GrapH: Heterogeneity-Aware Graph Computation with Adaptive Partitioning

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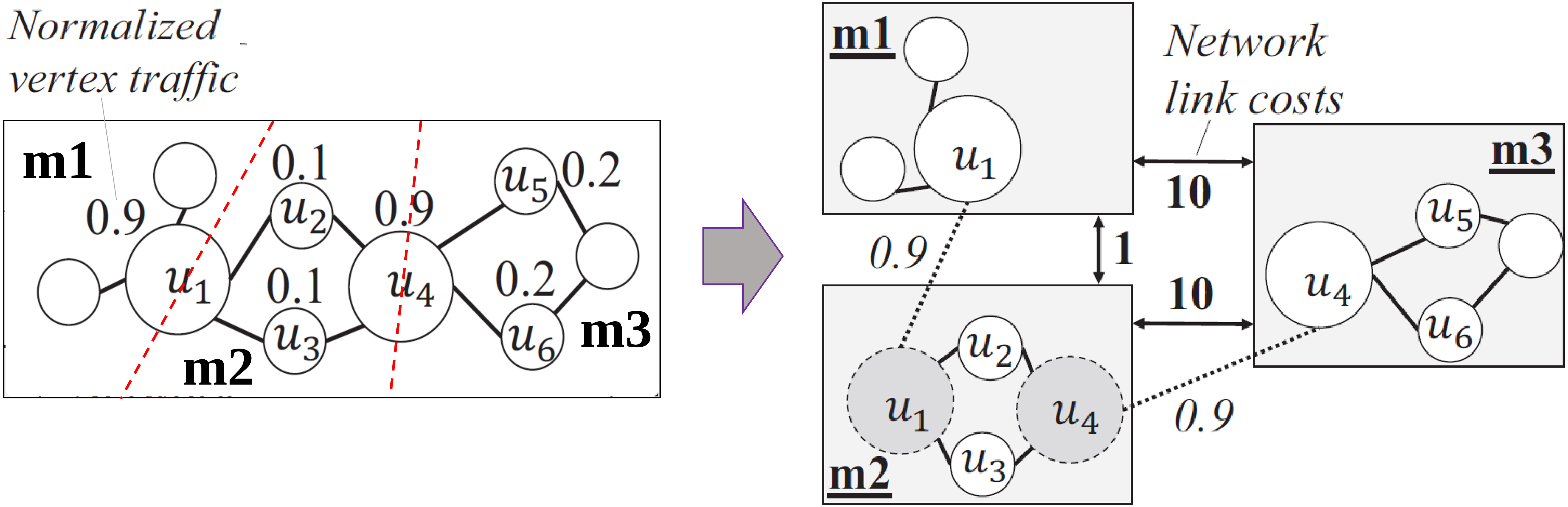
2016 IEEE 36th International Conference on Distributed Computing Systems

Partition graph with vertex-cut

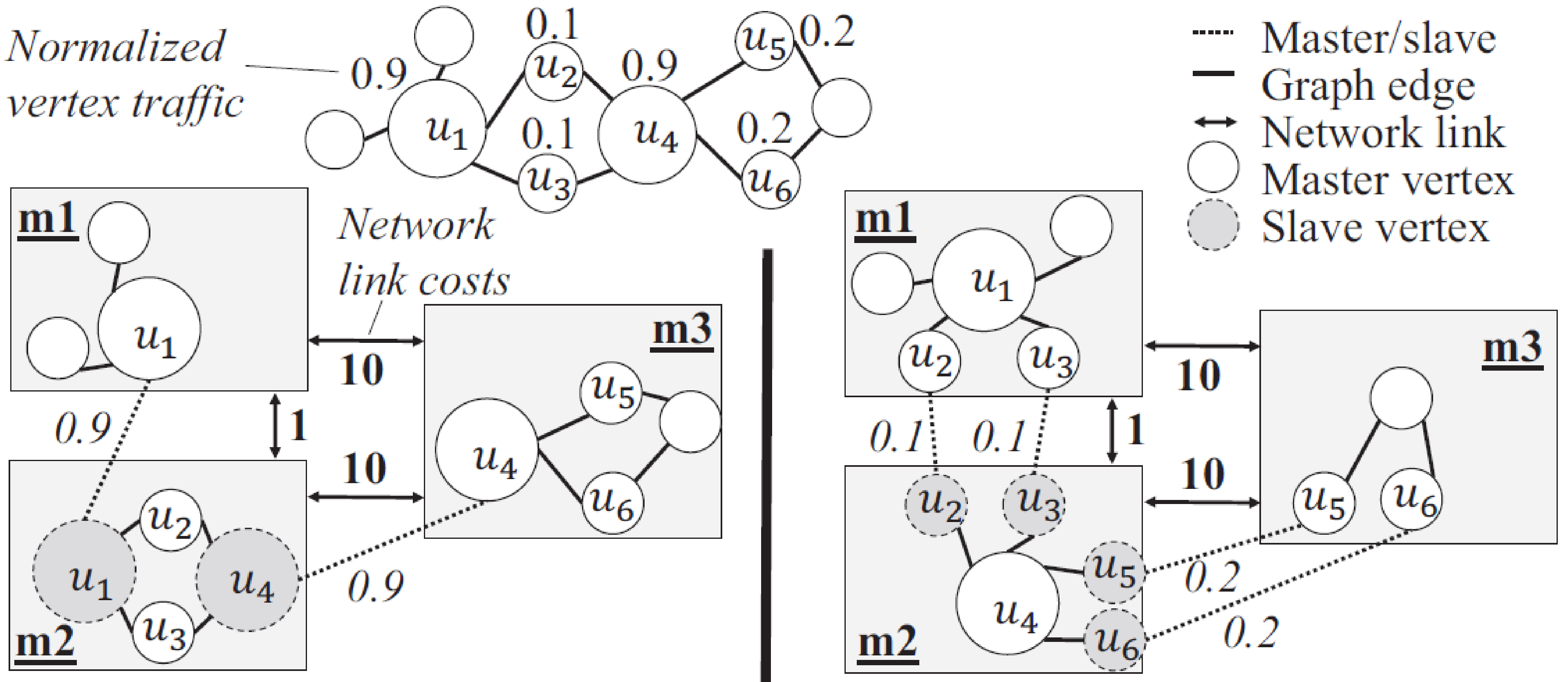


Motivation

- Many high-effect Vertex-centric graph processing systems use graph partitioning algorithms assuming:
  - uniform **vertex traffic** exchanged between graph vertices
  - homogeneous underlying **network costs**.
- However, in real-world scenarios:
  - **vertex traffic** and **network costs** are heterogeneous.

➔ **suboptimal** partitioning decisions and **inefficient** graph processing.

Motivation: Traffic- & network-aware vertex-cut



(a) **Traditional vertex-cut**

replication degree: 4

costs: $0.9 \times \mathbf{1} + 0.9 \times \mathbf{10} = 9.9$

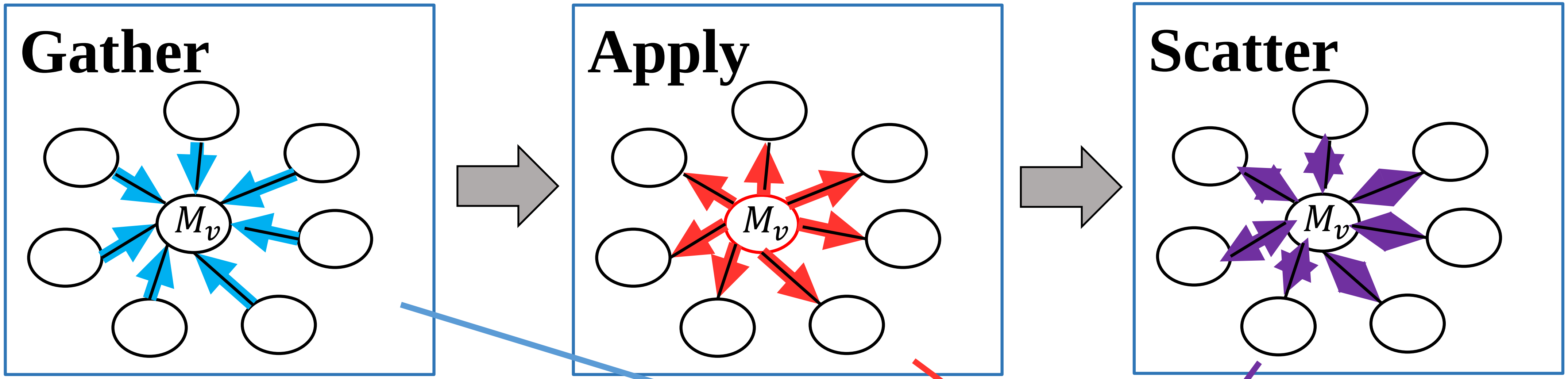
(b) **Traffic- & network-aware vertex-cut**

replication degree: 8

costs: $2(0.1 \times \mathbf{1}) + 2(0.2 \times \mathbf{10}) = 4.2$

Distributed vertex computation model

- organized in iterations
- three phases, Gather, Apply and Scatter (GAS), in each iteration.



Vertex Traffic $$t^v(i) = \frac{1}{|R_v(i)|} \sum_{r \in R_v(i)} (g_r^v(i) + a^v(i) + s)$$

Goal

1. (Mainly) Optimal dynamic assignment of edges to machines minimizing overall communication costs:

Dynamic Assignment $$a_{opt} = \operatorname*{argmin}_a \sum_i \sum_{v \in V} \sum_{m \in R_v^a(i)} t^v(i)\ T_{m,\mathcal{M}_v}$$

2. Machine load *Lm*(*i*), the summed vertex traffic, is bounded by a small balancing factor *λ* > 1:

Load of machine m $$L_m(i) = \sum_{v \in V_m} t^v(i) < \lambda \frac{\sum_{v \in V} t^v(i)}{|M|}.$$

Hardness

- Dynamic network- and traffic-aware partitioning problem is NP-hard.

$$a_{opt} = \underset{a}{\operatorname{argmin}} \sum_{i} \sum_{v \in V} \sum_{m \in R_v^a(i)} t^v(i)\; T_{m,\mathcal{M}_v}$$ is NP-hard

$\because$ the reduce problem: Network- and traffic-unaware partitioning problem is NP-hard

$a_{opt} = \operatorname{argmin}_a \sum_i \sum_{v \in V} \sum_{m \in R_v^a(i)} 1*1 = \operatorname{argmin}_a \sum_{v \in V} |R_v^a|$ is NP-hard

Solution

Consist two phases:

- H-load:
  - a partitioning algorithm for pre-partitioning the graph

- H-move:
  - a dynamic algorithm for runtime refinement using migration of edges.

H-load

Consist two phases:

1. Group partitions into *c* clusters and map edges to partitions such that replicas preferentially lie in the same cluster

Each edge (*u*, *v*) is assigned to a partition *p* as follows:

1) **If no** replica of *u* or *v* on any partition

➔ assign (*u*, *v*) to the least loaded partition.

2) **If exist** partitions containing replicas of ***u and v***

➔ assign (*u*, *v*) to the least loaded of those partitions.

3) **Otherwise**, choose partition *p* such that the new replica preferentially lies in the same cluster as already existing replicas.

H-load

2. Find a good mapping of partitions to machines

Use iterated local search algorithm to greedily minimize (communication) costs.

1) Initially, partitions are randomly mapped to machines.
2) Then iteratively the following method:
    a) Find two machines, if an exchange of partition assignments would lower total communication costs.
    b) If an improvement is found, it is applied immediately.
    c) Perturb a local optimal solution by randomly exchanging two assignments to avoid convergence to local minima.

H-move

- Idea:
  - Each machine locally migrate *bag-of-edges* (in parallel) after each GAS iteration.
    - *bag-of-edges* is the set of edges to be migrated.
  - Finally, if no further improvements can be performed, migration is switched off.

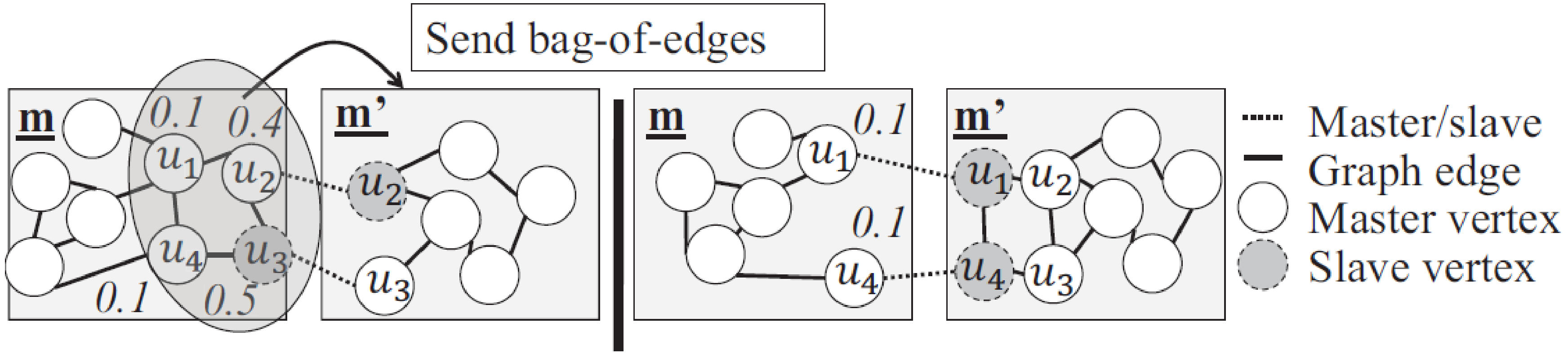


Fig. 4. Example of bag-of-edges migration to reduce inter-machine traffic.

H-move - **Migration algorithm**

Algorithm 1 Migration algorithm on machine m.

$waitForActivation()$
$m' \leftarrow selectPartner()$
$b \leftarrow bagOfEdges(m')$
$lock(b)$
$b \leftarrow updateLocked(b)$
$\Delta c \leftarrow c_{+} - c_{-}$
if $\Delta c < 0$ **then**
    $migrateBag(b)$
$releaseLocks(b)$

H-move - **Determining the bag-of-edges**

Algorithm 2 Determining the bag-of-edges to exchange.

function $bagOfEdges(m')$:
$bag \leftarrow []$
$candidates \leftarrow sort(adjacent(m'))$
while $hasCapacity(m', bag)$ **do**
  $v \leftarrow candidates.removeFirst()$
  $b \leftarrow \{(u, v) | u \neq v\}$
  $\Delta c \leftarrow c_+ - c_-$
  if $\Delta c < 0$ **then**
    $bag \leftarrow bag + b$
return bag

Capacity $C = (L_{m'} - L_m)/2.$

Evaluation - setup

- To get the graph in real world, implemented the three graph algorithms:
  - **PageRank,** denoted as PR
- compared migration strategies with static vertex-cut partitioning approaches:
  - **hashing of edges** (Hash) and **PowerGraph** (PG).
- Implemented GrapH in the Java programming language
- GrapH consists of a master machine and multiple client machines
- The master receives a sequence of graph processing queries $q1$, $q2$, $q3$, ... consisting of user specified GAS algorithms.
- All machines communicate directly via TCP/IP.
- Use two computing clusters with homogeneous and heterogeneous network costs.

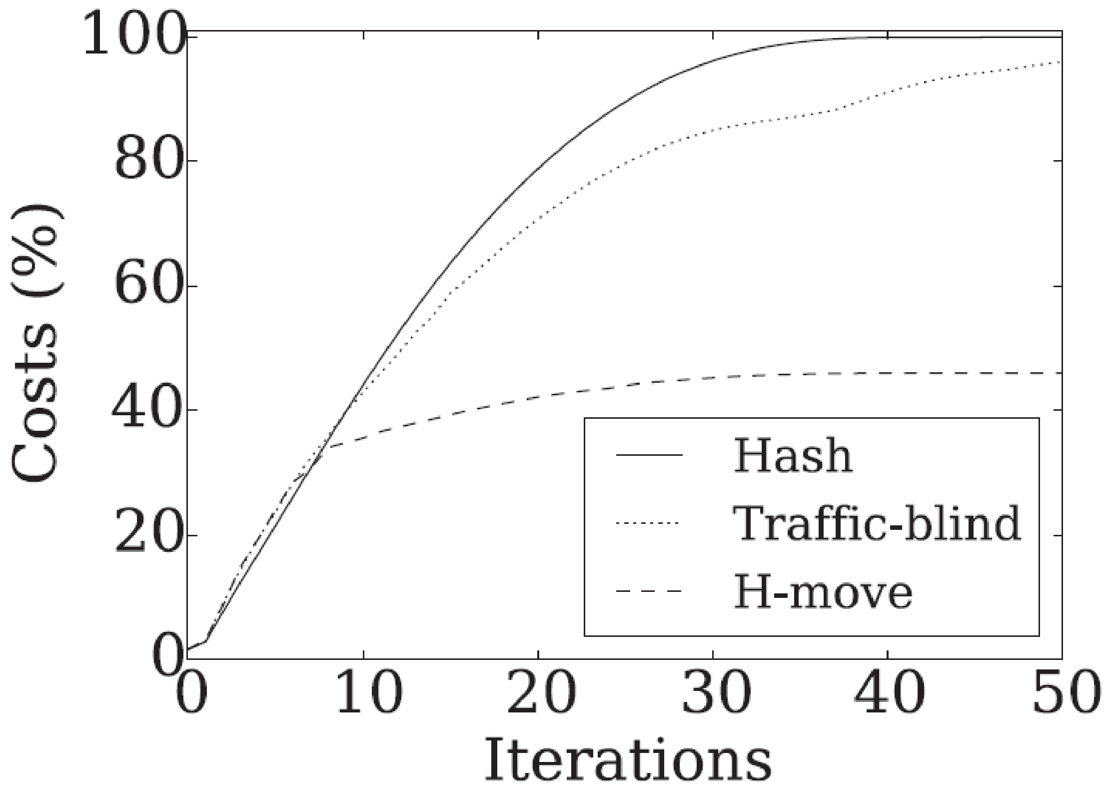
Evaluation - ***Setup***

Machine placement	Incoming traffic	Outgoing traffic
Same AZ	0.00-0.01 $/GB	0.00-0.01 $/GB
Different AZ, same region	0.01 $/GB	0.01 $/GB
Different region	0.00 $/GB	0.02 $/GB
Internet	0.00 $/GB	0.00-0.09 $/GB

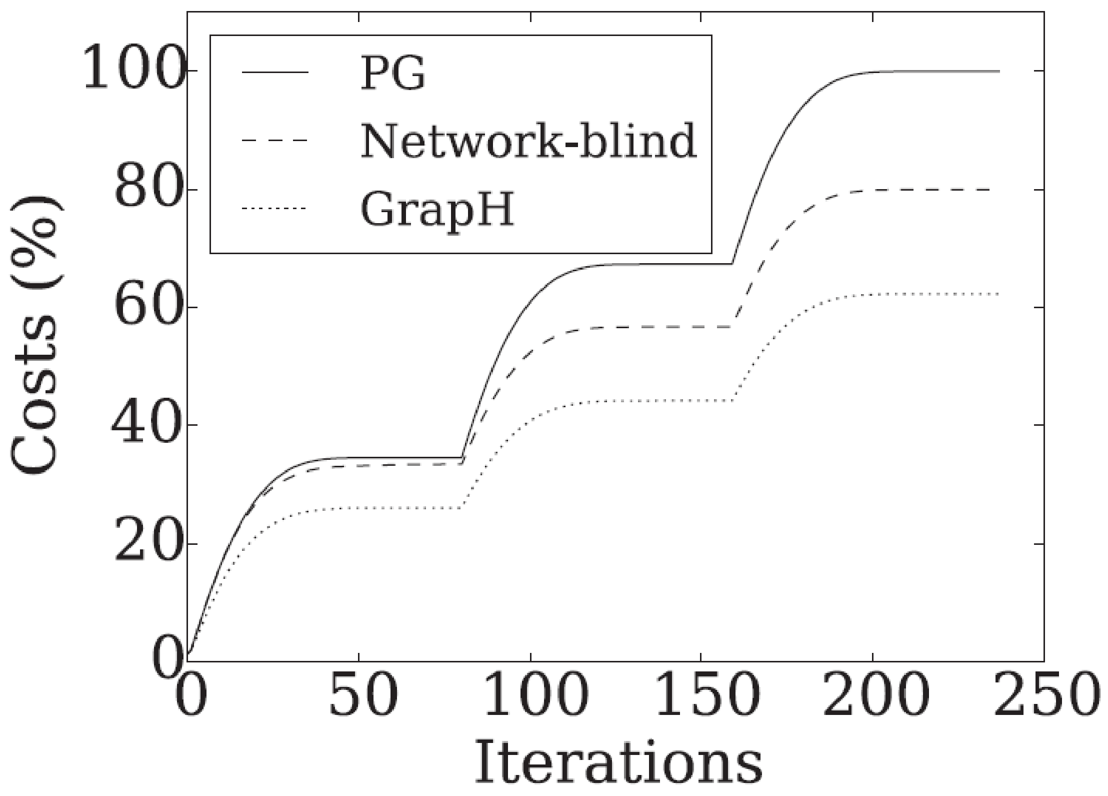
TABLE I
HETEROGENEOUS COMMUNICATION COSTS FOR AMAZON EC2 CLOUD INSTANCES (AUGUST 2015).

- The homogeneous computing cluster (ComputeC) consists of 12 machines, each with 8 cores (3.0GHZ) and 32GB RAM, interconnected with 1 Gbps ethernet.
- The heterogeneous computing cluster (CloudC) is deployed in the Amazon cloud using 8 geographically distributed EC2 instances (1 virtual CPU with 3.3 GHz and 1 GB RAM) that are distributed across two regions, US East (Virginia) and EU (Frankfurt), and four different availability zones. .
- As network costs between these instances, we used the real monetary costs charged by Amazon (Tab. I).

Evaluation - ***Communication costs***

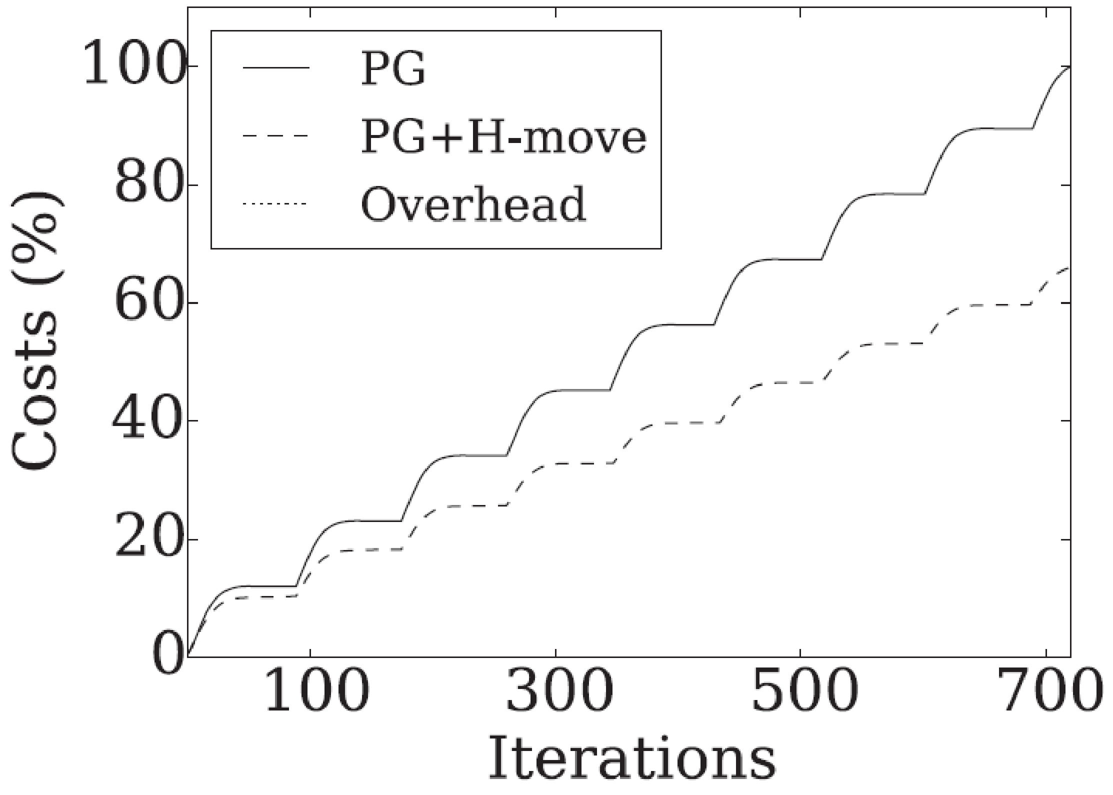


(a) PR on *Twitter*(Traffic-awareness)

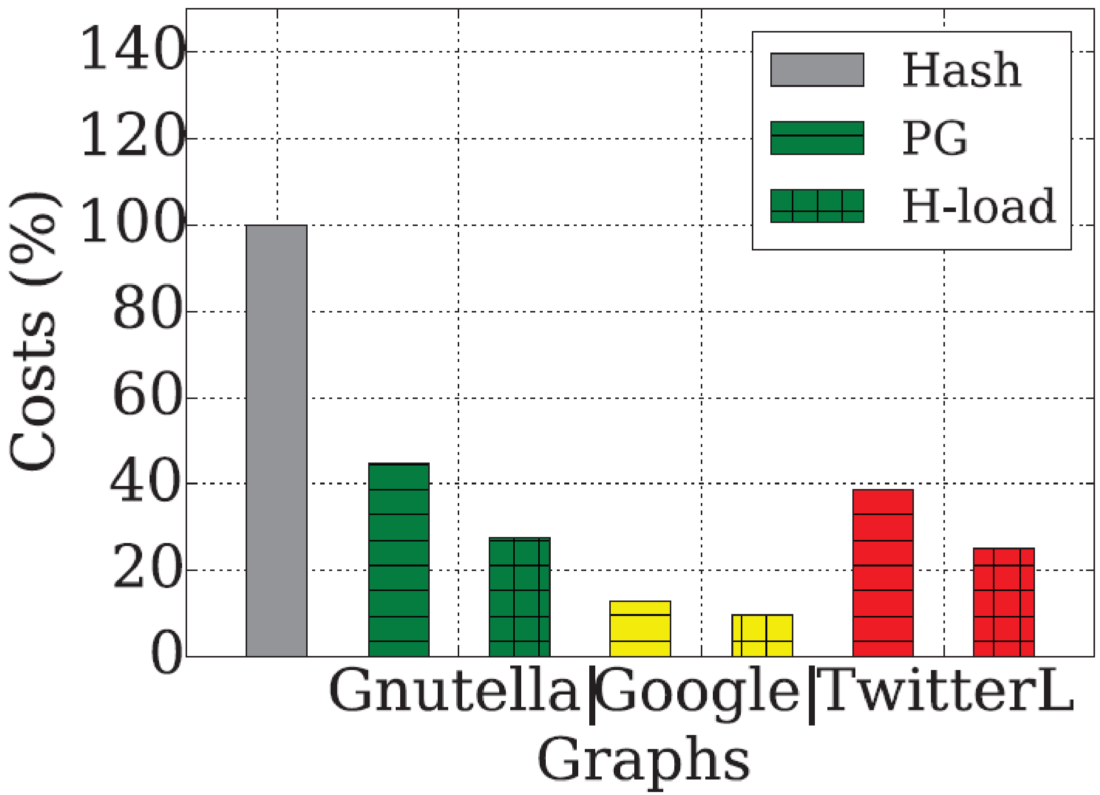


(b) PR on *GoogleWeb*

Evaluation - ***Communication costs***

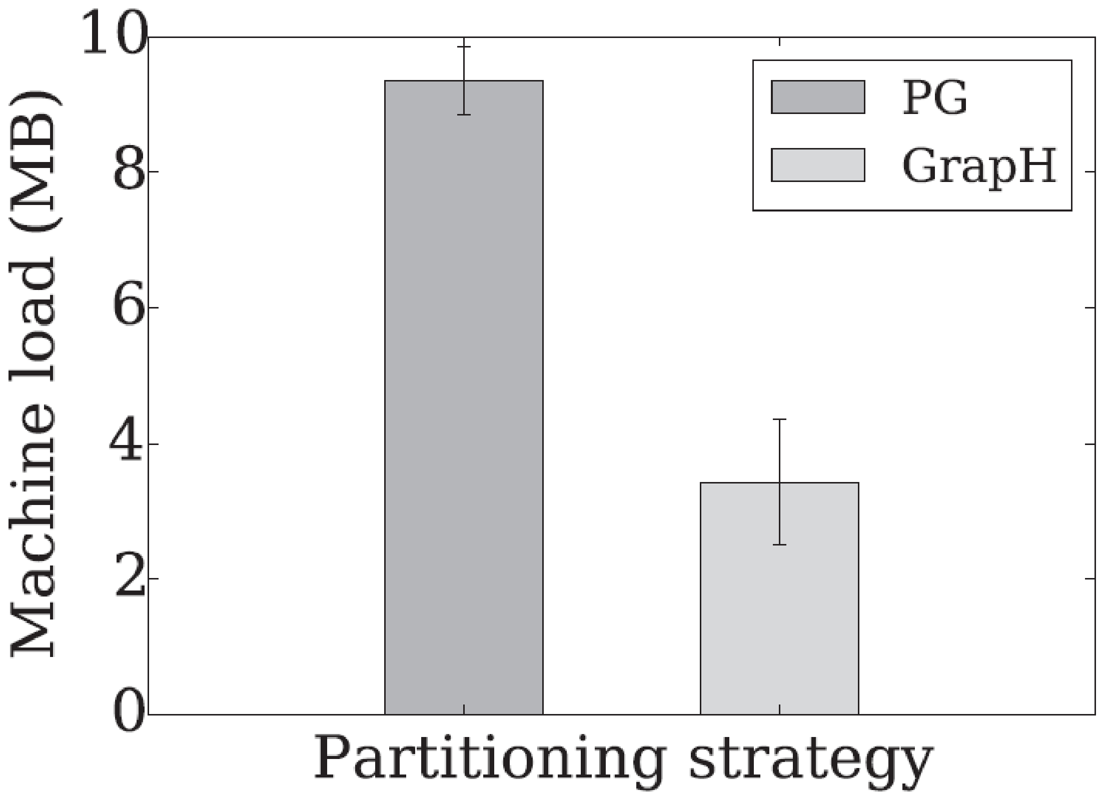


(c) PR on *GoogleWeb*.



(f) Pre-partitionings

Evaluation – ***Load balancing***



(c) PR on *GoogleWeb*.

Conclusion

- Modern graph processing systems use vertex-cut partitioning methods assume:
  - **uniform** vertex traffic
  - **homogeneous** network costs

  do not hold for many real-world applications.
- GrapH considers
  - **dynamic** vertex traffic
  - **diverse** network costs

  By adaptively minimizing communication costs of the vertex-cut at runtime.
- Evaluation show that GrapH **outperforms** PowerGraph's vertex-cut partitioning algorithm by more than 60% communication costs.