## Graph Evacuation Problems

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CRM June, 2015

#### Joint Work with

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- Di Chen
- Siu-Wing Cheng
- Yuya Higashikawa
- Naoki Katoh
- Guanqun Ni
- Bing Su
- Prashanth Srikanthan
- Yinfeng Xu

## <u>Outline</u>

- Dynamic Flow Networks
- Congestion in Dynamic Flows
- Evacuation Flows
  - Problem Definitions
  - Known Results
- Example Algorithm 1: k-Sink Evacuation on a Path
- Example Algorithm 2: 1-sink Min-Max Regret Evacuation on a Path with uniform capacity
- Open Problems

- Graph G=(V,E) represents structure
  - Vertices are rooms, Edges are Hallways
  - Vertices are Buildings, Edges are roads
  - Edge weight  $\tau_e$  is transit time on edge
  - Edge capacity ce is "width"

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  - Problem: Design Good Evacuation Protocols
- Often Approached via Dynamic Flow Networks

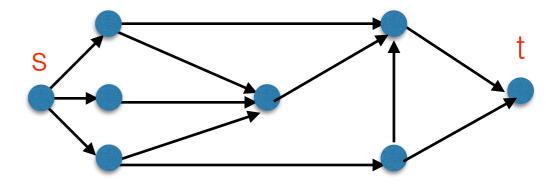
# Dynamic Flow Networks

- G=(V,E)
- Edges have travel times  $\tau_{e}$  and capacities  $c_{e}$
- Distinguished source s and sink t
- Max Flow Over Time Problem (input T) How much flow can be pushed from s to t in time T?
  - Ford Fulkerson (1958)
  - Not polynomial (Constructs Static Max-Flow each timestep)
- Quickest Flow Problem (input W) How quickly can W items be moved from s to t?
  - Burkard, Dlasks and Klinz (1993)
  - Strongly Polynomial (uses parametric search)

#### Quickest Transhipment Problem

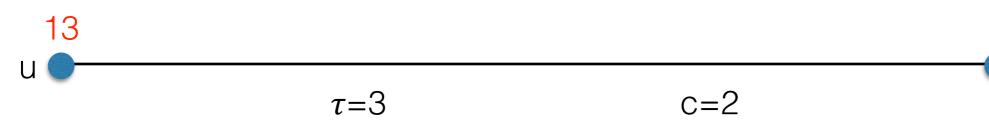
Like QF Problem but Multiple Sources/Sinks (with fixed supply/demands)

- Hoppe & Tardos (2000)
- Strongly Polynomial (but uses sub modular optimization)

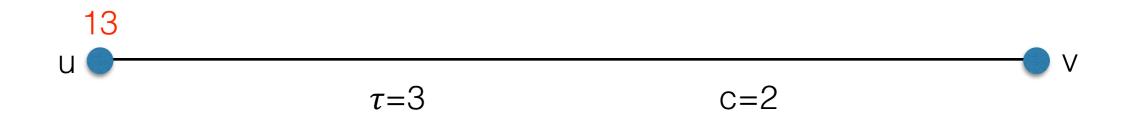


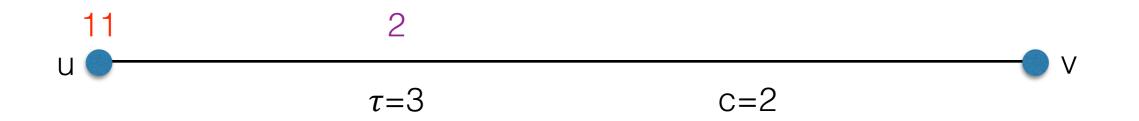
# Edges have Capacities

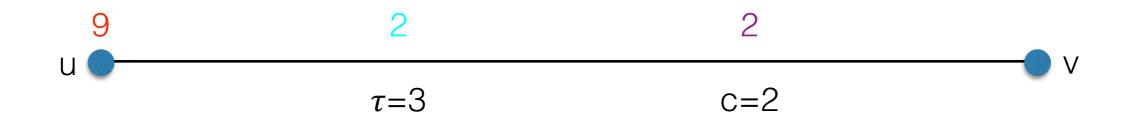
- Original Flow Model is static. Doesn't model time
- Time required is function of both transit times and capacities
- *c*<sub>e</sub> is edge capacity ("width")
  - At most c<sub>e</sub> people can enter edge e=(u,v) in one time unit.
     They travel together as a group on e
  - If more than *c<sub>e</sub>* people at *u*, remainder need to **wait** to enter *e*
- $\tau_e$  is time for one group to traverse edge
- Start with W people at u
   How much time does take them all to reach v?

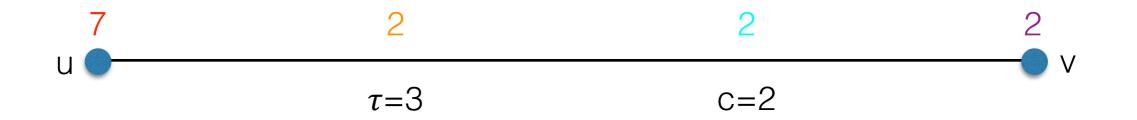


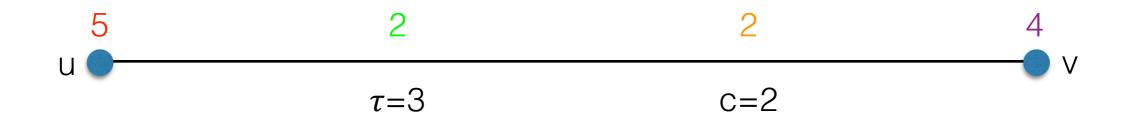


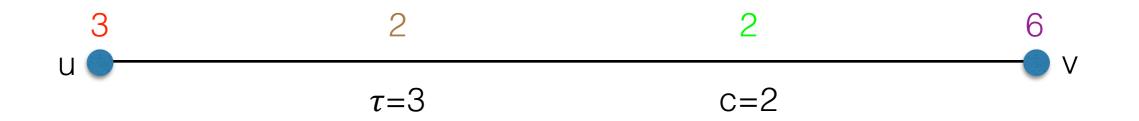


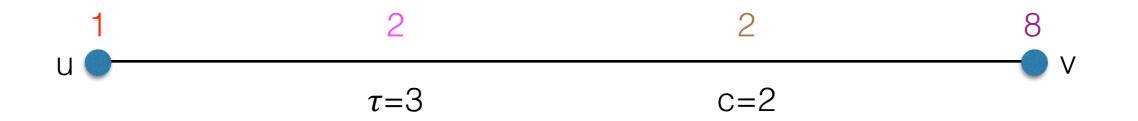


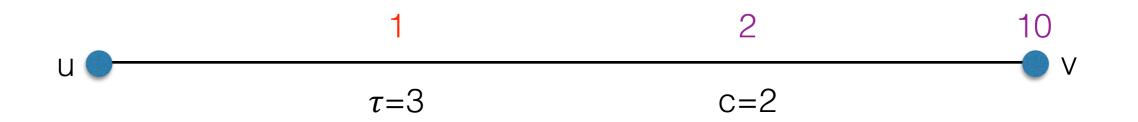


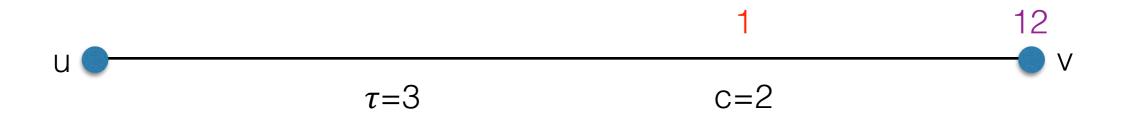


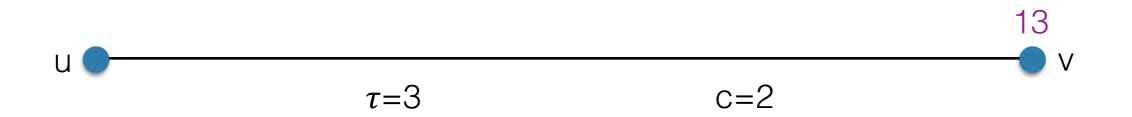


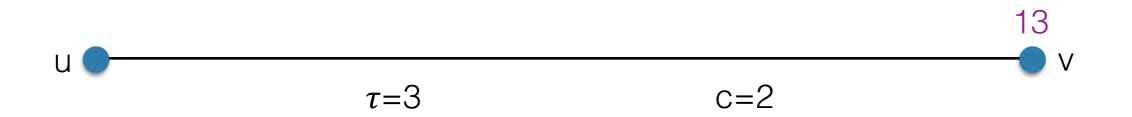


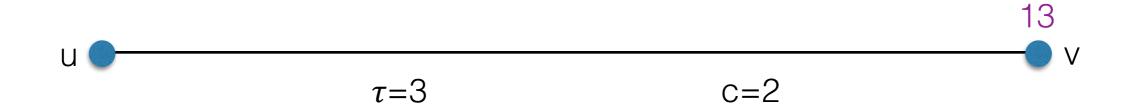




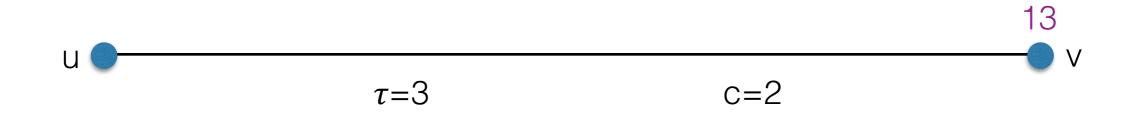








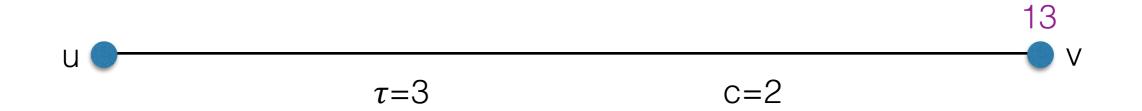
- 13 items split into g = r13/27 = 7 groups
- First group reached v at time  $t = \tau = 3$
- Last group reached v at time t=3+g-1=9



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### **Discrete Model**

- W people, Capacity c integral, Transit time  $\tau$
- All edge transit times integral
- Requires  $\Gamma W/C^7 + \tau 1$  time to move everyone from u to v



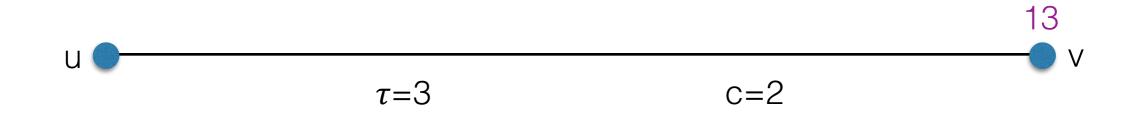
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### Discrete Model

- W people, Capacity c integral, Transit time  $\tau$
- All edge transit times integral
- Requires  $\Gamma W/C^{T} + \tau 1$  time to move everyone from u to v

### Continuous Model

- W units of non-quantized fluid. Fluid flows continuously
- c is rate: amount that can enter e in one unit of time
- Requires  $W/c + \tau 1$  time to move all fluid from u to v



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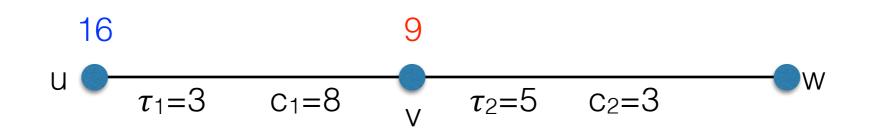
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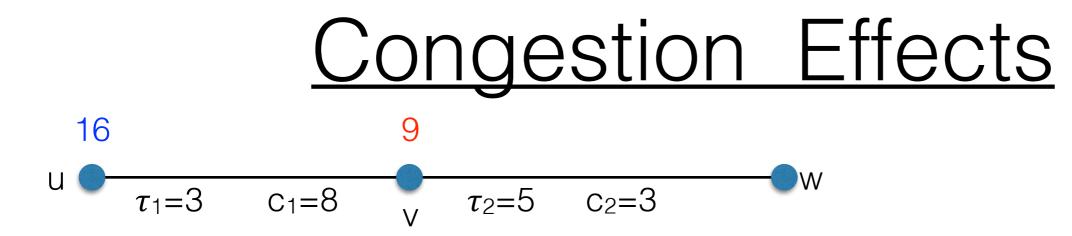
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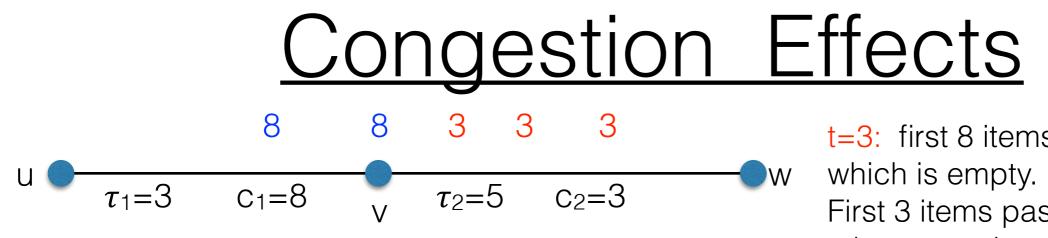
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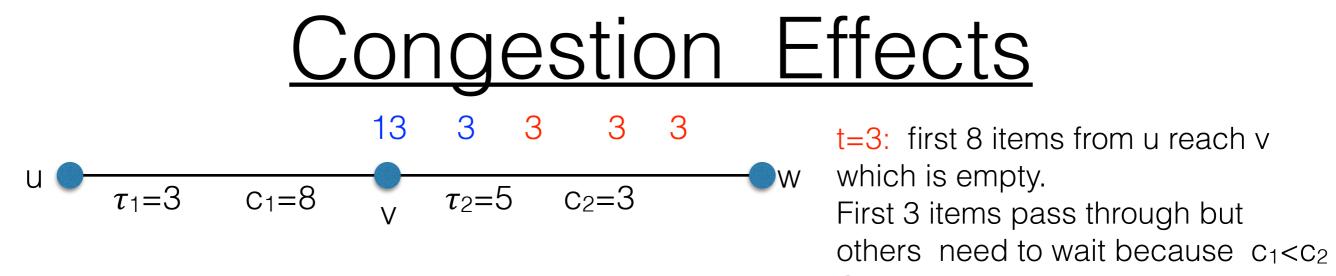
A major complication with dynamic flows is that they introduce congestion effects that can slow down transport time



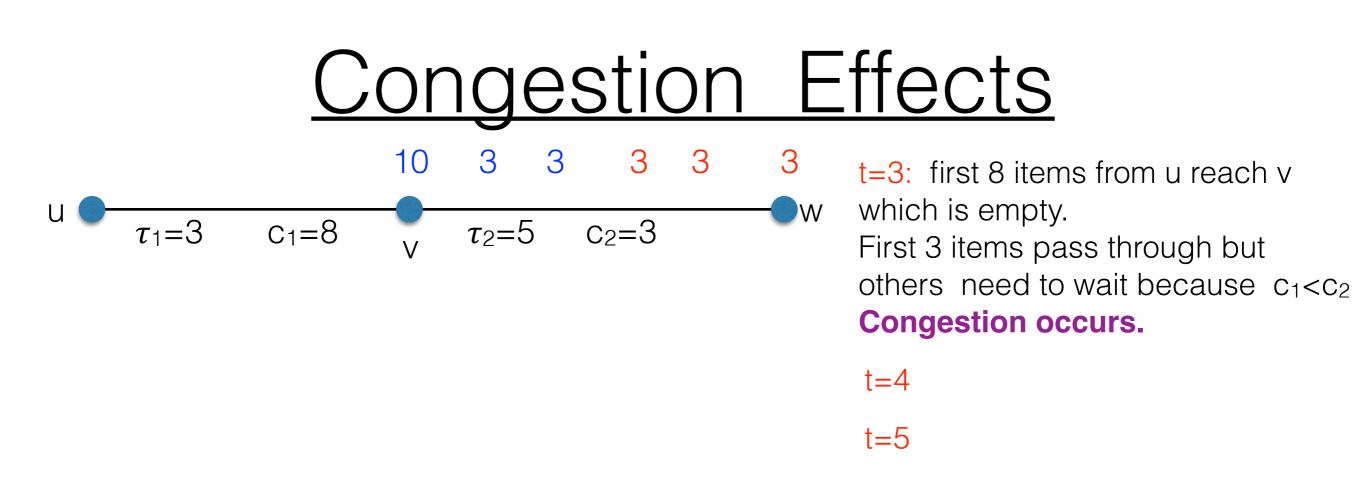


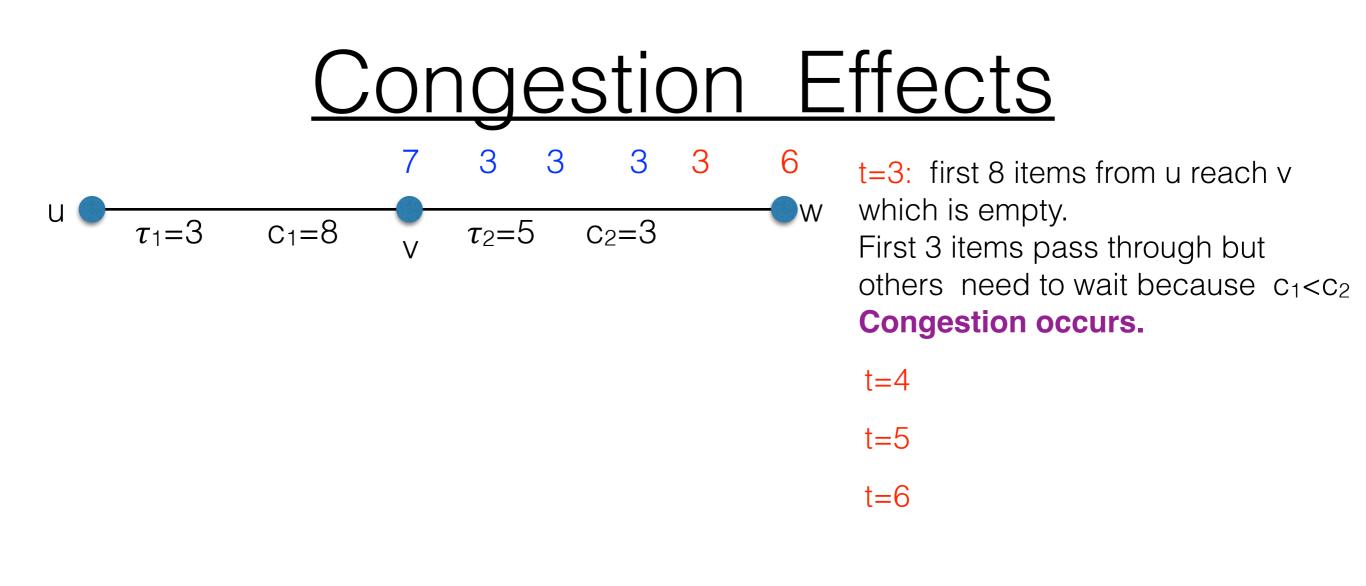


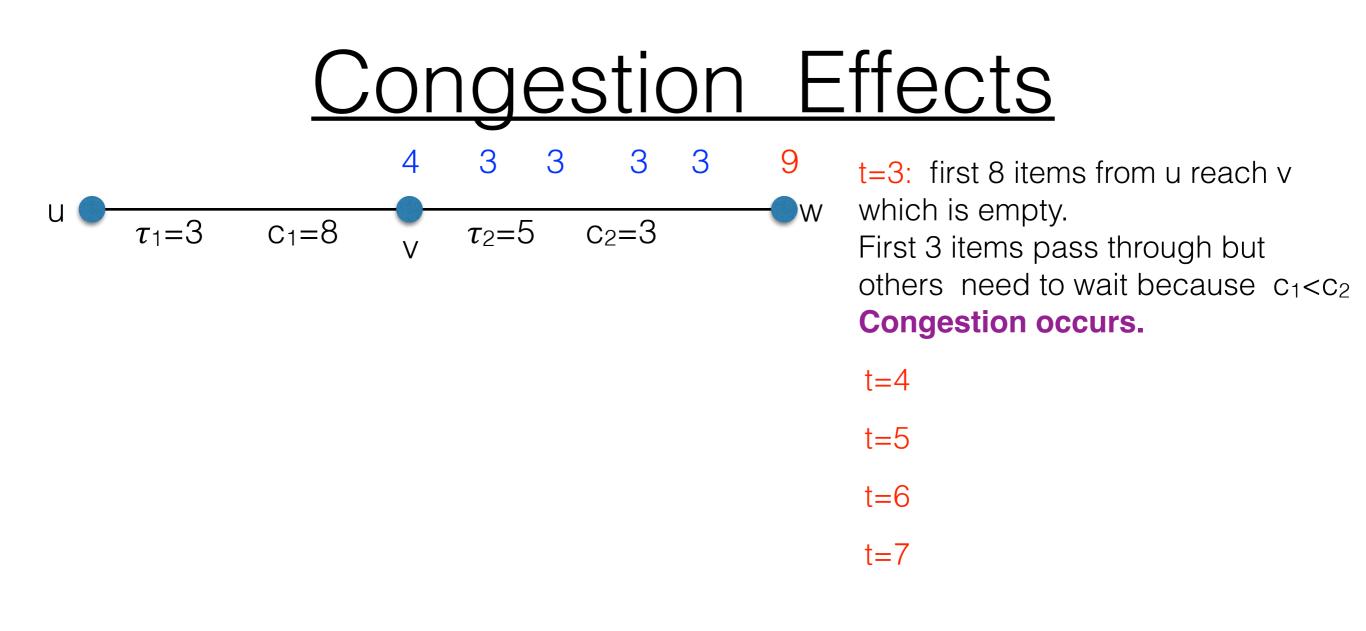
t=3: first 8 items from u reach v which is empty.
First 3 items pass through but others need to wait because c<sub>1</sub><c<sub>2</sub>
Congestion occurs.

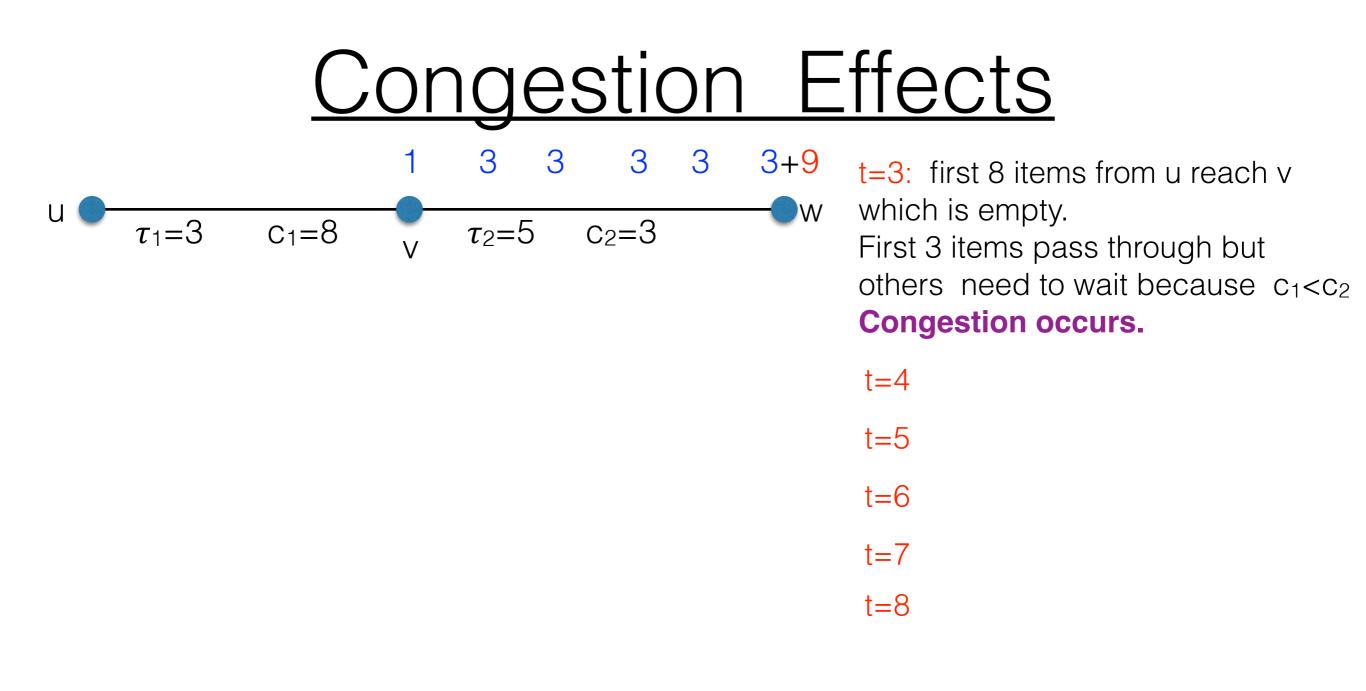


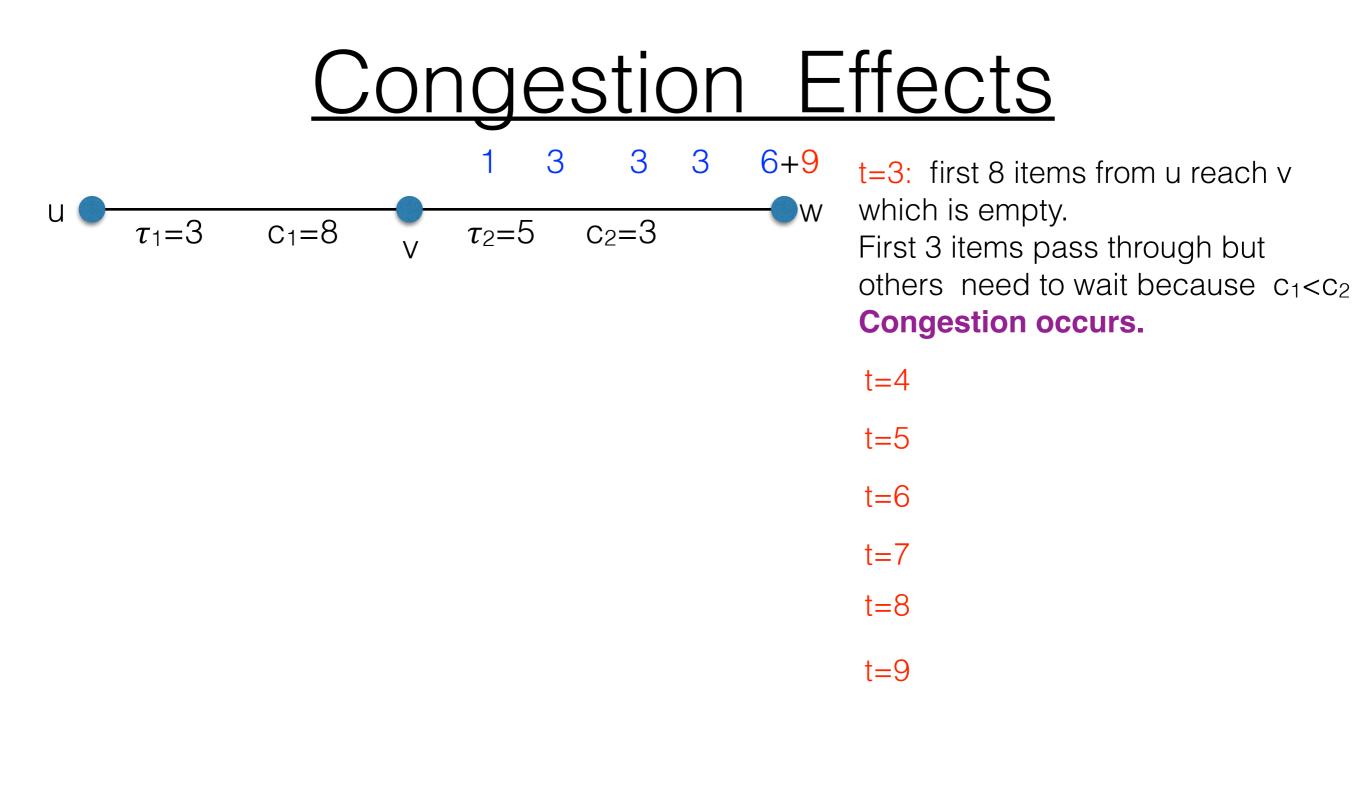
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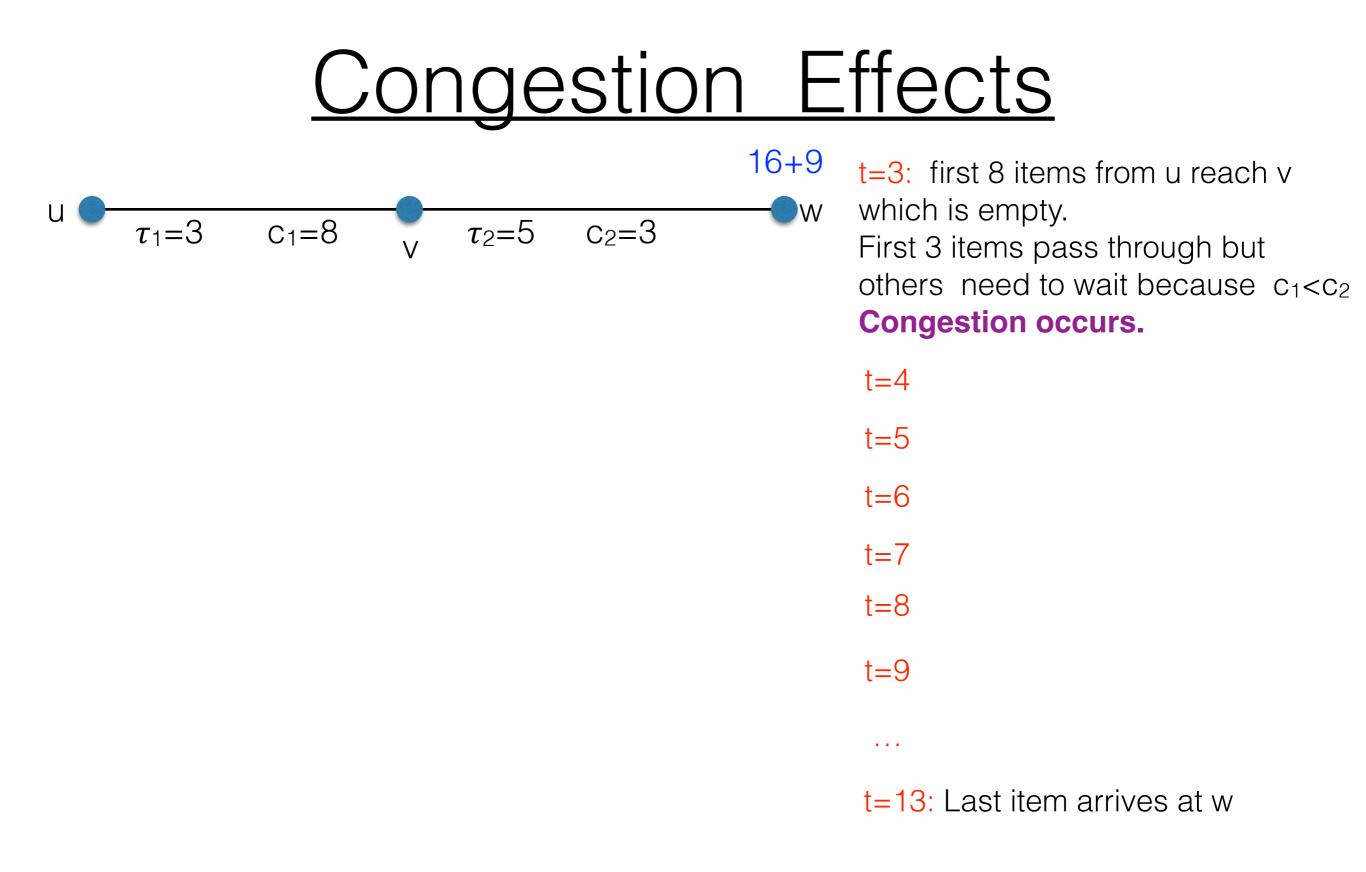


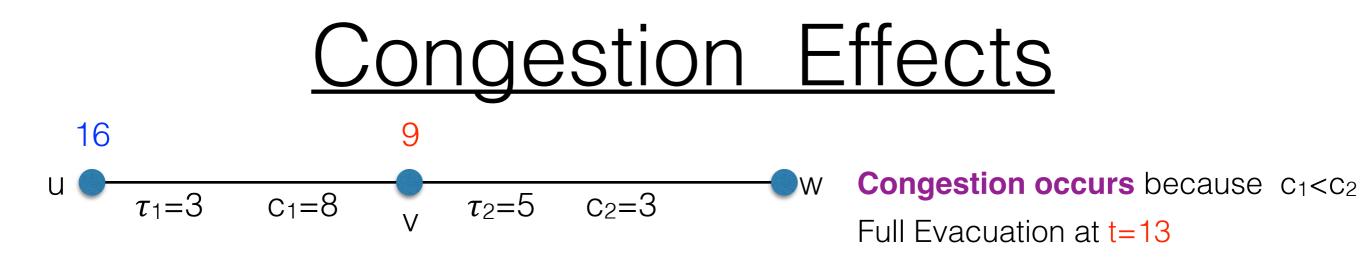


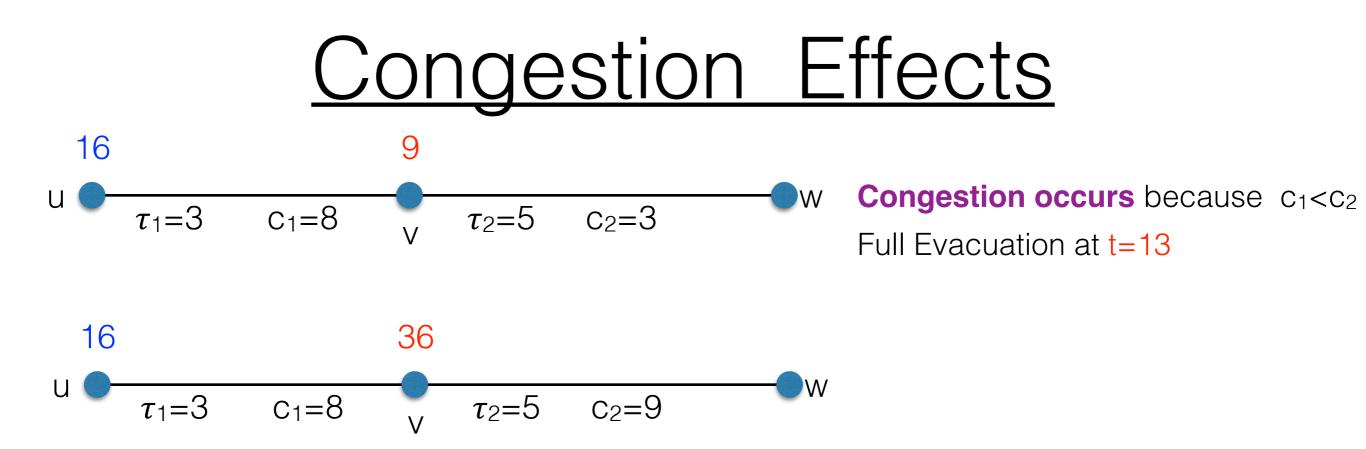


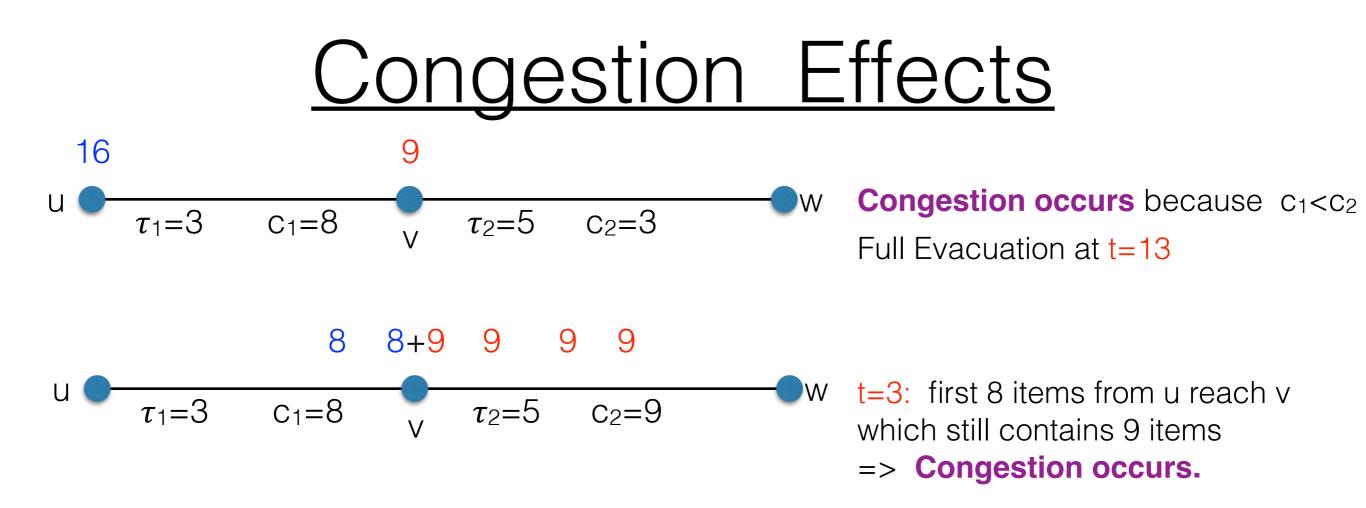


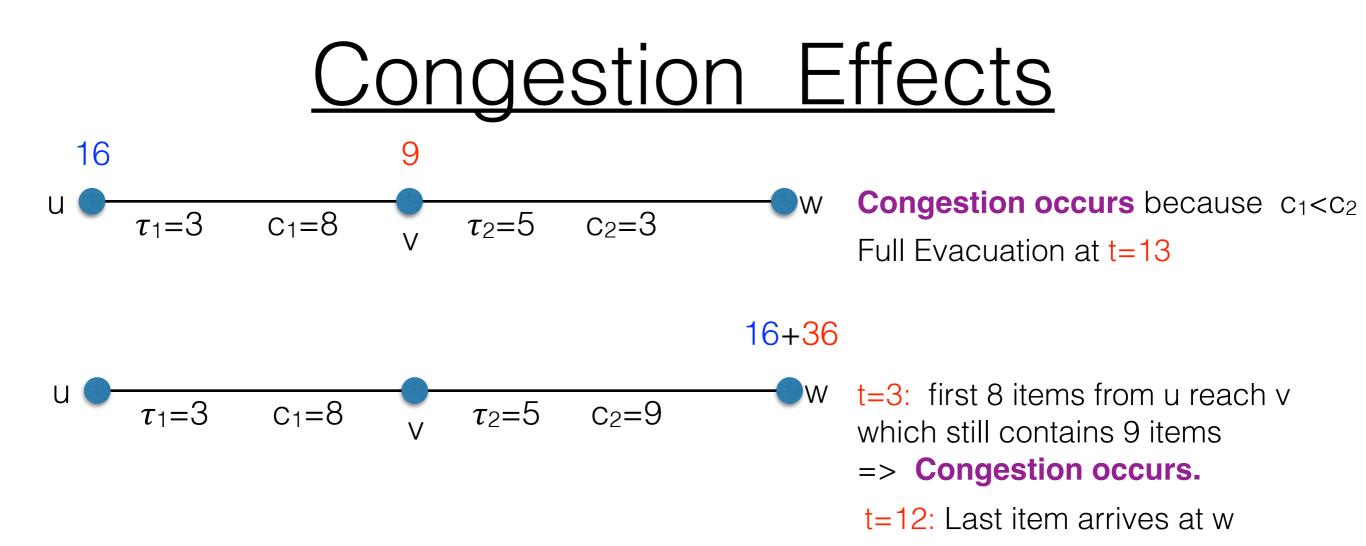


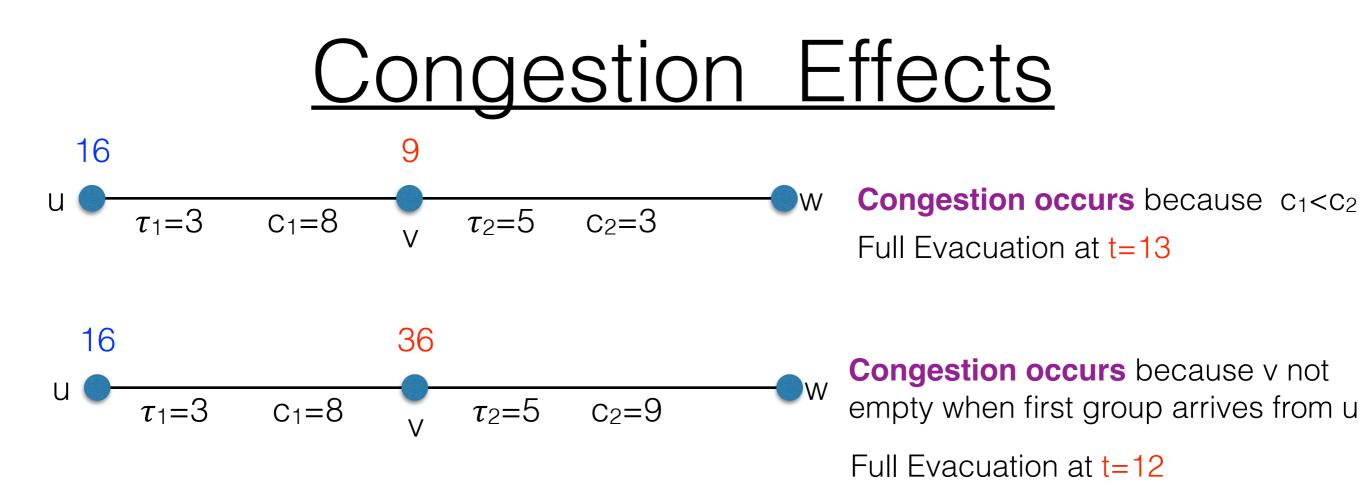


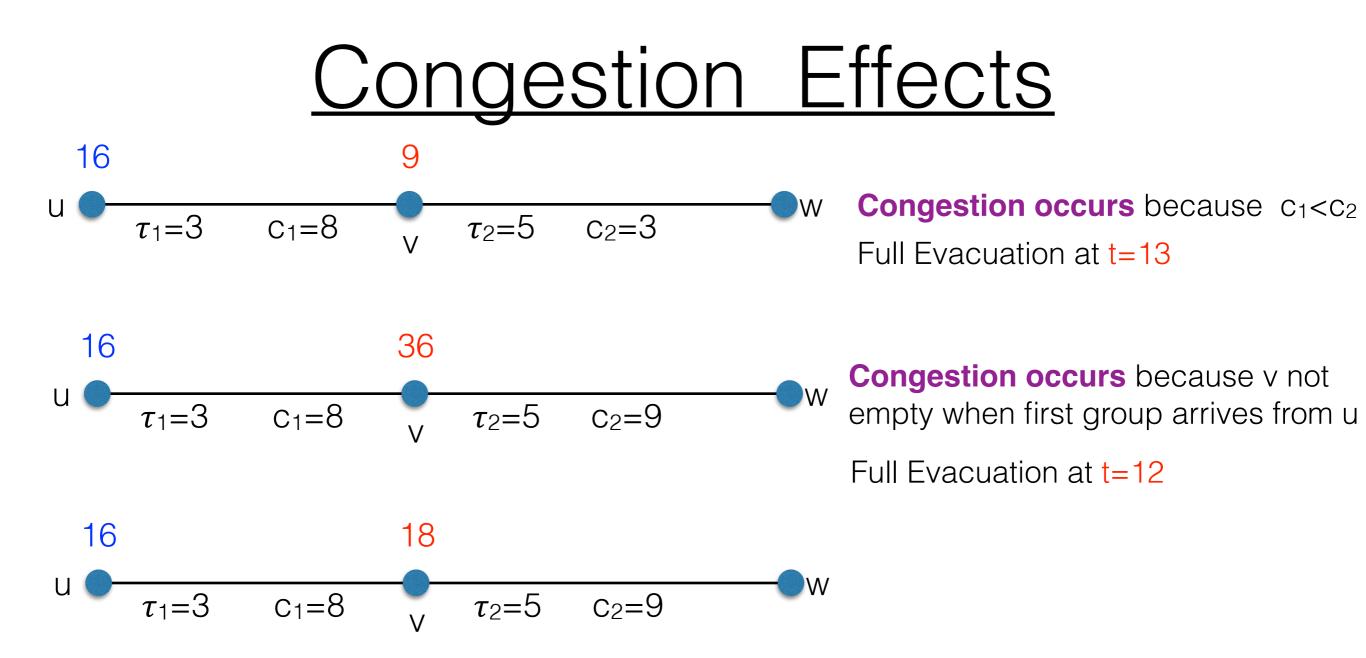


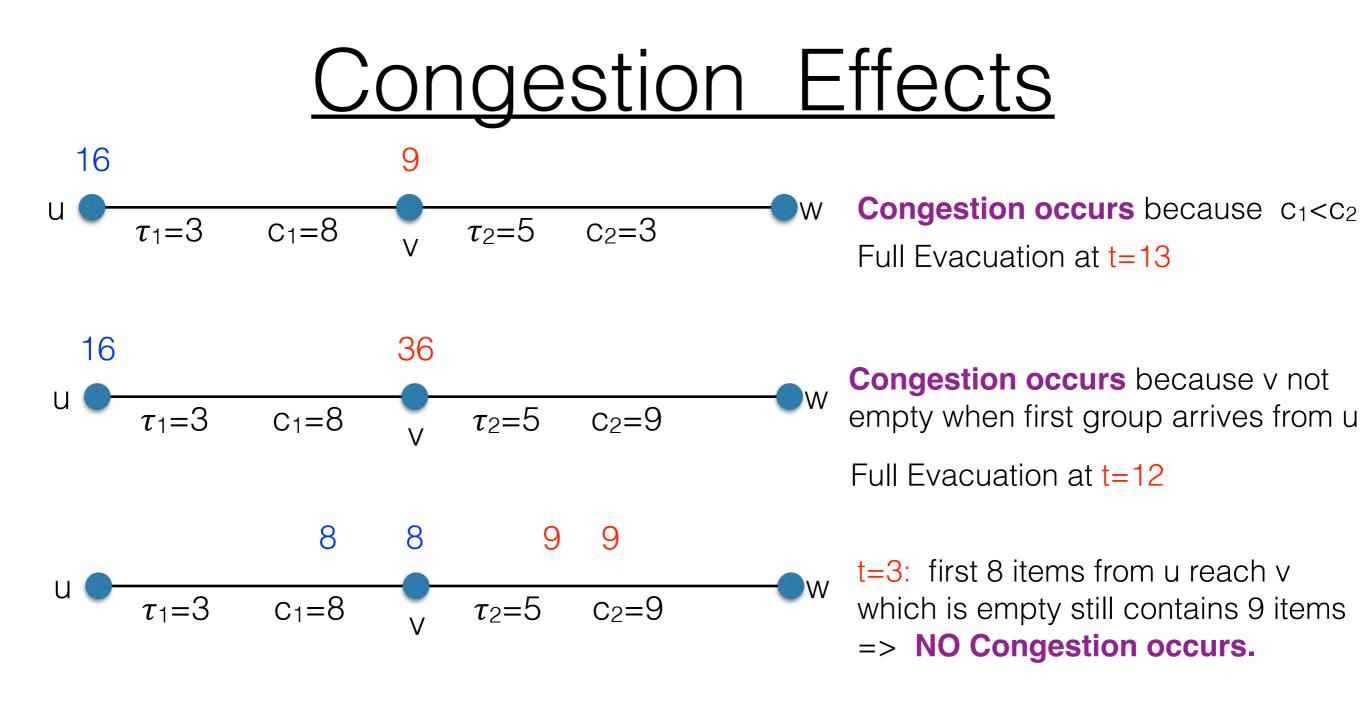


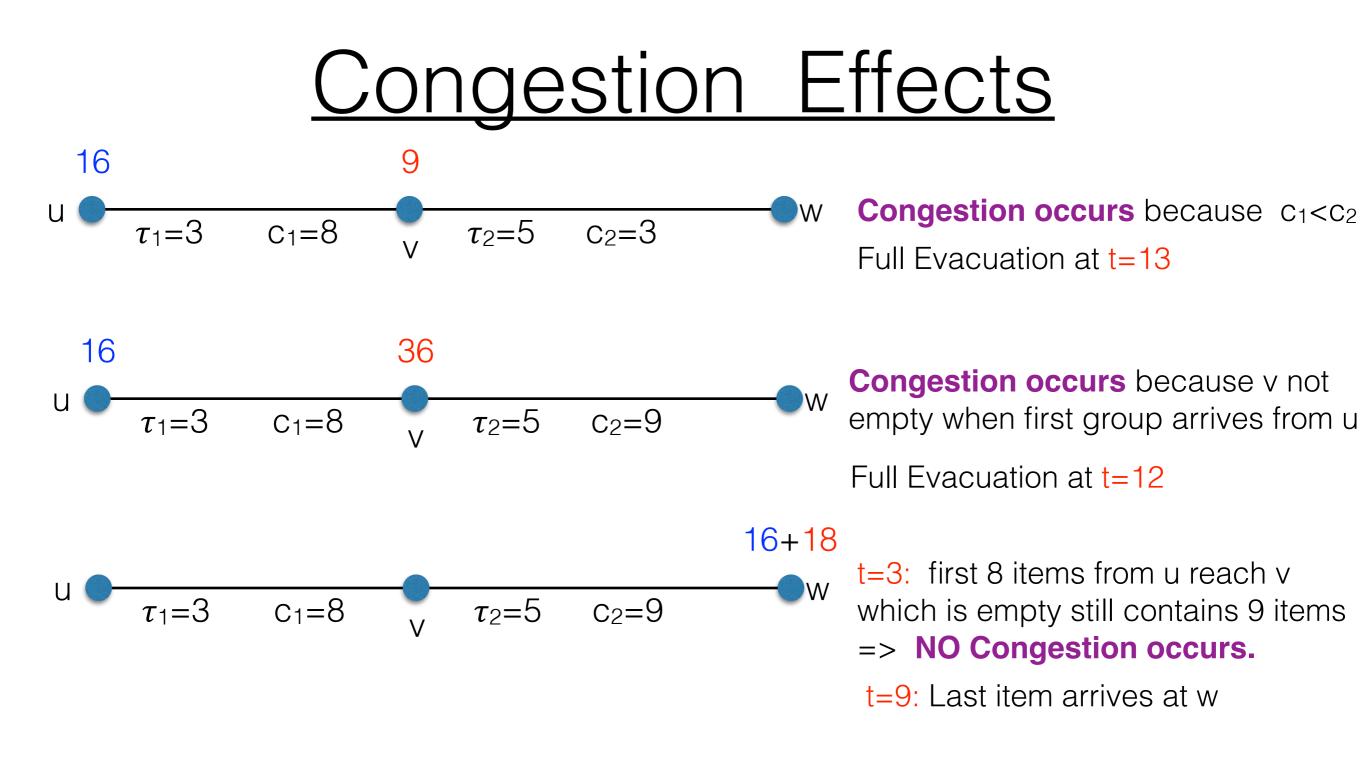


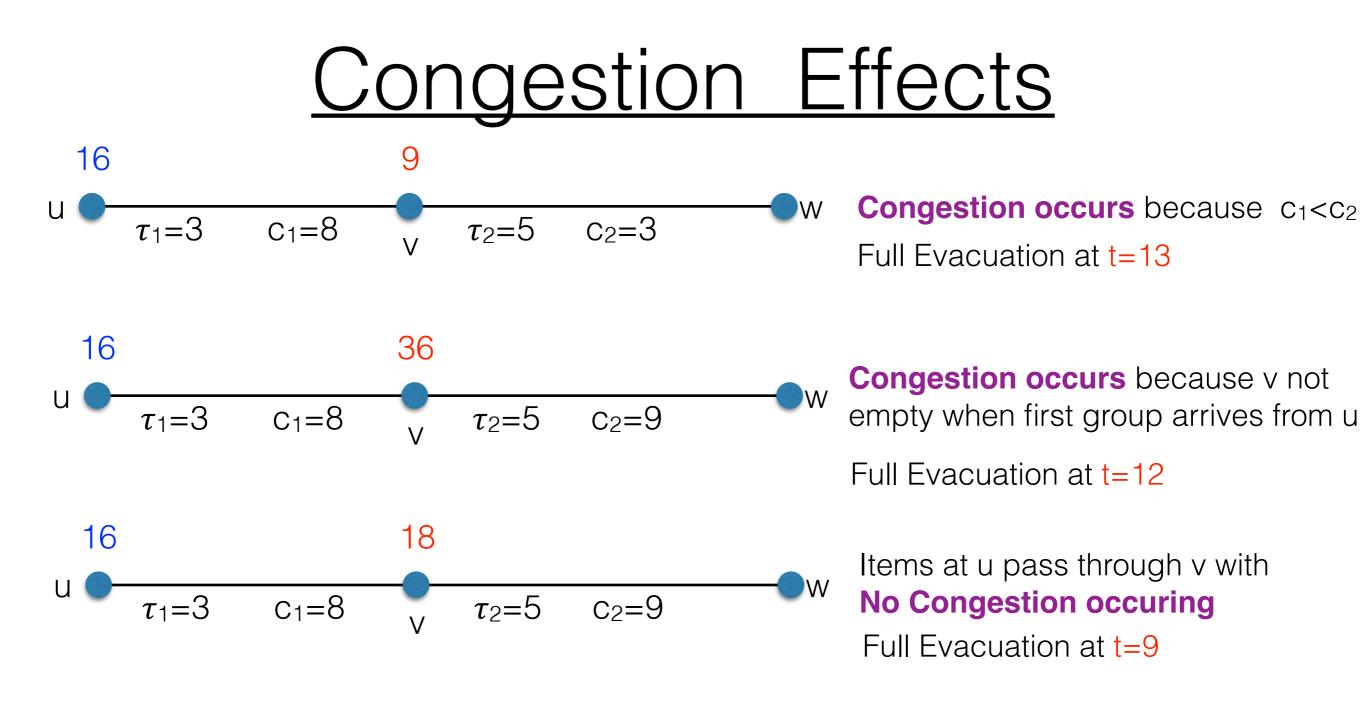


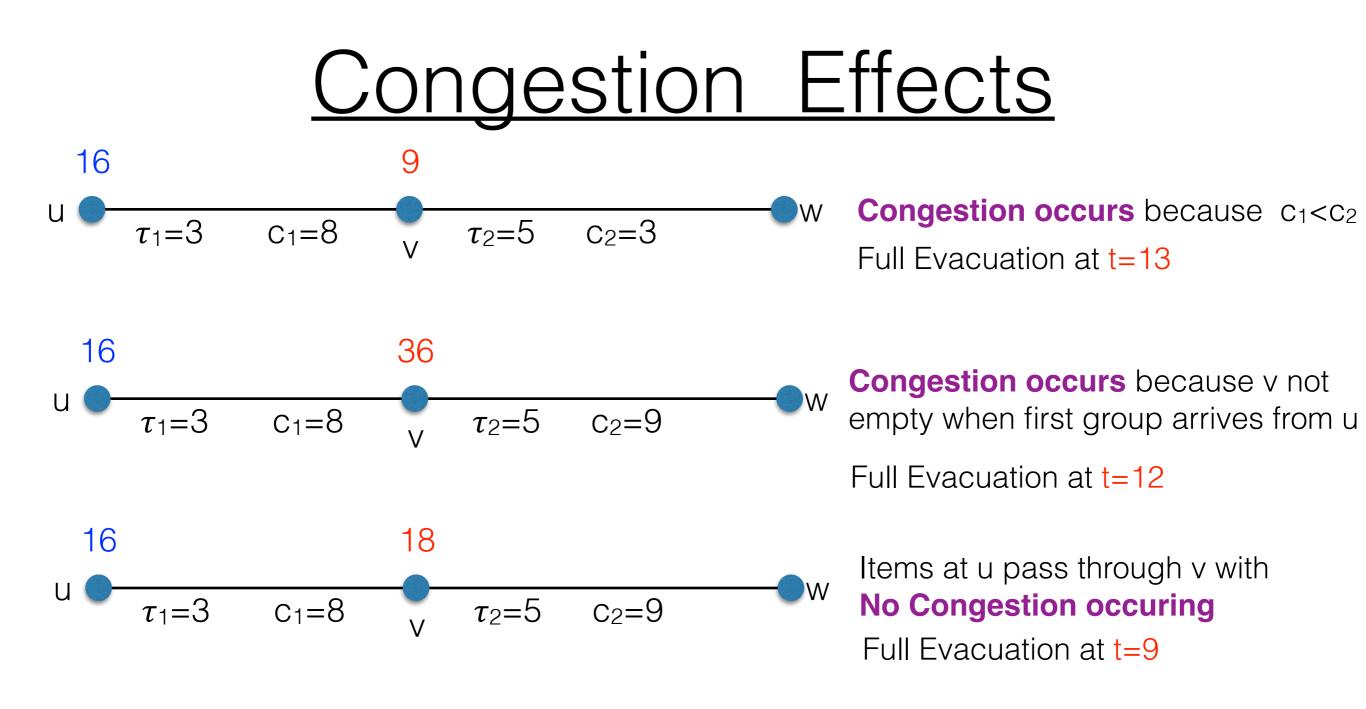






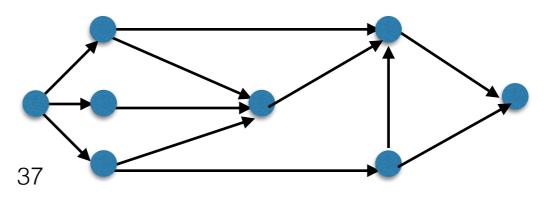






Analysis of Flow/Evacuation times must include congestion!!

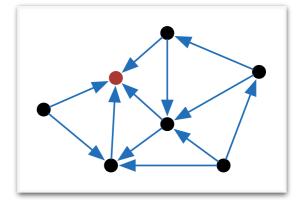
Can be very complicated!



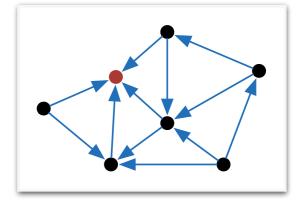
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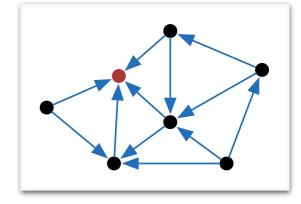
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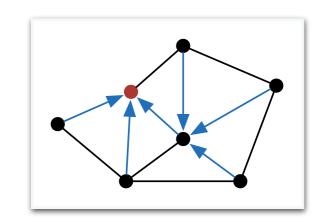


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  - Each vertex has unique evacuation edge.
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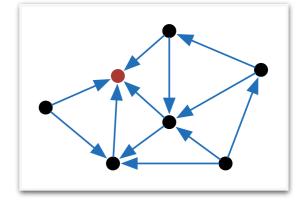


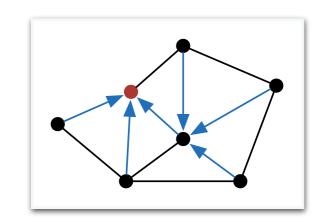
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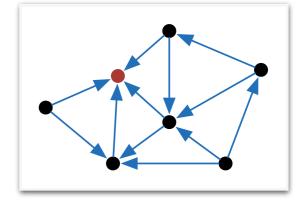


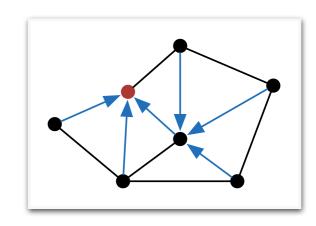
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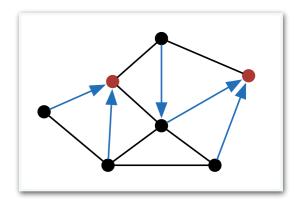




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- Input: Graph G=(V,E)
  - $\tau_{e, C_e}$ : transit times and capacities for each edge
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- Output: An Evacuation Protocol that minimizes maximum evacuation time
  - Evacuation Protocol
    - A unique evacuation edge for each vertex
    - If input is k, a set  $K \subseteq V$  of sinks with |K| = k
  - Maximum Evacuation time
    - The evacuation time of a vertex is the earliest time by which ALL items from that vertex have reached a sink.
    - Maximum evacuation time is the maximum evacuation time over all vertices

- Type of graph G: Path, Tree, General, ....
  - For general G and k>1 problem is NP-Complete because it solves k-Center (if c<sub>e</sub> set to be large)

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- *c<sub>e</sub>*: uniform (all the same) vs general (arbitrary)
- Min-Max vs Min-Max Regret
  - Robust solutions. MMR allows  $w_v$ , # of people on vertex, to be a range rather than a number. Find "best" solution for all allowable scenarios

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## Known Results

	Min-max cost (DISCRETE/CONTINUOUS)				
	General capacity		Uniform capacity		
	1-sink	k-sink	1-sink	k-sink	
Path	O(n) [2]	O(kn log <sup>2</sup> n) [2]	O(n)	O(kn) [6]	
Tree	O(n log <sup>2</sup> n) [7]	O(k <sup>2</sup> n log <sup>4</sup> n) [3]	O(n log n) [4]	O(k <sup>2</sup> n log <sup>3</sup> n) [3]	
General graph	Poly?	NP-Hard	Poly?	NP-Hard	

	Min-max regret cost (DISCRETE/CONTINUOUS)			
	General capacity		Uniform capacity	
	1-sink	k-sink	1-sink	k-sink
Path	None		O(n log n) [5,9]	O(kn <sup>3</sup> log n) [1]
Tree			O(n <sup>2</sup> log <sup>2</sup> n) [4]	None
General graph			None	

#### References

[1] G.P. Arumugam, J. Augustine, M.J. Golin and P. Srikanthan, "A Polynomial Time Algorithm for Minimax-Regret Evacuation on a Dynamic Path", arXiv:1404.5448, 2014

[2] G.P. Arumugam, J. Augustine, M.J. Golin and P. Srikanthan, "Evacuation on Dynamic Paths with General Edge Capacities", document in preparation (2015)

[3] Di Chen and M.J. Golin, "Optimal Sink Location Problems in Dynamic Tree Networks", document in preparation (2015)

**[4]** Y. Higashikawa, M. J. Golin and N. Katoh, "Minimax Regret Sink Location Problem in Dynamic Tree Networks with Uniform Capacity", *Proc. WALCOM 2014*, LNCS 8344, pp. 125-137, 2014.

**[5]** Y. Higashikawa, J. Augustine, S. W. Cheng, N. Katoh, G. Ni, B. Su and Y. Xu, "Minimax Regret 1-Sink Location Problem in Dynamic Path Networks", *Theoretical Computer Science*, 2014.

**[6]** Y. Higashikawa, M. J. Golin and N. Katoh, "Multiple Sink Location Problems in Dynamic Path Networks", *Theoretical Computer Science* (to appear) 2015.

**[7]** S. Mamada, T. Uno, K. Makino and S. Fujishige, "An O(n log<sup>2</sup> n) Algorithm for the Optimal Sink Location Problem in Dynamic Tree Networks", *Discrete Applied Mathematics*, 154(16), pp. 2387-2401, 2006.

[8] G. Ni, Y. Xu and Y. Dong, "Minimax regret k-sink location problem in dynamic path networks", *Proc. AAIM* 2014

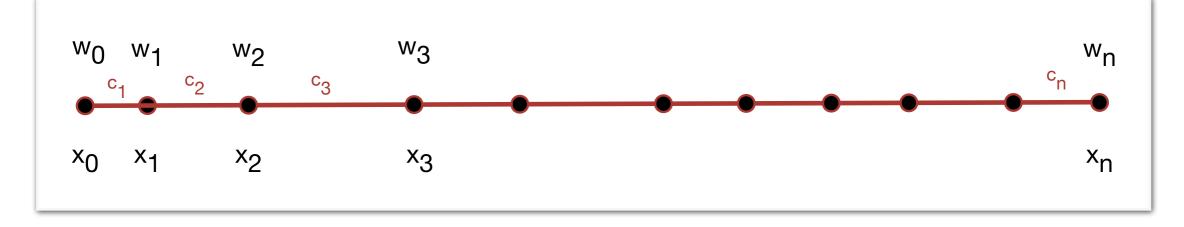
[9] H. Wang, "Minmax Regret 1-Facility Location on Uncertain Path Networks", *Proc. ISAAC 2013*, LNCS 8283, pp. 733-743, 2013.

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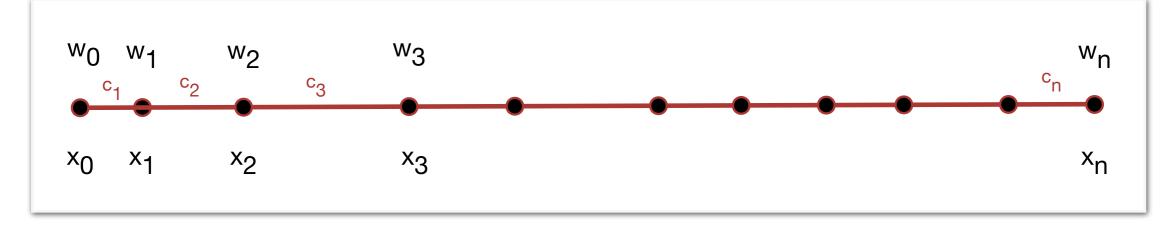
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Given a path, associated values  $C_{e, VV}$  and k, # of sinks,



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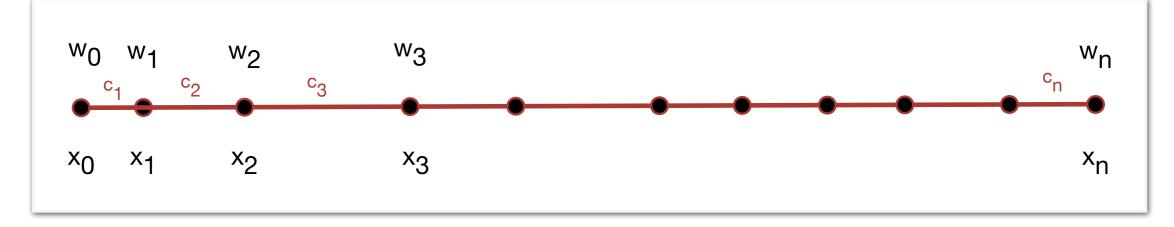
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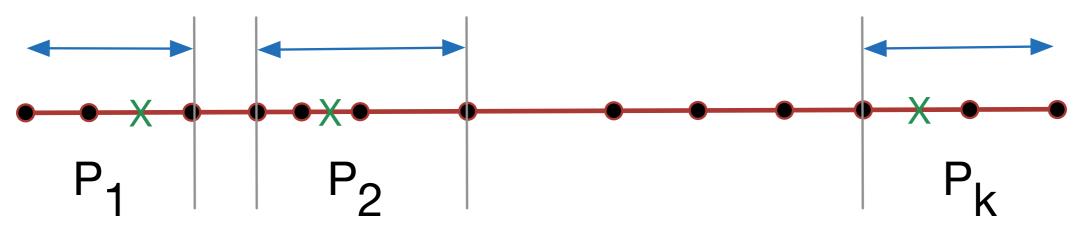
Find a partition into k-subpaths and a sink for each subpath, that minimizes the maximum evacuation time over all subpaths.

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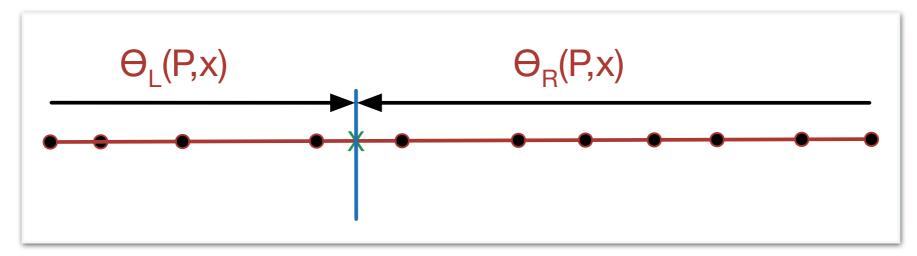
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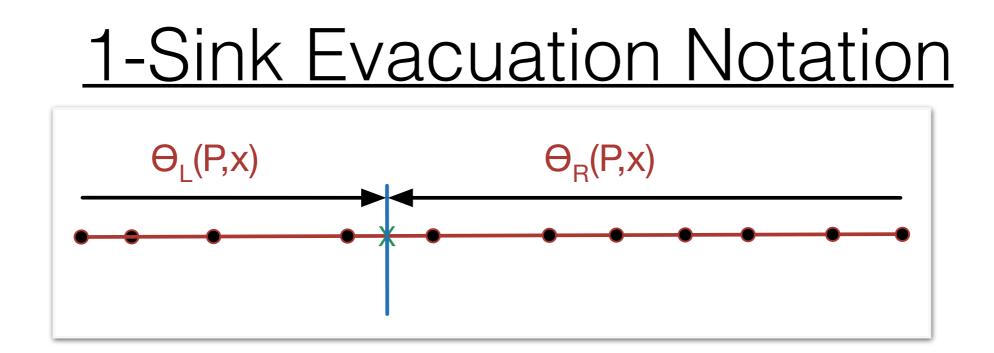


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**1-Sink Evacuation Notation** 





 $\Theta_{L}(P,x) = Time to evacuate all nodes to left of x on P to x$ 

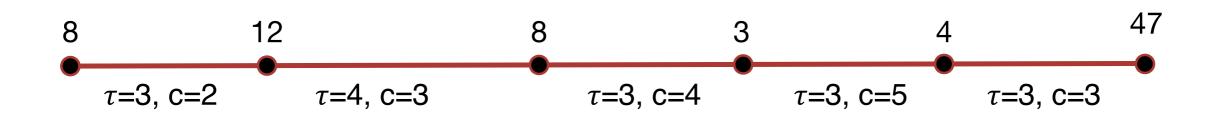
 $\Theta_{R}(P,x) = Time to evacuate all nodes to right of x on P to x$ 

#### $\Theta(P,x) = \max(\Theta_L(P,x), \Theta_R(P,x))$

- = Time to evacuate all nodes on P to x
- $\Theta^{1}(P) = \min_{\{x \in P\}} \Theta(P,x)$ 
  - = min evacuation time for P with one sink

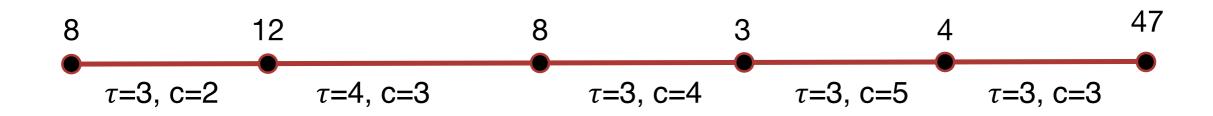


**Original Input:** 

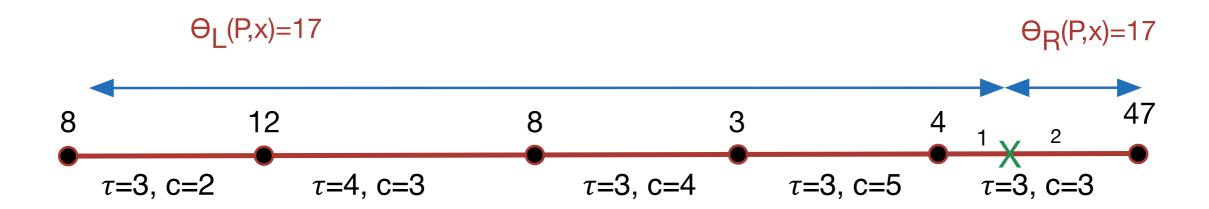




**Original Input:** 

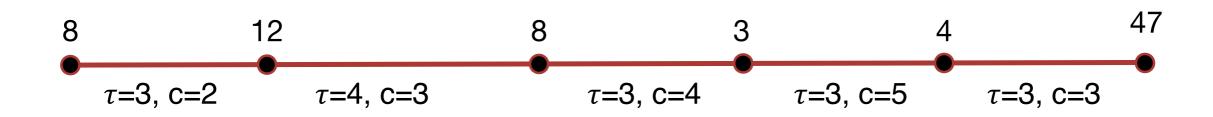


X is the sink location that minimizes Maximum Evacuation Time

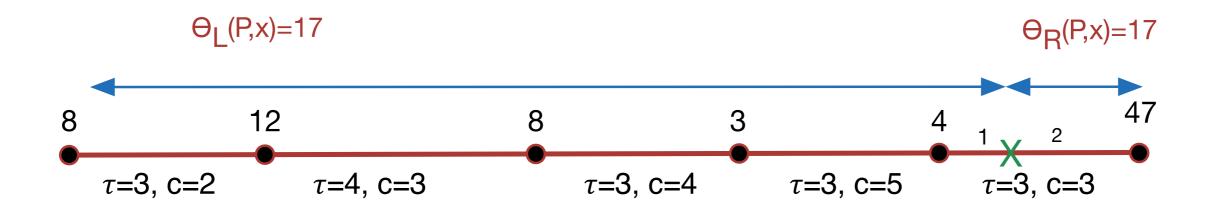




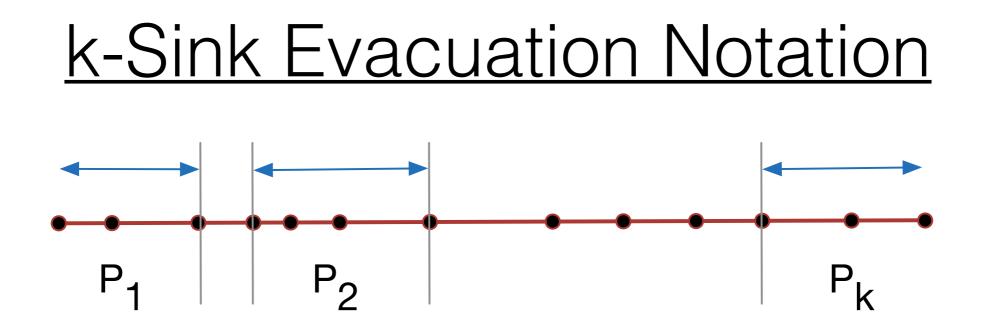
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X is the sink location that minimizes Maximum Evacuation Time



Note: Min evac-time sink location is NOT an original vertex. Can modify problem definition to require sink to be a vertex Algorithms remain almost the same

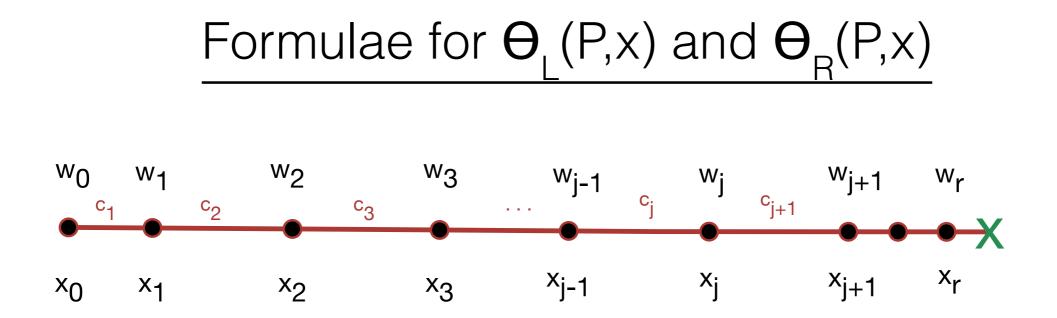


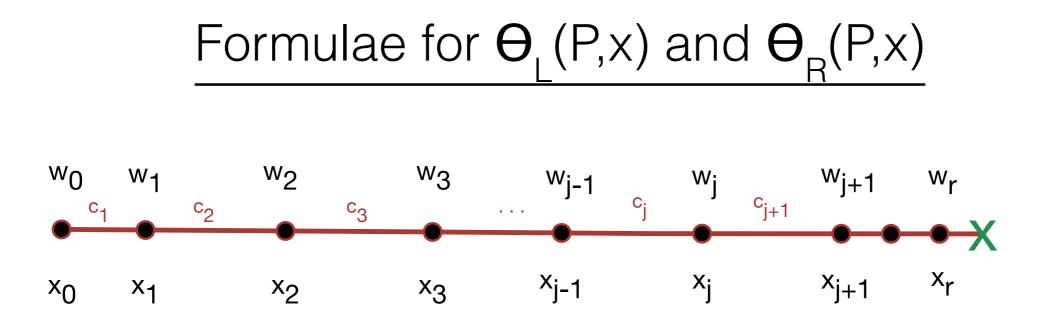
- Given Path P and integer k
- $\mathbb{P} = \{P_1, P_2, \dots, P_k\}$  is a partition of P into k-subpaths
- Given P, the evacuation time of P is max ( $\Theta^1(P_1), \Theta^1(P_2), \dots, \Theta^1(P_k)$ )
- Want to find

 $\Theta^{k}(P) = \min_{\mathbb{P}} \left( \max \left( \Theta^{1}(P_{1}), \Theta^{1}(P_{2}), \dots, \Theta^{1}(P_{k}) \right) \right)$ = Min k-sink evacuation time for P

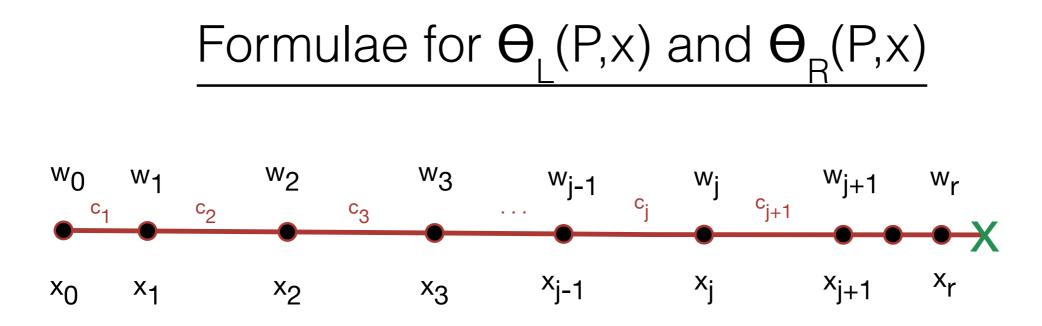
# Algorithm Development Sketch

- 1. Formulae for  $\Theta_L(P,x)$  and  $\Theta_L(P,x)$
- 2. => O(|P|) Algorithm for  $\Theta_L(P,x)$ ,  $\Theta_L(P,x)$
- 3. => O( $|P| \log |P|$ ) Algorithm for  $\Theta^{1}(P)$
- 4. => O(|P| log |P|) Algorithm that  $\forall \alpha > 0$ tests whether  $\Theta^{k}(P) \le \alpha$
- 5. => O(k|P| log<sup>2</sup> |P|) Algorithm for  $\Theta^{k}(P)$

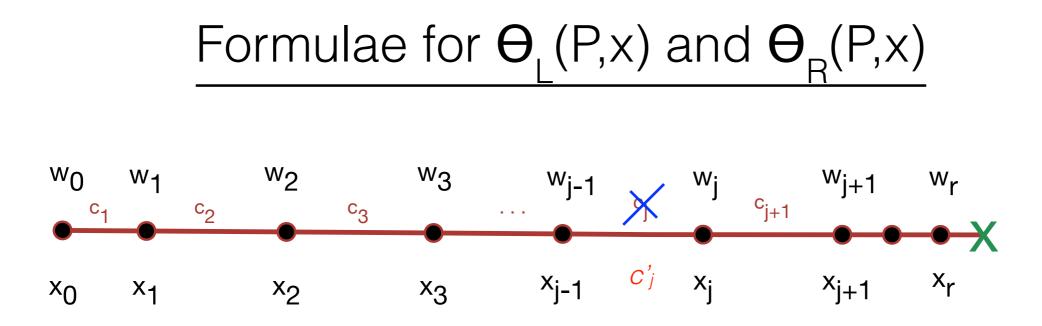




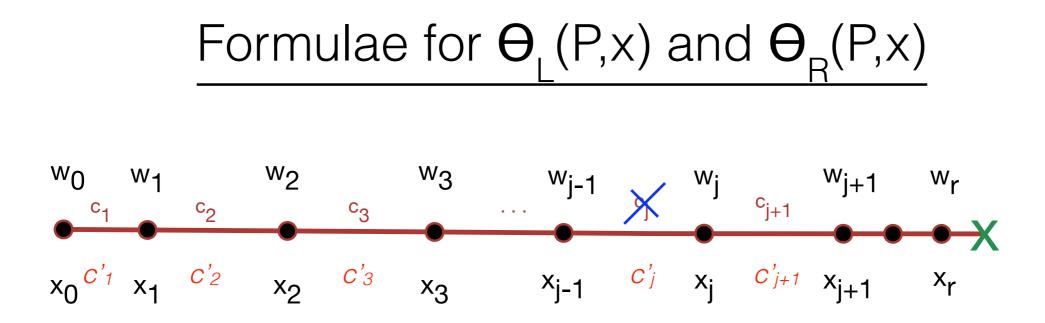
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- Lemma: Suppose  $C_j > C_{j+1}$ . Create P' by replacing  $C_j$  with  $C'_j = C_{j+1}$ . =>Then  $\Theta_L(P,x) = \Theta_L(P',x)$



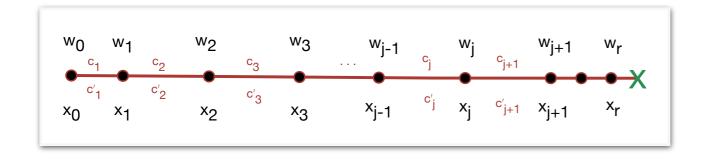
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- Corollary: May replace capacities by

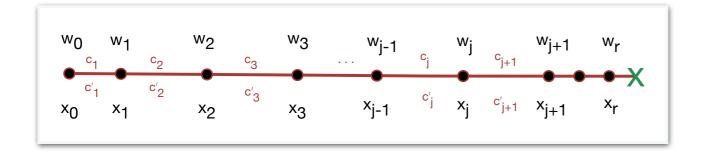
 $C'_{1} \leq C'_{2} \leq C'_{3} \leq ... \leq C'_{n}$ 

 $c_i' = \min_{i \le j \le r+1} c_j$ 



x<sub>r</sub> is last vertex to right of x

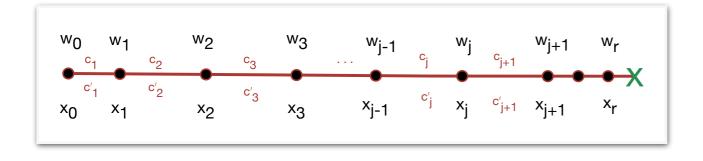
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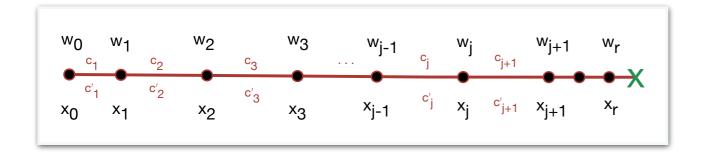


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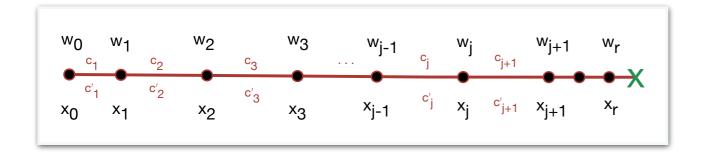
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Intuition: Analysis is on path P'

• Fix  $x_t$ .  $x-x_t$  is uncongested travel time from  $x_t$  to x



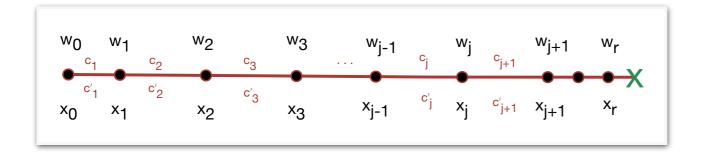
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- Fix  $x_t$ .  $x-x_t$  is uncongested travel time from  $x_t$  to x
- Remove all items to right of x<sub>t</sub>.
   Move all items to left of x<sub>t</sub> onto x<sub>t</sub>. x<sub>t</sub>'s new weight is W<sub>t</sub>



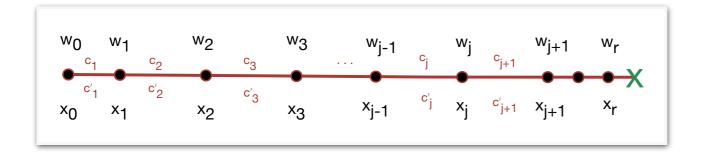
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- Fix  $x_t$ .  $x_t$  is uncongested travel time from  $x_t$  to x
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- # of groups leaving  $x_t$  is  $g = \Gamma W_t / c'_{t+1}$ . No congestion on path to x.



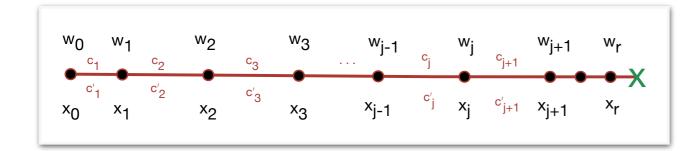
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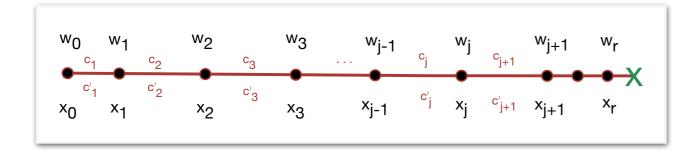
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- # of groups leaving  $x_t$  is  $g = \Gamma W_t / c'_{t+1} \gamma$ . No congestion on path to x.
- =>  $x-x_t+g-1$  is the exact evacuation time for items on  $x_t$



Path with  $c_i$  has same evac time as Path with  $c'_i = \min_{i \le j \le r+1} c_j$ 

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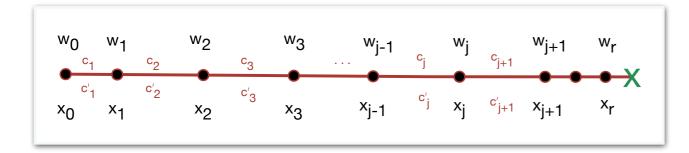


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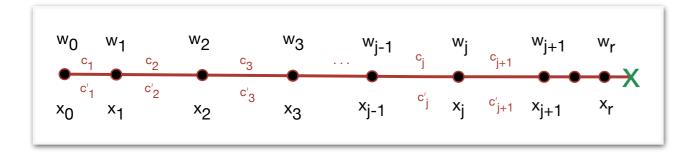
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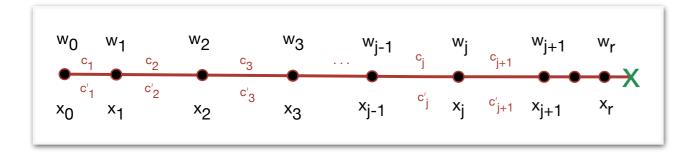
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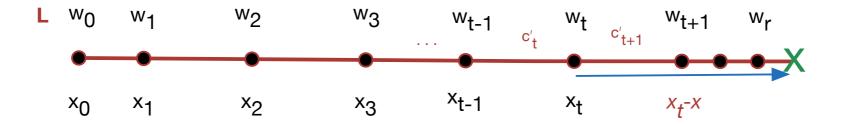


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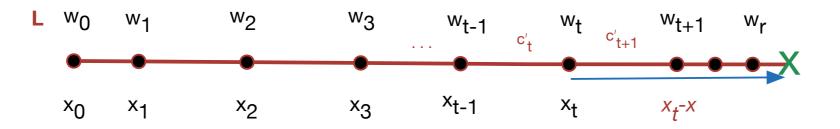
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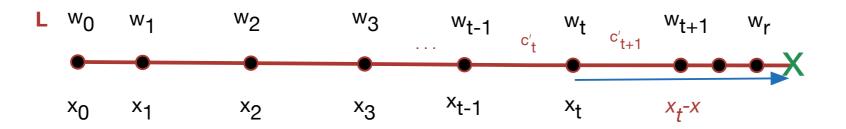


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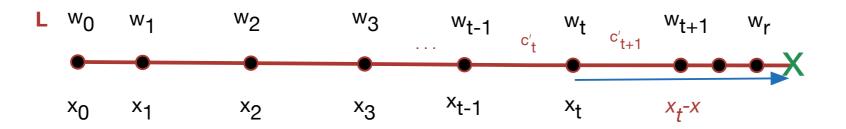


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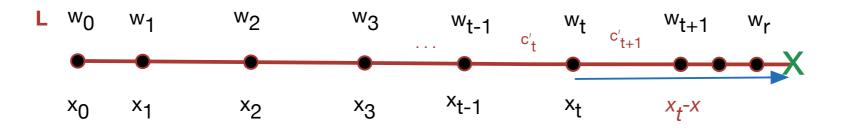


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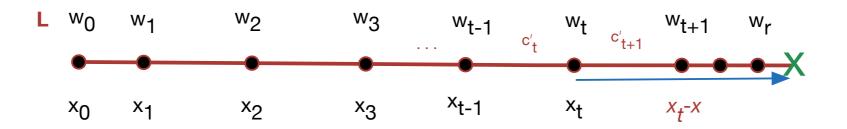
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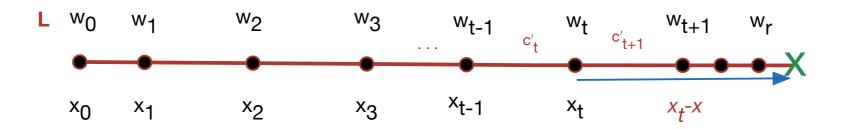
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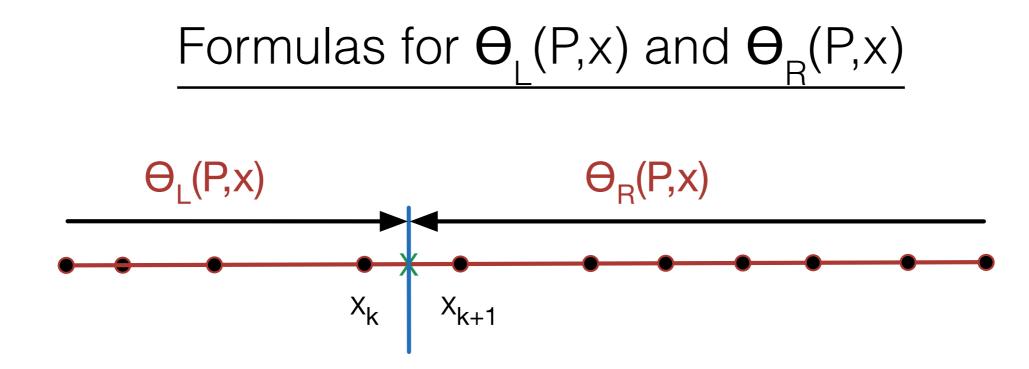
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# Algorithm Development Sketch

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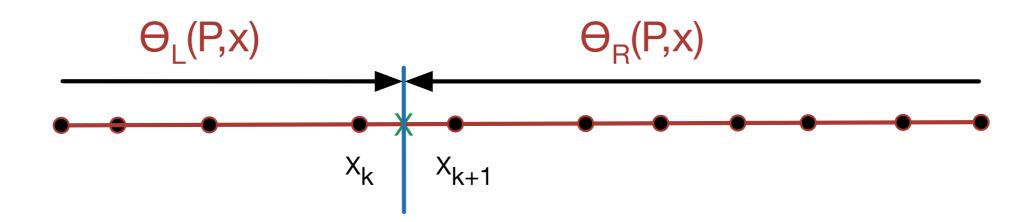


Theorem: Let k be s.t.  $x_k < x \le x_{k+1}$ . Then

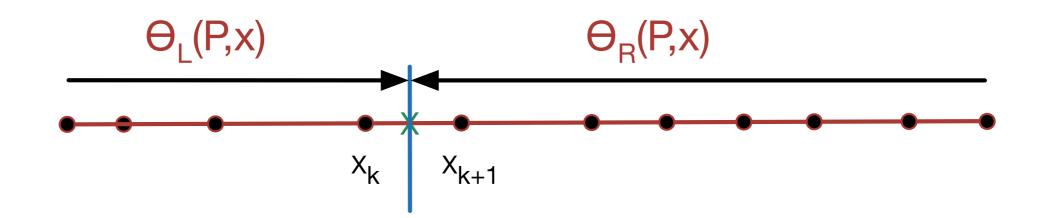
$$\Theta_L(P,x) = \max_{x_i < x} \left( (x - x_i) + \left\lceil \frac{\sum_{0 \le j \le t} w_j}{\min_{i+1 \le j \le k+1} c_j} \right\rceil + 1 \right) \qquad \Theta_R(P,x) = \max_{x_i > x} \left( (x_i - x) + \left\lceil \frac{\sum_{i \le j \le n} w_j}{\min_{k+1 \le j \le n} c_j} \right\rceil + 1 \right)$$

Corollary:  $\Theta_L(P,x)$  and  $\Theta_R(P,x)$  can be computed in O(|P|) time

# Formulas for $\Theta_{L}(P,x)$ and $\Theta_{R}(P,x)$

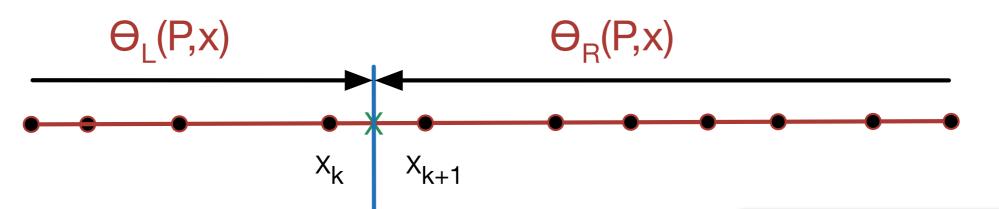


# Formulas for $\Theta_{L}(P,x)$ and $\Theta_{R}(P,x)$

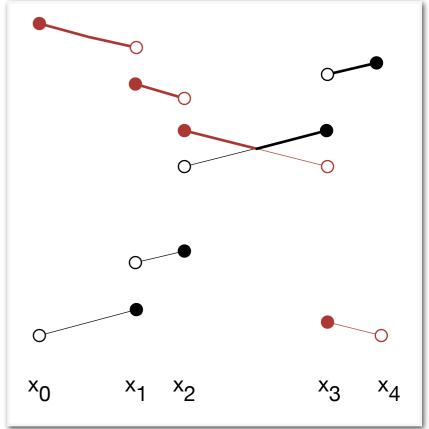


Claim 1:  $\Theta_L(P,x)$  ( $\Theta_R(P,x)$ ) is a monotonically increasing (decreasing) piecewise linear function in x.

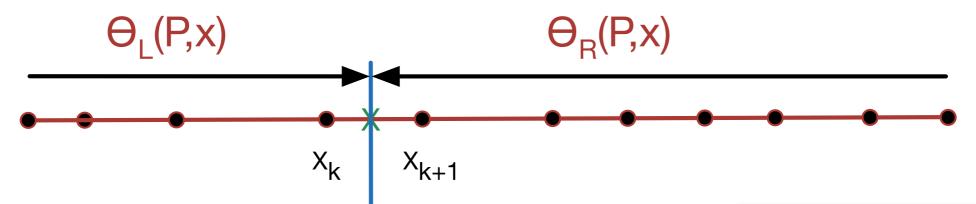
# Formulas for $\Theta_{P,x}$ and $\Theta_{R}(P,x)$



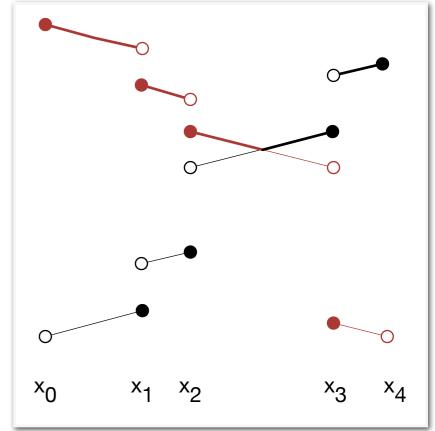
Claim 1:  $\Theta_L(P,x) (\Theta_R(P,x))$ is a monotonically increasing (decreasing) piecewise linear function in x.



# Formulas for $\Theta_{P,x}$ and $\Theta_{R}(P,x)$



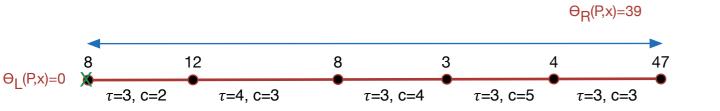
- Claim 1:  $\Theta_L(P,x)$  ( $\Theta_R(P,x)$ ) is a monotonically increasing (decreasing) piecewise linear function in x.
- Claim 2:  $\Theta(P,x) = \max(\Theta_L(P,x), \Theta_R(P,x))$ is a unimodal function. It decreases, achieves a unique minimum and then increases

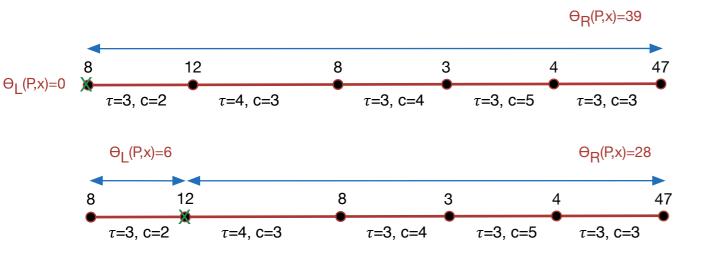


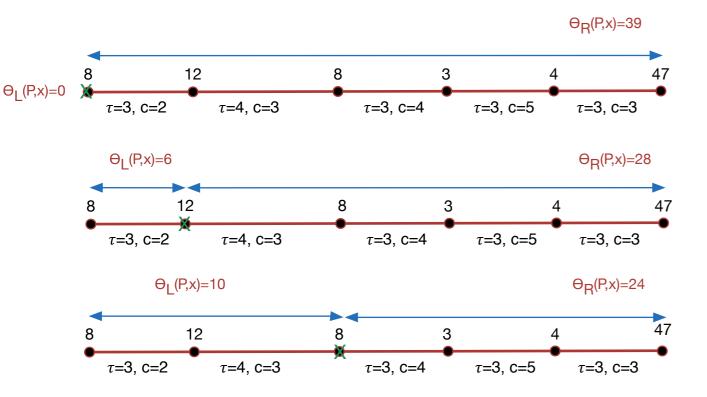
# Algorithm Development Sketch

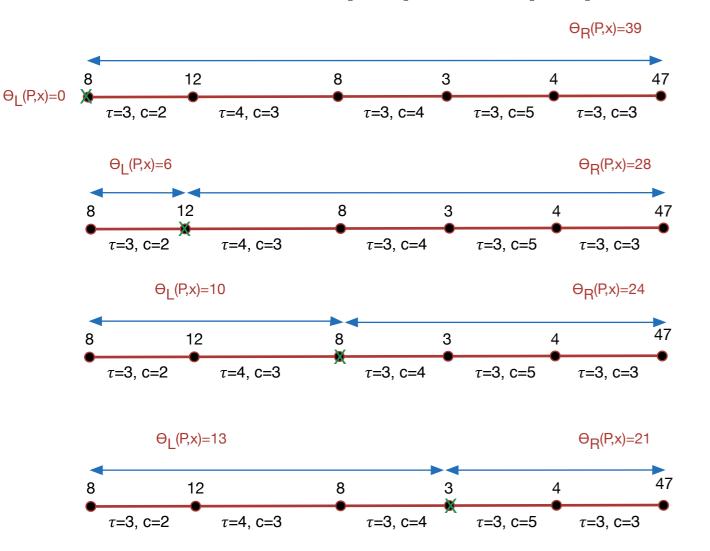
- 1. Formulae for  $\Theta_L(P,x)$  and  $\Theta_L(P,x)$
- 2. => O(|P|) Algorithm for  $\Theta_L(P,x)$ ,  $\Theta_L(P,x)$
- 3. => O( $|P| \log |P|$ ) Algorithm for  $\Theta^{1}(P)$
- 4. => O(|P| log |P|) Algorithm that  $\forall \alpha > 0$ tests whether  $\Theta^{k}(P) \le \alpha$
- 5. => O(k|P| log<sup>2</sup> |P|) Algorithm for  $\Theta^{k}(P)$

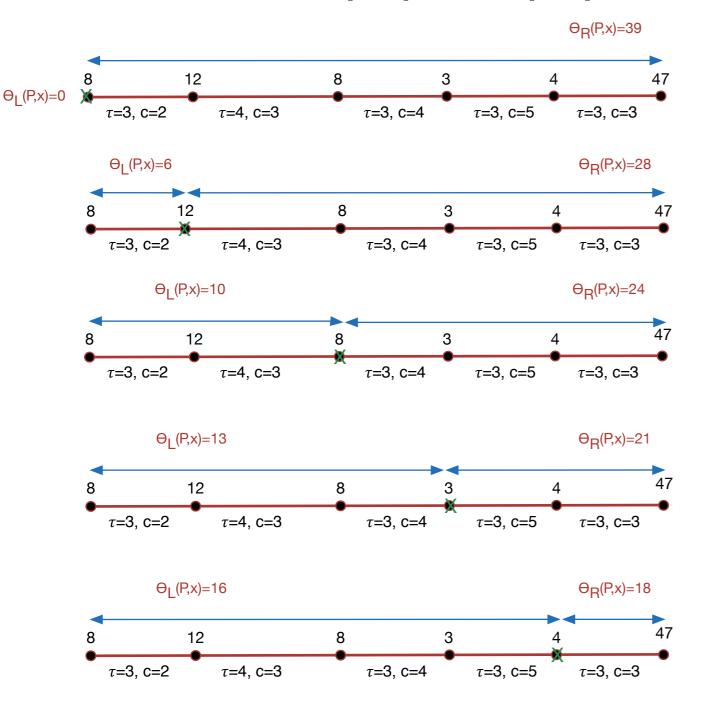
# An O( $|P| \log |P|$ ) Algorithm for $\Theta^{1}(P)$



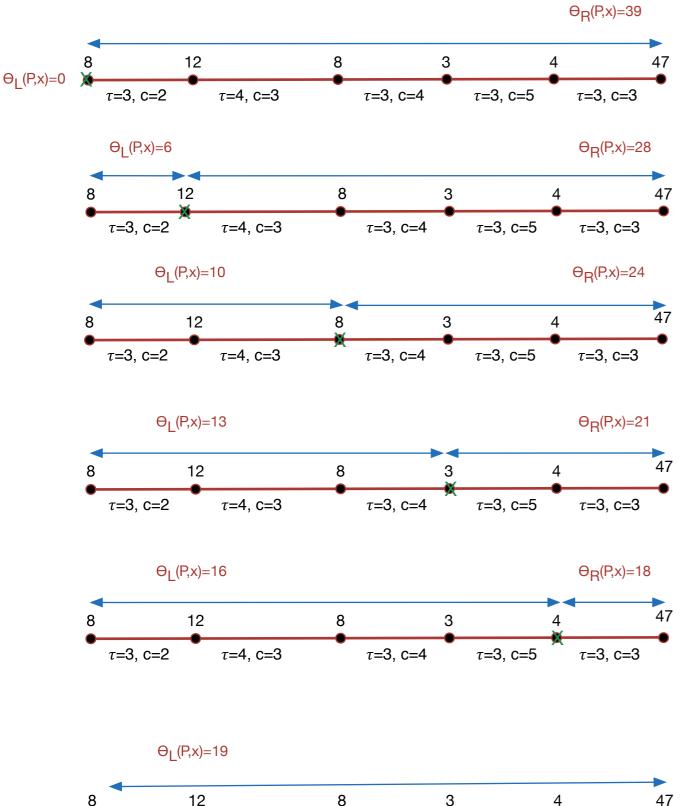




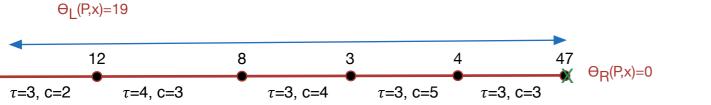


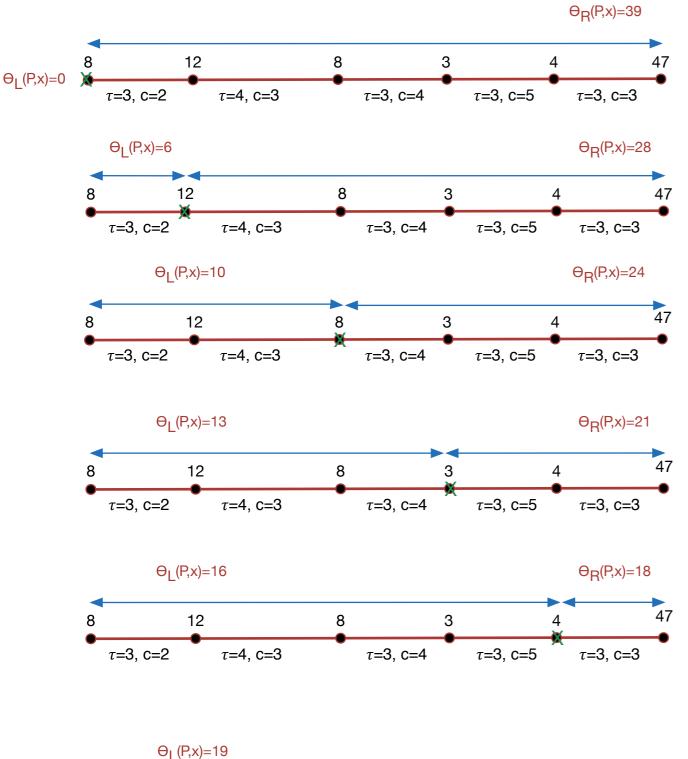


#### P) Algorithm for $\Theta^{1}(P)$ An

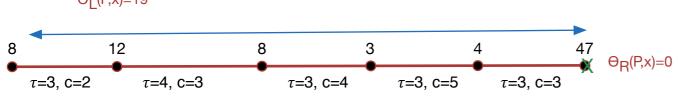


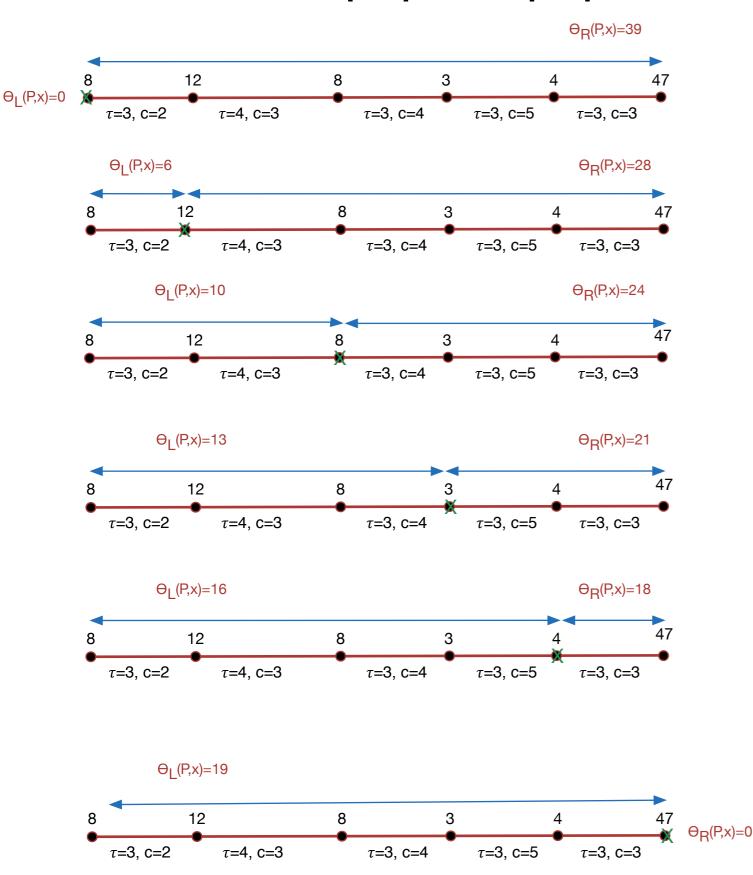




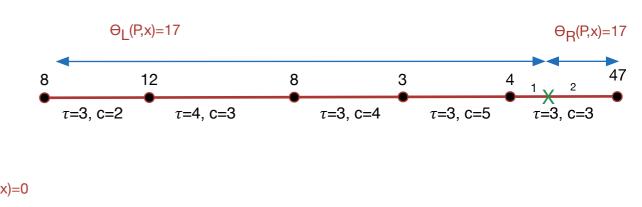


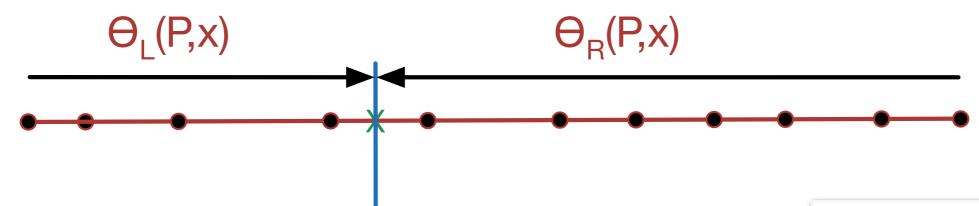
Search for where  $\Theta_L(P, X_i) < \Theta_R(P, X_i)$ switches to  $\Theta_L(P, X_i) > \Theta_R(P, X_i)$ . Optimum sink x is in the interval where the switch occurs



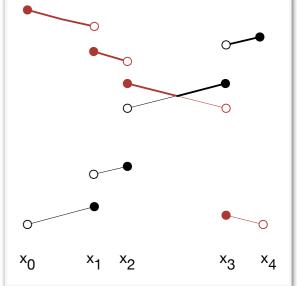


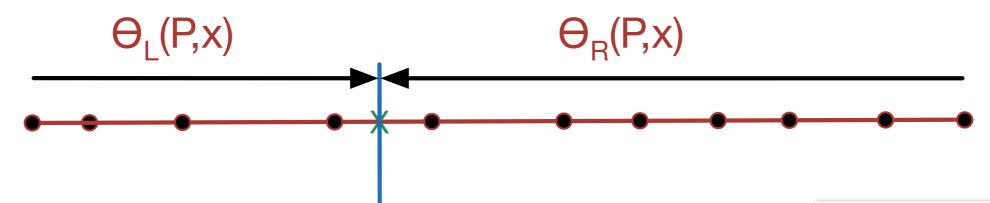
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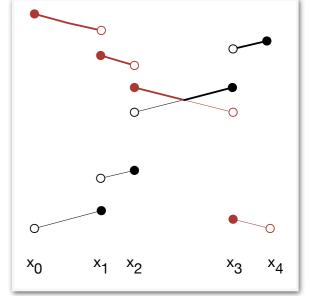
- **Corollary:** For fixed x,  $\Theta_L(P,x)$ ,  $\Theta_R(P,x)$  can be computed in O(|P|) time
- **Claim 2:**  $\Theta(P,x) = \max(\Theta_L(P,x), \Theta_R(P,x))$  is a unimodal function.





**Corollary:** For fixed x,  $\Theta_L(P,x)$ ,  $\Theta_R(P,x)$  can be computed in O(|P|) time

**Claim 2:**  $\Theta(P,x) = \max(\Theta_L(P,x), \Theta_R(P,x))$  is a unimodal function.



**Algorithm:** Using O(|P| log|P|) time binary search Find x<sub>t</sub> s.t  $\Theta^1(P) = \Theta(P,x)$  satisfying x<sub>t</sub> < x ≤ x<sub>t+1</sub>. Gives  $\Theta_L(P, x_t)$ ,  $\Theta_R(P, x_t)$ ,  $\Theta_L(P, x_{t+1})$ ,  $\Theta_R(P, x_{t+1})$ In O(1) time do a linear interpolation to find x.

# Algorithm Development Sketch

- 1. Formulae for  $\Theta_L(P,x)$  and  $\Theta_L(P,x)$
- 2. => O(|P|) Algorithm for  $\Theta_L(P,x)$ ,  $\Theta_L(P,x)$
- 3. => O( $|P| \log |P|$ ) Algorithm for  $\Theta^{1}(P)$
- 4. => O(|P| log |P|) Algorithm that  $\forall \alpha > 0$ tests whether  $\Theta^{k}(P) \le \alpha$
- 5. => O(k|P| log<sup>2</sup> |P|) Algorithm for  $\Theta^{k}(P)$

### An O( $|P| \log |P|$ ) Testing Algorithm for $\Theta^{k}(P)$ [1]

Set  $P_{i,j}$  to be path from  $x_i$  to  $x_j$  and  $P_{i,x}$  path from  $x_i$  to x. Set |P| to be # of vertices in P. An O( $|P| \log |P|$ ) Testing Algorithm for  $\Theta^{k}(P)$  [1]

Set  $P_{i,j}$  to be path from  $x_i$  to  $x_j$  and  $P_{i,x}$  path from  $x_i$  to x. Set |P| to be # of vertices in P.

<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(|P_{i,n}| | Og | P_{i,n}|)$  time An O( $|P| \log |P|$ ) Testing Algorithm for  $\Theta^{k}(P)$  [1] Set P<sub>i,i</sub> to be path from x<sub>i</sub> to x<sub>i</sub> and P<sub>i,x</sub> path from x<sub>i</sub> to x.

Set |P| to be # of vertices in P.

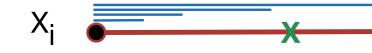
<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(IP_{i,n} I I Og IP_{i,n} I)$  time

<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \le \alpha$ in  $O(|P_{i,j}| | \log |P_{i,j}|)$  time An O( $|P| \log |P|$ ) Testing Algorithm for  $\Theta^{k}(P)$  [1] Set P<sub>i,j</sub> to be path from x<sub>i</sub> to x<sub>j</sub> and P<sub>i,x</sub> path from x<sub>i</sub> to x. Set |P| to be # of vertices in P.

<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(IP_{i,n} I I Og IP_{i,n} I)$  time

<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \le \alpha$ in  $O(IP_{i,j} | Iog | P_{i,j} |)$  time

Proof Idea (Lemma): In  $O(IP_{i,x} I \text{ log } I P_{i,x} I)$  use linear formula for  $\Theta_L(P_{i,n},x) \&$  doubling search technique to find max x s.t.  $\Theta_L(P_{i,n},x) \leq \alpha$ .



An O( $|P| \log |P|$ ) Testing Algorithm for  $\Theta^{k}(P)$  [2] Set P<sub>i,i</sub> to be path from x<sub>i</sub> to x<sub>i</sub> and P<sub>i,x</sub> path from x<sub>i</sub> to x.

Set |P| to be # of vertices in P.

<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(|P_{i,n}| | Og | P_{i,n}|)$  time

<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^{1}(P_{i,j}) \leq \alpha$ in  $O(IP_{i,j} | Iog | P_{i,j} |)$  time

 $\begin{array}{l} \underline{Proof \ Idea \ (Lemma):} \\ \text{In } \textit{O(IP}_{i,x} \ \textit{I} \ \textit{Iog \ I} \ \textit{P}_{i,x} \ \textit{I}) \\ \text{use linear formula for } \varTheta_L(\mathsf{P}_{i,n},\mathsf{x}) & \& \\ \text{doubling search technique to find max x s.t. } \varTheta_L(\mathsf{P}_{i,n},\mathsf{x}) \leq \mathfrak{a}. \\ \text{Similarly, in } \textit{O(IP}_{x,j} \ \textit{I \ Iog \ I} \ \textit{P}_{x,j} \ \textit{I}), \\ \end{array}$ 

#### An O( $|P| \log |P|$ ) Testing Algorithm for $\Theta^{k}(P)$ [3]

Set  $P_{i,j}$  to be path from  $x_i$  to  $x_j$  and  $P_{i,x}$  path from  $x_i$  to x. Set |P| to be # of vertices in P.

- <u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(|P_{i,n}| | Og | P_{i,n}|)$  time
- <u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \leq \alpha$ in O(I P<sub>i,j</sub> | log | P<sub>i,j</sub> |) time

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<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \le \alpha$ in O(I P<sub>i,j</sub> I log I P<sub>i,j</sub> I) time

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#### An O( $|P| \log |P|$ ) Testing Algorithm for $\Theta^{k}(P)$ [4]

Set  $P_{i,j}$  to be path from  $x_i$  to  $x_j$  and  $P_{i,x}$  path from  $x_i$  to x. Set |P| to be # of vertices in P.

<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(|P_{i,n}| | Og | P_{i,n}|)$  time

X<sub>i</sub> a evac X<sub>j</sub> X<sub>j+1</sub>

a evac

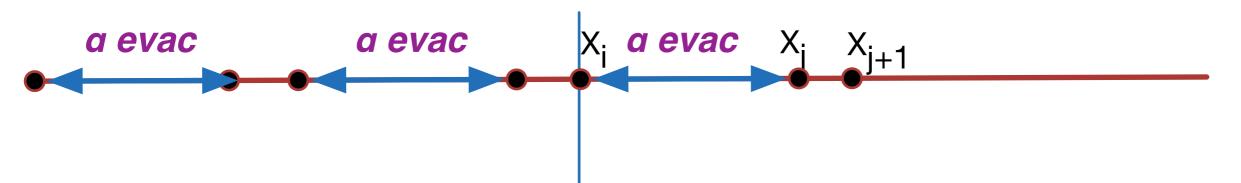
<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \le \alpha$ in O(I P<sub>i,j</sub> I log I P<sub>i,j</sub> I) time

#### An O( $|P| \log |P|$ ) Testing Algorithm for $\Theta^{k}(P)$ [5]

Set  $P_{i,j}$  to be path from  $x_i$  to  $x_j$  and  $P_{i,x}$  path from  $x_i$  to x. Set |P| to be # of vertices in P.

<u>Thm:</u>  $\forall \alpha > 0$ , k>0 and i,j can test if  $\Theta^{k}(P_{i,n}) \leq \alpha$ in  $O(|P_{i,n}| | Og | P_{i,n}|)$  time

<u>Lemma:</u>  $\forall \alpha > 0$ , and i can find maximum j s.t.  $\Theta^1(P_{i,j}) \le \alpha$ in O(I P<sub>i,j</sub> I log I P<sub>i,j</sub> I) time



# Algorithm Development Sketch

- 1. Formulae for  $\Theta_L(P,x)$  and  $\Theta_L(P,x)$
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- $\Theta^{1}(P_{0,j})$  ( $\Theta^{k-1}(P_{j+1,n})$ ) is non decreasing (increasing) in j
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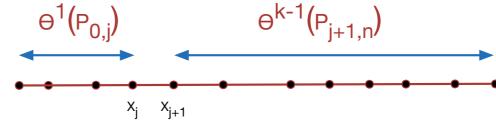
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  - $O(|P_{0,j}| \log |P_{0,j}|) + O(|P_{j+1,n}| \log |P_{j+1,n}|) = O(|P| \log |P|)$

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  - Using previous algorithms for k=1 and testing
  - $O(|P_{0,j}| \log |P_{0,j}|) + O(|P_{j+1,n}| \log |P_{j+1,n}|) = O(|P| \log |P|)$
- Binary search to find largest j s.t.  $\Theta^{k-1}(P_{j+1,n}) > \Theta^{1}(P_{0,j})$ • O(IPI log<sup>2</sup>IPI) time

#### An O(k $|P| \log^2 |P|$ ) Algorithm for $\Theta^k(P)$ [2]

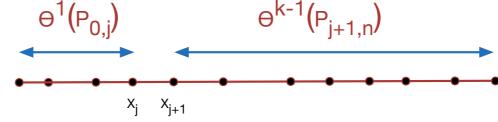
•  $\Theta^{k}(P) = \Theta^{k_{j}} = \min_{j} (\Theta^{1}(P_{0,j}), \Theta^{k-1}(P_{j+1,n}))$  $\Theta^{1}(P_{0,j}), \Theta^{k-1}(P_{j+1,n})$  increase/decrease in j  $\Theta^{k_{j}}$  "unimodal" in j



• => O(IPI log<sup>2</sup>IPI) time Binary search to find largest j s.t  $\Theta^{k-1}(P_{j+1,n}) > \Theta^{1}(P_{0,j})$ 

#### An O(k $|P| \log^2 |P|$ ) Algorithm for $\Theta^k(P)$ [2]

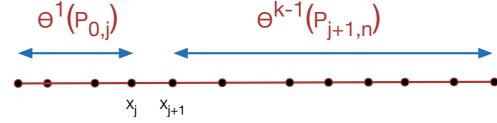
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- => O(IPI log<sup>2</sup>IPI) time Binary search to find largest j s.t  $\Theta^{k-1}(P_{j+1,n}) > \Theta^{1}(P_{0,j})$ 
  - $\Theta^{k}(P)$  is min of  $\Theta^{1}(P_{0,j+1})$  and  $\Theta^{k-1}(P_{j+1,n})$

#### An O(k $|P| \log^2 |P|$ ) Algorithm for $\Theta^k(P)$ [2]

•  $\Theta^{k}(P) = \Theta^{k_{j}} = \min_{j} (\Theta^{1}(P_{0,j}), \Theta^{k-1}(P_{j+1,n}))$  $\Theta^{1}(P_{0,j}), \Theta^{k-1}(P_{j+1,n})$  increase/decrease in j  $\Theta^{k_{j}}$  "unimodal" in j

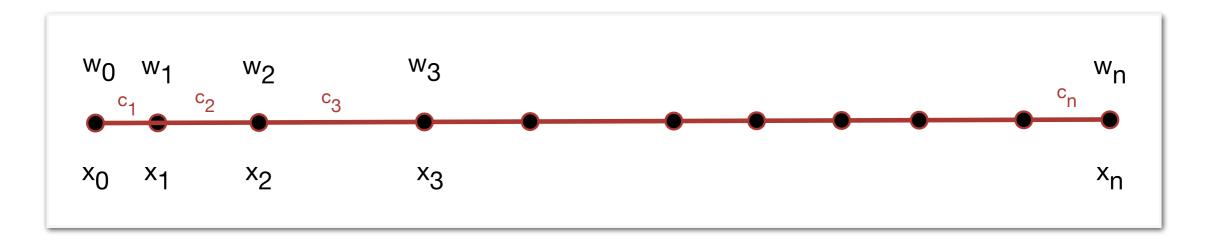


- => O(IPI log<sup>2</sup>IPI) time Binary search to find largest j s.t  $\Theta^{k-1}(P_{j+1,n}) > \Theta^{1}(P_{0,j})$ 
  - $\Theta^{k}(P)$  is min of  $\Theta^{1}(P_{0,j+1})$  and  $\Theta^{k-1}(P_{j+1,n})$
  - • $\Theta^{k-1}(P_{j+1,n})$  can be found recursively
    - stop when k=1 (know how to solve)
    - Total algorithm is k O(IPI log<sup>2</sup> IPI) = O( k IPI log<sup>2</sup> IPI)

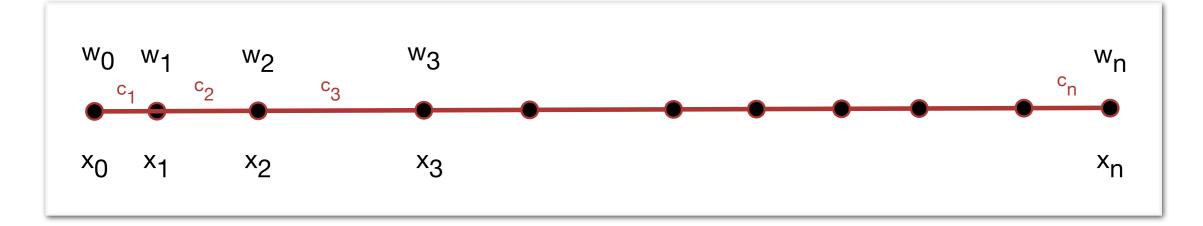
# <u>Outline</u>

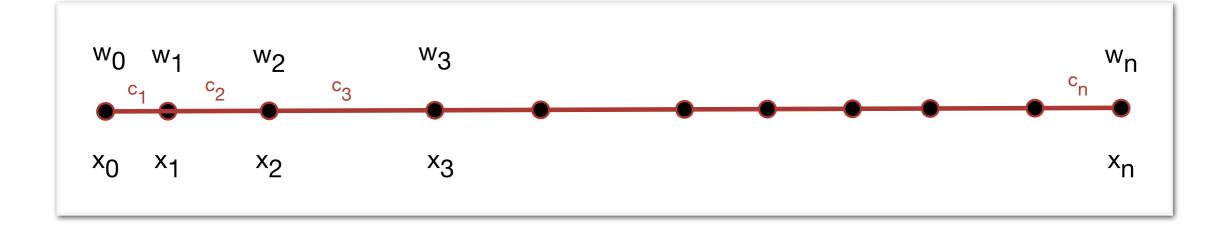
- Dynamic Flow Networks
- Congestion in Dynamic Flows
- Evacuation Flows
  - Problem Definitions
  - Known Results
- Example Algorithm 1: k-Sink Evacuation on a Path
- Example Algorithm 2: 1-sink Min-Max Regret Evacuation on a Path with uniform capacity
- Open Problems

In the regret version of the problem, input still provides  $C_{e_{i}} \tau_{e_{i}} k$ 

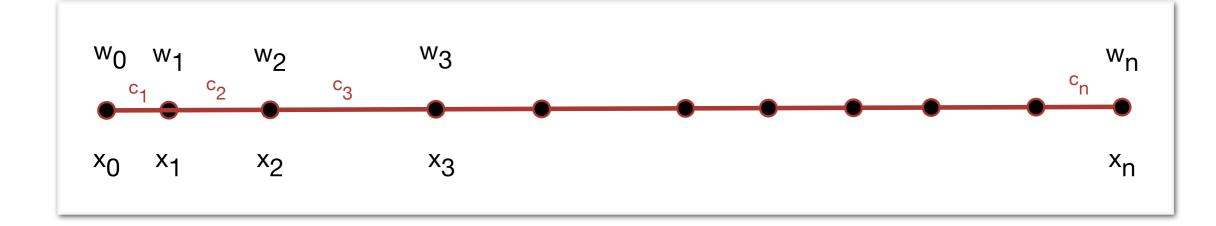


- •But  $W_{\nu}$  is no longer explicitly input. Instead, each vertex has an input range  $W_{\nu} \in [W'_{\nu}, W'_{\nu}]$
- Algorithm needs to find robust evacuation protocol that works least badly against adversarial input.
- Min-Max Regret is one standard way of modelling robustness

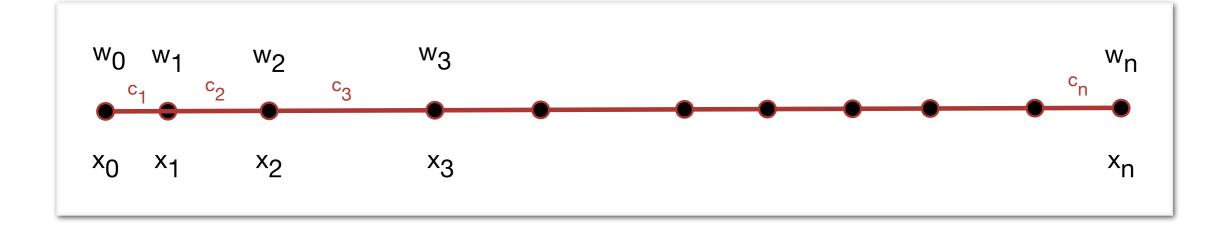




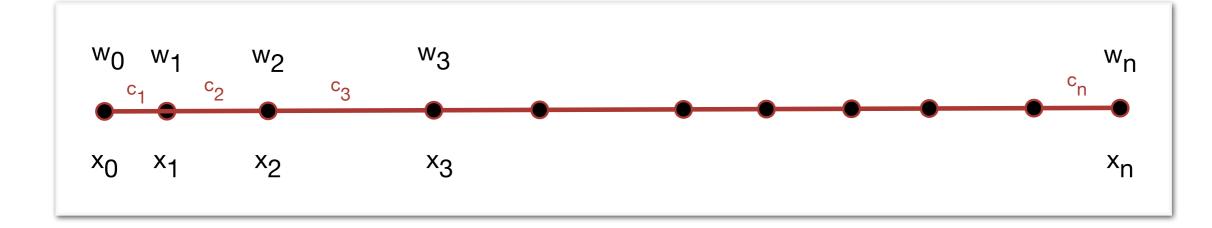
S = ∏<sub>v</sub>[w'<sub>v</sub>,W'<sub>v</sub>] is the set of all feasible scenarios.
 An s ∈ S is of the form s= (w<sub>1</sub>, ..., w<sub>n</sub>)



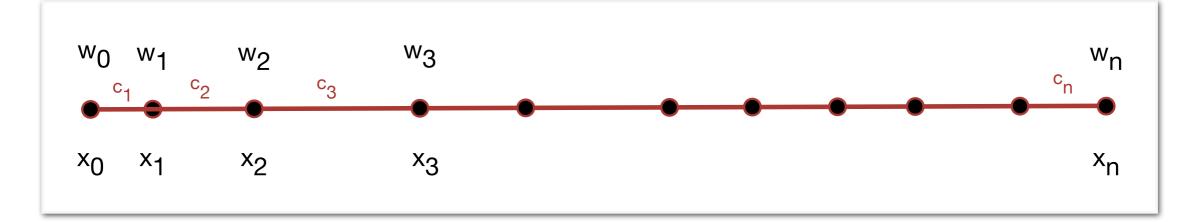
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- • $\Theta(P,x,s)$  = evacuation time of P to x in scenario s
- • $\Theta^{1}(P,s)$  = min evacuation time of P in scenario s



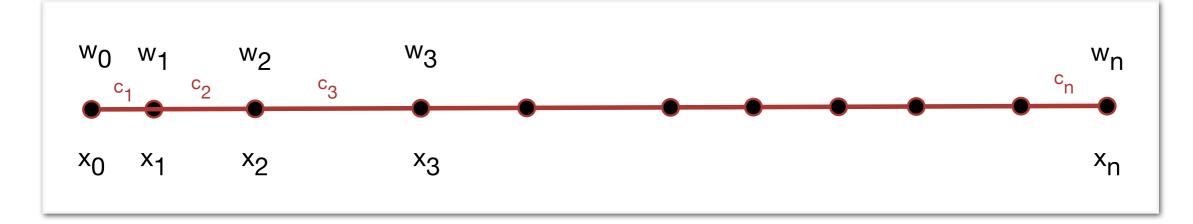
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- $R(x,s) = Regret of x under scenario s = \Theta(P,x,s) \Theta^{1}(P,s)$
- $R(x) = Max regret of x = max_s R(x,s)$



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- $R(x,s) = Regret of x under scenario s = \Theta(P,x,s) \Theta^{1}(P,s)$
- $R(x) = Max regret of x = max_s R(x,s)$
- •The Min-max regret of P is minimum regret over all x  $MMR(P) = Min_x R(x)$

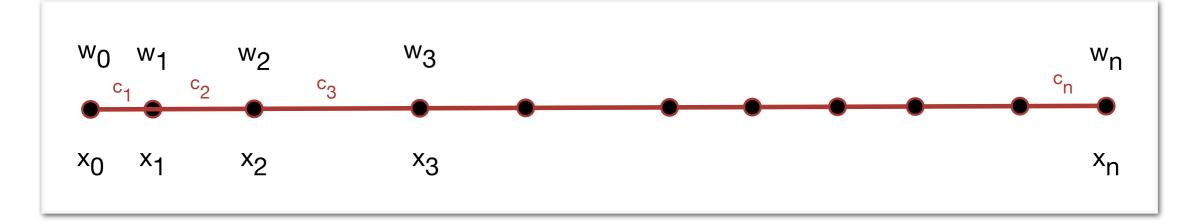


 $R(x,s) = \Theta(P,x,s) - \Theta^{1}(P,s) \qquad R(x) = Max_{s} R(x,s)$  $MMR(P) = Min_{x} R(x) = Min_{x} Max_{s} \{\Theta(P,x,s) - \Theta^{1}(P,s)\}$ 



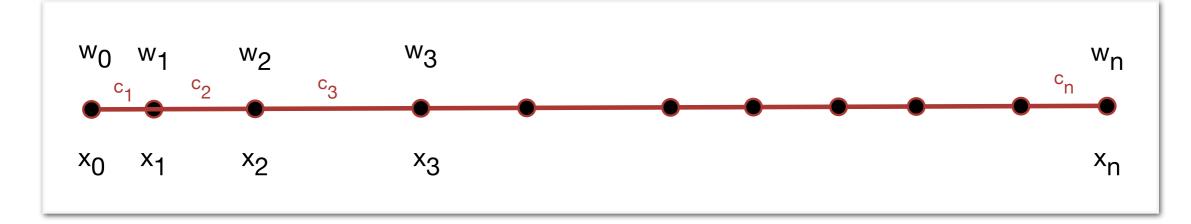
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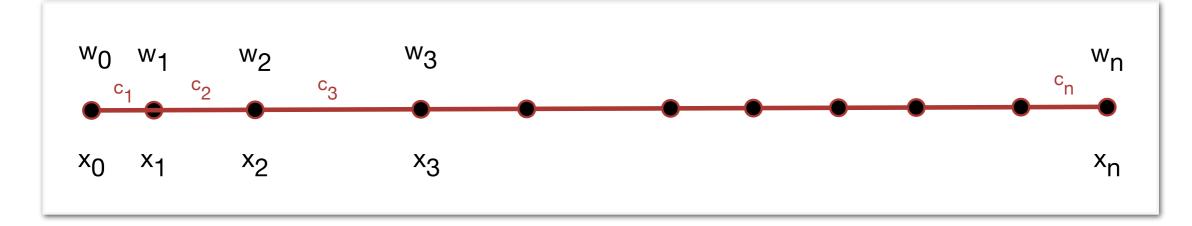
 $\begin{aligned} \mathsf{R}(\mathsf{x},\mathsf{s}) &= \Theta(\mathsf{P},\mathsf{x},\mathsf{s}) - \Theta^{1}(\mathsf{P},\mathsf{s}) & \mathsf{R}(\mathsf{x}) &= \mathsf{Max}_{\mathsf{s}} \ \mathsf{R}(\mathsf{x},\mathsf{s}) \\ \mathsf{MMR}(\mathsf{P}) &= \mathsf{Min}_{\mathsf{x}} \ \mathsf{R}(\mathsf{x}) &= \mathsf{Min}_{\mathsf{x}} \ \mathsf{Max}_{\mathsf{s}} \ \{\Theta(\mathsf{P},\mathsf{x},\mathsf{s}) - \Theta^{1}(\mathsf{P},\mathsf{s})\} \end{aligned}$ 

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- Can show that, for uniform capacities, there are only O(n) scenarios s at which any R(x) attains maximum



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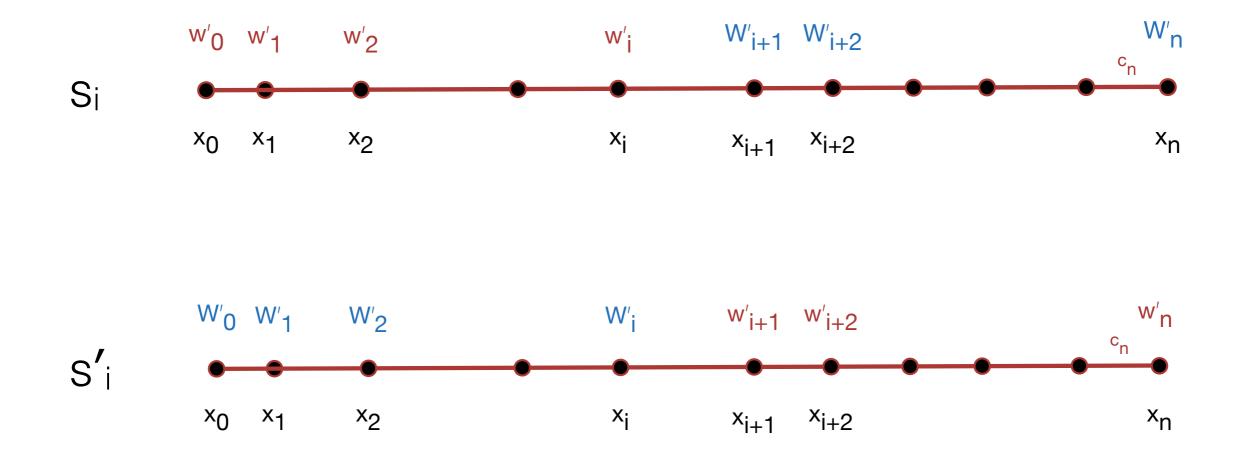
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- This, permits evaluating MMR(P) in polynomial time
  - further observations reduce this to O(n log n)
- Existence of O(n) scenarios not totally surprising
  - Same phenomenon arises in MMR for medians on a line

 $\begin{array}{l} \underline{\text{Min-Max Regret Evacuation on a Path}}\\ R(x,s) = \Theta(P,x,s) - \Theta^{1}(P,s) & R(x) = Max_{s} R(x,s)\\ \underline{\text{MMR}(P)} = Min_{x} R(x) = Min_{x} Max_{s} \left\{\Theta(P,x,s) - \Theta^{1}(P,s)\right\}\\ \end{array}$ There are 2n scenarios at which R(s,x) attains max. These are s<sub>i</sub> in which w<sub>j</sub> = w'<sub>j</sub> for j ≤ i & w<sub>j</sub> = W'<sub>j</sub> for i > j and s'<sub>i</sub> in which w<sub>j</sub> = W'<sub>j</sub> for j ≤ i & w'<sub>j</sub> = w'<sub>j</sub> for i > j



 $\begin{array}{l} \underline{\text{Min-Max Regret Evacuation on a Path}}\\ R(s,x) = \Theta(P,x,s) - \Theta^{1}(P,s) & R(x) = Max_{s} R(s,x)\\ \underline{\text{MMR}(P)} = Min_{x} R(x) = Min_{x} Max_{s} \left\{\Theta(P,x,s) - \Theta^{1}(P,s)\right\}\\ \end{array}$ There are 2n scenarios at which R(s,x) attains max.

These are  $s_i$  in which  $w_j = w'_j$  for  $j < i \& w_j = W'_j$  for i > jand  $s'_i$  in which  $w_j = W'_j$  for  $j < i \& w'_j = w'_j$  for i > j

- k-sink uniform capacity on path have O(n<sup>3</sup>) worst case
   scenarios => O(kn<sup>3</sup>logn) time time algorithm
- •1-sink uniform capacity on tree have  $O(n^2)$  worst case MMR scenarios =>  $O(n^2 \log^2 n)$  time algorithm
- NOTHING is known about any other cases.
   In particular, even on path no structure for MMR solution for 1-sink gen cap problem => no polynomial time alg

# <u>Outline</u>

- Dynamic Flow Networks
- Congestion in Dynamic Flows
- Evacuation Flows
  - Problem Definitions
  - Known Results
- Example Algorithm 1: k-Sink Evacuation on a Path
- Example Algorithm 2: 1-sink Min-Max Regret Evacuation on a Path with uniform capacity
- Open Problems

# <u>Open Frontier Problems</u>

- G a General Graph, k>1 (NP Hard)
  - Find approximation algorithm or PTAS
- G a General Graph, k=1
  - Solve exactly or prove NP-Hard
  - Even if the one sink is given
- G a tree with uniform capacities, k>1
  - solve min-max regret k-sink problem
- G a path (tree) tree with general capacities, k=1
  - solve min-max regret 1-sink problem
- For Robust Computation
  - Replace Min-Max-Regret by size distribution on nodes and find sink(s) that minimize expected evacuation time.