Nona: A Stochastic Congestion-Aware Job Scheduler for Real-Time Inference Queries

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** MIT, † EURECOM, ‡ Technion.*

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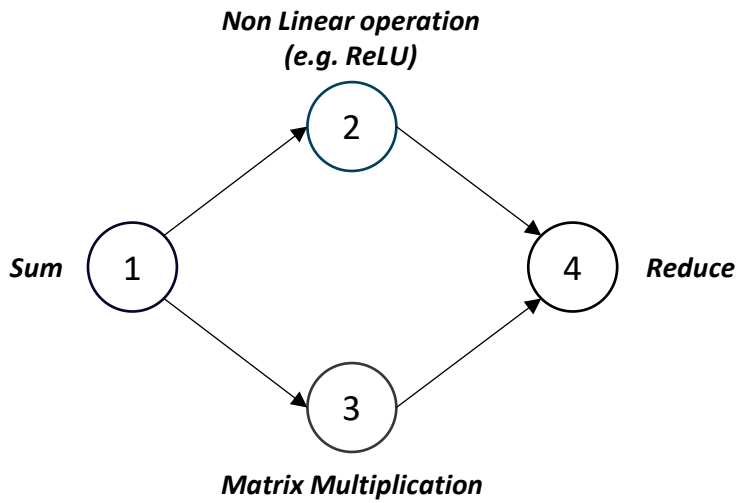
Real-time Inference Requests are Flooding Datacenters

- ChatGPT serves in the order of 10 million inference queries per day
- 2024’s growth of AI unit at Microsoft is “all inference”
- Interactive workloads have strict latency requirements

What is scheduling?

- Users submit *jobs*, or Directed Acyclic Graphs (DAG), of operations to the cluster.
- Along with the input data, this specifies what the cluster should do, and how to obtain the result.



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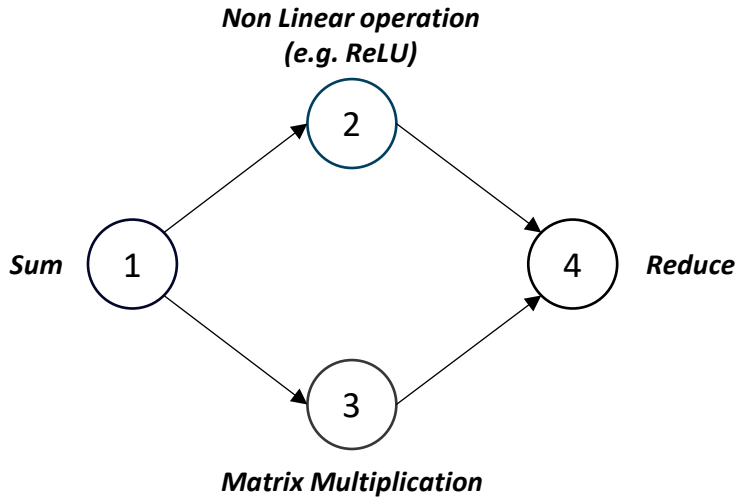

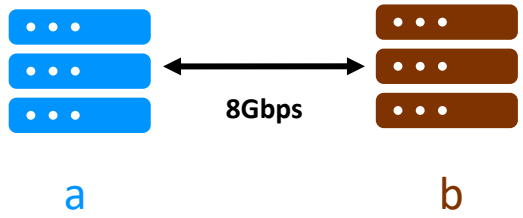

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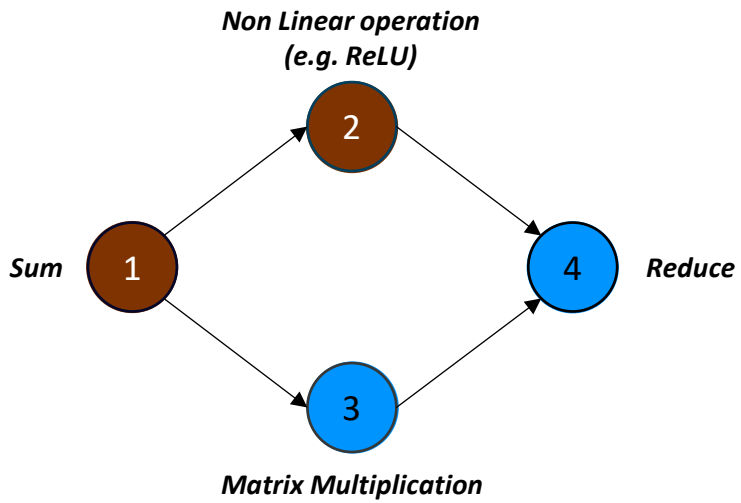

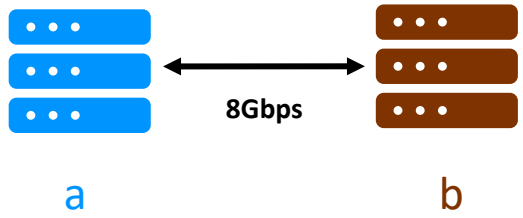

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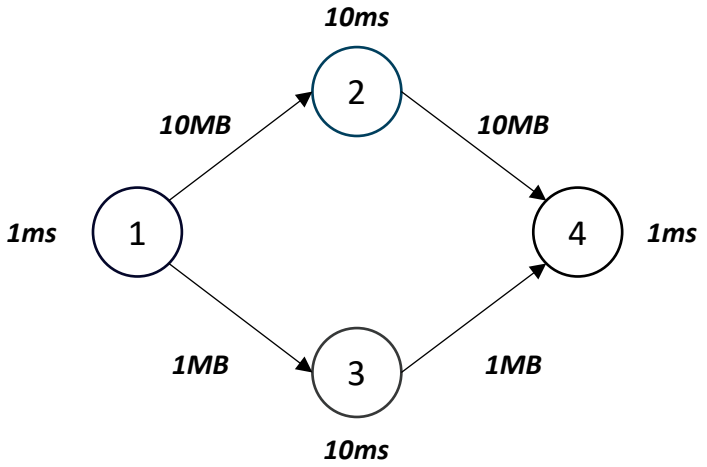

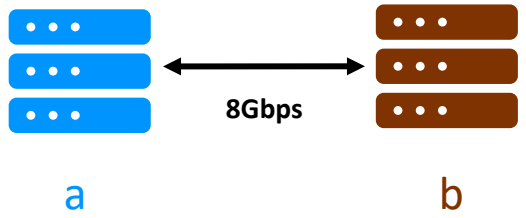

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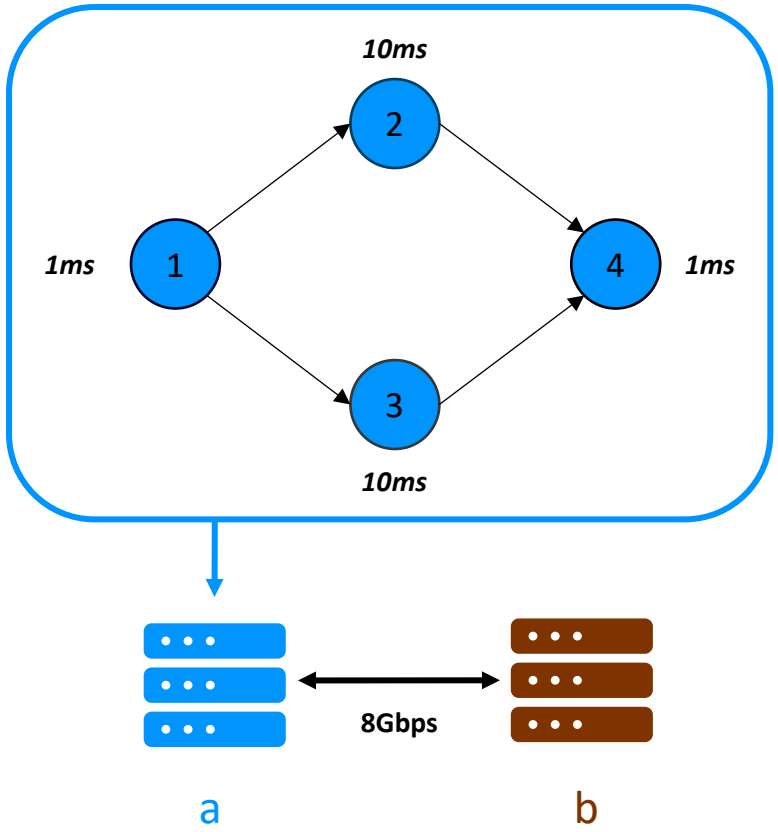

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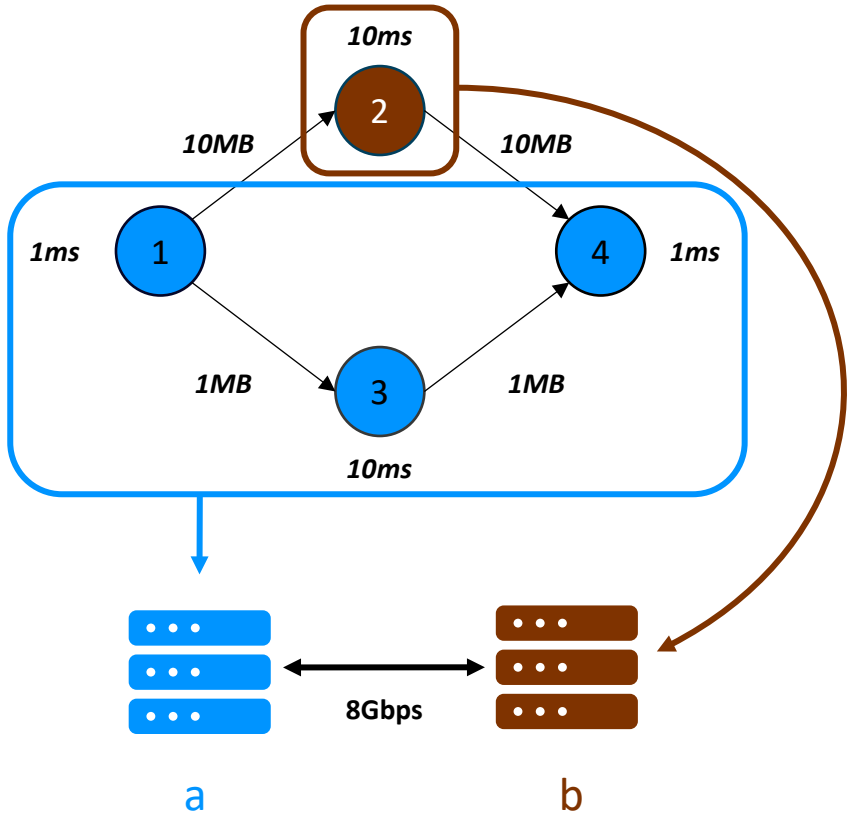

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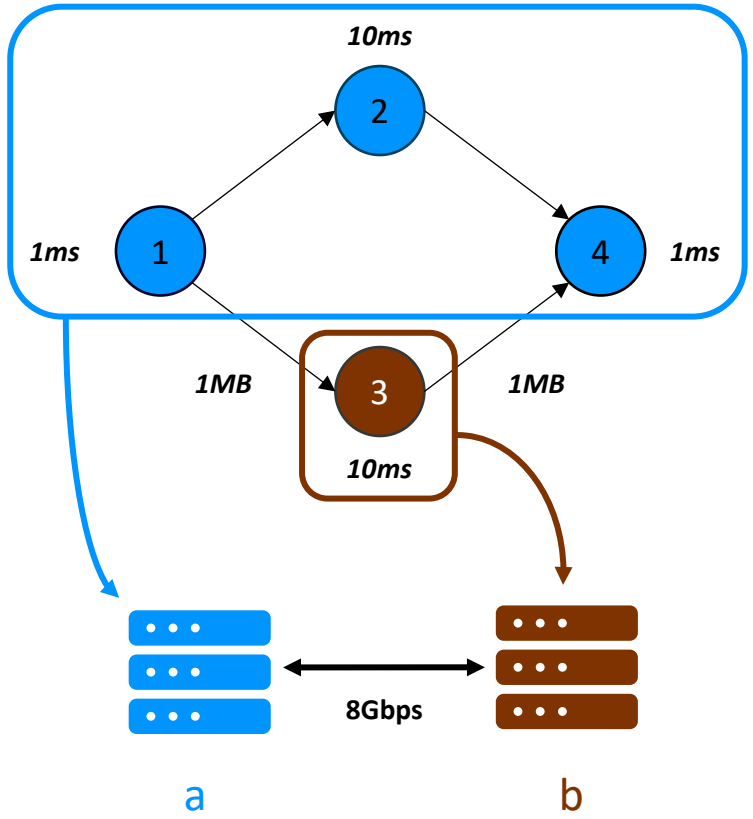

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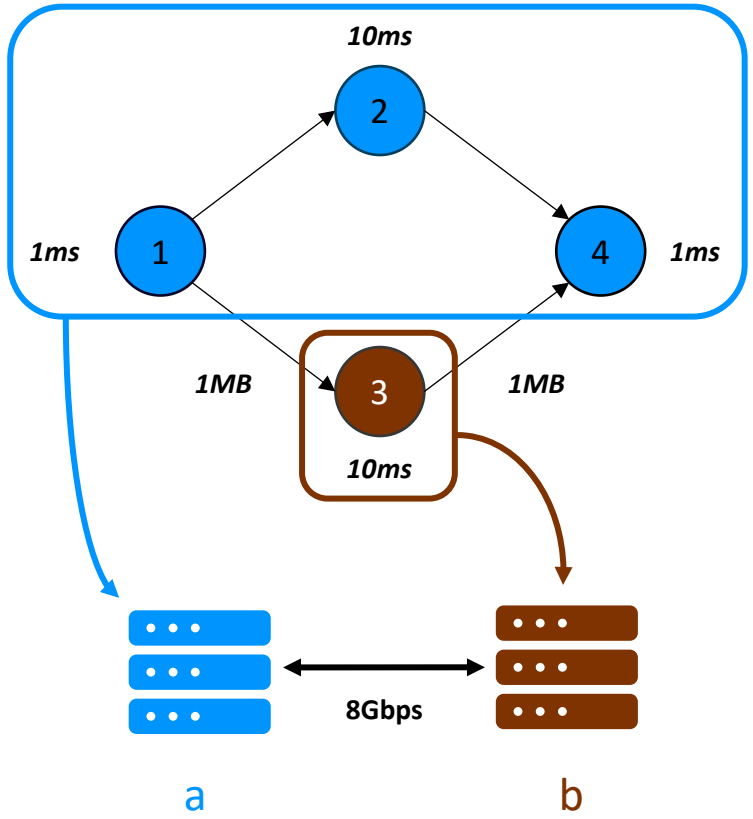

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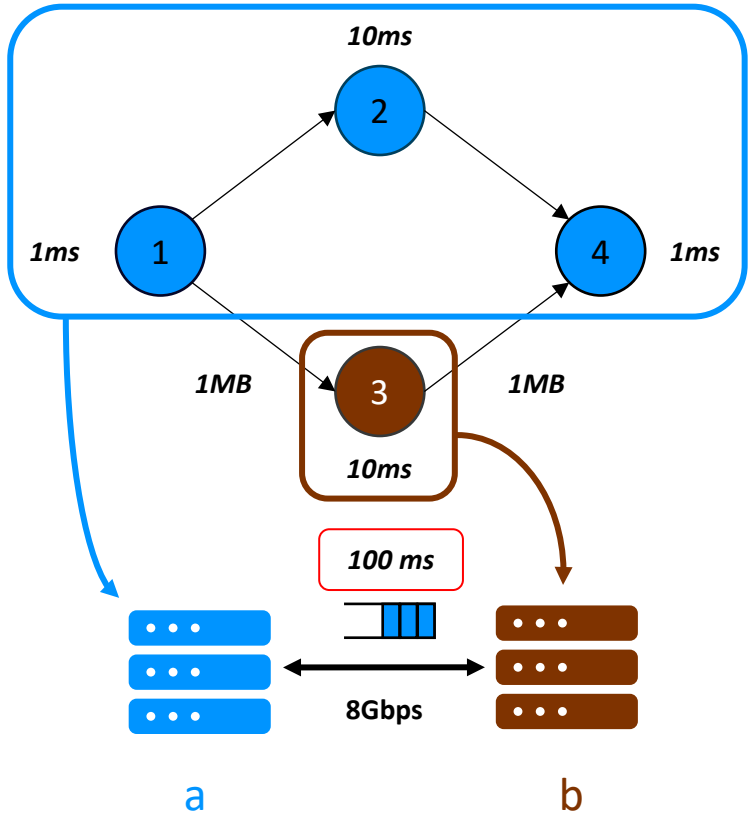

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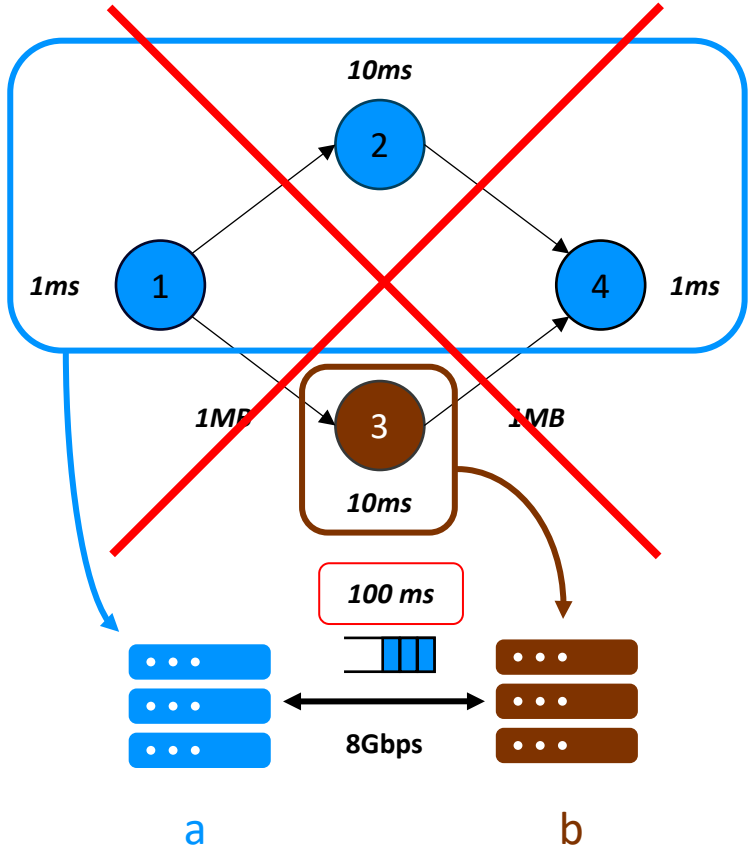

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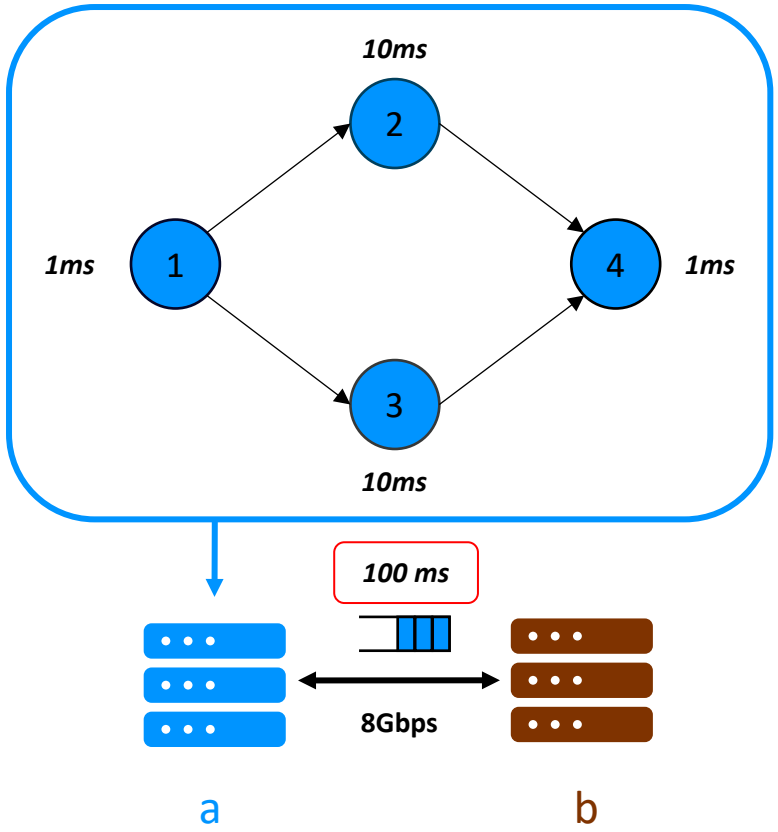

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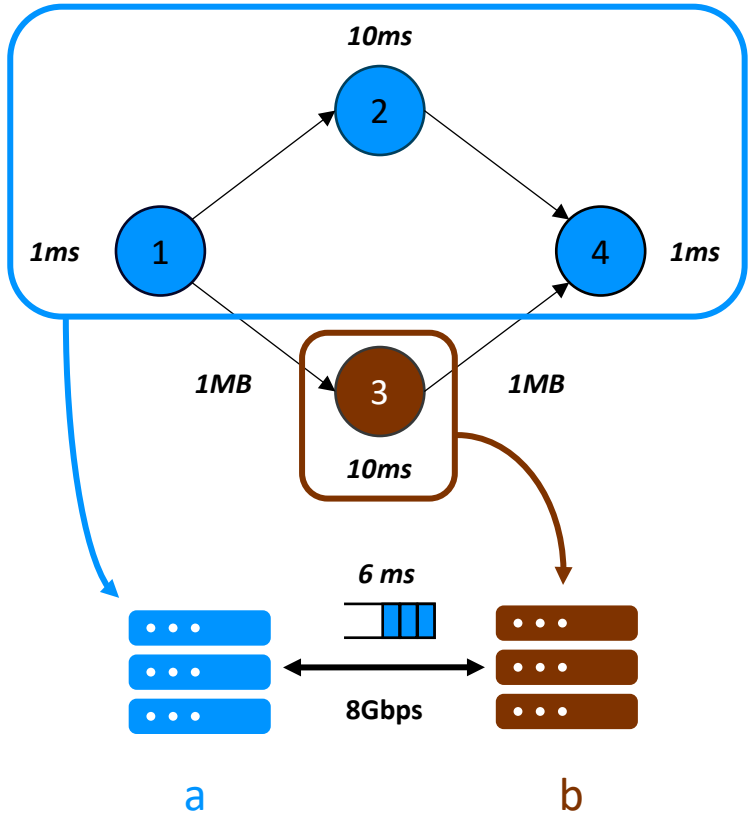

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Queueing delay should be taken into account when making scheduling decisions

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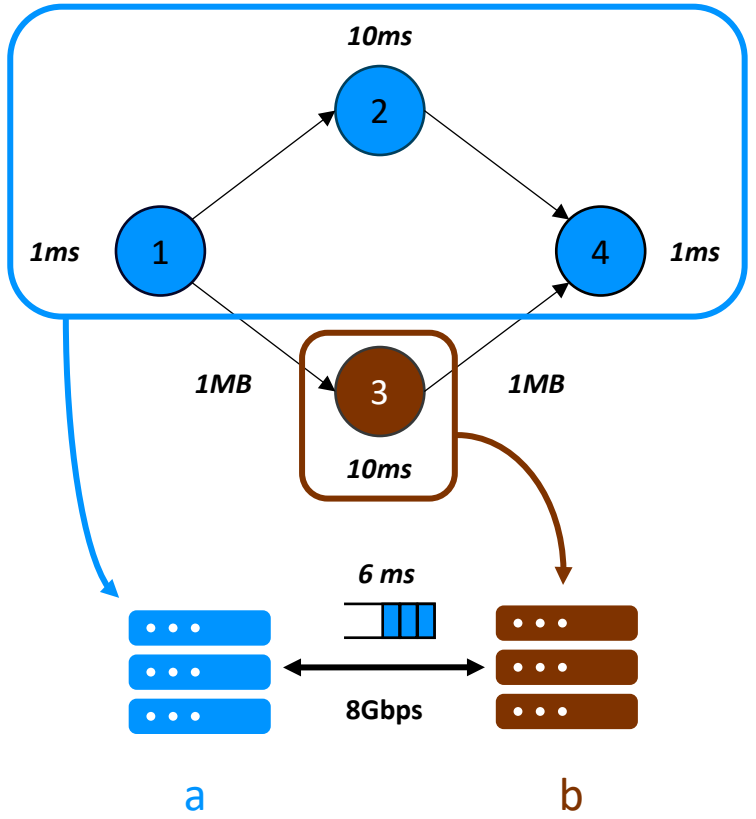
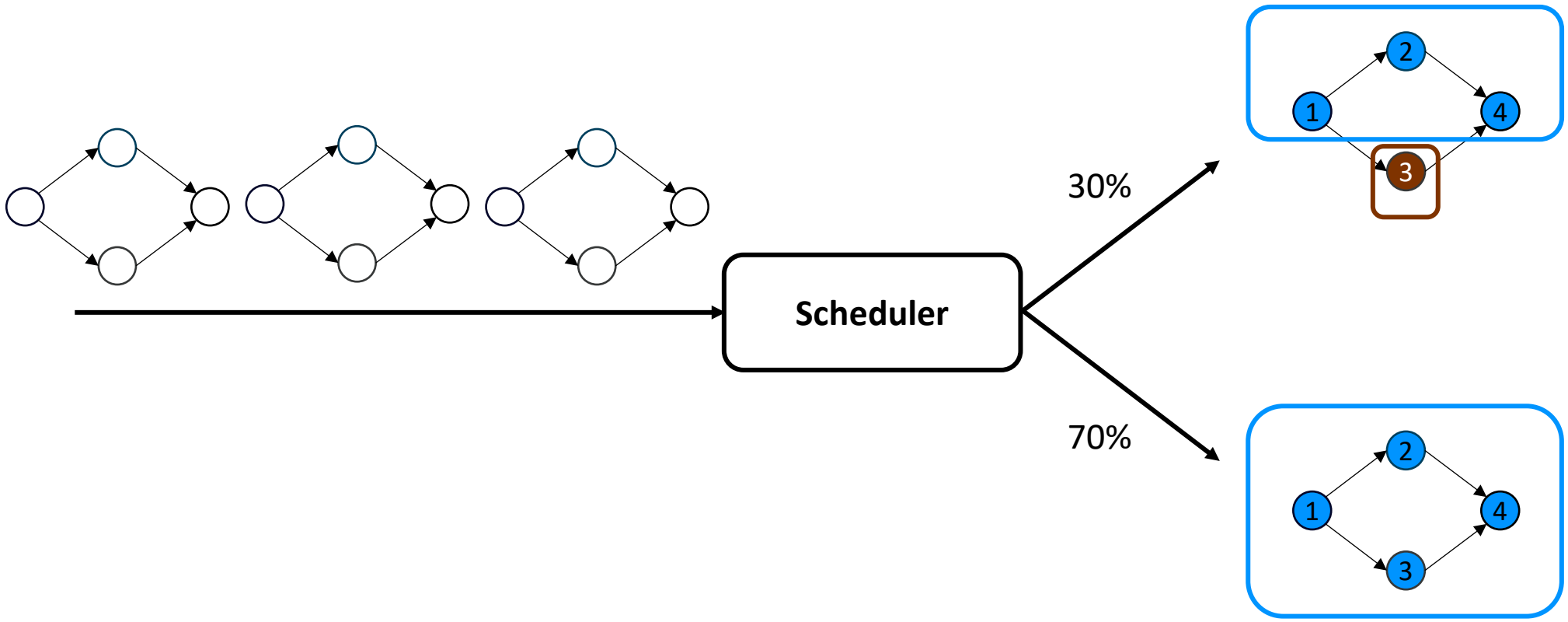


Scheduling matters - Example

- The actual optimum is somewhere between different allocations



Existing schedulers - Network Congestion

Learning/History based

- Gandiva[OSDI'18]: learns isolated network costs
- Optimus[EuroSys'18]: assumes no congestion
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Taking the network into account is hard, predicting network queueing is even more challenging

One approach: Queueing models

Advantages:

- Pollaczek–Khinchine formula to predict queueing delays at different parts in the network

Challenges:

- Strong arrival process assumptions
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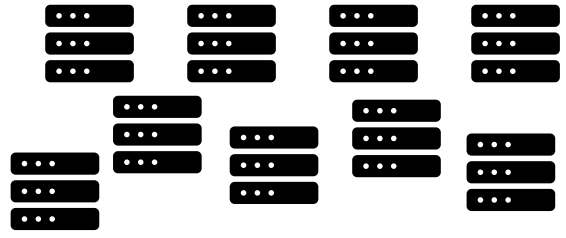
Solution: Stochastic scheduling!

Users

Nona’s System Model



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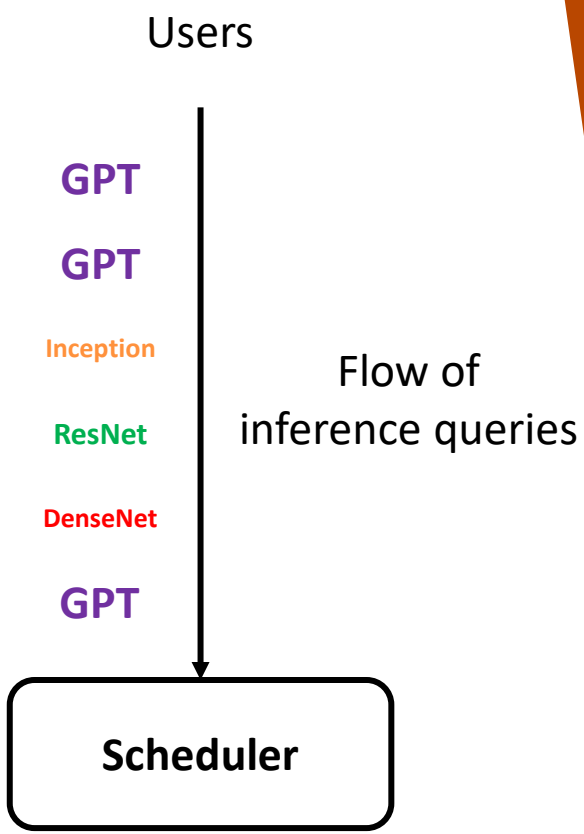

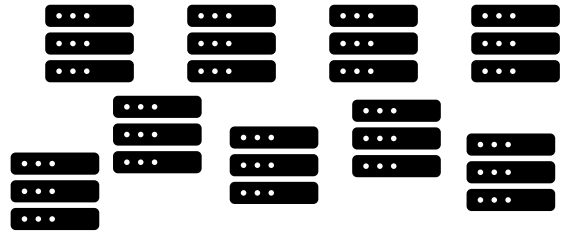

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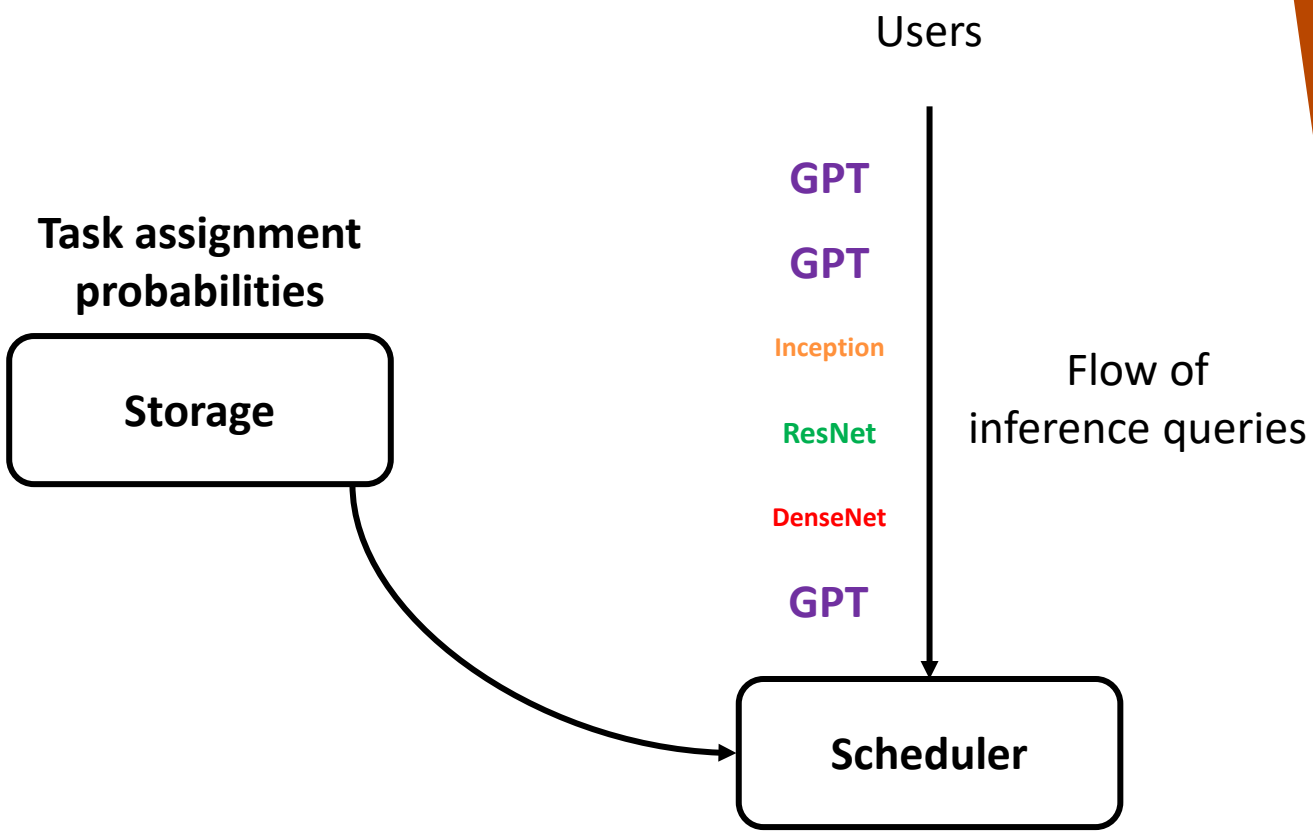

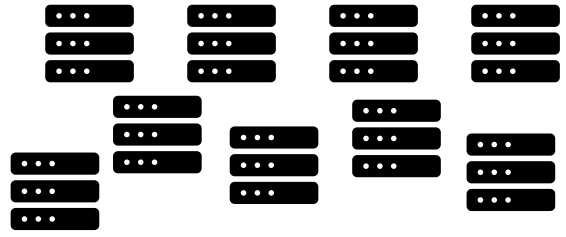

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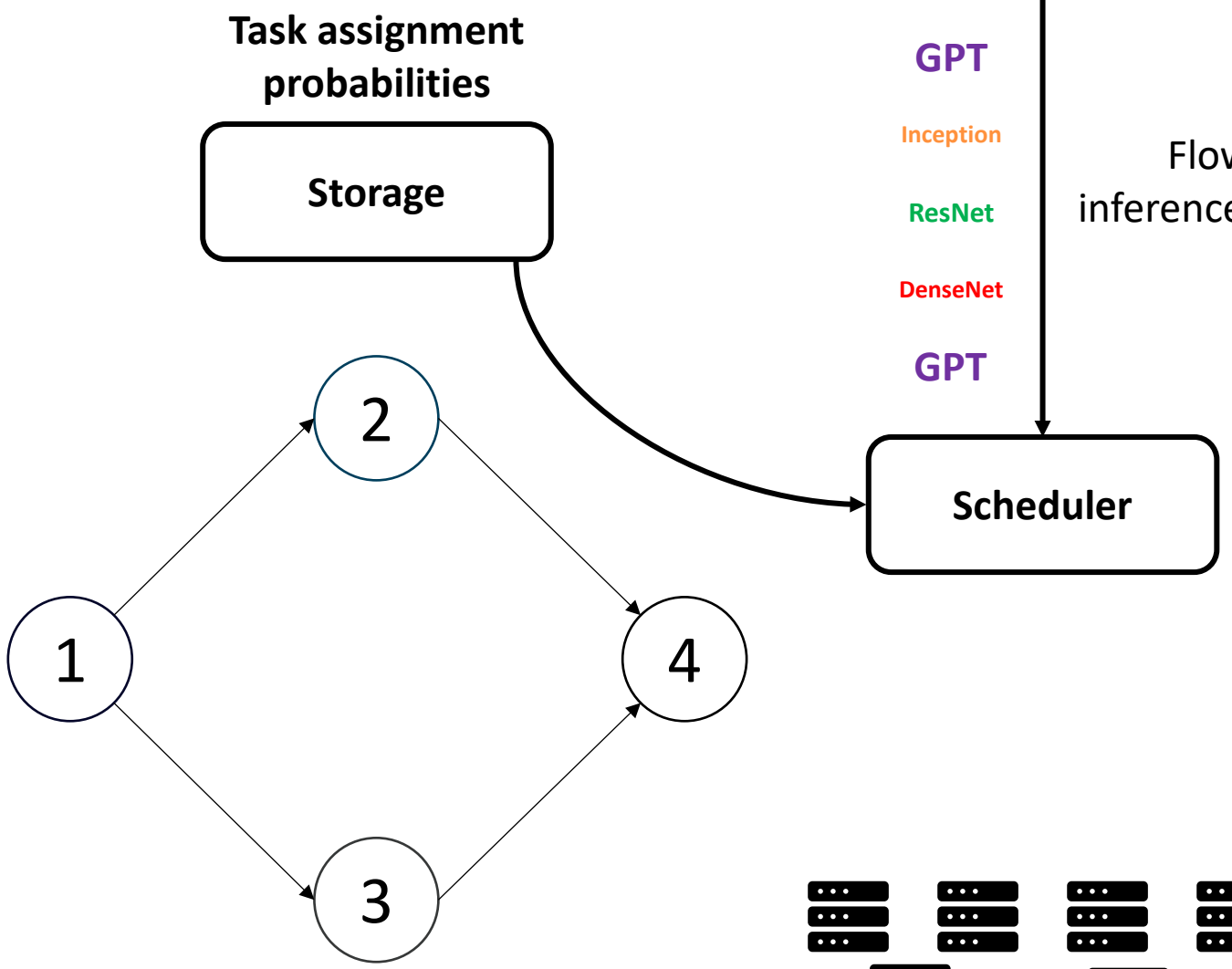
$$p_{1,2} = \begin{pmatrix} 0.7 \\ 0.1 \\ 0.1 \\ 0.1 \\ 0 \end{pmatrix} \begin{matrix} : 1+2+3+4 \\ : 1+2+4 \mid 3 \\ : 1+2 \mid 3+4 \\ : 1+3 \mid 2+4 \\ : 1+3+4 \mid 2 \end{matrix}$$



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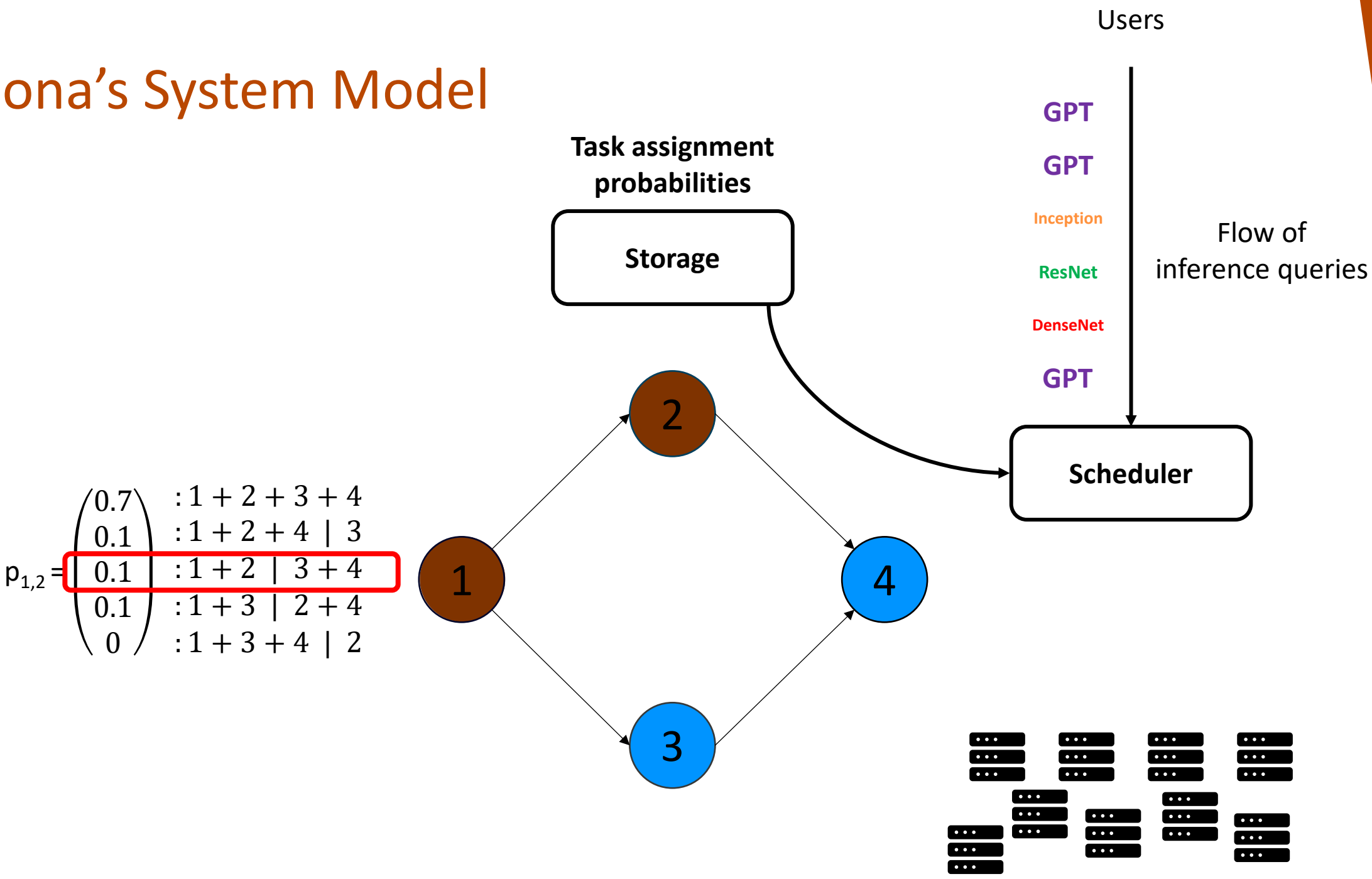

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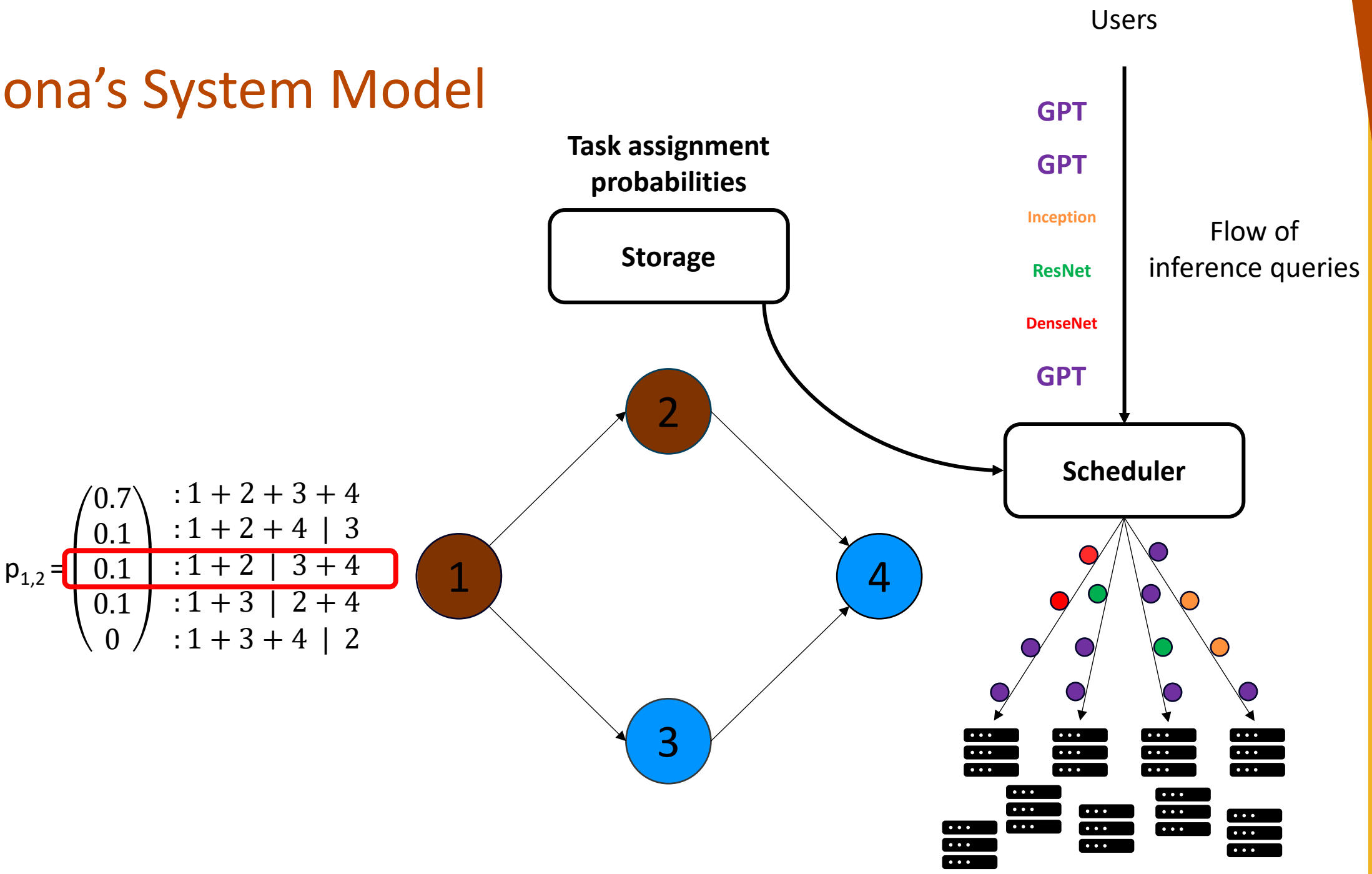

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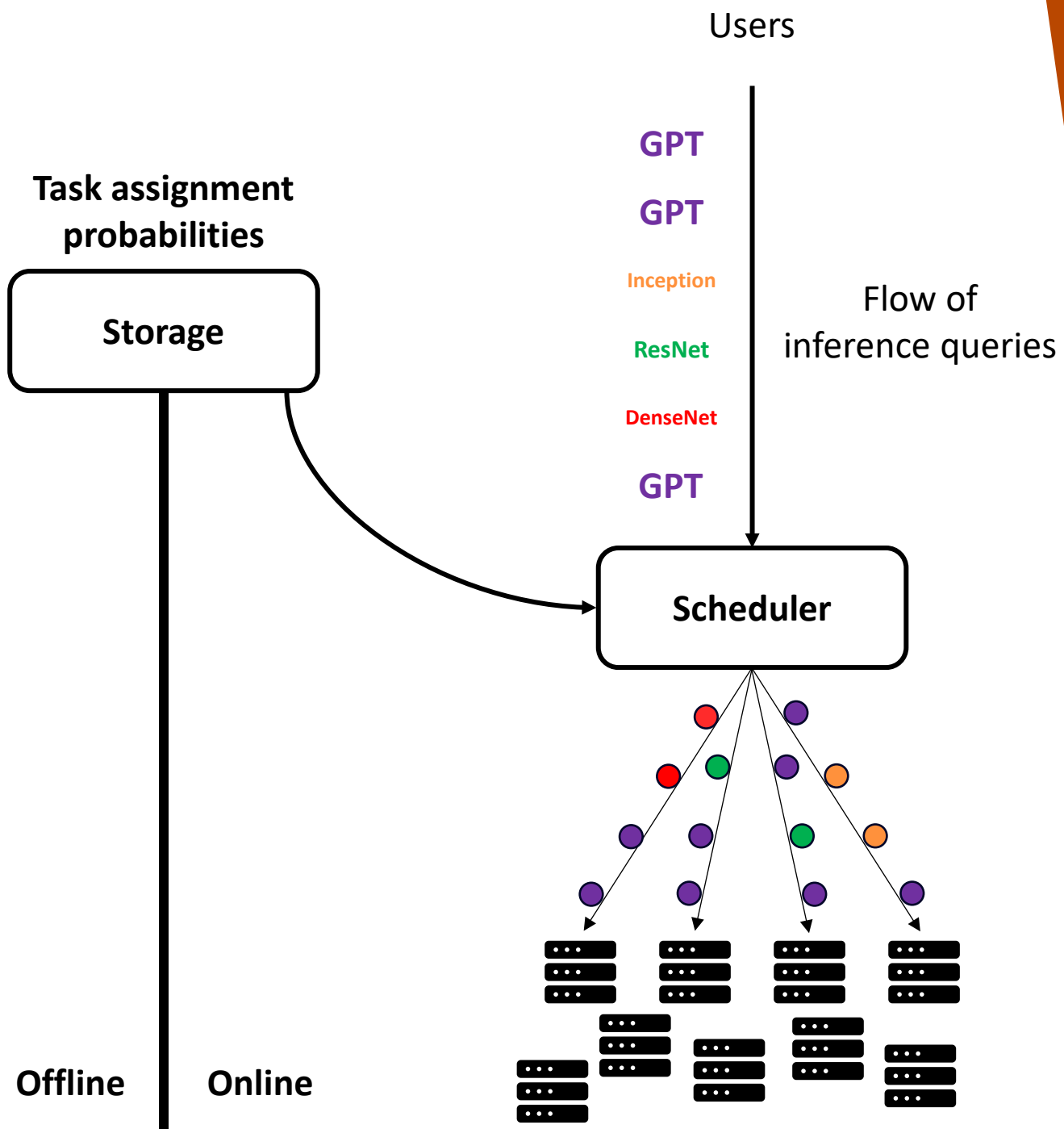

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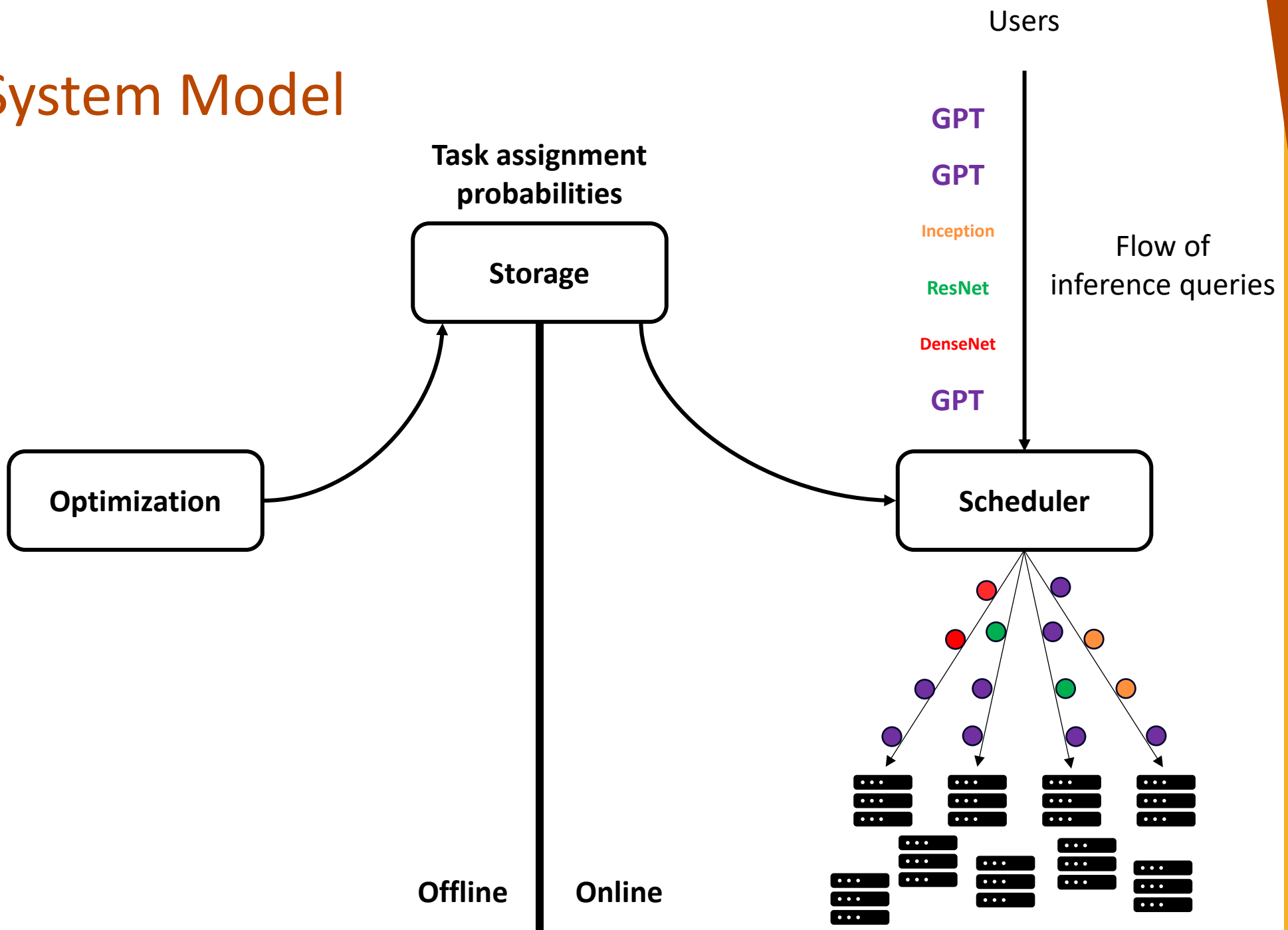

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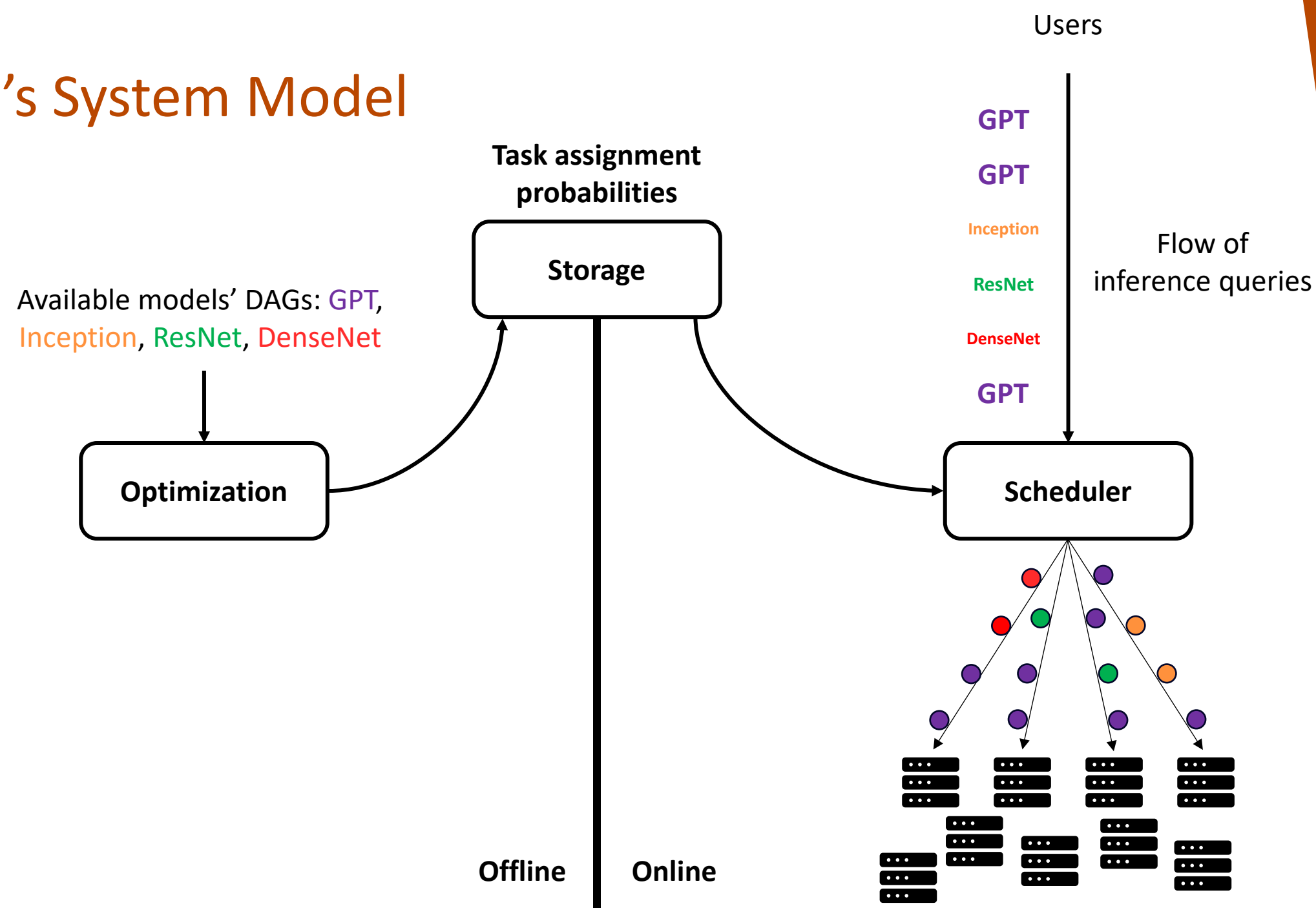

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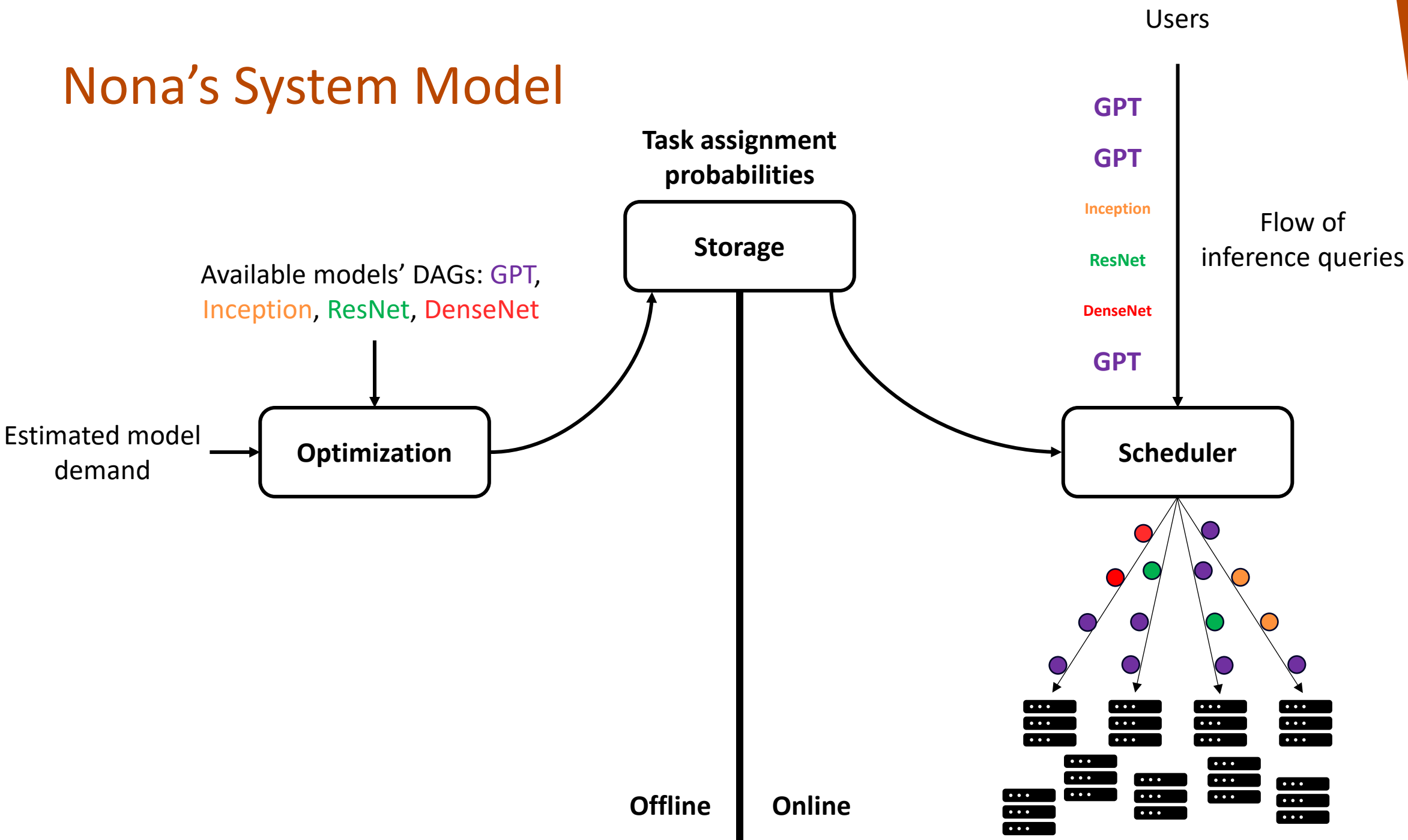

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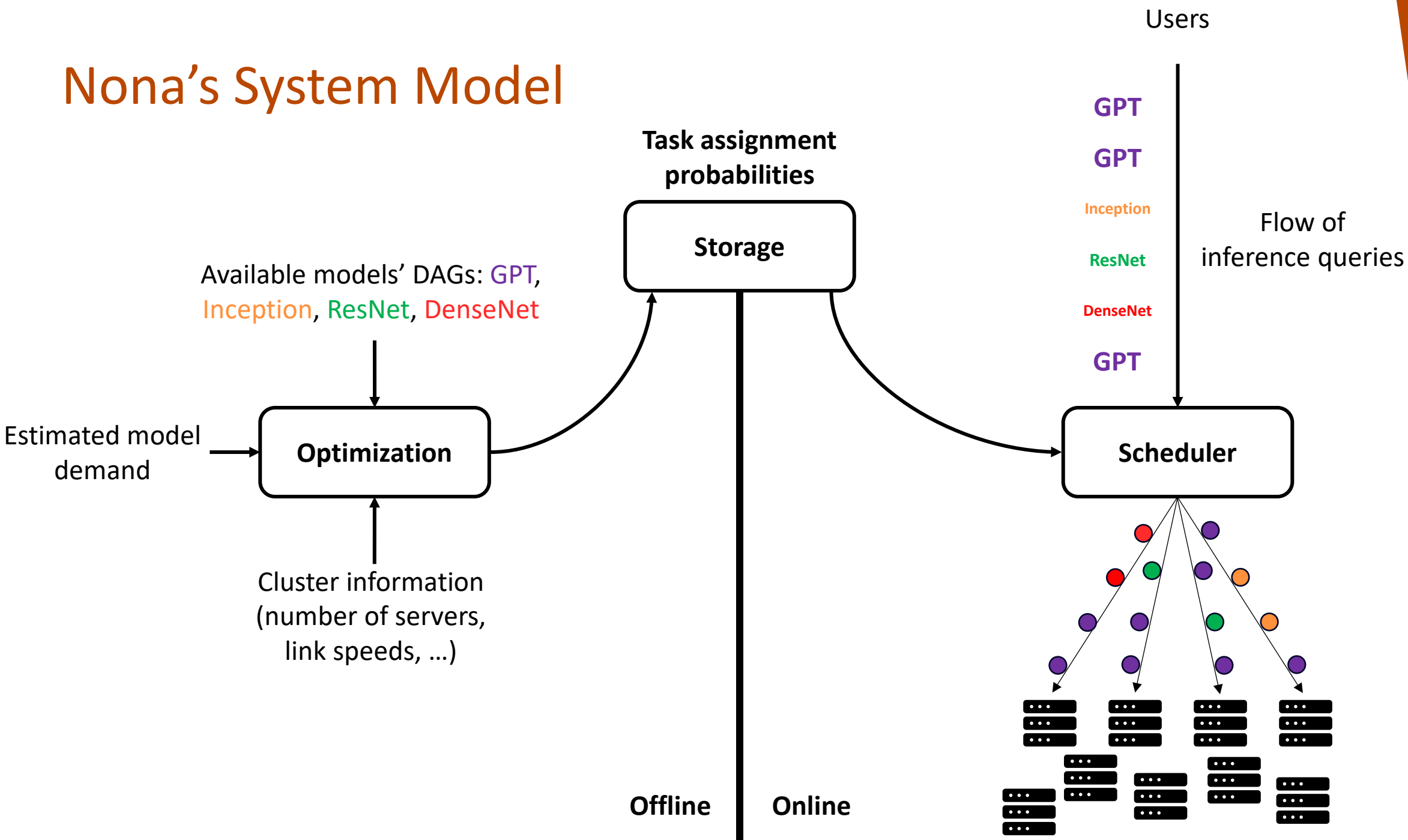

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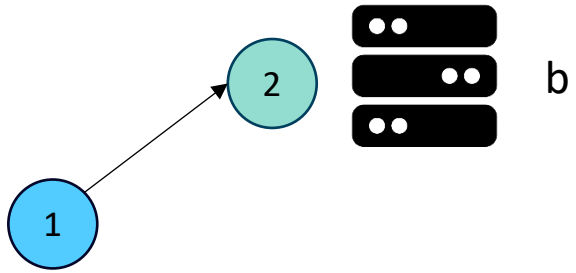

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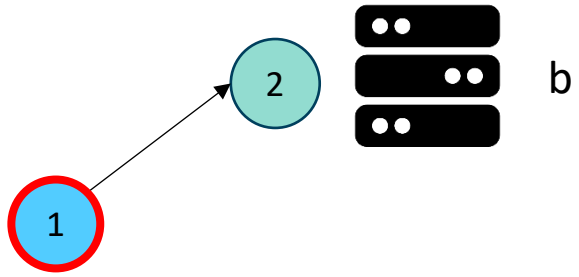

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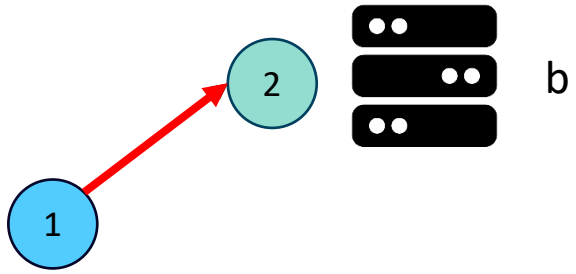

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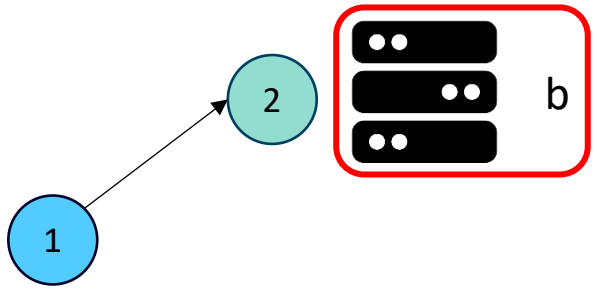

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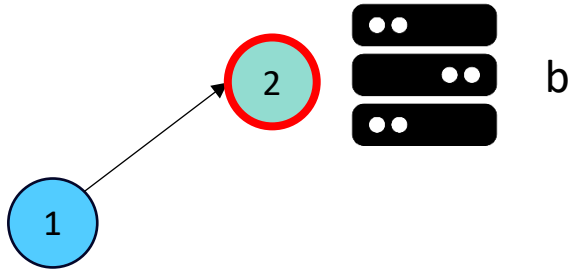

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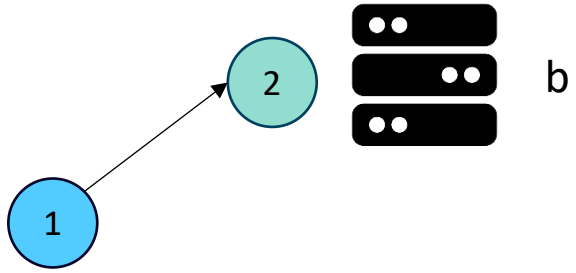

See the paper or nona.csail.mit.edu for more details

Graph Contraction

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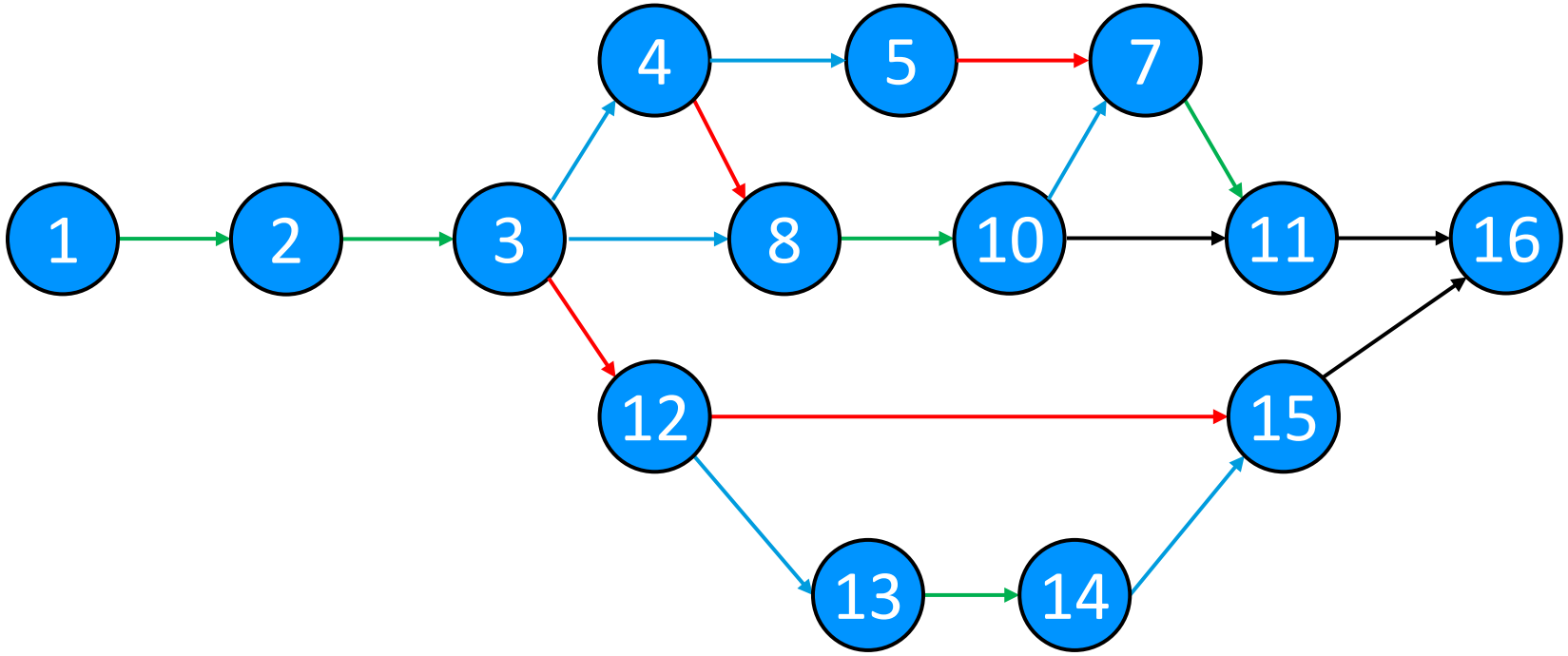

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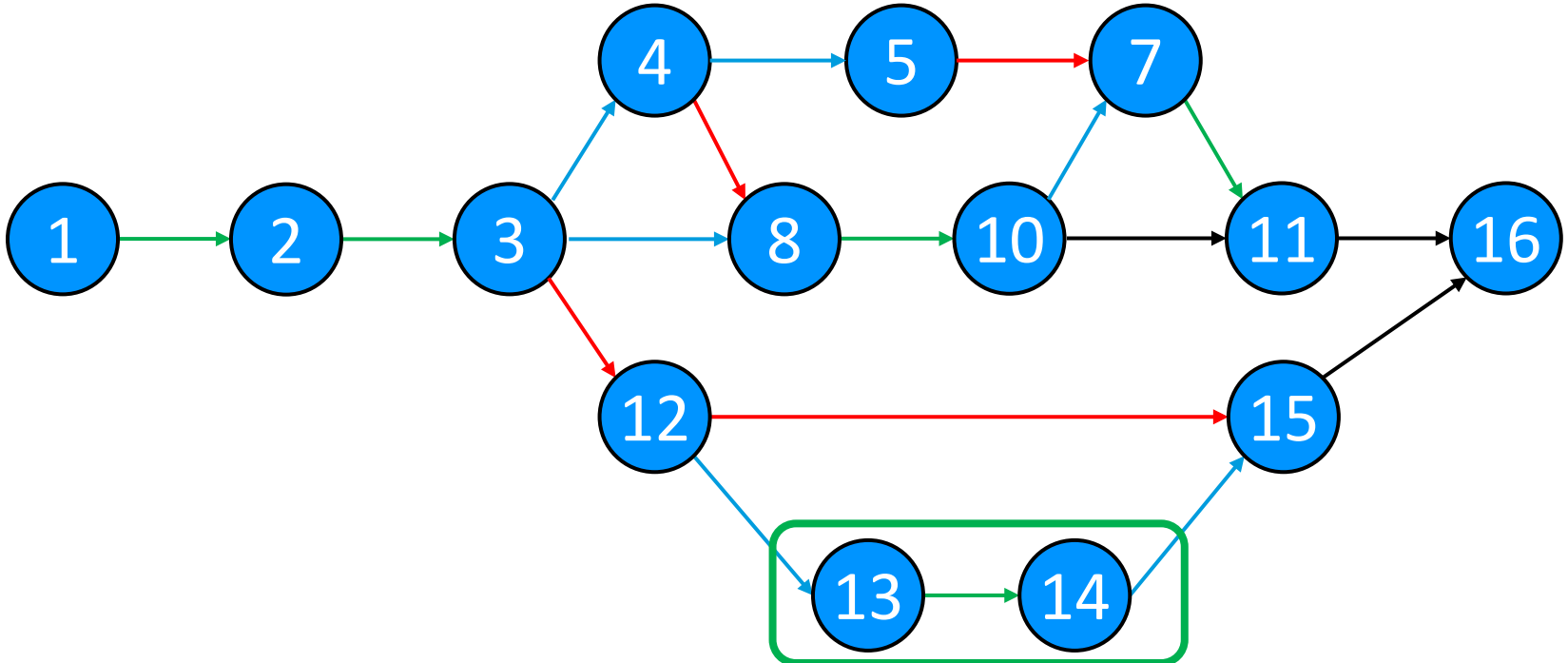

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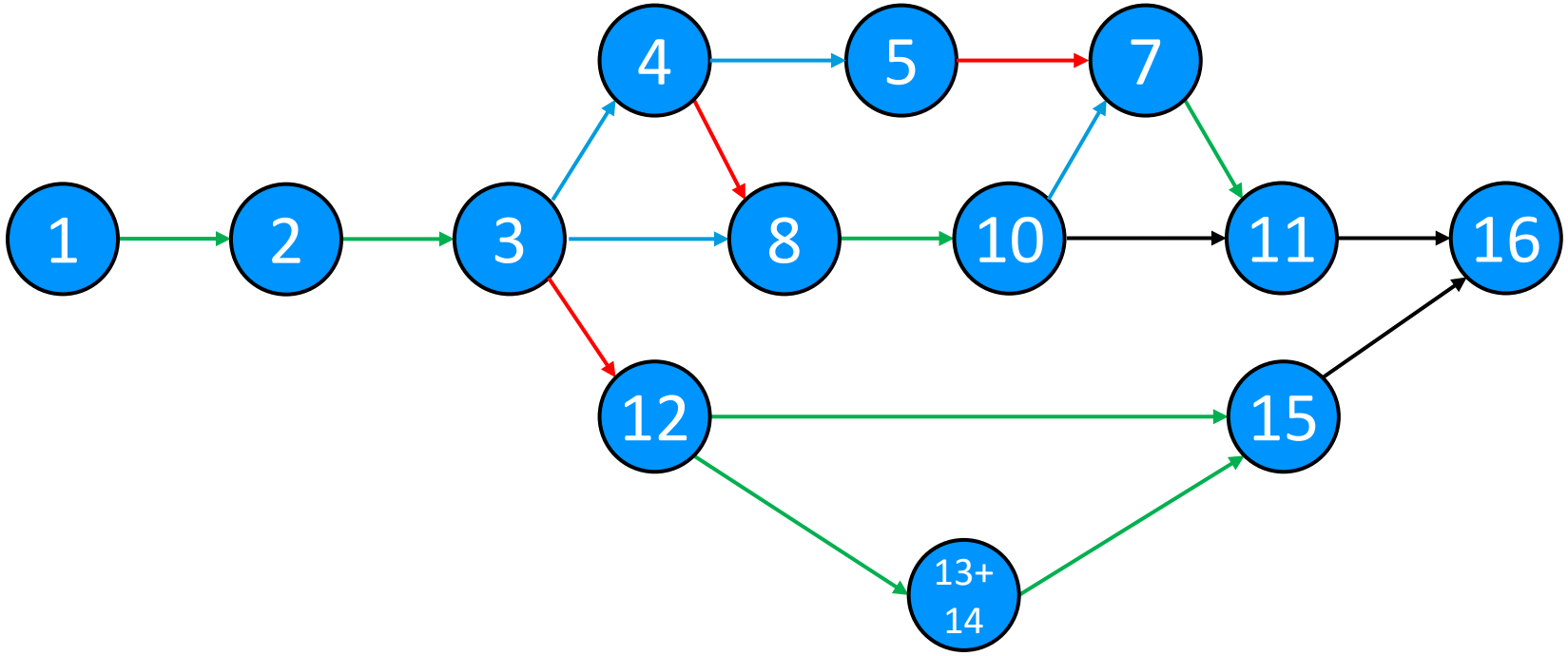

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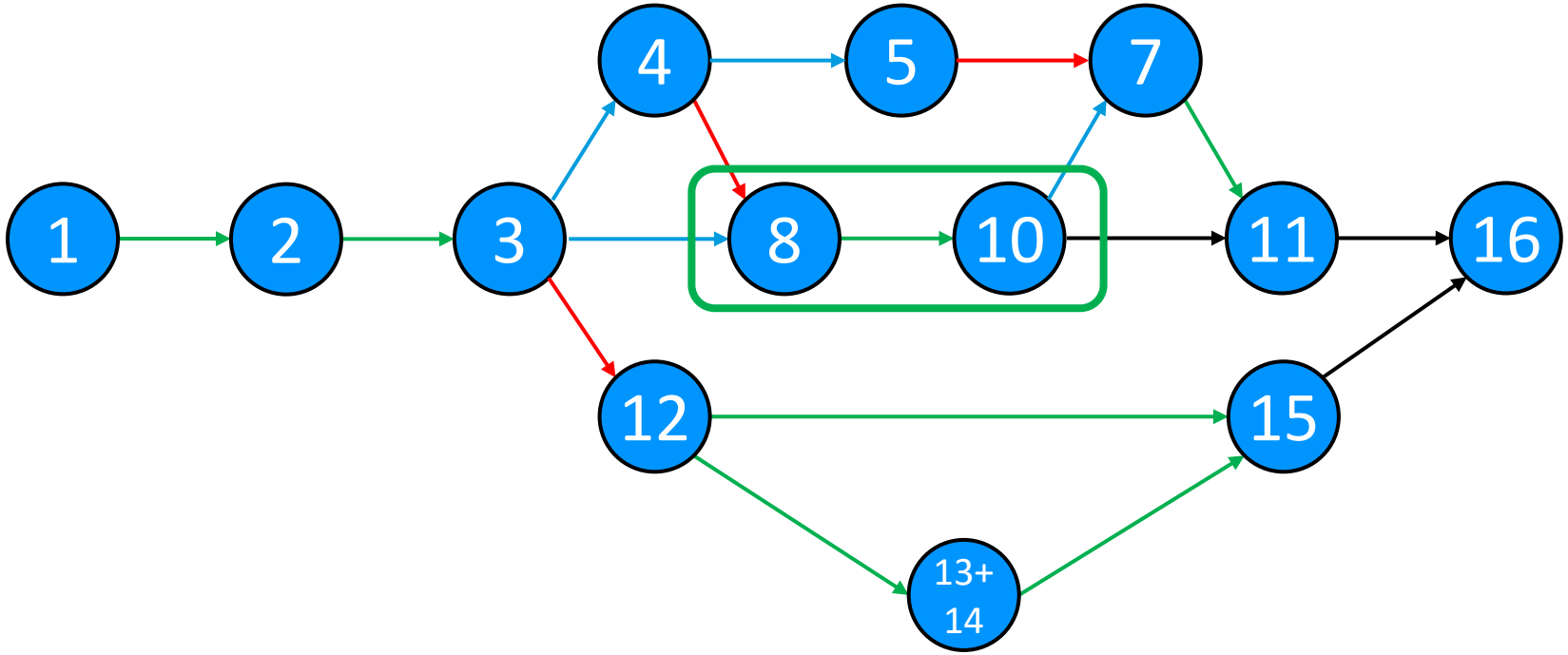

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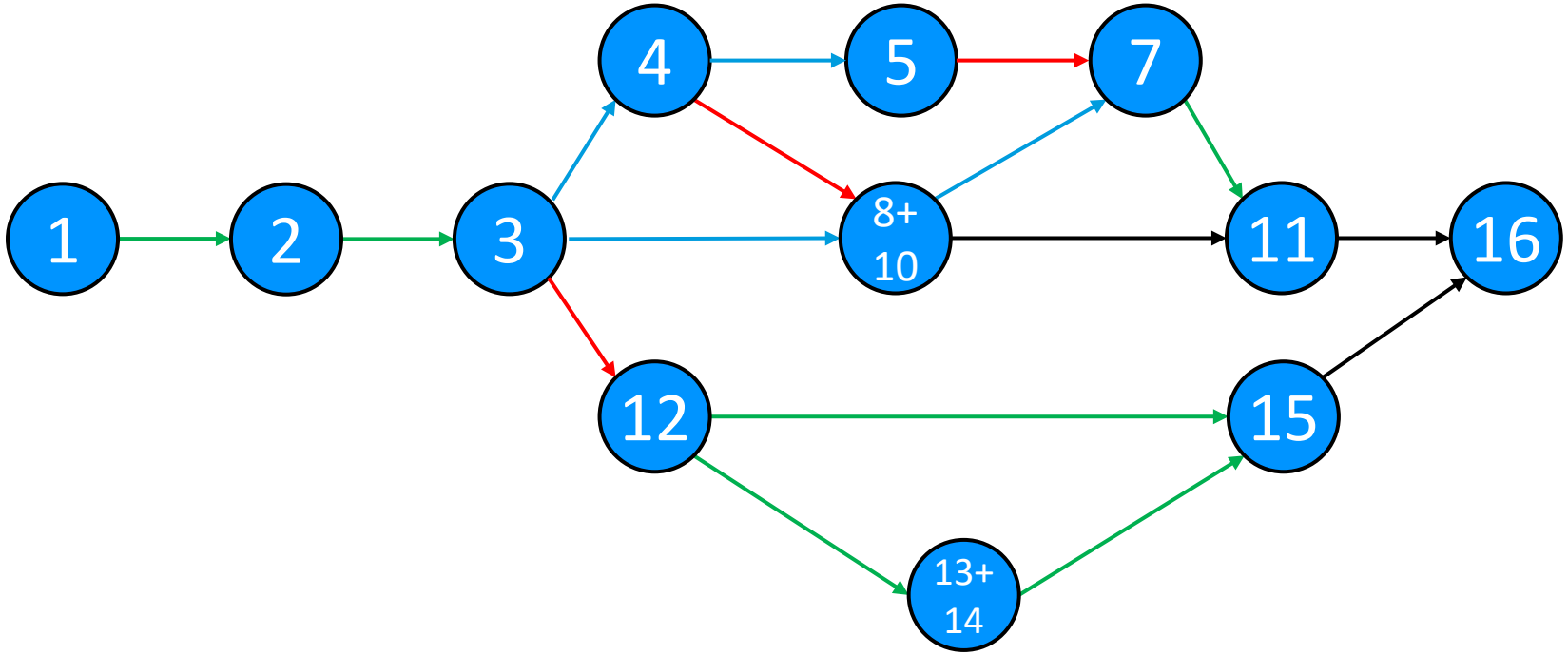

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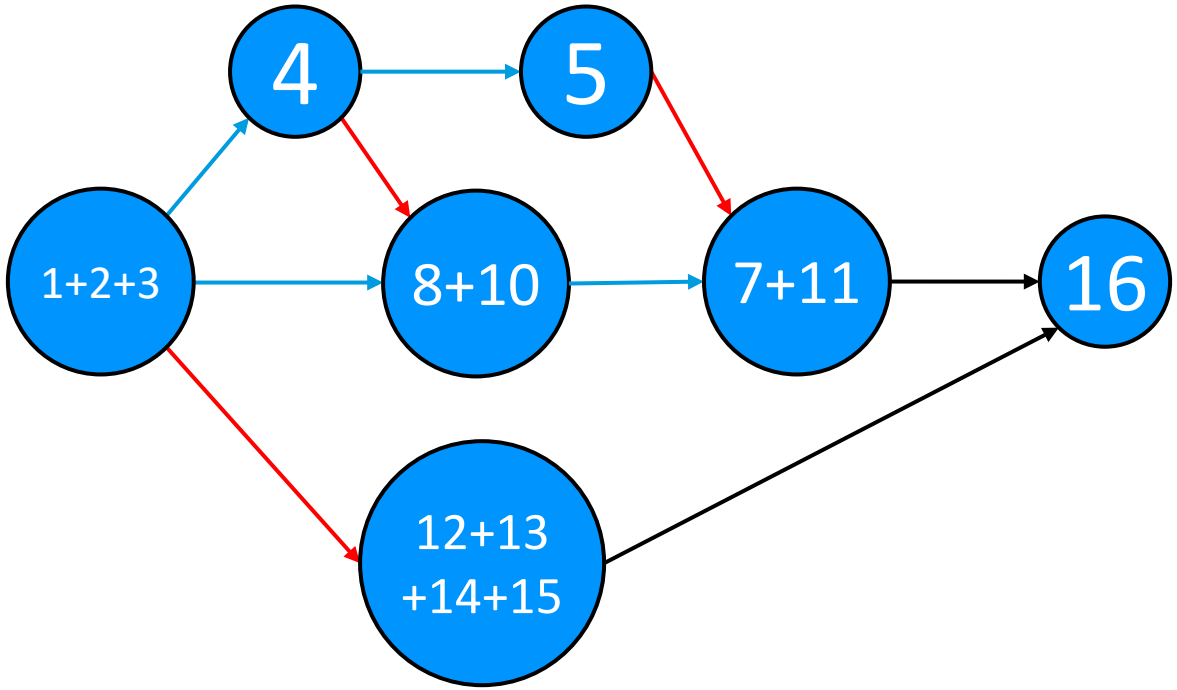

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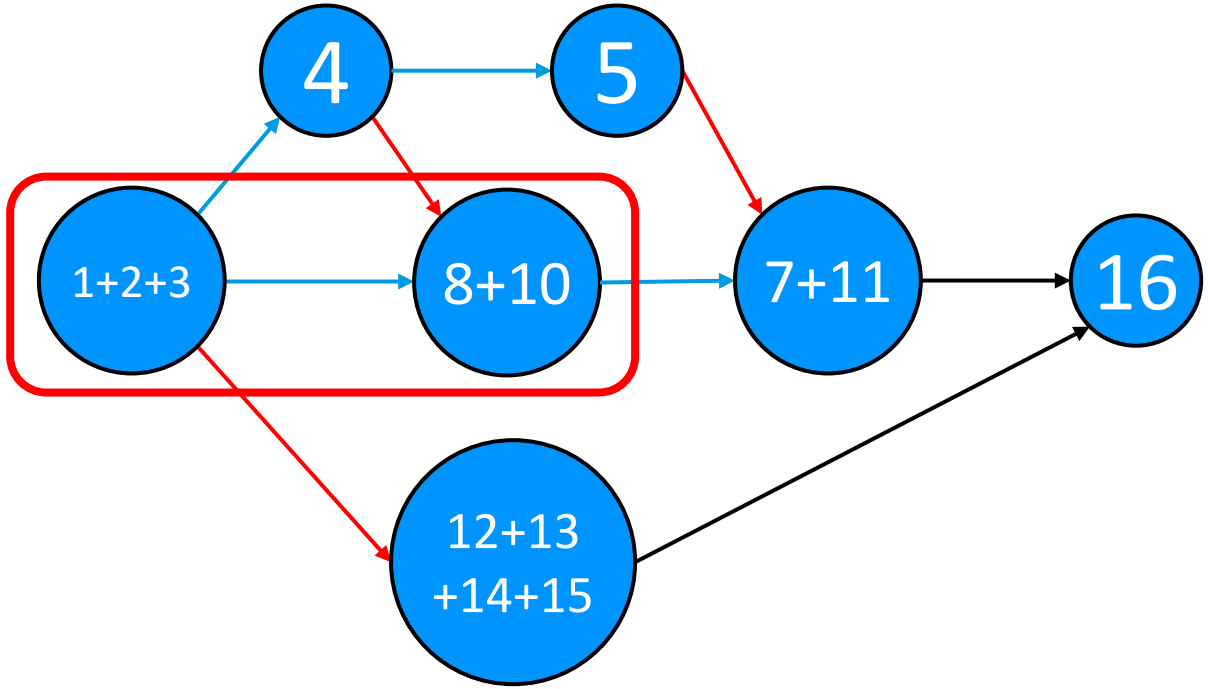

Graph Contraction

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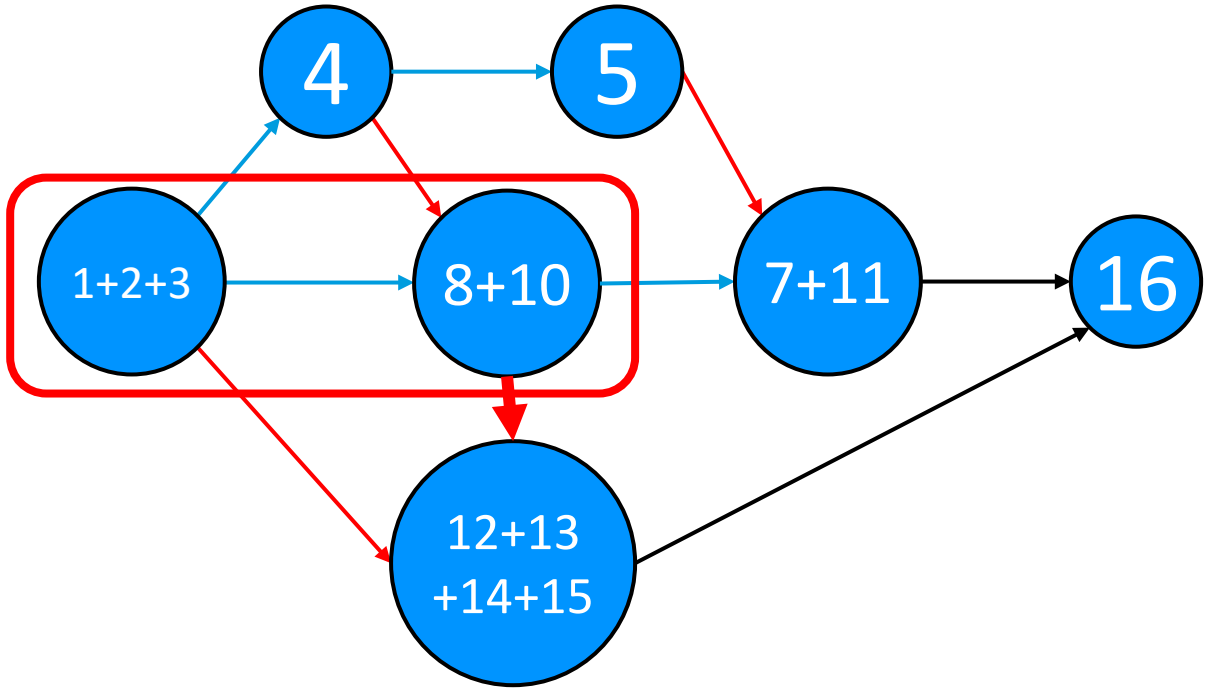

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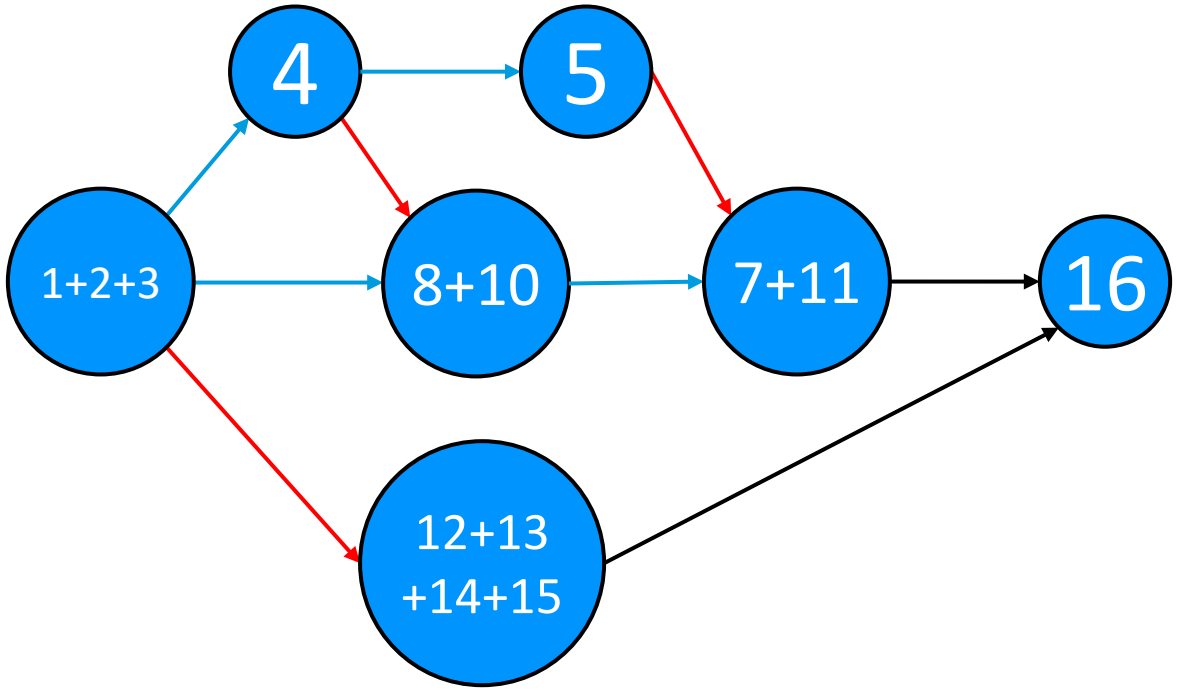

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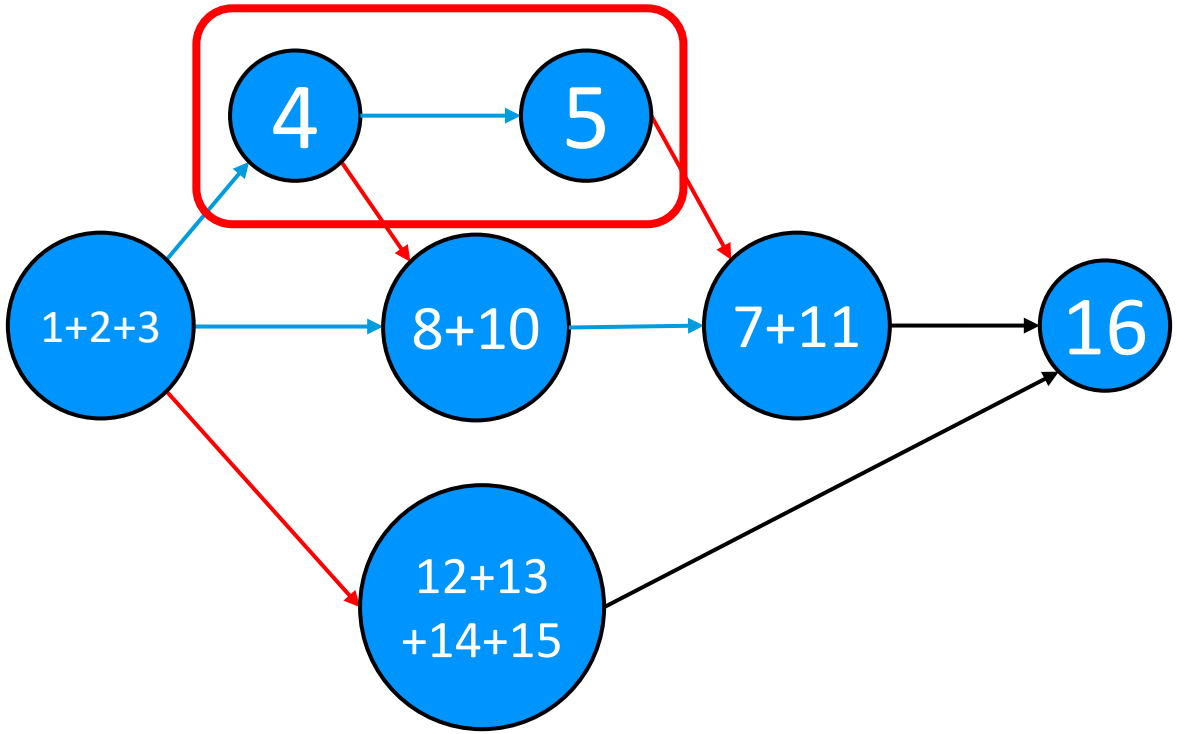

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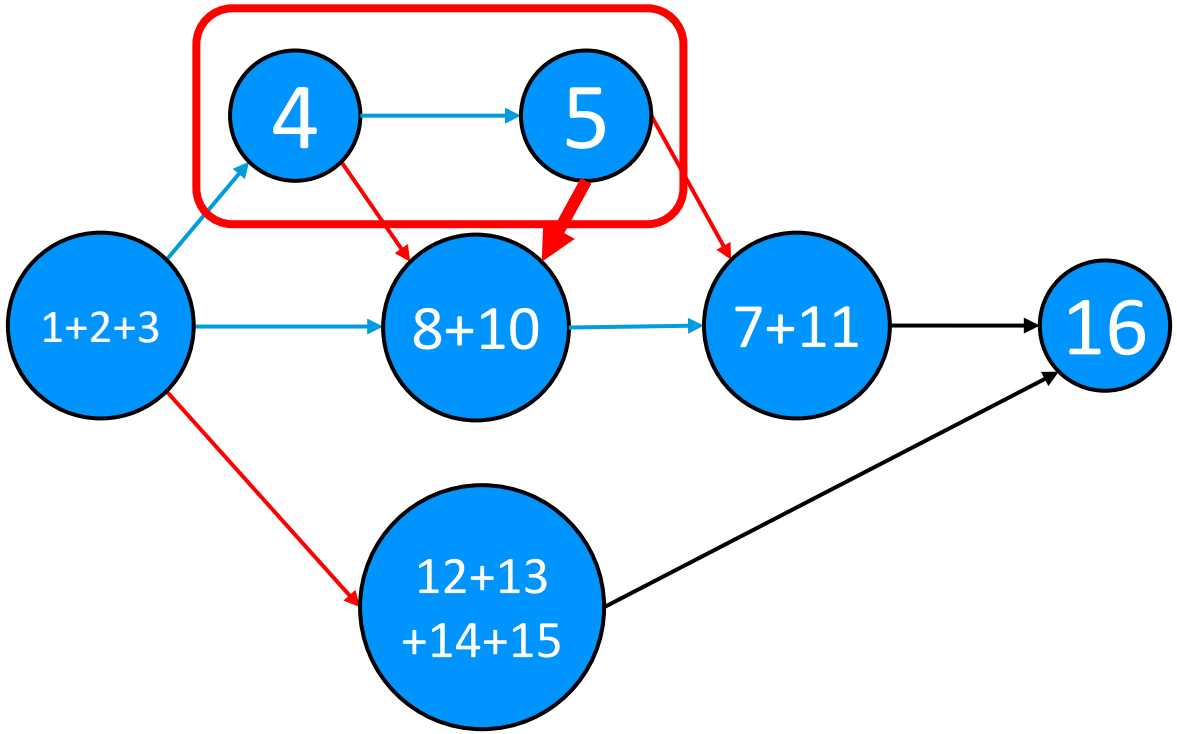

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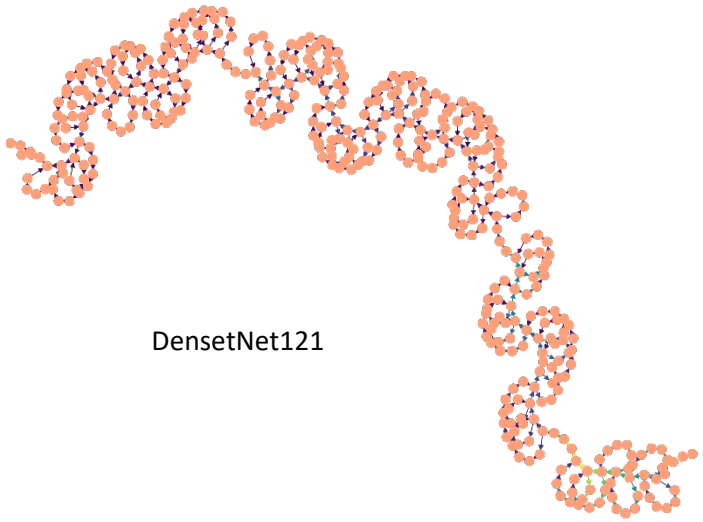

DensetNet121

Graph Contraction

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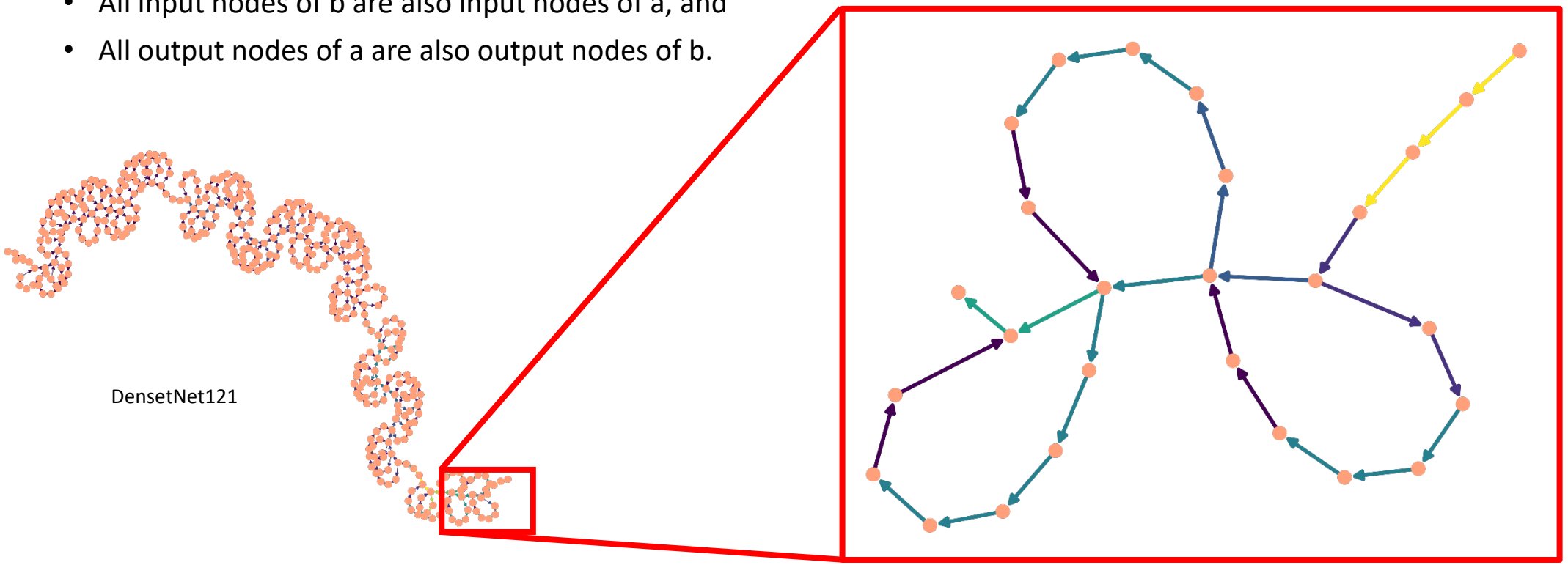

DensetNet121

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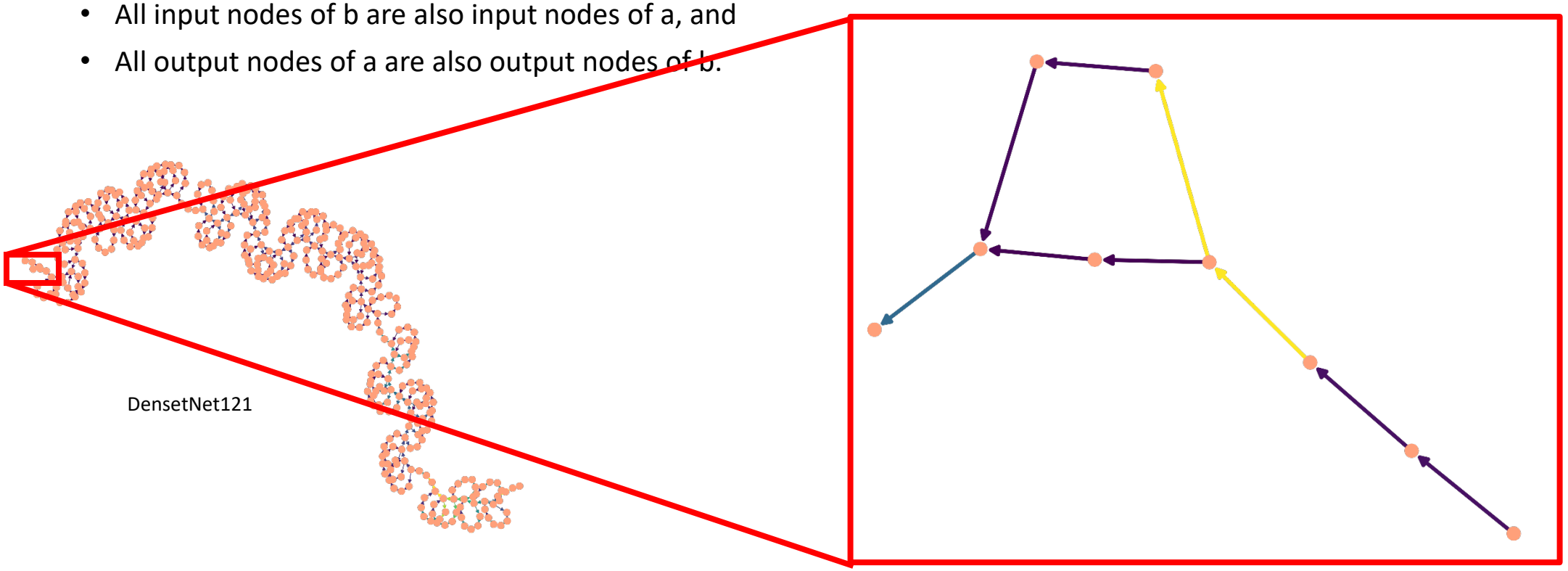

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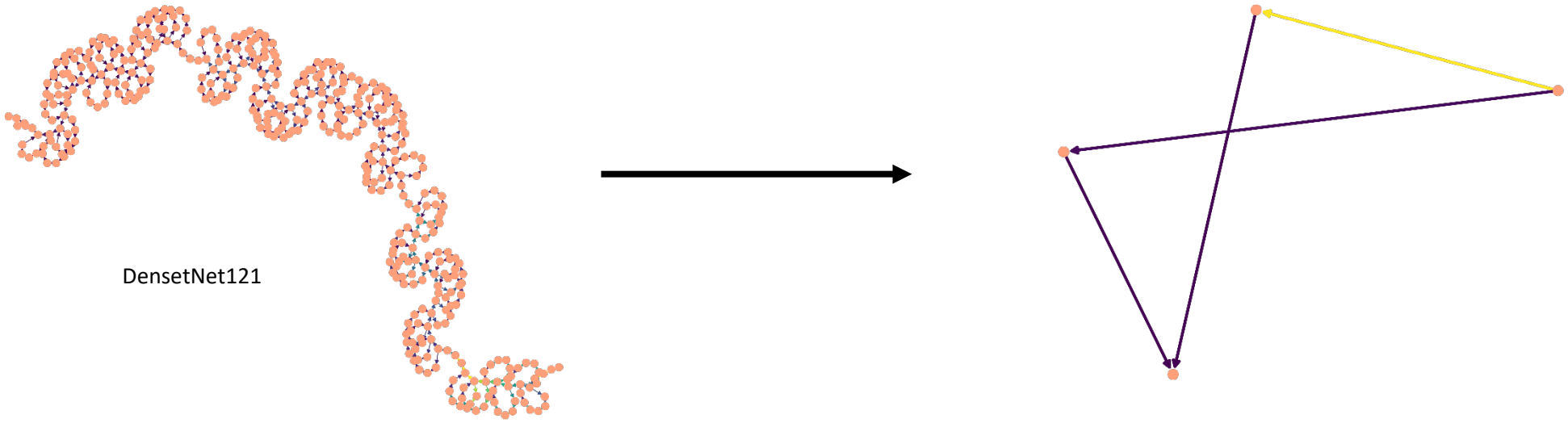
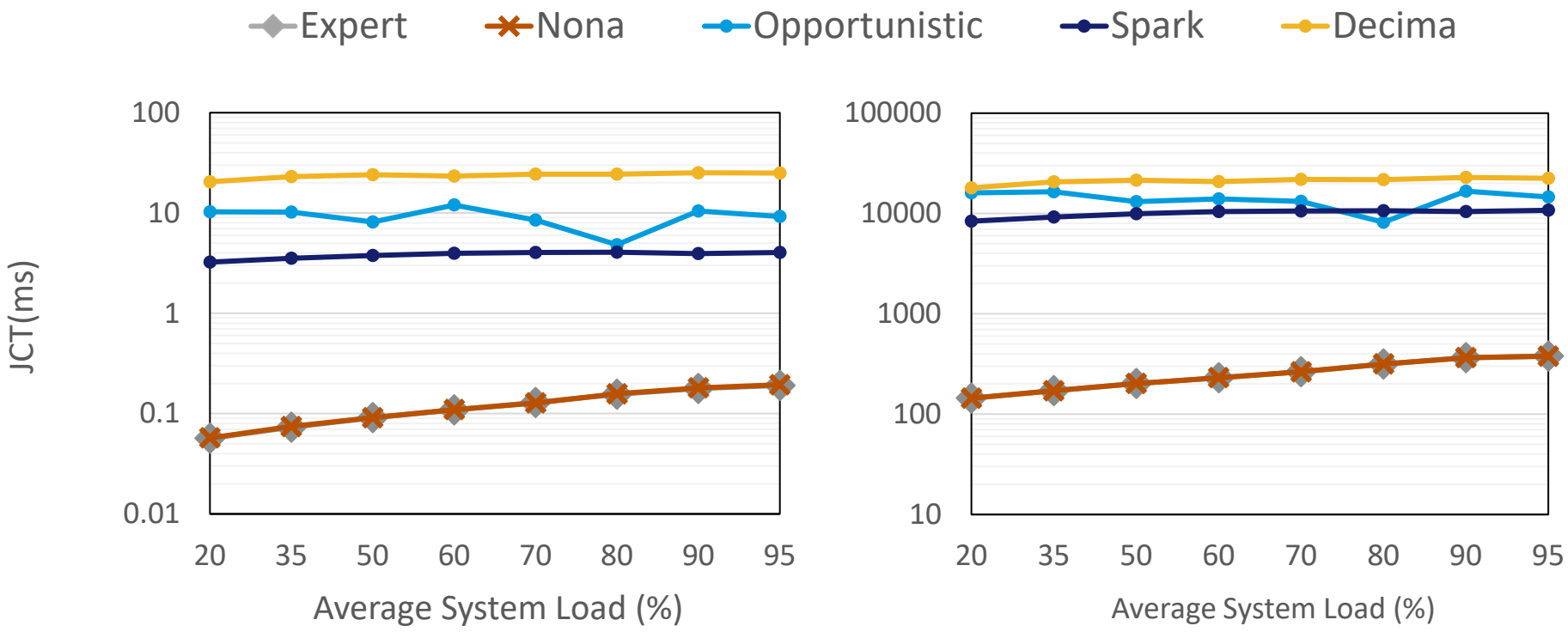


Evaluation

Setup

- Workload consists in contracted versions of AlexNet, ResNet18, VGG16, Densenet, and GPT2
  + Background traffic and compute tasks
- We use a simulator from Decima [SIGCOMM'19], a Reinforcement Learning (RL)-based scheduler, originally made for Spark
- We compare Nona with
  - Decima
  - Spark's Fair Scheduler
  - Opportunistic
  - Hand picked expert solutions
- 80-server cluster

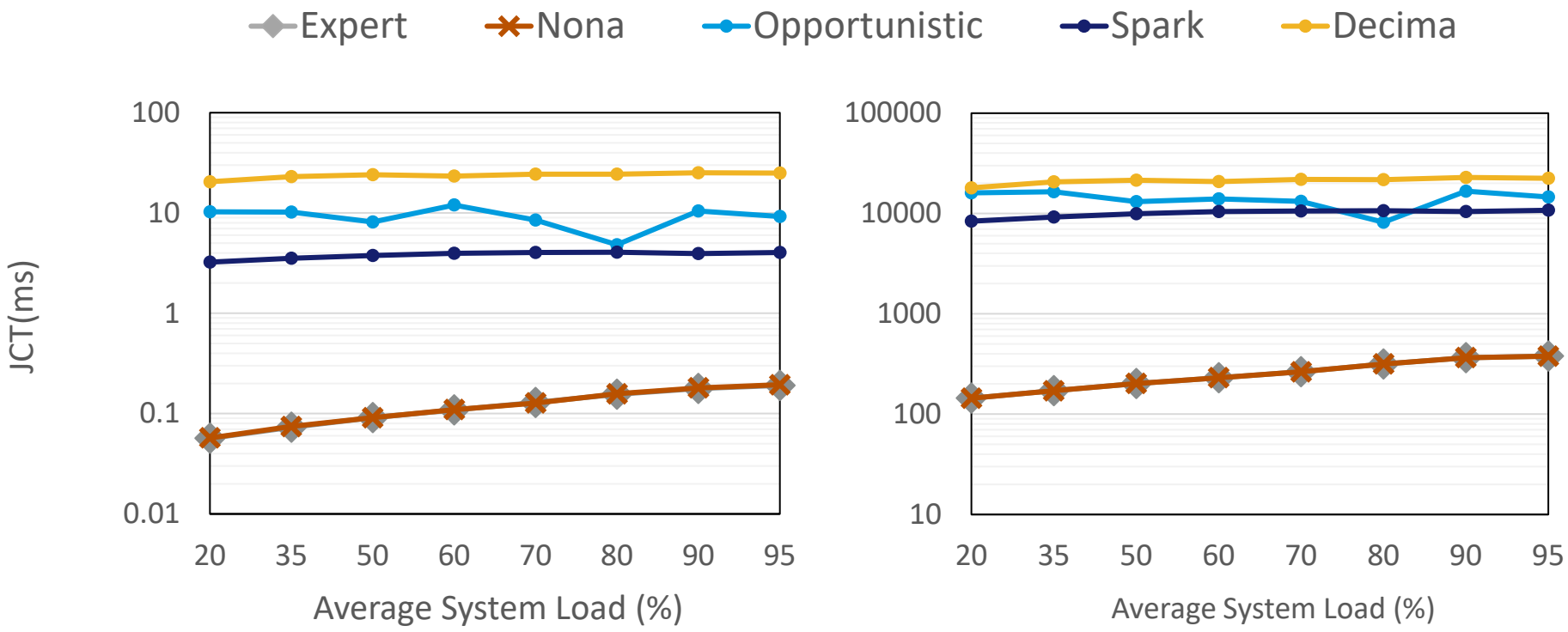
Impact of Job Arrival Rate



(a) Average over all jobs

(b) Average over foreground jobs

Impact of Job Arrival Rate



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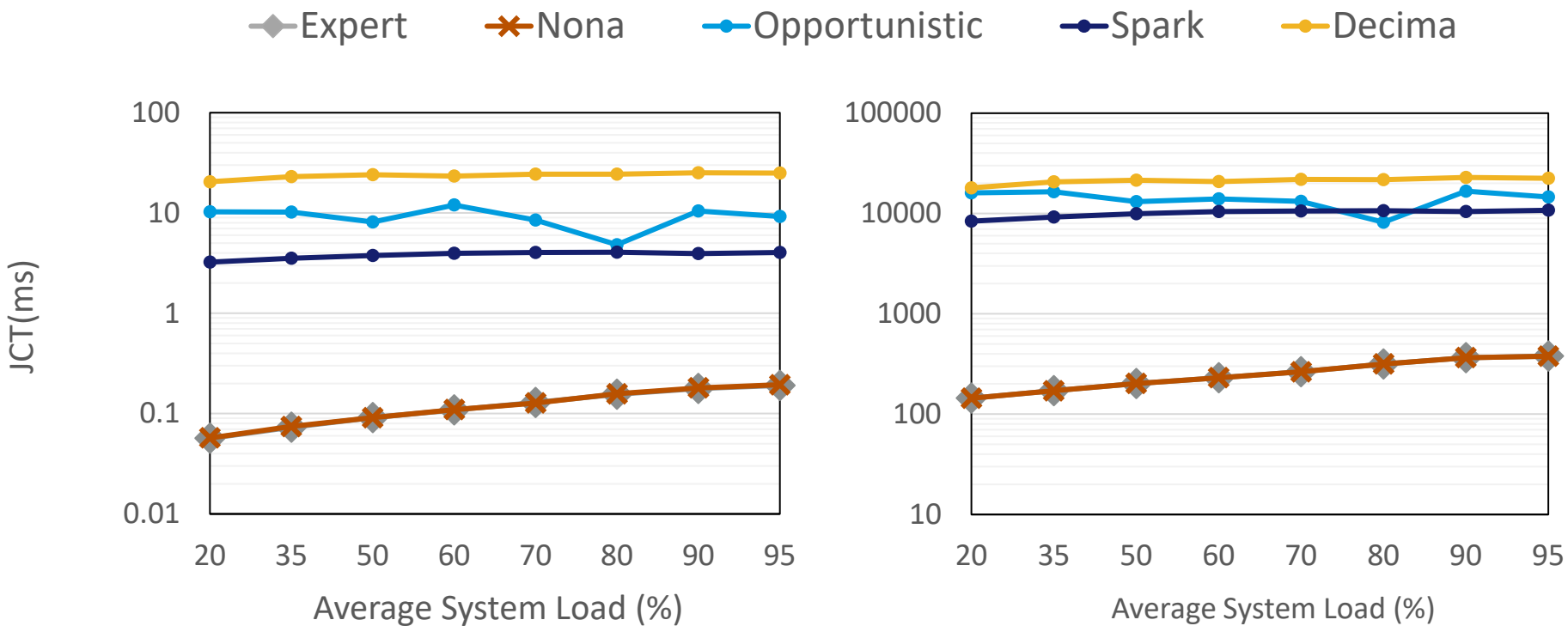

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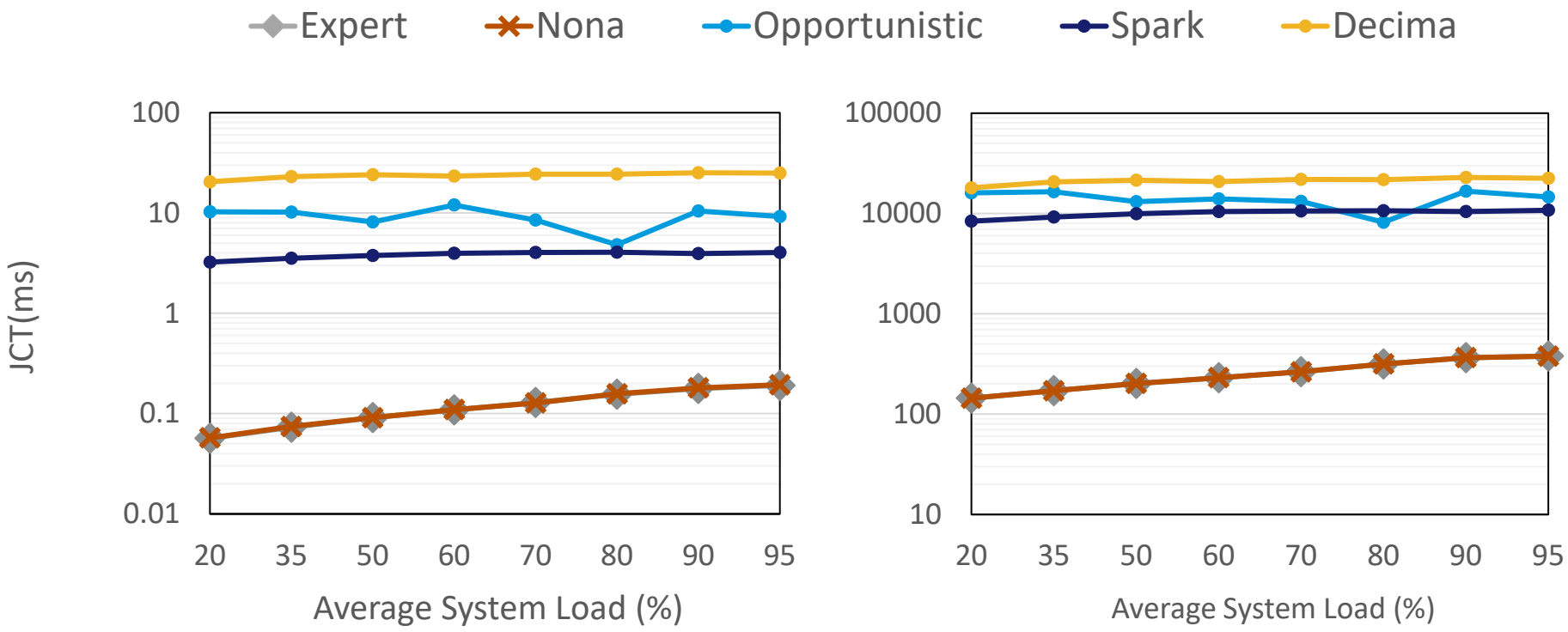

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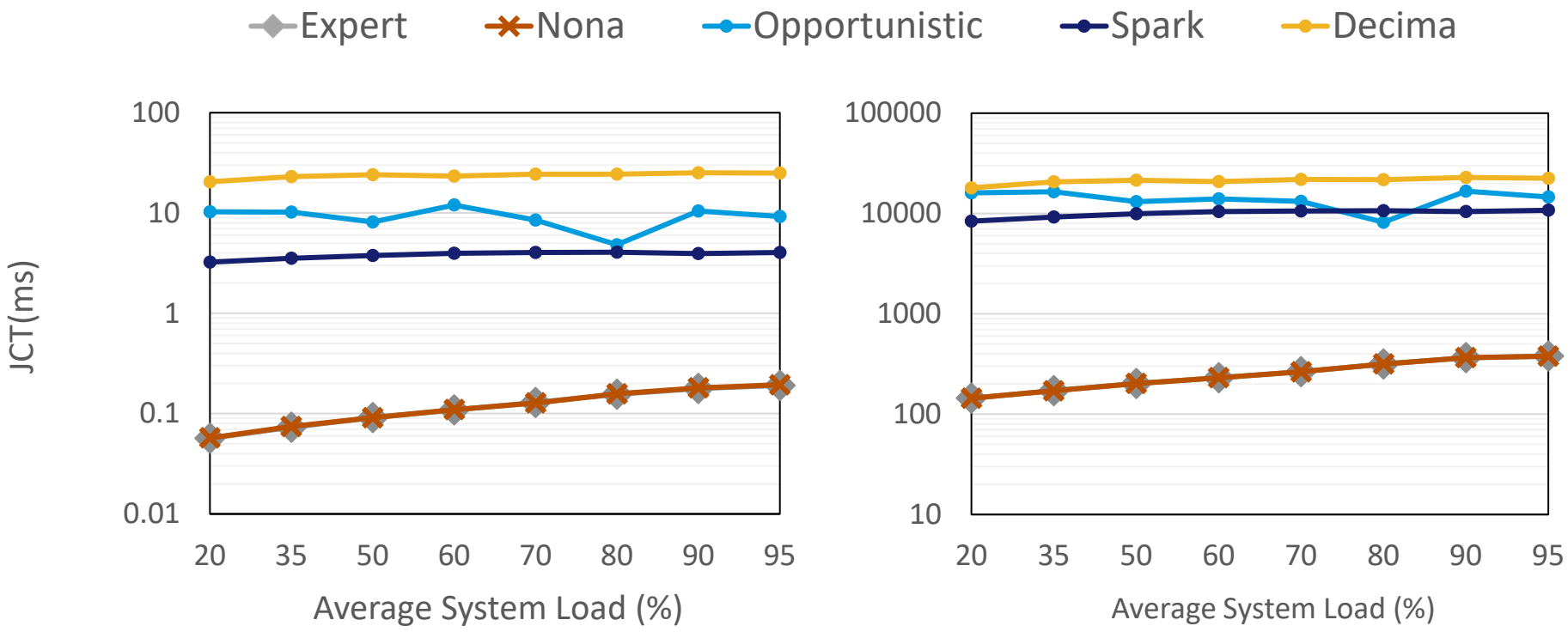

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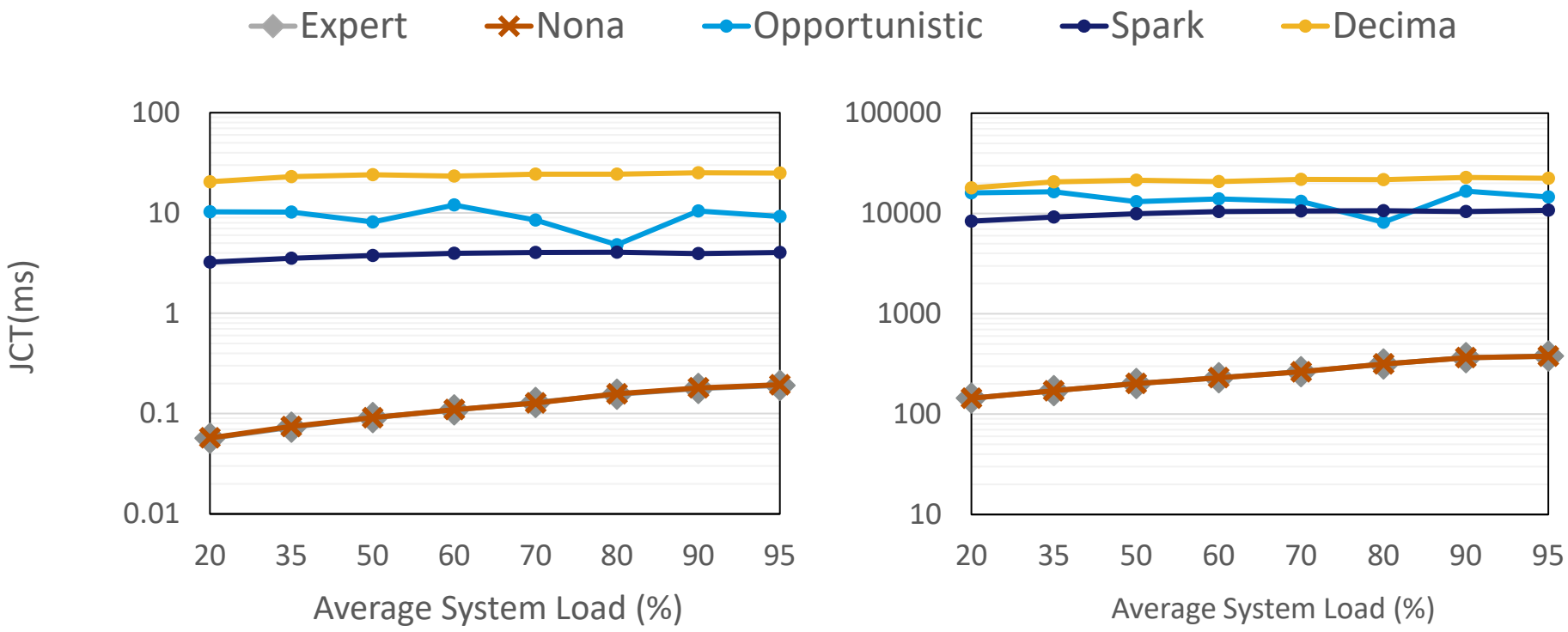

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Conclusion

- Schedulers should consider network queueing and asymmetry in jobs' DAGs:
  - Nona achieves up to 350x better JCT than previous works by including network delays in the decision-making
- ML operation graphs can be largely compacted to simplify scheduling
- Stochastic scheduling allows moving the complexity of the problem offline for low latency scheduling