NEURAL INFORMATION PROCESSING SYSTEMS

Zero-Shot Video Question Answering via Frozen Bidirectional Language Models

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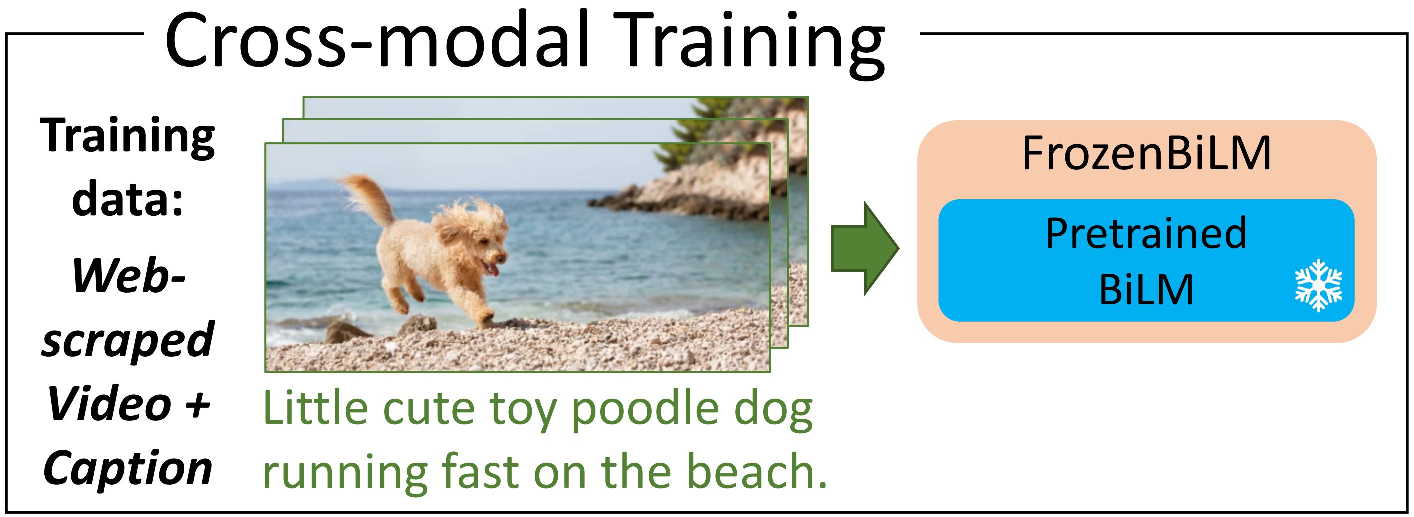
Project page: https://antoyang.github.io/frozenbilm.html

Paper: https://arxiv.org/abs/2206.08155

Zero-Shot VideoQA [1]

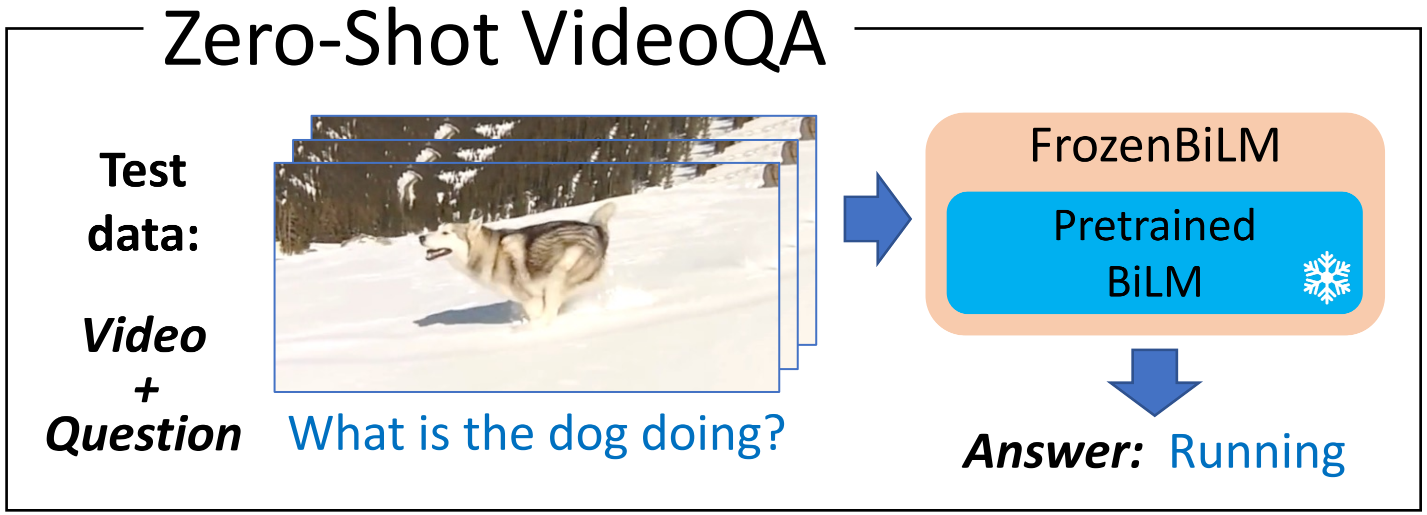


Cross-modal Training

Training data:

Web-scraped Video + Caption

Little cute toy poodle dog running fast on the beach.



Zero-Shot VideoQA

Test data:

Video + Question

What is the dog doing?

Answer: Running

[1] Just Ask: Learning to Answer Questions from Millions of Narrated Videos, A. Yang et al, ICCV 2021.

FrozenBiLM idea

- **Background:** SoTA models for zero-shot VQA rely on *frozen* autoregressive language models [2].
- **Issues:** They require billion parameters to work well => hard to train and deploy in practice.
- **Problematic:** Can we tackle zero-shot VideoQA with lighter models?
- **Idea:** Use bidirectional language models (BiLM)!

Autoregressive language models

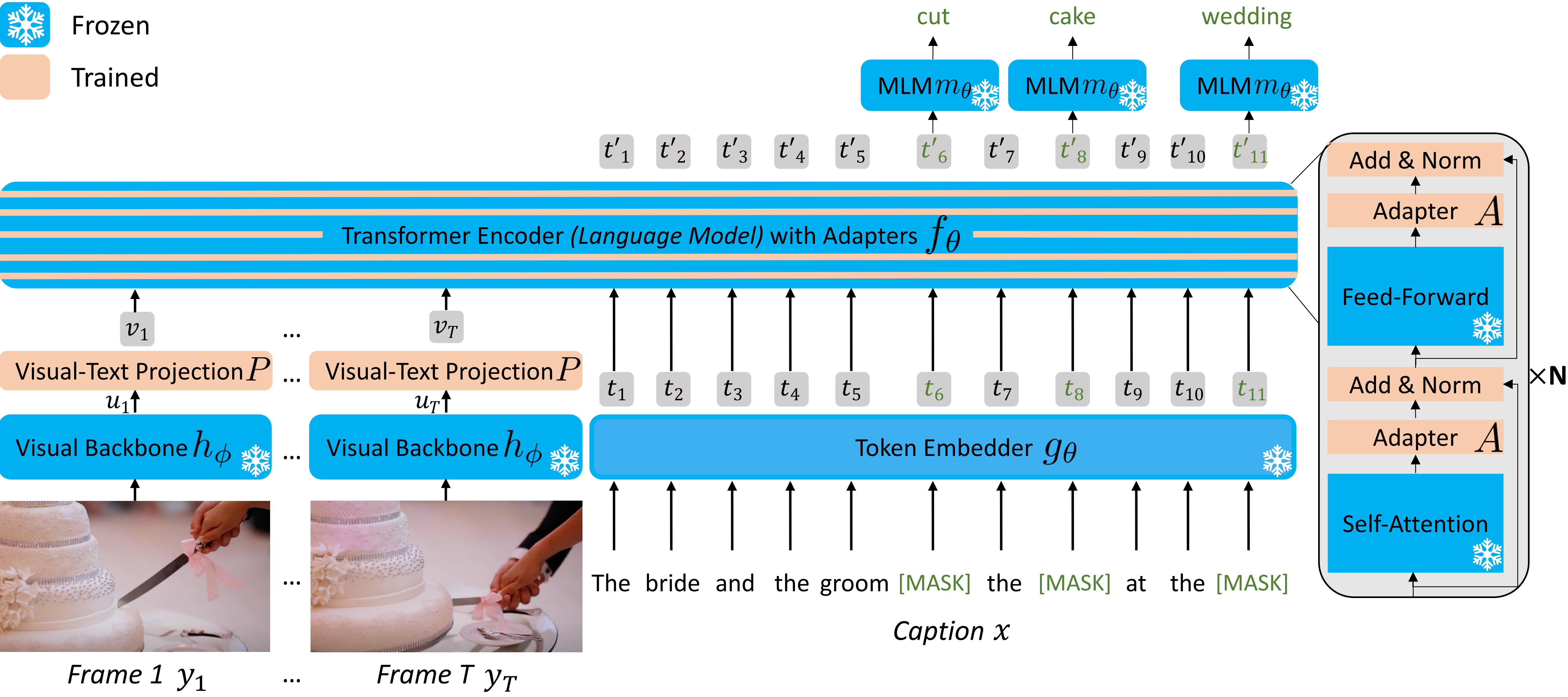
[BOS] -> The
The -> dog
The dog -> is
The dog is -> running
The dog is running -> in
The dog is running in -> the
The dog is running in the -> snow
The dog is running in the snow -> EOS

Bidirectional language models (BiLM)

The dog is [MASK] in the snow -> running

[2] Multi-modal Few-Shot Learning with Frozen Language Models, M. Tsimpoukelli et al, NeurIPS 2021.

Multi-modal adaptation of a *Frozen* BiLM



Frozen
Trained
cut
cake
wedding
MLM m_θ
MLM m_θ
MLM m_θ
t'_1 t'_2 t'_3 t'_4 t'_5 t'_6 t'_7 t'_8 t'_9 t'_{10} t'_{11}
Transformer Encoder *(Language Model)* with Adapters f_θ
Add & Norm
Adapter A
Feed-Forward
Add & Norm
Adapter A
Self-Attention
×N
v_1
...
v_T
Visual-Text Projection P
...
Visual-Text Projection P
u_1
u_T
t_1 t_2 t_3 t_4 t_5 t_6 t_7 t_8 t_9 t_{10} t_{11}
Visual Backbone h_ϕ
...
Visual Backbone h_ϕ
Token Embedder g_θ
...
The bride and the groom [MASK] the [MASK] at the [MASK]
Caption x
Frame 1 y_1
...
Frame T y_T

Training data

- **Initialization of the frozen modules:** DeBERTa-V2-Xlarge (900M params) [3] for the BiLM, CLIP ViT-L/14 @224px [4] for the visual backbone.
- **Training data:** Videos with alt-text description from the WebVid10M. Such data are easy to obtain at scale and less noisy than narrated videos [5].

Lonely beautiful woman sitting on the tent looking outside. wind on the hair and camping on the beach near the colors of water and shore. freedom and alternative tiny house for traveler lady drinking.

Female cop talking on walkietalkie, responding emergency call, crime prevention

Billiards, concentrated young woman playing in club.

[3] DeBERTa: Decoding-enhanced BERT with Disentangled Attention, P. He et al, ICLR 2021.

[4] Learning transferable visual models from natural language supervision, A. Radford et al, arXiv 2021.

[5] Frozen in Time: A Joint Video and Text Encoder for End-to-End Retrieval, M. Bain et al, ICCV 2021.

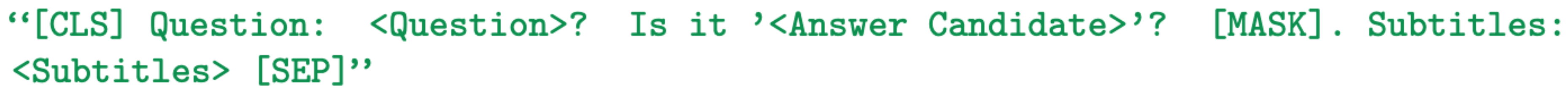
Downstream task adaptation

Answer prediction: We map the masked token in the following prompts with an **answer embedding module** which is initialized from the *frozen* masked language modeling head.

- Open-ended VideoQA:

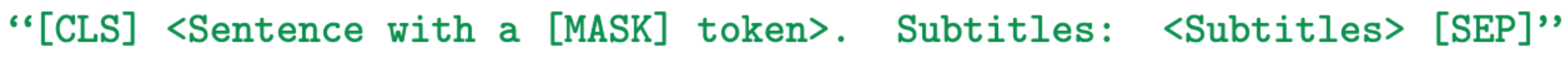
```
“[CLS] Question: <Question>? Answer: [MASK]. Subtitles: <Subtitles> [SEP]”
```

- Multiple-choice VideoQA:



```
“[CLS] Question: <Question>? Is it ’<Answer Candidate>’? [MASK]. Subtitles:
<Subtitles> [SEP]”
```

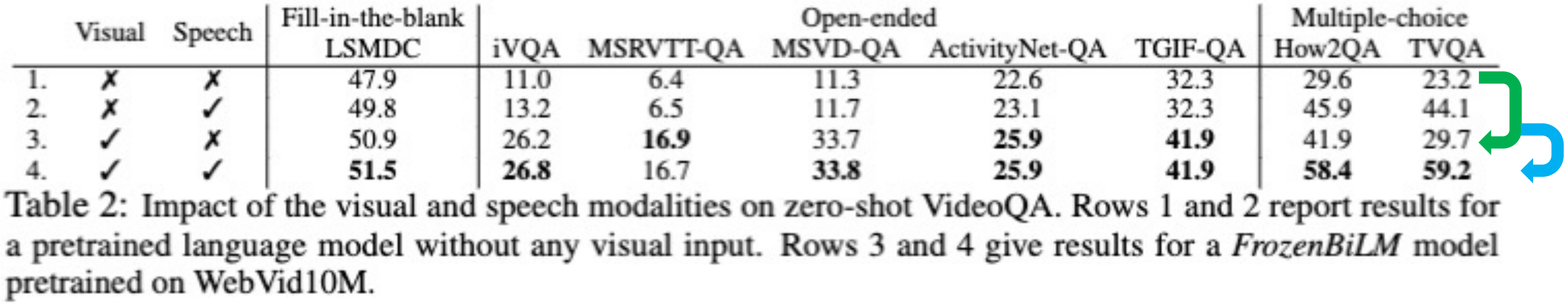
- Video-conditioned fill-in-the-blank:



```
“[CLS] <Sentence with a [MASK] token>. Subtitles: <Subtitles> [SEP]”
```

Ablation: Modalities

- Vision is essential.
- Speech helps.

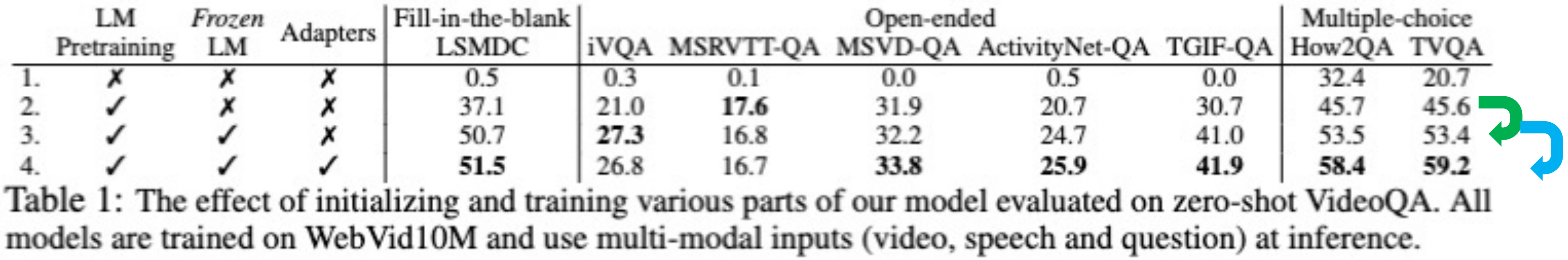


	Visual	Speech	Fill-in-the-blank			Open-ended			Multiple-choice	
			LSMDC	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA	How2QA	TVQA
1.	✗	✗	47.9	11.0	6.4	11.3	22.6	32.3	29.6	23.2
2.	✗	✓	49.8	13.2	6.5	11.7	23.1	32.3	45.9	44.1
3.	✓	✗	50.9	26.2	**16.9**	33.7	**25.9**	**41.9**	41.9	29.7
4.	✓	✓	**51.5**	**26.8**	16.7	**33.8**	**25.9**	**41.9**	**58.4**	**59.2**

Table 2: Impact of the visual and speech modalities on zero-shot VideoQA. Rows 1 and 2 report results for a pretrained language model without any visual input. Rows 3 and 4 give results for a *FrozenBiLM* model pretrained on WebVid10M.

Ablation: Model Training

- Freezing the pretrained BiLM considerably helps.
- Adapters help.

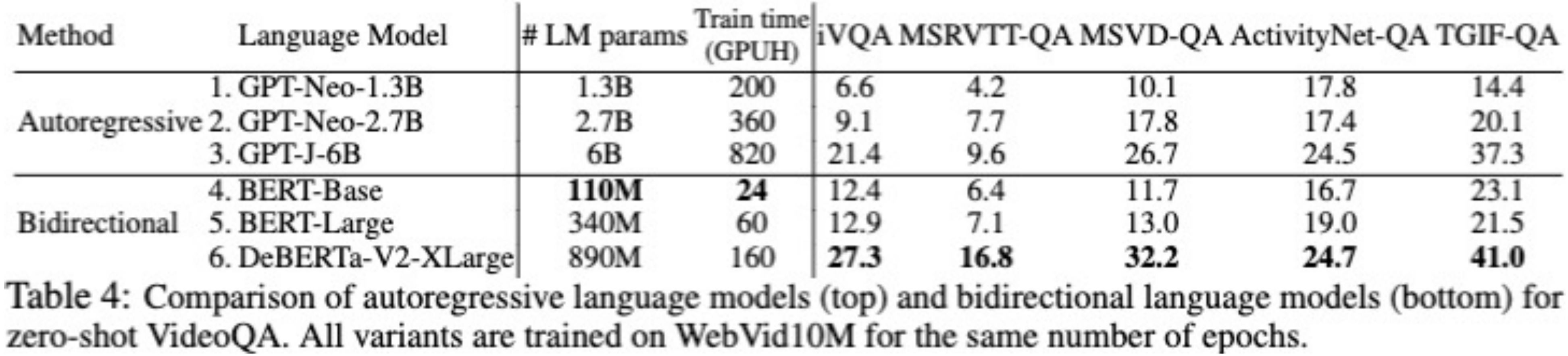


	LM	*Frozen*	Adapters	Fill-in-the-blank			Open-ended			Multiple-choice	
	Pretraining	LM		LSMDC	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA	How2QA	TVQA
1.	✗	✗	✗	0.5	0.3	0.1	0.0	0.5	0.0	32.4	20.7
2.	✓	✗	✗	37.1	21.0	**17.6**	31.9	20.7	30.7	45.7	45.6
3.	✓	✓	✗	50.7	**27.3**	16.8	32.2	24.7	41.0	53.5	53.4
4.	✓	✓	✓	**51.5**	26.8	16.7	**33.8**	**25.9**	**41.9**	**58.4**	**59.2**

Table 1: The effect of initializing and training various parts of our model evaluated on zero-shot VideoQA. All models are trained on WebVid10M and use multi-modal inputs (video, speech and question) at inference.

FrozenBiLM vs autoregressive LM

Bidirectional models perform better, train faster and require less parameters.

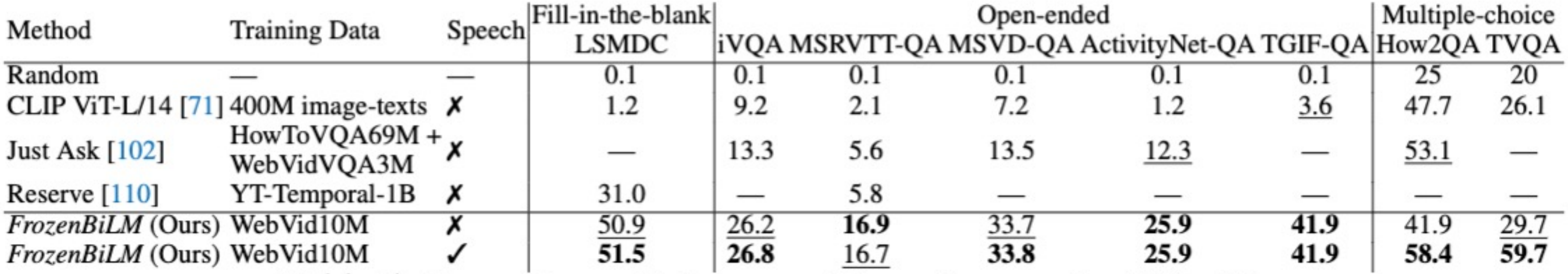


Method	Language Model	# LM params	Train time (GPUH)	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA
Autoregressive	1. GPT-Neo-1.3B	1.3B	200	6.6	4.2	10.1	17.8	14.4
	2. GPT-Neo-2.7B	2.7B	360	9.1	7.7	17.8	17.4	20.1
	3. GPT-J-6B	6B	820	21.4	9.6	26.7	24.5	37.3
Bidirectional	4. BERT-Base	**110M**	**24**	12.4	6.4	11.7	16.7	23.1
	5. BERT-Large	340M	60	12.9	7.1	13.0	19.0	21.5
	6. DeBERTa-V2-XLarge	890M	160	**27.3**	**16.8**	**32.2**	**24.7**	**41.0**

Table 4: Comparison of autoregressive language models (top) and bidirectional language models (bottom) for zero-shot VideoQA. All variants are trained on WebVid10M for the same number of epochs.

Zero-shot quantitative results

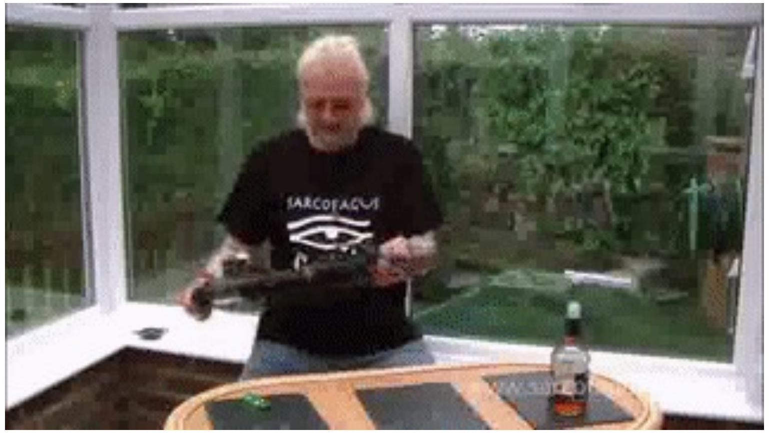
SoTA on 8 datasets spanning video-conditioned fill-in-the-blank, open-ended VideoQA and multiple-choice VideoQA.



Method	Training Data	Speech	Fill-in-the-blank	Open-ended					Multiple-choice	
			LSMDC	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA	How2QA	TVQA
Random	—	—	0.1	0.1	0.1	0.1	0.1	0.1	25	20
CLIP ViT-L/14 [71]	400M image-texts	✗	1.2	9.2	2.1	7.2	1.2	3.6	47.7	26.1
Just Ask [102]	HowToVQA69M + WebVidVQA3M	✗	—	13.3	5.6	13.5	12.3	—	53.1	—
Reserve [110]	YT-Temporal-1B	✗	31.0	—	5.8	—	—	—	—	—
FrozenBiLM (Ours)	WebVid10M	✗	50.9	26.2	**16.9**	33.7	**25.9**	**41.9**	41.9	29.7
FrozenBiLM (Ours)	WebVid10M	✓	**51.5**	**26.8**	16.7	**33.8**	**25.9**	**41.9**	**58.4**	**59.7**

Table 5: Comparison with the state of the art for zero-shot VideoQA.

Zero-shot qualitative results (open-ended)



Question: What is the man holding at the start of the video?

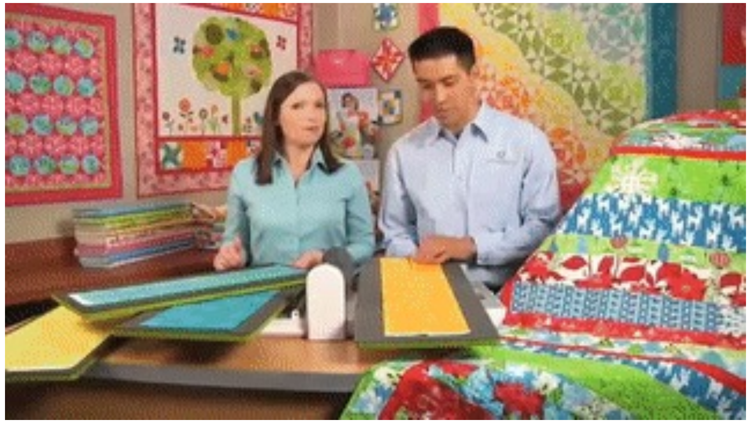
GT answer: guitar, electric guitar

Just Ask [1]: typewriter

UnFrozenBiLM: beer

FrozenBiLM (text-only): scissors

FrozenBiLM: guitar



Question: What item hanging on the wall features a tree?

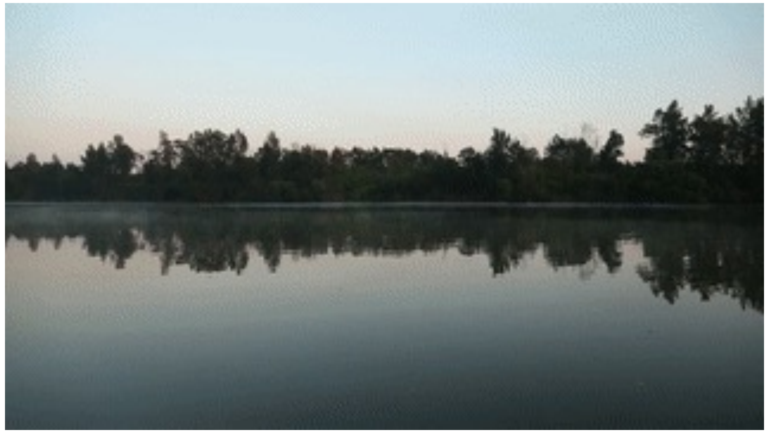
GT answer: quilt

Just Ask [1]: christmas tree

UnFrozenBiLM: fabric

FrozenBiLM (text-only): tree

FrozenBiLM: quilt



Question: Which category of sports does this sport belong to?

GT answer: surfing

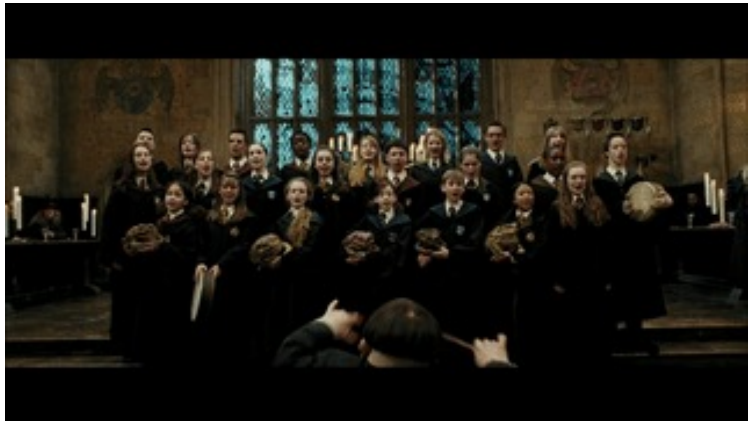
Just Ask [1]: second

UnFrozenBiLM: swimming

FrozenBiLM (text-only): 1

FrozenBiLM: surfing

Zero-shot qualitative results (fill-in-the-blank)



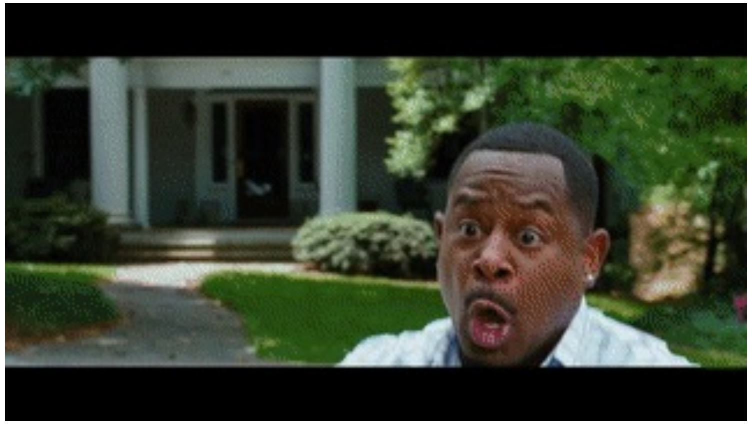
Sentence: Each singer in the front row ____ a huge toad.

GT answer: holds

UnFrozenBiLM: plays

FrozenBiLM (text-only): wears

FrozenBiLM: holds



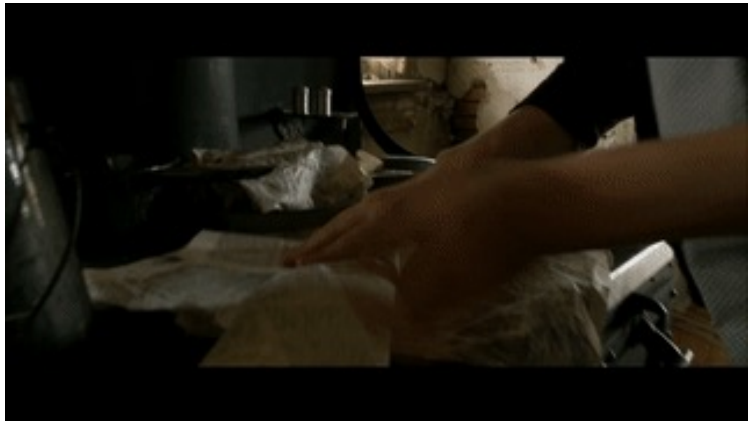
Sentence: Someone ____ him to the truck and across the street.

GT answer: chases

UnFrozenBiLM: follow

FrozenBiLM (text-only): drags

FrozenBiLM: chases



Sentence: A woman wraps food in newspapers and brings it over to their ____.

GT answer: table

UnFrozenBiLM: man

FrozenBiLM (text-only): home

FrozenBiLM: table

Zero-shot qualitative results (multiple-choice)

Question: When did the chef flipped over the layer of rice and seaweed?

GT answer: A0

A0: after she sprinkled sesame

A1: after she added cucumber

A2: after she added fish

A3: after she cut the cucumbers

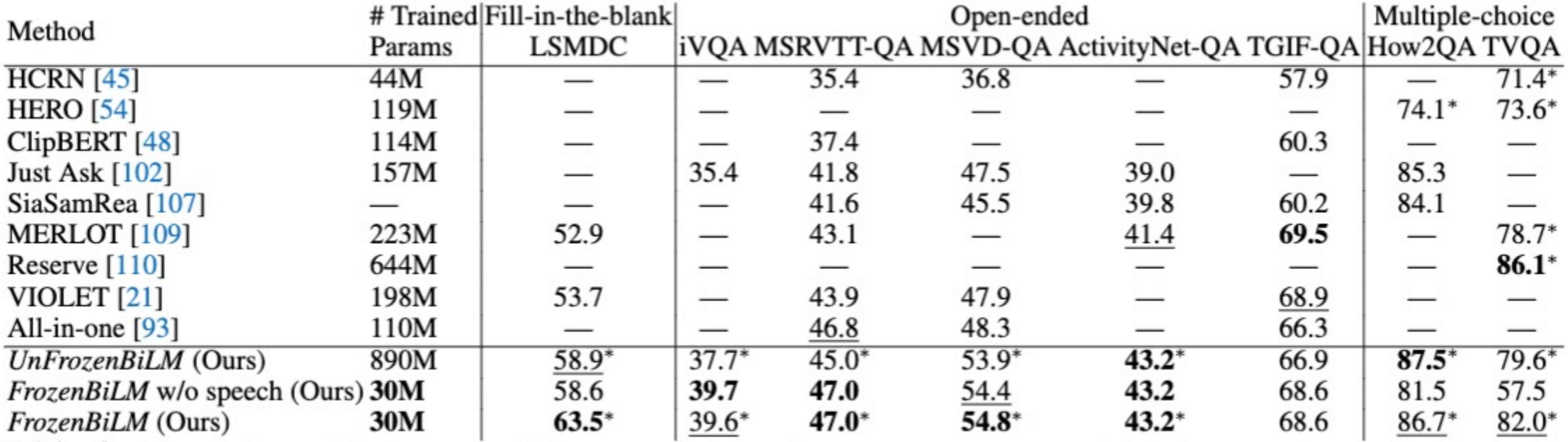
UnFrozenBiLM: A3

FrozenBiLM (text-only):A1

FrozenBiLM: A0

Fully-supervised results

- Freezing the BiLM also helps in the fully-supervised setting.
- Competitive performance + high parameter efficiency.

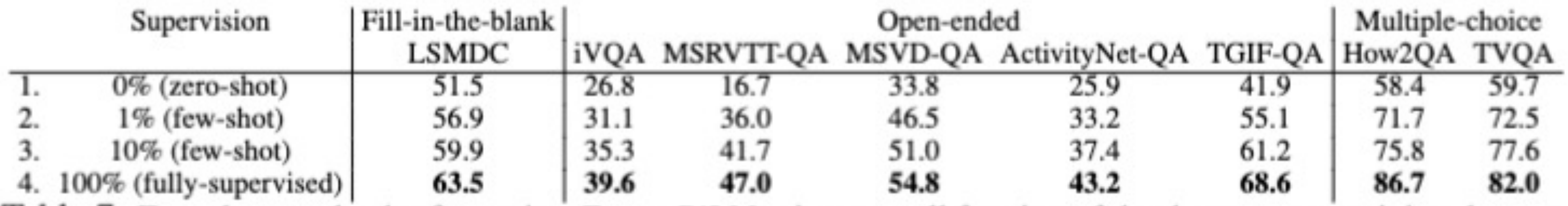


Method	# Trained	Fill-in-the-blank	Open-ended					Multiple-choice	
	Params	LSMDC	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA	How2QA	TVQA
HCRN [45]	44M	—	—	35.4	36.8	—	57.9	—	71.4*
HERO [54]	119M	—	—	—	—	—	—	74.1*	73.6*
ClipBERT [48]	114M	—	—	37.4	—	—	60.3	—	—
Just Ask [102]	157M	—	35.4	41.8	47.5	39.0	—	85.3	—
SiaSamRea [107]	—	—	—	41.6	45.5	39.8	60.2	84.1	—
MERLOT [109]	223M	52.9	—	43.1	—	41.4	**69.5**	—	78.7*
Reserve [110]	644M	—	—	—	—	—	—	—	**86.1***
VIOLET [21]	198M	53.7	—	43.9	47.9	—	68.9	—	—
All-in-one [93]	110M	—	—	46.8	48.3	—	66.3	—	—
UnFrozenBiLM (Ours)	890M	58.9*	37.7*	45.0*	53.9*	**43.2***	66.9	**87.5***	79.6*
FrozenBiLM w/o speech (Ours)	**30M**	58.6	**39.7**	**47.0**	54.4	**43.2**	68.6	81.5	57.5
FrozenBiLM (Ours)	**30M**	**63.5***	39.6*	**47.0***	**54.8***	**43.2***	68.6	86.7*	82.0*

Table 6: Comparison with the state of the art, and the variant *UnFrozenBiLM* which does not freeze the language model weight, on fully-supervised benchmarks. * denotes results obtained with speech input.

Few-shot results

- Significant improvements over zero-shot when using 1% of the downstream training data for finetuning.



	Supervision	Fill-in-the-blank	Open-ended					Multiple-choice	
		LSMDC	iVQA	MSRVTT-QA	MSVD-QA	ActivityNet-QA	TGIF-QA	How2QA	TVQA
1.	0% (zero-shot)	51.5	26.8	16.7	33.8	25.9	41.9	58.4	59.7
2.	1% (few-shot)	56.9	31.1	36.0	46.5	33.2	55.1	71.7	72.5
3.	10% (few-shot)	59.9	35.3	41.7	51.0	37.4	61.2	75.8	77.6
4.	100% (fully-supervised)	**63.5**	**39.6**	**47.0**	**54.8**	**43.2**	**68.6**	**86.7**	**82.0**

Table 7: Few-shot results, by finetuning *FrozenBiLM* using a small fraction of the downstream training dataset.