Zero-Shot Visual Question Answering

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Abstract

Part of the appeal of Visual Question Answering (VQA) is its promise to answer new questions about previously unseen images. Most current methods demand training questions that illustrate every possible concept, and will therefore never achieve this capability, since the volume of required training data would be prohibitive. Answering general questions about images requires methods capable of Zero-Shot VQA, that is, methods able to answer questions beyond the scope of the training questions. We propose a new evaluation protocol for VQA methods which measures their ability to perform Zero-Shot VQA, and in doing so highlights significant practical deficiencies of current approaches, some of which are masked by the biases in current datasets. We propose and evaluate several strategies for achieving Zero-Shot VQA, including methods based on pretrained word embeddings, object classifiers with semantic embeddings, and test-time retrieval of example images. Our extensive experiments are intended to serve as baselines for Zero-Shot VQA, and they also achieve state-of-the-art performance in the standard VQA evaluation setting.

1. Introduction

The task of Visual Question Answering (VQA) spans the fields of computer vision and natural language processing by requiring an algorithm to answer a previously unseen text question about an image. The recent interest [13, 3, 30], in part, reflects the enthusiasm for VQA as an indicator of progress towards deep scene understanding, which is the overarching goal of computer vision [7, 14]. The ability to answer truly general questions about images would also constitute an concrete step towards real Artificial Intelligence.

A number of VQA datasets have been introduced, and a variety of methods have demonstrated impressive (yet possibly converging) results (see [30] for a survey). The training of most current VQA methods relies on a dataset of {question,image,answer} tuples illustrating all question types applied to all items of interest, in all situations of interest. No finite set of exemplars, however, can cover the diversity of the world that an ideal VQA system should be prepared to consider. A secondary problem with this approach is that the incentive to perform well on benchmark datasets that do not encourage addressing rare, or novel, words and concepts. Most current methods are therefore designed to best learn – and often overfit – dataset biases. For example, it is common to consider a vocabulary limited to only the most frequent words and answers in the dataset. That practice thus completely discards rare concepts, let alone those that do not appear in the training set at all.

As an example, the training question How many giraffes are in the image? is currently taken as an opportunity to learn to count giraffes specifically. We propose here that the opportunity is instead to learn to count. An ideal VQA system should therefore be able to generalize and answer questions about objects and situations that are not present...
in the VQA training set. We label this capability Zero-Shot VQA, inspired by the task of zero-shot classification. Our first contribution is an evaluation setting for VQA in which all test instances (questions and answers) include words not present in the training set. Our experiments in this setting expose common weaknesses of current VQA systems, namely poor generalization and over-reliance on dataset biases.

We show that most VQA datasets contain strong biases that render the interpretation and comparison of performances difficult. A small number of frequent words constitute a large fraction of the correct answers, and exploiting these statistical regularities achieves deceptively strong performance [3, 11, 34]. For example, most questions starting with How many... have two or three as their correct answer, and rarely zero or seventeen. Although such biases are actually present in the questions that humans ask, VQA methods that overfit to these biases may improve on the benchmarks without making any significant progress towards visual scene understanding. For example, the state-of-the-art method in [11] achieves an impressive accuracy of almost 65% correct answers on the Visual7W dataset. However, the authors also train a similar, but blind model, that answers the question without analysing the image, that achieves 56% accuracy. This second figure is really more illuminating than the first, and one of the primary implications is that current methods for evaluating VQA performance are not a particularly good measure of a method’s ability to understand visual scenes.

The contributions of this paper are summarized as follows.

1) We define the Zero-Shot Visual Question Answering (ZS-VQA) problem, and propose a corresponding evaluation setting where each test instance contains one or several unseen words, i.e. words not present in any training instance.

2) We propose a dataset that focuses exclusively on this setting based on the Visual7W dataset [36], of which we define new training and test splits.

3) We show that the paradigm followed by current VQA methods performs poorly in this setting, as correct answers cannot be as easily guessed by learning dataset biases.

4) We describe and evaluate extensively a set of strategies for ZS-VQA, including incorporating auxiliary data at training and test time. They result in large improvements for ZS-VQA, and also in state-of-the-art performance in the standard VQA setting (on the original splits of the Visual7W dataset).

2. Related work

The task of visual question answering has received increasing interest since the seminal paper of Antol et al. [3].

Most recent methods are variations on the idea of a joint embedding of the image and the question using a deep neural network. The image and the question are passed respectively through a convolutional (CNN) and a recurrent neural network (e.g. an LSTM). They produce representations of the image and the question in a joint space, which can then be fed together into a classifier over an output vocabulary of possible answers. Consult [30] for a recent survey of the literature.

Most VQA systems are trained end-to-end, i.e. with supervision solely for their final output, on closed datasets of images, questions, and their correct answers. Several such datasets are available and they have increased in size and quality [3, 12, 13, 22, 36]. They remain however expensive to produce and are thus necessarily of limited size. This drives an increased interest in using additional sources of data.

On the language side, the word embeddings, i.e. the vectors used to represent the words, can be pretrained on a language modeling task [19, 17]. They capture semantics by mapping words of similar meaning to similar representations. Such pretrained embeddings showed benefit for VQA for example in [23, 6, 11, 24]. They can be pretrained unsupervised on large corpora and incorporate words not necessarily present in the training questions/answers. This simple strategy can enable VQA systems to generalize to words not present in training questions. The syntactic structure of language for VQA has received much less attention, but recent work suggest that explicit parsing can bring useful information [24].

On the image side, the common representation uses features produced within a convolutional neural network (CNN) pretrained for image classification. As is the case for pretrained word embeddings, this leverages the larger amounts of data available for the pretraining task. Most VQA methods do not use the actual output of the classifier but its hidden features. An exception is [28], where the authors use language as an explicit intermediate representation for VQA. They represent an image as a set of recognized attributes, actions, and objects. In this paper, we evaluate both traditional CNN features and explicit object detections.

Finally, a few methods consider the test-time retrieval of additional data from knowledge bases [31, 27, 29]. Importantly, this data is not incorporated within the learned weights of the network. Only the behaviour for retrieving and incorporating external information is learned, and can then be applied at test time to concepts unseen during training. We experiment with a similar principle by retrieving additional visual exemplars at test time. In comparison, the information from knowledge bases in [31, 27, 29] is purely textual in nature.

The presence of strong biases and the long-tailed distri-
Figure 2. Test questions from the proposed zero-shot test split of the Visual7W dataset. Each instance contains one or more unseen words (in blue boldface), i.e. not used in any training question or answer. Tick marks indicate the correct answers among the given multiple choices.

3. Dataset for Zero-Shot VQA

We propose a dataset for VQA with a “zero-shot” aspect with respect to the questions and answers, but not to the visual concepts in the associated images. For example, we consider the question *How many zebras are in this image?* to be zero-shot if no training question involves zebras. Images containing zebras may, however, appear in the training set (with questions involving other elements of those images) or be used to train auxiliary components, e.g. an image classifier that recognizes zebras. This distinction reflects the fact that CNNs pre-trained on ImageNet [4] are commonly used in existing VQA methods, and the fact that VQA is the task that we are actually interested in.

3.1. Repurposing the Visual7W dataset

In multiple-choice VQA, each training or test instance is a tuple of an image, a question, and multiple answer choices (four in the dataset considered here). The question and answers are given as text in natural language. Exactly one of the answers is marked as correct, and is used for supervised training and for evaluation. A dataset is partitioned into training, evaluation, and test splits.
The words used in the questions and answers of VQA datasets follow a long-tail distribution typical in natural language [12, 36]. In other words, most questions and answers are made of words from a small vocabulary, but a large number of other words appear very infrequently. The typical strategy in VQA methods is to focus on a limited vocabulary and a limited set of possible answers. This makes the training practically easier, and the performance penalty remains reasonable since the rare words arise in only a small fraction of the test instances. It however implies a fundamental limitation to the restricted set of words and answers.

The Zero-Shot VQA dataset we propose is formed by defining new training, validation, and test splits for the “telling” task of the Visual7W dataset [36]. Visual7W is itself a subset of the Visual Genome dataset [12] the highest quality dataset for VQA currently available, in terms of size, answer distribution, human performance, and the quality of the multiple choice answers.

We define the new splits such that every validation and test instance is zero-shot question, which we define as using at least one word that was not present in any training instance. The zero-shot instances can be further broken down according to whether unseen words appear in the question itself, in the correct answer, or in the other (incorrect) answers. These three sets are not mutually exclusive, as multiple unseen words can appear in the question and its answers. An analysis of the original splits of the Visual7W shows that only 9% of test questions qualify as zero-shot (see Table 1).

### 3.2. Building zero-shot splits

To build our new splits, we hold out two distinct subsets of the words used throughout the whole dataset and reserve them for the validation and test splits, respectively. The words in the held-out subsets are randomly selected from those which appear less than 20 times over the whole dataset. This ensures that these unseen words are semantically rich, as opposed to common verbs or stop words. These words typically describe fine-grained categories and very specific concepts (see examples in Fig. 2 and in the supplementary material). The validation and test splits are formed from all instances containing at least one word from their reserved set, ensuring no overlap between sets. The training set is composed of all remaining instances, making sure, as in the original splits, to keep the images disjoint between the training and validation/test sets so as not to encourage overfitting. An analysis of the resulting splits is given in Table 1. Note that we preserve the other qualities of the original dataset, e.g. in the approximate distribution of question types.

We also annotate the test instances as to whether they contain unseen words in the question itself, in the correct answer, or in the other (incorrect) answers. We recommend reporting accuracy over the whole test set and on those non-disjoint subsets. We provide those same annotations for the standard splits, making it possible to report performance on zero-shot questions (albeit on a small number of them) of a method trained on the standard splits. Splits and annotations are available from the authors’ website.

### 4. Methods for zero-shot VQA

We consider a neural network for VQA with straightforward architecture. Our main objective is to evaluate additional features and pretrained representations of the inputs (image, question, and candidate answers). A simple architecture lets us evaluate these in relative isolation. Our method particularly does not include an attention mechanism, in contrast to many current approaches. The application of attention to the proposed features has no single obvious implementation and may warrant another research study of its own. Note also that each of the proposed improvements is evaluated on the basis of a relatively simple implementation. The goal is not to obtain the single best performing model, but to guide future research to areas with the most promise and provide reference performances of basic implementations.

|                              | Training | Standard splits | Test  | Zero-shot splits | Test  |
|------------------------------|----------|-----------------|-------|-----------------|-------|
| Number of questions          | 69,817   | 28,020          | 42,031| 63,128          | 10,651| 10,559|
| Number of images             | 14,366   | 5,678           | 8,609 | 15,616          | 7,937 | 7,920 |
| Question types (what, where, when, who, why, how) | 48% 16% 5% | 48% 16% 5% | 48% 16% 5% | 46% 17% 5% | 52% 11% 3% | 52% 12% 3% |
| Number of instances with ≥1 unseen word | 2,640 | 3,962 | – | 6,880 | 6,847 |
| — appearing in the question  | –        | 2,360  8%     | 3,606 9% | – | 10,651 100% | 10,559 100% |
| — appearing in the correct answer | – | 352 8%*15% | 528 9%*15% | – | 2,053 19% | 2,092 20% |
| — appearing in other (incorrect) choices | – | 448 8%*19% | 740 9%*21% | – | 2,362 22% | 2,295 22% |
| Number of words unseen in training | – | 2,064 8%*87% | 3,174 9%*88% | – | 9,306 87% | 9,181 87% |

*15 528 9%*15% 740 9%*21% 2,053 19% 2,092 20% 2,362 22% 2,295 22% 9,306 87% 9,181 87%
4.1. Baseline method

Our network architecture is similar to baselines evaluated in other studies of VQA [3, 11, 35]. The overall principle (see Fig. 1) is to map the inputs, i.e., a question, an image, and candidate answers, to vector representations in a common space. The mappings to produce these representations are learned such that interactions (e.g., distances, products, order comparisons, ...) between elements in this space capture semantic compatibility.

Our baseline represents the question with a bag of words (BoW). Each word is represented by a fixed-length vector with a look-up table that associates every possible word to a learned vector (unknown words at test time receive an empty vector of zeros). The BoW representation is the average of all non-empty vectors of the question words. We refer to this representation as the learned word embedding. Additional features, described below, are concatenated where required (Fig. 3), giving the final question features \( x^Q \). Each candidate answer is treated similarly, using a BoW and optionally concatenated with additional features, giving the answer features \( x^A \) for each multiple choice \( i \).

The image is represented with global (image-wide) features of dimension 2048 extracted from the last pooling layer of a ResNet-152 [10] pretrained for image recognition on ImageNet. Note that this common practice is already a form of transfer learning, as opposed to the baseline language representation which learns the word embeddings from scratch. The CNN features are optionally concatenated with additional features described below, giving the image features \( x^I \).

The features \( x^Q, x^A, \) and \( x^I \) are combined in two stages with multiplicative interactions, first between the question and image representations, then with the candidate answers:

\[
x^{QI} = f(W_1 x^Q + b_1) \circ f(W_2 x^I + b_2)
\]

\[
x^{QIA}_i = f(W_3 x^{QI} + b_3) \circ f(W_4 x^A + b_4)
\]

with \( W_1 \ldots W_4 \) and \( b_1 \ldots b_4 \) learned weights and biases, \( f \) a ReLU, and \( \circ \) the Hadamard (element-wise) product. Each candidate answer \( i \) then receives a score \( s_i \) obtained with a logistic regression using the combined features

\[
s_i = \sigma(W_5 x^{QIA}_i + b_5)
\]

with learned weights \( W_5 \) and biases \( b_5 \), and \( \sigma \) being the logistic function. The score represents the compatibility between the input question, image, and a candidate answer. All weights, biases, and embeddings are trained end-to-end to minimize the cross-entropy loss, using +1 labels for the correct candidate answers and 0 for the incorrect multiple choices.

4.2. Improved language representations

**Pretrained word embeddings** We compare the learned word embeddings (trained end-to-end within the VQA system) to embeddings pretrained on a language modeling task. This common practice [19, 17] has two advantages. First, the pretrained embeddings reflect word co-occurrences, and have shown empirically to capture complex semantic relationships in their vector space. Second, the pretraining task is unsupervised and embeddings can be learned from very large amounts of data, covering a much richer vocabulary than a VQA training set. Concretely, we evaluate GloVe embeddings of various dimensions \{50, 100, 200, 300\} pretrained on Wikipedia and the Gigaword newswire corpus.

**Sharing embeddings across stems** We propose sharing a embeddings across words with a same stem (e.g., flower, flowers, and flowering). We hypothesize that the semantic meaning of words is often more important in the context of VQA than verb conjugation or plural forms of nouns. The procedure reduces the number of unique embeddings to be learned (e.g., from ~22k to ~17k words in the original V7W training set). Moreover, novel words at test time that have appeared in another form or declension during training can now be associated with a relevant embedding. An obvious drawback of the approach is to potentially associate a same
representation to multiple words of different meanings, e.g. runner, ran, runs, and runnable. This exacerbates the issue of polysemy already present with standard word embeddings. A set of homonyms are indeed mapped a single – thus necessarily ambiguous – representation. Concretely, we replace every word in the input question and/or answer by its stem, obtained either with the classical Porter algorithm [20], or with the dictionary-based algorithm of the Stanford CoreNLP library [16].

Sharing embeddings between questions and answers

Our baseline implementation learns independent embeddings for words in questions and answers. One may hypothesize that both inputs could benefit from similar representations, and we compare independent embeddings versus a common shared one. The latter reduces the number of parameters to learn, but it forces the semantics of questions and answers to be represented identically.

Test-time exemplar retrieval

A hallmark feature of Z.S.–capable methods is their extensibility to novel concepts without retraining. We implement such a capability by retrieving, at test-time, exemplar images from the web for all words (known or unknown) in the test questions and/or answers. Concretely, we build an additional representation of the question and/or of the candidate answers by retrieving the top-k images of each of its words from Google Images (k=1 to 4). We extract global CNN features from the images (as described above for the input image) and average them over words and exemplars. The resulting vector of dimension 2048 is referred to as a visual embedding.

4.3 Improved image representations

Explicit object detection

In addition to the global CNN features to represent the input image, we consider using explicit detections of objects in the scene. We obtain candidate detection from the YOLO method pretrained on Pascal VOC [21] as set of detections scores, each with the class of the detected object. We keep all detections above a certain threshold (varied throughout multiple experiments as to vary recall). We turn the set of detections into a fixed-size vector with a similar bag of words as for our questions (see above): we associate the possible answers with a learned embedding (i.e. a look-up table) and sum these embeddings over all detections.

Semantic object class embeddings

The detections presented above do not associate any semantic prior on the classes considered by the detector. Those classes are however known by their name, and we experiment associating the detections with the pretrained GloVe word embedding (as used for the language model, see above) of their recognized class. We simply replace the look-up table with the pretrained embeddings of the words corresponding to class names. We refer to this representation as semantic class embeddings.

Order embeddings

We experiment with the idea of imposing an order between the representation $x^{QI}$ of question/image and $x^{A}$ of candidate answers, as proposed by Vendrov et al. for other vision and language tasks [25]. Whereas our baseline uses a symmetric product to relate $x^{QI}$ and $x^{A}$, the idea of an order embedding is to place a hierarchy between the two modalities by measuring their compatibility with an antisymmetric operation (consult [25] for details). Practically, we replace Eq. 2 with

$$x_{i}^{QIA} = \max \left(0, \ |f(W_{3}x^{A} + b_{3})| - |f(W_{4}x^{QI} + b_{4})| \right)^{2} \quad (5)$$

This imposes a partial order over the spaces of $x^{QI}$ and $x^{A}$, the candidate answers being placed higher in the hierarchy (with smaller absolute coordinates) and thus deemed more general than a particular pair of question/image. Crucially, we experiment with a reversed ordering by swapping $x^{QI}$ and $x^{A}$ in the above, which results in a dramatically lower performance (see Section 5.2).

5. Experiments

We conduct extensive experiments on both the original and the zero shot splits of the Visual7W dataset. As hypothesized in our premise, we observe different behaviors in the two cases, and the proposed improvements have different impact on the overall average performance of the two settings. Each experiment below considers one variation at a time of the baseline model including pretrained word embeddings of dimension 300, unless otherwise noted. Pretrained word embeddings are common practice and have a large positive impact, and they thus constitute our de facto reference for fair comparisons of additional improvements. Implementation details are provided in the supplementary material.

5.1 Masking inputs

We first obtain an indication of the difficulty of the datasets by training a model with limited input, masking the question and/or the image. This forces the model to rely on dataset biases. Indeed, when masking both the question and the image, the only input is the set of multiple-choice answers, and the model can only learn to pick the common ones seen during training. As observed before [11], this strategy is sufficient to achieve a high performance with the standard splits. It is far less effective in the Z.S. setting, giving for example, when masking the question, 62.7% vs 52.6% in the standard and Z.S. settings, respectively (see Table 2 and Fig. 4, bottom right). In other words, answers in the Z.S. setting cannot be as easily guessed.

5.2 Improved representations

Pretrained word embeddings

We compare pretrained GloVe word embeddings of dimension 50 to 300 and an
embedding learned from scratch of dimension 300 (noted “0” in the plot). Pretrained word embeddings over learned ones have the largest impact of all tested improvements in both the standard and Z.S. settings (Fig. 4, bottom left). There is an appreciable correlation between accuracy and the dimension of the embedding. Pretrained embeddings are more beneficial to represent the candidate answers than the questions, which can be explained by the larger amount of data (i.e., question words) available to learn the latter. We evaluate fine-tuning the pretrained embeddings with a relative learning rate between 0 and 1 to the other network parameters. Some fine-tuning always proves beneficial, but the Z.S. setting favors a smaller learning rate (Fig. 4, top left). We suppose that fine-tuning rate may otherwise significantly alter the embeddings of frequent training words. The remaining of the model then co-adapts, but the embeddings of rare and zero-shot words will however no be updated as much, leading to a negative performance impact in the Z.S. setting. Finally, we observe that fine-tuning a common shared embedding between question and answer performs worse than independent ones. We conclude that the information captured by pretrained embeddings is relevant but not perfectly adequate for VQA, and that a same representation cannot capture the ideal semantics from both questions and answers. **Sharing embeddings across word stems** We obtain a clear benefit from sharing embeddings across words of common stem (Fig. 4, top center). The procedure reduces the number of unique embeddings by about 25%, which regularizes their learning, and addresses some of the novel words at test time by mapping them to known stems. The observed impact is indeed larger in the Z.S. setting than on the standard one. The quality of the stemming algorithm does matter. The classical rule-based Porter algorithm performs worse than our baseline, and the improvements are obtained with a modern algorithm [16]. **Test-time exemplar retrieval** We evaluate the proposed visual embeddings for representing the question, the candidate answers, or both. We obtain a net advantage in the Z.S. setting (Fig. 4, top right), correlated with the number of retrieved examples. The benefit is only appreciable when including visual embeddings for both the question and the answers. This indicates that the network may not succeed in learning to correlate visual features of the input image and of the visual embeddings, but only between the visual embeddings of the question and answers. A possible culprit is the different nature of top retrievals from Google and of the images in the Visual7W dataset. Surprisingly, visual embeddings impact performance negatively in the standard setting. We suspect that the language cues and dataset bi-

![Figure 4](https://example.com/figure4.png)

Figure 4. Individual impact of each proposed improvement on the standard (std.) and zero-shot (Z.S.) splits of the Visual7W dataset (average accuracy in %; note the different vertical scale on the bottom row). See discussion in Section 5.2.
possible with attention mechanisms. At the optimal thresh-
ol, we obtain a minor improvement with the proposed sem-
semantic class embeddings.

Order embeddings    The proposed order embeddings sig-
nificantly improves over a symmetric interaction between
features. Crucially, we verify that the improvement is
caused by the actual order imposed on the embeddings and
not merely by the different interactions. To do so, we
replace the proposed order \( x^A \) above than \( x^B \) by its re-
verse, which results in performance well below the base-
line (Fig. 4, middle center).

Data augmentation    We propose a simple form of data
augmentation with additional training examples of incorrect
answers. Our model ultimately measures the compatibility
between a question/image and a candidate answer, and the
intuition is to expand training to more combinations, drawn
randomly within mini-batches to form additional incorrect
candidate answers. The procedure proves beneficial (Fig. 4,
middle right), with a larger relative improvement in the Z.S.
setting. The augmentation ratio correspond to the fraction
of additional pairs of question / candidate answer (originally
four per question).

5.3. Comparison with the state-of-the-art

We finally evaluate a model incorporating all proposed
improvements (see Table 2). It achieves best performance
overall in both the standard and Z.S. splits. The relative
gains from combined improvements are not strictly cumula-
tive, which indicates some overlap in the capability brought
in by each. Part of the individual gains is likely attributable
to increased model capacity, the benefit of which saturates
at some point. On the standard splits, our best model clearly
surpasses the existing state-of-the-art on this dataset [11].
We also trained our baseline and best models on reduced
training data (random subsets). We appreciate a smooth
drop-off in performance, especially in the Z.S. setting with
our best method (Fig. 4, bottom center). This indicates good
generalization, which, as argued in the introduction, should
be a chief objective of VQA systems.

6. Conclusions

This paper defined a setting of visual question answering
where questions and answers contain words that were not
seen during training. We rearranged the Visual7W dataset
to allow an evaluation that focuses exclusively on such test
cases. This setting requires more generalization capabilities
and leads to a more honest evaluation of deep image under-
standing. This setting also motivates alternative strategies.
We showed that additional, auxiliary data, used for pretrain-
ing language visual representations as well as during test
time was beneficial, not only for ZS-VQA, but in the tra-
ditional setting as well. The extensions of those strategies
constitute promising directions for future research.

| Table 2. Quantitative results on the standard and zero-shot (Z.S.) splits of the Visual7W dataset (average accuracy in %). The proposed improvements generally have a larger impact in the Z.S. setting. In combination, all the proposed improvements significantly outperform the state-of-the-art. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                  | Standard        | Zero-shot       |                  |                  |
|                  | splits          | splits          |                  |                  |
|                  | All             | Z.S.            | Z.S.            | Z.S.            |
|                  | Choices         | Quest.          | Ans.             | Choices         |
|                  |                 |                 |                 |                 |
| Chance (lower bound) | 25.0            | 25.0            | 25.0            | 25.0            |
| Human (upper bound)   | 96.0            | 95.7            | 94.2            | 92.6            |
| LSTM Q+1 [15]         | 52.1            | –               | –               | –               |
| LSTM-Att. [36]        | 55.6            | –               | –               | –               |
| MCB [6]              | 62.2            | –               | –               | –               |
| Jabri et al. [11]     | 64.8            | –               | –               | –               |
| Baseline model        |                 |                 |                 |                 |
| (1) Learned word emb. d.300 | 59.5 | 47.3            | 43.0            | 36.7            | 47.5            |
| (2) Pretr. w. emb. d.300, l.r. 0.4 | 64.7 | 54.1            | 48.3            | 40.3            | 54.8            |
| Masking input (Q, I, A) | 62.7            | 52.6            | 47.7            | 37.7            | 53.0            |
| Masking input (Q, J, A) | 56.6            | 48.3            | 43.5            | 36.1            | 48.7            |
| Masking input (Q, J, A) | 52.9            | 46.5            | 43.8            | 35.3            | 46.7            |
| Improvements over (2) |                 |                 |                 |                 |
| (3) Word stemming, CoreNLP | 64.6 | 54.9            | 49.2            | 41.3            | 55.4            |
| (4) Order embeddings | 65.4            | 55.3            | 48.6            | 32.5            | 56.1            |
| (5) Data augmentation, ratio 0.5 | 64.9 | 54.7            | 48.1            | 39.6            | 55.4            |
| (6) Visual emb. 4 exemplars | 63.8 | 54.8            | 48.6            | 38.1            | 55.4            |
| (7) Object det. threshold 0.2 | 64.8 | 54.1            | 48.2            | 39.6            | 54.7            |
| (8) Obj. det. with class emb. | 64.8 | 54.6            | 48.5            | 39.2            | 55.3            |
| (3) + (4)            | 65.5            | 54.8            | 48.1            | 35.8            | 55.5            |
| (3) + (4) + augm. 2.0 | 65.7            | 55.2            | 47.4            | 33.6            | 56.1            |
| (3) + (4) + (6)      | 64.4            | 55.3            | 50.3            | 40.1            | 55.6            |
| (3) + (4) + (6) + (8) | 64.6            | 55.8            | 49.9            | 40.0            | 56.5            |
| (3) + (4) + (6) + (8) + augm 0.5 | 63.5 | 56.0            | 49.5            | 36.7            | 56.8            |
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Supplementary material

A. Implementation details

We provide below practical details of our implementation of the proposed method.

• All weights and biases in our neural networks are optimized with Adadelta [33], using mini-batches of 512 questions. We do not use dropout and avoid overfitting with early stopping by monitoring accuracy on the validation set. The accuracy reported in the experiments is thus measured on the test set at the epoch of highest performance on the validation set.

• All weights except pretrained embeddings are initialized randomly as proposed by Glorot et al. [8].

• The pretrained word embeddings are GloVe vectors [19] trained for 6 billion words on Wikipedia and on the Gigaword newswire corpus. Those are publicly available from the GloVe authors [18].

• The CNN features extracted from the input images and from the exemplar retrieved from Google are obtained from the last pooling layer of a residual network (ResNet). The network is a 152-layer model trained on ImageNet and publicly available from the ResNet authors [10].

• The dimension of pretrained word embeddings is varied from 50 to 300 as noted in the experiments. The dimension of learned word embeddings is set to 300. The dimension of CNN features of the input image, and of the visual embeddings from retrieved exemplars (produced by ResNet) is 2048.

• The dimension of the combined representations $x^{Q1}$ and $x^{QIA}$ is 4096 and 2048 for the standard and zero-shot splits, respectively. Those were chosen among {1024, 2048, 4096, 8192} by cross validation of the baseline model.

• Experiments on exemplar retrieval use the top–1 to top–4 images returned by Google for single words, limiting the search to color photographs. This avoids results such as logos or clip art. Note that the procedure is applied similarly during training, i.e. we retrieve images for all words of in the training questions and answers. Once the images are downloaded and their CNN features extracted, they are cached locally for efficiency.

• Experiments on masking inputs (questions and/or images) are performed by randomly swapping those inputs within mini-batches during the training. This solution was chosen to avoid causing side effects, and preferred over removing the inputs entirely (and reducing the network capacity) or setting them to zero or other arbitrary values.

• Plots reporting performance on the “best model” use the two models highlighted in bold in Table 2 for the standard and Z.S. settings.

B. Examples of test questions

We provide below additional examples from the proposed zero-shot test split of the Visual7W dataset, in the same format as in Fig. 2.
How would you hear this cat coming?
- bell on his collar
- meowing
- walking on piano
- walking through water

What animals are these?
- giraffes
- elephants
- zebras
- emus

What is in the background?
- meadows
- lakes
- trees
- hills

When was this photo taken?
- july
- december
- august
- during say

What kind of picture?
- black white
- photoshopped
- sepia tone
- color

What has happened to the truck over time?
- fell apart
- paint came off
- dirty
- rusting

What time of day is it?
- lunchtime
- daytime
- morning
- teatime

Where is the cow?
- petting zoo
- barn
- milking pen
- field

Where is this picture taken?
- swimming pool
- playground
- volleyball court
- tennis court

What has many archways?
- house
- garden
- building
- bridge

Where are the giraffes?
- in jungle
- on reserve
- on plains
- in zoo

Where is the number 06?
- on back
- bottom middle
- bottom left
- upper right
What is written on the train?  
✓ csx  
1017  
zap  
love

What is in the background?  
forest  
sea  
✓ window  
mountains

What gender dominates this picture?  
men  
both  
transgender  
✓ women

Why is she on the side of the road?  
walking  
hitchhiking  
broken down  
✓ selling food

Who is in the picture?  
leprechauns  
captain ship  
✓ woman  
elephant

How does the bathroom look?  
discusting  
messy  
✓ clean  
dirty

What brown object is around the cow’s neck?  
rope  
✓ rope  
bell  
twine

What colors are the zebra?  
milticolored  
grey  
✓ black white  
striped

What sport are they displaying?  
snowboarding  
✓ skiing  
sledding  
logging

What color is the car?  
silver  
white  
red  
✓ black
How is the photo?
- fuzzy
- underdeveloped
- clear
- tilted

What time is it?
- midnight
- dusk
- daytime
- 6:48 pm

What does the white sign say?
- mott's
- turn right
- keep left
- upstairs

What is printed on the road?
- white arrows
- white line
- numbers spraypainted by utility company
- double yellow lines

Where is the water?
- behind birds
- in pool
- in birdbath
- in pond

Why is the truck in a ditch?
- avoided crash
- wheels came off
- hit deer
- driver fell asleep

What is white?
- wedding dress
- child's skin
- snow
- clock's face

Who is crossing the intersection?
- policeman
- chicken
- old woman
- woman man

What is printed on the road?
- white arrows
- white line
- numbers spraypainted by utility company
- double yellow lines

Where is the drawer unit?
- behind bed
- in front bed
- left bed
- right bed

Why is the girl on the horse?
- get somewhere
- fun
- pleasure
- ride

Who captured this photo?
- mario bertoli
- anthony bourdain
- guy fieri
- photographer
What does the sign say?
yield
✓ compact cars only
speed bumps ahead
slow children at play

How is the man dressed?
in jeans t shirt
✓ in uniform
in sweats

When was this picture taken?
while it was raining
during evening
at celebration
✓ during waking hours

What kind of tree is shown?
weeping willow
✓ maple
oak
cherry

Where was this picture taken?
at beach
at pond
at gulf
✓ at ocean

What does the bottom sign say?
bigelow ave n 450
lesly st

How are the scissors arranged?
on top each other
✓ close together
next each other
✓ overlapping 1 another

What is on the woman’s hands?
dirt
✓ wedding ring
✓ gloves
moisturizing lotion

What is the green plant for?
decoration
✓ elephant eat
cooking
seasoning

What is on the desk?
lunchbox
weekly planner
laptop
✓ empty pencil holder

Why is it a rounded picture?
panoramic view
cut way
✓ camera lens
fitted frame

What type of photo is shown?
outside
inside
✓ unfocused
black white
What is in the foreground?
- **ATV**
- train
- car
- bike

Who has longer wool?
- *unsheared* sheep
- cold weather sheep
- adult weather sheep
- better sheep
- better fabric shop

Who is shown?
- man
- crowd
- *protestors*
- child
- few people

What colors contrast in this picture?
- gray black
- blue white
- tan
- *emerald*

What drink is advertised on the truck?
- pepsi
- *vita coco*
- mountain dew
- coke cola

Where is there a bird?
- flying over ocean
- in *birdcage*
- in branches
- on ground

What are the yaks eating?
- hay
- grass
- feed
- clover

What condition is the old stove?
- some chips on *enamel*
- perfect
- dangerous *leak*
- antique

What does the monitor in the upper left of the photo say?
- no pain no gain
- just do
- rock bike
- rock boat

What is the number of *busts* in the room?
- 3
- 1
- 4
- 2
What does the sign say?
- stop
- wet paint
- pedestrian walking
- nothing but bumps

How do you know it’s an outdoor scene?
- i can hear birds
- sunny
- plenty deep shadows
- sun out

What type of boat is in the picture?
- rowboat
- canoe
- fishing boat
- yacht

What color are the giraffe spots?
- brown
- tanish brown
- black
- reddish brown

What is on the sink?
- spoon
- scrub
- brush
- cup
- plate

What color are the double-deck buses?
- yellow
- green
- red
- white

Who is playing?
- borg
- evert
- rafael nadal
- sampras

Who is riding on the elephant?
- monkey
- sultan
- some kids
- man

Who has their suit jackets buttoned?
- all men
- some men
- 3 men
- only 1 man

Who has a sewing kit?
- everyday person
- tailor
- traveler
- seamstress

Why is there a fire?
- ambiance
- cold
- roast marshmelloes
- burning yard waste

Where are smudges of dirt?
- gloves
- shoes
- shirt
- pants
Who is standing on the tennis court?
- ball boy
- umpire
- tennis player
- opponent

What is the woman doing?
- hitting tennis ball
- hitting hockey puck
- throwing football
- shooting basketball

What is the table made of?
- plastic
- mahogany
- wood
- lucite

What has tassels?
- drapery valance
- western style vest
- graduation cap
- fancy blouse

Why is this photo illuminated?
- sunlight
- photo effects
- moon
- stream effects

What is on the plate?
- dog food
- scraps
- cat food
- food

What is the status of the tv?
- paused
- on
- off
- broken

What kind of video game is it?
- soccer
- basketball
- golf
- mine craft

What kind of bus is this?
- double decker
- 1 moves
- red 1
- big 1

Where is this picture taken?
- soccer game
- big wheels demo
- swimming competition
- tennis match

Who is in this picture?
- women
- kids
- preachers
- men

How is the place?
- bushy
- rocky
- clear
- hilly