1 Introduction

Reasoning is one of the major challenges of Human-like AI (Lake et al., 2016) and has recently attracted intensive attention from natural language processing (NLP) researchers (Dagan et al., 2006; MacCartney and Manning, 2007; Bowman and Zhu, 2019). However, cross-modal reasoning needs further research.

For cross-modal reasoning, we observe that most methods fall into shallow feature matching without in-depth human-like reasoning, e.g. Fukui et al. (2016); Yang et al. (2015); Baltrušaitis et al. (2017) have shown that a number of cross-modal reasoning tasks can be easily solved by concatenating image representations and text representations. The reason lies in that existing cross-modal tasks directly ask questions for a image. However, human reasoning in real scenes is often made under specific background information, a process that is studied by the ABC theory (See Section 3) in social psychology.

We propose a shared task named “Premise-based Multimodal Reasoning” (PMR), which requires participating models to reason after establishing a profound understanding of background information. We believe that the proposed PMR would contribute to and help shed a light on human-like in-depth reasoning.

We summarize the significance of this task as follows:

- We introduce premise into cross-modal reasoning, therefore image-text interaction can be specified by the given premise, which may fit in real-world applications like visual related smart home devices.

- Different from existing cross-modal reasoning tasks, PMR’s negative answers are not irrelevant to the image but are possible understandings of the image. PMR is more challenging and can further push forward the fusion of image and text information in multimodal reasoning.

- We apply the ABC Theory to task designing by introducing premise as prior belief in the rational-emotive process. The proposed task paves the way for cognitive cross-modal reasoning.

2 Task Description

We describe our PRM task by an example in Figure 1 I&III. Given an image and a premise, we hope that the machine will understand the image in combination with the premise so as to choose the exclusive correct answer among the four hypothetical actions (See Appendix A). The premise would serve as the background knowledge or domain-specific common sense for the given image. In this way, we hope the reasoning models would make correct classification considering the interaction between the premise and the image, which is similar to the human cognitive process. In the multiple-choice setting, all four hypothetical actions describe what will happen next, but only one of them is correct under the specific premise.

Due to its cross-modal nature and resemblance with human cognition, PMR would be interesting to researchers working on cross-modal reasoning and understanding. The task would push forward the study on the fusion between different modalities and human-like cognitive reasoning, which is both a challenge and an opportunity for future research. Moreover, we will provide detailed annotation information to reduce the hassle of image processing, which makes the task friendly to NLP researchers.
3 Related Work

The ABC Theory  The design of PMR is inspired by the ABC Theory (Ellis, 1995) in social psychology. The theory represents a widely accepted framework for how one’s behavioral patterns are created. It asserts that human behavior do not come directly from the events but from the interpretations we made. We apply the ABC theory to the designing of PMR which formulates the given premise as the prior belief, as shown in Figure 2.

Visual Commonsense Reasoning (VCR)  VCR (Zellers et al., 2018) requires machines to understand an image and answer a multi-choice question. Specifically, questions are like ‘what is going to happen next’, ‘infer the relationship between [personA] and [personB]’ and ‘why is [personA] smiling’, as well as the rationale why the answer is true. Since VCR collects its data from movie clips (without notifying movie names), we argue that the answers may vary according to the specific movie type, e.g. the question like ‘why is [personA] smiling’ might have divergent answers in a horror movie and a romantic movie.

Taking one step forward, different people who observe the image from different aspects or under different premises would have divergent understandings, and thus make different interpretations of the same image. As shown in the example in Figure 1 I&II, without specifying a premise, all four hypothetical actions are reasonable in VCR. While in PMR, we provide the premise “[person2] is the mother of [person5].” To make the correct choice, machines have to perceive the image with the guidance of the premise. In essence, the premise in the PMR task would effectively narrow down the eligible actions with respect to the given image and thus require a higher level of human cognition on premises, questions as well as images. PMR is orthogonal to the contributions of VCR, as we encourage in-depth human-like reasoning with the specificity of premise while VCR focuses on common sense reasoning in the cross-modal setting.

4 Data

4.1 Data Preparation

Image and its annotation data are modified from VCR image collection (See Appendix B). To generate premises compatible with images, we manually wrote 52 premise templates belonging to six categories: relationship, antecedent, personality, emotion, environment and identity. We expanded them to 32,142 premise sentences by data augmentation.
4.2 Crowdsourcing Annotations

Randomly combining each image with premises of each category, we have constructed 36k examples to be labeled. In each example, we ask the AMT workers to choose one of the given premises as the image’s supplementary information. After that, two hypothetical actions should be written, which describe what will happen next. Among them, Action-True contains image information and meets the chosen premise. In contrast, Action-False contains image information but contradicts the chosen premise. In order to ensure quality, we have designed multi-stage quality control (See Appendix C).

4.3 Post-processing

We designed a series of rules to generate action interference items, such as changing the order or gender of characters in action-True and action-False, and replacing keywords that appear in them, so that the newly generated options do not match the image. As a result, we finally provide four different types of hypothetical actions, of which only one option is a reasonable inference based on the premise after understanding the image. We use Accuracy as the main evaluation metric for this task. We will provide human performance as a reference, and set up baseline models for PMR.

4.4 Copyright

We do not have any copyright issues. (See Appendix D).

5 Pilot Task

Pilot Annotation To obtain high-quality annotations, we conducted three pilot annotations, by adjusting the annotation process and platform. With reference to the pilot annotations, we have made an estimate of the final data size and relevant cost.

According to the pilot annotations, we have optimized the process and annotation website. We invited proficient students as annotators and provided them with extra training before annotating. In addition, inspectors will be arranged to check the annotating quality in real-time. Therefore, unqualified labels will be reworked.

Pilot Experiment We sampled 50 manually annotated data as our testing data, so as to evaluate this task. We converted them into the form of VCR questions. Concretely, we constructed the VCR-form question by concatenating “What is going to happen next given the fact” with the premise. Then, we used the VL-BERT (Su et al., 2019) model trained on the VCR as our baseline. VL-BERT is a simple yet powerful pre-trainable generic representation for visual-linguistic tasks, therefore we will provide this model for participants who have no experience in image processing, while participants can use their own image processing module as well. VL-BERT’s performance on VCR and on PMR is shown in Table 2. Compared with VCR, PMR is more challenging to multimodal reasoning, which is of great research significance.

| Name   | Accuracy | Model         |
|--------|----------|---------------|
| VCR (Q → A) | 73.6%    | VL-BERT-base  |
| PMR (Q → A) | 40.0%    | VL-BERT-base  |

Table 2: Pilot study on VL-BERT baseline.

6 Task Organizers

Zuifang Sui has co-organized CLP-2014 task 1 and CCL2021 task 2. Her research interests include Natural Language Processing, Text Mining and Language Knowledge Engineering. She has published more than 60 research papers in top-tier conferences and journals, such as ACL, IJCAI, EMNLP and COLING.

Weidong Zhan has co-organized CCL2021 task 2. His research interests are Modern Chinese Formal Grammar, Chinese Information Processing, Chinese Language Knowledge Engineering, etc.

Information of other co-organizers can be found in Appendix E.

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1Testing data can be found from https://github.com/dqxiu/PMR
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A Data Format

Here is an example$^2$ of what the data would look like.

Premise: “[person2] is the mother of [person5].”,
Image id: 1528,
#You can get the image and its annotation information from this value
Options:

{ 
  1: “[person4] is going to say how cute [person2]'s children are.”,
  2: “[person5] is going to say how cute [person2]'s children are.”,
  3: “[person4] sigh and say,” The children’s parents are too busy at work.”,”,
  4: “[person1] sigh and say,” The children’s parents are too busy at work.””
},

#Four hypothetical actions, two of them are reasonable inference from the image, the others are interference options.
Answer: “1”
#The only correct answer that can be derived from understanding the image based on the premise.
}

B Image Preparation

VCR image collection comes from the Large Scale Movie Description Challenge and YouTube movie clips. It has been screened by the “interestingness filter” to retain meaningful images, including 110k high-quality images in total. To ensure the labeling quality of PMR, we screened out images with low brightness, more than five people, or more than 15 tags, and finally got 30k images for our labeling.

C Quality Control

Labeling Quality Control Before Post-processing, we adopted a fast secondary crowdsourcing process to ensure labeling quality. Show the image, context and any action (true or false attribute are hidden) obtained from the first crowdsourced annotation to the annotator, and ask the annotator to judge whether the action is true or false. Suppose the judgments of the two annotators are the same as those of the first annotation. If the true or false attributes are consistent, the annotation will be regarded as a valid one, otherwise it will be discarded.

Question Quality Control After Post-processing, we control the quality of multiple-choice questions through crowdsourcing. We randomly hand the constructed multiple-choice questions to the annotators on the AMT. In addition to the four hypothetical actions for each multiple-choice question, the “Wrong” option is added to indicate that the question is wrong, the answer is not unique, and there is no answer. If both annotators choose the correct answer, the modified multiple-choice question will be regarded as a valid question. If both annotators select the “Wrong” option, the question will be discarded. In other cases, the organizers of this task will check the question.

D Data Availability and Copyright

According to Section 107 of the Copyright Law$^3$, and 28A and 30 of the Copyright Acts$^4$, there is one exception to copyright infringement which is fair use (or fair dealing). Fair use is appropriate for public benefit purposes, like research. Our use is not of commercial nature. Besides, we only use texts that are publicly available, and the source will be stated according to law. Users will download the images directly from the original source.

E Other Organizers

Baobao Chang is an associate professor at Peking University. He has published over 60 high-quality academic papers in international conferences and Journals, including top-tier conferences such as ACL, EMNLP, COLING, SIGIR and IJCAI. He has served in the Program Committee of various international conferences including ACL, EMNLP, COLING etc.

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$^2$More examples can be found from https://github.com/dqxiu/PMR

$^3$https://www.copyright.gov/title17/92chap1.html107

$^4$https://www.gov.uk/government/publications/copyright-acts-and-related-laws
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