

IN THE CITY OF NEW YORK

# MuMuQA: Multimedia Multi-Hop News Question Answering via Cross-Media Knowledge **Extraction and Grounding**

# MuMuQA: Multimedia Multi-hop QA

- Motivation: To answer questions about news articles, humans seamlessly combine context from multiple modalities, such as images and text. Images in the real world, especially in news, have objects that are co-referential in the text.
- ▶ New QA Task: Given an image-caption pair and its associated news body text, a question is answered by extracting a short span from the body text.
- Answering the questions requires *multi-hop reasoning*:
- ► The first hop requires cross-media grounding between image and caption to get the *bridge item*.
- ► The second hop requires reasoning over body text using the bridge item to extract the final answer.



Figure: Two examples from our evaluation benchmark with the question-answer pairs and their corresponding news articles.

## Contributions

- ► We release a new QA evaluation benchmark, **MuMuQA**, based on multi-hop reasoning and cross-media grounding of information present in news articles.
- ► We introduce a novel pipeline to automatically generate silver-standard training data for this task.
- We provide competitive baselines that leverage different modalities and demonstrate the benefit of using multimodal information.

# **Benchmark Construction**

- Our benchmark consists of an evaluation set that is human-annotated and a silver-standard training set that is automatically generated.
- News articles are shown in the interface along with their images and corresponding captions.
- ► The annotator first looks at the image-caption pair to identify which objects in the image are grounded in the caption and then creates a question about the grounded entity.
- For automatic quality control, the interface also provides access to a single-hop text-only QA model to ensure the questions cannot be directly answered using news body text.
- ► The evaluation set contains 1384 questions with 263 in dev and 1121 in test.

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### **Body Text**



Venezuelan security forces fired scores of tear gas volleys and turned water cannons on rock-throwing protestors on a bridge in Caracas on Wednesday as the death toll rom this month's anti-government unrest hit at least 29.

Red-shirted supporters of Maduro, the 54year-old former bus driver who succeeded Hugo Chavez in 2013, also rallied on the streets of the capital, punching their fists in the air and denouncing opposition

Question: What are the people in the image accused of behaving like?

Bridge item: Opposition supporters

The automatic training set generation process consists of the following steps:

- mention with its visual description.
- Question Filtering: Discard questions

### Multi-Hop Text-only QA

- HotpotQA.

### **End-to-end Multimedia QA**

- task

# performance of 78.8%.

- and news body text.

<sup>3</sup>Columbia University <sup>6</sup>IBM Research AI

# Silver Training Set Generation

Multimedia Entity Grounding: Identify objects in images that are grounded in text.

Visual Attribute Extraction: Generate visual descriptions for the objects in images.

Question Generation: Generate questions about the cross-media grounded entities.

Question Editing: Replace grounded entity

answerable using a text-only QA model.



► We use an extractive text-only QA model that takes the question, caption and body text as input.

The model is based on Bert-large and is trained on

We finetune a pre-trained multimodal model for our

We add an extractive answer predictor to OSCAR and finetune using 20k synthetic training examples.



Pipeline-based QA system has bridge F1 of 29.8% compared to human

Underperformance of end-to-end multimedia QA system could be due to OSCAR being pre-trained with image-caption pairs, which makes it potentially not suited for reasoning over larger text input.

Grounding system captures the bridge item in 45% of the cases.

# Conclusion

► We introduce a new challenging multi-hop QA task, MuMuQA, that requires cross-media grounding over images, captions

We demonstrate the benefit of using multimedia knowledge extraction, both for generating silver-standard training data and for a pipeline-based multimedia QA system.





