

A Constant Approximation for Maximum Throughput Multicommodity Routing

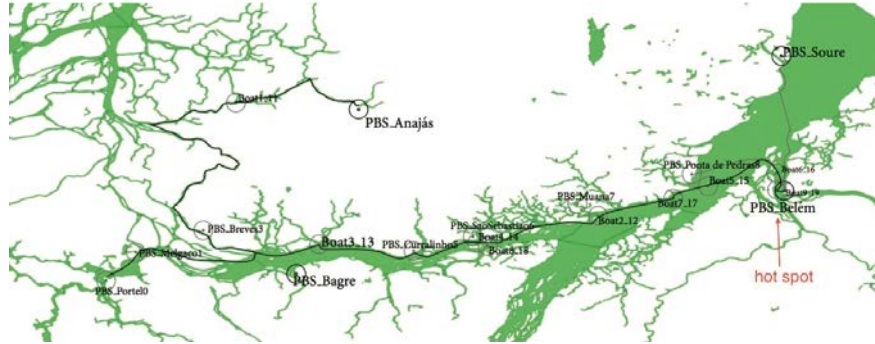
Mengxue Liu (ASU), Andrea Richa (ASU), *Stefan Schmid (Uni Vienna)*, Matthias Rost (TU Berlin)



An aerial photograph showing a vibrant blue river meandering through a vast, dense green forest. The forest canopy is thick and textured, with varying shades of green. The river is a bright, clear blue, contrasting sharply with the surrounding greenery. The river flows from the top center towards the bottom center of the frame, with several bends and curves.

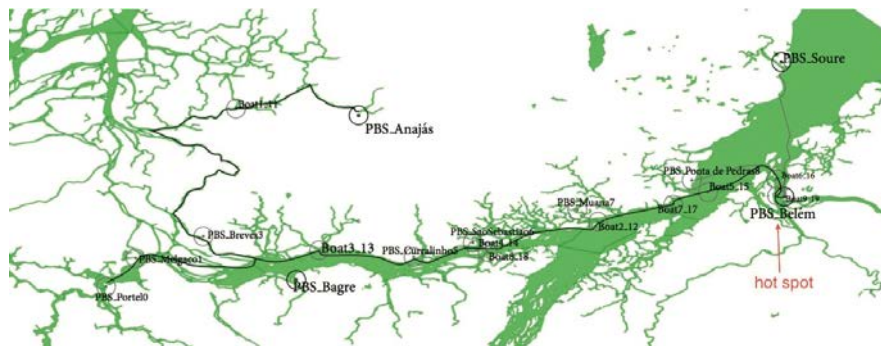
Original Motivation: Health Care Project in Amazon Riverine

Amazon Riverine



- Complex system of rivers...
- ... with poor **communication** infrastructure

Amazon Riverine



How to deliver
health care data to
hospitals?

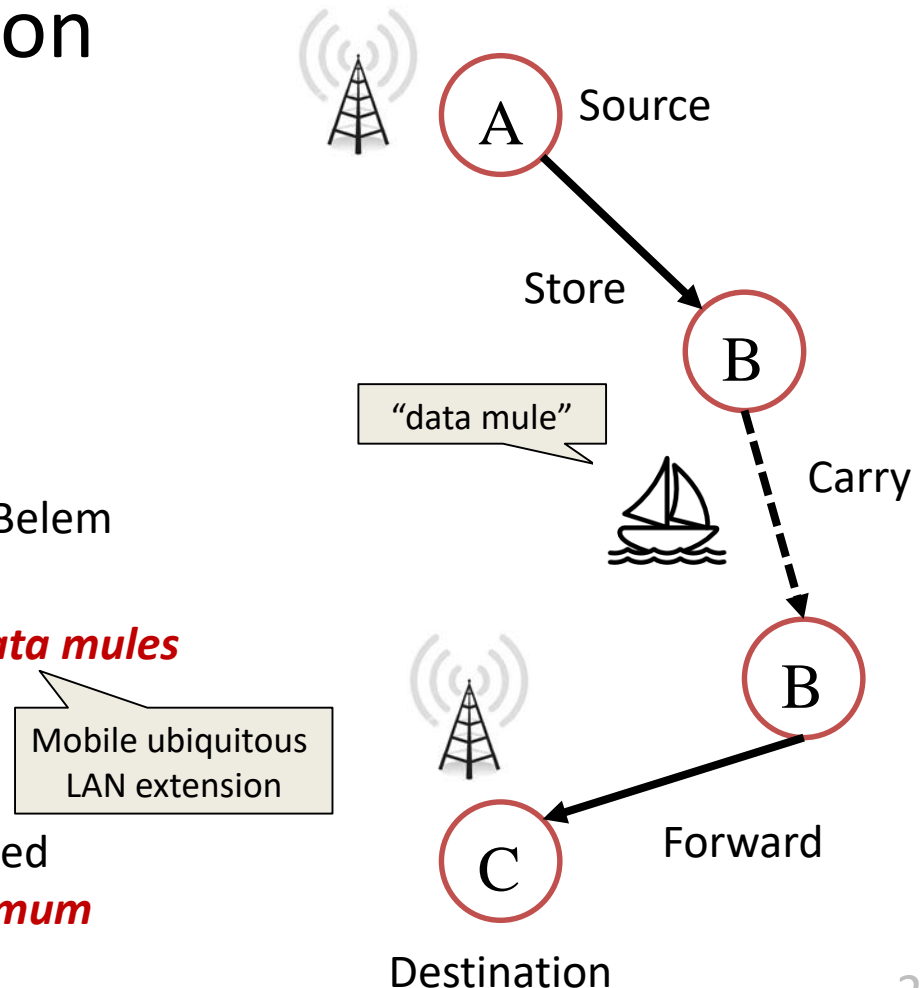
- Complex system of rivers...
- ... with poor **communication** infrastructure



Project and data collection by
Andrea Richa (ASU)

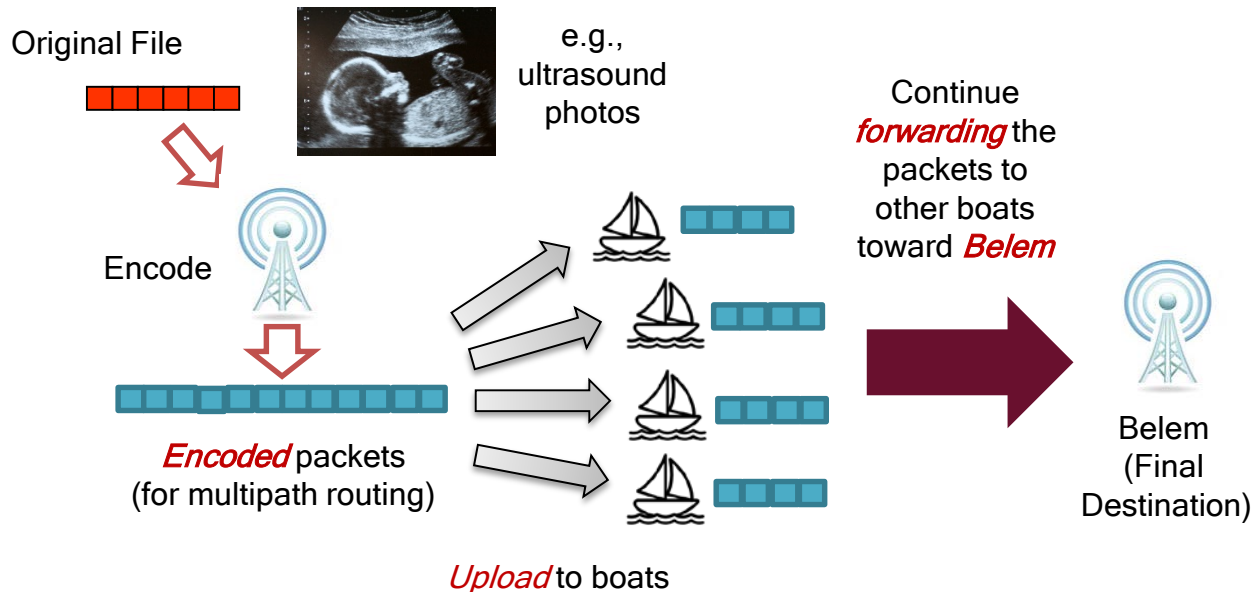
Solution: Communication with Boats

- Solution:
 - **Local nurses** perform routine clinical examinations, such as **ultrasounds** on pregnant women
 - **Records (files) sent** to the doctors in Belem (city) for evaluation
 - Using regularly **scheduled boats** as **data mules**
- Algorithmic problem:
 - Given time schedule of boats (of limited capacity), how to communicate **maximum amount of data**?



Throughput of Time-Schedule Networks

- Essentially, a throughput maximization problem over **Delay-Tolerant Network (DTN)** resp. **time-schedule network**



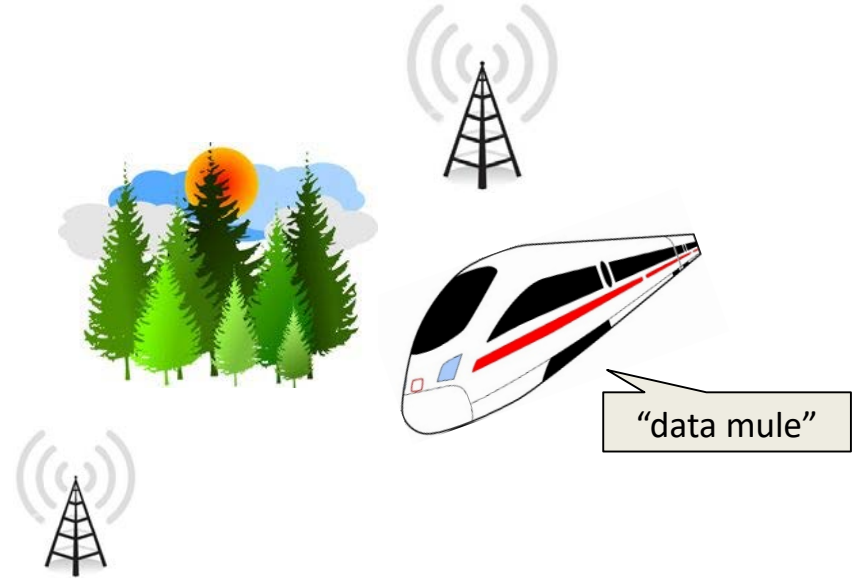
Goal (e.g.):
***maximize
throughput over
DTN***

A high-angle, wide shot of a crowded train platform. A silver train car with a curved roof is on the right. The platform is filled with a diverse group of people, mostly men, standing and waiting. The scene is brightly lit, suggesting daytime. A semi-transparent white box with black text is overlaid in the center.

Other Emerging Opportunities for Communication Using Time-Schedule Networks

Smart Devices on the Move: Commute with Their Owners

- E.g., smart devices/“**things**” **move with their (commuting) owners**: (social) **mobile network**
- Can be exploited for **communication**: e.g., commuter as “**data mule**” (intermittent connectivity between **hot spots**)



Observation Motivating This Paper

optimal routing **schedules**
in time-schedule network

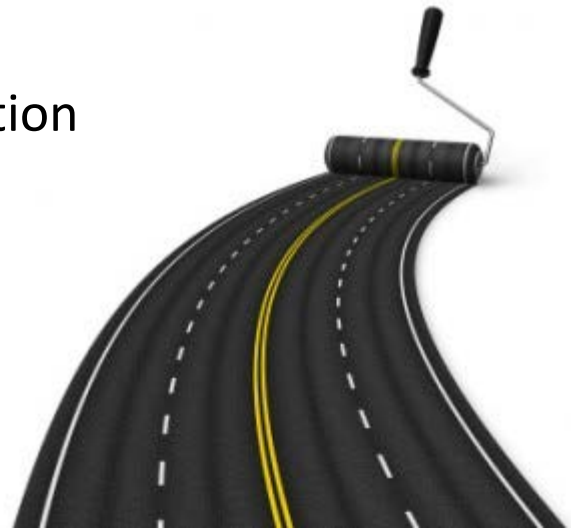


maximum throughput in
All-or-Nothing (Splittable) Multicommodity Flow (**ANF**) problem
on the “**connection graph**”

more soon!

Roadmap

1. A Constant Throughput Approximation Algorithm for ANF
2. Application to Optimizing Time-Schedule Networks
3. Extension to Virtual Network Embedding Approximation



Roadmap

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2. Application to Optimizing Time-Schedule Networks
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The ANF Problem

The ANF Problem

- **ANF** = All-or-Nothing (Splittable) Multicommodity Flow Problem

Input:

- Capacitated directed graph
- (Splittable) ***multi-commodity flows*** with demands

Output:

- ***Maximal*** subset of flows...
- ... such that ***capacities*** and ***demands*** are respected (i.e., the all-or-nothing)

The ANF Problem

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- ***Maximal*** subset of flows...
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- Well-known: problem is **NP-hard**
- **Challenge:** ***(α , β)-approximation***, α factor from optimum and capacity violation at most factor β

Our Result

Theorem: Randomized $(\alpha = O(1), \beta = \sqrt{n})$ -approximation algorithm for throughput maximization (ANF).

Related Work

C. Chekuri, S. Khanna, and F. B. Shepherd (SIAM J. Comput. 2013):

- *Polylog α , but constant β*
- Seems non-trivial to modify to *constant* approximation with *sublinear* capacity violation

Our Approach: Randomized Rounding

1

Formulate **ILP**

Maximize $\sum_{i=1}^k f_i$ subject to

$$\sum_{(s_i,v) \in E} f_{i,(s_i,v)} = f_i \quad \forall F_i \in \mathcal{F} \quad (1)$$

$$\sum_{(u,v) \in E} f_{i,(u,v)} = \sum_{(v,u) \in E} f_{i,(v,u)} \quad \forall F_i \in \mathcal{F}, v \in V \setminus \{s_i, t_i\} \quad (2)$$

$$\sum_{i=1}^k f_{i,(u,v)} \leq c_{(u,v)} \quad \forall (u,v) \in E \quad (3)$$

$$f_{i,(u,v)} \leq f_i \cdot c_{(u,v)} \quad \forall F_i \in \mathcal{F}, (u,v) \in E \quad (4)$$

$$f_{i,(u,v)} \geq 0 \quad \forall F_i \in \mathcal{F}, (u,v) \in E \quad (5)$$

$$f_i \in \{0, 1\} \quad \forall F_i \in \mathcal{F} \quad (6)$$

2

Relax and solve **LP**: \tilde{f}

Maximize $\sum_{i=1}^k f_i$ subject to

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(0,1)

3

Round acc. to \tilde{f} values (**randomized**)

With probability \tilde{f}_i , set $f_i = 1$, otherwise set it to 0

Scale up the fractional flow $\tilde{f}_{i,e}$ from the LP solution on edge e for commodity i by $\frac{1}{\tilde{f}_i}$, i.e., $f_{i,e} = \tilde{f}_{i,e} \times \frac{1}{\tilde{f}_i}$, for i s.t. $\tilde{f}_i = 1$

If the solution is greater than an α fraction of the optimal solution, return this solution; otherwise, repeat at most $\theta(\log |V|)$ times

fractional OPT



ILP

Maximize $\sum_{i=1}^k f_i$ subject to

$$\sum_{(s_i, v) \in E} f_{i, (s_i, v)} = f_i \quad \forall F_i \in \mathcal{F} \quad (1)$$

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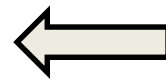
$$f_i \in \{0, 1\} \quad \forall F_i \in \mathcal{F} \quad (6)$$



maximize sum of
integral flows



s.t. flow
conservation



capacity



all-or-nothing

ILP

Maximize $\sum_{i=1}^k f_i$ subject to

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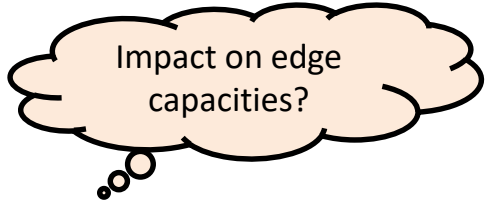
$$f_i \in \{0, 1\} \quad \forall F_i \in \mathcal{F} \quad (6)$$



A **trick**: implied by (3),
but there to
strengthen relaxation
(bounds violation)!



Randomized Rounding



Impact on edge capacities?


- After rounding up, we need to *rescale* flows by $1/f_i$, s.t. $f_i=1$ for each i

Randomized Rounding

- After rounding up, we need to **rescale** flows by $1/f_i$, s.t. $f_i=1$ for each i
- Constant approximation of **objective** follows from **Chernoff**:

$$\Pr[OPT_{ALG} < \frac{1}{3} \cdot OPT_{IP}] \leq e^{-2/9}$$

- **Capacity violation** from **modified LP** formulation and **Hoeffding** bounds:

$$1 + \epsilon' \cdot \sqrt{2 \log |V| \cdot k}$$


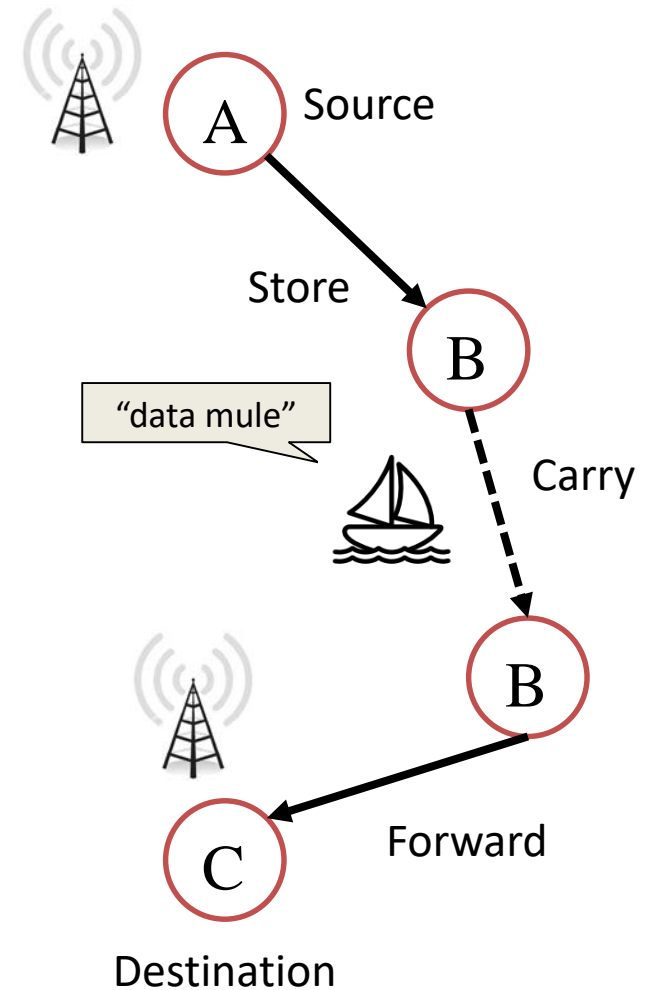
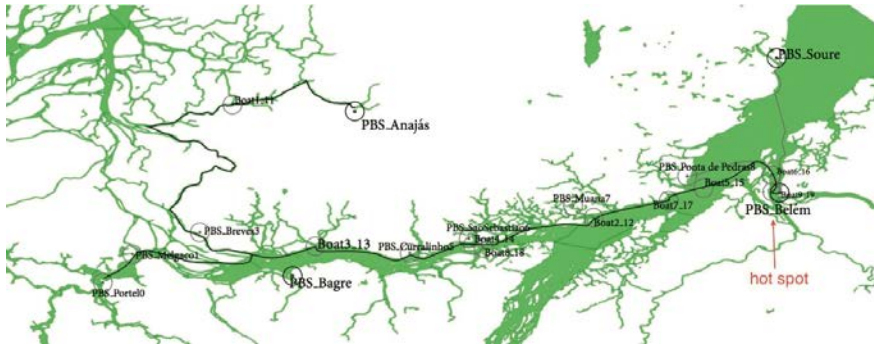
size # flows

Roadmap




1. A Constant Throughput Approximation Algorithm for ANF ✓
2. Application to Optimizing Time-Schedule Networks
3. Extension to Virtual Network Embedding Approximation

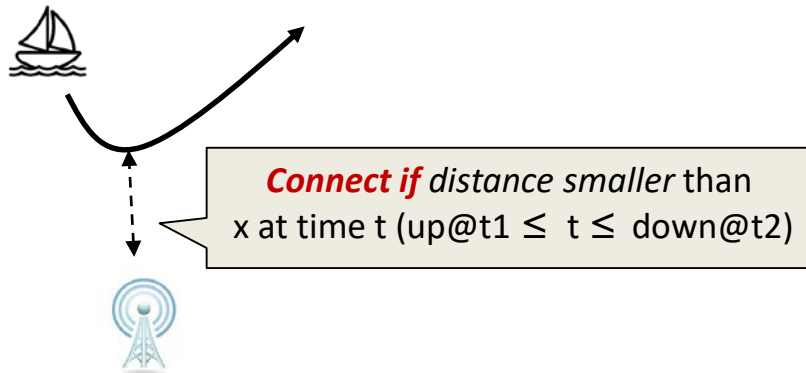


Recall: Health Care in Amazon Riverine

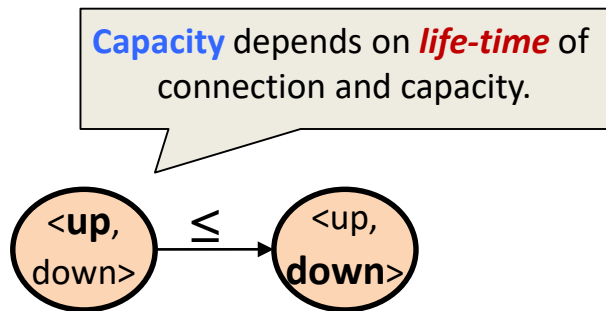


Model

- m **moving nodes**  : has schedule P_i
- n **stationary nodes** (up-/down-load data) 
- k **commodities**  between (possibly different sources and destinations)

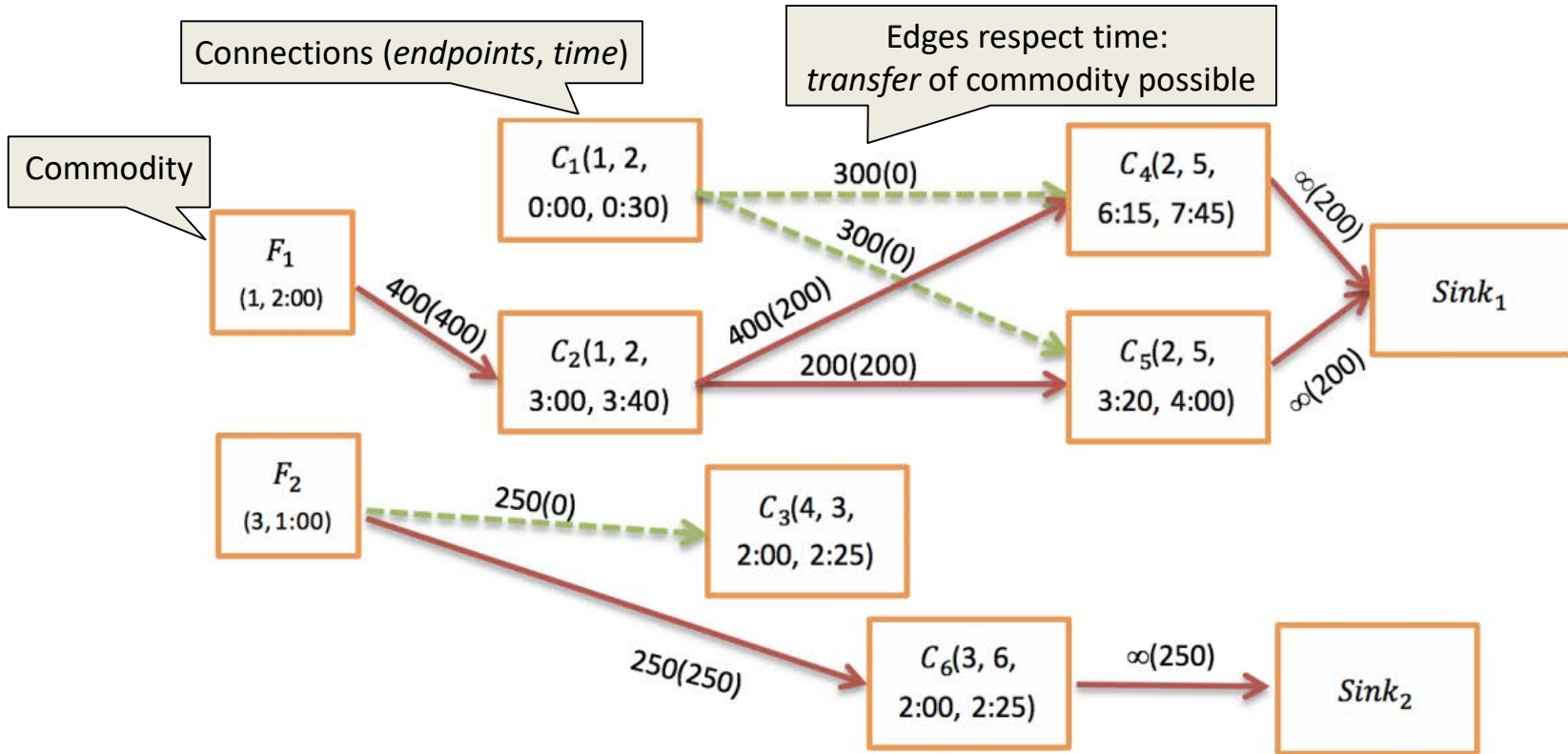


... can be transformed into a connection graph and MCF problem:



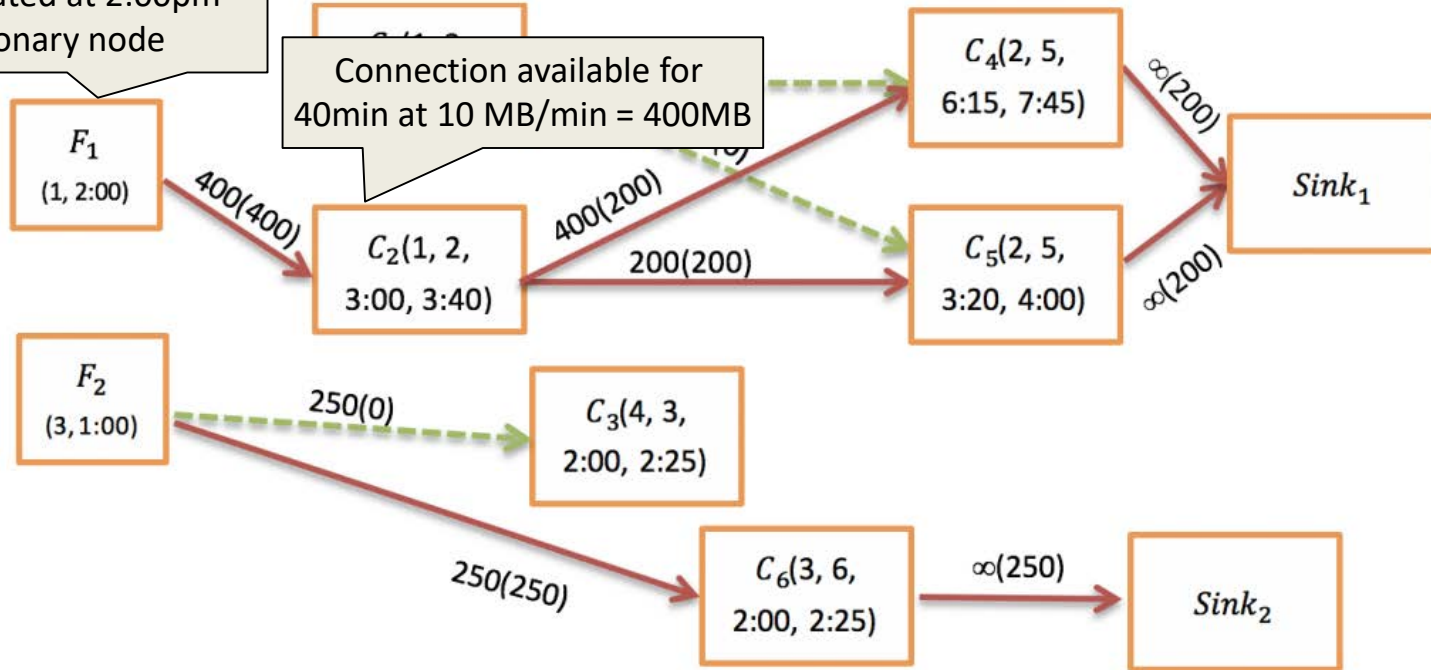
- Vertices:
 - moving and stationary nodes **plus** commodity sources **plus** connection nodes
- Directed edges:
 - From connection node C_x to connection node C_y if they **share a common object and $Up_x \leq Down_y$**

Connection Graph Example

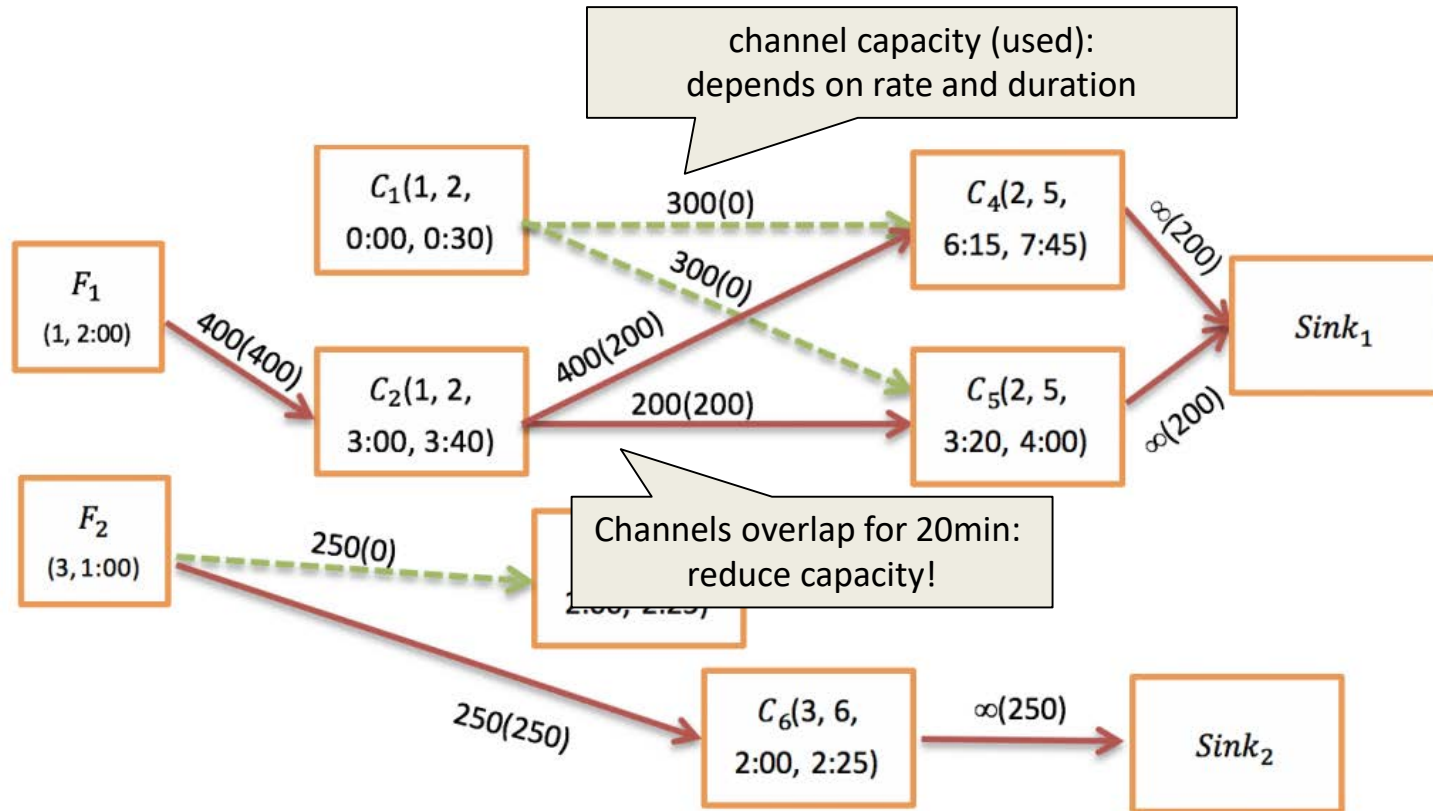


Connection Graph Example

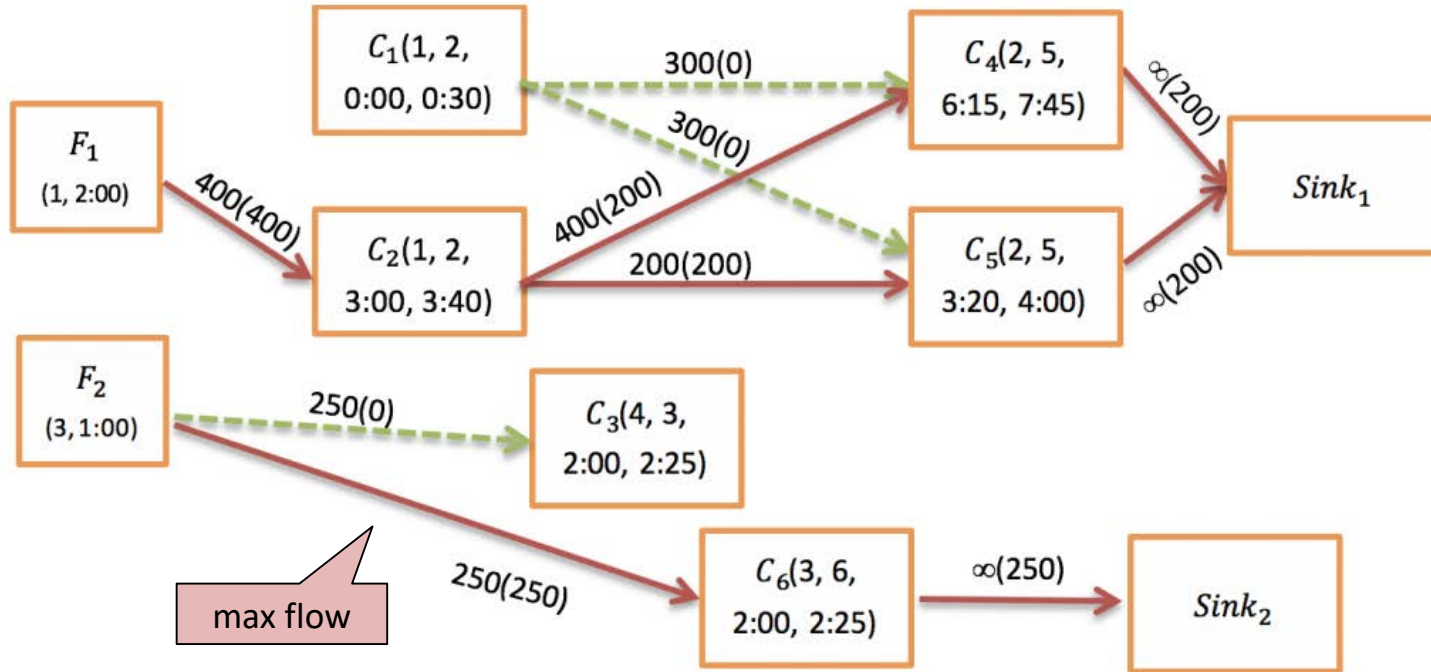
Data generated at 2:00pm
at stationary node



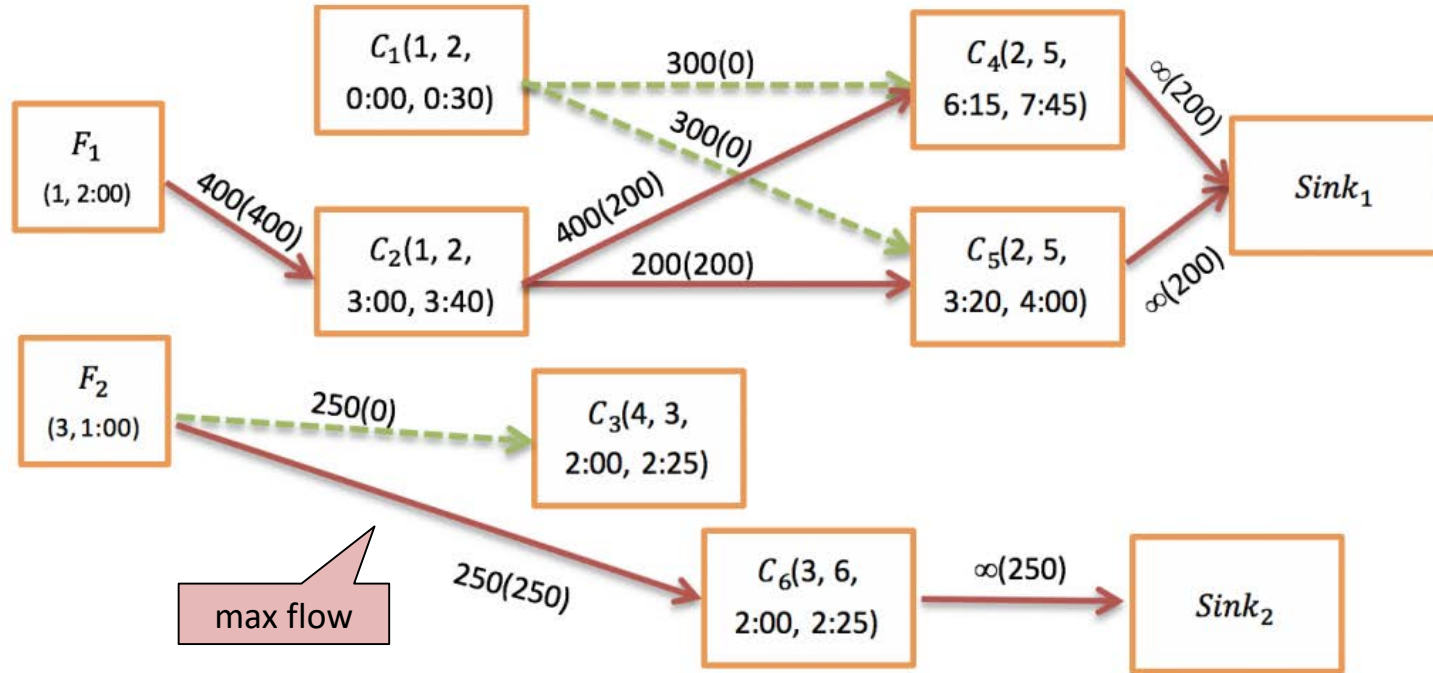
Connection Graph Example



Connection Graph Example



Connection Graph Example



Polynomial-time computable!

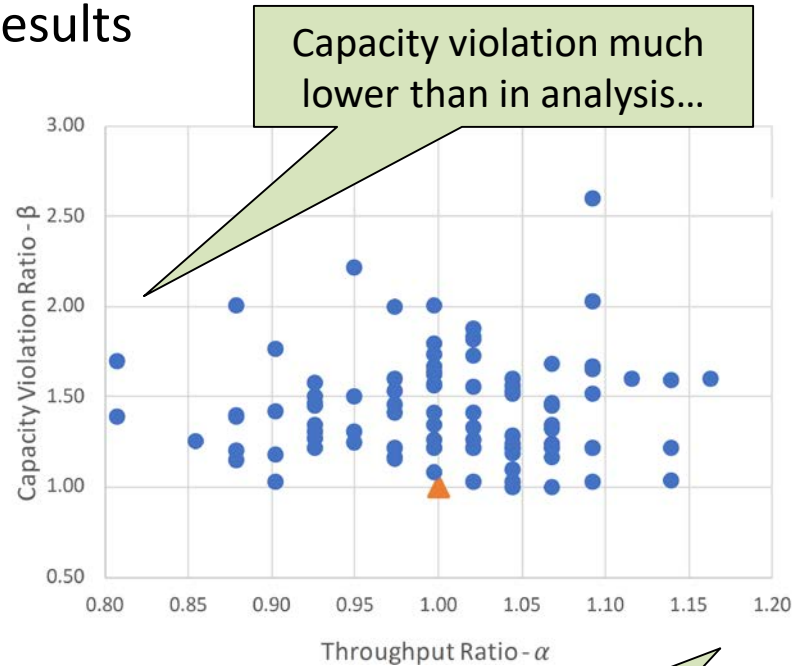
How good is the algorithm in practice?

Case Study: State of Para, Brazil

Data from State of Para, Brazil



Results



Roadmap

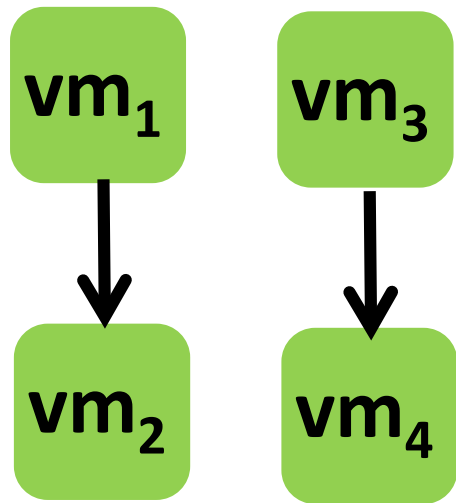
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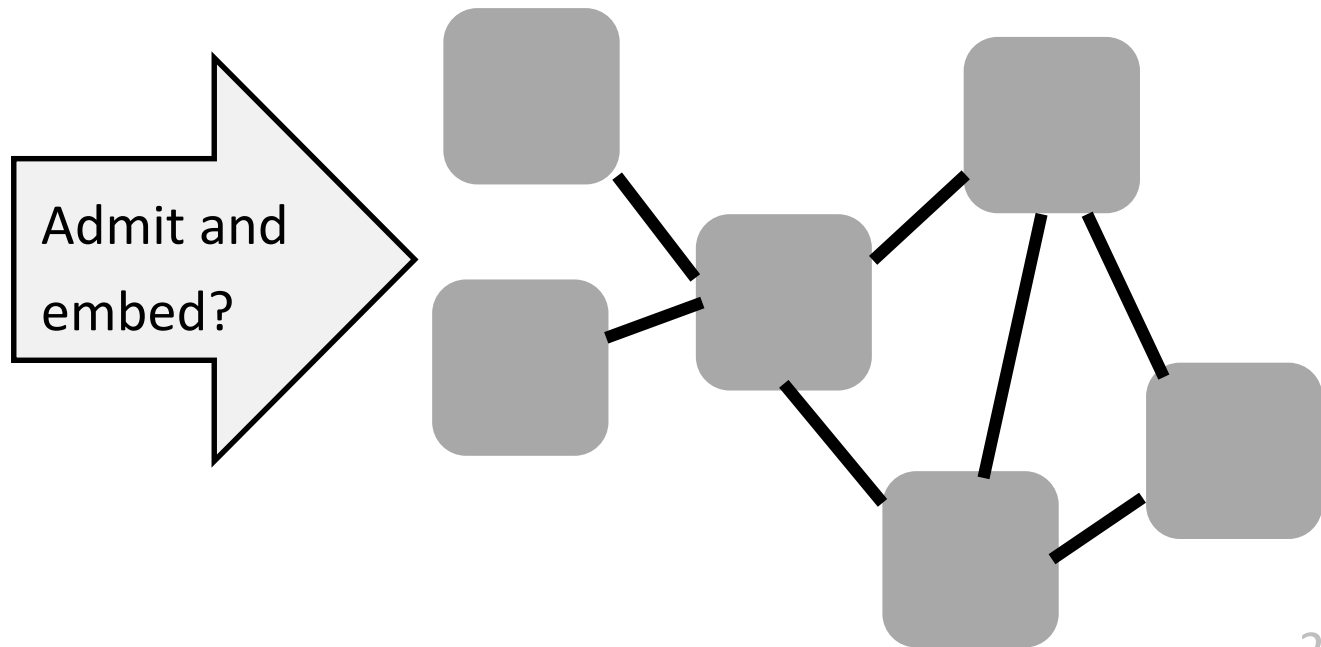
Can we use similar techniques for
admitting and routing VNets?

Recall: VNet Embedding Problem

VNets:

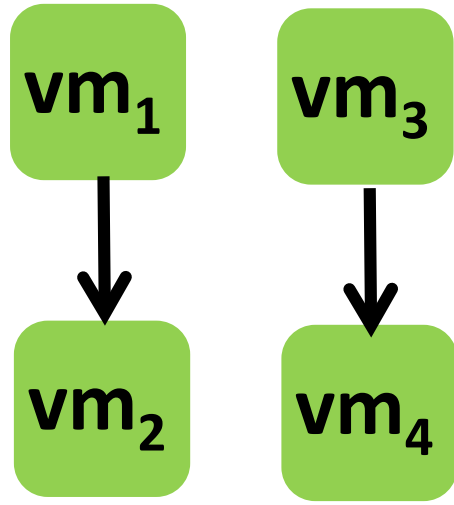


Substrate:



Recall: VNet Embedding Problem

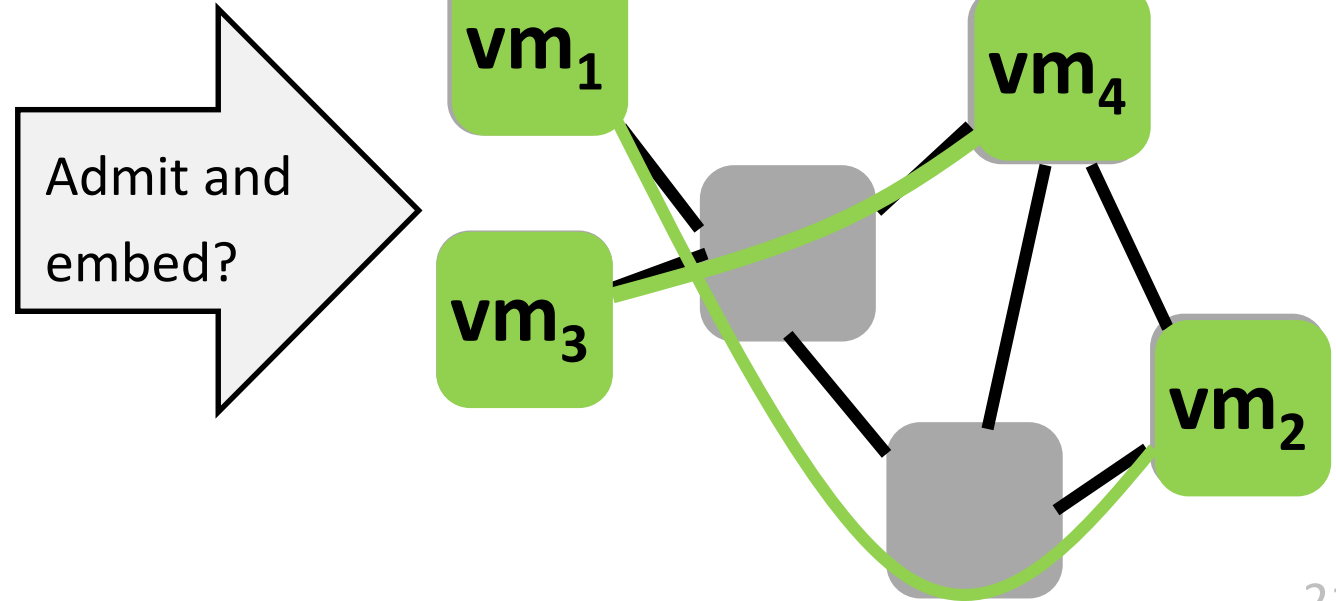
VNets:



Substrate:



Endpoints of flows are flexible!



Challenge: Decomposable ILP Formulations

Randomized Rounding based on MCF Can Fail!

$$\max \sum_{r \in \mathcal{R}} b_r x_r \quad (1)$$

$$\sum_{u \in V_S^{r,i}} y_{r,i}^u = x_r \quad \forall r \in \mathcal{R}, i \in V_r \quad (2)$$

$$\sum_{u \in V_S \setminus V_S^{r,i}} y_{r,i}^u = 0 \quad \forall r \in \mathcal{R}, i \in V_r \quad (3)$$

$$\begin{bmatrix} \sum_{(u,v) \in \delta^+(u)} z_{r,i,j}^{u,v} \\ - \sum_{(v,u) \in \delta^-(u)} z_{r,i,j}^{v,u} \end{bmatrix} = \begin{bmatrix} y_{r,i}^u \\ -y_{r,j}^u \end{bmatrix} \quad \forall \begin{bmatrix} r \in \mathcal{R}, (i,j) \in E_r, \\ u \in V_S \end{bmatrix} \quad (4)$$

$$z_{r,i,j}^{u,v} = 0 \quad \forall \begin{bmatrix} r \in \mathcal{R}, (i,j) \in E_r, \\ (u,v) \in E_S \setminus E_S^{r,i,j} \end{bmatrix} \quad (5)$$

$$\sum_{i \in V_r, \tau_r(i)=\tau} d_r(i) \cdot y_{r,i}^u = a_r^{\tau,u} \quad \forall r \in \mathcal{R}, (\tau, u) \in R_S^V \quad (6)$$

$$\sum_{(i,j) \in E_r} d_r(i,j) \cdot z_{r,i,j}^{u,v} = a_r^{u,v} \quad \forall r \in \mathcal{R}, (u,v) \in E_S \quad (7)$$

$$\sum_{r \in \mathcal{R}} a_r^{x,y} \leq d_S(x,y) \quad \forall (x,y) \in R_S \quad (8)$$



Each virtual node *should be placed*



Forbidden node mappings



Induce a *flow* for each virtual edge



Forbidden edge mappings



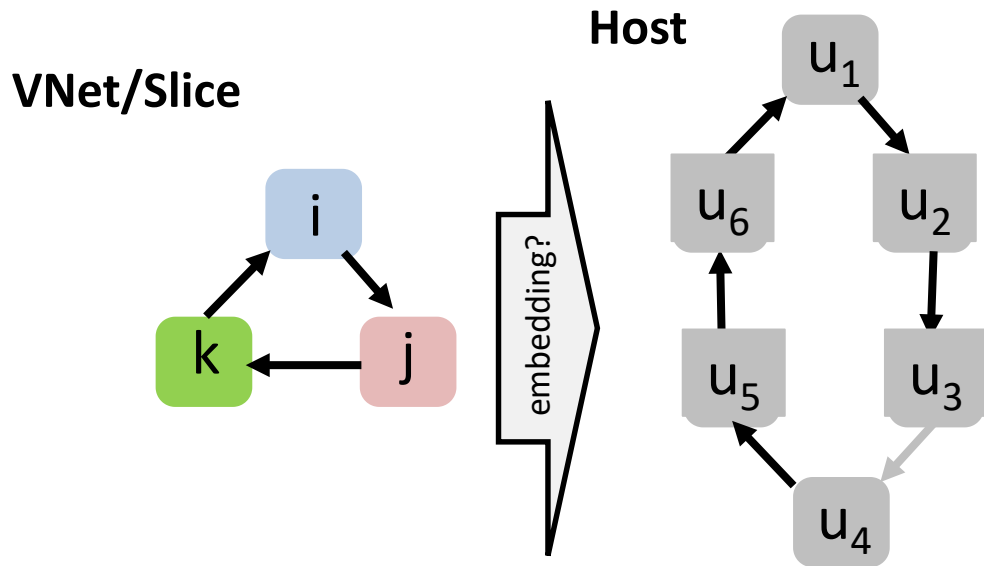
Compute cumulative *allocations*



Respect resource *capacities*

Challenge: Decomposable ILP Formulations

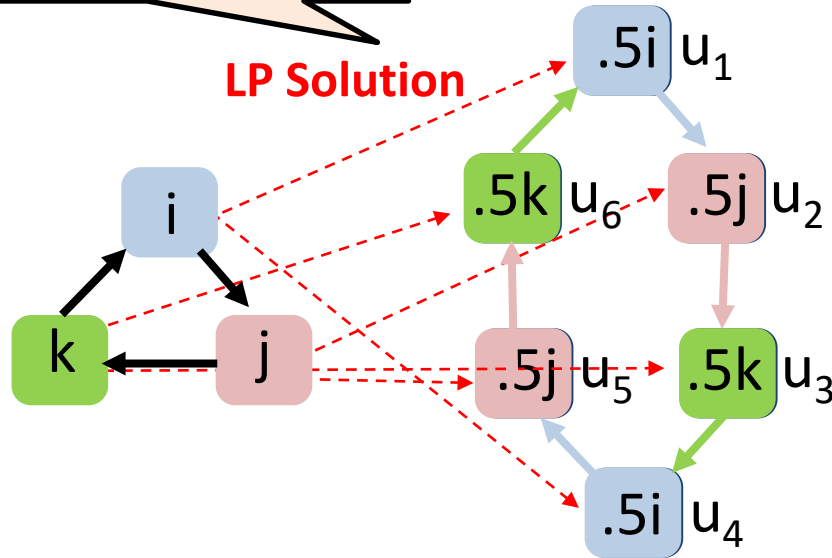
Randomized Rounding based on MCF Can Fail!



Challenge: Decomposable ILP Formulations

Valid LP solution: virtual node mappings sum to 1 and each virtual node connects to its neighboring node **with half a unit of flow...**

Relaxation based on MCF Can Fail!



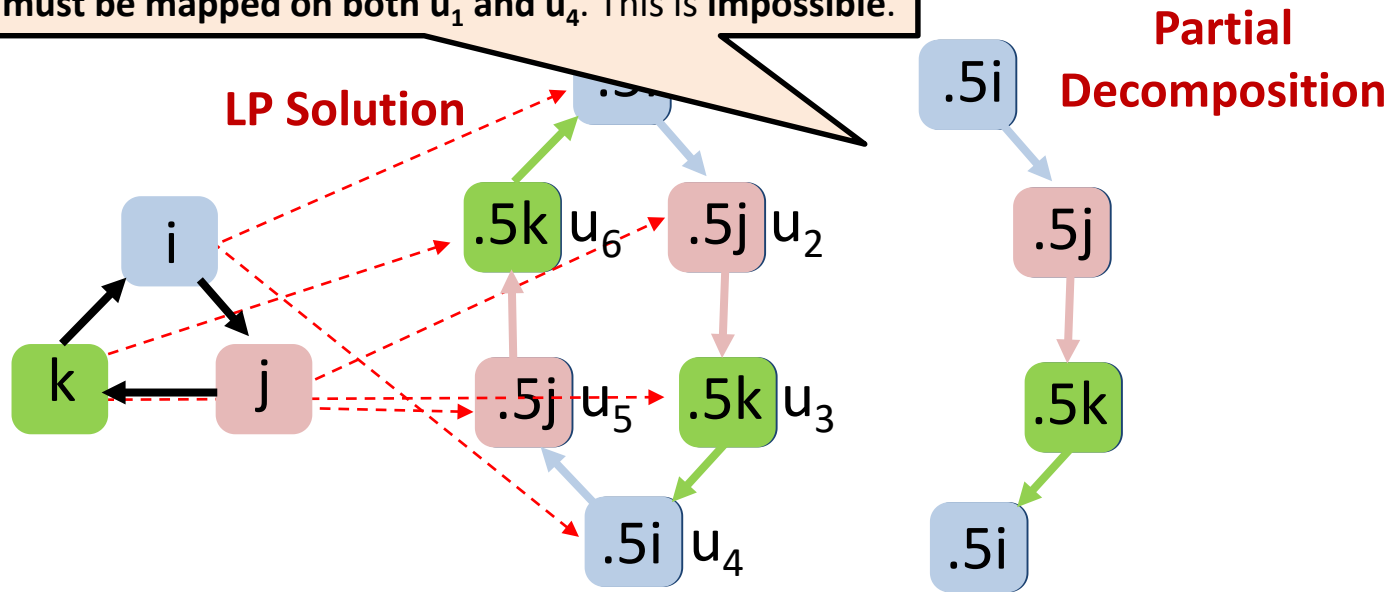
Relaxations of classic MCF formulation **cannot be decomposed** into convex combinations of valid mappings (so we **need different formulations!**)

Formulations

MCF Can Fail!

Impossible to decompose and extract any single valid mapping.

Intuition: Node i is mapped to u_1 and the only neighboring node that hosts j is u_2 , so i must be fully mapped on u_1 and j on u_2 . Similarly, k must be mapped on u_3 . But flow of virtual edge (k,i) leaving u_3 only leads to u_4 , so i must be mapped on both u_1 and u_4 . This is impossible.



Relaxations of classic MCF formulation **cannot be decomposed** into convex combinations of valid mappings (so we **need different formulations!**)

Approximation of VNet Embedding

- 1 To avoid dependencies, decompose VNet into **forests and cycles**, orient



- 2 Formulate alternative, decomposable **ILP**

$$\begin{aligned}
 & \max \sum_{r \in \mathcal{R}} b_r x_r \\
 & \text{Cons. (2) - (7) for } G_r^F \text{ on} \quad \forall r \in \mathcal{R} \\
 & \text{variables } (x_r, \tilde{y}_r, \tilde{z}_r, \tilde{a}_r)[\mathcal{F}_r] \\
 & \text{Cons. (2) - (7) for } G_r^{C_k} \text{ on} \quad \forall r \in \mathcal{R}, C_k \in \mathcal{C}_r, w \in V_{S,t}^{C_k} \\
 & \text{variables } (x_r, \tilde{y}_r, \tilde{z}_r, \tilde{a}_r)[C_k, w] \\
 & x_r = \sum_{u \in V_{S,t}^{C_k}} \tilde{y}_{r,i}^u \quad \forall r \in \mathcal{R}, i \in V_r \\
 & \tilde{y}_{r,i}^u = \tilde{y}_{r,i}^u[\mathcal{F}] \quad \forall r \in \mathcal{R}, i \in V_r^F, u \in V_{S,t}^{C_k} \\
 & \tilde{y}_{r,i}^u = \sum_{w \in V_{S,t}^{C_k}} \tilde{y}_{r,i}^u[C_k, w] \quad \forall \left[\begin{array}{l} r \in \mathcal{R}, i \in V_r, u \in V_{S,t}^{C_k} \\ C_k \in \mathcal{C}_r : i \in V_{S,t}^{C_k} \end{array} \right] \\
 & 0 = \tilde{y}_{r,i}^{u,C_k}[C_k, w] \quad \forall \left[\begin{array}{l} r \in \mathcal{R}, C_k \in \mathcal{C}_r, w \in V_{S,t}^{C_k} \\ u \in V_{S,t}^{C_k} \setminus \{w\} \end{array} \right] \\
 & a_r^{\tau, \text{in}} = \sum_{i \in V_r, \tau_r(i)=r} d_r(i) \cdot \tilde{y}_{r,i}^u \quad \forall r \in \mathcal{R}, (\tau, u) \in R_S^V \\
 & a_r^{u,v} = a_r^{u,v}[\mathcal{F}] + \sum_{C_k \in \mathcal{C}_r, w \in V_{S,t}^{C_k}} a_r^{u,v}[C_k, w] \quad \forall r \in \mathcal{R}, (u, v) \in E_S \\
 & \sum_{r \in \mathcal{R}} a_r^{x,y} \leq d_S(x, y) \quad \forall (x, y) \in R_S
 \end{aligned}$$




- 3 Apply **randomized rounding**

```

1 foreach  $r \in \mathcal{R}$  do // preprocess requests
2   compute LP Formulation 2 for request  $r$  maximizing  $x_r$ 
3   if  $x_r < 1$  then remove request  $r$  from the set  $\mathcal{R}$ 
4   compute LP Formulation 2 for  $\mathcal{R}$  maximizing  $\sum_{r \in \mathcal{R}} b_r \cdot x_r$ 
5   foreach  $r \in \mathcal{R}$  do // perform decomposition
6     compute  $\mathcal{D}_r = \{(f_r^k, m_r^k)\}_k$  from LP solution
7   do // perform randomized rounding
8     foreach  $r \in \mathcal{R}$  select  $m_r^k$  with probability  $f_r^k$ 
9   while (solution is not  $(\alpha, \beta, \gamma)$ -approximate and
         maximal rounding tries are not exceeded)
    
```

Conclusion

- Constant approximation with for **throughput maximization**
- Can be used to solve transmission scheduling on **time-schedule networks**
- Non-trivial **augmentation** required (*future work*: improve)
- But does not appear in ***simulations***
- Applications to **virtual network embedding** problem: works too!
- *Future work*: derandomization

An aerial photograph showing a river or stream meandering through a vast, dense green forest. The water is a light blue-green color, contrasting with the deep green of the surrounding trees. The forest appears to be a tropical or subtropical rainforest, with a thick canopy. The river flows from the top center towards the bottom center of the frame, with several bends and curves.

Thank you!
Questions?

Further Reading

- [Robust data mule networks with remote healthcare applications in the Amazon region: A fountain code approach](#) Mengxue Liu, Thienne Johnson, Rachit Agarwal, Alon Efrat, Andrea Richa, Mauro Margalho Coutinho. **HealthCom** 2015.
- [Charting the Complexity Landscape of Virtual Network Embeddings](#) Matthias Rost and Stefan Schmid. **IFIP Networking**, Zurich, Switzerland, May 2018.