1. Introduction

This paper presents the Rapid Dialogue Game (RDG) corpus, a collection of audio and video recordings of human conversations during a series of fast-paced two-person games. The use of games is well attested in natural language processing and dialogue systems research. One recent, high profile example is Watson (Ferrucci et al., 2010), a question-answering system developed by researchers at IBM that competes in the game of Jeopardy! against human players. The game was used to focus on research challenges posed by rapidly answering open-domain English language questions in a competitive setting. More broadly, a range of different corpora of participant interactions in games and tasks has facilitated dialogue system research, including work on natural language understanding and generation, turn-taking, dialogue management, and other areas; for a few recent examples see (Fernández et al., 2007; Gravano and Hirschberg, 2009; Koller et al., 2010; Campana et al., 2012).

The corpus presented here is designed to serve as a testbed for future research in incremental speech processing techniques for spoken dialogue systems (SDSs). Traditionally, SDSs have mostly understood and generated utterances with an utterance-level or turn-level granularity, and have relied on a strict turn-taking regime in which they only begin to process and respond to user utterances after the user finishes speaking. This “non-incremental” processing means that systems generally lack many of the highly interactive and low-latency response behaviors that are common in face-to-face human-human conversation. These include providing verbal backchannels (e.g., yeah, hmm, uh-huh, right, etc.) and non-verbal backchannels (e.g. head nods) while listening to user speech, using interruptions or overlapping speech in some situations, and having rapid and fluid turn transitions between speakers.

Recent research on incremental speech processing techniques has begun to address this issue by enabling SDSs to incrementally understand, predict, and respond to speech in real-time, as it happens; see e.g. (DeVault et al., 2011; Skantze and Schlangen, 2009; Sagae et al., 2009; Heintze et al., 2010; Skantze and Hjalmarsson, 2010). Incorporating such techniques into SDSs has been shown to be beneficial, including user preference over non-incremental systems, increases in responsiveness (Skantze and Schlangen, 2009; Skantze and Hjalmarsson, 2010), and increased fluency of user speech (Gratch et al., 2006).

The game corpus presented here is designed to support this area of research by enabling a detailed analysis of the real-time speech and dialogue behavior of interlocutors who are trying to communicate in a way that will maximize their game score under substantial time pressure. The two games we have chosen were carefully designed to provide: substantial time-pressure; potential for fun gameplay; naturally occurring overlapping and low-latency responses; and quantifiable game performance.

In the rest of the paper, we present the two RDGs, RDG-Phrase and RDG-Image, that we have designed and then summarize the corpus of human-human data we have collected.

2. Rapid Dialogue Games

2.1. RDG-Phrase

In the RDG-Phrase game, one of the participants takes the role of the clue-giver (giver) and the other the role of the clue-receiver (receiver). The team starts with 2 training rounds, followed by 4 main game rounds. Each round is composed of two parts: a betting phase and a guessing phase. In the betting phase, the giver is shown 10 target expressions as a numbered list. See the top left of Figure 1 for an illustration of the betting phase. Here, target expressions...
are generally nouns or phrases that are chosen to be semantically related to a word category. Semantic associations between word categories and target expressions were created in three steps. First, we used a list of commonly used English nouns as a seed to retrieve semantically related words from WordNet (Miller, 1995). Second, we filtered out results that contained less than 10 expressions related to each category. Third, we manually selected those sets of target expressions which seemed semantically coherent and more suitable for the task. Some examples of word categories used are “care”, “cars”, or “television” which include target expressions like “maternalism” and “babysitting” for “care”, “ambulance” and “bus” for “cars”, and “video” and “replay” for “television” respectively. When the numbered list of 10 target expressions is shown, the giver has 120 seconds to redefine an order for these and to place “bets” on which ones the receiver will guess correctly. The bets are optional and modify the score associated with selected target expressions.

In the guessing phase, the giver is privately shown the sequence of 10 target expressions one at a time in the order he has defined. Figure 1 includes an example excerpt from the guessing phase. The goal of the giver is to get the receiver to correctly guess the current active expression (AE) using verbal and non-verbal clues. When the receiver guesses the AE correctly, the team scores points and moves on to the next expression. While in the guessing phase, players can skip the AE to continue with the next target expression from the sequence. Skipped expressions are placed at the end of the sequence and teams have another chance to guess them later. The team is penalized and loses the opportunity to guess the AE if the giver explicitly mentions any part of the word or any part of the expressions that come later in the sequence. The receiver is allowed to guess multiple times without penalty with the only disadvantage of potential time loss. A third person acts as a judge who enforces
that the game rules are obeyed and decides whether a guess is correct or not. During the guessing phase, the team has 70 seconds to guess as many expressions as possible from the sequence before the time expires. This time limit was chosen to make the task challenging but not impossible for the participants.

2.2. RDG-Image
In RDG-Image, one person acts as a giver and the other as a receiver. Figure 2 shows a dialogue excerpt of a game interaction in RDG-Image. Players are presented a set of eight images on separate screens. This set of images is exactly the same for both players except that the images are arranged in a different order on the screen. One of the images is randomly selected as a target image (TI) and it is highlighted on the giver’s screen with a thick red border as shown in Figure 2. The goal of the giver is to describe the TI so that the receiver is able to uniquely identify it from the whole set of distractors. Different categories were used for the image sets including images of pets, fruits, people wearing make-up (as shown in Figure 2), and castles, among others. When the receiver believes he has correctly identified the TI, he clicks on the image and communicates this to the giver who has to press a button to continue with the next TI. The team scores one point for each correct guess. There is no direct penalty for a wrong guess besides losing the opportunity to score the point. For RDG-Image, the giver is instructed to only provide clues verbally. Participants are told that non-verbal communication, such as gesturing, is not allowed at any time. Otherwise, there are no forbidden words and players are encouraged to converse freely.1

During the data collection, teams were asked to play six different game rounds of RDG-Image. The first 2 were training rounds, followed by 4 main game rounds. In each main game round, participants were given 140 seconds to complete up to 24 target images. This time limit was selected after analysis of pilot testing sessions. As in RDG-Phrase, the time limit was chosen in order to make the task challenging but not impossible for the participants.

2.3. Related Games and Corpora
Our two games have been designed with specific features to support research in incremental speech processing for dialogue systems. These features include substantial time-pressure, naturally occurring overlapping and low-latency responses, and quantifiable game performance. Together, these features highlight the value that rapid, real-time understanding of user speech and incremental response capabilities can provide to spoken dialogue systems. Another design goal for these games has been the potential for fun gameplay, which can make recruitment of participants easier.

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1In the RDG-Image game, in practice, the two players are primarily looking at their respective computer screens while using a mouse with one hand, so the role of gesture is somewhat reduced in comparison with many face-to-face dialogue contexts. Since we intended to use the RDG-Image corpus to build an automated dialogue agent that will lack gesture recognition and generation capabilities, we instructed participants not to rely on gesture in their object descriptions.

2http://en.wikipedia.org/wiki/Taboo_(game)
3http://en.wikipedia.org/wiki/Pyramid_Game
now this is another purple
with a grey eye
uh greenish eye uh it’s like a
lavender
purple
is it like blond hair
oh that’s all blond hair
purple <pur>
no she has like a brownish eyebrow
uh
kinda thick eyebrow
you said it’s purple
does it have stars
ok I think I got it
yeah

| Start Time | End Time | Giver’s transcription | Receiver’s transcription | Score | Time remaining |
|------------|----------|-----------------------|--------------------------|-------|---------------|
| 104.574    | 106.148  | now this is another purple | purple                  | 9     | 56 sec        |
| 107.174    | 108.252  | with a grey eye        | is it like blond hair    |       | 53 sec        |
| 109.735    | 112.072  | uh greenish eye uh it’s like a | oh that’s all blond hair |       | 51 sec        |
| 112.451    | 113.317  | lavender               |                          |       | 48 sec        |
| 112.478    | 116.795  |                        |                          |       | 47 sec        |
| 113.904    | 114.438  | purple <pur>           |                          |       | 44 sec        |
| 116.203    | 118.64   | no she has like a brownish eyebrow | uh | 41 sec |
| 119.132    | 119.991  |                        | you said it’s purple    |       | 40 sec        |
| 119.403    | 120.572  | kinda thick eyebrow   | does it have stars      |       | 39 sec        |
| 120.678    | 121.322  |                        | ok I think I got it      |       | 38 sec        |
| 121.49     | 122.039  | yes                   | yeah                     |       | 37 sec        |
| 122.323    | 123.277  | no stars has nothing  |                          |       | 36 sec        |
| 123.66     | 124.877  |                        |                          |       | 34 sec        |
| 124.398    | 125.495  |                        |                          |       |               |
| 126.329    | 126.637  |                        |                          |       |               |

Figure 2: An excerpt of an RDG-Image dialogue and corresponding screen captures. The image at the bottom right of the Giver’s screen is the target.

Figure 3: Experiment and hardware set-up for the data collection. In addition to cameras A and B, a third camera was installed on the ceiling to obtain an overhead view of the interactions.
Figure 4: Example of a capture taken from the overhead camera during a game interaction. Participants have been pixelated for privacy reasons.

phones. Video was recorded in 1280x960 and 640x480, at 30fps, and was stored as AVI files. Besides audio and video recordings, automatic screenshots of both giver and receiver’s displays were captured every 200 milliseconds. These were later used to create videos of the game interactions. More importantly, game events and some user interface events, such as mouse-click events, were saved in log files. Game logs include millisecond precision timestamps in order to synchronize audio, video, and screenshots against game events. In this way, the game state throughout each game interaction was logged to permit the analysis of player’s language use and performance.

4. Demographics and Post-Questionnaire

64 participants were recruited using Craigslist\textsuperscript{4}. To provide demographic data and subjective information about perceived game performance, all participants filled out demographic questions and a post-game questionnaire. From a total of 32 two-people teams, 17 were of mixed gender and 15 were of the same gender. 55% of the 64 subjects were female. When asked about their age, 56 of the total pool of subjects answered and the mean age was 35 years with a standard deviation of 12. Regarding their experience playing similar guessing games, 89% of participants informed that they had never played similar games before or that they had only played a few times. Therefore, only 11% of participants reported to be frequent players of similar games. All subjects were over 18 years old and native English speakers.

5. Transcriptions and Corpus Overview

Each pair participated in 6 game rounds of each of the two games, for a total of 384 rounds. 256 of these were main game rounds, while the rest were training rounds. 17,804 speech segments including 84,615 words have been manually transcribed from the total of 384 dialogues that we have collected. Participant utterances were transcribed using Transcriber (Barras et al., 1998) with start and end timestamps as shown in Figures 1 and 2. Speech segmentation was done by creating a new segment after any unfilled pause of 300ms or longer.

We report here a few summary statistics drawn from a subset of 239 main game rounds (17 of the RDG-Image rounds are excluded due to technical problems during these rounds). The average speaking rate throughout this subset of dialogues (including both participants and both games) is 143.94 words per minute. This measure, called overall speaking rate (Yuan et al., 2006), was obtained by dividing the total number of words found in the dialogues (63,117 words) by the total elapsed time of the dialogues (about 438 minutes). Overlapping speech occurred in approximately 7.82% of the elapsed dialogue time. Filled pauses (such as “mm”, “um”, and “uh”) were included in the transcriptions; they appear 4,479 times, constituting 7.09% of word tokens in the transcripts. Finally, in relation to latency of responses and overlapping speech, the average inter-segment latency, which is defined as the average temporal delay between the conclusion of segment \( N \) and the start of segment \( N + 1 \), was found to be 410ms with a standard deviation of 1,800ms (note that negative values could occur due to overlapping segments).

More detailed analysis and annotation of participant speech during the games is a focus of current work.

6. Conclusion

This paper has presented the Rapid Dialogue Game (RDG) corpus, a collection of multimodal human-human interactions created using two fast-paced conversational games. The RDGs were specifically designed to engage participants in a fast paced dialogue with the objective of capturing overlapping speech, low-latency responses and ut-

\textsuperscript{4}http://www.craigslist.org
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The images of eye make-up used in Figure 2 are excerpted from pictures protected by copyright and released under Creative Commons licenses by their original authors. In the following attributions, we will identify the 8 images shown in the Giver’s screen capture from left-right and top-down direction, with a number from 1 to 8. Thanks to Angela Caesar for images 4**, 7**, and 2*, all licensed under CC BY-NC-SA 3.0. Thanks to Courtney Rhodes for images 8** and 6*, and to Deborah Austin for image 1**. Image 3* is licensed under CC BY 2.0. Image 3** is licensed under CC BY 3.0.

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