Cross-Task Generalization
via Natural Language Crowdsourcing Instructions

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Abstract

Humans (e.g., crowdworkers) have a remarkable ability in solving different tasks, by simply reading textual *instructions* that define them and looking at a few examples. Despite the success of the conventional supervised learning on individual datasets, such models often struggle with generalization across tasks (e.g., a question-answering system cannot solve classification tasks). A long-standing challenge in AI is to build a model that learns a new task by understanding the human-readable *instructions* that define it. To study this, we introduce NATURAL INSTRUCTIONS, a dataset of 61 distinct tasks, their human-authored instructions, and $193k$ task instances (input-output pairs). The instructions are obtained from crowdsourcing instructions used to create existing NLP datasets and mapped to a unified schema. Using this meta-dataset, we measure cross-task generalization by training models on *seen* tasks and measuring generalization to the remaining *unseen* ones. We adopt generative pre-trained language models to encode task-specific instructions along with input and generate task output. Our results indicate that models *benefit from instructions* when evaluated in terms of generalization to unseen tasks (19% better for models utilizing instructions). These models, however, are far behind an estimated performance upperbound, indicating significant room for more progress in this direction.[1]

1 Introduction

We have witnessed great progress in solving many NLP datasets through fine-tuning pre-trained language models (LMs) (Peters et al., 2018; Brown et al., 2020). More recent studies show tremendous promise in generalization *within* the set of observed tasks through multi-task training and unified encoding (Khashabi et al., 2020; Aghajanyan et al.,
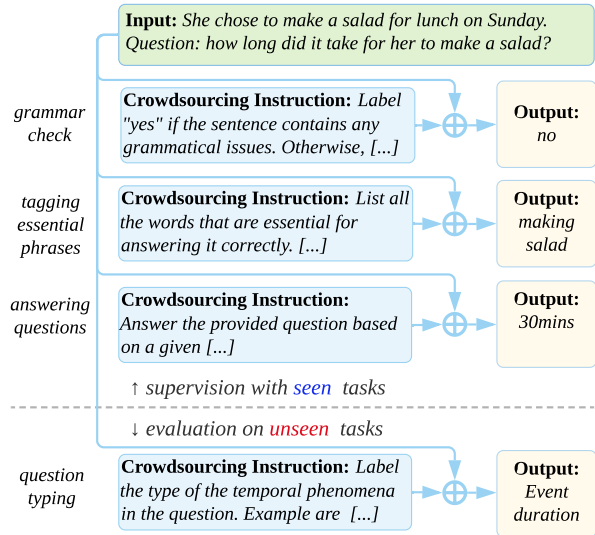

Figure 1: We construct the NATURAL INSTRUCTIONS dataset from crowdsourcing instructions and instances of different NLP datasets. We study if models can learn from *seen* tasks and generalize to *unseen* tasks given their natural crowdsourcing instructions.

2021). However, cross-task generalization – *generalization* to *unseen* tasks – has generally remained under-explored. For example, can we supervise a model with instances of grammar checking or question answering tasks, yet expect it to solve a different task like question typing (Fig.1). Evidently, humans are capable of such generalizations; an average human can follow natural language *instructions* to solve a variety of problems, as evident by the success of crowdsourcing platforms (also argued in Efrat and Levy (2020)). In this paper, we study if models can generalize to *unseen* tasks given their crowdsourcing instructions (Fig.1).

We build NATURAL INSTRUCTIONS, a dataset consisting of *natural* crowdsourcing instructions for various tasks and their instances. Training on *seen* tasks $\mathcal{T}_{seen}$ in our dataset, we build a model that learns to follow natural instructions that define a task and perform tasks (i.e., mapping input to output). Testing on *unseen* tasks $\mathcal{T}_{unseen}$, we evaluate if the model can perform *unseen* tasks solely from

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*Work done while interning at Allen Institute for AI.

[1]Dataset is available at `https://instructions.apps.allenai.org`

Task	Instance-Level Generalization	Task-Level Generalization
Training data	$X^{\text{train}}, Y^{\text{train}}$	$(I_t, X_t^{\text{train}}, Y_t^{\text{train}})$ $t \in \mathcal{T}_{\text{seen}}$
Evaluation	$x \to y$ where: $(x,y) \in (X^{\text{test}}, Y^{\text{test}})$	$(x, I_t) \to y$ where: $(x,y) \in (X_t^{\text{test}}, Y_t^{\text{test}})$ $t \in \mathcal{T}_{\text{unseen}}$

(a) A comparison of *task* vs *instance*-level generalization I_t, X_t and Y_t indicate natural language instructions, input, and output sets respectively for task t. In the conventional setup, training and evaluation are done on the instances of the same task. However, in task-level generalization, a model is expected to generalize to unseen tasks, where $\mathcal{T}_{\text{unseen}} \cap \mathcal{T}_{\text{seen}} = \varnothing$.
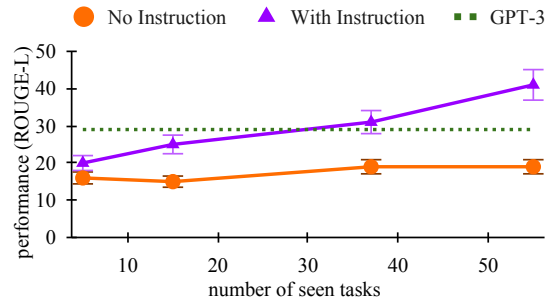
(b) BART evaluation on *unseen* tasks (y-axis is perf. on $\mathcal{T}_{\text{unseen}}$) when supervised with *seen* tasks (x-axis is $|\mathcal{T}_{\text{seen}}|$). A model using instructions (I_t) consistently improves with more observed tasks. In contrast, models with no access to the instructions show no sign of improved generalization. Details in §6.3.

Figure 2: The formal definition of generalization to unseen tasks (a) and a summary of its empirical outcome (b).

their instructions and without any task-specific labeled data (Table 2a; right). In contrast to the instance-level generalization (Table 2a; left), our model uses instruction as additional input, and evaluations are done on tasks that were not observed in the training stage.

We compile NATURAL INSTRUCTIONS from task instructions written by researchers for crowdsourcing existing NLP datasets. Such crowdsourcing instructions often elaborate a variety of details about how a task should (and should not) be done. To provide a systematic study of various elements of crowdsourcing instructions, we map them to a unified *schema* to cover the most important elements of task descriptions — such as definition, constraints, positive and negative examples. We collect tasks in NATURAL INSTRUCTIONS as minimal stand-alone steps provided to crowdworkers to complete a downstream NLP task. For example, tasks collected from QASC (Khot et al., 2020) include sub-tasks about generating topic words or combining facts, as well as answering multi-hop questions. Therefore our dataset not only contains typical downstream tasks in NLP, but also the intermediate subtasks that are not well-represented in the common benchmarks. The unified schema and the collection of minimal subtasks enable training LMs that can generalize across different tasks by learning from instructions. In total, our dataset consists of 61 distinct NLP tasks and $193k$ instances.

Our experimental results indicate that LMs learn to leverage natural language instructions as they show improved generalization to new tasks. For example, a BART (Lewis et al., 2019) achieves a 19% gain in terms of cross-task generalization compared to a model not using instructions (§6).

Importantly, LMs can generalize better to unseen tasks if they observe more tasks in training (Fig.2b). This upward trajectory suggests the potential for stronger cross-task generalizable models upon scaling up the diversity of tasks represented in a meta-dataset of task instructions. Despite the benefits of instructions, we observe a sizable gap between models' generalization and their estimated upper-bounds (6.4), encouraging the community to work on this challenging problem.

Contributions: In summary, the contributions of this work are as follows: (a) we introduce NATURAL INSTRUCTIONS, a dataset of human-authored instructions curated from existing well-known datasets mapped to a unified schema, providing training and evaluation data for learning from instructions; (b) we build models that can encode instructions and show: (b.1) the benefit of cross-task generalization by leveraging instructions; (b.2) the importance of different elements of instructions in the performance; (b.3) noteworthy headroom for improvement on our benchmark, which hopefully will motivate further work in this direction.

2 Related Works

Learning from instructions. There is recent literature on the extent to which models follow language instructions (Hase and Bansal, 2021; Ye and Ren, 2021; Gupta et al., 2021; Zhong et al., 2021). For example, Efrat and Levy (2020) examine if language models can follow crowdsourcing instructions with no further training. On the contrary, our work is pursuing a fundamentally different goal: creating a dataset of crowdsourcing instructions and task instances and formulating cross-task generalization by training models on seen tasks and

measuring generalization to the remaining unseen ones. Weller et al. (2020) construct a crowdsourced dataset with short question-like task descriptions. Compared to this work, our instructions are longer, more complex and natural since they were used to collect datasets through crowdsourcing.

PromptSource and FLAN (Wei et al., 2022; Sanh et al., 2022) are two concurrent works that pursue a similar goal as ours. A key difference between our work to these works is in terms of data collection strategy. Our work uses natural instructions created by NLP researchers before the dataset instances were created by crowd workers, and hence it contains the complete definition of each task (definition, things to avoid, negative examples, etc.). On the other hand, instructions in the concurrent work are collected retroactively based on the already-available task instances. Our *natural* instructions enable evaluating models on how they learn tasks given different elements of task descriptions. (See §A.5 for further comparisons.) Nevertheless, we believe that all these approaches to constructing instructions and task categories are complementary and the community will benefit from considering both towards solving the challenging problem of cross-task generalization.

Prompt engineering. Constructing effective discrete prompts for language models to perform NLP tasks is an active area of research (Schick and Schütze, 2021; Reynolds and McDonell, 2021; Liu et al., 2021). Such prompts are often extremely short and may not include a complete definition of complex tasks. In contrast, our instructions encode detailed instructions as they were used to collect the datasets. Moreover, the goals are different: Most prompt-engineering approaches seek prompts with higher performance on a particular task, typically through assumptions about their target task which make them non-trivial to generalize to any other task. However, our introduced meta dataset enables the measurement of generalization to unseen tasks.

Beyond standard multi-task learning. Multi-task learning is a long-standing goal for AI (Caruana, 1997) and has led to successful models that can support a wider range of tasks (McCann et al., 2018; Raffel et al., 2020; Khashabi et al., 2020; Mishra et al., 2020; Aghajanyan et al., 2021; Ye et al., 2021). Most of the conventional setups in the multi-tasking literature evaluate on instances that belong to the tasks that are seen, i.e., their labeled instances were observed during training (1st column of Table 2a). We augment this setup by introducing natural language instructions which enable our models to bridge to tasks that were not seen during training.

3 Defining Cross-Task Generalization

Here we formally define the problem setup for generalization across tasks. Each task t consists of input/output instances (X_t, Y_t) and is described in terms of its natural language instructions I_t.

Task-specific models. Standard supervised learning algorithms use task-specific labeled instances to learn a mapping from input x to output y: $M(x) = y$ for $(x, y) \in (X_t^{\text{train}}, Y_t^{\text{train}})$ and is evaluated on the test instances of the same (or similar) task $(X_t^{\text{test}}, Y_t^{\text{test}})$. We refer to this as the *instance-level* generalization (Table 2a; left).

Cross-task models. In this setup, the goal is to learn a model M that at inference obtains the output y given the input x and the task instruction I_t: $M(I_t, x) = y$, for $(x, y) \in (X_t, Y_t)$. In contrast to the task-specific models, no task-specific training data is used to learn the mapping M. We collect NATURAL INSTRUCTIONS (§4) to study this question: can a model be trained to follow instructions via training tasks $\mathcal{T}_{\text{seen}}$ and be generalized to follow instructions for a task $t' \in \mathcal{T}_{\text{unseen}}$. We refer to this as a *task*-level generalization (Table 2a; right).

4 NATURAL INSTRUCTIONS

NATURAL INSTRUCTIONS consists of instructions that describe a task (e.g., question answering) and instances of that task (e.g., answers extracted for a given question). Fig.3 shows an example instruction for the task of 'generating questions that require an understanding of event duration' accompanied with positive and negative examples that contextualize the task. Here we introduce a schema for representing instructions (§4.1) and then describe how existing datasets (their crowdsourcing templates) are mapped into our schema (§4.2).

4.1 Instruction Schema

Instructions used in crowdsourcing various datasets, are written by distinct authors for different purposes, and they are different in a variety of ways (see Appendix A.2 for their differences.) We introduce a unified schema (Fig.4) to consistently represent these diverse forms of instructions. Our instruction schema is the result of our pilot

Instructions for MC-TACO question generation task

• **Title:** Writing questions that involve commonsense understanding of "event duration".
• **Definition:** In this task, we ask you to write a question that involves "event duration", based on a given sentence. Here, event duration is defined as the understanding of how long events typically last. For example, "brushing teeth", usually takes few minutes.
• **Emphasis & Caution:** The written questions are not required to have a single correct answer.
• **Things to avoid:** Don't create questions which have explicit mentions of answers in text. Instead, it has to be implied from what is given. In other words, we want you to use "instinct" or "common sense".

Positive Example

• **Input:** Sentence: Jack played basketball after school, after which he was very tired.
• **Output:** How long did Jack play basketball?
• **Reason:** the question asks about the duration of an event; therefore it's a temporal event duration question.

Negative Example

• **Input:** Sentence: He spent two hours on his homework.
• **Output:** How long did he do his homework?
• **Reason:** We DO NOT want this question as the answer is directly mentioned in the text.
• **Suggestion:** -

• **Prompt:** Ask a question on "event duration" based on the provided sentence.

Example task instances

Instance

• **Input:** Sentence: It's hail crackled across the comm, and Tara spun to retake her seat at the helm.
• **Expected Output:** How long was the storm?

⋮

Instance

• **Input:** Sentence: During breakfast one morning, he seemed lost in thought and ignored his food.
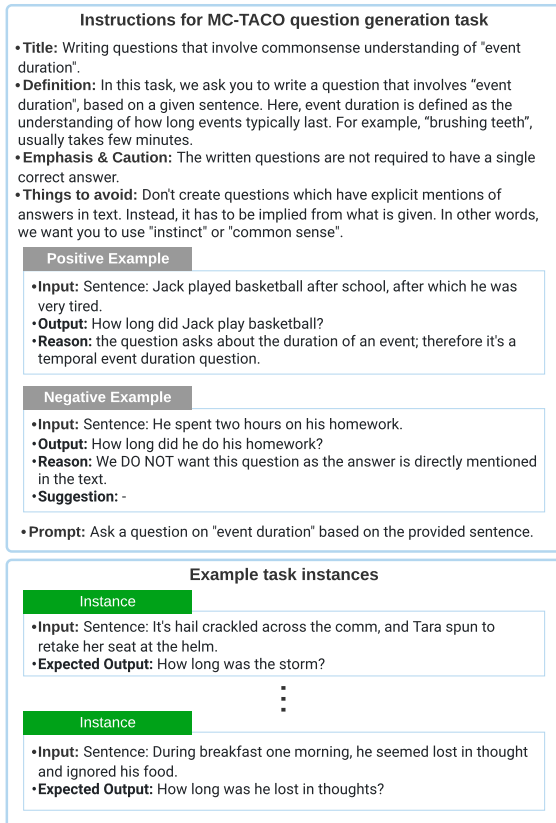• **Expected Output:** How long was he lost in thoughts?

Figure 3: An example from our dataset. Note that it follows the schema provided in Fig.4. See Fig .11 for more examples.

study conducted on a subset of datasets. Below we describe the ingredients of this schema:

• TITLE provides a high-level description of a task and its associated skill (such as question generation, answer generation).

• PROMPT is a single sentence command that often appears before the input instance and connects it to the instructions.

• DEFINITION provides the core detailed instructions for a task.

• THINGS TO AVOID contain instructions regarding undesirable annotations that must be avoided. These help to define the scope of a task and the space of acceptable responses.

• EMPHASIS AND CAUTION are short, but important statements highlighted in the crowdsourcing templates which were intended to be emphasized or warned against.

• POSITIVE EXAMPLES contain inputs/outputs similar to the input given to a worker/system and its expected output, helping crowdworkers better understand a task (Ali, 1981).
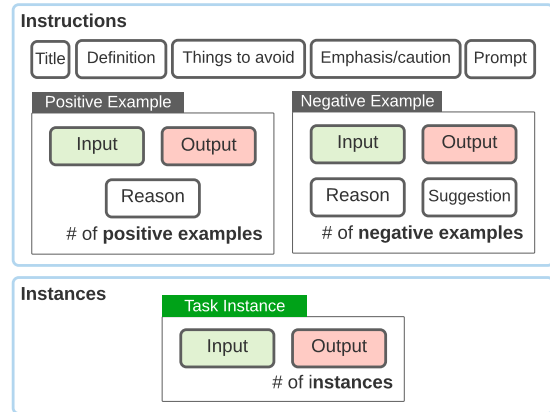
• NEGATIVE EXAMPLES contain inputs/outputs

Figure 4: The schema used for representing instruction in NATURAL INSTRUCTIONS (§4.1), shown in plate notation.

to emphasize THINGS TO AVOID by providing examples that must not be produced.

• REASON provides explanations behind why an example is positive or negative.

• SUGGESTION contains suggestions on how a negative example could be modified to turn it into a positive example.

The next section describes the process of mapping the raw instructions (designed for crowdworkers) to our instruction schema.

4.2 Constructing NATURAL INSTRUCTIONS

4.2.1 Collecting Data

Collecting raw instructions and instances. We use existing, widely adopted NLP benchmarks that are collected via crowdsourcing platforms and hence, come with crowdsourcing templates. In the first step, we identified several datasets and engaged with their authors to get their crowdsourcing templates and raw data. This yields the following datasets: CosmosQA (Huang et al., 2019), DROP (Dua et al., 2019), Essential-Terms (Khashabi et al., 2017), MCTACO (Zhou et al., 2019), MultiRC (Khashabi et al., 2018), QASC (Khot et al., 2020), Quoref (Dasigi et al., 2019), ROPES (Lin et al., 2019) and Winogrande (Sakaguchi et al., 2020).[2]

Splitting crowdsourcing instructions into minimal tasks. Almost all the crowdworking instructions include sequences of steps to guide crowdworkers in creating task instances. For example, QASC and MCTACO include 7 and 19 steps in the data creation process, respectively. We divide

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[2]We only focus on textual instructions and avoid datasets that involve visual or auditory steps, mostly focusing on QA datasets that were available to the authors.

source dataset	task
Quoref (Dasigi et al., 2019)	question generation answer generation
QASC (Khot et al., 2020)	topic word generation fact generation combining facts question generation answer generation incorrect answer generation

Table 1: Examples of the datasets and the tasks formed from them. The extracted tasks are independent annotation assignments in the crowdsourcing templates of the datasets. The complete list is in Table 10 in Appendix.

category	# of tasks	# of instances
question generation	13	38k
answer generation	16	53k
classification	12	36k
incorrect answer generation	8	18k
minimal modification	10	39k
verification	2	9k
Total	61	193k

Table 2: Task categories and their statistics.

crowdsourcing instructions into their underlying steps and generate multiple subtasks that are minimal and standalone.[3] Table 1 shows subtasks extracted for Quoref and QASC. For example, the main task in Quoref is to answer a question given a context paragraph, but the crowdsourcing template consists of two sub-tasks of *question generation* and *answer generation* with their separate instructions. This process results in a more consistent definition of tasks, enabling a successful mapping of instructions into our schema, in contrast to the work of Efrat and Levy (2020) that uses crowdsourcing instructions as-is.

In total, there are 61 tasks, which are categorized into 6 semantic categories (Table 2). We assigned these broad categories to the tasks to understand their collective behavior in the experiments. It is noteworthy that, despite the apparent resemblance of the tasks included in the same category, any pair of tasks are distinct. For example, while *question generation* is part of Quoref, CosmosQA, and QASC, each has its own separate variant of the question generation task (see Fig.10 in Appendix).

4.2.2 Mapping Raw Instructions to Schema

We manually fill in the fields of our instruction schema with the content from the crowdsourcing

instructions. For instance, parts of the raw instructions that are highlighted for emphasis are incorporated as part of our *emphasis/caution* field. The modifications suggested in this step were applied by one author and were verified by another author.[4]

Improving description quality and consistency. We edit raw instructions to ensure their quality. Particularly, we fix writing issues (typos, ambiguities, etc.) and redact repetitions. While repetition often helps in augmenting human understanding, short and concise instructions are often more effective for computers due to their limited attention span (Beltagy et al., 2020).

Augmenting examples and reasons. There is a large variance in the number of examples provided in the raw instructions. Instructions often include more positive examples, or some instructions do not include any negative examples (e.g., QASC). Whenever possible, we add negative examples such that each task has at least two negative examples. Furthermore, not all raw instructions contain REASONS or SUGGESTIONS for each of their examples. For example, positive examples are usually not accompanied by explanations, and most datasets do not include suggestions. We add them, wherever such information is missing in the instructions.

Collecting input/output instances for subtasks. Most of our tasks are the intermediate steps in the crowdsourcing process. Therefore, to extract input/output instances for each task, we need to parse the raw annotations of crowdworkers for every step. Since each dataset stores its annotations in a slightly different format, extracting and unifying such intermediate annotations can be non-trivial.

Verification. An annotator verified the quality of the resulting data in consultation with dataset authors. The annotator iterated on the authors' feedback (avg of 3 iters) until they were satisfied.

Quality assessment. We ask independent human annotators to answer 240 random instances (20 instances from 12 random tasks, used later for our evaluation §5.1). The subsequent evaluation of the human-generated responses results in more than 96% accuracy, which indicates that humans can effortlessly understand and execute our instructions.

4.2.3 NATURAL INSTRUCTIONS Statistics

In summary, NATURAL INSTRUCTIONS consists of subtasks each with a set of instructions and in-

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[3]We eliminate tasks that involve model-in-the-loop.

[4]On average, the process of data curation for each task takes around 5 hrs-34 hrs (details in Appendix; Table 9).

put/output instances (Fig.3 and 4). The complete list of instructions is included in the appendix. In total, the dataset includes 61 tasks and 193k instances. Table 2 shows data statistics for each task category.[5] On average, instructions contain 4.9 positive examples and 2.2 negative examples. The longest element of instructions is usually DEFINITIONS with 65.5 tokens and the shortest is TITLE with 8.3 tokens (more statistics in Table 3).

statistic	value
"title" length	8.3 tokens
"prompt" length	12.6 tokens
"definition" length	65.5 tokens
"things to avoid" length	24.1 tokens
"emphasis/caution" length	45.0 tokens
"reason" length	24.9 tokens
"suggestion" length	19.6 tokens
num of positive examples	4.9
num of negative examples	2.2

Table 3: Statistics of NATURAL INSTRUCTIONS

5 Problem Setup and Models

Here we define different cross-task generalization settings (§5.1) and the models (§5.2).

5.1 Task Splits and Generalizations Types

Random split. This setup follows the common practice in benchmarking NLP models with random data splits. Here, two tasks from each task category (Table 2) in NATURAL INSTRUCTIONS are randomly selected for evaluation, and the rest of the tasks are used for training. This leads to 12 tasks in $\mathcal{T}_{\text{unseen}}$ and 49 tasks in $\mathcal{T}_{\text{seen}}$.[6]

Leave-one-out generalization. To better understand the nature of cross-task generalization, we study more restrictive settings of dividing training and evaluation tasks.

leave-one-category: evaluates how well a model generalizes to a task category if it is trained on others – no task of that category is in $\mathcal{T}_{\text{seen}}$.

leave-one-dataset: evaluates how well a model can generalize to all tasks in a particular dataset if it is trained on all other tasks – no task of that dataset is in $\mathcal{T}_{\text{seen}}$. This split prevents any leakage across tasks that belong to the same source datasets.

```
Prompt : I_t^prompt
Definition : I_t^Definition
Things to Avoid : I_t^avoid.
Emphasis&Caution : I_t^emph.
NegativeExample1—
      input : I_t^pos. ex., output : I_t^pos. ex., reason : I_t^pos. ex.
PositiveExample1—
      input : I_t^pos. ex., output : I_t^pos. ex. reason : I_t^pos. ex.
input : x, output :"
```

Figure 5: Encoding instruction I_t, where I_t^c refers to the text of a component c in the instruction schema.

leave-one-task: evaluates how well a model can learn a single task by training on all other tasks.

5.2 Models

We build models using pre-trained LMs with encoder-decoder architectures BART (Lewis et al., 2019) for fine-tuning and GPT3 (Brown et al., 2020) for few-shot experiments.

Encoding instructions and instances. For every problem setup, we map a given instruction I_t and an input instance x into a textual format and decode an output y and obtain $enc(I_t, x)$. This encoding function is then fed to an encoder-decoder model to predict y: $M : enc(I_t, x) \rightarrow y$.

Encoding instances follows a standard NLP paradigm of mapping an input instance to text. Each instruction I_t consists of multiple elements as described in our instruction schema (§4.1). Here, we map each element of the instruction to a textual format and append it before the input instance. Fig.5 shows how we encode the full instruction.

To study the impact of each instruction element for cross-task generalization, we compare these encodings: (1) PROMPT, (2) POS. EXAMPLES, (3) PROMPT + DEFINITION, (4) PROMPT + THINGS TO AVOID, (5) PROMPT + EMPHASIS , (6) PROMPT + POS. EXAMPLES, (7) PROMPT + + DEFINITION + POS. EXAMPLES, and (8) FULL INSTRUCTION. Each of these (e.g., PROMPT and POS. EXAMPLES) correspond to prompting setups in the recent literature (Le Scao and Rush, 2021; Lu et al., 2021).

BART. We use BART (base) (Lewis et al., 2019) which allows us to fine-tune its model parameters. This is an encoder-decoder architecture with $140m$ parameters. For each setup, the input is encoded

model ↓	evaluation set $\mathcal{T}_{\text{unseen}} \rightarrow$	random split of tasks	leave-one-category (QG)	leave-one-dataset (QASC)	leave-one-task (QASC QG)
BART (fine-Tuned)	NO INSTRUCTIONS	13	6	37	20
	FULL INSTRUCTIONS	**32**	**17**	**51**	**56**
GPT3 (not fine-tuned)	FULL INSTRUCTIONS	24	33	22	33

Table 4: Cross-task generalization of BART under various splits (§5.1). Fine-tuned BART shows improved performance when provided with instructions. It also archives better performance than GPT3, despite being over $1k$ times smaller. All numbers are ROUGE-L.

using different instruction elements, trained on all $\mathcal{T}_{\text{seen}}$ tasks, and evaluated on $\mathcal{T}_{\text{unseen}}$ (§5.1).

GPT3. As a comparison, we evaluate GPT3 (Brown et al., 2020) which is a $175B$ parameter autoregressive LM ($\times 1.2k$ larger than BART) and has shown promising results in mimicking demonstrations provided in its prompt. We cannot fine-tune the parameters of this massive model and use it as-is under its default setting on the evaluation tasks in $\mathcal{T}_{\text{unseen}}$ (§5.1) using the encoding introduced earlier.

6 Experiments

Evaluation metrics. We treat all of our tasks as text generation problems and evaluate them with automated evaluation metrics for text generation. In particular, we use ROUGE-L (Lin, 2004) to automatically evaluate the generated outputs.[7]

Implementation details. For BART, our models are trained for 3 epochs with a learning rate of 5e-5 for a given training split and input encoding. For GPT3, we use the `davinci-instruct` engine and produce outputs with greedy decoding, generating up to a maximum number of tokens of 16 (the default value). We use the default stop condition which is 2 newline tokens.[8]

6.1 Generalization Under Various Task Splits

Table 4 reports the results of the BART model train and evaluated with various task splits (§5.1). For comparison, we evaluate GPT3 which uses no fine-tuning, unlike BART that is fine-tuned with the $\mathcal{T}_{\text{seen}}$ tasks. The first column corresponds to random split of tasks, while the remaining columns report cross-task generalization results of the BART model under leave-one-x splits (§5.1). For $x =$ category, the tasks in *question-generation* category

are held out during training. For $x = \underline{\text{dataset}}$, the tasks that were extracted from the *QASC* dataset were excluded from training. For $x = \underline{\text{task}}$, we train a model on all tasks, except *QASC question generation* task which is used for evaluation.

Instructions benefit cross-task generalization. The results indicate that BART benefits from instructions in generalizing to new tasks, regardless of task splits. For example, under random split, the model using FULL INSTRUCTIONS results in +19% gains over a model that is not using instructions. This is particularly interesting for leave-one-category-out split since the trained model can generalize to the tasks of a particular semantic category, without being exposed to it. In comparison to GPT3, the fine-tuned BART model that utilizes instructions achieves a stronger performance despite being $\times 1k$ smaller than GPT3. For example, a BART models using FULL INSTRUCTIONS achieves 8% higher performance than GPT3 under random split of tasks.

Note that the absolute values in leave-one-category are lower due to the difficulty of this setup compared to, for example, the random split setup. While all settings involve evaluating on tasks not seen during training, the leave-one-category setting enforces more dissimilarity among training and evaluation tasks.

6.2 Generalization Under Instruction Encoding and Task Categories

Table 5 reports the results of the BART model per encodings of different instruction elements (§5.2) and for different task categories. The table shows that encoding more elements of the instructions generally achieves better results than just using PROMPT or POSITIVE EXAMPLES. It additionally shows that the benefit of the instruction elements seems to depend on the target task category. We observe that the *question-generation* (QG) tasks benefit the most from POSITIVE EXAMPLES, whereas in *classification* (CF), POSITIVE EXAMPLES are of

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[7]Our experiments show that other metrics, e.g. BLEURT (Sellam et al., 2020) are also correlated with ROUGE-L, which has also been used in generative QA tasks.

[8]The relevant code is available at: https://github.com/allenai/natural-instructions-v1

model ↓	task category →	QG	AG	CF	IAG	MM	VF	avg
	NO INSTRUCTION	26	6	0	21	33	7	13
BART (fine-tuned)	PROMPT	27	22	7	22	34	**9**	20
	+DEFINITION	35	24	50	25	36	7	30↑ (+50)
	+THINGS TO AVOID	33	24	4	24	**58**	9	25↑ (+25)
	+EMPHASIS	38	23	16	**26**	49	3	26↑ (+30)
	+POS. EXAMPLES	53	22	14	25	17	7	23↑ (+15)
	+DEFINITION+POS. EXAMPLES	51	23	**56**	25	37	6	33↑ (+65)
	POS. EXAMP.	**55**	6	18	25	8	6	20
	FULL INSTRUCTION	46	**25**	52	25	35	7	32↑ (+60)
GPT3 (not fine-tuned)	FULL INSTRUCTION	33	18	8	12	60	11	24 (+11)

Table 5: Cross-task generalization under random split (§5.1). Models show improved results when provided with instructions. The numbers in parenthesis indicate absolute gains compared to 'NO INSTRUCTIONS' baseline. Fine-tuned BART archives better performance than GPT3, despite being over $1k$ times smaller. Category names: QG: Question Generation, AG: Answer Generation, CF: Classification, IAG: Incorrect Answer Generation, MM: Minimal Text Modification, VF: Verification. All numbers are ROUGE-L (in percentage).

little help. We hypothesis this is because it is easier to mimic question-generation based on a few examples, whereas it is difficult to define classes via a few examples, where DEFINITION can be more helpful. The models show little improvement in *verification* (VF). We hypothesize these tasks are inherently more difficult, partially because of their distinctness from the rest of the tasks in the dataset. We hope future work on this line will study a wider variety of tasks and will improve our understanding of such failure cases.

6.3 Generalization vs. Number of Seen Tasks

Fig.2b compares the impact of the number of seen tasks for cross-task generalization. For supervision, we randomly sample a few tasks as $\mathcal{T}_{\text{seen}}$ and evaluate on 6 tasks (one from each category). (each point in the figure is averaged over 5 random subsamples.) The results show that with NO-INSTRUCTION encoding there is no tangible value in observing more tasks. In contrast, the generalization of the models that encode instructions improves with observing more tasks. This is an exciting observation since it suggests that scaling up our dataset to more tasks may lead to stronger instruction-following systems.

6.4 Analyses

Upperbound: Task-specific Models. For each task, we obtain a task-specific model (§ 3) by training BART separately on each task's annotated training data. We evaluate these task-specific models to obtain a loose estimate of *upperbounds* for each task. On average, task-specific models score

Model ↓	Split ↓	w/ neg. examples	w/o neg. examples
BART	random	32	**35**
	leave-one-x		
	↳ x = category (AG)	19	**21**
	↳ x = dataset (Quoref)	37	37
	↳ x = task (QASC QG)	56	**57**
GPT3	-	24	**44**

Table 6: Effect of excluding negative examples from FULL INSTRUCTION encoding. Negative instructions are surprisingly difficult for the models to learn from.

66% which is considerably higher than our models' best generalization (32%; Table 4). This indicates that there is considerable room for improving generalization-based models that use instructions.

Impact of Negative Examples. Crowdsourcing instructions often include negative examples to exemplify undesirable responses. We study how negative examples in instructions affect cross-task generalization. Our cases study (Table 6) indicates that the models work better *without* (w/o) negative examples, contrary to the previously-observed benefits of other instructional elements (e.g., definition, positive examples). This is aligned with the previous studies (Xuan et al., 2020; Lin et al., 2003) that discuss the challenges of learning from negative examples. Interestingly, GPT3's drop (44 vs 24) is more significant than BART (35 vs 32), showing that BART can partly recover through the training step.

Error Analysis. We randomly sample 30 erroneous predictions of our fine-tuned BART on 3 distinct tasks (Winogrande answer generation; QASC

Category	Helpful Fields	Explanation
Question Generation (QG)	1. DEFINITION 2. EMPHASIS & CAUTION 3. POSITIVE EXAMPLES 4. NEGATIVE EXAMPLES	- Provides a holistic picture of the task. - Provides key information for solving the task. - This gives an idea of what is expected in the output. - Good to know the common mistakes people do.
Answer Generation (AG)	1. PROMPT 2. DEFINITION 3. POSITIVE EXAMPLES	- It limits the exploration space to question spans. - Provides a general understanding of the task. - Reason field is very helpful.
Classification (CF)	1. DEFINITION	- The task is unclear without this field.
Incorrect Answer Generation (IAG)	1. DEFINITION 2. EMPHASIS & CAUTION 3. POSITIVE EXAMPLES	- Helps understand the utility of such a task. - Source of some useful shortcuts. - Helps in understanding the type of questions asked.
Minimal Text Modification (MM)	1. THINGS TO AVOID	- Provides critical information.
Verification (VF)	1. DEFINITION 2. THINGS TO AVOID 3. POSITIVE EXAMPLES 4. NEGATIVE EXAMPLES	- Makes the task easy to understand. - Contains useful tips required for this task. - Exemplifies task understanding. - Helps avoid potential mistakes.

Table 7: Results of humans' perceived importance of instruction elements. Our annotators, for example, find DEFINITION and THING TO AVOID to be helpful for *Classification* and *Minimal Text Modification* tasks, respectively.

question generation; MC-TACO incorrect answer generation). We categorize the errors into common patterns (Table 8).

error type	BART
Generates a nonsensical/vague question	47
Generate an invalid question	8
Generates a yes/no question	4
Copies the given fact or a subset of it	3
Generates unanswerable questions	3

Table 8: Percentage of errors on QASC QG task. The numbers do not sum to 100 since the error types are not mutually exclusive.

Unlike GPT3 which generally suffers from generating redundant content irrelevant to instructions, our BART model provides more control, however, it can fail to generate proper output. Here are several erroneous predictions from our model:

Generates a nonsensical/vague question
BART input:[...]input: Fact: graduations are used for measuring the volume of substances. output: ?
BART output: How many substances are there in volume?

Copies the given fact or a subset of it
BART input:[...] input: Fact: If someone is not breathing, begin with ventilation. output: ?
BART output: If someone is breathing, begin with ventilation.

Generates a yes/no question
BART input:[...] input: Fact: Lack of saliva hinders the break down of food into components the body can absorb. output: ?
BART output: Does saliva hinders the break down of food into components the body can absorb?

Perceived Impact of Instruction Elements.
We survey human annotators to find out the value of instruction elements to humans. Except for the negative examples which were shown to be difficult for models, we observe similar trends between

humans' perceived value of those elements (Table 7) and their contributions to the model performance (Table 5). For example, humans viewed DEFINITION and THINGS TO AVOID as necessary fields for *classification* and *minimal text modification* categories, respectively, which is compatible with our empirical observations (e.g., PROMPT + DEFINITION has the highest score on CF category in Table 5).

7 Conclusion

In this paper, we studied the goal of building models that generalize to new tasks by encoding and understanding crowdsourcing instructions. We introduced NATURAL INSTRUCTIONS, which is built based on existing crowdsourced datasets, that enables building such models and systematically evaluate them. To the best of our knowledge, this is the first work to show the benefit of instructions towards improved cross-task generalization. Additionally, we observe that our proposed task has a large room for improvement, which we believe will bring more attention to building stronger models that can generalize to a wider range of tasks.

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Supplemental Material

A Datasets and their Templates

A.1 Division of Crowdsourcing Instructions into Minimal Tasks

Fig. 9 shows an example of how a task is divided into multiple subtasks for the MC-TACO dataset. MC-TACO has five categories (Event Duration, Event Frequency etc.). Each category contributes to 2 subtasks one for question generation and one for answer generation.

Number of tasks in each dataset. Fig. 6 illustrates how the number of steps in the data creation process varies across the 6 datasets. QASC and MC-TACO contain a relatively higher number of steps in the data creation process in comparison to DROP, Quoref, CosmosQA, and Winogrande.
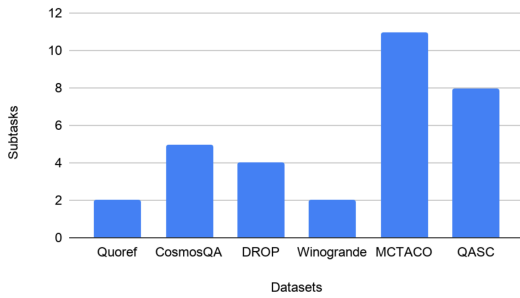
Figure 6: Variations in the number of subtasks

A.2 Analysis of Crowdsourcing Templates

We analyzed crowdsourcing templates of 6 datasets: CosmosQA (Huang et al., 2019), DROP (Dua et al., 2019), MC-TACO (Zhou et al., 2019), QASC (Khot et al., 2020), Quoref (Dasigi et al., 2019), and Winograe (Sakaguchi et al., 2020). Our intention behind the analysis is to identify similarities and differences across templates and subsequently decide regarding the collection of more templates.

Size of the instructions. We observe significant variation in size across the 6 datasets (Fig. 8). In the case of QASC, the instruction size associated with each step of the data creation process is very high, whereas for Winogrande, it is exactly the opposite– instruction size associated with each step of the data creation process is very low. Instead, the size of the common instruction (i.e., the instruction preceding the first step of the data creation process) is high in Winogrande; this is also seen for DROP. The major mode of instruction

varies across datasets. Examples and instructions associated with each step of data creation respectively take up the majority of space in Quoref and CosmosQA. MC-TACO relies on examples to explain the crowdsourcing task, while Winogrande and QASC depend mostly on common instructions and instructions associated with each step of the data creation process respectively, to explain the task to the crowdworker.

The number of positive/negative examples. Variation in the occurrence of POSITIVE and NEGATIVE Examples across datasets has been illustrated in Fig. 7. Only Winogrande provides an equal number of POSITIVE and NEGATIVE Examples. QASC instructions do not contain any NEGATIVE Examples. Overall, DROP instructions consist of a relatively higher number of examples than other datasets.
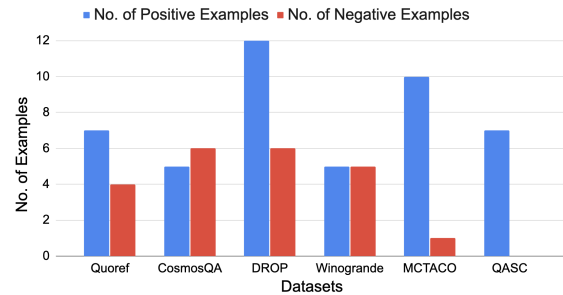
Figure 7: Variation in the number of positive and negative examples
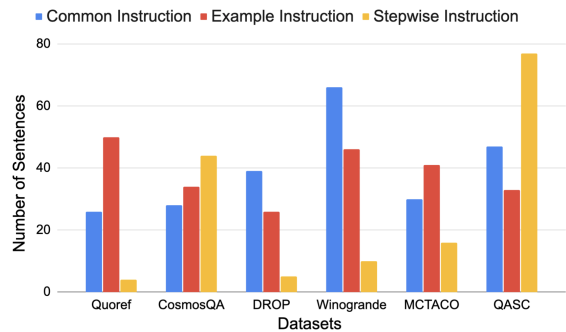
Figure 8: Variation in the number of sentences in the crowdsourcing instructions across datasets

Presence of reasons/suggestions in examples. All datasets except QASC contain both POSITIVE and NEGATIVE Examples. However, Quoref is the only dataset to provide REASONS for all the POSITIVE and NEGATIVE Examples. There are explanations associated with each of the NEGATIVE Examples, but the presence of explanations

Figure 9: Dividing a data creation task into multiple subtasks for the MC-TACO dataset.

associated with POSITIVE Examples varies across datasets. Finally, Quoref is the only dataset to provide SUGGESTIONS along with the REASONS associated with the NEGATIVE Examples.

A.3 Qualitative Analysis

Writing Style. There are significant variation in writing style across the datasets, even among those datasets that have the common a objective (e.g., DROP, Quoref and QASC). DROP instructions say *"There is an AI running in the background which will also try to answer the question. You won't be able to submit the question if the AI gives the same response."* The writing style in Quoref however is different: *"We also want you to avoid questions that can be answered correctly by someone without actually understanding the paragraph. ..."*

Information. We observe that sometimes instructions of a dataset contain information that is relevant to several other datasets, which do not contain similar instruction information. For example, Quoref, DROP and CosmosQA are datasets that are all based on reading comprehension tasks. CosmosQA contains a step in the data creation process asking users to skip passages containing inappropriate or offensive content. This information is also relevant to Quoref and DROP, but is not mentioned in their respective instructions.

Hardness. In a typical crowdsourcing task, certain tasks may be harder than the others, often these are the core tasks, e.g.: question generation, adversarial data creation, etc. Additional information, especially in the form of tips is always helpful in solving these hard tasks. Figure 10 illustrates that the task of question generation is stated differently in Quoref, CosmosQA, and QASC. QASC mentions an easy and detailed way to create questions, whereas CosmosQA mentions several different attributes of a good quality question. Knowing about the CosmosQA and QASC question generation processes may help with data creation for Quoref and

Figure 10: Variation in Task Specification: Quoref contains a single line instruction whereas the CosomosQA contains a detailed instruction. QASC on the other hand, contains examples along with instruction.

other such question generation tasks, where less additional information is provided regarding question creation.

A.4 Data Curation Effort

Table 9 shows the effort distribution in the data curation process of NATURAL INSTRUCTIONS. Step-8 which involves parsing instances is the main bottleneck in the data curation process. Table 10 shows the detailed structure of tasks in NATURAL INSTRUCTIONS. Fig. 11 shows examples of four different tasks in NATURAL INSTRUCTIONS.

step	task	time per task
1	Identify crowdsourced dataset and engage with their authors.	20-30 mins
2	Go through the template and understand the task.	10-15 mins
3	Manually fill fields in the schema with content from the template.	30-45 mins
4	Iterate over the instructions to ensure their clarity while eliminating the repeated content. Fix writing issue in examples, also typos etc.	2-3 hrs
5	Create negative examples if not present. Add the missing explanations to the examples.	1-2 hrs
6	Extract the input/output instances from raw crowdsourcing annotations.	0.5-24 hrs
7	Final inspections of the data to verify the data quality	0.25- 2hrs
	Overall	6-34 hrs

Table 9: Steps taken to curate each task in NATURAL INSTRUCTIONS and their estimated times.

question generation (from MC-TACO)

- **Title:** Writing questions that involve commonsense understanding of "event duration".
- **Definition:** In this task, we ask you to write a question that involves "event duration", based on a given sentence. Here, event duration is defined as the understanding of how long events typically last. For example, "brushing teeth", usually takes few minutes.
- **Emphasis & Caution:** The written questions are not required to have a single correct answer.
- **Things to avoid:** Don't create questions which have explicit mentions of answers in text. Instead, it has to be implied from what is given. In other words, we want you to use "instinct" or "common sense".

Positive Example

- **Input:** Sentence: Jack played basketball after school, after which he was very tired.
- **Output:** How long did Jack play basketball?
- **Reason:** the question asks about the duration of an event; therefore it's a temporal event duration question.

Negative Example

- **Input:** Sentence: He spent two hours on his homework.
- **Output:** How long did he do his homework?
- **Reason:** We DO NOT want this question as the answer is directly mentioned in the text.
- **Suggestion:** -

- **Prompt:** Ask a question on "event duration" based on the provided sentence.

Task Instance

- **Input:** Sentence: Still, Preetam vows to marry Nandini if she meets him again.
- **Expected Output:** How long had they known each other?

answer generation (from Winogrande)

- **Title:** Answering a fill in the blank question on objects
- **Definition:** You need to answer a given question containing a blank (_). Your answer must be one of the two objects mentioned in the question for example "trophy" and "suitcase".
- **Emphasis & Caution:** -
- **Things to avoid:** Your answer must not contain a word that is not present in the question.

Positive Example

- **Input:** Context word: fit. Question: The trophy doesn't fit into the brown suitcase because _ is too large.
- **Output:** trophy
- **Reason:** Answer is one of the objects ("trophy" and "suitcase") in the question. Since the blank is a "large" object that didn't fit the "suitcase", the answer must be "trophy".

Negative Example

- **Input:** Context word: fit. Question: The trophy doesn't fit into the brown suitcase because _ is too large.
- **Output:** bottle
- **Reason:** The issue is that the answer is not one of the objects present in the question which are "trophy" and "suitcase". Note that, a valid answer must be one of the objects present in the question.
- **Suggestion:** -

- **Prompt:** Answer a fill in the blank question that is based on a provided context word.

Task Instance

- **Input:** Context Word: Story. Question: After watching the movie Kelly began to work on her own story. The _ was for her research.
- **Expected Output:** movie

classification (from DROP)

- **Title:** Finding the answer type of a reasoning question
- **Definition:** This task involves annotating the answer type to a given question that involve some kind of complex reasoning (including numerical reasoning). Note that the questions require looking at more than one part of the passage to answer. There are 3 possible answer types (i) spans, (ii) numbers and (iii) dates. If the answer can be found in the passage, label it as "span". If the answer is a number, label as "number". Similarly, label "date" if you think the answer to the given question is a date.
- **Emphasis & Caution:** -
- **Things to avoid:** -

Positive Example

- **Input:** Passage: The outbreak of the Seven Years' War in Europe in 1756 resulted in renewed conflict between French and British forces in India. The Third Carnatic War spread beyond southern India and into Bengal where British forces captured the French settlement of Chandernagore in 1757. However, the war was decided in the south, where the British successfully defended Madras, and Sir Eyre Coote decisively defeated the French, commanded by Comte de Lally at the Battle of Wandiwash in 1760. After Wandiwash, the French capital of Pondicherry fell to the British in 1761. The war concluded with the signing of the Treaty of Paris in 1763, which returned Chandernagore [...] Question: Which french settlement did the British capture first, Chandernagore or Pondicherry?
- **Output:** Span
- **Reason:** The answer "Chandernagore" is a word from the passage. So, the answer type is "span".

Negative Example

-

- **Prompt:** What is the type of the answer corresponding to the given question? Number, Date, or Span?

Task Instance

- **Input:** Passage: Hoping to rebound from their loss to the Patriots, the Raiders stayed at home for a Week 16 duel with the Houston Texans. Oakland would get the early lead in the first quarter as quarterback JaMarcus Russell completed a 20-yard touchdown pass to rookie wide receiver Chaz Schilens. The Texans would respond with fullback Vonta Leach getting a 1-yard touchdown run, yet the Raiders would answer with kicker Sebastian Janikowski getting a 33-yard and a 30-yard field goal. Houston would tie the game in the second quarter with kicker Kris Brown getting a 53-yard and a 24-yard field goal. Oakland would take the lead in the third quarter [...] Question: How many field goals did Kris Brown kick?
- **Expected Output:** Number

minimal text modification (from Winogrande)

- **Title:** Modifying a fill in the blank question on persons
- **Definition:** You're given a fill-in-the-blank question where the answer is PersonX. You need to minimally change the given question so that the answer flips to PersonY. This task typically involves replacing one word i.e. the 'trigger word' by its antonym (e.g. changing from "sympathetic" to "stern").
- **Emphasis & Caution:** 1. Your question must contain at least 15 and at most 30 words. 2. Your question must have atleast 70% overlapping words with the given question 3. Your question must contain only one blank. 4. Make sure that PersonX and PersonY have the same gender. 6. In your question, PersonX and PersonY should be used only ONCE and PersonX should appear earlier than PersonY. [...]
- **Things to avoid:** 1. You should not change any content in the given question beyond a word or two i.e. the trigger word/phrase. [...]

Positive Example

- **Input:** Context word: upset. Question: PersonX yelled at PersonY because _ was so upset about the news. Answer: PersonX.
- **Output:** PersonX comforted at PersonY because _ was so upset about the news.
- **Reason:** On replacing the trigger word "yelled" by its antonym "comforted", the answer flips to PersonY which is as per the given instruction. So, this is a valid question.

Negative Example

- **Input:** Context word: step. Question: PersonX was always ahead of PersonY, as _ walked with a quick step. Answer: PersonX.
- **Output:** PersonY was always ahead of PersonY, as _ walked with a quick step.
- **Reason:** Here, the issue is that the usage order of PersonX and PersonY has been changed in the generated question. Remember that, for a question to be valid, PersonX should appear earlier than PersonY.
- **Suggestion:** -

- **Prompt:** What is the type of the answer corresponding to the given question? Number, Date, or Span?

task instance

- **Input:** Context Word: day. Question: PersonX learned new organizational skills from PersonY because _ 's day schedule was very chaotic. Answer: PersonX
- **Expected Output:** PersonX learned new organizational skills from PersonY because _ 's day schedule was very efficient.
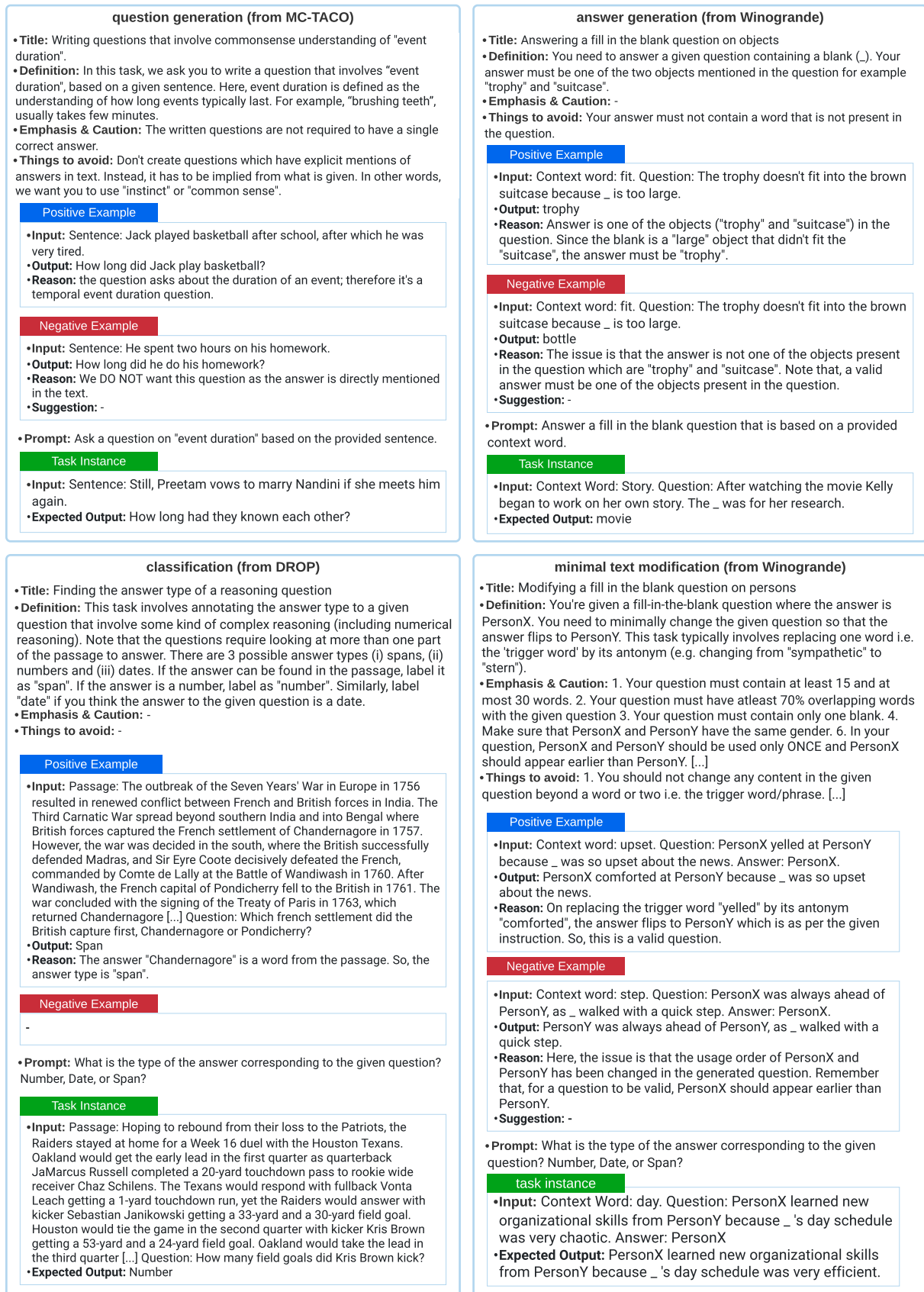
Figure 11: Examples from NATURAL INSTRUCTIONS. Each task follows the schema provided in Fig. 4.

task id	title	source dataset	task category
1	task001_quoref_question_generation	Quoref	Question Generation
2	task002_quoref_answer_generation	Quoref	Answer Generation
3	task003_mctaco_question_generation_event_duration	MC-TACO	Question Generation
4	task004_mctaco_answer_generation_event_duration	MC-TACO	Answer Generation
5	task005_mctaco_wrong_answer_generation_event_duration	MC-TACO	Incorrect Answer Generation
6	task006_mctaco_question_generation_transient_stationary	MC-TACO	Question Generation
7	task007_mctaco_answer_generation_transient_stationary	MC-TACO	Answer Generation
8	task008_mctaco_wrong_answer_generation_transient_stationary	MC-TACO	Incorrect Answer Generation
9	task009_mctaco_question_generation_event_ordering	MC-TACO	Question Generation
10	task010_mctaco_answer_generation_event_ordering	MC-TACO	Answer Generation
11	task011_mctaco_wrong_answer_generation_event_ordering	MC-TACO	Incorrect Answer Generation
12	task012_mctaco_question_generation_absolute_timepoint	MC-TACO	Question Generation
13	task013_mctaco_answer_generation_absolute_timepoint	MC-TACO	Answer Generation
14	task014_mctaco_wrong_answer_generation_absolute_timepoint	MC-TACO	Incorrect Answer Generation
15	task015_mctaco_question_generation_frequency	MC-TACO	Question Generation
16	task016_mctaco_answer_generation_frequency	MC-TACO	Answer Generation
17	task017_mctaco_wrong_answer_generation_frequency	MC-TACO	Incorrect Answer Generation
18	task018_mctaco_temporal_reasoning_presence	MC-TACO	Classification
19	task019_mctaco_temporal_reasoning_category	MC-TACO	Classification
20	task020_mctaco_span_based_question	MC-TACO	Classification
21	task021_mctaco_grammatical_logical	MC-TACO	Classification
22	task022_cosmosqa_passage_inappropriate_binary	Cosmosqa	Classification
23	task023_cosmosqa_question_generation	Cosmosqa	Question Generation
24	task024_cosmosqa_answer_generation	Cosmosqa	Answer Generation
25	task025_cosmosqa_incorrect_answer_generation	Cosmosqa	Incorrect Answer Generation
26	task026_drop_question_generation	DROP	Question Generation
27	task027_drop_answer_type_generation	DROP	Classification
28	task028_drop_answer_generation	DROP	Answer Generation
29	task029_winogrande_full_object	Winogrande	Minimal Text Modification
30	task030_winogrande_full_person	Winogrande	Minimal Text Modification
31	task031_winogrande_question_generation_object	Winogrande	Question Generation
32	task032_winogrande_question_generation_person	Winogrande	Question Generation
33	task033_winogrande_answer_generation	Winogrande	Answer Generation
34	task034_winogrande_question_modification_object	Winogrande	Minimal Text Modification
35	task035_winogrande_question_modification_person	Winogrande	Minimal Text Modification
36	task036_qasc_topic_word_to_generate_related_fact	QASC	Minimal Text Modification
37	task037_qasc_generate_related_fact	QASC	Minimal Text Modification
38	task038_qasc_combined_fact	QASC	Minimal Text Modification
39	task039_qasc_find_overlapping_words	QASC	Verification
40	task040_qasc_question_generation	QASC	Question Generation
41	task041_qasc_answer_generation	QASC	Answer Generation
42	task042_qasc_incorrect_option_generation	QASC	Incorrect Answer Generation
43	task043_essential_terms_answering_incomplete_questions	Essential Terms	Answer Generation
44	task044_essential_terms_identifying_essential_words	Essential Terms	Verification
45	task045_miscellaneous_sentence_paraphrasing	Miscellaneous	Minimal Text Modification
46	task046_miscellaenous_question_typing	Miscellaenous	Classification
47	task047_miscellaenous_answering_science_questions	Miscellaenous	Answer Generation
48	task048_multirc_question_generation	MultiRC	Question Generation
49	task049_multirc_questions_needed_to_answer	MultiRC	Classification
50	task050_multirc_answerability	MultiRC	Classification
51	task051_multirc_correct_answer_single_sentence	MultiRC	Answer Generation
52	task052_multirc_identify_bad_question	MultiRC	Classification
53	task053_multirc_correct_bad_question	MultiRC	Minimal Text Modification
54	task054_multirc_write_correct_answer	MultiRC	Answer Generation
55	task055_multirc_write_incorrect_answer	MultiRC	Incorrect Answer Generation
56	task056_multirc_classify_correct_answer	MultiRC	Classification
57	task057_multirc_classify_incorrect_answer	MultiRC	Classification
58	task058_multirc_question_answering	MultiRC	Answer Generation
59	task059_ropes_story_generation	ROPES	Minimal Text Modification
60	task060_ropes_question_generation	ROPES	Question Generation
61	task061_ropes_answer_generation	ROPES	Answer Generation

Table 10: Detailed set of tasks included in NATURAL INSTRUCTIONS

A.5 Qualitative Comparison to PromptSource

We provide a comparison between our proposed dataset and PromptSource (Sanh et al., 2022). Prompt-Source tasks are mainly focused on the common NLP downstream tasks (such as question-answering, coreference, NLI, etc). However, since we create tasks from various steps (including the intermediate steps) in a data creation process, our instructions contain a broader variety of tasks. For example, tasks for chaining facts (task 38; Table 10), question typing (task 27; Table 10) or detecting inappropriate content (task 22; Table 10) are unique additions in NATURAL INSTRUCTIONS. Additionally, since our instructions were originally written by various researchers targeted for crowdworkers, they are elaborate and contain the complete definition of each task. This is somewhat evident from observation that GPT3 leads to higher performance on our instructions (Table 11). Last but not least, since we represent the instructions in a structured format, we are able to ablate various elements of the instructions (definition, negative/positive examples, etc.) and empirically quantify their contributions (§6).

Task	Model	PromptSource	NATURAL INSTRUCTIONS
Quoref QA (002)	GPT3-Instruct	43	**47**
	GPT3	2	**13**
DROP QA (028)	GPT3-Instruct	6	**10**
	GPT3	2	**3**

Table 11: Comparing zero-shot performance of GPT3 on our instructions vs. PromptSource. The instructions curated in this work, despite being lengthier, lead to higher performance.

task	Natural Instructions	PromptSource (Sanh et al. 2021)
MC-TACO (question answering)	* Definition: In this task we ask you to write answer to a question that involves "absolute timepoint" of events, which is defined as understanding of when events usually happen. For example, "going to school" usually happens during the day (not at 2 A.M). * Emphasis: Note that a lot of the questions could have more than one correct answers. We only need a single most-likely answer. Please try to keep your "answer" as simple as possible. Concise and simple "answer" is preferred over those complex and verbose ones. * Prompt: Answer the given question on "absolute timepoint" of events. Sentence: {{ sentence }} Question: {{ question }}	Given the context, {{sentence}} observe the following QA pair and check if the answer is plausible: Question: {{question}} Answer: {{answer}}
Quoref (question answering)	* Definition: In this task, you're expected to write answers to questions involving multiple refences to the same entity. Emphasis: The answer to the question should be unambiguous and a phrase in the paragraph. Most questions can have only one correct answer. * Prompt: Answer the given question. Your answer must be a single span in the passage. Passage: {{ passage }} Question: {{ question }}	Given the following context: {{context}} answer the following question: {{question}}
CosmosQA (question answering)	* Definition: Craft one correct answer to the question given in input. To make it more interesting, try to use non-stereotypical language if possible. Make sure your correct answer is reasonably long, consistent with the context, and requires common sense (instead of explicit extraction from the context.) * Emphasis: 1. In your answer, use as few words as possible from the given context. 2. Use a response that is uncommon/non-stereotypical, so that it is less predictable. 3. To be less repetitive, please vary your language for each question. * Prompt: Craft one correct answer to the question given in input. Context: {{ context }} Question: {{ question }}	{{ context }} According to the above context, choose the best option to answer the following question. Question: {{ question }} Options: {{answer_choices}}
DROP (question answering)	* Definition: This task involves creating answers to complex questions, from a given passage. Answering these questions, typically involve understanding multiple sentences. Make sure that your answer has the same type as the "answer type" mentioned in input. The provided "answer type" can be of any of the following types: "span", "date", "number". A "span" answer is a continuous phrase taken directly from the passage or question. You can directly copy-paste the text from the passage or the question for span type answers. If you find multiple spans, please add them all as a comma separated list. Please restrict each span to five words. A "number" type answer can include a digit specifying an actual value. For "date" type answers, use DD MM YYYY format e.g. 11 Jan 1992. If full date is not available in the passage you can write partial date such as 1992 or Jan 1992. * Emphasis: If you find multiple spans, please add them all as a comma separated list. Please restrict each span to five words. * Prompt: Write an answer to the given question, such that the answer matches the "anwer type" in the input. Passage: {{ passage }} Question: {{ question }}	Context: {{passage}} I am trying to figure out the answer to the question from the above context. Can you tell me the answer? Question: {{question}} Answer:

Table 12: Qualitative comparison of the task instructions for several shared tasks among NATURAL INSTRUCTIONS and PromptSource (Sanh et al., 2022).

B Building Baselines for NATURAL INSTRUCTIONS

In this section, we provide several details on the baselines included in our work.

B.1 Encoding of the instructions

According to our schema (§4.1), each instruction I_t for the t-th task is a set that contains the following fields:

$$I_t = \left\{ I_t^{\text{title}}, I_t^{\text{def.}}, I_t^{\text{avoid}}, I_t^{\text{emph.}}, I_t^{\text{prompt}}, I_t^{\text{pos. ex.}}, I_t^{\text{neg. ex.}} \right\}$$

To feed the instances to LMs, we first encoder them into plain text. Let $enc(I, x)$ define a function that maps a given instruction I and input instance x to plain text. Evidently, there are many choices for this function. In our study, we consider the following encodings:

NO-INSTRUCTIONS encoding. This encoding is the conventional paradigm where no instructions exist:

$$\begin{aligned} enc(I_t, x) := &\texttt{input}: x \\ &\texttt{output}: \text{''} \end{aligned} \tag{1}$$

PROMPT encoding. In this encoding, we append the prompt message before the input:

$$\begin{aligned} enc(I_t, x) := &\texttt{Prompt}: I_t^{\text{prompt}} \\ &\texttt{input}: x \\ &\texttt{output}: \text{''} \end{aligned} \tag{2}$$

PROMPT + DEFINITION encoding. In this encoding, the prompt message and the task definition appear before the input:

$$\begin{aligned} enc(I_t, x) := &\text{``}\texttt{Definition}: I_t^{\text{def.}} \\ &\texttt{Prompt}: I_t^{\text{prompt}} \\ &\texttt{input}: x \\ &\texttt{output}: \text{''} \end{aligned} \tag{3}$$

Intuitively, this encoding is more informative and more complex than "prompt" encoding.

FULL INSTRUCTIONS encoding. This encoding contains all the instruction content:

$$\begin{aligned} enc(I_t, x) := &\text{``}\texttt{Definition}: I_t^{\text{def.}} \\ &\texttt{Prompt}: I_t^{\text{prompt}} \\ &\texttt{Things to Avoid}: I_t^{\text{avoid.}} \\ &\texttt{Emphasis\&Caution}: I_t^{\text{emph.}} \\ &\text{``}\texttt{NegativeExample1}- \\ &\quad \texttt{input}: I_t^{\text{pos. ex.}}(\texttt{input}) \\ &\quad \texttt{output}: I_t^{\text{pos. ex.}}(\texttt{output}) \\ &\quad \texttt{reason}: I_t^{\text{pos. ex.}}(\texttt{reason}) \\ &\texttt{NegativeExample2}- \\ &\quad \dots \\ &\text{``}\texttt{PositiveExample1}- \\ &\quad \texttt{input}: I_t^{\text{pos. ex.}}(\texttt{input}) \\ &\quad \texttt{output}: I_t^{\text{pos. ex.}}(\texttt{output}) \\ &\quad \texttt{reason}: I_t^{\text{pos. ex.}}(\texttt{reason}) \\ &\texttt{PositiveExample2}- \\ &\quad \dots \\ &\texttt{input}: x \\ &\texttt{output}: \text{''} \end{aligned} \tag{4}$$

where $enc_{\text{ex}}(I_t)$ is an alternating encoding positive and negative examples. We include as many examples as possible, before exceeding the input limit.

POSITIVE EXAMPLES encoding. This encoding contains only positive examples of the subtask (no task description, etc).

$$\begin{aligned} enc(I_t, x) := \quad &\texttt{input}: I_t^{\text{pos. ex.}}(\texttt{input}) \\ &\texttt{output}: I_t^{\text{pos. ex.}}(\texttt{output}) \\ &\dots \\ &\texttt{input}: x \\ &\texttt{output}: \text{''} \end{aligned} \tag{5}$$

Such example-only have been used in several recent studies in the field (Zhao et al., 2021).

C   Analysis on Baseline Results

C.1   Comparison to Raw Instructions

We seek to understand the value of breaking the tasks into sub-tasks and mapping them into our proposed schema (§4.2). We compute performance of raw instructions (first sub-task of four datasets), in the same vein as (Efrat and Levy, 2020)'s setup. We compare this to our FULL INSTRUCTION - NEG EXAMPLES encoding. The results in Table 13 indicate that GPT3 leads to higher performance with our encoding (2nd row) compared to raw instructions (first row). Weak performance of LMs on raw instructions aligns with (Efrat and Levy, 2020)'s finding that "language model performs poorly".

	Quoref	MCTaco	CosmosQA	QASC
raw instructions	12.5	5.00	6.9	3.7
our schema	25.8	42.6	17.7	51.3

Table 13: Comparing GPT3 performance on raw crowdsourcing instructions vs. our encoding. All numbers are ROUGE-L.

This might be partly due to the verbose language of the raw instructions: the average length of the raw instructions is $2.5k$ tokens, in comparison to 950 tokens for our encoding. While repetition often helps human understanding, concise instructions seem to be more effective for computers.