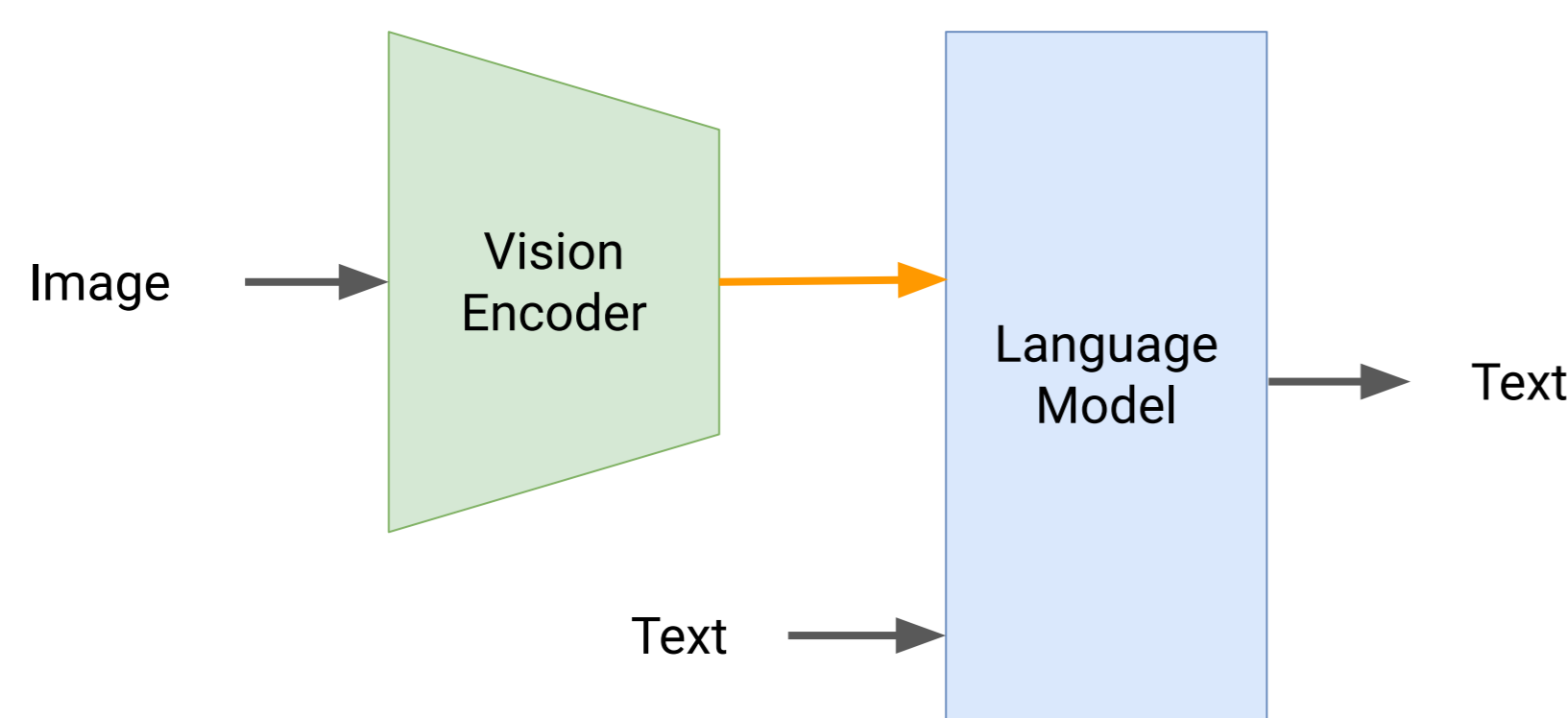
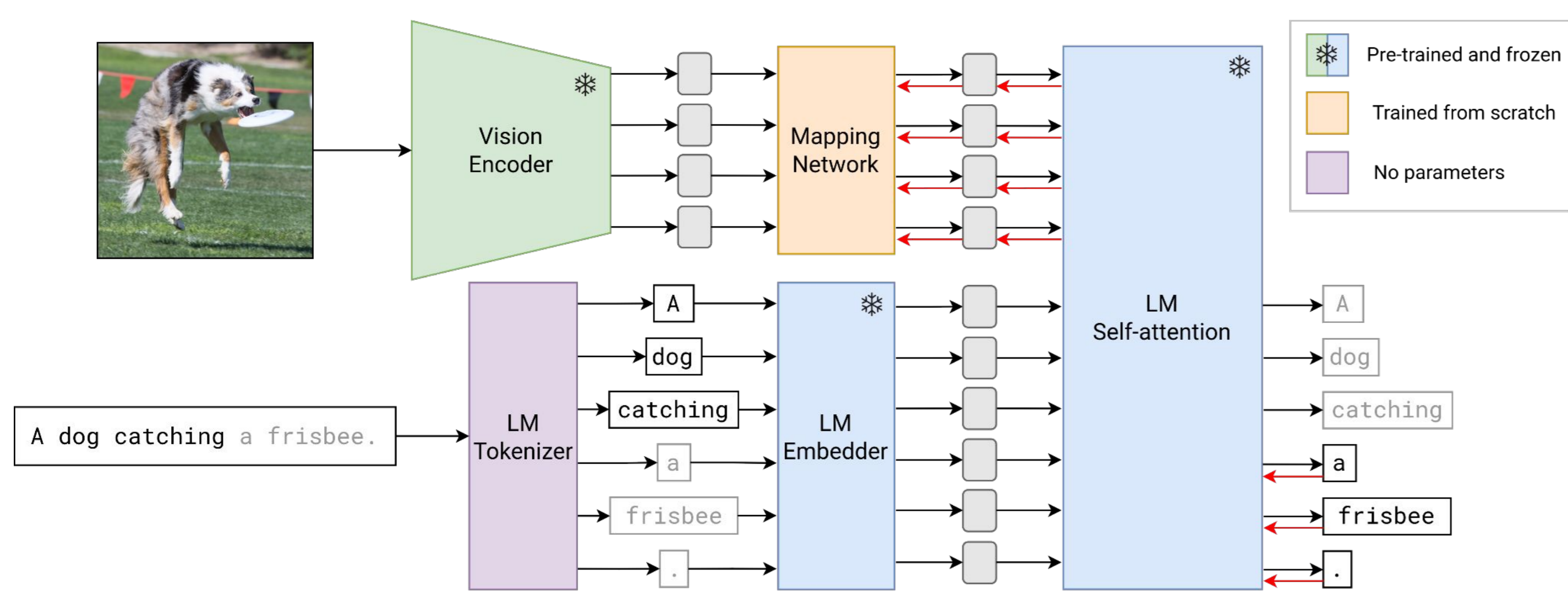


Motivation

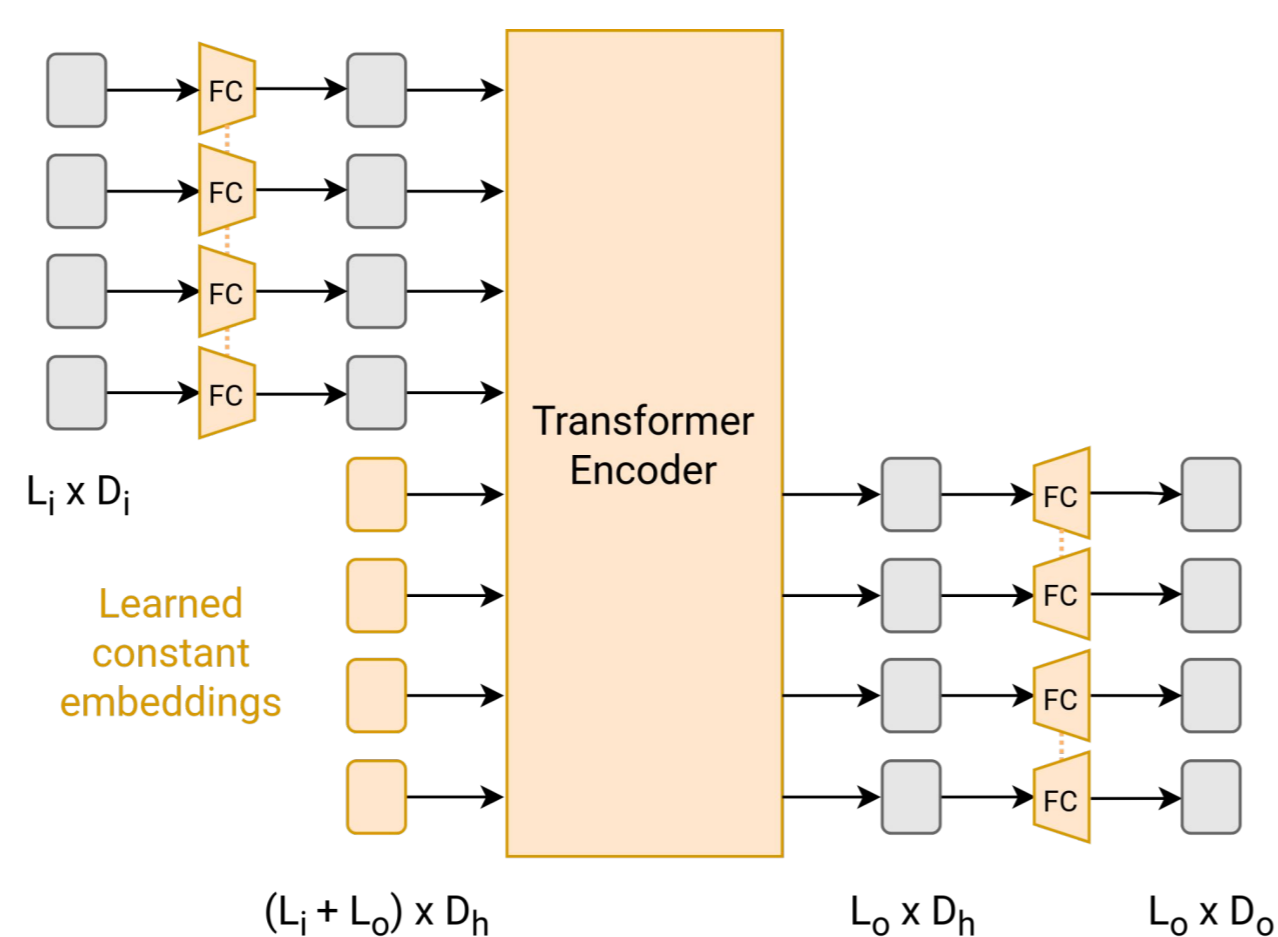
- Problem definition:** processing images and text to generate text (e.g., image captioning, VQA)
- Impressive recent progress in learning vision-only and language-only **pre-trained models** (e.g., CLIP, ALIGN, GPT, OPT, LLaMA)
- Research question:** can we reuse such powerful unimodal models and *efficiently adapt* them for multimodal vision-language downstream tasks?
- Issues with existing approaches** (e.g., Frozen, MAGMA, Flamingo):
 - Large** number of **trainable parameters** (~40M to ~10B)
 - Inserting adapter layers is **not straightforward**
 - Learning vision encoders from scratch **does not scale well**



Method



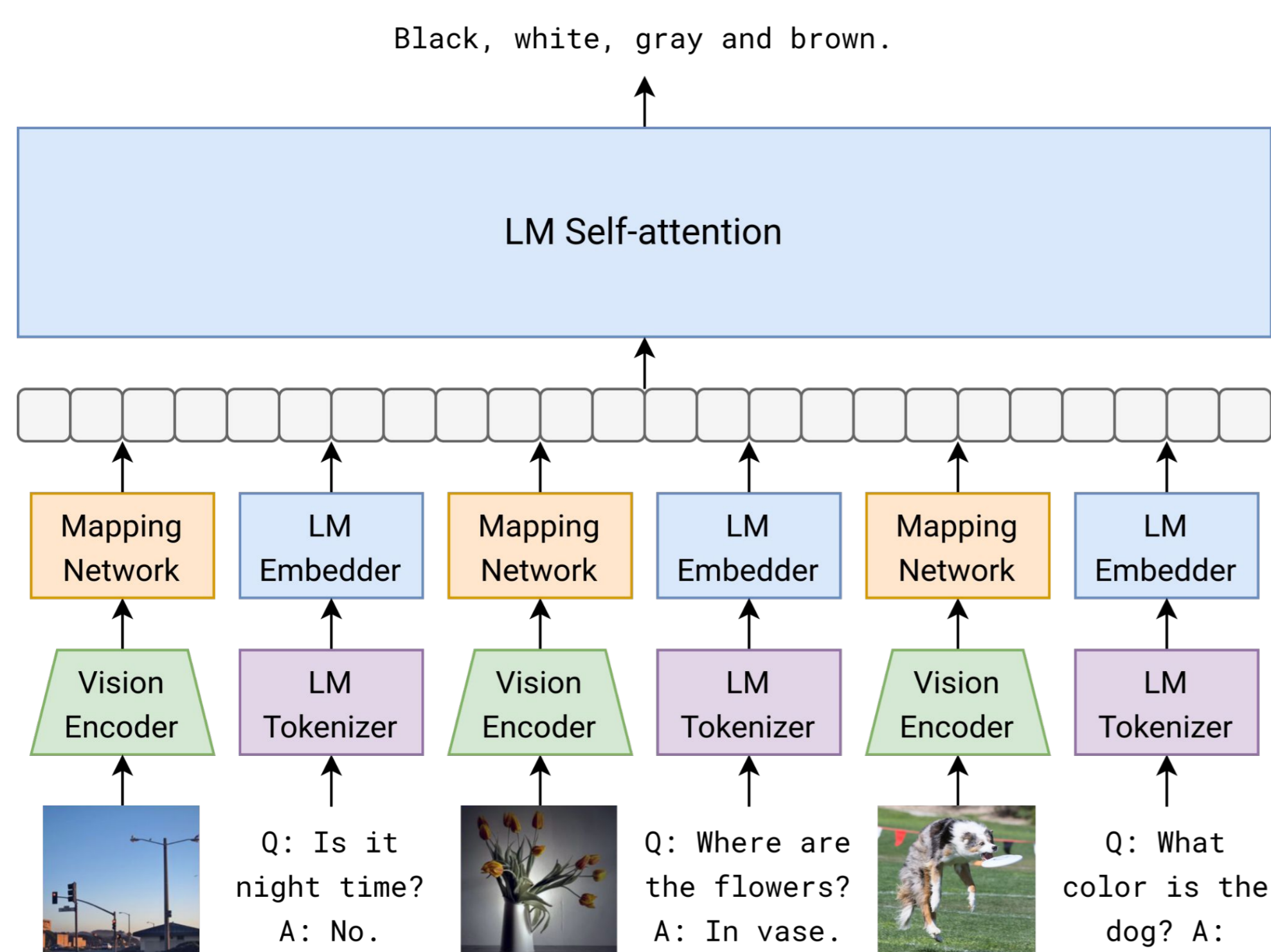
- Idea:** learn a lightweight vision-language mapping between unimodal representation spaces
- CLIP-ViT-L/14 vision encoder (303M params)
- GPT-J language model (6.1B params)
- Transformer-based **mapping network** (3.4M params)
- Image-conditioned language modeling loss



Benefits of our approach:

- Orders of magnitude fewer trainable parameters
- Can be trained in just a few hours
- Uses modest computational resources and public datasets
- Modular, hence easily extensible to newer/better pretrained unimodal models

Vision-language few-shot prompting

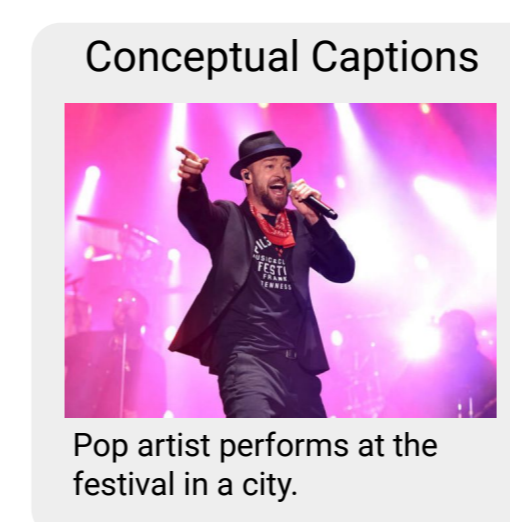


- We can leverage the **in-context learning** capabilities of the frozen language model to transfer to **unseen vision-language tasks** (e.g., VQA)
- The learned mapping network allows us to feed **visual context** to the language model, enabling **multimodal prompting**
- Now the language model is able to “see”!

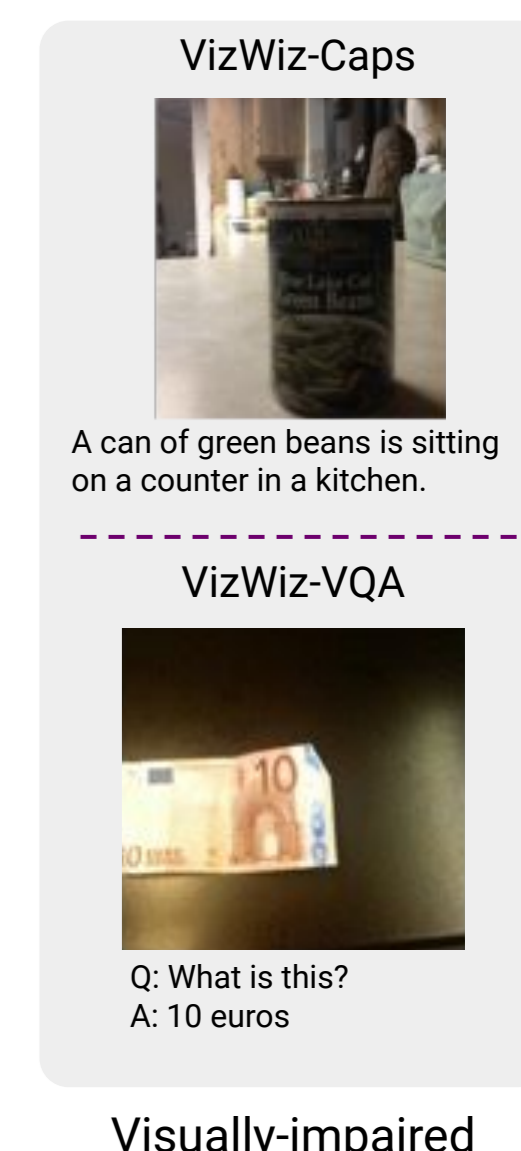
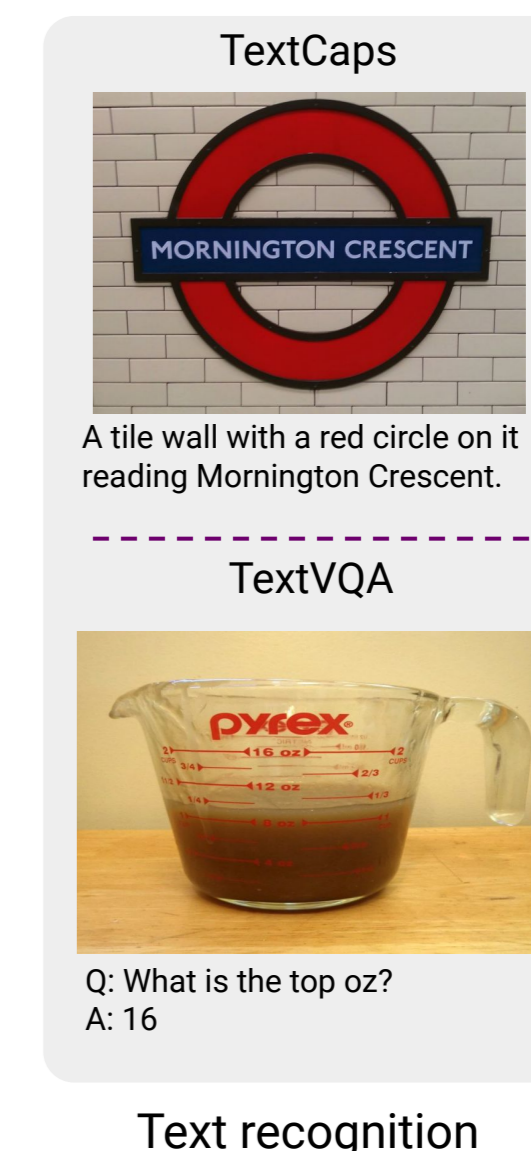
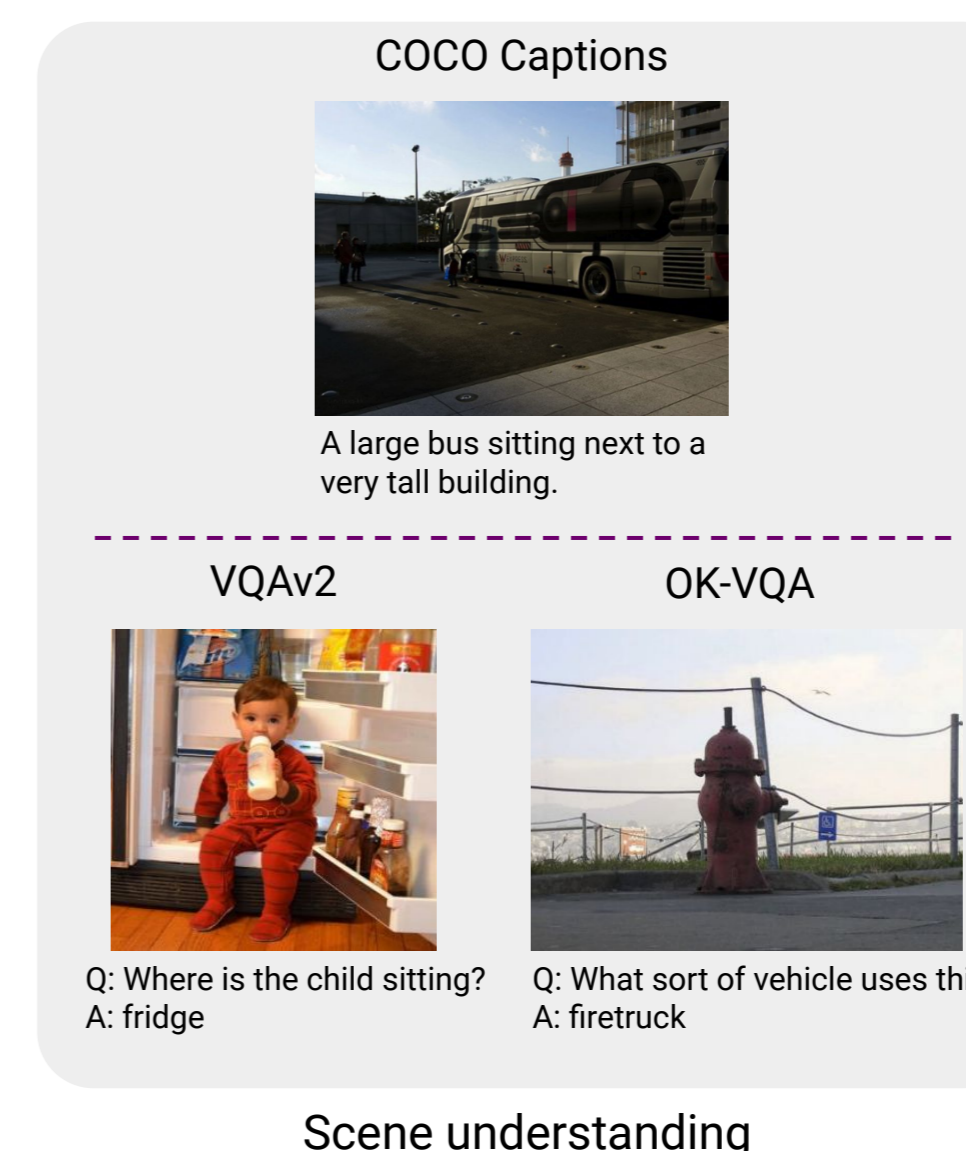
Experimental setting

- We evaluate our method on several vision-language benchmarks across two tasks:
 - Image captioning** (CC, COCO, TextCaps, VizWiz-Caps)
 - Few-shot VQA** (VQAv2, OK-VQA, TextVQA, VizWiz-VQA)

Domain-agnostic training dataset



Pairs of **in-domain captioning** (training) and **VQA** (evaluation) datasets

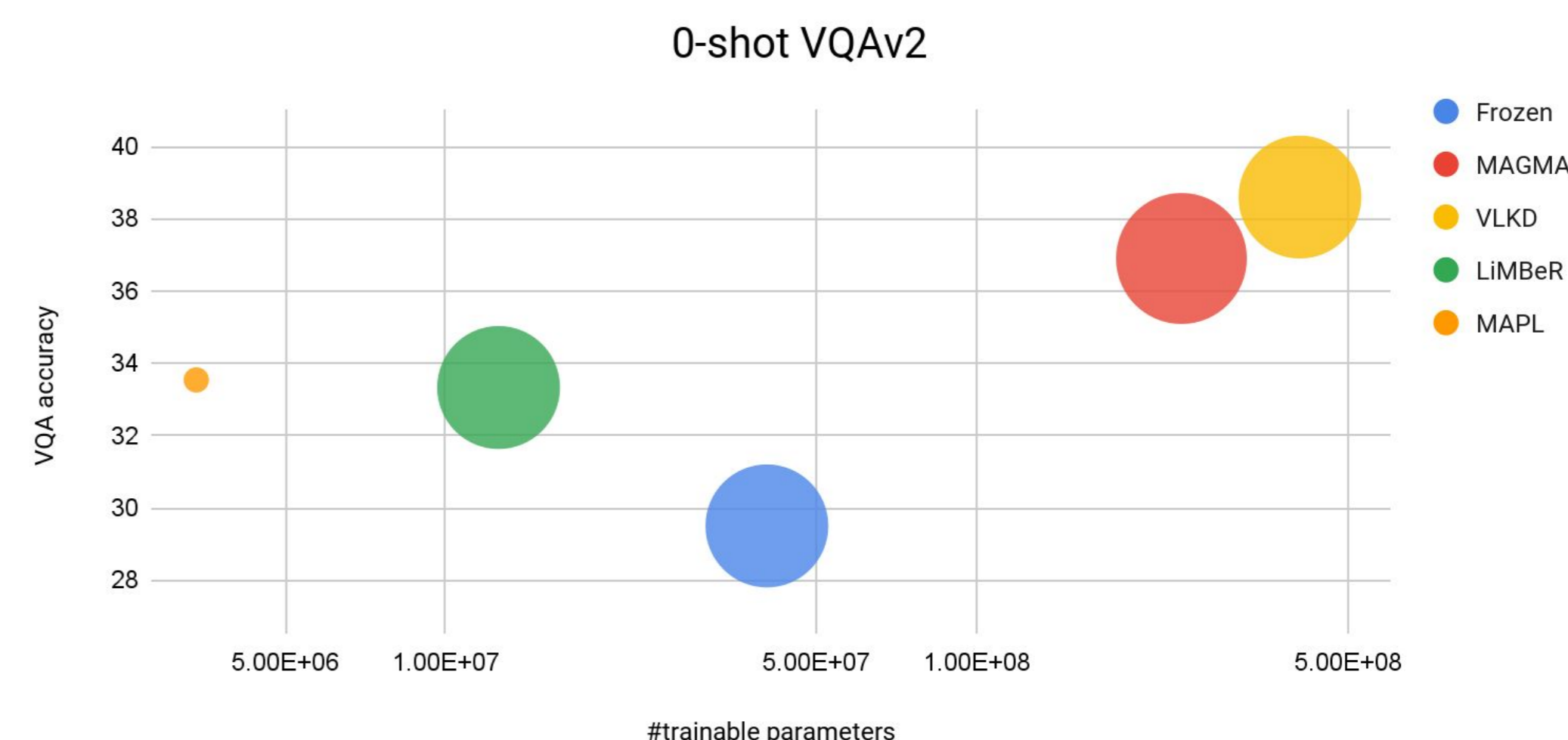


Quantitative results

Domain-agnostic training

Image-caption pairs come from a domain agnostic of the downstream task

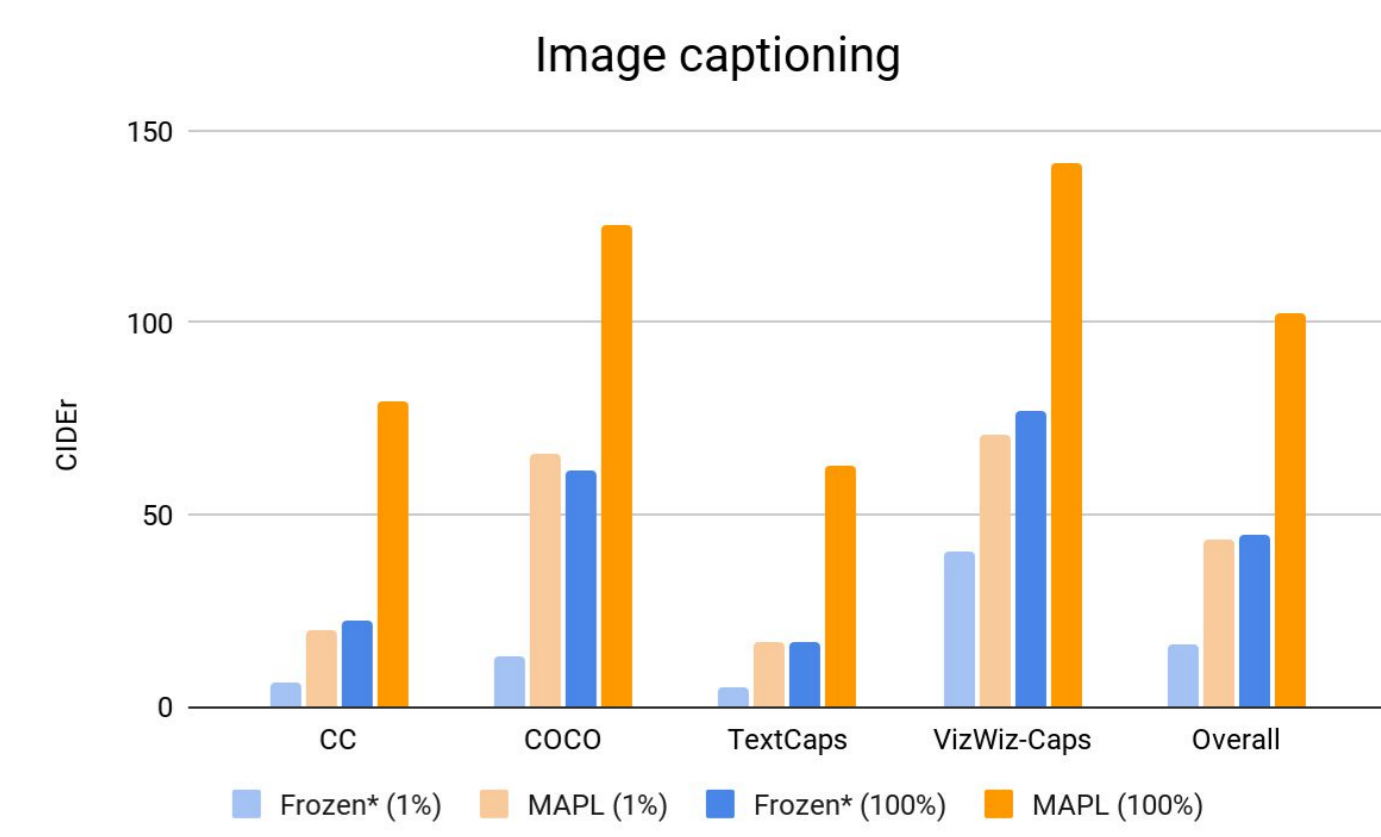
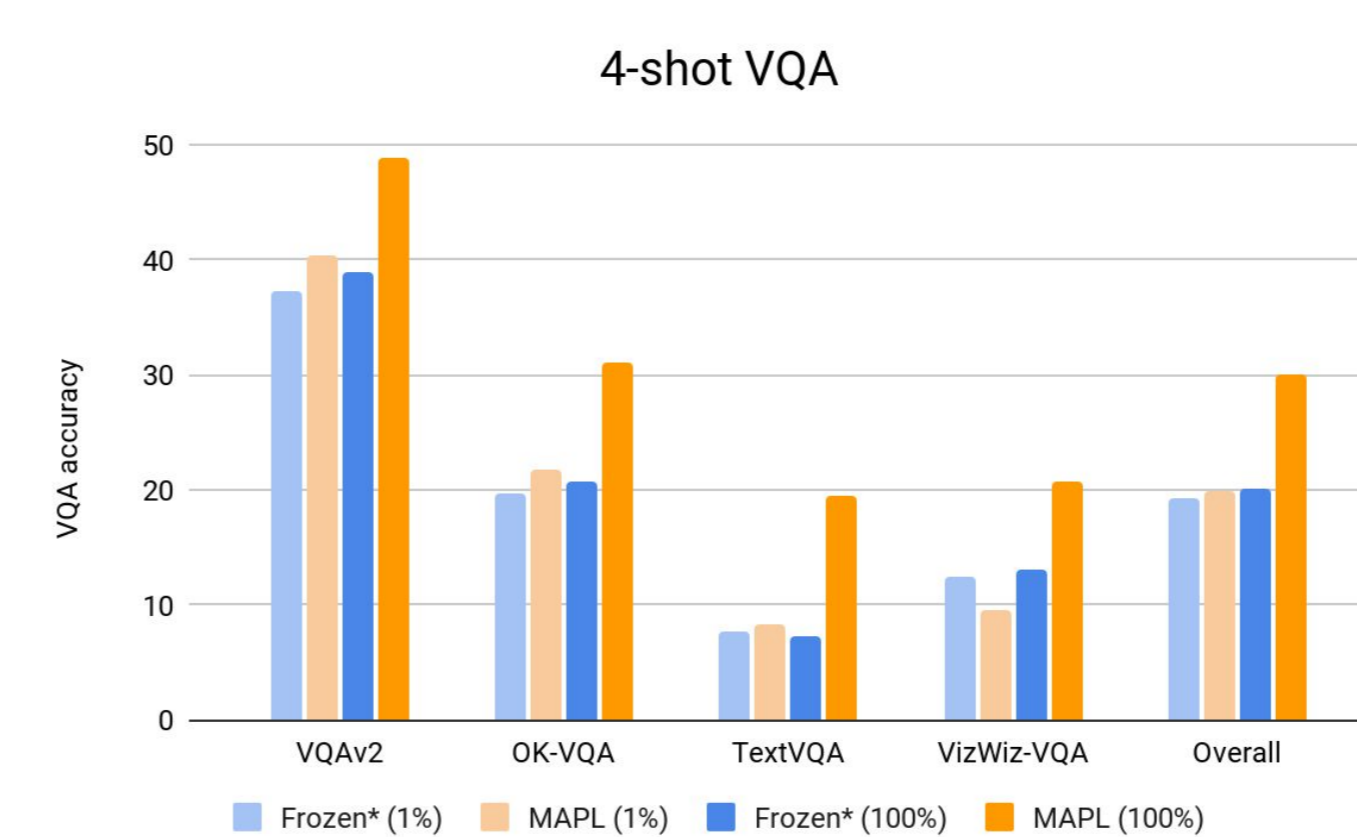
- MAPL** is competitive with existing and concurrent methods while training orders of magnitude fewer parameters on less multimodal data (bubble size)



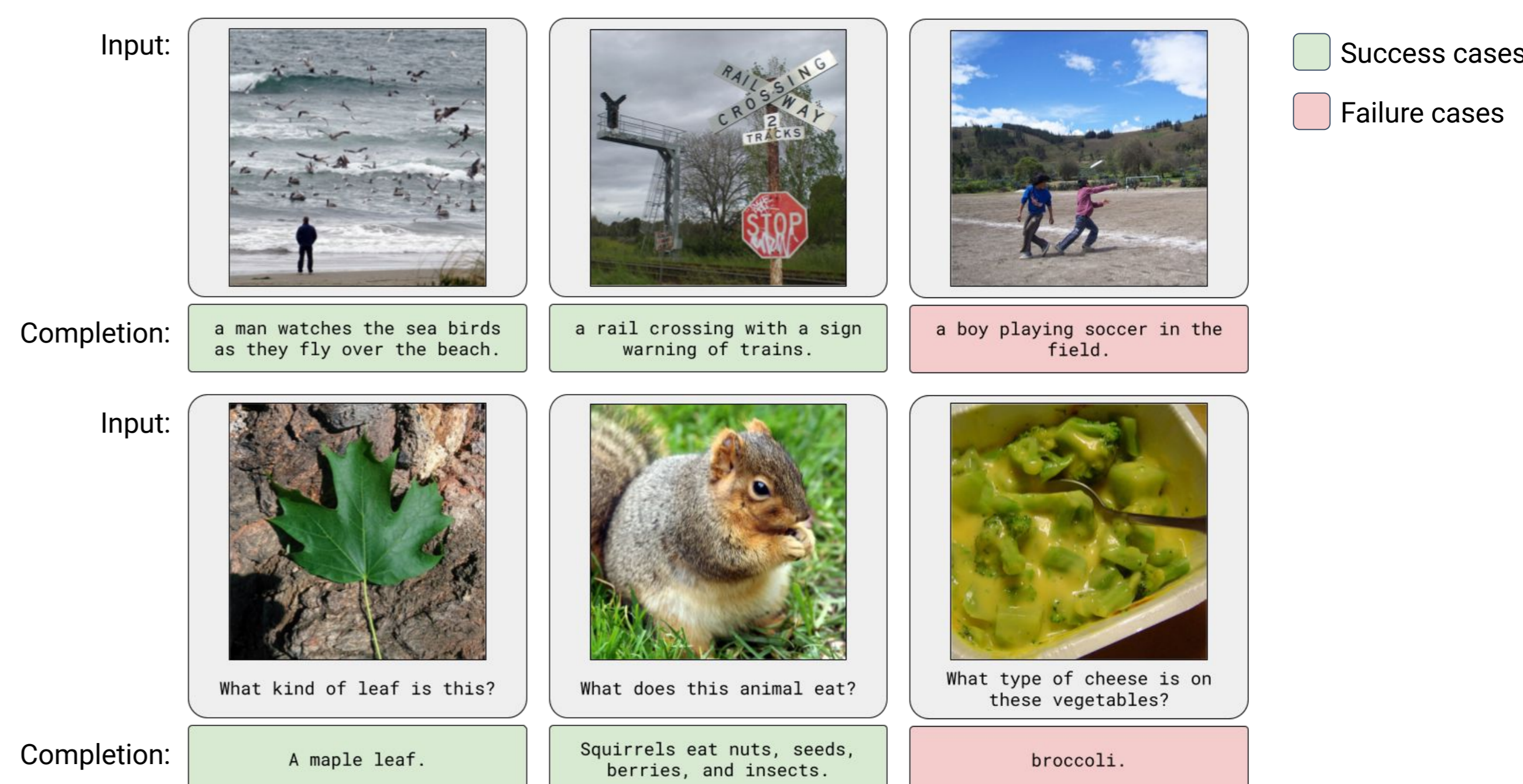
In-domain training

Image-caption pairs come from same domain as the downstream task

- Both **MAPL** and **Frozen** benefit from directly training on in-domain data, but the gap is larger for **MAPL**
- MAPL** outperforms **Frozen** on all considered tasks and benchmarks when training on 100% of in-domain data
- MAPL** trained on 1% of in-domain data generally outperforms **Frozen** trained on 100% of in-domain data on 4-shot VQA



Qualitative results



Conclusion

- Pretrained vision and language models can be repurposed for new VL tasks with modest computational resources and public datasets
- MAPL matches or outperforms similar methods on several VL benchmarks with fewer trainable parameters and less training data
- MAPL is effective in low-data and in-domain settings, useful when training with large-scale datasets is difficult
- Effective recycling of large pretrained models is becoming increasingly important

