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Improving VQA and its Explanations by Comparing Competing Explanations

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Visual Question Answering (VQA)

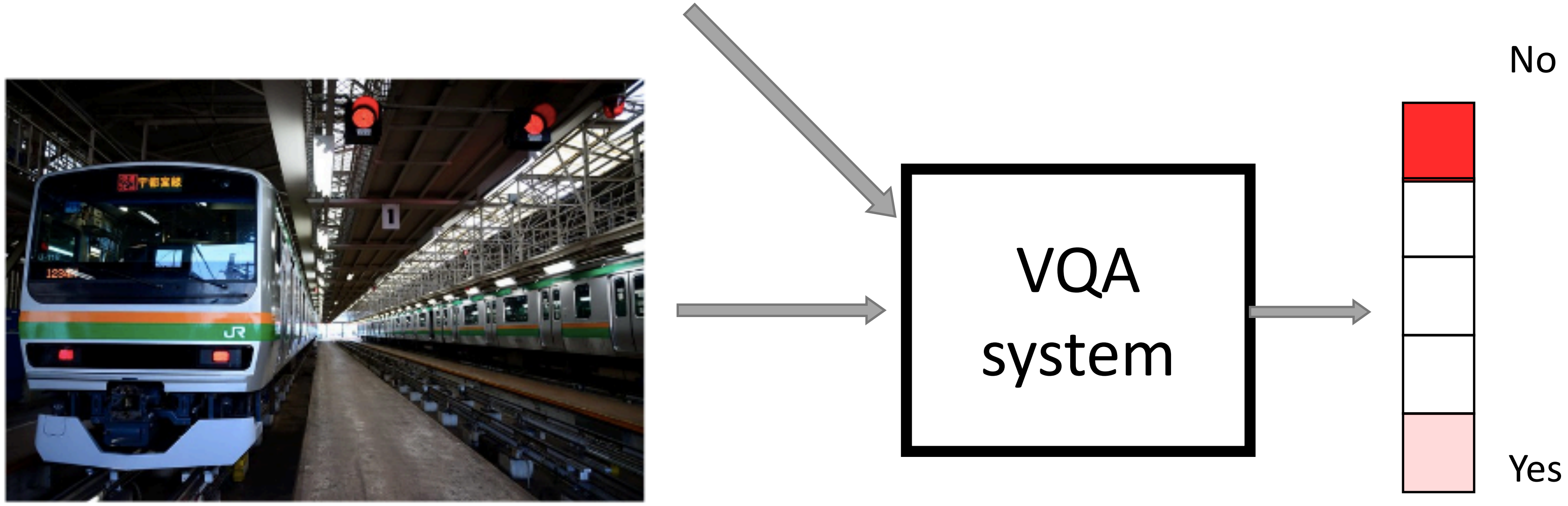
- Answering natural language questions about an image

Question: Is this in an Asian country?
Answer: Yes

VQA systems

- Framed as multi-class classification problems

Question: Is this in an Asian country?



Lack of Explanatory Capabilities

- Dataset biases introduce shortcuts
    - ‘Is this’ type questions are more likely to be answered as No.
    - ‘Red light’ means No.
    - More US subways are in the dataset.

Lack of Explanatory Capabilities

- Key features are subtle
  - Hard to let the system automatically learn to focus on the text on the train's marquee, and further notice the type of characters.

VQA with Textual Explanations

- Human annotated explanations

Question: Is this in an Asian country?
Answer: Yes

The information provided on the train’s marquee is comprised of Asian characters.

Competing Explanations

- Plausible explanations that support top-ranked answer candidates.
  - Describe expected behaviors when a certain answer candidate is true.

Candidate 1: No VQA confidence: 0.88
Sample Retrieved Explanations:
1. The train looks European as well as the railings and surrounding area.
2. The wording on the train is in English.
3. 4.… 8…

Candidate 2: Yes VQA Confidence: 0.79
Sample Retrieved Explanations:
1. It does not look like a standard American train.
2. The signs are all in Japanese.
3. 4.… 8…

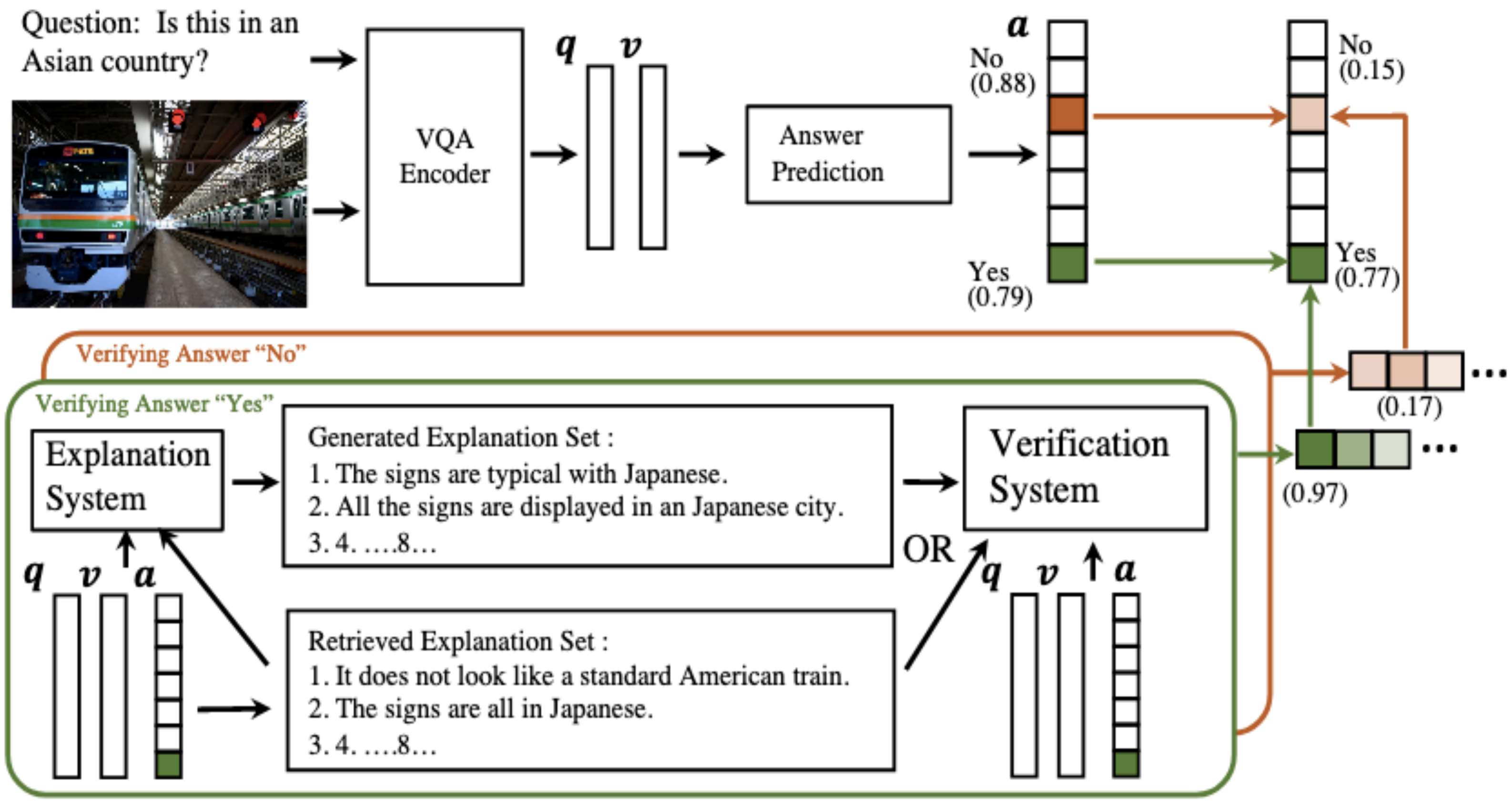
Competing Explanations

- Extracting top-ranked answer candidates
  - We used the top-5 answers from a pretrained VQA systems
- Generating explanations for each answer candidates
  - Retrieval approach: select explanations of the 8 examples in the training set with the most similar features for questions, images and answers.
  - Generation approach: we train an explanation module [1] to generate the explanation for each candidate.

[1] J. Wu and R. J. Mooney. Faithful Multimodal Explanation for Visual Question Answering. In ACL BlackboxNLP Workshop, 2019

Using Competing Explanations

- Competing explanations are encoded to re-weight the original VQA confidence based on their supportiveness to the answer candidates.



Verification Systems

- score how well a generated or retrieved explanation supports a corresponding answer candidate given the question and visual content.

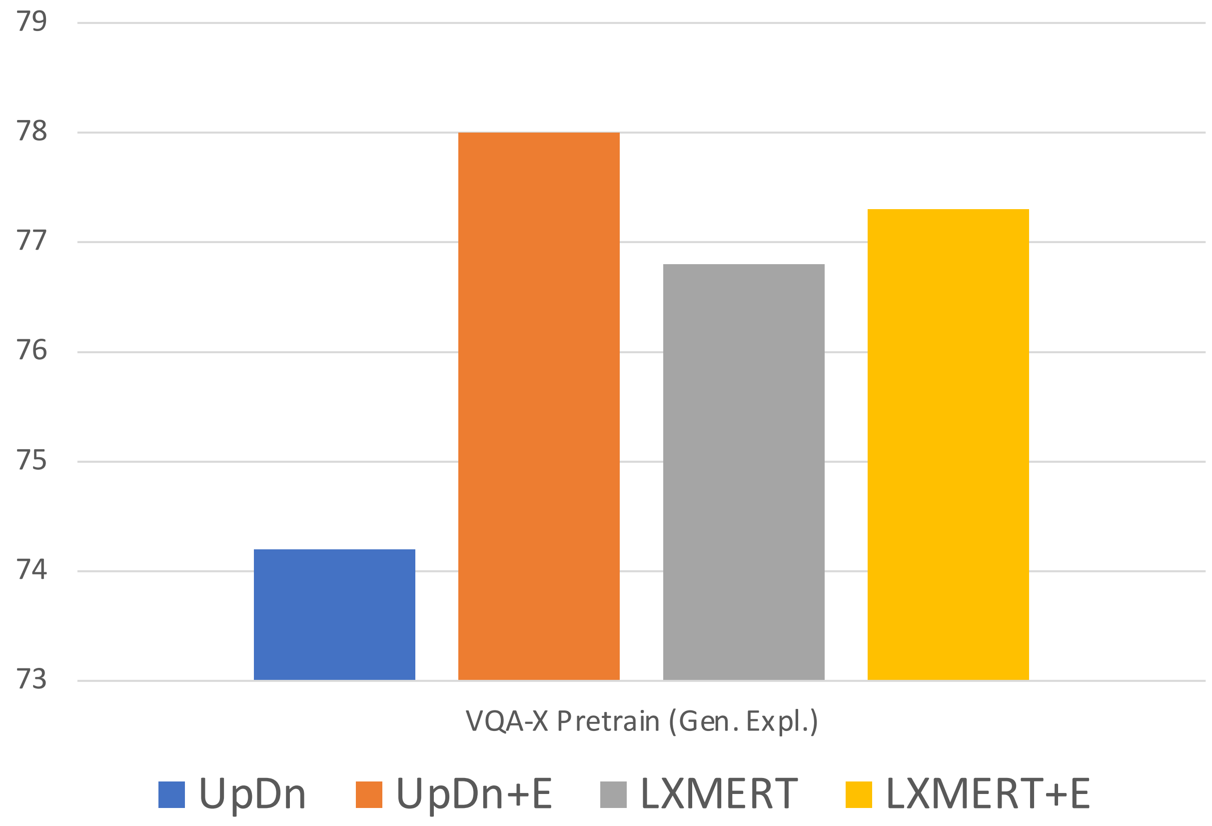
$$S(Q, \mathcal{V}, a, x) = \sigma(f_2(f(\mathbf{q}), f(\mathbf{v}), f(\mathbf{a}), f(\phi(x))).$$

Training

- Positive examples
  - The VQA examples with annotated human explanations
- Negative examples
  - Replacing visual features
  - Replacing question features
  - Replacing answer features
  - Replacing explanation features

Experimental Results

- VQA-X Performance pretraining on VQA-X



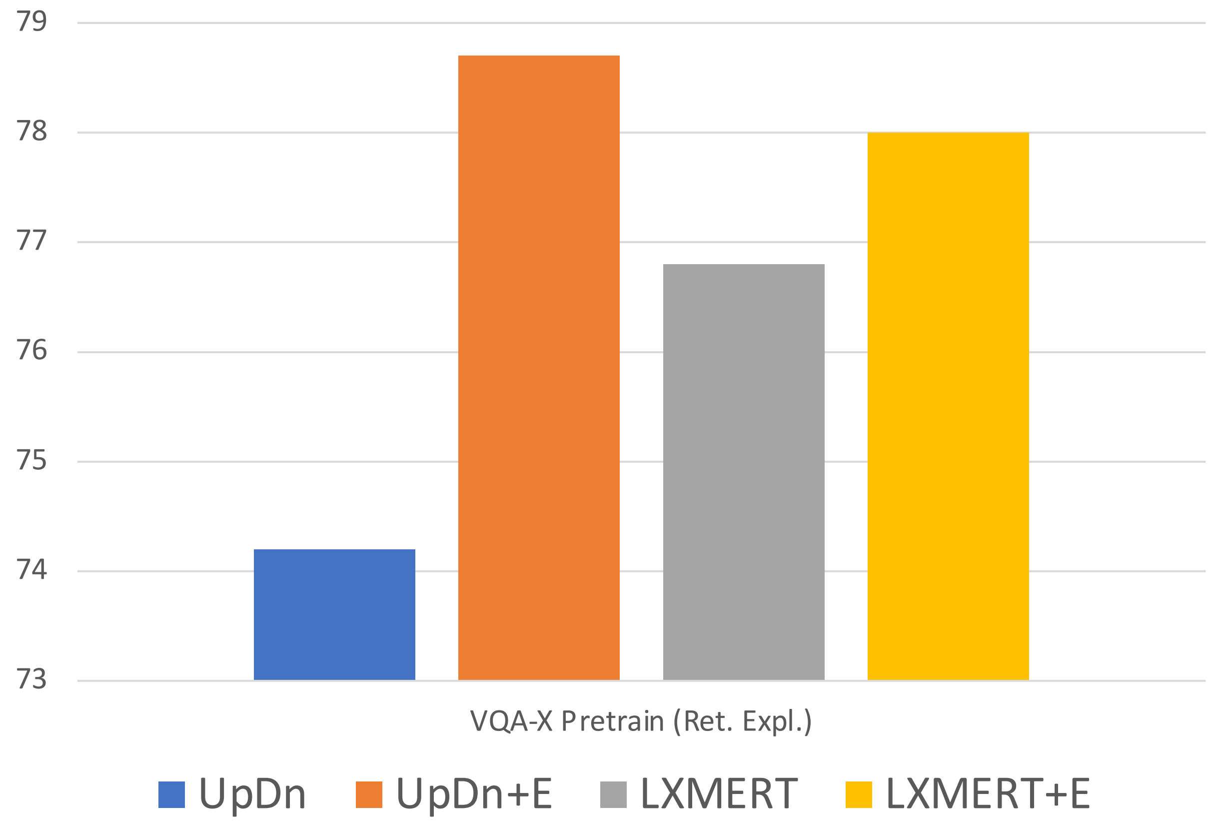
Experimental Results

- VQA-X

- VQAv2

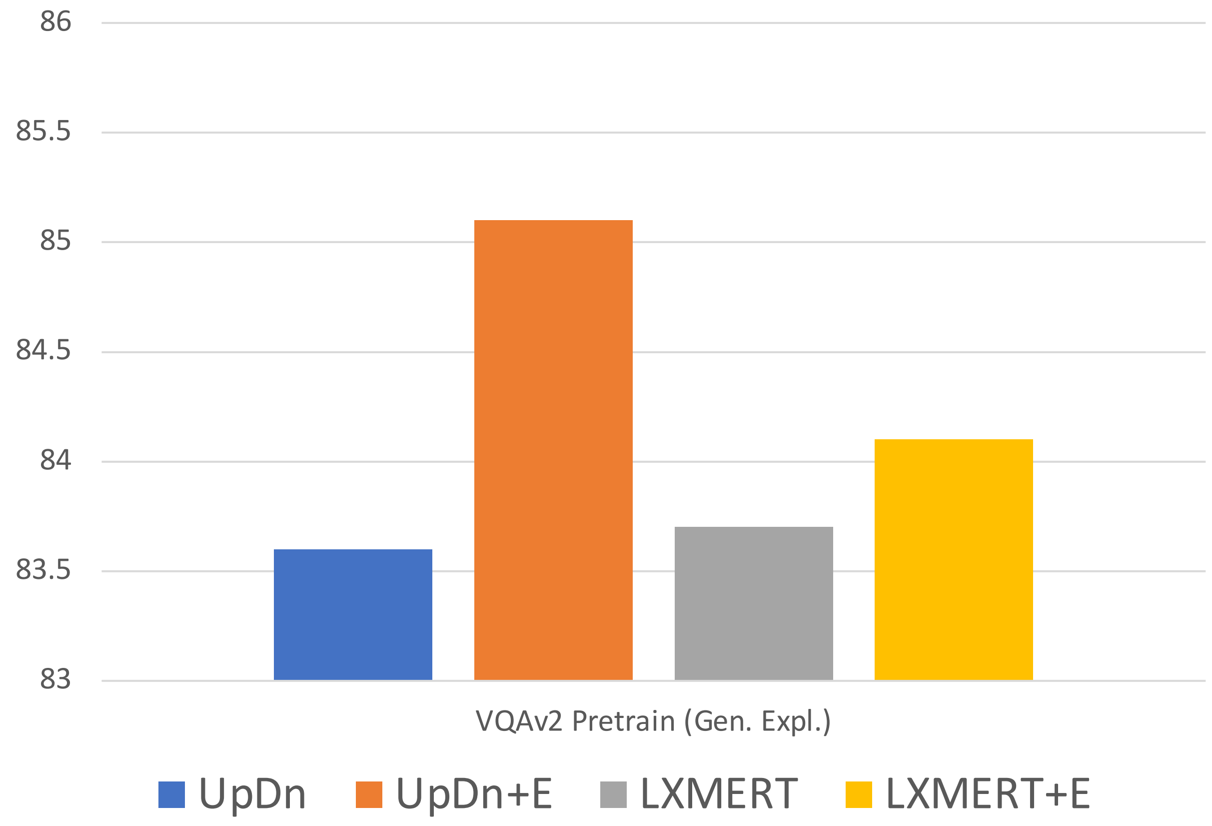
Experimental Results

- VQA-X Performance pretraining on VQA-X



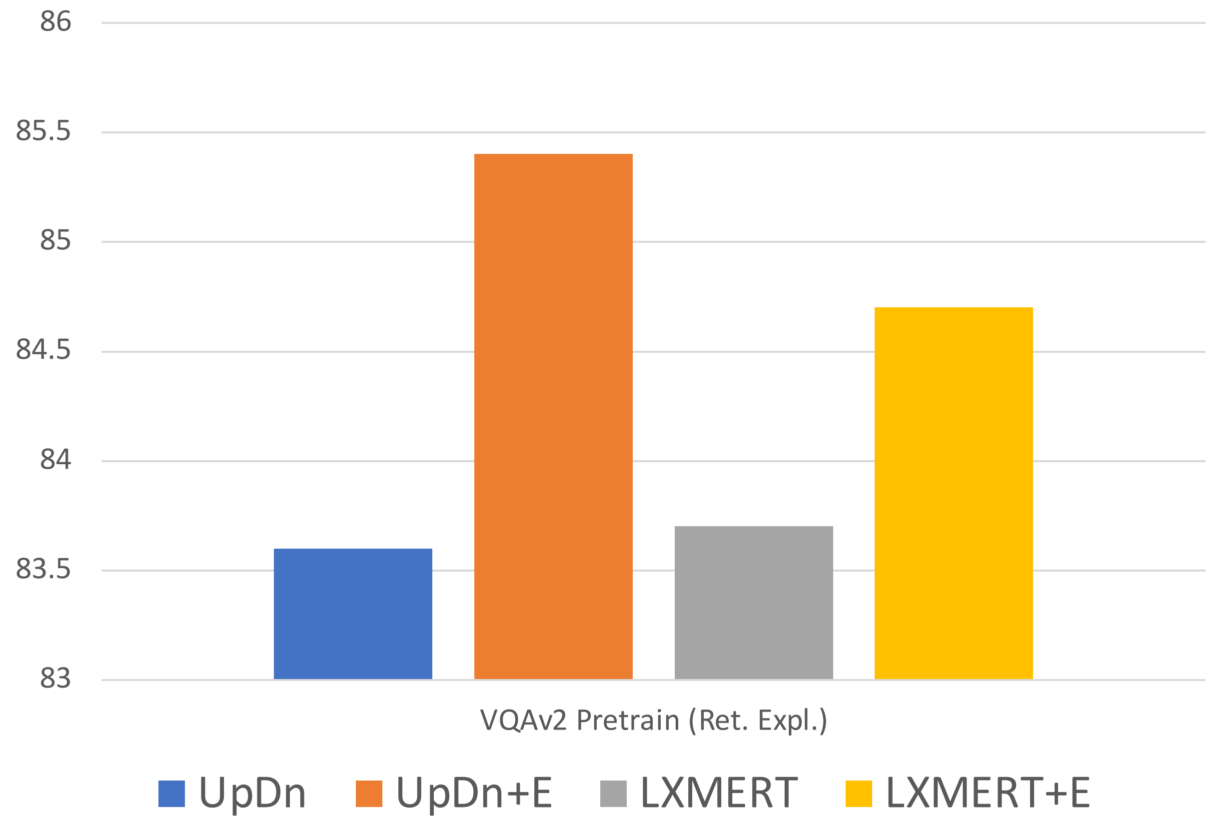
Experimental Results

- VQA-X Performance pretraining on VQA-v2



Experimental Results

- VQA-X Performance pretraining on VQA-v2



Qualitative Results

What type of fruit toy is the cat holding?

Cat(0.0): VQA: 0.12 VQA+E: 0.00

A fluffy animal with ears and a tail is there.

Banana(1.0): VQA: 0.09 VQA+E: 0.08

It is long with a yellow peel.

Qualitative Results

What beverage is in the cup?

Milk(0.0): VQA: 0.20 VQA+E: 0.11

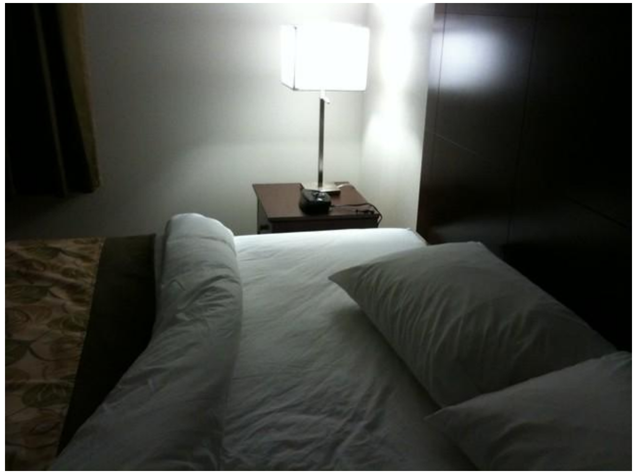
It is a liquid and white.

Beer(1.0): VQA: 0.13 VQA+E: 0.12

It is amber in color.

Competing Explanations for Better Explanation

- Provide references to explanations to similar visual questions.



What is this piece of furniture used for?

Sleep(0.6):
There is a bed and pillows in the room.

Competing Explanations for Better Explanation

- We used the explanation module from [1] and use the retrieved explanations as additional input features.

	Automatic Evaluation				
	BLEU-4	METEOR	ROUGE	CIDEr	SPICE
Faith. Expl. [1]	25.0	20.0	47.1	91.1	18.6
Faith. Expl. + E (ours)	26.4	20.4	48.5	95.3	18.7

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