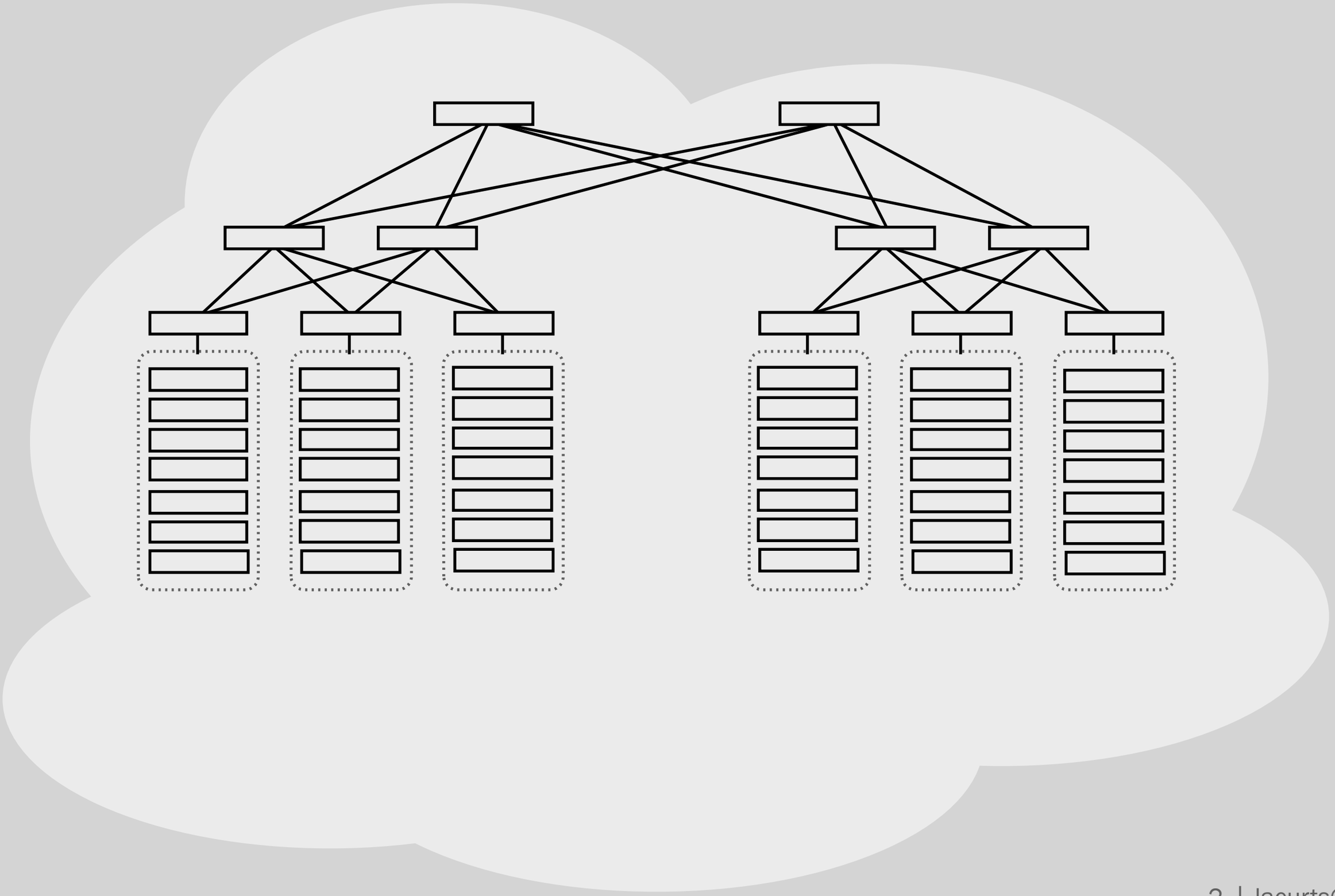
CICADA

PREDICTIVE GUARANTEES FOR CLOUD NETWORKS

Katrina LaCurts
Jeff Mogul
Hari Balakrishnan
Yoshio Turner
MIT CSAIL, Google Inc., HP Labs

BANDWIDTH GUARANTEES



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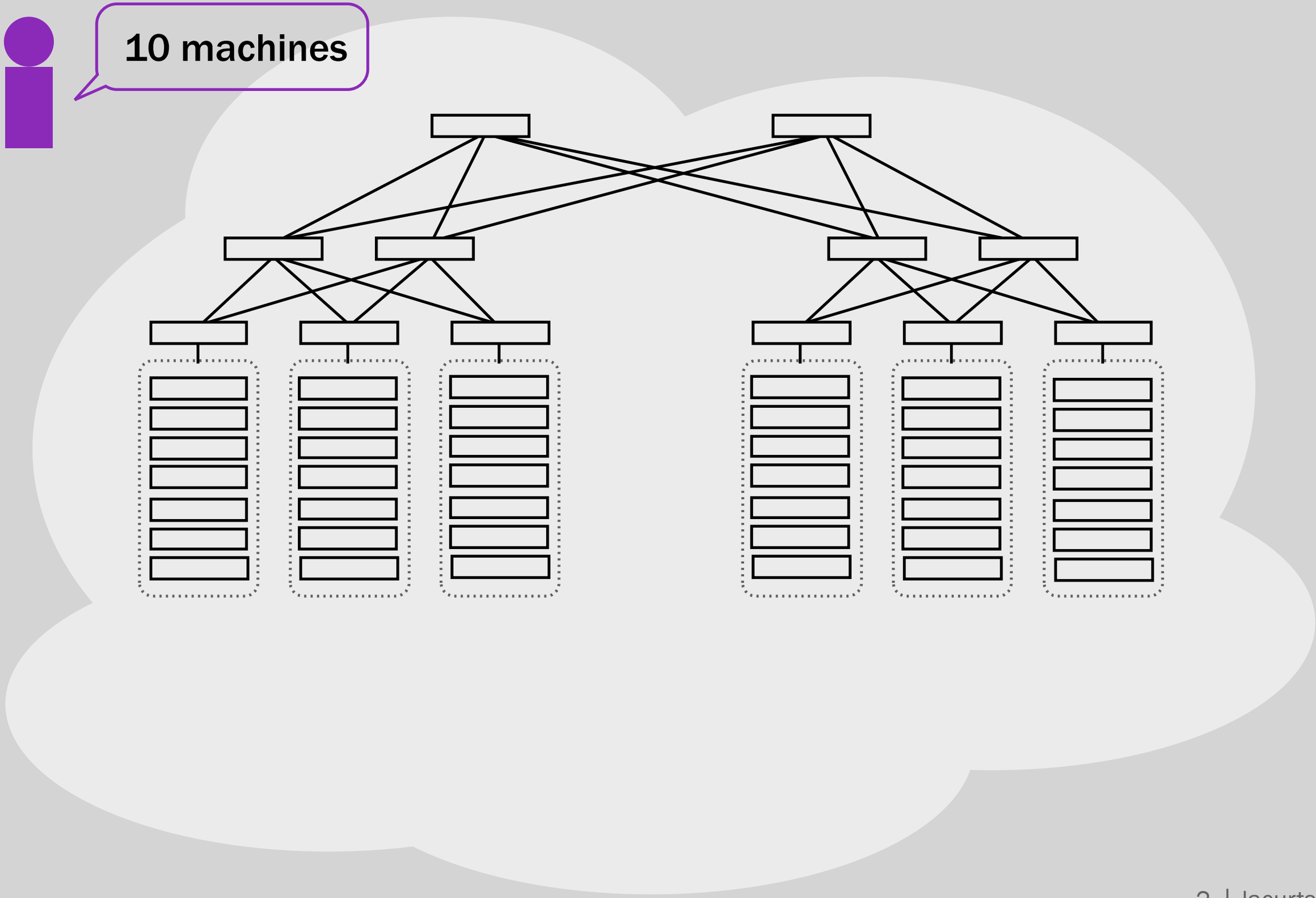

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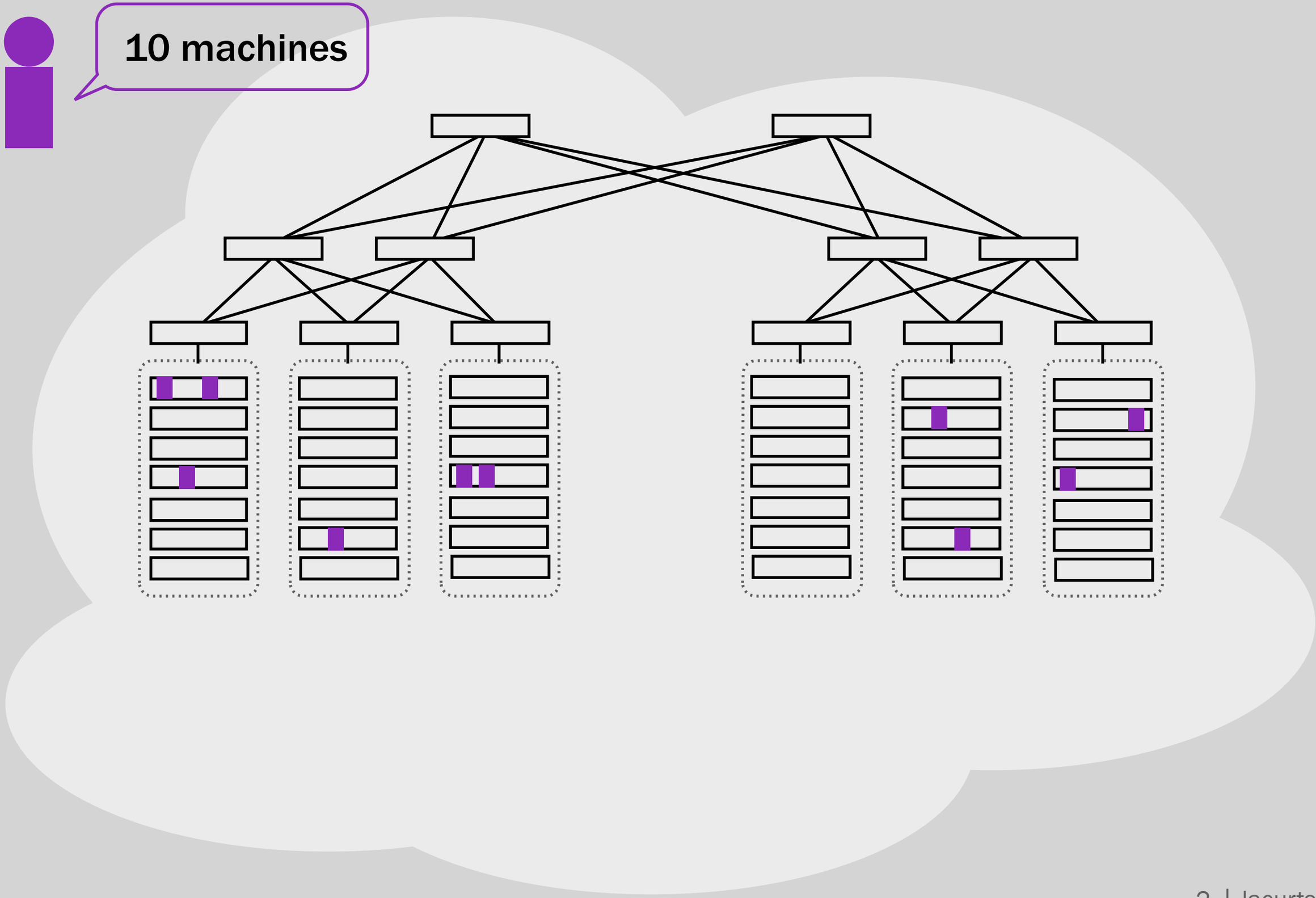

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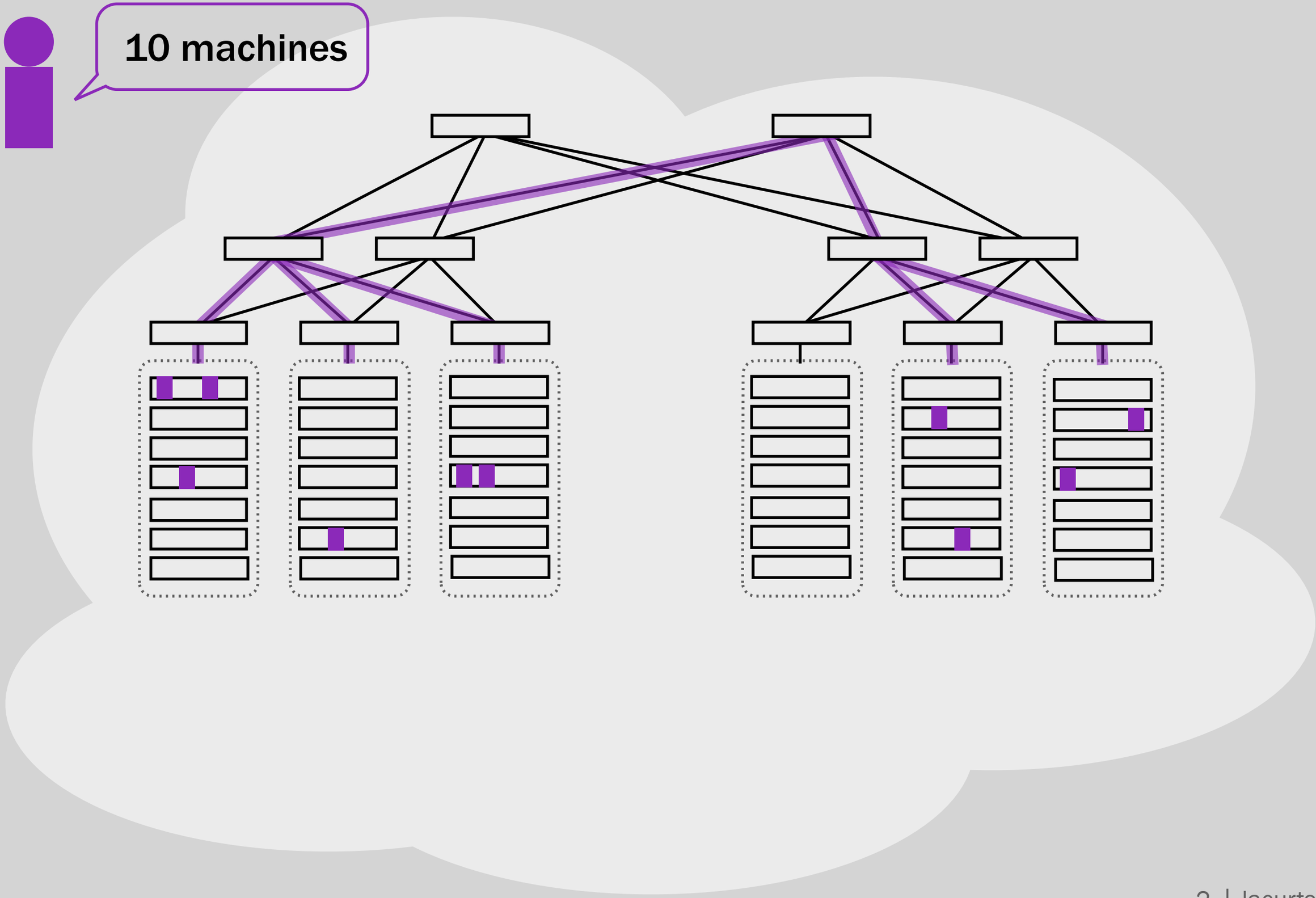

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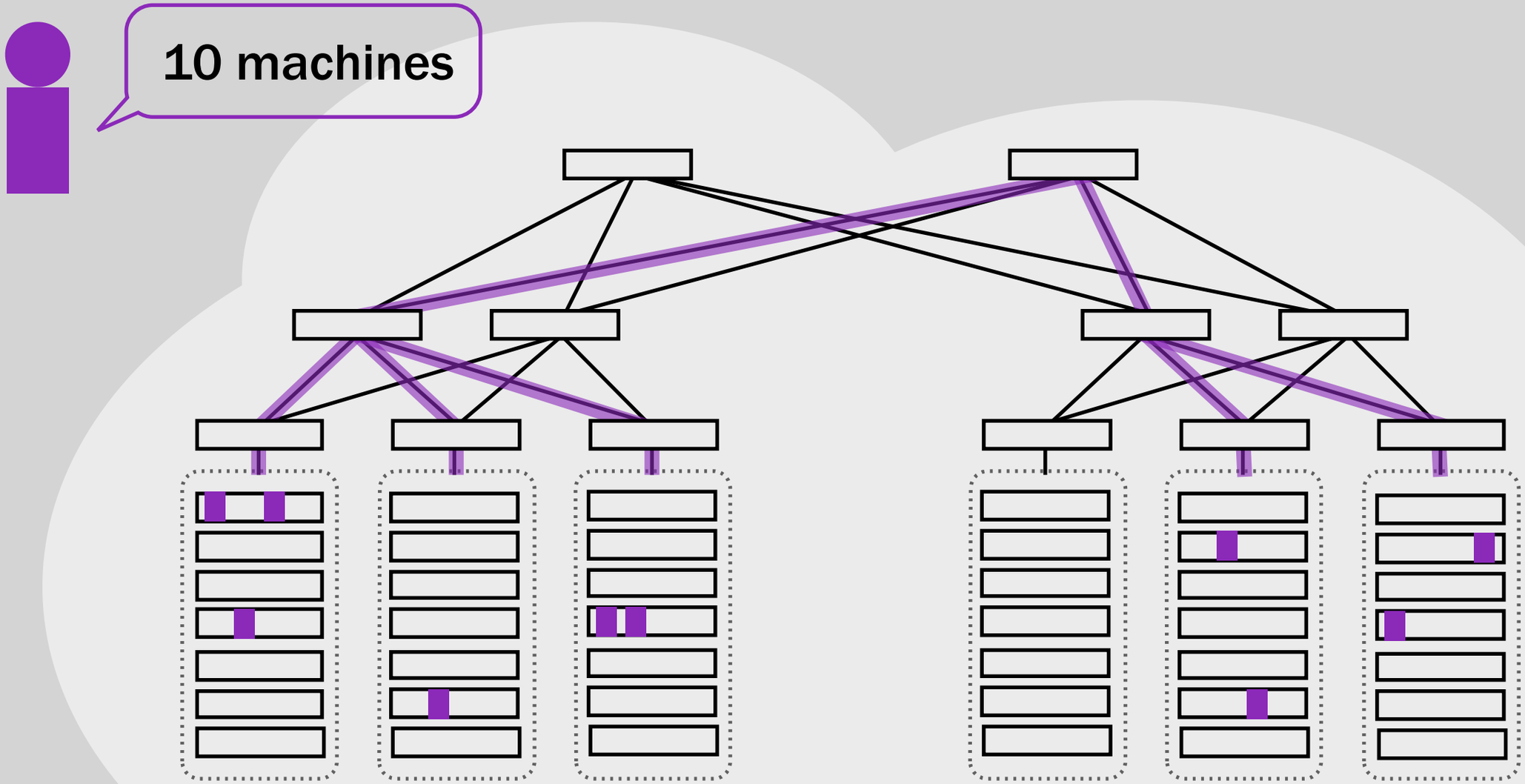
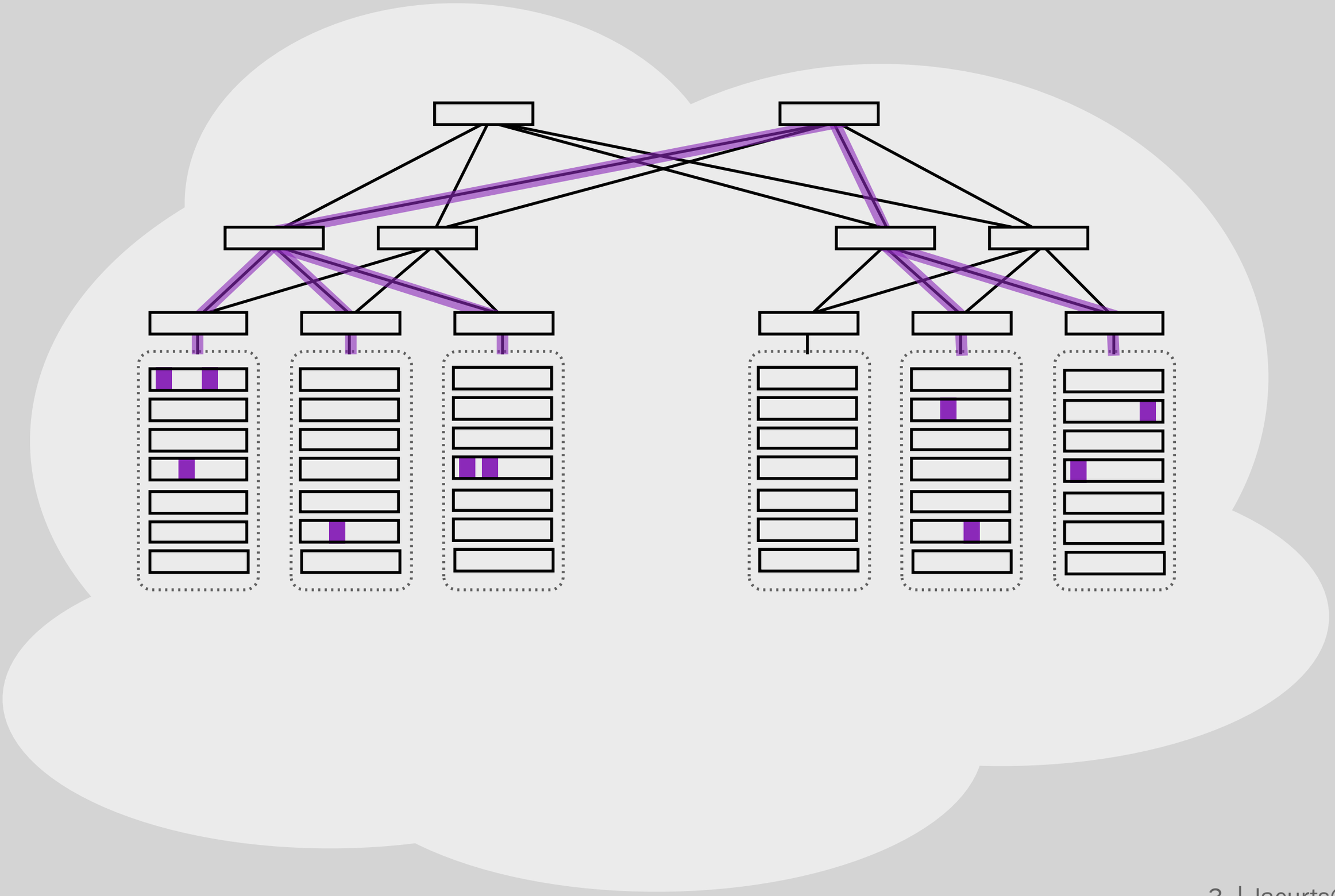


bandwidth guarantee: a promise from the provider to the customer that its VMs will be able to communicate with each other at a particular rate

(informal definition)

WHY GUARANTEES?



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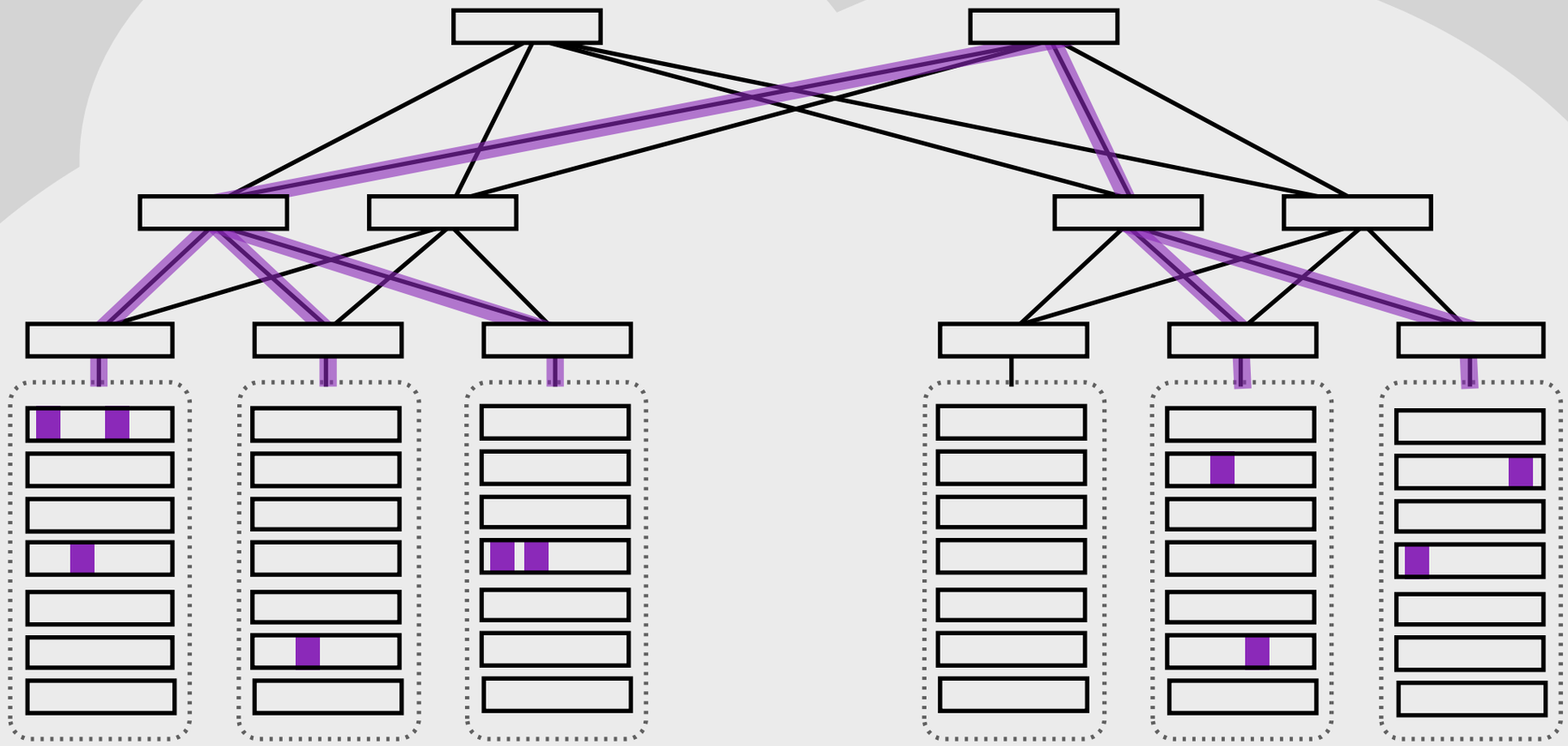
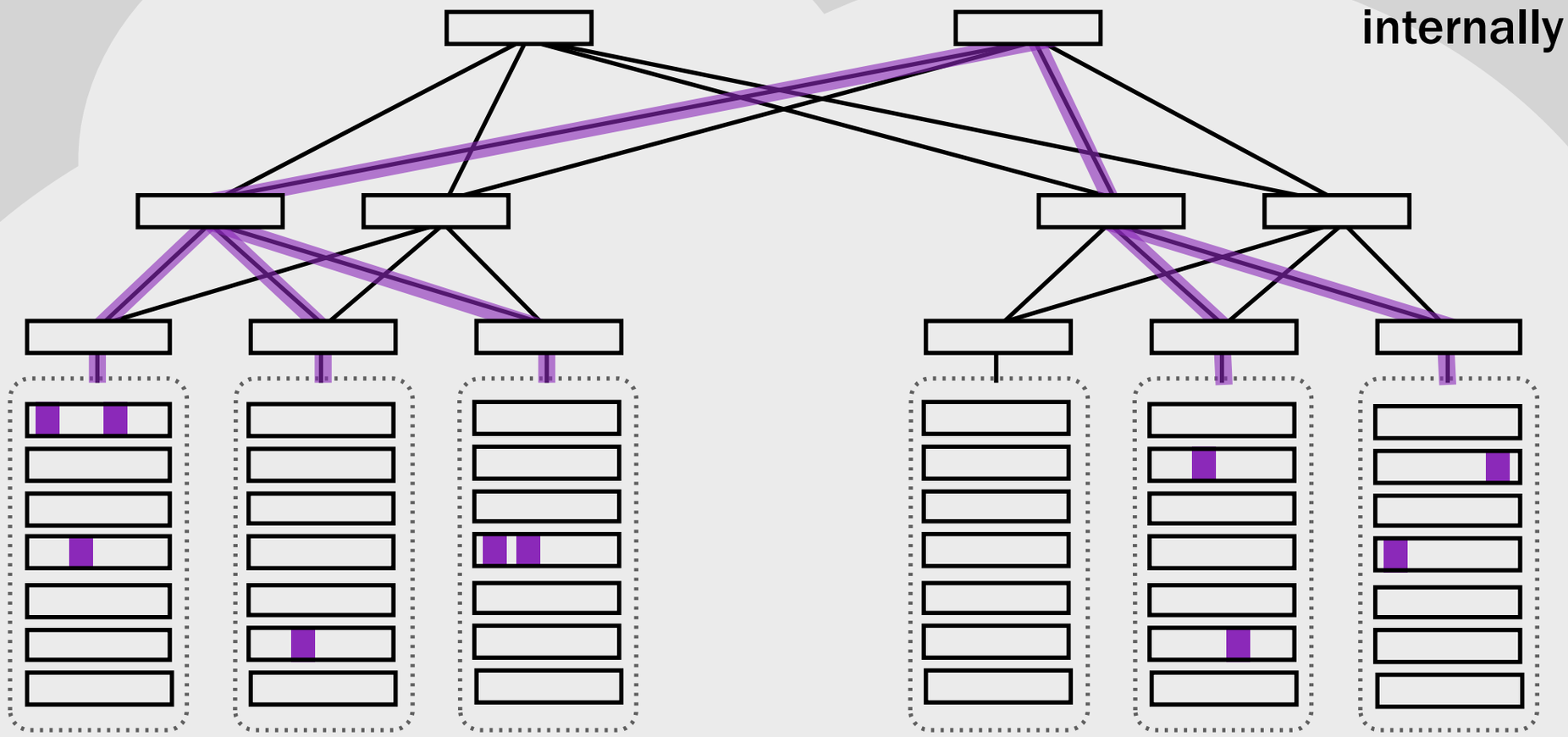


is there really that much data?

WHY GUARANTEES?

applications can send terabytes or petabytes of data internally [1]



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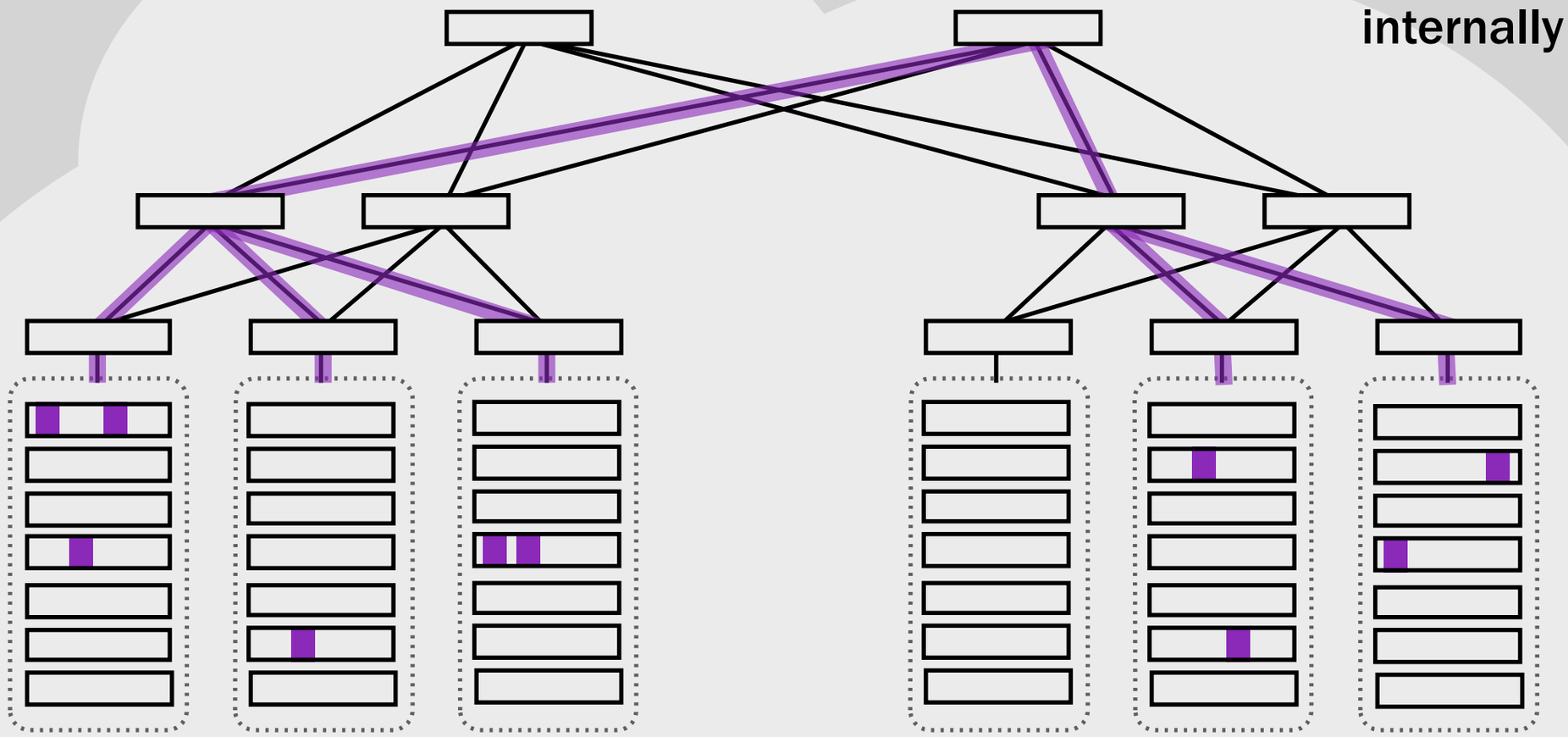

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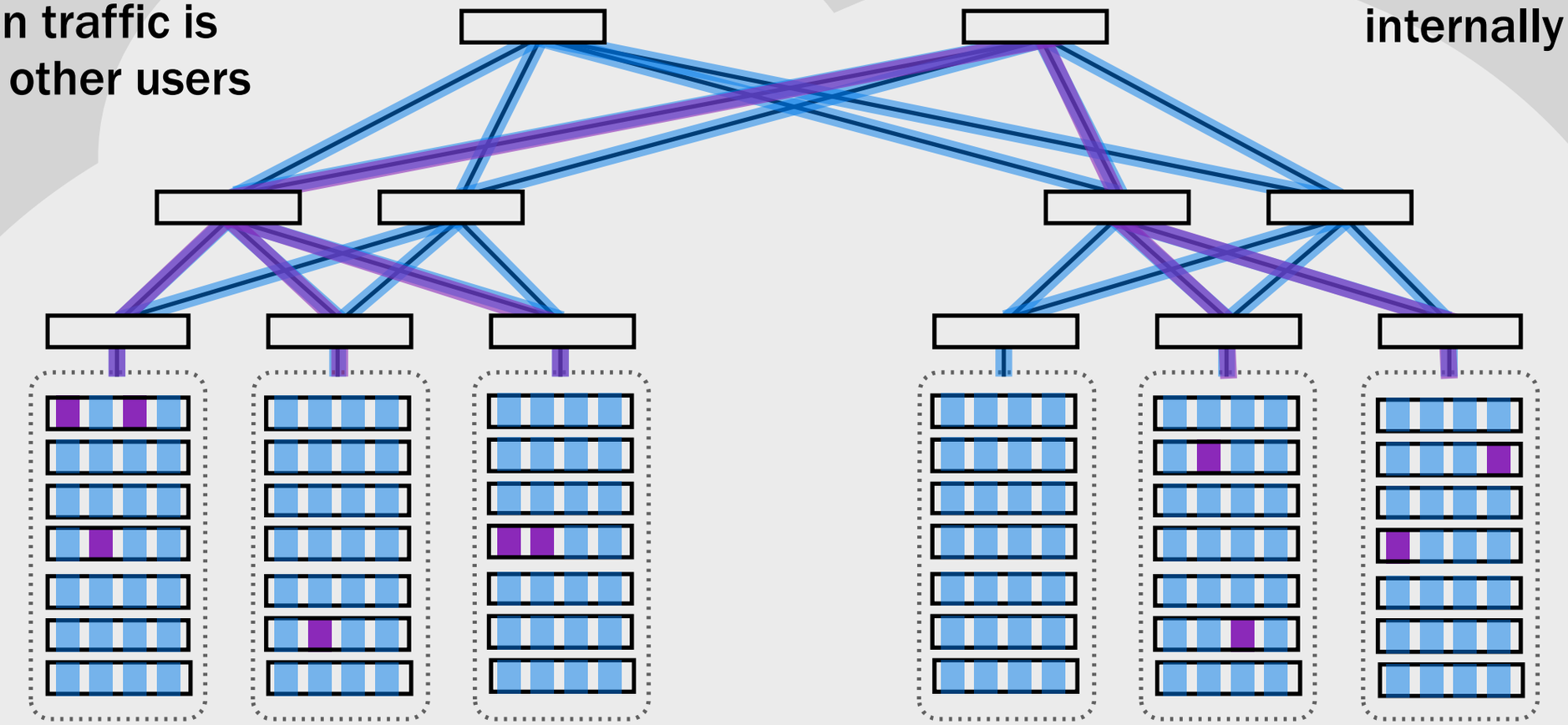

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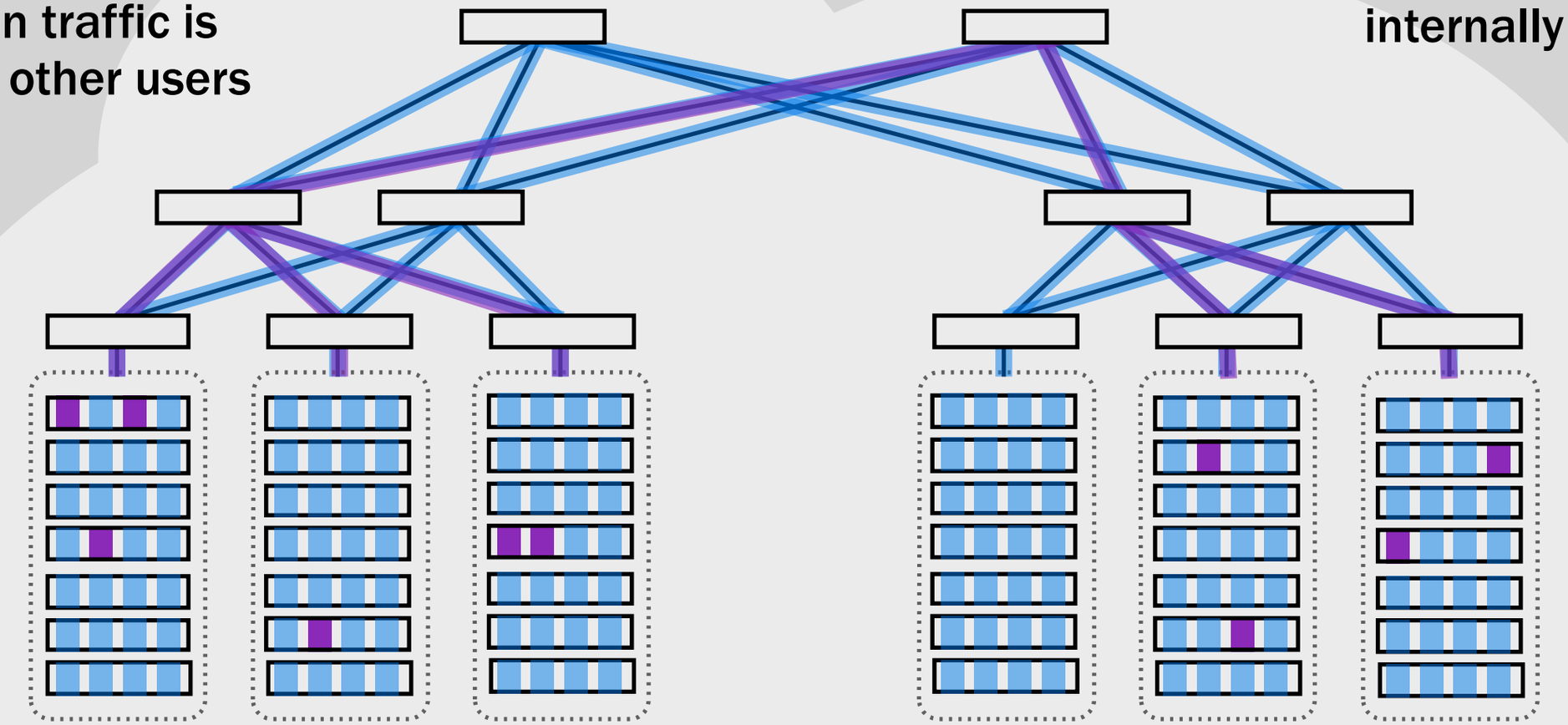

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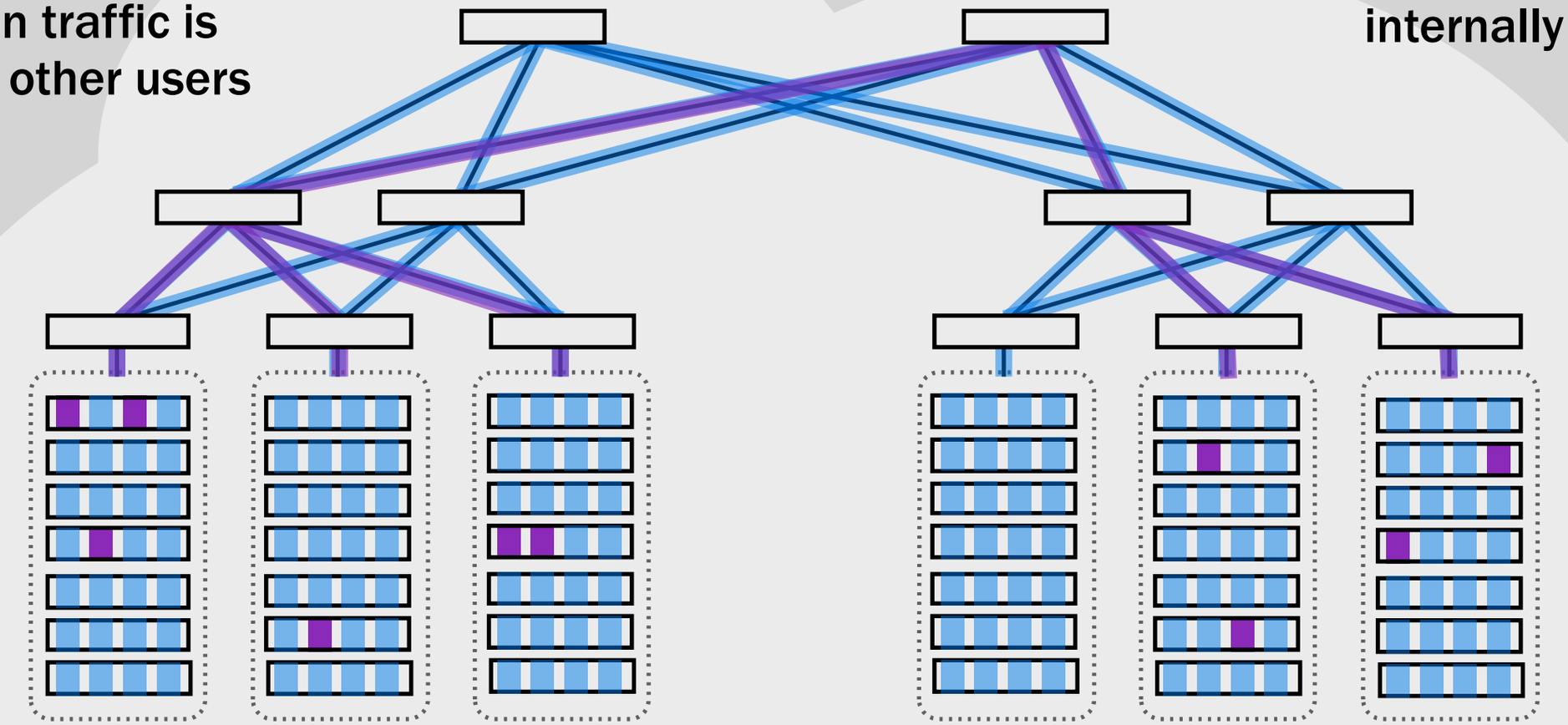

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enterprise customers need to satisfy SLAs with their own customers

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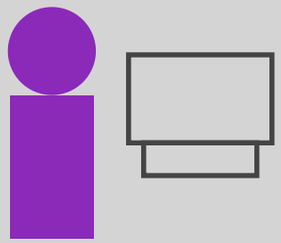

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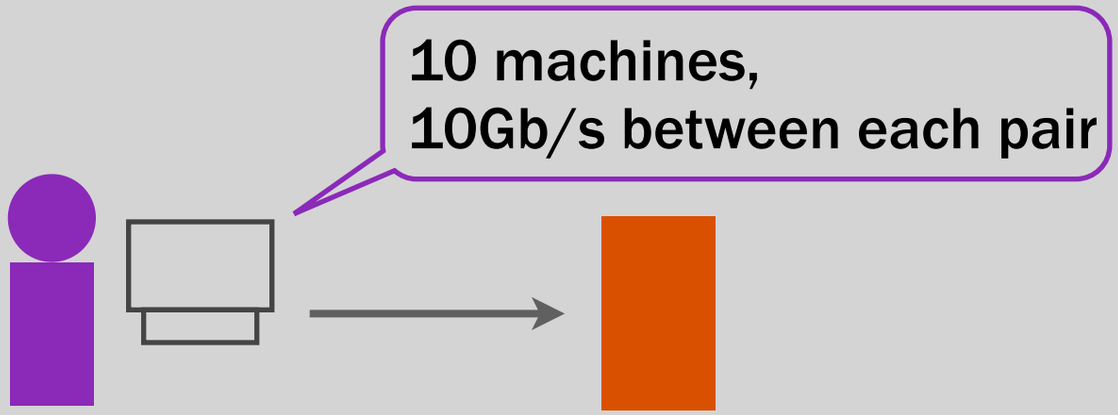

customer requests machines
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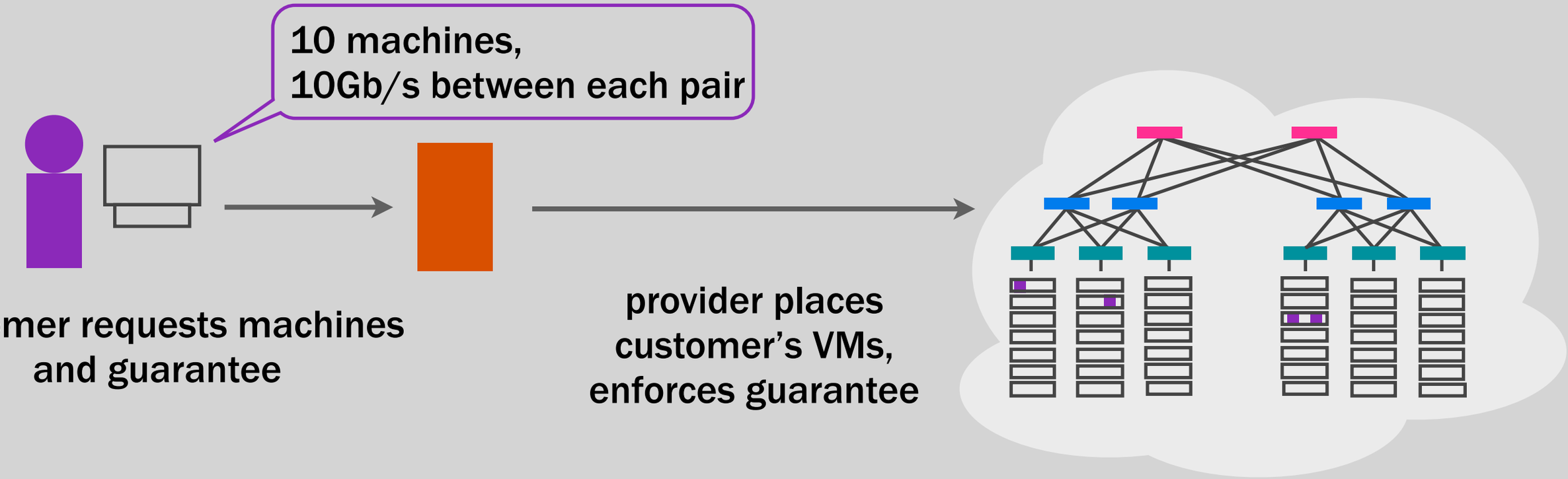

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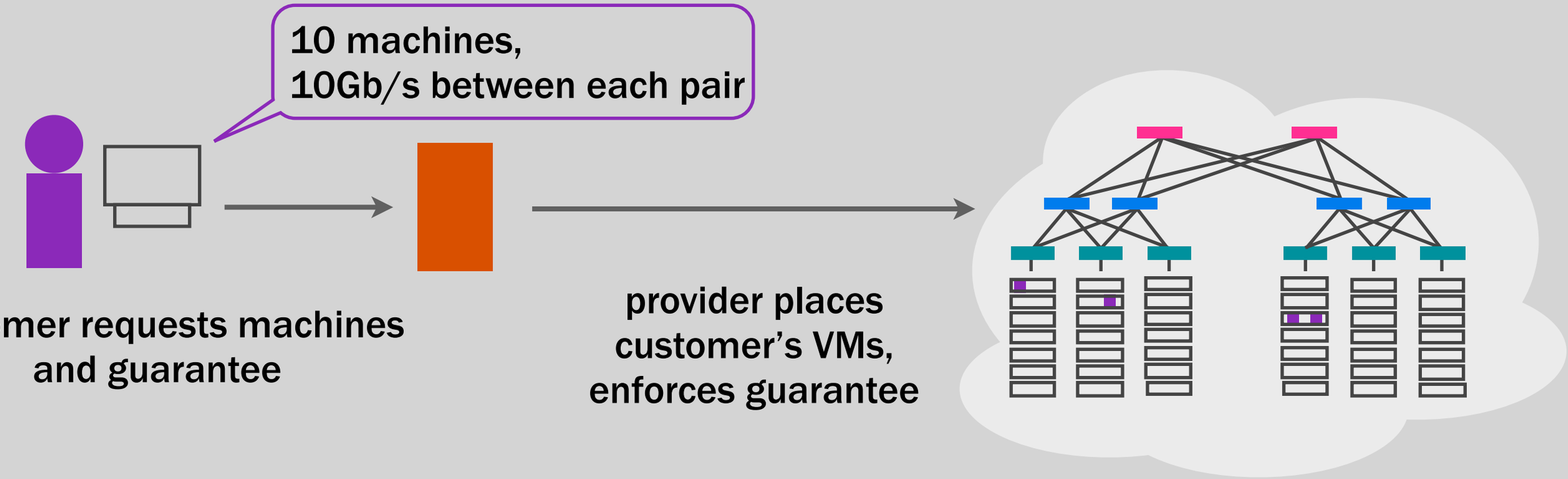

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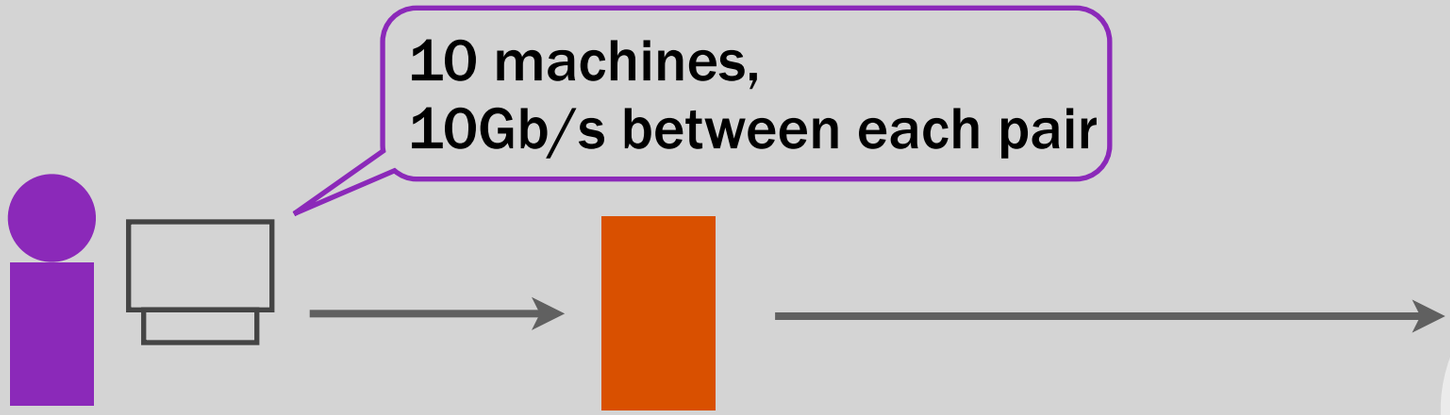
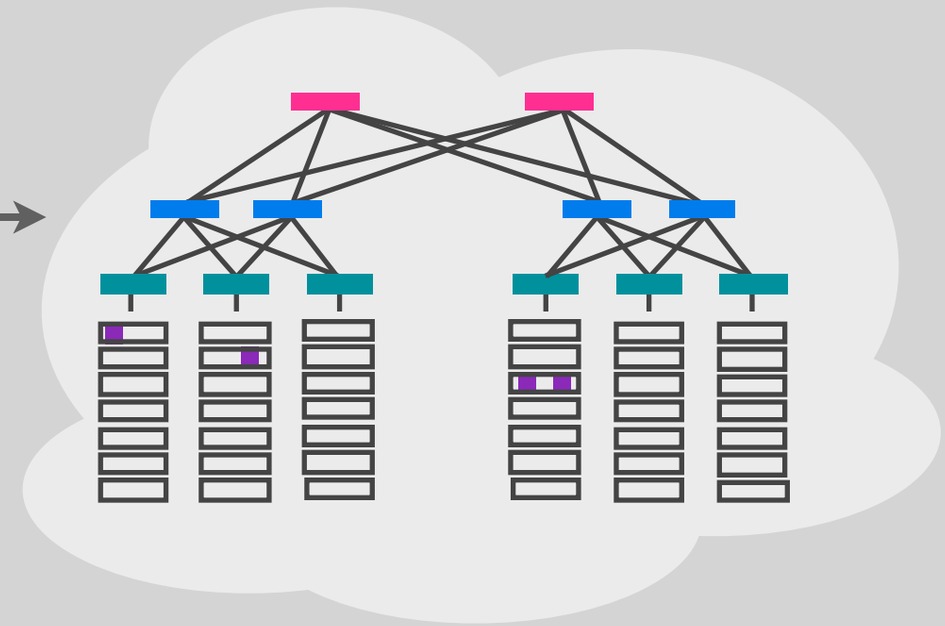


customer requests machines and guarantee

provider places customer's VMs, enforces guarantee



what if some pairs of VMs use fewer than 10Gb/s?

over-provisioned network
increased cost to customer,
wasted bandwidth within network

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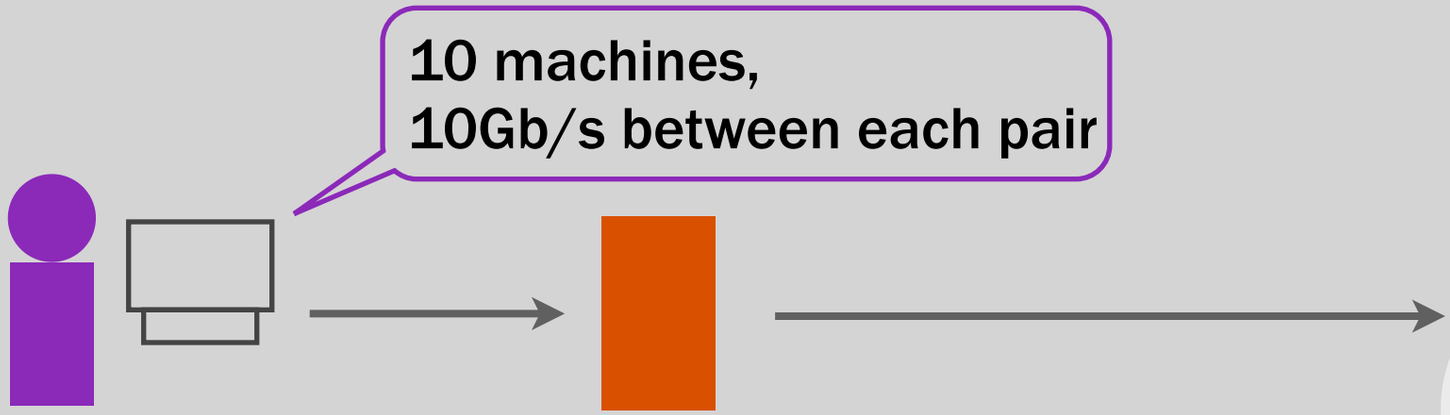

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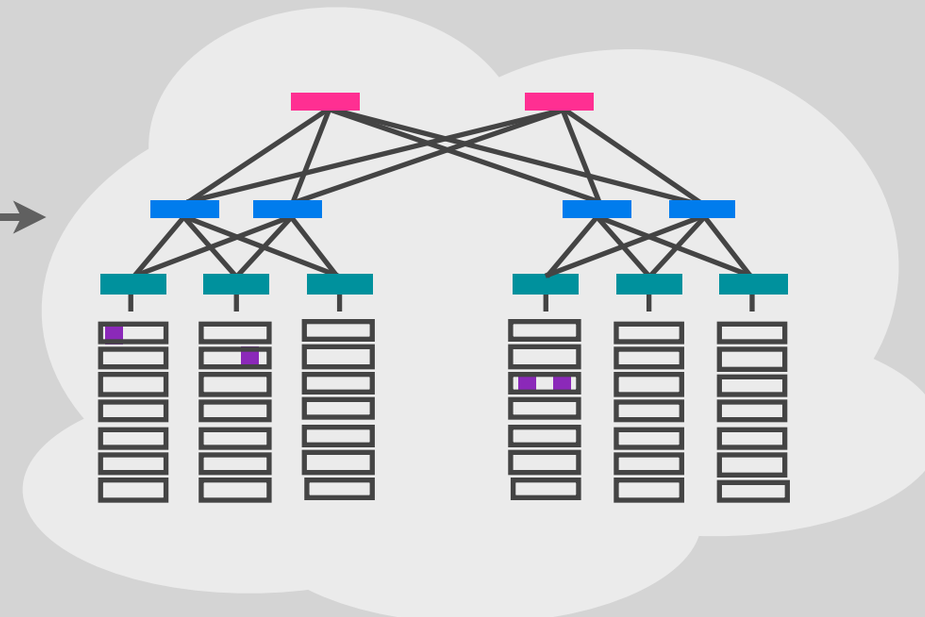

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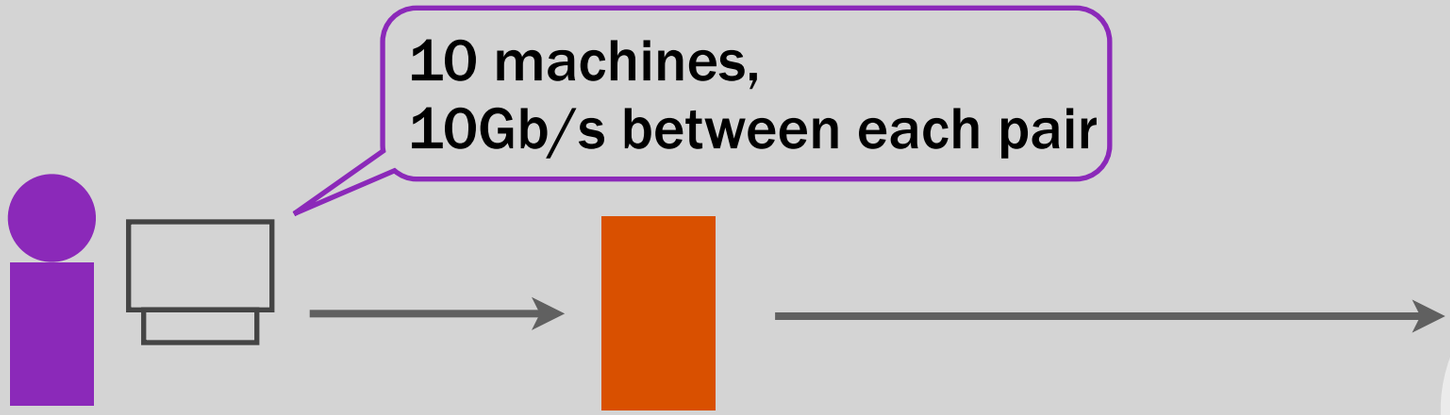

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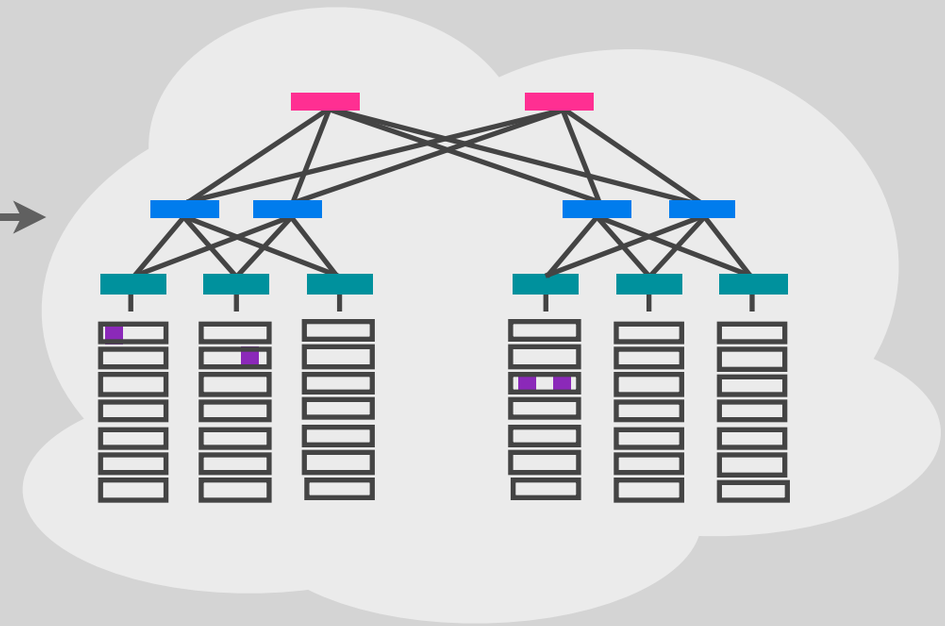

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poor performance for customer's application

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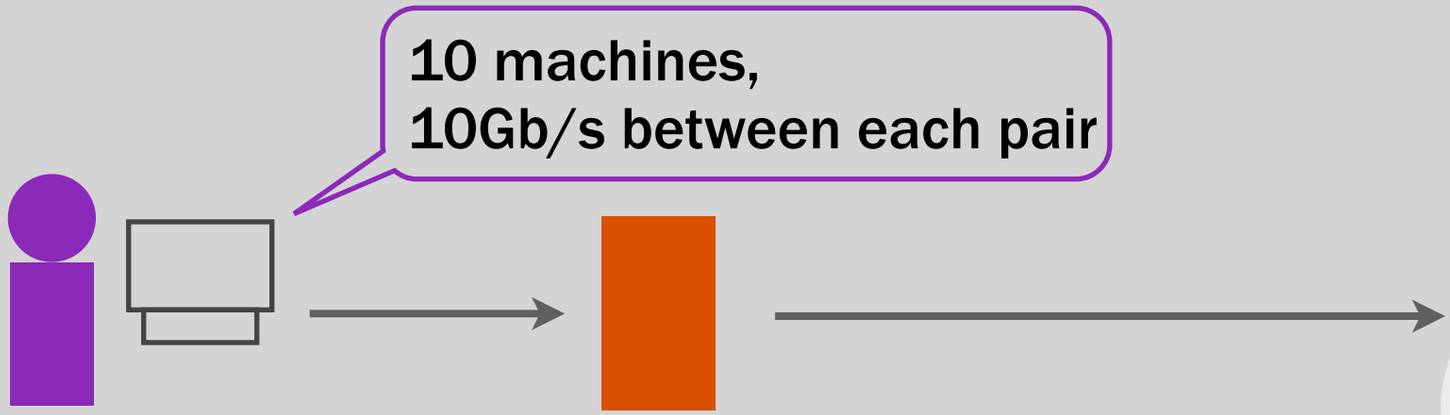

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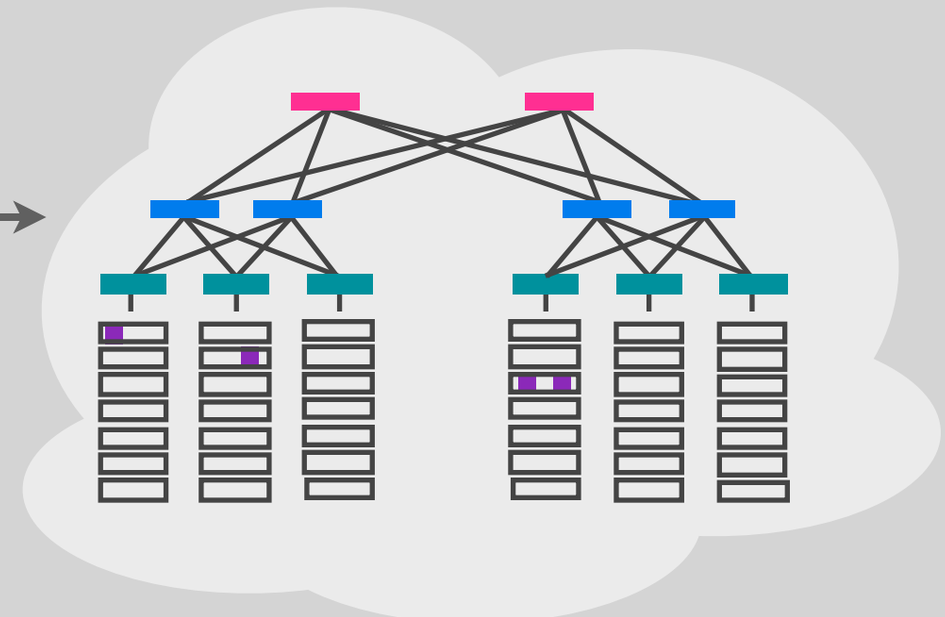

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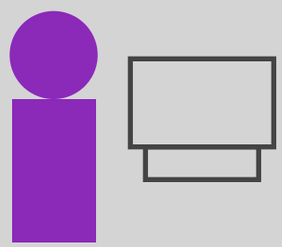
problem: how do customers know what guarantee they need?

CICADA'S ARCHITECTURE

cicada makes predictions about an application's traffic to automatically generate a guarantee



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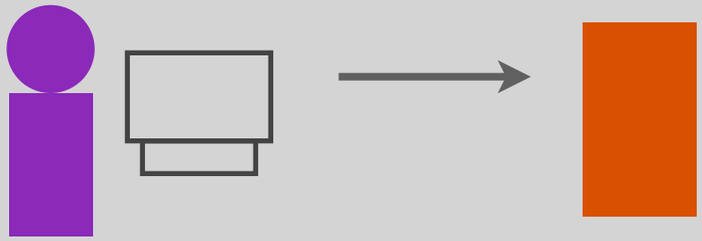

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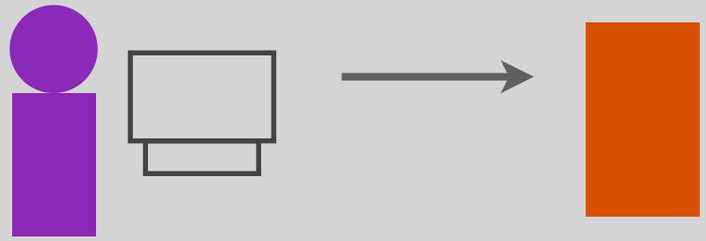
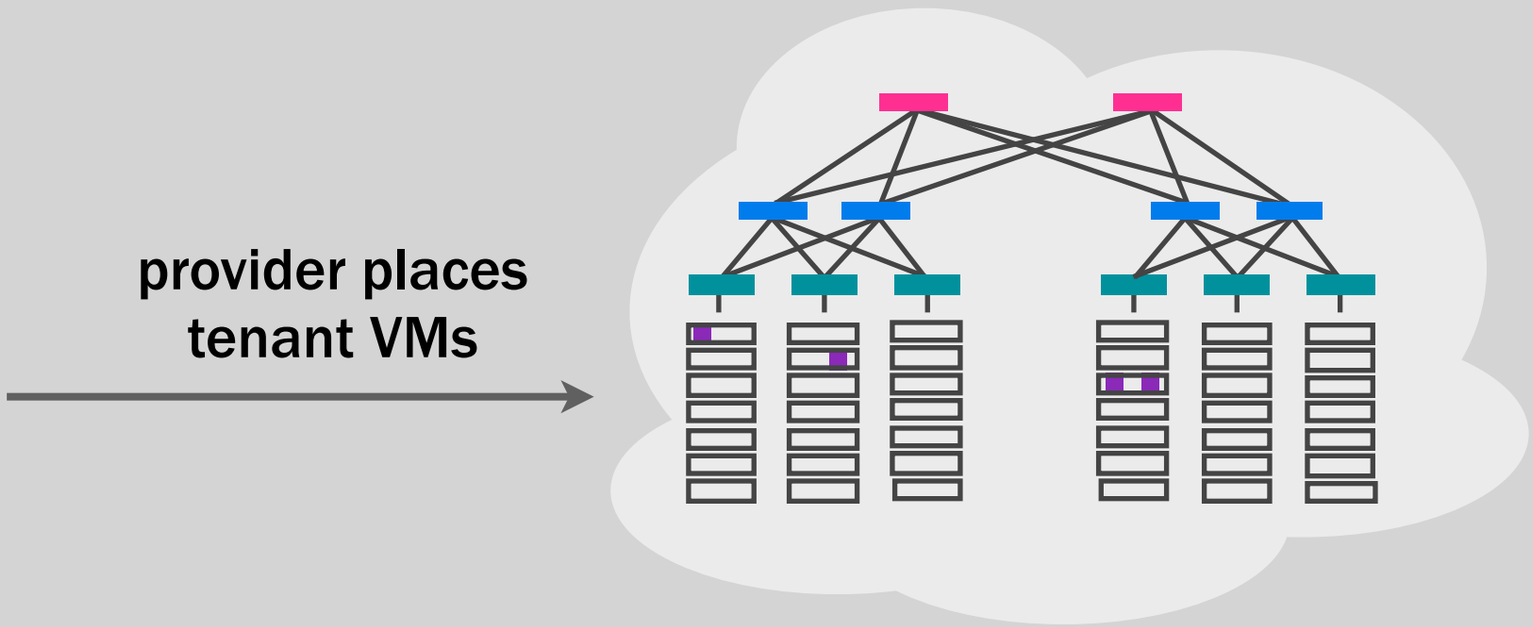


provider places tenant VMs



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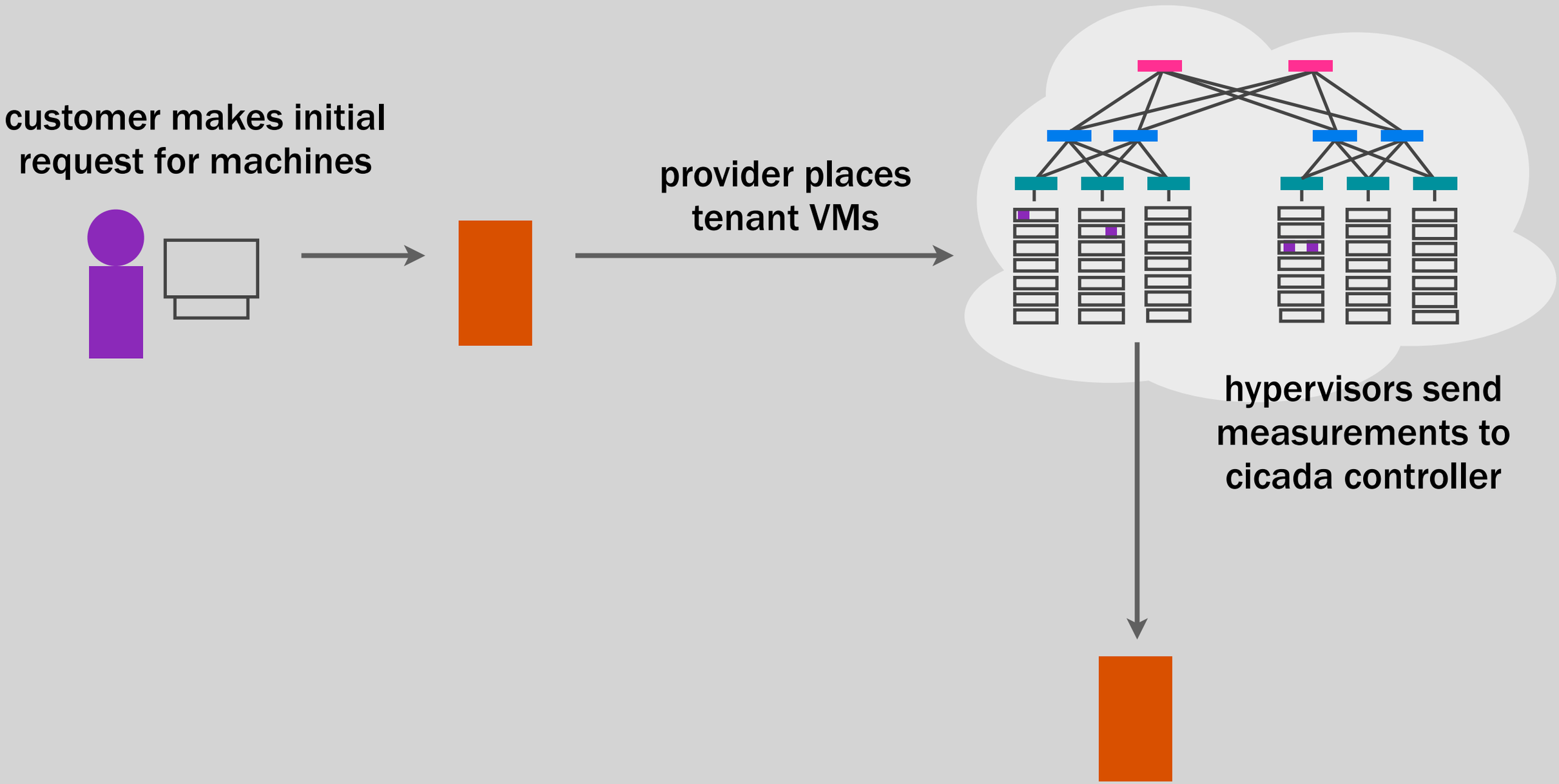

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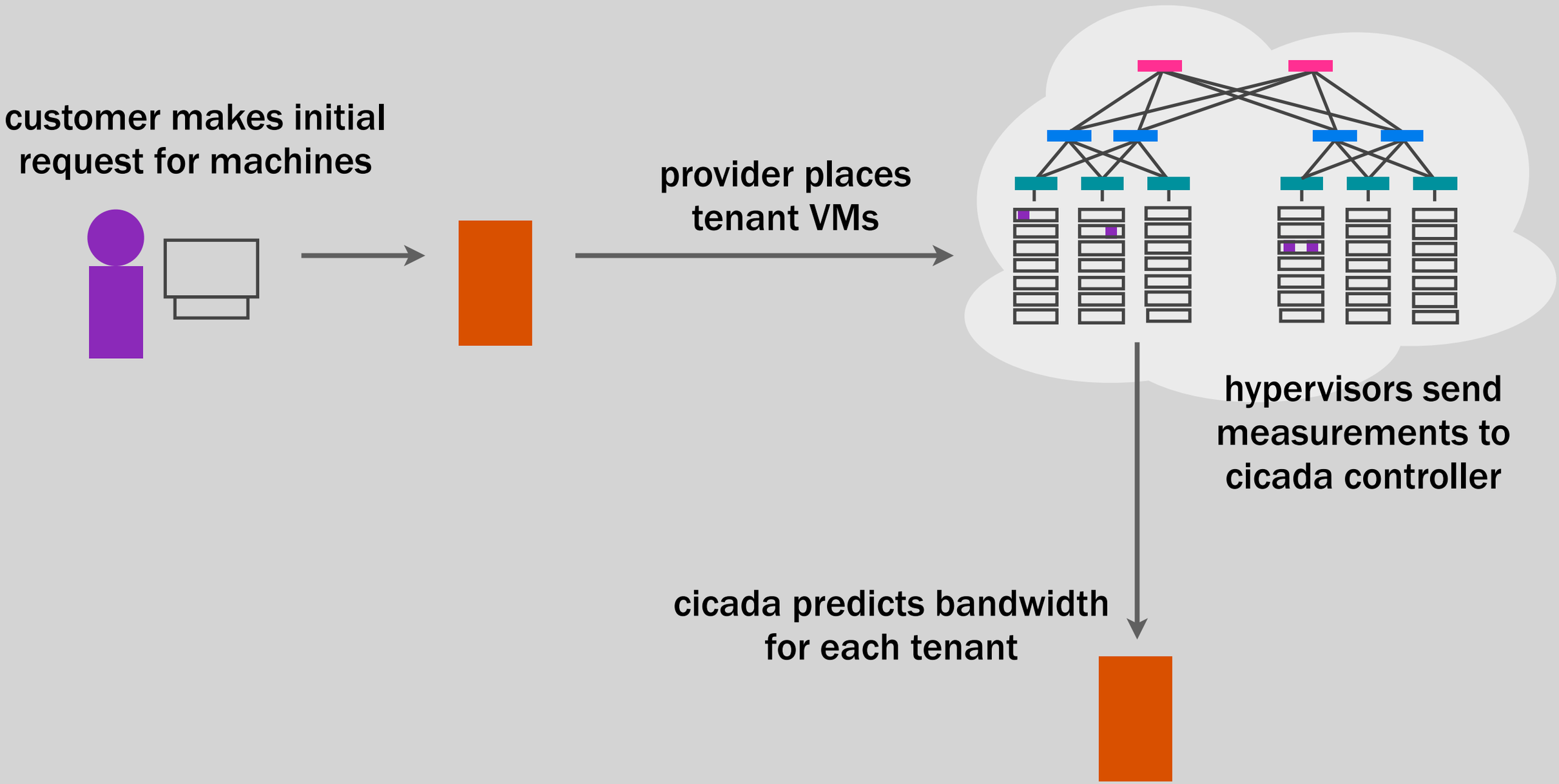

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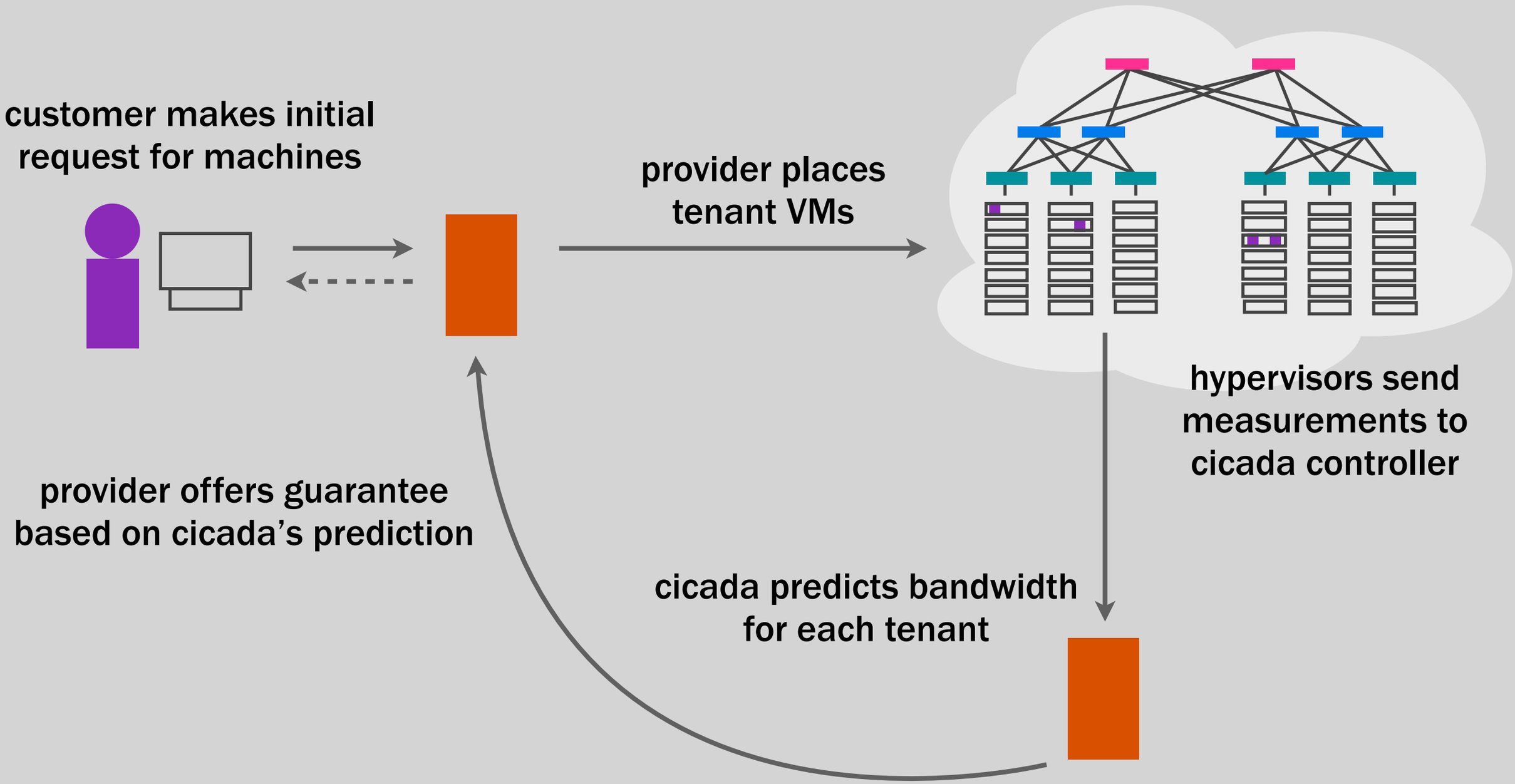

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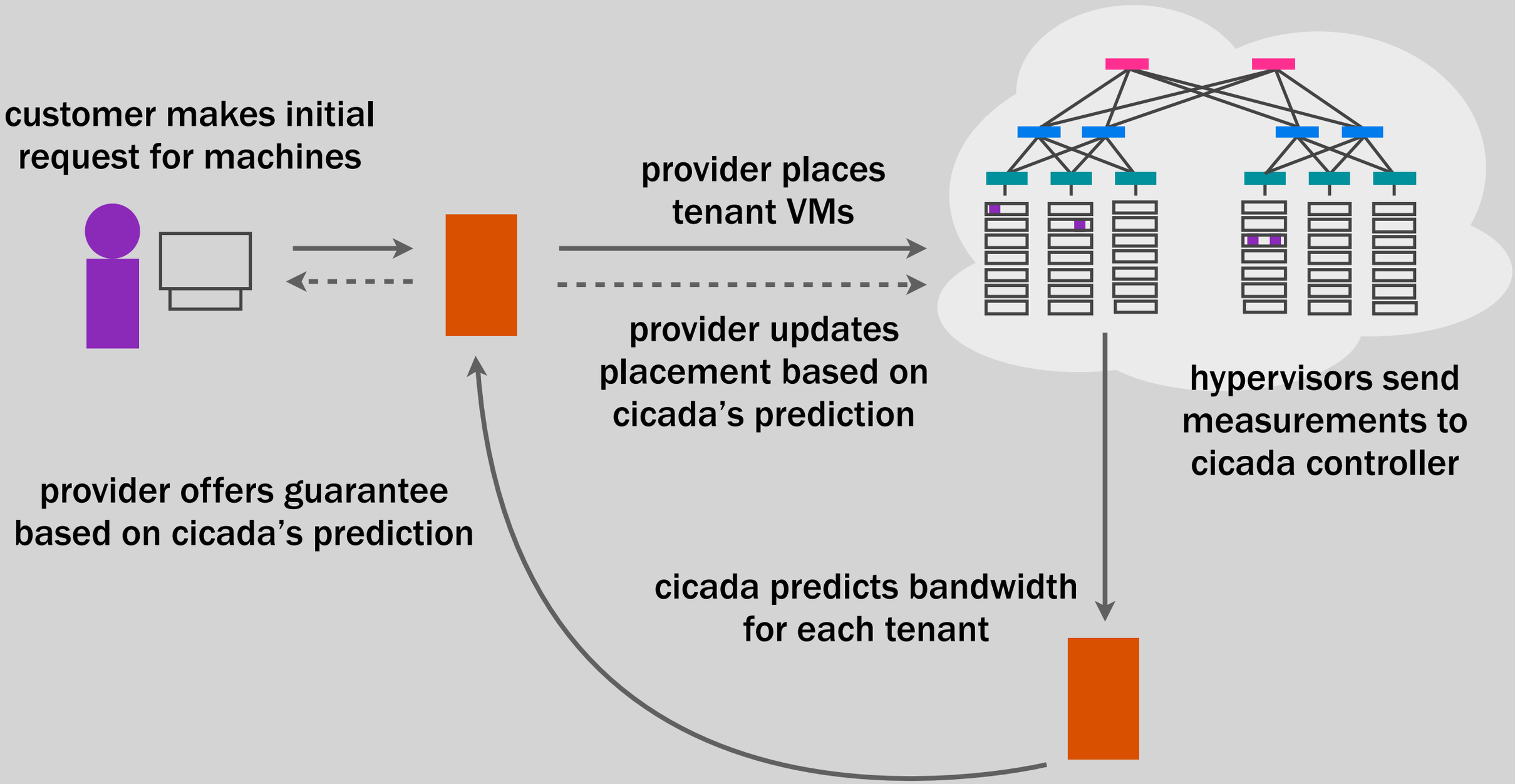

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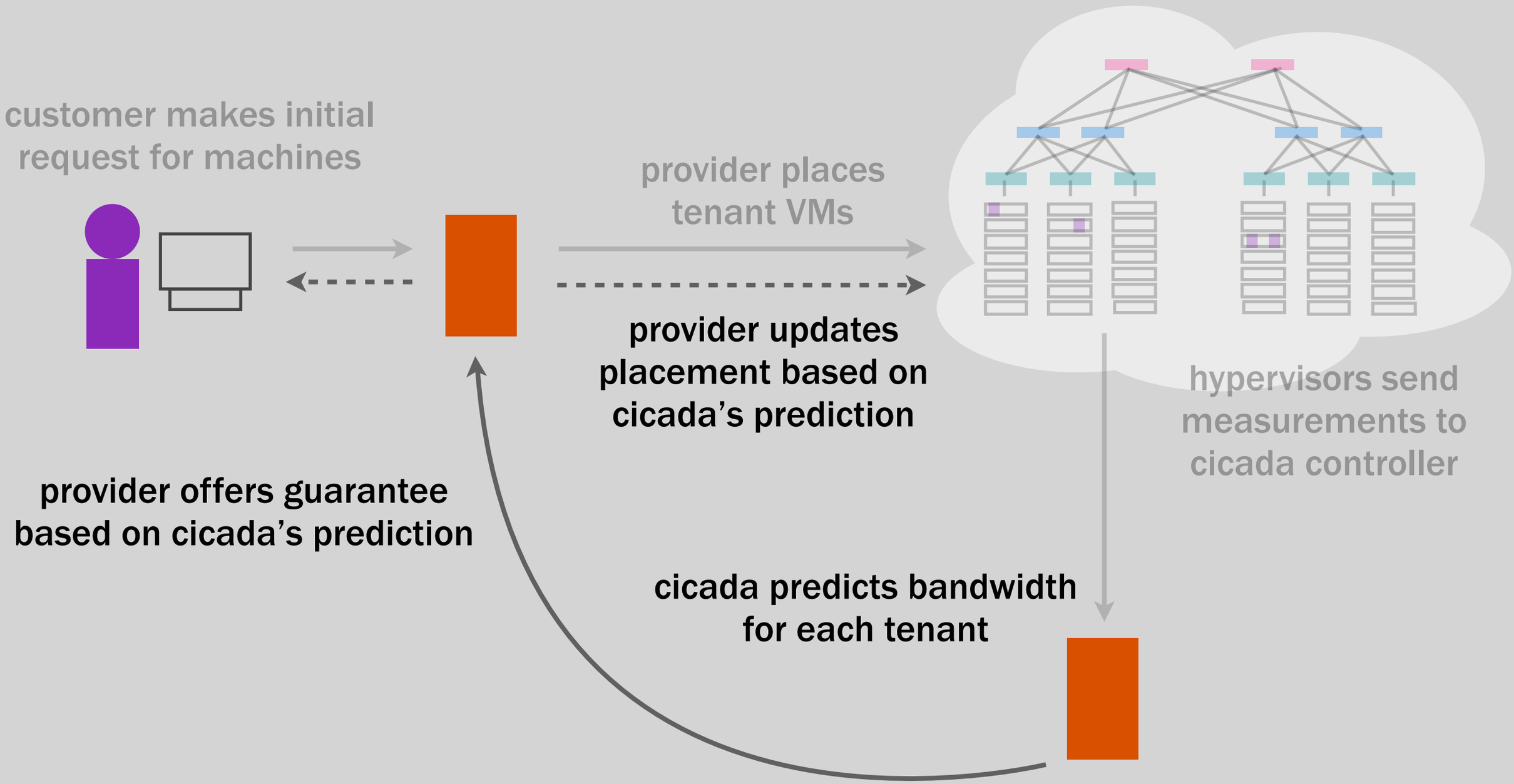

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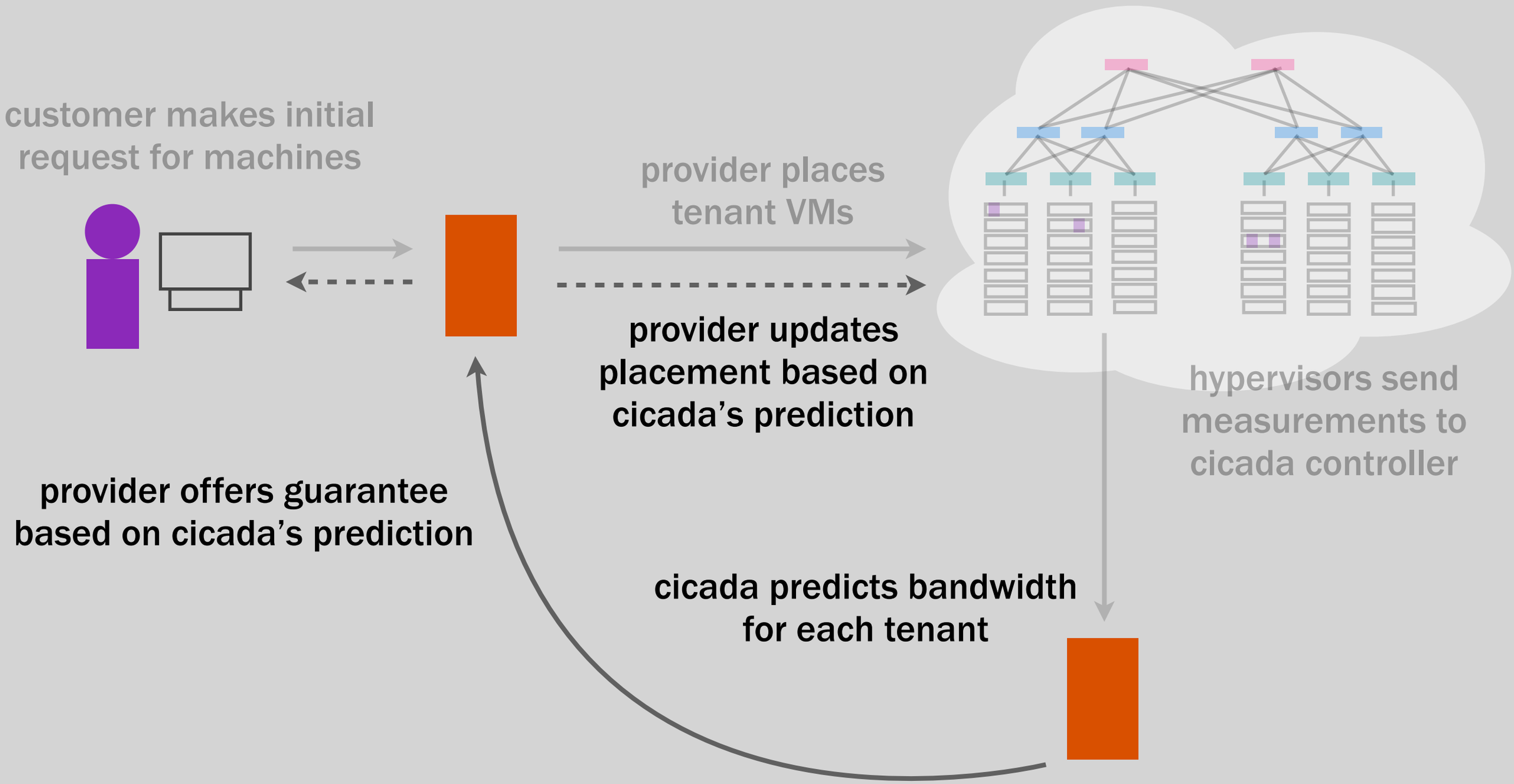
problem: is application traffic actually predictable? if so, is it captured by existing models?



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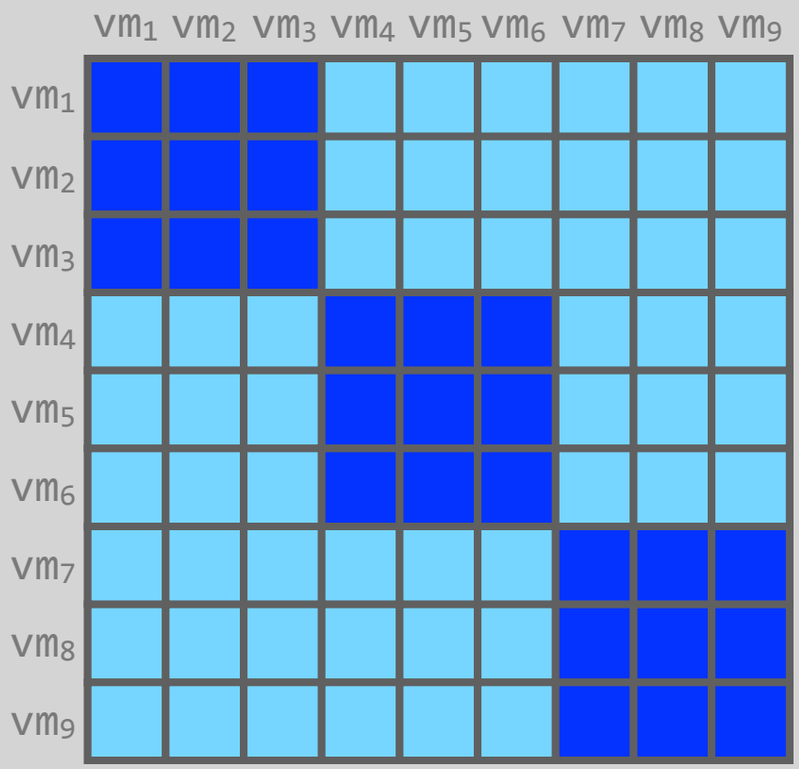

rigid application
(similar to VOC [1])

more data
less data

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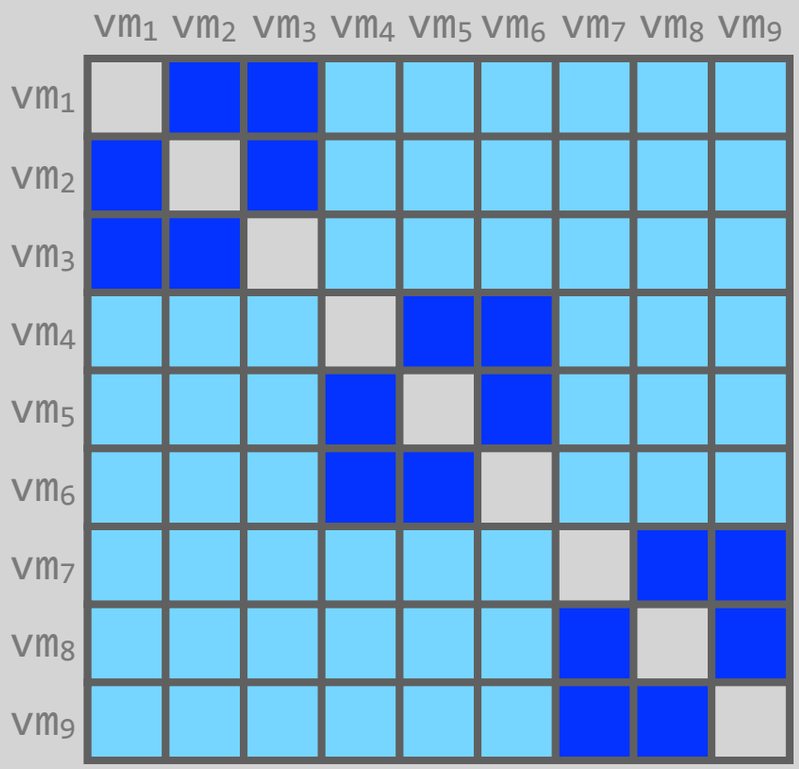

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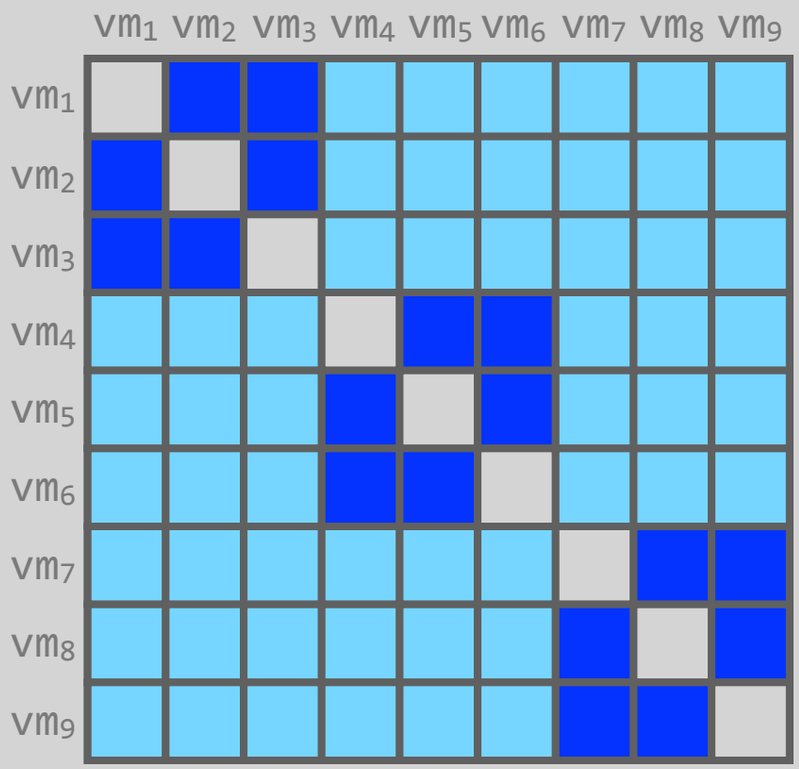

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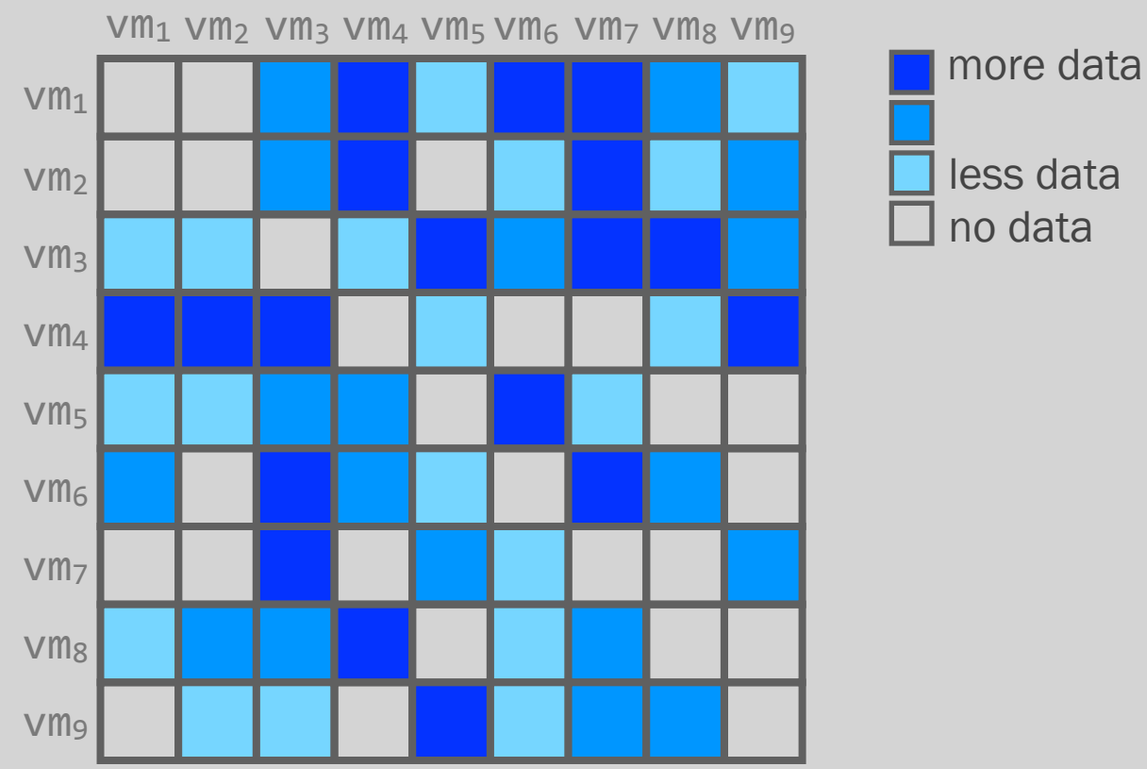

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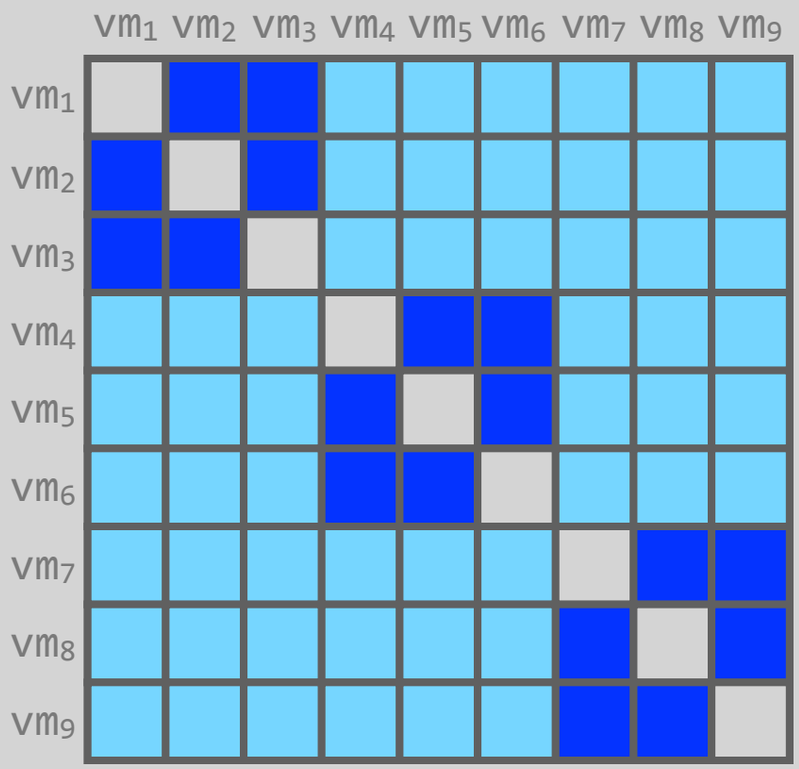

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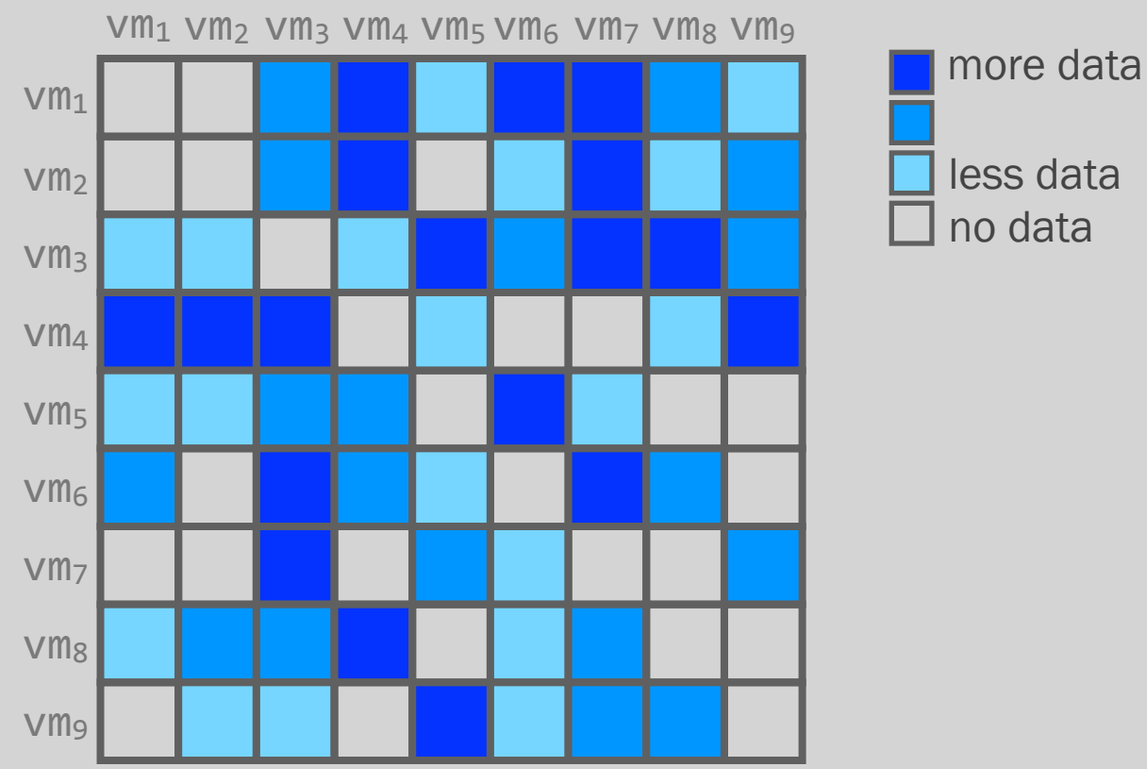

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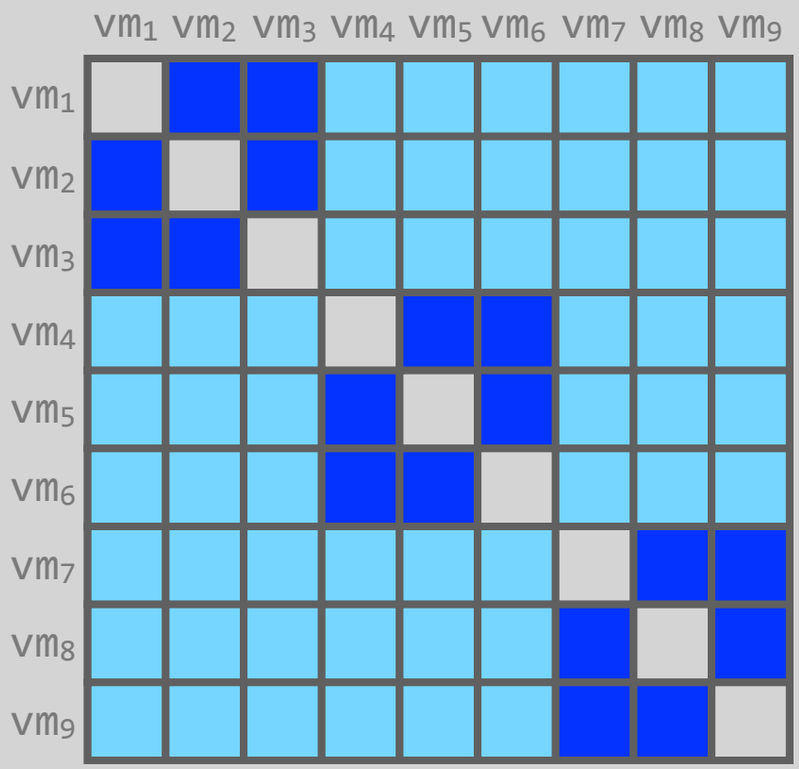

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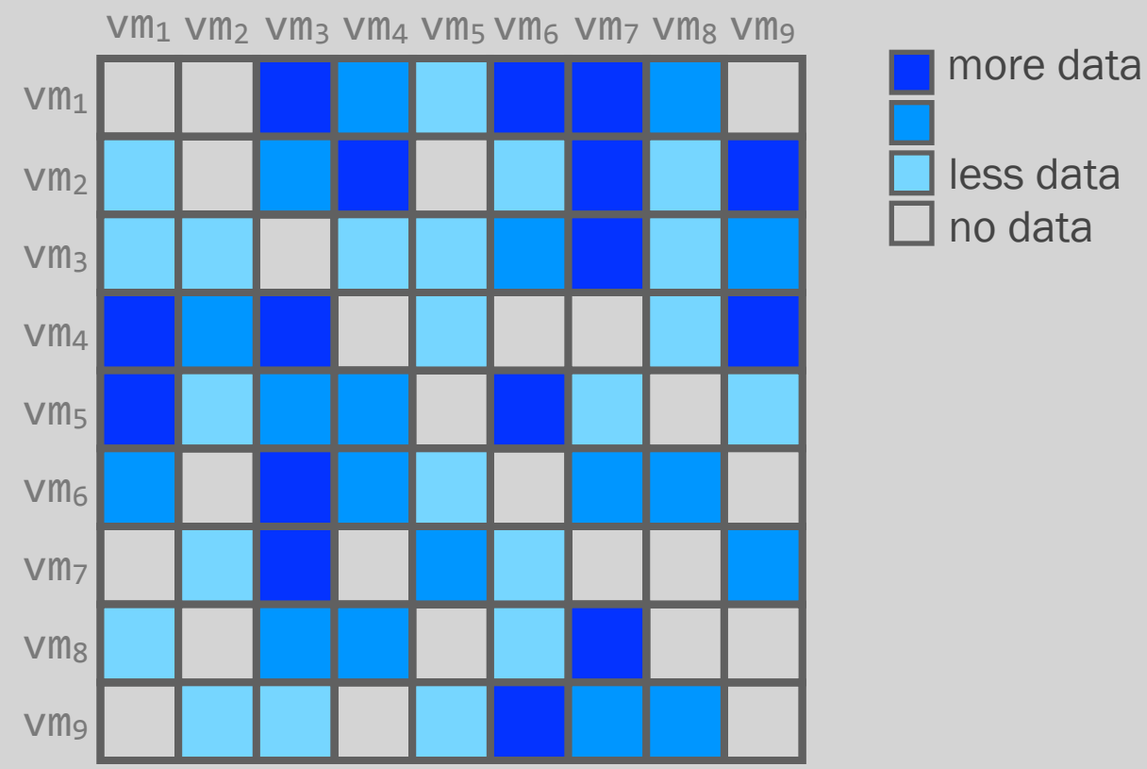

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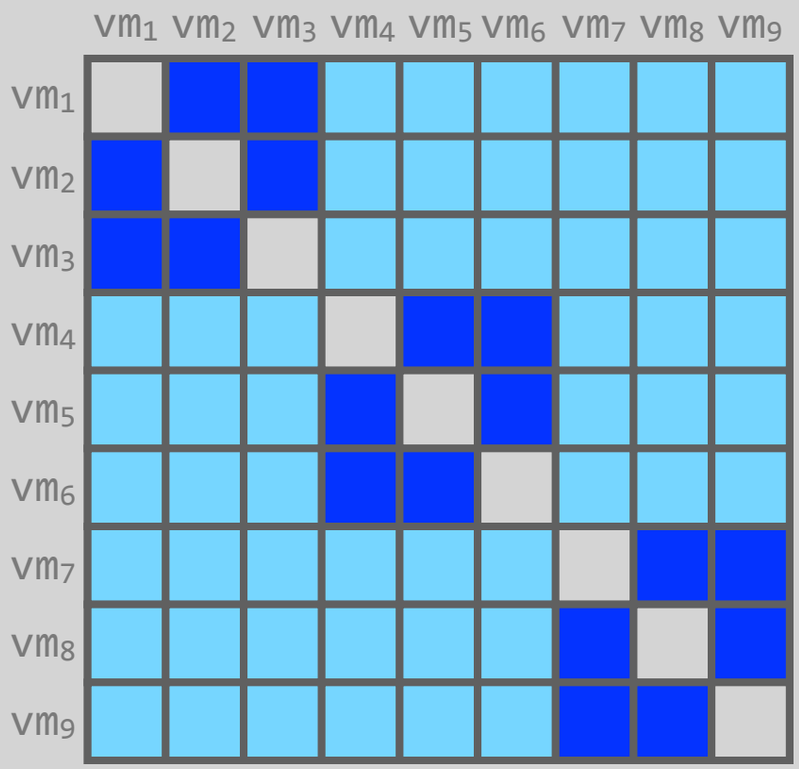

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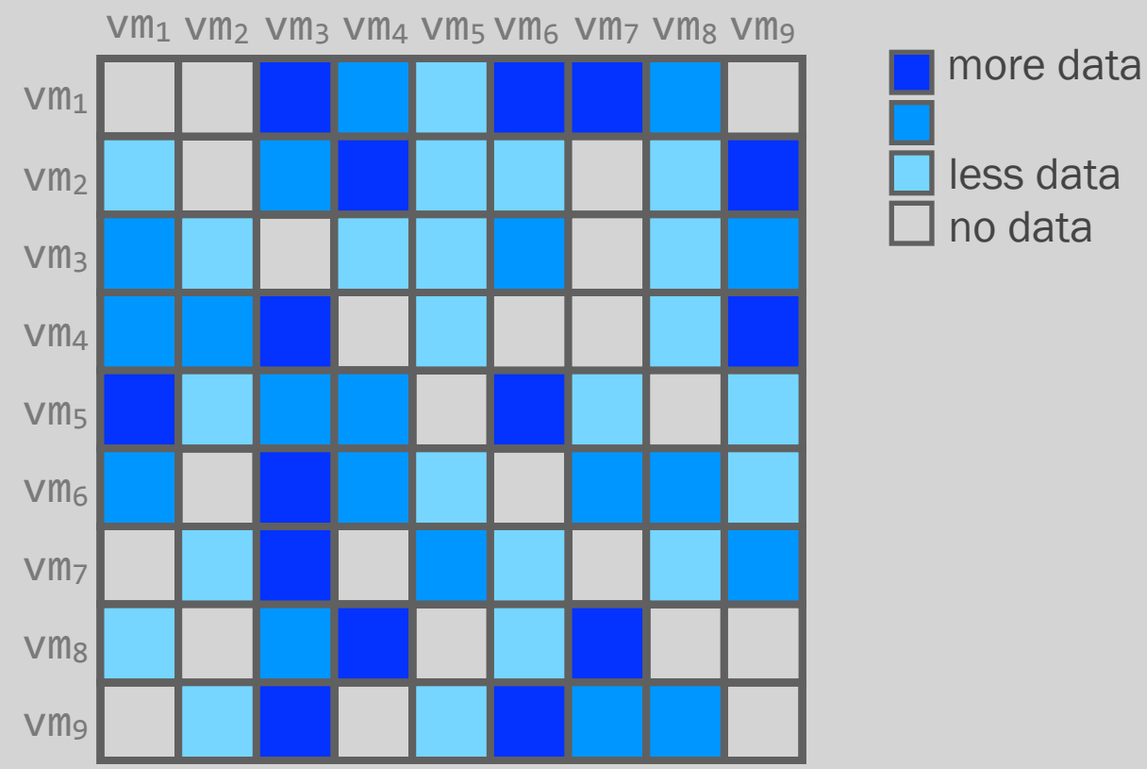

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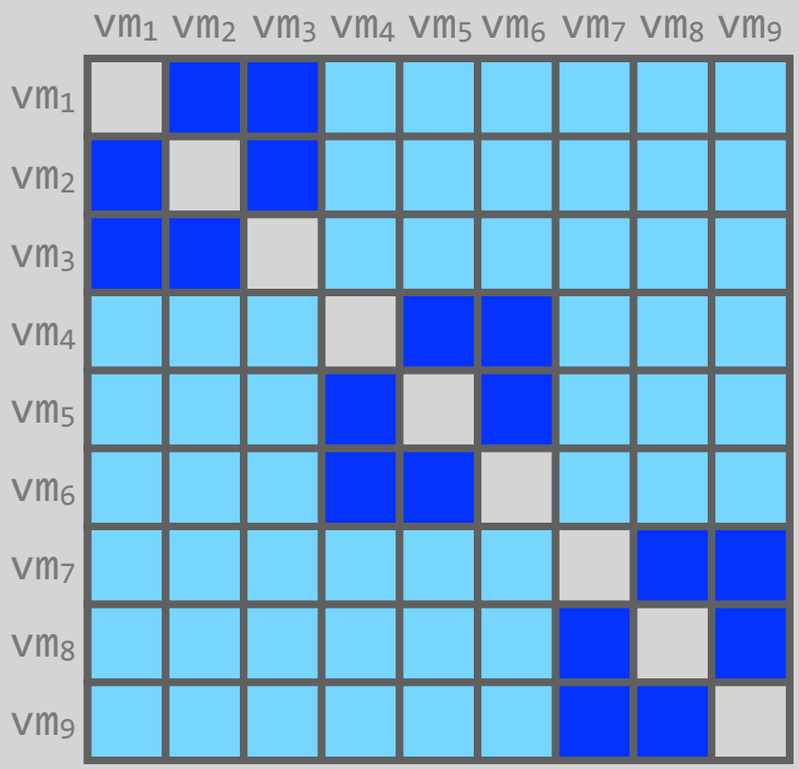

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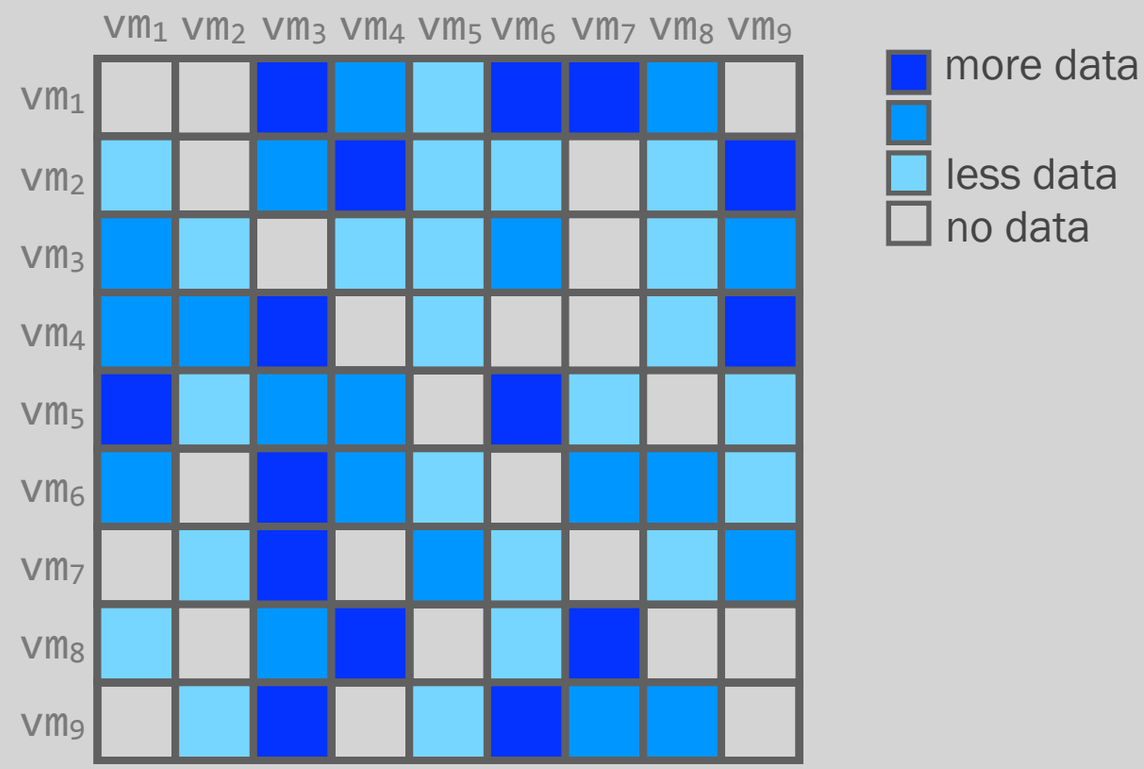

variable application

spatial variability: different pairs of VMs transfer different amounts of data

temporal variability: pairs of VMs transfer different amounts of data at different times

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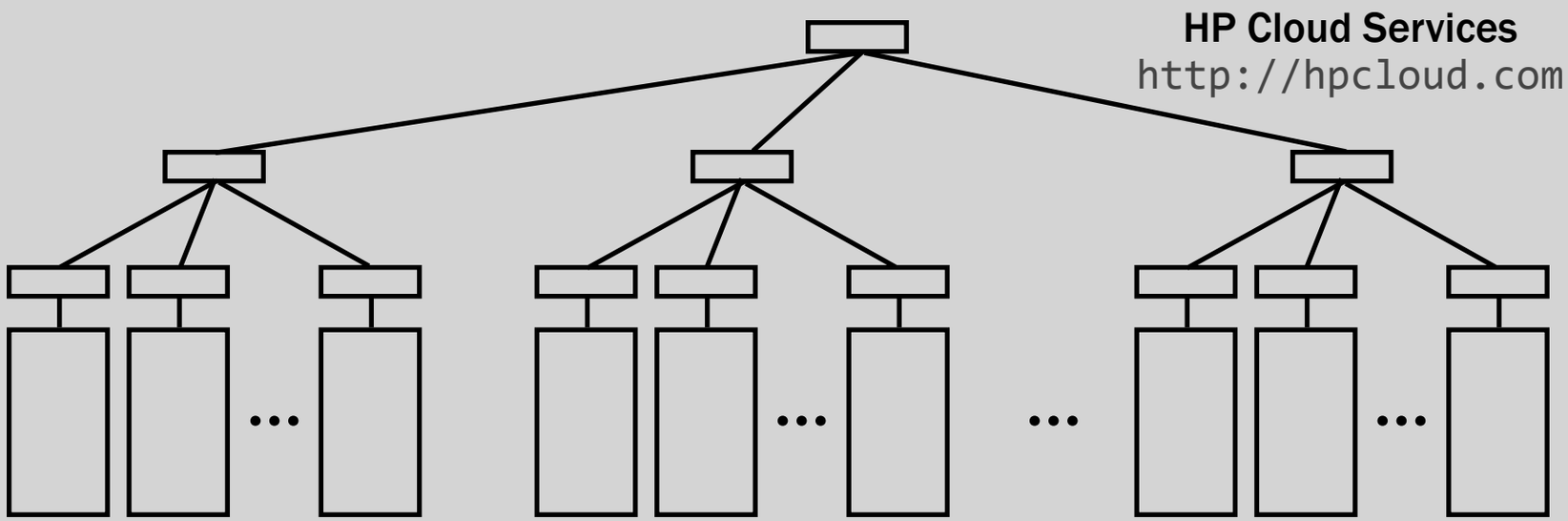
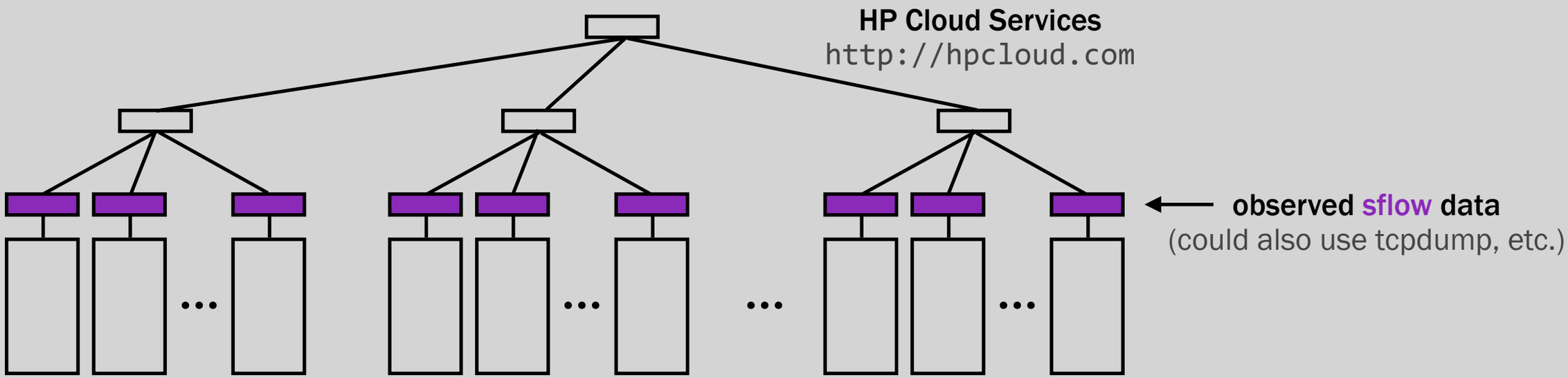
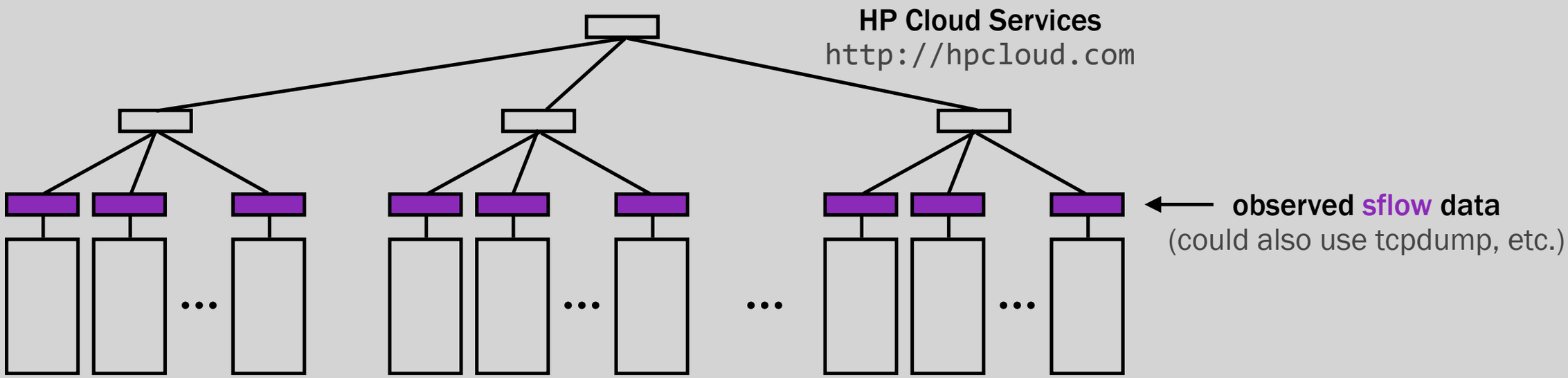
DATASET



DATASET

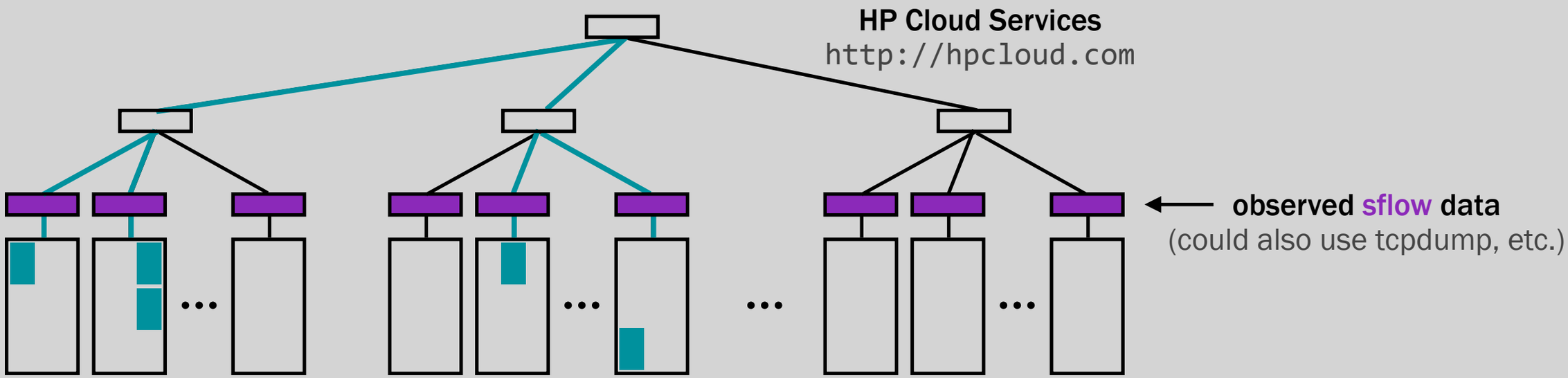

HP Cloud Services
http://hpcloud.com
observed sflow data
(could also use tcpdump, etc.)

DATASET

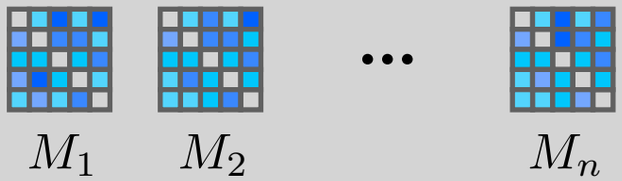


(in this talk)
collected one traffic matrix per hour, for each application

DATASET



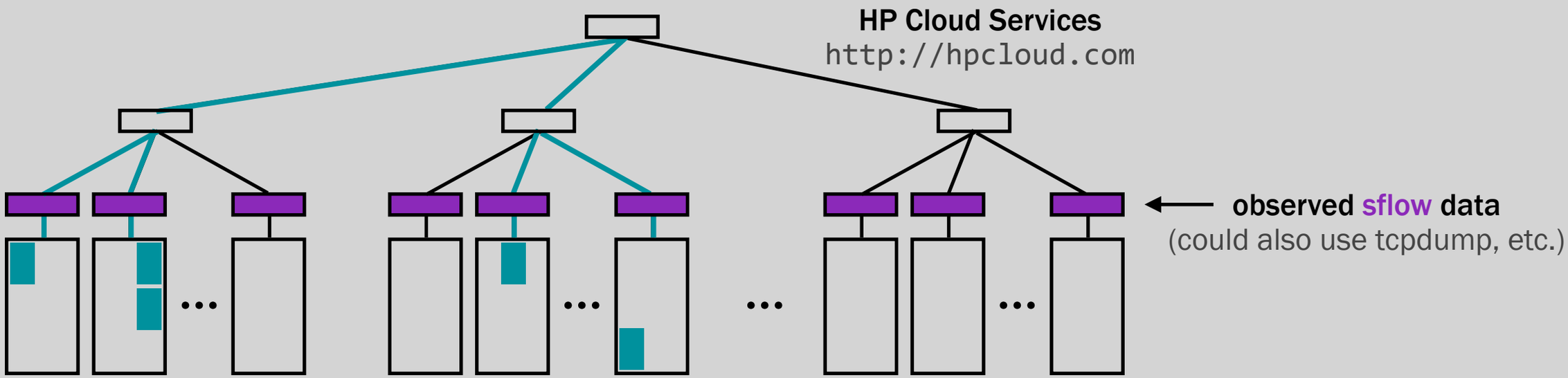
(in this talk)
collected one traffic matrix per hour, for each application



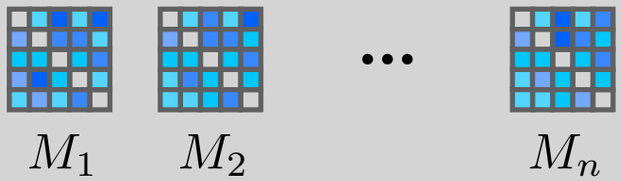
observed traffic

each entry represents the number of bytes transferred between i and j

DATASET



(in this talk)
collected one traffic matrix per hour, for each application



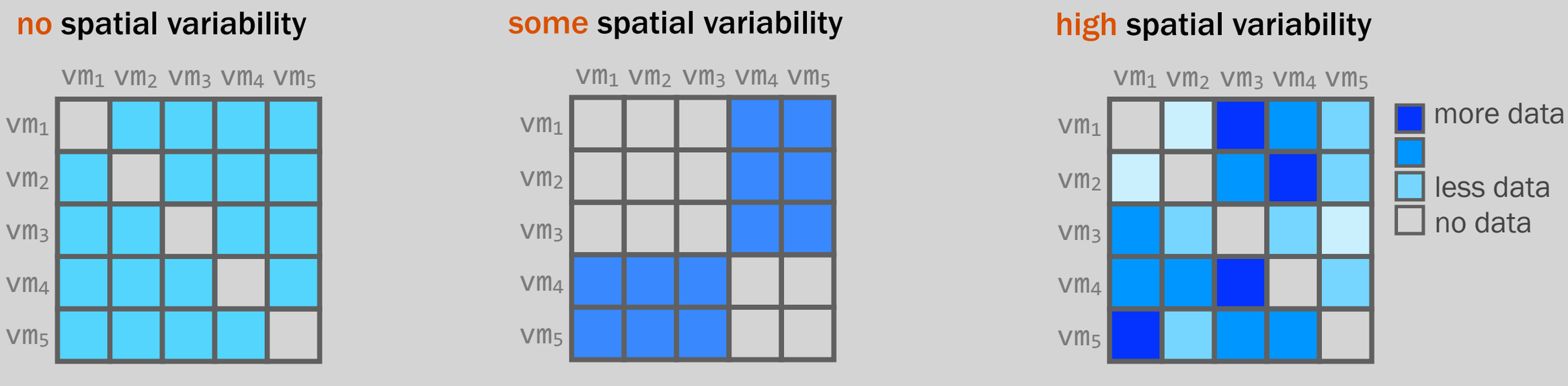
observed traffic

each entry represents the number of bytes transferred between i and j

goal: use this dataset to quantify spatial and temporal variability

SPATIAL VARIABILITY

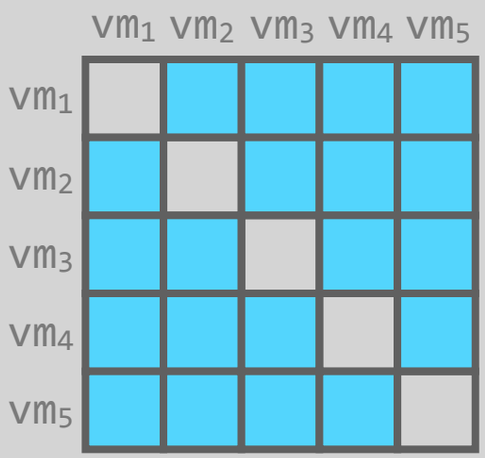
how do we quantify spatial variability?



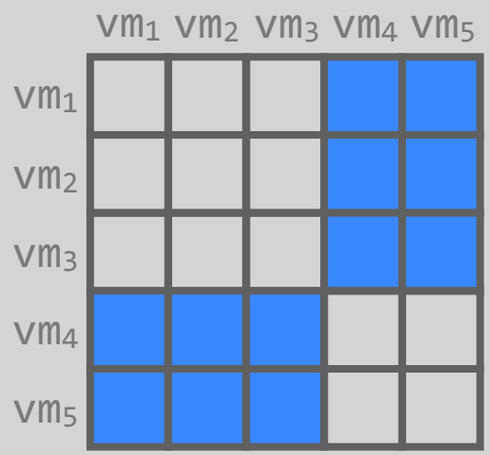
SPATIAL VARIABILITY

how do we quantify spatial variability?

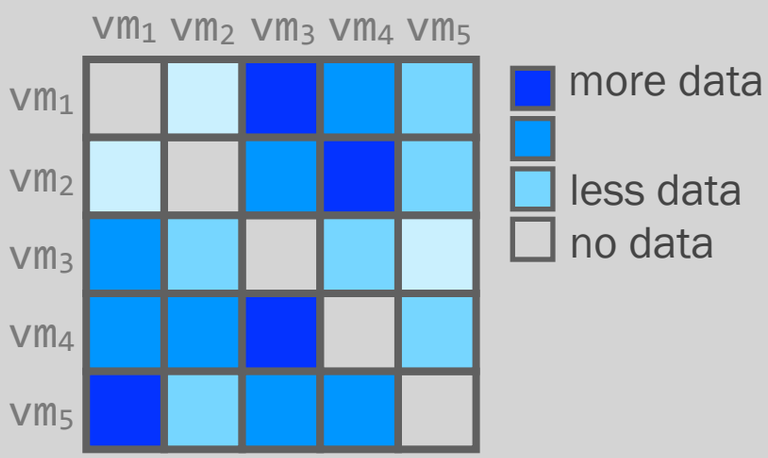
no spatial variability



some spatial variability



high spatial variability

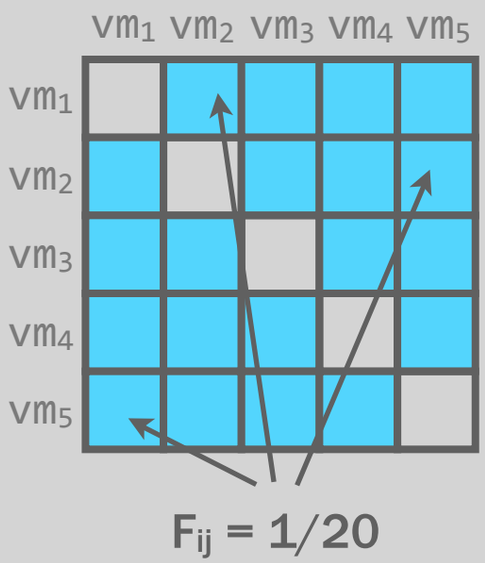


1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

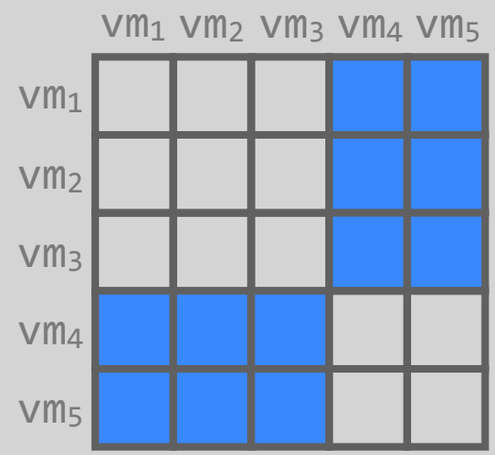
SPATIAL VARIABILITY

how do we quantify spatial variability?

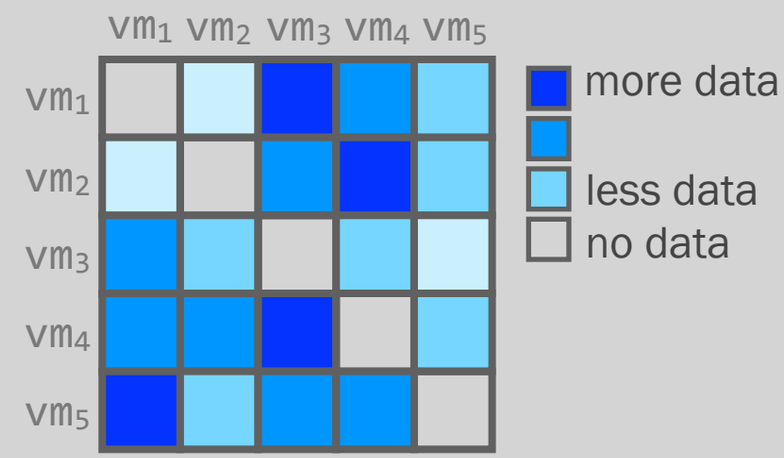
no spatial variability



some spatial variability



high spatial variability

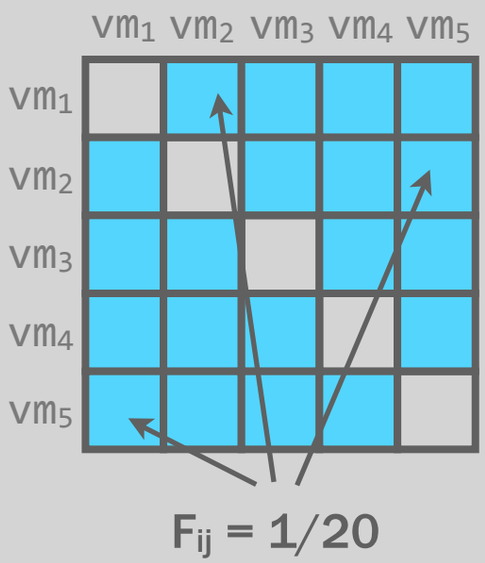


1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

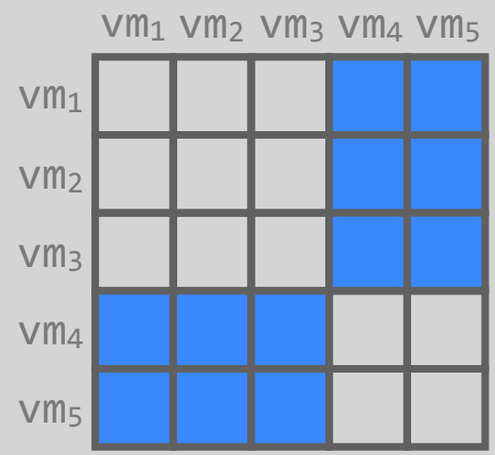
how do we quantify spatial variability?

no spatial variability

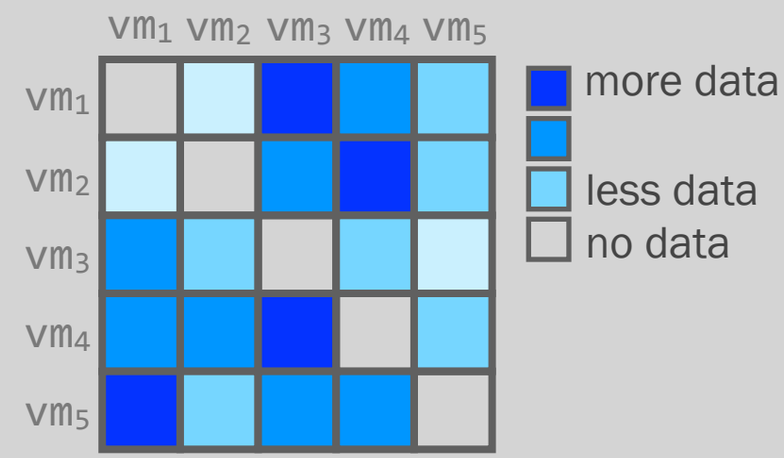


all F_{ij} values are equal

some spatial variability



high spatial variability

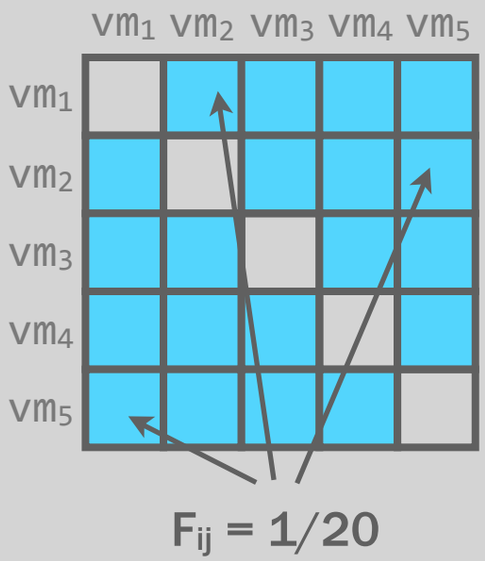


1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

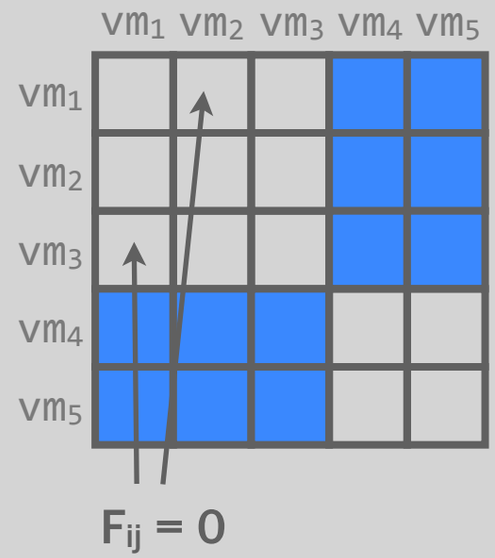
how do we quantify spatial variability?

no spatial variability

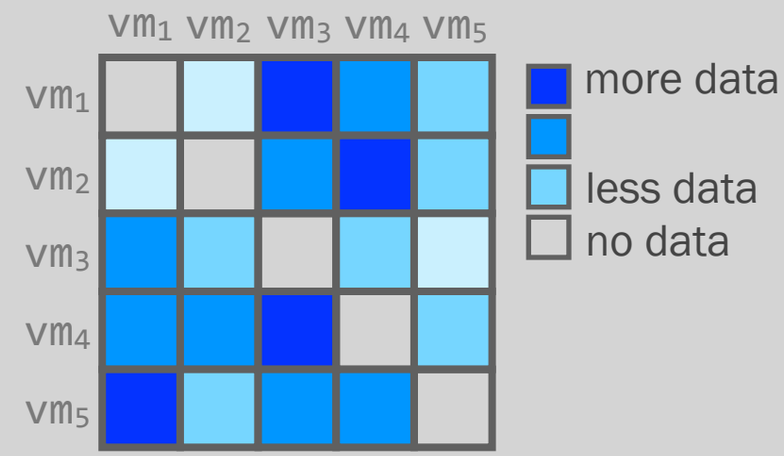


all F_{ij} values are equal

some spatial variability



high spatial variability

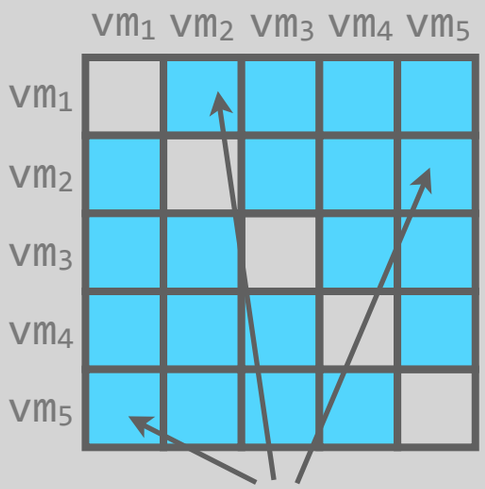


1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

how do we quantify spatial variability?

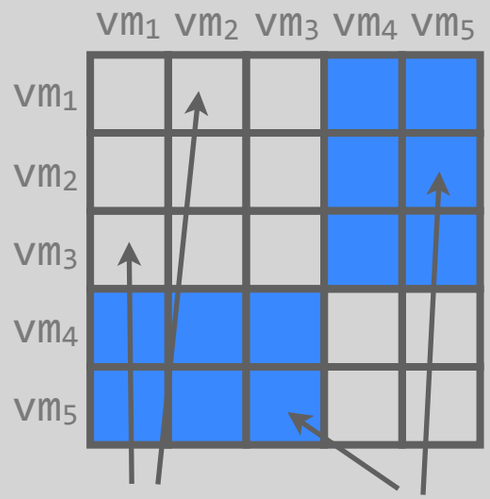
no spatial variability



$F_{ij} = 1/20$

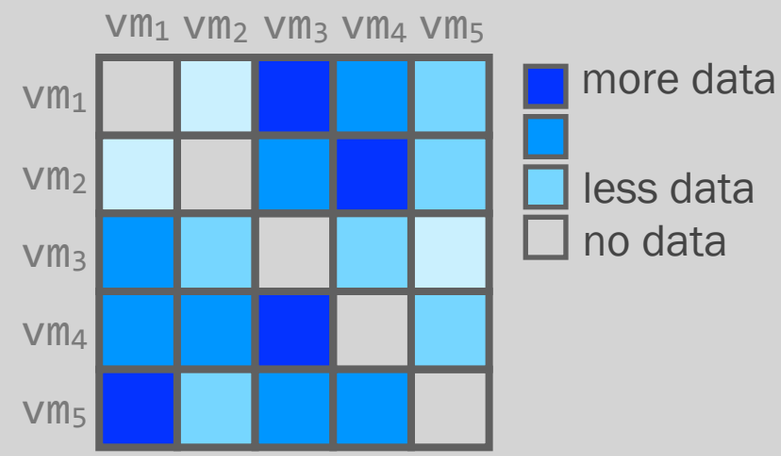
all F_{ij} values are equal

some spatial variability



$F_{ij} = 0$

high spatial variability



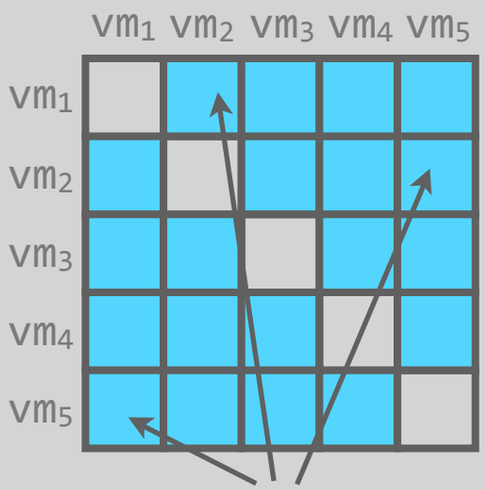
$F_{ij} = 1/12$

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

how do we quantify spatial variability?

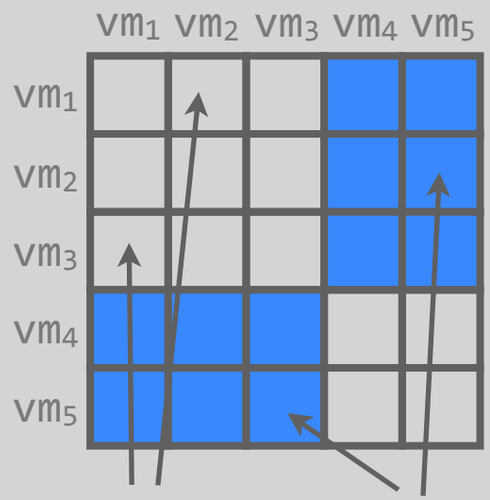
no spatial variability



$F_{ij} = 1/20$

all F_{ij} values are equal

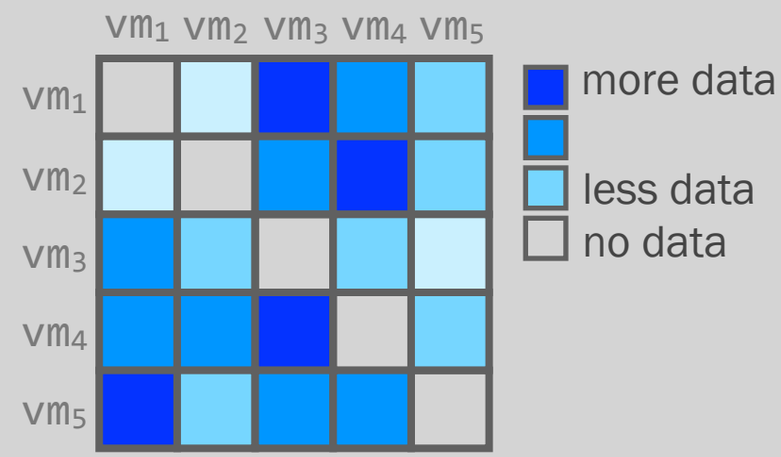
some spatial variability



$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

high spatial variability

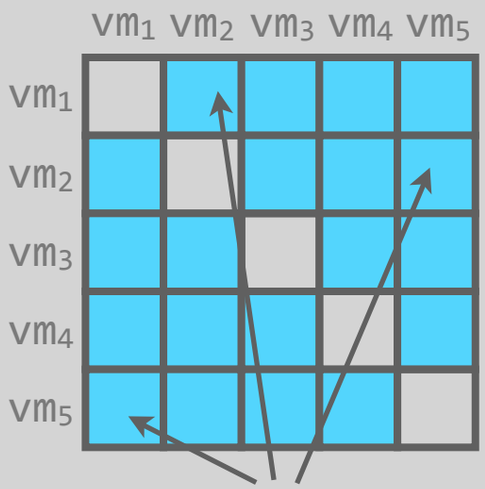


1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

how do we quantify spatial variability?

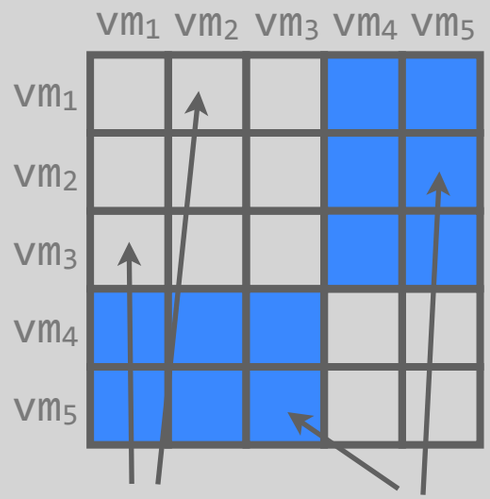
no spatial variability



$F_{ij} = 1/20$

all F_{ij} values are equal

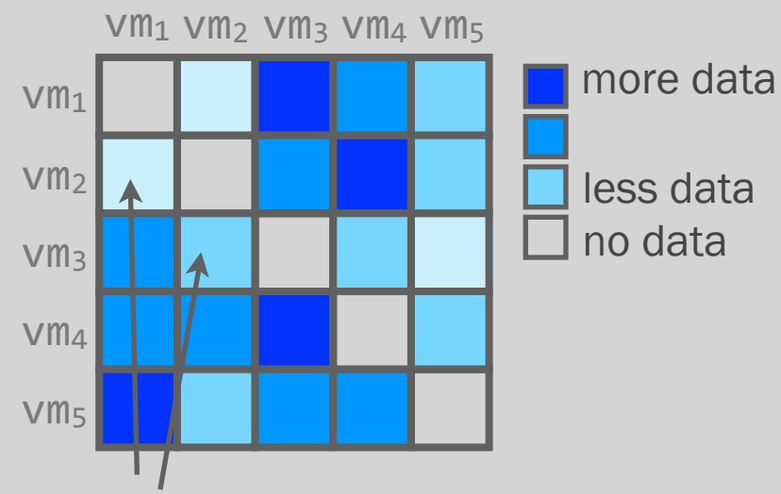
some spatial variability



$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

high spatial variability



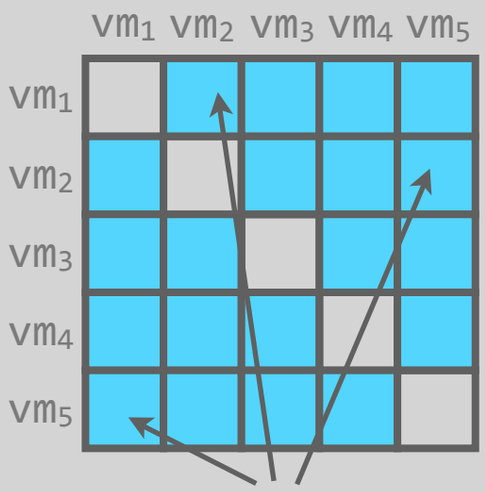
$F_{ij} < 1/20$

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

how do we quantify spatial variability?

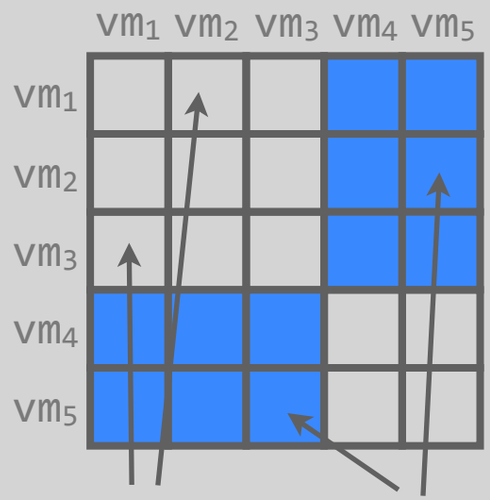
no spatial variability



$F_{ij} = 1/20$

all F_{ij} values are equal

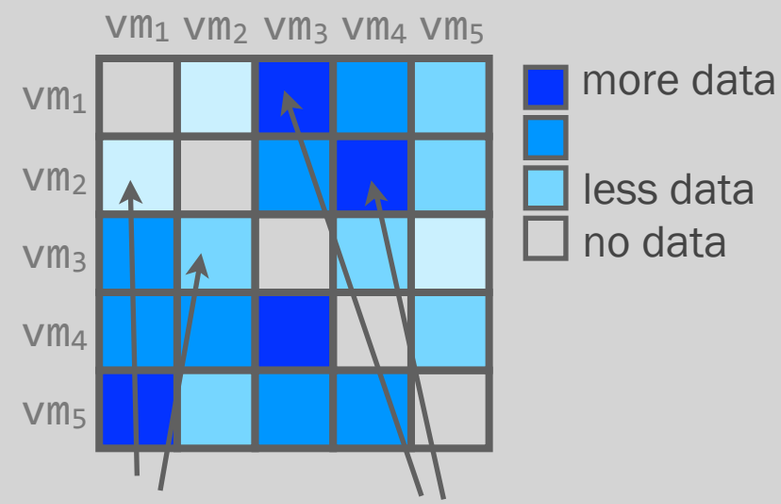
some spatial variability



$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

high spatial variability



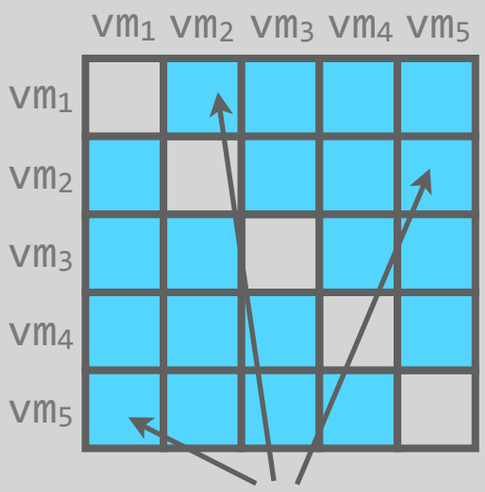
$F_{ij} < 1/20$ $F_{ij} > 1/20$

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

how do we quantify spatial variability?

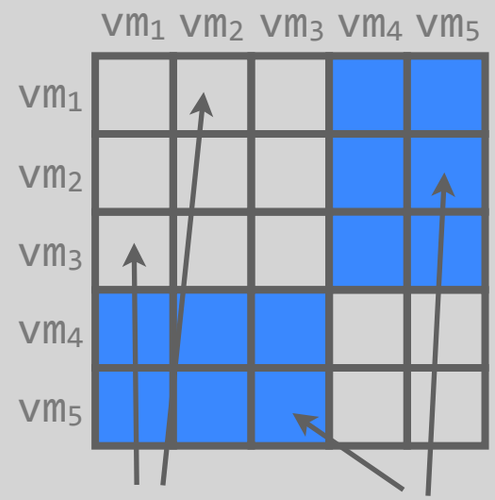
no spatial variability



$F_{ij} = 1/20$

all F_{ij} values are equal

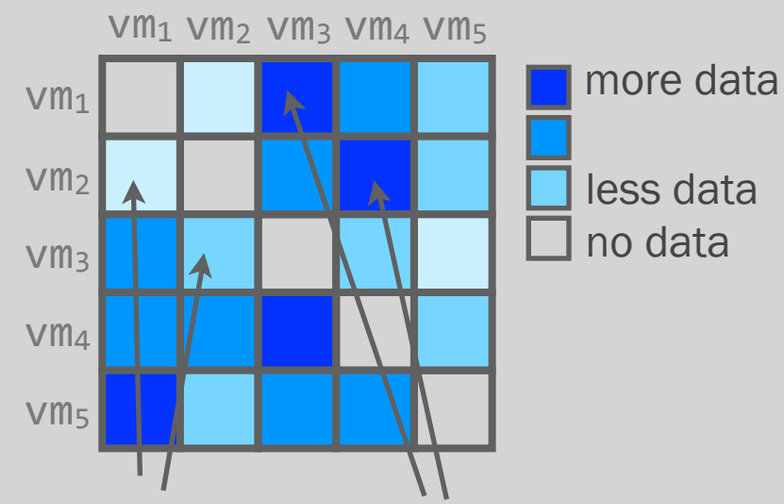
some spatial variability



$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

high spatial variability



$F_{ij} < 1/20$ $F_{ij} > 1/20$

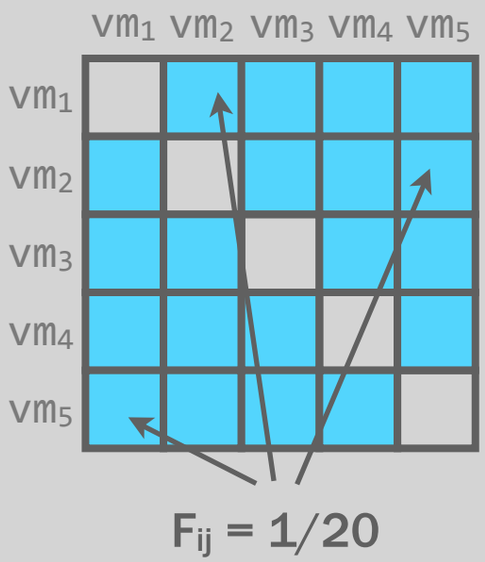
many distinct F_{ij} values

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j

SPATIAL VARIABILITY

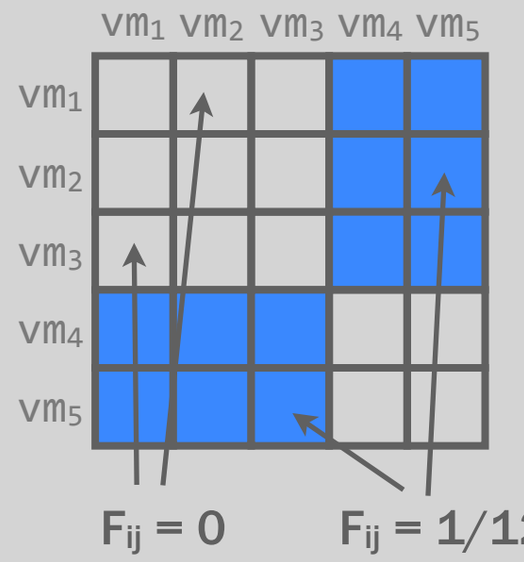
how do we quantify spatial variability?

no spatial variability



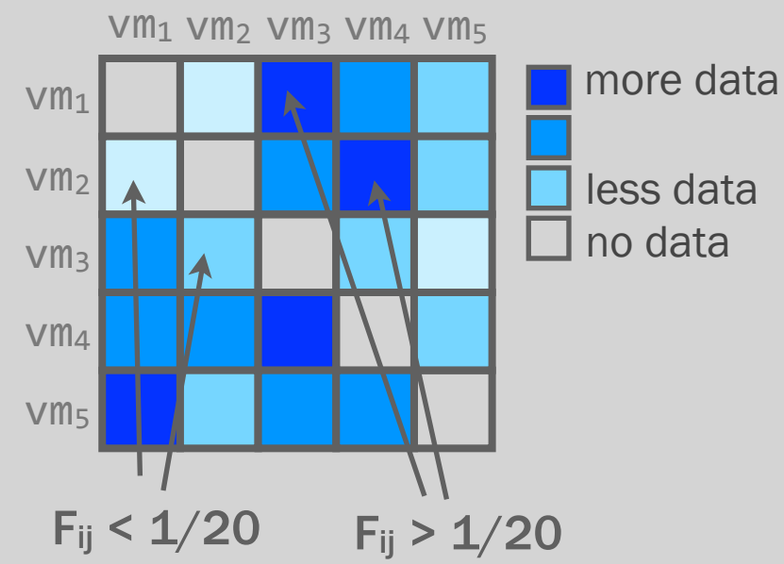
all F_{ij} values are equal

some spatial variability



two distinct F_{ij} values

high spatial variability



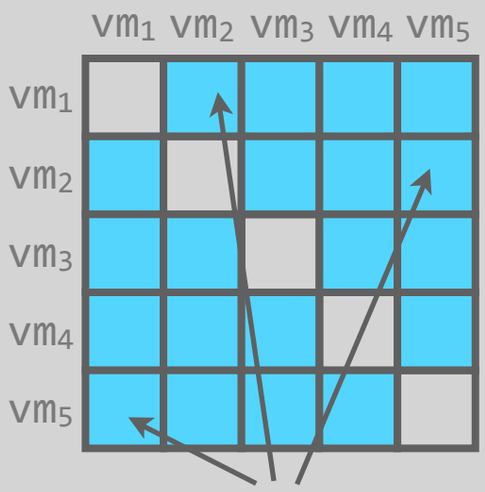
many distinct F_{ij} values

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j
2. calculate the coefficient of variation (σ/μ) of the F_{ij} values

SPATIAL VARIABILITY

how do we quantify spatial variability?

no spatial variability

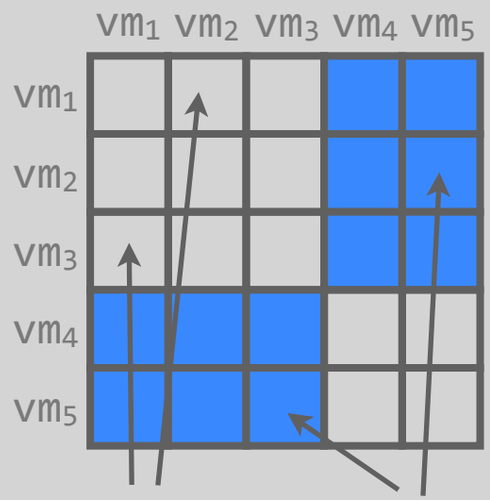


$F_{ij} = 1/20$

all F_{ij} values are equal

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 0$

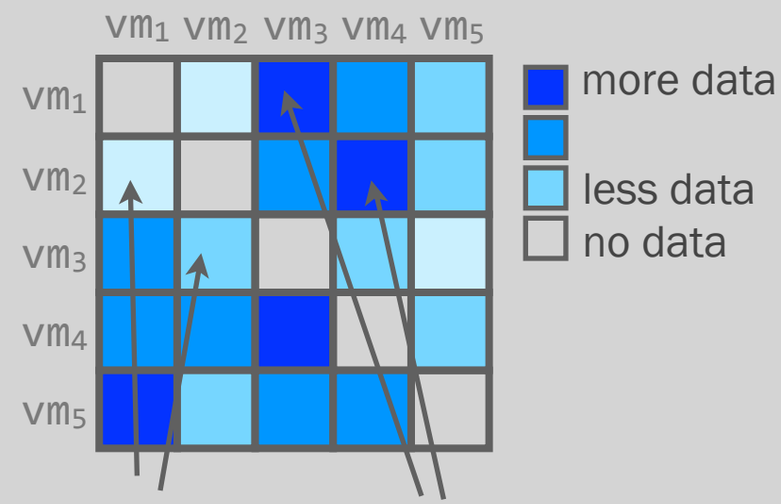
some spatial variability



$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

high spatial variability



$F_{ij} < 1/20$ $F_{ij} > 1/20$

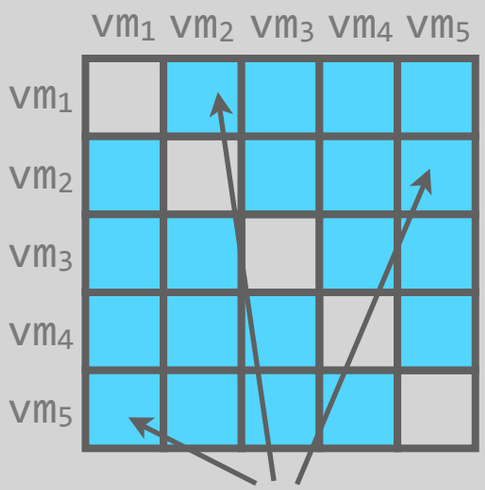
many distinct F_{ij} values

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j
2. calculate the coefficient of variation (σ/μ) of the F_{ij} values

SPATIAL VARIABILITY

how do we quantify spatial variability?

no spatial variability

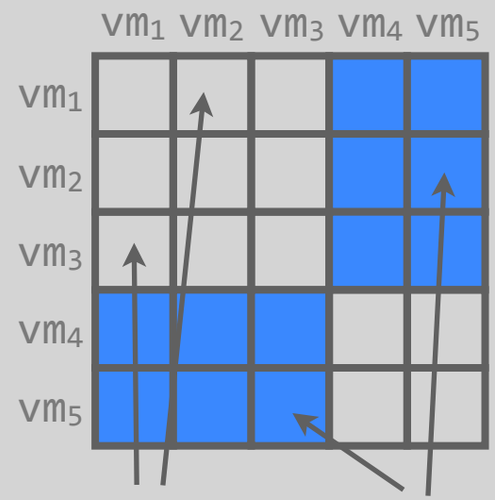


$F_{ij} = 1/20$

all F_{ij} values are equal

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 0$

some spatial variability

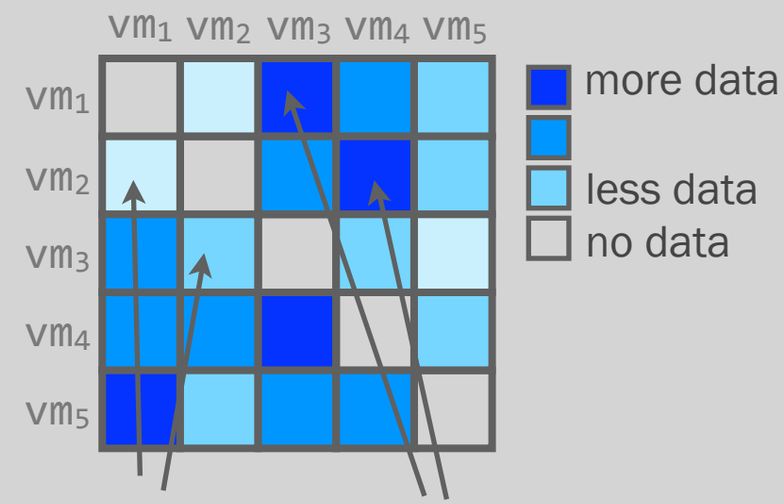


$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 1^*$

high spatial variability



$F_{ij} < 1/20$ $F_{ij} > 1/20$

many distinct F_{ij} values

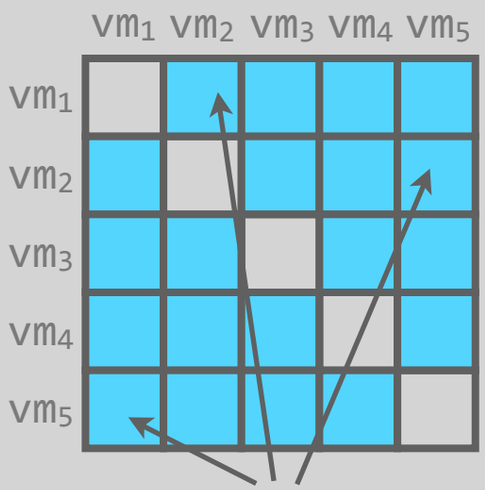
1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j
2. calculate the coefficient of variation (σ/μ) of the F_{ij} values

*see paper for this result

SPATIAL VARIABILITY

how do we quantify spatial variability?

no spatial variability

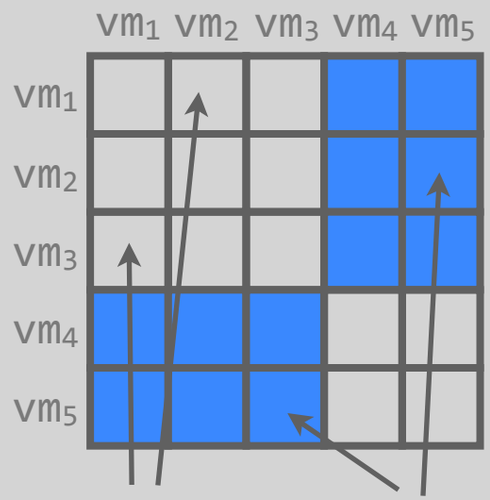


$F_{ij} = 1/20$

all F_{ij} values are equal

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 0$

some spatial variability

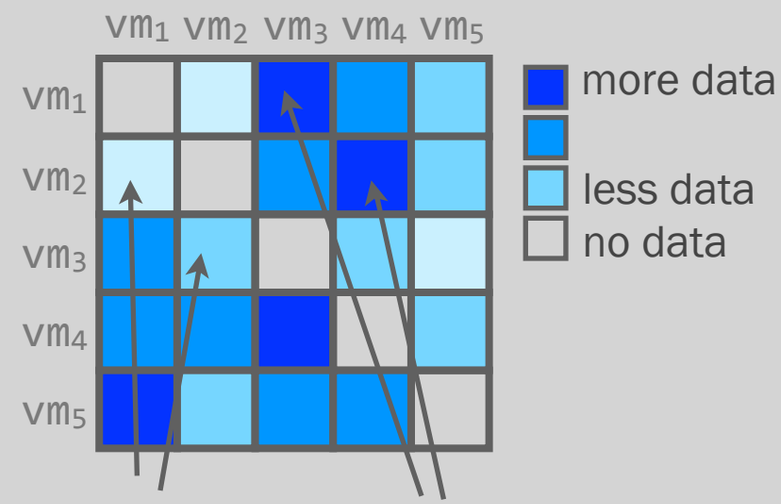


$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 1^*$

high spatial variability



$F_{ij} < 1/20$ $F_{ij} > 1/20$

many distinct F_{ij} values

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) > 1$

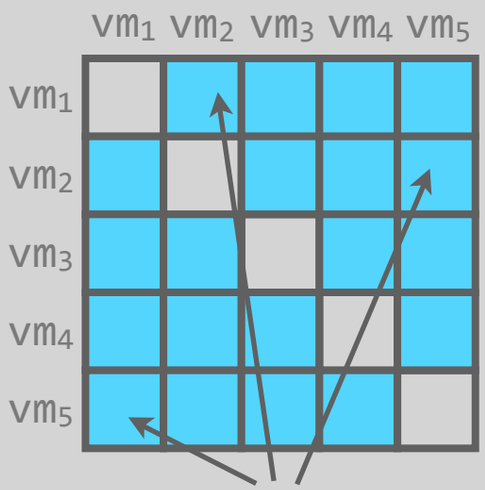
1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j
2. calculate the coefficient of variation (σ/μ) of the F_{ij} values

*see paper for this result

SPATIAL VARIABILITY

how do we quantify spatial variability?

no spatial variability

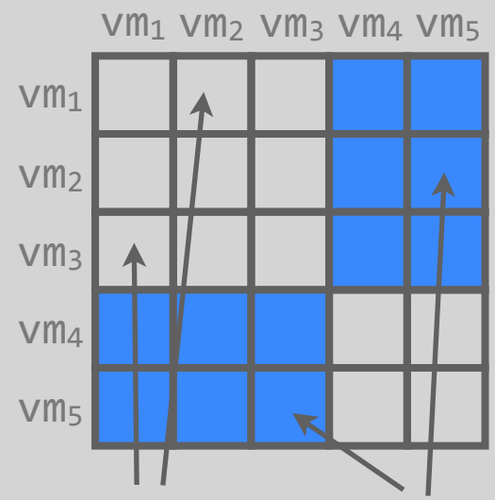


$F_{ij} = 1/20$

all F_{ij} values are equal

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 0$

some spatial variability

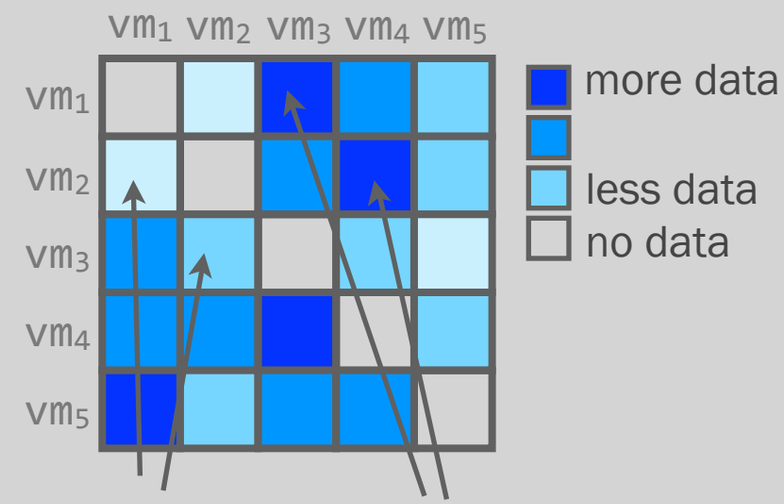


$F_{ij} = 0$ $F_{ij} = 1/12$

two distinct F_{ij} values

$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) = 1^*$

high spatial variability



$F_{ij} < 1/20$ $F_{ij} > 1/20$

many distinct F_{ij} values

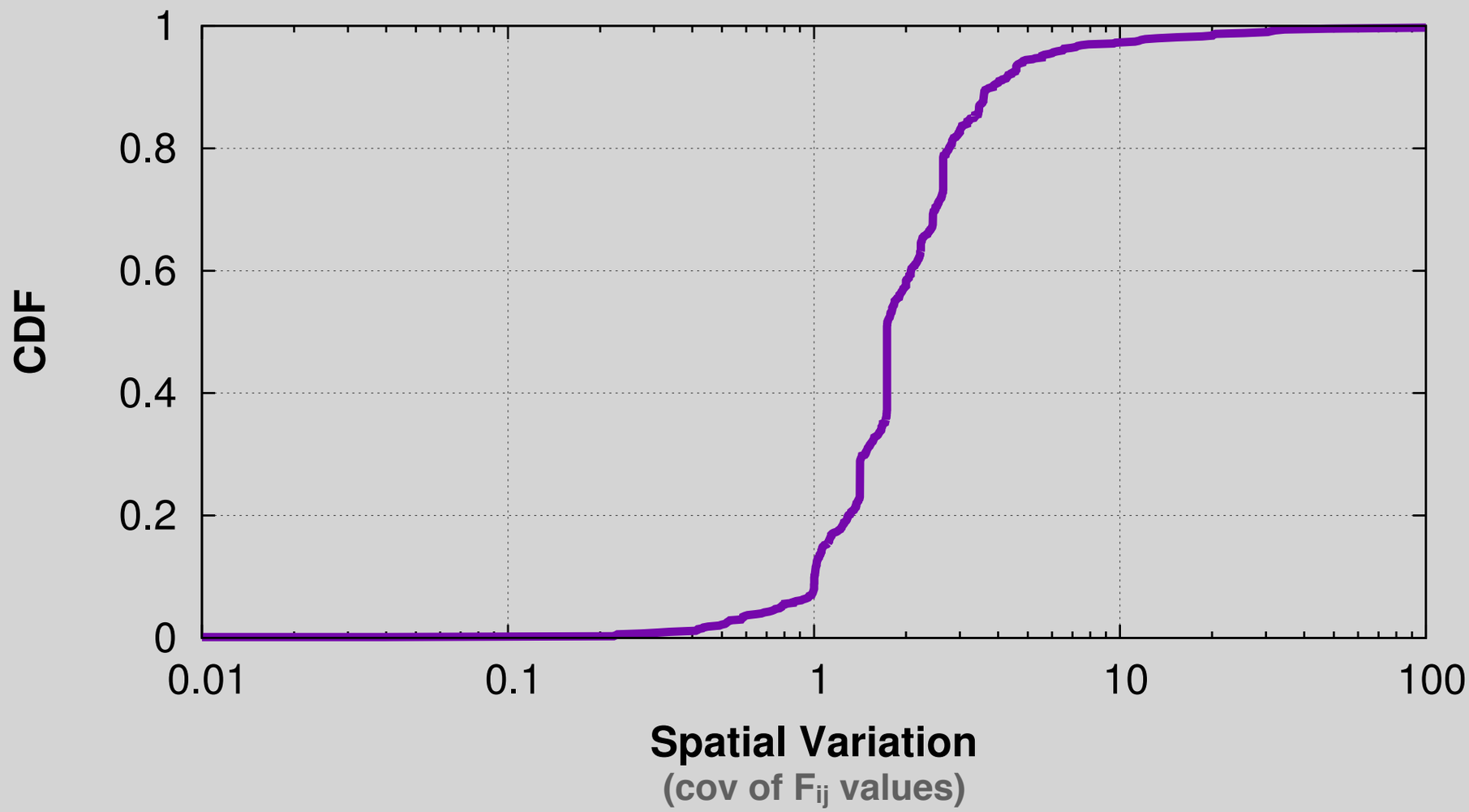
$\Rightarrow \sigma(F_{ij})/\mu(F_{ij}) > 1$

1. let F_{ij} = fraction of tenant traffic sent from VM_i to VM_j
2. calculate the coefficient of variation (σ/μ) of the F_{ij} values

the higher the cov, the higher the spatial variation

*see paper for this result

SPATIAL VARIABILITY



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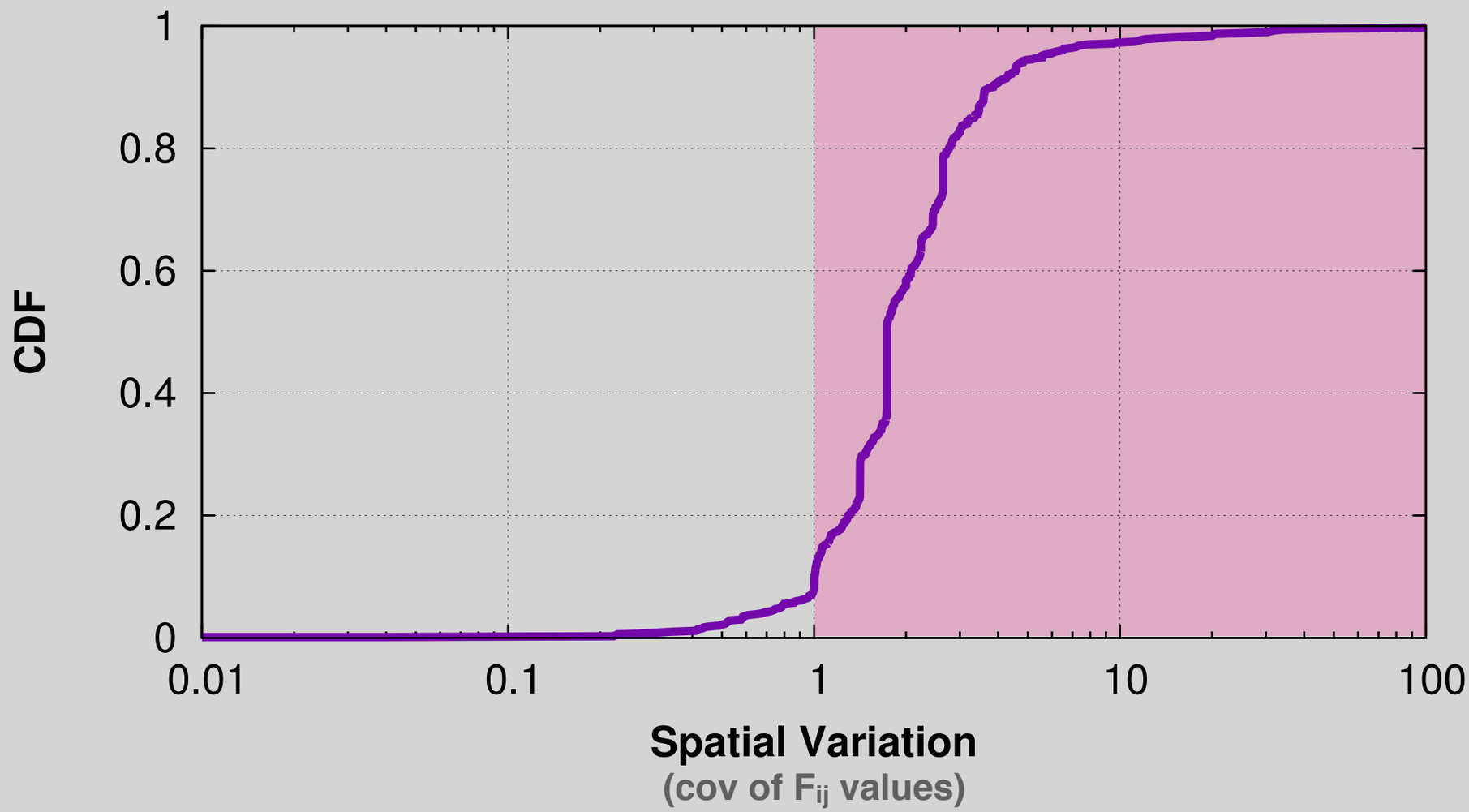

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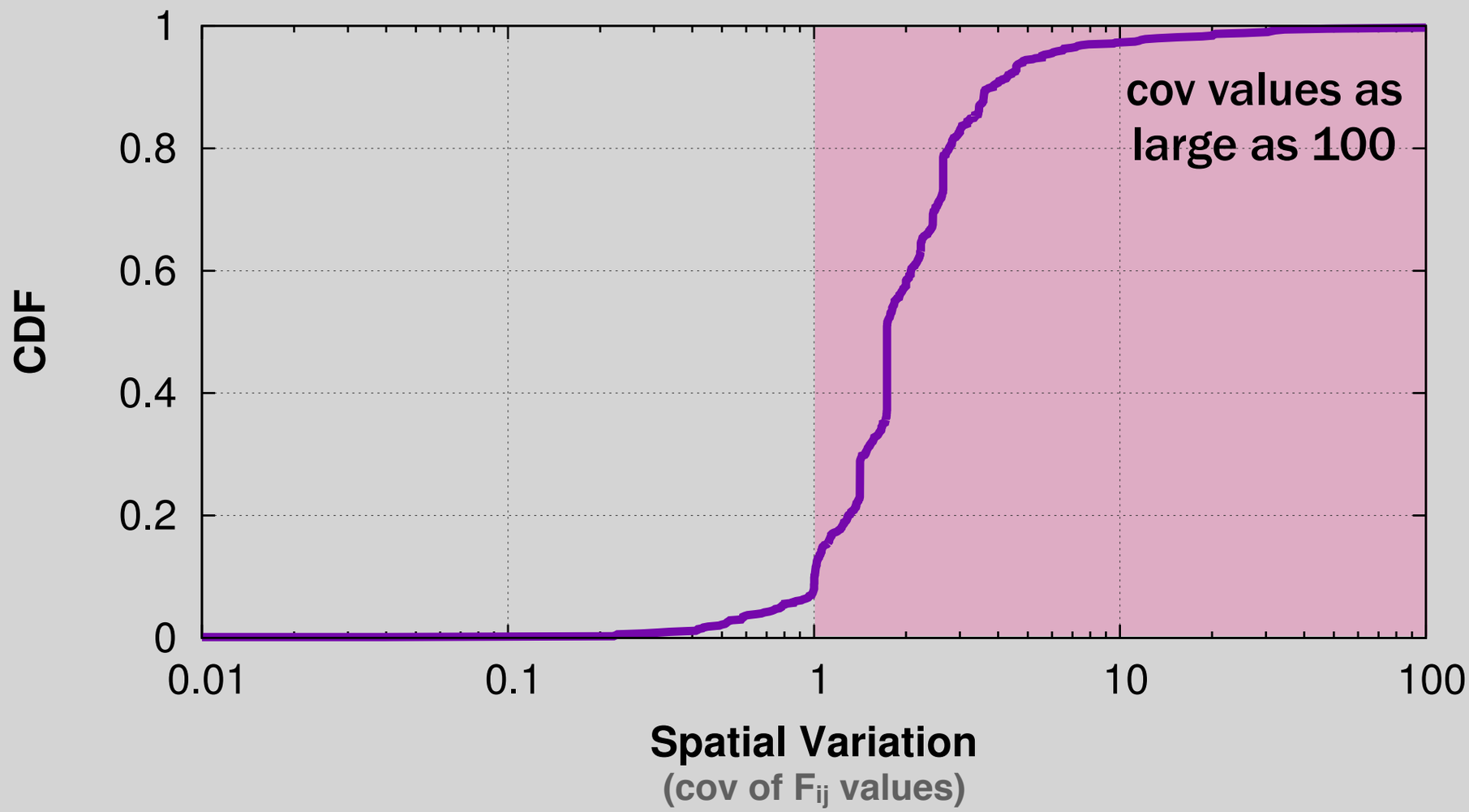

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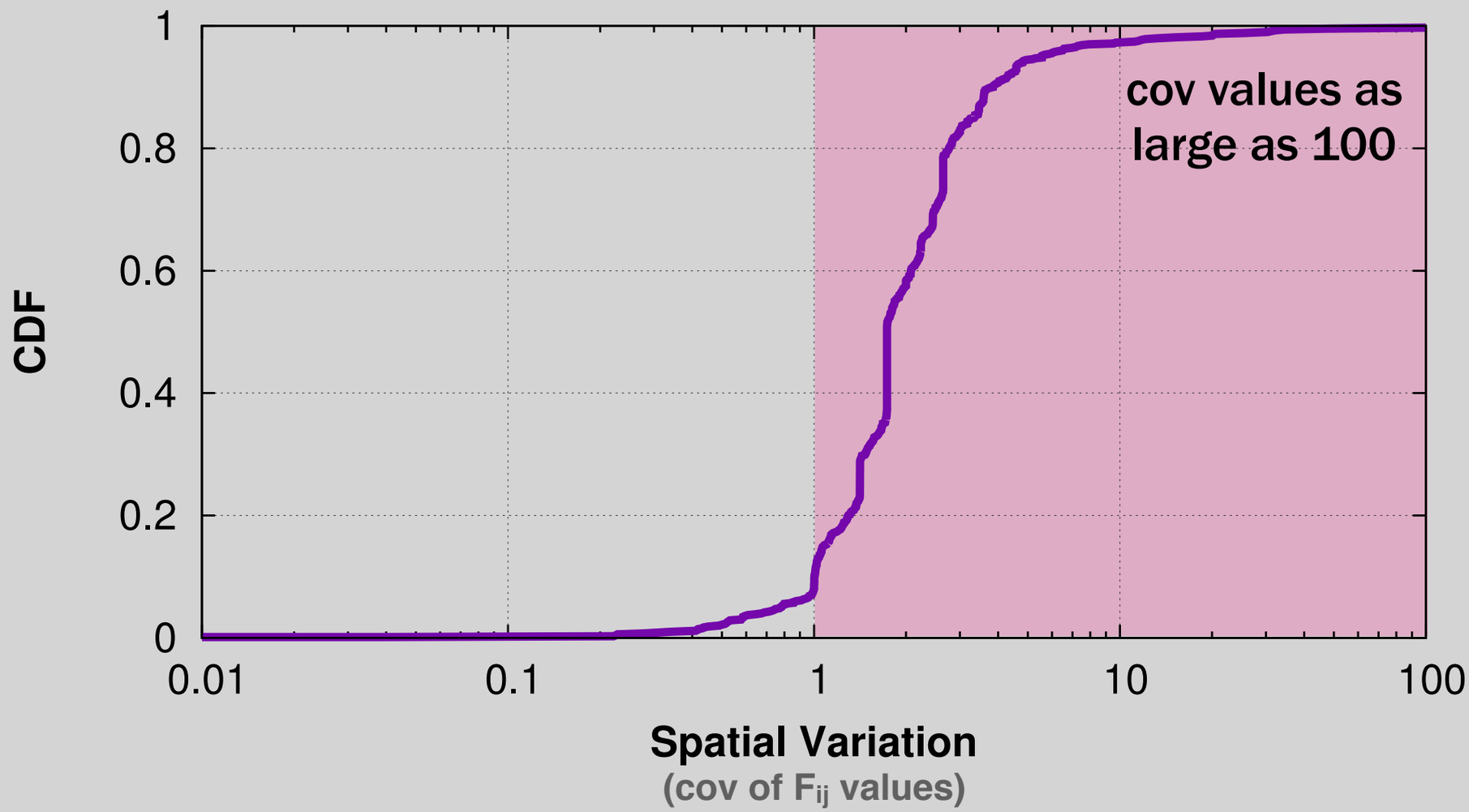

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(the same result holds for temporal variability, see paper)

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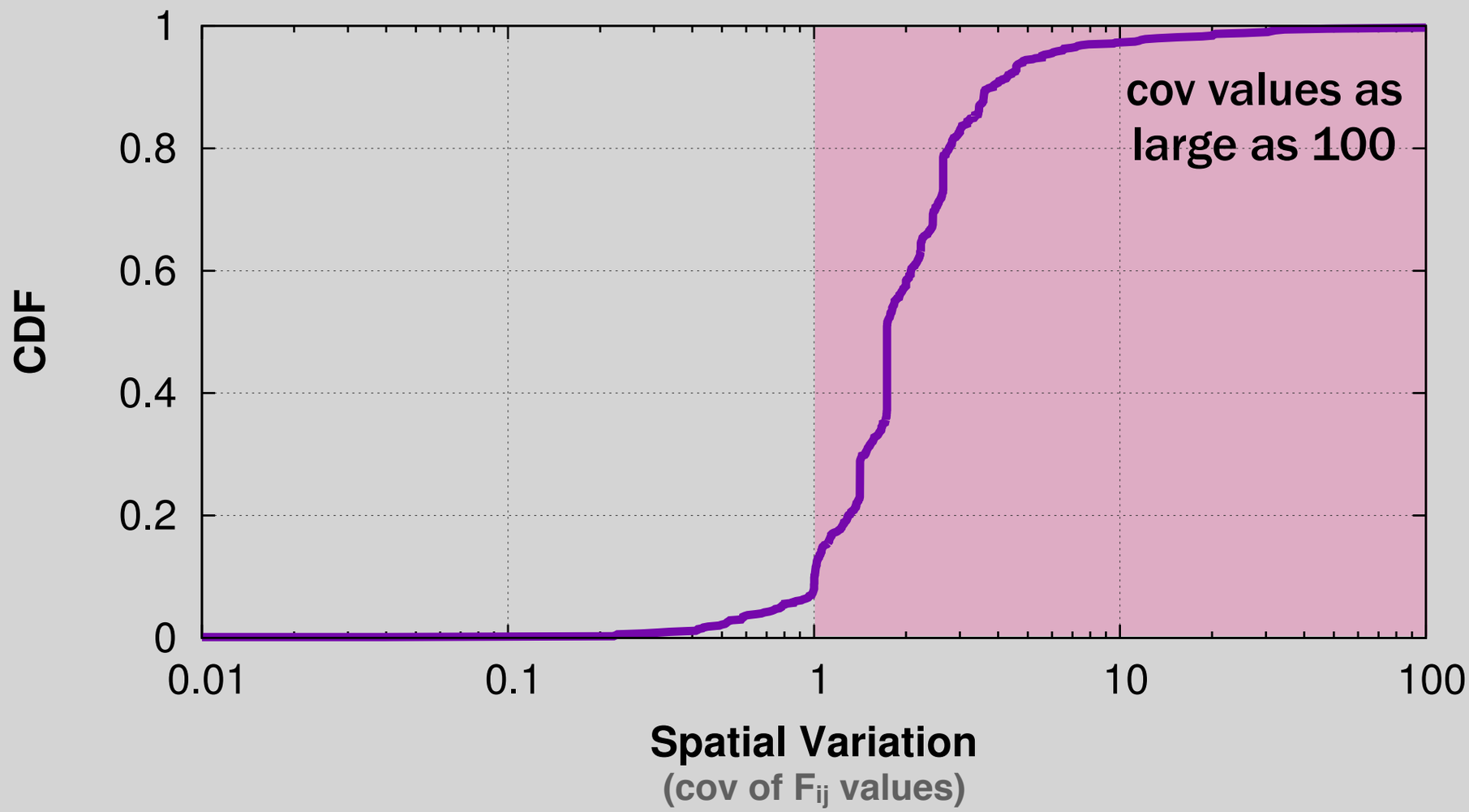

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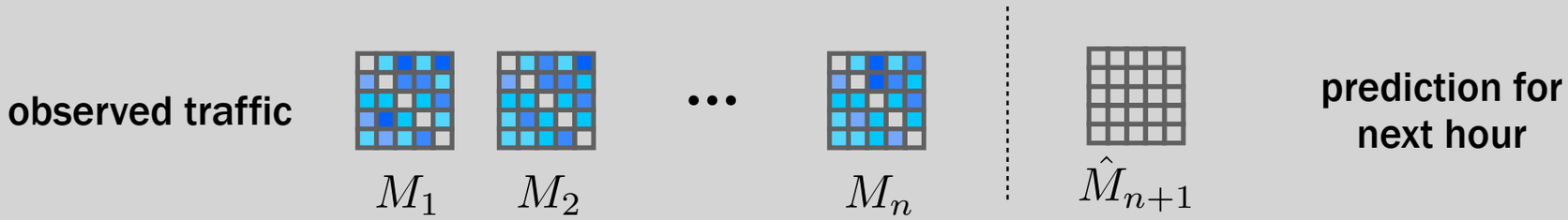
customers cannot model such variability themselves, and existing models do not capture it

CICADA'S ALGORITHM



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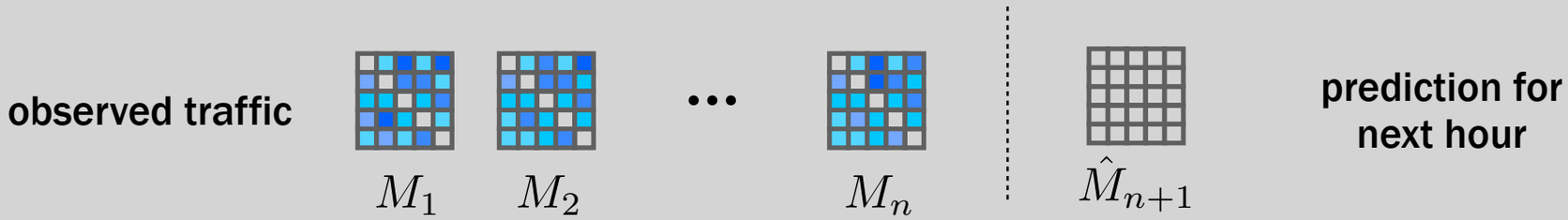

$$\hat{M}_{n+1} = f(M_1, M_2, \ldots, M_n)$$

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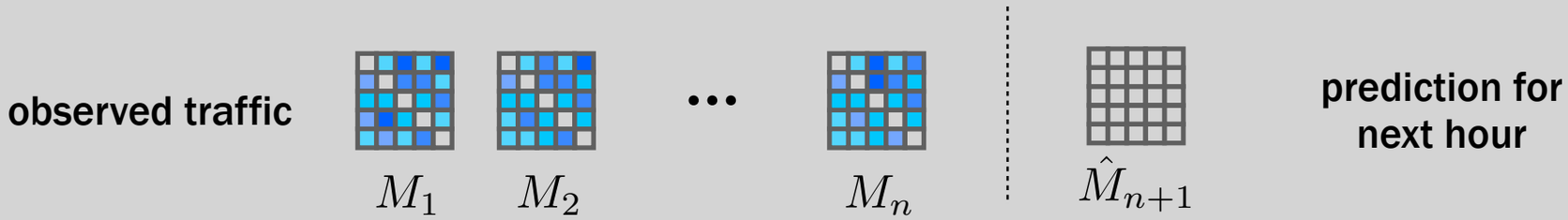

$$\hat{M}_{n+1} = w_1 \cdot M_1 + w_2 \cdot M_2 + \ldots + w_n \cdot M_n$$

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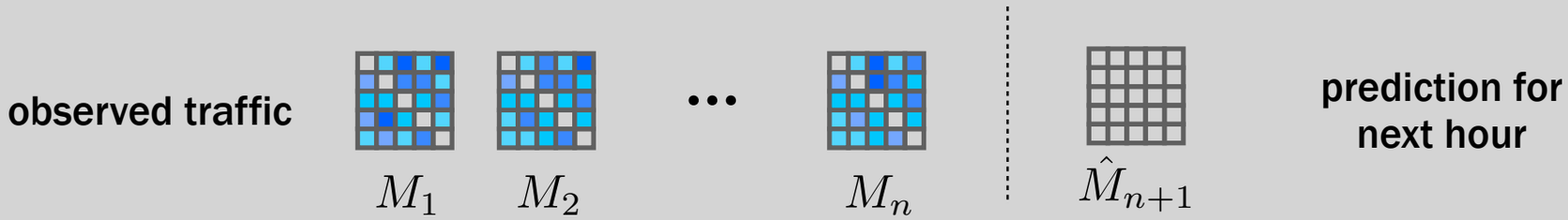

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instead of setting the weights beforehand, cicada learns the weights online; they are updated with every prediction based on errors made in previous predictions

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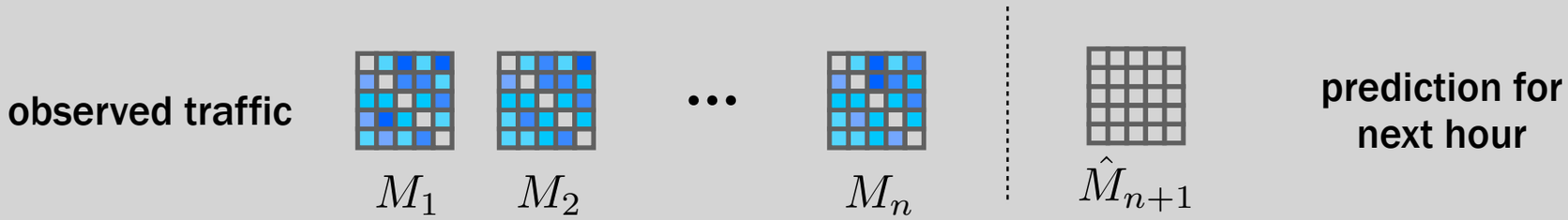

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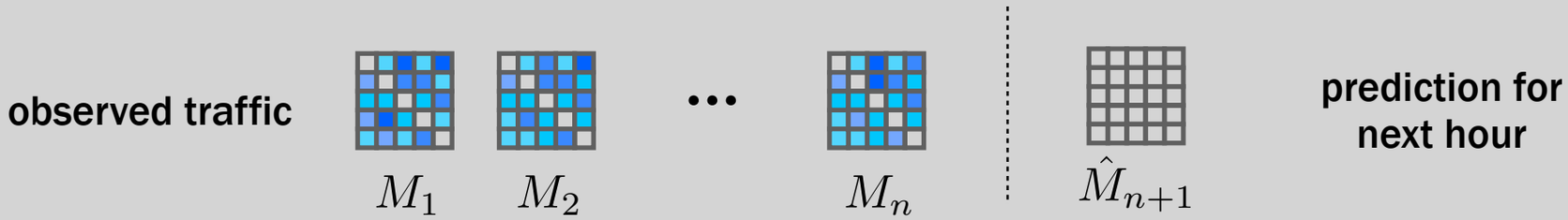

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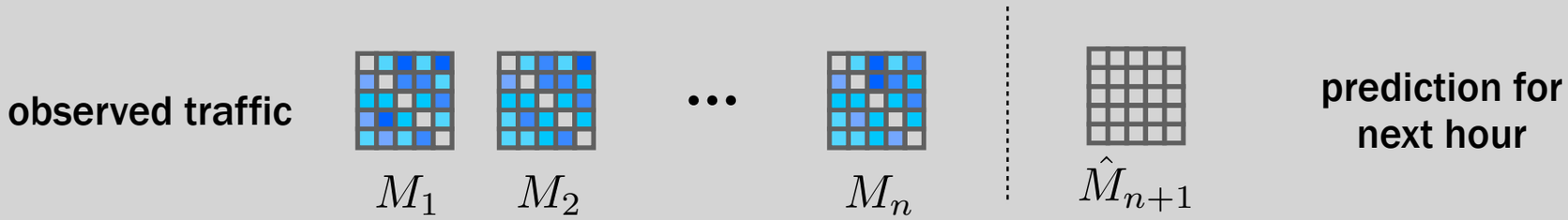

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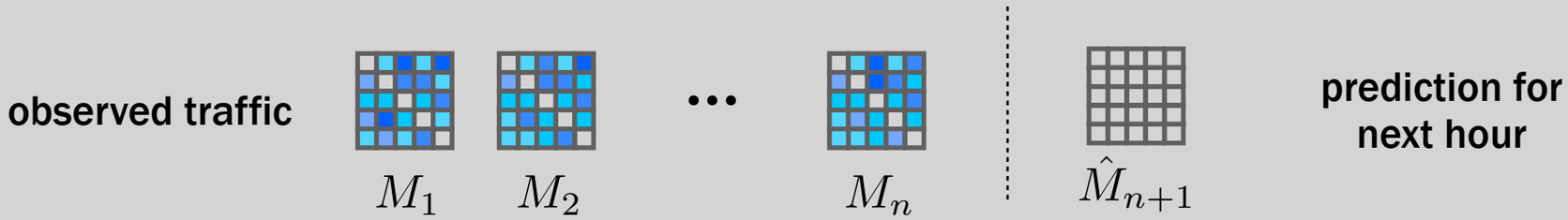

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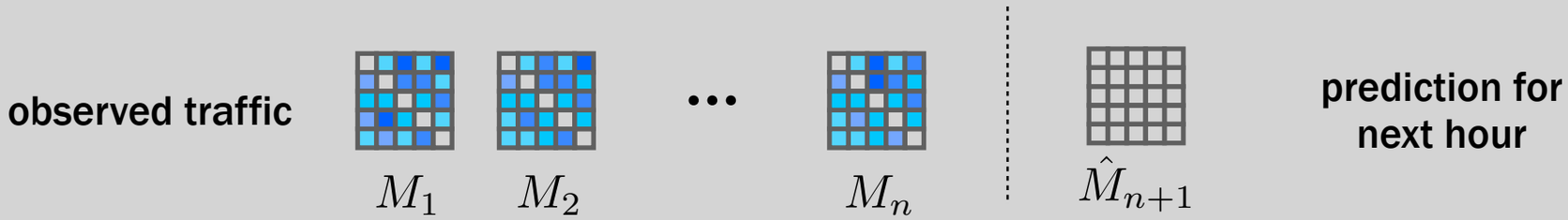

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$$w_i(n+1) = w_i(n) \cdot \underbrace{e^{-L(i,n)}}_{\text{loss function}} \cdot \underbrace{\frac{1}{Z_{n+1}}}_{\text{normalization}} \qquad L(i,n) = \frac{\|\vec{M}_i - \vec{M}_n\|}{\|\vec{M}_n\|}$$

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EVALUATION

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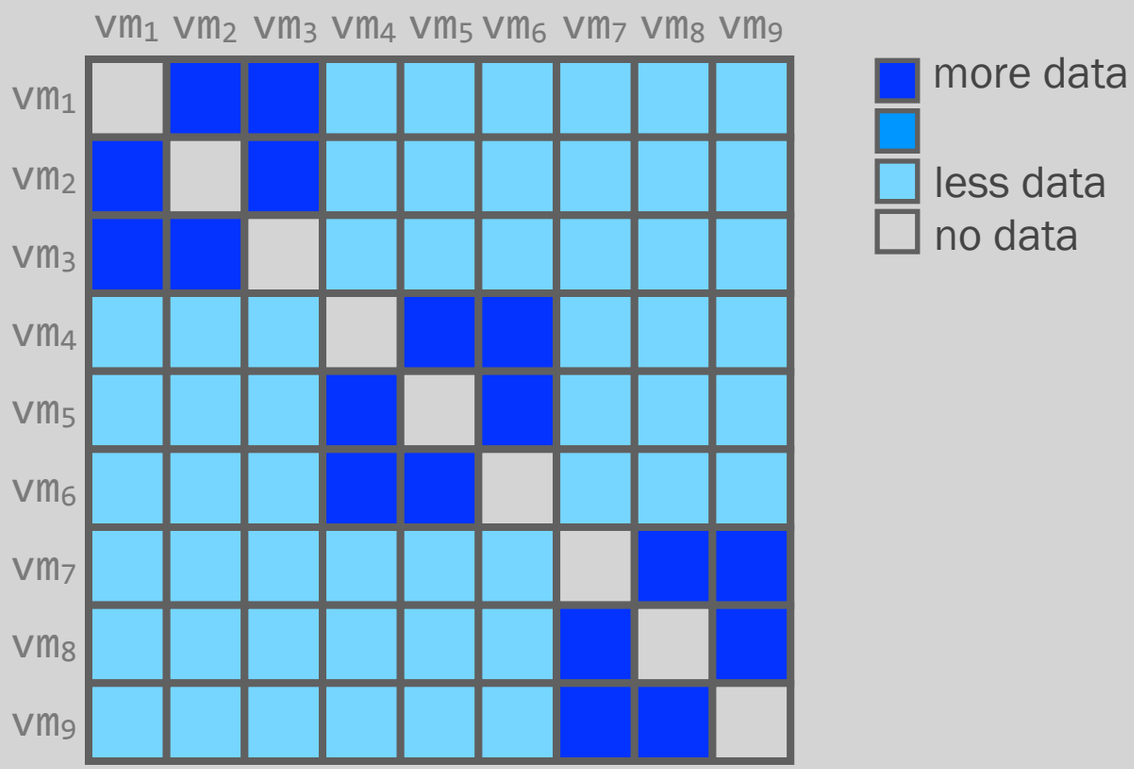

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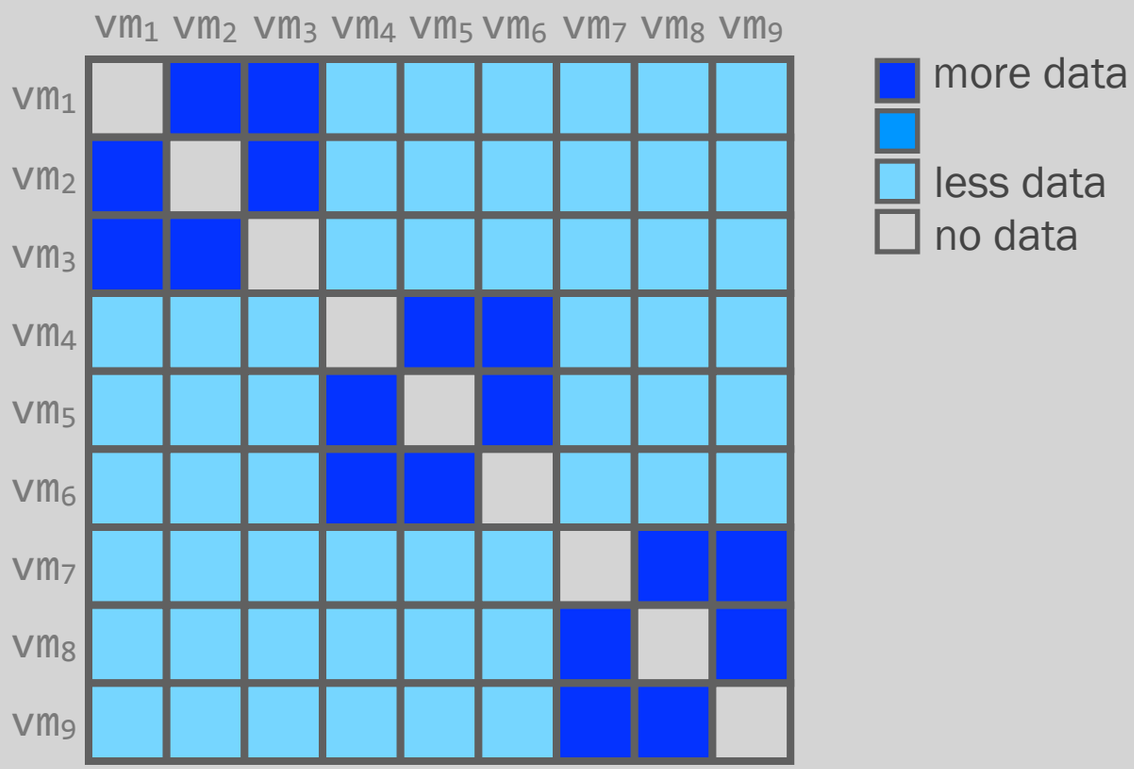

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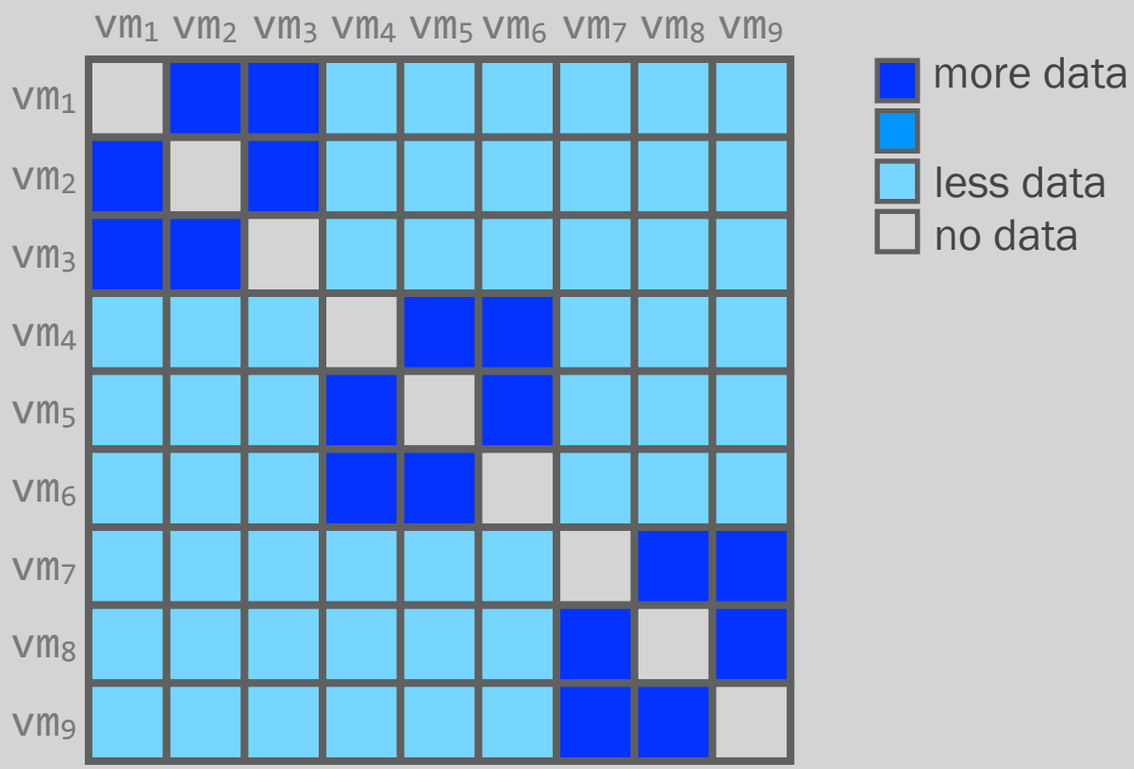

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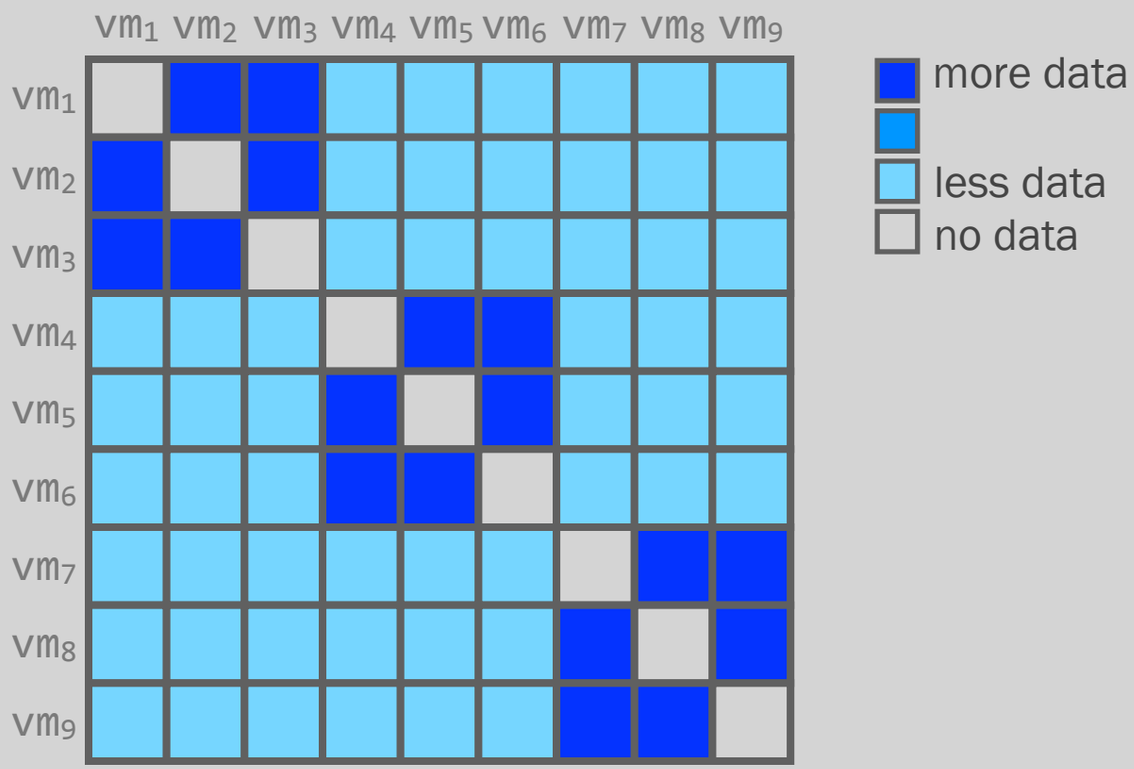

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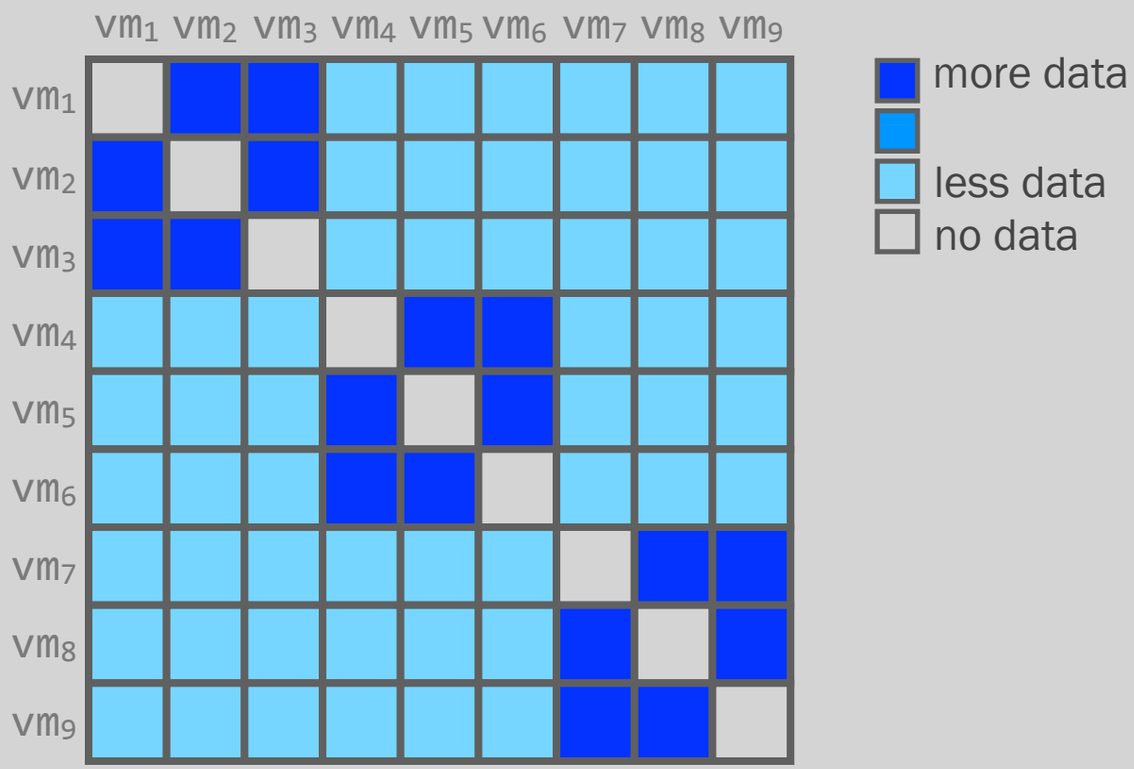

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RESULTS

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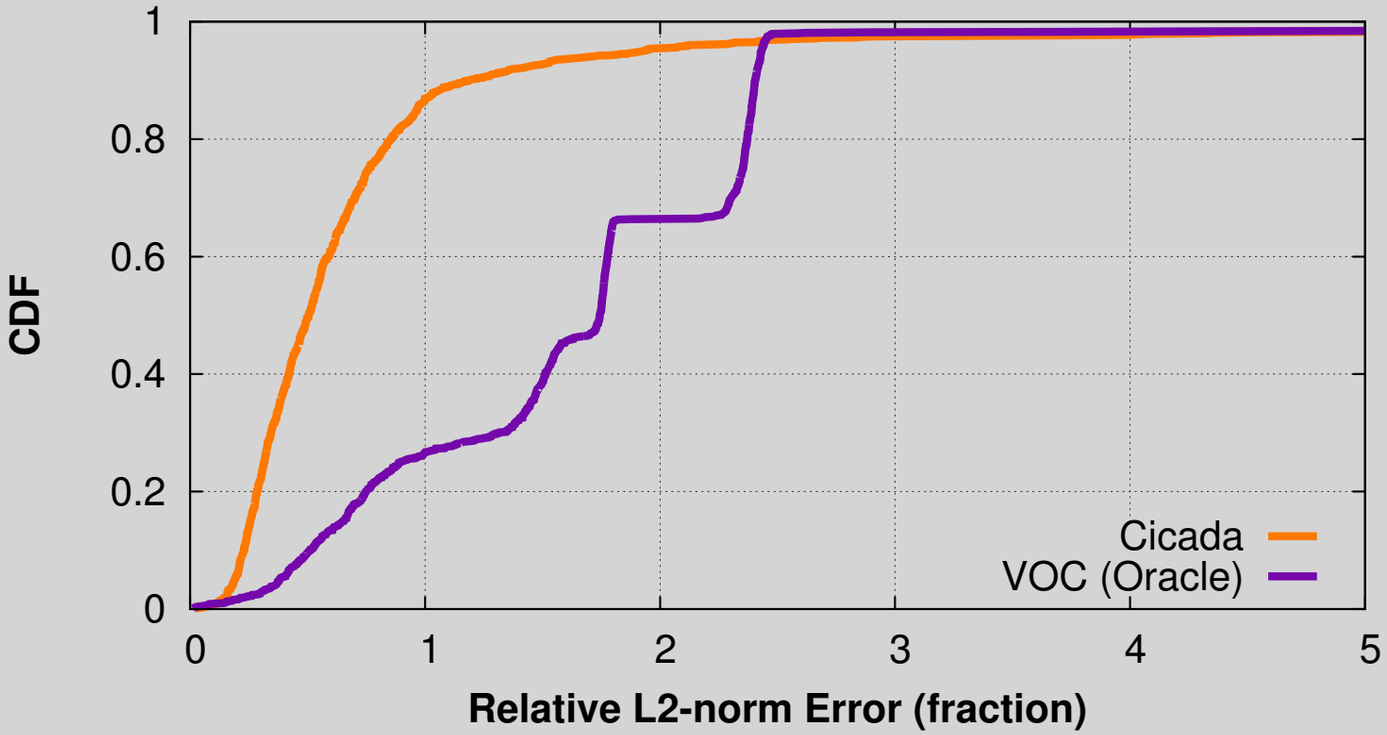

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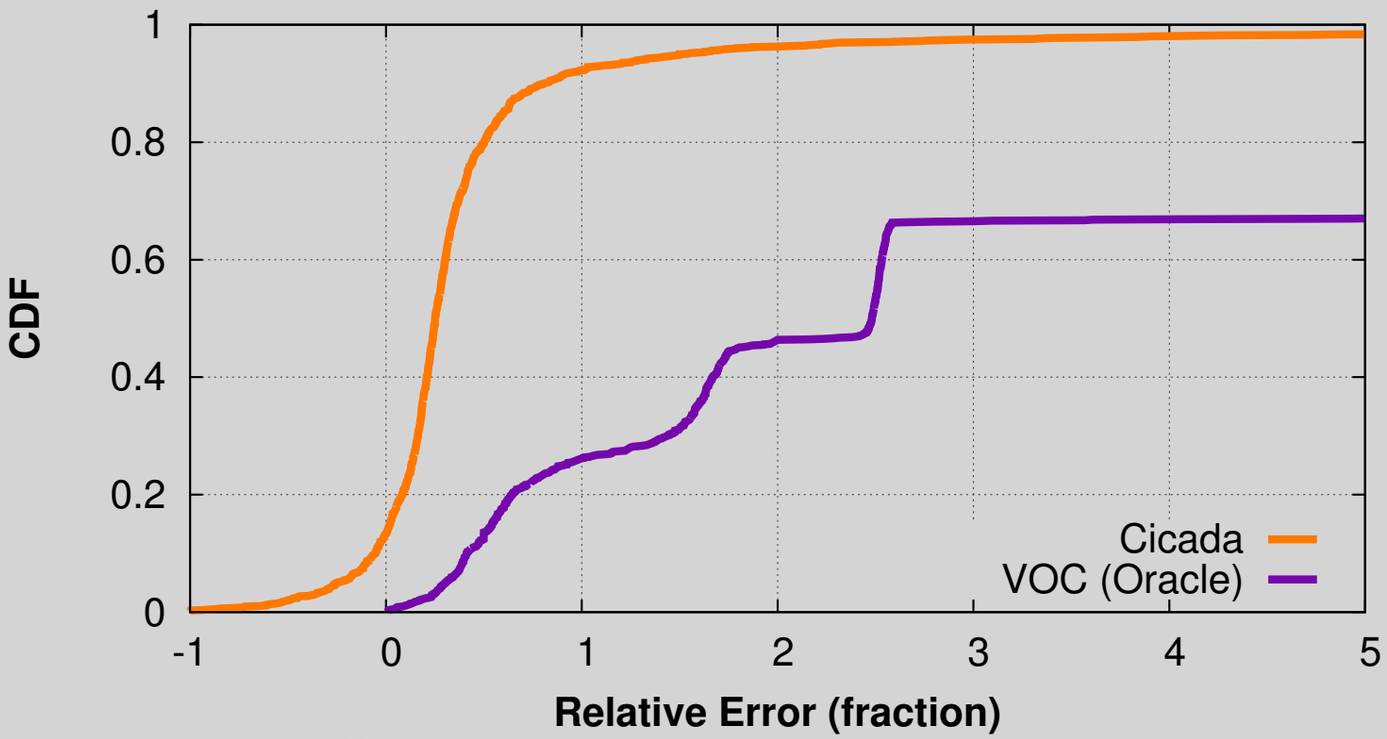

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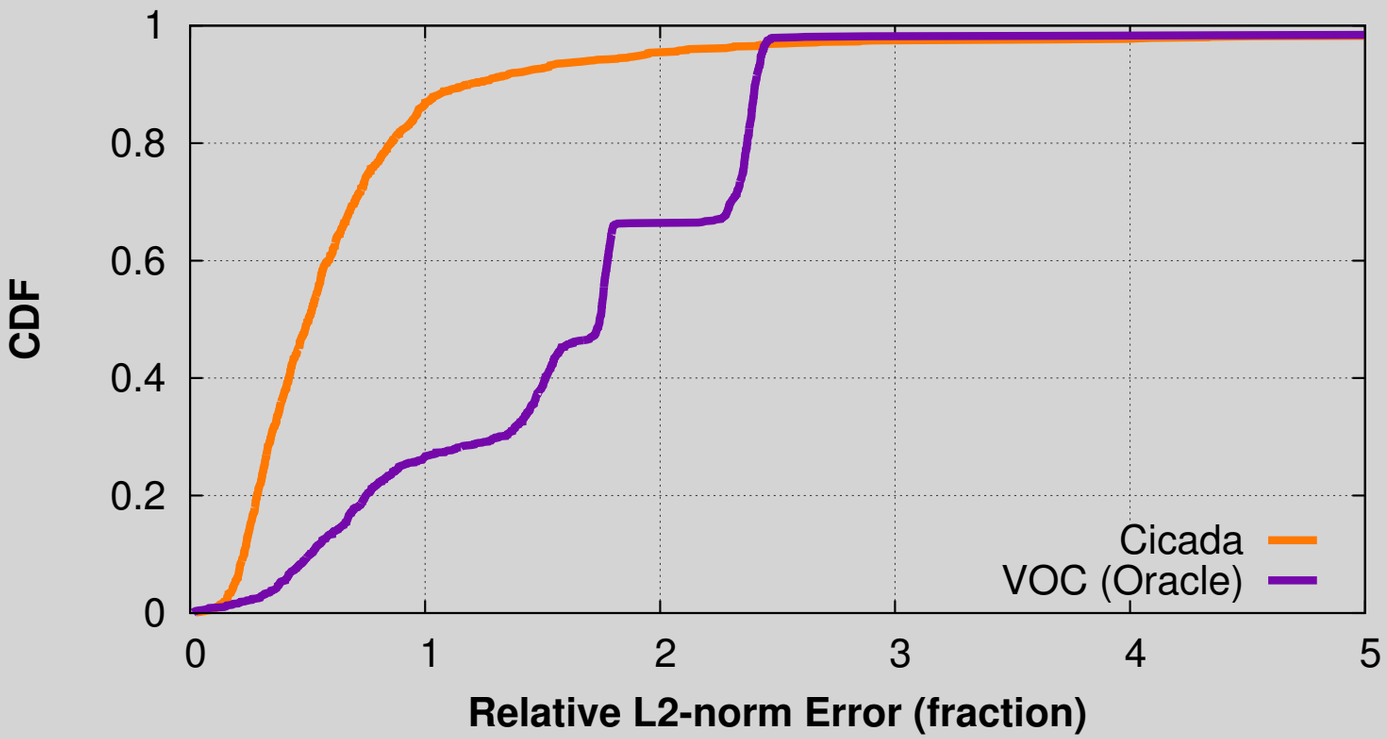

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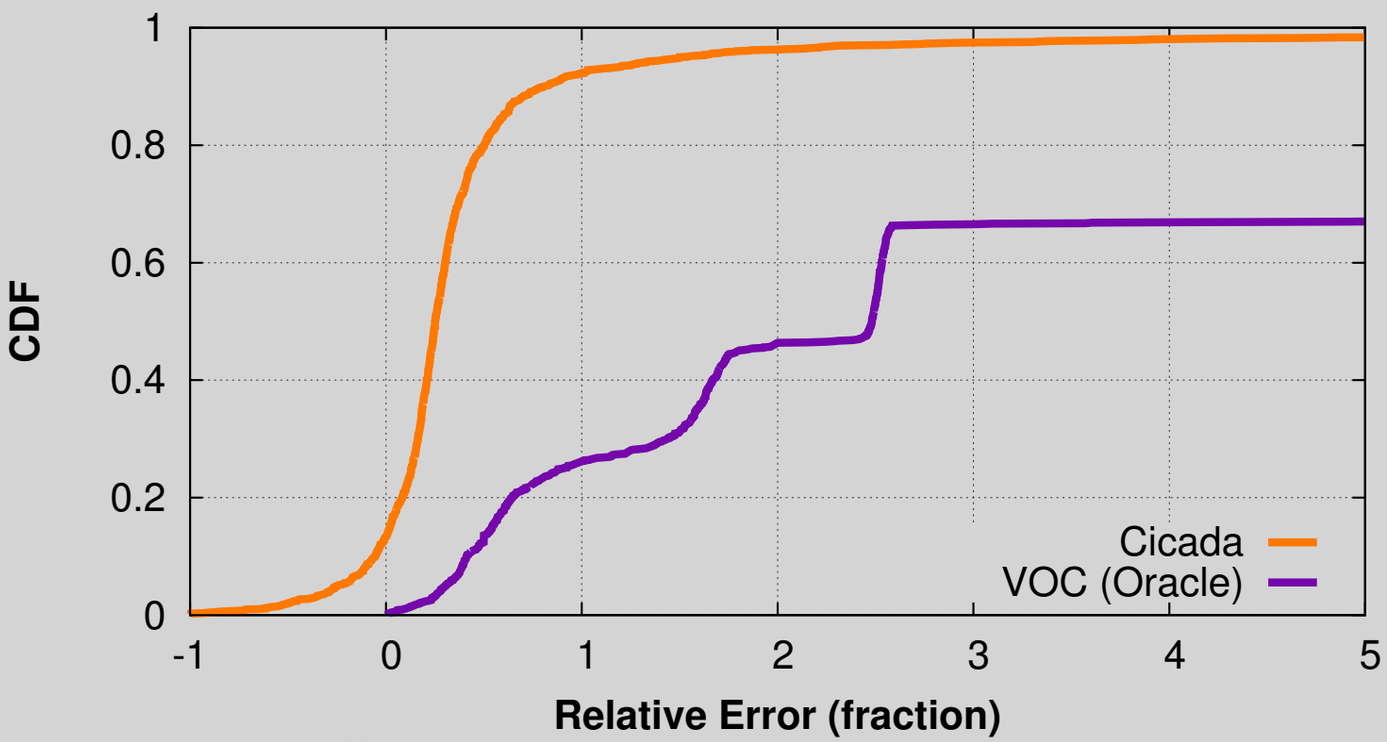

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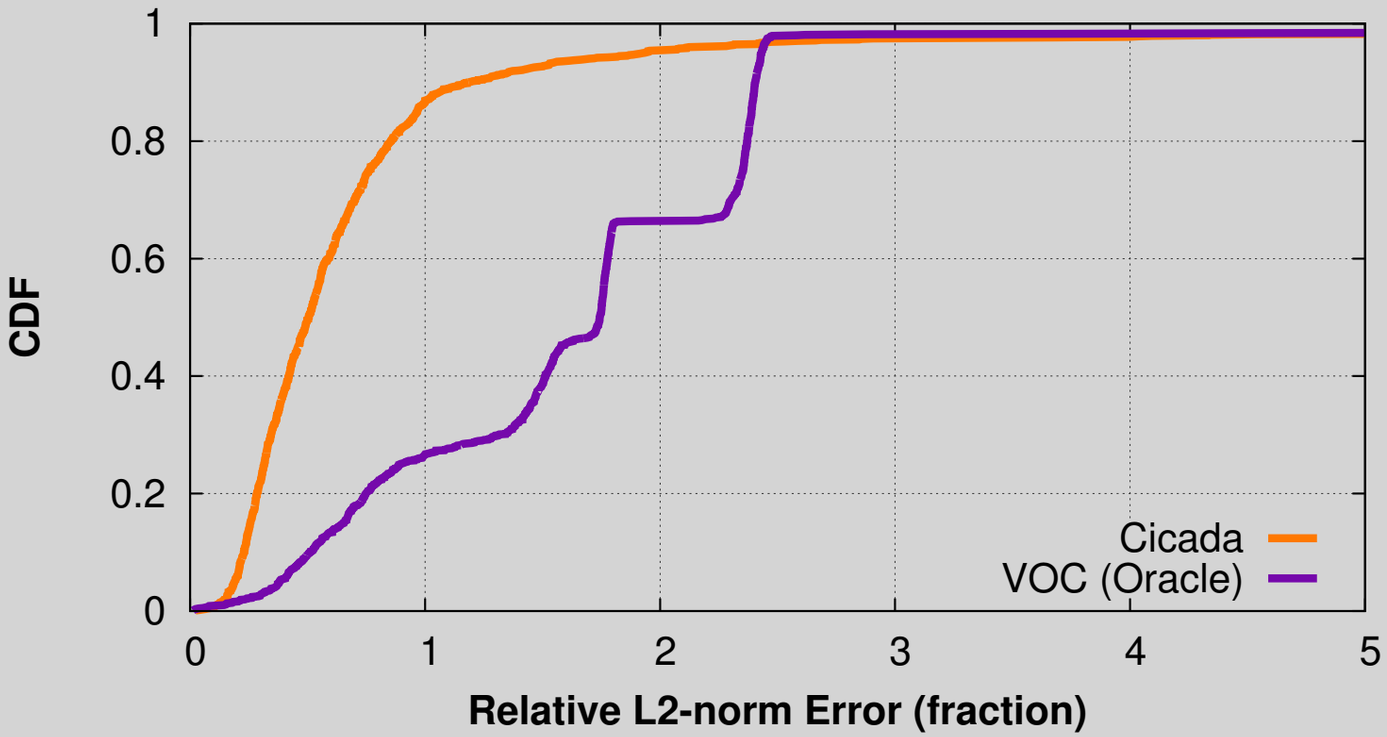

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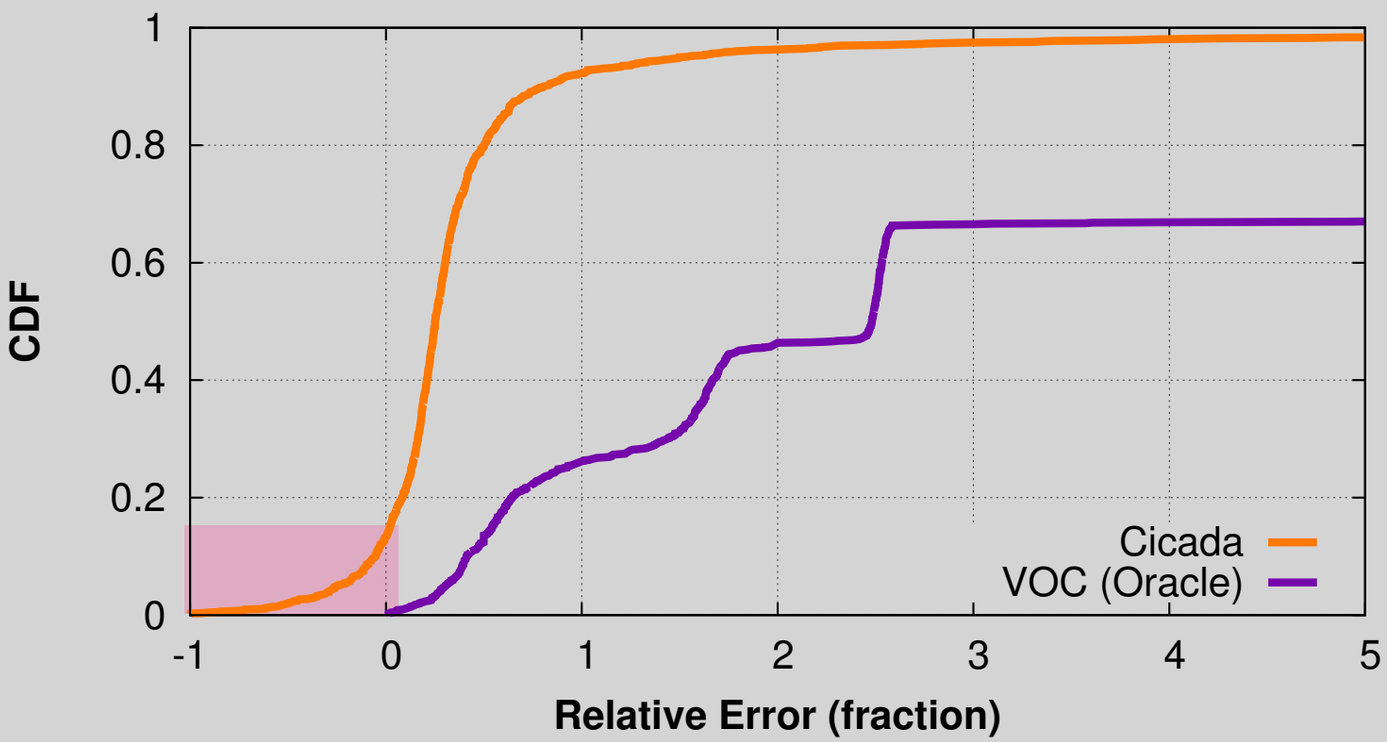

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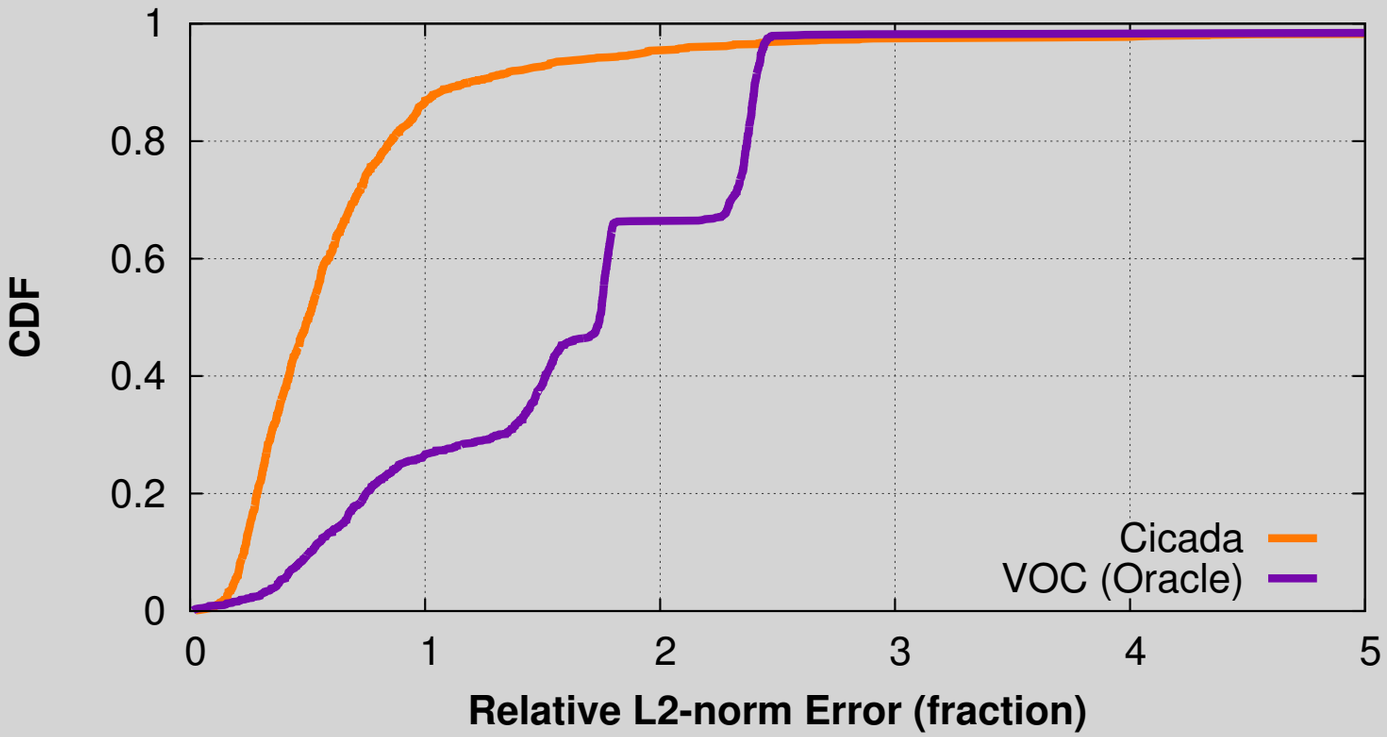

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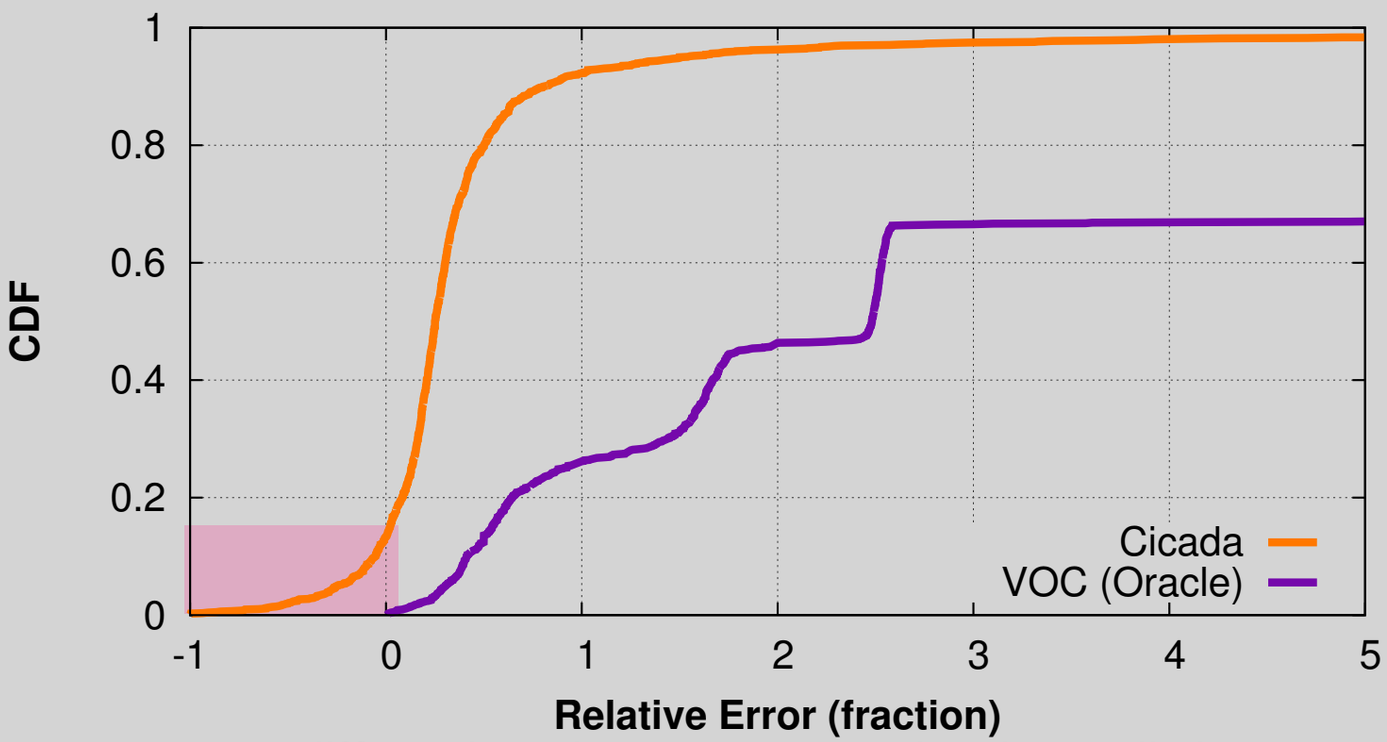

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cicada's predictions typically require only 1-2 hours of application history

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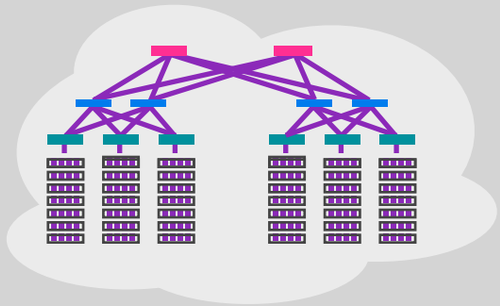

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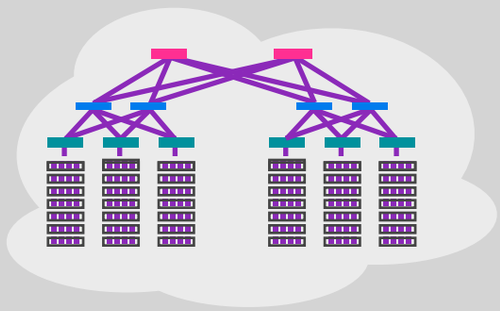

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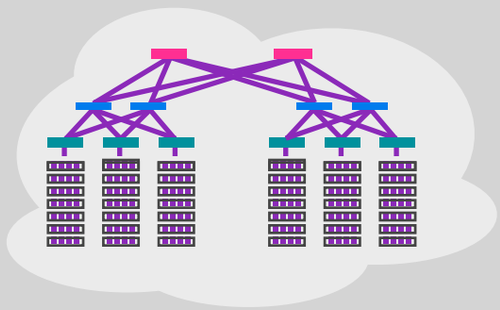

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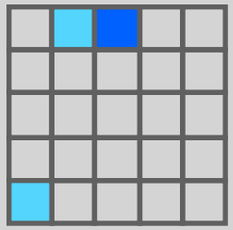

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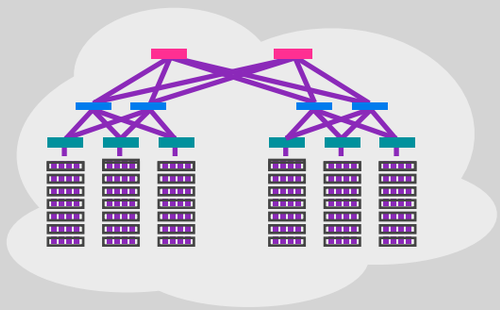

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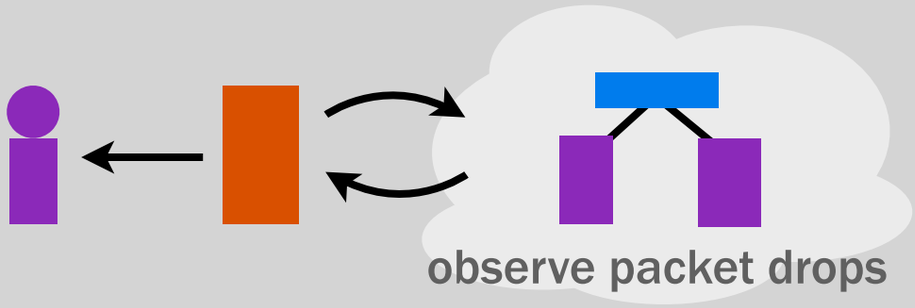
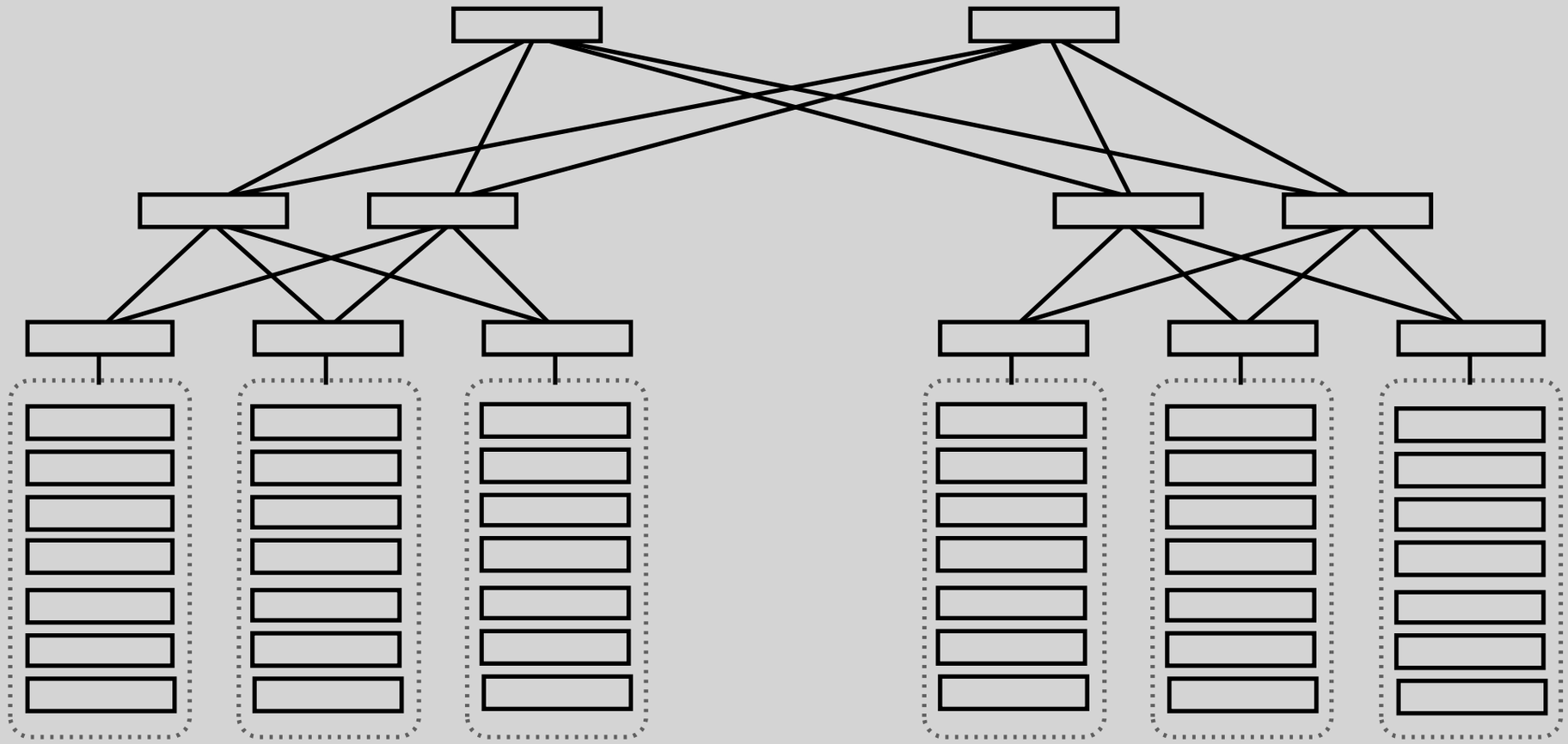
cicada can detect when a guarantee is too low, and offer a new one



NETWORK UTILIZATION

do cicada's bandwidth guarantees improve network utilization?



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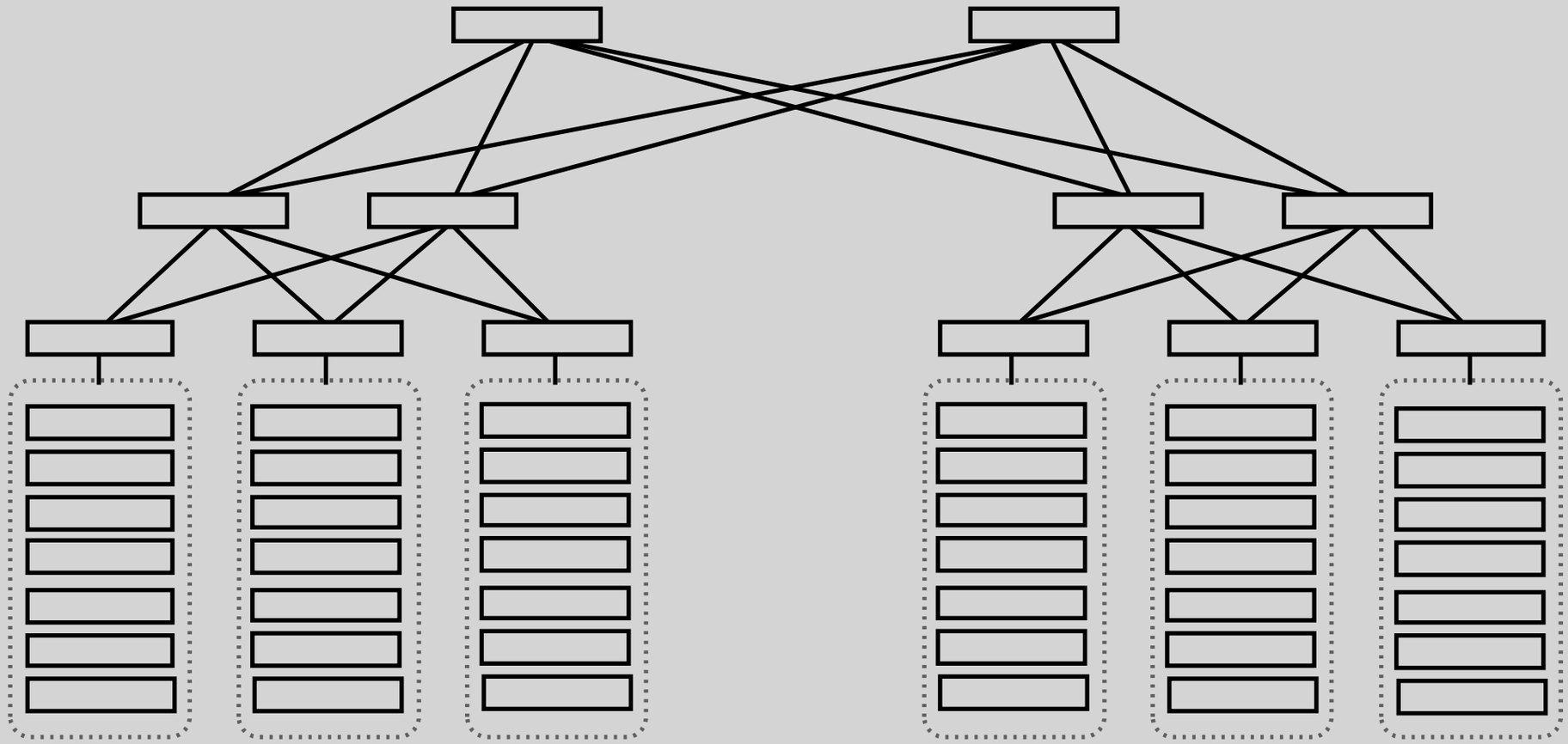

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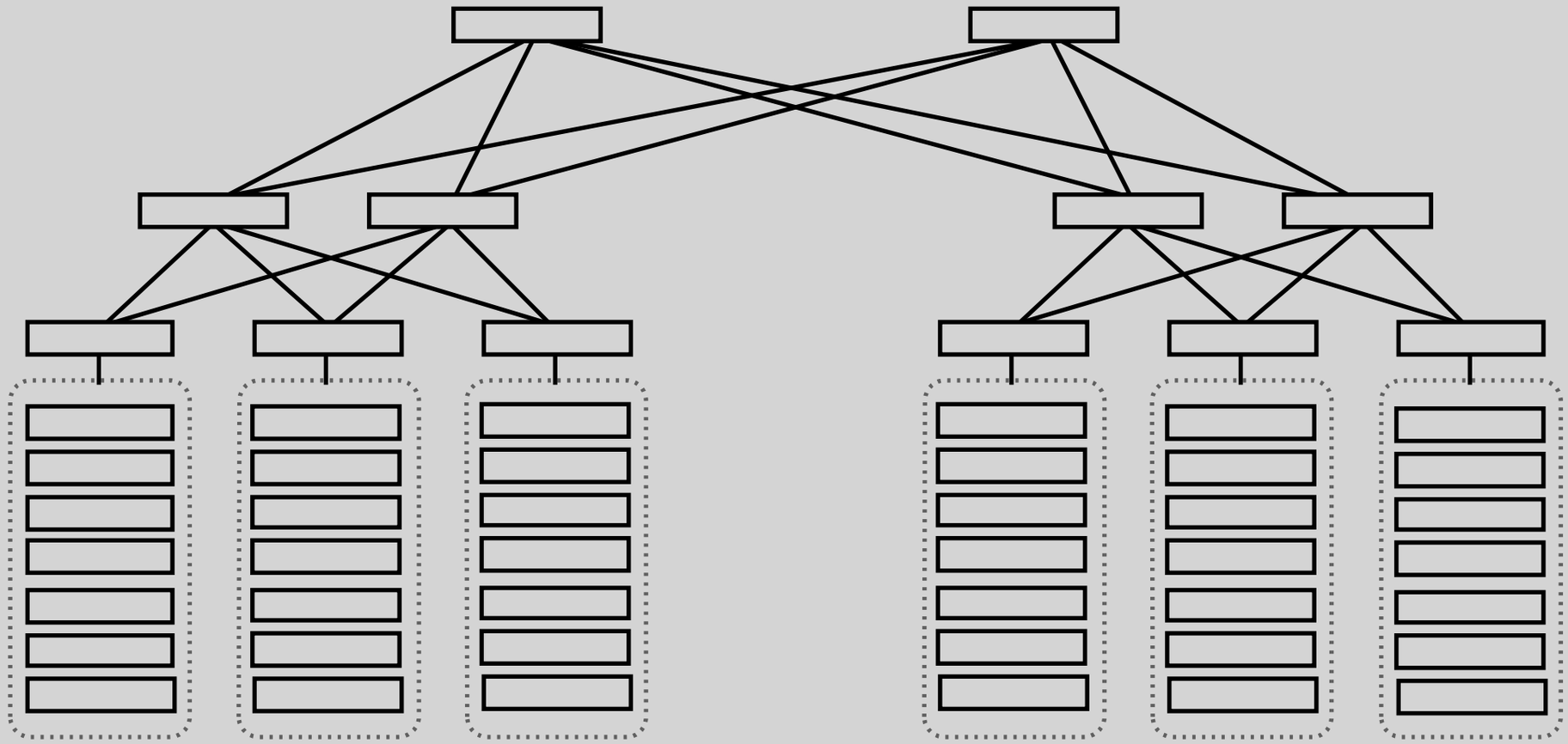

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intra-rack bandwidth
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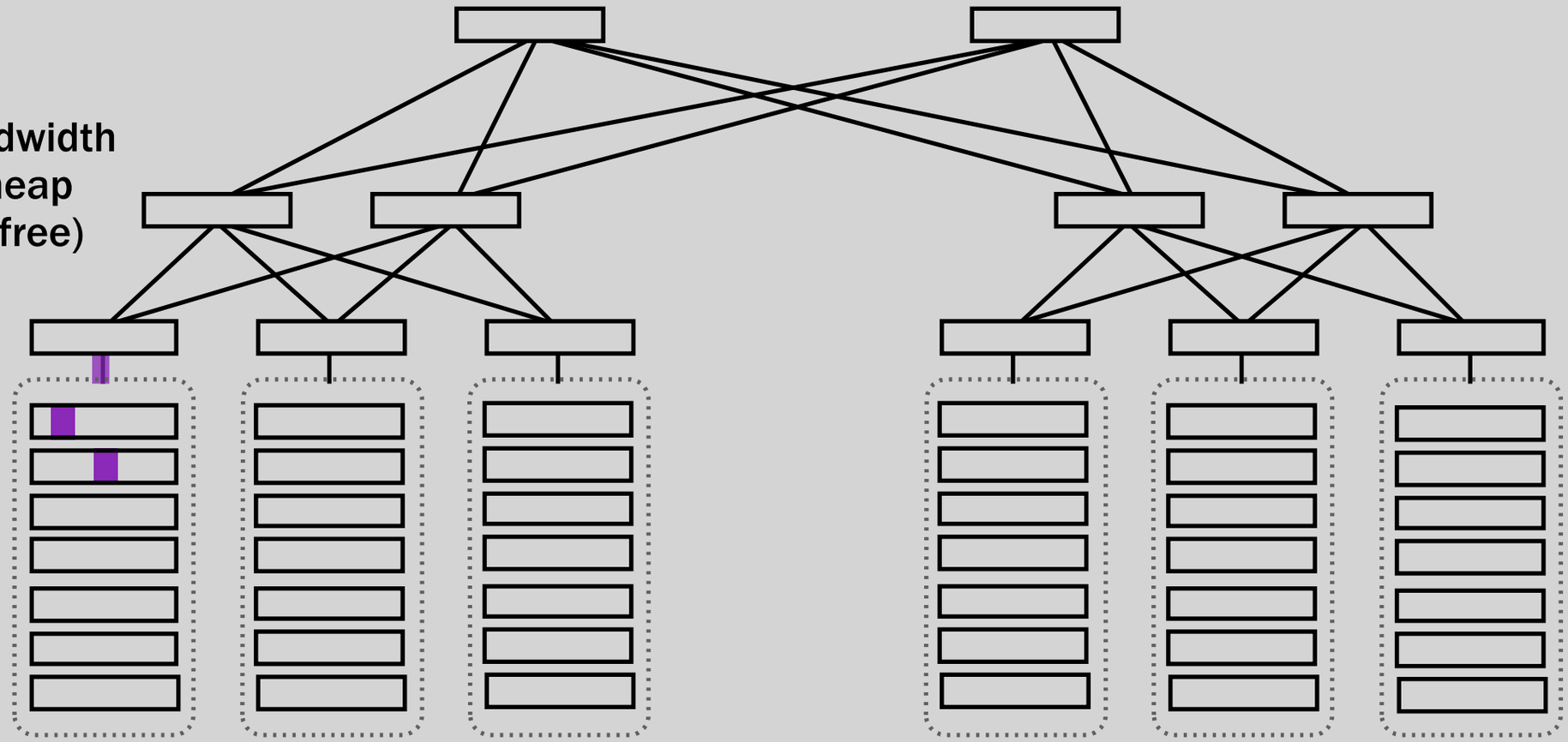

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NETWORK UTILIZATION

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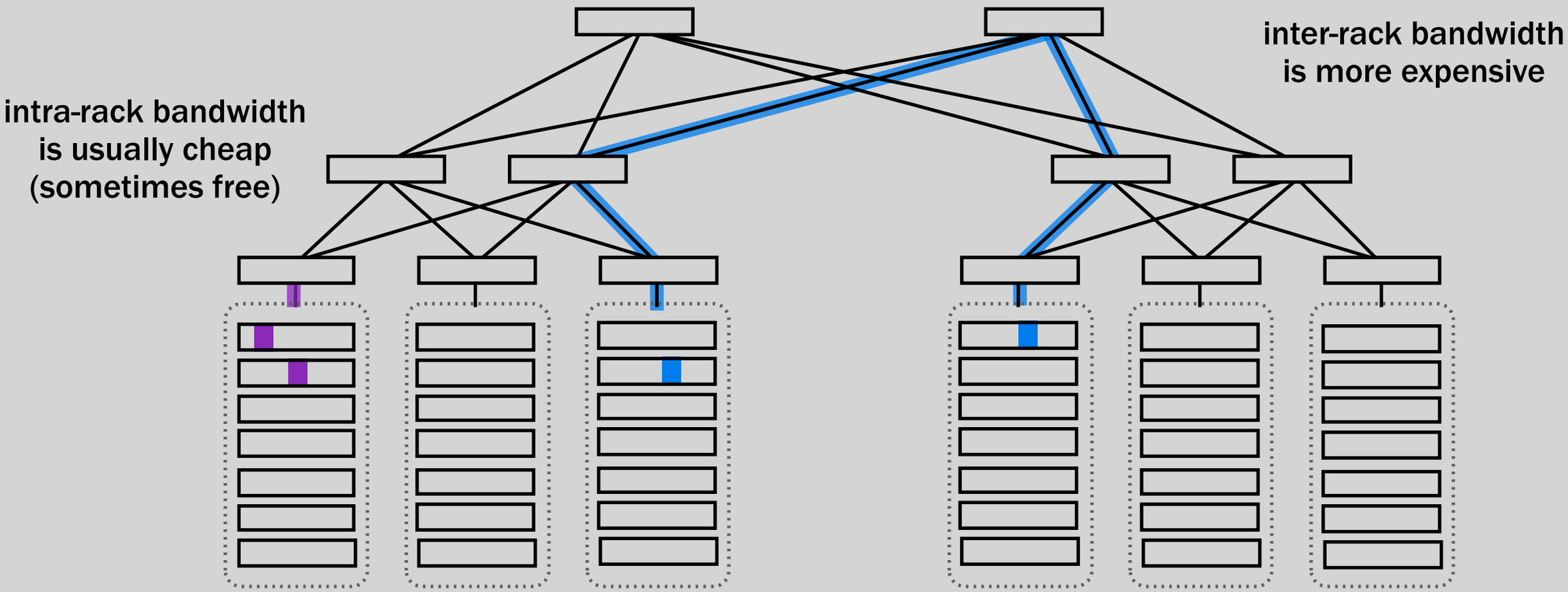

wasted bandwidth: bandwidth that is guaranteed for an application, but not *used* by the application

provider's goal: minimize wasted bandwidth

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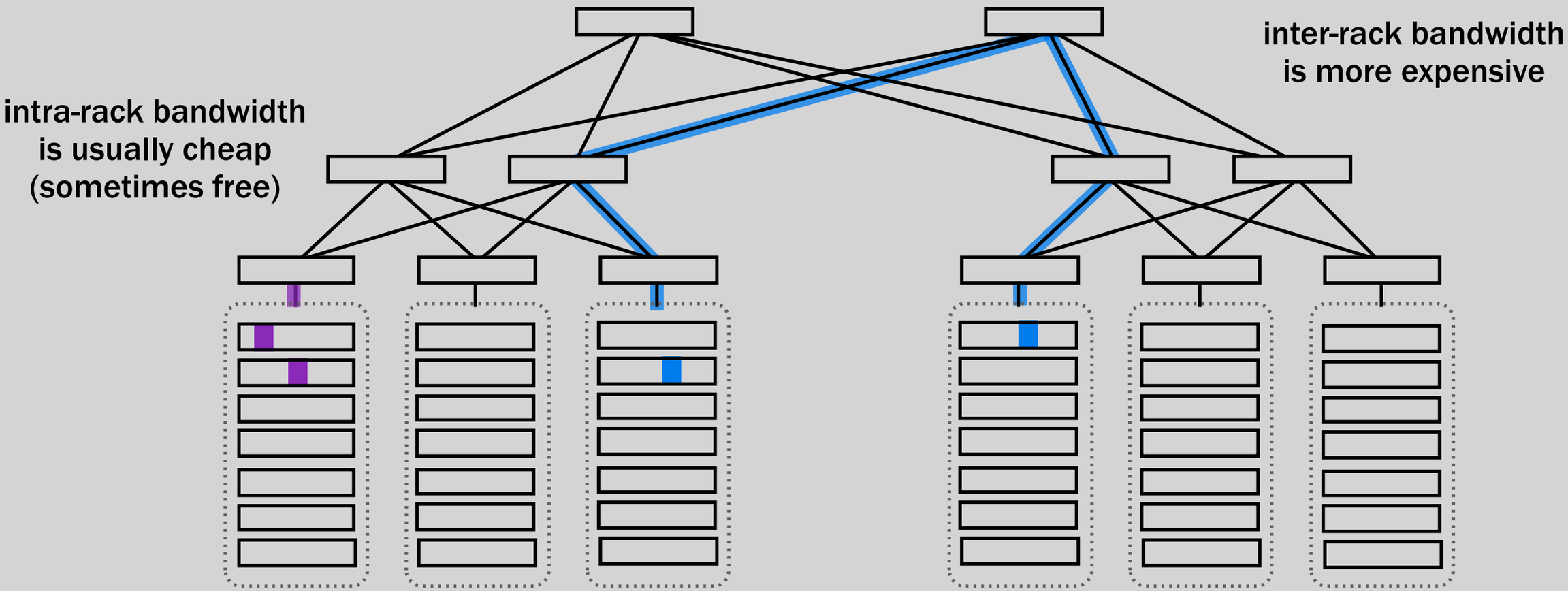
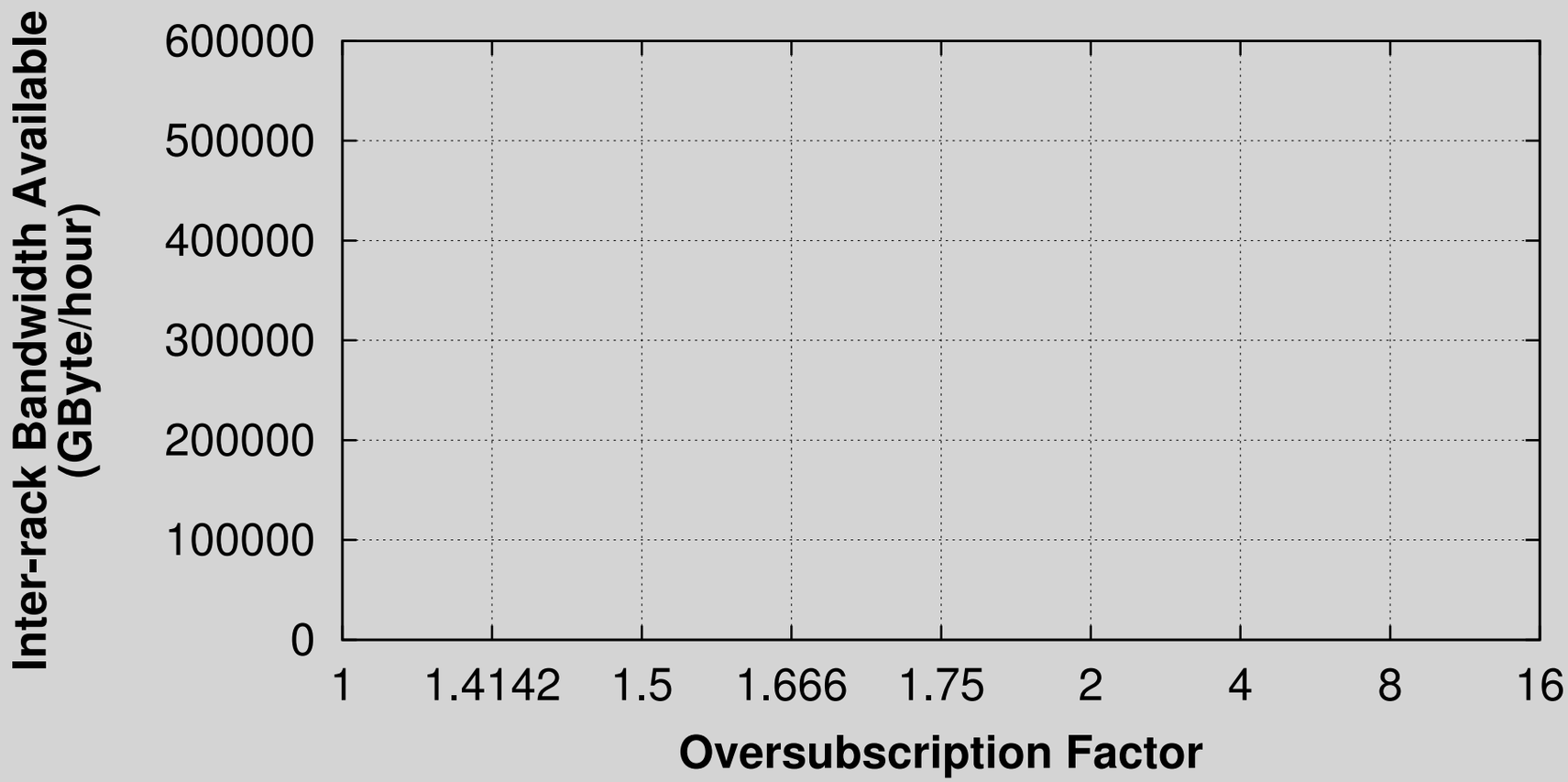


wasted bandwidth: bandwidth that is guaranteed for an application, but not *used* by the application

provider's goal: minimize wasted *inter-rack* bandwidth

NETWORK UTILIZATION

cicada's greedy placement heuristic: place the pairs of VMs that need the highest guarantees on the fastest paths (see paper for details)



[1] Ballani, et al. "Towards Predictable Datacenter Networks". SIGCOMM 2011.

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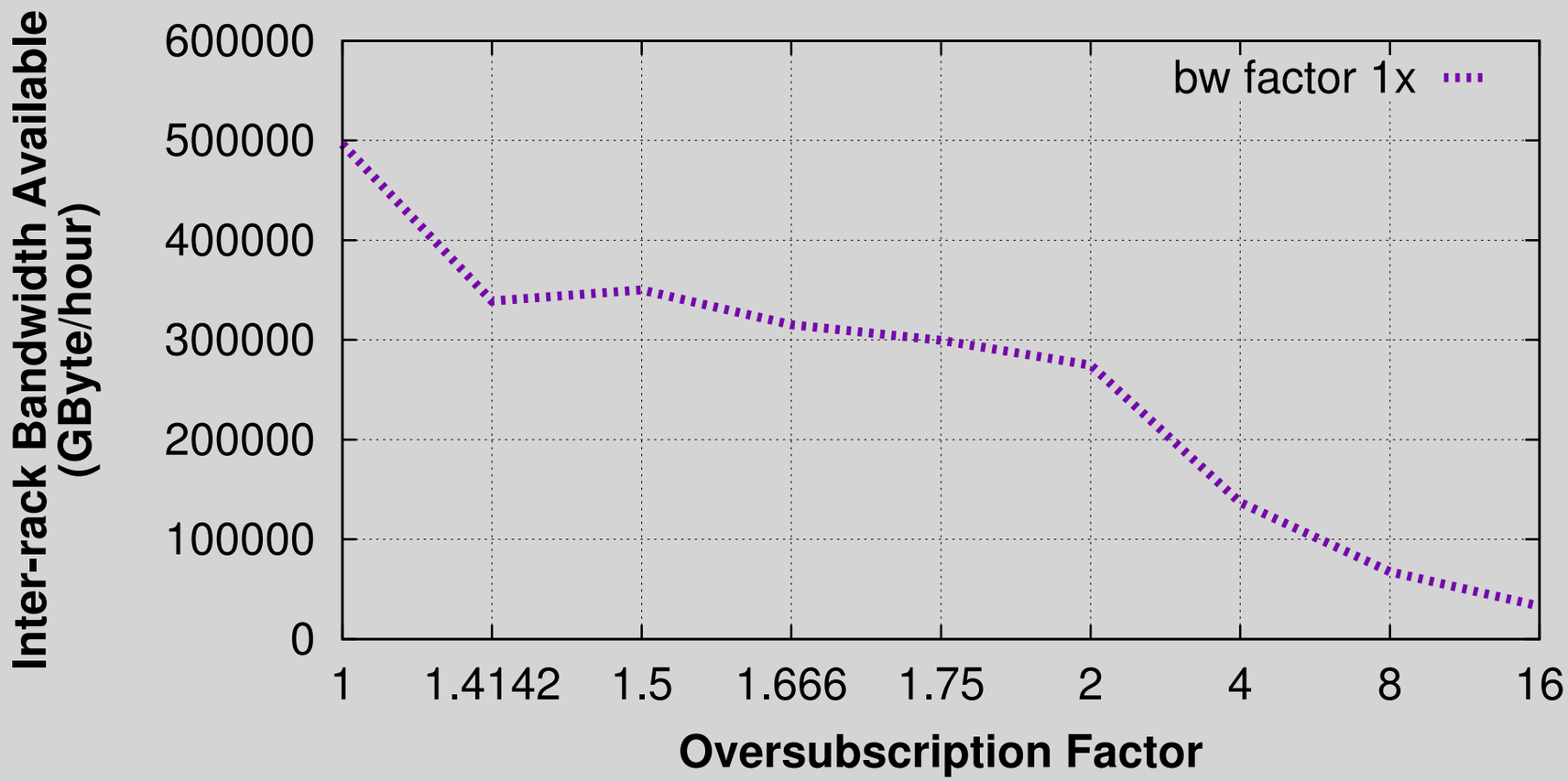

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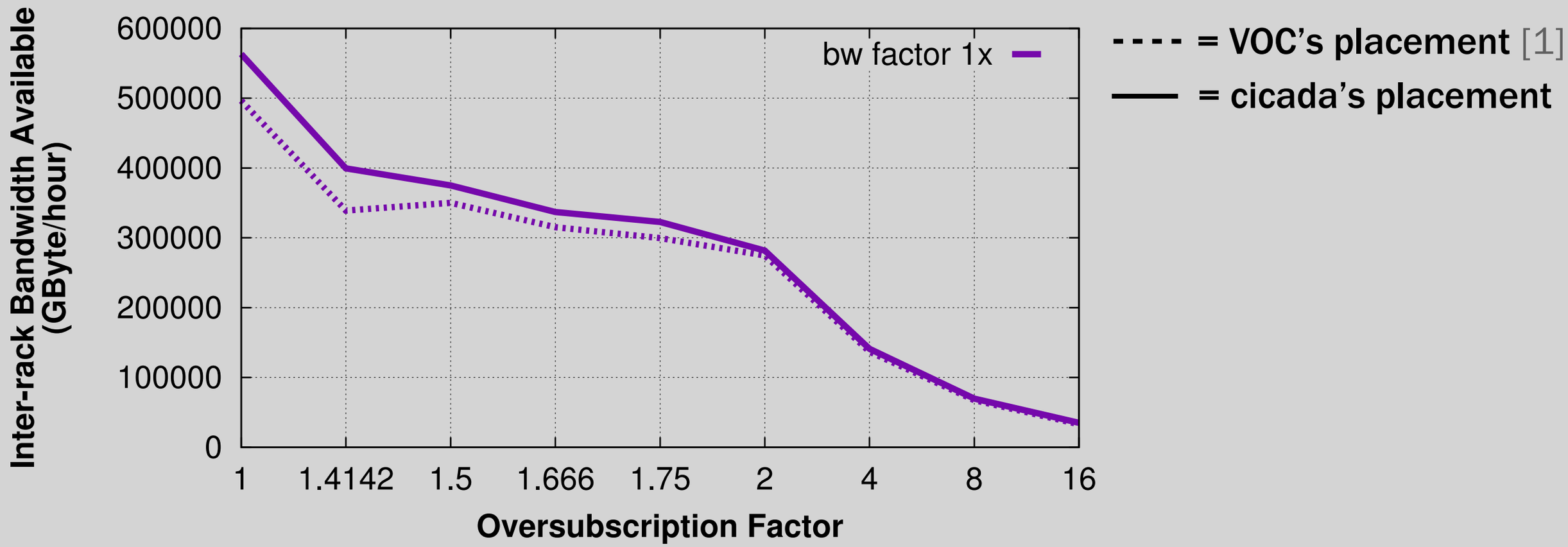

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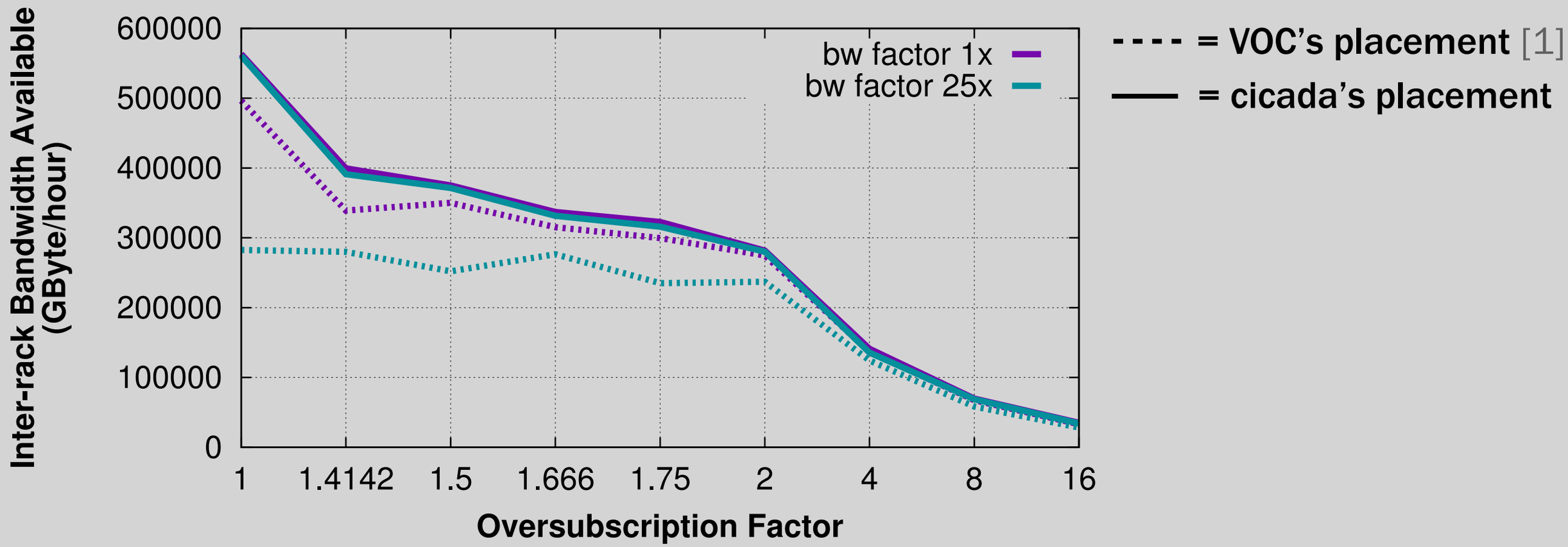

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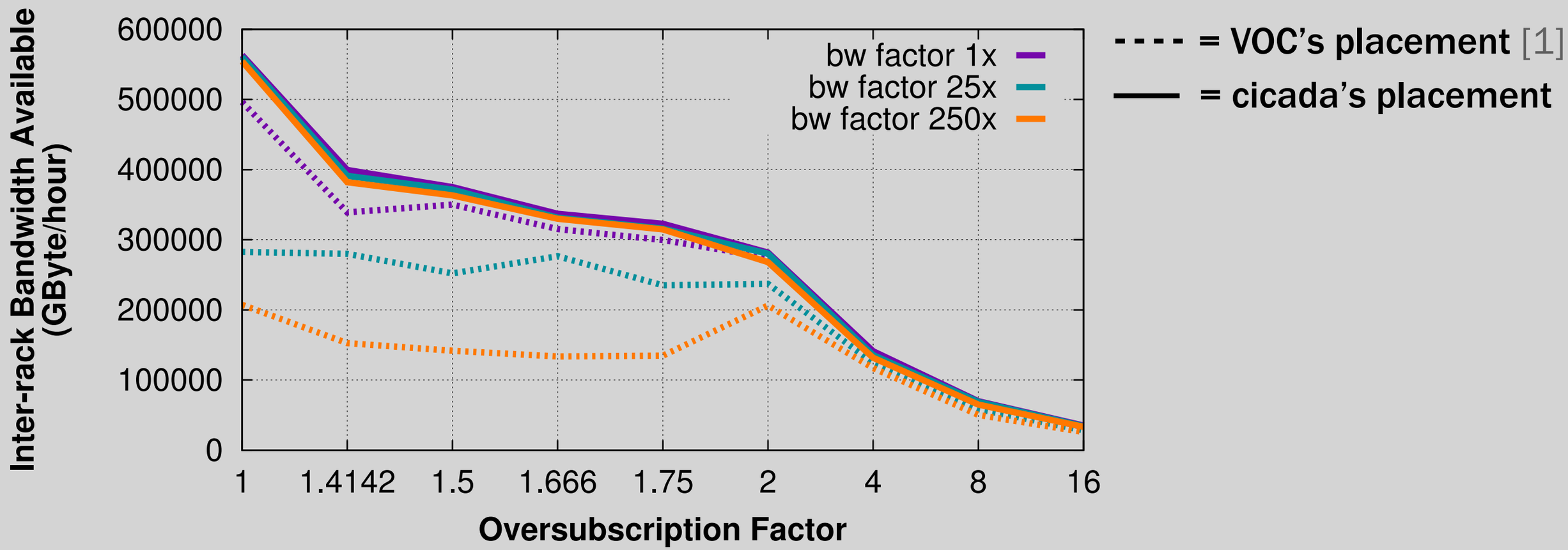

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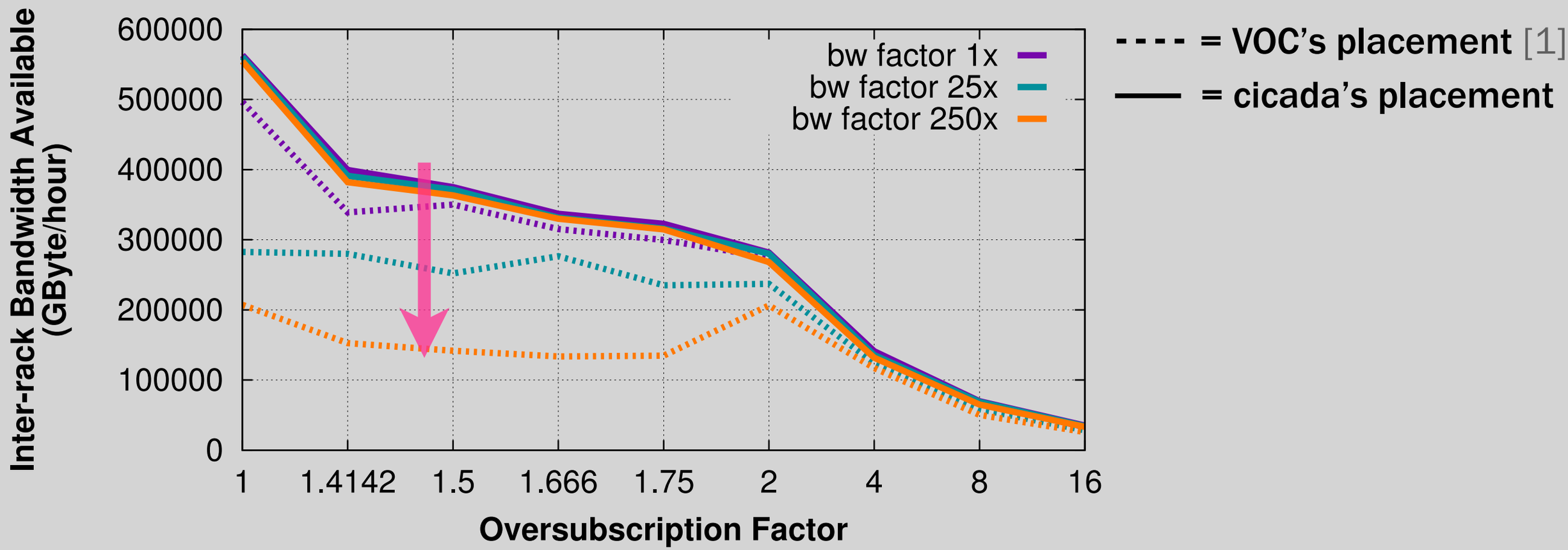

as applications use more bandwidth, VOC's placement wastes more inter-rack bandwidth

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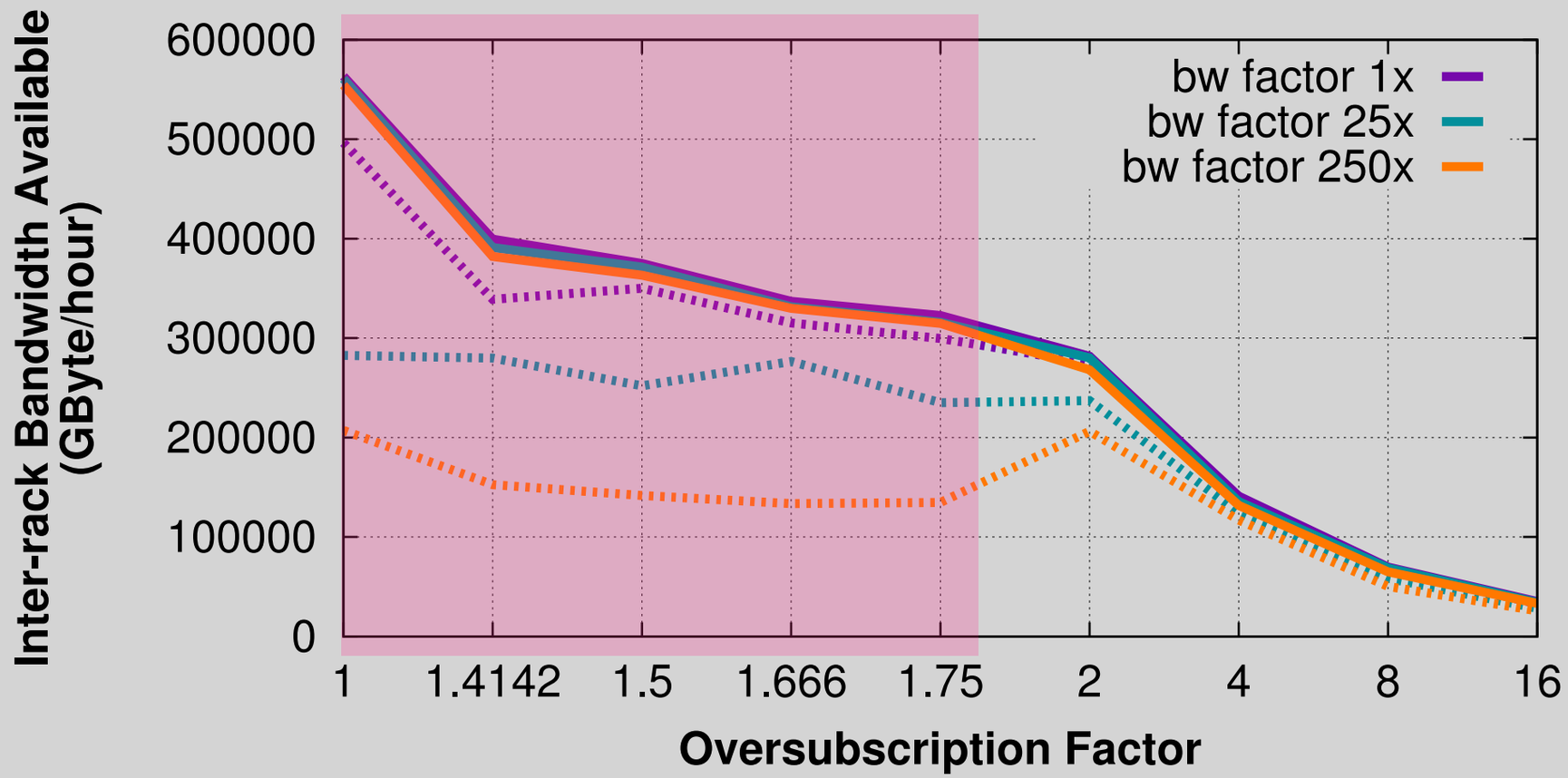

- - - - = VOC's placement [1]

—— = cicada's placement

in some scenarios, cicada's placement more than doubles the amount of available inter-rack bandwidth

as applications use more bandwidth, VOC's placement wastes more inter-rack bandwidth

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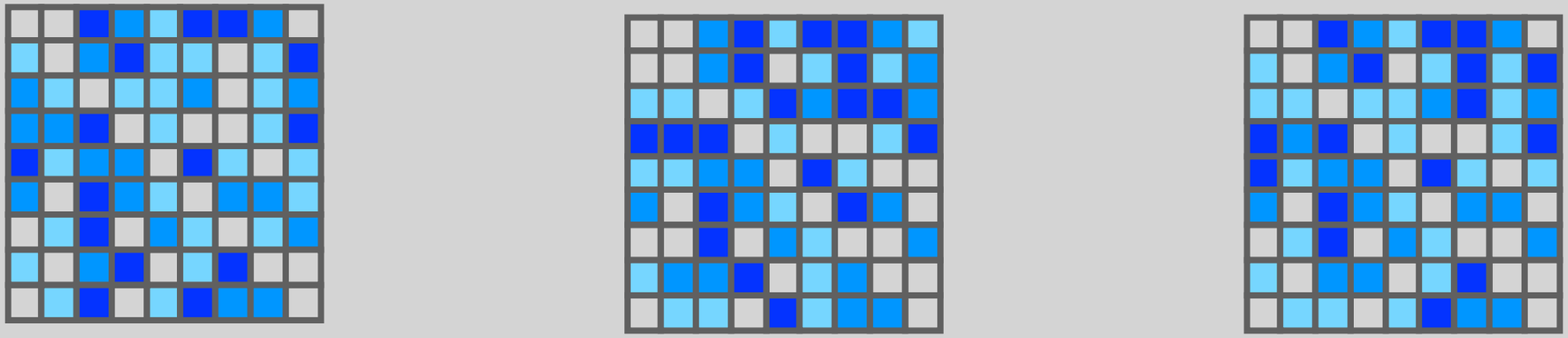
SUMMARY

cloud applications exhibit variability that existing models don't capture



cicada captures this variability, and provides guarantees that are

- accurate
- calculated quickly*
- require little history
- increase network utilization

*see paper for this result

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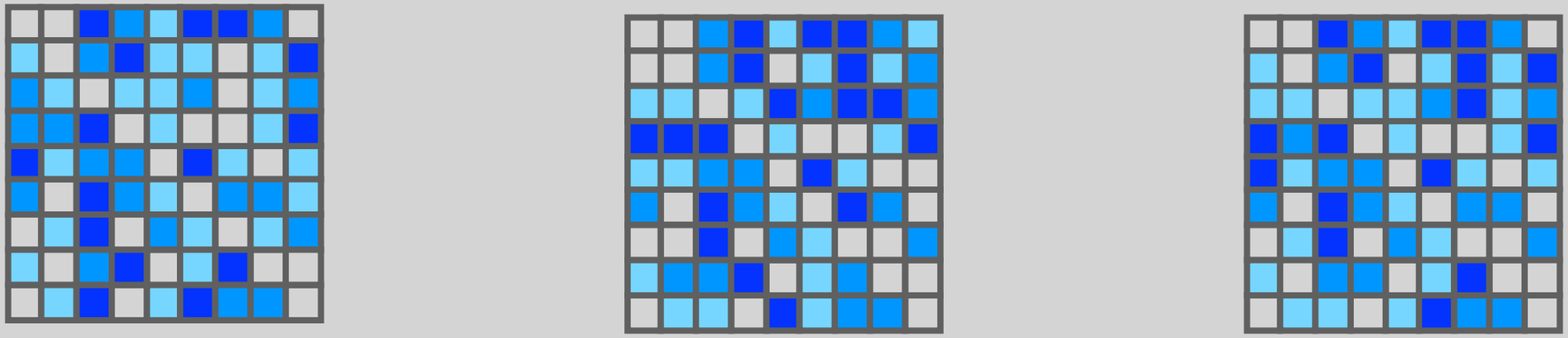

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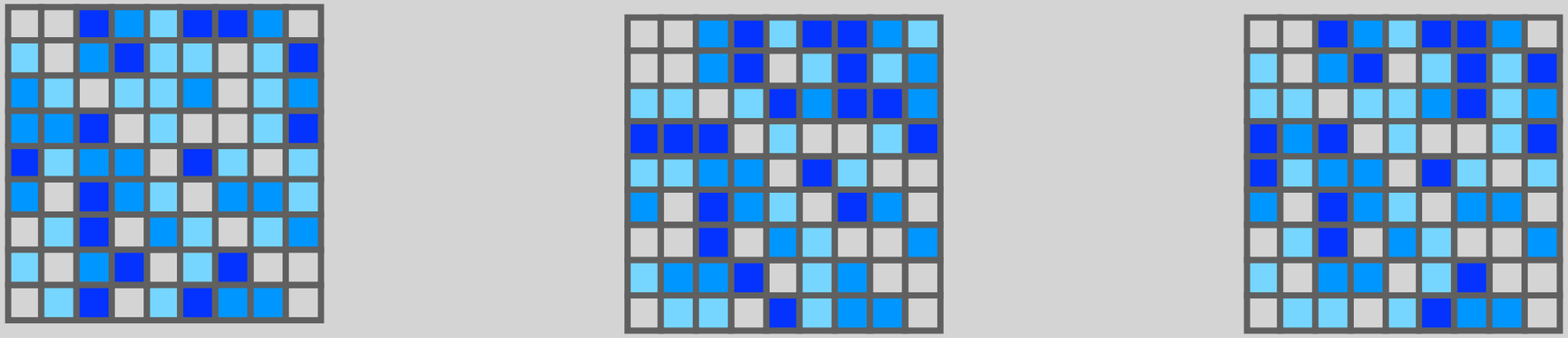

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accurate	improve relative error by 90%
calculated quickly*	< 10milliseconds per application
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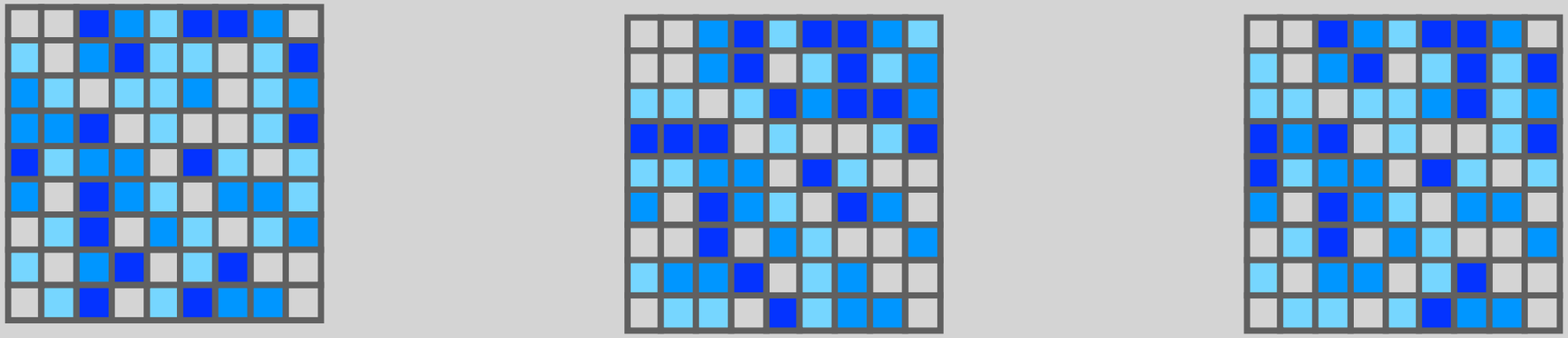

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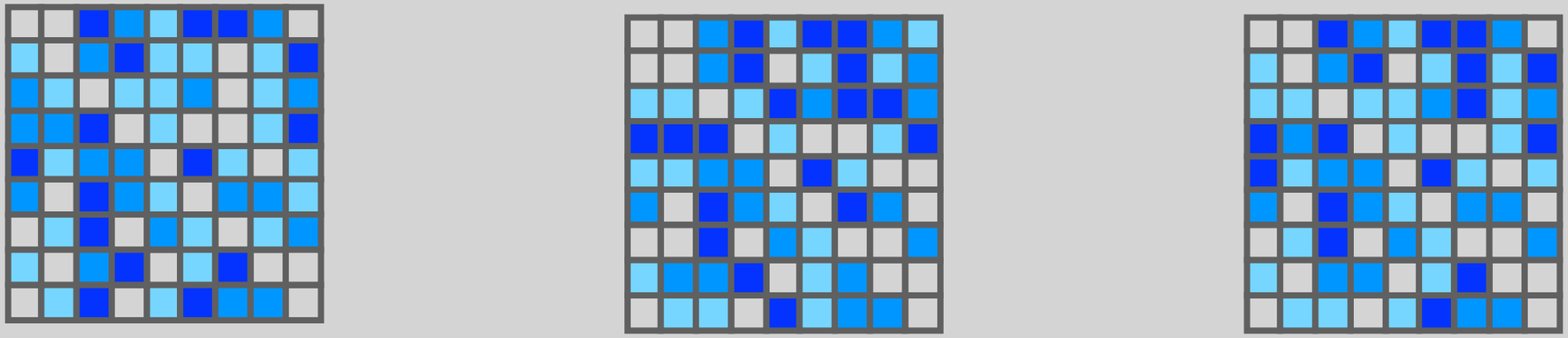

cicada captures this variability, and provides guarantees that are

accurate	improve relative error by 90%
calculated quickly*	< 10milliseconds per application
require little history	1–2 hours for most applications
increase network utilization	in some cases, inter-rack utilization is doubled

*see paper for this result