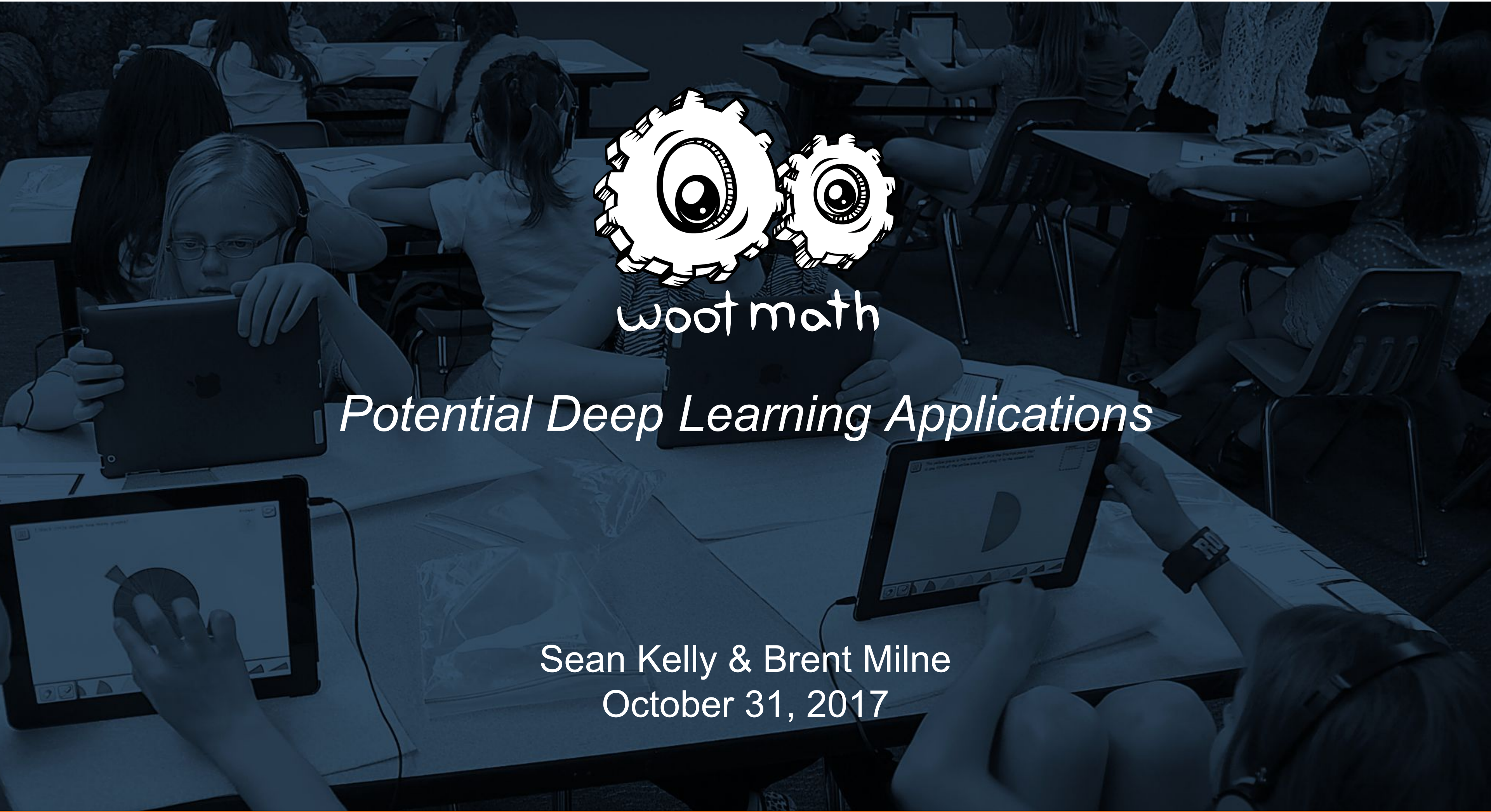
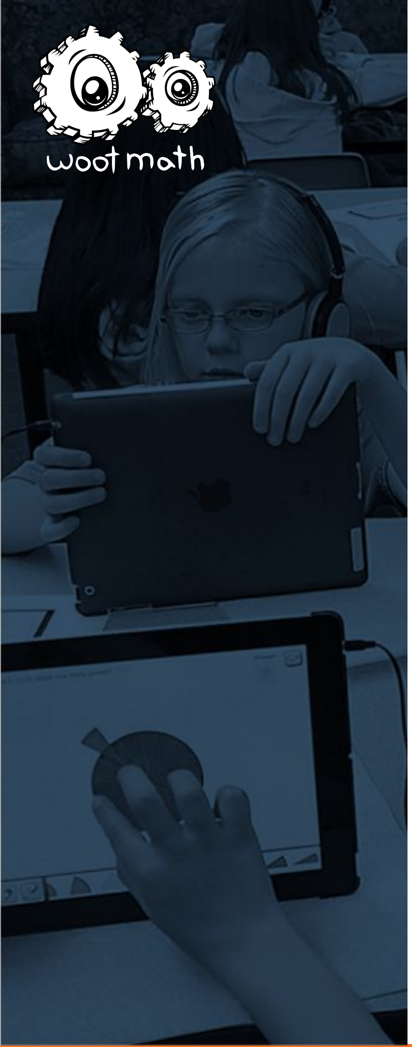


woot math

Potential Deep Learning Applications

Sean Kelly & Brent Milne

October 31, 2017



What is Woot Math?

Adaptive instructional software

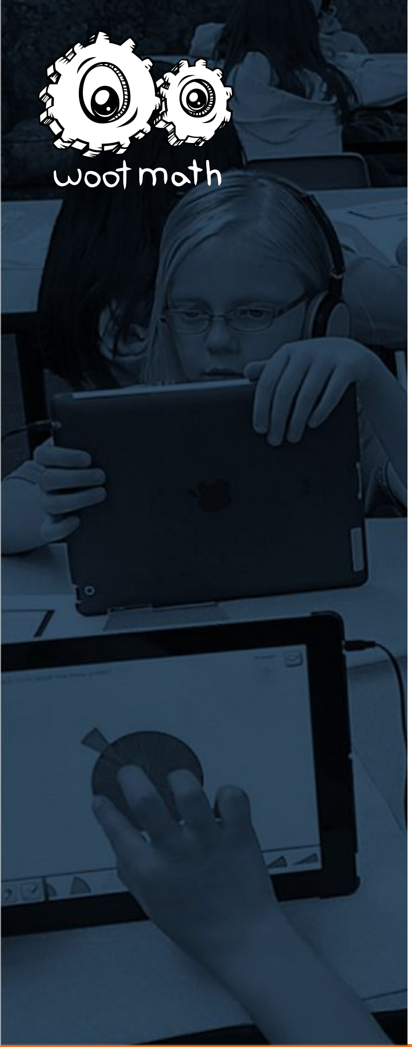
Goal is to enable all students to **master fractions** and related concepts

Research-backed with proven efficacy

Hands-on, **interactive** mathematical models

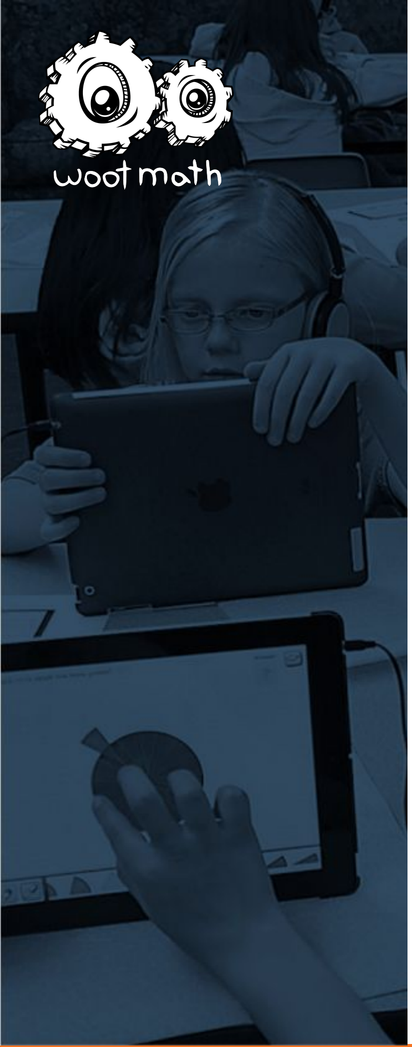
Engages students, **builds confidence**,
helps them make deep connections in mathematics

Boulder **startup, founded 2013**; funding from the NSF, the US Dept. of Ed, and Foundry Group (VC)



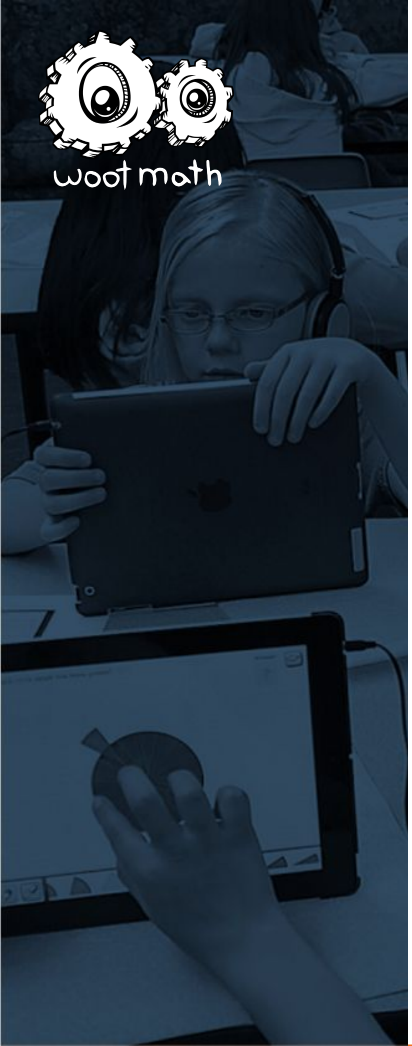
“National tests show nearly **half of eighth-graders** aren't able to put three fractions in **order by size**.”

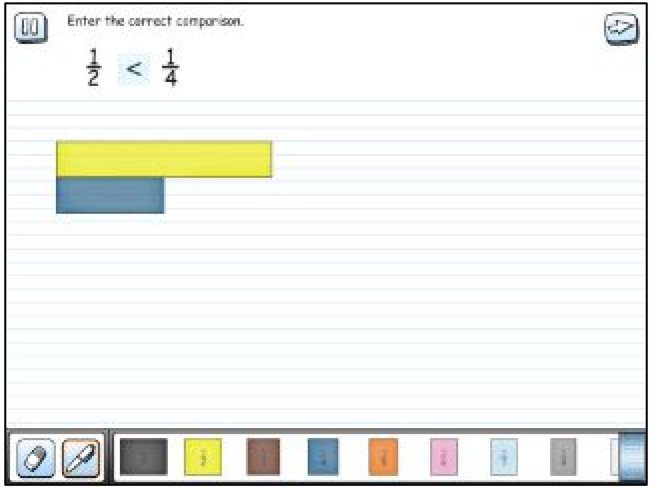
– *The Wall Street Journal*, “New Approaches to Teaching Fractions,” September 2013

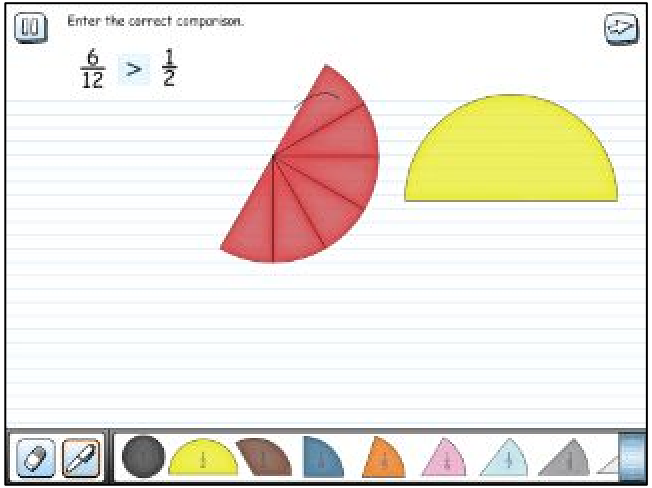


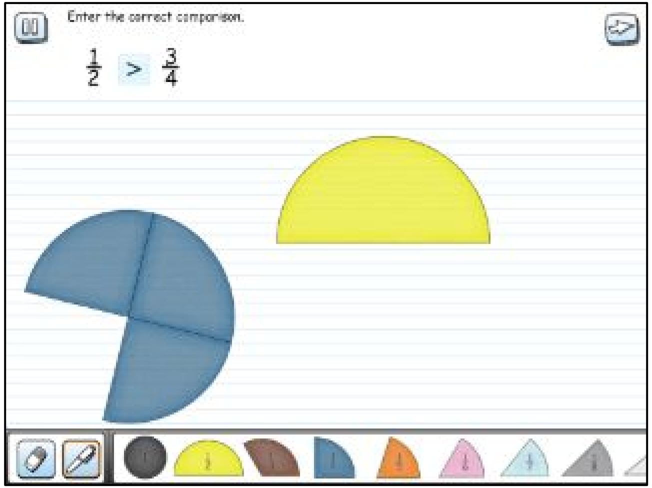
"Understanding fractions is **crucial** for mathematics learning… It is also **predictive** for students' mathematical achievement **years later**."

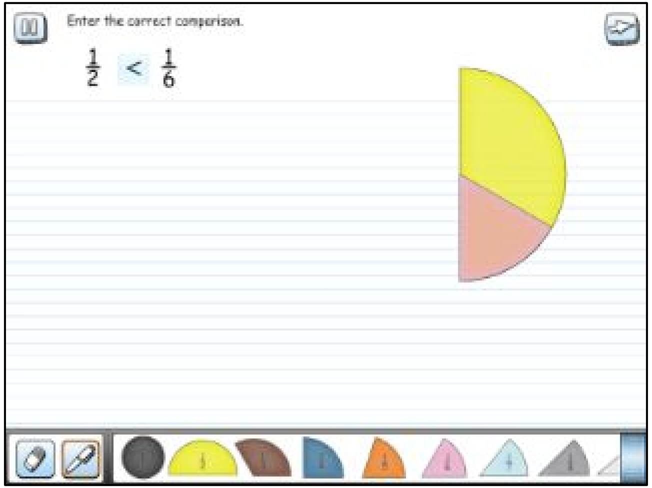
– Bridging the gap: Fraction understanding is central to mathematics achievement in students from three different continents.
Torbeyns, Schneider, Xin, and Siegler, 2015


woot math


Enter the correct comparison.
$\frac{1}{2} < \frac{1}{4}$


Enter the correct comparison.
$\frac{6}{12} > \frac{1}{2}$

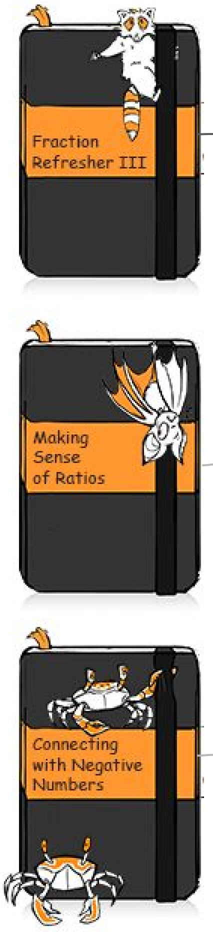

Enter the correct comparison.
$\frac{1}{2} > \frac{3}{4}$


Enter the correct comparison.
$\frac{1}{2} < \frac{1}{6}$

DEMO

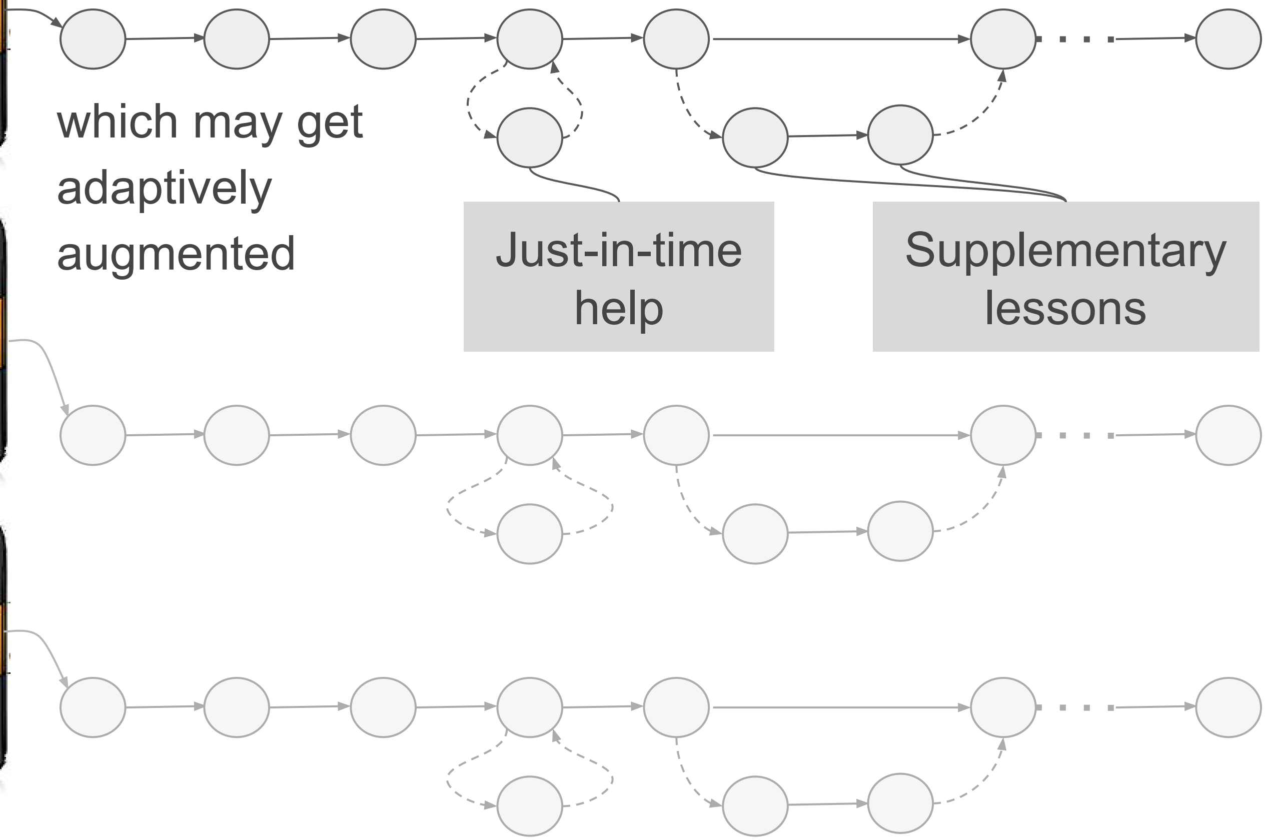
Content is organized into "Books."

Books are units of study.

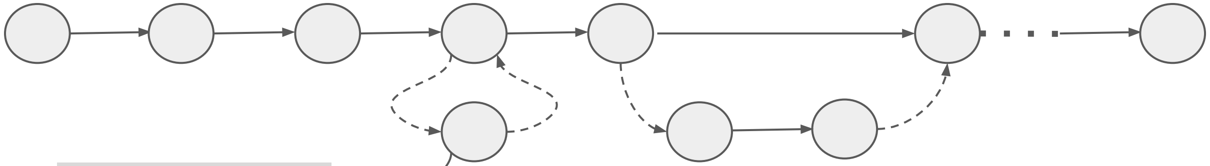


Each Book has an ordered, main sequence of Lessons

which may get adaptively augmented



Lessons are labeled with identifiers referencing the *Common Core State Standards*



“4.NF.3.a”

Number and Operations—Fractions[3]	4.NF

Extend understanding of fraction equivalence and ordering.

1. Explain why a fraction a/b is equivalent to a fraction $(n \times a)/(n \times b)$ by using visual fraction models, with attention to how the number and size of the parts differ even though the two fractions themselves are the same size. Use this principle to recognize and generate equivalent fractions.

2. Compare two fractions with different numerators and different denominators, e.g., by creating common denominators or numerators, or by comparing to a benchmark fraction such as 1/2. Recognize that comparisons are valid only when the two fractions refer to the same whole. Record the results of comparisons with symbols >, =, or <, and justify the conclusions, e.g., by using a visual fraction model.

Build fractions from unit fractions by applying and extending previous understandings of operations on whole numbers.

3. Understand a fraction a/b with $a > 1$ as a sum of fractions $1/b$.

   a. Understand addition and subtraction of fractions as joining and separating parts referring to the same whole.

   b. Decompose a fraction into a sum of fractions with the same denominator in more than one way, recording each

Woot Math Dataset

De-identified anonymous data (private, access under NDA)

~1M Student Sessions from 2016-17 school year

~50k students from grades 3-6

Labels include **Math Standards, Difficulty**, Lesson, Unit

Structured canvas analysis, correctness, time spent, screen-shot at submission, student histories

Knowledge Tracing

The training data consists of a sequence student interactions, each with an expert assigned task label and a representation of whether the task was answered correctly.

Deep Knowledge Tracing

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Abstract

Knowledge tracing—where a machine models the knowledge of a student as they interact with coursework—is a well established problem in computer supported education. Though effectively modeling student knowledge would have high educational impact, the task has many inherent challenges. In this paper we explore the utility of using Recurrent Neural Networks (RNNs) to model student learning. The RNN family of models have important advantages over previous methods in that they do not require the explicit encoding of human domain knowledge, and can capture more complex representations of student knowledge. Using neural networks results in substantial improvements in prediction performance on a range of knowledge tracing datasets. Moreover the learned model can be used for intelligent curriculum design and allows straightforward interpretation and dis-

$$x_t = \{q_t \,,\; a_t\}$$

$$q_t \in \{3.NF.1,\; 3.NF.2..\}$$

$$a_t \in \{0, 1, 2\}$$

Knowledge Tracing (ii)

We want the network to learn the probability of a student correctly answering a new task conditioned on the task label(s) for the new task and the vector of prior interactions.

$$P(a_{t+1} | \, x_t, q_{t+1})$$

Knowledge Tracing (iii)

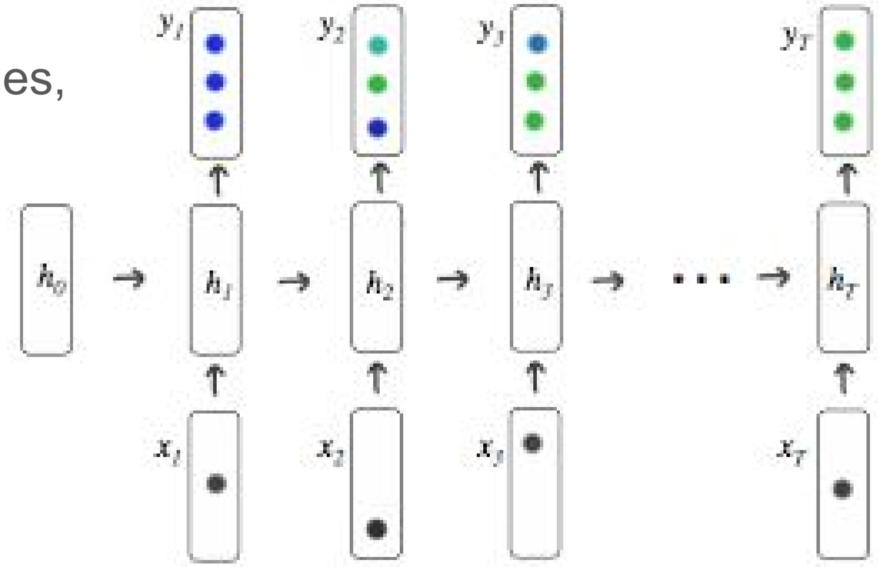
Vanilla RNN & LSTM from Piech

One hot inputs will cluster (4-16 problems per label).

It might be more interesting to focus on sequences that cross label-label boundaries, i.e., to condition the inputs such that:

$$a_t \in \{n_r,\ n_w\}$$

$$n_r \in \mathbb{Z}_{\neq 0}$$



Other Ideas

What can we learn about latent variables from opening the box ? I.e. “what internal representation has the network learned in carrying out the prediction task?” – Mike's lecture *Recurrent Nets 1*

Can we use performance data to learn something about a multi-factorial difficulty (e.g. complexity $\otimes$ difficulty)?

Can we leverage structured response data in a way that improves the predictive models?
(E.g., do students who build models have a higher probability of success?)

Automatic Discovery of Cognitive Skills to Improve the Prediction of Student Learning

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How Deep is Knowledge Tracing?

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