Large Language Models (LLMs)

Instruction Fine-Tuning

Learning goals

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

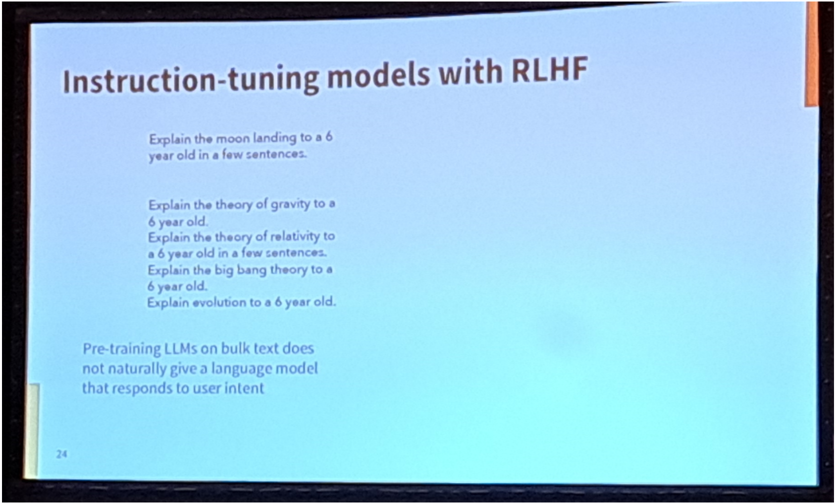
RECAP

- encoder vs. decoder models (discriminative vs. generative)

$\rightarrow$ 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

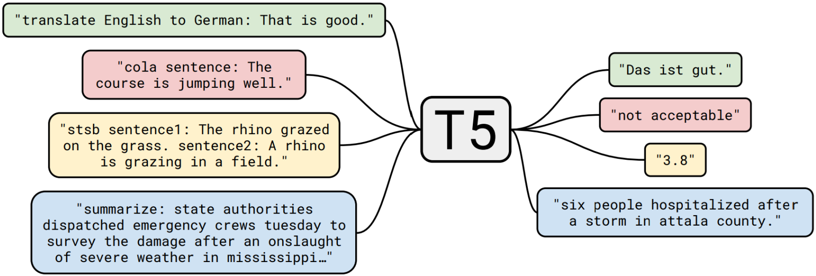
ISSUES WITH PROMPTING

- 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



Source: Raffel et al., 2020

BEST OF BOTH WORLDS

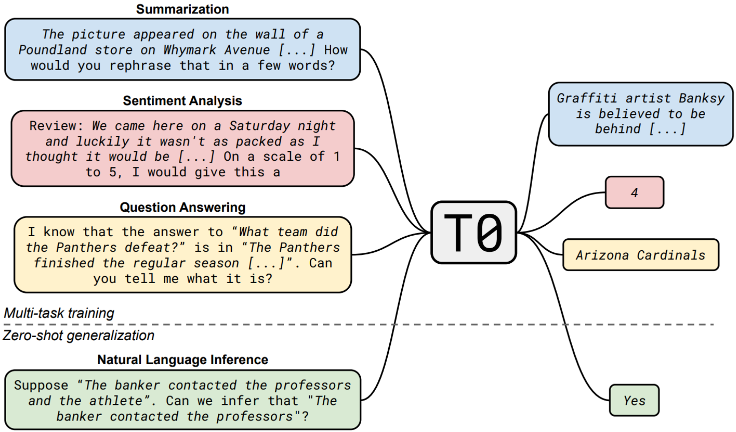
- **Question: How does multi-task learning happen?**

→ 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



Source: Sanh et al., 2021

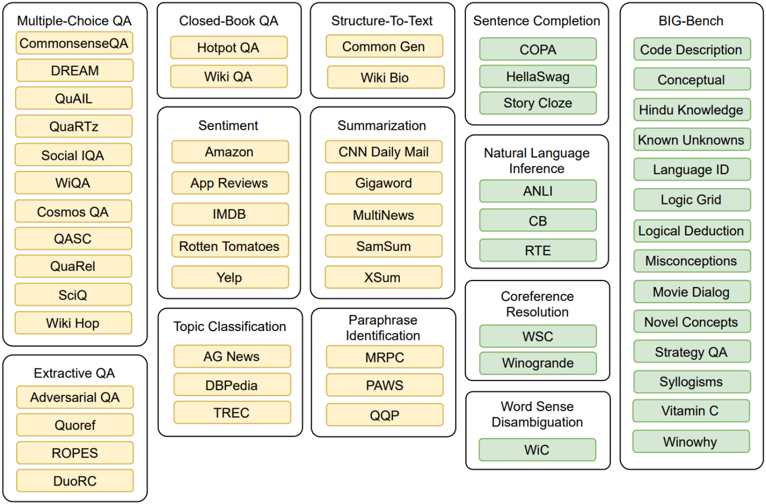
MULTITASK PROMPTED TRAINING

- *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.
  $\rightarrow$ *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

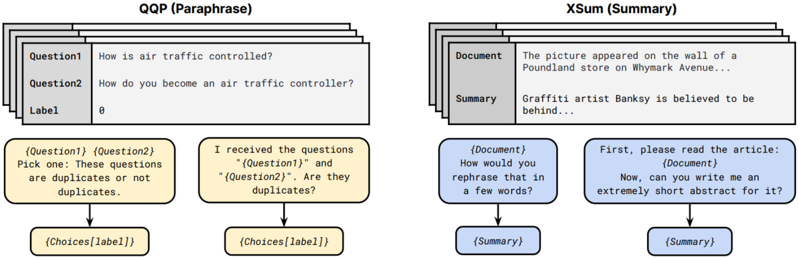
- Benchmark for Evaluation:
  - Held-out *tasks* instead of just held-out samples as a test set (data sets are grouped according to task beforehand)
  - All data sets belonging to as held-out task go to the test set
  - Generalization across tasks / data distributions
- Highlights the Importance of Prompts: 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.

T0 – DATA SPLITS



▸ Source: Sanh et al., 2021

T0 – PROMPT TEMPLATES



Source: Sanh et al., 2021

FINETUNED LANGUAGE NET (FLAN)

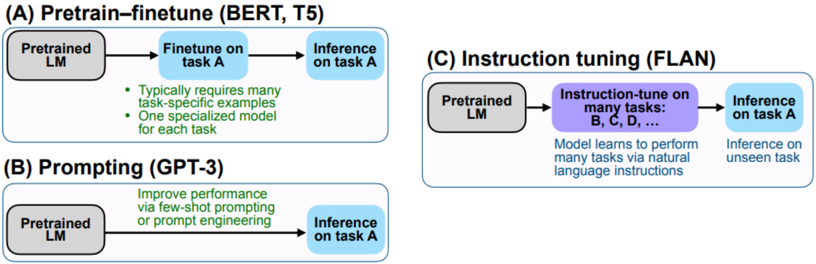
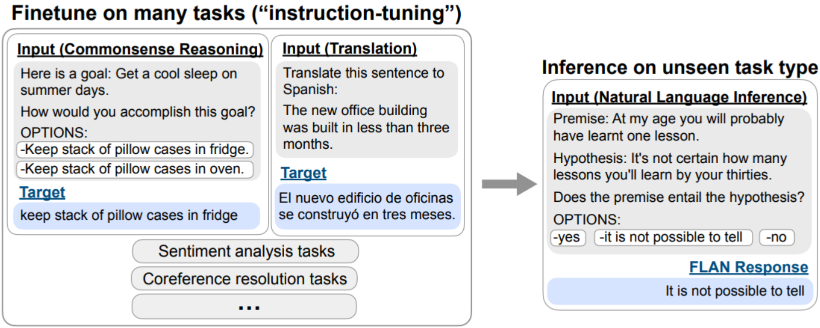


Figure 2: Comparing instruction tuning with pretrain–finetune and prompting.

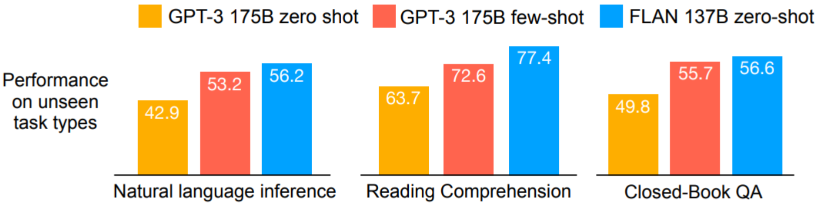
▸ Source: Wei et al., 2021

FLAN FINETUNING



▸ Source: Wei et al., 2021

FLAN PERFORMANCE



Source: Wei et al., 2021

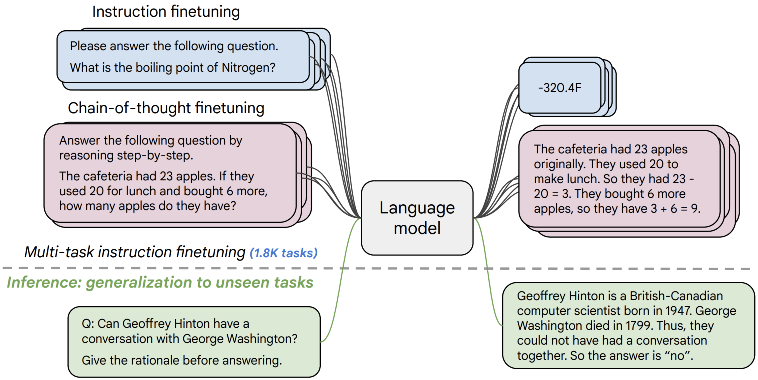
FLAN FINE-TUNING

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



▸ Source: Chung et al., 2022

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 %