Programming and Toolkits

CS 347

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Last time

Visualizations can be represented as **encodings** that map from **data to marks & visual attributes** based on **data types**

Our **cognitive and perceptual systems determine which encodings are effective**: we (mis)read data if encoded poorly

Active research at frontiers investigating **how users can create effective visualizations** and **how readers take information away from them**

✓Cognition

Unit 5

cognitive models
visualization
(and don’t forget the design cognition that we already covered)

Software

Unit 6

Programming and Toolkits
Content Creation

Today

Threshold and ceiling

Changing problem representations

Learning programming

A Small Matter of Programming

Software engineering is a highly complex task, a microcosm of many challenges in HCI

Making software engineering more accessible could empower millions to customize applications and write programs

Programming ain't easy

Developers **struggle to recover others' implicit knowledge** by inspecting code [LaToza, Venolia and DeLine 2006; Ko, DeLine and Venolia 2007; Ko et al. 2006]

Developers rarely hold all information needed for the task, and **often must turn to the web** [Brandt et al. 2009]

- Just-in-time learning of new skills, clarifying existing skills
- Reminding themselves of details

Barriers span from conceptual (how is this even possible to code?) to pragmatic (how do I express this?) [Ko, Myers, and Aung 2004]

How do we aid programming?

Threshold and Ceiling

What is your programming intervention actually doing?

What is Claude Code designer's goal? How do we know if it's succeeding at that design goal?

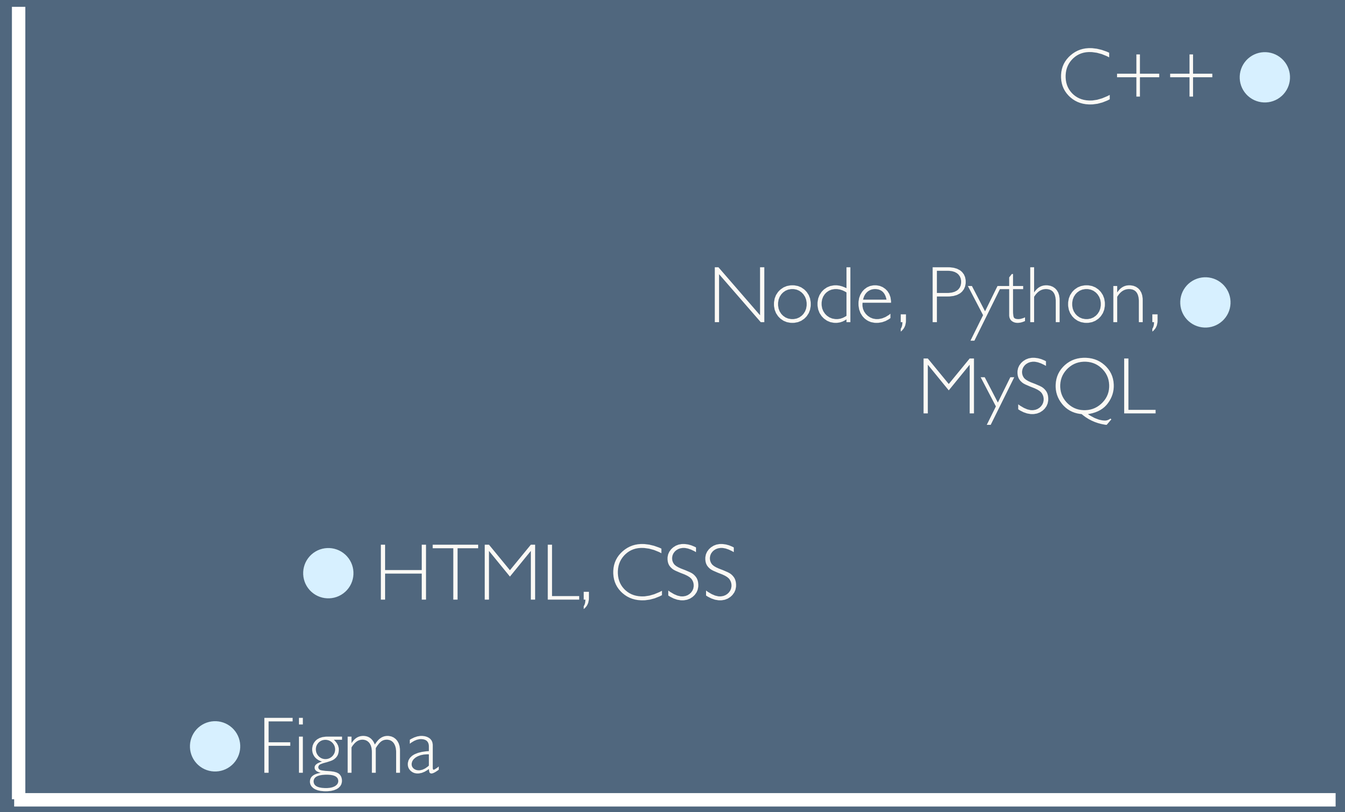
Are some programming languages "better" than others? How would we know?

Is the VSCode plugin helping? With what?

Threshold/Ceiling Diagram

[Myers, Hudson and Pausch, TOCHI 2000]

Threshold: Difficulty of non-expert use



Are you trying to **lower the threshold**, or **raise the ceiling**?

Ceiling: Expressivity; sophistication of what can be created

Tradeoffs

Threshold is about **ease of use for non-experts**;
Ceiling is about **expressivity for experts**

Often, threshold and ceiling are in tension with each other.

The **command line** and **Photoshop** are **high ceiling, but also high threshold** because they require substantial up-front learning

A tool's threshold or ceiling status **may depend on the user's background**: you might be able to make striking representational art with a **simple digital brush**, even if I can only produce stuff that looks like bad graffiti

Some tools enable you to **"pop out" to code or advanced tools to achieve higher ceilings** for experts: e.g., Microsoft Word has a low threshold, but you can do a lot of complex layout with it if you know how

Lowering the threshold

Goal: reduce the effort and cognitive complexity of creating software artifacts

How to lower thresholds

One approach is to reduce the ceiling (expressivity) in exchange for **smaller semantic distances** in **gulf of execution or evaluation**

- Regular expressions are simpler to understand than context-free grammars, but also less expressive
- No-code or low-code front-end web frameworks can be fast to get off the ground but limited in what you can create
- Python manages memory and garbage collection for you, but also trades off some manual optimizability of memory to achieve it

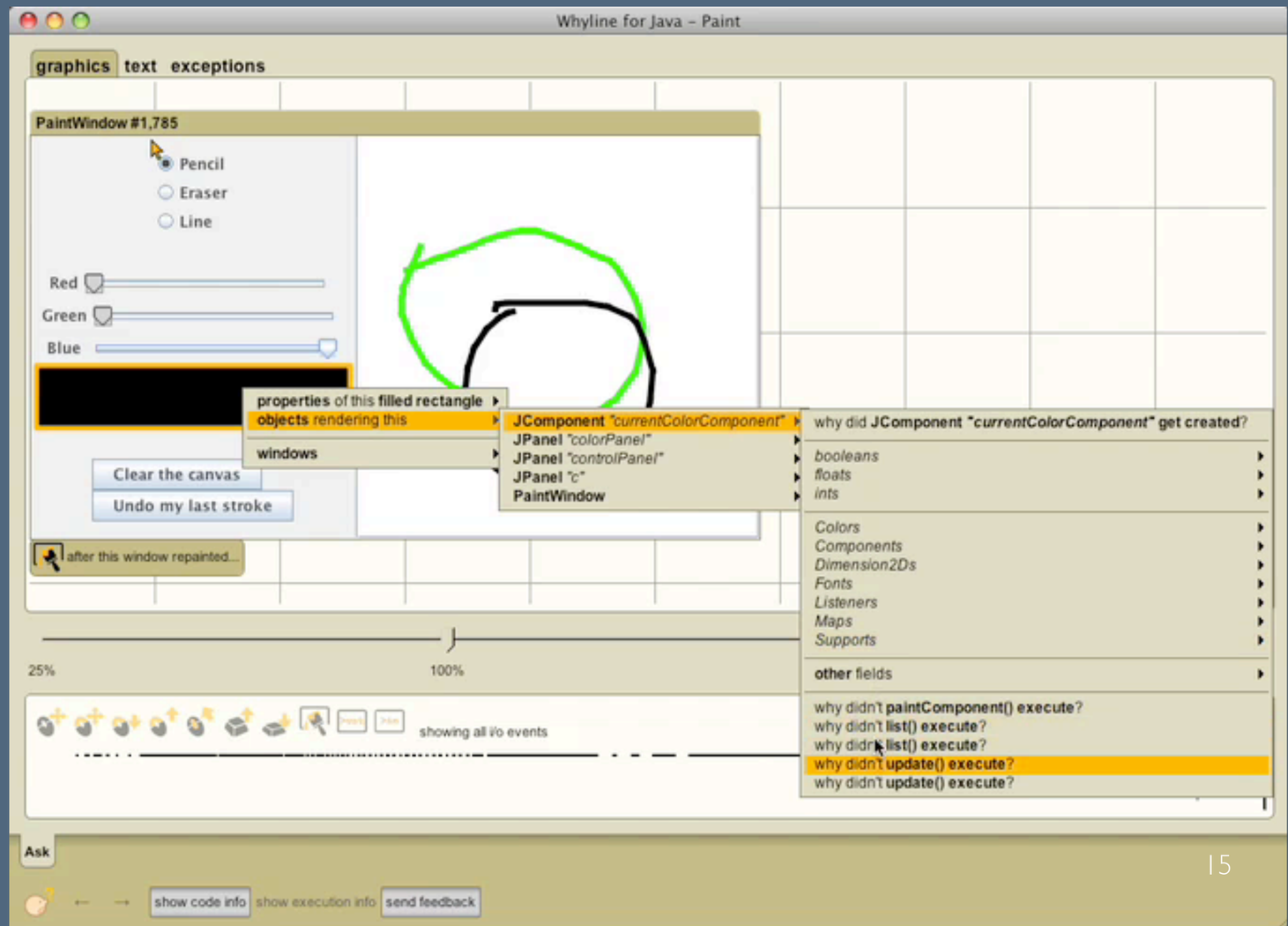
But, not all lowered thresholds require substantially lower ceilings: Python has a very high ceiling despite lowering the floor vs. C++

Asking ‘why’ questions of code

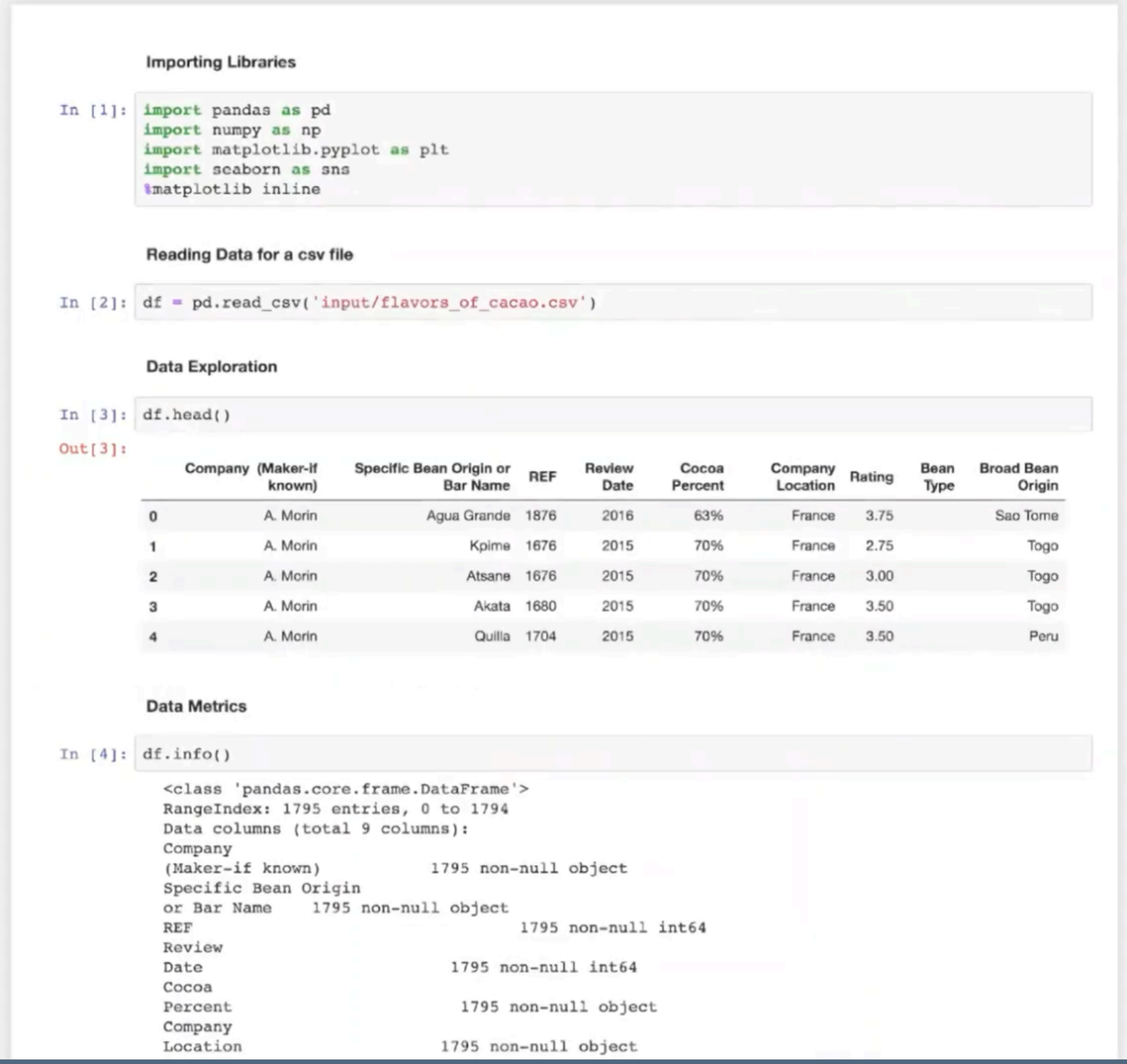
[Ko and Myers CHI ’04, ICSE ’09]

Debugging problems often reduce to “why” questions, but these questions are **challenging to answer** (=high threshold)

Analyze program traces to answer many unanswered “why” and “why not” questions about what just happened



Data science notebooks



Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Reading Data for a csv file

In [2]:
```
df = pd.read_csv('input/flavors_of_cacao.csv')
```

Data Exploration

In [3]:
```
df.head()
```

Out[3]:

	Company (Maker-if known)	Specific Bean Origin or Bar Name	REF	Review Date	Cocoa Percent	Company Location	Rating	Bean Type	Broad Bean Origin
0	A. Morin	Agua Grande	1876	2016	63%	France	3.75		Sao Tome
1	A. Morin	Kpime	1676	2015	70%	France	2.75		Togo
2	A. Morin	Atsane	1676	2015	70%	France	3.00		Togo
3	A. Morin	Akata	1680	2015	70%	France	3.50		Togo
4	A. Morin	Quilla	1704	2015	70%	France	3.50		Peru

Data Metrics

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1795 entries, 0 to 1794
Data columns (total 9 columns):
Company
(Maker-if known)           1795 non-null object
Specific Bean Origin
or Bar Name    1795 non-null object
REF                                     1795 non-null int64
Review
Date                          1795 non-null int64
Cocoa
Percent                        1795 non-null object
Company
Location                      1795 non-null object
```

Automatic cleanup of Jupyter notebooks by tracking provenance across cells [Head et al. 2019]

Tools for statistical analysis

[Jun et al. 2019]

Non-experts often struggle to **select appropriate statistical tests**

So, instead of asking people to directly run statistical tests, instead ask them to write down the **properties of their method and data**

This representation **lowers the threshold to statistical test selection**, but **limits the ceiling** of some complex models

```
import tea
tea.data('UScrime.csv')
variables = [
    {
        'name' : 'So',
        'data type' : 'nominal',
        'categories' : ['0', '1']
    },
    {
        'name' : 'Prob',
        'data type' : 'ratio',
        'range' : [0,1]
    }
]
tea.define_variables(variables)
study_design = {
                    'study type': 'observational study',
                    'contributor variables': 'So',
                    'outcome variables': 'Prob',
                }
tea.define_study_design(study_design)
assumptions = {
    'groups normally distributed': [['So', 'Prob']],
    'Type I (False Positive) Error Rate': 0.05
}
tea.assume(assumptions)
hypothesis = 'So:1 > 0'
tea.hypothesize(['So', 'Prob'], hypothesis)
```

Programming by demonstration (PBD)

Programming by demonstration (PBD): teach a computer a program by doing it yourself while it watches

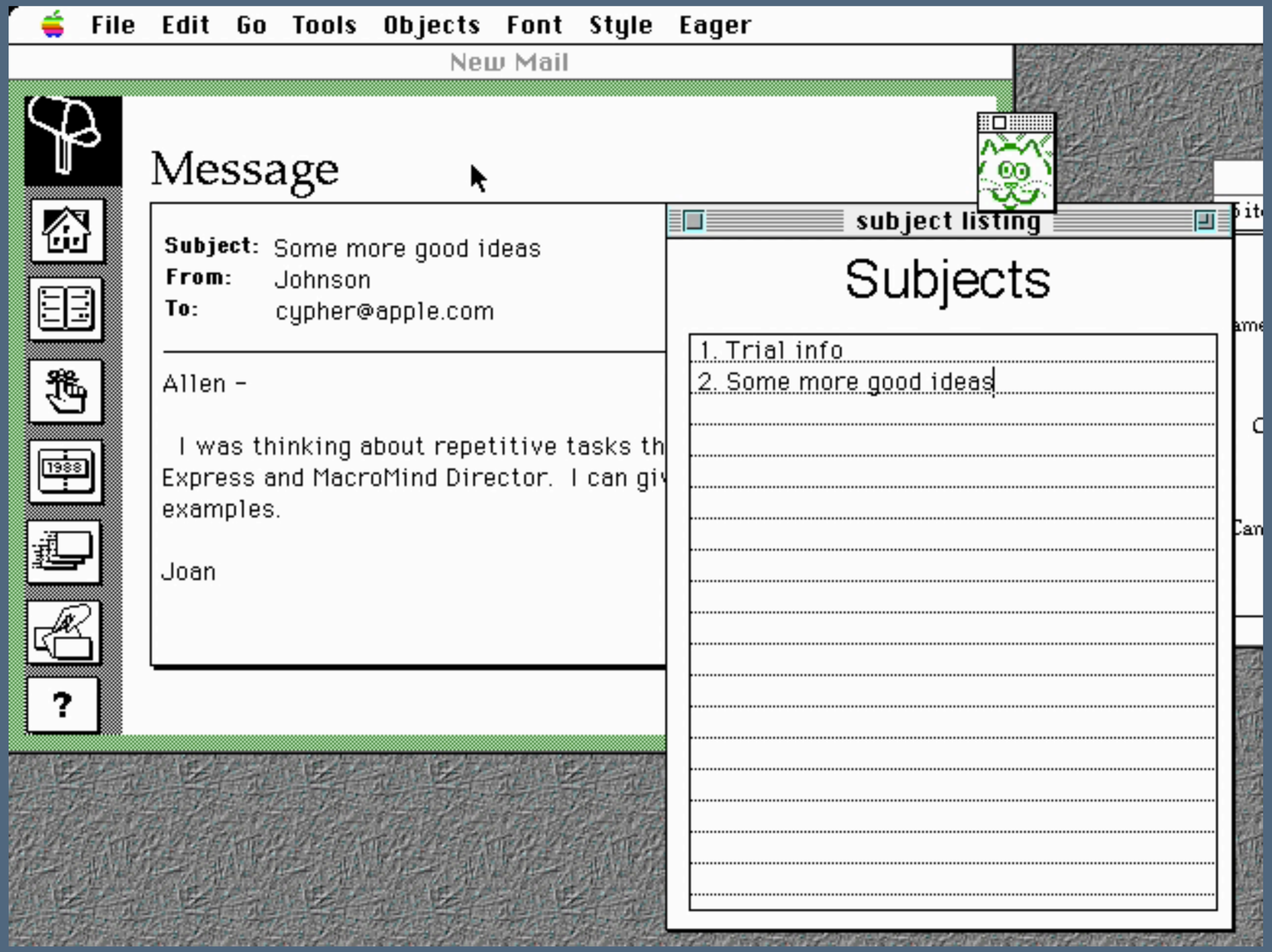
Challenges

- There is an infinite, and hugely branching, space of programs that might be inferred
- Inferred macros can be extremely brittle

PBD on the desktop

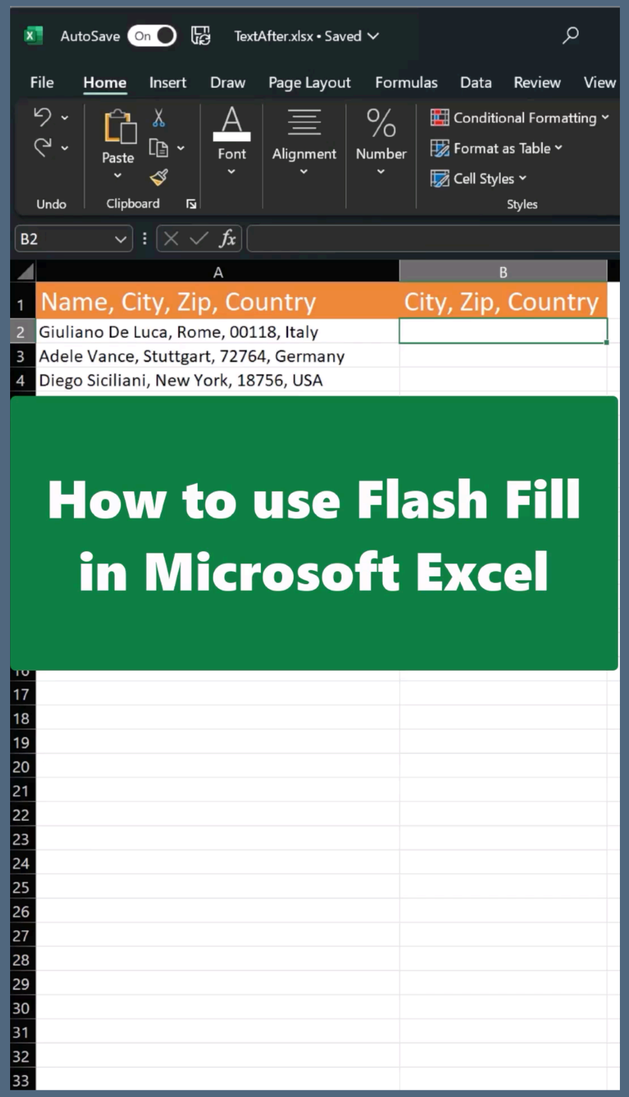
[Cypher 1991]

Infer a macro by **watching the user's behavior**



Modern PBD: Excel flash fill

[Gulwani 2011]

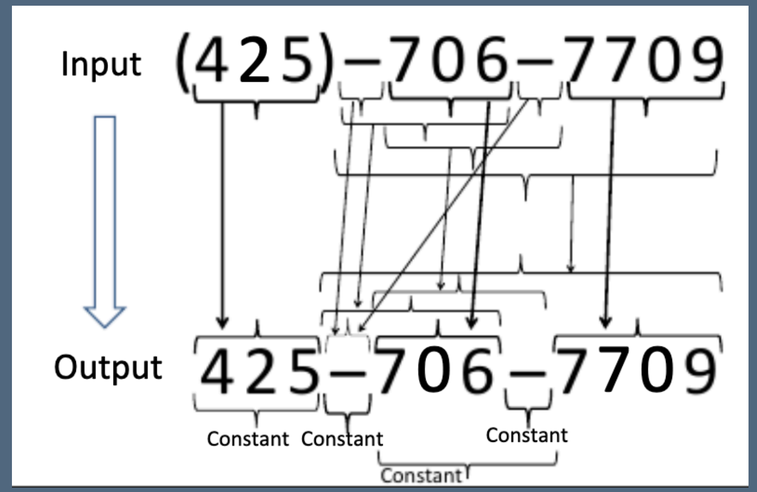


Modern PBD: Excel flash fill

[Gulwani 2011]

Develop a domain-specific language of string transformations, and learn from examples how to decompose it into subproblems

Machine learning ranks between all possible valid programs



Raising the ceiling

Goal: increase expressivity (range and sometime complexity of what can be created)

How to increase the ceiling

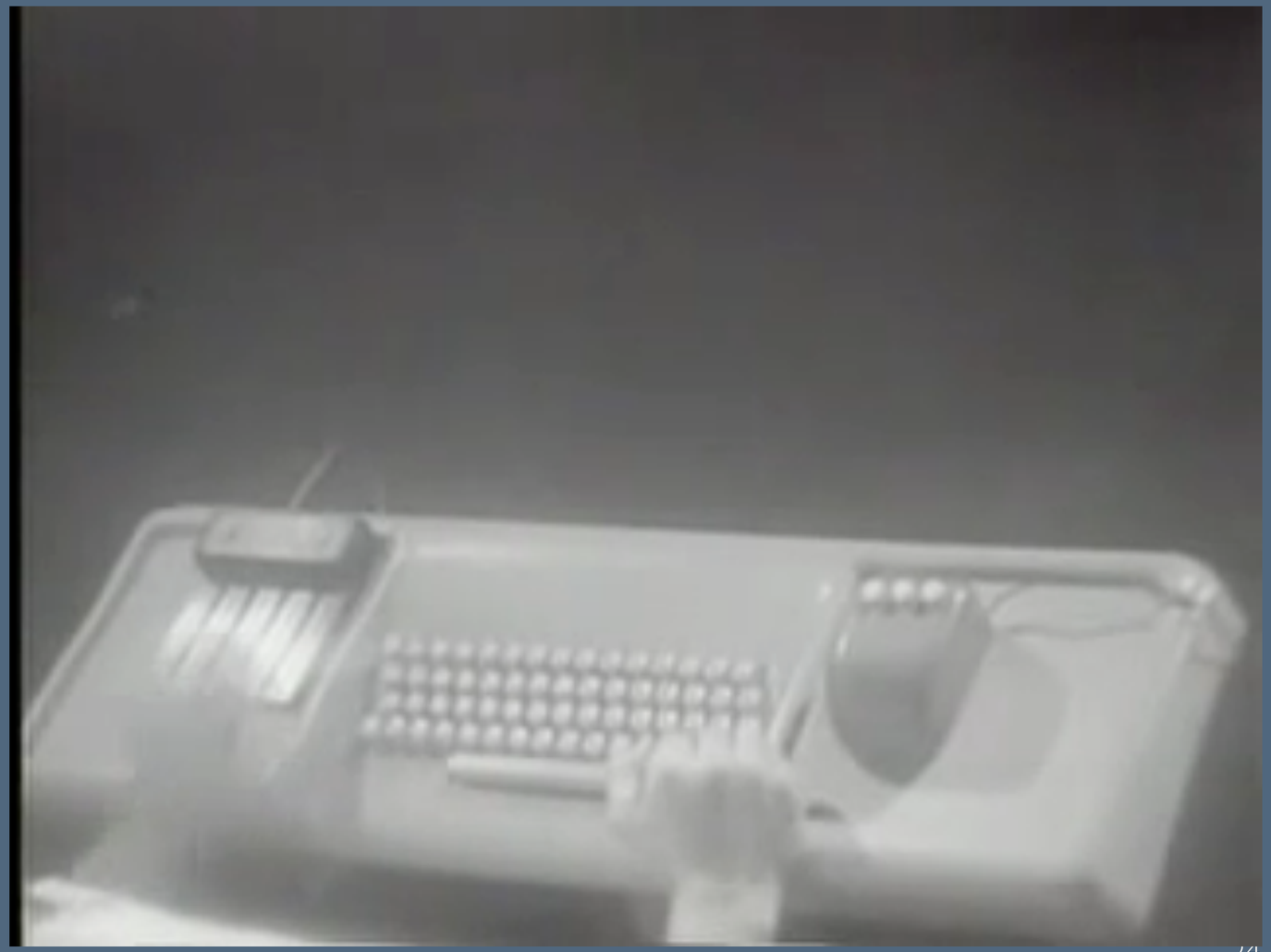
Identify opportunities for **untapped expressivity** in the current language, and position the software to expose that level of expressivity

This is not about "adding knobs": it's about (metaphorically) providing new paint colors in the palette

Non-programming examples

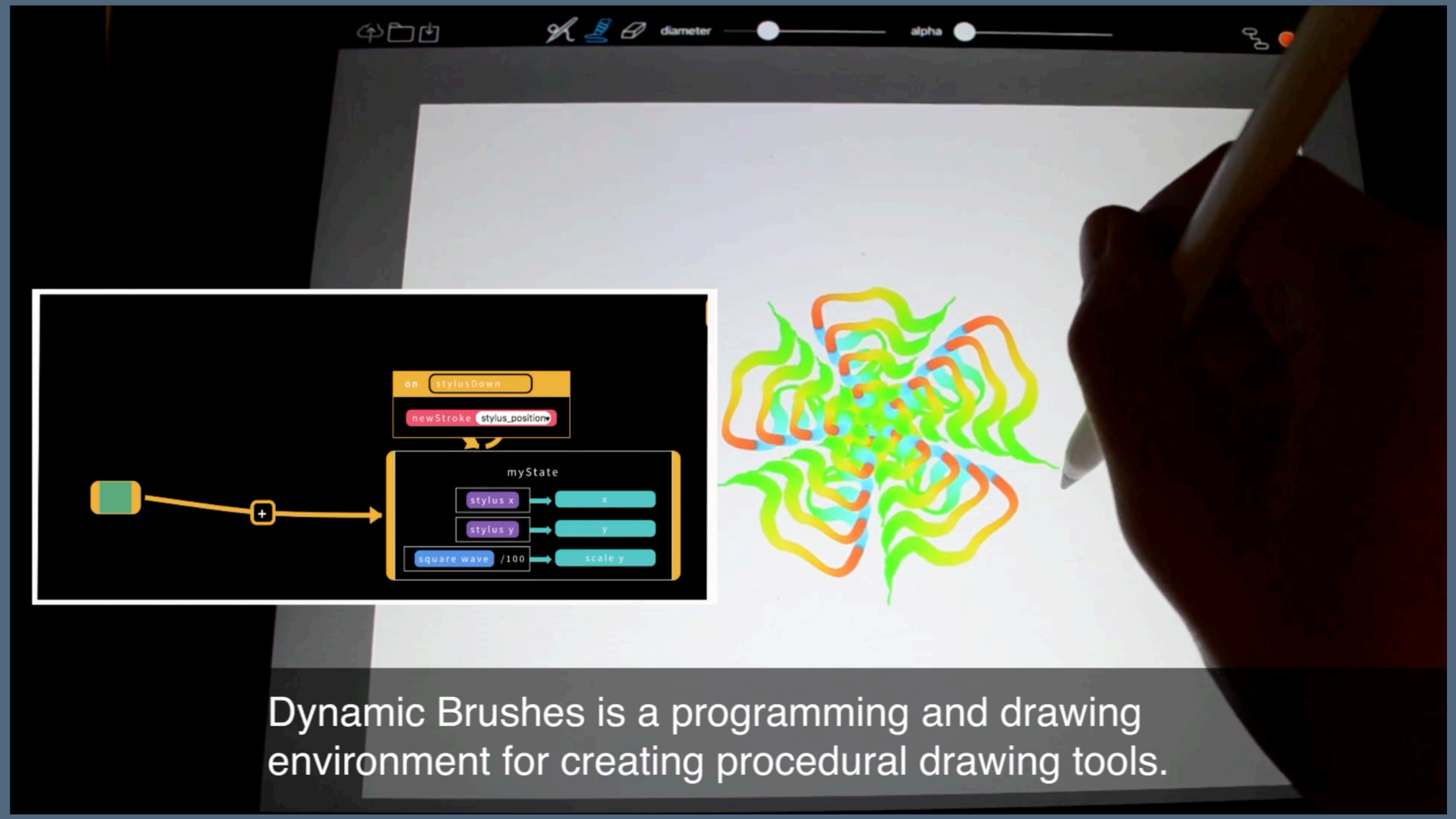
Engelbart's chorded keyset [Engelbart 1968]

Musical instruments: the goal isn't to reduce the threshold to playing the piano — it's to enable high musical expressivity



Programmable artist brushes

[Jacobs et al. 2018]



Attaching computational functions to brushes enables new forms of artistic expression

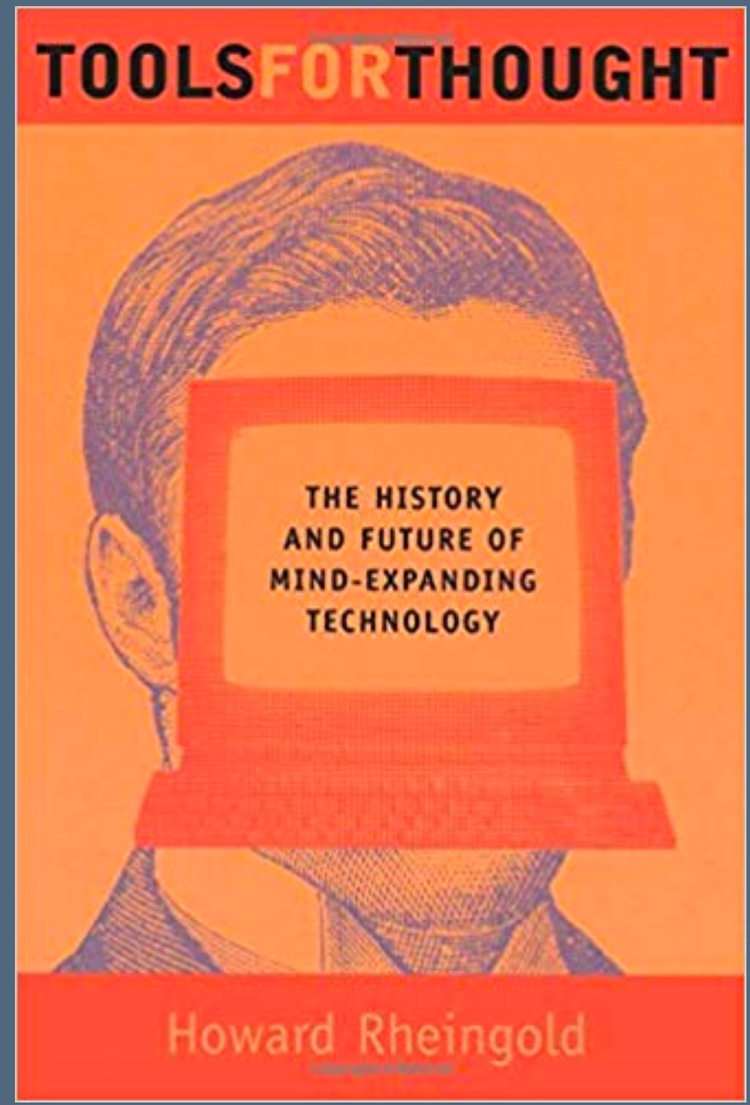
Programming as problem representation

Remember: Cognitive amplification

By better understanding human cognition, we can design technology that makes us smarter

Automation can help, but ultimately this power comes from better **representation**

"The powers of cognition come from abstraction and representation: the ability to represent perceptions, experiences, and thoughts in some medium other than that in which they have occurred, abstracted away from irrelevant details." [Norman 1994]



Domain-specific languages

DSLs, or domain-specific languages, are programming languages that are tailored to a specific domain

SQL (databases)

d3 / Vega Lite (visualization)

pytorch, keras, tensor flow (machine learning)

Successful DSLs **reshape the cognitive representation** of the task, reducing the gulfs of execution and evaluation and empowering development in their application domain

Data science representations

I have too much data to fit in my computer. How do I count the number of times the word "HCI" appears on the web?

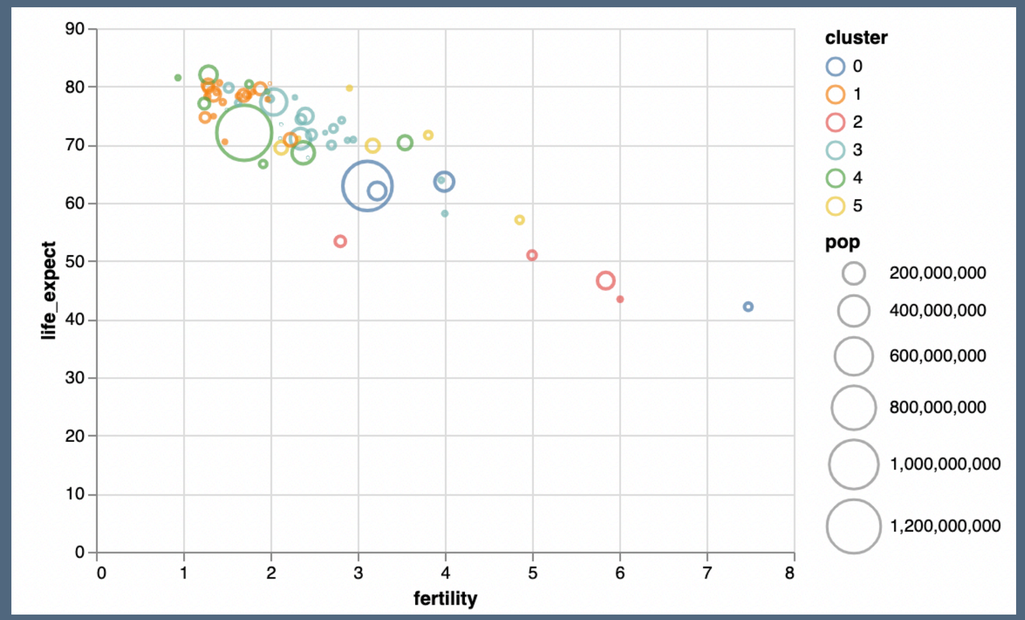
Representation: ***Map-Reduce*** [Dean and Ghemawat 2008]

> First, run a ***Map*** phase that runs a simple function over each webpage. That function outputs the number of HCIs, and can be run completely in parallel across every page on the web
>
> Second, run a ***Reduce*** phase that collects the outputs from the Map phase and aggregates them: here, via a sum

Representations for vis

[Bertin 1983; Mackinlay 1986; Satyanarayan 2016]

How do we tell a machine to create this? Paint pixels?



It's extremely challenging until we adopt a representation that visualizations are **encodings of data types into marks**

```
vl.markPoint()
  .data(data2000)
  .encode(
    vl.x().fieldQ('fertility'),
    vl.y().fieldQ('life_expect'),
    vl.size().fieldQ('pop').scale({range: [0, 1000]}),
    vl.color().fieldN('cluster')
  )
  .render()
```

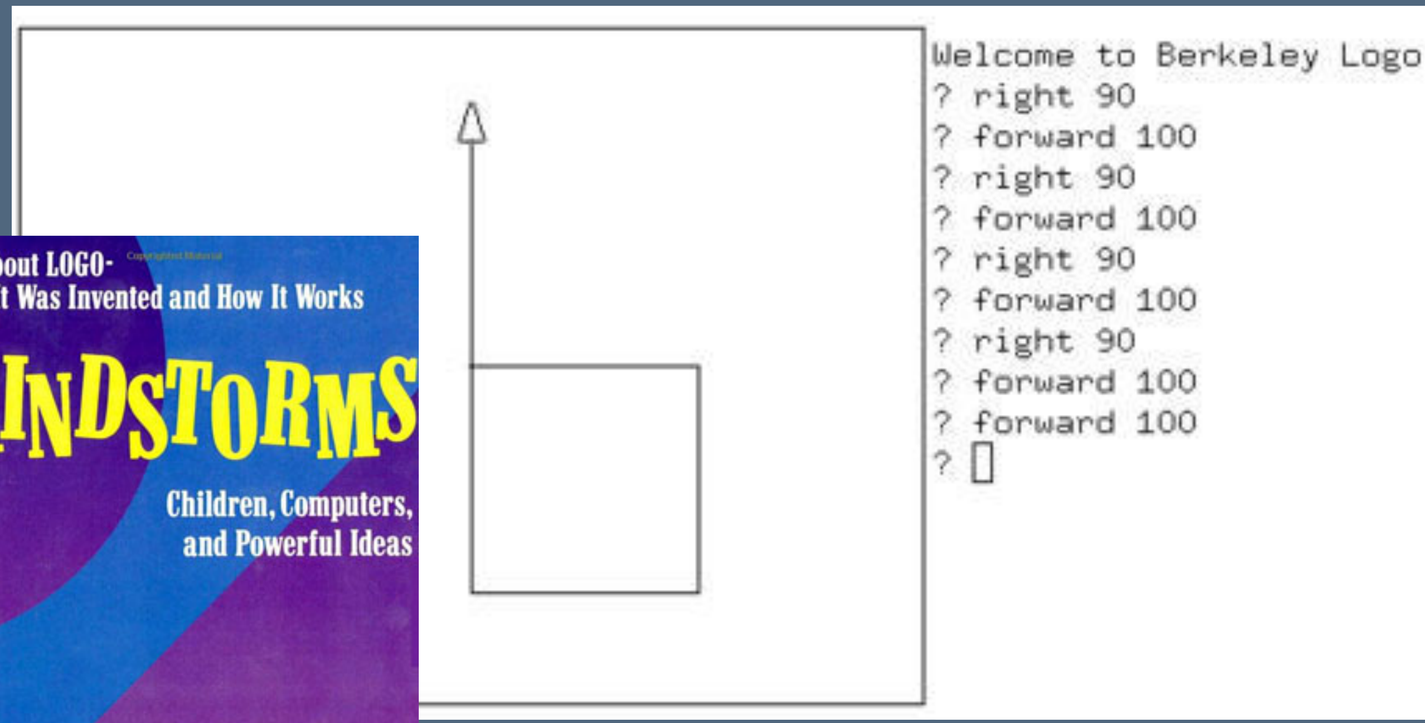
Learning programming

Logo: programming for children

[Papert 1980]

Constructionist learning: learning happens most effectively when people are making tangible objects

Lego Mindstorms followed this mold and was named after it

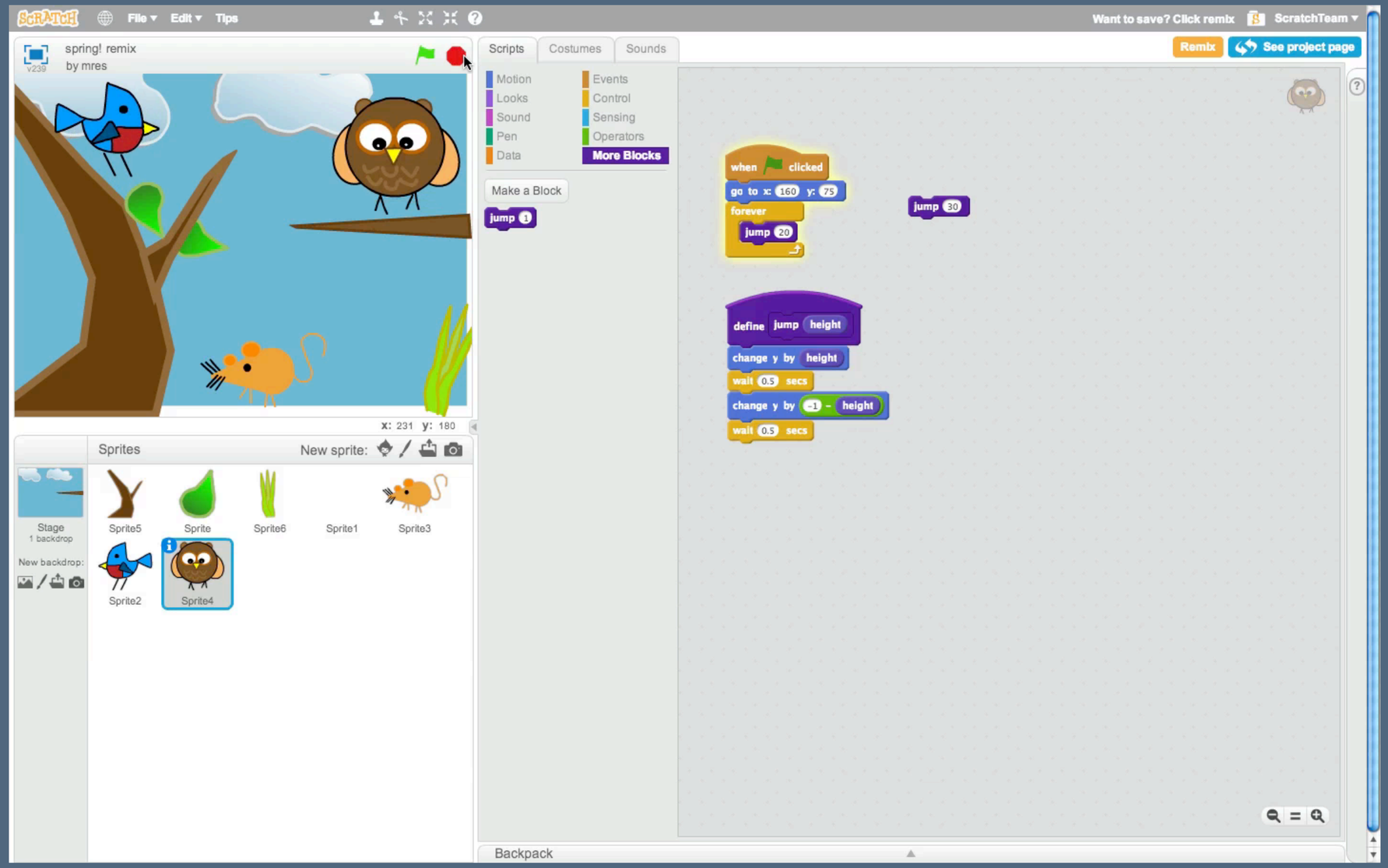


Scratch

[Resnick et al. 2009]

Inherited from Logo:

Block-based programming of simple animations and games as a gateway to programming for children

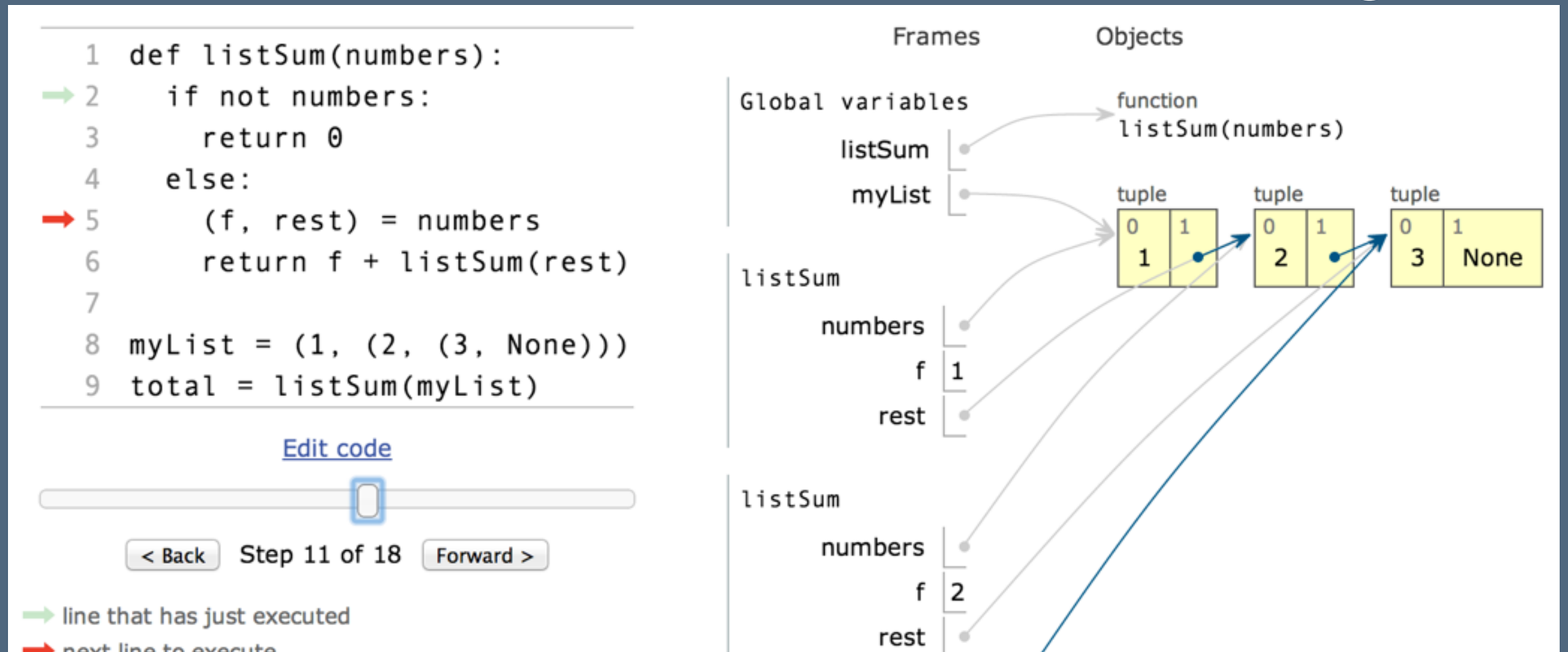


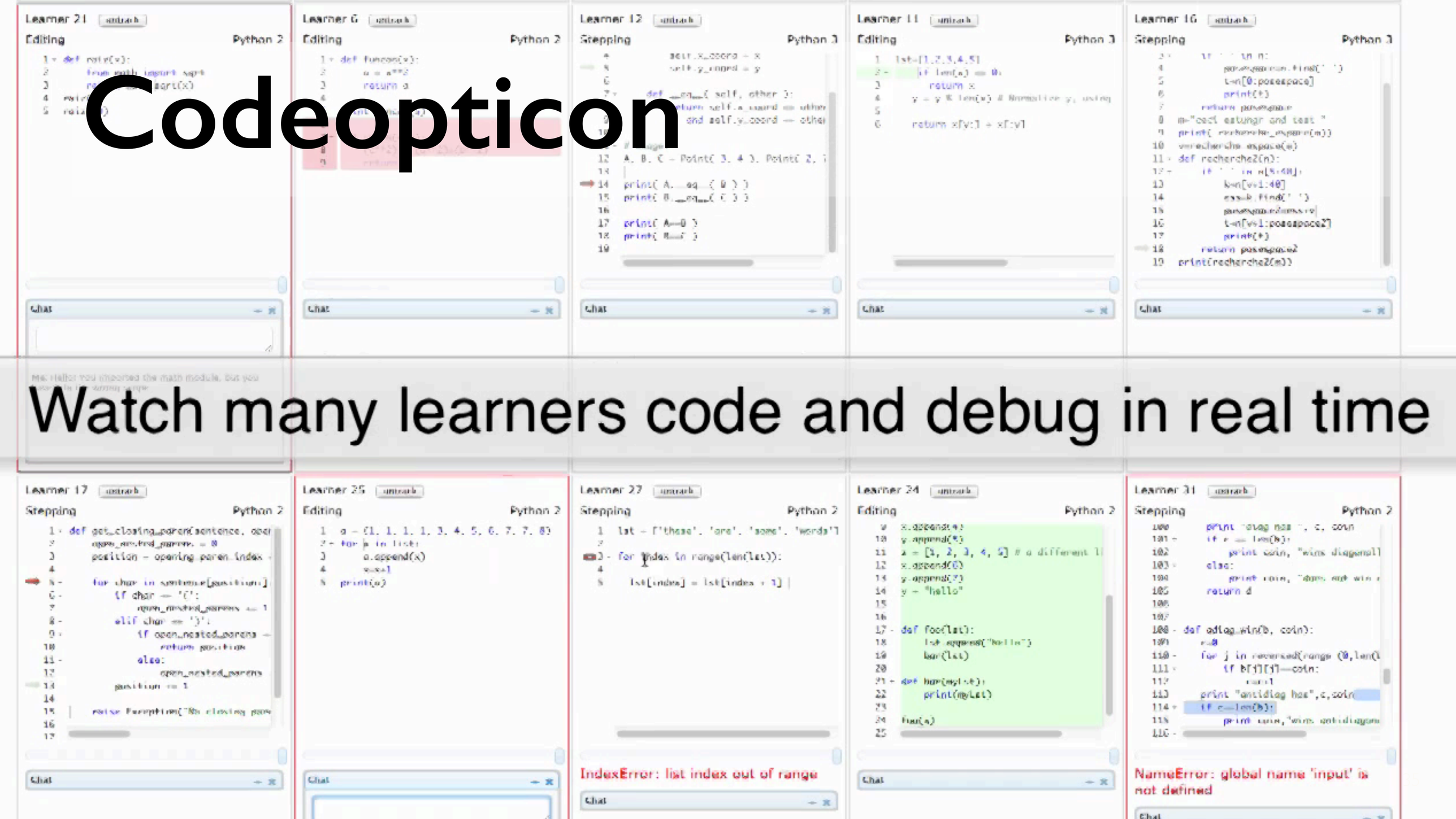
Online python tutor

[Guo 2013]

Embeddable Python data structure visualization

Over 200,000 users and a dozen universities using it




Codeopticon
Watch many learners code and debug in real time
Learner 21
Learner 6
Learner 12
Learner 11
Learner 16
Learner 17
Learner 25
Learner 27
Learner 24
Learner 31
IndexError: list index out of range
NameError: global name 'input' is not defined

Clustering student programs

[Glassman and Miller 2015]

iterPower

done

showing 862 total stacks

that represent 3842 total submissions

filtering by:

nothing yet

Filter | Rewrite | Legend

lines that appear in at least 50 submissions

Largest stack (matching filters)

1534

```
def iterPower(base,exp):
    result=1
    while exp>0:
        result*=base
        exp-=1
    return result
```

Remaining stacks (matching filters)

374

```
def iterPower(base,exp):
    result=1
    while exp>0:
        result=result*base
        exp-=1
    return result
```

153

```
def iterPower(base,exp):
    result=1
    while exp>0:
        result=result*base
        exp=exp-1
    return result
```

77 base=resultB

2592 def iterPower(base,exp):

701 def iterPower(base,expB):

349 def iterPower(base,expC):

51 def iterPower(base,expD):

51 def iterPower(resultB,expC):

55 elif expC==1:

527 else:

2466 exp-=1

279 exp=exp-1

135 exp=expB

366 expC-=1

65 expC=expC-1

63 for i in range(0,expB):

174 for i in range(expB):

52 iC+=1

64 iC=0

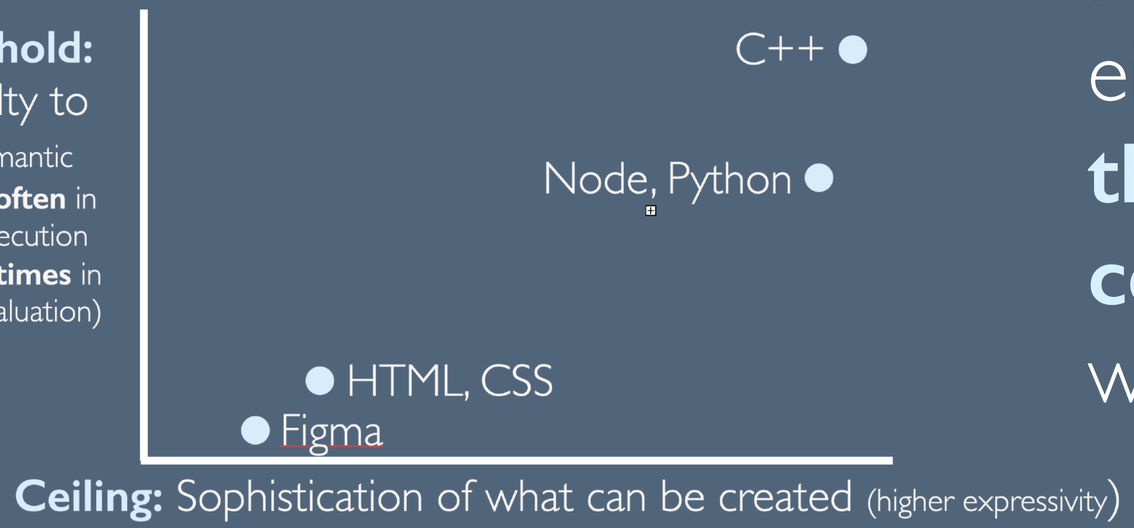
204 if exp==0:

210 if expB==0:

350 if expC==0:

2035 result*=base

Summary



Programming tools often either aim to **reduce the threshold** or **increase the ceiling** — how depends on which one we're pursuing

Successful programming tools **shift our cognitive problem representations** to make the task more readily solvable

Tools for **learning programming** help externalize our cognition to better understand what code is doing (or ought to be doing)

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