

DreamCoder: Bootstrapping Inductive Program Synthesis with Wake-Sleep Library Learning

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Inductive program synthesis

FlashFill (Gulwani 2012)

EXAMPLE 3 (Directory Name Extraction). Consider the following example taken from an excel online help forum.

<i>Input</i> v_1	<i>Output</i>
<i>Company\Code\index.html</i>	<i>Company\Code\</i>
<i>Company\Docs\Spec\specs.doc</i>	<i>Company\Docs\Spec\</i>

String Program:

$\text{SubStr}(v_1, \text{CPos}(0), \text{Pos}(\text{SlashTok}, \epsilon, -1))$

Inductive program synthesis

FlashFill (Gulwani 2012)

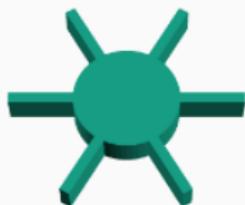
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Szalinski (Nandi 2020)



(a) CAD model of ship's wheel

```
(Union
  (Cylinder [1, 5, 5])
  (Fold Union
    (Tabulate (i 6)
      (Rotate [0, 0, 60i]
        (Translate [1, -0.5, 0]
          (Cuboid [10, 1, 1]))))))
```

(b) Caddy program

Inductive program synthesis

FlashFill (Gulwani 2012)

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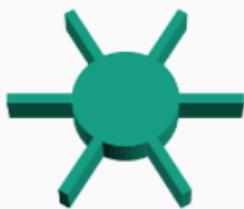
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Company\Docs\Spec\specs.doc	Company\Docs\Spec\

String Program:

```
SubStr(v1, CPos(0), Pos(SlashTok, ε, -1))
```

String expr P := `Switch((b1, e1), .., (bn, en))`
Bool b := $d_1 \vee \dots \vee d_n$
Conjunct d := $\pi_1 \wedge \dots \wedge \pi_n$
Predicate π := `Match(vi, r, k) | \neg Match(vi, r, k)`
Trace expr e := `Concatenate(f1, .., fn)`
Atomic expr f := `SubStr(vi, p1, p2)`
| `ConstStr(s)`
| `Loop(\lambda w : e)`
Position p := `CPos(k) | Pos(r1, r2, c)`
Integer expr c := $k | k_1 w + k_2$
Regular Expression r := `TokenSeq(T1, .., Tm)`
Token T := $C + | \neg C +$
| `SpecialToken`

Szalinski (Nandi 2020)



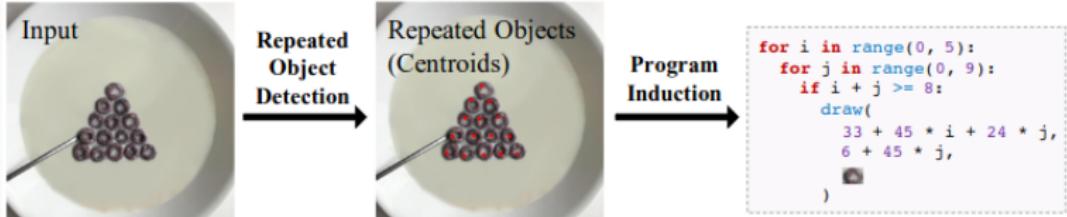
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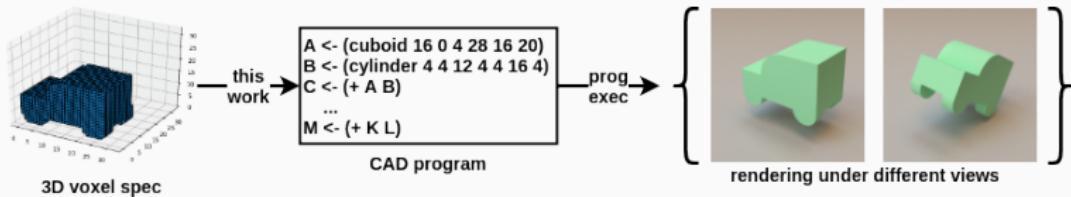
(b) Caddy program

op ::= + | - | × | / num ::= R | <var> | <num> <op> <num>
vec2 ::= [(num), (num)] vec3 ::= [(num), (num), (num)]
affine ::= Translate | Rotate | Scale | TranslateSpherical
binop ::= Union | Difference | Intersection
cad ::= (Cuboid <vec3>) | (Sphere <num>)
| (Cylinder <vec2>) | (HexPrism <vec2>) | ...
| ((affine) <vec3>) (cad)
| ((binop) <cad> <cad>)
| (Fold <binop> <cad-list>)
cad-list ::= (List <cad>+)
| (Concat <cad-list>+)
| (Tabulate (<var> Z⁺) <cad>)
| (Map2 <affine> <vec3-list> <cad-list>)
vec3-list ::= (List <vec3>+)

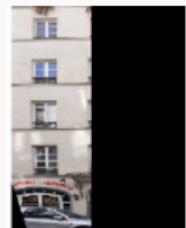
Visual programs



Mao*, Zhang*, et al 2019



Ellis*, Nye*, Pu*, Sosa*, et al 2019



partial image x_{part}

```
for i = 1..3
    for j = 1..1
        draw(i*2, j*1, [color])
    ...

```

synthesized program P_{part}



```
Draw("Top", "Circle", position, geometry)

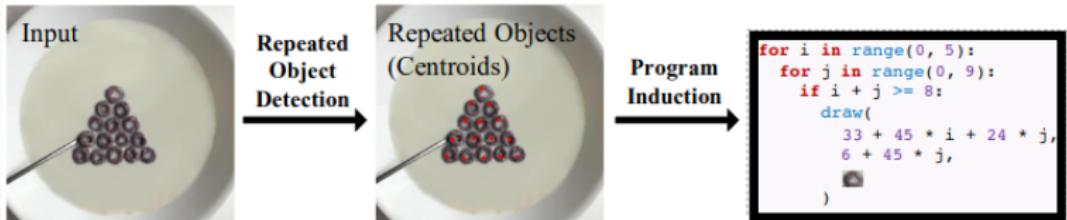
for(i < 2, "translation", a)
    for(j < 2, "translation", b)
        Draw("Leg", "Cub", position + i*a + j*b, )

for(i < 2, "translation", c)
    Draw("Layer", "Rec", position + i*c, geomet
```

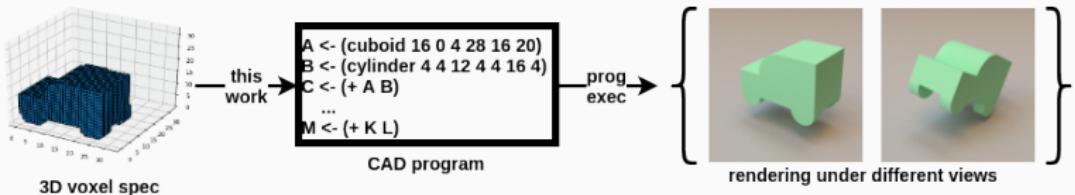
Young et al 2019

Tian et al 2019

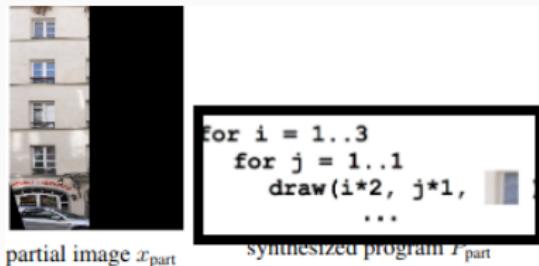
Where does this language come from?



Mao*, Zhang*, et al 2019

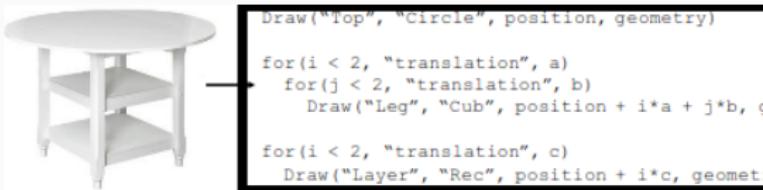


Ellis*, Nye*, Pu*, Sosa*, et al 2019



partial image x_{part}

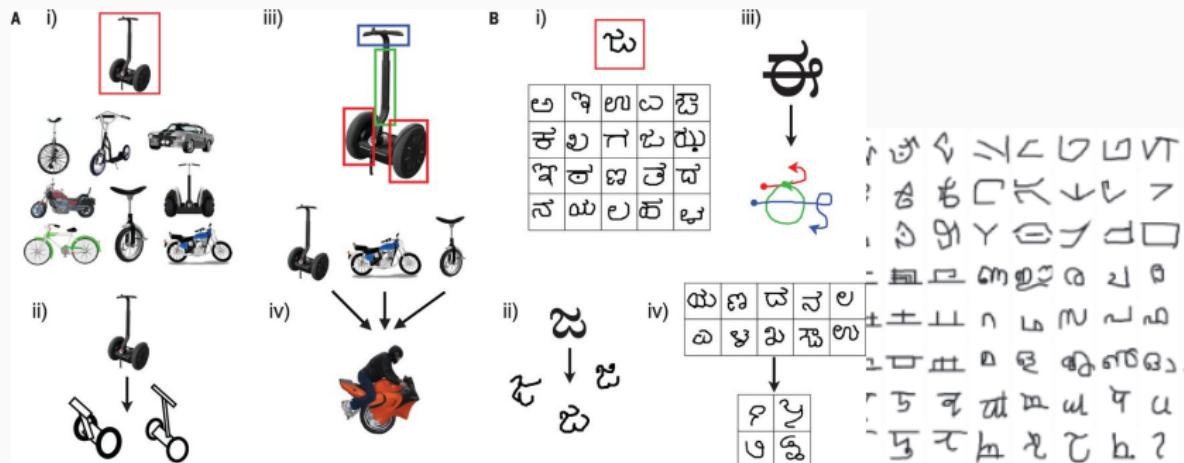
synthesized program F_{part}



Young et al 2019

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Human-level Program induction



DreamCoder and learning to learn

- learning a library
- learning to search
- synergy between library+learned search

Learning to write code

Goal: acquire domain-specific knowledge needed to induce a class of programs

- Library of components
- Search strategy (synthesis algorithm)

Library learning

Initial Primitives

: 

map

fold 

if

cons

>

: 

Sample Problem: sort list

[9 2 7 1] → [1 2 7 9]

[3 8 9 4 2] → [2 3 4 8 9]

[6 2 2 3 8 5] → [2 2 3 5 6 8]

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Library learning

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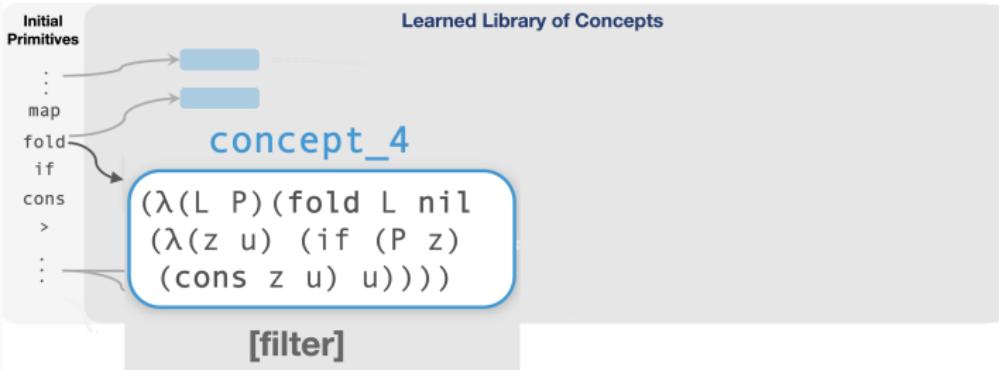
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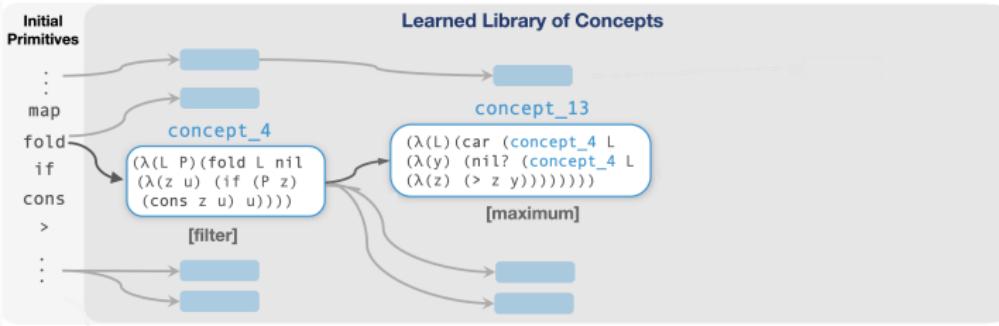
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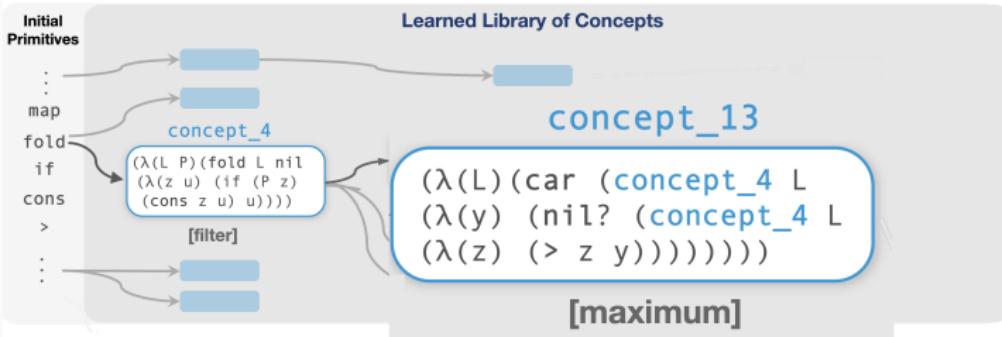
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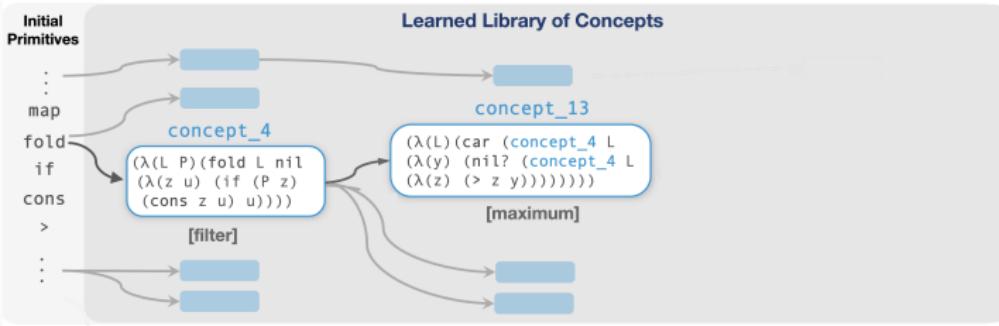
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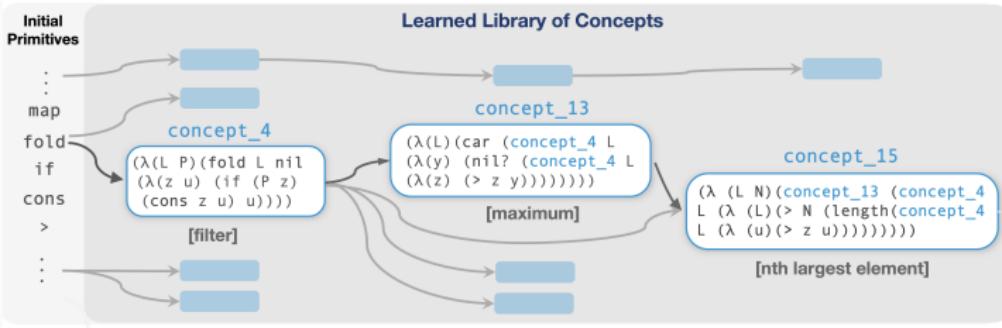
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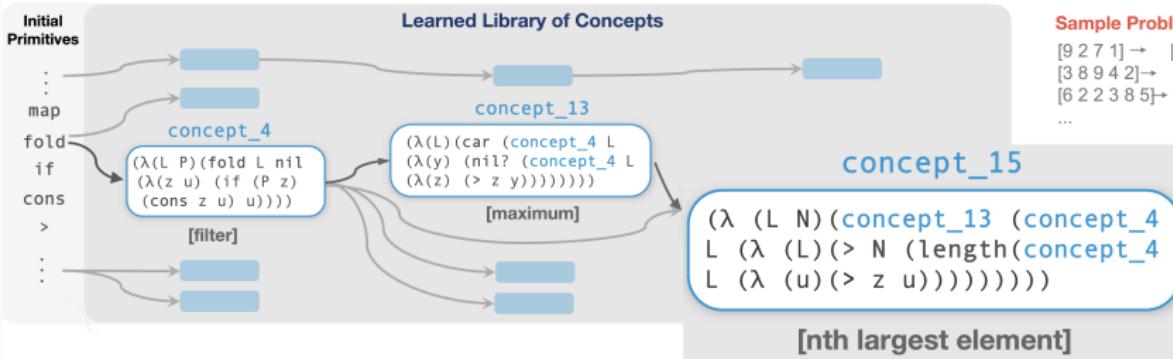
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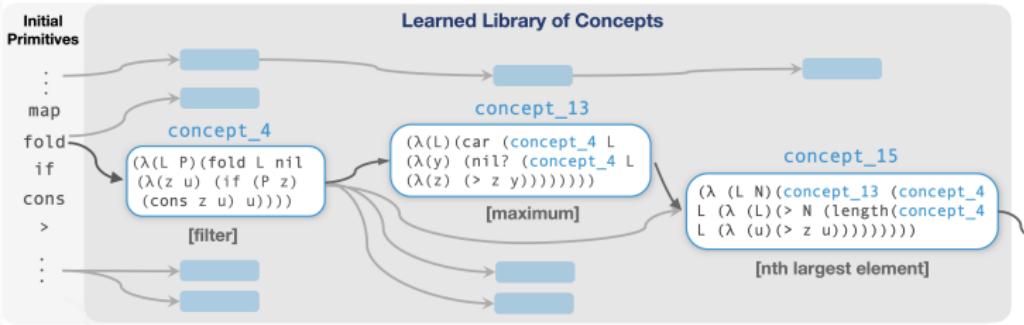
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Library learning



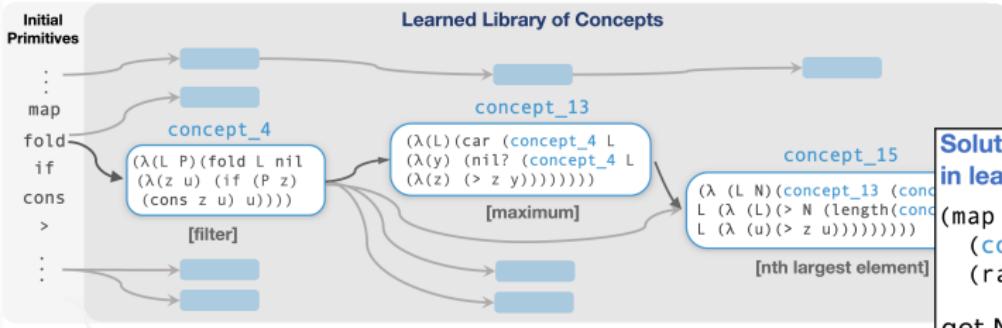
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Solution to sort list discovered in learned language:

```
(map (λ (n)
  (concept_15 L (+ 1 n)))
  (range (length L)))
```

Library learning



Sample Problem: sort list

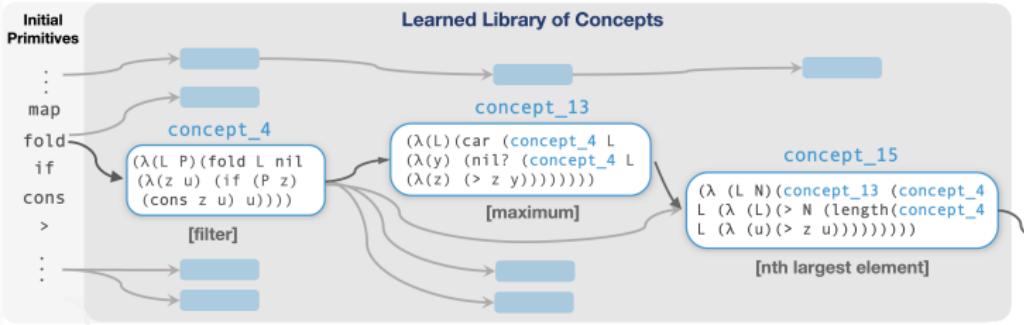
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get Nth largest element,
where N is 1, 2, 3, ...

Library learning



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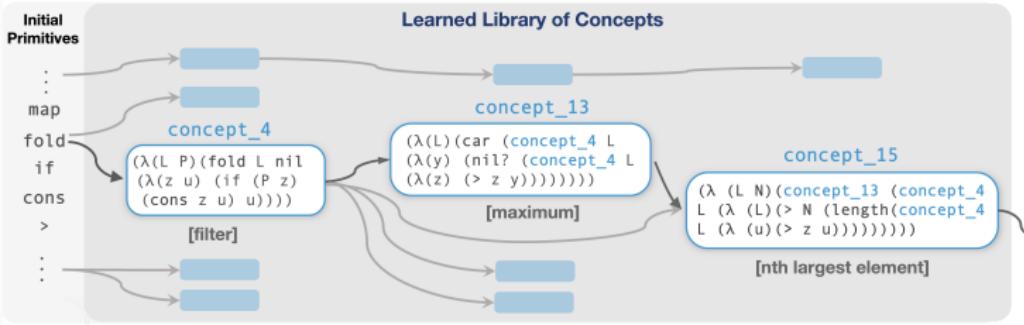
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Solution rewritten in initial primitives:

```
(lambda (x) (map (lambda (y) (car (fold (fold x nil (lambda (z u) (if (gt? (+ y 1) (length
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Library learning



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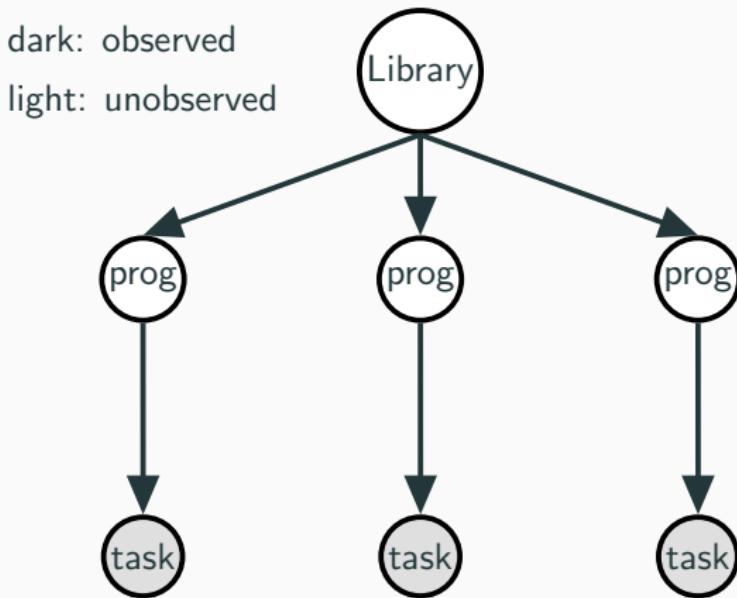
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```

induced sort program found in $\leq 10\text{min}$. Brute-force search
without learned library would take $\approx 10^{73}$ years

- **Wake:** Solve problems by writing programs
- **Sleep:** Improve library and neural recognition model:
 - **Abstraction sleep:** Improve library
 - **Dream sleep:** Improve neural recognition model

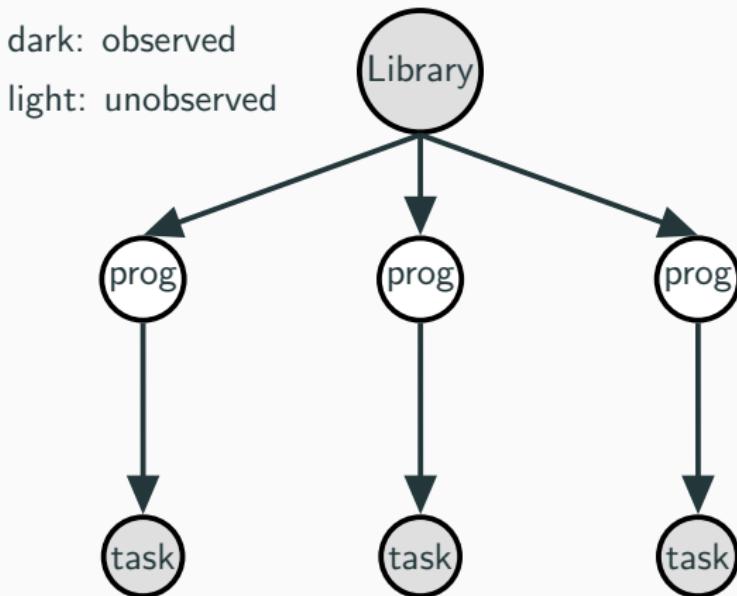
cf. Helmholtz machine, wake/sleep neural network training algorithms

Library learning as Bayesian inference



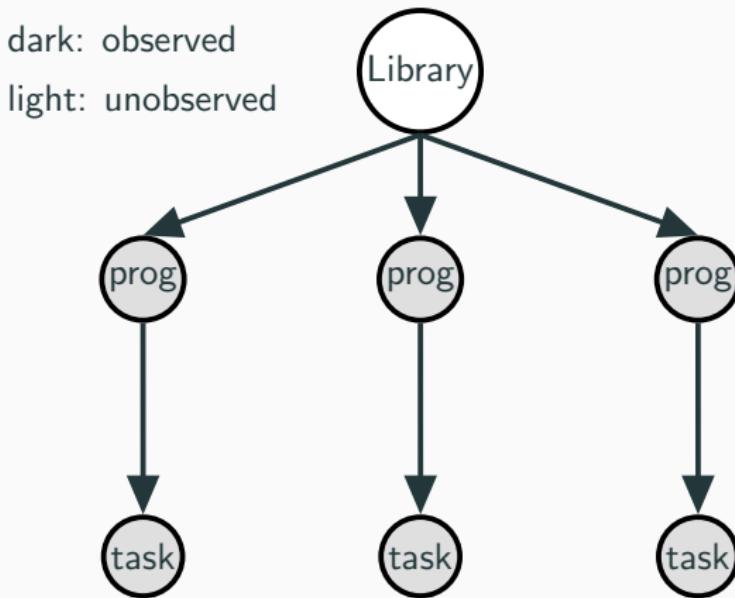
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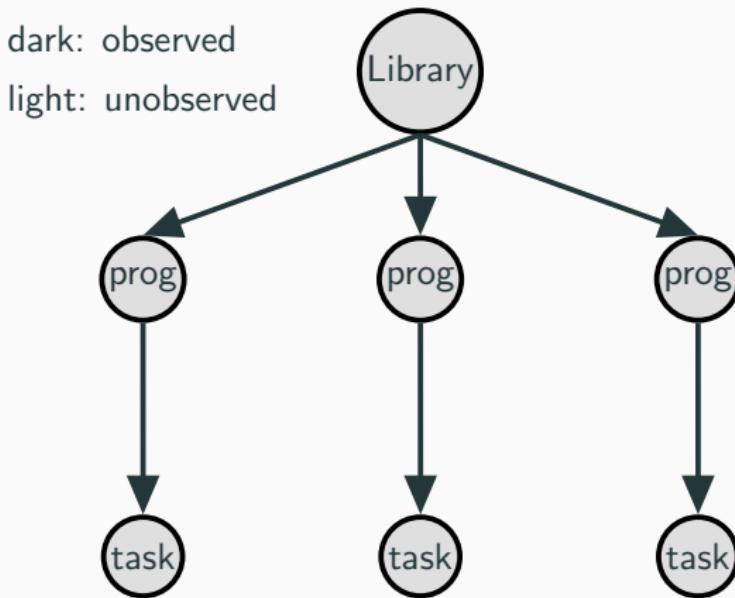
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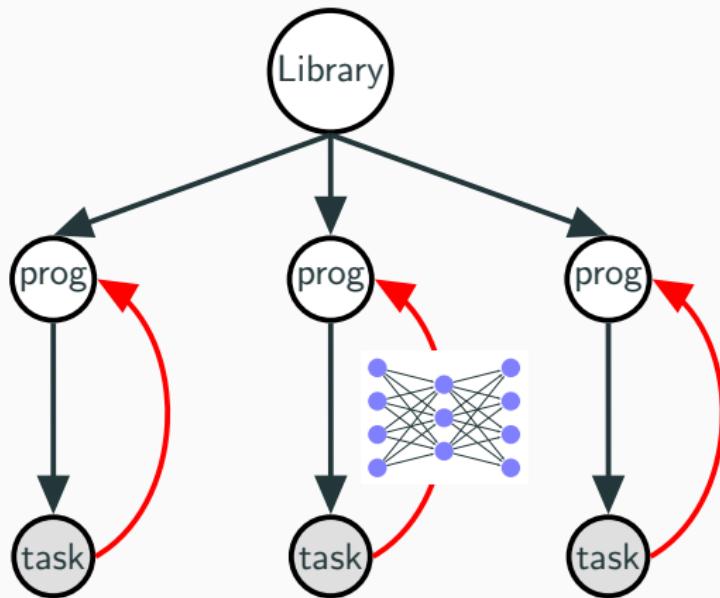
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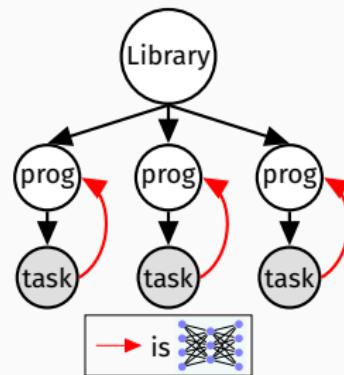


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Library learning as neurally-guided Bayesian inference



library learning via program analysis +
new neural inference network for program synthesis +
better program representation (Lisp+polymorphic types [Milner 1978])

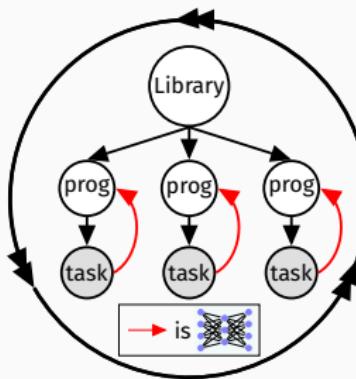


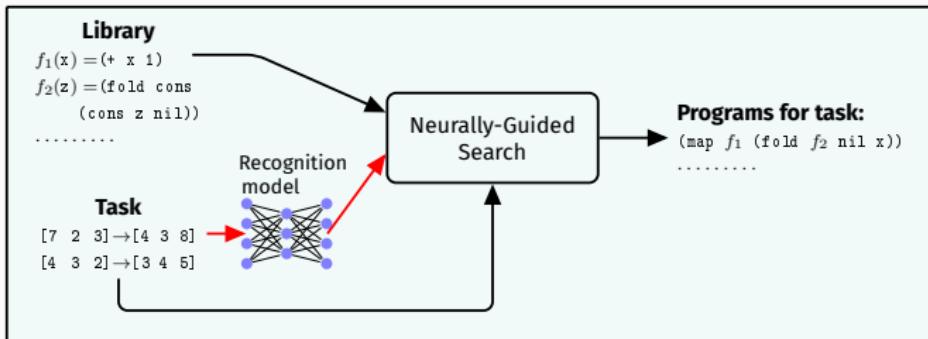
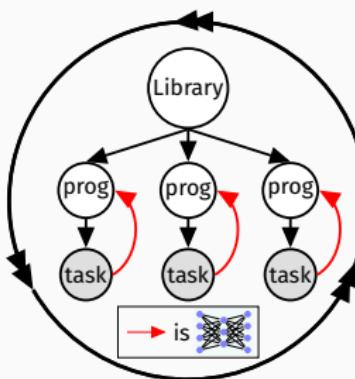
WAKE

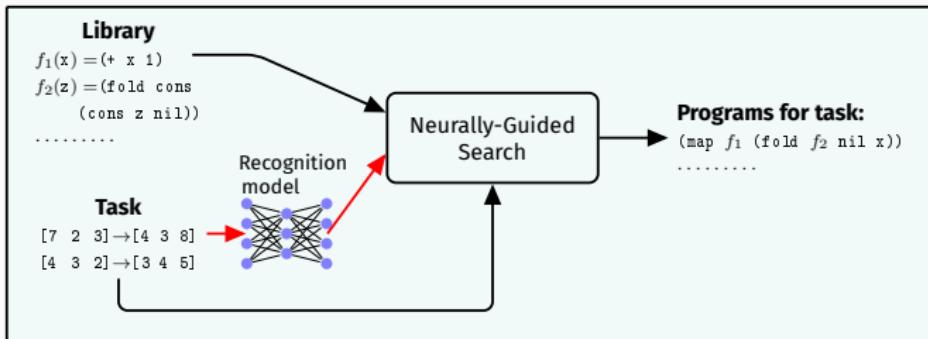
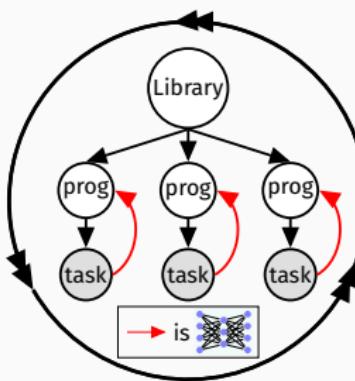
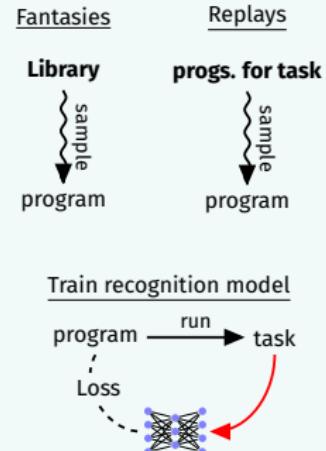


SLEEP: ABSTRACTION

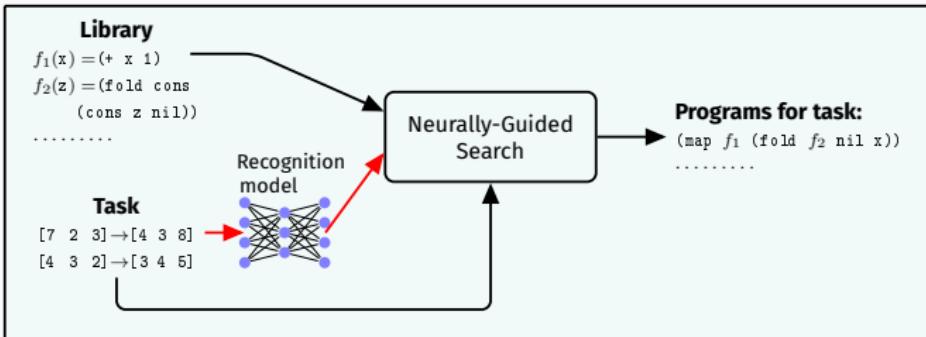
SLEEP: DREAMING



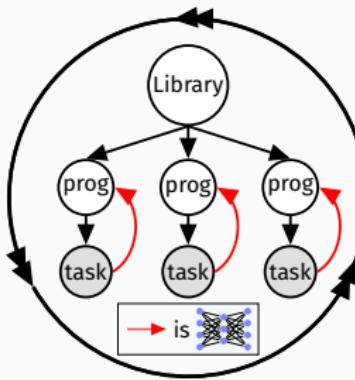
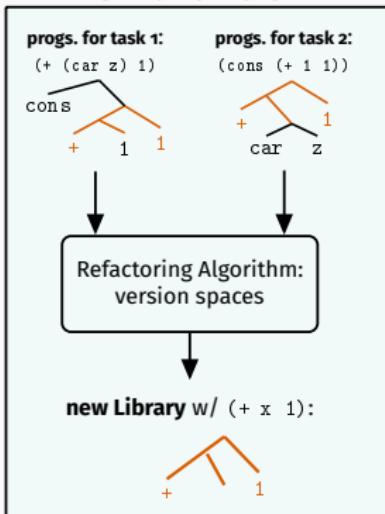
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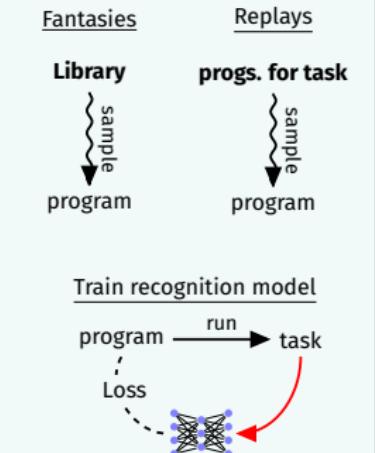
WAKE



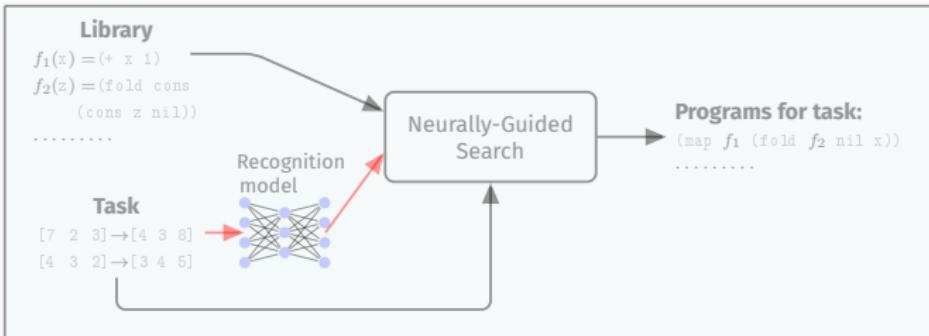
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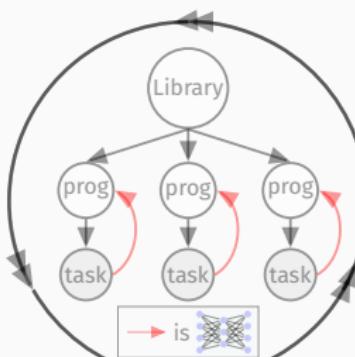
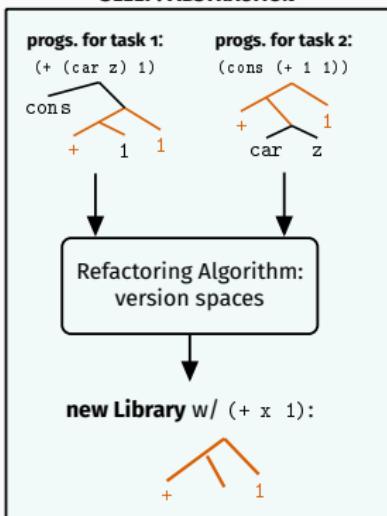
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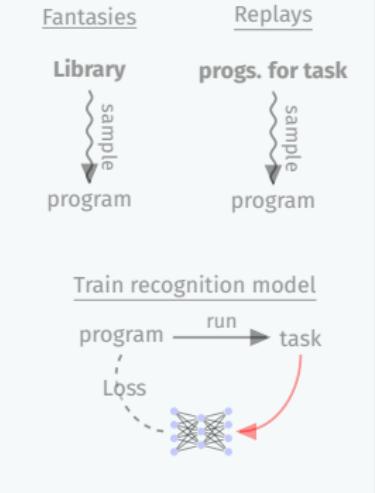
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SLEEP: ABSTRACTION



SLEEP: DREAMING



DreamCoder and learning to learn
learning a library
learning to search
synergy between library+learned search

Abstraction Sleep: Growing the library via refactoring

Task: $[1 \ 2 \ 3] \rightarrow [2 \ 4 \ 6]$
 $[4 \ 3 \ 4] \rightarrow [8 \ 6 \ 8]$

Task: $[1 \ 2 \ 3] \rightarrow [0 \ 1 \ 2]$
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Abstraction Sleep: Growing the library via refactoring

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Wake: program search

```
(Y (λ (r 1) (if (nil? 1) nil  
           (cons (+ (car 1) (car 1))  
                 (r (cdr 1)))))))
```

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refactor

$(10^{14}$ refactorings)

```
((λ (f) (Y (λ (r 1) (if (nil? 1)  
                           nil  
                           (cons (f (car 1))  
                                 (r (cdr 1)))))))  
  (λ (z) (+ z z)))
```

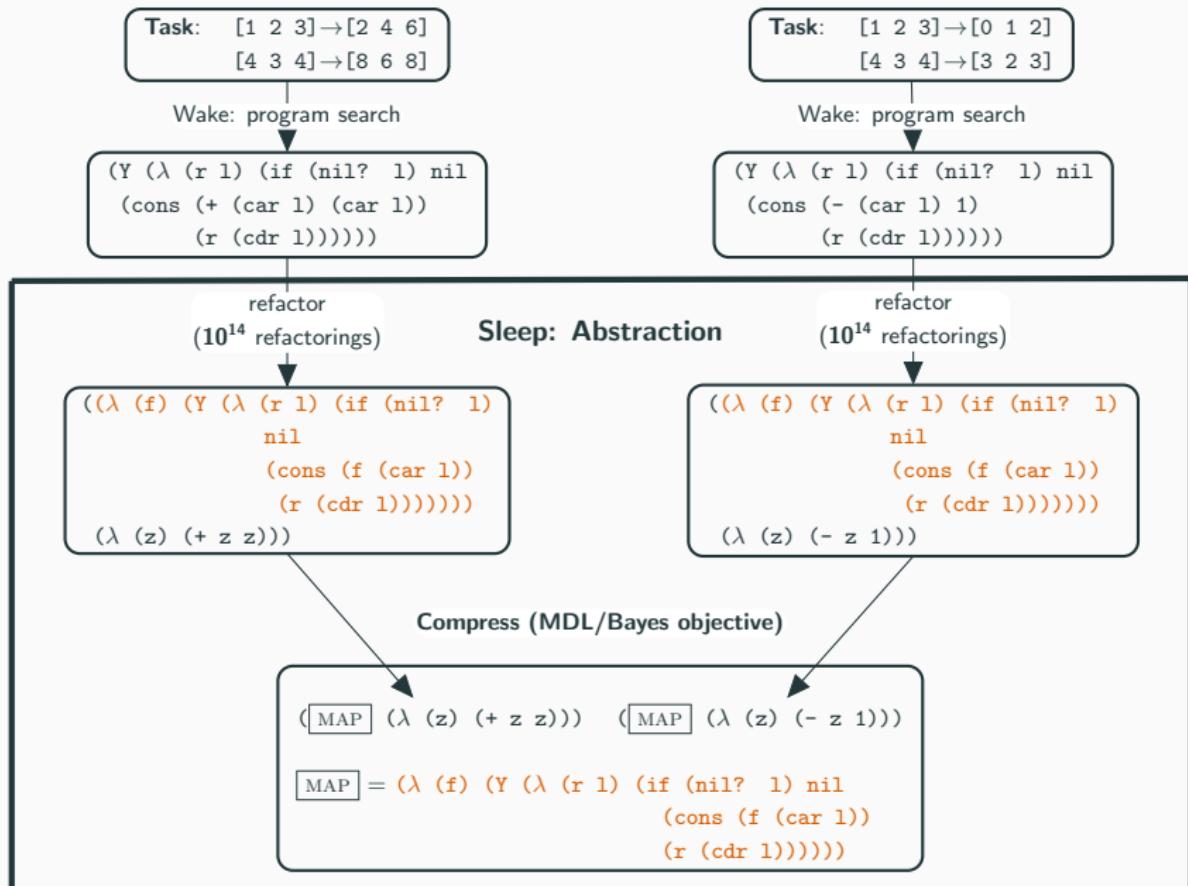
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Sleep: Abstraction

Abstraction Sleep: Growing the library via refactoring



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```

these 10^{14} refactorings represented in exponentially more efficient refactoring data structure:

$(\lambda$ equivalence graphs+version spaces using 10^6 nodes,
calculated in under 5min

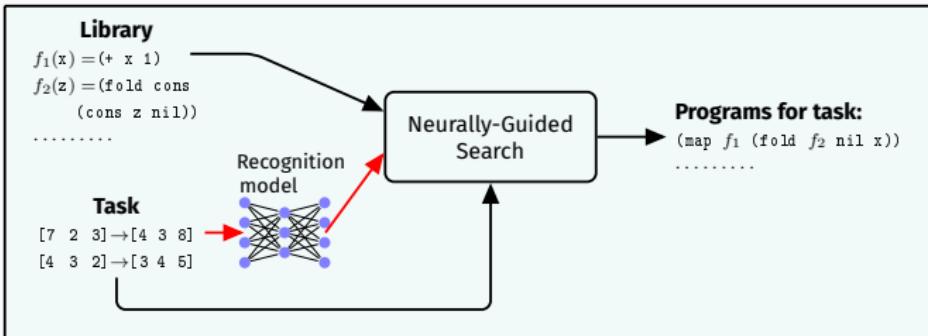
c.f. [Tate et al 2009], [Gulwani 2012]

Compress (MDL/Bayes objective)

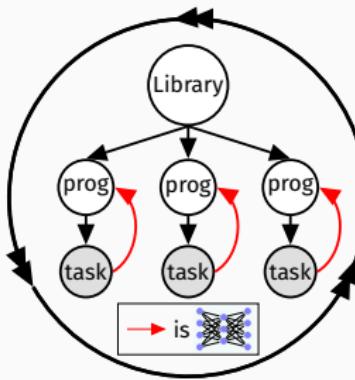
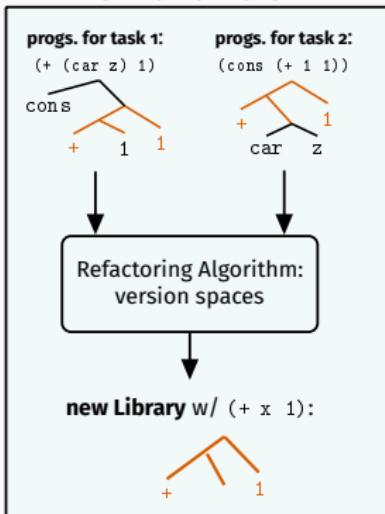
```
(MAP (λ (z) (+ z z))) (MAP (λ (z) (- z 1)))  
MAP = (λ (f) (Y (λ (r 1) (if (nil? 1) nil  
                           (cons (f (car 1))  
                                 (r (cdr 1)))))))
```

DreamCoder and learning to learn
learning a library
learning to search
synergy between library+learned search

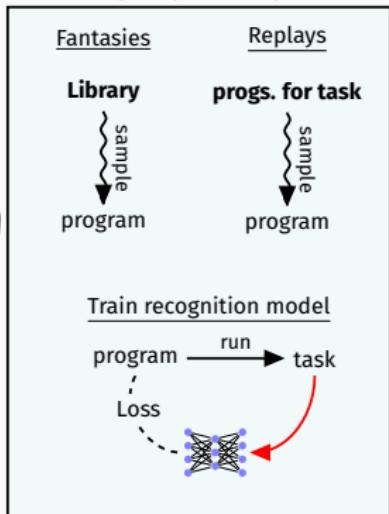
WAKE



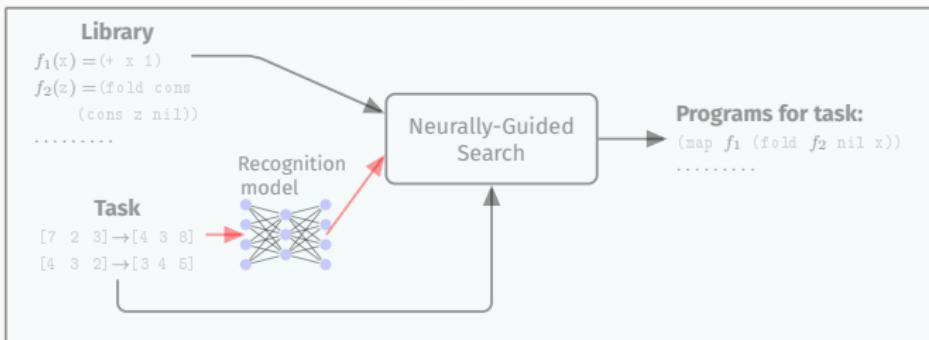
SLEEP: ABSTRACTION



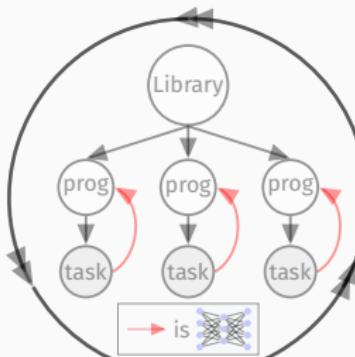
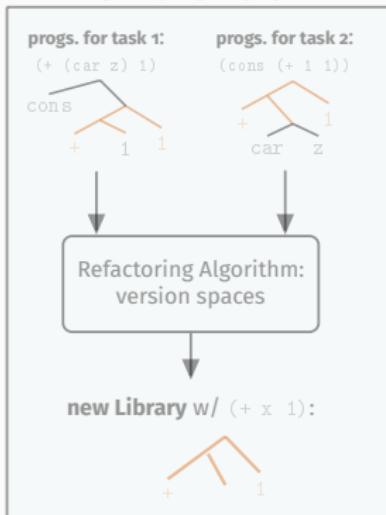
SLEEP: DREAMING



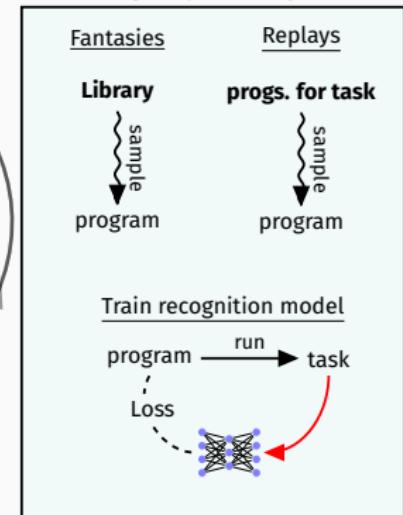
WAKE



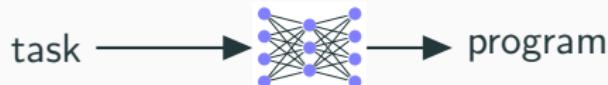
SLEEP: ABSTRACTION



SLEEP: DREAMING



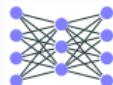
Neural recognition model guides search



Neural recognition model guides search



Neural recognition model guides search

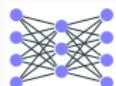


is a...

recurrent network (Devlin et al 2017)

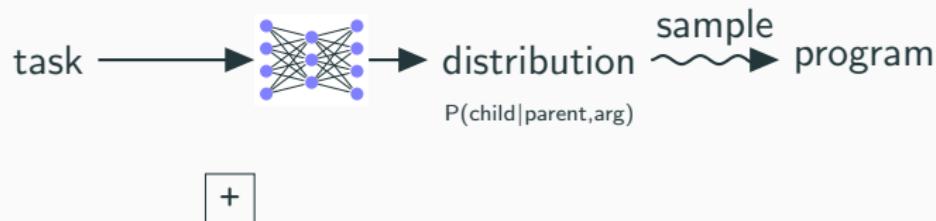
unigram model (Menon et al 2013; Balog et al 2016)

Neural recognition model guides search

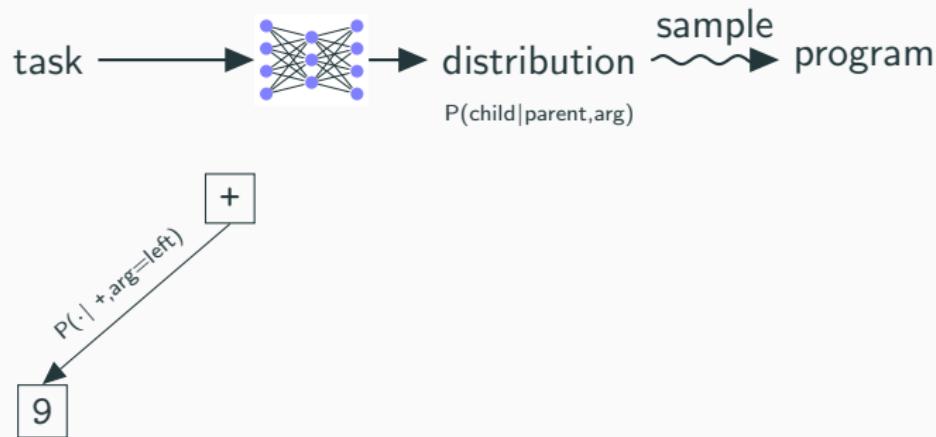


is a “**bigram**” model over syntax trees

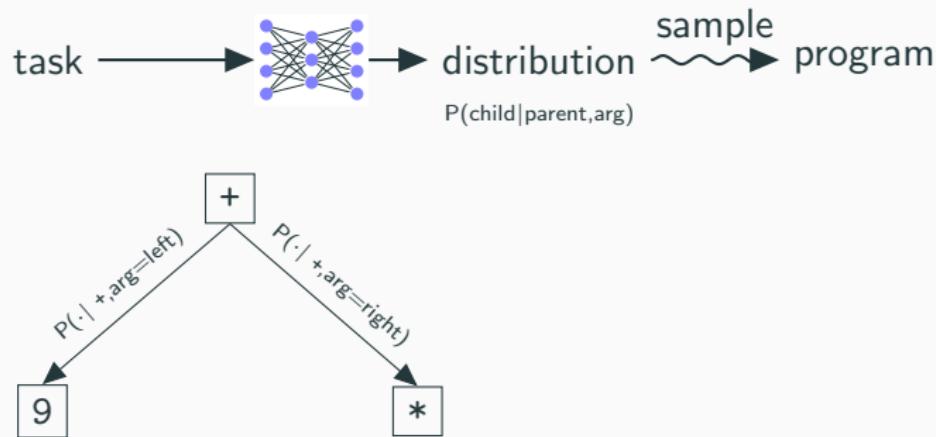
Neural recognition model guides search



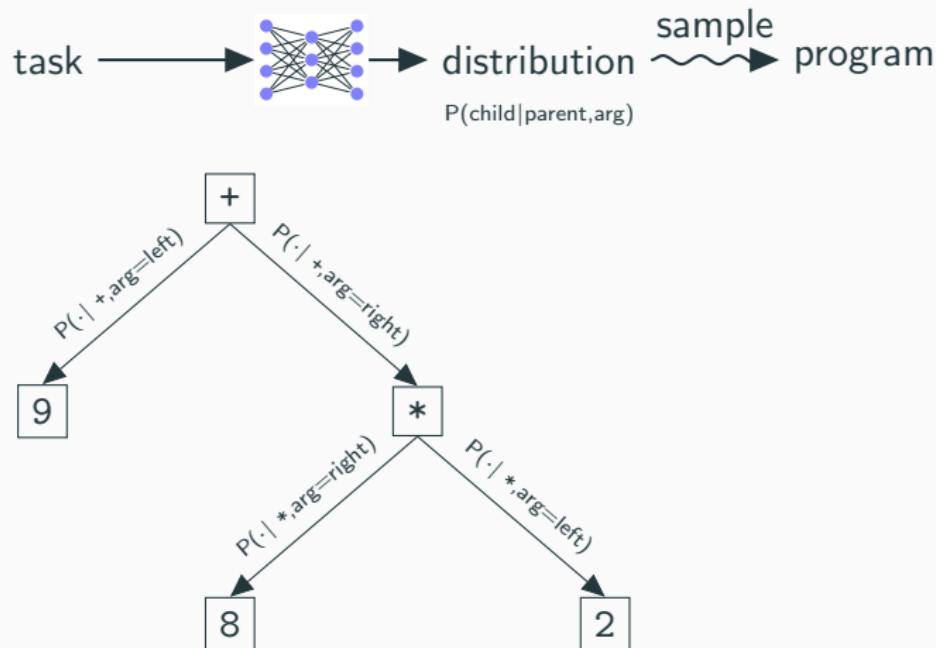
Neural recognition model guides search



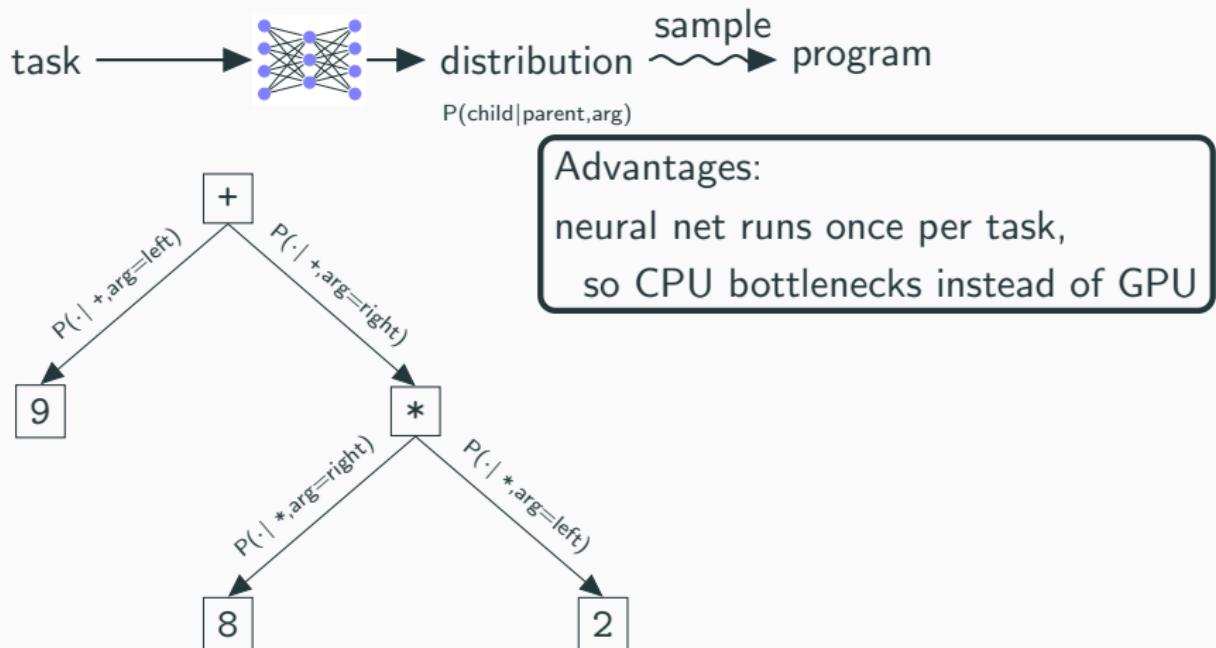
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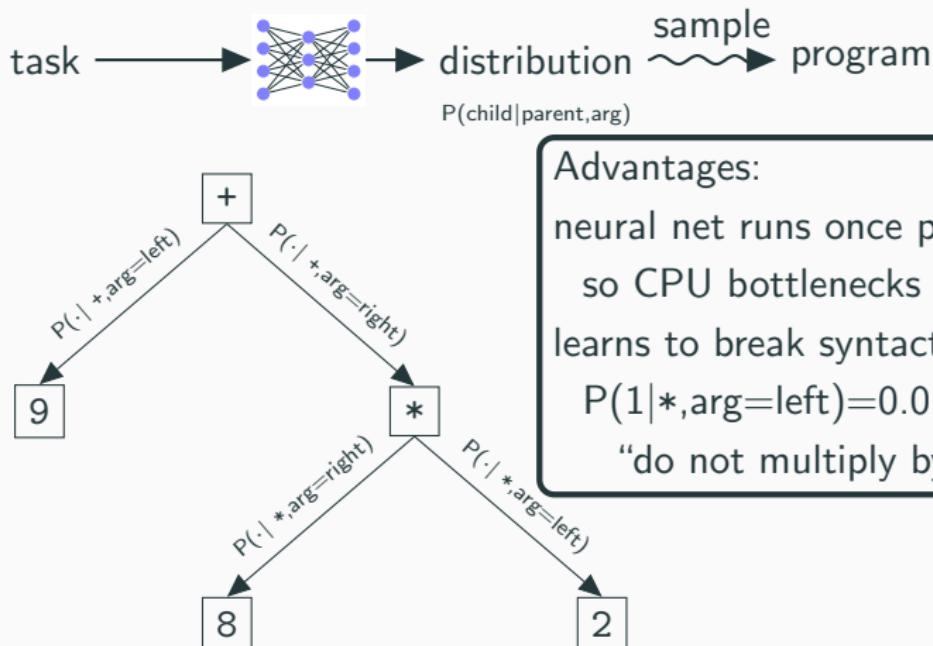
Neural recognition model guides search



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Neural recognition model guides search



DreamCoder and learning to learn
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DreamCoder Domains

List Processing

Sum List

$[1 \ 2 \ 3] \rightarrow 6$

$[4 \ 6 \ 8 \ 1] \rightarrow 17$

Double

$[1 \ 2 \ 3] \rightarrow [2 \ 4 \ 6]$

$[4 \ 5 \ 1] \rightarrow [8 \ 10 \ 2]$

Text Editing

Abbreviate

Allen Newell → A.N.

Herb Simon → H.S.

Drop Last Three

shrdlu → shr

shakey → sha

Regexes

Phone numbers

(555) 867-5309

(650) 555-2368

Currency

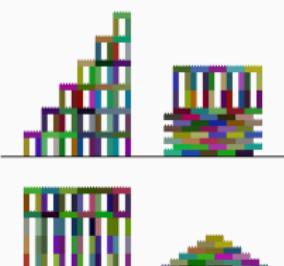
\$100.25

\$4.50

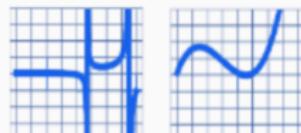
LOGO Graphics



Block Towers



Symbolic Regression



$$y = f(x)$$

Recursive Programming

Filter Red

[■■■■■■■■] → [■■■■]

[■■■■■■■■■■] → [■■■■■■■■]

[■■■■■■■■■■■■] → [■■■■■■■■■■]

Physical Laws

$$\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$$

$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}|^2} \hat{r}$$

DreamCoder Domains

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Sum List

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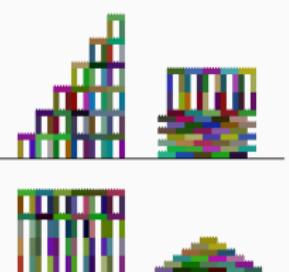
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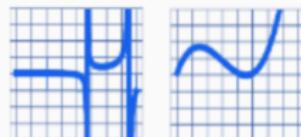
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[■■■■■■■■■■■■■■■■■■] → [■■■■■■■■■■■■■■■■■■]

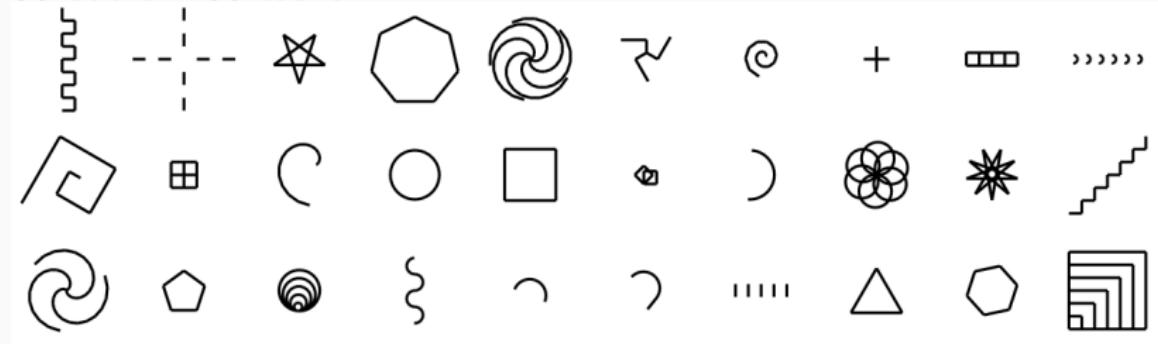
Physical Laws

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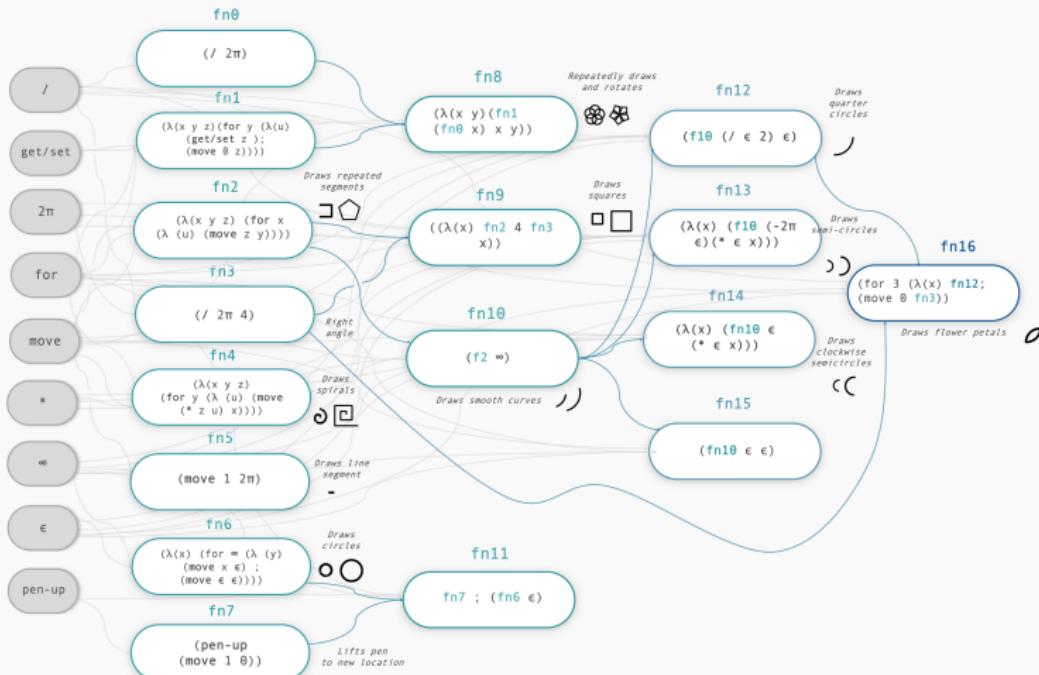
$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}|^2} \hat{r}$$

LOGO Turtle Graphics

30 out of 160 tasks



LOGO Turtle Graphics – learning an interpretable library



$(\text{fn8}\ 5\ (\text{fn4}\ (*\ \in 2)\ \infty\ \epsilon))$



$(\text{for}\ 7\ (\lambda(x)(\text{fn9}\ x)))$

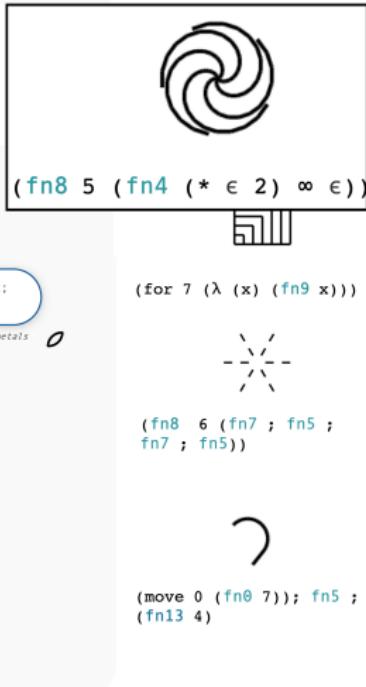
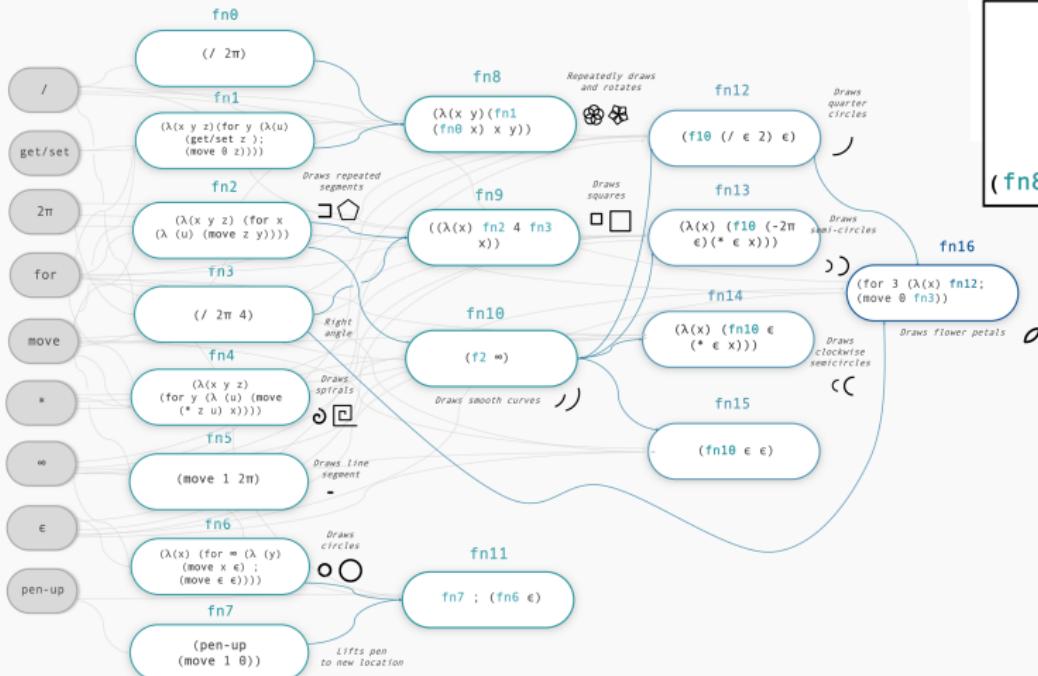


$(\text{fn8}\ 6\ (\text{fn7}\ ;\ \text{fn5}\ ;\ \text{fn7}\ ;\ \text{fn5}))$

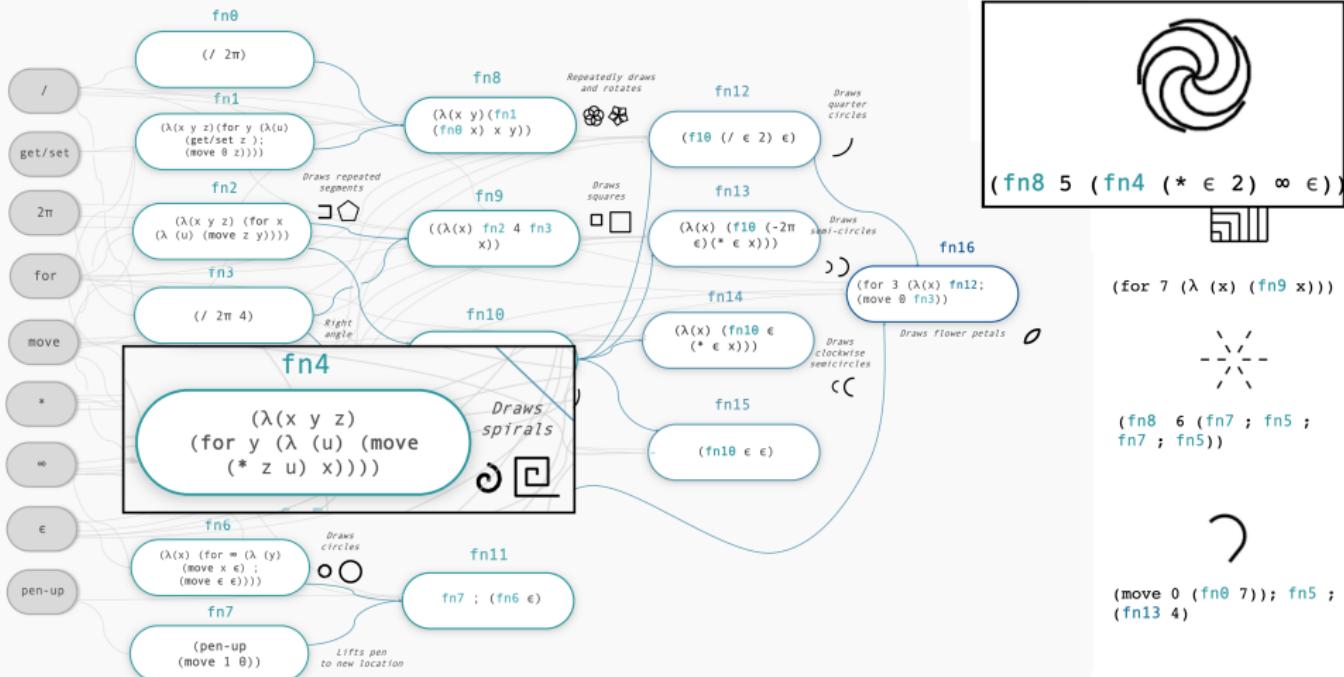


$(\text{move}\ 0\ (\text{fn0}\ 7));\ \text{fn5}\ ;\ (\text{fn13}\ 4))$

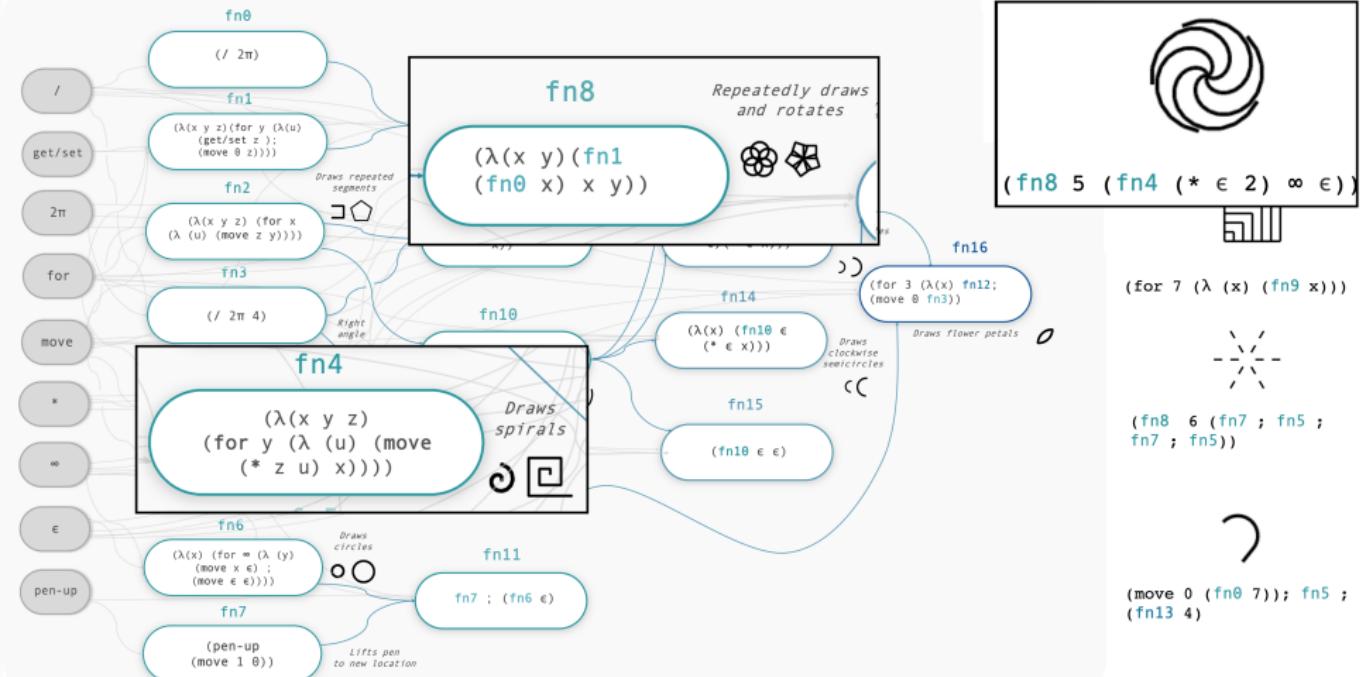
LOGO Turtle Graphics – learning an interpretable library



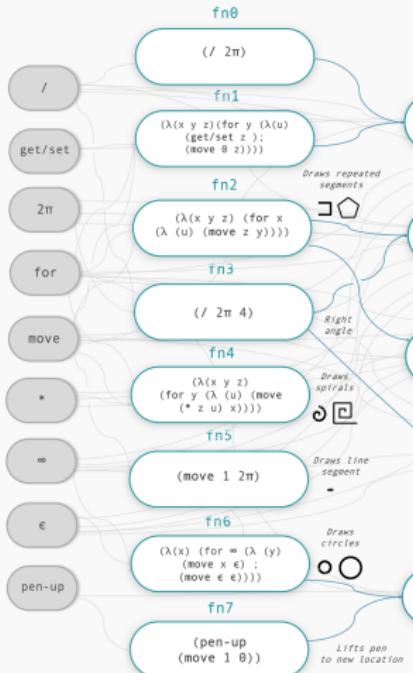
LOGO Turtle Graphics – learning an interpretable library



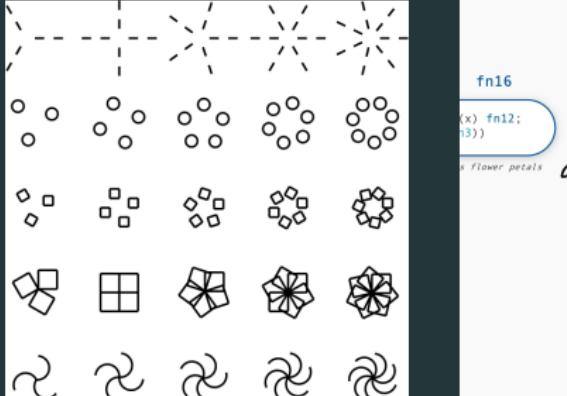
LOGO Turtle Graphics – learning an interpretable library



LOGO Turtle Graphics – learning an interpretable library



radial symmetry(n , body)



(fn8 5 (fn4 (* \ e 2) \ oo))



(for 7 (\lambda (x) (fn9 x)))

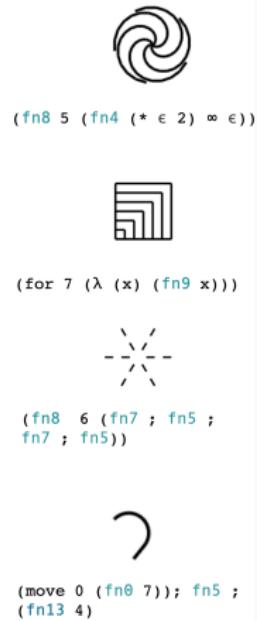
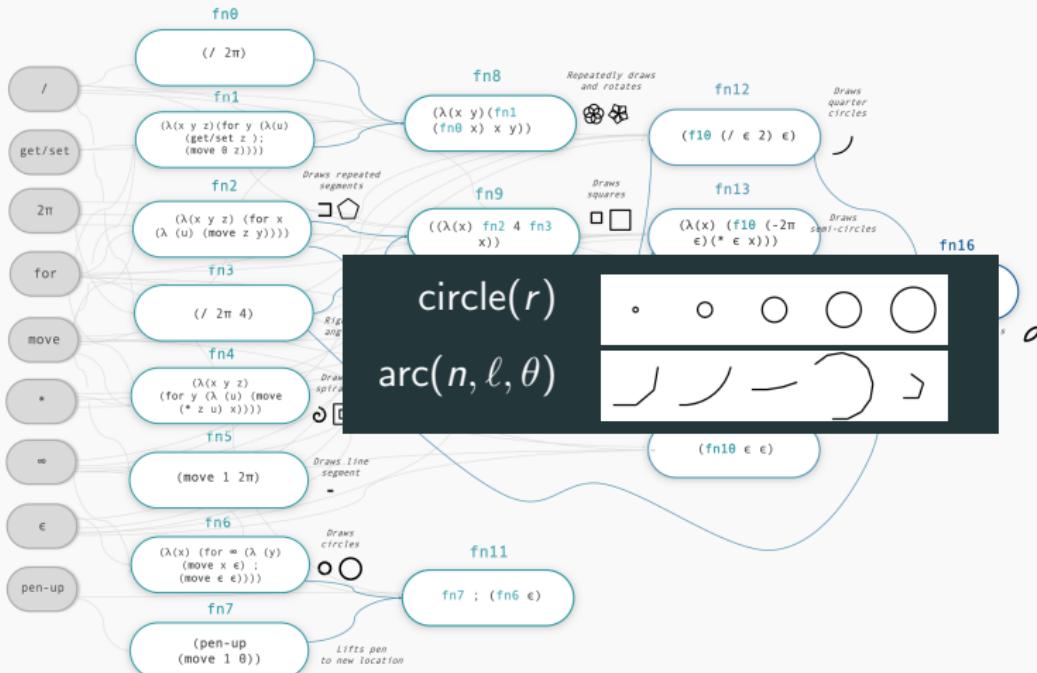


(fn8 6 (fn7 ; fn5 ; fn7 ; fn5))

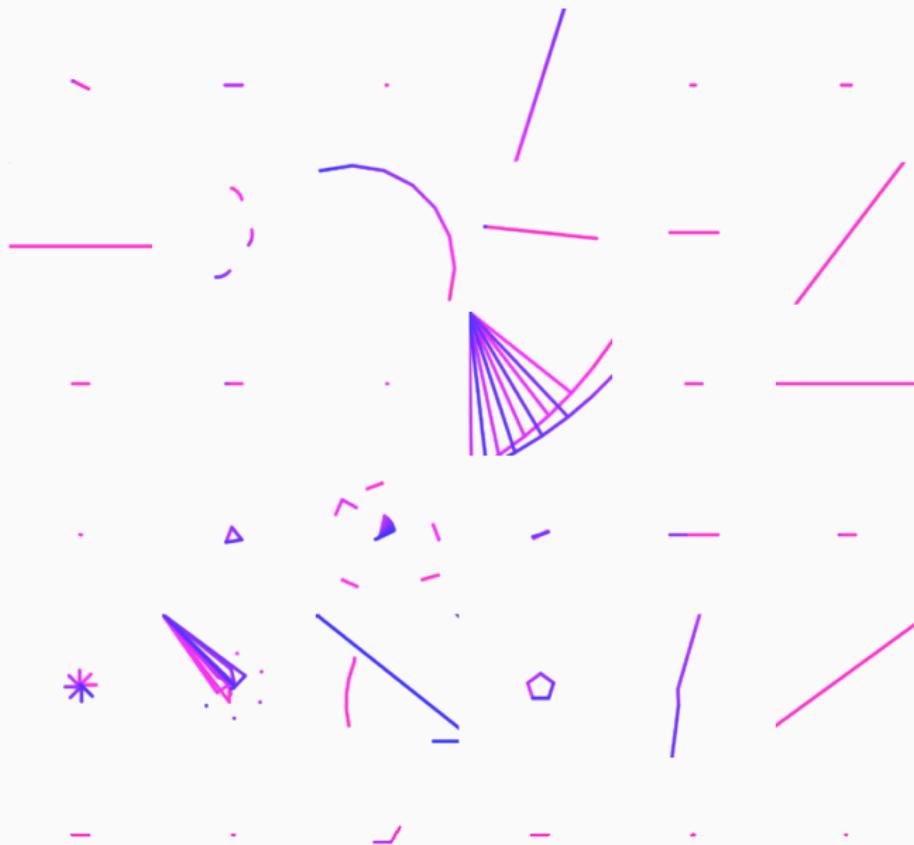


(move 0 (fn0 7)); fn5 ; (fn13 4)

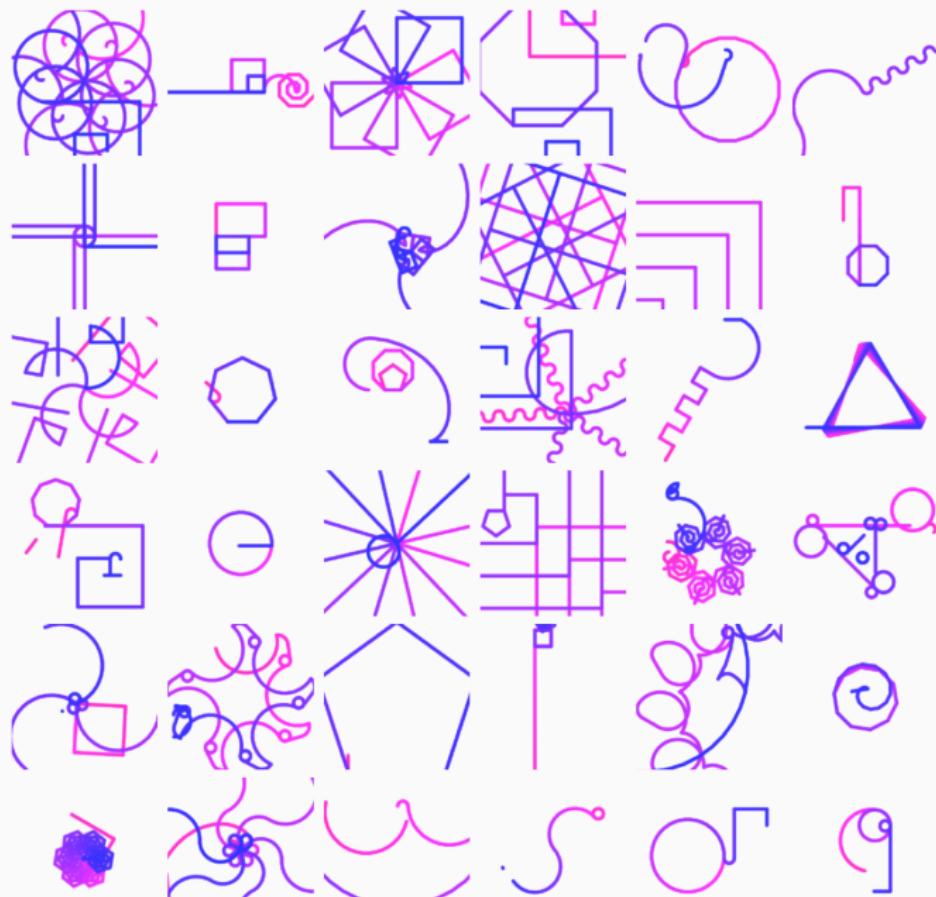
LOGO Turtle Graphics – learning an interpretable library



What does DreamCoder dream of? (before learning)

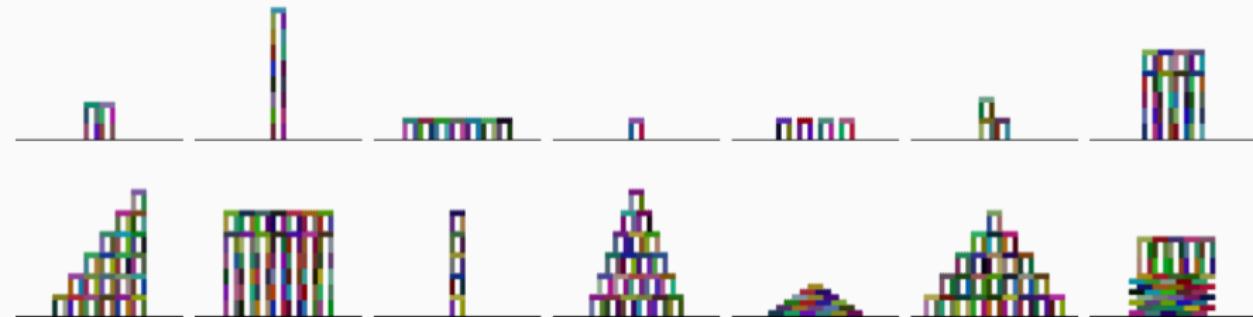


What does DreamCoder dream of? (after learning)



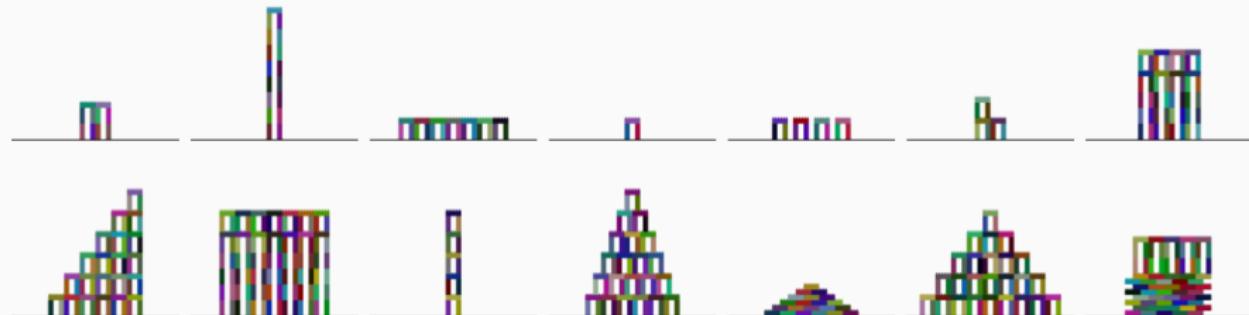
Planning to build towers

example tasks (112 total)

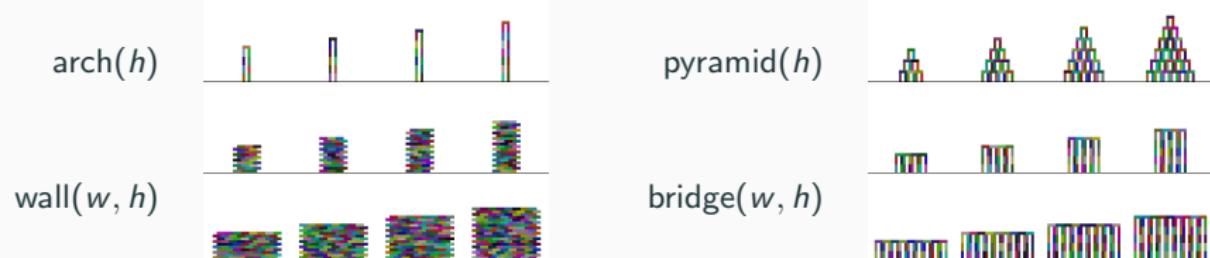


Planning to build towers

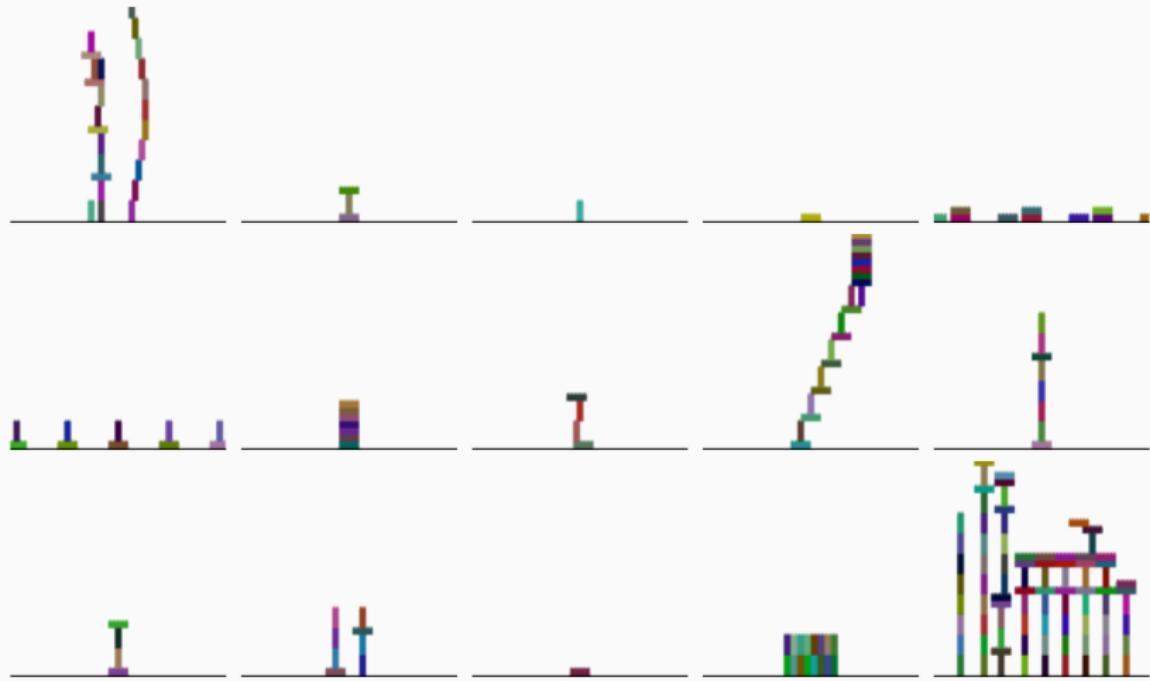
example tasks (112 total)



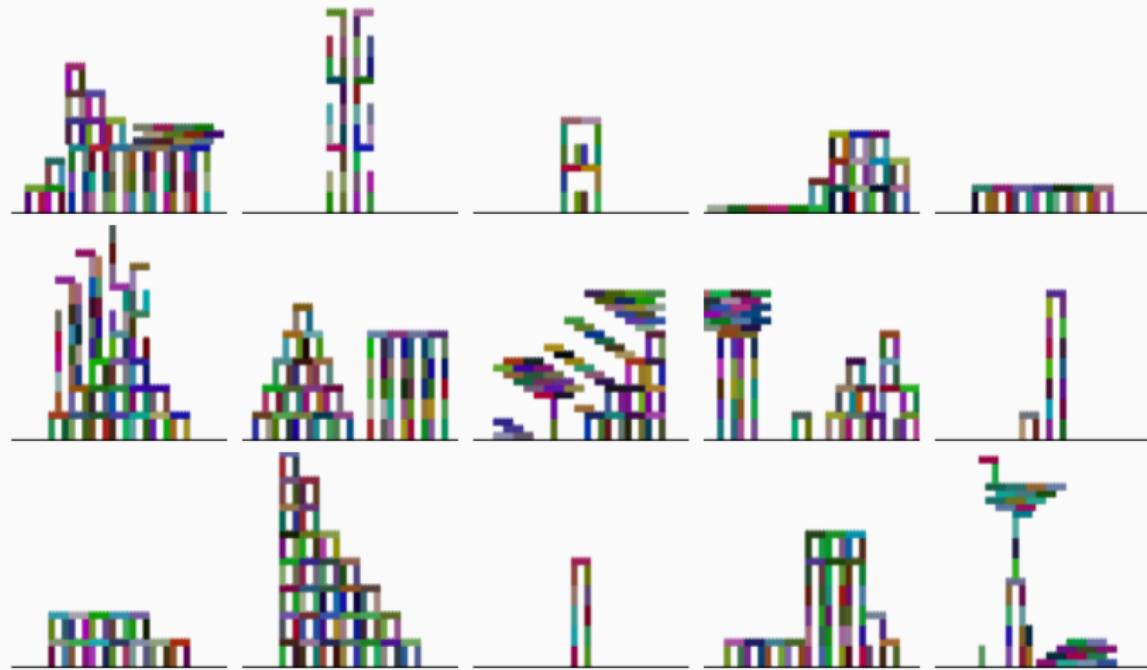
learned library routines (≈ 20 total)



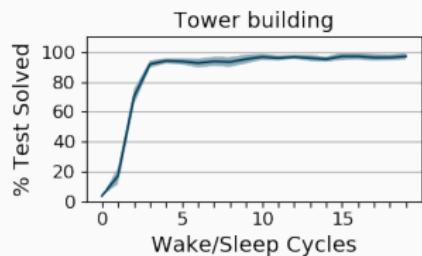
Dreams before learning



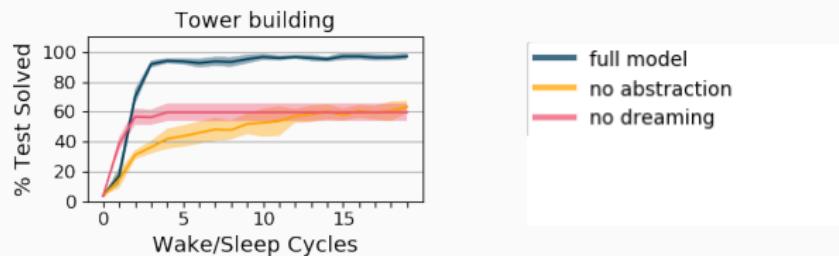
Dreams after learning



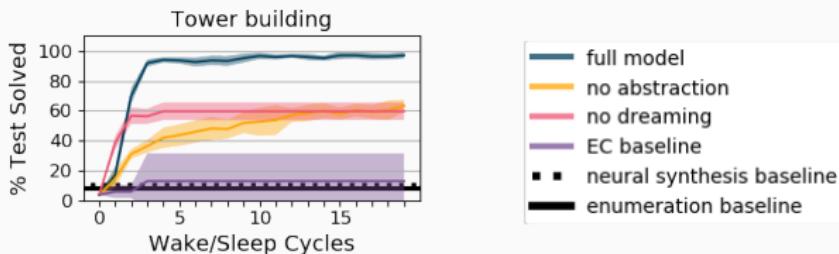
Learning dynamics



Learning dynamics



Learning dynamics

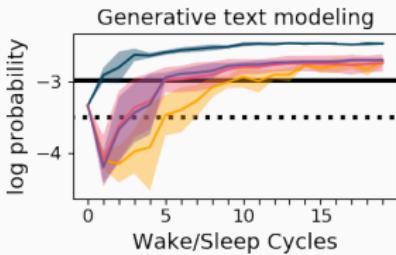
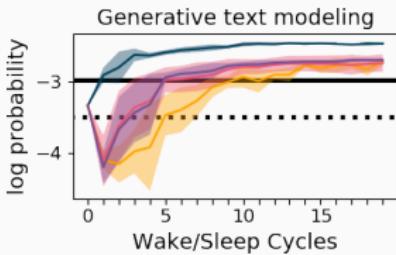
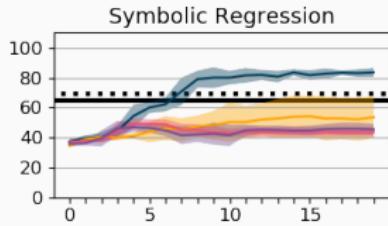
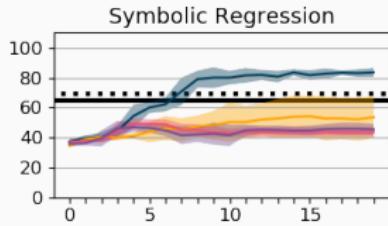
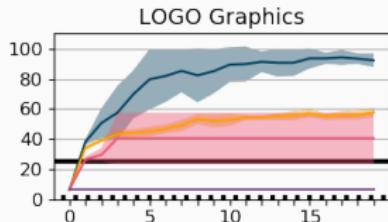
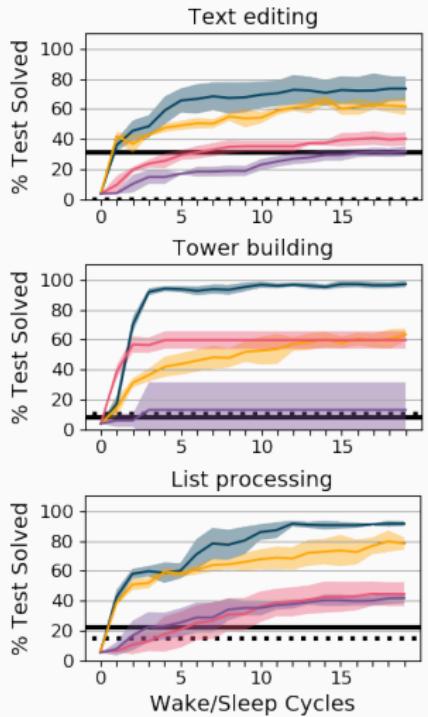


baselines: Exploration-Compression, EC [Dechter et al. 2013]

neural program synthesis, RobustFill [Devlin et al. 2017]

24 hours of brute-force enumeration

Learning dynamics



- full model
- no abstraction
- no dreaming
- EC baseline
- neural synthesis baseline
- enumeration baseline

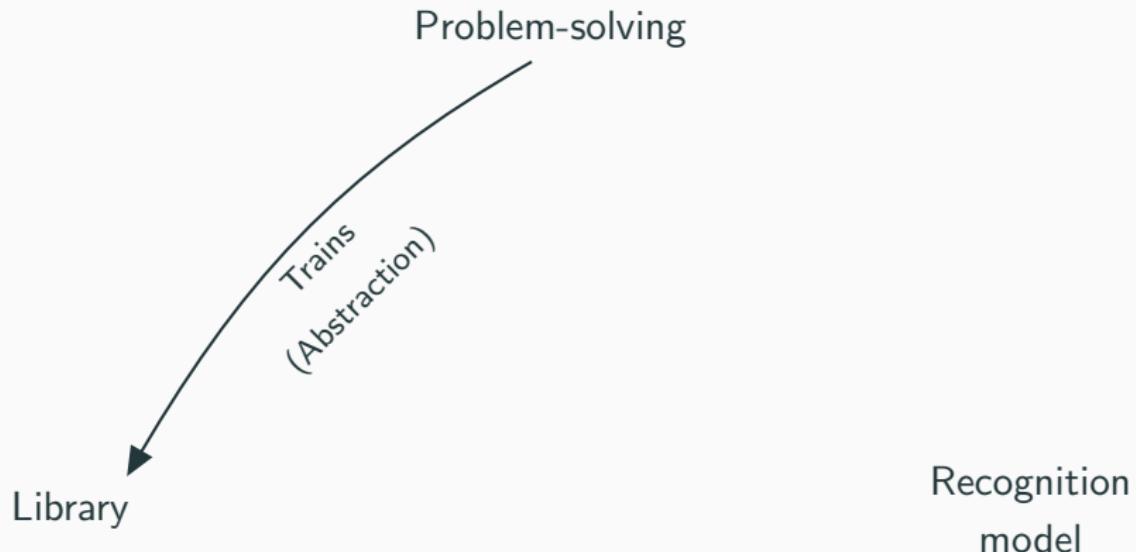
Synergy between recognition model and library learning

Problem-solving

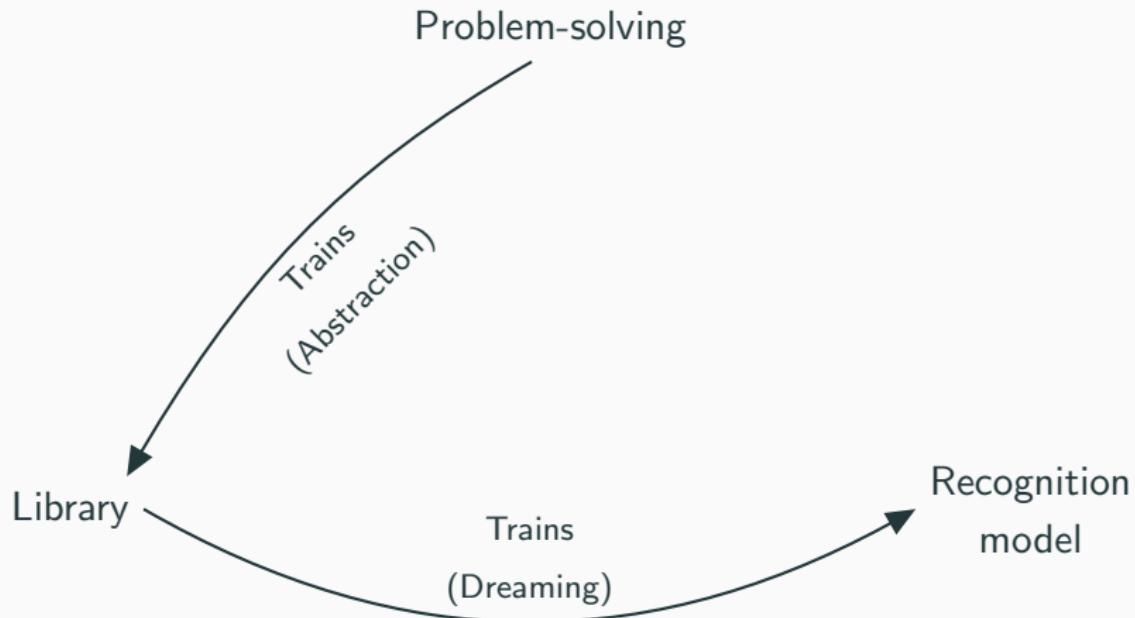
Library

Recognition
model

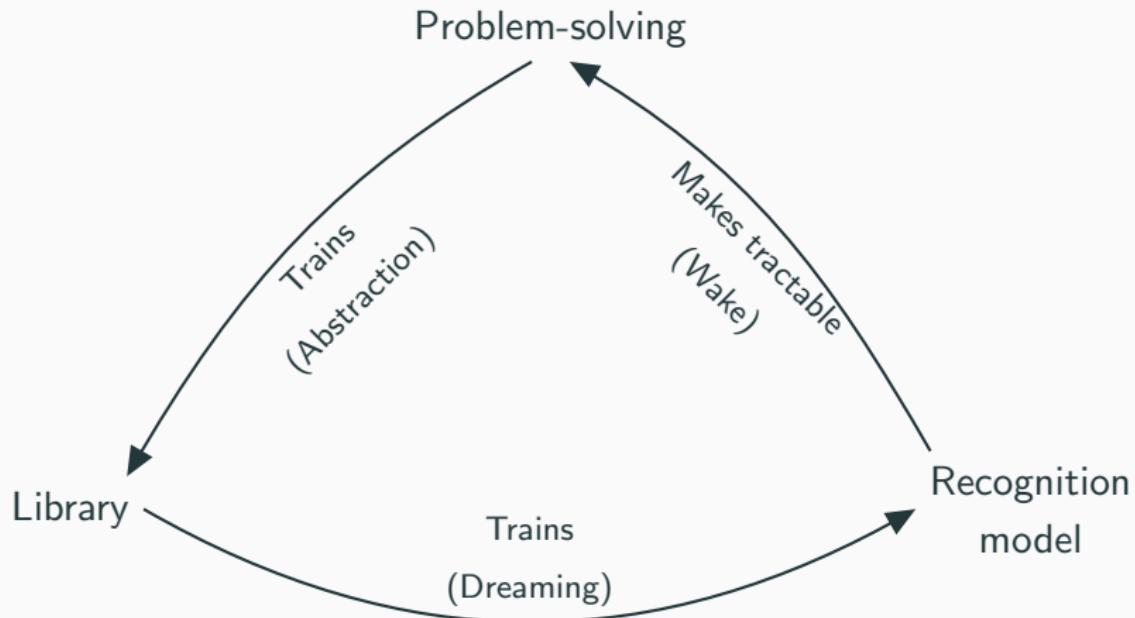
Synergy between recognition model and library learning



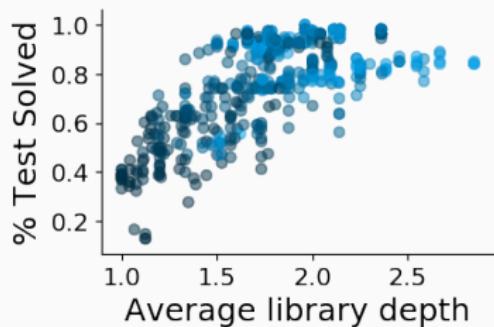
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Synergy between recognition model and library learning



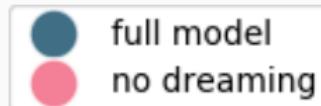
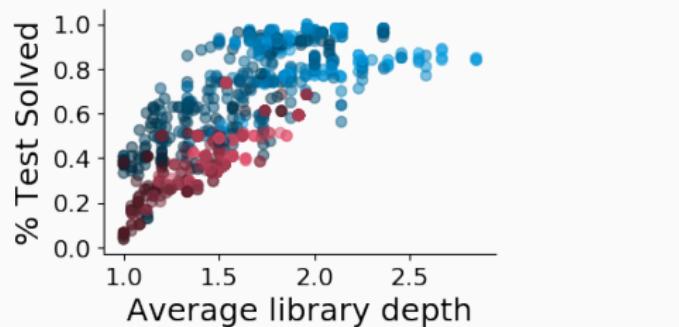
Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

Brighter: Later in learning

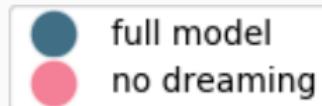
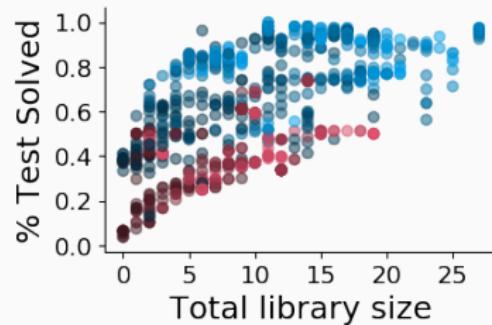
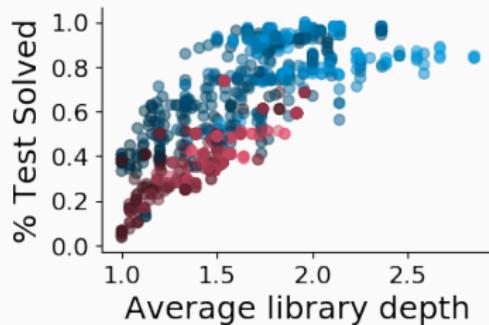
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Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

Brighter: Later in learning

From learning libraries,
to learning languages

From learning libraries,
to learning languages

modern functional programming → physics

From learning libraries,
to learning languages

1950's Lisp → modern functional programming → physics

Physics Formula Sheet

Mechanics

$x = x_0 + v_{x0}t + \frac{1}{2}a_xt^2$	$a_t = \frac{v^2}{r}$	$ \vec{F}_{\text{spring}} = k \vec{x} $
$v = v_0 + at$	$\theta = \theta_0 + \omega_0 t + \frac{1}{2}\alpha t^2$	$\text{PE}_{\text{spring}} = \frac{1}{2}kx^2$
$v_s^2 - v_{s0}^2 = 2a(x - x_0)$	$\omega = \omega_0 + \alpha t$	$T_{\text{spring}} = 2\pi \sqrt{\frac{m}{k}}$
$\bar{a} = \frac{\sum \vec{F}}{m} = \frac{\vec{F}_{\text{net}}}{m}$	$T = \frac{2\pi}{\omega} = \frac{1}{f}$	$T_{\text{pendulum}} = 2\pi \sqrt{\frac{L}{g}}$
$ \vec{F}_{\text{friction}} \leq \mu \vec{F}_{\text{Normal}} $	$v = f\lambda$	
$\bar{p} = m\bar{v}$	$x = A\cos(2\pi ft)$	$ \vec{F}_{\text{gravity}} = G \frac{m_1 m_2}{r^2}$
$\Delta \bar{p} = \vec{F} \Delta t$	$\bar{a} = \frac{\sum \vec{F}}{I} = \frac{\vec{F}_{\text{net}}}{I}$	$ \vec{F}_{\text{gravity}} = m\bar{g}$
$KE = \frac{1}{2}mv^2$	$\vec{r} = r \times F$	$\text{PE}_{\text{gravity}} = -G \frac{m_1 m_2}{r}$
$\Delta PE = mg\Delta y$	$L = I\omega$	$p = \frac{m}{V}$
$\Delta E = W = Fd\cos\theta$	$\Delta L = \tau \Delta t$	$KE = \frac{1}{2}I\omega^2$

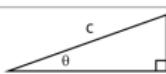
Electricity

$ \vec{F}_E = k \left \frac{q_1 q_2}{r^2} \right $	$\Delta V = IR$	$R = \frac{\rho l}{A}$
$I = \frac{\Delta q}{\Delta t}$		$P = I\Delta V$
$R_{\text{series}} = R_1 + R_2 + \dots + R_n$	$\frac{1}{R_{\text{parallel}}} = \frac{1}{R_1} + \frac{1}{R_2} + \dots + \frac{1}{R_n}$	

Geometry

Rectangle	$A = bh$	Rectangular Solid	$V = lwh$	Triangle	$A = \frac{1}{2}bh$
Circle	$A = \pi r^2$	Cylinder	$V = \pi r^2 l$	Sphere	$V = \frac{4}{3}\pi r^3$
	$C = 2\pi r$		$S = 2\pi rl + 2\pi r^2$		$S = 4\pi r^2$

Trigonometry



$$c^2 = a^2 + b^2 \quad \sin\theta = \frac{a}{c} \quad \cos\theta = \frac{b}{c} \quad \tan\theta = \frac{a}{b}$$

Variables

a = acceleration
 A = amplitude
 A = Area
 b = base length
 C = circumference
 d = distance
 E = energy
 f = frequency
 F = force
 h = height
 I = current
 I = rotational inertia
 KE = kinetic energy
 k = spring constant
 L = angular momentum
 l = length
 m = mass
 P = power
 p = momentum
 q = charge
 r = radius
 R = resistance
 S = surface area
 T = period
 t = time
 PE = potential energy
 V = electric potential
 V = volume
 v = velocity
 w = width
 W = work
 x = position
 y = height
 α = angular acceleration
 λ = wavelength
 μ = coefficient of friction

Growing languages for vector algebra and physics

Initial Primitives

map
zip
cons
empty
cdr
power
fold
car
+
-
*
/
θ
1
π -

Physics Equations

Newton's Second Law

$$\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$$

Parallel Resistors

$$R_{total} = \left(\sum_i \frac{1}{R_i} \right)^{-1}$$

Work

$$U = \vec{F} \cdot \vec{d}$$

Force in a Magnetic Field

$$|\vec{F}| = q |\vec{v} \times \vec{B}|$$

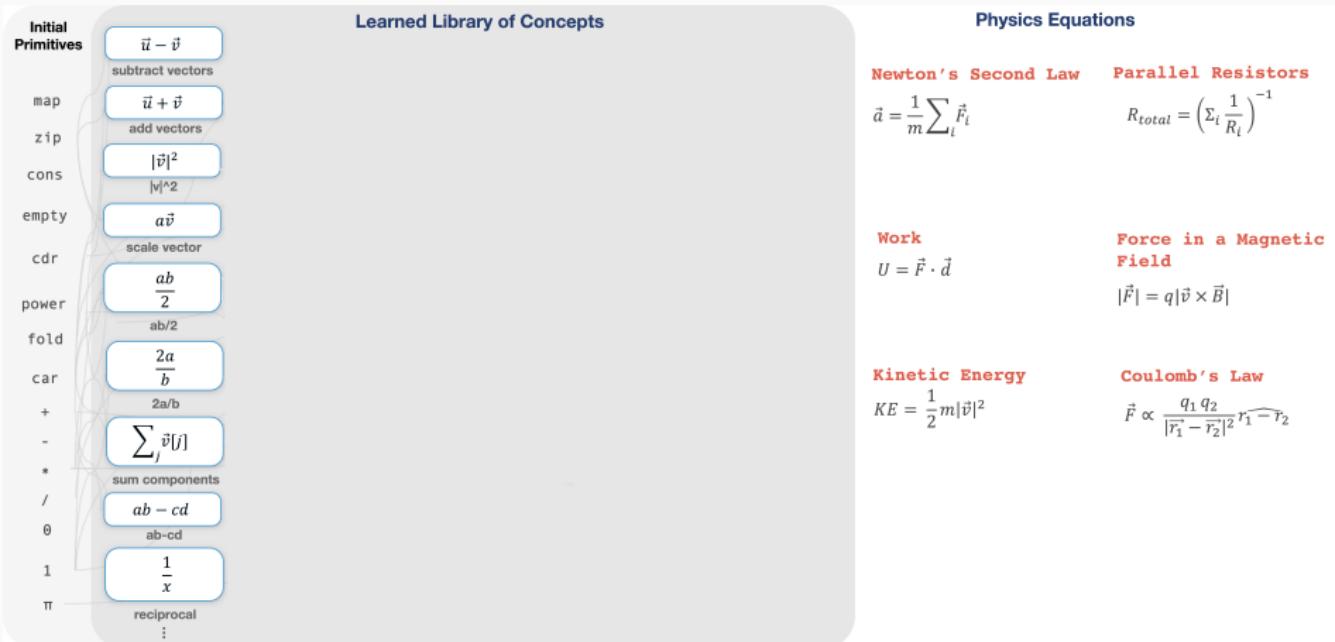
Kinetic Energy

$$KE = \frac{1}{2} m |\vec{v}|^2$$

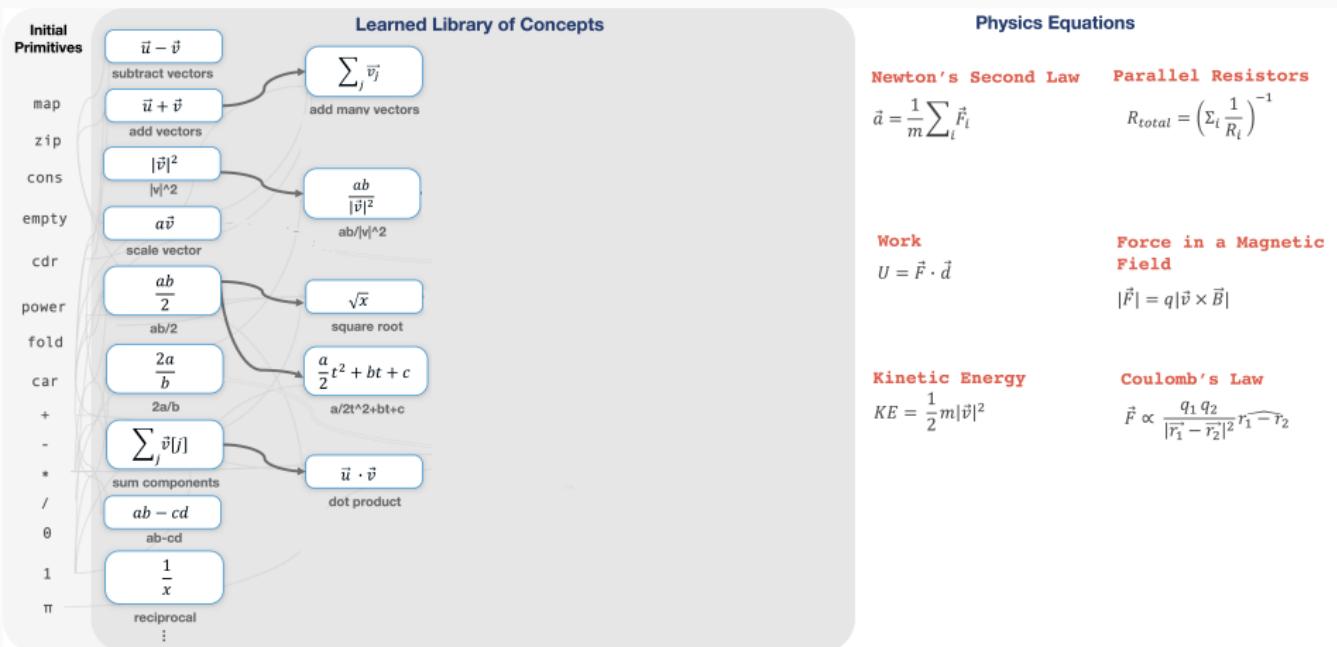
Coulomb's Law

$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}_1 - \vec{r}_2|^2} \hat{r}_1 - \hat{r}_2$$

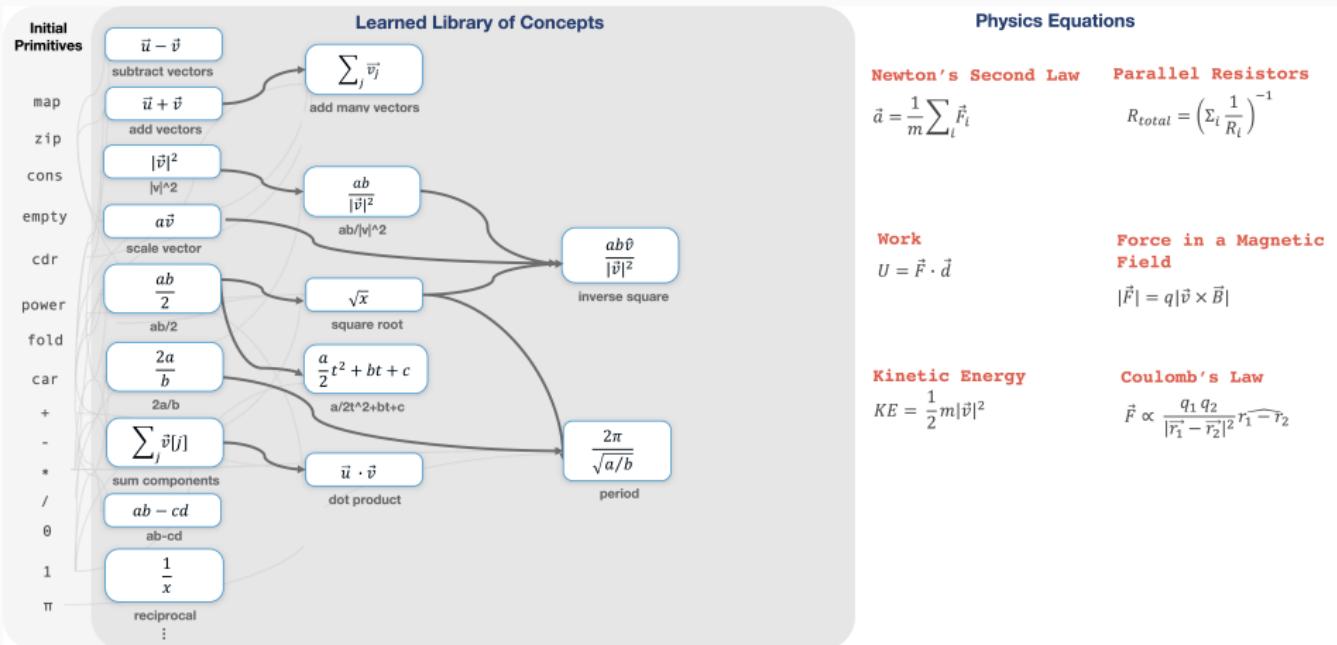
Growing languages for vector algebra and physics



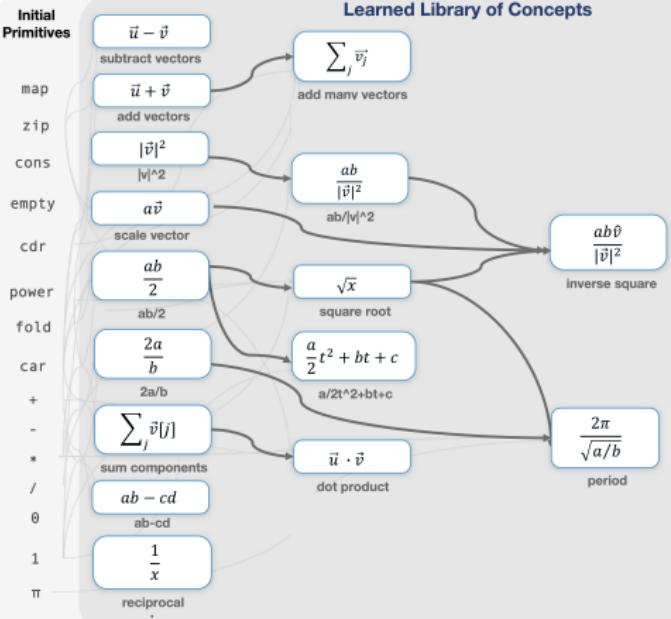
Growing languages for vector algebra and physics



Growing languages for vector algebra and physics



Growing languages for vector algebra and physics



Physics Equations

Newton's Second Law

$$\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$$

Parallel Resistors

$$R_{total} = \left(\sum_i \frac{1}{R_i} \right)^{-1}$$

(scale-vector(reciprocal m) (reciprocal (sum-components (add-many-vectors Fs)))
 (map (lambda(r) (reciprocal r)) Rs)))

Work

$$U = \vec{F} \cdot \vec{d}$$

(dot-product F d)

Force in a Magnetic Field

$$|\vec{F}| = q |\vec{v} \times \vec{B}|$$

(* q (ab-cd v_x b_y v_y b_x))

Kinetic Energy

$$KE = \frac{1}{2} m |\vec{v}|^2$$

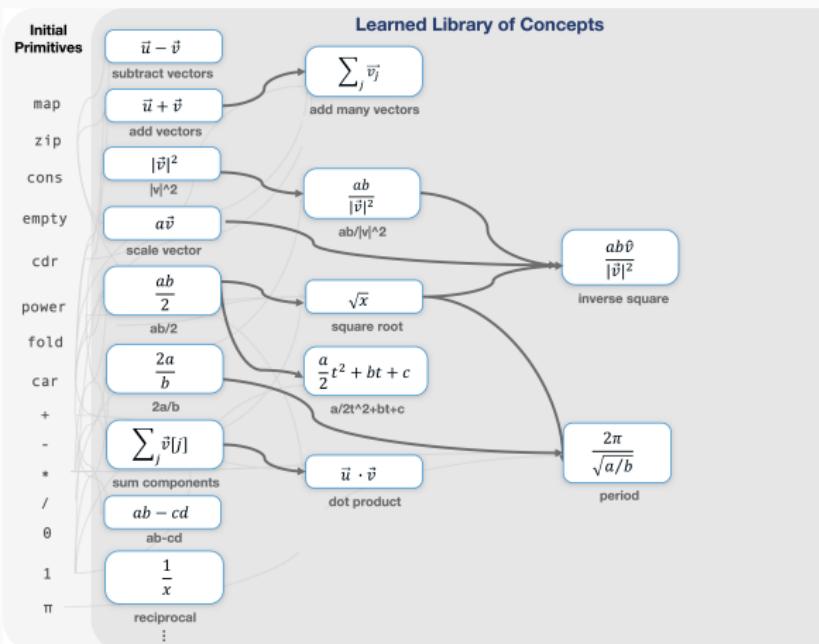
(ab/2 m ((|v|^2 v)))

Coulomb's Law

$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}_1 - \vec{r}_2|^2} \hat{r}_1 - \hat{r}_2$$

(inverse-square q_1 q_2
 (subtract-vectors r_1 r_2))

Growing languages for vector algebra and physics



Physics Equations

Newton's Second Law	Parallel Resistors
$\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$	$R_{total} = \left(\sum_i \frac{1}{R_i} \right)^{-1}$

```
(scale-vector(reciprocal m) (reciprocal (sum-components  
(add-many-vectors Fs)) (map (lambda(r) (reciprocal r))  
Rs)))
```

Work

$$U = \vec{E}, \vec{d}$$

(dot-product E d)

$$|\vec{F}| = q|\vec{v} \times \vec{B}|$$

(* g (ab-cd v x b v v v b x))

Force in a Magnetic Field

Kinetic Energy

$$KE = \frac{1}{2}m|\vec{v}|^2$$

$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}_1 - \vec{r}_2|^2} \hat{\vec{r}_1 - \vec{r}_2}$$

(inverse-square q_1 q_2

(Subtract vectors $\underline{v_1}$ & $\underline{v_2}$)

p

—
—

Solution to Coulomb's

Law if expressed in

initial primitives

Page 1

Growing a language for recursive programming

Initial Primitives

Y
combinator

cons

car

cdr

nil

if

nil?

+

-

0

1

=

Recursive Programming Algorithms

Stutter

[■■] → [■■■■]
[■■■■] → [■■■■■■■■]

Take every other

[■■■■■■] → [■■]
[■■■■■■■■] → [■■■■]

List lengths

[[■■■], [■]] → [3 1]
[[■■■], [], [■]] → [2 0 1]

List differences

[1 8 2], [0 5 1] → [1 3 1]
[2 3 6], [1 2 4] → [1 1 2]

Growing a language for recursive programming

Initial Primitives

λ

combinator

cons

car

cdr

nil

if

nil?

+

-

0

1

=

Learned Library of Concepts

fold

```
fold(xs,f,x0) =  
(if (nil? xs) x0  
  (f (fold (cdr xs)  
           f x0) (car xs)))
```

unfold

```
unfold(x,g,f,p) =  
(if (p x) nil  
  (cons (f x)  
        (unfold (g x)  
               g f p)))
```

Recursive Programming Algorithms

Stutter

```
[■■] → [■■■■]  
[■■■■] → [■■■■■■]  
(fold A (λ (u v) (cons v (cons v u))) nil)
```

Take every other

```
[■■■■■■] → [■■]  
[■■■■■■■■] → [■■■■]
```

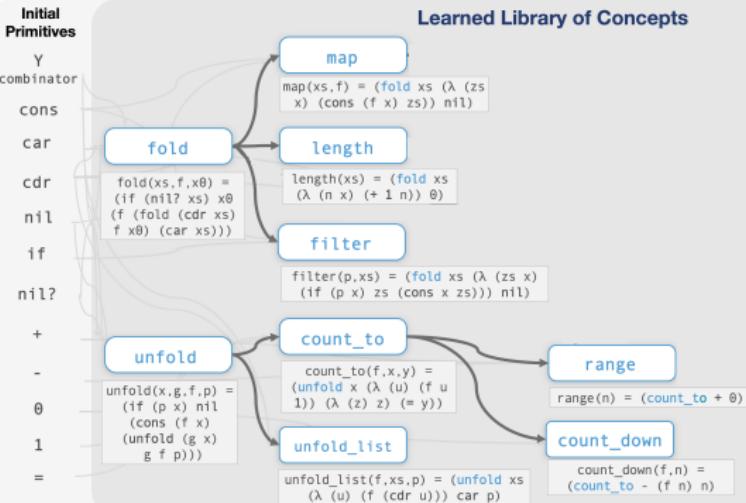
List lengths

```
[[■■■], [■]] → [3 1]  
[[■■■], [], [■]] → [2 0 1]
```

List differences

```
[1 8 2], [0 5 1] → [1 3 1]  
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```

Growing a language for recursive programming



Recursive Programming Algorithms

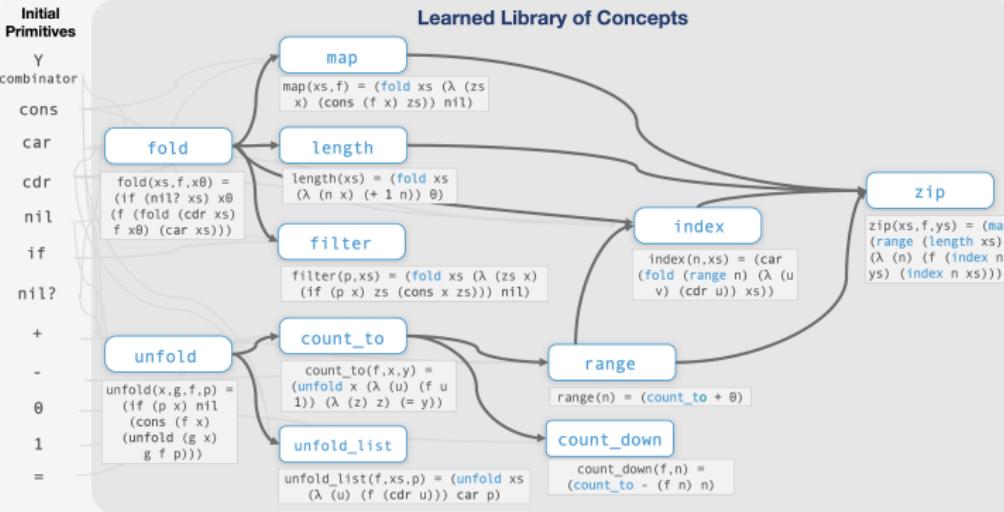
Stutter
 $[\text{■■}] \rightarrow [\text{■■■■}]$
 $[\text{■■■■}] \rightarrow [\text{■■■■■■}]$
 $(\text{fold } A (\lambda (u v) (\text{cons } v (\text{cons } v u))) \text{ nil})$

Take every other
 $[\text{■■■■■■}] \rightarrow [\text{■■}]$
 $[\text{■■■■■■■■}] \rightarrow [\text{■■■■}]$
 $(\text{unfold_list } \text{cdr } A \text{ nil?})$

List lengths
 $[[\text{■■■■}], [\text{■}]] \rightarrow [3\ 1]$
 $[[\text{■■■■■■}], [], [\text{■}]] \rightarrow [2\ 0\ 1]$
 $(\text{map } A \text{ length})$

List differences
 $[1\ 8\ 2], [0\ 5\ 1] \rightarrow [1\ 3\ 1]$
 $[2\ 3\ 6], [1\ 2\ 4] \rightarrow [1\ 1\ 2]$

Growing a language for recursive programming



Recursive Programming Algorithms

Stutter

$[\text{■■■}] \rightarrow [\text{■■■■■■}]$
 $[\text{■■■■}] \rightarrow [\text{■■■■■■■■}]$
 $(\text{fold } \text{A} \ (\lambda (\text{u} \ \text{v}) \ (\text{cons} \ \text{v} \ (\text{cons} \ \text{v} \ \text{u})))) \ \text{nil?})$

Take every other

$[\text{■■■■■■■■}] \rightarrow [\text{■■}]$
 $[\text{■■■■■■■■■■■■}] \rightarrow [\text{■■■■}]$
 $(\text{unfold_list} \ \text{cdr } \text{A} \ \text{nil?})$

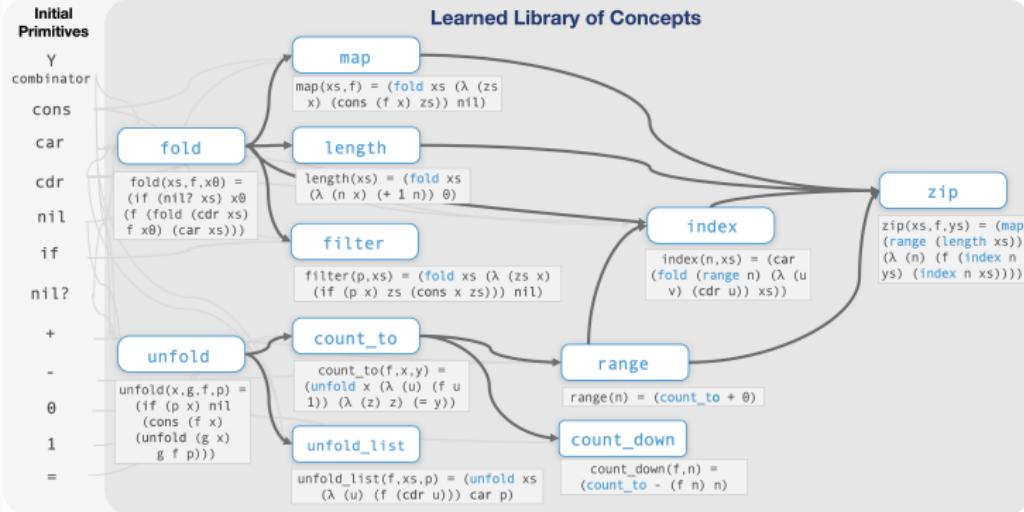
List lengths

$[[\text{■■■■}], [\text{■}]] \rightarrow [3 \ 1]$
 $[[\text{■■■}], [], [\text{■}]] \rightarrow [2 \ 0 \ 1]$
 $(\text{map } \text{A} \ \text{length})$

List differences

$[1 \ 8 \ 2], [0 \ 5 \ 1] \rightarrow [1 \ 3 \ 1]$
 $[2 \ 3 \ 6], [1 \ 2 \ 4] \rightarrow [1 \ 1 \ 2]$
 $(\text{zip } \text{A} - \text{B})$

Growing a language for recursive programming



Recursive Programming Algorithms

Stutter

$[\text{■■■}] \rightarrow [\text{■■■■■■}]$
 $[\text{■■■■}] \rightarrow [\text{■■■■■■■■}]$
 $(\text{fold } \text{A} \text{ } (\lambda \text{ } (\text{u } \text{v})) \text{ } (\text{cons } \text{v} \text{ } (\text{cons } \text{v } \text{u}))) \text{ } \text{nil})$

Take every other

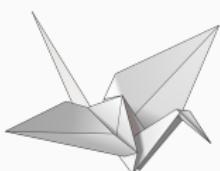
$[\text{■■■■■■■■}] \rightarrow [\text{■■}]$
 $[\text{■■■■■■■■■■}] \rightarrow [\text{■■■■}]$
 $(\text{unfold_list } \text{cdr } \text{A} \text{ } \text{nil?})$

List lengths

$[[\text{■■■■}], [\text{■}]] \rightarrow [3 \text{ } 1]$
 $[[\text{■■■}], [], [\text{■}]] \rightarrow [2 \text{ } 0 \text{ } 1]$
 $(\text{map } \text{A} \text{ } \text{length})$

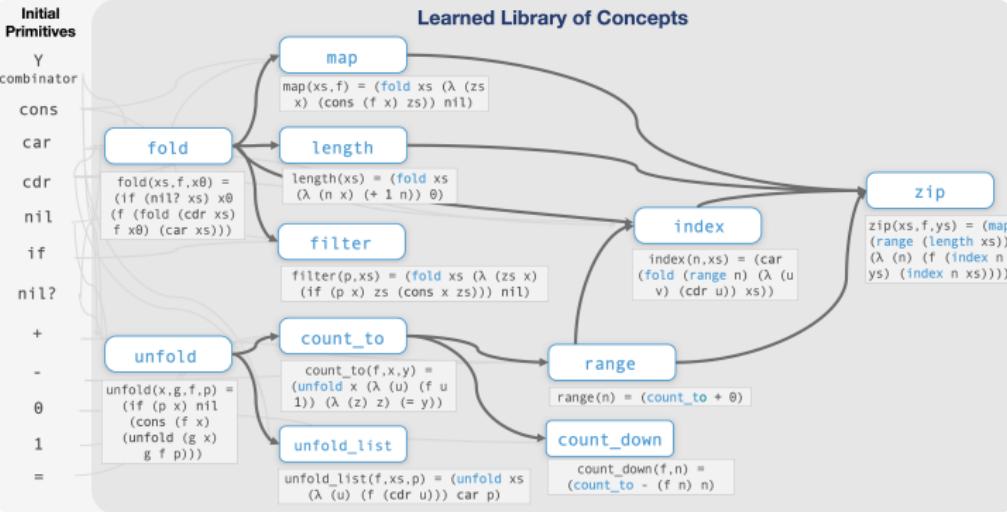
List differences

$[1 \text{ } 8 \text{ } 2], [0 \text{ } 5 \text{ } 1] \rightarrow [1 \text{ } 3 \text{ } 1]$
 $[2 \text{ } 3 \text{ } 6], [1 \text{ } 2 \text{ } 4] \rightarrow [1 \text{ } 1 \text{ } 2]$
 $(\text{zip } \text{A} \text{ } \text{B})$



Origami Programming: Jeremy Gibbons, 2003

Growing a language for recursive programming



Recursive Programming Algorithms

Stutter

$[\text{■■■}] \rightarrow [\text{■■■■■■}]$
 $[\text{■■■■}] \rightarrow [\text{■■■■■■■■}]$
 $(\text{fold } A (\lambda (\text{u } v)) (\text{cons } v (\text{cons } v \text{ u}))) \text{ nil}$

Take every other

$[\text{■■■■■■■■}] \rightarrow [\text{■■}]$
 $[\text{■■■■■■■■■■}] \rightarrow [\text{■■■■}]$
 $(\text{unfold_list } \text{cdr } A \text{ nil?})$

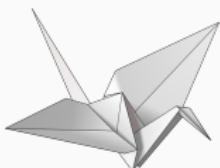
List lengths

$[[\text{■■■}], [\text{■}]] \rightarrow [3 \ 1]$
 $[[\text{■■■■}], [], [\text{■}]] \rightarrow [2 \ 0 \ 1]$
 $(\text{map } A \text{ length})$

List differences

$[1 \ 8 \ 2], [0 \ 5 \ 1] \rightarrow [1 \ 3 \ 1]$
 $[2 \ 3 \ 6], [1 \ 2 \ 4] \rightarrow [1 \ 1 \ 2]$
 $(\text{zip } A \text{ - } B)$

1 year of compute. 5 days on 64 CPUs.



Origami Programming: Jeremy Gibbons, 2003

Lessons

Library learning interacts synergistically with neural synthesis:
bootstrapping, more than sum of parts

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bootstrapping, more than sum of parts

Symbols aren't necessarily interpretable. Grow the language based
on experience to make it more powerful *and* more human
understandable

Lessons

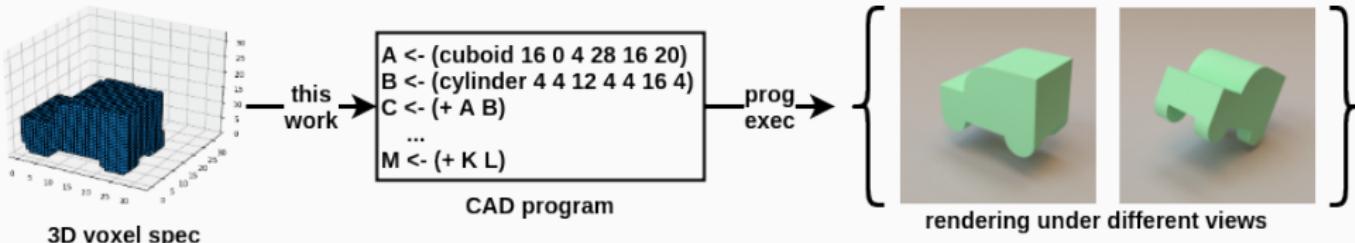
Library learning interacts synergistically with neural synthesis:
bootstrapping, more than sum of parts

Symbols aren't necessarily interpretable. Grow the language based
on experience to make it more powerful *and* more human
understandable

Learning-from-scratch is possible in principle. Don't do it. But
program induction makes it convenient to build in what we know
how to build in, and then learn on top of that

the end.

3D program induction

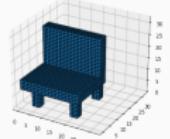


Challenge: combinatorial search!

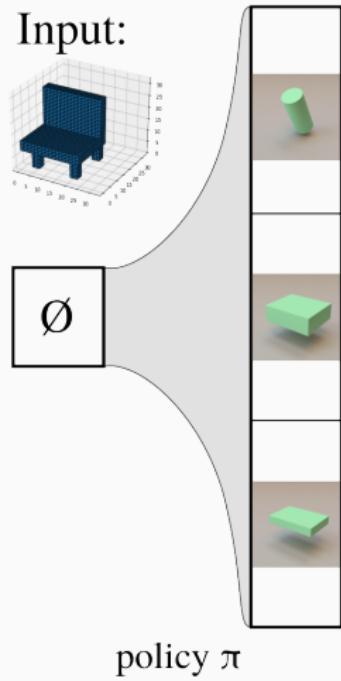
Branching factor: > 1.3 million per line of code, ≈ 20 lines of code
search space size: $(1.3 \text{ million})^{20} \approx 10^{122}$ programs

Solution: stochastic **tree search** + learn **policy** that writes code
+ learn **value** function that assesses execution of program so far;
analogous to **AlphaGo** [Silver et al. 2016]

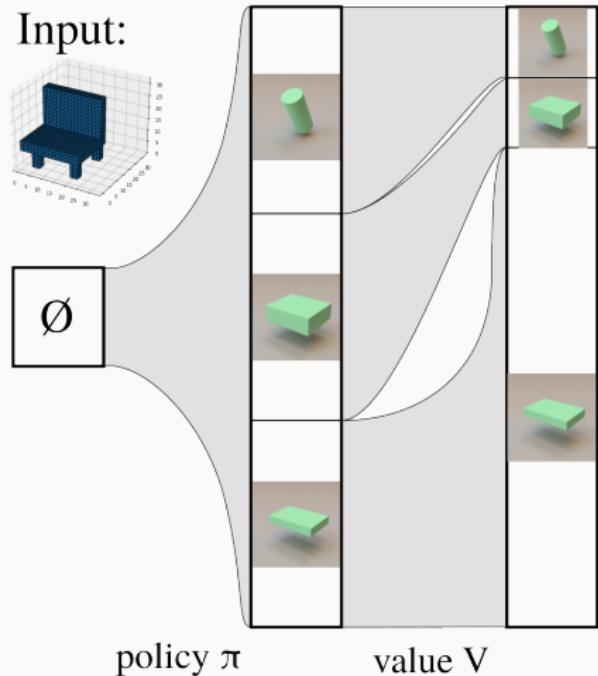
Input:



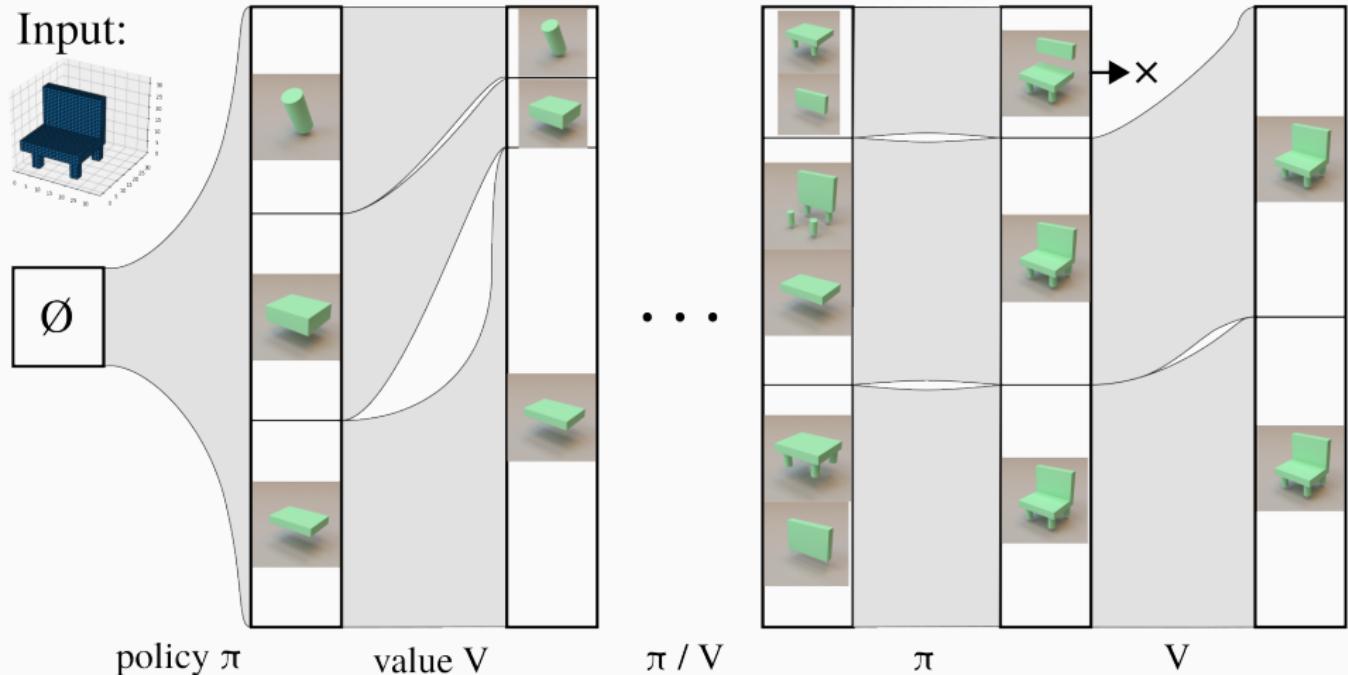
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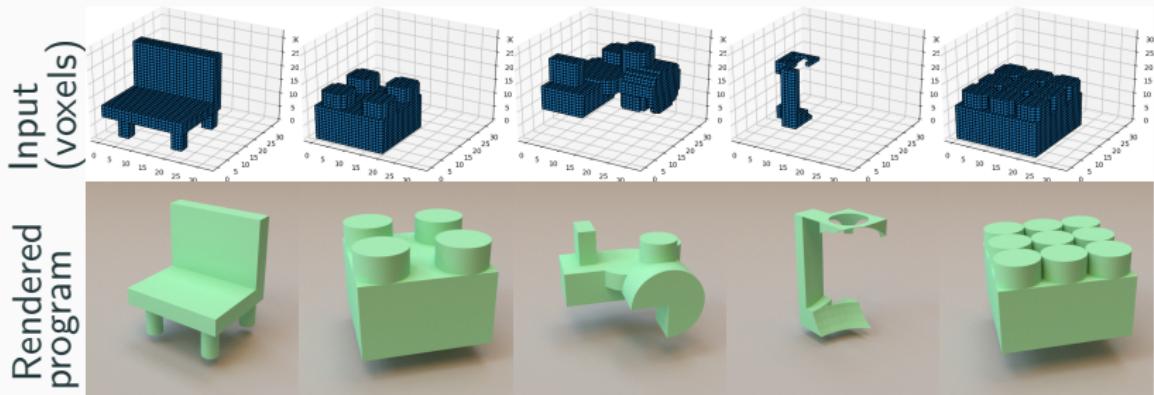
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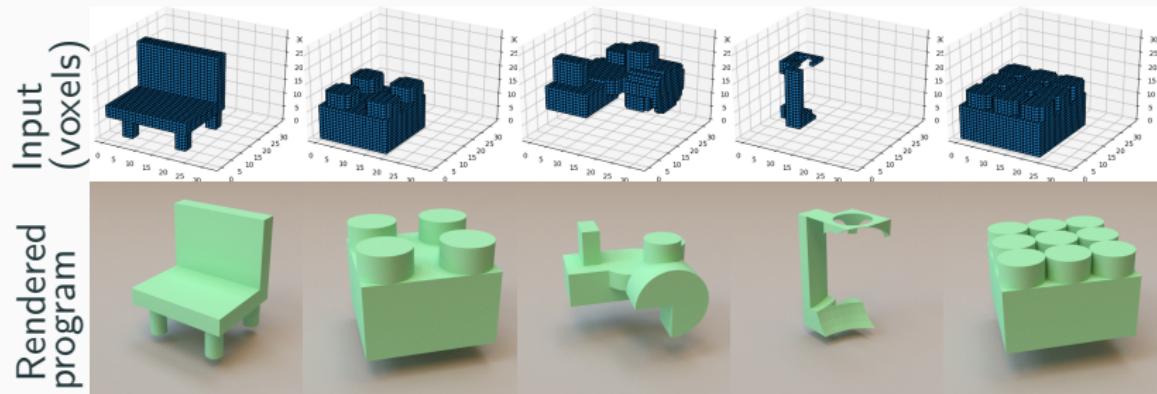
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3D program induction



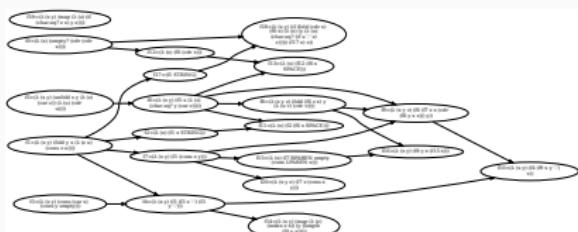
3D program induction



same architecture learns to synthesize text editing programs
(FlashFill, Gulwani 2012)

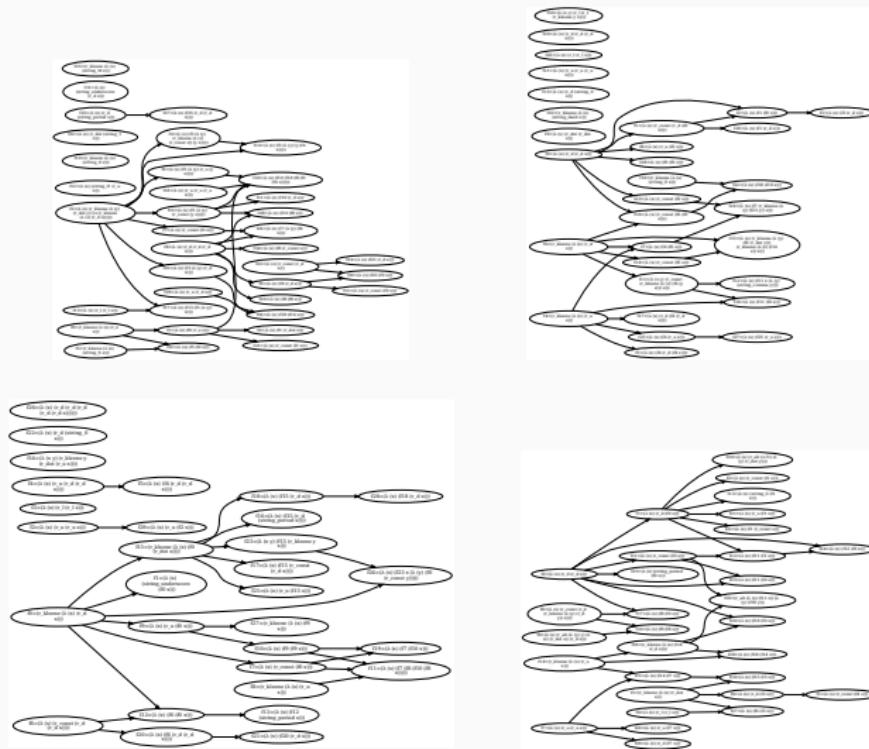
Library structure: Text Editing

DreamCoder learns libraries for FlashFill-style text editing [Gulwani 2012]

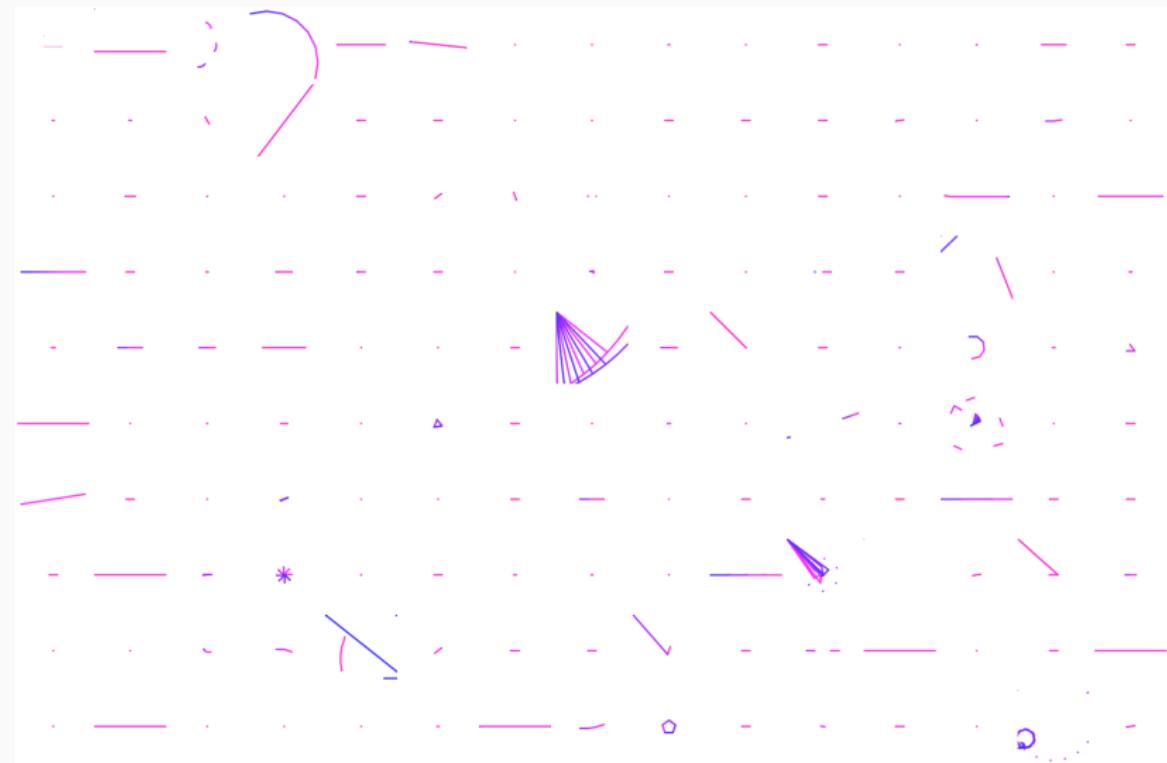


Library structure: Generating Text

Libraries for probabilistic generative models over text:
data from crawling web for CSV files



150 random dreams before learning



150 random dreams after learning

