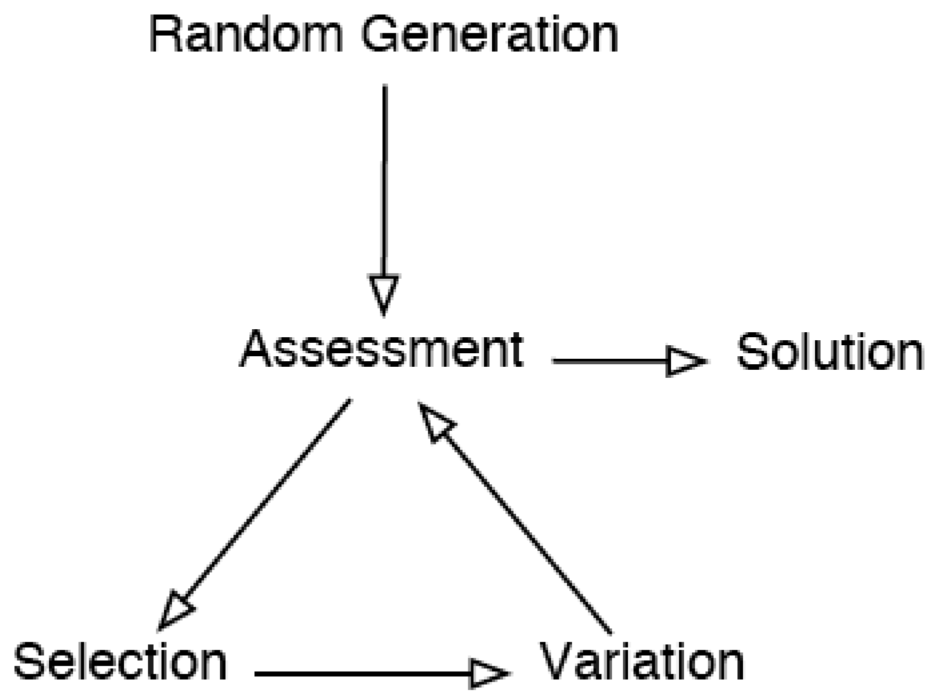
GP & Push slides for Tom

Evolutionary Computation



Genetic Programming

- Evolutionary computing to produce executable computer programs.
- Programs are tested by executing them.

Program Representations

- Lisp-style symbolic expressions (Koza, ...).
- Purely functional/lambda expressions (Walsh, Yu, ...).
- Linear sequences of machine/byte code (Nordin et al., ...).
- Artificial assembly-like languages (Ray, Adami, ...).
- Stack-based languages (Perkis, Spector, Stoffel, Tchernev, ...).
- Graph-structured programs (Teller, Globus, ...).
- Object hierarchies (Bruce, Abbott, Schmutter, Lucas, ...)
- Fuzzy rule systems (Tunstel, Jamshidi, ...)
- Logic programs (Osborn, Charif, Lamas, Dubossarsky, ...).
- Strings, grammar-mapped to arbitrary languages (O'Neill, Ryan, ...).

Mutating Lisp

```
(+ (* X Y)
   (+ 4 (- Z 23)))

(+ (* X Y)
   (+ 4 (- Z 23)))

(+ (- (+ 2 2) Z)
   (+ 4 (- Z 23)))
```

Recombining Lisp

```
Parent 1: (+ (* X Y)
             (+ 4 (- Z 23)))
Parent 2: (- (* 17 (+ 2 X))
             (* (- (* 2 Z) 1)
                (+ 14 (/ Y X))))

Child 1:  (+ (- (* 2 Z) 1)
             (+ 4 (- Z 23)))
Child 2:  (- (* 17 (+ 2 X))
             (* (* X Y)
                (+ 14 (/ Y X))))
```

Symbolic Regression

Given a set of data points, evolve a program that produces *y* from *x*.

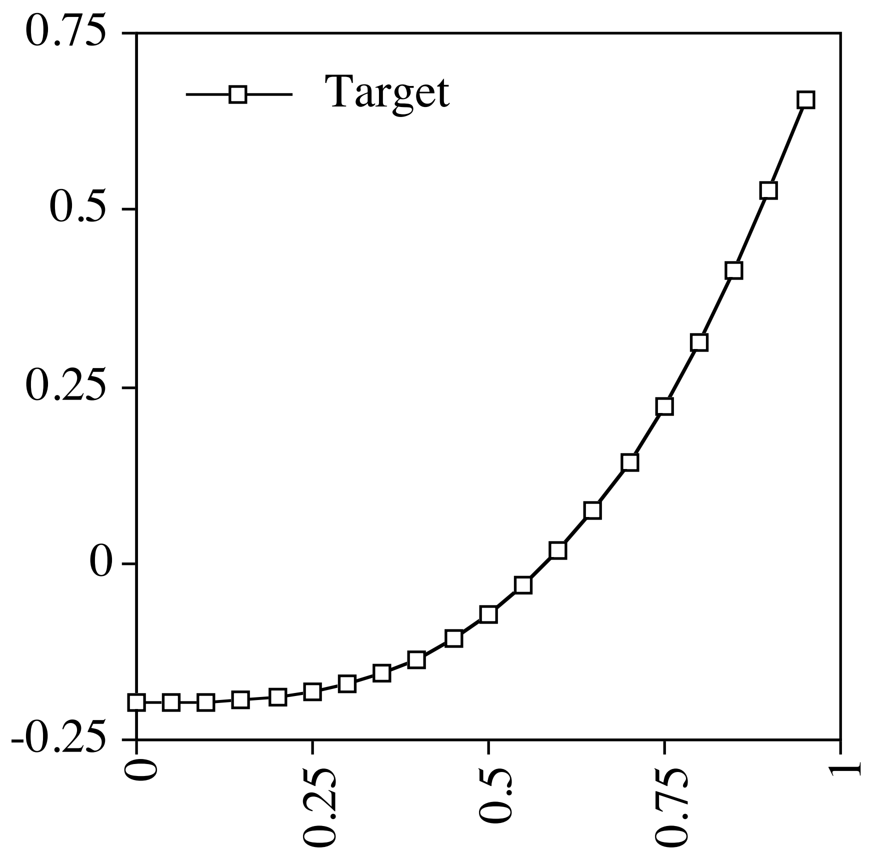
Primordial ooze: +, -, *, %, *x*, 0.1

Fitness = error (smaller is better)

GP Parameters

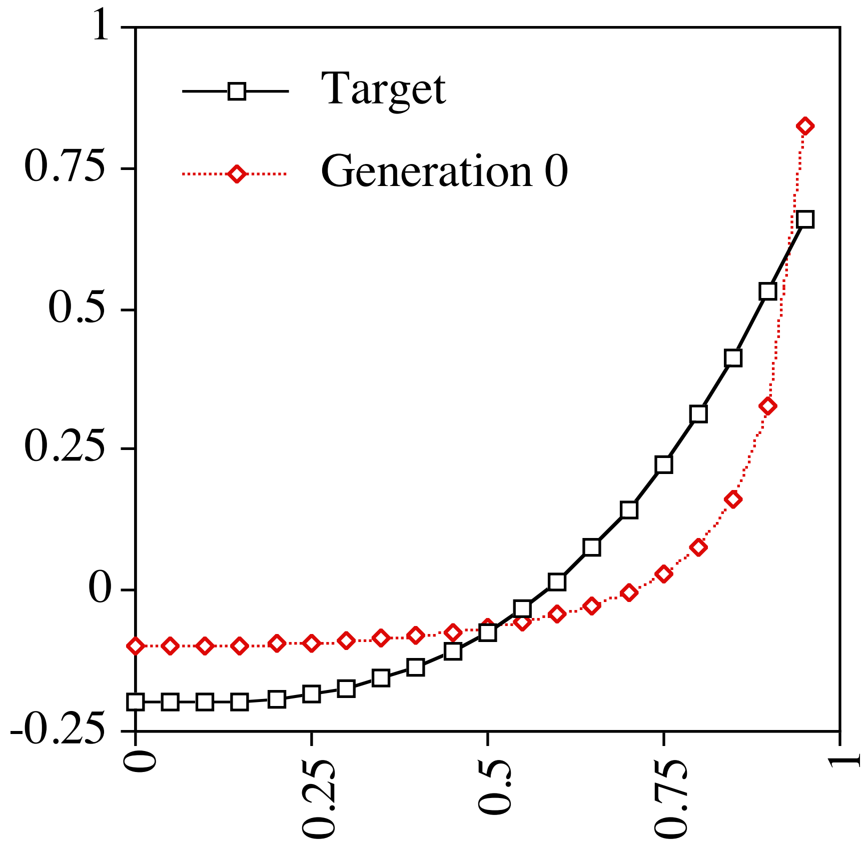
Maximum number of Generations: 51
Size of Population: 1000
Maximum depth of new individuals: 6
Maximum depth of new subtrees for mutants: 4
Maximum depth of individuals after crossover: 17
Fitness-proportionate reproduction fraction: 0.1
Crossover at any point fraction: 0.3
Crossover at function points fraction: 0.5
Selection method: FITNESS-PROPORTIONATE
Generation method: RAMPED-HALF-AND-HALF
Randomizer seed: 1.2

Evolving $y = x^3 - 0.2$



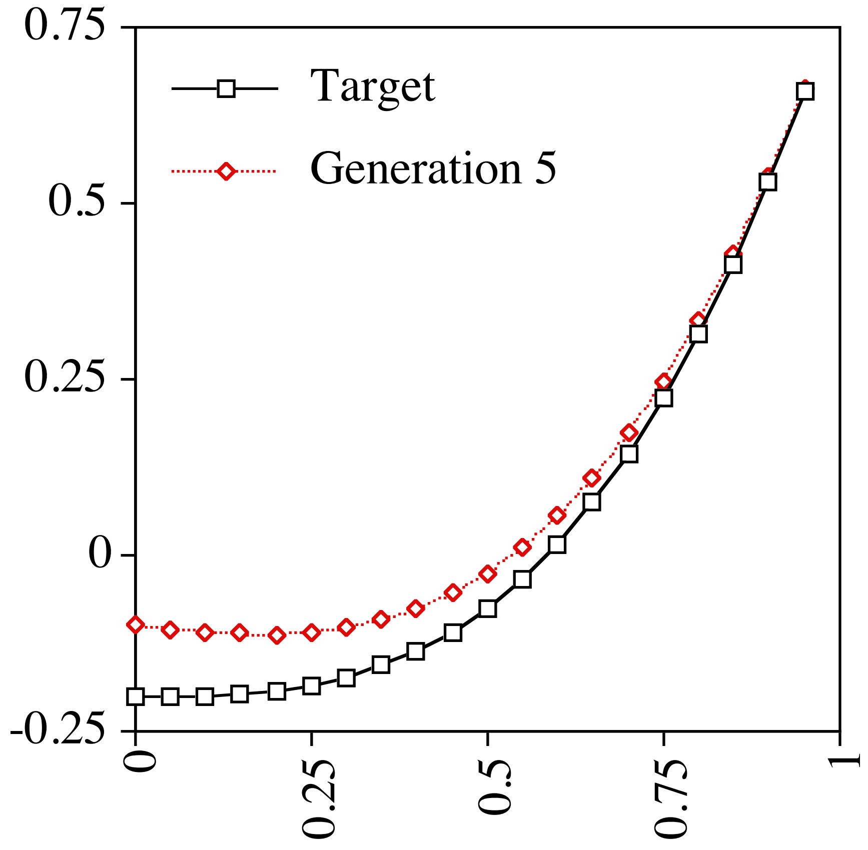
Best Program, Gen 0

```
(- (% (* 0.1
         (* X X))
      (- (% 0.1 0.1)
         (* X X)))
   0.1)
```



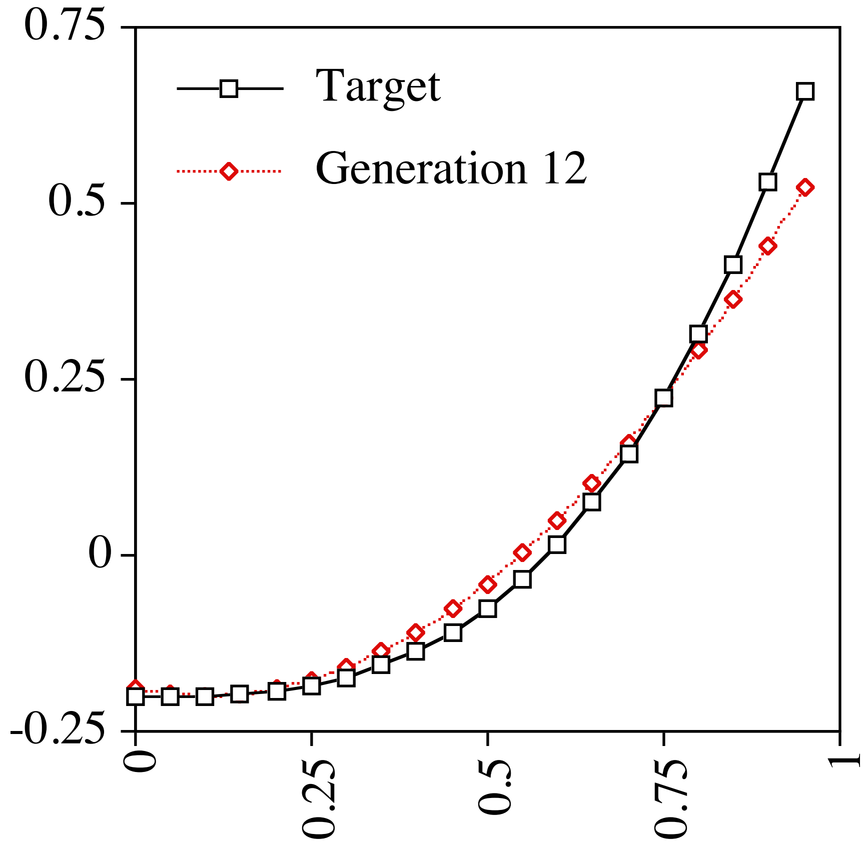
Best Program, Gen 5

```
(- (* (* (% X 0.1)
         (* 0.1 X))
      (- X
         (% 0.1 X)))
   0.1)
```



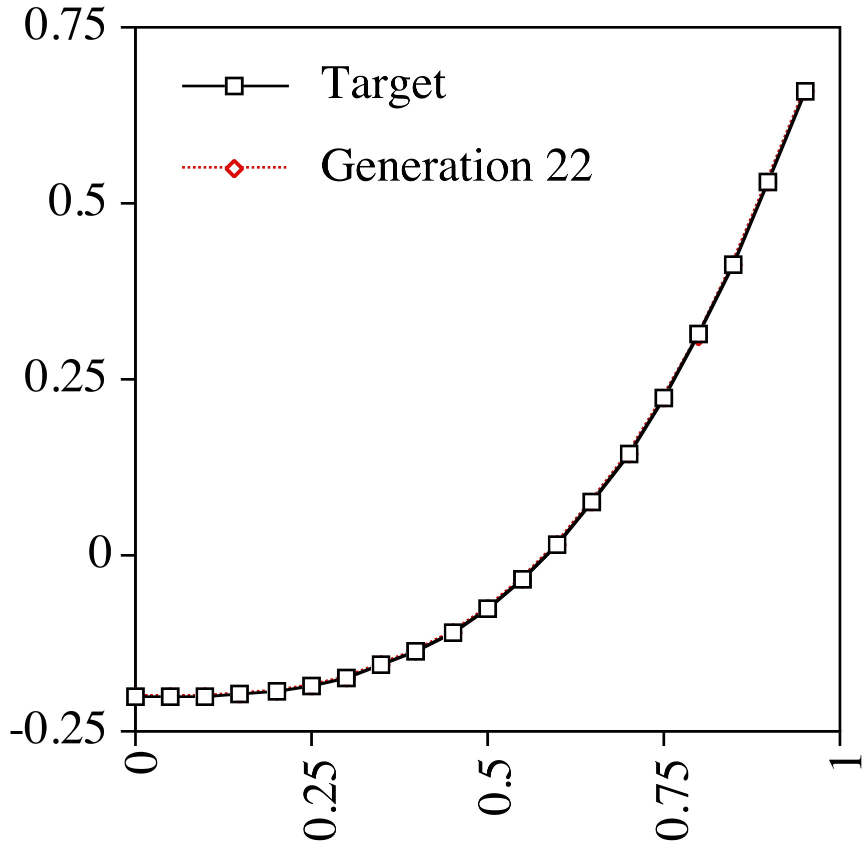
Best Program, Gen 12

```
(+ (- (- 0.1
         (- 0.1
            (- (* X X)
               (+ 0.1
                  (- 0.1
                     (* 0.1
                        0.1))))))
      (* X
         (* (% 0.1
               (% (* (* (- 0.1 0.1)
                        (+ X
                           (- 0.1 0.1)))
                     X)
                  (+ X (+ (- X 0.1)
                          (* X X)))))
            (+ 0.1 (+ 0.1 X))))))
   (* X X))
```



Best Program, Gen 22

```
(- (- (* X (* X X))
      0.1)
   0.1)
```



Genetic Programming for Finite Algebras

Lee Spector
Cognitive Science
Hampshire College
Amherst, MA 01002
lspector@hampshire.edu

David M. Clark
Mathematics
SUNY New Paltz
New Paltz, NY 12561
clarkd@newpaltz.edu

Ian Lindsay
Hampshire College
Amherst, MA 01002
iml04@hampshire.edu

Bradford Barr
Hampshire College
Amherst, MA 01002
bradford.barr@gmail.com

Jon Klein
Hampshire College
Amherst, MA 01002
jk@artificial.com

Humies 2008
GOLD MEDAL

Everybody's Favorite Finite Algebra

Boolean algebra, $\mathbf{B} := \langle \{0,1\}, \wedge, \vee, \neg \rangle$

$\wedge$	0	1
0	0	0
1	0	1

$\vee$	0	1
0	0	1
1	1	1

	$\neg$
0	1
1	0

Primal: every possible operation can be expressed by a term using only (and not even) $\wedge$, $\vee$, and $\neg$.

Bigger Finite Algebras

- Have applications in many areas of science, engineering, mathematics
- Can be *much* harder to analyze/understand
- Number of terms grows astronomically with size of underlying set

Goal

- Find terms that have certain special properties
- *Discriminator* terms, determine primality

$$t^A(x,y,z) = \begin{cases} x \text{ if } x \neq y \\ z \text{ if } x = y \end{cases}$$

- *Mal'cev*, *majority*, and *Pixley* terms
- For decades there was no way to produce these terms in general, short of exhaustive search
- Current best methods produce enormous terms

Algebras Explored

$\mathbf{A}_1$ *	0	1	2
0	2	1	2
1	1	0	0
2	0	0	1

$\mathbf{A}_2$ *	0	1	2
0	2	0	2
1	1	0	2
2	1	2	1

$\mathbf{A}_3$ *	0	1	2
0	1	0	1
1	1	2	0
2	0	0	0

$\mathbf{A}_4$ *	0	1	2
0	1	0	1
1	0	2	0
2	0	1	0

$\mathbf{A}_5$ *	0	1	2
0	1	0	2
1	1	2	0
2	0	1	0

$\mathbf{B}_1$ *	0	1	2	3
0	1	3	1	0
1	3	2	0	1
2	0	1	3	1
3	1	0	2	0

Results

- Discriminators for A_1, A_2, A_3, A_4, A_5
- Mal’cev and majority terms for B_1
- Example Mal’cev term for B_1:

$$
((((((((x*(y*x))*x)*z)*(z*x))*((x*(z*(x*(z*y))))*z))*z)
z)(z*((((x*(((z*z)*x)*(z*x)))*x)*y)*(((y*(z*(z*y))))*
(((y*y)*x)*z))*(x*(((z*z)*x)*(z*(x*(z*y)))))))))))
$$

Significance, Time

	Uninformed Search Expected Time (Trials)
3 element algebras	
Mal'cev	5 seconds ($3^{15} \approx 10^7$)
Pixley/majority	1 hour ($3^{21} \approx 10^{10}$)
discriminator	1 month ($3^{27} \approx 10^{13}$)
4 element algebras	
Mal'cev	10^3 years ($4^{28} \approx 10^{17}$)
Pixley/majority	10^{10} years ($4^{40} \approx 10^{24}$)
discriminator	10^{24} years ($4^{64} \approx 10^{38}$)

Significance, Time

	Uninformed Search Expected Time (Trials)	GP Time
3 element algebras		
Mal'cev	5 seconds ($3^{15} \approx 10^{7}$)	1 minute
Pixley/majority	1 hour ($3^{21} \approx 10^{10}$)	3 minutes
discriminator	1 month ($3^{27} \approx 10^{13}$)	5 minutes
4 element algebras		
Mal'cev	10^{3} years ($4^{28} \approx 10^{17}$)	30 minutes
Pixley/majority	10^{10} years ($4^{40} \approx 10^{24}$)	2 hours
discriminator	10^{24} years ($4^{64} \approx 10^{38}$)	?

Significance, Size

Term Type	Primality Theorem
Mal'cev	$10,060,219$
Majority	$6,847,499$
Pixley	$1,257,556,499$
Discriminator	$12,575,109$

(for A_l)

Significance, Size

Term Type	Primality Theorem	GP
Mal'cev	$10,060,219$	12
Majority	$6,847,499$	49
Pixley	$1,257,556,499$	59
Discriminator	$12,575,109$	39

(for A_I)

Human Competitive?

- Rather: human-**WHOMPING!**
- *Outperforms* humans *and all other known methods* on significant problems, providing benefits of *several orders of magnitude* with respect to search speed and result size
- Because there were no prior methods for generating practical terms in practical amounts of time, GP has provided the first solution to a previously open problem in the field

Expressive Languages

- Strongly typed genetic programming
- Automatically defined functions
- Automatically defined macros
- Architecture-altering operations
- Developmental genetic programming

Expressive Languages

- Strongly typed genetic programming
- Automatically defined functions
- Automatically defined macros
- Architecture-altering operations
- Developmental genetic programming
- Push provides all of the above and more, all without any mechanisms beyond the stack-based execution architecture

Types

- Most useful programs manipulate multiple data types.
- Single type or multiple type closures.
- Strongly typed genetic programming: constraints on code generation and genetic operators (Montana).
- Polymorphism (Yu and Clack).
- Stack-based GP with typed stacks (Spector).

Modules

- Automatically-defined functions (Koza).
- Automatically-defined macros (Spector).
- Architecture-altering operations (Koza).
- Module acquisition/encapsulation systems (Kinnear, Roberts, many others).
- Push approach: instructions that can build/execute modules with no changes to the system's representations or algorithms.

Push

- A programming language designed for programs that evolve.
- Simplifies evolution of programs that may use:
  - multiple data types
  - subroutines (any architecture)
  - recursion and iteration
  - evolved control structures
  - evolved evolutionary mechanisms

Push

- Stack-based postfix language with one stack per type
- Types include: integer, float, Boolean, name, code, exec, vector, matrix, quantum gate, [add more as needed]
- Missing argument? NOOP
- Trivial syntax:
  program → instruction | literal | (program*)

Sample Push Instructions

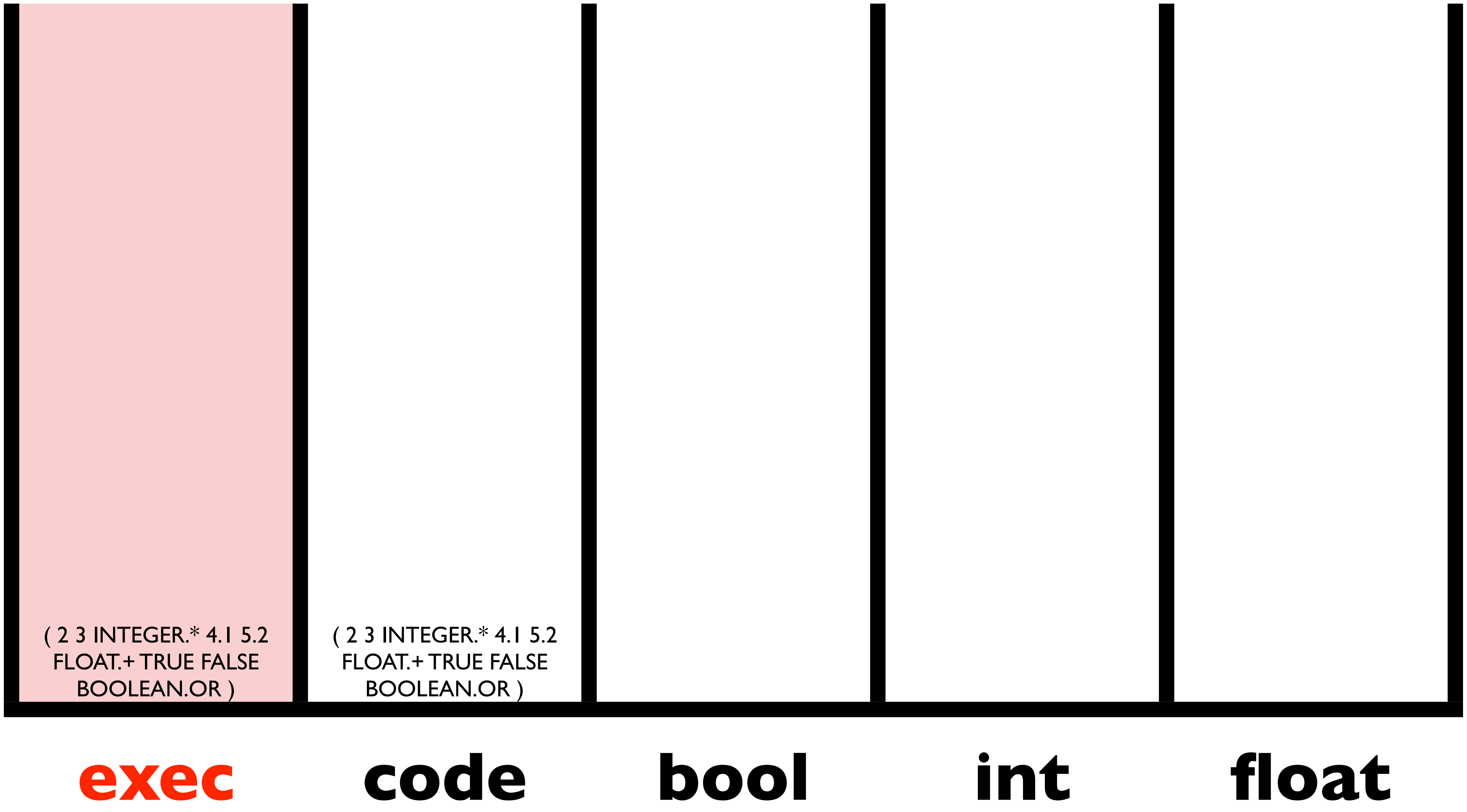
Stack manipulation instructions (all types)	POP, SWAP, YANK, DUP, STACKDEPTH, SHOVE, FLUSH, $=$
Math (INTEGER and FLOAT)	$+$, $-$, $/$, $*$, $>$, $<$, MIN, MAX
Logic (BOOLEAN)	AND, OR, NOT, FROMINTEGER
Code manipulation (CODE)	QUOTE, CAR, CDR, CONS, INSERT, LENGTH, LIST, MEMBER, NTH, EXTRACT
Control manipulation (CODE and EXEC)	DO*, DO*COUNT, DO*RANGE, DO*TIMES, IF

Push(3) Semantics

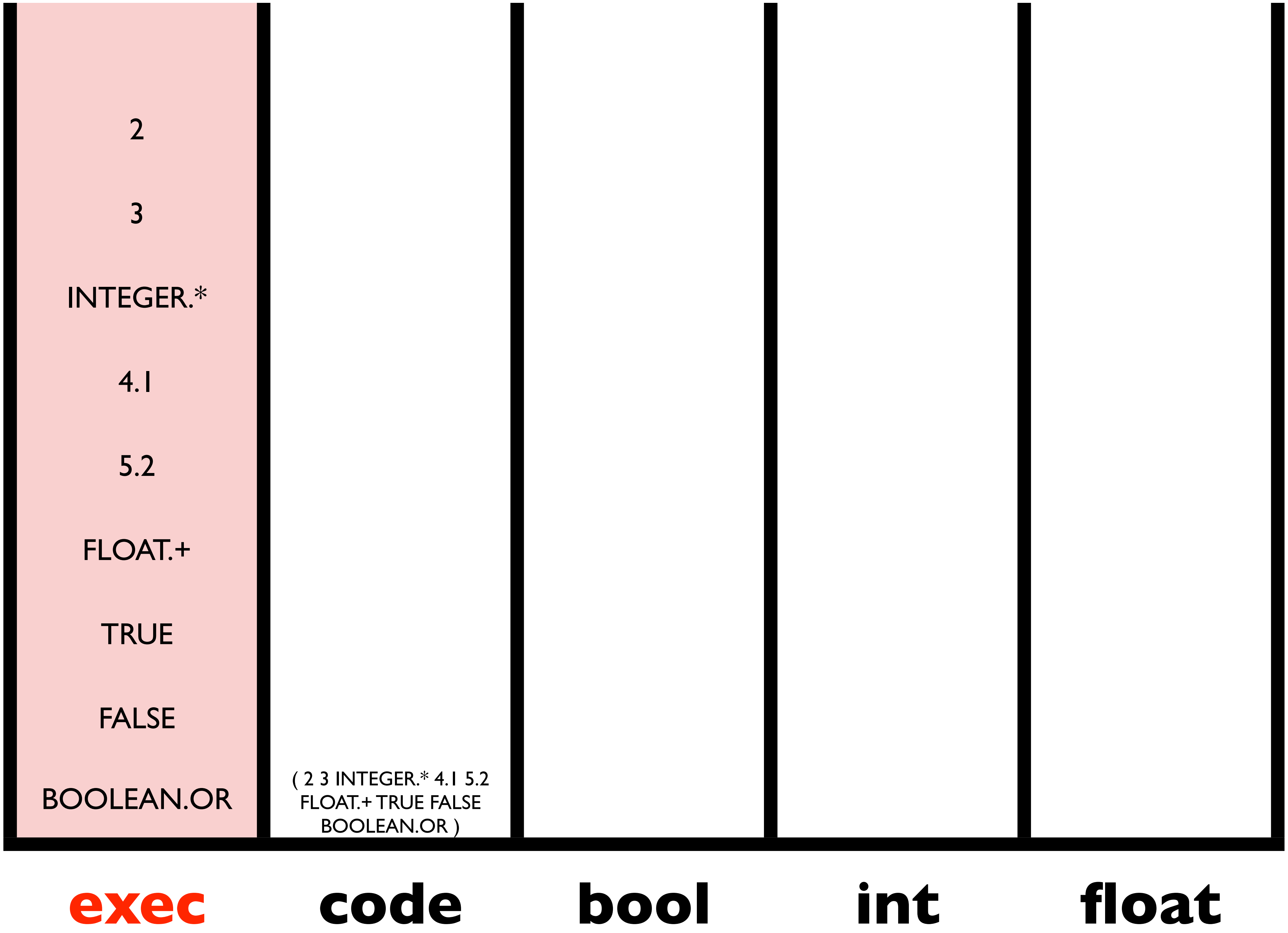
- To execute program P:

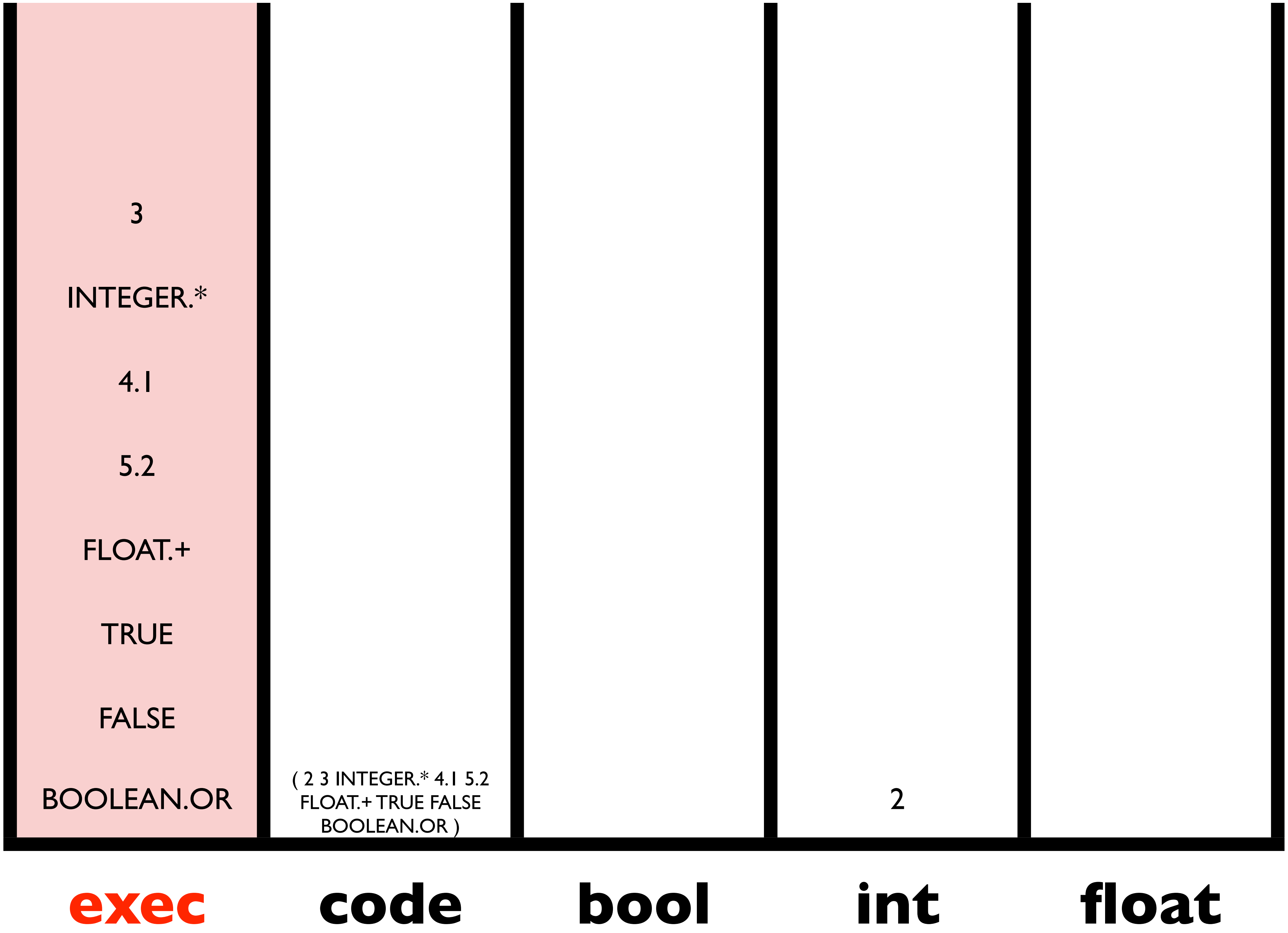
  1. Push P onto the `EXEC` stack.
  2. While the `EXEC` stack is not empty, pop and process the top element of the `EXEC` stack, E:
     - (a) If E is an instruction: execute E (accessing whatever stacks are required).
     - (b) If E is a literal: push E onto the appropriate stack.
     - (c) If E is a list: push each element of E onto the `EXEC` stack, in reverse order.

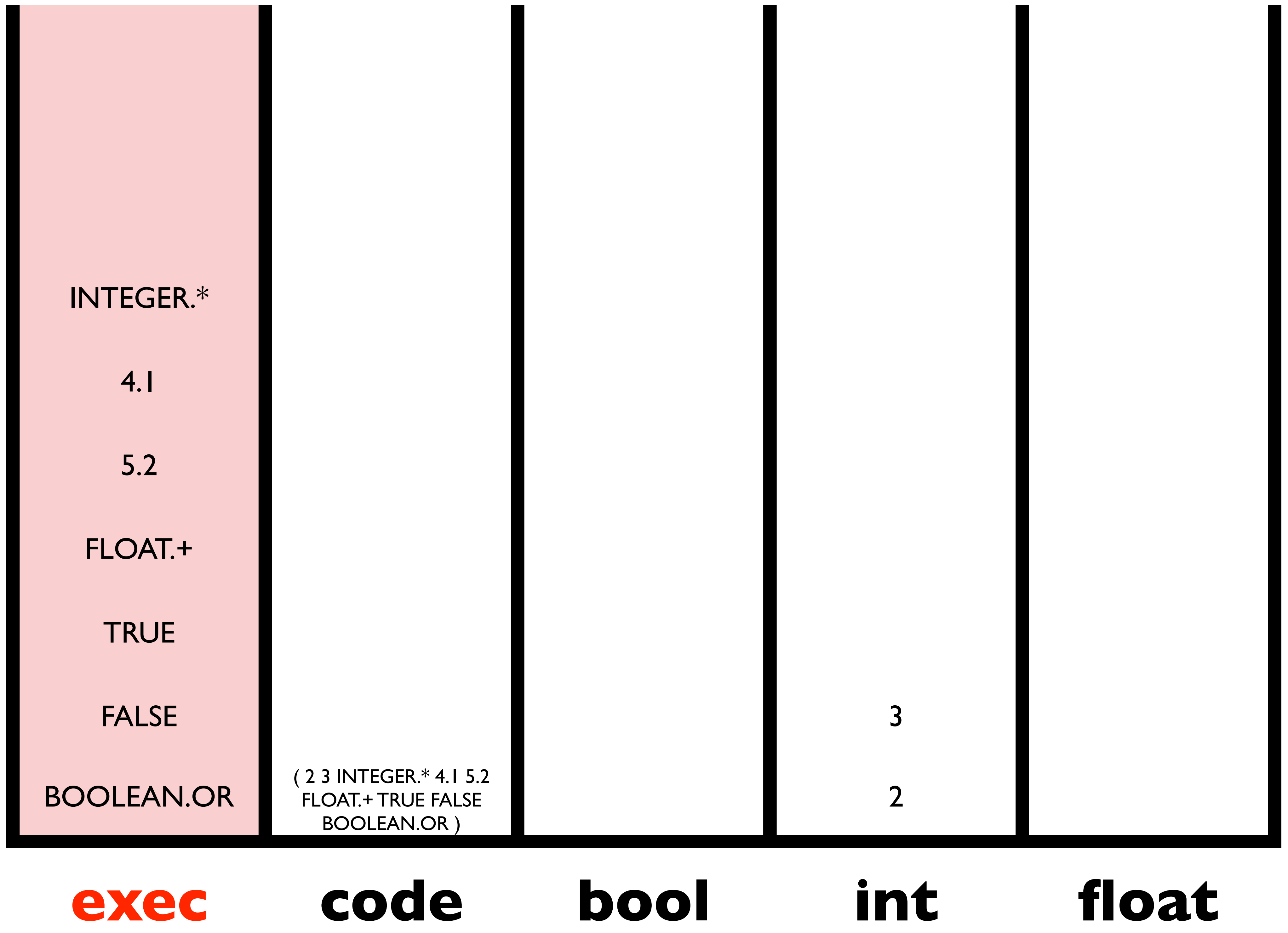
```
( 2 3 INTEGER.* 4.1 5.2 FLOAT.+
TRUE FALSE BOOLEAN.OR )
```

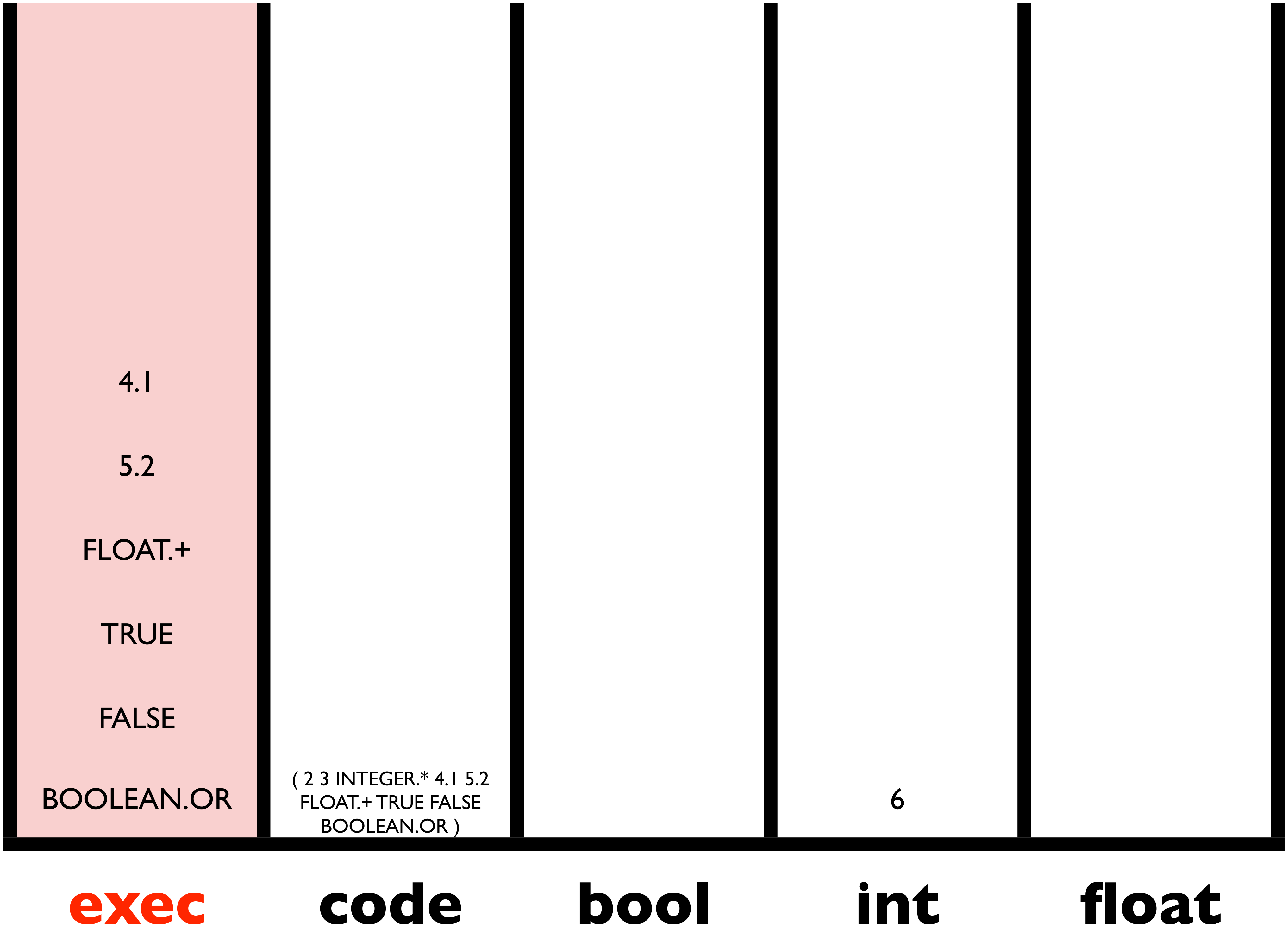


(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
exec
code
bool
int
float


2
3
INTEGER.*
4.1
5.2
FLOAT.+
TRUE
FALSE
BOOLEAN.OR
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
exec
code
bool
int
float

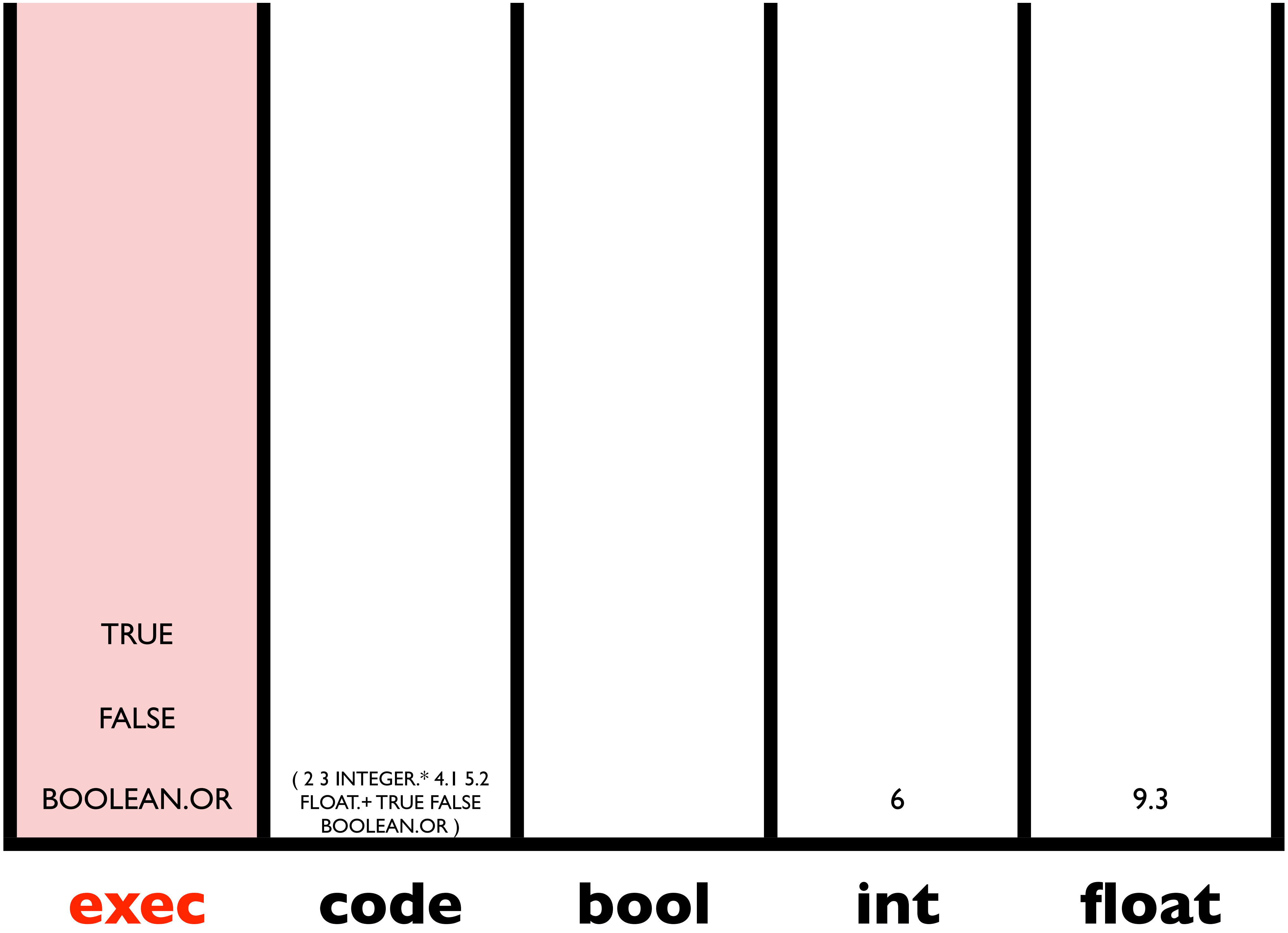

3
INTEGER.*
4.1
5.2
FLOAT.+
TRUE
FALSE
BOOLEAN.OR
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
2
exec
code
bool
int
float


INTEGER.*
4.1
5.2
FLOAT.+
TRUE
FALSE
BOOLEAN.OR
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
3
2
exec
code
bool
int
float


4.1
5.2
FLOAT.+
TRUE
FALSE
BOOLEAN.OR
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
6
exec
code
bool
int
float

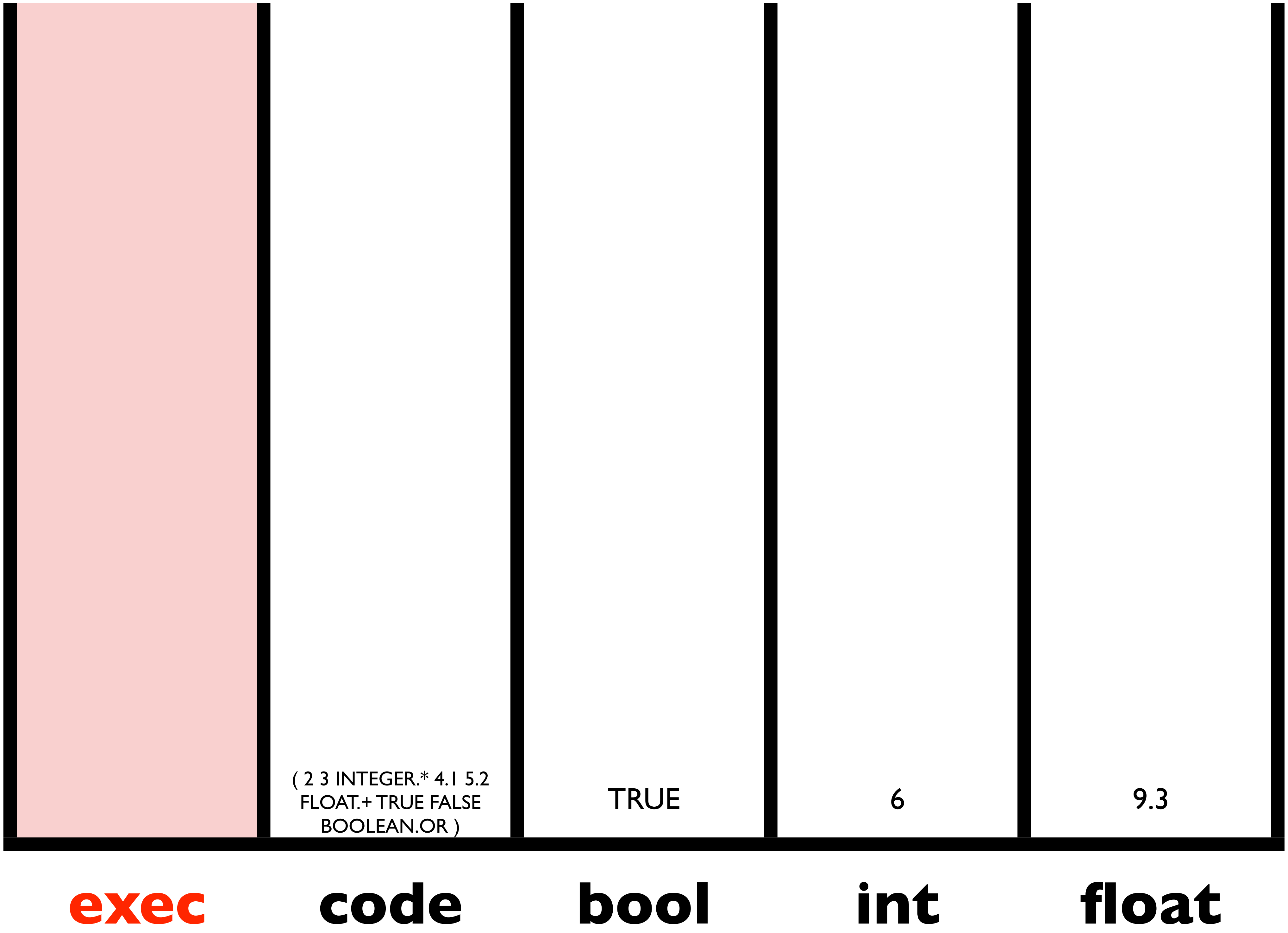
exec	code	bool	int	float
5.2				
FLOAT.+				
TRUE				
FALSE				
BOOLEAN.OR	(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)		6	4.1

exec	code	bool	int	float
FLOAT.+				
TRUE				
FALSE				5.2
BOOLEAN.OR	(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)		6	4.1


TRUE
FALSE
BOOLEAN.OR
(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)
6
9.3
exec
code
bool
int
float

exec	code	bool	int	float
FALSE				
BOOLEAN.OR	(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)	TRUE	6	9.3

exec	code	bool	int	float
		FALSE		
BOOLEAN.OR	(2 3 INTEGER.* 4.1 5.2 FLOAT.+ TRUE FALSE BOOLEAN.OR)	TRUE	6	9.3



```
( 2 3 INTEGER.* 4.1 5.2
FLOAT.+ TRUE FALSE
BOOLEAN.OR )
```

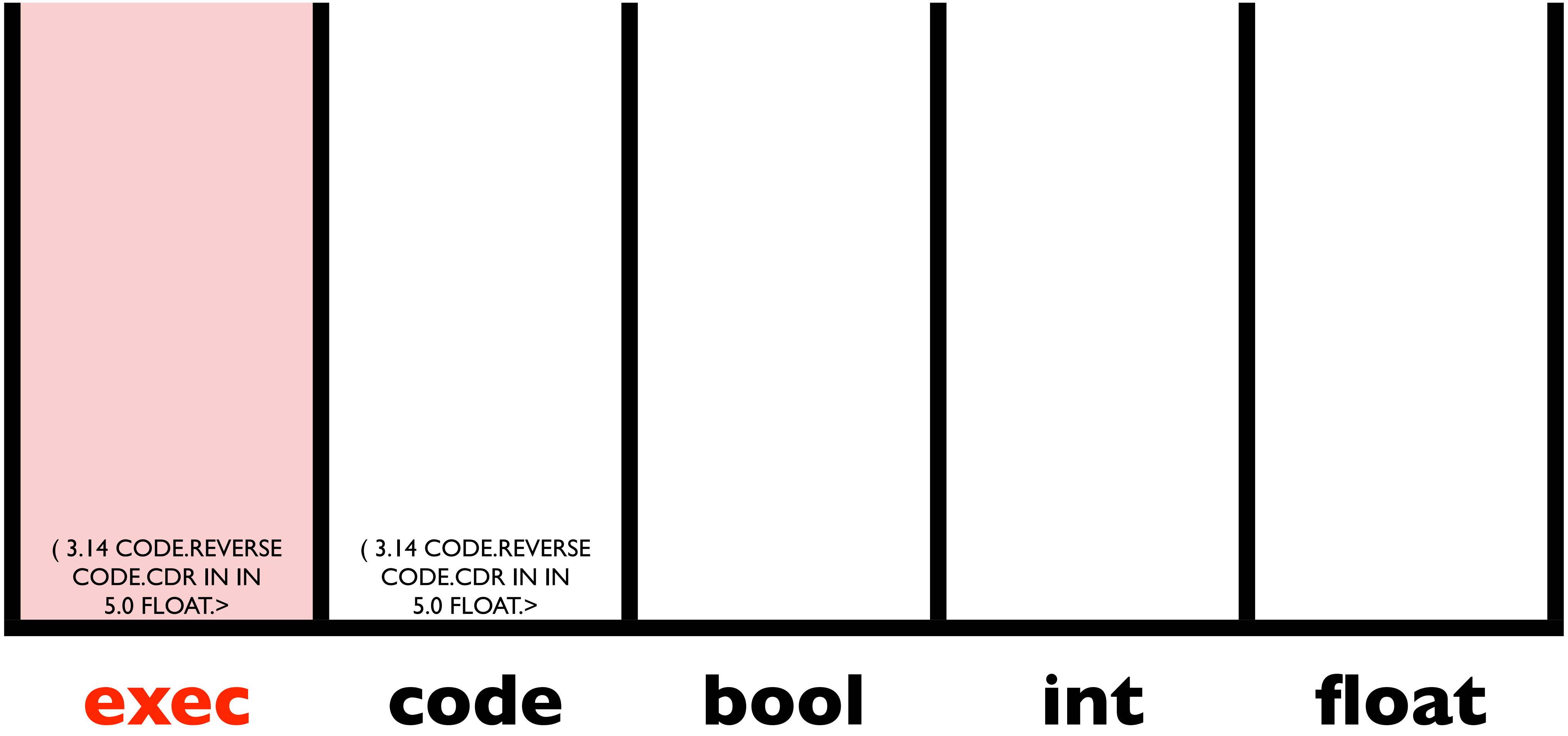
Same Results

```
( 2 3 INTEGER.* 4.1 5.2 FLOAT.+
   TRUE FALSE BOOLEAN.OR )
```

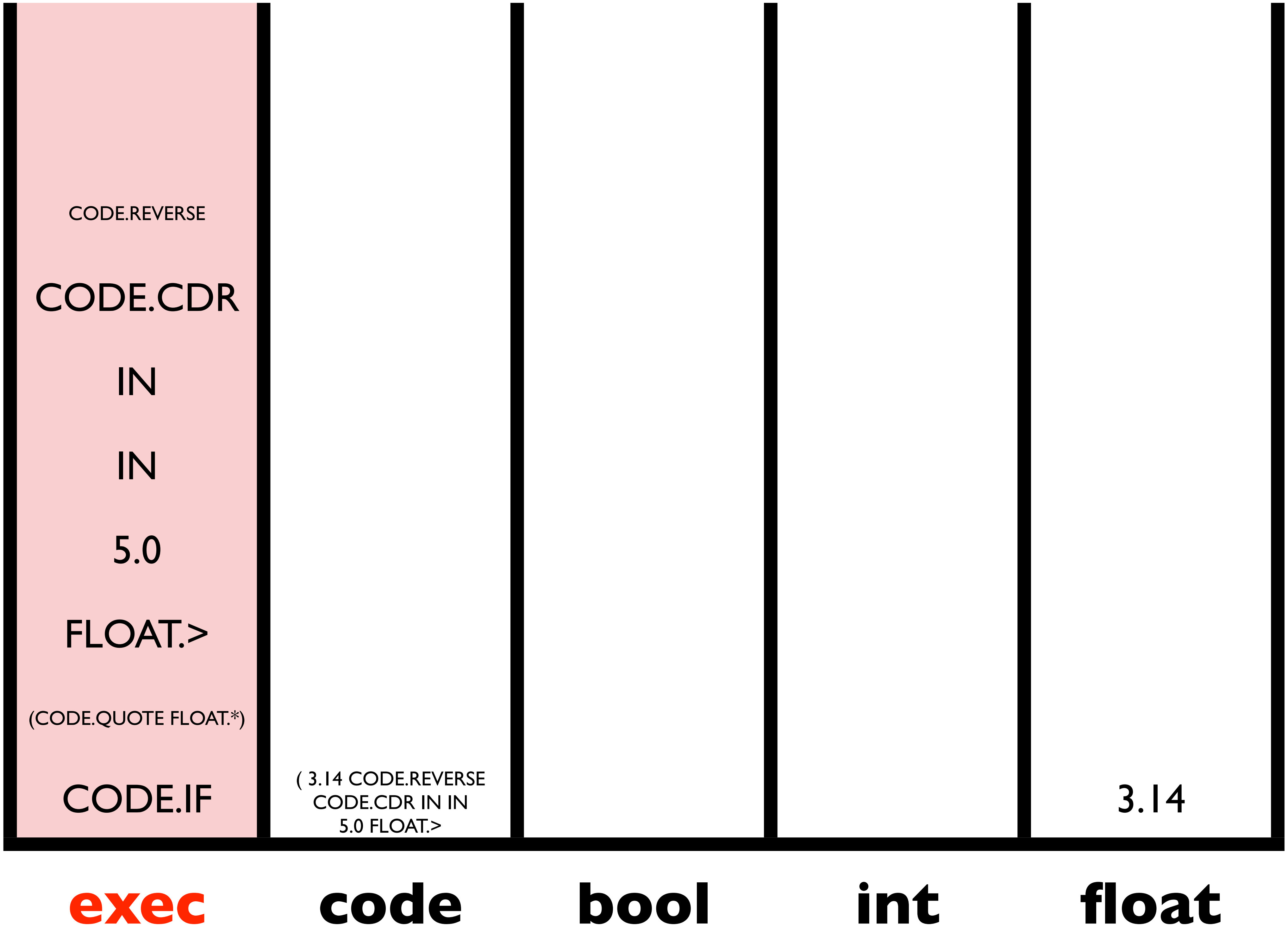
```
( 2 BOOLEAN.AND 4.1 TRUE INTEGER./ FALSE
  3 5.2 BOOLEAN.OR INTEGER.* FLOAT.+ )
```

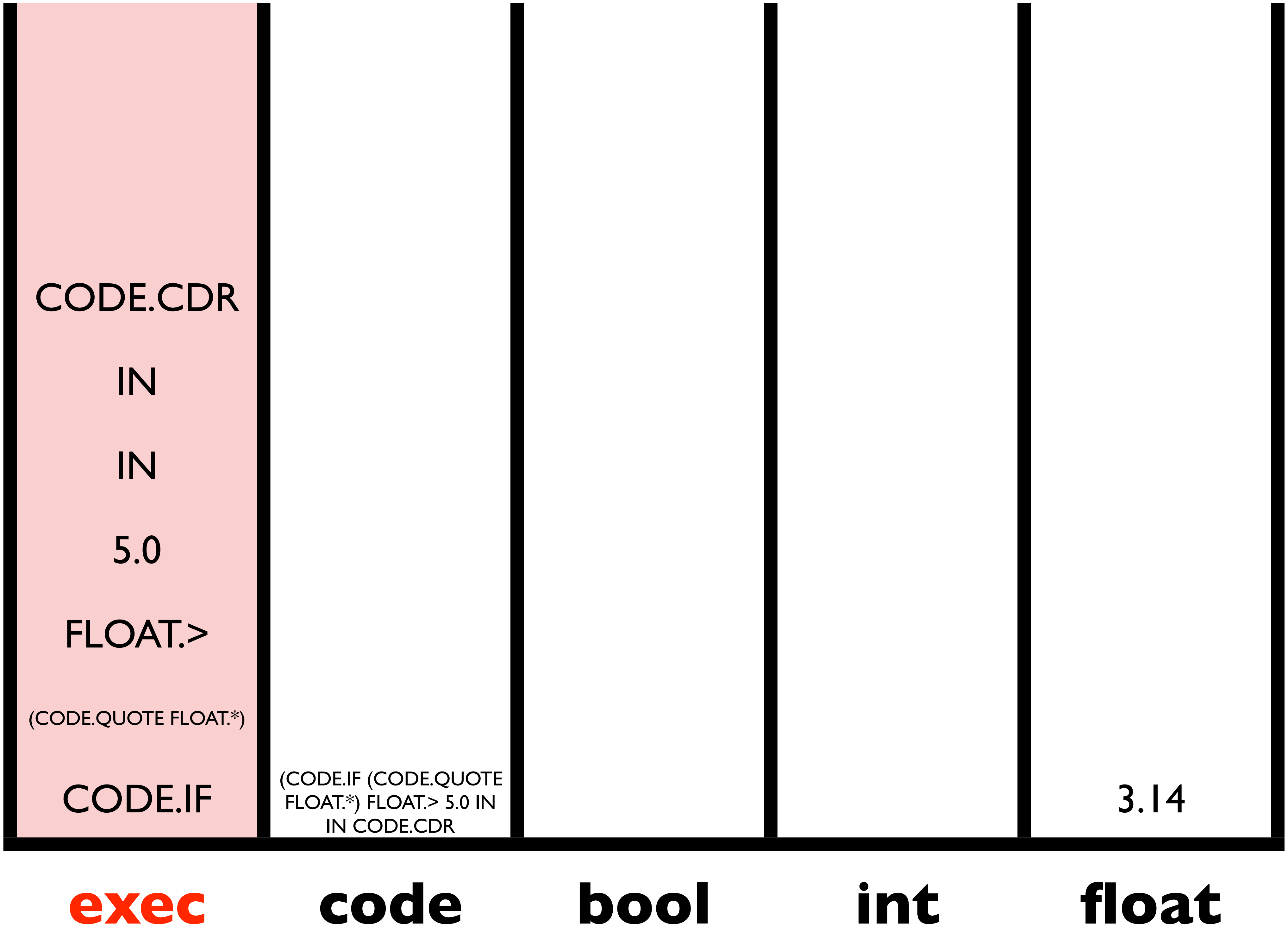
```
( 3.14 CODE.REVERSE CODE.CDR IN IN 5.0
FLOAT.> (CODE.QUOTE FLOAT.*) CODE.IF )
```

```
IN=4.0
```

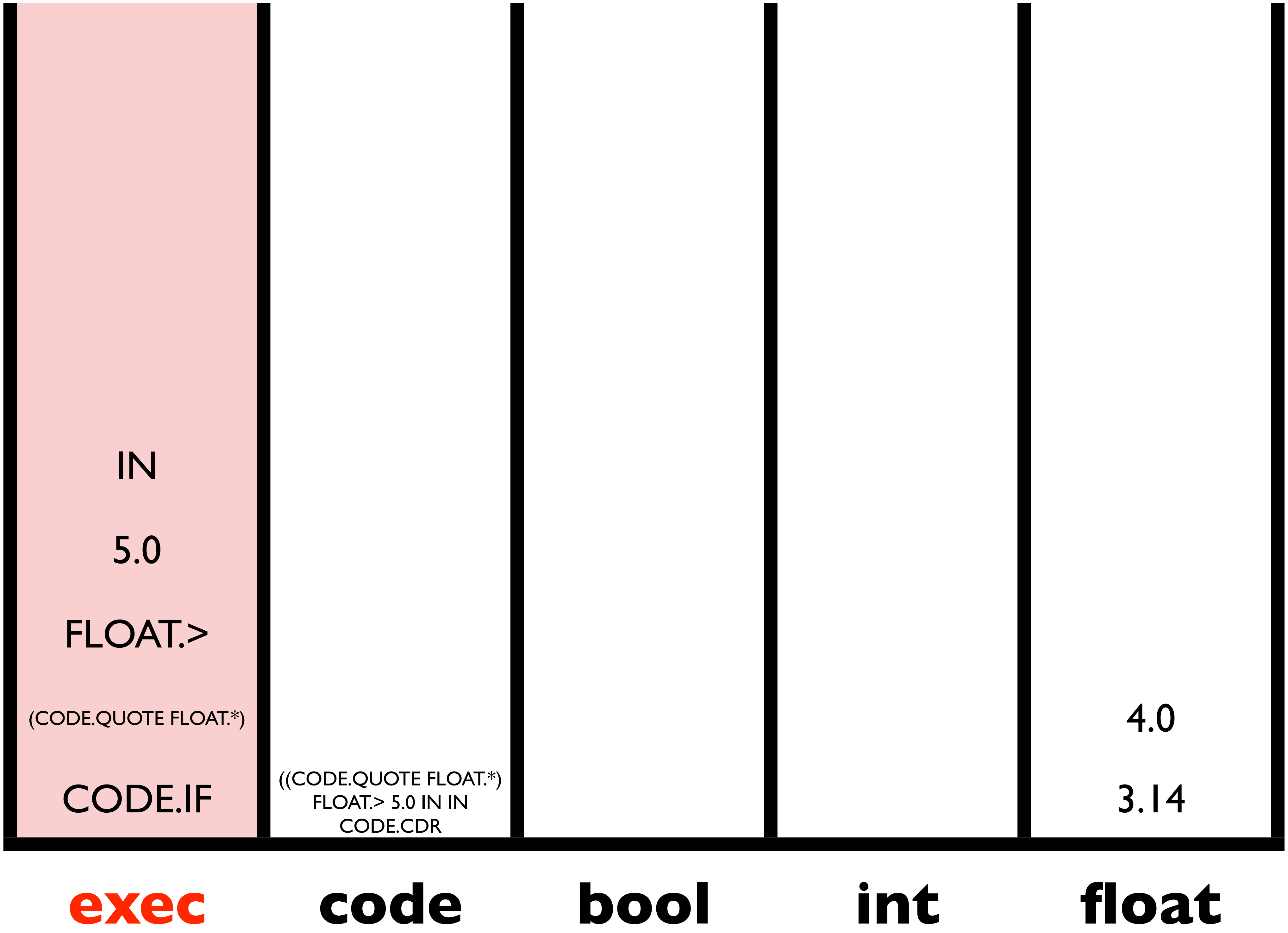

(3.14 CODE.REVERSE CODE.CDR IN IN 5.0 FLOAT.>
(3.14 CODE.REVERSE CODE.CDR IN IN 5.0 FLOAT.>
exec
code
bool
int
float

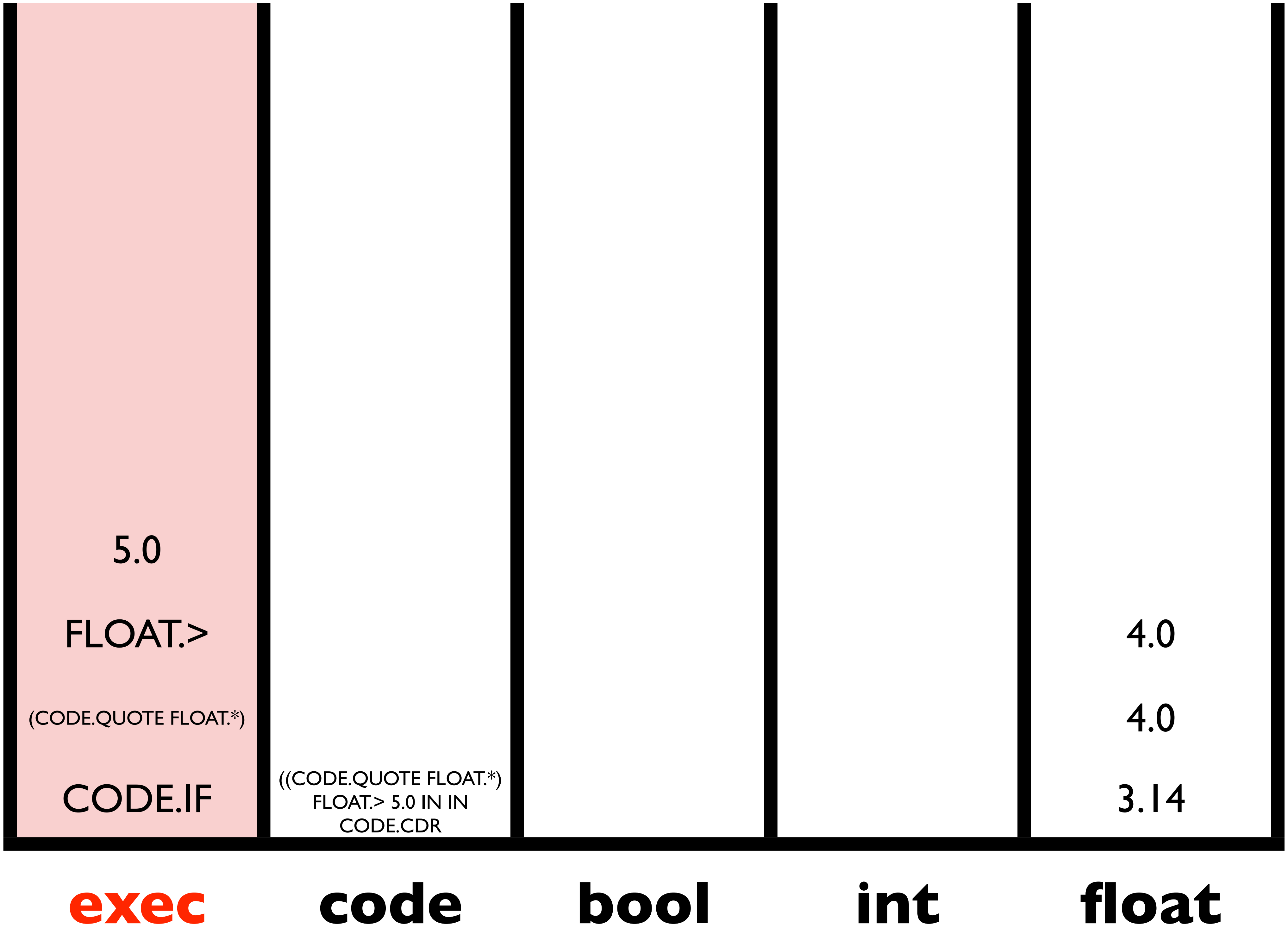
exec	code	bool	int	float
3.14				
CODE.REVERSE				
CODE.CDR				
IN				
IN				
5.0				
FLOAT.>				
(CODE.QUOTE FLOAT.*)				
CODE.IF	(3.14 CODE.REVERSE CODE.CDR IN IN 5.0 FLOAT.>			


CODE.REVERSE
CODE.CDR
IN
IN
5.0
FLOAT.>
(CODE.QUOTE FLOAT.*)
CODE.IF
(3.14 CODE.REVERSE CODE.CDR IN IN 5.0 FLOAT.>
3.14
exec
code
bool
int
float


CODE.CDR
IN
IN
5.0
FLOAT.>
(CODE.QUOTE FLOAT.*)
CODE.IF
(CODE.IF (CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR
3.14
exec
code
bool
int
float

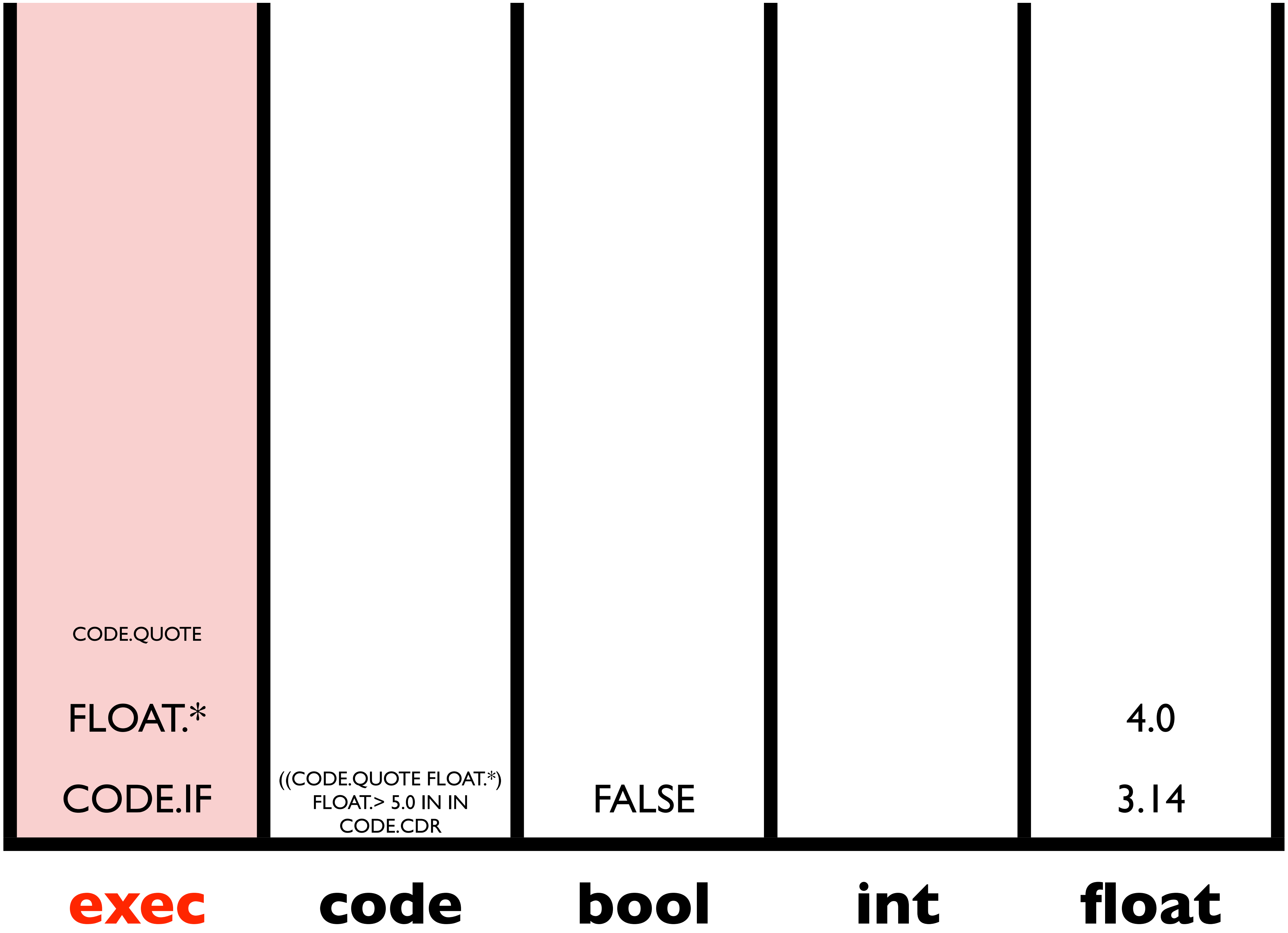
exec	code	bool	int	float
IN				
IN				
5.0				
FLOAT.>				
(CODE.QUOTE FLOAT.*)				
CODE.IF	((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR			3.14


IN
5.0
FLOAT.>
(CODE.QUOTE FLOAT.*)
CODE.IF
((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR
4.0
3.14
exec
code
bool
int
float

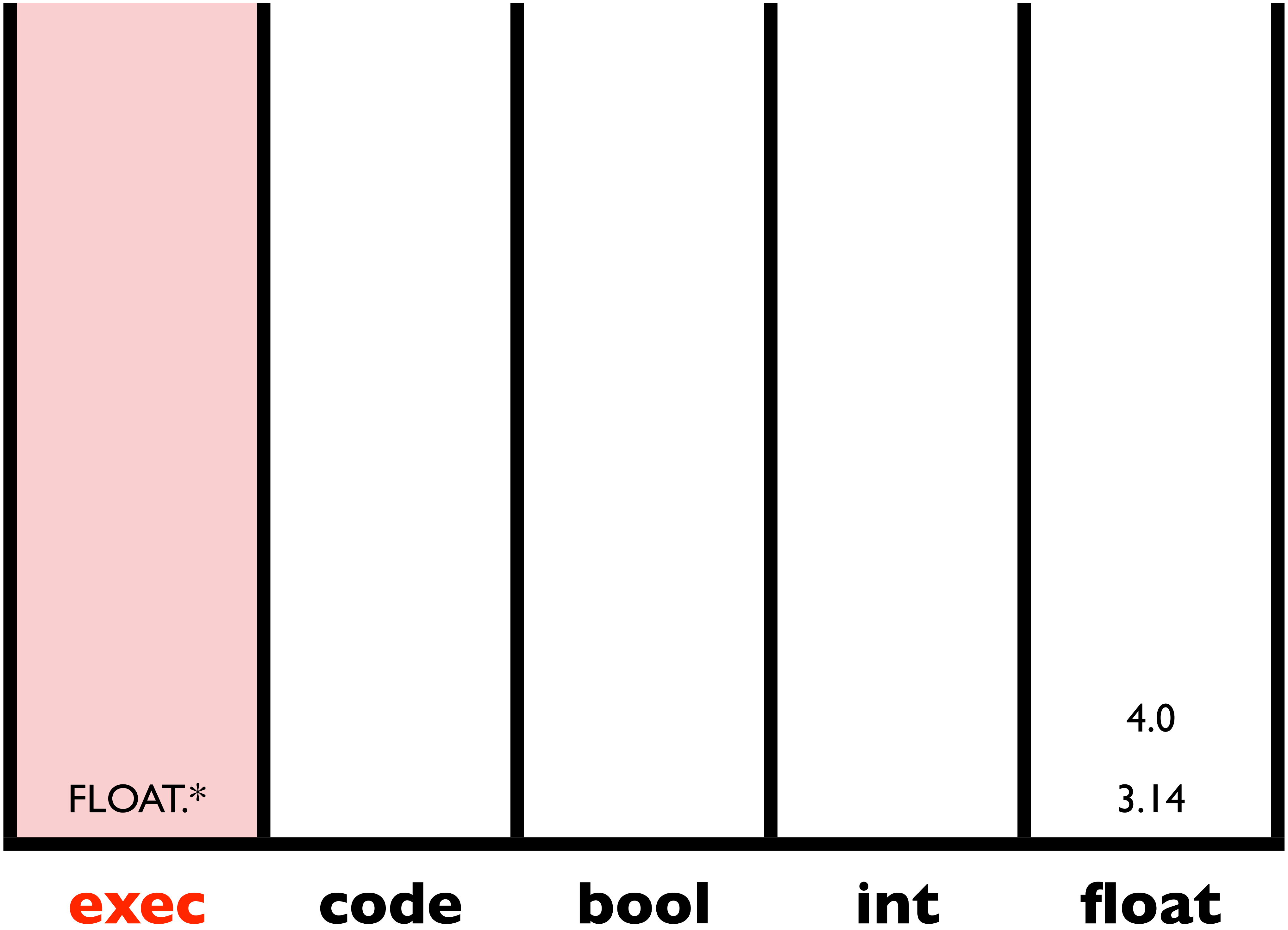

5.0
FLOAT.>
(CODE.QUOTE FLOAT.*)
CODE.IF
((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR
4.0
4.0
3.14
exec
code
bool
int
float

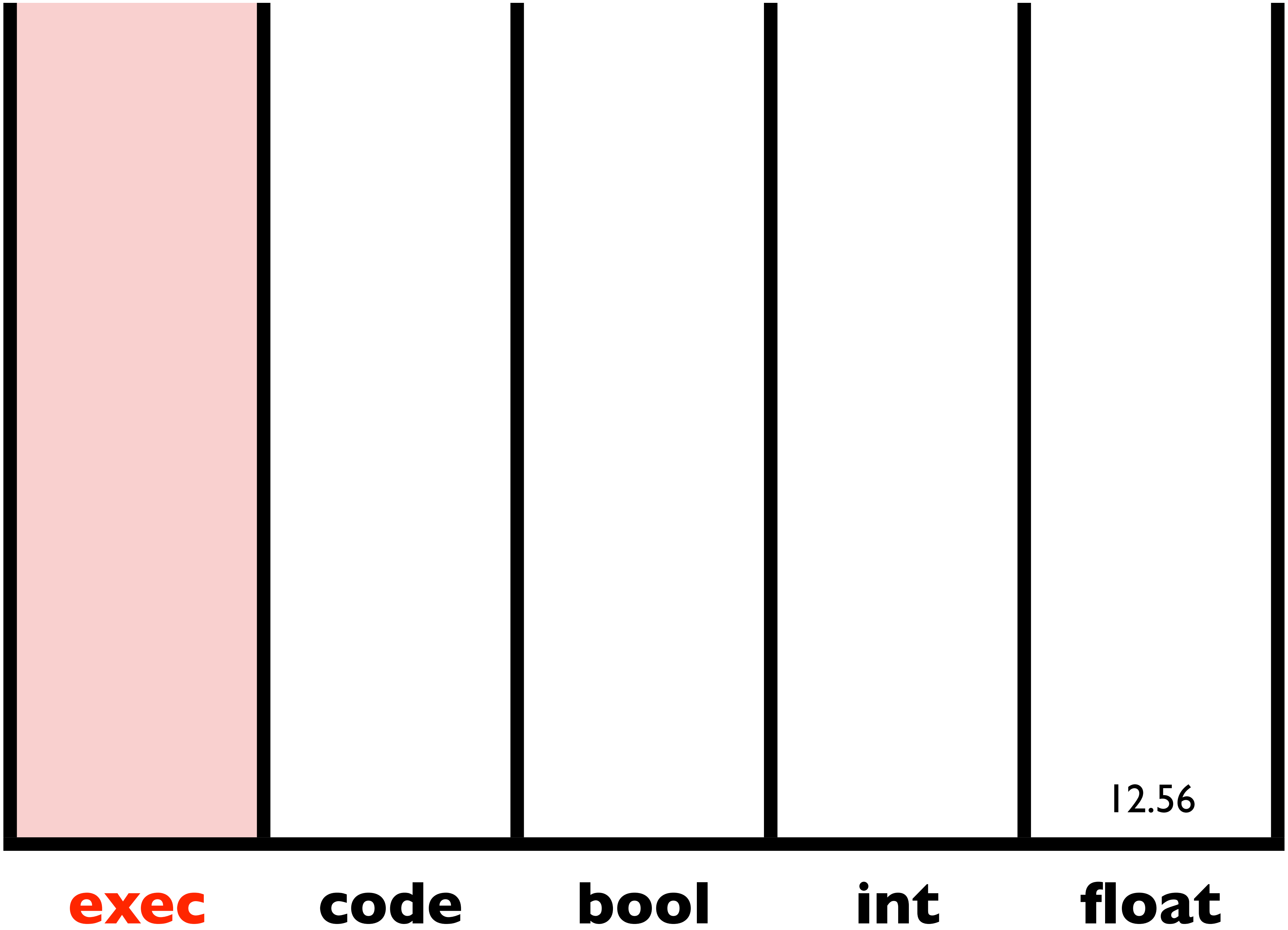
				5.0
FLOAT.>				4.0
(CODE.QUOTE FLOAT.*)				4.0
CODE.IF	((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR			3.14
exec	**code**	**bool**	**int**	**float**

exec	code	bool	int	float
(CODE.QUOTE FLOAT.*)				4.0
CODE.IF	((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR	FALSE		3.14


CODE.QUOTE
FLOAT.*
CODE.IF
((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR
FALSE
4.0
3.14
exec
code
bool
int
float

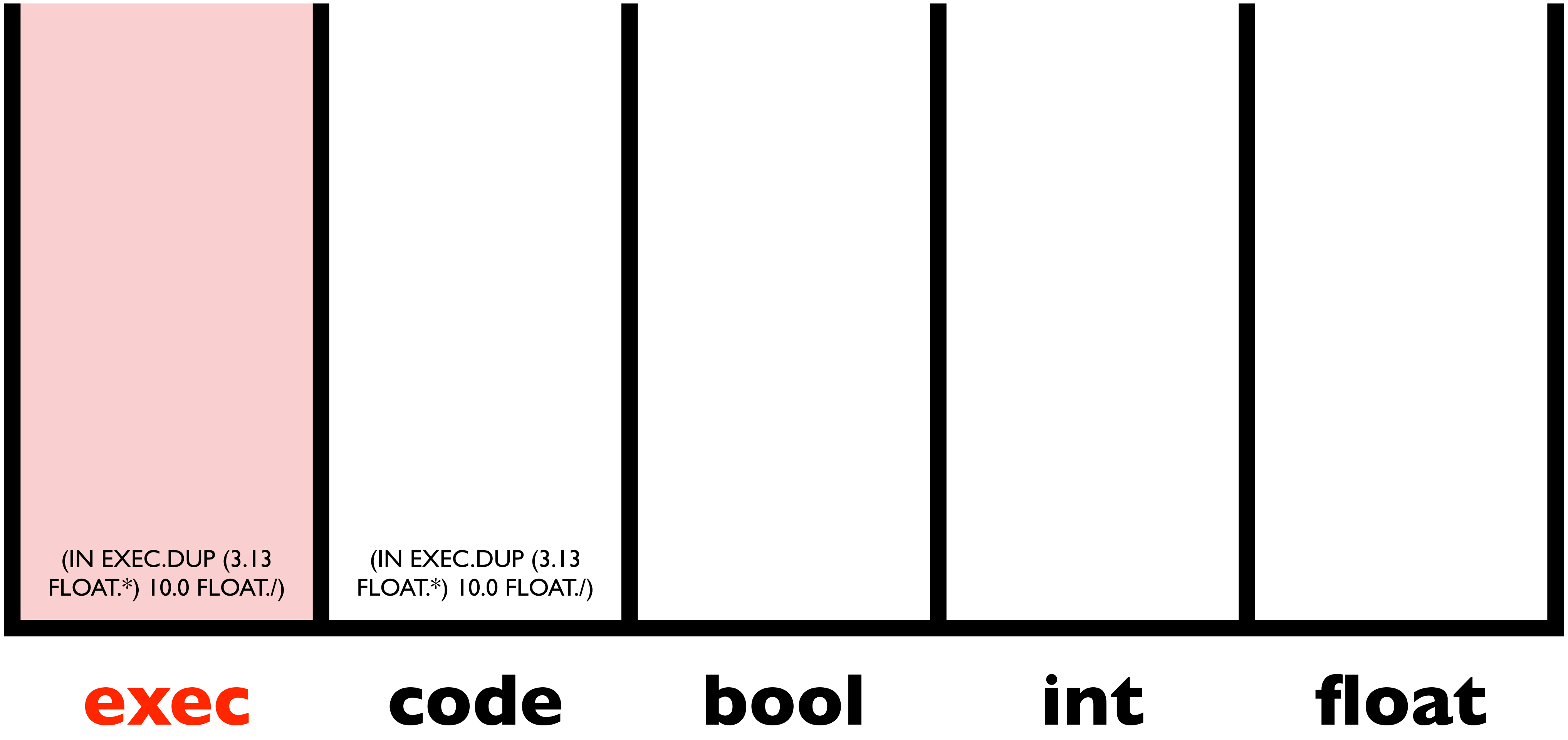
exec	code	bool	int	float
	FLOAT.*			4.0
CODE.IF	((CODE.QUOTE FLOAT.*) FLOAT.> 5.0 IN IN CODE.CDR	FALSE		3.14

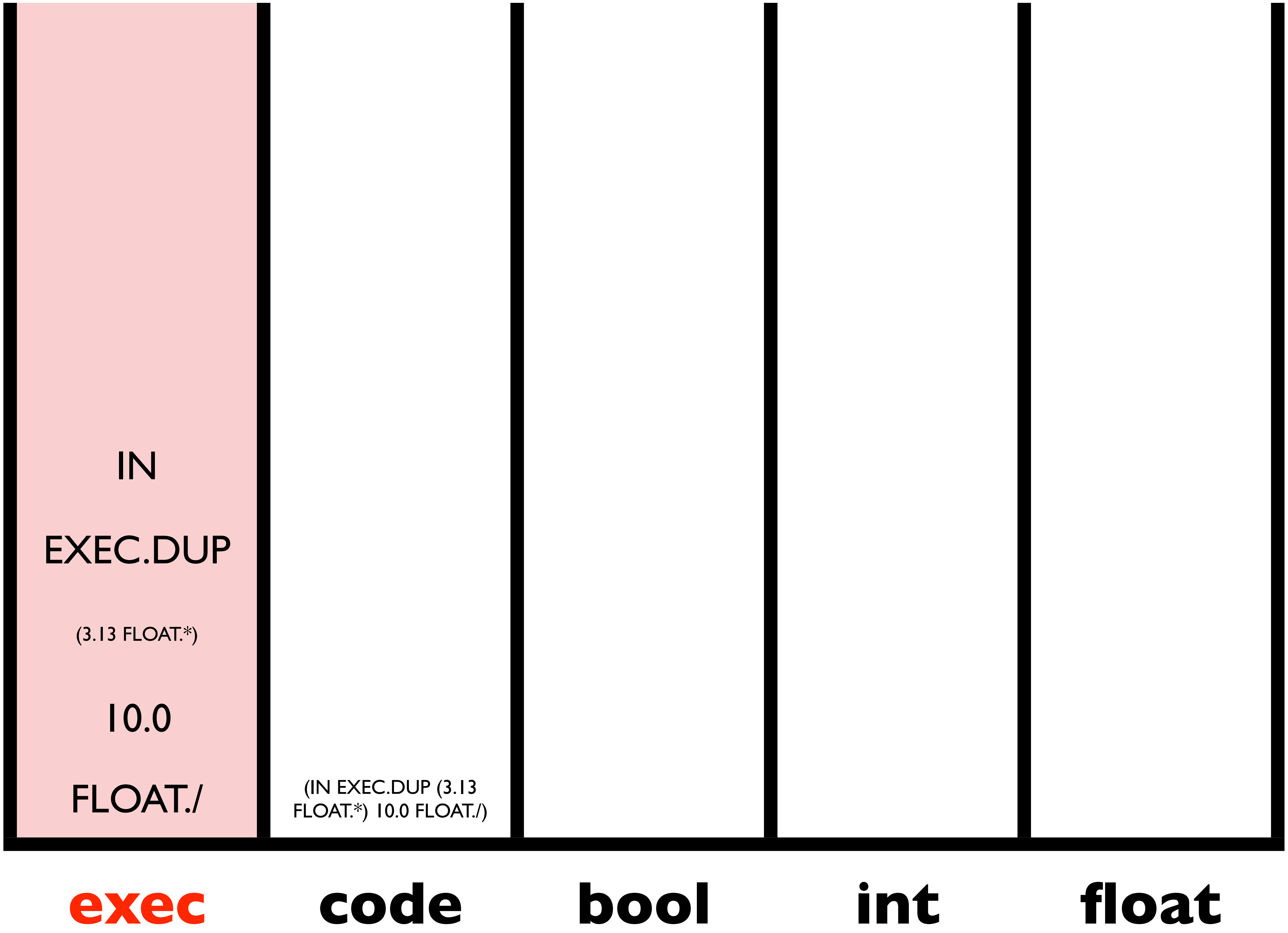

FLOAT.*
4.0
3.14
exec
code
bool
int
float


12.56
exec
code
bool
int
float

```
(IN EXEC.DUP (3.13 FLOAT.*)
10.0 FLOAT./)
```

```
IN=4.0
```


(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)
(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)
exec
code
bool
int
float

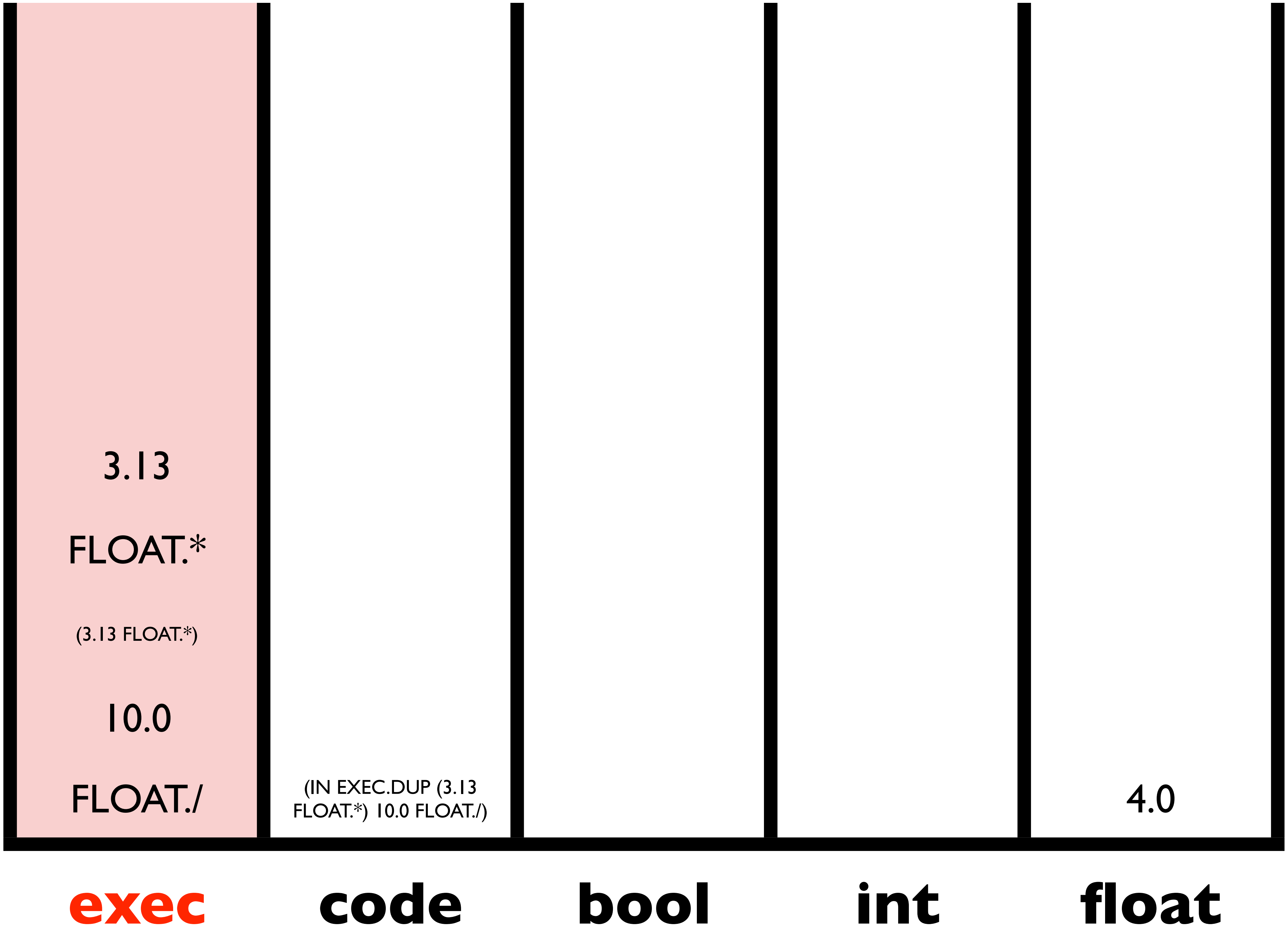


```
IN
EXEC.DUP
(3.13 FLOAT.*)
10.0
FLOAT./
```

```
(IN EXEC.DUP (3.13
FLOAT.*) 10.0 FLOAT./)
```

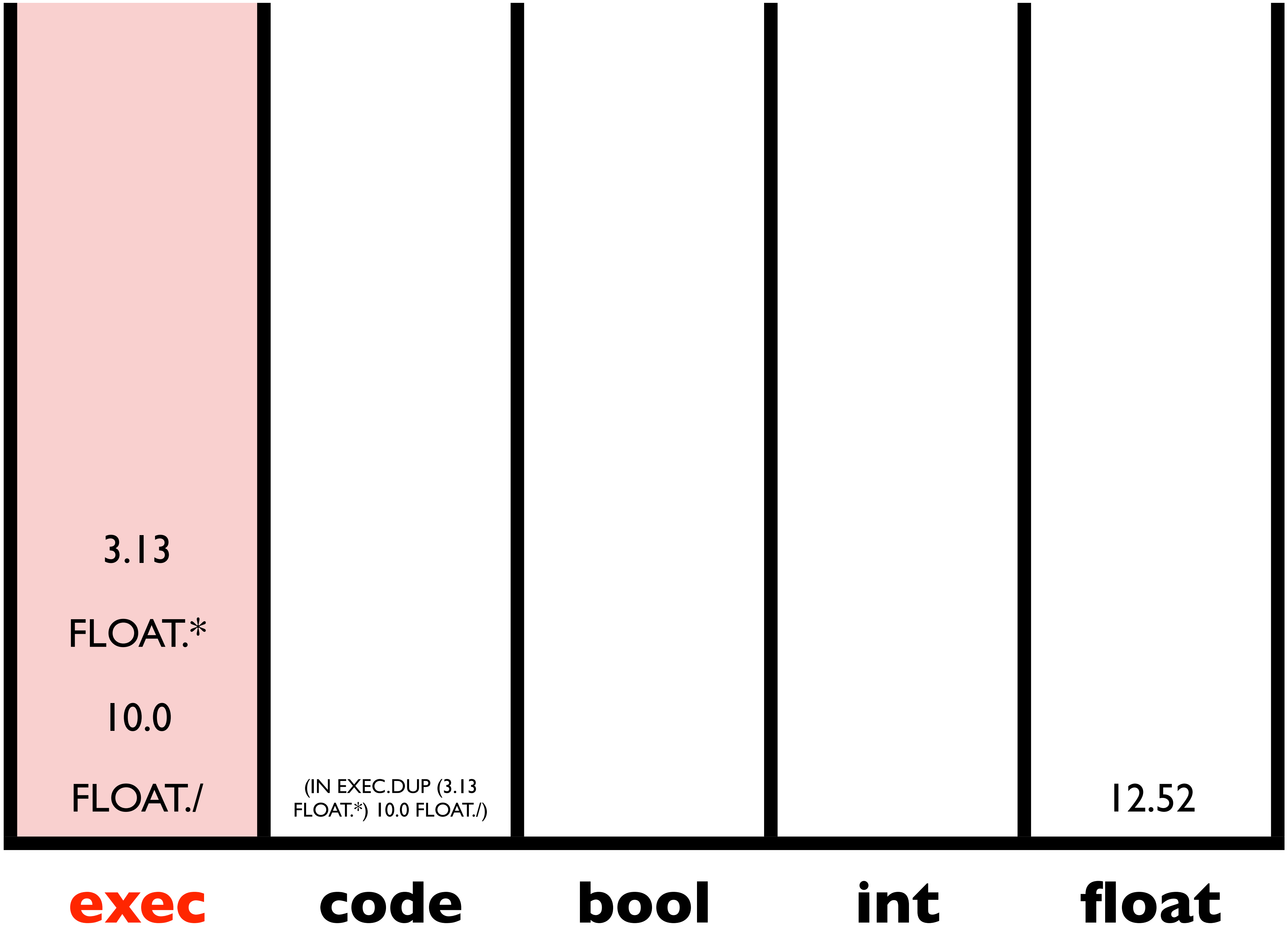
exec	code	bool	int	float
EXEC.DUP				
(3.13 FLOAT.*)				
10.0				
FLOAT./	(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)			4.0

exec	code	bool	int	float
(3.13 FLOAT.*)				
(3.13 FLOAT.*)				
10.0				
FLOAT./	(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)			4.0

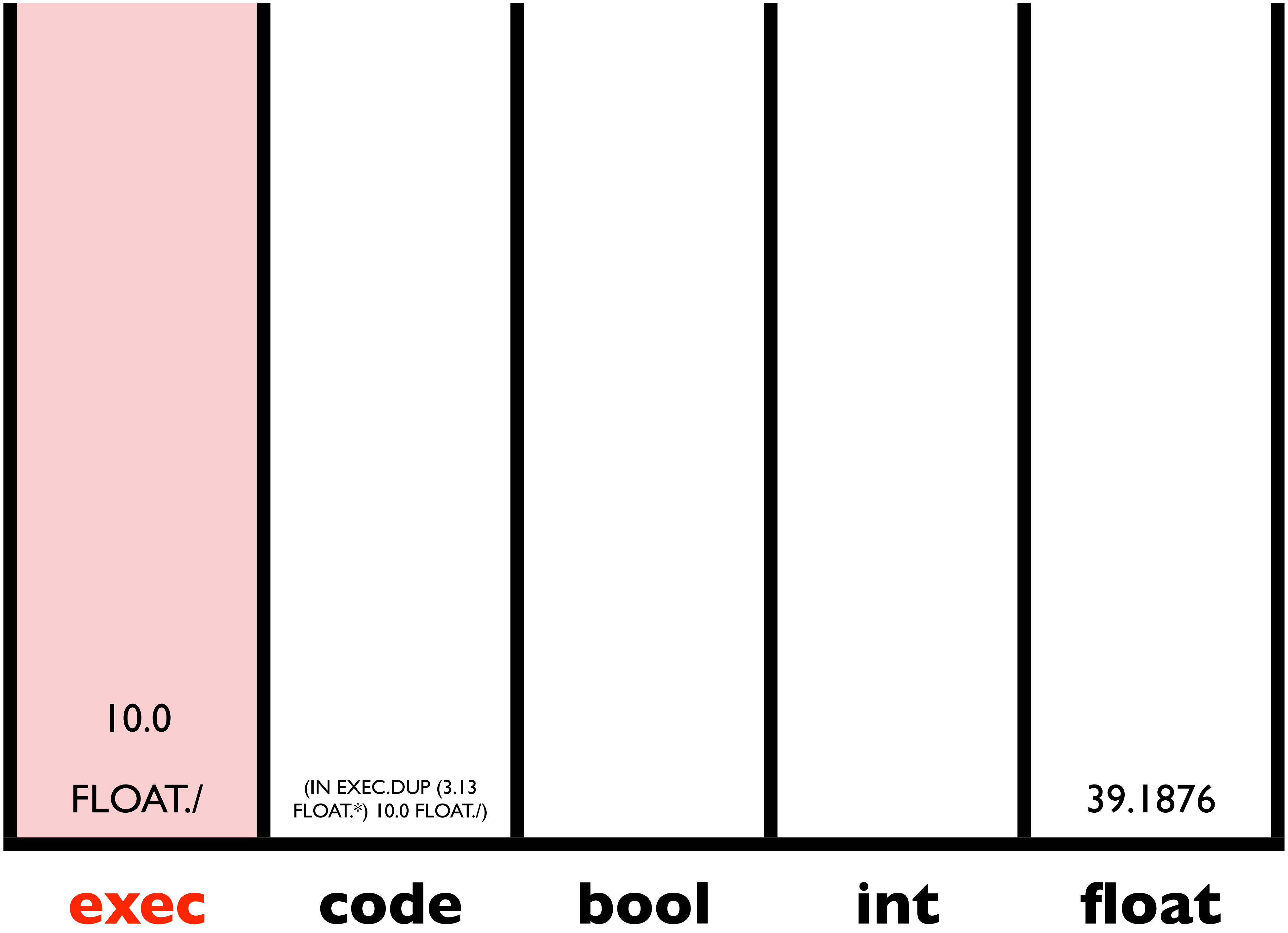

3.13
FLOAT.*
(3.13 FLOAT.*)
10.0
FLOAT./
(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)
4.0
exec
code
bool
int
float

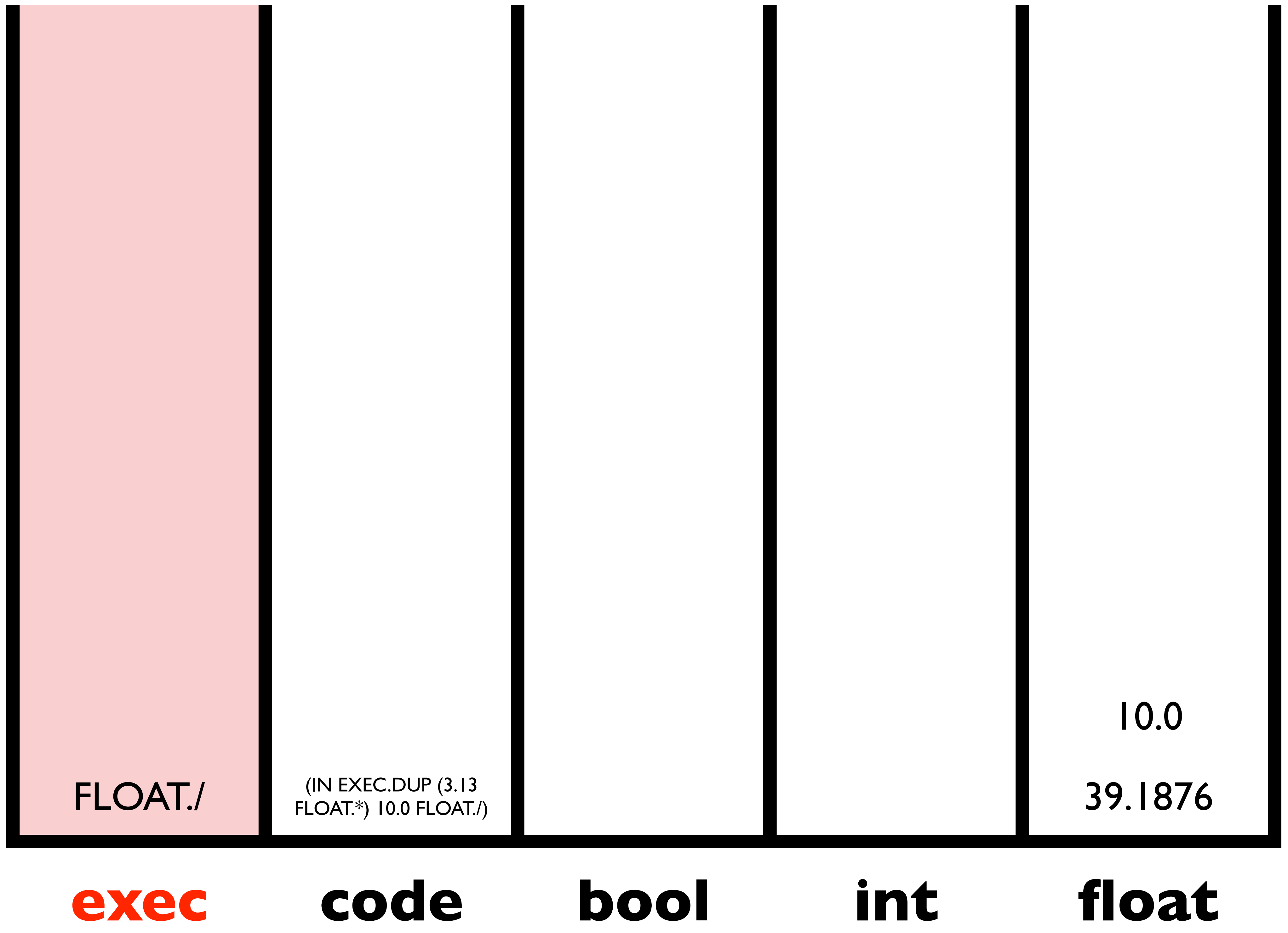
exec	code	bool	int	float
FLOAT.*				
(3.13 FLOAT.*)				
10.0				3.13
FLOAT./	(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)			4.0

(3.13 FLOAT.*)				
10.0				
FLOAT./	(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)			12.52
exec	**code**	**bool**	**int**	**float**

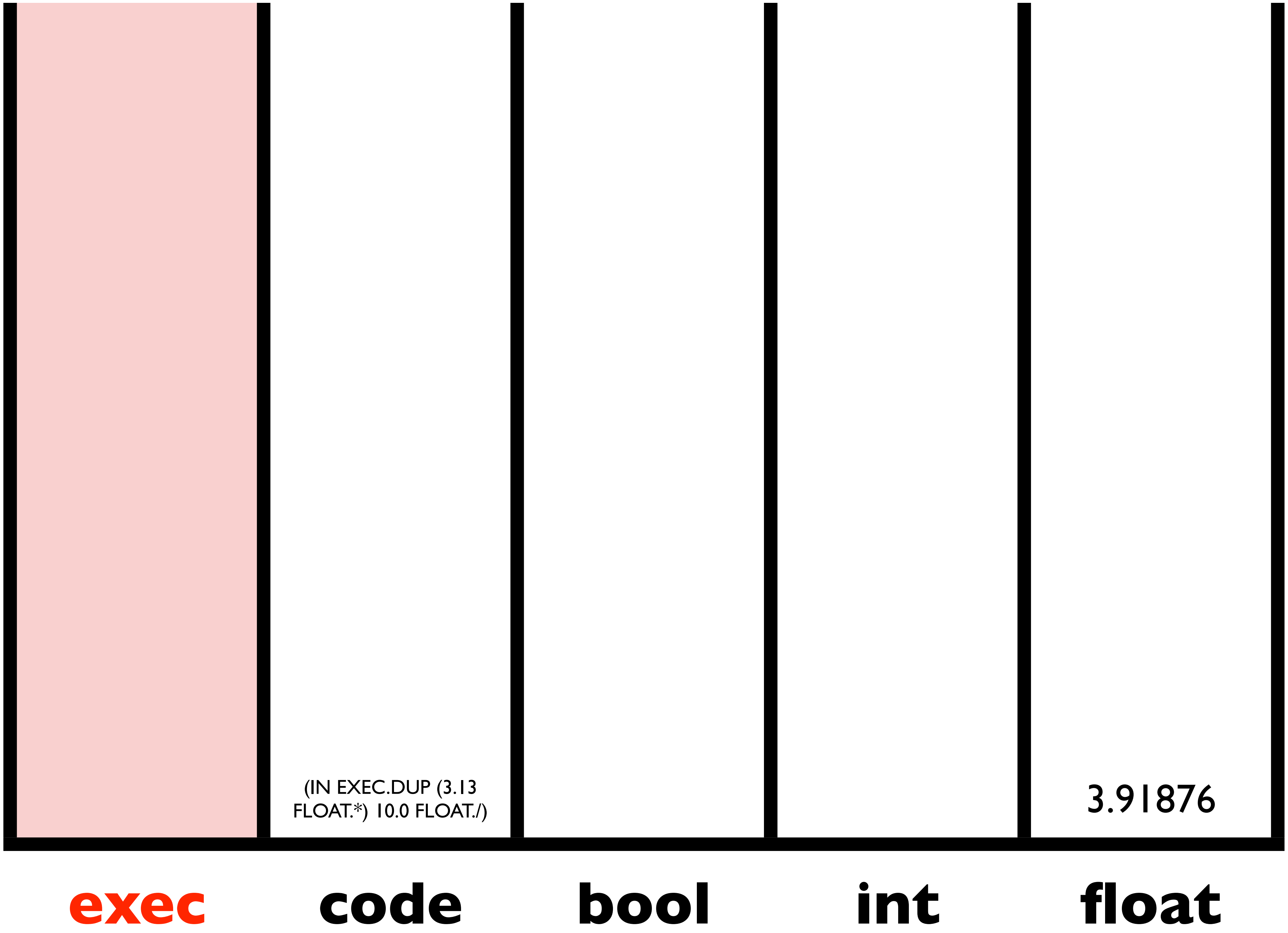

3.13
FLOAT.*
10.0
FLOAT./
(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)
12.52
exec
code
bool
int
float

exec	code	bool	int	float
FLOAT.*				
10.0				3.13
FLOAT./	(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)			12.52


10.0
FLOAT./
(IN EXEC.DUP (3.13 FLOAT.*) 10.0 FLOAT./)
39.1876
exec
code
bool
int
float



```
(IN EXEC.DUP (3.13
FLOAT.*) 10.0 FLOAT./)
```



```
(IN EXEC.DUP (3.13
FLOAT.*) 10.0 FLOAT./)
```

Combinators

- Standard *K*, *S*, and *Y* combinators:
  - `EXEC.K` removes the second item from the `EXEC` stack.
  - `EXEC.S` pops three items (call them `A`, `B`, and `C`) and then pushes `(B C)`, `C`, and then `A`.
  - `EXEC.Y` inserts `(EXEC.Y` *`T`*`)` under the top item (*T*).
- A *Y*-based "while" loop:

```
( EXEC.Y
  ( <BODY/CONDITION> EXEC.IF
  ( ) EXEC.POP ) )
```

Iterators

`CODE.DO*TIMES`, `CODE.DO*COUNT`, `CODE.DO*RANGE`

`EXEC.DO*TIMES`, `EXEC.DO*COUNT`, `EXEC.DO*RANGE`

Additional forms of iteration are supported through code manipulation (e.g. via `CODE.DUP CODE.APPEND CODE.DO`)

Named Subroutines

```
( TIMES2 EXEC.DEFINE ( 2 INTEGER.* ) )
```

Modularity
Ackley and Van Belle

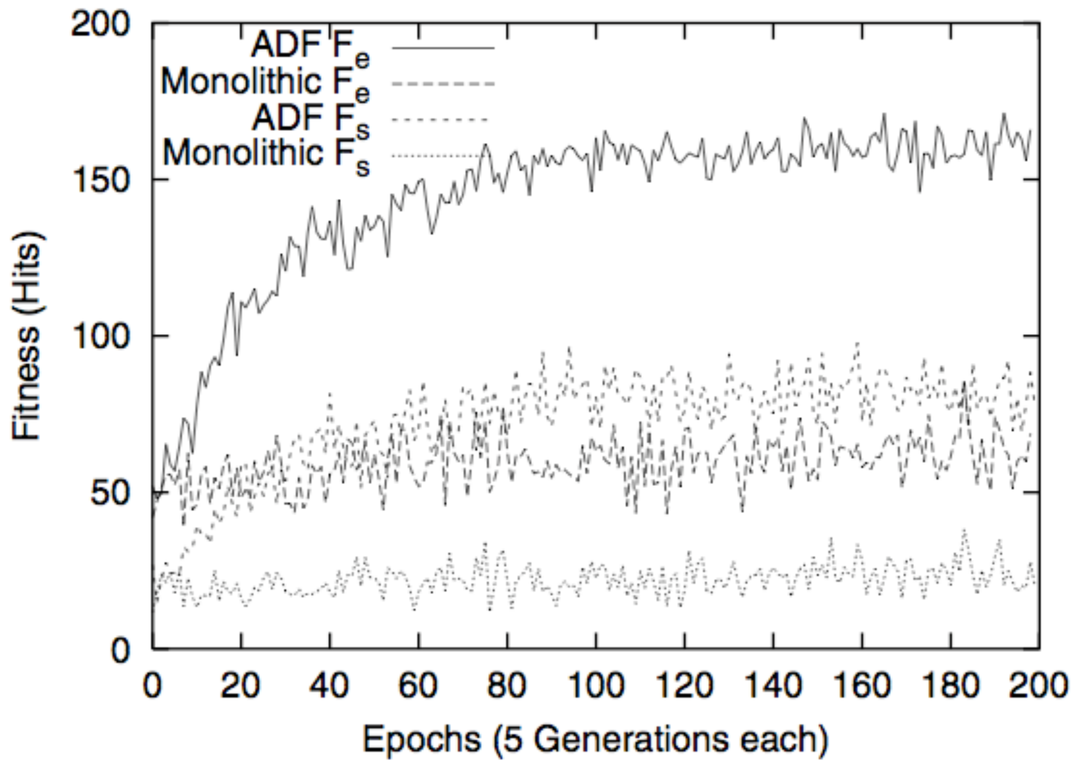
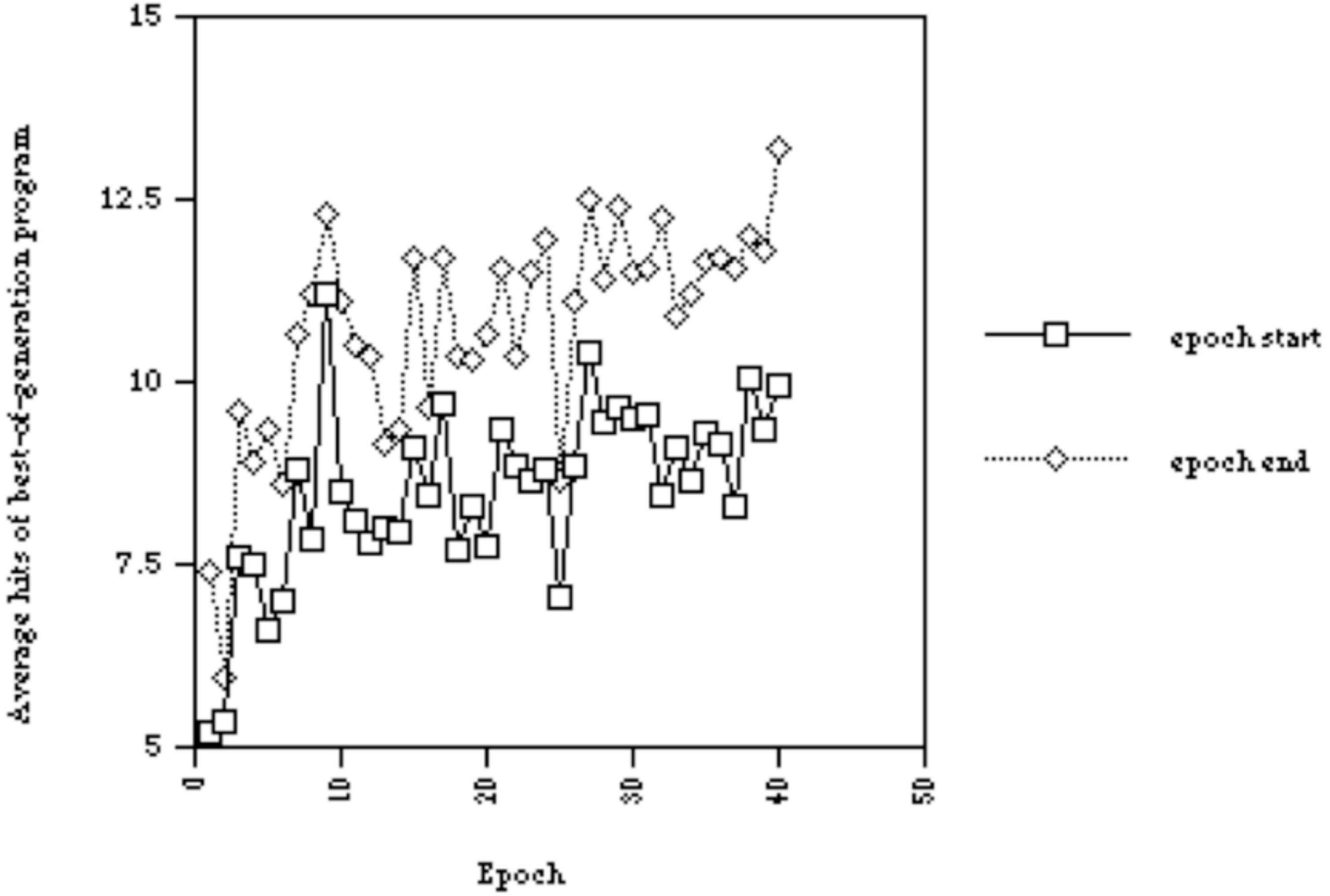


Figure 2: Average fitness values at the start (F_s) and end (F_e) of each epoch when regressing to $y = A\sin(Ax)$. A is selected at the start of each epoch uniformly from the range $[0,6)$.

Modularity via Push



The Odd Problem

- Integer input
- Boolean output
- Was the input odd?
- `((code.nth) code.atom)`

Evolved List Reverse

- Input is list of integers on the `CODE` stack.
- PushGP produced the following general solution:

```
((CODE.DO*TIMES (CODE.DO* CODE.LIST (((INTEGER.STACKDEPTH EXEC.DO*TIMES)
[illegible]
(CODE.QUOTE INTEGER.SWAP) CODE.POP) INTEGER.FLUSH)))) (BOOLEAN.=
```

Auto-simplification

```
Loop:
    Make it randomly simpler
    If it’s as good or better: keep it
    Otherwise: revert
```

Evolved List Reverse (2)

- The evolved general solution simplifies to:
  `(CODE.DO* INTEGER.STACKDEPTH EXEC.DO*TIMES CODE.FROMINTEGER CODE.STACKDEPTH EXEC.DO*TIMES CODE.CONS)`
- This works by executing the input list, then moving all of the integers individually to the `CODE` stack, then building the reversed list.

Evolved Factorial

Two simplified evolved general solutions:

```
(1 EXEC.DO*RANGE INTEGER.*)
```

Runs a loop that just multiplies all of the loop counter values.

```
(INTEGER.* INTEGER.STACKDEPTH CODE.DO*RANGE
INTEGER.MAX)
```

*Recursively executes the whole program, which is on the CODE stack; INTEGER.STACKDEPTH produces the 1 for the loop index lower bound, and INTEGER.MAX pulls each product out from under each INTEGER.STACKDEPTH; only the first CODE.DO*RANGE is executed in a context with code on the CODE stack.*

Evolved Fibonacci

Two simplified evolved general solutions:

```
(EXEC.DO*TIMES (CODE.LENGTH EXEC.S)
INTEGER.STACKDEPTH CODE.YANKDUP)
```

Builds an expression with Fibonacci(input) instances of INTEGER.STACKDEPTH on the EXEC stack, then executes them all.

```
(EXEC.DO*COUNT EXEC.S CODE.QUOTE NAME.=
CODE.DO*COUNT CODE.YANKDUP CODE.DO*COUNT
CODE.CONS CODE.STACKDEPTH)
```

Builds an expression with Fibonacci(input) instances of NAME.= on the CODE stack, then executes CODE.STACKDEPTH.

Evolved Even Parity

- Input is list of Boolean values on the `CODE` stack.
- Goal is a *general* solution that solves the problem for any number of inputs.

Evolved Even Parity (2)

Two simplified evolved general solutions:

```
(CODE.DO* EXEC.Y BOOLEAN.=)
```
Terminates only when execution limit is reached; works only for even number of inputs.

```
((((CODE.POP CODE.DO BOOLEAN.STACKDEPTH)
(EXEC.DO*TIMES) (BOOLEAN.= BOOLEAN.NOT))))
```
100% correct, general, terminating; see paper for explanation.

Evolved Expt(2,*n*)

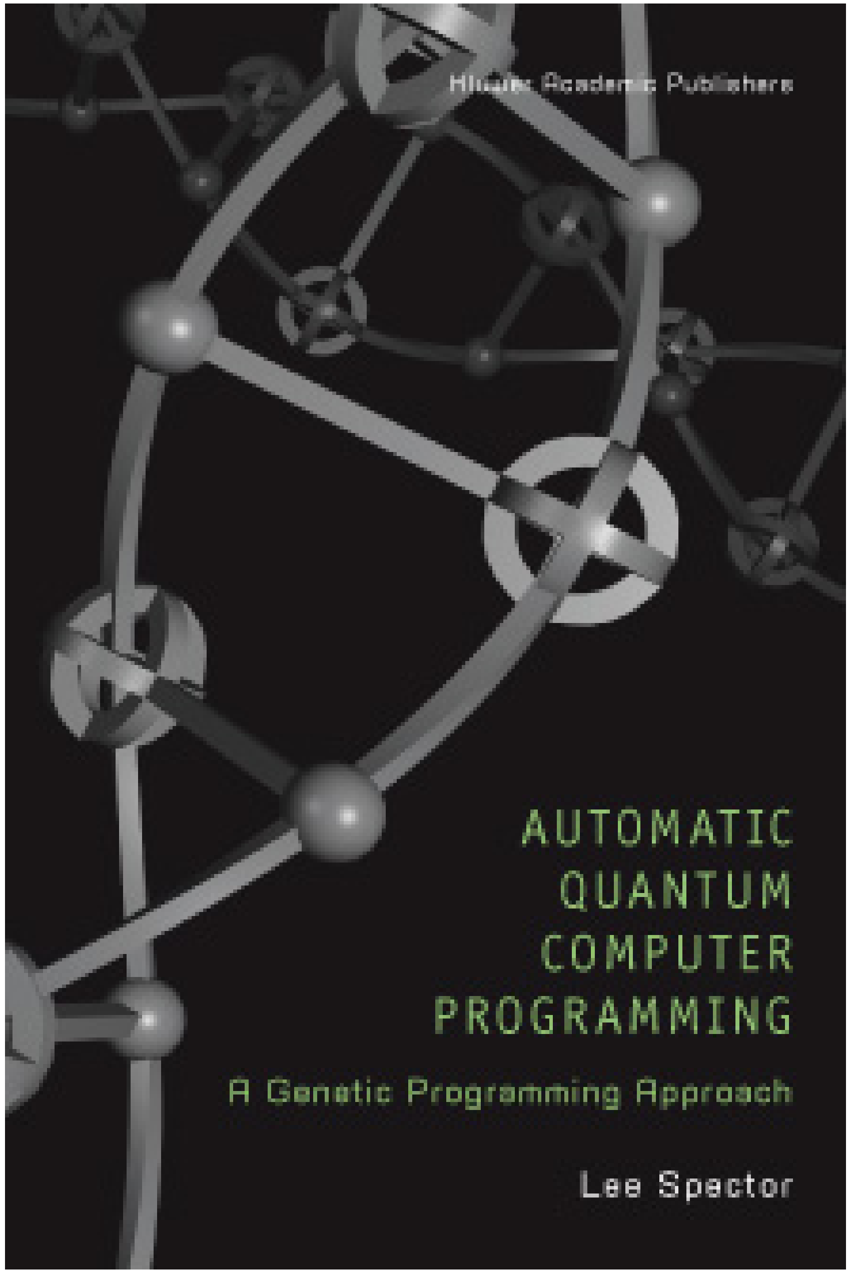
- Normally an easy problem, but here we attempted to evolve solutions without iteration instructions.
- The following evolved solution uses novel evolved control structures (but does not generalize beyond the training cases, *n*=1-8):

```
((INTEGER.DUP EXEC.YANKDUP EXEC.FLUSH 2
CODE.LENGTH) 8 (2 8  INTEGER.* INTEGER.DUP)
(EXEC.YANK 8 INTEGER.* ((CODE.IF (EXEC.ROT))
BOOLEAN.DEFINE EXEC.YANK)))
```

Evolved Sort

- Input/output in an external data structure accessed with `INTEGER.LIST-SWAP`, `INTEGER.LIST-LENGTH`, `INTEGER.LIST-GET`, `INTEGER.LIST-COMPARE`.
- Simplified evolved general solution that makes n*(n-1) comparisons:

```
(INTEGER.LIST-LENGTH INTEGER.SHOVE
INTEGER.STACKDEPTH CODE.DO*RANGE
INTEGER.YANKDUP INTEGER.DUP EXEC.DO*COUNT
INTEGER.LIST-COMPARE INTEGER.LIST-SWAP)
```


Kluwer Academic Publishers
AUTOMATIC QUANTUM COMPUTER PROGRAMMING
A Genetic Programming Approach
Lee Spector

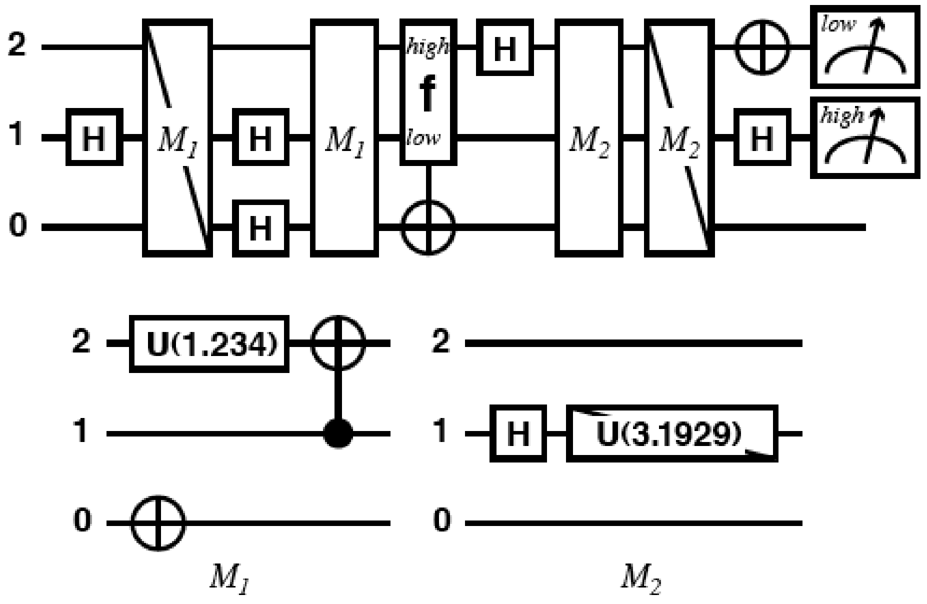


Figure 8.7. A gate array diagram for an evolved version of Grover's database search algorithm for a 4-item database. The full gate array is shown at the top, with M_1 and M_2 standing for the smaller gate arrays shown at the bottom. A diagonal line through a gate symbol indicates that the matrix for the gate is transposed. The "f" gate is the oracle.

Humies 2004 GOLD MEDAL

Autoconstructive Evolution

- Individuals make their own children.
- Agents thereby control their own mutation rates, sexuality, and reproductive timing.
- The machinery of reproduction and diversification (i.e., the machinery of evolution) evolves.
- Radical self-adaptation.

Motivation

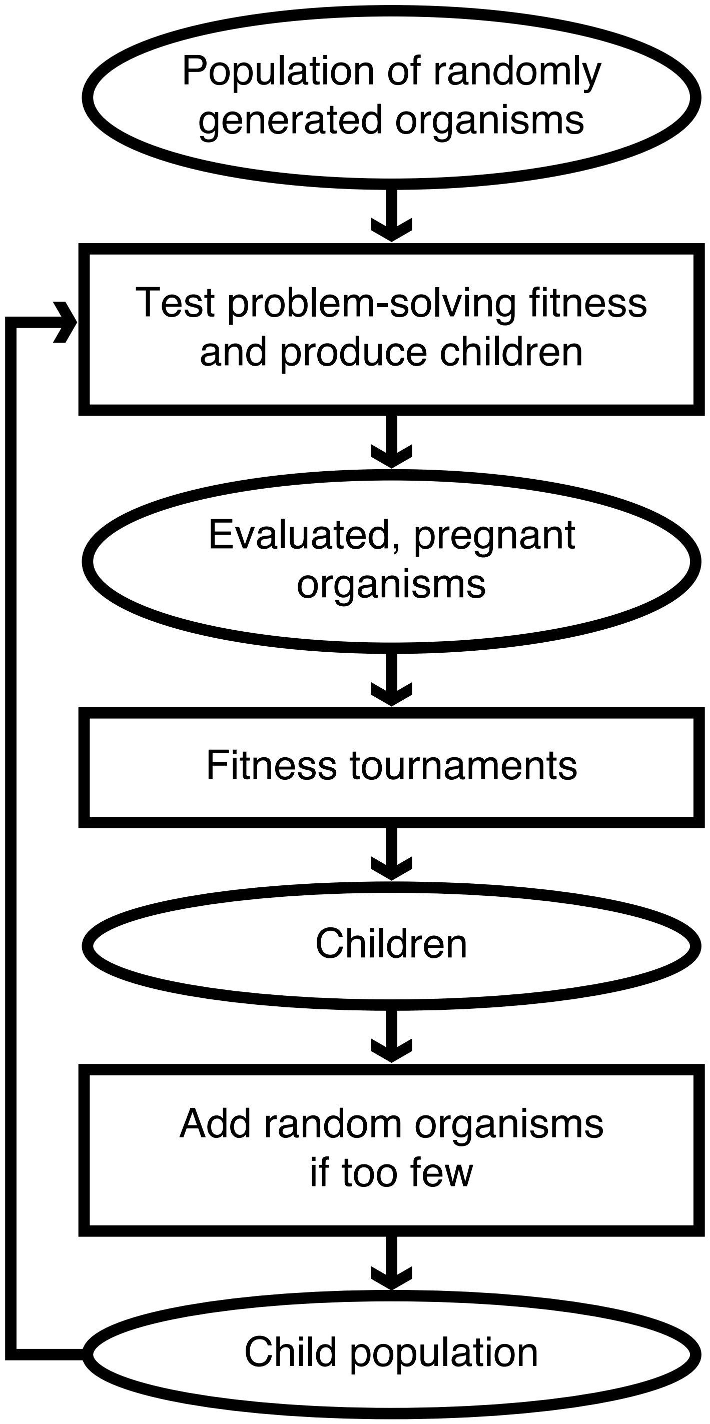
- We have **very little clue** about the best way to generate offspring in standard GP.
- We have **no clue whatsoever** about the best way to generate offspring in GP with the rich program representations that will become increasingly important.
- Natural reproductive methods evolved.
- Natural reproductive methods co-evolved with the organisms that use them, in the environments in which they use them.

Related Work

- MetaGP: but (1) programs and reproductive strategies dissociated and (2) generally restricted reproductive strategies.
- ALife systems such as Tierra, Avida, SeMar: but (1) hand-crafted ancestors, (2) reliance on cosmic ray mutation, and (3) weak problem solving.
- Evolved self-reproduction: but generally exact reproduction, non-improving (exception: Koza, but very limited tools for problem solving *and* for construction of offspring).

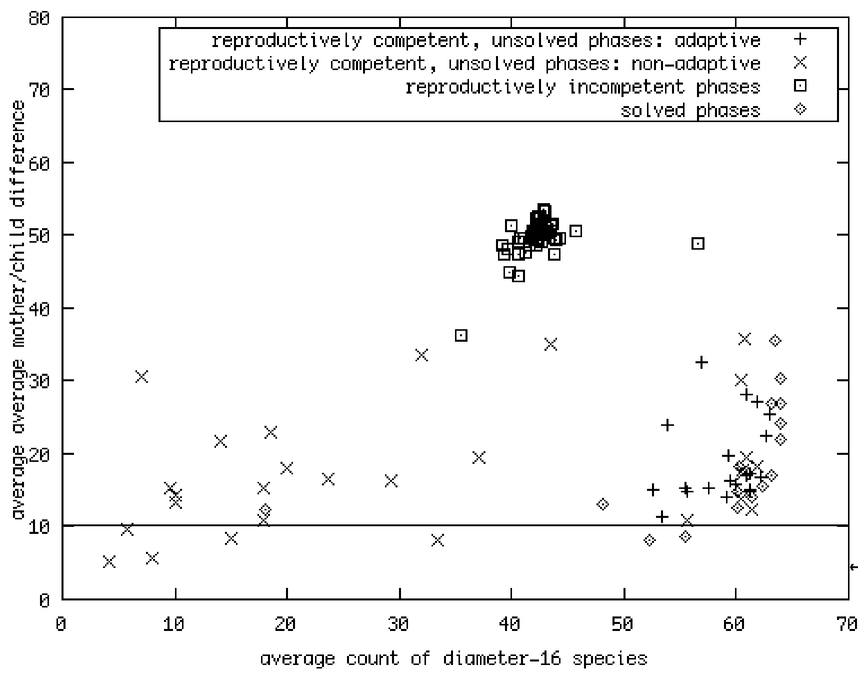
Pushpop

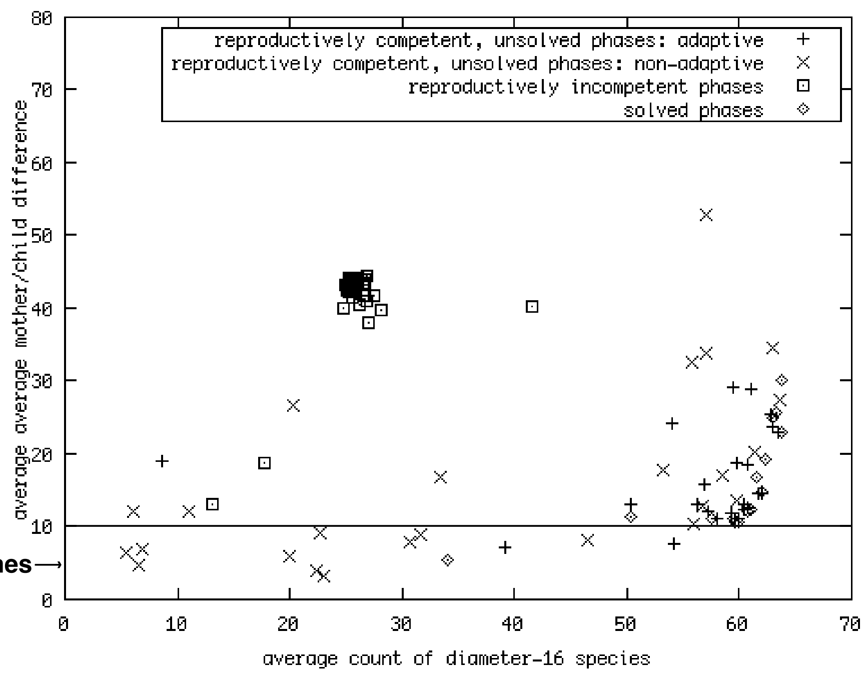
- A soup of evolving Push programs.
- Reproductive procedures emerge ex nihilo:
  - No hand-designed "ancestor."
  - Children constructed by any computable process.
  - No externally applied mutation procedure or rate.
  - Exact clones are prohibited, but near-clones are permitted.
- Selection for problem-solving performance.


Population of randomly generated organisms
Test problem-solving fitness and produce children
Evaluated, pregnant organisms
Fitness tournaments
Children
Add random organisms if too few
Child population

# Species vs. Mother/Child Differences

Note distribution of "+" points: adaptive populations have many species and mother/daughter differences in a relatively high, narrow range (above near-clone levels).





Runs including sexual instructions

Runs without sexual instructions

Pushpop Results

- In adaptive populations:
  - Species are more numerous.
  - Diversification processes are more reliable.
- Selection can promote diversity.
- Provides a possible explanation for the evolution of diversifying reproductive systems.
- Weak problem-solving power.
- Difficult to analyze results.

SwarmEvolve 2.0

- Behavior (including reproduction) controlled by evolved Push programs.
- Color, color-based agent discrimination controlled by agents.
- Energy conservation.
- Facilities for communication, energy sharing.
- Ample user feedback (e.g. diversity metrics, agent energy determines size).

AutoPush

- Goals:
  - Superior problem-solving performance.
  - Tractable analysis.
- Push3.
- Clojure (incidental, but fun!)
- Asexual (for now).
- Children produced on demand (not during fitness testing).
- Constraints on selection and birth.

Definitions

- **Improvement**: Recency-weighted average of vector of improvements (1), declines (-1), and repeats (0).
- **Discrepancy**: Sum, over all unique expressions in two programs, of the difference between the numbers of occurrences of the expression in the two programs.

Constraints on Selection

- Prefer reproductively competent parents.
- Prefer parents with non-stagnant lineages (changed performance in the most recent half of the lineage, after some threshold lineage length).
- Prefer parents with good problem-solving performance.
- (Possibly) Prefer parents from lineages with better-improving problem-solving performance.

Constraints on Birth

- Prevent birth from lineages with insufficient improvement.
- Prevent birth from lineages with constant discrepancies.
- Prevent birth from parents with fitness penalties, e.g. for non-termination.
- Prevent birth of children of illegal sizes.
- Prevent birth of children identical to ancestors or potential siblings.

Preliminary Results

- Simple symbolic regression successes
  - $y=x^3-2x^2-x$
  - $y=x^6-2x^4+x^3-2$
- Prime-generating polynomials
- Instructive lineage traces

Ancestor of Success

(for $y=x^3-2x^2-x$)

```
((code_if (code_noop) boolean_fromfloat (2)
integer_fromfloat) (code_rand integer_rot)
exec_swap code_append integer_mult)
```

Produces children of the form:

```
(RANDOM-INSTRUCTION (code_if (code_noop)
boolean_fromfloat (2) integer_fromfloat)
(code_rand integer_rot) exec_swap
code_append integer_mult)
```

Six Generations Later

A descendent of the form:

```
(SUB-EXPRESSION-1 SUB-EXPRESSION-2)
```

Produces children of the form:

```
((RANDOM-INSTRUCTION-1 (SUB-EXPRESSION-1))
(RANDOM-INSTRUCTION-2 (SUB-EXPRESSION-2)))
```

One Generation Later

A solution, which incidentally inherits the same reproductive strategy:

```
((integer_stackdepth (boolean_and
code_map)) (integer_sub (integer_stackdepth
(integer_sub (in (code_wrap (code_if
(code_noop) boolean_fromfloat (2)
integer_fromfloat) (code_rand integer_rot)
exec_swap code_append integer_mult)))))
```

Recent Enhancements

- Decimation (r-selection vs. k-selection)
- Reference via tags (Holland).

This project is extending the science of automatic programming, using concepts derived from evolutionary biology and software engineering, to permit the evolution of general and robust computational systems with multiple interacting functionalities and interfaces. The project uses the PI's Push programming language as the target language for evolved programs. Push programs are syntactically unconstrained, which facilitates evolution, but they can make use of arbitrary control and data structures; this supports the evolution of complex, modular programs.

This project will add new features to the Push language and develop new methods that allow requirements specifications and tests, of the type employed in software engineering practice, to be transformed into fitness functions that drive evolution. The cumulative effect of these extensions will be to support the evolution of significantly more general and robust computational systems.

The effectiveness of the technologies developed in this project will be demonstrated in two application areas: the automatic programming of small but complete productivity software applications and the automatic programming of robustly intelligent software agents for complex, time-varying economic games. The project is contributing to long-standing goals in computer science of building robustly intelligent systems and automatic synthesis of useful computer programs.

Conclusions

- Rich representations, such as those provided by the Push programming language, can allow genetic programming to solve a wide range of difficult problems.
- **Bold (unsupported!) prediction:** *The most powerful, practical genetic programming systems of the future will be autoconstructive.*