Attention Mechanism Based Cognition-level Scene Understanding

Xuejiao Tang\textsuperscript{1}, Tai Le Quy\textsuperscript{1}, Eirini Ntoutsi\textsuperscript{2}, Kea Turner\textsuperscript{3}, Vasile Palade\textsuperscript{4},
Israat Haque\textsuperscript{5}, Peng Xu\textsuperscript{6}, Chris Brown\textsuperscript{7} and Wenbin Zhang\textsuperscript{8}

\textsuperscript{1}Leibniz University of Hannover, Germany \textsuperscript{2}Freie Universitat Berlin, Germany
\textsuperscript{3}Moffitt Cancer Center, USA \textsuperscript{4}Coventry University, United Kingdom
\textsuperscript{5}Dalhousie University, Canada \textsuperscript{6}Technion – Israel Institute of Technology, Israel
\textsuperscript{7}Durham University, United Kingdom \textsuperscript{8}Carnegie Mellon University, USA
\textsuperscript{1}\{xuejiao.tang, tai\}@stud.uni-hannover.de,
\textsuperscript{2}eirini.ntoutsi@fu-berlin.de,\textsuperscript{3}Kea.Turner@moffitt.org,
\textsuperscript{4}ab5839@coventry.ac.uk,\textsuperscript{5}israat@dal.ca,\textsuperscript{6}peng.xu@technion.ac.il
\textsuperscript{7}chris.brown@durham.ac.uk,\textsuperscript{8}wenbinzhang@cmu.edu

Abstract. Given a question-image input, the Visual Commonsense Reasoning (VCR) model can predict an answer with the corresponding rationale, which requires inference ability from the real world. The VCR task, which calls for exploiting the multi-source information as well as learning different levels of understanding and extensive commonsense knowledge, is a cognition-level scene understanding task. The VCR task has aroused researchers’ interest due to its wide range of applications, including visual question answering, automated vehicle systems, and clinical decision support. Previous approaches to solving the VCR task generally rely on pre-training or exploiting memory with long dependency relationship encoded models. However, these approaches suffer from a lack of generalizability and losing information in long sequences. In this paper, we propose a parallel attention-based cognitive VCR network PAVCR, which fuses visual-textual information efficiently and encodes semantic information in parallel to enable the model to capture rich information for cognition-level inference. Extensive experiments show that the proposed model yields significant improvements over existing methods on the benchmark VCR dataset. Moreover, the proposed model provides intuitive interpretation into visual commonsense reasoning.

1 Introduction

Visual understanding is an important research domain with a long history that attracts extensive models such as Mask RCNN\textsuperscript{[1]}, ResNet\textsuperscript{[2]} and UNet\textsuperscript{[3]}. They have been successfully employed in a variety of visual understanding tasks such as action recognition, image classification, pose estimation and visual search\textsuperscript{[4]}. Most of them gain high-level understanding by identifying the objects in view based on visual input. However, reliable visual scene understanding requires not only recognition-level but also cognition-level visual understanding, and seamless integration of them. More specifically, it is desirable to identify the objects of interest to infer their actions, intents and mental states with an aim of having a comprehensive and reliable understanding of
the visual input. While this is a natural task for humans, existing visual understanding systems suffer from a lack of ability for higher-order cognition inference [5].

To improve the cognition-level visual understanding, recent research in visual understanding has shifted inference from recognition-level to cognition-level which contains more complex relationship inferences. This directly leads to four major directions on cognition-level visual understanding research: 1) image generation [6], which aims at generating images from given text description; 2) image caption [7], which focuses on generating text description from given images; 3) visual question answering, which aims at predicting correct answers for given images and questions; 4) visual commonsense reasoning (VCR) [5], which additionally provides rational explanations along with question answering and has gained considerable attention [8].

The VCR task is seen as a challenging mountain to climb. To solve the cognition-level visual task, the model need to learn human’s inference ability. This might be easy for human as we humans have a reserve of knowledge and excellent reasoning abilities. However, it is challenging for up-to-date AI systems. Recently, a large number of researches (see, e.g., [5,8,9,10,11]) has been proposed to solve the challenging task. These research on VCR typically necessitates pre-training on large scale data prior to performing VCR tasks. They usually fit well towards the properties that the pre-training data possessed but their generalization on other tasks are not guaranteed [12]. To remove the necessity of pre-training, another line of research focuses on directly learning the architecture of a system to find straightforward solutions for VCR [10]. However, these methods suffer commonsense information loss where the commonsense reasoning ability of the model is limited. Also, multimodel fusion to fuse visual and textual information is a daunting task.

To address the aforementioned challenges, we propose a parallel structure-based model PAVCR, which encodes the commonsens between sentences with less information lost. We first design a multimodal fusion layer to fuse visual and textual information. Then, we introduce a commonsense encoder to enhance the inference ability of the proposed model. Then, we introduce a commonsense encoder to enhance the inference ability of the proposed model. The novelty of this research comes from five aspects:

- We theoretically analyze the inadequacy of previous work [13] and introduce a new effective model to reduce the sequential computation. In [13], the computational complexity of related signals from two positions grows with the distance between the positions, which results in difficulties in learning dependencies among positions for the sequential task. In the newly proposed multimodal feature fusion layer and commonsense encoder submodules, we designed a parallel attention structure to limit the number of operations.
- A newly proposed model for VCR task, which represents cognition-level scene understanding.
- A new multimodal fusion layer that fuses visual and textual information.
- A new commonsense encoder layer with a parallel structure attention mechanism along with memory cell that avoid information loss while storying the extracted knowledge extracted commonsense between queries and responses.
- Extensive experiments comparing with popular methods for VCR tasks and ablation studies.
This work is an extension of our previous work [14]. The major changes include: i) a newly proposed multimodal fusion layer for visual-textual information fusion, ii) a parallel structure based commonsense encoder, which enable the model capture more information without long dependency, along with a memory cell to accumulate commonsense storage, iii) study to discuss the superior ability of the propose model, iv) ablation study to validate the proposed multimodal fusion layer and commonsense encoder layer.

The rest of this paper is organized as follows. In section 2 we review related work on QA (and specifically on VCR). Section 3 briefly covers notation. In section 4 we detail how the proposed model works to handle VCR task. In section 5 we apply our model to the VCR dataset and conduct experiments. In section 6 we show the case study to compare the prediction results from newly proposed model and the base model. In section 7 we display the quantitative results predicted by PAVCR. Finally, in section 8 we conclude our paper.

2 Related Work

From individual object level scene understanding [11] which aims at object instance segmentation and image recognition, to visual relationship detection [15] which captures the relationship between any two objects in image or videos, state-of-the-art visual understanding models have achieved remarkable progress [16]. However, that is far from satisfactory for visual understanding as an ideal visual system necessitates the ability to understand the deep-level meaning behind a scene. Recent research on visual understanding has therefore shifted inference from recognition-level to cognition-level which contains more complex relationship inferences. Rowan et al. [5] further formulated Visual Commonsense Reasoning as the VCR task, which is an important step towards reliable visual understanding, and benchmarked the VCR dataset. Specifically, the VCR dataset is sampled from a large sample of movie clips in which most of the scenes refer to logic inferences. For example, “Why isn’t Tom sitting next to David?”, which requires high-order inference ability about the scene to select the correct answer from available choices. Motivated studies generally fall into one of the following two categories based on the necessity of pre-training dataset.

The first line of research, pre-training approaches, trains the model on a large-scale dataset then fine-tunes the model for downstream tasks. The recent works include ERNIE-ViL-large [8] and UNITER-large [12]. While the former learns semantic relationship understanding for scene graph prediction, the latter is pre-trained to learn joint image-text representations. However, the generalizability of these models relies heavily on the pre-training dataset and therefore is not guaranteed.

Another research line focus on studying the model structure to find a straightforward solution for VCR task. It focuses on encoding the relationship between sentences using sequence-to-sequence based encoding methods. These methods infer rationales by encoding the long dependency relationship between sentences (see, e.g., R2C [5] and TAB-VCR [10], DMVCR [13]). However, these models face difficulty with reasoning information lost based on long dependency structure, and it is hard for them to infer reason based on commonsense about the world. More recently, CAN [14] proposes a
co-attention network to ease model training and enhance the capability of capturing relationship between sentences and semantic information from surrounding words, which has already gained a remarkable improvement in VCR task. Our work is resemble this method which is independent of large-scale pre-training dataset. Two distinctions in our proposed work are: i) a cross attention based multimodal unit is designed to fuse visual information from images and textual information from language sentences, ii) a parallel structure co-attention network with memory cell for storing commonsense rather than long dependency structure network to enhance the capability of capturing semantic information in case of long sentences.

Fig. 1. A VCR running example.
3 Notations and Problem Formulation

The VCR dataset consists of millions of labeled subsets. Each subset is composed of an image with one to three associated questions. Each question is then associated with four candidate answers and four candidate rationales. The overarching task is formulated as three subtasks: (1) predicting the correct answer for a given question and image \((Q \rightarrow A)\); (2) predicting the correct rationale for a given question, image, and correct answer \((QA \rightarrow R)\); and (3) predicting the correct answer and rationale for a given image and question \((Q \rightarrow AR)\). Additionally, we defined two language inputs - query \(q\{q_1, q_2, \cdots, q_n\}\) and response \(r\{r_1, r_2, \cdots, r_n\}\), as reflected in Figure 2. In the \(Q \rightarrow A\) subtask, query \(q\) is the question and response \(r\) is the answers. In the \(QA \rightarrow R\) subtask, query \(q\) becomes the question together with correct answer, while rationales constitute the response \(r\). For example, in Figure 1, the \(Q \rightarrow A\) subtask in Question 1 predicts correct answer choice for given image and question. Here, \(q\) is the given question (“Are \([0,1]\) happy to be here?”) and \(r\) is the given answer choices (“A: Yes, they will \(\cdots\)”, “B: No, neither of them is happy, \(\cdots\)”, “C: No, \([0,1]\) took the stairs \(\cdots\)”, “D: They both \(\cdots\)”). Compared to \(Q \rightarrow A\) subtask, the \(QA \rightarrow R\) subtask predicts rationale for given image, question and correct answer. Here, \(q\) is the question (“Are \([0,1]\) happy to be here?”) along with the correct answer (“B: No, neither of them is happy, and they want to go home.”), \(r\) is the rationale choices (“A: \([0,1]\) looks distressed \(\cdots\)”, “B: [1] is in an argument with [0] \(\cdots\)”, “C: Both their expression \(\cdots\)”, “D: They both \(\cdots\)”)

4 Proposed Framework

Figure 2 illustrates the steps of the learning process by the proposed framework. It consists of four layers: a feature representation layer, a multimodal fusion layer, a commonsense encoder layer, and a prediction layer. The first layer captures language and image features and converts them into dense representations. The represented features are then fed into the multimodal fusion layer to generate meaningful contexts of language-image fused information. Next, the fused features are fed into a commonsense encoder layer, which consists of a co-attention unit and memory cell to support commonsense storage. Finally, a prediction layer is designed to predict the correct answer or rationale.

4.1 Feature Representation Layer

Extracting informative features from multi-source information plays an important role in any machine learning application, especially in our context where the feature itself is one of the learning targets. As shown in Figure 2, for the image feature extraction, the original image information source is the image along with its objects, which is given by means of related bounding boxes serving as a point of reference for objects within the images. The bounding boxes of given image and objects are then fed into the deep nets to obtain sufficient information from original image information source. Concretely, PAVCR extracts image features by a deep network backbone ResNet50 [17] and fine-tunes the final block of the network after RoiAlign. In addition, the skip connection [2] is adopted to circumvent the gradient vanishing problem when training the deep nets.
Language embedding. The language embeddings are obtained by transforming raw input sentences into low-dimensional embeddings. The query represented by \( q \{ q_1, q_2, \cdots, q_n \} \) refers to a question in the question answering task \( (Q \rightarrow A) \), and a question paired with correct answer in the reasoning task \( (QA \rightarrow R) \). Responses \( r \{ r_1, r_2, \cdots, r_n \} \) refer to answer candidates in the question answering task \( (Q \rightarrow A) \), and rationale candidates in the reasoning task \( (QA \rightarrow R) \). The embeddings are extracted using an attention mechanism with parallel structure [18]. Note that the sentences contain tags related to objects in the image. For example, see Figure 1 and the question “Are [0,1] happy to be here?” The [0,1] are tags set to identify objects in the image (i.e., the object features of person 1 and person 2).

Object embedding. The images are filtered from movie clips. To ensure images with rich information, a filter is set to select images with more than two objects each [5]. The object features are then extracted with a residual connected deep network [2]. The output of the deep network is object features with low-dimensional embeddings \( o \{ o_1, o_2, \cdots, o_n \} \).

4.2 Multimodal Feature Fusion Layer

The multimodal feature fusion layer is illustrated in Figure 3. It aims to learn visual-textual fused features with semantic discriminative visual features under the guidance of the textual description without harming their location ability [19]. After the multimodal layer, the fused features enable the model to learn the ability in capturing context-level semantics of both vision and text. It consists of 1) a text branch to supply text features regarding query and responses with attention information for related object features from image; 2) a visual branch unit to supply mixed visual-textual information; 3) a text object fusion unit to enable the capability of the model in capturing context-level semantics of both visual and textual.

Textual Branch Unit. Textual branch unit is designed to supply textual information while extracting semantic information from around words. To this end, previous
extracted textual features from queries or responses are regarded as value $V_t$, query $Q_t$ and key $K_t$. Recall that the aim of textual branch unit is to learn textual information while considering around words. Here, we employ the multi-head attention [20] to obtain attended information from around words. Formally put,

$$X_1 = V_t \text{softmax}(Q_t K_t / \sqrt{d})$$

where $V_t$, $Q_t$ and $K_t$ is the embedded textual features from queries or responses, $d$ is the dimension of embeddings. It’s illuminated in Figure 2 as operation ①.

Next, the output $X_1$ can supply rich textual information for visual-textual fusion.

**Visual Branch Unit.** A visual branch is designed to learn joint visual-textual features, which fuses textual information into visual features. In details, the previously extracted object features $O$ are regarded as Query $Q_v$, Keys $K_v$ and Values $V_v$ for visual branch’s self-attention computation. To identify the objects and words order, position encodings are added before weighted attention computations (labeled as “Pos” in Figure 3). It can be formulated as:

$$PE_{pos,2i} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right), PE_{pos,2i+1} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

where $PE$ represents position encoding, $pos$ is the word position in sentence, $i$ is dimension, $d_{model}$ is the embedding dimension.
Visual sequential order is crucial for semantic information due to it could result in incorrect meaning in sentence. Therefore, the visual branch unit first takes the previously extracted object features $O$ as the input of position encoding. The operation is illuminated in Figure 2 in 4 and 6 and can be formulated as:

$$Q_{ve} = K_{ve} = \text{norm}(O^i) + PE(O^i)$$  \hspace{1cm} (3)

Next, the output is fed into softmax operation 2 to obtain weighted sum, it can be formulated as:

$$X_2 = \text{softmax}(\frac{Q_{ve}X_1}{\sqrt{d}})$$  \hspace{1cm} (4)

where $X_1$ is textual information which contains weighted attention information of each words and comes from operation 1 in textual unit.

Recall that the aim of the visual branch unit is to learn joint visual-textual representation. To this end, operation 5 concatenates visual-textual information from the output of operation 3, which can be formulated as:

$$Q_{ve} \oplus X_3$$  \hspace{1cm} (5)

where $\oplus$ represents concatenate operation and $X_3$ is the output of operation 3. It can be formulated as:

$$X_3 = X_2X_1$$  \hspace{1cm} (6)

Next, a multi-head attention in operation 7 is deployed to obtain fused visual representations, which contains weighted attention information from text features.

**Text-Object Fusion Unit.** After visual branch unit, the model has learned rich visual information containing weighted textual information as well as textual information containing semantic information from around words. To obtain context-level semantics regarding both textual and visual information, we leverage another multi-head attention operation to learn text-object representations.

### 4.3 Commonsense Encoder

After multimodal fusion layer, the visual and textual information has been fused and output as $q_o$ for fused query and object features, $r_o$ for fused response and object features. To further implement VCR task, a commonsense encoder layer is designed to capture the commonsense between sentences and use it to enhance inference. As in Figure 4 show, the encoder contains N co-attention blocks, each block consists of a guided-attention unit and self-attention unit. Its parallel structure enables the model to capture the semantic information between sentences in parallel and ease the information lost problem. Following the N-layer co-attention blocks is a memory cell to store extracted commonsense.

**Self Attention.** Self-attention is designed to capture semantic information within a sequence. Its structure is shown in Figure 4 as a grey block. The input consists of Query Q, Keys K, and Values V, which are identical, for the sake of capturing pairwise relationship in a sequence. In details, pairwise relationship between samples in a sequence is learned by the multi-head attention layer. For input sequence $\tilde{q} = [q_1, q_2, ..., q_m]$. 


the multi-head attention learns the relationship between $\langle \tilde{q}_i, \tilde{q}_j \rangle$ and outputs attended representations. Subsequently, the attended representations are transformed by a feed-forward layer which contains two fully-connected layers with ReLU activation and dropout. The multihead attention can be formulated as:

$$MultiHead = h_1 \oplus h_2 \cdots \oplus h_i$$

where $h_i$ represents an attention head and can be formulated as:

$$h_i = \text{softmax}(QK^T\sqrt{d_k})V$$

where $d_k$ is the dimension size of input embedding $K$. $Q$, $K$, $V$ are input sequence $\tilde{q}$.

**Guided Attention.** In comparison to self attention, guided attention focuses on inter-sentence-wise attention and can be regarded as guided attention learning weighted information among different sentences. When taking two different sentences representations $X = [x_1, x_2, ..., x_m]$ and $Y = [y_1, y_2, ..., y_m]$ as the inputs, $X$ is the query $Q$ while key $K$ and Value $V$ are $Y$, guiding the attention learning for $X$. Specifically, the multi-head layer in a guided attention unit attends the pairwise relationship between the two paired input sequences $\langle x_i, y_j \rangle$ and outputs the attended representations. A feed-forward layer is then applied to transform the attended representations. The co-attention network finally outputs $Z_q$ and $Z_r$, which are attention information over both images and texts.

**Memory cell.** Although the commonsense encoder layer improves long-horizon sequence modeling by attention mechanism, it would potentially have difficulties handling continuous inference which requires a knowledge base. Knowledge base, however, is a crucial requirement for cognition-level inference. Even human beings, we do inferences based on previous knowledge.
Therefore, we introduce a simple external memory cell to handle this dilemma. A memory cell is read-writable and learnable. We define the memory cell as $M$, where $M(i)$ has the same size as $Z_q$ or $Z_r$. At time step $t$, the model firstly read memory from $M$ regarding the past knowledge with the function $f_{\text{read}}(M(t - 1))$ and then concatenate it with the current embedding $h_t$, which is defined as $f_{\text{write}}(M(t))$. This allows the model to condition current embeddings on the previous embeddings for a consistent inference. Formally, put:

$$f_{\text{read}}(M(t - 1)) = Z^1_{q/r} \oplus Z^2_{q/r} \cdots \oplus Z^{t-1}_{q/r}$$  \hspace{1cm} (9)

where $\oplus$ represents concatenate operation.

$$m_{q/r} = f_{\text{write}}(M(t)) = f_{\text{read}}(M(t - 1)) \oplus Z^t_{q/r}$$  \hspace{1cm} (10)

where $m_{q/r}$ represents the memory cell output of queries or responses.

### 4.4 Prediction Layer

The prediction layer generates a probability distribution of responses from the high-dimension context generated in the encoder layer. It consists of an attention reduction unit and a prediction unit.

**Attention Reduction.** The commonsense encoder layer includes $N$ layers co-attention operation. However, some of these are unnecessary for prediction. Therefore, an attention reduction unit is designed to pick up most significant information. It can be formulated as:

$$\tilde{Z}_l = \sum_{i=1}^{m} \alpha_i z^i_l, \alpha = \text{softmax}(\text{MLP}(Z_l))$$ \hspace{1cm} (11)

where $Z_l$ is either input query or sequence, $\alpha$ is the learned attention weights and $i$ is the position in a sequence.

For better gradient flow through the network, PAVCR also fuses the features by using LayerNorm on the sum of the final attended representations,

$$c = \text{LayerNorm}(W^T_{x1} \tilde{Z}_q + W^T_{x2} \tilde{Z}_r)$$ \hspace{1cm} (12)

where $W^T_{x1}$ and $W^T_{x2}$ are two trainable linear projection matrices.

**Prediction.** The prediction includes a multi-layer perceptron (Dropout(0.3) - FC (1024) - ReLU - Dropout(0.3) - FC(1)). VCR task needs to predict the correct choices from four given choices (answer candidates and reason candidates). Hence, we treat it as a multi-class task. A popular loss function for multi-classification task cross-entropy [21] is therefore applied to complete the prediction. It aims to output probability distributions for four candidate choices and the choice with the max prediction probability is the final prediction.
5 Experimental Results

In this section, we conduct extensive experiments to demonstrate the effectiveness of our proposed PAVCR network for solving VCR tasks. We first introduce the datasets, baseline models, and evaluation metrics of our experiments. Then we compare our model with baseline models and present an analysis of the impact of the different strategies. Finally, we present an intuitive interpretation of the prediction. The experiments were conducted on a 64-bit machine with a 10-core processor (i9, 3.3GHz), 64GB memory with GTX 1080Ti GPU.

5.1 Dataset

The VCR dataset consists of 290k multiple-choice questions, 290k correct answers, 290k correct rationales, and 110k images. The correct answers and rationales are labeled in the dataset with > 90% of human agreements. As shown previously in Figure 1, each set consists of an image, a question, four available answer choices, and four reasoning choices. The correct answer and rationale are provided in the dataset as ground truth.

In addition, the dataset distribution is shown in Figure 5. 38% of the types of inference is about explanation, 24% is about activity inference. These types of tasks represent cognition-level inference tasks.

![Fig. 5. Overview of the types of inference required by questions in VCR.](image)
5.2 Metric.

The VCR task can be regarded as a multi-classification problem. We use mAP \[21\] to evaluate the performance, which is a common metric for evaluating prediction accuracy in multi-classification areas. The mAP is usually computed on a dataset.

5.3 Approach for comparison.

We compare the proposed PA VCR with recent deep learning-based models for VCR. Specifically, the following baseline approaches are evaluated:

- **RevisitedVQA \[22\]**: While the most recently proposed VCR methods have reasoning modules, RevisitedVQA deploys logistic regressions and multi-layer perceptrons (MLP) for reasoning tasks.
- **BottomUpTopDown \[23\]**: BottomUpTopDown uses weighted feature information over language and image to predict answers and reasons.
- **MLB \[24\]**: The key operation for MLB is the Hadamard product for attention mechanism, which enables a low-rank bilinear pooling for the task.
- **MUTAN \[25\]**: MUTAN consists of a multimodal fusion module tucker decomposition and a multimodal low-rank bilinear (MLB). The MLB is regarded as a reasoning module for inference.
- **R2C \[5\]**: R2C represents a general baseline for VCR tasks. It consists of a fusion module, a contextualization module, and a reasoning module for cognition-level inference. It encodes the sequence based on the sequence relationship model LSTM and attention mechanism.
- **DMVCR \[13\]**: Storing commonsense between sentences using working dynamic memory as dictionary. In the inference stage, the dictionary module looks up information from the dictionary as well as updates the information in the dictionary.
- **CAN \[14\]**: Proposed a parallel co-attention based network to enhance the capability of capturing information from surrounding words.

5.4 Analysis of Experimental Results

**Task description.** We implement the experiments separately in three steps. We firstly conducted $Q \rightarrow A$ evaluation, and then $QA \rightarrow R$. Finally, we join the $Q \rightarrow A$ result and $QA \rightarrow R$ results to obtain the final $Q \rightarrow AR$ prediction result. The difference between the implementation of $Q \rightarrow A$ and $QA \rightarrow R$ tasks is the input query and response. For the $Q \rightarrow A$ task, the query is the paired question, image, four candidate answers; while the response is the correct answer. For the $QA \rightarrow R$ task, the query is the paired question, image, correct answer, and four candidate rationales; while the response is the correct rationale.

**Analysis.** We compare our method with several popular visual scene understanding models based on the mean average precision metric for the three subtasks: $Q \rightarrow A$, $QA \rightarrow R$, and $Q \rightarrow AR$, respectively. As the results in Table I showing, our approach outperforms in all of the subtasks: $Q \rightarrow A$, $QA \rightarrow R$, and $Q \rightarrow AR$. Specifically, our method outperforms MUTAN and MLB by a large margin due to that MUTAN and
Attention Mechanism Based Cognition-level Scene Understanding

MLB are lacking a commonsense reasoning module, which works for cognition-level inference. Furthermore, it also performs better than recently proposed DMVCR \cite{13} and CAN \cite{14}. The reason is that the proposed PAVCR deploys a more efficient multi-modal fusion layer and commonsense encoder layer.

Table 1. Comparison of results between our methods and other popular methods using the VCR Dataset. The best performance of the compared methods is highlighted. Percentage in parenthesis is our relative improvement over the performance of the best baseline method.

| Models                  | Q → A | QA → R | Q → AR |
|-------------------------|-------|--------|--------|
| RevisitedVQA \cite{22}  | 39.4  | 34.0   | 13.5   |
| BottomUpTopDown \cite{23} | 42.8  | 25.1   | 10.7   |
| MLB \cite{24}          | 45.5  | 36.1   | 17     |
| MUTAN \cite{25}        | 44.4  | 32.0   | 14.6   |
| R2C \cite{5}           | 61.9  | 62.8   | 39.1   |
| DMVCR \cite{13}        | 62.4  | 67.5   | 42.3   |
| CAN \cite{14}          | 71.1  | 73.8   | 47.7   |
| PAVCR                  | 73.1  | 74.2   | 49.2   |

This is expected as PAVCR incorporates a more effective visual grounding module in its encoder network to enhance visual-textual fusion. In addition, to alleviate the lost information when encoding a long dependence structure for long sentences of other methods, PAVCR further encodes semantic information in parallel to capture more comprehensive information from surrounding words, which also leads to superior performance over the others.

Table 2. Comparison of results between our methods and other popular methods using the VCR Dataset. The best performance of the compared methods is highlighted. Percentage in parenthesis is our relative improvement over the performance of the best baseline method.

| Models                      | QA → R | Q → AR |
|-----------------------------|--------|--------|
| Without multimodal module   | 40.2   | 38.2   |
| Dictionary based encoder    | 63.4   | 69.1   |
| PAVCR                       | 73.1   | 74.2   |

5.5 Ablation Study

We also perform ablation studies to evaluate the performance of the proposed multi-modal fusion layer and the commonsense encoder layer. As in Table 2 showing, when
we take out the multimodal fusion layer, the prediction result decreases to 40.2% in $QA \rightarrow R$ task and 38.2 in $Q \rightarrow AR$ task. The large margin decrease indicates that the proposed multimodal fusion layer can help the model improve the capability of capturing visual-textual information. In addition, we also conduct ablation study to prove the effectiveness of the proposed commonsense module. If the proposed encoder layer is replaced by a dictionary-based encoder, the performance will decrease 9.7% in $QA \rightarrow R$ task and 5.1% in $Q \rightarrow AR$. Compared to the dictionary-based method, the proposed encoder layer captures information from surrounding words in parallel, which results in less information loss, as it doesn’t have a long dependency in long sequential prediction tasks.

Fig. 6. Case study example 1. The model predicts the correct answer and rationale.
6 Case Study

In this section, the case study is conducted to compare the performance of the proposed method and analyze the superiority of the model. Figure 6 shows prediction results from previous work and the newly proposed work. The results from the previous work are marked in red, while the results from the newly proposed model are marked in green. The model predicts two questions for the given image. Both of the two questions regards human activity prediction.

![Image of prediction results]

**Question 1: What kind of profession does [0,1] and [2] practice?**

| answer_choices | rationale_choices |
|----------------|-------------------|
| A: [0,1] and [2] are fast food employees. | A: They wear masks and work with a white powder and their are scales for measuring carefully, as well as no legal business would require working naked. |
| B: They work at a law firm. | B: The men are dressed professionally, they appear to be sitting at a long conference table and they have notes in front of them. |
| C: They are conductors on the train. | C: [0,1] and [2] are all dressed in suits and holding papers or briefcases, and meet with people to discuss their cases. |
| D: They are all lawyers. | D: They are sitting at a panel discussing their opinions with sponsored cups on their desk. |

✅

**Fig. 7.** Qualitative example 1. The model predicts the correct answer and rationale.

Analyze the results displayed in Figure 6, we can come to the result that the newly proposed model works better than the previous work CAN [14], due to that CAN [14] predicts the wrong answer but the correct rationale in Question 2 for the given image. However, compared with the result, our newly propose PAVCR correctly predicts all of the choices both in answer and rationale, which proved the superior ability of our newly
proposed model. A crucial factor is that the proposed multimodal feature fusion layer with visual branch and textual branch is more powerful in learning visual-textual fusion information due to it considers not only the multimodal fusion but also pay attention to the sequential order, which is an important factor in semantic meaning.

Fig. 8. Qualitative example 2. The model predicts the correct answer and rationale.

7 Qualitative Results

We evaluate qualitative results on the PAVCR model to show the prediction results visualization. The qualitative examples are provided in Figure 7, 8, 9. The candidate in green represents the correct choice; the candidate with a green checkmark represents the prediction result by our proposed PAVCR model. As the qualitative results show, the PAVCR model has a strong ability in both question answering and reasoning tasks.
It proves the inference ability of the proposed model in cognition-level visual understanding.

In Figure 7, PAVCR performs well in both questions answering and answer reasoning. In detail, the question listed is: “What kind of profession does [0,1] and [2] practice?” The predicted answer is D - “They are all lawyers.” Furthermore, the model offers rationale C - “[0,1] and [2] are all dressed in suits and holding papers or briefcases, and meet with people to discuss their cases.” PAVCR correctly infers the rationale based on dress and activity, even though this task is also difficult for humans. It proves the inference ability of the proposed model in cognition-level visual understanding.

PAVCR can also identify human beings’ necessary and infer emotion. See for example the result in Figure 8. Question 1 is: “Does [0] require medical attention?” Our model selects the correct answer A along with reason A: “[0] does require medical...
attention”; because “Humans are not typically in hospital beds unless they require medical attention.”

Moreover, it can also predict human activities. For instance in Figure 9 the question is “What is [1] doing?” The proposed PA VCR predicts the correct answer B - “[1] is getting chemotherapy,” along with the reason A - “He is in a hospital with tubes in him.” The results mean that the proposed model can analyze activities based on the surrounding environment. This is important and provides the possibility in a real-world application.

8 Conclusion

This work has studied the widely applicable visual commonsense reasoning. To solve the challenging cognition-level visual scene understanding task, we propose novel attention-based multimodal fusion layer and a commonsense encoder layer composed of a feature representation layer to capture multiple features containing language and objects information; a multimodal fusion layer to fuse features from language and images. We also conducted extensive experiments including comparison results with popular VCR models, case study analysis and ablation study on the VCR dataset to demonstrate the effectiveness of our model and present intuitive interpretation. A future direction is to extend the proposed framework in conjunction with our previous works [26, 27] to investigate various perspectives of bias in visual reasoning.

Acknowledgement

This work was supported by a NVIDIA GPU Grant.

References

1. A. O. Vuola, S. U. Akram, and J. Kannala, “Mask-rcnn and u-net ensembled for nuclei segmentation,” in IEEE ISBI, 2019, pp. 208–212.
2. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on CVPR, 2016, pp. 770–778.
3. R. L. Barkau, “Unet: One-dimensional unsteady flow through a full network of open channels. user’s manual,” Hydrologic Engineering Center Davis CA, Tech. Rep., 1996.
4. G. Papandreou, T. Zhu et al., “Towards accurate multi-person pose estimation in the wild,” 2017.
5. R. Zellers, Y. Bisk et al., “From recognition to cognition: Visual commonsense reasoning,” in Proceedings of the IEEE Conference on CVPR, 2019.
6. K. Gregor and I. e. a. Danihelka, “Draw: A recurrent neural network for image generation,” in International Conference on Machine Learning. PMLR, 2015, pp. 1462–1471.
7. O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, “Show and tell: A neural image caption generator,” in Proceedings of the IEEE conference on CVPR, 2015, pp. 3156–3164.
8. F. Yu, J. Tang et al., “Ernie-vil: Knowledge enhanced vision-language representations through scene graph,” 2020.
9. H. Ben-younes, R. Cadène, M. Cord, and N. Thome, “MUTAN: multimodal tucker fusion for visual question answering,” 2017.
10. J. Lin, U. Jain et al., “TAB-VCR: tags and attributes based VCR baselines.”
11. J. Lu, D. Batra et al., “ViL bert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks,” in Advances in Neural Information Processing Systems, 2019, pp. 13–23.
12. Y.-C. Chen, L. Li et al., “Uniter: Learning universal image-text representations,” 2019.
13. X. Tang, X. Huang, W. Zhang, T. B. Child, Q. Hu, Z. Liu, and J. Zhang, “Cognitive visual commonsense reasoning using dynamic working memory,” in International Conference on Big Data Analytics and Knowledge Discovery. Springer, 2021, pp. 81–93.
14. X. Tang, W. Zhang, Y. Yu, K. Turner, T. Derr, M. Wang, and E. Ntoutsi, “Interpretable visual understanding with cognitive attention network,” in International Conference on Artificial Neural Networks. Springer, 2021, pp. 555–568.
15. X. Yang, K. Tang et al., “Auto-encoding scene graphs for image captioning,” in Proceedings of the IEEE Conference on CVPR, 2019, pp. 10 685–10 694.
16. J. Carreira and A. Zisserman, “Quo vadis, action recognition? A new model and the kinetics dataset,” 2017.
17. Y. You, Z. Zhang et al., “Imagenet training in minutes,” in Proceedings of the 47th International Conference on Parallel Processing, 2018, pp. 1–10.
18. J. Devlin, M.-W. Chang et al., “Bert: Pre-training of deep bidirectional transformers for language understanding,” 2018.
19. Y. Du, Z. Fu, Q. Liu, and Y. Wang, “Visual grounding with transformers,” 2021.
20. A. Vaswani, N. Shazeer et al., “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.
21. P. Henderson and V. Ferrari, “End-to-end training of object class detectors for mean average precision,” in Asian Conference on Computer Vision. Springer, 2016, pp. 198–213.
22. A. Jabri, A. Joulin, and L. Van Der Maaten, “Revisiting visual question answering baselines,” in European conference on computer vision. Springer, 2016, pp. 727–739.
23. P. Anderson, X. He et al., “Bottom-up and top-down attention for image captioning and visual question answering,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018.
24. J.-H. Kim, K.-W. On, W. Lim, J. Kim, J.-W. Ha, and B.-T. Zhang, “Hadamard product for low-rank bilinear pooling,” 2016.
25. H. Ben-Younes, R. Cadene, M. Cord, and N. Thome, “Mutan: Multimodal tucker fusion for visual question answering,” in Proceedings of the IEEE international conference on computer vision, 2017.
26. W. Zhang and J. Weiss, “Longitudinal fairness with censorship,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2022.
27. W. Zhang, J. C. Weiss, S. Zhou, and T. Walsh, “Fairness amidst non-iid graph data: A literature review,” arXiv preprint arXiv:2202.07170, 2022.
28. L. Hirschman and R. Gaizauskas, “Natural language question answering: the view from here,” natural language engineering, vol. 7, no. 4, p. 275, 2001.
29. R. Rubinstein, “The cross-entropy method for combinatorial and continuous optimization,” Methodology and computing in applied probability, vol. 1, no. 2, pp. 127–190, 1999.
30. X. Yin, J. Goudriaan, E. A. Lantinga, J. Vos, and H. J. Spiertz, “A flexible sigmoid function of determinate growth,” Annals of botany, vol. 91, no. 3, pp. 361–371, 2003.
31. D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” 2014.
32. P. Anderson, X. He, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Zhang, “Bottom-up and top-down attention for image captioning and VQA,” 2017.
33. J. Lu, X. Ye, Y. Ren, and Y. Yang, “Good, better, best: Multi-choice vqa with textual distractors generation via policy gradient.”
34. C. Xiong, S. Merity, and R. Socher, “Dynamic memory networks for visual and textual question answering,” in *International conference on machine learning*. PMLR, 2016, pp. 2397–2406.
35. A. Kumar, O. Irsoy, P. Ondruska, M. Iyyer, J. Bradbury, I. Gulrajani, V. Zhong, R. Paulus, and R. Socher, “Ask me anything: Dynamic memory networks for natural language processing,” in *International conference on machine learning*. PMLR, 2016.
36. Z. Huang, Xu et al., “Bidirectional lstm-crf models for sequence tagging,” 2015.
37. P. Natarajan, S. Wu et al., “Multimodal feature fusion for robust event detection in web videos,” in *IEEE Conference on CVPR*. IEEE, 2012, pp. 1298–1305.
38. A. Wu and Y. Han, “Multi-modal circulant fusion for video-to-language and backward.” in *IJCAI*, 2018, p. 8.
39. J. M. Wolfe, “Visual search.” 2015.
40. J. Lu, D. Batra, D. Parikh, and S. Lee, “Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks.”
41. L. Huang, W. Wang, J. Chen, and X.-Y. Wei, “Attention on attention for image captioning,” in *Proceedings of the IEEE International Conference on Computer Vision*, 2019, pp. 4634–4643.
42. W. Zaremba, I. Sutskever, and O. Vinyals, “Recurrent neural network regularization,” 2014.
43. C. Lu, R. Krishna et al., “Visual relationship detection with language priors,” in *European Conference on Computer Vision*, 2016.
44. N. Maslan, M. Roemmele, and A. S. Gordon, “One hundred challenge problems for logical formalizations of commonsense psychology,” in *AAAI Spring Symposium Series*, 2015.
45. K. He, R. Girshick, and P. Dollar, “Rethinking imagenet pre-training,” in *The IEEE International Conference on Computer Vision (ICCV)*, October 2019.
46. X.-H. Le, H. V. Ho et al., “Application of long short-term memory (lstm) neural network for flood forecasting.” *Water*, p. 1387, 2019.
47. J.-H. Kim, S.-W. Lee et al., “Multimodal residual learning for visual qa,” 2016.
48. N. P. T. Pavlovic and A. Cartaxo, “Adaptable qam transmitter to current elastic optical networks demand,” in *Telecommunications Forum - TELFOR*, 2018.
49. C. Xiong, S. Merity, and R. Socher, “Dynamic memory networks for visual and textual question answering,” in *Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48*, ser. ICML’16. JMLR.org, 2016, p. 2397–2406.
50. H. Noh and B. Han, “Training recurrent answering units with joint loss minimization for vqa,” 2016.
51. P. Sharma, N. Ding, S. Goodman, and R. Soricut, “Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning,” in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2018, pp. 2556–2565.
52. ———, “Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning,” in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Jul. 2018, pp. 2556–2565.
53. K. Tiippana, “What is the mcgurk effect?” *Frontiers in Psychology*, p. 725, 2014.
54. H. Tan and M. Bansal, “Lxmert: Learning cross-modality encoder representations from transformers,” 2019.
55. T. Baltrušaitis, C. Ahuja, and L.-P. Morency, “Multimodal machine learning: A survey and taxonomy,” *IEEE transactions on pattern analysis and machine intelligence*, pp. 423–443, 2018.
56. M. Seeland, M. Rzanny, N. Alaqraka, J. Wäldchen, and P. Mäder, “Plant species classification using flower images—a comparative study of local feature representations,” *PLoS ONE*, p. e0170629, 02 2017.
57. T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, “Microsoft coco: Common objects in context,” in European conference on computer vision. Springer, 2014, pp. 740–755.

58. R. Shrestha, K. Kafle, and C. Kanan, “Answer them all! toward universal visual question answering models,” in Proceedings of the IEEE conference on CVPR, 2019, pp. 10472–10481.

59. R. Dey and F. M. Salemt, “Gate-variants of gated recurrent unit (gru) neural networks,” in IEEE 60th international midwest symposium on circuits and systems (MWSCAS). IEEE, 2017, pp. 1597–1600.

60. R. Krishna, Y. Zhu et al., “Visual genome: Connecting language and vision using crowdsourced dense image annotations,” International journal of computer vision.

61. N. Srivastava and R. R. Salakhutdinov, “Multimodal learning with deep boltzmann machines,” in Advances in neural information processing systems, 2012, pp. 2222–2230.

62. J. Andreas, M. Rohrbach, T. Darrell, and D. Klein, “Neural module networks,” in Proceedings of the IEEE conference on CVPR, 2016, pp. 39–48.

63. S. Sukhbaatar, J. Weston, R. Fergus et al., “End-to-end memory networks,” in Advances in neural information processing systems, 2015, pp. 2440–2448.

64. S. Antol, A. Agrawal et al., “Vqa: Visual question answering,” in Proceedings of the IEEE international conference on computer vision, 2015, pp. 2425–2433.

65. P. N. Sabes and M. I. Jordan, “Advances in neural information processing systems,” in In G. Tesauro & D. Touretzky & T. Leed (Eds.), Advances in Neural Information Processing Systems. Citeseer, 1995.

66. D. B. Lee, S. Lee, W. T. Jeong, D. Kim, and S. J. Hwang, “Generating diverse and consistent qa pairs from contexts with information-maximizing hierarchical conditional vaes,” arXiv preprint arXiv:2005.13837, 2020.

67. J. Andreas, M. Rohrbach, T. Darrell, and D. Klein, “Learning to compose neural networks for question answering,” 2016.

68. P. Wang, Q. Wu, C. Shen, A. Dick, and A. van den Hengel, “Fvqa: Fact-based visual question answering,” IEEE transactions on pattern analysis and machine intelligence, pp. 2413–2427, 2018.

69. Y. Sun, S. Wang et al., “Ernie: Enhanced representation through knowledge integration,” 2019.

70. Z. Yu, J. Yu et al., “Deep modular co-attention networks for visual question answering,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2019, pp. 6281–6290.

71. D. Hoffman-Plotkin and C. T. Twentyman, “A multimodal assessment of behavioral and cognitive deficits in abused and neglected preschoolers.” Child development, vol. 55 3, pp. 794–802, 1984.

72. T. Lin, A. RoyChowdhury, and S. Maji, “Bilinear cnn models for fine-grained visual recognition,” in IEEE International Conference on Computer Vision (ICCV), 2015, pp. 1449–1457.

73. V. Ordonez, G. Kulkarni et al., “Im2text: Describing images using 1 million captioned photographs,” in Advances in Neural Information Processing Systems 24. Curran Associates, Inc., 2011, pp. 1143–1151.

74. S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, pp. 1735–1780, 1997.

75. M. Malinowski, M. Rohrbach, and M. Fritz, “Ask your neurons: A neural-based approach to answering questions about images,” IEEE International Conference on ICCV, Dec 2015.

76. Q. Wu, D. Teney et al., “Visual question answering: A survey of methods and datasets,” Computer Vision and Image Understanding, vol. 163, pp. 21–40, 2017.
77. D. Sriram and R. Adey, *Applications of artificial intelligence in engineering problems*. Springer Berlin Heidelberg, 1986.

78. K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” 2014.

79. X. Tang, X. Huang, W. Zhang, T. B. Child, Q. Hu, Z. Liu, and J. Zhang, “Cognitive visual commonsense reasoning using dynamic working memory,” in *International Conference on Big Data Analytics and Knowledge Discovery*. Springer, 2021.

80. S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, pp. 1735–1780, 1997.

81. P. Zhou, W. Shi *et al.*, “Attention-based bidirectional long short-term memory networks for relation classification,” in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Association for Computational Linguistics, Aug. 2016, pp. 207–212.

82. F. Klingler, F. Dressler *et al.*, “MCB - A Multi-Channel Beaconing Protocol,” *Elsevier Ad Hoc Networks*, pp. 258–269, 2016.

83. W. Zhang and E. Ntoutsi, “Faht: an adaptive fairness-aware decision tree classifier,” in *International Joint Conference on Artificial Intelligence (IJCAI)*, 2019, pp. 1480–1486.

84. W. Zhang, X. Tang, and J. Wang, “On fairness-aware learning for non-discriminative decision-making,” in *International Conference on Data Mining Workshops (ICDMW)*, 2019, pp. 1072–1079.

85. W. Zhang and A. Bifet, “Feat: A fairness-enhancing and concept-adapting decision tree classifier,” in *International Conference on Discovery Science*. Springer, 2020, pp. 175–189.

86. W. Zhang *et al.*, “Flexible and adaptive fairness-aware learning in non-stationary data streams,” in *IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*, 2020, pp. 399–406.

87. W. Zhang, “Learning fairness and graph deep generation in dynamic environments,” 2020.

88. W. Zhang, A. Bifet, X. Zhang, J. C. Weiss, and W. Nejdl, “Farf: A fair and adaptive random forests classifier,” in *Pacific-Asia Conference on Knowledge Discovery and Data Mining*. Springer, 2021, pp. 245–256.

89. W. Zhang and J. Weiss, “Fair decision-making under uncertainty,” in *2021 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2021.

90. W. Zhang and J. Weiss, “Rethinking fairness: New definitions and algorithm for fair machine learning under uncertainty,” *Knowledge and Information Systems*, 2022.

91. J. Wang, Z. Huang *et al.*, “Wearable sensor based human posture recognition,” in *IEEE International Conference on Big Data (Big Data)*, 2016.

92. W. Zhang and J. Wang, “A hybrid learning framework for imbalanced stream classification,” in *IEEE International Congress on Big Data (BigData Congress)*, 2017, pp. 480–487.

93. W. Zhang, “Phd forum: Recognizing human posture from time-changing wearable sensor data streams,” in *IEEE International Conference on Smart Computing (SMARTCOMP)*, 2017.

94. W. Zhang, J. Tang, and N. Wang, “Using the machine learning approach to predict patient survival from high-dimensional survival data,” in *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2016.

95. W. Zhang and J. Wang, “Content-bootstrapped collaborative filtering for medical article recommendations,” in *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2018.

96. X. Tang, L. Zhang *et al.*, “Using machine learning to automate mammogram images analysis,” in *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2020, pp. 757–764.
97. W. Zhang, J. Wang, D. Jin, L. Oreopoulos, and Z. Zhang, “A deterministic self-organizing map approach and its application on satellite data based cloud type classification,” in *IEEE International Conference on Big Data (Big Data)*, 2018.

98. W. Zhang, L. Zhang, D. Pfoser, and L. Zhao, “Disentangled dynamic graph deep generation,” in *Proceedings of the SIAM International Conference on Data Mining (SDM)*, 2021, pp. 738–746.

99. X. Huang et al., “Lstms based sentiment analysis for cryptocurrency prediction,” in *International Conference on Database Systems for Advanced Applications*, 2021.

100. Z. Liu, R. Wang, N. Japkowicz, D. Tang, W. Zhang, and J. Zhao, “Research on unsupervised feature learning for android malware detection based on restricted boltzmann machines,” *Future Generation Computer Systems*, vol. 120, pp. 91–108, 2021.