

# Towards a Personalized Model of Number Concepts Learning in Preschool Children

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**Abstract**—The personalization and adaptation of education is an important research goal in much human-machine interaction research. “Bloom’s two sigma” phenomenon has shown the immense benefits of one-on-one, personalized tutoring (tutored students perform in the 95th percentile compared to students receiving traditional classroom instruction [1]), and has been replicated in human-computer interaction research [2]. However, very little research in automatic personalized education targets young children or includes features of learners’ intrinsic differences such as learning style. This paper presents and formalizes a model of personalized number concepts learning for preschool children with a socially assistive robot tutor. We also present an initial data collection on number concepts learning with a socially assistive robot, and discuss our future plans to use this multidimensional dataset to train and validate our model.

## I. INTRODUCTION

Socially Assistive Robotics (SAR) aims to supplement the efforts of educators, parents, clinicians, etc. in providing personalized support to individuals with important and specific needs. Exemplary domains of SAR include, but are not limited to: post-stroke rehabilitation [3][4][5], elderly care [6][7][8], and diagnosis, treatment, and understanding of autism spectrum disorder [9][10][11][12]. SAR is also emerging in the domain of education for young children, engaging children socially and mentally in educational activities.

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Differentiated or *personalized* education is a critical goal and challenge in modern education [13][14]. Personalized education requires the most resources and places the highest burden on educators. As a result, young children from underserved communities are less likely to receive such personalized support. SAR lends itself to broad replication and diminishing costs as technologies advance, and thus, holds much promise for greater accessibility to personalized education in these communities.

In response to recent market demands, education in science, technology, engineering, and mathematics (STEM) has come to the forefront [15]. Academic competence in mathematics is both critical [16] and achievable [17] in early childhood education. Thus, number concepts, the understanding of number basics [18], is a vital developmental goal in preschool education.

In this paper, we present a model for personalized number concepts learning in preschool children in a SAR context. We formalize number concepts learning based on early childhood education literature and a data collection executed with a SAR system in a preschool classroom. The goal of this model is to predict individual children’s abilities to perform number concept operations. We also discuss how the model we present might incorporate other multimodal features outside of child’s performance. Accurate, multidimensional assessment of children’s abilities will enable more optimal activity selection for personalized SAR education.

## II. RELATED WORK

Research in computer-based, Intelligent Tutoring Systems (ITS) has shown to replicate Blooms two-sigma phenomenon [1][2]. ITS has made large strides in accessible, personalized STEM education



Fig. 1: The SAR system setup in preschool classroom with the Aldebaran NAO robot, a Lenovo IdeaCentre Horizon 27" touch tablet, a high-definition camera, and two webcams for multimodal data collection

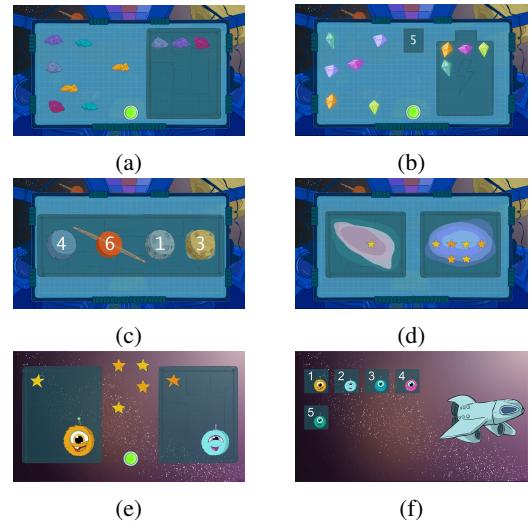


Fig. 2: Screen captures of activity types

for undergraduate students, including: ANDES for Newtonian physics [19], CIRCSISM-Tutor for cardiovascular physiology [20], KERMIT for conceptual database design [21], and eTeacher for Artificial Intelligence [22]. There is also a variety of research related to personalized, computer-based education for early language learning [23][24]. However, little research exists that is specific to early childhood, socially-mediated STEM education. Our research focuses on the various challenges inherent in the social and early childhood dimensions of STEM education, leveraging domain knowledge to minimize computational complexity.

Recent research in social robots for education has shown that embodiment and personalization increases cognitive learning gains [25]. Additionally, socially-mediated and embodied learning adheres to the best practices of socio-constructivist education theories [26], and specifically relevant to mathematics education [27]. Various studies have demonstrated the power of learning-through-play [28] applied to technologies for early childhood development such as interactive playgrounds [29], [30], educational computer games [31], and most applicably SAR for early childhood education [32], [33]. In our work, we embrace these practices and

consider modeling number concepts learning in the embodied and socially-mediated context of SAR.

The theory of learning styles (LS) is a common approach to characterizing some aspects of individual learners for differentiated or personalized education [34]. While LS has yet to be accepted as the ultimate method to learner differentiation, it has already been incorporated into various ITS research. Hybrid data-driven and literature-based LS estimation in ITS aims to understand a learner from a more holistic perspective, considering semi-static features about the learner [35][36]. Felder and Silverman defined one dimensional theory of LS for engineering students [37] that has been employed in much ITS and e-learning research [22][36]. In designing our model and data collection for number concepts learning, we consider how some dimensions of LS may be leveraged to better understand an individual child's ability.

### III. APPROACH

In the following section we describe our formalization of number concepts learning in a SAR context, an initial data collection in a preschool classroom, and our proposed model for personalization. We connect each of these back to the larger goal of

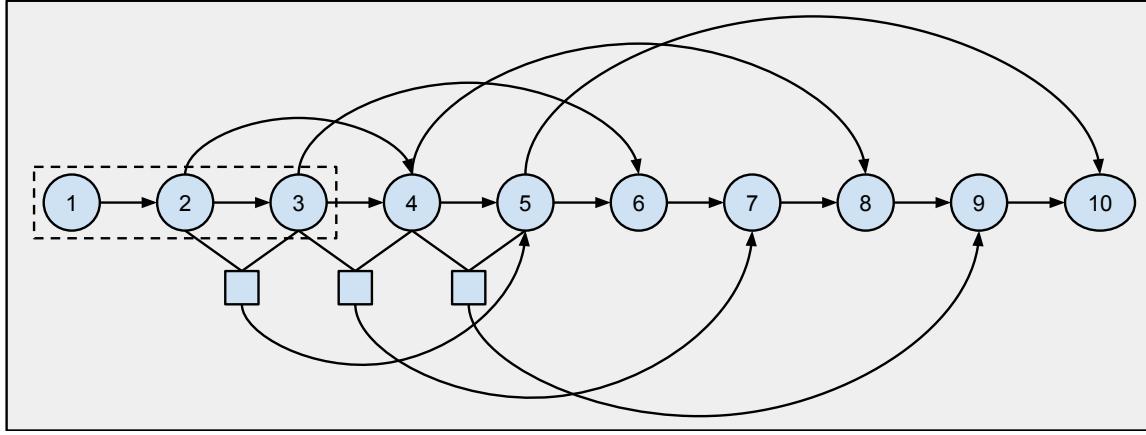


Fig. 3: Visualization of our proposed literature-based preschool numeracy dependency network, developed under the guidance of STEM education expert Prof. Gisele Ragusa

multidimensionally personalized, early childhood education through SAR.

#### A. Formalization of Number Concepts Learning

There are a total of 10 key numbers for a preschool child to learn and many concepts through which to learn them. We framed our number concepts activities around the 2013 Paramount Unified School District Transitional Kindergarten Math Pacing Guide [38] to ensure developmentally appropriate practice. These activities include:

- Give  $n$  objects where  $n \in [10]$ .
- Give [“most”, “all”, “just one”] objects.
- Identify  $n$ .
- Compare two quantities and tell which is “more” or which is “less”.
- Divide set of  $[4, 6, 8]$  objects into two halves.
- Count up to  $n$  objects in a row.

We created seven basic “types” of activities with a SAR tutor in a space-themed background story to enable the children to learn-through-play (see Figure 2).

Concretely, let  $\mathcal{A}$  denote the collection of all activities. Each activity  $A_\alpha \in \mathcal{A}$ , through which an individual child may practice number concepts, can be characterized by that activity’s number  $n$  and its “type” defined by the following set of four binary concept aspects  $n$ :

- 1)  $M$ : is the activity about  $n$ ’s magnitude?
- 2)  $O$ : is the activity about the linear order from 1 to  $n$ ?
- 3)  $W$ : is the activity about the verbal representation of  $n$  (i.e., how does it sound)?
- 4)  $S$ : is the activity about the symbolic representation of  $n$  (i.e., how is it written)?

Every aspect corresponds to an inherent learning style. For example, activities where  $S = 1$  contain a visual queue and activities where  $W = 1$  contain a verbal queue, and thus, activities of these concepts may be defined to lie along the visual-verbal dimension of Felder’s LS model [37]. This formalization allows the number  $n$  to be independent of the LS of its concepts.

#### B. Data Collection with Preschool Children

We conducted an initial data collection with 31 preschool children interacting one-on-one with the SAR system (see Figure 1) in a real-world classroom. Each child participant performed a set of 27 activities randomly selected from  $\mathcal{A}$  without repeat. Most children completed all 27 activities with an average interaction time of 20 minutes.

We collected a set of multimodal interaction data, including: frontal audio-video recording with a high-definition camera, full profile video recording with webcam, touch interaction recording with

tablet computer, and overhead video recording of tablet interaction with webcam (see Figure 1). Additionally, we collected parent and teacher questionnaires about each child’s LS.

Our model of number concepts learning, described in the following Section III-C, was constructed with this dataset in mind. We designed our model with the intent to expand it in the future to include multimodal features of interaction and LS. However, as can be observed from our formalization in Section III-A, we intend our model to generalize to any number concepts activities in any context, as number concepts activities are by definition characterized jointly by a number and its concepts.

### C. Personalized Model of Child’s Ability

In our model, we strive to separate the activities’ numeric differences defined by  $n$  and their concept differences defined by  $\{M, O, W, S\}$ . Based on number concepts learning literature and with the guidance of STEM learning expert Prof. Gisele Raguza, we have constructed a numeracy dependency network depicted in Figure 3. This network describes the overall progression of number learning, from one number as a *whole* to another.

Let  $A_\alpha(n, M, O, W, S)$  be a randomly sampled activity from the set of all activities  $\mathcal{A}$ . Let  $R_\alpha$  denote a child’s performance on activity  $A_\alpha$ . We desire to predict  $R_\alpha$  given the child’s activity performance history  $R_\beta$  such that we may later select the activity with optimal difficulty for that child. For simplicity, we consider the case when the history has only one activity.

Let  $k \in [4]$  be the possible rankings of children’s performance, where  $k$  roughly represents the number of tries it took a child to perform an activity correctly. Special case  $k = 4$  represents that the system moved on from an activity as a child was unable to complete it.

We model the probability  $P(R_\alpha = k' | R_\beta = k)$  by considering both the activities’ difference in numbers ( $A_\alpha(n)$  and  $A_\beta(n)$ ) and difference in the concepts (i.e. the variables  $M, O, W$  and  $S$ ) being tested.

*a) Measure differences in numbers:* We measure the effect of the difference in numbers by

$$n_{\alpha\beta} = \frac{|A_\alpha(n) - A_\beta(n)|}{9}$$

where  $0 \leq n_{\alpha\beta} \leq 1$  such that  $n_{\alpha\beta} = 0$  if  $A_\alpha$  and  $A_\beta$  test the same number  $n$ .

*b) Measure differences in concepts:* We measure the effect of the difference in concepts (which might be directly related to LS) by

$$\delta_{\alpha\beta} = 1 - \frac{\sum_{c \in \{M, O, W, S\}} w_c A_\alpha(c) A_\beta(c)}{4}$$

where  $w_c$  is a parameter to be determined from data, and  $0 \leq \delta_{\alpha\beta} \leq 1$  such that  $\delta_{\alpha\beta} = 0$  if  $A_\alpha$  and  $A_\beta$  test all the same concepts  $c$ . Note that  $A_\alpha(c) A_\beta(c)$  measures whether the two activities are the same on a given concept  $c$  (as those variables are binary).

*c) Performance model:*  $P(R_\alpha = k' | R_\beta = k)$  depends on whether  $A_\beta(n)$  is in parent node of  $A_\alpha(n)$  in the dependency network in Figure 3:

$$P(R_\alpha = k' | R_\beta = k) = \begin{cases} e^{-(\delta_{\alpha\beta} n_{\alpha\beta} \gamma |k' - k|)} & \text{yes} \\ e^{-(n_{\alpha\beta} \gamma' |k' - k|)} & \text{no} \end{cases}$$

where  $\gamma$  is a parameter to be determined from the data.

This theoretical model of number concepts learning takes into account both domain knowledge about the progression of number learning and the stylistic aspects of certain number concepts.

## IV. PRELIMINARY ANALYSIS

To gain more insight into the data collected and the potential fit of our proposed model, we visualized the data relative to the differences between  $A_\alpha$ - $A_\beta$  activity pairs. Figure 4 shows that as  $n_{\alpha\beta}$  increases—for which we selected the subset: 0.33, 0.56, 0.78, and 1—and  $k - k'$  deviates from 0, the number of instances declines. (Note that for the sake of this visualization, we mapped the  $k - k'$  distribution on a scale of -10 to 10 to visually separate the special cases where  $k$  or  $k'$  are equal to 4.)

The decay visualized in Figure 4 is promising as the shapes of the distributions over  $k - k'$  follow approximately our proposed probability model. The

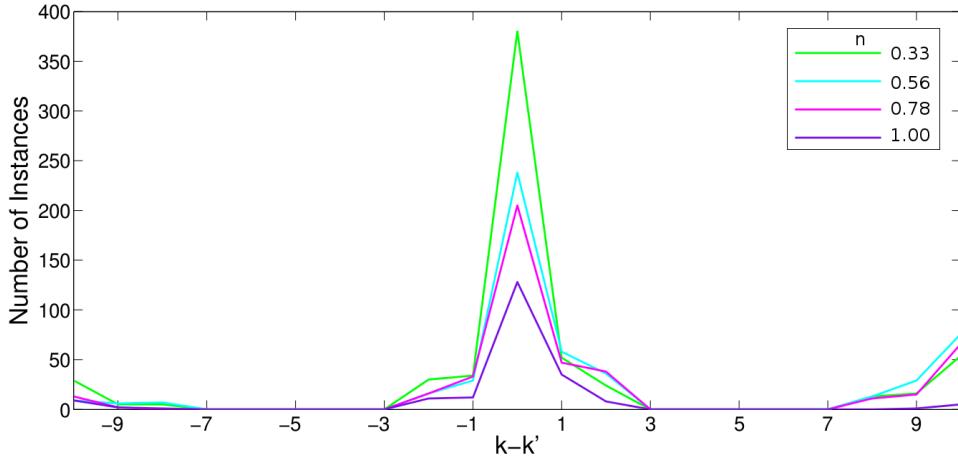


Fig. 4: Visualization of collected data that shows a promising and intuitive decay in number of instances following the difference between activities defined by  $k - k'$  (x-axis) and  $n_{\alpha\beta}$  (legend)

decay rate of our probability model is multiplicatively modulated by the interaction between  $\gamma'$  and  $n_{\alpha\beta}$  (i.e., the rate of decay is proportional to  $n_{\alpha\beta}$ ). Thus, from this preliminary analysis, we can expect to fit our model to the collected data.

## V. DISCUSSION & FUTURE WORK

We have presented and formalized the machine learning modeling problem of personalization in SAR for preschool number concepts learning. Our formalization considers LS as an important factor in predicting individuals' performance on activities with inherent LS preferences. Our proposed model attempts to separate the impacts of the number and concept(s) tested in a given number concepts activity. To further our understanding of the potential fit of our proposed probability model to the data collected, we conducted some preliminary analysis. Our initial discoveries described in Section IV show that the decay proportional to activity-difference included in our model is inherent in our data, and thus, holds promise for future work in model fitting and validation.

In future work, we plan to train and validate our model and possibly extend it to observe some features about the child participants' LS and affective

queues or nonverbal behaviors throughout the interaction. Multidimensionally personalized education is an important research goal of SAR, and young children are an important target population to be explored in ITS research. We hope to further the academic research and development to both these ends.

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