SmartPrimer: Using Imitation learning to generate hints to help high schoolers learn geometry

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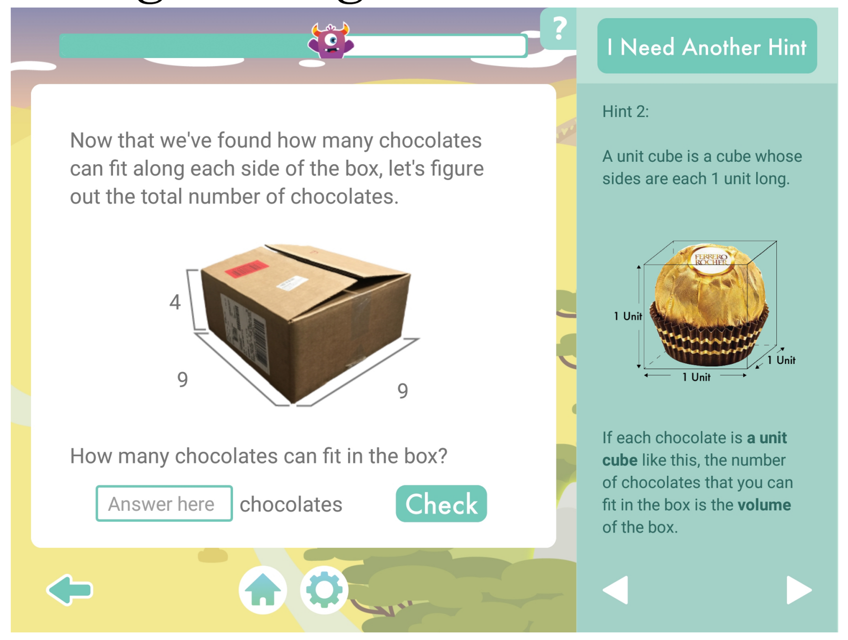
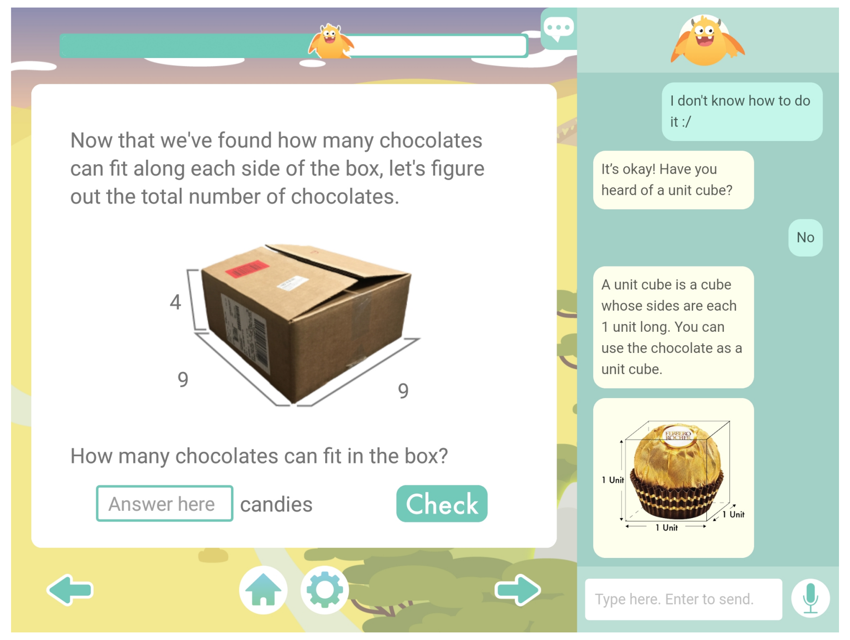
1 Introduction

Children naturally start their academic life intrinsically motivated to learn, but researchers found that during middle school many children's interest in schooling declines (1). Stanford's Smart-Primer project (2) aims to tackle this decline by using narrative-based learning. This research is part of the Smart-Primer project and aims to contribute by using Reinforcement Learning to provide children with hints while they try to solve a geometry problem. This could be a solution to the problem of increased labor that narrative-based learning inherently brings along.



(1.a) Problem and hint interface



(1.b) Problem and conversation interface

The data is generated from children trying to solve a simple geometry problem in 6 sub-problems. While solving, the children can ask for hints or type messages to a monster (see right panel in Fig 1.b). The monster, controlled by a human teacher, can choose a hint from a set of predefined hints per sub-problem. Our objective is to create a model that chooses hints that help the child understanding the topic as fast as possible.

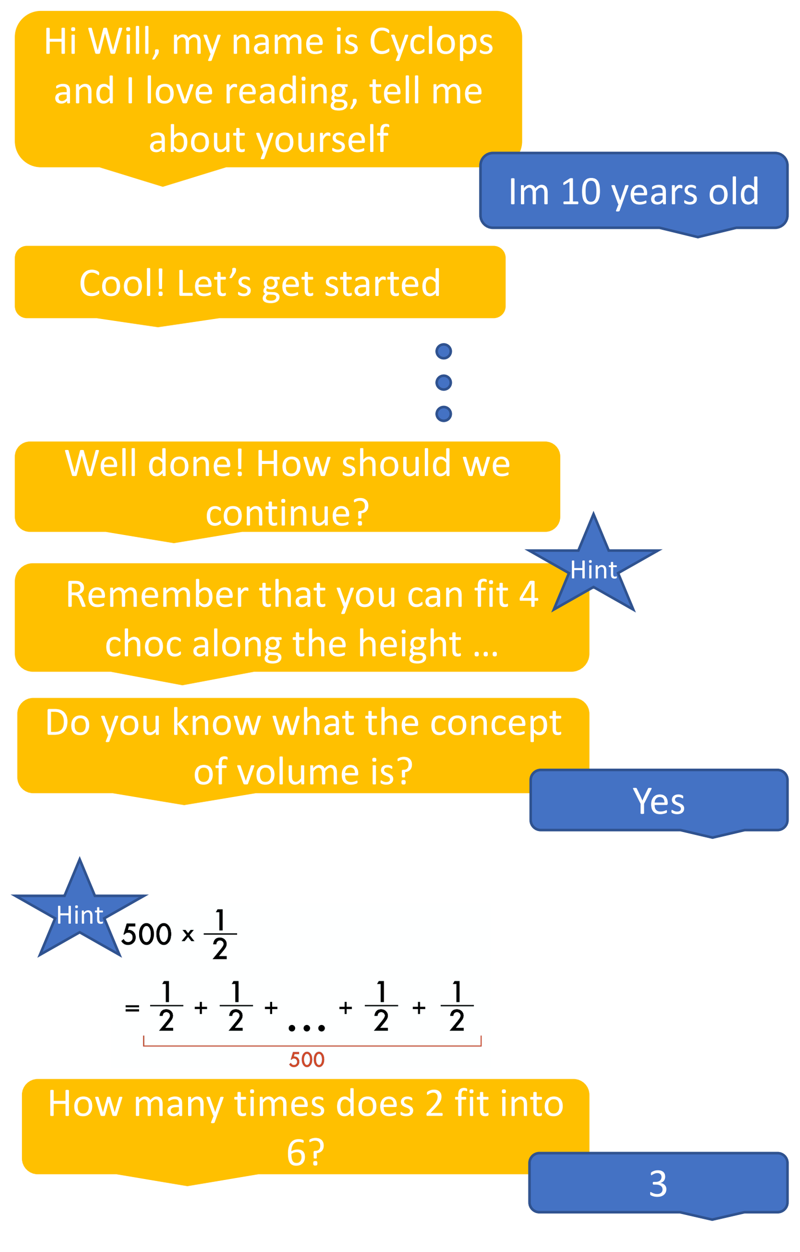
2 Reinforcement Learning

The key assumption in this research is that the hints generated by the monster are the true optimal hints. We can therefore model this problem as an imitation learning problem. More specifically, since we have the behavior of the 'expert' we take a behavior cloning approach. We model the RL problem using a hint based framework:

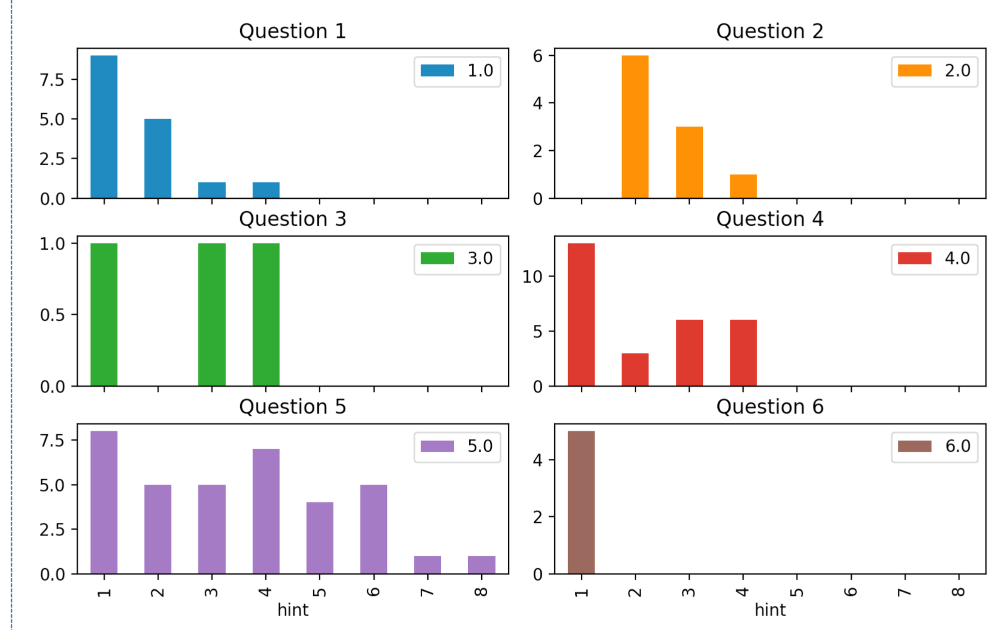
Hint based

- Only consider generating hints at moments where true hints are generated

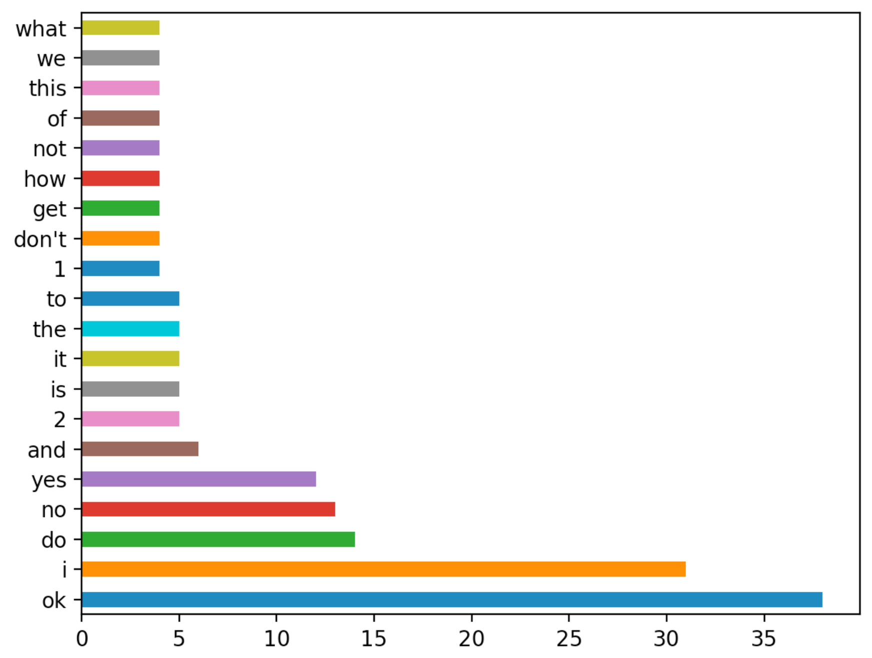
3 Descriptive statistics



Number of hints per question (17 children, 98 hints)



20 Most frequently used words (after filtering)



4 Methods

Essentially, the imitation learning approach is a supervised learning problem, in which we predict which hint to give. The state-space was encoded using the following variables:

- All words used by child after last given hint*
- Number of words used by the child
- Grade on a math test
- Age of child
- Current sub-question child is trying to solve
- Previous hint given

After testing multiple approaches, final models** are:

1) Increasing hints (baseline)
2) Linear Regression
3) LASSO
4) Logistic Regression with L1 penalty
5) Random forest

*Only words that were mentioned more than once in total
**All methods were compared including all words and no words

Models were compared using Mean Absolute Error (MAE) and accuracy (ACC) on leave one child out cross validation:

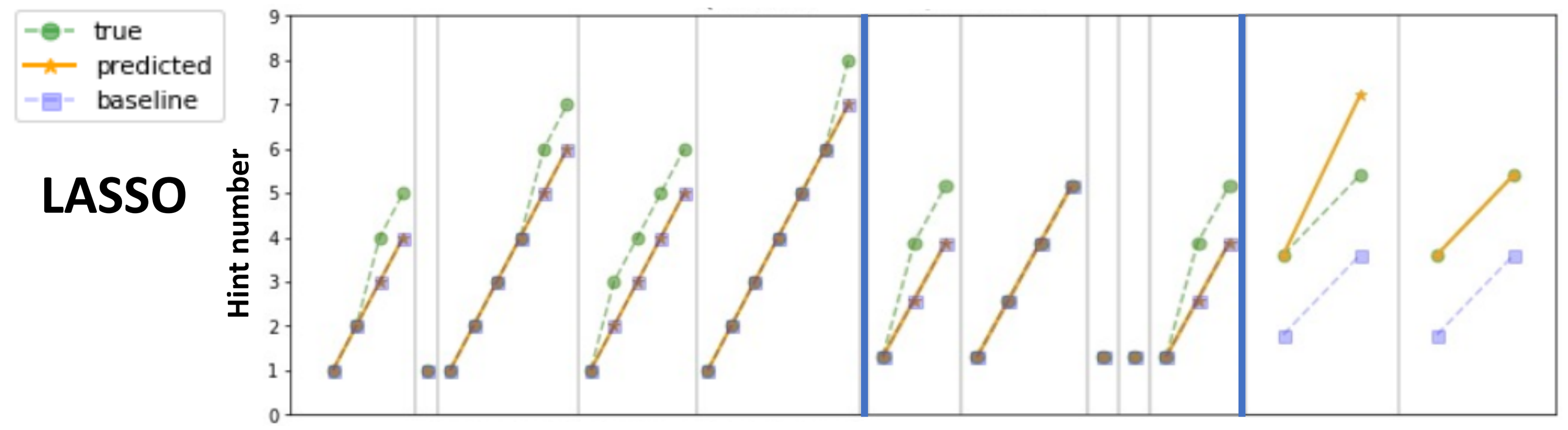
$$MAE = \frac{1}{K}\sum_{i}^{K}\frac{1}{T_i}\sum_{t}^{T_i}\left|H_{i,t}^{true} - H_{i,t}^{pred}\right| \qquad Acc = \frac{1}{K}\sum_{i}^{K}\frac{1}{T_i}\sum_{t}^{T_i} I\left[H_{i,t}^{true} - H_{i,t}^{pred}\right]$$

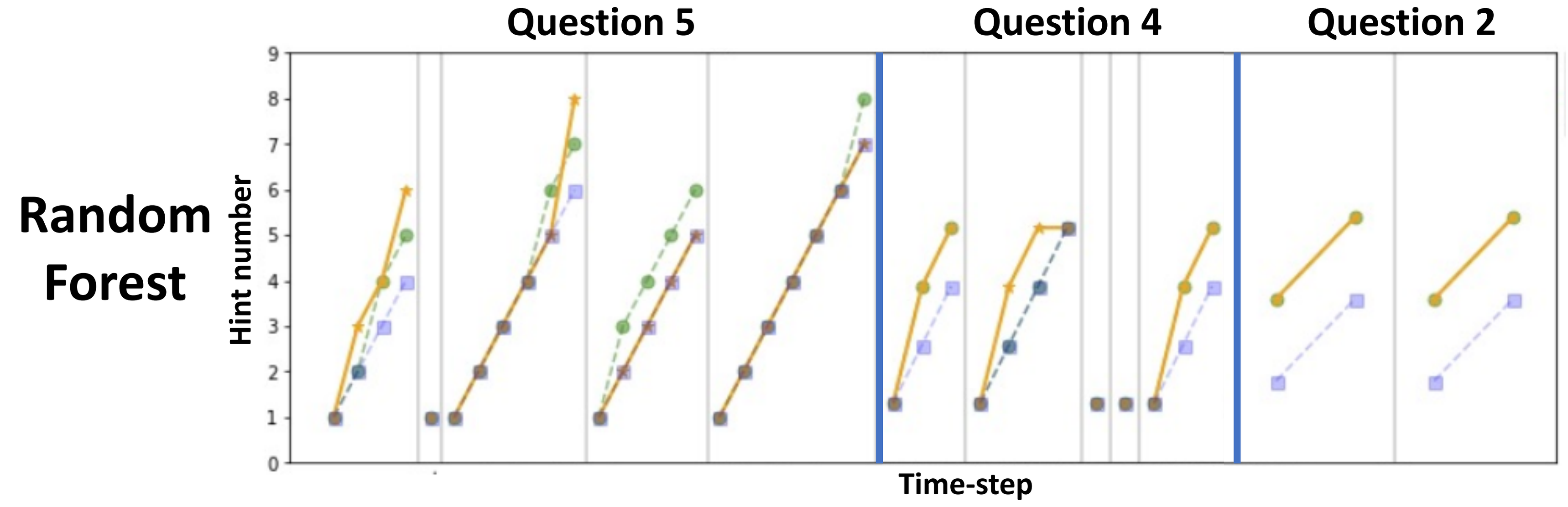
T_i = number true hints given for child i
K = number of children

$H_{i,t}^{true}$ = the t'th true hint given for child i
$H_{i,t}^{true}$ = the t'th predicted hint given for child i

5 Results

Measure	Baseline	Linear		LASSO		Logistic + L1		RF	
-	-	Words	No words	Words	No words	Words	No words	Words	No words
MAE	0.42	Inf	0.31	0.42	0.29	0.58	0.47	0.79	0.38
ACC	65%	28%	72%	65%	74%	55%	65%	51%	66%





Every block corresponds to trajectory of given hints for a child

6 Conclusion and Discussion

Conclusion

- Most methods beat the industry standard
- LASSO beats industry standard with 14% accuracy wise and 31% MAE wise
- Models tend to give more difficult hints faster

Discussion

- Deployment needs either a time-based method or pre-specified time steps
- Ensemble methods could combine best of both worlds
- Better NLP methods could provide improvement

References

1) Anderman, E. M. and Maehr, M. L. Motivation and school-ing in the middle grades.Review of educational Research,64(2):287–309, 1994.
2) Smartprimer.https://hci.stanford.edu/research/smartprimer/projects/smart primer.html. Accessed: 2020-02-25