Give Me Something to Eat: Referring Expression Comprehension with Commonsense Knowledge

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Abstract

Conventional referring expression comprehension (REF) assumes people to query something from an image by describing its visual appearance and spatial location, but in practice, we often ask for an object by describing its affordance or other non-visual attributes, especially when we do not have a precise target. For example, sometimes we say ‘Give me something to eat’. In this case, we need to use commonsense knowledge to identify the objects in the image. Unfortunately, there is no existing referring expression dataset reflecting this requirement, not to mention a model to tackle this challenge. In this paper, we collect a new referring expression dataset, called KB-Ref, containing 43k expressions on 16k images. In KB-Ref, to answer each expression (detect the target object referred by the expression), at least one piece of commonsense knowledge must be required. We then test state-of-the-art (SoTA) REF models on KB-Ref, finding that all of them present a large drop compared to their outstanding performance on general REF datasets. We also present an expression conditioned image and fact attention (ECIFA) network that extract information from correlated image regions and commonsense knowledge facts. Our method leads to a significant improvement over SoTA REF models, although there is still a gap between this strong baseline and human performance. The dataset and baseline models will be released.

1. Introduction

Referring expression comprehension (REF) aims at localizing a specific object in the image, based on an expression in the form of natural language. Several benchmark datasets have been released to test the referring expression comprehension models’ ability, such as RefCOCO [9], RefCOCOg [19] and CLEVR-Ref+ [16]. Expressions in these existing datasets are usually about the visual appearance and spatial location of the target objects. For example, commonly seen expressions in RefCOCO [9] mainly include three components that are subject, location and relationship, where the subject component handles the visual categories, colour and other visual attributes; the location phrase handles both absolute and relative location; and the relationship covers subject-object visual relations [37], such as ‘the second white cup on the table’. Expressions in CLEVR-Ref+ [16] require a longer reasoning chain but only visual attributes (such as size, colour, material) and spatial relationship (such as left, right) are covered.

While in practice, humans often use richer knowledge to ask for something they want, not limited to visual information. For example, we commonly use the ‘affordance’ and

Expression: I want to eat something soft but rich in starch.
Target object: Banana
External knowledge: A banana is soft flesh rich in starch covered with a rind, which may be green, yellow, red, purple, or brown when ripe.

Figure 1. An example from our KB-Ref dataset. The key information in the expression, ‘soft but rich in starch’, is non-visual attributes of the target object ‘banana’, which can be retrieved from an external knowledge base, such as ConceptNet.
other non-visual attributes to describe something we want, like ‘Can you pass me something to knock in this pin’ and ‘I want to eat something low fat’. In this case, one needs to identify the objects in the image in accordance with the commonsense knowledge mentioned in the expression, for example a ‘rock’ in the image can be used to knock in the pin, and ‘banana’ is low fat. Thus, to enable a machine to reason over visual appearance, spatial and semantic relationships and commonsense knowledge is an emerging challenge.

Unfortunately, no existing datasets, including the popular RefCOCO [19] and CLEVR-Ref+ [16], present above features, not to mention a referring expression model that offers this capacity. To this end, we propose a new dataset for referring expression comprehension with commonsense knowledge, KB-Ref, collected based on the images from Visual Genome [10] and knowledge facts from Wikipedia, ConceptNet [27] and WebChild [29]. Similar to RefCOCO dataset family, we ask Amazon Mechanical Turk (MTurk) workers to select an object from the image and use language to describe it so that another person can use it to localize the object. The difference in annotation is that we also provide a list of commonsense facts about the selected object to workers, who must use at least one of the provided knowledge facts together with the visual context to describe the target object. We also ask workers to record the knowledge they used. To verify whether the collected expression is meaningful and whether the recorded knowledge is required to localize the object, we give the annotations to another MTurk group to verify. Only those expressions that need knowledge to solve are kept. This leads to 43,284 expressions of 1,805 object categories in 16,917 images. The average length of the expressions is 13.32, nearly double the length in RefCOCOg [19]. In our setting, the recorded knowledge facts are provided during the training but are removed during the testing. So the real technical challenge of this new task is how to mine related knowledge and combine it with visual context to find the object that is referred by the expression.

To verify whether commonsense knowledge is crucial in our collected dataset, we first evaluate a variety of state-of-the-art (SoTA) referring expression models (such as MattNet [37] and LGARNs [30]) on our KB-Ref dataset, finding that all of them present a large drop compared to their performance on general REF datasets. We then propose an Expression Conditioned Image and Fact Attention network (ECIFA), which uses an top-down attention module to extract expression-related image representations and an episodic memory module to focus attention on a subset of commonsense knowledge facts. The proposed network leads to a significant improvement over SoTA REF methods, on our constructed dataset. Nevertheless, we also evaluate the human performance on the test split and find that there is still a large gap between our baselines and the human accuracy, which suggests that our proposed KB-Ref dataset is considerably challenging.

2. Related Work

2.1. Referring Expression Comprehension

Datasets. As presented in Table 1, commonly used datasets for referring expression comprehension include RefCOCO [9], RefCOCO+ [9] and RefCOCOg [19], all collected on top of MSCOCO images [14]. RefCOCO and RefCOCO+ are collected interactively in a two-player game, with concise phrase descriptions, while RefCOCOg is collected by MTurk workers in a non-interactive setting, using longer declarative sentences. There is no restriction in RefCOCO on language expressions, while RefCOCO+ focuses more on purely appearance descriptions where location words are not allowed. GuessWhat?! [2] is another dataset based on MS-COCO images. Instead of using a single expression, it creates a sequence of sentences (i.e., dialog) for a given image to perform referring expression comprehension. CLEVR-Ref+ [16] is a recently introduced synthetic dataset, built on the CLEVR environment. In contrast, our proposed KB-Ref is based on images from Visual Genome [10], which provides richer annotations including objects, attributes and relationships. The expressions in KB-Ref are different with above and need both visual context and commonsense knowledge to resolve.

Approaches. Referring expression is a visual-linguistic cross-model understanding problem. Some works solve REF jointly with a referring expression generation task [9, 19, 26, 38]. Some others [6, 18, 25, 30, 37] propose different types of joint embedding frameworks and directly localize the object which has the highest matching score. The work in [6, 37] proposes to decompose the expression into sub-phrases, which are then used to trigger separate visual modules to compute matching score. Liu et al. [15] develop a neural module tree network to regularize the visual grounding along the dependency parsing tree of the sentence. The works in [3, 36, 42] argue to learn the representations from expression and image regions in a step-wise manner, and perform multi-step reasoning for better matching performance. Wang et al. [30] propose a graph-based language-guided attention network to highlight the inter-object and intra-object relationships that are closely relevant to the expression for better performance. Niu et al. [25] develop a variational Bayesian framework to exploit the reciprocity between the referent and context. Our proposed baseline model uses a simple visual-expression joint embedding model to calculate the matching score, but we incorporate a knowledge facts attention module to mine external knowledge base for referring expression, which can
also be plugged into other REF models for extra knowledge exploring.

2.2. Visual Understanding and Reasoning with Extra Commonsense Knowledge

Commonsense knowledge has already attracted research attention in visual understanding and reasoning, such as visual relationship detection [17, 35, 40], scene graph generation [4], visual question answering [8, 12, 16, 23, 24, 31, 33, 34] and zero-shot recognition [11, 32]. In particular, the incorporation of commonsense knowledge is important for visual question answering (VQA), because a lot of questions are from open-domain that require to perform reasoning beyond the image contents. In [33], attributes extracted from the image are used to query external knowledge based on DBpedia, which enables answer questions beyond the image. Dynamic memory networks are employed in [28] and [12] to incorporate structured human knowledge and deep visual features for answer decoding. Wang et al. [31] introduce a Fact-Based VQA (FVQA) dataset which requires external knowledge to answer a question. A Graph Convolution Network (GCN) is developed in [23] which integrates image, question and all possible facts in an entity graph for answer inferring in FVQA. The work in [13] represents visual information by dense captions and convert VQA as a reading comprehension problem, where extra knowledge is added by text concatenation. In comparison with FVQA where visual reasoning is based on fixed-structured knowledge bases, an even larger knowledge based VQA dataset (OK-VQA) is introduced in [20] which performs VQA over unstructured open knowledge. The Visual Commonsense Reasoning (VCR) [8, 41] dataset contains 290k multiple choice QA problems from 110k movie scenes, which require higher-order cognition and commonsense reasoning.

Similarly, as a proxy to evaluate AI systems on both vision and language understanding, REF would require not only object localization based on image appearance, but also a more natural way to achieve human-level semantic understanding. With this requirement, we go one step forward and design a KB-Ref which requires reasoning incorporating external commonsense knowledge. In particular, REF can be regarded as a subtask of VQA with the question as “Where is sth. (by referring expression) in the image?”. However, in VQA the answer is generally open-ended, presented in natural language, while in REF the answer is numerical, chosen from a group of candidate bounding boxes, or directly output a detected one, which makes the evaluation much easier.

3. The KB-Ref Dataset

Different from existing referring expression datasets [9, 16, 19, 38] that mainly cover the visual contents of the referred objects (such as appearance, attributes and relationships), we collect a new dataset called KB-Ref that needs additional commonsense knowledge to identify the referent object. Wikipedia, ConceptNet and WebChild are employed here as knowledge resources. In this section, we will describe our data collection pipeline in detail and give a statistic analysis of the dataset.

3.1. Dataset Collection

Images and Objects Images of our dataset are sampled from Visual Genome (VG) [10], which contains over 108K images with dense annotations on objects, attributes and relationships. There are averagely 36.5 bounding boxes in each image, which requires complex visual reasoning to localize. Descriptions on object’s affordance or other non-visual attributes can help the referring expression comprehension, which, however, usually needs commonsense knowledge to understand. In VG, most objects are canonicalised to a synset ID in WordNet [22]. In order to complicate our dataset, we ignore objects that do not belong to any synset. Same as RefCOCO [9] and other REF datasets, objects that appear alone in one image (i.e., there are no other instances of the same object category within the same image) are also removed. Moreover, we neglect objects whose shorter sides are less than 32 pixels. Then we eliminate images which has labeled objects less than 5. With those filtering process, there are 24,453 images left which have 2,075 object categories within 208,532 bounding boxes. They form the basis of our KB-REF dataset.

Table 1. Comparison between different REF datasets. †The data of RefCOCOg is based on the revised version. ‡We use Visual Genome’s definition of object categories, which is finer than COCO. For example, ‘people’ in COCO corresponds to ‘man’, ‘woman’, ‘boy’ and ‘girl’ in Visual Genome.
Figure 2. Statistical analysis of the proposed KB-Ref dataset. We show the distributions of the length of expressions, the number of objects mentioned per expression in subfigures (a), (b) and (c) respectively. We also collect statistics of the TF-IDF similarity (the smaller the number, the less similar) between expressions and their corresponding supporting facts in subfigure (d) to see how much the expressions differ from facts. The number of object instances per image are also counted whose statistical result is shown in subfigure (e). The word cloud of the queried object categories is shown in subfigure (g), where the font size indicates the corresponding number of expressions.

Knowledge Base In order to aid annotation and evaluation, we construct a knowledge base by collecting facts from three knowledge resources (i.e., Wikipedia, ConceptNet and WebChild) that are related to the 1,805 object categories appeared in our dataset. ConceptNet is a graph-structured commonsense knowledge base where facts are represented by triplets of start nodes, relations, and end nodes. There is a closed set of relations in ConceptNet, such as IsA, HasA, PartOf, MadeOf, UsedFor, and CapableOf. WebChild contains fine-grained commonsense knowledge distilled from web-scale amounts of text, in which the facts can be further categorized into properties (e.g., HasShape, HasSzie, HasTaste), comparative (e.g., FasterThan, SmallerThan) and part-whole (e.g., PhysicalPartOf, SubstanceOf, MemberOf). Compared to structured knowledge bases like ConceptNet and WebChild, Wikipedia contains a larger variety of knowledge but in unstructured format. For each object category, we collect the facts in ConceptNet and Webchild whose start nodes or end nodes match the category label, and the Wikipedia article whose theme concept corresponds to this category.

Data Annotation We ask Amazon Mechanical Turk (MTurk) workers to write down referring expressions for the queried objects. The following requests are put forward in the annotation process. 1) At least one fact from the constructed knowledge base should be used in referring expression. 2) The specific object name cannot appear in the expression. Annotators are required to describe the queried object based on the corresponding fact and its visual context. 3) Multiple auxiliary objects appeared in the image are encouraged to be mentioned in the expression, to aid the search of the target object.

To control the dataset bias, we also perform a quality check in background: The frequency of each fact adopted in the expressions cannot exceed 200. If exceeds, this fact will be removed in the following annotation process. Note that we use TF-IDF (Term Frequency–Inverse Document Frequency) to measure the similarity between facts. If TF-IDF between two facts is larger than 0.5, they are regarded as the same.

The detailed annotating process is as follows. Given the object to be queried in an image (highlighted by a bounding box) and the related facts in our knowledge base, the MTurk worker is asked to generate a unique text description about the object, according to the requests described above. It takes about 2 minutes to collect one expression.

1 Considering that some object categories have different interpretations in different images, e.g., a pole may be a ski pole or a bar holding something, in this case, we choose the meaning that appears most frequently in our dataset, and ignore the uncommon ones. But this issue is then fixed in the following human annotation section because we allow human workers to fix or even rewrite the required knowledge.
Then another annotator is asked to verify the correctness of the provided expression. The ones that do not conform to the requests will be asked to re-annotate. The annotation interface can be found in the supplementary materials.

3.2. Data Analysis

Totally, we collected 43,284 expressions for 1,805 object categories on 16,917 images, as compared with other datasets listed in Table 1. Each object instance in one image has a sole referring expression. To be specific, Figure 2(a) shows the distribution of expression lengths. The average length of referring expression in KB-Ref is 13.32 words, which is longer than that in RefCOCOs (including RefCOCO, RefCOCO+ and RefCOCOg) (about 10). In our dataset, 25, 626, 9, 045 and 8, 613 expressions are generated based on the knowledge facts from Wikipedia, ConceptNet and WebChild, respectively. Figure 2(b) shows the distribution of the number of objects mentioned in each expression. Averagely, there are 4.34 objects used per expression, which suggests the complexity of our collected expressions. The distribution of the length of fact sentences is presented in Figure 2(c), with an average of 16.78 words per fact, which reflects the rich information recorded in these facts. We also use TF-IDF to calculate the similarity between each expression and the corresponding fact. As shown in Figure 2(d), most TF-IDFs range from 0.1 to 0.4, which illustrates the difference between the expressions and their corresponding facts. Note that our collected expressions not only reflect the knowledge from their corresponding facts but also contain visual information about the target objects.

Figure 2(e) shows the number of instances per image. We can see most of the images include multiple objects ranging from 20 to 50. The Figure 2(f) shows the percentage of knowledge sources of our dataset, most of the facts are from wikipedia. The object category cloud shown in Figure 2(g) illustrates that our dataset covers a wide range of objects with less bias (the font size in the cloud represents the frequency of the object appeared in our dataset).

We split the dataset on the base of images randomly for training, validation and test. There are 31, 284 expressions with 9, 925 images in training set, 4, 000 expressions with 2, 290 images in validation set, and 8, 000 expressions with 4, 702 images in test set.

4. Method

In this section, we propose an Expression Conditioned Image and Fact Attention (ECIFA) network for extra knowledge required referring expression comprehension. Given a natural language expression $q$ and an image $I$, the model is asked to pick the described object $O^*$ from a group of candidates $\{O\}_{n=1}^N$. The bounding boxes of candidate objects are either groundtruth or obtained via off-the-shell detectors. Different from previous settings, extra commonsense knowledge is needed to understand the given expression for object grounding. The overall architecture is illustrated in Figure 3. The model can be generally divided into three components: (1) a top-down image attention module that predicts an attention distribution over the image grids conditioned on the given expression; (2) a multi-hop facts attention module that gather information from a set of related facts in our knowledge base; (3) a matching module which calculates the expression-object matching score for final grounding. We elaborate on each component in the following. It is worth noting that our facts attention module can be plugged into other referring expression models as well.

4.1. Top-down Image Attention Module

Similar to many conventional REF models [7, 19], we first represent each word in the given expression $q$ using an one-hot vector, and then encode them iteratively by an LSTM. The hidden states at all time steps are added together as the holistic representation for the expression, which is denoted as $q$ with a dimension of 2048. Meanwhile, the input image is fed into a pre-trained VGG-16 net. Feature maps from Conv5_3 are extracted, denoted as $V$ of size $7 \times 7 \times 512$. A top-down attention mechanism is adopted here to extract information from the image regions that are the most related to the expression, which is formulated as:

$$
\alpha_{i,j} = w^T \tanh(W_wv_{i,j} + W_qq),
\beta_{i,j} = \exp(\alpha_{i,j}) / \left( \sum_{k,l} \exp(\alpha_{k,l}) \right), \quad i, j \in \{1, ..., 7\}
$$

$$
\nu = \sum_{k,l} \beta_{k,l} v_{k,l},
$$

where $v_{i,j}$ is the local feature vector at position $(i, j)$ in feature maps $V$; The expression feature $q$ is used here as the guidance signal; $W_w, W_q$, and $w$ are linear transformation weights to be learned; $\beta_{i,j}$ is the attention weight at location $(i, j)$. The weighted sum $\nu$ is the attended image feature, with the dimension of 512. It encodes image features that is most relevant to the given expression.

4.2. Two-stage Fact Attention Module

The distinguishing feature of our proposed dataset is the requirement of commonsense knowledge. In this section, we introduce a two-stage coarse-to-fine fact attention module that distills related information from the massive facts of our constructed knowledge base.

For the first stage, we train a Word2Vec [21] model with Skip-Gram on the 1, 008, 406 facts in our knowledge base. Given a candidate object, we first retrieve its corresponding facts, and then compute the cosine similarity between the averaged Word2Vec word embeddings of each fact and the

\footnote{We also tried to use the last hidden state of the LSTM as the expression feature but the results are slightly worse. We believe the reason is that our expressions are long.}
feature which is then fed into an attentional LSTM to decide how

representation, considering that some facts are very long.

stage. Firstly, each fact \( k \) is encoded by an LSTM with

retrieved facts in the previous

Figure 3. The overall architecture of our baseline model, which contains three main parts, i.e., the top-down attention module, the facts attention module and the matching module. These modules will be described one by one in Section 4.

expression. At most top \( K \) facts (denoted as \( \{s_k\}, k = 1, \ldots, K \) ) are then kept for further processing.

At the second stage, inspired by [34], we employ an

Epicdemic Memory Module (as shown in Figure 4) to focus attention on a subset of the \( K \) retrieved facts in the previous stage. Firstly, each fact \( s_k \) is encoded by an LSTM with

2048D hidden states (which does not share parameters with the LSTM encoding expressions), and the averaged hidden states over all time steps (denoted as \( s_k \) ) is taken as the fact representation, considering that some facts are very long. Next, the episodic memory module is adopted to perform a multi-hop attention over facts \( s_1, \ldots, s_K \) under the guidance of the expression \( q \). At each pass \( t \), a set of attention weights are computed as follows:

\[
\begin{align*}
\mathbf{z}_k^t &= [s_k \circ \mathbf{q}; s_k \circ \mathbf{m}^{t-1}; |s_k - \mathbf{q}|; |s_k - \mathbf{m}^{t-1}|], \\
\mathbf{z}_k^t &= \mathbf{w}_p^T \tanh(\mathbf{W}_c \mathbf{z}_k^t), \\
\alpha_k^t &= \exp(z_k^t) / (\sum_{i=1}^{K} \exp(z_i^t)), k = 1, \ldots, K,
\end{align*}
\]

which is then fed into an attentional LSTM to decide how

much the hidden state should be updated for each \( k \):

\[
h_k^t = \alpha_k^t \text{LSTM}(s_k, h_{k-1}^t) + (1 - \alpha_k^t)h_{k-1}^t, k = 1, \ldots, K
\]

and the episodic memory for pass \( t \) is updated by another

LSTM that takes the last hidden state of the attentional

LSTM as contextual vector:

\[
\mathbf{m}^t = \text{LSTM}(h_K^t, \mathbf{m}^{t-1}), t = 1, \ldots, T.
\]

The memory for the last pass \( \mathbf{m}^T \) is considered as the at-
tended fact feature and fed into the following Matching

Module.

4.3. Matching Module

The matching module is then used to calculate the

matching score between the expression \( q \) and each object

\( O_n \). Specifically, for each candidate object, we calculate

its appearance feature by firstly resizing the object region
to 224 \times 224 and then feeding it into a pre-trained VGG-16. Feature maps from Conv5_3 are extracted and aver-
gagely pooled. A fully connected layer with 512 neurons and ReLU are then followed, which results in an appearance feature for object \( O_n \) of \( \mathbf{f}_n^{512} \).

In addition, we also extract the geometric information for each candidate object, \( \{\alpha_{ul}^{512}, \alpha_{ur}^{512}, \alpha_{bl}^{512}, \alpha_{br}^{512}, \mathbf{w}_c\} \), which is a 5-dimensional vector consisting of four values for top

left and bottom right corner coordinates of the object region (normalised between 0 and 1) and one value for its relative area (i.e., ratio of the bounding box area to the image area, also between 0 and 1). A fully connected layer with 128 neurons and ReLU are followed, which lead to a geometric feature \( \mathbf{f}_n^{128} \).
Table 2. Dataset bias analysis with different settings. The results show that visual and knowledge facts are both important to our dataset. The remove of prepositional phrases and verbs from expressions has a relatively small influence on model performance.

| Method                  | Accuracy (%) | FG Accuracy (%) |
|-------------------------|--------------|-----------------|
|                         | Val | Test | Val | Test |
| Random                  | 9.93 | 9.81 | -   | -    |
| ECIFA (no image)        | 49.73| 47.61| 41.91| 40.35|
| ECIFA (no facts)        | 37.95| 35.16| -   | -    |
| ECIFA (partial expression) | 59.07| 58.49| 48.97| 48.61|
| ECIFA (no facts)        | 59.45| 58.97| 49.26| 48.92|

The candidate’s appearance feature $f_n^a$ and geometric feature of $f_n^g$ are then concatenated with the attended fact feature $f_n^v$ and the attended image feature $v$. Another linear transformation is applied to yield a 2048d feature:

$$f_n = W[f_n^a; f_n^g; f_n^v; v],$$

where $W$ is the parameter to be learned. Finally we calculate the inner product of the expression feature $q$ and the integrated object feature $f_n$. Softmax is then applied over all candidate objects, and the object with the highest score will be selected for the expression. During the training, the cross entropy loss is used.

5. Experiment

In this section, we conduct experiments to analyze the proposed dataset KB-Ref and baseline model ECIFA. Firstly, we analyze the bias of our dataset by evaluating our algorithm with different partial input information. Then the proposed ECIFA is compared with SoTA REF models on our dataset. Lastly, a group of ablation experiments are performed to validate the effectiveness of multi-hop fact attention. Additionally, results of using detected bounding boxes are given.

All the experiments are conducted on 8 Nvidia RTX2080Ti GPUs. The baseline model is implemented with PyTorch, and trained by using SGD optimizer with a learning rate of $1e^{-4}$ initially. The learning rate will decay half if the validation loss does not decrease in consecutive two epochs. We adopt a batch size of 16, which consists of 16 expressions and the corresponding object candidates in images, and train the model with 40 epochs. Same as previous work, we also use accuracy as the evaluation metric, which is calculated by checking whether the target object is correctly selected or not.

5.1. Dataset Bias Analysis

Dataset bias is an important issue of current vision-and-language datasets. In [1], Cirik et al. shows that a system trained and tested on input images without the input referring expression can achieve an accuracy of 71.2% in top-2 predictions on RefCOCOg [19], which suggests the significant data bias. Inspired by this work, we analyze our dataset using similar methods.

**Random** The accuracy is obtained by selecting a random object from the candidates in an image.

**ECIFA (no image)** We eliminate all the visual features in ECIFA, i.e., $f_n^g$, $f_n^v$, and $v$ are removed from Equation 5 when calculating the matching score. This study is to investigate the importance of visual information in our Kb-Ref.

**ECIFA (no facts)** ECIFA is re-trained without using knowledge facts, which means that $f_n^a$ is removed from Equation 5, so as to study the impact of knowledge facts in our Kb-Ref.

**ECIFA (partial expression)** ECIFA is re-trained by keeping only nouns and adjectives in the input expression, since description words (e.g., color, shape) and object categories are basically expressed by adjectives and nouns. It will obscure the relationships between objects, which are usually represented by prepositional phrases and verbs.

Table 2 shows the ablation study results. The Random baseline offers accuracy around 10% on both validation and test sets, as there are around 10 candidates to be selected for each expression. Without using external knowledge, the accuracy of ECIFA (no facts) drops to 35.16% on test set. ECIFA (no image) leads to a 11-percentage drop on the test accuracy. As we can see, the performance drop caused by removing facts is larger than by removing image, which indicates the importance of commonsense knowledge in our REF setting. In addition, by discarding all words except nouns or adjectives, the test accuracy of ECIFA (partial expression) drops slightly by around 0.5 percentage. This phenomenon indicates that the superior performance of ECIFA does not specifically depend on object relationships.

Besides the answering accuracy, we also evaluate the accuracy of ‘fact grounding’ in Table 2. A success will be counted if our model gives the highest attention weight to the groundtruth fact. We can see a positive correlation between the answering accuracy and the ‘fact grounding’ accuracy.

5.2. Comparison with State-of-the-arts

The following models are evaluated on the KB-Ref and compared with the proposed ECIFA model. All the models are trained from scratch on the training split of our proposed KB-Ref dataset, using their own training strategies.

**CMN** [6] is a modular architecture that utilizes the language attention to parse the input expression into subject, relation and object. The textual components are then aligned with image regions by three modules respectively to calculate the final matching score.

**SLR** [39] is a speaker-listener model that jointly learns for referring expression comprehension and generation. A re-
The overall accuracy of all evaluated models with ground truth candidate objects bounding boxes are presented in Table 3. All the SoTA models show a significant performance drop compared to their performance on RefCOCOs, which demonstrates the challenge of our dataset. Our model reaches an accuracy of 58.97% on KB-Ref test set, outperforming all the SoTA models by nearly 12%, which suggests the necessity of exploring external knowledge in our REF setting. In addition, there is still a large gap between our model and the human performance (about 30% in accuracy). We also visualize some experimental results on Figure 5. We also add the proposed episodic memory module (EMM) into MAttNet, which improves the test accuracy from 46.03% to 63.57%. It further validates the importance of commonsense knowledge integration for our proposed REF task and the effectiveness of EMM.

| Method                  | Val   | Test  |
|-------------------------|-------|-------|
| CMN [6]                 | 41.28 | 40.03 |
| SLR [39]                | 44.03 | 42.92 |
| VC [25]                 | 44.03 | 43.50 |
| LGARNs [30]             | 45.11 | 44.27 |
| MAttNet [37]            | 46.86 | 46.03 |
| ECIFA (Ours)            | 50.45 | 58.97 |
| MAttNet [37] + EMM      | 64.08 | 63.57 |
| Human performance       | -     | 90.13 |

Table 3. Performance (Acc%) comparison with SoTA REF approaches and our proposed ECIFA on KB-Ref. Our ECIFA shows the highest accuracy on both validation and test set. All listed models use VGG-16 features.

5.3. Ablation Studies

Effectiveness of Episodic Memory Module. The adopted Episodic Memory Module (EMM) performs a multi-hop attention process. To validate it effectiveness, we compare it with a single-pass soft attention module and also evaluate it with different numbers of passes $T = 1, 3, 5, 10$. The single-pass ($T = 1$) soft attention module compute the attended facts feature using a weighted sum $f_n = \sum_{k=1}^{K} a_k s_k$, instead of using the attentional LSTM as Equation 3. It does not take into consideration the interaction between facts. As shown in Table 4, the episodic memory module with one pass already surpasses soft attention by roughly 2.4 percentages. We also observe that the accuracy is improved with the increase of the number of passes $T$, which validates the advantage of multi-hop attention. As the performance almost saturates at $T = 5$, we choose the model ECIFA (EMM, 5-pass) for the following experiments, in order to strike a balance between accuracy and speed. In Figure 6, we also showcase the focused facts over different passes.

Impact of Direct Facts Supervision. Note that our episodic memory module is trained in a weakly supervised manner by the remote cross entropy loss for object selection. As the groundtruth supporting fact has been recorded in our dataset, it is straightforward to add a direct supervision on the episodic memory module. To be specific, a target vector is defined where the position corresponding to the ground truth fact is filled with 1 while others are 0. A binary cross entropy function is then employed to calculate the loss between the facts attention weights and the target vector, which is applied on the last pass of EMM. The corresponding results in Table 4 shows that adding direct fact supervision does not yield significantly better performance, which means that the weak supervision is considerably strong for training episodic memory module.
is roughly $2 \sim 3\%$, which is significantly smaller than the gap achieved using ground-truth bounding boxes. The reason is that the trained detector is far from satisfactory, which only generates low-quality and misleading bounding boxes and labels. A wrong label may lead our proposed model to extract incorrect knowledge from the knowledge base.

6. Conclusion

In this work, we present a referring expression dataset, KB-Ref, in which the objects are expressed by their visual and non-visual attributes. Such that, it encourages REF algorithms to explore information from images as well as external knowledge bases. The dataset features a large variety of objects (1,805 categories) and long expressions (13.32 in average). Due to its complexity, directly applying SoTA REF approaches does not achieve promising results. To this end, we propose to tackle the problem with a expression conditioned image and fact attention network (ECIFA). Experiments show that our proposed model indeed improves the performance on KB-Ref by a large margin.

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