CoDraw: Visual Dialog for Collaborative Drawing

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Abstract

In this work, we propose a goal-driven collaborative task that contains vision, language, and action in a virtual environment as its core components. Specifically, we develop a collaborative ‘Image Drawing’ game between two agents, called CoDraw. Our game is grounded in a virtual world that contains movable clip art objects. Two players, Teller and Drawer, are involved. The Teller sees an abstract scene containing multiple clip arts in a semantically meaningful configuration, while the Drawer tries to reconstruct the scene on an empty canvas using available clip arts. The two players communicate via two-way communication using natural language. We collect the CoDraw dataset of \textasciitilde10K dialogs consisting of 138K messages exchanged between a Teller and a Drawer from Amazon Mechanical Turk (AMT). We analyze our dataset and present three models to model the players’ behaviors, including an attention model to describe and draw multiple clip arts at each round. The attention models are quantitatively compared to the other models to show how the conventional approaches work for this new task. We also present qualitative visualizations.

1. Introduction

Training goal-driven agents that can interact with humans in natural language and take actions grounded in their environments is one of the fundamental goals in artificial intelligence. For this, we need the agent to perceive the environment, understand language, communicate proactively, comprehend the goal precisely, and finally, decide what actions to take.

Consider the following simple interaction: Human: ‘Can you recommend a new shirt similar to the one I am wearing now?’; AI: ‘Okay, {Shirt} is the one I recommend. Would you like me to purchase it?’; Human: ‘Yes, please’; AI: ‘Placed order via {ShoppingApp}’. Despite its simplicity, the short dialog requires various kinds of intelligent behaviors, e.g., natural language understanding (what does ‘shirt similar to mine’ mean?) and generation, grounding language to perceptual input (what does ‘shirt I am wearing’ look like?), and grounding execution statements from a user into action spaces in the environment (which APIs need to be called to execute ‘recommend’ or ‘purchase’ requests?).

As a first step towards this goal, we propose a Collaborative Drawing game (CoDraw) that incorporates these requirements into a simple and intuitively unified task. This task involves perception, communication, and actions in a partially observable virtual environment. As shown in Figure 1, our game is grounded in a virtual world constructed by clip art objects \cite{kim2017co, parikh2017distant}. Two players, Teller and Drawer, play the game. The Teller sees an abstract scene made from clip art objects, with a semantically meaningful configuration, while the Drawer sees a drawing canvas initialized with an empty canvas. Both players need to collaborate and communicate so that the Drawer can reconstruct the image of the Teller by dragging and dropping clip art objects.
The proposed game contains several known vision and language tasks as sub-problems, though with subtle differences. For instance, compared to image captioning [10–12] and visual question answering [5, 13–18], the proposed task involves multiple rounds of interaction. Both agents hold their own partially observable states and need to build a mental model for the canvas of their interlocutor. The quality of the reconstruction is quantitatively measured by the similarity between reconstructed and original image using a metric described in Section 3.1.

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Notice that this reconstruction is challenging. Both Teller and Drawer must ground the words to describe and draw accordingly, and Drawer must infer the perceptual properties of clip art (e.g., shape and position) from the Teller’s message (e.g., ‘The girl is holding a ball.’). The information asymmetry – neither agents can see the other’s canvas – makes communication a necessary component to build mental models for the canvas of their interlocutor. The quality of the reconstruction is quantitatively measured by the similarity between reconstructed and original image using a metric described in Section 3.1.

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3. CoDraw dataset

In this section, we describe our dataset collection procedure and present an analysis of our CoDraw dataset. Note that collecting a dataset of this nature involves sophisticated infrastructure including a live chat between two workers on Amazon Mechanical Turk, as well as a live drawing interface for the Drawer. Our dataset, as well as this infrastructure, will be made publicly available.

3.1. Dataset collection

Abstract scenes. To enable workers to draw semantically rich scenes on canvas easily, we leverage the Abstract Scenes dataset of Zitnick and Parikh [1, 2]. This dataset consists of 10,020 semantically consistent scenes created by human subjects on Amazon Mechanical Turk. Most scenes contain 6 objects (min 6, max 17). These scenes depict children playing in a park, and are made from a library of 58 clip arts, including a boy (Mike) and a girl (Jenny) in one of 7 poses and 5 expressions, and various other objects including trees, toys, hats, animals, food, etc.

An abstract scene is created by dragging and dropping multiple clip art objects to any \((x, y)\) position on the canvas. Also, for each clip art, different spatial transformations can be applied, including three levels of scales (Small, Normal, Large), three levels of depths (Front, Middle, and Back) and two orientations (facing left or right), a total of \(3 \times 3 \times 2 = 12\) transformations.

Teller is shown one of the scenes in the dataset, and the task of Drawer is to recreate the scene by communicating with the Teller using natural language. Both workers receive rewards if the reconstruction is accurate.

Collection procedure. We built a drag-and-drop interface based on the Visual Dialog chat interface (Das et al. [6]), as shown in Figure 1. Two workers are involved in the data collections. During the conversation, Teller describes the scene and answers the question of Drawer on the chat interface, while Drawer reconstructs the scene based on Teller’s descriptions and instructions.

Either Teller or Drawer can start the conversation. Each side is allowed to send only one message, and wait for the other hand to reply. To prevent excessively lengthy descriptions of the scene from Teller, the maximal length of a single message is 140 characters. Drawer updates the canvas based on Teller’s messages by updating clip arts. Drawer can also ask questions for clarification in the conversation. See Appendix A for details about user interface and instructions for workers.

Workers are asked to submit the task when they are both confident that Drawer has accurately reconstructed the scene of Teller. Workers who accomplish the task of good quality are given a bonus payment. On average, it took workers 6 minutes to complete the task (see Figure 3c). We log the chat history of the two workers as well as each move made by Drawer. Details of the similarity metric, as well as qualitative inspection, can be found in Section 3.1.

Figure 2 shows an example of our dataset. Teller starts a conversation describing the target scene. Drawer asks about the position of trees and the size of the sun. Teller answers some of these questions but misses others.

Additional interaction. While language-based communication is effective when exchanging high-level ideas, to get the details right, direct input of visual information could be constructive. For this, we give one chance for the Teller to peek at the Drawer’s canvas using the ‘peek’ button in the interface. Communication is only allowed after the peek window is closed. Please see Appendix C for details. Note that although this additional signal could lead to very interesting behaviors, we leave its analysis to future work.

Scene similarity metric. We define Scene Similarity Metric (SSM) to quantitatively assess the similarity between two abstract scenes, the ground-truth abstract scene \(S\) (what
Teller sees) and the reconstructed scene \( \hat{S} \) (what Drawer creates):

\[
SSM(\hat{S}, S) := \alpha \text{IoU}(\hat{S}, S) - \Delta(\beta, \hat{S}, S)
\]  

(1)

where IoU denotes the intersection over union of clip art ids between \( \hat{S} \) and \( S \), i.e., the number of clip art objects both scenes have in common divided by the total number of objects in both scenes combined. The second term \( \Delta \) measures 6 aspects of perceptual differences: direction, person pose, depth, absolute position, and relative position of clip art objects. The pose of non-person clip arts is ignored by our metric. The overall score is bounded by [0, 5]. \( \alpha \) and \( \beta \) are weights to balance the two terms, respectively. Please see Appendix B for details. An important detail is that the score is not visible to the workers when collecting the dataset. This scheme ensures that workers accomplish the task via communication, and not to optimize actions that maximize the metric.

3.2. Dataset statistics

We collect 9,993\(^1\) dialogs consisting of a total of 138K utterances. We split the dataset into 80% train (7,989), 10% val (1,002) and 10% test (1,002).

Messages. As shown in Figure 3a, the distribution of the number of tokens in Drawer’s message is skewed toward 1 with the passive replies like “ok”, “done”, etc. There does exist a heavy tail, which shows that Drawers do ask clarifying questions about the scene like “where is trunk of second tree, low or high”. The feedbacks from Drawer help to improve the estimation of the game status for Teller. On the other hand, The distribution of Teller’s is relatively smooth with long tails. The size of vocabulary is 4,555. Since the subject of conversations is about abstract scenes with a limited number of clip arts, the vocabulary is relatively small compared to those of real images.

Rounds. Figure 3b shows the distribution of the numbers of conversational rounds for dialog sessions. Most interactions are shorter than 20 rounds, median being 7.

Durations. In Figure 3c we see that the median session duration is 6 minutes. We had placed a 20-minute maximum limit on each session.

Scores. Figure 4 shows the distribution of the score. Notice that these scores are after the peek chance. The score effect from the peek is shown in Figure 13 (Appendix).

Challenges. Note that our dataset presents multiple challenges beyond image and language understanding: Tellers tend to describe multiple aspects in the same message for efficiency (1st col. in Figure 2). Drawers make more than one change to the scene in each round (2nd col. in Figure 2). Moreover, the Drawer may not update their drawing right away. They often wait to find out more and get a clear picture of what needs to be created before making a significant change to the scene. Agents that succeed at the CoDraw task would have to deal with these challenges.

4. Models

In our setup, we model both the Teller and the Drawer, and evaluate the performance of the team jointly via the quality of the reconstructed scene (measured via the automatic metrics presented in Section 3.1). In this section, we describe baseline and novel neural models for the Teller and Drawer.
4.1. Simple baseline: mode drawing

As a simple baseline, we just pick the most frequent clip art ids in the train split and place them using the modes of categorical properties and the median of positions. Figure 6 shows this mode drawing. It contains Jenny, Mike, sun, cloud, bushy tree, and dog. Notice that the bushy tree is occluding the sun and the cloud, which is not common in individual realistic instances of scenes.

4.2. Feature extractor

We extract features \(\phi(S)\) from the target image \(S \in \mathbb{R}^{C \times P}\) using the following feature extraction procedure. The feature \(\phi(S)\) is a \(C \times E\) matrix where \(C\) is the total number of clip arts (58) and \(E\) is the total feature dimension for each clip art. The \(i\)-th row of the feature is a concatenation of \(P = 6\) pieces of information extracted from the clip art whose id is \(i\). The first 4 pieces are the \(E_c\)-dimensional embeddings of 4 categorical values, clip art ids (58 choices), pose-expression combination (35 choices), depth (3 choices) and direction (2 choices). Note that the pose is only used for person clip arts. The last two pieces are \(x\) and \(y\) positions \((x \in [1, 500], y \in [1, 400])\), encoded as two \(E_r\)-dimensional vectors. The final feature is obtained by concatenating all pieces together, yielding a total dimension \(E = 4E_c + 2E_r\). Note that for clip art ids that are not in \(S\), the corresponding rows are zeros.

4.3. Sequential single attention

Our first approach to model the conversation is as follows: following a pre-defined, content-independent random order, Teller sequentially selects a single clip art \(S_i\), one at a time, to generate an utterance \(\hat{u}_t^{(T)}\). Once Drawer receives this message, he updates his canvas and generates a reply \(\hat{u}_t^{(D)}\) back to Teller.

This approach does not take the dialog history into consideration. Also, the attention – deciding which clip art to talk about – is not content-specific, e.g., Teller may not pick the most salient clip art. We call this method \(SeqAtt\).

To train the model, from the dataset we find the conversation rounds in which Drawer only changes a single clip art. Overall, 37.6% percents of conversational rounds are in such conditions. For details, refer to Appendix D.2. Note that even in these rounds, the associated messages (either sent by Teller or Drawer), might describe relationships with other clip art (e.g., 'sun' and 'bushy tree' in 'sun is at top of screen partially taken up by bushy tree').

4.4. Dynamic multi-attention

To model the conversation history and make the attention content-aware, we propose a Dynamic Multi-Attention model (called \(DynAtt\)). It gives memory to both the Teller and Drawer models. Its loss function can be written as the following:

\[
\mathcal{L} = \sum_{t=1}^{T} \left[ \mathcal{L}_u(\hat{u}_t^{(T)}, u_t^{(T)}) + \mathcal{L}_u(\hat{u}_t^{(D)}, u_t^{(D)}) + \mathcal{L}_a(\hat{a}_t^{(D)}, a_t^{(D)}) + \sum_{l \in L_c} \mathcal{L}_c(\hat{a}_t^{(D)}, S_l) \right]
\]

We use supervised signals for messages \(u\), attentions \(a\) and Drawer’s actions \(a\). The symbols without the \(^t\) indicate the ground-truth values. In the following, we introduce each component in detail:

Teller. For each round \(t\), Teller attends to a subset of clip arts in the target image \(S\) based on Drawer’s utterance \(u_t^{(D)}\) and Teller’s memory state \(m_t^{(T)}\):

\[
\hat{u}_t^{(T)}, m_t^{(T)} = \text{Teller}(u_{t-1}^{(D)}, m_{t-1}^{(T)}, S)
\]

Using the symbols in Table 2, the internal network structure of Teller is defined as:

\[
x_t^{(T)} = \text{Encoder}(W_{u} \hat{u}_{t-1}^{(T)}, \emptyset) \tag{4}
\]

\[
\hat{u}_t^{(T)} = \text{LSTM}(x_t^{(T)}, m_{t-1}^{(T)}) \tag{5}
\]

\[
\hat{a}_t^{(T)} = \sigma(\text{Conv}(1, m_t^{(T)} \circ \phi(S))) \tag{6}
\]

\[
\hat{u}_t^{(T)} = \text{Decoder}(\sum_i \hat{a}_i^{(T)} \phi(S)_i) \tag{7}
\]
where $\hat{a}_t^{(T)} \in \mathbb{R}^C$ denote the attention over the clip arts at $t$. Since this attention is dependent on memory $m_{t-1}^{(D)}$, the attention distribution changes as the conversation moves forwards. Notice that this attention mechanism is inspired by MLB [45]. The word embedding $W_u \in \mathbb{R}^{N \times V}$ and the parameters of convolutional filters in the 1x1 Convolution (Conv) are learnable. All bias terms are omitted for readability.

| Symbols | Description |
|---------|-------------|
| $u$     | an one-hot coded message ($\in V \times \rho$) |
| $x$     | the last hidden state of LSTM ($\in \mathbb{R}^M$) |
| $0$     | a zero vector for an initial state ($\in \mathbb{R}^M$) |
| $1$     | an all-one vector ($\in \mathbb{R}^C$) |
| $\sigma$ | sigmoid function |
| $\odot$ | element-wise multiplication |
| $\rho$ | the number of tokens in the message |
| $V$ | the size of vocabulary |
| $M$ | the dimension of the hidden state |
| $N$ | the size of word embedding |

Table 2. The symbols used in our $DynAtt$ model.

**Drawer.** Drawer draws multiple clip arts based on Teller’s utterance $\hat{u}_t^{(T)}$ and Drawer’s memory state $m_{t-1}^{(D)}$.

$$\hat{u}_t^{(D)}, \hat{a}_t^{(D)}, m_t^{(D)} = \text{Drawer}(\hat{u}_t^{(T)}, m_{t-1}^{(D)})$$ (8)

Likewise, Drawer is defined as:

$$x_t^{(D)} = \text{Encoder}(W_u \hat{u}_t^{(T)}, 0)$$ (9)

$$m_t^{(D)} = \text{LSTM}(x_t^{(D)}, m_{t-1}^{(D)})$$ (10)

$$\hat{a}_t^{(D)} = \sigma(W_u \hat{u}_t^{(T)})$$ (11)

$$\hat{a}_t^{(D)} = \text{Actor}(W_m m_t^{(D)} + w_k)$$ (12)

$$\hat{u}_t^{(D)} = \text{Decoder}(m_t^{(D)})$$ (13)

where we use $I_K = \{k|\hat{a}_{t,k}^{(D)} > 0.5\}$ to pick clip arts to draw. Notice that $w_k$ is a learnable vector dedicated to the index of clip art $k$ to generate $\hat{a}_{t,k}^{(D)}$. The $\text{Actor}$ is an aggregation of linear models to generate the properties of a clip art. Notice that this function is called $|I_K|$ times to update multiple clip arts described in the utterance of Teller, $\hat{u}_t^{(T)}$. The $W_u$, $W_v$, $W_m$, and $w_k$ are learnable parameters. All parameters are not shared with the Teller model.

The memory states $m^{(T)}$ and $m^{(D)}$ are the last hidden state vectors of separate LSTMs. When a new conversation starts, they are initialized with zero. The error is back-propagated through $t$ over the rounds. Figure 5 show a schematic diagram of our $DynAtt$ model.

Note that the Encoders and Decoders can be instantiated as LSTM [46] or BoW model, i.e., linear models with one-hot encoded utterances.

**Training.** The utterances $\hat{u}_t^{(T)}$ and $\hat{u}_t^{(D)}$ are learned in a supervised manner with cross-entropy, to mimic human utterances from the dataset during the first set of epochs (loss saturates around 50 epochs). After that, the output utterances of Teller and Drawer are used to fine-tune (with early-stopping) on the validation score of the drawing result. In testing, we ask the model to output the utterances of Teller and Drawer.

During training, the drawing attention $\hat{a}_t^{(D)}$, the indicator vector of the updated clip arts in the dataset at $t$-th round as the ground-truth. Then, to generate actions for each clip art, we use the ground truth set $I_K = \{i|\hat{a}_{i,t}^{(D)} = 1\}$, instead of its estimate $\hat{I}_K$. In the evaluation, we used predicted attention $\hat{a}_t^{(D)}$ rather than the ground-truth ones.

The number of conversational rounds $T$ for the $DynAtt$ models is determined based on validation results, which is 9 for LSTM, and 20 for BoW (saturated at the max round). For $SeqAtt$, we use 10 rounds which covers 98.7% of the examples.

**Joint attention models.** We found that an additional constraint that pushes $\hat{a}_t^{(T)}$ close to $\hat{a}_t^{(D)}$ with binary cross-entropy improves the performance (Table 3 and Figure 7). This constraint is only present in training.

**5. Results.**

In this section, we evaluate multiple baselines and our proposed models. We use the evaluation metric proposed in Equation 1, which includes IoU, 6 scores measuring different quality aspects, and an overall score.

**Overall score and IoU.** The baseline Mode Drawing (Mode) model gives an overall score of 0.9024. The IoU with the fixed 6 clip arts is relatively higher (0.3194) than random samplings, which reflects the bias from the distribution of the abstract images [1, 2]. $SeqAtt$ (GRU) achieves a better performance overall (1.4014±0.083) compared with Mode (0.9024), despite being trained on a subset of the dataset.

On the other hand, $DynAtt$ (LSTM) significantly improves IoU (0.5682±0.013) over Mode (0.3194) and $SeqAtt$ (GRU) (0.4118±0.021). As a result, $DynAtt$ (LSTM) achieves better performance overall (1.5890±0.037) than $SeqAtt$ (GRU) with joint attention loss (1.4873±0.048) is inferior to $DynAtt$ (LSTM) with the joint loss.

**Other aspects.** Notably, the $Dir$ performance (0.2436±0.030) of $SeqAtt$ is significantly better than human’s (0.3565) because human workers often fail to notice subtle horizontal flip for those horizontally symmetric clip arts, e.g., trees, sun, etc.
| Model                  | Overall Score | Gain | Dir | Pose | Depth | Pos | RelX | RelY |
|------------------------|---------------|------|-----|------|-------|-----|------|------|
| Mode                   | 0.9024        | 0.3194 | 0.4329 | 0.9791 | 0.2768 | 0.2808 | 0.1532 | **0.0518** |
| SeqAtt (GRU)           | 1.4014        | 0.4118 | **0.2436** | 0.9554 | **0.1289** | 0.1550 | 0.1050 | 0.1036 |
| SeqAtt (BoW)           | **2.3983**    | 0.7146 | 0.3500 | **0.9517** | 0.1983 | **0.0797** | **0.0610** | 0.0598 |
| DynAtt (LSTM)          | **1.5890**    | **0.5682** | 0.4769 | 0.9427 | **0.2677** | 0.2724 | 0.3423 | **0.1092** |
| DynAtt-NJ (LSTM)       | 1.4873        | 0.5396 | 0.6366 | 0.9835 | 0.4276 | 0.2761 | 0.3813 | 0.1892 |
| DynAtt (BoW)           | 1.4944        | 0.5237 | 0.6103 | 0.9704 | 0.3803 | **0.2661** | **0.3208** | 0.1754 |
| Human                  | 3.9851        | 0.9624 | 0.3565 | 0.1543 | 0.1577 | 0.1146 | 0.0403 | 0.0358 |

Table 3. The final scores and penalties on the test split of the CoDraw dataset. *DynAtt-NJ* is the same as *DynAtt* but with joint attention during training. The averaged scores of randomly-initialized 5 models are reported. **Score:** The overall quality of the scene (higher is better). *IoU:* interaction over union of the clip art IDs (higher is better). Rest are unweighted error measures (lower is better). *Dir:* directional error, *Pose:* pose + expression error of person clip arts, *Depth:* depth error, *Pos:* positional error, and *RelX* and *RelY:* relative positional error. Please see Section 3.1 and Appendix B for details.

While for IoU, *DynAtt* works decently well, for other aspects, *e.g.*, *Dir*, *Depth*, *Pos*, *RelX*, it does not work as well. In particular, the performance of *RelX* and *RelY* is worse than *SeqAtt*. This is because *DynAtt* allows attention on multiple clip arts described by Teller and multiple actions (*e.g.*, multiple coordinates) are to be decoded by the Drawer. This complex interaction often fails, and results in a prediction of average coordinate values.

**Sentence representations.** Similar to previous works [47, 48], we also find that using the Bag of Words (BoW) in the encoders and decoders of agents yields comparable (or better) performance compared to LSTMs. Interestingly, the *SeqAtt (BoW)* achieves 2.3983 (±0.179), which outperforms the other models, however, *DynAtt (BoW)* does not. Since the Teller of *SeqAtt (BoW)* generates concise utterances that specify the name of clip arts (*e.g.*, *bushy tree* or *boy*) and their position (*e.g.*, *left* or *right*), and the Drawer of *SeqAtt* generates the action for this single clip art. For *DynAtt (BoW)*, the BoW is not sufficient to model the change of attention and the utterances, which leads to poor performance. *DynAtt (LSTM)* is better than *DynAtt (BoW)*. The results of BoW-based *SeqAtt* and *DynAtt* are also shown in Table 3.

**Performance as conversations proceed.** *DynAtt* models have an advantage over *SeqAtt* models in the early stage as shown in Figure 7. The attention mechanism to describe and draw multiple clip arts convey more information in the early rounds.

Figure 7. How the overall score (Equation 1) on the test set varies as the conversation advances, for different methods. Error bars indicate the standard deviation across randomly initialized five models. *SeqAtt* (BoW), although simple, shows strong performance.

The visualization shows the contributors of the drawing reproduction along with its limitations of each model in Figure 8 and Appendix E. The visualization shows that *DynAtt* is biased toward the mode of x-position, which persists even in the *BoW* version of it. This result indicates that *Actor* function in Equation 12 needs to be improved to decode the corresponding actions.

**Model limitations.** *SeqAtt (BoW)* shows a stronger overall performance, despite its simplicity. However, it has limitations. The perceptual similarity involves various visual aspects. The pose and expressions of person clip arts play a key role in conveying semantics, where the sequential nature of natural language is quite relevant (*e.g.*, *‘angry sitting girl legs out facing right’*). Note that in clip art, we have a crisply delineated representation of the scene. Applying our techniques to real image would need an additional CNN to extract semantics information to feed into our system, which is not our focus in this paper. We will leave it to future work.

![Figure 7](image-url)
Human performance. Human outperforms all the baseline models, whose IoU is 0.9624 (maximum: 1.0), showing that the human Drawers capture the majority of clip arts described by Tellers, while the overall score is 3.9851 (maximum: 5.0). Humans significantly outperform our models at capturing the pose and expressions of Mike and Jenny.

6. Discussions

*SeqAtt (BoW)* generates utterances using a concise expression with a strong performance but with the limitations of a simple language model (BoW). *DynAtt (LSTM)* on the other hand tries to mimic the attention shift of humans across rounds of dialog as well as the drawing behaviors which are found in the collected dataset. Although it cannot yet effectively generate detailed realistic drawings involving rich interactions between multiple clip arts, we hope our work will spur future efforts in this direction.

Note that one could hand-craft a rule-based system for this task, but a rule-based Teller will not seem natural to a human Drawer, and more importantly, a Drawer that can only work with a rule-based Teller would not work with a human Teller. Hence, in this work, we train neural Drawers and Tellers that mimic human interaction. Pairing our trained agents with humans is part of future work.

7. Conclusions

We propose the Collaborative Drawing task which involves vision-grounded and action-grounded communication between agents with asymmetric information working towards a common goal. We collect the CoDraw dataset containing 10K dialogs consisting of 138K messages, where one human (Teller) is shown a semantically rich abstract scene made of clip art objects, the other (Drawer) is shown a blank canvas that clip art objects can be dragged on to, and the two must communicate so the Drawer can re-create the scene the Teller sees. We present analysis of the dataset, and propose three neural Drawer and Teller models. Some avenues of future work include modeling Theory of Mind (of the human, and the AI [49]), and reinforcement learning to help agents discover novel strategies not explored by humans in our dataset.
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A. AMT interface

Amazon Mechanical Turk (AMT) is a crowdsourcing platform provided by Amazon. It provides a way to collect datasets with carefully designed tasks and offers to reward participants in a transparent manner. The External Question feature of AMT enables us to create a customized Human Intelligence Task (HIT).

The overall procedure is as following: the first worker is connected to our interface via AMT and waits until the other worker is connected. When both workers are connected, they are randomly assigned a role of Teller or Drawer. Teller can see a target scene, but Drawer cannot. Either Teller or Drawer can start the conversation. Each side is allowed to send only one message at each round, then the other side sends a reply back, and so on. To prevent excessively lengthy descriptions of the scene from Teller, the maximal length of a single message is 140 characters. Drawer updates the canvas based on Teller’s messages by adding/deleting/moving around clip arts. Drawer can also ask questions for clarification during the conversation.

Our interface handles multiple connections concurrently. This means that multiple Tellers and Drawers can play the game concurrently for faster data collections.

In this section, we describe our interface, as well as instructions to each participant for a given role.

A.1. Instructions

Instructions are given to all of the participants, placed below the HIT title, and on the top of each role’s interface.

Chat to Complete!

Mike and Jenny are back! Chat with a fellow Turker to complete a clip art scene together!

You will be assigned to one of two roles: Teller and Drawer. Teller knows a secret clip art scene and Drawer’s task is to recreate it from an empty canvas, by putting relevant clip art pieces on the canvas, flipping them, and/or resizing them. The goal is to make sure the Drawer’s recreated clip art scene is similar to the Teller’s secret scene. If they are very different, both HITs can be rejected.

If they are very similar, both of you can get bonuses!

To achieve this goal, Teller and Drawer will chat. Also, Teller gets one chance to peek at the Drawer’s canvas. Use it wisely!

Please keep the following instructions in mind while chatting with your fellow Turker:

1. Once you accept a HIT, stay tuned. A message and a beep will notify you when you have been connected with a fellow Turker.
2. Please directly start the conversation. Do not make small talk.
3. Please do not have conversations not relevant to the task.
4. Please do not send inappropriate messages.
5. Please use professional and grammatically correct English. Do not use informal language (e.g., “r8” instead of “right”).
6. Please complete and submit the HIT in one session, after you have been connected with a partner. You cannot resume HITs.
7. If your fellow Turker violates instructions or idles for long wasting your time, do let us know. We will act accordingly. Please include a conversation snippet and your role (Drawer or Teller) in your message to us for our reference.
8. You are only allowed to submit the HIT once you have sent at least 2 messages.

https://www.mturk.com
9. You will be paid only if you submit the HIT. Unfinished HITs due to your disconnection and/or abandonment, will not be rewarded. When your fellow Turk disconnects, please continue sending messages. We will review these situations and reward you accordingly.

10. Please complete one HIT before proceeding to the next one. Do not open multiple tabs.

---

A.1.1 Instructions for teller

1. Your fellow Turk will ask you questions about your secret scene.
2. Your objective is to help the fellow Turk recreate the scene. You typically describe the details of the image and/or answer their questions.

A.1.2 Instructions for drawer

1. Your objective is to create a scene that matches the Teller’s secret scene.
2. Feel free to raise questions about the scene, which your fellow Turk will answer. They can see their secret scene.

A.2. Interface design

Figure 10 shows the AMT interface for the Teller. Figure 11 shows the AMT interface for the Drawer. Following previous works [1, 2], Drawers are given randomly selected 20 clip arts from the 58 clip arts object in the library, while ensuring that all objects required to reconstruct the scene are available.

![AMT Interface for Teller](image)

Figure 10. AMT interface for Teller. The left image is one of abstract scenes from Zitnick Parikh [2]. Teller sends messages using an input box. Teller has a single chance to peek Drawer’s canvas to correct mistakes. When Teller feels good to finish, Teller can finish the session.

A.3. Results

We found that approximately 13.6% of workers disconnect voluntarily in an early stage of the session. We paid workers who stayed in the conversation and had posted at least three messages. However, we exclude those incomplete sessions in the dataset, and only use the completed sessions.
Let $\omega$ denote a set of clip arts, specifically, $C_H$ denotes a set of human clip arts, which represent Mike and Jenny (the boy and the girl), and $\Omega$ denotes $\bigcap(\Omega_T, \Omega_D)$. We define Scene Similarity Metric (SSM) to quantify assess the similarity between two given abstract scenes which are made of a subset of clip arts. The first term (IoU, intersection over union) in this metric encourage as many overlapping clip arts with the ground truth as possible. Terms 2-7 penalize the differences between the abstract scenes in various perceptual aspects: direction, character pose (gesture and facial expression), depth, absolute position, and relative position of clip arts.

Let $\chi_{T,D}$ denote the first term, the intersection over union (IoU) of clip arts from Teller and Drawer’s, $|\bigcap(\Omega_T, \Omega_D)|/|\bigcup(\Omega_T, \Omega_D)|$. Then, the score is defined as:

$$
\text{score} := w_0 \chi_{T,D} - \frac{w_1 \chi_{T,D}}{|\{\Omega_i \in \Omega \mid \Omega_i \notin C_H\}|} \sum_{i, \Omega_i \notin C_H} |\text{dir}^T(\Omega_i) - \text{dir}^D(\Omega_i)|
$$

$$
- \frac{w_2 \chi_{T,D}}{|\{\Omega_i \in \Omega \mid \Omega_i \in C_H\}|} \sum_{i, \Omega_i \in C_H} \max(|\text{dir}^T(\Omega_i) - \text{dir}^D(\Omega_i)| + |\text{pose}^T(\Omega_i) - \text{pose}^D(\Omega_i)|, 1)
$$

$$
- \frac{w_3 \chi_{T,D}}{|\Omega|} \sum_{i, \Omega_i \notin C_H} \max(|\text{depth}^T(\Omega_i) - \text{depth}^D(\Omega_i)|, 1)
$$

$$
- \frac{w_4 \chi_{T,D}}{|\Omega|} \sum_{i} \left( \frac{|\text{pos}^T_x(\Omega_i) - \text{pos}^D_x(\Omega_i)|^2 + |\text{pos}^T_y(\Omega_i) - \text{pos}^D_y(\Omega_i)|^2}{W \cdot H} \right)^{1/2}
$$

$$
- \frac{w_5 \chi_{T,D}}{|\Omega|} \sum_{i,j, i \neq j} \text{SignDiff}(\text{pos}^T_x(\Omega_i) - \text{pos}^T_x(\Omega_j), \text{pos}^D_x(\Omega_i) - \text{pos}^D_x(\Omega_j))
$$

$$
- \frac{w_6 \chi_{T,D}}{|\Omega|} \sum_{i,j, i \neq j} \text{SignDiff}(\text{pos}^T_y(\Omega_i) - \text{pos}^T_y(\Omega_j), \text{pos}^D_y(\Omega_i) - \text{pos}^D_y(\Omega_j))
$$

**Clip arts** $C$ denotes a set of clip arts, specifically, $C_H$ denotes a set of human clip arts, which represent Mike and Jenny (the boy and the girl), and $\Omega$ denotes $\bigcap(\Omega_T, \Omega_D)$, where $\Omega_T$ is a set of Teller’s clip arts, and $\Omega_D$ is a set of Drawer’s clip arts. $W$ and $H$ denote the width and height of drawing canvas, respectively.
The number of sessions

106

.0K

1.0K

1.5K

2.0K

Scene Similarity Metric (score)

0.0

0.4

0.8

1.2

1.6

2.0

2.4

2.8

3.2

3.6

4.0

4.4

4.8

Peek

Not Peek

Median

4.2

Median

4.0

2

Figure 12. The accumulated distribution of Scene Similarity Metric (SSM) scores for the ends of sessions which used peek chance (blue), and did not use peek chance (green). Note that 8.43% of sessions did not use the peek chance.

Functions $\text{dir}(\cdot)$ returns the direction (horizontal flip) of a given clip art $[0,1]$, $\text{pose}(\cdot)$ returns the pose of a given human clip art $[0-34]$, $\text{depth}(\cdot)$ returns the depth of a given clip art $[0-2]$, $\text{posx}(\cdot)$ and $\text{posy}(\cdot)$ return $x$ and $y$-position of a given clip art in the drawing canvas. $\max(a,b)$ returns the maximum number between the two arguments, and $\text{sign}(\cdot)$ returns the sign of a given number. $|\cdot|$ returns the number of elements in a given set. And, $\text{SignDiff}(a,b)$ is defined as $(1 - \text{sign}(a) \cdot \text{sign}(b))/2$. Notice that the superscript of functions is used to indicate the specific use of the clip arts from Teller as $T$, or Drawer as $D$.

Hyperparameters $w \in \mathbb{R}^7$ denotes a weight vector to adjust this metric. We use $w = (5, 1, 1, 1, 0.5, 0.5)$, considering the trade-off between the first term and the others. Notice that we separate the penalty of relative positions into two terms with respect to x-axis and y-axis. The overall score is bounded by $[0, 5]$.

C. A peek chance as additional interaction

Teller can click on the “Use Chance” button in the AMT interface (see Figure 10) to invoke the “peek”. If the button is hit, the Drawer’s canvas is temporarily shown. Only after closing the pop-up window of the Drawer’s canvas, the Teller can continue the conversation. For example, in Figure 2, after peeking, the Teller provides a detailed description about the position of the bushy tree and Jenny, and the size of the sun. We find that the Teller tends to use the “peek” option strategically – using it at just the right time allows Teller to better understand the situation and give fine-grained descriptions to help Drawer refine the scene. The improvement of score due to the peek is shown in Figure 12. In 8.43% sessions, Tellers do not use the peek chance. Learning models with strategic planning abilities is a challenging problem, and we leave it for future work.

D. Model description

D.1. Submodules

Word embedding. We preprocess the utterances of Teller and Drawer using Bing Spell Check API\(^3\). The preprocessed utterances are encoded by one-hot vectors for each token, which is tokenized by Python Natural Language Toolkit (nltk) [50]. These one-hot vectors are embedded using weight matrices separately for each role, where the weights are not shared by the two agents. The two agents communicate with natural language symbols generated by Decoder.

Decoder. The utterance of Teller or Drawer $u$ is generated by Decoder for a given hidden state $h_0$ defined as:

$$h_{i+1} = \text{RNN}(W_u u_i, h_i)$$

(21)

$$u_{i+1} = \text{onehot} \left( \arg \max_j [W_h h_{i+1}]_j \right)$$

(22)

Figure 13. Segmentation of real-time drawings based on the time of Teller’s messages. The $\text{diff}(\abs_D^t, \abs_D^{t+1})$ defines the updated clip arts between the drawings at $t$ and $t + 1$ based on the time of Teller’s message.

\(^3\)https://www.microsoft.com/cognitive-services/en-us/bing-spell-check-api
where $W_u$ is a word embedding matrix, and $W_h$ is a linear projection for the state vector of RNN. The $u_0$ is the reserved token, \textit{START}. The utterance generation iterates over $i$ until it generates the reserved token, \textit{END}, or reaches the predefined maximum length (20). The size of $u_{i+1}^{(T)}$ is the number of vocabularies. For the recurrent neural networks (RNN), \textit{SeqAtt} uses GRUs, while \textit{DynAtt} uses LSTMs, although these choices do not have significant difference in performance. \textit{DynAtt} replaces $h_{t+1}$ with the concatenation of $h_0$ and $h_{t+1}$, to give direct access to $h_0$ at every step as in the seq2seq model of CLEVR [43].

For the BoW model, we use a binary vector to represent an utterance $u$ of Teller and Drawer. The $u$ is defined as:

$$u = \text{round}(\sigma(W_1 \tanh(W_0 h_0)))$$

where $W_0$ and $W_1$ are learnable parameters using binary cross-entropy with the output of the sigmoid function $\sigma$ and the target binary vector, which represents the corresponding ground-truth.

\textbf{Actor.} The action vector, $\hat{a}^{(D)} = [\hat{a}^{(D)}_{\text{idx}}, \hat{a}^{(D)}_{\text{pose}}, \hat{a}^{(D)}_{\text{depth}}, \hat{a}^{(D)}_{\text{flip}}, \hat{a}^{(D)}_{x}, \hat{a}^{(D)}_{y}] \in \mathbb{R}^6$, is generated by Actor for a given $h$ defined as:

$$\hat{a}^{(D)}_p = \arg \max_j [W_p h_j], \text{ for } p \in \{\text{idx, pose, depth, flip}\}$$

$$\hat{a}^{(D)}_p = W_p h, \text{ for } p \in \{x, y\}$$

where $W_p$ represents learnable parameters. The $W_p$ is optimized using cross-entropy loss and mean squared error, respectively. Then, the $\hat{a}^{(D)}$ is updated to the $k$-th row of $S$, where $k$ is $\hat{a}^{(D)}_{\text{idx}}$. In this case, $\hat{a}^{(D)}_{\text{idx}}$ is redundant information since the index of row indicates this. However, we leave this to be general.

\textbf{D.2. Sequential single attention}

Following a pre-defined, content-independent random order, Teller sequentially selects a single clip art $S_{I(t)}$, one at a time, to generate an utterance $u_t^{(T)}$. Once Drawer receives this message, they update their canvas and generate a reply $\hat{u}_t^{(D)}$ back to Teller. Its loss function can be written as the following:

$$\mathcal{L} = \sum_{t=1}^{T} \left[ \mathcal{L}_u(\hat{u}_t^{(T)}, u_t^{(T)}) + \mathcal{L}_u(\hat{u}_t^{(D)}, u_t^{(D)}) + \mathcal{L}_c(\hat{a}_t^{(D)}, S_{I(t)}) \right]$$

We use supervised signals for messages $u$, and Drawer’s actions $a$. The symbols without the hat (‘’) indicate the ground-truth values. In the following, we introduce each component in detail:

\textbf{Teller.} For each round $t$, Teller attends to one clip art in the target image $S$ independently on Drawer’s utterance $\hat{u}_t^{(D)}$.

$$\hat{u}_t^{(T)} = \text{Teller}(S_{I(t)})$$

where $I(t)$ is a function of $t$, which sequentially outputs one of the clip art indicies in $S$, but in random order. If $t$ is greater than the number of the clip arts in $S$, the remainder after division of $t$ by the number of the clip arts is used to iteratively select one clip art. However, since Teller only depends on $S_{I(t)}$, this results in the same utterance of Teller if $I(t)$ is the same.

The internal network structure of Teller is defined as:

$$h_t = \tanh(W_h \phi_{I(t)}(S))$$

$$\hat{u}_t^{(T)} = \text{Decoder}(h_t)$$

where $t$ is the index of conversational round, $I(t)$ is the index of the selected clip art at the $t$-th round, and the feature extractor function $\phi$ projects a clip art vector, whose elements are the perceptual properties, to embedding space. The Decoder is the decoder of seq2seq [46]. Notice that $\phi(S)$ and $S$ have the same number of rows, $\phi_{I(t)}(S)$ equals to $\phi(S_{I(t)})$. 

15
**Drawer.** Drawer draws the clip art $\hat{\alpha}_t^{(D)} \in \mathbb{R}^6$, representing the properties of the clip art, on the canvas $\hat{S} \in \mathbb{R}^{58 \times 6}$ (the total number of clip arts is 58). Using the Actor described earlier, each property is proportional to a separate linear projection of $z_t$, which is the embedding of an utterance by GRUs:

$$z_t = \text{GRU}(W_u \hat{u}_t^{(T)}, 0)$$  
$$\hat{\alpha}_t^{(D)} = \text{Actor}(z_t)$$  
$$\hat{u}_t^{(D)} = \text{Decoder}(z_t)$$

where $W_u$ is an embedding matrix and $0$ denotes zeros vector as an initial state vector. The $\hat{\alpha}_t^{(D)}$ is updated to the $l$-th row vector of $\hat{S}$, which is $\hat{S}_l$, where $l$ is $\hat{\alpha}_t^{(D)}$.id. Using $z_t$, the $\hat{u}_t^{(D)}$ is also generated in the same way of Teller’s.

**D.3. Dynamic multi-attention**

The DynAtt model is described in Section 4.4.

**Visualization of attention values.** The attention values of Teller and Drawer for the example in Figure 8d are visualized in Figure 14. Teller’s attention values are normalized using standard score, and the values greater than one standard deviation are selected to visualize, which correspond to the same clip arts in the ground truth. Drawer’s attention values are the output of sigmoid function and the values greater than 0.3 are visualized, while the drawing threshold is 0.5. Notice that the bushy tree is not drawn by Drawer, instead the pine tree and Frisbee is wrongly drawn. The corresponding generated dialog is follows:

T1: large rain cloud on left side , top cut off .  
D1: ok  
T2: the owl is facing left . the owl is facing the girl .  
D2: ok  
T3: the owl is facing left . the owl is facing the girl .  
D3: ok  
T4: the owl is facing left . the owl is facing the girl .  
D4: ok  
T5: the owl is facing right . the owl is facing the girl .  
D5: ok  
T6: the owl is facing right . the owl is facing the other way  
D6: ok  
T7: the slide is a little higher up the grass .  
D7: ok  
T8: the slide is a little higher up the sky  
D8: ok  
T9: the girl ’s pigtail on your left should be pointing at the boys left foot , and the girl is in  
D9: ok  
T10: the girl should be a little more to the right , so that the top of the tree is cut off  
D10: ok  
T11: the girl should be a little more to the right , so that the top of the tree is cut off  
D11: ok  
T12: the girl should be just above the bottom of the slide .  
D12: ok  
T13: the girl should be just above the bottom of the picture .  
D13: ok  
T14: the girl should be just above the boy ’s legs  
D14: ok  
T15: the girl should be moved up with the boy ’s foot should be in the middle of the slide  
D15: ok
At the 2nd conversational round, Teller describes girl (Jenny) and owl concurrently. At the 9th round, Teller describes boy (Mike) and girl with the high attention values. For these rounds, Drawer successfully draws both. Notice that the Drawer’s attention values change more exaggeratedly than Teller’s. The mistakes of both agents are also observed. Teller fails to describe bushy tree, whereas Drawer wrongly draws pine tree at the 1st round. At the 8th round, Frisbee is wrongly drawn, perhaps due to sky in the Teller’s message. Another thing to notice is that attention values change slowly across rounds due to the passive utterances of Drawer, e.g., ok. The drawing history is shown in the last row of Figure 17.

Figure 14. The visualization of the attention values from DynAtt (LSTM). (a) Teller’s normalized attention values for each conversational rounds. (b) Drawer’s sigmoid attention values for each conversational rounds. The drawing threshold for Drawer is 0.5.

D.4. Hyperparameters

We summarize the hyperparameters of SeqAtt and DynAtt models in Table 4 and Table 5, respectively. The size of the vocabulary is 4,555, excluding the reserved tokens, START, END, and UNK. We use Adam [51] as the optimizer with a learning rate of 5e-4 for both models.

| Parameter          | Value |
|--------------------|-------|
| Word embedding     | 128   |
| Clip art embedding | 128   |
| Input size         | 128   |
| Hidden size        | 128   |

Table 4. hyperparameters of SeqAtt model.

| Parameter          | Value |
|--------------------|-------|
| Word embedding     | 300   |
| Clip art embedding | 256   |
| Input size         | 256   |
| Hidden size        | 256   |

Table 5. The hyperparameters of DynAtt model.

E. Visualization

The visualizations of the drawings from the models described in the paper are shown in Figures 16, 17, 18, and 19. Please see the corresponding captions for details. In the figures, each column shows, from the top, abs_{t+1}, msg_{t}^{D}, and msg_{t} in Figure 13. Notice that abs_{t+1} is used instead of abs_{t} for abs_{0} is likely an empty canvas.

In Figure 16 and 18, the clip arts from the SeqAtt model are well-distributed across the canvas. In many cases, the correct positional information is provided by the utterance of Teller, and Drawer draws the corresponding clip art according to the Teller’s utterance. However, we observe that the Drawer of SeqAtt (GRU) fails to select the correct id of clip arts. For instance, the second and third columns of the first row in Figure 16 show the confusion of boy with girl and the ambiguity between bushy tree and pine tree.

In Figure 17 and 19, the visualizations show that DynAtt is biased toward the mode of the x-position, which persists even in the BoW version of it. Since Actor of DynAtt generate multiple drawing actions for a given utterance of Teller, the positional properties of multiple clip arts should be effectively decoded from the utterance, while correctly mapping these positional properties to the corresponding clip arts, respectively.
Figure 15. More examples from the Collaborative Drawing dataset. The images depict the drawing canvas of Drawers after each conversation. From left to right, we show the first to the fourth rounds of conversations, then the last round, and ground truth of Teller’s canvas. The corresponding conversations between Teller (T) and Drawer (D) are described below the images.
Figure 16. The visualization of the drawings from SeqAtt (GRU). The images depict the drawing canvas of Drawer after each conversation. From left to right, we show the first to the fourth rounds of conversations, then the last round, and ground truth of Teller’s canvas. The corresponding conversations between Teller (T) and Drawer (D) are described below the images.
Figure 17. The visualization of the drawings from DynAtt (LSTM). The images depict the drawing canvas of Drawer after each conversation. From left to right, we show the first to the fourth rounds of conversations, then the last round, and ground truth of Teller’s canvas. The corresponding conversations between Teller (T) and Drawer (D) are described below the images.
Figure 18. The visualization of the drawings from SeqAtt (BoW). The images depict the drawing canvas of Drawer after each conversation. From left to right, we show the first to the fourth rounds of conversations, then the last round, and ground truth of Teller’s canvas. The corresponding conversations between Teller (T) and Drawer (D) are described below the images.
Figure 19. The visualization of the drawings from DynAtt (BoW). The images depict the drawing canvas of Drawer after each conversation. From left to right, we show the first to the fourth rounds of conversations, then the last round, and ground truth of Teller’s canvas. The corresponding conversations between Teller (T) and Drawer (D) are described below the images.