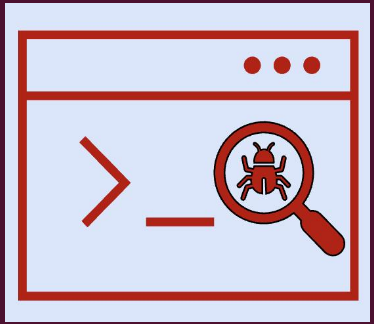

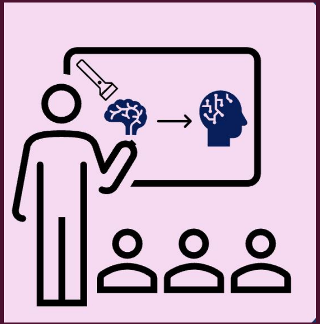

Three Lenses for Improving Programmer Productivity

From Anecdote to Evidence

Madeline Endres, PhD Proposal, University of Michigan

Why study human-focused programming productivity?

The Range of Individual Differences in Programming Performance

Sackman (et al.), 1968

Performance Measure	Slowest Coder	Fastest Coder	Ratio
Code Hours: Algebra Problem	111	7	16:1
Code Hours: Maze Problem	50	2	25:1
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Novice Software Developers, All Over Again

Andrew Begel   Beth Simon

A Tale of Two Cities: Software Developers Working from Home during the COVID-19 Pandemic

DENAE FORD, Microsoft Research

Socioeconomic Status and Computer Science Achievement

Spatial Ability as a Mediating Variable in a Novel Model of Understanding

Miranda C. Parker   Amber Solomon   Brianna Pritchett

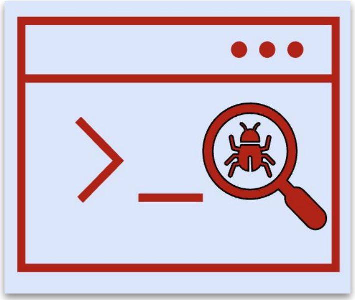
A Large-Scale Survey on the Usability of AI Programming Assistants: Successes and Challenges

Jenny T. Liang   Chenyang Yang   Brad A. Myers

What Predicts Software Developers' Productivity?

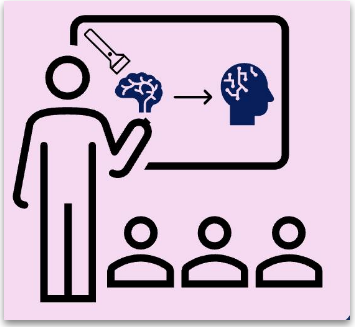
Emerson Murphy-Hill, Ciera Jaspan, Caitlin Sadowski, David Shepherd, Michael Phillips, Collin Winter, Andrea Knight, Edward Smith, and Matthew Jorde

Developing Efficient and Usable Programming Support



Can we support non-traditional novices in **writing more correct code faster?**

Designing Effective Developer Training



Can we use **cognitive insights** to inform training and **improve programming outcomes?**

Understanding External Productivity Factors

How does **psychoactive substance** use **impact software productivity?**

Improving Programming Productivity: My Human-Focused Approach

Desired Research Attribute	**Why I'm Excited** (and you could be too!)
Provide *Theoretically-Grounded* and *Actionable Insights*	Bridging the gap between novel theoretical ideas to supporting programmers in practice leads to higher impact

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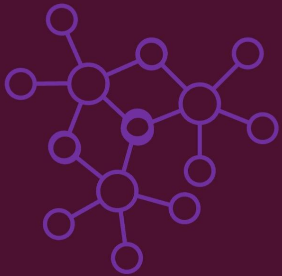
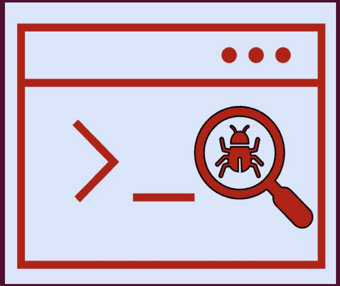
Minimize Scientific Bias to Support Generalizability	Controlled experimental design can capture a signal, even for complex human behavior
Support *Diverse Developer Groups*	I prefer approaches that not only help programmers in general, but also help those who need the most support



InFix and Seq2Parse: *Developing Efficient and Usable Tools*

Supporting Non-traditional Programming Novices via a two novel forms of bug-fixing support

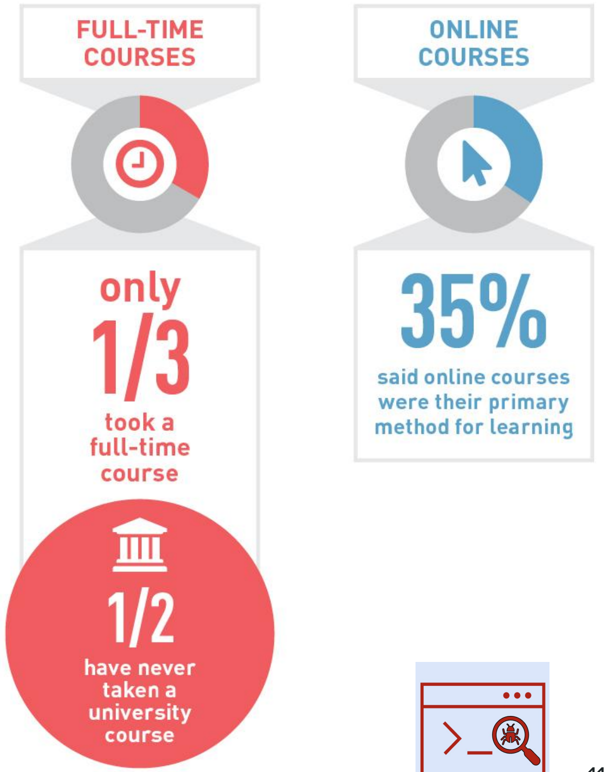


```
The online Python Tutor interpreter
currently has 60,000 users per month
```

Many People Want to Learn to Code

Without traditional classroom support

How do Codecademy's
45 million users
learn to code?



One Such Platform: **Python Tutor**

Write code in Python 3.11 [newest version, latest features

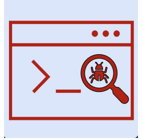
```python
def listSum(numbers):
  if not numbers:
    return 0
  else:
    (f, rest) = numbers
    return f + listSum(rest)

myList = (1, (2, (3, None)))
total = listSum(myList)
```

Visualize Execution   Get AI Help

Python Tutor is a free online **interpreter**. It helps novices **visualize arbitrary code execution.**

Users are primarily *Novice Programmers*

Started in 2010, it has had over **150 million users from 180 countries**



Parse Errors

- Syntax errors are, by far, the most common Python error type experienced by novice programmers (77%)

```
u = 42

x = 3.14

print(x * math.e / 2
```

```
SyntaxError: missing
parentheses in call to print
```

Input-Related Bugs

- We found that 6% of student errors are resolved by fixing the program input, not the source code

Example Code and Input

```
u = 42

x = float(input())

print(x * math.e / 2)
```

```
26,2
```

```
ValueError: could not convert
string to float: '26,2'
```

Parse Errors

- Syntax errors are, by far, the most common Python error type experienced by novice programmers (77%)

Proposed Approach:
Neurosymbolic technique,
Seq2Parse

Preliminary results in OOPSLA, 2022

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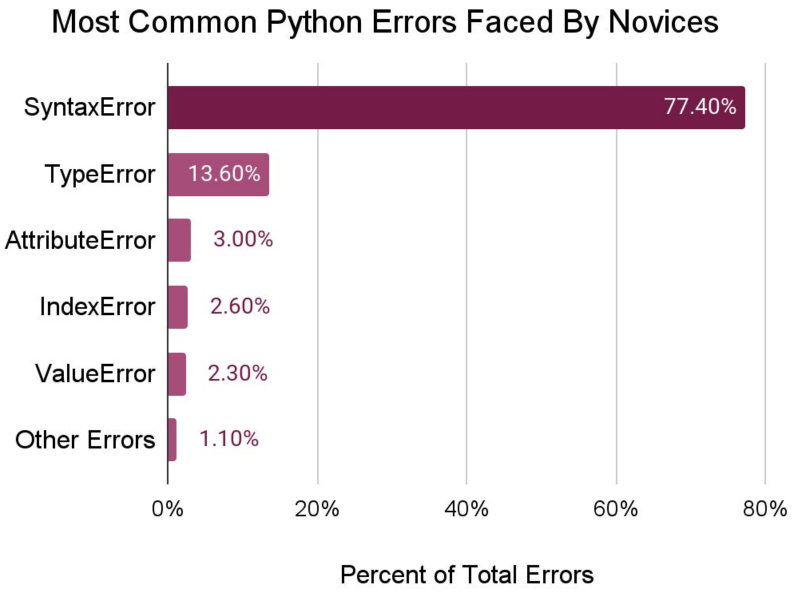
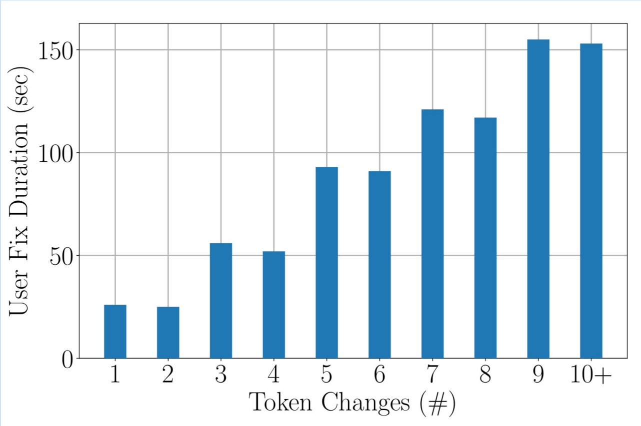
What do Non-Traditional Novices Struggle with? ***Parse Errors***

For Non-Traditional Novices, Parse Errors (Syntax Errors) are both **common** and **challenging**



37% of Parse Errors take over two minutes to resolve

More complex fixes take even longer:

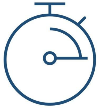


Fixing Parse Errors: How can we support Novices?

Goal: We want support for fixing parse errors faced by non-traditional novices that is both:

- *Effective*: can provide **helpful repairs close to the user's intent** in the majority of cases

and



- *Efficient*: Fast enough to be computed in ***real time***

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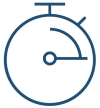

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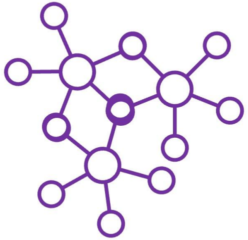
Symbolic Approach?

Neural Approach?



Parsing Overview

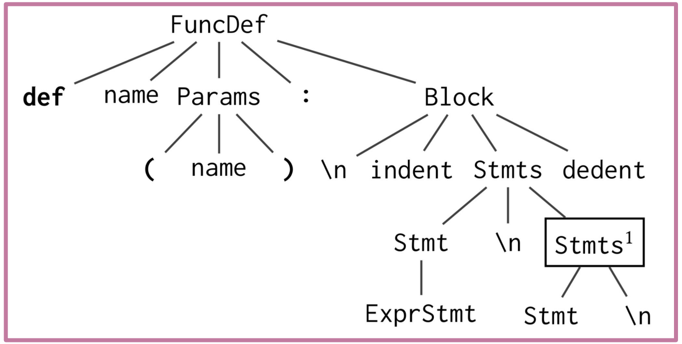
Program P

```python
def foo(a):
  return a + 42

def bar(a):
  b = foo(a) + 17
  return b +
```

Grammar G

```
S        → Stmts end_marker
Stmts    → Stmt \n | Stmt \n Stmts
Stmt     → FuncDef | ExprStmt
           | RetStmt | PassStmt | ...
FuncDef  → def name Params : Block
Block    → \n indent Stmts dedent
```



Finding Parse Errors: Fault Localization

Program P

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def bar(a):
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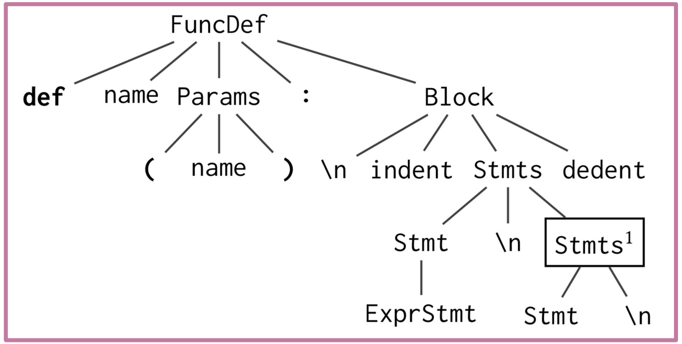

Fixing Parse Errors: Error Correcting Earley Parsers

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```

```
New_S    →  S | S Insert
RetStmt  →  | E_return | E_return Args
E_return →  return | ϵ | Replace
          | Insert return
E_number →  number | ϵ | Replace
          | Insert number
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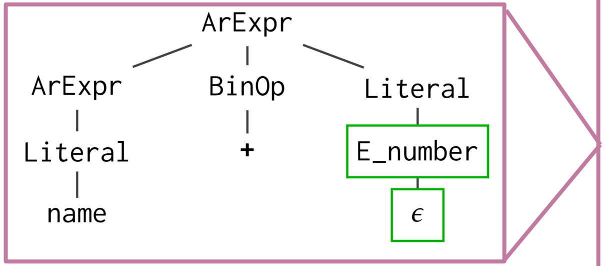
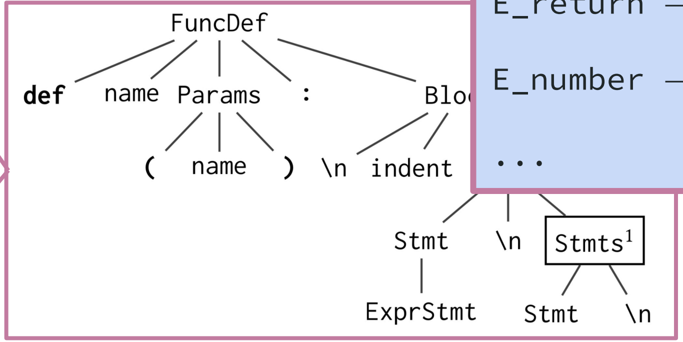
```





Fixing Parse Errors: Error Correcting Earley Parsers

Program P

```python
def foo(a):
  return a + 42

def bar(a):
```

Too many rules!

Grammar G'

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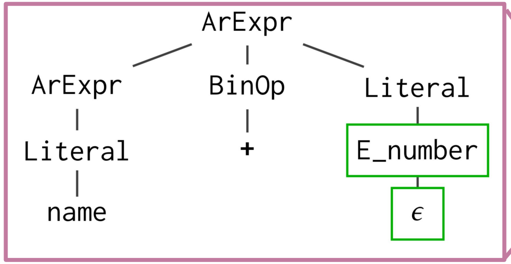

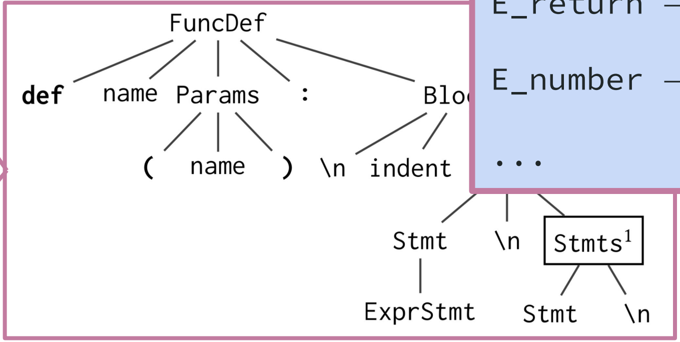

Fixing Parse Errors: Neural Approaches

Pros:

- Sequence classifiers can be good at predicting edits or repairs similar to human behavior
- Once trained, neural approaches can be quite efficient

Cons:

- Generally, **no guarantees** that the response will correct (e.g., actually parse), let alone be a minimal repair
- Neural approaches can be **confused program context** not directly related to the parse error

```python
def foo(a):
  return a + 42

def bar(a):
  b = foo(a) + 17
  return b +
```

SEQ2PARSE: Key Insight

- EC-Parsers guarantee a correct minimal parse error fix, but are slow in practice because **they consider too many production rules**, *the vast majority of which are not needed to fix any given novice error*.
- In contrast, Neural approaches are fast and can leverage historical user patterns, but **can be inaccurate or untrustworthy** if used alone

We propose to get the best of both worlds and *efficiently* and *accurately* suggest repairs in a **neurosymbolic fashion**:

1. Train sequence classifiers to predict the relevant EC-rules for a given program, *instead of the next token or the full fix*

2. Use the predicted rules to synthesize a Parse Error repair via EC-Parsing

SEQ2PARSE: Efficient Fixes for Novice Parse Errors

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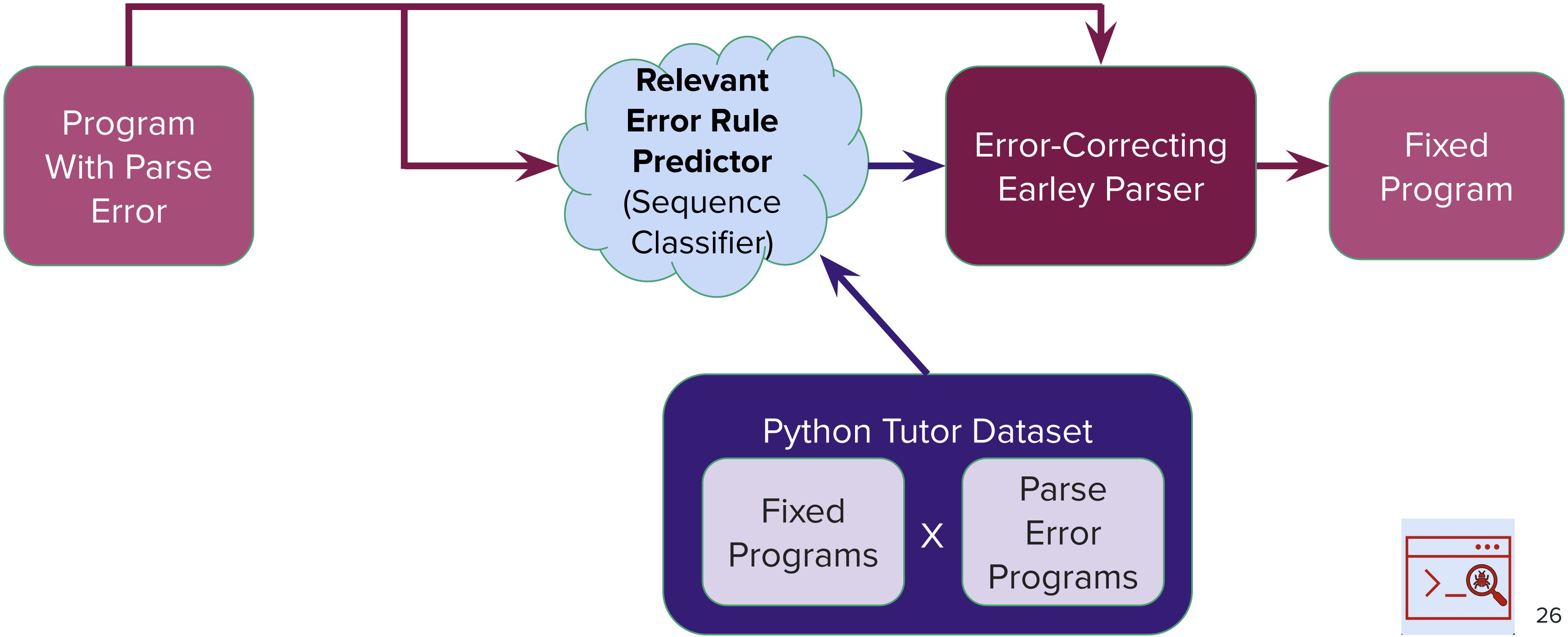
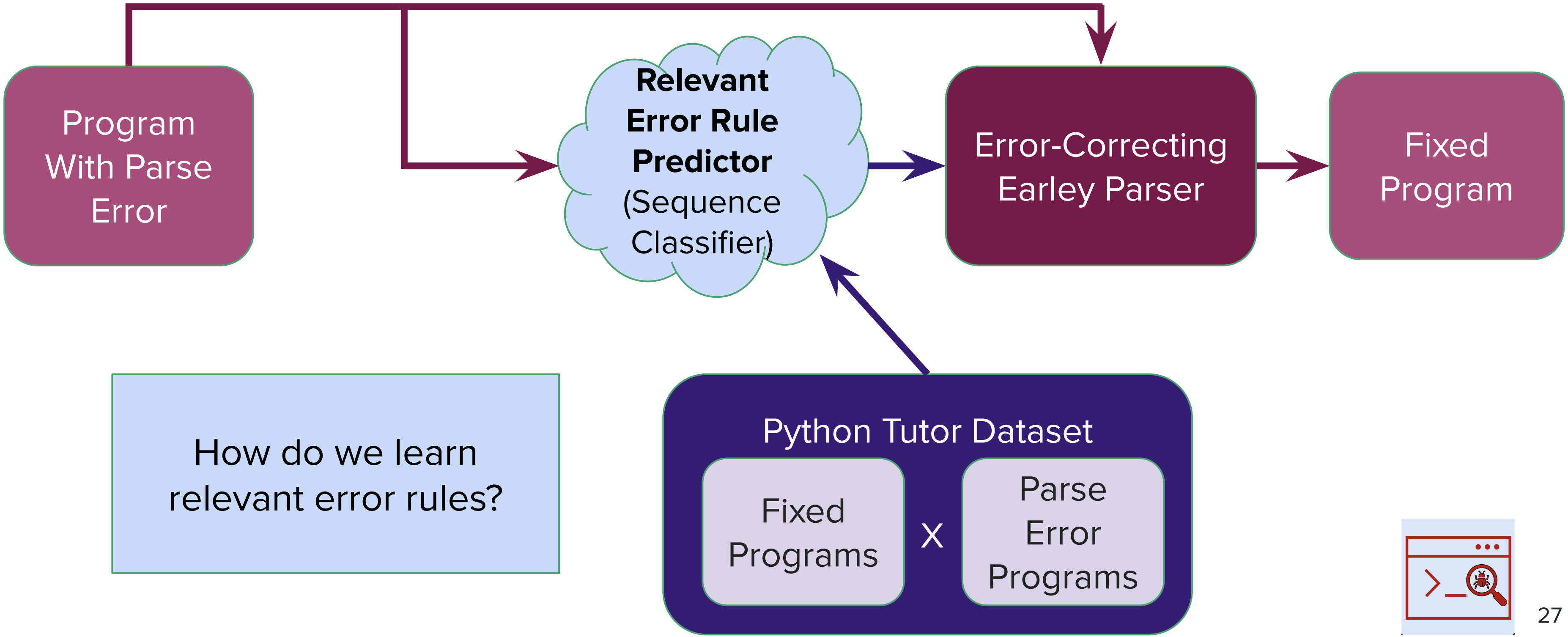


SEQ2PARSE: Efficient Fixes for Novice Parse Errors



How do we learn relevant error rules?

Additional Considerations for Learning EC-Production Rules

Ill-parsed Program Representation for Learning:

- *Problem*: Predicting relevant production rules using full buggy programs causes the model to be **confused by irrelevant program context**
- *Our Solution*: Instead of standard token strings, develop semantics for **Abstracted Token Sequences** that concentrate information relevant to a given parse error and remove confusing context

```
def foo(a):
  return a + 42

def bar(a):
  b = foo(a) + 17
  return b +
```

```
Stmt \n

def name Params: \n
indent Stmt \n
return Expr BinOp \n
dedent end_marker
```

Mitigating Representational Ambiguity:

- *Problem:* While needed, this abstraction adds ambiguity into what parse tree should result from any given abstracted token sequence
- *Our Solution:* Use fixed Python Tutor programs to learn a **Probabilistic Context Free Grammar** and resolve parsing ambiguities

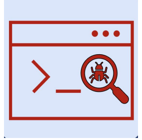
```
S        →  Stmts end_marker (p = 100.0%)
Stmts    →  Stmt \n (p = 38.77%) | Stmt \n Stmts (p = 61.23%)
Stmt     →  ExprStmt (p = 62.64%) | RetStmt (p = 7.59%) | ...
RetStmt  →  return (p = 1.61%) | return Args (p = 98.39%)
```

SEQ2PARSE: Python Implementation

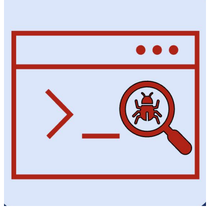
- Dataset: Over **One Million Buggy/Fixed Program Pairs** from Python Tutor
    - Average abstracted token sequence is 43 tokens long
    - 15,000 random programs used for evaluation, the rest for model training

- Error Rule Prediction **Model Structure**:
    - **Transformer classifier** with six blocks, each with a fully-connected hidden layer of 256 neurons and 12 attention heads, **connected to a DNN-based classifier** with two fully-connected hidden layers.
    - Trained using an Adam optimizer, a variant of stochastic gradient descent for 50 epochs.

- **Model Output:** We trained multiple model variations, including one that **outputs the 20 most likely error production rules** for a given Buggy Program
    - These rules are then fed into the Error Correcting Earley Parser



Preliminary results: Does it work? Yes!



Seq2Parse can fix most parse errors for non-traditional novices,

Repair Rate: Seq2Parse **can parse and repair up to 94.25% of programs** with syntax errors.

in real time

Efficiency: Seq2Parse can parse and repair the vast majority of the test set in under 20 seconds in a **median time of 2.1 seconds**

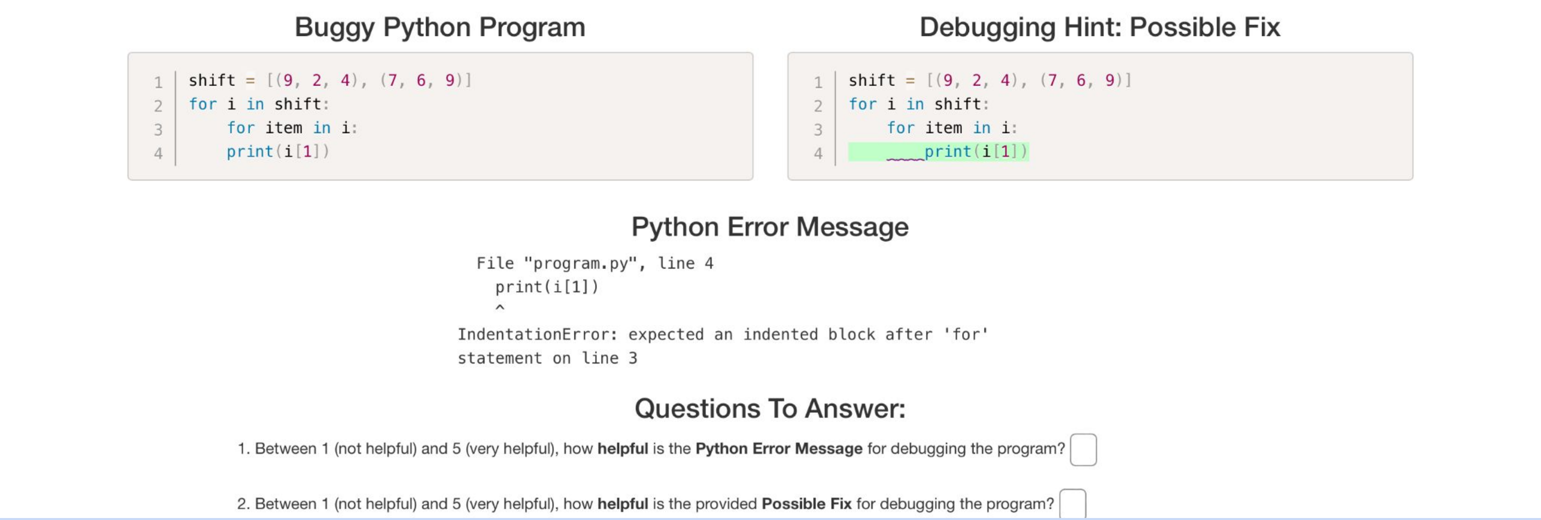
and with the same, or better, quality to the novices themselves!

Quality: Seq2Parse generates the exact fix as the historical user up to 35% of the time! Of the remainder, Seq2Parse repairs are equivalent to or more useful than historical repairs 52% and 15% of the time, respectively.

Preliminary results: Does it work? Yes!

We assess repair quality via a study with 39 programmers

Captured 527 subjective quality ratings for a corpus of 50 SEQ2PARSE / historical fix pairs
Compared the two pairs using standard statistical tests



Buggy Python Program

```
1  shift = [(9, 2, 4), (7, 6, 9)]
2  for i in shift:
3      for item in i:
4      print(i[1])
```

Debugging Hint: Possible Fix

```
1  shift = [(9, 2, 4), (7, 6, 9)]
2  for i in shift:
3      for item in i:
4          print(i[1])
```

Python Error Message

```
  File "program.py", line 4
    print(i[1])
    ^
IndentationError: expected an indented block after 'for'
statement on line 3
```

Questions To Answer:

1. Between 1 (not helpful) and 5 (very helpful), how **helpful** is the **Python Error Message** for debugging the program?

2. Between 1 (not helpful) and 5 (very helpful), how **helpful** is the provided **Possible Fix** for debugging the program?

Preliminary results: Does it work? Yes!

SEQ2PARSE can fix most parse errors for non-traditional novices,

✓

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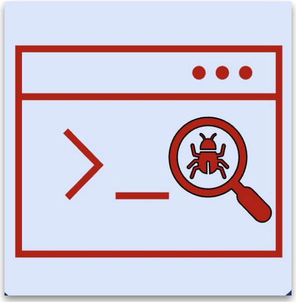
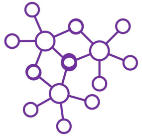
Lens 1 — Summary: Developing Better Bug Fixing Support



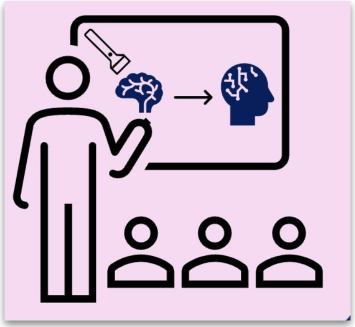
- We **identified parse errors and input-related bugs as a significant barrier** for non-traditional novices in practice
- We **propose SEQ2PARSE**, a neurosymbolic approach to fixing parse errors, and **InFix**, a template-based approach for fixing input-related bugs
- Our preliminary results show that both tools produce repairs that are **accurate, efficient, and of high quality,** as judged by humans.



Developing Efficient and Usable Programming Support

Can we support non-traditional novices in **writing more correct code faster?**

Designing Effective Developer Training



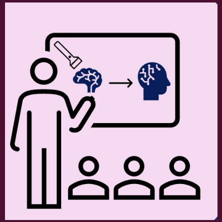
Can we use **cognitive insights** to inform training and **improve programming outcomes?**

Understanding External Productivity Factors

How does **psychoactive substance** use **impact software productivity?**

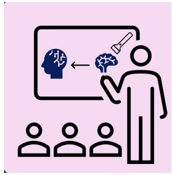
TO READ OR TO ROTATE?

An example of how cognitive insights can inform effective programming interventions



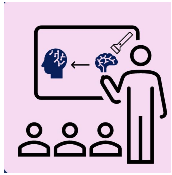
Novice programmers often struggle,
especially those students with weaker preparatory education

This struggle may result from **insufficient preparation in cognitive skills** necessary for programming



How can we help students?

Cognitive interventions (the supplemental training of a necessary cognitive skill) can **help underprepared students succeed in many fields**



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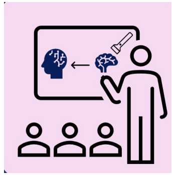
A writing-intensive course improves biology undergraduates' perception and confidence of their abilities to read scientific literature and communicate science

Sara E. Brownell,[1] Jordan V. Price,[2] and Lawrence Steinman[2,3]



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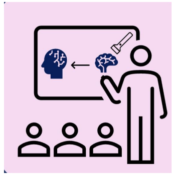
THE EFFECTS OF ORIGAMI LESSONS ON STUDENTS' SPATIAL VISUALIZATION SKILLS AND ACHIEVEMENT LEVELS IN A SEVENTH-GRADE MATHEMATICS CLASSROOM

A Qualitative Inquiry into the Effects of Visualization on High School Chemistry Students' Learning Process of Molecular Structure

Susan Deratzou



How can we help students?

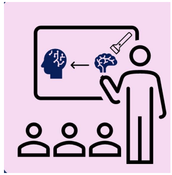
Cognitive interventions (the supplemental training of a necessary cognitive skill) can **help underprepared students succeed in many fields**

A writing-intensive course improves biology undergraduates' perception and confidence of their abilities to read scientific literature and communicate science

Sara E. Brownell,[1] Jordan V. Price,[2] and Lawre

THE EFFECTS OF ORIGAMI LESSONS ON STUDENTS' SPATIAL VISUALIZATION SKILLS AND ACHIEVEMENT LEVELS IN A SEVENTH-GRADE MATHEMATICS CLASSROOM

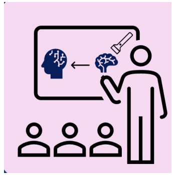
A Qualitative Inquiry into the Effects of Visualization on High School Chemistry Students' Learning



Does spatial skills instruction improve STEM outcomes? The answer is 'yes'

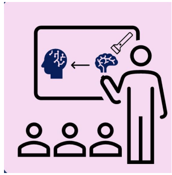
Sheryl Sorby[a,*], Norma Veurink[b], Scott Streiner[c]

Cognitive interventions may also help improve programming ability for novices...



Cognitive interventions may also help improve programming ability for novices…

… but what cognitive skills should we target?

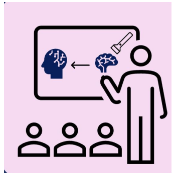


Neuroimaging and Software Engineering

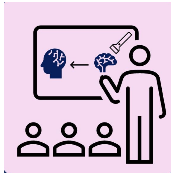
- Understanding the **cognitive basis of software engineering** is important

- Neuroimaging allows us to **objectively measure** this cognitive basis by **directly observing brain activation** patterns while programming! (as opposed to self-reported data)

- Potential impact areas of neuroimaging include pedagogy, technology transfer, expertise, adult retraining



What do we know so far?



- Neuroimaging uses **contrast-based experiments** to compare **programming** activities to **other cognitive tasks**

Neuroimaging Experiment	**Is programming like Reading?**	**Is programming like Spatial Reasoning?**
Siegmund *et al.*, (2014)	✔	
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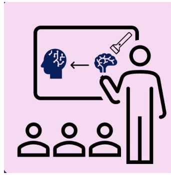

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Found connection with Expertise

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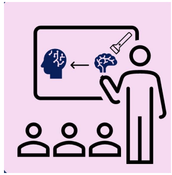

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Neuroimaging Experiment	**Is programming like Reading?**	**Is programming like Spatial Reasoning?**	**What about with novices?**
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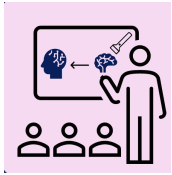
Proposed Study Overview



Phase 1: **Neuroimaging**

- We propose to build model of novice programmer cognition using **the first neuroimaging study of true novice programmers** during code comprehension

Phase 2: **Transfer Training**

- We propose to investigate the the usefulness of transfer training in computing **comparing the impact of two cognitive interventions on novice programming performance** in a controlled, longitudinal study

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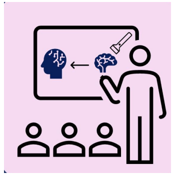

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ICSE, 2021

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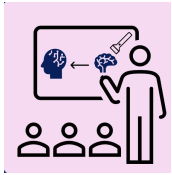
FSE, 2021

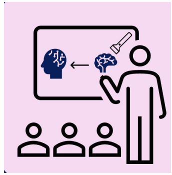
Phase 1: Neuroimaging Method



- We propose using **Functional Near Infrared Spectroscopy** (fNIRS) to capture the brain activation patterns of **novice programmers** (no prior programming experience)
  - **fNIRS** uses light to measure the oxygen levels in different parts of the brain
  - Supports studying the brain while doing natural programming tasks

- We compare programming-associated activations to **two well-understood cognitive tasks** commonly used in neuroimaging studies of expert developers: **spatial visualization** and **reading**

Experimental Timeline: A Semester of CS1



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Week 3: Participant recruitment from CS1

Week 4-5.5: Brain scans

Week 16: End of semester

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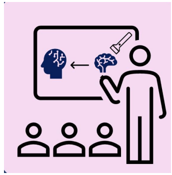

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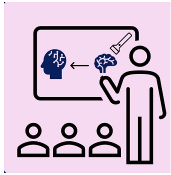
Neuroimaging Stimuli

We compare brain activation during three tasks:



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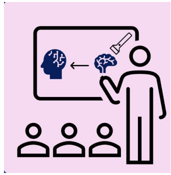
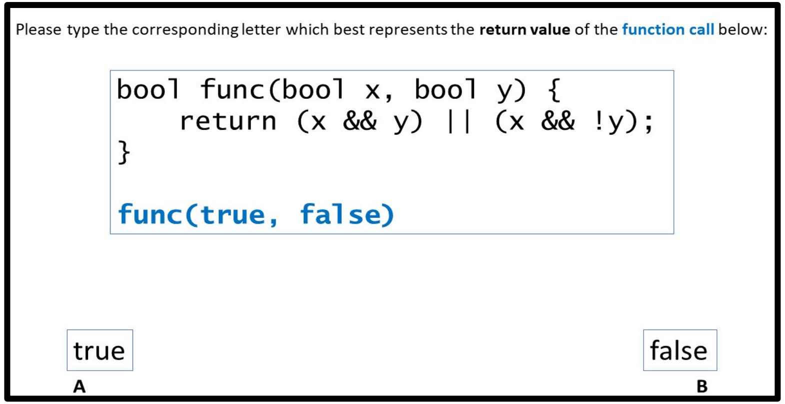


- **CS1-Level Programming**



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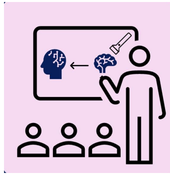


- CS1-Level Programming
- **Mental Rotation**

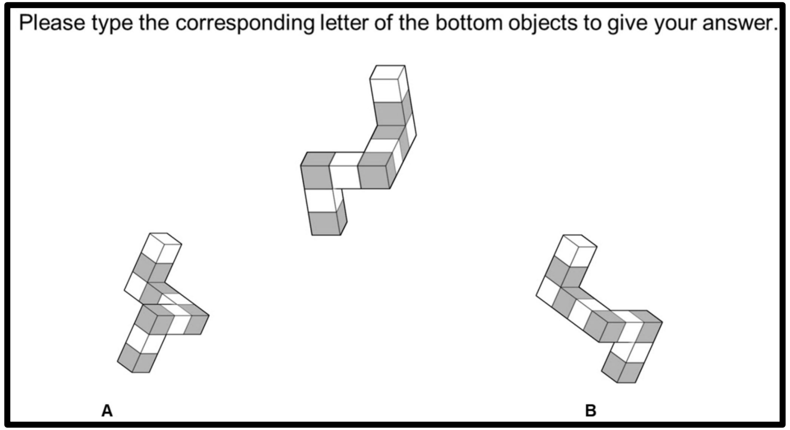
Please type the corresponding letter which best represents the **return value** of the **function call** below:

```
bool func(bool x, bool y) {
    return (x && y) || (x && !y);
}

func(true, false)
```

true A

false B



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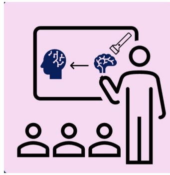

- CS1-Level Programming
- Mental Rotation
- **Prose Fill in the Blank**

Please type the corresponding letter which best represents the **return value** of the **function call** below:

```
bool func(bool x, bool y) {
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}

func(true, false)
```
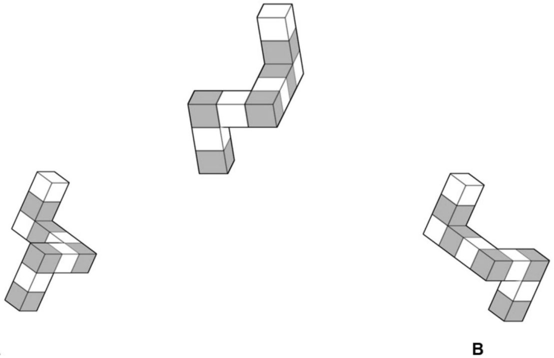

true — A

false — B

Please type the corresponding letter of the bottom objects to give your answer.



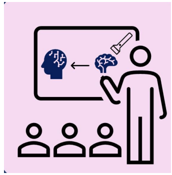
Please type the corresponding letter of the word which best fills in **BLANK** in the sentence below:

The author presents the life of Zane Grey with **BLANK** unusual in a biographer: he is not even convinced that Grey was a good writer.

an eloquence — A

a detachment — B

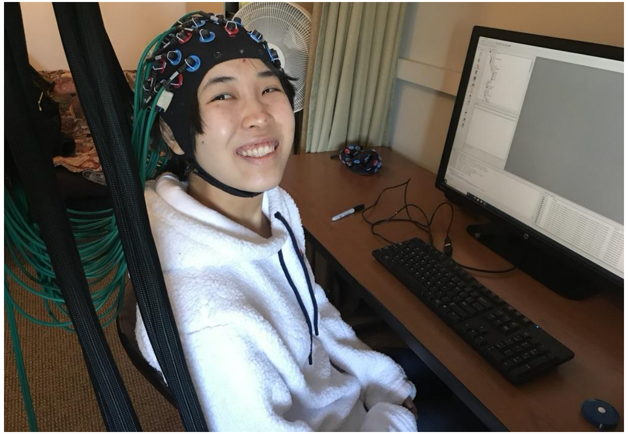
Proposed Scan Data Collection and Analysis



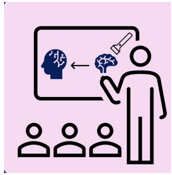
- Each scan session lasts two hours
  - 90 stimuli, 30 of each type (programming, mental rotation, reading)

- 36 participants, **31 valid** (24 female, 7 male)

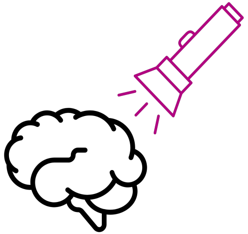
- Data Analysis
  - Compare activation by task by brain area using best practices from psychology
  - Significance threshold: $p < 0.01$.
  - FDR to correct for multiple comparisons: $q < 0.05$



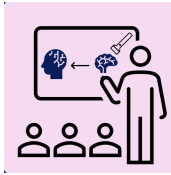
A Mathematical Model of Novice Cognition: Primary Research Questions



- *Comparative Activation*: Do true programming novices rely **more on spatial or language** brain regions while programming?
  a. How do novices' brain activation patterns **compare to those of expert developers**?



Preliminary Results: Comparative Brain Activation



- Question: **Do novices use more spatial or language areas while programming?**

- Result: While areas associated with both are activated, we find **more substantial differences between Coding and Reading** than between **Coding and Mental Rotation**

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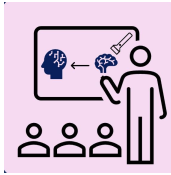

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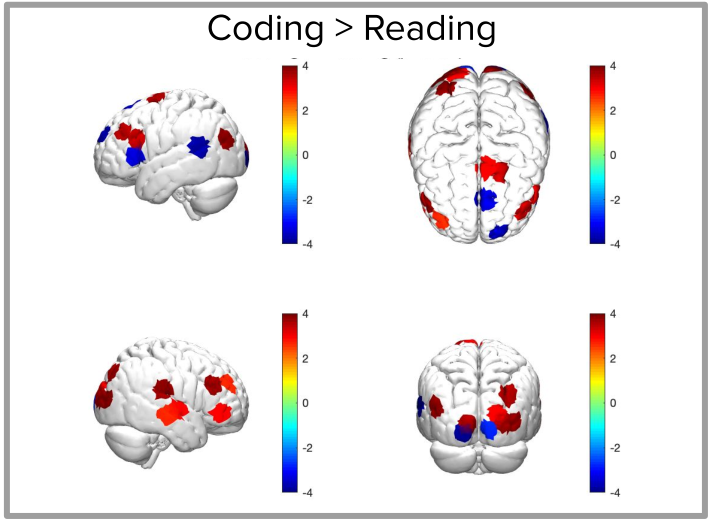

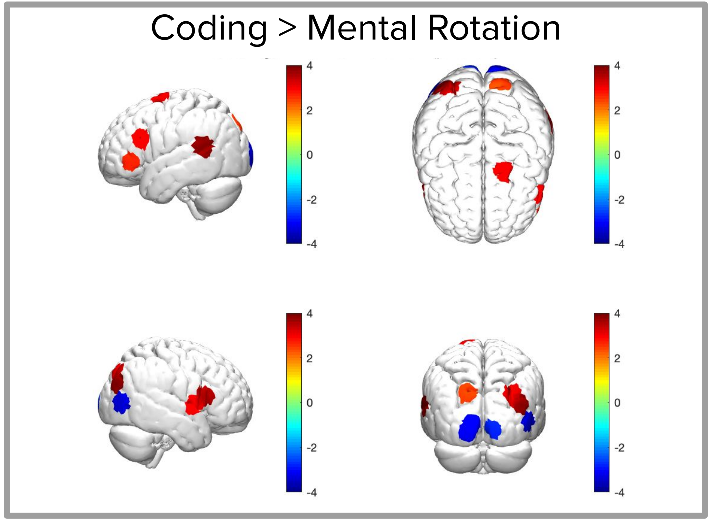

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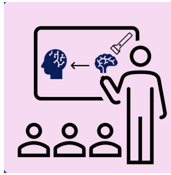

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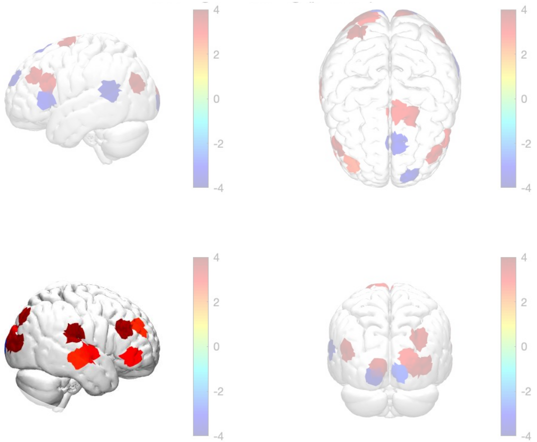

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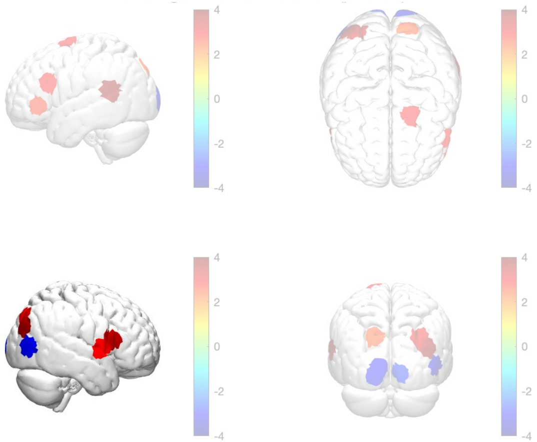

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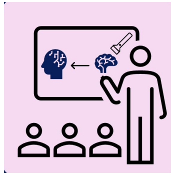

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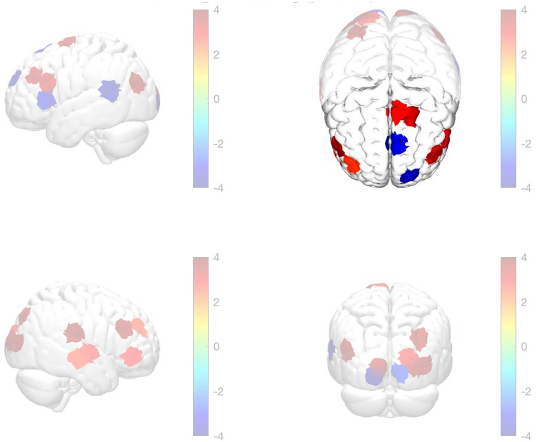

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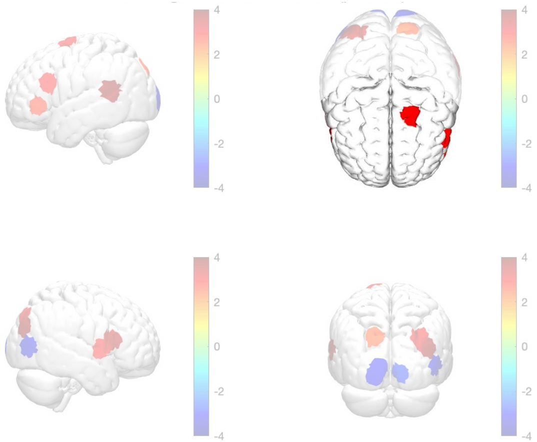

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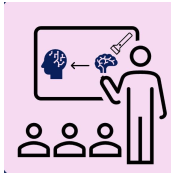

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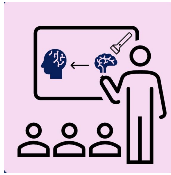

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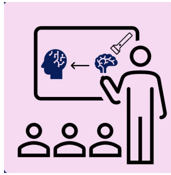
- Result: While areas associated with both are activated, we find **more substantial differences between Coding and Reading** than between Coding and Rotation

- We also find that for novices coding engages more **working memory** and is more **cognitively challenging** than does either mental rotation or prose reading

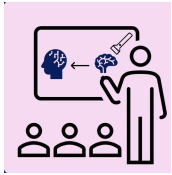
So for novices, programming looks more like spatial visualization than like reading. Now what?

Preliminary Results: Comparing to Experts



- Question: **How does this finding compare to previous studies with experts?**
- Floyd *et al.* found that coding and prose tasks are more similar in terms of neural activity for senior undergraduate than for mid-level undergraduates
- Our results: **the pattern continues to novices**. For less experienced programmers, **programming and reading show less cognitive similarity**
- Implications for developer training and pedagogy:
  - Perhaps **spatial skills enable general problem solving** for novices, but **domain-specific programming strategies** use **more reading-associated** cognitive processes
  - Directly training reading-based domain-specific strategies may help **novices become experts faster**

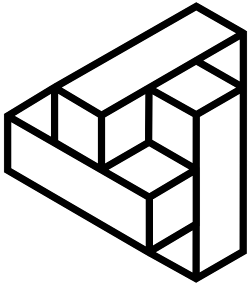
Preliminary Results Summary



For novices, **spatial reasoning is "more similar" to programming than reading** at a cognitive level.

This is **in contrast to results with expert developers**, and has **implications for** future programming **training** or **interventions**.

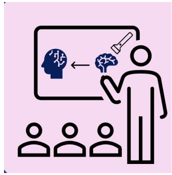
Phase 2: Transfer Training
A Tale of Two Cognitive Interventions



vs.

Standardized and Validated Spatial Reasoning Training

Our Novel CS-focused Technical Reading Training

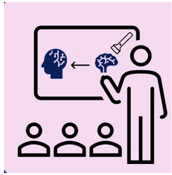


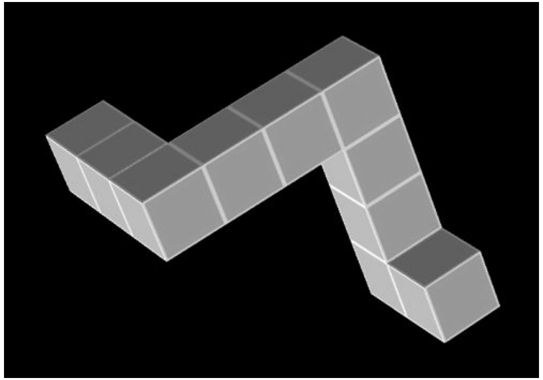
Intervention 1: Spatial Reasoning Training

- **Spatial Reasoning** is the ability to mentally manipulate 2D and 3D shapes

- We use a **validated pre-made Spatial Reasoning Training Curriculum** developed for engineering students
  - Developed by Sorby *et al.* (2000)

- Includes sketching practice of shape rotation projection, and folding

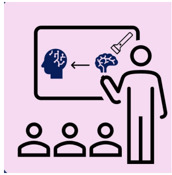


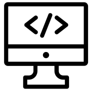


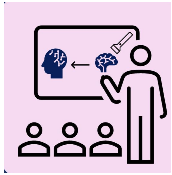
Intervention 2: Technical Reading Training

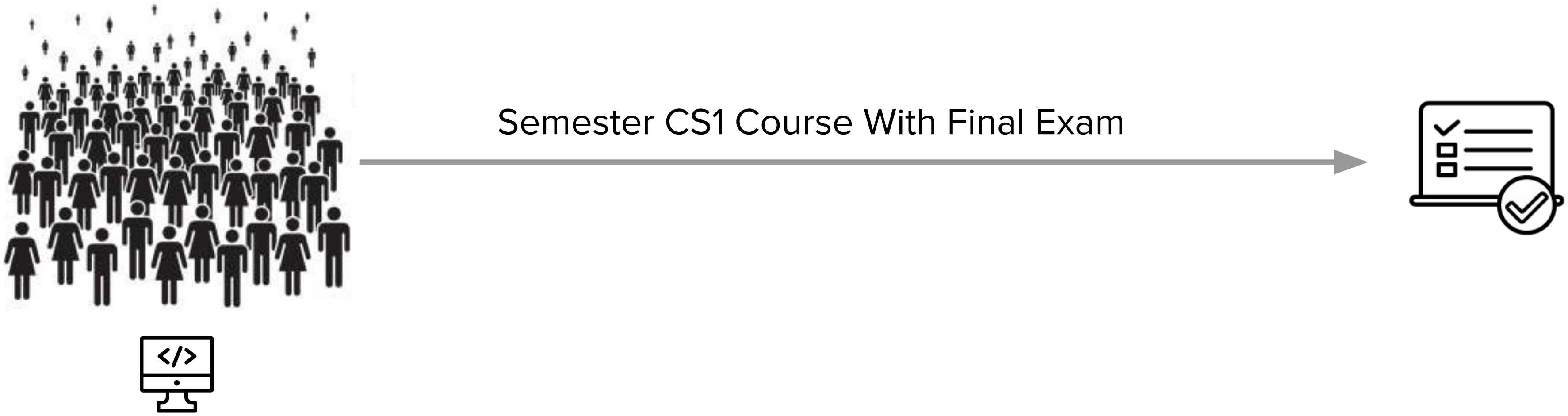
- We propose an intervention to teach **strategies** for **efficiently understanding scientific writing**

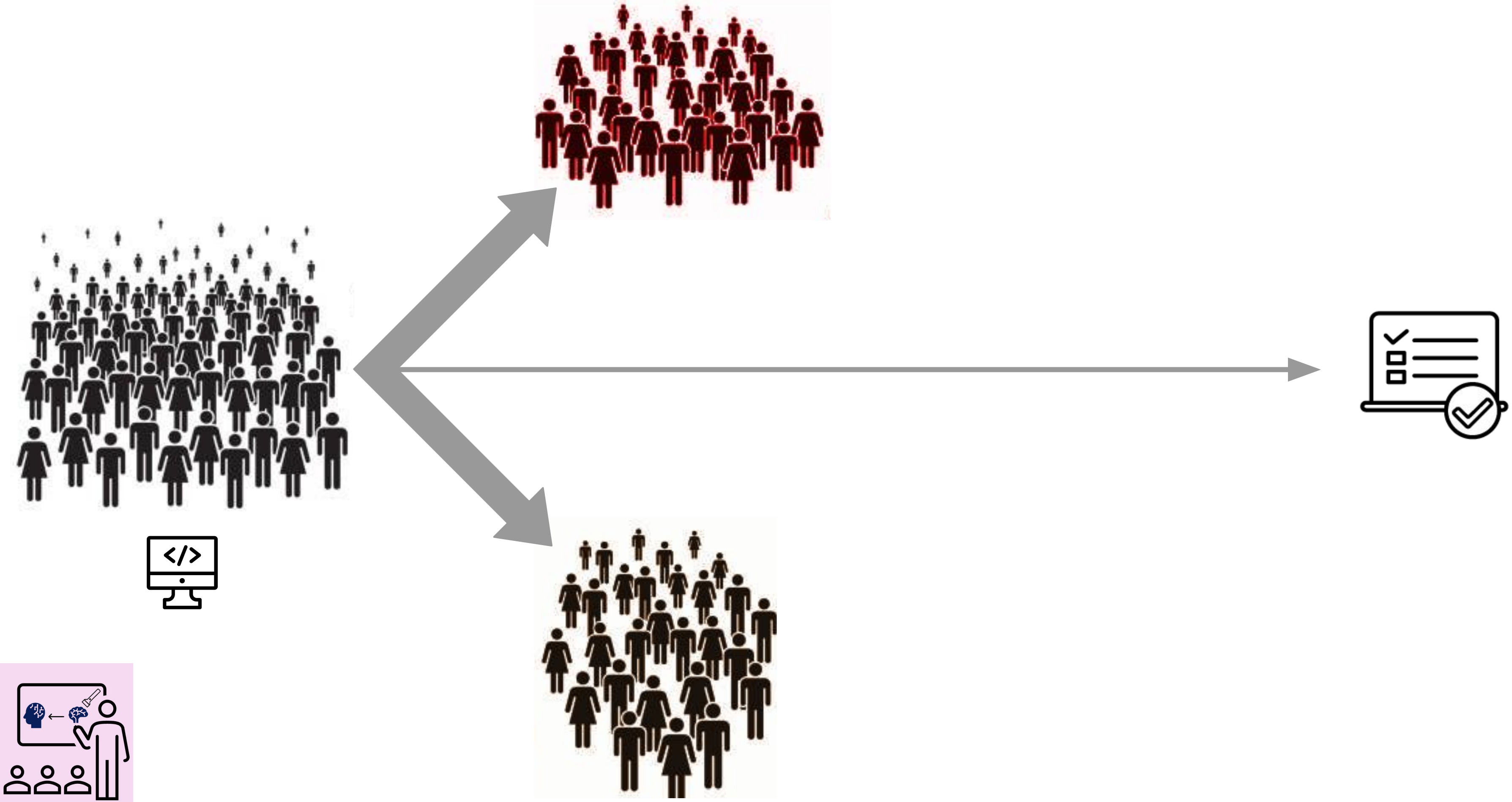
- Strategies focused on **using structural cues to scan texts** to retrieve and understand key points
    - **Experienced programmers tend to read code non-linearly**, focusing on high level features.

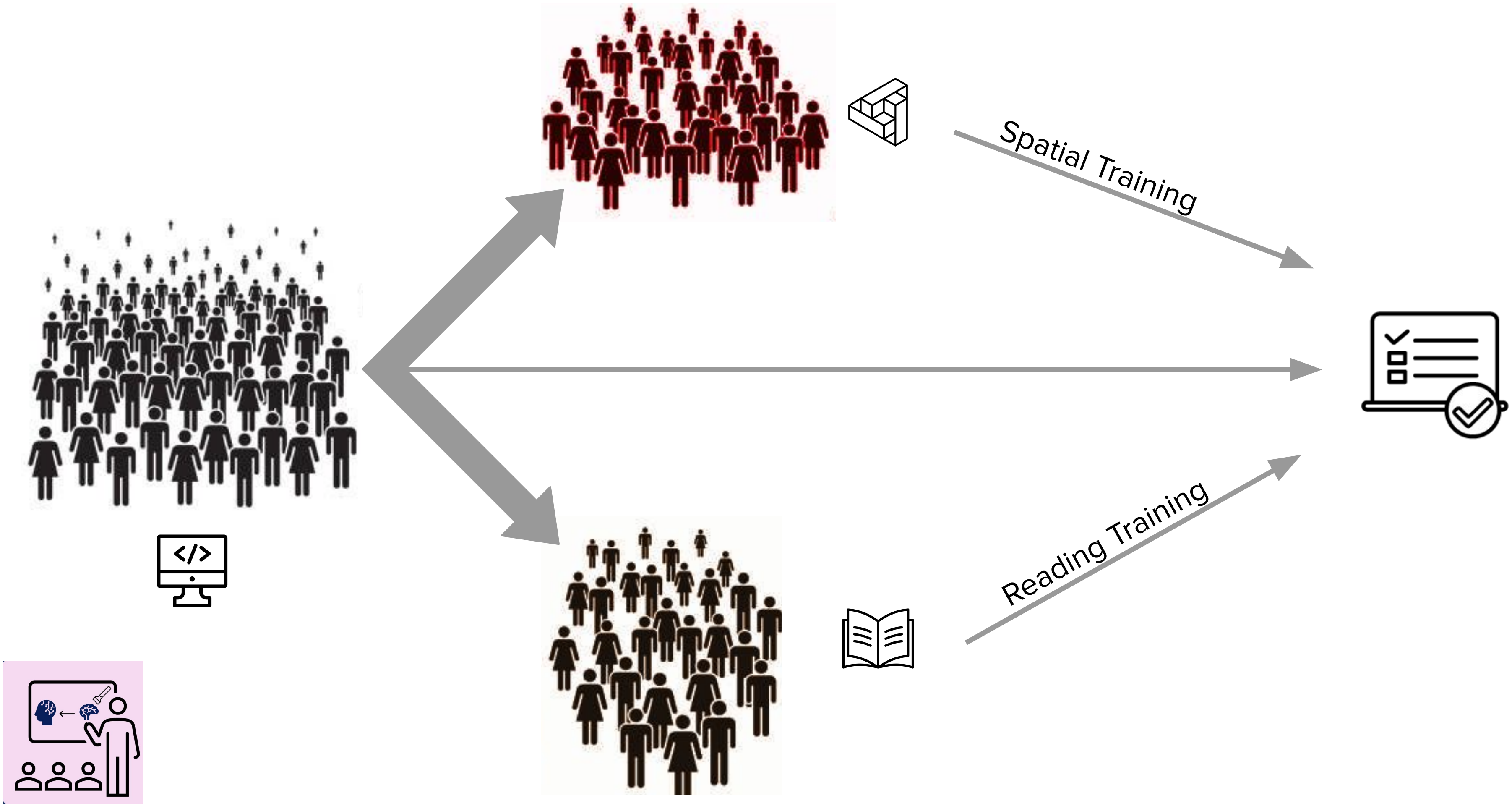


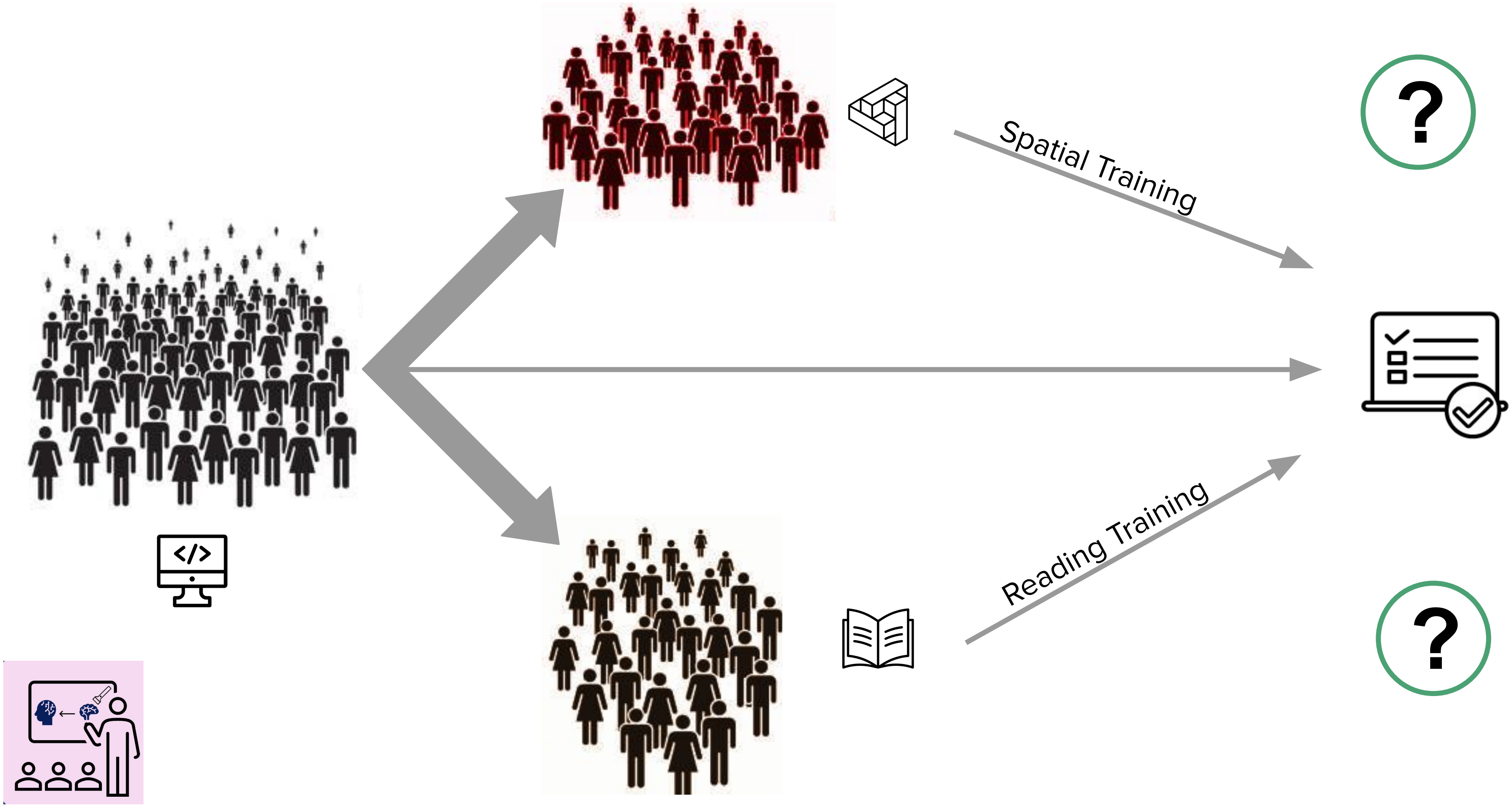





Semester CS1 Course With Final Exam




Spatial Training
Reading Training


Spatial Training
?
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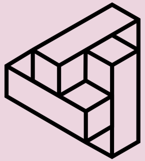
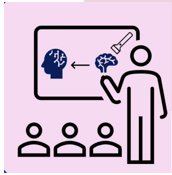
Transfer Training Results: Which Group Did Better?

Spatial Reasoning Training



Technical Reading Training



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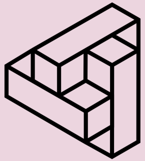

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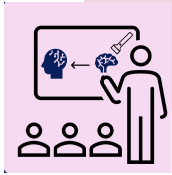

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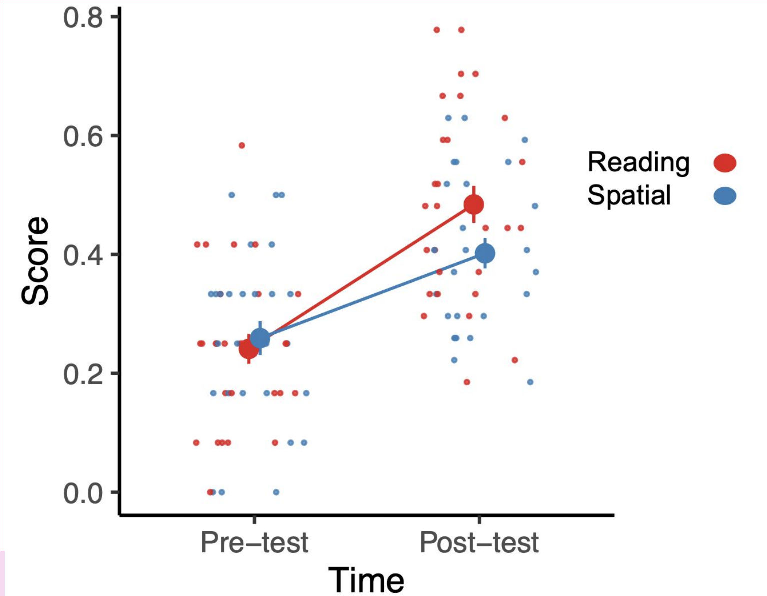
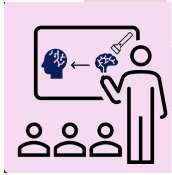
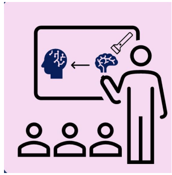


Technical Reading Training

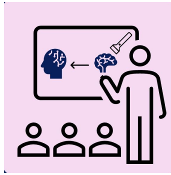


Now that we know that our Reading Training *transferred* to CS1, **what programming skill** did it help?

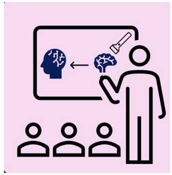


Now that we know that our Reading Training *transferred* to CS1, **what programming skill** did it help?

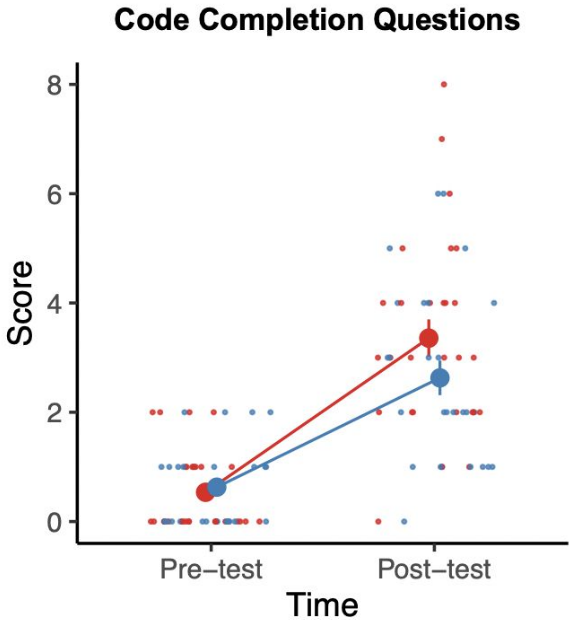
Our final programming assessment (the SCS1) had three types of questions: **code completion**, **definitional**, and **code tracing**



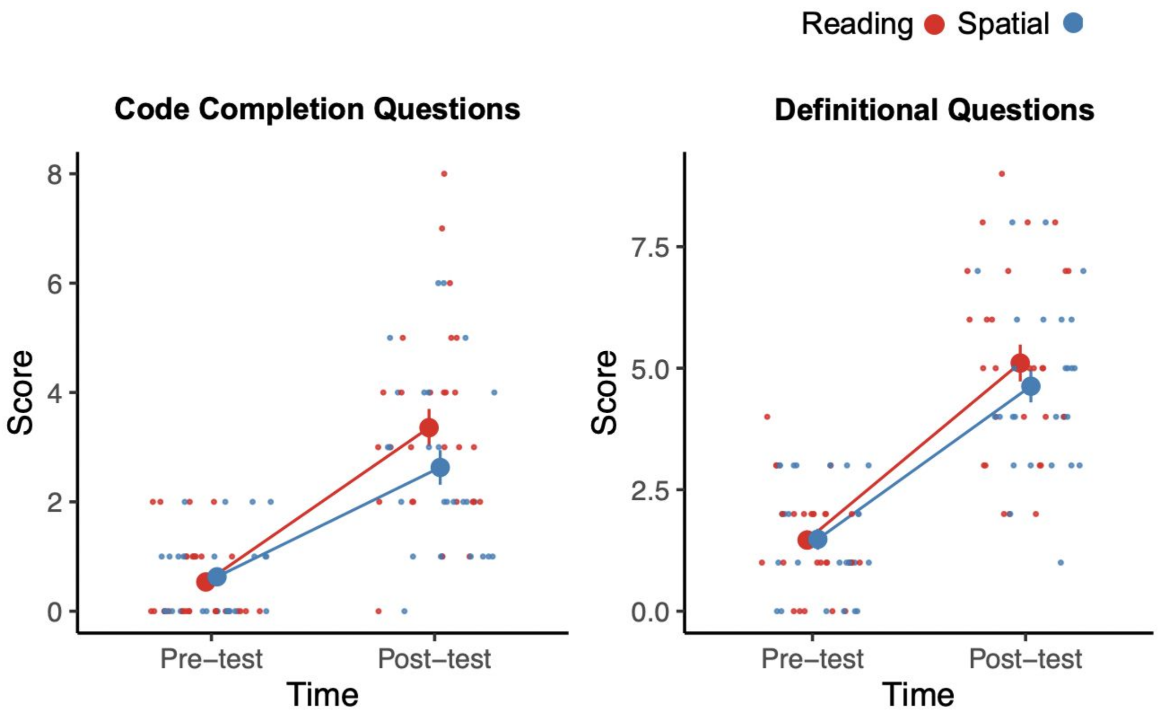
How did the Reading Training Help?



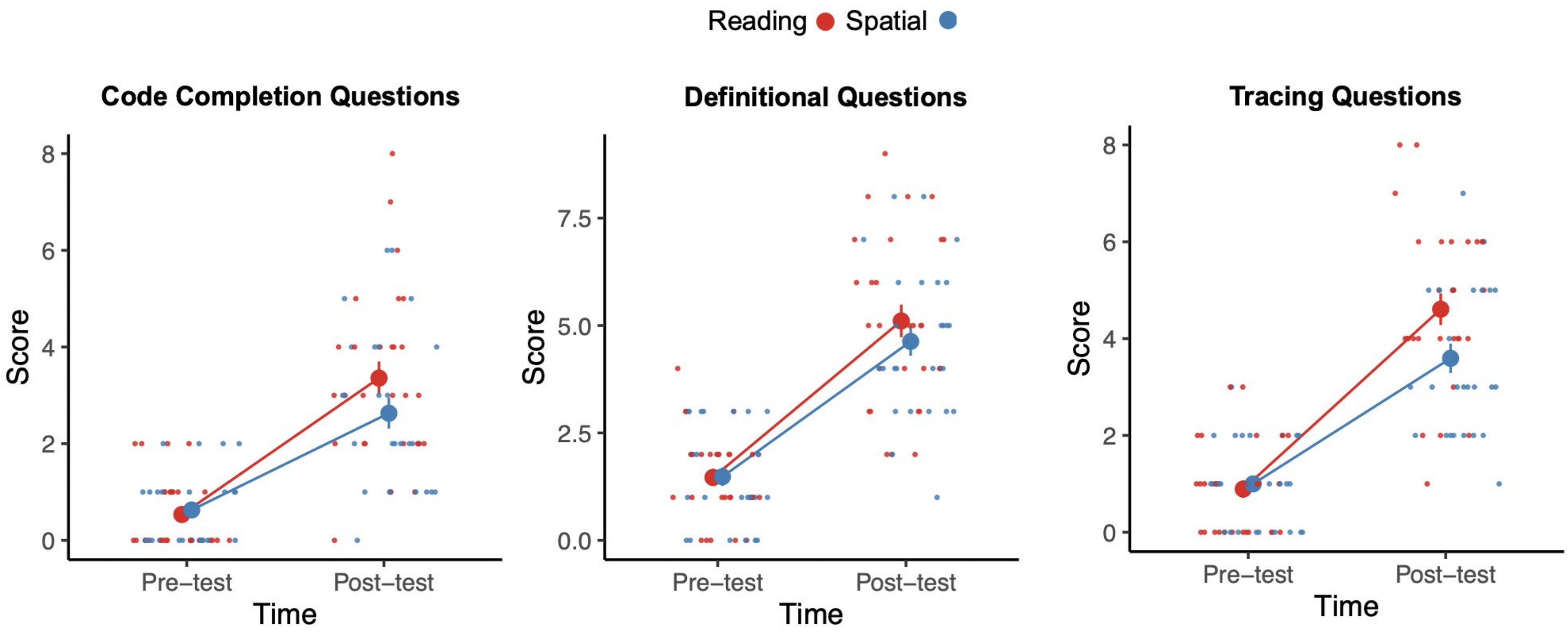
Reading ● Spatial ●



How did the Reading Training Help?



How did the Reading Training Help?



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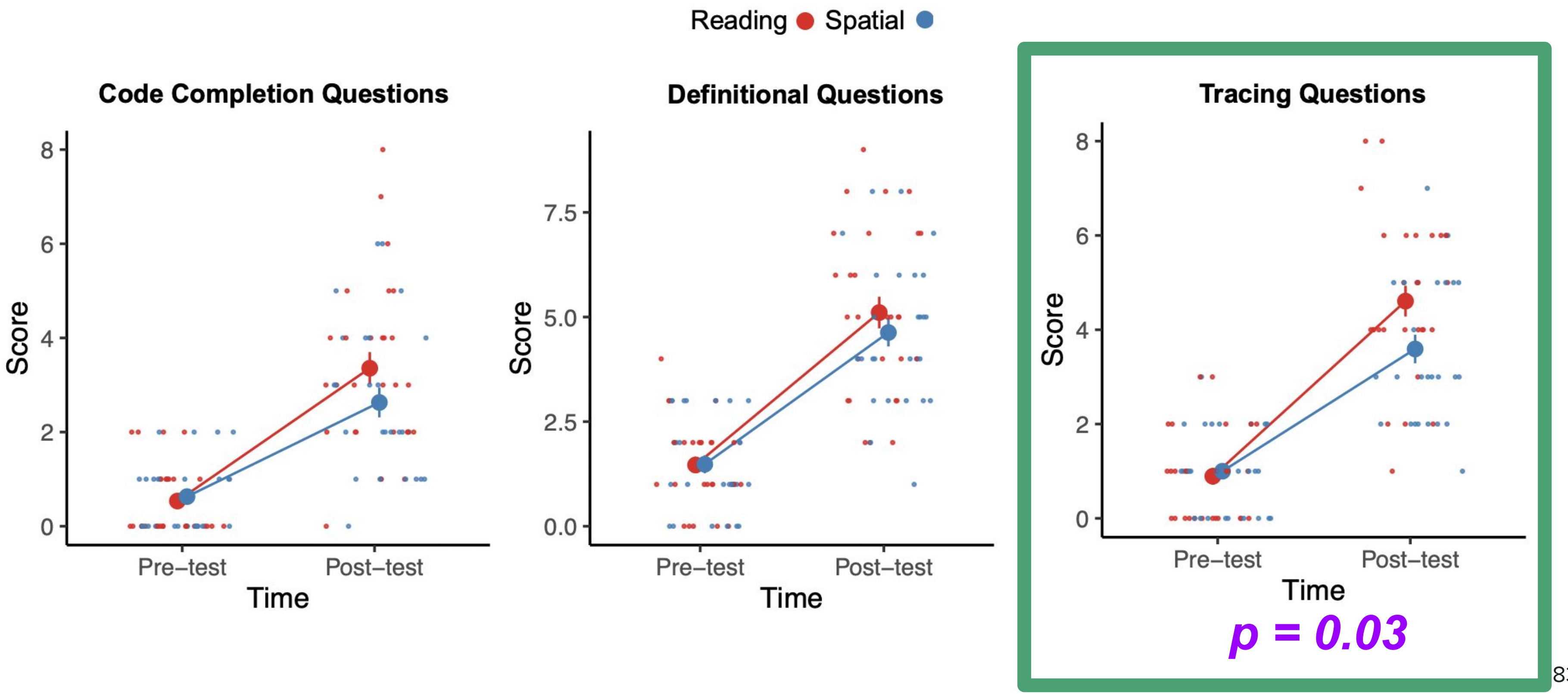
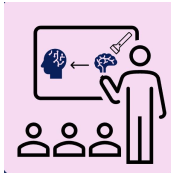


Lens 2 Summary



Phase 1: **Neuroimaging**

ICSE, 2021

- *Proposal:* model novice programmer cognition using using fNIRs
- *Preliminary Results:* For novices, programming is a challenging **working-memory intensive** task. In contrast to studies with experts, **spatial reasoning is "more similar" to programming than reading** for novices at a cognitive level

Phase 2: **Transfer Training**

FSE, 2021

- *Proposal:* investigate transfer training in computing by **comparing the impact of two cognitive interventions on novice programming** in a controlled, longitudinal study
- *Preliminary Results:* **Technical Reading Training helped programming ability more than spatial training**, especially **helping novices trace through code**

Developing Efficient and Usable Programming Support

Can we support non-traditional novices in **writing more correct code faster?**

Designing Effective Developer Training

Can we use **cognitive insights** to inform training and **improve programming outcomes?**

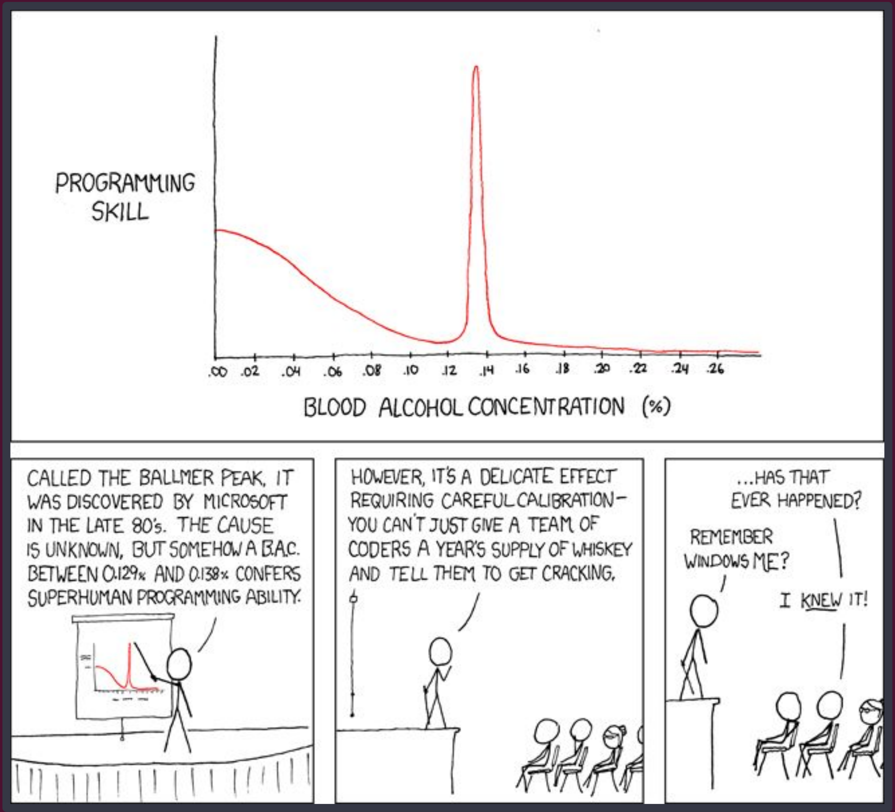
Understanding External Productivity Factors

How does **psychoactive substance** use **impact software productivity?**

Psychoactive Substances and Programming?

A case study on how understudied external factors can impact software productivity

ICSE 2022, 2023, 2024



Credit: XKCD Comic, https://xkcd.com/323/

CULTURE OF PSYCHOACTIVE SUBSTANCE USE AND SOFTWARE

Based upon my experiences and observations:

- caffeine
- nicotine
- alcohol
- ritalin
- modafinil

I've never met a developer that didn't use one of the aforementioned drugs *during work*.

Coder's High

Programming is just like drugs, except the dealer pays you.

BY DAVID AUERBACH JUNE 17, 2014 • 12:02 PM

"Taking LSD was a profound experience, one of the most important things in my life"

\- Steve Jobs

OLIVIA SOLON LONG READS 24.08.2016 08:28 AM

Under pressure, Silicon Valley workers turn to LSD microdosing

However, this culture may conflict with some organizational structures –

Take cannabis-related policies as an example:

We have a strict drug and alcohol policy. Employees are not permitted to use, possess, sell, transfer, manufacture, distribute, or be under the influence of illegal drugs on Cisco-owned or leased property, during working hours, while on company business, or while using company property.

Although certain jurisdictions may allow the prescription or other use of marijuana, this policy also applies to marijuana, which remains illegal under U.S. Federal law. Employees are not permitted to use, possess, sell, transfer, manufacture, distribute or be under the influence of these drugs while on Cisco owned or leased property, during working hours, while on company business, or while using company property. In additi
on du
or the

29% of software developers have taken a drug test for a programming-related job. (Endres et al, 2022)

MOTHERBOARD
TECH BY VICE

The FBI Says It Can't Find Hackers to Hire Because They All Smoke Pot

The FBI is struggling to find good hackers because of marijuana rules

By MARY SCHUMACHER
THE FRESH TOAST | APR 23, 2018 AT 11:52 AM

Proposed Study Overview

Phase 1: **Interviews and Survey**

- We propose to understand if, when, or why developers use psychoactive substances while programming using a **large-scale survey** and **qualitative interviews** with professional prop

ICSE, 2022, 2023

Phase 2: **Observational Study**

- We propose to build a mathematical model of how one substance, cannabis, impacts programming performance using a **controlled, observational study**.

Preliminary work not published

Phase 1: **Survey Methodology**

- **Goal:** To understand *if, when,* and *why* developers use cannabis while programming
- **Survey Design:**
    - 15-minute Qualtrics survey with questions about demographics, programming background, cannabis usage history, and experiences using cannabis while programming

- **Survey Populations:**
    - GitHub: Sent emails to 5,000+ US-based developers on popular projects
    - University of Michigan: Sent emails to 5,000+ current and recent graduates
- **Survey Ethics:**
    - We also need to make sure we distribute this survey **ethically**: responses are **anonymous** and **confidential**

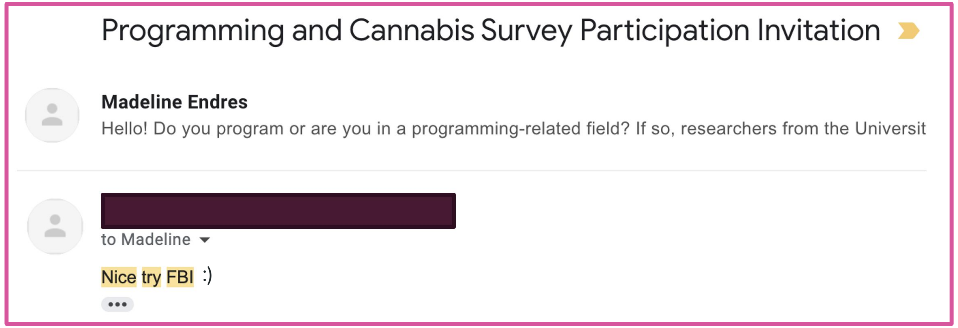
Phase 1: SURVEY RESPONSES

803 valid responses:

- 440 from GitHub
- 339 from University of Michigan
- 24 from Social Media

Demographics:

- 83% Men, 14% Women, 2% Non-binary
- Ages range from 15 to 70
- 56% Full-time programmers, 36% Students

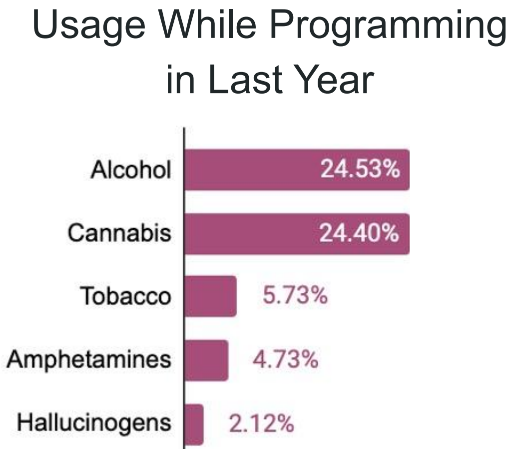

Programming and Cannabis Survey Participation Invitation

Madeline Endres
Hello! Do you program or are you in a programming-related field? If so, researchers from the Universit

[redacted]
to Madeline
Nice try FBI :)

Job Title (could select multiple)	
Software Engineer	311
Developer	270
Systems Engineer	72
CS Researcher	53
CS Instructor	49
Data Scientist	49

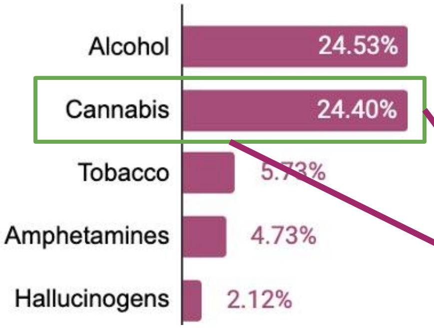
Phase 1 Preliminary Results: **Summary**



:)

Phase 1 Preliminary Results: **Summary**

Usage While Programming in Last Year



- 33% use cannabis for work-related tasks
- 11% use cannabis at a frequency likely to be caught by a drug test
- Qualitative evidence from cannabis-using includes conflicting experiences, with some reporting impairment with others reporting programming enhancement.

:)

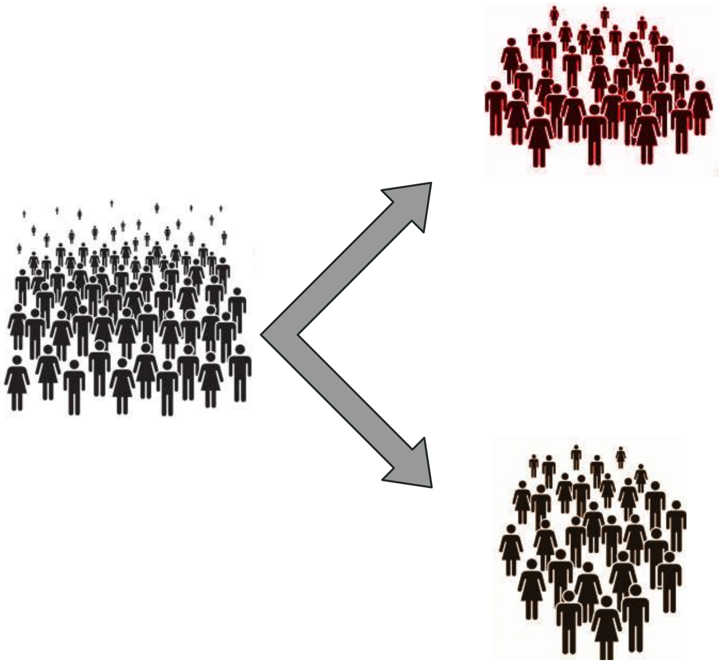
Phase 2: A Controlled Study of Cannabis's Impacts

- Goal: To **build a mathematical model of how cannabis use impacts programming.**
  - We want our model to be rigorous enough to be used by individual developers and policy makers alike in making more informed cannabis and programming decisions.
  - We **pre-registered our hypotheses** to facilitate future replication.

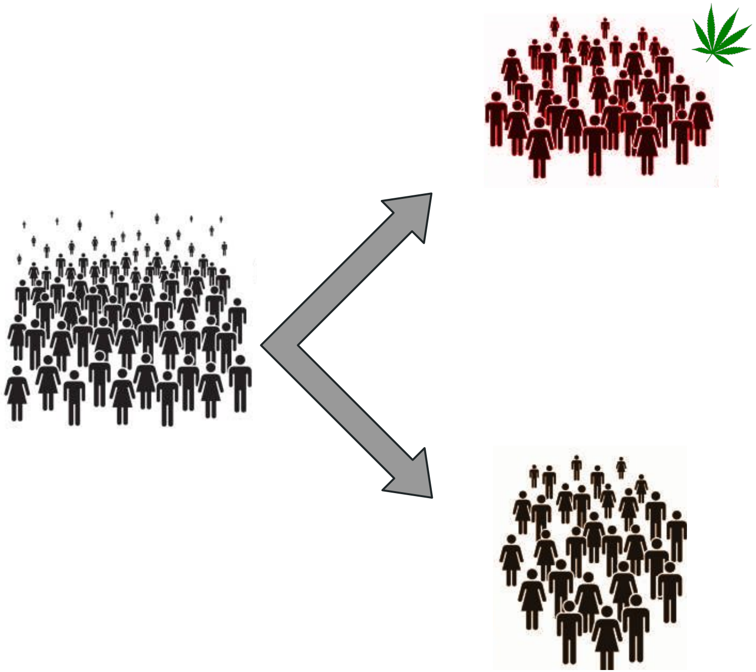
A Controlled Observational Study: Cannabis

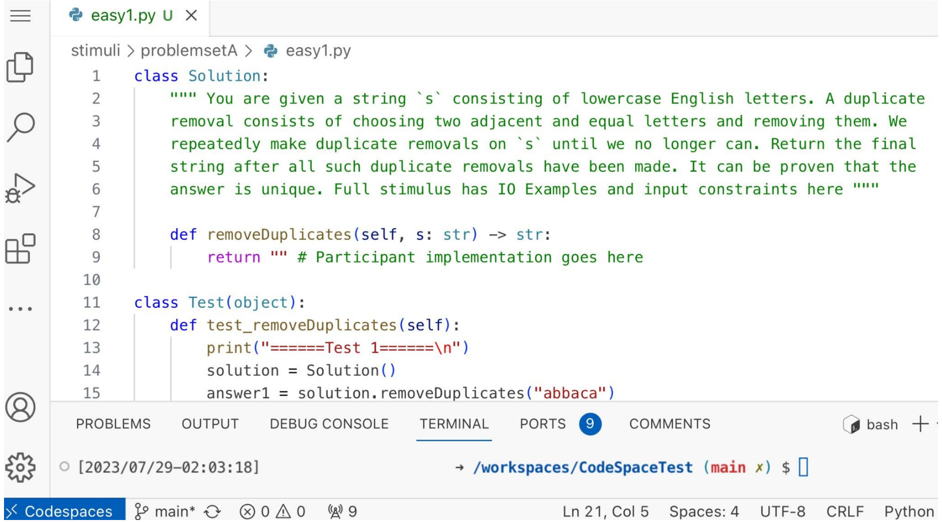
- Goal: To **build a mathematical model of how cannabis use impacts programming.**
  - We want our model to be rigorous enough to be used by individual developers and policy makers alike in making more informed cannabis and programming decisions.
  - We **pre-registered our hypotheses** to facilitate future replication.

- Design Considerations:
  - Achieving **sufficient statistical power** to answer our **pre-registered research questions**
  - Balancing Ecological Validity with Experimental Control
  - Maximizing Participant Privacy and Safety



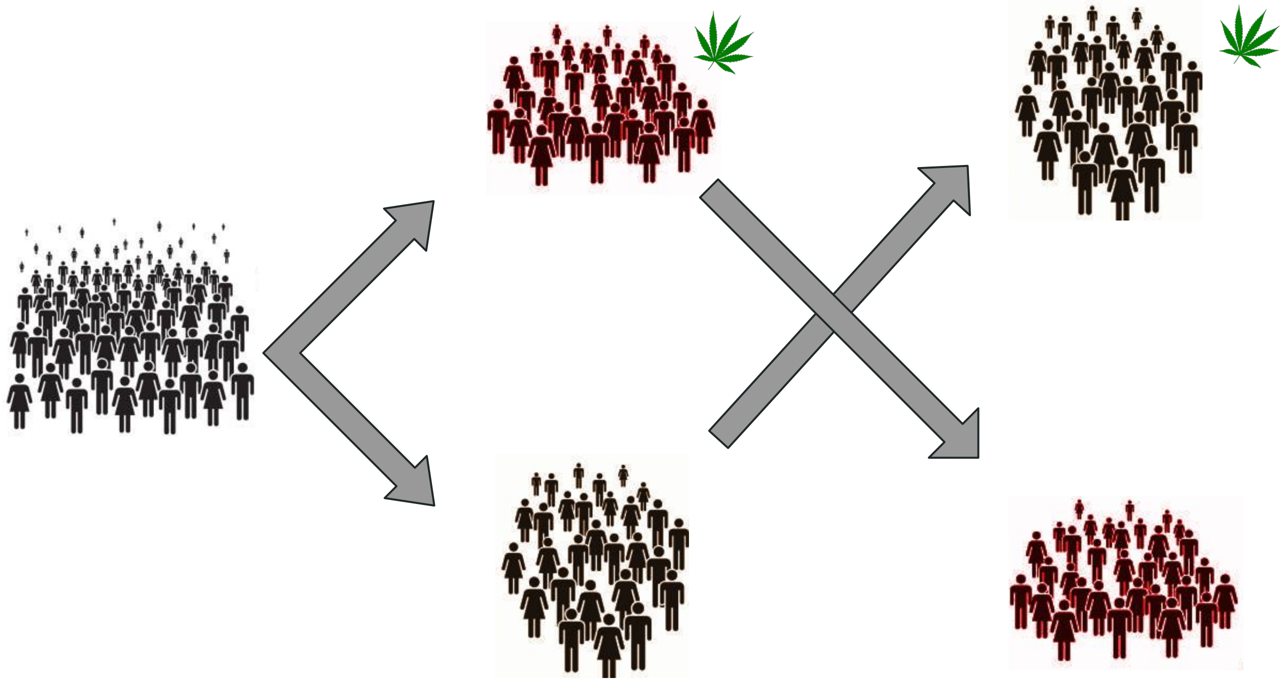
Remote Programming Session 1





Remote Programming Session 1

Remote Programming Session 2



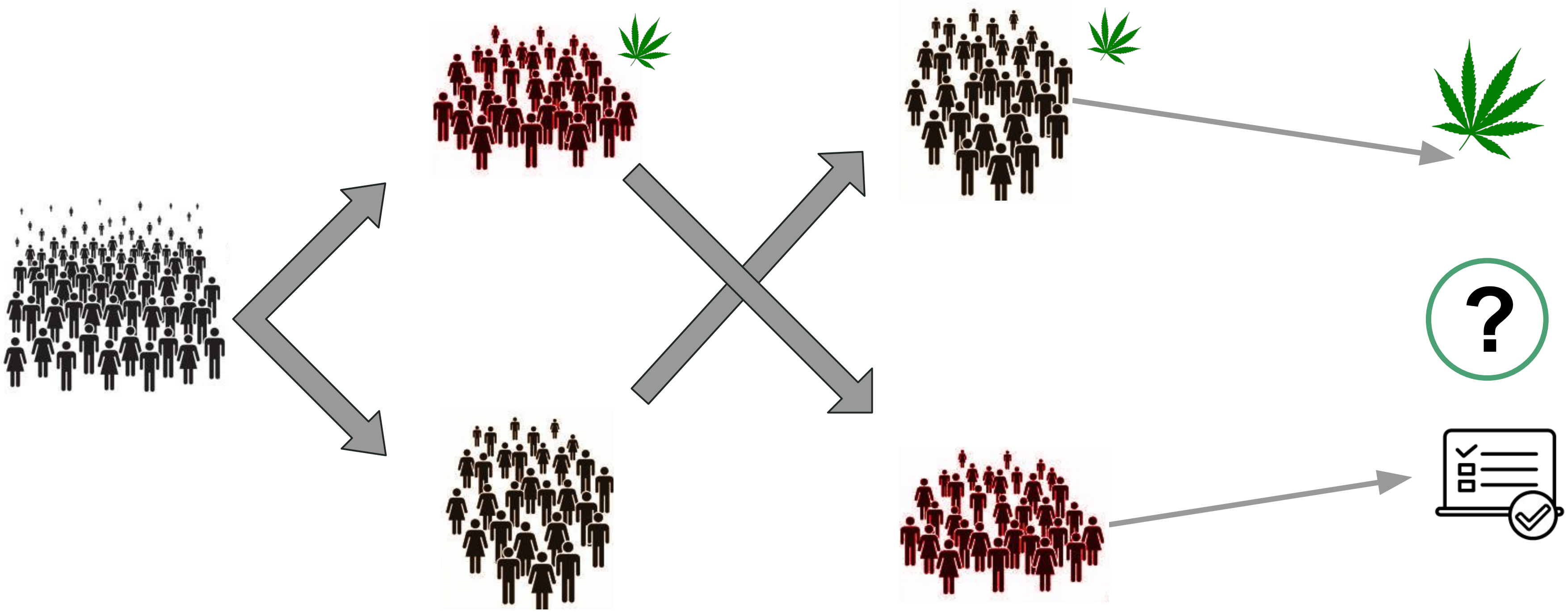
```
easy1.py U ×
stimuli > problemsetA > easy1.py
class Solution:
    """ You are given a string `s` consisting of lowercase English letters. A duplicate
    removal consists of choosing two adjacent and equal letters and removing them. We
    repeatedly make duplicate removals on `s` until we no longer can. Return the final
    string after all such duplicate removals have been made. It can be proven that the
    answer is unique. Full stimulus has IO Examples and input constraints here """

    def removeDuplicates(self, s: str) -> str:
        return "" # Participant implementation goes here

```

Remote Programming Session 1

Remote Programming Session 2



easy1.py U

stimuli > problemsetA > easy1.py

```python
class Solution:
    """ You are given a string `s` consisting of lowercase English letters. A duplicate
    removal consists of choosing two adjacent and equal letters and removing them. We
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Outstanding Work: **Pre-registered Hypotheses**

RQ1: How does cannabis intoxication while programming **impact program correctness**?

- Hypothesis: Programs will be **less correct** when written by cannabis-intoxicated programmers.

RQ2: How does cannabis intoxication while programming **impact programming speed**?

- Hypothesis: Cannabis-intoxicated programmers **will take longer to write** programs.

r).

Outstanding Work: **Pre-registered Hypotheses**

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RQ2: How does cannabis intoxication while programming **impact programming speed**?

- Hypothesis: Cannabis-intoxicated programmers **will take longer to write** programs.

r).

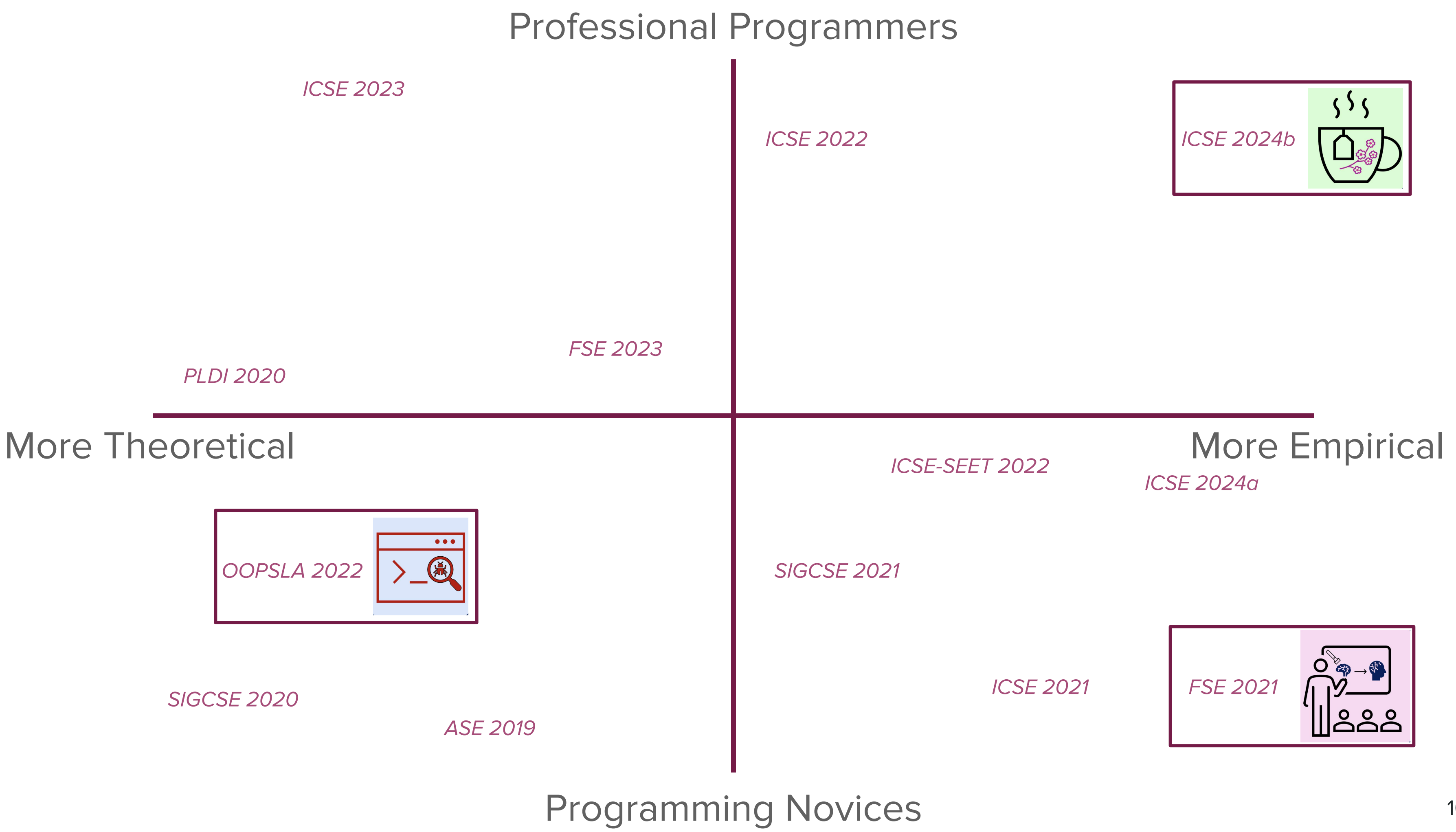
Current Status:
We have received IRB approval for our proposed study and have funding for participants. We have successfully obtained preliminary data from 74 participants.

Lens 3 - Summary: Psychoactive Substances and Programming

- In a survey of 800 programmers, we found that psychoactive **substance use is common** in software, especially alcohol and cannabis

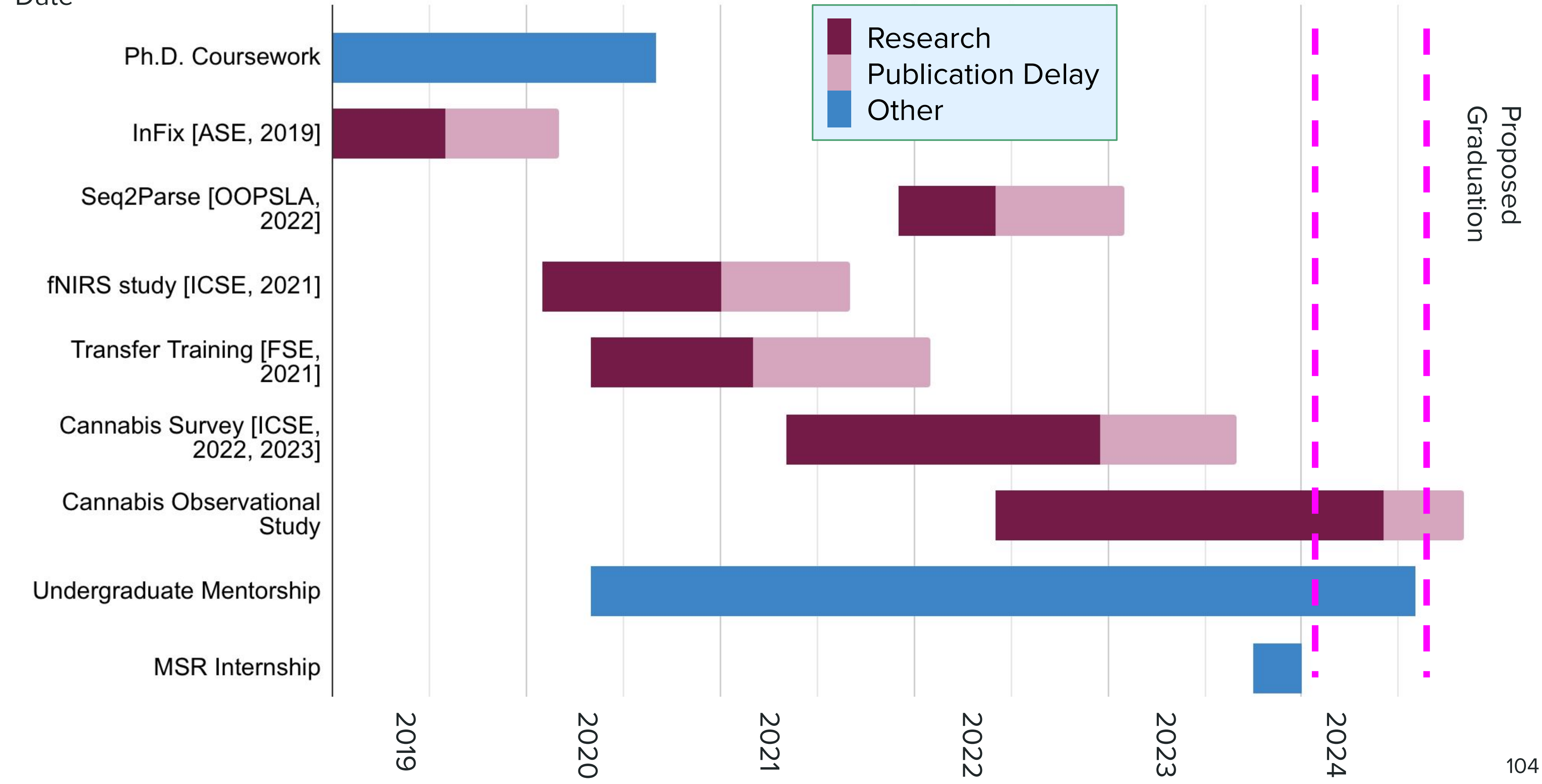
- We found that many programmers use cannabis at rates that can be tested by current software drug policies, and that there are conflicting qualitative experiences of its impacts

- We have received IRB approval to conduct an observational study of cannabis's impact on programmers, and have collected preliminary data



Professional Programmers
ICSE 2023
ICSE 2022
ICSE 2024b
FSE 2023
PLDI 2020
More Theoretical
More Empirical
ICSE-SEET 2022
ICSE 2024a
OOPSLA 2022
SIGCSE 2021
ICSE 2021
FSE 2021
SIGCSE 2020
ASE 2019
Programming Novices

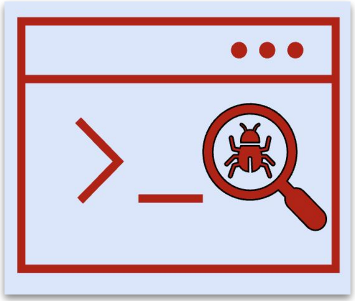
Proposed Ph.D. Timeline



Supporting Publications

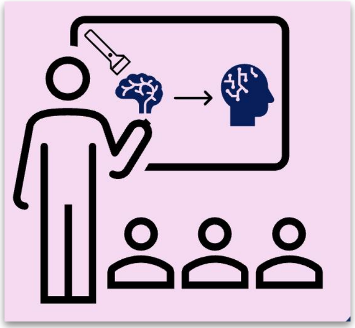
1. **ICSE, 2024** *Causal Relationships and Programming Outcomes: A Transcranial Magnetic Stimulation Experiment,* Ahmad, H., **Endres, M.**, Newman, K., Santiesteban, P., Shedden, E., Weimer, W.
2. **FSE, 2023** *A Four-Year Study of Student Contributions to OSS with a Lightweight Intervention,* Fang, Z., **Endres, M.**, Zimmermann, T., Ford, D., Weimer, W., Leach., K., Huang, Y
3. **ICSE, 2023** *From Organizations to Individuals: Psychoactive Substance Use By Professional Programmers,* Newman, K., **Endres, M.,** Weimer, W., Johnson, B.
4. **OOPSLA, 2022** *Seq2Parse: Neurosymbolic Parse Error Repair,* Sakkas, G., **Endres, M.,** Guo, P., Weimer, W., Jhala, R.
5. **ICSE, 2022** *Hashing It Out: A Survey of Programmers' Cannabis Usage, Perception, and Motivation,* **Endres, M.,** Boehnke, K., Weimer, W.
6. **ICSE-SEET, 2022** *Debugging with Stack Overflow: Web Search Behavior in Novice and Expert Programmers,* Li, A., **Endres, M.,** Weimer,
7. **FSE, 2021** *To Read or To Rotate? Comparing the Effects of Technical Reading Training and Spatial Skills Training…* **Endres, M.,** Fansher, M., Shah, P., Weimer, W.
8. **ICSE, 2021** *Relating Reading, Visualization, and Coding for New Programmers: A Neuroimaging Study* **Endres, M.,** Karas, Z., Hu, Z., Kovelman, I., Weimer, W
9. **SIGCSE, 2021** *An Analysis of Iterative and Recursive Problem Performance,* **Endres, M.,** Weimer, W., Kamil, A.
10. **PLDI, 2020** *Type Error Feedback via Analytic Program Repair* Sakkas, G.,**Endres, M.,**Cosman, B.,Weimer, W.,Jhala, R.
11. **SIGCSE, 2020** *Pablo: Helping Novices Debug Python Code Through Data-Driven Fault Localization* Cosman, B., **Endres, M.,** Sakkas, G., Medvinsky, L., Yao-Yuan,Y.,Jhala, R.,Chaudhuri, K.,Weimer, W.
12. **ASE, 2019** *InFix: Automatically Repairing Novice Program Inputs* **Endres, M.,** Cosman, B., Sakkas, G., Jhala, R., Weimer, W.

Developing Efficient and Usable Programming Support



Supporting non-traditional novices in **writing more correct code faster**

Designing Effective Developer Training



Use **cognitive insights** to inform training and **improve programming outcomes**

Understanding External Productivity Factors

Exploring how **substance use impacts software productivity**

A Human-Focused Approach to Improving Programmer Productivity

Madeline Endres, PhD Candidate, University of Michigan

Bonus Slides

Visualize Python, Java, JavaSc ×

Not Secure | pythontutor.com/visualize.html#mode=edit

Write code in Python 3.6

```
u = 42
x = float(input())
print(x * math.e / 2)
```

Help improve this tool by completing a **short user survey**

Please wait ... executing (takes up to 10 seconds)

Live Programming Mode

Anecdotal evidence abounds:

Many programmers use cannabis while programming

Posted by u/SmartTest 5 months ago

31

Coding + Cannabis Use

Hey fellow programmers!

I wanted to see what your

and working in the field.

Do you use cannabis and

career?

[redacted] Software Engineer at WeedMaps (2017-present)

Updated Aug 17, 2019 · Upvoted by Hasib Al Muhaimin, IOI participant '13, '14, '15, ACM-ICPC World Finalist 2016 and Stanley Munson, AAS Computer Programming & Network Administrator, Helena College (2019)

At WeedMaps we smoke and code everyday, all day. Some of the smartest, most insightful people I know smoke pot daily.

g thoughts might get in

ally isn't much of an

o really dive deep into

[redacted] Blockchain Engineer at Parallelcoin (2018-present)

Answered Oct 18, 2019

I believe that there is something about the type of brains that are common among programmers that get along well with extra THC. I also want to point out that until the 20th century, people were drinking milk and eating meat fed on hemp seed, and

negative_epsilon · 8 yr. ago

I have attempted to program while both high and drunk, and neither works well. I might think I write good code, but the next morning I look and there are ridiculous errors that I never would have made sober.

coding-on-marijuana · 8 yr. ago

A fair amount of professional experience here. If you're a responsible, mature, self-respecting adult then it's (mj) a great tool to use for software development. YMMV, this is my experience as reflected by my own strengths and weaknesses as a developer.

Stress: None. Bugs won't bug you, defects won't stress you out, inexplicable side-effects become fun logic puzzles.

Cannabis use **can conflict with corporate anti-drug policies**

This conflict **can lead to hiring shortages!**

We have a strict drug and alcohol policy. Employees are not permitted to use, possess, sell, transfer, manufacture, distribute, or be under the influence of illegal drugs on Cisco-owned or leased property, during working hours, while on company business, or while using company property.

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We find that 29% of software developers have taken a drug test for a programming-related job.

MOTHERBOARD
TECH BY VICE

The FBI Says It Can't Find Hackers to Hire Because They All Smoke Pot

The FBI is struggling to find good hackers because of marijuana rules

By MARY SCHUMACHER
THE FRESH TOAST | APR 23, 2018 AT 11:52 AM

How can we represent ill-parsed programs when **training** our classifier?

Buggy Program

```
def foo(a):
  return a + 42

def bar(a):
  b = foo(a) + 17
  return b +
```

Token Sequence

```
def name(name): \n
indent return name + number \n
dedent \n

def name(name): \n
indent name = name(name) + number \n
return name + \n
dedent end_marker
```

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```

Abstracted Token Sequence

```
Stmt \n

def name Params: \n
indent Stmt \n
return Expr BinOp \n
dedent end_marker
```

Great! But we have a new problem: **Ambiguity**

each abstracted token sequence can lead to multiple different ECE parse trees!

How can we represent ill-parsed programs when **training** our classifier?

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Abstracted Token Sequence

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Stmt \n

def name Params: \n
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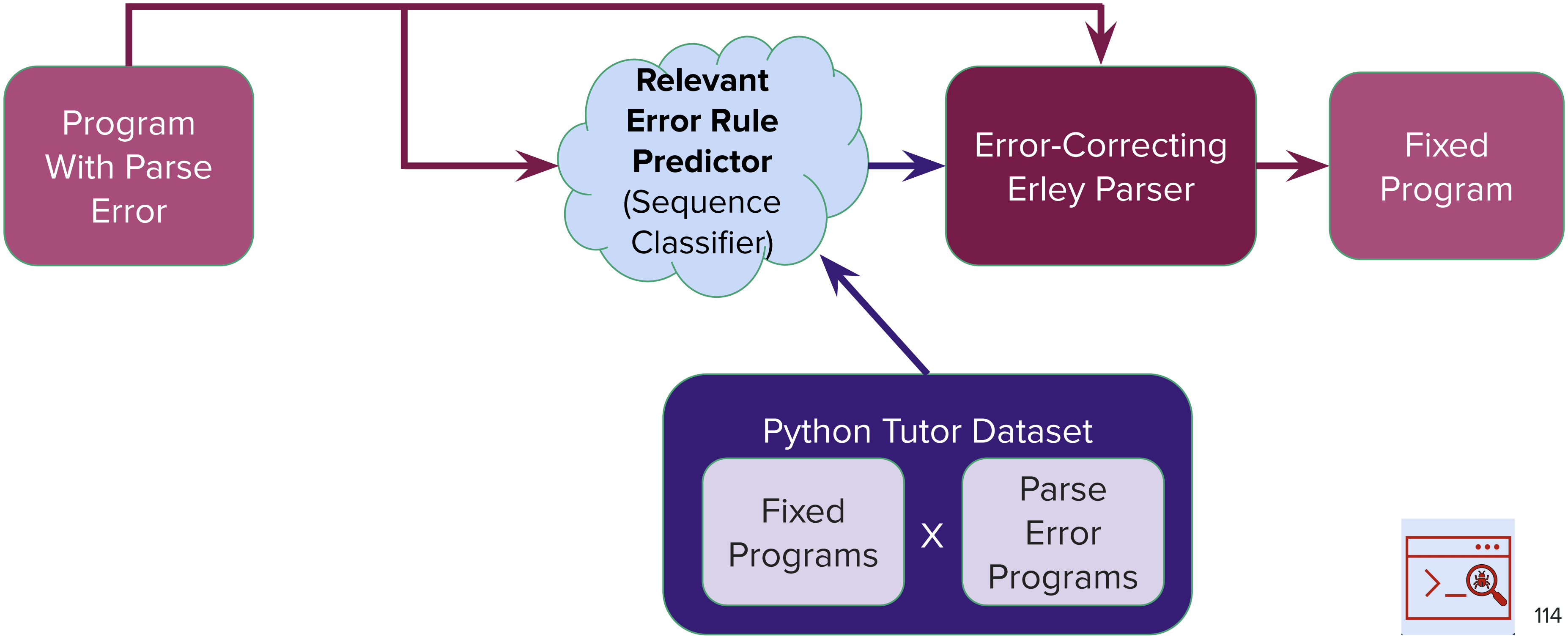
dedent end_marker
```

Great! But we have a new problem: **Ambiguity**

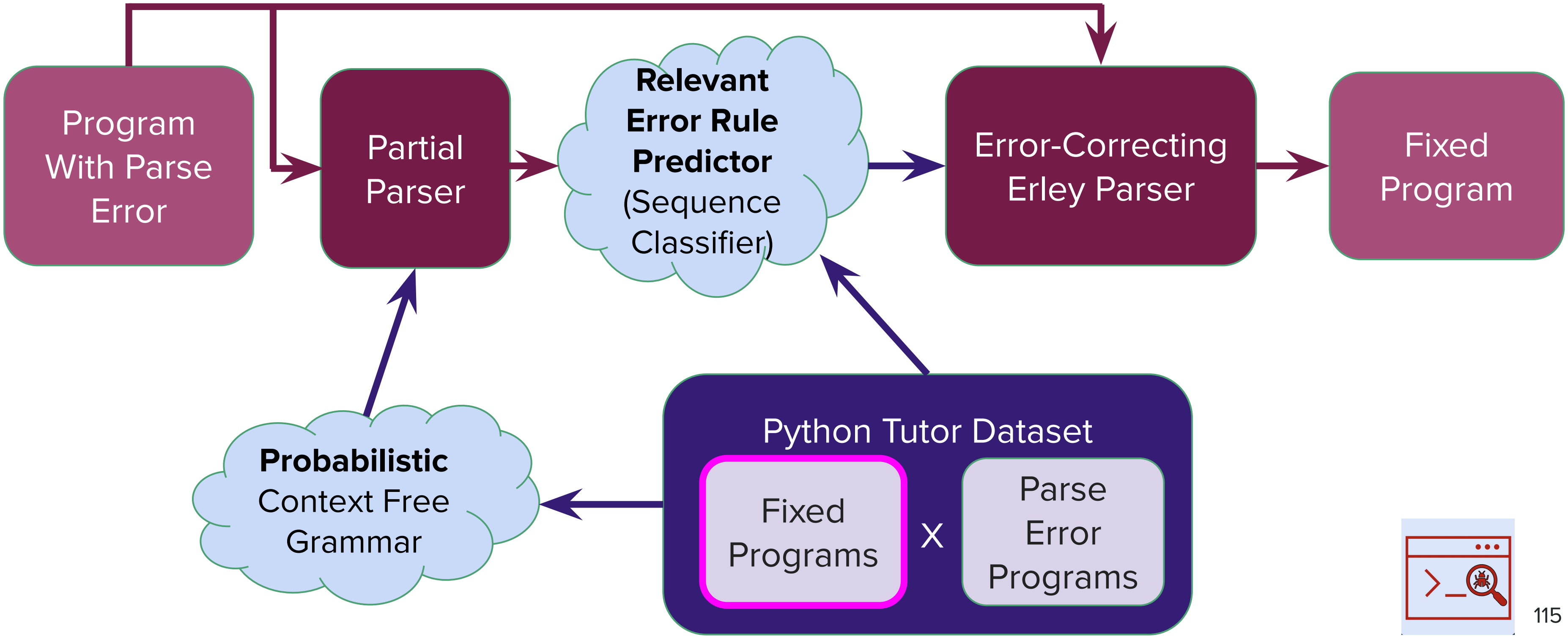
Solution: Learn a *Probabilistic Context Free Grammar* to Pick the Right One

S	$\rightarrow$	Stmts end_marker ($p = \underline{100.0\%}$)
Stmts	$\rightarrow$	Stmt \n ($p = \underline{38.77\%}$) | Stmt \n Stmts ($p = \underline{61.23\%}$)
Stmt	$\rightarrow$	ExprStmt ($p = \underline{62.64\%}$) | RetStmt ($p = \underline{7.59\%}$) | ...
RetStmt	$\rightarrow$	**return** ($p = \underline{1.61\%}$) | **return** Args ($p = \underline{98.39\%}$)

Seq2Parse: Efficient Fixes for Novice Parse Errors



Seq2Parse: Efficient Fixes for Novice Parse Errors



Cannabis sativa is the **world's most commonly used illicit substance**, used by more than 192 million people in 2018

Cannabis is used for many reasons both **medical** (e.g., pain relief) and **recreational** (e.g., altered consciousness)

Cannabis's **legality is changing rapidly** with many countries (e.g., UK, Colombia, Canada, Malawi) recently taking **steps towards legalization**

116

RQ2: Prediction

- Question: **Can brain activation patterns at the start of CS1 predict future programming ability?**

- Method: correlate brain activity interactions with scores on a programming test at the end of the semester (11-12 weeks after the initial brain scan)

- Result: **Yes, it is possible**!

- **Less-similar patterns of activation for coding and mental rotation** in the right frontal hemisphere at the start of the semester **predict better outcomes** on the end-of-semester programming assessment ($r = -0.482$, $p = 0.006$)

RQ2: Prediction Implications

- Perhaps novices **who transition away from general spatial skills** to reading-associated domain-specific strategies earlier **make more progress**
- Provides impetus for **earlier pedagogical interventions**
- Note: we do not see our result supporting essentialist-based theories of programming ability
    - Rather, it provides insight for more **effectively understanding and removing computing barriers**

RQ2: Prediction Summary

Novice brain activity when programming **can predict** future programming ability.

Provides another window into **understanding and ameliorating computing barriers**.