

An Algebraic Approach to Internet Routing —  
Lectures 13, 14  
**Routing in Equilibrium**  
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# What algebraic properties are associated with global optimality?

## Distributivity

$$\text{L.D} : a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c),$$

$$\text{R.D} : (a \oplus b) \otimes c = (a \otimes c) \oplus (b \otimes c).$$

## What is this in $sp = (\mathbb{N}^\infty, \min, +)$ ?

$$\text{L.DIST} : a + (b \min c) = (a + b) \min (a + c),$$

$$\text{R.DIST} : (a \min b) + c = (a + c) \min (b + c).$$

# Left Local Optimality

Say that  $\mathbf{L}$  is a **left-locally optimal solution** when

$$\mathbf{L} = (\mathbf{A} \otimes \mathbf{L}) \oplus \mathbf{I}.$$

That is, for  $i \neq j$  we have

$$\mathbf{L}(i, j) = \bigoplus_{q \in V} \mathbf{A}(i, q) \otimes \mathbf{L}(q, j)$$

- $\mathbf{L}(i, j)$  is the best possible value given the values  $\mathbf{L}(q, j)$ , for all out-neighbors  $q$  of source  $i$ .
- Rows  $\mathbf{L}(i, \_)$  represents **out-trees from**  $i$  (think Bellman-Ford).
- Columns  $\mathbf{L}(\_, i)$  represents **in-trees to**  $i$ .

# Right Local Optimality

Say that  $\mathbf{R}$  is a **right-locally optimal solution** when

$$\mathbf{R} = (\mathbf{R} \otimes \mathbf{A}) \oplus \mathbf{I}.$$

That is, for  $i \neq j$  we have

$$\mathbf{R}(i, j) = \bigoplus_{q \in V} \mathbf{R}(i, q) \otimes \mathbf{A}(q, j)$$

- $\mathbf{R}(i, j)$  is the best possible value given the values  $\mathbf{R}(q, j)$ , for all in-neighbors  $q$  of destination  $j$ .
- Rows  $\mathbf{L}(i, \_)$  represents **out-trees from**  $i$  (think Dijkstra).
- Columns  $\mathbf{L}(\_, i)$  represents **in-trees to**  $i$ .

# With and Without Distributivity

## With

For (well behaved) Semirings, the three optimality problems are essentially the same — locally optimal solutions are globally optimal solutions.

$$\mathbf{A}^* = \mathbf{L} = \mathbf{R}$$

## Without

Suppose that we drop distributivity and  $\mathbf{A}^*$ ,  $\mathbf{L}$ ,  $\mathbf{R}$  exist. It may be the case they they are all distinct.

# A World Without Distributivity

## Global Optimality

This has been studied, for example [?, ?] in the context of circuit layout. See Chapter 5 of [?]. This approach does not play well with (loop-free) hop-by-hop forwarding (need tunnels!)

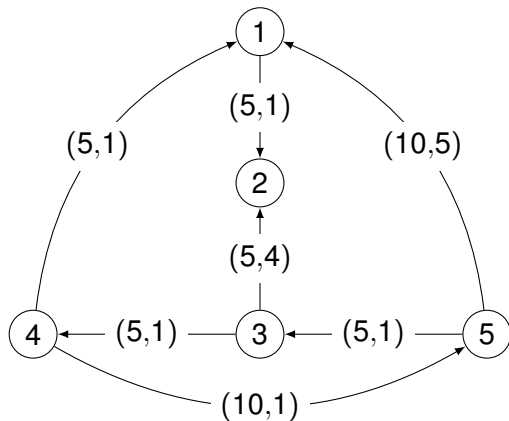
## Left Local Optimality

At a very high level, this is the type of problem that BGP attempts to solve!!

## Right Local Optimality

This approach does not play well with (loop-free) hop-by-hop forwarding (need tunnels!)

# Example



(bandwidth, distance) with lexicographic order (bandwidth first).

# Example's adjacency matrix

$$\mathbf{A} = \begin{array}{c} \begin{array}{ccccc} & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \left[ \begin{array}{ccccc} (0, \infty) & (5, 1) & (0, \infty) & (0, \infty) & (0, \infty) \\ (0, \infty) & (0, \infty) & (0, \infty) & (0, \infty) & (0, \infty) \\ (0, \infty) & (5, 4) & (0, \infty) & (5, 1) & (0, \infty) \\ (5, 1) & (0, \infty) & (0, \infty) & (0, \infty) & (10, 1) \\ (10, 5) & (0, \infty) & (5, 1) & (0, \infty) & (0, \infty) \end{array} \right] \end{array}$$



# Global optima

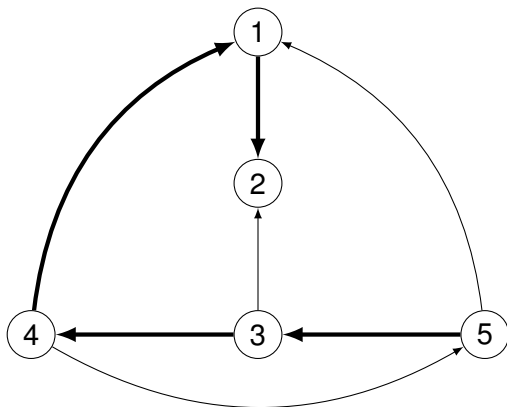
$$\mathbf{A}^* = \begin{array}{c} \phantom{1} \\ \phantom{2} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \phantom{1} \\ \phantom{2} \\ \phantom{3} \\ \phantom{4} \\ \phantom{5} \\ \phantom{6} \\ \phantom{7} \end{array} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \\ \left[ \begin{array}{ccccc} (\infty, 0) & (5, 1) & (0, \infty) & (0, \infty) & (0, \infty) \\ (0, \infty) & (\infty, 0) & (0, \infty) & (0, \infty) & (0, \infty) \\ (5, 2) & (5, 3) & (\infty, 0) & (5, 1) & (5, 2) \\ (10, 6) & (5, 2) & (5, 2) & (\infty, 0) & (10, 1) \\ (10, 5) & (5, 4) & (5, 1) & (5, 2) & (\infty, 0) \end{array} \right], \end{array}$$

# Left local optima

$$\mathbf{L} = \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{ccccc} & 1 & 2 & 3 & 4 & 5 \\ \left[ \begin{array}{ccccc} (\infty, 0) & (5, 1) & (0, \infty) & (0, \infty) & (0, \infty) \\ (0, \infty) & (\infty, 0) & (0, \infty) & (0, \infty) & (0, \infty) \\ \mathbf{(5, 7)} & (5, 3) & (\infty, 0) & (5, 1) & (5, 2) \\ (10, 6) & (5, 2) & (5, 2) & (\infty, 0) & (10, 1) \\ (10, 5) & (5, 4) & (5, 1) & (5, 2) & (\infty, 0) \end{array} \right], \end{array}$$

Entries marked in **bold** indicate those values which are not globally optimal.

## Left-locally optimal paths to node 2

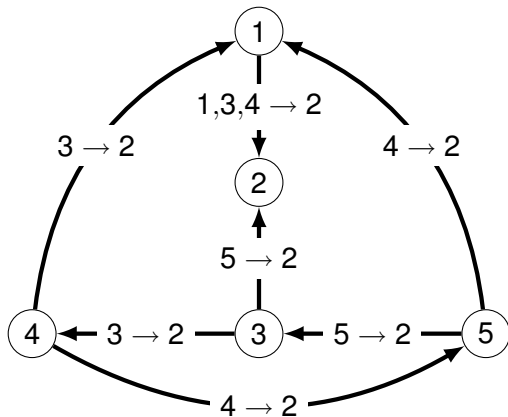


## Right local optima

$$\mathbf{R} = \begin{array}{c} \begin{array}{ccccc} & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \left[ \begin{array}{ccccc} (\infty, 0) & (5, 1) & (0, \infty) & (0, \infty) & (0, \infty) \\ (0, \infty) & (\infty, 0) & (0, \infty) & (0, \infty) & (0, \infty) \\ (5, 2) & (5, 3) & (\infty, 0) & (5, 1) & (5, 2) \\ (10, 6) & (5, 6) & (5, 2) & (\infty, 0) & (10, 1) \\ (10, 5) & (5, 5) & (5, 1) & (5, 2) & (\infty, 0) \end{array} \right], \end{array}$$

Note : the **(5, 6)** is **(5, 7)** in the paper, which appears to be a bug!

## Right-locally optimal paths to node 2



# What are the conditions needed to guarantee existence of local optima?

For a non-distributed structure  $S = (S, \oplus, \otimes, \bar{0}, \bar{1})$ , can be used to find **local optima** when the following property holds.

## Strictly Inflationary

$$\text{S.INFL} : \forall a, b \in S : a \neq \bar{0} \implies a < b \otimes a$$

where  $a \leq b$  means  $a = a \oplus b$ .

We know that (a modified) Bellman-Ford iteration will converge, but we currently have no bound on the number of iterations needed!

# Dijkstra's algorithm

**Input** : adjacency matrix  $\mathbf{A}$  and source vertex  $i \in V$ ,  
**Output** : the  $i$ -th row of  $\mathbf{R}$ ,  $\mathbf{R}(i, \_)$ .

**begin**

$S \leftarrow \{i\}$

$\mathbf{R}(i, i) \leftarrow \bar{1}$

**for each**  $q \in V - \{i\}$  :  $\mathbf{R}(i, q) \leftarrow \mathbf{A}(i, q)$

**while**  $S \neq V$

**begin**

find  $q \in V - S$  such that  $\mathbf{R}(i, q)$  is  $\leq_{\oplus}^L$ -minimal

$S \leftarrow S \cup \{q\}$

**for each**  $j \in V - S$

$\mathbf{R}(i, j) \leftarrow \mathbf{R}(i, j) \oplus (\mathbf{R}(i, q) \otimes \mathbf{A}(q, j))$

**end**

**end**

# Dijkstra's algorithm, annotated version

Subscripts make proofs by induction easier ....

**begin**

$$S_1 \leftarrow \{i\}$$

$$\mathbf{R}_1(i, i) \leftarrow \bar{1}$$

**for each**  $q \in V - S_1 : \mathbf{R}_1(i, q) \leftarrow \mathbf{A}(i, q)$

**for each**  $k = 2, 3, \dots, |V|$

**begin**

find  $q_k \in V - S_{k-1}$  such that  $\mathbf{R}(i, q)$  is  $\leq_{\oplus}^L$ -minimal

$$S_k \leftarrow S_{k-1} \cup \{q_k\}$$

**for each**  $j \in V - S_k$

$$\mathbf{R}_k(i, j) \leftarrow \mathbf{R}_{k-1}(i, j) \oplus (\mathbf{R}_{k-1}(i, q_k) \otimes \mathbf{A}(q_k, j))$$

**end**

**end**



## Assumptions on $(S, \oplus, \otimes, \bar{0}, \bar{1})$

- $(S, \oplus, \bar{0})$  is a commutative, idempotent, and selective monoid,
- $(S, \otimes, \bar{1})$  is a monoid,
- $\bar{0}$  is the annihilator for  $\otimes$ ,
- $\bar{1}$  is the annihilator for  $\oplus$ ,
- RINF :  $\forall a, b : a \leq a \otimes b$

Recall that  $a \leq b \equiv a \leq_{\oplus}^L b \equiv a = a \oplus b$ .

## The goal

Given adjacency matrix  $\mathbf{A}$  and source vertex  $i \in V$ , Dijkstra's algorithm will compute  $\mathbf{R}(i, \_)$  such that

$$\forall j \in V : \mathbf{R}(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in V} \mathbf{R}(i, q) \otimes \mathbf{A}(q, j).$$

## Main Claim

$$\forall k : 1 \leq k \leq |V| \implies \forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, j)$$

## Observation 1

$$\forall k : 1 \leq k < |V| \implies \forall j \in S_{k+1} : \mathbf{R}_k(i, j) = \mathbf{R}_{k+1}(i, j)$$

This is easy to see — once a node is put into  $S$  its weight never changes.

## Observation 2

### Observation 2

$$\forall k : 1 \leq k \leq |V| \implies \forall q \in S_k : \forall w \in V - S_k : \mathbf{R}_k(i, q) \leq \mathbf{R}_k(i, w)$$

By induction.

Base : Need  $\bar{1} \leq \mathbf{A}(i, w)$ . OK

Induction. Assume

$$\forall q \in S_k : \forall w \in V - S_k : \mathbf{R}_k(i, q) \leq \mathbf{R}_k(i, w)$$

and show

$$\forall q \in S_{k+1} : \forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, q) \leq \mathbf{R}_{k+1}(i, w)$$

Since  $S_{k+1} = S_k \cup \{q_{k+1}\}$ , this means showing

- (1)  $\forall q \in S_k : \forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, q) \leq \mathbf{R}_{k+1}(i, w)$
- (2)  $\forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, q_{k+1}) \leq \mathbf{R}_{k+1}(i, w)$

By Observation 1, showing (1) is the same as

$$\forall q \in S_k : \forall w \in V - S_{k+1} : \mathbf{R}_k(i, q) \leq \mathbf{R}_{k+1}(i, w)$$

which expands to (by definition of  $\mathbf{R}_{k+1}(i, w)$ )

$$\forall q \in S_k : \forall w \in V - S_{k+1} : \mathbf{R}_k(i, q) \leq \mathbf{R}_k(i, w) \oplus (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w))$$

But  $\mathbf{R}_k(i, q) \leq \mathbf{R}_k(i, w)$  by the induction hypothesis, and

$\mathbf{R}_k(i, q) \leq (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w))$  by the induction hypothesis and RINF.

Since  $a \leq_{\oplus}^L b \wedge a \leq_{\oplus}^L c \implies a \leq_{\oplus}^L (b \oplus c)$ , we are done.

By Observation 1, showing (2) is the same as showing

$$\forall w \in V - S_{k+1} : \mathbf{R}_k(i, q_{k+1}) \leq \mathbf{R}_{k+1}(i, w)$$

which expands to

$$\forall w \in V - S_{k+1} : \mathbf{R}_k(i, q_{k+1}) \leq \mathbf{R}_k(i, w) \oplus (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w))$$

But  $\mathbf{R}_k(i, q_{k+1}) \leq \mathbf{R}_k(i, w)$  since  $q_{k+1}$  was chosen to be minimal, and  $\mathbf{R}_k(i, q_{k+1}) \leq (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w))$  by RINF.

Since  $a \leq_{\oplus}^L b \wedge a \leq_{\oplus}^L c \implies a \leq_{\oplus}^L (b \oplus c)$ , we are done.

## Observation 3

### Observation 3

$$\forall k : 1 \leq k \leq |V| \implies \forall w \in V - S_k : \mathbf{R}_k(i, w) = \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, w)$$

Proof: By induction:

Base : easy, since

$$\bigoplus_{q \in S_1} \mathbf{R}_1(i, q) \otimes \mathbf{A}(q, w) = \bar{1} \otimes \mathbf{A}(i, w) = \mathbf{A}(i, w) = \mathbf{R}_1(i, w)$$

Induction step. Assume

$$\forall w \in V - S_k : \mathbf{R}_k(i, w) = \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, w)$$

and show

$$\forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, w) = \bigoplus_{q \in S_{k+1}} \mathbf{R}_{k+1}(i, q) \otimes \mathbf{A}(q, w)$$

By Observation 1, and a bit of rewriting, this means we must show

$$\forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, w) = \mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w) \oplus \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}($$

Using the induction hypothesis, this becomes

$$\forall w \in V - S_{k+1} : \mathbf{R}_{k+1}(i, w) = \mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, w) \oplus \mathbf{R}_k(i, w)$$

But this is exactly how  $\mathbf{R}_{k+1}(i, w)$  is computed in the algorithm.

# Proof of Main Claim

## Main Claim

$$\forall k : 1 \leq k \leq |V| \implies \forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, j)$$

Proof : By induction on  $k$ .

Base case:  $S_1 = \{i\}$  and the claim is easy.

Induction: Assume that

$$\forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, j)$$

We must show that

$$\forall j \in S_{k+1} : \mathbf{R}_{k+1}(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_{k+1}} \mathbf{R}_{k+1}(i, q) \otimes \mathbf{A}(q, j)$$



Since  $S_{k+1} = S_k \cup \{q_{k+1}\}$ , this means we must show

- (1)  $\forall j \in S_k : \mathbf{R}_{k+1}(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_{k+1}} \mathbf{R}_{k+1}(i, q) \otimes \mathbf{A}(q, j)$
- (2)  $\mathbf{R}_{k+1}(i, q_{k+1}) = \mathbf{I}(i, q_{k+1}) \oplus \bigoplus_{q \in S_{k+1}} \mathbf{R}_{k+1}(i, q) \otimes \mathbf{A}(q, q_{k+1})$

By use Observation 1, showing (1) is the same as showing

$$\forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{I}(i, j) \oplus \bigoplus_{q \in S_{k+1}} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, j),$$

which is equivalent to

$$\forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{I}(i, j) \oplus (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, j)), \oplus \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, j)$$

By the induction hypothesis, this is equivalent to

$$\forall j \in S_k : \mathbf{R}_k(i, j) = \mathbf{R}_k(i, j) \oplus (\mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, j)),$$

Put another way,

$$\forall j \in S_k : \mathbf{R}_k(i, j) \leq \mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, j)$$

By observation 2 we know  $\mathbf{R}_k(i, j) \leq \mathbf{R}_k(i, q_{k+1})$ , and so

$$\mathbf{R}_k(i, j) \leq \mathbf{R}_k(i, q_{k+1}) \leq \mathbf{R}_k(i, q_{k+1}) \otimes \mathbf{A}(q_{k+1}, j)$$

by RINF.

To show (2), we use Observation 1 and  $\mathbf{I}(i, q_{k+1}) = \bar{0}$  to obtain

$$\mathbf{R}_k(i, q_{k+1}) = \bigoplus_{q \in S_{k+1}} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, q_{k+1})$$

which, since  $\mathbf{A}(q_{k+1}, q_{k+1}) = \bar{0}$ , is the same as

$$\mathbf{R}_k(i, q_{k+1}) = \bigoplus_{q \in S_k} \mathbf{R}_k(i, q) \otimes \mathbf{A}(q, q_{k+1})$$

This then follows directly from Observation 3.

# Finding Left Local Solutions?

$$\mathbf{L} = (\mathbf{A} \otimes \mathbf{L}) \oplus \mathbf{I} \iff \mathbf{L}^T = (\mathbf{L}^T \otimes^T \mathbf{A}^T) \oplus \mathbf{I}$$

$$\mathbf{R}^T = (\mathbf{A}^T \otimes^T \mathbf{R}^T) \oplus \mathbf{I} \iff \mathbf{R} = (\mathbf{R} \otimes \mathbf{A}) \oplus \mathbf{I}$$

where

$$a \otimes^T b = b \otimes a$$

Notice that this exchanges RINF for LINF!

$$\text{LINF} : \forall a, b : a \leq b \otimes a$$

# Conclusion

- Complexity of solving for left local optima?
  - ▶ Previous work has shown that Bellman-Ford will find a solution as long as only simple paths are explored — but no time bounds are known.
  - ▶ But, now we know that  $O(V^3)$  will due with Dijkstra's greedy algorithm.
  - ▶ Could do better in sparse graphs using Fibonacci heaps ...