Augmentative and Alternative Communication personalization with PECS cards: Evaluation of Reinforcement Learning Algorithms

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Introduction

Augmentative and alternative communication (AAC) systems, such as the Picture Exchange Communication System (PECS), are widely used to support children with autism spectrum disorder (ASD) in real communication with adults. To improve their usability and learnability, the systems are digitalised. Artificial intelligence capabilities are applied to increase communication effectiveness. Most existing research works, based on AI models, try to build classifiers for the child's reaction states, where the data to train the models is fully labelled. However, data labelling is prone to subjective interpretations by the specialist. For each child with ASD, their individuality makes it impossible to determine the rule-based data and their decisions. The work proposes the research and evaluation of reinforcement learning algorithms, where the agent learns an optimal strategy of presenting an appropriate PECS card for effective communication between a child and an adult.

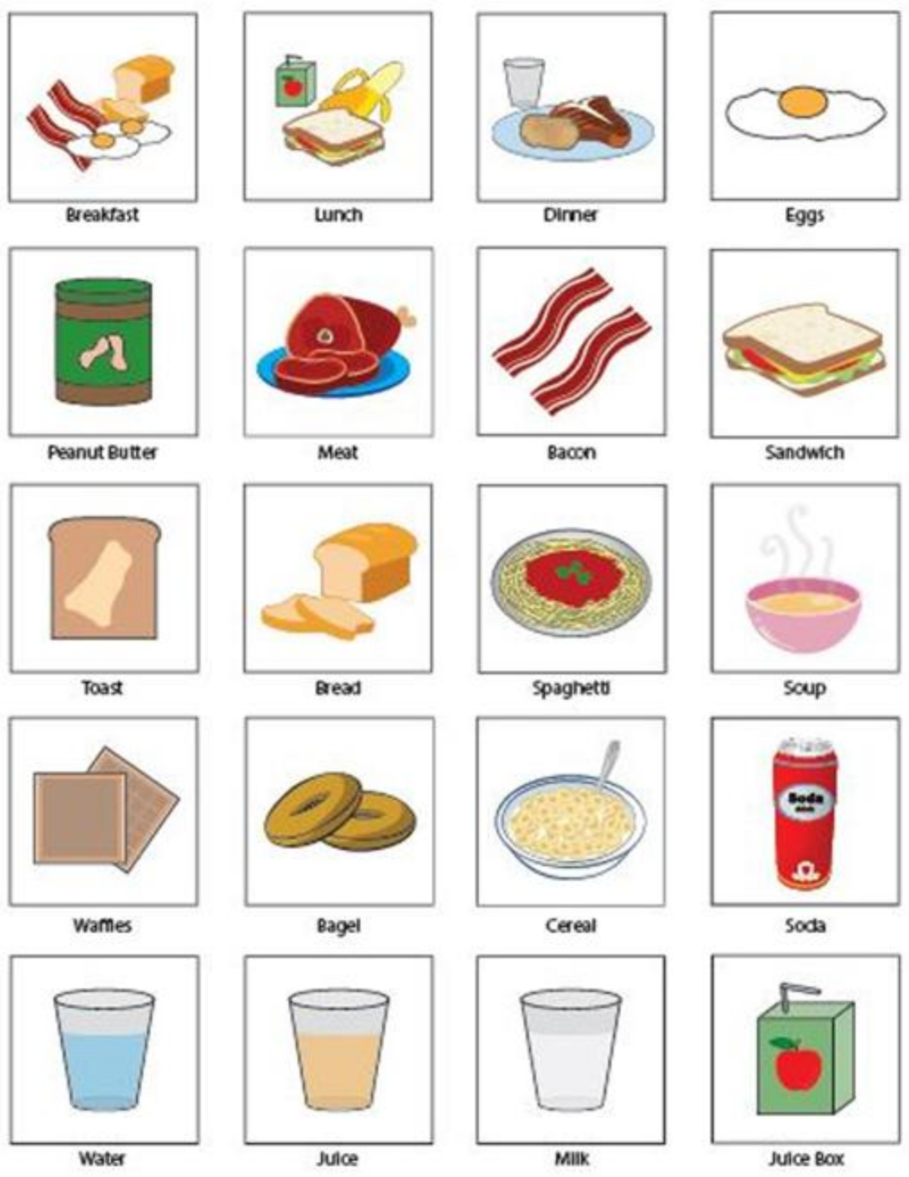

Figure 1. PECS cards

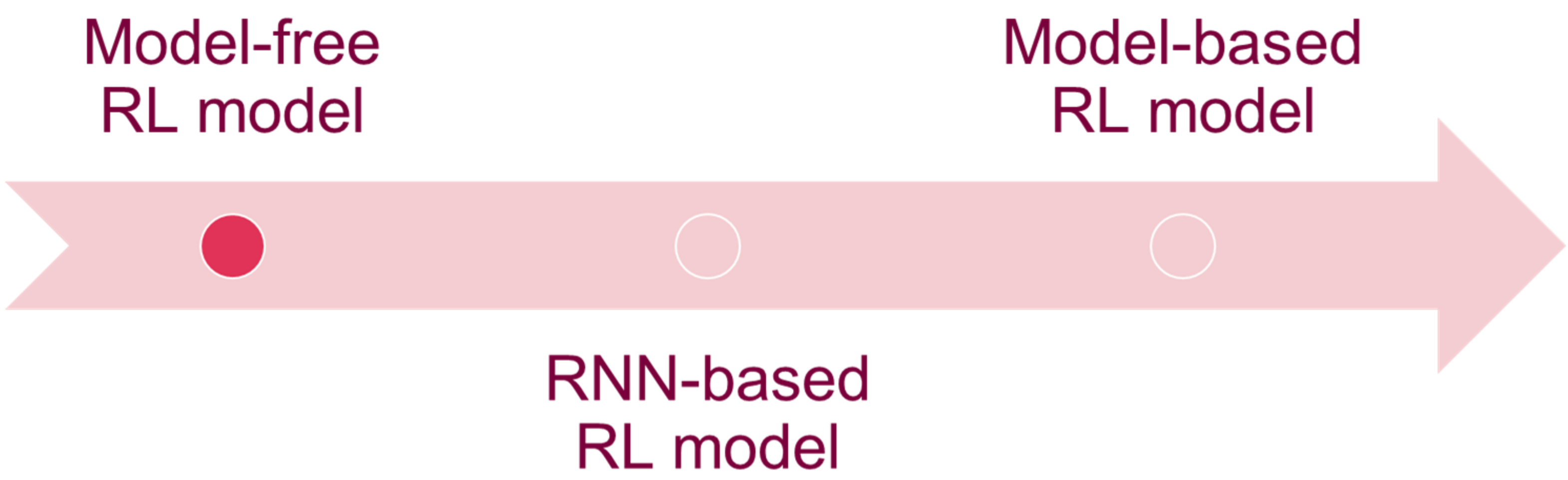

Figure 2 The research scope

The research goal is to propose an RL-based model for optimal PECS card selection within a digital AAC system to improve child–adult communication.

Reinforcement Learning

SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a') - Q(s,a)]$$

SARSA(λ)

$$Q(s,a) \leftarrow Q(s,a) + \alpha e[r + \gamma Q(s',a') - Q(s,a)]$$
$$\underbrace{e(s,a)}_{eligibility\ trace} = \gamma\lambda e(s,a) + 1$$

Expected SARSA

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \underbrace{\sum_{a'} \pi(a' \mid s')Q(s',a')}_{weighted\ policy\ sum} - Q(s,a)\right]$$

Actor–Critic

$$V(s) \leftarrow V(s) + \alpha_v[r + \gamma V(s') - V(s)]$$
$$\theta \leftarrow \theta + \alpha_\pi[r + \gamma V(s') - V(s)] \underbrace{\nabla_\theta \log \pi(a \mid s)}_{policy-gradient\ term}$$

Learning environment (LE)

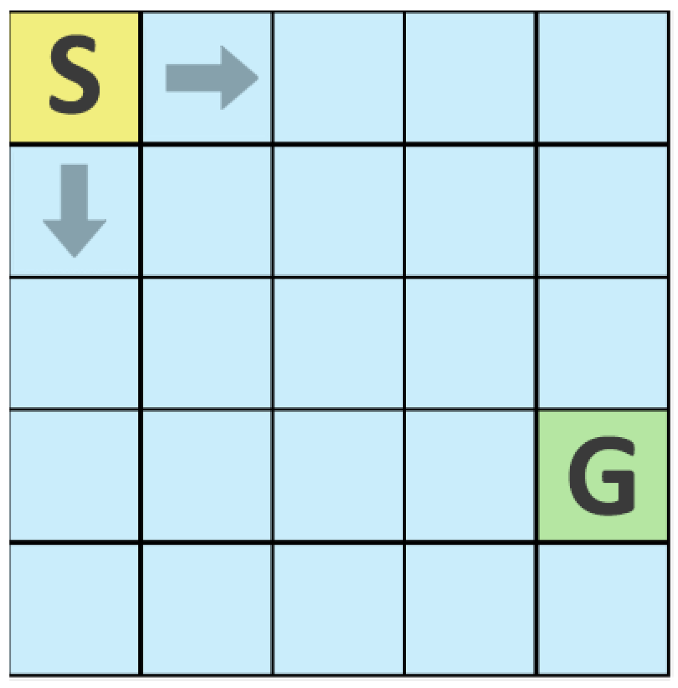

Figure 3. 1st LE with starting position (1,1)

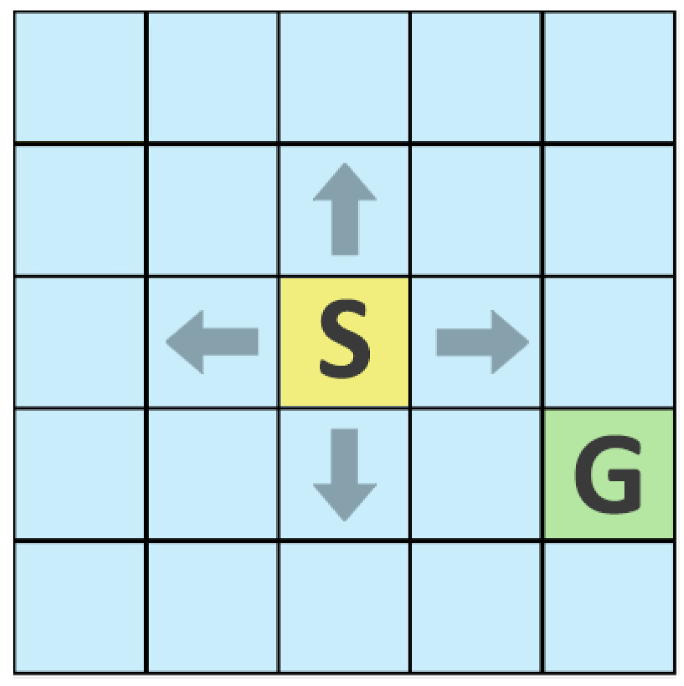

Figure 4. 2nd LE with starting position (3,3)

Results

The Actor-Critic algorithm achieved the best average performance with 7 steps, outperforming SARSA, Expected SARSA, and Sarsa (λ) by 9.1% to 9.4%.
Actor-Critic again showed the most efficient learning, completing the task in 3 steps on average during testing, while SARSA required 33.3% more steps.

Table 1 RL algorithms average results

Algorithm	Start (1,1) - Avg. Value	Start (1,1) - Std. Dev.	Start (3,3) - Avg. Value	Start (3,3) - Std. Dev.
Sarsa	37	7.7	30.56	4.5
Sarsa(λ)	28.6	7.4	23.9	**3.0**
Expected Sarsa	36	7.7	27.16	**3.0**
Actor-critic	**18.6**	**7.0**	**14.6**	**3.0**

The performance of Sarsa(λ) was better than Sarsa, because Sarsa(λ) reduced the average episode length from 7,7 to 7,4 steps at the (1,1) start position and from 4,5 to 3 steps at the (3,3) start position effectively bridging the gap between the initial action and the delayed reward

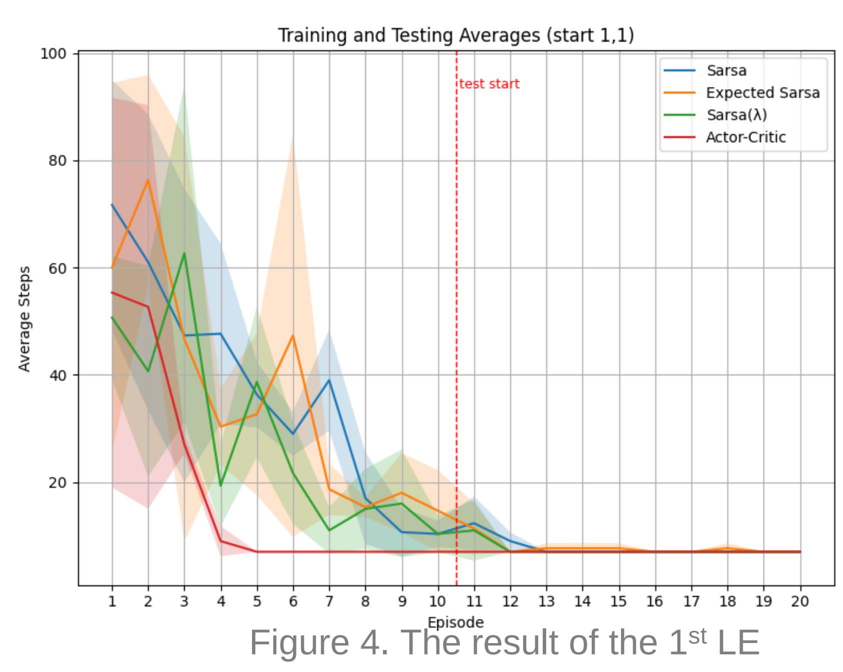

Figure 4. The result of the 1st LE

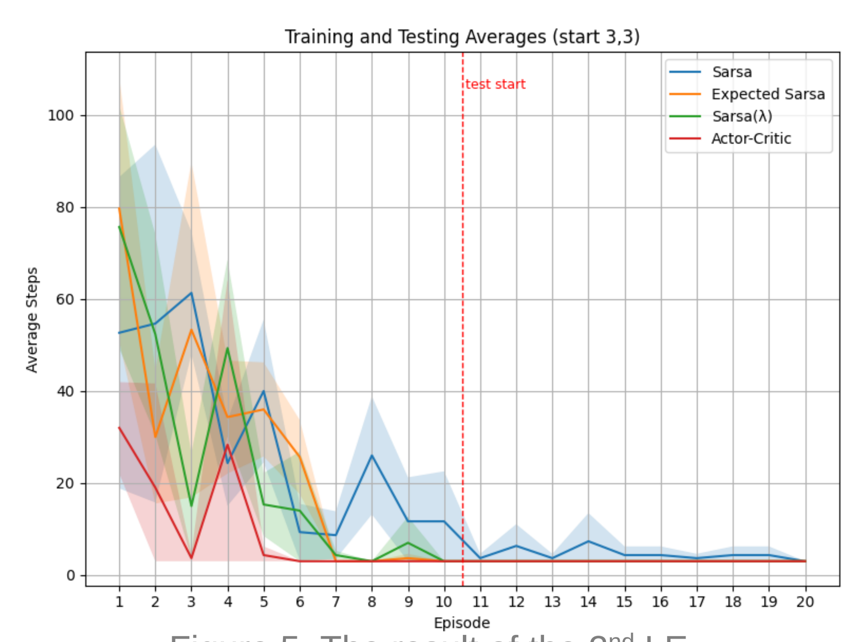

Figure 5. The result of the 2nd LE

Conclusions

1. For AAC development, the Actor-Critic method is the most effective approach, as it enables rapid convergence to the user's behaviour, minimising the "cold start" (model-free RL) problem and ensuring that the system effectively addresses the child's communication needs before attention is lost.
2. Meanwhile, the Sarsa(λ) results confirm that in the PECS process, it is important to evaluate sequences of actions (choices of PECS cards), and not just individual steps, as this allows for faster learning of more complex communication chains.