Instructions for ACL-2016 Proceedings

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Abstract

This should be a 6-8 page conference paper with appendices, if relevant. Good reports from last year: 1 and 7

1 Introduction

from coursework spec: main research or technical question addressed
Socially assistive robots (SARs) are a crucial part of the future of many sectors, for example, education or healthcare (Gunson et al., 2022). Especially the latter depends on technology advancements as it is facing numerous obstacles in the future, such as increasing spendings and a growing percentage of older people. A serious lack of healthcare workers is already occurring, with 10 million more healthworkers needed worldwide by 2030 (Cooper et al., 2020; WHO, 2023). SARs can pose a solution to the problem by supporting healthcare in various ways, such as encouraging older people to keep living independently for longer or reducing caregiver burden (Cooper et al., 2020).

Healthcare SAR scenarios require SARs to be able to handle multi-party interactions as it is likely that more than one person will interact with the system. Compared to handling dyadic (two-party) interactions, handling multi-party conversations includes more complex challenges, such as Speaker Recognition, Addressee Recognition, Response Selection (summarised in "who says what to whom") and coordination of turn-taking (Addlesee et al., 2023; Johansson and Skantze, 2015).

Include here what exactly we examined about turn-taking

In this work, we propose a conversational system using a model trained on multi-party human-human conversation data. We collected the data from recordings of special "Who wants to be millionaire?" episodes where two candidates collaborated to answer the host's questions.

Include results here.

2 Background

from coursework spec: literature review / related work, including a critical analysis of the field, and commentary on applicability of the technologies and methods used in emerging technologies and application areas

2.1 Socially Assistive Robots

For healthcare, as well as for any other sector, the difficulty of successfully designing SARs lies in creating robots that can effectively converse with humans and adhere to social norms (Moujahid et al., 2022). The more expressive a robot is, the more it will be perceived as intelligent, conscious and polite (Moujahid et al., 2022). To achieve such a positive perception, multiple parts need to be combined into one conversational system, such as the ability to carry out visually grounded as well as task-based dialogues, to perceive and discuss its environment and to chit-chat (Gunson et al., 2022).

The SPRING project conducts research on a SAR robot deployed in an eldercare hospital reception area (Addlesee et al., 2020). The conversational system is deployed on the humanoid ARI robot produced by Pal Robotics (Robotics, 2023). ARIs capabilities can be extended with custom AI algorithms, in the case of SPRING-ARI a visual perception system, a dialogue system, and a social interaction planner (Addlesee et al., 2020). While the SPRING-ARI system successfully demonstrates that task-based, social and visually grounded dialogue can be combined with physical actions, it still lacks the ability to handle conversations with more than one person simultaneously (Addlesee et al., 2020).

2.2 Multi-party Human Robot Interaction

As stated before, the endeavour to create conversational systems becomes considerably more difficult when dealing with multi-party interactions (Addlesee et al., 2023). Especially turn-taking poses a central problem. It is defined as follows:

> The rules of turn-taking organize the conversation into turns, during which one of the participants has the right to speak while the others agree to listen. (Żarkowski, 2019)

In dyadic conversations, there are only two roles a participant can take: speaker or listener, hence it is clear when and to whom the turn is yielded. In multi-party conversations, participants can take multiple roles, therefore turn-taking needs to be coordinated (Johansson and Skantze, 2015). Humans signal their intents mostly through gaze, but also through pauses, prosody, and body positioning (Żarkowski, 2019). To copy this behaviour, earlier models for conversational systems relied on silence time-outs to coordinate turn-taking, however, this approach is found to be too simplistic (Skantze, 2021). Instead, mimicking human turn-taking behaviour better by using a combination of verbal and non-verbal cues leads to robots that are better perceived (Moujahid et al., 2022).

State exactly the gap that we will fill - whatever that will be

3 Data Collection

- (Laura) Talk about multi-party data collection

Data collection was performed by the team. We first collected all available recordings of "Who Wants to Be a Millionaire" with two participants, which were transcribed using the YouTube API. To annotate these transcripts, we used the unified set of annotations shown in Table 1. This list allows us to capture as much information as possible, without saturating the data.

Intent	Description
question	The system presents the question
options	The system presents the options
chit-chat	Speech not related to the quiz
offer-answer()	A player presents an answer to the other player
offer-to-answer	A player signals that they know the answer
agreement	Agreement between players about the answer
ask-agreement	A player asks the other player for confirmation on their proposed answer
accept-answer	System considers answer the final answer
final-answer()	Players give final answer
confirm-agreement	The system tries to confirm the final answer with participants
confirm-final-answer	Participants confirm their answer is final

Table 1: Intents used for Data Annotation

3.1 Cohen's Kappa Coefficient

To ensure reliability and consistency, Cohen's kappa was calculated for a sample of the completed transcripts. It measures the reliability between raters on categorical data, while accounting for agreement happening by chance (Cohen, 1960). A sample of four transcripts are re-annotated by a team member, which amounts to approximately 15% of the total transcripts.

$$\begin{aligned} KappaScore &= \frac{Agree - ChanceAgree}{1 - ChanceAgree} \\ KappaScore &= \underline{\underline{0.9601}} \end{aligned} \quad (1)$$

A Kappa score of 0.9601 is interpreted as "almost perfect agreement" (McHugh, 2012). From this, the annotation of transcripts can be concluded as reliable.

4 Design and Implementation

- *from coursework spec:* design and implementation of the system: components and architecture

4.1 Automatic Speech Recognition

To enable interaction between users and the conversational system, the first step is to transform

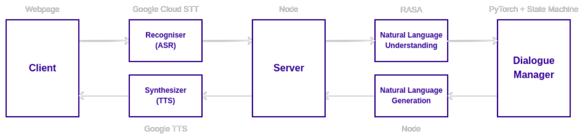


Figure 1: Architecture of the conversational system

user's speech into text, in order to pass text further onto intent recognition (NLU). Transforming audio into text works through Speech-To-Text (STT) software. In recent years, STT systems became more accurate and fast, however, none of the existing systems can yet reliably handle conversations in real time (Addlesee et al., 2020).

Our conversational system required two non-standard aspects from the ASR: (1) real-time transcription and (2) diarization. As our system conceptualised for usage on a robot, it must transcribe what the user is saying in real-time to avoid response delays. Time taken for a system to respond can only be marginally longer than the delay a human would leave before responding . source!

Diarization is the process of determining the speaker in multi-party conversations. Therefore, to handle a "Who wants to be millionaire?" style game, our system must be able to diarise. This allows us to track the intents of each individual user and determine when users agree or disagree. We tried several STT systems including Amazon's Transcribe, IBM's Watson and locally running Pyannote. Our findings were that these are all valid options for transcription but lack real-time diarization. We settled with Google's Cloud Speech-to-Text API due to its high accuracy, real-time transcription capabilities, and customisability. As it is widely used, troubleshooting and integration resources were readily available. In addition, Google's API promised diarization capabilities, and along with its real-time transcription capabilities seemed to fit our use case. However, in use, diarization was inaccurate, and it often grouped two separate speakers together or split sentences up seemingly at random. This became even more apparent when two users were speaking over each other, supporting the findings of (Addlesee et al., 2020). As this made Google's diarization unusable for our system, therefore we decided to handle the diarization separately and integrate it with the real time Google transcription.

4.2 Natural Language Understanding

Natural Language Understanding (NLU) is the first contact point between a user and conversational AI system. NLU uses many different methods to take in sentences or phrases of natural human language and try and classify them into intents that a computer can use. We use Rasa NLU which uses machine learning to train on our collected data to create a model that can accurately recoginize new, unseen inputs from users similar to the training examples. The NLU model will take the phrases from the ASR and label them with what it thinks the intention of that phrase is and passes that on to the DM.

> Rasa Open Source is the most popular open source framework for building chat and voice-based AI assistants. Rasa Open Source is an open source conversational AI platform that allows you to understand and hold conversations, and connect to messaging channels and third party systems through a set of APIs. It supplies the building blocks for creating virtual (digital) assistants or chatbots.

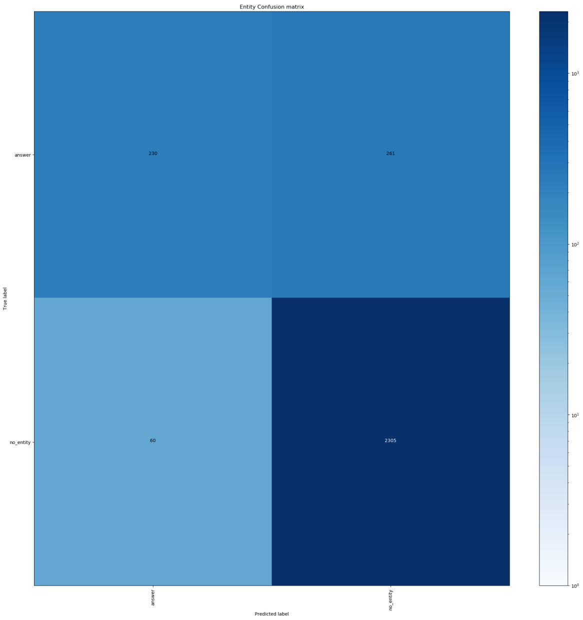
We are not using all that Rasa has to offer but only Rasa NLU. Rasa NLU only produces a NLU model that can translate human language into intents or labels without the rest of the conversational system like DM and NLG. It takes training data in the form of each intent required with examples of natural language that would be classified under that intent. The model is also capable of entity extraction where it can recognize and label words of interest, like the answer to the question in our case.

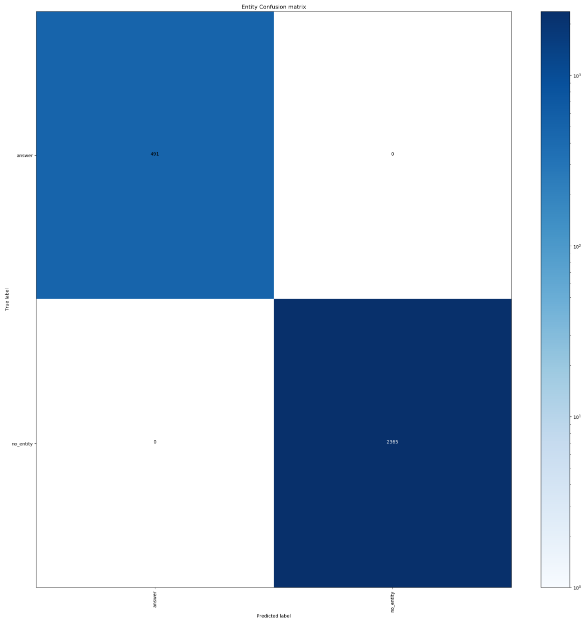
The intents NLU is trying to detect and label were described in the section 3 section above. Data collection provided hundreds of examples of each intent, which was then cleaned by the NLU team and put in as training data for Rasa NLU.

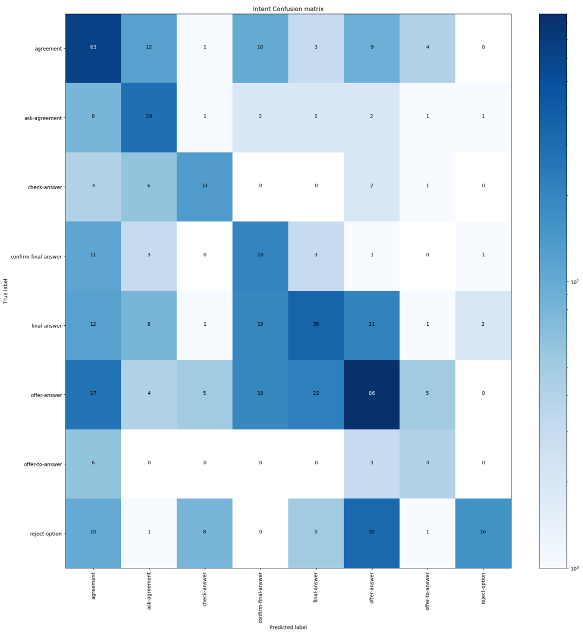
4.3 Evaluation of NLU

The NLU model has gone through multiple iterations, starting with very few training examples and being highly innacurate to a large amount of clean data producing a highly accurate and reliable model. Two models and their evaluations:

Original The original model is the first model trained on only 4 or 5 annotated transcripts, very







little training data. This model was highly innacurate, constantly mislabeling intents, and extracting wrong answers or no answer at all. The Rasa training model used was not very efficient with a small amount of training data so this was expected.

The diagram above shows the entity extraction confusion matrix, where you can see that more than half of the phrases with answers werent extracted. It did well with phrases without entities and rarely mislabed entities that werent actually answers, but its general tendency to not extract an entity was poor.

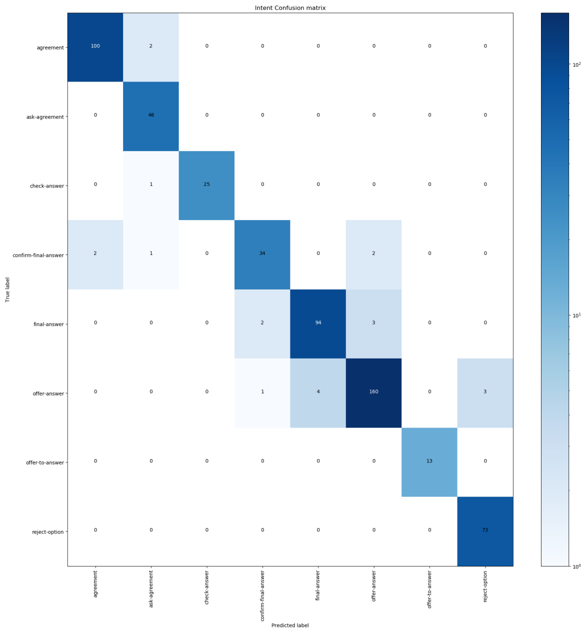
This diagram shows the confusion matrix for the intents. It shows a random scatter over the matrix meaning that the predicted labels and real labels often did not match up. The model in general was quite random and inconsistent to say the least.

Used Model The latest/best model, and the one actually used in our chatbot, was trained on around 25 transcripts with hundreds of training examples for each intent. Furthermore, we went through all the training data and manually cleaned it of any examples that were misplaced or extracted from the transcripts wrong. The added amount of data and the cleaning proved to do wonders as the performance of the model was much more reliable and accurate.

As can be seen above, the confusion matrix is perfect as the model did not make any mistakes with entity extraction. Of course the model can't be perfect and this is only its performance on our test data, but still a crystal clear difference from the original model.

This diagram again shows the intents and how much more accurate this model is compared to the original. It only has a few mistakes here and there, especially with the more ambiguous intents, but even us as humans confuse those intents often. Regardless, the model is leaps more accurate than its beginning.

- Short description of RASA
- Explain the aim (detecting intents)
- Refer to the intents described in 3 section 3
- Evaluation - show different versions of the



model: difference in F-Score, Confusion Matrix, ...

4.4 Dialogue Management

- Clearly explain 2 parts (State-Machine and NN)
- State-Machine: high-level control, handles things we have no data for, eg. pauses
- NN: Report on differences between RNN and LSTM and why the choice for the LSTM has been made
- (optional): Comparison to RASA rule-policy

4.5 Natural Language Generation

To make the system feel more unique and less robotic, we made use of Natural Language Generation (NLG) for the phrases that the "host" says to the participants. We used OpenAI's API, specifically "gpt-3.5-turbo", the same version that is used in ChatGPT. This allowed us to prompt for different outputs for the system that convey the same information. For example, when receiving a correct answer, "Yes, that's it! Well done!" and "You got it! Great job!" are both possible outputs. There are 50 different options for each response the "host" can say.

5 Evaluation

from coursework spec: evaluation of the system and presentation of the results

5.1 Methodology

In this study, we performed extrinsic and intrinsic evaluations. The extrinsic evaluation focused on both subjective and objective measures of the system's performance. The subjective measures included the user's enjoyment and perception of the system's natural behaviour, while the objective measures included the number of turns taken and the agreement rate. Additionally, the correlation between correct answers and enjoyment was also examined. Overall, the evaluation aimed to assess the effectiveness of the system in engaging users and providing accurate responses.

The evaluation focused on intrinsic measures of individual components in a multi-party conversational system. The components were assessed separately, with ASR being evaluated using the word error rate, NLU using precision, recall, accuracy, and F1 score, DM IDK YET, and NLG using n-gram-based overlap with BLEU. The aim was to assess the performance of each component and identify areas of improvement.

Additionally, the evaluation also aimed to test the hypothesis that using verbal cues instead of silence cues in a multi-party conversational system increases user interaction and satisfaction with the system. This hypothesis needed to be statistically proved or disproved through significance testing.

5.2 Experiment Layout

The experiment followed a between-subjects design. Every participant was required to read and sign a consent form before they can play the quiz. This was an in-person experiment, with the quiz running on a laptop, where participants can see the questions and the options. Members of the experiment were required to play the quiz at least once. However, they were encouraged to play as many times as they can. After they no longer wished to play, they were asked to complete a questionnaire about their experience. The questionnaire queried them on their experience using a five-point Likert scale.

5.3 Results

- ASR results
- NLU result
- DM result NLG result
- questionnaire result

6 Conclusion

6.1 Ethical Reflection

7 Future Work

from coursework spec: suggestions for future work

To further improve on NLG within this system, some content moderation could be performed on the generations, to ensure that there are no inappropriate outputs, this can be done entirely within OpenAI's API. Also, the system could be updated to make use of GPT-4, which at this current time is not publicly available.

Acknowledgments

The acknowledgments should go immediately before the references. Do not number the acknowledgments section. Do not include this section when submitting your paper for review.

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A Supplemental Material, Appendix