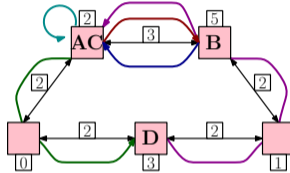


Charting the Complexity Landscape of Virtual Network Embeddings



IFIP Networking 2018

Matthias Rost

Technische Universität Berlin, Internet Network Architectures

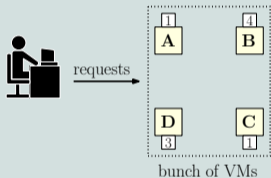
Stefan Schmid

Universität Wien, Communication Technologies

Introduction: Virtual Network Embeddings and Their Complexity

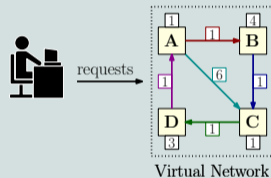
Virtualization: Resource Allocation Opportunities

'Classic' Cloud Computing



- User requests virtual machines
- No guarantee on network performance

Goal: Virtual Networks (since \approx 2006)

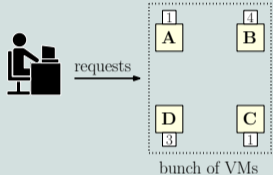


- Communication requirements given
- Network performance will be guaranteed

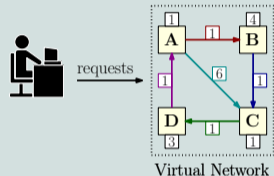
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Novel Service Abstractions

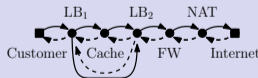
- Virtual Networks – overlays (\approx 2006)
- Virtual Clusters – batch processing (\approx 2011)
- Service Chain – stitch functions (\approx 2013)



Virtual Network



Virtual Cluster

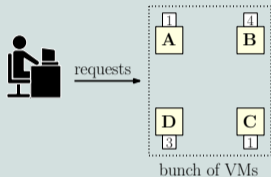


Service Chain

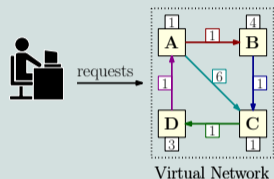
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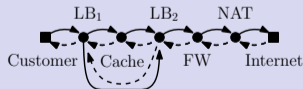
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Virtual Network



Virtual Cluster

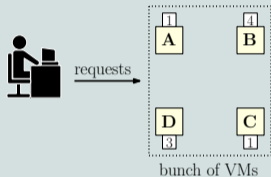


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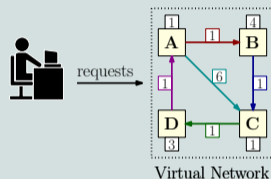
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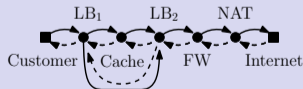
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Virtual Network



Virtual Cluster



Service Chain

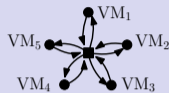
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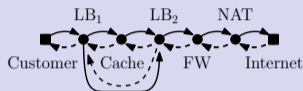
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Virtual Cluster

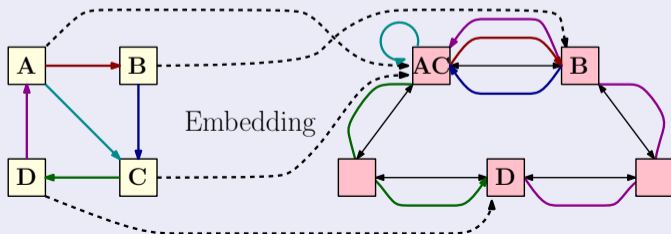


Service Chain

Virtual Network Embeddings at a Glance

Virtual Network

Substrate (Physical Network)



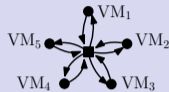
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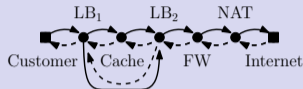
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Virtual Network



Virtual Cluster

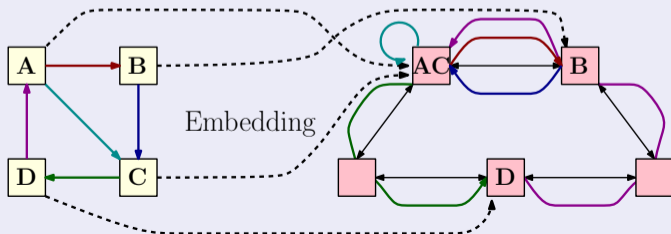


Service Chain

Virtual Network Embeddings at a Glance

Virtual Network

Substrate (Physical Network)



Embedding Restrictions

Capacity

V Node

E Edge

Additional

N Node placement

R Routing

L Latencies

Introduction: Virtual Network Embeddings and Their Complexity

Novel Service Abstractions

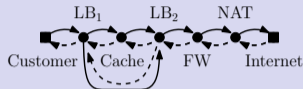
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Virtual Network



Virtual Cluster

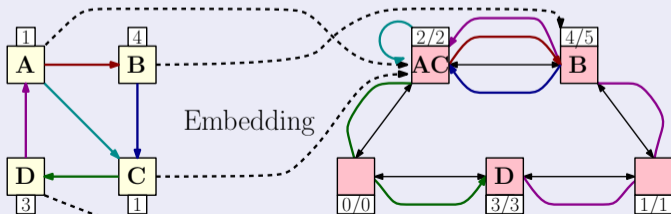


Service Chain

Virtual Network Embeddings at a Glance – Node Capacities

Virtual Network

Substrate (Physical Network)



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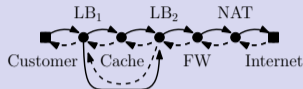
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Virtual Network



Virtual Cluster

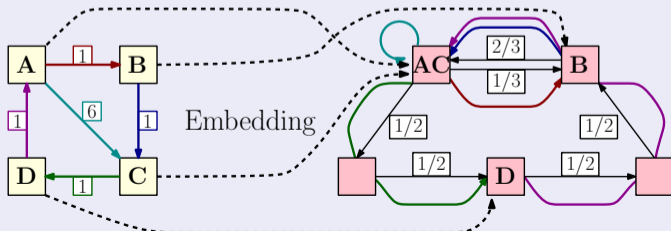


Service Chain

Virtual Network Embeddings at a Glance – Edge Capacities

Virtual Network

Substrate (Physical Network)



Embedding Restrictions

Capacity

V Node

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Additional

N Node placement

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Introduction: Virtual Network Embeddings and Their Complexity

Novel Service Abstractions

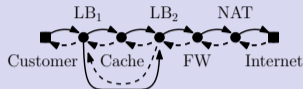
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Virtual Network



Virtual Cluster

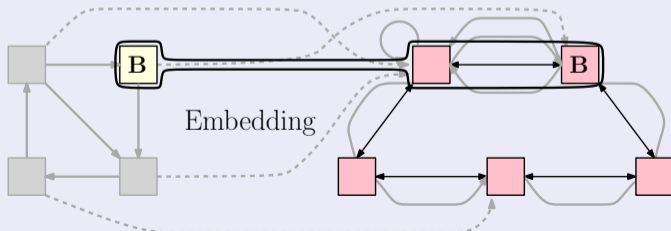


Service Chain

Virtual Network Embeddings at a Glance – Node Placement

Virtual Network

Substrate (Physical Network)



Embedding Restrictions

Capacity

V Node

E Edge

Additional

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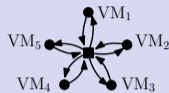
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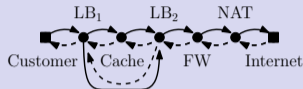
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Virtual Network



Virtual Cluster

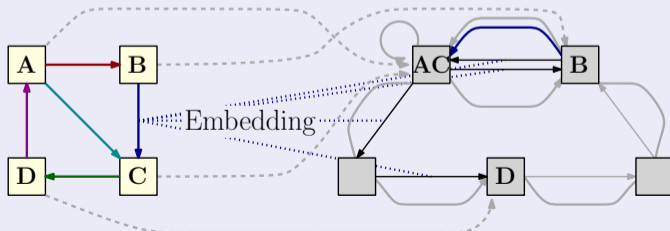


Service Chain

Virtual Network Embeddings at a Glance – Routing Restrictions

Virtual Network

Substrate (Physical Network)



Embedding Restrictions

Capacity

- V** Node
- E** Edge

Additional

- N** Node placement
- R** Routing
- L** Latencies

Introduction: Virtual Network Embeddings and Their Complexity

Novel Service Abstractions

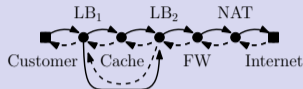
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Virtual Network



Virtual Cluster

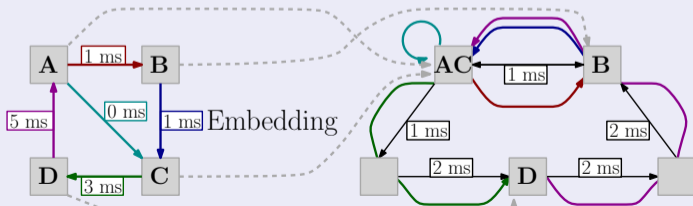


Service Chain

Virtual Network Embeddings at a Glance – Latencies

Virtual Network

Substrate (Physical Network)



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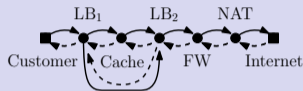
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Virtual Network



Virtual Cluster



Service Chain

Taxonomy of VNEP Variants

VNEP $\langle C | A \rangle$: capacity restrictions C & additional restrictions A

Embedding Restrictions

Capacity

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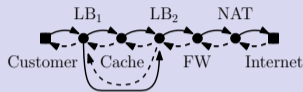
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Virtual Network



Virtual Cluster



Service Chain

Taxonomy of VNEP Variants

VNEP $\langle C | A \rangle$: capacity restrictions C & additional restrictions A

For example...

VNEP $\langle VE | - \rangle$: node and edge capacities

VNEP $\langle V | R \rangle$: node capacities and routing restrictions

VNEP $\langle - | NL \rangle$: node placement and latency restrictions

Embedding Restrictions

Capacity

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Introduction: Virtual Network Embeddings and Their Complexity

Related Work

Theoretical Results: **Few**

Andersen [2002] Considered $\langle \mathbf{VE} \mid - \rangle$ and argued for \mathcal{NP} -hardness

Amaldi et al. [2016] Considered $\langle \mathbf{VE} \mid \mathbf{N} \rangle$ under *profit objective*, proved \mathcal{NP} -hardness and derived inapproximability result.

Practical Results: **Many**

Generally More than 100 papers on VNEP alone, for example ...

Chowdhury et al. [2009] Developed algorithms for variant $\langle \mathbf{VE} \mid \mathbf{N} \rangle$ and hoped to obtain *approximations*.

VNEP is of **crucial** importance, yet is **hardly understood!**

Introduction: Virtual Network Embeddings and Their Complexity

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Our Contributions

- 1 \mathcal{NP} -completeness under restrictions $\langle \mathbf{VE} | - \rangle$, $\langle \mathbf{E} | \mathbf{N} \rangle$, $\langle \mathbf{V} | \mathbf{R} \rangle$, $\langle - | \mathbf{NR} \rangle$, $\langle - | \mathbf{NL} \rangle$.
- 2 Relaxed model: \mathcal{NP} -completeness of computing approximate embeddings.
- 3 Restricted input: \mathcal{NP} -completeness pertains when restricting request topologies.

Practical Implications (unless $\mathcal{P} = \mathcal{NP}$)

There cannot exist a polynomial-time algorithm ...

- 1 always yielding a solution to the VNEP under any of the above restrictions,
- 2 which does not violate capacities or latencies by less than some amount,
- 3 even when virtual networks are acyclic, planar, and degree-bounded.

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Definition of the Virtual Network Embedding Problem

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Input

Substrate $G_S = (V_S, E_S)$

Request $G_r = (V_r, E_r)$

Restrictions ...

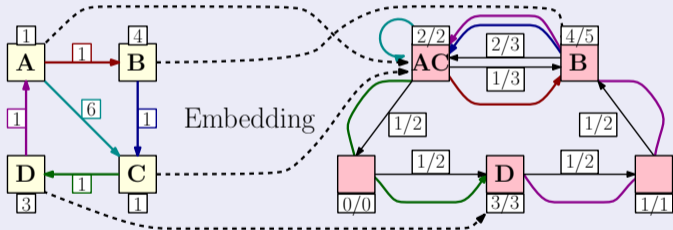
Feasible Embedding

A *feasible* embedding is a mapping of G_r to G_S respecting **all** restrictions.

Feasible embedding meets *all* requirements

Virtual Network

Substrate (Physical Network)



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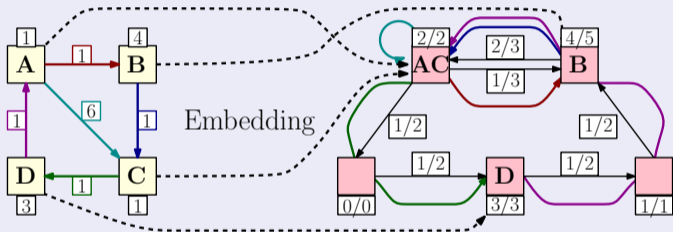
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Virtual Network

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Virtual Network Embedding Problem (Decision Variant)

Decide whether a feasible embedding of request G_r on substrate G_S exists.

Output: Yes / No.

Methodology

Reminder: 3-SAT and \mathcal{NP} -Completeness

3-SAT-Formula ϕ

$\phi = \bigwedge_{C_i \in \mathcal{C}_\phi} C_i$ with $C_i \in \mathcal{C}_\phi$ being disjunctions of at most 3 (possible negated) literals.

Example 3-SAT formula ϕ over literals $\mathcal{L}_\phi = \{x_1, x_2, x_3, x_4\}$

$$\phi = \underbrace{(x_1 \vee x_2 \vee x_3)}_{C_1} \wedge \underbrace{(\bar{x}_1 \vee x_2 \vee x_4)}_{C_2} \wedge \underbrace{(x_2 \vee \bar{x}_3 \vee x_4)}_{C_3}$$

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Definition of 3-SAT

Decide whether satisfying assignment $a : \mathcal{L}_\phi \rightarrow \{F, T\}$ exists for formula ϕ . Output: Yes/No.

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Theorem: Karp [1972]

3-SAT is \mathcal{NP} -complete.

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3-SAT is \mathcal{NP} -complete.

A Decision Problem is \mathcal{NP} -complete if ...

... it lies in \mathcal{NP} and *all* other decision problems in \mathcal{NP} can be reduced to it.

Methodology: Proving \mathcal{NP} -completeness

Proving \mathcal{NP} -completeness of the VNEP

- 1 VNEP lies in \mathcal{NP} (answer can be checked in polynomial time).
- 2 Reduction from 3-SAT to VNEP.

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Outline of Reduction Framework

3-SAT instance ϕ \longmapsto VNEP instance $(G_r(\phi), G_S(\phi), \text{mapping restrictions})$

ϕ satisfiable? \iff feasible embedding of $G_r(\phi)$ on $G_S(\phi)$ under restrictions?

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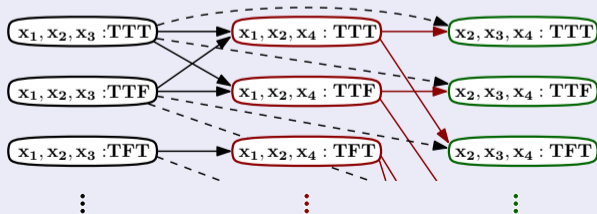
Request $G_r(\phi)$

- $V_r(\phi) = \{v_i \mid C_i \in \mathcal{C}_\phi\}$
- $E_r(\phi) = \{ (v_i, v_j) \mid C_i \text{ introduces literal used by } C_j \}$



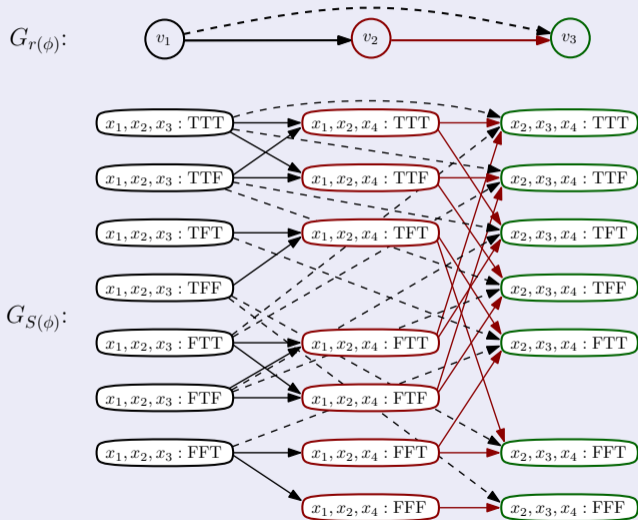
Substrate $G_S(\phi)$

- one node per clause and per satisfying assignment
- edges as for the requests, if assignments do not contradict



Complete Picture

$$\phi: (x_1 \vee x_2 \vee x_3) \wedge (\bar{x}_1 \vee x_2 \vee x_4) \wedge (x_2 \vee \bar{x}_3 \vee x_4)$$



Our Reduction Framework

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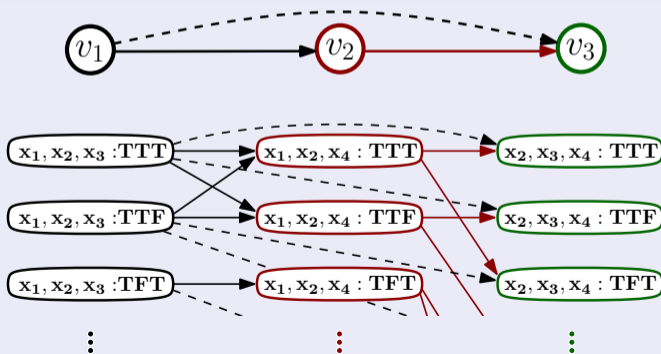
Our Reduction Framework

Base Lemma

Formula ϕ is satisfiable **if and only if** there exists a mapping of $G_r(\phi)$ on $G_S(\phi)$, s.t.

- (1) each virtual node v_i is mapped to a 'satisfying assignment node' of the i -th clause, and
- (2) all virtual edges are mapped on exactly one substrate edge.

Visualization of Conditions (1) and (2)



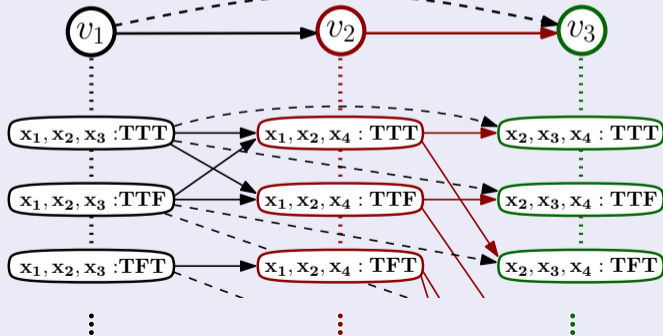
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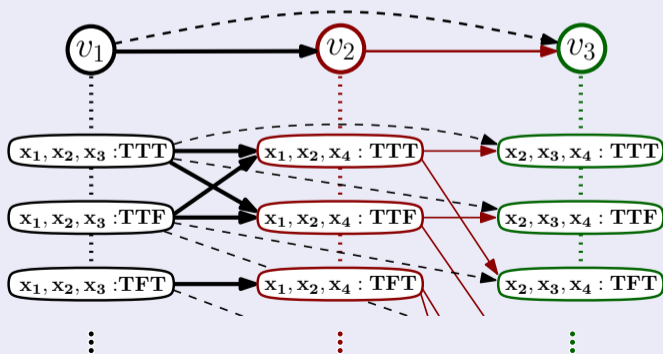
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Visualization of Conditions (1) and (2)



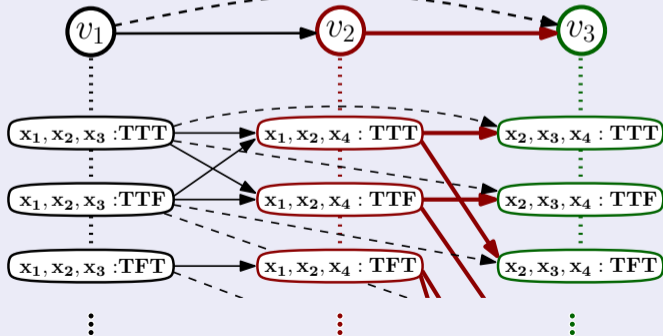
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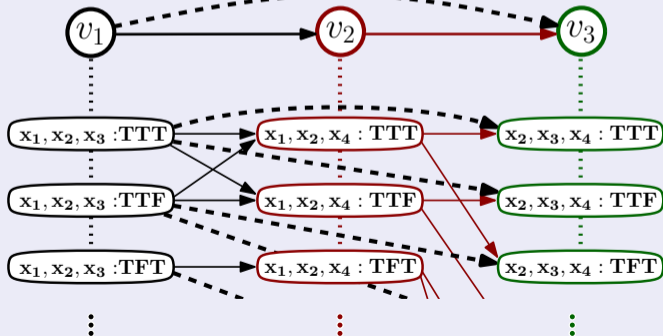
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Example

$$\phi = (x_1 \vee x_2 \vee x_3) \wedge (\bar{x}_1 \vee x_2 \vee x_4) \wedge (x_2 \vee \bar{x}_3 \vee x_4)$$

Assignment for ϕ

$$x_1 \mapsto \text{T}$$

$$x_2 \mapsto \text{T}$$

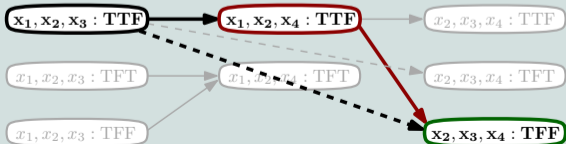
$$x_3 \mapsto \text{F}$$

$$x_4 \mapsto \text{F}$$

Request



Embedding satisfying conditions (1) and (2)



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Application of Base Lemma for VNEP Variant $\langle \mathbf{X} \mid \mathbf{Y} \rangle$

VNEP $\langle \mathbf{X} \mid \mathbf{Y} \rangle$ is \mathcal{NP} -complete if we can enforce all *feasible* embeddings to satisfy (1) and (2).

3-SAT instance $\phi \longmapsto$ VNEP instance $(G_r(\phi), G_S(\phi), \text{under mapping restrictions})$

ϕ satisfiable? \iff feasible embedding of $G_r(\phi)$ on $G_S(\phi)$ **under restrictions?**

Results

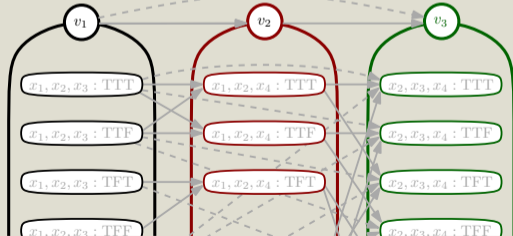
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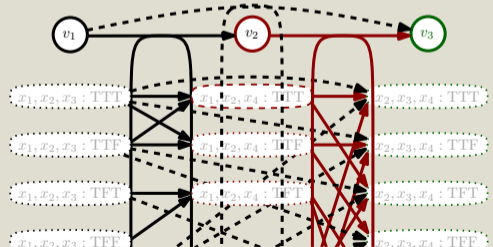
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Node placement enforce (1)



Routing restrictions enforce (2)



Results

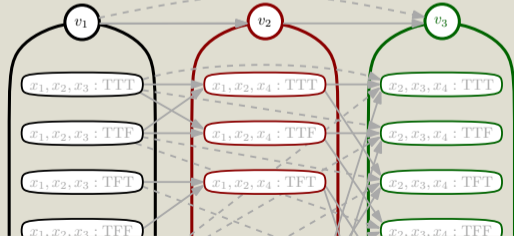
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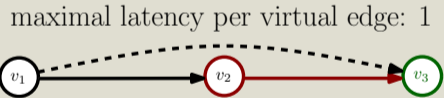
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VNEP $\langle - | \text{NL} \rangle$ is \mathcal{NP} -complete.

Node placement enforce (1)



Placement and latency restrictions enforce (2)



latency of substrate edges: 1



Results

\mathcal{NP} -Completeness shown for $\langle - | \mathbf{NR} \rangle$ and $\langle - | \mathbf{NL} \rangle$

In the paper: $\langle \mathbf{VE} | - \rangle$, $\langle \mathbf{E} | \mathbf{N} \rangle$, $\langle \mathbf{V} | \mathbf{R} \rangle$.

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Implications of \mathcal{NP} -Completeness

- Finding a feasible embedding for the VNEP is \mathcal{NP} -complete.
- Finding an optimal feasible embedding **subject to any objective** is \mathcal{NP} -hard.
- There cannot exist polynomial-time approximation algorithms (unless $\mathcal{P} = \mathcal{NP}$).

\mathcal{NP} -Completeness of Computing Approximate Embeddings

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Insight: If the problem is too hard, relax the model.

How hard are the VNEP variants when we allow for capacity violations or latency violations?

Allowing for Node Capacity Violations

Relaxation: We allow for substrate node capacity violations by a factor $\alpha < 2$.

Result: $\langle \mathbf{VE} \mid - \rangle$ and $\langle \mathbf{V} \mid \mathbf{R} \rangle$ stay \mathcal{NP} -complete and inapproximable (unless $\mathcal{P} = \mathcal{NP}$).

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\mathcal{NP} -Completeness when Restricting Graph Classes

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Insight: If the problem is too hard, restrict the model inputs.

How hard are the VNEP variants when we restrict the graph classes for the substrate and the requests?

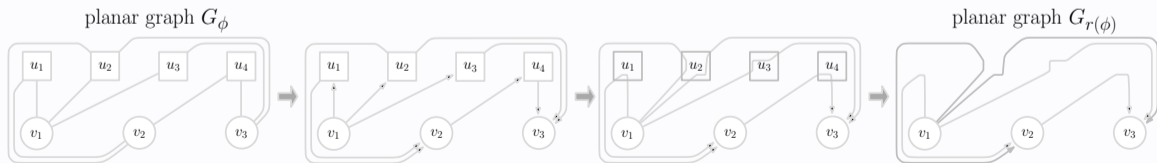
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By construction, the graphs $G_r(\phi)$ and $G_S(\phi)$ are directed acyclic graphs (DAGs). Accordingly, the hardness results pertain when restricting the input graphs to be DAGs.

Restriction of Requests to Planar Degree-Bounded Graphs

Restriction: The request graph must be a planar and degree-bounded.

Result: All previous results pertain based on a reduction from a **special planar 3-SAT** variant.



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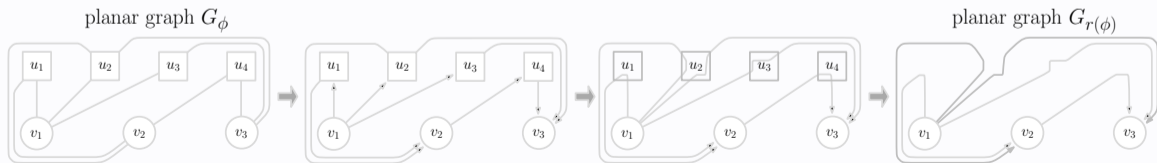
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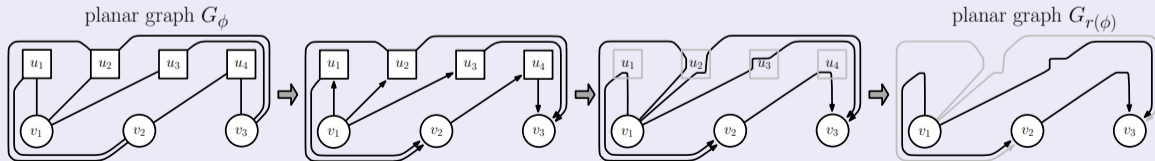
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Conclusion

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Further Results Proof \mathcal{NP} -completeness for $\langle \mathbf{V} \mid \mathbf{RL} \rangle$, consider *uniform* capacities, ...

Improvements Improvement of lower bounds for approximate embeddings.

Gained Insights The VNEP is really hard.

- Justifies using heuristics and exponential-time algorithms.
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Thank you! Questions?

References I

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