Structured Attentions for Visual Question Answering

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Abstract

Visual attention, which assigns weights to image regions according to their relevance to a question, is considered as an indispensable part by most Visual Question Answering models. Although the questions may involve complex relations among multiple regions, few attention models can effectively encode such cross-region relations. In this paper, we demonstrate the importance of encoding such relations by showing the limited effective receptive field of ResNet on two datasets, and propose to model the visual attention as a multivariate distribution over a grid-structured Conditional Random Field on image regions. We demonstrate how to convert the iterative inference algorithms, Mean Field and Loopy Belief Propagation, as recurrent layers of an end-to-end neural network. We empirically evaluated our model on 3 datasets, in which it surpasses the best baseline model of the newly released CLEVR dataset [13] by 9.5%, and the best published model on the VQA dataset [3] by 1.25%. Source code is available at https://github.com/zhuchen03/vqa-sva.

1. Introduction

Visual Question Answering (VQA) is a comprehensive task inspecting intelligent systems’ ability to recognize images and natural languages together. Advances in this area not only benefit real-world applications which require the synergistic reasoning of vision and language, such as querying events in surveillance videos [34] and searching specific goods in images [41], but also call for finer-grained understanding on the semantic structures of images.

Adoption of the visual attention mechanism like [38, 40, 24, 27] is a major source to boost performance of VQA. Visual attentions impose regularization on the models to find the most relevant image regions to the question. Still, experiments [6] point out that state-of-the-art models often fail to identify the related regions like humans do. We argue this problem comes from the fact that such attention models do not take into account the spatial relations between regions when predicting the attention. This is important because the effective receptive field (ERF) of deep CNNs only covers a small fraction of the image [25]. Even with memory mechanism [37, 27, 40, 38], it is difficult to infer the right attention corresponding to questions that involve the spatial relations between regions without overlapping ERFs.

In this paper, we propose a novel neural network to model the attention with a multivariate distribution which considers the arrangements of image regions. We adopt the most straightforward graph structure to model image region arrangements - a grid-structured Conditional Random Field (CRF) [29]. The framework of the proposed method is illustrated in Fig. 2. We show that attention can be formulated as the marginal distribution of each hidden variable in the CRF. Then, we implement the iterative approximate inference algorithms, Mean Field and Loopy Belief Propagation, as recurrent layers of neural networks, which iteratively refines the attention. An example of this process is shown in Fig. 1. We evaluate the proposed model on three repre-
sentative datasets, where our model is competitive with the
rule-based model [2] on the SHAPES dataset, and surpasses
the best baseline model of CLEVR by more than 9.5% and
best published method [17] on the VQA dataset by 1.25%.
We also demonstrate that the ERF on CLEVR and the VQA
dataset is not large enough for previous methods to answer
all questions involving object arrangements correctly.

Our work has the following contributions. First, we pro-
pose to model structured attentions with a CRF over image
regions for Visual Question Answering, to address the prob-
lem of limited effective receptive fields of CNNs. Second,
we demonstrate how to unfold both Mean Field and Loopy
Belief Propagation algorithms for CRF as recurrent layers
of neural networks, and perform comprehensive evaluation
of the two different networks on three challenging datasets.
Third, we give empirical evaluations of ERFs on CLEVR
and the MSCOCO dataset.

2. Related Work

There have been many different directions for improving
VQA performance, including predicting answer types
[14], utilizing task-specific submodules [1, 2], and better
multimodal feature pooling methods [8, 17]. Our focus is
on structure-aware spatial attention applied on the visual
feature. There are two major forms of spatial attention for
VQA. One [31, 22, 11] is based on region proposals gener-
ated by Edge Box [43], and the other [38, 40, 24, 27, 8, 17]
predicts attention on the individual feature vectors of convo-
lutional feature maps. The most representative model SAN
[40] adopted multiple attention layers to support multi-step
reasoning. There are also methods [24, 27] that adopted
both image attention and question attention to refine the
image and question representation simultaneously. [38]
proved its ability to recognize absolute and relative posi-
tions with two simple experiments, but the model itself does
not consider the arrangement of regions and the success
may be attributed to the power of CNNs.

Some of the methods considered the structures of im-
ages. [26] adopted the Bayesian framework based on the
logic forms of segmentation results. The method was sur-
passed by some simple baseline models due to its demand
for better semantic segmentation [15]. The DMN [37]
adopted a bidirectional GRU that traverses the convolu-
tional feature map in a snake-like fashion to encode the de-
pendency of regions, which might not be the optimal choice
for the 2D structure of images. [22] concatenated the 8D
bounding box representation with the 4096D visual fea-
ture, in which the spatial information could be easily over-
weighed by the visual feature.

There have been a number of approaches combining neu-
ral networks and CRF to predict structured outputs in both
computer vision and natural language processing. [30] uti-
lized neural networks with sigmoid activation to predict the
unary potential for sequential labeling. [7] also used neu-
nal networks to predict the pairwise potential of labels. [4]
learned fixed pairwise potentials for word recognition and
image classification. [12] utilized CNNs to predict both
the unary potentials and higher-order potentials for uncon-
strained word recognition. [42] proposed to unfold the
Mean Field algorithm as recurrent layers for semantic seg-
mentation. It modeled the pairwise potential with Gaussian
kernels, which encourages similar features to take the same
label. Besides the supervised structure in the output layers,
[18] enforced the intermediate layers of neural networks to
learn structured attentions for natural language tasks.

To the best of our knowledge, structured attention has
not been explored for the complex task of VQA. We give
the first empirical evaluations on unfolding both Mean Field
and Loopy Belief Propagation as intermediate recurrent lay-
ers on the task of VQA, which can be seen as a further ex-
ploration of [18] in modeling 2D structures of visual data.

3. Attention Models and Methods

The general architecture of the proposed model is shown
in Fig. 2. Here we define some notations used across the
paper. We take the question feature \( q \in \mathbb{R}^{n_Q} \) from the last
time step of a GRU such as [20], and the image feature map
\( X = [x_1, ..., x_M] \in \mathbb{R}^{n_I \times M} \) from one of the convolution
layers of a CNN such as [10]. Here \( n_Q, n_I \) are the di-
mensions of question and image feature vectors respectively,
and \( M \) is the total number of image feature vectors which
divides the image into \( M \) regions. We use \( \text{softmax}(\cdot) \) to de-
ote the softmax activation function and \( \sigma(\cdot) \) to denote the
sigmoid activation function. The attention mechanism in
VQA aims to produce a context \( c \) from \( X \) which represents
the visual feature related to the question.

3.1. Unstructured Categorical Attention

In previous methods for VQA, visual attention is usually
modeled as a single or multi-step soft-selection from \( X \). As
shown in [39, 18], the soft-selection approach represents the
selected region index by a categorical latent variable \( z \in
\{1, ..., M\} \) and defines \( c \) as an expectation of the selection:

\[
c = \mathbb{E} \left[ \sum_i \mathbb{1}_{\{z=i\}} \cdot x_i \right] = \sum_i \mu(z = i|X, q)x_i, \tag{1}
\]

where \( \mathbb{1}_{\{z=i\}} \) is an indicator function, and the distribution
of \( z \) is parameterized by

\[
p(z = i|X, q) = \text{softmax}(U g(x_i, q)), \tag{2}
\]

where \( U \in \mathbb{R}^{1 \times n_I} \) and \( g(\cdot) \) is some multimodal feature
pooling function such as [8, 17]. Noticing this model ig-
nores the spatial arrangement of the feature vectors in \( X \) in
each step, and the resulting hidden states in multi-step models [39, 38] are still unstructured, we have dropped the hidden states in the condition presented in [38] for notational convenience.

Since categorical distribution only requires the probabilities to be positive and sum to 1, the following normalized sigmoid attention is still a valid categorical attention:

$$p(z = i | X, q) = \frac{\sigma(Ug(x_i, q))}{\sum_j \sigma(Ug(x_j, q))},$$  \hspace{1cm} (3)

We can use such attention as a glimpse\(^1\) of our model, which will be introduced in Section 3.4.

### 3.2. Structured Multivariate Attention

To consider the arrangement of \(X\), we adopt a structured multivariate attention model similar to [18], in which we consider the distribution \(z \sim p(z|X, q)\) as a vector of binary latent variables \(z = [z_1, \ldots, z_M]^T\) with \(z_i = 1\) if \(x_i\) is related to the question and \(z_i = 0\) otherwise. Multiple regions can now be selected at the same time. We define the context as the expectation of the sum over all related regions, which can be derived as a sum of \(x_i\) weighted by the marginal probability \(p(z_i = 1 | X, q)\):

$$\mathbb{E}_{z \sim p(z|X, q)}[Xz] = \sum_i p(z_i = 1 | X, q)x_i.$$  \hspace{1cm} (4)

Let \(S = \sum_i p(z_i = 1 | X, q)\). Since \(0 \leq S \leq M\) and \(M\) is relatively large, to reduce covariate shift, we normalize the expectation to get the context \(c\):

$$c = \frac{1}{S} \sum_i p(z_i = 1 | X, q)x_i,$$  \hspace{1cm} (5)

We model the distribution \(p(z|X, q)\) in the most straightforward form, a grid-structured Conditional Random Field, which represents the joint probability \(p(z|X, q)\) with a grid-structured factor graph that considers the pairwise joint distribution of a region's 4-neighbourhood, as shown in Fig. 2. Let \(\mathcal{N} = \{(i, j) | i < j, j \in N_i\}\), where \(N_i\) is the set of \(i\)'s neighbors on the graph. The grid-structured CRF assumes

$$p(z|X, q) = \frac{1}{Z} \prod_{(i, j) \in \mathcal{N}} \psi_{ij}(z_i, z_j) \prod_i \psi_{i}(z_i),$$  \hspace{1cm} (6)

where the unary potential \(\psi_{i}(z_i) \geq 0\) measures the likelihood of region \(i\) taking the value \(z_i \in \{0, 1\}\), and the pairwise potential \(\psi_{ij}(z_i, z_j) \geq 0\) measures the likelihood of regions \((i, j)\) taking values \(z_i, z_j\) respectively.

### 3.3. Recurrent Inference Layers

The inference problem in such a grid-structured factor graph, which aims to calculate the marginal probability \(p(z_i|X, q; \theta)\), is known to be NP-hard [32]. Still, there are approximate inference algorithms to solve the problem, such as Mean Field (MF) and Loopy Belief Propagation (LBP). These algorithms take potential functions \(\psi_{i}(z_i)\) and \(\psi_{ij}(z_i, z_j)\) as inputs and update \(p(z_i|X, q; \theta)\) iteratively through message passing. We train neural networks to predict optimal \(\psi_{i}(z_i)\) and \(\psi_{ij}(z_i, z_j)\) and then run the algorithms for a fixed number of \(T\) steps. The iterative algorithms are implemented as recurrent inference layers in the neural network.

#### 3.3.1 Potential Functions

In VQA, the potential functions should depend on both the image and the question. We use low-rank bilinear pooling [17], a parsimonious bilinear model, to capturing the interaction between 2 feature vectors \(x, y\):

$$g(x, y; P_x, P_y) = \tanh(P_x x) \odot \tanh(P_y y),$$  \hspace{1cm} (7)
where \( P_x, P_y \) are learnt projection matrices projecting \( x, y \) to the same dimension, and \( \odot \) represents Hadamard product. Based on this, we model \( \psi_i(z_i) \) and \( \psi_{ij}(z_i, z_j) \) as following:

\[
\psi_i(z_i) = 1 - \psi_i(z_i^0), \quad \psi_i(z_i^0) = 1, \quad \psi_{ij}(z_i, z_j) = h(v_{z_i z_j} g(y_{ij}, q; V_y, V_q)),
\]

where \( U_x \in \mathbb{R}^{n_x \times n_i}, U_q \in \mathbb{R}^{n_q \times n_i}, U \in \mathbb{R}^{1 \times n_i}, V_y \in \mathbb{R}^{n_y \times 2n_i}, V_q \in \mathbb{R}^{n_q \times n_y} \) are learnt projection matrices, \( v_{z_i z_j} \) is a row vector of \( V \in \mathbb{R}^{4 \times n_c} \) indexed by \( z_i \) and \( z_j \), \( y_{ij} = [x_{ij}^T, x_{ij}^T]^T \), \( n_c \) is the common projection dimension, \( h(\cdot) \) is a certain activation function which will differ in the inference algorithms.

### 3.3.2 Mean Field Layers

The Mean Field algorithm approximates the distribution \( p(z|X, q) \) in Eq. 6 with a fully factorized distribution \( q(z) \):

\[
q(z) = \prod_i b_i(z_i),
\]

where \( b_i(z_i) \) are variational parameters corresponding to the marginal probabilities \( p(z_i|X, q) \). The variational parameters are optimized by iteratively minimizing the mean-field free energy

\[
F_{MF}(b_i) = - \sum_{(z_i) \in N} \sum_{z_j} b_i(z_i) b_j(z_j) \ln \psi_{ij}(z_i, z_j)
+ \sum_i \sum_{z_i} b_i(z_i) \ln b_i(z_i) - \ln \psi_i(z_i)
\]

subject to the constraint \( \sum_{z_i} b_i(z_i) = 1 \), which is shown to be equivalent to minimizing the KL divergence between \( p(z|X, q) \) and \( q(z) \) [35]. Specifically, MF initializes \( b_i^{(0)}(z_i) = \psi_i(z_i) \) and updates \( b_i^{(t)}(z_i) \) as:

\[
b_i^{(t)}(z_i) = \alpha \psi_i(z_i) \exp \left( \sum_j N_{z_j} b_j^{(t-1)}(z_j) \ln \psi_{ij}(z_i, z_j) \right),
\]

where \( \alpha \) is the normalizing constant. Since Eq. 12 only involves \( \ln \psi_{ij}(z_i, z_j) \), we adopt a log model for pairwise potential,

\[
\ln \psi_{ij}(z_i, z_j) = \tanh(v_{z_i z_j} g(y_{ij}, q; V_y, V_q)).
\]

MF can be unfolded as a recurrent layer of neural networks without parameters, where in each step \( t \) the inputs are \( \psi_i(z_i), \psi_{ij}(z_i, z_j) \) and \( b_i^{(t-1)}(z_i) \), as demonstrated by Algorithm 1.

### 3.3.3 Loopy Belief Propagation Layers

Loopy Belief Propagation can be applied similarly by initializing all messages to a fixed value and updating the messages iteratively in a fixed or random order [29]. In our grid-structured graph, since each factor is connected to only 2 variables, the variable-to-factor and factor-to-variable messages can be merged as a single message \( m_{i j} \), representing the message from \( z_i \) to \( z_j \). We initialize \( m_{i j}^{(0)}(z_j) = 0.5 \), and iteratively update the messages based on the formula

\[
m_{i j}^{(t)}(z_j) = \alpha \sum_{z_i} \psi_{ij}(z_i, z_j) \psi_i(z_i) \prod_{k \in N_i \setminus \{j\}} m_{k i}^{(t-1)}(z_i),
\]

where \( \alpha \) is the normalizing constant as above. After a fixed number of steps \( T \), the variable \( z_i \) gathers all the messages from its neighbourhood to get the marginal probability:

\[
b_i(z_i) = \beta \psi_i(z_i) \prod_{k \in N_i} m_{k i}^{(T)}(z_i),
\]

where \( \beta \) is the normalizing constant.

Similar to MF, LBP can also be unfolded into parameterless recurrent layer, where at each time step \( t \) the input is \( \psi_i(z_i), \psi_{ij}(z_i, z_j) \) and \( m_{i j}^{(t-1)}(z_j) \), and after \( T \) steps
$m^{(T)}(z_i)$ is used to compute marginal probability $b_i(z_i)$, as shown in Algorithm 2.

3.4. The overall structure

As shown in Fig. 2, the overall structure of the proposed model is an end-to-end classification neural network. Firstly, $\psi_{ij}(z_i)$ and $\psi_{ij}(z_i, z_j)$ are computed using the extracted features $X$ and $q$. Then, the recurrent inference layers run for $T$ steps to get the structured marginal probability $p(z_i = 1|X, q) = b_i^{(T)}(z_i = 1)$, which is then used to compute the structured context $c$ with Eq. 5. We also compute a unstructured context $\hat{c}$ with Eq. 1 by replacing $Ug(x_i, q)$ in Eq. 3 with $\psi_i(z_i = 1)$. In the classifier, the contexts are both pooled with the question to get

$$\hat{s} = g(\hat{c}, q; W_c, W_q),$$

$$\hat{s} = g(\hat{c}, q; W_c, W_q),$$

where $W_c, W_q \in \mathbb{R}^{n_c \times n_l}, W_q, W_q \in \mathbb{R}^{n_c \times n_q}$. The answer is predicted with

$$a = \arg\max_{k \in \Omega_K} \text{softmax}(w_k [\hat{s}^T, \hat{s}^T]^T),$$

where $w_k$ is the $k$-th row of $W \in \mathbb{R}^{K \times 2n_c}$, $K$ is the number of answers, $\Omega_K$ is the answer space with up to $K$ answers.

4. Experiments

4.1. Datasets

The SHAPES dataset [2] is a synthetic dataset consisting of images containing 3 basic shapes in 3 different colors with a resolution of $30 \times 30$, and queries about the arrangements of the basic shapes, as shown in Fig. 3. The answer is “yes” when the image satisfies the query, and “no” otherwise. There are 3 different lengths of queries. The original dataset [1] has 14592 and 1024 image/question pairs for the training and test sets. All the queries in the test set do not consist of the basic shapes, as shown in Fig. 3. The answer consists of 320 shapes, sizes, materials, colors and positions with a resolution of $30 \times 448$. The VQA real-image dataset [3] is a comprehensive unbiased synthetic dataset aiming at testing visual abilities such as counting, comparing and logical reasoning. It consists of 100,000 images of simple 3D objects with random sizes, materials, colors and positions with a resolution of $320 \times 480$, and nearly a million natural language questions, 853,554 of which are unique. The questions can be categorized into 5 general types: exist, count, compare integer, query attribute, and compare attribute. There are 699,989 training questions, 149,991 validation questions and 149,988 test questions. The vocabulary sizes for the questions and answers are 82 and 28 respectively.

The VQA real-image dataset [3] is a comprehensive dataset which requires knowledge beyond the dataset to answer all the questions correctly. It has about 204,721 images from MSCOCO [23] each with 3 natural language questions, and each question has 10 answers collected from online workers. It consists of 3 splits: train, val and test, each of which has 248,349, 121,512 and 244,302 questions respectively. test-dev is a subset of test, which has 60,864 questions. We keep a collection of 2,000 most frequent answers from the union of train and val, and ignore questions with no answers from this collection, which leaves us 334,554 samples for training. With the same pre-processing procedure as [8, 17], we also get 837,298 training samples from Visual Genome [21] for augmentation.

4.2. Model Configuration and Training

For extracting image features, we use a 2-layer LeNet trained with the whole network on SHAPES as in [1], and ImageNet-pretrained ResNets [10] on CLEVR and the VQA dataset. For sentence embedding, we use single-layer trained with the whole network on SHAPES as in [1], and the res5c layer of ResNet-152 ($n_1 = 2048$, $M = 49$) in different experiments. We also set $n_Q = 2048$, comparable to the 2-layer LSTM with 1024 units per layer used in [13]. On the VQA dataset, we fix $n_c = 1200$. Images are resized to $448 \times 448$ and we use the feature at the res5c layer of ResNet-152 ($n_1 = 2048$, $M = 196$), the same as [24, 8, 17]. We set $n_Q = 2400$ since we use the pre-trained skip-thought vector [20] provided by [17] as initialization.

For training, we implement our network with MXNet [5]. In all 3 tasks, we use the Adam optimizer [19] with the default setting except for the learning rate, which is picked using grid search. We adopt Bayesian dropout [9] for GRU’s as in [17], and apply dropout [33] before every other fully connected layer. On SHAPES and CLEVR, we find setting both dropout probability to 0.2 to be optimal, while on the VQA dataset, setting a small Bayesian dropout 0.25 for the GRU and a large dropout of 0.5 for the other parts achieved the optimal results. In addition, we use answer sampling by default on the VQA dataset as in [8, 17].

4.3. Visualization of ERF

To visualize the ERF, we need to compute the influence of a pixel $I_{ij} \in \mathbb{R}^3$ on the entry $y_{rc}^n$, the feature at $(r, c)$ of the $n$-th channel in a certain conv layer, represented by $\|\partial y_{rc}^n / \partial I_{ij}\|$. As in [25], we assume a loss function $l_{rc}^n$ which is related only to channel $y_{rc}^n$, i.e., $\partial l_{rc}^n / \partial y_{rc}^n = 1$ and $\partial l_{rc}^n / \partial y_{ij}^n = 0$ for $i \neq r$ or $c \neq j$, so that $\partial y_{rc}^n / \partial I_{ij} = \partial l_{rc}^n / \partial I_{ij}$, since $\partial l_{rc}^n / \partial I_{ij}$ can be computed efficiently by DL frameworks. Finally, we draw the heat map of the total effect of a subset $\Omega_C$ of channels:

$$E_{ij} = \sum_{n \in \Omega_C} \left( \frac{\partial l_{rc}^n}{\partial I_{ij}} \right)^2.$$  (19)
4.4. Results and Analysis

We perform experiments on the 3 datasets, in which we fix the general structure except for the visual attention models, to quantify the role of structured attention in our model and the best configuration for it. We will use the following abbreviations to distinguish the models we implemented:

- **SM/SIG**: 1-glimpse softmax or sigmoid attention.
- **MF/LBP**: 1-glimpse multivariate attention with a MF or LBP recurrent layer and a default $T = 3$.
- **MODEL-G2**: $2$-glimpses with a default $T = 3$, where $MODEL=SIG,MF$ or LBP is the attention model.
- **MF-SIG/LBP-SIG**: $2$-glimpse model by concatenating a MF or LBP attention with a SIG attention, as mentioned in Section 3.4.
- **MODEL-$Tn$**: $MODEL$ with $T = n$ inference steps.

### 4.4.1 On SHAPES

In this part, we will look into the influence of the volume of the data on our model’s generalization, and compare the performance of SIG-G2, MF-G2 and LBP-G2 models. We find it is difficult for all 3 models to generalize with the same amount of data as [1]. This may because [1] uses a parser to understand the queries with guaranteed correctness on this dataset, while we have to train the GRU to understand the queries from scratch. The parser-based method may not perform well in more general tasks such as the VQA dataset, since they found using fewer modules on the VQA dataset turned out to be better, but our RNN-based approach should generalize better with enough training data. So we generate more data with the same answer distributions for each query as [1] to train and test our model, and re-trained their model using the released code. We name the original dataset small, and the newly generated datasets with 2 and 3 times as much data in both training and test sets as medium and large respectively. We find with more training data, our model becomes competitive with [1] and the MF-G2 model surpasses it on both medium and large, as shown in Table 1. Our models are extremely good at handling length-$4$ queries, which looks for object arrangements in 4-neighborhood, as demonstrated in Fig. 3. The high accuracy also implies the model is capable of set theory reasoning, since it achieved high test accuracy with length-$3$ queries which contain self-conflict queries such as is red green, which aims to find an object that is both red and green. For complex queries, such as is red below below green, which aims to find a red object below another object that is below a green object, it is not as competitive as [1], probably because the GRU in our model has not generalized to higher order logic.

### 4.4.2 On CLEVR

In this part, we study the role of different visual features and different kinds of attentions on the performance, and test our best models on the test set, as shown in Table 2. Our best model surpasses the best baseline model in [13] by more than 9.5% on the test set. Both MF and LBP outperform SM and SIG, demonstrating the effectiveness of our method. The maximum margin of MF/LBP vs. SIG on overall accuracy is 2.62% and 1.33% with the ResNet-152 and ResNet-101 features respectively. The most significant improvement of MF/LBP over other models is on Compare Attribute, which involves comparing specific attributes of objects specified by spatial relations with other objects. This also proves that our model alleviates the problem of previous methods of ignoring arrangements of regions. Further, we show the receptive fields of the 2 selected layers on the test set in Fig. 4. In each image, we choose the feature vector closest to the center, where there is a higher chance for objects to appear. Still, both of them only occupy a small portion of the image, indicating the importance of considering the structure of regions. Overall, the performance with res4b22 features is better than that with res5c features. From the ERF point of view, the ERF of res5c has more...
Figure 4: The average ERF [25] of 32 channels chosen at regular intervals, on 15,000 images from the CLEVR test set and 52,500 images from the MSCOCO test set with resolution of 224 × 224 and 448 × 448 respectively. The ERF images are smoothed with σ = 4 Gaussian kernels.

Table 2: Accuracy on CLEVR. CI, QA, CA stand for Count Integer, Query Attribute and Compare Attribute respectively. The top half uses ResNet-152 features and the bottom half uses ResNet-101 features. Our best model uses the same visual feature as [13].

Table 3: Results of the Open Ended task on test-dev.

Table 4: Results of the Open Ended and Multiple Choice tasks on test. We compare the accuracy of single models (without augmentation) and ensemble models with published methods.

4.4.3 On the VQA dataset

Since we have found MF-SIG and LBP-SIG are the best on CLEVR, in this part, we mainly compare the two models with different $T$. Notice now the total number of glimpses is the same as MCB [8] and MLB [17], and both of them use res5c features and better feature pooling methods. The optimal choice in these experiments is MF-SIG-T3, which is 0.92% higher in overall accuracy than the previous best method [17], and outperforms previous methods on all 3 general categories of questions. We then use external data from Visual Genome to train MF-SIG-T3 and MF-T3, in which MF-SIG surpassed MLB under the same condition by 1.35%. The accuracy boost of our model is higher than MCB and MLB, showing that our model has higher capacity. The LBP models, which performs better than MF layers [17] and [8], is the optimal choice for LBP. We also find the single MF at-

tention model, which should not be as powerful as MF-SIG, be caused by the bias of the current VQA dataset [3], where there are questions with fixed answers across all involved images. We also show the results on test-dev2017 of VQA2.0, as shown in Table 4. Our model is the best among published methods with- out external data. With an ensemble of 3 MF-T3 and 4 MF-SIG-T3 models, we achieve 68.18% accuracy on test, 1.25% higher than best published ensemble model on the
Q: What is the size of the object that is both right of the cyan sphere and left of the tiny red metallic object?
MF: small. LBP: small. SIG: large.

Q: the tiny gray object that is made of the same material as the gray cube is what shape?
MF: sphere. LBP: sphere. SIG: cube.

Figure 5: Two instances of different attentions on CLEVR, where the SIG model gives wrong answers but MF-SIG and LBP-SIG both give the correct answer. For each instance, from left to right, the first row to the second row, the images are: input image, $b^{(0)}$ of MF-SIG, $b^{(3)}$ of MF-SIG, $\psi(z_i)$ of LBP-SIG, $b$ of LBP-SIG, attention of SIG. Notations are the same as in Fig. 3. Best viewed in color.

Open Ended task. By the date of submission, we rank the second on the leaderboard of Open Ended task and the first on that of the Multiple Choice task. The champion on Open Ended has an accuracy of 69.94% but the method is not published. We have also recorded our model’s performance on the test-dev2017 and test2017 of VQA2.0 in Table 3 and 4. Accuracy on test2017 is achieved with 8 snapshots from 4 models with different learning rates.

4.4.4 Qualitative Results
We demonstrate some attention maps on CLEVR and the VQA dataset to analyze the behavior of the proposed models. Fig. 5 shows 2 instances where the SIG model failed but both MF and LBP succeeded. We find the MF-SIG model has learned interesting patterns where its attention often covers the background surrounding the target initially, but converges to the target after iterative inference. This phenomenon almost never happens with the LBP-SIG model, which usually has better initializations that contained the target region. The shortcoming of the unstructured SIG model is also exposed in the 2 instances, where it tends to get stuck with the key nouns of the question. Fig. 6 demonstrates 3 instances of the MF-SIG model together with the effective receptive field. The model gives 2 correct answers for the first 2 instances and 1 wrong answer for the last instance. In the first instance, the ERF at the target should be enough to encode the relations. The initial attention involves some extra areas due to the key word “luggage”, but it manages to converge to the most relevant region. In the second instance, the initial attention is wrong, as we can see the ERF at the initial attention does not overlap with the target, but with the help of MF, the final attention captures the relation “in the front” and gives an acceptable answer. In the third instance, the ERF at the target region is very weak on the keyword “bulb”, which means the feature vector does not encode this concept, probably due to the size of the bulb. The model fails to attend to the right region and gives a popular answer “2” (3rd most popular answer on the VQA dataset) according to the type of the question.

5. Conclusion
In this paper, we propose a novel structured visual attention mechanism for VQA, which models attention with binary latent variables and a grid-structured CRF over these variables. Inference in the CRF is implemented as recurrent layers in neural networks. Experimental results demonstrate that the proposed method is capable of capturing the semantic structure of the image in accordance with the question, which alleviates the problem of unstructured attention that captures only the key nouns in the questions. As a result, our method achieves state-of-the-art accuracy on three challenging datasets. Although structured visual attention does not solve all problems in VQA, we argue that it should be an indispensable module for VQA in the future.
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