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ACM Award Winning Research in Data Science

Tiffany Barnes | North Carolina State University
April Wang | University of Michigan

go.ncsu.edu/ghc2023

Tiffany Barnes

CRA-WP
Computing Research Association
Widening Participation

- Distinguished Professor of Computer Science
- North Carolina State University
- Researcher in educational data mining, AI in education, ed tech, human-computer interaction, serious games, computing education

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The Q-Matrix Method: Mining student response data for knowledge

Educational Data Mining 2021 Test of Time Award

Tiffany Barnes

NC STATE UNIVERSITY

NSF

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GAME2LEARN

Highlights from EDM 2022 Keynote:

Compassionate, Data-Driven Tutors for Problem Solving and Persistence

Tiffany Barnes
GHC 2023

Compassion in context

Striving to solve the most important problems in education – for students, teachers, parents, and society

Using Data Science and HCI to show concern and adapt the environment for learners and teachers

Goals of Q-matrix method

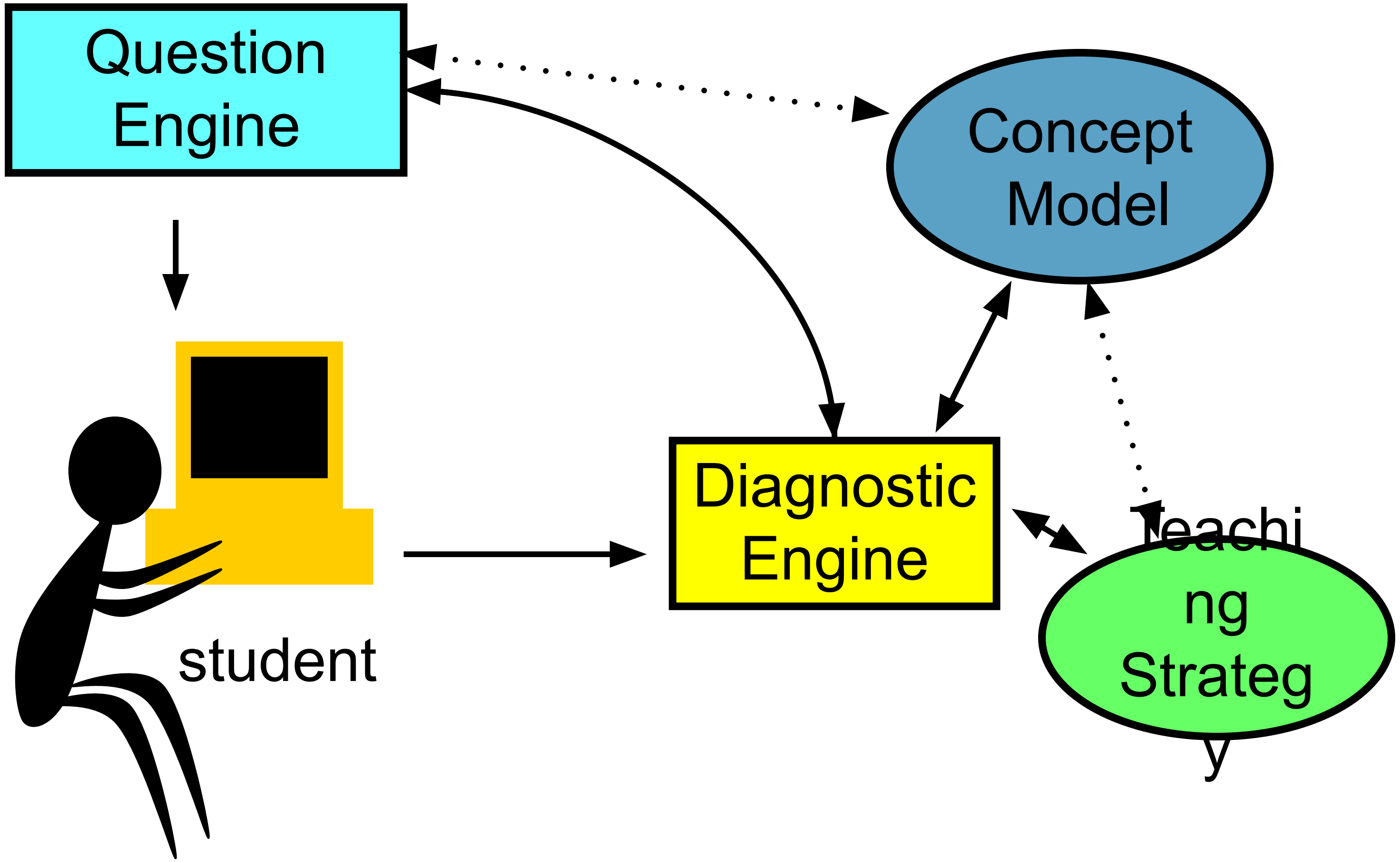
Modify existing tools with simple intelligence

- Diagnose and correct misconceptions
- Diagnosis tolerates careless errors & guesses

Build a scientific approach to improving computer based education

- Build in fault tolerance, robustness
- Optimize for student performance
- Optimize teaching strategies for effectiveness

Adaptive Tutorial Flow



Expert Rule Spaces

Expert analysis of arithmetic tasks into rules

- Plotted student responses in 2D plane
- Assumed nearby responses had similar knowledge

Evolved into Q-matrix

- Relationship between questions & concepts

Applications:

- Student assessment & remediation
- Group performance measure
- Finding new rules (student innovations)

Binary Q-matrix example

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	q1	q2	q3	q4	q5
Con1	0	0	0	1	1
Con2	1	0	0	1	0

q1: 2 - 7 = ?

q2: 5 + 4 = ?

q3: 10 - 6 = ?

q4: -3 - 7 = ?

q5: -5 + 1 = ?

Questions **q1-q5**: addition & subtraction tasks

Concept **Con1** = First number is negative

Concept **Con2** = 2nd number is negative and larger than the first number

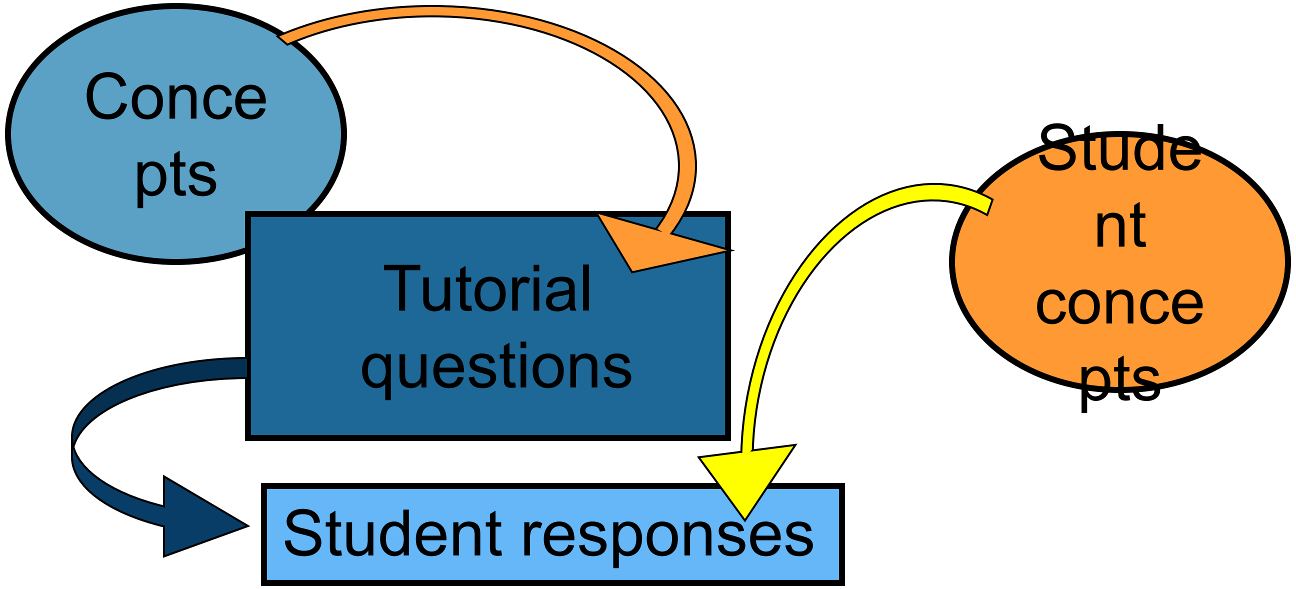
q4 cannot be answered correctly without Con1 & Con2

q1 needs only Con2; q5 needs only Con1

q2 & **q3** use only "background knowledge"

Knowledge & student model

Goal: Mine to extract student concepts



Concept states

Concept state – student understanding bit string

Concept state 01: understands Con2 but not Con1

Q-matrix: Concepts v. Questions

Each state has an "ideal response vector" computed from Q-matrix

Q-matrix model

Assumes concepts underlie questions

For each concept state, compute “ideal response vector” (IDR)

Assign student to state with closest IDR

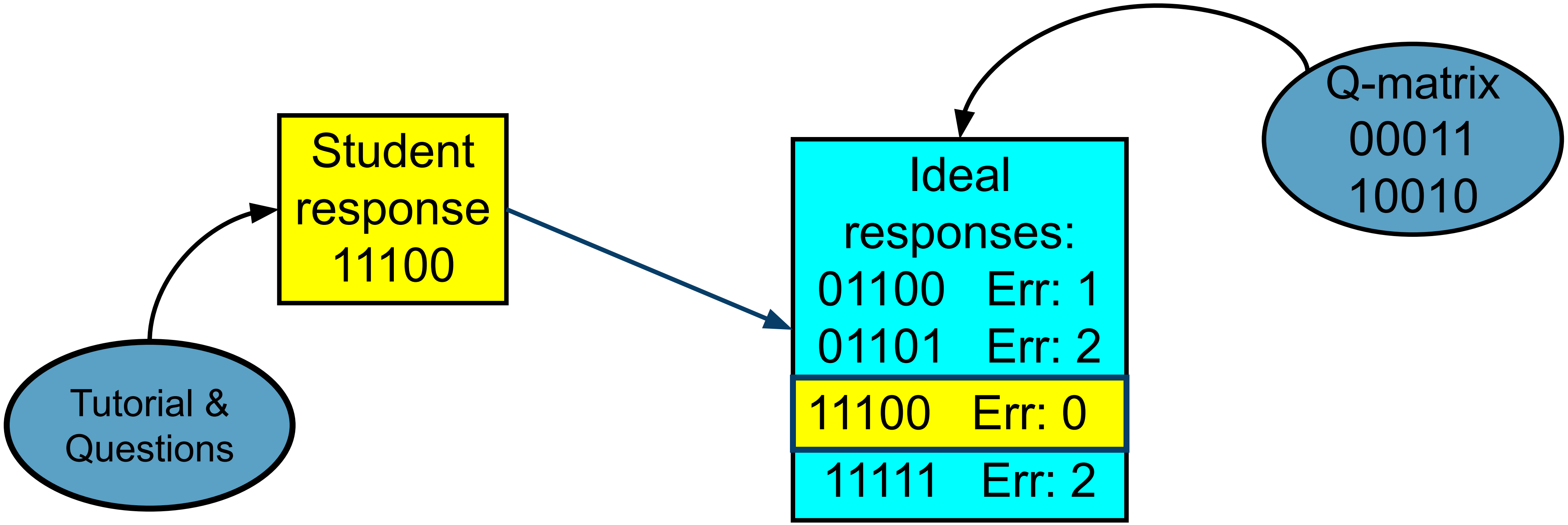
Redirect learning based on concept state

Ideal Responses

	q1	q2	q3	q4	q5
Con1	0	0	0	1	1
Con2	1	0	0	1	0

Concept State	Ideal Response
00	01100
01	11100
10	01101
11	11111

Classify responses



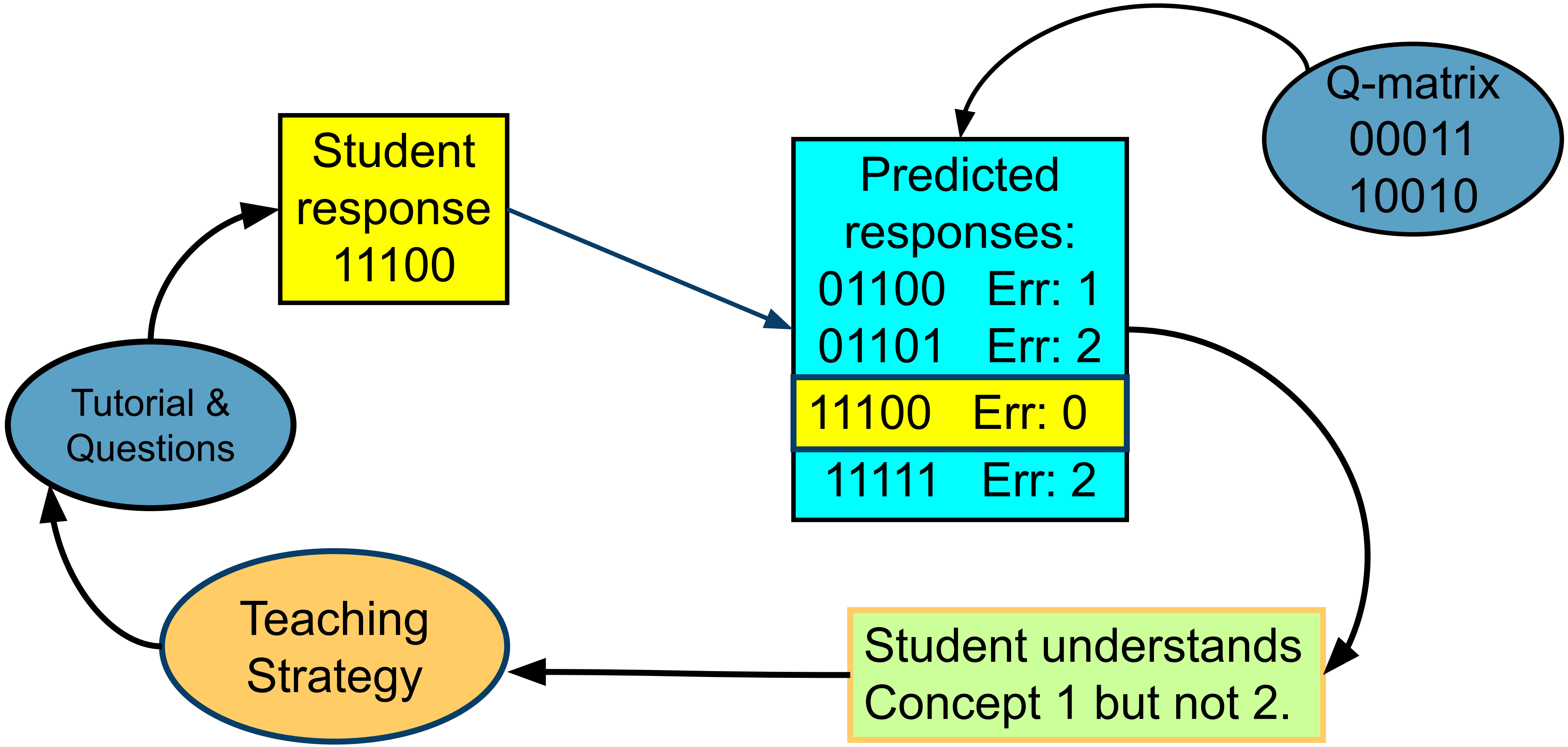
Q-matrix: gradient descent

Until convergence criterion met:

1. Increment number of concepts
2. Fill q-matrix with random values in [0,1]
3. Compute IDRs, assign students to concept states & sum assoc. errors
4. Vary one value in q-matrix
5. Repeat step 3
6. Repeat steps 4-5 until error not improving
7. Repeat steps 2-6 to avoid local minima

Like k-means, incrementing k, but IDRs are centers

Closing the loop



What does it mean today?

The first paper to use data to create q-matrix

The paper also introduced a closed loop: it chose a new question for students based on the model

New papers do similar things: Learn what we can, from the data we have, with methods we understand

Approaches for compassion

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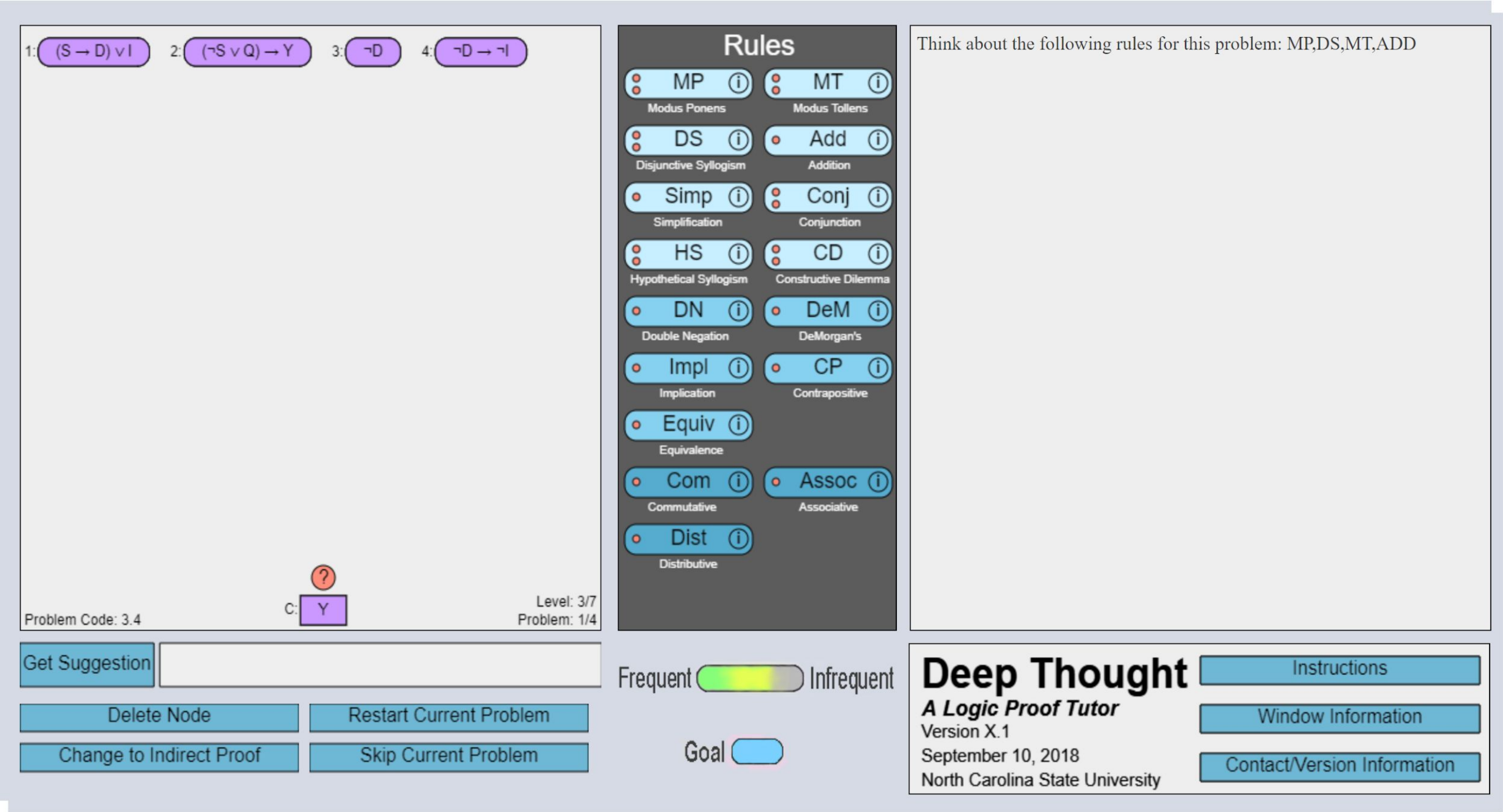
HCI to make content more usable, accessible, and compassionate

Co-design with, and respect rights and autonomy of students and teachers

Determine WHEN a student needs help and PROVIDE IT

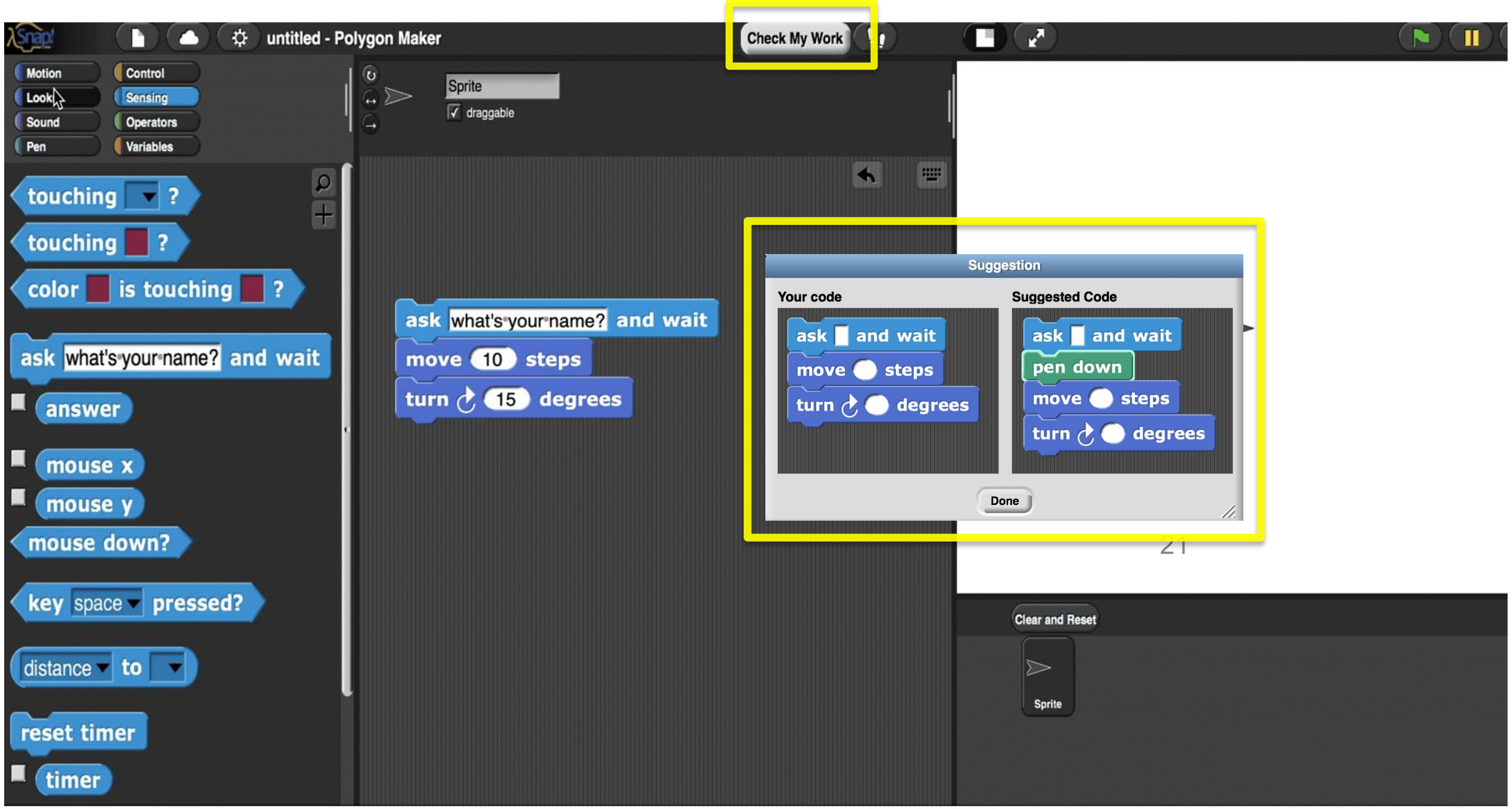
Deep Thought for Logic

Provides data driven next-step hints and problem solving supports



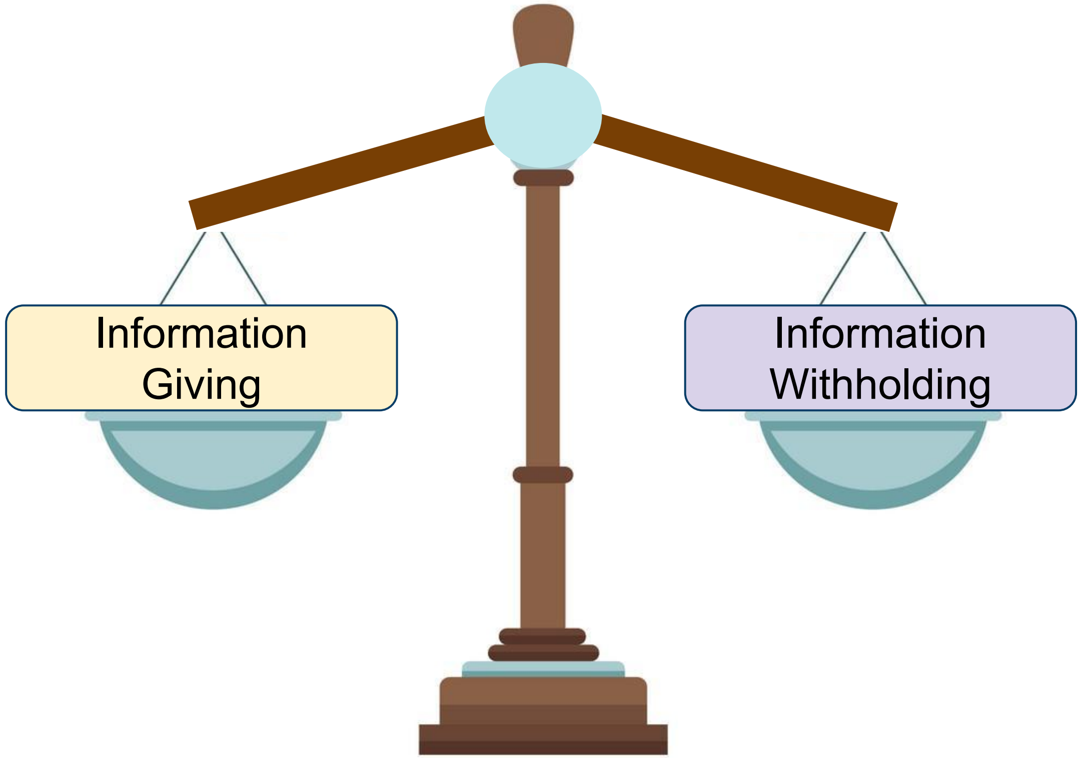
iSnap for Programming

iSnap provides *next-step hints* and logs students' code edits [Price et al., 2017].



Productivity & HelpNeed

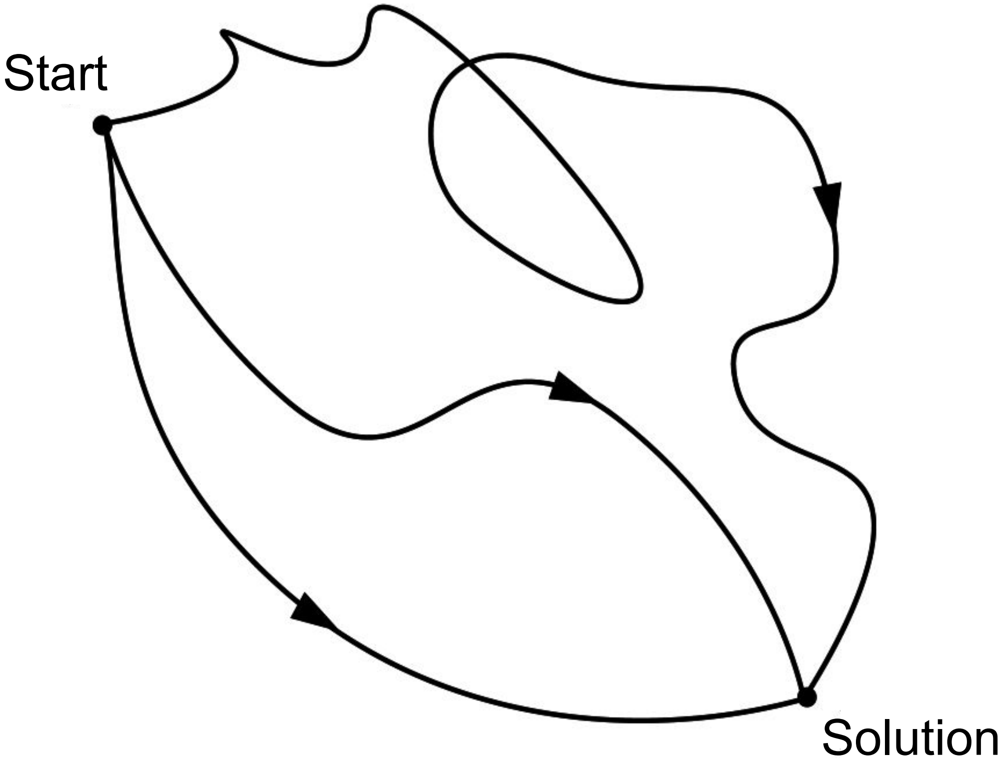
Assistance Dilemma in Problem Solving



[Koedinger et al., 2007]

Assistance Dilemma

Open-ended Domains [McLaren et al., 2014]



Step-level Productivity

Overall State Quality

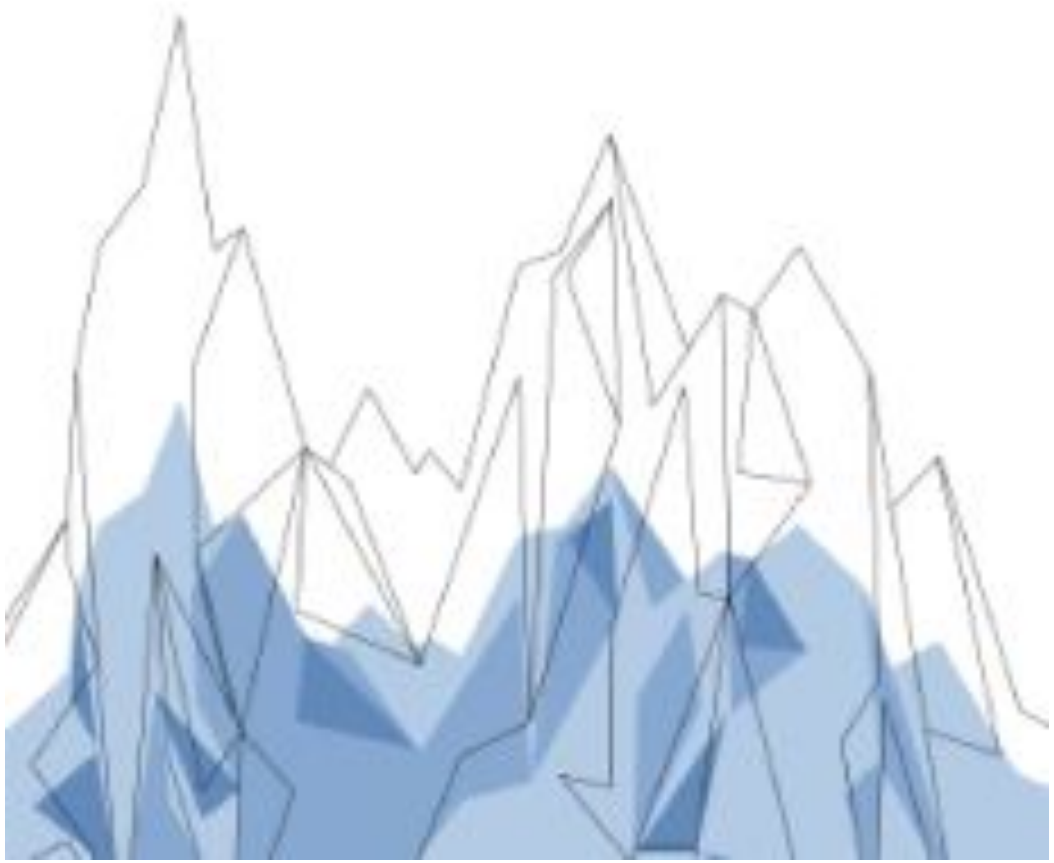
{Local, Global}

✖

Progress of Current Step

{Absolute, Relative}

State Quality

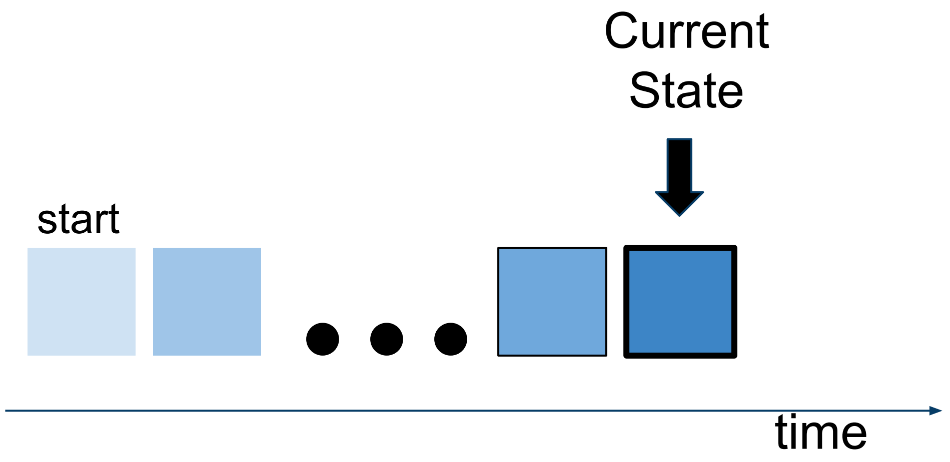


Problem solving like mountain climbing

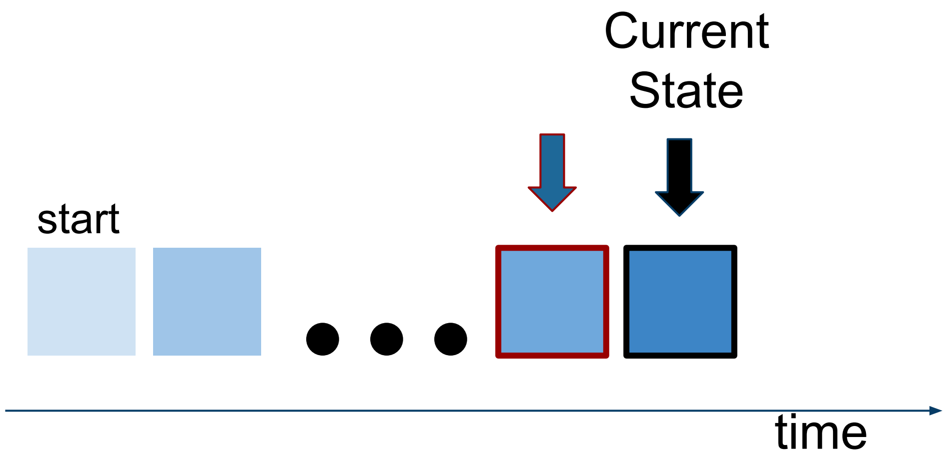
All peaks are solutions

Quality estimate
2 comparisons:
Closest peak (Local)
Highest peak (Global)

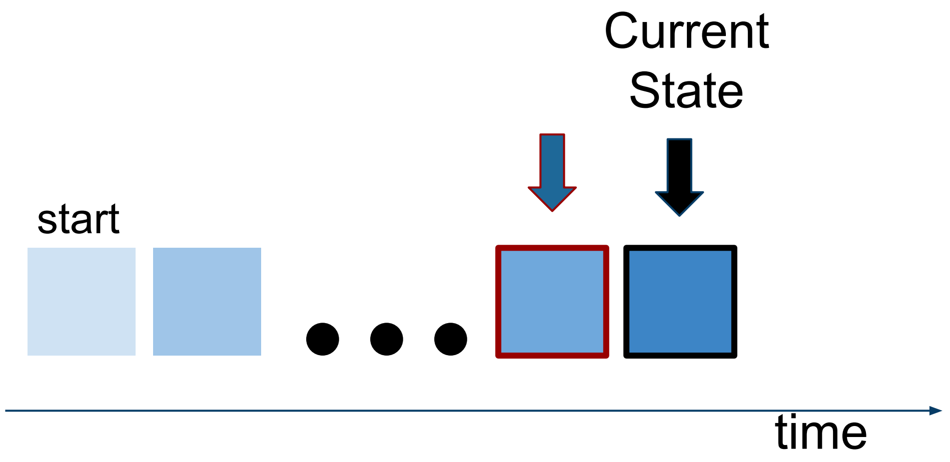
Step Progress - Change in Quality



Step Progress - Change in Quality

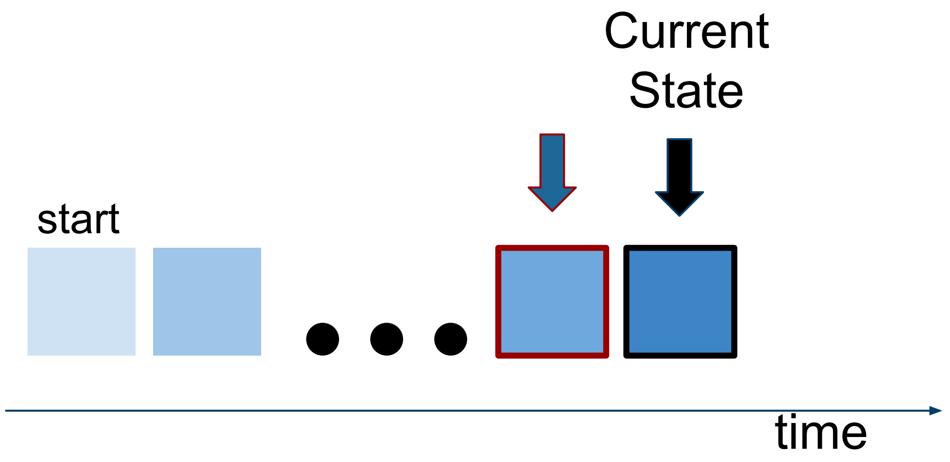


Step Progress - Change in Quality

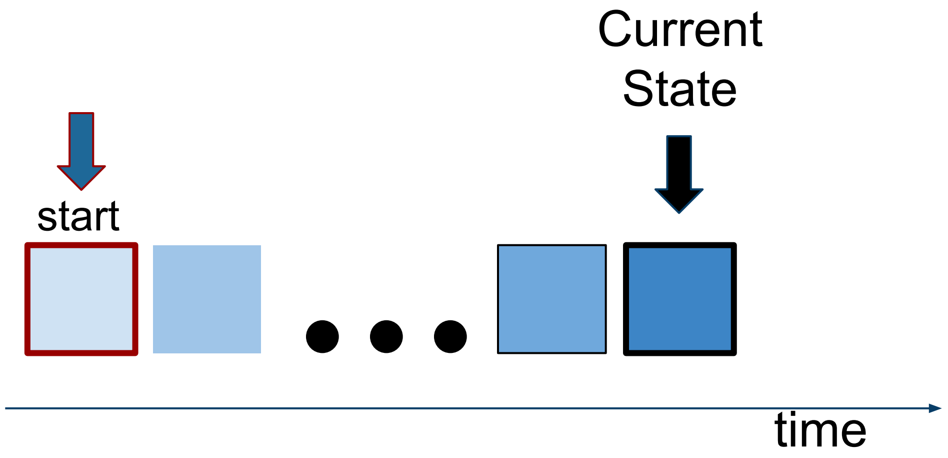


Relative Progress

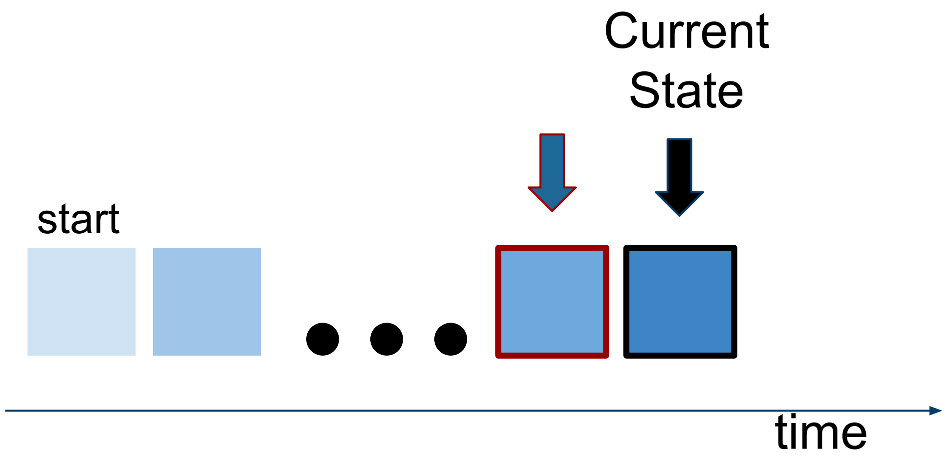
Step Progress - Change in Quality



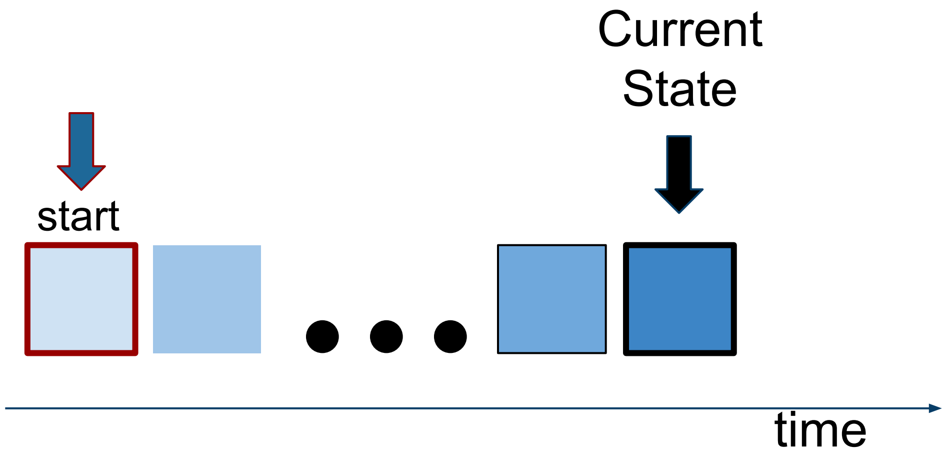
Relative Progress



Step Progress - Change in Quality



Relative Progress



Absolute Progress

Step Efficiency as Productivity Model

State Quality
{Local, Global}

✖

Progress
{Absolute, Relative}

Table 5.2: Defining Step Efficiency

Quality-Progress	Efficiency Formula
Global-Absolute	$(GQV_{post-state} - GQV_{start-state}) \geq 0$
Global-Relative	$(GQV_{post-state} - GQV_{pre-state}) \geq 0$
Local-Absolute	$(LQV_{post-state} - LQV_{start-state}) \geq 0$
Local-Relative	$(LQV_{post-state} - LQV_{pre-state}) \geq 0$

HelpNeed Classification

Efficiency
{Efficient, Inefficient}

+

Duration
{Long, Quick}

Figure 5.1 Classification of Step Behavior using efficiency and duration

Classification	Behavior	Description
No HelpNeed	Expert-like	A quick efficient step; demonstrating mastery
	Strategic	A long efficient step; taking longer on an expert-like step
	Opportunistic	A single, quick inefficient step
HelpNeed	Far Off	Maximum number of inefficient steps in a sequence and/or multi-step duration for inefficient steps before intervention is desired In our tutor: consecutive quick but inefficient steps
	Futile	A long inefficient step; taking too long on a step that does not help make progress

HelpNeed Predictor

Proactive Help fosters productive persistence among students with low prior knowledge

Can we *predict need (Far-Off/Futile) before* a step and convert it to productive persistence by proactively giving help?

Experiment

- **Participants: Undergraduate students in Fall 2019**
- **Conditions: *Adaptive (N = 70)* and *Control (N = 53)***
- **Procedure:**
  - Pre-test, Training, Post-test
  - During training, Adaptive receives proactive hints when need predicted

Better Posttest Optimality and Time

Table 5.5 Pre- and Post-test performance

Test	Optimality		Time (min)	
	Adaptive	Control	Adaptive	Control
Pretest	.54 (.38)	.60 (.27)	39 (20)	34 (16)
Posttest	**.71 (.27)**	**.59 (.33)**	**18 (12)**	**29 (17)**

$t(110) = 1.74$, $p = .04$ $t(110) = 3.07$, $p < .01$

Cohen's d = 0.4 Cohen's d = 0.7

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Classifying Training steps

Step Behavior	Description	# Training Steps		p
		Adaptive	Control	
Expert	Quick efficient steps	61 (12)	65 (13)	.10
Strategic	Long efficient steps	25 (19)	21 (9)	.17
Opportunistic	**Singular, quick, inefficient steps**	**5 (3)**	**7 (4)**	**<.01***
Far Off	**Consecutive quick but inefficient steps**	**16 (20)**	**25 (25)**	**.02***
Futile	Long inefficient steps	13 (12)	12 (19)	.47
	Total Training Steps	121 (38)	133 (39)	.10

Hypotheses

H1: Students in the Adaptive condition will have better posttest optimality and time than those in the Control condition

H2: Students in the Adaptive condition will exhibit better training behaviors than Control, with

(a) fewer HelpNeed steps

(b) lower possible help avoidance, and higher possible help appropriateness (as measured using the HelpNeed classifier)

HelpNeed Contributions

Novel data-driven productivity metrics:

Quality and Progress

Adaptable to well-structured open-ended problem solving

Defined new ways to classify and improve student performance

Using Data to Classify Progress and Struggle during programming

Students need proactive help during programming, too

Can we determine when to provide it automatically as in HelpNeed for Logic?

Dataset

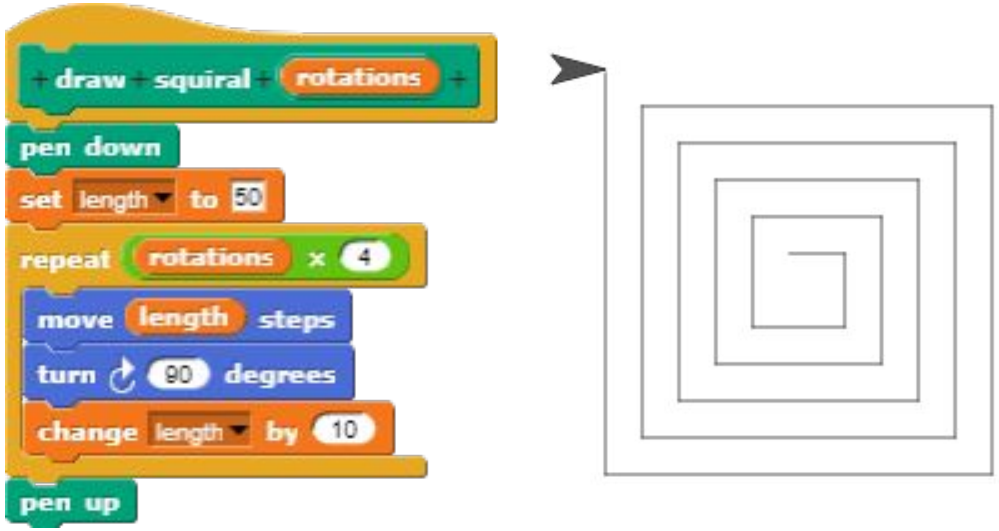
Trace data from two non-majors programming assignments

Each trace contains timestamped student actions and code snapshots

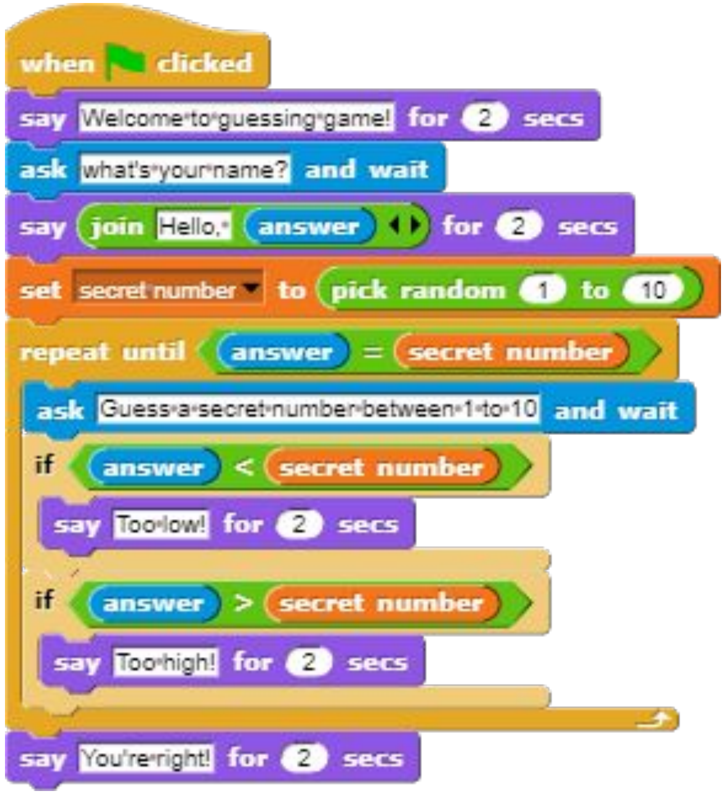
Students had on-demand next-step hint support

Assignment	Traces	Actions	Avg Time on Task	Used Hints (>5)	Avg Grade
Squiral	45	25160	29.6 mins	8 (2)	9.8/12
Guessing Game	50	22744	30.5 mins	9 (5)	11.7/12

Assignments



- Guessing Game (Lab)



Struggle Definition

A student is struggling if the student cannot make significant progress within typical time

Relative to the majority of students

- i.e., 75th percentile [Teu18]

Identifying Struggling Moments

Step 1: Measure student progress

Step 2: Determine significant progress

Step 3: Determine typical time for significant progress

Step 4: Identify struggling & progressing moments

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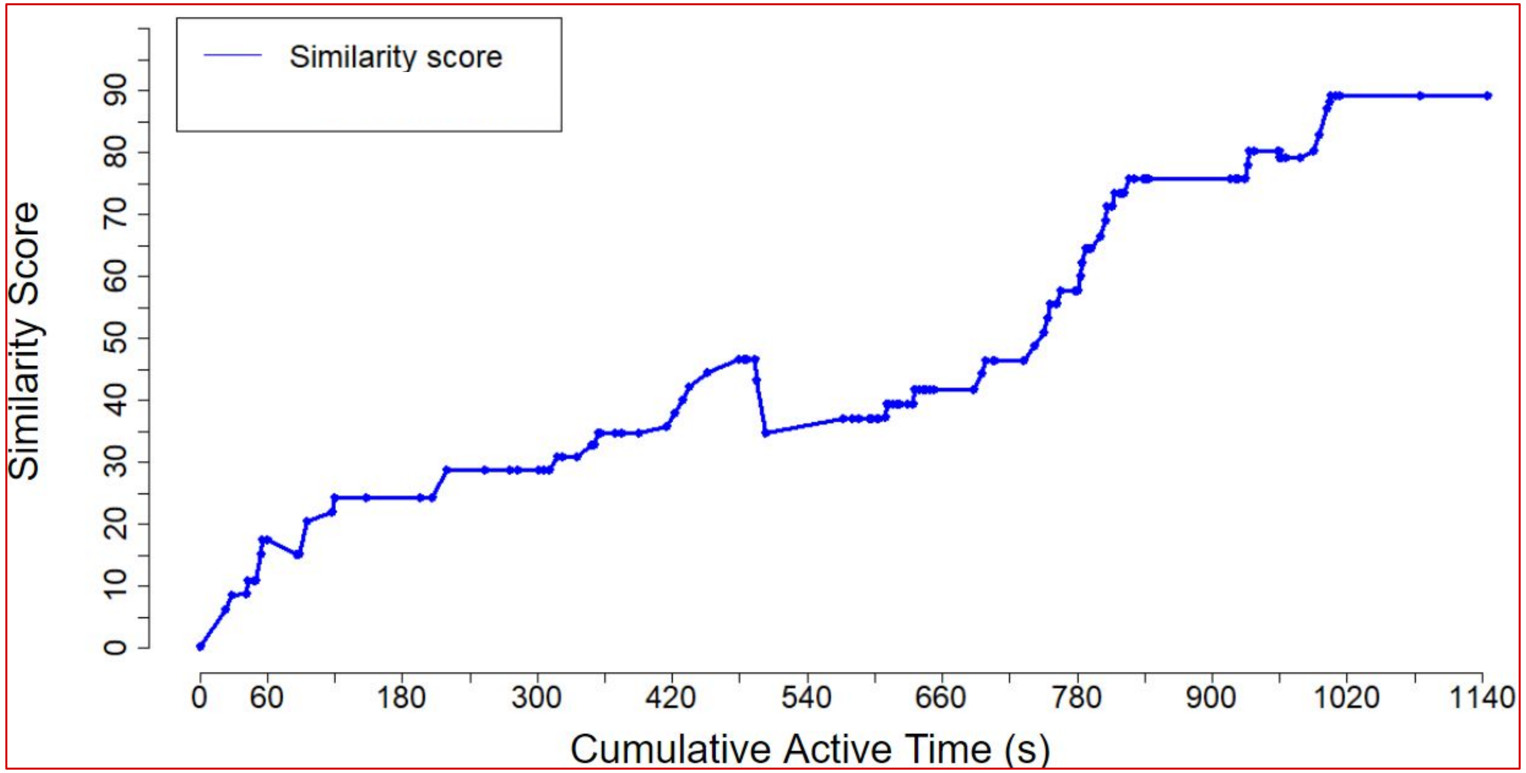
Step 1: Determining Progress

- SourceCheck is a relative distance metric for program hint generation
- Identify the closest correct solution to a code snapshot
  - One that needs fewest edits/lowest cost to accomplish
  - Similar to closest IDR in q-matrix method, Cost is like Error
- Assign Similarity Score to current snapshot (like Quality)
  - The inverse of the Cost to the closest correct solution
  - Increases when a student moves closer to a correct solution

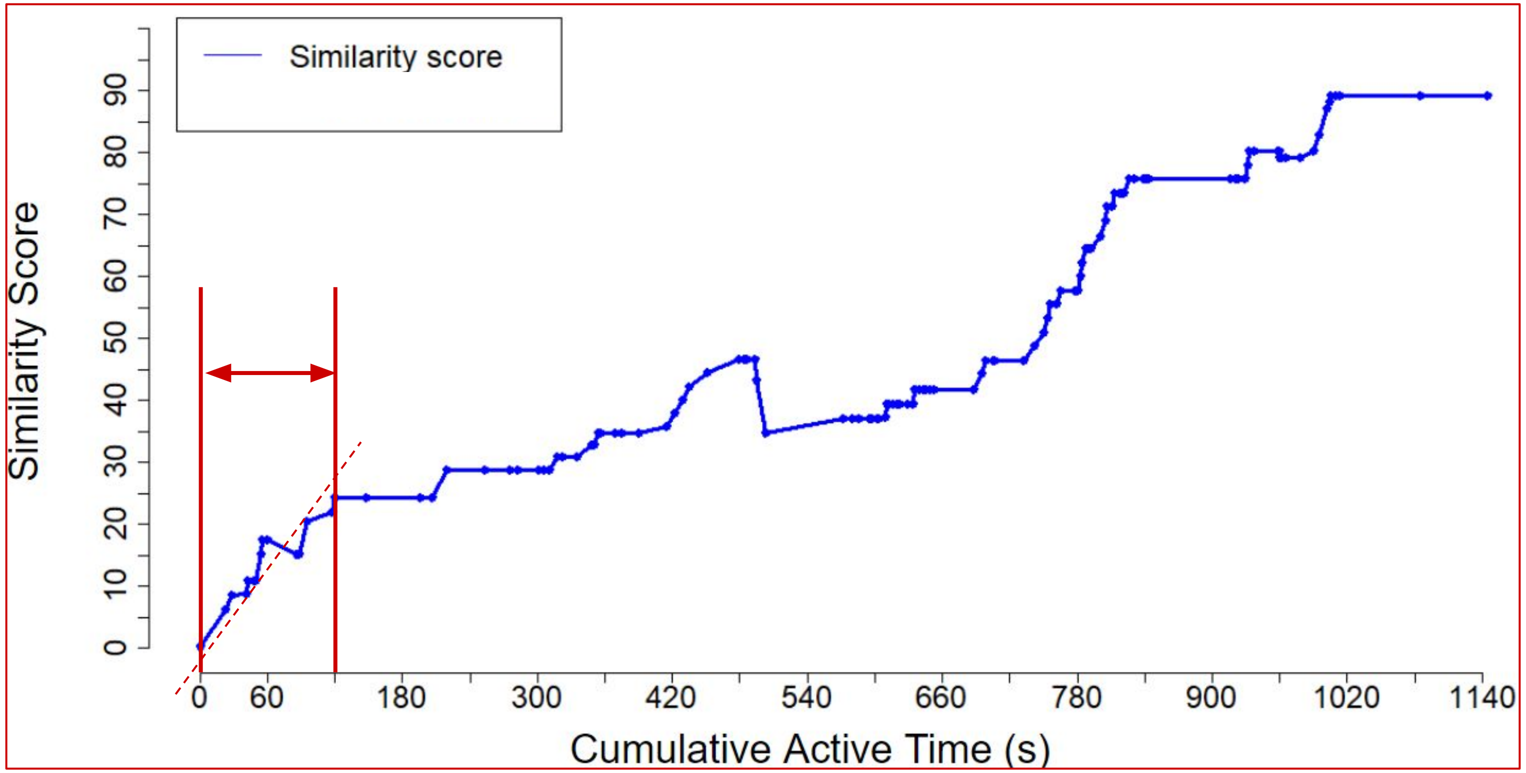
Step 1: Determining Progress

➢ Plot the similarity scores for each snapshot against cumulative time



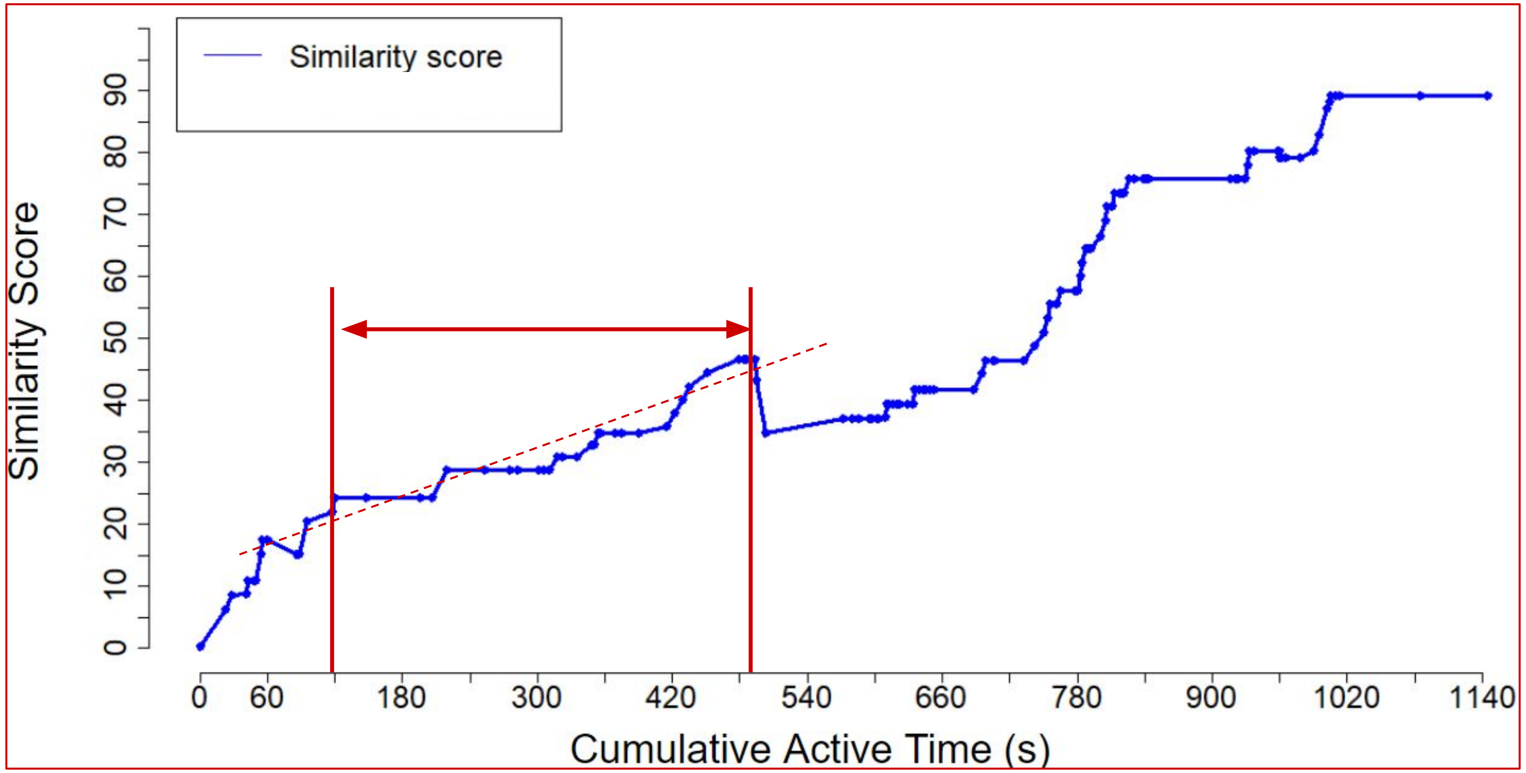
Step 1: Determining Progress

➢ 2 minutes of rapid progress



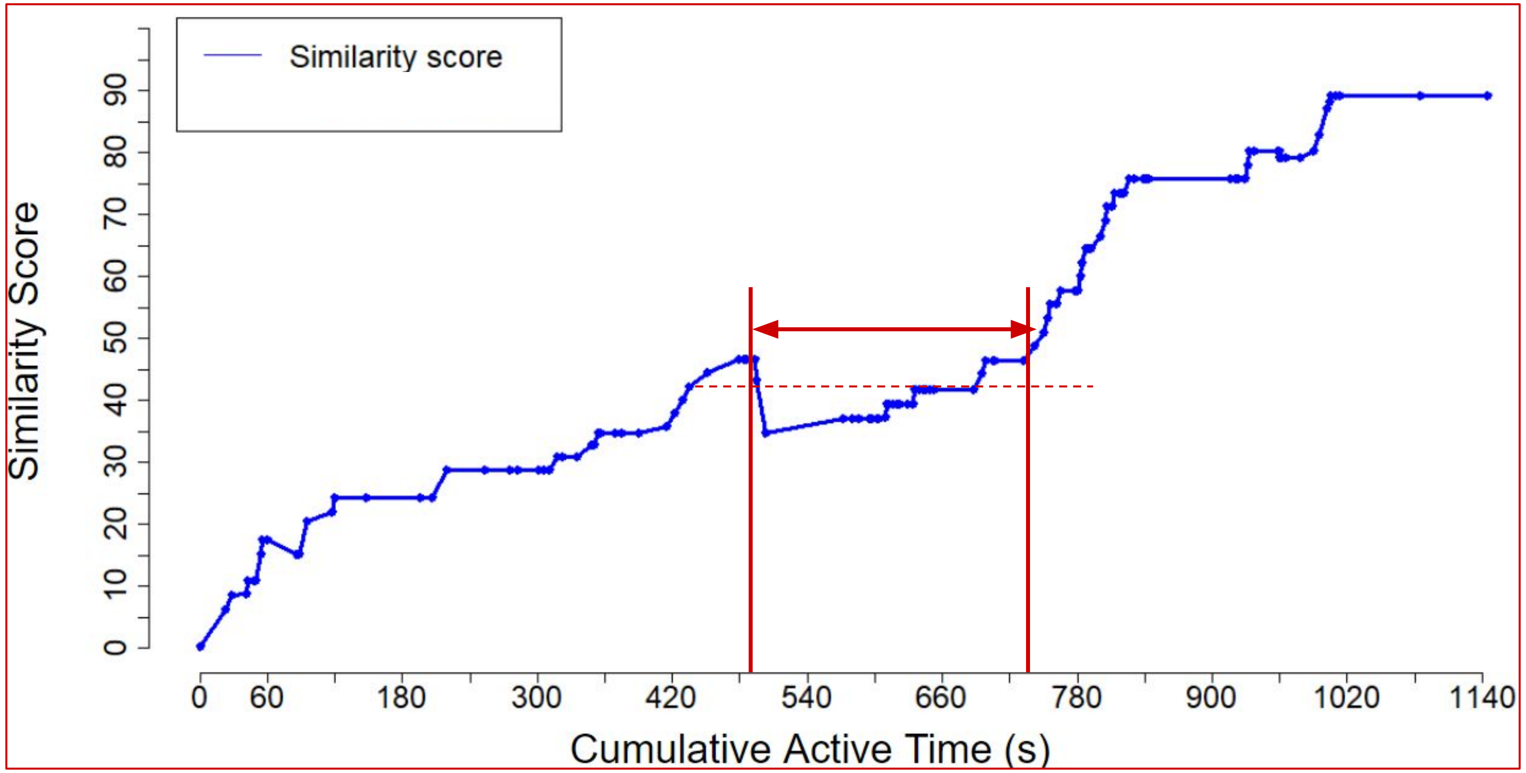
Step 1: Determining Progress

➢ Next six minutes: slower but steady progress



Step 1: Determining Progress

- A reduction in progress for the next 4 minutes since the student restructured and deleted code



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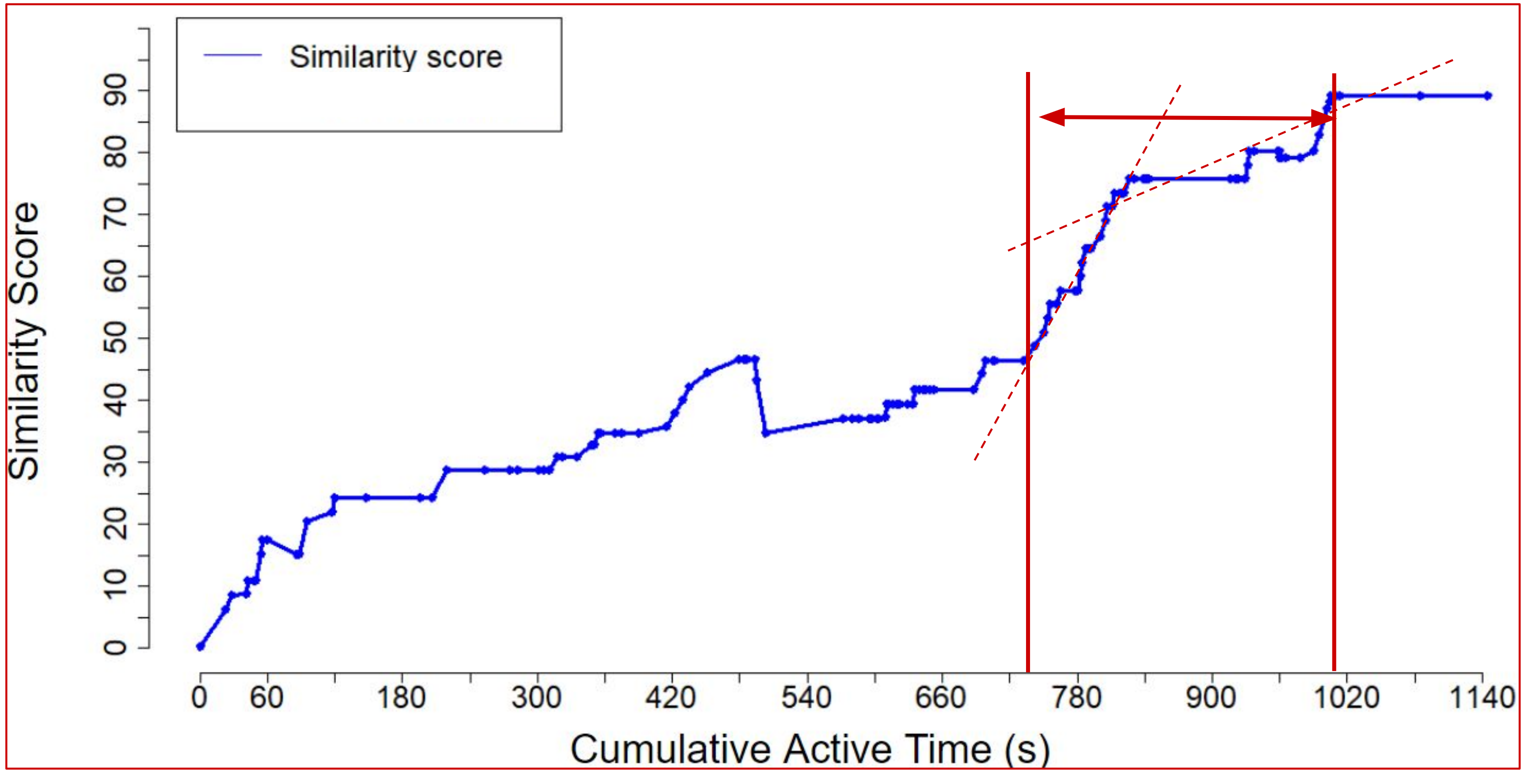
Step 1: Determining Progress

- A 1.5 minute period of rapid progress and then slower 3 minutes progress then done!



Step 2: Determine Significant Progress

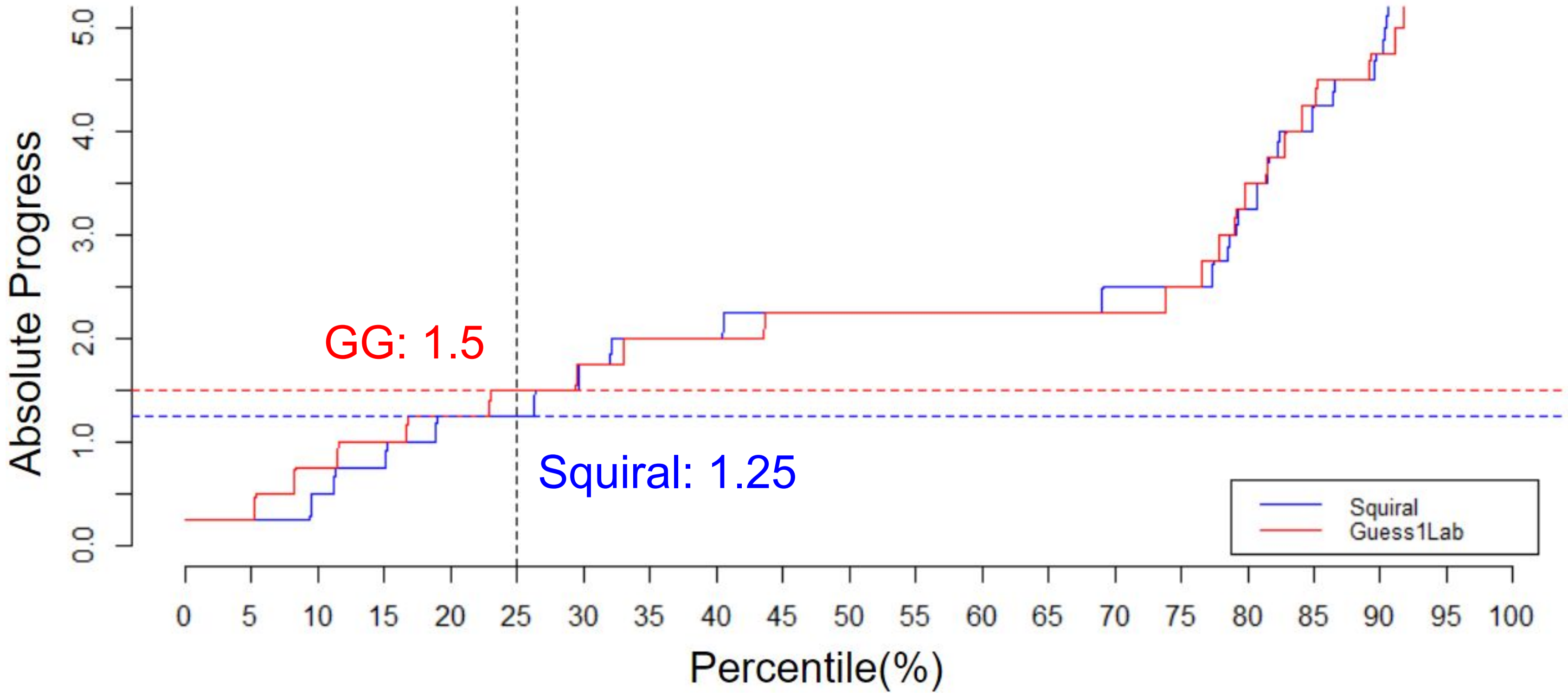
Basically, subtract similarity scores between consecutive snapshots

Plot all the progress scores for all snapshots for all students in a histogram, ordering from least progress to most

All progress except the lowerst 25% is deemed “significant”

Step 2: Determine Significant Progress

- Significant Progress is any progress over 25th percentile



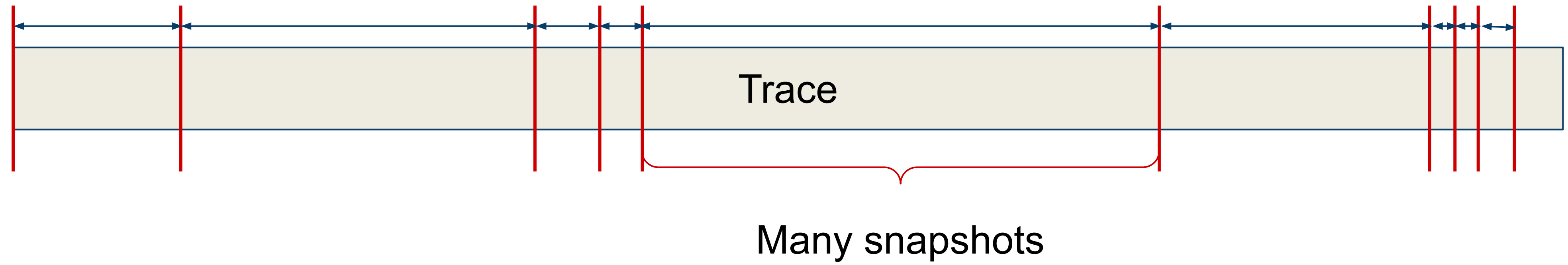
Step 3: Determine Typical Time

- Slice a trace into code chunks every time it achieves significant progress
- Calculate duration of each code chunk using cumulative active time

Trace

Step 3: Determine Typical Time

- Slice a trace into code chunks every time it achieves significant progress
- Calculate duration of each code chunk using cumulative active time



Step 3: Determine Typical Time

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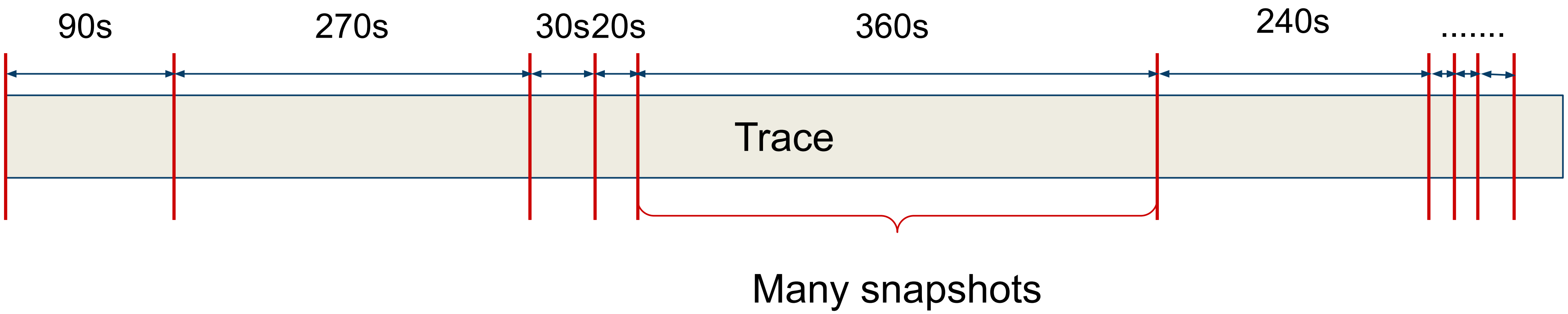
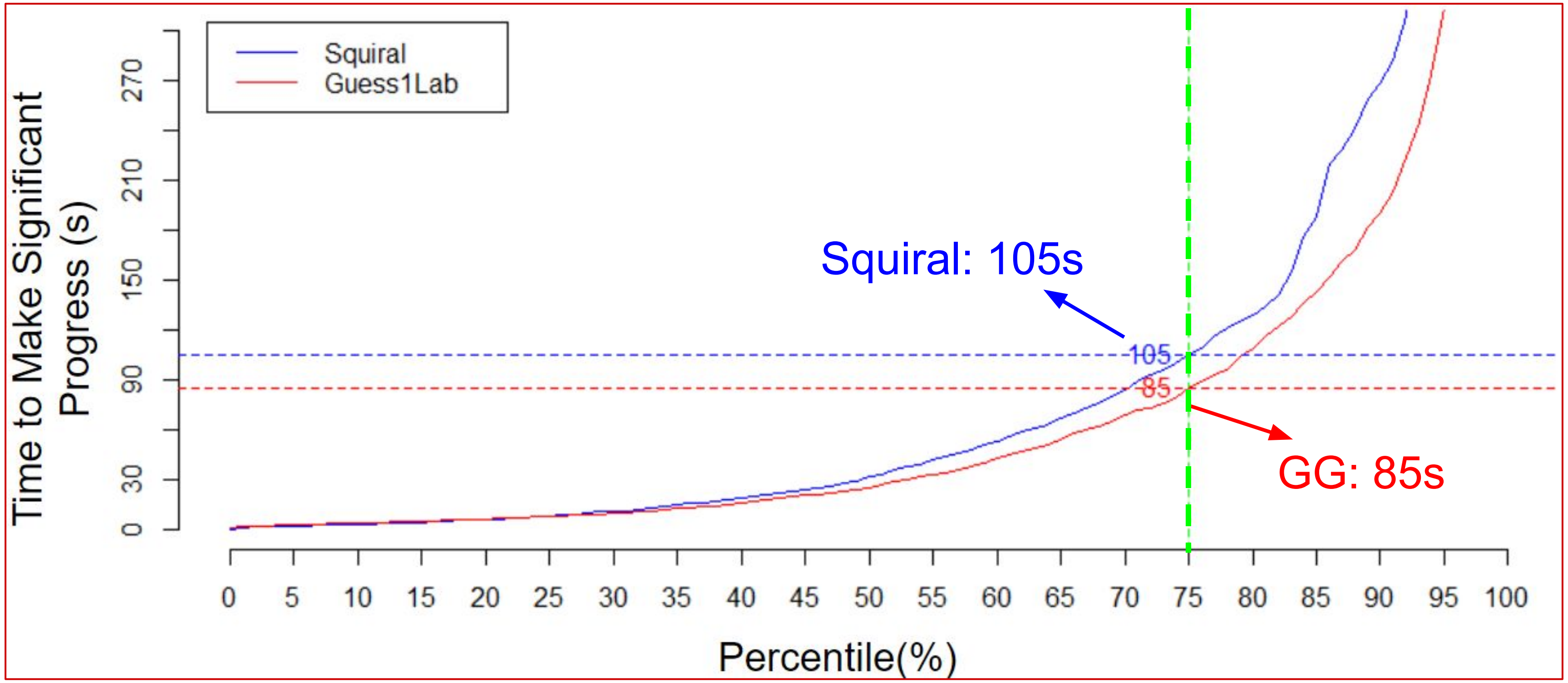


Step 3: Determine Typical Time

- Typical time: 75th percentile of all significant code chunks
- Any less chunk time is reasonable progress in reasonable time



Step 4: Determine Struggling Moments

- Struggling moment: a chunk where progress took longer than typical time
- Progressing moment is chunk where progress took <= typical time

	Traces	Sig. Progress	Time for Sig. Progress	# Code Chunks	# (%) Struggling Moments	# (%) Progressing Moments
Squiral	45	1.25	105 secs	648	131 (20.2%)	517 (79.8%)
Guessing Game	50	1.5	85 secs	1207	269 (22.3%)	938 (77.7%)

Evaluation - Expert Rating

Experts rated a random sample

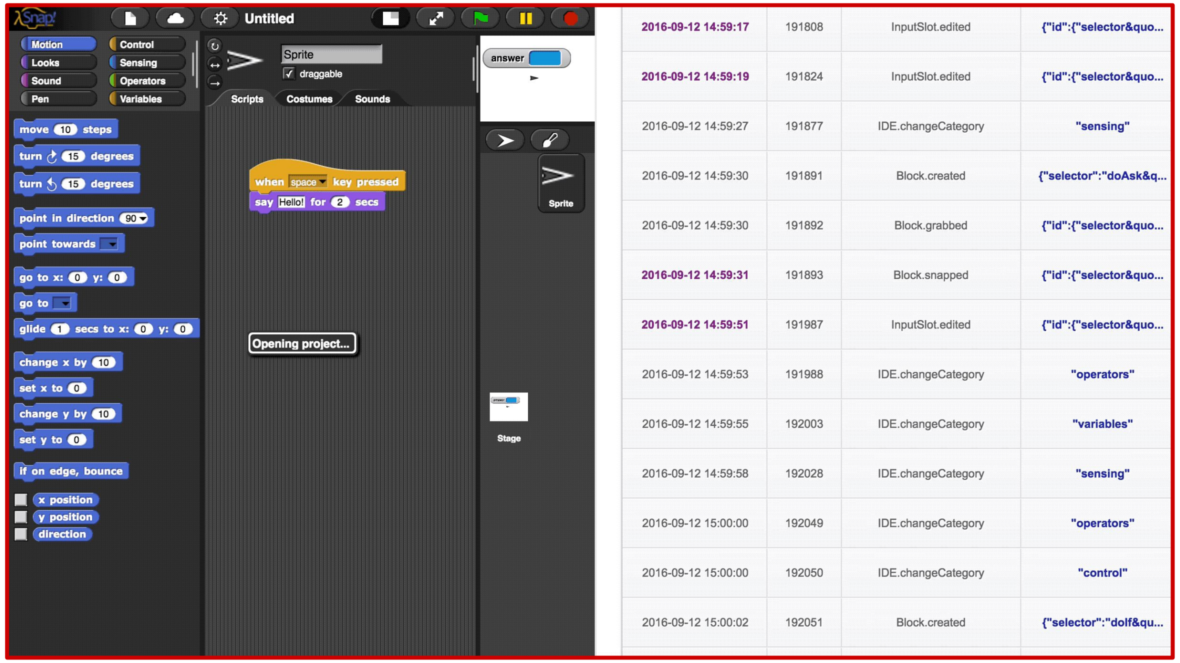
- Struggling moments rating dataset: randomly sampled 20% of the struggling moments from each assignment
- Progressing moments rating dataset: the progressing moments before each struggling moment above

	Total Struggling Moments	Struggling Rating Dataset	Progressing Rating Dataset
Squiral	131	29	29
Guessing Game	269	57	54

Expert Rating Setup

Three experts rated if and when intervention is needed for each moment

Experts used the trace viewer to inspect student actions



2016-09-12 14:59:17	191808	InputSlot.edited	{"id":{"selector&quo...
2016-09-12 14:59:19	191824	InputSlot.edited	{"id":{"selector&quo...
2016-09-12 14:59:27	191877	IDE.changeCategory	"sensing"
2016-09-12 14:59:30	191891	Block.created	{"selector":"doAsk&q...
2016-09-12 14:59:30	191892	Block.grabbed	{"id":{"selector&quo...
2016-09-12 14:59:31	191893	Block.snapped	{"id":{"selector&quo...
2016-09-12 14:59:51	191987	InputSlot.edited	{"id":{"selector&quo...
2016-09-12 14:59:53	191988	IDE.changeCategory	"operators"
2016-09-12 14:59:55	192003	IDE.changeCategory	"variables"
2016-09-12 14:59:58	192028	IDE.changeCategory	"sensing"
2016-09-12 15:00:00	192049	IDE.changeCategory	"operators"
2016-09-12 15:00:00	192050	IDE.changeCategory	"control"
2016-09-12 15:00:02	192051	Block.created	{"selector":"doIf&qu...

Struggle/Progress Classification Worked!

A data-driven method to classify both progressing and struggling moments

Classified moments matched experts 77-85% of the time

Has the potential to be generalized to domains with similar characteristics

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Common Causes of Disagreement

- Disagreement in Struggling Moments
  - Solution Matching: similarity fluctuation when switching solution
  - Few Coding Actions: not enough actions to determine help-need

- Disagreement in Progressing Moments
  - Logic Errors: an issue that SourceCheck does not account for
  - Human Factors: human can infer information that is not possible for the algorithm

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Papers with details

- Barnes, T., 2005, July. The q-matrix method: Mining student response data for knowledge. In *American association for artificial intelligence 2005 educational data mining workshop* (pp. 1-8). AAAI Press, Pittsburgh, PA, USA.

- M Maniktala, C Cody, A Isvik, N Lytle, M Chi, T Barnes. (2020). Extending the Hint Factory for the assistance dilemma: A novel, data-driven Help-Need Predictor for proactive problem-solving help. *Journal of Educational Data Mining*, *12*(4), 24-65.

- Dong, Y., Marwan, S., Shabrina, P., Price, T., & Barnes, T. (2021). Using Student Trace Logs To Determine Meaningful Progress and Struggle During Programming Problem Solving. In *Proceedings of the 14th International Conference on Educational Data Mining*.

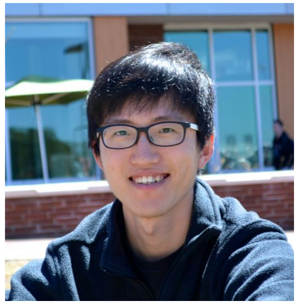
Thanks to these collaborators, and the National Science Foundation.

Heidi Reichert

Benyamin Tabarsi

Ally Limke

Mehak Maniktala



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Thomas Price

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How Data Scientists Use Computational Notebooks for Real-Time Collaboration

April Wang | Anant Mittal | Chris Brooks | Steve Oney

April Wang

- Incoming Assistant Professor at ETH Zurich
- Graduated from University of Michigan, School of Information
- Interested in human-computer interaction, educational technology, and data science
- Looking for motivated students to become part of my research lab!

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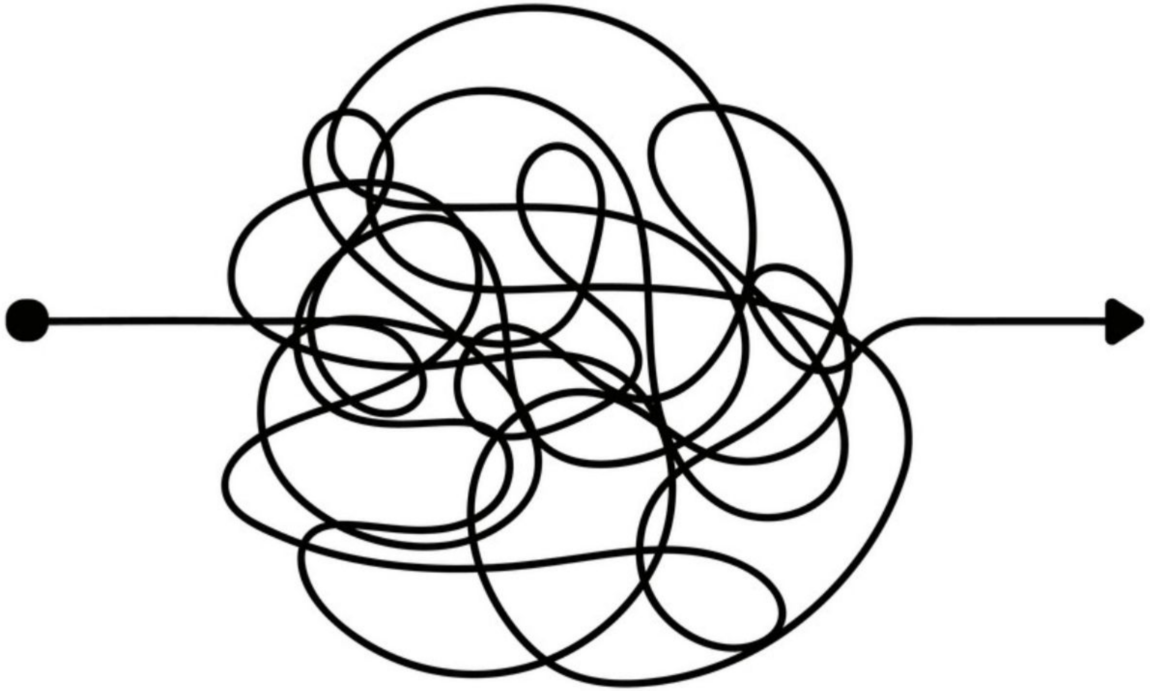
https://aprilwang.me/

The Story Behind Data Analysis



The Story Behind Data Analysis

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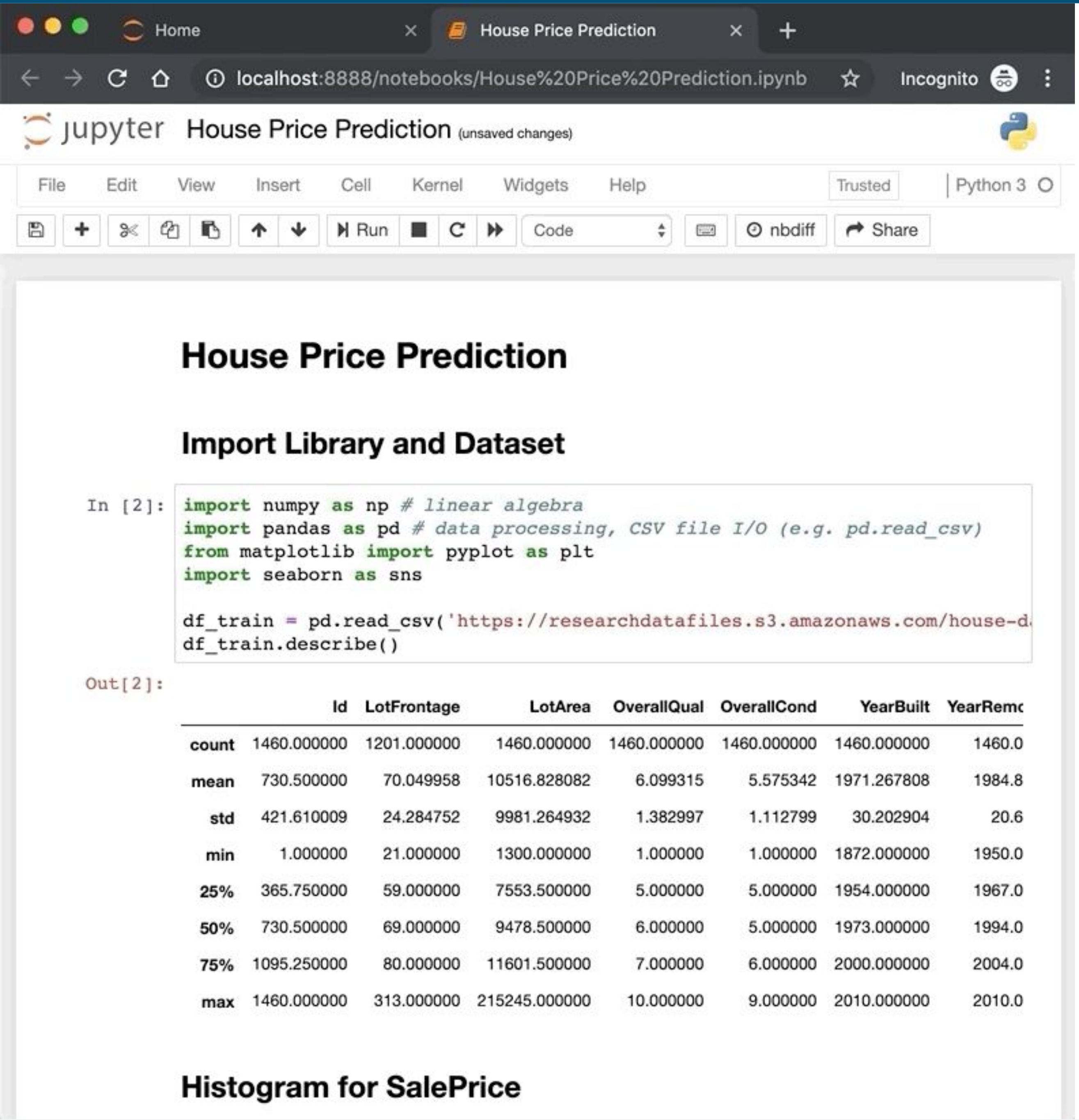
Computational Narratives

Narrative Text

Code

Visualization

Other Media



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Jupyter Notebook

Jupyter notebooks consist of **"cells"** — typically small chunks of code or narrative text in the Markdown format.

Users can execute cells (typically, but not necessarily, from top to bottom) and observe their outputs.

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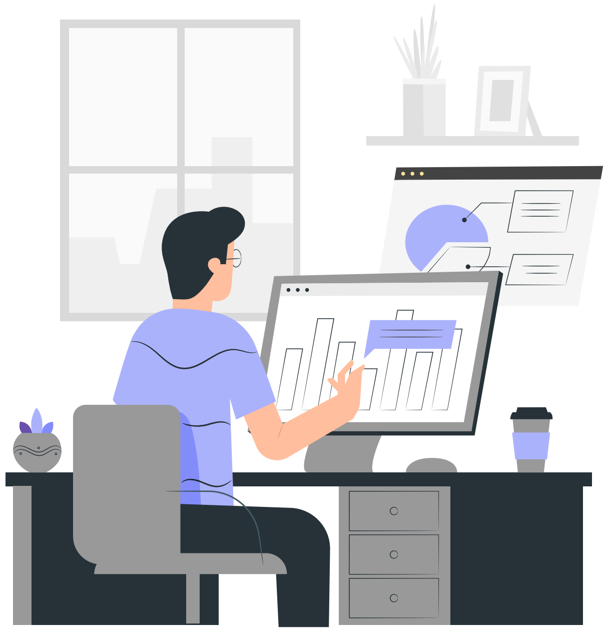
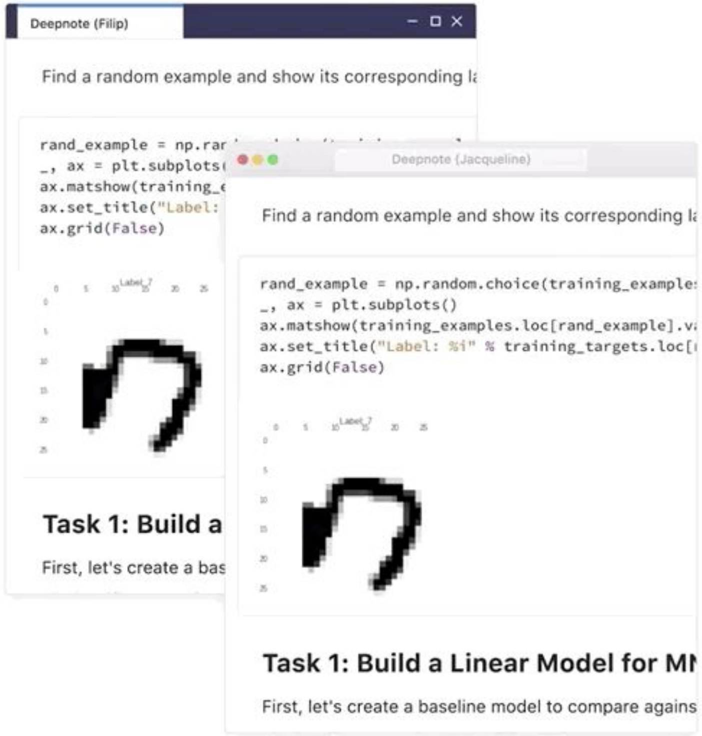
Writing and Sharing Computational Notebooks in Various Contexts

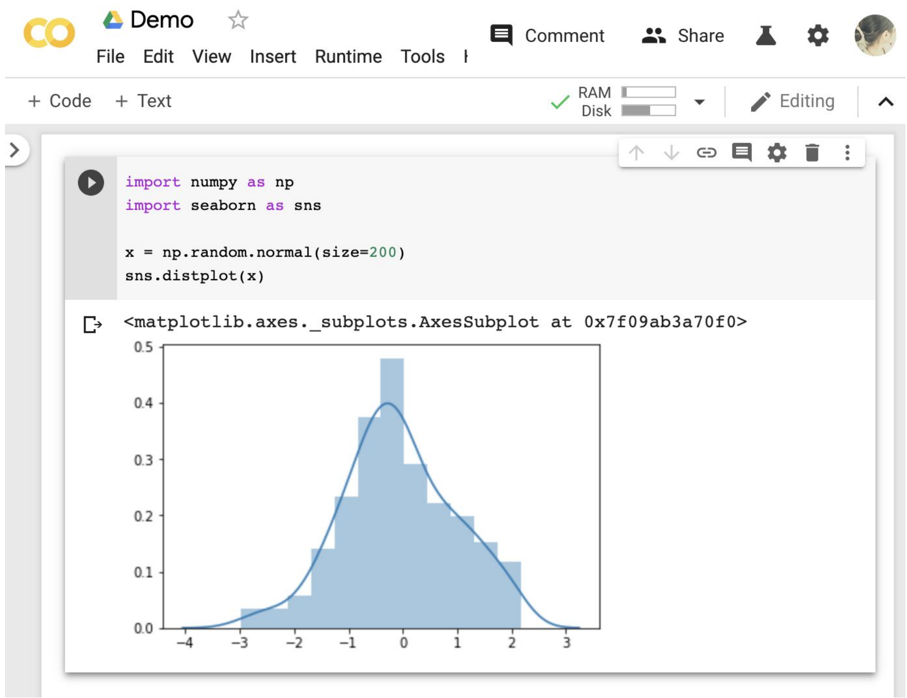
- Data Science Education
  Kross and Guo, CHI 19
- Open Science
  Randles et al., JCDL 17
- Professional Data Analytics
  Kery et al., CHI 18



From Sharing to Synchronous Editing



Deepnote

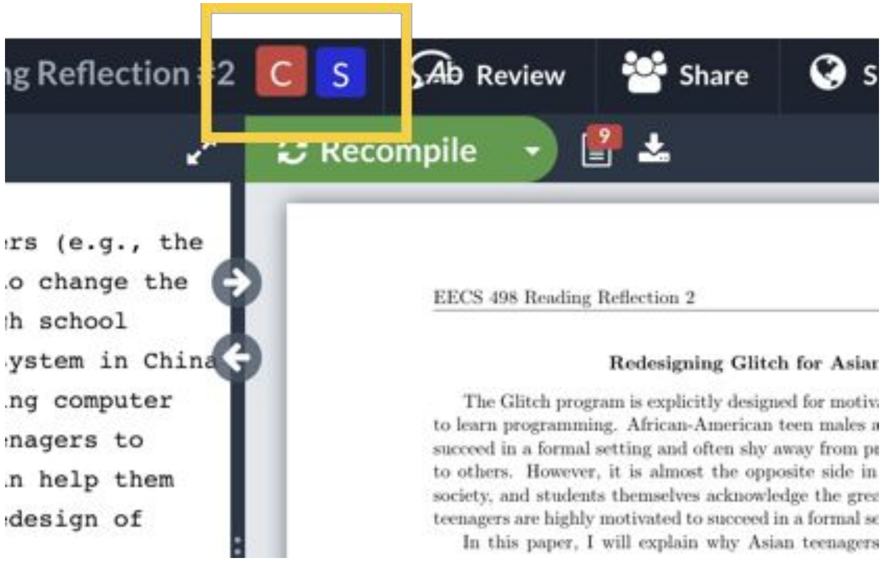


Google colab

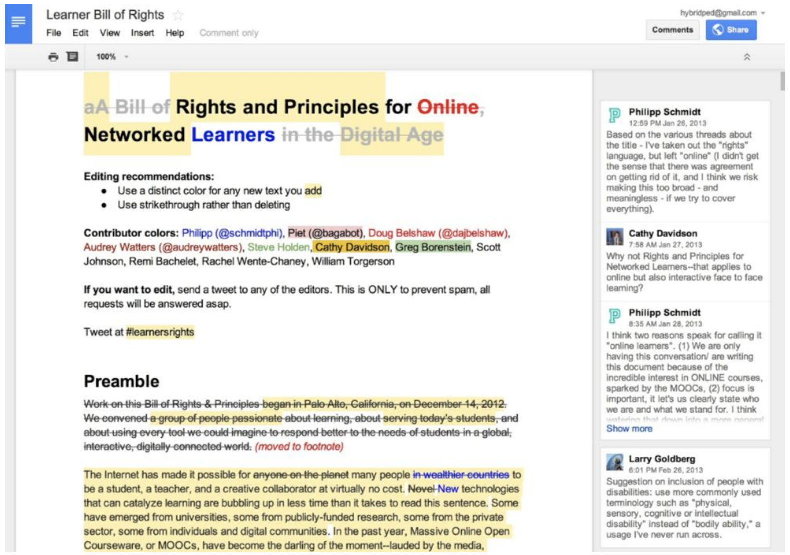
Issues with Synchronous Editing

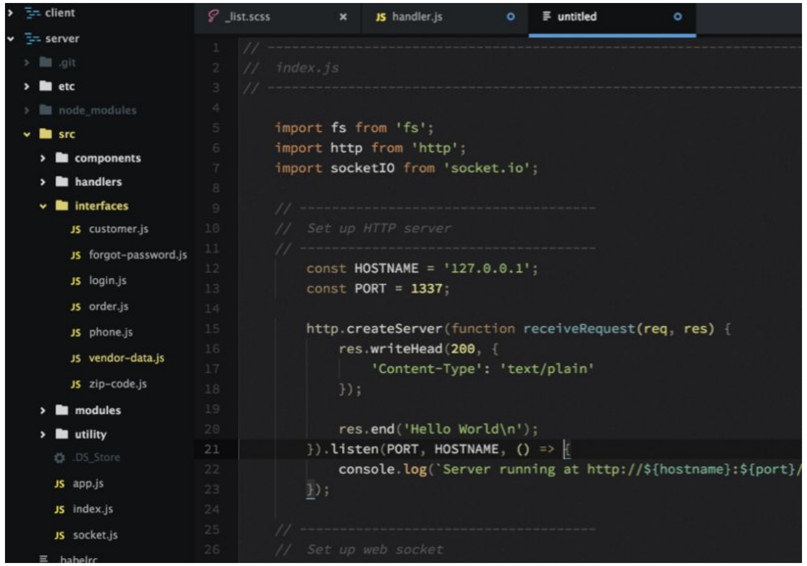
- Reluctant to write together when collaboratively constructing a document
- Social embarrassment to be watched by others when typing

~ Wang et al. CSCW’17



Issues with Synchronous Editing





Collaborative Writing

Wang et al. CSCW'17

D'Angelo et al. CSCW'18

Collaborative Programming

Goldman et al. UIST'11

Oney et al. CSCW'18

What about collaborative data science?

data science ≠ writing + coding

RQ1 What **tools and strategies** do data scientists currently use for collaboration?

RQ2 Compared to **working on individual notebooks** in a collaborative setting, how does **synchronous notebook editing** change the way data scientists collaborate in computational notebooks?

RQ3 What **challenges**, if any, do data scientists perceive in synchronous notebook editing?

Study 1 Formative Survey

RQ1 What **tools and strategies** do data scientists currently use for collaboration?

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Study 2 Observational Study

Study 1 Formative Survey

Demographic

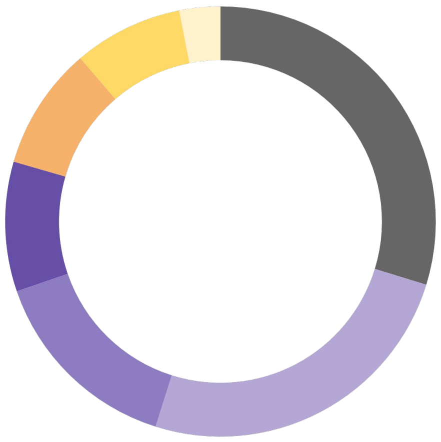
Data Source

195
Valid Responses

35
Umich

160
Coursera

Job Roles



- Students
- Data Scientists
- Software Engineers
- Researchers
- Managers
- Business Analysts
- Others

Experience with Data Science

Study 1 Formative Survey

RQ1 What **tools and strategies** do data scientists currently use for collaboration?

Traditional Collaboration Setting

Working on individual Jupyter notebooks

Emerging Collaboration Setting

Working on notebooks with synchronous editing

Study 1 Formative Survey

RQ2 Compared to **working on individual notebooks** in a collaborative setting, how does **synchronous notebook editing** change the way data scientists collaborate in computational notebooks?

RQ3 What **challenges**, if any, do data scientists perceive in synchronous notebook editing?

Study 2 Observational Study

Study 2 Observational Study

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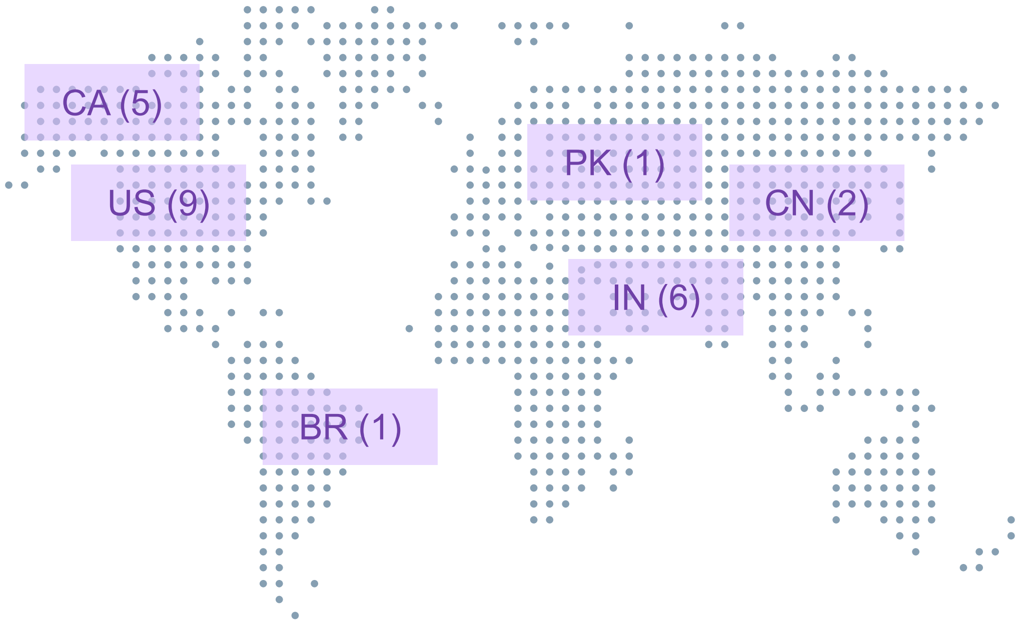
Participants

- 24 participants (12 from the survey)
- Randomly assigned to pairs
- Work collaboratively on a predictive modeling problem remotely



Study 2 Observational Study

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Study Setup

Non-Shared Condition

Participants worked on individual notebooks

- ✓ Exchange the notebook file
- ✓ Set up a git repository
- ✓ Send code snippets through other tools if necessary

Shared Condition

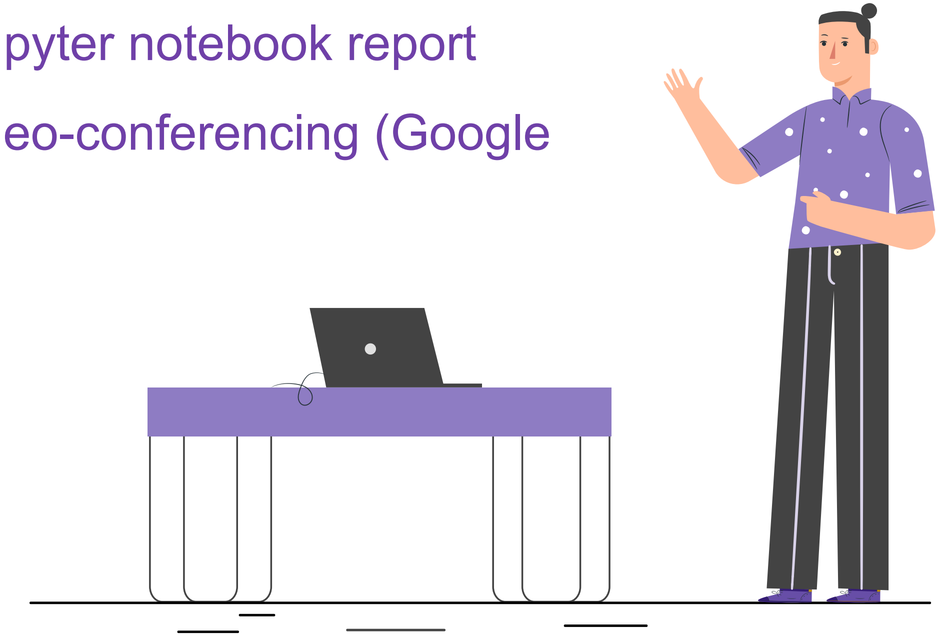
Synchronous editing was supported.

- ✓ Share notebook edits and actions (e.g., moving cursor, adding cells) in real-time
- ✓ Execute code on a single interpreter
- ✓ Update output and runtime variables among collaborators

Study 2 Observational Study

Task

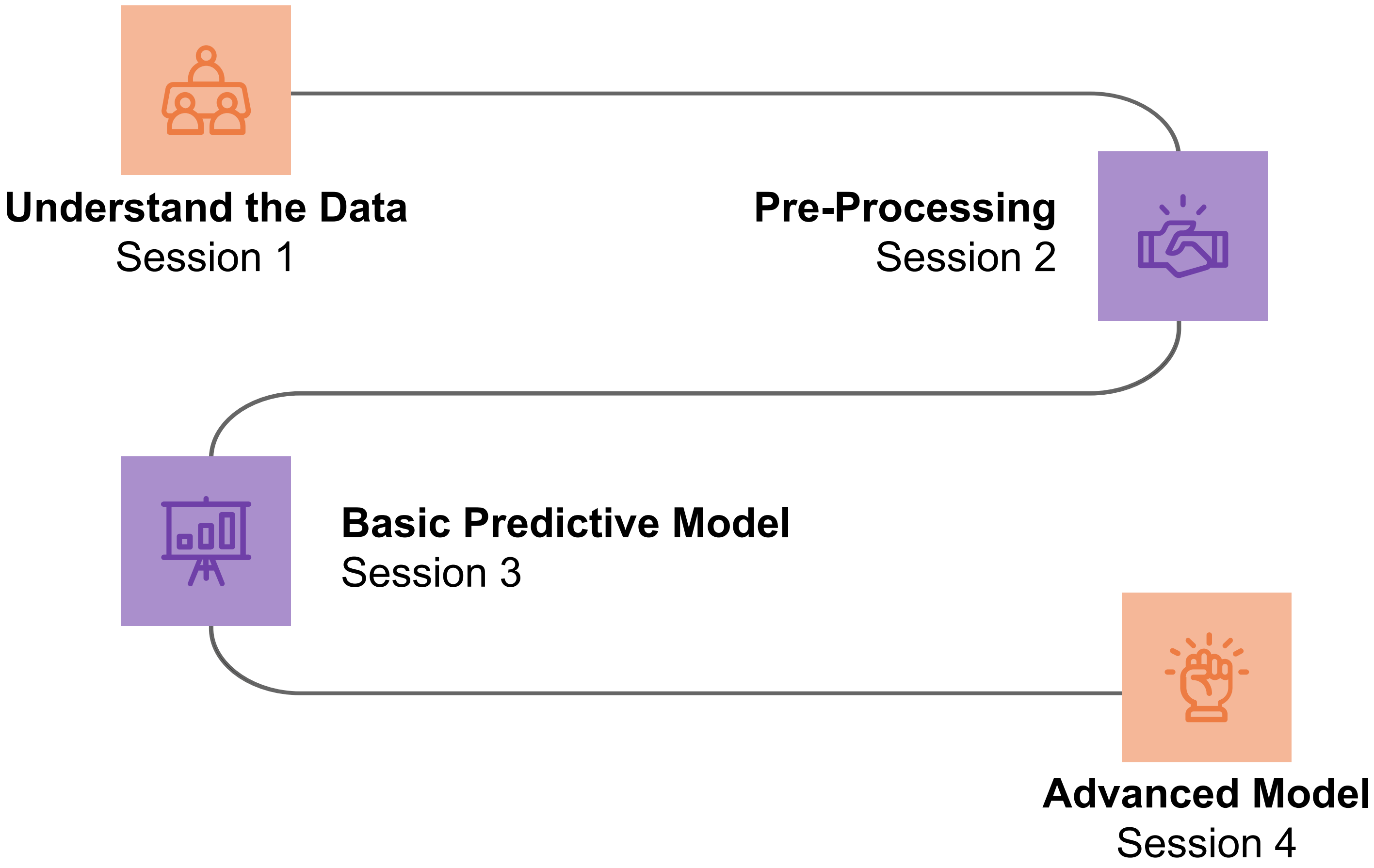
- Predict house sale prices using 80 features (e.g., lot size, year built)
- Additional incentives for the group with the lowest error score
- Submit prediction results as well as one Jupyter notebook report
- Choose from text-messaging (Slack) or video-conferencing (Google Hangouts) for communication



Study 2 Observational Study

Procedure

The study consisted of four sessions, each of which lasted an hour.



Study 2 Observational Study

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Collaboration Style

Collaboration Style	GID	Definition
Single Authoring		One team member contributed the majority of ideas and did the majority of the implementation, while the others did not contribute much.
Pair Authoring		
Divide and Conquer		
Competitive Authoring		

Study 2 Observational Study

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Competitive Authoring		Team members wrote the code for the same purpose and reached the consensus to use the code by whomever finished first.

Study 2 Observational Study

Collaboration Style

Collaboration Style	GID	Definition
Single Authoring	S2, S5	One team member contributed the majority of ideas and did the majority of the implementation, while the others did not contribute much.
Pair Authoring	S6	One team member did the majority of implementation while the others contributed ideas, engaged in discussions and reviewed the results.
Divide and Conquer	N2, N5, S1, S3, S4	Members divided the task into subgoals and explored the subgoals independently.
Competitive Authoring	N1, N3, N4, N6	Team members wrote the code for the same purpose and reached the consensus to use the code by whomever finished first.

Study 2 Observational Study

Communication Channels

	Non-Shared Condition	Shared Condition
Choices of Tools	Text Messaging (6/6)	Text Messaging (3/6) Video Conferencing (3/6)

Participants in the non-shared condition send files, code snippets, and output more often.

➔ Working in the shared notebook may reduce the communication costs by establishing a shared context.

Study 2 Observational Study

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Final Submissions

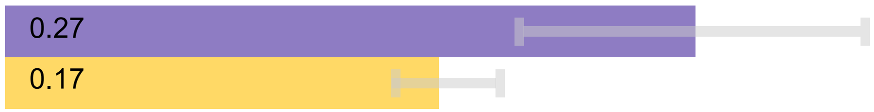
➔ Groups in the shared condition achieved a better prediction result.

➔ Groups in the shared condition explored more alternative models.

Non-Shared Condition

Shared Condition

Error Score



Number of Alternative Models*

p= 0.05

Lines in the Notebook*

p= 0.04

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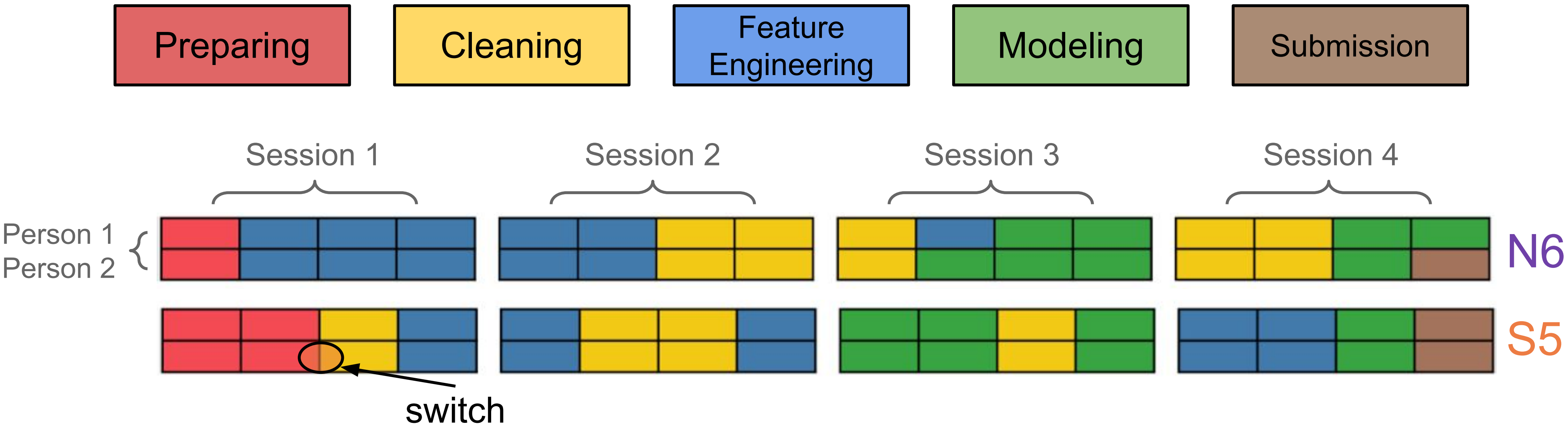
Work Across Phases



Participants in the shared condition switched more frequently ($p<0.001$).

➔ Working on the same notebook provides collaborators with convenience to branch through tasks

Study 2 Observational Study

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Benefits of Synchronous Editing in Notebook

- ➔ Reducing communication costs
- ➔ Flexibility to branch through tasks
- ➔ Enabling explorations of more alternative models
- ➔ Leading to a better prediction result

Study 2 Observational Study

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Challenges of Synchronous Editing

Study 2 Observational Study

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Challenges of Synchronous Editing

1. Interference with each other

train_df → df_train

*"... **When using Jupyter Notebook together, it's hard to keep track of variable names.** Everyone might use a different name and may cause issues. For example, my teammate used train_df as name, and later changed it to something else, but I wanted him to keep using the original name…" (P2 from S1)*

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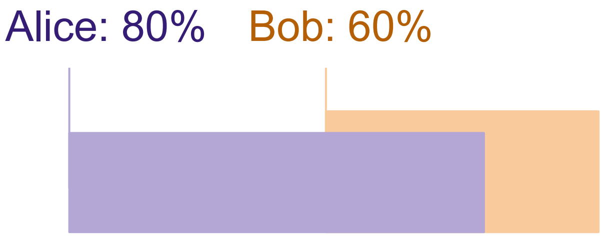
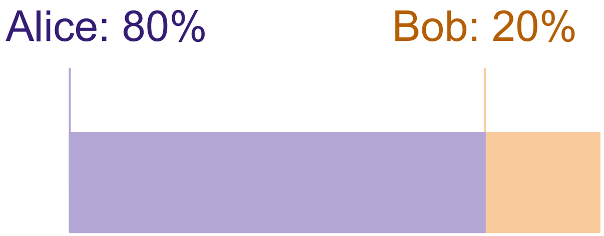
Challenges of Synchronous Editing

2. Lack of strategic coordination

Why competitive authoring happens in the non-shared condition?



Why single authoring happens in the shared condition?



"... I feel I am not splitting work well enough. ***I was thinking about how to get the work done and just tried the ideas on myself****...." (P11 from S2)*

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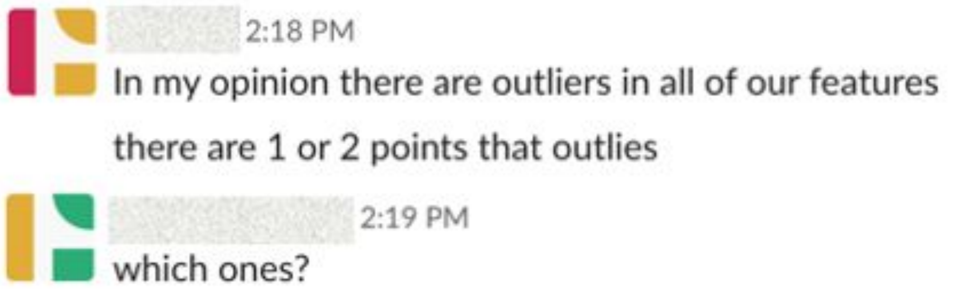
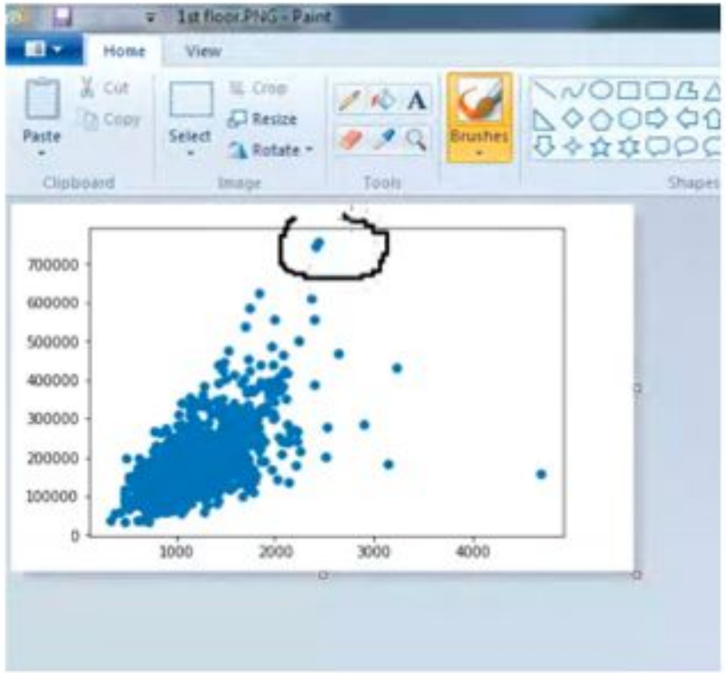
Challenges of Synchronous Editing

3. Contextual Chatting

P14 and P15 were looking at the scatterplots of independent variables together.



P14 downloaded the graph, opened MS Paint, annotated the graph and sent it back to P15.



How Data Scientists Use Computational Notebooks for Real-Time Collaboration

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What tools and strategies do data scientists currently use for collaboration?

Study 1 - Formative Survey on Collaborative Data Science

Traditional Collaboration Setting + Emerging Collaboration Setting

How does synchronous notebook editing change the way data scientists collaborate?

What challenges do data scientists perceive in synchronous notebook editing?

Study 2 - Observational Study on Collaborative Data Science

Having synchronous editing is great for collaborative data science, but not perfect!

Presenter: April Wang | april.wang@inf.ethz.ch

Co-authors: Anant Mittal, Chris Brooks, Steve Oney

spot MISC SCHOOL OF INFORMATION NSF

Programming, Education, and Computer-Human Interaction Lab (PEACH Lab)

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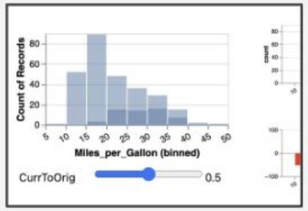
https://aprilwang.me/#/team

Study on
Real-time Editing

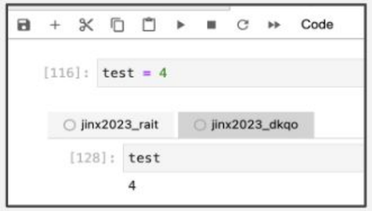
Understand Challenges in Collaborative Data Science

Callisto

Themisto



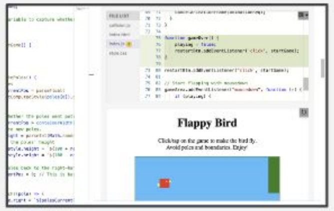
DITL



PADLOCK

Design Collaborative Computational Notebook Environments for Data Scientists

PuzzleMe



Colaroid

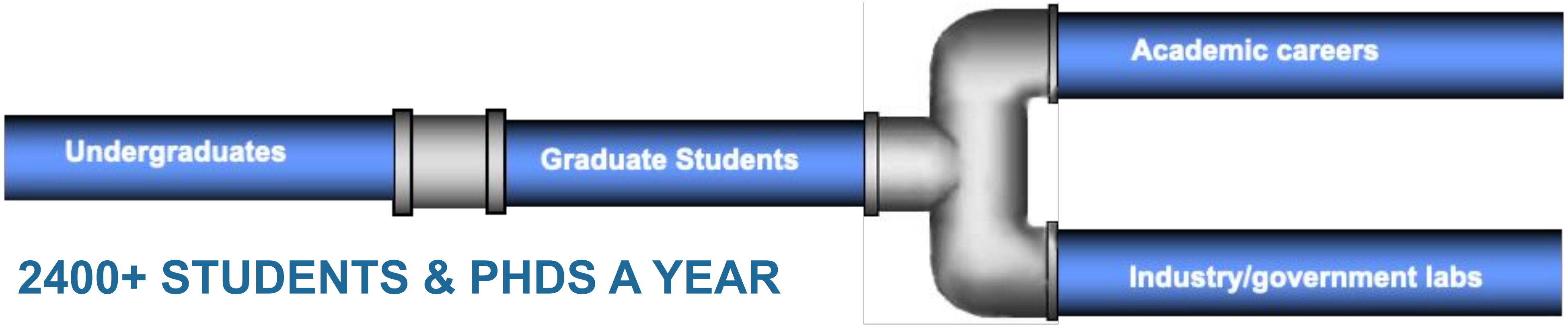
Facilitate Knowledge Sharing for Future Data Scientists

What Is CRA-WP?
Individual & Group Research Mentoring

CRA-WP
Computing Research Association
Widening Participation

Our mission is to widen the participation and improve the access, opportunities, and positive experiences of individuals from populations underrepresented in computing research and education. We individual and group research mentoring provide for:

- *Undergrads* — Undergraduate Research Experiences (DREU), Scholarships for Women Studying Information Security (SWSIS)
- *Grad Students* — CSGrad4US Fellowships, Grad Cohort for IDEALS, Grad Cohort for Women, Mentoring Tracks at GHC, and Scholarships for Women Studying Information Security (SWSIS)
- *Academics/PhD Researchers* — Career Mentoring Workshop (CMW), CSGrad4US Mentoring Program, and Mentoring Tracks at GHC



2400+ STUDENTS & PHDS A YEAR

Insert Additional Slides Below

QUESTIONS?

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THANK YOU

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