



PennState
College of Education

Supporting Learners to Evaluate Computational Models: Mechanistic Reasoning about Machine Learning

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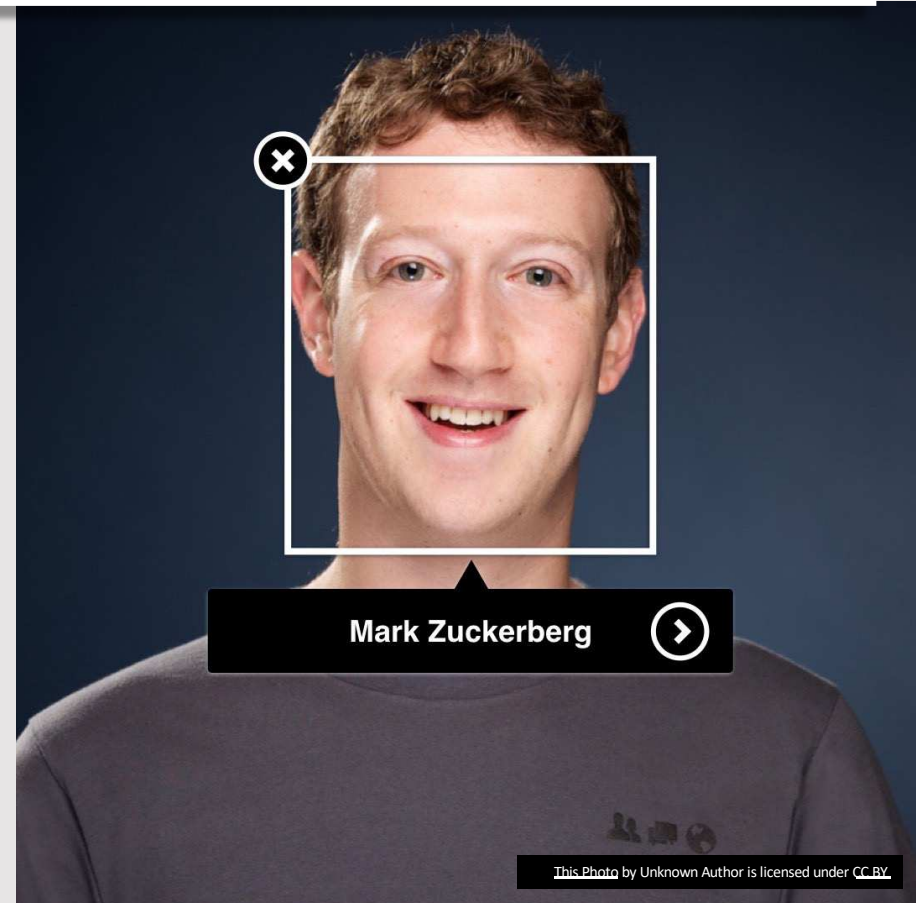


Introduction

- Teachers and teacher candidates' experiences with and knowledge about modeling impacts their future practice (e.g., Kenyon et al., 2011; Louca & Zacharia, 2012).
- Supporting learners to test and evaluate their own and others' models is challenging (Schwarz & White, 2005; Weintrop et al., 2016; Wilensky & Reisman, 2006).
 - Evaluation of models includes critical analysis of learners' models (e.g.,: assumptions, output, and predictive capacity) (Wilensky & Reisman, 2006).

Image Recognition

- Image recognition applications of artificial intelligence, and specifically machine learning, are pervasive.
- Explaining underlying mechanisms of how these systems work requires:
 - Systems thinking (e.g., Jacobson & Wilensky, 2006)
 - Mechanistic reasoning (e.g., Bolger et al. 2012; Russ et al., 2008; Weinberg et al., 2020)



Mechanistic Reasoning

- An analytical lens that can be used to categorize a learners' explanations of phenomena they have experienced (e.g., Russ et al., 2008; Krist et al., 2019)

Characterizes explanations of ecological systems, kinetic toys, and computational models of invisible processes in physical systems

Description of the target phenomenon

Identifying entities and activities

Properties and organization of entities

Chaining

Adapted from Russ et al. (2008)

Context of the Study

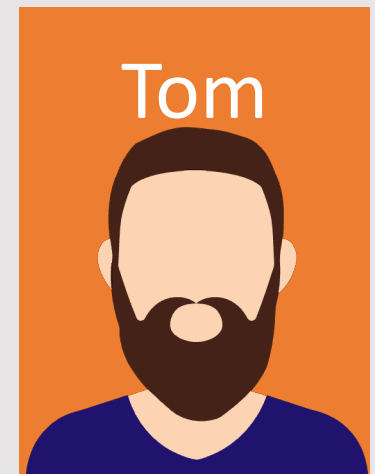
- Fall 2021 course at a large university in the northeastern United States.
- *Teaching Science and Engineering* for non-science major middle school teacher candidates (TCs)
- 23 consented TCs:
 - Disciplinary specializations in Social Studies (n = 3), English Language Arts (n = 8), and Mathematics (n = 12)
- Two classes during weeks 13 and 14 of the semester

Research Questions

1. How do teacher candidates begin to explain and model how machine learning systems work?
2. In what ways do they participate in evaluation of their own models?

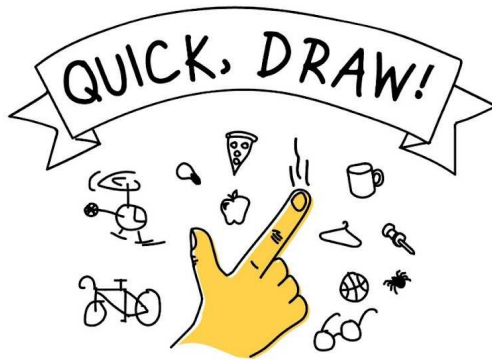
Design and Method

- Exploratory, Design-based Research Study (Cobb et al., 2003)
- Data Sources:
 - Pre- and post-models
 - Instructor field notes
 - Course assignments, including lesson rationale and reflection
- Adapted categories of Mechanistic Reasoning (Russ et al., 2008)
- Thematic Analysis (Braun & Clarke, 2019)
 - Three explanatory cases



Activity Sequence

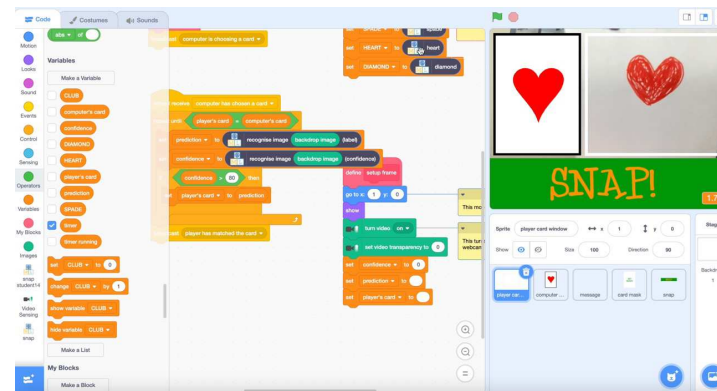
Google Quick, Draw!



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quickdraw.withgoogle.com

Machine Learning for Kids



machinelearningforkids.co.uk

Guess Who?



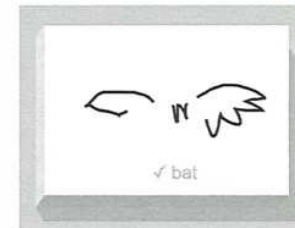
aiforteachers.org

Activity Sequence



Quick, Draw! prompts the user to draw an object. This repeats for 6 doodles.

How does Quick, Draw!
guess the doodle?



Quick, Draw! guesses the what the doodle is.

- Key features

- how people start:

- link to google images

- past plays

starting features matter
some method

- new app each = added to dictionary
- not in database
- new game how does it start (still under this)

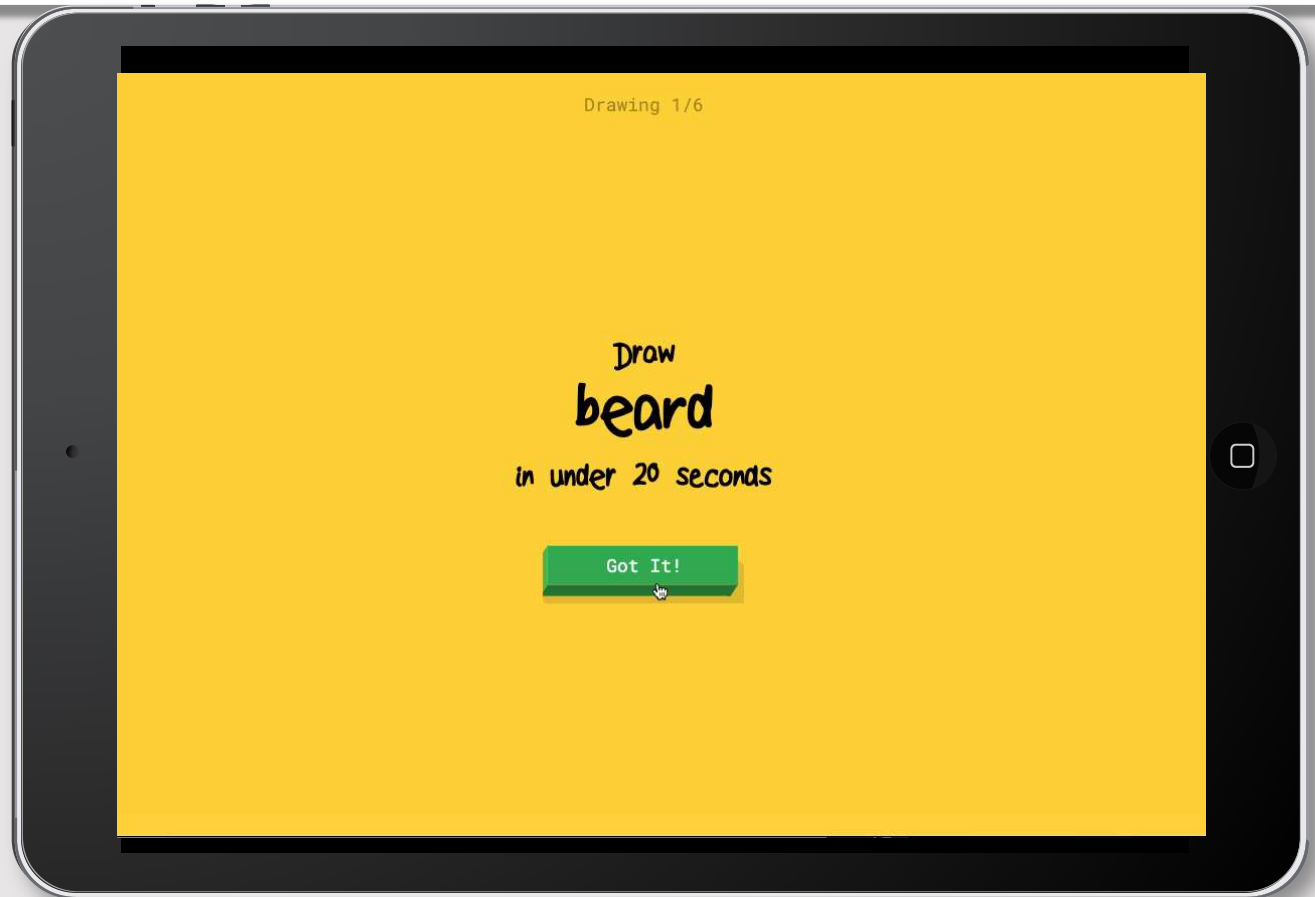
→ add drawings to enlarge the database each time
→ uses averages to pick out key pieces of information

→ different cultures/geographic locations have different experiences/attributes that they value

Activity Sequence



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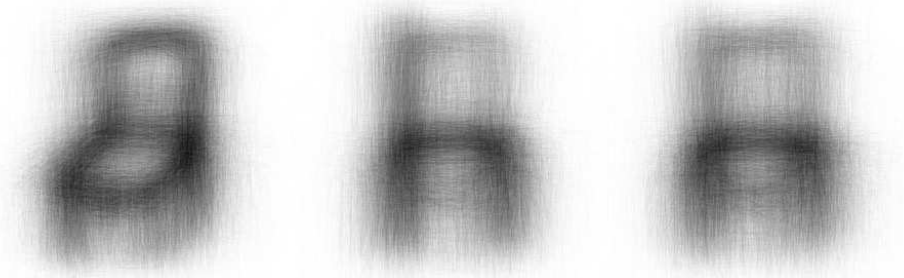
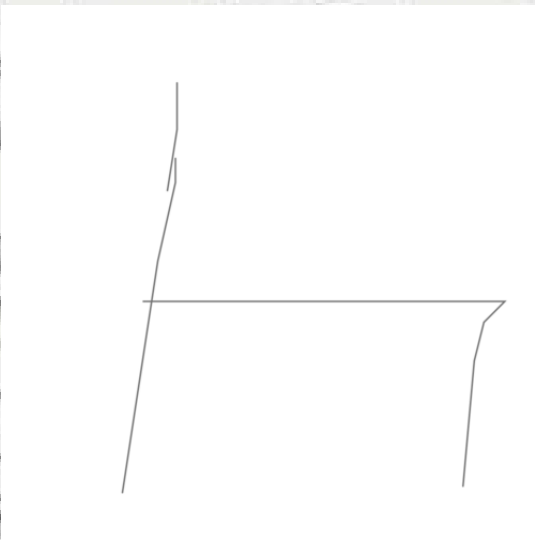


Case 1: Blurriness as a feature of mechanism and link to statistical reasoning



- Field placement in a 5th grade self-contained classroom in a rural community
- Math education major

Case 1: Blurriness as a feature of mechanism and link to statistical reasoning



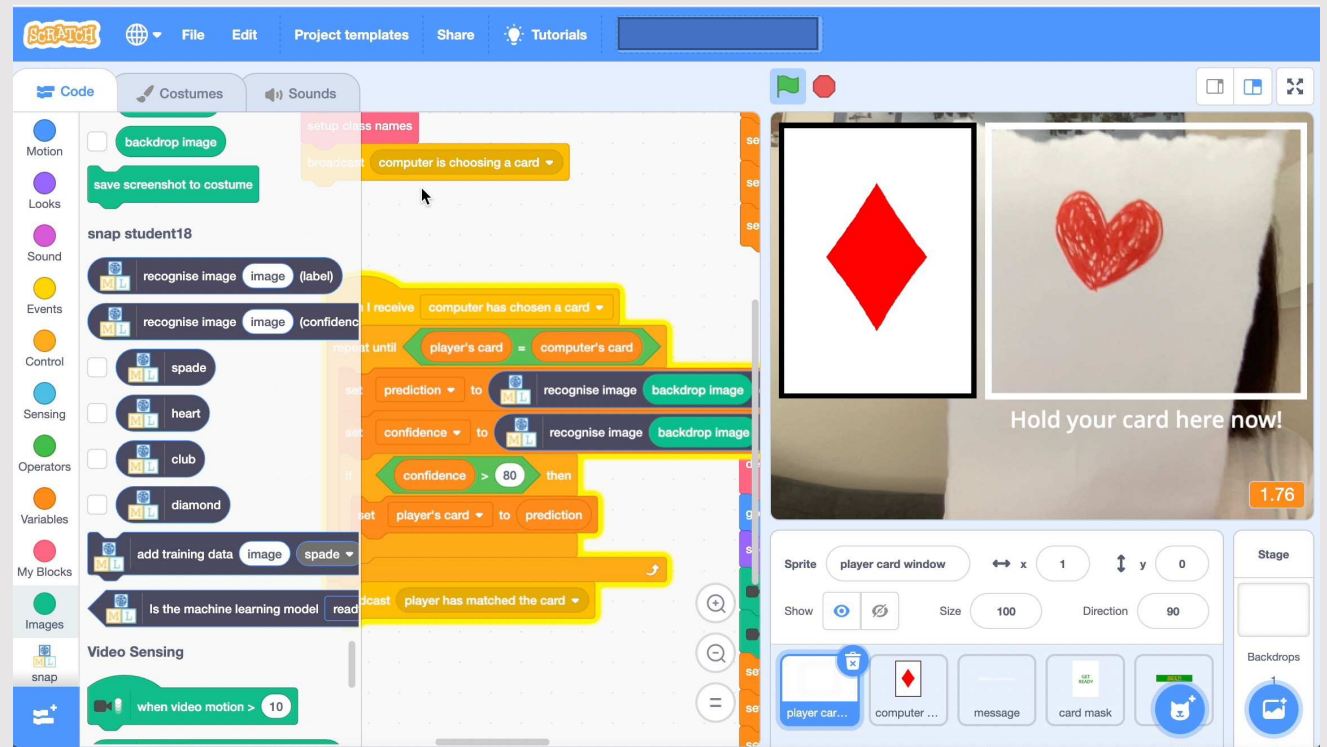
South Korea

Brazil

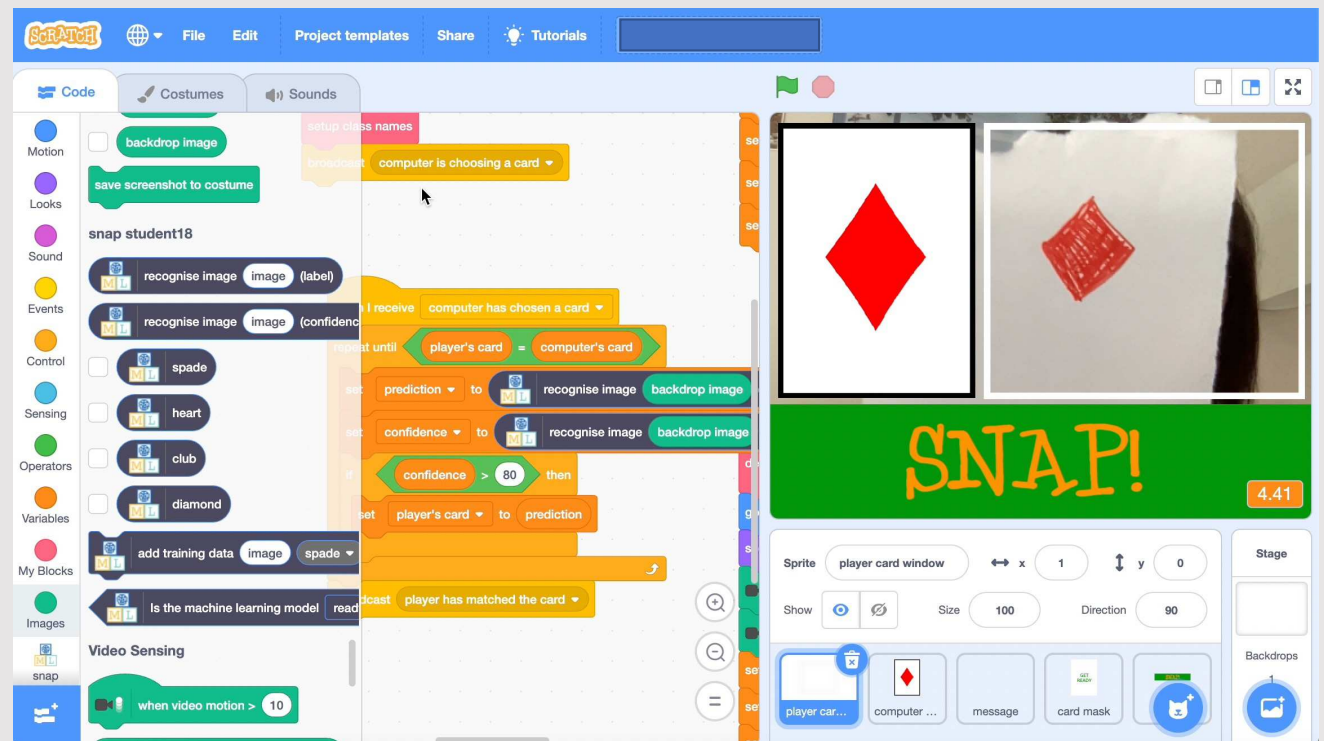
Australia

- 5th grader reasons that blurry lines described as an “average” of a distribution of doodles
- Kathy acknowledges the potential of ML systems to generate contexts that elicit mathematical and statistical reasoning

Case 2: Sensemaking about Models → Ownership



Case 2: Sensemaking about Models → Ownership



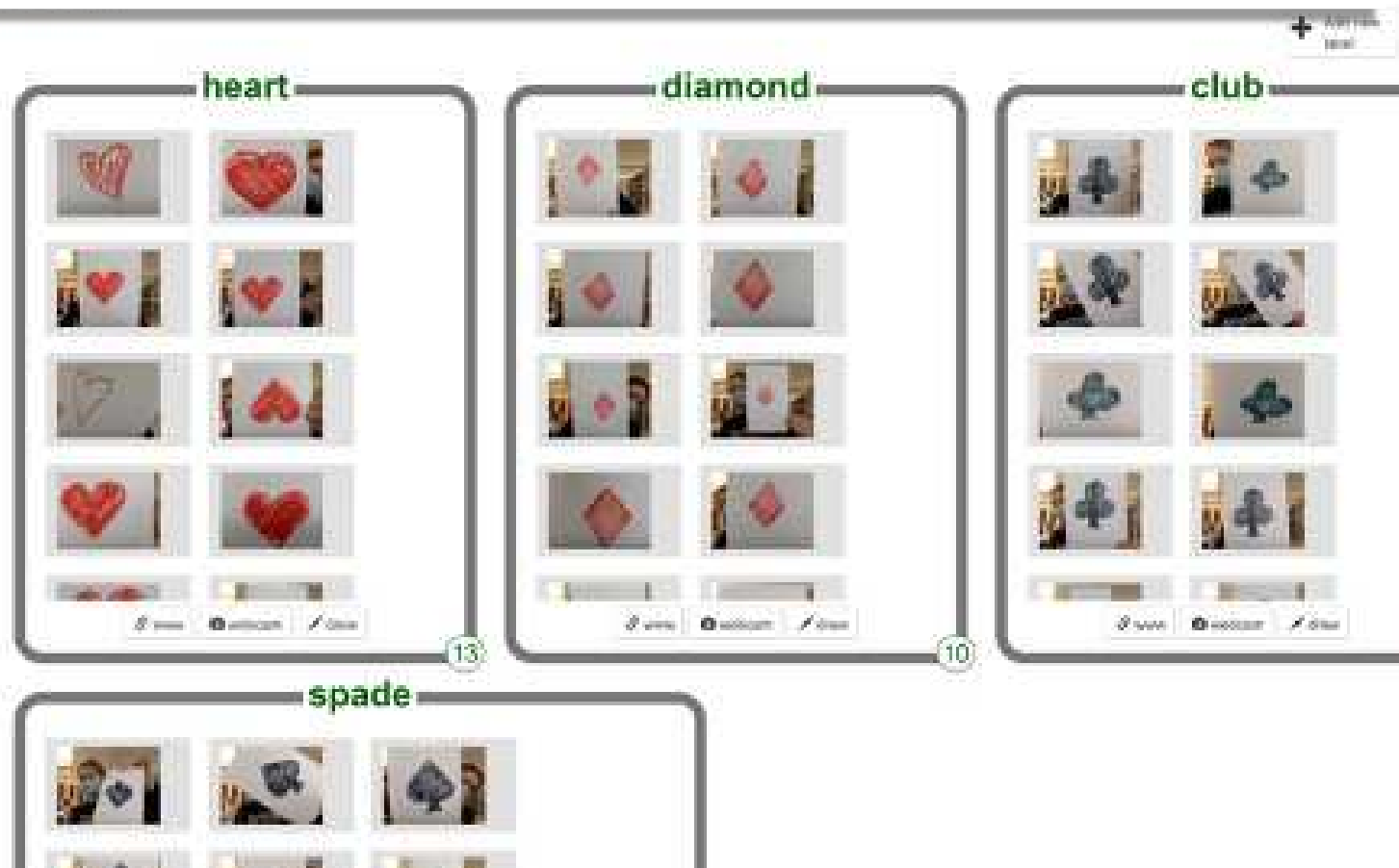
Case 2: Sensemaking about Models leads to Ownership



Afterwards, we will look at different peoples' projects on a scale of ones that worked the best and others that may have not worked as well. We will then discuss why they may have worked better or worse.

I also liked the process of making it on my own and learning from my own work, which I think will be good for students so that they can see the whole process of computer learning.

Case 3: Evaluating Computational Models



Case 3: Evaluating Computational Models

Annabel



Recognizing the potential for models and systems to be better, and diagnosing those problems, is important in the lives of students. [In this project] they get experience with code, machine learning, and modifying their projects for improvement.

...highlight the fallacies in another's project and then can use that to improve their own models.

Conclusion & Discussion

Overall, participation in learning activities supported engagement with evaluating and improving explanations of how ML systems work.

Research Question 1

How do teacher candidates begin to explain and model how machine learning systems work?

- Analysis of pre- and post-explanations, as well as the cases, indicate that teacher candidates' explanations of ML mechanisms were based on their experiences in critically “messing around” with ML, and training and improving image recognition games
- Tom (Case 2) and Annabel (Case 3) each engaged in mechanistic reasoning that extends beyond mere chaining of events and considers a complex case of human and machine interaction.

Conclusion & Discussion

Research Question 2

In what ways do they participate in evaluation of their own models?

- The experience of training the model supported Annabel in diagnosing errors in her training and improving her model, even without a deep understanding of the code.
- Annabel and Tom's cases show that understanding the phenomenon—that is, how the computational model recognizes the shape of the hand-drawn card by a human—led to their evaluation and revision learners' critical analysis of their models including the assumptions, output, and predictive capacity (Wilensky & Reisman, 2006).



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