## How to Plan Programs

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Lines of Code



# Understanding Problems Before Programming



- Not accounting for empty input
- Not accounting for even-length lists (left median? right median? average?)
- Not accounting for unsorted input
- Confusing median for mean
- Confusing median for mode
  - 1

Students often solve the <u>wrong</u> problem

Autograding:

- Comes too late
- Fear of change (sunk costs)
- Learning objectives lost

We keep focusing on understanding pro**gra**ms We don't focus enough on understanding pro**ble**ms

#### Standard solution:

#### Express the problem in your own words.

Problem:

Students don't have their "own" words!

Exercise:

Provide examples (input/output pairs)

for a median function

median([list: 1, 2, 3]) is 2
median([list: 1, 2, 3, 4, 5]) is 3
median([list: 1, 2, 3, 4]) is ...
median([list: 1, 3, 2]) is ...

#### Examples provide a *concrete* form of "in your own words" Examples are <u>also</u> useful as *test cases*

But inert examples are useless (and students won't write them [Castro & Fisler])

#### <u>Idea</u>

Run examples against known correct & known buggy implementations (We can do this *before they've written any code*)

"Semantic mutation testing":

The buggy implementations correspond to known misconceptions









"Semantic mutation testing":

The buggy implementations correspond to <u>known misconceptions</u>

How do we know this?

# Experts curate the mutants based on experience, student questions, etc.

#### But the *expert blind spot* is a real concern!



#### median([list: 1, 3, 2]) is 3

▶ median-tests.arr					
INCO	ORRECT	CONSEQUENTLY, THOROUGHNESS IS UNKNOWN			
These tests do not match the behavior described by the assignment:					
		definitions://:10:2-10:30			
11 r	median([list:	1, 3, 2]) <b>is</b> 3			

Gather failing student examples

> Cluster and look for misconceptions

> > Translate misconceptions into buggy code







#### Classsourcing

Identifies misconceptions from failing examples

Works around expert blind-spots

Relatively lightweight

#### <u>Summary</u>

Students program before understanding the problem

We need lightweight ways to help them debug understanding

Examples are very good for this

Examples can be operationalized via "semantic mutation testing"

Student mistakes can be mined for insight

#### Executable Examples for Programming Problem Comprehension

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#### Will Students Write Tests Early Without Coercion?\*

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	Who Tests the Testers?*				
	Avoiding the Perils of Automated Testin	g			
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**Reading Between the Lines:** Student Help-Seeking for (Un)Specified Behaviors

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#### Making Hay from Wheats: A Classsourcing Method to Identify Misconceptions Siddhartha Prasad Ben Greenman Tim Nelson Computer Science Department **Computer Science Department** Computer Science Department **Brown University** Brown University Brown University Providence, Rhode Island, USA Providence, Rhode Island, USA Providence, Rhode Island, USA siddhartha\_prasad@brown.edu timothy\_nelson@brown.edu benjamin.l.greenman@gmail.com John Wrenn Shriram Krishnamurthi **Computer Science Department Computer Science Department Brown University Brown University** Providence, Rhode Island, USA Providence, Rhode Island, USA

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# Planning Programs Before Programming

Write a program that takes a list/array of numbers and produces the average of the non-negative numbers that occur before (an optional) -999

Ignore I/O – just take the list/array as input

Use any language you wish

## On Mark Guzdial's Blog

#### A Challenge to Computing Education Research: Make Measurable Progress

After 30 years, why hasn't somebody *beaten* the Rainfall Problem? Why can't someone teach a course with the *explicit* goal of their students doing *much* better on the Rainfall Problem — then publish how they did it? We ought to make measurable progress.

I don't think that this is an impossible goal. In fact, I bet that some of the existing research projects in computing education could "beat" (generate published reports with better results) these current studies.

 The TeachScheme approach focuses on design based on data. I bet that their students could beat the Rainfall Problem or the McCracken working group problem. Write a program that takes a list/array of numbers and produces the average of the non-negative numbers that occur before (an optional) -999

- truncate at sentinel
- ignore negatives
- sum the data
- count the data
- compute average
- handle empty data (division by zero)

[Fisler 2014] studied students at 4 unis/5 courses using HtDP

Findings:

Students with clear structure had far fewer errors

Students made good use of built-in and higher-order functions

Students showed a much greater diversity of structures than traditional in imperative programming

Guzdial: this "beat" rainfall

**Rainfall**: Write a program that takes a list/array of rainfall values (numbers) and produces the average of the non-negative numbers that occur before (an optional) -999

Adding Machine: given list of numbers, return list of sums of each sublist separated by zeros; stop after two consecutive zeros

e.g.:  $[3,0,2,5,0,0,9] \rightarrow [3,7]$ 

**Palindrome**: standard definition, but ignore whitespace, punctuation, and capitalization

**Shopping Cart**: compute total cost of a cart (list of items), giving one discount based on the number of hats in the cart and another based on the total price of shoes in the cart All the prior research has been in the "backward" direction: Have students write programs, try to determine plans

What if we go in the "forward" direction? Have students write plans *before* programming?













#### **Two Different Views of HOFs**

Common in textbooks (e.g., *HtDP*)

HOFs as abstractions of *code* 

(i.e., uniformity over several traversal/processing patterns)

View we're trying to develop

HOFs as abstractions of *behavior* (i.e., uniformity over several data transformations)



	Output Type	Output Element Type	Output Length
map	list	can differ	same
filter	list	same	<=
ormap	bool		

### Important from both **plan composition** and **data science** perspectives

Functional programming (FP) provides a rich set of tools for reducing duplication in your code. The goal of FP is to make it easy to express repeated actions using high-level verbs. I think that learning a little about FP is really important for data scientists, because it's a really good fit for many problems that you'll encounter in practice.

—Hadley Wickham, *Advanced R*, etc.

#### **Three Kinds of Activities**

# *Clustering*: given i/o pairs, put them in equivalent groups

## Labeling:

given pictorial versions, indicate intended functions

#### Classification:

for each i/o pair, indicate which function(s) can do this

#### **Takeaways**

### Students did increasingly well at our tasks; we also found some common errors

Students do confuse distinct functions with similar features

*Clustering* and *classification* are very useful activities

We've created useful instruments for both research <u>and</u> teaching

Onward to planning...



filter lambda function that checks if the string is only made up of the characters given strings





words

•(Each•word,•deconstructed•into•a•list•using•string->list)





#### **Structural versus Pipeline Composition** of Higher-Order Functions (Experience Report)

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# New Curricular Horizons

## Data Structure Progress Since the 1970s

1970s	Pascal	arrays
1980s	С	arrays
1990s	C++	arrays
2000-2015	Java	ArrayList
2015-now	Python	associative arrays

## Whereas in Functional Programming...

1960s	Lisp	lists
1980s	Scheme	lists
1990s	ML	lists
2000s	Haskell	lists
Now?	Lean/Coq/	Building artisanal lists inductively



LowCode/NoCode

Data-centric algorithms

StackOverflow

Program synthesis

Property-based testing

Verification in programming



## Understanding Problems Before Programming



## Planning Problems Before Programming



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