

# #8: Weighted Enumerative Search - II

**Sankha Narayan Guria**

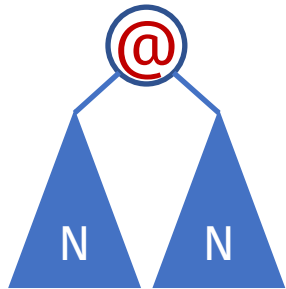
EECS 700: Introduction to Program Synthesis



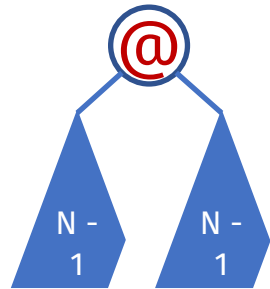
# Scaling enumerative search

## Prune

- Discard useless subprograms



$$m * N^2$$



$$m * (N - 1)^2$$

## Prioritize

- Explore more promising candidates first

$$P = \{ \begin{array}{l} [0][N..N] \\ x[N..N] \\ \dots \end{array} , \quad \leftarrow \begin{array}{l} \text{dequeue} \\ \text{this first} \end{array}$$

# Weighted enumerative search

DeepCoder

Probabilistic Grammars

Weighted top-down search

Lee, et al: Accelerating Search-Based Program Synthesis using Learned Probabilistic Models. PLDI'18

Weighted bottom-up search

Barke, Peleg, Polikarpova. Just-in-Time Learning for Bottom-Up Enumerative Synthesis. OOPSLA'20

Shi, Bieber, Singh. TF-Coder: Program Synthesis for Tensor Manipulations. arXiv

# Weighted top-down search

**Wanted:** explore programs in the order of **probability**

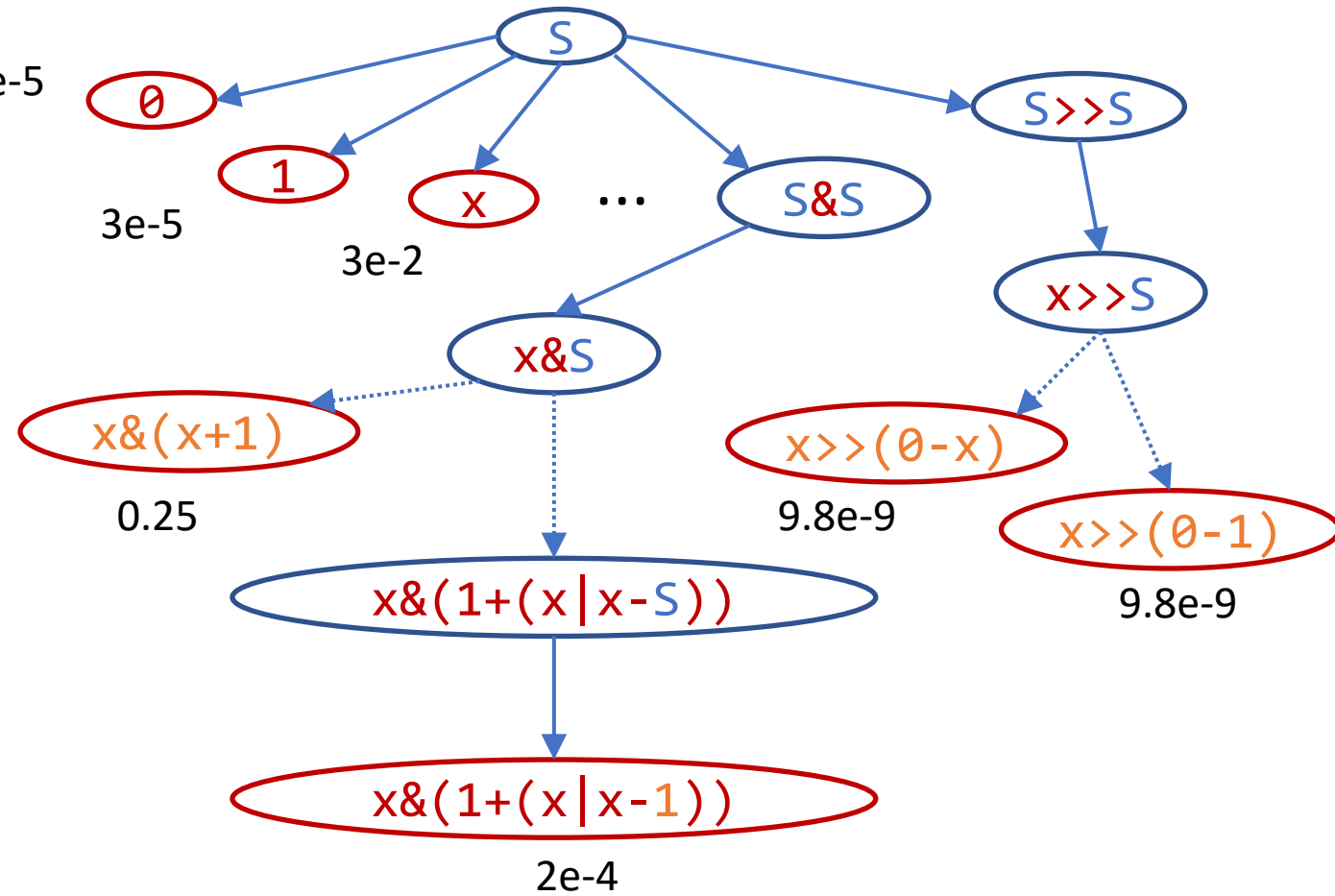
$$\wp(t) = \prod_{(r_i, \tau_i) \in S \rightarrow^* t} \wp(r_i \mid \tau_i)$$

Hard to maximize multiplicative cost... but easy to minimize additive cost!

= shortest path

$$cost(t) = \sum_{(r_i, \tau_i) \in S \rightarrow^* t} weight(r_i \mid \tau_i)$$

$$-\log_2 \wp(t) = \sum_{(r_i, \tau_i) \in S \rightarrow^* t} -\log_2 \wp(r_i \mid \tau_i)$$



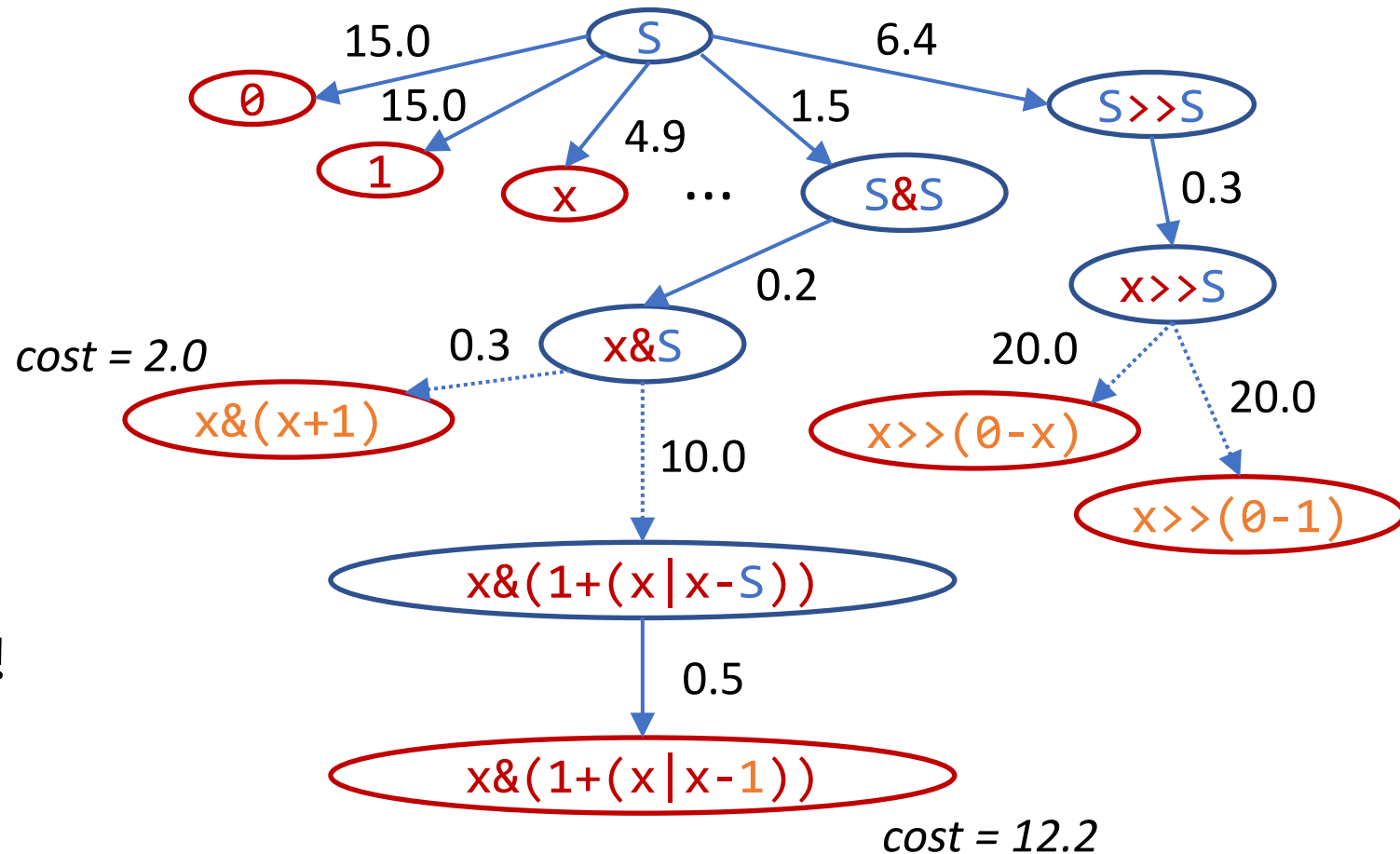
# Weighted top-down search

Assigns weights to edges:



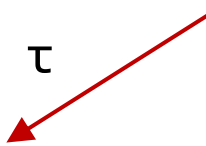
$$\text{weight}(r_i | \tau_i) = -\log_2 \wp(r_i | \tau_i)$$

Now  $\text{cost}(t) < \text{cost}(t')$   
iff  $t$  is more likely than  $t'$ !

We can use shortest path algo  
(e.g. Dijkstra) to search by cost!



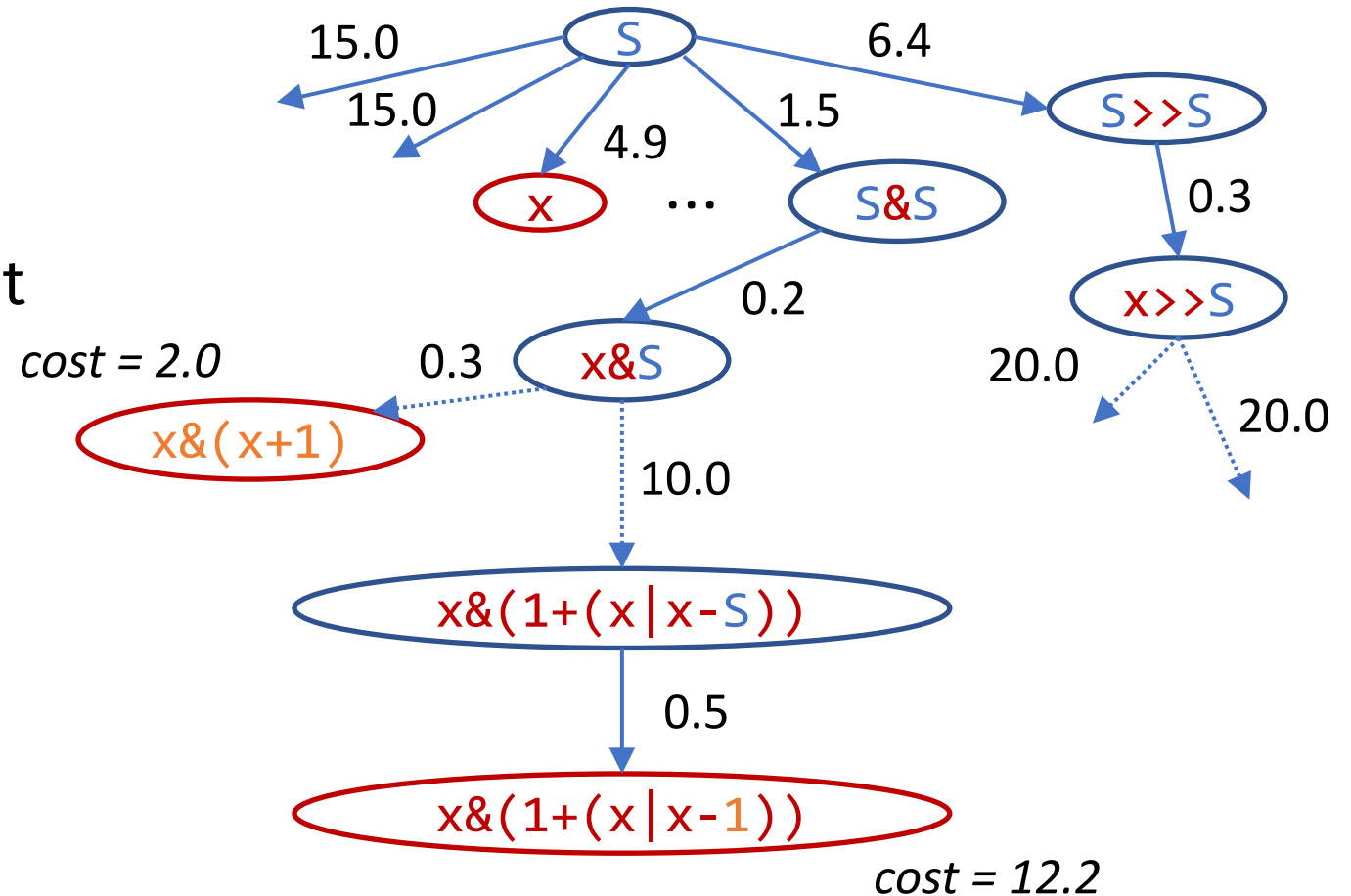
# Weighted top-down search (Dijkstra)

```
top-down(< $\Sigma$ , N, R, S>, [i  $\rightarrow$  o]) {  
  wl := [<S, 0>]  wl now stores candidates (nodes)  
  while (wl != []) together with their costs  
    < $\tau$ , c> := wl.dequeue_min(c);  Dequeue the node with minimal cost  
    if (complete( $\tau$ ) &&  $\tau$ ([i]) = [o])  
      return  $\tau$ ;  
    wl.enqueue(unroll( $\tau$ , c));  
}  
  
unroll( $\tau$ , c) {  
  wl' := []  
  A := left-most nonterminal in  $\tau$   
  forall (A  $\rightarrow$  rhs) in R:  
    wl' += < $\tau$ [A  $\rightarrow$  rhs], c + w(A  $\rightarrow$  rhs |  $\tau$ )>  Distance to a new node: add the  
    return wl';  
}
```

# Can we do better?

**Dijkstra:** explores a lot of intermediate nodes that don't lead to any cheap leaves

**A\*:** introduce heuristic function  $h(p)$  that estimates how close we are to the closest leaf



# Weighted top-down search (A\*)

```
top-down(<Σ, N, R, S>, [i → o]) {  
  w1 := [<S, 0, h(S)>]  
  while (w1 != [])  
    <τ, c, h> := w1.dequeue_min(c + h);  
    if (complete(τ) && τ([i]) = [o])  
      return τ;  
    w1.enqueue(unroll(τ, c));  
}
```

Roughly how close is this  
program to the closest leaf

```
unroll(τ, c) {  
  w1' := []  
  A := leftmost nonterminal in τ  
  forall (A → rhs) in R:  
    w1' += <τ[A → rhs], c + w(A → rhs|τ),  
          h(τ[A → rhs])>  
  return w1';  
}
```



# Weighted enumerative search

## DeepCoder

Balog et al. DeepCoder: Learning to Write Programs. ICLR'17

## Weighted top-down search

Lee, et al: Accelerating Search-Based Program Synthesis using Learned Probabilistic Models. PLDI'18

## Weighted bottom-up search

Barke, Peleg, Polikarpova. Just-in-Time Learning for Bottom-Up Enumerative Synthesis. OOPSLA'20

Shi, Bieber, Singh. TF-Coder: Program Synthesis for Tensor Manipulations. TOPLAS'22

# Bottom-up search (revisited)

```
bottom-up (< $\Sigma$ , N, R, S>, [ $i \rightarrow o$ ]):
```

```
  bank[A,d] := {} forall A, d
```

```
  for d in [0..]:
```

```
    forall (A  $\rightarrow$  rhs) in R:
```

```
      forall p in new-terms(A $\rightarrow$ rhs, d, bank):
```

```
        if (A = S  $\wedge$  p([i]) = [o]):
```

```
          return p
```

```
          bank[A,d] += p;
```

```
new-terms(A  $\rightarrow$   $\sigma(A_1 \dots A_n)$ , d, bank):
```

```
  if (d = 0  $\wedge$  n = 0) yield  $\sigma$ 
```

```
  else forall <d1, ..., dn> in [0..d-1]n s.t. max(d1, ..., dn) = d-1:
```

```
    forall <p1, ..., pn> in bank[A1, d1]  $\times$  ...  $\times$  bank[An, dn]:
```

```
      yield  $\sigma(p_1, \dots, p_n)$ 
```

Search by  
depth



# Bottom-up variations

```
new-terms( $A \rightarrow \sigma(A_1 \dots A_n)$ , d, bank):
```

```
  if ( $d = 0 \wedge n = 0$ ) yield  $\sigma$ 
```

```
  else forall  $\langle d_1, \dots, d_n \rangle$  in  $[0..d-1]^n$  s.t.  $\max(d_1, \dots, d_n) = d-1$ :
```

```
    forall  $\langle p_1, \dots, p_n \rangle$  in  $\text{bank}[A_1, d_1] \times \dots \times \text{bank}[A_n, d_n]$ :
```

```
      yield  $\sigma(p_1, \dots, p_n)$ 
```

by depth

```
new-terms( $A \rightarrow \sigma(A_1 \dots A_n)$ , s, bank):
```

```
  if ( $s = 1 \wedge n = 0$ ) yield  $\sigma$ 
```

```
  else forall  $\langle s_1, \dots, s_n \rangle$  in  $[0..s-1]^n$  s.t.  $\text{sum}(s_1, \dots, s_n) = s-1$ :
```

```
    forall  $\langle p_1, \dots, p_n \rangle$  in  $\text{bank}[A_1, s_1] \times \dots \times \text{bank}[A_n, s_n]$ :
```

```
      yield  $\sigma(p_1, \dots, p_n)$ 
```

by size

```
new-terms( $A \rightarrow \sigma(A_1 \dots A_n)$ , c, bank):
```

```
  budget =  $c - w(A \rightarrow \sigma(A_1 \dots A_n))$ 
```

```
  if (budget = 0  $\wedge$  n = 0) yield  $\sigma$ 
```

```
  else forall  $\langle c_1, \dots, c_n \rangle$  in  $[0.. \text{budget}]^n$  s.t.  $\text{sum}(c_1, \dots, c_n) = \text{budget}$ :
```

```
    forall  $\langle p_1, \dots, p_n \rangle$  in  $\text{bank}[A_1, c_1] \times \dots \times \text{bank}[A_n, c_n]$ :
```

```
      yield  $\sigma(p_1, \dots, p_n)$ 
```

by cost!

# Bottom-up by cost: discussion

- What kind of cost functions are supported?
  - positive
  - integer
  - context-free

# Bottom-up: example

by depth

by size

cost

$L ::= \text{sort}(L)$  | 10  
 $L + L$  | 3  
 $x$  | 1  
 by cost

d=0:  $x$

d=1:  $\text{sort}(x)$   
 $x + x$

d=2:  $\text{sort}(\text{sort}(x))$   
 $\text{sort}(x + x)$   
 $x + \text{sort}(x)$   
 $\text{sort}(x) + x$   
 $x + (x + x)$   
 $(x + x) + x$

d=3: ...

s=1:  $x$

s=2:  $\text{sort}(x)$

s=3:  $x + x$   
 $\text{sort}(\text{sort}(x))$

s=4:  $\text{sort}(x + x)$   
 $\text{sort}(\text{sort}(\text{sort}(x)))$   
 $x + \text{sort}(x)$   
 $\text{sort}(x) + x$

s=5: ...

c=1:  $x$

c=2,3,4:

c=5:  $x + x$

c=6,7,8:

c=9:  $x + (x + x)$   
 $(x + x) + x$

c=10:

c=11:  $\text{sort}(x)$

c=12:

c=13:  $x + (x + (x + x))$   
 $(x + x) + (x + x)$   
 $(x + (x + x)) + x$

# Weighted search

## Top-down

- Supports real-valued weights: optimal enumeration order
- Supports context-dependent weights

## Bottom-up

- Inherits benefits of bottom up: dynamic programming, observational equivalence