Large Language Models (LLMs)

Instruction Fine-Tuning

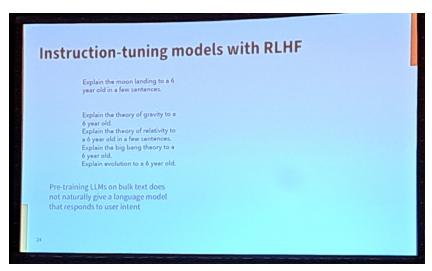
Learning goals

 comprehend the different subtleties in the space between supervised fine-tuning and zero-shot prompting

RECAP

- encoder vs. decoder models (discriminative vs. generative)
- → fine-tuning vs. prompting
 - (in-context) learning vs. creative generation/chatting
 - pre-training with plain language modeling:
 - next token prediction
 - no explicit understanding of tasks
 - no alignment with human preferences for charting or for generation coherent text

PRE-TRAINED GENERATIVE MODELS



Source: Chris Manning's keynote at EMNLP 2023

AGENDA

- instruction-tuning: adapt the models to follow instructions
 - rather task-oriented
 - multi-task, everything as text-to-text now
- chain-of-thought prompting:
 - trigger the model to "explain" it thought-process
 - final goal still correct label/output
- emergent abilities:
 - claim: With increasing model sizes, at some point new capabilities of the models (seem to) "emerge".

ISSUES WITH FINE-TUNING

- Only single-task models (sequential transfer learning instead of multi-task learning)
- Generalization of the model
 - only w.r.t. to one task / data distribution
 - Question: what about other tasks? Do they also benefit?
 - Question: what about related domains? other languages?
- Still requires (quite) large amounts of annotated data
- Poor (to none) zero-/few-shot capabilities of fine-tuned models

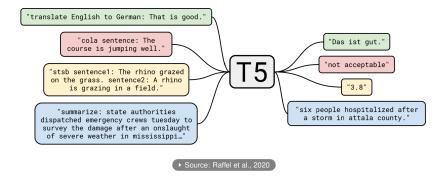
ISSUES WITH PROMPTING

- Assumption: Model has learned about the task during (unsupervised) pre-training
 Question: Is this always a realistic assumption??
- A direct response within the frame of a given label set is expected
 - Humans usually don't directly answer but provide intermediate reasoning steps (so-called "chain-of-thought")
- Misalignment with human needs
 - Out of context answers
 - Harmful answers
- Lack of interpretability
 - Just the answer w/o explanation
 - Big concern about LLMs in general

ISSUES WITH PROMPTING

- Hallucinations: Output that is not true or not reasonable w.r.t the context and given input data
- Imprecise mathematical operations: Models not trained to do arithmetics
- Inadequate experience grounding: Not fully capable of generating correct answers to questions from custom data
- Limited ability for complex reasoning: Long-known challenge in NLP/LLMs

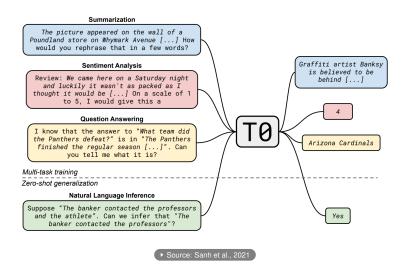
BEST OF BOTH WORLDS



BEST OF BOTH WORLDS

- Question: How does multi-task learning happen?
- → IMPLICITLY, i.e. the model learns via fine-tuning which task prefix to associate with which set of labels
 - Question: How can we make the EXPLICIT?
- → Mapping any natural language tasks into a human-readable prompted form Sanh et al., 2021

CAREFULLY DESIGNING TASK PREFIXES



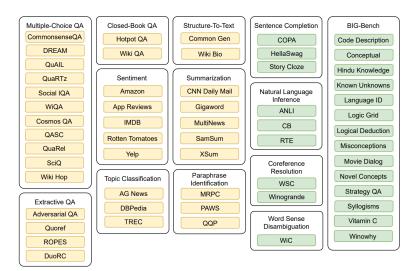
MULTITASK PROMPTED TRAINING

- Multitask Prompted Training: Novel training method that involves learning from multiple tasks using unified prompt formats as a means to improve generalization to new, unseen tasks.
 - → zero-shot task generalization
- This means that the model can perform well on tasks it hasn't been explicitly trained for.
- The key for this lies in the set of shared prompts it has learned from during fine-tuning.

MULTITASK PROMPTED TRAINING

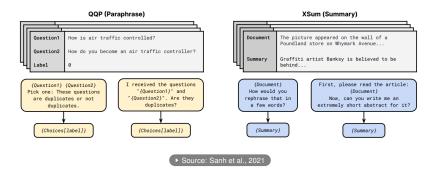
- Benchmark for Evaluation:
 - Held-out tasks instead of just held-out samples as a test set (data sets are grouped according to task beforehand)
 - All data sets belonging to as held-out task go to the test set
 - Generalization across tasks / data distributions
- Highlights the Importance of Prompts: The paper emphasizes the importance of prompts in facilitating zero-shot learning, as the model can generalize to new tasks by relying on the learned prompts and the ability to generate text outputs.

TO - DATA SPLITS



➤ Source: Sanh et al., 2021

TO – PROMPT TEMPLATES



FINETUNED LANGUAGE NET (FLAN)

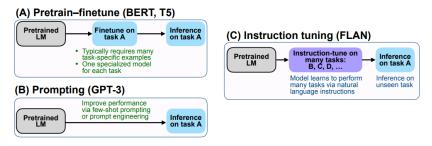
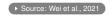
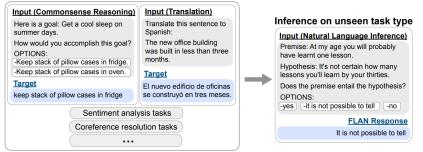


Figure 2: Comparing instruction tuning with pretrain–finetune and prompting.



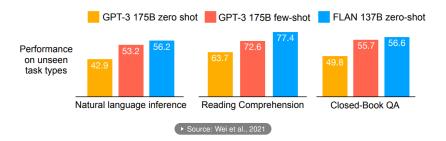
FLAN FINETUNING

Finetune on many tasks ("instruction-tuning")



► Source: Wei et al., 2021

FLAN PERFORMANCE



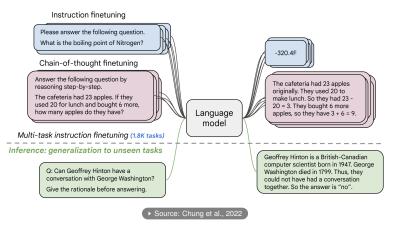
FLAN FINE-TUNING

Extend instruction fine-tuning:

- Scaling the number of fine-tuning tasks and data
 - NIV2 (1554 tasks)
 - T0-SF (193 tasks)
 - Muffin (80 tasks)
 - CoT (reasoning tasks, cf. next chapter)
- Scaling model sizes
 - PaLM 8 B
 - PaLM 62 B
 - PaLM 540 B

FLAN UPSCALING

Fine-tuning in 1.8 K tasks



FINE-TUNING CONCLUSIONS

- It is still possible to upscale
 - Larger models will improve performance
 - More fine-tuning tasks will improve performance
- Instruction finetuning generalizes across models
 - It works well on different architectures
- It improves usability and mitigates some harms
- It is relatively compute-efficient
 - For PaLM 540 B it takes 0.2 % of pre-training compute, but improves by 9.4 %