Do Prompt-Based Models Really Understand the Meaning of Their Prompts?

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Abstract

Recently, a boom of papers has shown extraordinary progress in zero-shot and few-shot learning with various prompt-based models. Such success can give the impression that prompts help models to learn faster in the same way that humans learn faster when provided with task instructions expressed in natural language. In this study, we experiment with over 30 prompts manually written for natural language inference (NLI). We find that models learn just as fast with many prompts that are intentionally irrelevant or even pathologically misleading as they do with instructively "good" prompts. Further, such patterns hold even for models as large as 175 billion parameters (Brown et al., 2020) as well as the recently proposed instruction-tuned models which are trained on hundreds of prompts (Sanh et al., 2021; Wei et al., 2021). Despite some success, instruction-tuned models are capable of producing good predictions with misleading prompts even at zero shots. In sum, notwithstanding prompt-based models' impressive improvement, we find evidence of serious limitations that question the degree to which language models really understand the meaning of prompts in the way humans do.

1 Introduction

Suppose a human is given two sentences: "No weapons of mass destruction found in Iraq yet." and "Weapons of mass destruction found in Iraq." They are then asked to respond 0 or 1 and receive a reward if they are correct. In this setup, they would likely need a large number of trials and errors before figuring out what they are really being rewarded to do. This setup is akin to the pretrain-and-fine-tune setup which has dominated NLP in recent years, in which models are asked to classify a sentence representation (e.g., a CLS token) into some arbitrary dimensions of a one-hot vector. In contrast, suppose a human is given a prompt such as: Given that "no weapons of mass destruction found in Iraq yet.", is it definitely correct that "weapons of mass destruction found in Iraq."?[1] Then it would be no surprise that they are able to perform the task more accurately and without needing many examples to figure out what the task is.

Similarly, reformatting NLP tasks with prompts such as the underlined text above has dramatically improved zero-shot and few-shot performance over traditionally fine-tuned models (Schick and Schütze, 2021b; Le Scao and Rush, 2021; Sanh et al., 2021; Wei et al., 2021). Such results naturally give rise to the hypothesis that the extra prompt text included within each input example serves as semantically meaningful task instructions which help models to learn faster, in the way task instructions help humans to learn faster. This hypothesis is implicitly assumed by many and explicitly argued by Mishra et al. (2021), Schick and Schütze (2021a), and Brown et al. (2020).

While last year saw a gold rush of papers (summarized in §2) that proposed automatic methods for optimizing prompts, Logan et al. (2021) compare a representative sample of these newly proposed methods and report that Schick and Schütze (2021b)'s manually written prompts still on average outperform the automatically searched prompts across a range of SuperGLUE tasks (Wang et al., 2019). Such findings suggest that expert-crafted prompts are among the best, if not *the* best, which reinforces the above hypothesis that models benefit from meaningful instructions.

In this paper, we test this hypothesis by evaluating various language models on NLI in zero-shot and few-shot settings using more than 30 manually written templates and 10 sets of LM target words for a total of over 300 prompts. We find that in most cases models learn identically as fast when given irrelevant or misleading templates as they do when

[1] This prompt is adapted from MultiNLI (Williams et al., 2018, p. 3)'s instructions to crowdsourced workers, while the example is the first one in RTE's validation set.

given instructively good templates. Further, models ranging from 235 million to 175 billion parameters all exhibit this behavior, as do the instruction-tuned models, which are trained on dozens of datasets formatted with hundreds of manually written prompts. While we confirm Sanh et al. (2021)'s finding that instruction tuning substantially improves the performance and robustness of prompts, we also find that instruction-tuned models can be, in some sense, too robust and less sensitive to the semantics of the prompts, as compared to their non-instruction-tuned equivalents. In sum, despite prompt-based models' dramatic improvement in zero-shot and few-shot learning, which is laudable progress, we find limited evidence that such improvement is derived from models understanding task instructions in a way that is analogous to humans' use of task instructions.

2 Related Work

2.1 Prompt-Based Models

At the time of writing, the terms "prompt tuning" and "prompting" can refer to any one or combination of three approaches described below:

Discrete Prompts reformat each example with some template text. For example, in a sentiment analysis task, the template can be `{sent} In summary, the restaurant is [prediction]`, where the predicted mask word is then converted to a class prediction by a predefined mapping, e.g., {"great" $\rightarrow$ positive, "terrible" $\rightarrow$ negative}. The prompts can be manually written (Schick and Schütze, 2021a; Bragg et al., 2021) or automatically generated (Gao et al., 2021b; Shin et al., 2020). This approach typically tunes all parameters of the model, but its few-shot performance can exceed that of very large models (e.g., GPT-3 175B) despite using a 3 orders of magnitude smaller LM (Schick and Schütze, 2021b; Tam et al., 2021).

Priming (a.k.a. in-context learning) prepends k priming examples to the evaluation example, where each example is optionally wrapped in a template such as `Question:` $\texttt{\{sent}_1\texttt{\}}$ `True or false?` $\texttt{\{label}_1\texttt{\}}$ `... Question:` $\texttt{\{sent}_k\texttt{\}}$ `True or false?` $\texttt{\{label}_k\texttt{\}}$ `Question: {eval_sent} True or false? [prediction]`. Notably, although models see labeled examples, their parameters do not receive gradient updates based on those examples. Although this approach is intriguing, Brown et al. (2020) report that it only performs well on the largest GPT-3 model, the API of which is costly and difficult to use for academic research (see Appendix C for details).

Continuous Prompts prepend or append examples with special tokens optionally initialized with word embeddings, but during learning, those tokens can be updated arbitrarily such that the final embeddings often *do not* correspond to any real word in the vocabulary (e.g., Lester et al., 2021; Li and Liang, 2021; Qin and Eisner, 2021). This approach often efficiently tunes a much smaller set of model parameters, but these methods have not yet reported success in few-shot settings. Moreover, foregoing prompts as expressed in natural language makes it much harder to study their semantics, and it is not clear if continuous prompts serve as task-specific instructions or simply more efficient model parameters (see He et al., 2021 for a detailed analysis).

2.2 Analyses of Prompts

In this paper, we focus on discrete prompts because we can manually write and control their wording and semantics. We measure the effect of prompt semantics by the model's k-shot performance where $k = \{4, 8, 16, 32, 64, 128, 256\}$. This setup resembles that of Le Scao and Rush (2021), but their study focuses on comparing Schick and Schütze (2021b)'s existing small set of prompts against traditional fine-tuning over the training trajectories of entire training sets, whereas our study focuses on the few-shot learning trajectories among a much more diverse set of prompts designed to test specific hypotheses about the effect of prompt semantics on few-shot learning speed.

At a high-level, our findings contradict Mishra et al. (2021)'s claim that models benefit from elaborate instructions adapted from crowdsourcing annotation guides. But note that they define "instructions" more broadly as including priming examples, and they find that "GPT-3 benefits the most from positive examples, mildly from definition, and deteriorates with negative examples." (p. 18). In other words, if we ablate priming and narrow "instructions" to just the description and explanation of a task, we in fact have the same finding that instructions are only modestly beneficial over no instructions (cf. our irrelevant templates), but we further show that good instructions have no consistent benefit over bad instructions, thus raising questions

Category	Description	Examples
instructive	How we would describe the NLI task to a human who has never seen the task before.	{premise} Are we justified in saying that "{hypothesis}"? Given {premise} Should we assume that "{hypothesis}" is true?
misleading-moderate	Instruct the models to perform a task related or tangential to NLI such that, if the model were to perform the task as explicitly instructed, it would perform poorly on NLI in general.[2]	{premise} Can that be paraphrased as: "{hypothesis}"? {premise} Are there lots of similar words in "{hypothesis}"?
misleading-extreme	Instruct the models to perform a task unrelated to NLI.	{premise} is the sentiment positive? {hypothesis} {premise} is this a sports news? {hypothesis}
irrelevant	Concatenate the premise, a sentence unrelated to any NLP task, and the hypothesis.	{premise} If bonito flakes boil more than a few seconds the stock becomes too strong. "{hypothesis}"?
null	Concatenate the premise and the hypothesis without any additional text.	{premise} {hypothesis} {hypothesis}{premise}

Table 1: Prompt templates used in this paper. See Appendix F for the full list.

of whether models' use of prompts can be fairly described as "understanding".

3 Experiment Setup

Our research question is whether models understand prompts as meaningful task instructions analogous to how humans would. For intuition, suppose an experimenter provides a human annotator with an informative instruction of a reasonably easy task. If the annotator understands the instruction, we expect them to perform better than when the experimenter provides intentionally misleading instructions, makes irrelevant chitchat, or says nothing at all. Accordingly, we write various prompt templates that correspond to these different scenarios and evaluate models' performance with these templates in zero-shot and few-shot settings.

Templates We write 5 categories of templates (Table 1), with at least 5 templates for each category (10 for instructive). To control for the effect of target words, a template's performance is always reported with "yes"/"no" as its target words, which consistently perform best (see Appendix A for the effect of different target words.) Except in ablation studies, we further control for punctuation, declarative vs. interrogative templates, and the order of concatenation (always `{premise} some template text {hypothesis}[prediction]`).

After preliminary experiments, to avoid cherry picking, all prompts reported in this paper were written prior to evaluation, i.e., we do not allow retroactively editing prompts for performance manipulations, except for an ablation study on the effect of punctuation (Appendix B).

Implementation We implement a manual discrete prompt model[3] which in essence is the same as that of Schick and Schütze (2021b), except their implementation includes several augmentations such as self-labeling and ensembling of multiple prompts for competitive results. In order to focus on measuring the effect of prompts themselves, our implementation does not include those augmentations. Following Sanh et al. (2021) and Wei et al. (2021), we evaluate by a rank classification of the target words.

Baseline Model In preliminary experiments, we fine-tuned and prompt-tuned BERT, DistilBERT, RoBERTa, ALBERT, and T5 (Devlin et al., 2019; Sanh et al., 2019; Liu et al., 2019; Lan et al., 2020; Raffel et al., 2020; all implemented via Wolf et al., 2020). Confirming prior work (Schick and Schütze, 2021b; Tam et al., 2021), we find that ALBERT consistently yields the best performance, so we use it as our baseline model.

To verify that our implementation is comparable with prior work, Figure 1 reports the RTE validation accuracy of our baseline model. At 32 shots, our implementation yields a median accuracy of 70.22% (mean = 69.29%, std. dev. = 6.3%), which is comparable to the 69.8% reported by Schick

[2] An author manually labeled the 30 training examples seen by models under random seed 1 (example nos. 550–580), among which we find 17 pairs of entailment, 5 or 8 pairs (depending on how strictly one judges their acceptability) of summarizations, and only one pair of paraphrase.

[3] Publicly available on GitHub along with all hyperparameters, interactive figures, and statistical test results. Anonymized for submission but included in supplementary materials.

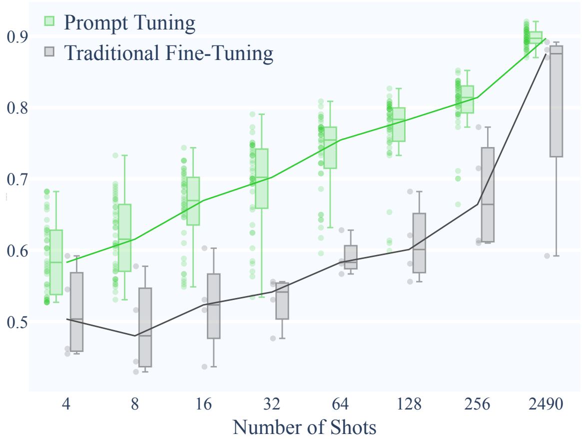


Figure 1: How to read these figures: Each dot is the performance of one prompt under one random seed (which controls the sets of few-shot examples). Boxes span from the first quartile to the third quartile, while lines inside boxes mark the medians. Later figures omit the points except outliers in order to improve legibility. See the interactive figures in supplementary materials or Appendix H for the results of individual prompts.

and Schütze (2021b). Further, Figure 1 confirms Le Scao and Rush (2021)'s finding that, while both fine-tuning and prompt-tuning converge to similar results when fully trained on the entire set ($n = 2490$ for RTE), prompt-tuning yields the largest improvement in the few-shot setting. Going forward, we focus on studying the few-shot learning trajectory between 4 and 256 examples.

Instruction-Tuned Model We additionally experiment with T0, a recently proposed instruction-tuned model which is trained on dozens of datasets[4] formatted with hundreds of manually written prompts (Sanh et al., 2021). We experiment with both sizes of T0 (3B and 11B), as well as their non-instruction-tuned version, T5 LM-Adapted (Lester et al., 2021) as a baseline.

Very Large Model Lastly, we experiment with the largest GPT-3 (175B) via priming (a.k.a. in-context learning). Although fine-tuning is technically available, it is extremely limited by OpenAI's various quotas. See Appendix C for details on how we circumvent challenges in reproducing Brown et al. (2020)'s results.

Data We focus on NLI because, compared to the usual suite of NLP classification tasks such as topic classification and question answering, NLI is in theory more sensitive to differences in task instructions. For example, depending on if an instruction asks for strictly logical entailment or pragmatic inference, humans can give different predictions on the same premise and hypothesis. Thus, we conjecture that NLI's sensitivity to nuanced differences in task instructions can magnify measurements of to what extent are prompt-based models sensitive to the meaning of prompts.

We use Recognizing Textual Entailment (RTE, Dagan et al., 2006, inter alios), a series of expert-annotated NLI datasets where a model is asked to classify whether one piece of text (the "premise") entails another (the "hypothesis"). Specifically, we use the SuperGLUE collection of RTE (i.e., RTE1, 2, 3, and 5; all converted to binary classification) for comparability with prior work on prompts.

We also experiment with Adversarial NLI (Nie et al., 2020), one of the newest high-quality NLI dataset. We find no qualitative difference between the RTE and ANLI results (reported in Section G.2) except that ANLI requires much larger number of shots before obtaining any above-random accuracy, as it is designed to be a highly challenging set.

Random Seeds & Example Sampling All experiments are run over the same set of 4 random seeds. Within a given seed, all models see the same set of examples. For instance, under seed 1, the 5-shot models see examples 550–555, the 10-shot models see examples 550–560, and so on. Across different seeds, a different starting example index is drawn. The exact training example indices are also recorded in our GitHub repository for reproducibility.

Statistical Tests We use both ANOVA and its nonparametric equivalent, the Kruskal–Wallis test. After finding a significance among multiple categories of templates, we report pairwise significance with the independent two-sample t-test and the Wilcoxon rank-sum test. We set $\alpha = 0.05$ and apply the Bonferroni correction to account for multiple comparisons. Results reported in this paper are always agreed by both t-test and Wilcoxon.

4 Results

Irrelevant Templates We find that models trained with irrelevant templates learn just as fast as those trained with instructive templates, with no statistical significance at any number of shots (Figure 2). This is true for all models and all datasets

[4]Importantly, T0 always holds out all NLI prompts and all NLI datasets in its training, which makes it a fair comparison to other models in this paper.

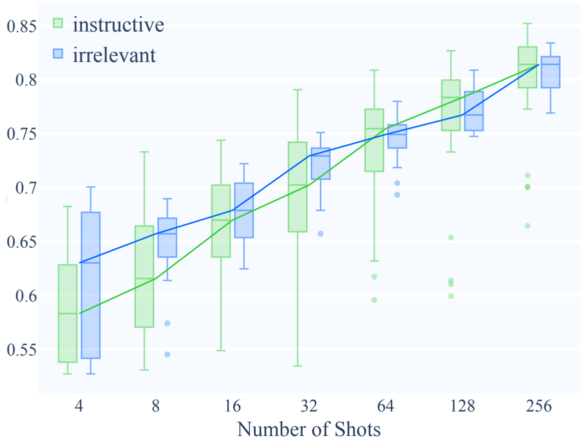


Figure 2: ALBERT on RTE. Models trained with irrelevant templates actually slightly outperform the instructive templates, albeit without statistical significance at any number of shots.

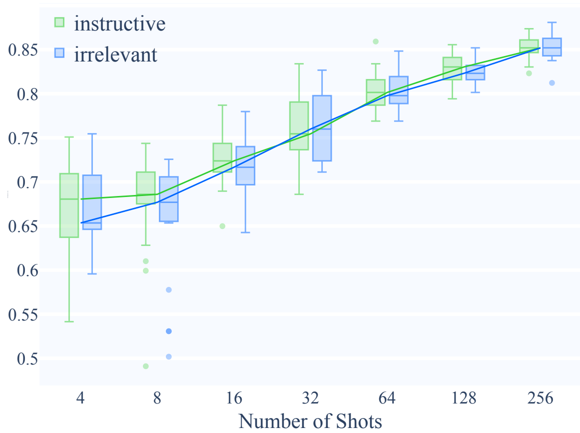


Figure 4: T0 (3B) on RTE. Likewise, there is no statistical significance between the performance of models trained with instructive templates and those trained with irrelevant templates at any number of shots.

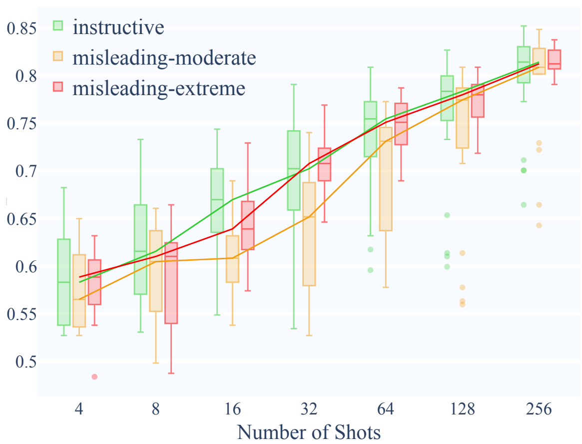


Figure 3: ALBERT on RTE. There is no statistical significance between misleading-extreme and instructive at any number of shots. In contrast, models trained with misleading-moderate templates are significantly worse than the instructive ones from 16 to 64 shots.

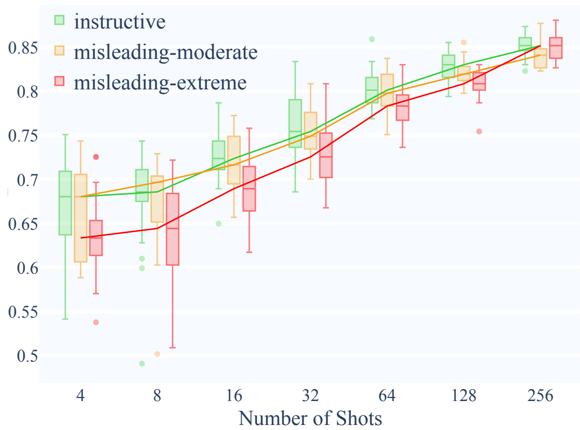


Figure 5: T0 (3B) on RTE. There is no statistical significance between instructive and misleading-moderate templates at any number of shots, whereas those trained with misleading-far are significantly worse from 8 to 128 shots.

we experimented, including the largest GPT-3 (Figure 6) as well as the instruction-tuned T0 (Figure 4).

Misleading Templates Curiously, there is no consistent relation between the performance of models trained with templates that are moderately misleading (e.g. `{premise} Can that be paraphrased as "{hypothesis}"?`) vs. templates that are extremely misleading (e.g., `{premise} Is this a sports news? {hypothesis}`). ALBERT and T5 3B appear to prefer misleading-extreme, T0 of both sizes appear to prefer misleading-moderate, whereas T5 770M, 11B, as well as GPT-3 have no preference (Figures 3 and 5; also summarized in Table 2). Despite a lack of pattern between the two misleading categories, however, it is consistent that models are able to differentiate between instructive and at least one category of misleading templates.

Null Templates Models trained with null templates perform far worse than all other categories of templates (see Appendix G for all null results). Here, we focus on an encoder-only masked language model, which allows more permutation of concatenation orders by placing mask in the middle of sentences. We see that, although null templates are much worse in aggregate, some subset of them (e.g., `{premise} [mask] {hypothesis}`) are still able to learn comparably fast as the average instructive template after 32 shots (Figure 7). Additionally, punctuation can also have an outsized

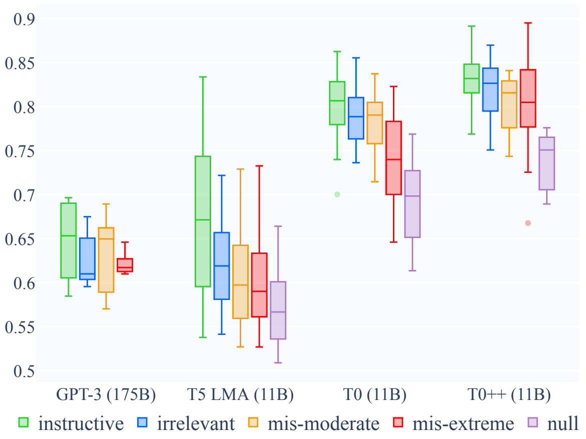


Figure 6: 16-shot accuracy of four large models. For GPT-3, there is no statistical significance between any template categories except null (not plotted because they are below 0.5). For T5, there is no significance between instructive and irrelevant. For T0, there is no significance between instructive and irrelevant nor between instructive and misleading-moderate. For T0++, there is no significance between instructive and irrelevant nor between instructive and misleading-extreme.

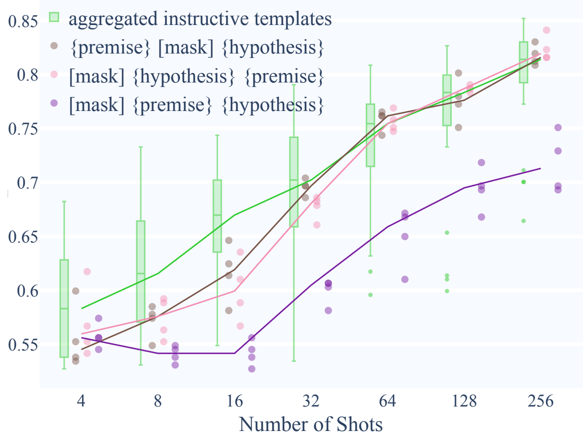


Figure 7: ALBERT on RTE. After 32 shots, models trained with 2 null templates learn as fast as the instructive templates, but models trained with other null templates (e.g., purple) are much worse.

effect (which we control for in the main experiments; see Appendix B for an ablation study).

Zero-Shot So far, we have focused on few-shot results because, at zero shots, all models perform only marginally above random, except the instruction-tuned T0. Although T0 attains good performance, Figure 8 shows that T0 3B is still unable to distinguish instructive from both categories of misleading templates. T0 11B improves, although it remains unable to distinguish between misleading-moderate and instructive templates. Lastly, T0++ (trained on more datasets than other T0 variants), is the only model that is able to statistically significantly distinguish all categories of prompts in this paper, although with the major caveat that it still performs too well in absolute terms with pathological prompts, which we will discuss in the next section.

5 Discussion

5.1 Summary of Results

Recall that a common assumption in the literature is that prompts require experts to clearly and correctly describe the task at hand (§1). In contrast, Table 2 summarizes that, with the sole exception of T0++ at zero shots, all models perform comparably well with some pathological prompts as they do with proper prompts. Notably, despite being much larger than its competitors, GPT-3 fares worse, suggesting that mere scaling does not address this issue. Meanwhile, the evidence from instruction tuning is mixed. Although Sanh et al. (2021) are right that instruction tuning yields substantial improvement in performance as well as robustness as measured by variance, T0 is somewhat too robust and less sensitive to the semantics of the prompts in terms of distinguishing proper instructions from pathological ones, compared to T5 of the same size in the few-shot setting (Figure 6).

In the zero-shot setting, although one could argue that the largest model instruction-tuned with the most datasets (T0++) improves a model's sensitivity to prompt semantics, this has a major caveat: There still exist numerous examples of pathological prompts that perform just as well as the proper ones do. To be charitable to randomness in neural models, we hold this study to a higher standard by comparing means and medians among categories with statistical tests. Nevertheless, for our research question, existence proofs alone are still alarming. For example, without any gradient update nor priming, it is striking that out-of-the-box T0++ scores a high accuracy of 78% with the extremely misleading `{premise} Is that grammatically correct? {hypothesis}`, the same accuracy as it achieves with a proper instruction `{premise} Are we justified in saying "{hypothesis}"?` If models were truly classifying whether the text is grammatical, it would have only scored 52.7% because RTE is written by experts and all examples are grammatical.

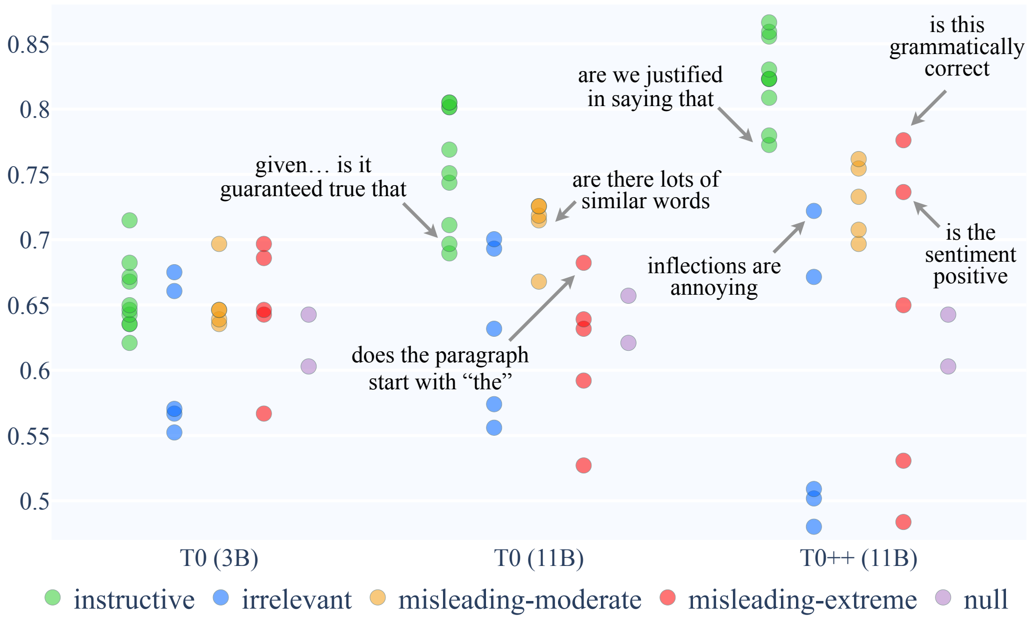


Figure 8: Zero-shot accuracy of instruction-tuned models. Each prompt's performance is a single point (unlike the few-shot figures where each prompt is approximated by multiple points with multiple samplings of few-shot examples.) Arrows highlight some prompts with their names. See Table I for the full results.

	size	#shots	inst. > mis-moderate	inst. > mis-extreme	inst. > irrelevant	inst. > null
T0	3B	0				✓
T0	11B	0		✓	✓	✓
T0++	11B	0	✓	✓	✓	✓
ALBERT	235M	4 - 256	✓			✓
T5 LMA	770M	4 - 256				
T5 LMA	3B	4 - 256	✓			✓
T0	3B	4 - 256		✓		✓
T5 LMA	11B	16	✓	✓		✓
T0	11B	16		✓		✓
T0++	11B	16	✓			✓
GPT-3	175B	16				✓

Table 2: Checkmarks indicate where two categories of templates lead to statistically significantly different performance, as measured by an independent two-sample t-test and a Wilcoxon rank-sum test; both tests always agree in this table. A lack of checkmark indicates where model performance fails to differentiate the two categories, i.e., models do not understand the differences between the prompt categories. We consider significant differences (checkmarks) between categories of prompts to be necessary—but not sufficient—for language understanding.

Even templates that underperform the instructive ones seem to be too good. For example, it is difficult to imagine a human scoring 72% *zero-shot* with the prompt `{premise} Inflections are annoying and thank god that Middle English got rid of most of them. {hypothesis}` for a nuanced task like NLI—Recall the opening example in Section 1; it is not at all obvious to a human how they are supposed to classify a pair of sentences when there is no task instruction.

Finally, our main argument throughout the paper shares the same logic as a recent line of studies (Sinha et al., 2021; Pham et al., 2021; Gupta et al., 2021) which argue that the fact that LMs achieve good performance under ideal conditions is insufficient to establish language understanding because they also succeed under pathological conditions (e.g., sentences with shuffled word order) where humans fail catastrophically. In other words, the fact that models are so good at inferring the gold labels from pathological inputs casts major doubts on whether models make inferences in any way that resembles how humans make inferences. For our results, the fact that models are so good at learning from pathological instructions likewise casts major doubts on whether models understand prompts as instructions in any way that resembles how humans understand instructions.

5.2 Alternative Interpretations and Future Directions

As with any extrinsic evaluation, accuracy cannot directly measure understanding. For example, a human could perfectly understand an instruction but still, e.g., have the same accuracy with instructive vs. irrelevant templates because the task itself is too hard (a lack of competence) or because they for some reason ignore the instructions (a lack of compliance). We discuss these two possibilities below.

Lack of Competence This is primarily a concern for non-instruction-tuned models at zero shots, where all models perform only slightly above random, and thus a lack of statistical significance among template categories is ambiguous as to whether models lack understanding of NLI instructions vs. if models lack the competence in NLI per se. This is why our study largely focuses on the few-shot setting, where a lack of competence is less of a concern, as models do competently achieve good accuracies that are only moderately below the state-of-the-art non-few-shot models.

Another counterargument is that maybe no models ever actually reason about if a premise entails a hypothesis. Maybe they just always exploit spurious or heuristic features and, if only they were competent in properly reasoning about entailment relations, then the meaning of NLI instructions would matter. This argument is possible, although, first, it hinges on to what extent NLI (or any other behavioral evaluation) can measure language understanding, which is a complex debate beyond the scope of this paper. Second, in preliminary experiments, our models actually zero-shot transfer very well to HANS (McCoy et al., 2019), a dataset designed to diagnoses models use of NLI heuristics. Thus, it is unlikely that models are entirely incompetent in reasoning about entailment relations and solely rely on heuristics. Regardless, further differentiating competence in understanding task instructions vs. competence in tasks per se is an important direction for future work.

Lack of Compliance Another interpretation is that irrelevant prompts perform the same as the instructive ones because models simply ignore the prompts altogether. However, a lack of compliance alone cannot explain our results. If models truly ignore the prompts, we should not see any systematic differences between any categories of prompts. Instead, we do see consistent patterns that instructive and irrelevant templates make models learn significantly faster than misleading and null templates do (Table 2).

A more nuanced counterargument is that although models do not ignore their prompts entirely, perhaps it "takes less effort" for models to use the spurious or heuristic features for predictions as opposed to the more complex syntactic or semantic features (Lovering et al., 2021; Warstadt et al., 2020) required to properly comply with the instructions. However, spurious features alone likewise cannot explain the observed performance gaps. Recall that, within each random seed, all models see exactly the same training examples (with the same spurious features). Thus, to the extent that models perform differently with some prompts compared to others, it may be due to some complex interactions between the (spurious or semantic) features in prompts and the spurious features in inputs. One possible example of this interaction is that punctuation has a large effect for irrelevant templates, but instructive templates seem to be able to suppress such effect (Appendix B). Investigating the nature of this interaction is a promising direction for future work, and it suggests a way in which the semantics of the prompt might matter, e.g., by affecting the models' inductive biases, even if models do not interpret or use the instructions in the same way as humans would.

6 Conclusion

In this study, we train several prompt-based models with over 30 manually written templates for NLI. We find that models often learn equally fast with misleading and irrelevant templates as they do with instructive ones. This is true for all models and datasets with which we experimented in the few-shot setting. Although we see mixed evidence in the zero-shot setting with instruction-tuned models, overall, these results contradict a hypothesis commonly assumed in the literature that prompts serve as semantically meaningful task instructions and that writing high-performing prompts requires domain expertise. Although we find that existing models are far from fully understanding the meaning of their prompts, we agree that learning from instructions is an important research direction, and we propose several future directions of investigating models' understanding of the meaning of prompts.

References

Jonathan Bragg, Arman Cohan, Kyle Lo, and Iz Beltagy. 2021. FLEX: Unifying evaluation for few-shot NLP. *ArXiv preprint*, abs/2107.07170.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. The pascal recognising textual entailment challenge. In *Machine Learning Challenges Workshop*, pages 177–190. Springer.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. 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)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Stephen Ferrigno, Julian Jara-Ettinger, Steven T Piantadosi, and Jessica F Cantlon. 2017. Universal and uniquely human factors in spontaneous number perception. *Nature communications*, 8(1):1–10.

Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2021a. A framework for few-shot language model evaluation.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021b. Making pre-trained language models better few-shot learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3816–3830, Online. Association for Computational Linguistics.

Marvin J Greenberg. 1974. *Euclidean and non-Euclidean Geometries: Development and history*. W. H. Freeman and Company.

Ashim Gupta, Giorgi Kvernadze, and Vivek Srikumar. 2021. Bert & family eat word salad: Experiments with text understanding.

Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2021. Towards a unified view of parameter-efficient transfer learning. *CoRR*, abs/2110.04366.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A lite BERT for self-supervised learning of language representations. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Teven Le Scao and Alexander Rush. 2021. How many data points is a prompt worth? In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2627–2636, Online. Association for Computational Linguistics.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In *EMNLP*.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *ArXiv preprint*, abs/1907.11692.

Robert L Logan, Ivana Balažević, Eric Wallace, Fabio Petroni, Sameer Singh, and Sebastian Riedel. 2021. Cutting down on prompts and parameters: Simple few-shot learning with language models. *ArXiv preprint*, abs/2106.13353.

Charles Lovering, Rohan Jha, Tal Linzen, and Ellie Pavlick. 2021. Predicting inductive biases of pre-trained models. In *International Conference on Learning Representations*.

Tom McCoy, Ellie Pavlick, and Tal Linzen. 2019. Right for the wrong reasons: Diagnosing syntactic heuristics in natural language inference. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3428–3448, Florence, Italy. Association for Computational Linguistics.

Sewon Min, Mike Lewis, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2021. Metaicl: Learning to learn in context. *CoRR*, abs/2110.15943.

Swaroop Mishra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. 2021. Natural instructions: Benchmarking generalization to new tasks from natural language instructions. *ArXiv preprint*, abs/2104.08773.

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A new benchmark for natural language understanding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4885–4901, Online. Association for Computational Linguistics.

Thang Pham, Trung Bui, Long Mai, and Anh Nguyen. 2021. Out of order: How important is the sequential order of words in a sentence in natural language understanding tasks? In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1145–1160, Online. Association for Computational Linguistics.

Plato. c. 399 BC. *Euthyphro*. Penguin Books.

Guanghui Qin and Jason Eisner. 2021. Learning how to ask: Querying LMs with mixtures of soft prompts. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5203–5212, Online. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *ArXiv preprint*, abs/1910.01108.

Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Stella Biderman, Leo Gao, Tali Bers, Thomas Wolf, and Alexander M. Rush. 2021. Multitask prompted training enables zero-shot task generalization.

Timo Schick and Hinrich Schütze. 2021a. Exploiting cloze-questions for few-shot text classification and natural language inference. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 255–269, Online. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2021b. It's not just size that matters: Small language models are also few-shot learners. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2339–2352, Online. Association for Computational Linguistics.

Noam Shazeer and Mitchell Stern. 2018. Adafactor: Adaptive learning rates with sublinear memory cost. In *International Conference on Machine Learning*, pages 4596–4604. PMLR.

Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. AutoPrompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4222–4235, Online. Association for Computational Linguistics.

Koustuv Sinha, Prasanna Parthasarathi, Joelle Pineau, and Adina Williams. 2021. UnNatural Language Inference. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 7329–7346, Online. Association for Computational Linguistics.

Derek Tam, Rakesh R Menon, Mohit Bansal, Shashank Srivastava, and Colin Raffel. 2021. Improving and simplifying pattern exploiting training. *ArXiv preprint*, abs/2103.11955.

Shizuo Tsuji and Mary Sutherland. 1980. *Japanese Cooking: A Simple Art*. Kodansha International.

Prasetya Utama, Nafise Sadat Moosavi, Victor Sanh, and Iryna Gurevych. 2021. Avoiding inference heuristics in few-shot prompt-based finetuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 9063–9074, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 3261–3275.

Alex Warstadt, Yian Zhang, Xiaocheng Li, Haokun Liu, and Samuel R. Bowman. 2020. Learning which features matter: RoBERTa acquires a preference for linguistic generalizations (eventually). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 217–235, Online. Association for Computational Linguistics.

Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *ArXiv preprint*, abs/2109.01652.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Contents

A Effect of Target Words

A.1 Setup

In this experiment, we study the effect of different LM targets given a fixed template. We write 4 categories[5] of targets (see Table 3 for examples):

1. Yes-no: Model is expected to predict the word "yes" for entailment and "no" for non-entailment.
2. Yes-no-like: Semantically equivalent to yes-no but using superficially different words, e.g., "true"/"false", "positive"/"negative".
3. Arbitrary: Model is expected to predict arbitrary words that have no semantic relation to the entailment task, e.g., "cat" for entailment, "dog" for non-entailment.
4. Reversed: Model is expected to predict the opposite of the (intuitive) yes-no and yes-no-like labels, e.g., "no" for entailment, "yes" for non-entailment.

Within the arbitrary category, in addition to common anglophone first names as Le Scao and Rush (2021) tested, we also include word pairs with high semantic similarity, low similarity, and pairs which are highly frequent in the English language, but we find no consistent difference among these various subcategories of the arbitrary category.

Target Words	Category
yes; no	yes-no
true; false	yes-no-like
right; wrong	yes-no-like
good; bad	yes-no-like
no; yes	reversed
false; true	reversed
cat; dog	arbitrary (semantically similar)
cake; piano	arbitrary (semantically dissimilar)
the; a	arbitrary (highly frequent)
she; he	arbitrary (highly frequent)

Table 3: Example Sets of LM targets.

A.2 Results

For ALBERT,[6] we find that models trained with yes-no targets learn dramatically faster than those trained with arbitrary and reversed targets. For example, Figure 9 shows the top-performing instructive template trained with different target words. The large effect sizes are particularly noteworthy. In fact, in most cases, the effect of target words far outweighs the effect of templates (Figure 10)

On the first impression, the above seems to be a positive result—models are sufficiently sensitive to the semantics of the target words such that they consistently learn slower when the target words are unintuitive. However, there are several negative results as well: The effect of the target words overrides the semantics of the overall prompt. Consider two kinds of template-target combinations:

1. An irrelevant or misleading template + yes-no targets, e.g., `{premise} Does the paragraph start with "the"? [yes/no] {hypothesis}`
2. An instructive template + arbitrary targets, e.g., `{premise} Are we justified in saying that "{hypothesis}"? [cat/dog]`

Figure 11 shows that that combinations such as (1) often dramatically outperform (2), which is the opposite of what we expect because (1) is a pathological condition under which we would expect that a human would be confused and would still need a large number of trials and errors to figure out what is the actual task. In contrast, (2) simply

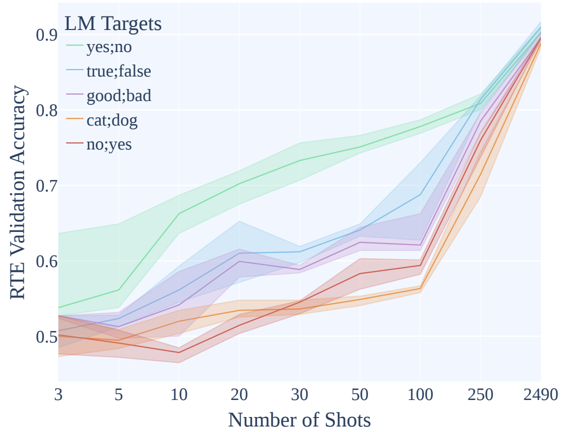


Figure 9: The best-performing instructive prompt for ALBERT, `{premise} Are we justified in saying that "{hypothesis}"? [mask]` with select LM targets from each category. See Appendix J for results with other templates.

[5] With declarative templates, another category is their template-specific targets. They are excluded from experiments in this section because combining declarative templates with other target categories yield ungrammatical prompts.

[6] We have not yet run these experiments for the large models, which is why we omit these claims in the main paper. However, although incomplete, our existing results are striking enough that we report them here in the appendix.

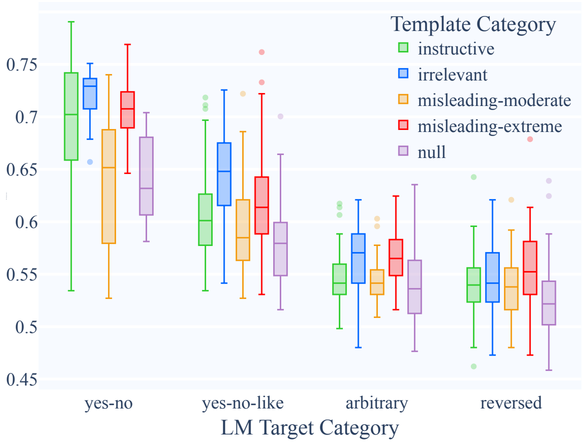


Figure 10: Median accuracies of all template-target combinations at 32 shots. In general, the choice of target words (x-axis groups) matters much more than the choice of templates (colors), which is counterintuitive because humans would care much more about the templates (the task instructions) than the targets (which words they need to respond with).

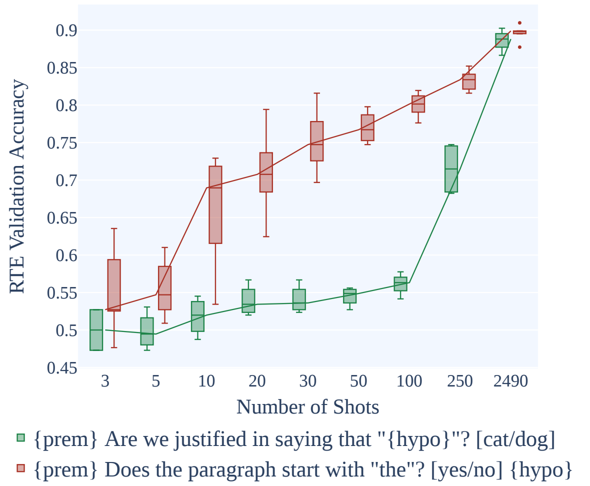


Figure 11: Misleading templates + yes-no targets (red) learn substantially faster than instructive templates + arbitrary targets (green), which is the opposite of what we expect from humans.

requires figuring out a mapping: "Reply 'cat' if entailed and reply 'dog' if not entailed". For humans, this can be learned in a few shots, e.g., Ferrigno et al. (2017) showed that adults can reach 60% accuracy in 18 trials[7] for an arbitrary map of {more numerous → star shape, less numerous → diamond shape} without receiving any language instructions. In contrast, models under many arbitrary LM targets struggle to reach 60% median accuracy even by 100 shots with instructive templates (Figure 11 green; Figure 9 yellow, orange, red).

Further, even given intuitive yes-no-like targets such as "true"/"false" and "positive"/"negative", models learn drastically slower compared to when given "yes"/"no". As Figure 9 (green vs. blue) and Figure 10 (first vs. second group) show, there exists a large performance gap between yes-no and yes-no-like targets which is not closed until 250 shots, whereas for humans, the difference between answering "yes"/"no" vs. answering "true"/"false" should be trivial and likely would not require more than 100 examples to close any gap. Moreover, when we try to help the models by appending target hints such as "True or false?" to the templates, performance consistently reduce instead.

[7] And this comparison is heavily charitable to the models because "18 trials" means that humans see 18 examples for 18 times in total, whereas "20-shot" means that models can see the same 20 examples over and over again for many epochs.

B Effect of Punctuation

For irrelevant templates, we find a large effect from the use of quotation and question marks in templates. It is natural to write such punctuation in instructive templates as they help humans to parse an NLI hypothesis as an embedded clause within an instruction sentence (e.g., `Given {premise} Should we assume that "{hypothesis}" is true?`). For control, we also use quotation and question marks ("qmarks" hereafter) in irrelevant templates where they would not have made sense naturally, e.g., `{premise} Single-family zoning is bad for American cities. "{hypothesis}"?` As an ablation, when we remove these qmarks from irrelevant templates, the performance of ALBERT and T0 drops substantially (Figures 12 and 13). In contrast, for T5, qmarks make no difference for irrelevant templates; yet, removing qmarks from instructive templates—where qmarks are natural—boosted performance instead for T5 (Figure 14), but not for T0 nor ALBERT.

Additionally, as a coincidence, most misleading templates contain both quotation and question marks, while most misleading-far templates contain only question marks (Appendix F). But as noted in Section 4, there is no consistent pattern between those two misleading categories. In other words, punctuations alone cannot explain everything. As discussed in Section 5.2, the full explanation is likely a combined interactions between

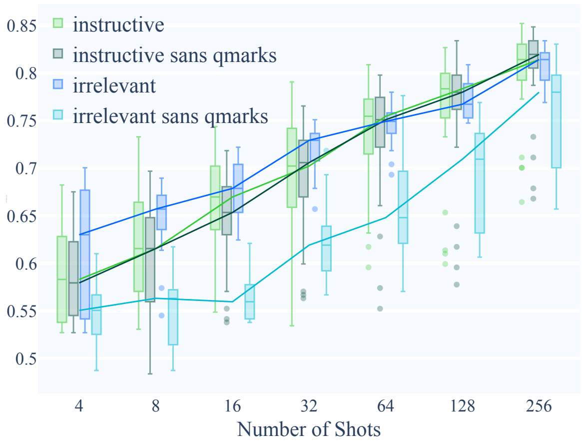


Figure 12: ALBERT on RTE. Note that (1) irrelevant templates slightly outperform the instructive templates, albeit without statistical significance. (2) Irrelevant templates are far worse without quotation and question marks. (3) But there is no significant difference between instructive templates with or without qmarks.

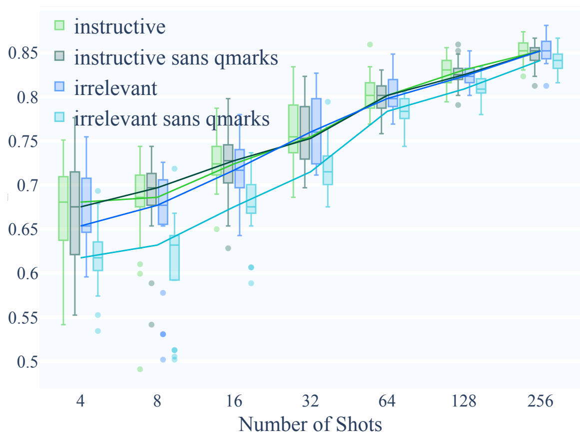


Figure 13: T0 (3B) on RTE. Like ALBERT, irrelevant sans qmarks are significantly worse than irrelevant at each and every shot, but there is no significant difference between instructive with or without qmarks.

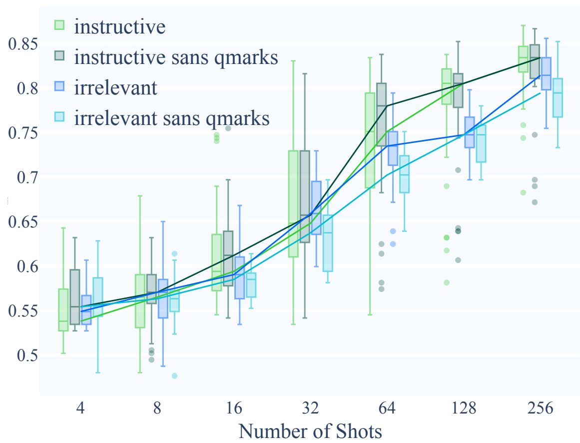


Figure 14: T5 LM-Adapted (3B). Unlike the other models, there is no statistical significance between irrelevant with or without qmarks. However, instructive sans qmarks statistically significantly outperform instructive at 32 and 64 shots.

the spurious features and the semantics of the templates.

Lastly, note that Schick and Schütze (2021b) and many subsequent papers' prompts for NLI (e.g., `"{hypothesis}" ? | [mask]. "{premise}"`) are basically null templates with some variation in punctuation between the hypothesis and the premise. We find that models learn poorly with the vanilla `{hypothesis} [mask] {premise}`, but they learn as fast as the instructive templates with Schick & Schütze's punctuated version. That being said, note again that punctuation alone cannot explain the performance gap, since models trained with `[mask] {hypothesis} {premise}` (Figure 7, pink) perform second to best, yet swapping their premises and hypotheses (Figure 7, purple) makes it the worst performing among all null templates.

C Details and Lessons from Experimenting with GPT-3's API

C.1 Choice of Model

We use the `davinci` model provided by OpenAI's API, which corresponds to[8] the 175 billion parameter model reported in Brown et al. (2020). Notably, concurrent to our work, OpenAI released a new product called the "Instruct Series", which is speculated by Sanh et al. (2021) and Wei et al. (2021) as an instruction-tuned version of GPT-3. While it would be interesting to study an instruction-tuned 175B model,[9] we decide to not experiment with the Instruct Series because no academic paper or technical documentation of any kind is available with the Instruct Series aside from the following claim on their website:[10]

> The Instruct models share our base GPT-3 models' ability to understand and generate natural language, but they're better at understanding and following

[8]OpenAI never actually discloses which one of their commercially named `ada, babbage, curie, davinci` "engines" correspond to models of which size. However, Gao et al. (2021a) estimate that they correspond to 350M, 1.3B, 6.7B, and 175B respectively.

[9]Especially since Wei et al. (2021)'s 137B FLAN is not publicly available.

[10]http://beta.openai.com/docs/engines/instruct-series-beta

> your instructions. You simply tell the model what you want it to do, and it will do its best to fulfill your instructions. This is an important step forward in our goal of building safe models that are aligned with human interests.

Crucially, the Instruct Series is inappropriate for reproducible research because it is unknown what datasets and prompts these models are trained on, and whether any task categories are systematically held out as done by Sanh et al. (2021) and Wei et al. (2021). If it is trained on any prompt or dataset of NLI, it would not be zero-shot, making it an unfair comparison to other models in our experiments. Second, it is still in beta and its training, held-out, and prompt mixtures could change. At least two Instruct Series models were made available in sequence during our writing, and it is not clear if we experiment on an older version, whether it will still be available and reproducible in the future.

C.2 Priming vs. Fine-Tuning

As mentioned in Section 3, we use priming (a.k.a. in-context learning) in lieu of fine-tuning because, at the time of writing, OpenAI's fine-tuning API is limited to 10 runs per month. To train 30 prompts at only two number of shots would take 6 months, assuming we get hyperparameters right at first try. Further, each training run is limited to a maximum of 5 epochs, which often entails an insufficient number steps for few-shot training. We were unable to fine-tune GPT to any reasonable accuracy with our allowed 10 tries in the first month. Finally, at the time of writing, fine-tuning is limited to GPT variants up to 6.7B, not the 175B model we plan to experiment with.

With priming, we are able to reproduce Brown et al. (2020)'s zero-shot performance on RTE but only with their exact prompt reported in their Figure G.31, all other (even instructive) prompts perform at random at zero shots, suggesting that their reported prompt is highly cherry-picked. We are unable to reproduce their reported few-shot result because they report it at 32 shots, but their API only permits a context length up to 2049 tokens, which is insufficient for RTE. We find that 16 shots are the highest one can reach within the token limit.[11]

[11]Depending on the length of the prompt template, 2 or 3 examples still exceed the token limit, in which case we remove one priming example, keeping the other 15 priming examples and the to-be-predicted example unmodified.

Like the gradient updated models, we document the exact examples we use for few-shot priming in supplementary materials. Unlike the gradient updated models, which are trained on the same k examples, priming models use different sets of k priming examples for each inference example (Brown et al., 2020, p. 20). This means that GPT's performance reflects the fact that, overall, it has seen far more than k examples, making it not directly comparable to the few shots of the gradient updated models. This is not ideal, but our GPT few-shot performance already underperforms what Brown et al. (2020) report, so we choose to not further restrict it to have the same fixed priming examples for all inference examples, which could run into a lack of competence issue (§5.2) that make its results unusable for our research question.

Lastly, unlike the gradient updated models, we do not run multiple seeds with our GPT experiments because, first, they are expensive. As the API bills by token, using k shots of priming example effectively multiplies the total cost by k. Second, OpenAI imposes a monthly quota for each lab, so running multiple seeds will take several more months to complete.

C.3 Other Tips for Working with GPT-3

Using the `logprobs` argument in their API, we obtain the top 99 predicted target word and their log probabilities.[12] Following Sanh et al. (2021) and Wei et al. (2021), we evaluate by a rank classification of the target words, i.e., if the gold target word is "yes", we consider it as correct as long as the probability of "yes" is higher than that of "no", regardless of whether "yes" is the top-1 prediction generated by the model.

Alarmingly, we find that these top-99 predictions are semantically inconsistent ranked, e.g., for one data example and its top-99 word predictions, it is often the case that, e.g., P(yes) > P(no) but P(Yes) < P(No). Thus, the choice of the target words' surface form makes a substantial difference in the overall performance. (Not to mention the problem of choosing between yes/no, true/false, correct/incorrect, etc. as studied in Appendix A.) OpenAI recommends having no trailing space in the input and let the model predict the first token

[12]Although sometimes the API returns less than the number of `logprobs` the user specifies, in which case we contacted OpenAI's customer support who provided us refund by store credit. At the time of publishing, OpenAI now restricts `logprobs` to a maximum of 5.

with a leading space as in "␣Yes". We find that although stripping the leading space sometimes leads to higher performance for some prompts, overall not applying stripping or other token normalization performs the best.

Another point researchers should pay attention to is the use of what OpenAI calls a "separator" inserted between priming examples. In preliminary experiments, we initially use newline characters as appeared in Brown et al. (2020)'s Appendix G. We later discover that OpenAI recommends using `###` or `\n###\n` as separators. We use the latter and find consistent performance improvement over just using newline characters, and we use it throughout in our main experiments.

D Hyperparameters

For encoder-only models, we follow Schick and Schütze (2021b) and Le Scao and Rush (2021)'s recommendations and use a learning rate of $1e^{-5}$. For T5 and T0 models, we follow Raffel et al. (2020) and Sanh et al. (2021)'s recommendations and use a learning rate of $1e^{-4}$. We run several preliminary experiments with learning rates $(3e^{-4}, 1e^{-4}, 5e^{-5}, 1e^{-5})$ deviating from their recommendations and they perform worse, although our search is not exhaustive due to the high cost of running multiple prompts with multiple random seeds.

Note that T5 and T0 are trained with the Adafactor optimizer (Shazeer and Stern, 2018) in Mesh TensorFlow. Our implementation is in PyTorch, and we find that fine-tuning T5 with PyTorch's implementation of Adafactor yields substantially worse results than the usual choice of the AdamW optimizer. We corresponded with Raffel et al. (2020), who advised us that it might be due to the fact that PyTorch does not have the same learning rate scheduler implementation as TensorFlow's Adafactor does. They recommended us to simply use AdamW, which is what we did. This is somewhat unfortunate because Adafactor is much more memory efficient, which would have drastically reduced the compute resources required and thus enable more comprehensive experiments of the 11B models, which are currently limited to 0 shots and 16 shots only.

Although most models seem to obtain the highest validation accuracy at very early epochs, we train all models to 30 epochs (20 epochs for 11B models) to be safe and select the checkpoint with the highest validation accuracy.

All models use a batch size of 4 with 4 gradient accumulation steps for an effective batch size of 16.

Note that because we use a rank classification of single-token target words, decoding sampling methods (e.g., beam search, top-k, top-p) are unnecessary.

We follow Raffel et al. (2020) and add EOS tokens for input sequences, which yields higher few-shot performance compared to not adding EOS as done by Sanh et al. (2021). However, we omit EOS in the zero-shot setting, which exactly reproduces the results reported by Sanh et al. (2021). See T0's GitHub repository readme[13] for more information.

E Compute Used

Each ALBERT 235M model is trained on a single Nvidia RTX3090. Their main experiments took approximately 96 GPU hours.

Each T5 LMA 770M model is trained on a single A6000. Their main experiments took approximately 48 GPU hours.

The 3B models are each trained by partitioning their layers over four RTX3090s. T5 and T0's main experiments took approximately 1,536 GPU hours in total.

The 11B models are each trained on eight V100s (each with 32GB of memory). T5, T0, and T0++'s main experiments took approximately 1,728 GPU hours in total. (Due to their massive GPU memory requirement, we were only able to complete one number of shots.)

[13]https://github.com/bigscience-workshop/t-zero/tree/master/examples

F All Prompts

F.1 Main Experiments

category	template	adapted from
instructive	{premise} Using only the above description and what you know about the world, "{hypothesis}" is definitely correct. Yes or no?	Williams et al. (2018, p. 3)
instructive	{premise} \nquestion: {hypothesis}Yes or no?\nanswer:	Brown et al. (2020, p. 59)
instructive	{premise} Are we justified in saying that "{hypothesis}"?	
instructive	Given {premise} Should we assume that "{hypothesis}" is true?	
instructive	{premise} Based on the previous passage, is it true that "{hypothesis}"?	
instructive	Given {premise} Is it guaranteed true that "{hypothesis}"?	
instructive	Suppose {premise} Can we infer that "{hypothesis}"?	
instructive	Given that {premise} Does it follow that "{hypothesis}"?	
instructive	{premise} Question: Does this imply that "{hypothesis}"?	
instructive	Given that {premise} Therefore, it must be true that "{hypothesis}"?	
misleading-moderate	{premise} Do most of the above words appear in the following passage? {hypothesis}	
misleading-moderate	{premise} Are there lots of similar words in "{hypothesis}"?	
misleading-moderate	{premise} Does that have the same meaning as "{hypothesis}"?	
misleading-moderate	{premise} Can that be paraphrased as: "{hypothesis}"?	
misleading-moderate	{premise} Can that be summarized as "{hypothesis}"?	
misleading-extreme	{premise} Does the paragraph start with "the"? {hypothesis}	
misleading-extreme	{premise} Is this grammatically correct? {hypothesis}	
misleading-extreme	{premise} Is the sentiment positive? {hypothesis}	
misleading-extreme	{premise} Is this a sports news? {hypothesis}	
misleading-extreme	{premise} Is this French? {hypothesis}	
irrelevant	{premise} Single-family zoning is bad for American cities. "{hypothesis}"?	
irrelevant	{premise} Inflections are annoying and thank god that Middle English got rid of most of them. "{hypothesis}"?	
irrelevant	{premise} When Bolyai sent Gauss his discovery of non-Euclidean geometry, Gauss replied that he arrived at the same results 30 years ago. "{hypothesis}"?	Greenberg (1974, p. 141)
irrelevant	{premise} If bonito flakes boil more than a few seconds, the stock becomes too strong? "{hypothesis}"?	Tsuji and Sutherland (1980, p. 148)
irrelevant	{premise} Is the pious loved by the gods because it is pious? Or is it pious because it is loved by the gods? "{hypothesis}"?	Plato (c. 399 BC, 10a)
null	{premise} {hypothesis}	
null	{hypothesis}{premise}	
null (MLM only)	{premise} {mask} {hypothesis}	
null (MLM only)	{hypothesis}{mask} {premise}	
null (MLM only)	{mask} {premise} {hypothesis}	
null (MLM only)	{mask} {hypothesis}{premise}	

Table 4: All prompts used in the main text of the paper. All templates use "yes"/"no" as target words for the entailment and non-entailment classes, respectively. For ternary NLI datasets, we use "unclear" for the neutral class, which performs best after preliminary experiments with other ternary words, e.g., "maybe", "sometimes", "neither".

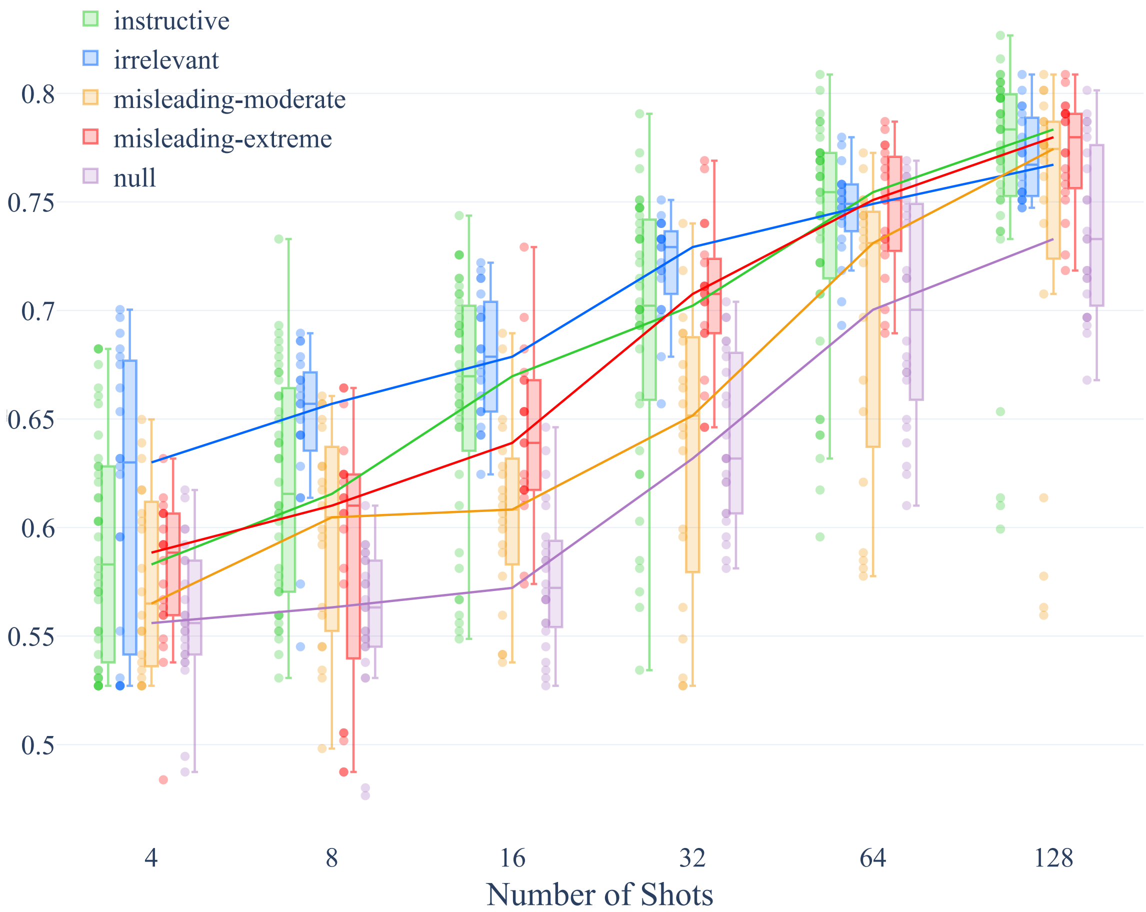
F.2 Ablation Experiments

category	template
instructive sans qmarks	{premise} Using only the above description and what you know about the world, {hypothesis}is definitely correct. Yes or no
instructive sans qmarks	{premise} \nquestion: {hypothesis}Yes or no\nanswer:
instructive sans qmarks	{premise} Are we justified in saying that {hypothesis}
instructive sans qmarks	Given {premise} Should we assume that {hypothesis}is true
instructive sans qmarks	{premise} Based on the previous passage, is it true that {hypothesis}
instructive sans qmarks	Given {premise} Is it guaranteed true that {hypothesis}
instructive sans qmarks	Suppose {premise} Can we infer that {hypothesis}
instructive sans qmarks	Given that {premise} Does it follow that {hypothesis}
instructive sans qmarks	{premise} Question: Does this imply that {hypothesis}
instructive sans qmarks	Given that {premise} Therefore, it must be true that {hypothesis}
irrelevant sans qmarks	{premise} Single-family zoning is bad for American cities. {hypothesis}
irrelevant sans qmarks	{premise} Inflections are annoying and thank god that Middle English got rid of most of them. {hypothesis}
irrelevant sans qmarks	{premise} When Bolyai sent Gauss his discovery of non-Euclidean geometry, Gauss replied that he arrived at the same results 30 years ago. {hypothesis}
irrelevant sans qmarks	{premise} If bonito flakes boil more than a few seconds, the stock becomes too strong. {hypothesis}
irrelevant sans qmarks	{premise} Is the pious loved by the gods because it is pious. Or is it pious because it is loved by the gods. {hypothesis}

Table 5: Used in the study of the effect of question and quotation marks in Appendix B.

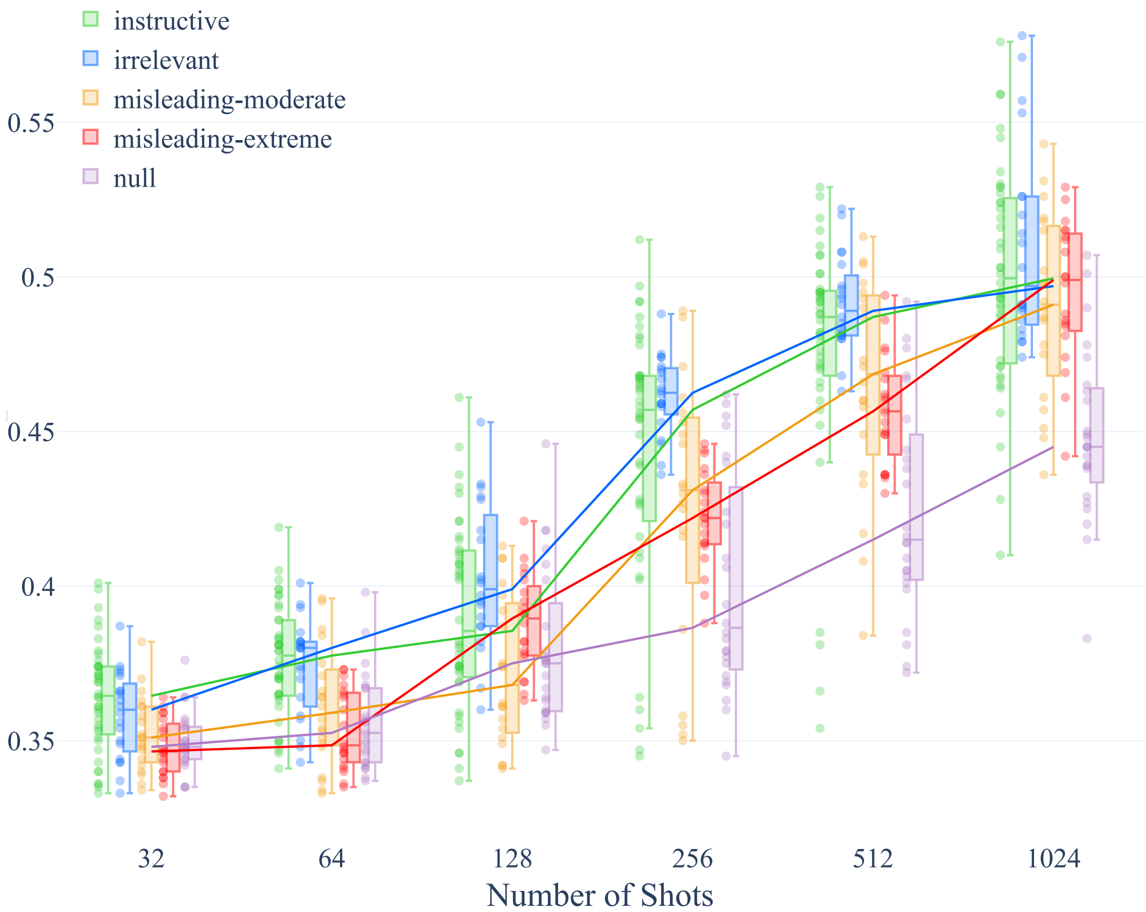
G Aggregated Results

G.1 ALBERT on RTE



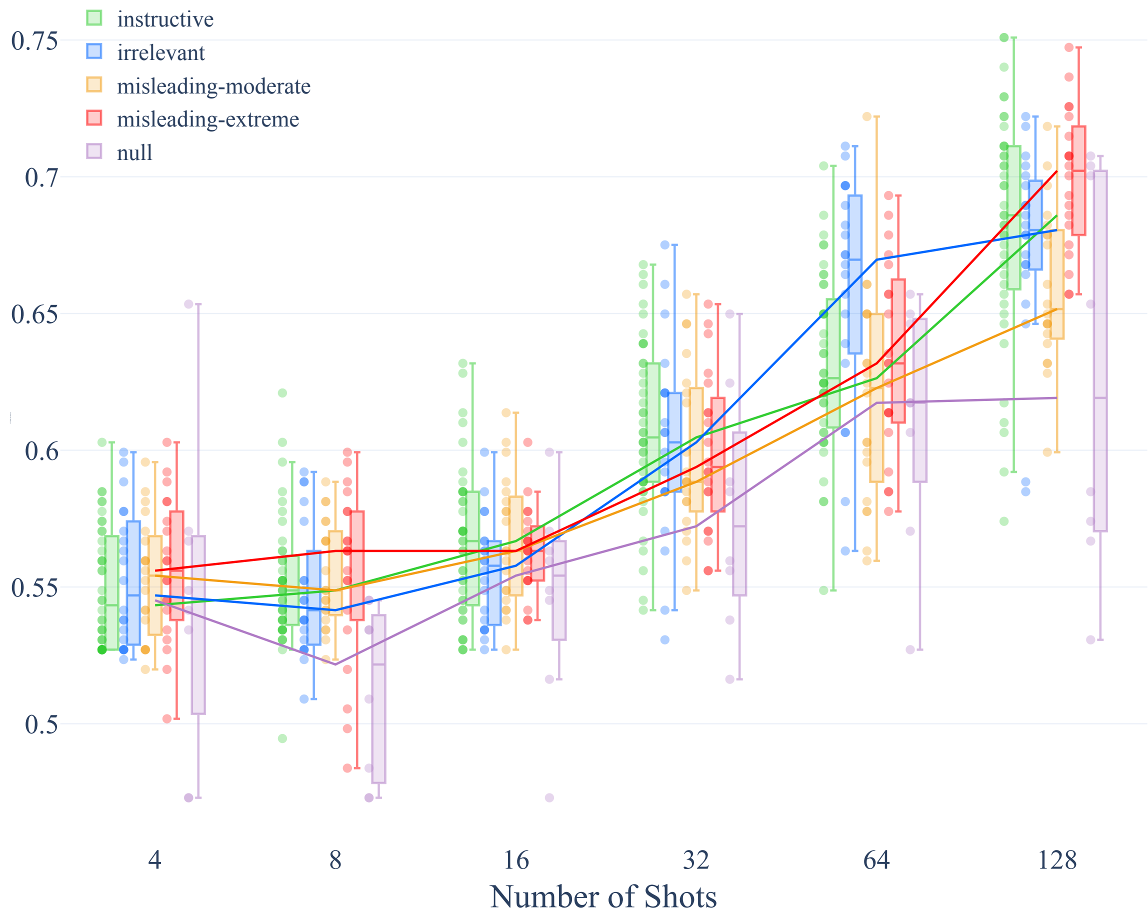
num. shots	template category	median	q3 - q1	mean	std. dev.
4	instructive	0.5830	0.0885	0.5907	0.0517
4	irrelevant	0.6300	0.1291	0.6170	0.0645
4	misleading-extreme	0.5884	0.0469	0.5787	0.0342
4	misleading-moderate	0.5650	0.0722	0.5753	0.0418
4	null	0.5560	0.0433	0.5599	0.0324
8	instructive	0.6155	0.0920	0.6186	0.0524
8	irrelevant	0.6570	0.0307	0.6471	0.0374
8	misleading-extreme	0.6101	0.0677	0.5899	0.0595
8	misleading-moderate	0.6047	0.0767	0.5969	0.0490
8	null	0.5632	0.0397	0.5586	0.0326
16	instructive	0.6697	0.0605	0.6594	0.0558
16	irrelevant	0.6787	0.0488	0.6787	0.0294
16	misleading-extreme	0.6390	0.0506	0.6413	0.0384
16	misleading-moderate	0.6083	0.0443	0.6072	0.0427
16	null	0.5722	0.0379	0.5767	0.0327
32	instructive	0.7022	0.0813	0.6929	0.0638
32	irrelevant	0.7292	0.0235	0.7206	0.0236
32	misleading-extreme	0.7076	0.0334	0.7056	0.0340
32	misleading-moderate	0.6516	0.0992	0.6350	0.0666
32	null	0.6318	0.0731	0.6414	0.0392
64	instructive	0.7545	0.0542	0.7353	0.0548
64	irrelevant	0.7491	0.0198	0.7455	0.0218
64	misleading-extreme	0.7509	0.0416	0.7451	0.0299
64	misleading-moderate	0.7310	0.0993	0.6953	0.0688
64	null	0.7004	0.0848	0.6998	0.0516
128	instructive	0.7834	0.0451	0.7661	0.0551
128	irrelevant	0.7671	0.0343	0.7704	0.0200
128	misleading-extreme	0.7798	0.0334	0.7729	0.0255
128	misleading-moderate	0.7744	0.0550	0.7354	0.0842
128	null	0.7329	0.0695	0.7369	0.0389

G.2 ALBERT on ANLI R1



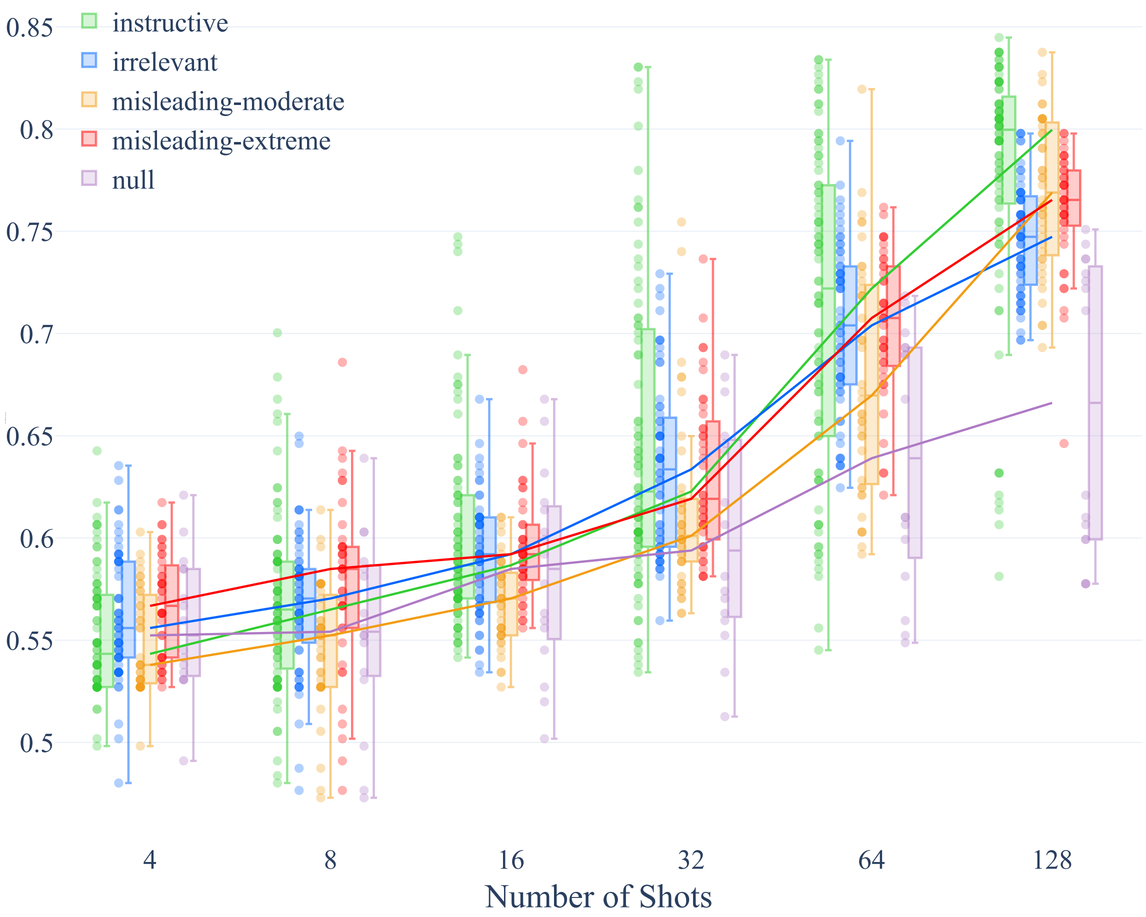
num. shots	template category	median	q3 - q1	mean	std. dev.
32	instructive	0.3645	0.0215	0.3642	0.0177
32	irrelevant	0.3600	0.0195	0.3583	0.0141
32	misleading-extreme	0.3465	0.0147	0.3478	0.0092
32	misleading-moderate	0.3510	0.0175	0.3525	0.0123
32	null	0.3480	0.0102	0.3496	0.0096
64	instructive	0.3775	0.0242	0.3760	0.0183
64	irrelevant	0.3800	0.0195	0.3739	0.0160
64	misleading-extreme	0.3485	0.0217	0.3534	0.0128
64	misleading-moderate	0.3590	0.0232	0.3608	0.0192
64	null	0.3525	0.0240	0.3558	0.0155
128	instructive	0.3855	0.0400	0.3908	0.0304
128	irrelevant	0.3990	0.0335	0.4027	0.0239
128	misleading-extreme	0.3895	0.0212	0.3881	0.0158
128	misleading-moderate	0.3680	0.0400	0.3725	0.0242
128	null	0.3750	0.0310	0.3795	0.0250
256	instructive	0.4570	0.0445	0.4439	0.0432
256	irrelevant	0.4625	0.0135	0.4617	0.0129
256	misleading-extreme	0.4220	0.0185	0.4218	0.0158
256	misleading-moderate	0.4310	0.0453	0.4247	0.0437
256	null	0.3865	0.0540	0.4002	0.0355
512	instructive	0.4870	0.0262	0.4758	0.0403
512	irrelevant	0.4890	0.0178	0.4912	0.0155
512	misleading-extreme	0.4565	0.0218	0.4569	0.0178
512	misleading-moderate	0.4685	0.0478	0.4650	0.0353
512	null	0.4150	0.0440	0.4246	0.0347
1024	instructive	0.4995	0.0523	0.5004	0.0358
1024	irrelevant	0.4970	0.0408	0.5101	0.0325
1024	misleading-extreme	0.4990	0.0303	0.4952	0.0228
1024	misleading-moderate	0.4910	0.0443	0.4905	0.0298
1024	null	0.4450	0.0278	0.4490	0.0280

G.3 T5 770M on RTE



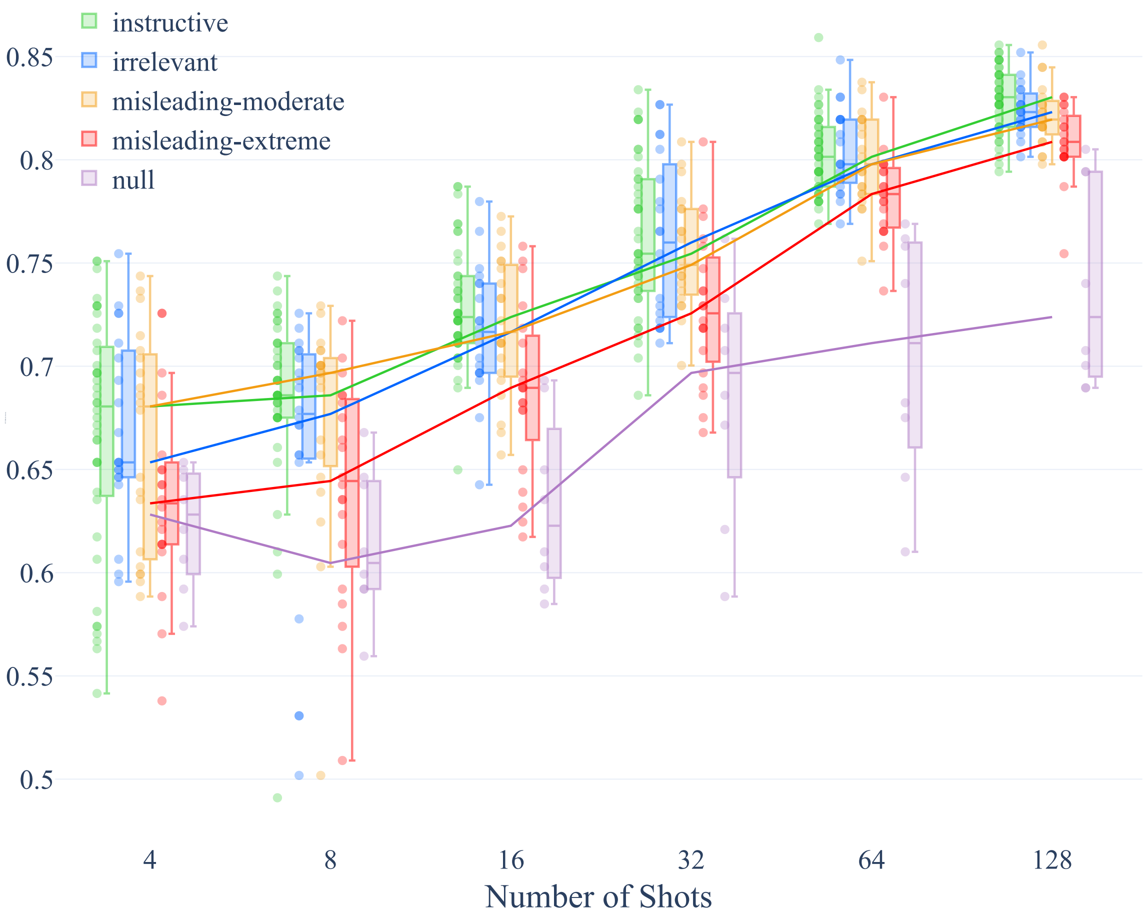
num. shots	template category	median	q3 - q1	mean	std. dev.
4	instructive	0.5433	0.0406	0.5493	0.0219
4	irrelevant	0.5469	0.0424	0.5532	0.0252
4	misleading-extreme	0.5560	0.0361	0.5561	0.0263
4	misleading-moderate	0.5542	0.0325	0.5531	0.0220
4	null	0.5451	0.0487	0.5451	0.0578
8	instructive	0.5487	0.0235	0.5516	0.0232
8	irrelevant	0.5415	0.0280	0.5480	0.0244
8	misleading-extreme	0.5632	0.0379	0.5545	0.0322
8	misleading-moderate	0.5487	0.0280	0.5543	0.0192
8	null	0.5217	0.0560	0.5122	0.0317
16	instructive	0.5668	0.0406	0.5662	0.0277
16	irrelevant	0.5578	0.0298	0.5558	0.0199
16	misleading-extreme	0.5632	0.0190	0.5634	0.0160
16	misleading-moderate	0.5632	0.0343	0.5666	0.0239
16	null	0.5542	0.0271	0.5469	0.0381
32	instructive	0.6047	0.0433	0.6078	0.0317
32	irrelevant	0.6029	0.0361	0.6025	0.0366
32	misleading-extreme	0.5939	0.0352	0.5996	0.0292
32	misleading-moderate	0.5884	0.0424	0.5986	0.0311
32	null	0.5722	0.0460	0.5772	0.0443
64	instructive	0.6264	0.0433	0.6318	0.0324
64	irrelevant	0.6697	0.0542	0.6585	0.0421
64	misleading-extreme	0.6318	0.0478	0.6336	0.0355
64	misleading-moderate	0.6227	0.0578	0.6195	0.0400
64	null	0.6173	0.0496	0.6115	0.0442
128	instructive	0.6859	0.0514	0.6820	0.0421
128	irrelevant	0.6805	0.0307	0.6749	0.0362
128	misleading-extreme	0.7022	0.0361	0.6987	0.0260
128	misleading-moderate	0.6516	0.0379	0.6597	0.0295
128	null	0.6191	0.1291	0.6277	0.0717

G.4 T5 3B on RTE



num. shots	template category	median	q3 - q1	mean	std. dev.
4	instructive	0.5433	0.0442	0.5524	0.0297
4	irrelevant	0.5560	0.0469	0.5611	0.0308
4	misleading-extreme	0.5668	0.0442	0.5671	0.0251
4	misleading-moderate	0.5379	0.0415	0.5497	0.0247
4	null	0.5523	0.0514	0.5575	0.0334
8	instructive	0.5650	0.0514	0.5680	0.0427
8	irrelevant	0.5704	0.0343	0.5676	0.0332
8	misleading-extreme	0.5848	0.0397	0.5773	0.0431
8	misleading-moderate	0.5523	0.0442	0.5485	0.0309
8	null	0.5542	0.0523	0.5553	0.0459
16	instructive	0.5866	0.0505	0.6005	0.0467
16	irrelevant	0.5921	0.0406	0.5907	0.0279
16	misleading-extreme	0.5921	0.0262	0.5953	0.0271
16	misleading-moderate	0.5704	0.0298	0.5693	0.0212
16	null	0.5848	0.0614	0.5833	0.0481
32	instructive	0.6227	0.1056	0.6463	0.0757
32	irrelevant	0.6336	0.0623	0.6349	0.0416
32	misleading-extreme	0.6191	0.0542	0.6315	0.0393
32	misleading-moderate	0.6011	0.0298	0.6134	0.0440
32	null	0.5939	0.0848	0.6031	0.0548
64	instructive	0.7220	0.1227	0.7113	0.0784
64	irrelevant	0.7040	0.0578	0.7032	0.0408
64	misleading-extreme	0.7076	0.0478	0.7039	0.0352
64	misleading-moderate	0.6697	0.0957	0.6792	0.0569
64	null	0.6390	0.0984	0.6397	0.0618
128	instructive	0.7996	0.0496	0.7769	0.0627
128	irrelevant	0.7473	0.0415	0.7468	0.0271
128	misleading-extreme	0.7653	0.0262	0.7604	0.0295
128	misleading-moderate	0.7690	0.0632	0.7685	0.0373
128	null	0.6661	0.1318	0.6640	0.0716

G.5 T0 3B on RTE



num. shots	template category	median	q3 - q1	mean	std. dev.
4	instructive	0.6805	0.0704	0.6677	0.0580
4	irrelevant	0.6534	0.0596	0.6695	0.0450
4	misleading-extreme	0.6336	0.0379	0.6368	0.0469
4	misleading-moderate	0.6805	0.0966	0.6644	0.0525
4	null	0.6282	0.0442	0.6223	0.0292
8	instructive	0.6859	0.0361	0.6850	0.0438
8	irrelevant	0.6769	0.0487	0.6579	0.0674
8	misleading-extreme	0.6444	0.0749	0.6401	0.0543
8	misleading-moderate	0.6968	0.0478	0.6747	0.0530
8	null	0.6047	0.0514	0.6137	0.0357
16	instructive	0.7238	0.0325	0.7290	0.0284
16	irrelevant	0.7166	0.0433	0.7171	0.0315
16	misleading-extreme	0.6895	0.0415	0.6879	0.0410
16	misleading-moderate	0.7166	0.0523	0.7191	0.0337
16	null	0.6227	0.0596	0.6322	0.0423
32	instructive	0.7545	0.0542	0.7627	0.0369
32	irrelevant	0.7599	0.0695	0.7621	0.0397
32	misleading-extreme	0.7256	0.0451	0.7278	0.0361
32	misleading-moderate	0.7491	0.0406	0.7551	0.0279
32	null	0.6968	0.0632	0.6859	0.0578
64	instructive	0.8014	0.0289	0.8027	0.0190
64	irrelevant	0.7978	0.0298	0.8040	0.0204
64	misleading-extreme	0.7834	0.0271	0.7827	0.0201
64	misleading-moderate	0.7978	0.0361	0.8000	0.0225
64	null	0.7112	0.0912	0.7053	0.0600
128	instructive	0.8303	0.0253	0.8292	0.0161
128	irrelevant	0.8231	0.0153	0.8244	0.0118
128	misleading-extreme	0.8087	0.0190	0.8088	0.0174
128	misleading-moderate	0.8195	0.0135	0.8215	0.0152
128	null	0.7238	0.0966	0.7401	0.0505

G.6 T5 11B, T0 11B, and GPT-3 175B (Figure 6)

model	template category	median	q3 - q1	mean	std. dev.
GPT-3 (175B)	instructive	0.6534	0.0722	0.6472	0.0429
GPT-3 (175B)	irrelevant	0.6101	0.0361	0.6260	0.0326
GPT-3 (175B)	misleading-extreme	0.6173	0.0072	0.6217	0.0143
GPT-3 (175B)	misleading-moderate	0.6498	0.0578	0.6318	0.0480
T5 LMA (11B)	instructive	0.6679	0.1462	0.6797	0.0823
T5 LMA (11B)	irrelevant	0.6426	0.0776	0.6368	0.0488
T5 LMA (11B)	misleading-extreme	0.5993	0.0794	0.6070	0.0619
T5 LMA (11B)	misleading-moderate	0.5957	0.1137	0.6072	0.0653
T5 LMA (11B)	null	0.5560	0.0442	0.5578	0.0332
T0 (11B)	instructive	0.7942	0.0623	0.7959	0.0392
T0 (11B)	irrelevant	0.7906	0.0632	0.7942	0.0384
T0 (11B)	misleading-extreme	0.7401	0.0650	0.7338	0.0496
T0 (11B)	misleading-moderate	0.7942	0.0397	0.7858	0.0356
T0 (11B)	null	0.6986	0.0695	0.6847	0.0484
T0++ (11B)	instructive	0.8321	0.0316	0.8319	0.0282
T0++ (11B)	irrelevant	0.8267	0.0433	0.8207	0.0323
T0++ (11B)	misleading-extreme	0.8051	0.0614	0.8029	0.0593
T0++ (11B)	misleading-moderate	0.8159	0.0487	0.8039	0.0333
T0++ (11B)	null	0.7509	0.0505	0.7379	0.0362

H Results of Individual Templates

H.1 ALBERT

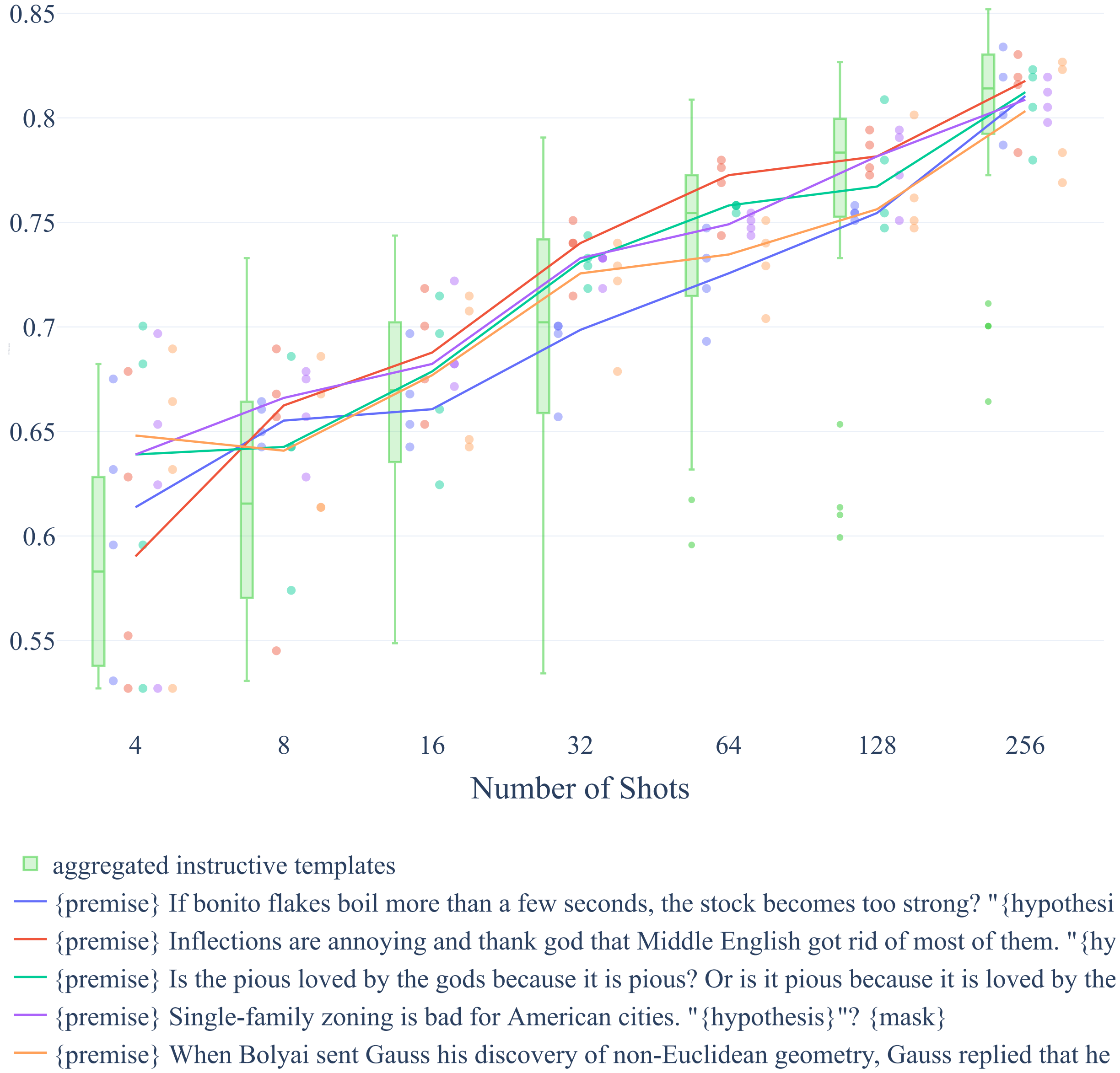


Figure 15: ALBERT with all irrelevant templates and the aggregated instructive for reference.

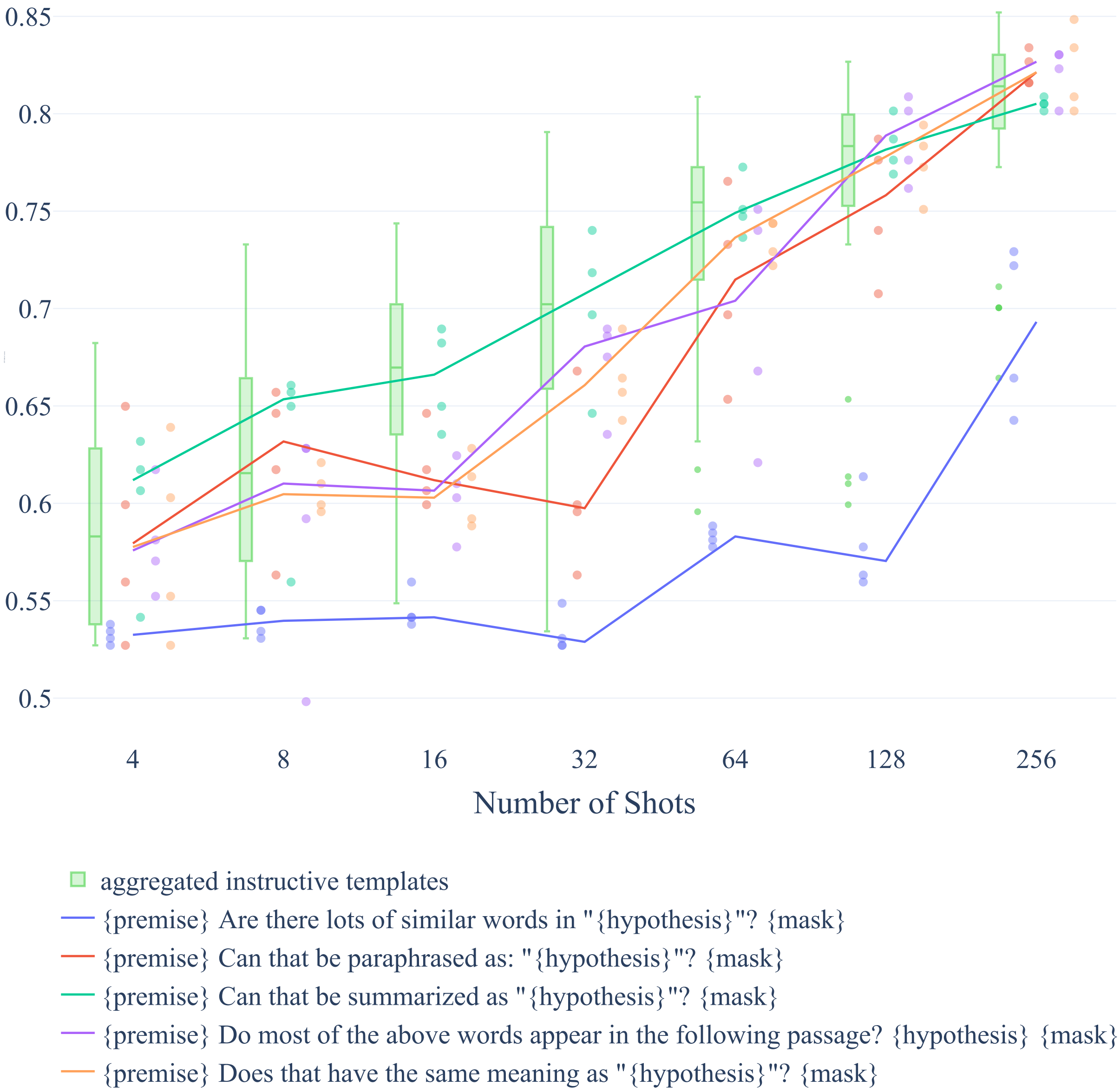


Figure 16: ALBERT with all misleading-moderate templates and the aggregated instructive for reference.

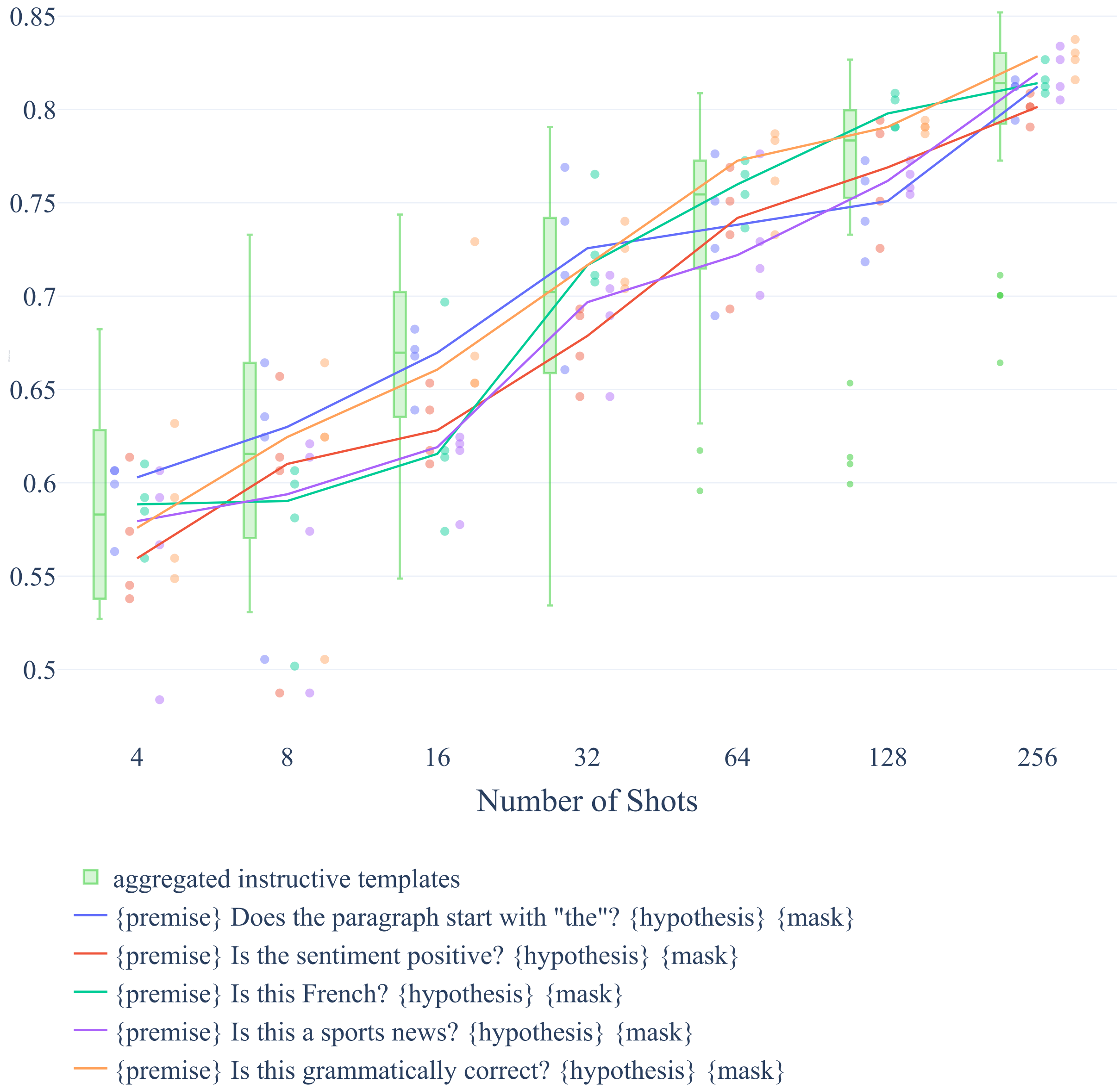


Figure 17: ALBERT with all misleading-extreme templates and the aggregated instructive for reference.

Figure 18: ALBERT with all instructive templates.

H.2 T0 (3B)

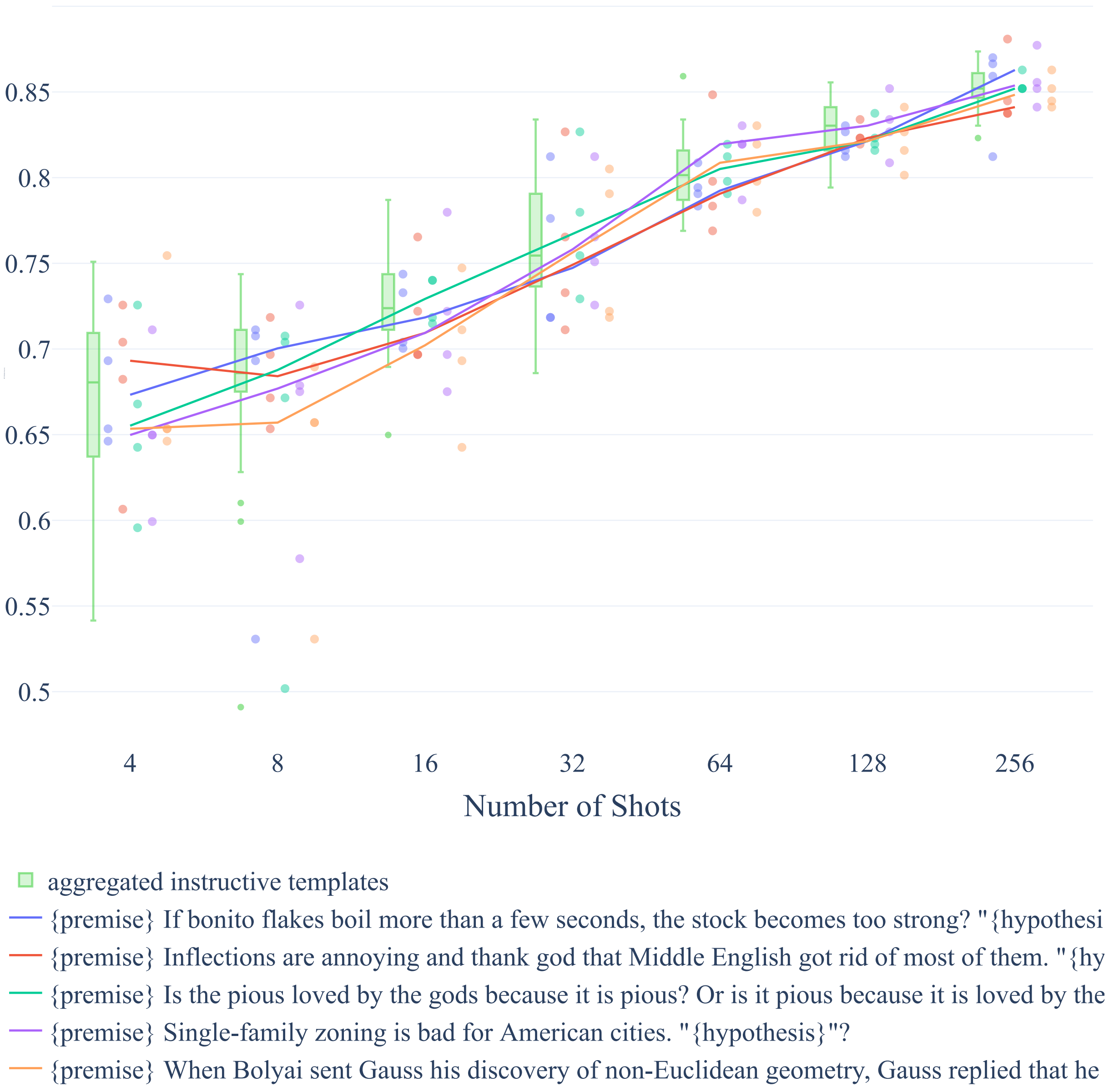


Figure 19: T0 (3B) with all irrelevant templates and the aggregated instructive for reference.

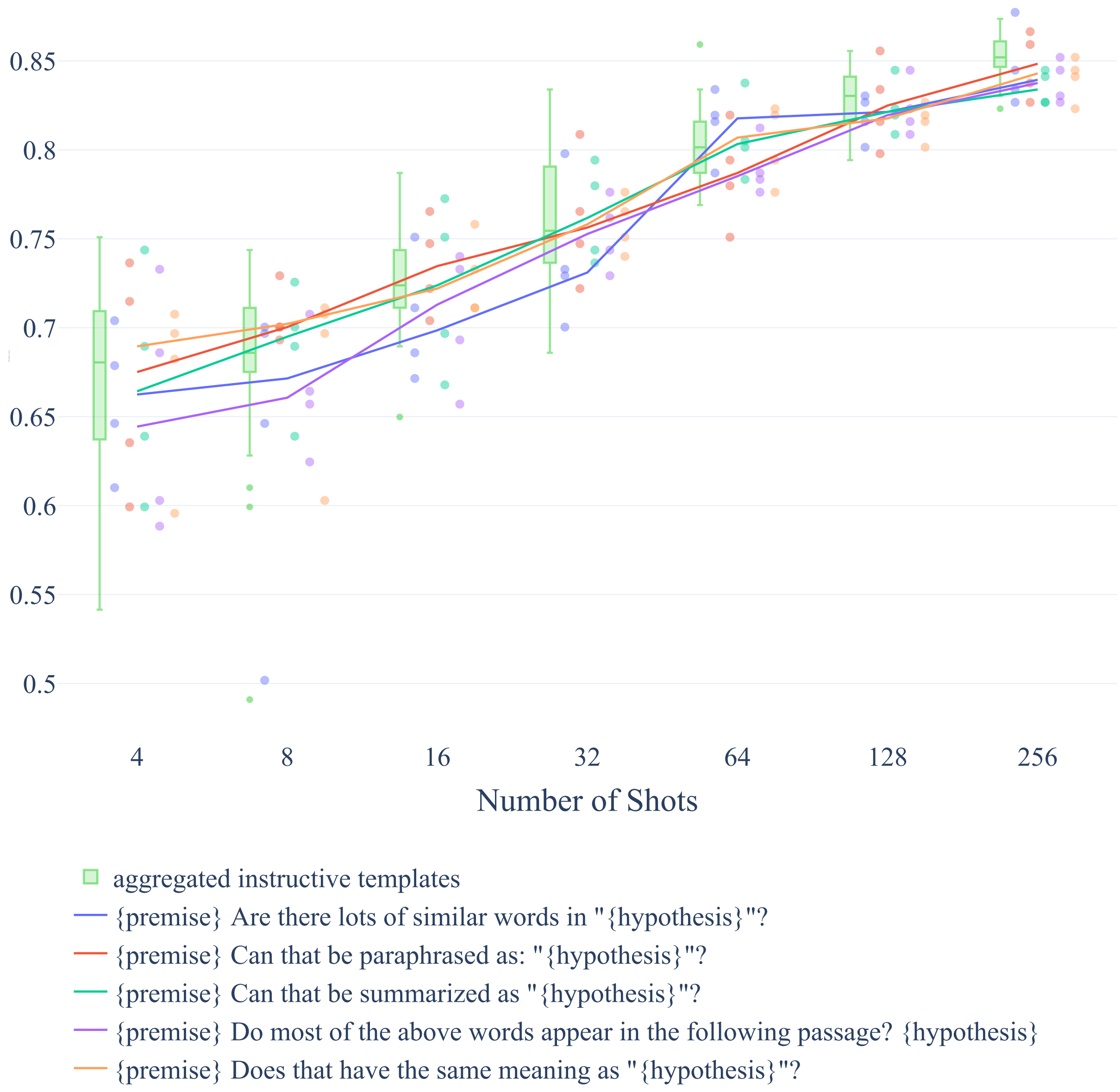


Figure 20: T0 (3B) with all misleading-moderate templates and the aggregated instructive for reference.

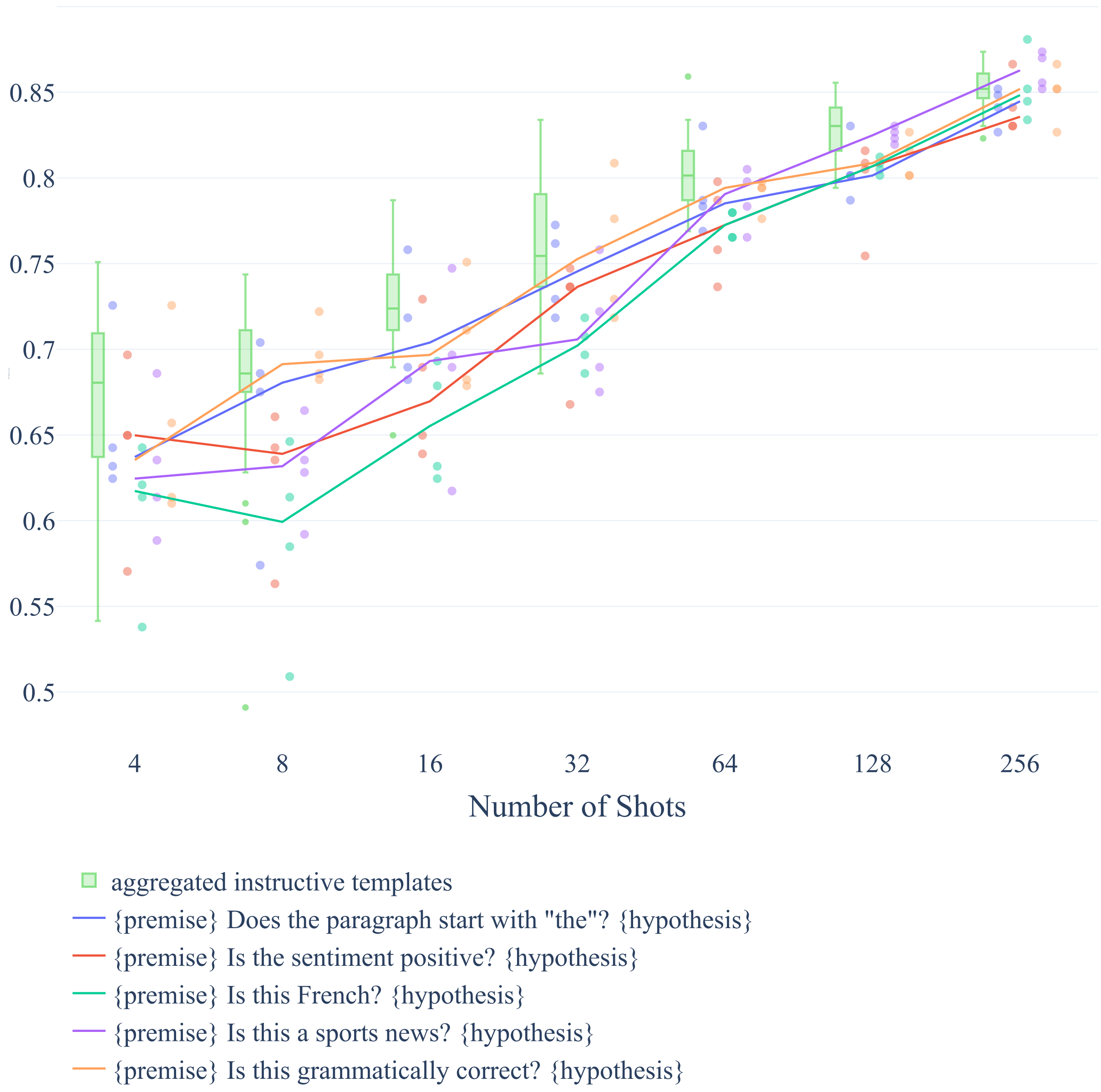


Figure 21: T0 (3B) with all misleading-extreme templates and the aggregated instructive for reference.

Figure 22: T0 (3B) with all instructive templates.

H.3 T5 LM-Adapted (3B)

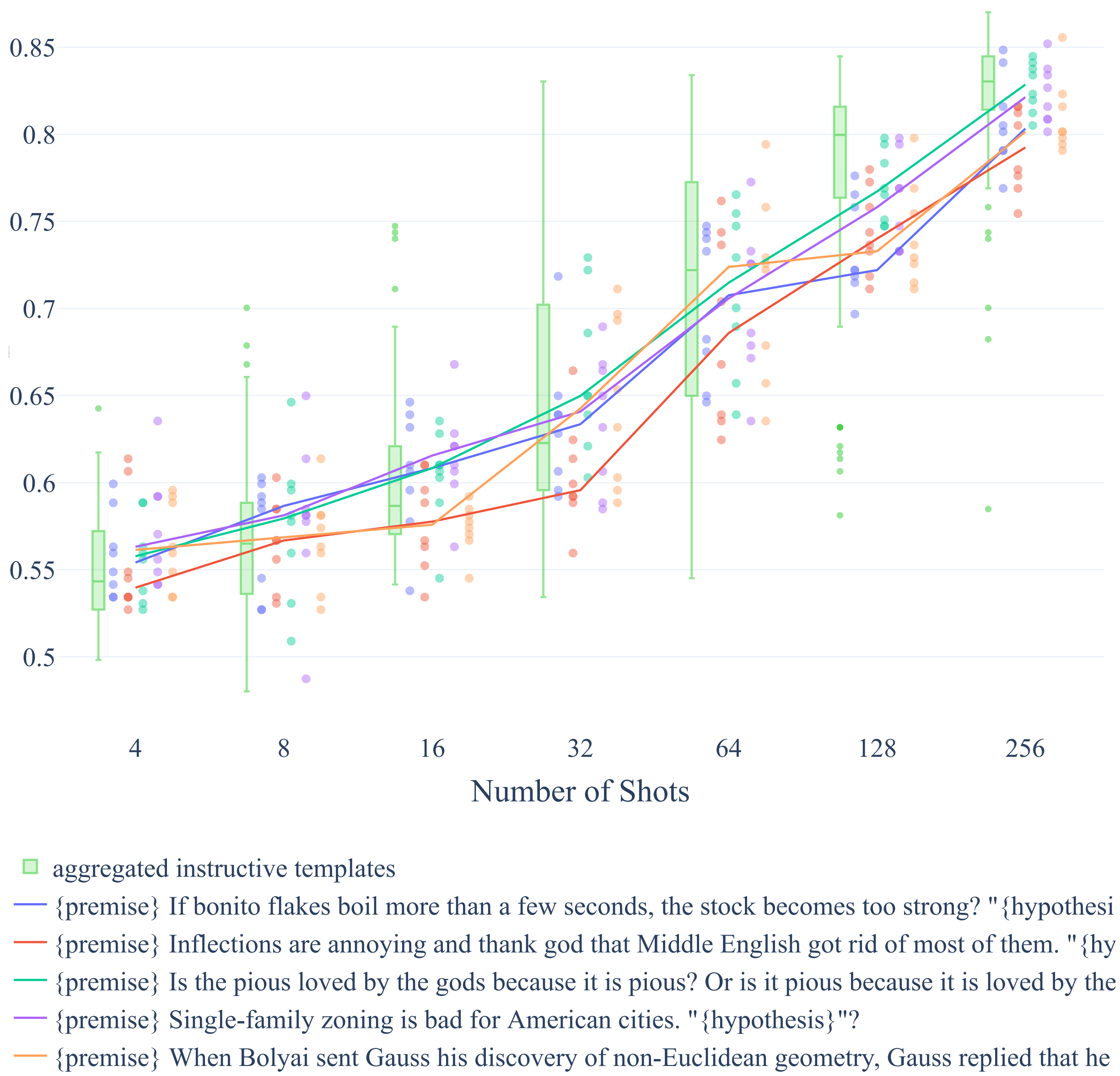


Figure 23: T5 LM-Adapted (3B) with all irrelevant templates and the aggregated instructive for reference.

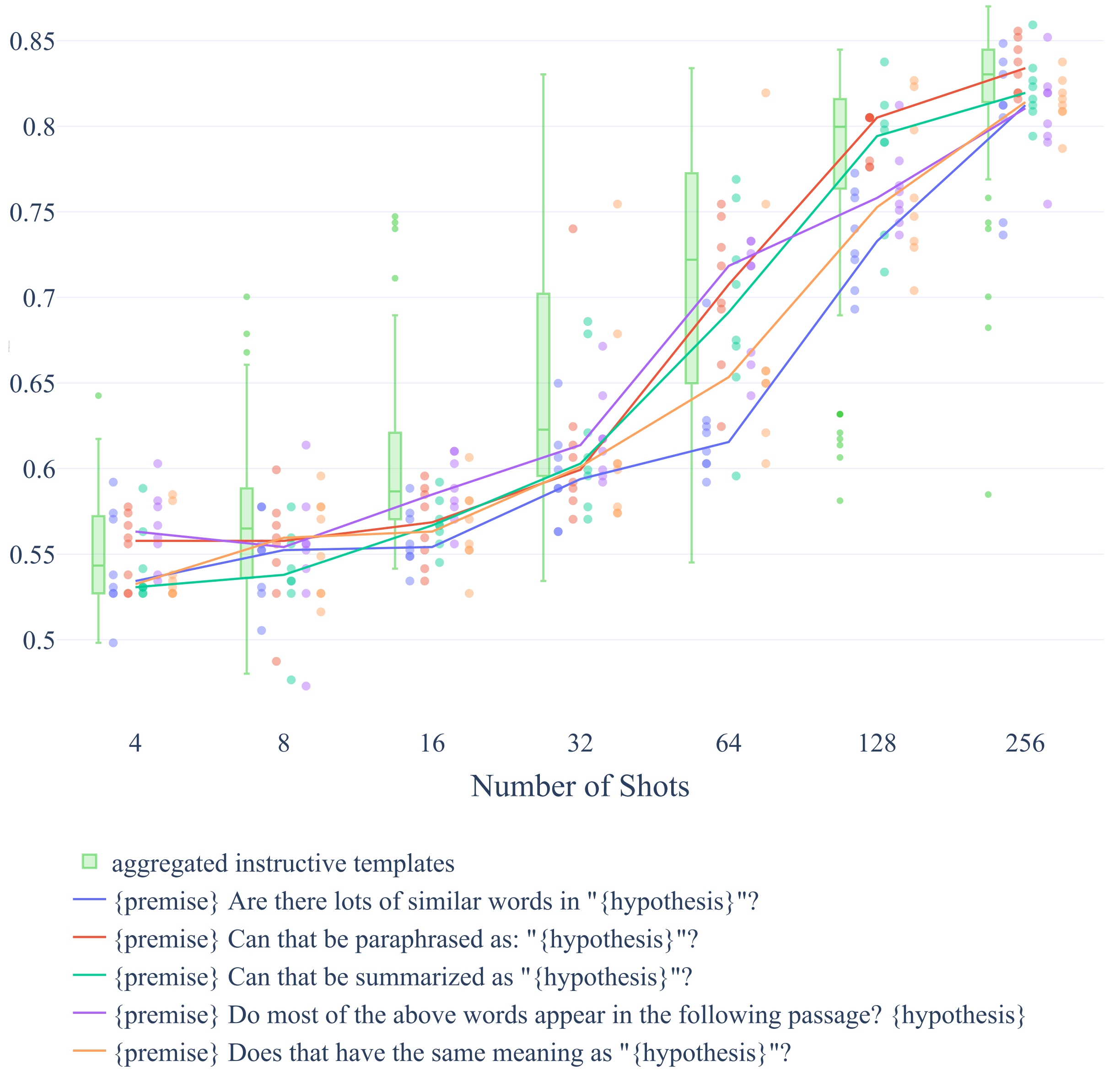


Figure 24: T5 LM-Adapted (3B) with all misleading-moderate templates and the aggregated instructive for reference.

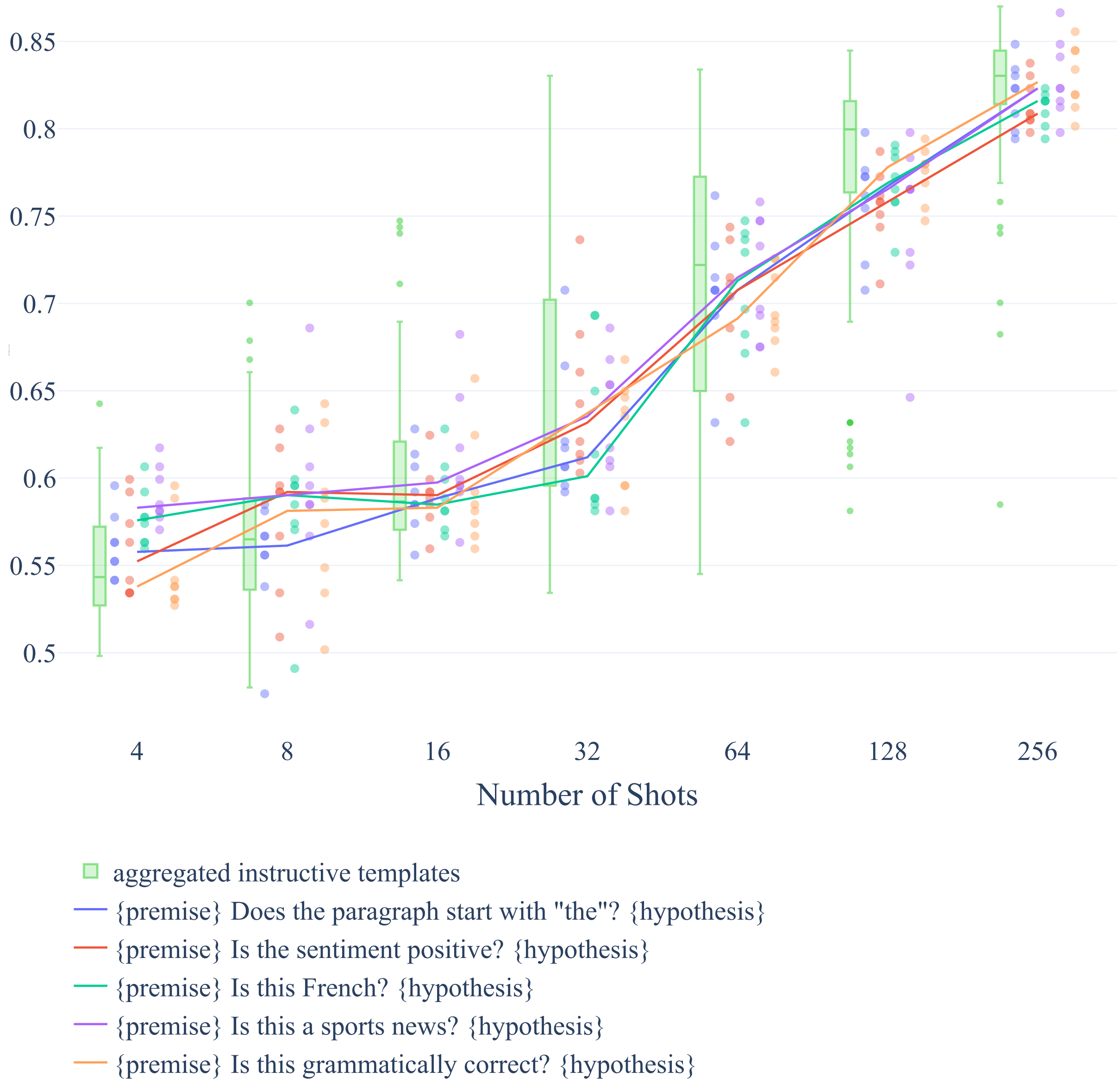


Figure 25: T5 LM-Adapted (3B) with all misleading-extreme templates and the aggregated instructive for reference.

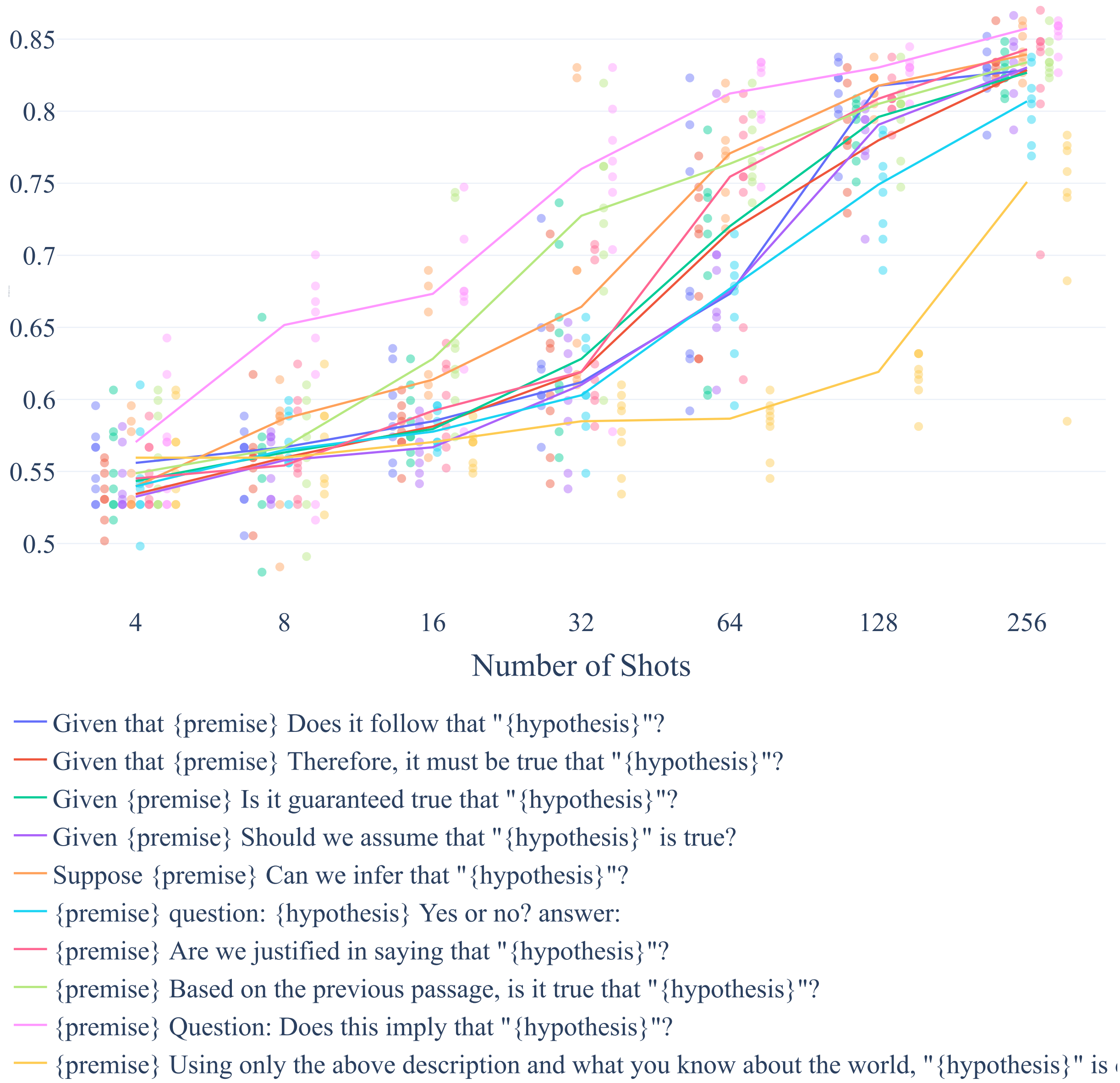


Figure 26: T5 LM-Adapted (3B) with all instructive templates.

I Zero-Shot Results (Figure 8)

model	category	template name	accuracy
T0 (3B)	instructive	MNLI_YN	0.7148
T0 (3B)	instructive	GPT_YN	0.6823
T0 (3B)	instructive	justified_in_saying	0.6426
T0 (3B)	instructive	should_assume	0.6498
T0 (3B)	instructive	is_it_true	0.6462
T0 (3B)	instructive	guaranteed_true	0.6209
T0 (3B)	instructive	can_we_infer	0.6354
T0 (3B)	instructive	does_it_follow	0.6715
T0 (3B)	instructive	does_this_imply	0.6679
T0 (3B)	instructive	modal_be_true	0.6354
T0 (3B)	misleading-moderate	words_appear	0.6462
T0 (3B)	misleading-moderate	similar_words	0.6354
T0 (3B)	misleading-moderate	same_meaning	0.6968
T0 (3B)	misleading-moderate	paraphrase	0.6390
T0 (3B)	misleading-moderate	summarize	0.6462
T0 (3B)	misleading-extreme	start_with_the	0.6968
T0 (3B)	misleading-extreme	grammatical	0.6859
T0 (3B)	misleading-extreme	sentiment	0.6462
T0 (3B)	misleading-extreme	sportsball	0.6426
T0 (3B)	misleading-extreme	french	0.5668
T0 (3B)	irrelevant	zoning	0.5704
T0 (3B)	irrelevant	gauss	0.5523
T0 (3B)	irrelevant	katsuobushi	0.5668
T0 (3B)	irrelevant	inflection	0.6751
T0 (3B)	irrelevant	euthyphro	0.6606
T0 (3B)	null	concat_PHM	0.6426
T0 (3B)	null	concat_HPM	0.6029

model	category	template name	accuracy
T0 (11B)	instructive	MNLI_YN	0.8051
T0 (11B)	instructive	GPT_YN	0.8014
T0 (11B)	instructive	justified_in_saying	0.7112
T0 (11B)	instructive	should_assume	0.7437
T0 (11B)	instructive	is_it_true	0.8051
T0 (11B)	instructive	guaranteed_true	0.6968
T0 (11B)	instructive	can_we_infer	0.7690
T0 (11B)	instructive	does_it_follow	0.7509
T0 (11B)	instructive	does_this_imply	0.8014
T0 (11B)	instructive	modal_be_true	0.6895
T0 (11B)	misleading-moderate	words_appear	0.7184
T0 (11B)	misleading-moderate	similar_words	0.7148
T0 (11B)	misleading-moderate	same_meaning	0.7256
T0 (11B)	misleading-moderate	paraphrase	0.7256
T0 (11B)	misleading-moderate	summarize	0.6679
T0 (11B)	misleading-extreme	start_with_the	0.6823
T0 (11B)	misleading-extreme	grammatical	0.6390
T0 (11B)	misleading-extreme	sentiment	0.6318
T0 (11B)	misleading-extreme	sportsball	0.5921
T0 (11B)	misleading-extreme	french	0.5271
T0 (11B)	irrelevant	zoning	0.6318
T0 (11B)	irrelevant	gauss	0.5560
T0 (11B)	irrelevant	katsuobushi	0.5740
T0 (11B)	irrelevant	inflection	0.7004
T0 (11B)	irrelevant	euthyphro	0.6931
T0 (11B)	null	concat_PHM	0.6570
T0 (11B)	null	concat_HPM	0.6209
T0++ (11B)	instructive	MNLI_YN	0.8592
T0++ (11B)	instructive	GPT_YN	0.8231
T0++ (11B)	instructive	justified_in_saying	0.7726
T0++ (11B)	instructive	should_assume	0.8231
T0++ (11B)	instructive	is_it_true	0.8556
T0++ (11B)	instructive	guaranteed_true	0.8231
T0++ (11B)	instructive	can_we_infer	0.8303
T0++ (11B)	instructive	does_it_follow	0.7798
T0++ (11B)	instructive	does_this_imply	0.8664
T0++ (11B)	instructive	modal_be_true	0.8087
T0++ (11B)	misleading-moderate	words_appear	0.7076
T0++ (11B)	misleading-moderate	similar_words	0.7329
T0++ (11B)	misleading-moderate	same_meaning	0.7545
T0++ (11B)	misleading-moderate	paraphrase	0.7617
T0++ (11B)	misleading-moderate	summarize	0.6968
T0++ (11B)	misleading-extreme	start_with_the	0.6498
T0++ (11B)	misleading-extreme	grammatical	0.7762
T0++ (11B)	misleading-extreme	sentiment	0.7365
T0++ (11B)	misleading-extreme	sportsball	0.5307
T0++ (11B)	misleading-extreme	french	0.4838
T0++ (11B)	irrelevant	zoning	0.5018
T0++ (11B)	irrelevant	gauss	0.5090
T0++ (11B)	irrelevant	katsuobushi	0.4801
T0++ (11B)	irrelevant	inflection	0.7220
T0++ (11B)	irrelevant	euthyphro	0.6715
T0++ (11B)	null	concat_PHM	0.6426
T0++ (11B)	null	concat_HPM	0.6029

J Comparison of LM targets, Controlling for the Template

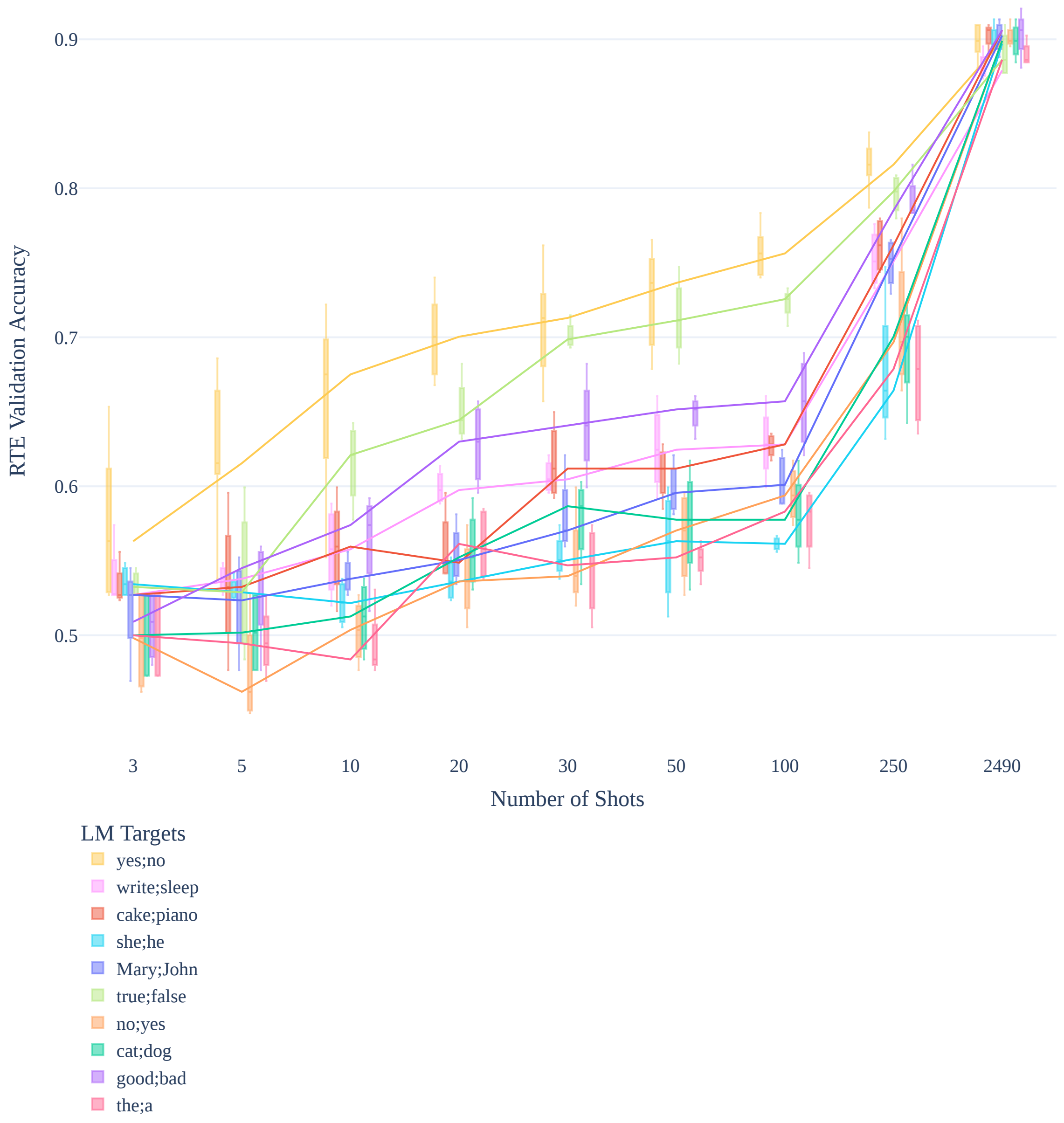


Figure 27: The best performing irrelevant prompt for ALBERT, `{premise} Single-family zoning is bad for American cities. "{hypothesis}"? [mask]` with all LM targets.

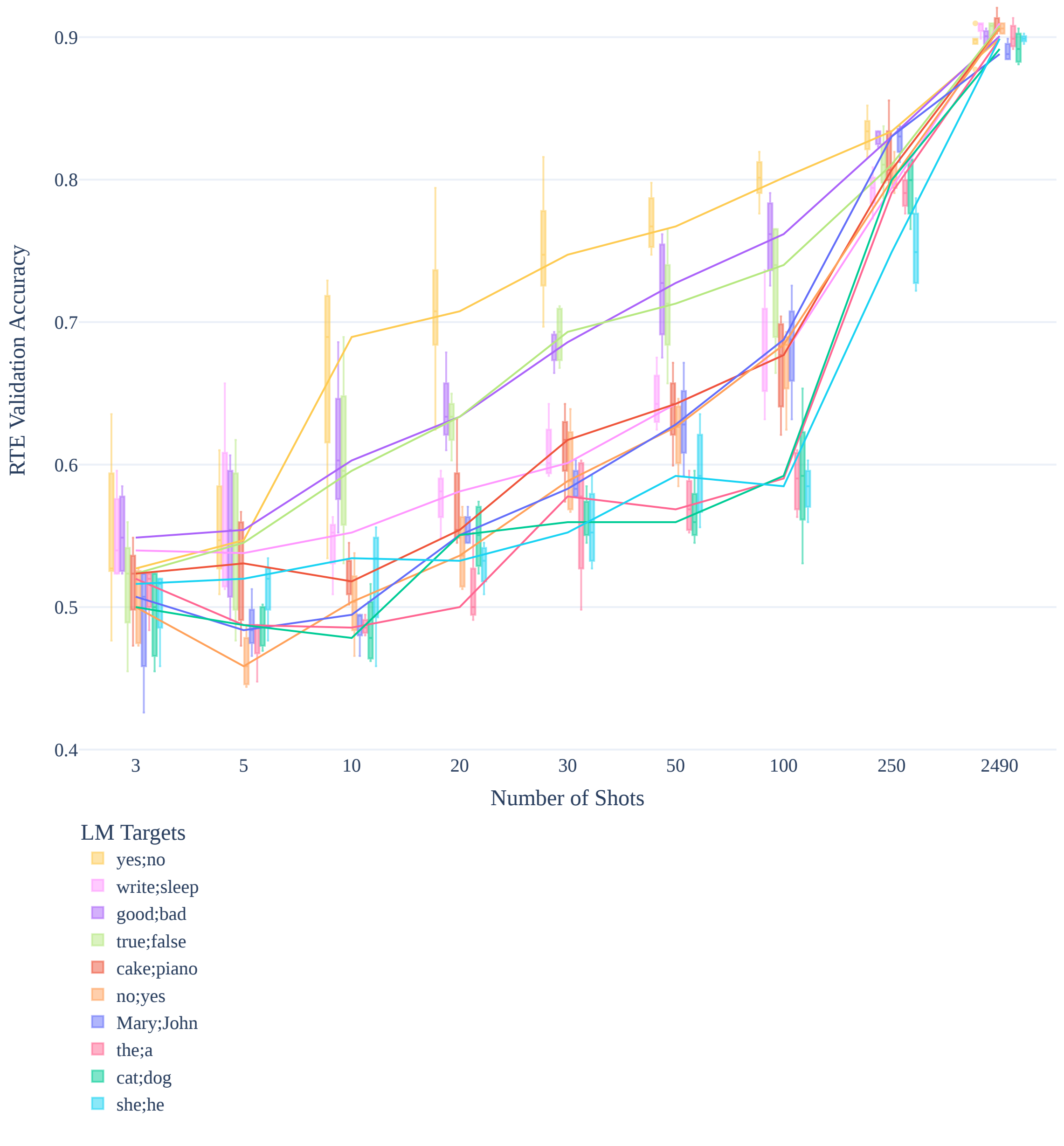


Figure 28: The best-performing misleading prompt for ALBERT, `{premise} Does the paragraph start with "the"? [mask] "{hypothesis}"` with all LM targets.

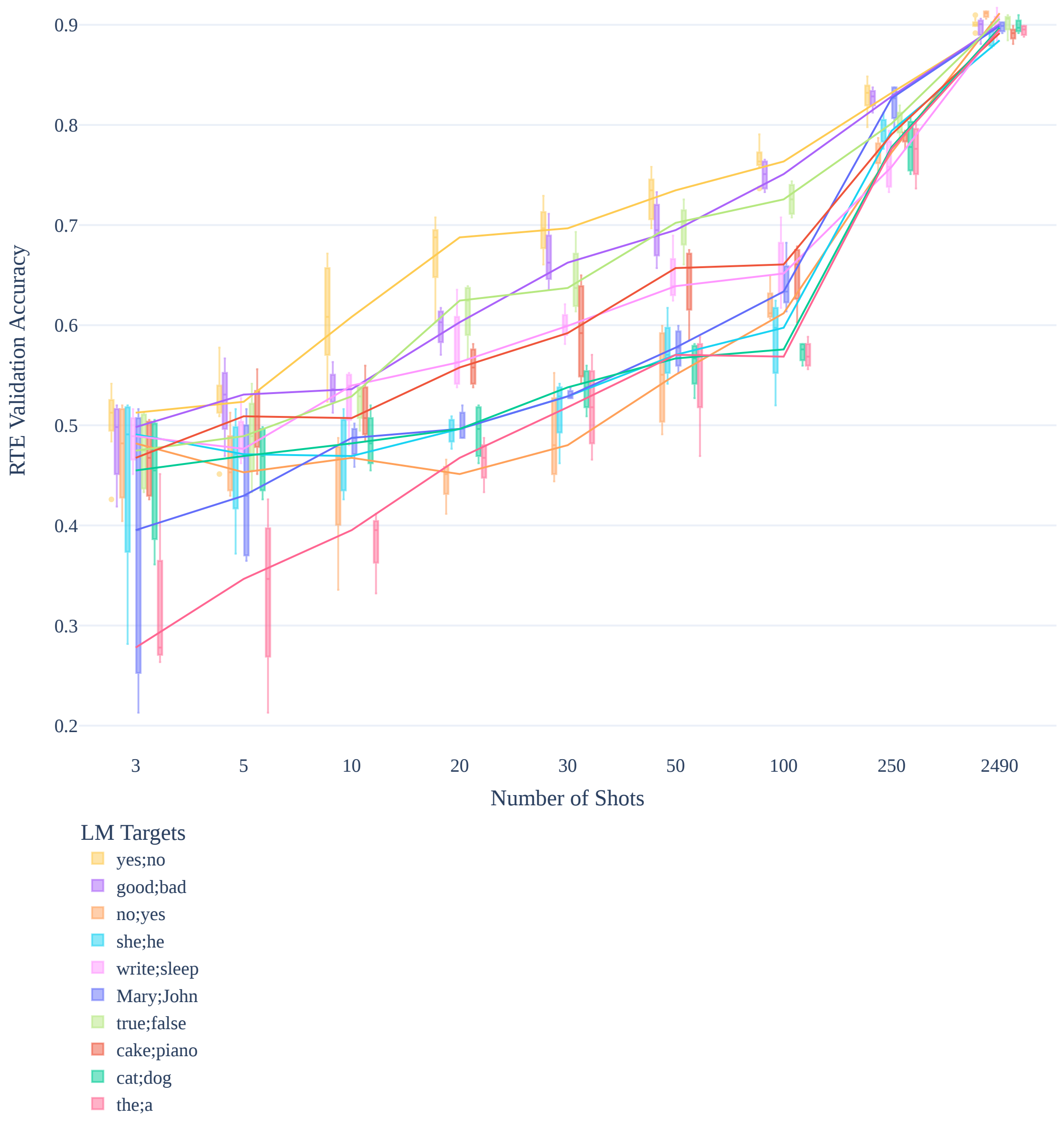


Figure 29: The best-performing null prompt for ALBERT, `{premise} [mask] "{hypothesis}"` with all LM targets.