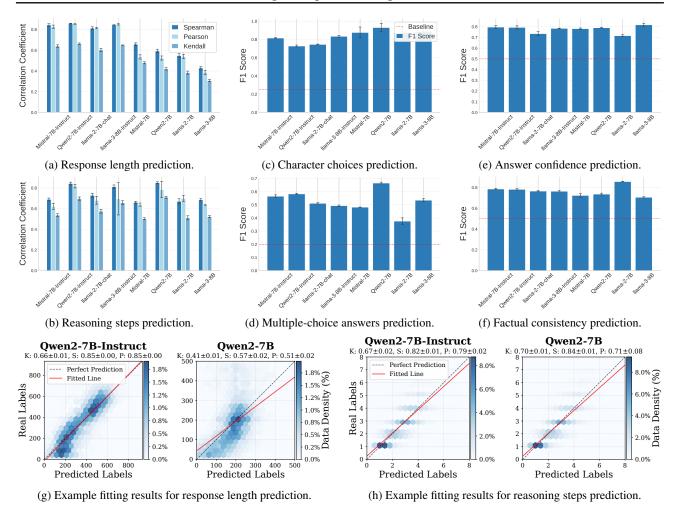


Figure 1. Prediction results within the dataset. Regression tasks (response length, reasoning steps) show high accuracy and strong correlation with targets, as measured by Kendall (K), Spearman (S), and Pearson (P) coefficients. Classification tasks (character choices, multiple-choice answers, confidence, factual consistency) perform significantly above random baseline according to F1 scores. These results suggest that the model demonstrates emergent planning capabilities for future response attributes.

we carefully pair datasets with corresponding prompts. We use prompts from Ultrachat (Ding et al., 2023) and AlpacaE-val (Taori et al., 2023) for response length; GSM8K (Cobbe et al., 2021) and MATH (Saxton et al., 2019) for reasoning steps; TinyStories (Eldan & Li, 2023) and ROCStories (Mostafazadeh et al., 2016) for character choices; CommonsenseQA (Talmor et al., 2019) and SocialIQA (Sap et al., 2019) for multiple-choice answers; MedMCQA (Pal et al., 2022) and ARC-Challenge (Clark et al., 2018) for answer confidence; CREAK (Onoe et al., 2021) and FEVER (Thorne et al., 2018) for factual consistency. Please see Appendix A.3.1 for more details about task design.

Data collection. For each task $T = (p(\mathbf{x}), g(\mathbf{y}))$, we collect datasets for probing. We sample prompts \mathbf{x}_i from the prompt distribution $p(\mathbf{x})$, store prompt representations $\mathcal{H}_i = \{\mathbf{H}_{\mathbf{x}_i}^l\}_{l=1}^L$, generate responses to the prompts $\mathbf{y}_i = \arg\max \pi(\mathbf{y} \mid \mathbf{x}_i)$, and store probing targets $\hat{g}_i = g(\mathbf{y}_i)$. This creates a dataset of prompt representations and their

future response attributes: $\mathcal{D} = \{\mathcal{H}_i, \hat{g}_i\}_{i=1}^N$. With this dataset, we then train a probe to predict targets from representations.

See Appendix A.3 for details on data collection, including task-specific and model-specific prompt templates, as well as data filtering and augmentation methods.

3.3. Experimental Details

Probe training. We train one-hidden-layer MLPs with ReLU activation, with hidden sizes chosen among $\mathcal{W}=\{1,2,4,8,16,32,64,128,256,512,1024\}$. The output size is 1 for regression and the number of classes with a softmax layer for classification. Each probe is trained for 400 epochs using MSELoss for regression and CrossEntropy-Loss for classification. Datasets are split 60:20:20 for train-validation-test. We perform a grid search over MLP hidden sizes \mathcal{W} and representation layers \mathcal{H} (as inputs to

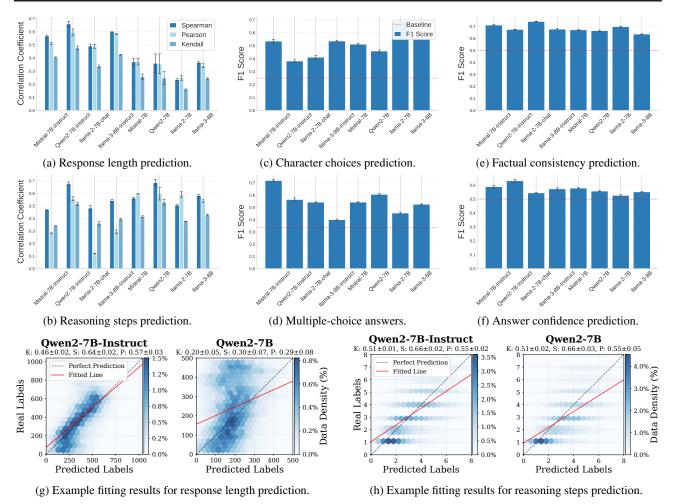


Figure 2. Cross-dataset generalization results. For regression tasks (response length, reasoning steps), correlations with targets remain strong despite reduced accuracy compared to in-dataset testing, as shown by Kendall (K), Spearman (S), and Pearson (P) coefficients. Classification tasks (character choices, multiple-choice, confidence, factual consistency) maintain above-baseline F1 scores. These results suggest the probes detect generalizable patterns rather than dataset-specific features, indicating transferable emergent planning capabilities within the task domain.

the probes), reporting the test scores for the best hyperparameters. Results are averaged across three random seeds.

Probe evaluation. For regression tasks (response length and reasoning steps), we evaluate using Spearman, Kendall and Pearson correlation coefficients, which measure the strength and direction of monotonic (Spearman, Kendall) and linear (Pearson) relationships between predicted and target values. For classification tasks, we evaluate using F1 scores: 4-class classification for character choices, 5-class classification for multiple-choice answers, and binary classification for answer confidence and factual consistency. In our setup, accuracy aligns with F1 score for classification due to strict class balance across tasks.

Language models. We experiment with both instruction-tuned models (Llama-2-7B-chat, Llama-3-8B-Instruct,

Mistral-7B-Instruct, and Qwen2-7B-Instruct) and their corresponding base models (Llama-2-7B, Llama-3-8B, Mistral-7B, and Qwen2-7B). See Appendix A.1 for model specifications and links.

4. Experimental Results

In this section, we present experimental results across six tasks, showing that LLM hidden prompt representations encode rich information about upcoming responses and can be used to probe and predict global response attributes.

Insight 1: Models present emergent planning on structural, content, and behavioral attributes, which can be probed with high accuracy (Fig. 1). Our in-dataset probing experiments (where probes are trained and tested on different splits of the same prompt dataset) reveal that both

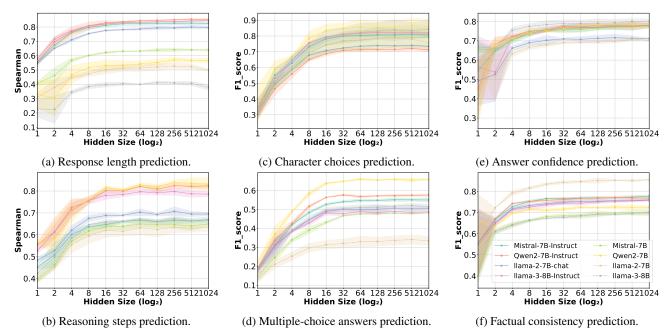


Figure 3. Hidden-size study results. Performance of MLP probes plateaus at relatively small hidden sizes (≤ 128) across all tasks, with structure attributes converging around size 16, content attributes at 32, and behavior attributes at 8. This suggests a hierarchy of pattern complexity, with behavioral patterns being most accessible and content patterns requiring more sophisticated probes.

base and fine-tuned models encode structural, content, and behavioral attributes, with fine-tuned models showing superior performance. For structural attributes (response length and reasoning steps; Fig. 1a, 1b), fine-tuned models exhibit strong linear correlations with ground truth, clustering around y = x (with example fitting results shown in Fig. 1g, 1h), while base models show weaker but positive correlations. For content and behavior attributes (character choices, multiple-choice answers, answer confidence, and factual consistency; Fig. 1c, 1d, 1e, 1f), both model types demonstrate robust classification performance above random baselines. These findings also suggest that models develop systematic internal planning representations for content or behavior attributes during pre-training, with structure attributes requiring additional reinforcement through fine-tuning.

Insight 2: The learned patterns generalize across datasets, indicating intrinsic task-related patterns rather than dataset-specific ones (Fig. 2). Our cross-dataset experiments (training and testing probes on different prompt datasets for the same task, e.g., GSM8K→MATH or TinyStories→ROCStories) demonstrate robust generalization of learned patterns. For structural attributes (Fig. 2a, 2b), predictions maintain strong positive correlations with target labels despite lower accuracy compared to in-dataset testing (with example fitting results shown in Fig. 2g, 2h), with fine-tuned models showing stronger correlations than base models. Similarly, for content and behavior attributes

(Fig. 2c, 2d, 2f, 2e), performance remains above baseline in cross-dataset settings. These results suggest that probes capture generalizable task-related patterns rather than merely dataset-specific features, indicating that models may develop intrinsic emergent planning capabilities that transfer across different contexts within the same task domain.

Insight 3: Emergent planning patterns are salient across models and tasks, extractable with simple MLP probes (**Fig. 3**). We investigate pattern saliency by varying the hidden size of two-layer MLP probes and measuring their average performance across model layers. Performance plateaus before hidden size 128 across all datasets, with larger sizes that can even lead to overfitting, indicating pattern saliency. The results can also indicate saliency differences across attributes: structure attributes (Fig. 3a, 3b) reach converges start at around hidden size 16, content attributes (Fig. 3c, 3d) plateau around 32, and behavior attributes (Fig. 3e, 3f) plateus at around 8, suggesting a hierarchy of representation complexity where behavioral patterns are most readily accessible, structural patterns require moderate complexity to capture, and content patterns demand the most sophisticated probe architectures. The consistent pattern across different model scales and architectures points to fundamental organizational principles in language model representations. This suggests that emergent planning capabilities may be an inherent property of large language models rather than an artifact of specific architectures or training pro-

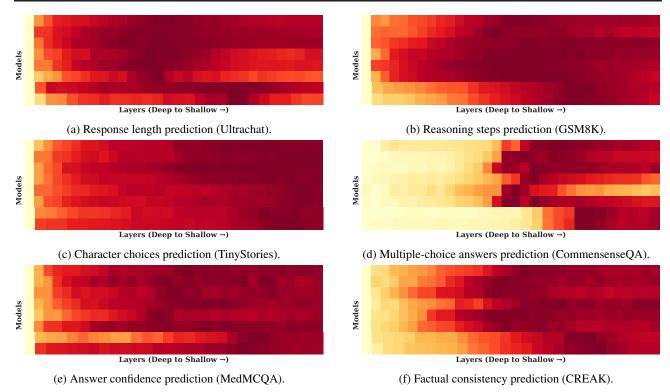


Figure 4. Layer-wise attribute prediction dynamics. Structural attributes peak mid-layers, content attributes emerge late, and behavioral attributes stabilize early. Layer-wise probing reveals hierarchical organization of planning capabilities, with progressive refinement shaping final outputs.

cedures.

Insight 4: Attribute patterns accumulate and peak differently across model layers (Fig. 4). We conduct layer-wise probing analysis (with hidden sizes optimized per layer) to understand how different attributes emerge through model layers. The results reveal distinct accumulation patterns for each attribute type. Structure attributes (Fig. 4a, 4b) show weak performance in early layers, peak in middle layers, and partially diminish in final layers, suggesting a gradual accumulation followed by refinement. Content attributes (Fig. 4c, 4d) peak in later layers, either through sudden late-layer emergence or gradual accumulation, indicating their reliance on higher-level semantic processing. Behavior attributes (Fig. 4e, 4f) demonstrate uniform distribution across layers except for the initial few, suggesting they are fundamental properties encoded early in the model. These layer-wise patterns reveal that (1) different aspects of planning emerge through distinct computational paths, (2) the hierarchical nature of planning, from basic behavioral patterns to complex structural decisions, is reflected in the layer-wise organization, and (3) the emergence of these patterns through progressive transformations, rather than from initial embeddings alone, indicates that planning capabilities arise from learned computational processes rather than simple statistical correlations.

5. Ablation

5.1. Planning Ability Scales with Model Size

We analyze how emergent response planning scales across different model sizes using four model families: LLama-2-chat (7B, 13B, 70B), Llama-3-Instruct (8B, 70B), Qwen-2-Instruct (7B, 72B), and Qwen-2.5-Instruct (1.5B, 32B, 72B). Using grid search over layers and hidden sizes, we identify optimal configurations and evaluate models on UltraChat and TinyStories datasets, focusing on structure and content attributes. We exclude base models as the relatively small models have short context which limit few-shot prompts, while the same prompts fail to effectively prompt larger base models to follow instructions. We omit the behavior attribute type as larger models tend to give correct answers consistently, making it difficult to obtain balanced data for analysis.

Results shown in Fig. 5 exhibit two key insights: (1) within each model family, larger models demonstrate stronger planning capabilities, and (2) this scaling pattern does not generalize across different model families, suggesting that other factors like architectural differences also influence planning behavior.

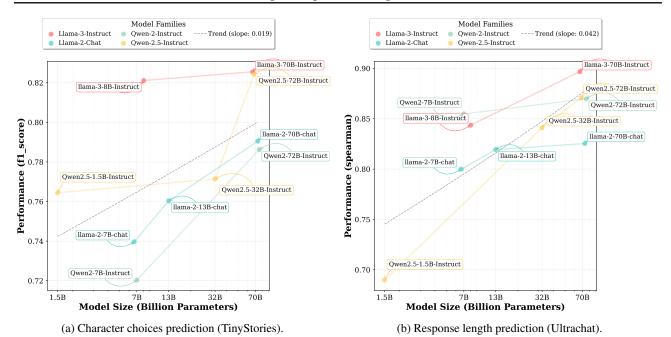


Figure 5. Scaling effects on planning capabilities. Evaluated across four model families (LLaMA-2-chat, LLaMA-3-Instruct, Qwen-2-Instruct, Qwen-2.5-Instruct; 1.5B–72B) using UltraChat and TinyStories, structure and content attributes show family-specific scaling: larger models within each family improve planning.

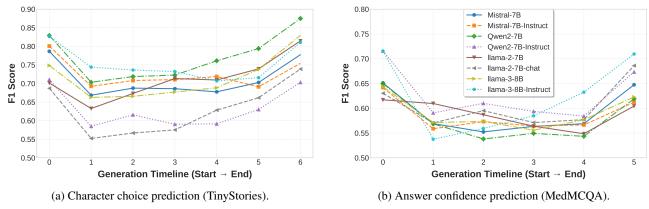


Figure 6. U-shaped planning dynamics during generation. Probing at equidistant positions (character choice, answer confidence) shows three-phase patterns: high accuracy in early segments (global planning intent), mid-segment decline (local token focus), and late-stage recovery (contextualized refinement). This suggests models first outline global attributes, then refine locally, before finalizing coherent plans.

5.2. Evolution of Planning Representations During Response Generation

We analyze how planning features evolve during generation by probing at different positions in the response sequence. For each response, we collect activations from the first token up to the token before attribute-revealing keywords (e.g., animal words in story character selection tasks) or throughout the entire sequence for tasks requiring external ground-truth labels (e.g., answer confidence tasks). We divide these positions into equal segments and apply probes previously trained with in-dataset settings at each division point. We conduct experiments on two datasets: TinyStories

for character choice prediction and MedMCQA for answer confidence prediction. Results in Fig. 6 reveal a distinctive pattern: **probing accuracy is high initially, decreases in the middle segments, and rises again toward the end.** This pattern suggests a three-phase planning process: (1) initial phase with strong planning that provides an overview of the intended response; (2) middle phase with weaker planning, characterized by more local, token-by-token generation; (3) final phase with increased planning clarity as accumulated context makes the target attributes more apparent.

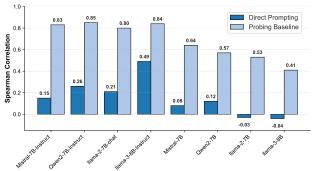


Figure 7. Implicit-explicit planning discrepancy. Models struggle to explicitly predict their own response lengths, with base models showing near-zero Spearman correlation and most fine-tuned models achieving only marginal gains. This gap implies limited introspective awareness despite underlying capability.

5.3. Gap Between Probing and LLMs' Self-Predicted Results

We investigate how the models' ability to predict their own response attributes compare to probe-based predictions with the UltraChat dataset on response length task. For fine-tuned models, we prompt: "Estimate your answer length in tokens using [TOKENS] number [/TOKENS], then provide your answer." For base models, we provide few-shot examples with pre-calculated lengths. To evaluate self-prediction accuracy, we compare the predicted token count collected in a separated run against the length of the previous-collected model's greedy-decoded response.

As shown in Fig. 7, base models achieve near-zero Spearman correlation when predicting token lengths, even with examples. While fine-tuned models perform marginally better, there remains a substantial gap between models' direct predictions and probe-based predictions. This gap suggests that models encode more planning information in their hidden representations than they can explicitly access during token-by-token generation, indicating a discrepancy between implicit planning capabilities and explicit self-awareness.

6. Discussion

6.1. Measuring Emergent Response Planning Under Sampling

In this study, we focus on the greedy-decoded responses of LLMs, using greedy decoding to derive deterministic probe labels $\hat{g}_i = g(\mathbf{y}_i)$ for representations $\mathcal{H}_i = \{\mathbf{H}_{\mathbf{x}_i}^l\}_{l=1}^L$. But when generalizing to sampling settings, while greedy decoding simplifies sampling approximation by reflecting the LLM's most probable output, this approach may not fully capture sampling nuances. We propose two potential ways for improvement:

Averaging: Replace greedy labels with attribute averages

over multiple sampling trials (e.g., 10 samples) to approximate expected sampling behavior.

Distributional probing: Train probes to predict label distributions instead of single values, capturing uncertainty inherent to sampling. While greedy decoding reflects the LLM's most probable output (approximating sampling averages), distribution-aware probing remains an open challenge, which we leave for future work.

6.2. Potential Applications of Emergent Response Planning in LLMs.

Our findings on LLMs' emergent response planning suggest several practical applications. First, anticipating response length and complexity could enable dynamic resource allocation in LLM systems. Second, detecting low confidence or inaccuracies early during generation might trigger interventions like early stopping or retrieval-augmented refinement. Third, predictive capabilities could improve user interaction: predicting reasoning complexity might facilitate task decomposition in multi-step problems, while forecasting response characteristics could enable precise progress estimation during interactive tasks. These possibilities underscore the need to develop robust probing methods for deployed LLMs.

6.3. Future Research Directions

Several key research directions emerge from our findings. Understanding the causal relationship between planning representations and generation outcomes stands as a primary challenge - while our probing results show these representations exist, determining whether and how they influence the generation process requires further investigation. Also, exploring whether similar planning phenomena emerge in multilingual or multimodal contexts could provide insights into how these capabilities develop across different domains and training objectives. Addressing these questions could require developing robust evaluation frameworks and more sophisticated probing techniques.

7. Conclusion

In conclusion, our work reveals that LLMs have emergent response planning capabilities, with prompt representations encoding global attributes of future outputs across structure, content, and behavior attributes. These findings challenge the conventional view of LLMs as purely local predictors and provide new insights into their internal mechanisms. Though we do not focus on interpretability mechanisms to explain the causal relationship of emergent response planning, our findings open promising directions for enhancing model control and transparency, potentially enabling more effective methods for guiding and predicting model outputs before generation begins.

Impact Statement

Our findings on LLM emergent planning raise specific considerations for model deployment. While these capabilities could enhance system reliability through better resource allocation and early warning mechanisms, they also present concerns when handling sensitive data, as these probing methods reveal aspects of the model's internal thinking or decision-making process. We encourage careful evaluation of these trade-offs when implementing probing-based monitoring systems, particularly in applications involving sensitive information.

Acknowledgements

We would like to thank Yuyu Fan, Jiachen Ma and anonymous reviewers for their valuable feedback and helpful discussions.

Author Contributions

Zhichen Dong provided early inputs on the emergent response planning; proposed and ran the experimental tasks, and participated in writing all sections of the paper.

Zhanhui Zhou proposed the emergent response planning in discussion with **Zhichen Dong**; proposed experimental tasks; made substantial writing contributions to abstract, introduction, and Section 3.

Zhixuan Liu provided valuable feedback throughout the project; **Chao Yang** and **Chaochao Lu** supervised and managed the group.

References

- Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- AI@Meta. Llama 3 model card. 2024. URL https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md.
- Anthropic. Claude 3.5 sonnet. https://anthropic.com, 2024. Version: claude-3-5-sonnet-20241022.
- Bachmann, G. and Nagarajan, V. The pitfalls of next-token prediction. *arXiv preprint arXiv:2403.06963*, 2024.
- Belrose, N., Furman, Z., Smith, L., Halawi, D., Ostrovsky, I., McKinney, L., Biderman, S., and Steinhardt, J. Eliciting latent predictions from transformers with the tuned lens. *arXiv* preprint arXiv:2303.08112, 2023.
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G.,

- Askell, A., et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33: 1877–1901, 2020.
- Burns, C., Ye, H., Klein, D., and Steinhardt, J. Discovering latent knowledge in language models without supervision. *arXiv* preprint arXiv:2212.03827, 2022.
- Clark, P., Cowhey, I., Etzioni, O., Khot, T., Sabharwal, A., Schoenick, C., and Tafjord, O. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv:1803.05457v1*, 2018.
- Cobbe, K., Kosaraju, V., Bavarian, M., Chen, M., Jun, H., Kaiser, L., Plappert, M., Tworek, J., Hilton, J., Nakano, R., Hesse, C., and Schulman, J. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.
- Cornille, N., Moens, M.-F., and Mai, F. Learning to plan for language modeling from unlabeled data. *arXiv* preprint *arXiv*:2404.00614, 2024.
- Damani, M., Shenfeld, I., Peng, A., Bobu, A., and Andreas, J. Learning how hard to think: Input-adaptive allocation of lm computation. *arXiv preprint arXiv:2410.04707*, 2024.
- Ding, N., Chen, Y., Xu, B., Qin, Y., Zheng, Z., Hu, S., Liu, Z., Sun, M., and Zhou, B. Enhancing chat language models by scaling high-quality instructional conversations. *arXiv* preprint arXiv:2305.14233, 2023.
- Eldan, R. and Li, Y. Tinystories: How small can language models be and still speak coherent english?, 2023. URL https://arxiv.org/abs/2305.07759.
- Geva, M., Bastings, J., Filippova, K., and Globerson, A. Dissecting recall of factual associations in auto-regressive language models. *arXiv preprint arXiv:2304.14767*, 2023.
- Han, T., Fang, C., Zhao, S., Ma, S., Chen, Z., and Wang, Z. Token-budget-aware llm reasoning. *arXiv preprint arXiv:2412.18547*, 2024.
- Heo, J., Heinze-Deml, C., Elachqar, O., Ren, S., Nallasamy, U., Miller, A., Chan, K. H. R., and Narain, J. Do llms" know" internally when they follow instructions? *arXiv* preprint arXiv:2410.14516, 2024.
- Hernandez, E., Li, B. Z., and Andreas, J. Inspecting and editing knowledge representations in language models. *arXiv* preprint arXiv:2304.00740, 2023.
- Ji, Z., Chen, D., Ishii, E., Cahyawijaya, S., Bang, Y., Wilie, B., and Fung, P. Llm internal states reveal hallucination risk faced with a query. arXiv preprint arXiv:2407.03282, 2024.

- Jiang, A. Q., Sablayrolles, A., Mensch, A., Bamford, C., Chaplot, D. S., de las Casas, D., Bressand, F., Lengyel, G., Lample, G., Saulnier, L., Lavaud, L. R., Lachaux, M.-A., Stock, P., Scao, T. L., Lavril, T., Wang, T., Lacroix, T., and Sayed, W. E. Mistral 7b, 2023. URL https: //arxiv.org/abs/2310.06825.
- Li, K., Hopkins, A. K., Bau, D., Viégas, F., Pfister, H., and Wattenberg, M. Emergent world representations: Exploring a sequence model trained on a synthetic task. *arXiv preprint arXiv:2210.13382*, 2022.
- Li, K., Patel, O., Viégas, F., Pfister, H., and Wattenberg, M. Inference-time intervention: Eliciting truthful answers from a language model. *Advances in Neural Information Processing Systems*, 36, 2024.
- Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., and Neubig, G. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. ACM Computing Surveys, 55(9):1–35, 2023.
- MacDiarmid, M., Maxwell, T., Schiefer, N., Mu, J., Kaplan, J., Duvenaud, D., Bowman, S., Tamkin, A., Perez, E., Sharma, M., et al. Simple probes can catch sleeper agents, 2024.
- Men, T., Cao, P., Jin, Z., Chen, Y., Liu, K., and Zhao, J. Unlocking the future: Exploring look-ahead planning mechanistic interpretability in large language models. *arXiv* preprint arXiv:2406.16033, 2024.
- Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., and Allen, J. A corpus and cloze evaluation for deeper understanding of commonsense stories. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 839–849, 2016.
- nostalgebraist. interpreting gpt: the logit lens.
 Website, 2020. https://www.lesswrong.
 com/posts/AcKRB8wDpdaN6v6ru/
 interpreting-gpt-the-logit-lens.
- Onoe, Y., Zhang, M. J. Q., Choi, E., and Durrett, G. Creak: A dataset for commonsense reasoning over entity knowledge, 2021. URL https://arxiv.org/abs/2109.01653.
- Pal, A., Umapathi, L. K., and Sankarasubbu, M. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In Flores, G., Chen, G. H., Pollard, T., Ho, J. C., and Naumann, T. (eds.), *Proceedings of the Conference on Health, Inference, and Learning*, volume 174 of *Proceedings of*

- Machine Learning Research, pp. 248–260. PMLR, 07–08 Apr 2022. URL https://proceedings.mlr.press/v174/pal22a.html.
- Pal, K., Sun, J., Yuan, A., Wallace, B. C., and Bau, D. Future lens: Anticipating subsequent tokens from a single hidden state. *arXiv preprint arXiv:2311.04897*, 2023.
- Pochinkov, N., Benoit, A., Agarwal, L., Majid, Z. A., and Ter-Minassian, L. Extracting paragraphs from llm token activations. *arXiv preprint arXiv:2409.06328*, 2024.
- Qian, C., Zhang, H., Sha, L., and Zheng, Z. Hsf: Defending against jailbreak attacks with hidden state filtering. *arXiv* preprint arXiv:2409.03788, 2024.
- Rateike, M., Cintas, C., Wamburu, J., Akumu, T., and Speakman, S. Weakly supervised detection of hallucinations in llm activations. *arXiv preprint arXiv:2312.02798*, 2023.
- Sap, M., Rashkin, H., Chen, D., LeBras, R., and Choi, Y. Socialiqa: Commonsense reasoning about social interactions, 2019. URL https://arxiv.org/abs/ 1904.09728.
- Saunders, W., Yeh, C., Wu, J., Bills, S., Ouyang, L., Ward, J., and Leike, J. Self-critiquing models for assisting human evaluators. *arXiv preprint arXiv:2206.05802*, 2022.
- Saxton, Grefenstette, Hill, and Kohli. Analysing mathematical reasoning abilities of neural models. *arXiv:1904.01557*, 2019.
- Talmor, A., Herzig, J., Lourie, N., and Berant, J. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4149–4158, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1421. URL https://aclanthology.org/N19-1421.
- Tang, E., Yang, B., and Song, X. Understanding llm embeddings for regression. *arXiv preprint arXiv:2411.14708*, 2024.
- Taori, R., Gulrajani, I., Zhang, T., Dubois, Y., Li, X., Guestrin, C., Liang, P., and Hashimoto, T. B. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.
- Team, Q. Qwen2 technical report, 2024a.
- Team, Q. Qwen2.5: A party of foundation models, September 2024b. URL https://qwenlm.github.io/blog/gwen2.5/.

- Thorne, J., Vlachos, A., Cocarascu, O., Christodoulopoulos, C., and Mittal, A. The FEVER2.0 shared task. In *Proceedings of the Second Workshop on Fact Extraction and VERification (FEVER)*, 2018.
- Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., et al. Llama: Open and efficient foundation language models. arXiv preprint arXiv:2302.13971, 2023a.
- Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., et al. Llama 2: Open foundation and finetuned chat models. arXiv preprint arXiv:2307.09288, 2023b.
- Turner, A. M., Thiergart, L., Leech, G., Udell, D., Vazquez, J. J., Mini, U., and MacDiarmid, M. Steering language models with activation engineering, 2024. URL https://arxiv.org/abs/2308.10248.
- Wu, W., Morris, J. X., and Levine, L. Do language models plan ahead for future tokens? *arXiv preprint arXiv:2404.00859*, 2024.
- Zhou, Z., Liu, Z., Liu, J., Dong, Z., Yang, C., and Qiao, Y. Weak-to-strong search: Align large language models via searching over small language models. *arXiv preprint arXiv:2405.19262*, 2024.
- Zou, A., Phan, L., Chen, S., Campbell, J., Guo, P., Ren, R., Pan, A., Yin, X., Mazeika, M., Dombrowski, A.-K., et al. Representation engineering: A top-down approach to ai transparency. arXiv preprint arXiv:2310.01405, 2023.

A. Further Details on the Experimental Setup

A.1. Model Specification

The following table lists the models and their corresponding links.

Models	Links
Llama-2-7B (Touvron et al., 2023b)	https://huggingface.co/meta-llama/ Llama-2-7b-hf
Llama-2-7B-Chat (Touvron et al., 2023b)	https://huggingface.co/meta-llama/ Llama-2-7b-chat-hf
Llama-2-13B-Chat (Touvron et al., 2023b)	https://huggingface.co/meta-llama/ Llama-2-13b-chat-hf
Llama-2-70B-Chat (Touvron et al., 2023b)	https://huggingface.co/meta-llama/ Llama-2-70b-chat-hf
Llama-3-8B (AI@Meta, 2024)	https://huggingface.co/meta-llama/ Meta-Llama-3-8B
Llama-3-8B-Instruct (AI@Meta, 2024)	https://huggingface.co/meta-llama/ Llama-2-7b-hf
Llama-3-70B-Instruct (AI@Meta, 2024)	https://huggingface.co/meta-llama/ Meta-Llama-3-70B-Instruct
Mistral-7B (Jiang et al., 2023)	https://huggingface.co/mistralai/ Mistral-7B-v0.1
Mistral-7B-Instruct (Jiang et al., 2023)	https://huggingface.co/mistralai/ Mistral-7B-Instruct-v0.2
Qwen2-7B (Team, 2024a) Qwen2-7B-Instruct (Team, 2024a)	https://huggingface.co/Qwen/Qwen2-7B https://huggingface.co/Qwen/ Owen2-7B-Instruct
Qwen2-72B-Instruct (Team, 2024a)	https://huggingface.co/Qwen/ Qwen2-72B-Instruct
Qwen2.5-1.5B-Instruct (Team, 2024b)	https://huggingface.co/Qwen/Qwen2.5-1. 5B-Instruct
Qwen2.5-32B-Instruct (Team, 2024b)	https://huggingface.co/Qwen/Qwen2. 5-32B-Instruct
Qwen2.5-72B-Instruct (Team, 2024b)	https://huggingface.co/Qwen/Qwen2. 5-72B-Instruct

A.2. Dataset Specification

The following table lists the datasets and their corresponding links.

Datasets	Links
Ultrachat (Ding et al., 2023)	https://huggingface.co/datasets/stingning/ultrachat
AlpacaEval (Taori et al., 2023)	https://huggingface.co/datasets/tatsu-lab/alpaca
GSM8K (Cobbe et al., 2021)	https://huggingface.co/datasets/openai/gsm8k
MATH (Saxton et al., 2019)	https://huggingface.co/datasets/deepmind/math_dataset
TinyStories (Eldan & Li, 2023)	https://huggingface.co/datasets/roneneldan/ TinyStories
ROCStories (Mostafazadeh et al., 2016)	https://huggingface.co/datasets/Ximing/ROCStories

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```
CommonsenseQA (Talmor et al., 2019) https://huggingface.co/datasets/tau/
commonsense_qa

SocialIQA (Sap et al., 2019) https://huggingface.co/datasets/allenai/social_
i_qa

MedMCQA (Pal et al., 2022) https://huggingface.co/datasets/
openlifescienceai/medmcqa

ARC-Challenge (Clark et al., 2018) https://huggingface.co/datasets/allenai/ai2_arc

CREAK (Onoe et al., 2021) https://huggingface.co/datasets/amydeng2000/
CREAK

FEVER (Thorne et al., 2018) https://huggingface.co/datasets/fever/fever
```

A.3. Detailed Process of Response Collection and Labeling

In this section, we detail the process of collecting a dataset $\mathcal{D} = \{\mathcal{H}_i, \hat{g}_i\}_{i=1}^N$ for each task $T = (p(\mathbf{x}), g(\mathbf{y}))$, pairing prompt representations with their corresponding attribute labels. First, we construct the prompt distribution $p(\mathbf{x})$ to elicit responses with target attributes from the models (Sec.A.3.1). Second, we label these responses according to specific criteria $\hat{g}_i = g(\mathbf{y}_i)$ to capture their key attributes (Sec.A.3.2). Finally, we collect representations $\mathcal{H}_i = \{\mathbf{H}^l_{\mathbf{x}_i}\}_{l=1}^L$ for each prompt (Sec. A.3.3).

A.3.1. PROMPT TEMPLATES

To elicit responses with target attributes, we construct prompt distributions using carefully designed templates paired with datasets. We present the prompt templates for both chat and base models across all tasks, along with representative input-output examples.

```
Task 1:
                                    Response Length
Prompt for fine-tuned models
{data}
(\rightarrow Gets formatted according to model's template)
Example Response
Data: Why are oceans important to the global ecosystem?
Output: The oceans play a crucial role [...]
Prompt for base models
Q: How can cross training benefit athletes?
A: Cross training offers various benefits [...]
                                                        [END OF RESPONSE]
Q: What role does collaboration play in creativity?
A: Collaboration and originality complement each other [...]
OF RESPONSE]
Q: {data}
A:
Example Response
Data: What are positive impacts of Reality TV?
Output: Reality TV provides entertainment and [...] [END OF RESPONSE]
                          Task 2:
                                    Reasoning Steps
Prompt for fine-tuned models
Provide step-by-step solution, starting with 'Step 1:'.
Problem:
{data}
```

, ,

(→ Gets formatted according to model's template)

Example Response

Data: Randy has 60 mango trees on his farm. He also has 5 less than half as many coconut trees as mango trees. How many trees does Randy have in all?

Output: Step 1: Write down the information [...]

```
Prompt for base models ,, Solve this problem step-by-step, starting with 'Step 1:'. Few-shot examples: Problem: Let f(x) = \{ax+3 \text{ if } x>2; x-5 \text{ if } -2 \le x \le 2; 2x-b \text{ if } x<-2\}. Find a+b if f is continuous. Step 1: At x=2: a(2)+3=2-5 [...] [END OF RESPONSE] Problem: If x=2 and y=5, find (x^4+2y^2)/6. Step 1: Substitute: (2^4+2(5^2))/6 [...] [END OF RESPONSE] Problem: \{data\}
```

Example Response

Data: Weng earns \$12 an hour for babysitting. Yesterday, she just did 50 minutes of babysitting. How much did she earn?

Output: Step 1: Substitute: 12(50/60) [...] [END OF RESPONSE]

```
Task 3: Character Choices
```

```
Prompt for fine-tuned models

,,

Here's the first sentence of a story: {data}

Continue this story with one sentence that introduces a new animal character.

,,
```

 $(\rightarrow Gets \ formatted \ according \ to \ model's \ template)$

Example Response

Data: Once upon a time, there was a big car named Dependable.

Output: As Dependable was cruising down the highway, a chatty parrot [...]

```
Prompt for base models
First sentence: Lily was a little mouse who liked to follow her big
brother Leo.
Continuation: The garden was peaceful that morning until [...]
[Animal: owl] [END OF RESPONSE]
First sentence: Lila and Ben were playing in the park with their
toys.
Continuation: While building their epic sandcastle [...] [Animal:
rabbit | [END OF RESPONSE]
First sentence: Sara was lonely.
Continuation: As she sat on the front steps drawing patterns [\ldots]
[Animal: puppy] [END OF RESPONSE]
First sentence: Lily and Ben were twins who liked to go on walks
with their mom and dad.
Continuation: Their morning hike through the woods [...] [Animal:
squirrel] [END OF RESPONSE]
First sentence: {data}
Continuation:
```

, ,

Example Response

Data: One day, a girl named Mia went for a walk.

Output: As she strolled through the park, she noticed a group of birds [...] [END OF RESPONSE]

```
Task 4: Multiple-Choice Answers
```

```
Prompt for fine-tuned models

""

Before choosing your answer, *briefly explain why in one short sentence*. Then select from the options:

{data}

""
```

(→ Gets formatted according to model's template)

Example Response

Data: Sammy wanted to go to where the people were. Where might he go? A) race track B) populated areas C) the desert D) apartment E) roadblock

Output: **He wants to be around people, so he would go to a populated area.**B) populated areas

```
Prompt for base models

//

Select the correct answer. Choose the single best answer.

Q: The sanctions against the school were a punishing blow, and they seemed to what the efforts the school had made to change?

A) ignore B) enforce C) authoritarian D) yell at E) avoid

A: The sanctions ignore the school's reform efforts, contradicting their purpose. Therefore A. [END OF RESPONSE]

Q: Sammy wanted to go to where the people were. Where might he go?

A) race track B) populated areas C) the desert D) apartment E) roadblock

A: If Sammy wants to find people, he would logically go to populated areas where many people gather. Therefore B. [END OF RESPONSE]

Q: {data}

A:

//
```

Example Response

Data: Where do you put your grapes just before checking out? A) mouth B) grocery cart C) super market D) fruit basket E) fruit market

Output: The question asks where you put your grapes just before checking out. The answer is the grocery cart. Therefore B.[END OF RESPONSE]

```
Task 5: Answer Confidence
```

```
Prompt for fine-tuned models

""

Please first write analysis of the problem, then select the single correct answer to the following question from the options, and state your option explicitly:

{data}

""

( → Gets formatted according to model's template)

Example Response
```

Data: Damage to median nerve produces - A) Claw hand B) Winging of scapule C) Ape thumb D) Wrist drop

Output: Damage to the median nerve [...] The correct answer is: B) Winging of scapula

```
Prompt for base models
```

Select the correct answer. Choose the single best answer.

Q: Which vitamin is supplied from only animal source:

A) Vitamin C B) Vitamin B7 C) Vitamin B12 D) Vitamin D

A: Vitamin B12 (cobalamin) is exclusively found in animal products as it is synthesized by bacteria in animals, and cannot be obtained from plant sources. Therefore C.[END OF RESPONSE]

 $\ensuremath{\mathtt{Q}} \colon \ensuremath{\mathtt{All}}$ of the following are surgical options for morbid obesity except -

A)Adjustable gastric banding B)Biliopancreatic diversion C)Duodenal Switch D)Roux en Y Duodenal By pass

A: While Roux-en-Y gastric bypass is a common bariatric procedure, there is no such thing as 'Roux en Y Duodenal Bypass'. The correct procedures include gastric banding, biliopancreatic diversion, and duodenal switch. Therefore D.[END OF RESPONSE]

Q: {data}

A:

Example Response

Data: Which of the following amino acid is active at neutral pH? A) Histidine B) Glycine C) Leucine D) Arginine

Output: Histidine is the only amino acid that is active at neutral pH. Therefore A.[END OF RESPONSE]

Task 6: Factual Consistency

Prompt for fine-tuned models

, ,

First discuss on this statement briefly in one short sentence, then explicitly state that you are in favour of the statement or explicitly state if you feel unsure instead: {data}

(→ Gets formatted according to model's template)

Example Response

Data: American children's adventure film The Wizard of Oz was made by Warner Bros.

Output: The Wizard of Oz is a classic American children's adventure film [...] I am unsure about the statement as it appears to be incorrect.

```
Prompt for base models
```

, ,

 $\ensuremath{\mathtt{Q}} \colon \ensuremath{\mathtt{Only}}$ people named Floyd wearing pink are allowed to attend Pink Floyd concerts.

A: This contradicts known concert admission practices and Pink Floyd's actual ticket policies. I cannot be confident about the accuracy of this statement.[END OF RESPONSE]

Q: Fax works without any internet connection.

A: Fax machines transmit data through telephone lines independently of internet infrastructure. I support this statement as accurate.[END OF RESPONSE]

Q: Larry King served tea during his show.

A: Larry King was known to have beverages during his long-running CNN show to maintain vocal comfort during interviews. I support this statement as accurate. [END OF RESPONSE]

Q: The band Lynyrd Skynyrd formed up in Beijing, China.

```
A: Available historical documentation about Lynyrd Skynyrd's origins contains conflicting or unclear information about their early formation. I cannot be confident about the accuracy of this statement.[END OF RESPONSE]
Q: {data}
A:
```

Example Response

Data: The crack in the Liberty Bell sets it apart from other famous bells.

Output: The Liberty Bell is a famous bell in the United States. I support this statement as accurate.[END OF RESPONSE]

A.3.2. LABELING

After collecting model responses, we first extract base model outputs using the <code>[END OF RESPONSE]</code> signal. Then, for both base and fine-tuned models, we label and filter responses using these criteria:

- 1. **Response length**: Calculate token count using the model's tokenizer, excluding special tokens. Exclude responses exceeding the 1000-token limit or those that are incomplete.
- 2. **Reasoning steps**: Count remaining steps by identifying step markers (e.g., "Step 1:"). Exclude responses with more than 8 steps.
- 3. **Character choices**: Identify animal mentions in responses, excluding cases with no animals, multiple animals, or animals in the first two words. Select the top-4 most frequent animals per model and label them 0-3.
- 4. **Multiple-choice answers**: Extract answer selections (e.g., "the answer is D") using pattern matching. Exclude responses with zero or multiple answers, or answers at sentence start. Label options A-E as 0-4.
- 5. **Answer confidence**: Match the model's selected option against ground truth, excluding cases with multiple or no choices. Label correct answers as 1, incorrect as 0.
- 6. **Factual consistency**: Identify explicit agree/disagree statements and compare with ground truth, excluding cases without explicit agreement/disagreement. Label as 1 if the model agrees with true statements or disagrees with false ones, 0 otherwise.

Then we perform data augmentation by: (1) removing responses shorter than 8 tokens and balancing class distributions across classification tasks while equalizing dataset sizes across models; (2) generating additional examples by randomly truncating responses several tokens before key information appears (e.g., end-of-response token, animal names in character choices, or option selections in multiple-choice answers), computing corresponding labels, and grouping original and augmented data to ensure they are assigned to the same data split (train/test/validation).

A.3.3. REPRESENTATION COLLECTION

For each truncated response, we concatenate the original LLM input with the truncated text and perform a forward pass to obtain representations from all layers at the truncation point. For answer-start representations, we directly use a forward pass on the original input. We then pair these collected representations with their corresponding labels to create the final dataset.

B. Extended Experimental Results

B.1. Regression Fitting Performance

We present complete regression fitting results for both in-dataset (Fig. 8) and cross-dataset (Fig. 9) settings using hexbin density plots.

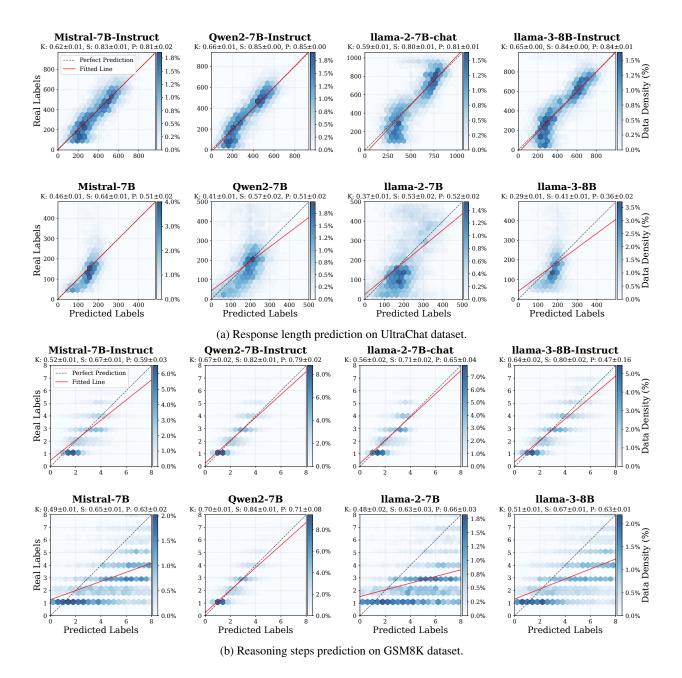


Figure 8. Hexbin plots showing in-dataset regression performance. Color intensity represents point density, with diagonal dashed lines indicating perfect predictions. The solid line in each subplot represents the linear regression fit applied to the predictions and the real labels.

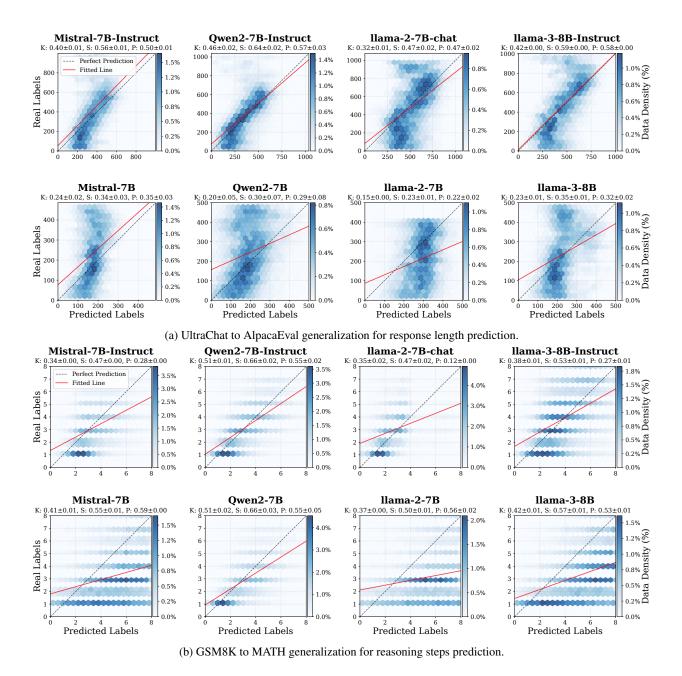


Figure 9. Cross-dataset regression generalization visualized through hexbin plots. Color intensity represents point density, with diagonal dashed lines indicating perfect predictions. The solid line in each subplot represents the linear regression fit applied to the predictions and the real labels.