Text-Aware Dual Routing Network for Visual Question Answering

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Abstract

Visual question answering (VQA) is a challenging task to provide an accurate natural language answer given an image and a natural language question about the image. It involves multi-modal learning, i.e., computer vision (CV) and natural language processing (NLP), as well as flexible answer prediction for free-form and open-ended answers. Existing approaches often fail in cases that require reading and understanding text in images to answer questions. In practice, they cannot effectively handle the answer sequence derived from text tokens because the visual features are not text-oriented. To address the above issues, we propose a Text-Aware Dual Routing Network (TDR) which simultaneously handles the VQA cases with and without understanding text information in the input images. Specifically, we build a two-branch answer prediction network that contains a specific branch for each case and further develop a dual routing scheme to dynamically determine which branch should be chosen. In the branch that involves text understanding, we incorporate the Optical Character Recognition (OCR) features into the model to help understand the text in the images. Extensive experiments on the VQA v2.0 dataset demonstrate that our proposed TDR outperforms existing methods, especially on the "number" related VQA questions.

Introduction

Deep neural networks have been the workhorse of many real-world applications, including image classification (Guo et al. 2020b, 2019; Guo, Stutz, and Schiele 2022), language modeling (Dai and Callan 2019), and many other areas (Goodfellow et al. 2020; Guo et al. 2020a, 2022). Recently, Visual Question Answering (VQA) has become an important task that combines the knowledge of computer vision and natural language processing. It has a high research value as well as a broad range of application scenarios (e.g., graphic reading, aided navigation for the blind, and medical consultation). Typically, a VQA model takes an image and a free-form, open-ended question as input and generates a reasonable answer based on visual information and natural language rules. The VQA task is extremely challenging. It involves the representation learning of different modalities (i.e., visual and linguistic modality), cross-modal fusion, and diverse answer generations. In general, there are two great challenges to be solved for the VQA task.

First, it is non-trivial to explore the visual information from a given image. For example, many existing methods (Yu et al. 2017; Ma et al. 2018; Hong et al. 2019) use logit (i.e., feature from the highest layer of CNN) as their visual representation, which, however, is biased towards object detection tasks, and neglects the low-level semantics such as color, texture, and number of instances. To alleviate this issue, the most recent work namely VinVL (Zhang et al. 2021) obtains richer visual features by a powerful object detection model optimized with more data and annotations. Nevertheless, as VinVL considers object features only, it is hard to read and understand text in the given image, which is crucial and can not be ignored in many real-world scenes, e.g., signs and titles. In this sense, how to capture abundant visual features from images is one of the most important problems in the VQA task.

Second, how to formulate the answer prediction pattern in the VQA task still remains an open question. Specifically, to handle the answer prediction part, many recent works (e.g., (Zhang et al. 2021; Anderson et al. 2018; Li et al. 2020)) cast the answer prediction in VQA as a multi-label classification problem. However, with such an oversimplified problem setting, the models can only choose the answers from a predefined and fixed-length candidate set (e.g., with 3129 candidate answers), which is extremely small and can not cover all the answers in the real world. As a result, the limited number of answer candidates would further hamper the model performance as the model can only select the most likely answer in the candidate set regardless of whether this answer is true. Thus, a suitable pattern of the answer prediction is vital and necessary.

To overcome these challenges and improve performance on the VQA task, we propose a Text-Aware Dual Routing Network (TDR). We use rich object-level region features from VinVL (Zhang et al. 2021) to capture appearance information from images. Because appearance information alone cannot describe the semantic information of text in images, we introduce abundant Optical Character Recognition (OCR) features as compensation. To improve visual-linguistic alignment, we organize the object tags in Oscar (Li et al. 2020). The model can now observe images on a more
Our contributions are summarized as follows:

- We use abundant visual representations to provide a comprehensive view of images. We not only utilize richer object-level region features but also introduce OCR features as compensation on the semantic level.

- We propose a dual routing prediction module in which we elaborately tackle text-reading and general cases with a two-branch answer prediction network. Specifically, a gating network serves as a dynamic router to activate the final answer from these two branches for each instance.

- Extensive experiments on the VQA v2.0 dataset demonstrate the superiority of our proposed method. Compared with the SoTA (Zhang et al. 2021), our method achieves 4% higher accuracy on “number” answer-type instances.

Related Work

Text-Based Visual Question Answering

These years have seen prosperous development in the VQA task (Li et al. 2020; Lu et al. 2019; Tan and Bansal 2019; Hu and Singh 2021). Text-based VQA is a sub-task of VQA that involves reading and reasoning about the text in images. To address this issue, several methods have been proposed. LoRRA (Singh et al. 2019) attends to objects and text relevant to the question, and then chooses an answer from a fixed-length candidate set or OCR tokens with the highest attention weight. However, LoRRA predicts in a single step and cannot combine multiple tokens to form an answer sequence. To overcome this limitation, M4C (Hu et al. 2020) proposes a flexible pointer network to generate answers in multiple steps, with each step copied from an OCR token or a fixed vocabulary. After that, some M4C-based variants go a step further. LaAP-Net (Han, Huang, and Han 2020) uses text location as evidence to generate answers. Zhu et al. (Zhu et al. 2020) design separate attention branches for visual and linguistic parts of text features to fuse pairwise modalities. Different from them, we use abundant visual features from object level and semantic level for image understanding. We also develop a dual routing module for answer prediction and further improve the model performance.

Pointer Networks

For instances involving text-reading (e.g., signs and titles) in the VQA dataset, the answers mainly come from the input OCR tokens. Pointer Networks (Vinyals, Fortunato, and Jaitly 2015) generates outputs by directly copying from the input sequence, which is not limited by a fixed-length candidate set and thus addresses the out-of-vocabulary (OOV) problem. Pointer Networks has been validated on text sum-
marization (Nallapati et al. 2016), machine translation (Gu et al. 2016), image captioning (Lu et al. 2018) and other tasks. Recently, Pointer Networks and its variants are applying to text-based VQA tasks. LoRRA (Singh et al. 2019) adds dynamic OCR tokens to the candidate set for classification. M4C (Hu et al. 2020) incorporates the pointer network in iterative decoding, allowing each step to select an answer from the candidate set or copy a token from OCR tokens. Since the text-sensitive answers are rarely found in the candidate set, we devise a dynamic pointer network to reorganize OCR tokens into a correct answer sequence.

Dynamic Neural Networks

Dynamic neural networks incorporate multiple candidate modules, each of which is expert in handling different instances. A gating network is used to selectively activate these modules conditioned on the input instances (Han et al. 2021). Mixture of Experts (MoE) (Shazeer et al. 2017) takes this approach by dynamically routing instances to different experts and achieves computation allocation. Lioutas et al. (Lioutas, Passalis, and Tefas 2018) employ a diverse group of attention experts to provide more reliable attention information than a single attention model. N. Patro et al. (Patro et al. 2020) use a mix of experts to generate visual questions by combining multiple visual and language cues. Wang et al. (Wang et al. 2021) propose to encode different input modalities by modality-specific experts. Concerning the VQA task, we find that while OCR sequence answers generally require multiple steps to generate, other answer phrases can be selected from the candidate set in a single step, implying that these two cases can be solved separately. Thus, we propose a dual routing prediction module containing two experts (i.e., a classifier and a dynamic pointer network), and then use a gating network to activate a best-match answer generated by these two experts.

Method

Overall Framework

In this paper, we propose a Text-Aware Dual Routing Network (TDR) which simultaneously handles the VQA cases with and without understanding text information in the input images. Given an image and a related question, we first improve the visual representations for image understanding by utilizing richer object-level region features and elaborate OCR features. Then, we feed all of the input features into Transformer (Vaswani et al. 2017) for cross-modal interaction. To enhance the intelligence of our model, we propose a dual routing prediction module composed of a gating network and two experts, namely a classifier for selecting answers from the candidate set and a dynamic pointer network that generates answers from OCR tokens through an iterative decoding process. Finally, we employ a gating network to activate a best-match answer for each instance. The overall architecture of our proposed method is shown in Figure 2.

Visual Representation

Object Feature

Visual representations are essential for the advancement of VQA tasks. However, many methods rely on region features proposed in (Anderson et al. 2018) to identify salient regions from detected objects without further optimizing the visual features. Recently, VinVL (Zhang et al. 2021) has trained a new object detector on a large-scale corpus to extract richer visual features, which significantly improves SoTA results. Given an instance (i.e., an image and a related question), we use the object-level region features extracted by VinVL and project them into a series of object embeddings \( \{h_{obj}^{e}\} \in \mathbb{R}^{d} \), where \( e = 1, ..., E \). Furthermore, to enhance visual-linguistic alignment according to (Li et al. 2020), we append the detected object tags to the question words and embed them in d-dimensional word embeddings as \( \{h_{word}^{v} \in \mathbb{R}^{d} \}, \) where \( v = 1, ..., V \).

OCR Feature

OCR tokens extracted from images necessarily require special consideration, as they contain visual and semantic information critical to understanding the text in images and cannot be expressed solely through region features. Given an image with \( M \) OCR tokens derived from the Rosetta system (Borisyuk, Gordo, and Sivakumar 2018), we introduce the OCR feature for each OCR patch following the setting in (Hu et al. 2020). The OCR feature consists of two parts (i.e., semantic and spatial ones), which focus on the content and position of each OCR patch, respectively. Regarding the \( m \)-th OCR token (where \( m = 1, ..., M \)), to better capture the semantic information from the OCR patch, we further divide the semantic part \( x_{m}^{smt} \) into a FastText feature (Bojanowski et al. 2017), a Pyramidal Histogram of Characters (PHOC) feature (Almazán et al. 2014), and an appearance feature. Specifically, the FastText feature \( x_{m}^{ft} \in \mathbb{R}^{200} \) constructs word embedding using subword information, which endows the model with the ability to handle rare and unknown words. The PHOC feature \( x_{m}^{p} \in \mathbb{R}^{204} \) is a character-level representation while the appearance feature \( x_{m}^{fr} \in \mathbb{R}^{2048} \) is an object-level representation detected by Faster R-CNN (Ren et al. 2015), which primarily reflects the color, font, and background information of the OCR patch. Formally, to obtain the semantic part \( x_{m}^{smt} \), we compose these features by:

\[
x_{m}^{smt} = [x_{m}^{ft}; x_{m}^{p}; x_{m}^{fr}],
\]

where \( [\cdot; \cdot; \cdot] \) denotes concatenation operation. On the other hand, the spatial part \( x_{m}^{spt} \in \mathbb{R}^{4} \) refers to the absolute position of the OCR patch in the given image, which is denoted as bounding box coordinates. After that, we feed both the \( x_{m}^{smt} \) and \( x_{m}^{spt} \) features into an OCR embedding layer and obtain the d-dimensional integrated OCR embeddings \( \{h_{m}^{ocr}\} \in \mathbb{R}^{d} \) (where \( m = 1, ..., M \)) as follows:

\[
h_{m}^{ocr} = LN(W_{m}^{smt}x_{m}^{smt}) + LN(W_{m}^{spt}x_{m}^{spt}),
\]

where \( W_{m}^{smt} \) and \( W_{m}^{spt} \) are learnable weights while \( LN(\cdot) \) denotes layer normalization.

Cross-Modal Interaction

The multi-modal transformer layers are built with an encoder-decoder architecture, and the multi-head attention mechanism allows for inter-modal and intra-modal interaction. Entities in each input modality can attend to one
another while each decoding step can attend to all positions preceding the current step. We feed a sequence of
$d$-dimensional inputs into the transformer layers, namely word embeddings \( \{ h_{\text{word}} \} \), object embeddings \( \{ h_{\text{obj}} \} \), OCR embeddings \( \{ h_{\text{ocr}} \} \), and previous prediction embeddings \( \{ h_{\text{prev}} \} \) (where the decoding step \( t = 1, ..., T \)) to produce a set of \( d \)-dimensional enhanced representations. Specifically, \([CLS]\) is a special token added to the beginning of each input sequence, and \( z^{[CLS]} \) is used as the aggregated representation for classification tasks. In the case of sequence-to-sequence learning, the decoder generates a sequence of answers based on the auto-regressive scheme. At each time step, we feed some enhanced representations and a previous prediction embedding into a dynamic pointer network to predict the next step (explained in the next section).

### Dual Routing Prediction Module

The VQA dataset contains open-ended questions with flexible answers. In practice, there are two types of questions: general questions that can be answered with a common answer set and questions that must be answered using the text information in the image. To improve the intelligence of our model, we propose a two-branch answer prediction network.

Since the first case can be thought of as a multi-label classification problem, we use a classifier to select an entire answer (single-word or multi-word) in one step. In the second case, multi-step decoding is required to generate a sequence of answers. To this end, we propose a dynamic pointer network to copy an answer token from OCR tokens in each step. Finally, a gating network acts as a router to activate a best-match answer generated by these two experts for each instance.

**Two-Branch Answer Prediction Network**

**Classifier**  According to (Anderson et al. 2018), in general cases, we can cast the answer prediction in VQA as a multi-label classification problem and use a set of \( C \) frequent answers in the VQA v2.0 training set as the candidate set. Assume we have \( N \) instances in the training set, for the \( i \)-th (where \( i = 1, ..., N \)) instance, we perform a linear transformation on the aggregated representation \( z_i^{[CLS]} \) to calculate the predicted score \( \hat{s}_i \) for these candidate answers. To train the classifier, we compute the Binary Cross Entropy (BCE) loss \( \mathcal{L}_{cls} \) between the predicted and ground-truth scores of the instance taking this branch as follows:

\[
\mathcal{L}_{cls} = -\frac{1}{N} \sum_{i=1}^{N} g_i \sum_{c=1}^{C} [s_{i,c} \log(\hat{s}_{i,c}) + (1-s_{i,c}) \log(1-\hat{s}_{i,c})],
\]

where the ground-truth routing flag \( g_i = 1 \) indicates that the instance selects the answer generated by the classifier, otherwise \( g_i = 0 \). \( C \) is the fixed length of the candidate set, and \( s_{i,c} \) is the ground-truth answer score calculated by
The questions in the VQA task are open-ended, requiring the model to use a variety of abilities and knowledge to solve them. We divide the instances of the dataset into two categories based on whether they are answered with the text in images. The aforementioned dynamic pointer network handles cases where an answer sequence must be generated using detected OCR tokens in the image, while the classifier handles other common cases. To deal with this dynamic routing process, a gating network is proposed. The gating network is essentially a Multi-Layer Perceptron network (MLP) designed for binary classification. For the $i$-th (where $i = 1, ..., N$) instance, we take $z_i^{[CLS]}$ as input and compute the gating score $\hat{g}_i$ as follows:

$$\hat{g}_i = \sigma(W_2ReLU(W_1z_i^{[CLS]} + b_1) + b_2),$$

where $W_i$ and $b_i$ are learnable parameters, and $\sigma(\cdot)$ is the sigmoid function that projects the value into the range $[0, 1]$. During inference, we use the ceiling function to convert $\hat{g}_i$ to discrete values 0 and 1 as a routing indicator to activate a best-match answer from the above two branches, i.e., the classifier and the dynamic pointer network. The gating network is trained with the BCE loss $\mathcal{L}_{gate}$ as follows:

$$\mathcal{L}_{gate} = -\frac{1}{N}\sum_{i=1}^{N} [g_i\log(\hat{g}_i) + (1-g_i)\log(1-\hat{g}_i)],$$

where $N$ is the number of training set instances, and $g_i$ denotes the ground-truth answer for the $i$-th question.

**Overall Objective Function**

To eliminate the impact of imbalance distribution in the proposed two branches, we use the weighted version for $\mathcal{L}_{cls}$ in Eq. (3) and $\mathcal{L}_{ptr}$ in Eq. (5). Finally, the objective function is formatted as follows:

$$\mathcal{L} = \omega_{cls}\mathcal{L}_{cls} + \omega_{ptr}\mathcal{L}_{ptr} + \mathcal{L}_{gate},$$

where $\omega_{cls} = \frac{\sum_{i=1}^{N} g_i}{N}$, $\omega_{ptr} = \frac{\sum_{i=1}^{N} (1-g_i)}{N}$.

**Experiments**

The VQA v2.0 dataset (Goyal et al. 2017) includes 265016 images from COCO and abstract scenes, at least 3 open-ended questions per image, and 10 ground-truth answers per question. It is a well-balanced dataset that provides two similar images with distinct answers to the same question. These instances require a detailed visual understanding of images to extract crucial information for reasoning. As a comprehensive dataset, VQA v2.0 covers a wide range of question types, and about 43% of the images contain essential text information. Therefore, a VQA model should apply a variety of skills to complete the task intelligently.

**Evaluation Metric**

We use the evaluation metric proposed in (Antol et al. 2015) that is robust to inter-human variable answers as follows:

$$\text{Acc}(\text{ans}) = \min\left\{\frac{\#\text{humans that said ans}}{3}, 1\right\}.$$
Q1: What number is lit up on the bus?  
VinVL: 1  
TDR (ours): 407  
Human: 407

Q2: What number is on the right man’s shirt?  
VinVL: 7  
TDR (ours): 5  
Human: 5

Q3: What is the name of this street?  
VinVL: main  
TDR (ours): FLAMING LIPS ALLEY  
Human: FLAMING LIPS ALLEY

Q4: What is written on the flag?  
VinVL: nothing  
TDR (ours): MAXIGLIDE  
Human: MAXIGLIDE

As shown in Eq. (9), if at least three humans give the same answer, the answer is considered 100% accurate. Before evaluation, a series of regularization operations are performed, such as converting all answers to lowercase, using Arabic numerals uniformly, and removing punctuation marks and articles.

Implementation Details

Our models are implemented in PyTorch and optimized using the Adam optimizer. We fine-tune our BERT-base and BERT-large models with initial learning rates of 5e-05 and 1e-05, respectively. The maximum length of tokenized words is $V = 128$. We detect at most $E = 50$ objects and $M = 50$ OCR tokens per image. The maximum decoding step is $T = 12$. The dimensionality of the embedding space is set to $d = 768$. The candidate set has a size of $C = 3129$. The dropout rate is 0.3 and the weight decay is 0.05. We use 12 attention heads in transformer layers and leave the other hyper-parameters unchanged from BERT (Kenton and Toutanova 2019). Due to hardware limitations, we run the training procedure for 35 epochs with a batch size of 48.

Comparison with State-of-The-Art Methods

We compare TDR with previous state-of-the-art methods including UNITER (Chen et al. 2019), VILLA (Gan et al. 2020), ERNIE-VIL (Yu et al. 2021), Oscar (Li et al. 2020) and the strongest baseline VinVL (Zhang et al. 2021) on the VQA v2.0 testing set (i.e., “test-dev” and “test-std”). Table 1 gives an overall comparison of BERT-base size and BERT-large size models. TDR outperforms all the other methods and especially surpasses VinVL by around 0.8% under the same experimental setting. To further validate the effect on different answer-type instances, we compare TDR with VinVL in Table 2, we find that our final model (line 3) leads to over 4% improvement on “number” answer-type instances of VQA v2.0 dataset (line 1).

Effect of OCR Feature

To investigate the effect of the OCR feature, we conduct an ablation experiment with models of the BERT-base size in Table 2. Unlike VinVL, the restricted version of our TDR model (line 2) incorporates OCR features in the visual representation. In the answer prediction phase, both models use the classifier to predict an entire answer in one step. Comparing line 2 to 1, OCR features lead to an overall improvement, particularly in the “number” answer type known to be difficult for VQA models (Lu et al. 2019). We especially uplift the performance of text-reading instances (e.g., “What number is ... ?”, “What is ... ?”), demonstrating the validity of incorporating OCR features as supplement information.

Effect of Dual Routing Prediction Module

As shown in Table 2, we train our full TDR model with a dual routing prediction module (line 3), which gives another 2% improvement on “number” answer-type instances compared to its counterpart using a classifier for answer prediction (line 2). When compared to VinVL, our full TDR model achieves around 4% improvement (line 3 VS line 1) on this answer type.

The dual routing prediction module incorporates a two-branch answer prediction network (i.e., a classifier and a dy-
We can simultaneously handle the VQA cases with and without understanding text information in the input images. We not only improve the diversity and the accuracy of the generated answers but also inspire a new way of thinking about achieving human intelligence. Extensive experiments on the VQA v2.0 dataset demonstrate the superiority of our method over the considered baseline methods. We significantly improve the performance on the “number” related questions known to be difficult for existing VQA models. 

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**Table 2:** Performance on different answer-type instances of the VQA v2.0 dataset. (Test-dev is denoted by “Dev” and Test-std is denoted by “Std”.)

| Method | OCR Feature | Dual Routing | Yes/No | Number | Other | All |
|--------|-------------|--------------|--------|--------|-------|-----|
|         |             |              | Dev    | Std    | Dev   | Std |
| VinVL   | —           | —            | 90.62  | 90.73  | 56.28 | 55.63 |
| TDR     | ✓           | ✓            | 90.92  | 90.84  | 57.58 | 57.57 |

**Table 3:** Performance on different answer-source instances of the VQA v2.0 dataset.

| Answer Source | OCR Token | Candidate Set |
|---------------|-----------|---------------|
| VinVL         | 22.08     | 76.28         |
| TDR (ours)    | 58.23     | 75.69         |

**Qualitative Analysis**

The major failure cases of existing methods in the VQA v2.0 dataset involve text reading and answering. As shown in Figure 3, the SoTA VinVL degrades when accounting questions such as “What number is ... ?” and “What is ... ?”. Under these difficult conditions, our TDR model can still correctly identify and reorganize OCR tokens in the image to generate a complete answer sequence, proving the advancement of our proposed method.

**Conclusion**

In this paper, we propose a Text-Aware Dual Routing Network (TDR) for the VQA task. We enrich the visual representations with abundant region features and OCR features to provide a comprehensive visual-linguistic view of the input image. Thus, the model can utilize text information as supplementary knowledge for reasoning. Furthermore, we propose a dual routing prediction module incorporating a two-branch answer prediction network and a gating network to improve the flexibility of answer prediction. In this way,
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