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Week 2 Resources

Below you'll find links to the research papers discussed in this weeks videos. You don't need to understand all the technical details discussed in these papers - **you have already seen the most important points you'll need to answer the quizzes** in the lecture videos.

However, if you'd like to take a closer look at the original research, you can read the papers and articles via the links below.

Generative AI Lifecycle

- **Generative AI on AWS: Building Context-Aware, Multimodal Reasoning Applications** [↗](#) - This O'Reilly book dives deep into all phases of the generative AI lifecycle including model selection, fine-tuning, adapting, evaluation, deployment, and runtime optimizations.

Multi-task, instruction fine-tuning

- **Scaling Instruction-Finetuned Language Models** [↗](#) - Scaling fine-tuning with a focus on task, model size and chain-of-thought data.
- **Introducing FLAN: More generalizable Language Models with Instruction Fine-Tuning** [↗](#) - This blog (and article) explores instruction fine-tuning, which aims to make language models better at performing NLP tasks with zero-shot inference.

Model Evaluation Metrics

- **HELM - Holistic Evaluation of Language Models** [↗](#) - HELM is a living benchmark to evaluate Language Models more transparently.
- **General Language Understanding Evaluation (GLUE) benchmark** [↗](#) - This paper introduces GLUE, a benchmark for evaluating models on diverse natural language understanding (NLU) tasks and emphasizing the importance of improved general NLU systems.
- **SuperGLUE** [↗](#) - This paper introduces SuperGLUE, a benchmark designed to evaluate the performance of various NLP models on a range of challenging language understanding tasks.
- **ROUGE: A Package for Automatic Evaluation of Summaries** [↗](#) - This paper introduces and evaluates four different measures (ROUGE-N, ROUGE-L, ROUGE-W, and ROUGE-S) in the ROUGE summarization evaluation package, which assess the quality of summaries by comparing them to ideal human-generated summaries.
- **Measuring Massive Multitask Language Understanding (MMLU)** [↗](#) - This paper presents a new test to measure multitask accuracy in text models, highlighting the need for substantial improvements in achieving expert-level accuracy and addressing lopsided performance and low accuracy on socially important subjects.
- **BigBench-Hard - Beyond the Imitation Game: Quantifying and Extrapolating the Capabilities of Language Models** [↗](#)
- The paper introduces BIG-bench, a benchmark for evaluating language models on challenging tasks, providing insights on scale, calibration, and social bias.

Parameter- efficient fine tuning (PEFT)

- **Scaling Down to Scale Up: A Guide to Parameter-Efficient Fine-Tuning** [↗](#) - This paper provides a systematic overview of Parameter-Efficient Fine-tuning (PEFT) Methods in all three categories discussed in the lecture videos.
- **On the Effectiveness of Parameter-Efficient Fine-Tuning** [↗](#) - The paper analyzes sparse fine-tuning methods for pre-trained models in NLP.

LoRA

- **LoRA Low-Rank Adaptation of Large Language Models** [↗](#) - This paper proposes a parameter-efficient fine-tuning method that makes use of low-rank decomposition matrices to reduce the number of trainable parameters needed for fine-tuning language models.
- **QLoRA: Efficient Finetuning of Quantized LLMs** [↗](#) - This paper introduces an efficient method for fine-tuning large language models on a single GPU, based on quantization, achieving impressive results on benchmark tests.

Prompt tuning with soft prompts

- **The Power of Scale for Parameter-Efficient Prompt Tuning** [↗](#) - The paper explores "prompt tuning," a method for conditioning language models with learned soft prompts, achieving competitive performance compared to full fine-tuning and enabling model reuse for many tasks.

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