CSE 561A: Large Language Models

Spring 2024

Lecture 3: Instruction Tuning

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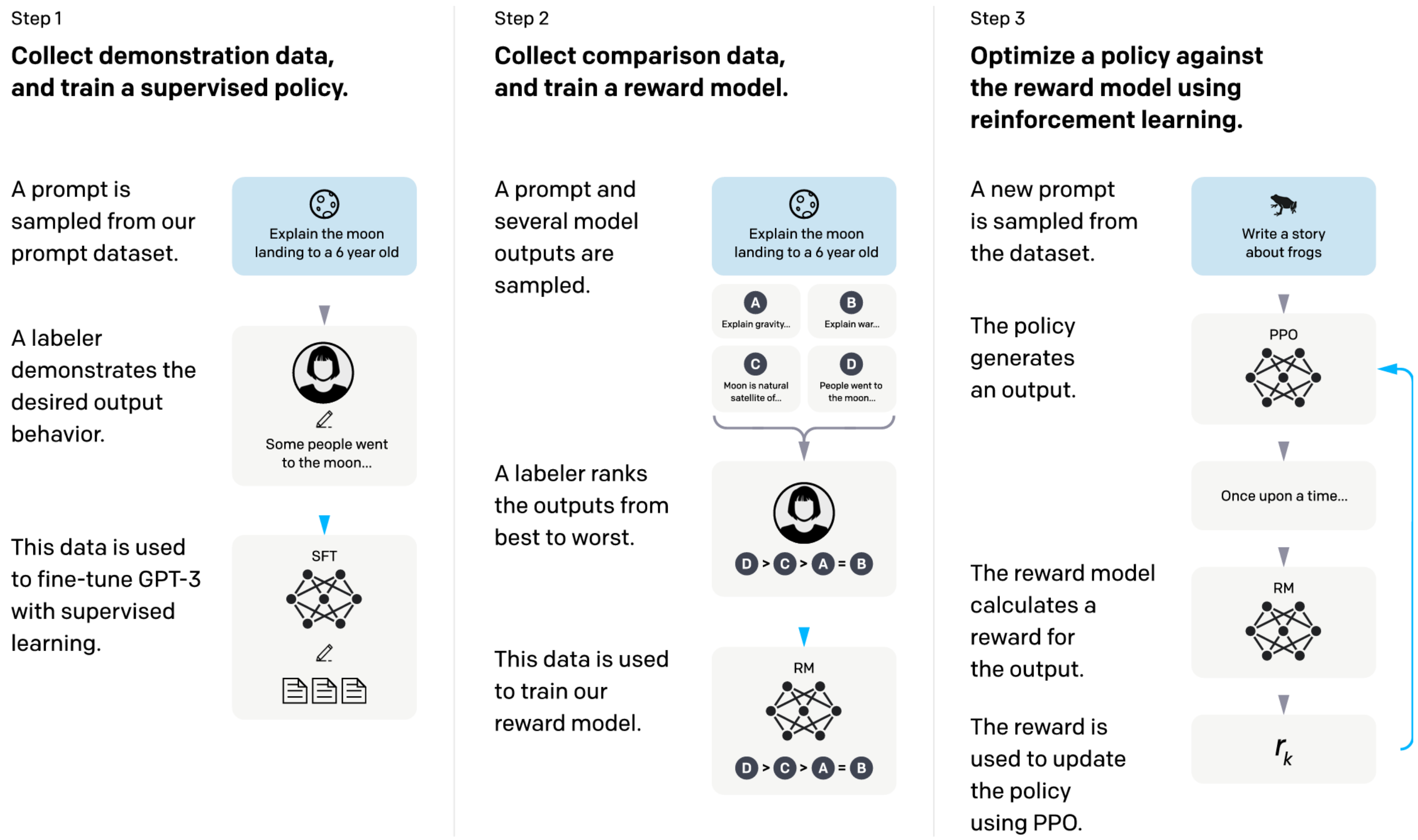
Course Announcements

- The sign-up sheet is out: https://docs.google.com/spreadsheets/d/1xSCaIOjiri17V7IjP2di-kFwbOgInPb_azBfZKeTgmc/edit
- The first student presentation lecture is on next Thursday (Feb.1st)
- Presenters (on Feb.1st) please send your slides to me (cc the TAs) before Monday 12:00PM (Jan. 29th)

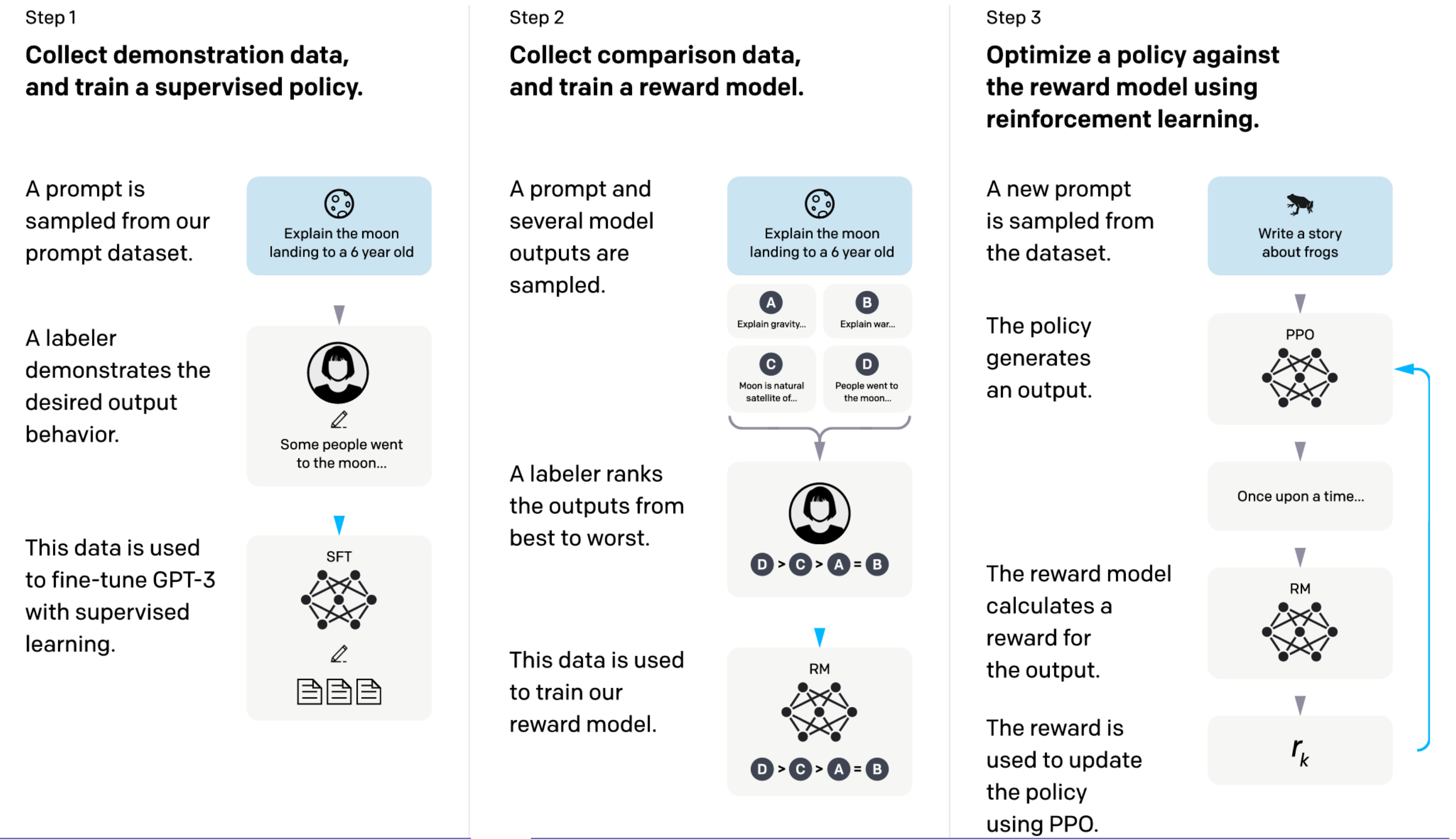
Large Language Model Pre-training Framework

- ChatGPT training procedure
  - Self-supervised pre-training
  - Supervised training on pairs of human-written data (Step 1)
  - Model generate multiple outputs for a prompt, train a reward model on human-labeled ranking list (Step 2)
  - Optimize the language model with the trained reward model (Step 3)



Training language models to follow instructions with human feedback. Ouyang et al. 2022.

Large Language Model Pre-training Framework



Instruction-Tuning
(covered in this course)

Reinforcement Learning from Human Feedback
(covered in next course)

Training language models to follow instructions with human feedback. Ouyang et al. 2022.

LLaMA: Open and Efficient Foundation Language Models

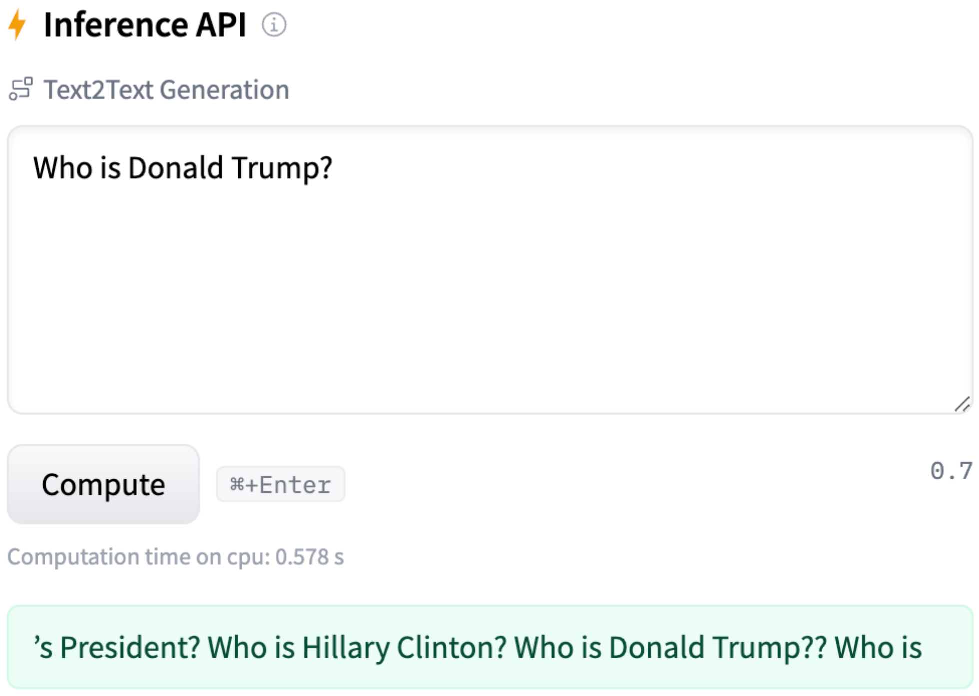
- ChatGPT (175B): **closed-source/proprietary models** where we don't know about their pre-training corpus, and don't have access to their pre-trained weights, and can only do inference or training through APIs
- LLaMA (7B/13B/33B/65B): **open-source models** where the pre-trained corpus is transparent and we have full access to their pre-trained weights
  - Pre-trained Corpus: English CommonCrawl, C4, Github, Wikipedia, Gutenberg and Books3, ArXiv, Stack Exchange.
  - Smaller models allow researchers with limited computing resources to understand how and why these language models work

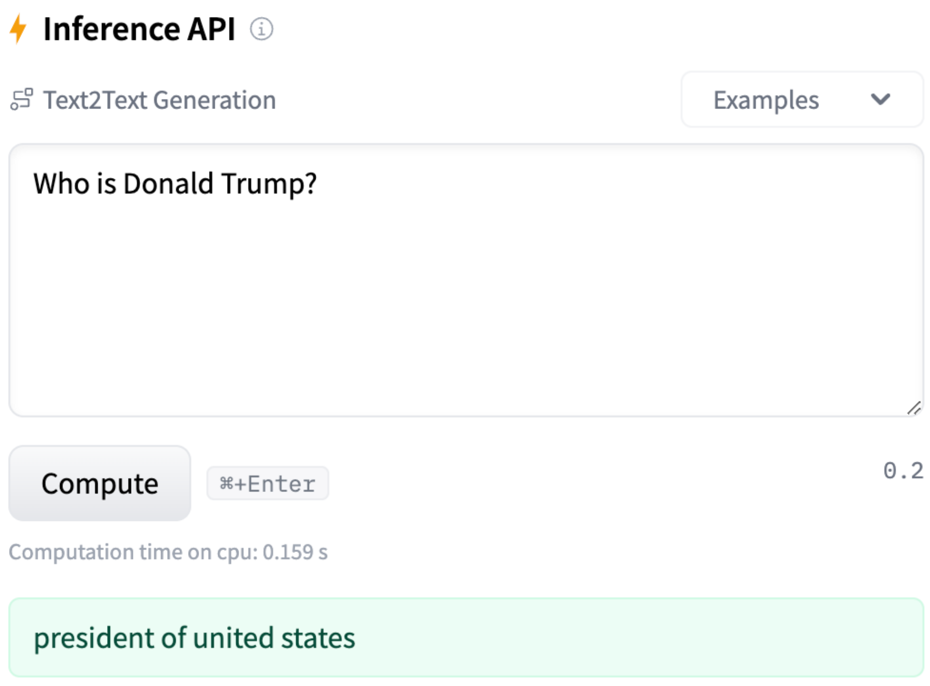
Content

- **Instruction Tuning Overview**
- Instruction Tuning on Public NLP Datasets
- Instruction Tuning on Crowdsourced Datasets
- Instruction Tuning on LM-Generated Datasets
- Instruction Tuning on Mixture of Datasets

Language Models and User intents

- Language models pre-trained on large corpus not necessarily aligned with user intents

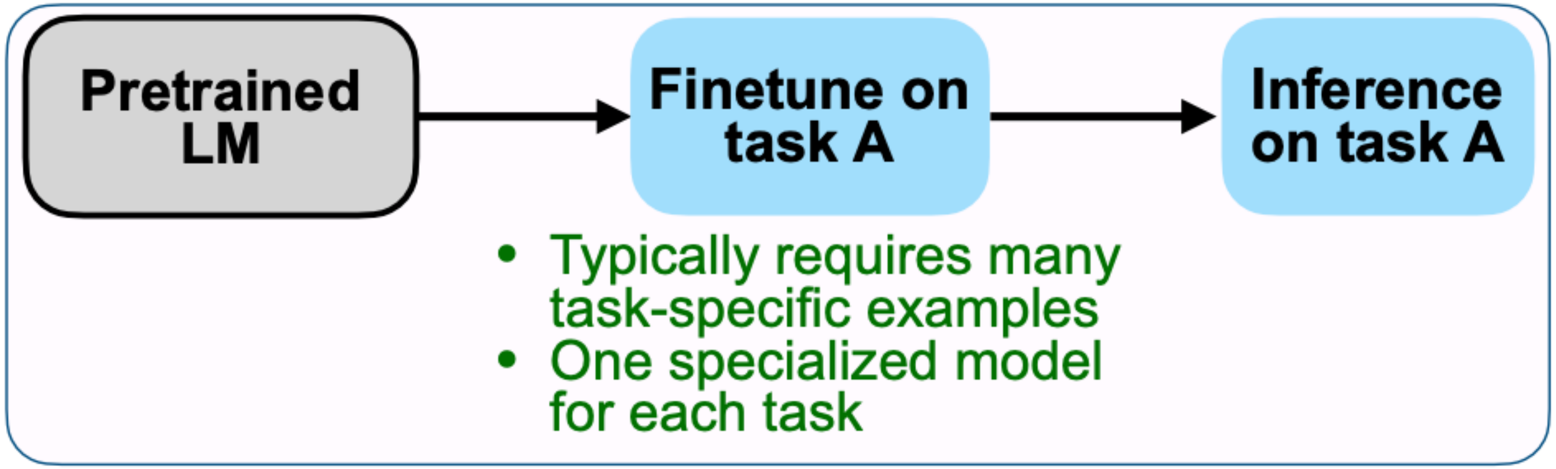




Inference with T5 model and instruction-tuned T5 model

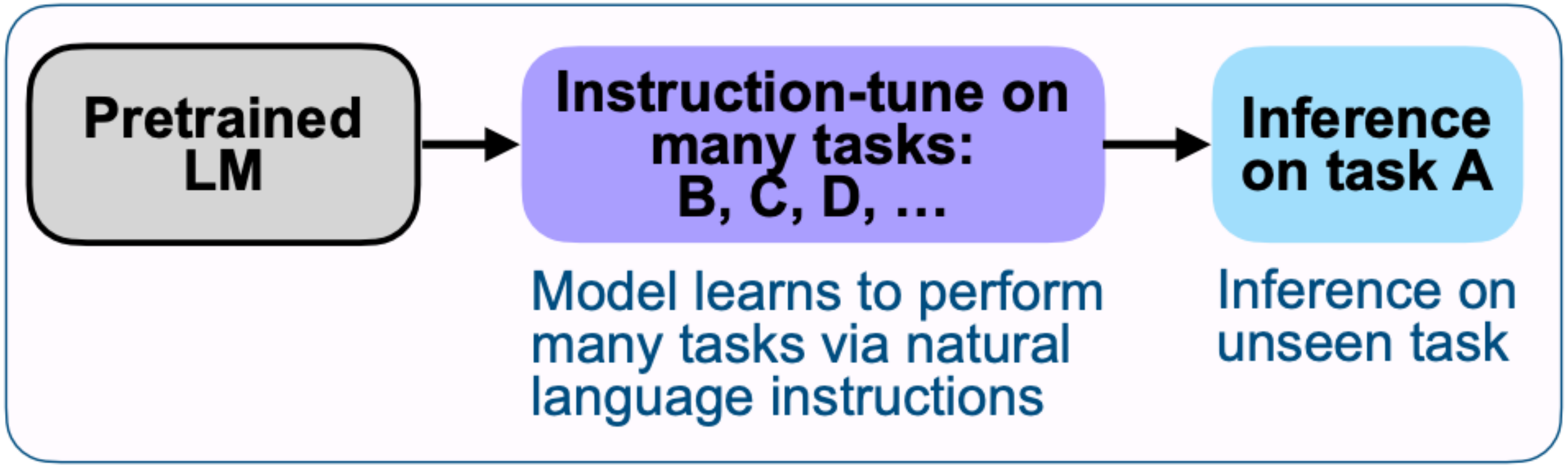
Recall Finetuning

- The pre-training stage let language models learn generic representation and knowledge from the corpus, but they are not specifically fine-tuned on any form of user tasks.
- To adapt language models to a specific downstream task, we could use task-specific datasets for fine-tuning



Instruction Tuning

- Fine-tuning on many tasks! Teach language models to follow different natural language instructions, so that it could perform better on downstream tasks and generalize to unseen tasks!
- Fine-tuning -> Instruction Pre-training



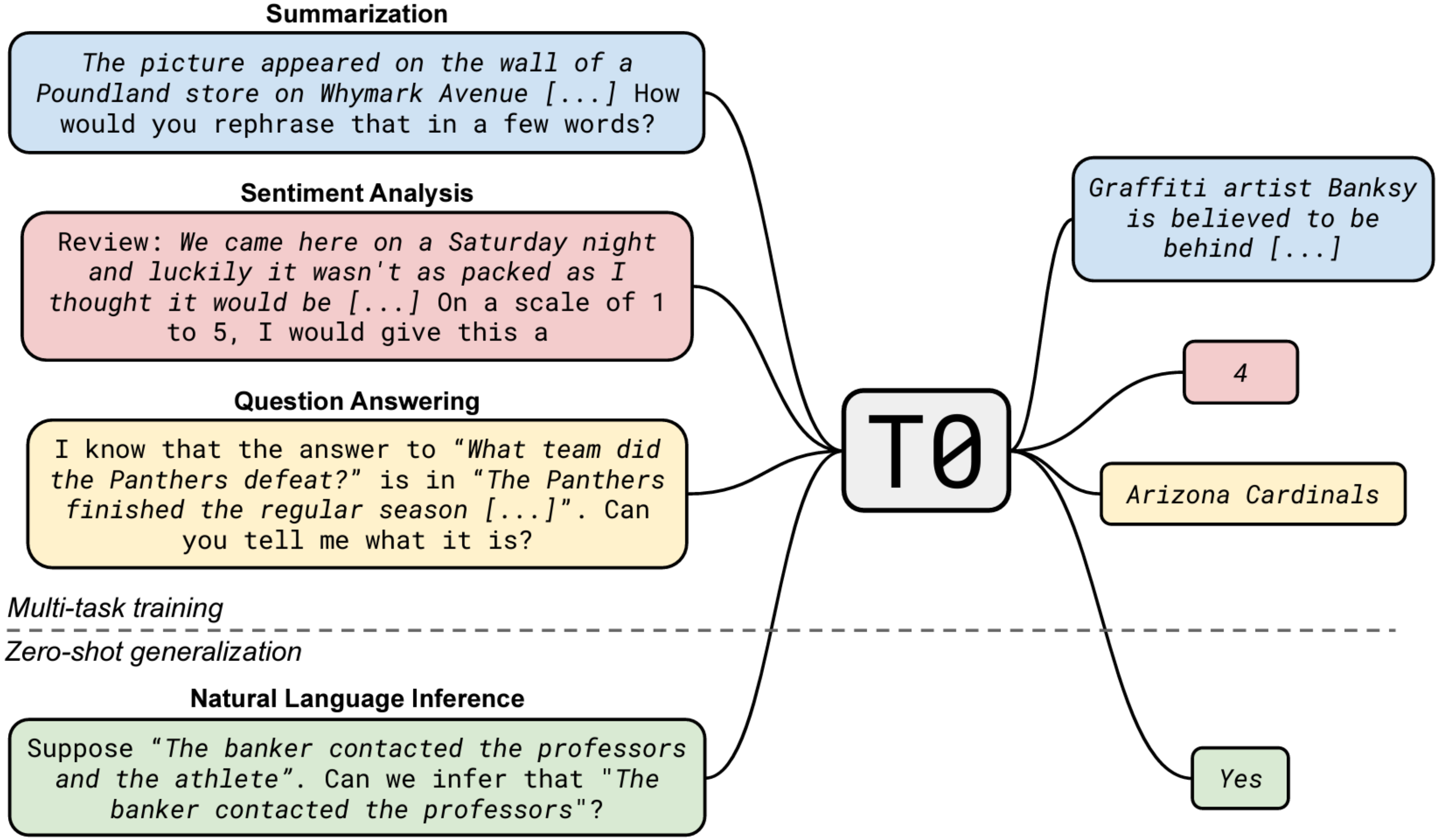
Increasing Generalization

Generalization	Task	Dataset	Category	Instances
new examples	$=$	$=$	$=$	$\neq$
new category	$=$	$=$	$\neq$	$\neq$
new domain	$=$	$\neq$	$\neq$	$\neq$
new skill	$\neq$	$\neq$	$\neq$	$\neq$

Increasing generalization

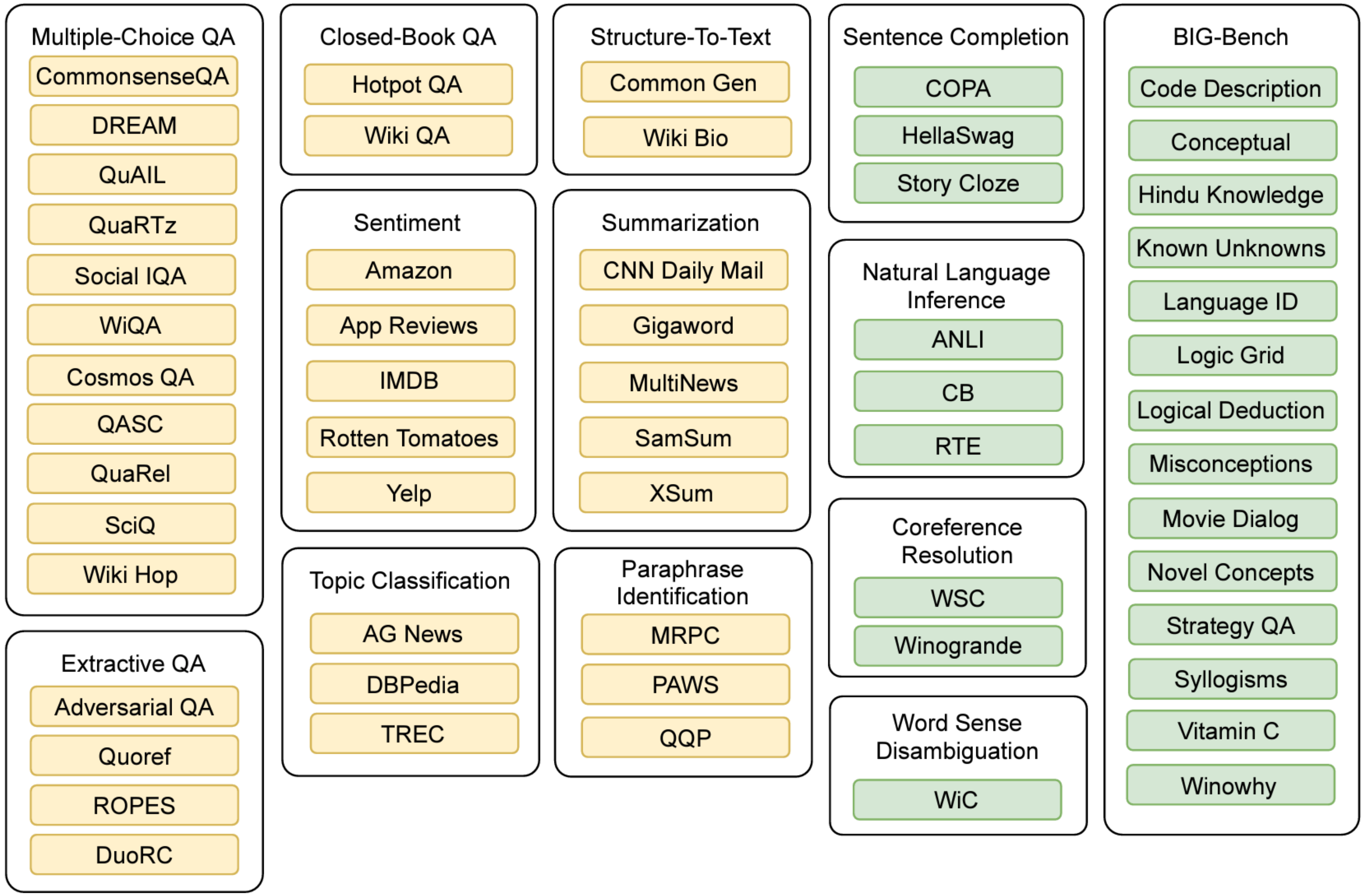
Content

Multitask Prompted Training Enables Zero-Shot Task Generalization (Sanh et. al, 2021)



T0 Training Datasets

- Collecting from multiple public NLP datasets

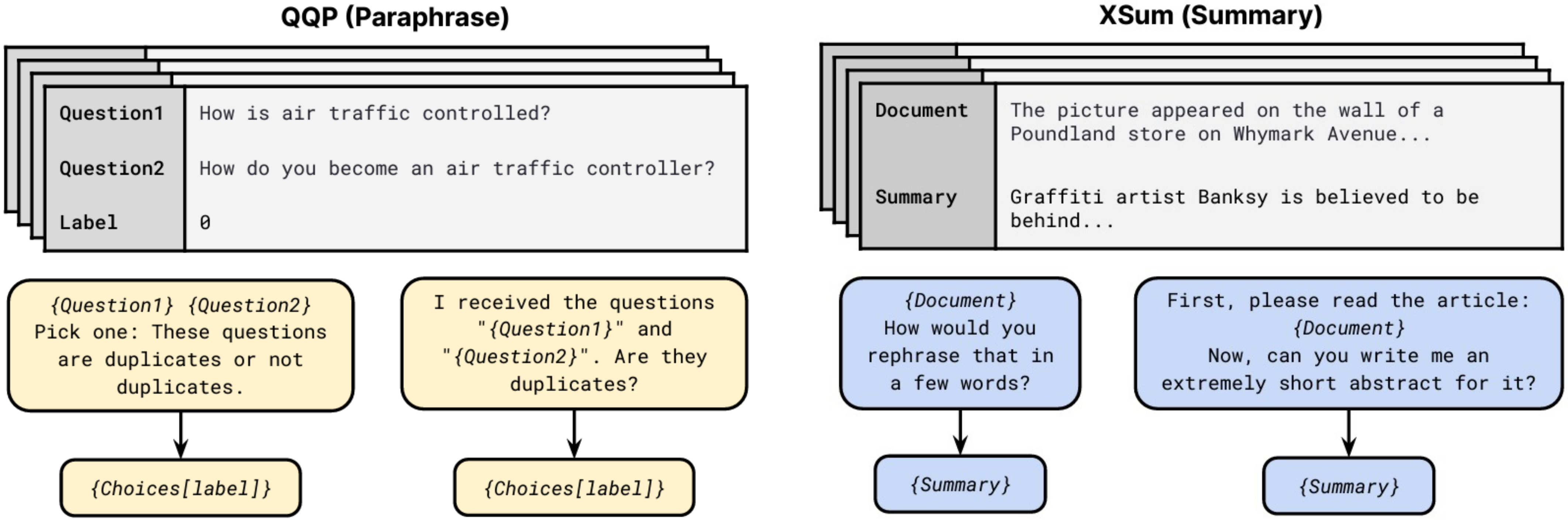


Training Mixtures and Held-Out Sets

- Training mixtures:
  - QA (Question Answering tasks), structure-to-text, summarization
  - Sentiment analysis, topic classification, paraphrase identification
- Held-out test set:
  - Sentence completion, BIG-Bench
  - Natural language inference, coreference resolution, word sense disambiguation

Task Adaptation with Prompt Templates

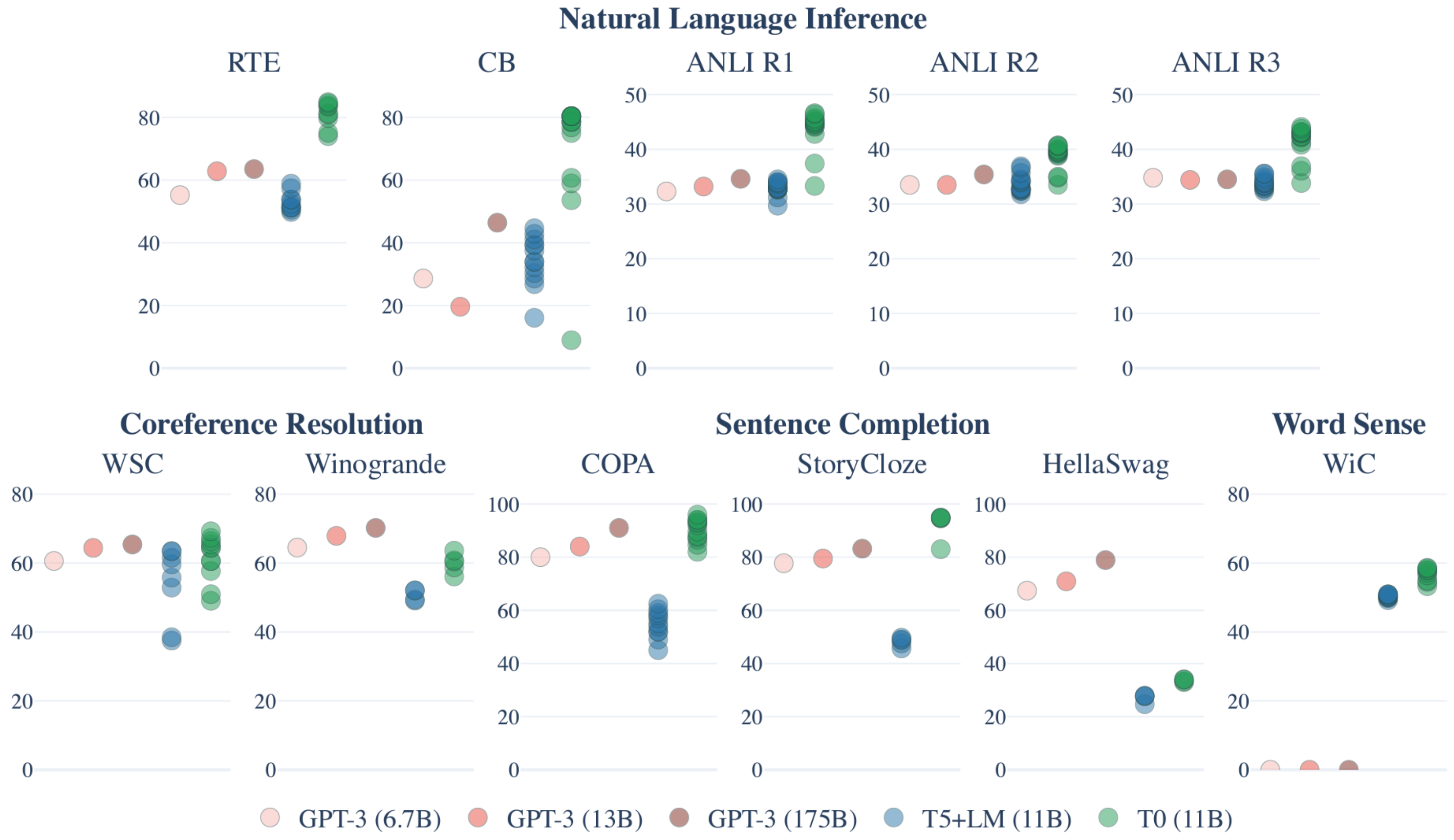
- Instead of directly using pairs of input and output, add specific instructions to explain each task (different templates per task)
- the outputs are tokens instead of class labels



Experiments

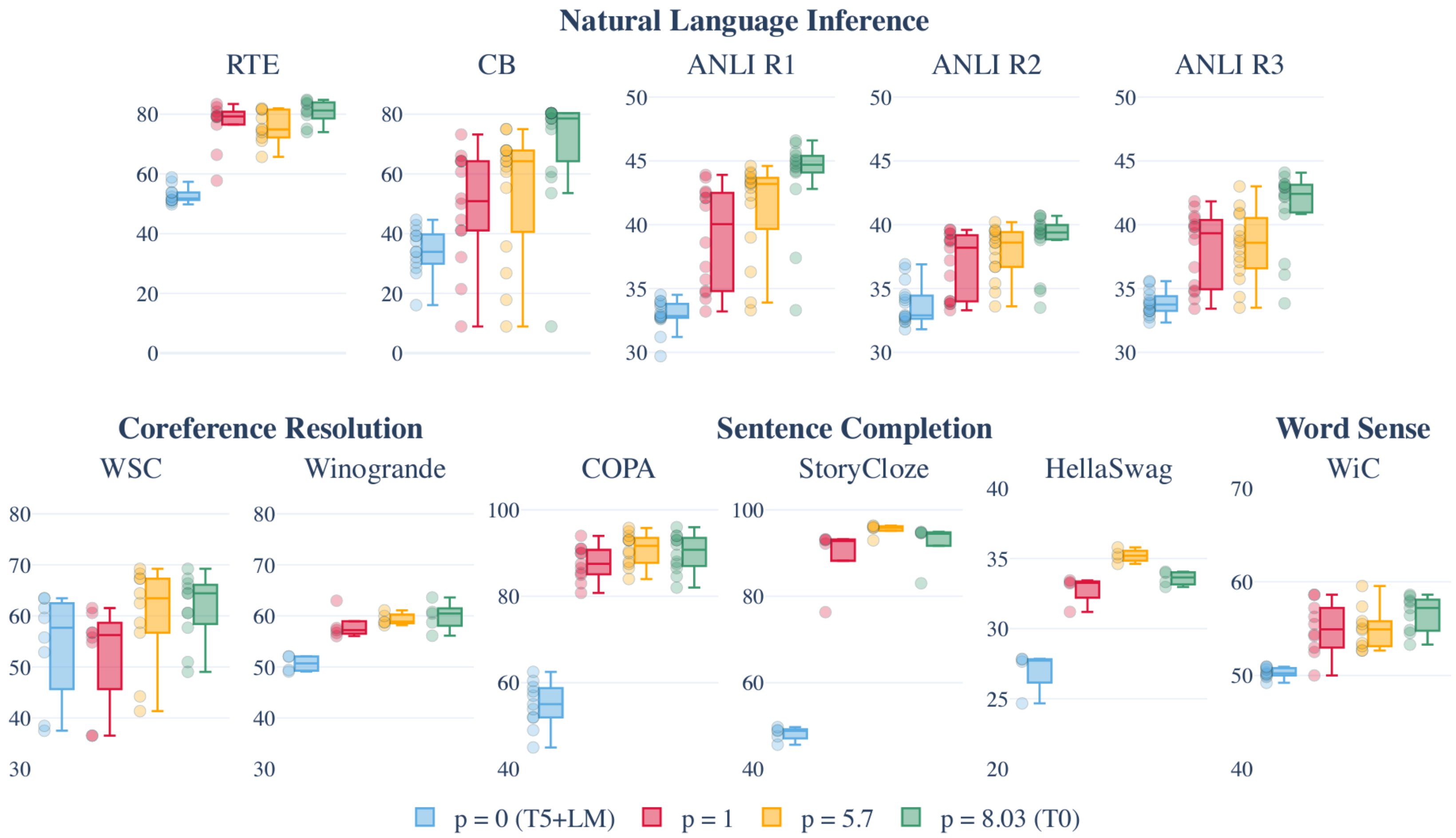
- The proposed model is called T0, trained on T5-LM (11B model) with multitask mixture of training sets
- Baselines

Performance on Held-Out Tasks

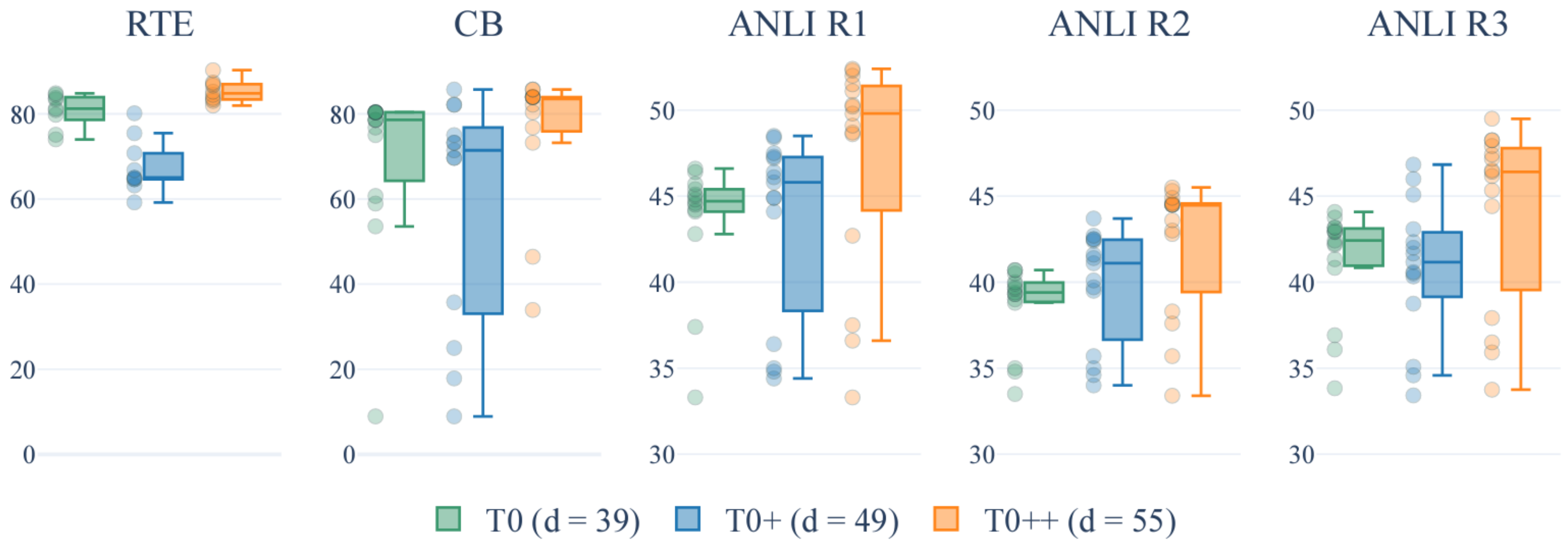


- For T5 and T0 models, each dot represents one evaluation prompt.

Effects of Prompt Numbers



Effects of More Training Datasets



- Adding more datasets consistently leads to higher median performance

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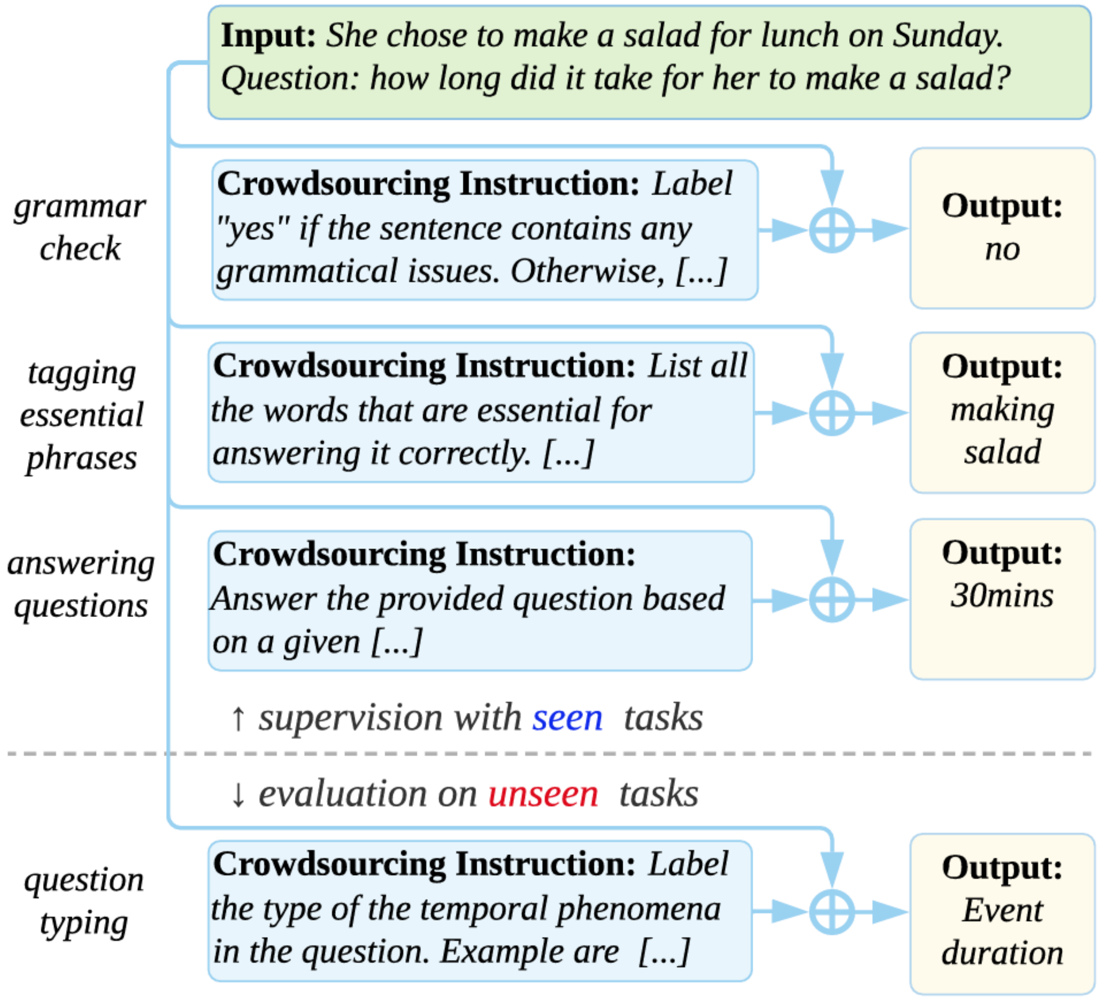
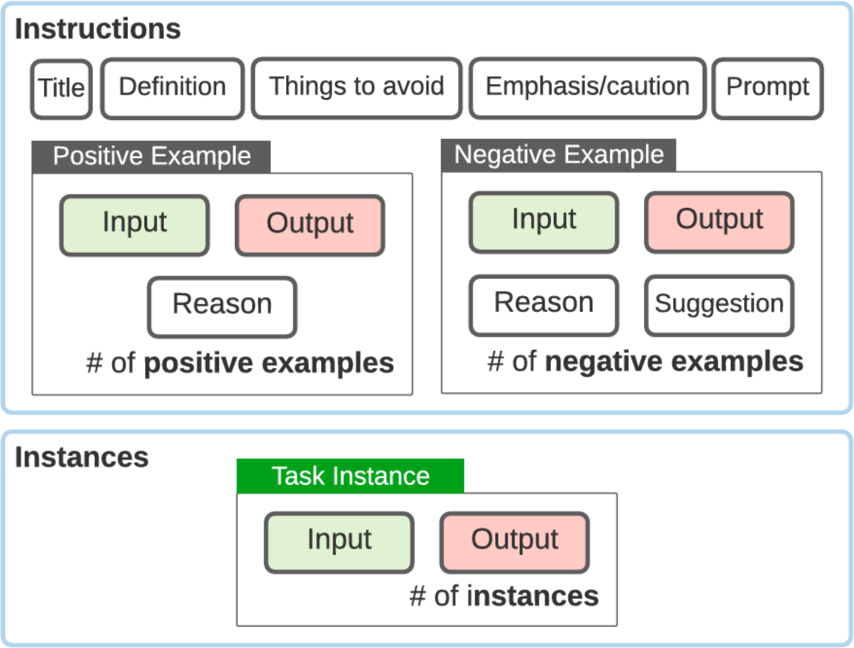
Cross-Task Generalization via Natural Language Crowdsourcing Instructions (Mishra et. al, 2021)

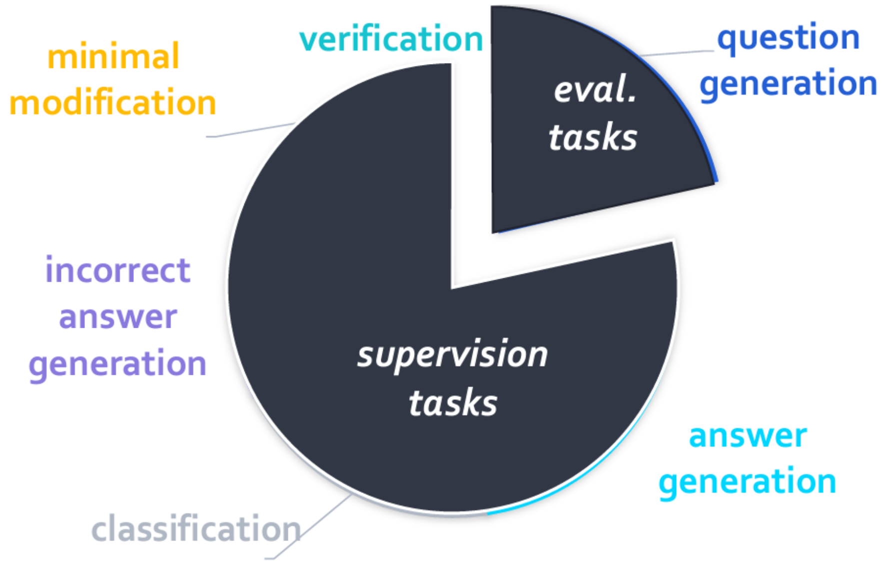
- Contribution:
- A crowdsourced dataset: Natural Instructions
  - 61 distinct tasks
  - 193k instances (input -> output)
- A more complete instruction schema



Crowdsourced Dataset

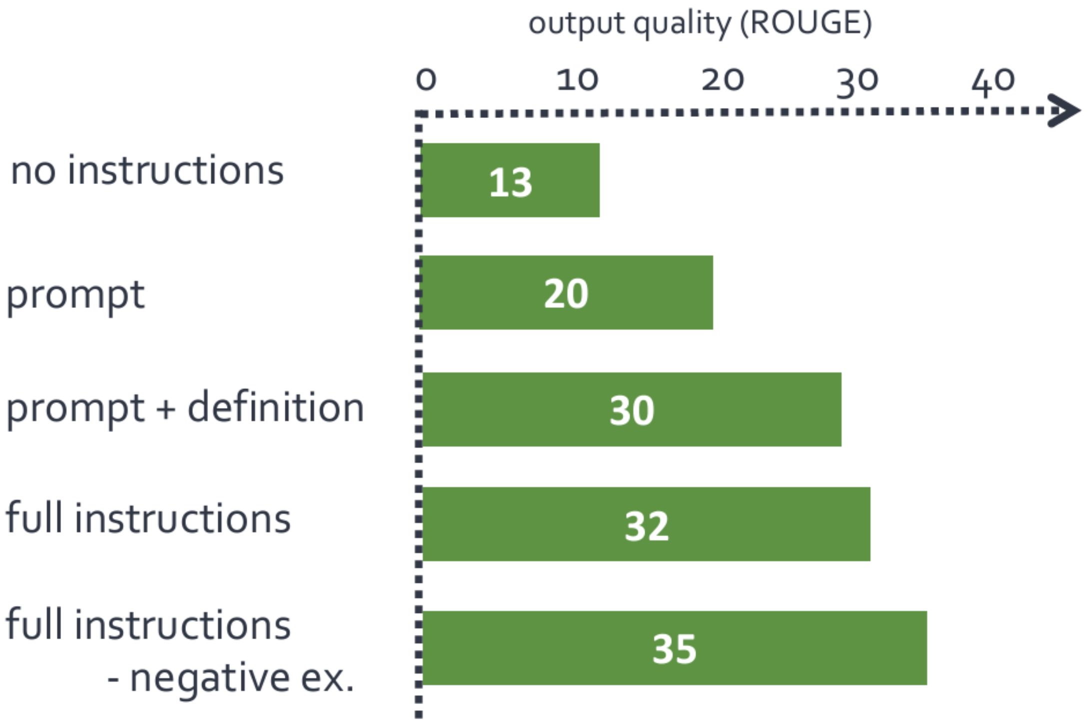
- 1. Randomly split the tasks (12 evaluation tasks, 49 supervision tasks)
- 2. Leave-one-category-out





Experiments: Generalization to Unseen Tasks

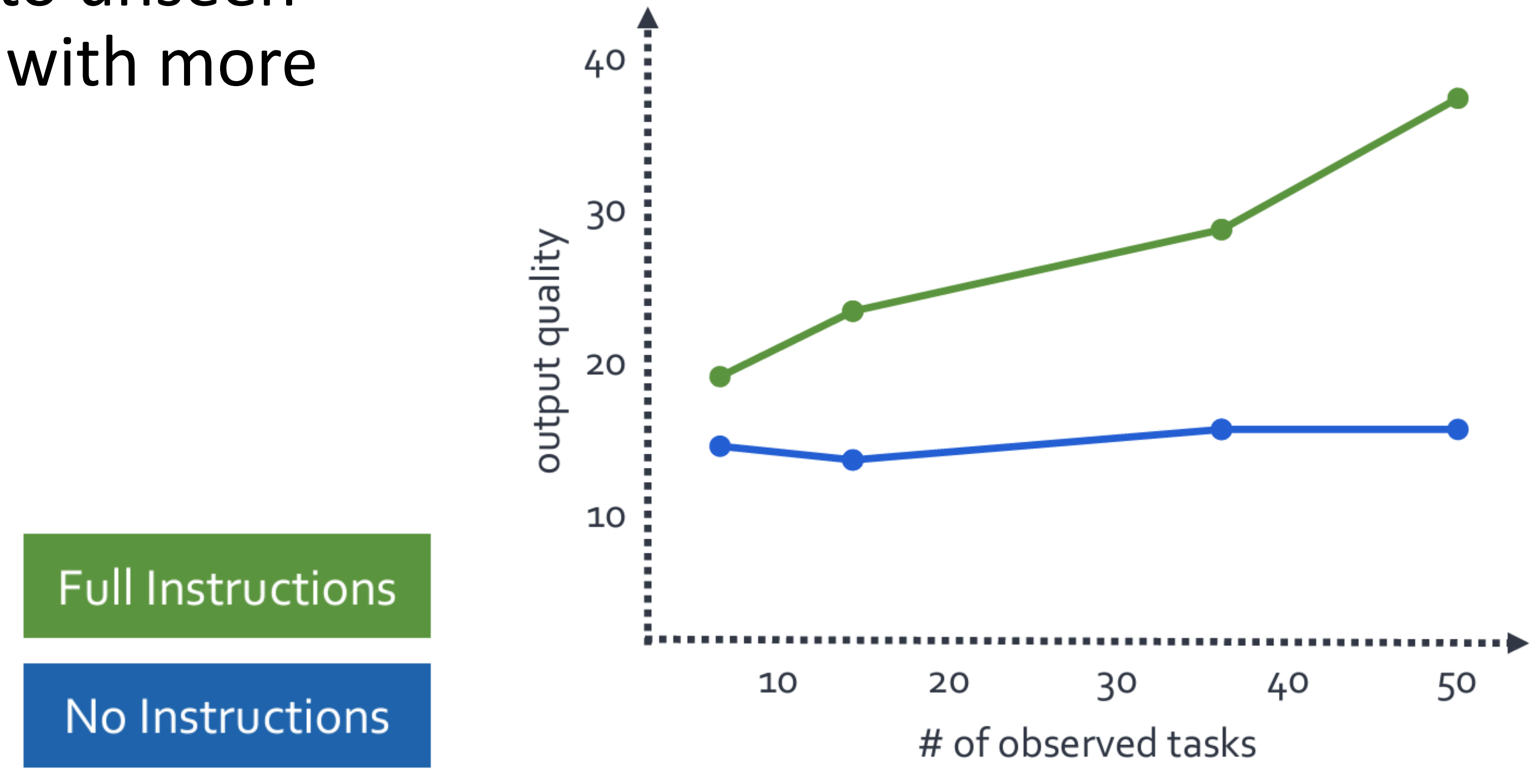
- Model: BART (140M params., instruction-tuned)



- All instruction elements (except negative examples) help improve model performance on unseen tasks.

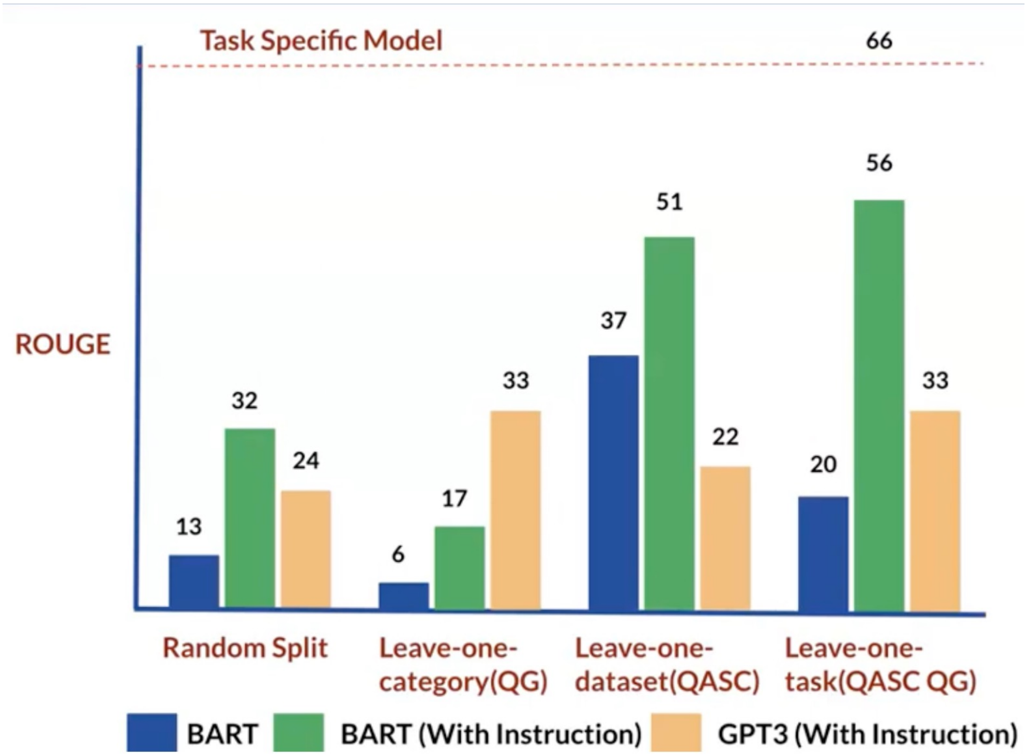
Experiments: Number of Training Tasks

- Generalization to unseen tasks improves with more observed tasks



Experiments: Comparison with Larger Model

- Model: BART (140M params., instruction-tuned)
- Baseline: GPT3 (175B params., not instruction-tuned)



- Instructions consistently improve model performance on unseen tasks.
- When both having access to instructions on the held-out set, BART (instruction-tuned) can often outperform GPT3 (not instruction-tuned)

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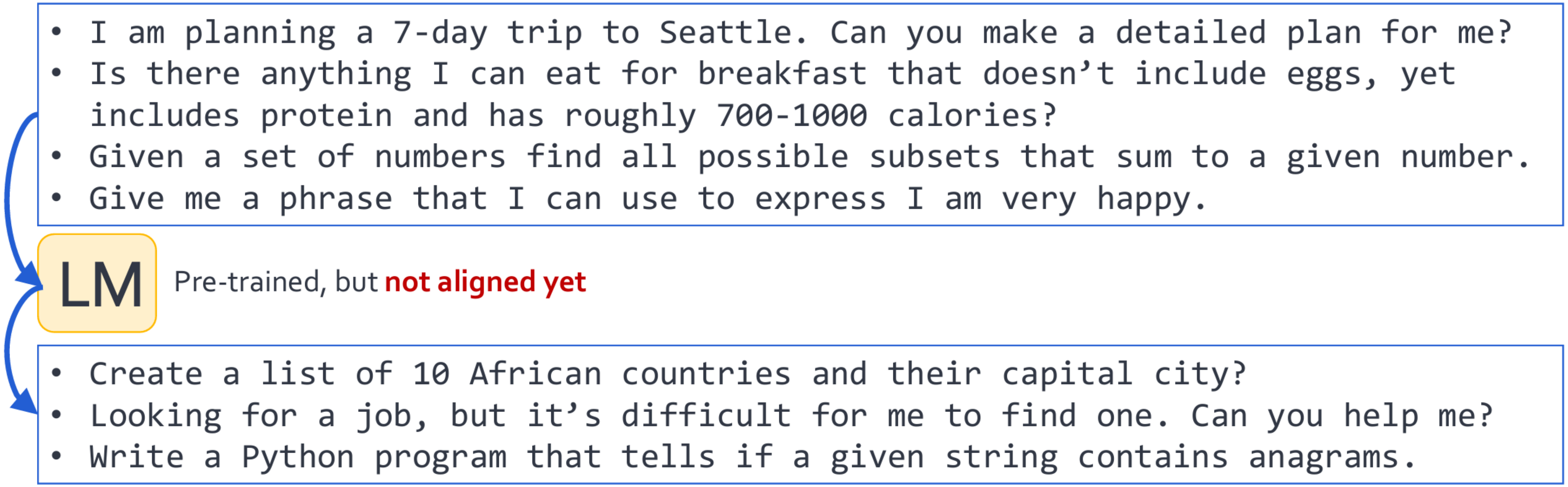
- Instruction Tuning on Mixture of Datasets

Self-Instruct: Aligning Language Models with Self-Generated Instructions (Wang et. al, 2022)

- Human-written instruction data can be very expensive!
- Can we reduce the human annotations?
- Idea: bootstrap from off-the-shelf LMs

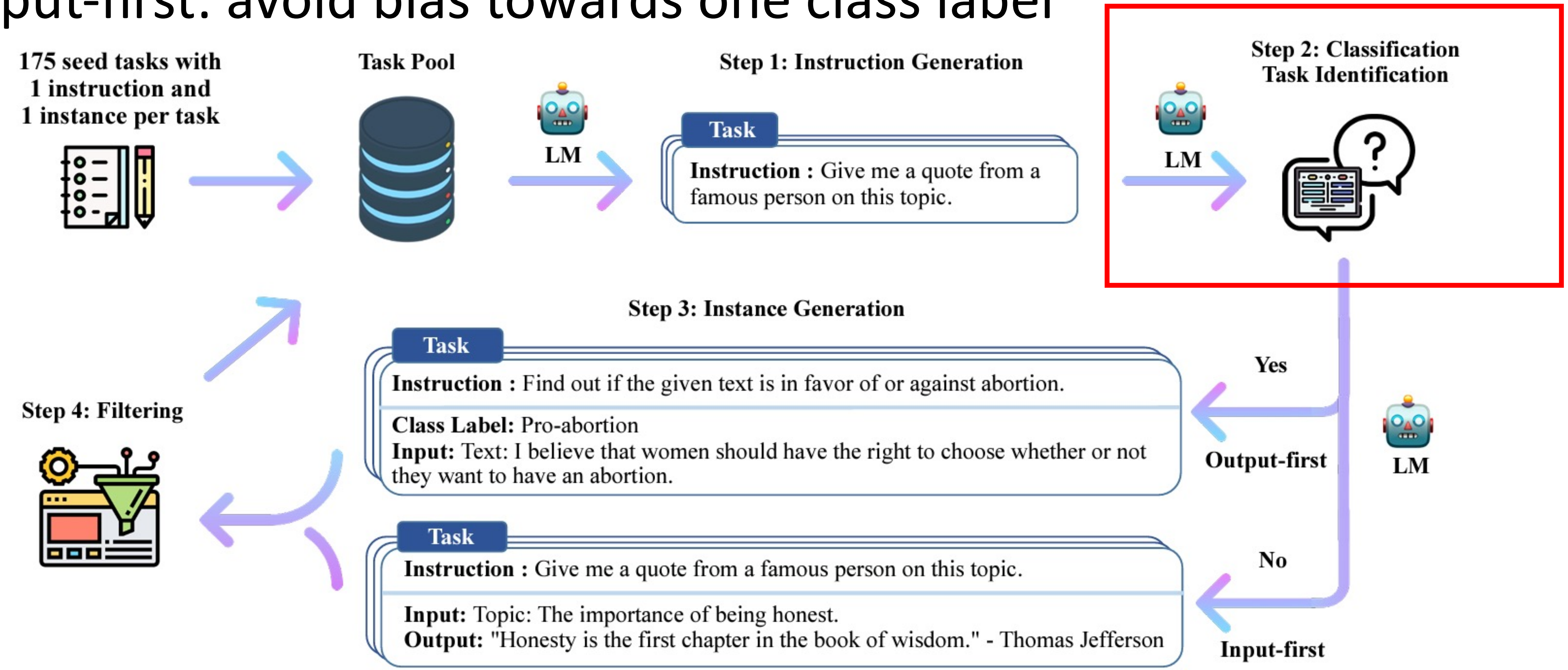
Self-Instruct: Aligning Language Models with Self-Generated Instructions (Wang et. al, 2022)

- Human written seed tasks to bootstrap off-the-shelf language models (GPT-3)



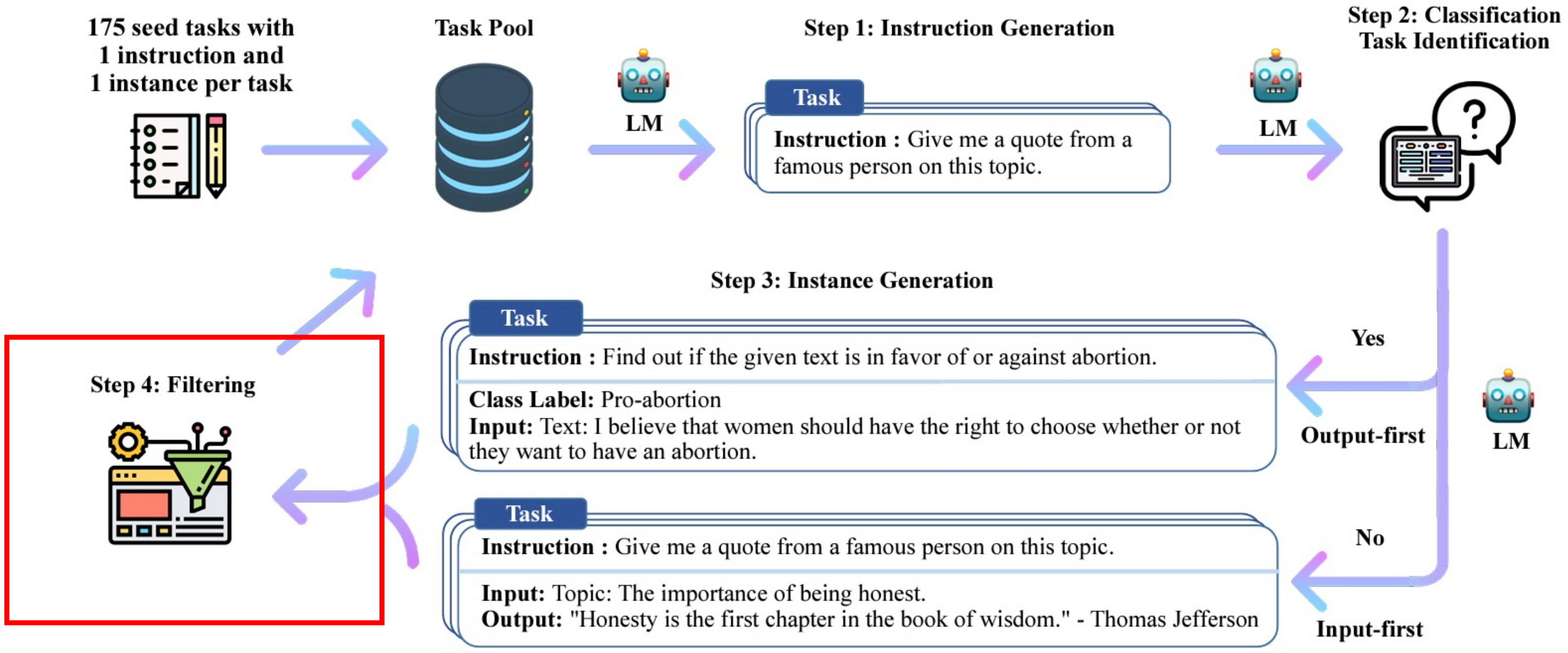
Self-Instruct Framework

- Classify whether the generated instruction is a classification task
- Output-first: avoid bias towards one class label



Self-Instruct Framework

- Filter out instructions similar with existing ones
- Add newly generated tasks into the task pool for next iteration

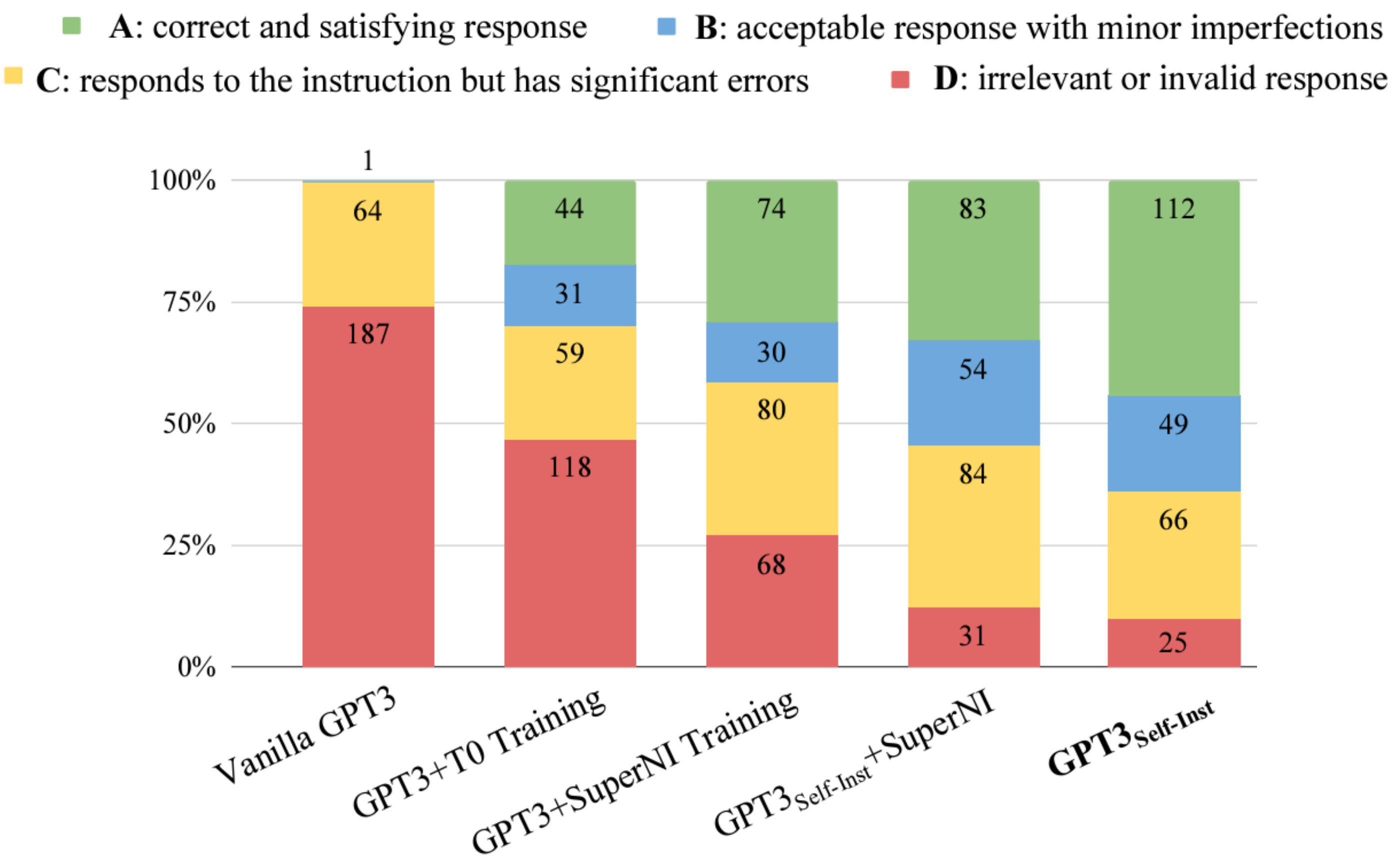


Experiment Results

- Use a GPT-3 (“davinci”) model to generate new instruction tasks, and fine-tune the GPT-3 model itself
- 175 seed tasks -> 52K instructions and 82K instances

statistic	
# of instructions	52,445
- # of classification instructions	11,584
- # of non-classification instructions	40,861
# of instances	82,439
- # of instances with empty input	35,878
ave. instruction length (in words)	15.9
ave. non-empty input length (in words)	12.7
ave. output length (in words)	18.9

Evaluation on User-Oriented Instructions



- Self-training the model by bootstrapping instruction tasks from limited human-written seed tasks can improve model alignment

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LIMA: Less Is More for Alignment (Zhou et. al, 2023)

- Can we use a small number of data to generalize to new tasks?
- Hypothesis: A model's knowledge and capabilities are learn almost entirely during pre-training, while alignment teaches it the right format to be used when interacting with users

LIMA: Less Is More for Alignment (Zhou et. al, 2023)

- 1000 training examples: no more distillation data and with minor human annotations (200)
  - 750 top questions selected from community forums
  - manually write 250 examples of prompts and responses to emphasize the response style of an AI assistant
  - Finally train a 65B LLaMa model on 1000 demonstrations.

Source	#Examples	Avg Input Len.	Avg Output Len.
Training			
Stack Exchange (STEM)	200	117	523
Stack Exchange (Other)	200	119	530
wikiHow	200	12	1,811
Pushshift r/WritingPrompts	150	34	274
Natural Instructions	50	236	92
Paper Authors (Group A)	200	40	334
Dev			
Paper Authors (Group A)	50	36	N/A
Test			
Pushshift r/AskReddit	70	30	N/A
Paper Authors (Group B)	230	31	N/A

LIMA: Less Is More for Alignment

- Quality and diversity are the keys
- Quality Control:
  - Public data: select data with higher user ratings
  - In-house authored data: uniform tone and format
- Diversity Control:
  - Public data: Stratified sampling to increase domain diversity
  - In-house authored data: Increase task/scenario

Comparing LIMA with other LLMs

- Ask human crowd workers and GPT-4 which model response is better

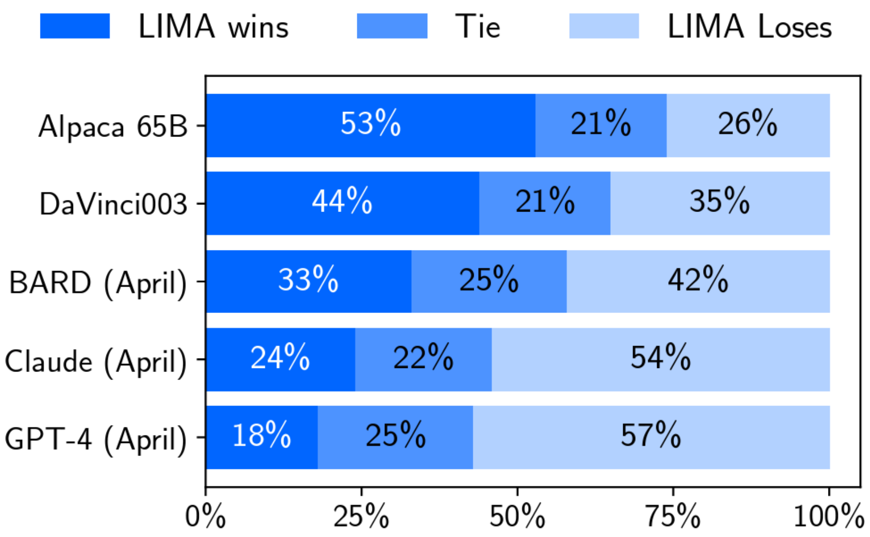


Figure 1: Human preference evaluation, comparing LIMA to 5 different baselines across 300 test prompts.

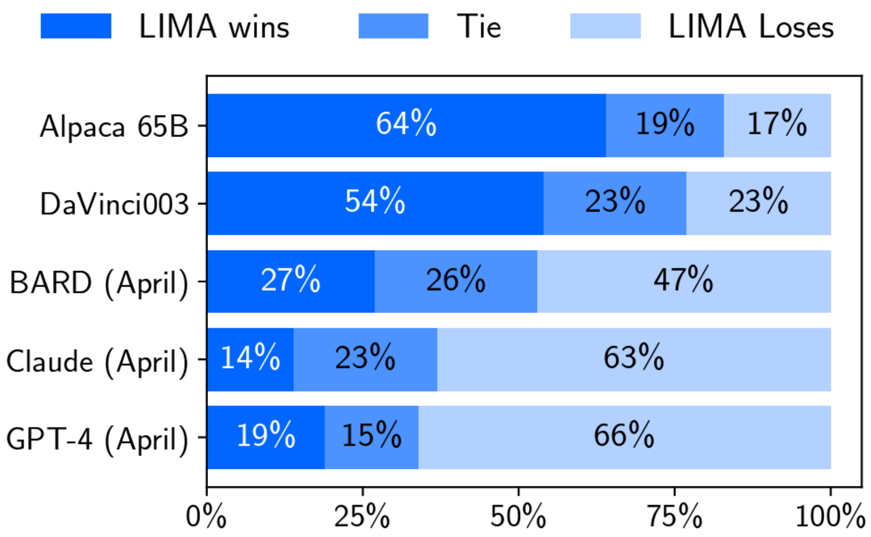


Figure 2: Preference evaluation using GPT-4 as the annotator, given the same instructions provided to humans.

Quality vs. Quantity vs. Diversity

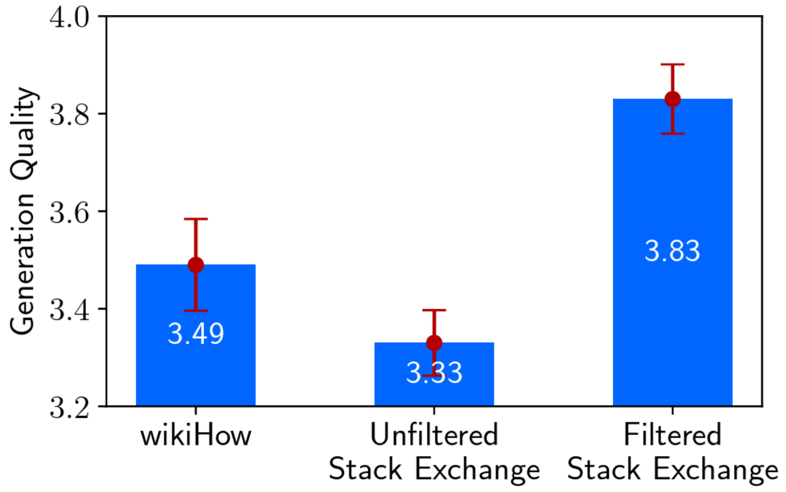
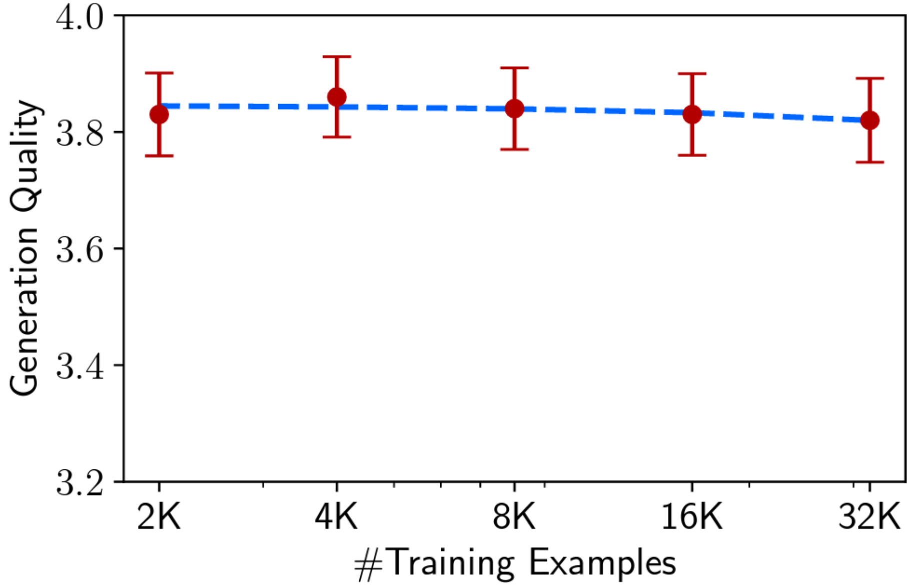


Figure 5: Performance of 7B models trained with 2,000 examples from different sources. **Filtered Stack Exchange** contains diverse prompts and high quality responses; **Unfiltered Stack Exchange** is diverse, but does not have any quality filters; **wikiHow** has high quality responses, but all of its prompts are "how to" questions.

- Scaling up training data does not necessarily improve the model response quality



Quality of Long-Form Highly Structured Response

- LIMA w. or w/o 6 format constraint exmaples
  - generating a product page with *highlights, about the product* and *how to use*
  - paper reviews with *summary, strengths, weakness* and *potentials*

LIMA w/o 6 Format Constraint Examples (994 Examples)	LIMA (1,000 Examples)
[Marketing Plan (Out of Distribution)] **I want to start a local coffee shop. Create a marketing plan with the following elements: Marketing Goals and Objectives, Define Target Audience, Research Marketing Tactics, Plan Marketing Tactics and Develop Your Timeline and Budget.**	
Coffee Shop Marketing Plan Executive Summary The following marketing plan for Java Jolt Coffee Bar outlines an aggressive approach to establishing a thriving coffee shop business in downtown Pittsburgh. Java Jolt will capitalize on the popularity of specialty coffees and the growing demand for WiFi hot spots by offering a comfortable environment where customers can enjoy premium coffee drinks while taking advantage of free Internet access. Market research indicates that there is a significant opportunity for a new coffee bar located in the heart of the downtown business district. Market trends suggest that consumers are willing to pay a higher price for quality specialty coffees served in a welcoming atmosphere. Additionally, many office workers and students living in the area do not have easy access to high-speed Internet service, presenting an additional revenue stream for the coffee bar. This marketing plan includes the following elements:	Here's a marketing plan for your local coffee shop. **Marketing Goals and Objectives** • Increase awareness of our brand among consumers [...] • Drive foot traffic [...] during slow business hours [...] • Build relationships with influencers in our community who [...] **Define Target Audience** Our target audiences include: • Residents of the neighborhood surrounding our coffee shop • Office workers near our coffee shop • Students at nearby schools We will focus our marketing efforts on these audiences because they are most likely to become regular customers at our [...] **Research Marketing Tactics** Here are some marketing tactics that we could use to reach to reach

Tulu: How Far Can Camels Go? Exploring the State of Instruction Tuning on Open Resources (Wang et. al, 2023)

- A comprehensive study on different instruction-tuning datasets
- Two mixtures of datasets
  - Human data mixture
  - Human + GPT data mixture

Comparison of Using Different Instruction Tuning Datasets

- There is not a single best instruction tuning dataset across all tasks
- Combining datasets results in the best overall performance

	MMLU (factuality)	GSM (reasoning)	BBH (reasoning)	TydiQA (multilinguality)	Codex-Eval (coding)	AlpacaEval (open-ended)	Average
	EM (0-shot)	EM (8-shot, CoT)	EM (3-shot, CoT)	F1 (1-shot, GP)	P@10 (0-shot)	Win % vs Davinci-003	
Vanilla LLaMa 13B	42.3	14.5	39.3	43.2	28.6	-	-
+SuperNI	49.7	4.0	4.5	**50.2**	12.9	4.2	20.9
+CoT	44.2	40.0	41.9	47.8	23.7	6.0	33.9
+Flan V2	**50.6**	20.0	40.8	47.2	16.8	3.2	29.8
+Dolly	45.6	18.0	28.4	46.5	31.0	13.7	30.5
+Open Assistant 1	43.3	15.0	39.6	33.4	31.9	58.1	36.9
+Self-instruct	30.4	11.0	30.7	41.3	12.5	5.0	21.8
+Unnatural Instructions	46.4	8.0	33.7	40.9	23.9	8.4	26.9
+Alpaca	45.0	9.5	36.6	31.1	29.9	21.9	29.0
+Code-Alpaca	42.5	13.5	35.6	38.9	34.2	15.8	30.1
+GPT4-Alpaca	46.9	16.5	38.8	23.5	**36.6**	63.1	37.6
+Baize	43.7	10.0	38.7	33.6	28.7	21.9	29.4
+ShareGPT	49.3	27.0	40.4	30.5	34.1	**70.5**	42.0
+Human data mix.	50.2	38.5	39.6	47.0	25.0	35.0	39.2
+Human+GPT data mix.	49.3	**40.5**	**43.3**	45.6	35.9	56.5	**45.2**

Different Base Models

- Base model quality is extremely important for downstream performance
- LLaMA is pre-trained on more tokens than other models

	MMLU (factuality)	GSM (reasoning)	BBH (reasoning)	TydiQA (multilinguality)	Codex-Eval (coding)	AlpacaEval (open-ended)	Average
	EM (0-shot)	EM (8-shot, CoT)	EM (3-shot, CoT)	F1 (1-shot, GP)	P@10 (0-shot)	Win % vs Davinci-003	
Pythia 6.9B	34.8	16.0	29.2	32.8	20.9	23.5	26.2
OPT 6.7B	32.6	13.5	27.9	24.1	8.9	25.9	22.2
LLaMA 7B	44.8	25.0	38.5	43.5	29.1	48.6	38.3
LLaMA-2 7B	**49.2**	**37.0**	**44.2**	**52.8**	**33.9**	**57.3**	**45.7**

Different Model Sizes

- Smaller models benefit more from instruction-tuning
- Instruction-tuning does not help to enhance strong capabilities already exist in the original model

	MMLU (factuality)	GSM (reasoning)	BBH (reasoning)	TydiQA (multilinguality)	Codex-Eval (coding)	AlpacaEval (open-ended)	Average
	EM (0-shot)	EM (8-shot, CoT)	EM (3-shot, CoT)	F1 (1-shot, GP)	P@10 (0-shot)	Win % vs Davinci-003	
🐫 **models trained on our final Human+GPT data mixture ↓**							
TÜLU 🐫 7B	44.8 (+13.3)	25.0 (+15.0)	38.5 (+5.5)	43.5 (+5.1)	29.1 (+8.6)	48.6	38.3
TÜLU 🐫 13B	49.3 (+7.0)	40.5 (+26.0)	43.3 (+4.0)	45.6 (+2.4)	35.9 (+7.3)	56.5	45.2
TÜLU 🐫 30B	57.7 (+3.1)	53.0 (+17.0)	51.9 (+2.4)	51.9 (-3.4)	48.0 (+5.2)	62.3	54.1
TÜLU 🐫 65B	59.2 (+0.5)	59.0 (+9.0)	54.4 (-3.7)	56.6 (-0.2)	49.4 (+2.5)	61.8	56.7
🐫 **models trained on our final Human+GPT data mixture using LLAMA-2 ↓**							
TÜLU-1.1 🐫 7B	49.2 (+7.4)	37.0 (+25.0)	44.2 (+4.9)	52.8 (+1.6)	33.9 (+7.1)	57.3	45.7
TÜLU-1.1 🐫 13B	52.3 (+0.3)	53.0 (+28.0)	50.6 (+1.7)	58.8 (+2.3)	38.9 (+7.4)	64.0	52.9

Next Course: Reinforcement Learning from Human Feedback