

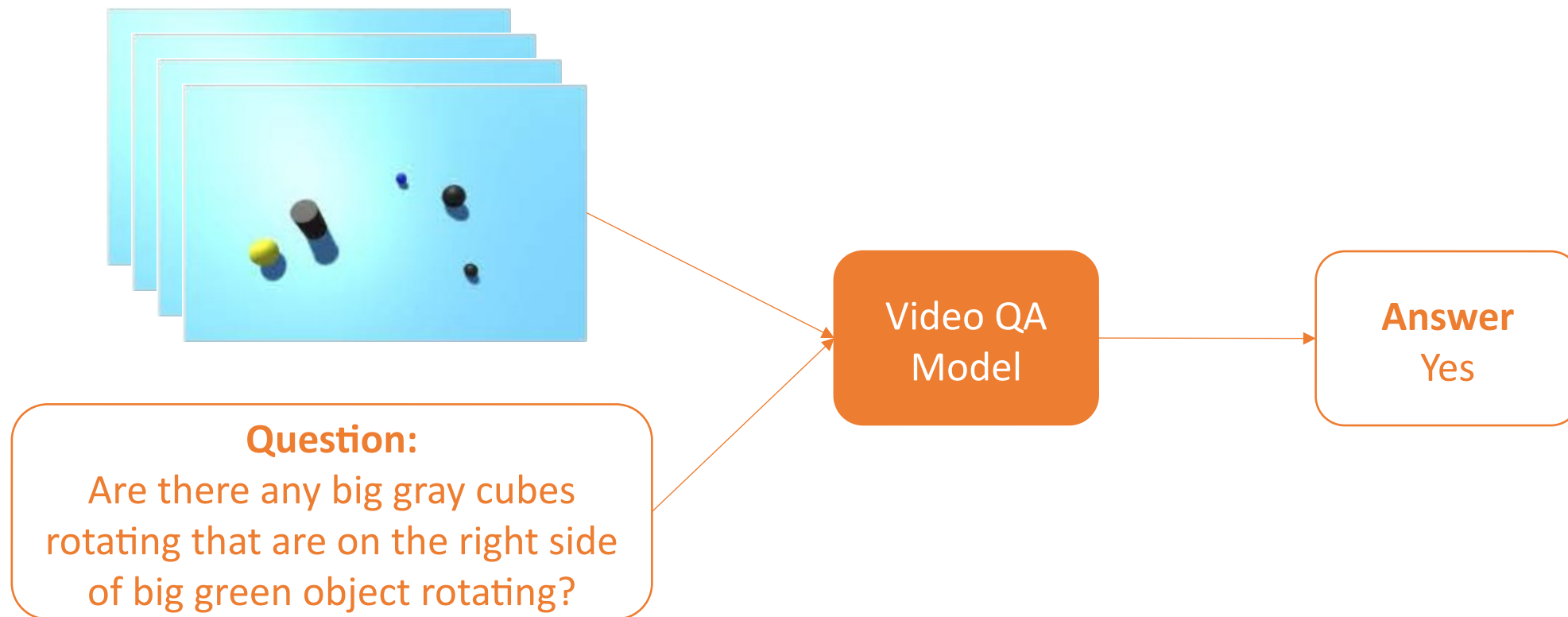
# Object-Centric Representation Learning for Video Question Answering

Long Hoang Dang, Thao Minh Le, Vuong Le, Truyen Tran  
Presented at IJCNN 2021



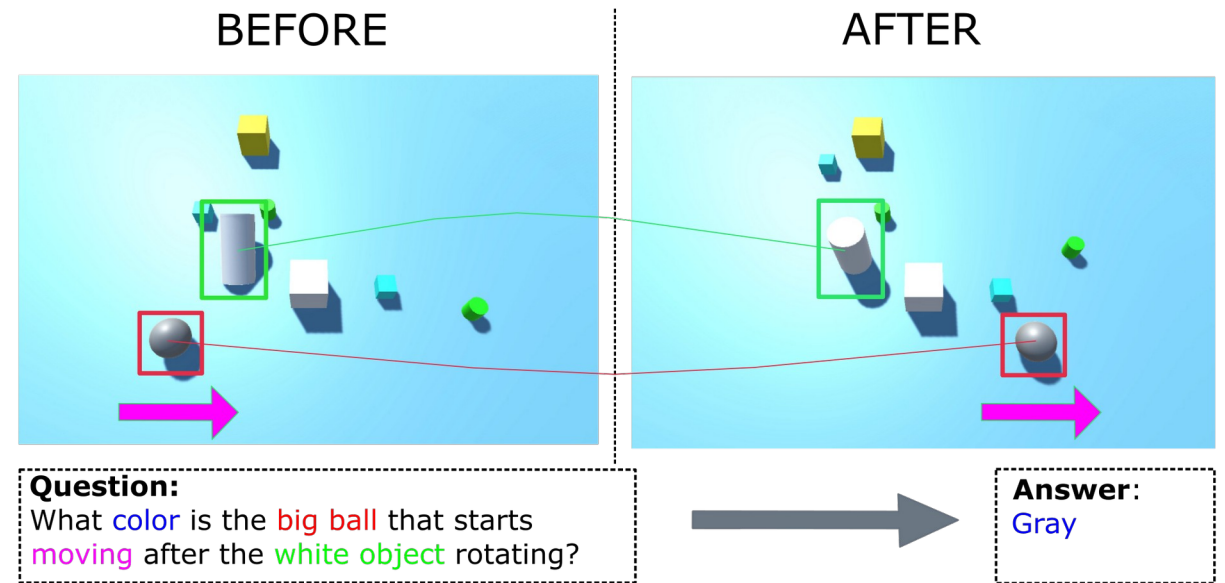
# Introduction

## General Video QA Framework

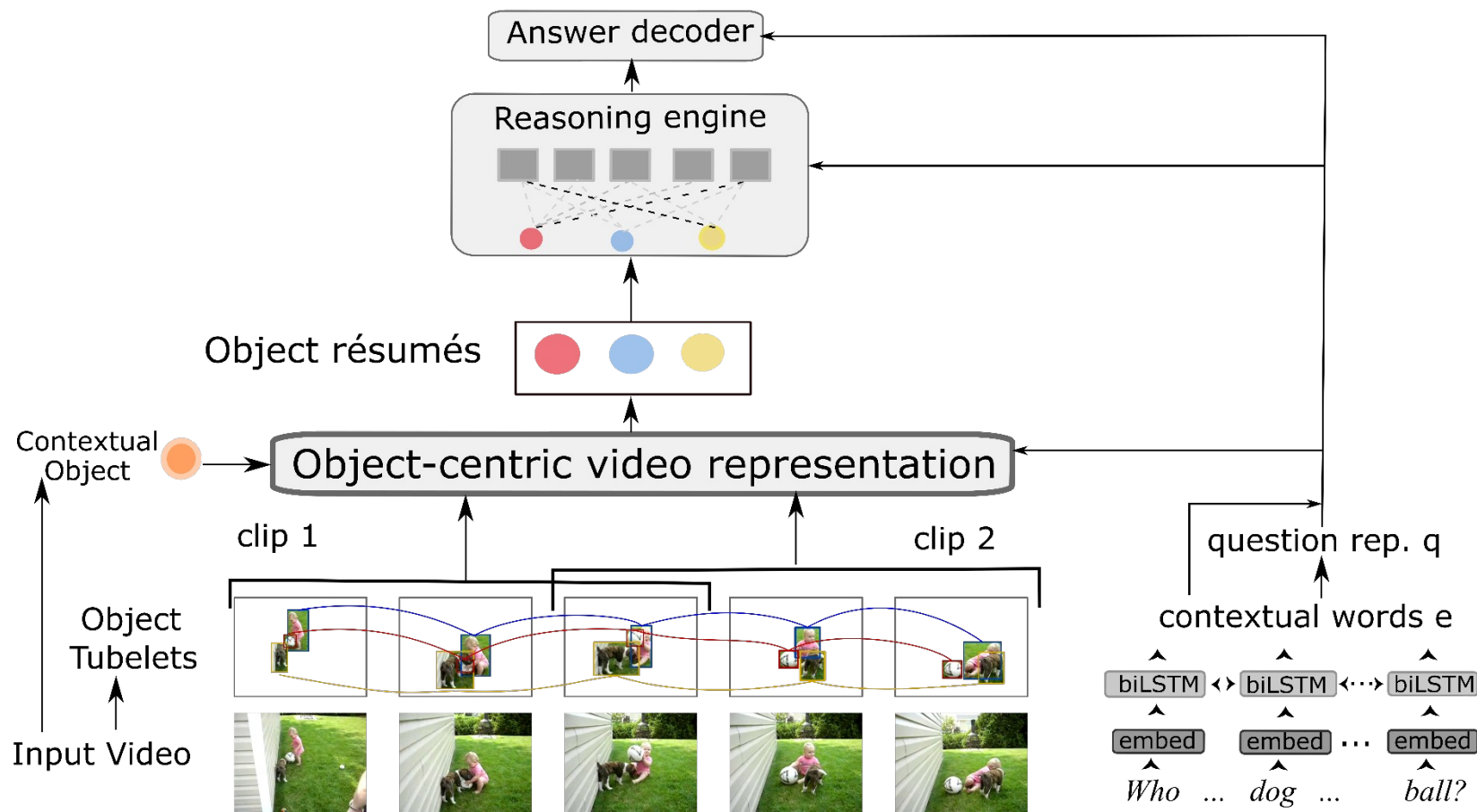


# Our focus: Object-centric representation

- **Objects** in video are primary constructs that have unique evolving lives throughout space-time
- To predict a correct answer, we need:
  - Understand the **evolution** of the object
  - Capture the contextualized **interaction** with its neighbours



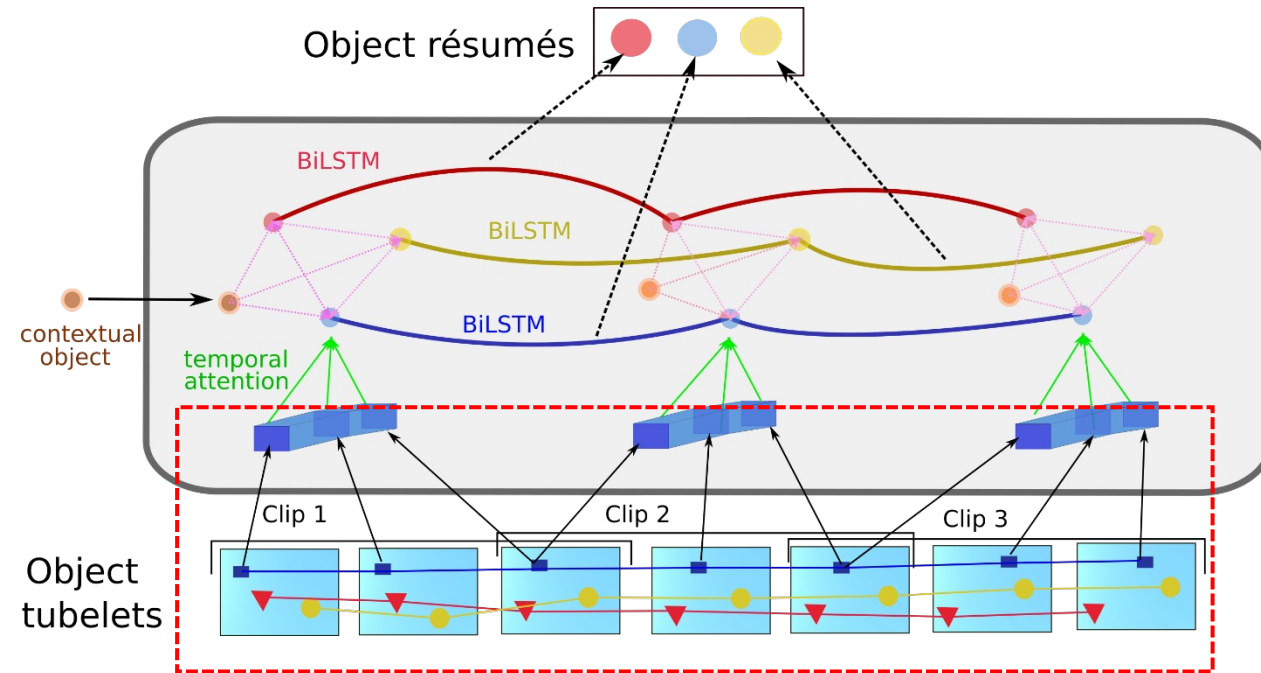
# Object-centric Neural Architecture for Video QA



# System 1: Object-centric Video Representation

## Constructing Object Tubelets

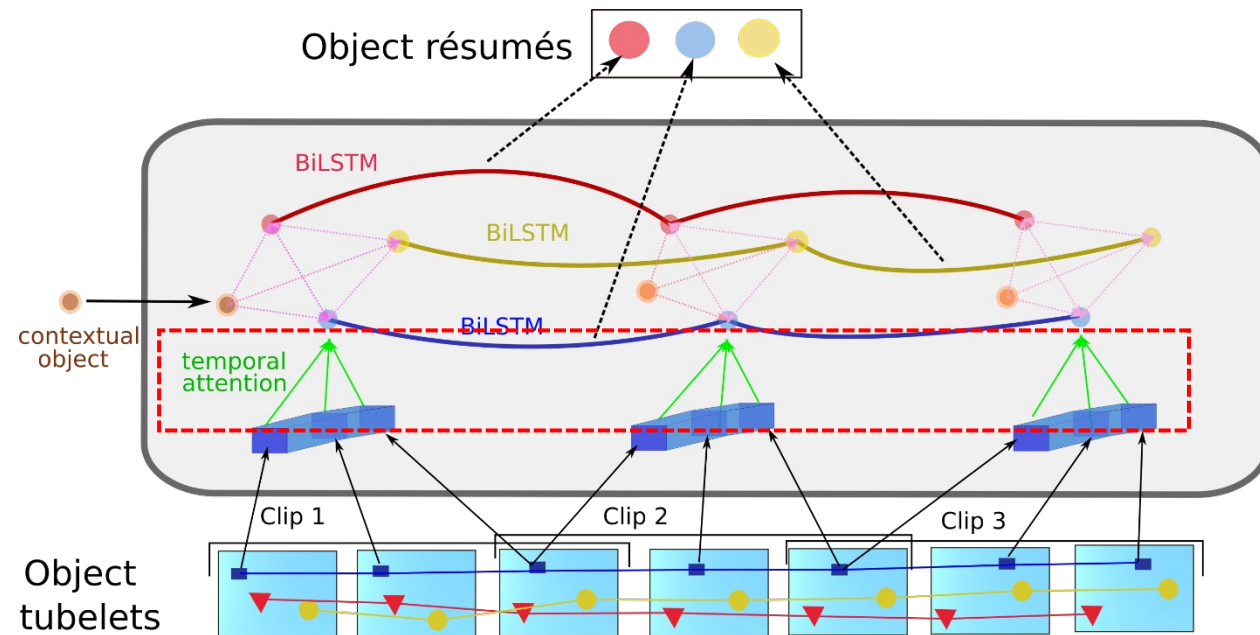
- For each object:
  - The appearance feature
  - The geometrical feature : coordinates of the region box
- The *position-specific appearance* of object:
- Contextual object (ResNet features)



# System 1: Object-centric Video Representation

## Language-conditioned Representation

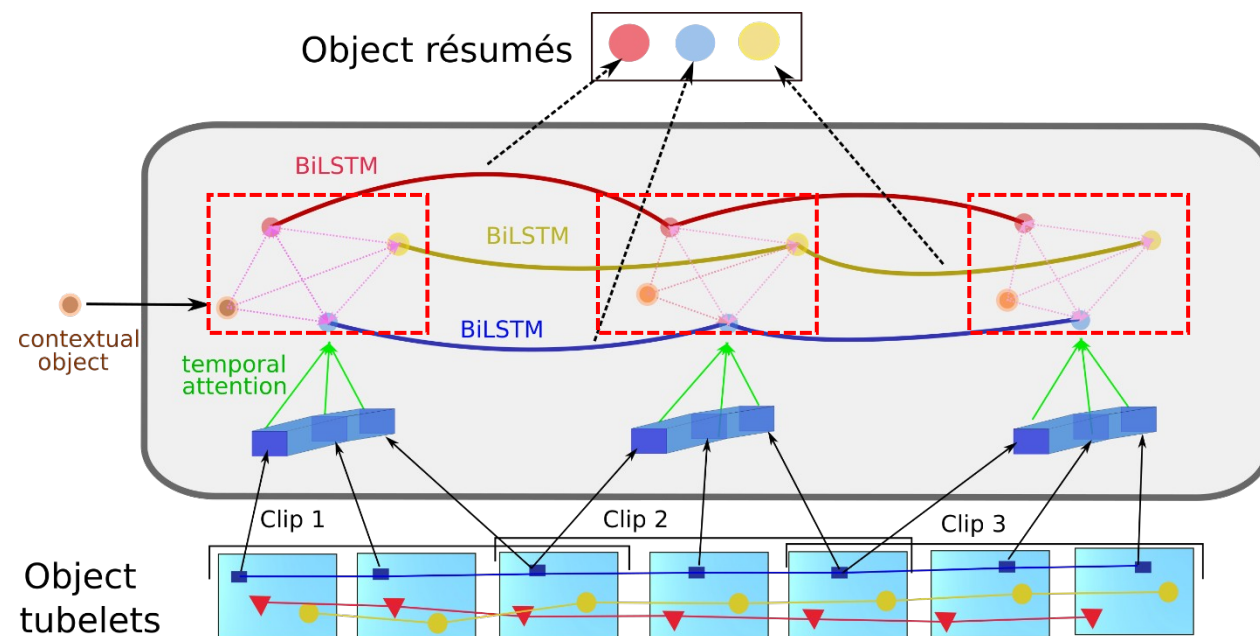
- Divide into K equal temporal parts:
- where is the *position-specific appearance* feature.
- Temporal attention mechanism: reduce irrelevant visual information.
- Binary mask: exclude missed detections of objects.



# System 1: Object-centric Video Representation

## Query-conditioned Object Graph

- A graph
  - are nodes
  - Adjacent matrix is given by:
- Let  $\mathcal{G}$ , we refine representations of nodes:

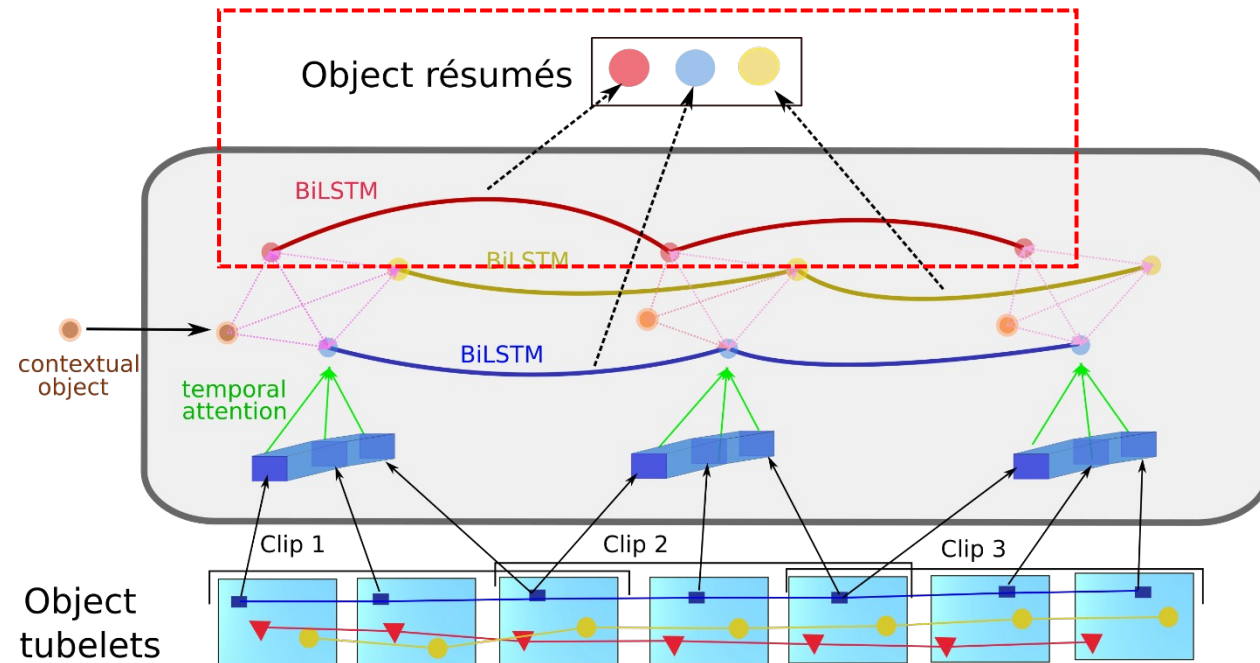


# System 1: Object-centric Video Representation

## Video as Evolving Object Graph

- Temporal parts are then connected through a BiLSTM:
- Compute a résumé for each object by summarizing its lifetime:

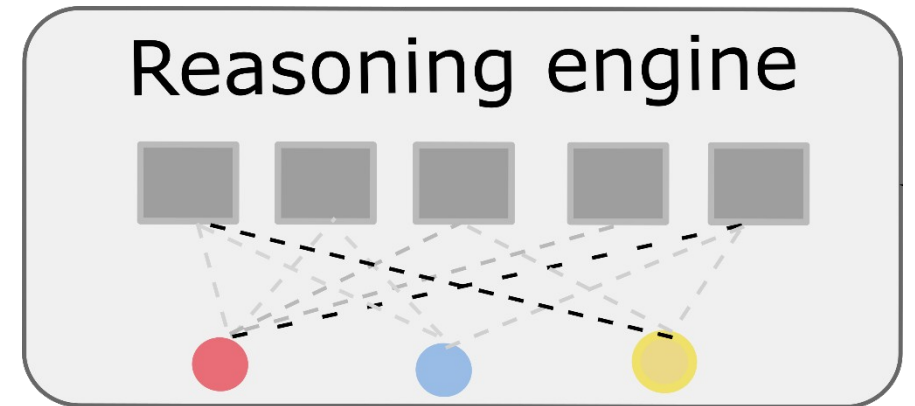
and are end states of the BiLSTM.





## System 2: General-proposed Reasoning Engine

- Our *object-centric video representation* can combine with a wide range of reasoning models.
  - MACNet (Hudson et al. 2018)
  - LOGNet (Le et al. 2020)



# Experiments

Model	Test accuracy (%)	
	MSVD-QA	MSRVTT-QA
ST-VQA	31.3	30.9
Co-Mem	31.7	32.0
AMU	32.0	32.5
HME	33.7	33.0
HRA	34.4	35.1
HCRN	36.1	35.6
<b>OCRL+LOGNet</b>	<b>38.2</b>	<b>36.0</b>

Comparison with state-of-the-art-methods on three common datasets (MSVD-QA, MSRVTT-QA and SVQA). Our model is referred as OCRL+LOGNet.

Models	Exist	Count	Integer Comparison			Attribute Comparison					Query					All
			More	Equal	Less	Color	Size	Type	Dir	Shape	Color	Size	Type	Dir	Shape	
SA+TA	52.0	38.2	74.3	57.7	61.6	56.0	55.9	53.4	57.5	53.0	23.4	63.3	62.9	43.2	41.7	44.9
STRN	54.0	44.7	72.2	57.8	63.0	56.4	55.3	50.7	50.1	50.0	24.3	59.7	59.3	28.2	44.5	47.6
CRN+MAC	72.8	56.7	<b>84.5</b>	<b>71.7</b>	<b>75.9</b>	70.5	76.2	90.7	75.9	57.2	76.1	92.8	91.0	<b>87.4</b>	85.4	75.8
<b>OCRL+MAC</b>	77.4	56.7	81.2	64.6	65.0	90.0	93.4	90.1	77.0	93.5	<b>77.8</b>	<b>92.9</b>	<b>91.3</b>	82.5	<b>89.5</b>	77.8
<b>OCRL+LOG</b>	<b>81.7</b>	<b>61.5</b>	83.2	64.9	71.4	<b>92.7</b>	<b>97.2</b>	<b>94.6</b>	<b>88.8</b>	<b>95.7</b>	75.1	90.9	90.3	82.6	86.8	<b>79.5</b>

## Conclusion

- Proposed a novel neural architecture for object-centric representation learning in video question answering.
- Introduced the concept of résumé that summarizes the live of an object over the entire video.

Thank you  
QA

---