



A Read-Write Memory Network for Movie Story Understanding

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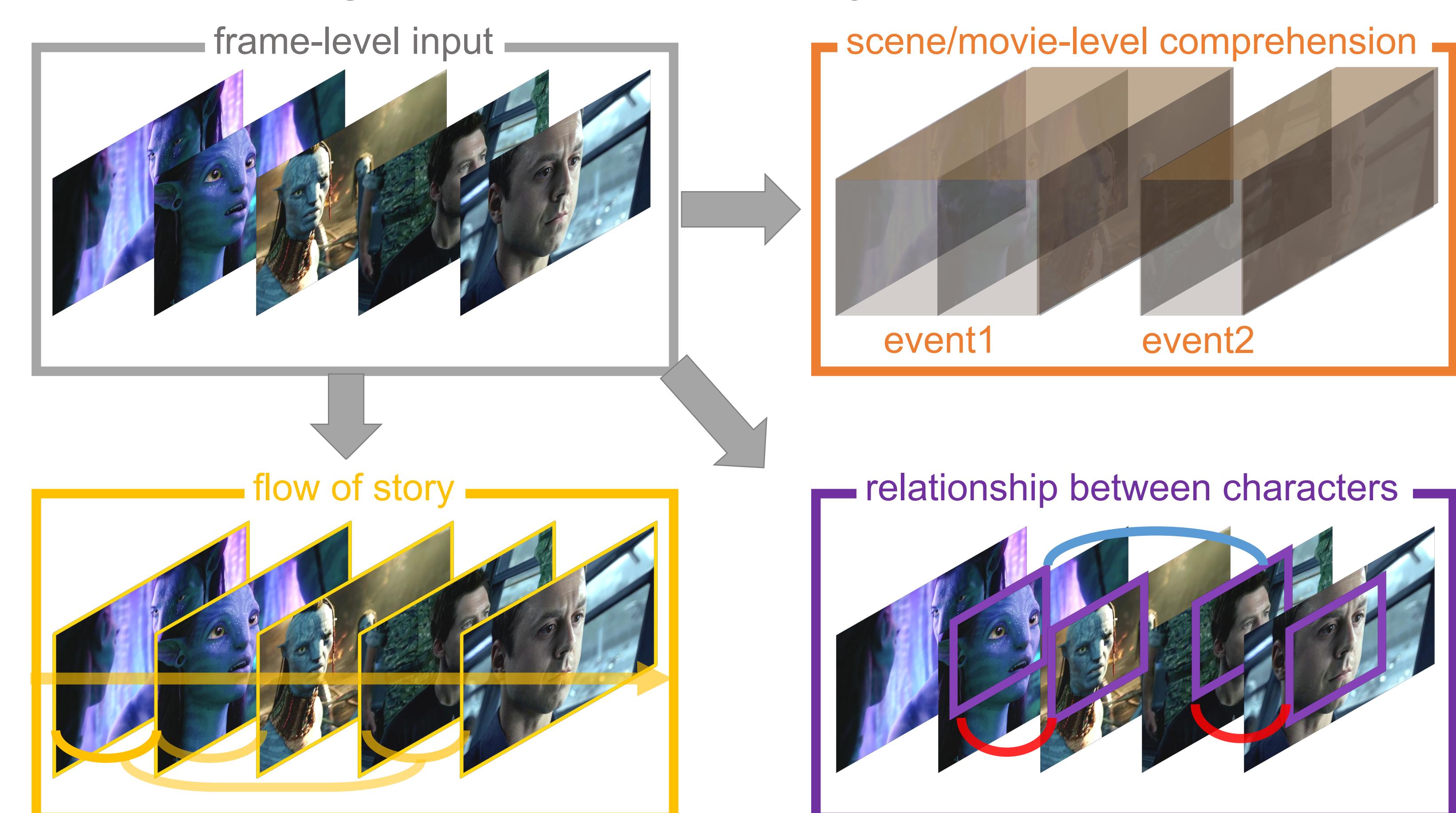
SK Telecom[‡]

Code is available at
<https://github.com/seilna/RWMN>

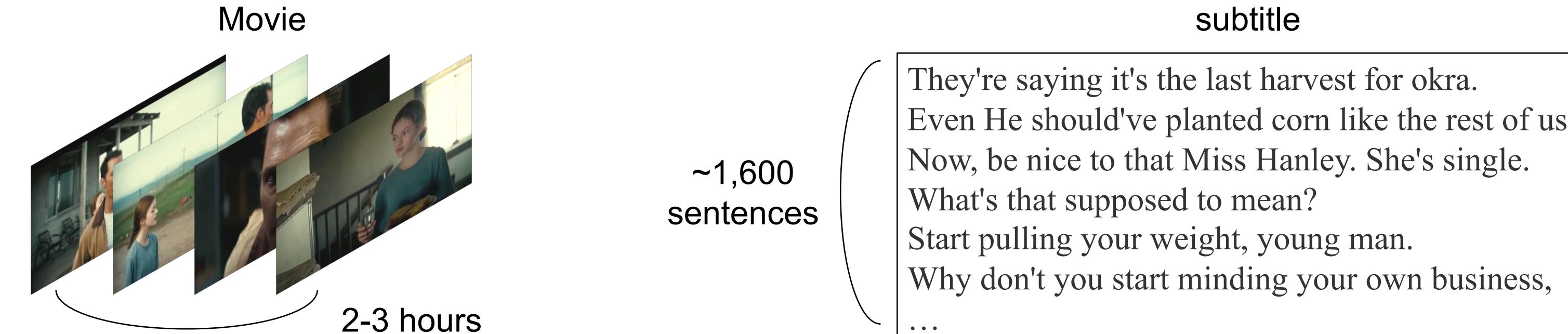
Motivation

It is hard to understand a long movie story

- It needs **high-level abstraction** given frame-level input only



- A movie consists of very **long sequence** of frames and text



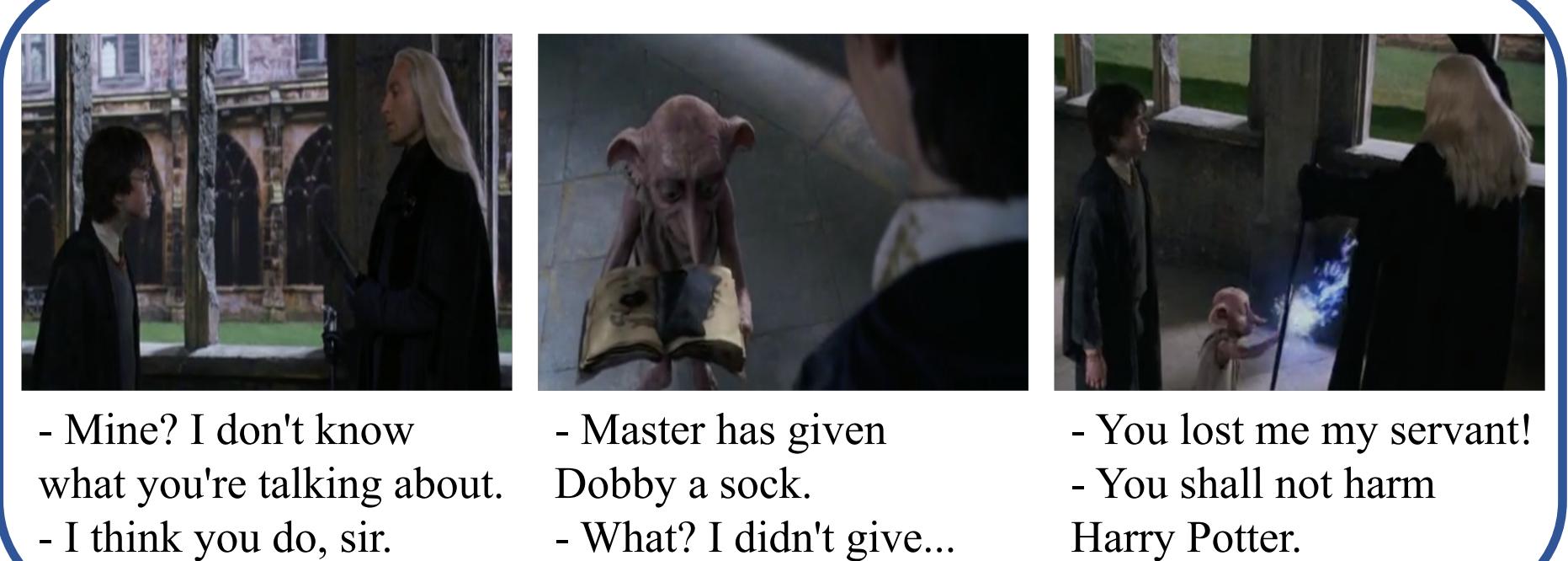
Objective

MovieQA [1]: Story Understanding Benchmark
Multi-choice Question & Answering with movie stories

Our model achieves **best** performance on **4 out of 6 tasks**

Video-based Q&A

Video and Subtitle story



Multi-choice Q&A

Q. What does Harry trick Lucius into doing?
A1. Releasing Dobby to Harry's care
A2. Releasing Dobby to Dumbledore's care
A3. Releasing Dobby to Hagrid's care
A4. Freeing Dobby
A5. Admitting he put Tom Riddle's diary in Ginny's cauldron

Text-based Q&A

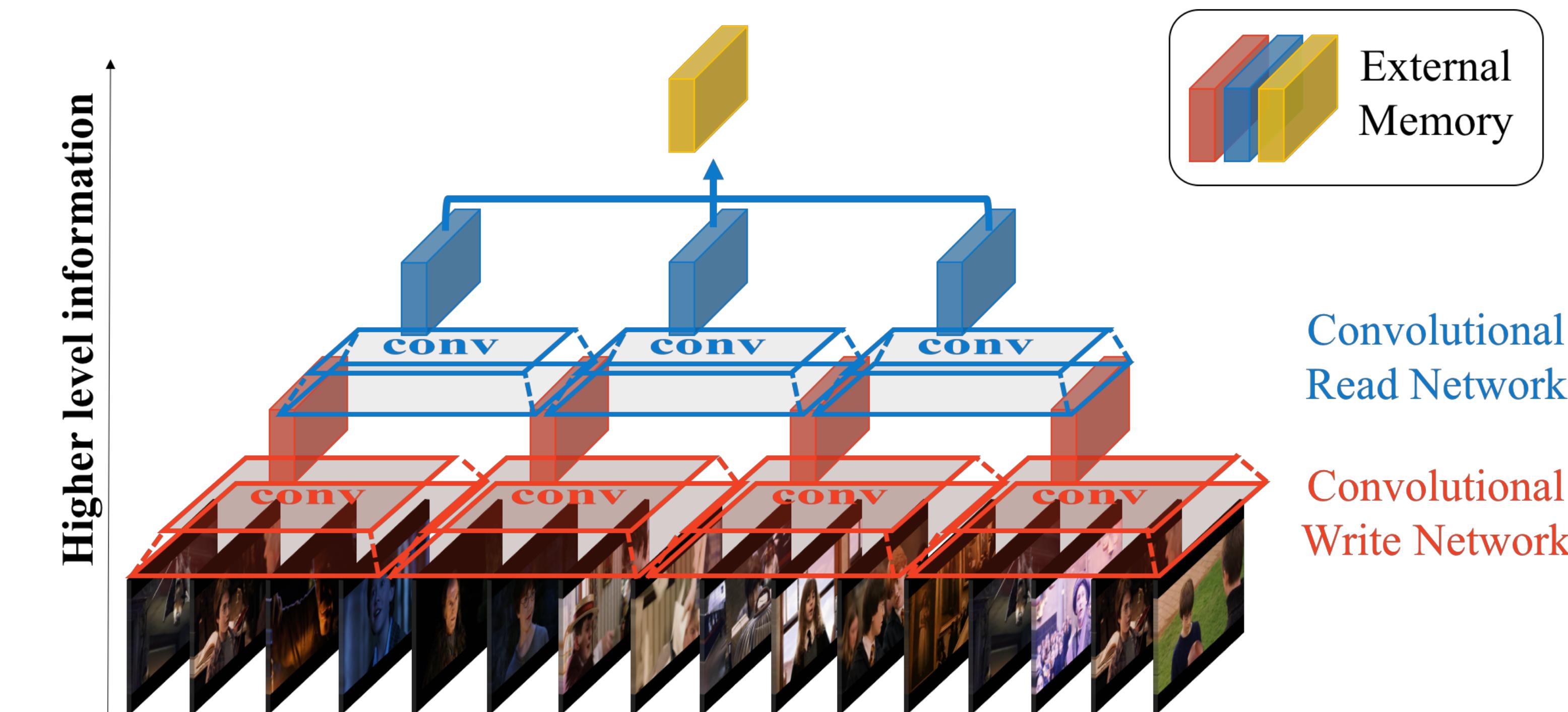
- Harry's snowy owl, flies into the great hall skimming over their heads.
- It drops a long thin parcel.
- They unwrap the brown paper, to reveal a streamline broomstick with a highly polished handle.
- Stroking the white owl's feathers.
- Wearing leather gloves and Scarlett and gold cloaks, the Gryffindor Quidditch team assemble in the player's tunnel.

Q. What sports they play in Hogwarts?
A1. They box
A2. They play golf
A3. They fight with brooms
A4. They play chess
A5. Quidditch

Our Solution – RWMN

Read Write Memory Network

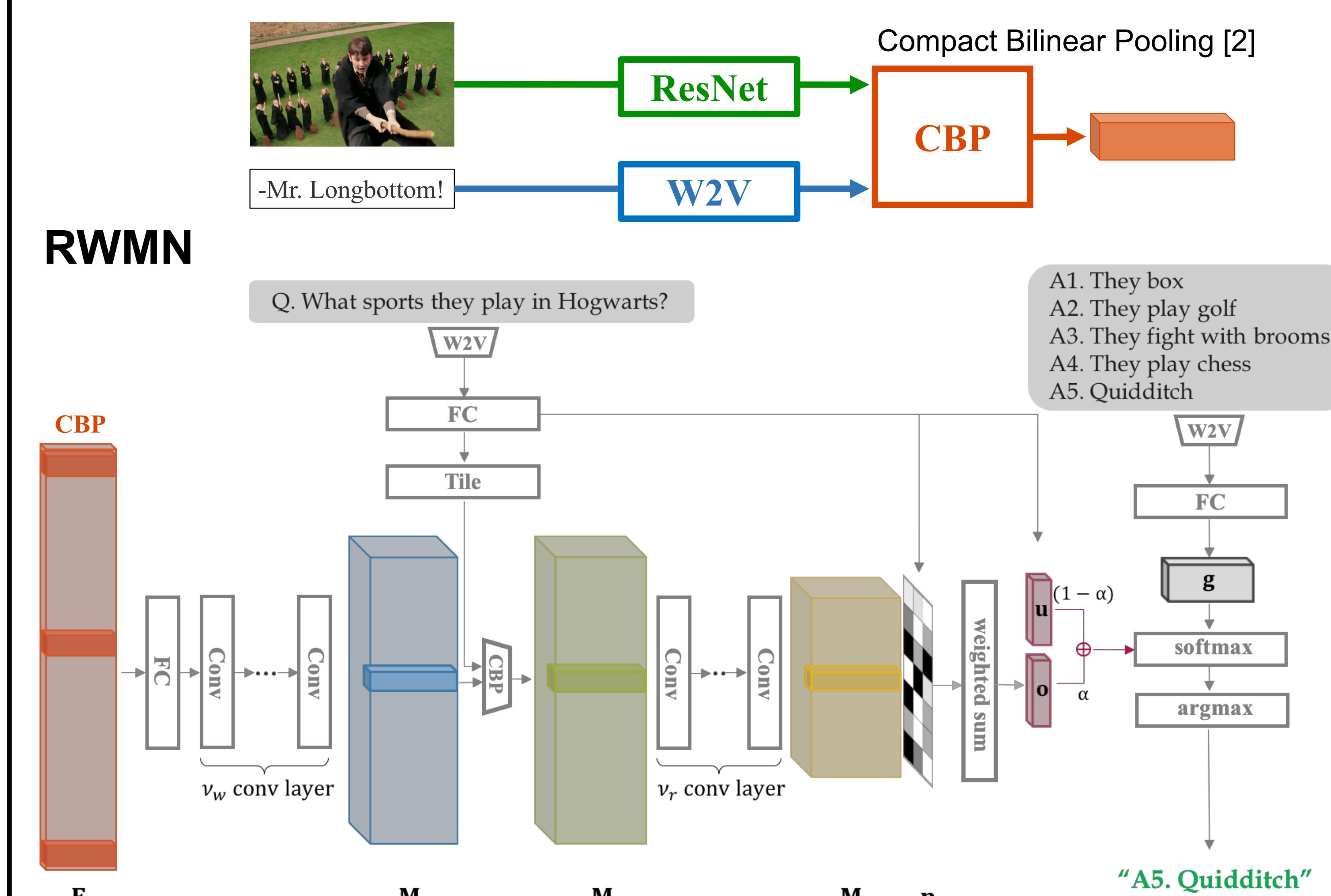
- External memory to fully utilize long input sequences
- Convolutional write/read to capture interactions btw. adjacent memory vectors
- Query-dependent memory embedding to update memories conditioned on query



RWMN Architecture

Preprocessing & Feature extraction

- Video frames are aligned with subtitles



- (1): Write operation abstracts memory cells to higher-level via write convolutions
- (2): Memory cells is updated conditioned on query via CBP
- (3): Read operation abstracts updated memory cells appropriately for query

⚠ See the equations in the paper!

Quantitative Results

Results on MovieQA Benchmark

RWMN shows **best** performance on **4 tasks**
→ **Video+Subtitle / Subtitle / Script / Open-end task**

Video-based Q&A

Methods	Video
OVQAP	23.61
Simple MLP	24.09
LSTM + CNN	23.45
LSTM + Discriminative CNN	24.32
VCFSM	24.09
DEMN	29.97
RWMN	36.25

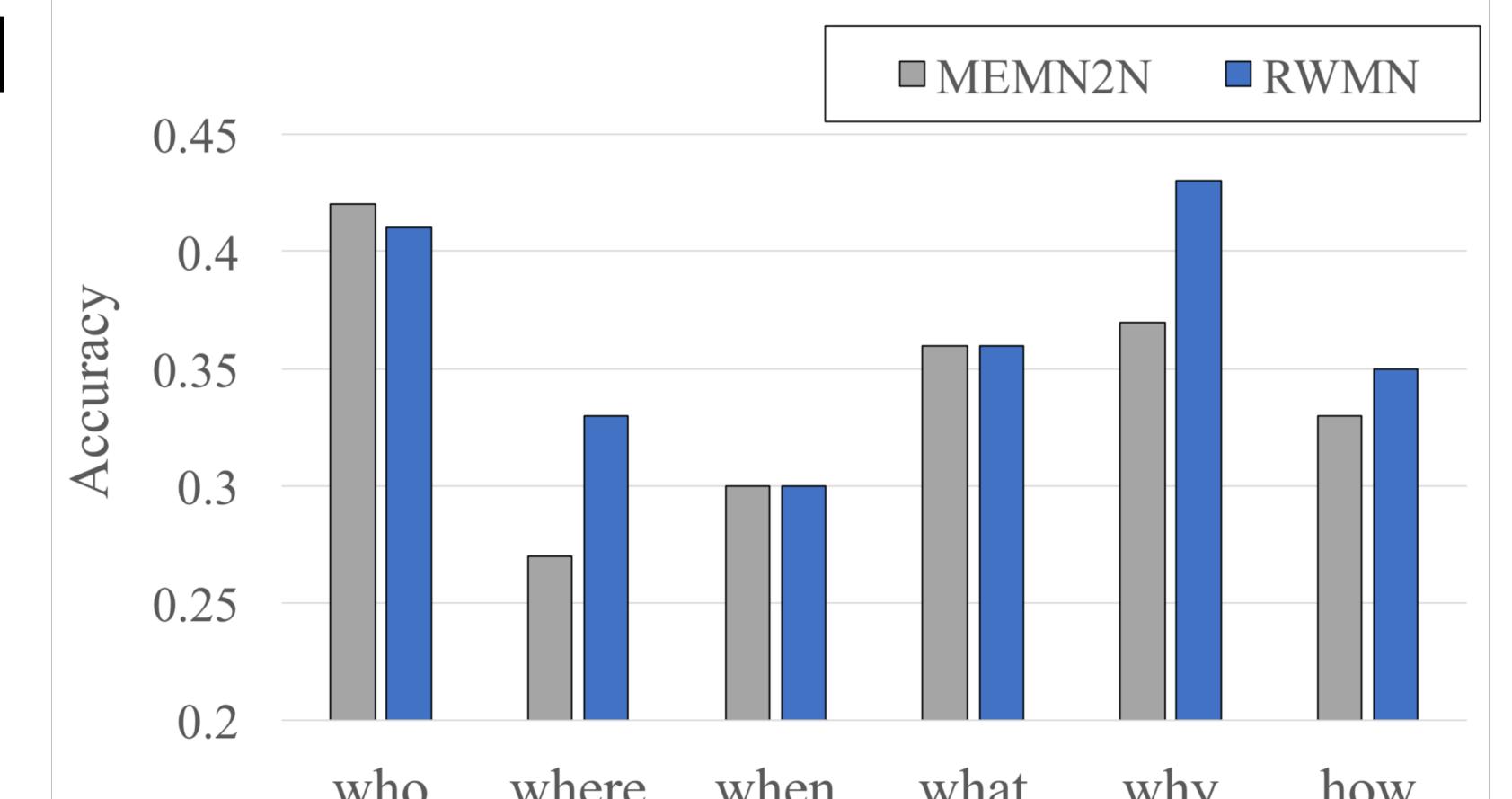
Method	Subtitle	Script	DVS	Plot	Open-end
MEMN2N [24]	36.9	37.0	35.0	38.4	–
SSCB-W2V [24]	23.7	24.4	24.9	45.6	–
SSCB-TF-IDF [24]	26.5	23.9	23.3	47.4	–
Convnet Fusion	–	–	–	77.6	–
Longest Answer	–	–	–	–	25.6
RWMN	38.5	39.4	34.2	34.8	36.6

• All results as of the ICCV Submission Deadline, March 27, 2017 23:59 GMT

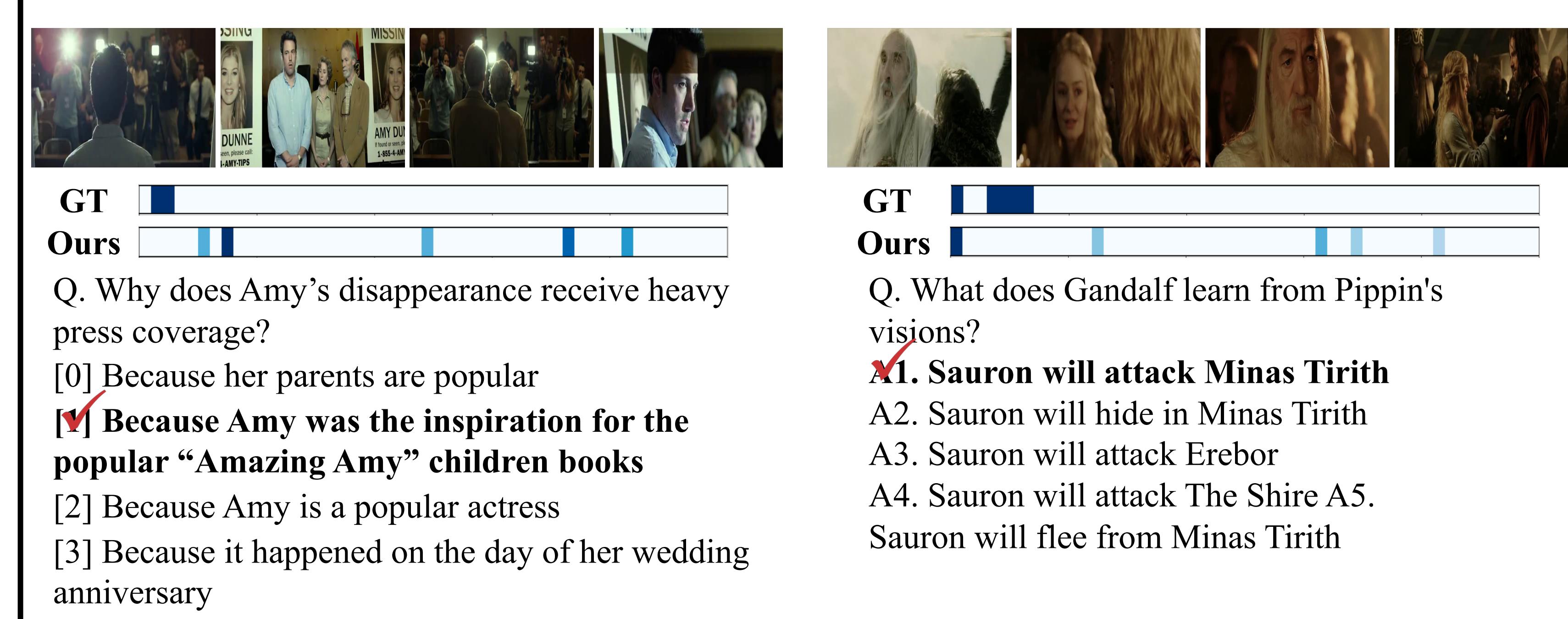
(RWMN-*) : Ours and variants
(DEMN) : [Kim et al. IJCAI 17]
(MEMN2N) : [Tapaswi et al. CVPR16]
(SSCB-*) : [Tapaswi et al. CVPR16]
(CNN Word Matching) : [Wang et al. ICLR 17]

Qualitative Results

- Comparison between RWMN and MEMN2N according to question types



- Video-based Q&A examples with attention maps



Reference

- [1] MovieQA: Understanding Stories in Movies through Question-Answering, M Tapaswi et al. CVPR 2016
- [2] Compact Bilinear Pooling, Y Gao et al. CVPR 2016