It's About Time: On Optimal Virtual Network Embeddings under Temporal Flexibilities

IPDPS 2014

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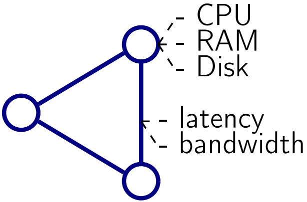
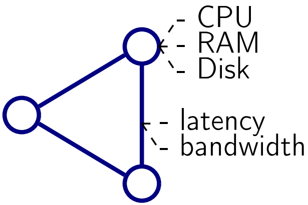
The Virtual Network Embedding Problem (VNEP)

Physical Network

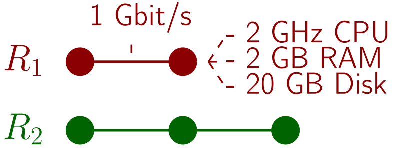


The Virtual Network Embedding Problem (VNEP)

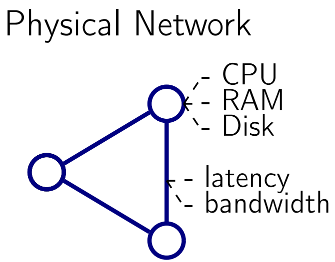
Physical Network

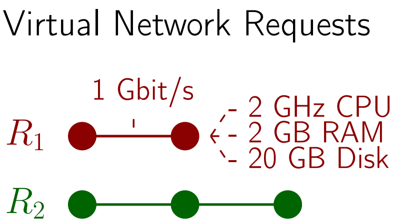


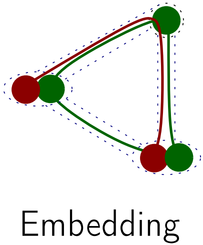
Virtual Network Requests



The Virtual Network Embedding Problem (VNEP)







- map virtual onto substrate nodes
- map virtual links onto substrate paths
- obeying the substrate's capacities

Facets of the VNEP

Setting

(De)centralized

Multi-Provider

Reliability

Reconfigurations

Objectives

Access Control

Load Balancing

Energy Savings

Algorithms

Exact

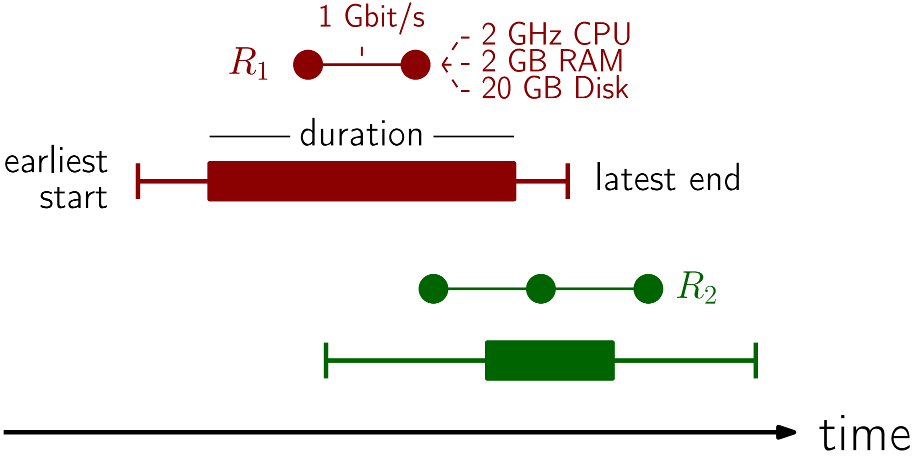
Heuristic

Facets of the VNEP

Setting	Objectives	Algorithms
(De)centralized	Access Control	Exact
Multi-Provider	Load Balancing	Heuristic
Reliability	Energy Savings	
Reconfigurations		

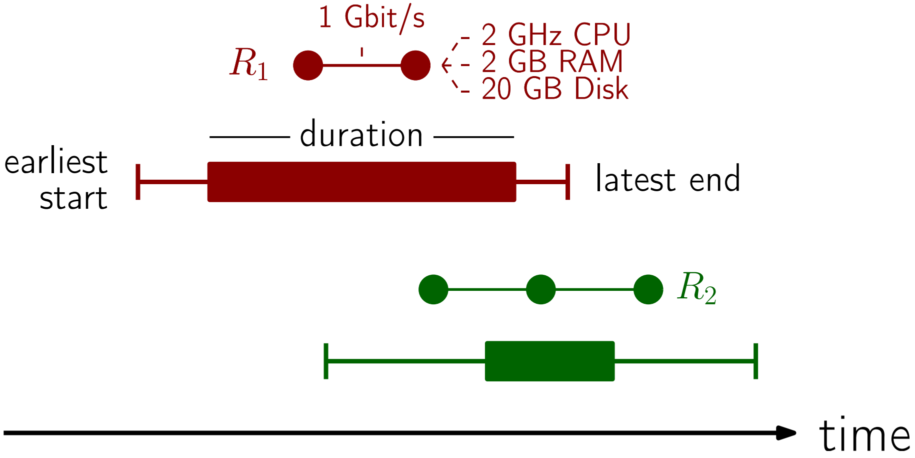
Novelty: Temporality!

Our Model


1 Gbit/s
R_1
2 GHz CPU
2 GB RAM
20 GB Disk
duration
earliest start
latest end
R_2
time

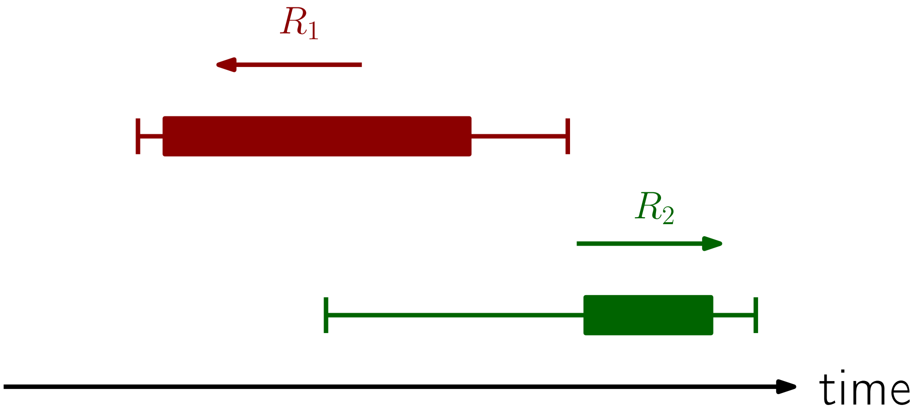
Our Model

Offline scenario

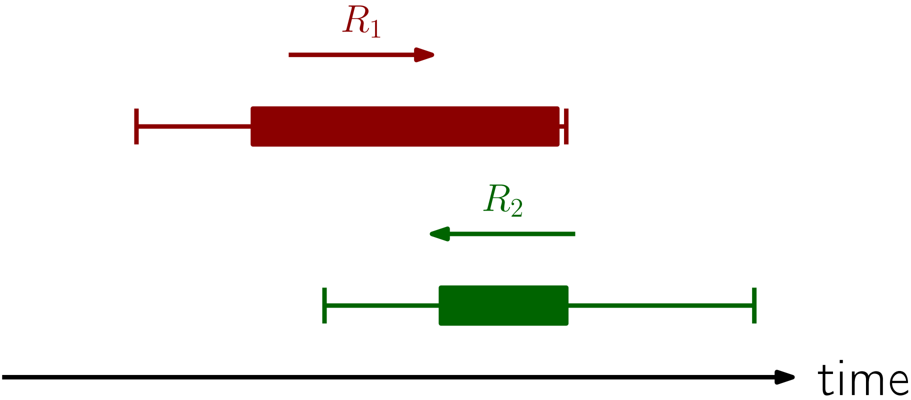


Motivation #1: Business

Provider Incentives: Minimizing Load

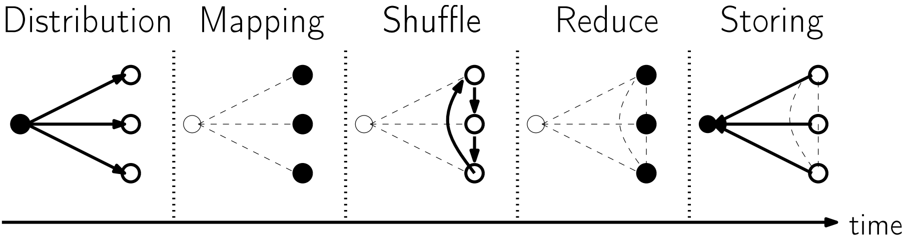


Provider Incentives: Maximizing Utilization by Collocation



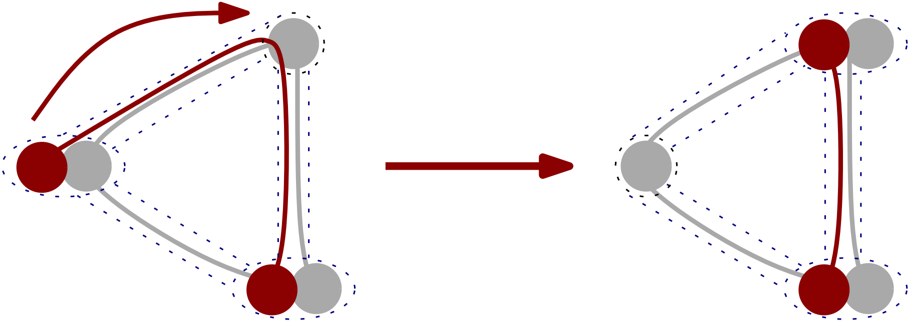
Motivation #2: Modeling Opportunities

Modeling Opportunities: Evolution of VNets

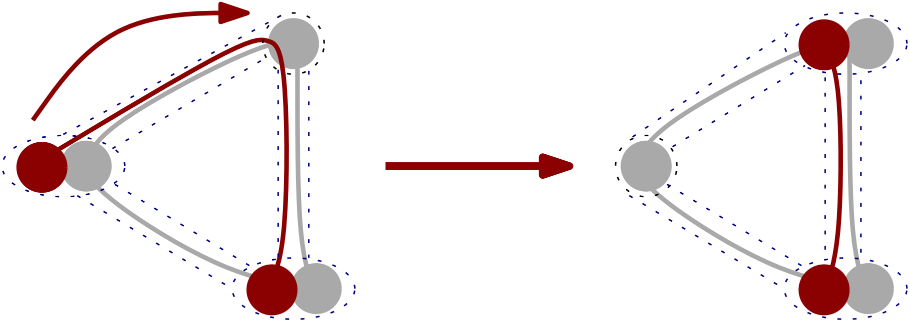


Reservation of maximal allocations over the whole time?

Modeling Opportunities: Migrations

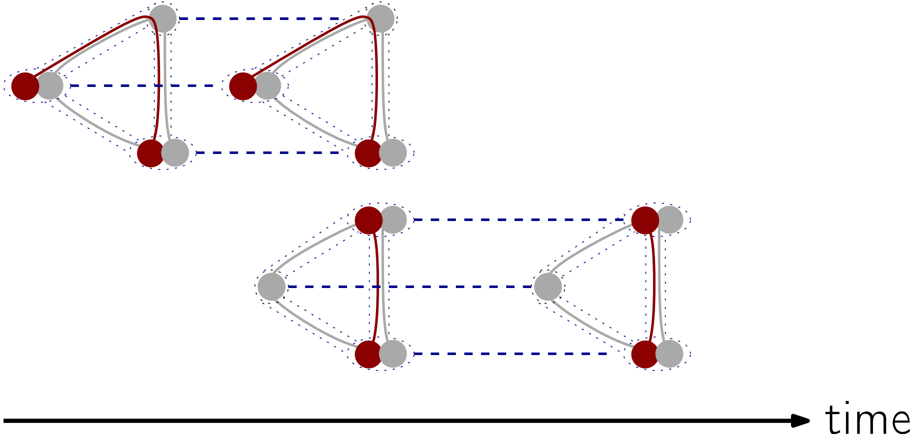


Modeling Opportunities: Migrations

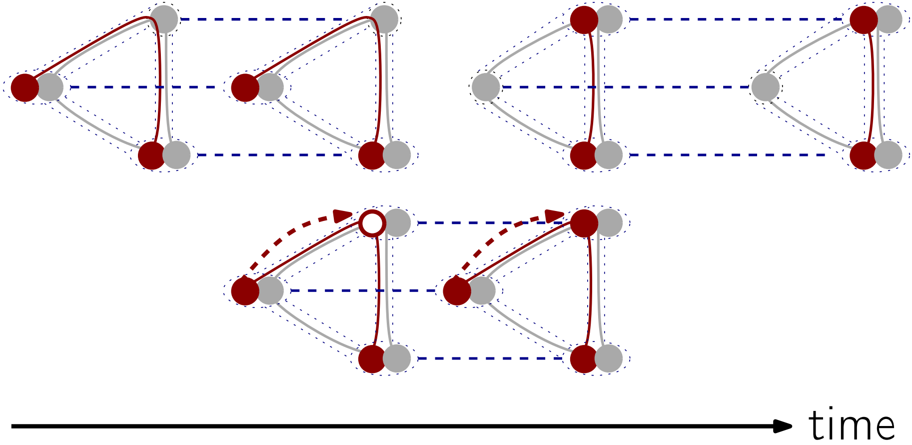


In previous work instantaneous operation!

Modeling Opportunities: Migrations

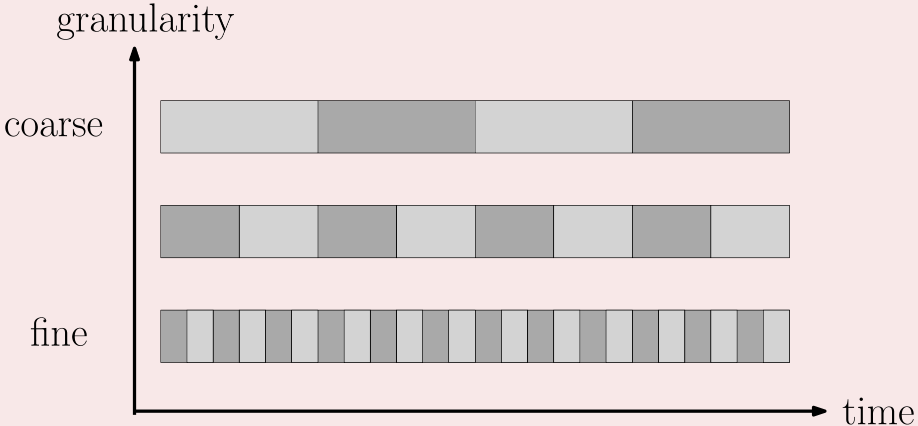


Modeling Opportunities: Fine-grained Migrations



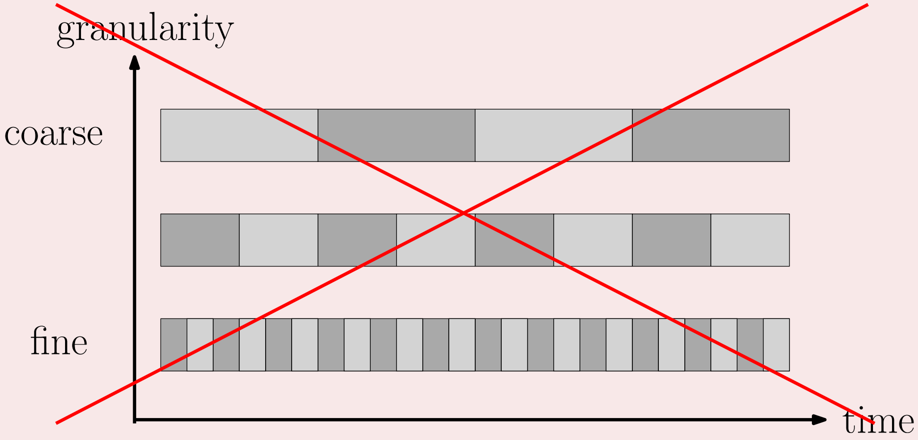
Important Decision: Continuous-Time Model!

Discretization



Important Decision: Continuous-Time Model!

No Discretization!



Problem Statement

Notation

Substrate $\mathcal{S}$

topology $\mathcal{S} = (\mathbf{V_S}, \mathbf{E_S})$

capacities $\mathbf{c_S} : \mathbf{V_S} \cup \mathbf{E_S} \to \mathbb{R}^+$

time horizon $\mathbf{T} > 0$

Requests $\mathcal{R} = \{R_1, \ldots, R_n\}$

topologies $(\mathbf{V}_{R_i}, \mathbf{E}_{R_i})$

resources $\mathbf{c}_{R_i} : \mathbf{V}_{R_i} \cup \mathbf{E}_{R_i} \to \mathbb{R}^+$

temporal spec interval $[\mathbf{t}^s_{R_i}, \mathbf{t}^e_{R_i}]$
duration $\mathbf{d}_{R_i} \leq \mathbf{t}^e_{R_i} - \mathbf{t}^s_{R_i}$

Temporal Virtual Network Embedding Problem (TVNEP)

Access Control Decide which of the requests to embed.

Resource Mapping Map virtual onto substrate resources, obtaining
$alloc_V : \mathcal{R} \times \mathbf{V_S} \to \mathbb{R}_{\geq 0}$ and
$alloc_E : \mathcal{R} \times \mathbf{E_S} \to \mathbb{R}_{\geq 0}$.

Scheduling Find start $t^+_\mathrm{R} \geq \mathbf{t}^s_\mathrm{R}$ and end time $t^-_\mathrm{R} \leq \mathbf{t}^e_\mathrm{R}$ for $\mathrm{R} \in \mathcal{R}$, such that $t^-_\mathrm{R} + t^+_\mathrm{R} = \mathbf{d}_\mathrm{R}$ holds.

Feasibility For each point in time $t \in [0, \mathbf{T}]$ ensure:

$$\forall N_s \in \mathbf{V_S}.\ \mathbf{c_S}(N_s) \geq \sum_{\substack{\mathrm{R} \in \mathcal{R} \text{ with} \\ t \in (t^+_\mathrm{R}, t^-_\mathrm{R})}} alloc_V(\mathrm{R}, N_s)\ ,$$

$$\forall L_s \in \mathbf{E_S}.\ \mathbf{c_S}(L_s) \geq \sum_{\substack{\mathrm{R} \in \mathcal{R} \text{ with} \\ t \in (t^+_\mathrm{R}, t^-_\mathrm{R})}} alloc_E(\mathrm{R}, L_s)\ .$$

Local Embedding

For sake of simplicity, treat mapping as a black box (see e.g.[1]).

Classic VNEP Task

Access Control	Decide which of the requests to embed: $x_{\mathcal{R}} : \mathcal{R} \rightarrow \mathbb{B}$.
Resource Mapping	Map virtual onto substrate resources, obtaining $alloc_V : \mathcal{R} \times \mathbf{V_S} \rightarrow \mathbb{R}_{\geq 0}$ and $alloc_E : \mathcal{R} \times \mathbf{E_S} \rightarrow \mathbb{R}_{\geq 0}$.

Overview

Overview

Contributions

1. Continuous-time Mixed-Integer Programming formulations for TVNEP
2. cΣ-Model utilizes state-space and symmetry reductions to render solving TVNEP (computationally) feasible
3. Greedy polynomial time heuristic which is based on cΣ-Model
4. Initial computational evaluation

Why Mixed-Integer Programming?

- TVNEP is a novel problem: baseline for further work
- Offline scenario: trade-off runtime with solution quality

Mixed-Integer Programming Models

Standard VNEP

Access Control Decide which of the requests to embed: $x_{\mathcal{R}} : \mathcal{R} \to \mathbb{B}$.

Resource Mapping Map virtual onto substrate resources, obtaining

$alloc_V : \mathcal{R} \times \mathbf{V_S} \to \mathbb{R}_{\geq 0}$ and

$alloc_E : \mathcal{R} \times \mathbf{E_S} \to \mathbb{R}_{\geq 0}$.

Novel: Continuous-Time Scheduling

Scheduling Find start $t^+_{\mathrm{R_i}} \geq \mathbf{t}^s_{\mathrm{R_i}}$ and end time $t^-_{\mathrm{R_i}} \leq \mathbf{t}^e_{\mathrm{R_i}}$, such that $t^-_{\mathrm{R_i}} + t^+_{\mathrm{R_i}} = \mathbf{d}_{\mathrm{R_i}}$ holds.

Feasibility For each point in time $t \in [0, \mathbf{T}]$:

$$\forall N_s \in \mathbf{V_S}.\ \mathbf{c_S}(N_s) \geq \sum_{\substack{\mathrm{R} \in \mathcal{R} \text{ with} \\ t \in (t^+_{\mathrm{R}}, t^-_{\mathrm{R}})}} alloc_V(\mathrm{R}, N_s) \ ,$$

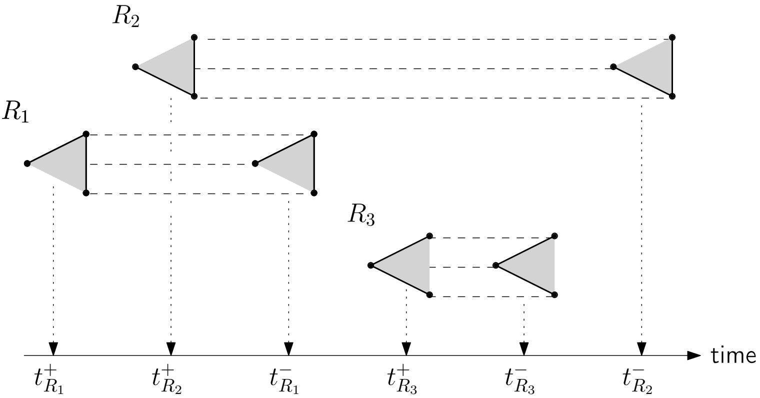
$$\forall L_s \in \mathbf{E_S}.\ \mathbf{c_S}(L_s) \geq \sum_{\substack{\mathrm{R} \in \mathcal{R} \text{ with} \\ t \in (t^+_{\mathrm{R}}, t^-_{\mathrm{R}})}} alloc_E(\mathrm{R}, L_s) \ .$$

Modeling Continuous-Time: Checking Feasibility

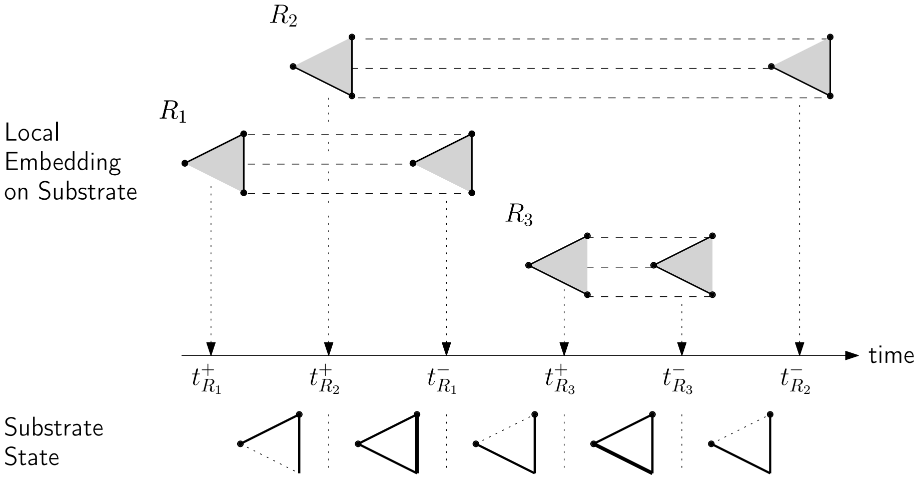
Assume for now:
Local embeddings and start / end times are fixed.

Modeling Continuous-Time: Checking Feasibility

Local
Embedding
on Substrate

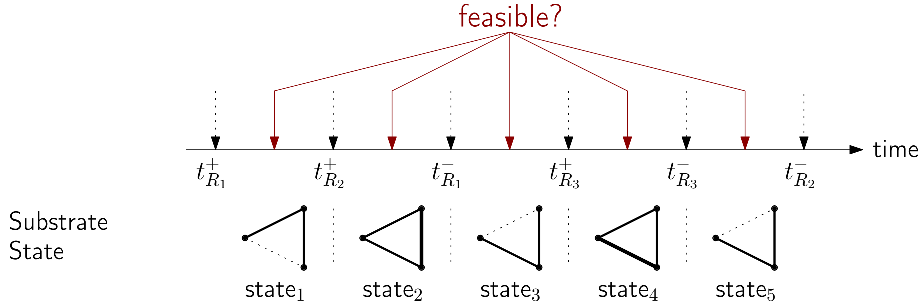


Modeling Continuous-Time: Checking Feasibility



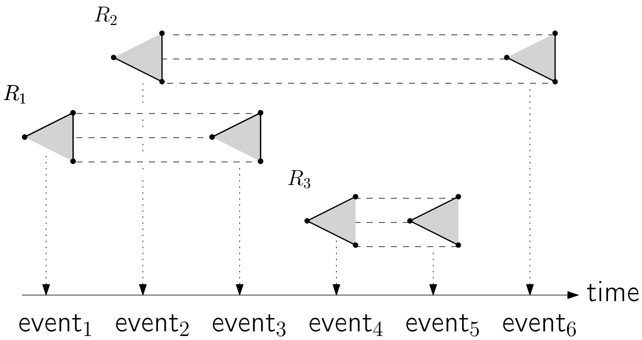
Modeling Continuous-Time: Checking Feasibility

Check the feasibility of the $2 \cdot |\mathcal{R}| - 1$ states.



Abstract Event Model

Modeling Continuous-Time: Abstract Event Model



Mapping Variables

$$\mathcal{E} = \{\mathbf{e}_1, \ldots, \mathbf{e}_{2\cdot|\mathcal{R}|}\}$$

$$\forall \mathsf{R} \in \mathcal{R}.\ \chi^+_{\mathsf{R}} \colon \mathcal{E} \to \mathbb{B}$$

$$\forall \mathsf{R} \in \mathcal{R}.\ \chi^-_{\mathsf{R}} \colon \mathcal{E} \to \mathbb{B}$$

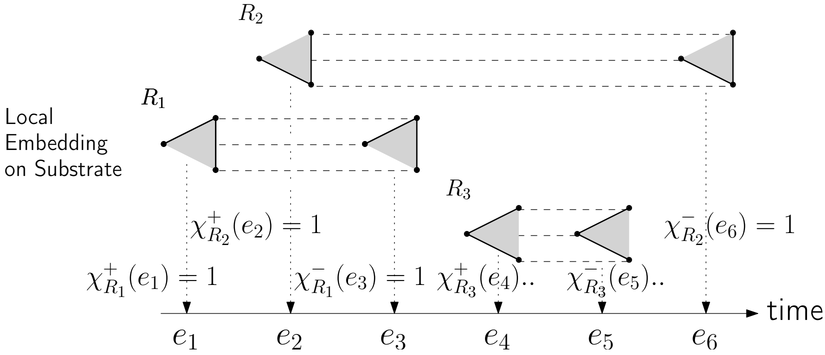
Bijective Mapping

$$\forall \mathsf{R} \in \mathcal{R}.\ \sum_{\mathbf{e}_i \in \mathcal{E}} \chi^+_{\mathsf{R}}(\mathbf{e}_i) = 1 \wedge \sum_{\mathbf{e}_i \in \mathcal{E}} \chi^-_{\mathsf{R}}(\mathbf{e}_i) = 1$$

$$\forall \mathbf{e}_i \in \mathcal{E}.\ \sum_{\mathsf{R} \in \mathcal{R}} \chi^+_{\mathsf{R}}(\mathbf{e}_i) = 1 \wedge \sum_{\mathsf{R} \in \mathcal{R}} \chi^-_{\mathsf{R}}(\mathbf{e}_i) = 1$$

Δ-Model

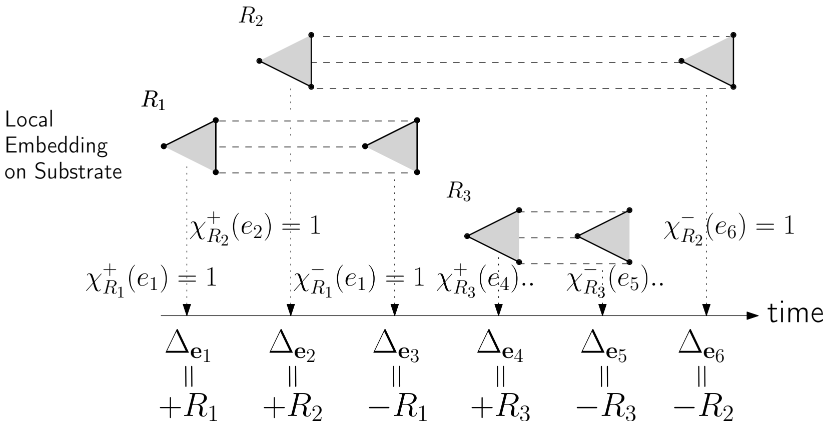
Reconstructing States: Δ-Model



Idea

- Compute state changes via mapping variables $\chi^+_{\mathsf{R}}(e_i), \chi^-_{\mathsf{R}}(e_i)$

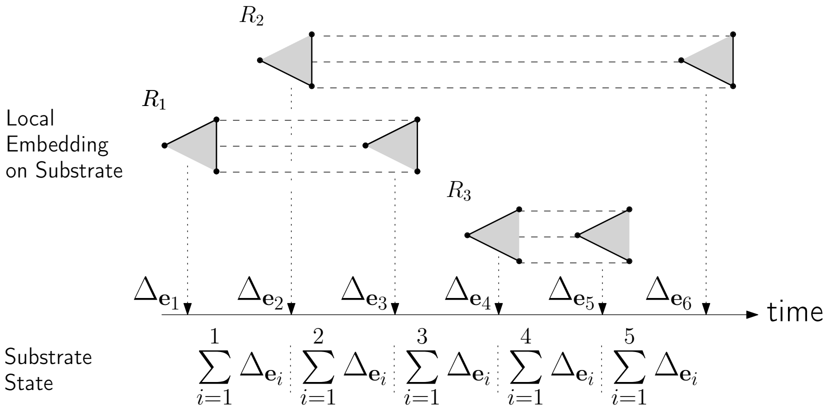
Reconstructing States: Δ-Model



Idea

- Compute state *changes*: $\Delta_{\mathbf{e}_i} : \mathbf{V_S} \cup \mathbf{E_S} \to \mathbb{R}$ via $\chi^+_{\mathsf{R}}(e_i), \chi^-_{\mathsf{R}}(e_i)$

Reconstructing States: Δ-Model



Idea

1. Compute state *changes*: $\Delta_{\mathbf{e}_i} : \mathbf{V_S} \cup \mathbf{E_S} \to \mathbb{R}$ via $\chi^+_{\mathsf{R}}(e_i), \chi^-_{\mathsf{R}}(e_i)$
2. Enforce $\sum_{j=1}^{i} \Delta_{\mathbf{e}_i} \leq \mathbf{c_S}$ for each state

Δ-Model: Computing State Changes

Conditional Assignment

$\forall \mathbf{e}_i \in \mathcal{E}.\ \forall N_s \in \mathbf{V_S}.$

$$\Delta_{\mathbf{e}_i}(N_s) = \begin{cases} +alloc_V(\mathsf{R_j}, N_s) & \text{, if } \chi^{+}_{\mathsf{R_j}}(\mathbf{e}_i) = i \\ -alloc_V(\mathsf{R_j}, N_s) & \text{, if } \chi^{-}_{\mathsf{R_j}}(\mathbf{e}_i) = i \\ \vdots & \\ +alloc_V(\mathsf{R_k}, N_s) & \text{, if } \chi^{+}_{\mathsf{R_k}}(\mathbf{e}_i) = i \\ -alloc_V(\mathsf{R_k}, N_s) & \text{, if } \chi^{-}_{\mathsf{R_k}}(\mathbf{e}_i) = i \end{cases}$$

Δ-Model: Computing State Changes

Conditional Assignment via Big-M Constraints

$\forall \mathrm{R} \in \mathcal{R}.\ \forall \mathbf{e}_i \in \mathcal{E}.\ \forall N_s \in \mathbf{V_S}.$

$$\Delta_{\mathbf{e}_i}(N_s) \leq +\, alloc_V(\mathrm{R}, N_s) + \mathbf{c_S}(N_s)(1 - \chi^{+}_{\mathrm{R}}(\mathbf{e}_i))$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq +\, alloc_V(\mathrm{R}, N_s) - \mathbf{c_S}(N_s)(1 - \chi^{+}_{\mathrm{R}}(\mathbf{e}_i)) \cdot 2$$
$$\Delta_{\mathbf{e}_i}(N_s) \leq -\, alloc_V(\mathrm{R}, N_s) + \mathbf{c_S}(N_s)(1 - \chi^{-}_{\mathrm{R}}(\mathbf{e}_i)) \cdot 2$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq -\, alloc_V(\mathrm{R}, N_s) - \mathbf{c_S}(N_s)(1 - \chi^{-}_{\mathrm{R}}(\mathbf{e}_i))$$

Δ-Model: Computing State Changes

Big-M Assignment of Start

$\forall \mathrm{R} \in \mathcal{R}.\ \forall \mathbf{e}_i \in \mathcal{E}.\ \forall N_s \in \mathbf{V_S}.$

$$\Delta_{\mathbf{e}_i}(N_s) \leq + \mathit{alloc}_V(R, N_s) + \mathbf{c_S}(N_s)(1 - \chi^{+}_{\mathrm{R}_1}(\mathbf{e}_i))$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq + \mathit{alloc}_V(R, N_s) - \mathbf{c_S}(N_s)(1 - \chi^{+}_{\mathrm{R}_1}(\mathbf{e}_i)) \cdot 2$$

$\chi^{+}_{\mathrm{R}}(\mathbf{e}_i) = 0$

$$\Delta_{\mathbf{e}_i}(N_s) \leq + \mathit{alloc}_V(\mathrm{R}, N_s) + \mathbf{c_S}(N_s)$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq + \mathit{alloc}_V(\mathrm{R}, N_s) - 2 \cdot \mathbf{c_S}(N_s)$$

$\Rightarrow$

unbounded

$$\Delta_{\mathbf{e}_i}(N_s) \leq \mathbf{c_S}(N_s)$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq - \mathbf{c_S}(N_s)$$

Δ-Model: Computing State Changes

Big-M Assignment of Start

$\forall \mathrm{R} \in \mathcal{R}.\ \forall \mathbf{e}_i \in \mathcal{E}.\ \forall N_s \in \mathbf{V_S}.$

$$\Delta_{\mathbf{e}_i}(N_s) \leq +\, alloc_V(R, N_s) + \mathbf{c_S}(N_s)(1 - \chi^+_{\mathrm{R}_1}(\mathbf{e}_i))$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq +\, alloc_V(R, N_s) - \mathbf{c_S}(N_s)(1 - \chi^+_{\mathrm{R}_1}(\mathbf{e}_i)) \cdot 2$$

$\chi^+_{\mathrm{R}}(\mathbf{e}_i) = 1$

$$\Delta_{\mathbf{e}_i}(N_s) \leq +\, alloc_V(\mathrm{R}, N_s)$$
$$\Delta_{\mathbf{e}_i}(N_s) \geq +\, alloc_V(\mathrm{R}, N_s)$$

$\Rightarrow$

equal

$$\Delta_{\mathbf{e}_i}(N_s) = alloc_V(\mathrm{R}, N_s)$$

Δ-Model Issue: LP Smearings!

LP Relaxation Example

$\chi^{+}_{\mathrm{R_j}}(\mathbf{e}_j) = 0.5$ for $j \in \{1, 2\}$:

$$-\mathbf{c_S}(N_s) + alloc_V(\mathrm{R_j}, N_s) \leq \Delta_{\mathbf{e}_j}(N_s) \leq alloc_V(\mathrm{R_j}, N_s) + 0.5 \cdot \mathbf{c_S}(N_s)$$

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Implications

1. $\Delta_{\mathbf{e}_j}(s) \leq 0$ is always feasible when $\chi^{+}_{\mathrm{R_j}}(\mathbf{e}_j) = 0.5$ for $j \in \{1, 2\}$
2. $\Delta_{\mathbf{e}_j}(s) = -\mathbf{c_S}(N_s)$ possible if $alloc_V(\mathrm{R_j}, N_s) = 0$

Δ-Model Issue: LP Smearings!

LP Relaxation Example

$\chi^{+}_{\mathrm{R_j}}(\mathbf{e}_j) = 0.5$ for $j \in \{1,2\}$:

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Implications

1. $\Delta_{\mathbf{e}_j}(s) \leq 0$ is always feasible when $\chi^{+}_{\mathrm{R_j}}(\mathbf{e}_j) = 0.5$ for $j \in \{1,2\}$
2. $\Delta_{\mathbf{e}_j}(s) = -\mathbf{c_S}(N_s)$ possible if $alloc_V(\mathrm{R_j}, N_s) = 0$

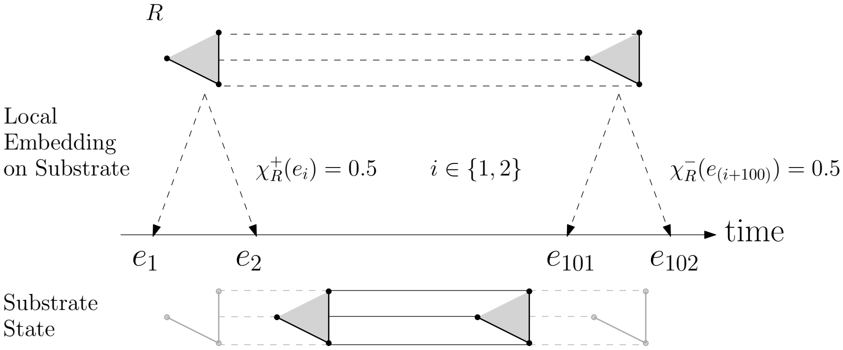
Necessitates more explicit representation of states.

Σ-Model

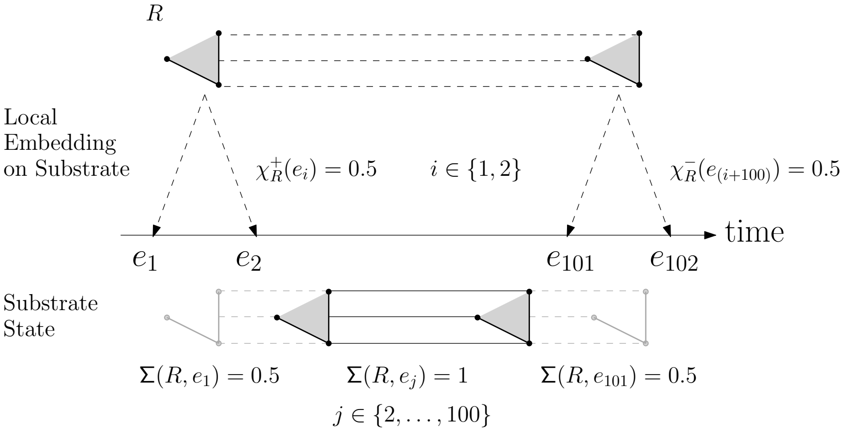
Σ-Model: Intuition

Requirement

Resource allocations must materialize in the substrate's state.



Σ-Model: Intuition



$\forall \mathsf{R} \in \mathcal{R}. \forall \mathbf{e}_i \in \mathcal{E}.$

$$\Sigma(R, \mathbf{e}_i) = \sum_{j=1,\ldots,i} \chi_{\mathsf{R}}^+(\mathbf{e}_j, \mathsf{R}) - \sum_{j=1,\ldots,i} \chi_{\mathsf{R}}^-(\mathbf{e}_j, \mathsf{R})$$

Σ-Model

Request allocations are computed for each state

- States $\mathcal{S} = \{\mathbf{s}_1, \ldots, \mathbf{s}_{2\cdot|\mathcal{R}|-1}\}$
- $\forall \mathrm{R} \in \mathcal{R}. \forall \mathbf{s}_i \in \mathcal{S}. \forall N_s \in \mathbf{V_S}.$

$$\mathrm{a}_{\mathrm{R}}(\mathbf{s}_i, N_s) \geq alloc_V(\mathrm{R}, N_s) - \mathbf{c_V}(N_s) \cdot (1 - \Sigma(R, \mathbf{e}_i))$$

- $\forall \mathbf{s}_i \in \mathcal{S}. \forall r \in \mathbf{V_S}.$

$$\mathbf{c_S}(N_s) \geq \sum_{\mathrm{R} \in \mathcal{R}} \mathrm{a}_{\mathrm{R}}(\mathbf{s}_i, N_s)$$

$\forall \mathrm{R} \in \mathcal{R}. \forall \mathbf{e}_i \in \mathcal{E}.$

$$\Sigma(R, \mathbf{e}_i) = \sum_{j=1,\ldots,i} \chi^+_{\mathrm{R}}(\mathbf{e}_j, \mathrm{R}) - \sum_{j=1,\ldots,i} \chi^-_{\mathrm{R}}(\mathbf{e}_j, \mathrm{R})$$

cΣ-Model

cΣ-Model: Overview

Computational Trade-Off

- The Σ-Model is provably stronger than Δ-Model.
- However, the Σ-Model uses (approximately) $2 \cdot |\mathcal{R}|$ more variables!

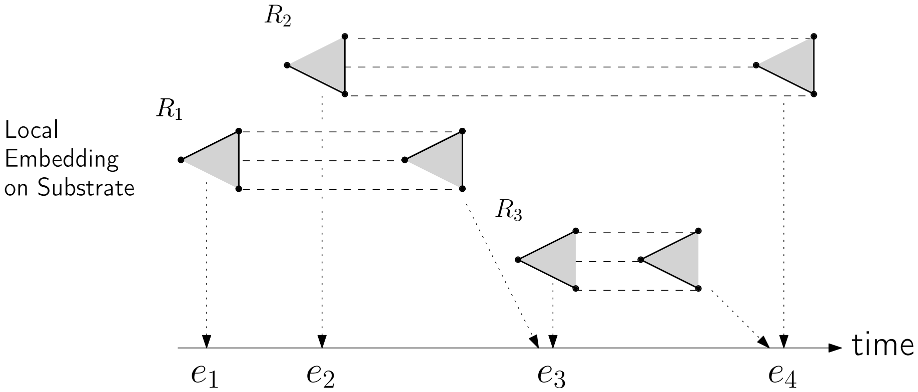
Σ-Model can be strengthened: cΣ-Model

State compactification: Consider only *partial* event order. Yields *state-space* and *symmetry reductions*.

User cuts: Use temporal information to reduce *state-space* and strengthen formulation.

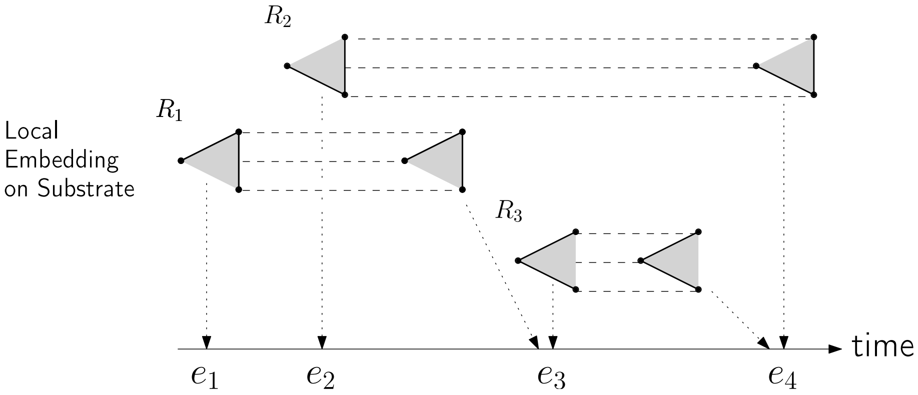
cΣ Optimization: State Compactification

cΣ-Model: State Compactification

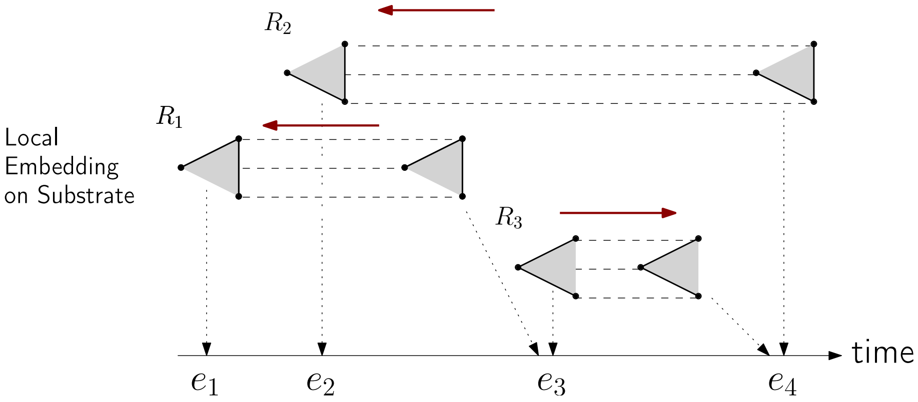


No need to check feasibility at *end* of a request.
Halves the number of variables (approximately):
State-space reduction.

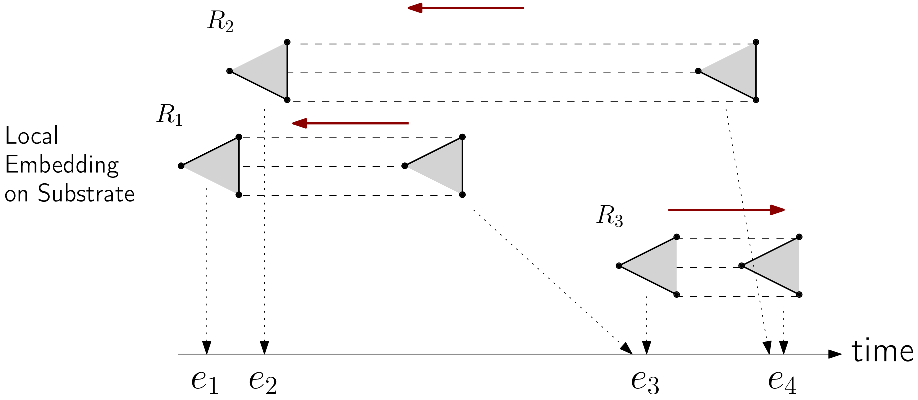
cΣ-Model: State Compactification is Symmetry Reduction



cΣ-Model: State Compactification is Symmetry Reduction

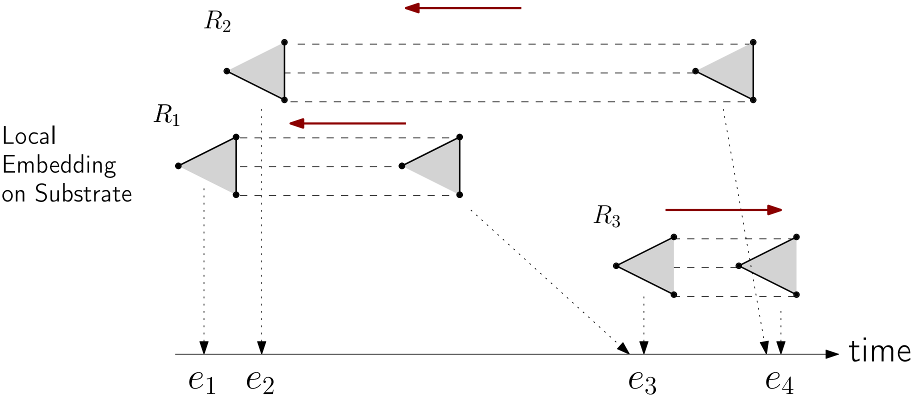


cΣ-Model: State Compactification is Symmetry Reduction



Same order as before!

cΣ-Model: State Compactification is Symmetry Reduction



Theorem

Compactification is symmetry reduction.

The Last Bit: Incorporating Time

cΣ-Model: Incorporating Time

$\forall \mathbf{e}_i \in \{\mathbf{e}_1, \ldots, \mathbf{e}_{|\mathcal{R}|}\}$.

$$t_{\mathbf{e}_i} \leq t_{\mathbf{e}_{i+1}}$$

$\forall R \in \mathcal{R}$.

$$\mathbf{d}_R = t^-{}_R - t^+{}_R$$

$\forall R \in \mathcal{R}. \forall \mathbf{e}_i \in \{\mathbf{e}_1, \ldots, \mathbf{e}_{|\mathcal{R}|}\}$.

$$t_R^+ \leq t_{\mathbf{e}_i} + \Big(1 - \sum_{j=1,\ldots,i} \chi_R^+(\mathbf{e}_j, R)\Big) \cdot \mathbf{T}$$

$$t_R^+ \geq t_{\mathbf{e}_i} - \Big(1 - \sum_{j=i,\ldots,|\mathcal{E}|} \chi_R^+(\mathbf{e}_j, R)\Big) \cdot \mathbf{T}$$

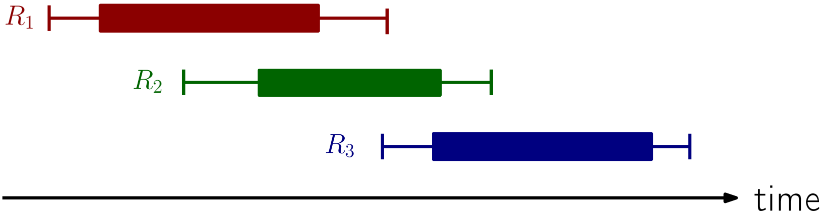
$\forall R \in \mathcal{R}. \forall \mathbf{e}_i \in \{\mathbf{e}_2, \ldots, \mathbf{e}_{|\mathcal{R}|+1}\}$.

$$t_R^- \leq t_{\mathbf{e}_i} + \Big(1 - \sum_{j=2,\ldots,i} \chi_R^-(\mathbf{e}_j, R)\Big) \cdot \mathbf{T}$$

$$t_R^- \geq t_{\mathbf{e}_{i-1}} - \Big(1 - \sum_{j=i,\ldots,|\mathcal{E}|} \chi_R^-(\mathbf{e}_j, R)\Big) \cdot \mathbf{T}$$

Optimizations: Temporal Dependency Graph Cuts

Temporal Dependency Graph Cuts



Temporal Dependency Graph Cuts

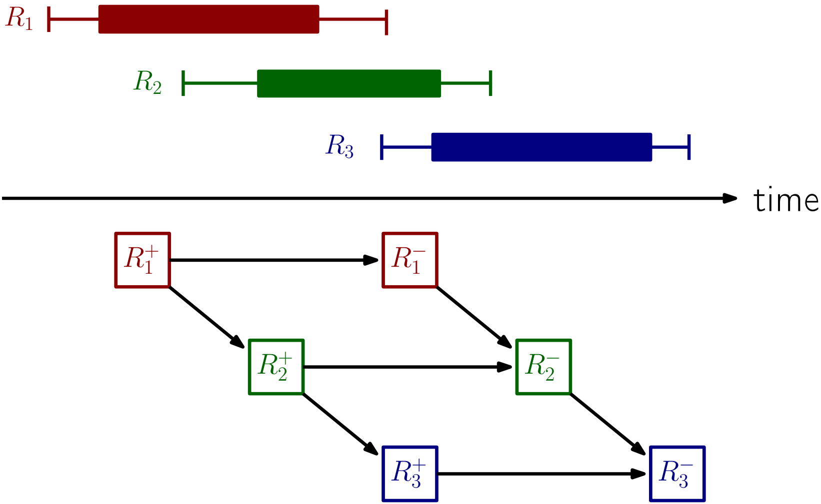


Figure: Temporal Dependency Graph

Temporal Dependency Graph Cuts

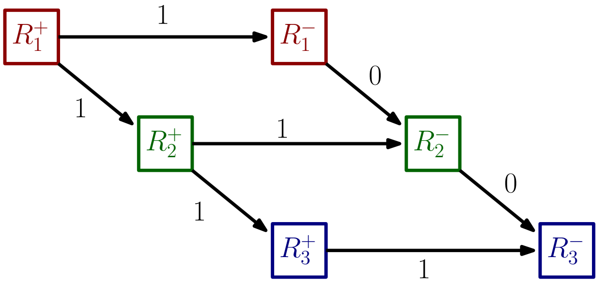


Figure: Temporal Dependency Graph

By computing maximal distances we obtain:

- Start of R_1: e_1
- Start of R_2: e_2
- Start of R_3: e_3
- End of R_1: e_2, e_3, e_4
- End of R_2: e_3, e_4
- End of R_1: e_4

Temporal Dependency Graph Cuts

State-space Reduction via

$\forall v \in V_{dep}.$

$$\sum_{i=|dist^{+}_{\max}(v)|+1}^{|\mathcal{R}|+1-|dist^{-}_{\max}(v)|} \chi_{Event}(\mathbf{e}_i, v) = 1$$

User Cuts:

If R was embedded at e_i, then successor w must have been embedded ..

$\forall v \in V_{dep}.\forall w \in dist^{+}_{\max}(v).\forall \mathbf{e}_i \in \mathcal{E}, dist_{\max}(v,w) + 1 \leq i \leq |\mathcal{R}|.$

$$\sum_{j=1}^{i} \chi_{Event}(\mathbf{e}_j, w) \leq \sum_{\substack{\mathbf{e}_j \in \mathcal{E} \\ \text{with } j \leq i - dist^{-}_{\max}(v,w)}} \chi_{Event}(\mathbf{e}_j, v)$$

Greedy Heuristic $c\Sigma_A^G$

Greedy Heuristic $c\Sigma_A^G$

Setting

Node placements are fixed.

Outline

1. Order requests according to their earliest start time.
2. Iteratively try to embed requests as soon as possible using $c\Sigma$-Model
    1. If the request was embedded: fix start and end time.

Greedy Heuristic $c\Sigma_A^G$

Setting

Node placements are fixed.

Outline

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    1. If the request was embedded: fix start and end time.

Theorem

$c\Sigma_A^G$ is polynomial-time algorithm.

Important

All link allocations are re-computed in each iteration.

Computational Evaluation

Scenario: One day workload

- 20 requests (star-graphs) are to be embedded on 4×5 grid
- Expected inter-arrival time of one hour [Poisson]
- Expected duration of 3.5 hours [Weibull: heavy-tailed]
- Node-mappings are fixed to concentrate on temporal aspects
- Link-mappings are not fixed
- Increasing temporal flexibility: $0, 30, 60, \ldots, 300$ minutes.

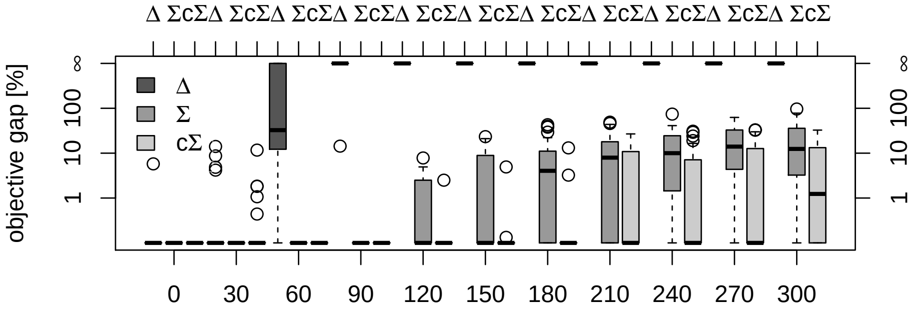
Computational Setup

- 24 independently generated scenarios
- Limited runtime of one hour for MIPs [Gurobi]

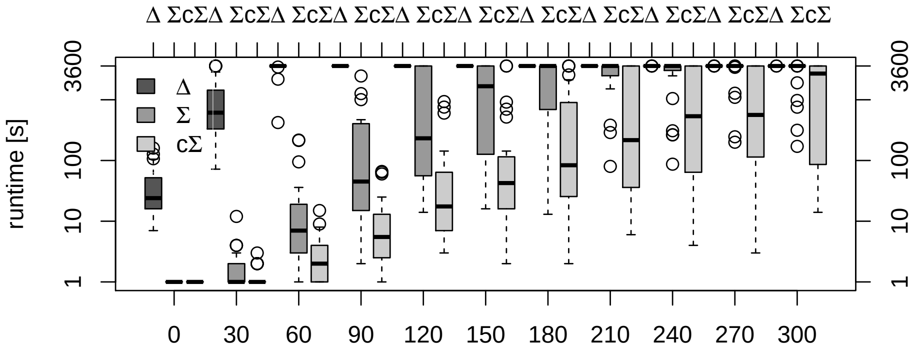
Task: Maximize revenue $\propto$ load $\cdot$ duration

1. Decide which requests to embed (access control).
2. Find time-invariant embedding (routing of data).
3. Decide when to embed the requests.

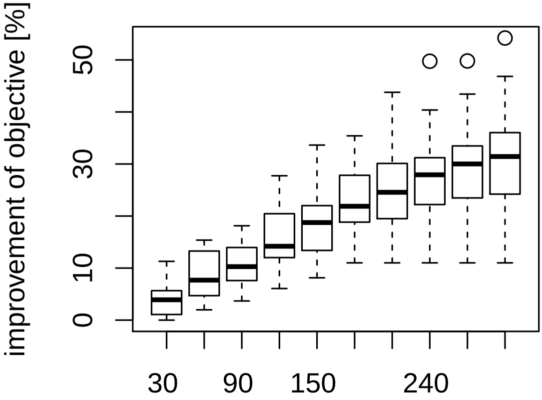
Objective Gap: MIP Formulations



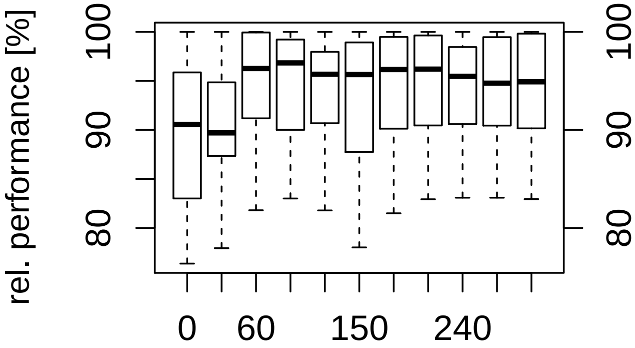
Runtime: MIP Formulations



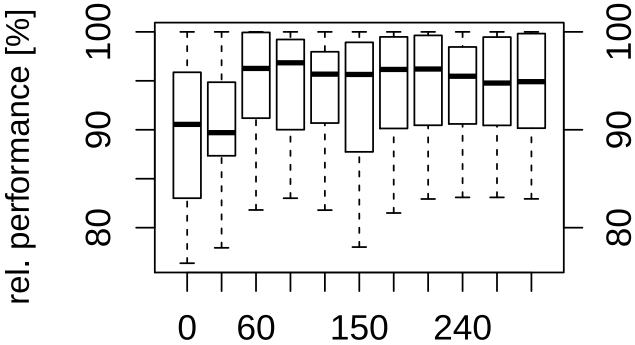
Benefit of Flexibility



Performance of $c\Sigma_A^G$



Performance of $c\Sigma_A^G$



Fast: runtime of few seconds.

Conclusion

Related Work

Chemical plants [3]	Utilize similar event abstraction, but no resource sharing.
Business Perspective [4]	Marketplace based on temporal flexibilities.
MapReduce [5]	Consider temporally predictable jobs (MapReduce-like) and allow for temporally interleaved resource sharing.
VNet Survey [2]	There is no comparable work on TVNEP.
Google B4 [6]	Software-defined network (wide-area) connecting data centers. Only some dozen locations.

Future Work / Discussion

Modeling

- Consider flexible duration of requests.
- Consider delay-tolerant VNets.
- Consider more complex scenarios, e.g. migrations.

Algorithmic

- Incorporate other heuristical embedding approaches.
- Develop local-search algorithms for the TVNEP.

The End

1. Abstract event point model
2. Δ-, Σ- and $c\Sigma$-Model
   - state-space reductions
   - symmetry reduction
3. Greedy heuristic $c\Sigma^G_A$ based on $c\Sigma$
4. Initial computational evaluation
   - $\Delta \ll \Sigma < c\Sigma$
   - $c\Sigma$: near optimal solutions within one hour
   - $c\Sigma^G_A$ only approx. 5-10% off optimum

References I

[1] N. Chowdhury, M. Rahman, and R. Boutaba.
Virtual network embedding with coordinated node and link mapping.
In *Proc. of the IEEE INFOCOM '09*, 2009.

[2] A. Fischer, J. Botero, M. Beck, H. De Meer, and X. Hesselbach.
Virtual network embedding: A survey.
2013.

[3] C. A. Floudas and X. Lin.
Continuous-time versus discrete-time approaches for scheduling of chemical processes: a review.
Computers & Chemical Engineering, 28(11), 2004.

[4] T. A. Henzinger, A. V. Singh, V. Singh, T. Wies, and D. Zufferey.
A marketplace for cloud resources.
In *Proc. of the ACM EMSOFT '10*, 2010.

[5] L. Mai, E. Kalyvianaki, and P. Costa.
Exploiting time-malleability in cloud-based batch processing systems.
In *Proceeding of the ACM SIGOPS LADIS Workshop '13*, 2013.

References II

[6] S. Jain et al.
B4: experience with a globally-deployed software defined wan.
In *Proc. of the ACM SIGCOMM '13*, 2013.

[7] A. Singla, A. Singh, K. Ramachandran, L. Xu, and Y. Zhang.
Proteus: A topology malleable data center network.
In *Proc. of the ACM SIGCOMM HotNets Workshop '10*, 2010.

Standard VNEP Access Control & Resource Mapping

Variables

Access Control		$\mathrm{x}_{\mathcal{R}} : \mathcal{R} \to \mathbb{B}$
Node Mapping	$\forall \mathrm{R} \in \mathcal{R}.$	$\mathrm{x}_V : \mathbf{V}_\mathrm{R} \times \mathbf{V}_\mathbf{S} \to \mathbb{B}$
Link Mapping	$\forall \mathrm{R} \in \mathcal{R}.$	$\mathrm{x}_E : \mathbf{E}_\mathrm{R} \times \mathbf{E}_\mathbf{S} \to [0, 1]$

Node mapping

Map each virtual onto a substrate node, if the request is embedded.

Link mapping

Map each virtual link onto multiple paths in the substrate (splittable flows).

Macro $alloc_V(R, N_s)$: $\forall R \in \mathcal{R}. \forall N_s \in \mathbf{V_S}$

$$alloc_V(R, N_s) = \sum_{N_v \in \mathbf{V}_\mathrm{R}} \mathsf{c}_\mathrm{R}(N_v) \cdot \mathrm{x}_V(N_v, N_s)$$

Macro $alloc_V(R, N_s)$: $\forall R \in \mathcal{R}. \forall L_s \in \mathbf{E_S}$

$$alloc_E(R, L_s) = \sum_{L_v \in \mathbf{E}_\mathrm{R}} \mathsf{c}_\mathrm{R}(L_v) \cdot \mathrm{x}_E(L_v, L_s)$$

Standard VNEP Access Control & Resource Mapping

Variables

Access Control		$\mathrm{x}_{\mathcal{R}} : \mathcal{R} \to \mathbb{B}$
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Link Mapping	$\forall \mathrm{R} \in \mathcal{R}.$	$\mathrm{x}_E : \mathbf{E}_\mathrm{R} \times \mathbf{E}_\mathbf{S} \to [0,1]$

Node mapping: $\forall \mathrm{R} \in \mathcal{R}.\ \forall N_v \in \mathbf{V}_\mathrm{R}.$

$$\mathrm{x}_{\mathcal{R}}(\mathrm{R}) = \sum_{N_s \in \mathbf{V}_\mathbf{S}} \mathrm{x}_V(N_v, N_s)$$

Link mapping: $\forall \mathrm{R} \in \mathcal{R}.\forall L_v = (N_v^+, N_v^-) \in \mathbf{E}_\mathrm{R}.\forall N_s \in \mathbf{V}_\mathbf{S}$

$$\sum_{L_s \in \delta^+(N_s)} \mathrm{x}_E(L_v, L_s) - \sum_{L_s \in \delta^-(N_s)} \mathrm{x}_E(L_v, L_s) = \mathrm{x}_V(N_v^-, N_s) - \mathrm{x}_V(N_v^+, N_s)$$

Macro $alloc_V(R, N_s)$: $\forall R \in \mathcal{R}.\forall N_s \in \mathbf{V}_\mathbf{S}$

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$alloc_E(R, L_s) = \sum_{L_v \in \mathbf{E}_\mathrm{R}} \mathbf{c}_\mathrm{R}(L_v) \cdot \mathrm{x}_E(L_v, L_s)$

Applications

Data center

- e.g. MapReduce cycles through different phases, traffic only during 30-60% of execution [7]
- price incentives for customers and providers to allow for / harness temporal flexibility [5]

Wide area networks

- Google uses SDN in the WAN to connect data centers [6]
- scheduling of bandwidth-intensive synchronizations
  - is necessary to achieve good utilization and resource isolation
  - is enabled by central SDN control