Integrating Open Source Software for an Adaptive Conversational Robot

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ABSTRACT

This paper explores the benefits and challenges of creating an adaptive conversational robot through the integration of open-source software and reinforcement learning algorithms. The aim is to create a conversational robot that imitates natural person-to-person communication, as speaking is considered the most convenient way of communicating. The Furhat Robot is used as the platform for receiving inputs and outputs, and the python script deploys the model that evaluates the interest of the counterpart in the conversation. The state-action space of the model includes parameters of the OpenAI API and various factors that affect the robot's response, such as tone and volume of the robot's voice. The findings of this study provide insight into the potential of using open-source software and reinforcement learning algorithms to create more advanced conversational robots, and highlights the importance of continued research in the field of Human-Robot Interaction.

CCS CONCEPTS

• Computer systems organization → Robotics; **• Human-centered computing → Field studies**; **• Applied computing**;

KEYWORDS

social robot, reinforcement learning, furhat robot, conversational robot, open-source software

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1 RELATED WORKS

There are a number of works that proves that personalised adaptive robots with RL algorithms are much better for therapy and learning.

One example is the work by Zini et. al. called "Adaptive Cognitive Training with Reinforcement Learning". It suggests an approach for adaptive cognitive training that is based on reinforcement learning (RL). In order to maximize training efficacy, the method employs an RL algorithm to dynamically modify the complexity of training tasks based on the user's performance. The authors demonstrate that their RL-based approach leads to superior performance compared to a predetermined training regimen by evaluating it on a variety of cognitive training tasks. They also demonstrate how the strategy effectively accommodates individual variances, resulting in more customized training plans. Overall, the findings point to RL as a potentially effective method for increasing cognitive training. The same use of the RL algorithms is going to be applied to our project [7].

Another work by Shawki and Badawi examines the use of RL to provide a personalized learning experience. The authors suggest a system that creates a personalized learning environment by adjusting to the user's learning style, motivation, and speed. The technology adapts the learning experience based on user input and reinforcement learning algorithms to understand individual preferences. Through simulations and trials with a sample of users, the authors show the usefulness of the suggested approach. The findings demonstrate that the system is capable of delivering a tailored learning experience that raises motivation, engagement, and performance [5].

Park et. al. proposes a model-free affective reinforcement learning approach to personalize an autonomous social robot companion for early literacy education. With this method, the robot may learn the preferences of the youngster it is working with and modify its behaviour appropriately. Reinforcement learning algorithms are used. By customizing its interactions with the child based on their emotional state, the goal is to increase the robot's efficacy as a teaching tool. The study's findings that the suggested strategy works well at increasing children's motivation and involvement with educational activity are presented in the article [2].

This work shows that it is possible to create a conversational robot based on the RL model in order to adapt to the cognitive differences of people for various learning purposes.

2 USED TECHNOLOGY

2.1 Furhat Robot

Furhat robot is a social conversational robot developed by Sweden company FurhatRobotics that able to communicate with people by imitating the way that people interact with each other. The robot consist of facial mask, that allows to show different faces and imitate emotions, FOV camera, stereo microphone and stereo system. Robot has a natural language processing and internal library. Also, it could easily integrated with other application and software.

2.2 TextToSpeech model

Text to Speech model from the Human-Robot interaction Lab was integrated with Furhat robot to generate audio speech in the Kazakh language. The module is capable of generating 3 different Kazakh voices: man, women and child voice.

2.3 OpenAi

The implementation of the answer generation in the paper is achieved through the use of the OpenAI API. In order to find most suitable language model, the three are tested Generative Pretrained Transformer 3 (GPT-3), Davinci, and Curie. GPT-3 is a highly advanced language model that capable of generating human-like text and processing natural language requests. Despite being smaller in size, the Davinci and Curie models are renowned for their high accuracy and low delay, which makes them better for real-time applications. All three models are compared by highlighting the strengths and limitations of each.

2.4 Actor-Critic RL algorithm

Another open source software method that is going to be used is RL Actor-Critic (AC). The Actor-Critic model combines two neural networks: the "actor" and the "critic". The actor network maps states to actions and is responsible for selecting actions in the environment. The critic network maps states and actions to estimates of their expected long-term rewards and is responsible for learning the optimal value function. The two networks are trained together so that the critic provides feedback to the actor about the quality of its choices, and the actor adjusts its policy based on the critic's feedback. This allows the actor-critic algorithm to balance exploration and exploitation, learning to make good decisions over time[3].

The reason to choose the Actor-Critic over other algorithms such as Deep Q-Network is that we believe for conversational robot we need an algorithm which can handle stochastic nature of that state space. In other words, conversations may be very random depending on the people the robot is talking to and that is why increasing the state-action space. The conversational model is hardly represented by a single value function but many. That is why, we believe AC is better suited for this application Moreover, the conversational robot may have sparse reward problem, in which reward can come in long intervals. This is effectively handled by AC algorithm.

3 METHODOLOGY

3.1 Implementation structure

In this project the open-source technologies are going to be used in the following way. The major goal is to use them in order to create a good flow of outputs and inputs for the AC model. In order to receive the input and output we are going to use the Furhat Robot. The robot has a number of built-in technologies for that purpose. It has its own TTS, Speech Recognition, gaze recognition, and other models for the purpose of conversation. The received input and output data then will go through a python script, which deploys the model. The model will receive the data that evaluates the interest of the user in the conversation. Some metrics like the tone, the speed of responses, the gaze of the person are analyzed. All this data are going to be used to measure the optimal reward function and act upon it. The state-action space of such model are going to be the parameters of the OpenAI API, which generates responses for the questions, the tone and volume of the robot voice, etc.

An important point to mention is that as there is scarcity of models for Kazakh language as well the problems with the existing ones in the Furhat Robot, the open source models from the local Nazarbayev University's labs are going to be used. The custom made Text-To-Speach model, the bilingual TTS engine is built by deploying the implementation of a modified Tacotron 2 model [6] and a flow-based neural network model from the WaveGlow [4] for PyTorch. and the Speech Recognition from the Institute of Smart Systems and Artificial Intelligence (ISSAI) [1] are used for that application.

3.2 Data collection and Training

The data will be collected by conducting a sample field experiments at local school, where children will interact with a robot in two different ways. Children will be given a specific scenario to assist them converse with the robot during the first experiment. In the second experiment, kids will have full freedom to interact with the robot as they like and ask any questions they may have. By analyzing the collected data and personal observations from the experiments, we will be able to identify the necessary improvements in scenarios and parameters for the reinforcement-learning model, which can then be used to fine-tune the model. After that, the model would be repetitively trained in order to increase the accuracy of the results.

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