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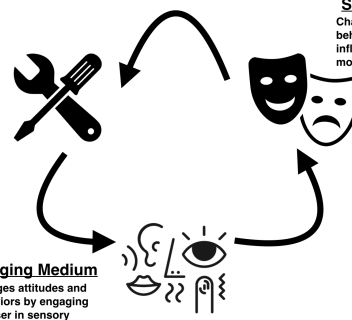
Abstract

Social robot learning companions hold great promise for augmenting parents and teachers to promote childhood learning by physically, socially, and emotionally engaging with children. One of the most important factors for language skill development is sufficient exposure to a rich variety of spoken language and vocabulary – critical precursors to learning to read. The social context of exposure is also critical to concept development and the learning experience, i.e., simply hearing language is not enough, children need to actively participate and be emotionally and physically engaged to maximize their learning gains. Through this project, we are developing a **fully autonomous, collaborative, peer-like social robot system** with effective educational activities building on top of: **multi-modal personalization algorithms for cognitive assessment, affective support, and interactive play behavior.**

Social Robots: A New Computational Medium for Practicing Language and Literacy Skills

“Functional Triad” of Persuasive Technology¹

Data-Fluent Tool
Changes attitudes and behaviors by calculating or tracking data and presenting to the user



Social Actor
Changes attitudes and behaviors by using social influence such as motivation or competition

Engaging Medium
Changes attitudes and behaviors by engaging the user in sensory experiences

Social Robots score highly on all aspects of the “Functional Triad” of persuasive technology: interactive computing systems intentionally designed to change attitudes, beliefs, and behaviors

¹“Persuasive Technology”, B.J. Fogg, 2003

Scientific Background

Social robot learning companions can promote childhood learning by **physically, socially, and emotionally engaging** with children.

Language learning is **cognitive, social, and affective!**

Language learning is “socially gated.” That is, interaction with other agents improves efficiency and retention.

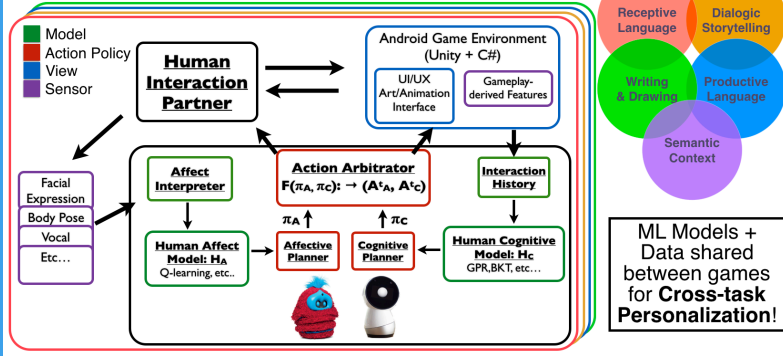


Emotions are deeply important through each step of learning: **attention, comprehension, integration, and memory consolidation.**

We are developing **collaborative, peer-like social robots** with effective educational activities building on top of: **personalized, multi-modal assessment and interaction models and algorithms**

An affective-cognitive framework for interactive model learning, educational content sequencing, and

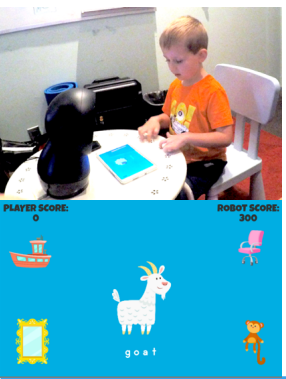
Affective, Personalized, Long-term Interaction



ML Models + Data shared between games for **Cross-task Personalization!**

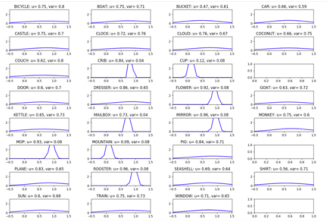
Romeo, R. R., Leonard, J. A., Robinson, S. T., West, M. R., Mackey, A. P., Rowe, M. L., & Gabrieli, J. D. (2018). **Beyond the 30-Million-Word Gap: Children’s Conversational Exposure Is Associated With Language-Related Brain Function.** *Psychological science*, 29(5), 700-710.

RhymeRacer

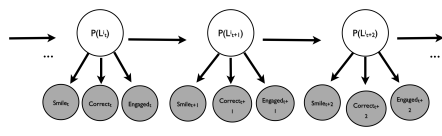


Teaching and Tracking phonological awareness through competitive play

Gaussian Process models vocabulary at word-level



Affective-BKT models rhyme-ending fluency at phonological level



Active Learning protocol personalizes content to improve data efficiency

Objective: select words with rhyme endings least likely to be known to teach
 $rhyme_{t+1} = \operatorname{argmin}_{e \in Endings} P(Learned_t^e)$

Objective: select rhyme ending with least model fit to improve model
 $rhyme_{t+1} = \operatorname{argmin}_{\theta \in \Theta} \operatorname{LogLikelihood}(\theta|D)$

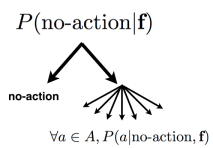
“A Social Robot System for Modeling Children’s Word Pronunciation.” Spaulding, S., Chen, H., Ali, S., Breazeal, C Proc. of AAMAS 2018.

WordQuest

A collaborative, free-form vocabulary game using a mixed-initiative play model



Mixed-initiative action-selection model chooses when and how to interact



- Action Space**
- Encourage
 - Re-Engage
 - Hint
 - Lesson
 - Answer
 - Prompt for Evaluation
 - Tease
 - Take Break
 - Skip to Next Question and more....

Pronunciation model from RhymeRacer personalizes content difficulty

Objective: Select category based on summed posterior mean knowledge estimate of Gaussian Process word model.
 $category_{easy} = \operatorname{argmax}_{c \in C} \sum_{w \in W} \mu_w$

Child and Robot collaboratively search for and pronounce words that fit a category (e.g. “vehicles”, “edible”)