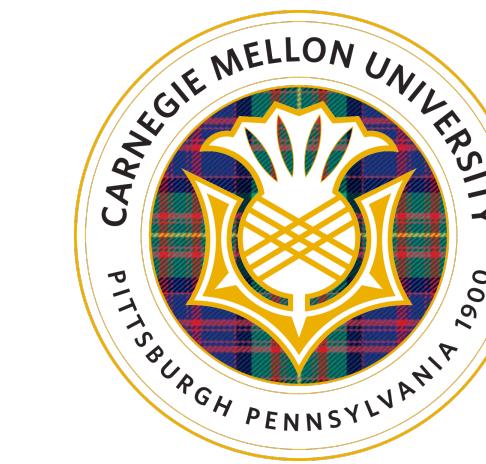


# Support-Set Bottlenecks for Video-Text Representation Learning

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ICLR 2021 spotlight

\* equal contribution



FACEBOOK

## Noise contrastive learning

$$f\left(\begin{array}{c} \text{Image of a cat with blue eyes} \end{array}\right) = f\left(\begin{array}{c} \text{Image of a cat with grey eyes} \end{array}\right) \neq f\left(\begin{array}{c} \text{Image of a white dog} \end{array}\right)$$

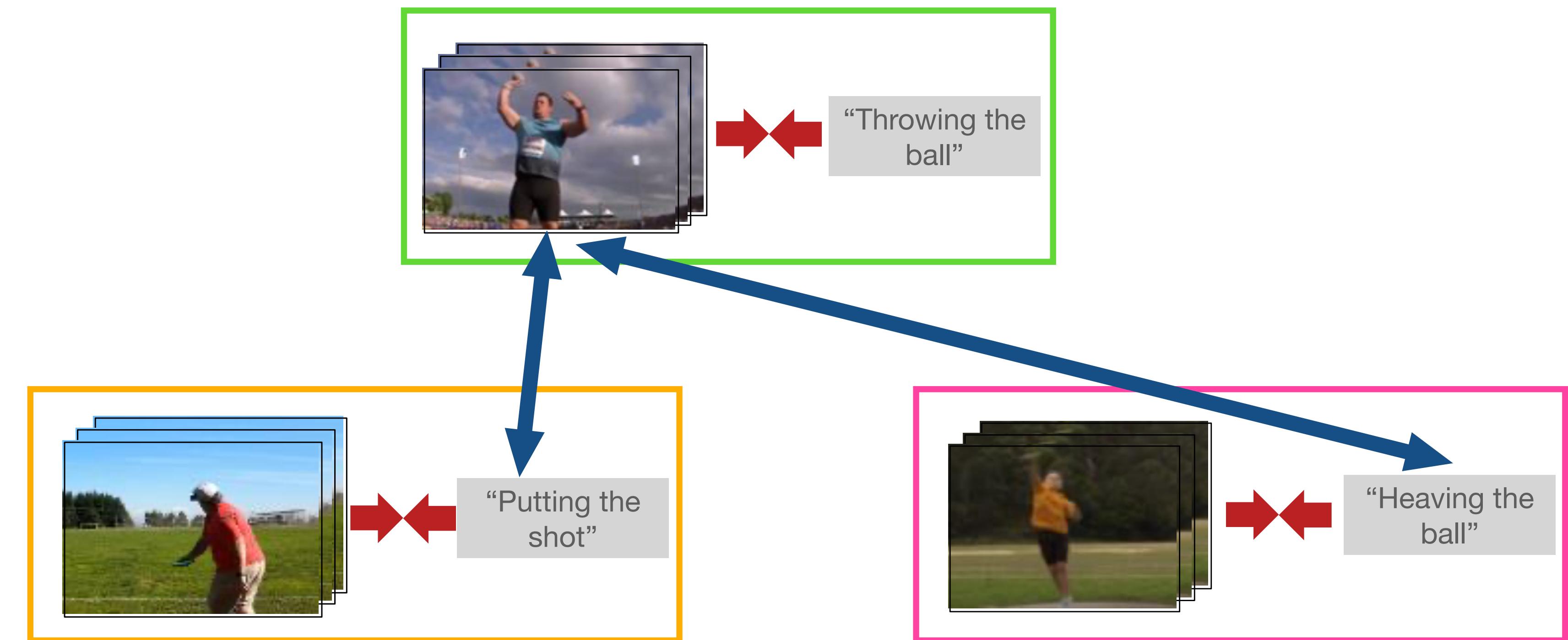
Key idea:  
features should encode image's core information.  
learn this by comparing augmentations against other images.

Examples: NPID, MoCo, CMC, SimCLR...

# Noise contrastive learning for Video-Text Representation Learning

Multi-modal contrastive formulation:

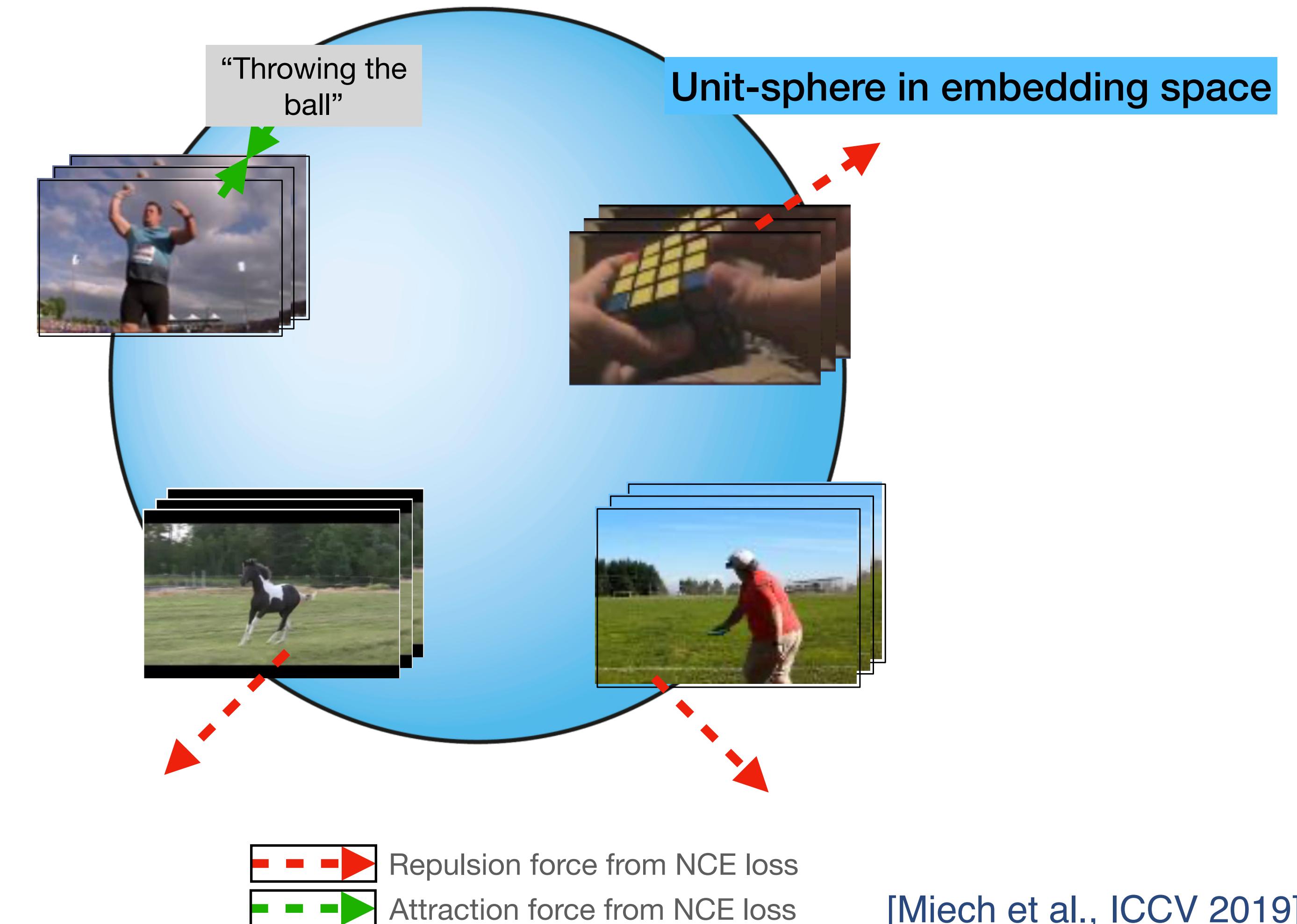
- **Pull** together videos and **their** captions
- **Push** apart videos and **other** captions



[Miech et al., ICCV 2019; Miech et al., CVPR 2020]

# Curse of Noise contrastive learning: Faulty Negatives

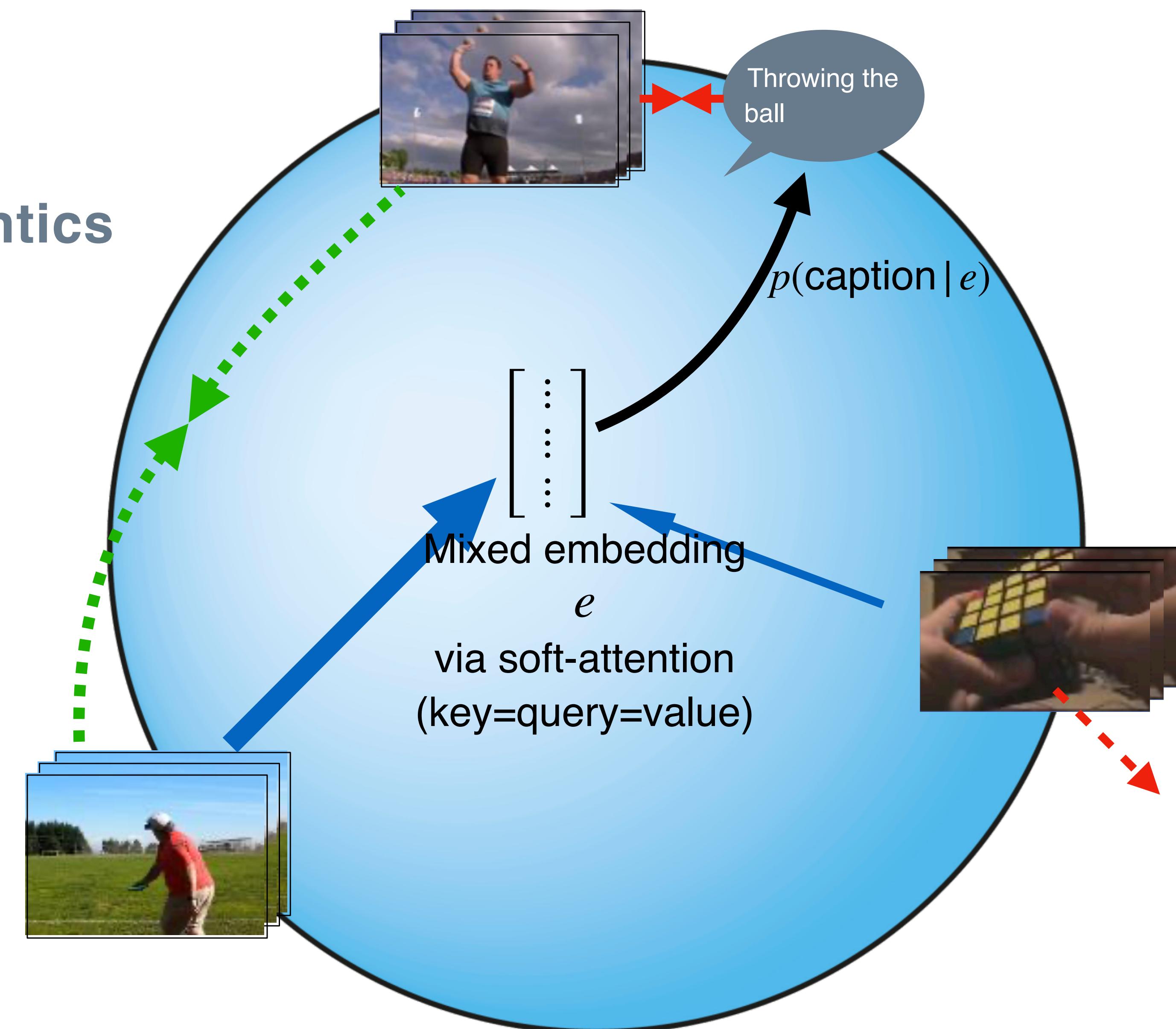
This can incorrectly push apart videos with the same content



## Key Insight: Attention for Shared Semantics

We assume that, for each video, the batch always contain **at least one more congruent video**

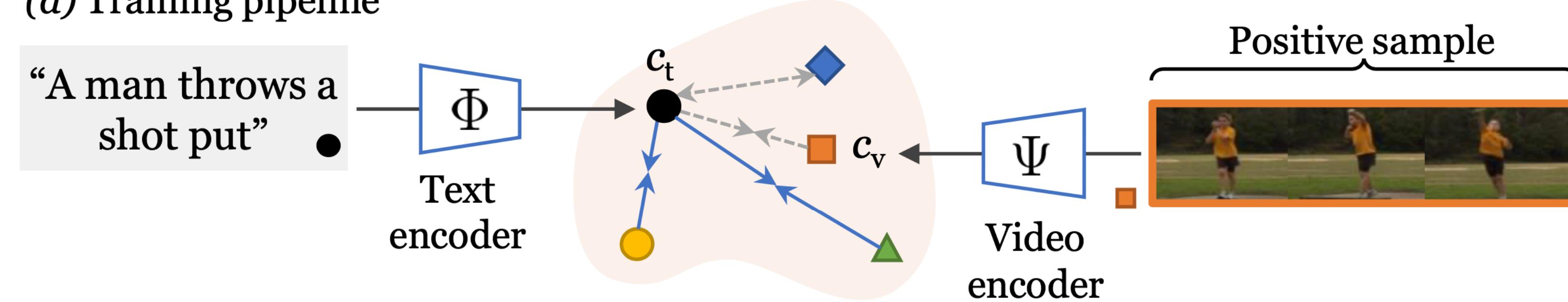
We then learn to predict a video's caption based on the other videos that the network thinks are the most related



- Net force from NCE loss
- Net force from reconstruction loss

# Our Approach: Support-set Bottlenecks

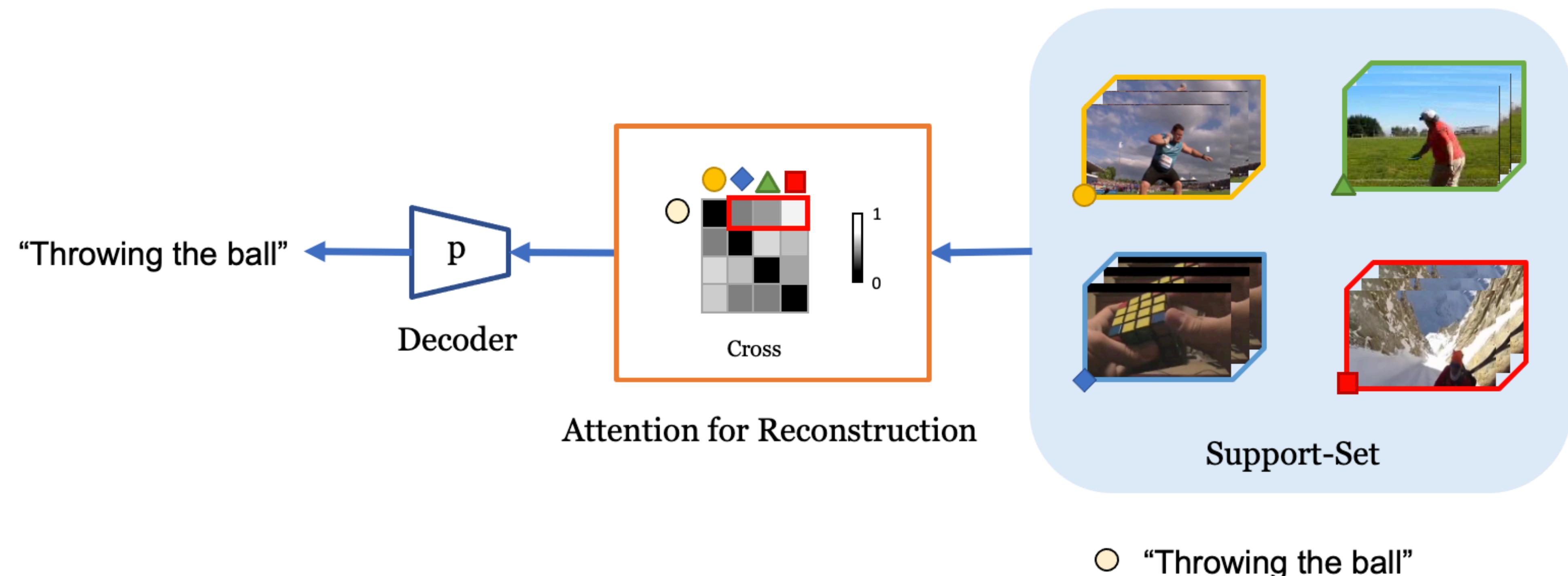
(a) Training pipeline



- ← Generative attraction (**similar** samples)
- ↔ Contrastive attraction (same sample)
- ↔→↔ Contrastive repulsion (all other samples)

# Cross Attention for Reconstruction

- Learn to reconstruct caption as weighted combination of videos in the support-set
- Implicitly pulls together videos with similar captions

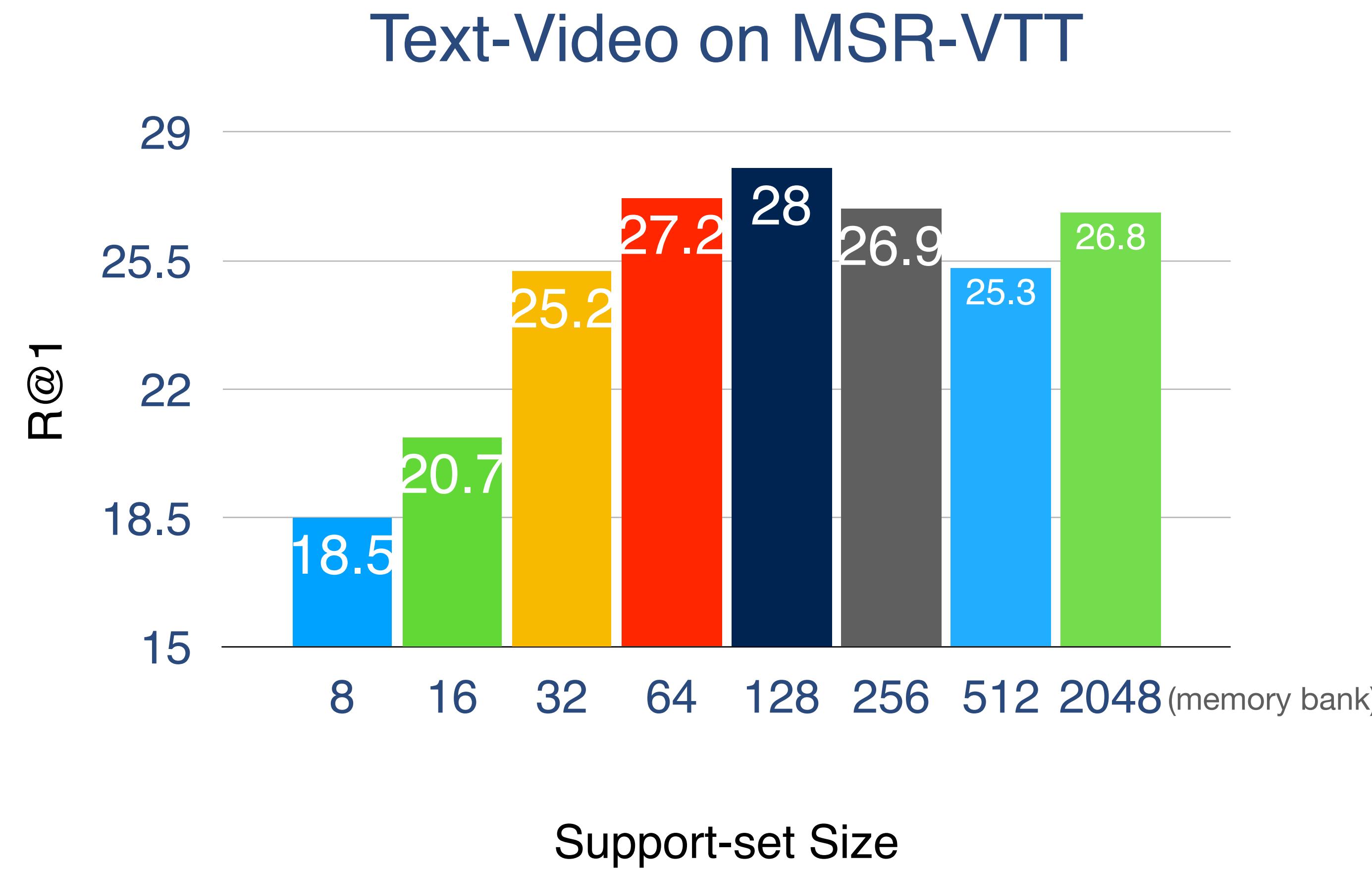


# Example Videos and Attentions

- Attention is highly-focused (top-left square)
- Attention acts as bottleneck (tries to relate semantic concepts across videos)



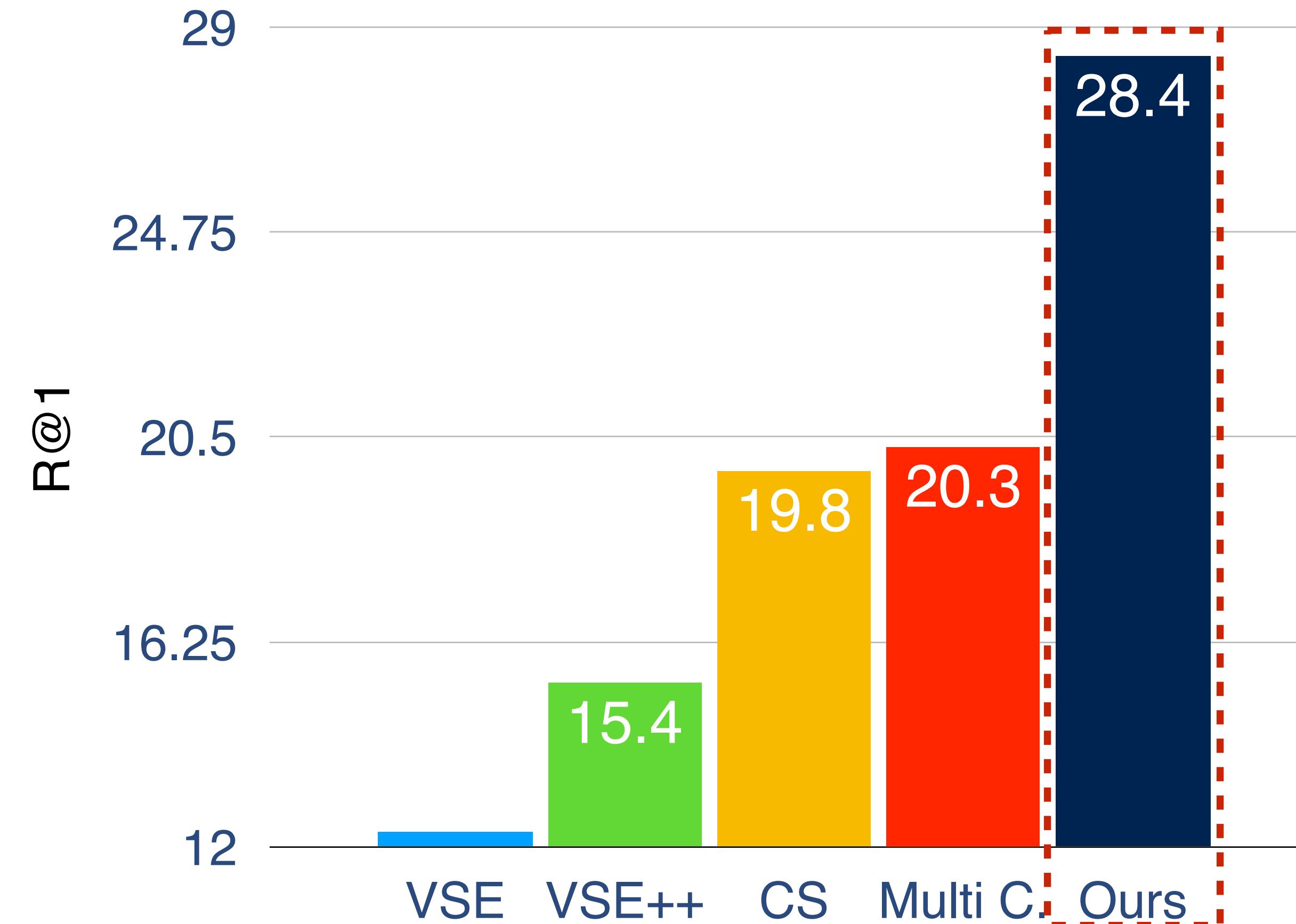
## Support Set acts as bottleneck



# Comparison to State-of-the-Art

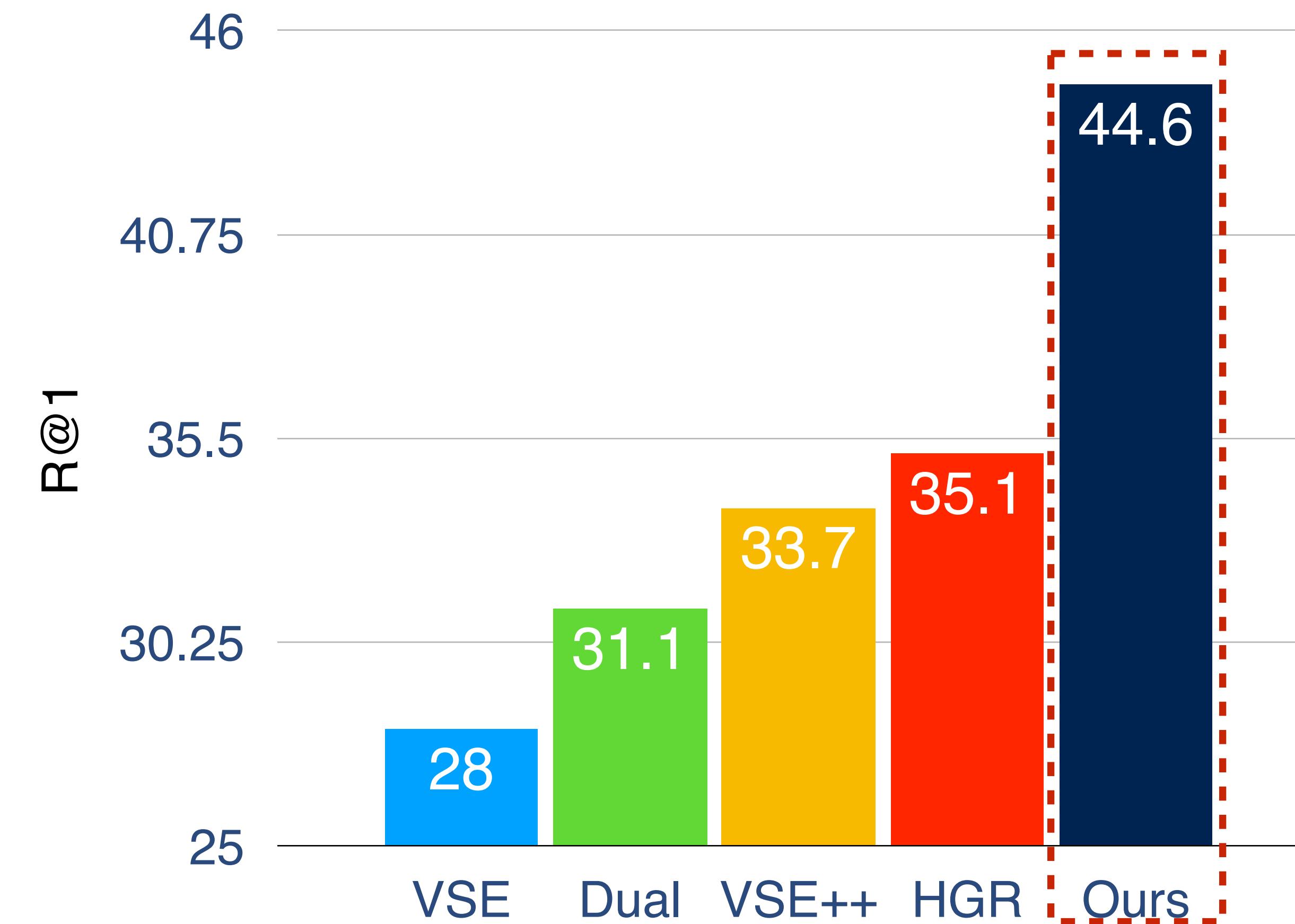
# SOTA on MSVD Text-Video Retrieval

## Text-Video



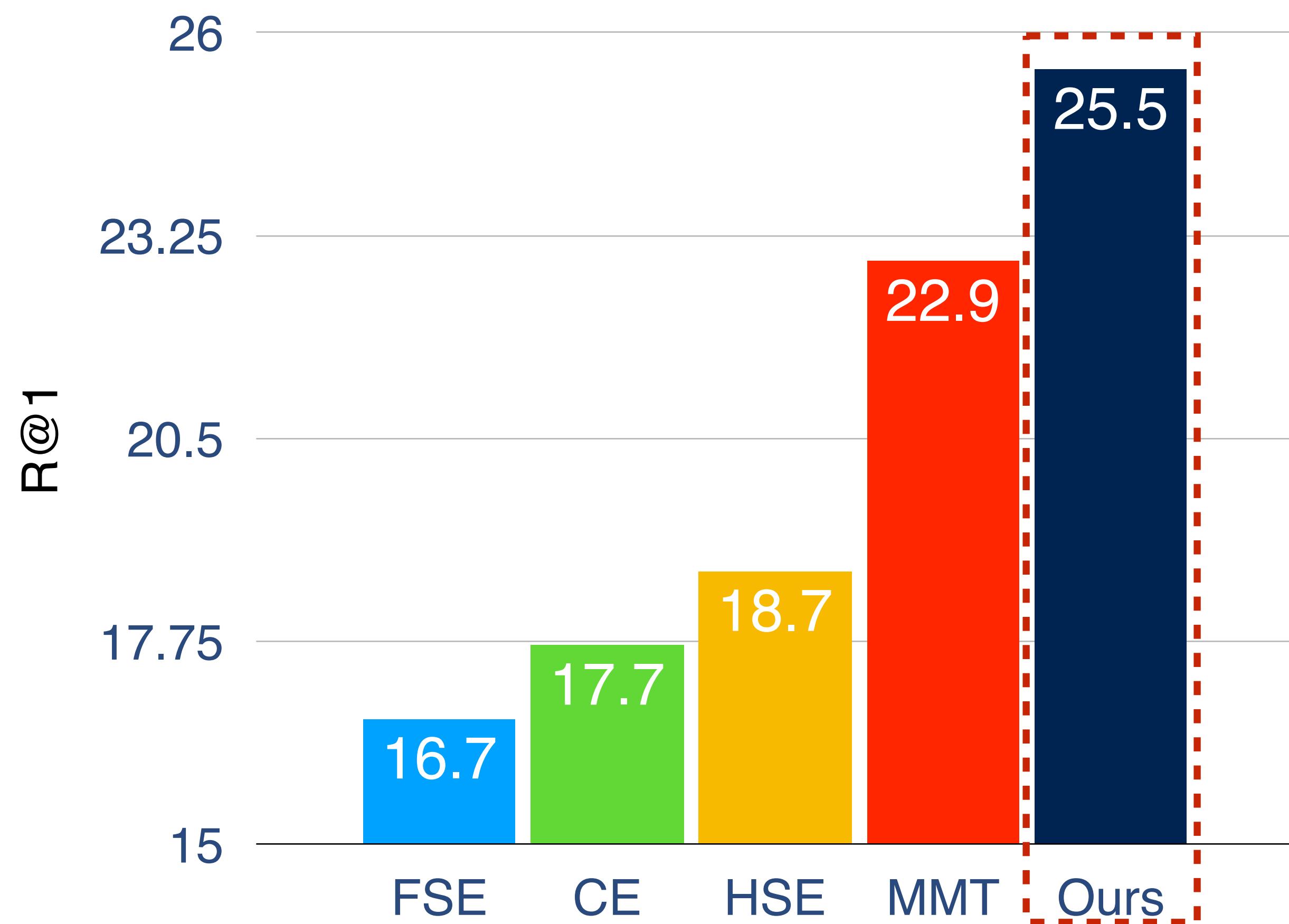
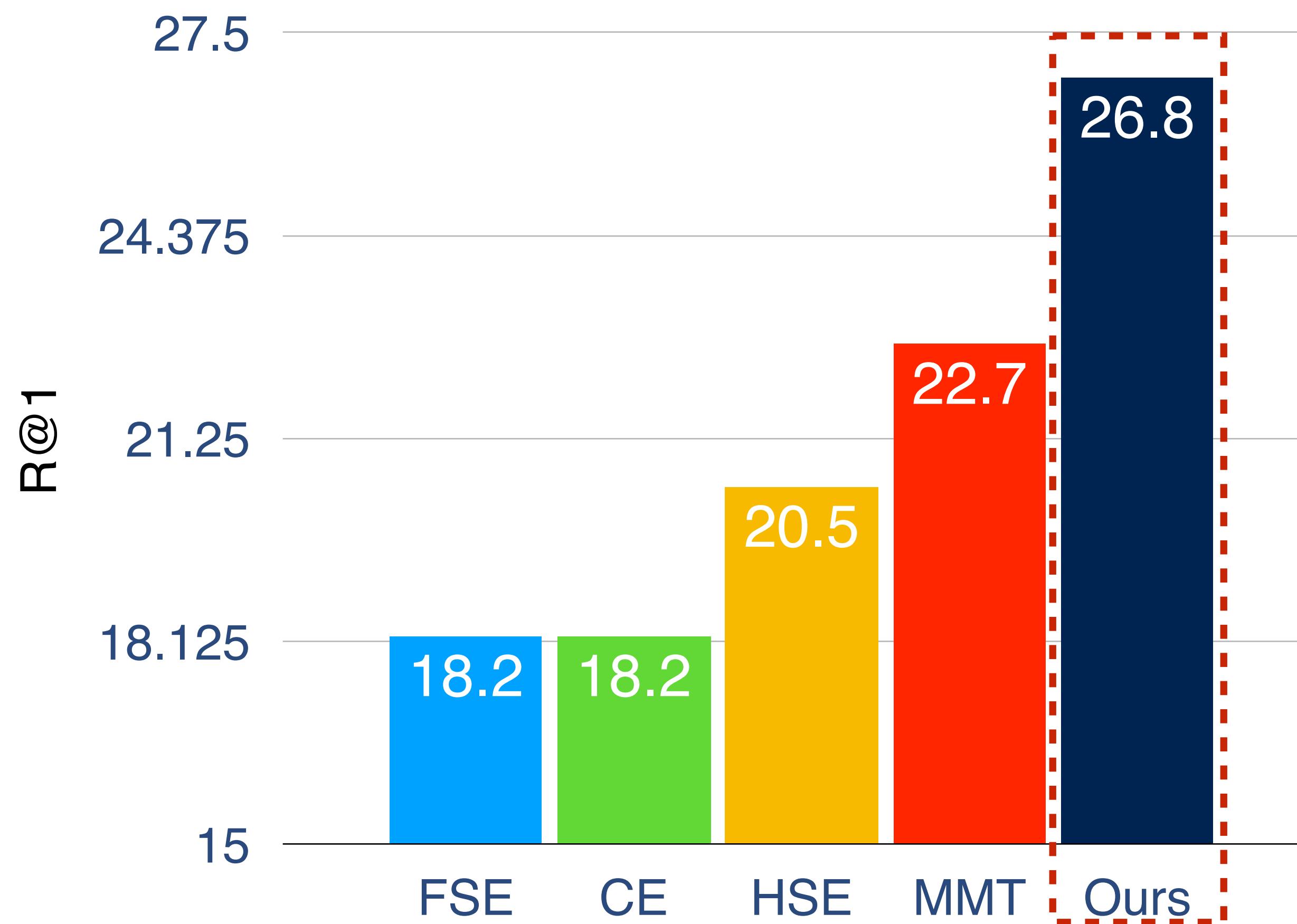
# SOTA on VATEX Text-Video Retrieval

Text-Video



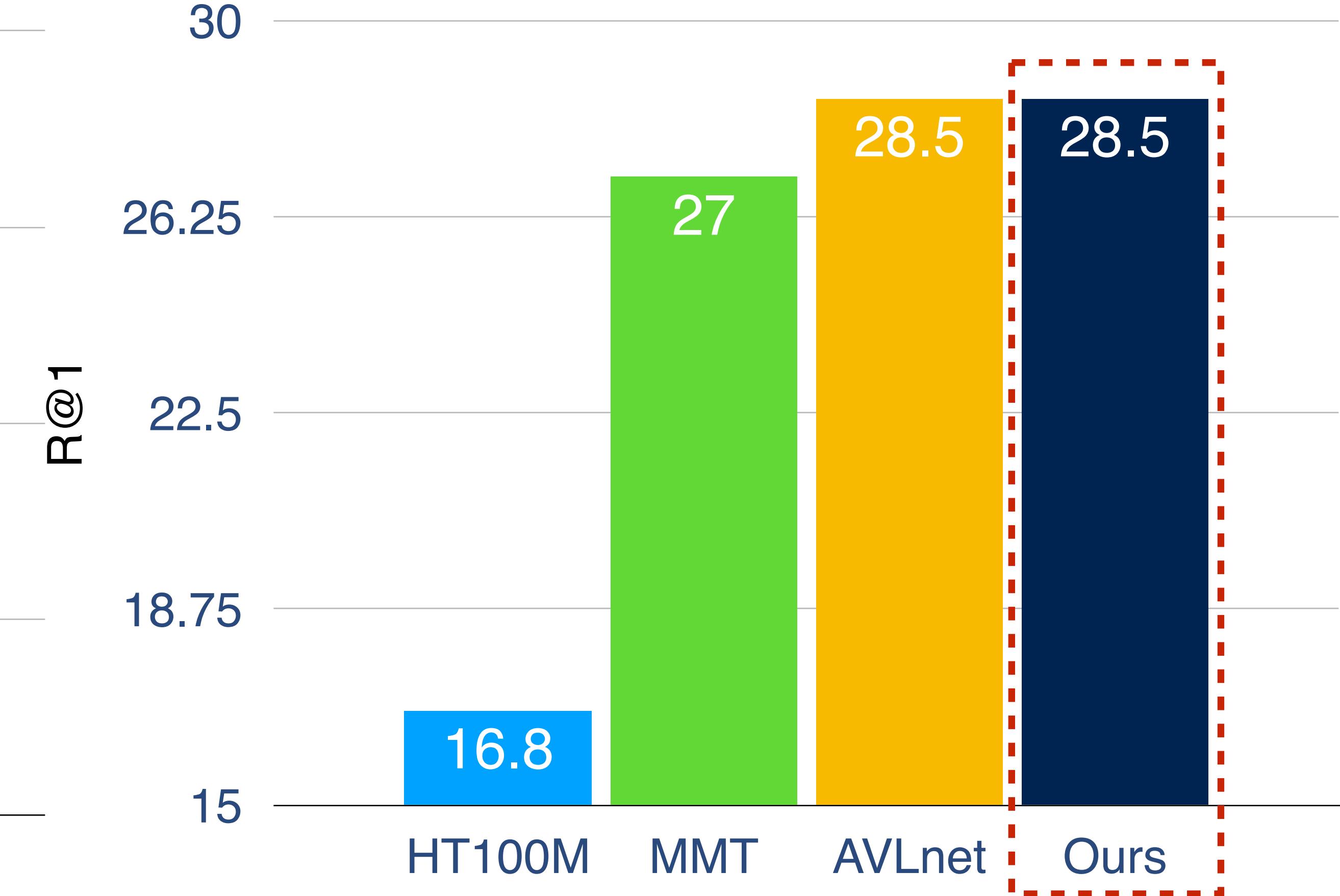
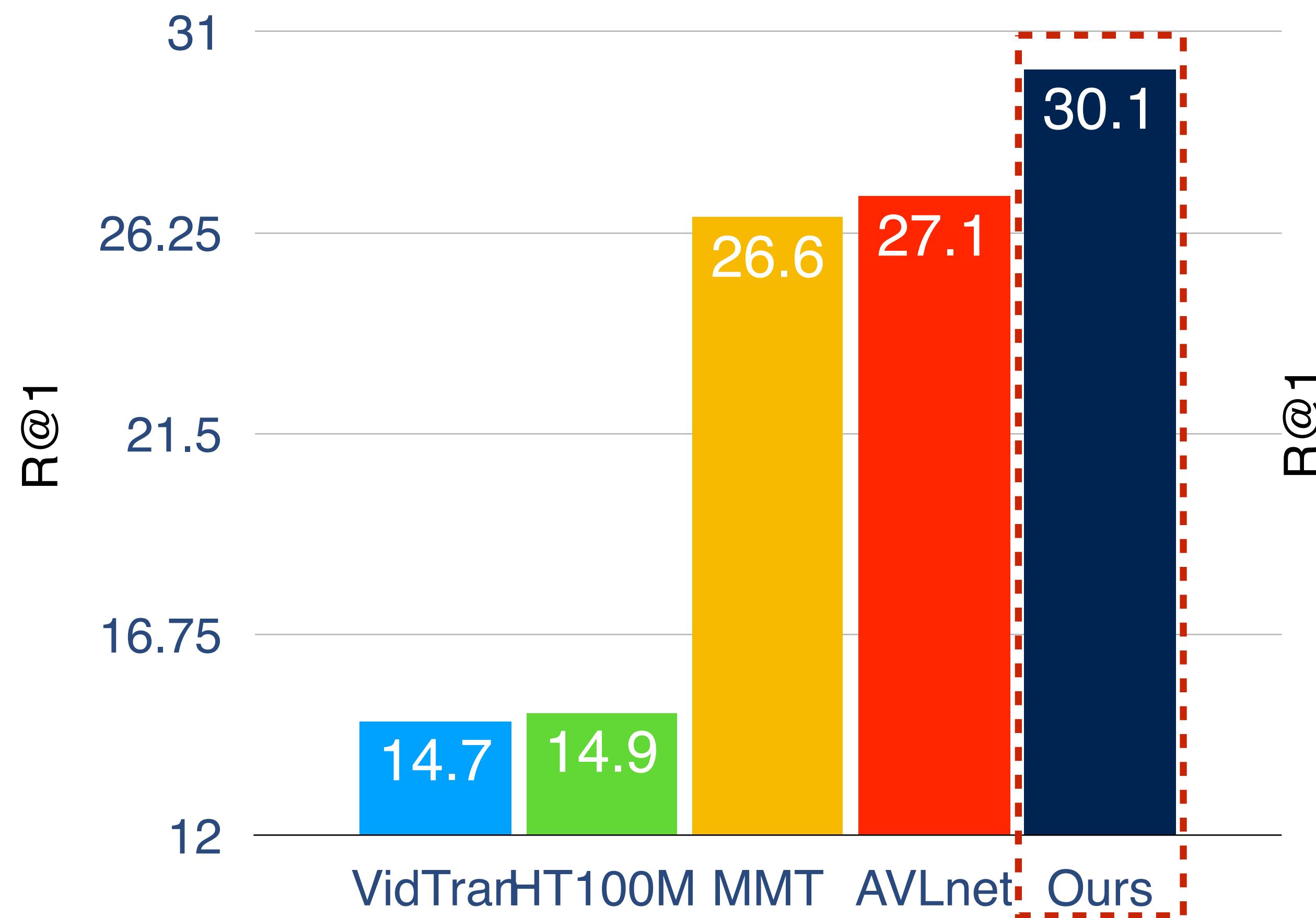
# SOTA on ActivityNet Text-Video and Video-Text Retrieval

## Text-Video



# SOTA on MSR-VTT Text-Video and Video-Text Retrieval

## Text-Video

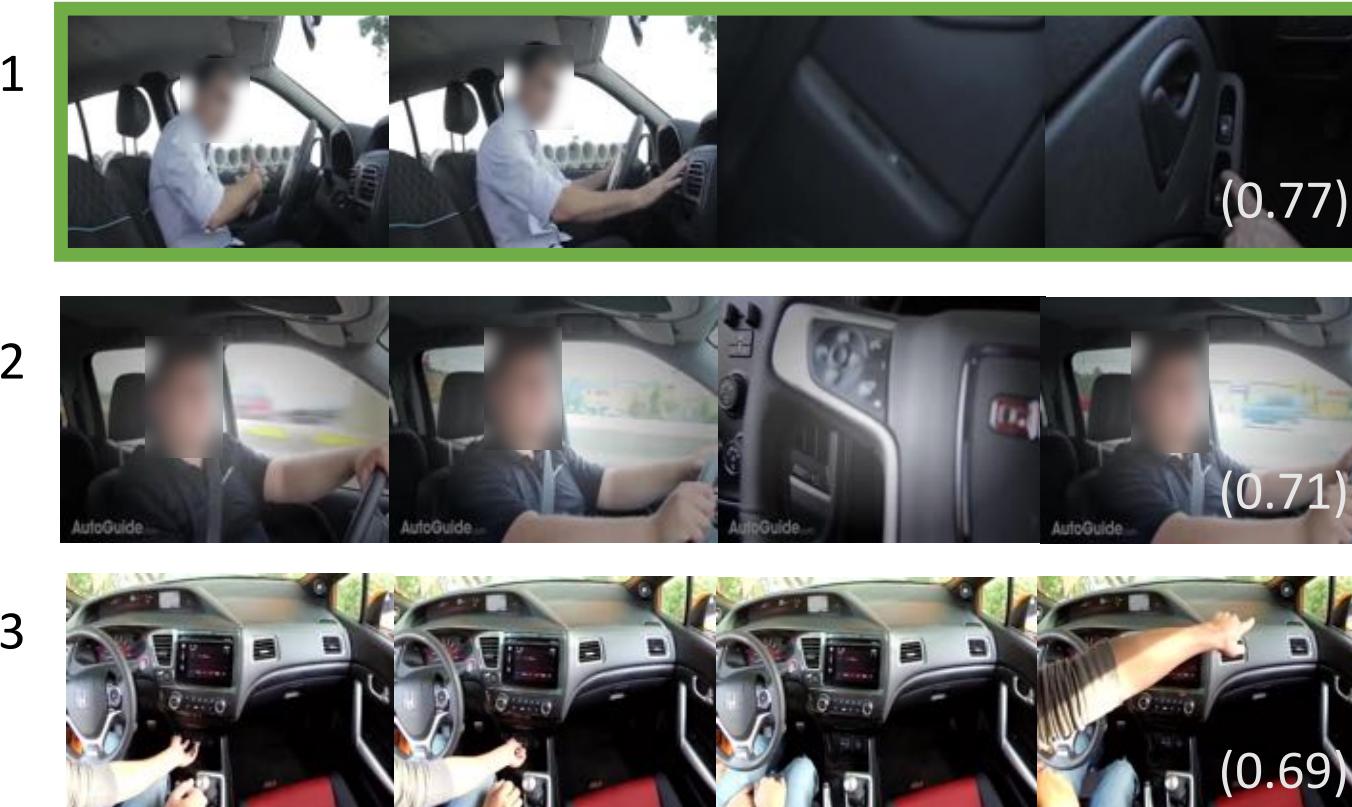


# Qualitative Results and Limitations

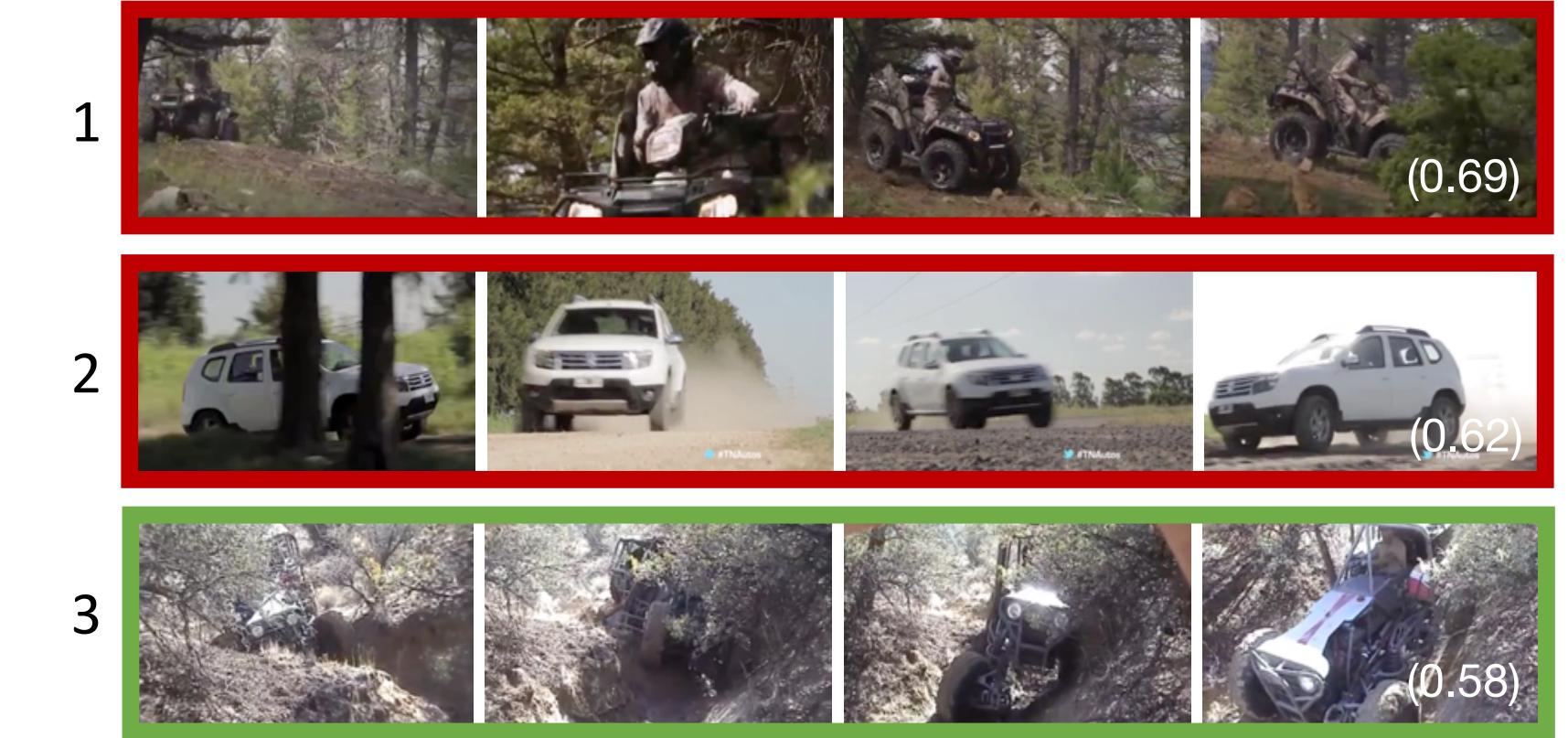
A Person is swimming in some white water rapids.



A man is showing the interior of a car.



A Jeep or other off-road vehicle is driving slowly through a very narrow valley without any road



# Conclusion

Noise contrastive learning uses instance discrimination to learn effective representations.

Instance discrimination naturally produces faulty negatives that hurt representations.

We propose to alleviate this using a generative objective that implicitly pulls together semantically related videos.

We set SOTA on all video-text and text-video retrieval benchmarks.