Lecture 6
Stochastic Search

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The problem statement

Behavioral constraints = examples

```
[1,4,7,2,0,6,9,2,5]  →  [1,2,4,7,0]
[0] → [0]
[5,1] → [1,5,0]
```

Structural constraints = grammar

```
L ::= sort(L)  |  L[N..N]
    |  L + L  |  [N]  |  x
N ::= find(L,N)  |  0
```

Search strategy?

Enumerative
Representation-based
Stochastic
Constraint-based

Stochastic search in synthesis

Weimer, Nguyen, Le Goues, Forrest. *Automatically Finding Patches Using Genetic Programming*. ICSE’09

Gissurarson, Applis, Panichella, van Deursen, Sands. *PropR: Property-Based Automatic Program Repair.* ICSE’22

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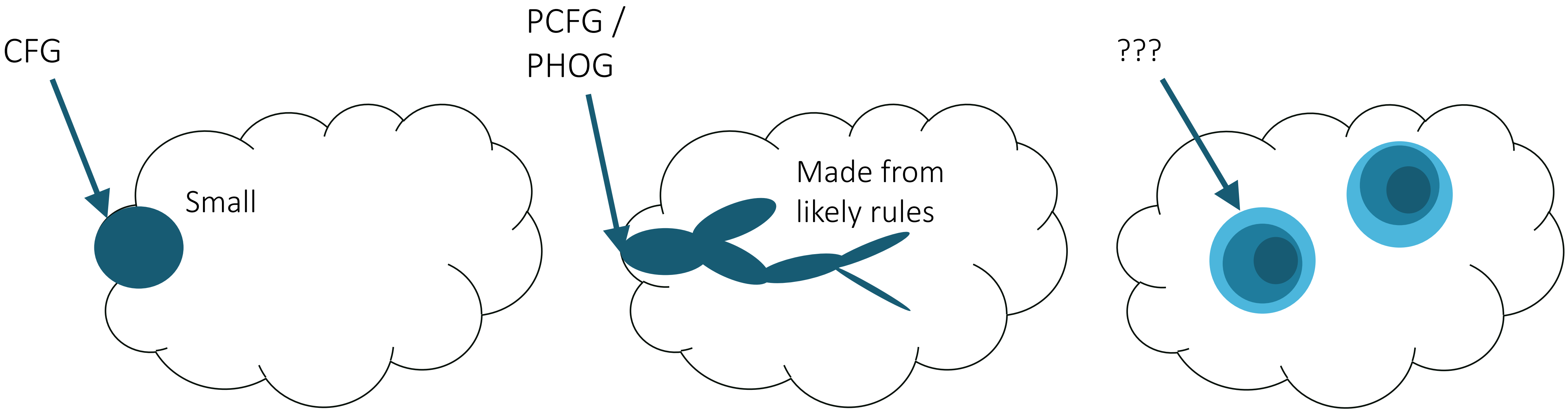
Search space



Enumerative search

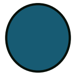
Weighted enumerative search

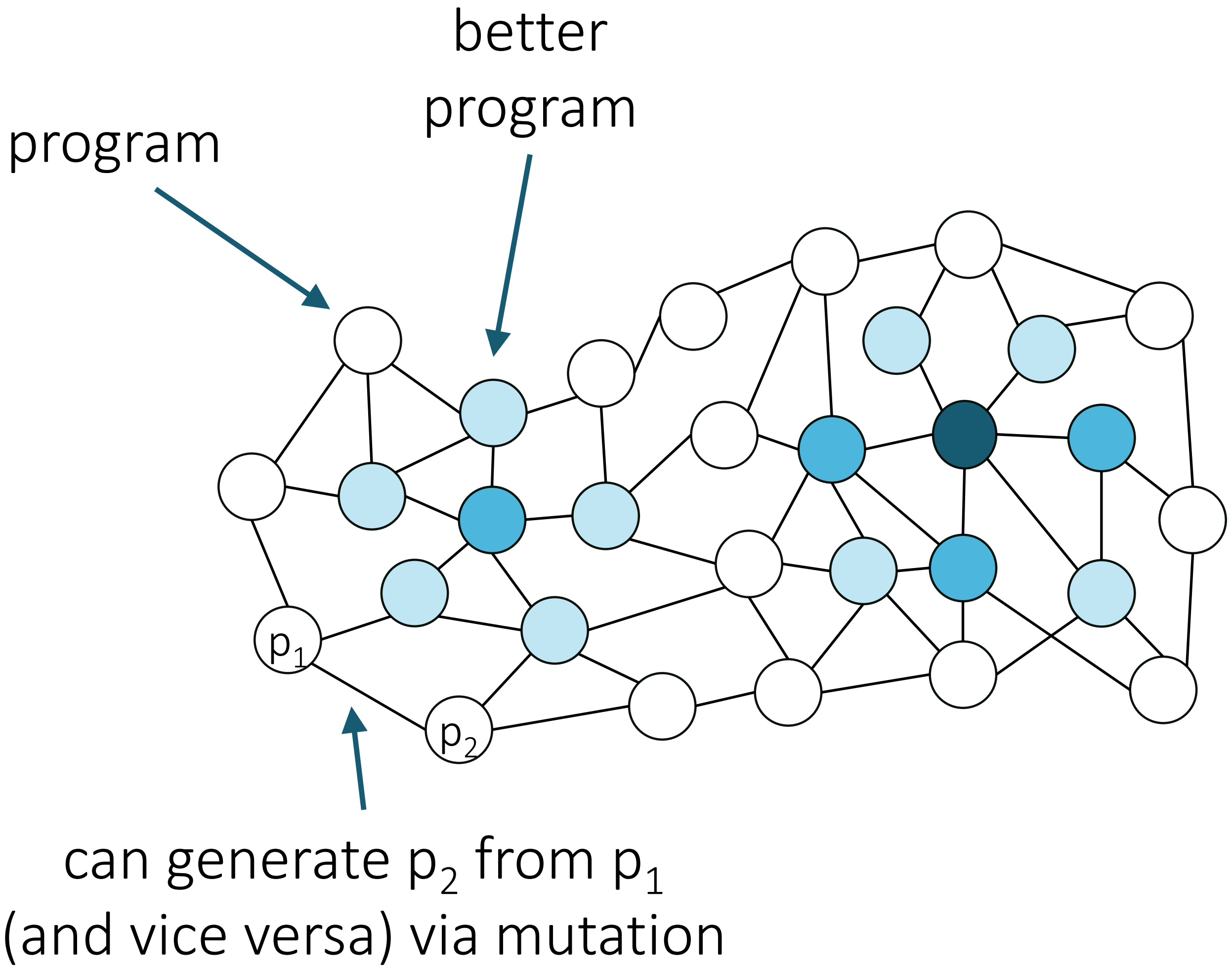
Local search

Naïve local search

To find the best program:

```
p := random()
while (true) {
  p' := mutate(p);
  if (cost(p') < cost(p))
    p := p';
}
```

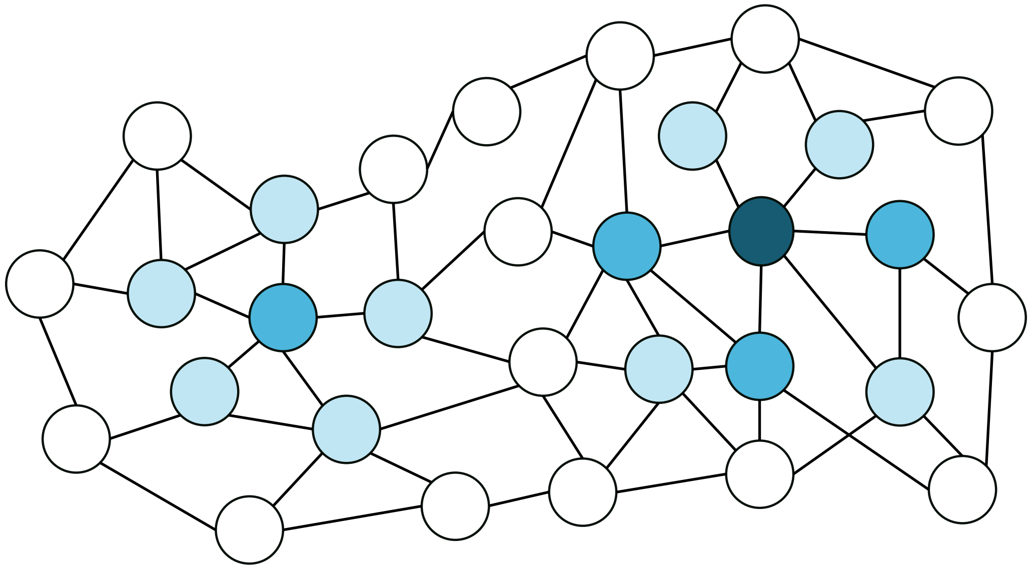
Will never get to  from p_1!



MCMC sampling

Avoid getting stuck in local minima:

```
p := random()
while (true) {
  p’ := mutate(p);
  if (random(A(p -> p’))
    p := p’;
}
```



where

- if p’ is better than p: $A(p \rightarrow p') = 1$
- otherswise: $A(p \rightarrow p')$ decreases with difference in cost between p’ and p

MCMC sampling

Metropolis algorithm:

$$A(p \to p') = \min(1, e^{-\beta(C(p') - C(p))})$$

The theory of Markov chains tells us that in the limit we will be sampling with the probability proportional to

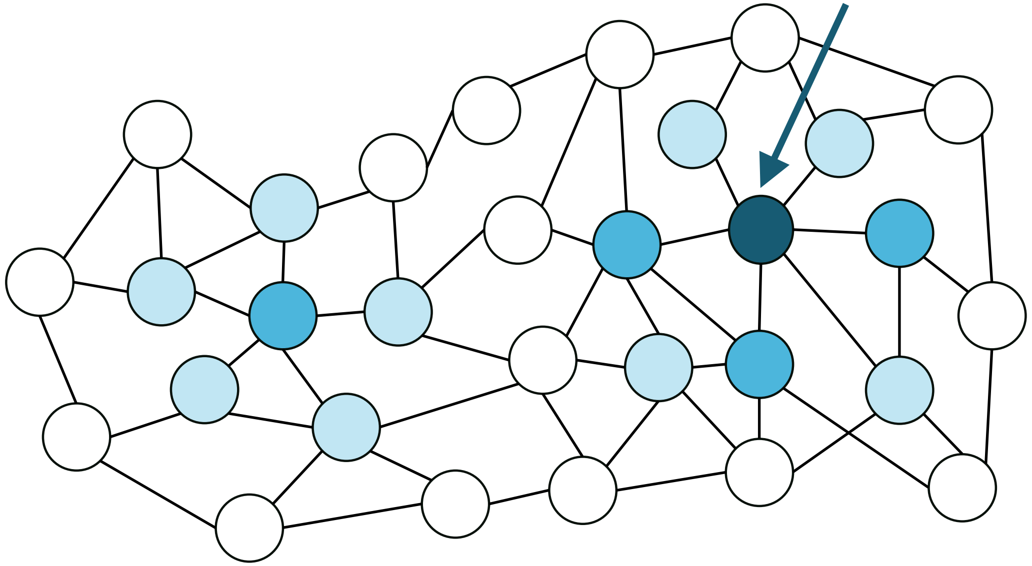
$$e^{-\beta * C(p)}$$

MCMC for superoptimization

[Schkufza, Sharma, Aiken '13]

```
.L0:
movq rsi, r9
movl ecx, ecx
shrq 32, rsi
andl 0xffffffff, r9d
movq rcx, rax
movl edx, edx
imulq r9, rax
imulq rdx, r9
imulq rsi, rdx
imulq rsi, rcx
addq rdx, rax
jae .L2
movabsq 0x100000000, rdx
addq rdx, rcx
.L2:
movq rax, rsi
movq rax, rdx
shrq 32, rsi
salq 32, rdx
addq rsi, rcx
addq r9, rdx
adcq 0, rcx
addq r8, rdx
adcq 0, rcx
addq rdi, rdx
adcq 0, rcx
movq rcx, r8
movq rdx, rdi
```

```
.L0:
shlq 32, rcx
movl edx, edx
xorq rdx, rcx
movq rcx, rax
mulq rsi
addq r8, rdi
adcq 0, rdx
addq rdi, rax
adcq 0, rdx
movq rdx, r8
movq rax, rdi
```



Cost function

$$C_s(p) = \mathrm{eq}_s(p) + \mathrm{perf}(p)$$

source program

penalty for wrong results

penalty for being slow

$$\mathrm{eq}_s(p) = \sum_{t \in Tests} \mathrm{reg}_s(p,t) + \mathrm{mem}_s(p,t) + \mathrm{err}(p,t)$$

# of different bits in registers/memory

# of segfaults etc

when $\mathrm{eq}_s(p) = 0$, use a symbolic validator

Cost function

$$C_s(p) = \mathrm{eq}_s(p) + \mathrm{perf}(p)$$

source program

penalty for wrong results

penalty for being slow

$$\mathrm{perf}(p) = \sum_{i \in \mathrm{instr}(p)} \mathrm{latency}(i)$$

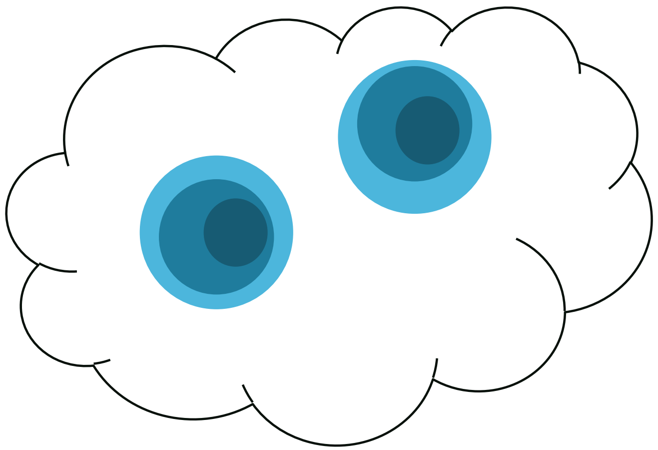
Local search: discussion

Strengths:

- can explore program spaces with no a-priori bias

Limitations?

- only applicable when there is a cost function that faithfully approximates correctness
- Counterexample: round to next power of two
  - 0011 -> 0100
  - 0101 -> 1000
  - 0111 -> 1000



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- Similar but for program repair, uses genetic programming

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- Samples from a grammar with bias towards partial solutions
- I assume they use stochastic just for ease of sampling

Next

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