

Toward Responsive DBMS: Optimal Join Algorithms, Enumeration, Factorization, Ranking, and Dynamic Programming

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Part 5: Dynamic programming & Semirings



Slides: <https://northeastern-datalab.github.io/responsive-dbms-tutorial>

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Data Lab: <https://db.khoury.northeastern.edu>



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Outline tutorial

1: Introduction (Nikos) ~40min

2: Tree Decompositions (Mirek) ~20min

3: Acyclic Queries & Enumeration (Wolfgang) ~25min

BREAK

4: Factorization (Nikos) ~15min

5: Dynamic Programming & Semirings (Wolfgang) ~20min

6: Any- k or Ranked Enumeration (Nikos) ~35min

7. Decomposition of Comparison Predicates (Mirek) ~10min

8. Conclusion (Mirek) ~5min

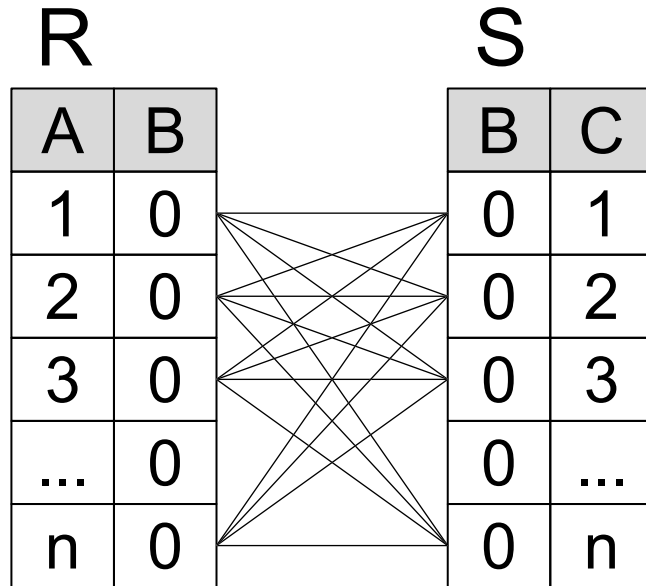
Outline Part 5

Part 5: Dynamic Programming & Semirings (Wolfgang) ~20min

- Top-1 = Dynamic Programming (DP)
- Top-1 Yannakakis as variant of Tree-DP
- Algebra: Totally Ordered Commutative Monoids

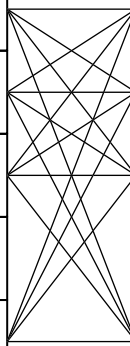
Evaluating Top-1 result with a modern DBMS

$$P_2(x, y, z): \neg R(x, y), S(y, z)$$



Evaluating Top-1 result with a modern DBMS

$P_2(x, y, z): -R(x, y), S(y, z)$

R				S		
A	B	w		B	C	w
1	0	1		0	1	1
2	0	2		0	2	2
3	0	3		0	3	3
...	0	...		0
n	0	n		0	n	n

```
select R.A, R.B, S.C,  
       R.w + S.w as weight  
from   R, S  
where  R.B=S.B  
order by weight asc  
limit  1
```

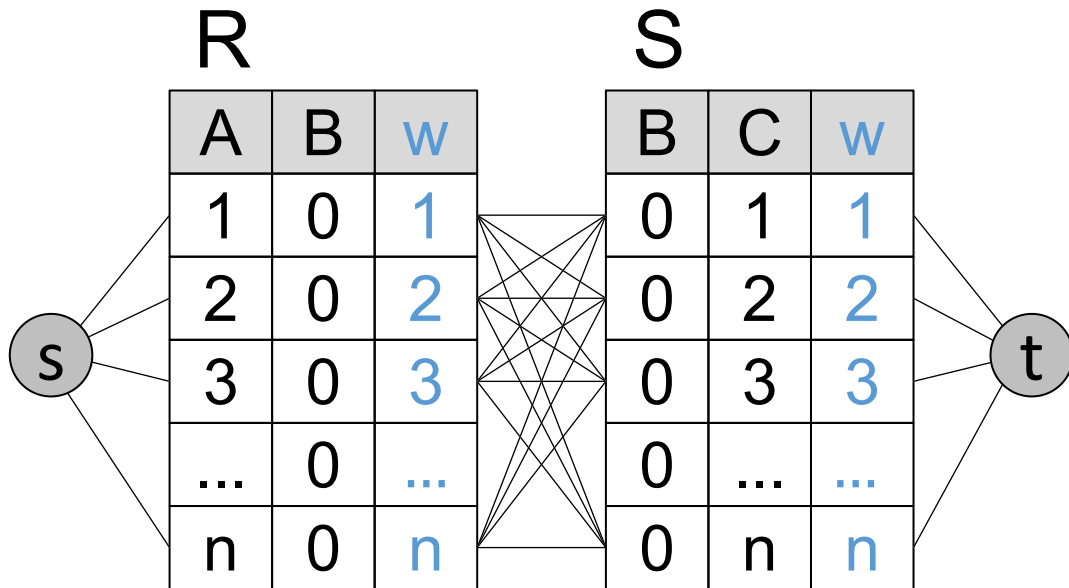
Q: Find the lightest joining pair

?

Adding weights to each tuple

Evaluating Top-1 result with a modern DBMS

$P_2(x, y, z): -R(x, y), S(y, z)$



```
select R.A, R.B, S.C,  
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from   R, S  
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order by weight asc  
limit  1
```

Q: Find the **lightest** joining pair

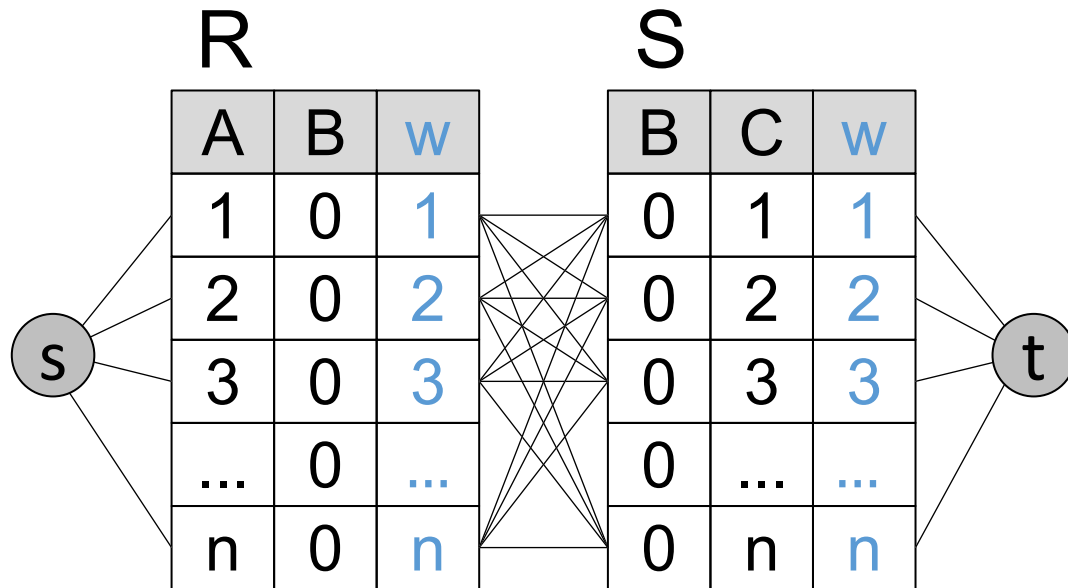
?

Adding **weights** to each tuple

Basically a **shortest path** calculation
(from source s to target t)

Evaluating Top-1 result with a modern DBMS

$P_2(x, y, z): -R(x, y), S(y, z)$

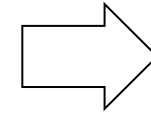


Adding **weights** to each tuple

Basically a **shortest path** calculation
(from source s to target t)

```
select R.A, R.B, S.C,  
       R.w + S.w as weight  
from   R, S  
where  R.B=S.B  
order by weight asc  
limit  1
```

Q: Find the **lightest joining pair**



Result

A	B	C	weight
1	0	1	2
1	0	2	3
2	0	1	3
3	0	1	4
2	0	2	4
1	0	3	4
...
n	0	n	n+n

$O(n^2)$ possible pairs,
but only 1 lightest.

**Problem: DBMS first
calculates all n^2 pairs,
then picks the top-1 😞**

Evaluating Top-1 result with Postgres



$$P_2(x, y, z): -R(x, y), S(y, z)$$

R				S		
A	B	w		B	C	w
1	0	1		0	1	1
2	0	2		0	2	2
3	0	3		0	3	3
...	0	...		0
n	0	n		0	n	n

-- Query 1

```
SELECT  A, R.B, S.C,  
        R.W + S.W as weight  
FROM    R, S  
WHERE   R.B=S.B  
ORDER BY weight ASC  
LIMIT  1;
```

$n = 1,000$: $t_{Q1} = 0.22 \text{ sec}$

$n = 10,000$: $t_{Q1} = 22 \text{ sec}$ $O(n^2)$ ☹️

Evaluating Top-1 result with Postgres



$P_2(x, y, z): -R(x, y), S(y, z)$

R				S		
A	B	w		B	C	w
1	0	1		0	1	1
2	0	2		0	2	2
3	0	3		0	3	3
...	0	...		0
n	0	n		0	n	n

Maximal intermediate
result size is $O(n)$ 😊

Dynamic programming!

-- Query 1

```
SELECT  A, R.B, S.C,  
        R.W + S.W as weight  
FROM    R, S  
WHERE   R.B=S.B  
ORDER BY weight ASC  
LIMIT  1;
```

$n = 1,000$: $t_{Q1} = 0.22 \text{ sec}$

$n = 10,000$: $t_{Q1} = 22 \text{ sec}$ $O(n^2)$ 😞

-- Query 2

```
SELECT R.A, X.B, S.C, X.W as weight  
FROM R, S,  
      (SELECT T1.B, W1, W2, W1+W2 W  
       FROM  
         (SELECT B, MIN(W) W1  
          FROM R  
          GROUP BY B) T1,  
         (SELECT B, MIN(W) W2  
          FROM S  
          GROUP BY B) T2  
       WHERE T1.B = T2.B  
       ORDER BY W ASC  
       LIMIT 1) X  
WHERE X.B = R.B  
AND X.W1 = R.W  
AND X.B = S.B  
AND X.W2 = S.W  
LIMIT 1;
```

$t_{Q2} = 1 \text{ msec}$

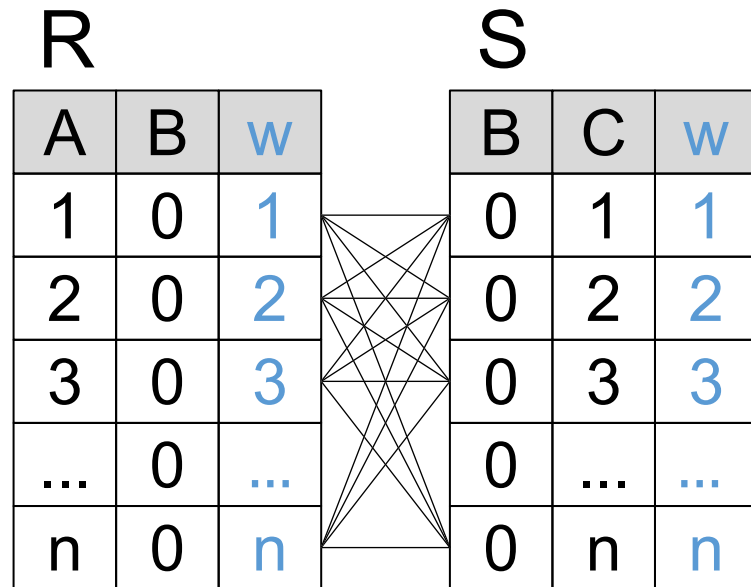
$t_{Q2} = 4 \text{ msec}$ $O(n)$ 😊

Evaluating Top-1 value with Postgres



$P_2(x, y, z): -R(x, y), S(y, z)$

Maximal intermediate
result size is $O(n)$ 😊



Dynamic programming!

-- Query 1

```
SELECT min(R.W + S.W) as weight
INTO record1
FROM R, S
WHERE R.B=S.B;
```

-- Query 2

```
SELECT min(W1+W2) as weight
INTO record2
FROM
  (SELECT B, MIN(W) W1
   FROM R
   GROUP BY B) T1,
  (SELECT B, MIN(W) W2
   FROM S
   GROUP BY B) T2
WHERE T1.B = T2.B;
```

$n = 1,000$: $t_{Q1} = 0.1 \text{ sec}$

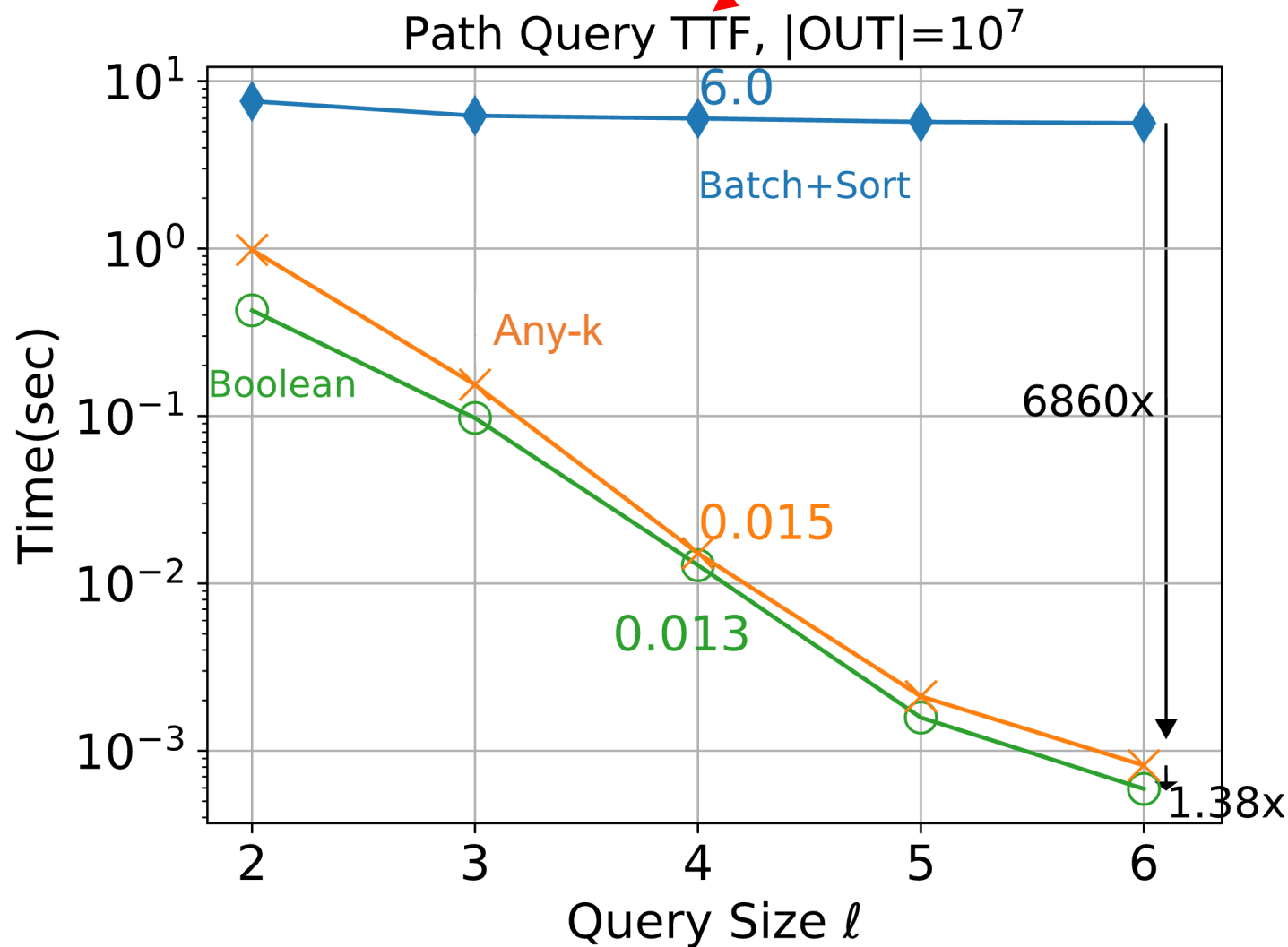
$n = 10,000$: $t_{Q1} = 9.4 \text{ sec}$ $O(n^2)$ 😞

$t_{Q2} < 1 \text{ msec}$

$t_{Q2} = 3 \text{ msec}$ $O(n)$ 😊

Any-k: Faster and more versatile than Top-k today

TTF = Time-To-First = Top-1

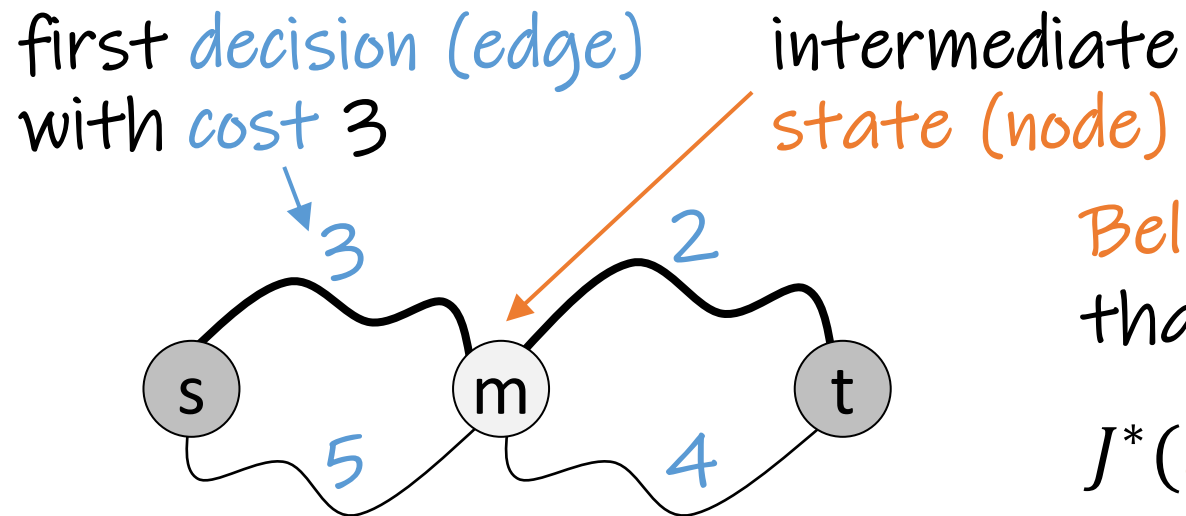


Path query with constant size output and increasing query size

Two slightly different definitions of Dynamic Programming

1. **Principle of optimality*** in **mathematical optimization**: *"There is an optimal policy s.t. irrespective of the initial state and decision, the remaining decisions are chosen optimally."*

2. A **more general algorithm** that solves problems with **optimal substructure**: *"Break a complicated problem into simpler sub-problems, and then solve them recursively bottom-up."*



Bellman equation: Edges or transitions mean that state j can be reached from state i

$$J^*(i) = \min\{w(i, j) + J^*(j) \mid (i, j) \in E\}$$

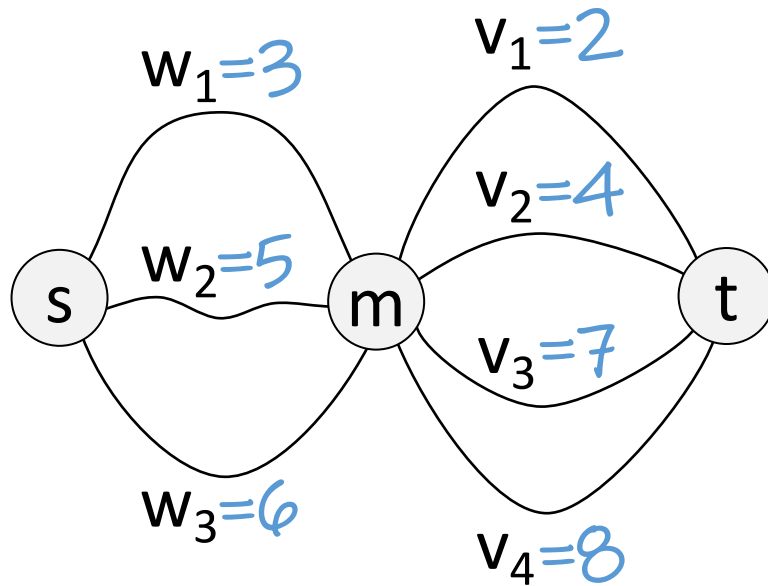
← backwards reasoning or "bottom-up"

* Definition slightly modified from originally "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision" by "Bellman. Dynamic Programming. Princeton University Press 1957, <https://dl.acm.org/doi/10.5555/862270>" due to details discussed in part 6 and by "Morin. Monotonicity and the Principle of Optimality. JMAA 1982, [https://doi.org/10.1016/0022-247X\(82\)90223-2](https://doi.org/10.1016/0022-247X(82)90223-2)"

Towards Responsive DBMS. ICDE 2022 tutorial: <https://northeastern-datalab.github.io/responsive-dbms-tutorial>

1. Dynamic programming for mathematical optimization

weights or cost

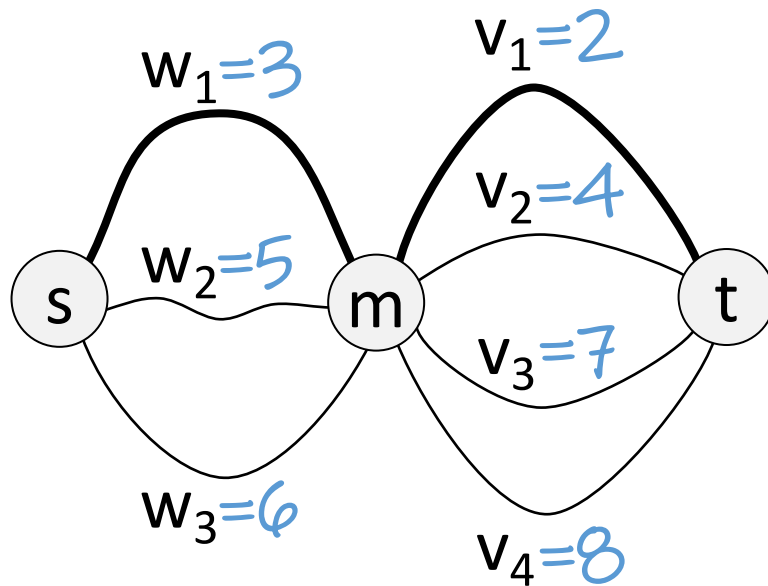


What is the shortest path from s to t?

?

1. Dynamic programming for mathematical optimization

weights or cost



Principle of optimality from Dynamic Programming:
irrespective of the initial state and decision, an optimal solution continues optimally from the resulting state

$$\min\{w_1+v_1, w_1+v_2, w_1+v_3, w_1+v_4, \dots, w_3+v_4\}$$

$$\min\{3 + 2, 3 + 4, 3 + 7, 3 + 8, \dots, 6 + 8\}$$

$$= \min\{w_1, w_2, w_3\} + \min\{v_1, v_2, v_3, v_4\}$$

$$\min\{3, 5, 6\} + \min\{2, 4, 7, 8\}$$

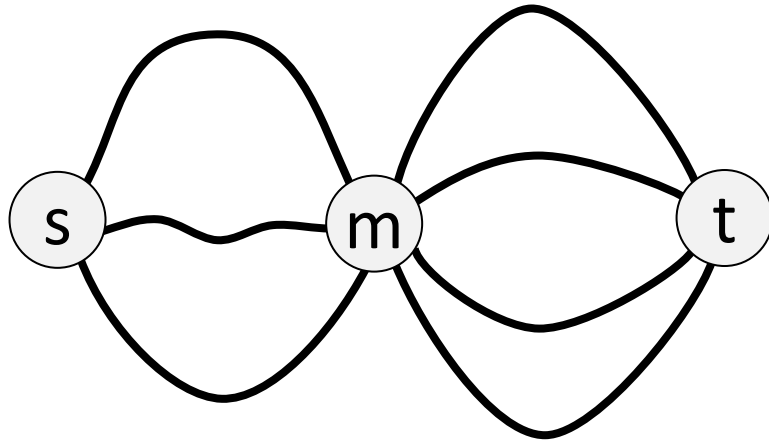
What is the shortest path from s to t?

Answer: $5 = 3 + 2$

Distributivity law: $+$ distributes over \min

$$\min\{x, y\} + z = \min\{x + z, y + z\}$$

2. Dynamic programming as using optimal substructure

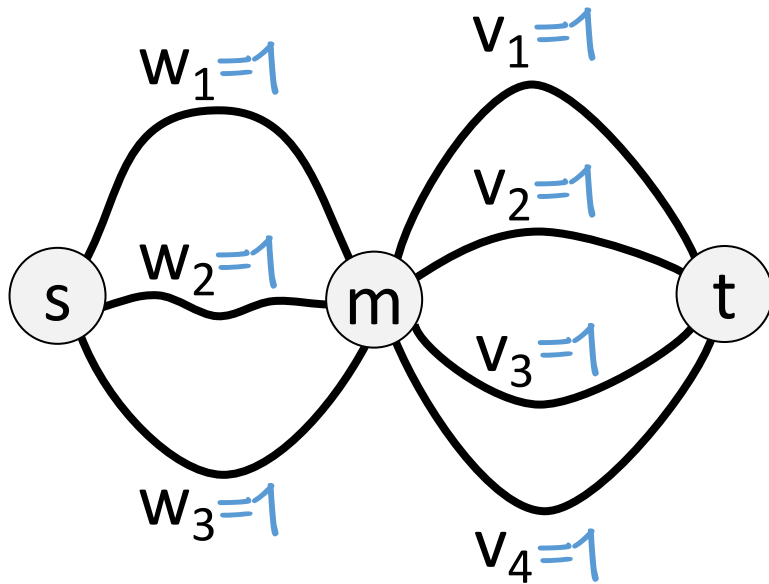


How many paths are there from s to t?

?

2. Dynamic programming as using optimal substructure

The more general algebraic structure behind these two examples are "semirings" (more on that later). On a high-level, we just apply the distributivity law.



How many paths are there from s to t?

Answer: $12 = 3 \cdot 4$

$$\text{sum}\{w_1 \cdot v_1, w_1 \cdot v_2, w_1 \cdot v_3, w_1 \cdot v_4, \dots, w_3 \cdot v_4\}$$

$$\text{sum}\{1 \cdot 1, 1 \cdot 1, 1 \cdot 1, 1 \cdot 1, \dots, 1 \cdot 1\}$$

$$= \text{sum}\{w_1, w_2, w_3\} \cdot \text{sum}\{v_1, v_2, v_3, v_4\}$$

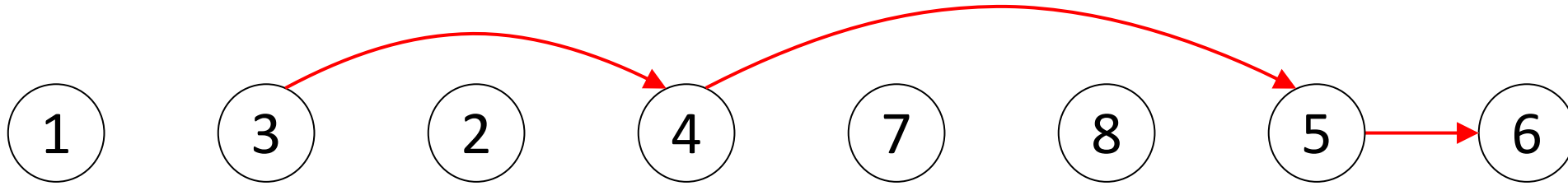
$$\text{sum}\{1, 1, 1\} \cdot \text{sum}\{1, 1, 1, 1\}$$

Distributivity law: \otimes distributes over \oplus

$$(x \oplus y) \otimes z = x \otimes z \oplus y \otimes z$$

3. Find a "Longest Increasing Subsequence" with DP

In an increasing subsequence the numbers are getting strictly larger.

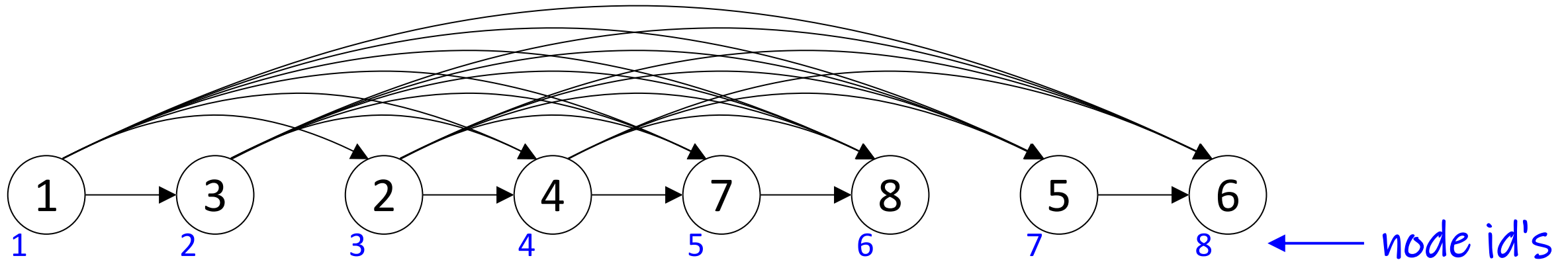


How do we find a longest increasing subsequence

?

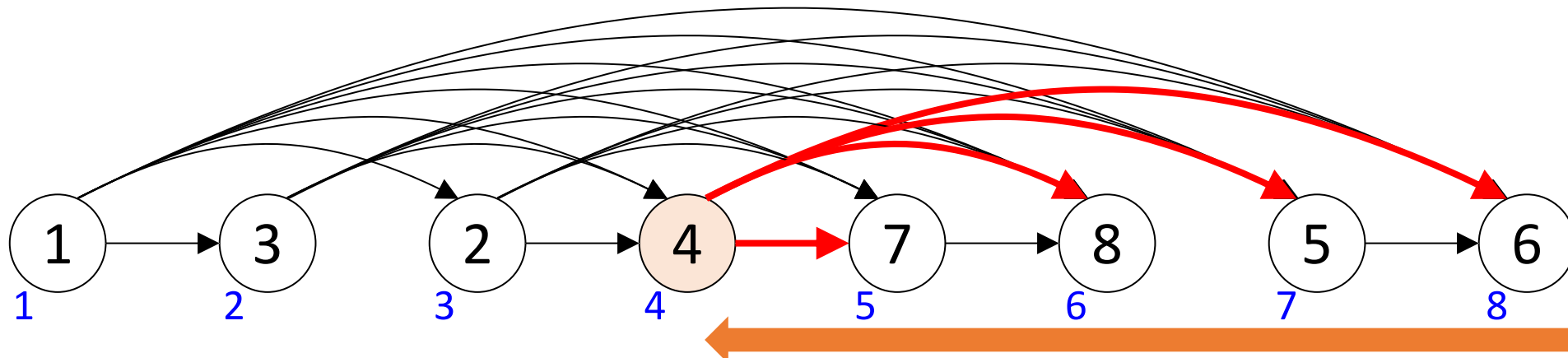
3. Find a "Longest Increasing Subsequence" with DP

Edges show permissible transitions



3. Find a "Longest Increasing Subsequence" with DP

Edges show permissible transitions



Permissible transitions for node 4: {5:2, 7:2, 6:1, 8:1, 1:0}

next state id: additional length

DP formulation:

for $i = n, \dots, 2, 1$:

$$L(i) = 1 + \max\{L(j) \mid (i, j) \in E\}$$

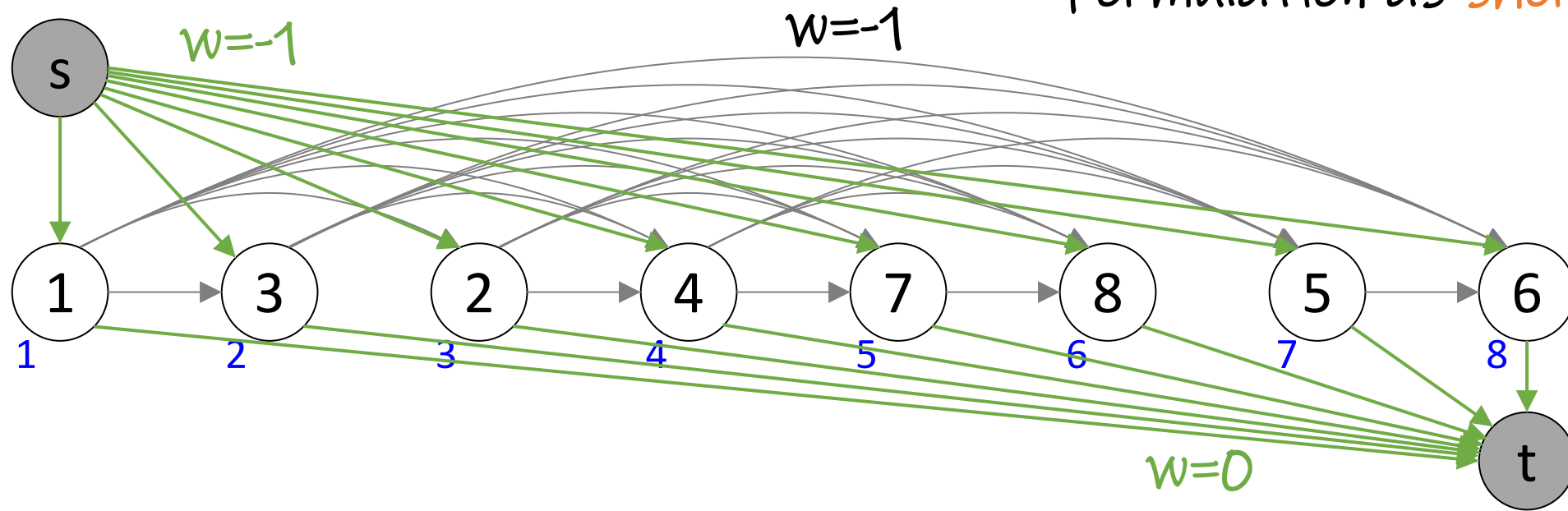
return $\max\{L(i) \mid i \in [n]\}$

Can we also formulate it as
shortest path problem



3. Find a "Longest Increasing Subsequence" with DP

Formulation as **shortest path problem**



DP formulation:

for $i = n, \dots, 2, 1$:

$$L(i) = 1 + \max\{L(j) \mid (i, j) \in E\}$$

return $\max\{L(i) \mid i \in [n]\}$

As shortest path problem:

$$d(t) = 0$$

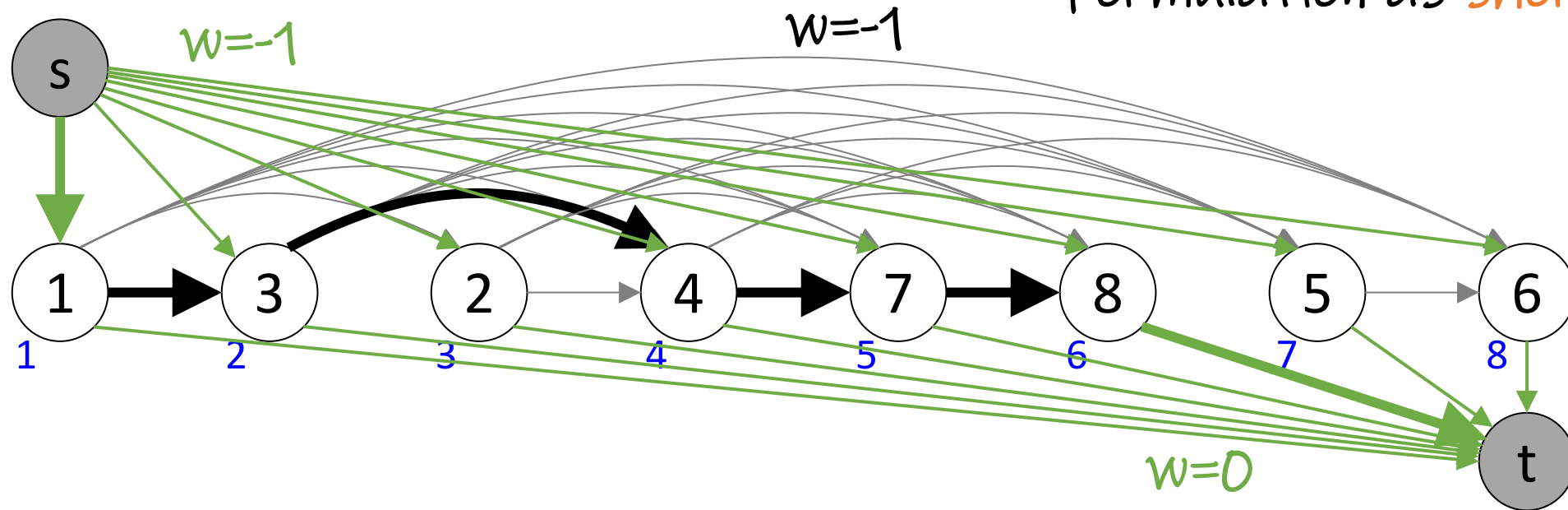
for $i = n, \dots, 2, 1, s$:

$$d(i) = \min\{w(i, j) + d(j) \mid (i, j) \in E\}$$

return $-d(s)$

3. Find a "Longest Increasing Subsequence" with DP

Formulation as **shortest path problem**



$$L(1) = -d(s) = 5$$

DP formulation:

for $i = n, \dots, 2, 1$:

$$L(i) = 1 + \max\{L(j) \mid (i, j) \in E\}$$

return $\max\{L(i) \mid i \in [n]\}$

As shortest path problem:

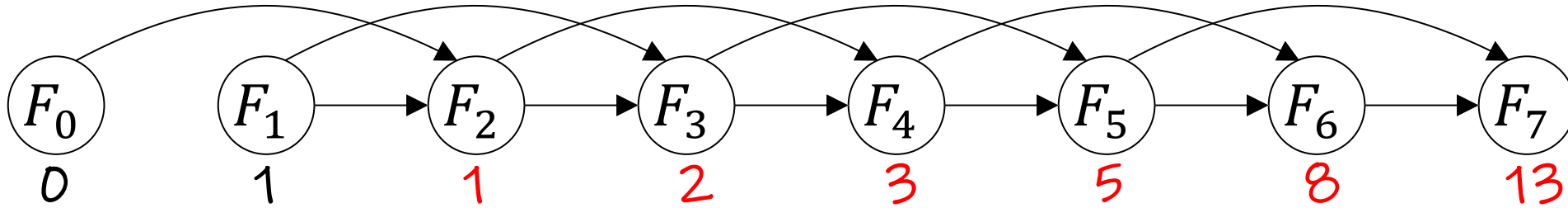
$$d(t) = 0$$

for $i = n, \dots, 2, 1, s$:

$$d(i) = \min\{w(i, j) + d(j) \mid (i, j) \in E\}$$

return $-d(s)$

4. Calculating Fibonacci numbers with DP



DP formulation:

$F_0 = 0; F_1 = 1$

for $i = 2, 3, \dots, n$:

$F_i = F_{i-1} + F_{i-2}$

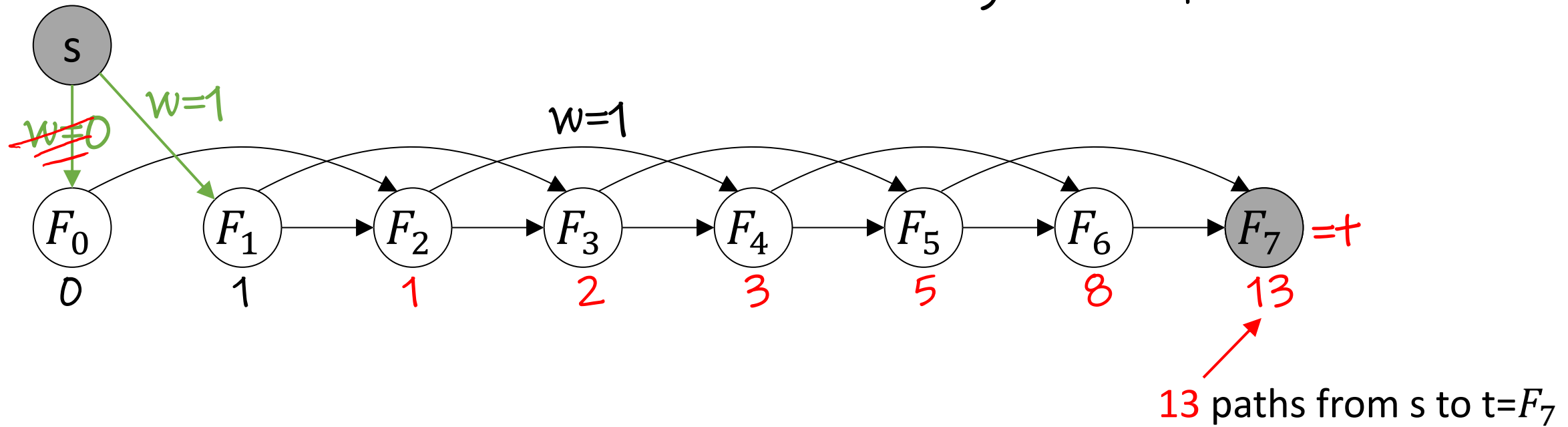
return F_n

Can we also formulate it as
path counting problem



4. Calculating Fibonacci numbers with DP

Edges show permissible transitions



DP formulation:

$$F_0 = 0; F_1 = 1$$

for $i = 2, 3, \dots, n$:

$$F_i = F_{i-1} + F_{i-2}$$

return F_n

As path counting problem:

$$F_0 = 0; F_1 = 1$$

for $j = 2, 3, \dots, n$:

$$F_j = \text{sum}\{w(i, j) \cdot F(i) \mid (i, j) \in E\}$$

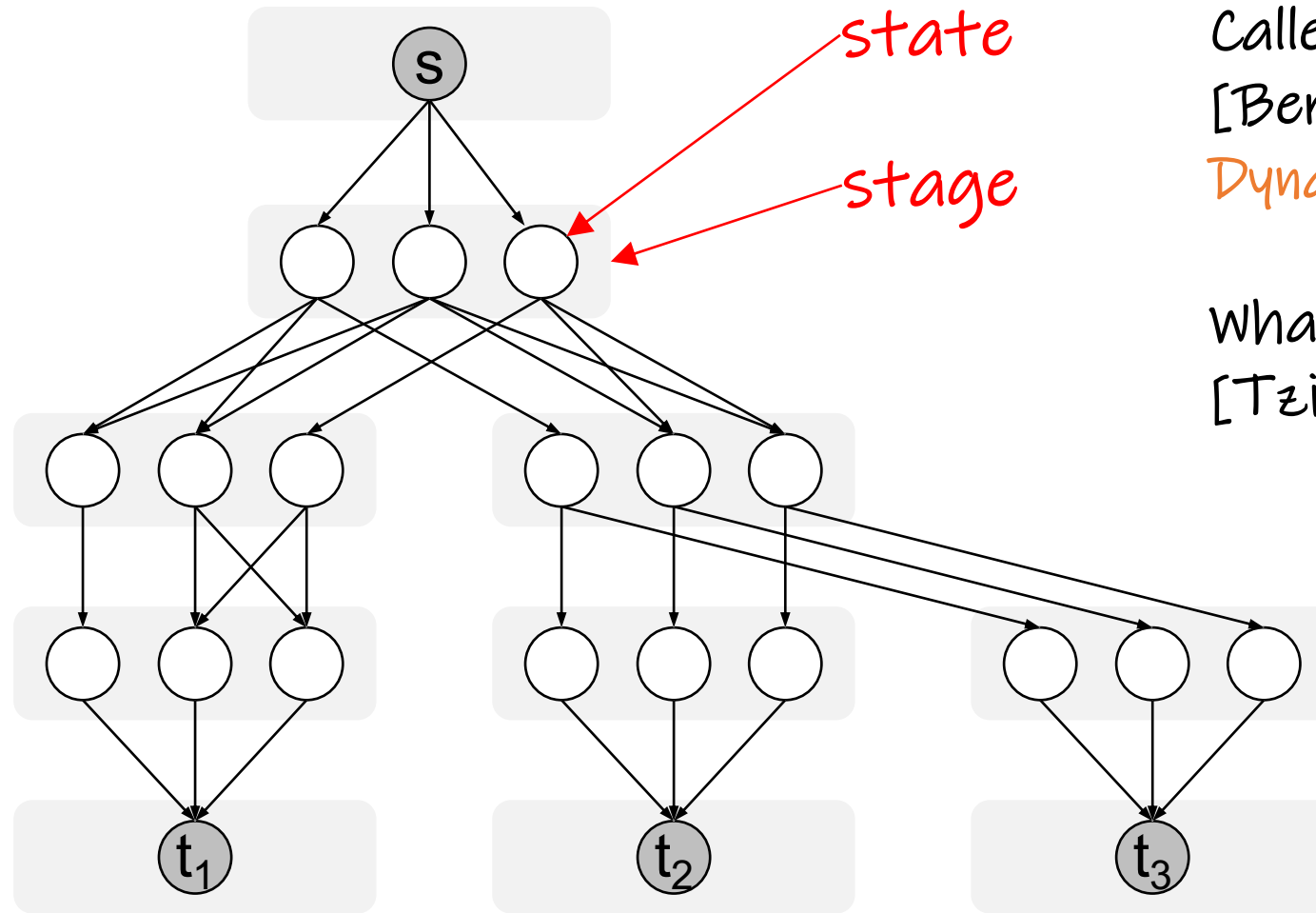
return F_n

Outline Part 5

Part 5: Dynamic Programming & Semirings (Wolfgang) ~20min

- Top-1 = Dynamic Programming (DP)
- Top-1 Yannakakis as variant of Tree-DP
- Algebra: Totally Ordered Commutative Monoids

Tree-DP = instance of Non-Serial DP (NSDP)

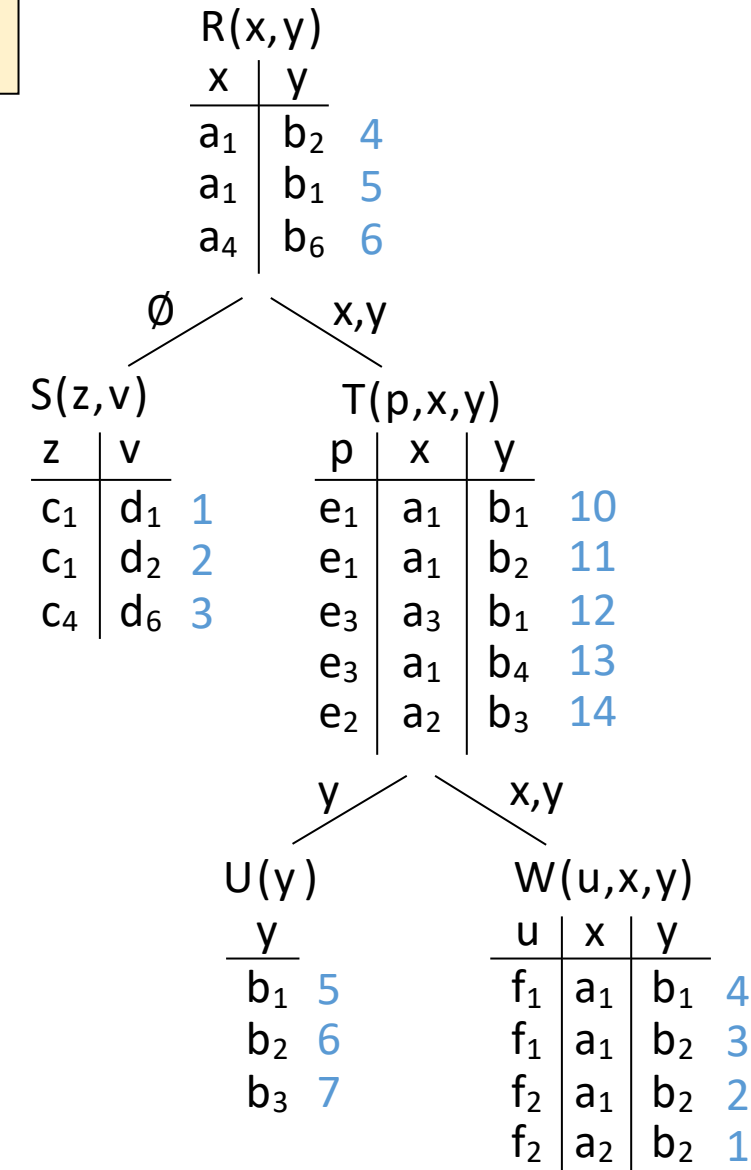


Called "diverging branch structure" by [Bertele'72] as one instance of **Non-Serial Dynamic Programming** (NSDP).

What we will refer to as "**Tree-DP**" [Tziavelis'20]

Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$



Each tuple now has a *weight*.

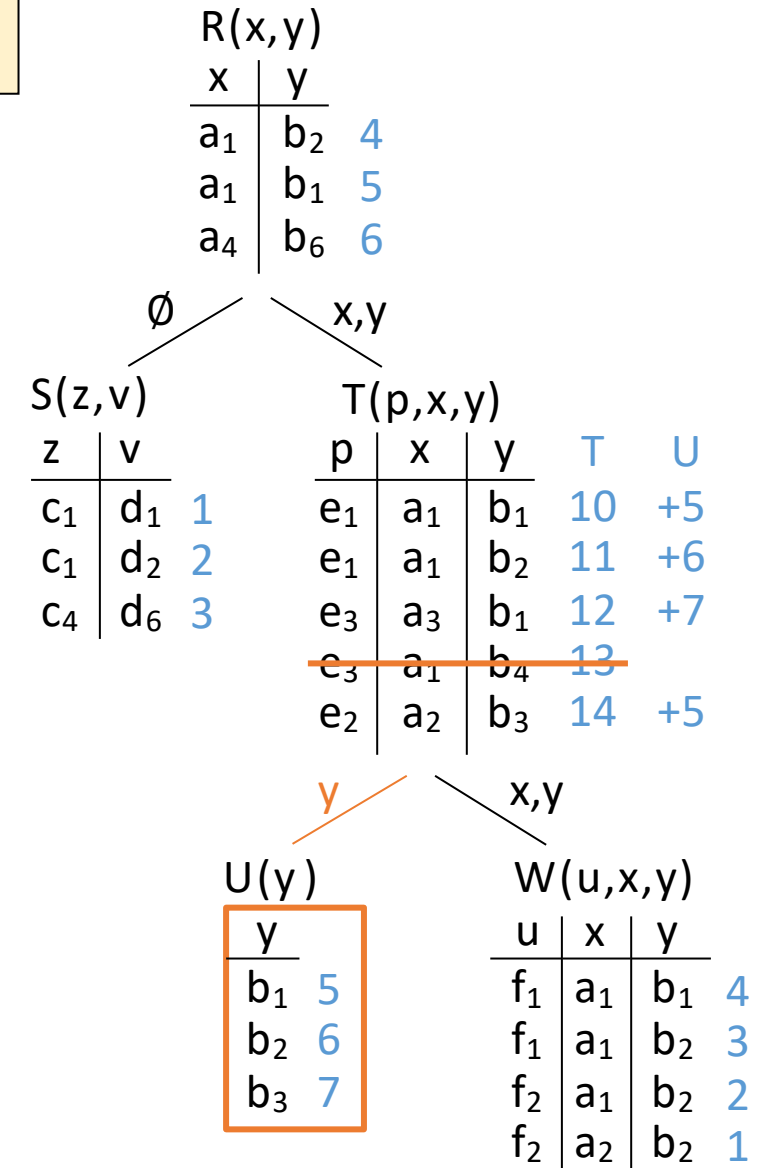
New goal: Find the "lightest join"
(*minimum sum of weights*)



Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

- Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value**



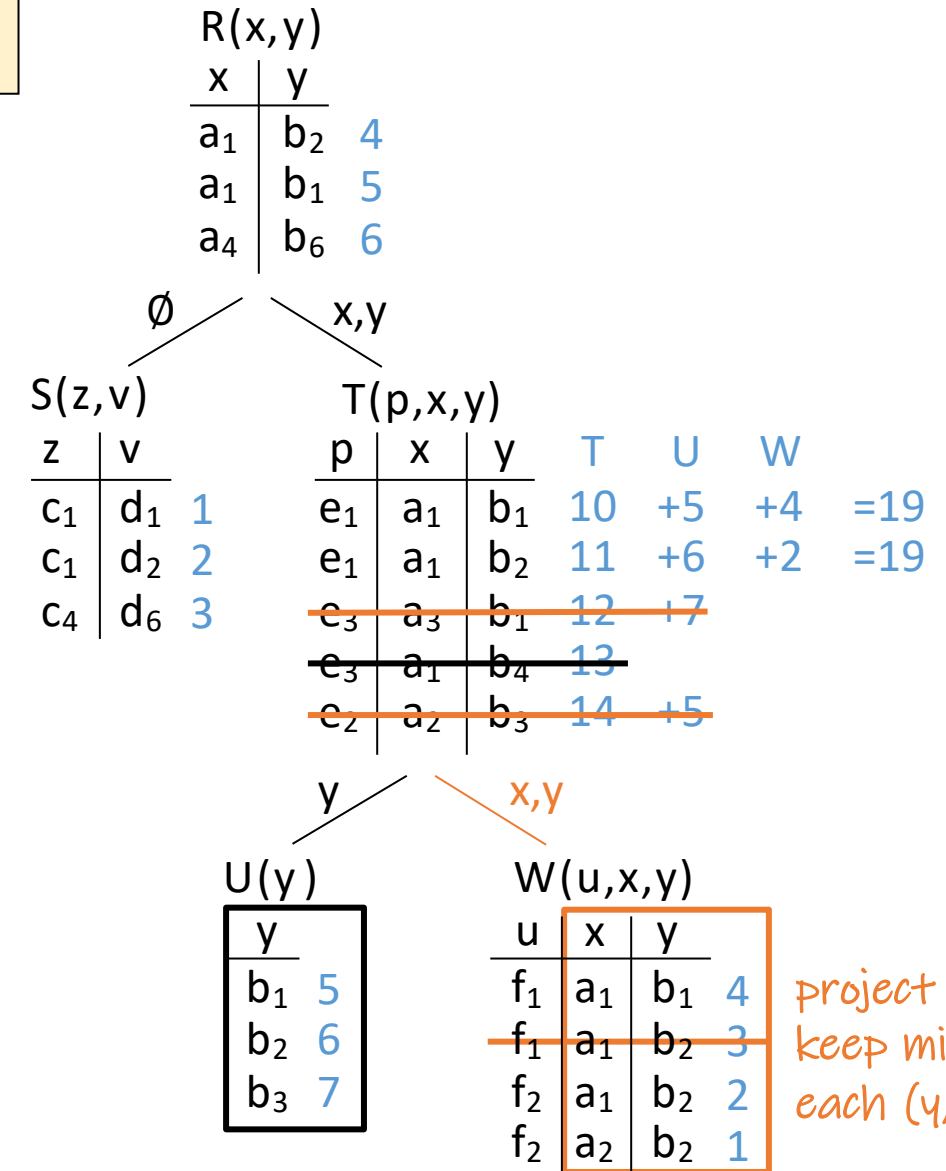
Each tuple now has a **weight**.

New goal: Find the "lightest join"
(**minimum sum of weights**)

Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

- Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value**



Each tuple now has a **weight**.

New goal: Find the "lightest join"
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Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

- Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value**

no common
variables,
thus keep
min across
all tuples

R(x,y)			
x	y	R	S
a ₁	b ₂	4	+1
a ₁	b ₁	5	+1
a ₄	b ₆	6	+1

S(z,v)		T(p,x,y)					
z	v	p	x	y	T	U	W
c ₁	d ₁	e ₁	a ₁	b ₁	10	+5	+4
c₁	d₂	e₁	a₁	b₂	11	+6	+2
c₄	d₆	e₃	a₃	b₁	12	+7	
		e₃	a₁	b₄	13		
		e₂	a₂	b₃	14	+5	

Each tuple now has a **weight**.

New goal: Find the "lightest join"
(**minimum sum of weights**)

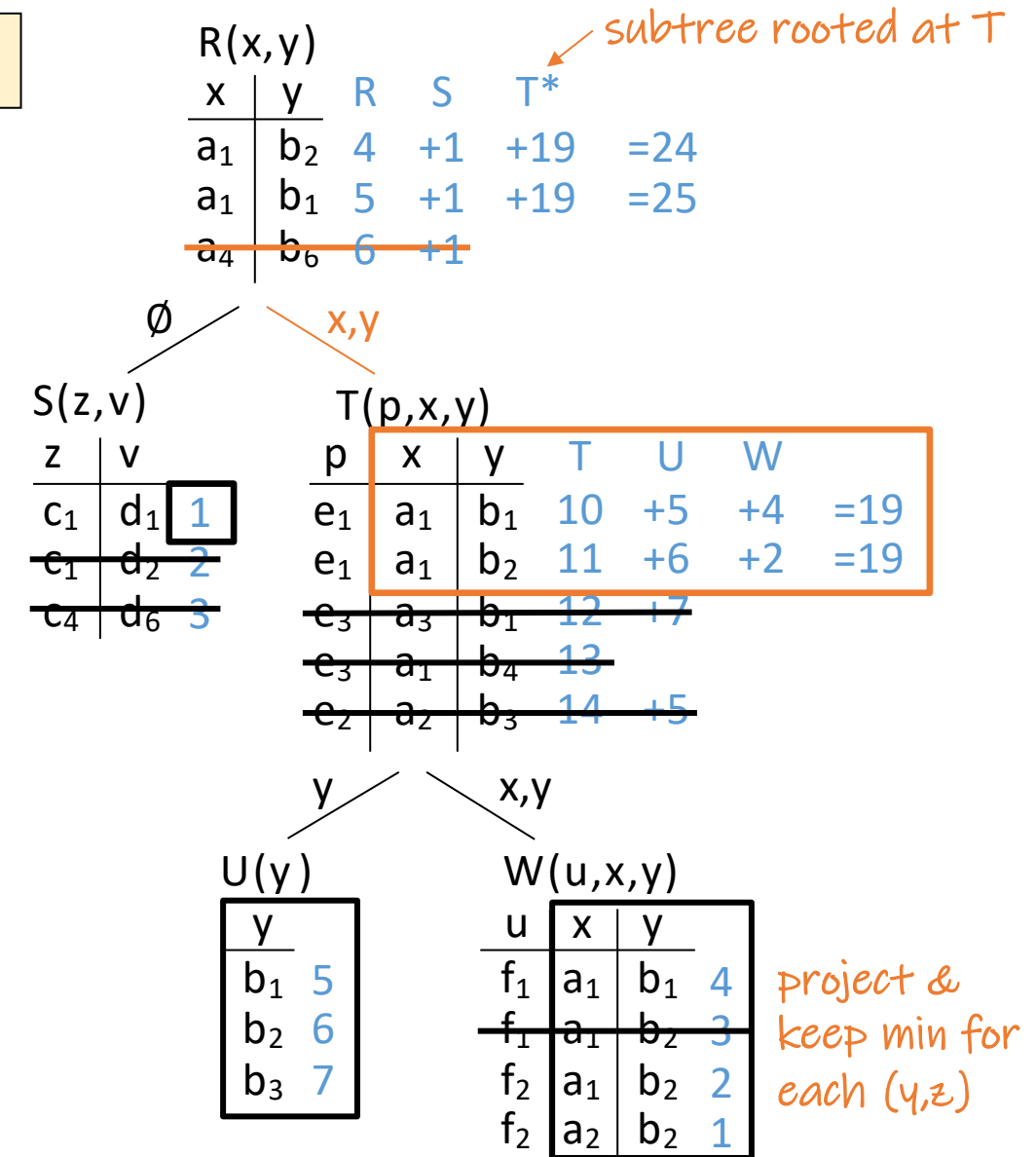
U(y)		W(u,x,y)		
y		u	x	y
b ₁	5	f ₁	a ₁	b ₁
b ₂	6	f₁	a₁	b₂
b ₃	7	f ₂	a ₁	b ₂
		f ₂	a ₂	b ₂

project &
keep min for
each (y,z)

Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

- Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value**



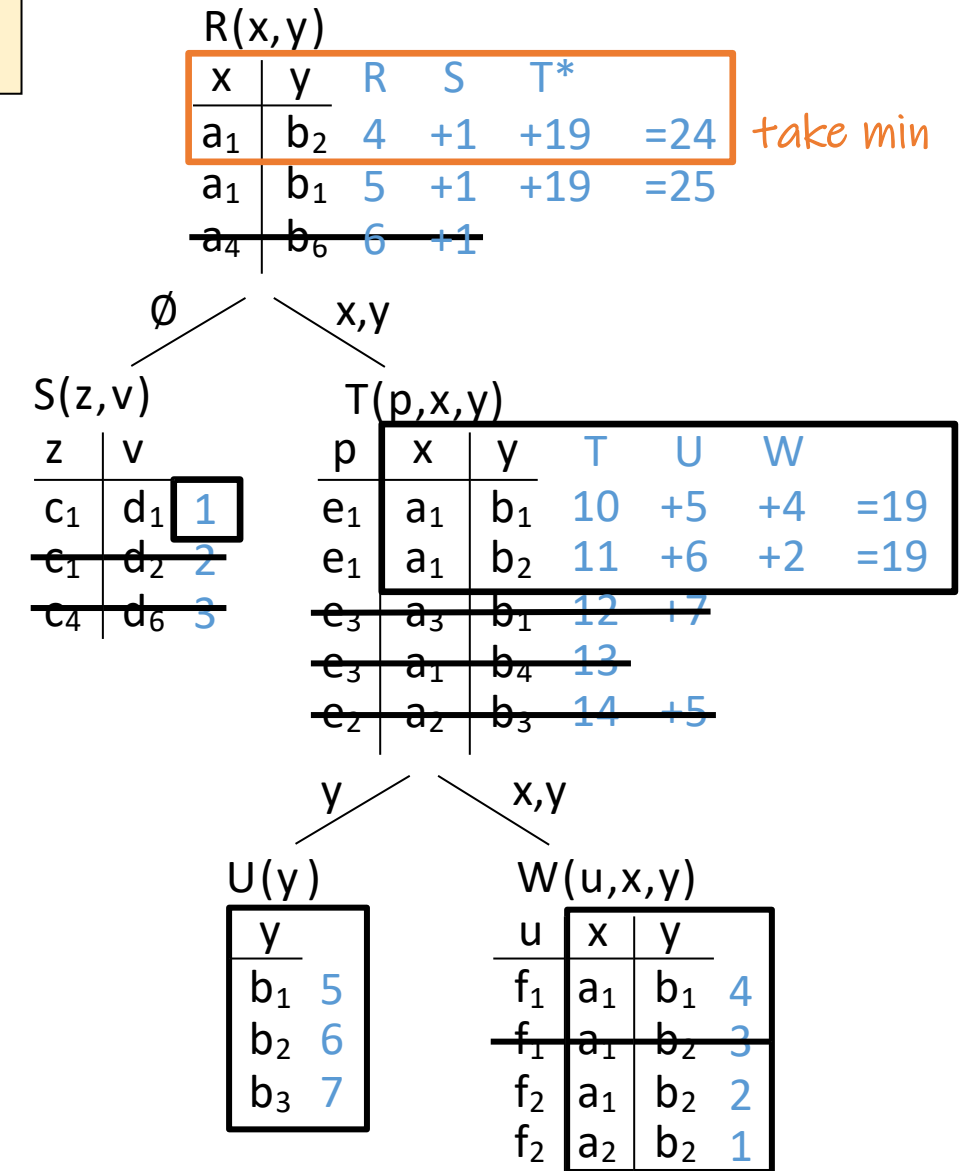
Each tuple now has a **weight**.

New goal: Find the "lightest join"
(**minimum sum of weights**)

Yannakakis Algorithm – Example

$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

- Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value** = 24



Each tuple now has a **weight**.

New goal: Find the "lightest join"
(**minimum sum of weights**)

Yannakakis Algorithm – Example



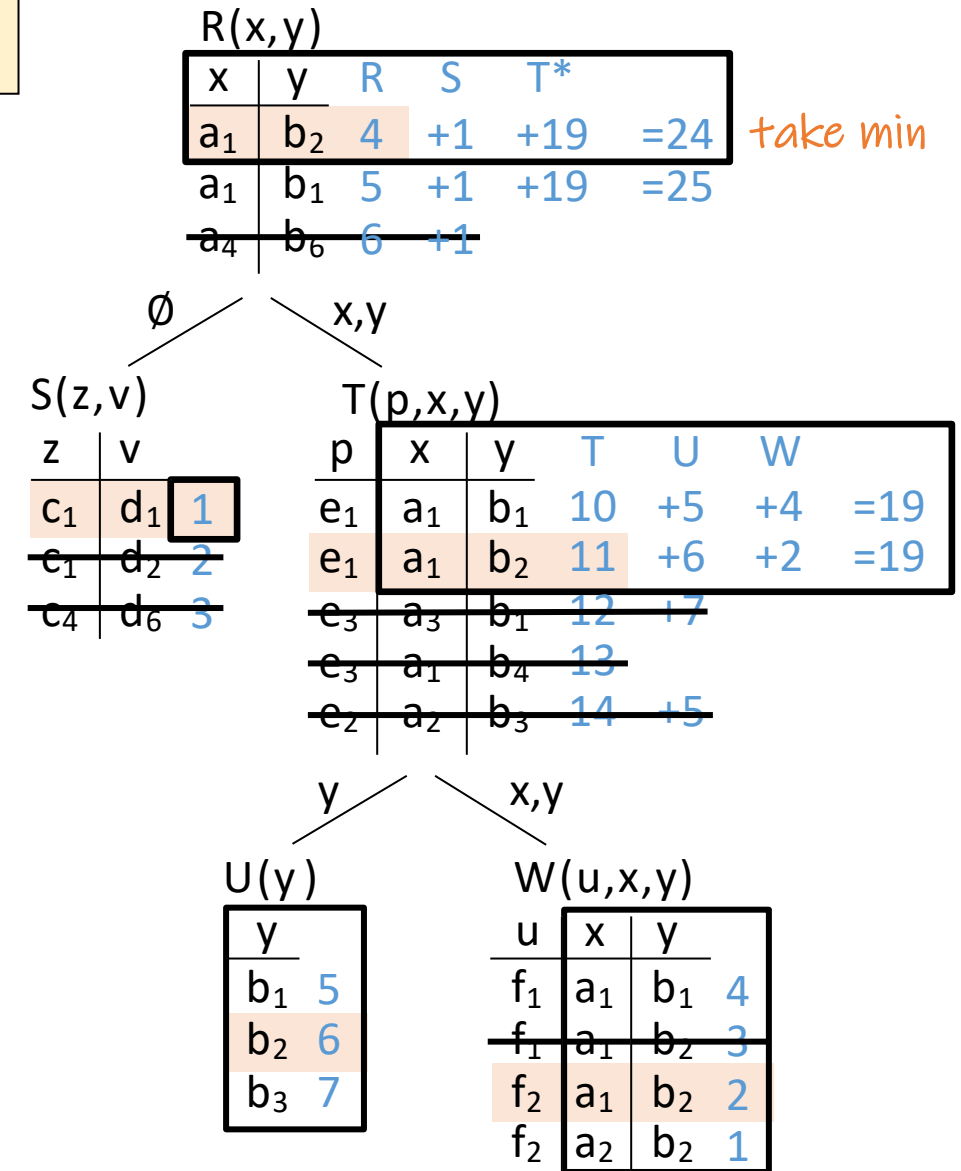
$Q(x,y,z,v,p,u) :- R(x,y), S(z,v), T(p,x,y), U(y), W(u,x,y).$

1. Adapted bottom-up **semi-join propagation** in $O(|input|)$.
Finds the **minimum value** = 24
2. Top-down traversal (equi-join) in $O(1)$.
Builds an optimal solution: = $(a_1, b_1, c_2, d_1, e_1)$

Tree Dynamic Programming in time $O(n)$!
Fractional edge cover for Q is 3. Thus a standard DBMS plan will need $O(n^3)$

Each tuple now has a **weight**.

New goal: Find the "lightest join"
(**minimum sum of weights**)

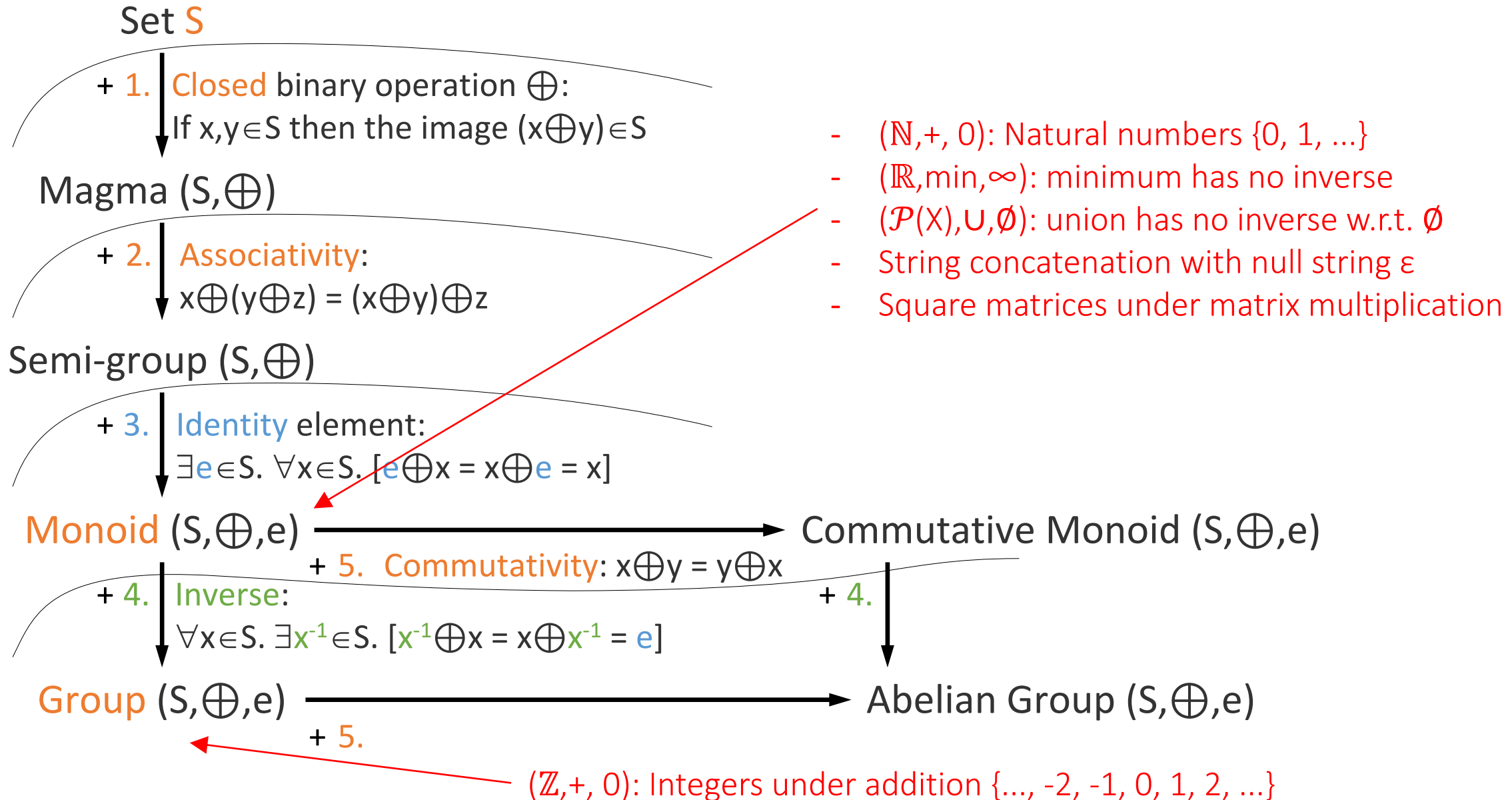


Outline Part 5

Part 5: Dynamic Programming & Semirings (Wolfgang) ~20min

- Top-1 = Dynamic Programming (DP)
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Group-like structures: a set & one binary operation



Group-like structures: a set & one binary operation

Set S

+ 1. **Closed** binary operation \oplus :

↓ If $x, y \in S$ then $(x \oplus y) \in S$

Magma (S, \oplus)

+ 2. **Associativity**:

↓ $x \oplus (y \oplus z) = (x \oplus y) \oplus z$

Semi-group (S, \oplus)

+ 3. **Identity** element:

↓ $\exists e \in S. \forall x \in S. [e \oplus x = x \oplus e = x]$

Monoid (S, \oplus, e)

+ 5. **Commutativity**: $x \oplus y = y \oplus x$

+ 4. **Inverse**:

↓ $\forall x \in S. \exists x^{-1} \in S. [x^{-1} \oplus x = x \oplus x^{-1} = e]$

Group (S, \oplus, e)

+ 5.

Totally Ordered Commutative Monoid (S, \oplus, e, \leq)

+ 6. \leq **total order** that is **translation-invariant**

$\forall x, y, z \in S: x \leq y \Rightarrow x \oplus z \leq y \oplus z$

Commutative Monoid (S, \oplus, e)

+ 4.

Abelian Group (S, \oplus, e)

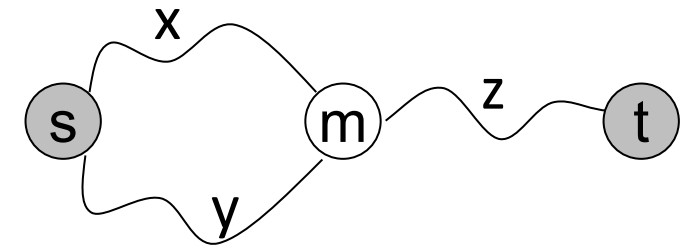
Totally ordered commutative monoid

- **Totally ordered** commutative monoid (S, \oplus, e, \leq)

6. \leq total order that is **translation-invariant** (sometimes called "compatible" with \oplus , or **monotonic**), i.e. $\forall x, y, z \in S: x \leq y \Rightarrow x \oplus z \leq y \oplus z$

– equivalent to "**optimal substructure**" in DP

when the solution to an optimization problem can be constructed from optimal solutions to its subproblems.



$$x \leq y \quad \oplus \quad z$$

- Let's generalize

– $\min [(x \oplus z), (y \oplus z)] = \min[x, y] \oplus z$

– $(x \oplus z) \min (y \oplus z) = (x \min y) \oplus z$

(+ **distributes** over min)

– $(x \cdot z) + (y \cdot z) = (x + y) \cdot z$

(multipl. **distributes** over add.)

Semirings: two binary operators

- **Semiring** $(S, \oplus, \otimes, 0, 1)$

1. $(S, \oplus, 0)$ is commutative monoid
2. $(S, \otimes, 1)$ is monoid
3. \otimes distributes over \oplus : $(x \oplus y) \otimes z = (x \otimes z) \oplus (y \otimes z)$
4. 0 annihilates \otimes : $0 \otimes x = 0$ (0 is an absorbing element for \otimes)

semirings are rings
w/o the additive inverse

e.g.: Natural numbers
under addition $(\mathbb{N}, +, 0)$

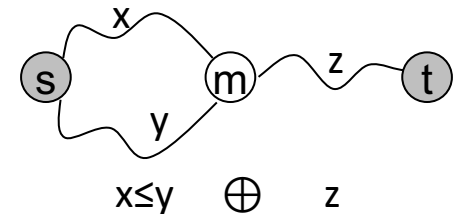
- **Examples**

1. $\mathbb{T} = (\mathbb{R}_+^\infty, \min, +, \infty, 0)$ Shortest-distance: $\min[x, y] + z = \min[(x+z), (y+z)]$

min-sum semiring, also called **tropical semiring**: sum distributes over min

not the other way: $\min[x+y, z] \neq \min[x, z] + \min[y, z]$; e.g. $\min[3+4, 5] = 5 \neq 7 = \min[3, 5] + \min[4, 5]$

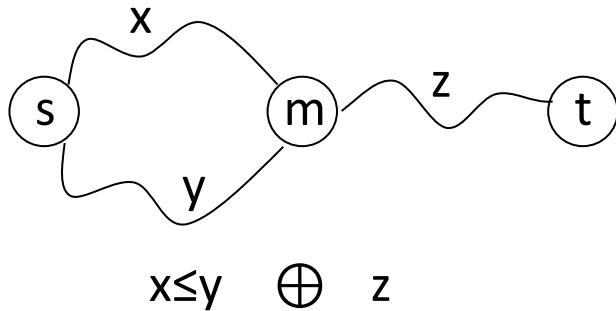
2. $\mathbb{N} = (\mathbb{N}, +, \cdot, 0, 1)$ Number of paths (bag semantics)
3. $\mathbb{R} = (\mathbb{R}, +, \cdot, 0, 1)$ Ring of real numbers
4. $\mathbb{B} = (\{0, 1\}, \vee, \wedge, 0, 1)$ Boolean (set semantics)
5. $\mathbb{V} = ([0, 1], \max, \cdot, 0, 1)$ Probability of best derivation (Viterbi)



Two equivalent algebraic perspectives of DP

Monoid perspective

- **Totally ordered** commutative monoid (S, \otimes, e, \leq)
 - \leq **total order** that is **translation-invariant**, i.e.
 $\forall x, y, z \in S: x \leq y \Rightarrow x \otimes z \leq y \otimes z$
 - implies the distributivity law (\otimes **distributes** over min):
 $(x \otimes z) \min (y \otimes z) = (x \min y) \otimes z$
 - equivalent to "**optimal substructure**" in DP



$(\mathbb{R}_+^\infty, +, 0)$: **totally ordered comm. monoid**

$(\mathbb{R}_+^\infty, \min, \infty)$: **selective monoid**

Semiring perspective

- **Selective commutative dioid** $(S, \oplus, \otimes, e_\oplus, e_\otimes)$
 - semiring, thus \otimes **distributes** over \oplus
 - semiring, thus \oplus is **commutative**
 - commutative semiring, thus \otimes is also **commutative**
 - additionally, \oplus is **selective**:
 $x \oplus y = x \text{ or } y \quad \forall x, y \in S$
 - selectivity & commutativity implies:
total order \leq on S

$(\mathbb{R}_+^\infty, \min, +, \infty, 0)$: **tropical semiring**

Summary Dynamic Programming & Semirings

1. DP works on **trees** and can be seen as a variant of **message passing**
2. DP is often the same problem as **shortest path finding**
3. **Semirings** allow us to further abstract what DP does:
 - **Shortest Paths problems** are instances of the tropical semiring $\mathbb{T}=(\mathbb{R}^{\infty}, \min, +, \infty, 0)$
 - **Path counting** on the $\mathbb{N}=(\mathbb{N}, +, \cdot, 0, 1)$ semiring
4. **Yannakakis** is DP on the Boolean semiring $\mathbb{B}=(\{0,1\}, \vee, \wedge, 0, 1)$

Outline tutorial

1: Introduction (Nikos) ~40min

2: Tree Decompositions (Mirek) ~20min

3: Acyclic Queries & Enumeration (Wolfgang) ~25min

BREAK

4: Factorization (Nikos) ~15min

5: Dynamic Programming & Semirings (Wolfgang) ~20min

6: Any-*k* or Ranked Enumeration (Nikos) ~35min

7. Decomposition of Comparison Predicates (Mirek) ~10min

8. Conclusion (Mirek) ~5min