Large Language Models (LLMs)

Fine-Tuning

Learning goals

- comprehend the different subtleties in the space of fine-tuning and prompting

RECAP

- language modeling objectives
  - token prediction
  - no explicit understanding of tasks
- this is true for encoder and decoder models
- So we need to do additional work if we want to use language models for solving tasks!

HOW TO SOLVE A TASK WITH LANGUAGE MODELS? (1)

- "old-style" single-task fine-tuning
  - supervised training on a task-specific training set of size k (where k is not small, e.g., $k = 100$)
  - the output can be an arbitrary category (e.g., "0", "1" for sentiment analysis)
  - alternatively, the output can be a meaningful "verbalizer" (e.g., "negative", "positive" for sentiment analysis) ▸ Schick et al., 2020
  - this was the typical way encoder models like BERT were used

HOW TO SOLVE A TASK WITH LANGUAGE MODELS? (2)

- few-shot prompting
  - provide k (where k is small) examples of what the model is supposed to do
  - the model will then often complete the task just based on analogy to these few shots
  - this is the most typical way of using autoregressive models for tasks

HOW TO SOLVE A TASK WITH LANGUAGE MODELS? (3)

- multi-task finetuning
  - mixes single-task finetuning with prompting
  - requires finetuning on a large training set
  - but now: many tasks (the more the better)
  - task format is consistent with language model objective (similar to verbalizer)
  - T5, see below

HOW TO SOLVE A TASK WITH LANGUAGE MODELS? (4)

- instruction tuning (short for instruction finetuning)
  - theory/hope: you no longer have to explicitly train on specific tasks
  - instead, you teach the model a general capability of being “helpful”
  - it then solves arbitrary tasks without few-shot prompting and without finetuning beyond instruction tuning
  - no task-specific training set required!
  - next lecture

ANOTHER TYPE OF FINETUNING

- Finetuning has yet another meaning.
- Continued pretraining is also sometimes called finetuning.
- Continued pretraining: given a language model that has been trained on generic data (web, reddit etc), adapt it to a new domain (e.g., company-internal data) by training it on a large corpus from this new domain.
- objective: standard language modeling objective
- This results in a language model that has all the nice capabilities of a generic language model (e.g., MISTRAL family), but also understands the special domain.

ISSUES WITH SINGLE-TASK FINE-TUNING

- The result is a single-task model. (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 few-shot capabilities of fine-tuned models

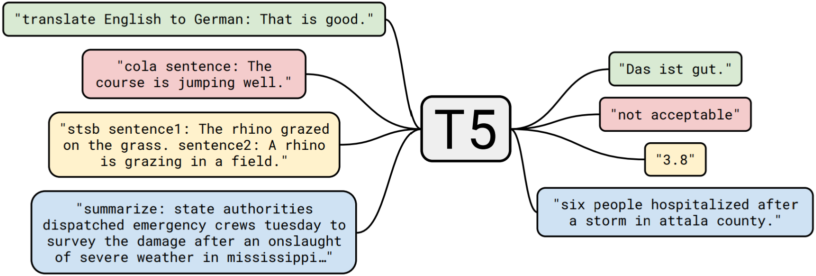
ISSUES WITH PROMPTING

- 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. (different possible causes: just made up, incorrect internal reasoning etc)
- *Imprecise mathematical operations:* Models not trained to do arithmetics
- *Inadequate experience grounding:* Not fully capable of generating correct answers to questions from specialized domains not covered by pretraining data
- *Limited ability for complex reasoning:* Long-known challenge in NLP/LLMs

T5: BEST OF BOTH WORLDS, FINE-TUNING ON TASKS AND PROMPTING



Source: Raffel et al., 2020

BEST OF BOTH WORLDS

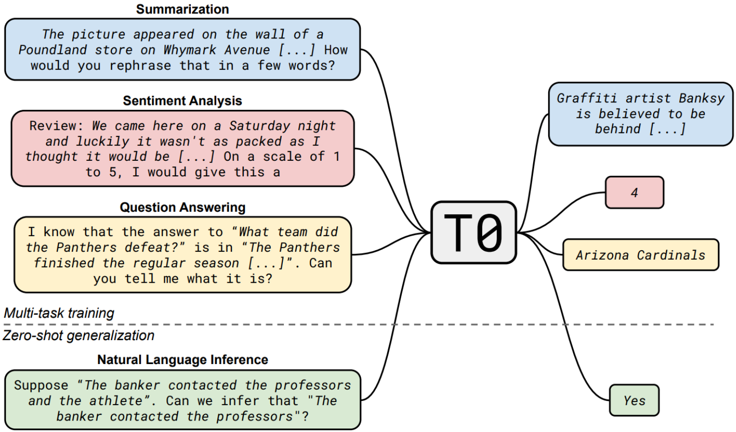
- **Question: How does multi-task learning happen?**

→ 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.
- 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 transfer to new tasks, as the model can generalize to new tasks by relying on the learned prompts and the ability to generate text outputs.

T0 – DATA SPLITS

Multiple-Choice QA
- CommonsenseQA
- DREAM
- QuAIL
- QuaRTz
- Social IQA
- WiQA
- Cosmos QA
- QASC
- QuaRel
- SciQ
- Wiki Hop

Extractive QA
- Adversarial QA
- Quoref
- ROPES
- DuoRC

Closed-Book QA
- Hotpot QA
- Wiki QA

Sentiment
- Amazon
- App Reviews
- IMDB
- Rotten Tomatoes
- Yelp

Topic Classification
- AG News
- DBPedia
- TREC

Structure-To-Text
- Common Gen
- Wiki Bio

Summarization
- CNN Daily Mail
- Gigaword
- MultiNews
- SamSum
- XSum

Paraphrase Identification
- MRPC
- PAWS
- QQP

Sentence Completion
- COPA
- HellaSwag
- Story Cloze

Natural Language Inference
- ANLI
- CB
- RTE

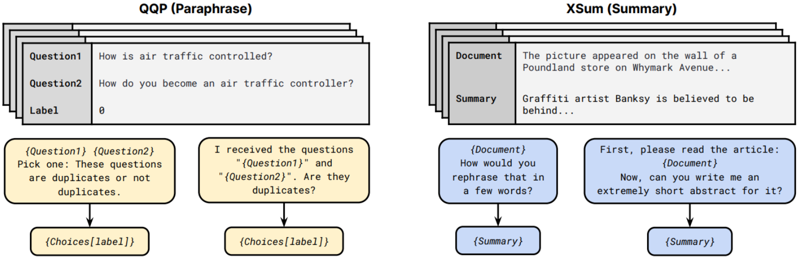
Coreference Resolution
- WSC
- Winogrande

Word Sense Disambiguation
- WiC

BIG-Bench
- Code Description
- Conceptual
- Hindu Knowledge
- Known Unknowns
- Language ID
- Logic Grid
- Logical Deduction
- Misconceptions
- Movie Dialog
- Novel Concepts
- Strategy QA
- Syllogisms
- Vitamin C
- Winowhy

Source: Sanh et al., 2021

T0 – PROMPT TEMPLATES



▸ Source: Sanh et al., 2021

FINETUNED LANGUAGE NET (FLAN)

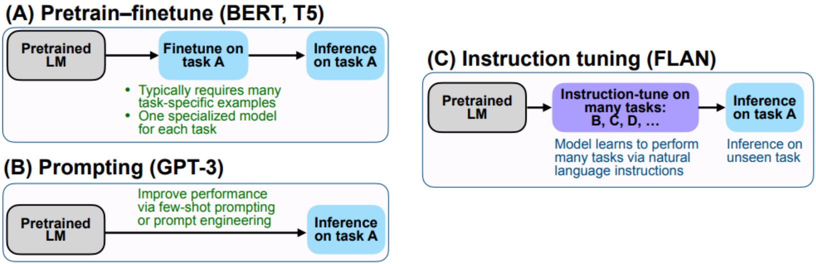
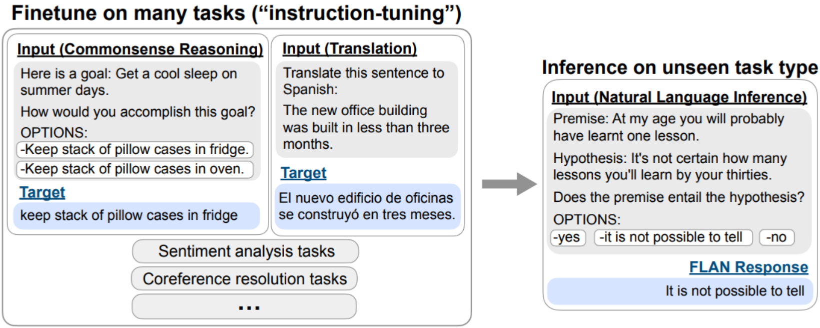


Figure 2: Comparing instruction tuning with pretrain–finetune and prompting.

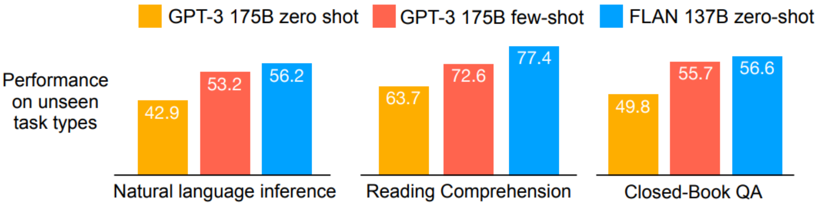
▸ Source: Wei et al., 2021

FLAN FINETUNING



▸ Source: Wei et al., 2021

FLAN PERFORMANCE



▸ Source: Wei et al., 2021

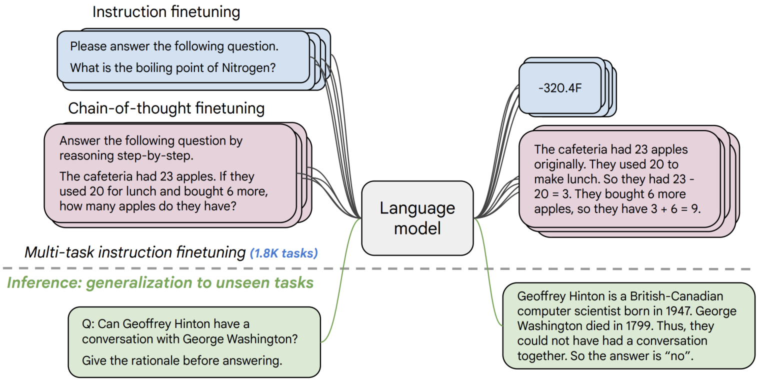
FLAN FINE-TUNING

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 %