From Known to the Unknown: Transferring Knowledge to Answer Questions about Novel Visual and Semantic Concepts

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Abstract

Current Visual Question Answering (VQA) systems can answer intelligent questions about ‘Known’ visual content. However, their performance drops significantly when questions about visually and linguistically ‘Unknown’ concepts are presented during inference (‘Open-world’ scenario). A practical VQA system should be able to deal with novel concepts in real-world settings. To address this problem, we propose an exemplar-based approach that transfers learning (i.e., knowledge) from previously ‘Known’ concepts to answer questions about the ‘Unknown’. We learn a highly discriminative joint embedding space, where visual and semantic features are fused to give a unified representation. Once novel concepts are presented to the model, it looks for the closest match from an exemplar set in the joint embedding space. This auxiliary information is used alongside the given Image-Question pair to refine visual attention in a hierarchical fashion. Since handling the high dimensional exemplars on large datasets can be a significant challenge, we introduce an efficient matching scheme that uses a compact feature description for search and retrieval. To evaluate our model, we propose a new split for VQA, separating Unknown visual and semantic concepts from the training set. Our approach shows significant improvements over state-of-the-art VQA models on the proposed Open-World VQA dataset and standard VQA datasets.

1. Introduction

Machine vision algorithms have significantly evolved various industries such as internet commerce, personal digital assistants and web-search. A major component of machine intelligence comprises of how well it can comprehend visual content. A Visual Turing Test to assess a machine’s ability to understand visual content is performed with the Visual Question Answering (VQA) task. Here, machine vision algorithms are expected to answer intelligent questions about visual scenes. The current VQA paradigm is not without its grave weaknesses. One key limitation is that the questions asked at inference time only relate to the concepts that have already been seen during the training stage (closed-world assumption).

In the real world, humans can easily reason about visually and linguistically Unknown concepts based on previous knowledge about the Known. For instance, having seen visual examples of ‘lion’ and ‘tiger’, a person can recognize an unknown ‘liger’ by associating visual similarities with a new compositional semantic concept and answer intelligent questions about their count, visual attributes, state and actions. In order to design machines to mimic human visual comprehension abilities, we must impart lifelong learning mechanisms that allow them to accumulate and use past knowledge to relate Unknown concepts. In this paper, we introduce a novel VQA problem setting that evaluates models in an ‘Open-World’ dynamic scenario where previously unknown concepts show up during the test phase (Fig. 1).

1Dataset and models will be available at: TBA
An open-world VQA setting requires a vision system to acquire knowledge over time and later use it intelligently to answer complex questions about Unknown concepts for which no linguistic+visual examples were available during training. Existing VQA systems lack this capability as they use a ‘fixed model’ to acquire learning and envisage answers without explicitly considering closely related examples from the knowledge base. This can lead to ‘catastrophic forgetting’ as the object/question set is altered with updated categories. Here, we develop a flexible knowledge base (only comprising of the training examples) that stores the joint embeddings of visual and textual features. Our proposed approach learns to utilize past knowledge to answer questions about unknown concepts.

Related to our work, we note a few recent efforts in the literature that aim to extend VQA beyond the already known concepts [27, 1, 23, 20, 16]. A major limitation of these approaches is that they introduce novel concepts only on the language side (i.e., new questions/answers), either to re-balance the split or to prevent the model cheating by removing biases [21, 23, 16]. Further, they rely on external data sources (both visual and semantic) and consider training splits that contain visual instances of ‘novel objects’, thereby violating the unknown assumption [20, 23]. To bridge this gap, we propose a new Open World VQA (OW-VQA) protocol for novel concepts based on MS-COCO and VQA-v1-v2 datasets. Our major contributions are:

- We reformulate VQA in a transfer learning setup that uses closely related Known instances from the exemplar set to reason about Unknown concepts.
- We present a novel network architecture and training schedule that maintains a knowledge base of exemplars in a rich joint embedding space that aggregates visual and semantic information.
- We propose a hierarchical search and retrieval scheme to enable efficient exemplar matching on a high dimensional joint embedding space.
- We propose a new OW-VQA split to enable impartial evaluation of VQA algorithms in a real-world scenario and report impressive improvements over recent approaches with our proposed model.

2. Related Works

Multi-modal Information Fusion: VQA is an AI complete task that requires high-level multimodal reasoning both in visual and language domains. The recent literature in VQA mostly focus on the optimal mechanisms to fuse multimodal cues. A simple fusion approach was used by Lu et al. [17] that progressively combines multimodal features using concatenations and sum-pooling operations. Xu et al. [29] proposed a recurrent neural network to generate intelligent image captions by considering the previously predicted words and targeted visual content. Bilinear models provide an effective way to model complex interactions, but impose restrictions due to computational intractability for high-dimensional inputs. Efficient versions of bilinear pooling were used in [10, 13] to learn the second-order interactions between visual and language features. To further speed-up the computations, Ben-younes et al. [3] introduced a Tucker fusion scheme that first projects the individual modalities to low dimensions and subsequently learns full bilinear relationships. Recently, Farazi et al. [8] fused complementary object level features alongside image level descriptors to achieve superior performance.

VQA for Novel Concepts: A VQA engine is highly likely to encounter questions about totally unknown objects. Some recent attempts to propose novel concept splits for VQA only consider the language side [1, 23, 20, 16]. Goyal et al. [11] showed that existing VQA datasets have highly correlated answers on train and test sets. As a result, VQA models tend to remember the popular answers instead of attending to correct image details for correct answer. They subsequently proposed new protocols with distinct distributions of answers in both sets to have a fair evaluation protocol. On similar lines, Agrawal et al. [1] proposed a new split for VQA where train and test sets have different prior distributions for each question type. Teney and Hengel [23] also highlighted that current VQA models are biased towards rare and unseen concepts and proposed a zero-shot split only for language content (i.e., Q&A). We note that the above-mentioned methods only suggest a language based split and the visual concepts may still appear visually during the training process. Therefore, they do not satisfy the zero-shot assumption.

Exemplars for VQA: Although most VQA approaches only work with the given training set, some efforts explore the use of supplementary information to help the VQA system. Generally, such methods employ external knowledge sources (both textual and visual) to augment the training set. For example, Teney et al. in [23, 22] used web searches to find related images which were used for answer prediction. Language based external knowledge bases were used by Wang et al. [26] and Wu et al. [28] to provide logical reasons for each answer choice and to answer a more diverse set of questions. More recently, Teney et al. [24] proposed a meta-learning approach that learns to use an externally supplied support set comprising of example questions-answers. In contrast to these approaches, we do not use any external data, rather learn an attention function that learns to use similar examples from the training set to provide better inference-time predictions. Patro et al. [19] proposed a differential attention mechanism that uses an exemplar from the training set to generates human-like attention maps, however does not consider a transferable attention function that can reason about new visual/semantic concepts.
3. Methods

Given a question \( Q \) about an image \( I \), an AI agent designed for the VQA task will predict answer \( a^* \) based on the learning acquired from training examples. This task can be formulated as:

\[
a^* = \arg \max_{a \in \mathcal{D}} P(\hat{a}|Q, I; \theta)
\]  

(1)

where \( \theta \) denotes the model parameters and \( a^* \) is predicted from the dictionary of possible answers \( \mathcal{D} \). An ideal VQA system should effectively model the complex interactions between the language and visual domains to acquire useful knowledge and use it to answer newly presented questions at test time. Towards this end, we propose a framework to answer questions about novel concepts in Fig. 2. The overall pipeline is based on four main steps: (1) Joint Feature Embedding: The given IQ pair is processed to extract visual \( v \) and language \( q \) features. These features are jointly embedded into a common space through multi-modal fusion. (2) Transfer Learning with Exemplars: We propose an exemplar-based model that learns to reason from similar examples known during training time. When presented with a test image containing an Unknown concept, our model transfers the knowledge acquired on closely related examples of Known concepts to novel cases. (3) Visual Attention: In the next stage, the proposed network selectively attends to visual scene details using the joint feature embedding of given inputs and the exemplars (output of step 1 and 2 respectively). This ensures that the model learns to identify salient features to answer a specific question. (4) Answer Prediction: During the final stage, the refined joint embedding is calculated by the model to predict the correct answer \( a^* \) from the answer set \( A \), minimizing a cross entropy loss.

3.1. Joint Feature Embedding

From the given image \( I \), the \( n_v \)-dimensional visual feature embedding \( v \in \mathbb{R}^{n_v} \) is extracted from the last convolutional layers just before the global pooling and classification layer of the feature extraction model (i.e., ResNet [12]). The language feature embedding \( q \in \mathbb{R}^{n_q} \) is generated from \( Q \) by first encoding the question in a one-hot-vector representation and then embedded into vector space using Gated Recurrent Units (GRUs) [6, 9]. In order to predict a correct answer, a VQA model needs to generate a joint embedding: \( e = \Phi(v, q; \tau) \in \mathbb{R}^{n_e} \). A naive approach that models visual-semantic interactions using a tensor \( \tau \in \mathbb{R}^{n_q \times n_v \times n_e} \) will result in an unrealistic number of trainable parameters (e.g., \( \sim 9.83 \) billion for our baseline model).

To reduce the dimensionality of the tensor, we use Tucker decomposition [25] which can be seen a high-order principal component analysis operation. This technique has been proven effective in embedding visual and textual features for VQA [8, 5]. It approximates \( \tau \) as follows:

\[
\tau = \sum_{i=1}^{t_q} \sum_{j=1}^{t_v} \sum_{k=1}^{t_e} \omega_{ijk} \tau_q^i \circ \tau_v^j \circ \tau_e^k
\]

\[
= \omega \times_1 \tau_q \times_2 \tau_v \times_3 \tau_e = [\omega; \tau_q, \tau_v, \tau_e]
\]  

(2)

where \( \times_i \) denotes n-mode product of a tensor with a matrix and \( \circ \) denotes the outer vector product. Eq. 2 means that tensor \( \tau \) is decomposed into a core tensor \( \omega \in \mathbb{R}^{t_q \times t_v \times t_e} \) and orthonormal factor matrices \( \tau_q \in \mathbb{R}^{n_q \times t_q} \), \( \tau_v \in \mathbb{R}^{n_v \times t_v} \), \( \tau_e \in \mathbb{R}^{n_e \times t_e} \). Intuitively, by setting \( t_q < n_q, t_v < n_v \) and \( t_e < n_e \) of the factored matrices, one can approximate \( \tau \) with only a fraction of originally required number of trainable parameters.
The output embedding $e$ from the Tucker decomposition effectively captures the interactions between semantic and visual features for a given Image-Question-Answer (IQA) triplet. Such joint embedding for VQA is specific to the given IQ pair because the same visual feature associated with different semantics (and vice-versa) will result in a different joint embedding specific for that pair. For example, given an image that captures children playing in the backyard, when asked ‘How many children are in the picture?’ and ‘Are the children happy?’ requires two very different joint embeddings $e$ even though they use the same visual feature, $v$. Building on this rich joint embedding, we develop a transfer learning module based on exemplars.

### 3.2. Exemplar based Learning Transfer

Given a question about an Unknown concept, our model identifies a similar joint embedding of Known concepts from the training set. Since, visual/semantic examples of unknown concepts are not available to us during training, first we learn a generic attention function $A$ that can transfer knowledge from the Known concepts to Unknown. The attention function is learned on the training set, where it identifies the useful features from closely related exemplars to answer questions. The function $A$ is agnostic to specific IQ pairs and provides a generalizable mechanism to identify relevant information from related examples. Therefore, at inference time, we use the same exemplar based attention function to obtain refined attention maps by using the closely related joint embedding of known concepts.

We design the training schedule in two stages to facilitate knowledge transfer. During the first stage, only the Visual-Semantic embedding part of the network is trained end-to-end and the joint feature embedding tensor $e$ is stored in memory $\xi \in \mathbb{R}^{d \times n}$, where $n$ is the number of training IQA triplets and $d$ denotes the embedding dimension. In the second stage, both the visual-semantic embedding and the exemplar-embedding segment of the model are trained end-to-end where the model performs a nearest neighbour (NN) search on $\xi$ to find the most similar joint embedding $e_\xi$. Further, the network learns to use the exemplar embedding to refine the attention on visual scene details. This can be represented as:

$$\tilde{v}_\xi = A(v, e_\xi), \quad \text{where, } e_\xi = N(e, \xi, \kappa),$$

where, $e_\xi$ is the exemplar-embedding found using nearest neighbour search ($N$) on a set of compact embeddings $\kappa$.

There are two main motivations for not performing the NN search directly on $\xi$ and instead using a set of compact embeddings $\kappa$. Firstly, searching in the joint embedding space would allow the model to overfit when searching for the closest match. However, when searching for the closest match for a compact representation of the joint embedding, the reduced dimensionality of the representation avoids overfitting. Secondly, storing and performing NN search directly on the joint embedding exemplar space is extremely memory and time intensive. For example, if visual features are extracted from the second-last convolution layer of ResNet152\[12\] for evaluation on VQAv2\[11\] dataset, $\xi$ will be $\mathbb{R}^{n \times d}$ dimensional where $n \approx 400K$ training examples and $d = t_c \times G$ such that grid locations $G = 14 \times 14$ and $t_c \approx 500$ for a standard setting. Doing a similarity match on such a large space has practical memory and computational limitations.

Due to the above-mentioned reasons, we generate a coarse representation of $\xi$ by passing each of its elements through a max-pooling layer. We empirically found max-pooling to perform well in our case. The set of max-pooled embeddings is represented by $\kappa$, whose entries act as soft-indices for the exemplar-embeddings. When a query embedding $e$ is presented, we calculate its compact feature $e^\kappa$ by applying a max-pooling operation. The NN search is performed between $e^\kappa$ and each element of $\kappa$ to find the embedding $e^\xi$. As the elements of $\xi$ and $\kappa$ have a one-to-one relationship, by matching the maxpooled version of $e$ to $\kappa$, the model finds the exemplar embedding $e$. Notably, with this setup, we do not require the large set of exemplars $\xi$ to be loaded into memory, instead a much more compact representation is used for efficient search and retrieval.

### 3.3. Visual Attention

Attention is applied at two levels in our network. At the first level, the joint embedding $e$ is used to apply attention on visual features to focus model attention on more important features. The joint embedding is passed through a FC (fully connected) layer followed by a softmax layer to generate an attention vector $v_{IQ}^e \in \mathbb{R}^G$ which scores each spatial grid location $G$ of visual feature $v$ according to input IQ pair. At the second level, we select $v_G$, the most similar exemplar embedding of $e$, and follow the same protocol to generate another attention score $v_{\xi}^e$ over spatial grid locations. The attention vectors $v_{IQ}^e$ and $v_{\xi}^e$ signify complementary proposals generated using a given IQ pair and the most similar visual-semantic embedding from the exemplar set respectively. Such a complementary attention mechanism allows the model to reason about unknown concepts using the attention calculated from the combined effect of the input IQ pair and further refine it by looking at the closest example from the exemplar set. Both the IQ pair and the exemplar-based attention vectors are used to take a weighted sum at each location $g$ of the input visual representation $v$ (i.e., $v^g$) to create an attended visual representation. This can be formulated as:

$$\tilde{v}_{IQ} = \sum_{g=1}^{G} v^g v_{IQ}^e, \quad \text{and} \quad \tilde{v}_\xi = \sum_{g=1}^{G} v^g v_{\xi}^e,$$  

$$\tilde{e} = \sum_{g=1}^{G} v^g e^\kappa,$$

4
where $\tilde{v}_{IQ}$ and $\tilde{v}_E$ denote the attended visual features generated from the IQ pair and exemplar embedding respectively. We concatenate the two to create an overall attended visual feature $\tilde{v}$ and again apply $\Phi$ in a similar manner as described in Sec. 3.1 to generate the final vision-semantic embedding. We then project the embedding to the prediction space that is passed through a classifier to predict the final answer $a^* \in D$.

4. OW-VQA dataset generation protocol

**Motivation:** When a VQA system is subjected to an open-world setting, it can encounter novel visual and semantic concepts that it has not seen during training. To help VQA systems develop capability to handle unknown visual and semantic concepts, we propose a new split that contains known/unknown concepts for training/testing respectively. Our dataset generation protocol builds on the fact that images in VQA datasets [4, 11] are repurposed from MSCOCO images [16] and paired with crowd sourced Q&A. Even though, MSCOCO images have rich object level annotation for 12 super-categories and 80 object categories, the VQA dataset annotations include only information related to Q&A, excluding any link to object level annotation. This constitutes a significant knowledge gap which if addressed, would allow for more subtle understanding of the scene even if it contains previously unknown visual and semantic concepts. To bridge the gap, we propose to use Objects categories as the core entity to develop a true Known-Unknown split that constitutes both visual and semantic concepts. First, we propose an known-unknown split for the MSCOCO object categories, which leads to a well-founded split that separates known/unknown concepts in IQA triplets on VQA datasets.

**Known/Unknown Object Split:** At the first stage, from each MSCOCO super-category (except for person which has no sub-category), we select the rarest category as Unknown and the rest as Known. This choice is motivated by the fact that rare classes are most likely to be unknown. For each category $c$, we calculate $N_i$ and $N_t$ which represent the total number of images that $c$ appears in, and total number of instances of $c$ respectively. We define $N = N_i \times N_t$ as the measure of occurrence for each category. We select the category with the smallest $N$ as Unknown category. Fig. 3 shows the normalized $N$ for categories in each super category and respective Unknown categories (more details in supplementary material). This ensures that the unknown category appears in least number of images least number of times. Such a measure is particularly necessary for datasets that are used to perform high level vision tasks associated with a language component. For example in super-category vehicle, train is less frequent compared to airplane in terms of instances (4,761 vs 5,278). If the split was solely based on number of instances $N_i$, then train would have been selected as an unseen class even though it appears in 662 less number of images than airplane. When human annotators are tasked with generating language components (i.e. Q&A or captions), the rarest language cues are often associated with categories that appears in the least number of images, the least number of times. Thus, selecting the category with the least occurrence measure $N$ ensures that categories with least language representation are selected as Unknown.

**Image-Question-Answer Split:** Building on the Known-Unknown categories, we repurpose IQA triplets from VQAv1[4] and VQAv2[11], and propose training (known) and test (unknown) splits called OW-VQAv1 and OW-VQAv2. For this purpose, we combine training and validation sets of respective datasets (test split cannot be used as they are not publicly available). We use two steps to ensure that both visual and semantic concepts associated with the Unknown categories are completely absent in the training set. Firstly, we place an IQA triplet in the training set if there is no instance of any unseen category in the image of the corresponding triplet. This ensures that the new visual concepts are unknown to the model during training. Secondly, we focus on the semantic part and filter out the IQA triplets from the training set that have any un-
known category names or synonyms in the questions. Such 
visual and semantic confinement of concepts in train/test 
split is the major advantage that our proposed dataset has 
over other approaches [20, 23, 1] where the unseen ‘ob- 
jects/concepts’ are only defined at semantic-level. For ex-
ample, airplane is an ‘unseen category’ in our proposed 
dataset and a ‘novel object’ in the dataset proposed by Ra-
makrishnan et al. [20]. A semantically motivated dataset 
generation protocol would place an IQA triplet that does not 
have the keyword airplane in the question, in the training 
set. However, there are several IQA triplets in VQA dataset 
that shows an airplane being serviced by a car, truck or 
an airplane at an airport, and do not ask about the air-
plane. Just ensuring that the semantic concepts are not present dur-
ing training only addresses a naive version of the challenge 
an open-world VQA system would face.

5. Experiments

In this section, we first describe the experimental setup 
and implementation details of our proposed model. Then 
we present the baseline model architectures using different 
combinations of visual and semantic features to gener-
ate joint embedding. Then we present the results of our 
experiments which includes benchmarking of VQA models 
on OW-VQA dataset, ablation and performance analysis of 
our proposed model on semantically motivated VQA splits 
and standard VQA setting.

5.1. Experimental Setup

Feature Extraction and Fusion: We use Facebook’s 
implementation of ResNet152 [12] to extract multilevel vi-
ual features from the input image by taking the output of 
the two last convolutional layers, \( v_1 \in \mathbb{R}^{2048 \times 14 \times 14} \) 
and \( v_2 \in \mathbb{R}^{2048} \) where \( v_1 \) represents spatial visual features at 
each image grid location \( G = 14 \times 14 \) and \( v_2 \) represents 
the pooled visual features at an image level. We use different 
combinations of \( v_1 \) and \( v_2 \) in the baseline models that 
undergo joint embedding with the question features. Se-
monic feature \( q \in \mathbb{R}^{2040} \) is generated in a manner similar to 
[8, 5, 9] where the question is encoded with skip-thought 

vectors [14] and passed through GRUs. When generating 
the visual-semantic embedding, we set \( t_v = t_q = 310, t_e = 510 \) 
and use two glimpse attention following the literature [8, 5], 
making the joint embedding \( G \times 510 \) dimensional. 

Exemplar Implementation: We store the joint embed-
dings \( e \) of randomly selected 10% IQ pairs from the training 
set in \( \xi \). Our experiments show that such a sub-sampling 
does not degrade the performance while significantly im-
proving computational efficiency. To generate the compact 
embedding or Soft-key set \( \kappa \), Max Pooling is applied on 
each entry of \( \xi_i \in \mathbb{R}^{1196 \times 510} \) to generate the compressed 
embedding \( \kappa_i \in \mathbb{R}^\rho \) for \( \xi_i \). For our experiments we set \( \rho = 140 \) which was found optimal through our experiments. 
We represent \( \kappa \) using a K-D tree data structure. During test-
ing and second stage of training, we query on \( \kappa \) to find the 
index of the closest match to the max-pooled \( e \) by perform-
ing k-nearest neighbour search (\( k = 1 \)), and get the joint 
embedding from \( \xi \) for that index and set as \( e_\xi \).

Answer Classifier: We create the answer set \( D \) with 
most frequent 2000 answers from the training set and for-
mulate the VQA task as a multi-class classification problem 
on the answer set \( \xi \in \mathbb{R}^{2000} \) following VQA benchmark 
[4]. The final attended visual-semantic feature representa-
tion \( \tilde{\phi} \) is passed through a fully connected layer to project to 
answer embedding space where softmax cross entropy loss 
is applied to predict the most probable answer from \( D \).

5.2. Baseline Models

We first propose three strong baselines that build on the 
state-of-the-art Tucker fusion technique [8, 5] to generate 
visual-semantic embeddings for VQA. These baselines are: 
(a) In the Concatenation Model, we concatenate \( q \) and \( v_2 \) 
and generate the joint embedding \( e \) by applying multimodal 
fusion \( \Phi \) on \( q \) and \( (v_2 \oplus q) \). The joint embedding is used to 
refine grid level feature \( v_1 \) by applying attention \( \alpha \). (b) For 
Dual Attention Model, the \( e \) is generated as \( e = \Phi(q, v_2) \). 
This joint embedding generated from pooled image feature 
is used to apply attention on the grid level image feature 
\( v_1 \), and is thus called the dual attention model. (c) Finally, 
the Grid Attention Model only uses the grid level visual fea-
tures \( v_1 \). The joint embedding is generates as \( e = \phi(q, v_1) \) 
and it is used to apply attention on \( v_1 \) to refine the visual 
features based on semantic input. The Grid attention model

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Table 2. Evaluation on our proposed OW-VQA split when trained on Train-
valset (Trainset+Valset-Known) and evaluated on Testset.

|          | OW-VQA1 | OW-VQA2 |
|----------|---------|---------|
|          | All     | Y/N     | Num. | Other | All     | Y/N     | Num. | Other |
| JEX (Ours) | 61.7    | 81.2    | 40.3  | 48.5  | 57.8    | 74.8    | 37.1  | 47.6  |
| MUTAN [5]  | 60.3    | 80.6    | 39.5  | 48.1  | 56.9    | 74.7    | 36.2  | 46.9  |
| MCB [9]    | 59.7    | 73.1    | 36.9  | 46.1  | 55.5    | 71.8    | 35.5  | 45.7  |
| SAN [30]   | 55.7    | 76.0    | 40.2  | 39.8  | 50.6    | 67.2    | 34.5  | 39.4  |
| HitchAtt [17] | 55.6 | 77.3    | 42.1  | 37.7  | 50.7    | 67.4    | 35.1  | 38.5  |
| VQA [4]    | 54.1    | 77.3    | 37.2  | 35.9  | 49.8    | 68.1    | 37.1  | 35.7  |

Table 3. Performance drop when trained on known con-
cepts and evaluated on unseen concepts.

|          | OW-VQA1 | OW-VQA2 |
|----------|---------|---------|
|          | All     | Y/N     | Num. | Other | All     | Y/N     | Num. | Other |
| JEX (Ours) | 61.7    | 81.2    | 40.3  | 48.5  | 57.8    | 74.8    | 37.1  | 47.6  |
| MUTAN [5]  | 60.3    | 80.6    | 39.5  | 48.1  | 56.9    | 74.7    | 36.2  | 46.9  |
| MCB [9]    | 59.7    | 73.1    | 36.9  | 46.1  | 55.5    | 71.8    | 35.5  | 45.7  |
| SAN [30]   | 55.7    | 76.0    | 40.2  | 39.8  | 50.6    | 67.2    | 34.5  | 39.4  |
| HitchAtt [17] | 55.6 | 77.3    | 42.1  | 37.7  | 50.7    | 67.4    | 35.1  | 38.5  |
| VQA [4]    | 54.1    | 77.3    | 37.2  | 35.9  | 49.8    | 68.1    | 37.1  | 35.7  |
outperforms other baselines in our experiments (Table 3) which shows its effectiveness in jointly embedding visual-semantic features. Thus our proposed model uses $\theta_1$ to generate the joint embedding of the exemplars $E$.

5.3. Results

**Benchmarking VQA models on OW-VQA:** We benchmark existing VQA models on OW-VQA dataset and report their performance on both versions of our proposed VQA dataset split. From Table 2, we can see VQA models that incorporate multimodal (visual-semantic) embedding (i.e. pooling [9] or fusion [5]) compared to the models which only use semantic embedding to generate visual attention achieves higher performance in both versions of OW-VQA. Our exemplar based approach further refines the visual attention by transferring knowledge from exemplar set and we report 1.4% and 0.9% overall accuracy gain over the closet state-of-the-art method on both v1 and v2 respectively. Such an improvement without using any external knowledge base (i.e. complementary training on Visual Genome [15], external image and text corpora) and/or model ensemble justifies our approach of transferring knowledge from exemplars. Furthermore, the accuracy scores of VQA models reported in Table 2, drop significantly when evaluated OW-VQA v2 compared to v1 as the IQA triplets in v2 have less semantic bias. It can also be seen that the joint embedding attention models are more robust against semantic bias than semantic attention models (overall accuracy drop of $\sim$3.5% compared to $\sim$5.1%). This further strengthens our motivation to make use of such joint embedding space which capture highly discriminative multi-modal features.

**Performance drop when evaluated on Unknown:** We perform an ablation study to quantify the role of different components of our proposed model on OW-VQA-v2 dataset and compare the performance of our baseline models and full model, along with exemplar-attention-only variant. In this experiment, we train the models on Trainset and evaluate on Valset, Valset-known and Valset-Unknown which enables us to perform a comparative analysis on the models’ ability to reason about Known and Unknown concepts (see Table 3). We also report the number of trainable parameters required for each model. From the bar plot, it can be observed that all model variants achieved higher accuracy on Valset compared to Valset-Unknown and lower accuracy when compared with Valset-Known when trained with only Known concepts. Among the baseline methods, the grid attention variant achieves the highest accuracy with the least number of trainable parameters. Interestingly, when only the joint feature encoding from exemplar (exemplar-attention-only variant) is used, it achieves a relatively reasonable overall accuracy of $\sim$51%. This shows that the exemplar feature indeed encapsulates valuable information for the VQA task. Our full model incorporates both grid attention and exemplar attention with a small increase in the
number of trainable parameters, and achieves higher accuracy than the other variants. Furthermore, there is a significant drop in overall accuracy when tested on Unknown concepts compared to Known concepts which signifies the knowledge gap a VQA model needs to address when reasoning about Unknown concepts. In Table 3, note that accuracy difference between Known and Unknown concepts is 6.1 for JEX which is 12.68% lower than that of the gird attention model. This quantifies the value added by using exemplars to bridge that gap in comprehending Unknown concepts.

**Evaluation on semantically separated VQA splits:**
We evaluate our exemplar based approach on semantically motivated VQA-CP [1] and Novel VQA [20] datasets where the former separated the challenging semantic concepts in the testset and the latter placed least frequent nouns and associated IQA triplets in the testset. Although, our motivation is orthogonal and our definition of Novel Concepts is heterogeneous to these semantically motivated approaches, we showcase the effectiveness of our exemplar based approach on their settings. In Table 5, we compare the performance of JEX model on Novel-VQA split with performances of baseline and proposed methods (Arch-1 and Arch-2) reported in [20]. Our exemplar based approach outperforms the best variant of Arch-1 and Arch-2 by 13.3% and 15.2%. This is to be noted that even if the proposed approaches by Ramakrishnan et al. [20] incorporate external knowledge, both semantic (i.e. books) and visual (i.e. examples from ImageNet [7]), our model achieves superior performance by only leveraging information from training examples.

We also evaluate our model on both versions of VQA-CP dataset and report performance against other benchmarks and their proposed GVQA [1] dataset in Table 4. It shows that in VQA-CPv1, GVQA achieves a slightly higher (0.9%) Overall accuracy than JEX, but performs significantly low (18.8%) compared to JEX for Other type questions. GVQA employs separate question classifiers for Y/N and non-Y/N (i.e. Num, Other) questions that account for its high accuracy in Y/N questions which results in higher accuracy. However, when evaluated on VQA-CPv2, JEX outperforms GVQA in both Overall and Other question accuracy by 5.5% and 19.3% respectively because VQA-CPv2 has a more balanced distribution of question categories and a considerably lower language bias [11].

**Evaluation on standard VQA setting:** We evaluate our model on VQA2 validation set [11] and compare its performance with other attention based models. It is worth noting that we only compare with their single model without data augmentation which is similar to our setting for fair comparison. From Table 6 it can be seen that our model outperforms the Tucker decomposition based model by Benyounes et al. [5] which has a similar architecture to our baseline models. Further, it also outperforms the Support-Set model proposed by Teney et al. [24] in a similar setting where the support set contains example representation of question, answers and image. Interestingly, the overall accuracy of GVQA [1] without an ensemble and/or oracles is 18.9% lower than JEX in a standard VQA setting.

### 6. Conclusion

Existing VQA systems lack the ability to generalize their knowledge from training to answer questions about novel concepts encountered during inference. In this paper, we propose an exemplar-based transfer learning approach that utilizes the closest Known examples to answer questions about Unknown concepts. A joint embedding space is central to our approach, that effectively encodes the complex relationships between semantic, visual and output domains. Given the IQ pair and exemplar embedding in this space, the proposed approach hierarchically attends to visual details and focuses attention on the regions that are most useful to predict the correct answer. We propose a new Open-World VQA train/test split to fairly compare the performance of VQA systems on Known and Unknown concepts. Our exemplar based approach achieves significant improvements over the state-of-the-art techniques on the proposed OW-VQA setting as well as standard VQA setting, which reinforces the notion of transferring knowledge from rich joint embedding space to reason about Unknown concepts.

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2Compared with k=1, where only one nearest neighbour was used.
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Supplementary Material

A. Dataset generation protocol for OW-VQA

For each MSCOCO [16] category $c$, $N_i$ represents the number of images in which $c$ appears and $N_t$ represents the number of times $c$ appears in the dataset (i.e., total instances). These statistics are calculated after merging the MSCOCO Train2014 and Val2014 splits. Fig. 6 shows $N_i$ and $N_t$ for categories within each super-category of MSCOCO [16]. The category names are color-coded to represent the super-category labels and respective Unknown categories. From this figure, we can see that the categories which appear in the least number of images, the least number of times are selected as Unknown.

Table 7 presents statistics of VQA dataset following the proposed Known/Unknown concept separation protocol described in ‘Image-Question-Answer Split’ of Sec. 4 of the main paper. We can see from the statistics that Unknown categories are present in $\sim 16\%$ of training and validation images. Furthermore, it can be observed, when IQA triplets from the training and validation splits of the VQA datasets are separated on the basis of Known and Unknown concepts, the Unknown IQA triplets also amount to $\sim 16\%$ of the total. This is an indication that our dataset preparation protocol is able to uniformly separate Known and Unknown concepts even from crowd-sourced, complex, multi-modal dataset like VQA. Such uniform split allows for effective evaluation of a VQA models’ ability to reason with Unknown concepts.

The Trainset and Testset of the OW-VQA dataset consists of Known and Unknown IQA triplets from corresponding Train splits of VQA datasets respectively. We also propose two validation splits called Valset-Known and Valset-Unknown from the Val splits of VQA datasets. The Valset-Known contains Known IQA triplets and the Valset-Unknown contains Unknown IQA triplets from the Valset of respective version. The subdivision of Valset into Known and Unknown splits allows evaluation on both concept types.

B. Evaluation protocol for OW-VQA

There are two main ways to evaluate a models performance on the proposed OW-VQA dataset.

(a) For the purpose of debugging and running validation experiments, one can train a VQA model on OW-VQA Trainset and evaluate on Valset-Known or Valset-Unknown or the whole Valset. The OW-VQA v1 Trainset contains $\sim 187k$ IQA triplets, and Valset-Known and Valset-Unknown contains $\sim 101k$ and $\sim 19k$ IQA pairs respectively. The OW-VQA v2 has more IQA triplets, where the Trainset contains $\sim 336k$ IQA triplets, and Valset-Known and Valset-Unknown contains $\sim 178k$ and $\sim 34k$.

(b) To do a more comprehensive evaluation, it is recommended to train the model on OW-VQA Trainset and evaluate on Testset or Testset+Valset-Unknown, as they have more Unknown IQA pairs than Valset-Unknown. For OW-VQA v1 and v2, the Testset contains $\sim 36k$ and $\sim 66k$ IQA respectively. When combined with respective Valset-Unknown it presents an even larger setting to evaluate on Unknown concepts.

C. Additional results

Fig. 5 reports the overall accuracy of Grid Attention baseline model trained on Trainset and evaluated on validation splits of OW-VQA v1 and OW-VQA v2. It can be seen that the Known-Unknown accuracy gap is lower in v1 and higher in v2. This is due to the language bias present in VQA dataset and the model used this bias to correctly answer questions about Unknown concepts.

Table 8 reports the comparison of proposed JEX model and other contemporary VQA models on both versions of VQA-CPv1 and v2 [1], including accuracy scores of all question categories. It can be seen that GVQA [1] achieved higher accuracy on the Y/N questions than the proposed JEX model. As mentioned in the ‘Evaluation on semantically separated VQA splits’ part of Section 5.3 of the main paper, GVQA employs a separate training module for Y/N questions which helps achieve higher accuracy for Y/N questions. However, for all other question categories the proposed JEX model achieved higher accuracy than GVQA.
Figure 6. This bar chart shows number of images and number of times each category appears in the MSCOCO Train2014 and Val2014 dataset combined. The super-categories are color-coded and from each super-category one category is selected as Unknown.

| Image | MSCOCO[16] | VQAv1[4] | VQAv2[11] |
|-------|-------------|-----------|-----------|
|       | Total | Known | Unknown | Unknown% | Total | Known | Unknown | Unknown% |
| Image | | | | | | | | |
|       | 82,783 | 69,557 | 13,226 | 15.98 | 40,504 | 34,137 | 6,367 | 15.72 |
| IQA Tiplet | | | | | | | | |
| VQA-CP v1 | 224,040 | 187,986 | 36,054 | 16.09 | 120,916 | 101,815 | 19,101 | 15.80 |
| VQA-CP v2 | 402,691 | 336,124 | 66,568 | 16.53 | 213,266 | 178,321 | 34,945 | 16.39 |

Table 7. Statistics on VQAv1[4] and VQAv2[11] dataset following dataset generation protocol described in Sec. 4.

| VQA-CP v1 | All | Y/N | Num. | Other | VQA-CP v2 | All | Y/N | Num. | Other |
|-----------|-----|-----|------|-------|-----------|-----|-----|------|-------|
| JEX (Ours) | 38.3 | 43.7 | **12.5** | **43.7** | **36.8** | 41.4 | **12.1** | **41.4** |
| GVQA[1] | 39.2 | 64.7 | 11.9 | 24.9 | 31.3 | 58.0 | 11.7 | 22.1 |
| MCB[9] | 34.4 | 38.0 | 11.8 | 39.9 | 36.3 | 41.0 | 12.0 | 40.6 |
| SAN [30] | 26.9 | 35.3 | 11.3 | 24.7 | 25.0 | 38.3 | 11.1 | 27.7 |
| NMN [3] | 29.6 | 38.8 | 11.2 | 27.9 | 27.5 | 38.9 | 11.9 | 25.7 |
| VQA[4] | 23.5 | 34.5 | 11.4 | 17.4 | 19.8 | 34.3 | 11.4 | 14.4 |

Table 8. Detailed evaluation on VQA-CP[1] dataset.