Practical approaches to teaching the CS theory module: nondecision problems and real computer programs

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Overview

- 1. Main talk (practical approaches to the CS theory module)
	- About 35 minutes; real-time questions and interaction are welcomed
- 2. Other interests (hope to pursue some of these in the next two years)
	- About 5 minutes: computer vision, machine learning, distributed systems, CS education, public understanding of computer science
- 3. Questions and discussion

Understanding the audience

- As an undergraduate, did you:
	- Take a module that emphasized the distinction between polynomial time and exponential time algorithms (more formally, P vs EXP)?
	- Take a module that explored NP and NP-completeness?
	- Take a module that discussed the equivalence, in terms of time complexity, of all "reasonable" computational models (up to polynomial factors)?
	- Take a module that covered undecidability, including proofs that certain problems (e.g. the halting problem) are undecidable?

Understanding the audience, part II

- As an *instructor*, have you:
	- *Taught* a module that emphasized the distinction between polynomial time and exponential time algorithms (more formally, P vs EXP)?
	- *Taught* a module that explored NP and NP-completeness?
	- *Taught* a module that discussed the equivalence, in terms of time complexity, of all "reasonable" computational models (up to polynomial factors)?
	- *Taught* a module that covered undecidability, including proofs that certain problems (e.g. the halting problem) are undecidable?

The CS "theory" module? What theory module?

- Most computer science programs in the UK and US offer a "theory" module
	- many require it
- Typical topics drawn from:
	- automata theory (dfas, pdas, regular grammars, cfgs, Turing machines)
	- computability theory (existence of undecidable problems e.g. halting problem, Turing reductions, Rice's theorem)
	- complexity theory (P, NP, EXP, NP-completeness, Cook-Levin theorem, polynomial time reductions)
- Sometimes the complexity theory is included as part of an advanced algorithms module

High-level point of the talk: the theory module can be taught in a practical and accessible way

What Can Be Computed?

A Practical Guide to the Theory of Computation

vapourware version of front cover (Erik Demaine origami)

- new undergraduate textbook from Princeton University Press, available February 2018
- Key features:
	- Python programs as the main computational model

Technical content of today's talk

• Focuses on nondecision problems

Next few slides: informal overview of the key distinction between decision and nondecision problems

Which is more "useful": program *A* or program *B*?

Input: Input to both programs is a roadmap and a list of cities:

- *Decision problem*.
- Existing theory-of-computation modules usually focus on decision

• *Nondecision problem*.

- This talk points to a way to teach the theory-of-computation module using nondecision problems.
- Students may achieve better learning because the content is perceived as relevant and practical.

We consider only a *novice audience*

- Novice audience \equiv undergraduate students who are seeing computability and complexity theory for the first time
- Experienced practitioners know that decision programs can often be converted to equivalent non-decision programs with only a logarithmic increase in running time.
- Therefore, experienced practitioners don't care if we restrict attention to decision problems
- But for the *novice audience*, a program that outputs only a single bit may appear abstruse, irrelevant, and impractical

Conclusion: For the novice audience, start the module with nondecision problems

Conclusion:

- No clear-cut winner.
- We recommend using nondecision problems for most of the module, then transitioning to decision problems for advanced topics. Specifically:
	- Nondecision problems for decidability, P, EXP, and NP
	- Decision problems for NP-completeness

The talk could end here. The remainder provides additional detail.

Remainder of the talk

- 1. Empirical evidence of student perceptions favoring nondecision problems
- 2. Technical details of how to teach the content using nondecision problems
	- a) Definitions, including *formal languages* vs *computational problems*
	- b) Computability
	- c) Complexity

A survey of computer science students gathered empirical evidence

- 41 computer science students given descriptions of four computer programs
	- The programs solve decision and non-decision variants of two different problems (TSP and knapsack)
- rate "usefulness" from 1 (extremely useful) to 5 (not at all useful)

Programs that solve nondecision problems are perceived as much more "useful" by the novice audience

- The difference has overwhelming statistical significance
	- Wilcoxon signed-rank test has $p < 10^{-11}$
- The effect size is also substantial
	- Additional tests show the effect size exceeds difference between "very useful" and "mildly useful"

Educational theory implies that perceived usefulness will lead to improved outcomes

- Education researchers have demonstrated that effectiveness of learning is enhanced when concepts are perceived as *useful* or *applicable*
	- See e.g. L. D. Fink, *Creating significant learning experiences: An integrated approach to designing college courses* (2013)
- Therefore, we conclude the use of nondecision problems in the CS theory course should improve learning outcomes

We have not attempted to measure improved learning outcomes directly. I welcome suggestions on how to do that!

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Details of the traditional approach

- *alphabet* \equiv finite set of symbols, denoted Σ
- *string* ≡ finite sequence of symbols
- set of all possible strings on Σ is denoted Σ^*
- *language* or *formal language* ≡ subset of Σ ∗
- Given Turing machine M with input string S , we say
	- *M* accepts s if it terminates in an accepting state
	- *M rejects s* if it terminates in any other state
	- but remember the machine may not terminate, so it could neither accept nor reject
- Machine *M* decides language *L* if
	- *M* accepts all $s \in L$ and rejects all $s \notin L$

so it had better terminate on all inputs!

What is the connection between "deciding a language" and "solving a problem"?

- For decision problems, these concepts are equivalent
- Example: Hamilton cycle
	- asks the yes/no question "does this graph have a Hamilton cycle?"
	- e.g. the string $s = "a, b, b, c, c, a"$ is a *positive instance*,

but $s' = "a, b, b, c"$ is a *negative instance*

- Let language L be the set of strings that are positive instances
- Then a Turing machine that decides L implicitly answers the question "does this graph have a Hamilton cycle?"

 D_L = "is string *s* in language L?"

 $L_D =$ set of strings that are positive instances of D

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Key recommendation: instead of *formal language*, use *computational problem*

- A *computational problem* (which may or may not be a decision problem) is a function F , mapping ASCII strings to sets of ASCII strings.
- If $F(x) = \{s_1, s_2, ...\}$, we call $\{s_1, s_2, ...\}$ the *solution set* for x, and each s_i is a **solution** for x .
- If $F(x) = \{$ "no"}, then x is a *negative instance* of F; otherwise x is a *positive instance*.

"Deciding a language" vs "solving a problem"

- Computer program P solves the computational problem F if $P(x) \in$ $F(x)$ for all x. That is, the program always terminates and outputs a correct solution.
- Contrast with: Turing machine *M* decides language L if M accepts all $s \in L$ and rejects all $s \notin L$

Helpful examples of computational problems: HamCycle and Factor

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Computability replaces *decidability*

- The notion of *computable function* is well known, but here we generalize to the notion of *computable problem*:
	- \bullet F is *computable* if there exists a Python program P that computes F
	- i.e. require $P(x) \in F(x)$ for all x but for given x, P needs to compute only one solution, not all of them (e.g. find one Hamilton cycle, not all Hamilton cycles)
- Uncomputable problems include old favorites such as the halting problem, but also include interesting nondecision problems, e.g.
	- can view Hilbert's 10th problem as a nondecision problem: find integer solutions to Diophantine equations
	- given a program, how many steps will it execute before it halts?

Using real computer programs also helps understanding

Example: A classical diagonalization + proof by contradiction can be done explicitly in Python

```
from yesOnString import yesOnString
def weirdYesOnString(progString):
   if yesOnString(progString, progString) == 'yes':return 'no'
   else:
      return 'yes'
```
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Need new notation to generalize standard complexity classes

P, NP, Exp generalize to Poly, NPoly, Expo

Exp

NP

Poly, NPoly, Expo yield pedagogical benefits

Examples:

- Students can write multithreaded programs that find factors, Hamilton cycles, etc. in nondeterministic polynomial time
	- Leads to concrete experience of the power of nondeterminism
- The impact of complexity theory on cryptography is obvious to the novice audience
	- No polynomial time algorithm for *finding* factors is known
	- But the AKS algorithm determines the *existence* of a factor in polynomial time! So in the decision framework, it's hard to make the link to cryptography.

The generalization of *verifier* presents some interesting challenges and opportunities

- The definition involves multiple conditions and quantifiers
- The definition separates the proposed solution s and any required "hint" h
	- Contrast this with the traditional approach, where s and h are incorporated into a single string c called the *witness* or *certificate*
	- It can be difficult for a novice audience to interpret the certificate c

Let F be a computational problem. A verifier for F is a program $V(w, s, h)$ with the following properties:

- \bullet V receives three string parameters: an instance w , a proposed solution s , and a hint h .
- V halts on all inputs, returning either "yes" or "no".
- Every positive instance can be verified: If w is a positive instance of F , then $V(w, s, h) =$ "yes" for some correct positive solution s and some hint h .
- Negative instances can never be verified: If w is a negative instance of F , then $V(w, s, h) =$ "no" for all values of s and h.
- Incorrect proposed solutions can never be verified: If s is not a correct solution (i.e. $s \notin F(w)$), then $V(w, s, h) = \text{``no''}$ for all h .

We recommend the traditional approach to polynomial time reductions, with one small tweak

- As with the strong majority of other treatments, stick with *Karp reductions* (also known as *mapping reductions* or *many-one reductions*)
- One small generalization: can reduce from decision problems to *nondecision* problems, without altering the definition
	- Leads to a nice definition of NP-hardness later
- In principle, can teach a more general approach, reducing *nondecision* problems to *nondecision* problems
	- Experiments led to some success, but on balance this is not recommended for the novice audience

For NP-completeness, stay firmly within the traditional realm

- It is possible to teach "NPoly-completeness," but not recommended
- Even while restricting to decision problems, the benefits of using nondecision problems earlier in the course are felt:
	- The practical impacts of routing, scheduling and knapsack problems are obvious
	- Holistic discussions of "P versus NP" have a more practical flavour

Ten CS theory textbooks

Related work

- Focus on nondecision problems
	- Goldreich, *On Teaching the Basics of Complexity Theory* (2006) + books (2008, 2010); Mandrioli (1982)
- Interactive automata software tools e.g. JFLAP, DEM
	- Chesñevar et al. (2003); Rodger et al. (2006, …);
- "NP-completeness for all"
	- Crescenzi et al. (2013); Enström and Kann (2010); Lobo and Baliga (2006)

Summary: The CS theory course can be made practical and accessible

- Key ideas: focus on nondecision problems, use real computer programs
- Two main components of today's talk:
	- Survey of CS students shows they perceive nondecision problems as more useful; educational theory implies this leads to better learning outcomes
	- Presented definitions and techniques useful for achieving this with a novice audience
- Approach has been refined over four years' experimentation in classroom; details appear in forthcoming textbook

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Do we live in an age of algorithms?

Public understanding of computer science

Princeton University Press (2012)

Computer vision and machine learning

EMMCVPR (2013)

Distributed systems

ACM Trans. Storage (2008)

CS education

A Multi-Institutional Perspective on H/FOSS Projects in the **Computing Curriculum**

GRANT BRAUGHT and JOHN MACCORMICK, Dickinson College JAMES BOWRING and QUINN BURKE, College of Charleston BARBARA CUTLER, DAVID GOLDSCHMIDT, MUKKAI KRISHNAMOORTHY, and WES-LEY TURNER, Rensselaer Polytechnic Institute STEVEN HUSS-LEDERMAN, Beloit College BONNIE MACKELLAR, St. John's University ALLEN TUCKER, Bowdoin College

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+ thank you for welcoming me into the School of Computing Sciences, and thanks for listening today!