

Vid2Seq: Large-Scale Pretraining of a Visual Language Model for Dense Video Captioning

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Project page: https://antoyang.github.io/vid2seq.html

Paper: https://arxiv.org/abs/2302.14115





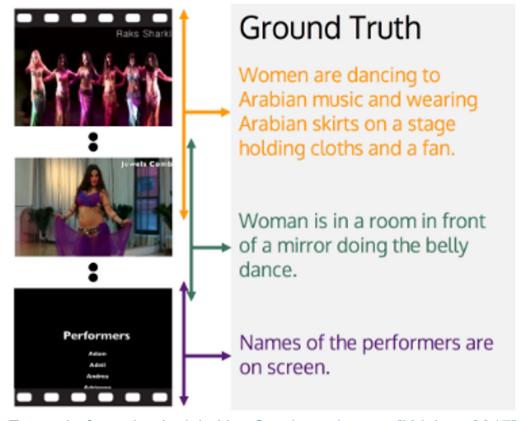






Dense Video Captioning

- Task: generate temporally localized captions for all events in an untrimmed minutes-long video.
- Prior approaches (e.g. [Wang 2021]): are task specific and trained only on manually annotated datasets.



Example from the ActivityNet-Captions dataset [Krishna 2017].

The Vid2Seq model

- Formulates dense video captioning as a sequence-to-sequence problem.
- Time is quantized and jointly tokenized with the text.
- Model architecture: visual encoder, text encoder and text decoder.



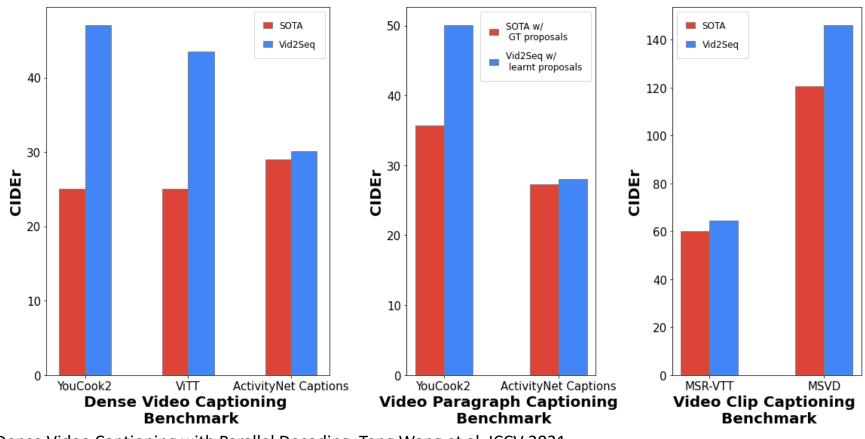
Input transcribed speech 3.02s → 4.99s: Please stay calm! 42.87s → 45.97s: Hey my friend!

Pretraining Vid2Seq on untrimmed narrated videos

- Speech is also cast as a single sequence of text and time tokens.
- Generative objective: given visual inputs, predict speech.
- **Denoising objective:** given visual inputs and noisy speech, predict masked tokens.



Vid2Seq improves the SoTA on various video captioning tasks.



[Wang 2021] End-to-End Dense Video Captioning with Parallel Decoding, Teng Wang et al, ICCV 2021.

[Zhu 2022] End-to-end Dense Video Captioning as Sequence Generation, Wanrong Zhu et al, COLING 2022.

[Lei 2020] MART: Memory-Augmented Recurrent Transformer for Coherent Video Paragraph Captioning, Jie Lei et al, ACL 2020.

[Seo 2022] End-to-end Generative Pretraining for Multimodal Video Captioning, Paul Hongsuck Seo et al, CVPR 2022.

[Lin 2022] SwinBERT: End-to-End Transformers with Sparse Attention for Video Captioning, Kevin Lin et al, CVPR 2022.

Benefits of pretraining on untrimmed narrated videos with time tokens

Pretraini	١	ouCook2		ActivityNet Captions			
Untrimmed	Time tokens	SODA	CIDEr	F1	SODA	CIDEr	F1
X	X	4.0	18.0	18.1	5.4	18.8	49.2
√	Х	5.5	27.8	20.5	5.5	26.5	52.1
√	√	7.9	47.1	27.3	5.8	30.1	52.4

Effect of pretraining losses and modalities

The visual inputs only model benefits from the generative objective. The denoising objective helps the model with visual+speech inputs.

Finetuning Input		Pretraining losses		YouCook2			ActivityNet Captions		
Visual	Speech	Generative	Denoising	SODA	CIDEr	F1	SODA	CIDEr	F1
\checkmark	X	No pretraining		3.0	15.6	15.4	5.4	14.2	46.5
√	√	No pretraining		4.0	18.0	18.1	5.4	18.8	49.2
√	Х	√	X	5.7	25.3	23.5	5.9	30.2	51.8
√	√	√	X	2.5	10.3	15.9	4.8	17.0	48.8
\checkmark	√	√	√	7.9	47.1	27.3	5.8	30.1	52.4

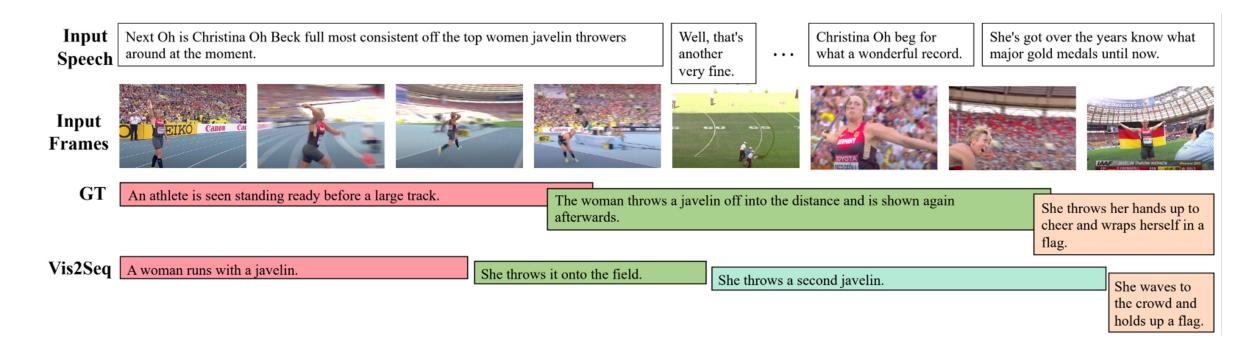
Vid2Seq generalizes well to few-shot settings.

We find that pretraining is crucial for few-shot generalization.

Data	YouCook2			ViTT			ActivityNet Captions		
	SODA	CIDEr	METEOR	SODA	CIDEr	METEOR	SODA	CIDEr	METEOR
1%	2.4	10.1	3.3	2.0	7.4	1.9	2.2	6.2	3.2
10%	3.8	18.4	5.2	10.7	28.6	6.0	4.3	20.0	6.1
50%	6.2	32.1	7.6	12.5	38.8	7.8	5.4	27.5	7.8
100%	7.9	47.1	9.3	13.5	43.5	8.5	5.8	30.1	8.5

Qualitative dense video captioning results

More examples at: https://www.youtube.com/watch?v=3oEHSU5Exsl



Conclusion

- We introduce Vid2Seq, a new visual language model for dense video captioning.
- We show how Vid2Seq can be effectively pretrained on unlabeled narrated videos at scale.
- The pretrained Vid2Seq model improves the SoTA on 3 dense video captioning datasets, 2 video paragraph captioning datasets and 2 video clip captioning datasets, and generalizes well to few-shot setting.