**Why is this an important area of study? [0.5 points]**

Sometimes we can save time when we can achieve the same goal without training an entire model or without training at all. For example, we can finetune only the last layer of an existing image classifier if there’s a new class of objects being added. Another example is that we can rely on the zero-shot capability of large language models so that we don’t need to finetune at all.

**Describe two different techniques/approaches discussed [0.5 points]**

1. Weight imprinting: if the representations are sufficiently consistent and disjoint, we don’t have to touch this part. Instead, we can extend the weight matrix of subsequence classifier layers (which are usually lightweight) and only finetune these layers for a few iterations.
2. In-context learning: When pre-training the model, we condition the output on a latent concept. Thus, by listing some new concepts at the beginning of the prompt, we can alter the model’s behavior without finetuning. This is intuitively similar to imitative writing that we practiced as kids.

**Discuss relative strengths [0.5 points] and weaknesses [0.5 points] of the two techniques described above. [1 point total]**

Both weight imprinting and in-context learning can improve the model with only a few new examples. However, weight imprinting does require some finetuning, while in-context learning is totally train-free. This makes in-context learning more suitable for very large models. However, in-context learning needs carefully crafted prompts to output high-quality answers, and it increases the input sequence length. In contrast, we can obtain more stable behaviors using weight imprinting.