Decentralized Prediction of End-to-End Network Performance Classes

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End-to-End Network Performance

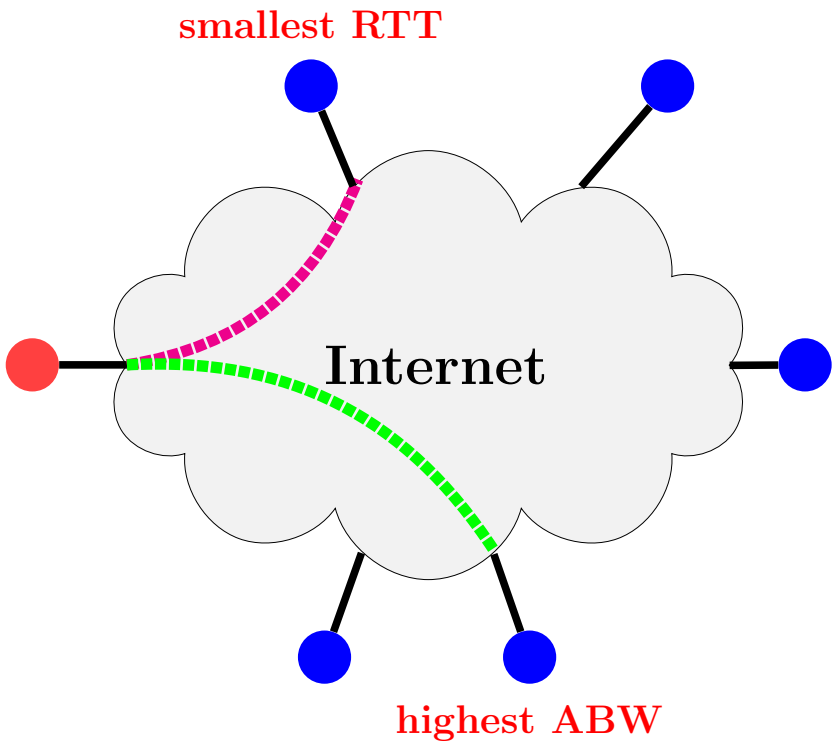
Metrics

- round-trip time (RTT)
- available bandwidth (ABW)
- packet loss rate (PLR)

Network Performance Matters!

- peer-to-peer downloading
- overlay routing
- content distribution network
- Internet games

Peer Selection



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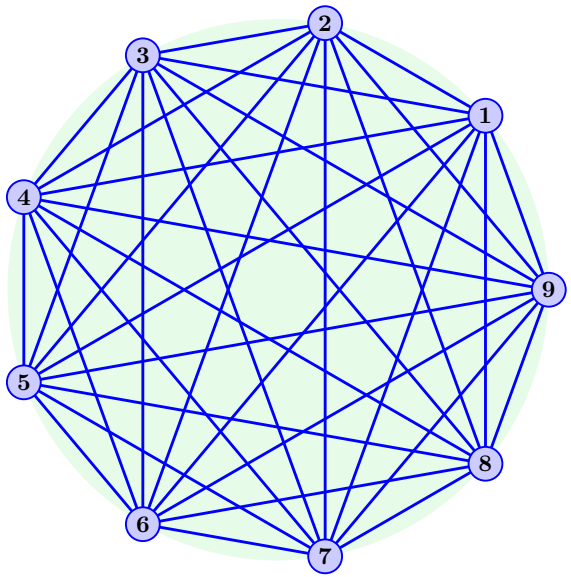
Acquisition on Large-Scale Networks

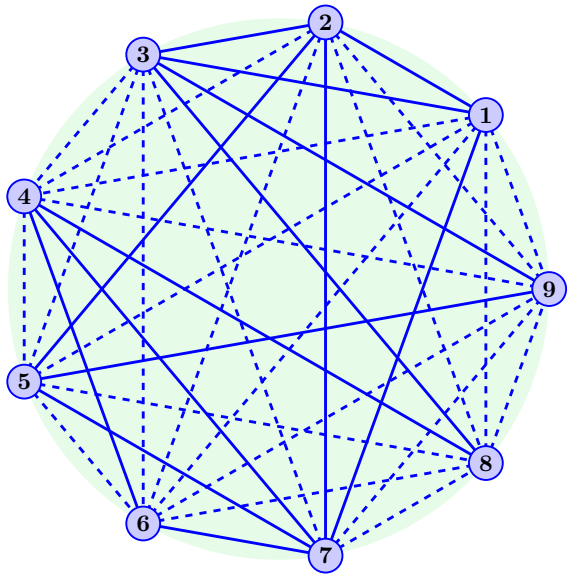
full-mesh active measurements



n nodes $\Rightarrow$ $o(n^2)$ measurements

accurate but expensive

network performance prediction



n nodes $\Rightarrow$ measurements $\ll o(n^2)$

less accurate but cheap

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Network Performance Prediction

Challenges

Network Performance Prediction

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- Networks are dynamic.
  - Churn: nodes join and leave frequently.
  - Metric values vary over time.

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- Metrics differ largely.
  - RTT: symmetric; ABW: asymmetric.
  - RTT: the smaller the better; ABW: the larger the better.
  - RTT and ABW are measured with different methodologies.

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- Metrics differ largely.
  - RTT: symmetric; ABW: asymmetric.
  - RTT: the smaller the better; ABW: the larger the better.
  - RTT and ABW are measured with different methodologies.
- Decentralized processing is prefered.
  - no landmarks or central servers
  - no infrastructure

Related Work on Network Performance Prediction

Round-Trip Time

- Euclidean Embedding
  - GNP: Ng et al. INFOCOM 2002
  - Vivaldi: Dabek et al. SIGCOMM 2004
- Matrix Factorization
  - IDES: Mao et al. IMC 2004
  - DMF: Liao et al. Networking 2010

Available Bandwidth

- SEQUOIA: Rama et al. SIGMETRICS 2009
- iPlane: Madhyastha et al. USENIX OSDI 2006

Our Contributions

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1. Class-based Performance Representation

Represent network performance by discrete-valued classes, instead of real-valued quantities.

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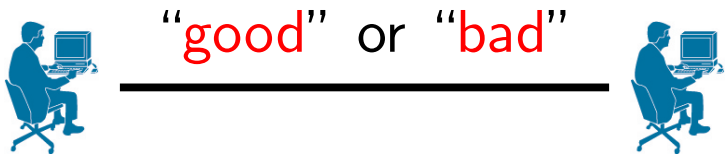
Class-based Performance Representation

Binary Classification



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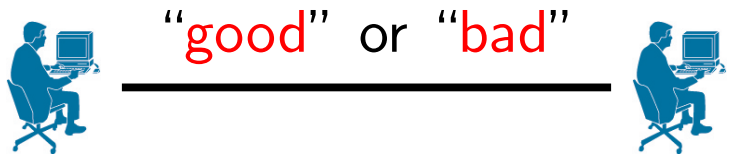

- Class reflects the QoS experience of end users.

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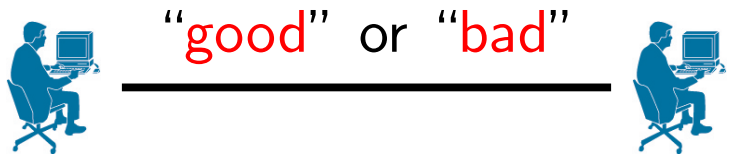

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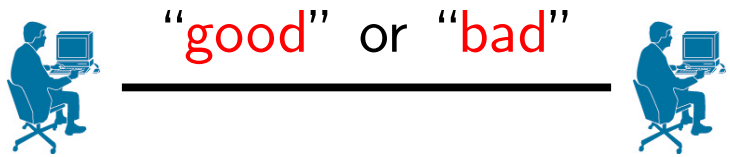

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  - Streaming applications care if ABW is high enough.
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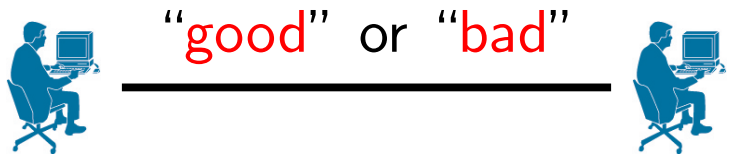

- Class reflects the QoS experience of end users.
- Class unifies different metrics.
- Class information is often sufficient.
  - Streaming applications care if ABW is high enough.
  - P2P applications care if RTT is small enough.
- Class measurements are cheap.
  - Classes are rough.
  - Classes are more stable.

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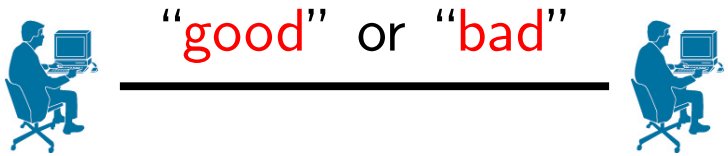
Measure Performance Classes



Thresholding

Measure if the metric value is larger or smaller than a threshold τ.

- If RTT $<$ 100ms, performance is "good".
- If ABW $>$ 100Mbps, performance is "good".

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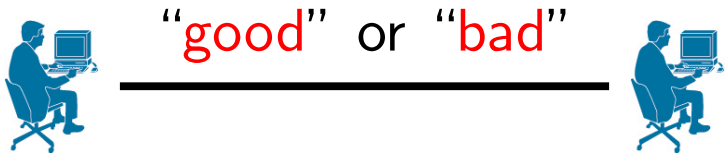

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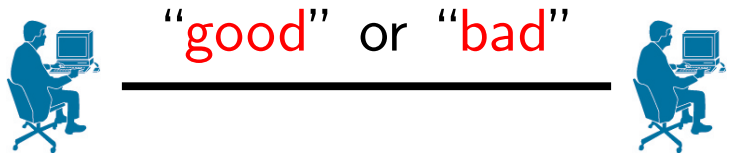

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Threshold τ

defined according to requirements of applications

- Google TV requires 10Mbps for HD contents.

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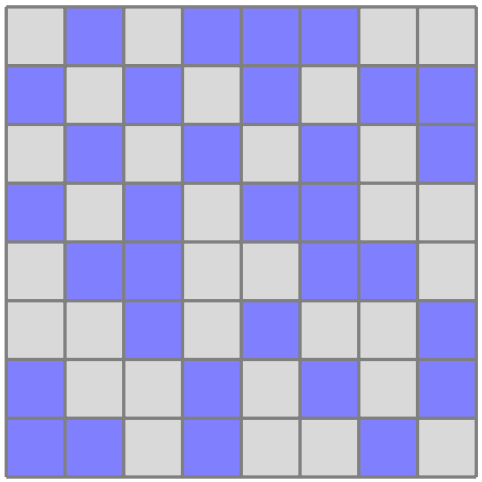
Matrix Completion for Network Performance Prediction

Matrix Completion

Predict the unknown entries from a few known entries.

X



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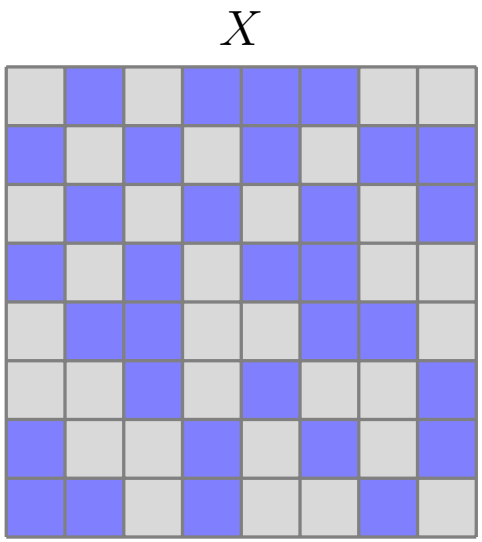

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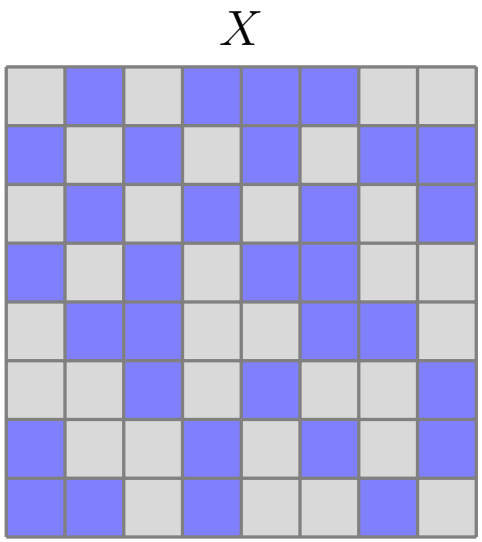

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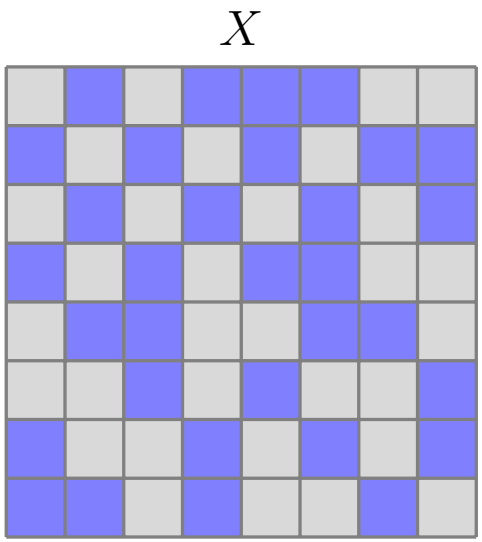

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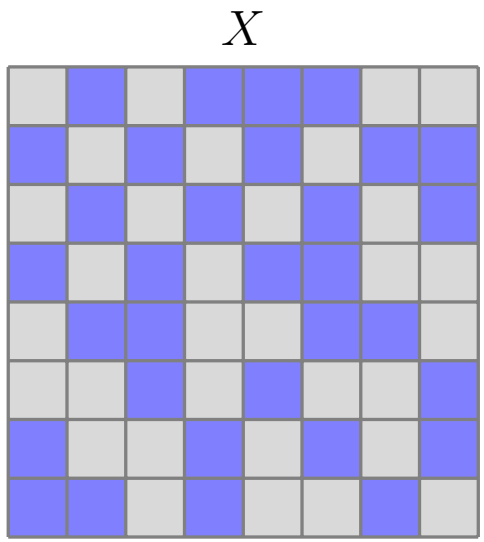
You don't need all $n \times n$ entries!



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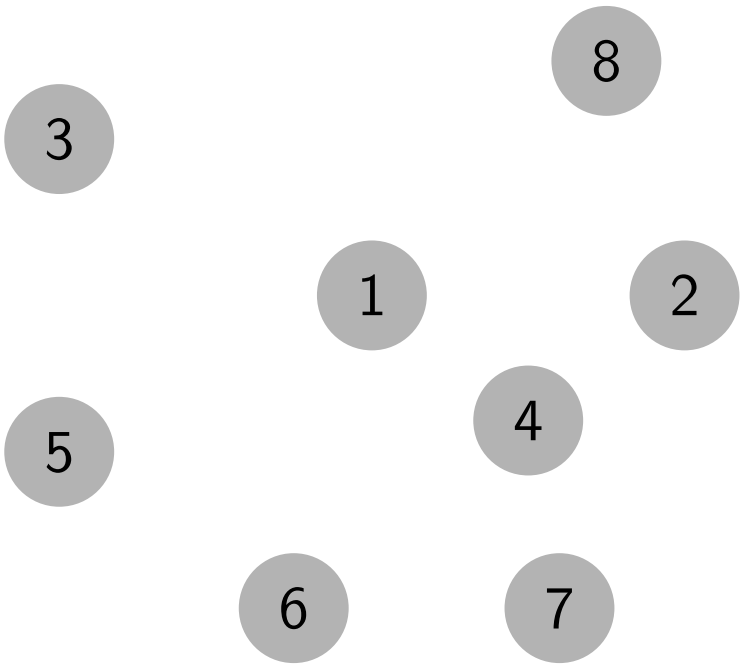

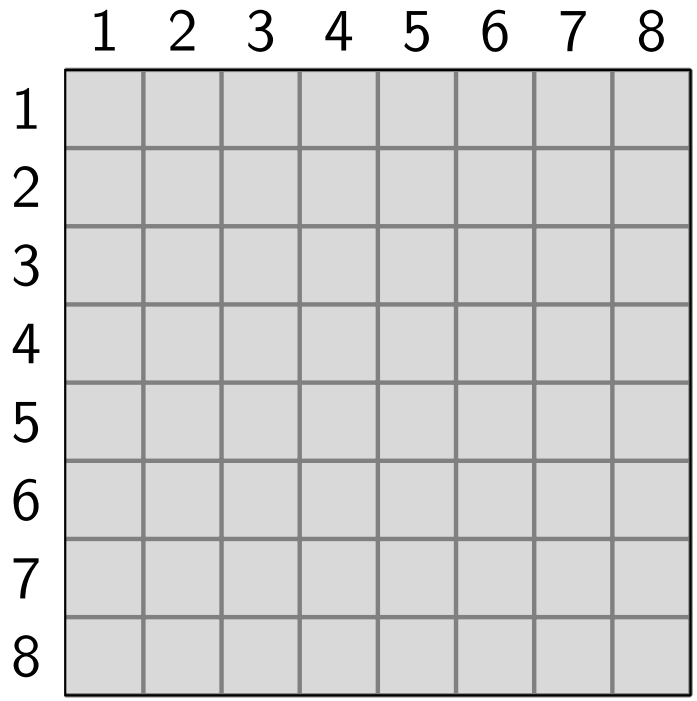

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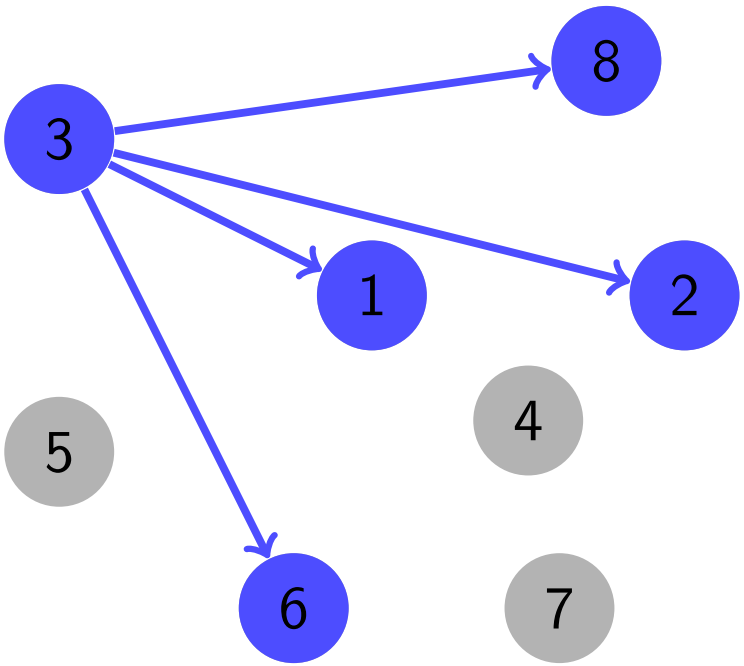

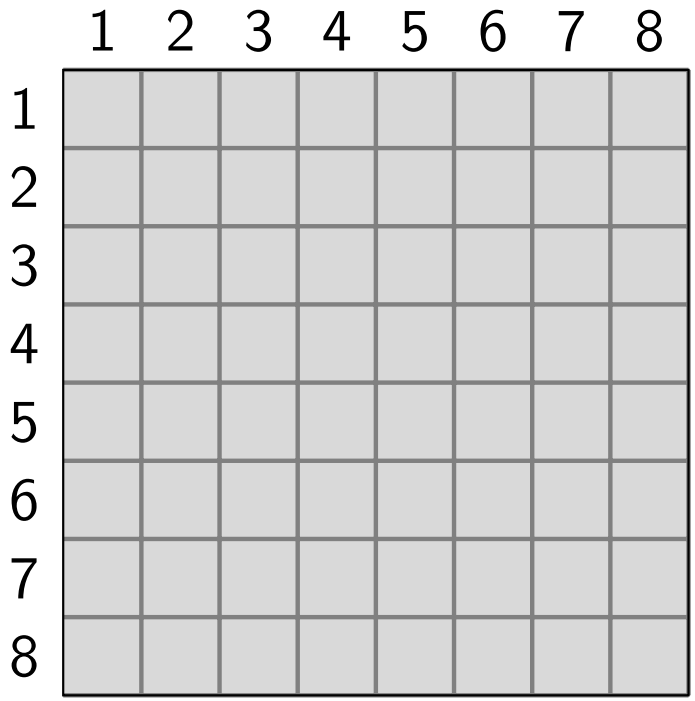

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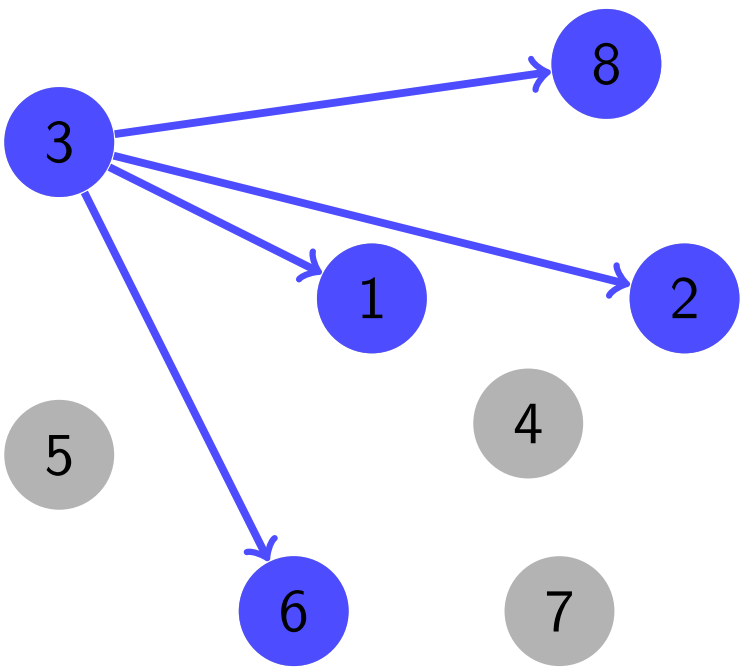

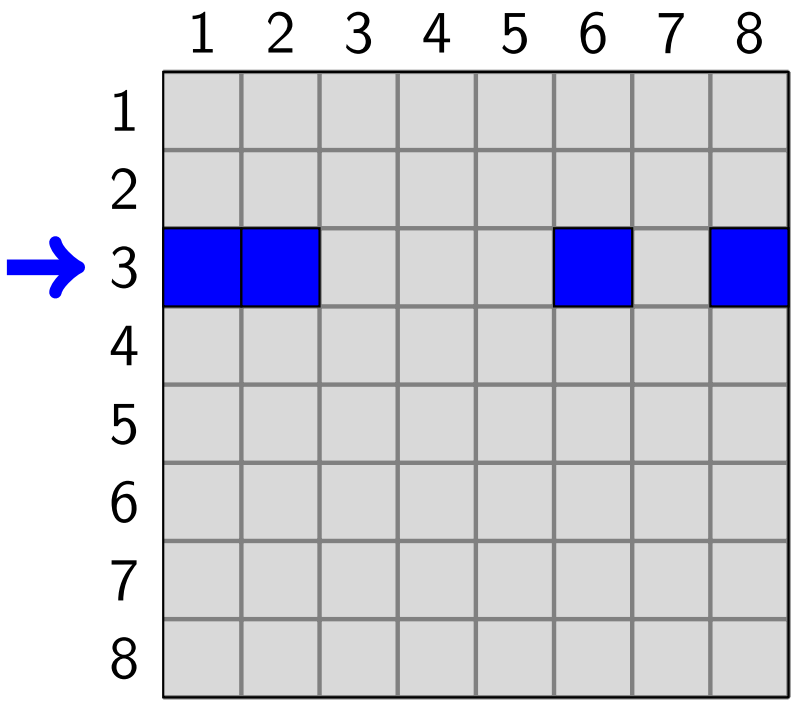

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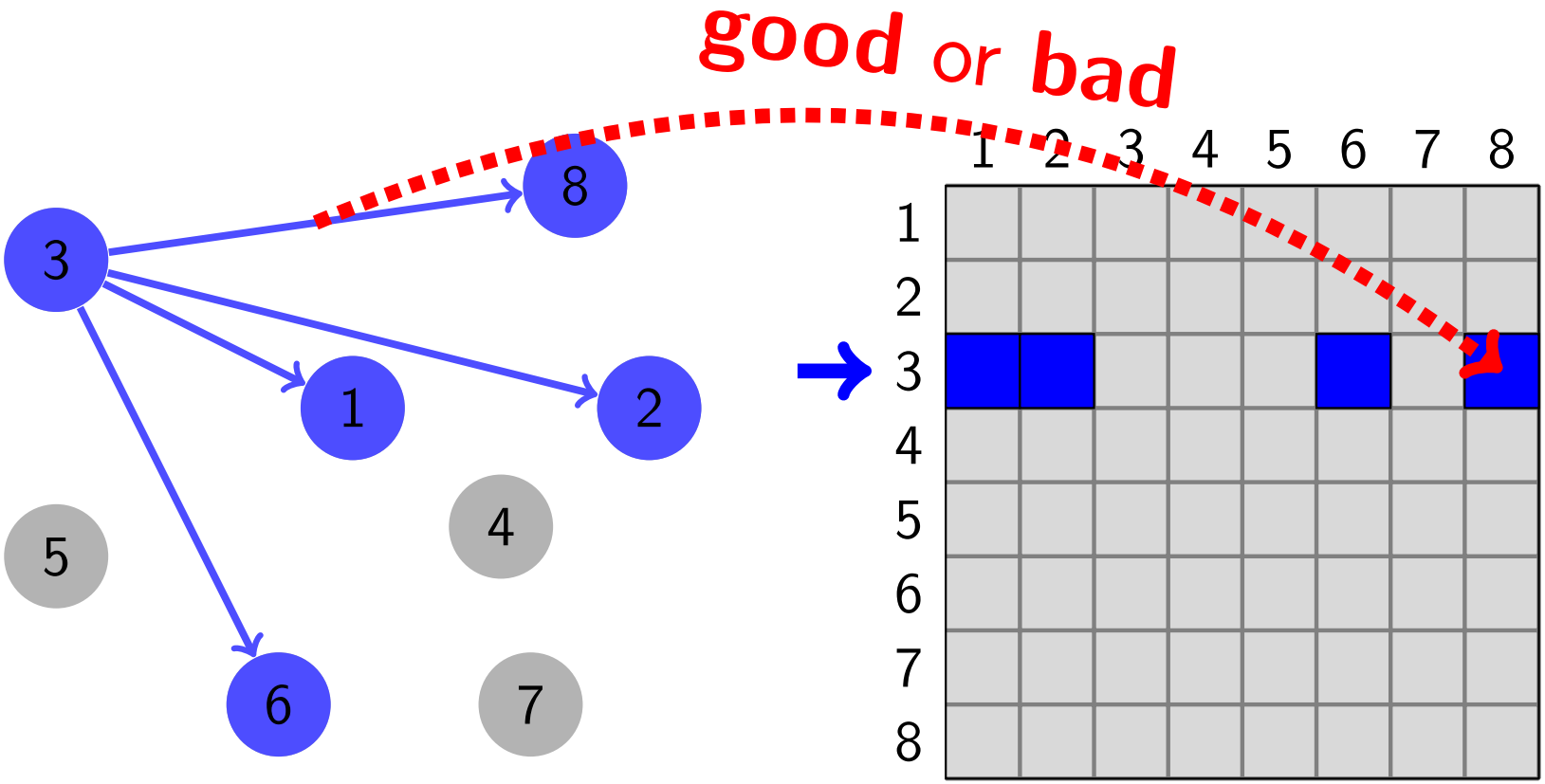

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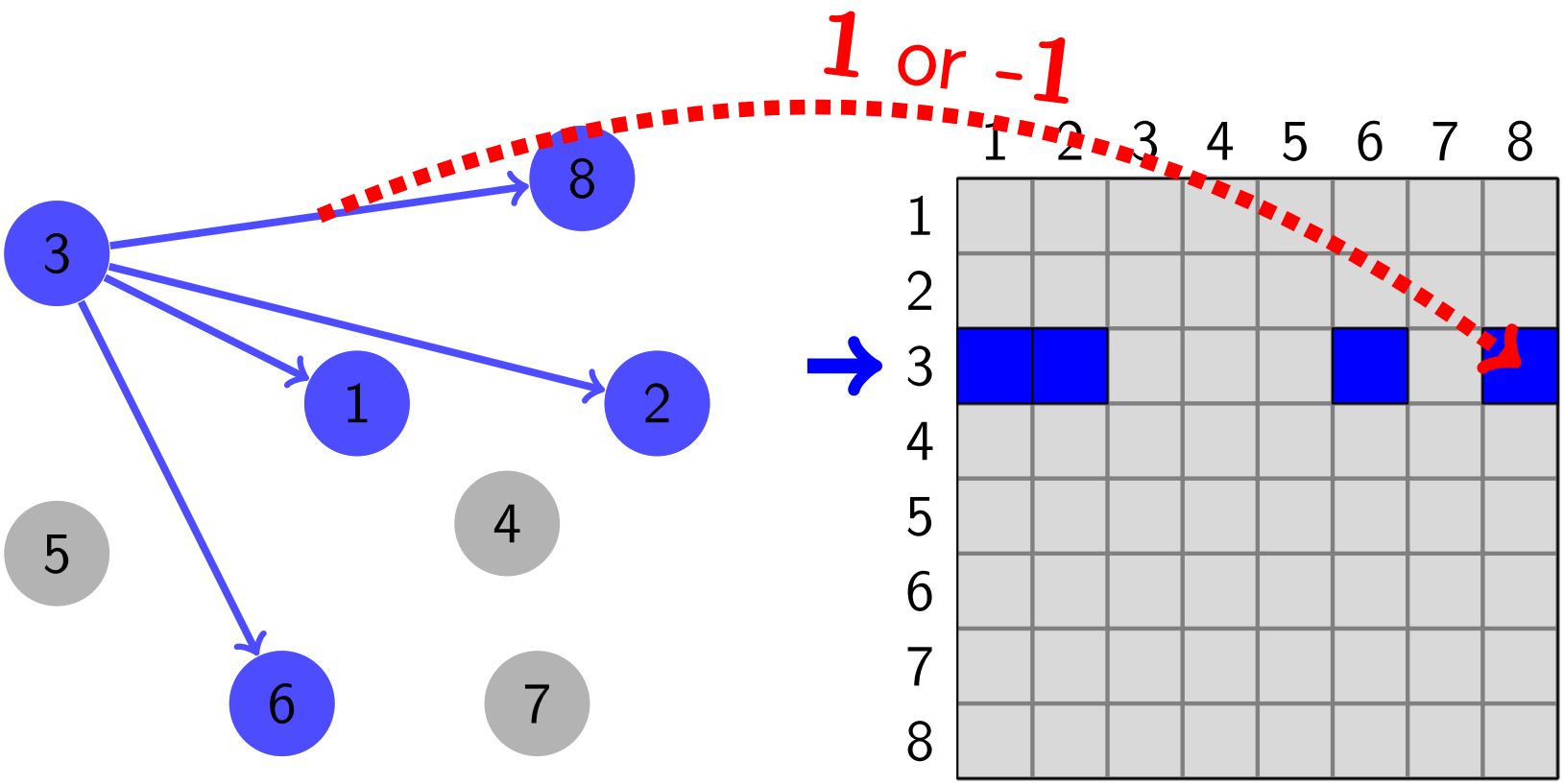

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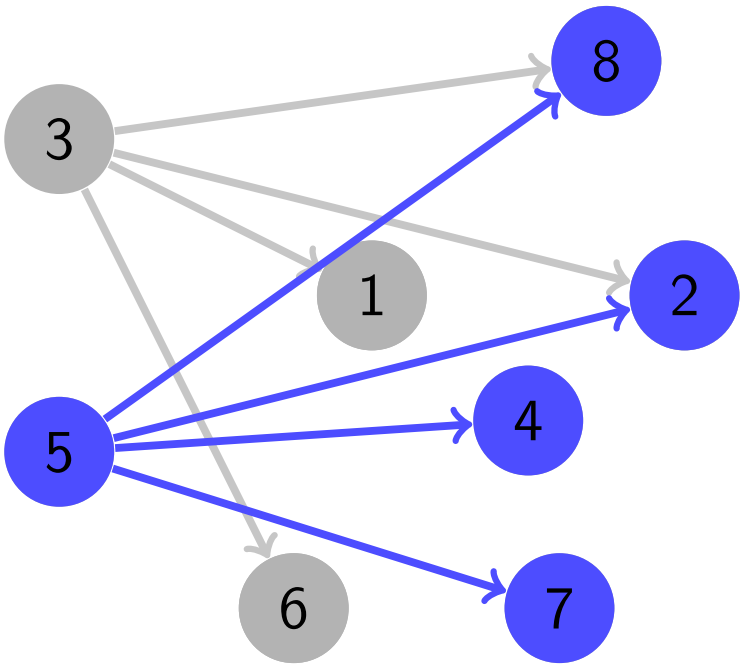

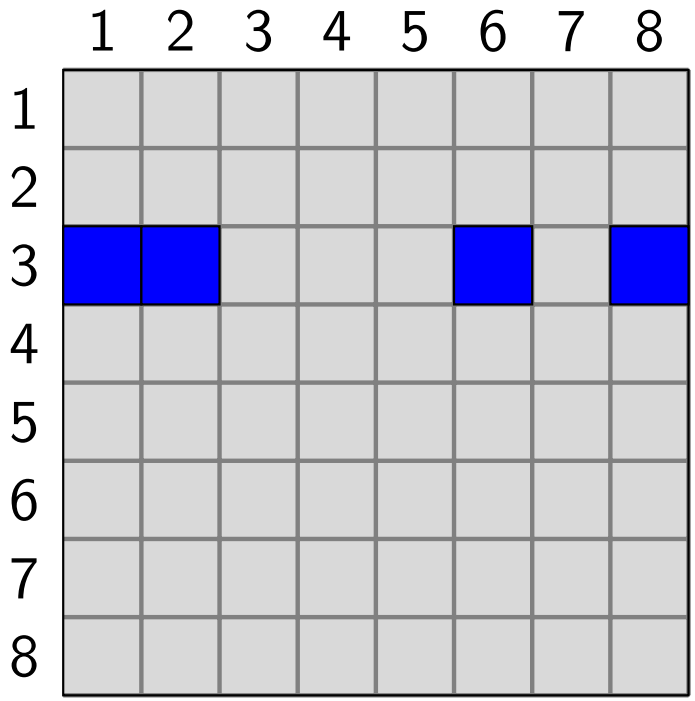

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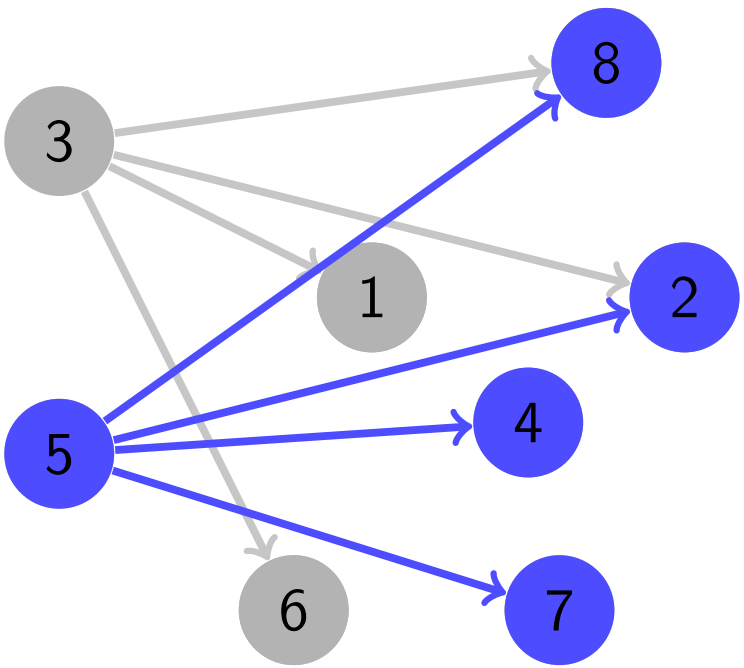

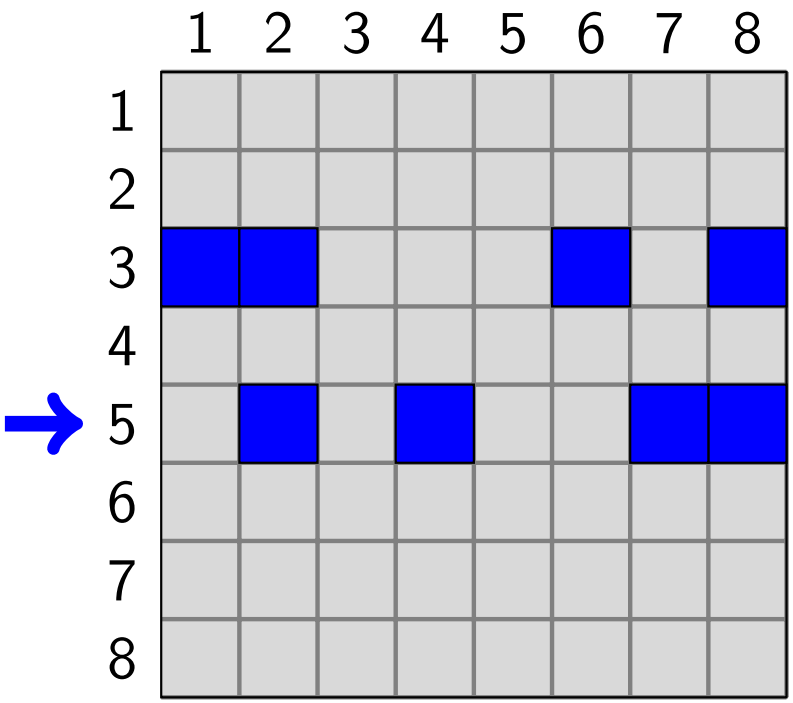

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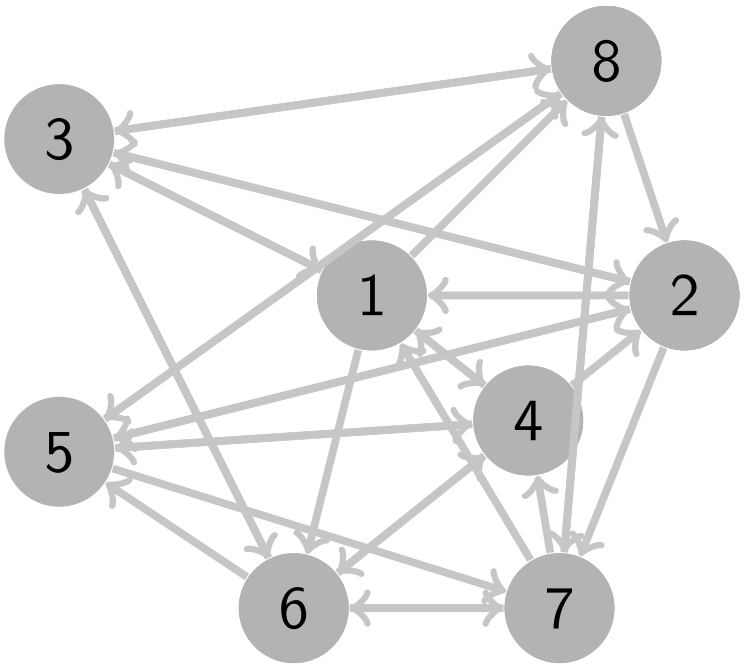

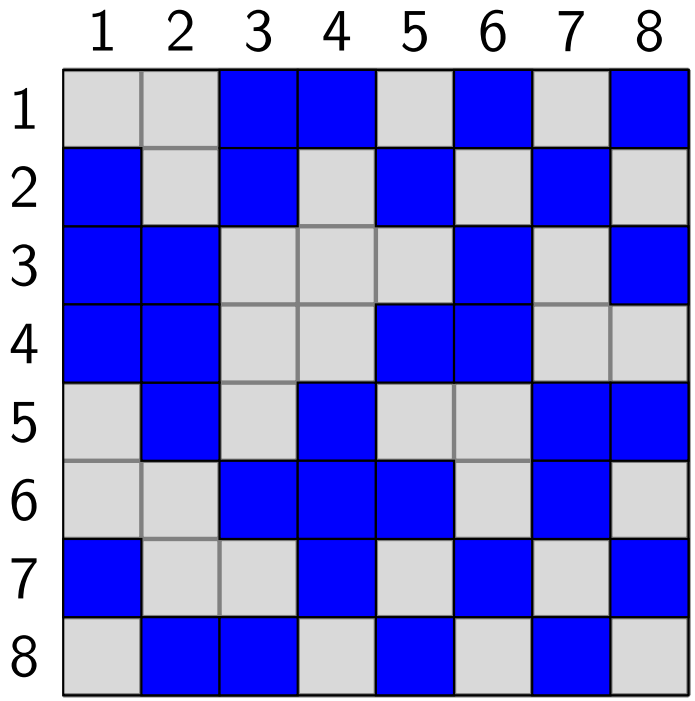

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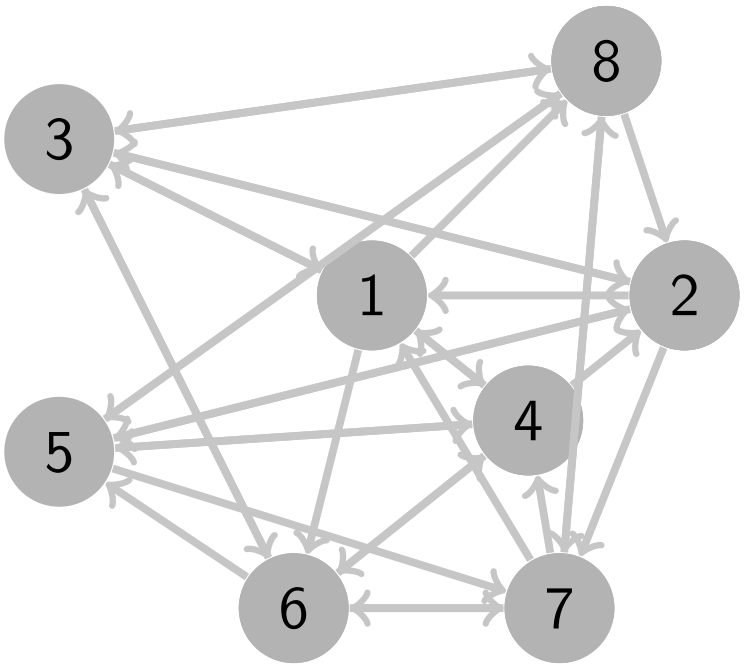

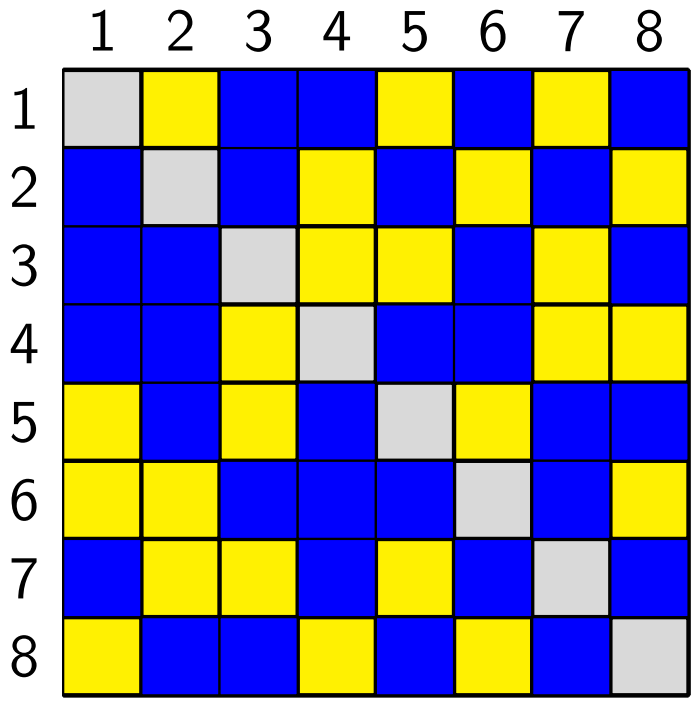

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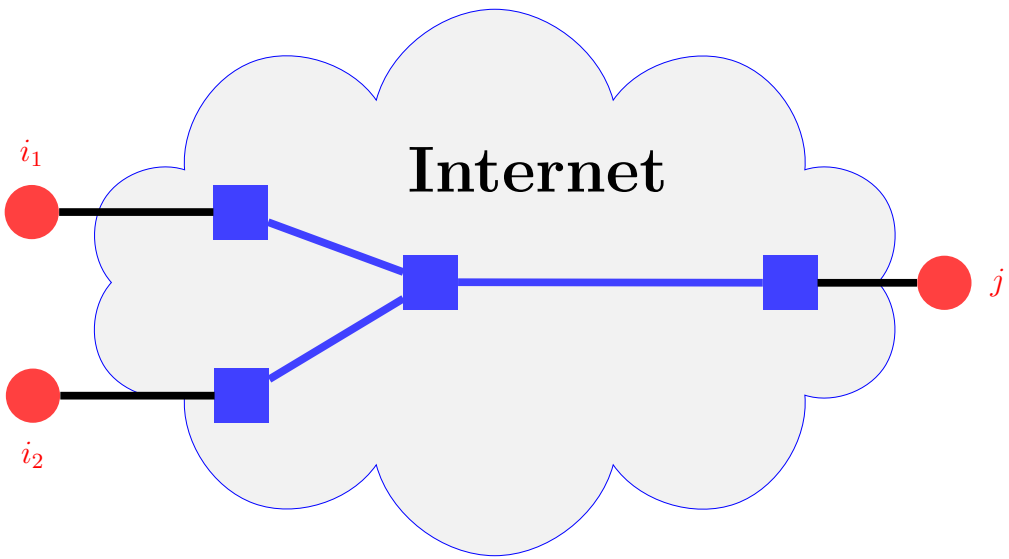
Why is Matrix Completion Possible

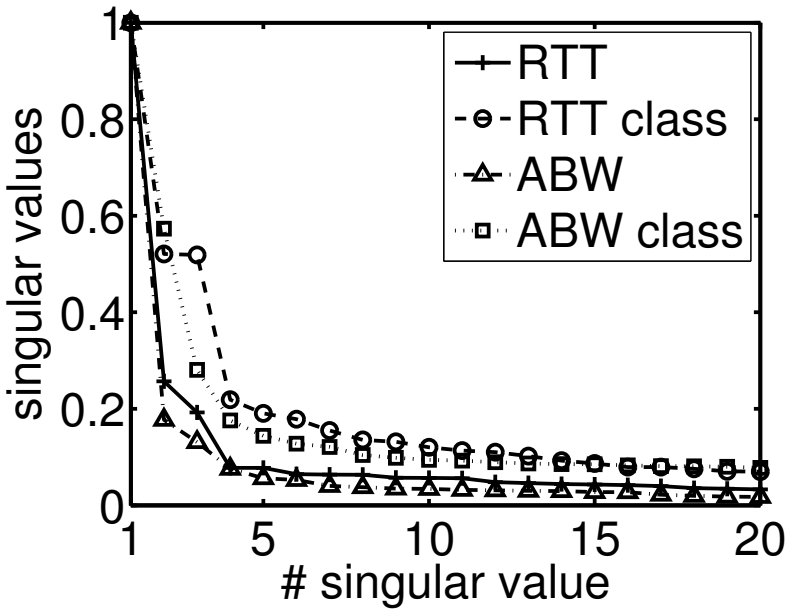
Correlations across network performance

- network topology
- routing algorithms
- redundancies among network paths
- ...



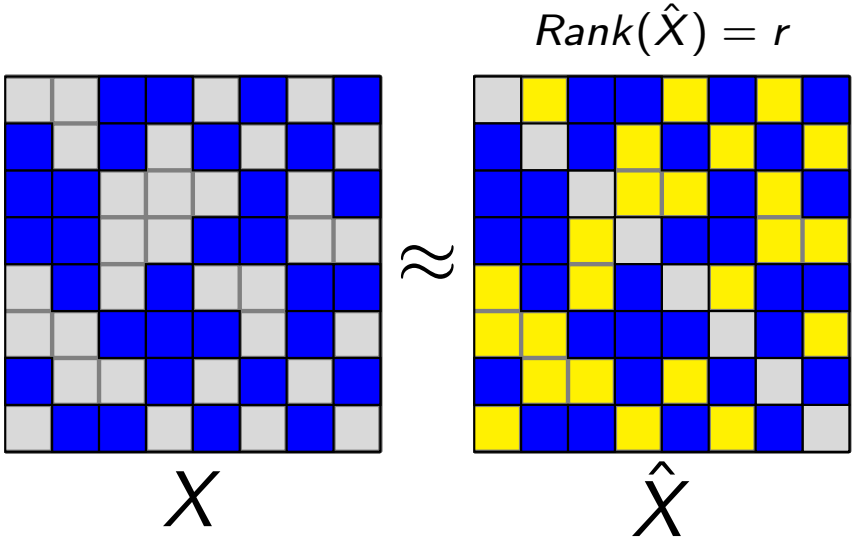
Why is Matrix Completion Possible

Low-rank of performance matrices



- RTT matrix: 2255×2255
- ABW matrix: 201×201
- Class matrices are obtained by thresholding.

Low-Rank Matrix Factorization



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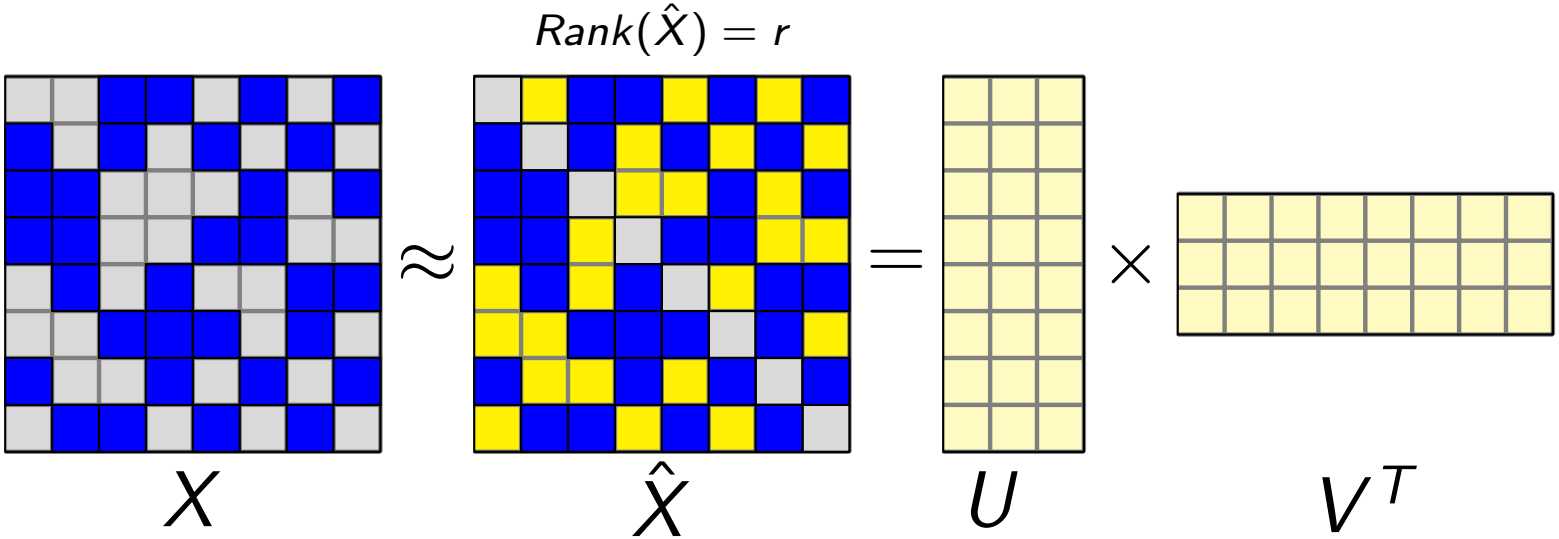
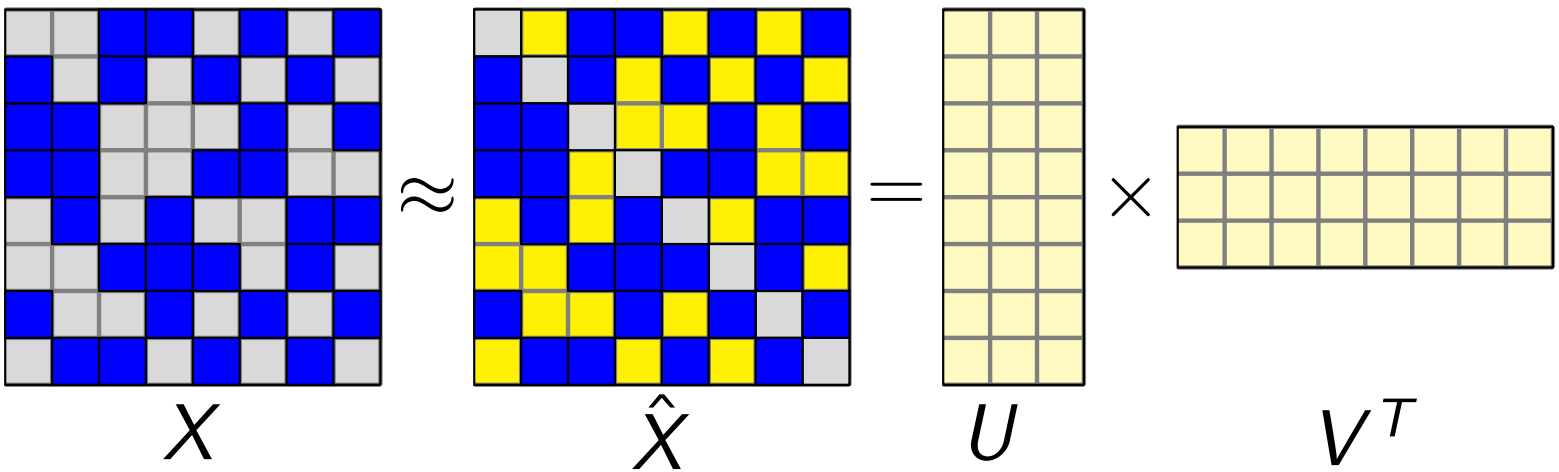


Low-Rank Matrix Factorization

Look for (U, V), instead of $\hat{X}$

$Rank(\hat{X}) = r$



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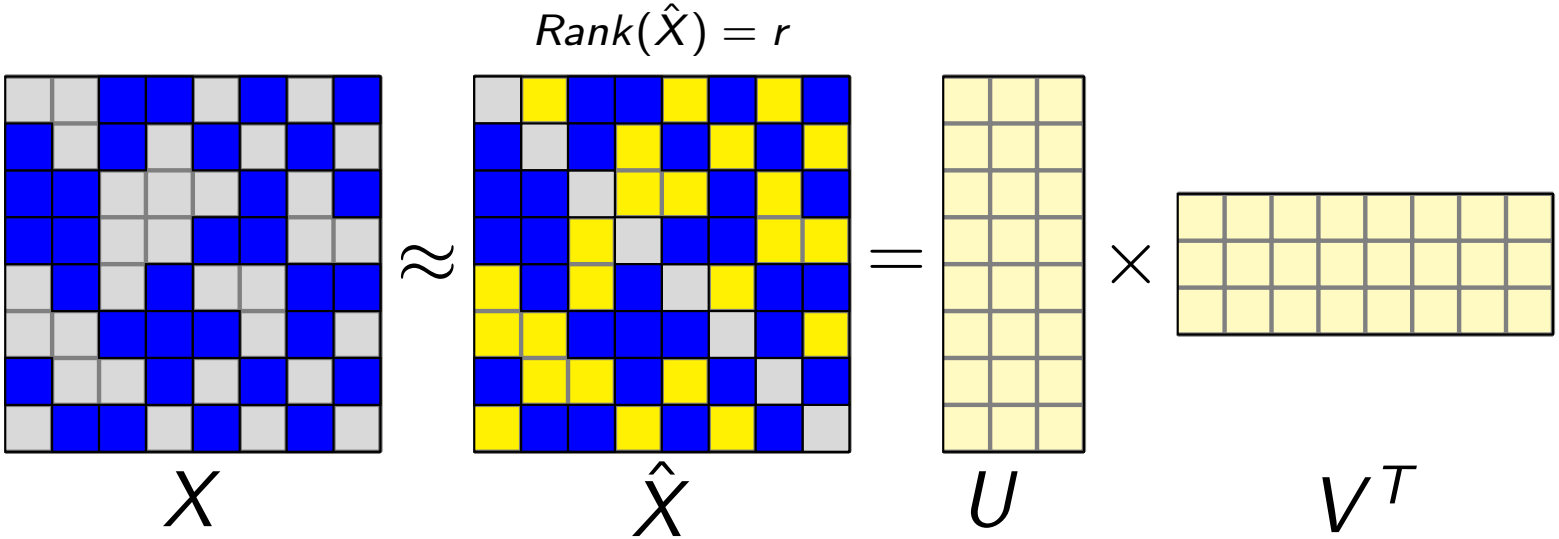
Stochastic Gradient Descent



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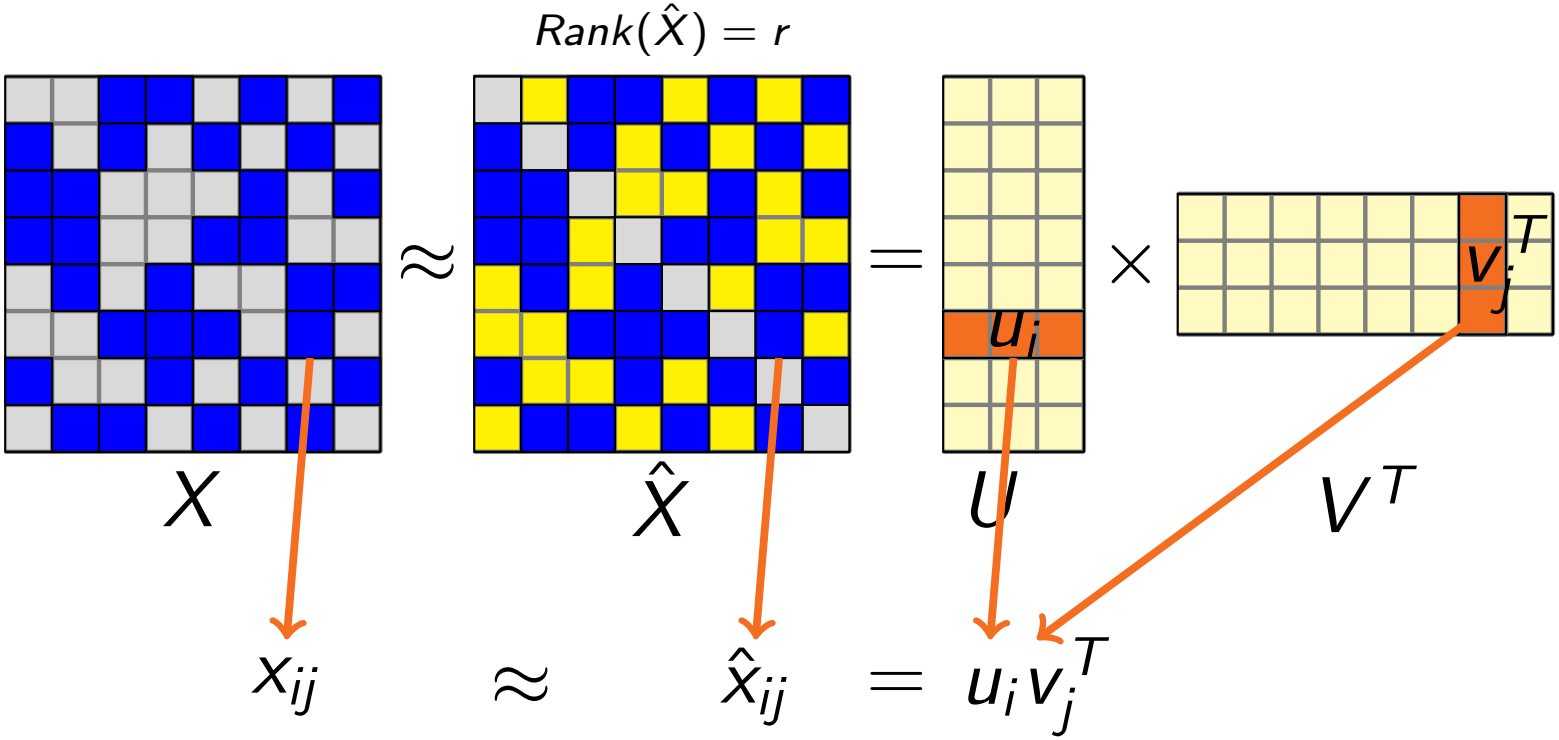

Decentralized Matrix Factorization by Stochastic Gradient Descent

No construction of matrices

Repeated SGD updates

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- X: measurement x_{ij} is probed by node i.

Repeated SGD updates

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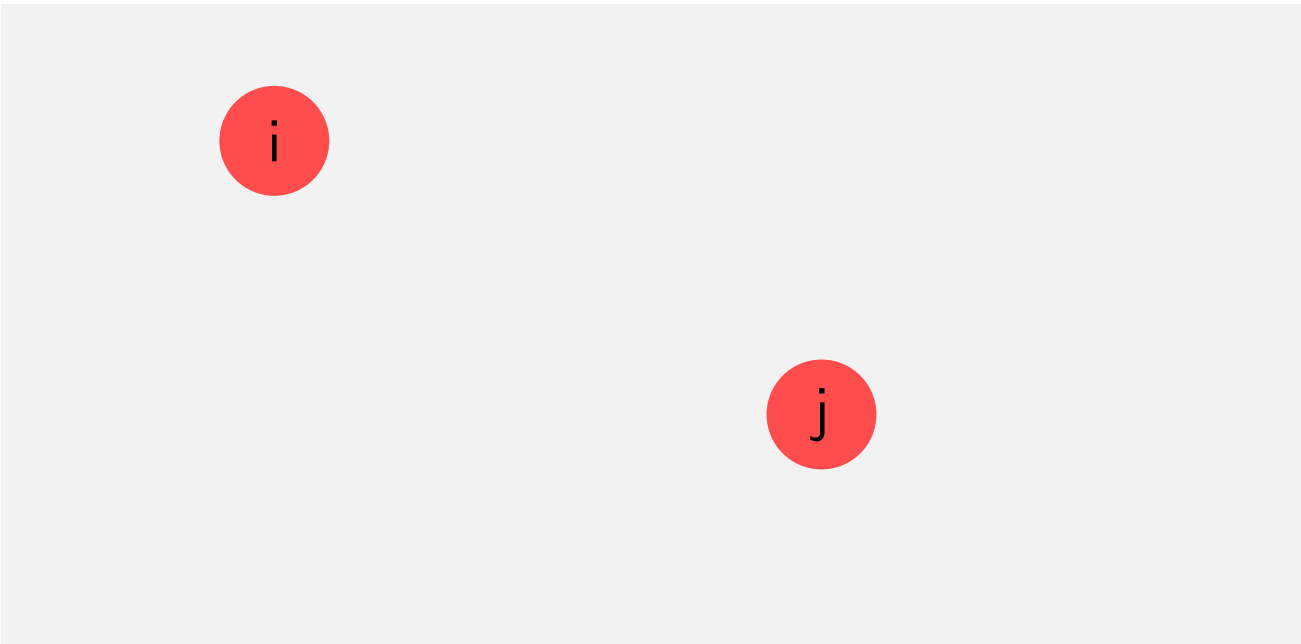

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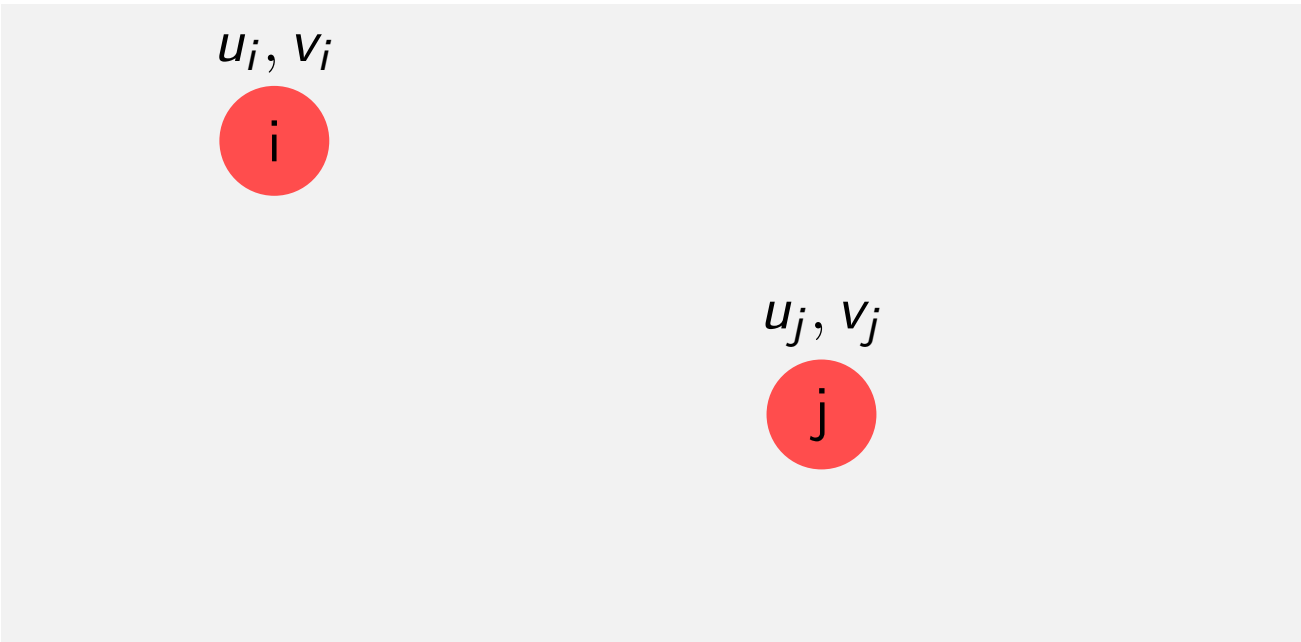

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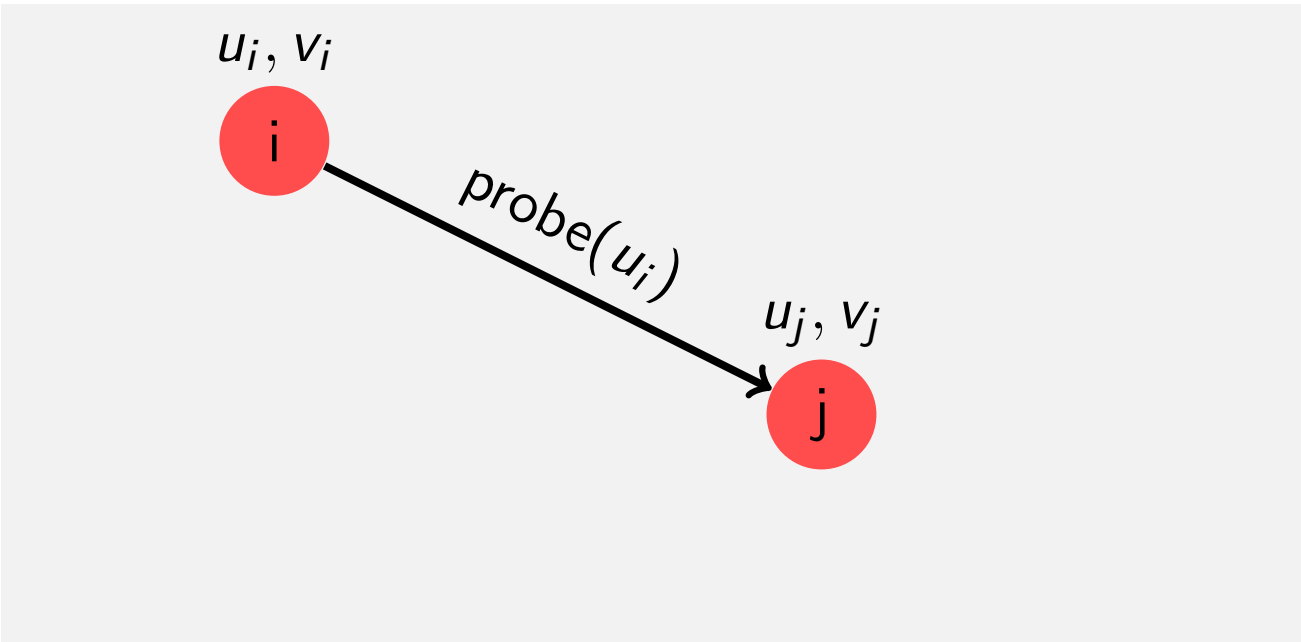

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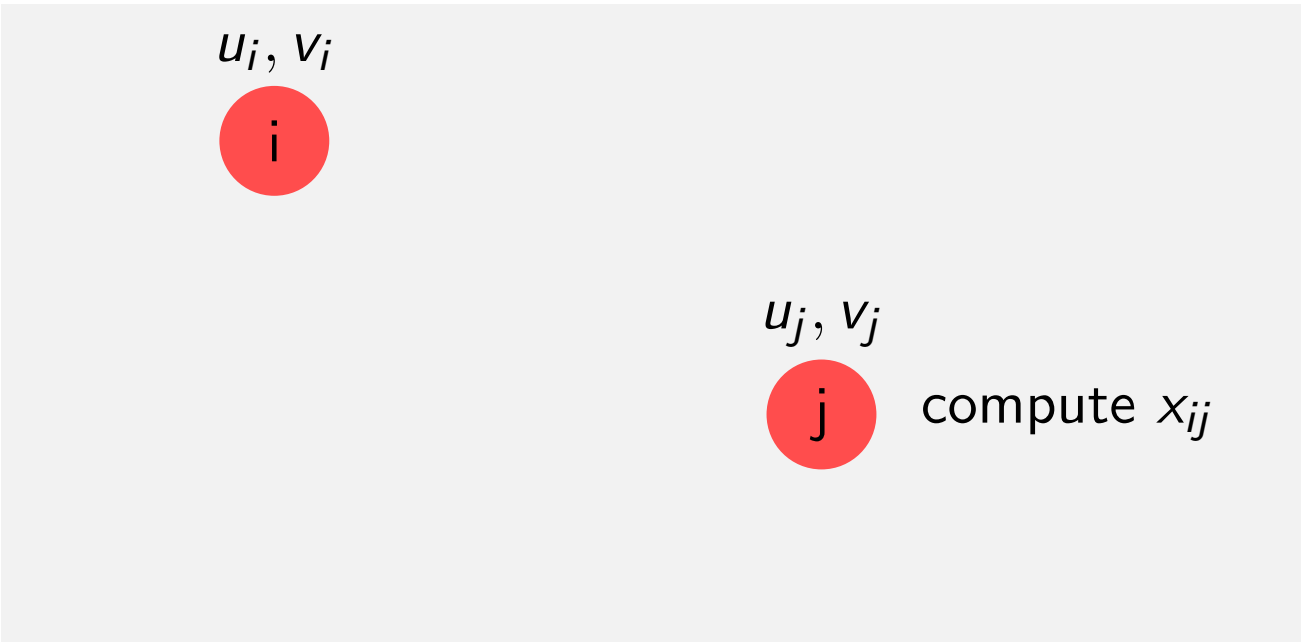

Decentralized Matrix Factorization by Stochastic Gradient Descent

No construction of matrices

- X: measurement x_{ij} is probed by node i.
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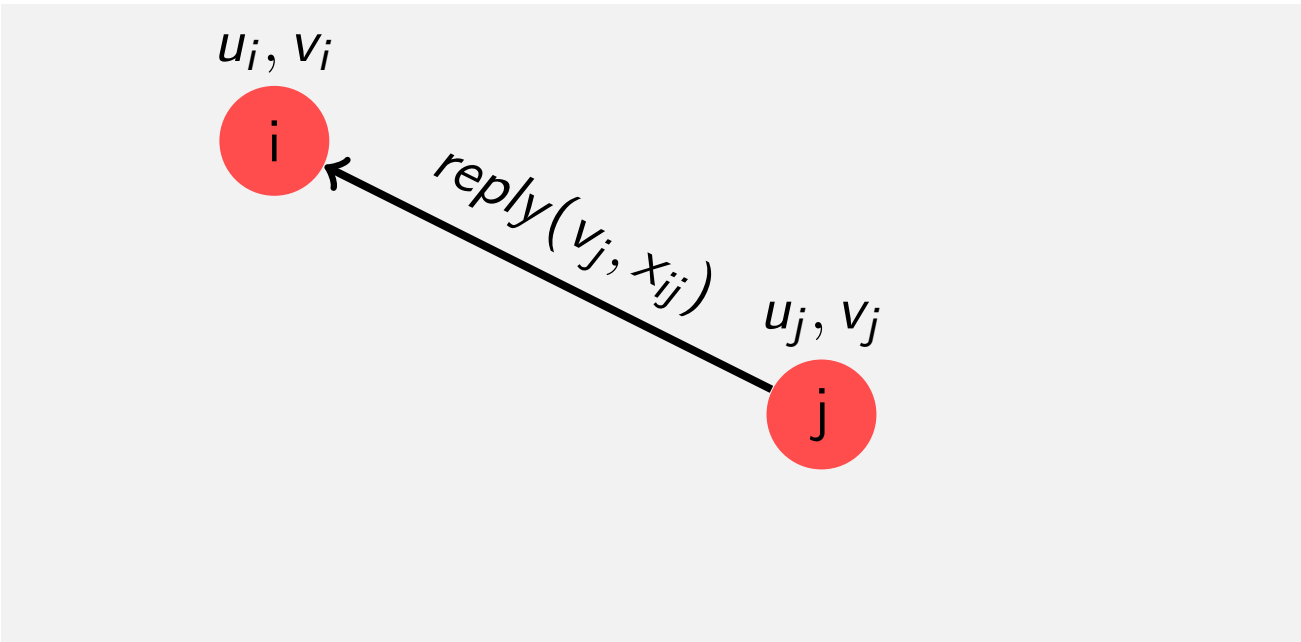

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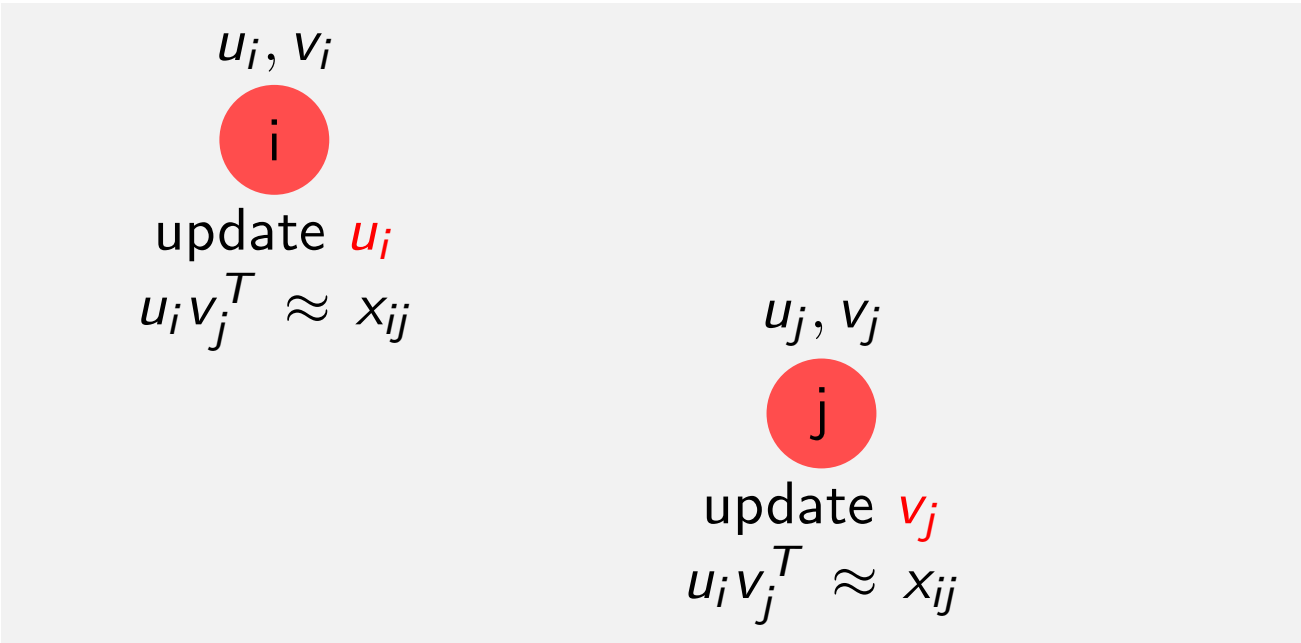

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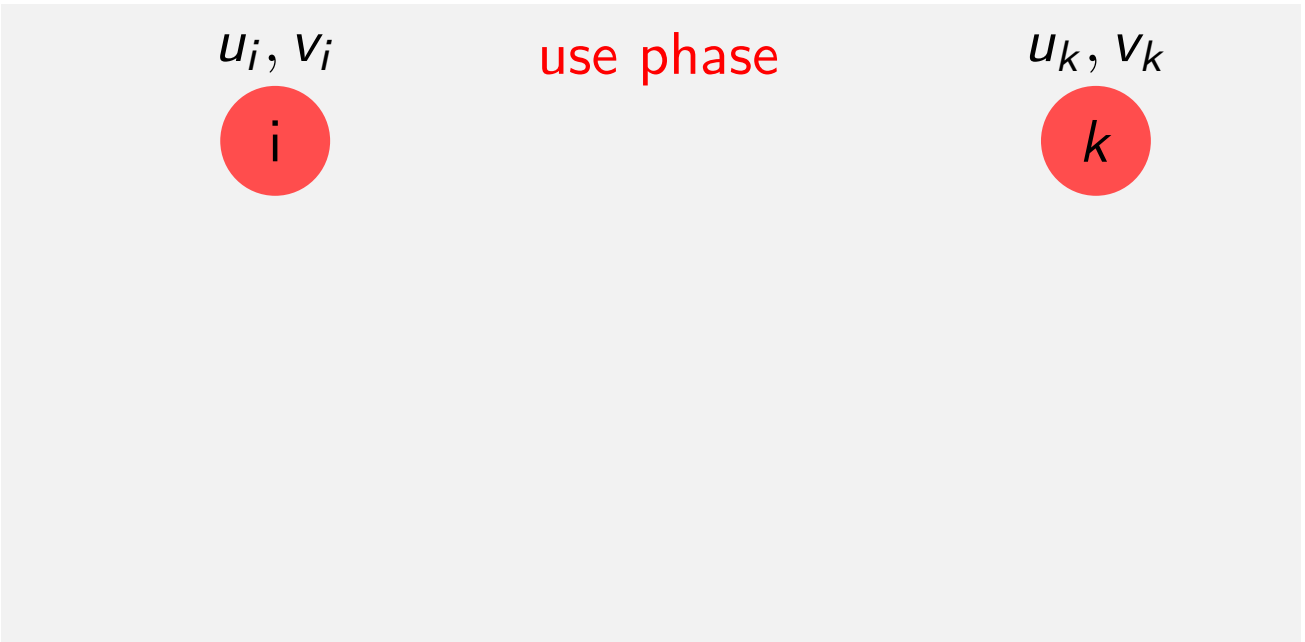

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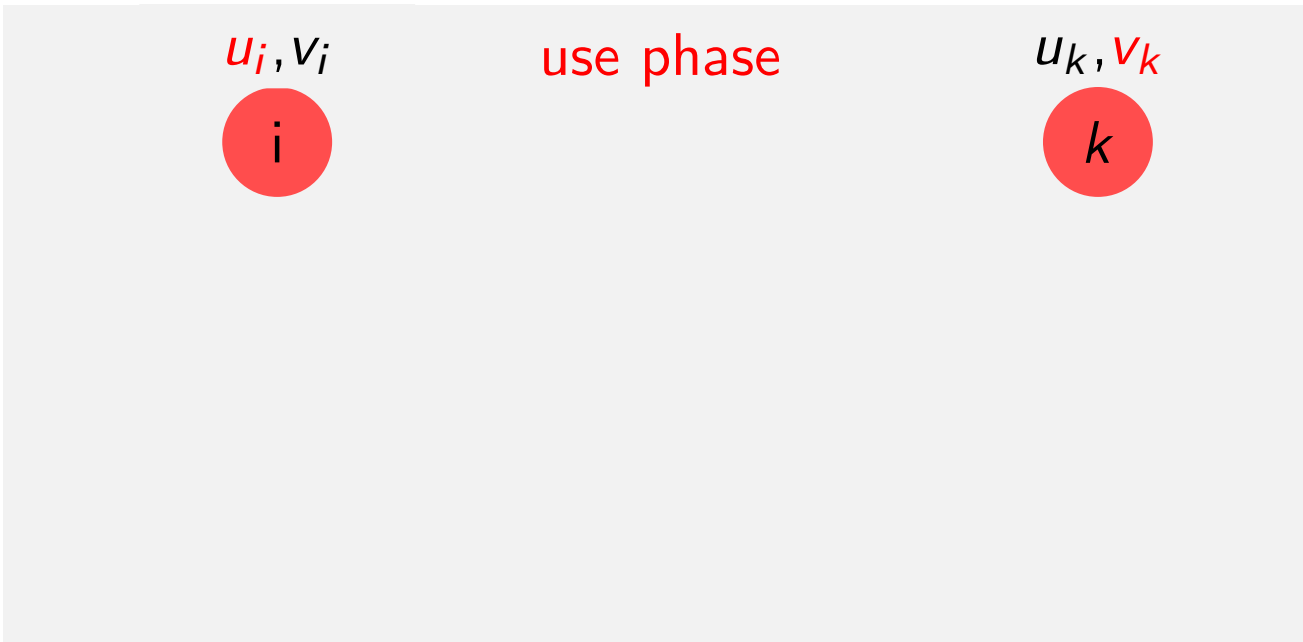

Decentralized Matrix Factorization by Stochastic Gradient Descent

DMFSGD

All nodes employ the same processing.

- Each node selects k neighbors to communicate with.
- Each node collaborates with one neighbor at each time.

Advantages

- easy to implement
- computationally lightweight
- suitable for large-scale dynamic measurements
- adaptable for various metrics

Experiments and Evaluations

Datasets

	Harvard	Meridian	HP-S3
nodes	226	2500	231
metric	RTT	RTT	ABW
dynamic	Yes	No	No
source	Ledlie et al. NSDI 2007	Wong et al. SIGCOMM 2005	Ramasubramanian et al. SIGMETRICS 2009

*Harvard dataset is collected from Azureus (now Vuze) and contains dynamic measurements with time-stamps.

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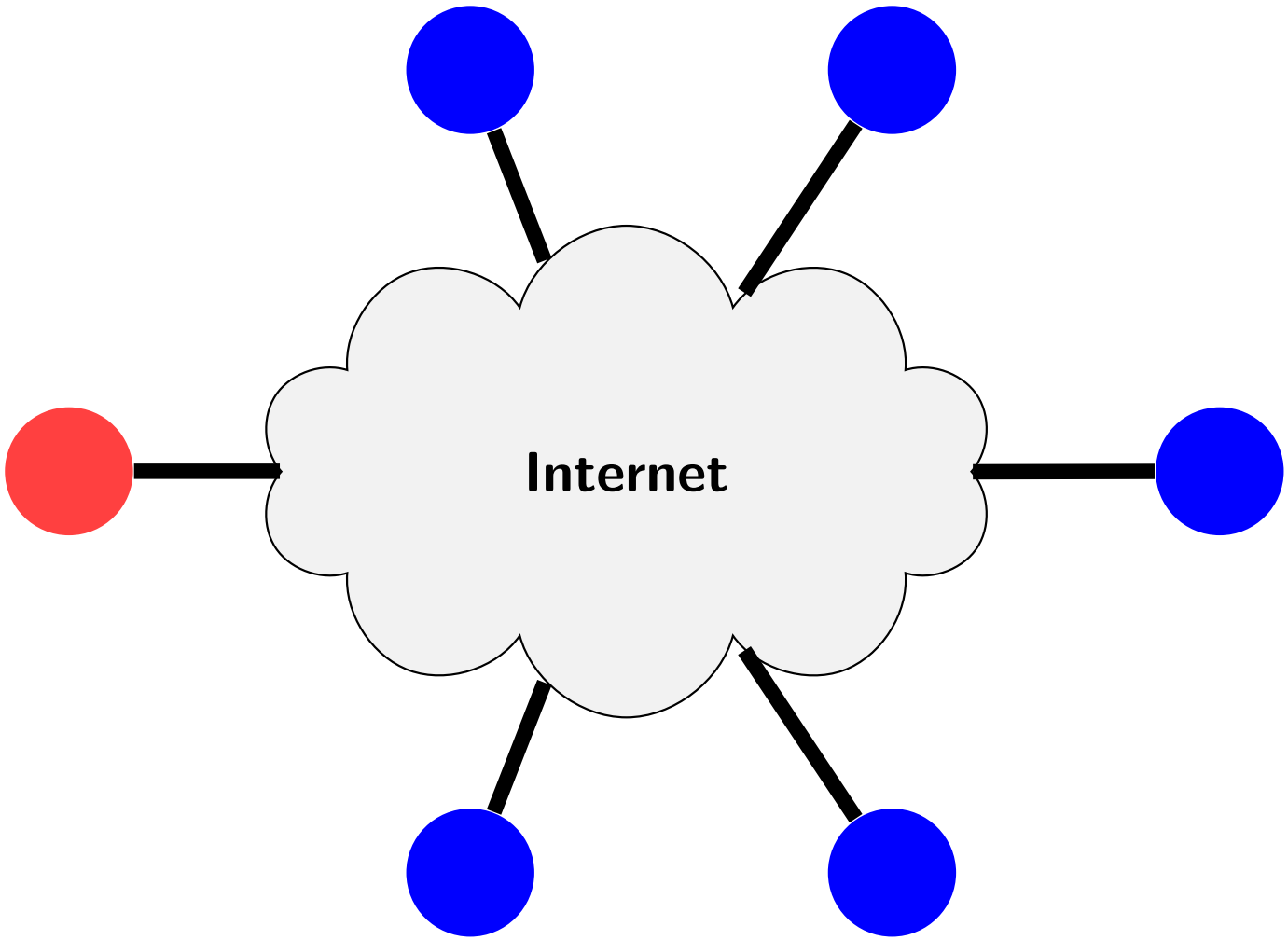
$$\text{Accuracy} = \frac{\#\text{ of correct prediction}}{\#\text{ of data}}$$

	Harvard	Meridian	HP-S3
Accuracy	89.4%	85.4%	87.3%

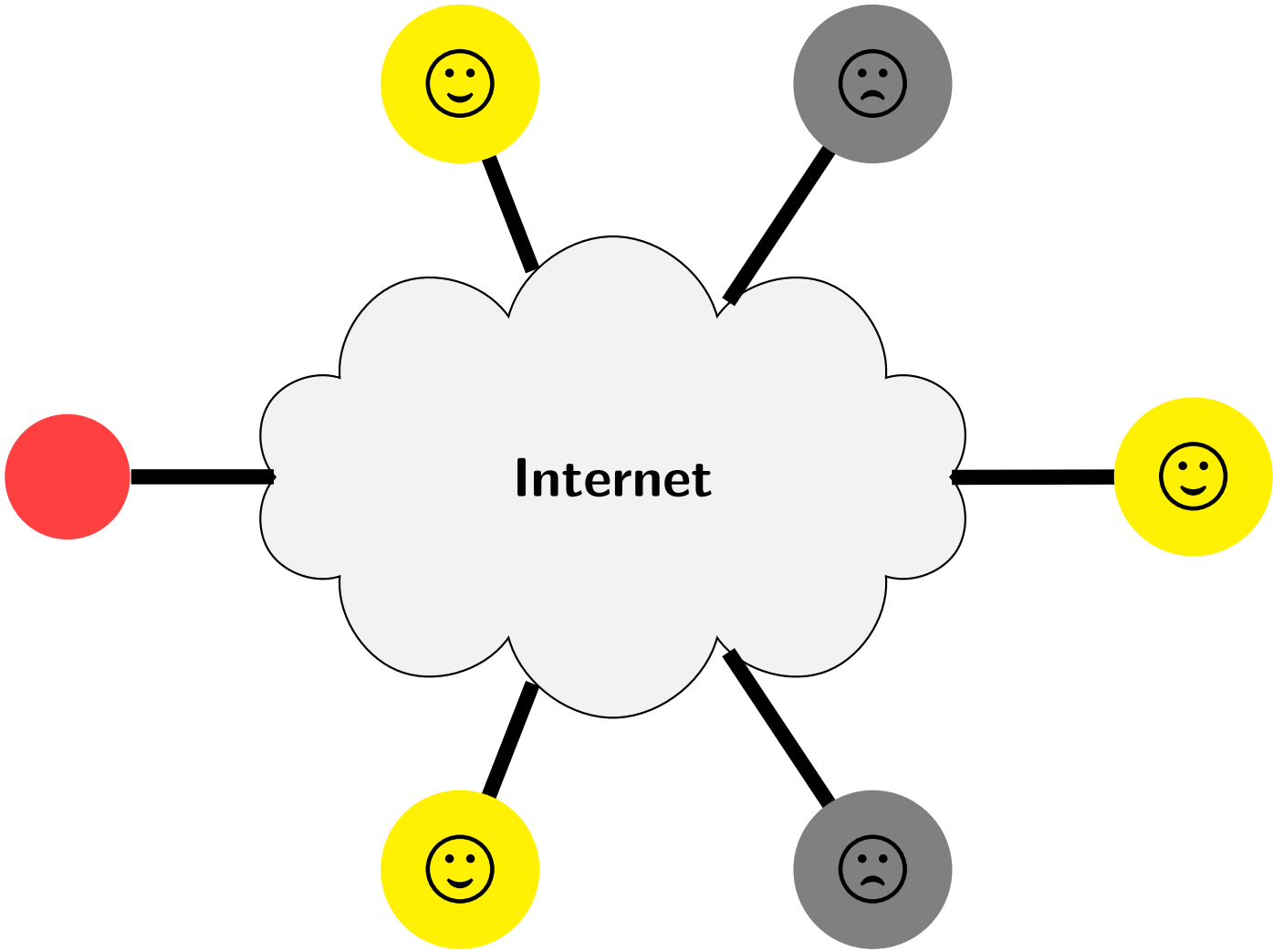
Peer Selection

Find a "good" peer, not the "best" peer!



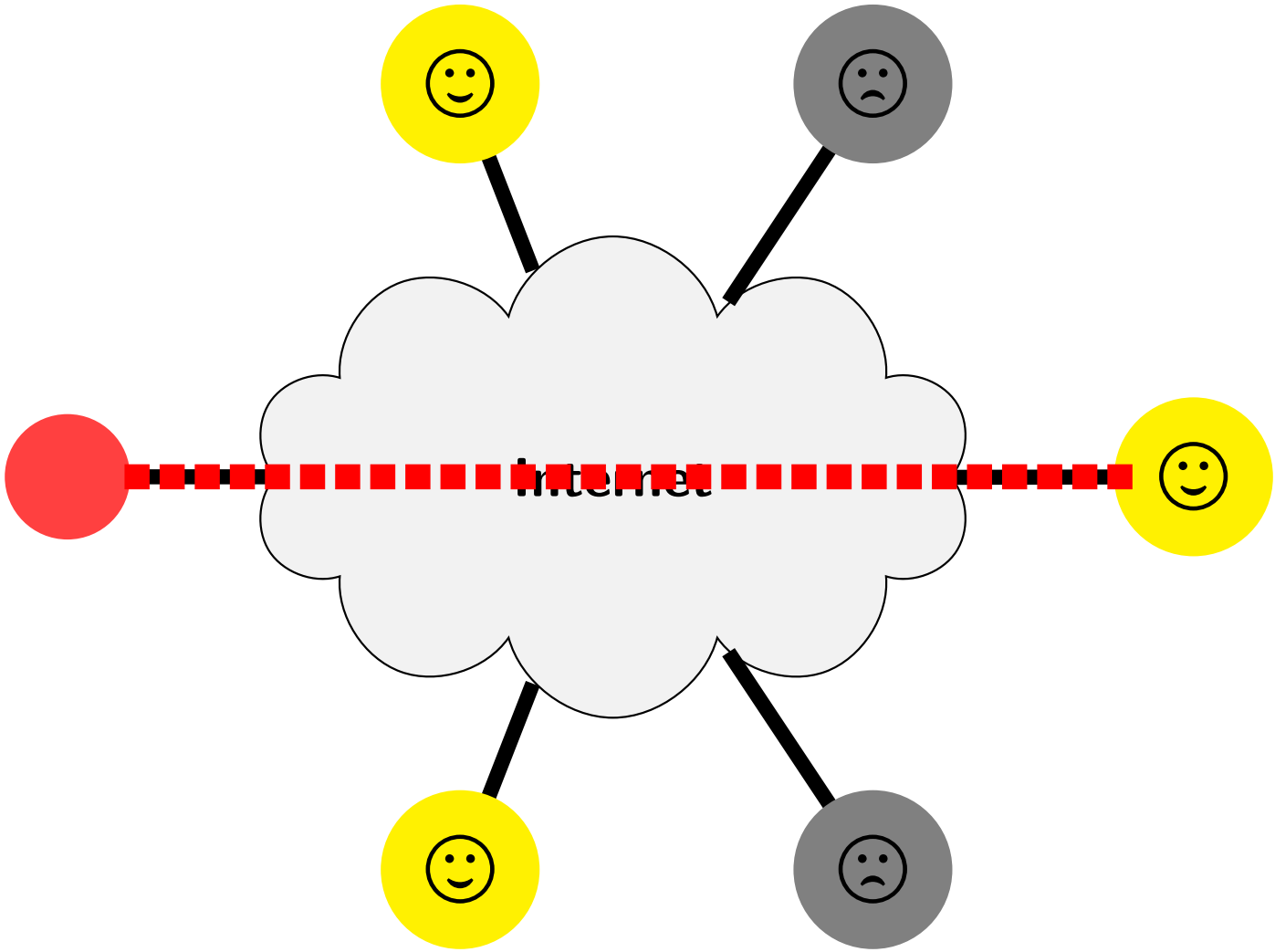
Peer Selection

Some peers are predicted as "good" and some "bad".



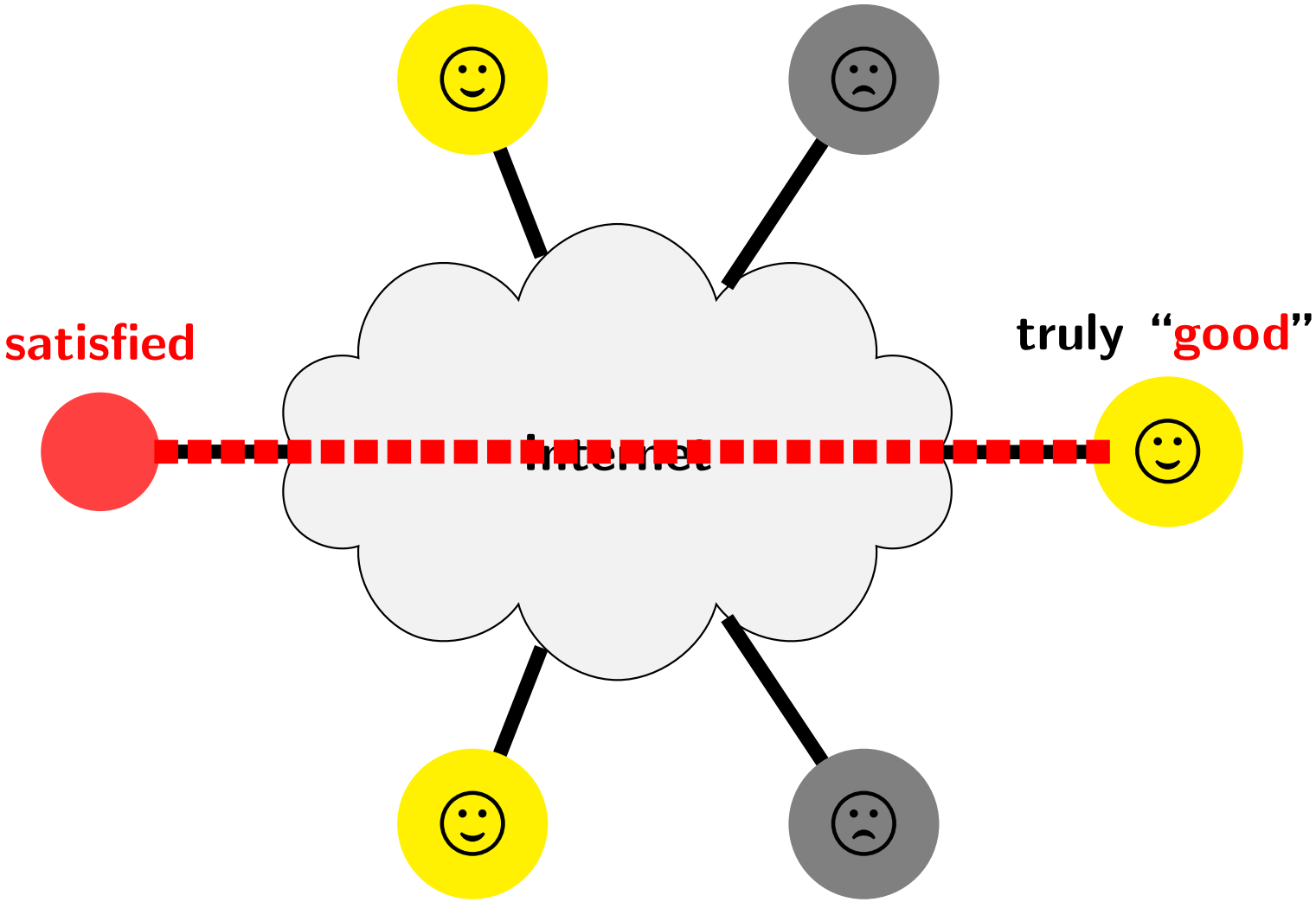
Peer Selection

Select a peer that is predicted as "good".



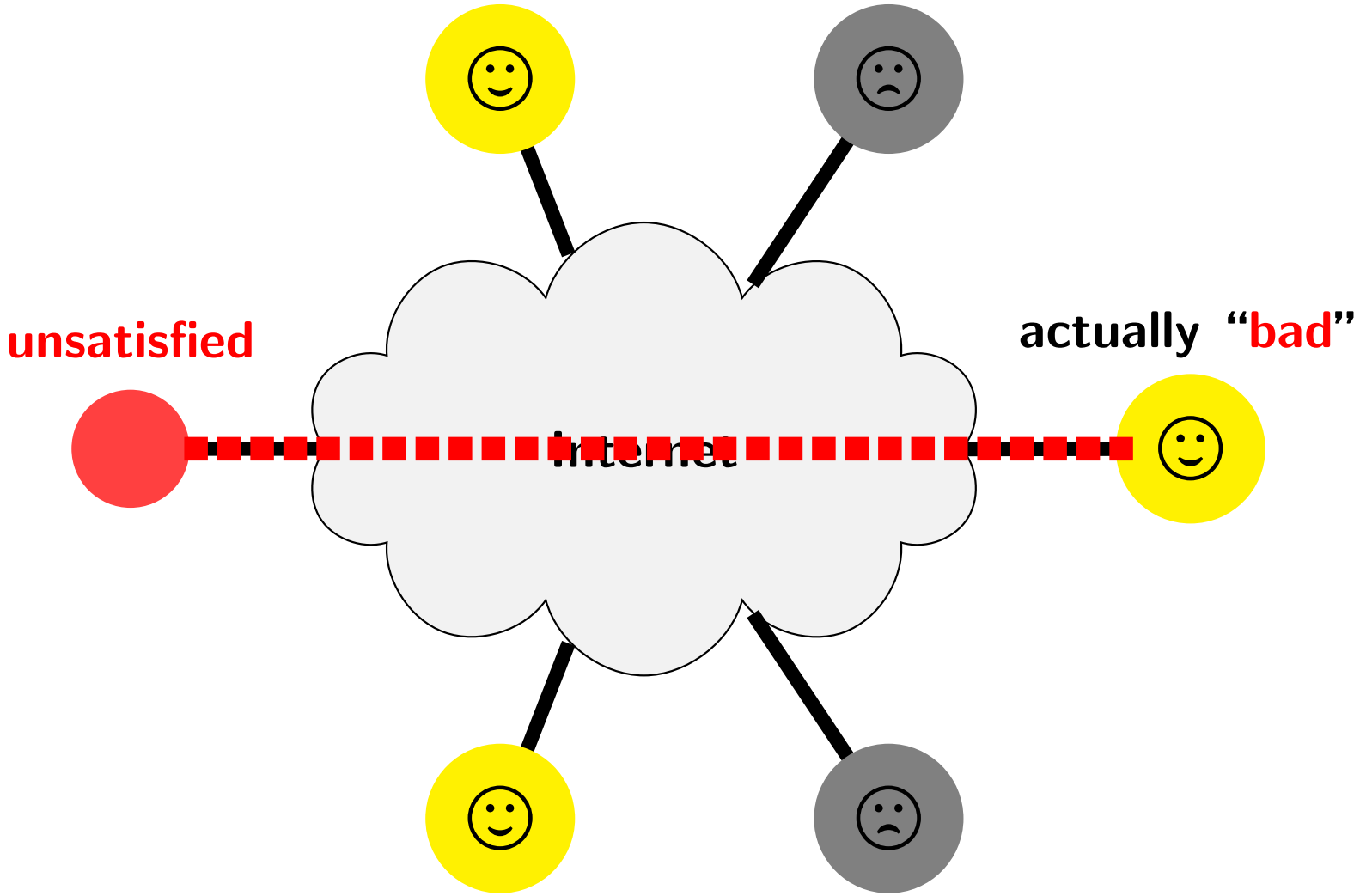
Peer Selection

The node is satisfied if the selected peer is truly "good".



Peer Selection

The node is unsatisfied if the selected peer is actually "bad".



Peer Selection

Evaluation

Count the number of unsatisfied nodes.

Peer Selection

Evaluation

Count the number of unsatisfied nodes.

Methods that are compared with

classification: class-based prediction

Peer Selection

Evaluation

Count the number of unsatisfied nodes.

Methods that are compared with

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- random peer selection

Peer Selection

Evaluation

Count the number of unsatisfied nodes.

Methods that are compared with

classification: class-based prediction

- random peer selection
- regression: value-based prediction
  - Predict values of some metric by our DMFSGD algorithm.
  - Select the predicted best peer for each node.
  - Check if the selected peers are truly "good".

Peer Selection

Evaluation

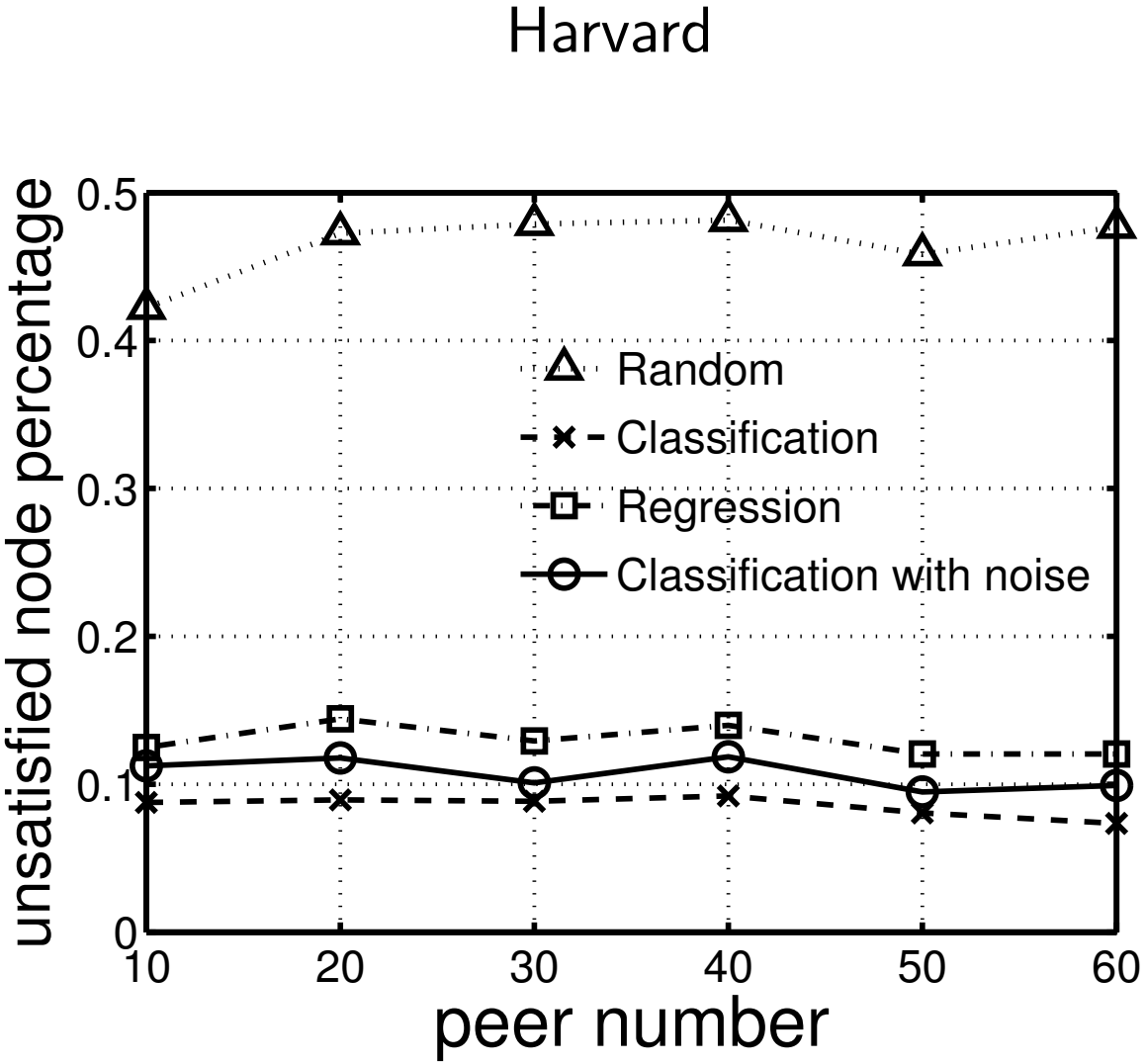
Count the number of unsatisfied nodes.

Methods that are compared with

classification: class-based prediction

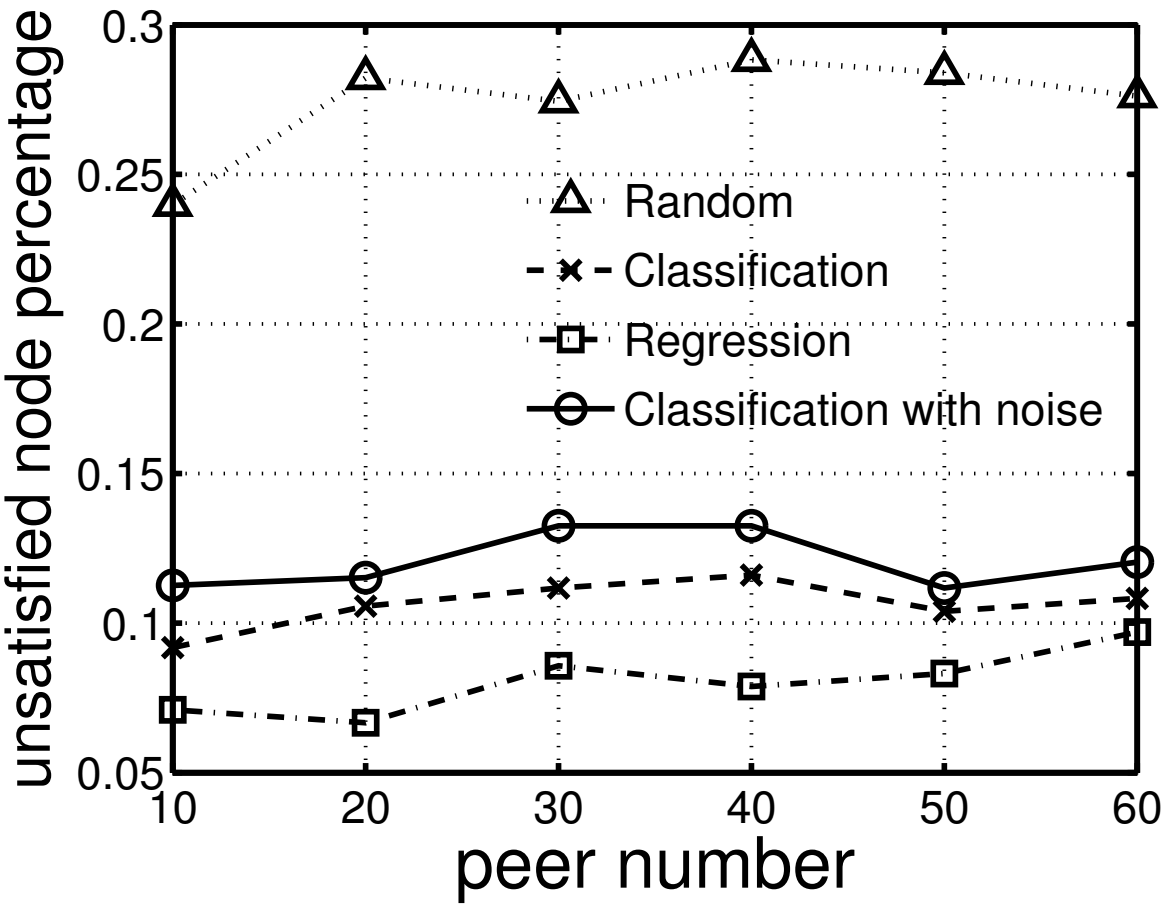
- random peer selection
- regression: value-based prediction
  - Predict values of some metric by our DMFSGD algorithm.
  - Select the predicted best peer for each node.
  - Check if the selected peers are truly "good".
- classification with noise
  - Overall 15% erroneous labels were simulated.

Peer Selection



Peer Selection

HP-S3



Conclusions and Future Work

Decentralized Prediction of Network Performance Classes

- **Class**-based Performance Representation
- Formulation as **Matrix Completion**
- **DMFSGD**: a **decentralized matrix factorization** algorithm by stochastic gradient descent
  - accurate and scalable
  - generic to deal with various metrics
  - robust against erroneous measurements
  - usable on real Internet applications

Future Work

- Multiclass classification

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Acknowledgement

We wish to thank

- Dr. Ramasubramanian for providing the HP-S3 dataset;
- our shepherd Augustin Chaintreau;
- the anonymous reviewers;
- project FP7-Fire ECODE.

Thank you for listening. Any questions?

Low-Rank Matrix Factorization

$$(U, V) = \arg\min L(X, U, V, W, \lambda)$$
$$= \arg\min \sum_{i,j=1}^{n} w_{ij} l(x_{ij}, u_i v_j^T) + \lambda \sum_{i=1}^{n} u_i u_i^T + \lambda \sum_{i=1}^{n} v_i v_i^T$$

- $(U, V) = \{(u_i, v_i),\ i = 1, \ldots, n\}$
- $w_{ij} = 1$ if x_{ij} is known and 0 otherwise
- l: loss function that penalizes the difference between x and $\hat{x}$
  - square loss function: $l(x, \hat{x}) = (x - \hat{x})^2$;
  - hinge loss function: $l(x, \hat{x}) = \max(0, 1 - x\hat{x})$;
  - logistic loss function: $l(x, \hat{x}) = \ln(1 + e^{-x\hat{x}})$.
- λ: regularization coefficient

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Parameter Sensitivity

parameter	tested values
learning rate η	0.001, 0.01, 0.1, 1
regularization coefficient λ	0.001, 0.01, 0.1, 1
rank r	3, 10, 20, 100
loss function l	hinge, logistic
neighbor number k	5, 10, 30, 50 (Harvard and HP-S3) 16, 32, 64, 128 (Meridian)
classification threshold τ	10%, 25%, 50%, 75%, 90% (portion of good-performing)

*chosen value

Insensitive because the inputs are either 1 or -1.

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Robustness Against Erroneous Measurement

Source of Erroneous Measurements

- inaccurate measurement techniques
- network anomaly

Errors Type

1. Flip near τ
2. Underestimation bias
3. Flip randomly
4. Good-to-Bad