"Are you telling me to put glasses on the dog?" Content-Grounded Annotation of Instruction Clarification Requests in the CoDraw Dataset

Brielen Madureira¹

David Schlangen^{1,2}

¹Computational Linguistics, Department of Linguistics University of Potsdam, Germany ²German Research Center for Artificial Intelligence (DFKI), Berlin, Germany {madureiralasota, david.schlangen}@uni-potsdam.de

Abstract

Instruction Clarification Requests are a mechanism to solve communication problems, which is very functional in instruction-following interactions. Recent work has argued that the Co-Draw dataset is a valuable source of naturally occurring iCRs. Beyond identifying when iCRs should be made, dialogue models should also be able to generate them with suitable form and content. In this work, we introduce CoDrawiCR (v2), extending the existing iCR identifiers with fine-grained information grounded in the underlying dialogue game items and possible actions. Our annotation can serve to model and evaluate repair capabilities of dialogue agents.

1 Introduction

If someone requests you to put glasses on a dog, you may doubt yourself: *Is that really what I am supposed to do?* Before attempting that, you'd likely seek confirmation, for instance, by posing a clarification request. In real life, dogs do fine without glasses, but, as we see in Figure 1, that is indeed a correct action in the context of a scene construction dialogue game.

In instruction following settings, ambiguous or underspecified instructions may elicit clarification requests when the instruction follower realises they cannot act properly without further information. These are Instruction Clarification Requests (iCRs), as defined by Madureira and Schlangen (2023), namely CRs that occur in Clark's 4th level of communication (Clark, 1996), when an instruction is understood generally, but not at the level of uptake (Schlöder and Fernández, 2014).

We have recently argued that the CoDraw dataset (Kim et al., 2019) is a rich and large source of spontaneous iCRs (Madureira and Schlangen, 2023). We identified iCRs among all instruction follower utterances and proposed using the annotation to model the tasks of knowing *when* to ask and to reply to an iCR. However, knowing *what* and *how* to



Figure 1: A communication problem occurring and being resolved with the aid of clarification requests in an instruction following interaction (CoDraw, ID 9429, CC BY-NC 4.0, scene from Zitnick and Parikh (2013)). When an instruction is not clear enough, the instruction follower asks for clarification, in order to act accordingly (here, placing cliparts in the scene).

ask are also topical devices for a competent instruction follower dialogue model. To account for that, we continue this initiative by adding information about the *content* and *form* of iCRs, in order to allow modelling and evaluating the subsequent task of *generating* iCRs, not yet explored in this corpus.

In this work, we describe our annotation procedure and present a corpus analysis of CoDraw-iCR (v2). Our annotation complements CoDraw-iCR (v1) by adding mood categories and by mapping each utterance to its corresponding objects and action-related attributes. We show that this sample is an appealing ensemble of mostly unique surface forms through which interesting relations in cooccurring objects and attributes emerge, making it a handy resource for further CR research. We find that iCRs are mostly posed right after an unclear instruction and typically trigger a response at the next turn, so dialogue models should also know how to react timely. The data is available at https://osf.io/gcjhz/.

	Category	Description	Values				
Form	Mood	the iCR surface form	declarative, polar question, alternative question, wh- question, imperative, other				
Locale	Source relation to preceding IG utterance Response relation to following IG utterance		bool, 1 if iCR is about instruction in immediately preceding utterance bool, 1 if iCR gets response in immediately following utterance				
Content	Quantity Objects Attributes	how many objects are mentioned which objects are mentioned position size direction relation object disambiguation person disambiguation	one, two, many, unknown clipart identifiers (up to five) bool, 1 if iCR is about an object's position in the scene bool, 1 if iCR is about an object's size bool, 1 if iCR is about an object's direction/orientation bool, 1 if iCR is about relations between objects bool, 1 if iCR is disambiguating objects bool, 1 if iCR is disambiguating person's pose or facial expression				

Table 1: Content-grounded schema used to annotate iCRs in the CoDraw dataset.

2 Related Work

Clarification Requests are a multifaceted phenomenon in dialogue, with vast literature on categorising, documenting and modelling their various realisations as well as their relations to other utterances and to the context. Annotation efforts have been conducted to identify their causes (Gabsdil, 2003; Rodríguez and Schlangen, 2004; Bohus and Rudnicky, 2005; Benotti, 2009; Koulouri and Lauria, 2009; Kingma and Ba, 2014) forms (Purver et al., 2003; Rodríguez and Schlangen, 2004; Rieser and Moore, 2005; Deits et al., 2013; Khalid et al., 2020; Gervits et al., 2021) and readings (Purver et al., 2003; Gabsdil, 2003; Rodríguez and Schlangen, 2004; Bohus and Rudnicky, 2005; Rieser and Moore, 2005; Rieser et al., 2005; Kato et al., 2013; Liu et al., 2014; Braslavski et al., 2017; Benotti and Blackburn, 2021; Shi et al., 2022).

Still, it remains an open research area; in particular, we cannot delineate yet to what extent CR mechanisms can be learnt via data-driven methods (Benotti and Blackburn, 2021), and dealing with underspecifications is still hard for pretrained language models (Li et al., 2022).

Benotti and Blackburn (2021) have recently raised awareness to the different world modalities upon which clarifications can be *grounded*, like vision, movement or physical objects. Still, few works exist that systematically map the content of CRs to elements related to the context where they occur (Gervits et al., 2021). Some examples are Benotti and Blackburn (2017), who use a methodology to classify CRs according to why they make implicated premises explicit (*e.g.* wrong plan, not explainable plan or ambiguous plan in instruction giving), in a corpus that is further analysed in Benotti and Blackburn (2021) with a recipe to detecting *grounded clarifications*. Gervits et al. (2021) propose a fine-grained annotation schema for CR types related to the environment (object location, feature, action, description, etc). The small size of these corpora, however, does not meet the needs of current data-driven methods.

CoDraw (Kim et al., 2019) is a dialogue game where an instruction giver, who sees a clipart scene (Zitnick and Parikh, 2013), provides written, turnbased instructions to a drawer, who needs to reconstruct the scene. The drawer sees a gallery of objects (a subset of 58 cliparts) and can place, remove, resize or flip the objects and can also ask questions when they wish. Madureira and Schlangen (2023) have put forward a desiderata for Instruction Clarification Requests datasets suitable for data-driven research and demonstrated that the CoDraw-iCR (v1) dataset meets most requirements: Naturalness, specificity, frequency, diversity and relevance (regularity, according to the authors, requires further investigation). Its size (9.9k dialogues with more than 8k iCRs) also makes it more suitable for neural network-based models.

3 Fine-Grained Annotation of iCRs

Relying on the existing iCR identification in CoDraw-iCR (v1), we hereby introduce CoDraw-iCR (v2). It contains a fine-grained annotation of the subset of iCR utterances in CoDraw, using categories that are expected to be directly relevant for generation (form and content), as summarised in Table 1.

Motivation In CoDraw-iCR (v1), the annotators identified, with high agreement, an emblematic dialogue act, whose cause and function are demarcated

well: iCRs that happen on Clark's 4th level of communication, their source utterances (i.e. the utterance where the communication problem originates) occur during instruction giving, and their purpose is getting an appropriate *response* that enables them to decide how to follow the instruction by making actions. Their realisation, however, evinces many other degrees of variation. An adequate instruction follower model playing the CoDraw dialogue game has a series of decision-making steps to perform when it comes to iCRs. It must detect the time to ask, decide what to ask about in terms of game objects and actions, and define the surface form to realise the iCR. The existing annotation can directly inform the training process for the first, but the other two are left at the mercy of the capabilities of end-to-end models to learn them implicitly from the data. Alternatively, our more detailed annotation can guide the learning process more explicitly and also enrich the evaluation of generated iCRs.

Procedure The annotation was performed by a fluent non-native English speaker working as a student assistant at our lab and paid according to the national regulations. The person is a female computational linguistics bachelor student who went through a learning phase to familiarise herself with the CR literature and with CoDraw objects and rules. The annotation instructions were given as shown in Figure 2. Utterances were then presented in an internally developed graphical user interface where all the predefined values were available (see Figure 3, Step Two). The immediately previous and next turns by the instruction giver were shown as context. Some less evident cases were discussed with the author: the main decisions are documented in the data repository. The annotation was performed in a period of around 4 months.

Locale Given that iCRs are typically a local phenomenon (Rodríguez and Schlangen, 2004; Schlangen and Fernández, 2007; Rieser and Moore, 2005), and also the incremental nature of the task and the turn-based setting, only one utterance before and one utterance after the iCR were presented as context. To validate that assumption, the annotator decided whether the previous utterance is the iCR's *source* utterance and whether the next utterance is or contains a *response*.

Form We follow the schema proposed by Rodríguez and Schlangen (2004) and annotate the *mood* of the iCRs. For each iCR utterance,

	Please neither change the order of t	he rows nor edit columns ABCD.					
Task 1. Do	puble check main annotation: Which utterances are instructi	on clarification requests?					
	 Read each drawer's utterance carefully and whether you agree with the annotation in column D. It should be 1 one the uterance is/contains an instruction cardification request. For our purposes, an uterance is an instruction clarification request if the affirmation in the green cell here is most 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."					
	- Type 1 in column E if you agree, otherwise type 0.						
Task 2. Fir	ne-grained annotation						
	If column D has a 1, or if column D has a 0 but you disagree w columns.	ith that, you must do task 2, which is to fill in the annotation					
Column	Description						
F	F Select one mood: declarative; polar question; alternative question; wh- question; imperative; other						
G	G 1 if the CR refers to an instruction in column A, else 0.						
н	H 1 If the CR gets a response in column C, else 0.						
1	I is it possible to know which clipart the CR refer to? Options: unknown, many, two, one						
J-N	J-N If it is possible to know the clipart, select them in these columns, in the order they occur. A list of cliparts is in the third tab.						
0	O 1 if the CR about an object's position, else 0.						
P	1 if the CR is about an object's size, else 0.						
Q	1 if the CR is about an object's direction/orientation, else 0.						
R	1 if the CR is about relations between two or more objects, els	e 0.					
S	S 1 if the CR is trying to disambiguate between similar objects (e.g. trees, glasses, balls, etc), else 0.						
т	1 if the CR is trying to disambiguate the facial expression or p	ose of the boy or the girl.					

Figure 2: Instructions provided to the annotator.

IS IT A CLARIFICAT	ON REQUEST?
Annotated	0
Total	13726
Time	Q
Т:	
D: thanks for all of your help !	
т	
Step One:	
This utterance was marked as classification request: NO	
Do you agree? Yes 🕺 +	
Step I Wo: You have to complete Part 2 if this dialogue was marked as a clarification request or if it was Select a mood for this request Mood	orit, but you disagree.
Last turn Mark true if the CR refers to an instruction Response Mark true if the CR gets a response from th	from the Teller e Teller
Clinarts	
Is it possible to know which clipart the CR refer to? Clipart *	
If it is possible to know the clipart, select them in these columns, in the order they Clipart 1 + Clipart 2 + anabiguous	cccur. (you can search a clipart by typing) R * Clipart 4 *
Clipart 5 v	
Select (if any) the passing categories for this clarification request Position Size Relation to other Object disambiguiation	Direction Person disambiguiation
BACK	NEXT

Figure 3: The GUI with the iCR annotation schema.

the annotator could select among declarative, polar question, alternative question, whquestion, imperative and other. Utterances expressing more than one mood were annotated with all suitable categories.¹

Content The main goal of our fine-grained annotation is to have categories grounded in the underlying dialogue game. It is similar to the types in Gervits et al. (2021), but adapted to CoDraw, where two aspects are relevant: Objects and actions. Objects are the cliparts, and actions refer to

¹Due to a limitation of the GUI script, the exact order could not be preserved.



Figure 4: Overview of the distributions of annotated categories in CoDraw iCR utterances.

the possible manipulations of their attributes: Size, position, direction and their relation to the scene and to other objects. Upon a close qualitative examination of some dialogues, we also identified iCRs being used to disambiguate between related cliparts, either because multiple types exist (e.g. trees and hats) or, in case of the boy and girl, their pose and facial expression. Therefore, the content annotation was twofold. First, the annotator decided whether it is possible to identify the cliparts being mentioned in the utterance. They were grouped in an aggregate category of quantity (one, two, many or unknown) and then listed (up to five) in the order they occur. Besides the game cliparts, we also added a category for the background (which is the same for all scenes). Following a similar approach in Rodríguez and Schlangen (2004), we introduced six ambiguity classes to account for cases when it was not possible to precisely detect the clipart, five for specific groups of related objects (tree, ball, cloud, hat, glasses) and one for other ambiguities. Then, non-mutually exclusive binary labels were assigned if the iCR was about an object's position in the scene, size and direction, its relation to other objects, and disambiguation of object or person.

4 Corpus Analysis

In this section, we conduct a detailed examination of the annotated utterances, among which 8,765 utterances (7,710 types) were identified as iCRs.² We present a descriptive analysis enriched with examples of each annotation category, anchoring them in the linguistic components of the game.

4.1 Locale

The immediately preceding instruction giver utterance is the source utterance (*i.e.* the utterance where the communication problem manifests) for 80.26% of the iCR utterances, similar to what is reported by Purver et al. (2003) but around 15% less than in the corpus study by Rodríguez and Schlangen (2004). 78.49% of the iCR utterances get a response from the instruction giver in the immediately following turn. For 63.85% of them, both conditions are true. This corroborates the assumption that iCRs are usually a local phenomenon in CoDraw, so the context we use is enough for our purposes of annotating form and content.

²The absolute numbers differ slightly from Madureira and Schlangen (2023) due to the inclusion of the in-context annotation of duplicate types.

polar	is girl angry?	position	campfire on right or left edge?
-	large cloud is left?	_	tree top and left edge cut?
	so half sun is visible?		so the girl is in the middle of the scene?
wh	what are they doing?	relation	left handle touching sun?
	which tree and what size?		where is the soda located on the table?
	how are the boys arms?		which hands are they holding things?
alternative	is she large or small	direction	facing left or right?
	is the balloon in the air or sitting on the		which direction is rocket facing?
	ground?		cat facing left or right
	right or left or center	size	ok and girl size
declarative	i don't see a baseball available.		sun big?
	you said the tree is on the right side		are you sure the tree is large?
	i don't understand where the basketball	amb. person	does he look happy or surprised?
	is supposed to be		happy or sad girl?
imperative	describe the boy please.		is she standing?
	confirm the boy is about a half inch from	amb. object	is the tree pointed at the top?
	the left of the scene.		what is the color of hat?
	please clarify		does the cloud have rain or lightning
		-	

Table 2: Example utterances for each type of mood in CoDraw iCRs.

4.2 Form

Examples for each mood are shown in Table 2. The average number of tokens in iCR utterances is 8.39, around four times the average length of all instruction follower's utterances, which contained a large portion of very short acknowledgements like ok. The distribution is illustrated in Figure 4d. They are realised in many surface forms, ranging from short and generic (sorry?), to very specific (owl is med?), to long and verbose (is the girl sitting or standing i need to know as there are multiple options and her expression as well). Figure 4a shows the relative frequency of the ten most common moods. Polar questions are the most common, followed by wh-questions and alternative questions. Declarative and imperative moods are much less frequent. In 11.5% of the cases, the instruction follower uses more than one mood, e.g. by asking more than one CR in a turn, or even integrating them in the same sentence. Examples with multiple moods are which way is the bolt and is it touching the ground or above it? (asking about two different attributes with a wh-question and an alternative question) and which tree? apple or bushy tree? (refining the first wh-question to make the CR more specific with an alternative).

4.3 Content

We now turn to analyse the two aspects of iCR content, namely objects and manipulable attributes, which directly map to the game objects and actions. As we will see, the iCRs cover all available objects and are well distributed among actions.

Table 3: Example utterances for each type of attribute in CoDraw iCRs.

Attributes Table 3 shows examples of utterances seeking to clarify each attribute. In Figure 4b, we see the relative frequency of each attribute in CoDraw iCRs. While object disambiguation is somewhat less frequent, all other types occur more evenly, each in around 20% of the iCRs. Attributes are not mutually exclusive: While 82.87% of the iCR utterances refer to only one attribute, 14.15% mentions two. Three and four attributes occur together in less than 2% of the iCRs and are interesting cases of very detailed clarification requests. For example, the utterance is she sitting, and is she in the sandbox or on the right of it outside? is about position, relation and ambiguous person and how close to the bottom are their feet? i have the crown and the boy's hands over grass line. are they *smaller*? is about position, size and relation. The frequency of attribute co-occurrence is depicted in Figure 4e. Position and direction occur very often with relation. Disambiguations of objects occur more rarely with other attributes. We observe some patterns in the ways iCRs are realised for each attribute. The ten most common initial bigrams are shown in Figure $6.^3$ Some bigrams, especially the first ones, look very predictable given the attribute (for instance, keywords like where, close and far are relevant for positioning and way, facing and direction are indicative of direction). On the other hand, is the is a versatile initial bigram which is frequent for all attributes. This is pertinent information to be integrated during generation, so that the iCRs sound natural and purposeful.

³Here, initial *ok* or *ok*, tokens are excluded.

32.86%	32.45%	8.36%	4.06%	3.78%	2.86%	2.8%	2.78%	2.64%	2.48%
girl sitting ok horizon right boy standifigcing	girl left facing sitting happy way right	tree ^{sky} grass left horizon girl line part _{green} boy	large left sun big top cut size tree right side	cut side trunk size tree pine left right applehole	pine apples cut size side left right apple	table size girl left ok right side boy top	size ^{ok} boy hot left girl way dog facing	left size ok way bear X girl facing horizon right boy	top right left size tree apple see
2.46%	2.3%	2.27%	2.24%	1.95%	1.61%	1.47%	1.4%	1.39%	1.35%
boy way ladder facing girl solution side left slide right	size ^{big} right boy box sand side faciñĝndbox	size right left looking girl and ok way boy facing cat	ginhorizon swing left size III facing boy set side right	plane ^{facing} big left small direction right way side	lightningjoud bolt rain left sun cut right size tree	size ^{tree} facing way small elicopter left gird irection	size right tree left boy fidection owl way lookinfgcing	boy snake right side small direction way left	left ^{bolt} right ghtning clouds size facing cloud _{rain} way
1.25%	1.24%	1.21%	1.05%	0.98%	0.91%	0.9%	0.88%	0.76%	0.67%
cutightning clouds left right size touching raindrops cloud rain	left ^{right} tent ppening size facing bear ^{ok} horizon ^{tree}	hand girl facing girl way left toy size	balloons ^{left} right balloon size air _{hand} top	bodirection duck right facing right girl way ok left cat	gril ^{horizon} bbq boy size left ok right top girl	feetgreen girl boy facing left part fire campfi@ght	facing left girl halloons horizon hand balloor size right boy	boykicking right close beach size soccer ballfacing	touching bottom irection boy tree hat facing left
0.6%	0.59%	0.59%	0.54%	0.47%	0.46%	0.44%	0.43%	0.39%	0.37%
girl ^{right} tail size left see bolding	side right hand ball soccer football	size hand balloon soccer ball halloons boy	way hand tilted left ground size right	strawdrink girl horizon hand 💽 cup	hotdog ^{dog} side boy way table hand	table right large see size left side	facing ^{ands} burger right ketchup left hand	righaseball boy ok bat afacing	left ^{top} girl basketball ball okav
hand string kite	facing left highersize	left right girl	frisbee _{side} top	sodatable	left hot right	cente _{ĥizza} pie	hamburger side ^{closest}	ball handglove	boy right ^{soccer}
hand string kite	facing left highersize 0.33%	left right girl 0.32%	frisbee _{side}	sodatable	left hot right	cente _{ĥizza} pie 0.21%	hamburger side ^{Closest} 0.21%	ball handglove	boy right ^{soccer}
hand string kite 0.37% pizza size left pie side right table hand_hings	facing left highersize 0.33% boy left racket medium hand big holdingbat	left right girl 0.32% baseballtar hat boy cap right blue facing left	risbee _{side} 0.3% boy left air glove right ok right facing one thumband	vay felt sodatable 0.29% right girl ball bucket size pail left basketball hand boy	eft hot right 0.22% 0kay right left ball tennis @ grass girl size hanfledium	centefizza ^{pie} 0.21% mediuthovel side hand box ok small	hamburger siddlosest 0.21% witdlirection part way facing hat basebal bottom witchegoint	ball Dall handglove 0.19% porglasses sun sunglasses girl purple left wearing kind black	boy staty righ®cccer 0.17% bat ^{ok} right touch left basebal hand bottom tennis
hand string kite 0.37% pizza size left pie side right table hand _h horizon 0.17%	facing left highersize 0.33% boy left racket medium hand big holdingbat 0.17%	0.32% basebałtar hat touching boy cap right blue facing left	origination of the state of the	way tell sodatable 0.29% right girl ball bucket size pail left basketball hard boy 0.14%	eft hot right 0.22% left ball tennis @ grass girl size handledum 0.11%	cente _{fjizza} pie 0.21% medium ^{hovel} boy side sizes hand nght box ok small	hamburger siddlosest 0.21% witclirection part way facing hat battom battom battom battom battom battom battom battom battom battom battom witclirection battom battom witclirection battom witclirection battom battom witclirection battom batt	ball ball handBlove 0.19% porglasses sun sunglasses girl en purple left wearing kind black	boy righ@cccer 0.17% bat ^{ok} right touch baseball bottomacket
hand string kite 0.37% pizza size left pie side right table hand_hings 0.17% glasses sun black purple girl left sunglasses color	facing left highersize 0.33% boy left racket medium hand big holdingbat 0.17% 0.17% like girl viking pirate horm cap right wearingboy	left right girl right girl 0.32% baseballtar hat touching boy a cap right blue facing left 0.14% vay littledhand way littledhand girl itt crown	Color Co	way retent sodatable 0.29% right girl ball bucket size pail left basketball hand boy 0.14% red ^{grey} pom hat left ok raingtow	eft hot right 0.22% okay right left ball tennis e grass girl size handedum 0.11% Nolding put side burgefight left	Centef _{juzza} pie O.21% mediuthovel boy side sizes hand inght box ok small O.11% mustardeft burger hat hand in hands right closest balloor@ack	hamburger sidelosest 0.21% way facing basebal bottom witchegoint 0.1% wasingleft boy facing boy hat know witch pirate witch vikingorizon	bill and love bill and love o.19% porfilasses sun sunglasses girl purple left wearing kind black 0.05% head chef jenny relation grill hat skyline	boy righ@cccer 0.17% bat ^{ok} right touch baseball left hand bottomacket

Figure 5: The ten most common tokens (excluding stopwords) associated with each game object in iCRs. The percentages are the relative frequency over all iCR utterances. Clipart images from Zitnick and Parikh (2013).



Figure 6: Ten most common initial bigrams for each iCR attribute category.

Objects When it comes to the game objects, the relevant aspects are quantity (how many objects are mentioned in an iCR), frequency (which objects lead to more need to clarify) and co-occurrences (how the relations between specific objects need to be clarified). In terms of quantity, in Figure 4c we see that 58.28% of the iCRs refer to only one object, and a considerable portion refers to two (32.29%). The relative frequency of all 58 game objects (and the background) in the set of iCRs and the most common vocabulary associated to each of them is shown in Figure 5. The person cliparts are the most common.⁴ Next comes the background, whose horizon is commonly used as a point of reference when positioning objects. The three types of trees are also a common subject. Multiplicity is, however, not an explaining factor on its own, because the different hats and glasses appear much less often. Objects frequency in iCRs is actually positively correlated with their frequency in the scenes (Spearman $\rho = 0.82$). To explore it in more

⁴For illustration purposes, only one pose for the boy and the girl is shown in Figure 5.



Figure 7: Dialogues with at least one iCR about each clipart, normalised by their frequency across scenes.

detail, Figure 7 shows, for each object, the percentage of times they triggered at least one iCR in a dialogue among all scenes in which they appeared. Higher percentages mean that the object is frequently involved in communication problems when it is in a scene. The boy and the girl, each of them occurring in more than 90% of the scenes, very often require clarification. This is likely due to their various poses and facial expressions that require disambiguation and also to their relation to other cliparts (for instance, hats on their heads or their hands holding objects). The thematic category of large objects and some objects in multiple forms (cloud and tree) also bring on many iCRs. However, some ambiguous objects, like chef hat and pirate hat or glasses and sunglasses, very rarely trigger clarification.⁵ Figure 9 shows the co-occurrences of cliparts, with distributions by row. We can see clusters in ambiguous objects like balls and clouds, but semantically related objects like shovel and sandbox, racket and baseball bat, and table and pizza also tend to co-occur. Persons and the background occur often with almost all other objects. In Figure 4f, objects are grouped into thematic categories. Besides the evident ubiquity of person and background, some less obvious relations become clear: hats and balls, sky objects and glasses, sky objects and trees, balls and clouds.

4.4 Interrelations

The distribution of attribute for each object category and mood is shown in 8. Polar questions are often used to clarify relations, while alternative and imperative are common to disambiguate persons. Wh-questions and declarative are used more uniformly for all attributes. When grouped by thematic category, we see that relation is a predominant topic for almost all groups (note, however, that relations always include more than one clipart in the count). Glasses and hats very often require object disambiguation. For sky objects and trees, position is also a usual topic.



Figure 8: Co-occurrence of clipart categories and mood with attributes, distribution by row in %.

5 Conclusion

We have analysed the manifestation of Instruction Clarification Requests in the CoDraw dataset in terms of form (mood and length) and content (objects, attributes and their co-occurrences) and some of their interrelations. Our findings further support the argument that the CoDraw data collection setting was an effective means to elicit iCRs. Even in its controlled environment with a limited number of actions and objects, the resulting iCR utterances are very diverse in their surface form and very fertile in their content. With the release of the annotated data, the community gains a larger resource with sequential, spontaneous iCRs in turn-based dialogues.

⁵Further investigation is necessary to understand if they indeed trigger precise referring expressions. There may also be an effect of the subset of available cliparts in the gallery. Although many hats exist in the game, if the gallery shown to the instruction follower only contains one type, no disambiguation will be needed even in face of an underspecified instruction.



Figure 9: Co-occurrence of objects, distribution by row in %.

We aim to encourage more research on modelling clarification requests in instruction following interactions, and also to enable more detailed evaluation of iCR generation.

Limitations Given the need for large scale corpora for data-driven methods, trading some of the ecological validity in the annotation process for machine-learnability was necessary. Due to the availability of resources for this project, the annotation was performed by only one annotator, thus inter-annotator agreement could not be measured. Still, the quality of a sample was verified by the author to during the initial annotation phase. The

scenes were not available during annotation, so clipart annotation can contain misunderstandings. The macro categories for ambiguous cases help alleviate that, but we still observed that misclassifications occur in some cases. The annotator worked on utterance level but, as we showed, some utterances contain non-iCR content or multiple categories. A possible enhancement is to further segment utterances in order to allow each category to be mapped to sentences or phrases (for mood and attribute) and to tokens or phrases (for objects and their referring expressions), and also to identify the tokens that are unrelated to the current iCR. For the portion of the iCRs whose source utterances occur further back in the dialogue context, or whose responses are not given in the next turn, we currently lack annotation that would allow full examination of their context.

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