



Three Lenses for Improving Programmer Productivity

From Anecdote to Evidence

Madeline Endres, PhD Defense, 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	<mark>25:1</mark>
Debug Hours: Algebra Problem	170	6	28:1
Debug Hours: Maze Problem	26	1	<mark>26:1</mark>

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Novice Software Developers, All Over Again

Andrew Begel

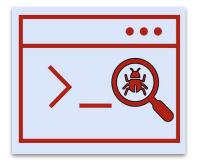
Beth Simon

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

DENAE FORD, Microsoft Research

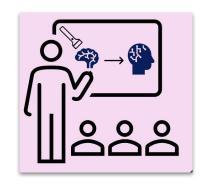
Performance Measure	Slowest Coder	Fastest Coder	Socioeconomic Status and Computer Science Achievement Spatial Ability as a Mediating Variable in a Novel Model of Understanding Miranda C. Parker Amber Solomon Brianna Pritchett
Code Hours: Algebra Problem	111	7	A Large-Scale Survey on the Usability of Al Programming
Code Hours: Maze Problem	50	2	Assistants: Successes and Challenges Jenny T. Liang Chenyang Yang Brad A. Myers
Debug Hours: Algebra Problem	170	6	What Predicts Software Developers' Productivity?
Debug Hours: Maze Problem	26	1	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?

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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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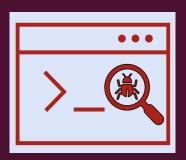
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Support Diverse Developer Groups	I prefer approaches that not only help programmers in general, but also help those who need the most support



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

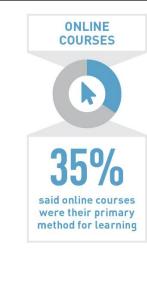
Many People Want to Learn to Code

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

```
1 def listSum(numbers):
2    if not numbers:
3       return 0
4    else:
5       (f, rest) = numbers
6       return f + listSum(rest)
7
8    myList = (1, (2, (3, None)))
9    total = listSum(myList)
```

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**

Visualize Execution

Get Al Help



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)
```

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

Published in OOPSLA, 2022

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Template-repair approach,
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Published in ASE, 2019

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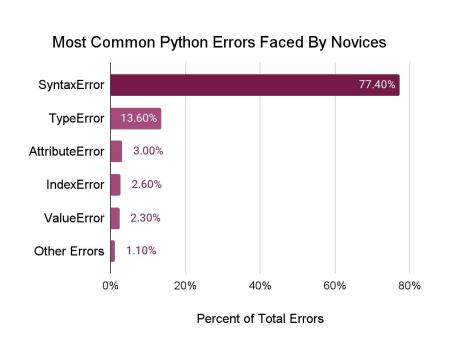
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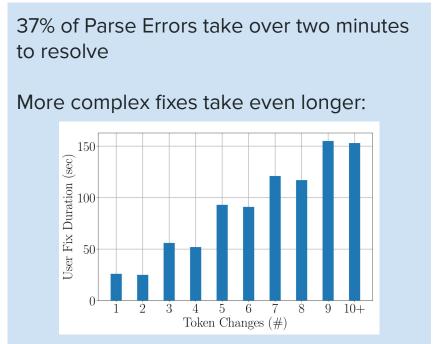
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What do Non-Traditional Novices Struggle with? Parse Errors

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

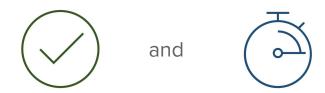




Fixing Parse Errors: How can we support Novices?

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



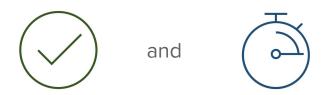
Efficient: Fast enough to be computed in real time



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Symbolic Approach?



Neural Approach?





Parsing Overview

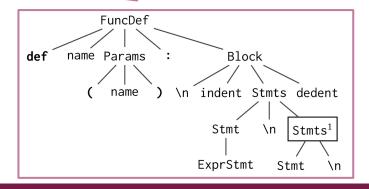


Program P

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

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

Grammar G



Finding Parse Errors: Fault Localization

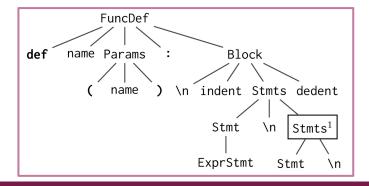


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Fixing Parse Errors: Error Correcting Earley Parsers

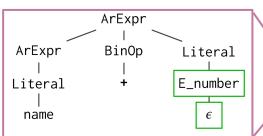


```
Program P
```

Grammar G'

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

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



```
FuncDef

def name Params : Blo E_number -

( name ) \n indent \cdots

Stmt \n Stmts^1

ExprStmt Stmt \n
```

```
\rightarrow Stmts end marker
Stmts
          → Stmt \n | Stmt \n Stmts
Stmt
          → FuncDef | ExprStmt
           | RetStmt | PassStmt | ...
FuncDef → def name Params : Block
Block
        → \n indent Stmts dedent
New_S \rightarrow S | S Insert
RetStmt → | E_return | E_return Args
E_return \rightarrow return | \epsilon | Replace
              Insert return
E_number \rightarrow number \mid \epsilon \mid Replace
             Insert number
```

Fixing Parse Errors: Error Correcting Earley Parsers



```
Program P
```

Grammar G'

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

def bar(a):
    Too many rules!
```

```
ArExpr

ArExpr

BinOp

Literal

Literal +

name

ArExpr

E_number
```

```
FuncDef

def name Params : Blo

( name ) \n indent

Stmt \n Stmts¹

ExprStmt Stmt
```

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 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 by program context not directly related to the parse error

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

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

SEQ2PARSE: Key Insight

- EC-Parsers guarantee a correct fix, but are slow because they consider too many production rules, the vast majority of which are not needed to fix any given error.
- In contrast, Neural approaches are fast and leverage 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**:

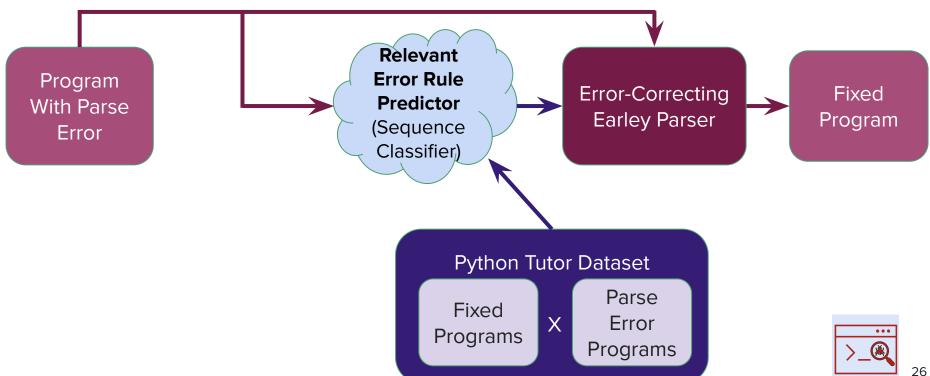
- 1. Train sequence classifiers to **predict the relevant EC-rules for a given program,**instead of the next token or the full fix
- 2. Use the predicted rules to synthesize a Parse Error repair via EC-Parsing

SEQ2PARSE: Efficient Fixes for Novice Parse Errors

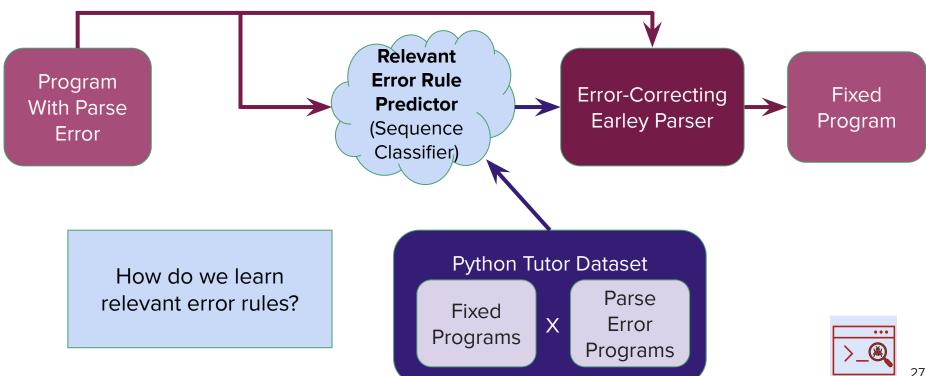




SEQ2PARSE: Efficient Fixes for Novice Parse Errors



SEQ2PARSE: Efficient Fixes for Novice Parse Errors



Additional Considerations for Learning EC-Production Rules

III-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 $S \rightarrow Stmts end_marker (p = 100.0\%)$



```
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: Python Implementation

- Dataset: Over **One Million Buggy/Fixed Program Pairs** from Python Tutor
 - Average abstracted token sequence is 43 tokens long
 - o 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: Top 20 most likely error production rules for a given Buggy
 Program
 - These rules are then fed into the Error Correcting Earley Parser



Seq2Parse: 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.

Seq2Parse: 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

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

Python Error Message

Questions To Answer:

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

File "program.py", line 4

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

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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.



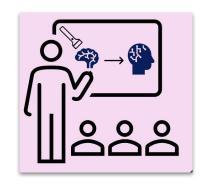


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TO READ OR TO ROTATE?

An example of how cognitive insights can inform effective programming interventions





ESEC/FSE, 2021, ICSE 2021

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

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



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



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, Jordan V. Price, and Lawrence Steinman^{2,3}



Cognitive interventions (the supplemental training of a necessary cognitive skill)

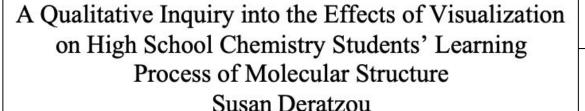
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A Qualitative Inquiry into the Effects of Visualization on High School Chemistry Students' Learning



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

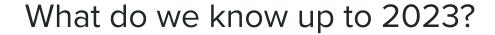






 Neuroimaging uses contrast-based experiments to compare programming activities to other cognitive tasks

Neuroimaging Experiment	Is programming like Reading?	Is programming like Spatial Reasoning?
Siegmund et al., (2014)	✓	
Siegmund et al., (2017)	•	
Floyd et al., (2017)	•	
Huang et al., (2019)		•





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Siegmund et al., (2014)	V	
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Huang et al., (2019)		V

Found connection with expertise





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

Neuroimaging Experiment	Is programming like Reading?	Is programming like Spatial Reasoning?	What about with novices?
Siegmund et al., (2014)	•		?
Siegmund et al., (2017)	•		?
Floyd et al., (2017)	•		?
Huang et al., (2019)		•	?





Phase 1: **Neuroimaging**

 We first build a model of novice programmer cognition using the first neuroimaging study of true novice programmers during code comprehension

Published in ICSE, 2021

Phase 2: Transfer Training

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

Published in FSE, 2021

Phase 1: Neuroimaging Method



- We use 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



Week 1: Start of the CS1 (EECS 183) semester

Week 4-5.5: Brain scans

Week 3:
Participant
recruitment
from CS1

Week 16: End of

semester

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We compare brain activation during three tasks:



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CS1-Level Programming

```
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);
}

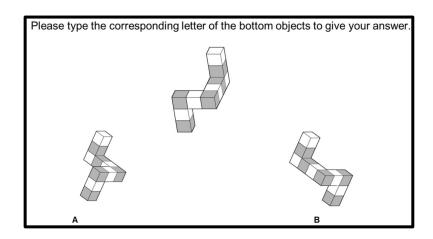
func(true, false)

false
A
```

We compare brain activation during three tasks:



- CS1-Level Programming
- Mental Rotation



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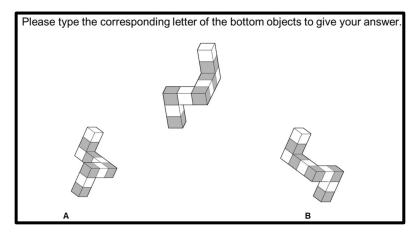
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We compare brain activation during three tasks:



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

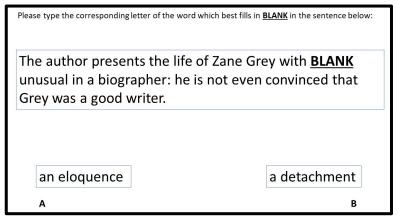


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fNIRS Scan Data Collection and Analysis



- Each scan session lasts two hours in a darkened room
 - o 90 stimuli, 30 of each type (programming, mental rotation, reading)
- 36 participants, **31 valid** (24 female, 7 male)
 - Recruited from EECS 183, here at Michigan!
- Data Analysis
 - Compare activation by task by brain area using best practices from psychology
 - Significance threshold: p < 0.01.
 - We used False Discovery Rate to correct for multiple comparisons: q < 0.05



A Mathematical Model of Novice Cognition: Primary Research Questions



- Comparative Activation: How does novice program comprehension compare to prose comprehension and spatial reasoning at the cognitive level?
 - How do novices' brain activation patterns compare to those of expert developers?

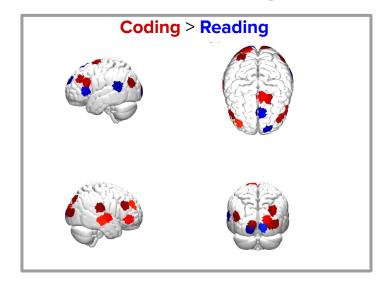




- Question: Do novices use spatial and/or language areas while programming?
- Result: While areas associated with both are activated, we find more substantial
 differences between Coding and Reading than between Coding and Mental Rotation



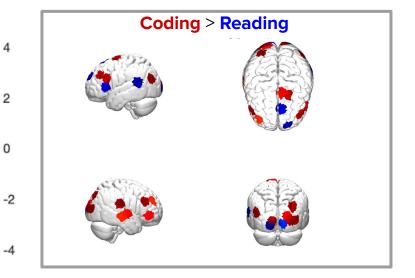
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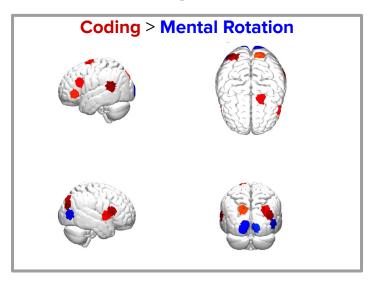


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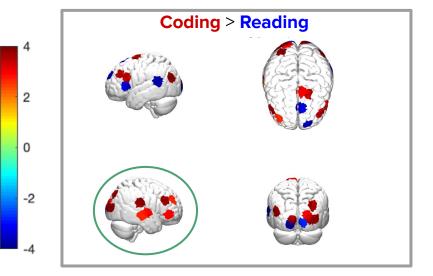
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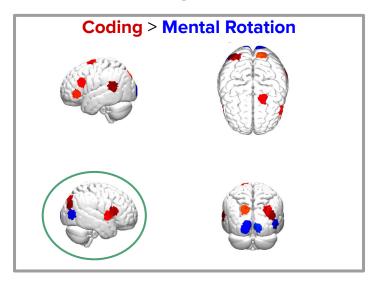






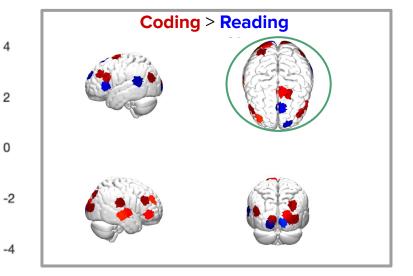
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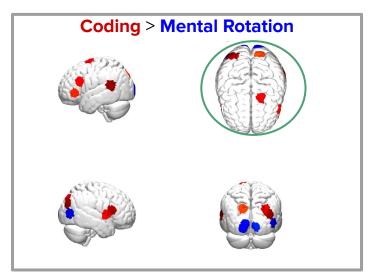






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- We also find that for novices coding engages more working memory and is more cognitively challenging than does either mental rotation or prose reading

So for novices, we see more differences with reading that spatial ability. Now what?

Phase 1 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 may continue to novices. For less experienced programmers, programming and reading show little 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**

Phase 1 Summary

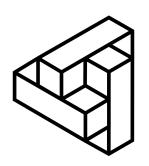


For novices, spatial reasoning is less distinct to programming than reading at a cognitive level.

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







Standardized and Validated Spatial

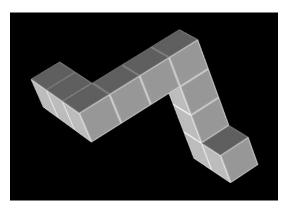
Reasoning Training



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 developed an intervention to teach strategies for efficiently understanding scientific writing
- Strategies focused on using structural cues to scan academic papers to retrieve and understand key points
 - Inspired by eye tracking findings: experienced programmers tend to read code non-linearly, focusing on high level features.



Novices Reading Code

```
def init (self, inFix config, inFix log):
def find fixes(self, filt=None):
    Filter is an optional filter that says which sessions to consider
    if self.config.partial_file is not None:
        with open(self.config.partial_file, 'r') as f:
                       experiment_results = json.loads(next(f))
                       if len(experiment results) == 0:
                       to_return.append((general_config, experiment_results))
    for config, result in to_return:
       zzz.add(config["UniqueId"])
    theories = self.config.get_theories()
    global theory config = [self.config.get specific theory info(x) for x in theories]
    global_theory_factory = [theory_factory.get_theory_solver(i, global_theory_config[e], self.log) for i
    base_path = self.config.get_session_path()
    counter = 1
    for folder in os.listdir(base path):
       print("Number: {}".format(ak))
```

Busjahn, et al., 2015

Experts Reading Code

```
def __init__(self, inFix_config, inFix_log):
def find fixes(self, filt=None):
    if self.config.partial_file is not None:
        with open(self.config.partial_file, 'r') as f:
                       experiment_results = json.loads(next(f))
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Busjahn, et al., 2015

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```

print("Number: {}".format(ak))









Semester CS1 Course With Final Exam















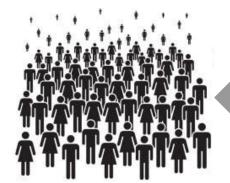








Spatial Training











Reading Training

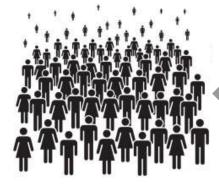






Spatial Training













Reading Training



Transfer Training Results: Which Group Did Better?

Spatial Reasoning
Training



Technical Reading
Training





Transfer Training Results: Which Group Did Better?

Spatial Reasoning
Training



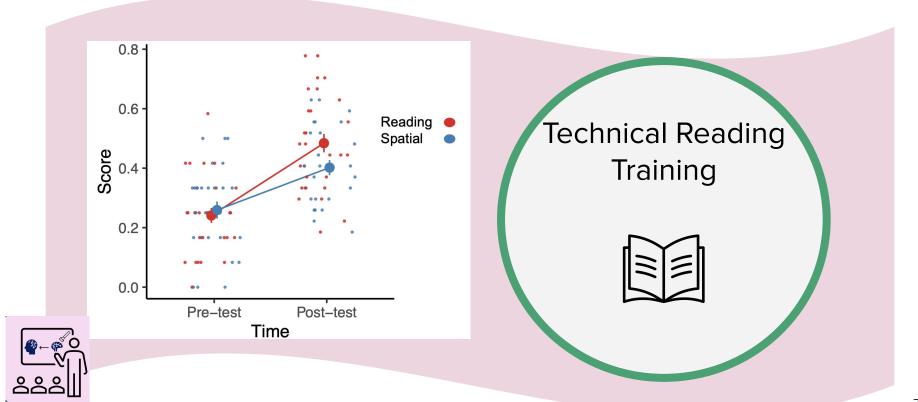
Technical Reading

Training





Transfer Training Results: Which Group Did Better?



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



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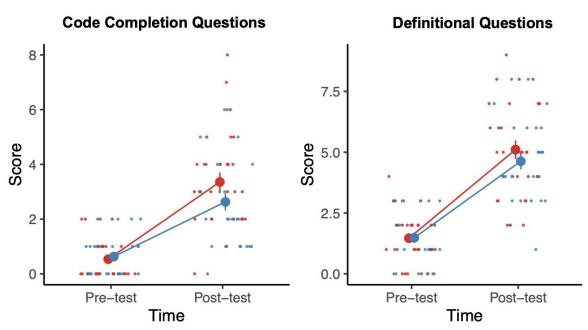
Our final programming assessment (the SCS1) had three types of questions: code completion, definitional, and code tracing

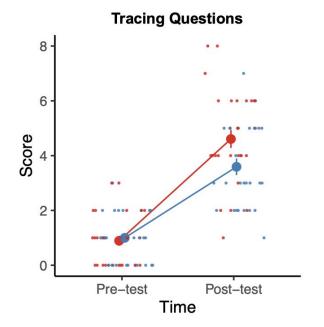






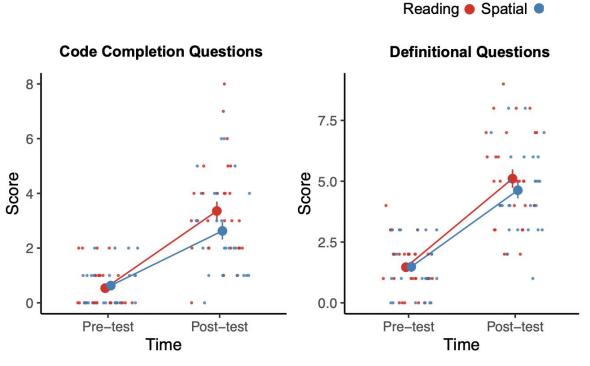


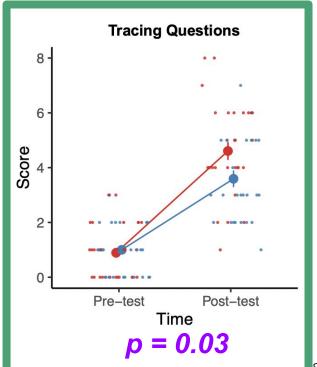




How did the Reading Training Help?







Transfer Training Results: Summary



We compared the effects of **Spatial Reasoning Training** and our novel **CS-focused Technical Reading Training** on CS1 students.





We found that our Technical Reading Training helped programming ability more, especially helping novices trace through code

Transfer Training Results: Summary

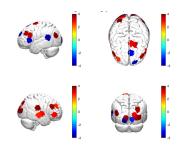


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Developing Efficient and Usable Programming Support



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



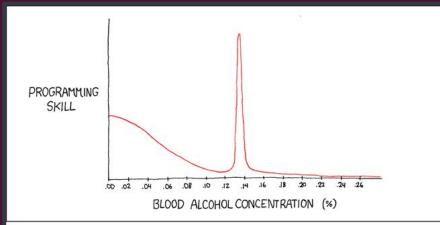
How does psychoactive substance use impact software productivity?

Psychoactive Substances and Programming?

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



ICSE 2022, 2024









HOWEVER, IT'S A DELICATE EFFECT



CULTURE OF PSYCHOACTIVE SUBSTANCE USE AND SOFTWARE

Based upon my experiences and observations:

- caffeine
- nicotine
- alcohol
- ritalin
- modafinil

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



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

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

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

MOTHERBOARD TECHBY VICE

on du ___

additid

or the

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



Despite this conflict, **little empirical research has been conducted** on psychoactive substance use in software development

We want to know if, when, or why developers use substances while programming: tech companies cannot effectively evaluate existing anti-drug policies

And we want to build a mathematical model of how such substances actually impact programmers

We present results from the:

First large-scale empirical study of psychoactive substance use in software engineering

(800+ programmers, 450 full-time devs)

First controlled observational study of cannabis and programming (70+ programmers, pre-registered hypotheses)

Psychoactive Substances Exploratory Survey: Summary



803 survey responses:

- 440 from GitHub Emails
- 339 from University of Michigan
- 24 from Social Media
- 56% Have full-time programming jobs, 36% are students



Psychoactive Substances Exploratory Survey: **Summary**

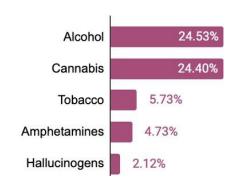


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Usage While Programming in Last Year

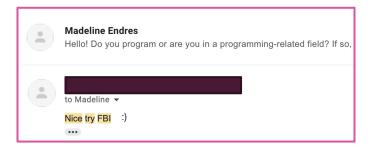


Psychoactive Substances Exploratory Survey: Summary

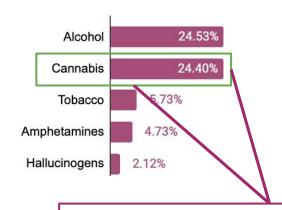


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- 56% Have full-time programming jobs, 36% are students



Usage While Programming in Last Year



- 33% use for work-related tasks
- 11% use at a frequency likely to be caught by a drug test

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.

A Controlled Observational Study: Cannabis



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 - 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





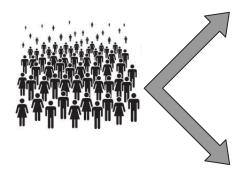




Remote Programming Session 1

Programming While High









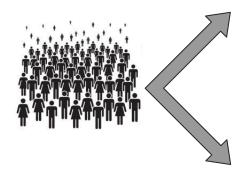
```
easy1.py U X
      stimuli > problemsetA > 🤚 easy1.py
             class Solution:
                 """ You are given a string `s` consisting of lowercase English letters. A duplicate
                 removal consists of choosing two adjacent and equal letters and removing them. We
                 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:
B
                    return "" # Participant implementation goes here
        10
             class Test(object):
                 def test_removeDuplicates(self):
        12
                    print("=====Test 1=====\n")
        13
        14
                     solution = Solution()
        15
                     answer1 = solution.removeDuplicates("abbaca")
                                                                COMMENTS
                          DEBUG CONSOLE
                                                                                       o [2023/07/29-02:03:18]
                                              → /workspaces/CodeSpaceTest (main x) $ []
Ln 21, Col 5 Spaces: 4 UTF-8 CRLF Python
```



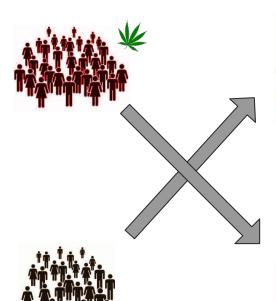
Remote Programming Session 1

Remote Programming Session 2

Programming While High



Programming While Sober



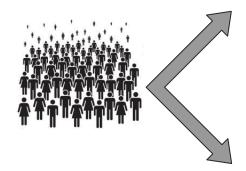




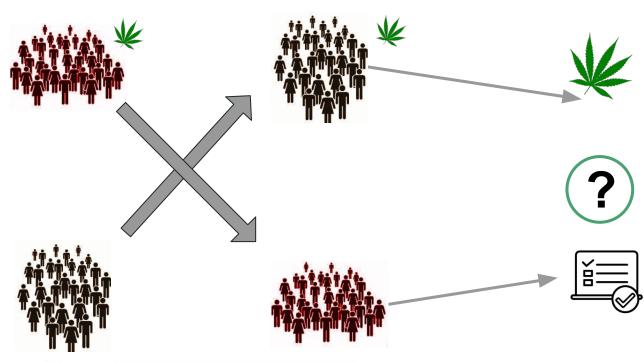
Remote Programming Session 1

Remote Programming Session 2

Programming While High



Programming While Sober



Results: 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.

.

Results: Pre-registered Hypotheses

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

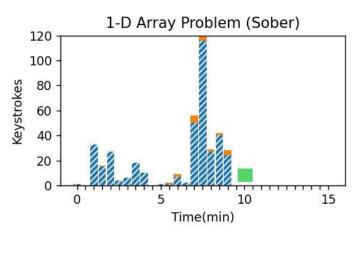
- Hypothesis: Programs will be less correct when written by cannabis-intoxicated programmers.
- Finding: **Cannabis use decreases program correctness** (0.0005 < p < 0.05, 0.28 < d 0.44, 10-14% fewer passed tests). In particular, cannabis impairs the ability to write and trace through programs.

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

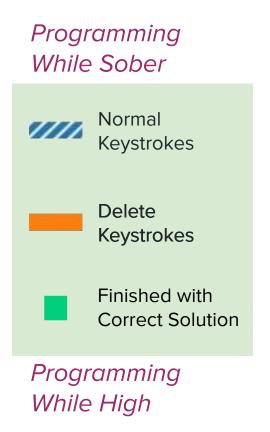
- Hypothesis: Cannabis-intoxicated programmers will take longer to write programs.
- Finding: **Cannabis use impairs programming speed** (p < 0.04, d = 0.3, 10-14% slower). This decrease in speed is associated with typing slower, deleting more characters, and more time spent not typing.

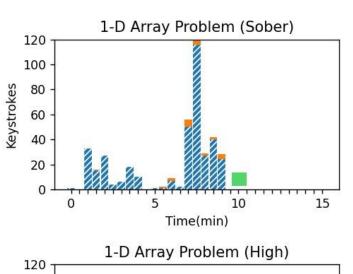
High vs. Sober: How does Cannabis Impair Programming?

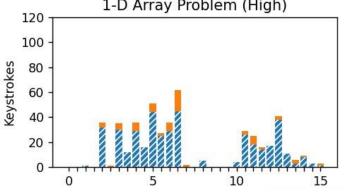




High vs. Sober: How does Cannabis Impair Programming?









Lens 3 - Summary: Psychoactive Substances and Programming

- By surveying 800 programmers, we found that
 psychoactive substance use is common in software
- Despite anecdotes to the contrary, we only observed evidence of cannabis impairing productivity
- This work demonstrates the usefulness of objective measures and careful controlled experimental design to come to evidence-based conclusions on anecdotal software productivity factors



Professional Programmers

ICSE 2023





FSE 2024

FSE 2023

PLDI 2020

More Theoretical

OOPSLA 2022

SIGCSE 2020



SIGCSE 2021



ICSE-SEET 2022

FSE 2021

More Empirical

ICSE 2024b

Programming Novices

1.	FSE, 2024	Can LLMs Transform Natural Language Intent into Formal Methods Postconditions?	>_@
		Endres, M., Fakhoury, S., Chakraborty, S., Lahiri, S.	
2.	ICSE, 2024a	Causal Relationships and Programming Outcomes: A Transcranial Magnetic Stimulation Experiment,	
		Ahmad, H., Endres, M., Newman, K., Santiesteban, P., Shedden, E., Weimer, W. (Distinguished Paper)	ys,
3.	ICSE, 2024b	High Expectations: An Observational Study of Programming and Cannabis Intoxication,	
		He, W., Parikh, M., Weimer, W., Endres, M.	
4.	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 (Distinguished Paper)	<i>ڰ</i> ۮڐ۩ٛ
5.	ICSE, 2023	From Organizations to Individuals: Psychoactive Substance Use By Professional Programmers,	555
		Newman, K., Endres, M., Weimer, W., Johnson, B.	
6.	OOPSLA, 2022	Seq2Parse: Neurosymbolic Parse Error Repair,	
		Sakkas, G., Endres, M., Guo, P., Weimer, W., Jhala, R.	>_@_
7.	ICSE, 2022	Hashing It Out: A Survey of Programmers' Cannabis Usage, Perception, and Motivation,	555
		Endres, M., Boehnke, K., Weimer, W.	
8.	ICSE-SEET, 2022	Debugging with Stack Overflow: Web Search Behavior in Novice and Expert Programmers,	
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10.	ICSE, 2021	Relating Reading, Visualization, and Coding for New Programmers: A Neuroimaging Study	
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11.	SIGCSE, 2021	An Analysis of Iterative and Recursive Problem Performance,	
		Endres, M., Weimer, W., Kamil, A.	
12.	PLDI, 2020	Type Error Feedback via Analytic Program Repair	
		Sakkas, G., Endres, M., Cosman, B.,Weimer, W.,Jhala, R.	>_@
13.	SIGCSE, 2020	Pablo: Helping Novices Debug Python Code Through Data-Driven Fault Localization	
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14.	ASE , 2019	InFix: Automatically Repairing Novice Program Inputs 105	<u></u>
		Endres, M., Cosman, B., Sakkas, G., Jhala, R., Weimer, W.	>_@_

Student Advisees



Yiannos Demetriou BS CS, 2023



Wenxin He MS CS, 2024



Annie Li BS CS, 2022



Kaia Newman BS CS, 2023



Manasvi Parikh BS CS, 2023

Interdisciplinary Collaborators



Madison Fansher Cognitive Psychology



Xiaosu (Frank) Hu Developmental Psychology



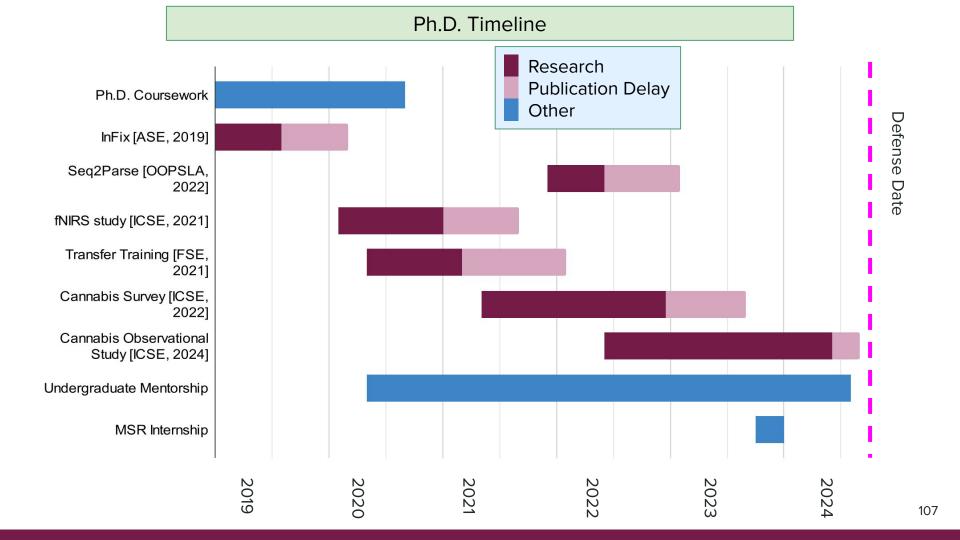
Priti Shah Cognitive Psychology



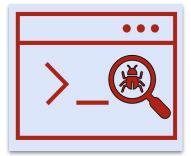
Kevin Bohenke Anesthesiology and Chronic Pain



loulia Kovelman Developmental Psychology

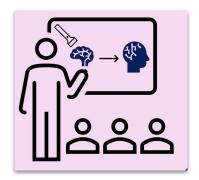


Developing Efficient and Usable
Programming Support



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

Data Analysis Pipeline

Step 1: Preprocessing

- Raw fNIRs Data (light intensity levels) → optical density data (how much is being absorbed?)
- Optical density data → HbO/HbR signal (oxygenated vs deoxygenated blood)

Step 2: Individual Modeling

- We model the hemodynamic response for each subject individually using a GLM
- Quality control checks are used to filter noisy data (e.g., signal to noise ratio, anticorrelation of HbO and HbR, visual activation spot checking)

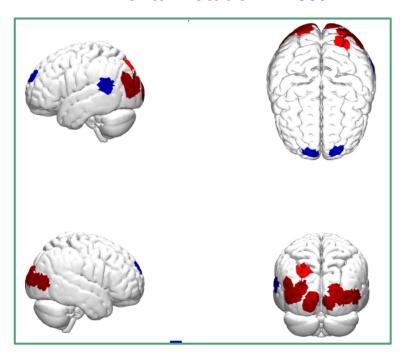
• Step 3: Group Modeling

- Used a linear mixed effects models, contrasting Task > Baseline activations
- \circ We applied a false-discovery rate (FDR) correction (q < 0.05) to account for multiple comparisons

Results: Baseline Activation

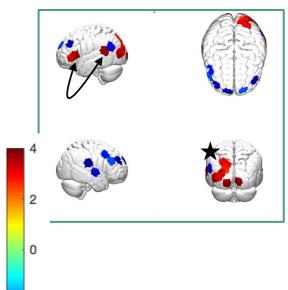
Reading > Rest 0 -2

Mental Rotation > Rest

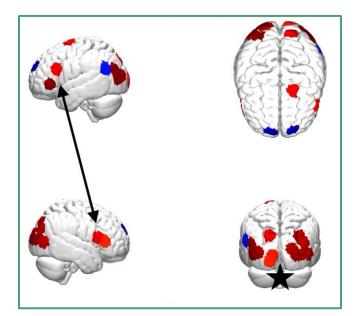


Results: Baseline Activation

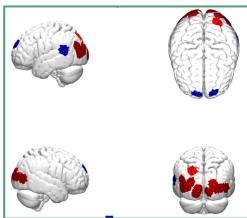
Reading > Rest



Coding > Rest

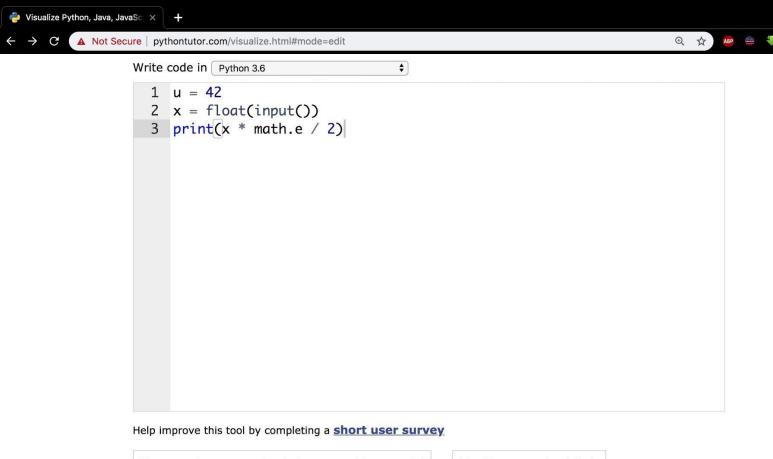


Mental Rotation > Rest



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.	ICSE, 2024	High Expectations: An Observational Study of Programming and Cannabis Intoxication,
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Please wait ... executing (takes up to 10 seconds)

Live Programming Mode



Coding + Cannabis Use

Hey fellow programmers!

I wanted to see what your and working in the field.

Do you use cannabis and career?



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.



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

g thoughts might get in ally isn't much of an o really dive deep into



Anecdotal evidence

abounds:



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.

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 addition, no employee may report for work, go on or remain on duty while under the influence of, or impaired by, alcohol, or these drugs or substances.



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

MOTHERBOARD

TECH BY VIC

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 SCHUMACHE

y n



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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def foo(a):

Token Sequence

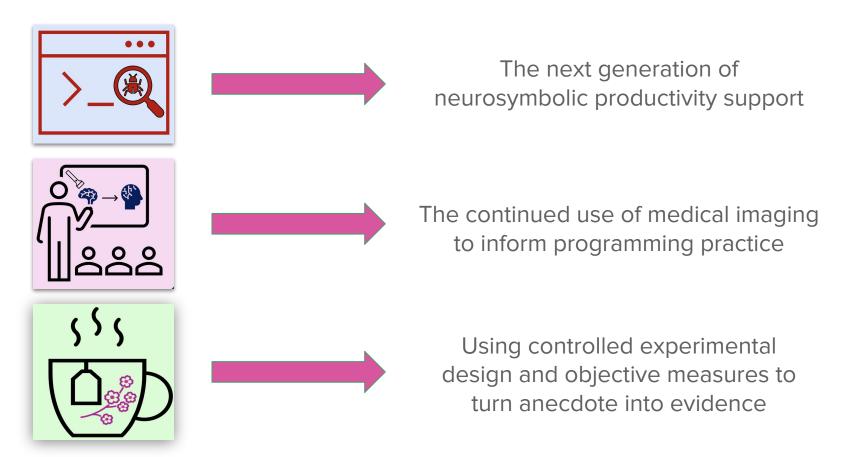
```
def name(name): \n
indent return name + number \n
dedent \n

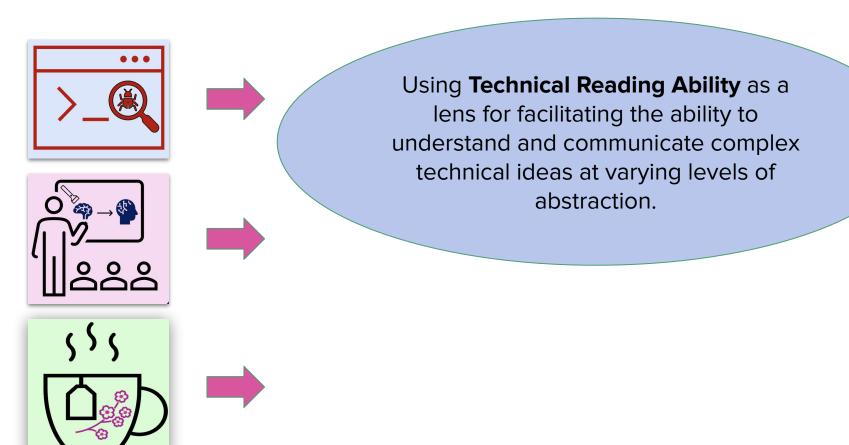
def name(name): \n
indent name = name(name) + number \n
return (name + \n)
dedent end_marker
```

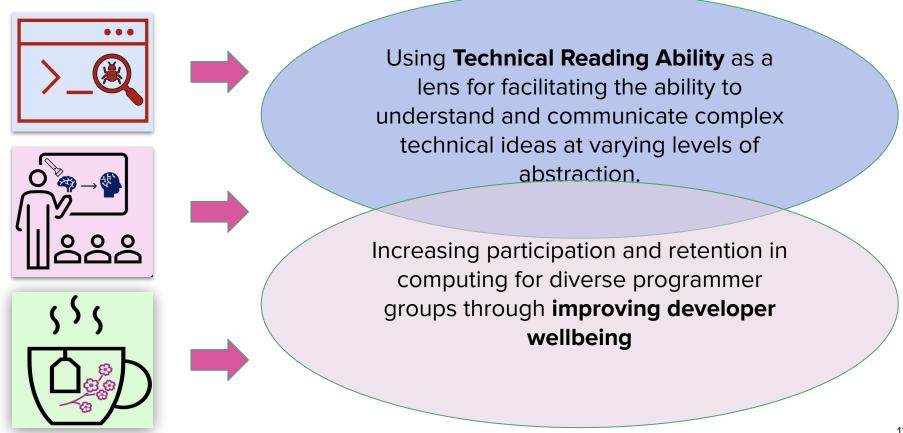
Abstracted Token Sequence

```
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!







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Abstracted Token Sequence

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Great! But we have a new problem: Ambiguity

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

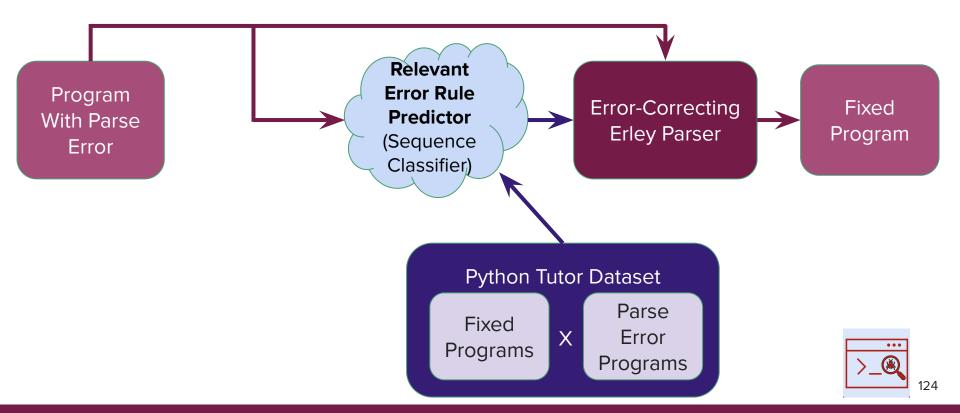
```
S \rightarrow Stmts end_marker (p = \underline{100.0\%})

Stmts \rightarrow Stmt \n (p = \underline{38.77\%}) | Stmt \n Stmts (p = \underline{61.23\%})

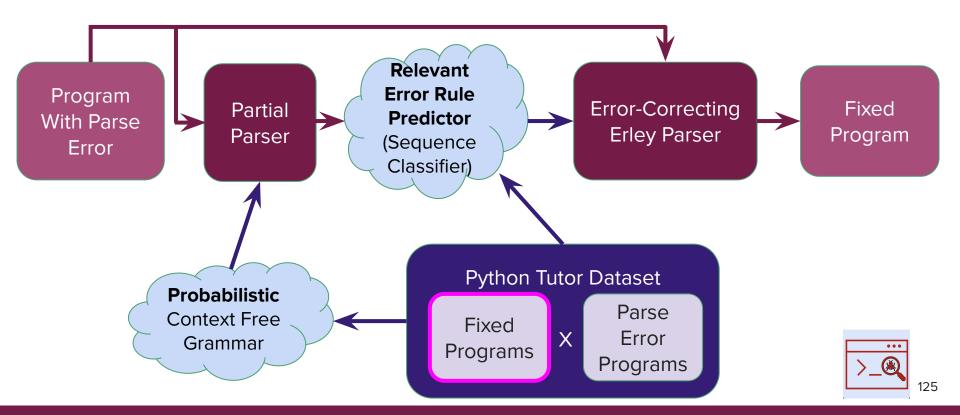
Stmt \rightarrow ExprStmt (p = \underline{62.64\%}) | RetStmt (p = \underline{7.59\%}) | ...

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

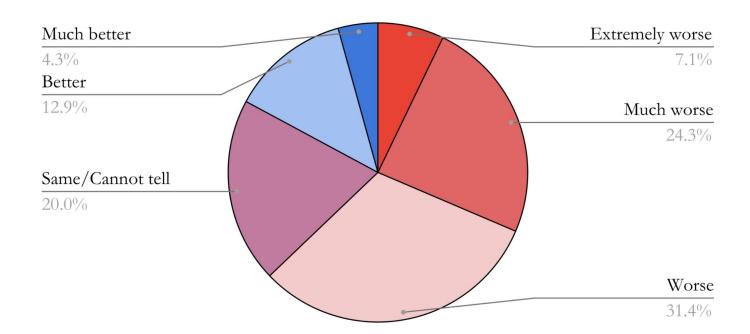


Cannabis is used for many reasons both **medical** (e.g., pain relief) and **recreational** (e.g., altered consciousness)

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



Self-reported subjective programming performance when high (compared to when sober)



Desired Research Attribute	Why I'm Excited
Provide Theoretically- Grounded and Actionable Insights	Bridging the gap between novel theoretical ideas to supporting programmers in practice leads to higher impact
Include Empirical or Objective Measures of Programmers	Captures aspects of programming beyond self-reporting alone, including unconscious behaviors and habits
Minimize Scientific Bias to Support Generalizability	Controlled experimental design can capture a signal, even for complex human behavior
Support Diverse Developers	I prefer approaches that not only help programmers in general, but also help those who need the most support

















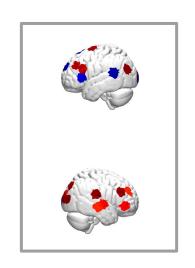
Objective measures of cognition



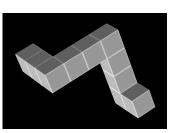
Identify Relevant Cognitive Skills











Technical Reading





