Instruction Clarification Requests in Multimodal Collaborative Dialogue Games: Tasks, and an Analysis of the CoDraw Dataset

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Abstract

In visual instruction-following dialogue games, players can engage in repair mechanisms in face of an ambiguous or underspecified instruction that cannot be fully mapped to actions in the world. In this work, we annotate Instruction Clarification Requests (iCRs) in CoDraw, an existing dataset of interactions in a multimodal collaborative dialogue game. We show that it contains lexically and semantically diverse iCRs being produced self-motivatedly by players deciding to clarify in order to solve the task successfully. With 8.8k iCRs found in 9.9k dialogues, CoDraw-iCR (v1) is a large spontaneous iCR corpus, making it a valuable resource for data-driven research on clarification in dialogue. We then formalise and provide baseline models for two tasks: Determining when to make an iCR and how to recognise them, in order to investigate to what extent these tasks are learnable from data.

1 Introduction

Somewhere in interstellar space are the Voyager Golden Records[1], which left Earth in spacecrafts in 1977 carrying a message about humanity to extraterrestrial civilizations. The committee in charge of designing the message, chaired by Carl Sagan, was careful to include symbolic instructions on how to play the records. But what if these instructions turn out to be incomprehensible to the aliens?

In human dialogue, Clarification Requests (CRs), such as those highlighted in Figure 1, are a common and indispensable mechanism to signal misunderstandings and to negotiate meaning, as recently stressed *e.g.* by Benotti and Blackburn (2017). This utterance-anaphoric conversational move can be realized with various forms, functions/readings and contents (Purver et al., 2003; Ginzburg, 2012) and can trigger responses that may or not be satisfactory (Rodríguez and Schlangen, 2004).

1 T: above the tree is a cloud with lightning
2 D: small size ?
3 T: it fits right above the tree so the whole cloud is seen and the bolt is just above the top of the tree
4 D: got it and
5 T: to the left of the cloud is a air balloon with a very tip of the top off screen
6 D: is it large or small in size ?
7 T: maybe medium
8 D: done what else
9 T: to the left of the balloon is another regular cloud about one inch from the left
10 D: okay and
11 T: just left of center in the green is a medium girl facing right
12 D: expression of the girl ? what side is she facing ?
13 T: she is standing with a sad face and one hand facing out . she is facing the tree
14 D: got it and

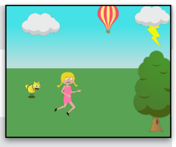


Figure 1: Instruction Clarification Requests identified in a portion of a CoDraw dialogue (ID 8906, CC BY-NC 4.0), with a scene from Zitnick and Parikh (2013).

In addition to the scientific motivation to comprehend CRs as a linguistic phenomenon, timely producing and understanding the vast range of CRs is also a desirable property for dialogue systems (Schlangen, 2004). This ability is especially relevant in scenarios where building common ground is necessary to act and collaboratively achieve a goal. Instructional interactions are a particular instance where an instruction follower (*IF*) often needs to ask for clarification in order to execute actions according to an instruction giver's (*IG*) instructions.

Instruction Clarification Requests (iCRs), as we will refer to them, are a type of CRs originating at Clark (1996)'s 4th level of communication, the level of uptake (Schlöder and Fernández, 2014). They are elicited when an instruction utterance is generally understood (*e.g.* acoustically, syntactically, semantically) but some underspecification or ambiguity prevents the *IF* to carry out an action with enough certainty, as shown in Figure 1.

Learning clarification mechanisms from data is still an understudied research problem (Benotti and Blackburn, 2021). We envision the following desiderata for a dataset suitable for data-driven research on iCRs:

[1] https://voyager.jpl.nasa.gov/golden-record//

- ▷ **Naturalness**: iCRs should occur by the spontaneous decision process of the *IF* in real interaction while trying to act and solve a task, ideally not being induced by external incentives in the data collection and also not synthetically generated.
- ▷ **Specificity**: the annotation should pin down iCRs as a single category, not subsumed within other CRs and dialogue acts.
- ▷ **Frequency**: relative and absolute occurrence of iCRs should be large enough for data-driven methods and statistical purposes.
- ▷ **Diversity**: iCRs should occur with various forms and content, being grounded in the game actions and parameters.
- ▷ **Relevance**: iCRs should be pertinent for players to decide on actions and solve the task successfully.
- ▷ **Regularity**: iCRs should emerge from underlying strategies of the players and not be the result of random or idiosyncratic behaviour.

Our research questions are: i) Can *IF* dialogue models trained on data learn to recognise when they would profit from receiving more information in order to execute an action, and thus generate an iCR? ii) Can *IG* dialogue models trained on data learn to recognise when the *IF* is making an iCR and respond to it?

In this work, our contribution to begin addressing these questions is threefold. We (a) perform annotation of naturally occurring iCRs in a collaborative and multimodal dialogue game, namely the CoDraw dataset (Kim et al., 2019), showing that it is a valuable resource for data-driven research on clarification in dialogue; (b) analyse the corpus and provide insights relating iCRs to the game dynamics; and (c) discuss two subtasks and models that can be explored with CoDraw-iCR (v1) and may serve as components of *IF* and *IG* dialogue models capable of handling iCRs.

2 Related Literature

It is a common practice to map CRs to the level of communication (Clark, 1996; Allwood, 2000) where the misunderstanding occurs (Gabsdil, 2003; Schlangen, 2004; Rodríguez and Schlangen, 2004; Rieser and Moore, 2005; Rieser et al., 2005; Bohus and Rudnicky, 2005; Benotti, 2009; Koulouri and Lauria, 2009; Benotti and Blackburn, 2021). When ASR used to be a bottleneck for dialogue processing, several works focused on CRs elicited by problems at levels 2 and 3 – perception and understanding (Healey et al., 2003; Schlangen and Fernández, 2007a,b; Stoyanchev et al., 2013, 2014, *inter alia*). Comparatively less research exists focusing on CRs at level 4, namely intention, uptake or task-level clarifications (Benotti, 2009; Schlöder and Fernández, 2014). We thus contribute to filling this gap, building upon the existing literature we now turn to discuss in more detail.

Schlöder and Fernández (2015) perform a corpus-based study splitting level 4 CRs into two types of intention-related conversational problems: recognition and adoption. Instruction-following dialogues, where utterances are intertwined with actions, is one setting where level 4 CRs play a fundamental role in negotiating meaning. Benotti and Blackburn (2017) discuss the relation between instruction, CRs and contexts in such settings and how conversational implicatures are a rich source of CRs. Task-level reformulations, a clarification strategy where the initiator rephrases an utterance with respect to its effects on the task, are typically used to confirm more complex actions in instruction giving dialogues (Gabsdil, 2003) and happen very frequently (Benotti, 2009). Multimodality, *e.g.* gestures, also play a role in instruction-following CRs (Ginzburg and Luecking, 2021).

Benotti (2009) proposes using planning to infer and generate the task-level clarification potential of instructions and identify level 4 CRs in one dialogue of a corpus of 15 instruction giving dialogues. Benotti and Blackburn (2021) analyse the same corpus and identify six characteristics that may account for the larger proportion of level 4 CRs found in it: task-oriented dialogues, asymmetry in dialogue participant roles (*IF* and *IG*), immediate world validation by the informational or physical actions, shared view and consequent verification of the actions, long dialogues that enable more shared background, and irreversible actions that require more certainty.

Other corpus studies exist in small datasets. Rodríguez and Schlangen (2004) find that 22.17% of the CRs are level 4 CRs in an instruction-following setting. Similarly, Gervits et al. (2021) collect and annotate 22 dialogues with a human-controlled virtual robot that followed high-level or low-level instructions. They propose a very detailed annotation schema for the content of CRs, but there is no clear distinction of level 4 CRs.

A larger dialogue game dataset, the Minecraft Dialogue Corpus (Narayan-Chen et al., 2019) with 509 games, has been annotated with CRs. Lambert et al. (2019) annotate the *IF* utterances with eight dialogue acts, one of which, `clarification questions`, comprises requests for clarification to a given instruction or statement (26.36% of all utterances). Shi et al. (2022) perform a similar annotation with a category `instruction-level questions` to request clarification for a previous instruction that was not clear or ambiguous (18.64%).

The TEACh dataset (Padmakumar et al., 2022) contains 3k dialogues annotated with dialogue acts (Gella et al., 2022), of which the 675 `RequestOtherInfo` spans under the `Instruction` category relate to iCRs.

Kiseleva et al. (2021) extend the Minecraft Dialogue Corpus with 47 games containing 126 CRs for an interactive agent building challenge, but concentrate on the task of modelling a "silent *IF*" that cannot ask questions. The second edition of their challenge, which happened recently (Kiseleva et al., 2022; Mohanty et al., 2022), focuses on when the *IF* should ask for clarification and what it should ask about, similar to Aliannejadi et al. (2021). The dataset for the second challenge is not collected through real, synchronous interaction. Instead, one player builds a structure and generates instructions *a posteriori*, and, in a separate step, another player follows these instructions, deciding whether to make a CR. Similarly, Aliannejadi et al. (2021) collects a large dataset of CRs to user requests, augmented synthetically, in a multiple-step process without interaction. Another large-scale dataset with 53k task-relevant questions and answers about an instruction was constructed Gao et al. (2022). However, the data is created by an annotator that does not have to act, but only watches execution videos, asking a question they think would be helpful and then answering their own question.

Although these strategies facilitate data collection, they abstract away the decision-making and repair processes that emerge when humans collaborate to solve a task jointly, which are present in CoDraw. Our work and the existing literature converge in addressing CRs for ambiguous instructions, but CoDraw-iCR (v1) maintains the interactive aspect of *sequential* rounds and the spontaneous initiative of *IF* to ask. It is large in absolute number of iCRs and dialogues, with short games that have a relatively constrained action space. Moreover, our annotation pins down iCRs among other types of CRs.

A dataset that can be further explored for iCRs is Thomason et al. (2020). It instantiates a navigation task where the *IF* gets an ambiguous or underspecified command about where to navigate to, and can ask questions to an oracle during the trajectory.

In HRI, following commands is a central task. Koulouri and Lauria (2009) investigate miscommunication management mechanisms in robots performing collaborative tasks, in which task-level reformulations is a challenging type of CR that requires identification of the effects of all possible executions of an instruction. Deits et al. (2013) evaluate various clarification question strategies for robots that receive instructions with an ambiguous phrase. Marge and Rudnicky (2015) examine recovery strategies in situated grounding problems, when an agent has to deal with requests containing referential ambiguity or that are impossible to execute. Interestingly, Jackson and Williams (2018) and Jackson and Williams (2019) raise awareness to the fact that merely posing a CR can already imply willingness to follow a command, which is undesirable in morally delicate situations.

Other tangent research areas study clarification edits to solve underspecified phrases in instructional texts (Roth et al., 2022) and clarification responses in community forum questions or search queries (Braslavski et al., 2017; Rao and Daumé III, 2018; Aliannejadi et al., 2019; Kumar and Black, 2020; Hu et al., 2020; Majumder et al., 2021), scenarios with only minimal or no interaction.

Tasks. Deciding when to initiate a CR in various contexts is a task classically discussed in the CR literature (Rieser and Lemon, 2006; Stoyanchev et al., 2012, 2013; Narayan-Chen et al., 2019; Aliannejadi et al., 2021; Shi et al., 2022; Kiseleva et al., 2022, *inter alia*). Fewer works exist specifically about detecting if a CR was made. Identification of CRs in corpora carry out a similar task, although this is not done from the perspective of an agent knowing that it needs to respond to the CR, of which De Boni and Manandhar (2003) is an example. More generally, this task can be subsumed by dialogue act classification, as in, for instance, Gella et al. (2022).

3 Motivation and Problem Statement

CRs occur naturally in human-human interaction and thus also in visual dialogue games. Neural network-based dialogue models trained at such datasets need to properly handle this phenomenon, which comprises various component tasks for identifying, interpreting, generating and responding to CRs. In this section, we formalise the setting and two of these tasks.

3.1 Formalisation: Instruction-Following Dialogue Games

A visual instruction-following dialogue game can be formalised as a tuple $G = (P, S, R, M)$ representing a goal-oriented interaction between players P (an instruction giver *IG* and an instruction follower *IF*). *IG* sees a scene S, hidden to *IF*, and instructs *IF* on how to reconstruct it. They exchange a sequence R of n rounds $r_i = (g_i, a_i, f_i)$ comprised of two utterances (g_i, f_i), from *IG* and *IF*, respectively, and of actions a_i that incrementally create partial reconstructions s_i of S. R is initialised as an empty set and, at each round, it is extended with g_i, a_i and f_i, in that order. The final state of a completed game contains all filled rounds. A scene similarity metric M computes how close the reconstructions are to the original image at each round, and the goal is to maximize similarity of the final reconstruction $M(S, s_n)$.

The dialogue acts by the *IF* include acknowledgements and clarification requests, whereas the dialogue acts by the *IG* include instructions and responses to clarifications. Two variations are possible: the state s_i can be accessible for the *IG* or not. The incremental scenes can be regarded either as the common ground between players (if both can see it) or as what the *IF* considers to be their common ground (when it is private), akin to what is proposed by Mitsuda et al. (2022).

Following Clark (1996), we assume that a pair of equally competent players, committed to the game's goal of maximizing $M(S, s_n)$, seek to minimize joint effort. It is acceptable for the *IG* to produce an underspecified instruction if producing a fully specified instruction would cost more than answering an iCR. Instruction CRs require an extra effort by the *IF*, so they should occur when repair is necessary and the cost of asking is lower than the potential information gain.

3.2 Tasks

We propose to use CoDraw-iCR (v1) to advance research in iCRs by modelling two CRs subtasks in an instruction-following dialogue game grounded in a visual modality. Both subtasks can be regarded as a binary decision step happening right before each player's next utterance generation.

Task 1: Ask iCR? From the *IF*'s perspective as the CR initiator, decide when to initiate a CR. More specifically, after each *IG* utterance, given the dialogue context $D_{0:(i-1)}$ (that is, all previous utterances), the current utterance g_i by IG, and the current state[2] of the scene s_i, the *IF* must decide on the type of their utterance f_i, namely whether to consider the action completed and signal willingness to receive further instructions (*e.g.*, produce something like "OK"), or to ask for clarification on some aspect of a previous instruction. That is, this formulation of the task focuses on the dialogue act to perform, abstracting away from the concrete realisation. It deals with the problem of automatically determining what is a good instruction and what is not, on its context. This task relates to slot filling in the sense that an instruction containing all the needed parameters for the mentioned objects should not require clarification.

Task 2: Was this an iCR? From the *IG*'s perspective as the CR recipient, identify whether an iCR has been made. At each round i, given the dialogue context $D_{0:i}$ (in which the last utterance, f_i, is possibly an iCR) and the original scene S, the *IG* must decide whether to give further instructions or to (also) respond to an iCR.

4 Data and Annotation

CoDraw (Kim et al., 2019) is a collaborative instruction-following dialogue game, in which a "teller" (in our terminology, the *IG*) observes a clipart scene and instructs a "drawer" (*IF*), who has no access to it, on how to reconstruct it, *i.e.* place cliparts in a canvas with the correct size, direction and position. The corresponding crowdsourced dataset contains 9,993 dialogues in English and has been released under a CC BY-NC 4.0 license. This dataset instantiates the formalisation proposed in

[2] Under the assumption that the *IF* has manipulated the scene in response to *IG* already. For CoDraw, the exact point when the *IF* types the message has not been preserved.

Section 3, but adds an additional signal: The teller is allowed to peek at the drawer's canvas once during the game whenever they want, *i.e.* the teller can get access to s_i and thus judge how it differs from S. Players exchange messages of up to 140 characters through a chat interface and must alternate turns. We will use round to refer to a pair of consecutive utterances by teller and drawer with the corresponding actions. The drawer's performance is evaluated with a scene similarity score that ranges from 0 to 5, where 5 is a perfect match. Table 1 summarizes quantitative aspects of the dataset.

	train	**val**	**test**
dialogues	7,989	1,002	1,002
with peek	7,315	923	913
avr. final score	4.20	4.19	4.17
before peek	3.97	3.95	3.96
avr. rounds/dialogue	7.76	7.69	7.70
avr. utterance len teller	14.36	14.48	14.31
avr. utterance len drawer	2.58	2.67	2.58
vocab size *IG*		4,506	
vocab size *IF*		2,200	

Table 1: Descriptive statistics: CoDraw dataset.

Each game is about a different abstract scene[3] composed of between 6 and 17 out of a set of 58 clipart types (Zitnick and Parikh, 2013; Zitnick et al., 2013), among which the boy and the girl can have 5 facial expressions and 7 body poses, so the resulting clipart set contains 126 elements and the default background. Multiple types of trees, hats, clouds, glasses and balls can introduce the need for ambiguity resolution in the games. As the individual components can be placed freely, the space of possible resulting scene images is practically unlimited in size.

In the baseline models proposed in the original paper, the authors introduce a simplifying assumption which removes the drawer's utterances from the dialogue history (they call this condition the *silent drawer*). The authors leave the tasks of identifying when a CR is necessary and of generating it for future work. Subsequent works with this dataset have focused on text-to-image generation (El-Nouby et al., 2019; Matsumori et al., 2021; Zhang et al., 2021; Lee et al., 2021; Liu et al., 2020; Fu et al., 2020) but, to the best of our knowledge, no other work has examined CRs in CoDraw. We thus take up this idea to bring back the dialogue modality to this dialogue game.

Identification of Instruction CRs. We observe that a good portion of the drawer's utterances belongs to one of two dialogue act types: *acknowledgements*, signaling that the teller may proceed with the next instruction, and *clarification requests*, initiating repair on aspects necessary to solve the task. We thus consider CoDraw to be a potentially interesting source of iCRs.

The first step we take is identifying instruction-level CRs in this dataset. To achieve that, we perform a binary decision over the drawer's utterances. For our purposes, an utterance is an iCR if the following assertion is likely true:

> "*This utterance indicates that the drawer is requesting further information about one or more instruction(s) previously given by the teller in order to perform an action accordingly, likely because part of the instruction was underspecified, ambiguous or not clear.*"

To reduce the annotation workload, we annotate utterance *types*; forms that occur only once (88.97% of the types) are presented with a one-utterance context window around it. All occurrences of each of the other utterance forms are collapsed into a single datum, presented to the annotators without context.

5 Corpus Analysis

In this section, we present an analysis of iCRs in the CoDraw dataset and their relation to the game dynamics, establishing connections to the items in our desiderata and showing that CoDraw-iCRs (v1) is a promising resource to study the phenomenon and to model dialogue agents that learn what to do in face of unclear instructions, complementing existing initiatives.[4]

5.1 Descriptive Statistics

The 13,727 *IF*'s utterance types have been annotated by two annotators, with a Cohen's κ (Cohen, 1960) of 0.92. Table 2 presents the main descriptive statistics of the annotated corpus.[5] 8,807 (11.36%) of all drawer's utterances in CoDraw are iCRs. 59.45% of the dialogues contain no iCRs. For the purpose of analysis, we also compute numbers relative to the subset of dialogues that contain at least

[3] http://optimus.cc.gatech.edu/clipart/

[4] The dataset is available for the community upon request.

[5] In this paper, for the around 3.6% of the utterances with disagreements, we opt for the second annotator's labels, who had more training.

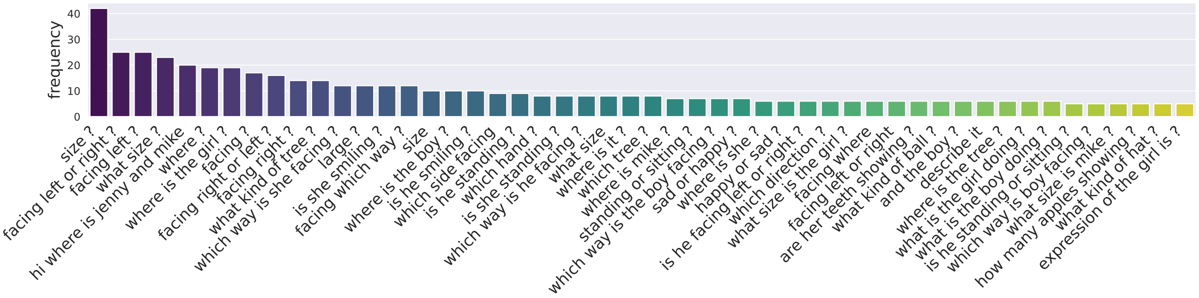


Figure 2: 50 most frequent Instruction CRs in the CoDraw dataset ordered by rank.

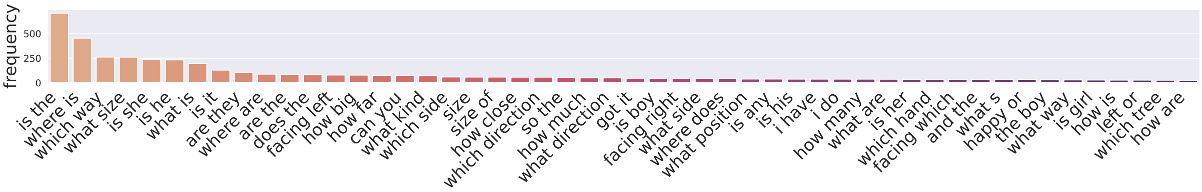


Figure 3: 50 most frequent iCRs initial bigrams in the CoDraw dataset.

one iCR; the idea here is that this excludes players who may not have been willing to use the opportunity to ask iCRs. In this subset, the percentage of iCRs is 24.36%. We also separate out numbers computed from the dialogues up the "peek" action described above, as from that move on, the state of the common ground changes.

	all	w/ iCRs	until peek
dialogues	9,993	4,052	-
rounds	77,502	36,149	61,829
iCR utterances	8,807	8,807	7,803
% iCR utterances	11.36	24.36	12.62
mean iCRs/dialogue	0.88	2.17	0.78
std iCRs/dialogue	1.53	1.73	1.36

Table 2: Descriptive statistics: Annotation.

Figure 2 presents the most frequent iCR utterance types, ordered by rank. 7,260 (94.13% of the types) are *hapax legomena*. Types occupying the highest ranks relate to size, position and orientation, which directly map to the possible actions on cliparts, and to disambiguation of *e.g.* facial expression and body pose. Few types occur more than 5 times, which is evidence that the dataset contains a rich diversity of iCR surface forms. Figure 3 aggregates iCRs by initial bigrams, after removing punctuation and initial *ok* and *okay* tokens (which realise a different dialogue act). Common iCR forms are polar questions and wh-questions also related to the main actions (placement, resize, flip, disambiguation).

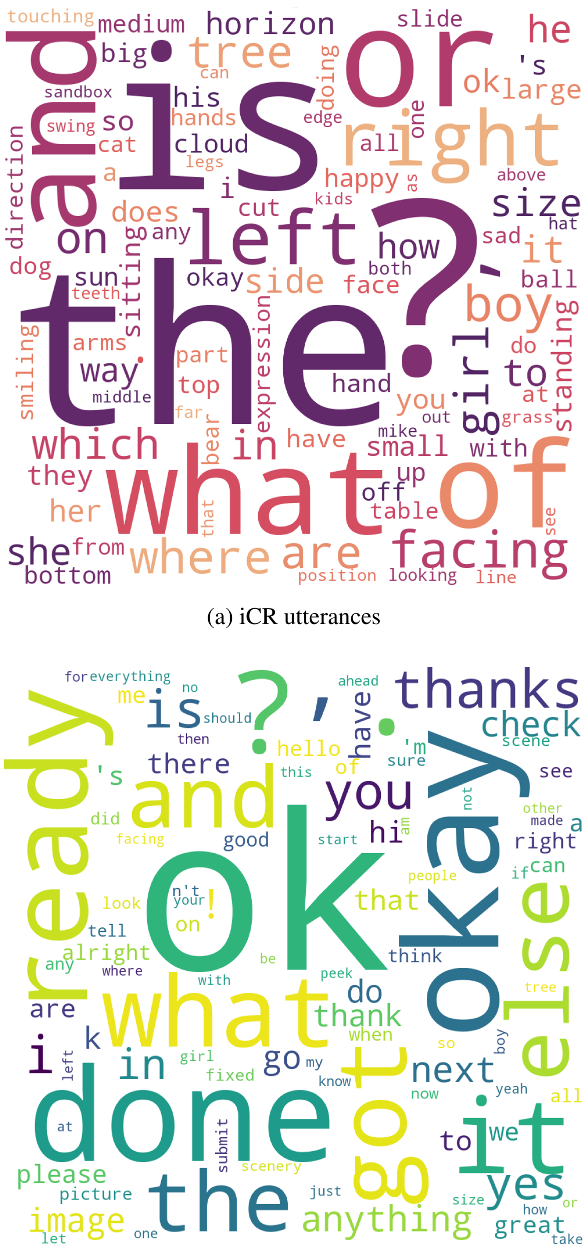
The drawer's vocabulary contains 2,200 token types, out of which 1,468 occur in iCRs. Figure 4 shows an overview of the 100 most common tokens. The frequent iCR vocabulary contains many nouns relating to cliparts (slide, table, bear, dog), in particular those that refer to nouns involving ambiguity (boy, girl, cloud, tree, ball). Question words occur frequently (what, how, where, which) as well as words about object placement (horizon, facing, size, top, touching, edge). Non-iCR utterances commonly contain words related to the task (scenery, picture, image, check, next), greetings and thanks, and acknowledgement words (ok, ready, done).

5.2 Relations to Game Dynamics

We now turn to examining how the occurrence of iCRs relate to the overall game dynamics.

To analyse CRs, three positions in a dialogue are particularly relevant: the source utterance in which the communication problem occurs, the CR utterance where repair is initiated, and the response utterance where the problem should ideally be dealt with. Since the dialogue is organized into a sequence of rounds with pairs of utterances (g_i, f_i), if an iCR occurs at round i, then f_i is an iCR, g_i is the likely source utterance, and g_{i+1} is possibly the response utterance. In Figure 1, turns 1, 5 and 11 are sources, 2, 6 and 12 are iCRs and 3, 7 and 13 are responses. However, these events do not necessarily occur in immediate sequence.

Here, we investigate how the game dynamics change at two positions: iCR rounds and rounds immediately following an iCR. We look at the mean number of actions per round and the difference in



(a) iCR utterances

(b) other utterances

Figure 4: Most common tokens weighted by frequency.

the score metric with respect to the previous state, as shown in Table 3. On average, more actions occur at iCR rounds than at non-CR rounds. The difference is even larger in post-iCR rounds, where necessary edits can be occurring. iCR rounds also cause an average higher improvement in the metric than other rounds and the same occurs for rounds after iCRs in dialogues containing iCRs.

	all	**w/ iCRs**
mean actions per round		
iCR rounds	1.72	1.72
not iCR rounds	1.64*	1.62*
post-iCR rounds	2.11	2.11
not post-iCR rounds	1.59*	1.50*
mean score diff		
iCR rounds	0.59	0.59
not iCR rounds	0.53*	0.43*
post-iCR rounds	0.53	0.53
not post-iCR rounds	0.54	0.44*

Table 3: Round dynamics. * means the difference in relation to the value at the row above is statistically significant at $\alpha = 0.01$ using a permutation test.

To conclude this section, we refer back to our desiderata. The **naturalness** of iCRs is a consequence of the data being produced by synchronous human-human interaction in a setting that does not directly induce players to ask for clarification; indeed, almost 60% of the games do not contain iCRs, which we take to be evidence that they are a result of the private decision making of the *IF* and not due to them following instructions on which dialogue acts to produce. **Specificity** is guaranteed by the annotation process which had a definition to distinguish iCRs from other utterances. In terms of **frequency**, iCRs are a common phenomenon in CoDraw-iCR (v1), which contains 8,807 (11.36%) iCR utterances, a sample larger than existing annotated datasets. We have gathered evidence that **diversity** is present, given that iCRs occur in various forms and exhibit lexical and semantic variety on content related to the game. When it comes to **relevance** to the task, we have shown that there are statistically significant differences in number of actions and score differences at turns realising and following iCRs, which is a sign that agents need to process iCRs in order to act accordingly throughout the game. **Regularity** is addressed in the experiments in the next section.

6 Models and Experiments

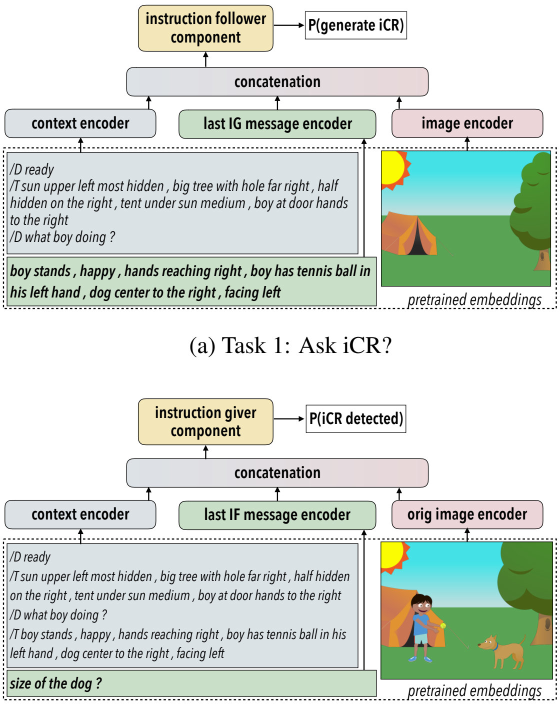
In this section, we present the models for the two tasks discussed in Section 3.2 as well as the evaluation metrics. Both are binary classification tasks using regression to predict the probability of the positive label (iCR) on imbalanced datasets, whose distribution is shown in Table 4.

	train	**val**	**test**
datapoints	62,067	7,714	7,721
% iCR	11.30	11.92	11.28
% not iCR	88.69	88.07	88.71

Table 4: Distribution of labels.

6.1 Models

We model the two prediction subtasks as a function $f : (s, c, u) \mapsto P(l = 1)$ where s is the representation of the scene, c is the representation of the dialogue context, u is the representation of the last utterance and l is the label. This function is approximated with a neural network that takes each input embedding, encodes them, and maps them to a concatenated representation which is fed into a two-layer classifier that outputs the probability of the positive label by applying the sigmoid function to the logit output, as illustrated in Figure 5.[6]


instruction follower component
P(generate iCR)
concatenation
context encoder
last IG message encoder
image encoder
/D ready
/T sun upper left most hidden , big tree with hole far right , half hidden on the right , tent under sun medium , boy at door hands to the right
/D what boy doing ?
boy stands , happy , hands reaching right , boy has tennis ball in his left hand , dog center to the right , facing left
pretrained embeddings
instruction giver component
P(iCR detected)
concatenation
context encoder
last IF message encoder
orig image encoder
/D ready
/T sun upper left most hidden , big tree with hole far right , half hidden on the right , tent under sun medium , boy at door hands to the right
/D what boy doing ?
/T boy stands , happy , hands reaching right , boy has tennis ball in his left hand , dog center to the right , facing left
size of the dog ?
pretrained embeddings

(a) Task 1: Ask iCR?

(b) Task 2: Was this an iCR?

Figure 5: Illustration of the classifier architecture, with an example dialogue from CoDraw (ID 3454).

6.2 Evaluation

Although the area under the ROC curve is a standard evaluation metric for binary classification, it can be deceptive in imbalanced datasets due to the interpretation of specificity, in which case Precision-Recall curves are more suitable (Saito and Rehmsmeier, 2015). The Average Precision (AP) summarizes this curve into one metric that ranges from 0 to 1, where 1 is the best performance, and the theoretical random is the fraction of positive labels. To facilitate comparison to existing literature, we also report macro-average F1 Score.

As trivial baselines, we perform logistic regression on basic features of the utterances and on the input representation vectors. For Task 1, the features are the length of the last teller's utterance and its boolean bag-of-words representation. For Task 2, we use the length of the last drawer's utterance and a binary variable indicating whether a content word occurs in it. The list of content words was extracted manually from a sample of dialogues.

6.3 Embeddings

The pretrained embeddings for texts are generated with SentenceTransformers (Reimers and Gurevych, 2019) and for images with ResNet101 (He et al., 2016). In order to probe whether the pretrained sentence encoders minimally capture the necessary information for our task, we use the dialogue context representation at the turn before the peek action to predict whether iCRs occurred in the dialogue so far. Using a logistic regression model on dialogues that contain a peek turn, we achieve AP= 0.91 and macro F1 Score= 0.86 in the validation set. This provides evidence that, despite they having been optimized for other tasks, the occurrence of iCRs is, to some extent, encoded in the representations.

7 Results

Table 5 presents the main results of our models on the two tasks. The feature-based baselines provide some gain over the random performance for Task 1, and a considerable improvement for Task 2. The logistic regression baseline is enough to produce good results for Task 2, whereas Task 1 remains very challenging even for the neural network model.

		Task 1: *IF*		**Task 2: *IG***	
		AP	mF1	AP	mF1
random	val	.117	.489	.117	.489
	test	.113	.503	.113	.503
features	val	.206	.531	.687	.858
	test	.195	.518	.687	.855
log-reg	val	.324	.587	.984	.962
	test	.287	.576	.978	.961
model	val	.399	.662	.991	.969
	test	**.347**	**.645**	**.988**	**.968**

Table 5: Main results. Average Precision and macro-average F1 Score on the validation and test sets.

[6] Details about the implementation, setup and experiments are in the Appendix and the code is available at https://github.com/briemadu/codraw-icr-v1/.

Ablation. We remove each component of the input to the neural network model in order to understand what information is more relevant for this task. Table 6 shows the differences with respect to the performance in the validation set.

The image representation does not seem to be fully exploited by the model. While in Task 2 the image is expected to be superfluous to detect the dialogue act, it should play a role for Task 1, as it imposes constraints on possible actions. It is possible that the off-the-shelf pretrained model is not adequate to encode cliparts and further investigation with other models and fine-tuning is required.

The last message is the most relevant signal for Task 2, as expected, given that it is the iCR being classified. Without it, the task is almost equivalent to Task 1 and the performance is indeed similar. Interestingly, the most relevant signal for Task 1 is the context and not the last utterance, which is evidence that the model fails to distinguish well which instructions require an iCR. To further investigate this, we remove the teller's utterances and the drawer's utterances from the context embeddings. While removing the teller's utterances causes little change, removing the drawer's utterances is almost as detrimental as removing the whole context. We thus conclude that the model is likely exploring patterns in the drawer's behavior to make decisions.

	Task 1: ***IF***		**Task 2:** ***IG***	
	AP	mF1	AP	mF1
no image	-.032	-.012	.001	.005
no message	-.050	-.021	-.652	-.328
no context	-.109	-.054	.001	.007
context w/o teller	-.001	.000	-.001	-.000
context w/o drawer	-.087	-.054	-.000	.007

Table 6: Results of ablation in the input components. Differences in relation to the main result in the val set.

8 Discussion

Our findings are aligned with the recent conclusions by Aliannejadi et al. (2021) and Shi et al. (2022) that the task of predicting when a CR should be made is rather difficult with data-driven models. Techniques to deal with the class imbalance (downsampling, upsampling and varying the cost-sensitive loss function) and variations of the models (*e.g.* Transformer-based architectures) so far led us to similar results. On the other hand, the task of identifying iCR utterances is uncomplicated even for a simpler logistic regression model.

The results reached by our model in Task 1 do not quite allow us to see desideratum **regularity** as satisfied at this point, but we are confident that there is much room for interesting further research with this dataset. On their own, these tasks model an overhearer that predicts what the agent should do. What is of interest in reality is having them integrated as subcomponents, implicitly or explicitly, in the models that also make the instruction-giving/following decisions, because these capabilities are not detached in the agents *de facto*. We expect that the decision to ask for clarification should emerge more easily in representations of models that are also making actions.

The fact that the drawer's utterances seem to be informative in the dialogue representations for the task speaks against the "silent drawer assumption" int he original models (Kim et al., 2019). Removing the drawer's utterances from the dialogue likely cause loss of relevant dialogue phenomena that is pertinent to the game.

9 Conclusion

We have shown that CoDraw-iCR (v1), the CoDraw dataset augmented with our iCR annotation, is a valuable resource for investigating instruction-level CRs at scale. Through the corpus analysis, we have also concluded that iCR turns and post-iCR turns imply different game dynamics, which is relevant for models trained to play this game successfully. Therefore, in order to succeed in this type of task, agents need to know how to handle iCRs, as they influence not only the dialogue acts but also the game moves.

Our models perform well on detecting iCRs and lay the groundwork for further research on predicting when an iCR should be made. The research roadmap is to integrate iCRs into the full IF agent, so that the decision to ask for clarification is learnt together with the actions in the game.

The second annotation phase will provide fine-grained categories of iCRs' form and content and ground them to the game objects, opening the possibility to explore other tasks like generation.

10 Limitations

In this section, we discuss some limitations that we inherit from the CoDraw dataset, and then some limitations of our task setup and baseline model.

CoDraw is a simplified but representative instance of instruction giving/following dialogue games and we show that iCRs are frequent and play an important role in it. Since modelling CRs is still an open problem, using abstract scenes is a reasonable strategy to simplify the underlying task while still giving room for iCRs to occur. Limitations are inherent to data collections in controlled environments. We aim for our annotations to add to other recent efforts, which are limited in other ways. CoDraw-iCR (v1) thus aims to move one step forward towards modelling iCRs, but general conclusions depend on various resources and further collaborative efforts in our field.

Actions were not irreversible in CoDraw games. The introduction of the peek action for the teller can be an incentive both for the teller to not give exhaustive instructions and for the drawer to build only an approximation, knowing it could be refined after the peek. We have no access to what the performance would have been if they could not make CRs at all.

Meta-data about crowdworker ID is not available.[7] Because of that, we cannot investigate the effects of individual CR strategies by players. Players that play multiple games get to know what to expect of the game and should both have more practice in identifying underspecified instructions that require repair and be able to make better guesses about the cliparts. Experienced tellers probably anticipate common problems and adapt their instructions to avoid them (*e.g.* they know that multiple cliparts of trees exist and would likely describe it in their instruction, avoiding unnecessary communication problems). Besides, we cannot draw conclusions on whether dialogues without iCRs indeed did not require repair or some players were personally less inclined to make the effort to ask for clarification.

Although CRs annotation should take into account the full context (Benotti and Blackburn, 2021), the decision to annotate utterance types instead of full dialogues, as discussed in Section 4, is due to the limited resources given the size of the dataset and to the nature of the game setting. We avoided the need to go over multiple non-iCR utterances that occur very often. The plan for the second step of the annotation is to provide fine-grained annotation for each identified iCR within its own context.

Our models do not take into account the gallery of cliparts available to the drawer, which is informative (as it limits the choices of cliparts per game) and could be part of the input. Preliminary experiments did not lead to better results. Building a suitable representation of the gallery is left for future research.

[7] Personal communication with the authors.

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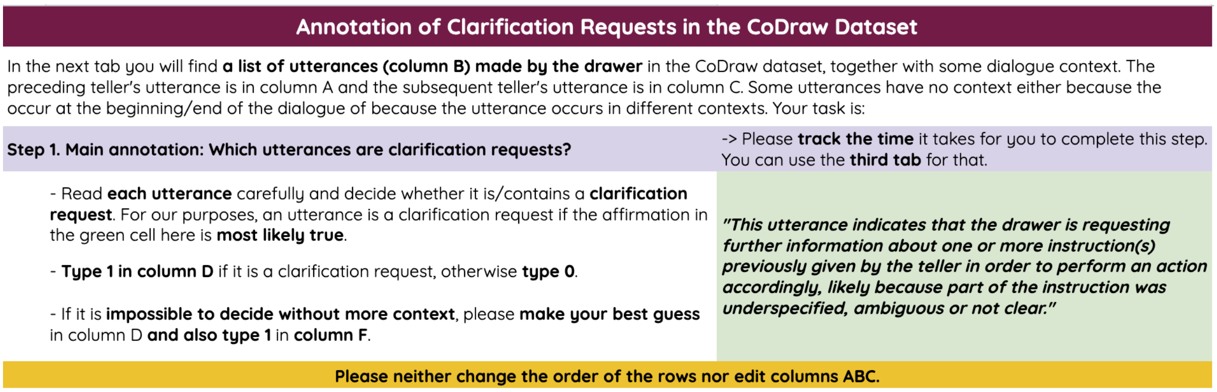


Annotation of Clarification Requests in the CoDraw Dataset

In the next tab you will find **a list of utterances (column B) made by the drawer** in the CoDraw dataset, together with some dialogue context. The preceding teller's utterance is in column A and the subsequent teller's utterance is in column C. Some utterances have no context either because the occur at the beginning/end of the dialogue of because the utterance occurs in different contexts. Your task is:

Step 1. Main annotation: Which utterances are clarification requests?

-> Please **track the time** it takes for you to complete this step. You can use the **third tab** for that.

- Read **each utterance** carefully and decide whether it is/contains a **clarification request**. For our purposes, an utterance is a clarification request if the affirmation in the green cell here is **most likely true**.
- **Type 1 in column D** if it is a clarification request, otherwise **type 0**.
- If it is **impossible to decide without more context**, please **make your best guess** in column D **and also type 1** in **column F**.

"This utterance indicates that the drawer is requesting further information about one or more instruction(s) previously given by the teller in order to perform an action accordingly, likely because part of the instruction was underspecified, ambiguous or not clear."

Please neither change the order of the rows nor edit columns ABC.

Figure 6: Instructions for the first annotator.

A Data Statement

Following Bender and Friedman (2018), in this section we provide information about the extended dataset. Figure 6 shows the instructions given to the first annotator.[8]

Curation Rationale. We annotate iCRs in all dialogues of the CoDraw dataset (Kim et al., 2019), which contains 9,993 dialogues produced by crowdworkers and has been released under a CC BY-NC 4.0 license. Please refer to the original paper for details about their data collection.

Language Variety and Speaker Demographic. The CoDraw dataset comprises written interaction in English, however no information about crowd worker demographic has been released in the dataset repository.

Annotator Demographic. The annotators who identified iCRs in CoDraw are a male and a female Computational Linguistics bachelor students who are non-native fluent English speakers working at colabPotsdam as student assistants. The students were paid according to the German's regulation for student assistants.

Situation. In CoDraw, crowdworkers exchanged written messages of up to 140 characters via a chat interface in a crowdsourcing tool. *IF* and *IG* had to send messages in alternating turns. The interaction was synchronous and task-oriented.

Text Characteristics. The CoDraw authors pre-process all collected utterances using a spell checker and tokenize the text with a natural language toolkit.

B Additional Corpus Analysis

We provide here further descriptive characteristics of the annotated dataset.

Table 7 shows a few negative examples, *i.e.* utterances that are not iCRs. Although utterances like *what do you see in the sky ?* and *anything else to change ?* can indeed be considered task-level CRs, we do not consider them iCRs because they do not directly refer back to a given instruction.

yeah it was a lot but thanks for finishing
i am a patient worker ready to start
check please and tell me what to change
anything else to change ?
what else is in the picture and where ?
i 've made all the changes you 've listed .
ok and look
alright , made changes
please be more specific thanks
ok anything else in the picture ?
yes , please lmk of any corrections
ok i got that :
ready whenever you are . :
what what is the first object and location ?
alright done
what do you see in the sky ?
tell me what we have

Table 7: Negative examples in CoDraw.

Figure 7 depicts in which rounds iCRs occur in the corpus. Given that the average dialogue length is 7.7 rounds, most instruction CRs in this dataset are occurring early in their corresponding dialogue. The distribution of the number of iCRs per dialogue is illustrated in Figure 8, where we see that it is very rare to have dialogues with more than 5 iCRs.

[8] The second annotator got more detailed instructions to perform the fine-grained annotation, which is not part of this publication. For the analysis and experiments in this work, we use the labels by the second annotator, who went through a more extensive background reading about CRs. There are few disagreements, as shown in the main text.

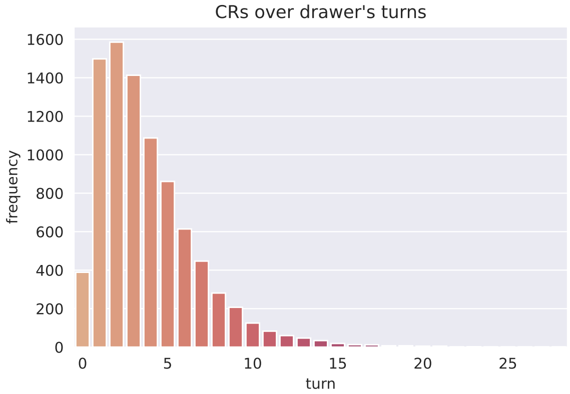


Figure 7: In which round iCRs occur.

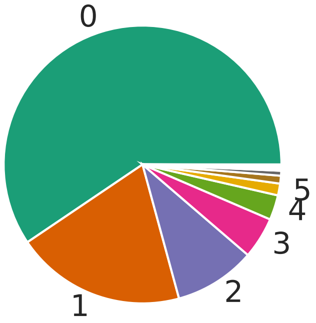


Figure 8: Number of iCRs per dialogue.

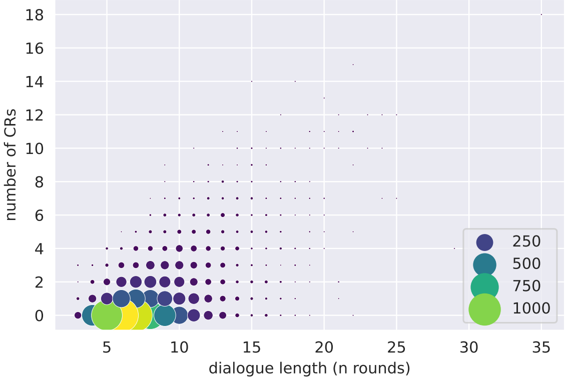


Figure 9: Number of iCRs vs. number of rounds.

Figure 9 breaks down the number of iCRs per number of dialogue rounds. Dialogues with more than 10 iCRs are outliers, which is expected given that most dialogues have no more then 15 rounds.

14.58% of validation and 11.96% of test iCR utterance types also occur in the training set. 17.50% of validation and 14.81% of test iCR utterances also occur in the training set. The overlap is low, which is a desirable characteristic to reduce the memorization shortcuts for models trained on this dataset.

Computing actions and score differences. We group the drawing actions into three main categories: *addition* (when a clipart is added to the scene), *edit* (when some change occurs with an object that existed in the previous round), and *no action* if the drawer did not perform an action in a round. Edits can be deletion, move (position change), flip and resize. We do not track whether newly added cliparts get immediately flipped or resized in relation to the gallery when they are added. We noticed that some actions that visually seem to be only flips or resize happen together with a move. However, our inspection shows that this does not occur consistently with a specific subset of cliparts and there is also a portion of cases where flips and resizes occur without moves. Therefore, each move, resize, flip are counted as one separate action in our analysis. We compute the moves based on the differences over consecutive rounds in sequence of scene strings labeled *abs_d* provided in the original dataset, assuming that they describe the state of the canvas at the moment when the drawer sends their message, *i.e.* at the end of the current round.

Scene similarity is computed with the scripts made available by the CoDraw authors on GitHub.

C Reproducibility

In this section we describe the details of the implementation and datasets for reproducibility purposes. Further information and documentation is available in the code repository.

The random and trivial baselines are trained with scikit-learn (v1.1.2) with class weight set to balanced. A maximum of 1,000 iterations was still not sufficient for convergence is all cases. The hypothesis tests are carried out with SciPy (v1.10.0), using the permutation test for the difference of means, with type set to independent.

Models. Our models are implemented with PyTorch (v1.11.0) and PyTorch Lightning (v1.6.4). Metrics are computed using TorchMetrics (v0.10.0). The experiments were run in Linux 5.4.0-99-generic, machine/processor x86_64 in Python 3.9.12 on an NVIDIA GeForce GTX 1080 Ti GPUs with CUDA v11.6. The architecture of the full neural network model with its corresponding layers and dimensions were:

```
(model): Classifier(
  (img_encoder): ImageEncoder(
    (encoder): Linear(in_features=2048,
                      out_features=128,
                      bias=True)
  )
  (msg_encoder): TextEncoder(
    (encoder): Linear(in_features=768,
                      out_features=128,
                      bias=True)
  )
  (context_encoder): TextEncoder(
    (encoder): Linear(in_features=768,
                      out_features=128,
                      bias=True)
  )
  (classifier): DeeperClassifier(
    (classifier): Sequential(
      (0): LeakyReLU(negative_slope=0.01)
      (1): Dropout(p=0.1, inplace=False)
      (2): Linear(in_features=384,
                  out_features=256,
                  bias=True)
      (3): BatchNorm1d(256,
                       eps=1e-05,
                       momentum=0.1,
                       affine=True,
                      track_running_stats=True)
      (4): LeakyReLU(negative_slope=0.01)
      (5): Linear(in_features=256,
                  out_features=1,
                  bias=True)
    )
  )
)
```

The complete model has 558,465 trainable parameters. For the ablation experiments, the number of dimensions was reduced according to the input, and the number of parameters were 263,425 (no image), 427,265 (no context) and 427,265 (no utterance).

Training is carried out with the Adam optimizer (Kingma and Ba, 2015) to minimize weighted binary cross entropy (the weight is the hyperparameter weight cr) estimated with a sigmoid function applied to the output logits. We use the Bayes algorithm from comet.ml to perform hyperparameter search seeking to maximize Average Precision (and also AUC of the Precision-Recall curve in some preliminary experiments) on the validation set for Task 1. For the final version, we run 111 experiments during hyperparameter search. The optimal hyperparameters used in the experiments are shown in Table 8 together with their corresponding bounds. We use the second best performing configuration, because it is only around 6e-7 below the best one, but has more stable learning curves. All other experiments (ablation and Task 2) use the same configuration, except that the dimensions change according to the input vectors for ablation. We report the results of one run using the best configuration.

We use a decision threshold of 0.5 for the evaluation metrics that require a fixed threshold.

We train the models for up to 20 epochs, which takes around 3-4 minutes, including inference, which requires around 4 seconds. Although it takes more than 20 epochs to achieve a higher performance on the training set, the maximum for the validation set is reached in early epochs. We then use the model checkpoint with the highest Average Precision on the validation set to run evaluation on the test set.

We use the `all-mpnet-base-v2` model from SentenceTransformers to encode the texts into a representation with 768 dimensions. The image representation has 2048 dimensions. Images are preprocessed according to PyTorch Vision documentation (without resizing and centering) and features are extracted following recommendation on their forum. We use the pretrained model `resnet101` available from torchvision (v0.12.0).

Datasets. We use the same train/val/test splits as the original CoDraw dataset. The sizes and the distribution of labels in the annotated dataset is in Table 4. For retrieving the context embeddings, we add a /T token before the teller's utterance and a /D token before the drawer's utterances. We also add a /PEEK token before the utterances of the round when a peek action occurs. The context is limited to the last 200 tokens. Utterances are tokenized with blank spaces on the preprocessed published dataset.

D Detailed Results

We present more details about the performance on the validation set.

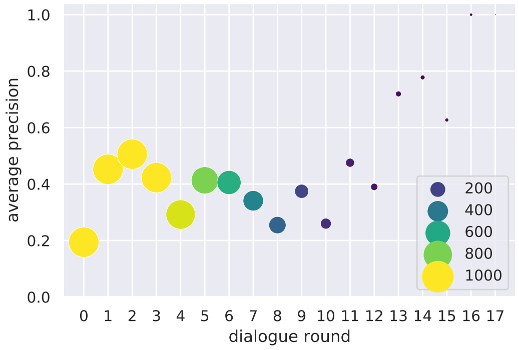
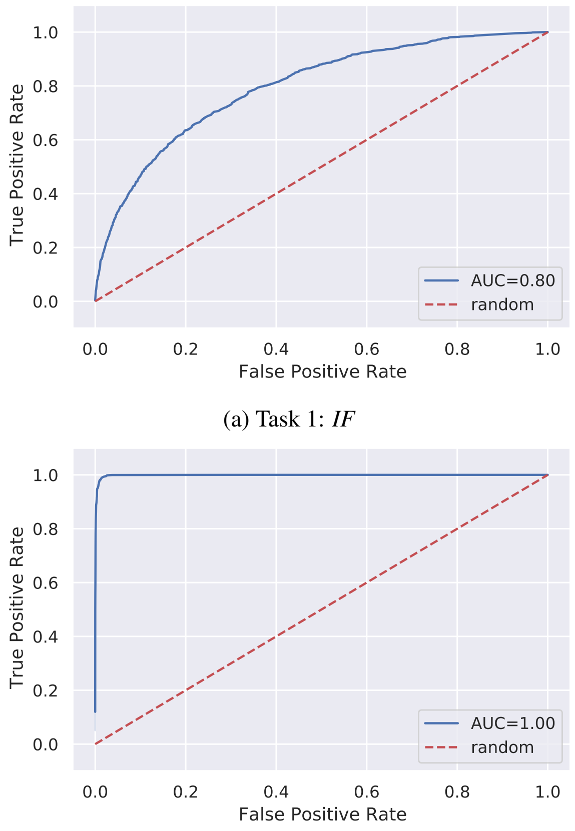


Figure 10: Average precision per round (validation set).

hyperparameter	**type**	**search bounds**	**optimal value**
accumulate gradient	discrete	1, 2, 5, 10, 25	25
batch size	discrete	32, 64, 128, 256, 512, 1024	128
clipping	discrete	0, 0.25, 0.5, 1, 2.5, 5, 10	1
dropout	discrete	0.1, 0.2, 0.3, 0.5	0.1
gamma	discrete	0.1, 0.5, 0.9, 0.99, 1	0.99
hidden dimension	discrete	32, 64, 128, 256, 512, 1024	256
internal embeddings dim	discrete	32, 64, 128, 256, 512, 1024	128
learning rate	discrete	0.1, 0.01, 0.001, 0.0001, 0.003, 0.0003, 0.00001, 0.0005	0.003
lr scheduler	categorical	none, exp, step	exp
lr step	integer	min=1, max=5	2
random seed	integer	min=1, max=54321	35466
weight cr	float	min=1, max=10	2.6125454767515217
weight decay	discrete	1, 0.1, 0.01, 0.001, 0.0001	0.0001

Table 8: Hyperparameters: Search bounds and optimal values.

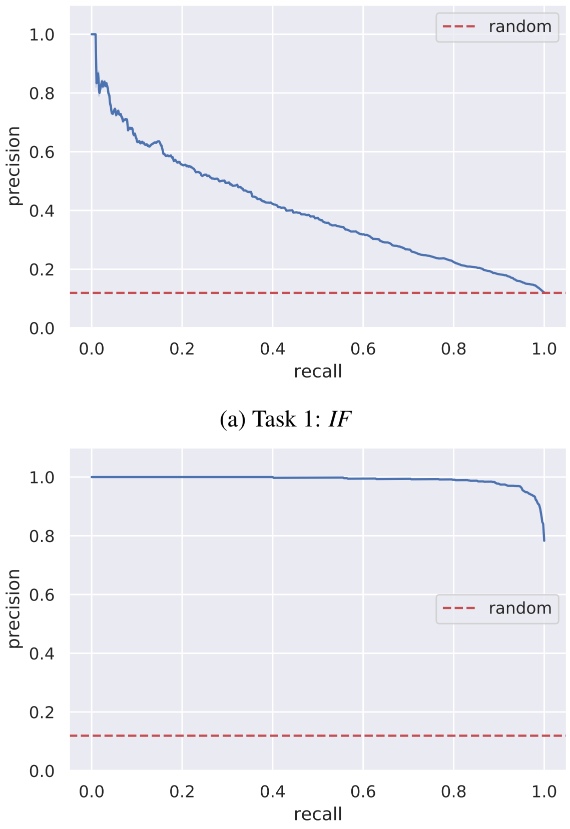
Figure 10 shows the AP metric split by round, Figure 11 presents the ROC curves and Figure 12, the Precision Recall curves of the best checkpoint.



(a) Task 1: *IF*

(b) Task 2: *IG*

Figure 11: ROC curves (validation set).



(a) Task 1: *IF*

(b) Task 2: *IG*

Figure 12: Precision-Recall curves (validation set).