DreamCoder: Growing generalizable, interpretable knowledge with wake-sleep Bayesian program learning

Kevin Ellis
Collaborators: Catherine Wong, Maxwell Nye, Mathias Sablé-Meyer, Lucas Morales, Armando Solar-Lezama, Joshua B. Tenenbaum

2020

colala group meeting

The premise of program induction

1. Represent knowledge as programs: as symbolic code

The premise of program induction

1. Represent knowledge as programs: as symbolic code

2. Learning=adding to that body of knowledge=

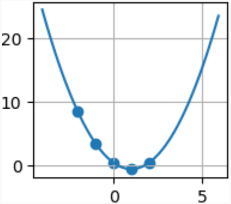
making new programs=program synthesis

Why program induction?

Why program induction?

strong generalization

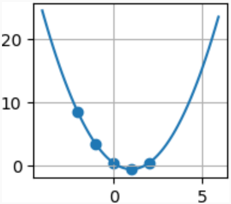
+data efficiency




```
f(x)=(x-1)**2 - 0.5
```

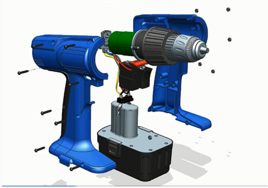
Why program induction?

strong generalization
+data efficiency

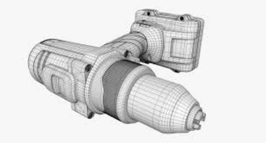


`f(x)=(x-1)**2 - 0.5`

interpretability

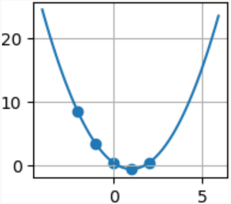


vs



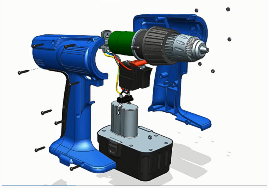
Why program induction?

strong generalization
+data efficiency

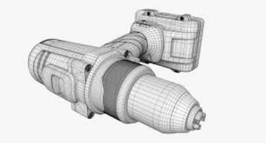


`f(x)=(x-1)**2 - 0.5`

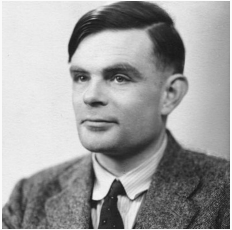
interpretability



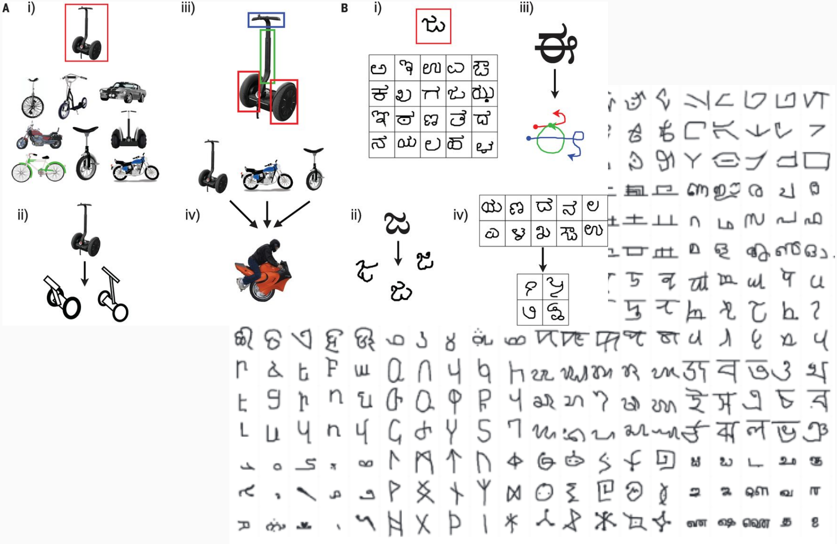
vs



universal expressivity

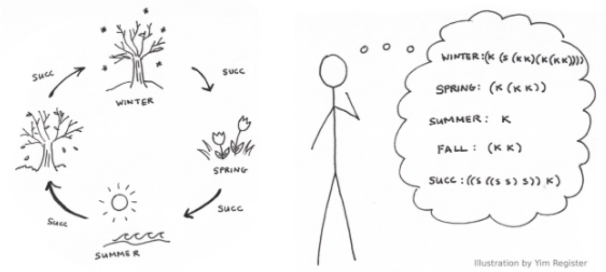


Human program induction



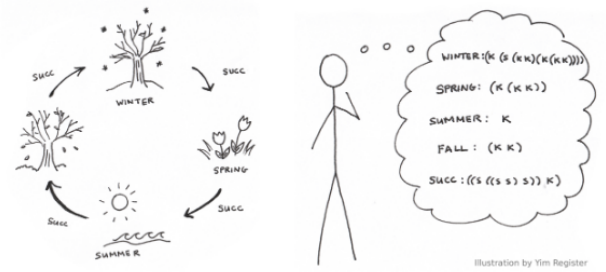
Lake et al 2015

Human program induction

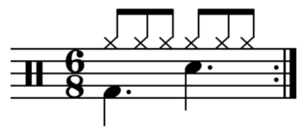


Piantadosi 2020: also kinship, subway routes, counting, ...

Human program induction



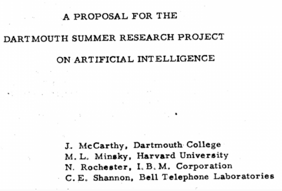
Piantadosi 2020: also kinship, subway routes, counting, ...



Evans 2019, “Apperception.” Also visual occlusion, analogies, ...

Why didn't this old idea work?

Program induction goes back to the 1956 Dartmouth Workshop that founded the field of AI



A PROPOSAL FOR THE

DARTMOUTH SUMMER RESEARCH PROJECT

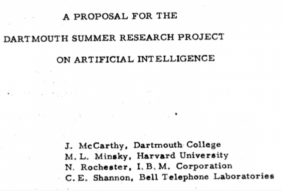
ON ARTIFICIAL INTELLIGENCE

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I. B. M. Corporation
C. E. Shannon, Bell Telephone Laboratories

John McCarthy, Ray Solomonoff

Why didn't this old idea work?

Program induction goes back to the 1956 Dartmouth Workshop that founded the field of AI



A PROPOSAL FOR THE

DARTMOUTH SUMMER RESEARCH PROJECT

ON ARTIFICIAL INTELLIGENCE

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I. B. M. Corporation
C. E. Shannon, Bell Telephone Laboratories

John McCarthy, Ray Solomonoff

main obstacle: combinatorial search is hard

Why try now?

better toolkits: neural+probabilistic+symbolic, and knowing how to combine them

Why try now?

better toolkits: neural+probabilistic+symbolic, and knowing how to combine them

maturing **program synthesis** techniques

Why try now?

better toolkits: neural+probabilistic+symbolic, and knowing how to combine them

maturing **program synthesis** techniques

better compute+parallel algorithms

Program Induction and learning to learn

Learning to write code

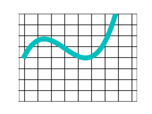
Goal: acquire domain-specific knowledge needed to induce a class of programs

- Library of concepts (declarative knowledge; domain specific language)
- Inference strategy (procedural knowledge; synthesis algorithm)

Learning to write code

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

- Library of concepts (declarative knowledge; domain specific language)
- Inference strategy (procedural knowledge; synthesis algorithm)



$\rightarrow$ Learned program inducer $\rightarrow$ program: $f(x) = 0.3x^3 + 1.1x^2 - 2x + 0.6$

Concepts: x^3, $\alpha x + \beta$, etc

Inference strategy: neurosymbolic search for programs

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]
...

Ellis, Morales, Sable-Meyer, Solar-Lezama, Tenenbaum. NeurIPS 2018.
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

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]
…

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

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]
...

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning

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]
...

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

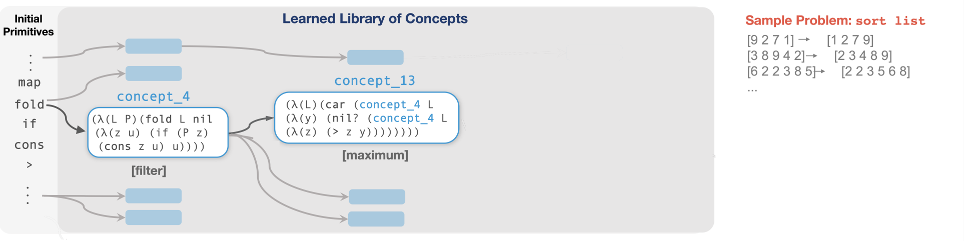
Library learning

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning

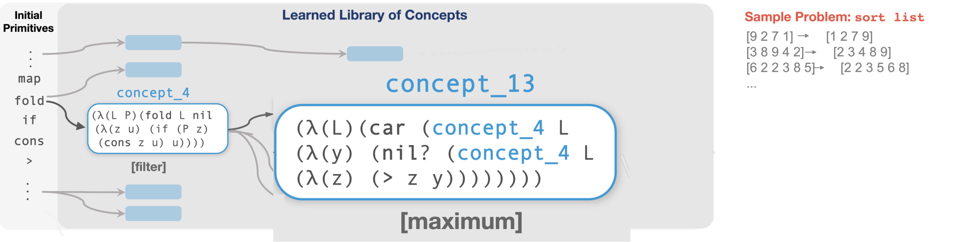
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



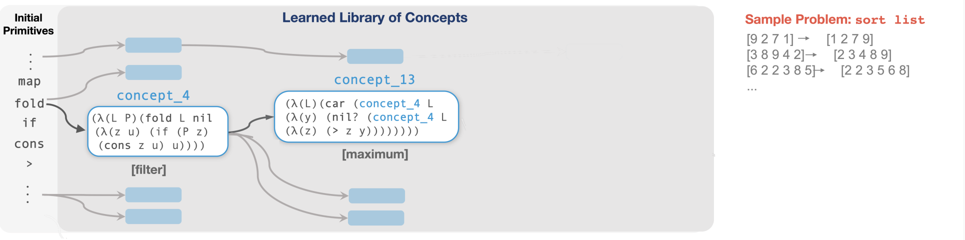
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



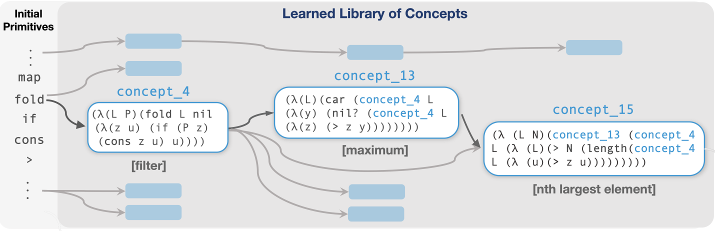
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning

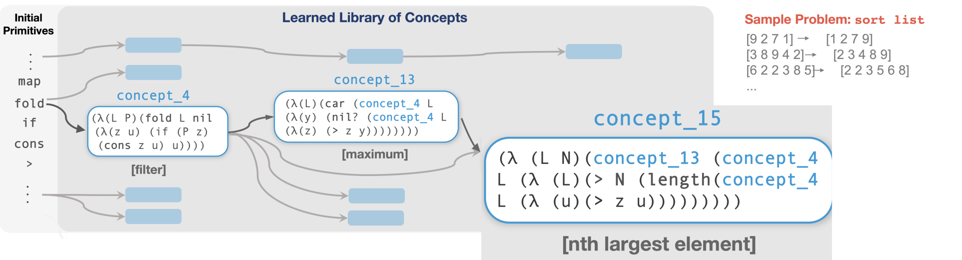


Sample Problem: `sort list`

[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]
...

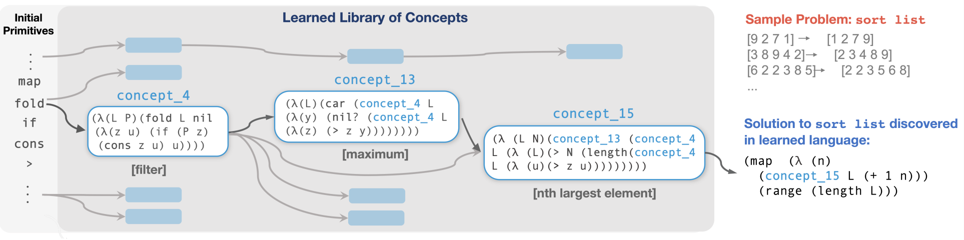
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



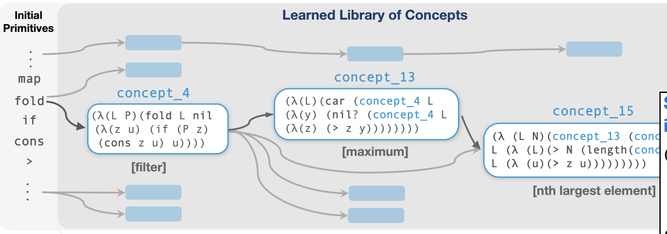
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



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]
...

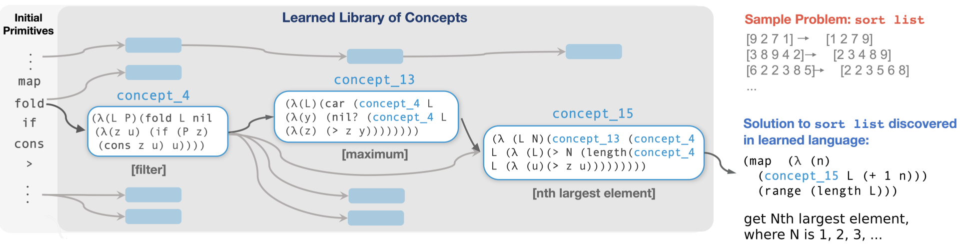
Solution to `sort list` discovered in learned language:

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

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

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning

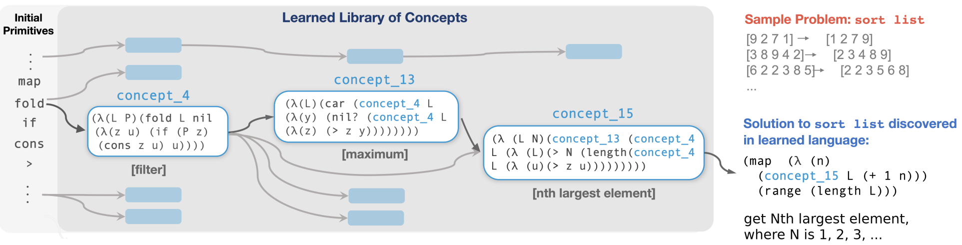


Solution rewritten in initial primitives:

```
(lambda (x) (map (lambda (y) (car (fold (fold x nil (lambda (z u) (if (gt? (+ y 1) (length
(fold x nil (lambda (v w) (if (gt? z v) (cons v w) w))))) (cons z u) u))) nil (lambda (a b) (if
(nil? (fold (fold x nil (lambda (c d) (if (gt? (+ y 1) (length (fold x nil (lambda (e f) (if
(gt? c e) (cons e f) f))))) (cons c d) d))) nil (lambda (g h) (if (gt? g a) (cons g h) h))))
(cons a b) b))))) (range (length x))))
```

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library learning



Solution rewritten in initial primitives:

```
(lambda (x) (map (lambda (y) (car (fold (fold x nil (lambda (z u) (if (gt? (+ y 1) (length
(fold x nil (lambda (v w) (if (gt? z v) (cons v w) w))))) (cons z u) u))) nil (lambda (a b) (if
(nil? (fold (fold x nil (lambda (c d) (if (gt? (+ y 1) (length (fold x nil (lambda (e f) (if
(gt? c e) (cons e f) f))))) (cons c d) d))) nil (lambda (g h) (if (gt? g a) (cons g h) h))))
(cons a b) b))))) (range (length x))))
```

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

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

DreamCoder

- **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

DreamCoder

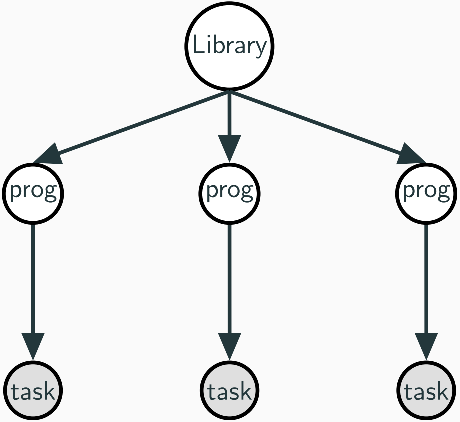
- **Wake:** Solve problems by writing programs
- **Sleep:** Improve library and neural recognition model:
  - **Abstraction sleep:** Improve library
  - **Dream sleep:** Improve neural recognition model

Memory consolidation during human sleep:

1. Slow-wave (∼explicit, declarative)
2. Fast-wave REM (∼implicit, procedural)

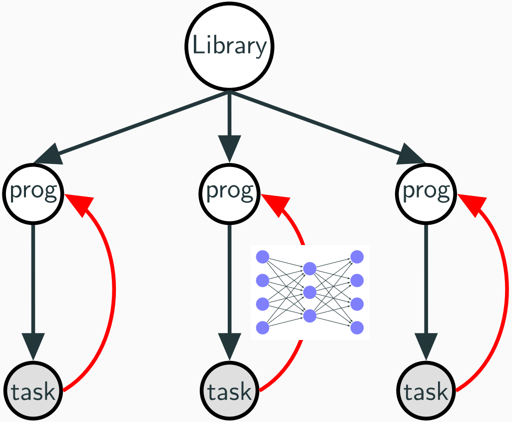
cf. Helmholtz machine, wake/sleep neural network training algorithms

Library learning as Bayesian inference



[Dechter et al, 2013] [Liang et al, 2010] [Lake et al, 2015]

Library learning as neurally-guided Bayesian inference

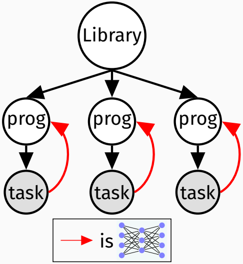


library learning via program analysis +

new neural inference network for program synthesis +

better program representation (Lisp+polymorphic types [Milner 1978])

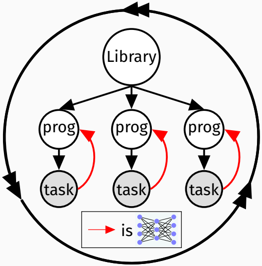
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

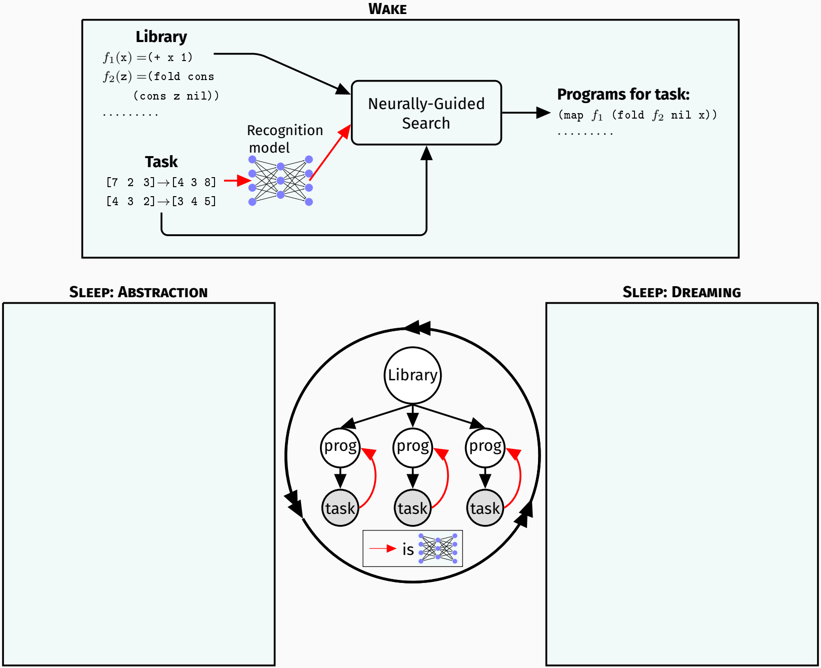

Library
prog
prog
prog
task
task
task
is

WAKE

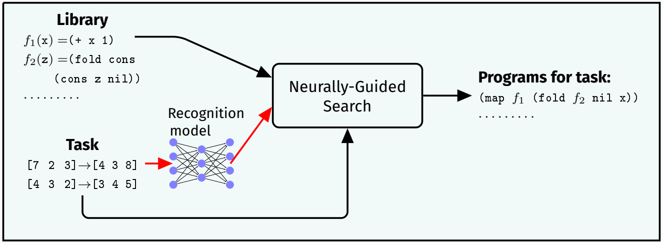
SLEEP: ABSTRACTION

SLEEP: DREAMING

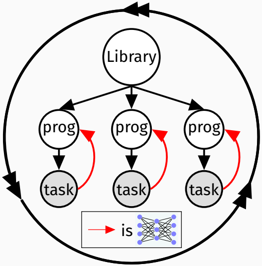



Wake
Library
f1(x) =(+ x 1)
f2(z) =(fold cons
(cons z nil))
....
Neurally-Guided Search
Programs for task:
(map f1 (fold f2 nil x))
....
Recognition model
Task
[7 2 3]→[4 3 8]
[4 3 2]→[3 4 5]
Sleep: Abstraction
Sleep: Dreaming
Library
prog
prog
prog
task
task
task
is

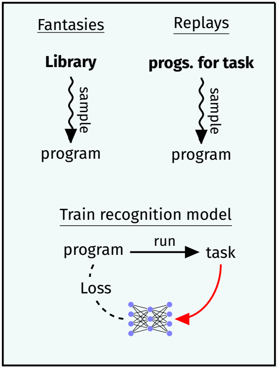
Wake

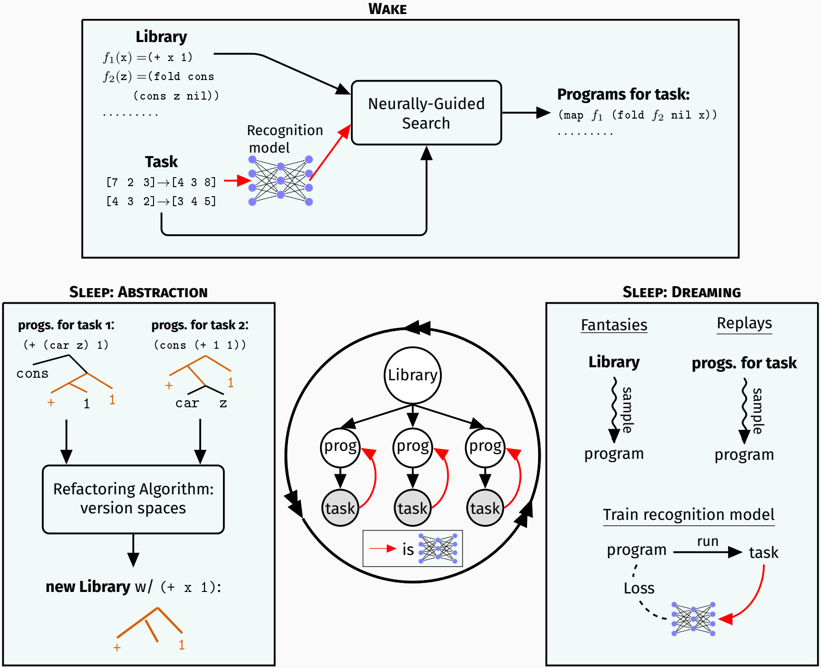


Sleep: Abstraction

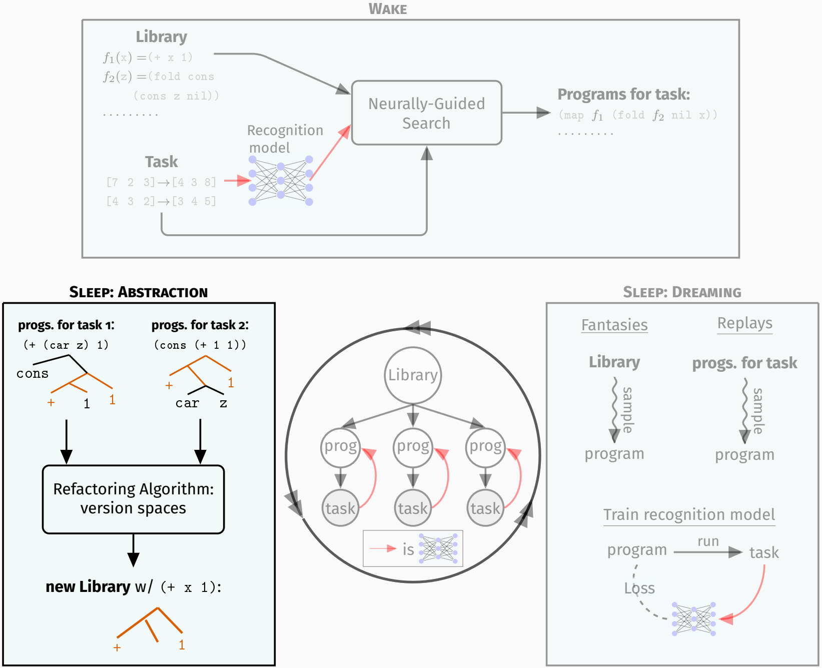


Sleep: Dreaming





Wake
Library
f_1(x) =(+ x 1)
f_2(z) =(fold cons (cons z nil))
....
Neurally-Guided Search
Programs for task:
(map f_1 (fold f_2 nil x))
....
Recognition model
Task
[7 2 3]→[4 3 8]
[4 3 2]→[3 4 5]
Sleep: Abstraction
progs. for task 1:
(+ (car z) 1)
cons
+
1
1
progs. for task 2:
(cons (+ 1 1))
+
1
car
z
Refactoring Algorithm: version spaces
new Library w/ (+ x 1):
+
1
Library
prog
prog
prog
task
task
task
is
Sleep: Dreaming
Fantasies
Replays
Library
sample
program
progs. for task
sample
program
Train recognition model
program
run
task
Loss



WAKE
Library
f_1(x) =(+ x 1)
f_2(z) =(fold cons (cons z nil))
....
Task
[7 2 3]→[4 3 8]
[4 3 2]→[3 4 5]
Recognition model
Neurally-Guided Search
Programs for task:
(map f_1 (fold f_2 nil x))
....
SLEEP: ABSTRACTION
progs. for task 1:
(+ (car z) 1)
cons
+
1
1
progs. for task 2:
(cons (+ 1 1))
+
1
car
z
Refactoring Algorithm: version spaces
new Library w/ (+ x 1):
+
1
Library
prog
task
is
SLEEP: DREAMING
Fantasies
Replays
Library
sample
program
progs. for task
sample
program
Train recognition model
program
run
task
Loss

Abstraction Sleep: Growing the library via refactoring

$5 + 5$

Abstraction Sleep: Growing the library via refactoring

$5 + 5$

`(+ 5 5)`

Abstraction Sleep: Growing the library via refactoring

$5 + 5$

`(+ 5 5)`

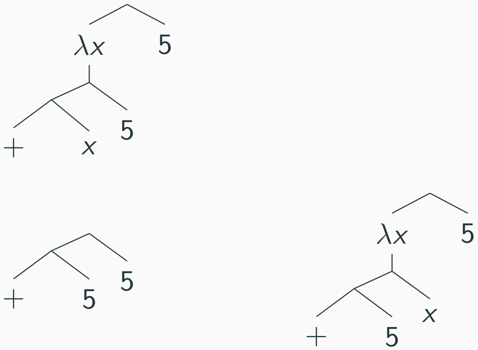
Abstraction Sleep: Growing the library via refactoring

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

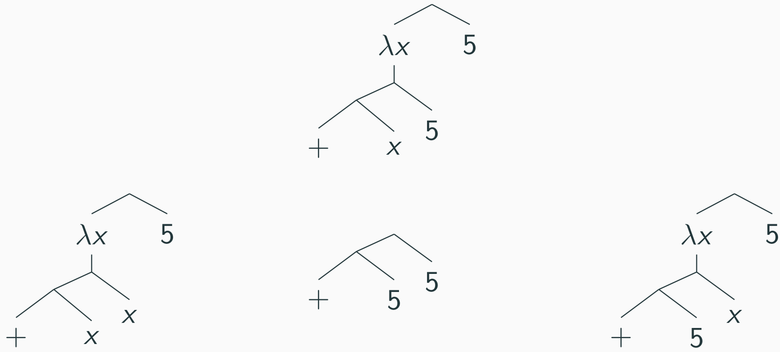
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring



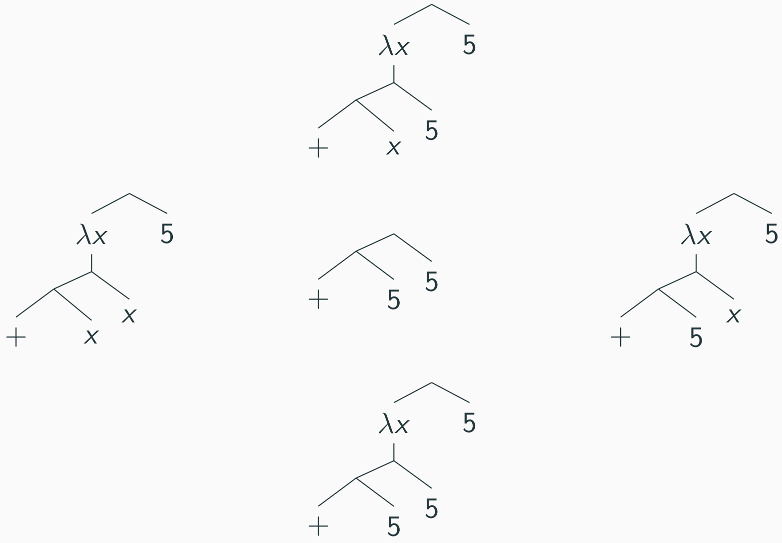
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring



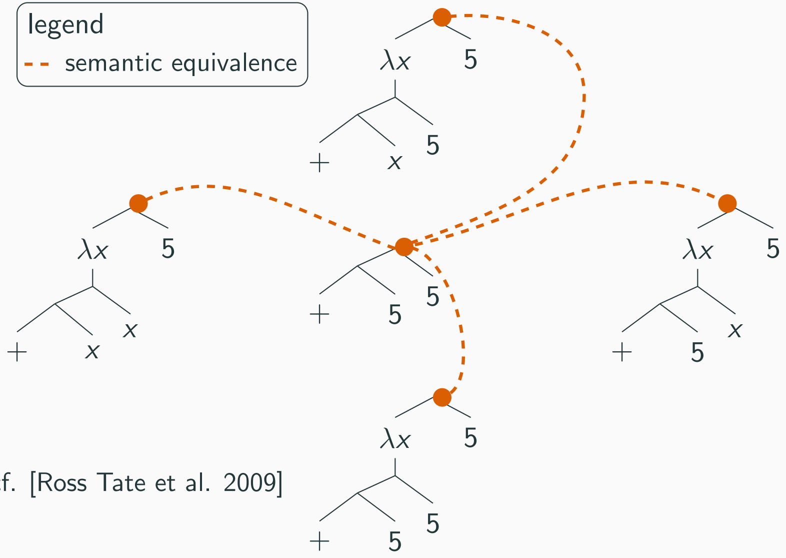
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

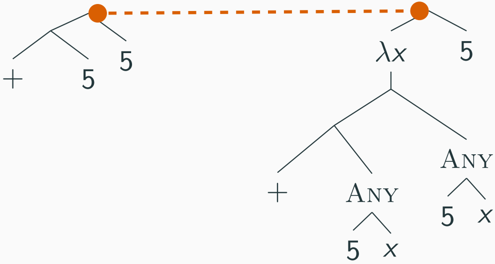


cf. [Ross Tate et al. 2009]

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

legend
- - - - semantic equivalence
ANY nondeterministic choice

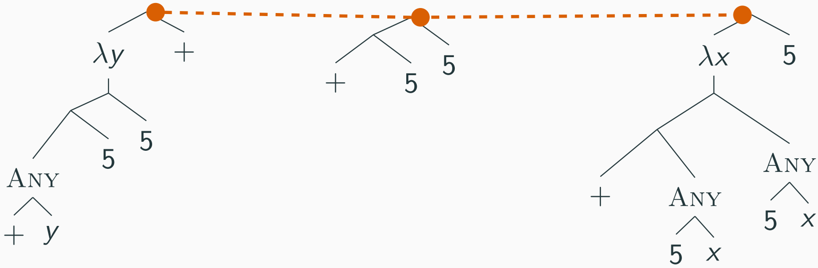


cf. [Gulwani 2012]

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

legend
- - - - semantic equivalence
ANY nondeterministic choice

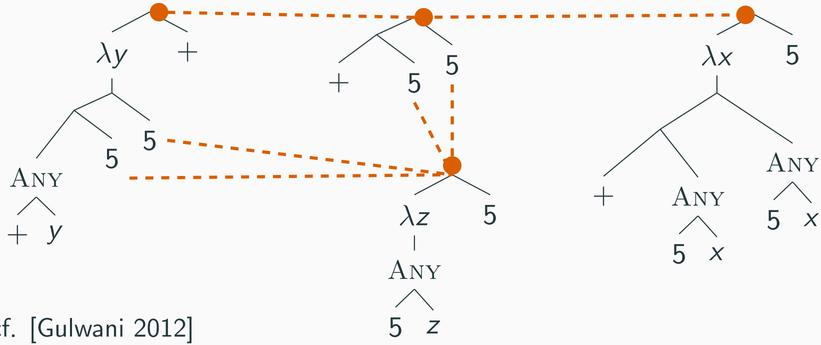


cf. [Gulwani 2012]

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

legend
semantic equivalence
Any nondeterministic choice

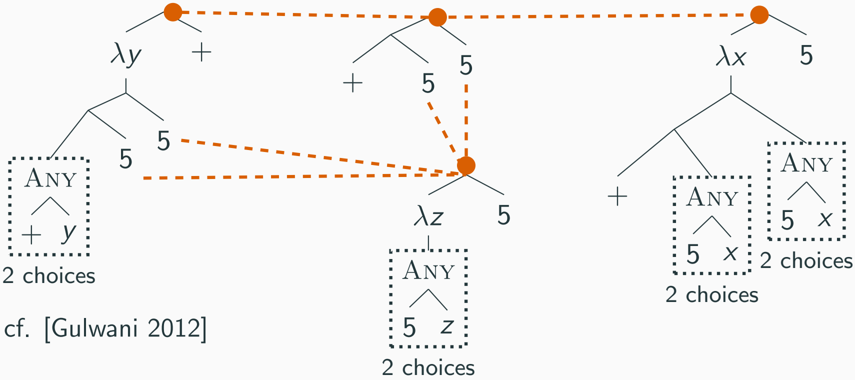


cf. [Gulwani 2012]

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

legend
semantic equivalence
ANY nondeterministic choice

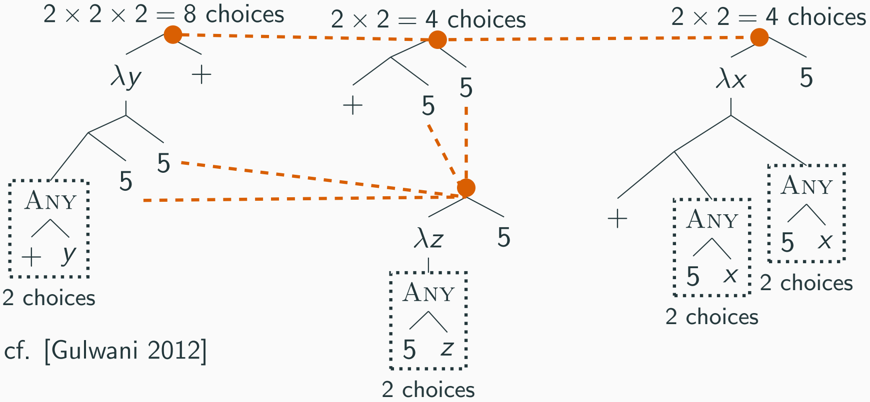


cf. [Gulwani 2012]

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

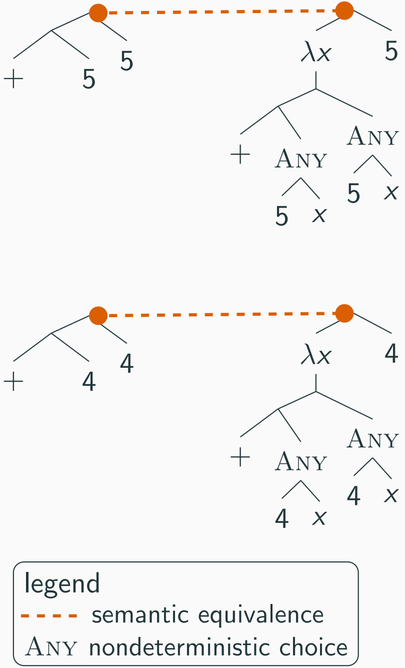
Abstraction Sleep: Growing the library via refactoring

legend
semantic equivalence
ANY nondeterministic choice

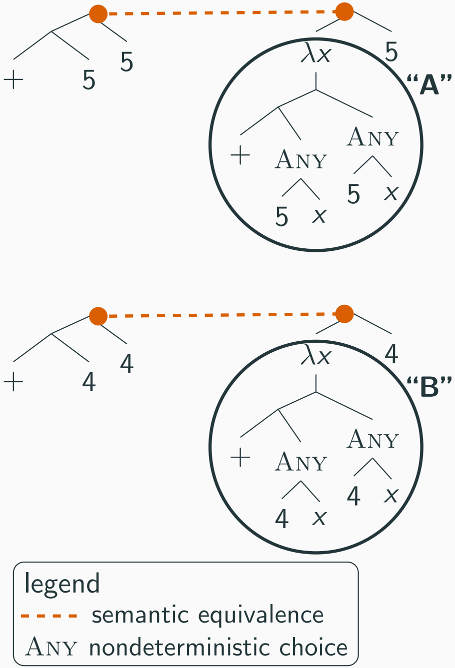


cf. [Gulwani 2012]

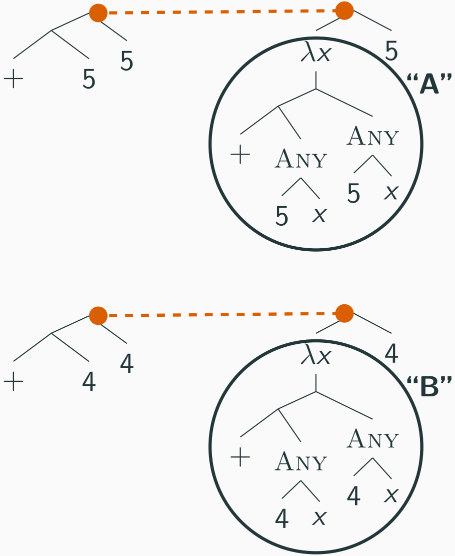
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.



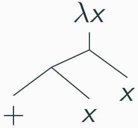
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

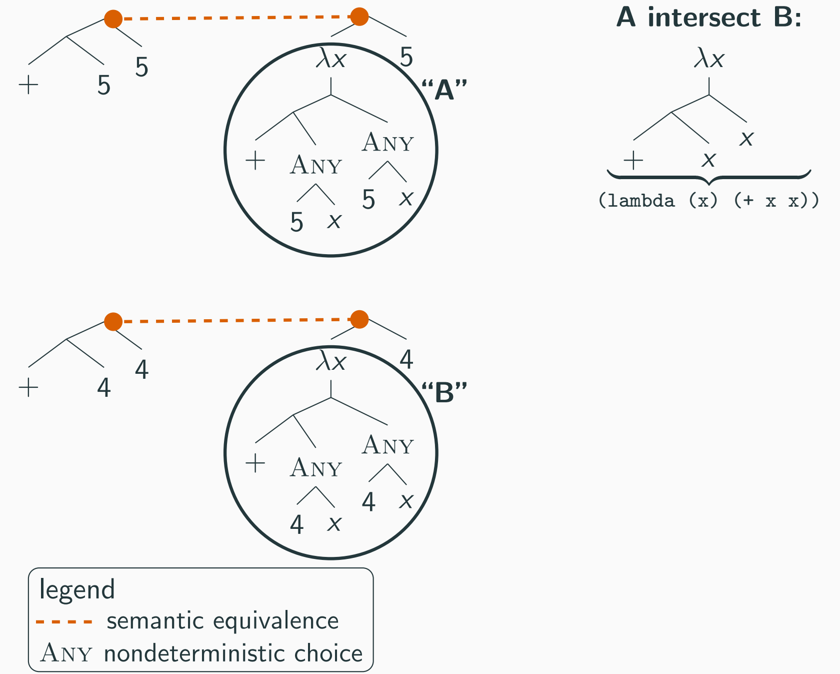


A intersect B:

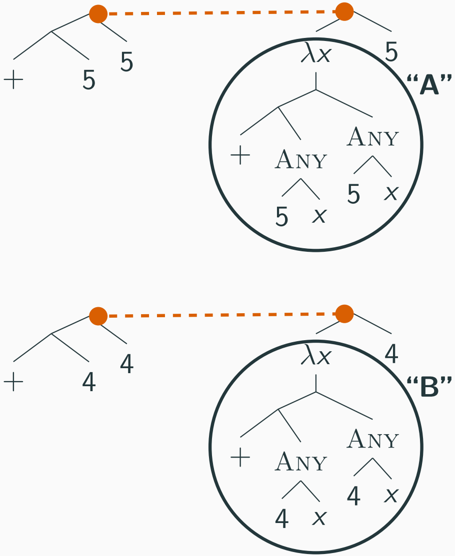


legend
semantic equivalence
Any nondeterministic choice

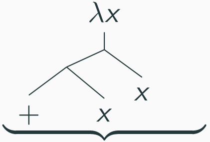
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.



A intersect B:

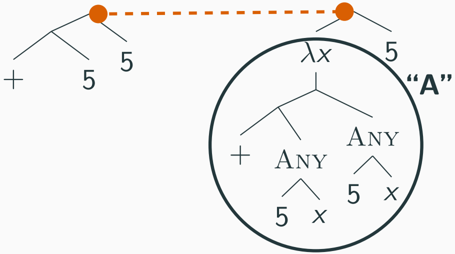


`(lambda (x) (+ x x))`

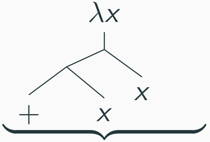
= `double`

legend
- - - - semantic equivalence
Any nondeterministic choice

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

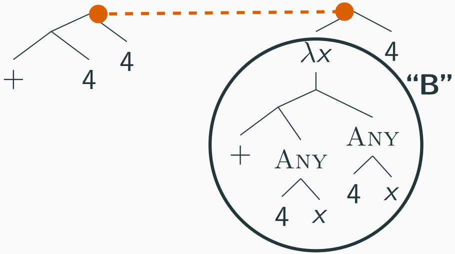


A intersect B:



`(lambda (x) (+ x x))`

= `double`



w/o double	w/ double
`(+ 5 5)`	`(double 5)`
`(+ 4 4)`	`(double 4)`
`(+ 3 3)`	`(double 3)`

...

legend
- - - - semantic equivalence
ANY nondeterministic choice

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Abstraction Sleep: Growing the library via refactoring

Task: [1 2 3]→[2 4 6]
[4 3 4]→[8 6 8]

Wake: program search

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

Task: [1 2 3]→[0 1 2]
[4 3 4]→[3 2 3]

Wake: program search

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

Abstraction Sleep: Growing the library via refactoring

Task: [1 2 3]→[2 4 6]
[4 3 4]→[8 6 8]

Wake: program search

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

refactor
($\mathbf{10^{14}}$ refactorings)

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

Task: [1 2 3]→[0 1 2]
[4 3 4]→[3 2 3]

Wake: program search

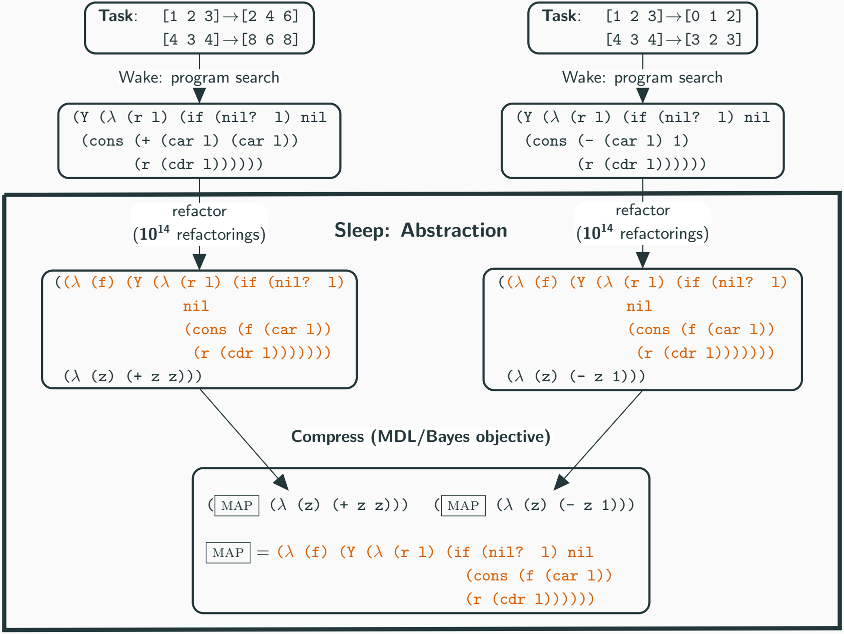
```
(Y (λ (r l) (if (nil?  l) nil
 (cons (- (car l) 1)
       (r (cdr l))))))
```

refactor
($\mathbf{10^{14}}$ refactorings)

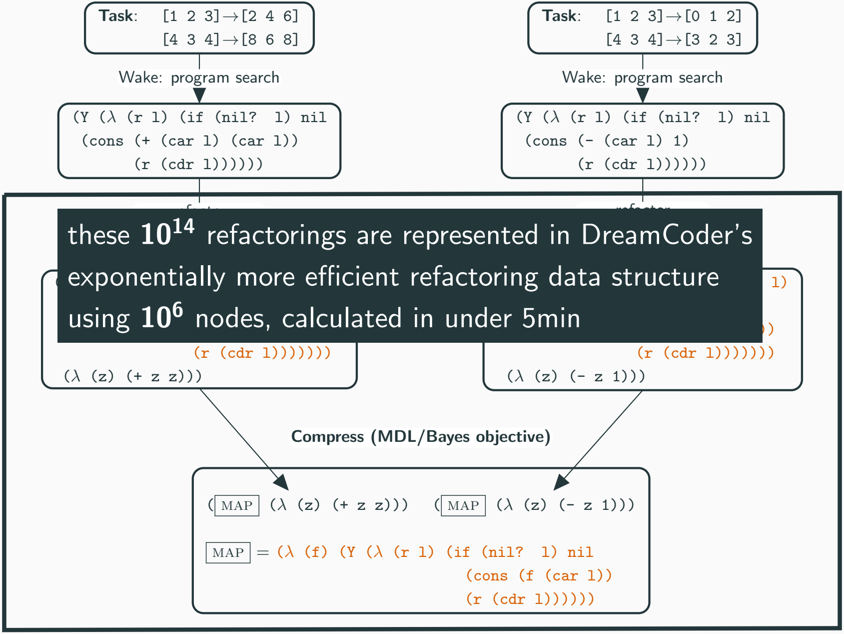
```
((λ (f) (Y (λ (r l) (if (nil?  l)
             nil
             (cons (f (car l))
              (r (cdr l)))))))
 (λ (z) (- z 1)))
```

Sleep: Abstraction

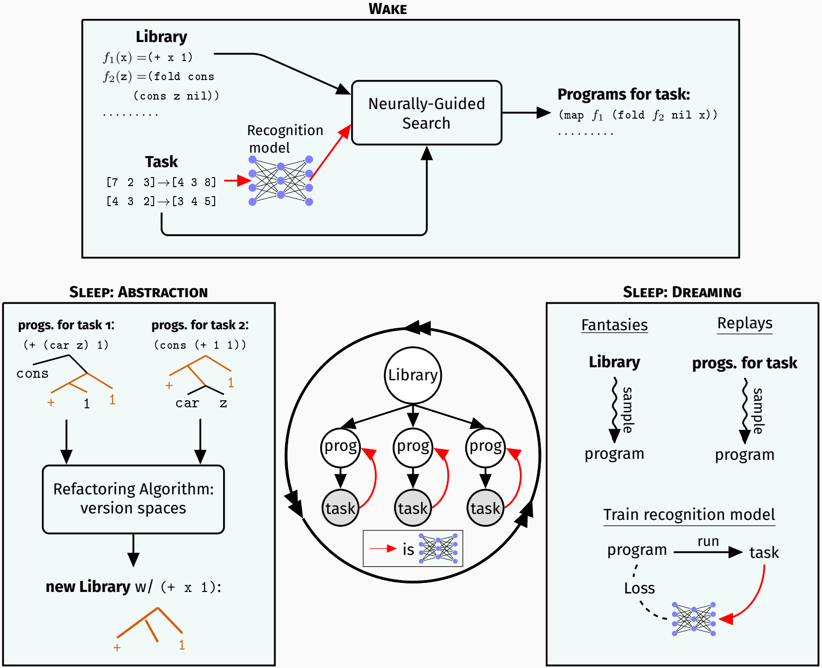
Abstraction Sleep: Growing the library via refactoring

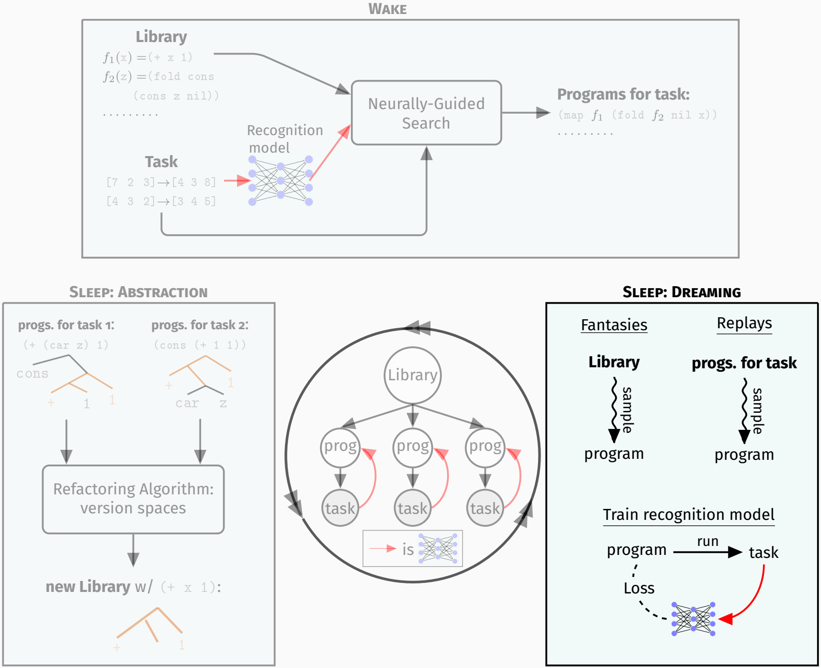


Abstraction Sleep: Growing the library via refactoring



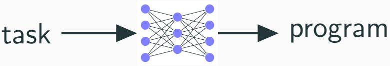
these 10^{14} refactorings are represented in DreamCoder's exponentially more efficient refactoring data structure using 10^{6} nodes, calculated in under 5min


WAKE
Library
f1(x) =(+ x 1)
f2(z) =(fold cons (cons z nil))
....
Task
[7 2 3]→[4 3 8]
[4 3 2]→[3 4 5]
Recognition model
Neurally-Guided Search
Programs for task:
(map f1 (fold f2 nil x))
....
SLEEP: ABSTRACTION
progs. for task 1:
(+ (car z) 1)
cons
+
1
1
progs. for task 2:
(cons (+ 1 1))
+
1
car
z
Refactoring Algorithm: version spaces
new Library w/ (+ x 1):
+
1
Library
prog
prog
prog
task
task
task
is
SLEEP: DREAMING
Fantasies
Replays
Library
sample
program
progs. for task
sample
program
Train recognition model
program
run
task
Loss

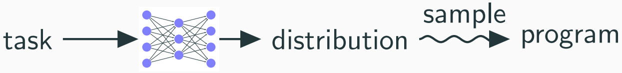


WAKE
Library
f_1(x) =(+ x 1)
f_2(z) =(fold cons (cons z nil))
....
Neurally-Guided Search
Programs for task:
(map f_1 (fold f_2 nil x))
....
Recognition model
Task
[7 2 3]→[4 3 8]
[4 3 2]→[3 4 5]
SLEEP: ABSTRACTION
progs. for task 1:
(+ (car z) 1)
cons
+
1
1
progs. for task 2:
(cons (+ 1 1))
+
1
car
z
Refactoring Algorithm: version spaces
new Library w/ (+ x 1):
+
1
Library
prog
prog
prog
task
task
task
is
SLEEP: DREAMING
Fantasies
Replays
Library
sample
program
progs. for task
sample
program
Train recognition model
program
run
task
Loss

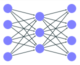
Neural recognition model guides search



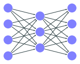
Neural recognition model guides search



Neural recognition model guides search

task →  → distribution $\rightsquigarrow$ program

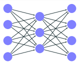
sample

 is a...

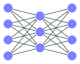
recurrent network (Devlin et al 2017)

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

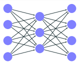
Neural recognition model guides search

task →  → distribution $\xrightarrow{\text{sample}}$ program

P(child|parent,arg)

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

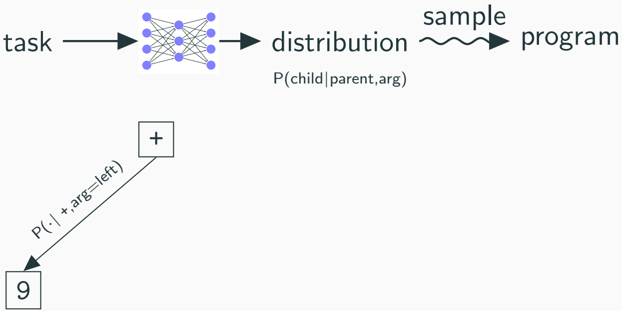
Neural recognition model guides search

task →  → distribution $\xrightarrow{\text{sample}}$ program

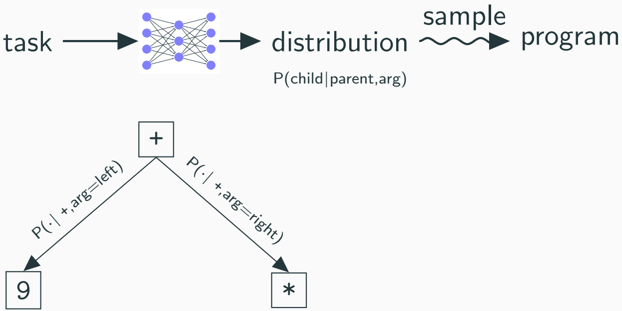
P(child|parent,arg)

$\boxed{+}$

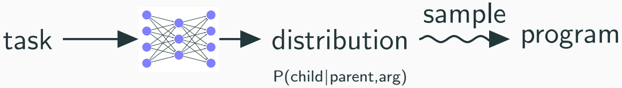
Neural recognition model guides search

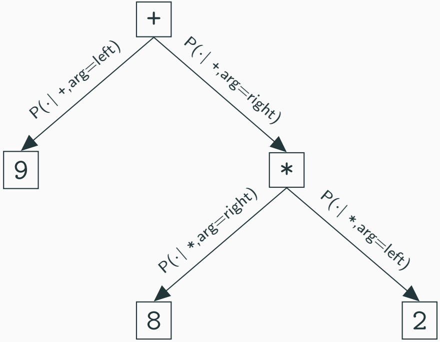


Neural recognition model guides search

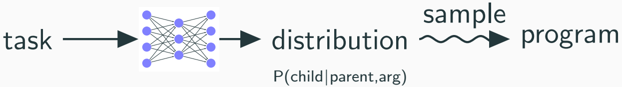


Neural recognition model guides search





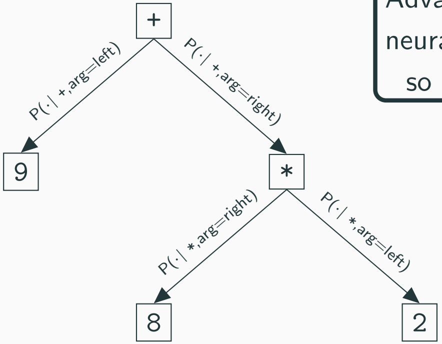
Neural recognition model guides search



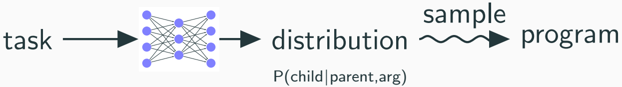
Advantages:

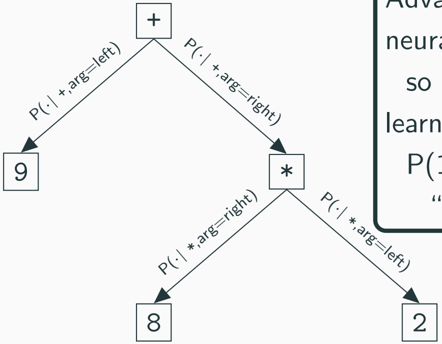
neural net runs once per task,

so CPU bottlenecks instead of GPU



Neural recognition model guides search





Advantages:

neural net runs once per task,
so CPU bottlenecks instead of GPU

learns to break syntactic symmetries:
P(1|*,arg=left)=0.0
"do not multiply by one"

DreamCoder Domains

List Processing

Sum List

[1 2 3] → 6
[4 6 8 1] → 17

Double

[1 2 3] → [2 4 6]
[4 5 1] → [8 10 2]

Text Editing

Abbreviate

Allen Newell → A.N.
Herb Simon → H.S.

Drop Last Three

shrdlu → shr
shakey → sha

Regexes

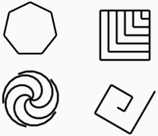
Phone numbers

(555) 867-5309
(650) 555-2368

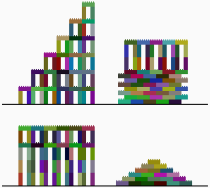
Currency

$100.25
$4.50

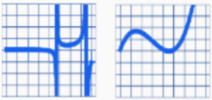
LOGO Graphics



Block Towers



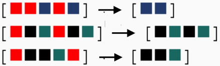
Symbolic Regression



$y = f(x)$

Recursive Programming

Filter Red



Physical Laws

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

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

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

DreamCoder Domains

List Processing

Sum List

[1 2 3] → 6
[4 6 8 1] → 17

Double

[1 2 3] → [2 4 6]
[4 5 1] → [8 10 2]

Text Editing

Abbreviate

Allen Newell → A.N.
Herb Simon → H.S.

Drop Last Three

shrdlu → shr
shakey → sha

Regexes

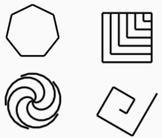
Phone numbers

(555) 867-5309
(650) 555-2368

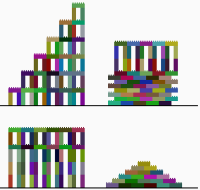
Currency

$100.25
$4.50

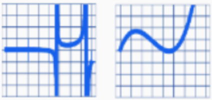
LOGO Graphics



Block Towers



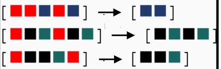
Symbolic Regression



$y = f(x)$

Recursive Programming

Filter Red



Physical Laws

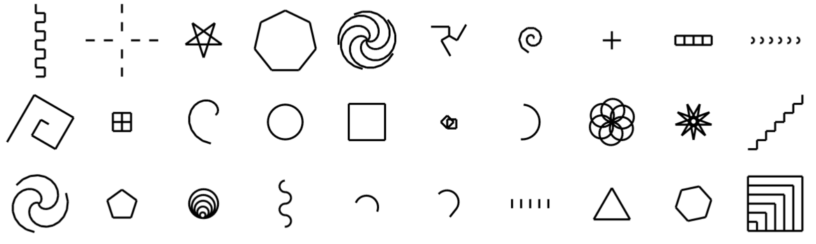
$$\vec{a} = \frac{1}{m}\sum_i \vec{F}_i$$

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

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

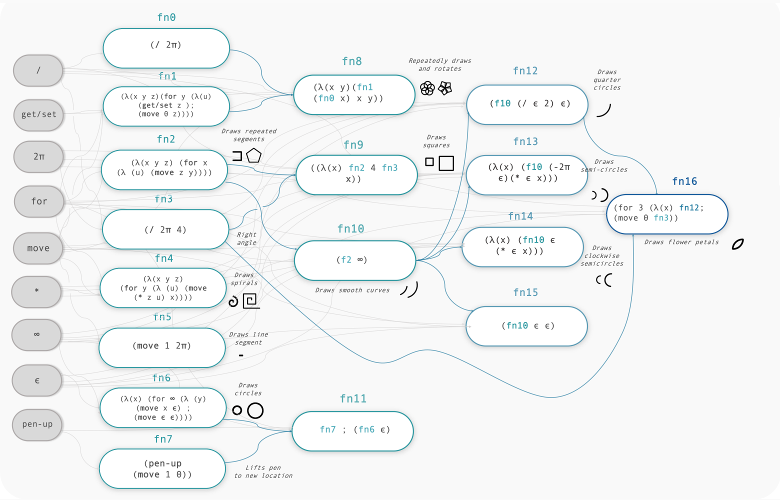
LOGO Turtle Graphics

30 out of 160 tasks



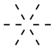
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library



(fn8 5 (fn4 (* ϵ 2) ∞ ϵ))

(for 7 (λ (x) (fn9 x)))

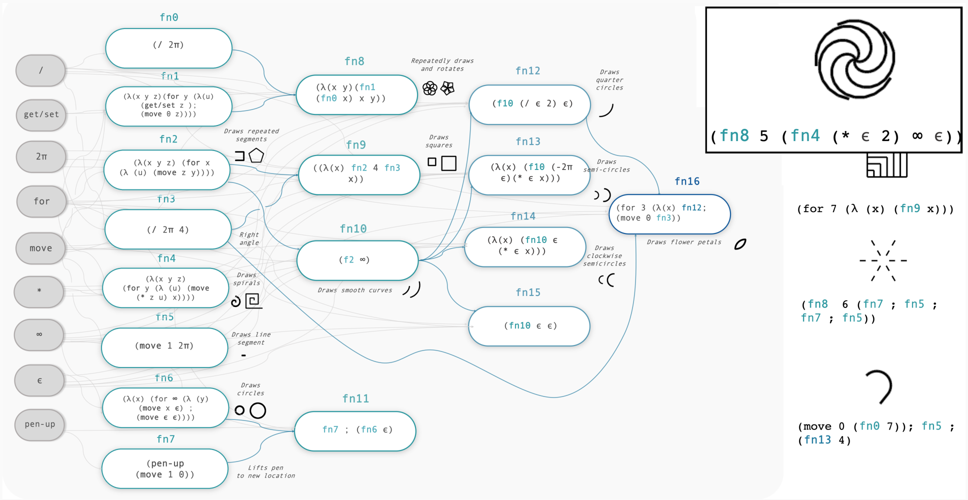


(fn8 6 (fn7 ; fn5 ; fn7 ; fn5))

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

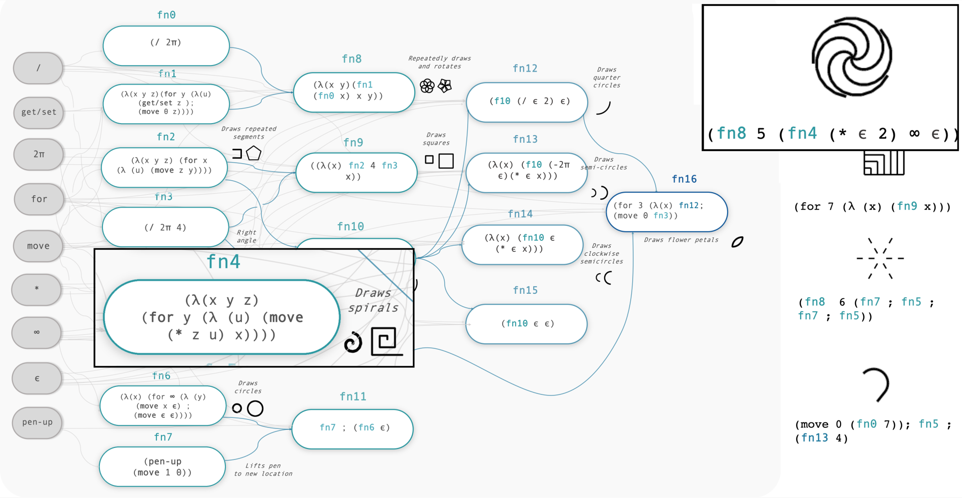
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library



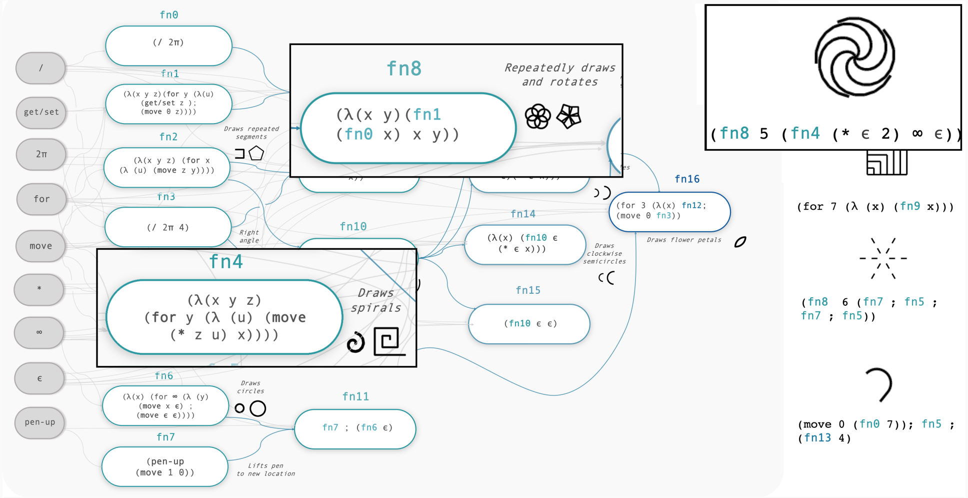
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library



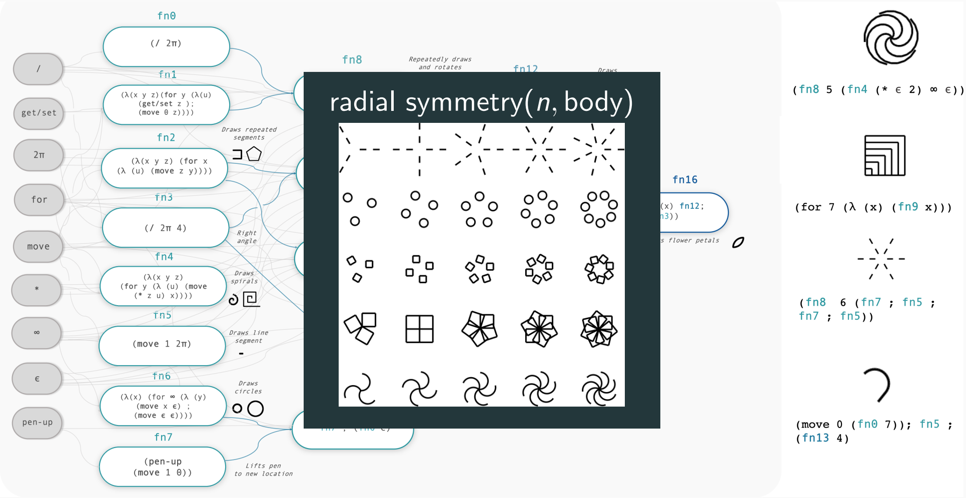
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library



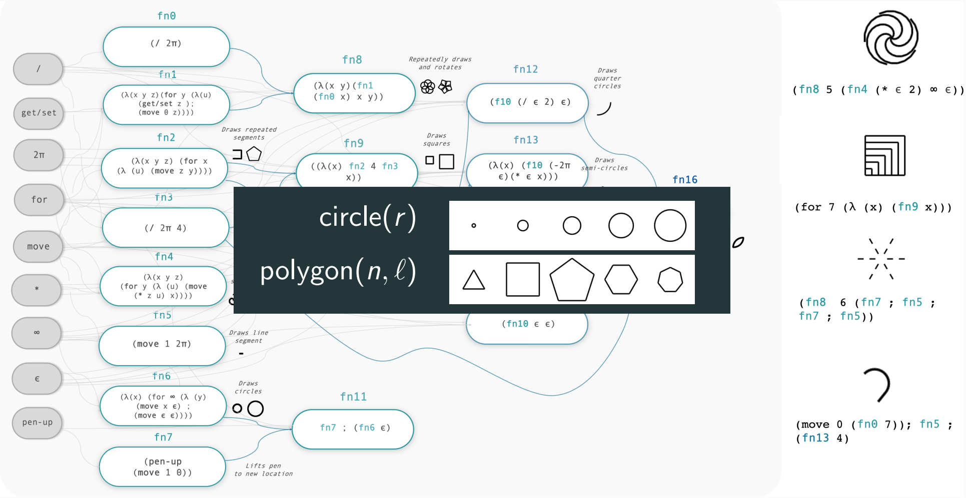
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library



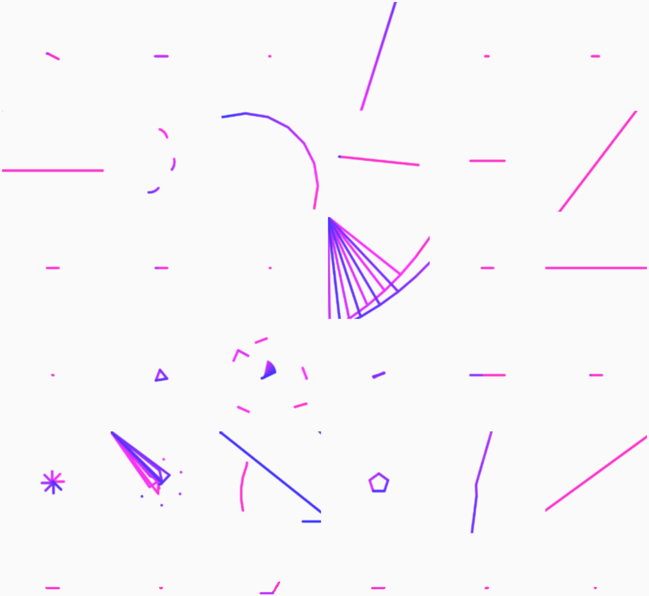
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

LOGO Turtle Graphics – learning an interpretable library

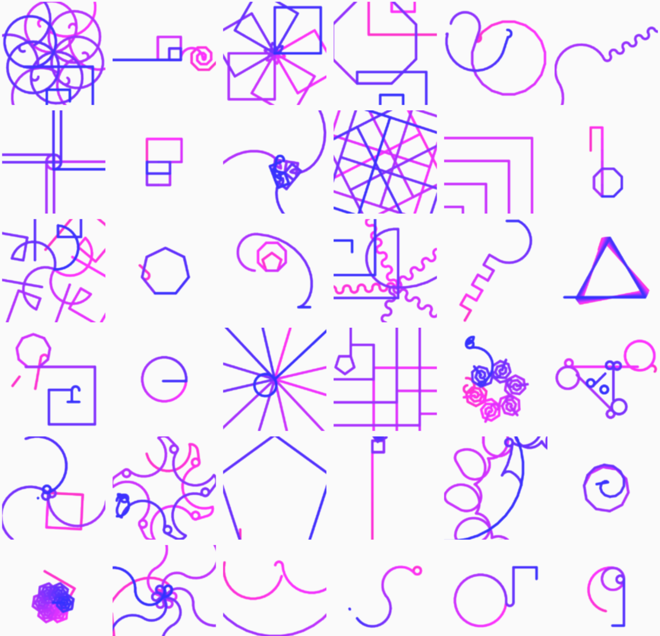


Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

What does DreamCoder dream of? (before learning)

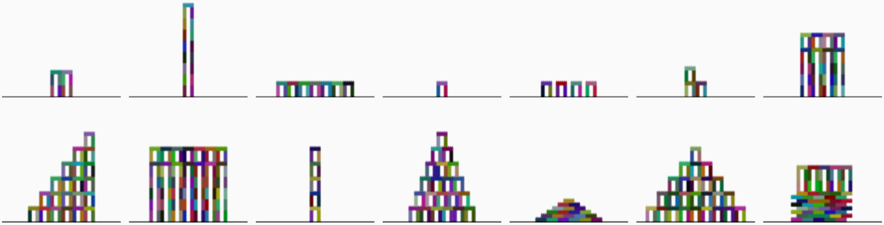


What does DreamCoder dream of? (after learning)



Planning to build towers

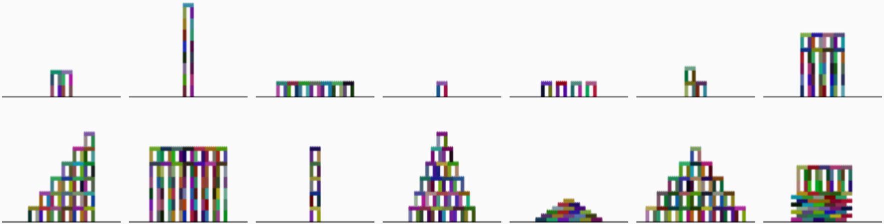
example tasks (112 total)



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Planning to build towers

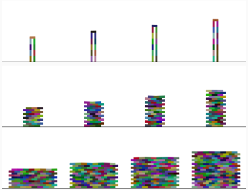
example tasks (112 total)



learned library routines (≈ 20 total)

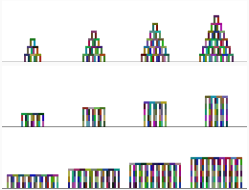
arch(h)

wall(w, h)



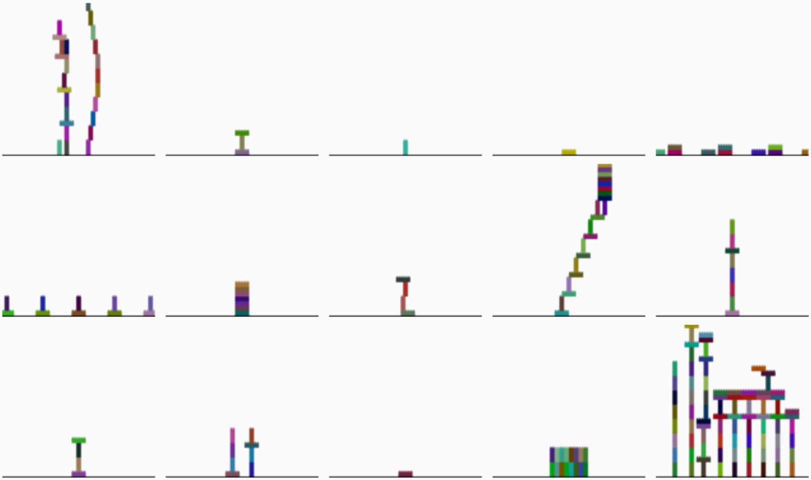
pyramid(h)

bridge(w, h)

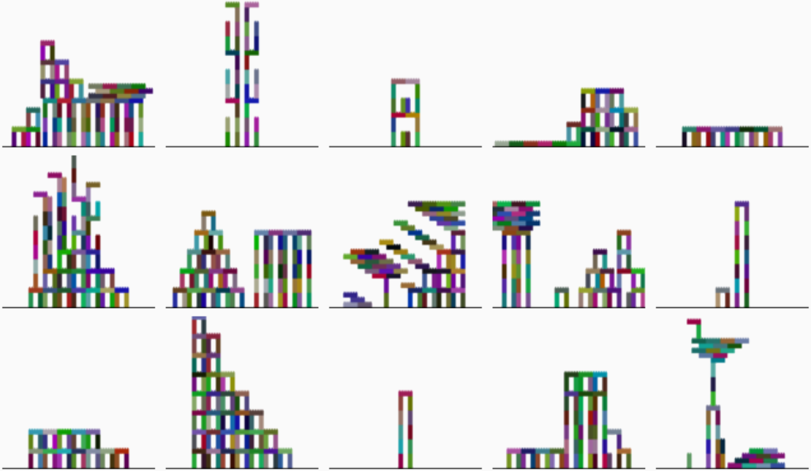


Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

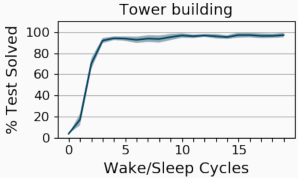
Dreams before learning



Dreams after learning

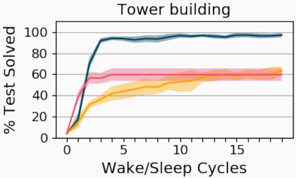


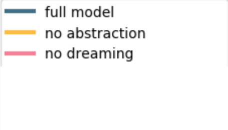
Learning dynamics



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

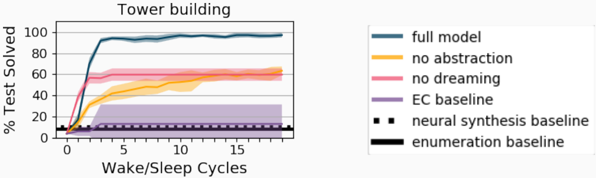
Learning dynamics





Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

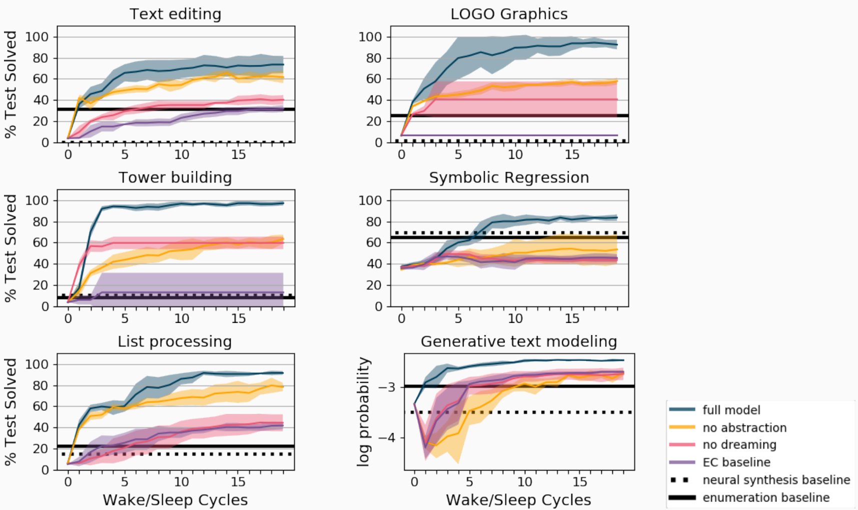
Learning dynamics



baselines: Exploration-Compression, EC [Dechter et al. 2013]
neural program synthesis, RobustFill [Devlin et al. 2017]
24 hours of brute-force enumeration

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Learning dynamics



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Synergy between dreaming and library learning

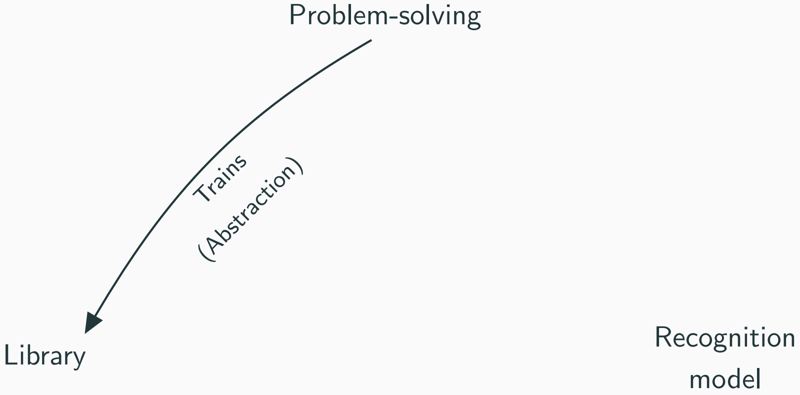
Problem-solving

Library

Recognition
model

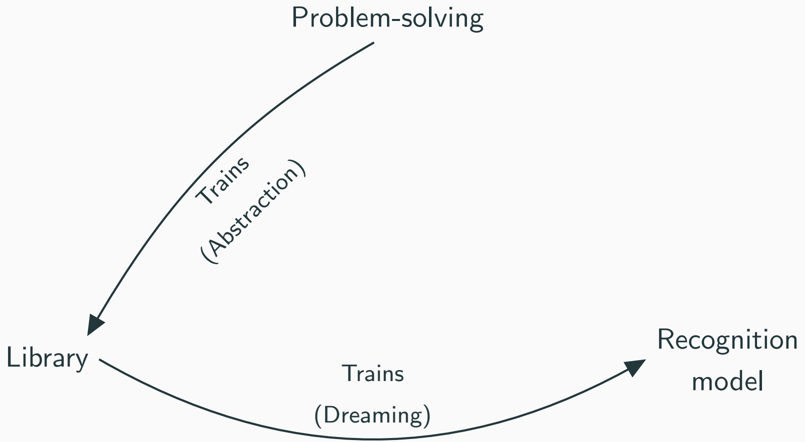
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Synergy between dreaming and library learning



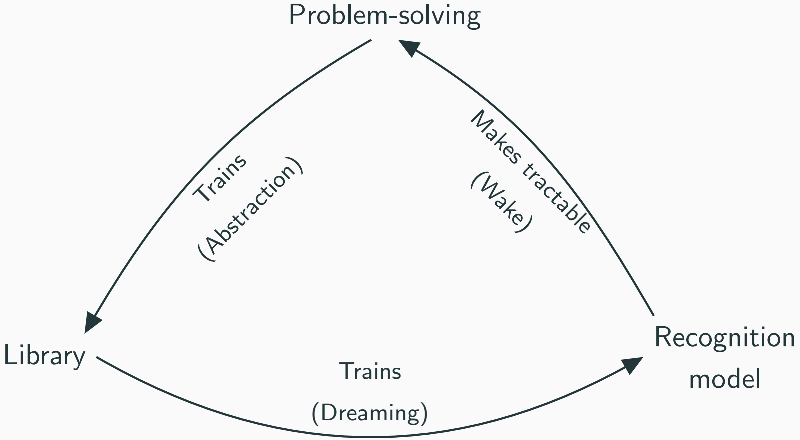
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Synergy between dreaming and library learning



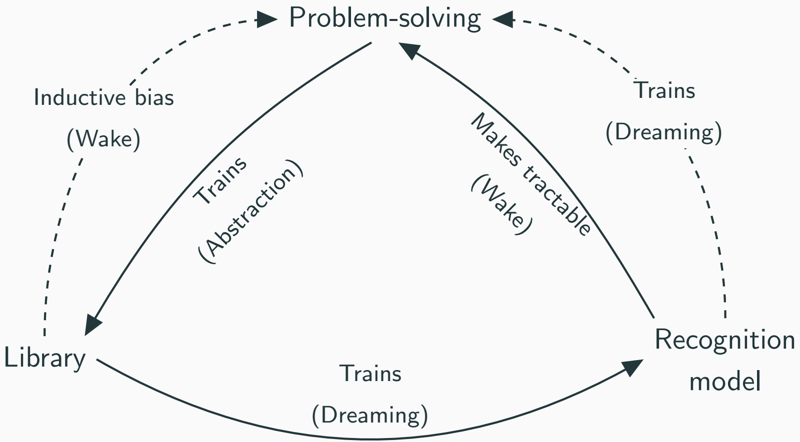
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Synergy between dreaming and library learning



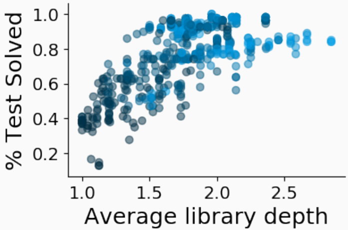
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Synergy between dreaming and library learning



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Evidence for dreaming bootstrapping better libraries

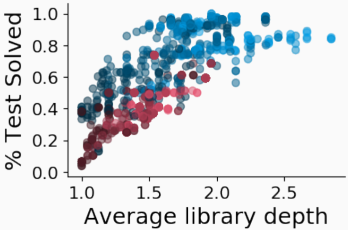


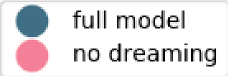
Darker: Early in learning

Brighter: Later in learning

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Evidence for dreaming bootstrapping better libraries



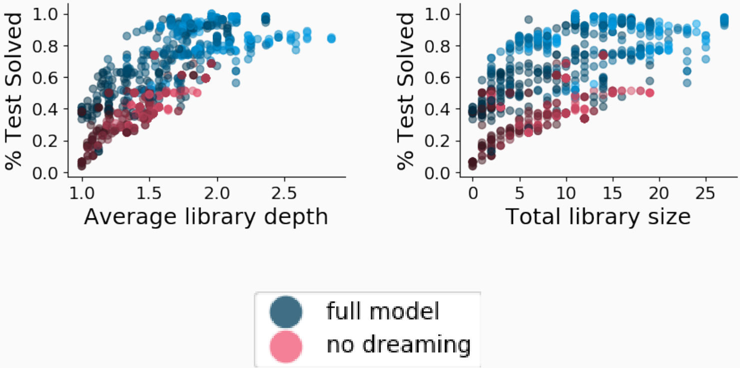


Darker: Early in learning

Brighter: Later in learning

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

Brighter: Later in learning

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

From learning libraries, to learning languages

From learning libraries, to learning languages

modern functional programming $\rightarrow$ physics

From learning libraries,
to learning languages

1950's Lisp $\rightarrow$ modern functional programming $\rightarrow$ physics

Physics Formula Sheet

Mechanics

$x = x_0 + v_{x0}t + \frac{1}{2}a_xt^2$	$a_c = \frac{v^2}{r}$	$\lvert\vec{F}_{spring}\rvert = k\lvert\vec{x}\rvert$
$v = v_0 + at$	$\theta = \theta_0 + \omega_0 t + \frac{1}{2}\alpha t^2$	$PE_{spring} = \frac{1}{2}kx^2$
$v_x^2 - v_{x0}^2 = 2a(x - x_0)$	$\omega = \omega_0 + \alpha t$	$T_{spring} = 2\pi\sqrt{\frac{m}{k}}$
$\vec{a} = \frac{\Sigma\vec{F}}{m} = \frac{\vec{F}_{net}}{m}$	$T = \frac{2\pi}{\omega} = \frac{1}{f}$	$T_{pendulum} = 2\pi\sqrt{\frac{\ell}{g}}$
$\lvert\vec{F}_{friction}\rvert \le \mu\lvert\vec{F}_{Normal}\rvert$	$v = f\lambda$	
$\vec{p} = m\vec{v}$	$x = A\cos(2\pi f t)$	$\lvert\vec{F}_{gravity}\rvert = G\frac{m_1m_2}{r^2}$
$\Delta\vec{p} = \vec{F}\Delta t$	$\vec{\alpha} = \frac{\Sigma\vec{\tau}}{I} = \frac{\vec{\tau}_{net}}{I}$	$\lvert\vec{F}_{gravity}\rvert = m\vec{g}$
$KE = \frac{1}{2}mv^2$	$\vec{\tau} = r \times F$	$PE_{gravity} = -G\frac{m_1m_2}{r}$
$\Delta PE = mg\Delta y$	$L = I\omega$	$\rho = \frac{m}{V}$
$\Delta E = W = Fd\cos\theta$	$\Delta L = \tau\Delta t$	$KE = \frac{1}{2}I\omega^2$

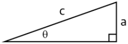
Electricity

$\lvert\vec{F}_E\rvert = k\left\lvert\frac{q_1q_2}{r^2}\right\rvert$	$\Delta V = IR$	$R = \frac{\rho\ell}{A}$
$I = \frac{\Delta q}{\Delta t}$	$P = I\Delta V$	
$R_{series} = R_1 + R_2 + \ldots + R_n$	$\frac{1}{R_{Parallel}} = \frac{1}{R_1} + \frac{1}{R_2} + \ldots + \frac{1}{R_n}$	

Geometry

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

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

+

-

*

/

0

1

π

Physics Equations

Newton's Second Law

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

Parallel Resistors

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

Work

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

Force in a Magnetic Field

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

Kinetic Energy

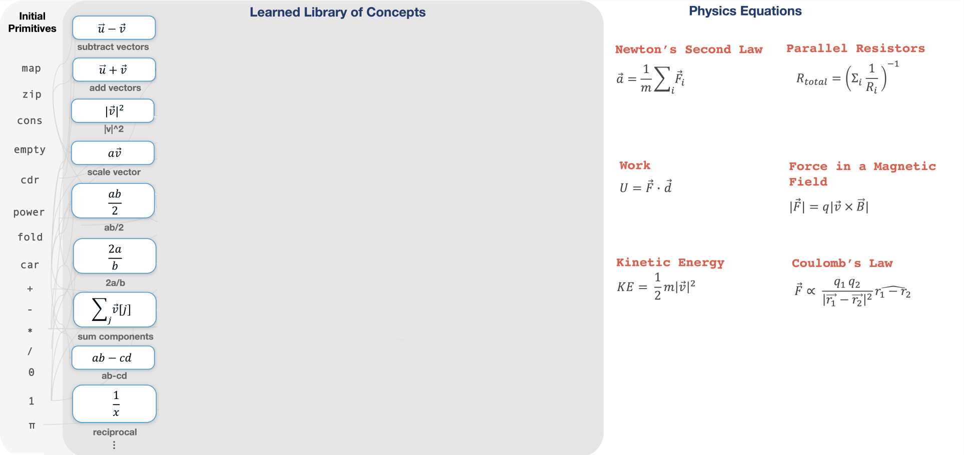
$KE = \frac{1}{2}m|\vec{v}|^2$

Coulomb's Law

$\vec{F} \propto \frac{q_1 q_2}{|\vec{r_1} - \vec{r_2}|^2}\widehat{r_1 - r_2}$

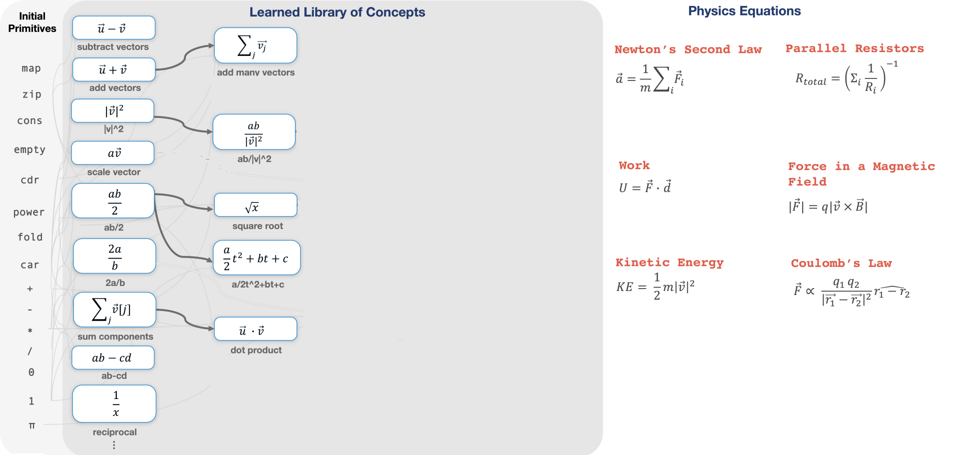
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing languages for vector algebra and physics



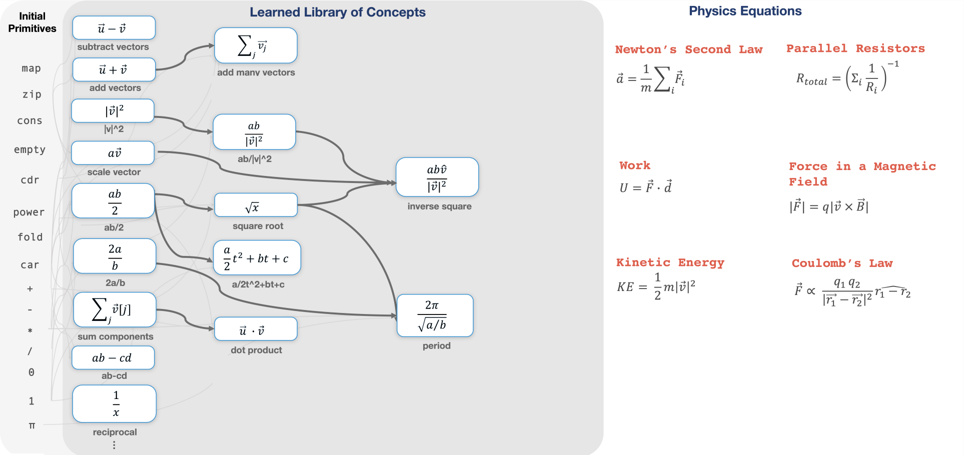
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing languages for vector algebra and physics



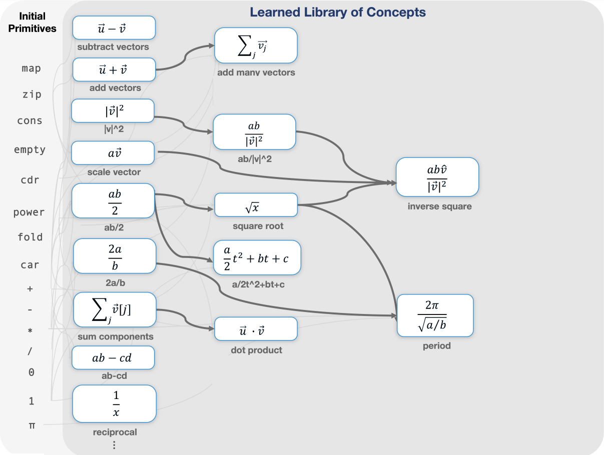
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing languages for vector algebra and physics



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing languages for vector algebra and physics



Physics Equations

Newton's Second Law

$$\vec{a} = \frac{1}{m}\sum_i \vec{F_i}$$

```
(scale-vector(reciprocal m)
(add-many-vectors Fs))
```

Parallel Resistors

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

```
(reciprocal (sum-components
(map (λ(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))
```

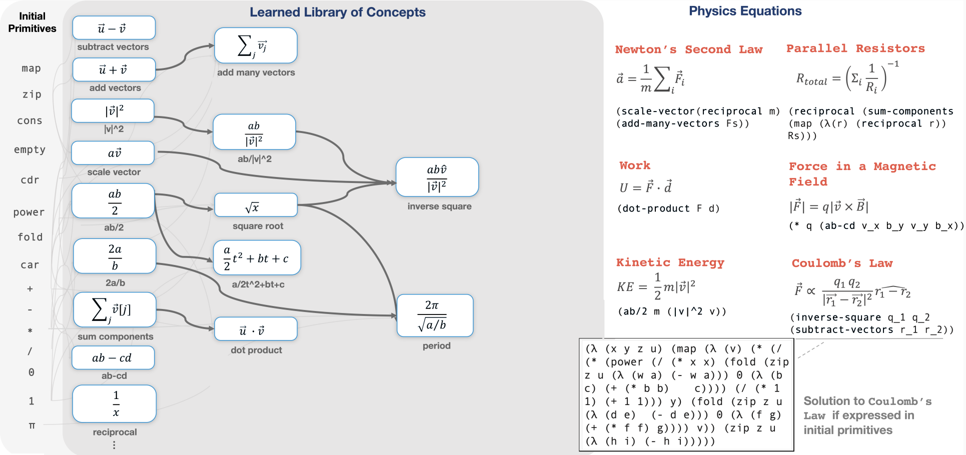
Coulomb's Law

$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r_1} - \vec{r_2}|^2}\widehat{r_1 - r_2}$$

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

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing languages for vector algebra and physics



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

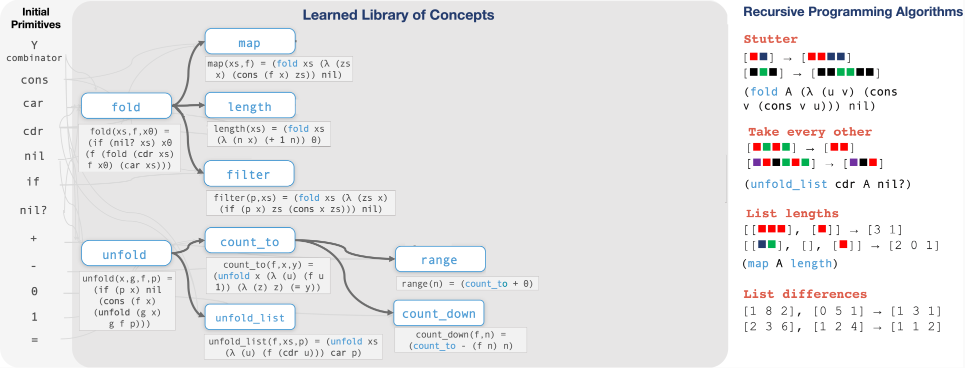
Growing a language for recursive programming

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing a language for recursive programming

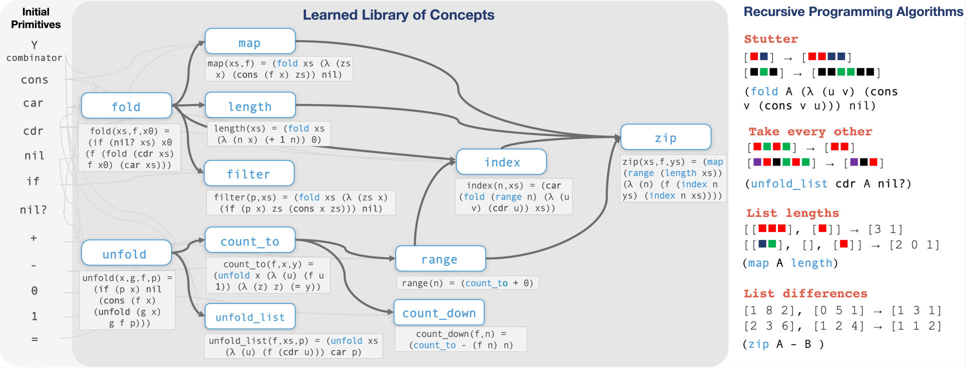
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing a language for recursive programming



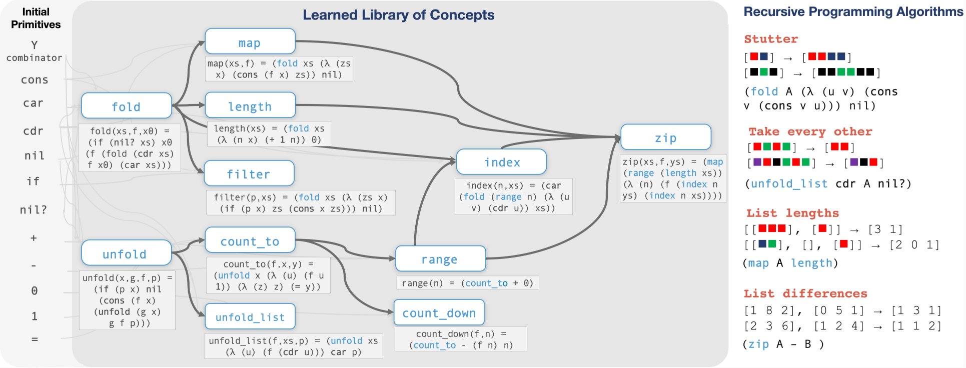
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

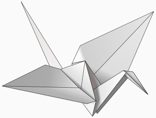
Growing a language for recursive programming



Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing a language for recursive programming

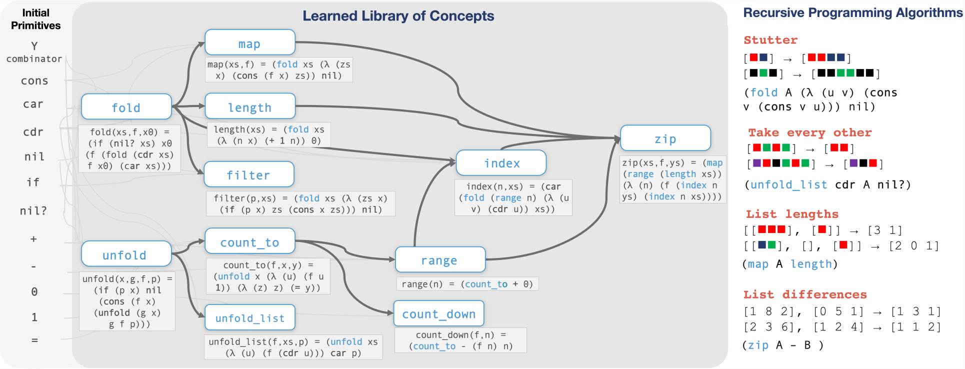




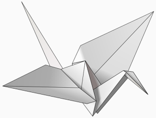
Origami Programming: Jeremy Gibbons, 2003

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Growing a language for recursive programming



1 year of compute. 5 days on 64 CPUs.



Origami Programming: Jeremy Gibbons, 2003

Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Lessons

Symbols aren't necessarily interpretable. Flexibly 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 and adapt on top of that

Program Induction and learning to learn

the future

Some unresolved questions

Not everything is crisp and symbolic. How do we learn neurosymbolic hybrid programs?

Some unresolved questions

Not everything is crisp and symbolic. How do we learn neurosymbolic hybrid programs?

Search is still hard

Some unresolved questions

Not everything is crisp and symbolic. How do we learn neurosymbolic hybrid programs?

Search is still hard

Is this a good model for human learning and thinking?

What we want for the future of machine learning

Strong generalization

What we want for the future of machine learning

Strong generalization

Bootstrapping, learning-to-learn, representation learning

What we want for the future of machine learning

Strong generalization

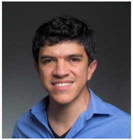
Bootstrapping, learning-to-learn, representation learning

Discovering knowledge that humans can understand and build on

Collaborators

Josh Tenenbaum

Armando Solar-Lezama



Max Nye

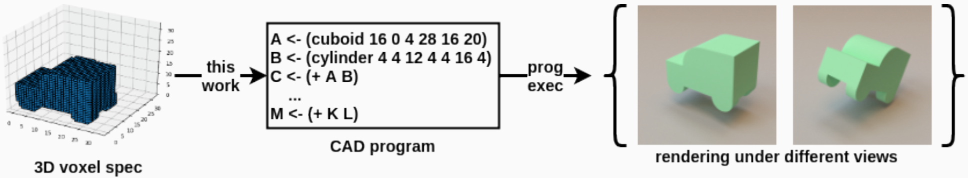
Cathy Wong

Mathias Sable-Meyer

Lucas Morales

thank you

3D program induction



Challenge: combinatorial search!

Branching factor: $>$ 1.3 million per line of code, $\approx$ 20 lines of code

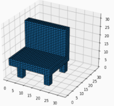
search space size: $(1.3 \text{ million})^{20} \approx 10^{122}$ programs

Ellis*, Nye*, Pu*, Sosa*, Tenenbaum, Solar-Lezama. NeurIPS 2019.

*equal contribution

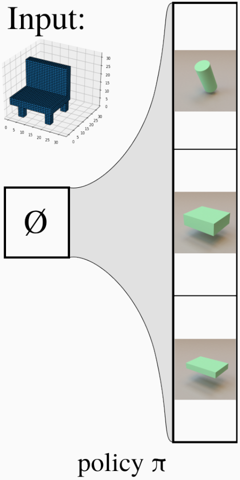
Solution: stochastic **tree search** + learn **policy** that writes code + learn **value** function that assesses execution of program so far; analogous to **AlphaGo** [Silver et al. 2016]

Input:

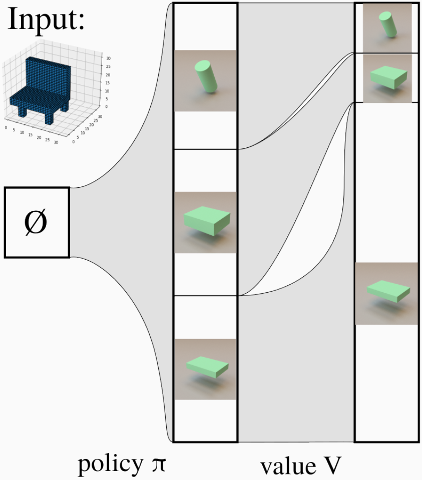


$\boxed{\emptyset}$

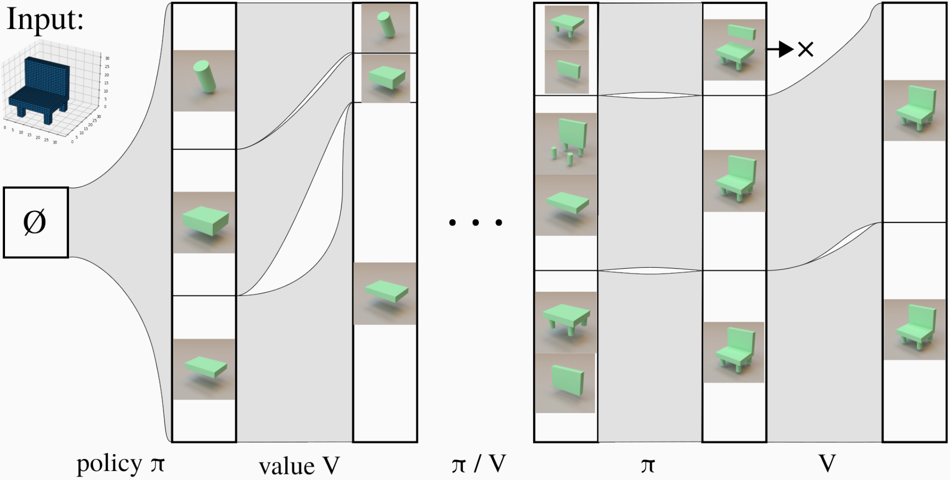
Solution: stochastic **tree search** + learn **policy** that writes code + learn **value** function that assesses execution of program so far; analogous to **AlphaGo** [Silver et al. 2016]



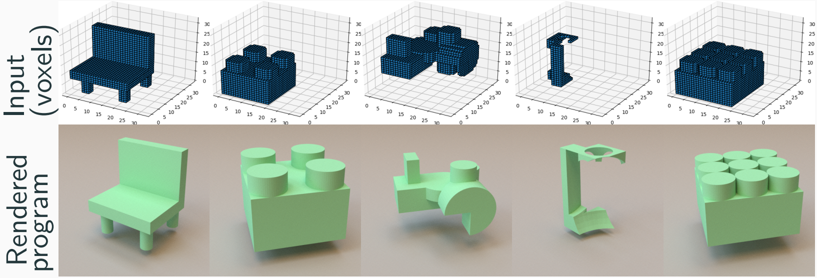
Solution: stochastic **tree search** + learn **policy** that writes code + learn **value** function that assesses execution of program so far; analogous to **AlphaGo** [Silver et al. 2016]



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]

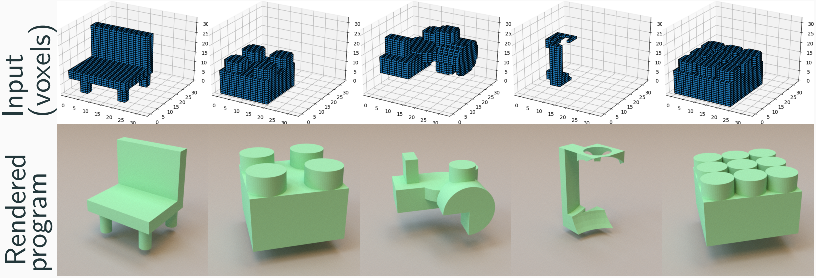


3D program induction



Ellis*, Nye*, Pu*, Sosa*, Tenenbaum, Solar-Lezama. NeurIPS 2019.
*equal contribution

3D program induction



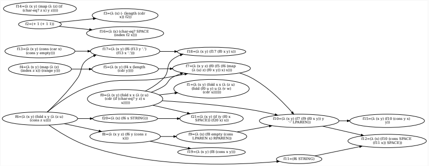
same architecture learns to synthesize text editing programs (FlashFill, Gulwani 2012)

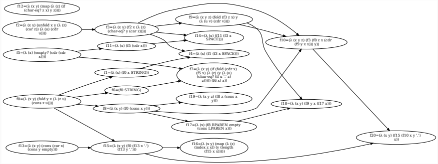
Ellis*, Nye*, Pu*, Sosa*, Tenenbaum, Solar-Lezama. NeurIPS 2019.

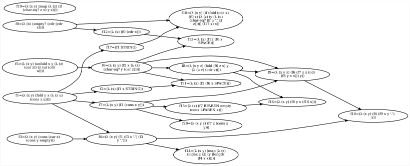
*equal contribution

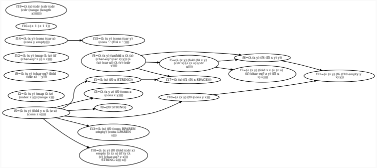
Library structure: Text Editing

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





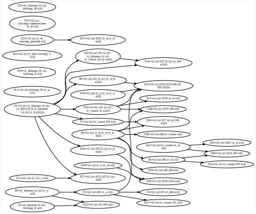


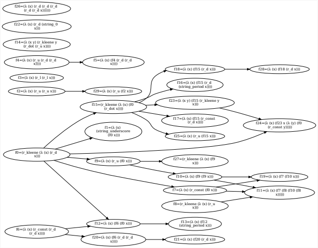


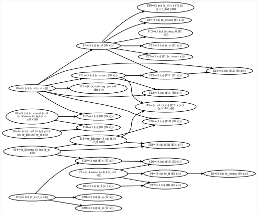
Ellis, Wong, Nye, ..., Solar-Lezama, Tenenbaum. arxiv 2020.

Library structure: Generating Text

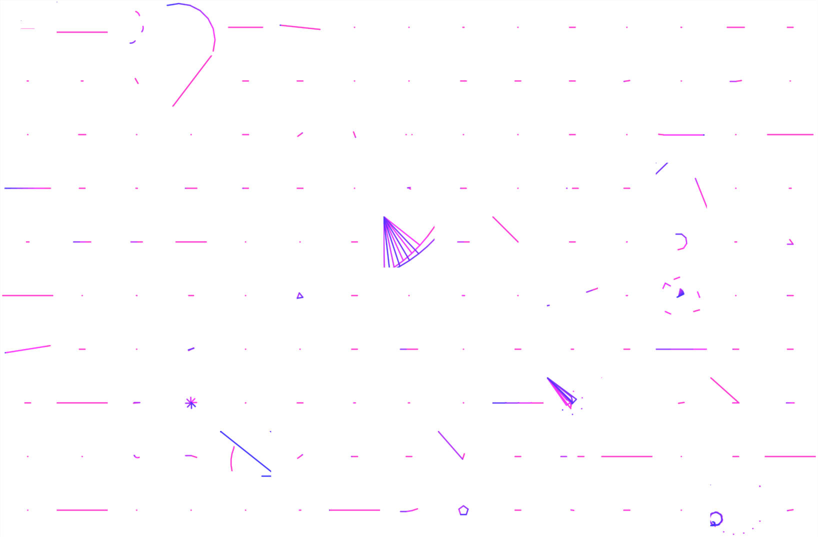
Libraries for probabilistic generative models over text:
data from crawling web for CSV files







150 random dreams before learning



150 random dreams after learning