Dual Energy-Flow Enhanced Graph Neural Network for Visual Question Answering

Abstract

Scene Graphs (SG), as a structural abstraction of natural images, contain massive detailed information. Modeling visual reasoning through SG can significantly improve the ability and strengthen the interpretability of reasoning. However, neither can existing models *jointly* exploit objects, relations, and attributes information in SG, nor can they balance the importance of objects and relations. In this paper, we introduce a novel Dual Energy-Flow Enhanced Graph Neural Network (DE-GNN), which learns a comprehensive representation by encoding full-scale scene graphs information from objects, attributes, and relations. Specifically, two types of SG structures are employed in the encoder: (i) *Object-significant graphs* which absorb attribute and relation information into nodes' representations. (ii) *Relation-significant graphs* which intensify the model's perception of relation features. In addition, we design an *energy-flow mechanism* to enhance the information transfer from edges and adjacent nodes to the updating nodes. We conduct extensive experiments on public GQA and Visual Genome datasets and achieve new state-of-the art performances highlighting the benefits of our method.

Introduction

Recent developments in deep learning have accelerated the research progress in Computer Vision (CV) and Natural Language Processing (NLP) areas. Multimodal fusion tasks between image and text have attracted a growing attention, such as image captioning and visual question answering (VQA) tasks. In particular, the task of VQA requires a model to answer a free-form natural language question using visual information from an image. VQA has proven to be a crucial multimodal task with a large scope of applications such as AI assistants, multimodal customer service dialogue and image-based search to name a few.

Scene graph (SG) reasoning is an important branch of VQA tasks, see (Hildebrandt et al. 2020). To generate the scene graph, the model extracts objects' names, attributes and relationships from the images and constructs them into graph representation as illustrated in Fig. 1(a). SG representation modeling displays several virtues over classical techniques leveraging object features extracted from images since in SG (a) the features are presented in plain and free text form (Damodaran et al. 2021), (b) it makes use of graph structures which have better interpretability (Zhang, Chao, and Xuan 2019). In this contribution, many researchers propose two reasoning methods on scene graphs: (i) Consider scene graphs as probabilistic graphs and iteratively update nodes' probabilities using soft instructions extracted from questions such as Neural State Machine (NSM) (Hudson and Manning 2019b; Le et al. 2020); (ii) Apply Graph Neural Network (GNN) into scene graphs (Singh et al. 2019; Li et al. 2019) to learn a joint representation of the nodes and their relations, and then feed the representation into a predictor to generate the answer.

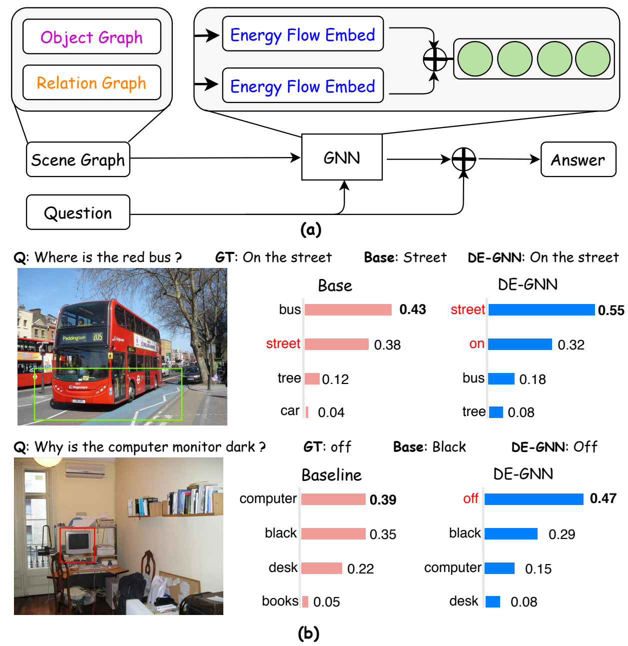

Figure 1: (a) Overview of our DE-GNN model. (b) Two key issues of the traditional SG-based model that we try to address: relation missing (top: missing "on the") and false attribute selection (bottom: select "black" instead of "off")

Scene graph reasoning frameworks have proven to be useful in VQA tasks, e.g. (Johnson et al. 2015; Hildebrandt et al. 2020; Yang et al. 2020). However, existing methods fail at generating comprehensive representations for objects by us-

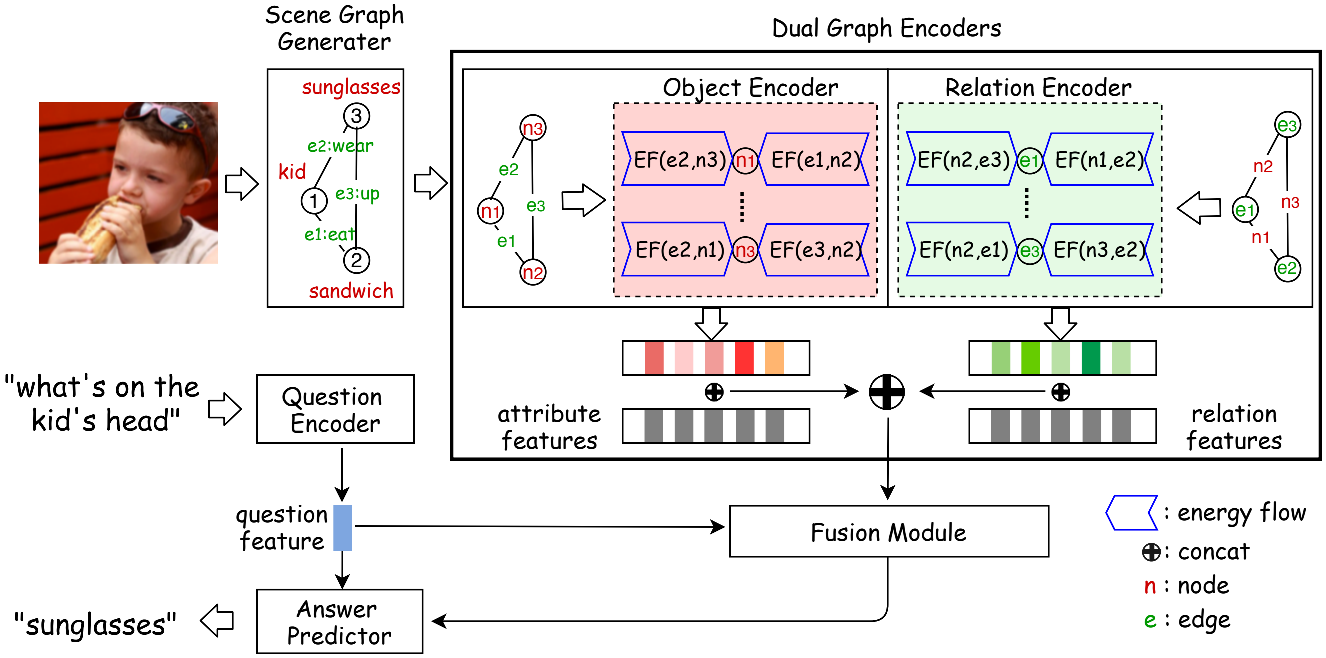

Figure 2: Model structure of the proposed Dual Energy-Flow enhanced Graph Neural Networks. EF stands for the energy-flow module. Images are transformed into scene graphs by the scene graph generator. The object-significant form and relation-significant form of the scene graph are injected into the object encoder and the relation encoder. Nodes' representations are generated from the sum of energy-flow modules. The representations are then be fused with question representation to predict an answer.

ing features from their neighbors and their attributes. Generally, information from objects and relations connected to them are reconstructed into object features in GNN-based methods (Xu et al. 2019). However, these encoding methods lack information from objects' attributes and objects on the other side of the edges. The NSM methods use attention mechanisms to update answer possibilities of objects, attributes, and relations, but they cannot learn the joint representation of all three types of information. These flaws make models answer wrong on complex reasoning questions. Take the "why" question in Fig. 1(b) as an example, false attribute selection occurs because the model can not associate "off" with "dark monitor".

Additionally, GNN-based models and NSM models are more focused towards object features, and considering relation features as references. This makes models answer wrong on questions requiring relation and object information. Take the "where" question in Fig. 1(b) as an example, relation missing occurs because the model can not capture "on the" relation information.

Empirically, we demonstrate that a correct relation representation is crucial to the VQA task and enables to alleviate the bottlenecks of VQA implied by inefficient usages of scene graph information described above.

Therefore, as a fix to current ineffective strategies, we propose the Dual Energy-Flow Enhanced Graph Neural Network (DE-GNN) for VQA, introducing a novel scene graph reasoning model that extracts full-scale feature maps from objects, attributes, and relations information in scene graphs. Concretely, as shown in Fig. 2, our DE-GNN model contains a scene graph generator, a question encoder, dual graph encoders, and a fusion module. Essentially, the scene graph generator extracts graphs out of images. Besides, to preserve integrated information in the encoding process, we transform scene graphs into a relation-significant modality, in which nodes represent relations and edges represent objects, and an object-significant modality, in which nodes represent objects and edges represent relations. Lastly, after receiving scene graphs in two modalities, dual graph encoders can produce feature maps focusing on both relations and objects.

Furthermore, to learn a node's joint representation from its attributes, edges, and adjacent nodes, we modify the gated graph neural network (GGNN) structure in our proposed DE-GNN by adding the energy-flow module. It is a bidirectional GRU that guides the internal information flow. The encoder can capture information from nodes, edges, and adjacent nodes that connect to them. The outputs of the encoder pass through multi-head attention layers using question features extracted from the question encoder, see Fig. 2. Hence, the model can dynamically focus on the critical parts of the questions and use the most similar part of the scene graph as the most adequate answer.

In summary, our main contributions are as follows:

- We propose a novel DE-GNN model to learn a comprehensive representation of scene graphs by encoding graphs' object-significant modality and relation-significant modality.

- Our energy-flow module is more suitable for processing graphs with meaningful edges and nodes with internal attributes.
- We conduct experiments on GQA and Visual Genome datasets and experimental results demonstrate DE-GNN which can effectively improve the reasoning accuracy on semantically complicated questions.

Related Works

Visual Question Answering. Most VQA approaches utilize a sequential model to encode the question and employ CNN-based pretrained models like Mask-RCNN or Faster-RCNN (Fan and Zhou 2018; Patro and Namboodiri 2018; Nam, Ha, and Kim 2017) to encode the image. The image encoder and question encoder then pass through a multi-modal fusion part and the output fusion vector pass through an answer predictor. Many attention-based models (Anderson et al. 2018; Yang et al. 2016; Xu and Saenko 2016; Lu et al. 2016; Hudson and Manning 2018) are proposed to model the relations between the images and the questions. Transformer-based models such as Unicoder-VL (Li et al. 2020) can achieve outstanding performance on VQA tasks, but these models are heavy to apply due to complicated pre-train strategies, extra datasets, time-consuming, and hard to explain and update with changeable environment. Instead, scene graph based models gives another choice which is more lightly and explainable.

Scene Graph Generation and Reasoning. Most scene graph generation (SGG) methods use object detection methods like mask-rcnn or faster-rcnn to extract region proposals from images (Xu et al. 2017; Yang et al. 2018; Zellers et al. 2018; Woo et al. 2018; Dai, Zhang, and Lin 2017; Li et al. 2017; Yin et al. 2018; Tang et al. 2020). Scene graph can promotes explainable reasoning for downstream multimodal tasks such as VQA (Zhang, Chao, and Xuan 2019). In our work, scene graph generation methods are used to transform VQA datasets into scene graph datasets. Our model is then tested in datasets generated by different SGG methods.

In typical scene graph reasoning models, neural state machine (Hudson and Manning 2019b) performs sequential reasoning over the scene graph by iteratively traversing its nodes to answer a given question. FSTT (Singh et al. 2019) uses GGNN based model to encode scene graphs. Relation-aware Graph Attention Network (Li et al. 2019) models multitype inter-object relations via a graph attention mechanism. However, the previous works are hard to fully utilize the attribute information and learn the comprehensive representation of scene graphs.

Graph Neural Network. A group of graph neural networks (GNN) (Scarselli et al. 2009; Wang et al. 2016, 2018; Sun and Li 2019; Morris et al. 2019; Liu et al. 2019) were proposed for different graph tasks. Graph convolutional network (GCN) (Kipf and Welling 2017) improves GNNs efficiency with fast approximated spectral operations. GAT (Velickovic et al. 2018) introduces the attention mechanism to GNN, leveraging masked self-attentional layers to address the shortcomings of prior methods based on graph convolutions or their approximations. GGNN (Li et al. 2016) uses gated recurrent units (GRU) to accelerate the training speed and gain favorable inductive biases on large-scaled graphs. Our DE-GNN model can learn a comprehensive representation using full-scale scene graph information from objects, attributes, and relations to overcome these problems.

DE-GNN Methodology

Beforehand, we define the VQA task. It is a classification task that, given a text question about an image, output an answer. Formally, given question q and image m, the model aims to maximizing a conditional distribution over candidate answers a:

$$\hat{a} = \arg\max_{a \in A} p_\theta(a|q,m) \tag{1}$$

where A is the set of all possible answers, p_θ represents the VQA model with the trainable vector of parameters θ and $\hat{a}$ denotes the final answer.

Our proposed architecture designed for the VQA task is illustrated in Fig. 2. Our model contains a scene graph generator, a question encoder, dual graph encoders and a fusion module. For the scene graph generator, we follow a code-base (Tang 2020) and other baselines referred in this work, which we will describe in the experiment section . For the question encoder, semantic questions are first projected into an embedding space using GLOVE pretrained word embedding model (Pennington, Socher, and Manning 2014). After adding a positional encoding matrix into questions, we use long short-term memory (LSTM) networks to generate questions embedding $q \in R^{dim}$. We introduce our dual GGNN encoders in the following subsection.

Object/Relation-Significant Graph

We organize scene graphs into object-significant and relation-significant modalities.

Object-Significant Graph. We define the object-significant modality as G_{obj}, where every nodes represent objects in the image and every edges represent relations between two objects. Define N as the node set and E as the edge set. For $n_i, n_j \in N$, $e_k \in E$, $< n_i$ - e_k - $n_j >$ denotes the relation tuple that represents the relation e_k from object n_i to object n_j. Note that relation tuples are not symmetrical: if $< n_i - e_k - n_j >$ is a valid relation tuple, $< n_j - e_k - n_i >$ may not exist. Also, n_i and n_j may have several relations.

Relation-Significant Graph. We define relation-significant modality as G_{rel}, where every nodes represent relations between objects in the image and every edges represent objects, which is completely opposed to the object-significant modality. For $e_i, e_j \in E$, $n_k \in N$, $< e_i - n_k - e_j >$ denotes the relation tuple that represents the relations e_i and e_j have a shared object n_k. Note that relation tuples are also not symmetrical.

Attribute types. Define L as attribute types (such as material, color, etc). For each node $n_i \in N$ that corresponds to an object in the image, we define a set of $L+1$ property variables $\left\{n_i^j\right\}_{l=0}^{L}$, where n_i^0 represents n_i's name embedding and n_i^l represents the embedding of node n_i's l^{th} attribute (such as wooden, blue, etc).

Dual Encoders

In our DE-GNN model, every input scene graph is transformed into an information tuple (N, E, A_{in}, A_{out}) where:

- N is a collection of node embeddings.
- E is a collection of directed edges that specify valid relation between nodes.
- A_{in} is the adjacency matrix of incident edges.
- A_{out} is the adjacency matrix of output edges.

Let h_i^t is the hidden state of node n_i in GGNN at timestep t, then at $t = 0$, we initialize h_i^0 as the GLOVE embedding of n_i with appropriate zero padding:

$$h_i^0 = [n_i^T, 0]^T \,. \tag{2}$$

The incident and output edges are retrieved in the respective adjacency matrices A_{in} and A_{out}.

Energy-Flow Module To enhance the information transfer from edges and adjacent nodes to the updating nodes, we use the Energy-Flow module (EF). EF module comes as a replacement of the fully-connected layers from the original GGNN model. Take a tuple $< n_i, e_k, n_j >$ as the processing sample of the energy-flow module. The embedding state, noted e_k, of the edge e_k and neighbor node n_j's hidden state h_j are injected into a bidirectional GRU network as input sequence while the node n_i's hidden state h_i is injected as the GRU's initial hidden state. The output of the GRU represents the updating information for hidden state h_i, which corresponds to the key information from edge e_k and node n_j that is related to node n_i. The sum of every GRU output is n_i's total information gain from n_i's adjacent nodes and edges. We detail the complete energy-flow module formula as follows:

$$EF_i(A_{in}) = \sum_{k,j}^{<n_i,e_k,n_j>\in A_{in}} \text{GRU}([e_k, h_j], h_i)\,,$$

$$EF_i(A_{out}) = \sum_{k,j}^{<n_j,e_k,n_i>\in A_{out}} \text{GRU}([e_k, h_j], h_i)\,,$$

where $EF_i(A_{in})$ is n_i's incident information gain, and $EF_i(A_{out})$ is n_i's output information gain.

Propagation Model At timestep t, the hidden states of all nodes are updated by the following gated propagator module:

$$k_i^t = [EF_i^t(A_{in}), EF_i^t(A_{out})]\,, \tag{3}$$

where k_i^t represents the node n_i's representation from all its incident edges, output edges and adjacent nodes.

Then, we adopt GRU-like updates to incorporate information from adjacent nodes and from the previous timestep leading to an update of each node's hidden state:

$$\begin{aligned} c_i^t &= [h_i^{(t-1)}, k_i^{(t-1)}]W + b\,, \\ z_i^t &= \sigma(U^z c_i^t)\,, \\ r_i^t &= \sigma(U^r c_i^t)\,, \end{aligned} \tag{4}$$

where W, U^z and U^r are referred to as the trainable weight matrices and b as a bias term. At timestep t, we denote by z_i^t and r_i^t the update and reset gates, respectively.

$$\tilde{h}_i^t = \tanh(U_1 k_i^{(t-1)} + U_2(r_u^t \odot h_i^{(t-1)}))\,, \tag{5}$$

$$h_i^t = (1 - z_i^t) \odot h_i^{(t-1)} + z_i^t \odot \tilde{h}_i^t\,. \tag{6}$$

Here, U_1 and U_2 denote the trainable parameters of the linear layers, the operator $\odot$ is the element-wise multiplication. After T steps, the GGNN encoder generates the final hidden state map G of the graph. Finally, we compute the graph embedding $g_i \in G$ for node n_i as follows:

$$g_i = \sigma(f(h_i^T, n_i))\,, \tag{7}$$

where $f(\cdot, n_i)$ is the multi-layer perceptron (MLP) layer which receives the concatenation of h_i^T and n_i, then generates the final representation of node n_i.

Fusion Module and Answer Predictor

Once the dual encoders embedded in our model output the node and relation features, we first fuse the attributes into feature maps. For node feature map G^N and relation feature map G^E, the fusion feature map F^N and F^E are defined as

$$F_i^N = \begin{cases} [g_i^N, n_i^0] \\ \cdots, \\ [g_i^N, n_i^L] \end{cases}, \; F_j^E = [g_j^E, e_j],\; F = [F^N, F^E], \tag{8}$$

where F_i^N indicates the fusion features of node i and g_i^N is node i's representation from the GGNN encoder. We denote by the vector $(n_i^0, \cdots, n_i^L)$ the embeddings attributes of node i. F_j^E corresponds to the fusion feature of edge j. g_j^E is edge j's representation from the GGNN encoder. e_j is edge j's original embedding. The full-scale feature map, noted F, is the concatenation of F^N and F^E.

Then, the question embedding q generated from the LSTM encoder and the full-scale feature map F are fed into a multi-head attention layer, where the query is stored in F and the key and values are stored in q. The reasoning vector, noted r, and which stems from the graph and the question, is computed using a weighted sum of the feature map using the scores output from the attention layer, i.e.,

$$r = \text{Attention}(F, q)\,. \tag{9}$$

Regarding the answer predictor module, we adopt a two-layer MLP noted by $f(\cdot)$. This MLP can be viewed as a classifier over the set of candidate answers. The input of the answer predictor is the concatenation vector (q, r). This type of classifier has been applied in many VQA models such as NSM (Hudson and Manning 2019b) and MacNet (Lu et al. 2016). Formally, the output answer reads:

$$\hat{a} = \arg\max(\text{softmax}(f((q, r))))\,. \tag{10}$$

Numerical Experiments

Datasets

The **Visual Genome** dataset contains $108\,077$ images with comprehensively annotated objects, attributes, and relations. To enrich the scene graph annotation in Visual Genome, we use a scene graph generation method and motifs (Zellers et al. 2018) to generate a new scene graph dataset called motif-VG. Compared with the Visual Genome dataset, motif-VG has the same images and questions-answers tuples, but has scene graph annotations with different qualities and biases. We split both datasets into train, valid, and test sets using a $7:1:2$ ratio.

The **GQA** dataset (Hudson and Manning 2019a) focuses on real-world reasoning, scene understanding and compositional question answering. It consists of 113k images and 22M questions of assorted types and varying compositionality degrees, measuring performance on an array of reasoning skills such as object and attribute recognition, transitive relation tracking, spatial reasoning, logical inference and comparisons.

Implementation Details

We use 50-dimensional GLOVE word embeddings model (Pennington, Socher, and Manning 2014) to embed words in the scene graph and questions. In order to record the questions' position information, we set up the positional encoding matrix PE:

$$\mathrm{PE}_{\mathtt{pos}=2i} = \sin(\mathtt{pos}/10000^{2i/d_{\mathrm{m}}})\,,$$
$$\mathrm{PE}_{\mathtt{pos}=2i+1} = \cos(\mathtt{pos}/10000^{2i/d_{\mathrm{m}}})\,,$$

where $\mathtt{pos}$ is the position of the word in the question sequence. If $\mathtt{pos}$ is odd, the position information is generated by a $\sin$ function, else, it is generated by a $\cos$ function. We also let model dimension equal to $d_{\mathrm{m}} = 50$. After adding position information, the question embeddings are injected into a single-directional GRU network. The dimension of the hidden layers of the GRU is 100, and the dropout rate is 0.2.

In our energy-flow enhanced GGNN encoder, the propagator time step is 5, and we use a bidirectional GRU as our energy-flow module. Here, we set the dimension of the single GRU hidden layer to 50.

In the fusion module, we apply a multi-head attention layer with 5 heads and no dropout. Regarding the answer predictor, we select the top-2000 answer candidates and use a 2-layer MLP as the output classifier.

We use Adam (Kingma and Ba 2015) as the optimizer, and Cross Entropy Loss as the loss function during the training of our model. For motif dataset, we set the batch size to 512. For Visual Genome ground truth dataset and GQA dataset, we set the batch size to 16 due to their abundant scene graph annotations.

The learning rate is decaying depending on the epoch number. We initialize the learning rate to be $1e^{-3}$, and when 30% epochs finish, the learning rate drops to $2e^{-4}$. When 60% epochs finish, the learning rate drops to $4e^{-5}$ and it becomes $8e^{-6}$ after 80% epochs finish. We train our model and other baselines on a single V100 GPU.

Empirical Results

In this subsection, we provide the experimental results on various datasets mentioned above. The different baselines compared in our experiments all use various methods to generate the scene graphs for images. In order to ensure general fairness across the methods, we implement them from scratch, removing their scene graph generation parts to eliminate the interference of different generation methods.

Table 1 reports the results on the test sets of the VG ground truth datasets and the motif-VG dataset. Compared to the baseline models, we can observe that our DE-GNN model outperforms the others at 3%-4%.

In addition, we provide detailed results on the VG dataset and motif-VG dataset with different question types. Compared to the other scene graph based VQA models, our model performs well in "what", "where", "who" and "why" types. Specially, our model has 6% accuracy improvement in "why" type questions, which highly requires VQA models' reasoning ability.

We report in Table 3 the detailed results on the test sets of the GQA dataset. Compared to the baseline models, our DE-GNN model achieves state-of-the-art accuracy performance.

We also evaluate our model and other baselines across GQA dataset's various metrics, where "Binary" represents binary-answer questions, "Open" represents open domain questions and "Distribution" represents the distance between prediction distribution and standard answer distribution. In open domain questions which are difficult for reasoning, our model outperforms the others at 10%. In distribution metric, our model also achieves 2nd score compared to other baselines.

To demonstrate that our dual encoders structure can intensify the model's perception of relation features and learn a comprehensive representation from nodes, attributes, and relations information, we make badcase analysis for baselines and our model on Motif dataset.

To classify the badcase answer category, we generate three dictionaries to record objects, attributes and relations that appear in scene graphs.

For each answer, we first extract potential relations and match them up with the relation dictionary. Then we split the objects and attributes in the answer and search objects and attributes dictionaries. As for some evasive answers containing both objects and its' attributes, we add them in both object and attribute categories.

We present Table 4 the results for our badcase analysis. Our DE-GNN model surpasses all baselines in the terms of objects detection. Also, our model reduces nearly half of the wrong answers in FSTT, Re-GAT, and NSM in the attribute aspect. Finally, our model does well in relation retrieval, outperforming GNN based FSTT and Re-GAT.

Ablation Study

We compare several ablated forms of DE-GNN with our complete one. The accuracy results are reported in Table 2.

We use the original GGNN network as the *base* model to encode scene graphs. The *Obj* model represents the original GGNN network processing *object-significant* graphs.

Table 1: Performance on different question types of VG datasets.

Question type	**What**	**Color**	**Where**	**How**	**Who**	**When**	**Why**	**Overall**
Percentage	(54%)	(14%)	(17%)	(3%)	(5%)	(4%)	(3%)	(100%)
VG-GroundTruth								
NSM (Hudson and Manning 2019b)	33.1	52.4	51.0	52.9	49.8	77.9	12.3	45.1
MLP (Jabri, Joulin, and van der Maaten 2016)	-	-	-	-	-	-	-	58.5
F-GN (Zhang, Chao, and Xuan 2019)	60.9	53.6	62.0	46.2	63.3	**83.7**	50.9	60.1
U-GN (Zhang, Chao, and Xuan 2019)	61.6	54.0	62.4	45.9	63.9	83.2	50.3	60.5
SAN (Yang et al. 2016)	-	-	-	-	-	-	-	62.6
FSTT (Singh et al. 2019)	65.5	45.6	70.1	47.8	68.3	82.1	91.5	65.6
ReGAT (Li et al. 2019)	72.1	**70.8**	64.4	**68.9**	72.7	65.0	92.3	71.2
DEGNN (ours)	**75.9**	64.9	**73.1**	66.8	**82.6**	81.4	**98.8**	**75.4**
Motif-VG								
NSM (Hudson and Manning 2019b)	31.8	62.4	53.1	51.4	47.6	83.3	10.9	43.1
FSTT (Singh et al. 2019)	48.8	40.4	49.2	40.1	40.6	54.5	70.3	48.1
F-GN (Zhang, Chao, and Xuan 2019)	58.7	60.8	60.4	47.2	61.8	84.8	49.0	60.0
U-GNN (Zhang, Chao, and Xuan 2019)	59.4	58.2	60.3	54.3	66.6	**85.3**	48.1	60.5
ReGATT (Li et al. 2019)	75.4	**69.2**	57.6	**69.9**	69.1	57.4	91.8	69.9
DEGNN (ours)	**79.4**	67.6	**62.7**	65.3	**72.8**	63.0	**96.1**	**72.9**

Table 2: Ablation study

Models	**Acc.**
Base	35.4%
+EF	*unstable*
+Obj	35.4%
+Obj+EF	39.3%
+Rel	35.2%
+Rel+EF	38.8%
+Obj+Rel	**67.9**%
+ (w/o *QF*)	54.9%
+ (w/o *attr*)	71.6%
+ (w/o *rela*)	**74.5**%
DEGNN(ours)	**75.2**%

Table 3: Performance on the GQA dataset.

Models	**Binary↑**	**Open↑**	**Validity↑**	**Distribution↓**	**Accuracy↑**
Human	91.20	87.40	98.90	-	89.30
BottomUp	66.64	34.83	96.18	5.98	49.74
MAC	71.23	38.91	96.16	5.34	54.06
SK T-Brain	77.42	43.10	96.26	7.54	59.19
PVR	77.69	43.01	**96.45**	5.80	59.27
GRN	77.53	43.35	96.18	6.06	59.37
Dream	77.84	43.72	96.38	8.40	59.72
LXRT	77.76	44.97	96.30	8.31	60.34
NSM	78.94	49.25	96.41	**3.71**	63.17
ReGAT	**83.57**	62.58	92.70	9.32	70.50
DEGNN(ours)	69.79	**72.21**	93.80	3.78	**71.21**

Table 4: Error rate analysis on Motif dataset.

Models	FSTT	ReGAT	DE-GNN	Case Number
Relation	45.9%	44.6%	**32.9**%	7913
Object	58.6%	47.3%	**25.2**%	4414
Attribute	49.6%	22.8%	**16.8**%	15483

The *Rel* model represents the original GGNN network processing *relation-significant* graphs. The *Obj-EF* model corresponds to the object encoder part of our DE-GNN model, which contains one energy-flow enhanced GGNN network to encode *object-significant* graphs. The *Rel-EF* model is the other half of our DE-GNN model, which contains one energy-flow enhanced GGNN network to encode *relation-significant* graphs.

First, we validate the effectiveness of applying dual structure to balance the importance of relations and objects by splitting our DE-GNN into an object-single model(*Obj*) and a relation-single model(*Rel*). Table 2 shows that both *Obj* model and *Rel* model perform poorly, at about 35.3%. It also shows that both relations and objects are vital to VQA performance. Lack of any of them leads to severe accuracy recession. Combining the object-single model and the relation-single model leads to an empirical gain of approximately 35% accuracy upward, which shows that the dual structure is significant in balancing relation and object information.

Then, we validate the effectiveness of applying energy-flow structure to learn a more comprehensive representation for scene graphs than the original GGNN structure, which represents the baseline in Table 2. We compare the *Obj+EF* model and the *Obj* model, which both learn representations from object-significant graphs, and note that after adding the energy-flow structure, there is an accuracy improvement of 3.9%. We also compare the *Rel+EF* model and the *Rel* model, noting that there is an accuracy improvement of 3.6%. The *Obj+Rel* model is DE-GNN without energy-flow module. Comparing with DE-GNN, there is a 7.3% accuracy improvement after adding the energy-flow module. These show that energy-flow structure can successfully improve the representation quality of scene graphs.

To demonstrate the impact of the explicit modeling of attributes and relations in our DE-GNN, the *w/o attr* model

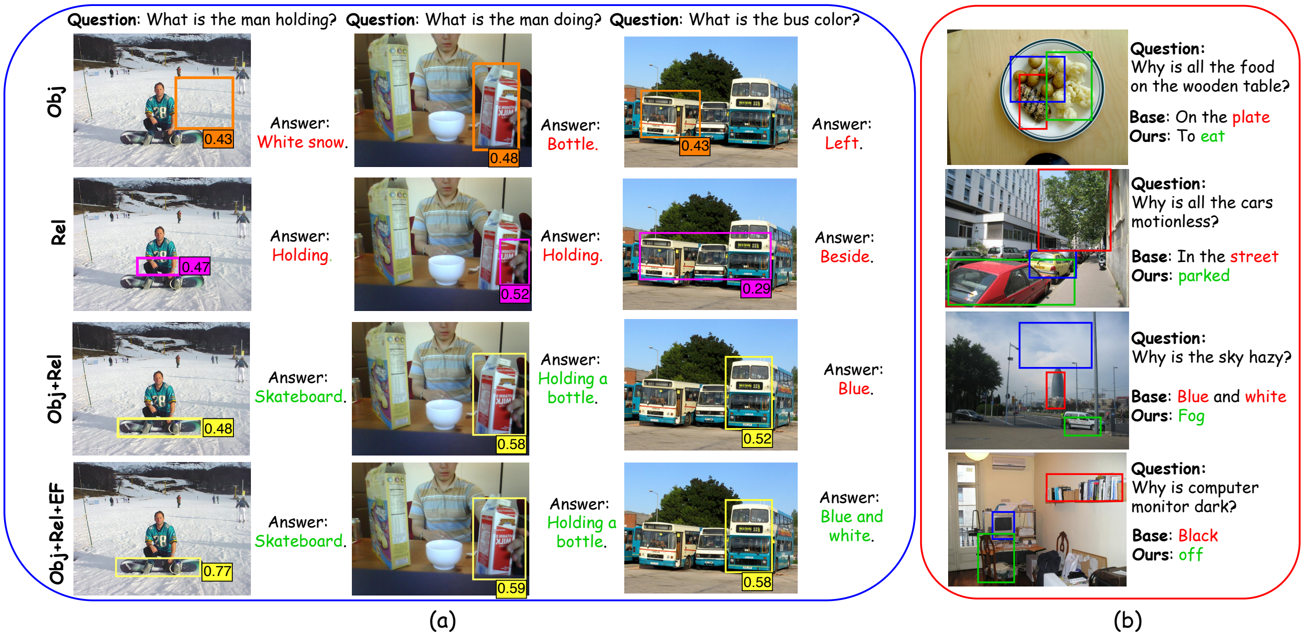

Figure 3: Examples of generated answers and top attention scores. The left plot and right plot show the visualization of "what" and "why" question types. From the left plot, our approach can correctly select answers from objects, relations and attributes. From the right plot, our model can handle comprehensive reasoning questions.

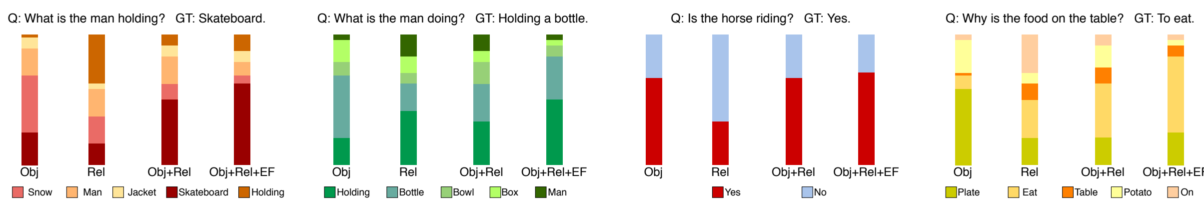

Figure 4: Examples of top 5 attention scores of different types of questions.

remove the explicit attribute modeling part from DE-GNN model and the *w/o rela* model remove the explicit relation modeling part. After removing attribute modeling, our model suffers 3.6% accuracy drop, while the relation modeling has only 0.7% accuracy influence on our model.

Visualization

To better illustrate the effectiveness of the dual encoder structure and the energy-flow module in our DE-GNN model, we compare the top attention score learned by DE-GNN model with those learned by our *Obj*, *Rel* and *Obj+Rel* models. Fig. 4 exhibits the detail of the visualization results.

The left blue plot shows the visualization on "what" question type. The examples in three columns are "what" questions aim at node, relation and attribute information. Comparing row 1, row 2 with row 3, *Obj* and *Rel* models have strong attention bias toward objects and relations, while their combination, the *Obj+Rel* model, balances the attention on both sides and captures correct answers. Comparing row3 with row 4, the addition of the energy-flow module increase the attention score of correct answers.

The right red plot shows the visualization on "why" question type. In "why" questions, models jointly exploit objects, relations and attributes to generate answers. Using dual encoder structures ans the energy-flow module, our DE-GNN can generate correct answers and achieves **96.1**% accuracy on "why" question type.

Conclusion

In this work, we study classical scene graph reasoning methods such as GNN-based models and Neural State Machine for Visual Question Answering tasks. We observe that neither can existing models *jointly* exploit objects, relations, and attributes in SG, nor can they balance the importance of objects and relations. To address this problem, we propose the Dual Energy-Flow Enhanced Graph Neural Network (DE-GNN), which encodes each scene graph into feature representations via an object encoder and a relation encoder generating full-scale feature maps using nodes, attributes, and relations information. We demonstrate the effectiveness of our method on the various datasets achieving significant improvement and state-of-the-art performances.

In future work, we will test our DE-GNN model on more VQA datasets, such as VQA-CP2. We hope that our work can further enhance the effect of scene graph for reasoning modeling.

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