Few-Shot Visual Question Generation: A Novel Task and Benchmark Datasets

Anurag Roy*, David Johnson Ekka**, Saptarshi Ghosh*, Abir Das*

* Indian Institute of Technology Kharagpur, West Bengal 721302, India
** Department of Computer Science, Indian Institute of Technology Kharagpur, West Bengal 721302, India

Abstract—Generating natural language questions from visual scenes, known as Visual Question Generation (VQG), has been explored in the recent past where large amounts of meticulously labeled data provide the training corpus. However, in practice, it is not uncommon to have only a few images with question annotations corresponding to a few types of answers. In this paper, we propose a new and challenging Few-Shot Visual Question Generation (FS-VQG) task and provide a comprehensive benchmark to it. Specifically, we evaluate various existing VQG approaches as well as popular few-shot solutions based on meta-learning and self-supervised strategies for the FS-VQG task. We conduct experiments on two popular existing datasets VQG and Visual7w. In addition, we have also cleaned and extended the VQG dataset for use in a few-shot scenario, with additional image-question pairs as well as additional answer categories. We call this new dataset VQG-23. Several important findings emerge from our experiments, that shed light onto the limits of current models in few-shot vision and language generation tasks. We find that trivially extending existing VQG approaches with transfer learning or meta-learning may not be enough to tackle the inherent challenges in few-shot VQG. We believe that this work will contribute to accelerating the progress in few-shot learning research.

Index Terms—Visual Question Generation, VQG, Few-Shot, meta-learning, self-supervised learning, transfer learning

I. INTRODUCTION

Both Question Answering and Question Generation have been well studied in natural language processing [1]. Visual Question Answering (VQA) [2], [3], [4], [5], [6] has emerged as an important cross-modal learning task in the recent past. However, generating natural language questions from visual scenes is still not much explored [7], [8], [9]. Visual Question Generation (VQG) [10] addresses the problem of automatically generating questions from images and some accompanying information e.g., possible answers, type of answers or questions. VQG is particularly challenging as the generated question not only needs to be grammatically meaningful but also needs to be relevant to the visual content of the scene. Traditionally, VQG approaches [7], [8] tend to focus on learning effective visuo-lingual representations using large amounts of labeled data. Collecting labels is rather tedious as the workers need to ask visually verifiable question from images. Hence there is a growing interest in learning few-shot models [11], [12] capable of automatically generalizing to classes with only a limited number of labeled examples. The limited scalability of the existing approaches inspired us to explore VQG in few-shot learning scenario.

*The author is currently a senior software engineer at Persistent Systems, Pune, India

While the majority of recent few-shot learning works focus on classification including pure visual (image/video classification) or visuo-lingual tasks, adapting it to a generative task like VQG is not trivial. In this paper, we focus on Few-Shot Visual Question Generation (FS-VQG) with an open-ended VQG model that automatically adapts to new categories of images and/or answers. In addition to questions, our formulation can exploit side information such as the category of questions (e.g., ‘where’, ‘when’, ‘why’, etc.) or answers (e.g., involving ‘persons’, or related to ‘food’, ‘animals’, etc.) whenever they are available. Note that questions generated from images only, tend to be generic [7]. This difficulty can be handled by exploiting easily available side information as input in addition to answers, with the goal of generating questions specific to the input image, the input answer and the category of question we are looking for. Existing VQG approaches have used the answer [8] and answer category [7], [13] as the side information. However, to the best of our knowledge, ours is the first comparative study exploiting such side information in Few-Shot VQG.

A powerful method to adapt a learner using experiences gained from similar tasks is meta-learning [14] where a meta-learner sets the model parameters for the task-specific learners. It involves a bi-level optimization process where the performances of the task-specific learners for the different tasks provide feedback for the meta-learner. Motivated by the success of meta-learning strategies [14], [15], [16], [17] in few-shot learning, the first model we try is a meta-learning based FS-VQG approach exploiting the available side information. Specifically, we leverage an image encoder to get visual representation of the images and a side information encoder to get text embeddings of the answers and other side information (if any). An LSTM-based decoder generates questions from textual features and attention guided visual features. Our meta-learner is conditioned on the answer and the side information embeddings, and adapts the image encoder to an unseen task by scaling and shifting the image features. These two lightweight neuron operations are shown to enable faster convergence in few-shot meta learning [15]. In a second variation, we slightly modify the architecture to get rid of the scaling and shifting operations. Instead, we concatenated the encoded visual and textual features to give as input to the LSTM decoder for question generation.

Motivated by recent advances in self-supervised learning of visual representations [18], [19], [20], [21], we investigated the effect of self-supervised pretext task of predicting image rotations towards the few-shot VQG task. As shown by Gidaris et al. [22], such a pretext task better prepares the image encoder
with diverse learning of features which, in turn, improves its ability to adapt to novel classes while fine-tuned with only a few labeled data. This variation follows the transfer learning paradigm closely where the pretraining is done on the merged data readily available from the tasks similar to the target task. In the meta-learning based approaches, the data from the similar tasks form the meta-training set. The transfer learning setup, in addition, minimizes a self-supervised objective that encourages the image encoder to predict the rotation angle of an image that is randomly rotated before passing through the image encoder. This simple yet effective strategy is shown to benefit the FS-VQG task compared to traditional VQG approaches not designed for situations with label scarcity.

Apart from comparing novel FS-VQG approaches, we also contribute a dataset for the FS-VQG task. The large-scale VQG dataset introduced by Krishna et al. [7] (henceforth referred to as the ‘VQG-16’ dataset) is prepared from the VQA dataset [2] by dividing its answers into 16 different categories according to different objects (e.g., ‘cat’, ‘person’), attributes (e.g., ‘cold’, ‘old’), colors (e.g., ‘brown’, ‘red’), etc. However, the coarse structure of the categories (e.g., ‘objects’ containing images of food and electronics items, or ‘sports and goods’ containing sporting activity and generic goods) results in confusion. In addition, miscategorizations of images – e.g., putting ‘Apples’ and ‘Bananas’ in the more generic ‘Object’ category instead of ‘Food’, or putting ‘Elephants’ and ‘giraffes’ in categories other than ‘animal’ (see Fig 1) – also negatively impacts the performance of models. We have taken this opportunity to propose a new dataset based on VQG-16 by (i) making the categorization more fine-grained by extending the 16 answer categories into 23, (ii) correcting the mis-categorizations in the process, and (iii) adding more images and question-answer pairs from the visual-genome dataset [23]. Following [7], we have taken the answer categories from the category names outlined in the VQA dataset [2]. We refer to this new dataset as ‘VQG-23’ throughout the paper. More details and statistics about VQG-23 are provided in Sec. IV. In addition to the VQG-23 dataset, we experimented on two more datasets, specifically the VQG-16 [7] and the visual7w [24] datasets with different choices of visual and textual encoders.

![Visual Question Generation (VQG):](image)

**II. RELATED WORK**

**Visual Question Generation (VQG):** VQG aims to automatically generate questions from an image and associated side information. Mostafazadeh et. al. [10] introduced the VQG task along with the introduction of benchmark datasets. Since then, the field has seen a steady increase of interest. The approaches can be broadly classified into 3 categories in terms of the type of the generated questions: 1) Grounded questions, 2) Common sense based questions and 3) Knowledge based questions. Answering the first type does not require any external knowledge other than the image. Majority of the VQG works address the problem in this setting. IQ [7] and C3VQG [13] approached the question generation task by maximizing mutual information between the generated question, image and the answer or its category. IQAN [8] addressed VQG as a dual problem of VQA using shared parameters between them. The second type of questions requires common sense reasoning in addition [25], [26], [27]. Knowledge based questions take help of external knowledge bases in addition to the visual scene [28], [29], [30]. A multidimensional taxonomy of VQG can be obtained in the review paper [9]. However, all these approaches rely heavily on the presence of large labeled datasets. Different from them, in this paper we address grounded VQG in a few-shot setup.

**Few-Shot Learning:** Early few-shot classification approaches were built on nearest neighbor principle, either in feature space or semantic space where both support and query examples are embedded [31], [32], [33]. Prototype-based works summarize all training examples to a single prototype per class and then perform nearest neighbor classification [34], [35], [36]. A classic path taken in few-shot scenario is to augment the data [37] or generate additional examples [38], [39], [40]. In contrast to nearest neighbor, data augmentation or generative approaches, meta-learning is a task-level learning method where ‘samples’ are replaced with ‘tasks’. Meta-learning typically aims to obtain an optimized meta-learner while the task-specific learner is optimized to provide learning signal for meta optimization [41], [14], [42], [15].

Few-shot or zero-shot learning with rare words in vision-and-language tasks is still in its infancy. The community has looked into zero-shot image captioning where no training data...
We address this problem using meta-learning where instead we propose the scarce. Different from these works, we propose the self-supervised image rotation prediction task that the few-shot representation learning [57], [58]. In this work, we leverage discarded to take advantage of pretext tasks towards better learning to predict masked input. Self-supervised pretraining has been recently used in supervised settings, where labels are free and are procured automatically from the images themselves. Many recent works have built on this idea to design a variety of pretext tasks in images, including learning to reconstruct the input [49], inpainting [50], solving jigsaw puzzle [51], geometry [52], colorizing greyscale images [53], rotation prediction in artificially rotated images [19] etc. and also in natural language processing [54], [55], [56] by learning to predict masked input. Self-supervised pretexting followed by supervised fine-tuning has been successfully used to great effect due to their potential to leverage large amount of unlabeled data. Self-supervised learning has also been recently used in supervised settings, where labels are discarded to take advantage of pretext tasks towards better representation learning [57], [58]. In this work, we leverage a self-supervised image rotation prediction task that the few-shot model minimizes during its first learning stage and is then transferred to the later task where labeled training data is scarce.

**Self-supervised Learning:** Self-supervised learning enables training by performing pretext tasks where both inputs and labels are free and are procured automatically from the images themselves. Many recent works have built on this idea to design a variety of pretext tasks in images, including learning to reconstruct the input [49], inpainting [50], solving jigsaw puzzle [51], geometry [52], colorizing greyscale images [53], rotation prediction in artificially rotated images [19] etc. and also in natural language processing [54], [55], [56] by learning to predict masked input. Self-supervised pretraining followed by supervised fine-tuning has been successfully used to great effect due to their potential to leverage large amount of unlabeled data. Self-supervised learning has also been recently used in supervised settings, where labels are discarded to take advantage of pretext tasks towards better representation learning [57], [58]. In this work, we leverage a self-supervised image rotation prediction task that the few-shot model minimizes during its first learning stage and is then transferred to the later task where labeled training data is scarce.

**III. Overview of the Problem and Approaches**

**Problem Overview:** Given an image, Visual Question Generation (VQG) produces questions relevant to the visual content of the image. However, questions generated using only the image without additional guidance in the form of category of question or answer will be uninformative and less directed. To generate more useful questions, additional side information needs to be provided as input along with image. In this paper we have used two different kinds of side information, namely category and answer. The category can be of both question or answer. **Question category** refers to the type of question e.g., ‘what’, ‘where’, ‘when’, etc. [24]. Categorization of answers stems from categorizing tokens in answers [7]. Example answer categories are ‘animal’ (e.g., answers containing words ‘elephants’, ‘giraffes’), ‘color’ (e.g., answers containing words ‘green’, ‘blue’), ‘food’ (e.g., answers containing ‘donuts’, ‘bananas’) etc.

Supervised VQG models require a lot of labeled data for training which may be difficult to get. Hence we propose the Few-Shot VQG (FS-VQG) task wherein the model should be able to learn from only a few instances of training data. All our tasks are K-way N-shot where K is the number of classes and N is the number of labeled instances per class which are usually very small. In VQG, parallel of ‘class’ is category of question/answer and thus K-way, N-shot task means generating questions from N instances of training data for each of K different question/answer categories.

**Overview of the Approaches:** We design an attention-based encoder-decoder architecture that takes an image and side information in the form of an answer to the question we want it to generate as well as question or answer category. Fig. 2 illustrates an overview of the approach. The image is passed through a convolutional image encoder to get the image embedding while the category information is passed through a single hidden layer MLP and the answer is passed through an LSTM. The answer and category representations are combined and further passed through MLP layers to get two sets of vectors for scaling and shifting the aforementioned image features. The interaction between the scaling and shifting vector with the...
image features not only aligns the image features with the additional side information but also does it with very little computation. The MLP generating the scaling and shifting values are meta-learned and are optimized by the test loss of the sample tasks. The scaled and shifted image features are passed through a LSTM decoder which generates the question words as well attention vector \( \beta \) that weighs the image features according to question words generated till the present timestep.

While the scaling and shifting operations reduce meta-parameters to be learned which in turn, helps prevent overfitting in a few-shot learning scenario, the question decoder does not directly get trained with the side information which may be crucial. So, in a second variation, instead of generating scaling and shifting vectors, we directly passed the combined encoding of the side information to the decoder. We call the former model Meta-FSVQG and the latter Meta-FSVQG-NoSS. A third variation explores an additional self-supervised objective in a transfer learning setup where the pre-training is done on the merged data from closely related tasks. The self-supervised loss from the pretext task of predicting rotation angle of input images is combined with minimizing the supervised cross-entropy loss during pretraining. The image encoder gets more images is combined with minimizing the supervised cross-entropy.

We will now explain the models in detail.

**A. Meta-FSVQG**

**Image encoder:** Representing the visual scene with rich features is crucial for VQG. Thus, we adopt a convolutional neural network as the image encoder. Specifically, for an image \( I \), the image encoder generates a feature map \( F \in \mathbb{R}^{h \times w \times c} \) of dimension \( h \times w \times c \) where \( h, w \) and \( c \) denote height, width and number of channels respectively. Let the 2-D feature map of the \( i^{th} \) channel is denoted by \( F^i \in \mathbb{R}^{h \times w} \) for \( i = \{1, \cdots c\} \).

**Scale and shift network:** This module generates scaling and shifting vectors from the available side-information. Specifically, this module generates the encoded representation of the side information. To this end, the category encoder is designed as a two layer feed-forward neural network. As answer can consist of multiple words, the answer encoder is an LSTM [60]. While one-hot encoding is used for category and answer words, we additionally experimented with state-of-the-art contextual embedder like BERT [56] for the answer to better exploit the context in them. The category and answer encodings are concatenated and passed through a series of MLPs to produce scaling vector \( \gamma \in \mathbb{R}^c \) and shifting vector \( \beta \in \mathbb{R}^c \). These vectors help in adaptively influencing the image features by the available side information. This is achieved via an affine transform on the feature maps by \( \gamma \) and \( \beta \). Such affine transformations have been empirically proven to perform good in visual reasoning [61] and few-shot classification [15]. Denoting the transformed image feature as \( G \in \mathbb{R}^{h \times w \times c} \), its \( i^{th} \) channel as \( G^i \in \mathbb{R}^{h \times w} \) and a matrix of size \( h \times w \) with all 1’s as \( \mathbb{I} \), the affine transformation is given by,

\[
G^i = \gamma^i F^i + \beta^i \mathbb{I}, \forall i \in \{1, \cdots c\}
\]

where \( \gamma_i \) and \( \beta_i \) mean \( i^{th} \) element of \( \gamma \) and \( \beta \) respectively.

**Question Decoder:** The scaled and shifted image features are decoded by an LSTM with attention. Specifically, we adopt the highly successful soft attention mechanism [62], [59], [63] that allows the decoder to weigh each spatial location of the feature map. Our approach has the potential of focusing on key elements of the image that may be crucial for the generated question to conform to the input side information. Denoting the scaled and shifted feature vector at location \( (x, y) \) as \( G(x, y) \in \mathbb{R}^c \), and the LSTM hidden state at time \( t \) as \( h_t \), the attention mechanism can be represented by,

\[
\alpha^{(i)}(x, y) = \frac{\exp \left( A^{(i)}(x, y) \right)}{\sum_{u=1}^{w} \sum_{v=1}^{h} \exp \left( A^{(i)}(u, v) \right)}
\]

\[
A^{(i)}(x, y) = \theta^T h_t \tanh(W h_{t-1} + U G(x, y) + b) + b
\]

Fig. 3. The proposed SelfSup-FSVQG that uses self-supervision to optimize the image-encoder. The combined embedding of the side information is appended with the attention weighted image features and fed into the LSTMCell to generate relevant question. While pre-training the model, the image encoder is jointly trained with a rotation classification loss where a rotation classifier has to identify the angle of rotation of the input image fed into the image encoder.

![Image Encoder](image.png)
Algorithm 1 The Meta Training Algorithm

1: randomly initialize $\Psi$
2: while not DONE do
3: Randomly sample batches of tasks $T_j \sim p(T)_{\text{meta}}$
4: for all $j$ do
5: Sample datapoints $T_{j}^{(tr)}, T_{j}^{(te)}$ from $T_j$
6: $\Psi_j \leftarrow \Psi$
7: for step in 1 … adaptation steps do
8: /* Base Learning */
9: Optimize $\Psi_j = \Psi_j - \nabla_{\Psi_j} \mathcal{L}_{T_j}(f_{\Psi_j})$ using $T_{j}^{(tr)}$ and $\mathcal{L}_{T_j}$ as Cross-Entropy Loss
10: end for
11: end for
12: /* Meta Learning */
13: Optimize $\Psi = \Psi - \nabla_{\Psi} \sum_{j \in T} \mathcal{L}_{T_j}(f_{\Psi_j})$ using $T_{j}^{(te)}$ and $\mathcal{L}_{T_j}$ as Cross-Entropy Loss
14: end while

where $\theta_h, W_h, U, b_h$ and $b$ are parameters of the ‘Question Decoder’ network. One of the inputs to the LSTM at timestep $t$ is $\phi_t^{(t)}(G) = \sum_{x=1}^{w} \sum_{y=1}^{h} \alpha_t^{(t)}(x, y)G(x, y)$. With the help of the soft attention mechanism, the question decoder LSTM gets a dynamically weighted sum of the spatial features where the weights are given by the positive real soft attention values $\alpha_t^{(t)} \in \mathbb{R}^{h \times w}$. Once the hidden state $h_t$ of the LSTM cell is computed, the probability of the output word $z_t$ is obtained using a single layer neural network as,

$$p(z_t) = \text{softmax}(\theta_{p}^{(t)} \text{tanh}(W_{p}^{(t)}h_t + b_{p}^{(t)} + d_t)) \quad (3)$$

where $\theta_p, W_p, b_p$ and $d$ are parameters of the ‘Question Decoder’ network that are learned along with other parameters of the model. $[\cdots]$ denotes a concatenation operation. $E$ is a word embedding function and $E(z_{t-1})$ is the embedding vector representation of the word $z_{t-1}$. The word embedding can be learnable or pretrained e.g., BERT [56]. In **Meta-FSVQG-NoSS**, instead of scaling and shifting the image embeddings with side information, the encoded side information is directly fed to the LSTM along with the attention weighted image features and the previous word.

**Meta-Training:** We leverage on the highly successful few-shot meta-learning framework Model Agnostic Meta-Learning (MAML) [14] to train using a set $T$ of scarcely labeled but related few-shot tasks. The goal of MAML is to get a ‘base model’ that performs well on the target task leveraging the across-task similarities. The dataset corresponding to a task $T_j \in T$ are used to acquire across-task similarities and are divided into two separate sets, a training set $T_{j}^{(tr)}$ and a test set $T_{j}^{(te)}$. Algorithm 1 outlines the meta-learning strategy for the FS-VQG task. Steps 7–9 in the algorithm highlights the task-specific optimization of a base model a.k.a base learning. Once the base models are trained, the test set losses of the tasks are used to update the meta-parameters in the meta-learning step (steps 12-13 in the algorithm), thereby helping achieve a good initialization of the base model. In the meta-training phase we train the whole model except the pre-trained image encoder which is kept fixed.

---

**Table 1**

| Categories     | Images | Questions | Categories     | Images | Questions |
|----------------|--------|-----------|----------------|--------|-----------|
| vehicles       | 3,265  | 7,822     | clothes        | 8138   | 11635     |
| sporting goods | 10,076 | 12,357    | binary         | 69,616 | 172,934   |
| attribute      | 4,285  | 85,158    | activity       | 13,431 | 17,350    |
| color          | 30,794 | 47,901    | cutery         | 2,894  | 4,144     |
| count          | 5,112  | 6,707     | electronics     | 4,006  | 5,734     |
| material       | 9,598  | 12,710    | furniture       | 5,140  | 6,780     |
| food           | 9,485  | 11,383    | other          | 10,474 | 12,086    |
| location       | 19,865 | 33,179    | animal         | 9,229  | 13,799    |
| object         | 7,341  | 10,290    | predicate       | 7,738  | 11,408    |
| people         | 1,624  | 1,887     |                  |        |           |
| shape          | 4,312  | 4,729     |                |        |           |
| spatial        | 10,613 | 11,001    |              |        |           |

**Per-category statistics of images and questions in the new dataset VQG-23 developed in this work.**

**B. Few-Shot Learning with Self-Supervision**

Recent works on few-shot learning highlight that self-supervision can be helpful in few-shot learning [64], [19]. Thus, we chose to explore self-supervision for FS-VQG in a transfer learning setup. Specifically, we optimize the image-encoder of our model with an additional rotation classification loss introduced in [19]. Rotated images (randomly rotated to $0^\circ, 90^\circ, 180^\circ$ or $270^\circ$) are input to the image encoder and it is tasked to recognize the rotation angle. To this end, we add a self-supervised rotation classifier consisting of convolution layer and a feed-forward linear layer on top of the image encoder as shown in Figure 3. We train the image-encoder jointly during pre-training. Once pre-trained, we discard the self-supervised classifier during fine-tuning. We call our model **SelfSup-FSVQG**.

**C. Traditional VQG models adapted for Few-Shot**

Traditional VQG models are adapted to FS-VQG by pre-training the merged training data from similar tasks and then fine-tuning on the few-shot test tasks. The first one is IQAN [8] which jointly trains an invertible question answering network for both VQA and VQG tasks with shared parameters. The second one is IQ [7] which learns to generate questions from image, answer and answer category by maximizing mutual information among them. In IQ, we also experimented with the case when one of the side information (i.e., answer or category) is absent. The third is C3VQG [13] which is similar to IQ wherein it generates relevant questions by maximizing the mutual information between images and answer categories.

## IV. Experiments

**A. Datasets**

**Benchmark datasets:** We experiment on two benchmark datasets, namely (1) VQG-16 [7] and (2) Visual7W [24]. The answers in the VQG-16 dataset are categorized into 16 categories, of which we select 10 categories for training and keep the remaining 6 categories – ‘binary’, ‘activity’, ‘animal’, ‘predicate’, ‘other’, ‘stuff’ – for testing. Visual7W is categorized into 6 categories based on question-words – ‘where’, ‘how’, ‘what’, ‘why’, ‘who’ and ‘when’. For training, we selected ‘where’, ‘what’, and ‘how’ categories. The other 3 categories...
are used for testing. For both datasets, we ensured that our train and test splits do not have any image overlap between them.

B. A new dataset VQG-23

As mentioned in Sec. I and shown in Fig. 1, miscategorizations of some answers in VQG-16 dataset introduce additional challenges (e.g., answers ‘elephants’ and ‘giraffe’ are included in the category ‘Food’). In addition, some of the categories are too generic (e.g., ‘object’ category contains vehicles, clothes, furniture, etc.) such that multiple distinct categories can be formed out of them. In Visual7W, the variation in questions belonging to any one category is very low which makes question generation less challenging. To better evaluate a few-shot VQG model, we need to ensure that the dataset is diverse enough so that the evaluation scenario is realistic in terms of the practical difficulty in finding large labeled datasets from a single domain.

Keeping these issues in mind, we form a new dataset by extending VQG-16 [7]. For this purpose, we use the Visual Genome [25] dataset that comprises of 1.7 million question-answer pairs of images taken from the MS-COCO [65] and the YFCC [66] datasets. We increased the number of categories from 16 in VQG-16 by (i) splitting the existing generalised categories to more specific categories and (ii) adding more question-answer pairs with images from Visual Genome to form new categories. Since both VQG-16 and Visual Genome use images from MS-COCO, we removed the duplicate images while retaining the question-answer pairs. In total, the new dataset has 23 answer categories and is hence called VQG-23. The per-category statistics of images and questions of it is shown in Table I. Out of the 23 categories in VQG-23, 13 are for use during pre-training (or meta-training) and the rest 10 are for use during fine-tuning and evaluation. We also ensure that there is no overlap among the images between these two phases. Detailed counts of unique images and questions from the Visual Genome dataset, added to each category in the VQG-16 dataset to form the VQG-23 dataset have been shown in Table III-C.

C. Comparing the Datasets

The Visual7W dataset contains 621,78 unique questions, 33,899 unique answers and 102,187 unique question-answer pairs. The VQG-16 dataset contains 97,088 unique questions, 502 unique answers and 172,939 unique question-answer pairs. The new dataset developed by us in this paper, VQG-23, contains 207,088 unique questions, 579 unique answers and 299,510 unique QA pairs. Fig 4 shows a stacked plot of the number of unique questions, number of unique answers and number of question-answer pairs in the three datasets, thus giving a comparative view of the datasets.

To quantitatively compare among datasets, we define the variety of questions present in a dataset using as follows:

\[
\text{variety of questions} = \frac{\#\text{Unique Question-Answer pairs}}{\#\text{Unique Answers}} \tag{4}
\]

A higher value of this ratio indicates a higher variety of the questions present in the dataset. Even if a certain VQG model performs very well on a dataset with low variety, there would be a lesser chance of this performance being reflected in the real world where the varieties will be more. Thus, it is preferable for datasets to have high values of variety as defined above. We compute this ratio to be 3.01 for Visual7W, 3.44 for VQG-16 and 517.29 for VQG-23, implying that the VQG-23 dataset developed in this work has substantially higher variety of questions. This ratio also helps explain the lesser gap in performance accuracy from the baselines in Visual7W in comparison to the VQG-16 and VQG-23 datasets.

D. Evaluation metrics

Following standard practice, we use BLEU[67], METEOR[68], ROUGE-L[69] and CIDEr[70] to measure the quality of the generated questions.

E. Results

Table II and Table III show the comparison of performance among the few-shot learning approaches also the traditional VQG approaches on VQG-16, Visual7W and VQG-23 datasets respectively. To understand the significance of different types of side-information, we evaluated the few-shot approaches using different combinations of categories and answers (indicated by checkmarks in ‘Cat’ and ‘Ans’ columns of the tables).
We also use different types of image and text embeddings for our approaches. Specifically, we use pre-trained ResNet-152 [71] and Efficientnet-b3 [72] image encoders (denoted by ‘Res’ and ‘Eff’ respectively, in the ‘Encoders’ column of the table). Also we either learn the word embeddings from scratch or use pretrained BERT [56] embeddings (denoted by ‘Scr’ and ‘Bert’ respectively, in the ‘Encoders’ column of the table). Table IV shows the questions generated by various models for some example images. Table II and III show that the approaches tailored towards few-shot learning (lower part of the tables) outperform all the tradition VQG approaches in all three datasets. This observation emphasizes the need for specialized models for few-shot VOG.

**Meta Learning vs Transfer Learning with Self-Supervision:** Transfer learning is known to perform inferior to meta-learning methods in few-shot scenario [14]. However, it would be interesting to see how transfer learning paired with self-supervision compares with meta learning methods. To this end, we evaluated SelfSup-FSVQG on all the datasets. In comparison to Meta-FSVQG-NoSS, the performance of SelfSup-FSVQG is relatively lower on VQG-16 and VQG-23, and superior on Visual7W. This shows that transfer learning paired with self-supervision performs poorly if the dataset is diverse (as for VQG-16 and VQG-23) and outperforms meta-learning when the dataset is less diverse (as is the case with Visual7w).

**Meta Learning vs #Parameters:** To better understand the effect of the number of trainable parameters on meta-learning based approaches for few-shot learning, we applied MAML to the traditional VQG approach containing the highest number of trainable parameters, iQAN, which also happens to be best performing among traditional VQG approaches (last column of Table II lists the number of parameters). We call this model Meta-iQAN. Much lower performance of Meta-iQAN compared to iQAN shows that deep state-of-the-art VQG models may not be efficiently adapted for Few-shot learning using meta-learning methods.

**Scaling-Shifting vs No Scaling-Shifting:** To understand how side information influences question generation in VQG, we considered two variations of our FSVOG model — (1) with scaling-shifting (Meta-FSVQG), and (2) without scaling-shifting (Meta-FSVQG-NoSS). From the results on Visual7W and VQG-23, we see that Meta-FSVQG outperforms Meta-FSVQG-NoSS over all the different variations, thereby indicating that side information can better influence the model to generate relevant questions by scaling and shifting of image features, than directly being appended to the input of LSTM as additional information. The better performance of Meta-FSVQG-NoSS over Meta-FSVQG on some metrics in VQG-16 dataset may be because of the possible misclassifications already present in VQG-16.

**Effect of side information:** We considered the availability of two types of side information in our approaches — (1) category and (2) answer. For Visual7W and VQG-23 datasets, the best
performance is obtained with category as side-information than with answer (even better than with both category and answer). For VQG-16, however, the best performance is obtained with both category and answer as input (as compared to that with only category or only answer as input). This difference may be because of the miscategorizations in VQG-16 (described earlier) due to which the models get confused. Overall, the ‘category’, if available, is seen to be a very useful side information for few-shot VQG.

Effect of pre-trained embeddings: Comparing the performance of our few-shot approaches in different settings, we observe the following. Replacing pre-trained Resnet-152 [71] feature maps with pre-trained Efficient-b3 [72] feature maps and using pretrained BERT [56] embeddings instead of learning them from scratch improves the performance, thereby indicating richer input features help the model learn better. Additional results and experimental details are provided in the supplementary.

V. LIMITATIONS AND CONCLUSION

We propose a novel few-shot VQG task and explored approaches based on meta-learning and self-supervised tasks that outperform traditional VQG models adapted for the purpose. We also construct a diverse and fine-grained dataset for few-shot VQG while highlighting drawbacks of the existing datasets.

Even though the meta and self-supervised learning based models perform reasonably in few-shot VQG, they are limited by their ability to generate relevant questions for images with intricate details. However, we consider this work as a start to the Few-Shot VQG and hope to see future works in this direction overcoming the associated challenges.

REFERENCES

[1] C. Manning and H. Schütze. Foundations of Statistical Natural Language Processing. MIT press, 1999.
[2] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh, “VQA: Visual Question Answering,” in International Conference on Computer Vision (ICCV), 2015.
[3] R. Cadene, C. Dancette, H. Ben-Younes, M. Cord, and D. Parikh, “VQA: Visual Question Answering,” in International Conference on Computer Vision (ICCV), 2019.
[4] P. Gao, H. You, Z. Zhang, X. Wang, and H. Li, “Multi-modality Interaction Network for Visual Question Answering,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019.
[5] H. Jiang, I. Misra, M. Rohrbach, E. Learned-Miller, and X. Chen, “In Defense of Grid Features for Visual Question Answering,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020.
[6] Y. Guo, L. Nie, Z. Cheng, Q. Tian, and M. Zhang, “Loss re-scaling vqa: revisiting the language prior problem from a class-imbalance view,” IEEE Transactions on Image Processing, vol. 31, pp. 227-238, 2021.
[7] R. Krishna, M. Bernstein, and L. Fei-Fei, “Information Maximizing Visual Question Generation,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019.
[8] Y. Li, N. Duan, B. Zhou, X. Chu, W. Qian, X. Wang, and M. Zhou, “Visual Question Generation as Dual Task of Visual Question Answering,” CVPR, 2018.
W.-Y. Chen, Y.-C. Liu, Z. Kira, Y.-C. F. Wang, and J.-B. Huang, “A Closer Look at Few-shot Classification,” in International Conference on Learning Representations, 2019.

Y. Wang, Q. Yao, J. T. Kwok, and L. M. Ni, “Generalizing from a Few Examples: A Few-shot Learning,” ACM Computing Surveys (CSUR), vol. 53, no. 3, pp. 1–34, 2020.

S. Upul, A. Madan, S. Bhagat, Y. Yu, and R. R. Shah, “C3VQG: Category Consistent Cyclic Visual Question Generation,” in Proceedings of the 2nd ACM International Conference on Multimedia in Asia, ser. MMAsia ’20. New York, NY, USA: Association for Computing Machinery, 2021.

C. Finn, P. Abbeel, and S. Levine, “Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks,” in International Conference on Machine Learning, ser. Proceedings of Machine Learning Research. PMLR, 2017, pp. 1126–1135.

Q. Sun, Y. Liu, T.-S. Chua, and B. Schiele, “Meta-Transfer Learning for Few-Shot Learning,” in IEEE Conference on Computer Vision and Pattern Recognition, June 2019.

X. Li, Q. Sun, Y. Liu, Q. Zhou, S. Zheng, T.-S. Chua, and B. Schiele, “Learning to Self-train for Semi-Supervised Few-shot Classification,” Neural Information Processing Systems, vol. 32, pp. 10276–10286, 2019.

M. A. Jamal and G.-J. Qi, “Task Agnostic Meta-learning for Few-Shot Learning,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 11719–11727.

A. Kurakin, C.-L. Li, C. Raffel, D. Berthelot, E. D. Cubuk, H. Zhang, K. Sohn, N. Carlini, and Z. Zhang, “Mixmatch: Simplifying semi-supervised learning with consistency and confidence,” in NeurIPS, 2020.

N. Komodakis and S. Gidaris, “Unsupervised representation learning by predicting image rotations,” in International Conference on Learning Representations (ICLR), 2018.

T. Chen, S. Kornblith, K. Swersky, M. Norouzi, and G. E. Hinton, “Big Self-Supervised Models are Strong Semi-Supervised Learners,” in International Conference on Learning Representations, 2020.

K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick, “Momentum Contrast for Unsupervised Visual Representation Learning,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9729–9738.

S. Gidaris, A. Bursuc, N. Komodakis, P. Pérez, and M. Cord, “Boosting few-shot visual learning with self-supervision,” in Proceedings of the IEEE International Conference on Computer Vision, 2019.

R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma et al., “Visual Genome: Connecting Language and Vision using Crowdsourced Dense Image Annotations,” International journal of computer vision, vol. 123, no. 1, pp. 32–73, 2017.

Y. Zhu, O. Groth, M. Bernstein, and L. Fei-Fei, “Visual7w: Grounded question answering in images,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4995–5004.

G. Gao, R. Wang, S. Shan, and X. Chen, “From two graphs to n questions: A vqa dataset for compositional reasoning on vision and commonsense,” arXiv preprint arXiv:1908.02962, 2019.

T. Wang, J. Huang, H. Zhang, and Q. Sun, “Visual commonsense r-cnn,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 10760–10770.

R. Zellers, Y. Bisk, A. Farhadi, and Y. Choi, “From recognition to cognition: Visual commonsense reasoning,” in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 6713–6724.

S. Shah, A. Mishra, N. Yadati, and P. P. Talukdar, “Kvqa: Knowledge-aware visual question answering,” vol. 33, no. 01, Jul. 2019, pp. 8876–8884.

G. Li, X. Wang, and W. Zhu, “Boosting visual question answering with context-aware knowledge aggregate,” in Proceedings of the 26th ACM International Conference on Multimedia, 2020, pp. 1227–1235.

A. K. Singh, A. Mishra, S. Shekhaw, and A. Chakraborty, “From strings to things: Knowledge-enabled vqa model that can read and reason,” in Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), October 2019.

L. Fei-Fei, R. Fergus, and P. Perona, “One-Shot Learning of Object Categories,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 4, pp. 594–611, 2006.

G. Koch, R. Zemel, and R. Salakhutdinov, “Siamese Neural Networks for One-Shot Image Recognition,” in ICML deep learning workshop, vol. 2, 2015.

O. Vinyals, C. Blundell, T. Lillicrap, K. Kavukcuoglu, and D. Wierstra, “Matching Networks for One Shot Learning,” in Neural Information Processing Systems, 2016, pp. 3637–3645.

J. Snell, K. Swersky, and R. Zemel, “Prototypical Networks for Few-Shot Learning,” in Neural Information Processing Systems, 2017, pp. 4087–4095.

Y.-X. Wang, R. Girshick, M. Hebert, and B. Hariharan, “Low-Shot Learning from Imaginary Data,” in IEEE conference on computer vision and pattern recognition, 2018, pp. 7278–7286.

J. Kim, T.-H. Oh, S. Lee, F. Pan, and I. S. Kweon, “Variational Prototyping-Encoder: One-Shot Learning with Prototypical Images,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 9462–9470.

A. Khoreva, R. Benenson, E. Ilg, T. Brox, and B. Schiele, “Lucid Data Dreaming for Object Tracking,” in The DAVIS challenge on video object segmentation, 2017.

A. Mehrotra and A. Dukkipati, “Generative Adversarial Residual Pairwise Networks for One Shot Learning,” arXiv preprint arXiv:1703.08033, 2017.

E. Schwartz, L. Karlinsky, J. Shott, S. Harary, M. Marder, A. Kumar, R. S. Feir, R. Giryes, and A. M. Bronstein, “Delta-Encoder: An Effective Sample Synthesis Method for Few-shot Object Recognition,” in NeurIPS, 2018.

A. Sahoo, A. Singh, R. Panda, R. Feris, and A. Das, “Mitigating Dataset Imbalance via Joint Generation and Classification,” in European Conference on Computer Vision Workshop on Imbalance Problems in Computer Vision. Springer, 2020, pp. 177–193.

S. Ravi and H. Larochelle, “Optimization as a Model for Few-Shot Learning,” in International Conference on Learning Representations, 2017.

A. Antoniou, H. Edwards, and A. Starkey, “How to Train your MAML,” in International Conference on Learning Representations, 2019.

L. A. Hendricks, S. Venugopalan, M. Rohrbach, R. Mooney, K. Saenko, and T. Darrell, “Deep Compositional Captioning: Describing Novel Object Categories without Paired Training Data,” in IEEE conference on computer vision and pattern recognition, 2016, pp. 1–10.

S. Venugopalan, L. Anne Hendricks, M. Rohrbach, R. Mooney, T. Darrell, and K. Saenko, “Captioning Images with Diverse Objects,” in IEEE conference on computer vision and pattern recognition, 2017, pp. 5753–5761.

X. Chen, M. Jiang, and Q. Zhao, “Self-Distillation for Few-Shot Image Captioning,” in IEEE Winter Conference on Applications of Computer Vision, 2021, pp. 545–555.

D. Teney and A. van den Hengel, “Zero-shot visual question answering,” arXiv e-prints, pp. arXiv–1611, 2016.

—, “Visual question answering as a meta learning task,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 219–235.

X. Dong, L. Zhu, D. Zhang, Y. Yang, and F. Wu, “Fast parameter adaptation for few-shot image captioning and visual question answering,” ser. MM ’18. New York, NY, USA: Association for Computing Machinery, 2018.

G. E. Hinton and R. R. Salakhutdinov, “Reducing the Dimensionality of Data with Neural Networks,” science, vol. 313, no. 5786, pp. 504–507, 2006.

D. Pathak, P. Krähenbühl, J. Donahue, T. Darrell, and A. A. Efros, “Context Encoders: Feature Learning by Inpainting,” in IEEE conference on computer vision and pattern recognition, 2016, pp. 2536–2544.

C. Doersch, A. Gupta, and A. A. Efros, “Unsupervised Visual Representation Learning from Imaginary Data,” in IEEE International Conference on Computer Vision, 2015, pp. 1422–1430.

A. Dosovitskiy, P. Fischer, J. T. Springenberg, M. Riedmiller, and T. Brox, “Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 9, pp. 1734–1747, 2015.

R. Zhang, P. Isola, and A. A. Efros, “Colorful Image Colorization,” in European Conference on Computer Vision. Springer, 2016, pp. 649–666.
[54] R. Kiros, Y. Zhu, R. R. Salakhutdinov, R. Zemel, R. Urtasun, A. Torralba, and S. Fidler, “Skip-thought Vectors,” in Neural Information Processing Systems, 2015, pp. 3294–3302. 3

[55] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, “Deep Contextualized Word Representations,” in Proceedings of NAACL-HLT, 2018, pp. 2227–2237. 3

[56] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Jun. 2019, pp. 4171–4186. 3, 4, 5, 7, 8

[57] B. Zoph, G. Ghiasi, T.-Y. Lin, Y. Cui, H. Liu, E. D. Cubuk, and Q. V. Le, “Rethinking Pre-training and Self-training,” Neural Information Processing Systems, vol. 33, 2020. 3

[58] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and K. Toutanova, “Rethinking Pre-training and Self-training,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Jun. 2019, pp. 4171–4186. 3, 4, 5, 7, 8

[59] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, E. Perez, F. Strub, H. de Vries, V. Dumoulin, and A. C. Courville, “Film: Visual reasoning with a general conditioning layer,” in AAAI, 2018. 4

[60] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” in Neural Information Processing Systems, 1997. 4

[61] A. Singh, O. Chakraborty, A. Varshney, R. Panda, R. Feris, K. Saenko, and A. Das, “Semi-Supervised Action Recognition with Temporal Contrastive Learning,” in IEEE Conference on Computer Vision and Pattern Recognition, 2021, pp. 10389–10399. 3

[62] B. Thomee, D. A. Shamma, G. Friedland, B. Elizalde, K. Ni, D. Poland, D. Bahdanau, K. Cho, and Y. Bengio, “Neural Machine Translation by Jointly Learning to Align and Translate,” in ICLR 2015, 2015. 4

[63] D. Bahdanau, K. Cho, and Y. Bengio, “Neural Machine Translation by Jointly Learning to Align and Translate,” in ICLR 2015, 2015. 4

[64] D. Chen, Y. Chen, Y. Li, F. Mao, Y. He, and H. Xue, “Self-supervised learning for few-shot image classification,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2021, pp. 1745–1749. 5

[65] 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 Computer Vision – ECCV 2014, D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, Eds. Cham: Springer International Publishing, 2014, pp. 740–755. 6

[66] B. Thomee, D. A. Shamma, G. Friedland, B. Elizalde, K. Ni, D. Poland, D. Borth, and L.-J. Li, “Yfcc100m: The new data in multimedia research,” Commun. ACM, vol. 59, no. 2, pp. 64–73, Jun. 2016. 6

[67] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “Bleu: a method for automatic evaluation of machine translation,” in Proceeding of the 40th annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318. 6

[68] A. Lavie and A. Agarwal, “Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments,” in Proceedings of the second workshop on statistical machine translation, 2007, pp. 228–231. 6

[69] T.-Y. Lin, “Rouge: A package for automatic evaluation of summaries,” in Text summarization branches out, 2004, pp. 74–81. 6

[70] R. Vedantam, C. L. Zitnick, and D. Parikh, “Cider: Consensus-based image description evaluation,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 4566–4575. 6

[71] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” CoRR, vol. abs/1512.03385, 2015. 7, 8

[72] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. PMLR, 09–15 Jun 2019, pp. 6105–6114. 7, 8

[73] A. Lavie and A. Agarwal, “Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments,” in Proceedings of the second workshop on statistical machine translation, 2007, pp. 228–231. 6

[74] T.-Y. Lin, “Rouge: A package for automatic evaluation of summaries,” in Text summarization branches out, 2004, pp. 74–81. 6

[75] R. Vedantam, C. L. Zitnick, and D. Parikh, “Cider: Consensus-based image description evaluation,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 4566–4575. 6

[76] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” CoRR, vol. abs/1512.03385, 2015. 7, 8

[77] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. PMLR, 09–15 Jun 2019, pp. 6105–6114. 7, 8

[78] A. Lavie and A. Agarwal, “Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments,” in Proceedings of the second workshop on statistical machine translation, 2007, pp. 228–231. 6

[79] T.-Y. Lin, “Rouge: A package for automatic evaluation of summaries,” in Text summarization branches out, 2004, pp. 74–81. 6

[80] R. Vedantam, C. L. Zitnick, and D. Parikh, “Cider: Consensus-based image description evaluation,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 4566–4575. 6

[81] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” CoRR, vol. abs/1512.03385, 2015. 7, 8

[82] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. PMLR, 09–15 Jun 2019, pp. 6105–6114. 7, 8

Anurag Roy is currently doing his Ph.D. in the Department of Computer Science and Engineering of IIT Kharagpur. He is co-supervised by Dr. Abir Das and Dr. Saptarshi Ghosh. He did his B.E. from IEST Shibpur in 2017. He research interests lie in few-shot learning, meta-learning and continual learning.

David Johnson Ekka is currently a Senior Software Engineer at Persistent Systems, India. He did his M.Tech in Computer Science and Engineering from IIT Kharagpur, India, in 2021. He did his B.Tech in Computer Science from Odisha University of Technology and Research in 2019.

Saptarshi Ghosh is currently an Assistant Professor with the Department of Computer Science and Engineering, IIT Kharagpur and the head of a Max Planck Partner Group at IIT Kharagpur. He received his Ph.D. from IIT Kharagpur, India, in 2013. He was a Humboldt Postdoctoral Fellow with the Max Planck Institute for Software Systems, Saarbrücken, Germany. His research interests include Social network analysis, Legal analytics, and Algorithmic bias and fairness.

Abir Das received the B.E. degree in electrical engineering from Jadavpur University, India, in 2007, and the M.S. and Ph.D. degrees in electrical engineering from the University of California, Riverside, CA, USA, in 2013 and 2015, respectively. He was a Postdoctoral Researcher at the Computer Science Department, Boston University. He is currently an Assistant Professor with the Computer Science and Engineering Department, IIT Kharagpur, India, and also the Director of the Computer Vision and Intelligence Research (CVIR) Group. His main research interests include visual scene understanding, language and vision and explainable AI.