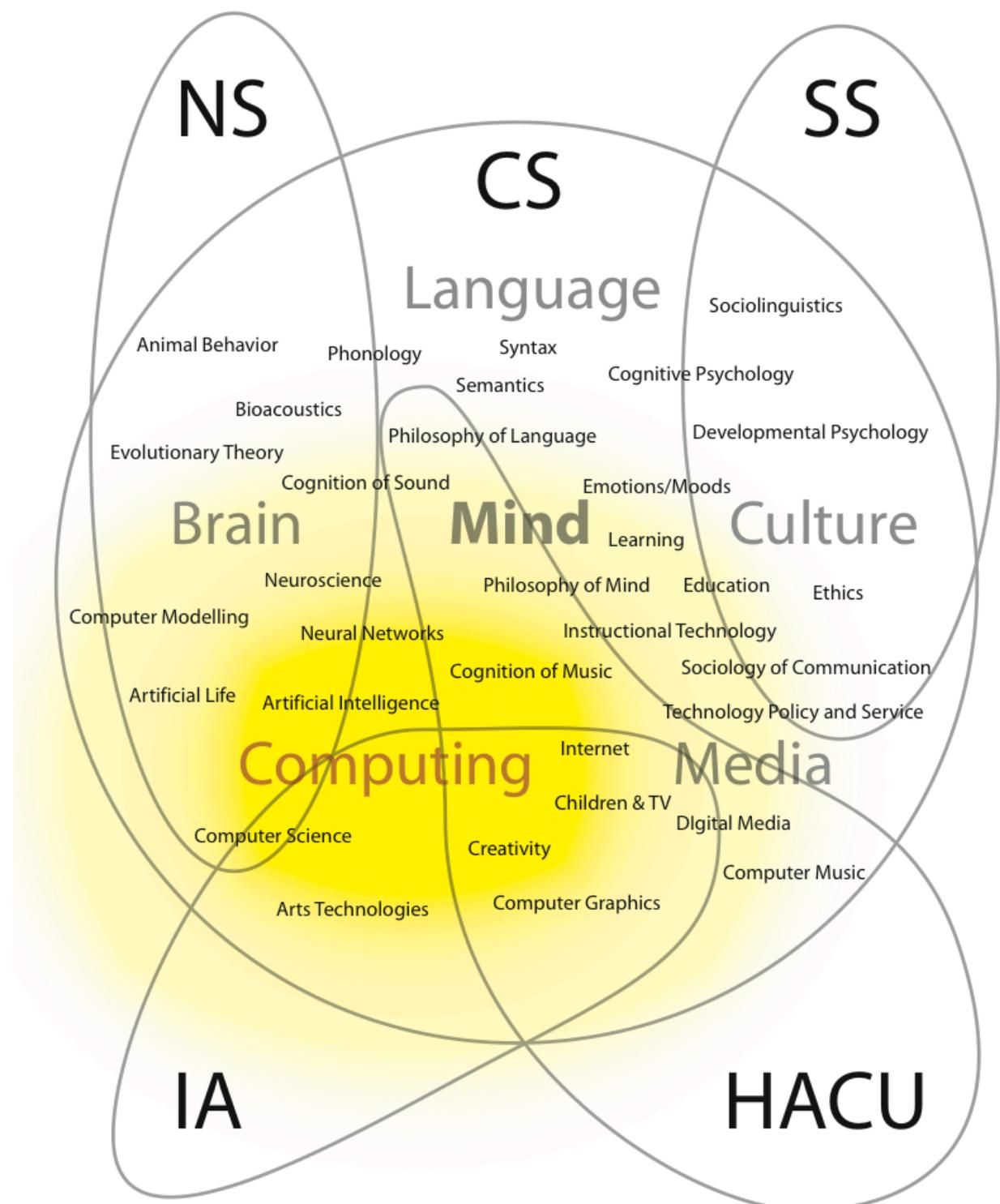


Evolving the Future of Mathematics

Lee Spector
Cognitive Science
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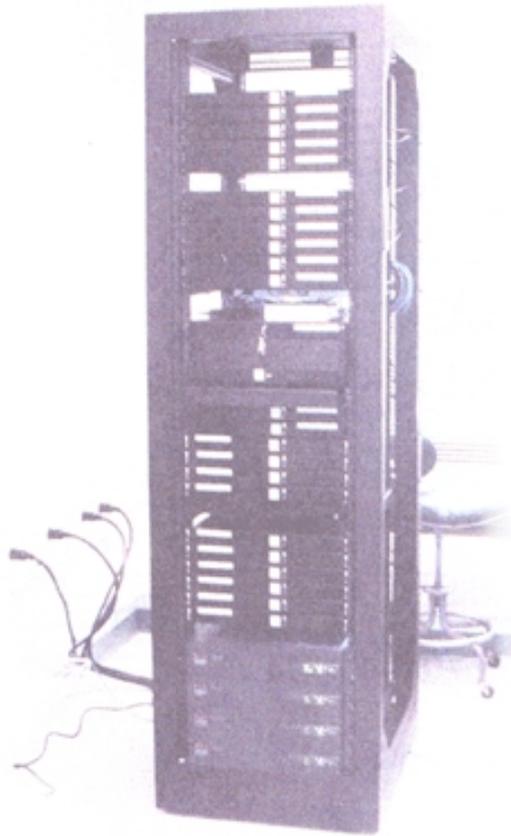
Outline

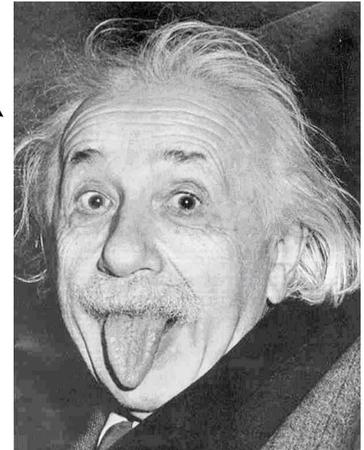
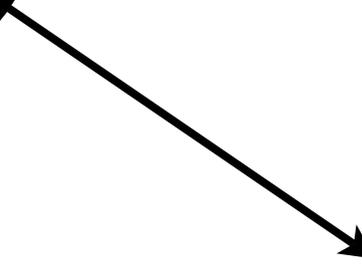
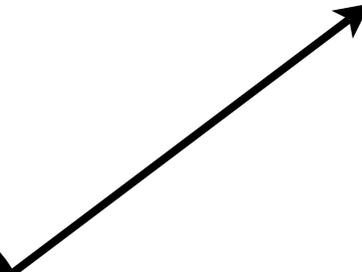
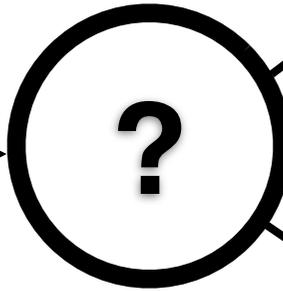
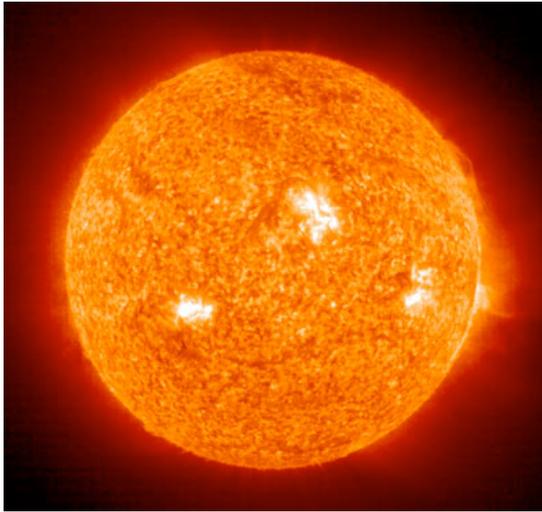
- Genetic programming
- Human competitive genetic programming
- An application to finite algebras
- How to think about possible future applications
- Autoconstructive evolution



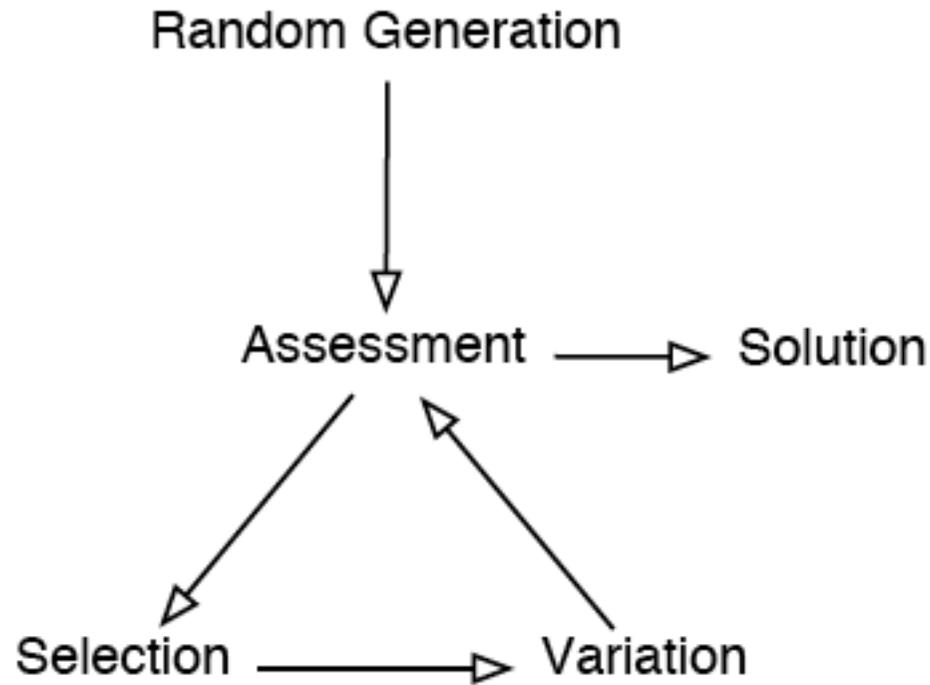
Cluster Computing Facility

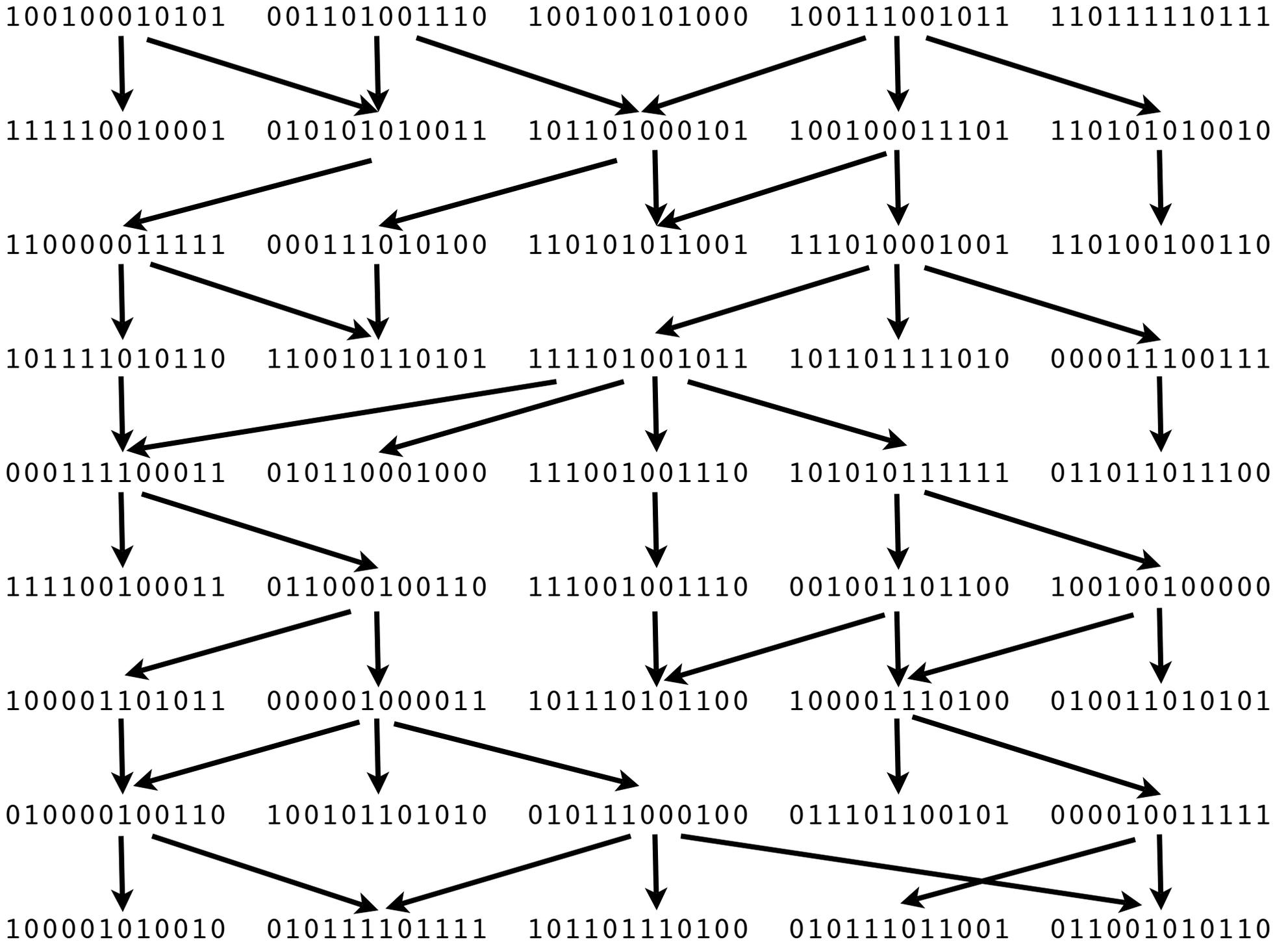
- A mixed-architecture 100+ core high-performance computer cluster
- Available to both faculty and students for course and project work
- Hosts a wide range of research and application software
- Runs Linux and the open source ROCKS clustering software package
- Uses include research and development projects in distributed computing, physical and ecological simulation, quantum computing, evolutionary algorithms, and applications of high-performance computing to the arts





Evolutionary Algorithms





Traditional Genetic Algorithms

- Interesting dynamics
- Rarely solve interesting hard problems

Evolution, the Designer

“Darwinian evolution is itself a designer worthy of significant respect, if not religious devotion.” *Boston Globe* OpEd, Aug 29, 2005

WHAT WOULD DARWIN SAY? | LEE SPECTOR

And now, digital evolution

The Boston Globe

By Lee Spector | August 29, 2005

RECENT developments in computer science provide new perspective on "intelligent design," the view that life's complexity could only have arisen through the hand of an intelligent designer. These developments show that complex and useful designs can indeed emerge from random Darwinian processes.

Genetic Programming

- Evolutionary algorithm in which the candidate solutions are executable computer programs.
- Candidate solutions are assessed, at least in part, 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., ...).
- 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

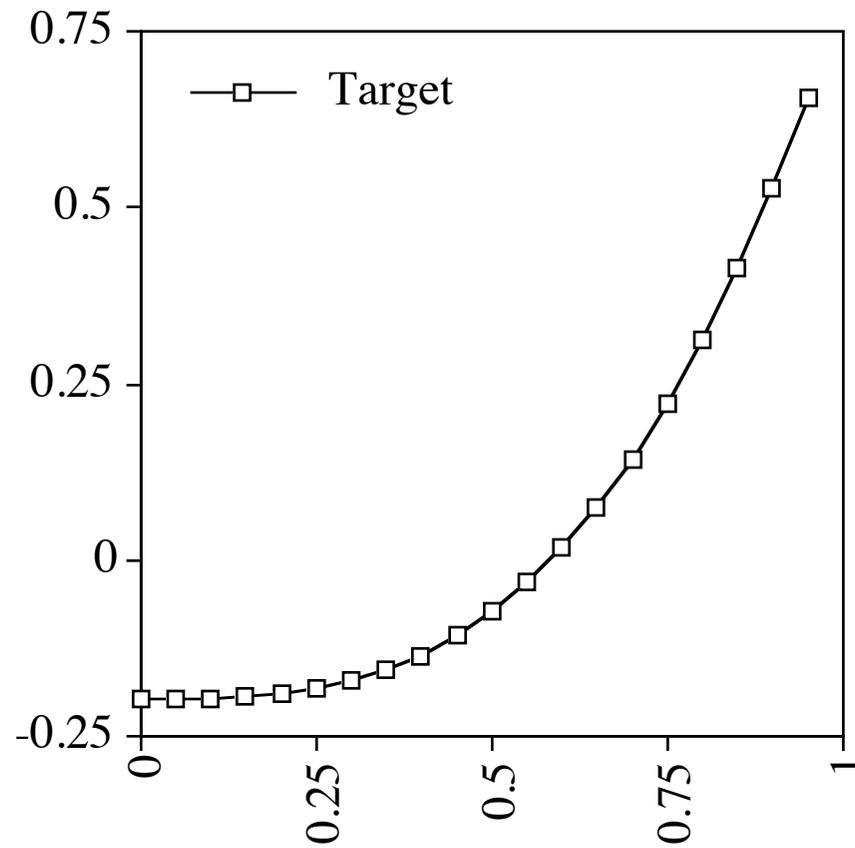
Crossover at function points fraction: 0.5

Selection method: FITNESS-PROPORTIONATE

Generation method: RAMPED-HALF-AND-HALF

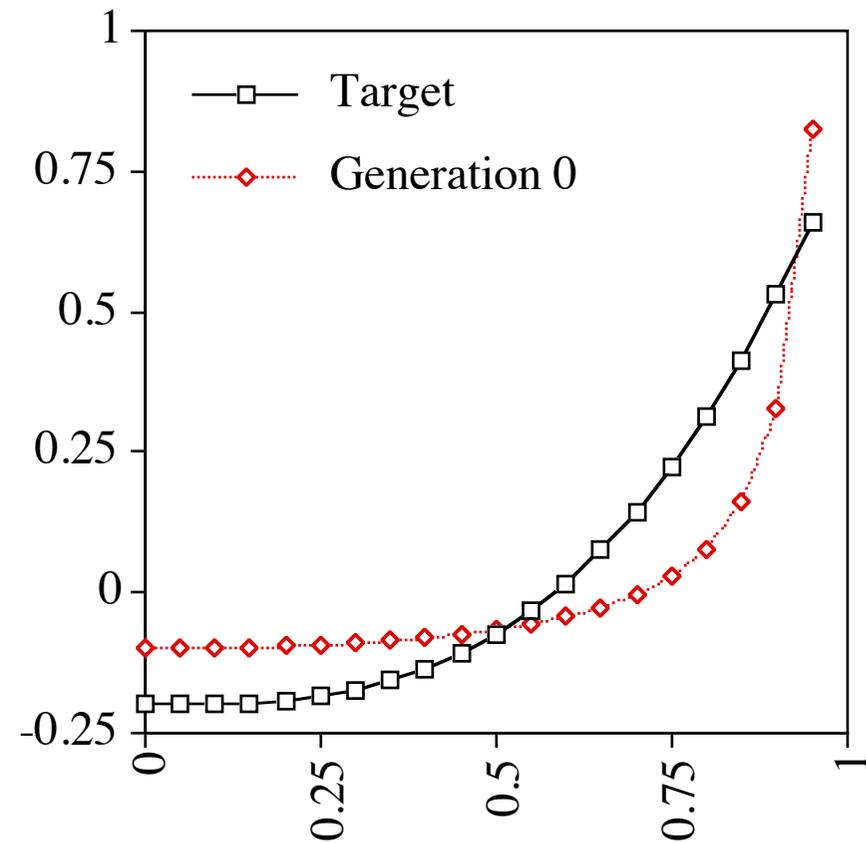
Randomizer seed: 1.2

Evolving $y = x^3 - 0.2$



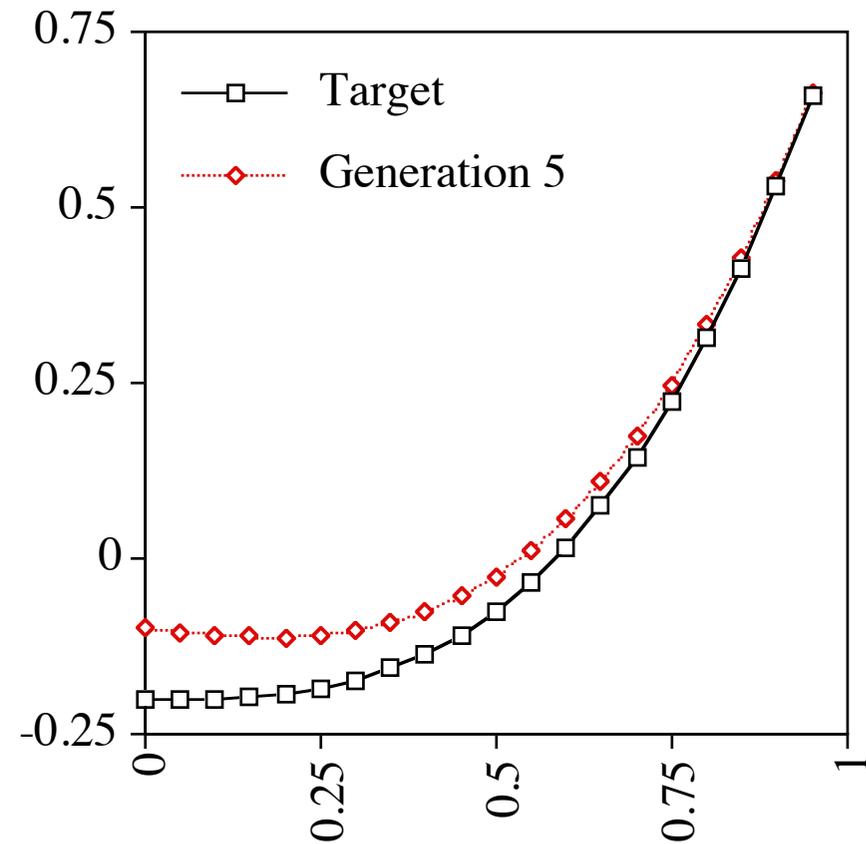
Best Program, Gen 0

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



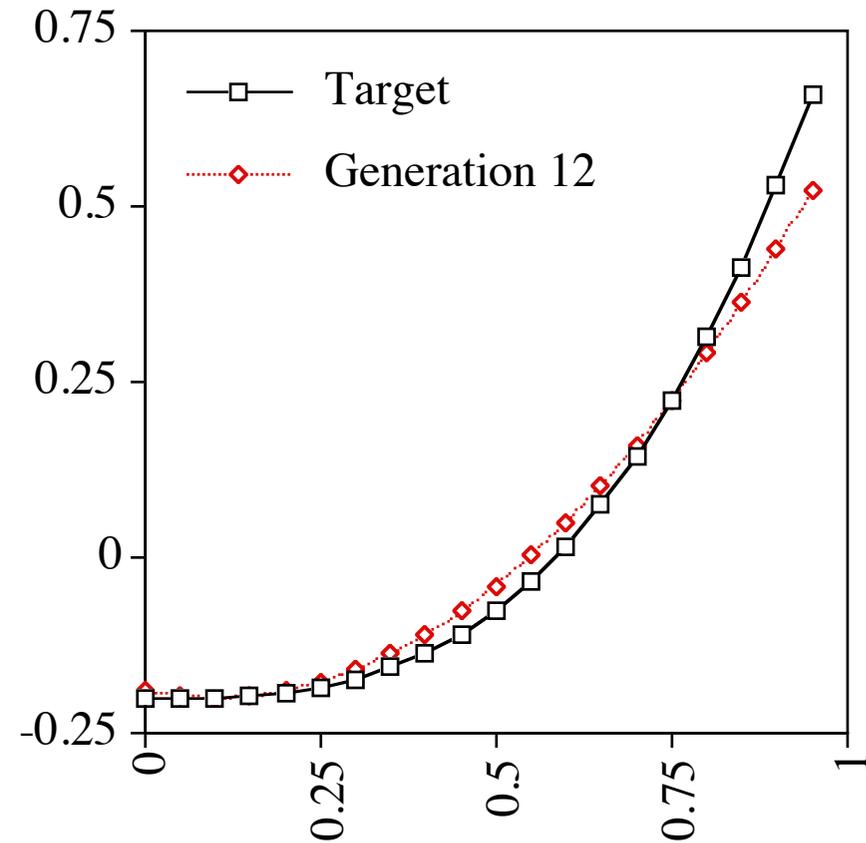
Best Program, Gen 5

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



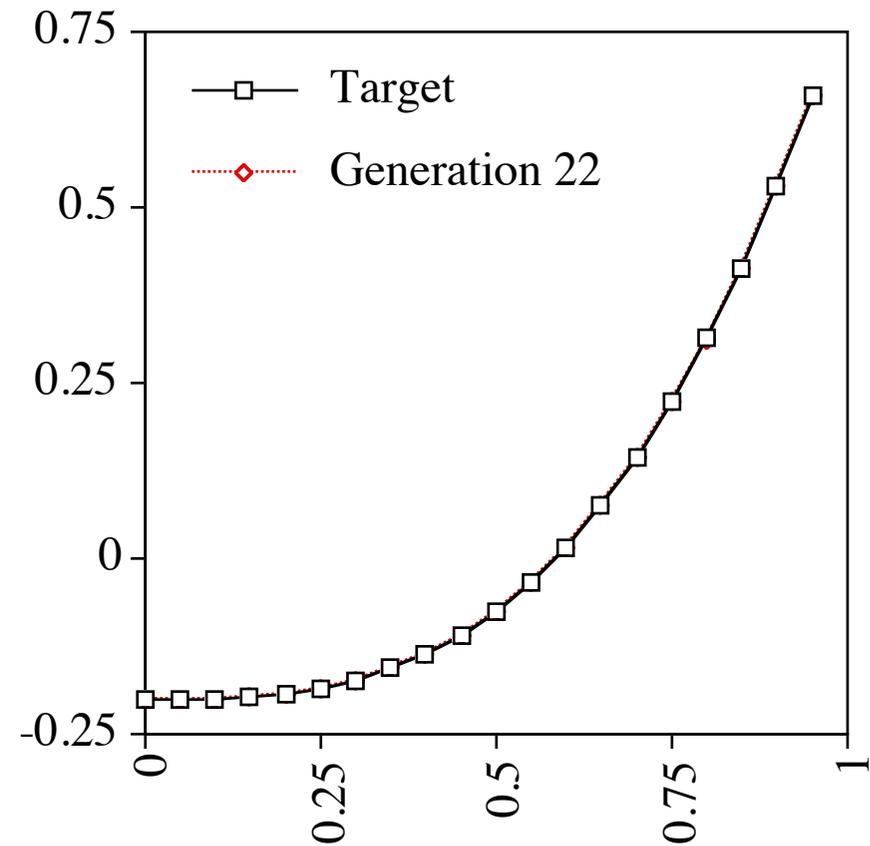
Best Program, Gen 12

```
(+ (- (- 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)
```





VOLUME 22

SUMMER 2008

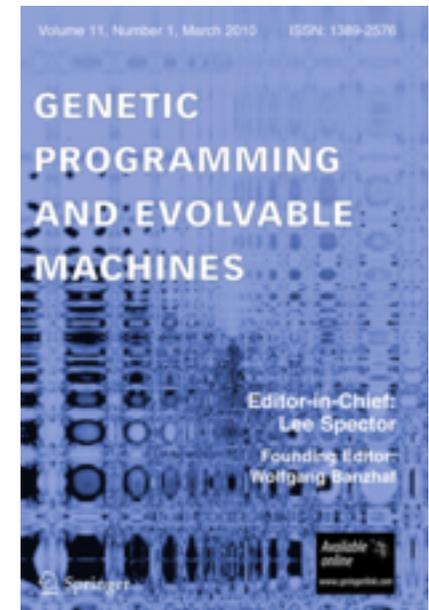
NUMBER 3

SPECIAL ISSUE

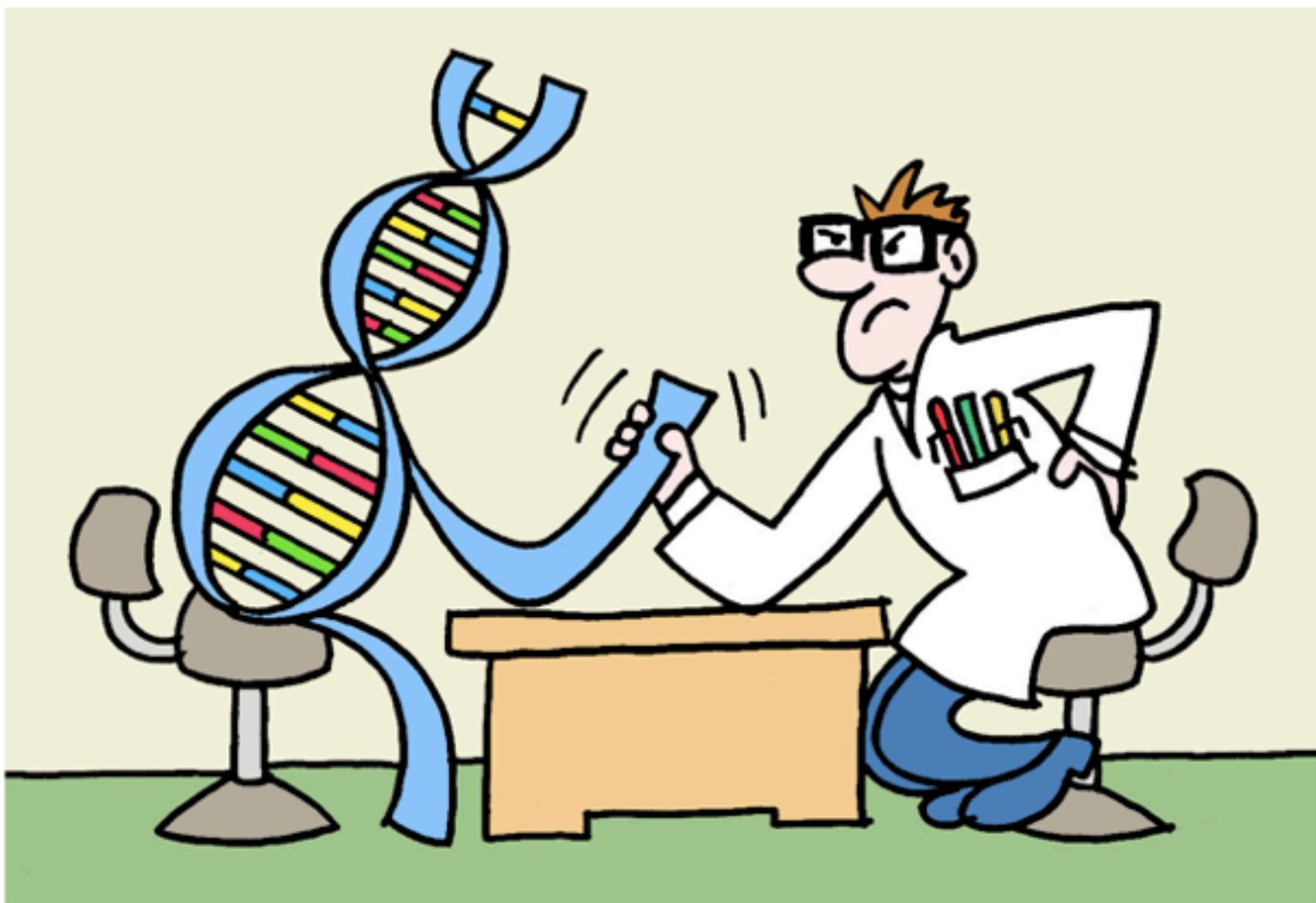
*Genetic Programming
for Human-Competitive Designs*

Guest Editor

LEE SPECTOR



**THE 5th ANNUAL (2008) "HUMIES" AWARDS
FOR HUMAN-COMPETITIVE RESULTS
PRODUCED BY GENETIC AND EVOLUTIONARY COMPUTATION
HELD AT THE
GENETIC AND EVOLUTIONARY COMPUTATION CONFERENCE**



Line-Drawing Mechanism

Without reference to an existing straight line.

Human-competitive results; challenged world's greatest inventors for a century (spanning 18th and 19th).

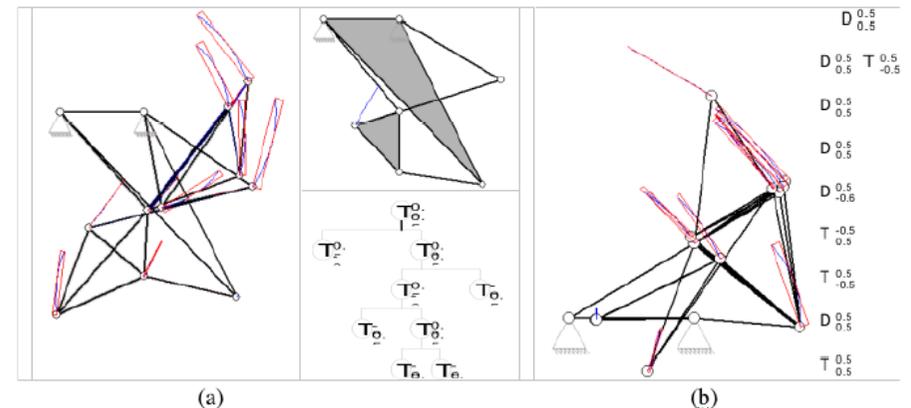
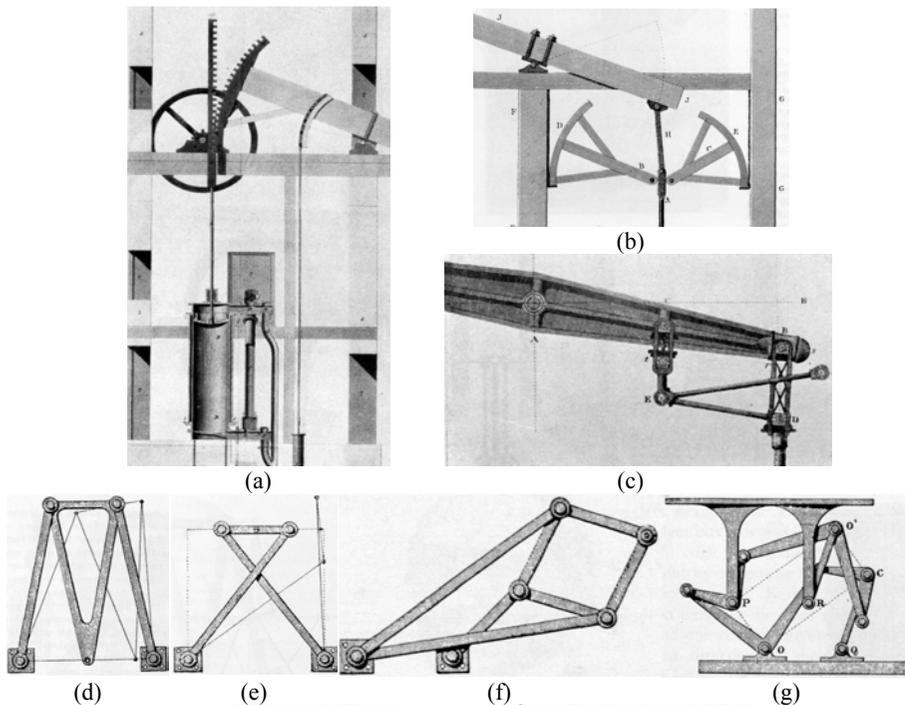
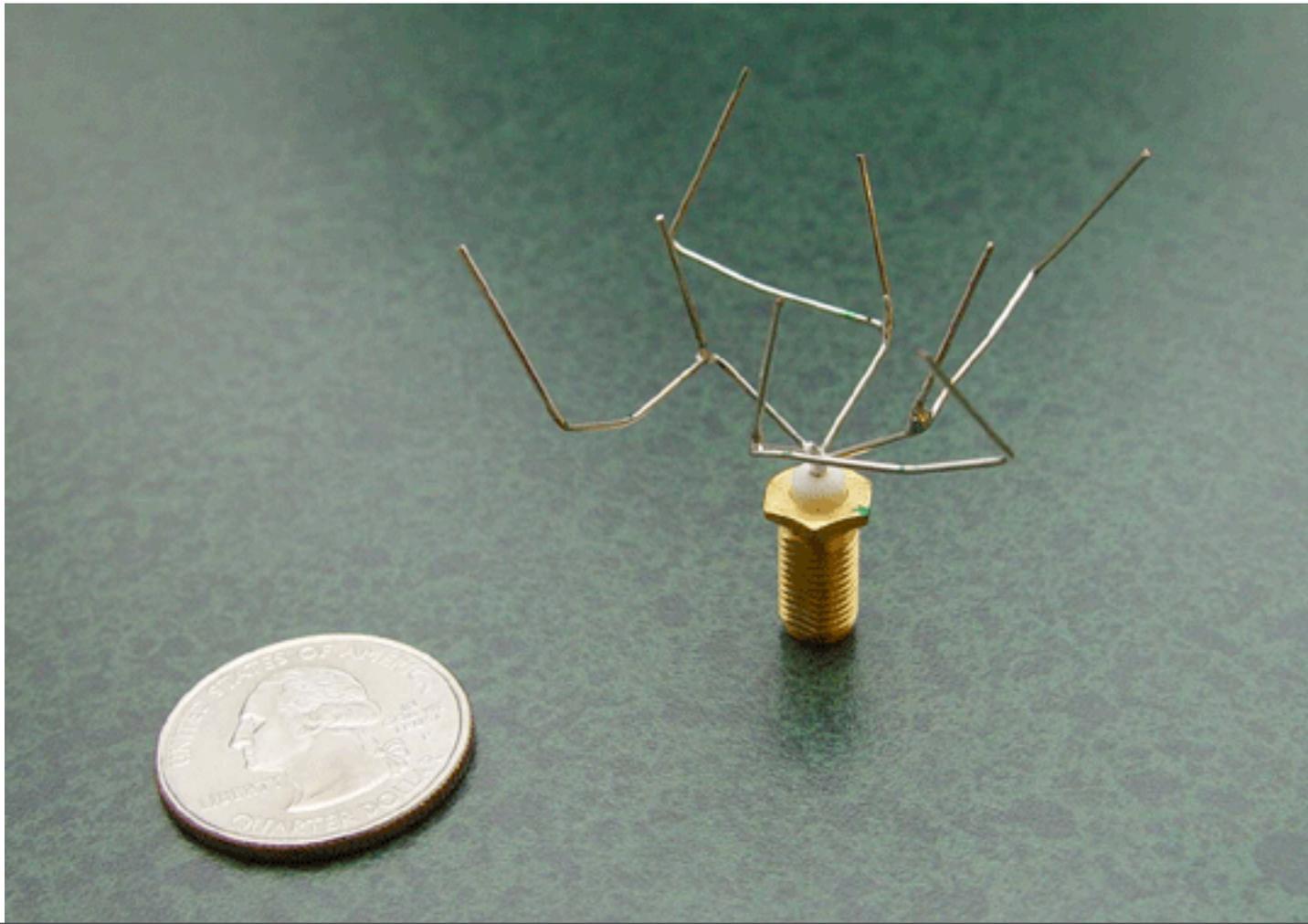


Fig. 10. Two Evolved mechanisms and their tree representations (a) Linearity 1:12819; The simplified equivalent shown top right, and (b) Linearity 1:4979.

Lipson, H. 2004. How to Draw a Straight Line Using a GP: Benchmarking Evolutionary Design Against 19th Century Kinematic Synthesis. GECCO-2004.

Evolved Antenna

- Human-competitive result.
- For NASA Space Technology 5 Mission.
- Lohn, Hornby, and Linden.



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
- Under active investigation for decades, with major advances (cited fully in the paper) in 1939, 1954, 1970, 1975, 1979, 1991, 2008

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

Specific Algebras

$\begin{array}{c ccc} \mathbf{A}_1 * & 0 & 1 & 2 \\ \hline 0 & 2 & 1 & 2 \\ 1 & 1 & 0 & 0 \\ 2 & 0 & 0 & 1 \end{array}$	$\begin{array}{c ccc} \mathbf{A}_2 * & 0 & 1 & 2 \\ \hline 0 & 2 & 0 & 2 \\ 1 & 1 & 0 & 2 \\ 2 & 1 & 2 & 1 \end{array}$
$\begin{array}{c ccc} \mathbf{A}_3 * & 0 & 1 & 2 \\ \hline 0 & 1 & 0 & 1 \\ 1 & 1 & 2 & 0 \\ 2 & 0 & 0 & 0 \end{array}$	$\begin{array}{c ccc} \mathbf{A}_4 * & 0 & 1 & 2 \\ \hline 0 & 1 & 0 & 1 \\ 1 & 0 & 2 & 0 \\ 2 & 0 & 1 & 0 \end{array}$
$\begin{array}{c ccc} \mathbf{A}_5 * & 0 & 1 & 2 \\ \hline 0 & 1 & 0 & 2 \\ 1 & 1 & 2 & 0 \\ 2 & 0 & 1 & 0 \end{array}$	$\begin{array}{c cccc} \mathbf{B}_1 * & 0 & 1 & 2 & 3 \\ \hline 0 & 1 & 3 & 1 & 0 \\ 1 & 3 & 2 & 0 & 1 \\ 2 & 0 & 1 & 3 & 1 \\ 3 & 1 & 0 & 2 & 0 \end{array}$

Methods

- Traditional genetic programming with ECJ
- Stack-based genetic programming with PushGP
- Alternative random code generators
- Asynchronous islands
- Trivial geography
- Parsimony-based selection
- Alpha-inverted selection pressure
- HAH = Historically Assessed Hardness

Results

- Discriminators for A_1, A_2, A_3, A_4, A_5
- Mal'cev and majority terms for B_1
- Parameter tables and result terms in paper
- Example discriminator term for A_1 :

$$\begin{aligned} & (((((((((x*(y*x))*x)*z)*(z*x))*((x*(z* \\ & (x*(z*y))))*z))*z)*z)*(z*(((x*(((z*z) \\ & *x)*(z*x))))*x)*y)*(((y*(z*(z*y))))* \\ & (((y*y)*x)*z))*((x*(((z*z)*x)*(z*(x* \\ & (z*y)))))))))) \end{aligned}$$

Assessing Significance

Relative to prior methods:

- Uninformed search:
 - Exhaustive: analytical (expected value) and empirical search time comparisons
 - Random: analytical (expected value) and empirical search time comparisons
- Primality method: empirical term size comparisons

Expected Value Analysis

Since $\text{Exp}(X)$ is the weighted sum of the values of X ,

$$\begin{aligned}\text{Exp}(X) &= \sum_{j=1}^{\infty} j p_j = \sum_{k=1}^{\infty} \sum_{j=k}^{\infty} p_j = \sum_{k=1}^{\infty} P_k \approx \sum_{k=1}^{\infty} \left(\frac{n-1}{n}\right)^{k-1} \\ &= \frac{1}{1 - \frac{n-1}{n}} = n.\end{aligned}$$

We recapitulate this conclusion as follows.

The expected value $\text{Exp}(X)$ of the number X of trials required to find a term representing the function f is approximately the size $n = |A|^{|B|}$ of the search space A^B of all functions from B to A .

- **Verified via empirical results with random search and exhaustive search**

Significance, Time

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

Significance, Time

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

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_1)

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_1)

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

Potential Impact

These results are in an foundational area of pure mathematics with:

- A long history
- Many outstanding problems of theoretical significance and quantifiable difficulty
- Applications across the sciences

The case for the prize

- Using GP, we have improved significantly on extensive past efforts of both humans and machines to solve problems related to finite algebras
- This is an important and previously unexplored application area for GP, with many open problems and quantitative measures of success

Genetic Programming for Finite Algebras

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Humies 2008
GOLD MEDAL!

Other applications in mathematics?

- Define representation
- Define fitness measure (need not be perfect)
- Use/define mutation/crossover algorithms that have sufficient likelihood of producing improvements

Towards practical autoconstructive evolution: self-evolution of problem-solving genetic programming systems

Lee Spector
Cognitive Science
Hampshire College

To appear in Riolo, Rick L., McConaghy, Trent, and
Vladislavleva, Ekaterina, editors, *Genetic Programming
Theory and Practice VIII*. Springer. 2010.

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.

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
- Turing complete
- Types include: integer, float, Boolean, name, **code**, **exec**, vector, matrix, quantum gate, [add more as needed]
- Missing argument? NOOP
- Trivial syntax:
program \rightarrow instruction | literal | (program*)

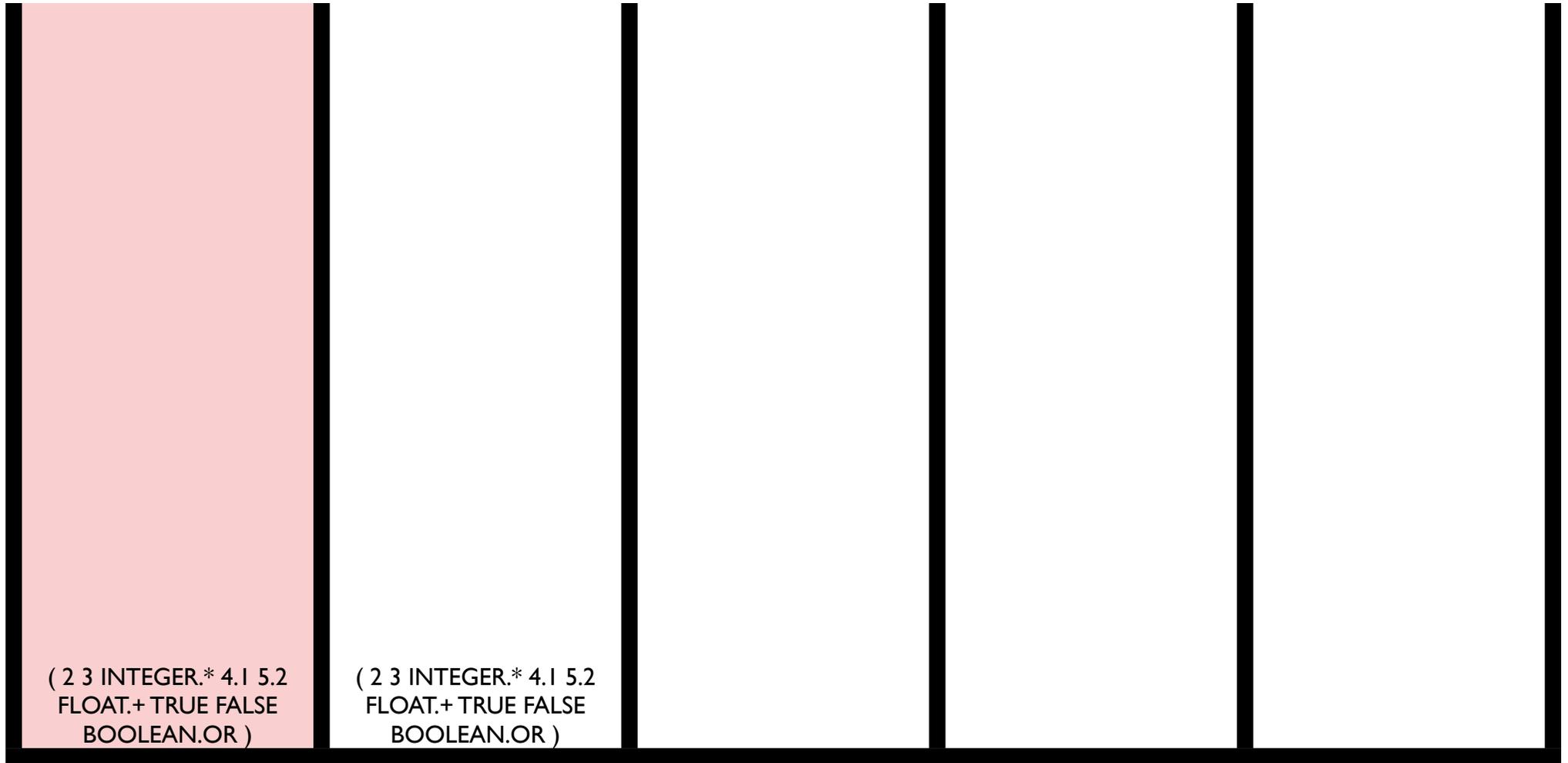
Sample Push Instructions

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 )
```



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)

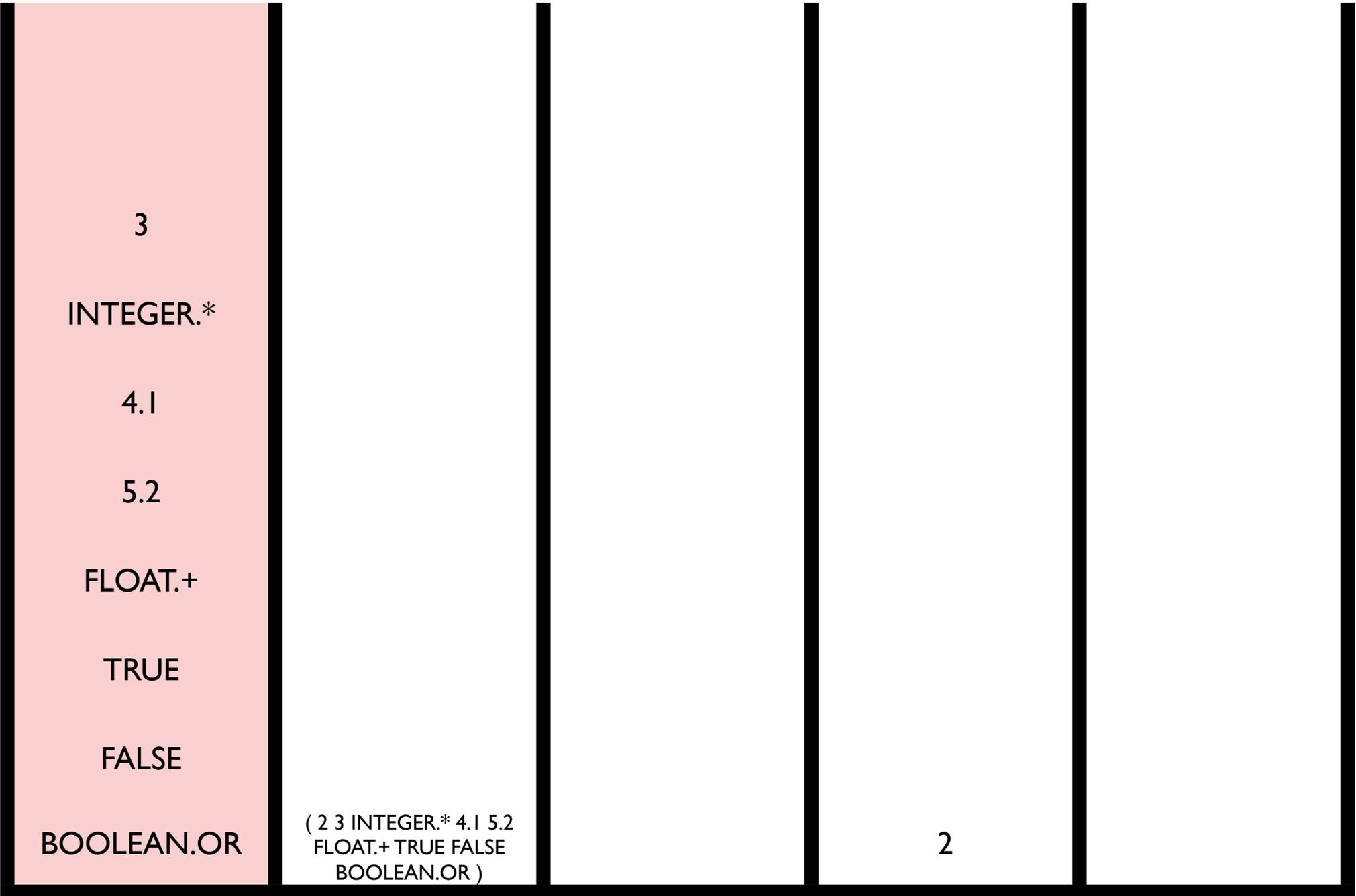
exec

code

bool

int

float



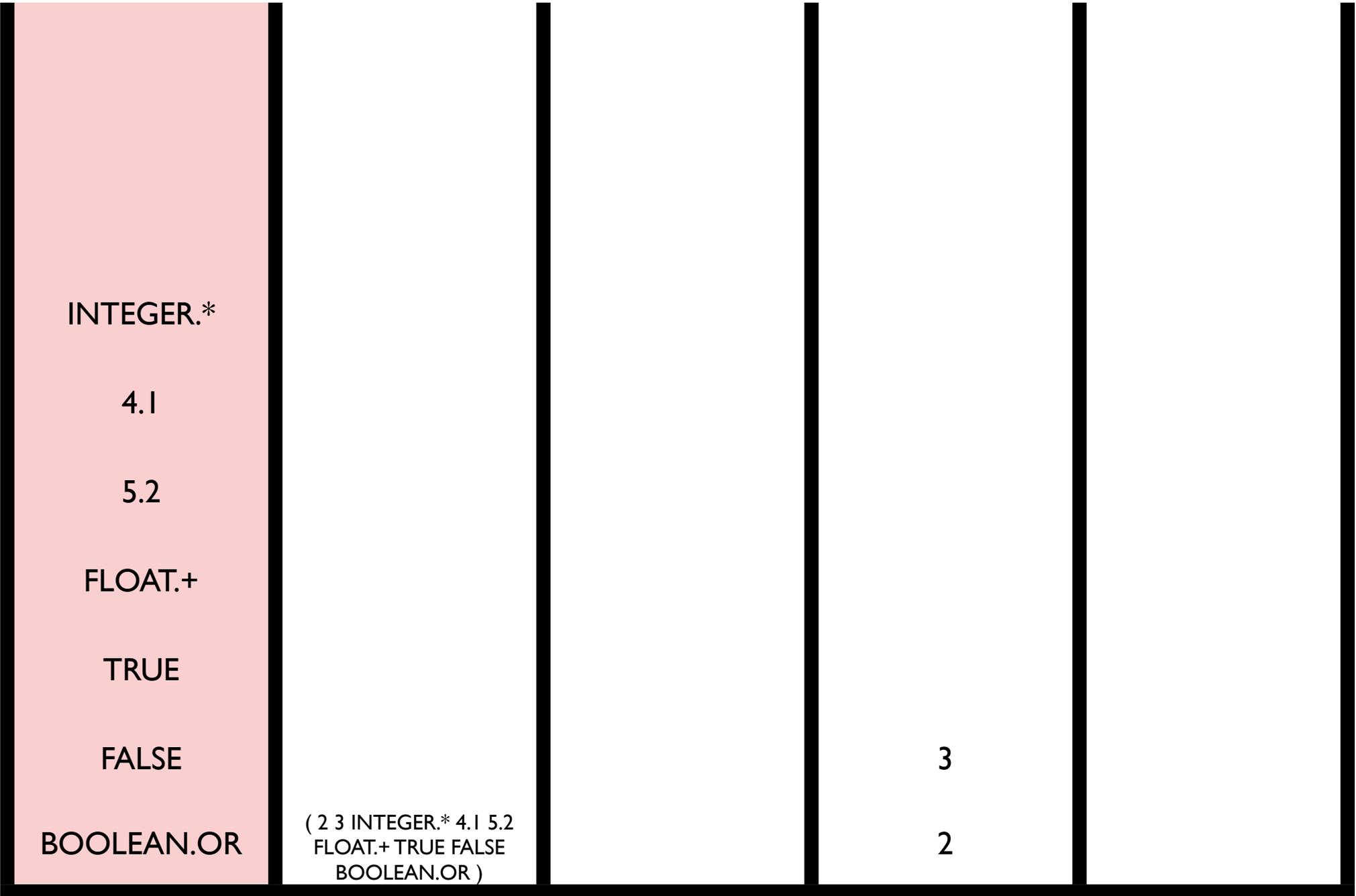
exec

code

bool

int

float



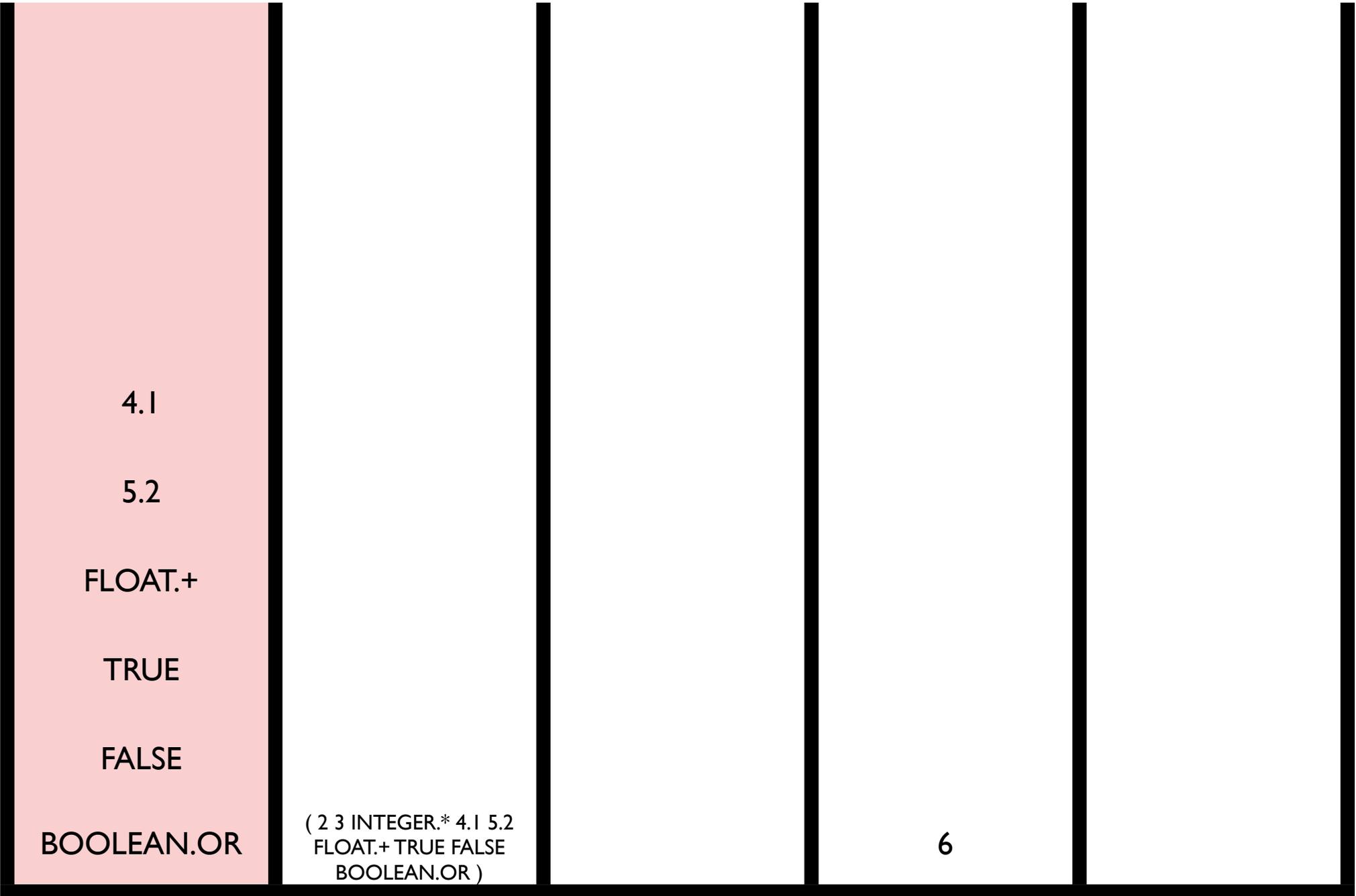
exec

code

bool

int

float



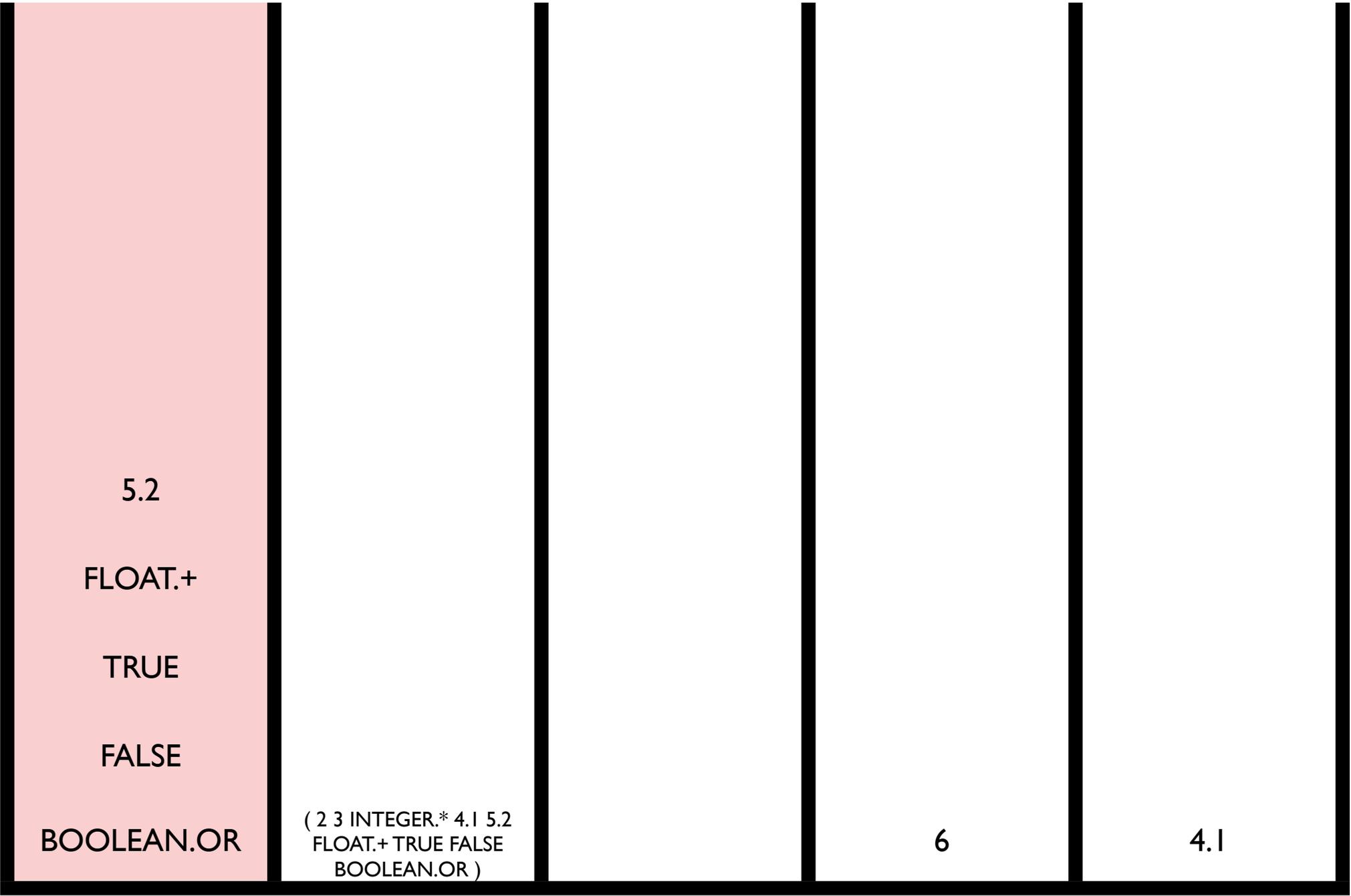
exec

code

bool

int

float



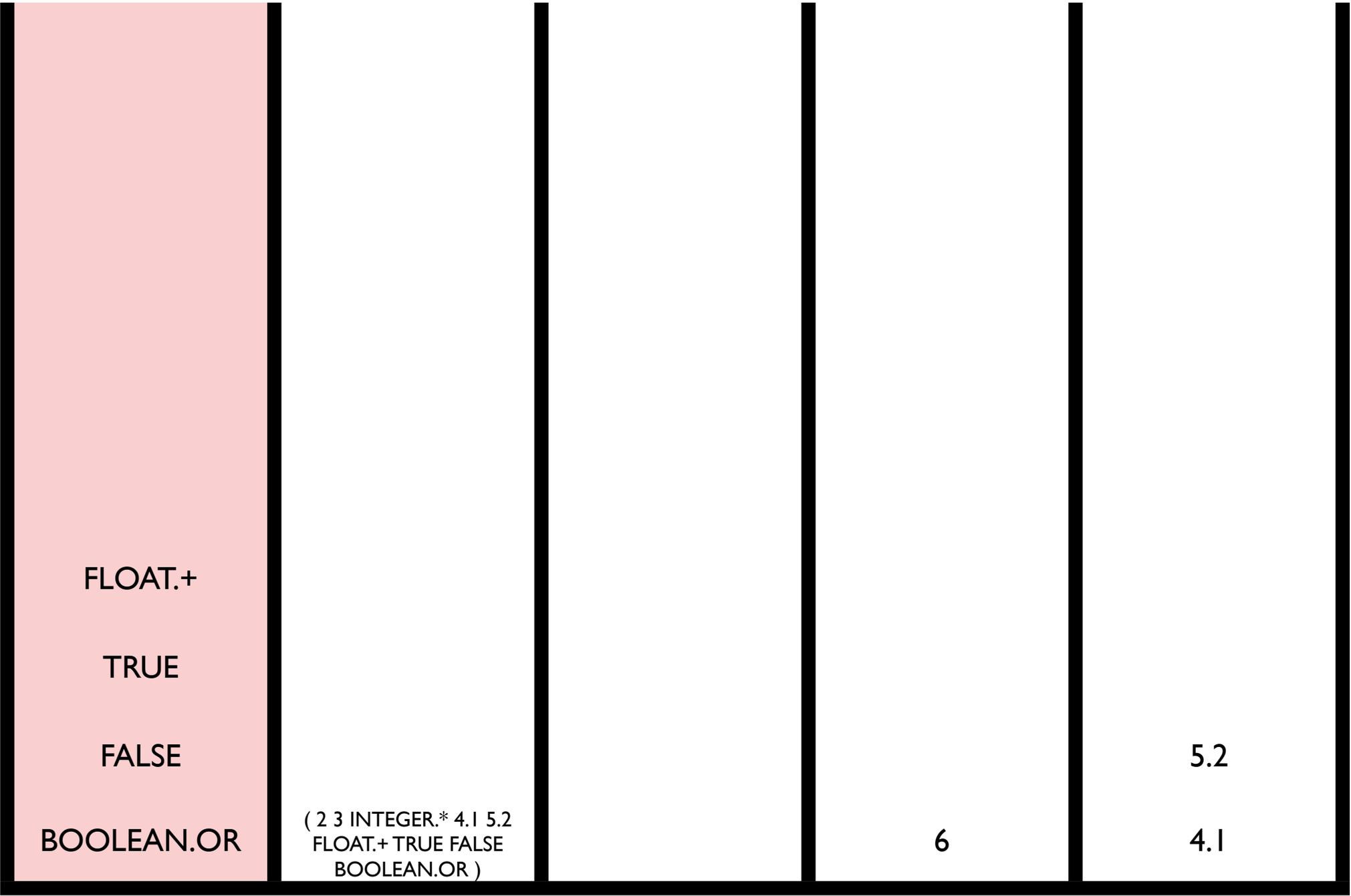
exec

code

bool

int

float



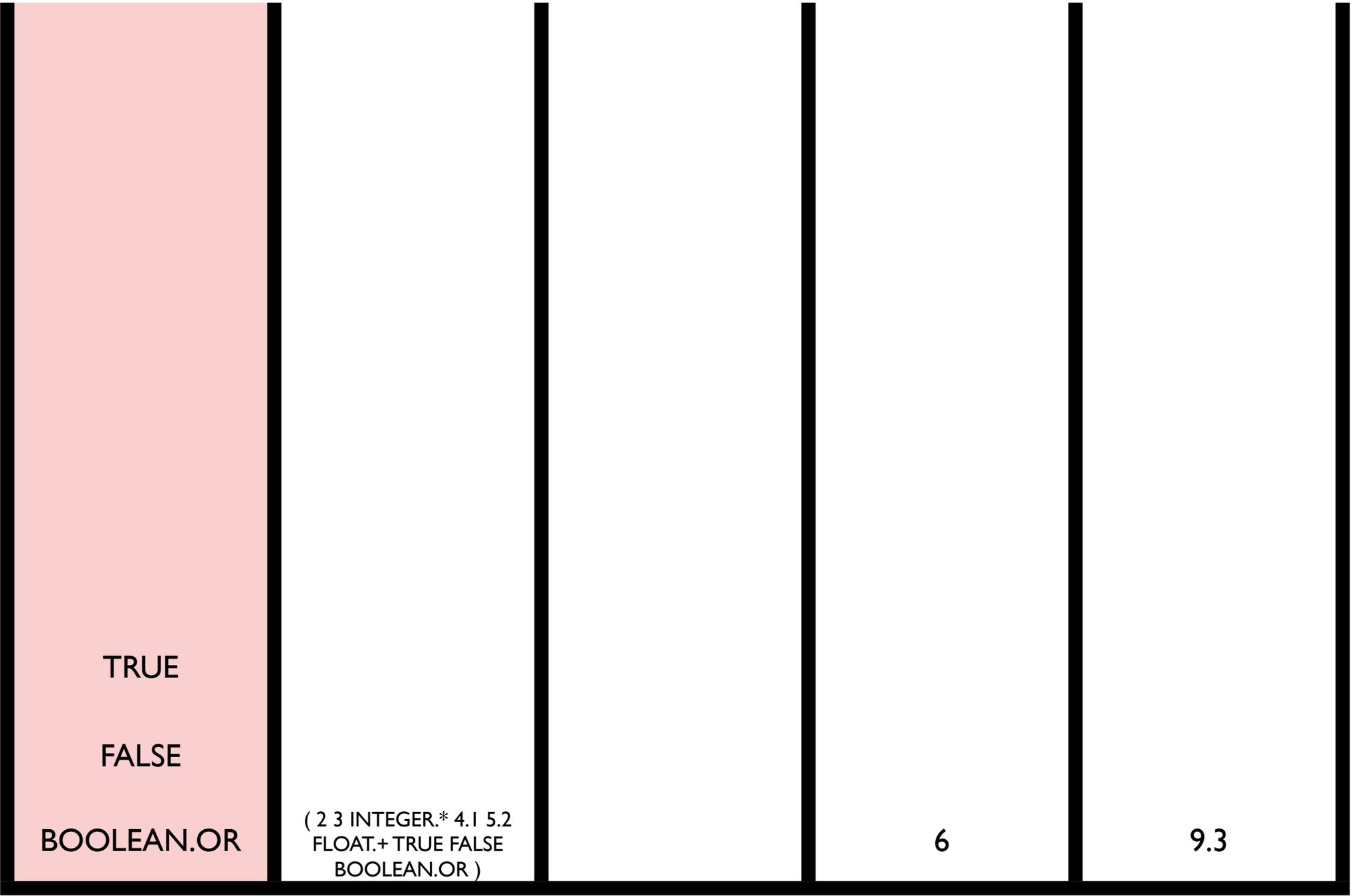
exec

code

bool

int

float



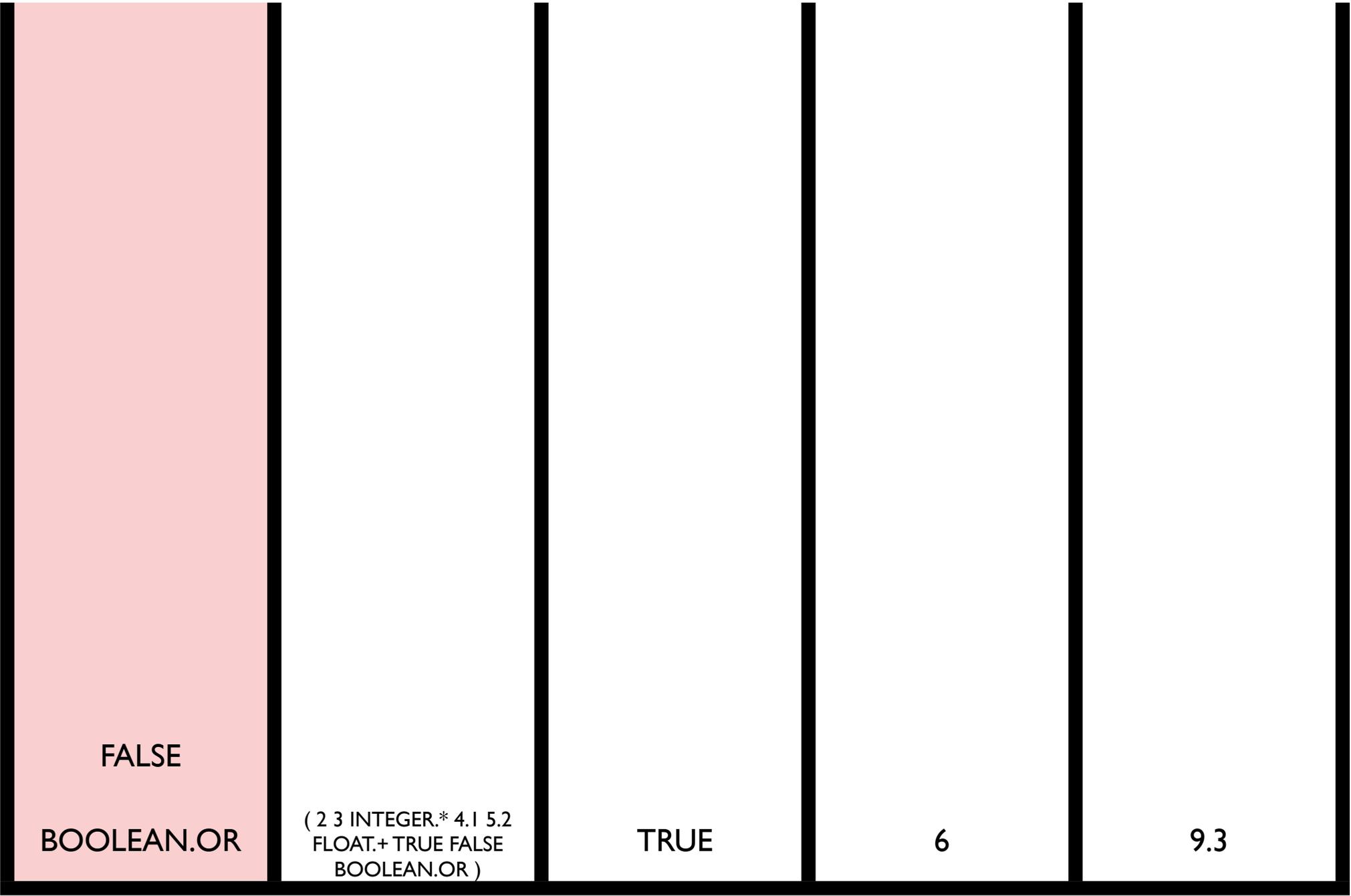
exec

code

bool

int

float



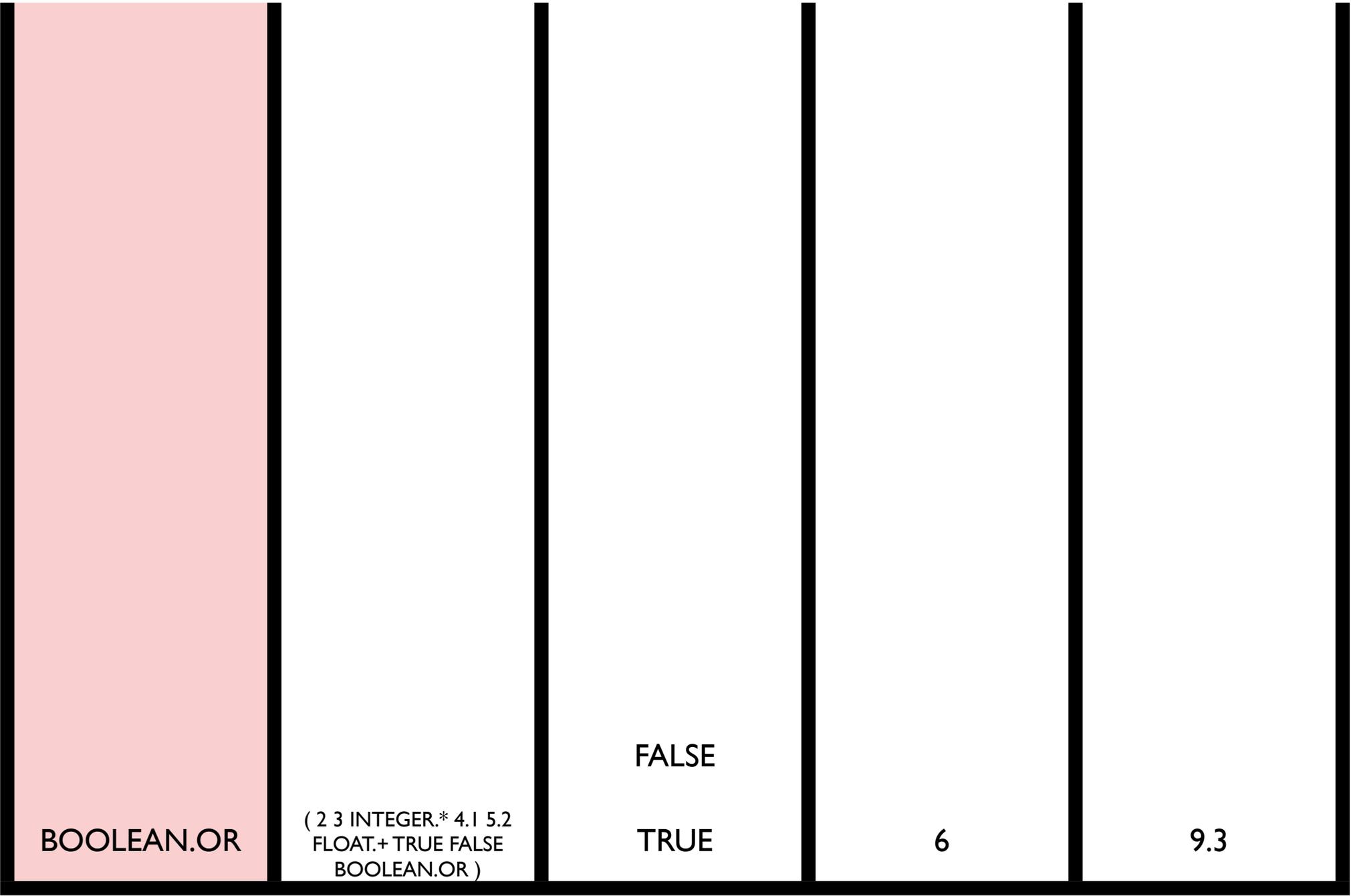
exec

code

bool

int

float



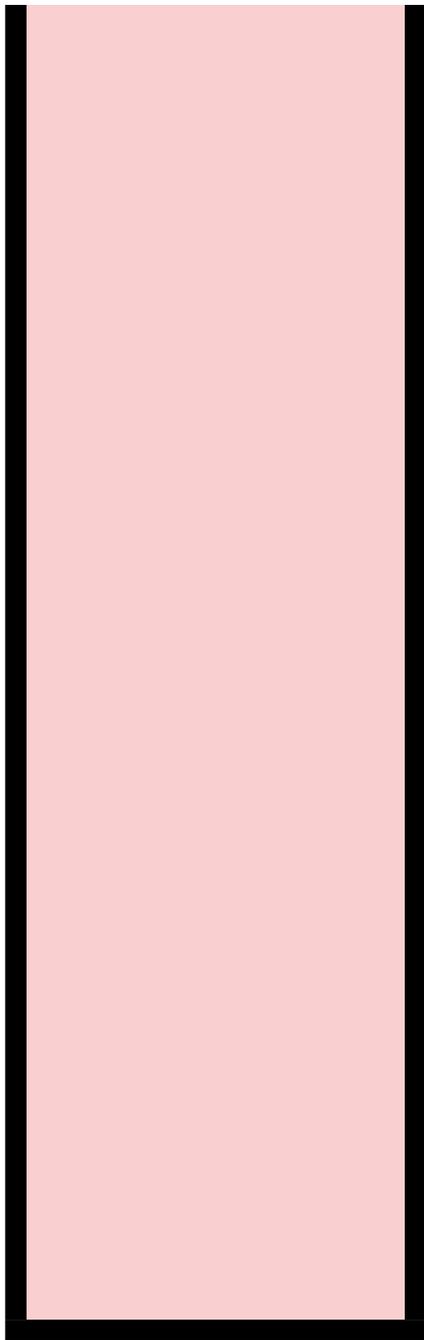
exec

code

bool

int

float



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

TRUE

6

9.3

exec

code

bool

int

float

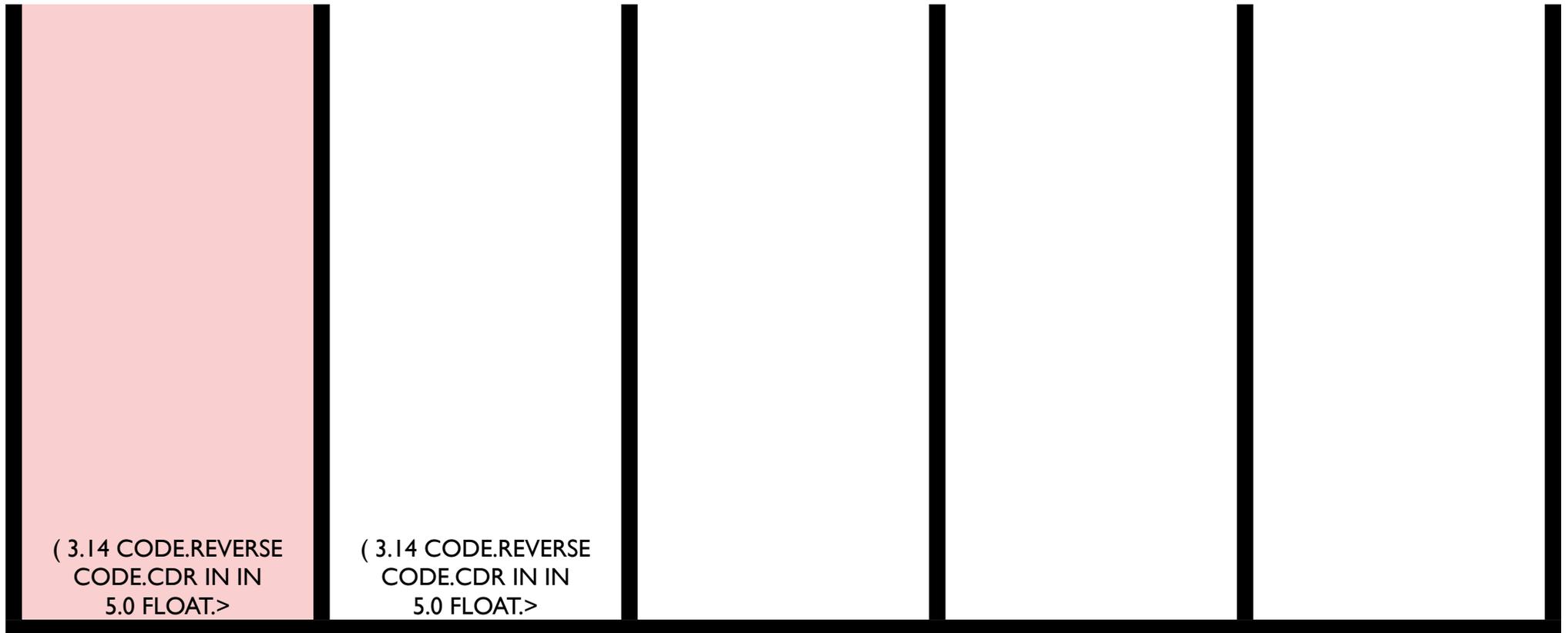
Same Results

```
( 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



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.>

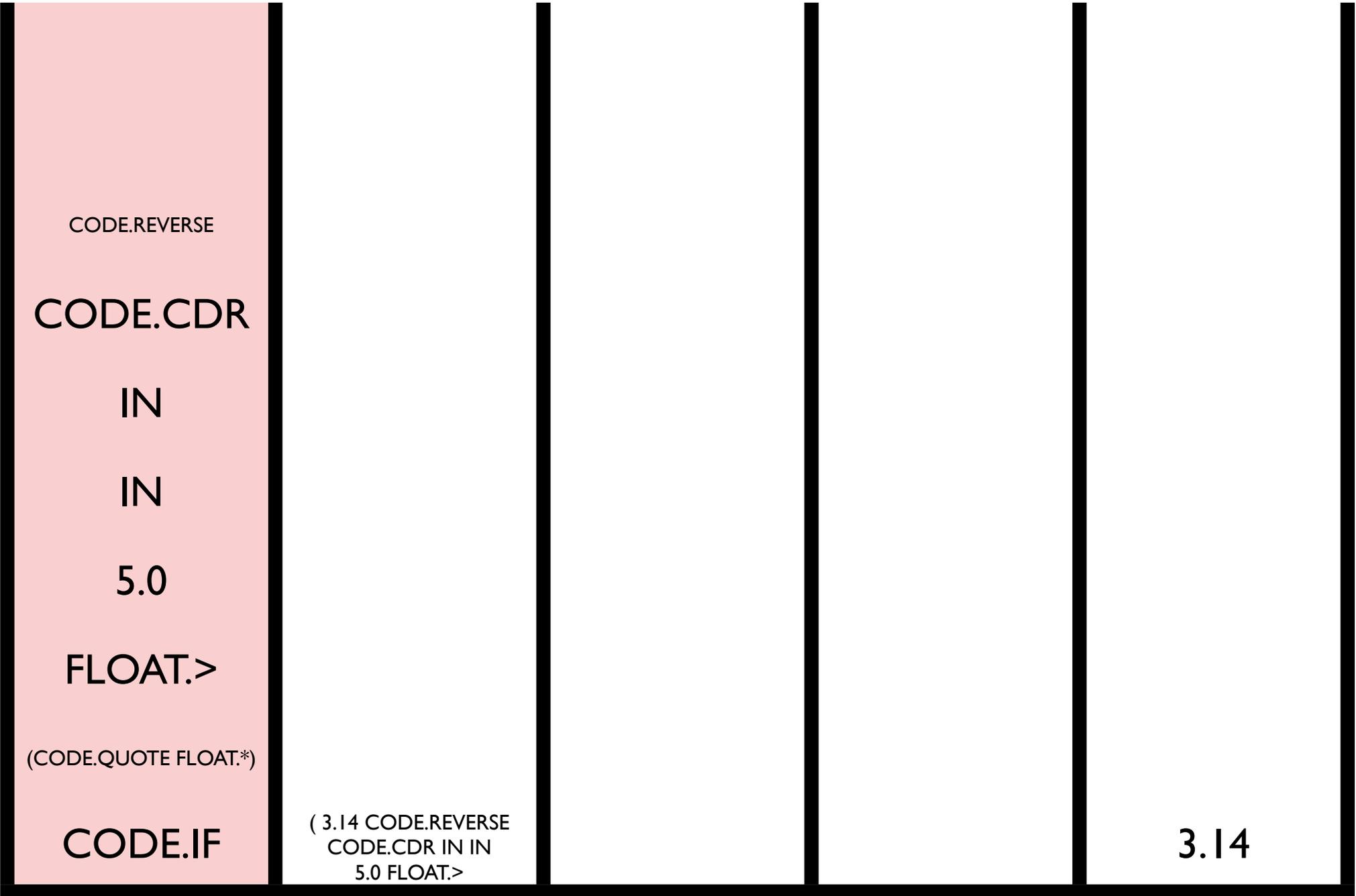
exec

code

bool

int

float



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

IN

IN

5.0

FLOAT.>

(CODE.QUOTE FLOAT.*)

CODE.IF

((CODE.QUOTE FLOAT.*)
FLOAT.> 5.0 IN IN
CODE.CDR

3.14

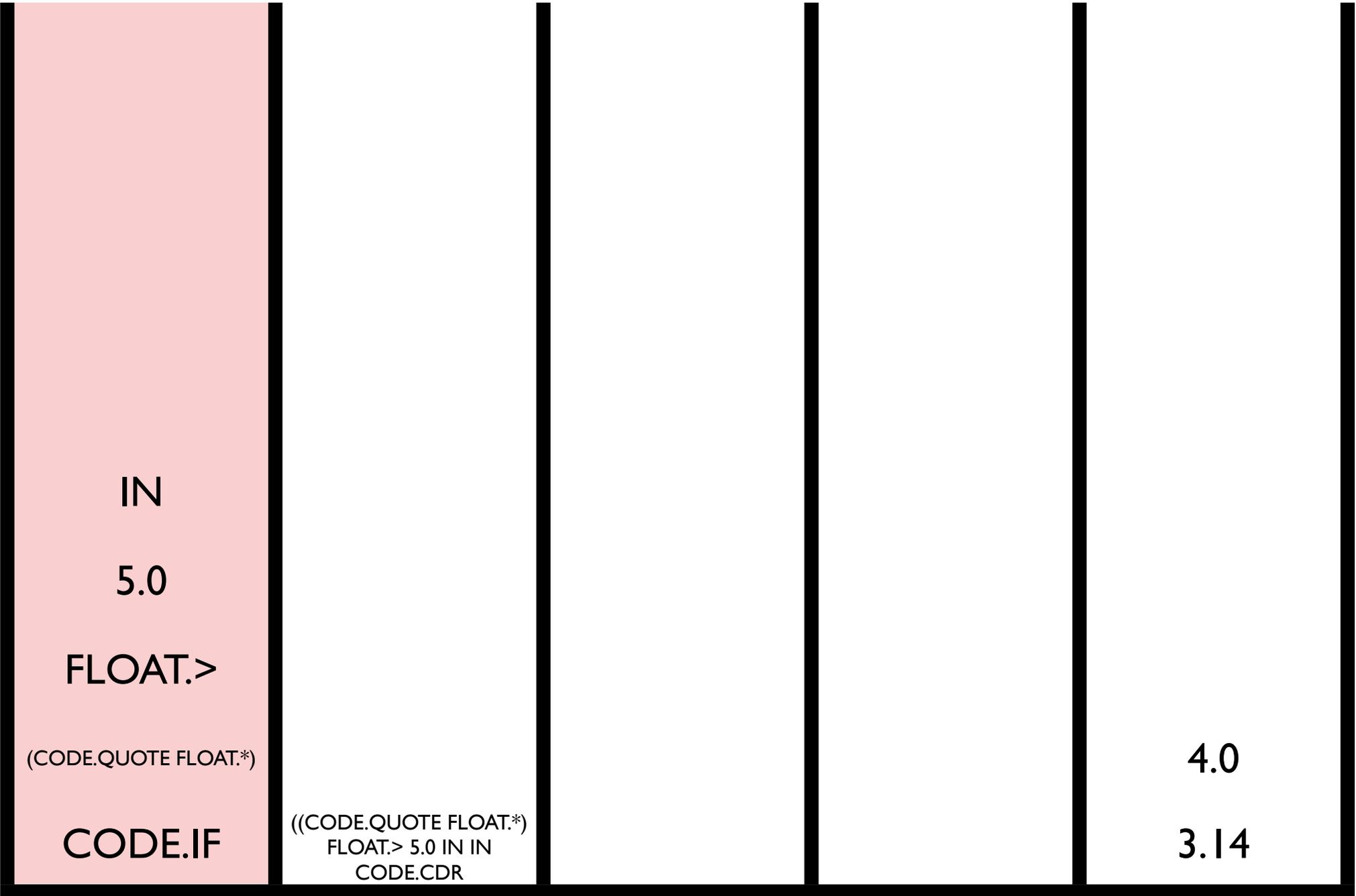
exec

code

bool

int

float



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

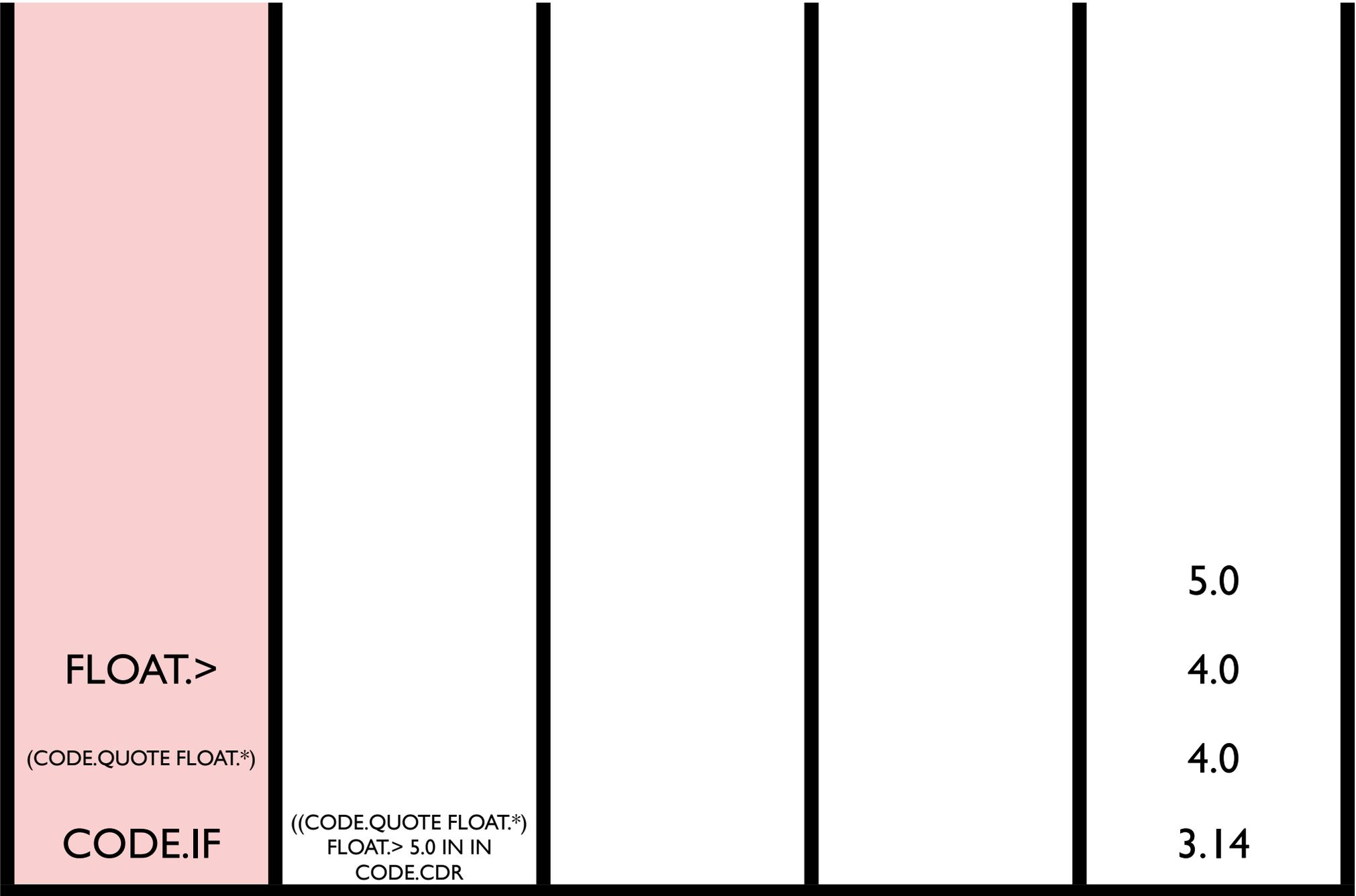
exec

code

bool

int

float



exec

code

bool

int

float

(CODE.QUOTE FLOAT.*)

CODE.IF

((CODE.QUOTE FLOAT.*)
FLOAT.> 5.0 IN IN
CODE.CDR

FALSE

4.0

3.14

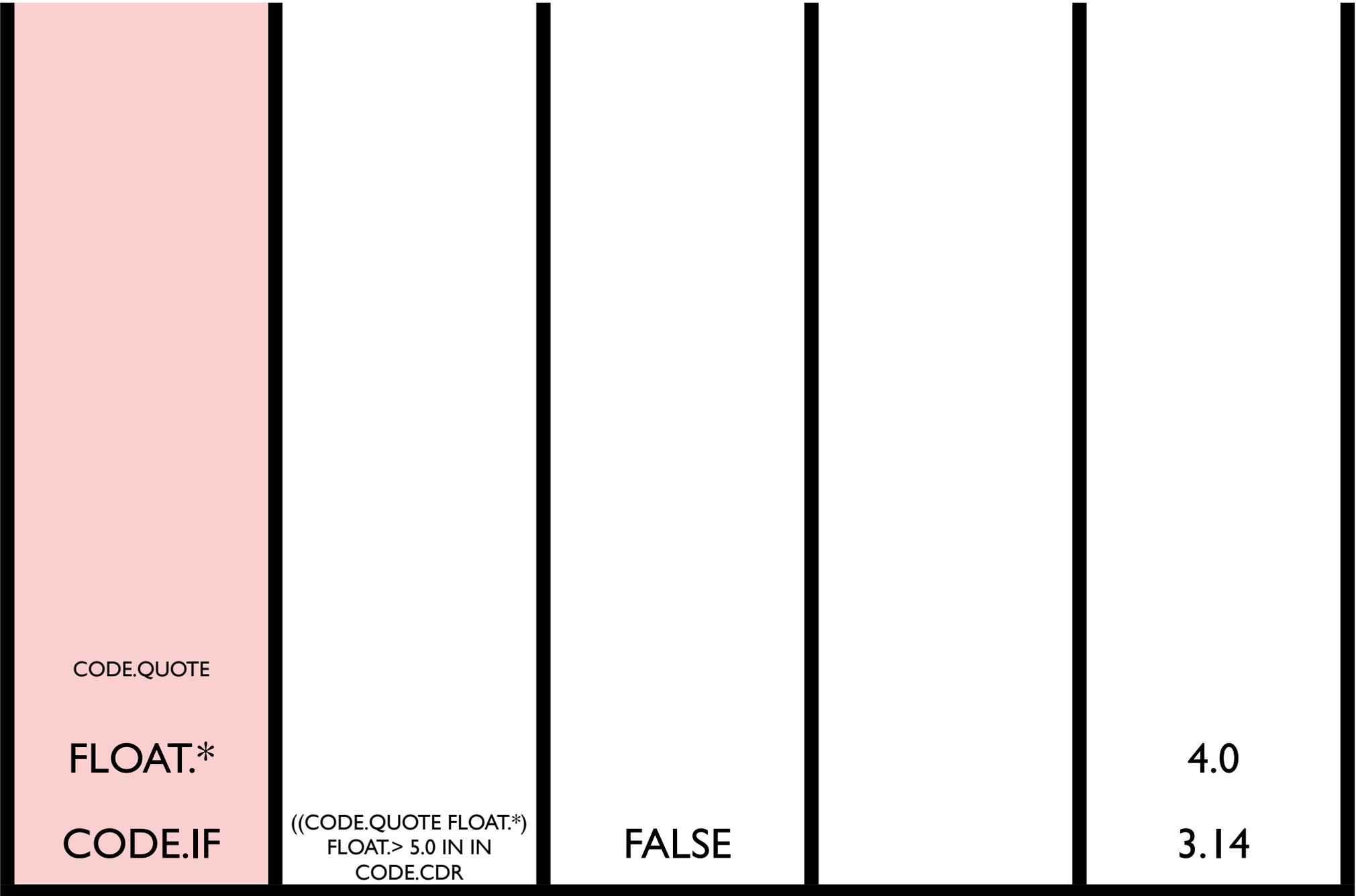
exec

code

bool

int

float



exec

code

bool

int

float

CODE.IF

FLOAT.*
((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

3.14



exec

code

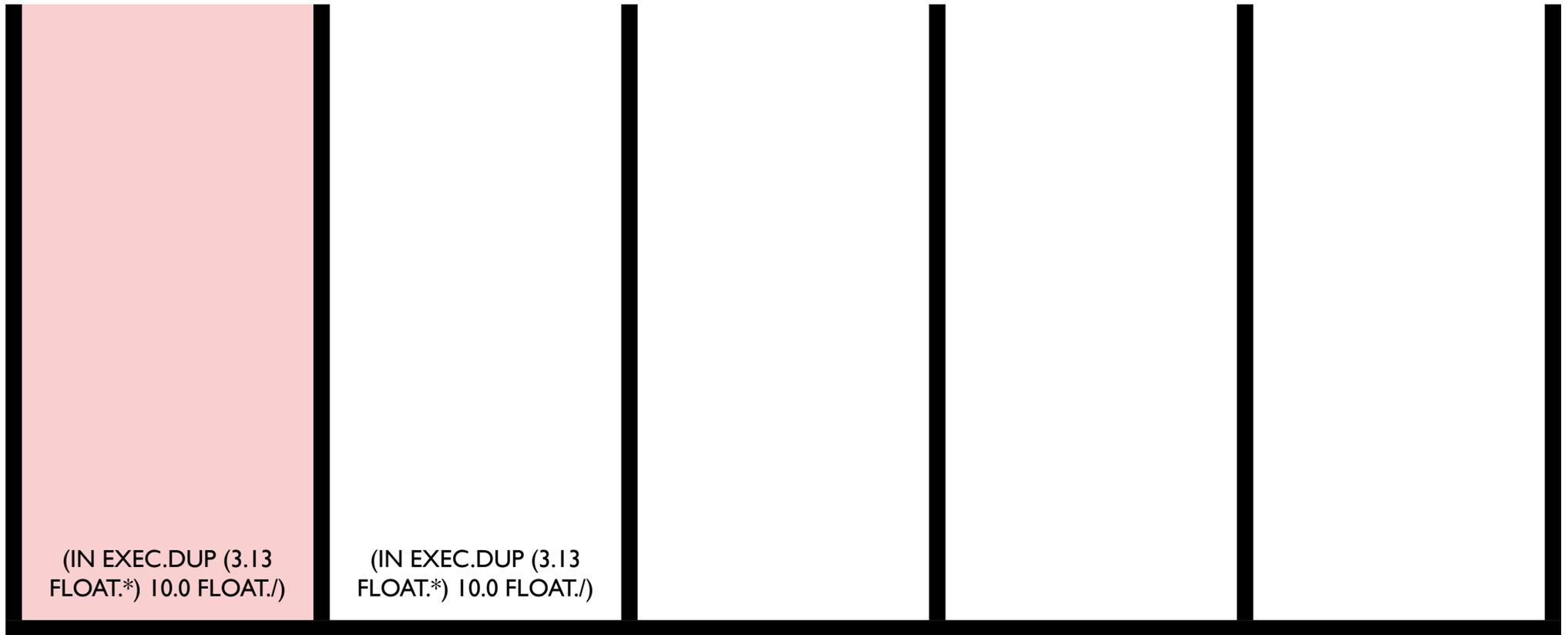
bool

int

float

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

IN=4.0



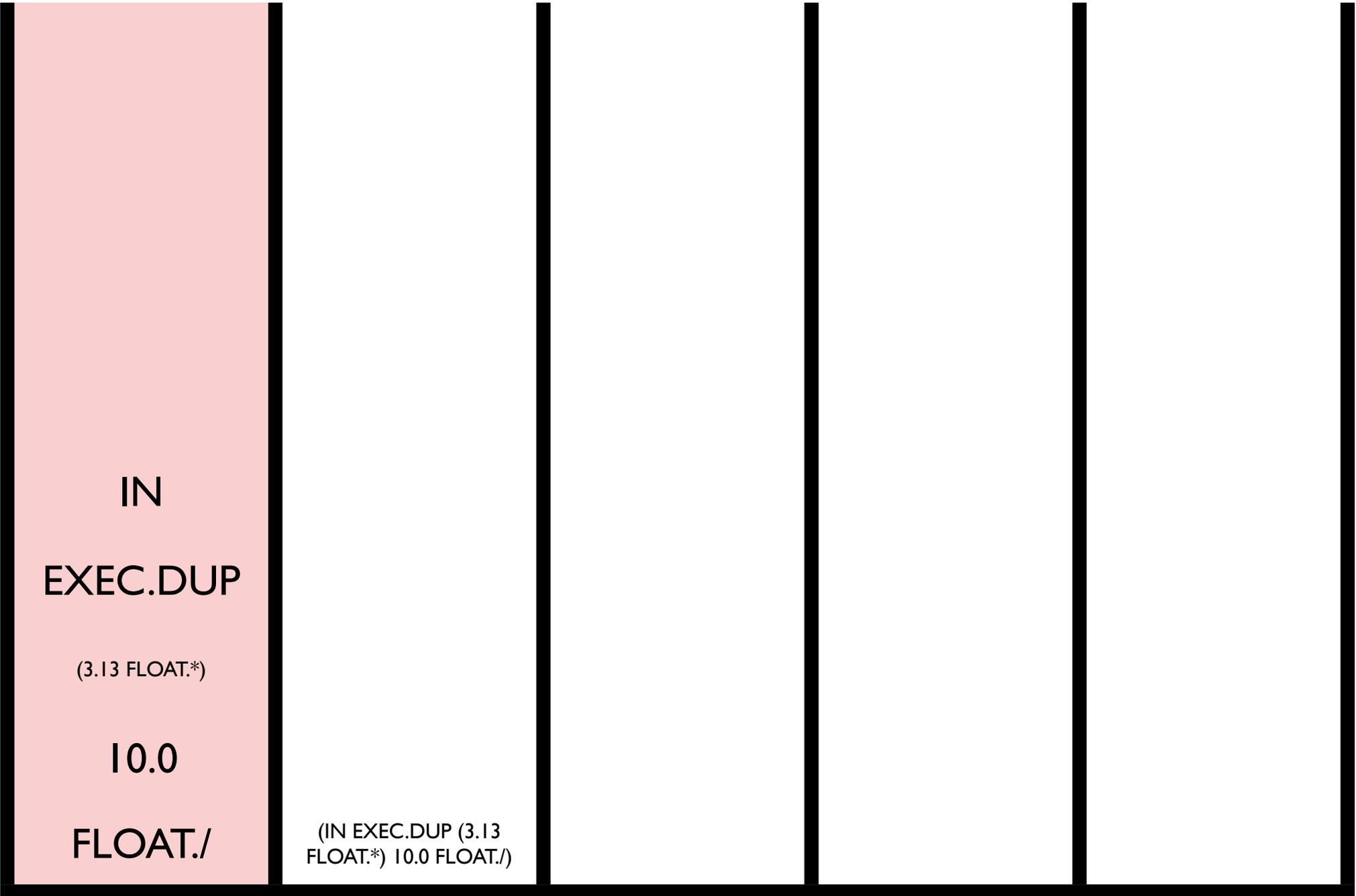
exec

code

bool

int

float



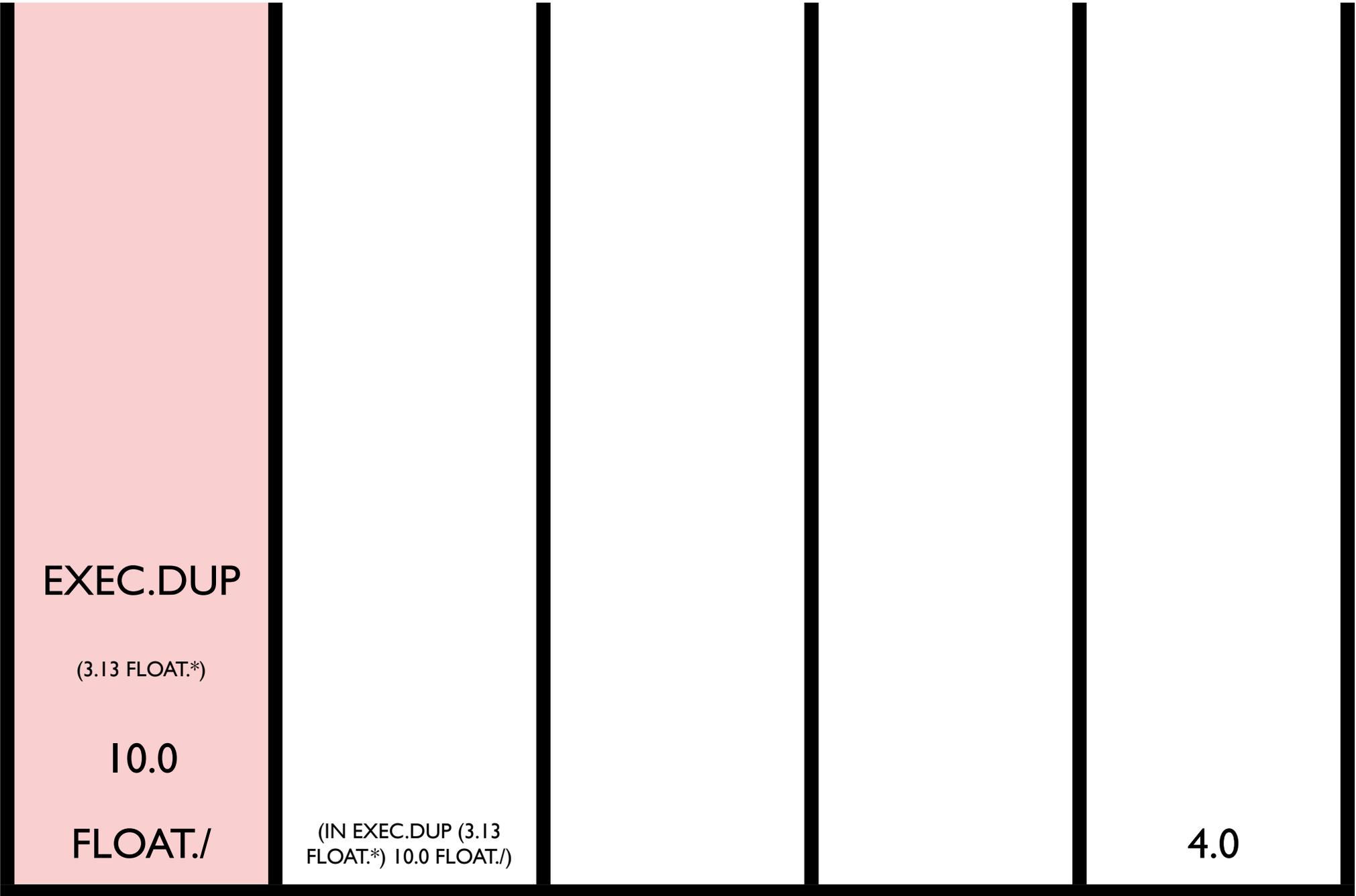
exec

code

bool

int

float



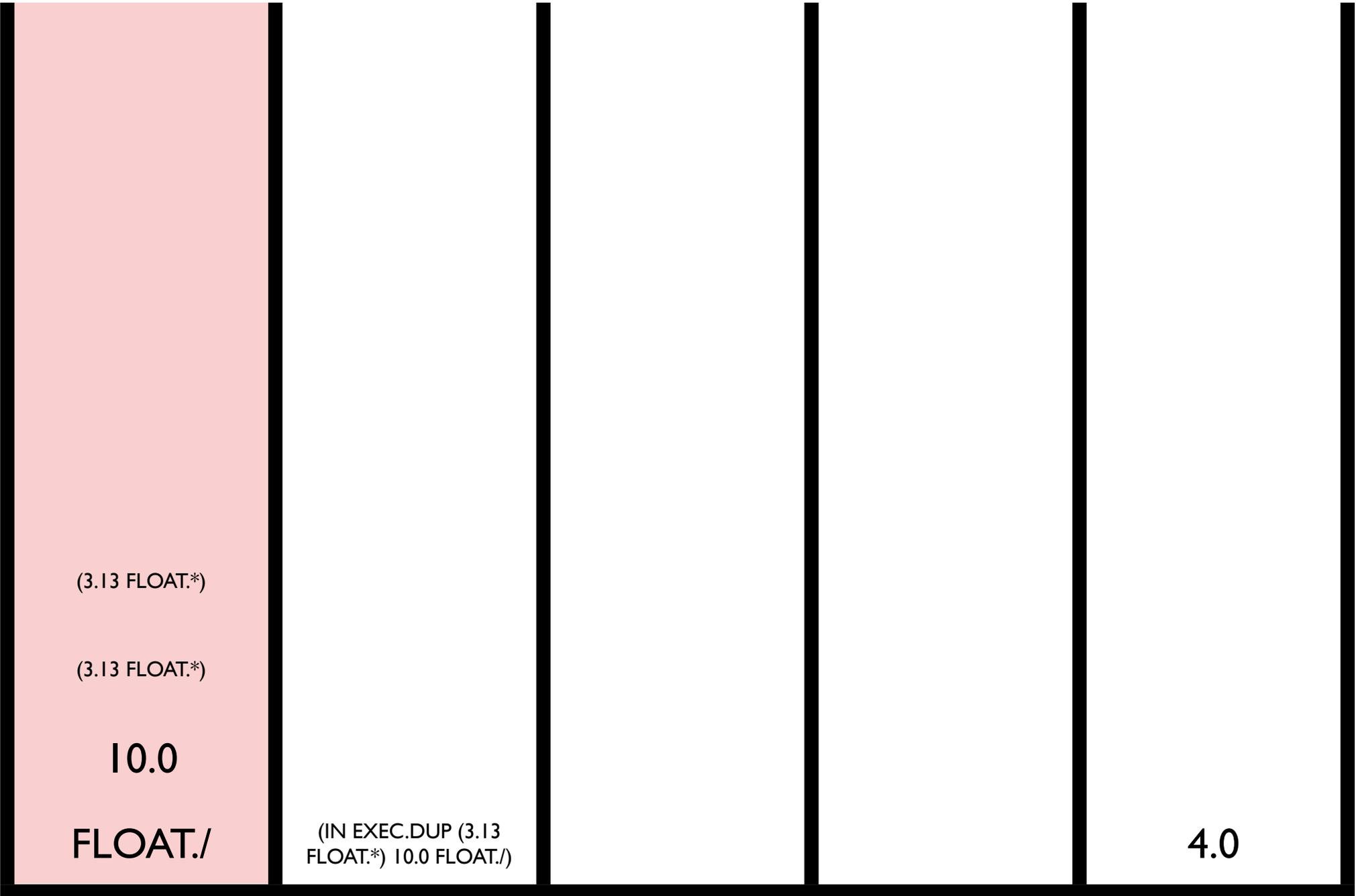
exec

code

bool

int

float



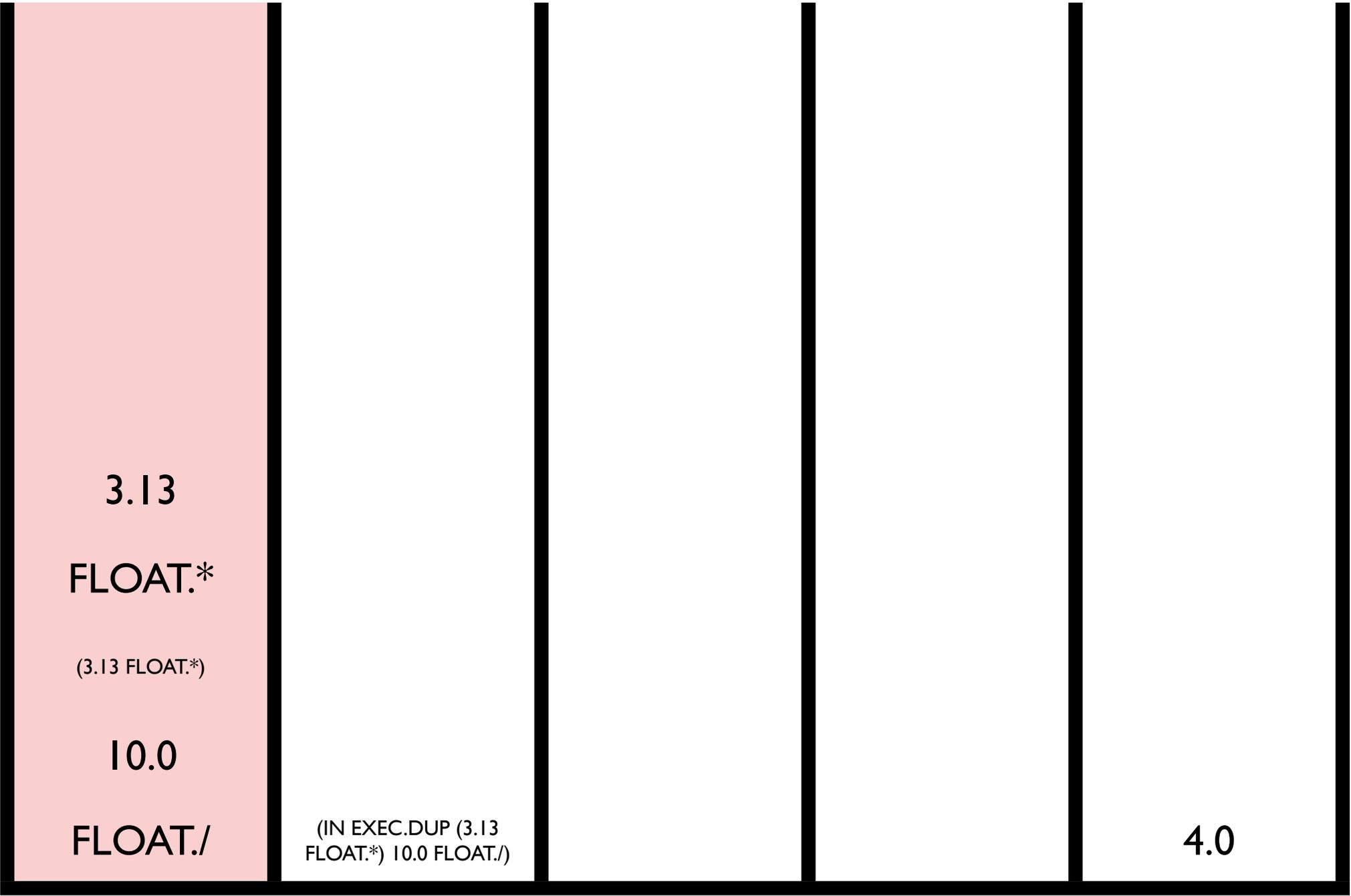
exec

code

bool

int

float



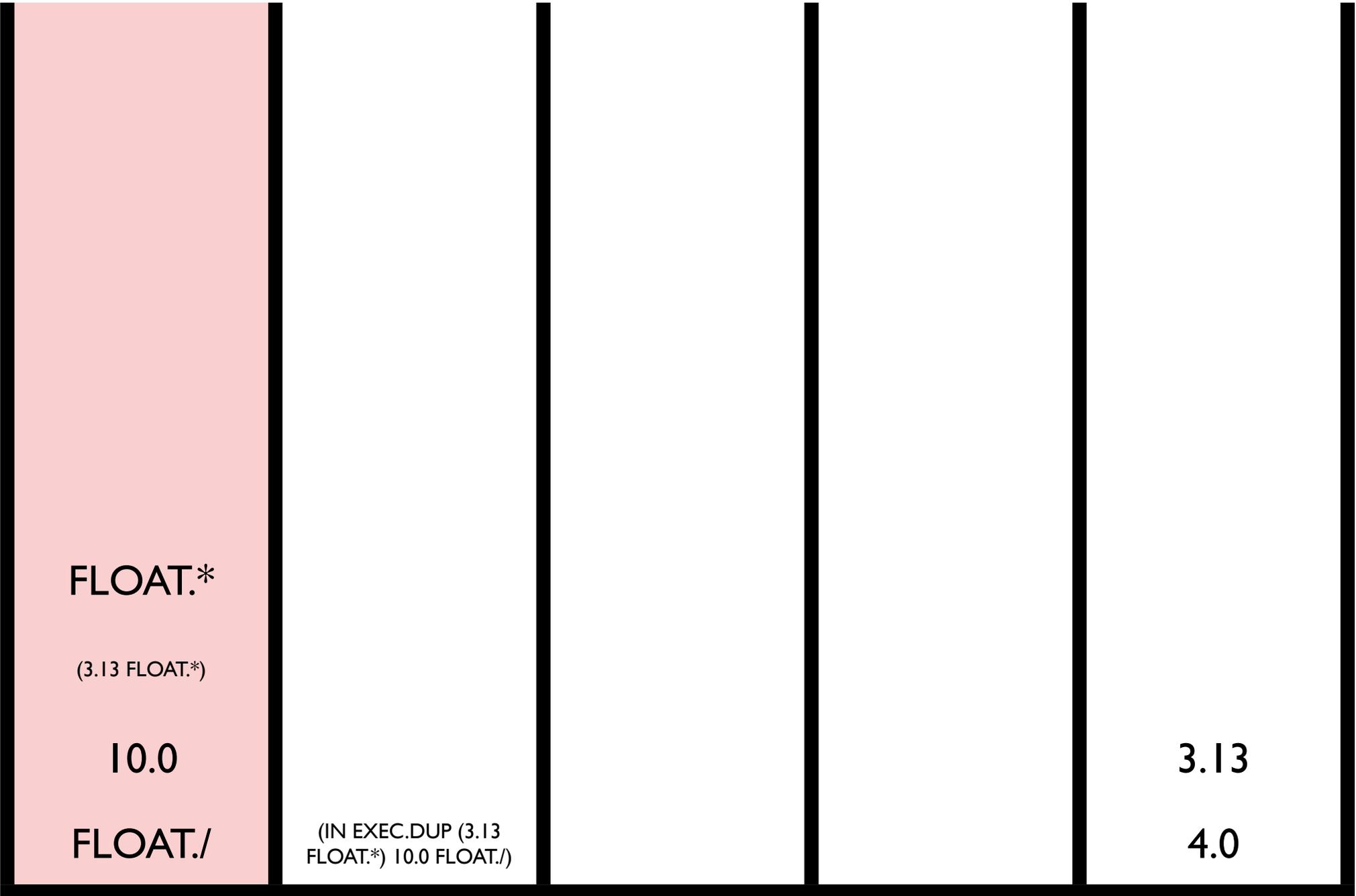
exec

code

bool

int

float



FLOAT.*

(3.13 FLOAT.*)

10.0

FLOAT./

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

3.13

4.0

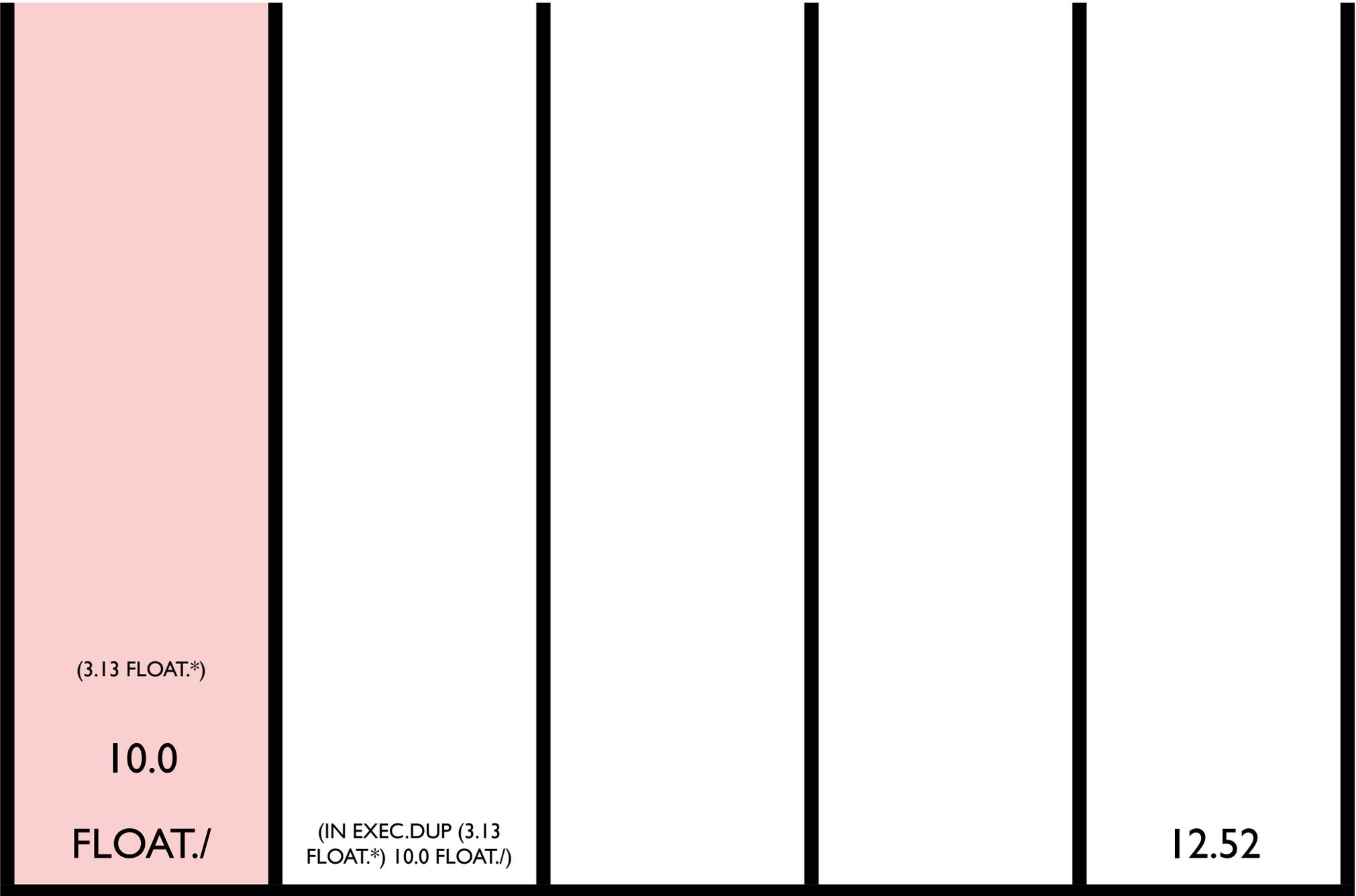
exec

code

bool

int

float



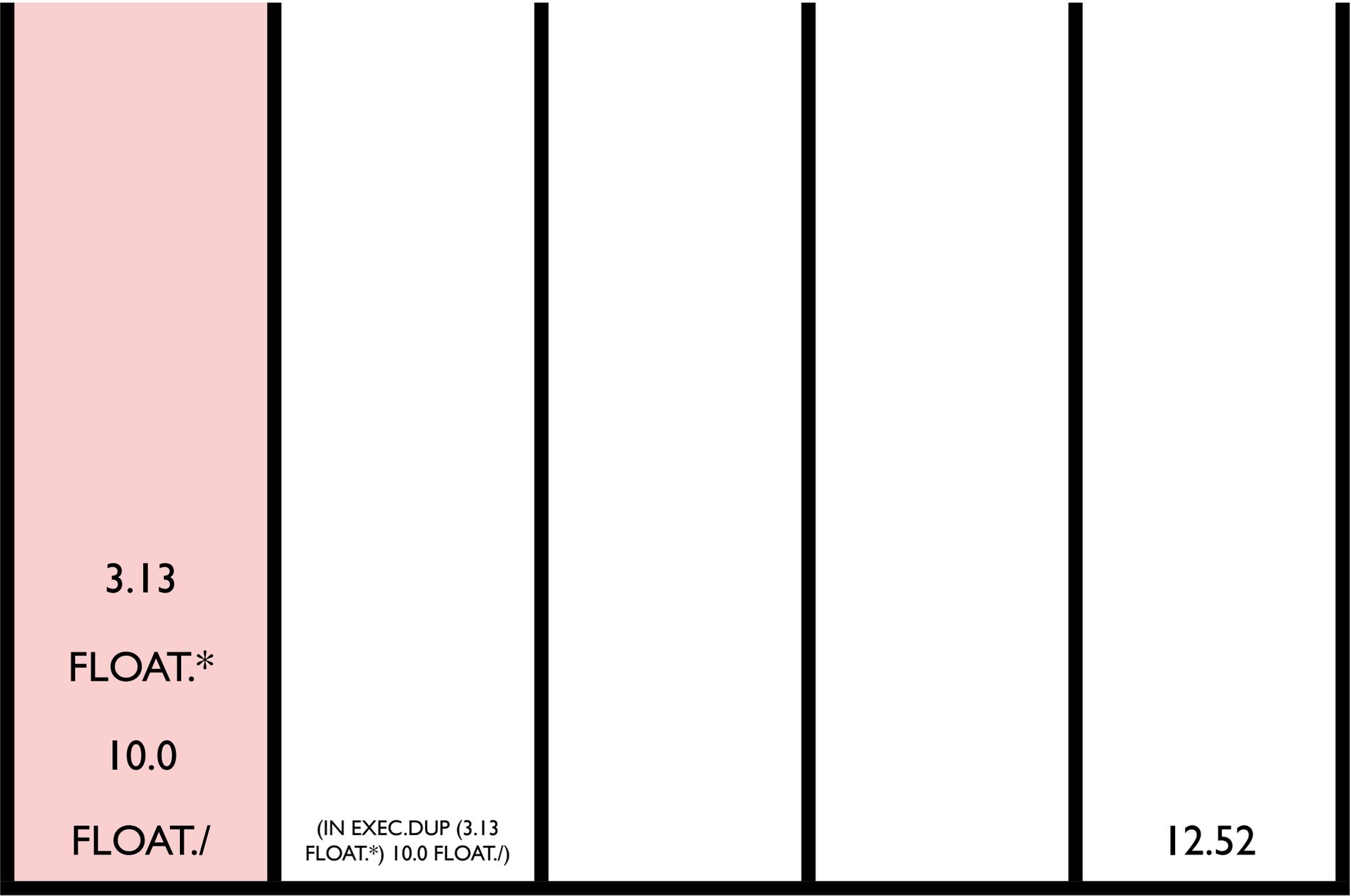
exec

code

bool

int

float



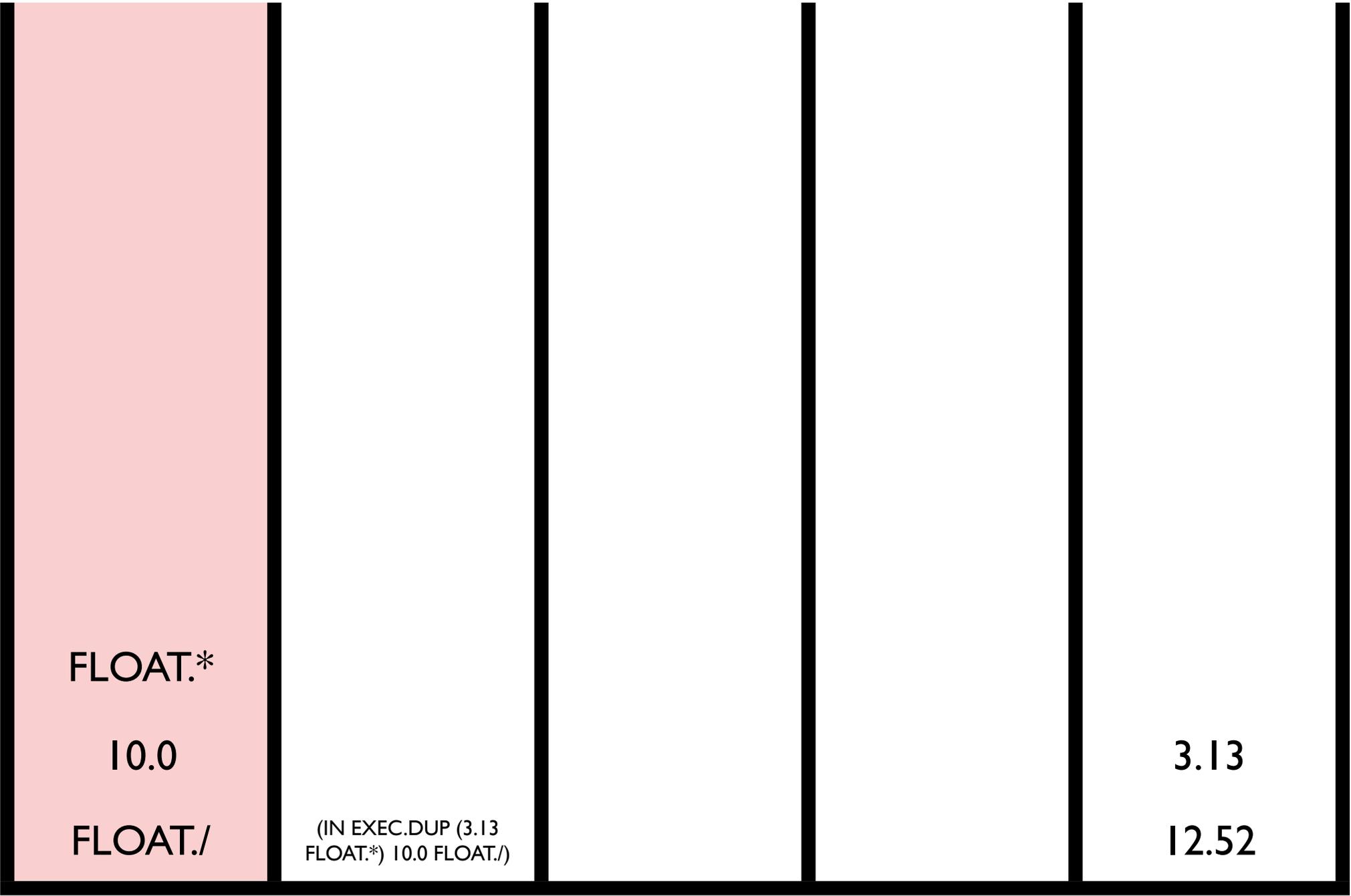
exec

code

bool

int

float



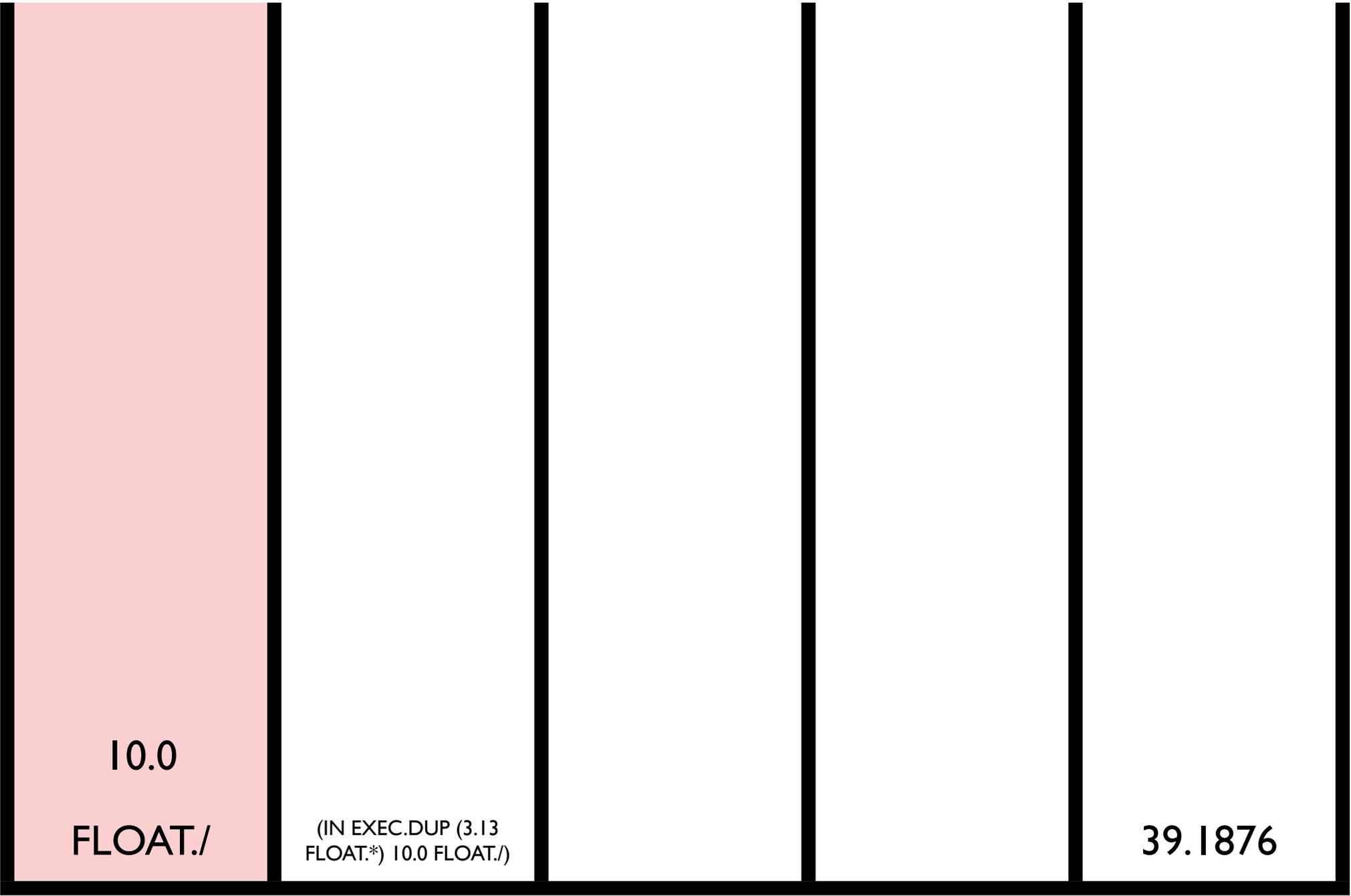
exec

code

bool

int

float



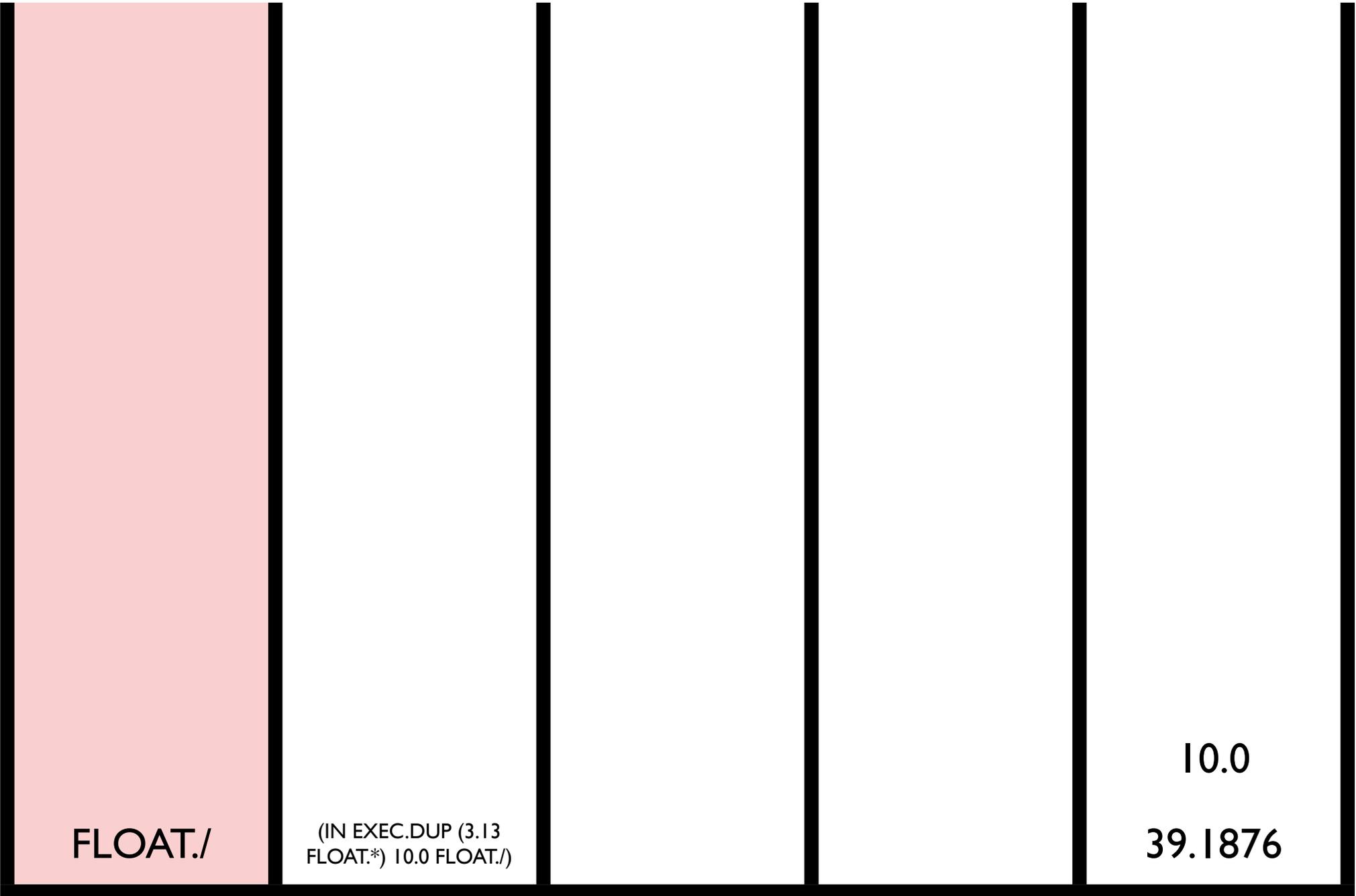
exec

code

bool

int

float



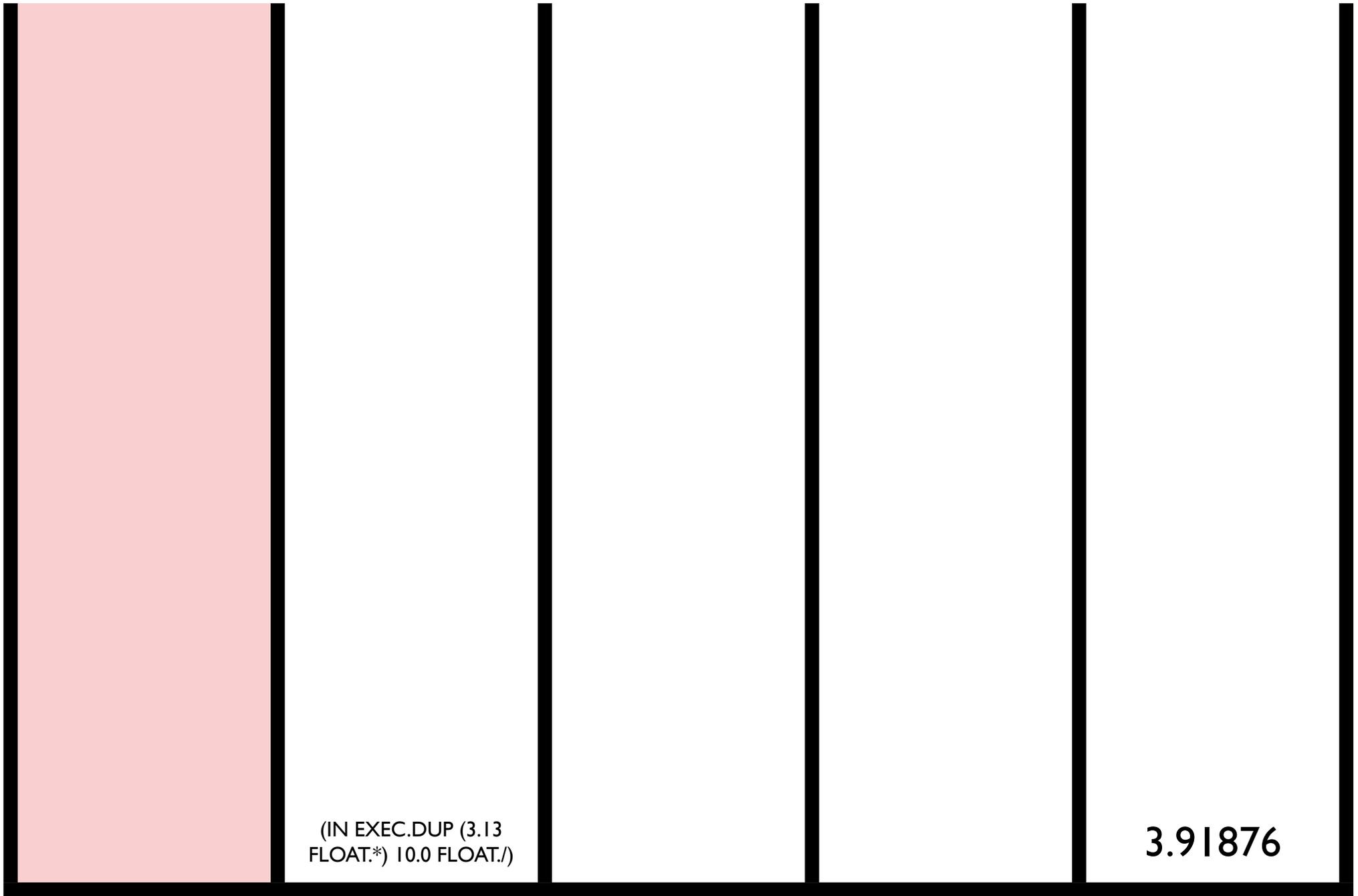
exec

code

bool

int

float



exec

code

bool

int

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.* ) )
```

Auto-simplification

Loop:

Make it randomly simpler

If it's as good or better: keep it

Otherwise: revert

Problems Solved by PushGP in the GECCO-2005 Paper on Push3

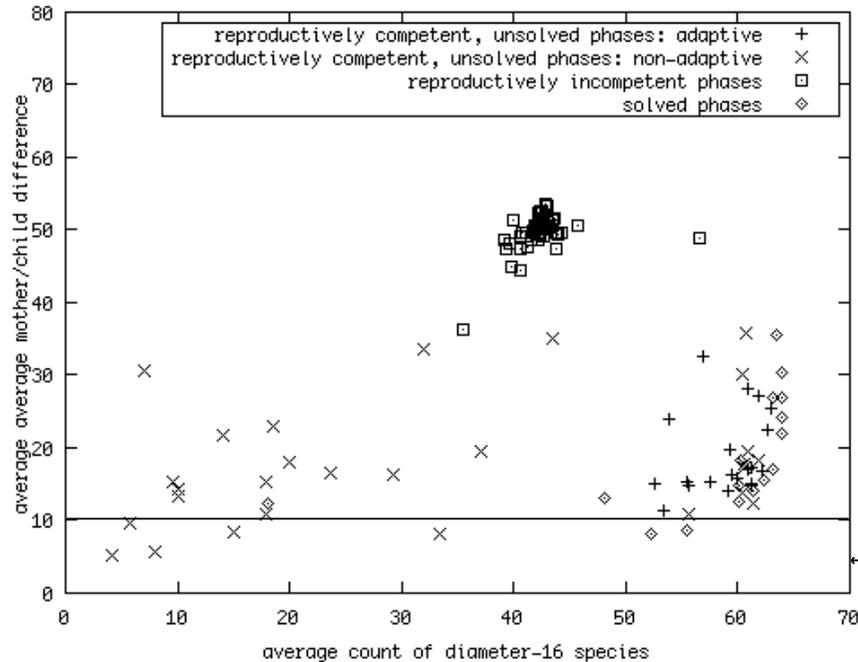
- Reversing a list
- Factorial (many algorithms)
- Fibonacci (many algorithms)
- Parity (any size input)
- Exponentiation
- Sorting

Pushpop

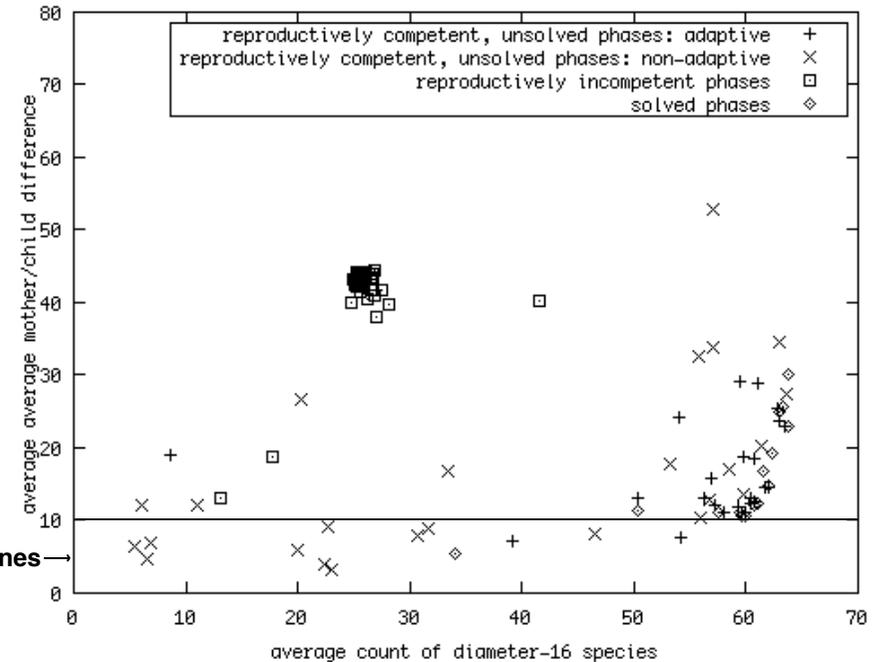
- A soup of evolving Push programs.
- Reproductive procedures emerge ex nihilo:
 - No hand-designed “ancestor.”
 - Children constructed by any computable process.
 - No externally applied mutation procedure or rate.
 - Exact clones are prohibited, but near-clones are permitted.
- Selection for problem-solving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

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**

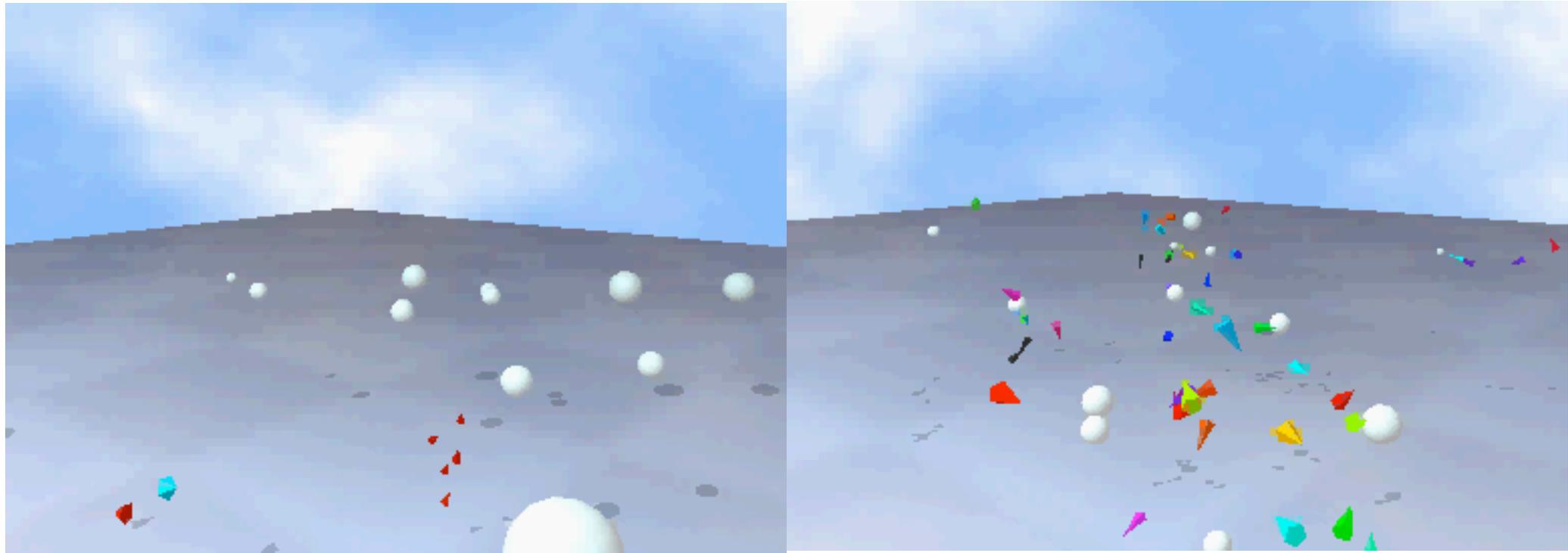


**Runs without
sexual instructions**

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).

SwarmEvolve 2.0



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.

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))))))
```

Conclusion

Genetic programming systems have an important role to play in the future of mathematics.