

Instruction tables will have to be made up by mathematicians with computing experience and perhaps a certain puzzle-solving ability...

This process of constructing instruction tables should be very fascinating. There need be no real danger of it ever becoming a drudge, for any processes that are quite mechanical may be turned over to the machine itself.

Alan Turing, 1945

Advances and Challenges in Program Synthesis

Armando Solar-Lezama

MIT COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE LABORATORY



The promise of automation

The FORTRAN Automatic Coding System

J. W. BACKUS†, R. J. BEEBER†, S. BEST‡, R. GOLDBERG†, L. M. HAIBT†,
H. L. HERRICK†, R. A. NELSON†, D. SAYRE†, P. B. SHERIDAN†,
H. STERN†, I. ZILLER†, R. A. HUGHES§, AND R. NUTT||

INTRODUCTION

THE FORTRAN project was begun in the summer of 1954. Its purpose was to reduce by a large factor the task of preparing scientific problems for IBM's next large computer, the 704. If it were possible for the 704 to code problems for itself and produce as good programs as human coders (but without the errors), it was clear that large benefits could be achieved.

For it was known that about two-thirds of the cost of solving most scientific and engineering problems on large computers was that of problem preparation. Furthermore, more than 90 per cent of the elapsed time for a problem was usually devoted to planning, writing,

system is now complete. It has two components: the FORTRAN language, in which programs are written, and the translator or executive routine for the 704 which effects the translation of FORTRAN language programs into 704 programs. Descriptions of the FORTRAN language and the translator form the principal sections of this paper.

The experience of the FORTRAN group in using the system has confirmed the original expectations concerning reduction of the task of problem preparation and the efficiency of output programs. A brief case history of one job done with a system seldom gives a good measure of its usefulness, particularly when the

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IBM's next large computer, the 704. If it were possible for the 704 to code problems for itself and produce as good programs as human coders (but without the errors), it was clear that large benefits could be achieved.


Furthermore, more than 70 per cent of the elapsed time for a problem was usually devoted to planning, writing,

good measure of its usefulness, particularly when the

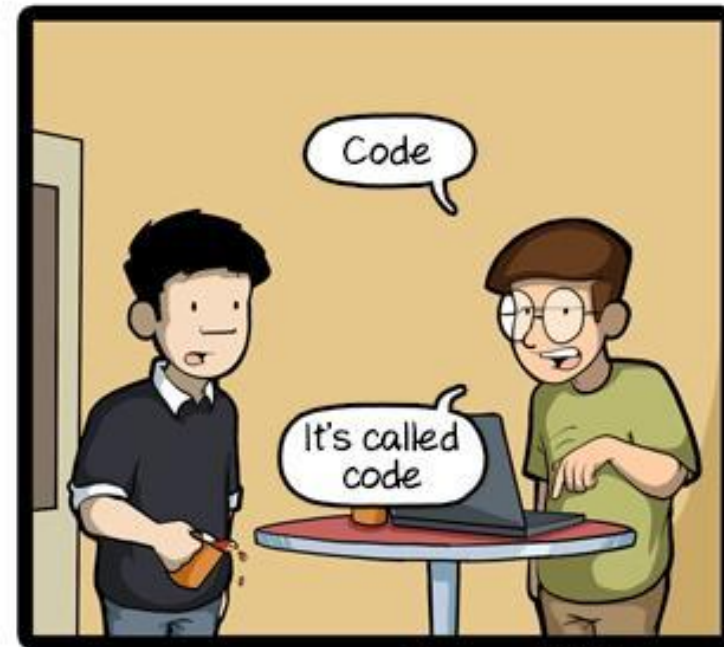
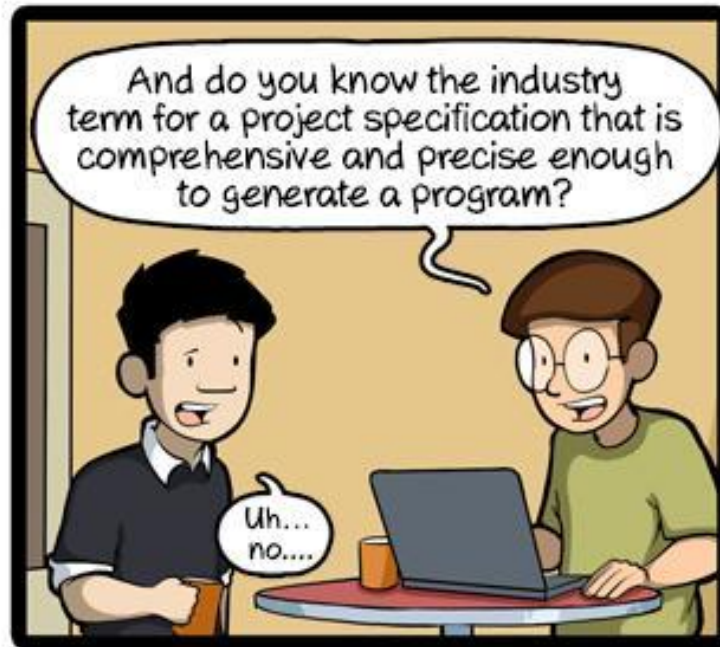
Automation Today



Domain Specific
Languages



High-level
general
purpose
languages



CommitStrip.com

Program Synthesis

IEEE TRANSACTIONS ON SOFTWARE ENGINEERING, VOL. SE-5, NO. 4, JULY 1979

Synthesis: Dreams \Rightarrow Programs

ZOHAR MANNA AND RICHARD WALDINGER

techniques are presented for deriving programs from given specifications. The specifications express the desired program without giving any hint of the algorithm. The basic approach is to transform the specifications according to certain rules, until a satisfactory pro-

INTRODUCTION

IN RECENT years there has been increasing activity in the field of program verification. The goal of these efforts is to construct computer systems for determining whether a



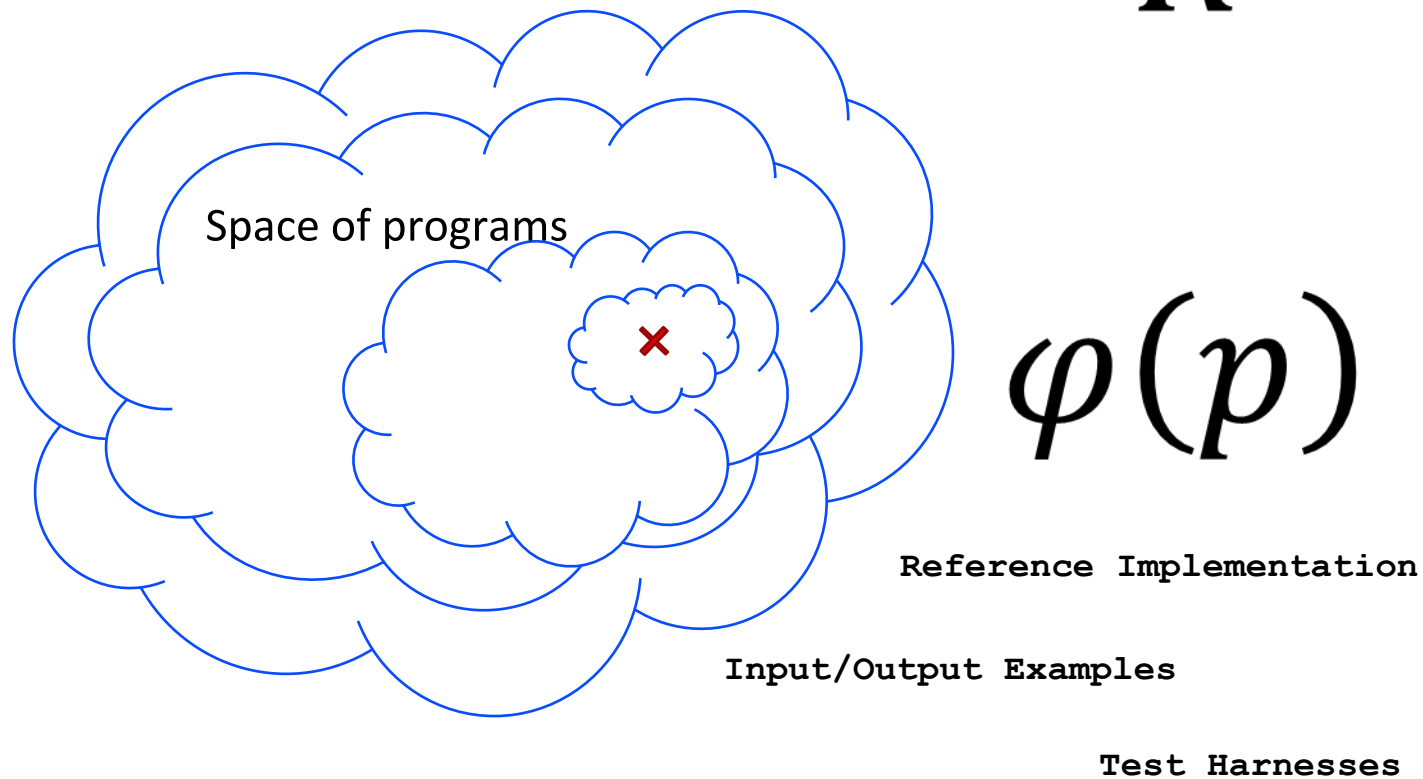
Zohar Manna



Richard Waldinger

Synthesis: modern view

$$R = \{p_0 \dots p_i\}$$

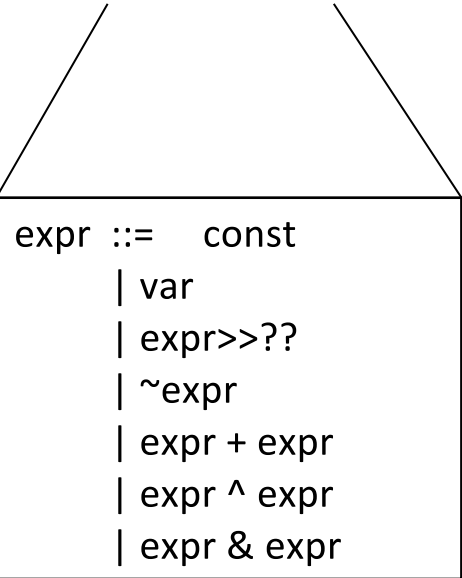


$$\varphi(p) = \forall in. \dots p(in) \dots$$

Example

Sketch

```
bit[W] avg(bit[W] x, bit[W] y)
implements avgSpec{
    return expr@signed({x,y}, 4);
}
```



```
expr ::=  const
        | var
        | expr>>??
        | ~expr
        | expr + expr
        | expr ^ expr
        | expr & expr
```

Spec

```
bit[W] avgSpec(bit[W] x, bit[W] y){
    bit[2*W] xx = extend@signed(x, 2*W);
    bit[2*W] yy = extend@signed(y, 2*W);

    bit[2*W] r = rshift@signed(xx+yy, 1);
    return (r[0::W]);
}
```

And 8 seconds later...

After considering 2^{1296} possibilities

$$(x \& y) + (x \wedge y) >> 1$$

Cool!

Now can you synthesize programs
with more than 1 line of code?

Early successes

Concurrent data-structures

Small but high-impact code

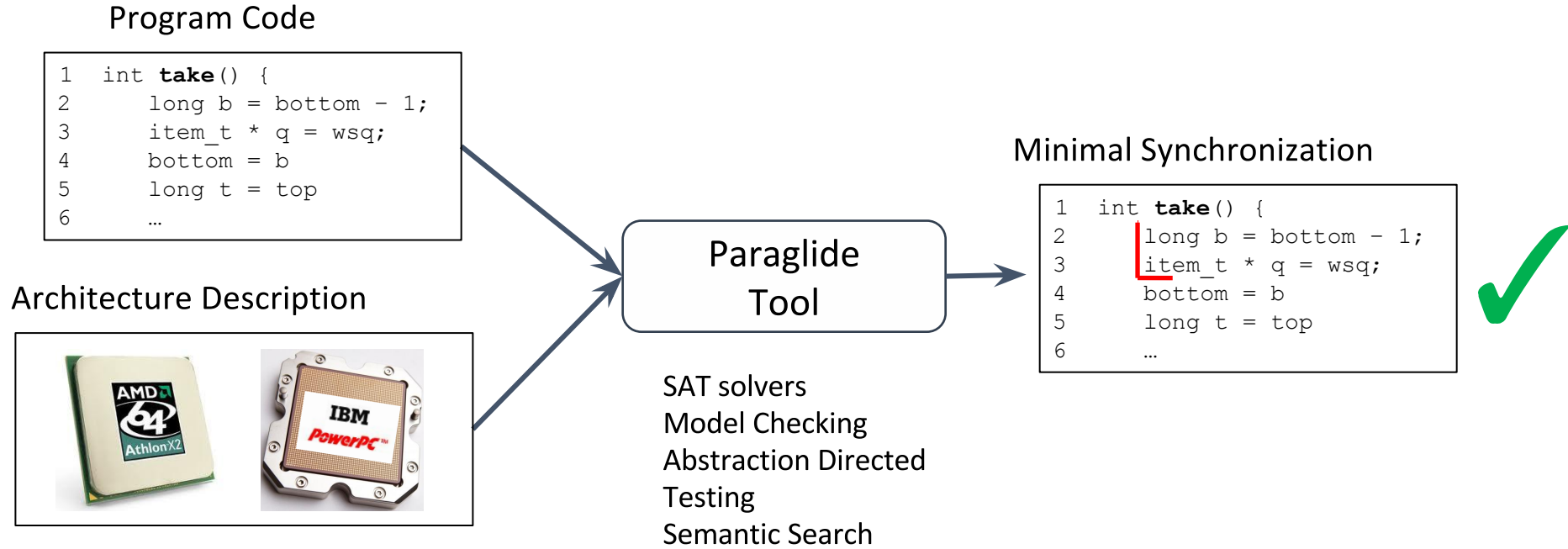
- Herlihy calls them the “ball bearings” of concurrent software

Difficult for humans to reason about

Well defined space of possible synchronization and coordination approaches

Paraglide [IBM]

Synthesis of concurrent code



Highly impactful work by Yahav, Vechev and Yorsh at IBM

Domain specific system

Lessons

Focus on high-impact domains

- Leverage domain specific structure

Engineer for interaction with experts

Reverse engineering

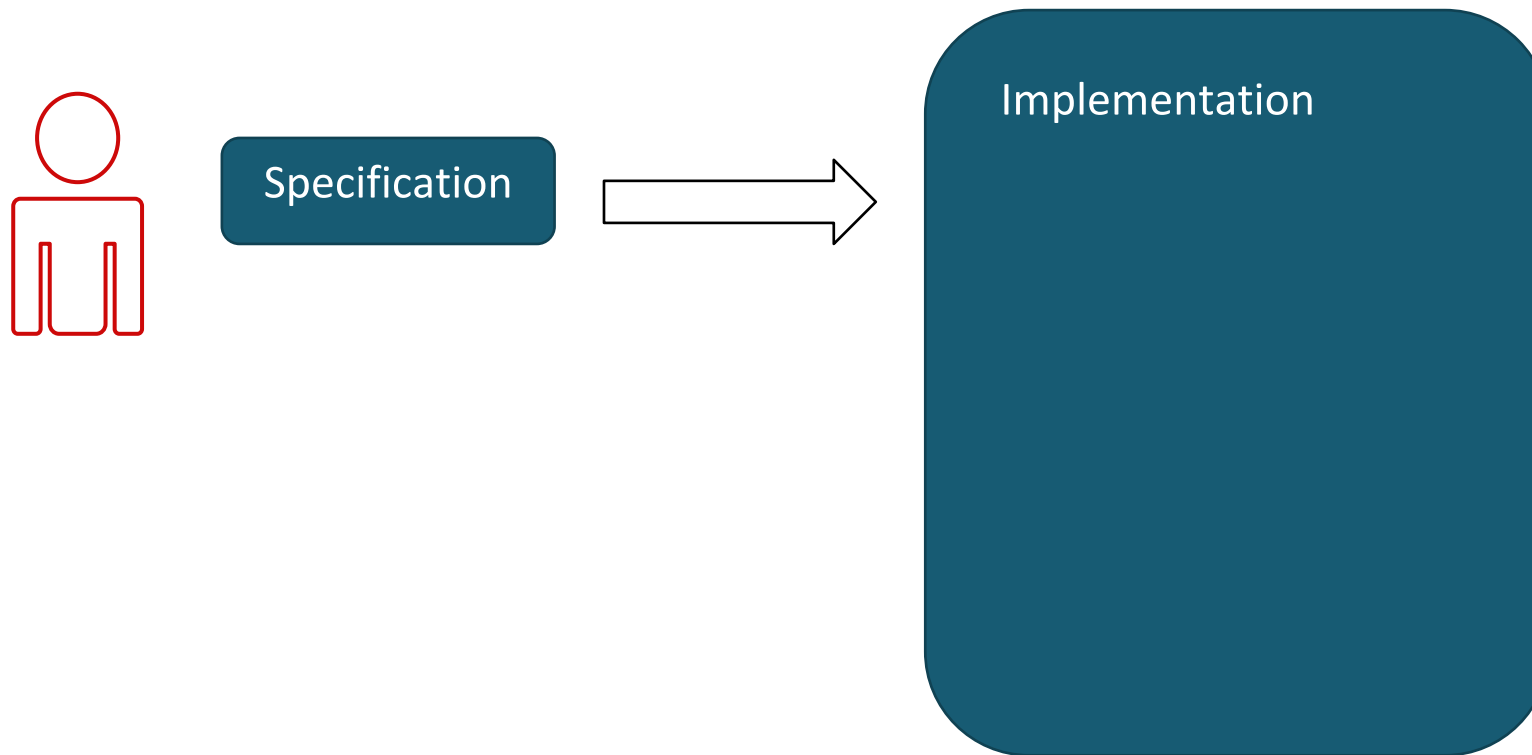
Oracle-guided component-based program synthesis

- ICSE 2010 paper by Jha, Gulwani, Seshia and Tiwari

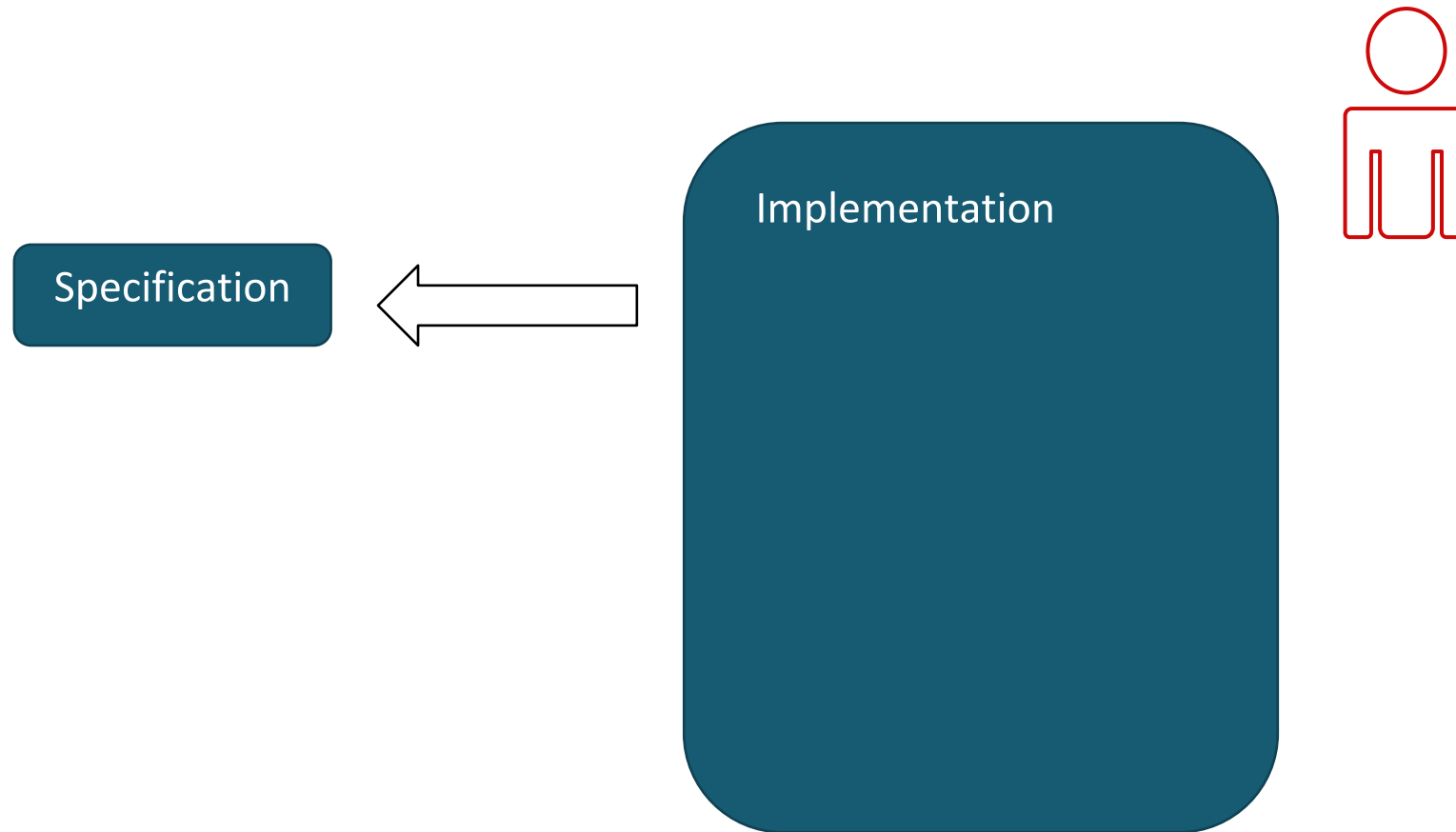
Pioneered a number of new ideas at the algorithmic level

Synthesis for reverse engineering

Reverse engineering



Reverse engineering



FlashFill

dr-2 - Microsoft Excel

File Home Insert Page Layout Formulas Data Review View Quick Code Load Test Team Table Tools Design

Quick Fill Auto Fill Quick Layout
Apply HiLight CurrencyWidget
Undo Commit AddressWidget

Table116 Ana Trujillo 357 21th Place SE,Redmond,WA,(757) 555-1634,140-37-6064,27171

	A	B	C	D	E	F
1	Column1	Col 2	Col 3	Col 4	Col 5	Col 6
2	Ana Trujillo	357 21th Place SE,Redmond,WA,(757) 555-1634,140-37-6064,27171	Redmond	WA	(757) 555-1634	140-37-6064 27171
3	Antonio Moreno	515 93th Lane ,Renton,WA,(411) 555-2786,562-87-3127,28581				
4	Thomas Hardy	742 17th Street NE,Seattle,WA,(412) 555-5719,921-29-4931,24607				
5	Christina Berglund	475 22th Lane ,Redmond,WA,(443) 555-6774,844-35-6764,30146				
6	Hanna Moos	785 45th Street NE,Puyallup,WA,(376) 555-2462,515-68-1285,29284				
7	Frédérique Citeaux	308 66th Place ,Redmond,WA,(689) 555-2770,552-23-2508,21415				
8	Martin Sommer	887 86th Place ,Kent,WA,(715) 555-5450,870-91-9824,21536				
9	Laurence Lebihan	944 13th Street NE,Redmond,WA,(620) 555-2361,649-25-5312,25252				
10	Elizabeth Lincoln	452 73th Lane NE,Renton,WA,(851) 555-4561,425-97-6344,22279				
11	Victoria Ashworth	463 16th Street ,Renton,WA,(696) 555-6044,690-29-7926,22832				
12	Patricio Simpson	630 20th Street ,Redmond,WA,(179) 555-3265,389-78-3236,24525				
13	Francisco Chang	683 49th Lane ,Seattle,WA,(272) 555-7434,665-18-6435,29453				
14	Yang Wang	944 28th Lane ,Redmond,WA,(151) 555-2272,846-78-8452,24388				
15	Pedro Afonso	411 70th Place ,Kent,WA,(170) 555-2964,774-35-2298,29485				
16	Elizabeth Brown	971 20th Lane ,Puyallup,WA,(373) 555-4134,476-53-7164,26417				
17	Sven Ottlieb	676 17th Lane NE,Redmond,WA,(828) 555-1593,548-73-8633,27440				
18	Janine Labrune	267 95th Place SE,Seattle,WA,(949) 555-1316,350-27-8300,28074				
19	Ann Devon	694 53th Place ,Kent,WA,(194) 555-8124,559-74-4016,22367				
20	Roland Mendel	581 12th Street NW,Kent,WA,(103) 555-2146,303-79-1328,20518				
21	Aria Cruz	594 85th Lane ,Renton,WA,(431) 555-1376,329-93-9992,21498				
22	Diego Roel	550 22th Lane ,Renton,WA,(639) 555-6238,918-34-5172,25931				
23	Martine Rancé	688 93th Place NW,Kent,WA,(573) 555-3571,695-94-3479,22424				
24						
25						
26						

ssn / FixTrunc2 / FixTrunc3 / bigbets / CustomerData / Dates2 / Layout / Currency / Dates / Abbreviat

Ready Average: 27171 Count: 27 Sum: 27171 106%

FlashFill

Program spaces through DSLs

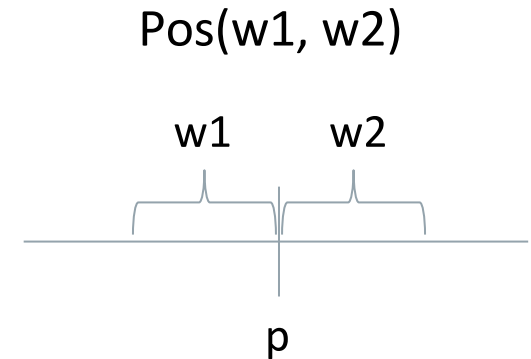
“<<hello>>” → “hello”

JavaScript:

```
in.substring(in.search("<<")+2,in.search(">>"));
```

FlashFill:

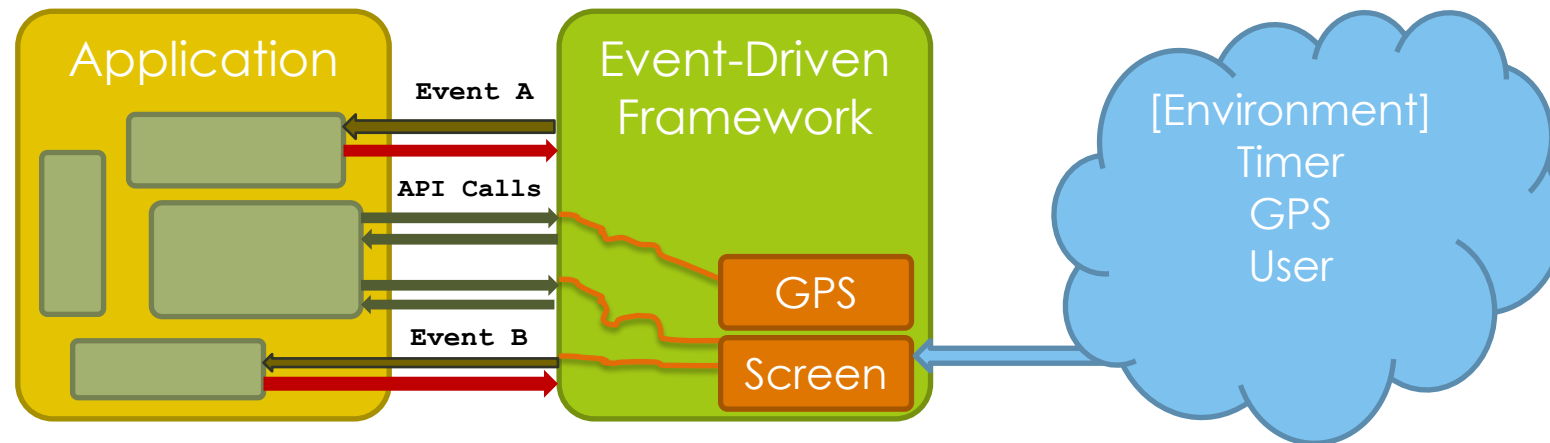
```
SubString(in, Pos("<<",""), Pos("",  
">>"));
```



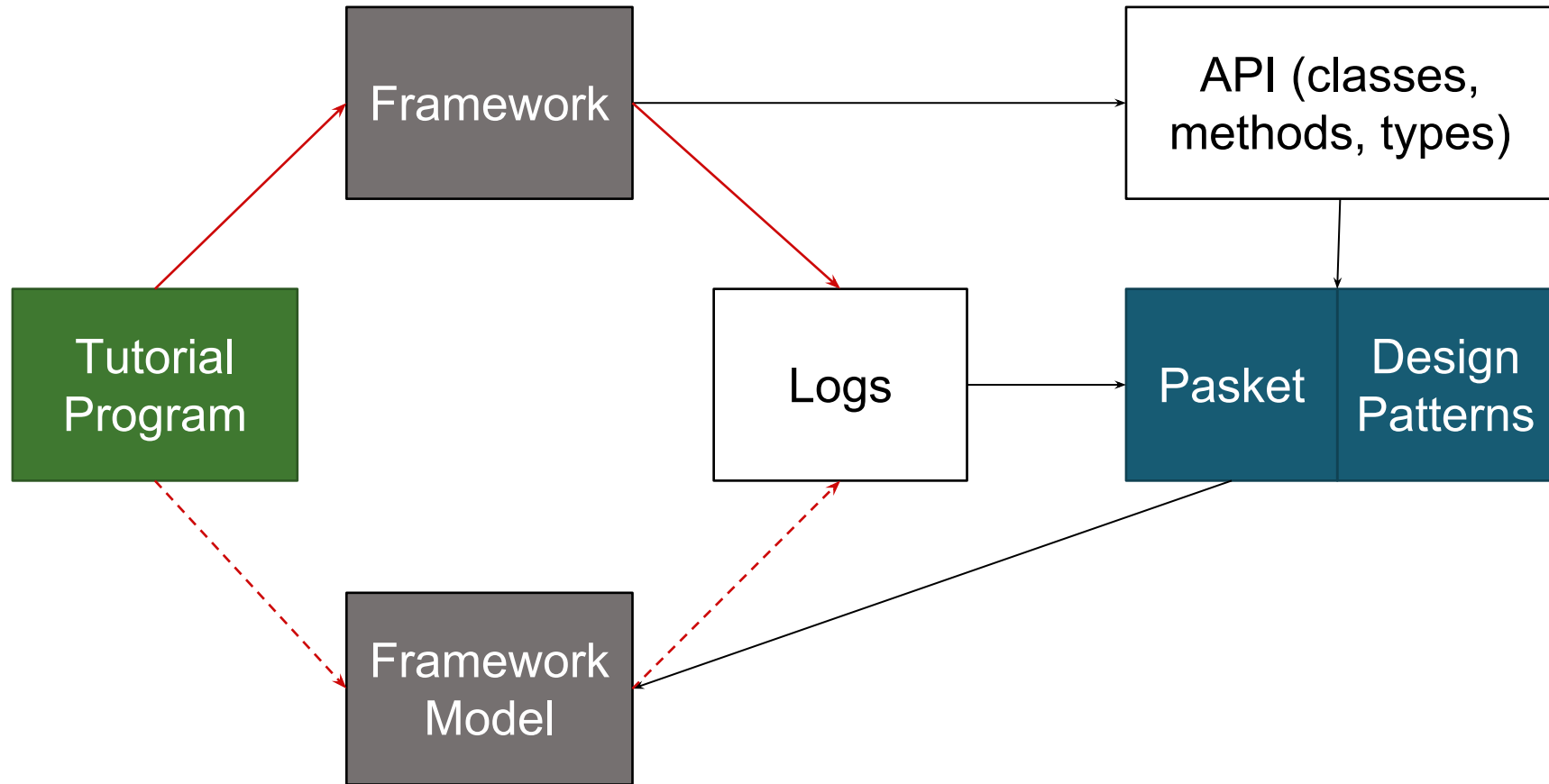
Exciting Directions: Reverse Engineering

Framework Models for Symbolic Execution

Pasket system by J. Jeon, X. Qiu, J. Fetter-Degges, J. S. Foster, and A. Solar-Lezama



Pasket



JPF w(/o) Synthesized Model

```
===== search started: ...
button_demo
----->property violated
===== error 1
gov.nasa.jpf.vm.NoUncaughtExceptionsProperty
java.lang.NoSuchMethodError:
    javax.swing.JButton.setVerticalTextPosition(I)V
    at ButtonDemo.<init>(ButtonDemo.java:63)
    at ButtonDemo.createAndShowGUI(ButtonDemo.java:131)
    ...
```

(a) With JPF's Swing model.

```
===== search started: ...
button_demo
...
===== results
no errors detected
```

(b) With PASKET's merged model.

JPF along with our synthesized model can run tutorials.

JPF's own hand-written models are insufficient.

- **lack of methods:** `setVerticalTextPosition`, etc.

An automated process (via Pasket) can avoid simple but nonetheless frustrating problems, like missing methods.

Verified Lifting

Synthesis based reverse engineering can help with optimization

Recent work with by Alvin Cheung and Shoaib Kamil



Optimization then and now

Naïve source code



~~Optimal executable~~
Kind-of-OK executable

Domain specific problem description



ATLAS

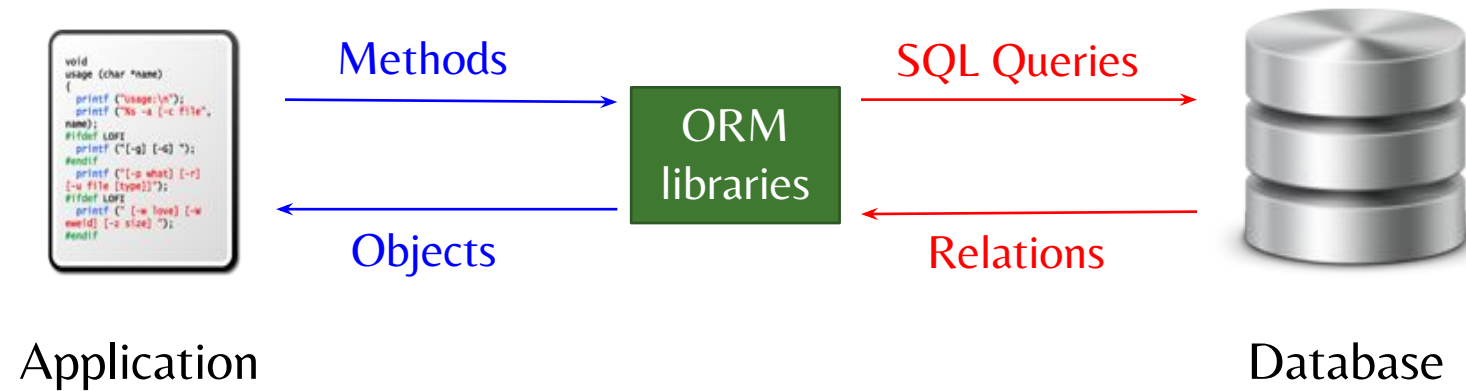
Pochoir

Halide

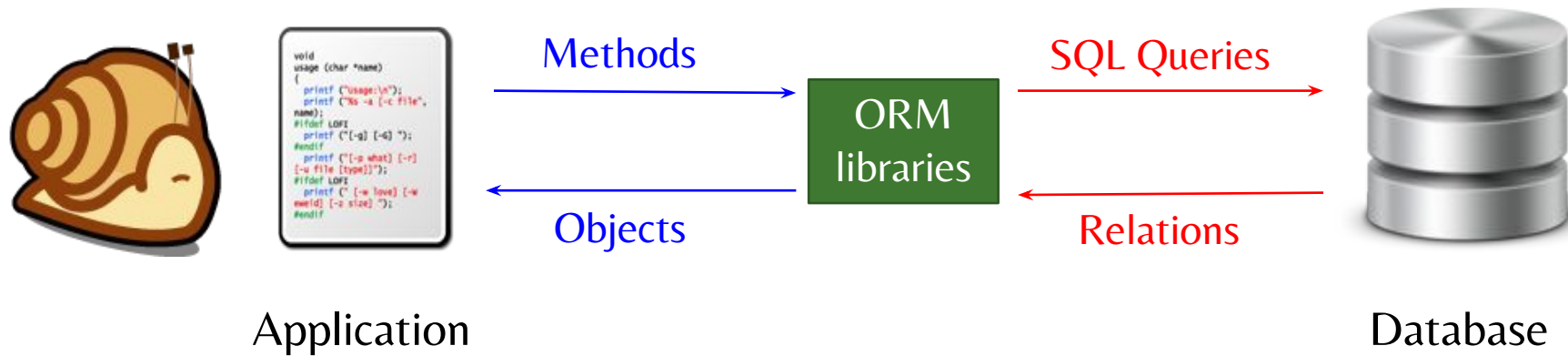


Close to optimal implementation

Java to SQL

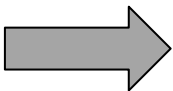


Java to SQL



Java to SQL

```
List getUsersWithRoles () {  
    List users = User.getAllUsers();  
    List roles = Role.getAllRoles();  
    List results = new ArrayList();  
    for (User u : users) {  
        for (Role r : roles) {  
            if (u.roleId == r.id)  
                results.add(u);  
        }  
    }  
    return results;  
}
```

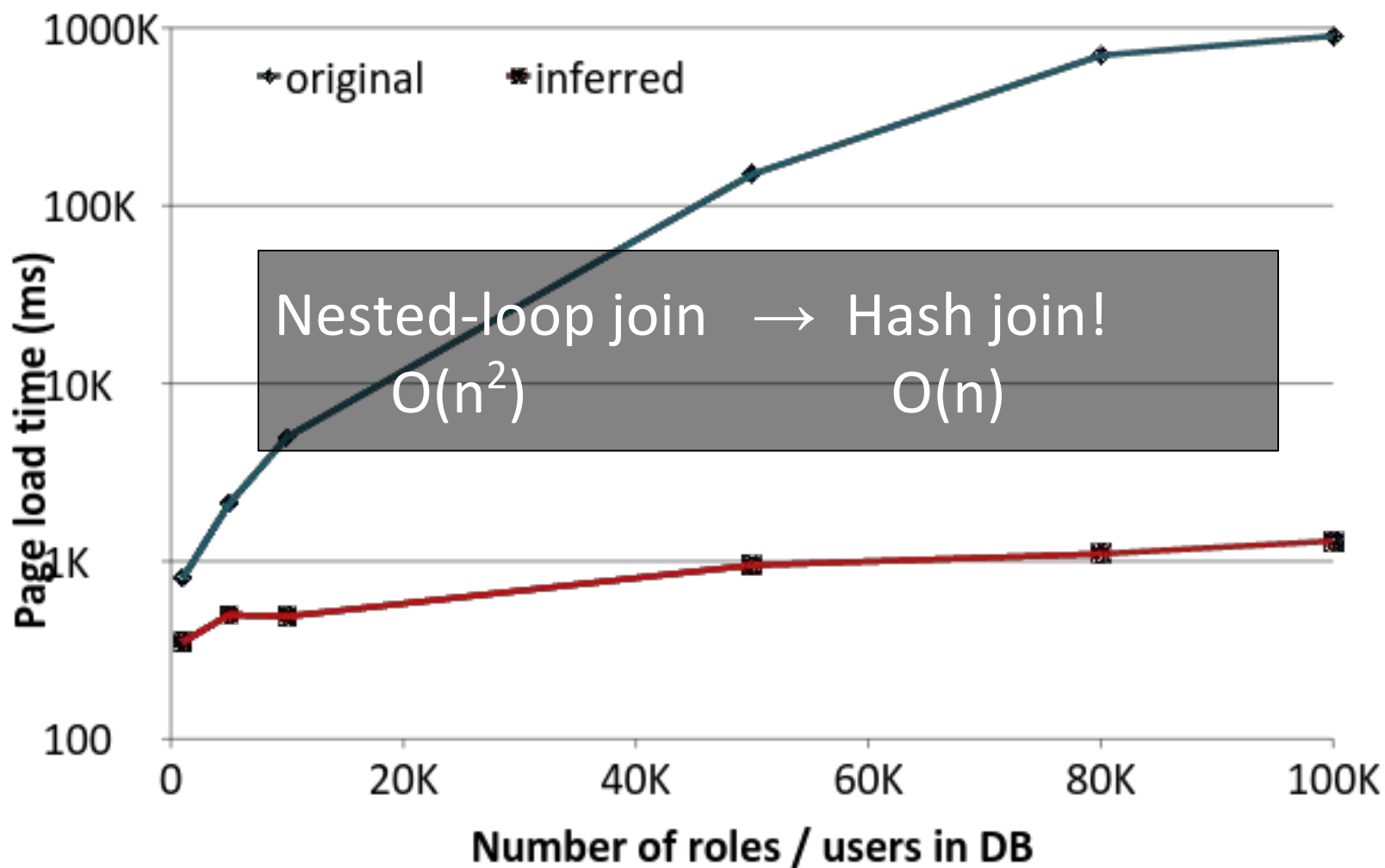

convert to

SELECT * FROM user

SELECT * FROM role

```
List getUsersWithRoles () {  
    return executeQuery(  
        "SELECT u FROM user u, role r WHERE u.roleId == r.id  
        ORDER BY u.roleId, r.id";  
    );  
}
```

Join Query



Example: MultiGrid

```
DO i3 = 2, n3 - 1
DO i2 = 2, n2 - 1
DO i1 = 1, n1
r1(i1) = r(i1,i2 - 1,i3) + r(i1,i2 + 1,i3) + r(i1,i2,i3 - 1) + r(i1,i2,i3 + 1)
r2(i1) = r(i1,i2 - 1,i3 - 1) + r(i1,i2 + 1,i3 - 1) + r(i1,i2 - 1,i3 + 1) + r(i1,i2 + 1,i3 + 1)
END DO
DO i1 = 2, n1 - 1
u(i1,i2,i3) = u(i1,i2,i3) + c(0) * r(i1,i2,i3) + c(1) * (r(i1 - 1,i2,i3) + r(i1 + 1,i2,i3) + r1(i1)) + c(2) * (r2(i1) + r1(i1 - 1) + r1(i1 + 1))
END DO
END DO
END DO
```

Example: MultiGrid

```
/*Range declarations go here */
```

```
r1_out(n1) = r(n1,n2-2,n3-1) + r(n1,n2,n3-1) + r(n1,n2-1,n3-2) + r(n1,n2-1,n3)
```

```
r2_out(n1) = r(n1,n2-2,n3-2) + r(n1,n2,n3-2) + r(n1,n2-2,n3) + r(n1,n2,n3)
```

```
u_out(i1,i2,i3) = u(i1,i2,i3) + c(0) * r(i1,i2,i3)
```

```
    + c(1) * (r(i1 - 1,i2,i3) + r(i1 + 1,i2,i3) + r(i1,i2 - 1,i3) + r(i1,i2 + 1,i3) + r(i1,i2,i3 - 1) + r(i1,i2,i3 + 1))
```

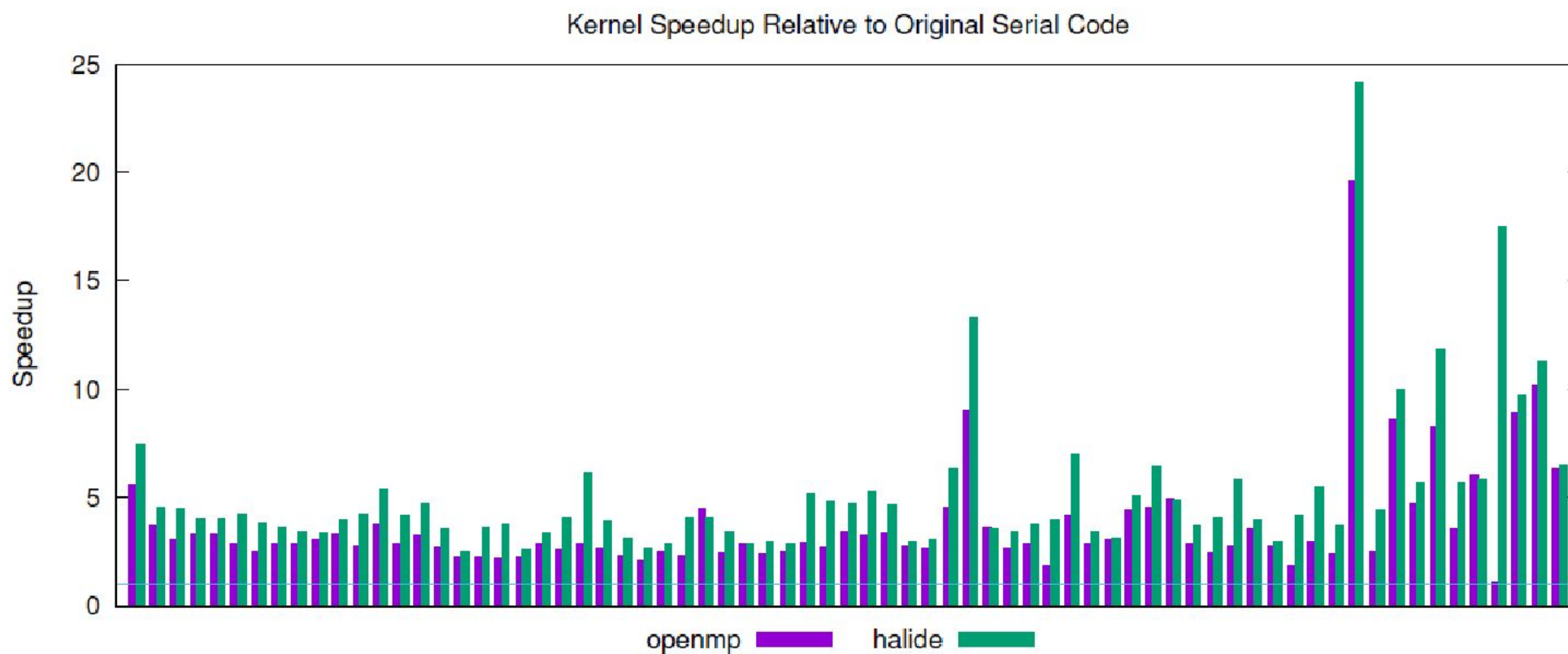
```
    + c(2) * ((r(i1,i2 - 1,i3 - 1) + r(i1,i2 + 1,i3 - 1) + r(i1,i2 - 1,i3 + 1) + r(i1,i2 + 1,i3 + 1))
```

```
              + (r(i1 - 1,i2 - 1,i3) + r(i1 - 1,i2 + 1,i3) + r(i1 - 1,i2,i3 - 1) + r(i1 - 1,i2,i3 + 1))
```

```
              + (r(i1 + 1,i2 - 1,i3) + r(i1 + 1,i2 + 1,i3) + r(i1 + 1,i2,i3 - 1) + r(i1 + 1,i2,i3 + 1)))
```

```
Tuple my_output(r1_out, r2_out, u_out);
```

Speedups



Exciting Directions: Synthesis for Synthesis

Can our solvers help us write better solvers?

Solvers are hard to write

Tradeoff between performance and maintainability

No single best approach

- NP complete problems after all

Clean formalizations

Good target for synthesis!

Sketch Simplifier

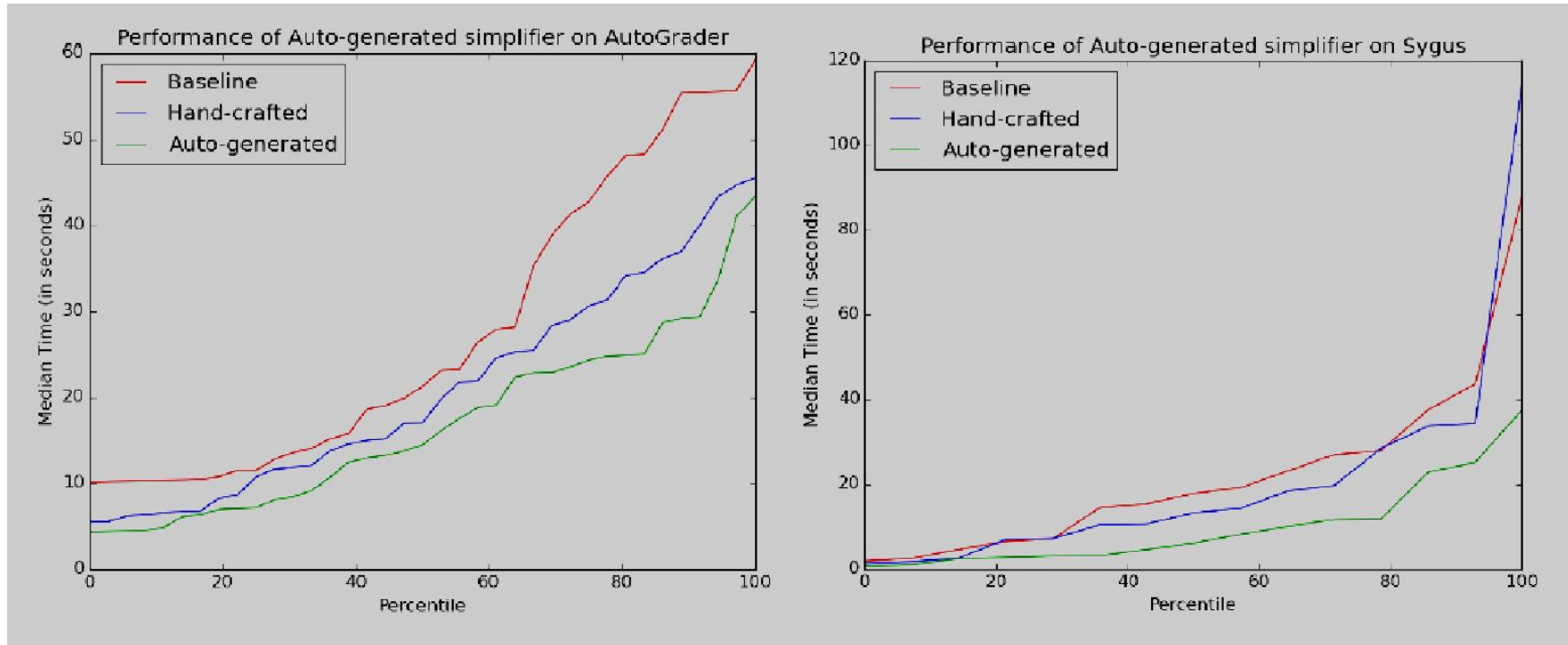
$$a+e < x \quad \& \quad e+b < x \quad \xrightarrow{b < a} \quad a+e < x$$

```
if(nfather->type == LT && nmother->type == LT) {
    // (a+e<x) & (b+e<x) ---> a+e<x when b<a
    if(nfather->mother->type == PLUS && nmother->mother->type == PLUS) {
        bool_node* nfm = nfather->mother;
        bool_node* nmm = nmother->mother;

        bool_node* nmmConst = nmm->mother;
        bool_node* nmmExp = nmm->father;
        if(isConst(nmmExp)) {
            bool_node* tmp = nmmExp;
            nmmExp = nmmConst;
            nmmConst = tmp;
        }
        bool_node* nfmConst = nfm->mother;
        bool_node* nfmExp = nfm->father;
        if(isConst(nfmExp)) {
            bool_node* tmp = nfmExp;
            nfmExp = nfmConst;
            nfmConst = tmp;
        }
    }
    if(isConst(nfmConst) && isConst(nmmConst) && nfmExp== nmmExp) {
        if(val(nfmConst) < val(nmmConst)) {
            return nmother;
        } else {
            return nfather;
        }
    }
} }
```

Performance

Impact on times



AutoGrader: 27.5s, 20s, 18s average times

Sygus: 22s, 21s, 10s average times

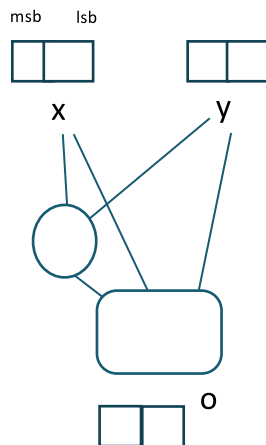
Bit-vector encoding

Boolean predicate P



CNF clauses C

$$o = ITE_N((GT_N, x, y), x, y)$$



```
t1 = true
t2 = true
for i from N to 1 :
    t3 = newVar
    t4 = newVar
    clause({x[i], y[i], o[i]})
    clause({x[i], t1, t3})
    clause({x[i], t2, o[i], t4})
    clause({x[i], o[i], t3})
    clause({x[i], y[i], o[i]})
    clause({x[i], t2, o[i]})
    clause({x[i], t2, t4})
    clause({y[i], t2, t4})
    clause({y[i], o[i], t3})
    clause({y[i], t1, t3})
    clause({y[i], o[i], t3})
    clause({t1, t3})
    clause({t1, o[i], t3})
    clause({t2, t4})
    clause({t3, t4})
    t1 = t3
    t2 = t4
```

Solve more problems

Benchmark Family	Solved by CVC4 → Our Solver
<i>Log-slicing (79)</i>	33 → 62
<i>ASP (365)</i>	240 → 288
<i>Mcm (61)</i>	40 → 43
<i>Brummayerbiere2 (33)</i>	28 → 29
<i>Float (62)</i>	59 → 60
<i>Brummayerbiere3 (40)</i>	23 → 24
<i>Bruttomesso (676)</i>	623 → 623
TOTAL	1046 → 1129



**83 more problems
in total**

Cross domain performance

Solver Domain → ↓	log-slicing	asp	mcm	brumma2	float	brumma3	brutto
<i>log-slicing</i>	62	58	36	59	32	35	35
<i>asp</i>	227	288	255	227	236	253	240
<i>mcm</i>	39	38	43	40	39	39	41
<i>brumma2</i>	29	28	28	29	29	29	29
<i>float</i>	57	57	59	57	60	60	59
<i>brumma3</i>	22	22	25	22	23	24	23
<i>brutto</i>	607	606	623	609	623	623	623



Exciting Directions: Quantitative Synthesis

Synthesis meets ML

STOKE

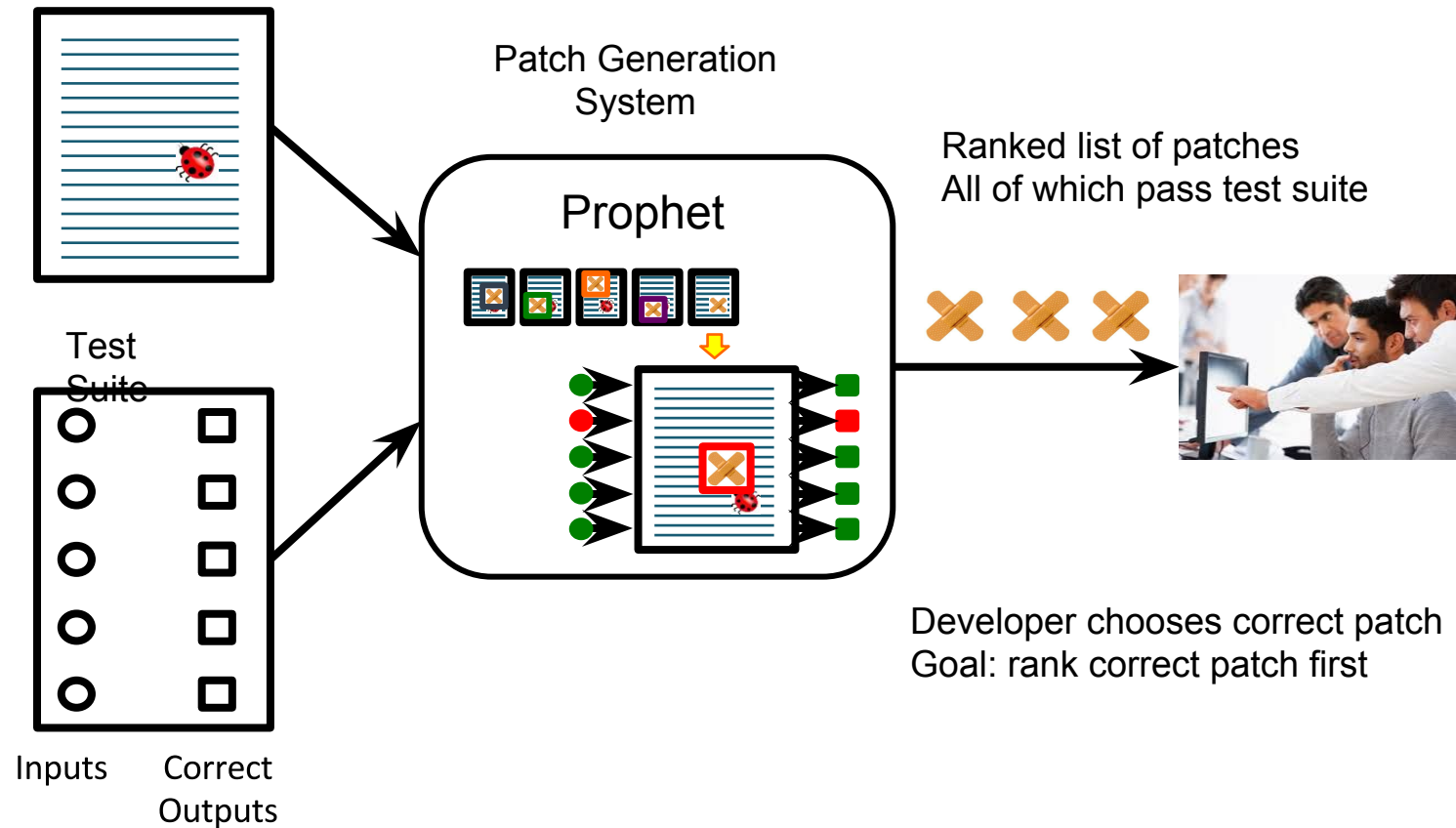
Project by Schkufza, Sharma, Heule, Aiken

Leverages Stochastic Search (MCMC) to incorporate quantitative parameters such as precision and performance

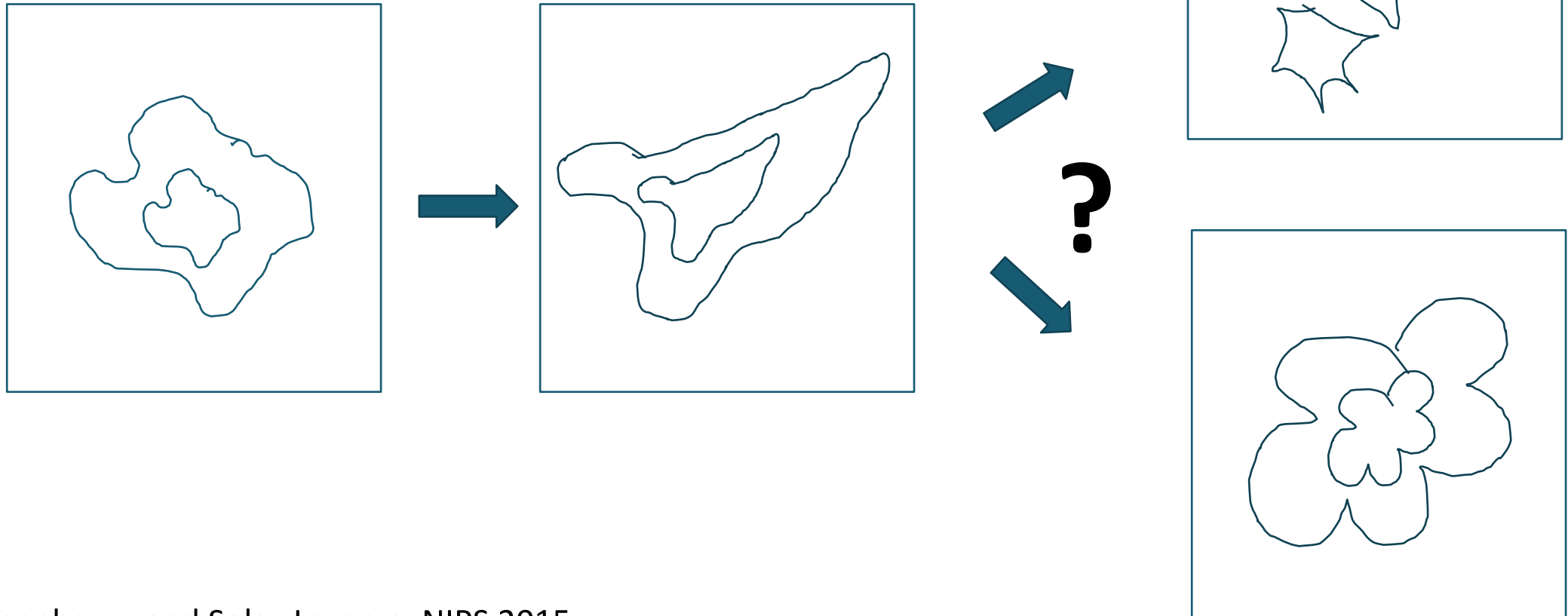
Focus on optimization

Prophet/Genesis

Project by Fan Long, Stelios Sidiroglou and Martin Rinard

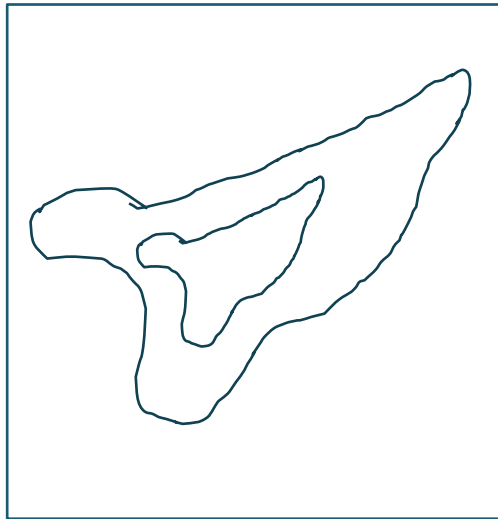
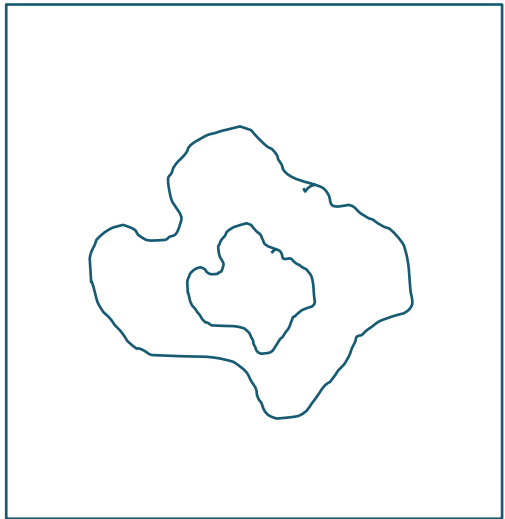


Visual Concept Learning

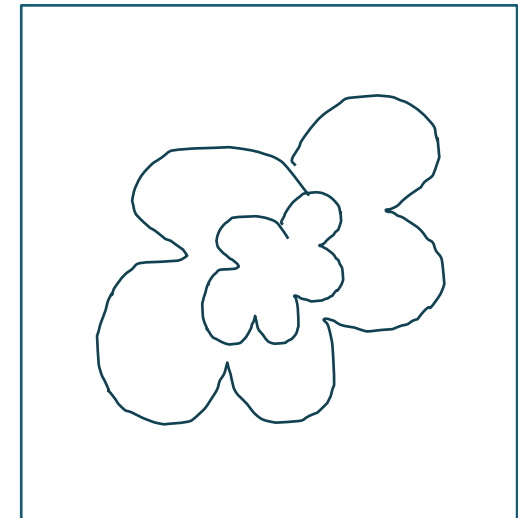
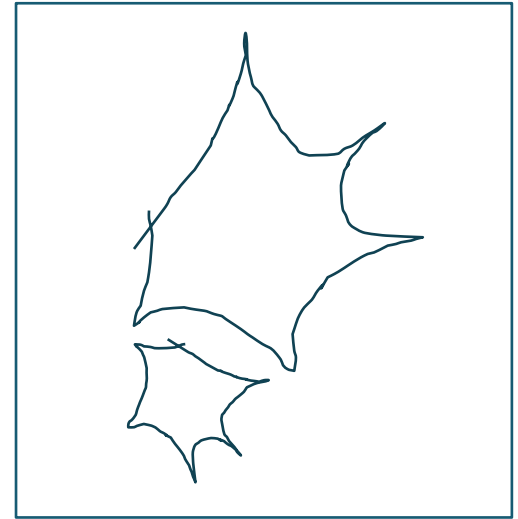


Ellis, Tenenbaum and Solar-Lezama, NIPS 2015

Visual Concept Learning



?



```
teleport(position[0], 0)  
draw(shape[0], scale=1.0)  
draw(shape[0], scale=0.5)
```

Synthesis vs. ML

Quantitative synthesis is at the intersection of synthesis and ML

Synthesis > ML

Big data vs. Small data

- Sometimes generating examples is expensive

I know what I want

- ML is heavily concerned with noise
- By design, it won't give you what you ask for

I know what I want (2)

- Difficult to incorporate hard constraints

ML > Synthesis

Big data vs. Small data

- Sometimes you really do have a lot of data, why waste it?

I know what I want

- Do you really?

You can do this too!

Synthesis Infrastructure

Sketch

- Just released v. 1.7.4
- Mature infrastructure with an expressive frontend language

SyGuS

- Family of solvers supporting emerging SYNT-LIB standard
- Less expressive than sketch, but higher performance
- Strong community support

Prose

- Infrastructure by Sumit Gulwani's team for DSL-based synthesis

Conclusion

The drive for automation continues

Synthesis provides a new set of tools to attack complex problems

We are just beginning to understand how to use this technology to improve productivity