

Building Machines that Discover Generalizable, Interpretable Knowledge

Kevin Ellis

2020

MIT

What computational problems are solved by intelligence?

an endless range of problems

language



using new devices



engineering



science



writing new characters



design



coding

```
(MEMBER  
(LAMBDA (X L)  
(COND ((NULL L) NIL)  
      ((EQ X (FIRST L)) T)  
      (T (MEMBER X (REST L)))))))
```

Allen, Anatomy of Lisp, 1975



play



What computational frameworks can contribute to this picture?

Three AI traditions

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Three AI traditions

Symbolic



In[34]:= `Solve[{(hw - hw^2) == z}, h]`

Out[34]= `{}`

Input interpretation: `solve h w - h w^2 = Z for h`

Result:

$$h = \frac{Z}{w - w^2} \text{ and } w^2 \neq w$$

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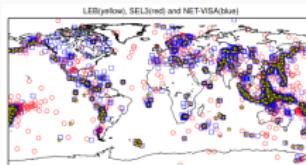
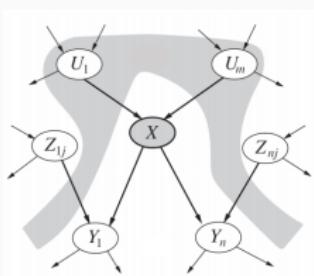
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Probabilistic



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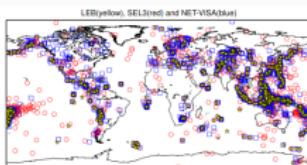
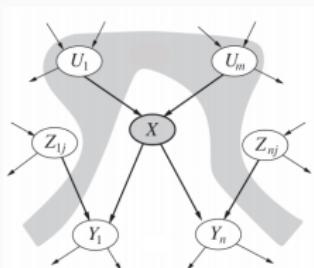
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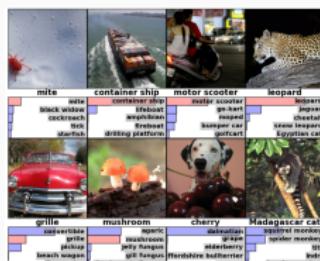
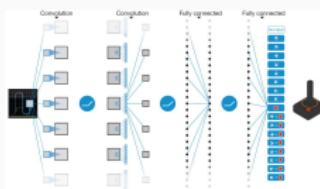
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Probabilistic



Neural



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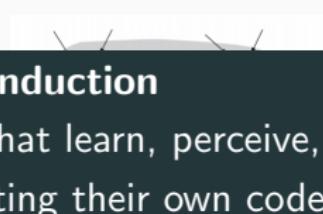
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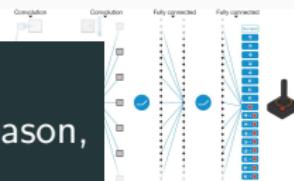
Probabilistic



Program induction

machines that learn, perceive, and reason,
by writing their own code

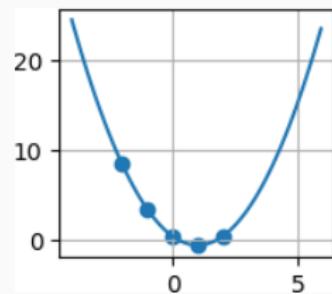
Neural



Why program induction?

Why program induction?

strong generalization
+data efficiency

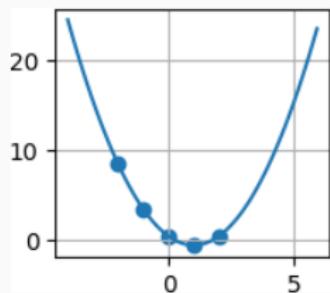


$$f(x) = (x-1)^{**2} - 0.5$$

Why program induction?

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+data efficiency

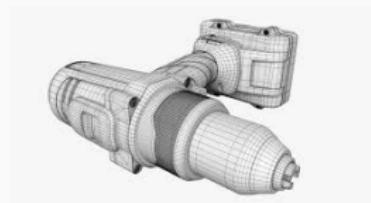
interpretability



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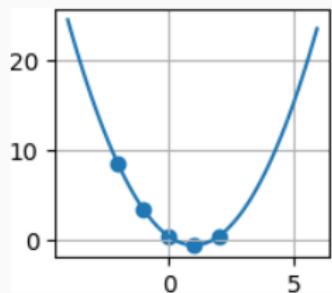


VS



Why program induction?

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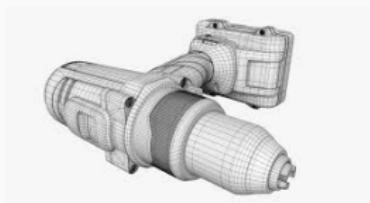


$$f(x) = (x-1)^{**2} - 0.5$$

interpretability



universal expressivity



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
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John McCarthy, Ray Solomonoff

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main obstacle: combinatorial search is hard

Why try again?

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

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

maturing **program synthesis** techniques

better compute+parallel algorithms

A lesson from the AI winter

We need an on-ramp of practical, tractable problems:

semantic parsing [Liang et al. 2011; Zettlemoyer et al. 2007]

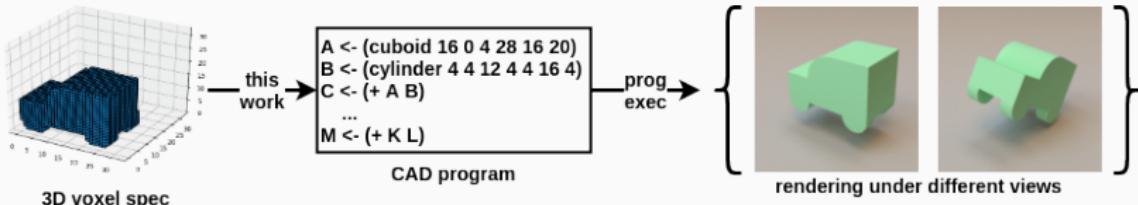
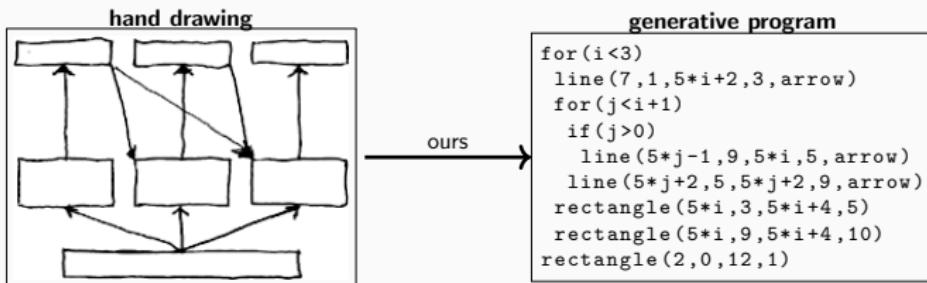
programming by examples [Gulwani 2011]

computer-aided-programming [Solar-Lezama 2008]

inverse procedural modeling [Kulkarni et al. 2015]

Perception, Synthesizing models, Learning-to-Learn

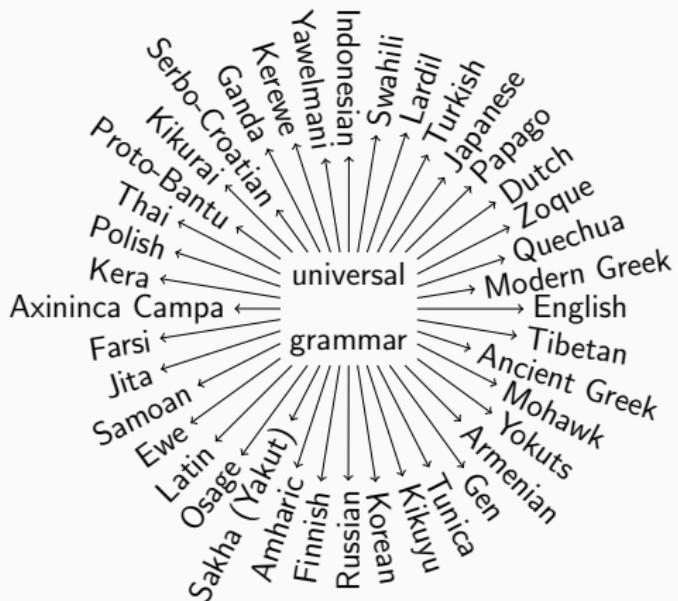
Theme #1: high-level visual understanding, pixels→programs



Perception, Synthesizing models, Learning-to-Learn

Theme #1: high-level visual understanding, pixels→programs

Theme #2: synthesizing human-understandable models



Perception, Synthesizing models, Learning-to-Learn

Theme #1: high-level visual understanding, pixels→programs

Theme #2: Synthesizing human-understandable models

Theme #3: learning to synthesize programs

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

$$\text{Allen Newell} \rightarrow \text{A.N.}$$

$$\text{Herb Simon} \rightarrow \text{H.S.}$$

Drop Last Three

$$\text{shrdlu} \rightarrow \text{shr}$$

$$\text{shakey} \rightarrow \text{sha}$$

Regexes

Phone numbers

$$(555) \ 867-5309$$

$$(650) \ 555-2368$$

Currency

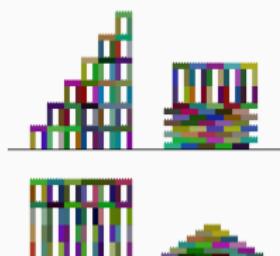
$$\$100.25$$

$$\$4.50$$

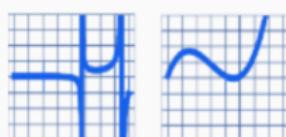
LOGO Graphics



Block Towers



Symbolic Regression



$$y = f(x)$$

Recursive Programming

Filter Red

$$[\blacksquare \ \textcolor{red}{\blacksquare} \ \blacksquare \ \blacksquare] \rightarrow [\blacksquare \ \blacksquare]$$

$$[\blacksquare \ \textcolor{red}{\blacksquare} \ \blacksquare \ \blacksquare] \rightarrow [\blacksquare \blacksquare \blacksquare \blacksquare]$$

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Physical Laws

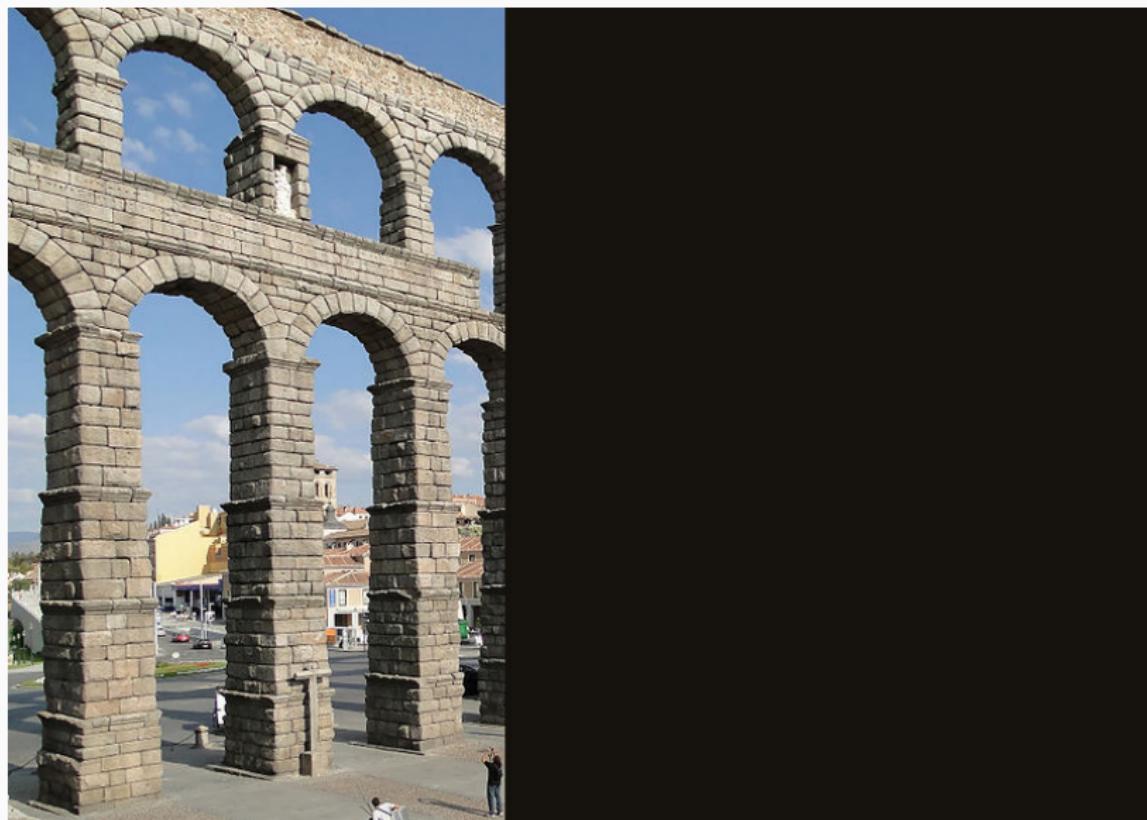
$$\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$$

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

Program Induction and perception
model discovery
learning to learn

Vision is more than knowing what is where

Can you visually extrapolate this aqueduct?



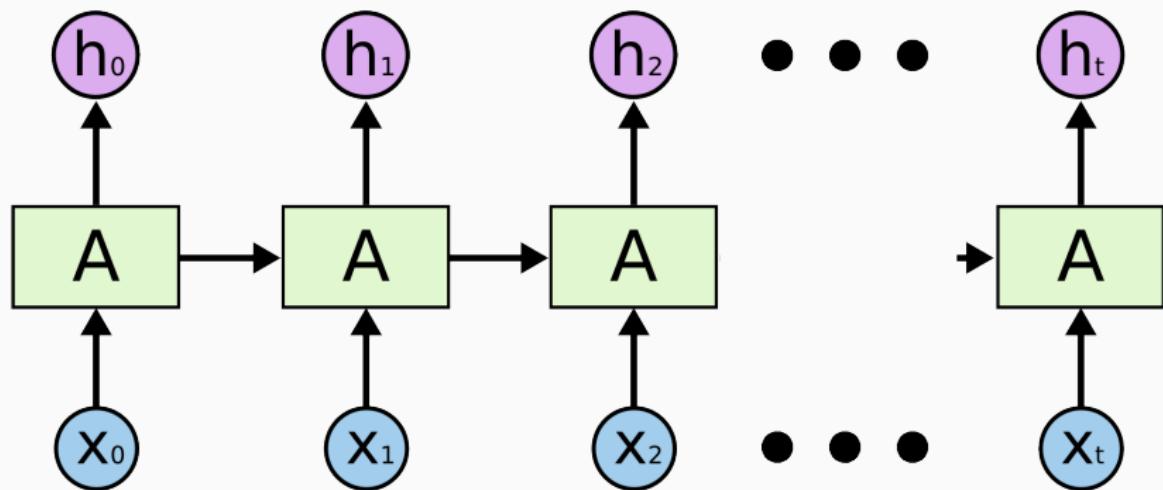
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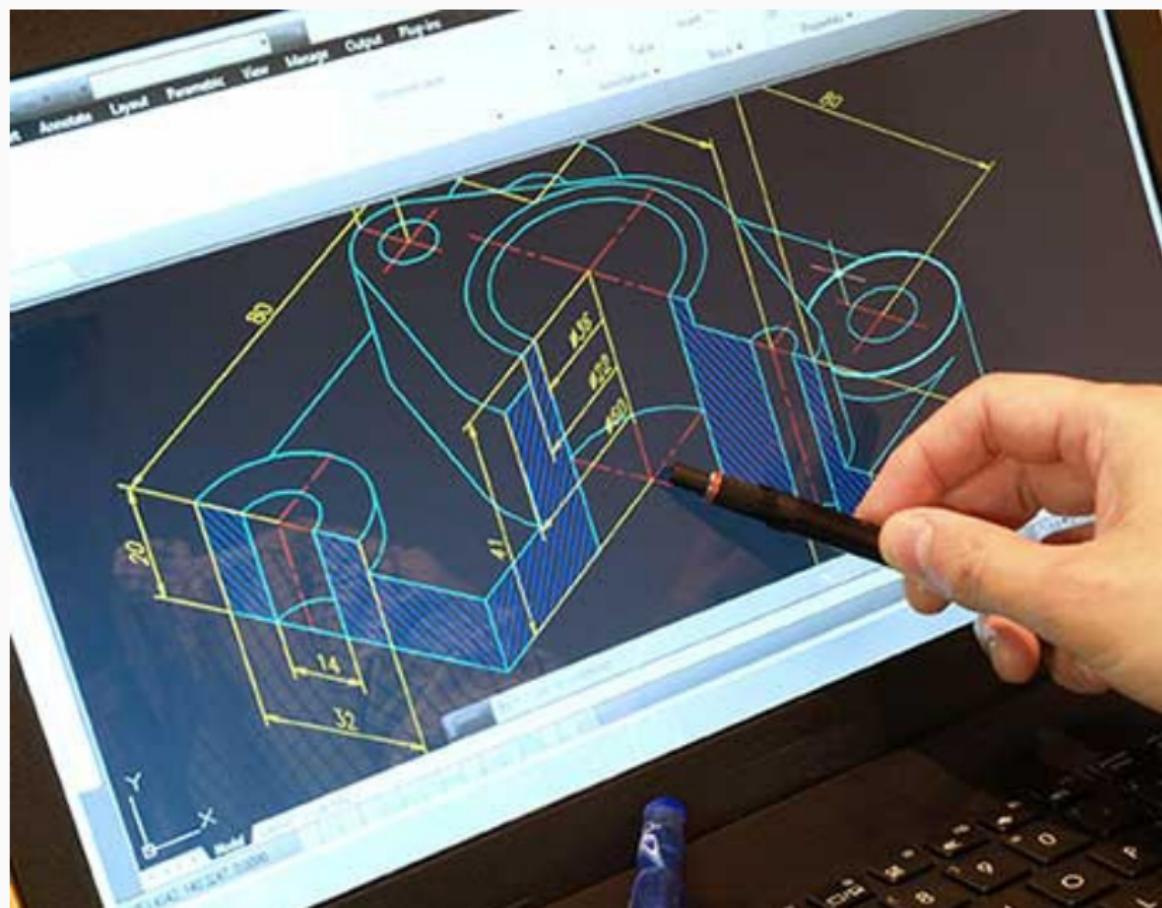


Vision is more than knowing what is where

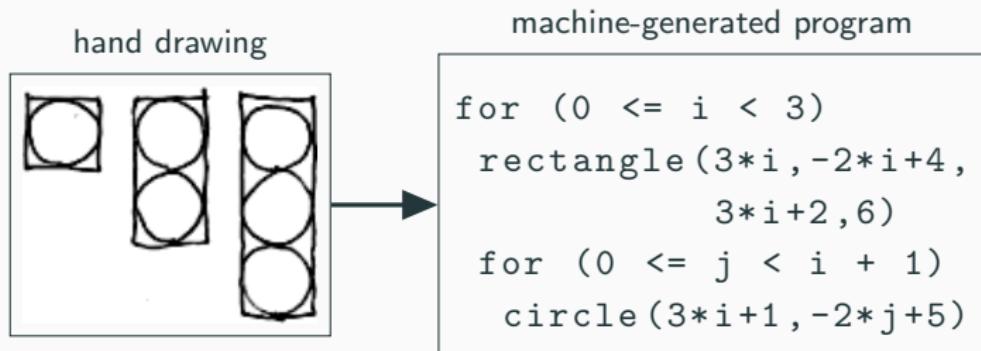
Can you infer what goes in the ellipses?



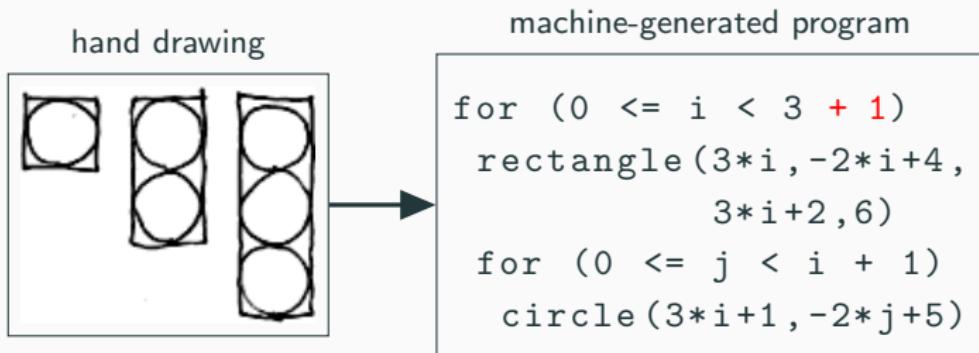
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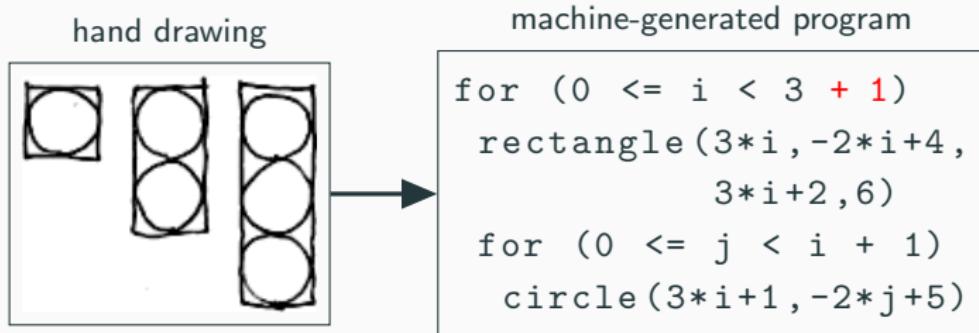
Learning to infer graphics programs from hand-drawn images



Learning to infer graphics programs from hand-drawn images

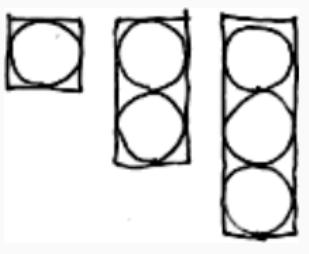


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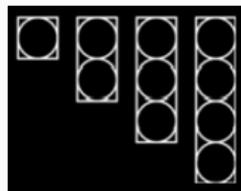
hand drawing



machine-generated program

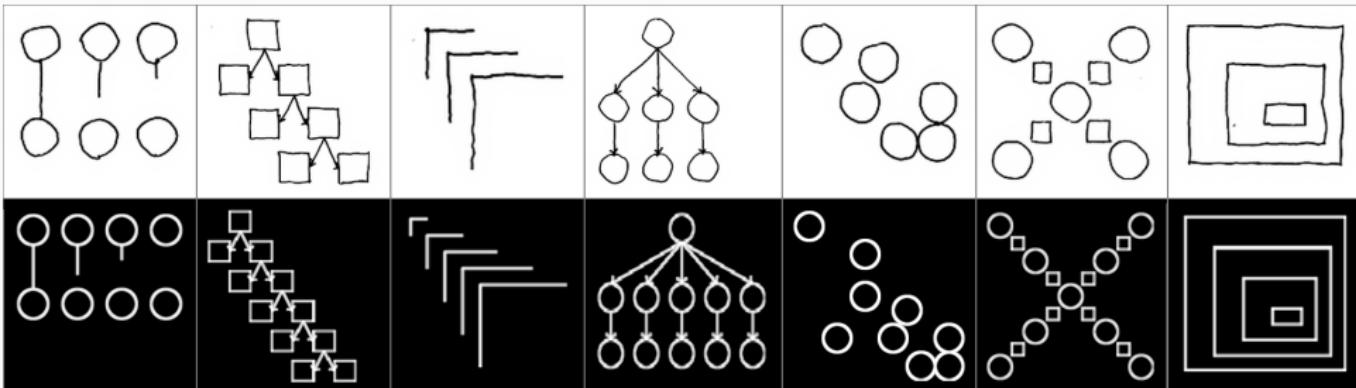
```
for (0 <= i < 3 + 1)
    rectangle(3*i, -2*i+4,
              3*i+2, 6)
    for (0 <= j < i + 1)
        circle(3*i+1, -2*j+5)
```

autogenerated extrapolation

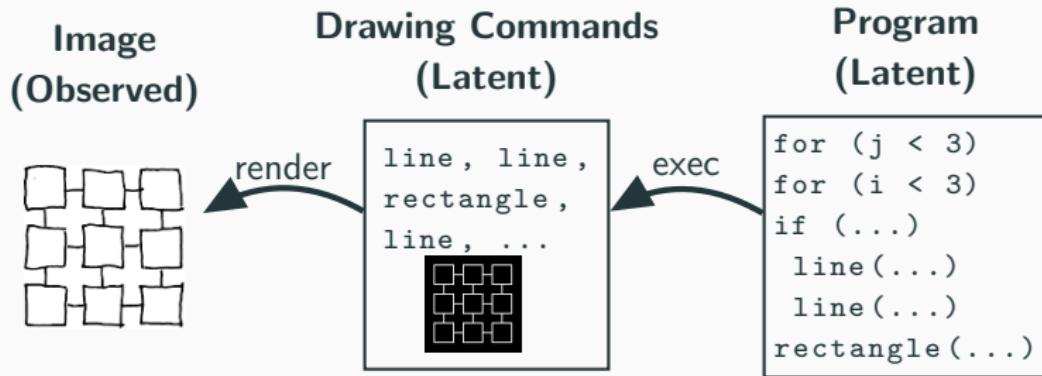


one-shot generalization / extrapolation

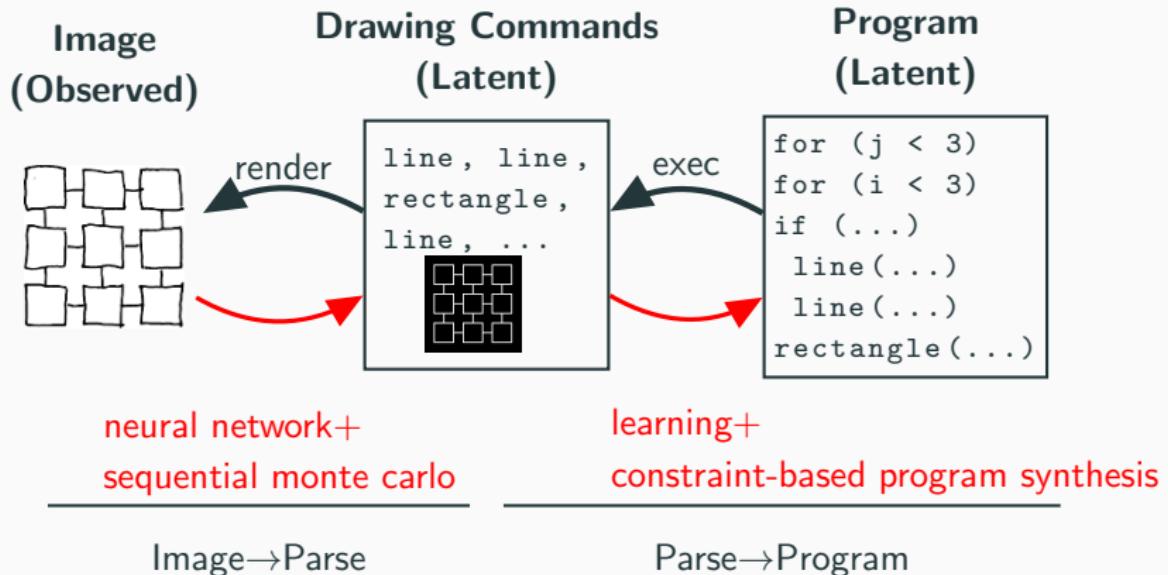
Extrapolation from a single image



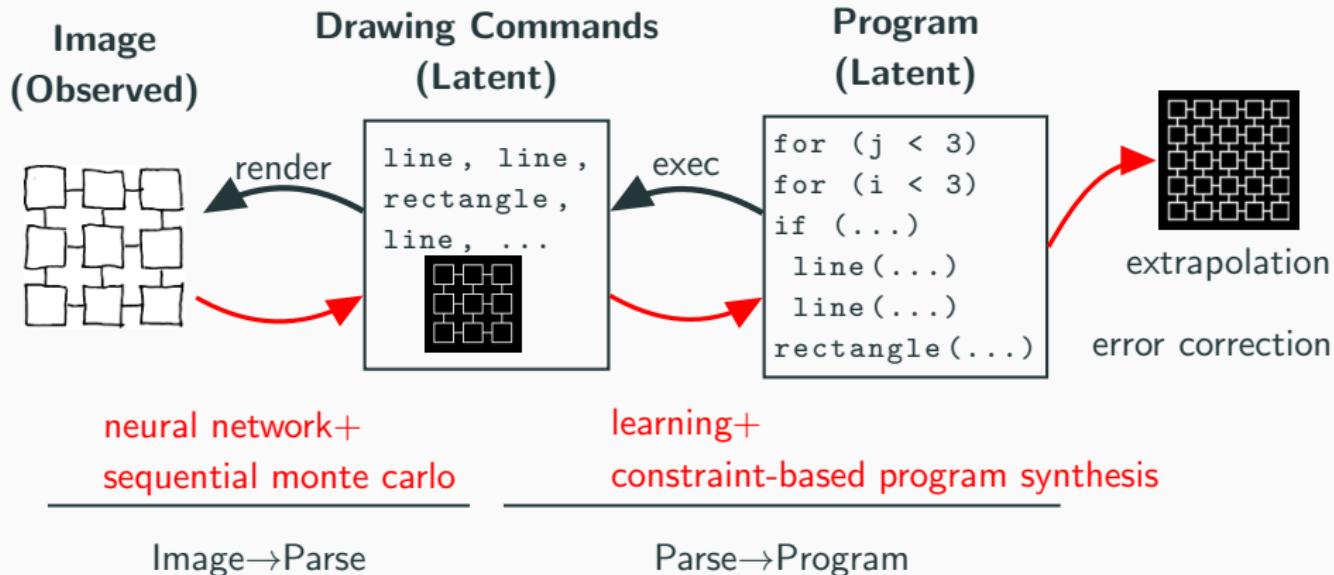
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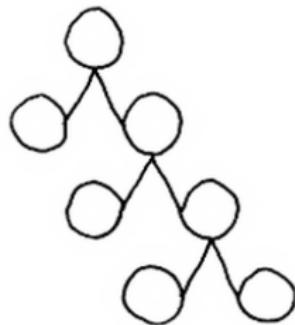


How to infer graphics programs from hand-drawn images



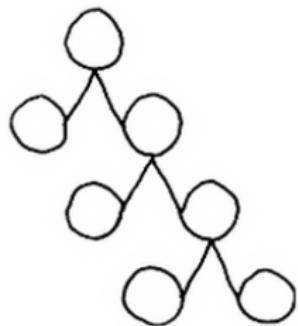
Top-down influences on perception

drawing

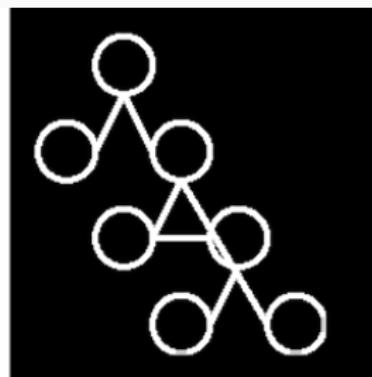


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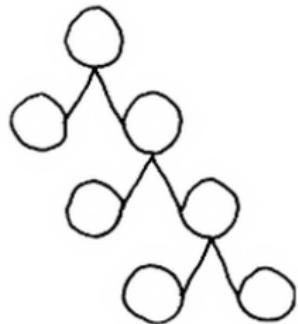


bottom-up neural net

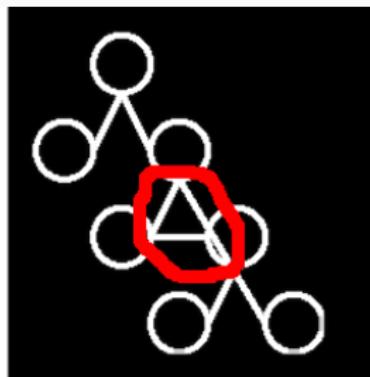


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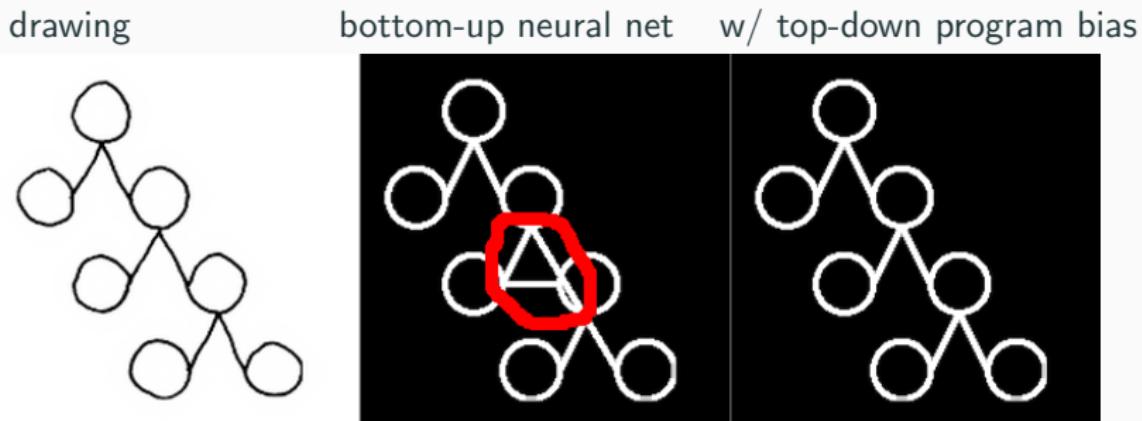
drawing



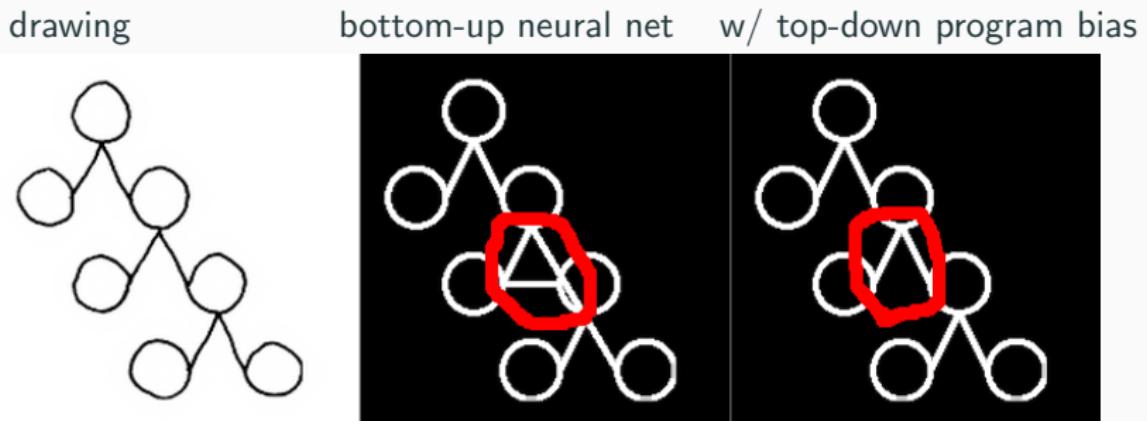
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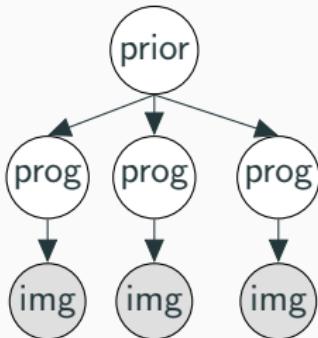
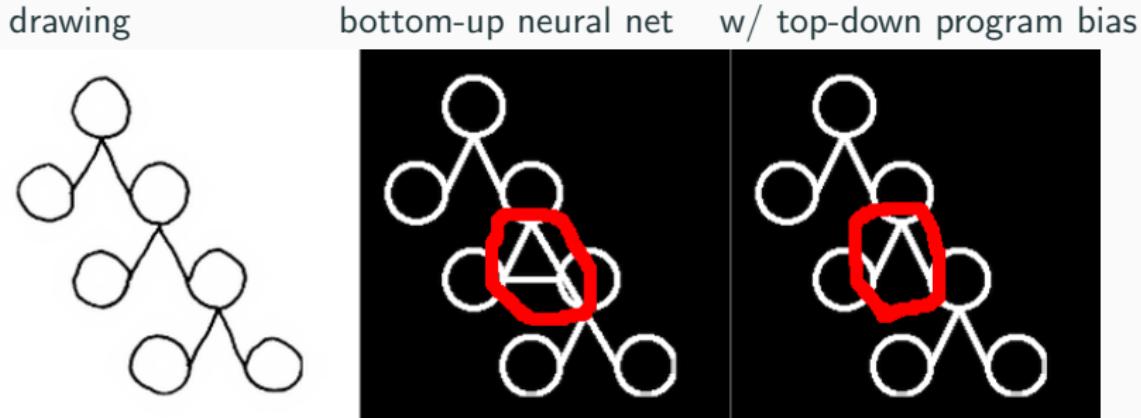
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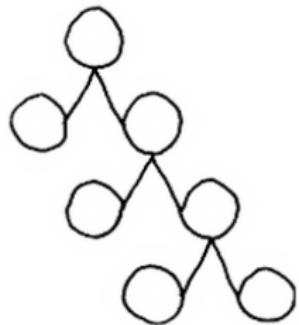
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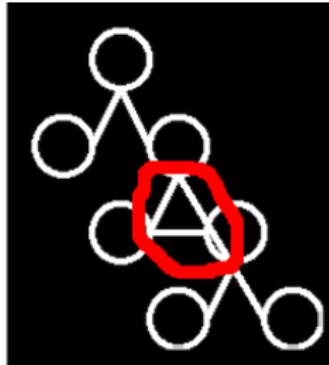
predicted program =
 $\arg \max_{\text{progs}} \mathbb{P} [\text{img} | \text{prog}] \mathbb{P} [\text{prog} | \text{prior}]$

Top-down influences on perception

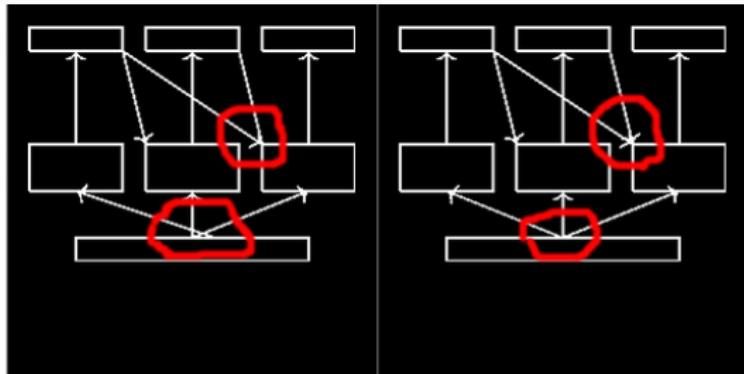
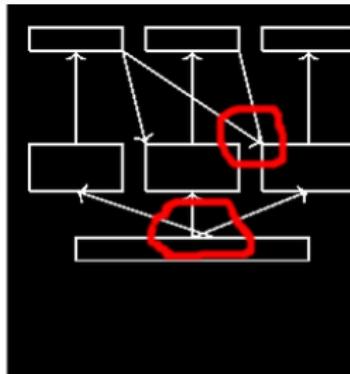
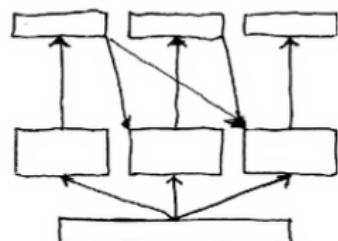
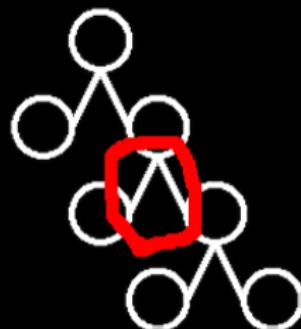
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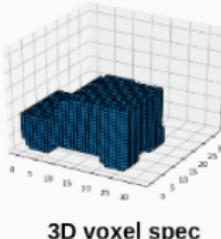
bottom-up neural net



w/ top-down program bias



3D program induction

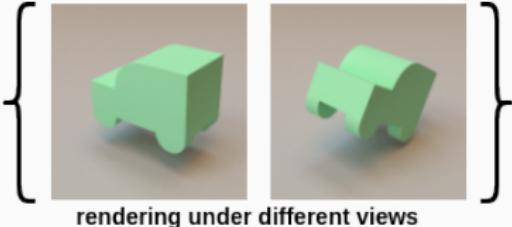


this work

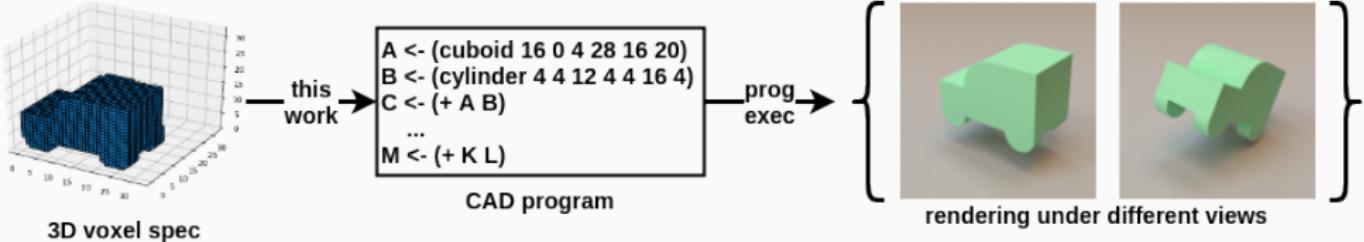
```
A <- (cuboid 16 0 4 28 16 20)
B <- (cylinder 4 4 12 4 4 16 4)
C <- (+ A B)
...
M <- (+ K L)
```

CAD program

prog
exec



3D program induction



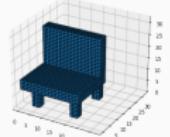
Challenge: combinatorial search!

Branching factor: > 1.3 million per line of code, ≈ 20 lines of code

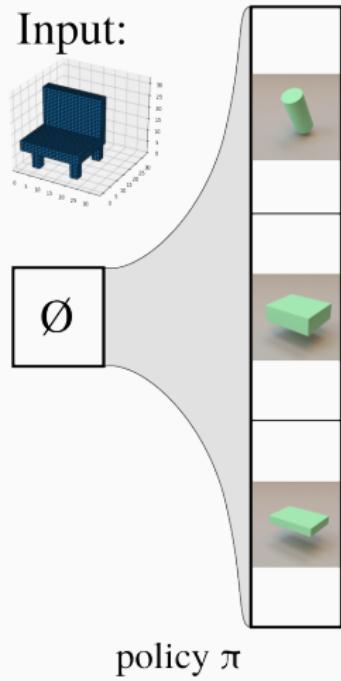
search space size: $(1.3 \text{ million})^{20} \approx 10^{122}$ programs

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]

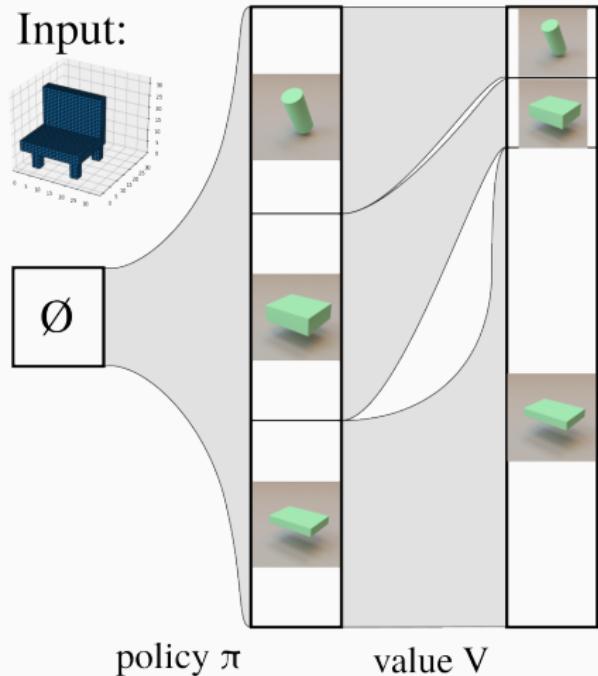
Input:



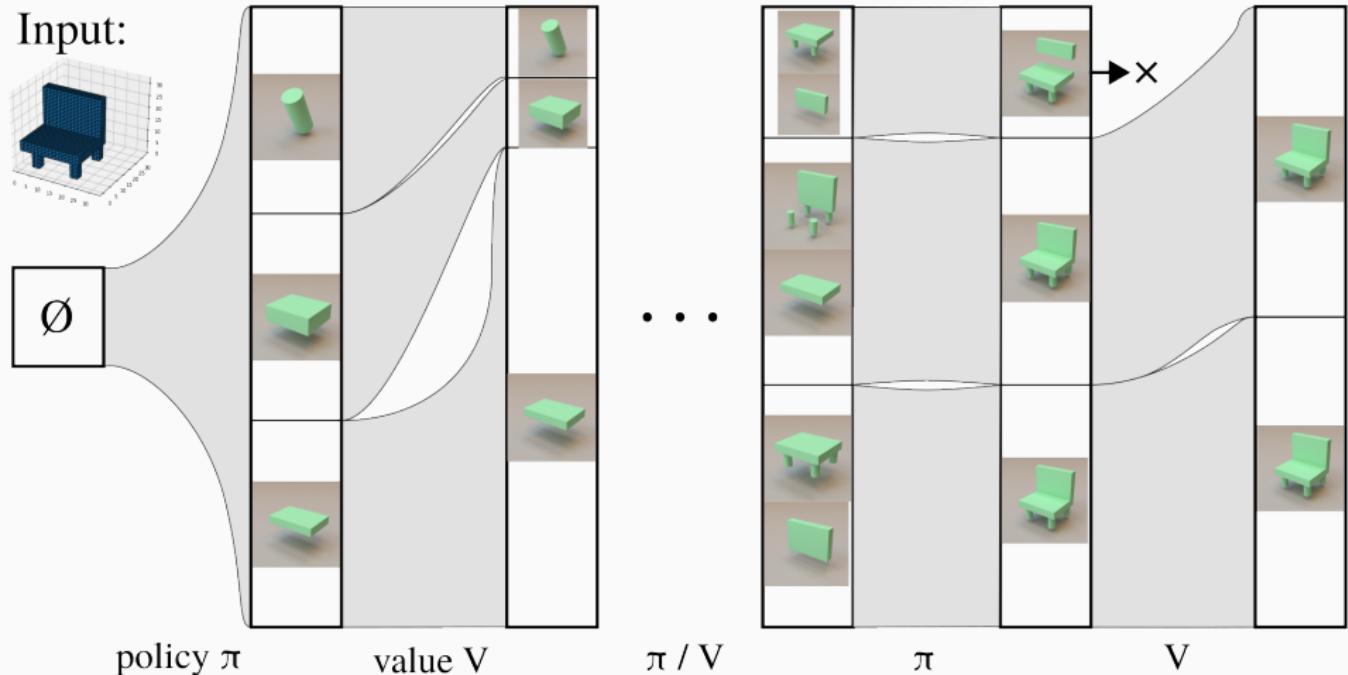
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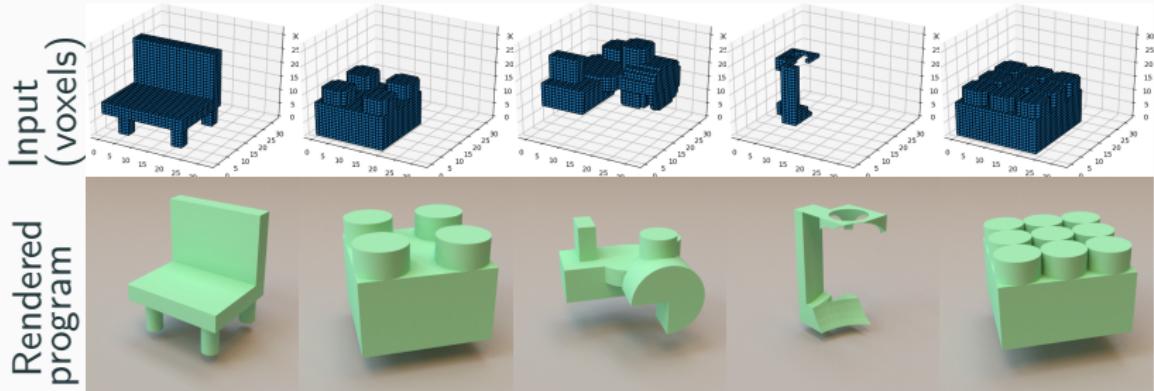
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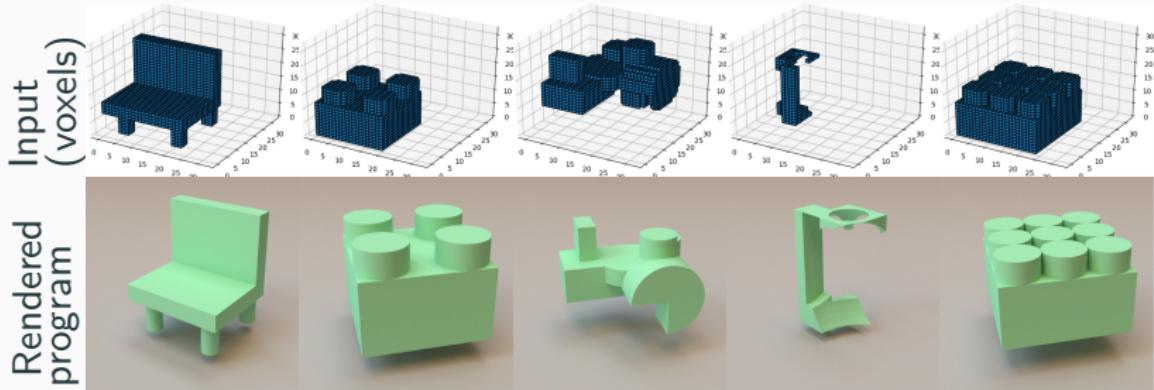
3D program induction



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

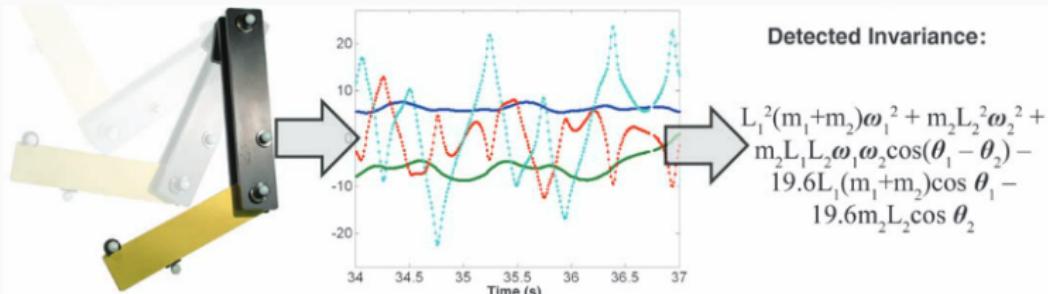
Lessons

The inductive bias from a programming language gives extrapolation, or strong generalization

Combine the best of different techniques: neural nets for perception and pattern recognition, symbols for reasoning, Bayesian methods for uncertainty

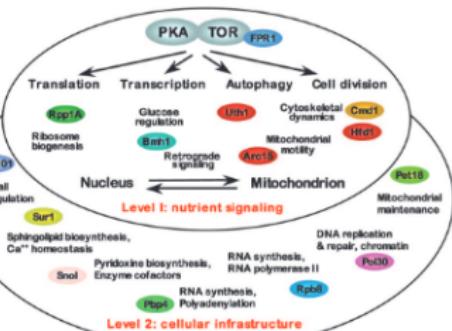
Program Induction and perception
model discovery
learning to learn

Scientific discovery



Schmidt & Lipson: "Distilling Free-Form Natural Laws from Experimental Data"

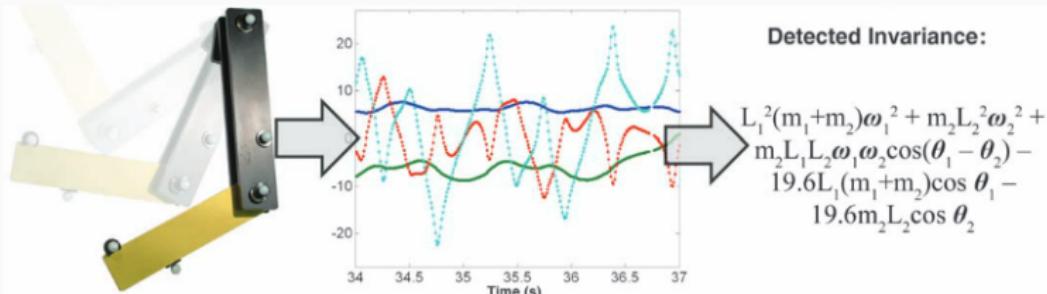
PNAS



Lezon et al. 2006

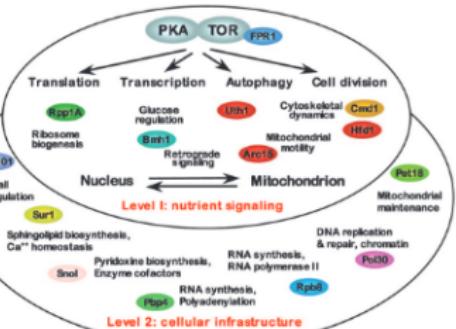
inferring genetic interaction networks

Scientific discovery



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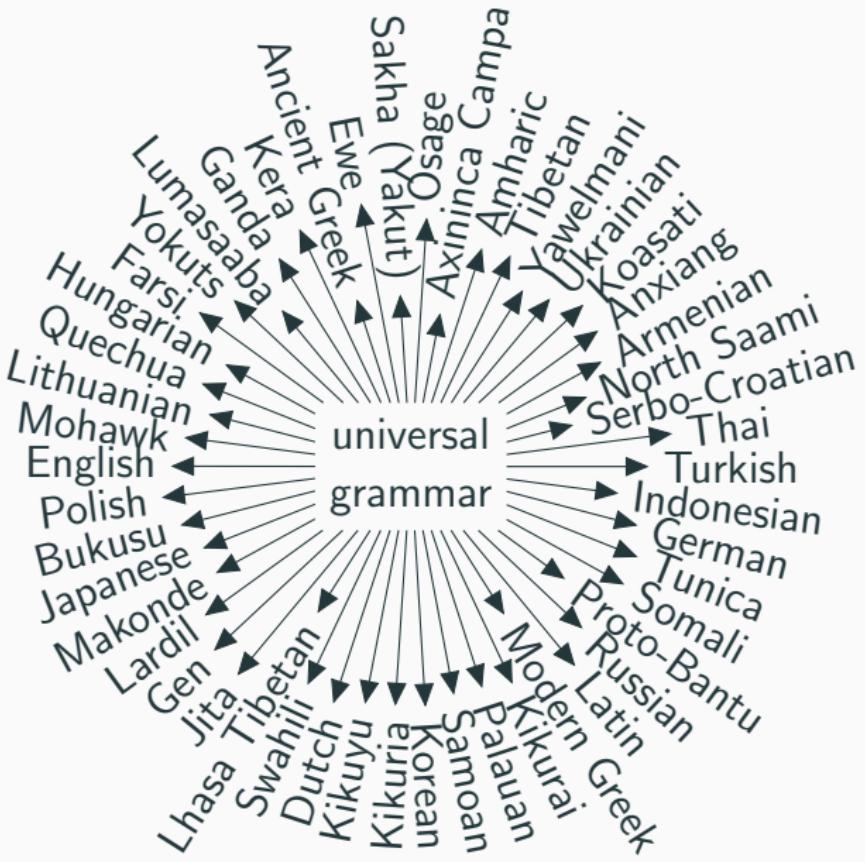
THE APPLICATION OF ALGORITHMIC PROBABILITY TO PROBLEMS IN ARTIFICIAL INTELLIGENCE

Ray J. Solomonoff

1986

This operation corresponds to Kepler's laws summarizing and compressing Tycho Brahe's empirical data on planetary motion. Algorithmic Complexity theory has this ability to synthesize, to find general laws in masses of unorganized and partially organized knowledge. It is in this area that its greatest value for A.I. lies.

Discovering human-understandable models of language



Few-shot language learning experiment

Mandarin:

	adjective	adverb
“slow”	man	manmandə
“small”	xiao	xiaoxiaodə
“fast”	kuai	???

Few-shot language learning experiment

Mandarin:

	adjective	adverb
“slow”	man	manmandə
“small”	xiao	xiaoxiaodə
“fast”	kuai	kuaikuaidə

Few-shot language learning experiment

Mandarin:

	adjective	adverb
“slow”	man	manmandə
“small”	xiao	xiaoxiaodə
“fast”	kuai	kuaikuaidə

stem+stem+də

Few-shot language learning experiment

Serbo-Croatian:

	masculine	feminine
“rich”	bogat	bogata
“mild”	blag	blaga
“green”	zelen	???

Few-shot language learning experiment

Serbo-Croatian:

	masculine	feminine
“rich”	bogat	bogata
“mild”	blag	blaga
“green”	zelen	zelena

Few-shot language learning experiment

Serbo-Croatian:

	mASCULINE	fEMININE
“rich”	bogat	bogata
“mild”	blag	blaga
“green”	zelen	zelena

add “a” to stem to make feminine

Few-shot language learning experiment

Serbo-Croatian:

	masculine	feminine
“rich”	bogat	bogata
“mild”	blag	blaga
“green”	zelen	zelena
“clear”	???	yasna

add “a” to stem to make feminine

Few-shot language learning experiment

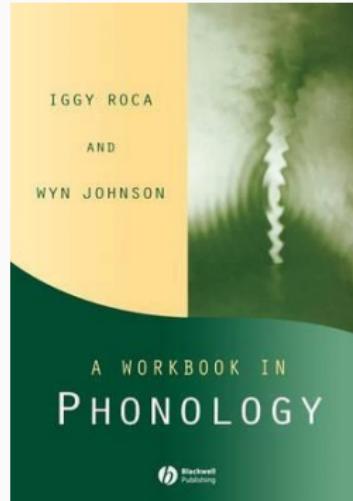
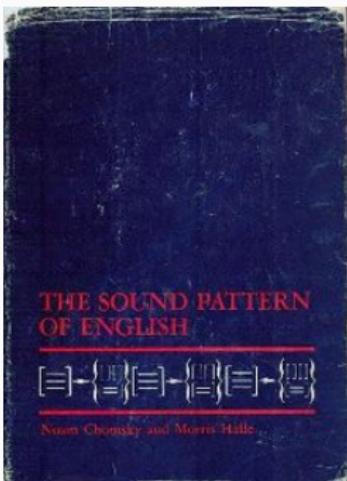
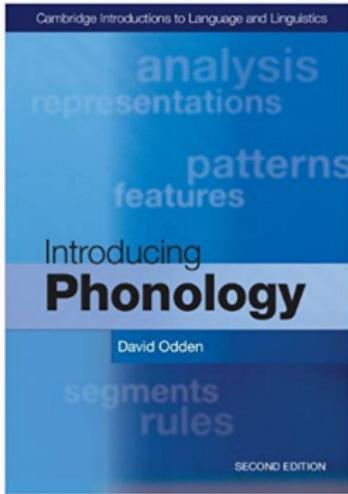
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“green”	zelen	zelena
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add “a” to stem to make feminine

insert “a” between two word-final consonants

$\emptyset \rightarrow a / C_C\#$



10 Sakha (Yakut)

Give a phonological analysis of the following case-marking paradigms of nouns in Sakha.

<i>Noun</i>	<i>Plural</i>	<i>Associative</i>	<i>oyuur</i>	<i>oyurdar</i>	<i>oyuurduun</i>	<i>'forest'</i>		
aýa	aýalar	aýaliin	'father'	üçügey	üçügeyder	'good person'		
paarta	paartalar	paartaliin	'school desk'	ejiy	ejiyder	'elder sister'		
tia	tiallar	tialliin	'forest'	tomtor	tomtordor	'knob'		
kinige	kinigeler	kinigeliiñ	'book'	moyotoy	moyotoydor	'chipmunk'		
Jie	jieler	Jieliiñ	'house'	kötör	kötördör	'bird'		
iyé	iyeler	iyeliin	'mother'	bölköy	bölköydör	'islet'		
kini	kiniler	kiniliin	'3rd person'	xatiij	xatignar	'birch'		
bie	bieler	bieliin	'mare'	aan	aannar	'doo'		
oyo	oyolor	oyoluun	'child'	tiig	tiigner	'squirrel'		
xopto	xoptolor	xoptoluun	'gull'	sordoj	sordognor	'pike'		
börö	börölör	böröliün	'wolf'	olom	olomnor	'ford'		
tial	tiallar	tialliin	'wind'	oron	oronnor	'bed'		
ial	iallar	ialliin	'neighbor'	bödög	bödögör	'strong one'		
kuul	kuullar	kuulluuñ	'sack'	<i>Noun</i>	<i>Partitive</i>	<i>Comparative</i>	<i>Ablative</i>	
at	attar	attiiñ	'horse'	aýa	ayata	ayataaýar	ayattan	'father'
balik	baliktar	balikiin	'fish'	paarta	paartata	paartataaýar	paattattan	'school desk'
iskaap	iskaaptar	iskaaptiin	'cabinet'	tia	tiata	tiataaýar	tiattan	'forest'
oyus	oyustar	oyustuuñ	'bull'	kinige	kinigete	kinigeteeyer	kinigetten	'book'
kus	kustar	kustuuñ	'duck'	Jie	jiete	jieteeeyer	jietten	'house'
tünnük	tünnükter	tünnüktüün	'window'	iye	iyete	iyeteeeyer	iyetten	'mother'
sep	septer	septiin	'tool'	kini	kinite	kinitteeeyer	kinitten	'3rd person'
et	etter	ettiiñ	'meat'	bie	biete	bieteeeyer	bietten	'mare'
örüs	örüster	örüstüün	'river'	oyo	oyoto	oyotooyor	oyotton	'child'
tis	tiister	tiistiin	'tooth'	xopto	xoptoto	xoptotooyor	xoptotton	'gull'
sorox	soroxtor	soroxtuuñ	'some person'	börö	börötö	börötööyör	böröttön	'wolf'
ox	oxtor	oxtuun	'arrow'	tial	tialla	tiallaaýar	tialtan	'wind'
oloppos	oloppstor	oloppstuun	'chair'	ial	ialla	iallaaýar	ialtan	'neighbor'
ötöx	ötöxtör	ötöxtüün	'abandoned farm'	kuul	kuulla	kuullaaýar	kuultan	'sack'
ubay	ubaydar	ubaydiin	'elder brother'	moxsoyol	moxsoyollo	moxsoyollooyor	moxsyoitolon'	falcon'
asaray	saraydar	saraydiin	'bam'	at	atta	attaayar	attan	'horse'
tiy	tiydar	tiydiin	'foal'	balik	balikta	baliktaaýar	baliktan	'fish'
atiir	atiirdar	atiirdiin	'stallion'	iskaap	iskaapta	iskaaptaaýar	iskaaptan	'cabinet'
			tünnük	oyus	oyusta	oyustaayar	oyustan	'bul'
				kus	kusta	kustaayar	kustan	'duck'
				tünnükte	tünnükte	tünnükteeyer	tünnükten	'window'

Turkic Sakha (Yakut)

observed data

	SINGULAR	PLURAL
BED	oron	<u>oronnor</u>
MARE	bie	<u>bieler</u>
CABINET	is̥kaap	<u>is̥kaaptar</u>

138 total examples

Turkic Sakha (Yakut)

grammar (unobserved)

SINGULAR → stem
PLURAL → stem + lar

observed data



	SINGULAR	PLURAL
BED	oron	oronnor
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Turkic Sakha (Yakut)

constraint-based
synthesis
[Solar-Lezama 2008]
test-driven synthesis
[Perelman et al. 2016]

grammar (unobserved)

SINGULAR → stem
PLURAL → stem + lar

$r_1: l \rightarrow d / [-\text{lateral} \ -\text{tense}]$
“l” becomes “d” next to “r”, “t”, but not “l”

$r_2: C \rightarrow [-\text{voice}] / [-\text{voice}]$
do not voice next to voiceless

$r_3: V \rightarrow [+\text{rounded}] / [+\text{rounded}] [-\text{low}]_0$

$r_4: [+\text{continuant} \ -\text{high}] \rightarrow [-\text{rounded}] / u \ C_0$
“harmonize” round vowels like “u”, “o”

$r_5: V \rightarrow [-\text{back} \ -\text{low}] / [-\text{back} \ +\text{vowel}] []_0$
“harmonize” vowels to be not at back of mouth

$r_6: [-\text{sonorant} \ +\text{voice}] \rightarrow [+\text{nasal}] / [+\text{nasal}]$
“nasalize” consonant next to a nasal, like “m”

observed data



	SINGULAR	PLURAL
BED	oron	oronnor
MARE	bie	bieler
CABINET	iskaap	iskaaptar

138 total examples

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stems (unobserved)

BED : oron
MARE : bie
CABINET : ıskAAP

	SINGULAR	PLURAL
BED	oron	oronnor
MARE	bie	bieler
CABINET	ıskAAP	ıskAAPtar

138 total examples

Turkic Sakha (Yakut)

grammar (unobserved)

SINGULAR→stem

PLURAL→stem+lar

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stems
(unobserved)

observed data

BED : oron

BEDS

Turkic Sakha (Yakut)

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PLURAL→stem+lar

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stems
(unobserved)

observed data

BED : oron

BEDS → oron+lar → oronlar

Turkic Sakha (Yakut)

grammar (unobserved)

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stems
(unobserved)

observed data

BED : oron

BEDS → oron+lar → oronlar → orondar

Turkic Sakha (Yakut)

grammar (unobserved)

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PLURAL→stem+lar

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$r_3: V \rightarrow [+ \text{rounded}] / [+ \text{rounded}] [- \text{low}]_0$

$r_4: [+ \text{continuant } -\text{high}] \rightarrow [- \text{rounded}] / u C_0$
“harmonize” round vowels like “u”, “o”

$r_5: V \rightarrow [-\text{back } -\text{low}] / [-\text{back } +\text{vowel}] []_0$
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“nasalize” consonant next to a nasal, like “m”

stems
(unobserved)

observed data

BED : oron

BEDS → oron+lar → oronlar → $\xrightarrow{r_1}$ orondar → $\xrightarrow{r_3}$ orondor

Turkic Sakha (Yakut)

grammar (unobserved)

SINGULAR→stem

PLURAL→stem+lar

$r_1: l \rightarrow d / [-\text{lateral } -\text{tense}]$
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“nasalize” consonant next to a nasal, like “m”

stems
(unobserved)

observed data

BED : oron

BEDS → oron+lar → oronlar → orondar → orondor → oronnor

Turkic Sakha (Yakut)

grammar (unobserved)

SINGULAR→stem
PLURAL→stem+lar

$r_1: l \rightarrow d / [\text{-lateral} \ \text{-tense}]_l$
“l” becomes “d” next to “r”, “t”, but not “l”

$r_2: C \rightarrow [\text{-voice}] / [\text{-voice}]_C$
do not voice next to voiceless

$r_3: V \rightarrow [\text{+rounded}] / [\text{+rounded}]_V$

$r_4: [\text{+continuant} \ \text{-high}] \rightarrow [\text{-rounded}] / u \ C_0$
“harmonize” round vowels like “u”, “o”

$r_5: V \rightarrow [\text{-back} \ \text{-low}] / [\text{-back} \ \text{+vowel}]_V$
“harmonize” vowels to be not at back of mouth

$r_6: [\text{-sonorant} \ \text{+voice}] \rightarrow [\text{+nasal}] / [\text{+nasal}]_C$
“nasalize” consonant next to a nasal, like “m”

stems
(unobserved)

BED : oron

MARE : bie

CABINET : ıskap

RIVER : örus

observed data

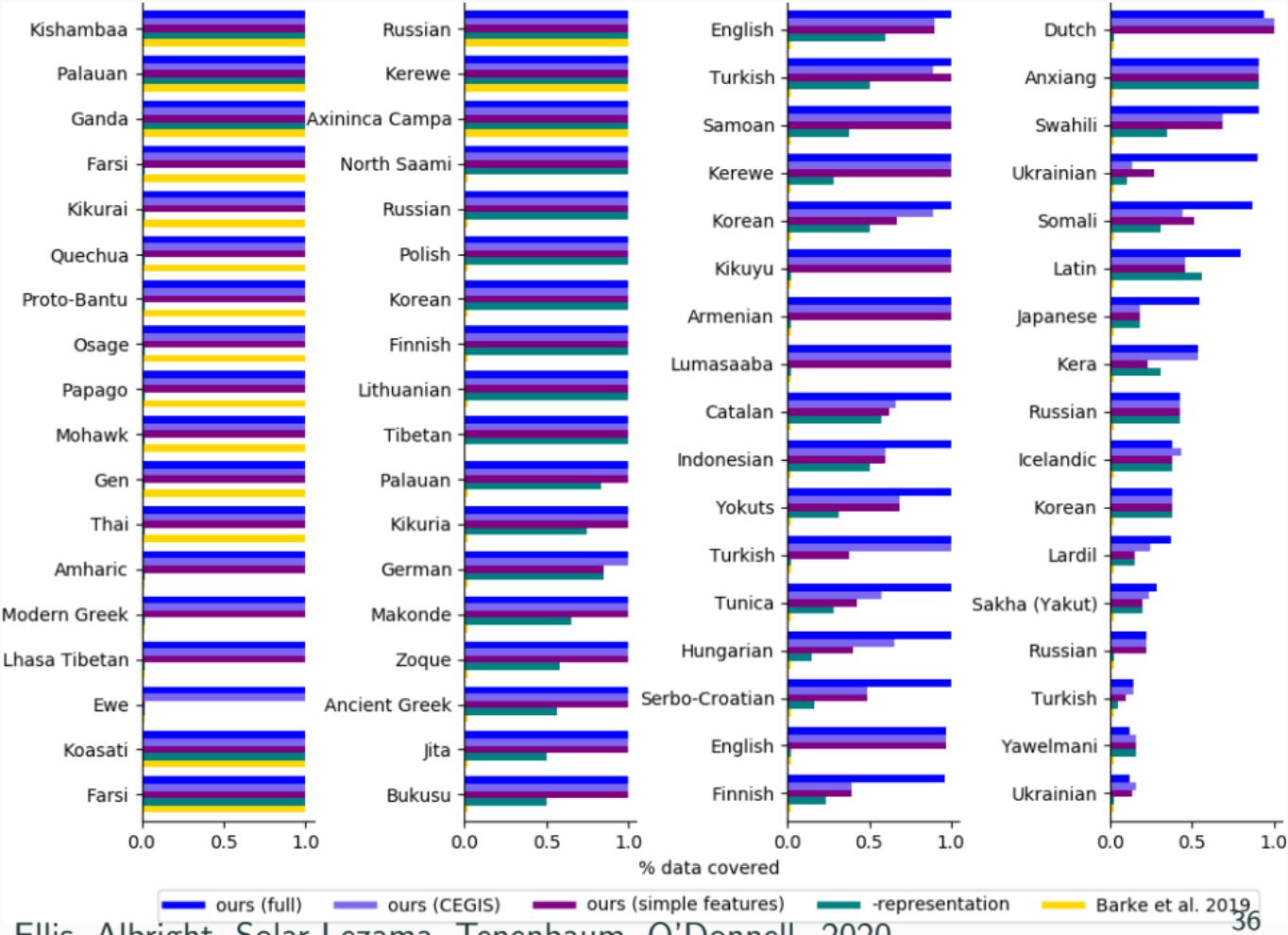
BEDS → oron+lar → oronlar $\xrightarrow{r_1}$ orondar $\xrightarrow{r_3}$ orondor $\xrightarrow{r_6}$ oronnor

MARES → bie+lar → bielar $\xrightarrow{r_5}$ bieler

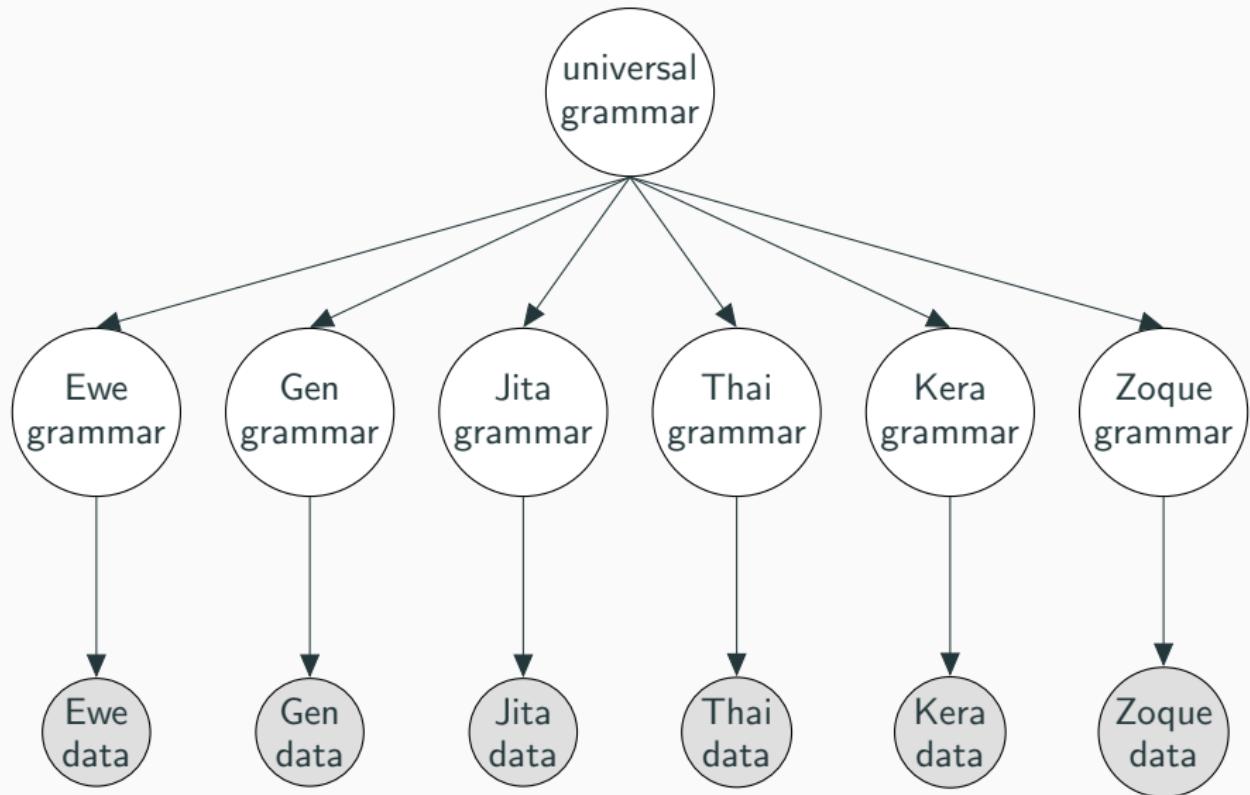
CABINETS → ıskap+lar → ıskaplar $\xrightarrow{r_1}$ ıskapdar $\xrightarrow{r_2}$ ıskaptar

RIVER (ASSOC) → örus+lİN → öruslüN $\xrightarrow{r_1}$ örusdüN $\xrightarrow{r_2}$
 $\xrightarrow{r_3}$ örustüN $\xrightarrow{r_5}$ örüstüün

Kishambaa	Russian	English	Dutch
Palauan	Kerewe	Turkish	Anxiang
Ganda	Axininca Campa	Samoan	Swahili
Farsi	North Saami	Kerewe	Ukrainian
Kikurai	Russian	Korean	Somali
Quechua	Polish	Kikuyu	Latin
Proto-Bantu	Korean	Armenian	Japanese
Osage	Finnish	Lumasaaba	Kera
Papago	Lithuanian	Catalan	Russian
Mohawk	Tibetan	Indonesian	Icelandic
Gen	Palauan	Yokuts	Korean
Thai	Kikuria	Turkish	Lardil
Amharic	German	Tunica	kha (Yakut)
Modern Greek	Makonde	Hungarian	Russian
Lhasa Tibetan	Zoque	Serbo-Croatian	Turkish
Ewe	Ancient Greek	English	Yawelmani
Koasati	Jita	Finnish	Ukrainian
Farsi	Bukusu		



Distilling higher-level knowledge



Lessons

Higher-level knowledge matters (“universal grammar”). Get the basics of the representation correct

But *some* of this higher-level knowledge can be learned. You don't need millions of examples to learn it. But it's not a one-shot learning problem either

Program Induction and perception
model discovery
learning to learn

Learning to write code

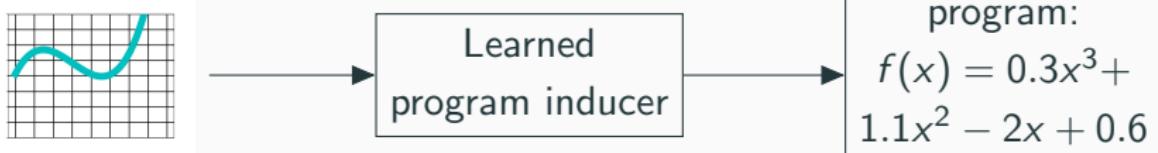
Goal: acquire domain-specific knowledge needed to induce a class of programs

- 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)



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]

...

Library learning

Initial Primitives

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⋮

Library learning

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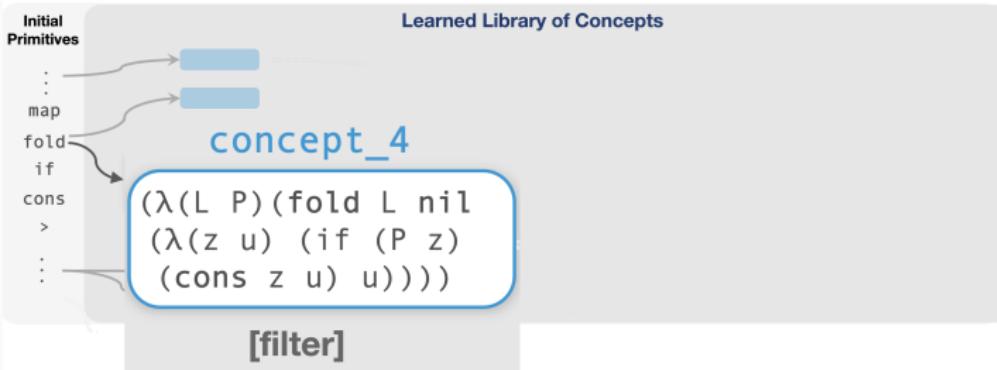
Library learning



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Library learning



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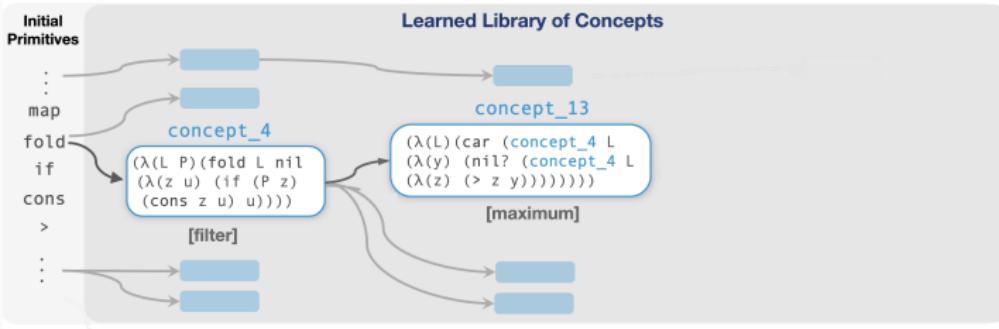
Library learning



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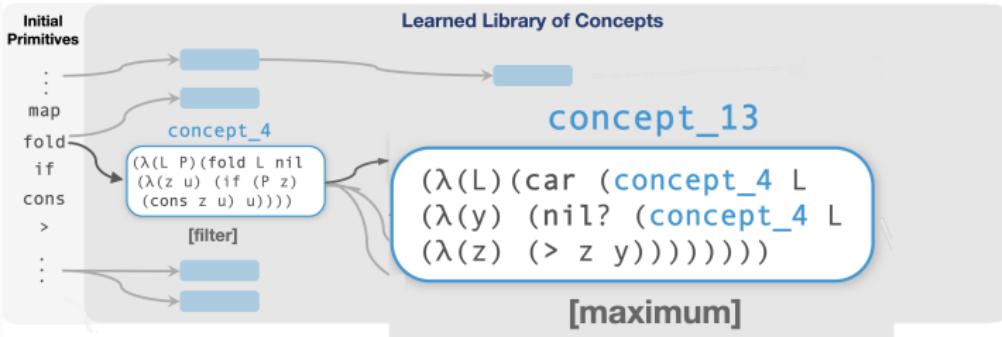
Library learning



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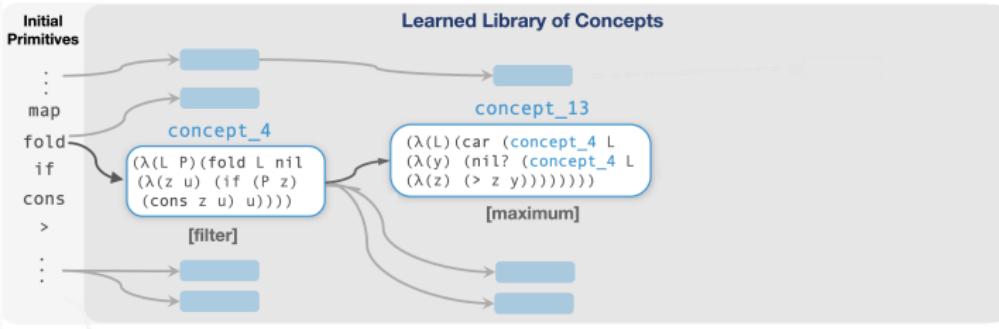
Library learning



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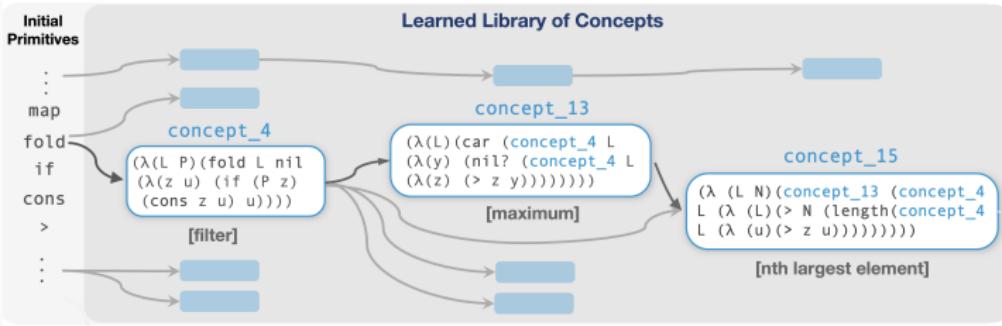
Library learning



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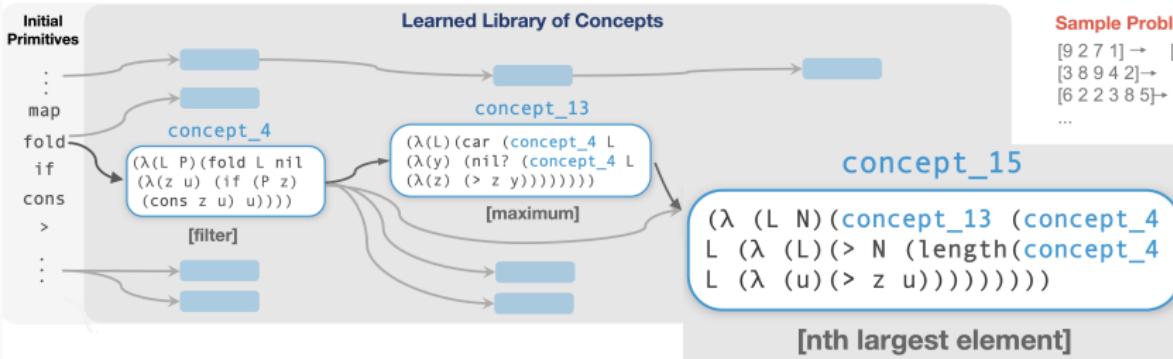
Library learning



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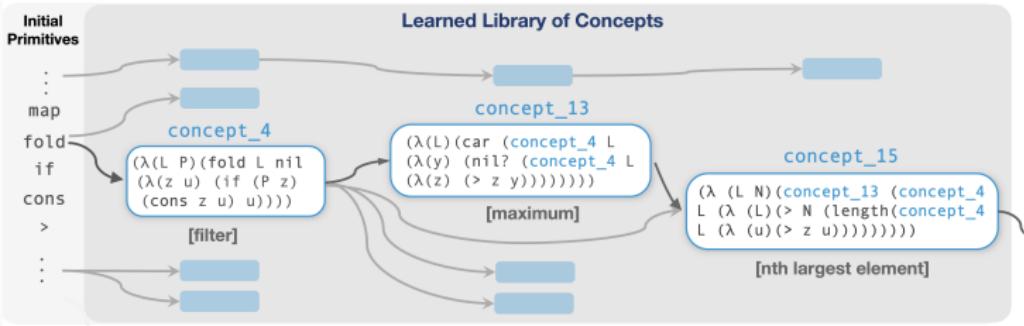
Library learning



Sample Problem: sort list

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Library learning



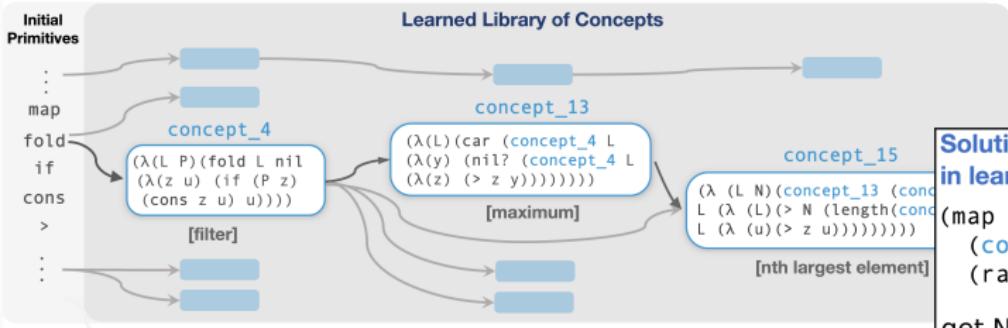
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Solution to sort list discovered in learned language:

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

Library learning



Sample Problem: sort list

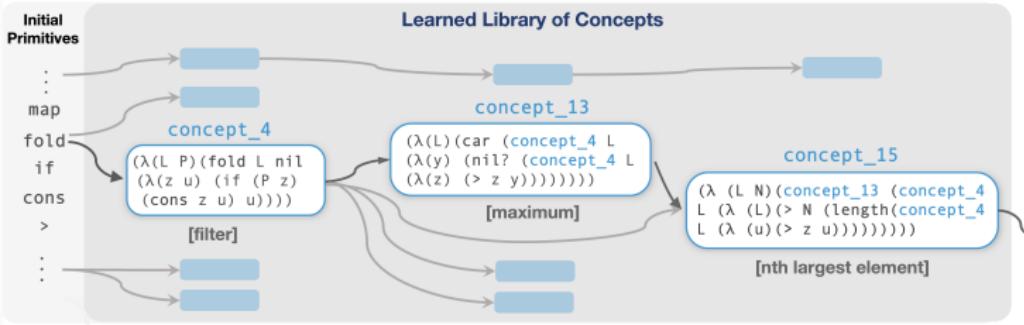
$$\begin{array}{l} [9\ 2\ 7\ 1] \rightarrow [1\ 2\ 7\ 9] \\ [3\ 8\ 9\ 4\ 2] \rightarrow [2\ 3\ 4\ 8\ 9] \\ [6\ 2\ 2\ 3\ 8\ 5] \rightarrow [2\ 2\ 3\ 5\ 6\ 8] \\ \dots \end{array}$$

Solution to sort list discovered
in learned language:

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(map  (λ (n)
  (concept_15 L (+ 1 n)))
  (range (length L)))
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get Nth largest element,
where N is 1, 2, 3, ...

Library learning



Sample Problem: sort list

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Solution to sort list discovered in learned language:

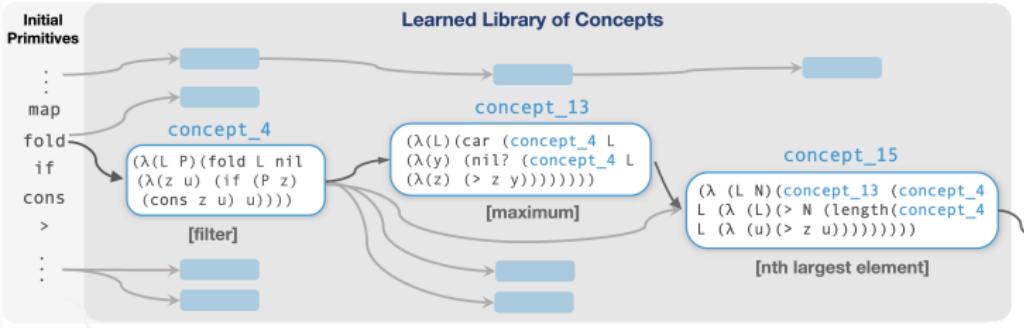
```
(map (λ (n)
  (concept_15 L (+ 1 n)))
  (range (length L)))
```

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where N is 1, 2, 3, ...

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))))
```

Library learning



Sample Problem: sort list

$[9 2 7 1] \rightarrow [1 2 7 9]$
 $[3 8 9 4 2] \rightarrow [2 3 4 8 9]$
 $[6 2 2 3 8 5] \rightarrow [2 2 3 5 6 8]$
...

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, ...

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

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

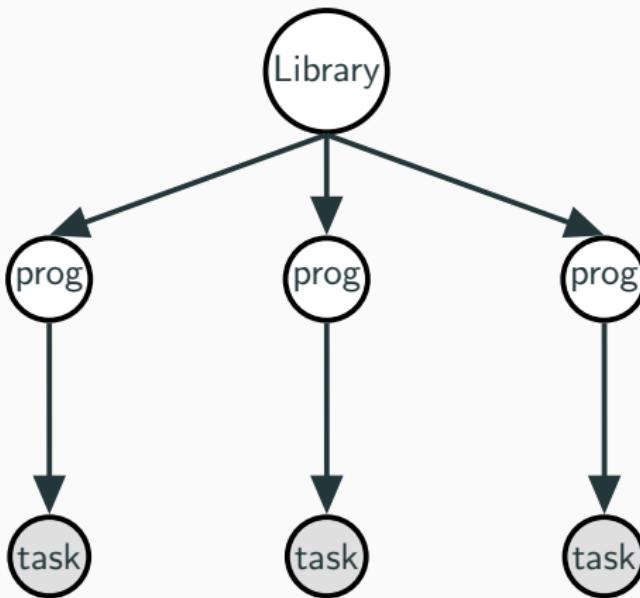
- **Wake:** Solve problems by writing programs
- **Sleep:** Improve library and neural recognition model:
 - **Abstraction sleep:** Improve library
 - **Dream sleep:** Improve neural recognition model



List Processing	Text Editing	Regexes		
Sum List $[1\ 2\ 3] \rightarrow 6$ $[4\ 6\ 8\ 1] \rightarrow 17$	Abbreviate Allen Newell → A.N. Herb Simon → H.S.	Phone numbers (555) 867-5309 (650) 555-2368		
Double $[1\ 2\ 3] \rightarrow [2\ 4\ 6]$ $[4\ 5\ 1] \rightarrow [8\ 10\ 2]$	Drop Last Three shrdlu → shr shakey → sha	Currency \$100.25 \$4.50		
Block Towers 	Symbolic Regression $y = f(x)$	Recursive Programming Filter Red $[\text{red red blue}] \rightarrow [\text{blue}]$ $[\text{red green blue}] \rightarrow [\text{green blue}]$ $[\text{red black red}] \rightarrow [\text{black blue}]$	Physical Laws $\vec{a} = \frac{1}{m} \sum_i \vec{F}_i$ $\vec{F} \propto \frac{q_1 q_2}{ \vec{r} ^2} \hat{r}$	LOGO Graphics

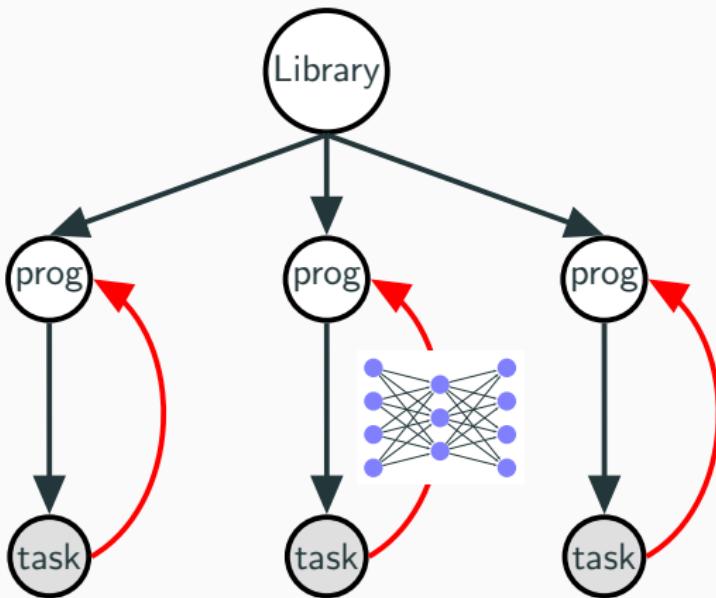
cf. Helmholtz machine, wake/sleep neural network training algorithms

Library learning as Bayesian inference

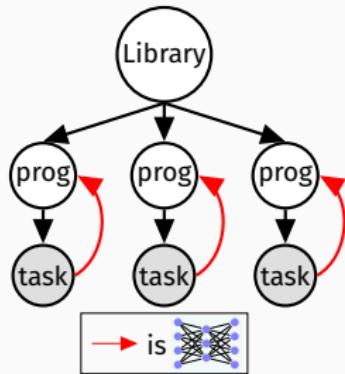


[Dechter et al, 2013] [Liang et al, 2010] [Lake et al, 2015]

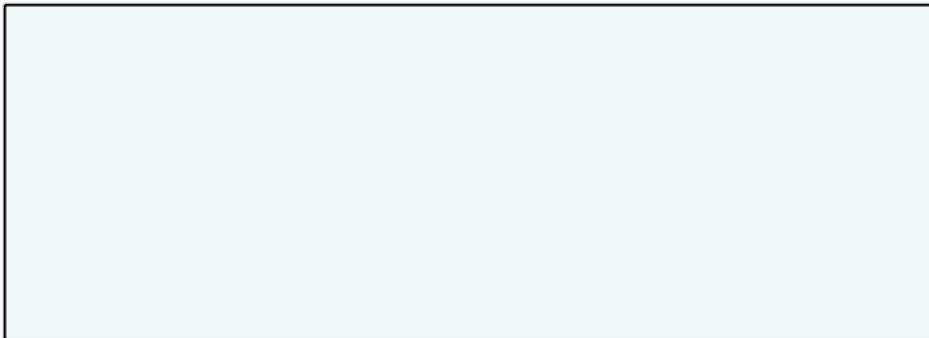
Library learning as neurally-guided Bayesian inference



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

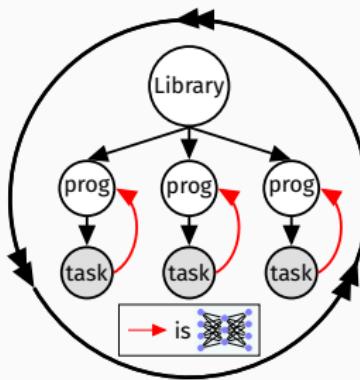


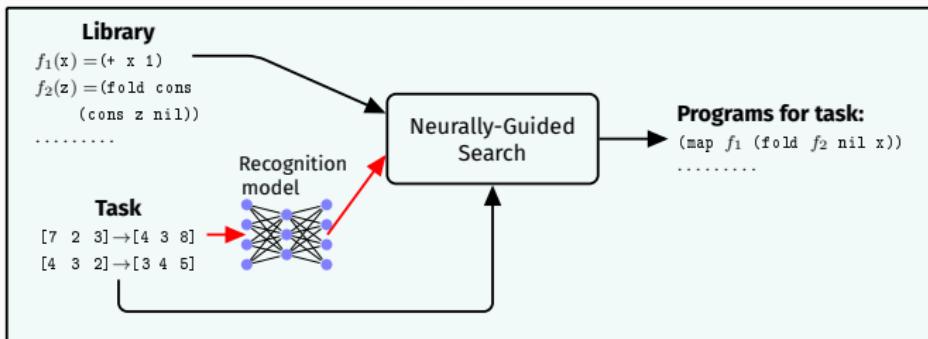
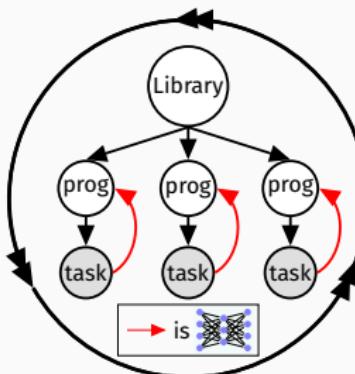
WAKE

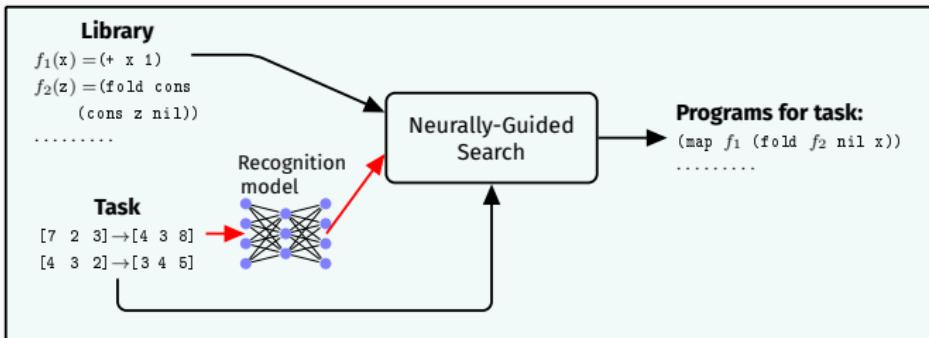
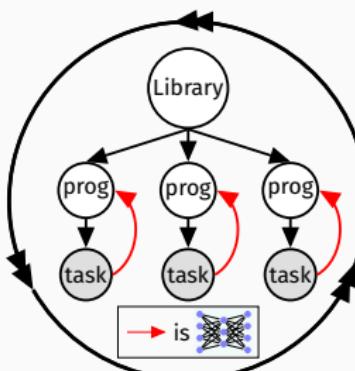
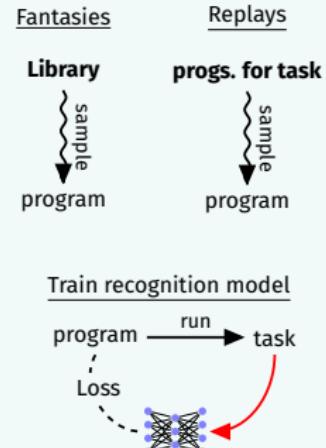


SLEEP: ABSTRACTION

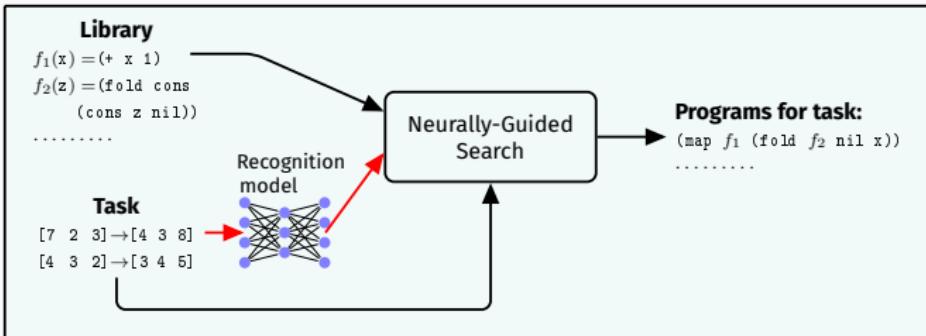
SLEEP: DREAMING



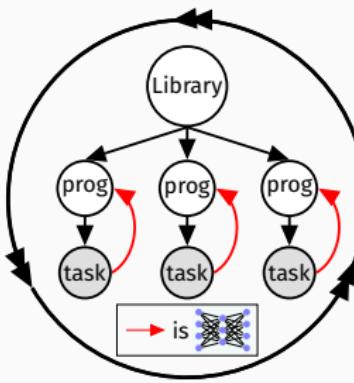
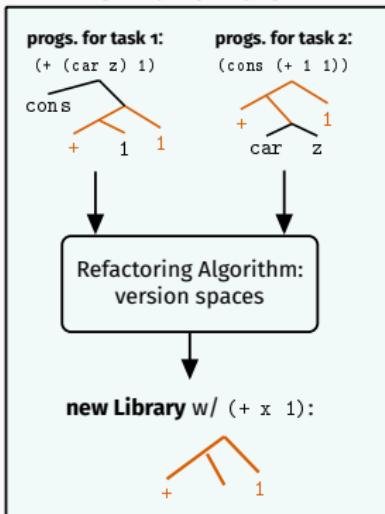
WAKE**SLEEP: ABSTRACTION****SLEEP: DREAMING**

WAKE**SLEEP: ABSTRACTION****SLEEP: DREAMING**

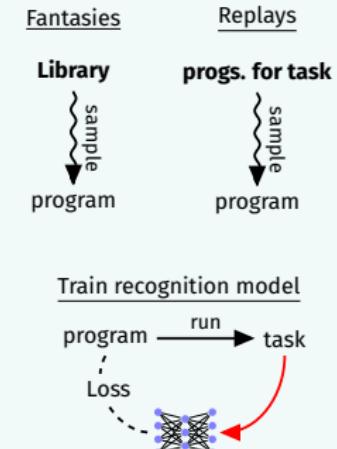
WAKE



SLEEP: ABSTRACTION



SLEEP: DREAMING



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

$5 + 5$

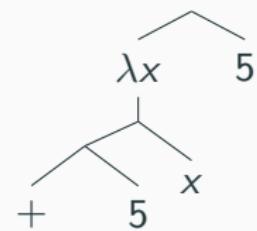
(+ 5 5)



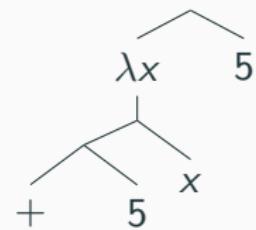
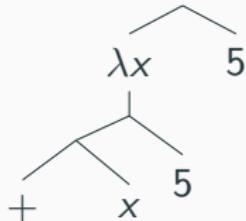
Abstraction Sleep: Growing the library via refactoring



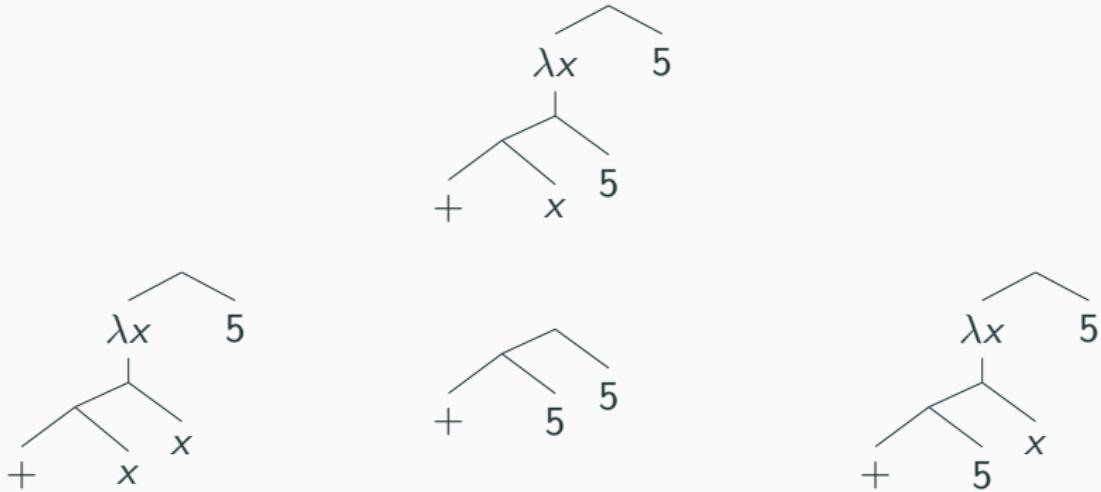
Abstraction Sleep: Growing the library via refactoring



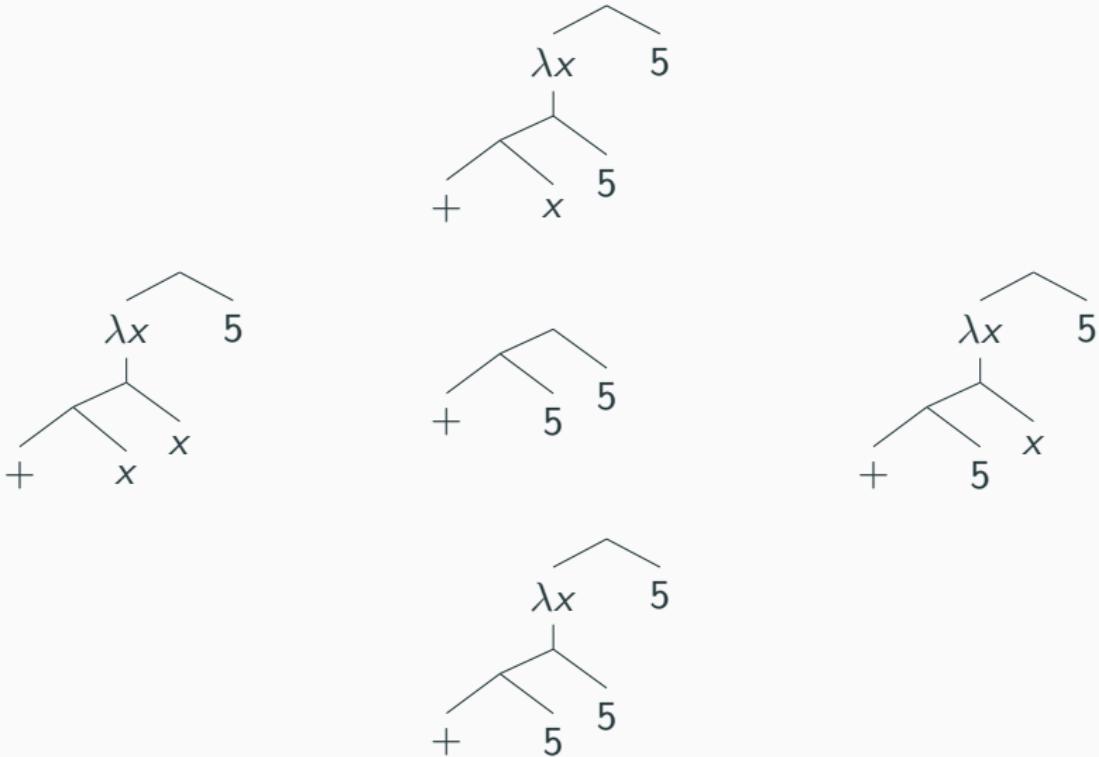
Abstraction Sleep: Growing the library via refactoring



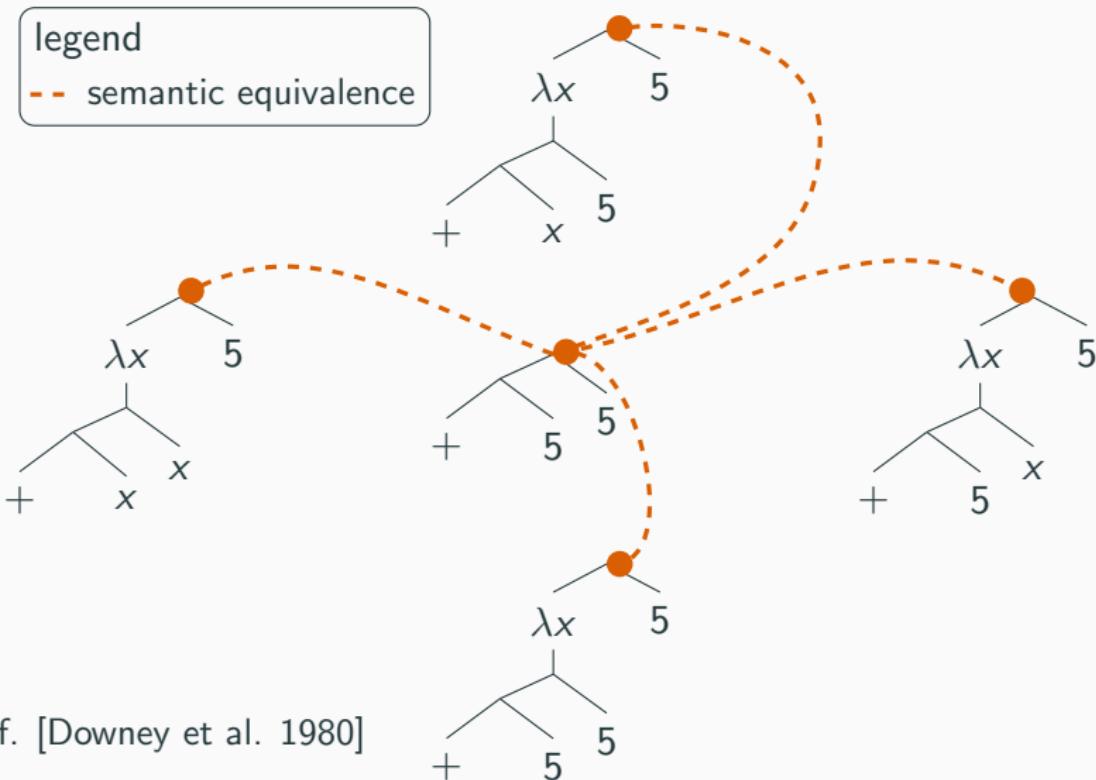
Abstraction Sleep: Growing the library via refactoring



Abstraction Sleep: Growing the library via refactoring



Abstraction Sleep: Growing the library via refactoring

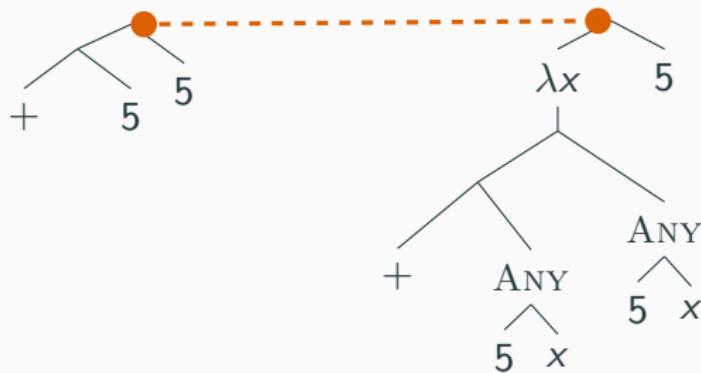


Abstraction Sleep: Growing the library via refactoring

legend

semantic equivalence

ANY nondeterministic choice



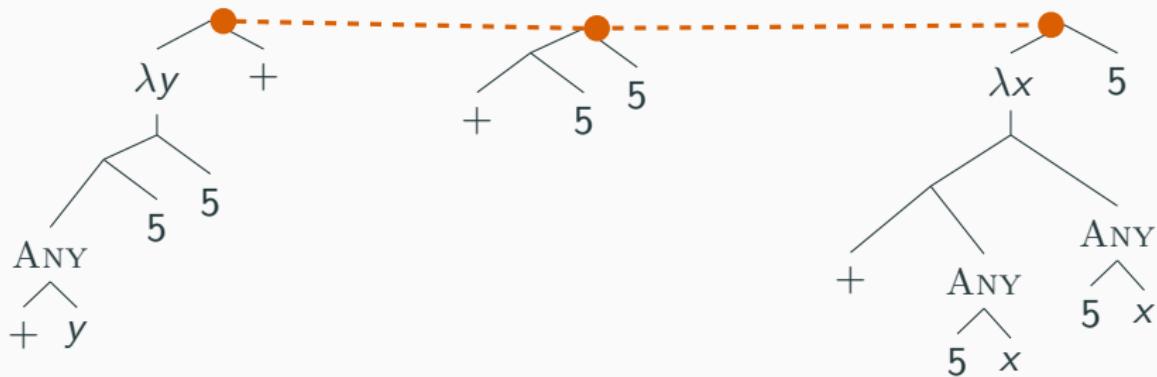
cf. [Gulwani 2012]

Abstraction Sleep: Growing the library via refactoring

legend

semantic equivalence

ANY nondeterministic choice

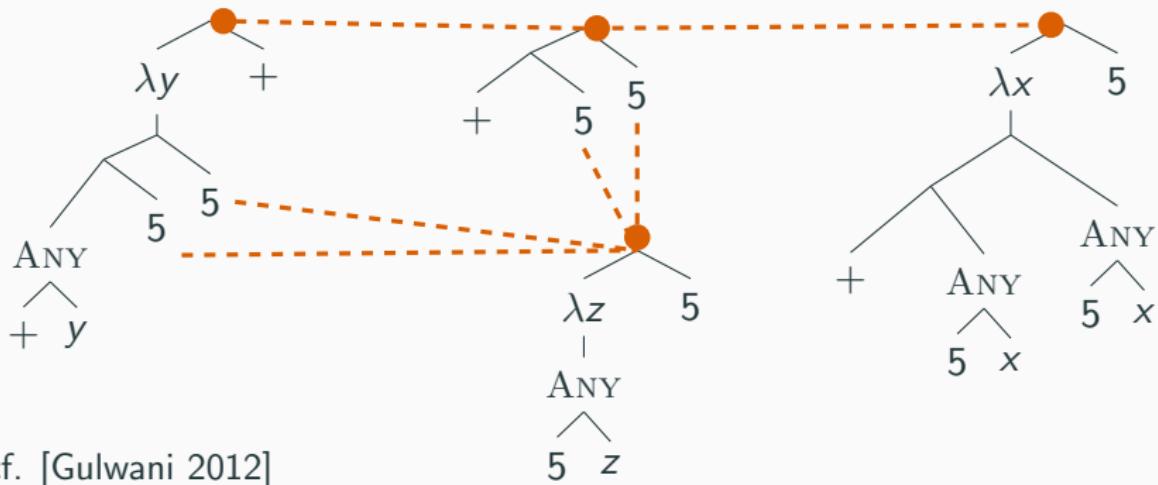


cf. [Gulwani 2012]

Abstraction Sleep: Growing the library via refactoring

legend

- semantic equivalence
- ANY nondeterministic choice

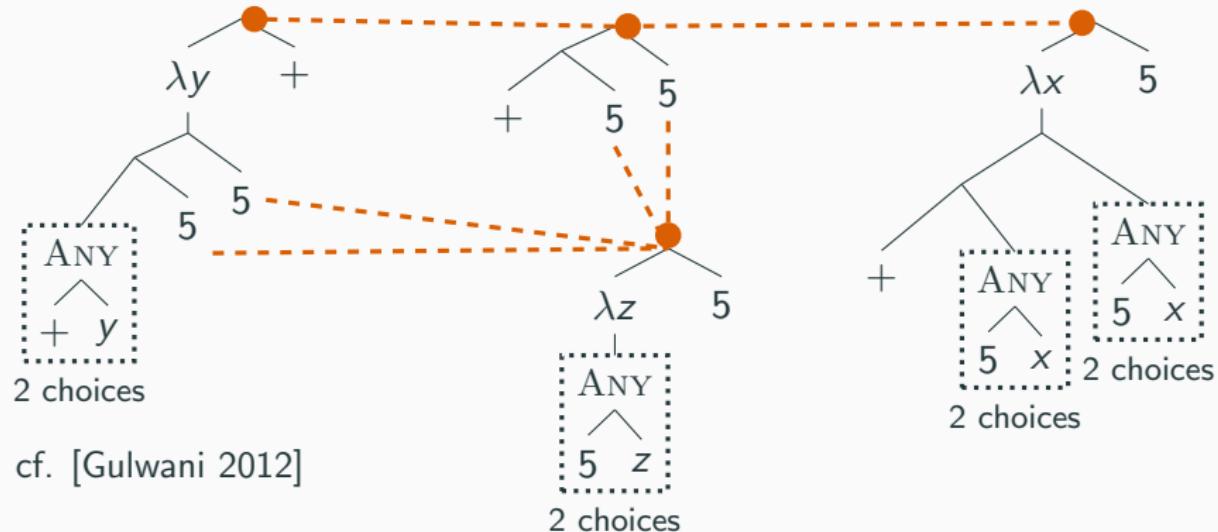


Abstraction Sleep: Growing the library via refactoring

legend

dashed orange line semantic equivalence

ANY nondeterministic choice



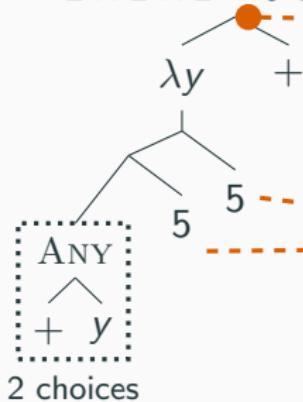
cf. [Gulwani 2012]

Abstraction Sleep: Growing the library via refactoring

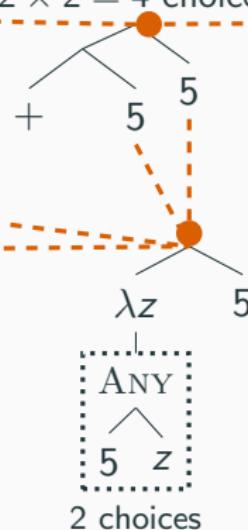
legend

- semantic equivalence
- ANY nondeterministic choice

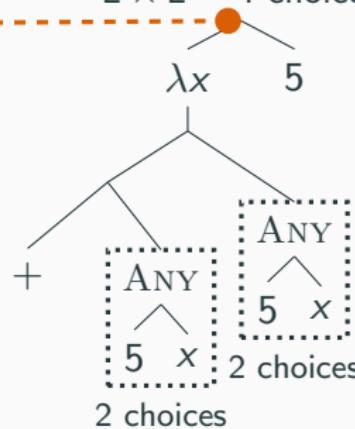
$2 \times 2 \times 2 = 8$ choices



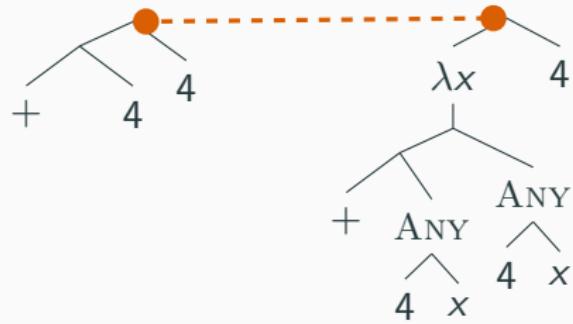
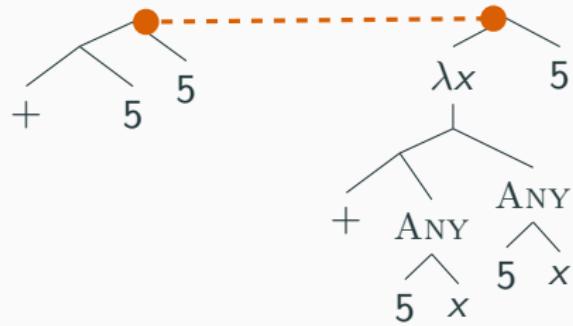
$2 \times 2 = 4$ choices



$2 \times 2 = 4$ choices



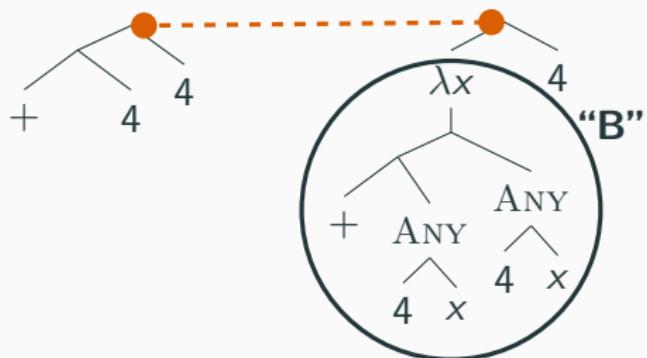
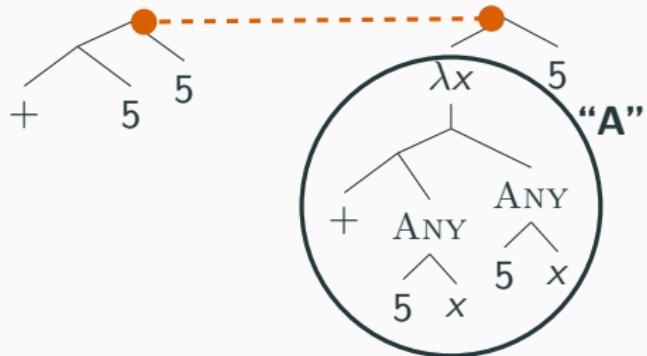
cf. [Gulwani 2012]



legend

— semantic equivalence

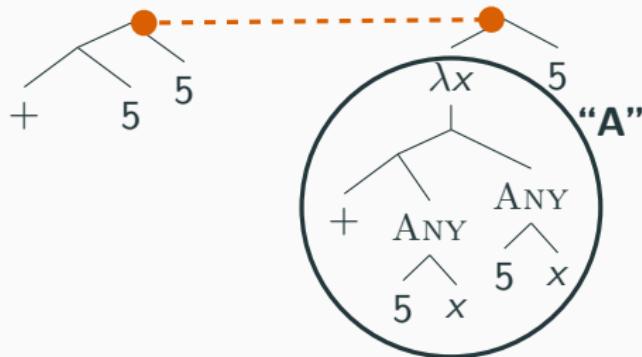
ANY nondeterministic choice



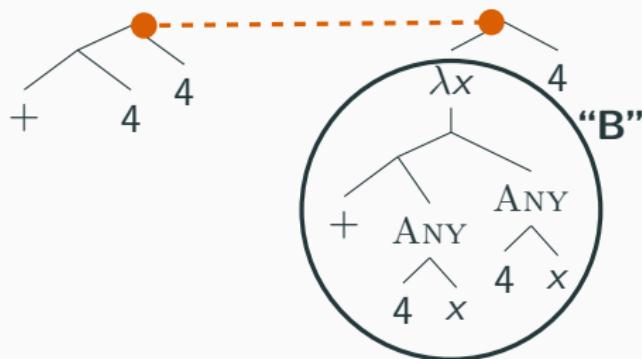
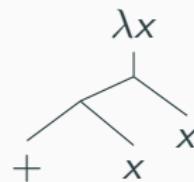
legend

— dashed orange line semantic equivalence

ANY nondeterministic choice



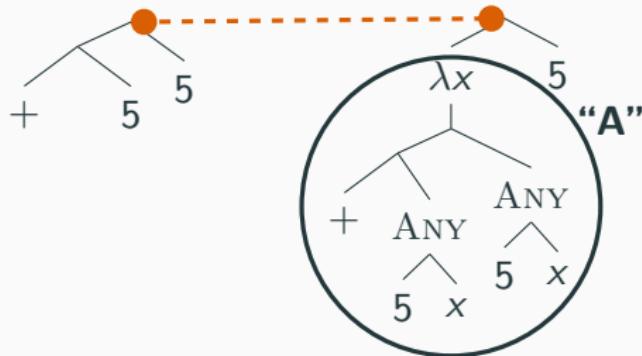
A intersect B:



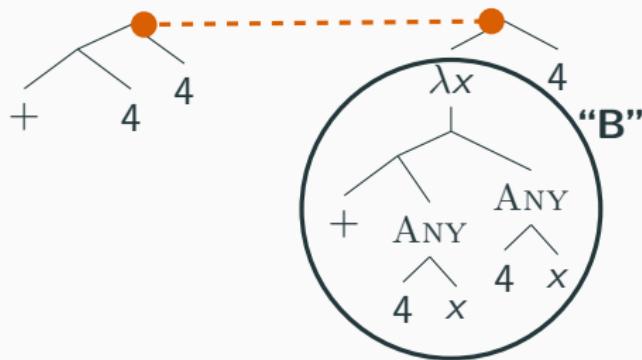
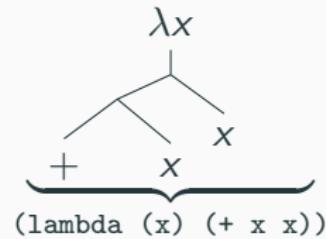
legend

— semantic equivalence

ANY nondeterministic choice



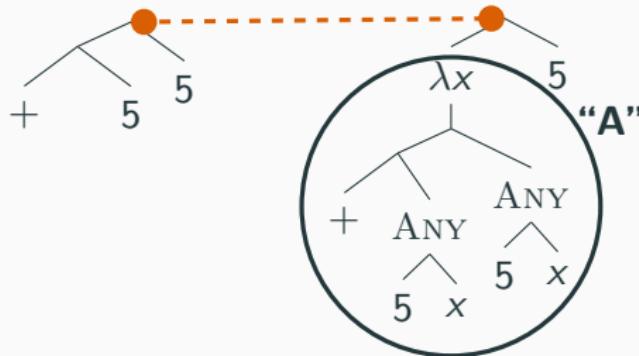
A intersect B:



legend

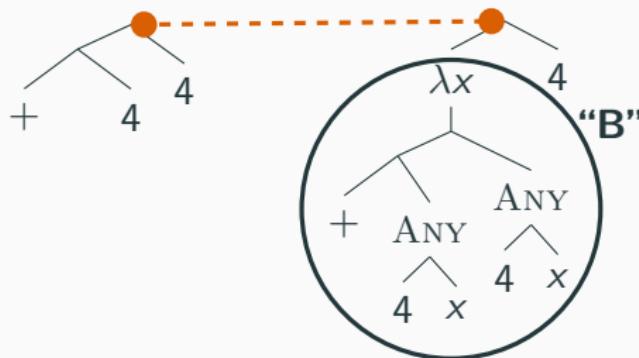
— semantic equivalence

ANY nondeterministic choice



A intersect B:

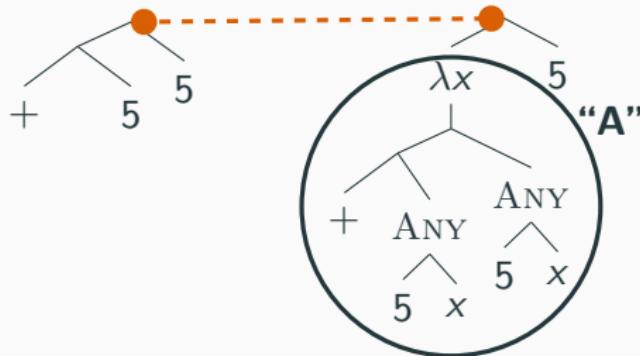
λx
 + x
 (lambda (x) (+ x x))
 = double



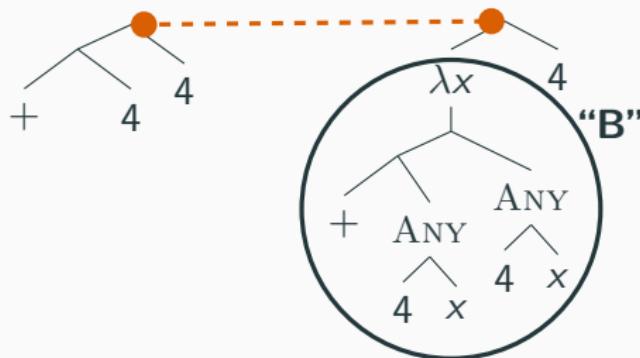
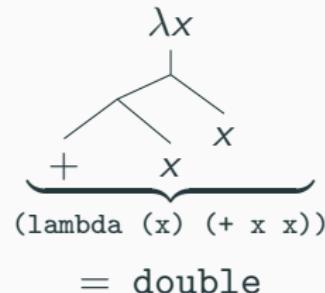
legend

— dashed orange line semantic equivalence

ANY nondeterministic choice



A intersect B:



w/o double	w/ double
$(+ 5 5)$	$(\text{double } 5)$
$(+ 4 4)$	$(\text{double } 4)$
$(+ 3 3)$	$(\text{double } 3)$
...	

legend

— semantic equivalence
ANY nondeterministic choice

Abstraction Sleep: Growing the library via refactoring

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

Wake: program search

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

Task: $[1\ 2\ 3] \rightarrow [0\ 1\ 2]$
 $[4\ 3\ 4] \rightarrow [3\ 2\ 3]$

Wake: program search

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

Abstraction Sleep: Growing the library via refactoring

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

Wake: program search

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

Task: $[1\ 2\ 3] \rightarrow [0\ 1\ 2]$
 $[4\ 3\ 4] \rightarrow [3\ 2\ 3]$

Wake: program search

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

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)))
```

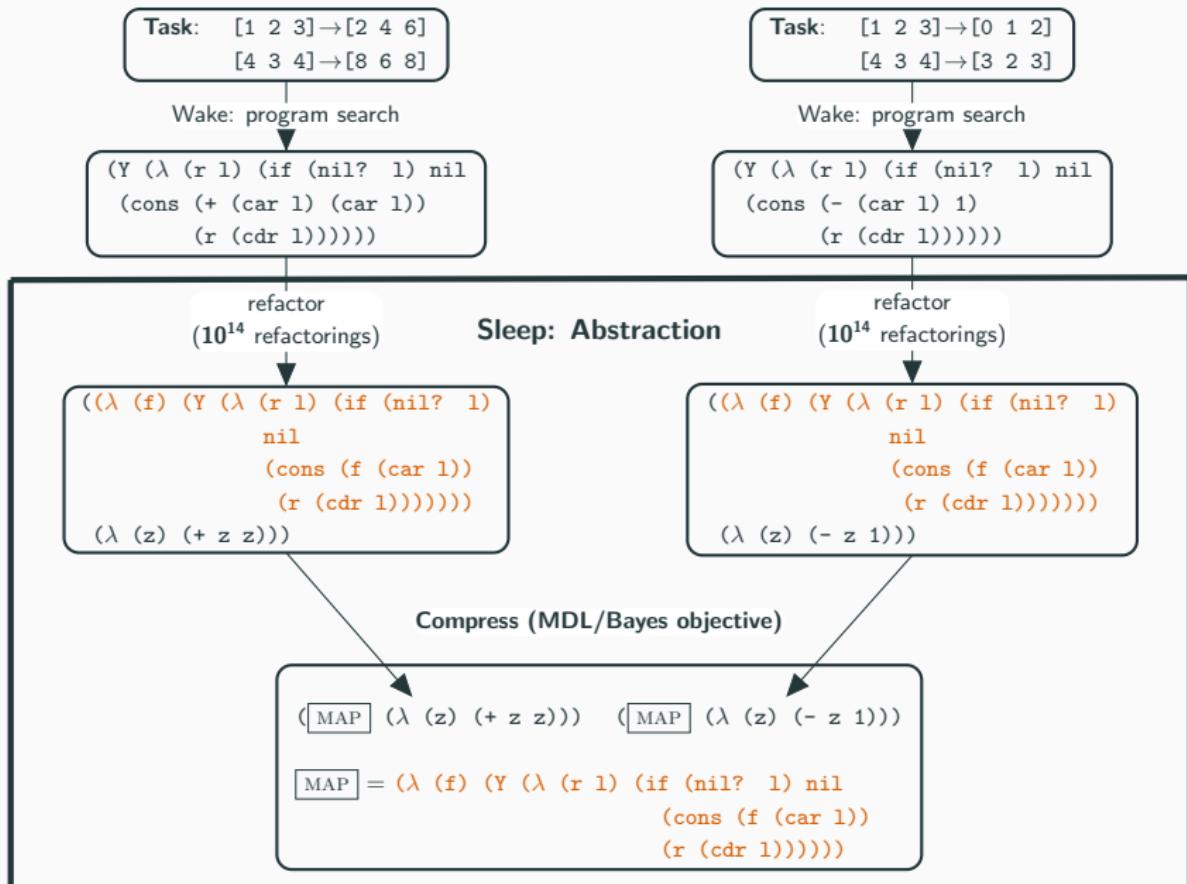
Sleep: Abstraction

refactor

$(10^{14}$ refactorings)

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

Abstraction Sleep: Growing the library via refactoring



Abstraction Sleep: Growing the library via refactoring

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

Wake: program search

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

Task: $[1\ 2\ 3] \rightarrow [0\ 1\ 2]$
 $[4\ 3\ 4] \rightarrow [3\ 2\ 3]$

Wake: program search

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

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

$(\lambda (z) (+ z z))$

$(\lambda (z) (- z 1))$

Compress (MDL/Bayes objective)

$(\boxed{\text{MAP}} (\lambda (z) (+ z z))) \quad (\boxed{\text{MAP}} (\lambda (z) (- z 1)))$

$\boxed{\text{MAP}} = (\lambda (f) (Y (\lambda (r 1) (if (nil? 1) nil
 (cons (f (car 1))
 (r (cdr 1)))))))$

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

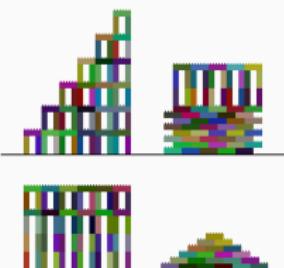
\$100.25

\$4.50

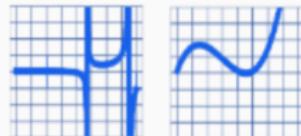
LOGO Graphics



Block Towers



Symbolic Regression



$$y = f(x)$$

Recursive Programming

Filter Red

[■ ■ ■ ■ ■] → [■ ■ ■]

[■ ■ ■ ■ ■ ■] → [■ ■ ■ ■ ■]

[■ ■ ■ ■ ■ ■] → [■ ■ ■ ■]

Physical Laws

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

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

DreamCoder Domains

List Processing

Sum List

[1 2 3] → 6

[4 6 8 1] → 17

Double

[1 2 3] → [2 4 6]

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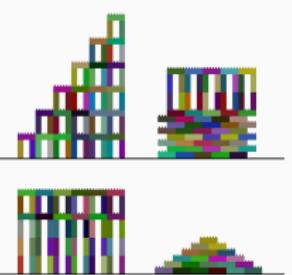
\$100.25

\$4.50

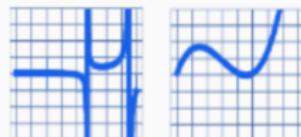
LOGO Graphics



Block Towers



Symbolic Regression



$$y = f(x)$$

Recursive Programming

Filter Red

[■■■■■■■■] → [■■■■■■■■]

[■■■■■■■■■■] → [■■■■■■■■■■]

[■■■■■■■■■■■■] → [■■■■■■■■■■■■]

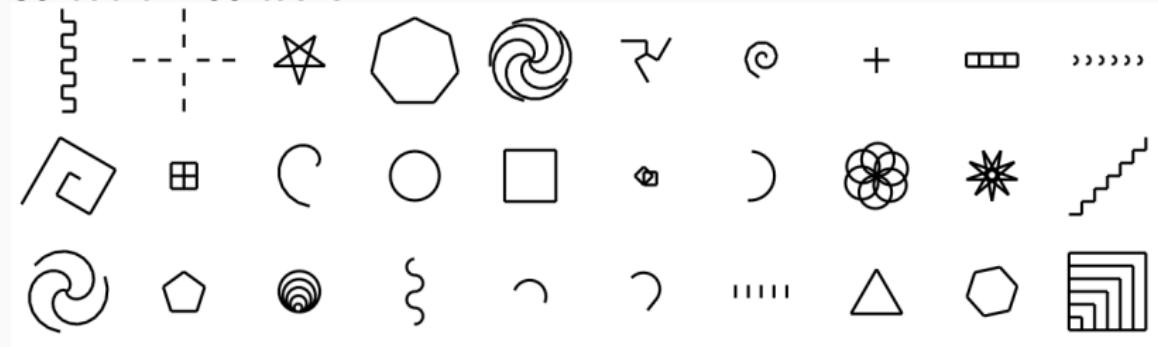
Physical Laws

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

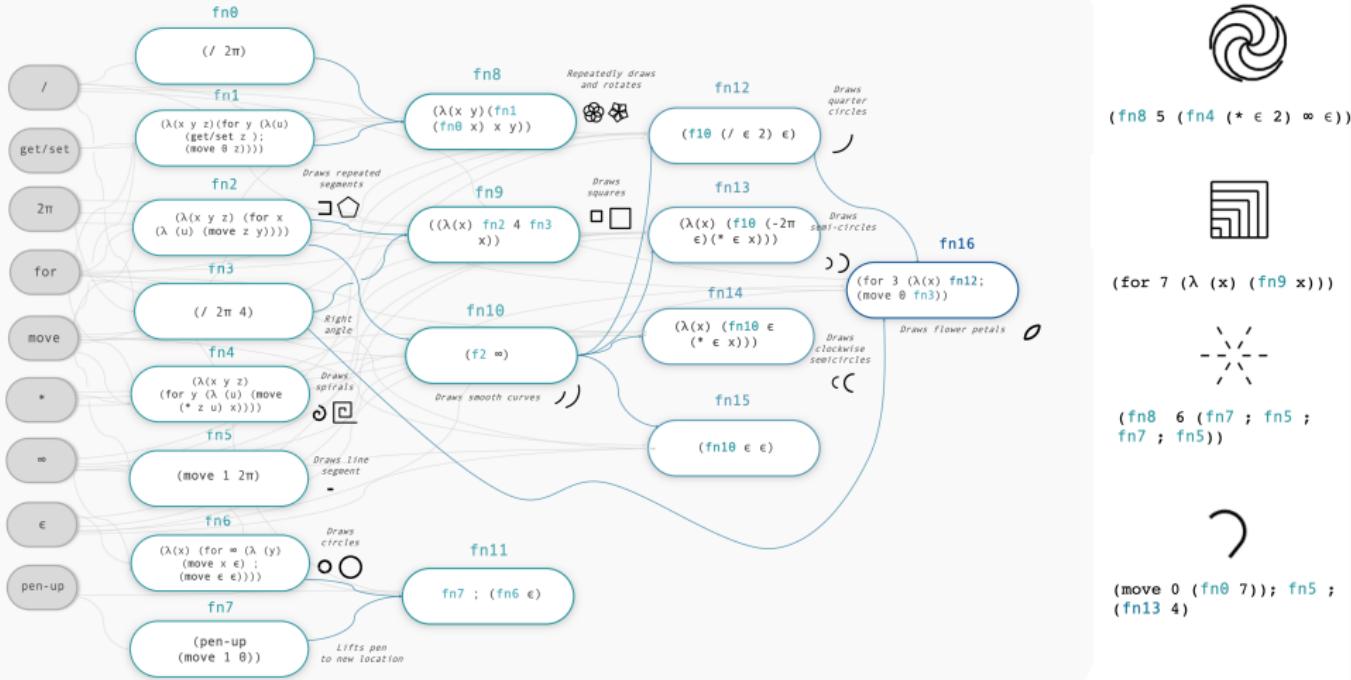
$$\vec{F} \propto \frac{q_1 q_2}{|\vec{r}|^2} \hat{r}$$

LOGO Turtle Graphics

30 out of 160 tasks



LOGO Turtle Graphics – learning an interpretable library



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



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

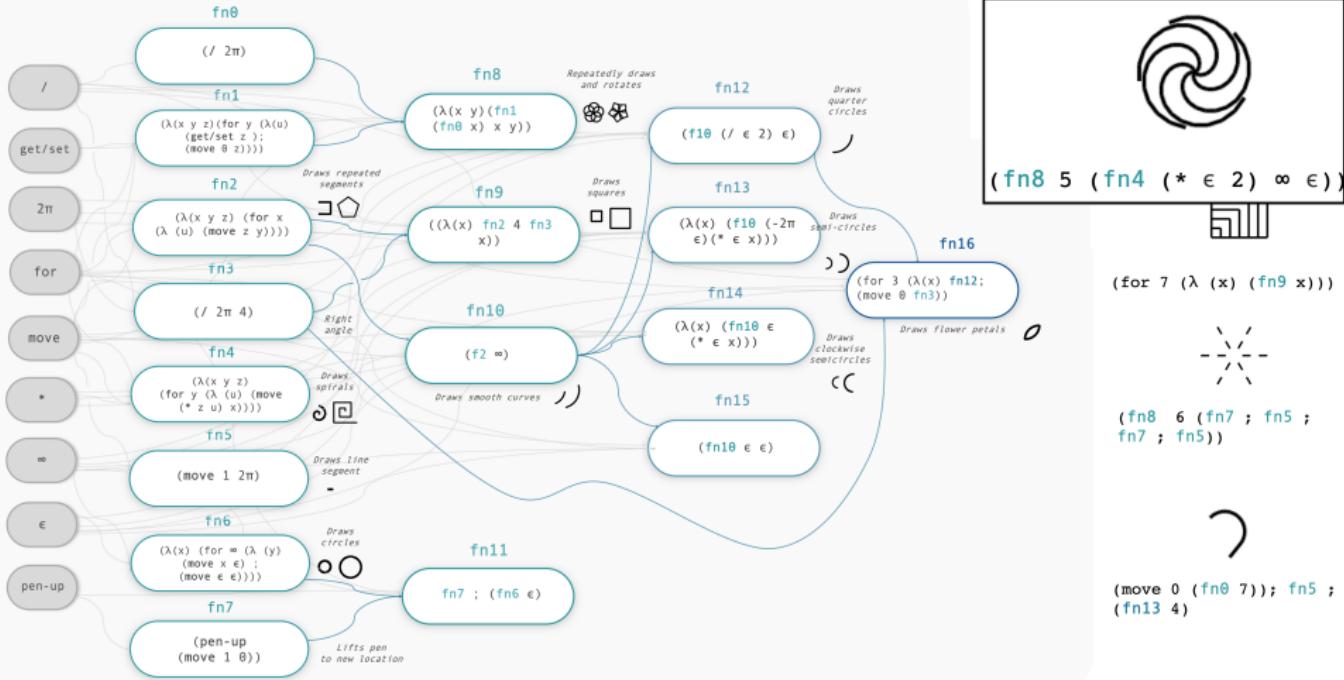


$(\text{fn8}\ 6\ (\text{fn7}\ ;\ \text{fn5}\ ;\ \text{fn7}\ ;\ \text{fn5}))$

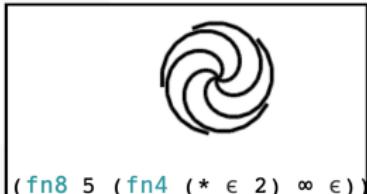
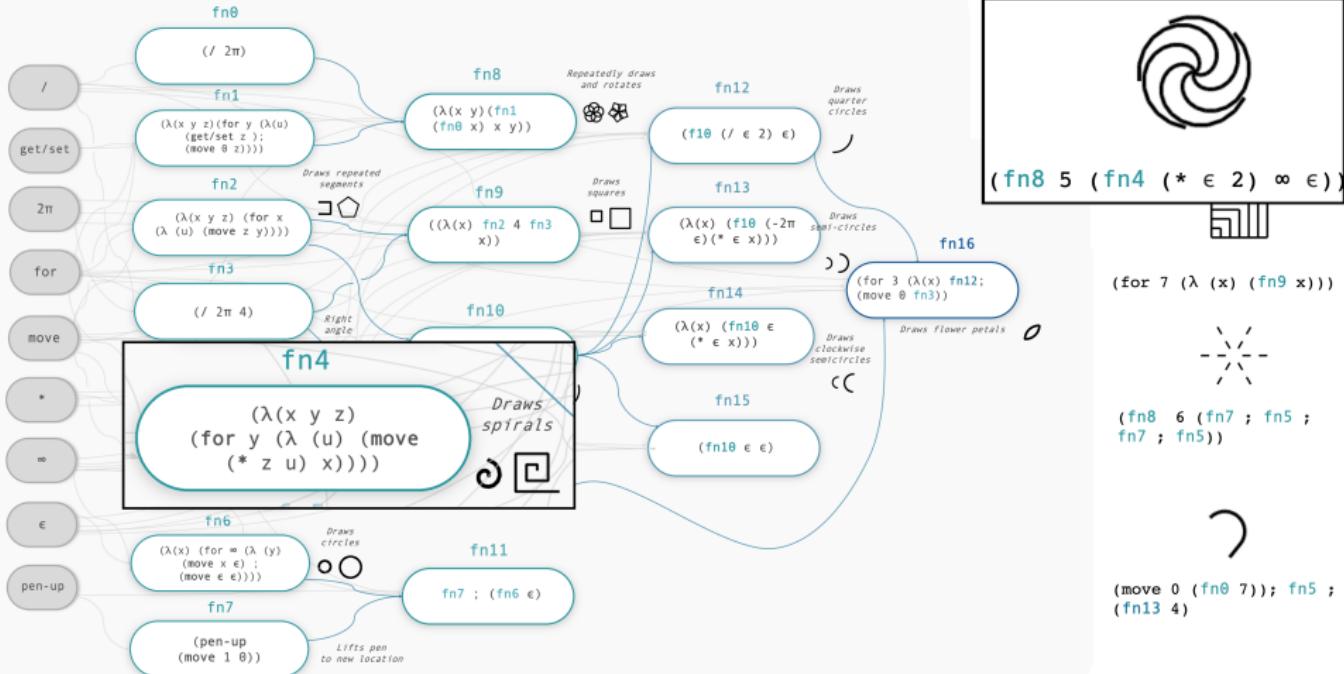


$(\text{move}\ 0\ (\text{fn0}\ 7));\ \text{fn5}\ ;\ (\text{fn13}\ 4)$

LOGO Turtle Graphics – learning an interpretable library



LOGO Turtle Graphics – learning an interpretable library



```
(fn8 5 (fn4 (* ε 2) ∞ ε))
```



```
(for 7 (λ (x) (fn9 x)))
```

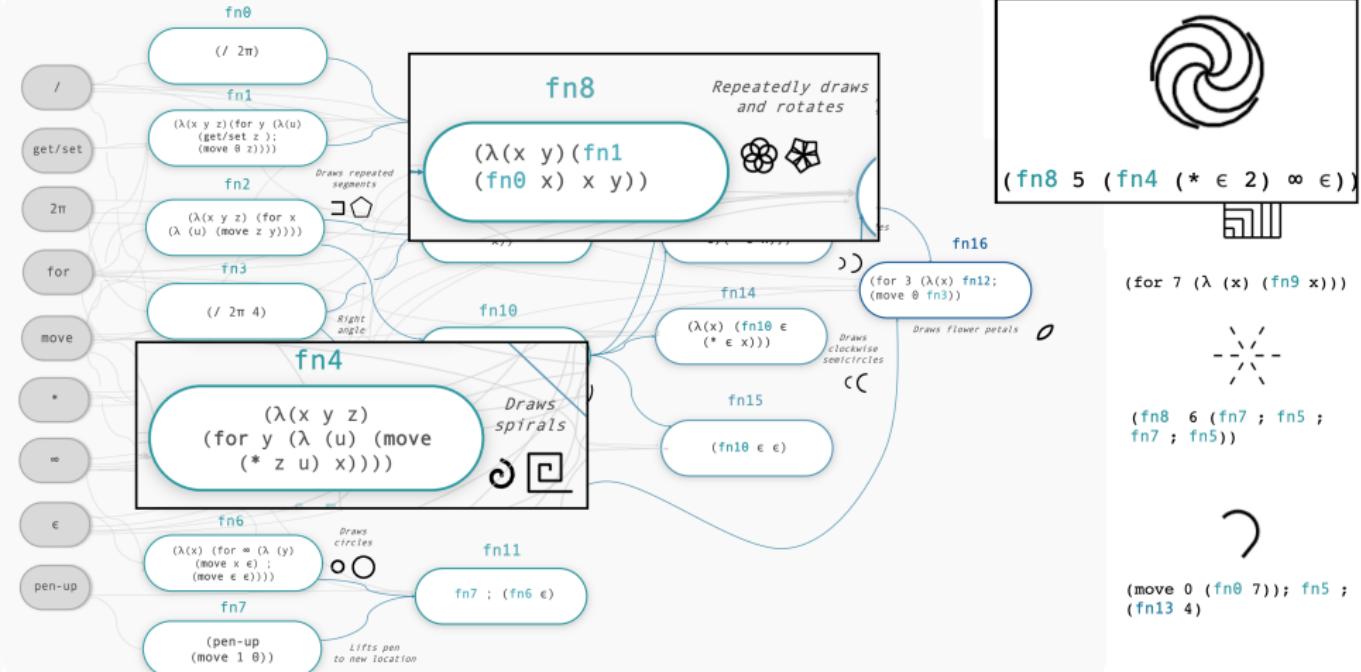


```
(fn8 6 (fn7 ; fn5 ; fn7 ; fn5))
```

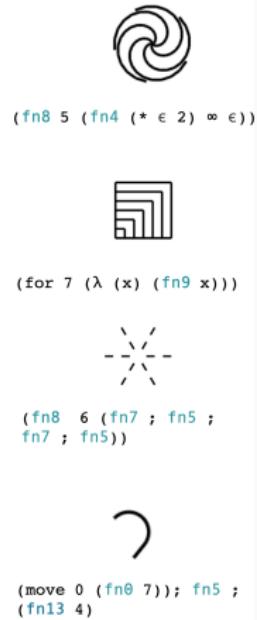
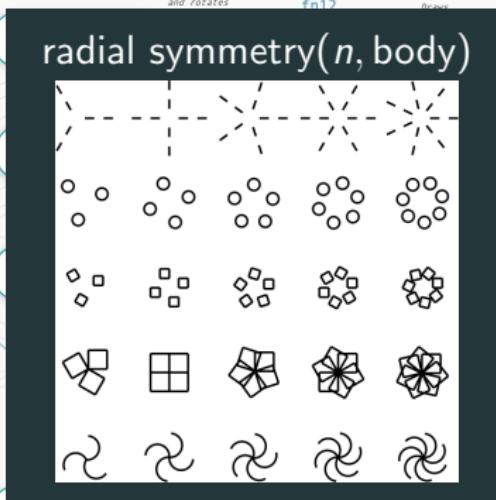
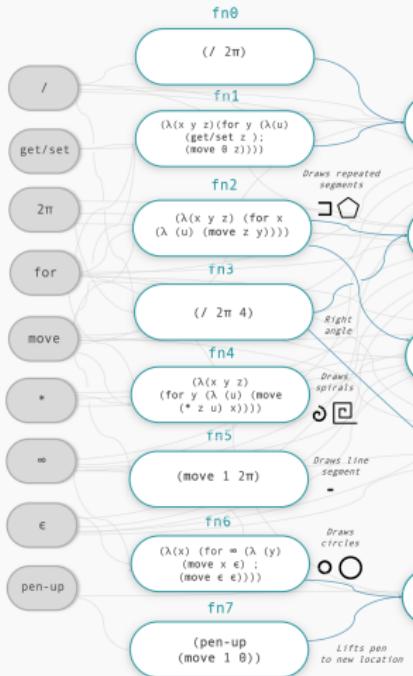


```
(move 0 (fn0 7)); fn5 ;  
(fn13 4)
```

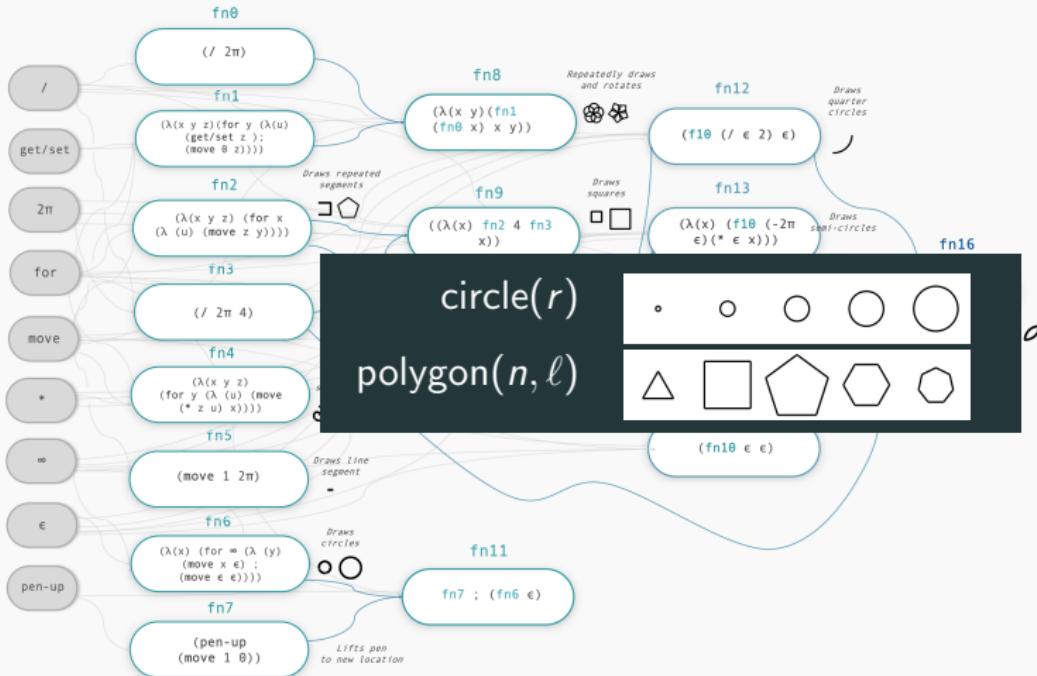
LOGO Turtle Graphics – learning an interpretable library



LOGO Turtle Graphics – learning an interpretable library



LOGO Turtle Graphics – learning an interpretable library



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



```
(for 7 (λ (x) (fn9 x)))
```

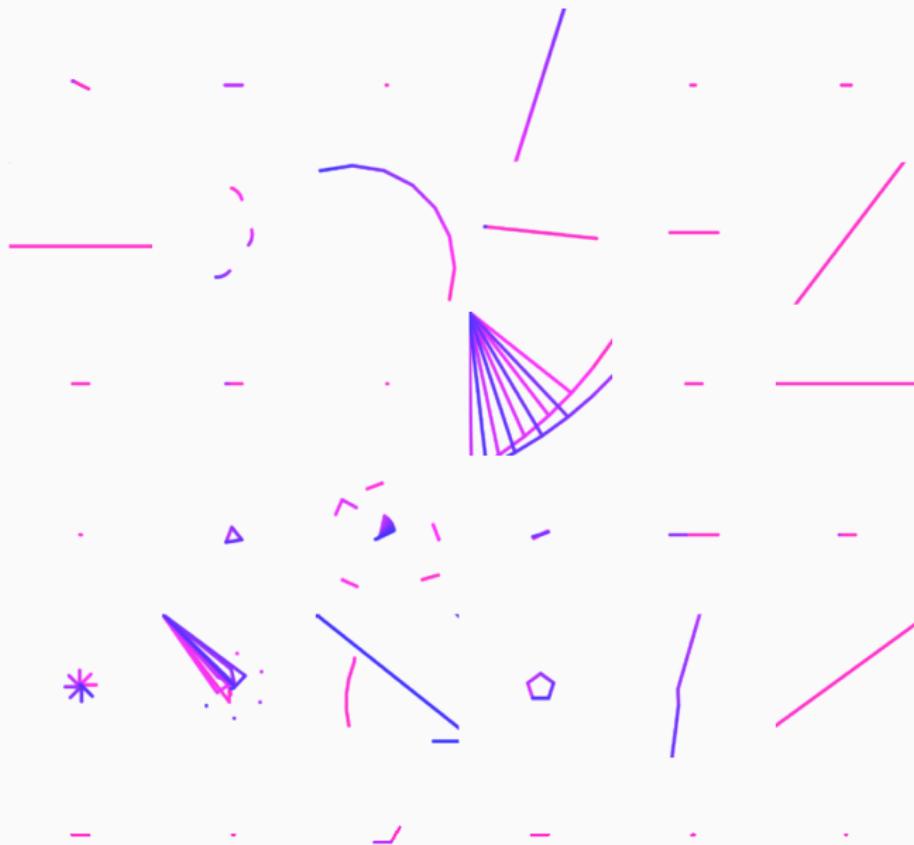


(fn8 6 (fn7 ; fn5 ;
fn7 ; fn5))

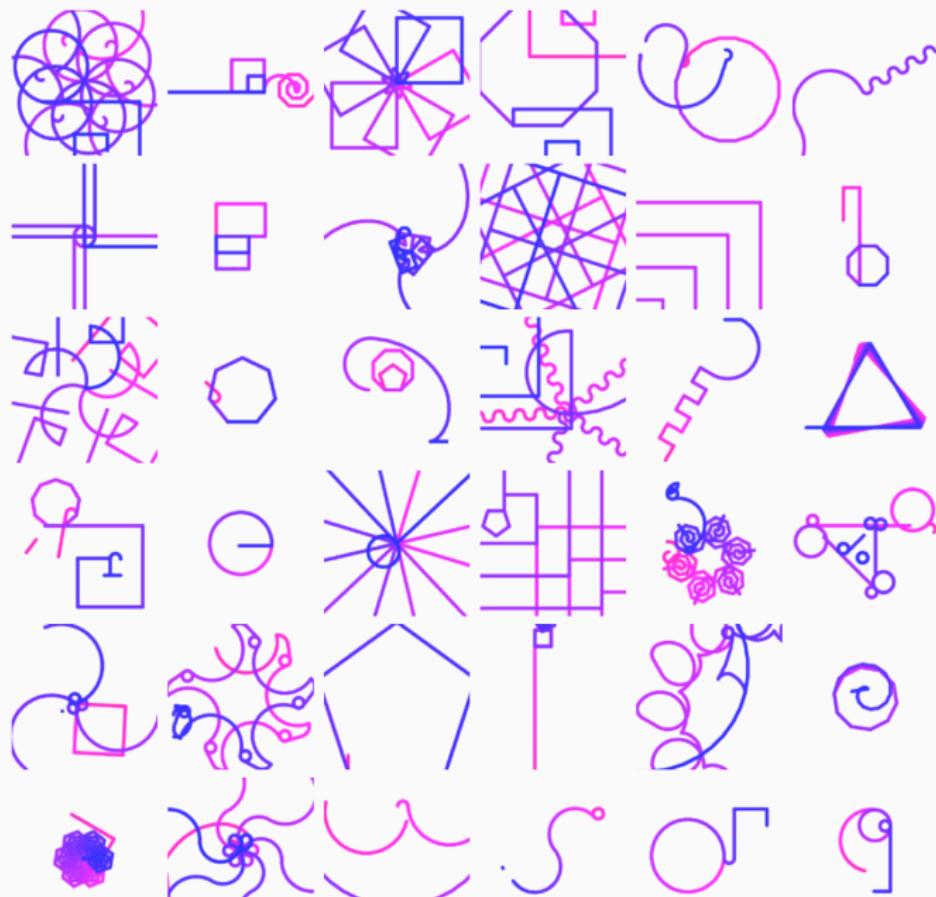


```
(move 0 (fn# 7)); fn5 ;  
(fn13 4)
```

What does DreamCoder dream of? (before learning)

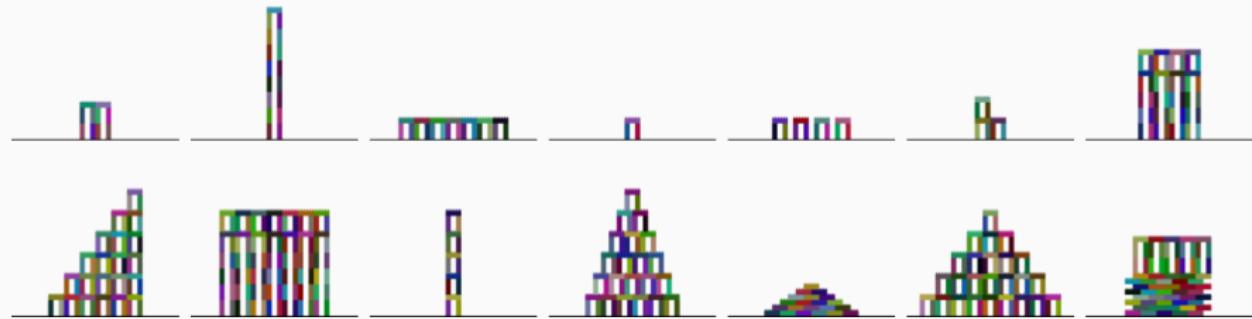


What does DreamCoder dream of? (after learning)



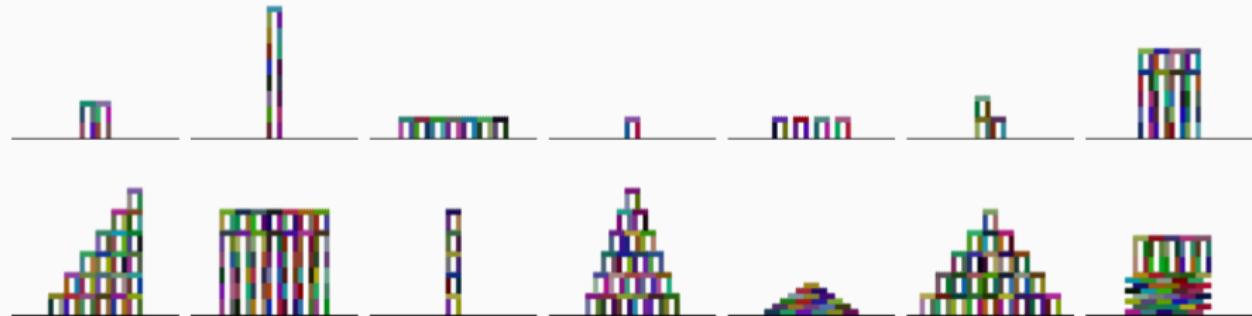
Planning to build towers

example tasks (112 total)



Planning to build towers

example tasks (112 total)



learned library routines (≈ 20 total)

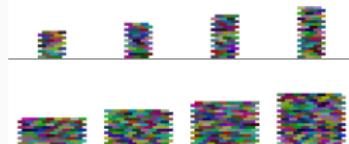
$\text{arch}(h)$



$\text{pyramid}(h)$



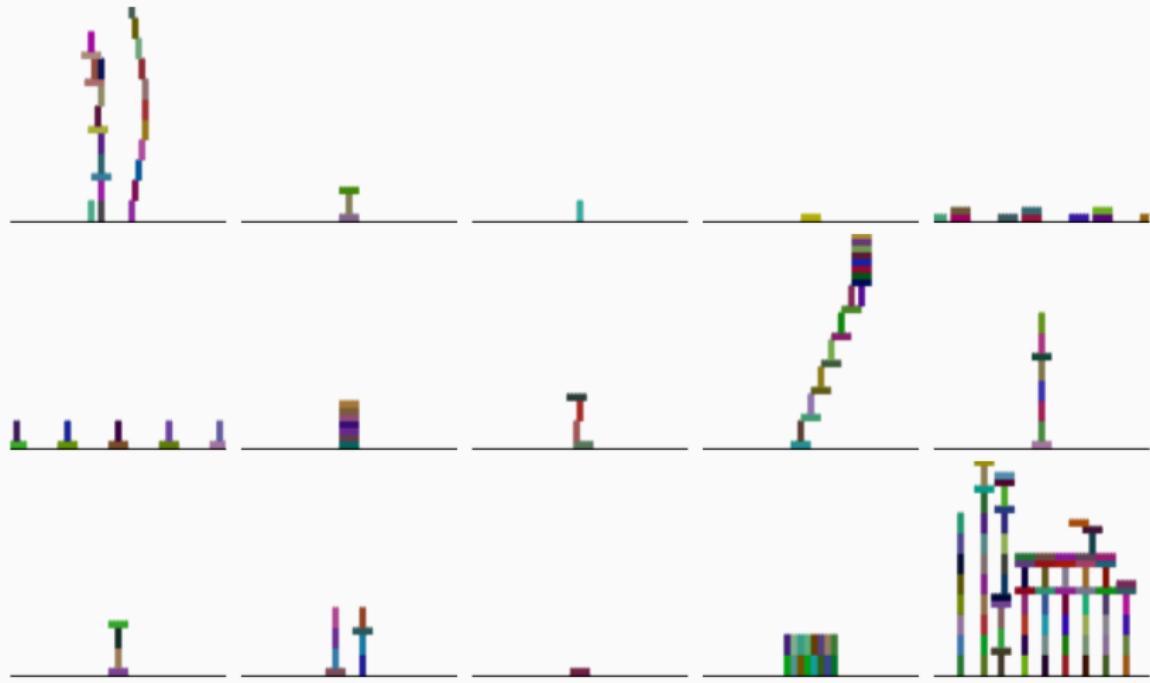
$\text{wall}(w, h)$



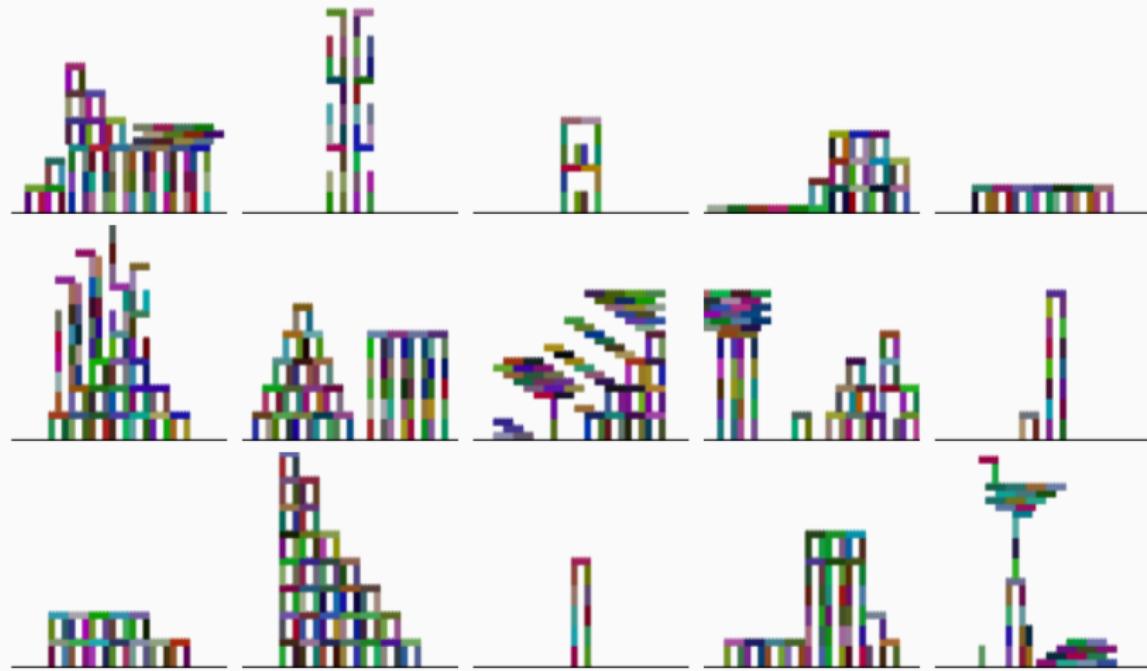
$\text{bridge}(w, h)$



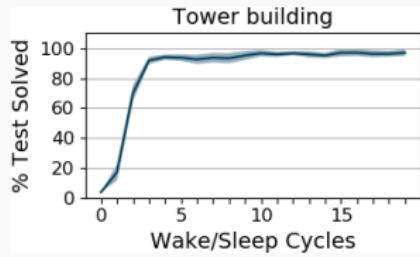
Dreams before learning



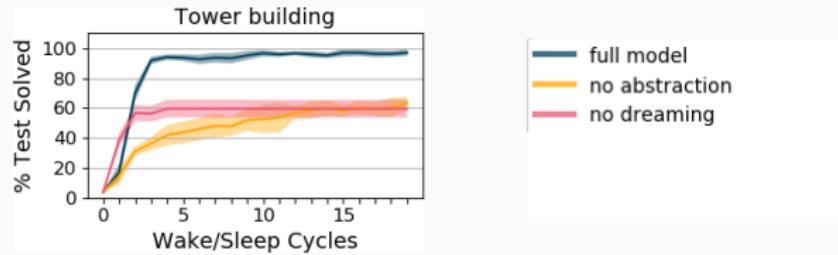
Dreams after learning



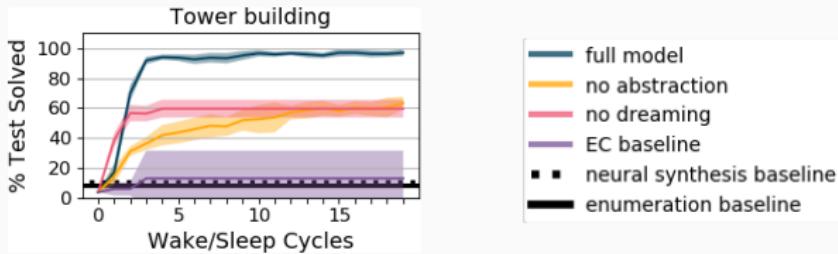
Learning dynamics



Learning dynamics

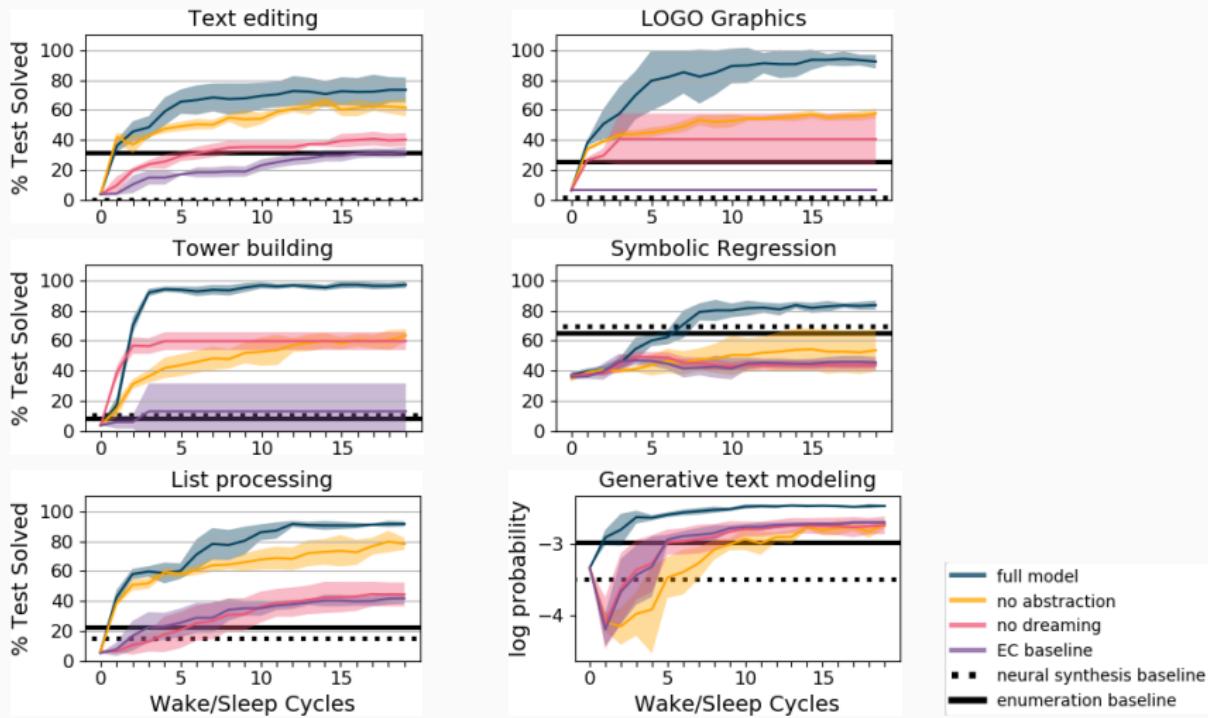


Learning dynamics



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

Learning dynamics



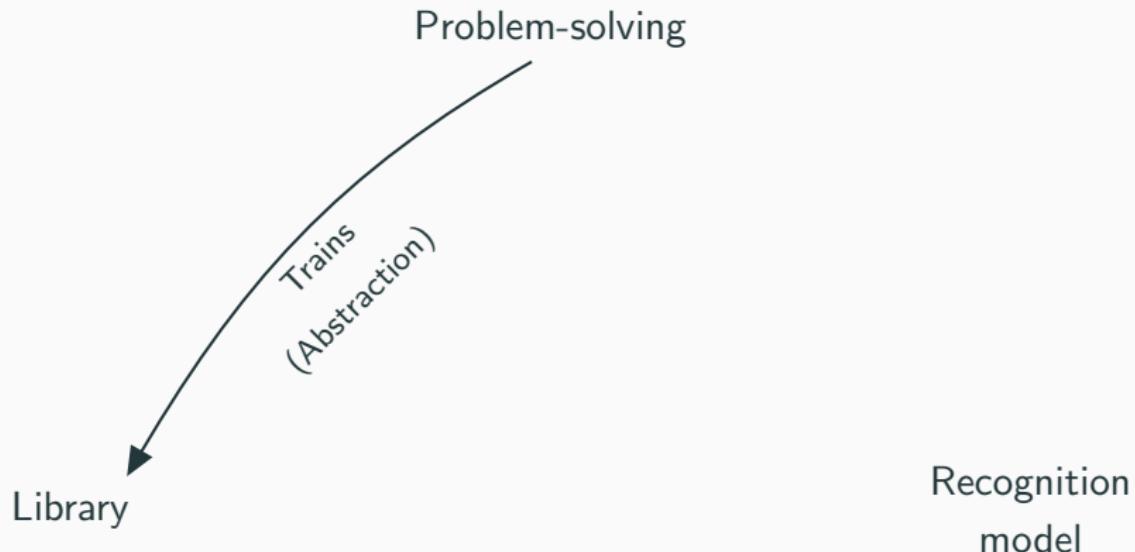
Synergy between dreaming and library learning

Problem-solving

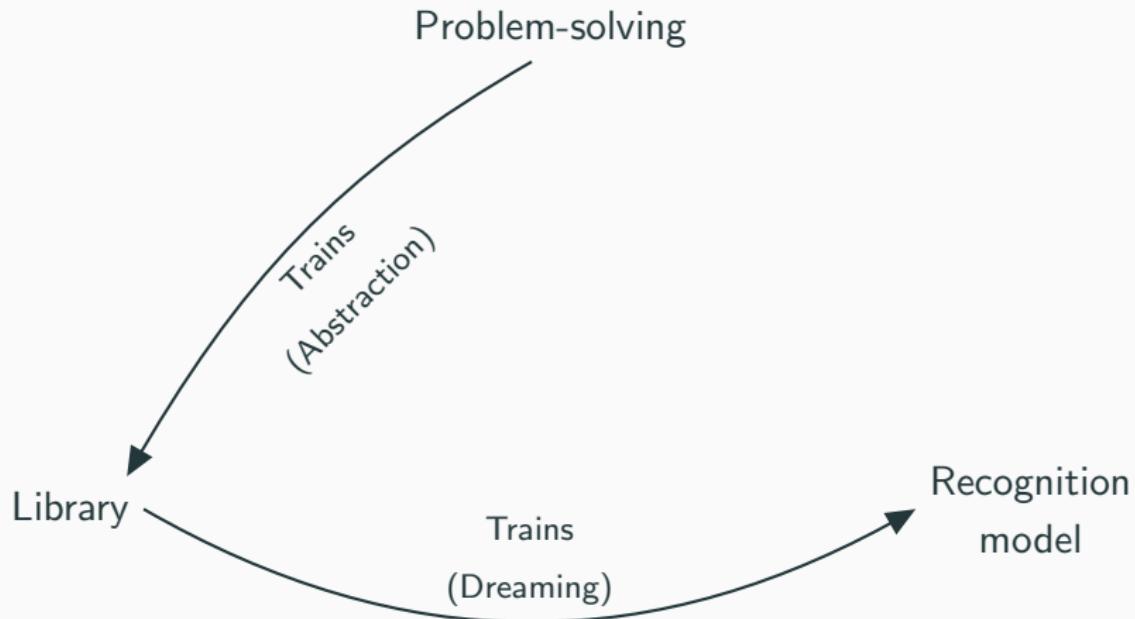
Library

Recognition
model

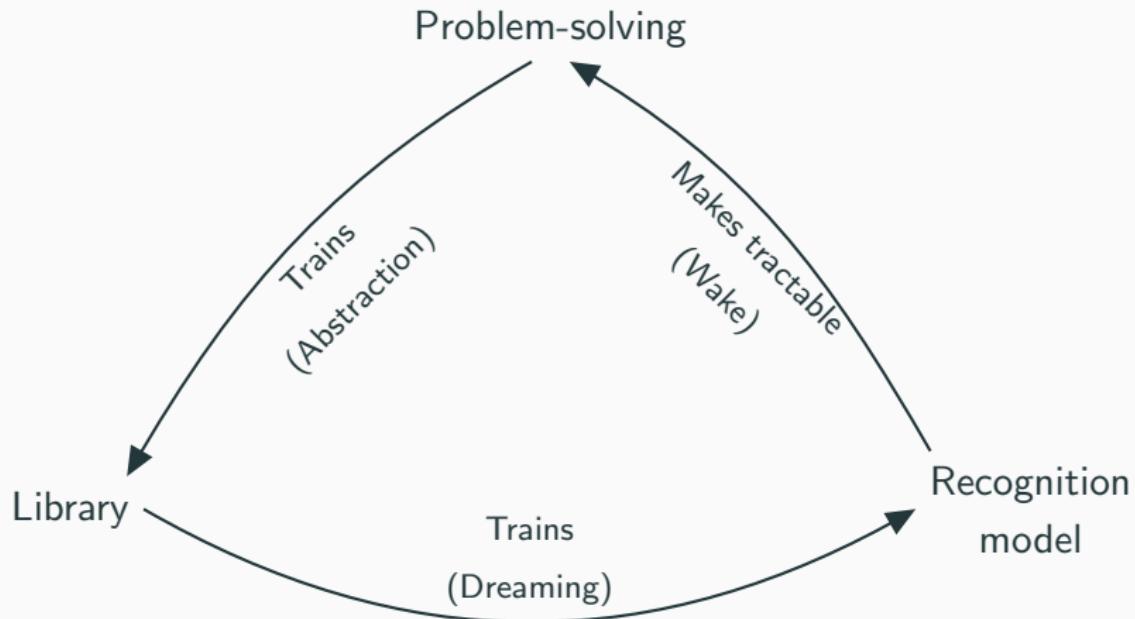
Synergy between dreaming and library learning



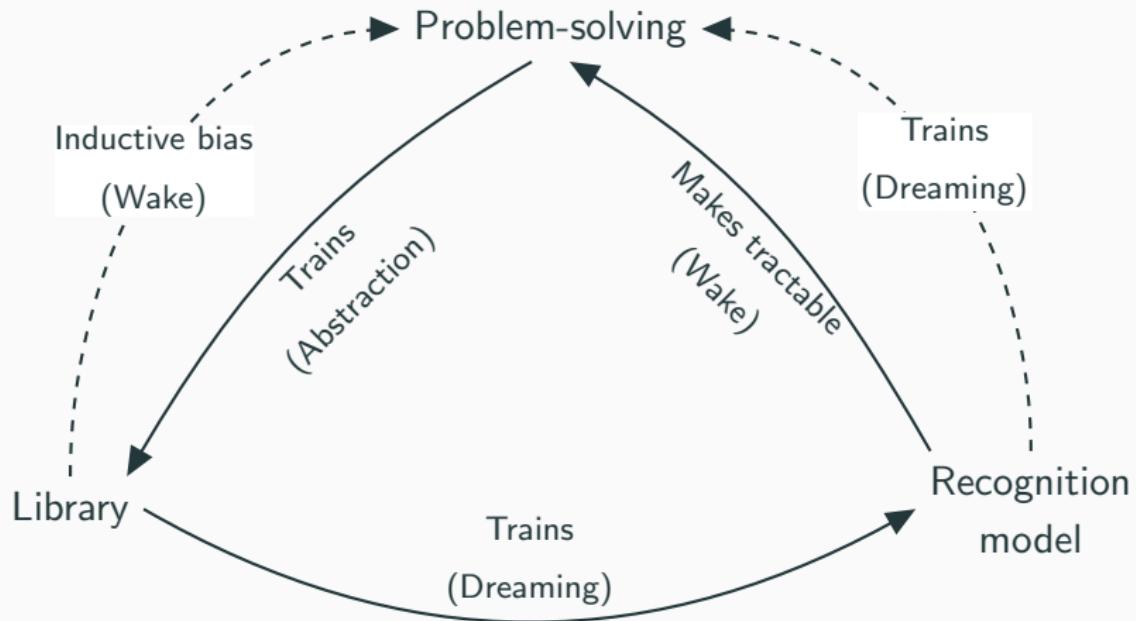
Synergy between dreaming and library learning



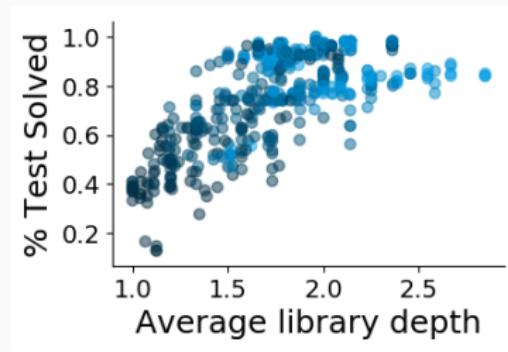
Synergy between dreaming and library learning



Synergy between dreaming and library learning



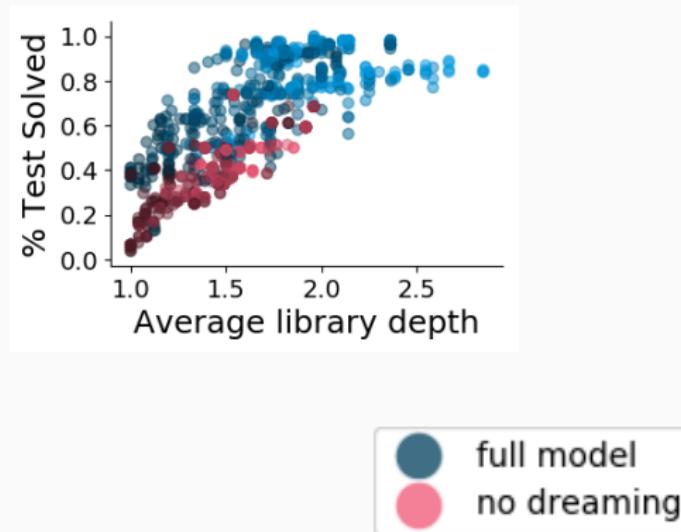
Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

Brighter: Later in learning

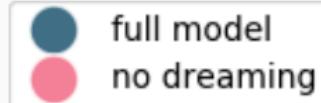
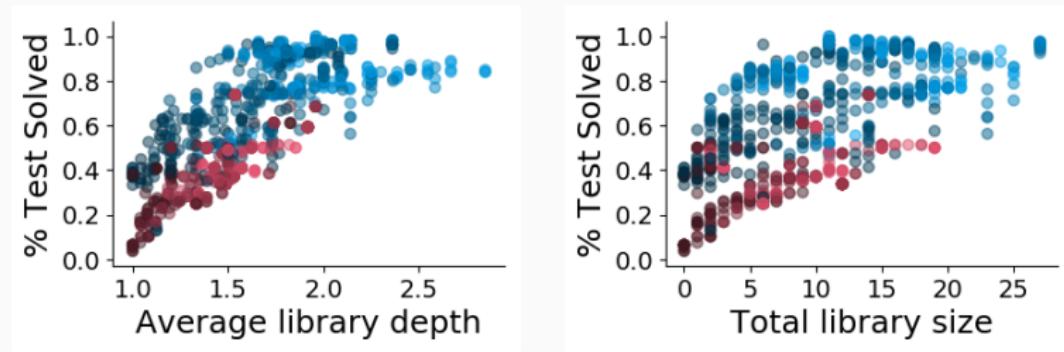
Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

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Evidence for dreaming bootstrapping better libraries



Darker: Early in learning

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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}$
$KE = \frac{1}{2}mv^2$	$\vec{r} = r \times F$	$\text{PE}_{\text{gravity}} = -G \frac{m_1 m_2}{r}$
$\Delta PE = mg\Delta y$	$L = I\omega$	$p = \frac{m}{V}$
$\Delta E = W = Fd\cos\theta$	$\Delta L = \tau \Delta t$	$KE = \frac{1}{2}I\omega^2$

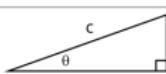
Electricity

$ \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



$$\begin{aligned} c^2 &= a^2 + b^2 & \sin\theta &= \frac{a}{c} & \cos\theta &= \frac{b}{c} & \tan\theta &= \frac{a}{b} \\ \end{aligned}$$

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

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

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

Initial Primitives

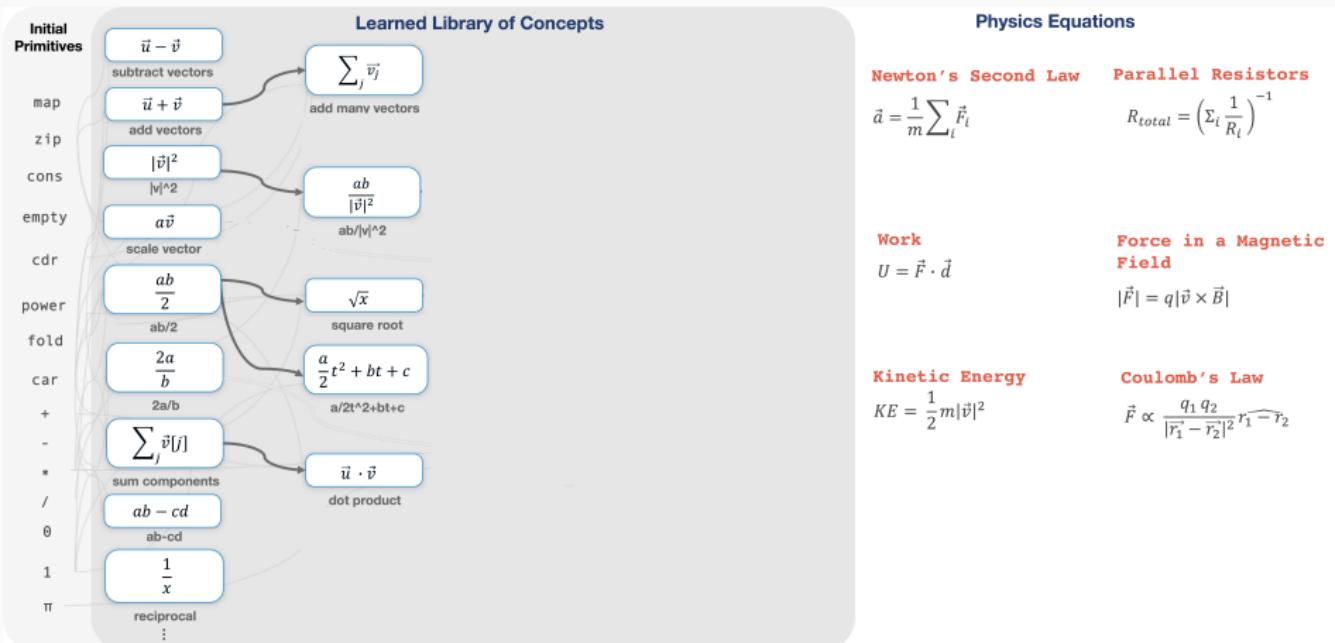
$\vec{u} - \vec{v}$	subtract vectors
$\vec{u} + \vec{v}$	add vectors
$ \vec{v} ^2$	$ v ^2$
$a\vec{v}$	scale vector
$\frac{ab}{2}$	$ab/2$
$\frac{2a}{b}$	$2a/b$
$\sum_j \vec{v}[j]$	sum components
$ab - cd$	$ab - cd$
$\frac{1}{x}$	reciprocal
⋮	⋮

Learned Library of Concepts

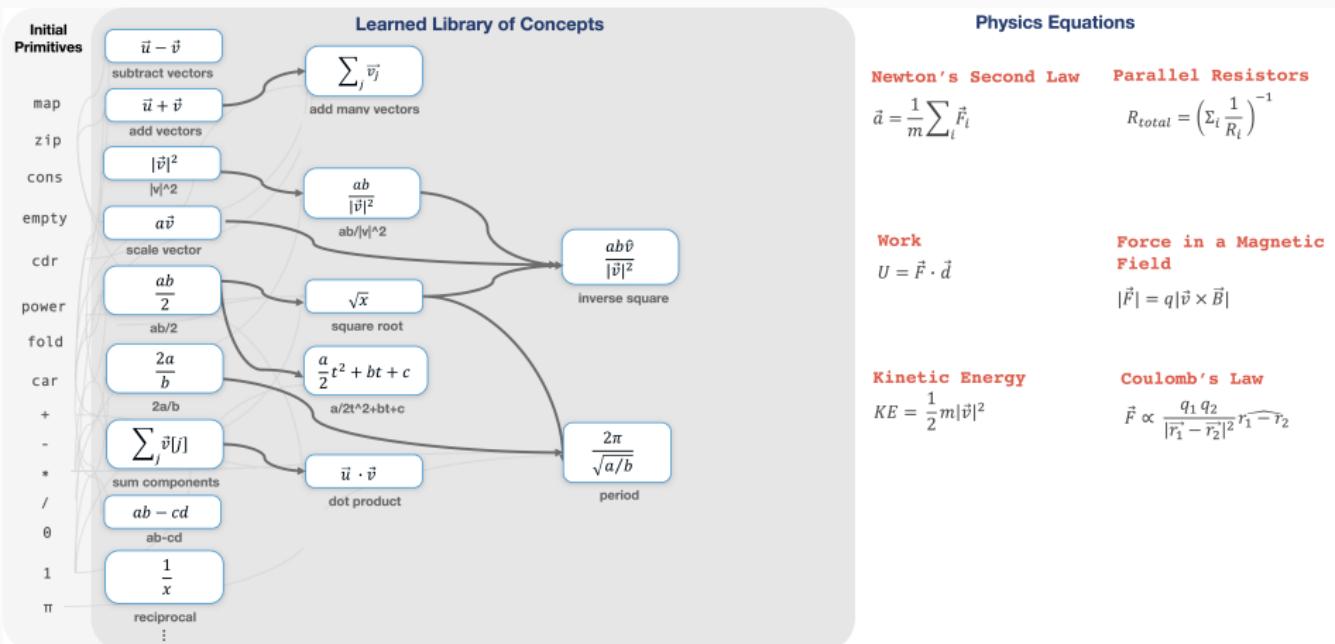
Physics Equations

Newton's Second Law	Parallel Resistors
$\vec{a} = \frac{1}{m} \sum_l \vec{F}_l$	$R_{total} = \left(\sum_i \frac{1}{R_i} \right)^{-1}$
Work	Force in a Magnetic Field
$U = \vec{F} \cdot \vec{d}$	$ \vec{F} = q \vec{v} \times \vec{B} $
Kinetic Energy	Coulomb's Law
$KE = \frac{1}{2} m \vec{v} ^2$	$\vec{F} \propto \frac{q_1 q_2}{ \vec{r}_1 - \vec{r}_2 ^2} \hat{r}_1 - \hat{r}_2$

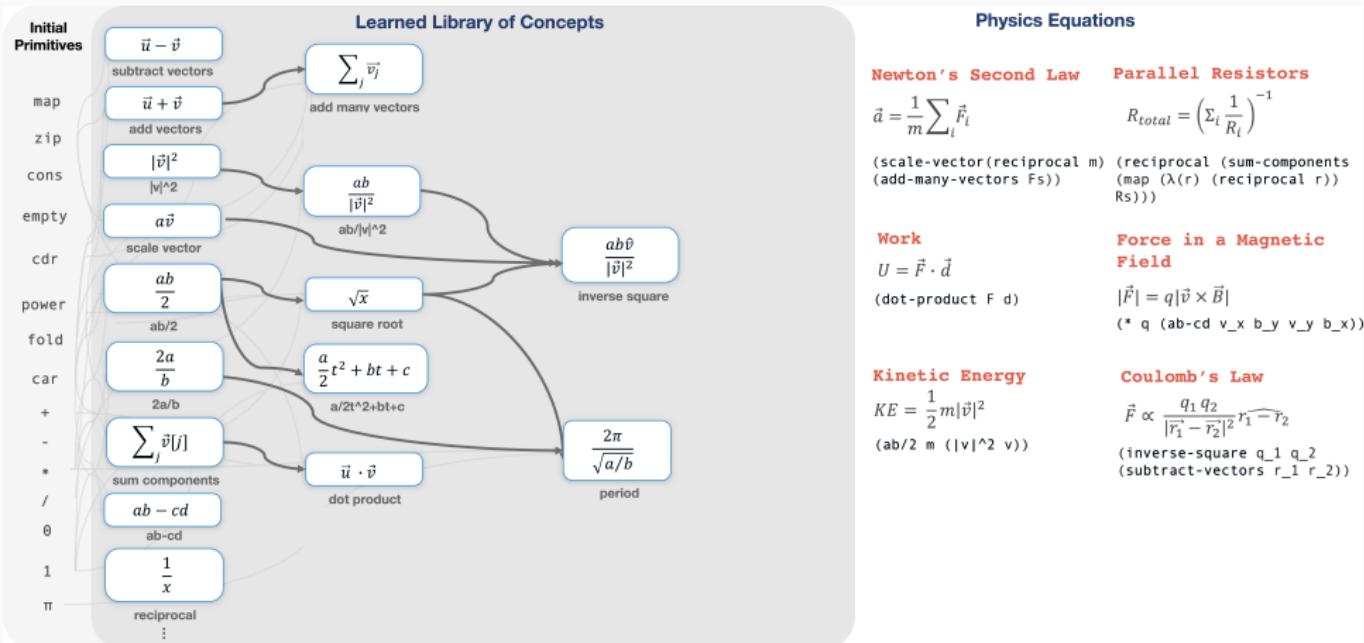
Growing languages for vector algebra and physics



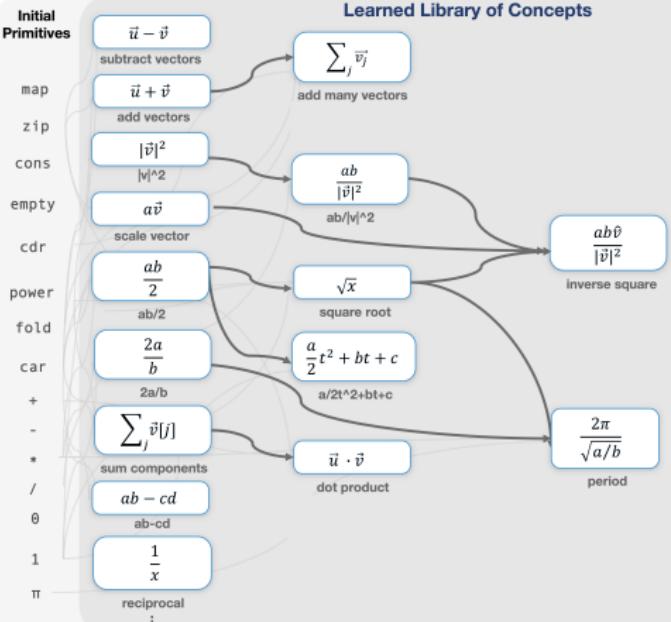
Growing languages for vector algebra and physics



Growing languages for vector algebra and physics



Growing languages for vector algebra and physics



Physics Equations

Newton's Second Law **Parallel Resistors**

$$\ddot{\vec{a}} = \frac{1}{m} \sum_l \vec{F}_l$$

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

(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))

(lambda (x y z u) (map (lambda (v) (* (/ (* (power (/ (* x) (fold (zip z u (lambda (w a) (- w a)))) theta (lambda (b c) (+ (* b b) c)))) (/ (* 1 1) (+ 1 1)))) y) (fold (zip z u (lambda (d e) (- d e)))) theta (lambda (f g) (+ (* f f) g)))) v)) (zip z u (lambda (h i) (- h i)))))

Solution to Coulomb's Law if expressed in initial primitives

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]

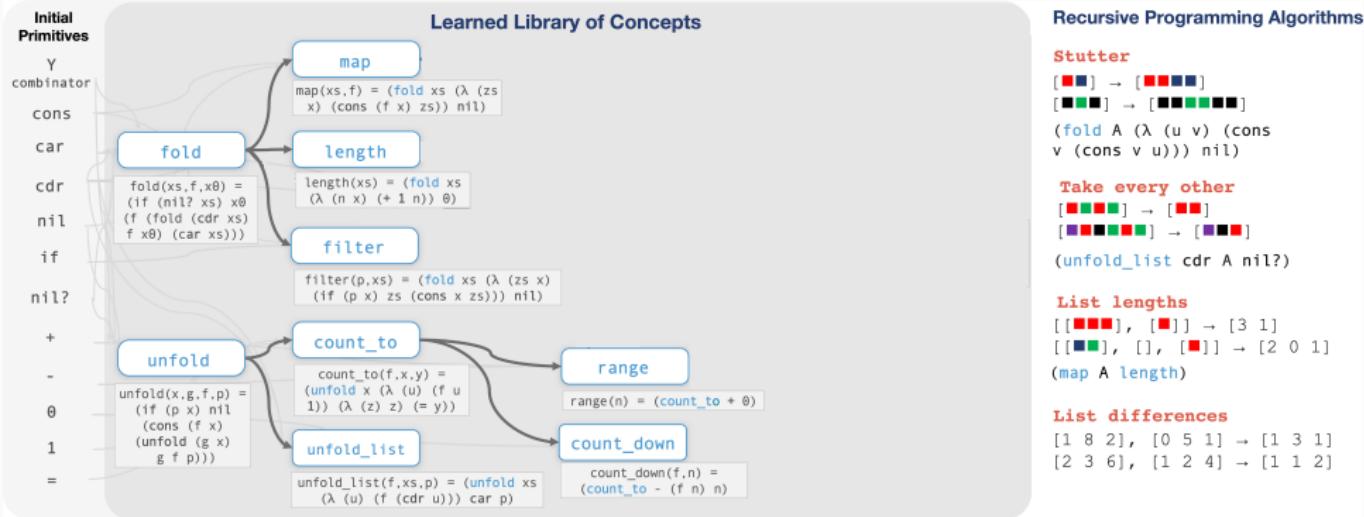
List differences

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

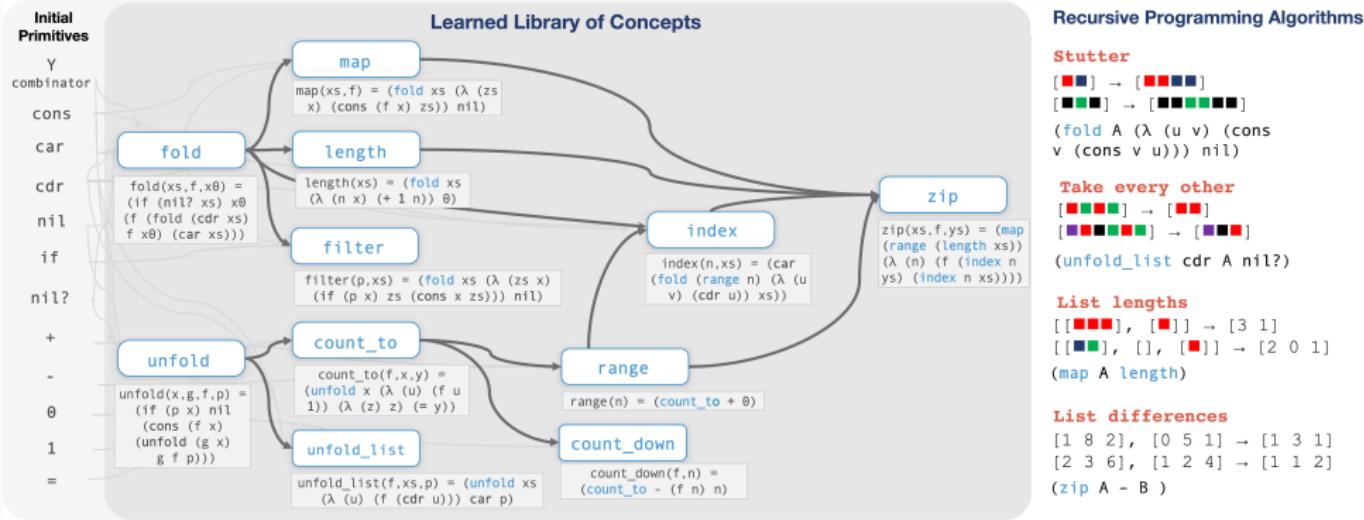
Growing a language for recursive programming



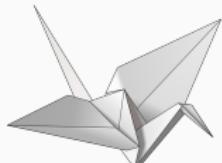
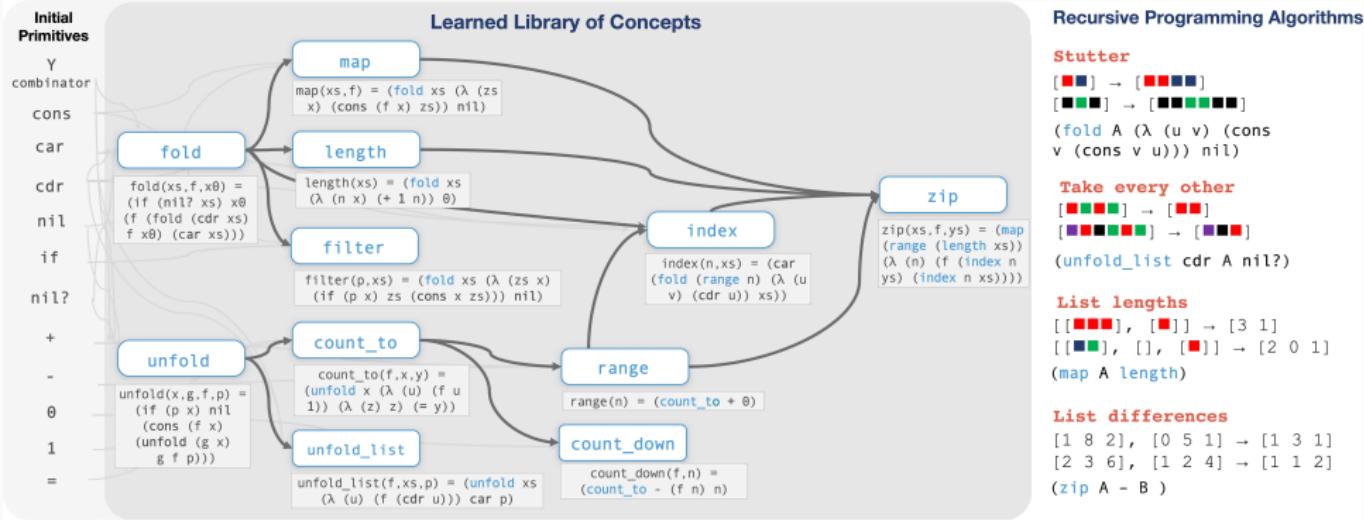
Growing a language for recursive programming



Growing a language for recursive programming

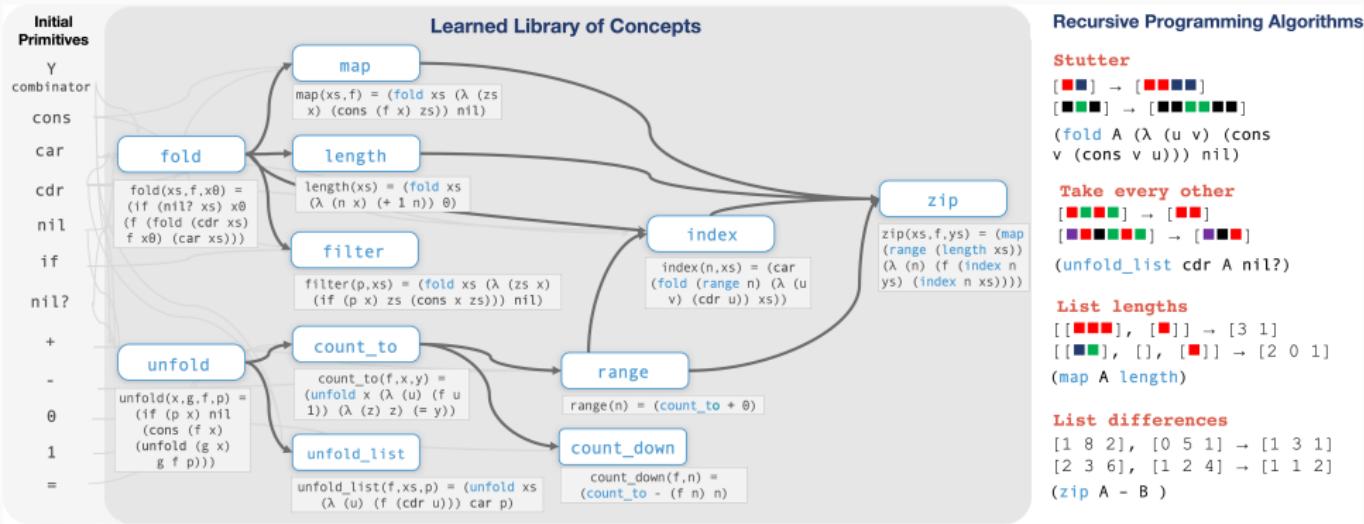


Growing a language for recursive programming

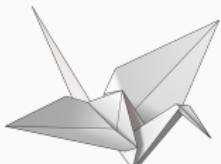


Origami Programming: Jeremy Gibbons, 2003

Growing a language for recursive programming



1 year of compute. 5 days on 64 CPUs.



Origami Programming: Jeremy Gibbons, 2003

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

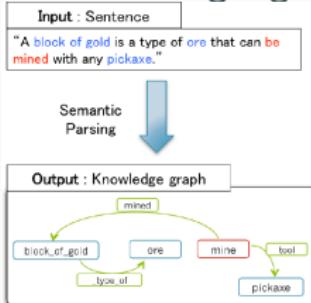
Program Induction and perception
learning to learn
model discovery
the future

What we've got now:
a toolkit for program induction,
addressing combinatorial program search via learning, integrating
symbolic, probabilistic, and neural techniques

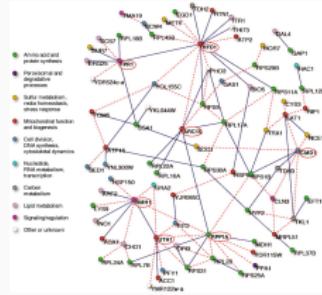
Where will this toolkit take us?

What's in reach

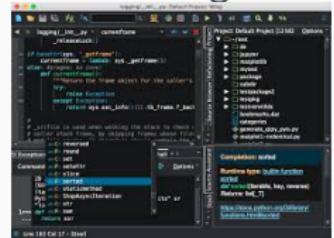
Library learning+ Natural language



Computer-Aided Science

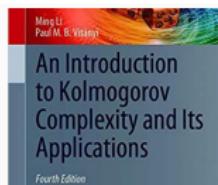


Synthesis for software engineers



Theory for program induction

$$P_M(x) = \sum_{i=1}^{\infty} 2^{-|s_i(x)|}$$



Modeling the physical world

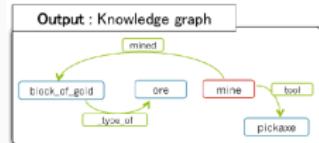


What's in reach

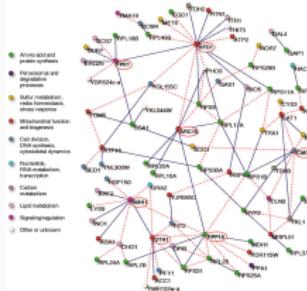
Library learning + Natural language

Input : Sentence
"A block of gold is a type of ore that can be mined with any pickaxe."

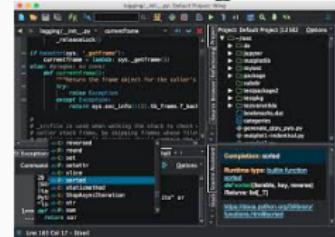
Semantic Parsing



Computer-Aided Science

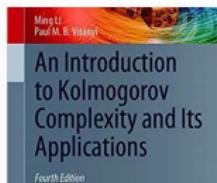


Synthesis for software engineers

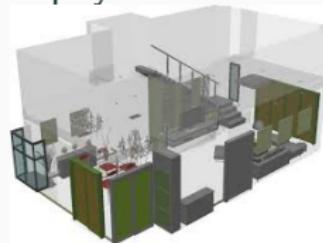


Theory for program induction

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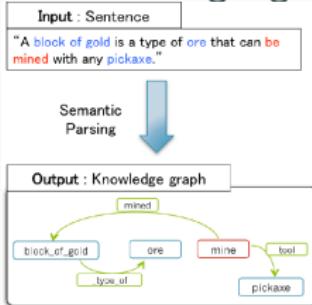


Modeling the physical world

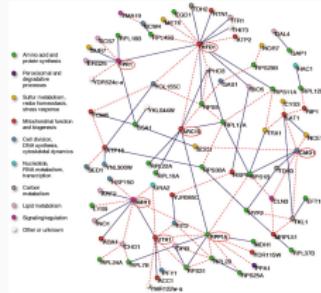


What's in reach

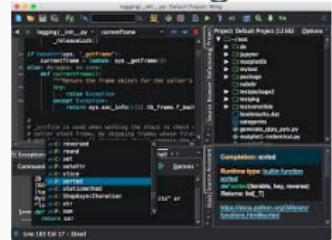
Library learning + Natural language



Computer-Aided Science

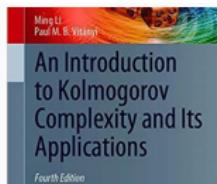


Synthesis for software engineers



Theory for program induction

$$P_M(x) = \sum_{i=1}^{\infty} 2^{-|s_i(x)|}$$

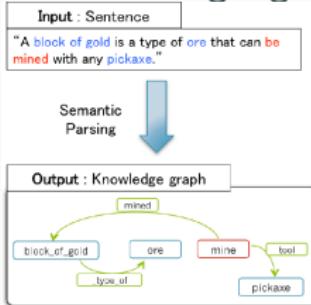


Modeling the physical world

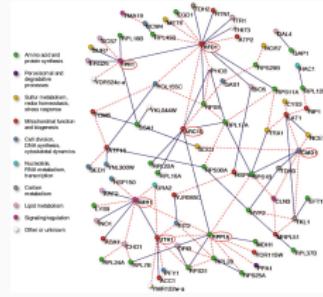


What's in reach

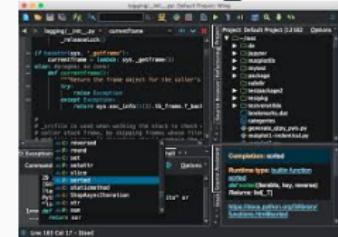
Library learning + Natural language



Computer-Aided Science

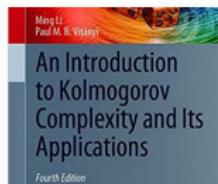


Synthesis for software engineers



Theory for program induction

$$P_M(x) = \sum_{i=1}^{\infty} 2^{-|s_i(x)|}$$

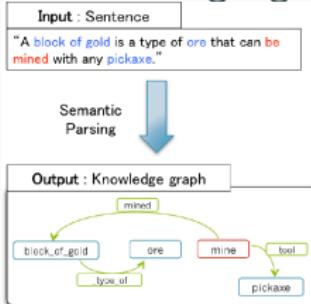


Modeling the physical world

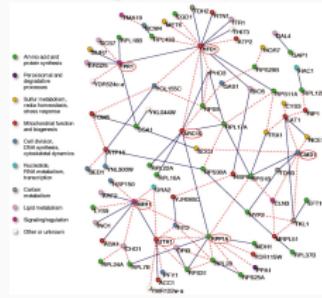


What's in reach

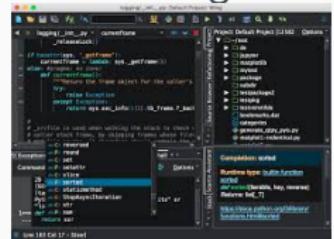
Library learning + Natural language



Computer-Aided Science

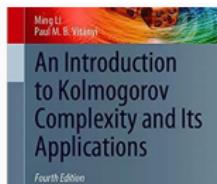


Synthesis for software engineers

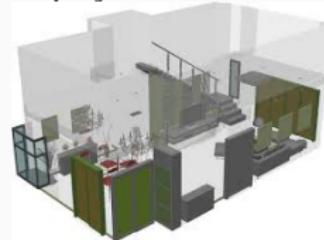


Theory for program induction

$$P_M(x) = \sum_{i=1}^{\infty} 2^{-|s_i(x)|}$$

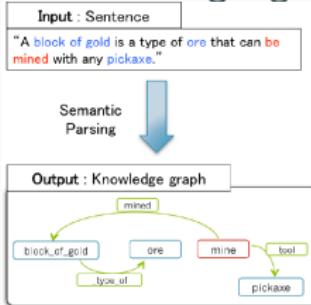


Modeling the physical world

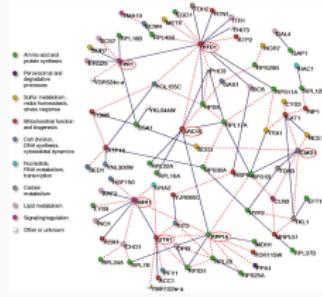


What's in reach

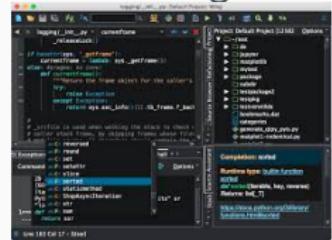
Library learning + Natural language



Computer-Aided Science

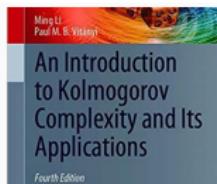


Synthesis for software engineers



Theory for program induction

$$P_M(x) = \sum_{i=1}^{\infty} 2^{-|s_i(x)|}$$



Modeling the physical world



Within reach: Modeling the physical world

hinge



gear



doorknob



Within reach: Modeling the physical world

Built in

Learned Library

The world

2D geometry

symmetry

...

3D geometry

extrude

...

Rigid body

dynamics

...

Programming

for loop

...



Within reach: Modeling the physical world

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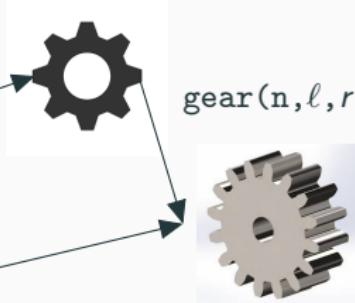
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`gear(n, ℓ, r)`



`geartrain(K, n̄, ℓ̄, r̄)`



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`gear(n, ℓ, r)`

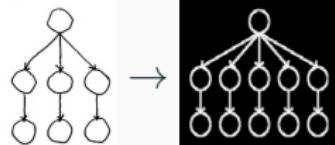


`geartrain(K, n̄, ℓ̄, r̄)`



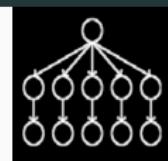
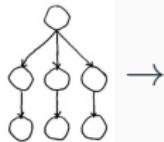
What do we want from machine learning?

Strong generalization

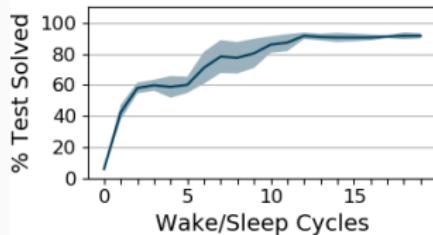


What do we want from machine learning?

Strong generalization

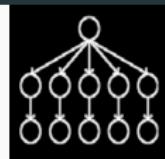
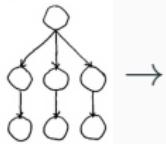


Bootstrapping, learning-to-learn, representation learning

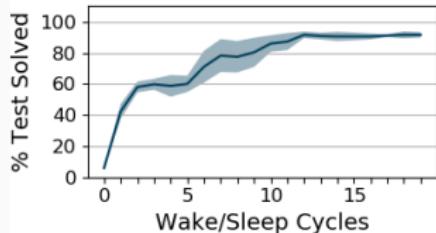


What do we want from machine learning?

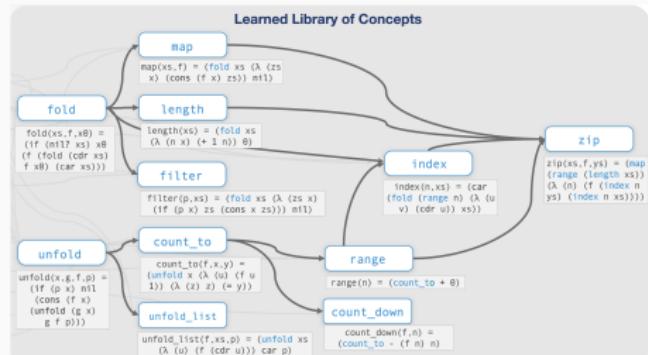
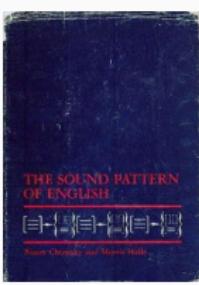
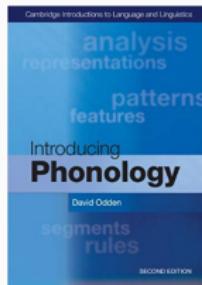
Strong generalization



Bootstrapping, learning-to-learn, representation learning



Discovering knowledge that humans can understand and build on



What's far off, but worthwhile?

What kinds of future machines could learn all this?

using new devices



play



coding

```
(MEMBER  
(LAMBDA (X L)  
(COND ((NULL L) NIL)  
((EQ X (FIRST L)) T)  
(T (MEMBER X (REST L)))))))
```

Allen, Anatomy of Lisp, 1975

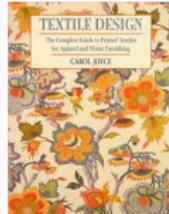
language



science



design



Collaborators

Josh
Tenenbaum



Armando
Solar-Lezama



Tim O'Donnell



Adam Albright



Max Nye



Cathy Wong



Yewen Pu



Dan Ritchie



Mathias Sable-Meyer



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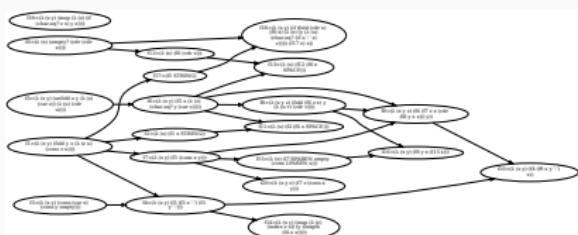
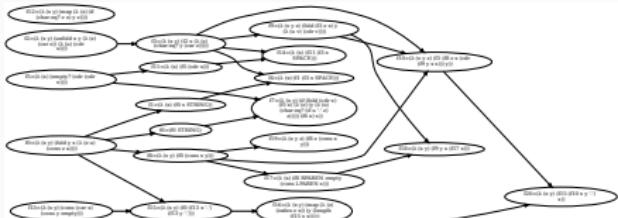
Tao Du



thank
you

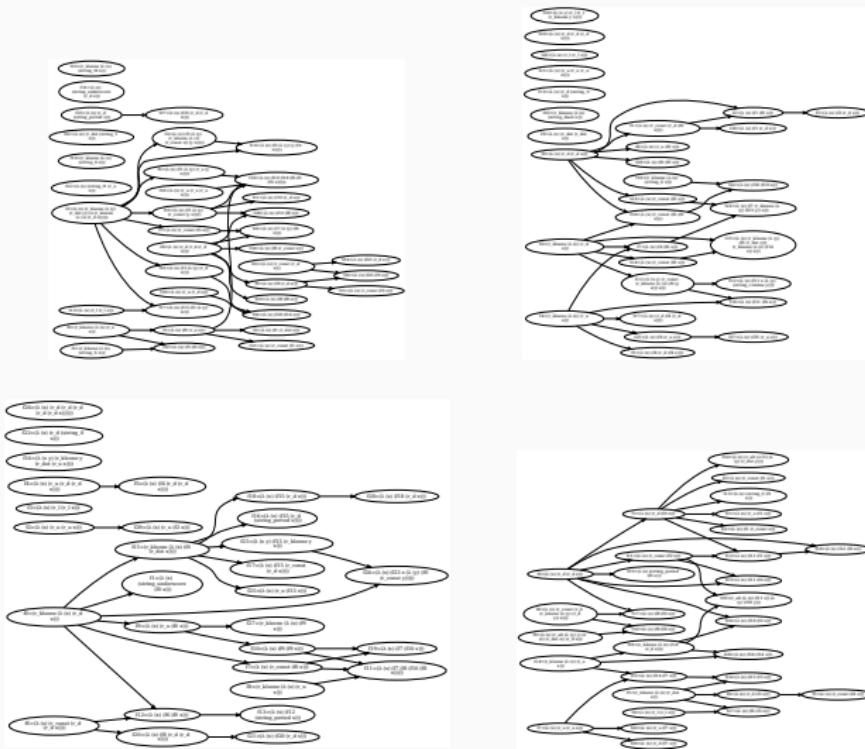
Library structure: Text Editing

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

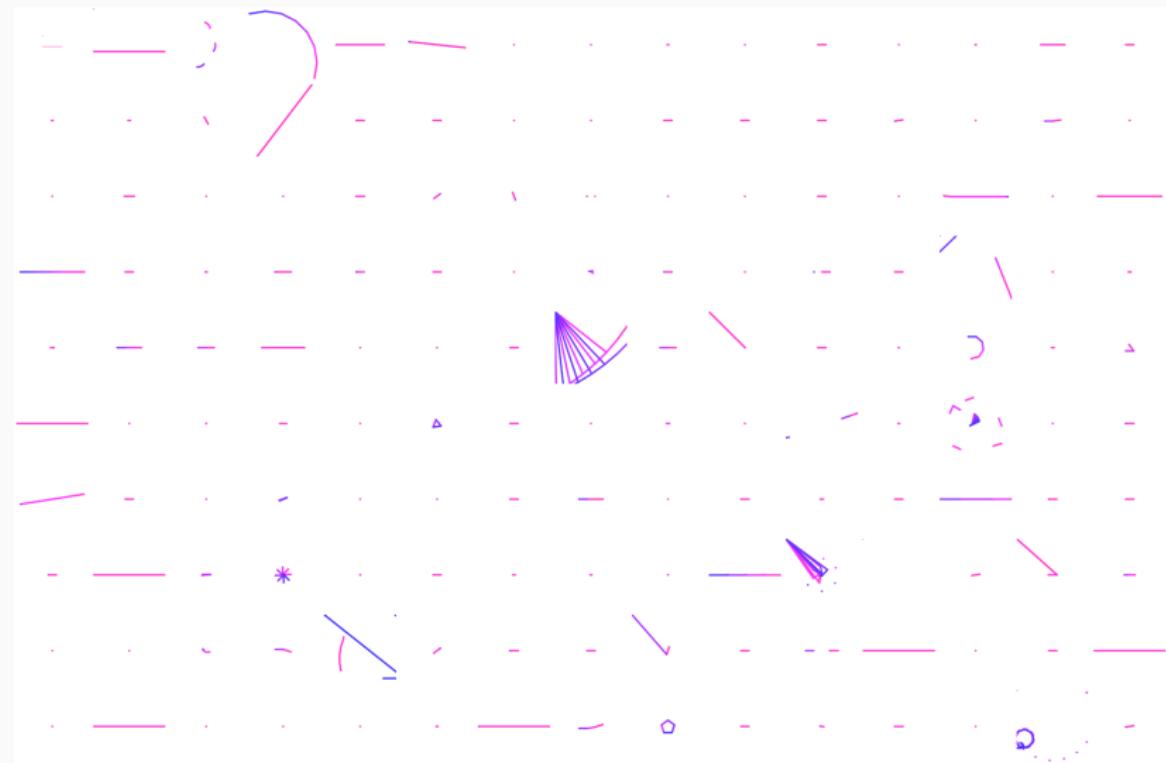


Library structure: Generating Text

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



150 random dreams before learning



150 random dreams after learning

