Synthesis

CS294-184: Building User-Centered Programming Tools

UC Berkeley Sarah E. Chasins

Program Synthesis Week 1, Day 1



Discuss in groups

- If you could express your intent to the computer in any way at all, how would you want to write programs?
 - What input would you have the computer take?
- How would the interaction between you and the computer work? What was confusing about synthesis from the first reading/your
- understanding of synthesis so far?
 - It's ok if this is lots of things! We'll be getting hands-on soon, which should clear up a lot of confusions. :)
- Are there applications that you'd expect are amenable to synthesis but that haven't made it into the literature yet? (Weren't mentioned in Chapter 2.)

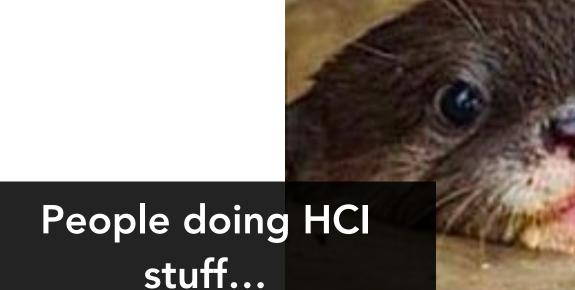
Reading Reflection

Reading Key Takeaways

- The core challenges in synthesis:
 - Scalability/size of the program space
 - Capturing user intent—What's a good spec? How do we get it?
- The variety of plausible specs we can get from users
 - I/O examples, demonstrations, logical specs, natural language, programs with holes, equivalent programs (!)
- The variety of search techniques
 - Enumerative, constraint-based, deductive, statistical
- And at a higher level, the fact that synthesis is not just **one** technique • A general sense of the problems to which synthesis has been applied
- so far

Thank you for your survey answers!

Why synthesis?



Synthesis

There are a few PL techniques that just keep coming up in HCI tasks!

- Program synthesis
- Projection/Structure editors
- Program slicing
 Others come up, but these
 seem to come up all the time.

Demo time

Automating String Processing in Spreadsheets using Input-Output Examples, Sumit Gulwani

FlashFill Do you have Excel installed? You can probably run this demo on your own laptop while I run it on mine!



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	Α	B
1	Whole Name	
2	Alvin Cheung	Prof. Cheung
3	Armando Fox	
4	Jonathan Ragan-Kelley	
5	Koushik Sen	
6	Sanjit A. Seshia	
7	Katherine A. Yelick	
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3	Armando Fox	Prof. Fox				
4	Jonathan Ragan-Kelley	Prof. Kelley	F			
5	Koushik Sen	Prof. Sen				
6	Sanjit A. Seshia	Prof. Seshia				
7	Katherine A. Yelick	Prof. Yelick				
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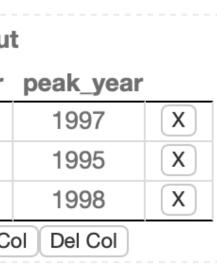
Scythe To run this one, head to: <u>https://scythe.cs.washington.edu/demo</u>

Synthesizing Highly Expressive SQL Queries from Input-Output Examples, Chenglong Wang

Scythe	Home	Demo				
Click the Synthesis button to synthesize Queries from the example!						

* Example Task: Find the span of career peak (the year when the first paper and most cited papers are published) of computer scientists given the list of their pushlished papers.

	papers						output
author	,	title	year	citation		author	min_year
H. Simo	n	Understanding wi	1974	277	X	H. Simon	1974
H. Simo	n	Organization	1997	20057	X	R. Tibshirar	1995
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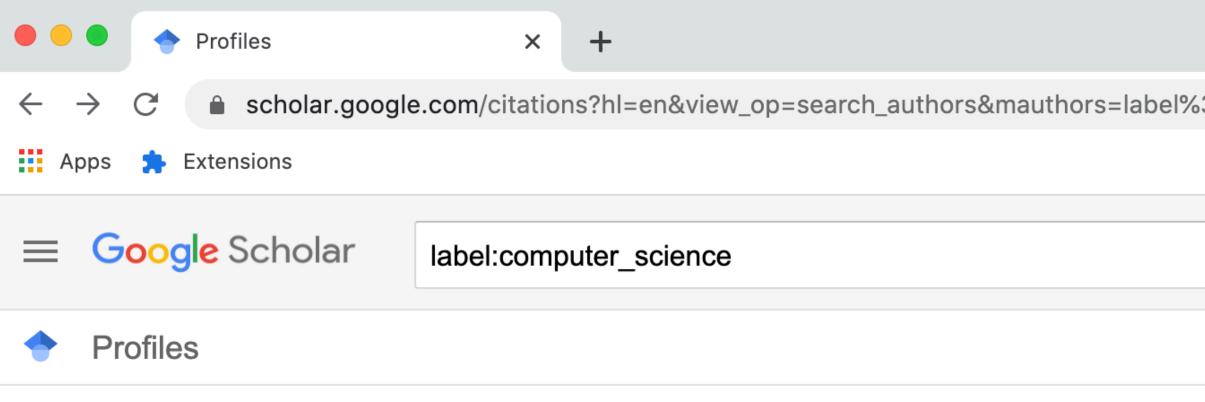
```
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From
  (Select t5.author, t5.min_year, t4.author As author1, t4.year
  From ((Select
          t3.author, Min(t3.year) As min_year
       From
          papers As t3
        Group By
         t3.author) As t5 Join
      (Select t7.author, t7.year
        From
          (Select t1.author, t1.max_citation, t8.author As author1, t8.ti
tle, t8.year, t8.citation
          From ((Select
                  t2.author, Max(t2.citation) As max_citation
                From
                  papers As t2
                Group By
                 t2.author) As t1 Join
             papers As t8)) As t7
        Where t7.max_citation = t7.citation
           And t7.author = t7.author1) As t4)) As t6
 Where t6.author = t6.author1;
```

Synthesized Query 1 - Run on DB Visualize -



Rousillon: Scraping Distributed Hierarchical Web Data, me & my collaborators :)

Helena If you want to run this one, you have to install an extension: http://helena-lang.org/install





Geoffrey Hinton

Emeritus Prof. Comp Sci, U.Toronto & Engineering Fellow, Google Verified email at cs.toronto.edu

machine learning psychology artificial intelligence cognitive science computer science



David S. Johnson

Visiting Professor, Columbia University Computer Science Department Verified email at research.att.com

Algorithms computer science optimization traveling salesman problem bin packing



David Haussler

Scientific Director, UC Santa Cruz Genomics Institute, University of California, Santa Cruz

Verified email at soe.ucsc.edu

genomics computer science molecular biology evolution cancer



Freeman Hu

Shandong University Verified email at mail.sdu.edu.cn

Computer Science



vapnik

Professor of Columbia, Fellow of NEC Labs America, Verified email at nec-labs.com

machine learning statistics computer science

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Helena Scrap
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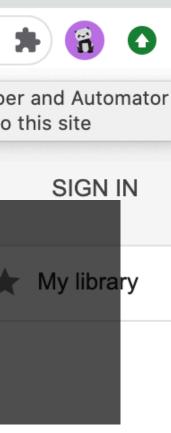
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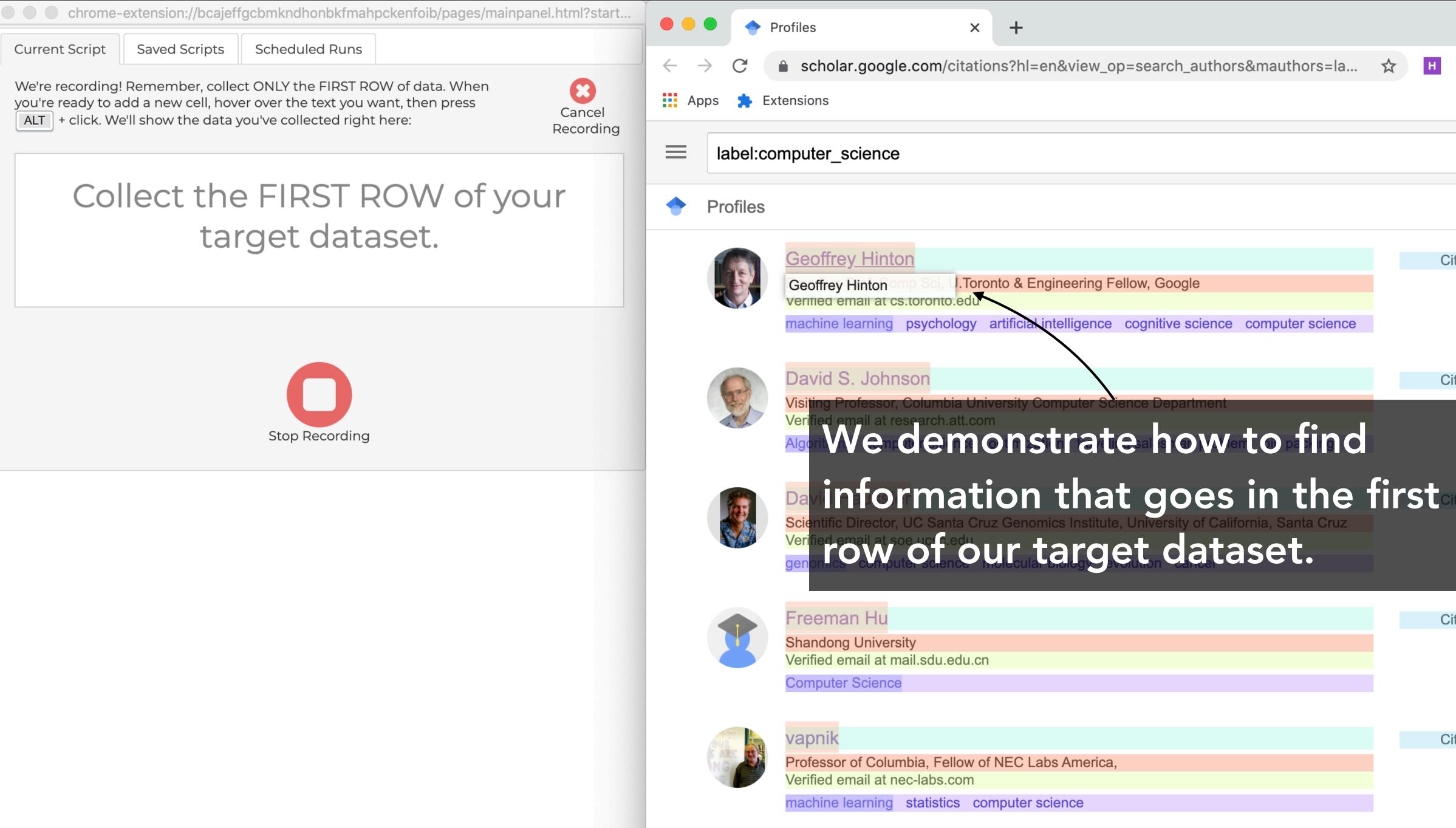
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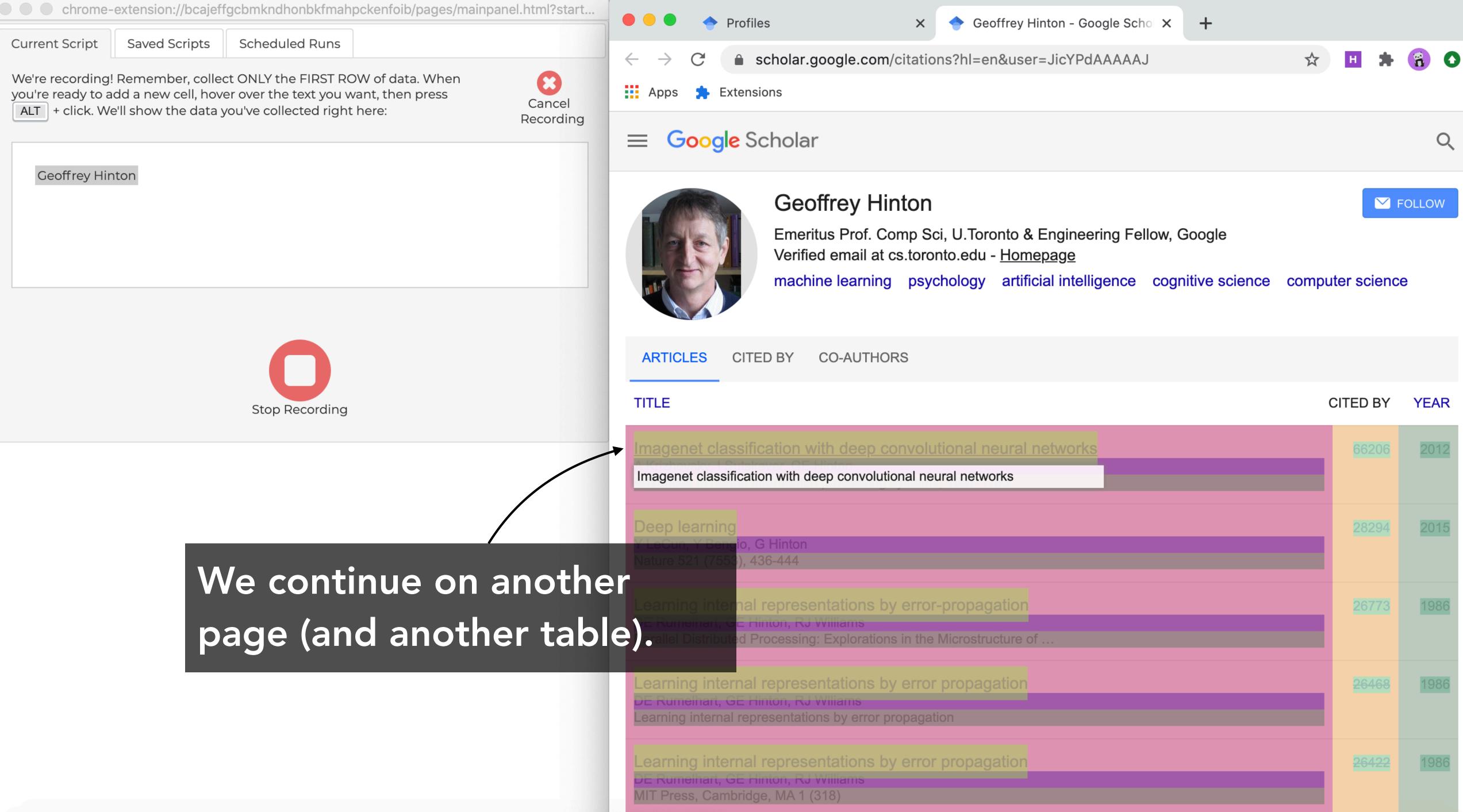


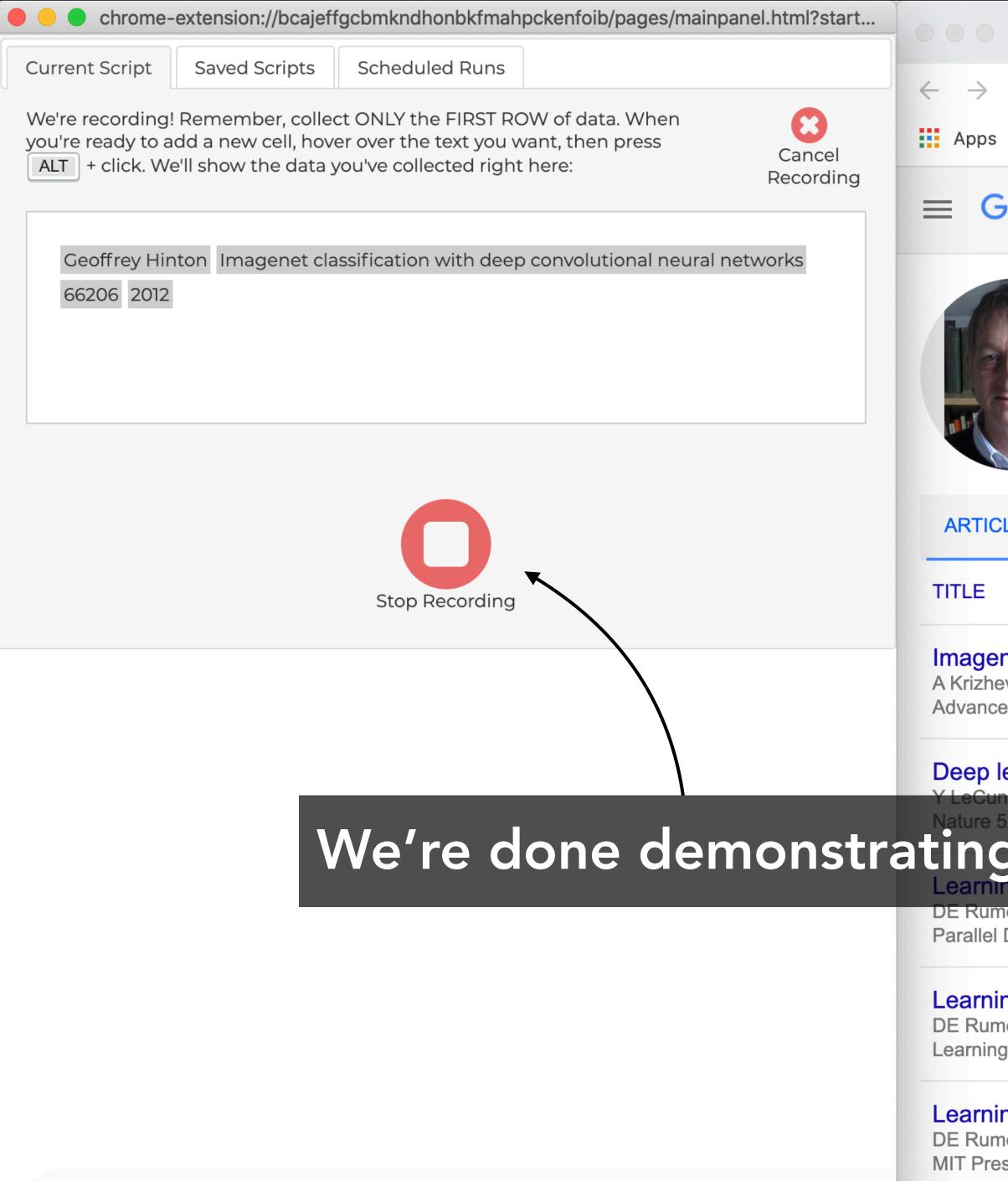






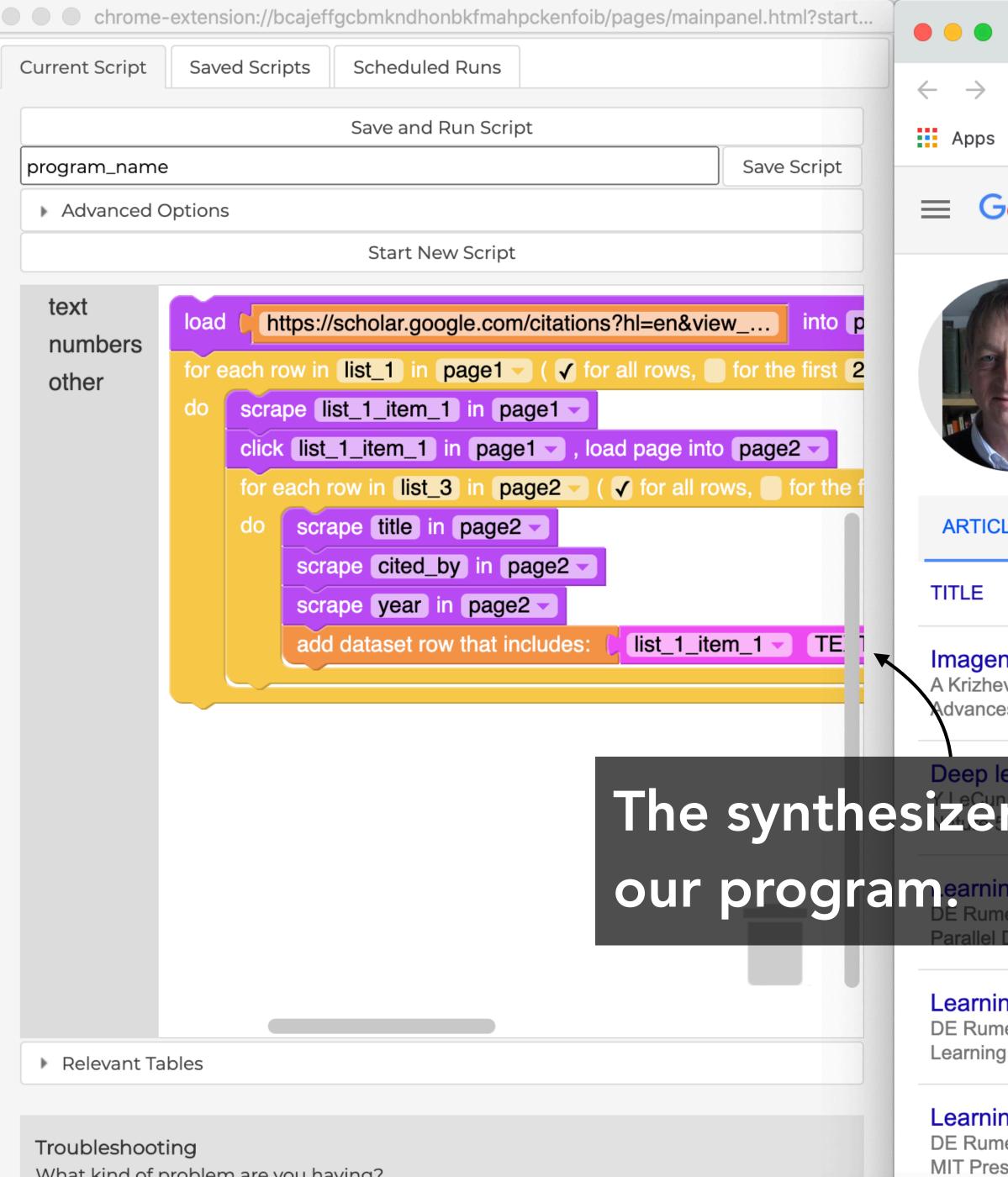
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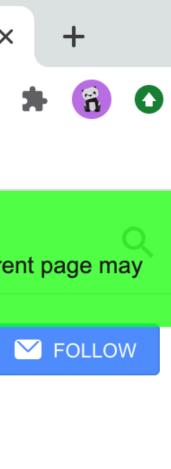
What kind of problem are you having?

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Geoffrey Hinton	Imagenet classification with deep convolutional neural networks	66206 2012 1	David Haussler
Geoffrey Hinton	Deep learning	28294 2015 2	Scientific Director, UC Santa Cruz Genomics Institute, University of California,
Geoffrey Hinton	Learning internal representations by error-propagation	26773 1986 3	Santa Cruz Verified email at soe.ucsc.edu
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Geoffrey Hinton	Dropout: a simple way to prevent neural networks from overfitting	21365 2014 7	
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Geoffrey Hinton	Reducing the dimensionality of data with neural networks	12573 2006 10	ES Lander, LM Linton, B Birren, C Nusbaum, MC Zody, J Baldwin, Macmillan Publishers Ltd.
Geoffrey Hinton	Rectified linear units improve restricted boltzmann machines	10069 2010 11	An integrated encyclopedia of DNA elements in the human genome 1053
-	Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups	8233 2012 12	ENCODE Project Consortium Nature 489 (7414), 57-74
Geoffrey Hinton	Learning multiple layers of features from tiny images	8034 2009 13	
Geoffrey Hinton	Speech recognition with deep recurrent neural networks	5975 2013 14	The human genome browser at UCSC WJ Kent, CW Sugnet, TS Furey, KM Roskin, TH Pringle, AM Zahler,
	Improving neural networks by preventing co-adaptation of feature detectors	5308 2012 15	Genome research 12 (6), 996-1006
Geoffrey Hinton	Training products of experts by minimizing contrastive divergence	4574 2002 16	Initial sequencing and comparative analysis of the mouse genome 706
Geoffrey Hinton	Adaptive mixtures of local experts	4263 1991 17	RH Waterston, K Lindblad-Toh, E Birney, J Rogers, JF Abril, P Agarwal,
Hinton	A learning algorithm for Boltzmann machines	line pr	ogram collects our data.
Geoffrey Hinton	Lecture 6.5-rmsprop: Divide the gradient by a running average of its rece magnitude	nt 3924 2012 19	A map of human genome variation from population-scale sequencing 705 1000 Genomes Project Consortium
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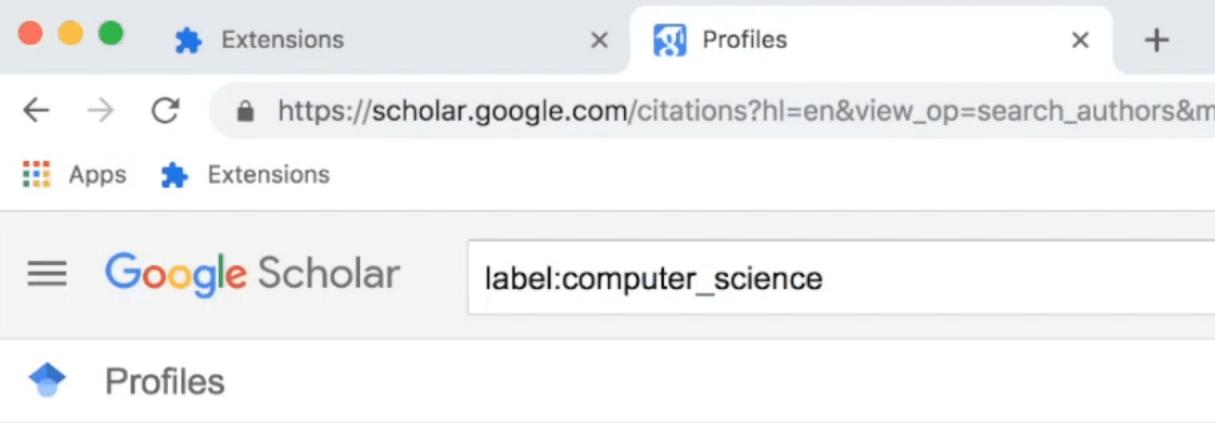
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Geoffrey Hinton	Dropout: a simple way to prevent neural networks from overfitting	21365	2014	7
Geoffrey Hinton	Visualizing data using t-SNE	14439	2008	8
Geoffrey Hinton	A fast learning algorithm for deep belief nets	13397	2006	9
Geoffrey Hinton	Reducing the dimensionality of data with neural networks	12573	2006	10
Geoffrey Hinton	Rectified linear units improve restricted boltzmann machines	10069	2010	11
Geoffrey Hinton	Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups	8233	2012	12
Geoffrey Hinton	Learning multiple layers of features from tiny images	8034	2009	13
Geoffrey Hinton	Speech recognition with deep recurrent neural networks	5975	2013	14
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2010





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machine learning neural networks artificial intelli computer science



DEYWIS MORENO

High Energy Physicist, Universidad Antonio Narino Verified email at uan.edu.co

High Energy Physics Computer science



David S. Johnson Visiting Professor, Columbia University (

Visiting Professor, Columbia University Computer Verified email at research.att.com

Algorithms computer science optimization trave



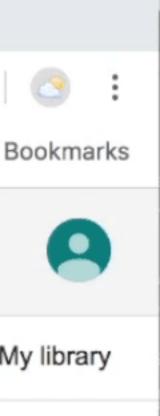
David Haussler Scientific Director, UC Santa Cruz Genomics Institu Cruz Verified email at soe.ucsc.edu

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18

before							
cmp	r1,	#0					
mov	r3,	r1,	asr #31				
add	r2,	r1,	#7				
mov	r3,	r3,	lsr #29				
movge	r2,	r1					
ldrb			, r2, asr #				
bic	r1,	r2,	#248				
sub	r3,	r1,	r3				
asr	r1,	r0,	r3				
and	r0,	r1,	#1				
(b)							

Scaling up Superoptimization, Phitchaya Mangpo Phothilimthana

LENS

after

#3]

r3, r1, #2 asr r2, r1, r3, lsr #29 add ldrb r0, [r0, r2, asr #3] and r3, r2, #248 r3, r1, r3 sub r1, r0, r3 asr r0, r1, #1 and

(c)

I know, I know, not as photogenic, but it makes programs much faster!!

Falx https://falx.cs.washington.edu/tool

Visualization by Example, Chenglong Wang

5 min break

Back up. What's program synthesis?

Find a program P that meets a spec ϕ (input, output):

Correctness Condition

$$\exists P. \forall x. \phi(x, P(x))$$

Find *P*

• When to use synthesis:

• Ease-of-use/productivity: When writing ϕ is faster or easier than writing P

• **Correctness:** when proving ϕ is easier than proving P

Hey, I've seen this before

I give computer a high-level description of what I want it to do



Computer gives me back a lowlevel program for doing it

Synthesis vs. compilation

Compilation

Typically deterministic

Typically performs lowering via a sequence of rewrite rules

Synthesis

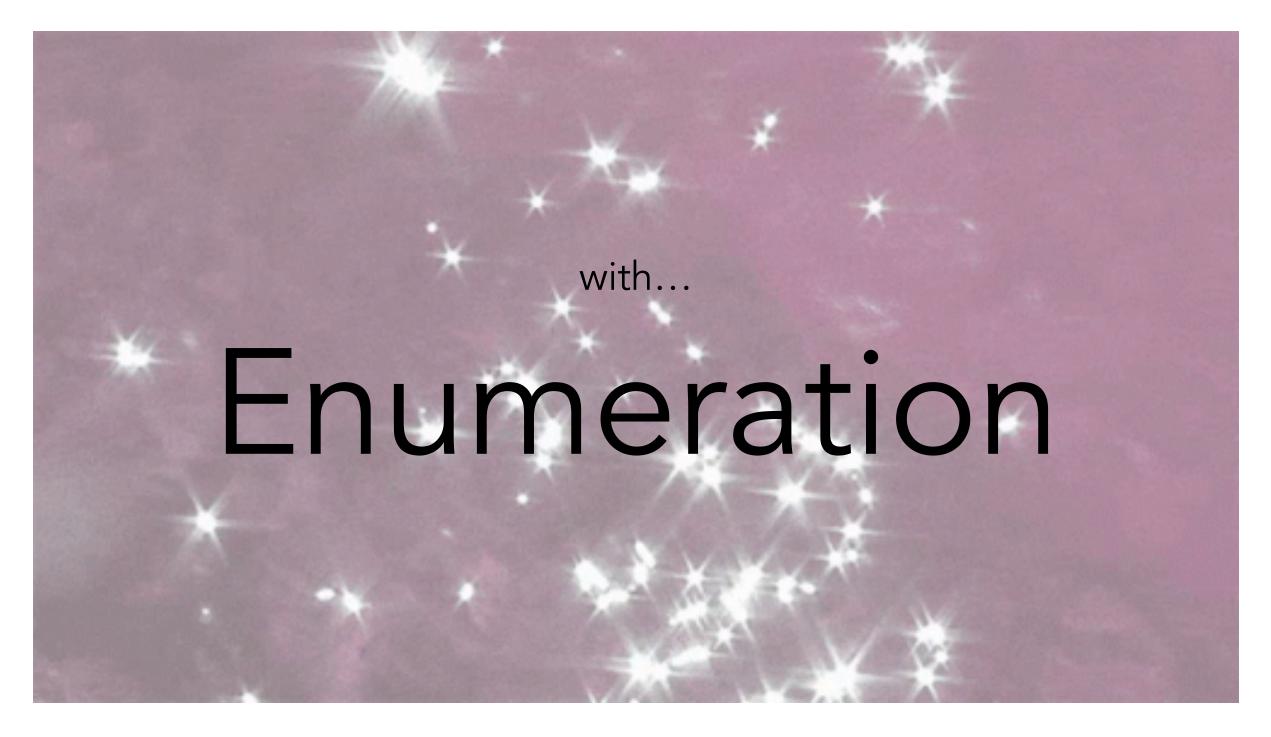
Searches a space of possible programs

... or sometimes a space of possible sequences of rewrite rules! look, the line is blurry ¯_(ツ)_/¯

If it involves search, we usually call it synthesis

Even if you don't take away anything else from today's lecture, take away that you can write a synthesizer!

Even if you don't take away anything else from today's lecture, take away that you can write a synthesizer!



What do we need to decide to make a synthesizer?

How does the user express what they want the program to do?

What space of programs is the synthesizer allowed to use?

What algorithm will the synthesizer use to search that space?

Hint: 3 things

What do we need to decide to make a synthesizer?

Hint: 3 things For today's sample synthesizer, let's pick...

How does the user express what they want the program to do? Input-Output examples

What space of programs is the synthesizer allowed to use?

Anything in a Domain-Specific Language (DSL) of our choice

What algorithm will the synthesizer use to search that space?



Which is to say...generating programs until we find one that works

Input-Output Examples

- Any work here?
- Nah, this is going to be pretty straightforward.

- Example:
- $(\{ \mathbf{x}'' \rightarrow \mathbf{3}, \mathbf{y}'' \rightarrow \mathbf{7} \},$ $(\{ ``X'' \rightarrow 4, ``Y'' \rightarrow 4 \},$ $(\{ "x" \rightarrow 2, "y" \rightarrow 12 \}, 31)$

23)

Can you guess it?? Did you already 19) synthesize this in your head?

Domain-Specific Language

• This one's a classic, but for another domain we might design something more customized

$$expr := \mathcal{N}$$

$$| v$$

$$| (expr + expr)$$

$$| (expr - expr)$$

$$| (expr * expr)$$

Enumeration

	level 0:	Ok, no luck so far. Let's just mash these				
	[0, 1, 2, 3, 4, y, x] count: 7	together! In every possible combination!				
Spec:	level 1 : $(0+0) = (0+0) = (0+0)$.00.00.10.41				
$(\{ "x'' \rightarrow 3, "v'' \rightarrow 7 \}, 23)$	(0+3), (0*3), (0-3), (0+4), (0*4	$\begin{array}{c} (0), (0-0), (0+1), (0*1), (0-1), (0+2), (0*2), (0-2), \\ (0-4), (0+y), (0*y), (0-y), (0+x), (0*x), (0-x), \\ \end{array}$				
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		(2-2), (2+3), (2*3), (2-3), (2+4), (2*4), (2-4), (2+4), (2-4), (2+1),				
$(\{ "x" \rightarrow 2, "y" \rightarrow 12 \}, 31)$		x), (2-x), (3+0), (3*0), (3-0), (3+1), (3*1), (3-1), b), (3-3), (3+4), (3*4), (3-4), (3+y), (3*y), (3-y),				
), $(4-0)$, $(4+1)$, $(4*1)$, $(4-1)$, $(4+2)$, $(4*2)$, $(4-2)$,				
		(4-4), (4+y), (4*y), (4-y), (4+x), (4*x), (4-x), (y-1), (y+2), (y*2), (y-2), (y+3), (y*3), (y-3),				
Space of programs:	(y+4), $(y*4)$, $(y-4)$, $(y+y)$, $(y*y)$	y), (y-y), (y+x), (y*x), (y-x), (x+0), (x*0), (x-0),				
	(x+1), (x*1), (x-1), (x+2), (x*2), (x*y), (x-y), (x+x), (x*x)	(x-2), (x+3), (x*3), (x-3), (x+4), (x*4), (x-4),				
$expr:=\mathcal{N}$	count: 154					
v	level 2 :	Hm, still no luck. Keep mashing.				
		(0-0), (0+1), (0*1), (0-1), (0+2), (0*2),				
(expr + expr)		<pre>4), (0*4), (0−4), (0+y), (0*y), (0−y), (0+x), (0*x), L), (1*1), (1−1), (1+2), (1*2), (1−2), (1+3), (1*3),</pre>				
(expr - expr)		<pre>// (1*y), (1-y), (1+x), (1*x), (1-x), (2+0), (2*0),</pre>				
		2), (2*2), (2-2), (2+3), (2*3), (2-3), (2+4), (2*				
(expr * expr)		x), (2*x), (2-x), (3+0), (3*0), (3-0), (3+1), (3*1), 3), (3*3), (3-3), (3+4), (3*4), (3-4), (3+y), (3*y),				
		(4*0), (4-0), (4+1), (4*1), (4-1), (4+2), (4*2),				
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	(y-3), $(y+4)$, $(y*4)$, $(y-4)$, $(y+3)$	$\begin{array}{c} \text{count: } 71,302 \\ \text{(y+x), (y+x), (y+x), (y-x), (x+0), (x*0),} \end{array}$				
	(x-0), (x+1), (x*1), (x-1), (x+2)	2), $(x*2)$, $(x-2)$, $(x+3)$, $(x*3)$, $(x-3)$, $(x+4)$, $(x*4)$,				
	(x-4), (x+y), (x*y), (x-y), (x+y)	x), (x*x), (x-x), (0+0), (0*0), (0-0), (0+1), (0*1), (0*1), (0+2), (0+2), (0+4), (0+				

. . . these ination!

```
(0-2),
```

(0*x), (1*3), (2*0), (2*4), (3*1), (3*y), (4*2), (4*x), <u>v*3</u>), x*0), (x*4), (0*1),

(0-x), (1-3), (2-0), (2-4), (3-1), (3-y), (4-2), (4-x), (y-3), (x-0), (x-4),

Enumeration...pruned with Operational Equivalence

Spec: $(\{ \mathbf{X}'' \rightarrow \mathbf{3}, \mathbf{Y}'' \rightarrow \mathbf{7} \},$ 23) $(\{``X'' \rightarrow 4, ``Y'' \rightarrow 4\}, 19)$ $(\{ "x" \rightarrow 2, "y" \rightarrow 12 \}, 31)$ Space of programs: $expr := \mathcal{N}$ (expr + expr)(expr - expr)(expr * expr)

←Which is the fancy program synthesis way of saying "they do the same thing on the inputs we care about."

> Ok, these are all just 0...which we already have. Why'd you give me these???

```
level 0:
[0, 1, 2, 3, 4, y, x]
count: 7
level 1 :
[0, 1, 2, 3, 4, y, x, (0+0), (0*0), (0-0), (0+1), (0*1), (0-1), (0+2), (0*2), (0-2),
(0+3), (0*3), (0-3), (\overline{0+4}), (0*4), (0-4), (0+y), (0*y), (0-y), (0+x), (0*x), (0-x),
(1+0), (1*0), (1-0), (1+1), (1*1), (1-1), (1+2), (1*2), (1-2), (1+3), (1*3), (1-3),
(1+4), (1*4), (1-4), (1+y), (1*y), (1-y), (1+x), (1*x), (1-x), (2+0), (2*0), (2-0),
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(2+y), (2*y), (2-y), (2+x), (2*x), (2-x), (3+0), (3*0), (3-0), (3+1), (3*1), (3-1),
(3+2), (3*2), (3-2), (3+3), (3*3), (3-3), (3+4), (3*4), (3-4), (3+y), (3*y), (3-y),
(3+x), (3*x), (3-x), (4+0), (4*0), (4-0), (4+1), (4*1), (4-1), (4+2), (4*2), (4-2),
(4+3), (4*3), (4-3), (4+4), (4*4), (4-4), (4+y), (4*y), (4-y), (4+x), (4*x), (4-x),
(y+0), (y*0), (y-0), (y+1), (y*1), (y-1), (y+2), (y*2), (y-2), (y+3), (y*3), (y-3),
(y+4), (y*4), (y-4), (y+y), (y*y), (y-y), (y+x), (y*x), (y-x), (x+0), (x*0), (x-0),
(x+1), (x*1), (x-1), (x+2), (x*2), (x-2), (x+3), (x*3), (x-3), (x+4), (x*4), (x-4),
(x+y), (x*y), (x-y), (x+x), (x*x), (x-x)]
count: 154
```

And these are the same on all inputs.

And eventually we'll find some that aren't the same on all inputs, but are the same on $\{"x" \rightarrow 3, "y" \rightarrow 7\}, \{"x" \rightarrow 4, "y" \rightarrow 4\}, and \{"x" \rightarrow 2, "y" \rightarrow 12\}$





This is exactly as simple as it looks. Seriously, you can write this synthesizer in vanilla Python in one page. Let's see it!



```
import itertools
     class Op:
          ops = {"+": lambda a,b: a+b, "-": lambda a,b: a-b, "*": lambda a,b: a*b}
 3
          def __init__(self, a, op, b):
 -4
              self.a = a; self.op = op; self.b = b
 5
          def ___repr__(self):
 6
              return "(" + str(self.a) + self.op + str(self.b) + ")"
         def interpret(self, argDict):
 8
              return Op.ops[self.op](self.a.interpret(argDict), self.b.interpret(argDict))
 9
10
     class Val:
          def ___init__(self, v):
11
12
             self_v = v
         def ___repr__(self):
13
              return str(self.v)
14
         def interpret(self, argDict):
15
16
             return self.v
     class Var:
17
         def __init__(self, n):
18
19
              self_n = n
20
          def ___repr__(self):
21
             return self.n
         def interpret(self, argDict):
22
23
              return argDict[self.n]
24
25
     spec = [({"x": 3, "y": 7}, 23), # our input-output pairs
26
              ({"x": 4, "y": 4}, 19),
              ({"x": 2, "y": 12}, 31)]
27
28
     def test_against_spec(expr):
29
30
31
         if (outputs == expected_outputs):
32
              print "found it!", expr
33
             exit()
34
35
     print "level 0:\n", exprs, "\ncount:", len(exprs)
36
     for expr in exprs:
37
          test_against_spec(expr) # let's just see if any of our starting exprs do the trick...
38
39
40
     ops = Op.ops.keys() # what operators are we allowed to use?
     level = 0
41
42
    while(True):
43
          level += 1
          print "level", level, ":"
44
45
          for pair in itertools.product(exprs, exprs): #let's make bigger expressions!
46
              for op in ops:
47
                 new_expr = Op(pair[0], op, pair[1])
48
                  test_against_spec(new_expr)
                 exprs.append(new_expr)
49
               exprs, "\ncount:", len(exprs)
50
```

This one isn't pruning at all. What do we do to prune with OE?

Just an extra 6 lines!

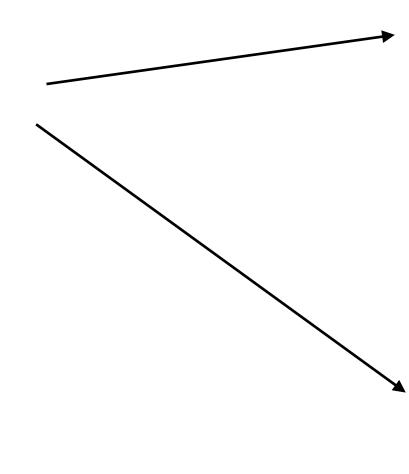
expected_outputs = [output for inputDict, output in spec] # for convenience, the outputs we expect for our i-o pairs outputs = [expr.interpret(inputDict) for inputDict, output in spec] # run the expression on our target inputs

exprs = [Val(x) for x in range(5)] + [Var(x) for x in spec[0][0].keys()] # the starting set is 0 through 5 and our args



Pruning based on Operational Equivalence can cut down our search space dramatically!

And this is just at level 2!



```
[Sarahs-MBP:othermaterials schasins$ python onePageSynthesizer.py
level 0:
[0, 1, 2, 3, 4, y, x]
count: 7
level 1 :
count: 154
level 2 :
count: 71302
 level 3 :
found it! (3+(2*(y+x)))
[Sarahs-MBP:othermaterials schasins$ python onePageSynthesizerOE.py
level 0:
[0, 1, 2, 3, 4, y, x]
count: 7
level 1 :
count: 63
level 2 :
count: 2051
level 3 :
found it! (3+(2*(y+x)))
```



So if you're ever watching a synthesis talk and get confused...just remember enumeration. At a sufficiently high level of abstraction, it's just going through programs until it finds one that works.

We can make enumeration smarter

- Doesn't have to be just start with the smallest program, then list all the programs in order of size until you find one that works
- We can have heuristics or language models that let us explore better/likelier programs first instead of smaller programs first
- There are other ways of pruning (other than Operational Equivalence) that let us cut out much more of the space
- We can make smart choices about what constants to include
- This was the easy-to-write version, but there are many ways to make it more effective • For a long time, the winner of the SyGuS competition (the primary competition for
- people who write synthesizers) was an enumerative solver!
 - This is a real technique!



Quick brainstorm. What would you like to synthesize?

Synthesis is like a buffet

- Stochastic synthesis Deductive synthesis **Constraint-** Enumerative based synthesis synthesis
- This is not one technique that either applies or doesn't apply to your problem
- It's a whole family of techniques
 - Tackling a new problem, you'll probably be looking through a host of existing approaches and tools...
 - If you read synth literature, you'll see very different domains formalized in very different ways. This isn't accidental!
 - ...and maybe inventing your own. Custom synthesizers are still common





To think about for next reading

- affect our synthesizer?
- synthesis?
 - tool?

 The issue of ambiguous specs. As designers of usable tools, do we want to prevent ambiguous specs? If yes, how? Do we want to allow them? If yes, how does this

What constrains the design of a our target languages for

 What's the tradeoff between designing for making the synthesizer's task easier vs. designing for the user of the

Please install before next class

https://docs.racket-lang.org/rosette-guide/ch_getting-started.html#%28part._sec~3aget%29



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About Rosette

Rosette is a solver-aided programming language that extends Racket with language constructs for program synthesis, verification, and more. To verify or synthesize code, Rosette compiles it to logical constraints solved with off-the-shelf SMT solvers. By combining virtualized access to solvers with Racket's metaprogramming, Rosette makes it easy to doyalap synthesis and yorification tools far now languages. Vou simply

The Rosette Language

A brilliant language from **Emina Torlak**

