Community Regularization of Visually-Grounded Dialog

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ABSTRACT

The task of conducting visually grounded dialog involves learning goal-oriented cooperative dialog between autonomous agents who exchange information about a scene through several rounds of questions and answers in natural language. We posit that requiring artificial agents to adhere to the rules of human language, while also requiring them to maximize information exchange through dialog is an ill-posed problem. We observe that humans do not stray from a common language because they are social creatures who live in communities, and have to communicate with many people everyday, so it is far easier to stick to a common language even at the cost of some efficiency loss. Using this as inspiration, we propose and evaluate a multi-agent community-based dialog framework where each agent interacts with, and learns from, multiple agents, and show that this community-enforced regularization results in more relevant and coherent dialog (as judged by human evaluators) without sacrificing task performance (as judged by quantitative metrics).

KEYWORDS

Visual Dialog; Multi Agent Reinforcement Learning; Curriculum Learning; Emergent Communication

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1 INTRODUCTION

AI is increasingly becoming an important part of our daily lives, be it in the household, the workplace or in public places. In order for humans to interact with and understand the AI system, it needs to learn how to communicate with us about our environment using the languages that we speak. This requires the AI system to visually interpret the world, and communicate descriptions of the physical world. While such a task would have been considered impossible a few years ago, the recent progress in the fields of Computer Vision and Natural Language Processing, which are important building blocks for this task, have reinvigorated interest in the community. Several problems like image captioning ([12], [36], [30], [10], [20], [37]), image classification ([14], [29], [8], [34]), object detection ([17], [23], [24]), image segmentation ([18], [9], [22]), dialog ([28], [31], [5]), question answering ([38], [27], [35]) etc. have received immense amounts of attention from the research community. The paradigm of reinforcement learning has also shown promising results in several problems including learning to play Go [26] and Atari games [21], among others, at superhuman levels.

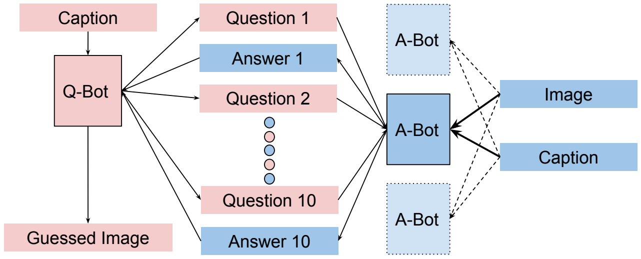

Figure 1: Multi-Agent (with 1 Q-Bot, 3 A-Bots) Dialog Framework. The diagram shows multiple A-bots interacting with a single Q-bot using natural language questions and answers. The Q-bot asks relevant questions to improve its understanding of the image and one of the randomly chosen A-bots answers the question. This ensures that the Q-bot can't overfit to responses provided by any one A-bot.

Capitalizing on the growth in all these different domains, it now seems plausible to build more advanced dialog systems capable of reasoning over multiple modalities while also learning from one another. Such systems will allow humans to have a meaningful dialog with intelligent systems containing visual as well as textual content. Use cases include assistive systems for the visually impaired, smart multimodal dialog agents (unlike current versions of Siri and Alexa which are primarily audio based and cannot make effective use of multimodal data) and even large scale visual retrieval systems. However, as these systems become more advanced, it will become increasingly common to have two agents interact with each other to achieve a particular goal [15]. We want these conversations to be interpretable to humans for the sake of transparency and ease of debugging. This motivates our work on goal-driven agents which interact in coherent language understandable to humans.

This paper presents work on Goal driven Visual Dialog Agents. Most prior work on visual dialog [[2], [4]] has approached the problem using supervised learning where, conditioned on the question - answer pair dialog history, a caption c and the image I, the agent is required to answer a given question q. The model is trained in a supervised learning framework using ground truth supervision from a human-human dialog dataset.

Some recent work [3] has tried to approach the problem using reinforcement learning, with two agents, namely the Question (Q-)

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Bot and the Answer (A-) Bot. While the A-Bot still has the image, caption and the dialog history to answer any question, the Question Bot only has access to the caption and the dialog history. The two agents are initially trained with supervision using the VisDial v0.9 dataset [2], which consists of 80k images, each with a caption and 10 human generated question-answer pairs discussing the image. Under supervision, the agents are trained in an isolated manner to maximize the likelihood of generating the ground truth answers. The agents are then made to interact and talk to each other, with a common goal of trying to improve the Q-Bot's understanding of the image. The agents learn from their conversation with each other via reinforcement learning. While the supervised training *in isolation* helps the agents to learn to interpret the images and communicate information, it is the *interactive* training phase which leads to richer dialog with more informative questions and answers as the agents learn to adapt to each others' strengths and weaknesses. However, it is important to note that the optimization problem in this conversational setting does not make the agents stick to the domain of grammatically correct and coherent natural language. Indeed, if the two agents are allowed to communicate and learn from each other for too long, they quickly start generating non-grammatical and semantically meaningless sentences. While the generated sentences stop making sense to human observers, the two agents are able to understand each other much better, and the Q-Bot's understanding of the image improves. This is similar to how twins often develop a private language [25], an idiosyncratic and exclusive form of communication understandable only to them. This, however, reduces transparency of the agents' dialog to any observer (human or AI), and is hence undesirable. Prior work [2, 3] which has focused on improving performance as measured by the Q-Bot's image retrieval rank has suffered from incoherent dialog. We address this problem of improving the agents' performance while increasing dialog quality by taking inspiration from humans. We observe that humans continue to speak in commonly spoken languages, and hypothesize that this is *because they need to communicate with an entire community*, and having a private language for each person would be extremely inefficient. With this idea, we let our agents learn in a similar setting, by making them talk to (ask questions of, get answers from) multiple agents, one by one. We claim that if, instead of allowing a single pair of agents to interact, we were to make the agents more social, and make them interact and learn from multiple other agents, they would be disincentivized to develop a private language, and would have to conform to the common language. We call this Community Regularization.

In the subsequent sections we describe the Visual Dialog task and the neural network architectures of our Q-Bots and A-Bots in detail. We then describe the training process of the agents sequentially: (a) in isolation (via supervision), (b) while interacting with one partner agent (via reinforcement), and (c) our proposed multi-agent setup where each agent interacts with multiple other agents (via reinforcement). We compare the performance of the agents trained in these different settings, both quantitatively using image retrieval ranks, and qualitatively evaluating the overall coherence, grammar and relevance of the dialog generated, as judged by impartial human evaluators. We make the following contributions: We propose a multi-agent dialog setup in a natural language setting and show that it results in community regularization which ensures that the interactions between the agents remain grounded in the rules and grammar of natural language, are coherent and human-interpretable without compromising on task performance. The code can be found in the following repository https://github.com/agakshat/visualdialog-pytorch.

2 PROBLEM STATEMENT

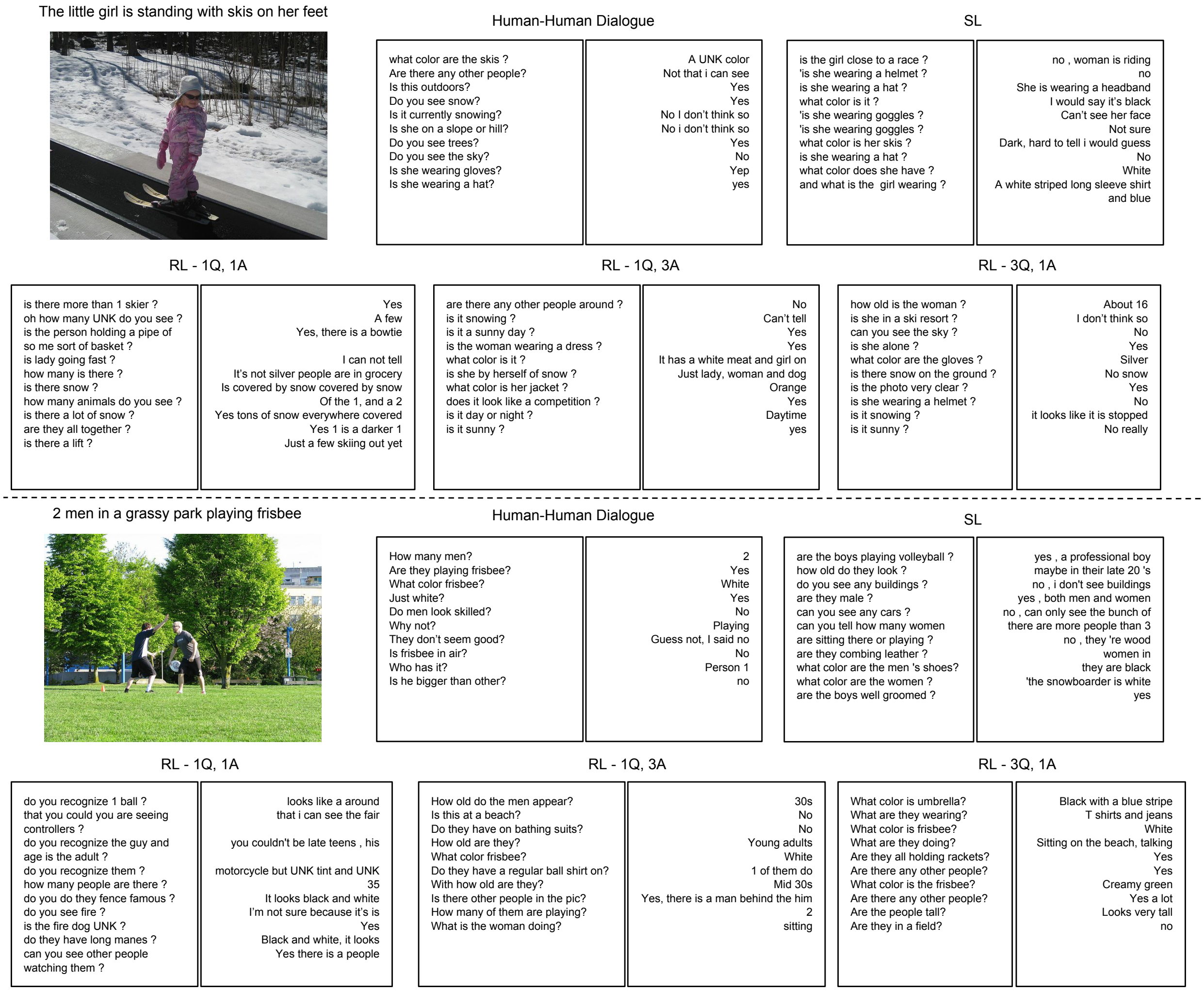
We begin by defining the problem of Visually Grounded Dialog for the co-operative image guessing game on the VisDial dataset.

Players and Roles: The game involves two collaborative agents – a question bot (Q-bot) and an answer bot (A-bot). The A-bot has access to an image and caption, while the Q-bot has access to the image's caption, but not the image itself. Both the agents share a common objective, which is for the Q-bot to form a good "mental representation" of the unseen image which can be used to retrieve, rank or generate that image. This is facilitated by the exchange of 10 pairs of questions and answers between the two agents, using a shared vocabulary, where the Q-bot asks the A-bot a question about the image, and the A-bot answers the question, hence improving the Q-Bot's understanding of the image scene.

General Game Objective: At each round, in addition to communicating with the A-bot, the Q-bot also provides the learning algorithm with its best estimate y_t of the unknown image I based only on the dialog history and caption. Both agents receive a common reward from the environment which is inversely proportional to the error in this description under some metric $L(y_t, y_{gt})$. We note that this is a general setting where the 'description' y_t can take on varying levels of specificity – from image feature embeddings extracted by deep neural networks to textual descriptions and pixel-level image re-generations.

Specific Instantiation: In our experiments, we focus on the setting where the Q-bot is tasked with estimating a vector embedding of the image I, which is later used to retrieve a similar image from the dataset. Given a feature extractor (say, a pretrained CNN model like VGG [29]), the target 'description' y_{gt} of the image, can be obtained by simply forward propagating through the VGG model, without the requirement of any human annotation. Reward/error can be measured by the Euclidean distance between the target description y_{gt} and the predicted description y_t, and any image may be used as the visual grounding for a dialog. Thus, an unlimited number of games may be simulated without human supervision, motivating the use of reinforcement learning in this framework.

Our primary focus for this work is to ensure that the agents' dialog remains coherent and understandable while also being informative and improving task performance. For concreteness, consider an example of dialog that is informative yet incoherent: **question**: "do you recognize the guy and age is the adult?", **answered with**: "you couldn't be late teens, his". The example shows that the bots try to extract and convey as much information as possible in a single question/answer (sometimes by incorporating multiple questions or answers into a single statement). But in doing so they lose basic semantic and syntactic structure. We also provide a sample of the dialogs in Figure 2.



The little girl is standing with skis on her feet

Human-Human Dialogue

what color are the skis ?	A UNK color
Are there any other people?	Not that i can see
Is this outdoors?	Yes
Do you see snow?	Yes
Is it currently snowing?	No I don't think so
Is she on a slope or hill?	No i don't think so
Do you see trees?	Yes
Do you see the sky?	No
Is she wearing gloves?	Yep
Is she wearing a hat?	yes

SL

is the girl close to a race ?	no , woman is riding
'is she wearing a helmet ?	no
is she wearing a hat ?	She is wearing a headband
what color is it ?	I would say it's black
'is she wearing goggles ?	Can't see her face
'is she wearing goggles ?	Not sure
what color is her skis ?	Dark, hard to tell i would guess
is she wearing a hat ?	No
what color does she have ?	White
and what is the girl wearing ?	A white striped long sleeve shirt
	and blue

RL - 1Q, 1A

is there more than 1 skier ?	Yes
oh how many UNK do you see ?	A few
is the person holding a pipe of	Yes, there is a bowtie
so me sort of basket ?	
is lady going fast ?	I can not tell
how many is there ?	It's not silver people are in grocery
is there snow ?	Is covered by snow covered by snow
how many animals do you see ?	Of the 1, and a 2
is there a lot of snow ?	Yes tons of snow everywhere covered
are they all together ?	Yes 1 is a darker 1
is there a lift ?	Just a few skiing out yet

RL - 1Q, 3A

are there any other people around ?	No
is it snowing ?	Can't tell
is it a sunny day ?	Yes
is the woman wearing a dress ?	Yes
what color is it ?	It has a white meat and girl on
is she by herself of snow ?	Just lady, woman and dog
what color is her jacket ?	Orange
does it look like a competition ?	Yes
is it day or night ?	Daytime
is it sunny ?	yes

RL - 3Q, 1A

how old is the woman ?	About 16
is she in a ski resort ?	I don't think so
can you see the sky ?	No
is she alone ?	Yes
what color are the gloves ?	Silver
is there snow on the ground ?	No snow
is the photo very clear ?	Yes
is she wearing a helmet ?	No
is it snowing ?	it looks like it is stopped
is it sunny ?	No really

2 men in a grassy park playing frisbee

Human-Human Dialogue

How many men?	2
Are they playing frisbee?	Yes
What color frisbee?	White
Just white?	Yes
Do men look skilled?	No
Why not?	Playing
They don't seem good?	Guess not, I said no
Is frisbee in air?	No
Who has it?	Person 1
Is he bigger than other?	no

SL

are the boys playing volleyball ?	yes , a professional boy
how old do they look ?	maybe in their late 20 's
do you see any buildings ?	no , i don't see buildings
are they male ?	yes , both men and women
can you see any cars ?	no , can only see the bunch of
can you tell how many women	there are more people than 3
are sitting there or playing ?	no , they 're wood
are they combing leather ?	women in
what color are the men 's shoes?	they are black
what color are the women ?	'the snowboarder is white
are the boys well groomed ?	yes

RL - 1Q, 1A

do you recognize 1 ball ?	looks like a around
that you could you are seeing	that i can see the fair
controllers ?	
do you recognize the guy and	you couldn't be late teens , his
age is the adult ?	
do you recognize them ?	motorcycle but UNK tint and UNK
how many people are there ?	35
do you do they fence famous ?	It looks black and white
do you see fire ?	I'm not sure because it's is
is the fire dog UNK ?	Yes
do they have long manes ?	Black and white, it looks
can you see other people	Yes there is a people
watching them ?	

RL - 1Q, 3A

How old do the men appear?	30s
Is this at a beach?	No
Do they have on bathing suits?	No
How old are they?	Young adults
What color frisbee?	White
Do they have a regular ball shirt on?	1 of them do
With how old are they?	Mid 30s
Is there other people in the pic?	Yes, there is a man behind the him
How many of them are playing?	2
What is the woman doing?	sitting

RL - 3Q, 1A

What color is umbrella?	Black with a blue stripe
What are they wearing?	T shirts and jeans
What color is frisbee?	White
What are they doing?	Sitting on the beach, talking
Are they all holding rackets?	Yes
Are there any other people?	Yes
What color is the frisbee?	Creamy green
Are there any other people?	Yes a lot
Are the people tall?	Looks very tall
Are they in a field?	no

Figure 2: A randomly selected image from the VisDial dataset followed by the ground truth (human) and generated dialog about that image for each of our 4 systems (SL, RL-1Q,1A, RL-1Q,3A, RL-3Q,1A). These examples were 2 of the 102 used in the human evaluation results shown in Table 2

3 RELATED WORK

Most of the major works which combine vision and language have traditionally focused on the problem of image captioning (([12], [36], [30], [10], [20], [37]) and visual question answering ([1], [39], [7]). The problem of visual dialog is relatively new and was first introduced by Das et al. [2] who also created the VisDial dataset to advance the research on visually grounded dialog. The dataset was collected by pairing two annotators on Amazon Mechanical Turk to chat about an image. They formulated the task as a 'multi-round' VQA task and evaluated individual responses at each round in an image guessing setup. In subsequent work by Das et al. [3] they proposed a reinforcement learning based setup where they allowed the Question bot and the Answer bot to have a dialog with each other with the goal of correctly predicting the image unseen to the Question bot. However, in their work they noticed that the reinforcement learning based training quickly led the bots to diverge from natural language. In fact Kottur et al. [13] recently showed that language emerging from two agents interacting with each other might not even be interpretable or compositional. We use community regularization to alleviate this problem. Recent work has also proposed using such goal driven dialog agents for other related tasks including negotiation [16] and collaborative drawing [11]. We believe that our work can easily extend to those settings as well. Lu et al. [19] proposed a generative-discriminative framework for visual dialog where they train only an answer bot to generate informative answers for ground truth questions. These answers were then fed to a discriminator, which was trained to rank the generated answer among a set of candidate answers. This is a major restriction of their model as it can only be trained when this additional information of candidate answers is available, which restricts it to a supervised setting. Furthermore, since they train only the answer bot and have no question bot, they cannot simulate an entire dialog which also prevents them from learning by self-play via reinforcement. Wu et al. [33] further improved upon this generative-discriminative framework by formulating the discriminator as a more traditional GAN [6], where the adversarial discriminator is tasked to distinguish between human generated and machine generated dialogs.

4 AGENT ARCHITECTURES

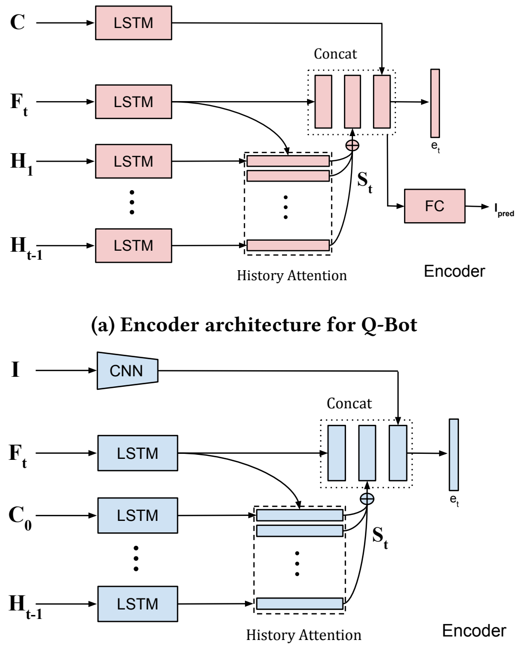
We describe all the different components of the agent architectures in this section. Note that the overall architecture is mostly borrowed from Das et al. [3], Lu et al. [19] with slight modifications to individual units and an additional caption encoder. We explain these modifications in detail in this section. We would like to stress that these changes are not the main contribution of our paper. The main contribution is the Multi-agent dialog framework described in section 5.3.

4.1 Question Bot Architecture

The question bot architecture we use is inspired by the answer bot architecture in Das et al. [3], Lu et al. [19] but the individual units have been modified to provide more useful representations. Similar to the original architecture, our Q-Bot, shown in Fig. 3a, also consists of 4 parts, (a) fact encoder, (b) state-history encoder, (c) question decoder and (d) image regression network.

1. **Fact Encoder:** The fact encoder is a unidirectional LSTM which is given the previous question-answer pair (q_{t-1}, a_{t-1}) as input. The LSTM generates a fact embedding $F_t \in R^{512}$.
2. **State/History Encoder:** We modify the state-history encoder to incorporate a two-level hierarchical encoding of the dialog. The encoder first computes the fact embeddings $H_t^Q = (F_1, F_2, F_3 ... F_{t-1})$, using an LSTM akin to the fact encoder described above. We pass these embeddings and F_t computed by the Fact Encoder through a fully connected layer, generating attention weights which are used to attend over H_t^Q, producing the history embedding $S_t^Q \in R^{512}$. Notice that this results in a two-level hierarchical encoding of the dialog $(q_t, a_t) \rightarrow F_t$ and $(F_1, F_2, F_3, ... F_t) \rightarrow S_t^Q$.
3. **Caption Encoder:** This is a unidirectional LSTM which is given the image caption c as input. The LSTM generates a caption embedding $C^Q \in R^{512}$.
4. **Feature Regression Network:** $\{F_t^Q, S_t^Q, C^Q\}$ are concatenated to produce an embedding E_t^Q. This is passed through 2 fully connected layers with dropout to produce $\hat{y}_t$ from the current encoded state $\hat{y}_t = f(S_t^Q)$.
5. **Question Decoder:** The hidden state of this LSTM is initialized with the hidden state of the fact encoder. E_t^Q is passed through a fully connected layer to generate e_t^Q, which is used to update the hidden state of the LSTM of the question decoder. The question q_t is then generated by sequentially sampling words (either via teacher forcing during supervised pretraining or via autoregressive generation during RL and evaluation).

Note that we use a dropout of 0.5 in all the LSTMs during training. All LSTM hidden layers sizes are 512, and the image embedding size is 4096. The input word embedding size is 300.



(a) Encoder architecture for Q-Bot

(b) Encoder architecture for A-Bot

Figure 3: Agent Encoder Architectures

4.2 Answer Bot Architecture

The architecture for A-Bot, also inspired from Lu et al. [19], shown in Fig. 3b, is similar to that of the Q-Bot. It has 3 components: (a) question encoder, (b) state-history encoder and (c) answer decoder.

1. **Question Encoder:** The question encoder is a unidirectional LSTM which is given the current question q_t generated by the Q-Bot as input. The LSTM generates a question embedding $Q_t^A \in R^{512}$.
2. **State/History/Image Encoder:** The encoder first computes the fact embeddings $H_t^A = (F_1, F_2, F_3 ... F_{t-1})$, using an LSTM akin to the fact encoder described above. By passing these embeddings and the Q_t^A computed by the Question Encoder through a fully connected layer, attention weights are generated which are used to attend over H_t^A, producing the history embedding $S_t^A \in R^{512}$. Notice that this results in a two-level hierarchical encoding of the dialog $(q_t, a_t) \rightarrow F_t$ and $(F_1, F_2, F_3 ... F_t) \rightarrow S_t^A$. $\{Q_t^A, S_t^A, y_{gt}\}$ are then concatenated to produce an embedding E_t^A.
3. **Answer Decoder:** The hidden state of this LSTM is initialized with the hidden state of the question encoder. E_t^A is passed through a fully connected layer to generate e_t^A, which is used to update the hidden state of the LSTM of the answer decoder. The answer a_t is then generated by sequentially sampling words (either via teacher forcing during supervised pretraining or via autoregressive generation during RL and evaluation).

5 TRAINING

We follow the training process proposed in Das et al. [3]. Two agents, a Q-Bot and an A-Bot are first trained in isolation, by supervision from the VisDial dataset. After this supervised pretraining for 15 epochs over the data, we smoothly transition the agents to learn from each other via reinforcement learning. The individual phases of training will be described in more detail below. Note that the key novelty of the work is the multi-agent dialog framework proposed in Section 5.3

5.1 Supervised pre-training

In the supervised part of training, both the Q-Bot and A-Bot are trained separately, using a Maximum Likelihood Estimation (MLE) loss computed using the ground truth questions and answers, respectively, for every round of dialog. The Q-Bot simultaneously optimizes another objective: minimizing the Mean Squared Error (MSE) loss between the true (y_{gt}) and predicted (y_t) image embeddings. The ground truth dialogs and image embeddings are from the VisDial dataset.

Given the true dialog history, image features and a question from the dataset, the A-Bot generates an answer to that question. Given the true dialog history and the previous question-answer pair from the dataset, the Q-Bot is made to generate the next question to ask the A-Bot. Both agents receive only ground truth questions and answers, never what the other agent generated - so the two agents never actually interact during this phase of training. However, there are multiple problems with this training scheme. First, MLE is known to result in models that generate repetitive dialogs and often produce generic responses. Second, since the agents are never allowed to interact during training, they end up encountering out-of-distribution questions and answers when made to interact during evaluation, which reduces the task performance. This can be observed in Figure 4. The performance of the agents trained via supervised learning dips after each successive dialog round.

5.2 Reinforcement Learning Setup

To alleviate the issues pointed out with supervised training, we let the two bots interact with each other via self-play (no ground-truth except images and captions). This interaction is also in the form of questions asked by the Q-Bot, and answered in turn by the A-Bot, using a shared vocabulary. The state space is partially observed and asymmetric, with the Q-Bot observing $\{c, q_1, a_1 \dots q_{10}, a_{10}\}$ and the A-Bot observing the same, plus the image I. Here, c is the caption, and q_i, a_i is the i^{th} dialog pair exchanged where $i = 1 \dots 10$. The action space for both bots consists of all possible output sequences of a specified maximum length (Q-Bot: 16, A-Bot: 9) under a fixed vocabulary (size 8645). Each action involves predicting words sequentially until a stop token is predicted, or the generated statement reaches the maximum length. Additionally, Q-Bot also produces a guess of the visual representation of the input image (VGG fc-7 embedding of size 4096). Both Q-Bot and A-Bot share the same objective and get the same reward to encourage cooperation. Information gain in each round of dialog is incentivized by setting the reward as the **change in distance** of the predicted image embedding to the ground-truth image representation. This means that a QA pair is of high quality only if it helps the Q-Bot make a better prediction of the image representation. Both policies are modeled by neural networks, as discussed in Section 4.

A dialog round at time t consists of the following steps: 1) the Q-Bot, conditioned on the state encoding, generates a question q_t, 2) A-Bot updates its state encoding with q_t and then generates an answer a_t, 3) Both Q-Bot and A-Bot encode the completed exchange as a fact embedding, 4) Q-Bot updates its state encoding to incorporate this fact and finally 5) Q-Bot predicts the image representation for the unseen image conditioned on its updated state encoding.

Similar to Das et al. [2], we use the REINFORCE [32] algorithm that updates policy parameters in response to experienced rewards. The per-round rewards that are used to calculate the discounted returns follow:

$$r_t(s_t^Q, (q_t, a_t, y_t)) = l(y_{t-1}, y^{gt}) - l(y_t, y^{gt}) \qquad (1)$$

This reward is positive if the distance between image representation generated at time t is closer to the ground truth than the representation at time $t-1$, hence incentivizing information gain at each round of dialog. The REINFORCE update rule ensures that a (q_t, a_t) exchange that is informative has its probabilities pushed up. Do note that the image feature regression network f is trained directly via supervised gradient updates on the L-2 loss.

However, as noted above, this RL optimization problem is ill-posed, since rewarding the agents for information exchange does not motivate them to stick to the rules and conventions of the English language. Thus, we follow an elaborate curriculum scheme described in [2]. Specifically, for the first K rounds of dialog for each image, the agents are trained using supervision from the VisDial dataset. For the remaining 10-K rounds, however, they are trained via reinforcement learning. K starts at 9 and is linearly annealed to 0 over 10 epochs. Despite these modifications the bots are still observed to diverge from natural language and produce non-grammatical and incoherent dialog. Thus, we propose a multi bot architecture to help the agents interact in diverse and coherent, yet informative, dialog.

5.3 Multi-Agent Dialog Framework (MADF)

In this section we describe our proposed Multi-Agent Dialog architecture in detail. We claim that if, instead of allowing a single pair of agents to interact, we were to make the agents more social, and make them *interact and learn from multiple other agents*, they would be disincentivized to develop a private language, and would have to conform to the common language. We call this Community Regularization.

In particular, we create either multiple Q-bots to interact with a single A-bot, or multiple A-bots to interact with a single Q-bot. All these agents are initialized with the learned parameters from the supervised pretraining as described in Section 5.1. Then, for each batch of images from the VisDial dataset, we randomly choose a Q-bot to interact with the A-bot, or randomly choose an A-bot to interact with the Q-bot, as the case may be. The two chosen agents then have a complete dialog consisting of 10 question-answer pairs about each of those images, and update their respective weights based on the rewards received (as per Equation 1) during the conversation, using the REINFORCE algorithm. This process is repeated for each batch of images, over the entire VisDial dataset. It is important to note that histories are *not shared* across batches. MADF

Table 1: Comparison of answer retrieval metrics with previously published work. SL has the best scores. The scores drop drastically in RL-1Q,1A, but MADF agents (RL-3Q,1A and RL-1Q,3A) are able to retain the same language quality as the SL agent.

Model	MRR	Mean Rank	R@10
Answer Prior [2]	0.3735	26.50	53.23
MN-QIH-G [2]	0.5259	17.06	68.88
HCIAE-G-DIS [19]	0.547	14.23	71.55
Frozen-Q-Multi [3]	0.437	21.13	60.48
CoAtt-GAN [33]	0.5578	14.4	71.74
SL(Ours)	**0.610**	**5.323**	**72.68**
RL - 1Q,1A(Ours)	0.459	7.097	72.34
RL - 1Q,3A(Ours)	0.601	5.495	72.48
RL - 3Q,1A(Ours)	0.590	5.56	72.61

can be understood in detail using the pseudocode in Algorithm 1.

Connection to Regularization: It is interesting to note that the MADF setting can actually be seen as a regularizer for the model. To establish this more formally, we look at the total loss minimized by each agent. The Total loss (TL) being minimized during the RL phase = $A1_t + A2_t$ at time t, where $A1_t$ is negative of the RL reward as described in section 5.2, and $A2_t$ is the L-2 loss between predicted and true image embeddings. Consider a setting with N Abots and 1 QBot. The $A2_t$ Loss can be written as:

$$A2_t = \sum_{i=1}^{N}(y_t^{(i)} - y^{gt})^2 = (y_t^{(1)} - y_t^{gt})^2 + \sum_{i=2}^{N}(y_t^{(i)} - y^{gt})^2$$

From the equation, we observe that $A2_t$ is a sum of 2 terms, where the first term is the standard regression loss which would apply for the 1Q,1A case. The second term can be viewed as a regularization imposed by pairing the other A-bots with the Q-bot, hence we can rewrite A2 as:

$$A2_t = (y_t^{(1)} - y_t^{gt})^2 + R_{A2_t}(\theta) \tag{2}$$

where $R_{A2_t}(\theta)$ represents regularization imposed by the other agents. Similarly, $A1_t$ can also be broken down into a likelihood and a regularization term as follows:

$$A1_t = -G_t^{(1)} log\pi(q_t^{(1)}, a_t^{(1)}) + R_{A1_t}(\theta) \tag{3}$$

where $G_t^{(1)}$ is the monte-carlo return calculated using the first pair of agents at time t. Thus, both the terms in the total loss can be broken down into a loss term akin to the 1Q, 1A case and a regularization term. This regularization term comes from the regularization imposed by pairing each Q-Bot with multiple A-bots or vice versa. This clearly shows that the multi-bot framework can be seen as a form of regularization. In the experiments we show that the regularization helps with the language quality by ensuring that the bots don't deviate much from natural language.

6 EXPERIMENTS AND RESULTS

6.1 Dataset description

We use the VisDial 0.9 dataset for our task introduced by Das et al. [2]. The data is collected using Amazon Mechanical Turk by pairing 2 annotators and asking them to chat about the image as a multi round VQA setup. One of the annotators acts as the questioner and has access to only the caption of the image and has to ask questions from the other annotator who acts as the 'answerer' and must answer the questions based on the visual information from the actual image. This dialog repeats for 10 rounds at the end of which the questioner has to guess what the image was. We perform our experiments on VisDial v0.9 (the latest available release) containing 83k dialogs on COCO-train and 40k on COCO-val images, for a total of 1.2M dialog question-answer pairs. We split the 83k into 82k for train, 1k for validation, and use the 40k as test, in a manner consistent with [2]. The caption is considered to be the first round in the dialog history.

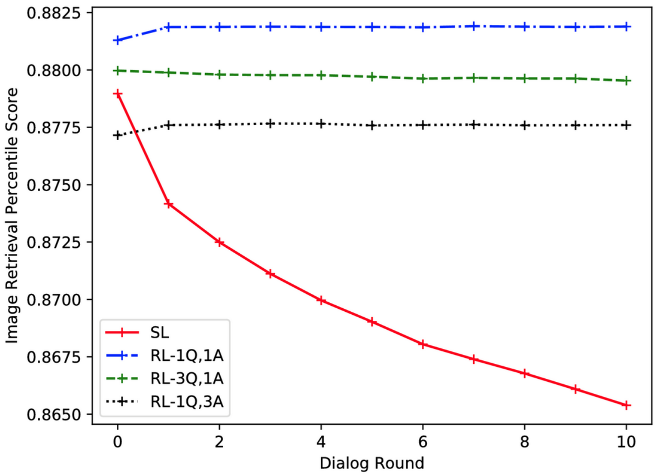


Figure 4: Comparison of Task Performance: Image Retrieval Percentile scores. This refers to the percentile scores of the ground truth image compared to the entire test set of 40k images, as ranked by distance from the Q-Bot's estimate of the image. The X-axis denotes the dialog round number (from 1 to 10), while the Y-axis denotes the image retrieval percentile score. The percentile score decreases monotonically for SL, but is stable for all versions using RL. This shows that the MADF agents are able to capitalize on the benefits of interactive learning.

6.2 Evaluation Metrics

We evaluate the performance of our model's individual responses by using 4 metrics, proposed by [3]: **1) Mean Reciprocal Rank (MRR)**, **2) Mean Rank**, **3) Recall@10** and **4) Image Retrieval Percentile**. Mean Rank and MRR compute the average rank (and its reciprocal, respectively) assigned to the ground truth answer, over a set of 100 candidate answers for each question (also averaged over all the 10 rounds). Recall@10 computes the percentage of answers with rank less (better) than 10. Intuitively all these language metrics are trying to measure similar things, i.e, how highly does the model rank the ground truth answer over a set of 100 candidate responses. Thus, if the model gives a lower rank to the ground truth answer, then we can say that the model is highly likely to produce the ground truth response to the question. But at the same time they do have some qualitative differences. For example, MRR and Rank@10 are more robust to outliers but Mean Rank is not (but it

Algorithm 1 Multi-Agent Dialog Framework (MADF)

```
procedure MultiBotTrain
    while train_iter < max_train_iter do                                ▷ Main Training loop over batches
        $Qbot \leftarrow random\_select\,(Q_1, Q_2, Q_3 \ldots Q_q)$
        $Abot \leftarrow random\_select\,(A_1, A_2, A_3 \ldots A_a)$      ▷ Either $q$ or $a$ is equal to 1
        $history \leftarrow (0, 0, \ldots 0)$                            ▷ History initialized with zeros
        $fact \leftarrow (0, 0, \ldots 0)$                               ▷ Fact encoding initialized with zeros
        $\Delta image\_pred \leftarrow 0$                                ▷ Tracks change in Image Embedding
        $Qz_1 \leftarrow Ques\_enc(Qbot, fact, history, caption)$
        for t in 1:10 do                                                 ▷ Have 10 rounds of dialog
            $ques_t \leftarrow Ques\_gen(Qbot, Qz_t)$
            $Az_t \leftarrow Ans\_enc(Abot, fact, history, image, ques_t, caption)$
            $ans_t \leftarrow Ans\_gen(Abot, Az_t)$
            $fact \leftarrow [ques_t, ans_t]$                            ▷ Fact encoder stores the last dialog pair
            $history \leftarrow concat(history, fact)$                   ▷ History stores all previous dialog pairs
            $Qz_t \leftarrow Ques\_enc(Qbot, fact, history, caption)$
            $image\_pred \leftarrow image\_regress(Qbot, fact, history, caption)$
            $R_t \leftarrow (target\_image - image\_pred)^2 - \Delta image\_pred$
            $\Delta image\_pred \leftarrow (target\_image - image\_pred)^2$
        end for
        $\Delta(w_{Qbot}) \leftarrow \frac{1}{10}\sum_{t=1}^{10} \nabla_{\theta_{Qbot}} \left[G_t \log p(ques_t, \theta_{Qbot}) - \Delta image\_pred\right]$
        $\Delta(w_{Abot}) \leftarrow \frac{1}{10}\sum_{t=1}^{10} G_t \nabla_{\theta_{Abot}} \log p(ans_t, \theta_{Abot})$
        $w_{Qbot} \leftarrow w_{Qbot} + \Delta(w_{Qbot})$                ▷ REINFORCE and Image Loss update for Qbot
        $w_{Abot} \leftarrow w_{Abot} + \Delta(w_{Abot})$                ▷ REINFORCE update for Abot
    end while
end procedure
```

Table 2: Human Evaluation Results - Mean Rank (Lower is better) : Results show that RL-3Q,1A outperforms RL-1Q,3A for A-relevance and overall coherence but otherwise SL (Supervised Learning), RL-1Q,3A, and RL-3Q,1A showed equivalent performance indicating that community regularization can effectively eliminate any losses to human intelligibility introduced through RL.

	Metric	N	SK	RL 1Q,1A	RL 1Q,3A	RL 3Q,1A
1	Question Relevance	49	**1.97**	3.57	2.20	2.24
2	Question Grammar	49	2.16	3.67	2.24	**1.91**
3	Overall Dialog Coherence: Q	49	2.08	3.73	2.34	**1.83**
4	Answer Relevance	53	2.09	3.77	2.28	**1.84**
5	Answer Grammar	53	2.20	3.75	2.05	**1.98**
6	Overall Dialog Coherence: A	53	2.09	3.64	2.35	**1.90**

is more interpretable). The fourth metric, i.e, the Image Retrieval percentile, is different from the first 3 metrics. It is a measure of how close the image prediction generated by the Q-bot is to the ground truth. All the images in the test set are ranked according to their distance from the predicted image embedding, and the rank of the ground truth embedding is used to calculate the image retrieval percentile. This gives a measure of the quality of the information exchange. All results are reported after 15 epochs of supervised learning and 10 epochs of curriculum learning as described in Section 5. Consequently, the training time of all 3 systems are equal.

Table 1 compares the Mean Rank, MRR, and Recall@10 of our agent architecture and dialog framework (below the horizontal line) with previously proposed architectures (above the line). SL refers to the agents after only the isolated, supervised training of Section 5.1. RL-1Q,1A refers to a single, idiosyncratic pair of agents trained via reinforcement as in Section 5.2. RL-1Q,3A and RL-3Q,1A refer to social agents trained via our Multi-Agent Dialog framework in Section 5.3, with 1Q,3A referring to 1 Q-Bot and 3 A-Bots, and 3Q,1A referring to 3 Q-Bots and 1 A-Bot.

It can be seen that our agent architectures clearly outperform all previously published results using generative architectures in MRR, Mean Rank and R@10. This indicates that our approach produces consistently good answers (as measured by MRR, Mean Rank and R@10). It is important to note that the point here is not to demonstrate the superiority of our architecture compared to other architectures. The point here is instead to show that the MADF framework (RL-3Q,1A and RL-1Q,3A) is able to maintain the same language quality as the supervised agent while improving the image retrieval scores. In fact, community regularization (in the form of the proposed MADF setup) can be integrated with any of the visual dialog algorithms in Table 1. Notice that SL has the best scores. The scores drop drastically in RL-1Q,1A, but RL-3Q,1A and RL-1Q,3A obtain scores comparable to SL. This shows that the agents trained by MADF are able to maintain the language quality of SL agents without sacrificing much on the task performance (image retrieval percentile). Fig. 4 shows the change in image retrieval percentile scores over dialog rounds. The percentile score decreases monotonically for SL, however it is stable for all versions using RL. The decrease in image retrieval score over dialog rounds for SL is because the test set questions and answers are not perfectly in-distribution (compared to the training set), and the SL system can't adapt to these samples as well as the systems trained with RL. As the dialog rounds increase, the out-of-distribution nature of dialog exchange increases, hence leading to a decrease in SL scores. Interestingly, despite having strictly more information in later rounds, the scores of RL agents do not increase - which we think is because of the nature of recurrent networks to forget.

The results in Fig. 4 and Table 1 show that the MADF setup allows the agents to achieve consistent task performance without sacrificing on language quality. We further support this claim in the next section where we show that human evaluators rank the language quality of MADF agents to be much better than the agents trained via reinforcement without community regularization.

6.3 Human Evaluation

There are no quantitative metrics to comprehensively evaluate dialog quality, hence we do a human evaluation of the generated dialog. There are 6 metrics we evaluate on: 1) Q-Bot Relevance, 2) Q-Bot Grammar, 3)A-Bot Relevance, 4) A-Bot Grammar, 5) Q-Bot Overall Dialog Coherence and 6) A-Bot Overall Dialog Coherence. We evaluate 4 Visual Dialog systems, trained via: 1) **Supervised Learning (SL)**, 2) **Reinforce for 1 Q-Bot, 1 A-Bot (RL-1Q,1A)**, 3) **Reinforce for 1 Q-Bot, 3 A-Bots (RL-1Q,3A)** and 4) **Reinforce for 3 Q-Bots, 1 A-Bot (RL-3Q,1A)**. We asked a total of 61 people to evaluate the 10 QA-pairs generated by each system for a total of 102 randomly chosen images, requiring them to give an ordinal ranking (from 1 to 4) for each metric. All the evaluators were provided with the caption from the dataset. Evaluators taking the perspective of the A-Bot were provided with the image and asked to evaluate answer relevance and grammar, while those taking the perspective of the Q-Bot evaluated question relevance and grammar. Both groups rated dialogs for overall coherence. Table 2 contains the average ranks obtained on each metric (lower is better).

The results convincingly validate our hypothesis that having multiple A-Bots/Q-Bots improves the language quality as compared with single Q-Bot and A-Bot. Kruskal-Wallis tests found strong differences among rankings (p< .0001) across all measures. Pairwise comparisons using the Mann-Whitney U test found a consistent pattern in which RL 1Q,1A performed substantially worse than other methods across all measures: for

(1) **Q-relevance**: SL: U=348, p<.0001; RL-1Q3A: U=2235, p< .0001; RL-3Q1A U=2209, p< .0001,
(2) **Q-grammar**: SL: U=319, p< .0001; RL-1Q3A U=2280, p < .0001; RL-3Q1A U=2221, p < .0001;
(3) **A-relevance**: SL U=256, p < .0001; RL-1Q3A U=2741, p < .0001; RL-3Q1A U-2909, p < .0001;
(4) **A-grammar**: SL U=305, p < .0001; RL-1Q3A U=2857, p < .0001; RL-3Q1A U=2673, p < .0001;
(5) **Overall (both groups)**: SL U=1206, p < .0001; RL-1Q3A U= 9458, p < .0001; RL-3Q1A U=10052, P < .0001.

Results showed that RL 3Q,1A outperformed RL 1Q,3A for A-relevance U=1889, p < .02 and overall coherence U=6543, p < .006 but otherwise SL, RL-1Q,3A, and RL-3Q,1A showed equivalent performance indicating that community regularization can effectively eliminate any losses to human intelligibility introduced through reinforcement learning. These results further support the claims made in the previous section that the MADF setup allows the agents to show consistent task performance (image retrieval percentile) while maintaining the language quality of the supervised agents.

We show a couple of randomly chosen examples from the set shown to the human evaluators in Fig. 2. The trends observed in the scores given by human evaluators are also clearly visible in this example. MADF agents are able to model the human responses much better than RL 1Q,1A and are about as well as (if not better) than SL trained agents. It can also be seen that although the RL-1Q,1A system has greater diversity in its responses, the quality of those responses is greatly degraded, with the A-Bot's answers especially being both non-grammatical and irrelevant.

7 DISCUSSION AND CONCLUSION

In this paper we propose a novel community regularization technique, the Multi-Agent Dialog Framework (MADF), to improve the dialog quality of artificial agents. We show that training 2 agents with supervised learning does not ensure good task performance (measured by the image retrieval percentile scores) at test time, and it only deteriorates as the agents exchange more information about the image. We hypothesize that this is because the agents were trained in isolation and never allowed to interact during supervised learning, which leads to failure during testing when they encounter out of distribution samples (generated by the other agent, instead of ground truth) for the first time. We show how allowing a single pair of agents to interact and learn from each other via reinforcement learning dramatically improves their percentile scores, which additionally does not deteriorate over multiple rounds of dialog, since the agents have interacted with one another and been exposed to the other's generated questions or answers. However, in an attempt to improve task performance, the agents end up developing their own private language which does not adhere to the rules and conventions of human languages. As a result, the dialog system loses interpretability and sociability. To alleviate this issue, we propose a multi-agent dialog framework to provide regularization. In this framework, a single A-Bot is allowed to interact with multiple Q-Bots and vice versa. We first show mathematically that this has direct connections to regularization. We then back it up with multiple empirical experiments including a human evaluation study, and show that MADF leads to significant improvements in dialog quality measured by relevance, grammar and overall coherence, without compromising the task performance.

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