

DOLOMITES: Domain-Specific Long-Form Methodical Tasks

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Abstract

Experts in various fields routinely perform methodical writing tasks to plan, organize, and report their work. From a clinician writing a differential diagnosis for a patient, to a teacher writing a lesson plan for students, these tasks are pervasive, requiring to *methodically* generate structured long-form output for a given input. We develop a typology of methodical tasks structured in the form of a task objective, procedure, input, and output, and introduce DoLoMiTes, a novel benchmark with specifications for 519 such tasks elicited from hundreds of experts from across 25 fields. Our benchmark further contains specific instantiations of methodical tasks with concrete input and output examples (1,857 in total) which we obtain by collecting expert revisions of up to 10 model-generated examples of each task. We use these examples to evaluate contemporary language models highlighting that automating methodical tasks is a challenging long-form generation problem, as it requires performing complex inferences, while drawing upon the given context as well as domain knowledge.

1 Introduction

Experts in various fields regularly use writing as a means for planning, organizing, and sharing their work. For instance, a teacher might draft a lesson plan for what they would like to teach in their next class, and a lawyer might draft a patent application for an invention. Experts generally follow a consistent and methodical approach to conduct these writing tasks. In the lesson plan example, a teacher would know the lesson objectives, format and profile of the class, and would produce a plan with the topics to be covered and activities to improve learning. Importantly, the teacher follows a systematic procedure to write this lesson plan, using their

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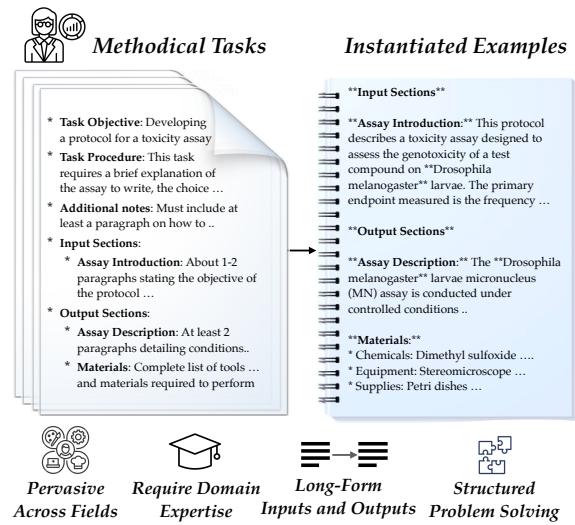


Figure 1: DOLOMITES contains descriptions of 519 methodical tasks elicited from domain experts across various fields. We instantiate these tasks with examples that contain plausible inputs and outputs, formulating a challenging long-form generation problem that requires domain expertise and structured problem-solving.

expertise and what they know about the current context (e.g., the class profile).

Across fields, from law to visual arts and engineering, experts accomplish on a regular basis such *methodical* tasks, i.e., writing tasks which loosely follow a standard template for what is usually given as input and what is required from the output. These tasks often follow a structured and consistent procedure as they are performed regularly and tend to be fairly time-consuming, taking from a few hours to several days (see Figure 1). As large language models become more capable and widely accessible to a more sophisticated set of users (Owens, 2023; Mollick and Mollick, 2023; Lee et al., 2023; Birhane et al., 2023; Mollick and Mollick, 2023; Frankenreiter and Nyarko, 2022; Demszky et al., 2023; Wang et al., 2023a; Bommasani et al., 2021), they hold great potential for assisting experts with methodical writing tasks, increasing their efficiency and allowing them to focus

Law	Biology	Medicine
<ul style="list-style-type: none"> * Task Objective: Drafting a legal opinion on a given matter * Task Procedure: The task involves interpreting, analysing and writing a position on a legal matter. * Additional Notes: The legal opinion should address each legal issue systematically. Best practices include citing authoritative legal sources and providing a balanced analysis of potential outcomes. * Input Sections: <ul style="list-style-type: none"> * The matter details: a document describing the specific case, the facts and circumstances. * Applicable laws and regulations: information about the laws, regulations, and legal frameworks relevant to the matter. * Output Sections: <ul style="list-style-type: none"> * Legal Opinion Document: a well-structured legal document that analyses the administrative matter, including an introduction, a statement of the legal issues, a discussion of relevant laws and precedents, and a conclusion with legal advice. 	<ul style="list-style-type: none"> * Task Objective: Developing a protocol for a toxicity assay * Task Procedure: This task requires a brief explanation of the assay to write, the choice and enumeration of the materials needed and the a detailed step-to-step description of the assay (how to analyze the individuals and how to treat the data). * Additional notes: Must include at least a paragraph on how to treat the data obtained, for example explaining the suggested statistical analysis to perform. * Input Sections: <ul style="list-style-type: none"> * Assay introduction: About 1-2 paragraphs stating the objective of the protocol, establishing endpoints to be assessed and briefly describing the species to be tested. * Output Sections: <ul style="list-style-type: none"> * Assay description: At least 2 paragraphs detailing the conditions in which the test should occur. * Materials: Complete list of tools and materials required to perform the assay. * Methods: List of numbered bullet points (length might vary) explaining the steps to follow in order to correctly assess the endpoints chosen. It should be a precise guide on how to handle the animals and how to collect the data. 	<ul style="list-style-type: none"> * Task Objective: Writing physical therapy plan of care documents. * Task Procedure: You will write the subjective, objective, assessment, and plan portions of the plan of care. Before doing this, you will need to synthesize all the data before putting it all together. * Additional Notes: Missing context may be information not gleaned from the history intake or physical examination. * Input Sections: <ul style="list-style-type: none"> * Subjective and objective: This information is gleaned from patient medical/social history and the physical examination. It is usually several paragraphs and bullet points. * Output Sections: <ul style="list-style-type: none"> * Assessment: This synthesizes the information from the first section to develop a course of action. This is typically one paragraph. * Plan: This lists all the different interventions necessary or applicable for the plan of care. It is usually bullet points for the various interventions. * Full Evaluation: This synthesizes all the information from the previous sections. It is usually 2-3 paragraphs long depending on the complexity of the patient's presentation. to collect the data.

Figure 2: A sample of methodical tasks from law, biology and medicine in DOLOMITES.

on complex problem-solving activities (Noy and Zhang, 2023).

Given their potential for assisting experts, it would be beneficial to evaluate language models on a realistic set of methodical writing tasks. However, we currently do not have benchmarks that contain a typology of such tasks. The most natural source for such data would be query logs (Nguyen et al., 2016; Kwiatkowski et al., 2019) or chat histories (Zhao et al., 2023). However, these data sources do not specifically reflect domain-specific use cases and do not allow us to study specific use cases in a controlled manner.

In this work, we bridge this gap by eliciting 519 methodical task descriptions (see a few examples in Figure 2) from 266 experts across 25 different fields (Section 3.1). These writing tasks are formatted in a standard way, with a task procedure, input, and output. Further analysis with an independent group of experts reveals that they are indeed plausible (~76% of them are likely to be conducted by an expert on a regular basis) and most experts (~63%) would find it useful if they could use a capable AI model as a writing assistant (Section 3.3). Our tasks serve as the first collection of realistic use cases of experts spanning multiple domains.

To evaluate the ability of existing models to assist experts with these tasks, we collect *examples* (see Figure 1), where we instantiate each task with plausible inputs and outputs (Section 3.4). Examples are created semi-automatically: we first retrieve web documents that could potentially serve as samples of the task, and then generate an exam-

ple using a language model based on the retrieved web documents. These examples are then significantly post-edited by the same experts (who contributed the task) for improving consistency, factual correctness, and level of detail.

We use our benchmark, called DOLOMITES (short for Domain-Specific Long-Form Methodical Tasks), to evaluate current models in their ability to generate accurate and detailed outputs (Section 4). We formulate the modeling problem as long-form generation, where models are provided the task description and the example input and asked to generate the example output. Our experiments reveal that there is significant headroom in improving performance on methodical tasks (Section 5) which are inherently difficult (requiring reasoning skills and domain-knowledge), and in terms of improving automatic evaluation of long-form text. In addition to well-known shortcomings (Schluter, 2017; Krishna et al., 2021), conventional metrics are not designed to capture expert knowledge.

We hope that DOLOMITES can serve as a reference for common domain-specific use cases of language models and as a means for evaluating future models. We release our dataset and code at <https://github-link-coming-soon>.

2 Problem Formulation

In this section, we first describe the types of writing tasks considered in this work. We refer to these tasks as methodical writing tasks due to two properties that are common to their execution. Firstly, each task requires **structured problem-solving**,

where the task follows a specific order where each step logically flows from the previous ones. For instance, in the *Medicine* task in Figure 2, the task requires producing an assessment of the patient, then a plan of care and finally a full evaluation of the patient. Secondly, every task usually follows a **consistent execution** across inputs, where there is a standard specification of the input, the output and the procedure for the task. In the same *Medicine* task, given a patient’s subjective and objective data, the task structure and procedure would mostly stay consistent across patients.

To elicit descriptions of tasks from experts, we operationalize our definition of a methodical task into a standard template (see Figure 2 for examples). We require that every task contains a brief *task objective*, a *task procedure* walking a beginner through how this task is conducted, *input and output sections*, which include information that is typically given, and information that needs to be generated. Both input and output sections are formatted in the form of section titles and section descriptions. Finally, we collect *additional notes* about the task, which can include best practices or common mistakes, and missing context that is important when conducting the task.

We further expect our tasks to meet the following criteria: (1) they are **purely textual** and do not involve other modalities in the input or output; (2) they **require domain expertise** and can only be completed by an expert; (3) they **do not require use of specific equipment or software**, with the exception of searching the web; (4) they are **frequent**, routinely performed by an expert at least once every few months; and (5) **time-consuming**, taking a significant but not indefinite amount of time to complete (e.g., from a half hour to a few days, but not several months).

Aside from task descriptions, our dataset contains specific **instantiations** of methodical tasks (see Figure 1). We create examples by populating descriptions like those shown in Figure 2 with plausible input and output sections (see Section 3.4).

3 DOLOMITES: Data Curation

3.1 Task Collection

In our data curation process, we first collect a typology of realistic tasks that span multiple fields. These tasks are not meant to be exhaustive, but instead represent realistic use cases across fields.

Participants. We recruit 266 participants from the Prolific crowdsourcing platform. We recruit experts from 25 different fields, shown in Table 1, aiming for a broad coverage across disciplines. Participants qualify as experts if they have formal education in the field, and at least 3 years of work experience. Additional details about the participants’ backgrounds are provided in Appendix A.

Annotation Task. We ask each annotator to provide descriptions of two writing tasks they routinely perform in their profession subject to the criteria listed in Section 2. For each task, annotators are asked to fill in predefined fields (task objective, procedure, input and output sections, additional notes), the same way as shown in Figure 2. We ask annotators to give thorough descriptions as if they are teaching a novice how to perform each task. Instructions and interface screenshots are in Appendix A.

3.2 Task Analysis

After collecting the initial set of tasks, and filtering them manually to ensure they meet the criteria outlined in Section 2, we obtain a total of 519 tasks. We find that there are very few tasks from a field that are highly similar. Tasks which are somewhat similar still vary based on precisely what is expected in the input and output sections.

Table 1 provides the number of tasks across fields and the task objective of a sample task from each field. Most fields have at least 20 tasks, with some exceptions, where we were not able to recruit as many experts. Across tasks, there are an average of ~ 2.78 sections in the input and ~ 2.82 sections in the output. Collectively, tasks in DOLOMITES are cognitively demanding and versatile in the types of reasoning they require. For instance, a diagnostic task in medicine requires *inductive reasoning* to go from particular symptoms to a general diagnosis. Whereas, in legal analysis, *deductive reasoning* is required to reason about how laws are interpreted in a specific case and *analogical reasoning* is needed as lawyers compare current cases with precedents. Similarly, in software application design, *abstract reasoning* is important for creating modular application designs while creativity is necessary for certain tasks in the visual arts. While it is hard to exhaustively describe the type of reasoning required for all tasks, every methodical task essentially involves **analyzing** the input, **making inferences** based on the input and domain-specific

Field	Sample Task Objective
Anthropology (8)	A survey to examine specific cultural practices, rituals, and societal norms within a cultural group or community
Architecture (20)	Developing a construction phasing plan for a building project
Biology (21)	Developing a protocol for a toxicity assay
Business (26)	Write a section of a non-financial report for a client, focusing on a company’s environmental and social activities
Chemistry (21)	To write a retrosynthesis scheme/plan for a specific target molecule
Economics (17)	Reviewing investment options for advising companies
Education (23)	To create a lesson plan for a school class
Engineering (22)	To write the instructions for conducting a radioactive experiment.
Environmental Sci (23)	Writing the life cycle assessment of a system, product or process
Geography (20)	Analyzing the environmental and social impacts of illegal mining activities in a specific region
History (22)	Summarize and analyze a specific medieval legal code
Hospitality (21)	Adapt existing recipes to cater to various dietary preferences
Journalism (20)	Write a news story based on an interview
Law (38)	Drafting a petition to challenge a decision
Linguistics (20)	Carry out a short literature review of a given problem in linguistics
Literature (20)	To write a research proposal for a presentation at a literary research conference
Mathematics (15)	Writing an experimental setup suitable for testing a research hypothesis in applied mathematics
Medicine (24)	Writing a list of potential radiotherapy regimens for a cancer patient
Music (23)	Writing lyrics for a game’s soundtrack
Philosophy (13)	Provide ethical recommendations for patient/doctor cases
Physics (21)	Design specifications for a pump or turbine system
Political Sci (20)	Redline a management measure / legislative policy
Psychology (21)	Writing a study protocol of a neuroimaging research project
Sociology (20)	Analyzing responses from sociological interviews to identify themes relevant to the research question
Visual Arts (20)	The objective of this task is to write a catalog entry for an art exhibition

Table 1: Fields represented in DOLOMITES, with number of tasks in parentheses and a sample task from each field.

knowledge, and finally, **providing a justification** in writing.

3.3 Task Validation and Societal Implications

We validate our collection of tasks by consulting an *independent* group of experts. Specifically, we collect Likert ratings for each task from three experts on the following axes (the precise description for each item on the scale is provided in Appendix A):

- **Representativeness:** How likely is this task to be conducted by an expert in your field?
- **Complexity:** How would you rate the complexity of this task?
- **Time Required:** How much time is typically required to complete this task?
- **Usefulness:** Would you or other experts find it useful if an AI system were to propose initial outputs for this task (which may be lacking), that can be validated and improved by experts?

The question above is motivated by prior work showing that AI writing assistants could significantly benefit the productivity of experts (Eloundou et al., 2023; Noy and Zhang, 2023; Dell’Acqua et al., 2023). Beyond productivity, we were additionally interested in expert opinions about the

societal implications of using language models as writing assistants. Hence, for each task, we elicit answers to the following questions which require a free-text response in addition to a Likert rating.

- **Anonymity Required:** Is it important to ensure anonymity of any individuals or organizations if an AI system is used for conducting this task?
- **Biased Outcomes:** Could relying on automatically generated outputs for this task result in biased or potentially harmful decisions for certain groups of people?
- **Ethical Considerations:** Are there ethical considerations (e.g., privacy, copyright issues) associated with the use of AI systems for this task?
- **Workforce Impact:** Could partial automation of this task have an impact on the workforce in the short term?
- **Accessibility Requirements:** Would the use of AI tools for this task require making exceptional considerations to ensure accessibility?

The main outcomes of our validation study are presented in Figure 3. We find that the tasks collected in DOLOMITES are ecologically valid, i.e., they are likely ($\sim 76\%$) to be conducted by field experts. Most of them are of medium or high

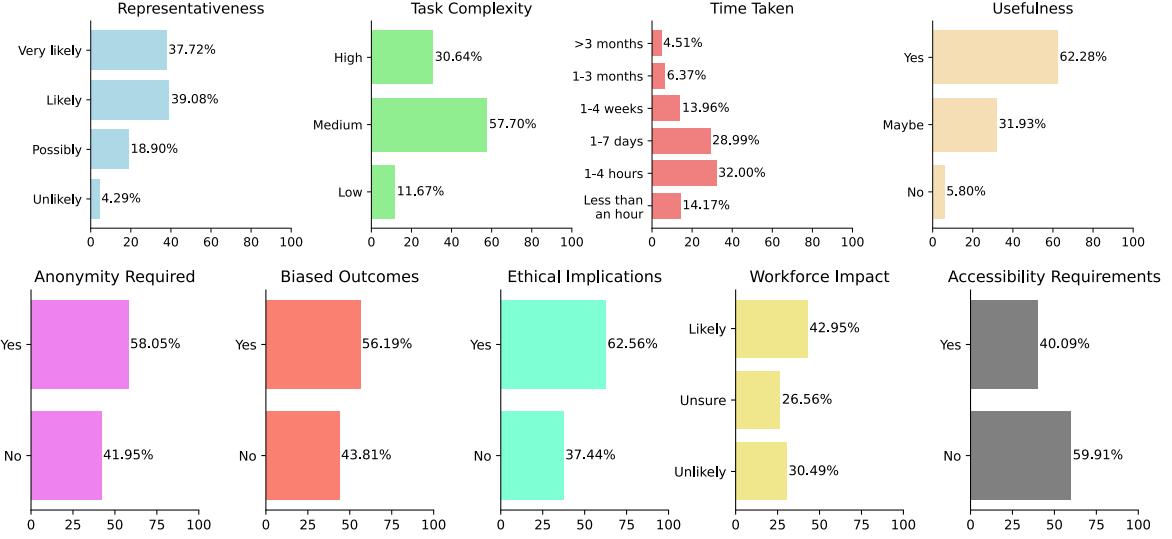


Figure 3: Validation of methodical tasks in the DOLOMITES task collection.

complexity, requiring moderate (few years of experience) or substantial (several years of experience) expertise. While they are complex tasks, judgments about time taken reveal that most (~61%) would take an expert from 1 hour to 7 days to complete. This degree of difficulty suggests that it is conceivable for language models to be useful assistants for these tasks. Finally, an overwhelming majority of experts would be interested (~62%) or open to trying (~32%) to use a language model that proposes initial outputs for the task.

With regard to the societal implications of language model use, the need for anonymity emerged as a concern for a significant number of tasks (~58%). In fields like medicine, psychology, and law, experts emphasized the importance of protecting patient/client confidentiality. Similarly, experts felt strongly that proprietary information and trade secrets should be kept private in fields like business. Experts further thought that using language model responses without careful perusal can result in biased outcomes (~56% of tasks) which could affect marginalized or underrepresented groups. They also raised various ethical concerns relating to copyright issues, privacy issues and stifling of human creativity due to over-reliance on AI.

Many experts (~43%) recognized that partial automation of writing tasks is likely to impact the workforce in the short term, potentially leading to changes in job roles or skill requirements. At the same time, they were optimistic that this would improve productivity and bring positive changes to the nature of the work. It is important to ensure that users of all backgrounds and capabilities have equal access to language models. A significant number of

tasks (~40%) were rated as requiring exceptional considerations to be made for ensuring accessibility to all users. Across fields, experts highlighted that while language models as writing assistants can improve productivity, human oversight is important for responsible use of these technologies.

3.4 Example Collection

To evaluate language model capabilities in assisting experts with their tasks, we create examples of input and output sections with concrete details. We adopt a human-in-the-loop methodology, where initial examples are generated by a model, which are then post-edited by the same expert who provided the task. We describe this process below.

3.4.1 Retrieval-Augmented Generation

We believe that samples of methodical tasks are partially available in documents on the web. Hence, we retrieve relevant documents for each task and generate examples by prompting models with passages from these documents as context. This process is depicted in Figure 4 and explained below.

Query Formulation. Given a task description, we first need to find more specific queries that could potentially result in relevant web documents. For example, for writing a catalog entry for an art exhibition, search queries like “renaissance art exhibition catalog entry” or “picasso guernica catalog entry” are likely to result in documents that contain examples of the task. To generate search queries, we prompt Bard ([Manyika and Hsiao, 2023](#)) (with 1 exemplar) with the task objective and instruct it to generate more specific queries that can help find

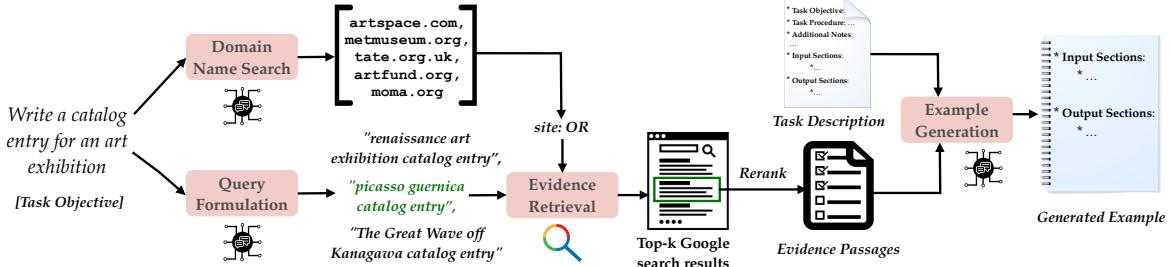


Figure 4: Method for constructing examples of tasks in DOLOMITES.

web documents which contain demonstrations of the task (Table 11 in Appendix B). We generate 10 search queries for each task and restrict search to reliable and authoritative sources. These are collected by prompting Bard (with 1 exemplar) with the task objective to generate URLs to domain names which will be useful to find real examples for the given task (Table 12 in Appendix B).

Evidence Collection. Using each search query, we gather the top-10 documents from Google search restricted to relevant domains with the `site:` operator in the query. Documents are then split into passages of 4,000 characters with a 100 character sliding window.

Conditional Generation. Having gathered evidence which may contain task demonstrations, we generate examples by prompting models with this evidence. We explore a *multi-document* setting, where passages are sampled from multiple documents and a *single document setting*, where passages are sampled from a single document as we found that the appropriate choice depends on the task.¹ Passages are reranked using an in-house reranker and the top-5 passages are provided as context, along with the task description, to a large language model (Gemini-Ultra (Team et al., 2023) or Bard in our case), which is asked to generate an example of the task (Table 13 in Appendix B). Not all information mentioned in the task description is required to be present in the context and the model is allowed to infill content to construct an example. We generate up to 10 examples for each task.

3.4.2 Expert Post-Editing

Even though they are based on retrieved web documents, model-generated examples could have many

issues. They may not adhere to the structure specified in the task description, they may contain factual inconsistencies or inaccuracies, lack in depth, or be vague. To remedy these issues, we present the examples to the same experts who wrote the tasks for post-editing. They are asked to choose the most plausible example out of four variants, and use single or multi-document evidence.

Prior to post-editing, experts are asked to label examples according to three criteria on a Likert scale: adherence to task structure, factual correctness, and level of detail. They are also shown 1) the evidence passages for the example and 2) a critique (generated using Gemini-Ultra with the prompt in Appendix B, Table 14) that may not be comprehensive, to aid them in identifying issues with the example. The critique is provided to make post-editing more efficient. They are required to fix any valid issues they recognize in the example as well as any valid issues identified by the critique.

3.4.3 Example Quality Analysis

Automatic Analysis. Expert judgements of automatically generated examples are shown in Figure 5. We find that the majority of examples already follow the task structure ($\sim 85\%$) and most of them are *probably* or *definitely* correct. However, a large number of examples are lacking in depth and detail. We show a histogram of the word-level edit distance between the original and edited example in Figure 6a and relevant statistics of the original and post-edited examples in Table 2. The histogram suggests that on average, there are significant changes made to the original examples during post-editing. Since most experts judge that examples are lacking in depth, the edited examples are expectedly much longer on average. The edited examples also adhere better to the task description (on average, 97.67% sections in the task description are found in the edited examples compared to 92.81% in the original examples). Finally, we

¹For instance, a task that requires drafting a legal opinion might benefit from multiple relevant documents whereas a single document might be sufficient for writing the catalog entry for an artwork.

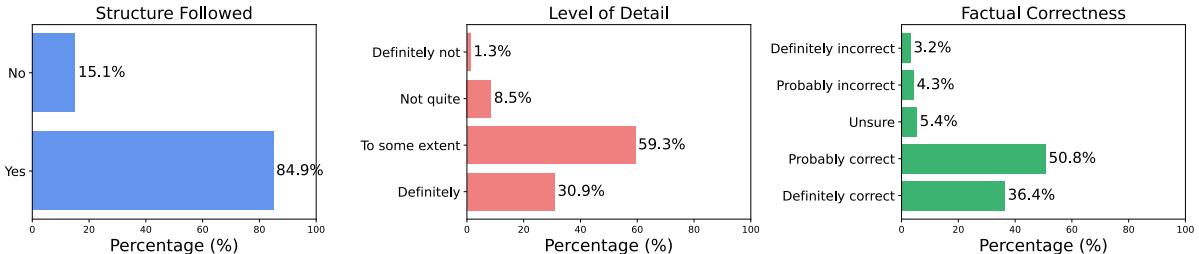


Figure 5: Expert judgements of original examples along three dimensions: adherence to task structure, level of detail and factual correctness.

	Avg Length	Avg section presence % (\uparrow)	Flesch-Kincaid Grade Level (\uparrow)
original	388.98	92.81	11.69
post-edited	590.24	97.67	13.46

Table 2: Statistics of the original and post-edited examples in DOLOMITES.

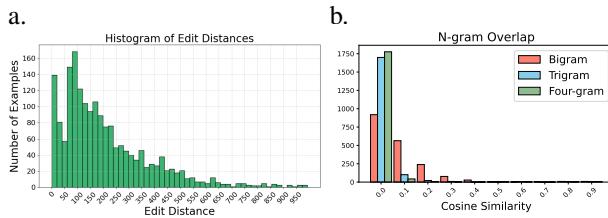


Figure 6: Histogram of (a) word-level edit distance between original and post-edited example and (b) cosine similarities based on n-grams in post-edited examples and evidence used as context.

compute readability scores of the examples as a noisy approximation of the complexity and level of detail in the text, using the Flesch-Kincaid Grade Level test (Kincaid et al., 1975). Higher readability values indicate that a piece of text requires more formal education and expertise to understand. We find that post-edited examples have higher scores, possibly indicating higher level of technical depth.

Memorization. Examples in DOLOMITES are created by conditioning on passages from web documents. We do not require these documents to contain complete examples of the task, and models are allowed to infill information to create an example. However, if these documents are seen by models during large-scale pretraining, it might be difficult to conduct a clean evaluation. We examine whether this is the case by computing the similarity of the post-edited examples to the evidence passages provided during generation. Figure 6b plots the cosine similarity between the n-grams found in the post-edited examples and evidence used as context. As can be seen, similarity to retrieved passages is fairly low in most examples, which suggests a low risk of memorization due to pretraining.

4 Experiments

4.1 Setup and Models

We create a development-test split for DOLOMITES, with 820 examples in the development (dev) set and 1,037 examples in the test set. There are 172 *seen* tasks with examples in both dev and test and 99 *unseen* tasks with examples only in the test set.

For evaluation, we considered multiple performant models from various companies as well as open-source models. In all cases, we favored instruction-tuned variants because of their better performance on other benchmarks. Specifically, we report experiments with Claude-3 Opus (Anthropic), Command-R-Plus (Cohere, 2024), Gemini-1.5-Pro and Gemini-1.5-0409 (Reid et al., 2024) and Gemini-Pro (Team et al., 2023), GPT-3.5-Turbo and GPT-4 (OpenAI, 2023), Mixtral-8x7B and Mixtral-8x22B (Jiang et al., 2024) and Mistral-Large (Mistral, 2024), and OLMo-7B-Instruct (Groeneveld et al., 2024). In all cases, we prompt models with the task description, the input sections corresponding to an example, and instruct them to generate the output sections for the example, in a zero-shot manner. Hyperparameters, prompts and model identifiers are in Appendix B.

4.2 Automatic Evaluation

Conventional Metrics. Prior work has recognized that conventional metrics for text generation are lacking in various ways (Liu et al., 2016; Novikova et al., 2017; Krishna et al., 2021). Nevertheless, for completeness, we report results with ROUGE-L (Lin, 2004) and BLEURT (Sellam et al., 2020). In addition, we report the average output length and average section presence (i.e., the percentage of output sections specified in the task that are present in the generated output, averaged across all examples) as a measure of instruction-following capabilities. Note that the average length of reference outputs is 341.42 tokens.

Model	Avg Length	Avg Section Presence %	BLEURT	ROUGE-L	nli (forward)	nli (reverse)	nli (h-mean)
Claude-3 Opus	417.41	91.53	0.4156	0.2395	0.3584 _[0.34,0.38]	0.3769 _[0.36,0.40]	0.3674
Command-R-Plus	440.44	92.92	0.4068	0.2134	0.3926 _[0.37,0.41]	0.3623 _[0.34,0.38]	0.3768
Gemini-1.5-Pro	349.27	95.25	0.4136	0.2371	0.4065 _[0.39,0.42]	0.3846 _[0.37,0.40]	0.3952
Gemini-1.5-0409	361.87	95.74	0.4068	0.2361	0.3994 _[0.38,0.42]	0.3984 _[0.38,0.42]	0.3989
Gemini-Pro	269.68	93.61	0.4124	0.2280	0.3415 _[0.32,0.36]	0.3090 _[0.29,0.33]	0.3244
GPT-3.5-Turbo	240.89	88.98	0.4276	0.2309	0.3854 _[0.37,0.40]	0.2949 _[0.28,0.31]	0.3341
GPT-4	407.35	95.46	0.4155	0.2271	0.3934 _[0.38,0.41]	0.3993 _[0.38,0.42]	0.3963
Mistral-Large	327.12	92.61	0.4158	0.2390	0.3524 _[0.33,0.37]	0.3523 _[0.33,0.37]	0.3523
Mixtral-8x22B	339.16	95.16	0.4212	0.2450	0.3951 _[0.38,0.41]	0.3583 _[0.34,0.37]	0.3758
Mixtral-8x7B	386.61	88.39	0.4098	0.2266	0.3290 _[0.31,0.35]	0.3097 _[0.29,0.33]	0.3191
OLMo-7B-Instruct	784.22	74.02	0.3905	0.1752	0.1929 _[0.18,0.21]	0.1721 _[0.16,0.19]	0.1819

Table 3: Results on the DOLOMITES test set with standard metrics and factual consistency using NLI models. We report 95% confidence intervals along with the average NLI scores.

Model	GPT-4	Claude-3 Opus	Gemini-1.5-0409
Claude-3 Opus	48.1	52.7	49.6
Command-R-Plus	34.4	45.8	38.7
Gemini-1.5-Pro	41.1	46.1	51.0
Gemini-1.5-0409	42.9	55.4	60.9
Gemini-Pro	17.6	21.0	22.1
GPT-3.5-Turbo	12.2	11.5	12.4
GPT-4	50.0	50.0	50.0
Mistral-Large	27.2	28.8	26.7
Mixtral-8x22B	21.6	25.1	17.6
Mixtral-8x7B	17.8	23.5	15.6
OLMo-7B-Instruct	4.2	5.5	3.3

Table 4: Model win rates (± 3) against GPT-4 on the DOLOMITES test set using three LM-based autoraters (GPT-4, Claude-3 Opus, and Gemini-1.5-PP). GPT-4’s win rate is 50% since it is the base comparison model.

Round-Trip Factual Consistency. We also measure the extent to which statements in the model output are consistent with statements in the reference output. We compute 1) *forward* entailment considering a reference section as the premise and the corresponding model section as the hypothesis and 2) *reverse* entailment considering a model output section as the premise and the corresponding reference section as the hypothesis. Scores are aggregated over all sections and examples. These metrics loosely capture the notions of precision and recall, we also report the harmonic mean of the two. We use the TRUE model (Honovich et al., 2022) to predict entailment scores (ranging from 0 to 1) and report 95% confidence intervals.

LM-based Evaluation. Language models are being increasingly used as evaluators (Chiang and Lee, 2023), despite concerns that they can be misleading and biased (Shen et al., 2023; Wang et al., 2023b; Zheng et al., 2023; Panickssery et al., 2024). We use *multiple* language models as judges to give preferences for a pair of model outputs. While this does not alleviate the problem of biased LM judgments, we believe it is slightly more reliable since

we are not biased by a single model’s judgements. In all comparisons, we use one of the strongest models, GPT-4, as the base comparison model. We sample outputs on the test set from a candidate model and GPT-4 (randomizing their order in the prompt) and ask the evaluator model to judge which output is better and provide a justification. We consider three models as evaluators: GPT-4, Claude-3 Opus and Gemini-1.5-0409. The win rate is computed by summing up the number of wins for a candidate model plus half the number of ties.

5 Results and Discussion

Main Results. Our results on the test set using automatic metrics are reported in Table 3. Based on the average section presence, we note that models are largely effective at generating almost all relevant output sections from the task description. A few models (GPT-4 and Gemini-1.5-0409) excel more at following this instruction. Based on the NLI scores, we note that the nli (reverse) scores are on average lower than nli (forward), which suggests that generated outputs contain statements not entailed by the reference, e.g., because they are inaccurate or irrelevant. We observe that Gemini-1.5-0409 and GPT-4 produce more information that is factually consistent with the reference, while Claude-3 and Command-R-Plus are also performant. We show the win rates according to different LM evaluators in Table 4. Based on these win rates, we note that a few models such as Claude-3 Opus, Gemini-1.5-Pro and Gemini-1.5-0409 prove to be comparable to GPT-4. We also report win rates with a length penalty for longer outputs in Table 6 and the overall rankings do not change.

Human Evaluation. To understand how well automatic evaluation measures correlate with human judgements, we sample 200 pairs of model outputs, where each pair comes from two randomly chosen models. We (the authors) then label which model output is better (or if they are tied) according to their task adherence, factual correctness and depth. On these 200 pairs, we also get automatic preference judgements from all the evaluation measures discussed in Section 4.2 (we convert float scores for two outputs into binary judgements). The percentage agreements between human labels (with and without pairs with ties) and all evaluation measures are in Figure 7. In summary, we find that LM-based evaluation measures are most helpful in discriminating between models, followed by the NLI measures and then ROUGE-L and BLEURT. We note that an evaluator that always picks the longer output also has reasonable agreement rates.

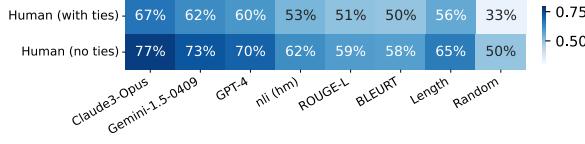


Figure 7: Percentage agreement of automatic evaluation measures with human labels.

Results by Field. Figure 8 illustrates how model performance fluctuates across fields; we show results for GPT-4, Gemini-1.5-0409, and Claude-3 Opus, normalized across fields. Across models, we find that a few fields have significantly lower NLI scores: Hospitality, Education, and Visual Arts. Tasks from these fields are sometimes subjective (e.g., *Create recipes with special dietary requirements*, *Create a user persona for an application*), which might justify the lower NLI scores. On the other hand, tasks in fields such as Literature, History, and Journalism have higher NLI scores. Some of these tasks focus more on factual reporting and narratives that may be easier to reason about.

Results by Length. Next, we evaluate whether output length is correlated with performance. Specifically, we show scores for GPT-4 split into bins by 1) length of the reference outputs and 2) number of output sections expected for the task. Scores normalized by bins are shown in Figure 9. We find that examples which require longer outputs are significantly harder for models, supported by the fact that examples with longer outputs have lower NLI scores.

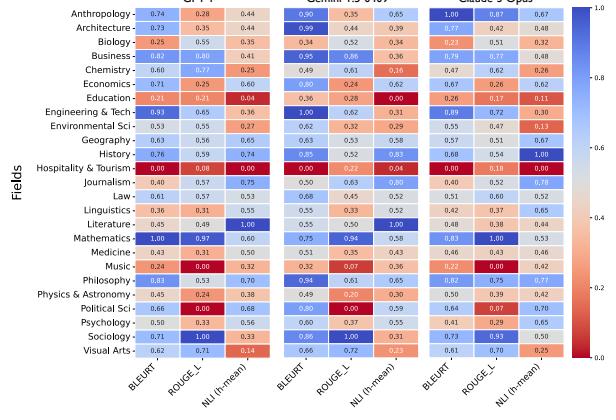


Figure 8: Heatmap of scores from GPT-4, Gemini-1.5-0409 and Claude-3 Opus, aggregated by field.

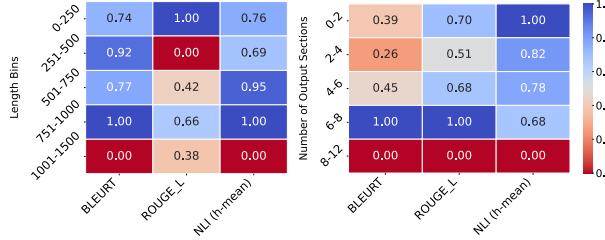


Figure 9: Heatmap of GPT-4 scores aggregated by length (in tokens) of reference output or length in terms of the number of output sections.

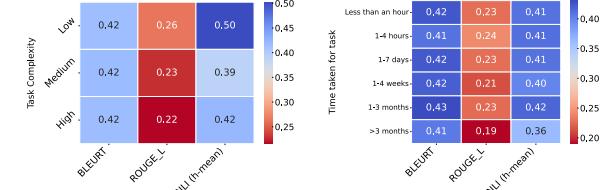


Figure 10: Heatmap of GPT-4 scores aggregated by task complexity labels from annotators.

Results by Task Complexity. Figure 10 groups results by task complexity labels collected during our task validation study. We find that tasks with *High* complexity or tasks that take longer for experts, are harder. Nonetheless, lower or medium complexity tasks are also challenging.

Error Analysis. We analyze generated outputs from 3 high-performing models (Gemini-1.5-0409, GPT-4 and Claude-3 Opus) for examples where the NLI scores are lowest. Broadly, we observe the following patterns:

- **Lacking depth** (Table 7): Writing technical documents requires depth and focus, which was sometimes found to be lacking. For example, concrete statistical results and method details were absent from a task on *writing up a report*

on an experimental study in clinical psychology.

- **Verbosity** (Table 8): A common characteristic of some model outputs was their verbosity. Common patterns included defining jargon when not necessary, and generating many filler statements that do not introduce new information.
- **Missing information** (Table 9): There were a few cases where a single output section required multiple pieces of information, but the model entirely missed producing a subset of them.
- **Subjectivity** (Table 10): Finally, we identified tasks that are subjective in nature (e.g., *Creating recipes with special dietary requirements* or *Writing a plan for a photography shoot*). While reference-based evaluation measures used in this work do not handle this subjectivity, future work can explore ways to evaluate such outputs.

6 Related Work

Domain-Specific NLP Benchmarks. The use of language technologies in domain-specific scenarios has the potential to help experts. Prior work has evaluated models through domain-specific benchmarks for standard tasks like QA (Hendrycks et al., 2021; Malaviya et al., 2024) and summarization (Hayashi et al., 2021). Many benchmarks have been proposed for specific fields (Rein et al., 2023; Xia et al., 2024), including law (Shen et al., 2022; Niklaus et al., 2023; Guha et al., 2024) and medicine (Tsatsaronis et al., 2015; Pampari et al., 2018; Jin et al., 2019, 2020; Fleming et al., 2023).

A notable difference between this line of work and DOLOMITES is the task formulation (i.e., QA vs methodical tasks). QA involves addressing a specific information need in response to a query while conducting methodical tasks requires following a structured and consistent procedure, involving multiple steps, to complete a goal-oriented task.

Naturalistic Evaluation. Evaluation that is grounded in realistic use cases, is important for reliable benchmarking (Rolnick et al., 2024). Prior efforts on creating NLP benchmarks which are representative of real user needs use query logs (Nguyen et al., 2016; Kwiatkowski et al., 2019) and chat histories (Lin et al., 2024). While these benchmarks are useful for evaluating responses to generic user queries, they do not allow us to study their abilities in assisting with domain-specific tasks in an isolated manner. For instance, Ouyang et al. (2023) find that user requests in chat histories often involve "planning" and "design", but these are

largely ignored in benchmarks. Our work fills this gap by presenting a typology of domain-specific tasks grounded in realistic scenarios.

Language Models as Writing Assistants. Recent work has investigated the potential of language models to act as writing assistants for domain experts (Calderwood et al., 2020; Lee et al., 2022; Gero et al., 2022; Li et al., 2024). While there is favorable evidence that they can improve productivity of experts (Noy and Zhang, 2023), their usage has broader societal consequences, including potential impact on the workforce (Eloundou et al., 2023). We analyze a subset of these societal implications relevant for our methodical tasks in Section 3.

7 Conclusion

We introduce DOLOMITES, a benchmark that is closely tied to realistic use cases of domain experts. The generalization of these use cases as methodical tasks provides a way to study capabilities of language models across tasks and domains. We consider a scenario where AI systems can act as tools for experts to amplify their problem-solving capabilities (Engelbart, 2023) and perform their tasks more efficiently. We verify that our tasks are representative across fields and that human oversight is necessary if language models propose initial outputs for these tasks. Evaluation of a broad range of contemporary language models suggests that there is a large room for models to improve on generating outputs for our tasks.

Future directions are many and varied. The methodical tasks in our collection constitute a mere sample from 25 fields in English language. We hope to further expand the set of tasks to cover a wider range of scenarios and languages. We could also consider tasks that involve modalities other than text in input or output, and multi-turn settings, where models continually improve their outputs through feedback and revision. Our experimental results revealed that automatic evaluation of generated text is particularly challenging. Our data contains a single reference output for an example input and does not model the potentially diverse perspectives of field experts and the innate subjectivity of tasks (Ganguli et al., 2023). While factual consistency metrics do not account for this subjectivity, it is unclear if language model judgements innately capture this subjectivity. More research is needed to ensure language model responses are given credit for alternative, but valid responses.

Acknowledgments

We thank the 266 annotators who participated in our data collection studies and the following people for their help with facilitating data collection: Shereen Ashraf, Michelle Chen Huebscher and Michael Sharman. We also thank the following people for helpful discussions and feedback: Sumit Asthana, Tuhin Chakrabarty, Michael Collins, Sunipa Dev, Jacob Eisenstein, Sebastian Gehrmann, Kalpesh Krishna, Tom Kwiatkowski, Matthew Lamm, Kenton Lee, Joshua Maynez, Slav Petrov, Hannah Rashkin, David Reitter, Marco Tulio Ribeiro, Elizabeth Sieber and Kristina Toutanova.

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A Annotation Details

Participants. We recruited 266 participants for our study from Prolific. Participants were required to be fluent in English, and came from 25 different countries, across Africa, Europe, North and South America. In terms of their background, participants were required to have an undergraduate degree and 3 years of work experience in their respective field. These requirements were first enforced through Prolific’s audience filters, followed by a screening where participants were asked to self-report their educational qualifications and work experience. They each provided two tasks, so for each field, we recruited half the number of the participants as the number of tasks reported in Table 1. Lastly, they were required to have at least 50 prior approved submissions and an approval rate of over 99%. Participants were informed that their provided data will be used to evaluate large language models in realistic scenarios. We obtained prior consent from all annotators before recruiting them for all studies.

Setup. Annotators were paid \$20 per hour for their work. For task collection, we allocated 40 minutes to write two tasks and for task validation, we allocated 15 minutes per task. For post-editing examples, we allocated 20 minutes per example.

Annotation Interface Screenshots. We show screenshots of the annotation interfaces presented to annotators for task validation and example post-editing in Figures 11 and 12 respectively.

B Experimental Details

Models. The specific identifiers for the models evaluated in this work are given in Table 5. Open-source models were obtained from the Hugging-Face model hub, while proprietary models were obtained through the organization’s official APIs.

Generation Configurations. In all generation tasks, we set the temperature for generation to be 0.1. For both example generation and model evaluation, we sampled a maximum of 4,096 tokens (or the maximum sequence length of the model).

Prompts. We provide the prompts used for various components of our work. The prompts used for example creation are given in Tables 11–13. The prompt used to generate the critique shown to annotators is shown in Table 14. The prompt used to

Model Name	Identifier
Claude-3 Opus	claude-3-opus-20240229
Command-R-Plus	command-r-plus
Gemini-1.5-Pro ²	gemini-1.5-pro-latest
Gemini-1.5-0409 ³	gemini-1.5-pro-preview-0409
Gemini-Pro	gemini-pro
GPT-3.5-Turbo	gpt-3.5-turbo
GPT-4	gpt-4-turbo-preview
Mistral-Large	mistral-large-latest
Mixtral-8x22B	Mixtral-8x22B-Instruct-v0.1
Mixtral-8x7B	Mixtral-8x7B-v0.1
OLMo-7B-Instruct	OLMo-7B-Instruct

Table 5: List of models used in our experiments and their identifiers.

generate outputs from candidate models is shown in Table 15. Finally, the prompt used for generating LM-based judgements for evaluation is shown in Table 16.

C Additional Results

We report additional results for LM-based evaluation of models. Prior work has reported that language models show a bias for longer outputs (Singhal et al., 2023). To correct for this bias, we report length-adjusted win rates in Table 6. The length adjustment requires applying a length penalty on the points awarded for each win. This penalty is 1% for every 10 words in the average length difference between the two models.

Model	GPT-4	Claude-3 Opus	Gemini-1.5-0409
Claude-3 Opus	47.6	52.1	49.1
Command-R-Plus	33.4	44.4	37.5
Gemini-1.5-Pro	43.2	48.4	53.6
Gemini-1.5-0409	44.6	57.6	63.4
Gemini-Pro	19.8	23.6	25.0
GPT-3.5-Turbo	14.1	13.3	14.4
GPT-4	50.0	50.0	50.0
Mistral-Large	29.4	31.1	28.8
Mixtral-8x22B	22.9	26.6	18.7
Mixtral-8x7B	18.2	24.0	15.9
OLMo-7B-Instruct	2.7	3.5	3.0

Table 6: Model win rate (± 3) against GPT-4 on the DOLOMITES benchmark using three LM-based autorators (GPT-4, Claude-3 Opus, and Gemini-1.5-PP), with a *length penalty*.

²Accessed from <https://aistudio.google.com/app>

³Accessed from <https://console.cloud.google.com/vertex-ai/generative>

Survey on the Use of AI Systems for Expert Tasks

Goal: We are a group of researchers ... and we are interested in studying the use of AI systems for assisting experts from different fields. With your help, we would like to study the practical and societal implications of using AI systems as tools for assisting experts from different fields. Thank you for participating!

Instructions: In this study, you will be shown the description of a textual task from your field written by an expert from your field. Each task has input sections and output sections, and any system would need to produce the content in the output sections given the content in the input sections. We would like you to first read this task description closely, and then answer the questions that follow below.

We would like you to imagine a scenario where an expert uses an AI system to get an initial output of this task from an AI system, which they can then improve and validate. Essentially, they would be using an AI system as a tool, the same way a mathematician might use a calculator as a tool. The questions listed below ask about the practical and societal implications of using AI systems this way, where they are used in the loop as experts conduct their tasks.

Notes:

- For all questions under societal implications, you are required to write 2-5 sentences elaborating upon your choice.
- Please try your best to provide high-quality labels. If you end up taking more time than allocated, we would be happy to bonus you.

Task Description

Task Objective: The task is to figure out which regional varieties of spoken languages are used by certain speakers in a region

Task Procedure: The persons who are chosen for the task are required to read some sentences in the pronunciation they usually speak when communicating with members of the family or friends. Those sentences are transcribed by an expert.

Additional Notes: Common mistakes: Is there any code-mixing or code-switching? Is the design of the exploration a bias for the people involved?

Input Sections:**

- Interview: 2 paragraphs & Answers to different questions in terms of the biography: age, gender, religion, date and place of birth, family members, date and place of birth of mother and father, residences.
- Exploration in regional variant: Transcribed readings and/or writings of a prepared set of sentences in the domestic variant of language.
- Exploration in standard language: Transcribed readings and/or writings of the same sentences as in section 2 in the standard language.

Output Sections:**

- Names of regional variants: The names of regional variants spoken by the person or group of people, identified through their transcribed readings and writings.

Representativeness: How likely is this task to be conducted by an expert in your field?

Very likely: This is a very common task that most or all experts in my field work on.
 Likely: This is a common task that some experts in my field would work on.
 Possibly: This is not a common task but it is conceivable that some experts in my field would work on this.
 Unlikely: This does not seem like a task that any expert from my field would work on.

Complexity: How would you rate the complexity of this task?

High: This is a highly technical task that requires immense field expertise (several years of experience).
 Medium: This is a technical task that requires a moderate amount of field expertise (a few years of experience).
 Low: This is not a very technical task and requires very little expertise in my field.

Time Required: How much time is typically required to complete this task?

Less than an hour
 1-4 hours
 1-7 days
 1-4 weeks
 1-3 months
 >3 months

Usefulness: Would you or other experts find it useful if an AI system could be used to propose initial outputs for this task (which may be lacking), that can be validated and improved by experts?

Yes: I would be interested in using this system as it could improve my efficiency.
 Maybe: It is not immediately obvious that this system would be helpful for the given task, but I am open to trying it and deciding based on that.
 No: I would not be interested in using this system because it would not improve my efficiency.

Societal Implications

Anonymity Required: Is it important to ensure anonymity of any individuals or organizations mentioned if an AI system is used for conducting this task? This may be the case if there is sensitive information in the input that should not be stored or accidentally leaked by an AI system.

Yes: It is imperative, as there might be sensitive information about individuals or organizations in the input for this task. (Please elaborate in the text box below)
 No: It is not necessarily a concern for this task.

Please elaborate on your choice in brief.

Biased Outcomes: Could relying on automatically generated outputs for this task result in biased or potentially harmful decisions for certain groups of people?

Yes: AI systems can potentially exhibit bias in the outputs of this task, which can negatively affect people from specific groups or demographics. (Please elaborate in the text box below)
 No: I don't think that automatically generated outputs for this task could lead to biased outcomes for people from any specific group or demographic.

Please elaborate on your choice in brief.

Ethical Considerations: Are there ethical considerations associated with the use of AI systems for this task? This can include privacy issues, moral issues, copyright issues or any other issues.

Yes: There is at least one ethical issue which is important to consider. (Please elaborate in the text box below)
 No: I don't foresee any ethical concerns related to the use of AI systems for this task.

Please elaborate on your choice in brief.

Workforce Impact: Could partial automation of this task potentially have an impact on the workforce in the short term?

Likely: Partial automation is likely to affect the workforce in my field in the short term.
 Unsure: Unable to make an informed judgment about this task.
 Unlikely: Partial automation is unlikely to affect the workforce in my field in the short term.

Please elaborate on your choice in brief.

Accessibility Requirements: Does the use of AI systems for this task require making exceptional considerations for ensuring accessibility to all users? For instance, a task that requires producing visual outputs might pose challenges for people with visual or motor disabilities.

Yes: It is critical to pay special attention to adapting the output for this task to users with special needs. (Please elaborate in the text box below)
 No: Beyond general considerations in making technology accessible to all users, I cannot identify any exceptional considerations for users with special needs.

Please elaborate on your choice in brief.

Figure 11: Interface shown to annotators for task validation.

Fixing Issues in Examples of Expert Tasks

Goal: We are a group of researchers and we are interested in improving the reliability of AI models for assisting experts from different fields. With your help, we would like to evaluate their capabilities in helping experts with writing tasks. We believe that you are the most suitable person to work on this study since you provided the task description given below. Thank you for your time and effort!

Instructions: You previously provided us with task descriptions from your field. We have come up with imperfect examples of your tasks that are lacking in various ways and in this study, we would like you to fix 1 example. An example is a real sample of the input & output sections of this task with concrete details. Examples are based on relevant webpages for the task, which are also provided to you below. To help you, we provide you a set of issues in the example, but these issues are by no means exhaustive and you should consider other issues as well.

Steps and Video Demonstration: [Watch this video for a demonstration of the study](#). Follow these steps for doing the study:

1. READ the task description and CHOOSE 1 example on the right that is the most appropriate and plausible example for the task. Then, READ the given issues in the chosen example.
2. ANSWER the questions in the blue boxes below about the chosen example's overall structure, level of detail and factual correctness.
3. EDIT the chosen example by fixing the given issues and other issues you identify in the example.
 - You need to ensure that the example 1) follows the task structure: all the input & output sections in the task description should be part of the example, 2) is detailed: it should completely and concretely address all sections in the task, and 3) is factually accurate: every word of the example should be correct.
 - For reference, you can also use relevant documents shown to you by clicking on 'Show References'.
4. VERIFY that you have fixed all issues in the example, including all the given issues. Next, provide a few important phrases from the output sections of the revised example.
5. SUBMIT and move on to the next example.

Notes:

- Once you start editing an example, please do not click on the buttons for any other example as you may lose progress.
- Please make sure that examples follow the task structure, contain specific details, and are factually accurate. We need expert-quality examples that are representative of the task. See an example below.
- Make sure every single one of the listed issues is fixed through your edits and note that we will use this as criteria to approve your work. At the same time, do not restrict only to these issues as there might be many other issues with the example which are not listed.
- Make sure you are thorough and detailed in your edits. You will not be able to submit until you have sufficiently edited the given example.

We are relying on your support for this study. Please try your best to provide high-quality examples. If you end up taking more time than allocated, we would be happy to bonus you.

[▶ Show Example](#) [▶ Show Revised Example](#)

Example 1 / 1

Task Description

Task Objective: Deciding how a particular annotation decision should be made in a corpus.

Task Procedure: Given some annotation guidelines for labeling examples in a benchmark NLP dataset, this task requires deciding how a specific example should be annotated. We need to pay close attention to the guidelines and make sure that our annotation is consistent with the rest of the annotated examples.

Additional Notes: This task could arise either while annotating additional data, or while examining system output.

Input Sections:

- Example under consideration: This is an example from a text corpus, possibly along with a questionable sentence or a document.
- Examples from annotated corpus: A few fully or partially annotated examples from the corpus. Some of these might exhibit behavior similar to the example under consideration, but most of them will be irrelevant to deciding the example under consideration. For example, if we are trying to make a decision about preposition attachment in dependency parsing, any examples without prepositions will be irrelevant.
- Annotation guidelines: The corpus is annotated according to some guidelines, typically consisting of English text and sometimes diagrams. These guidelines provide the rules for how to deal with the example under consideration. In many cases they will, but occasionally they might not.
- Specific question (optional): There might optionally be a specific question, asking about which part of the annotation or what question is unclear. For example, in POS tagging, we might ask should this word be a verb or a noun. This would be posed as a natural language question, potentially referring to the example under consideration.

Output Sections:

- Direct answer to the question: The response should start with an answer to the question, or multiple answers if the direct answer is not clear. If there is not a direct question, then the implicit question is "How should this be X?" and in many cases, the guidelines suggest that the label should be X, but in many cases, the annotated corpus uses Y in similar cases, so there is some inconsistency."
- Evidence from the annotation guidelines: An explanation of how cited parts of the annotation guidelines relate to the example and how that might lead to part of the direct answer.
- Evidence from the corpus: An explanation of how similar examples are treated in the corpus. This could include statistics from a small sample that an expert examined.

Potential Issues in the Chosen Example

CHOICE 1	CHOICE 2	CHOICE 3	CHOICE 4
Input Sections:			
Example under consideration:			
lobar (\leftarrow) lobulo, 'lobe', C0796494			
Examples from annotated corpus:			
* calcio sérico ('serum calcium measurement', C0728876) * sd de malabsorción (\leftarrow) síndrome de malabsorción, 'malabsorption syndrome', C0024523 * asignados al azar (\leftarrow) aleatorizados, 'randomized', C0034656			
Annotation guidelines:			
* We used exact string matching and the MedLexSp lexicon [52] to add only those CUIs that matched our annotations (changed to lowercase) and corresponded to the semantic group we annotated. * In multi-word entities, the full entity was matched (not parts of them). * Note that this procedure has limitations and not all the annotations are normalized automatically to CUIs. For example, we could not normalize some derived forms (lobar (\leftarrow) lobulo, 'lobe', C0796494), shortened forms (sd de malabsorción (\leftarrow) síndrome de malabsorción, 'malabsorption syndrome', C0024523), paraphrases (asignados al azar (\leftarrow) aleatorizados, 'randomized', C0034656) or misspellings ('chromosomata, 'chromosomalopathy', C0008626).			
Specific question:			

Structure:

- The example does not include any "Evidence from the corpus" section, which is required by the task description.

Depth:

- Evidence from the annotation guidelines: The explanation of how the annotation guidelines relate to the example could be more detailed. It only mentions exact string matching, but it does not explain how the guidelines handle derived forms, which is relevant to the example under consideration.
- Evidence from the corpus: The example could provide more specific examples from the corpus that are similar to the example under consideration. This would help to support the annotation decision.

[▶ Show References](#)

Task Structure Followed: Does the example include all the input & output sections present in the task description?

Yes: The example contains all the input & output sections in the same order as the task description.
 No: The example is missing the title/content of at least 1 section OR sections are given in the wrong order.

Level of Detail: Does the example show a detailed and concrete sample of the task?

Definitely: High-quality example that could have been written by an expert in the field.
 To some extent: Follows the basic structure of the task but the content could be improved.
 Not quite: Follows the structure of the task but content is far from being a plausible example of this task.
 Definitely not: Lacking in various ways (including its structure and content) and is nowhere close to being a plausible example of the task.

Factual Correctness: Is the example factually correct?

Definitely correct: Absolutely sure that every word of the example is correct.
 Probably correct: Not completely sure, but it is likely that this example is entirely correct.
 Unsure: Cannot make an informed judgment about the example.
 Probably incorrect: Not completely sure, but there are parts in the example that are likely incorrect.
 Definitely incorrect: Absolutely sure that there is at least a part of the example that is incorrect.

Changes Made: Did you edit the example so that all the given issues, as well as any other issues, are fixed? *

Yes
 No

Important Phrases: Please provide the most important 2-3 phrases from the output sections of the example. (Each phrase is a few words; separate these phrases with commas) *
 These are phrases that must be part of the output for it to be correct.

[◀ BACK](#) [NEXT ▶](#)

Figure 12: Interface shown to annotators for example post-editing.

Pattern: Lack of Detail

TASK DESCRIPTION

Task Objective: Designing an observation plan for different celestial bodies and objects using an infrared telescope

Task Procedure: Observing space can be quite a complicated task to achieve, space contains a lot of different celestial bodies and a variety of objects. Some of these objects emits "special" kind of electromagnetic radiation - radiation that we humans cannot see with our eyes. So in this task we're focusing on the invisible glow these objects emit in the infrared part of the spectrum. Our task is to basically decide which celestial bodies (star, planet, galaxies, nebulas and more) we want to study and investigate considering and taking into account their unique infrared features. We also need to plan what kind of telescope is going to be used in order to successfully achieve that mission and literally "see" what we want to see.

Additional Notes: Planning it correctly can save a lot of time and frustrations, taking in account different information like I presented and learning from mistakes can lead to a successful observation.

Input Sections:

* **Scientific/main Goal AND target object:** 1 paragraph, 3-4 sentences. To begin with the planning, we mostly need to understand what is our main objective - so we have to outline the scientific goals we aim to gather from the observation such as understanding atmospheric composition of different bodies, stars/planets life cycle and formation process and more.

* **Kind of telescope and wavelength range:** 2 paragraphs, 7-8 sentences. The user should provide detailed information regarding what instrument is being used, which includes technical specifications such as focal length of the telescope and eyepieces, apertures, focal ratios, the type of telescope and also what kind of additional items are being used like filters and cameras to detect that special electromagnetic spectrum. Providing what wavelength the observation is going to be in can surely help, infrared radiation varies in different nano-metrica (NIR, MIR, FIR), each wavelength is good for a certain type of observation.

Output Sections:

* **Observing conditions:** 1 paragraph, 3-4 sentences. We need to know what conditions the observation is taking place and what location, mostly because this plays a real key factor in terms of how the observation would be carried out. Providing information about things like light pollution (Bortle scale), density of air, outside temperature and more.

* **Instrument sensitivity:** 1 paragraph, 2-3 sentences. We need to know what are the **specifications of sensitivity of the instruments being used**. Sensors or cameras can detect so many details in comparison to the human eye, as well as filters of eyepieces.

EXAMPLE INPUT

* **Scientific/main Goal AND target object:** Our scientific goal is to study the formation and evolution of young stars within the Orion Nebula. The Orion Nebula is a vast region of star formation, and by observing it in the infrared, we can penetrate the dust and gas that obscure these young stars in visible light.

* **Kind of telescope and wavelength range:** We will use the Stratospheric Observatory for Infrared Astronomy (SOFIA), a 2.7-meter infrared telescope mounted on a Boeing 747SP aircraft. SOFIA is capable of observing in the mid-infrared and far-infrared wavelengths, from 5.4 to 25.5 microns. We will specifically target the mid-infrared range (8-13 microns), which is optimal for detecting the warm dust and gas associated with young stellar objects. Additionally, we will employ a medium-resolution spectrograph to obtain detailed information about the composition and physical properties of the observed targets.

REFERENCE OUTPUT

* **Observing conditions:** The observations will be conducted from an altitude of approximately 45,000 feet, above the majority of Earth's water vapor, which absorbs infrared radiation. The flight will take place during a moonless night to minimize light pollution. The observing site will be chosen to have a low Bortle scale rating, indicating minimal light pollution from artificial sources.

* **Instrument sensitivity:** SOFIA's mid-infrared camera, FORCAST, has a sensitivity of approximately 0.1 Jy for a point source in a 10-minute integration time. The spectrograph has a spectral resolution of R 1000, allowing us to resolve individual spectral lines and determine the chemical composition of the target objects.

Gemini-1.5-0409 OUTPUT

* **Observing conditions:** SOFIA operates at altitudes of 38,000-45,000 feet, above 99% of the Earth's water vapor, which allows for clear observations in the infrared spectrum. The observations will be conducted during nighttime flights to minimize background radiation from the Sun. Additionally, SOFIA's mobility allows it to choose observing locations with minimal light pollution, typically over remote ocean areas or sparsely populated regions, corresponding to Bortle Class 1 or 2.

* **Instrument sensitivity:** SOFIA's mid-infrared instruments, such as the FORCAST camera and the FLITECAM spectrograph, are highly sensitive to faint infrared emissions. They can detect temperature variations as small as a few degrees Kelvin and resolve spatial details down to a few arcseconds. This sensitivity enables the detection and characterization of young stellar objects and their surrounding environments within the Orion Nebula.

Table 7: Sample response showcasing lack of detail in the generated output.

Pattern: Verbosity

TASK DESCRIPTION

Task Objective: Write a review of a novel.

Task Procedure: You need to write an extensive review of a novel, you need to summarize and give basic facts of the writer and novel, but also give value judgement.

Additional Notes: nan

Input Sections:

* **Title:** only one or several words, this is the title of the book that you will review.

* **Writer:** only a name, this is the author's name.

* **Pages:** only a number, the number of pages in the novel.

* **Introduction:** 1 paragraph, a general introduction to both the author and their work (the title that will be reviewed in the article)

* **Summary:** 1 paragraph, a specific summary of the book which gives the reader an insight into the story without spoiling major events or the ending; it needs to stay exciting/enticing.

Output Sections:

* **Analysis:** 2-3 paragraphs, varying analyses of several aspects of the story, this includes content analysis, but also linguistic and semantical analysis; what is meant by certain passages? What are the cultural/societal connotations? In what way does the writer use language and form?

* **Verdict:** 1 paragraph, what do we think about the things we just analysed? Is it of high quality or low quality? And in what ways? Why?

* **Conclusion:** 1 sentence, summarize everything said above and give a final review in only one sentence.

EXAMPLE INPUT

* **Title:** Dead in Long Beach, California

* **Writer:** Venita Blackburn

* **Pages:** 157

* **Introduction:** A rising literary star, Venita Blackburn, tackles the complexities of grief and unconventional coping mechanisms in her captivating novel, "Dead in Long Beach, California." This poignant tale explores the depths of human sorrow through the story of a young woman grappling with loss. Blackburn delves into the lengths individuals go to find solace, weaving a narrative that is both heartbreakingly and thought-provoking.

* **Summary:** The novel follows the journey of a young woman who, after the sudden death of her brother, stumbles upon an unexpected and ethically dubious method of coping. Posing as her deceased sibling, she immerses herself in his online world, seeking comfort in the digital memories and connections he left behind. As she delves deeper into her brother's virtual existence, she uncovers hidden secrets and confronts the consequences of her actions.

REFERENCE OUTPUT

* **Analysis:** Blackburn's novel is a profound exploration of the grieving process. Through the protagonist's unconventional coping mechanism, she examines the ways in which technology can both connect and isolate us in times of loss. The author skillfully intertwines the protagonist's emotional turmoil with the digital landscape, creating a thought-provoking commentary on the nature of identity and the boundaries between the living and the dead.

Furthermore, Blackburn's prose is both lyrical and incisive. For instance, her description of the protagonist staring at her brother's empty online profile, "a hollow echo of a life once lived," perfectly captures the profound sense of emptiness and longing she experiences. The novel's exploration of ethical dilemmas, such as the protagonist's manipulation of online identities, is handled with sensitivity and nuance. It leaves readers to ponder the complexities of right and wrong in the face of overwhelming grief, sparking valuable discussions about the boundaries of acceptable coping mechanisms.

* **Verdict:** "Dead in Long Beach, California" is a powerful and deeply moving novel. Blackburn's ability to capture the raw emotions of grief and the complexities of our digital lives is commendable. Her exploration of unconventional coping mechanisms and the ethical implications they raise is both thought-provoking and timely.

* **Conclusion:** Venita Blackburn's "Dead in Long Beach, California" is a haunting and unforgettable tale that lingers long after the last page is turned. It serves as a powerful reminder of the enduring strength of human connection and the profound bond that transcends even death.

GPT-4 OUTPUT

* **Analysis:** Venita Blackburn's "Dead in Long Beach, California" is a masterful exploration of grief and identity in the digital age. Through her concise yet powerful prose, Blackburn challenges the reader to consider the boundaries between the self and the other, the living and the dead. The novel's central theme of coping with loss through digital impersonation raises poignant questions about the authenticity of online relationships and the ethics of assuming another's identity posthumously. Blackburn's use of language is both evocative and precise, capturing the protagonist's turmoil and desperation with striking clarity. The narrative structure, alternating between the protagonist's real-life struggles and her online escapades, effectively mirrors the fragmented nature of grief, enhancing the reader's empathy for the protagonist's plight. Furthermore, Blackburn subtly incorporates societal critiques, particularly concerning the internet's role in shaping our perceptions of death and mourning. The novel's setting in Long Beach, California, with its juxtaposition of urbanity and the vastness of the Pacific, further underscores the protagonist's feelings of isolation and her quest for connection in an increasingly disconnected world.

* **Verdict:** "Dead in Long Beach, California" is a compelling and thought-provoking novel that showcases Venita Blackburn's talent for delving into complex emotional landscapes with nuance and sensitivity. The quality of Blackburn's writing is evident in her ability to weave a deeply personal story with broader societal implications, making the novel both intimate and universally relevant. The ethical dilemmas and emotional depth explored in the book are handled with a deftness that invites readers to reflect on their own experiences of loss and the ways in which technology intersects with our most human experiences. Blackburn's linguistic prowess and her skillful narrative construction make this novel a high-quality literary work that is both engaging and enlightening. It is a poignant reminder of the power of fiction to explore the nuances of the human condition.

* **Conclusion:** Venita Blackburn's "Dead in Long Beach, California" is a beautifully crafted novel that offers a profound and nuanced exploration of grief in the digital age, making it a must-read for those who appreciate literature that delves into the complexities of the human heart.

Table 8: Sample response showcasing verbosity in the generated output (note the *Analysis* and *Verdict* sections).

Pattern: Missing Information

TASK DESCRIPTION

Task Objective: Writing a funding application for a medical research project.

Task Procedure: To write a funding application for a research project, you need to start with a clear and concise idea for the research project, identify matching funding sources, understand the funder's priorities. Then, write a detailed project description and prepare a specific budget. Complete the application form provided by the funder and follow all guidelines. Review the application, submit it, and await feedback.

Additional Notes: It is important to clearly define the research idea, understand the funder's priorities, write a detailed project description, prepare a specific budget, and review before submitting. Common mistakes include overlooking eligibility, using jargon, poor structure of the application, and an overwhelming page layout.

Input Sections:

* **Project Idea:** 1 paragraph. A clear and concise idea for the research project is essential.

* **Potential Funding Sources:** 1 paragraph. Estimated cost and identification of potential funding sources that align with the research topic.

Output Sections:

* **Funding application:** 2 paragraphs. The funding application will include a summary, an introductory section including background and motivation, detailed project description, and detailed budget.

* **Timeline:** In addition, a detailed timeline with key milestones is essential to demonstrate preparedness and careful planning for the project.

EXAMPLE INPUT

* **Project Idea:** We aim to develop a novel risk prediction model for asthma exacerbations in children aged 1-6 years. By integrating clinical data, environmental factors, and genetic markers, we will create a comprehensive tool to identify children at high risk of exacerbations, enabling early intervention and improved disease management.

* **Potential Funding Sources:** The National Heart, Lung, and Blood Institute (NHLBI) offers funding opportunities for research on respiratory diseases, including asthma. We estimate that the project will require a budget of \$250,000 over five years.

REFERENCE OUTPUT

* **Funding Application:**

Summary: This application proposes a comprehensive study to develop a risk prediction model for asthma exacerbations in children. The model will integrate clinical, environmental, and genetic data to identify high-risk individuals, facilitating early intervention and improved disease management.

Introduction: Asthma is a common chronic disease that affects millions of children worldwide. Exacerbations can be life-threatening and lead to significant healthcare costs. Current prediction methods are inadequate, and there is an urgent need for more accurate tools. This project will address this gap by developing a novel risk prediction model that combines multiple factors to provide a personalized assessment of exacerbation risk.

Project Description: We will recruit 500 children aged 1-6 years with asthma from the Aspen Medical Group and St. Paul Children's Hospital. Data collection will include clinical assessments, environmental monitoring, and genetic testing. Baseline clinical assessments will include use of short-acting beta agonists, previous asthma-related emergency department attendances and hospitalizations, history of lower respiratory tract infections, environmental tobacco exposure. Environmental monitoring will be performed using indoor air-quality sensors. Genetic testing will include the analysis of specific genes linked to asthma. Outcome events will include asthma-related emergency hospitalization. We will use survival models to estimate the hazard ratio associated with key predictors. The model will be validated using an independent cohort of children.

Budget: The total budget for the project is \$250,000 over five years. This includes costs for participant recruitment, data collection, analysis, and dissemination. The budget includes:

- * \$150,000: Staff salaries
- * \$50,000: Patient recruitment data, collection and analysis
- * \$30,000: Equipment and supplies
- * \$20,000: Travel expenses

* **Timeline:**

- * Year 1: Participant recruitment and data collection: This include three months for participant recruitment and nine months for data collection.
- * Year 2: Model development and validation: This includes nine months for model development and three months for validation.
- * Year 3: Model refinement, implementation, and real-world testing.
- * Year 4: Dissemination of results and exploration of clinical applications: This include three months for preparing and publishing findings, and nine months for exploring clinical applications.
- * Year 5: Project evaluation and future directions: The entire year will be dedicated to project evaluation and planning for future research.

GPT-4 OUTPUT

* **Funding Application:** Our project proposes the development of an innovative risk prediction model for asthma exacerbations in children aged 1-6 years, a critical period for asthma management and intervention. By leveraging a multidisciplinary approach that combines clinical data, environmental factors, and genetic markers, our model aims to revolutionize how healthcare providers identify children at high risk of asthma exacerbations. This early identification will facilitate timely interventions, potentially reducing the frequency and severity of exacerbations and improving overall disease management and patient outcomes.

The project will unfold in several phases, beginning with the collection and analysis of clinical data from pediatric asthma patients. Concurrently, we will conduct a comprehensive review of environmental factors known to influence asthma exacerbations, such as air quality and allergen exposure, and perform genetic analyses to identify markers associated with increased risk. This integrated data will form the basis of our predictive model, which will be rigorously tested and validated in clinical settings. To support this ambitious project, we are seeking funding of \$250,000 from the National Heart, Lung, and Blood Institute (NHLBI), an organization that prioritizes research on respiratory diseases, including asthma. This budget will cover costs associated with data collection, analysis, personnel, and dissemination of findings, ensuring a thorough and impactful study.

* **Timeline:**

Year 1:

- Q1-Q2: Project initiation, including team assembly and training, and development of data collection protocols.
- Q3-Q4: Begin data collection on clinical data and environmental factors, and initiate genetic marker identification.

Year 2:

- Q1-Q2: Continue data collection and start preliminary data analysis.
- Q3-Q4: Development of the initial model based on collected data and initial testing.

Year 3:

- Q1-Q2: Refinement of the model based on initial testing feedback and integration of additional data as necessary.
- Q3-Q4: Begin large-scale validation of the model in clinical settings.

Year 4:

- Q1-Q4: Continued validation and refinement of the model, including adjustments based on ongoing feedback from clinical applications.

Year 5:

- Q1-Q2: Finalization of the model and preparation of materials for dissemination.
- Q3-Q4: Dissemination of findings through publications, presentations at conferences, and direct outreach to healthcare providers.

This timeline demonstrates our commitment to careful planning and preparedness, ensuring that each phase of the project builds upon the last towards the successful development and implementation of our novel asthma risk prediction model.

Table 9: Sample response showcasing missing information in the generated output (note the *Funding application* section).

Pattern: Subjectivity

TASK DESCRIPTION

Task Objective: Writing a plan for a photography shoot

Task Procedure: I would start by considering my inspirations and previous research. I will then plan out the photography shoot by writing a description of each shot that I expect to get, the layout and the lighting techniques I will use.

Additional Notes: Make sure not to overly complicate the plan but stay clear and concise.

Input Sections:

* **Goals:** 1 paragraph. The goal of the photoshoot based on the event being photographed, the requirements from the photographs and how many final photographs are needed for release.

* **Target Audience:** 1-2 sentences. Who will the photographs be released to.

Output Sections:

* **Location:** 1 paragraph, 2 sentences. Choose Location: Select an appropriate setting that aligns with the objective.

* **Lighting:** 1 paragraph, 2-3 sentences. Plan for natural or artificial lighting, as needed, decide on lighting techniques and angles, and how many of each will aim for.

* **Layout:** 1-2 Sentences. Choose layout of props/people etc. and detail exact positions for each shot..

EXAMPLE INPUT

* **Goals:** The goal of this photoshoot is to capture the essence of the serene and rugged beauty of the Scottish Highlands. We aim to showcase the rolling hills, dramatic cliffs, and crystal-clear lochs that make this region so unique. We will need to capture a variety of images, including wide-angle landscape shots, intimate portraits of the local flora and fauna, and detailed shots of the region's unique geological features. We will need to deliver a total of 30 final photographs for release.

* **Target Audience:** The target audience for these photographs is potential tourists and travel enthusiasts interested in exploring the Scottish Highlands. These photographs will be used in a variety of marketing materials, including brochures, website banners, and social media posts.

REFERENCE OUTPUT

* **Location:** To achieve the desired effect, we will be shooting on location in the Cairngorms National Park. We will visit the Highland Wildlife Park, Rothiemurchus Estate, and Balmoral Castle. These locations offer a wide variety of landscapes, from towering mountains and windswept moors to tranquil forests, castles and shimmering lochs.

* **Lighting:** We will primarily use natural lighting for this photoshoot, taking advantage of the soft morning light, dramatic evening skies, the golden hour and sunsets. We will hope to visit in different weathers such as misty rain or blue skies to get a variety of shots. We may also use artificial lighting such as a flash if absolutely necessary for certain shots, such as portraits or close-ups of specific details.

* **Layout:** For the landscape shots, we will use the rule of thirds in some shots (as to not get repetitive) to create balanced and dynamic compositions. We will also use leading lines, such as paths and streams, to draw the viewer's eye into the scene. For the close-up shots, we will focus on capturing the intricate details of the subject, such as the veins in a leaf or the texture of a rock. We hope to include wildlife such as red deer, birds or insects in the photos. We will bring no props, and use only what nature and the landscape provides. We will photograph woodlands, streams, lakes, forests, castles and mountains. We will aim for 10 close up and wildlife shots and 20 landscape photos.

Claude-3 Opus OUTPUT

* **Location:** The photoshoot will take place in the Scottish Highlands, specifically focusing on the areas around Glencoe and the Isle of Skye. These locations offer a diverse range of landscapes, from the rugged peaks of the Three Sisters in Glencoe to the stunning coastline and rock formations of the Quiraing on the Isle of Skye.

* **Lighting:** Given the unpredictable weather conditions in the Scottish Highlands, we will primarily rely on natural lighting for our shots. We will aim to shoot during the golden hours of sunrise and sunset to capture the warm, soft light that enhances the natural beauty of the landscape. Additionally, we will experiment with backlighting and side-lighting techniques to add depth and dimension to our shots, particularly when photographing the local flora and fauna.

* **Layout:** For the wide-angle landscape shots, we will position our cameras to capture the vastness and scale of the Scottish Highlands, emphasizing the dramatic cliffs, rolling hills, and expansive lochs. When photographing the local flora and fauna, we will use a shallow depth of field to isolate our subjects and create intimate, detailed portraits that showcase the unique characteristics of each species.

Table 10: Sample response showcasing subjectivity in the task which is not accounted for during automatic evaluation.

Query Formulation Prompt

Generate 10 search queries for finding specific examples of the given task from the specified field. The search queries should be brief and request documents in more specific contexts than the given task. We would like the documents to contain real examples of the task. List the queries and nothing else.

FIELD: Visual Arts (Graphic design)

TASK: The objective of this task is to write a catalog entry for an art exhibition.

QUERIES: 1) Example of catalog entry for art exhibition

2) Catalog entry art exhibition Dali

3) Notable art catalog entries 2023

4) memorable art catalog entries 2000s

5) catalog entry for jackson pollock painting

6) frida kahlo painting catalog entry

7) picasso guernica catalog entry

8) da vinci mona lisa catalog entry

9) The Great Wave off Kanagawa catalog entry

10) renaissance art exhibition catalog entry

FIELD: [FIELD]

TASK: [TASK]

QUERIES:

Table 11: Prompt used for generating specific search queries for a task.

Domain Name Prompt

List 20-30 URLs to domain names which will be useful to find real examples for the given task. These websites should be reliable, trustworthy and authoritative sources for an expert in the field. They should be ranked by their likely usefulness.

FIELD: Engineering and Technology (NLP research)

TASK: Summarizing related work on an NLP subproblem.

URLs: 1) arxiv.org

2) aclweb.org

3) ldc.upenn.edu

4) nlp.stanford.edu

5) aclanthology.org

6) towardsdatascience.com

7) semanticscholar.org

8) openreview.net

9) medium.com

10) nature.com

11) transacl.org

12) cambridge.org

13) iclr.cc

14) aaai.org

15) academic.microsoft.com

16) nips.cc

17) onlinelibrary.wiley.com

18) link.springer.com

19) naacl.org

20) plos.org

FIELD: [FIELD]

TASK: [TASK]

URLs:

Table 12: Prompt used for searching for authoritative domain names for a task.

Example Generation Prompt

You are given a description of a task from the field of [FIELD] by an expert. Generate a concrete example of all the Input Sections and Output Sections listed for the given TASK DESCRIPTION. The example should resemble a real example that is written by an expert in the field, and should be highly technical and detailed.

Further instructions:

- You are also given CONTEXT in the form of Passages from web documents and will need to generate an example based on this CONTEXT. Make sure to generate the example based on the provided CONTEXT. If the CONTEXT is insufficient, you can say "The context is insufficient".
- Make sure the length of each section matches the required length and the section headers are exactly the same.
- The example should be highly detailed, and not be generic and vague.

====CONTEXT====

[CONTEXT]

====TASK DESCRIPTION====

[TASK DESCRIPTION]

====EXAMPLE====

Table 13: Prompt used for generating initial examples for a task.

Critique Generation Prompt

You are an expert in the field of [FIELD]. You are given a task description of a writing task from your field and an imperfect example for this task, where an example is a concrete sample of the task. You need to describe what is lacking in the example for the task. You are given a list of properties based on which you should critique the example:

- * Inconsistencies: Are there any inconsistencies in the information provided across the input and output?
- * Factual Inaccuracies: Are there any factual inaccuracies in the information presented in the input or how the output is inferred?
- * Structure: Are there any issues with how closely the example follows the instructions specified in the task description? This includes information requested in the task but missing in the example, or mismatch in the length required for a section.
- * Depth: How could the example benefit from more detail? Note that the example should resemble what an expert might write and so it should not be vague with details.

====TASK DESCRIPTION====

[TASK DESCRIPTION]

====EXAMPLE====

[EXAMPLE]

====Critique====

Table 14: Prompt used for generating critiques for model-generated examples.

Output Generation Prompt

You need to perform a writing task from the field of [FIELD]. You are given (1) a task description which contains input and output sections, and (2) an example input for this task, which is a sample of the input sections of the task with concrete details. You need to generate the output sections for the given example input.

- Make sure the length of each output section matches the required length and the section headers are exactly the same.
- Make sure the output follows the structure of the output sections in the task description, is factually accurate and detailed.

====TASK DESCRIPTION====

[TASK DESCRIPTION]

====EXAMPLE INPUT====

[EXAMPLE INPUT]

====EXAMPLE OUTPUT====

Table 15: Prompt used for generating outputs from candidate models for evaluation.

LM-based Evaluation Prompt

You are an expert in the field of [FIELD]. You are given a task description of a writing task from your field. For this task description, you are given an input example, which is a concrete sample of the input sections of this task, as well as the reference output, which is the gold standard output for this input. You will be given two candidate outputs for the input example and you need to judge which output is better by comparing it to the reference output.

First, you should say "##output 1##" if output 1 is better, "##output 2##" if output 2 is better and "##same##", if the two outputs are equivalent in quality (note the stars). Then you should explain why you picked this output.

Important: Keep in mind that longer outputs are not necessarily better quality outputs. Being concise is a good quality for outputs.

====TASK DESCRIPTION====

[TASK DESCRIPTION]

====INPUT EXAMPLE====

[EXAMPLE INPUT]

====REFERENCE OUTPUT====

[REFERENCE OUTPUT]

====EXAMPLE OUTPUT 1====

[EXAMPLE OUTPUT 1]

====EXAMPLE OUTPUT 2====

[EXAMPLE OUTPUT 2]

====Decision====

Table 16: Prompt used for generating LM-based judgements.