Efficient Flow Scheduling in Distributed Deep Learning Training with Echelon Formation

Rui Pan*, Yiming Lei*, Jialong Li, Zhiqiang Xie, Binhang Yuan, Yiting Xia







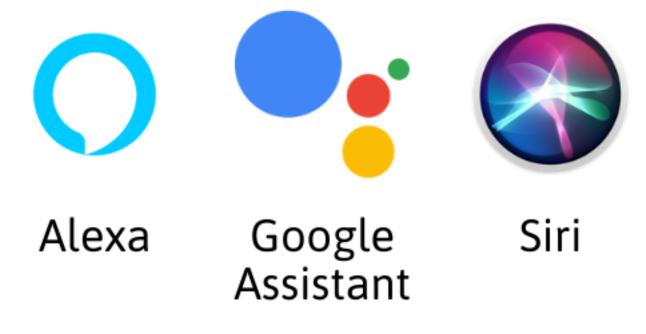


HotNets '22, Nov 14-15 2022, Austin, TX, USA

Deep Neural Networks (DNNs) are popular



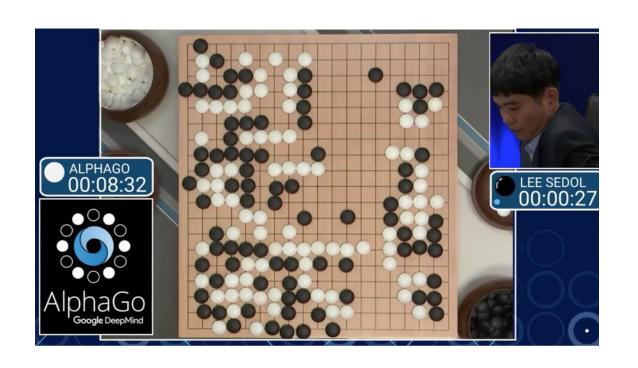
Image Classification



Speech-to-Text



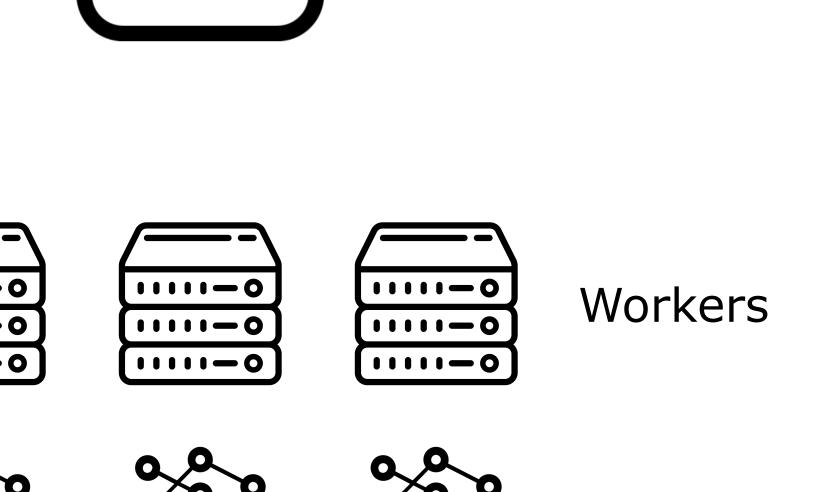
Machine Translation



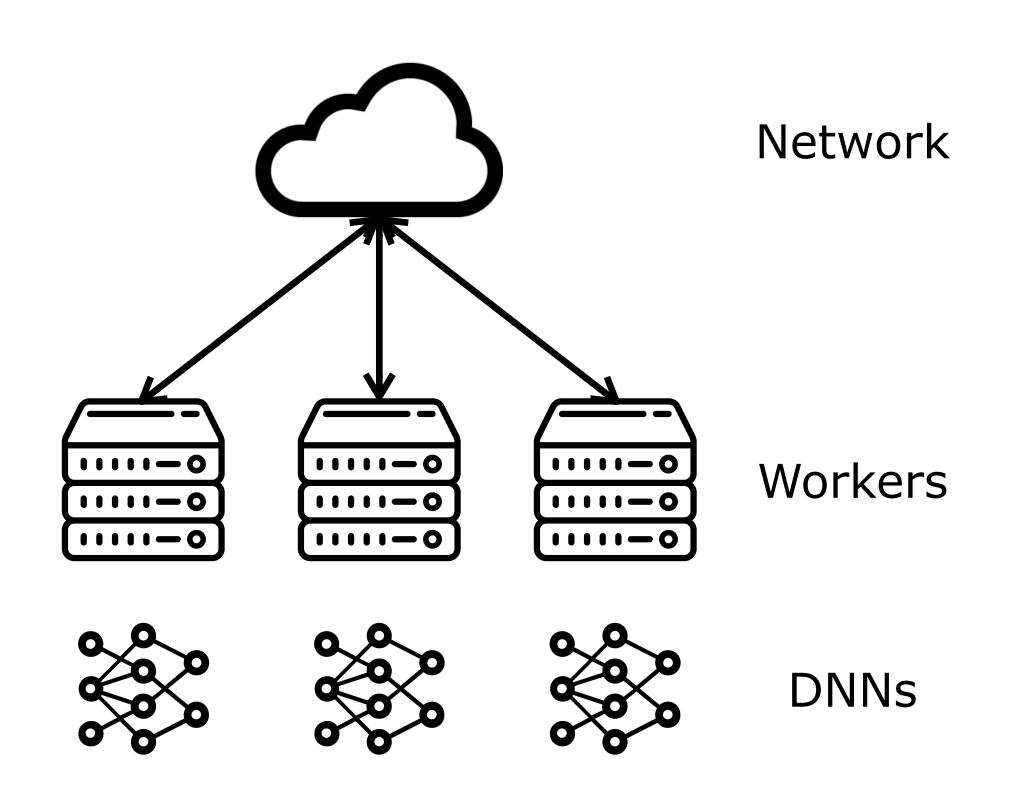
Game Playing

Network

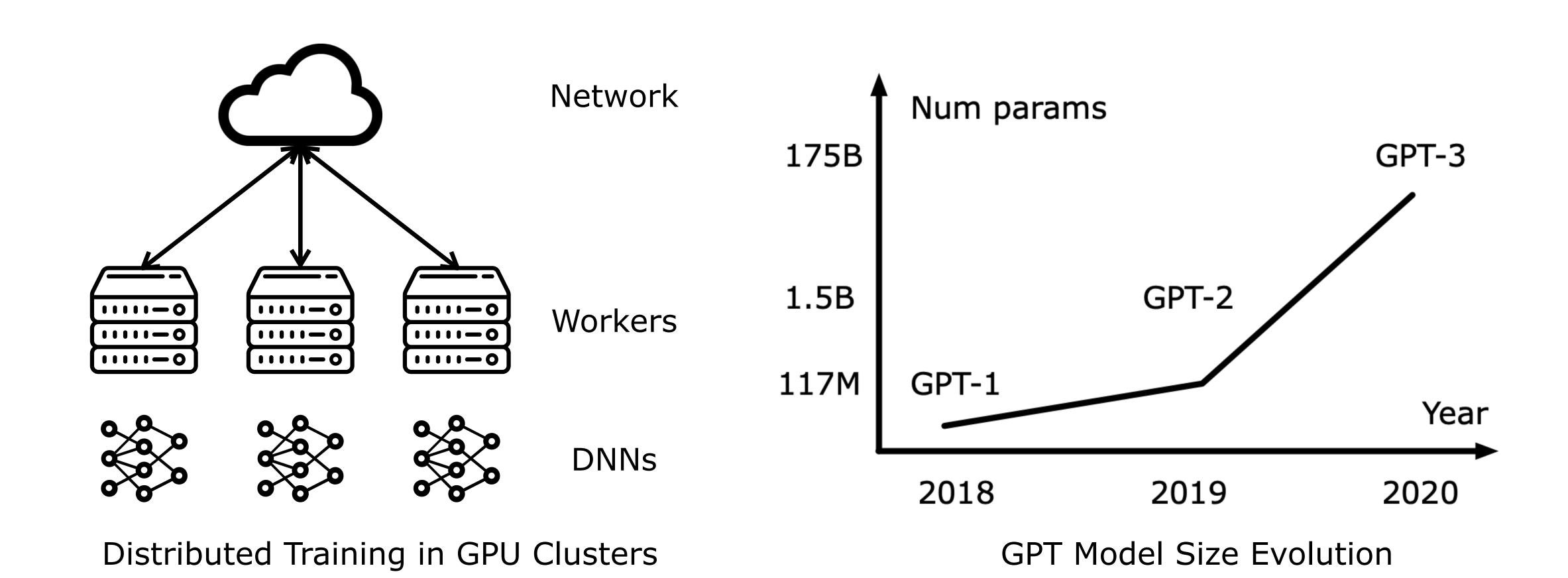
DNNs

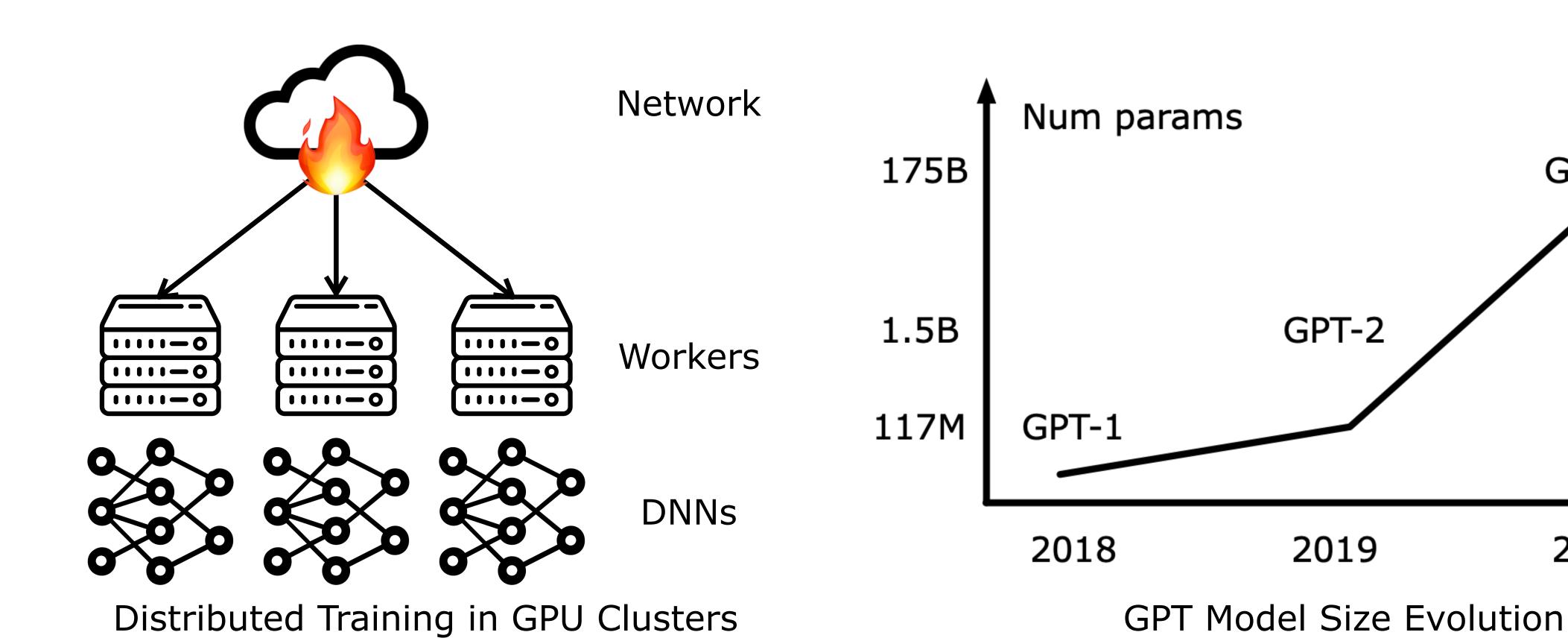


Distributed Training in GPU Clusters



Distributed Training in GPU Clusters





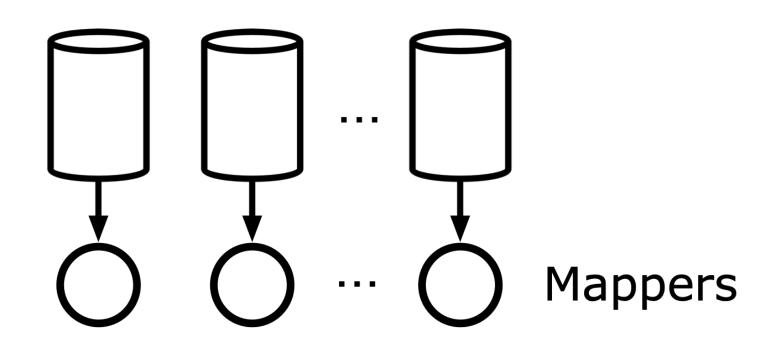
GPT-3

Year

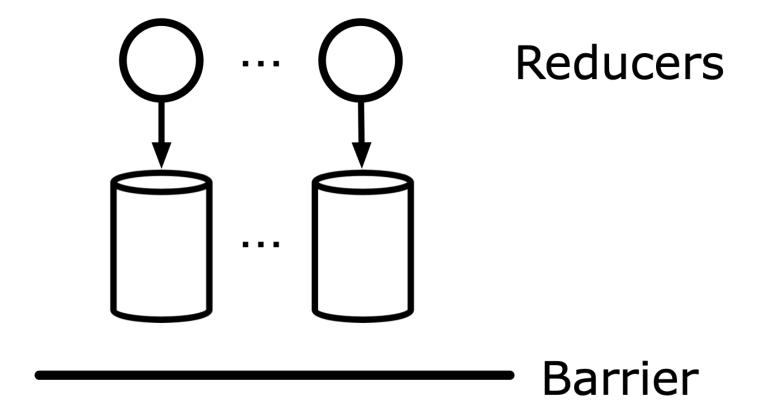
2020

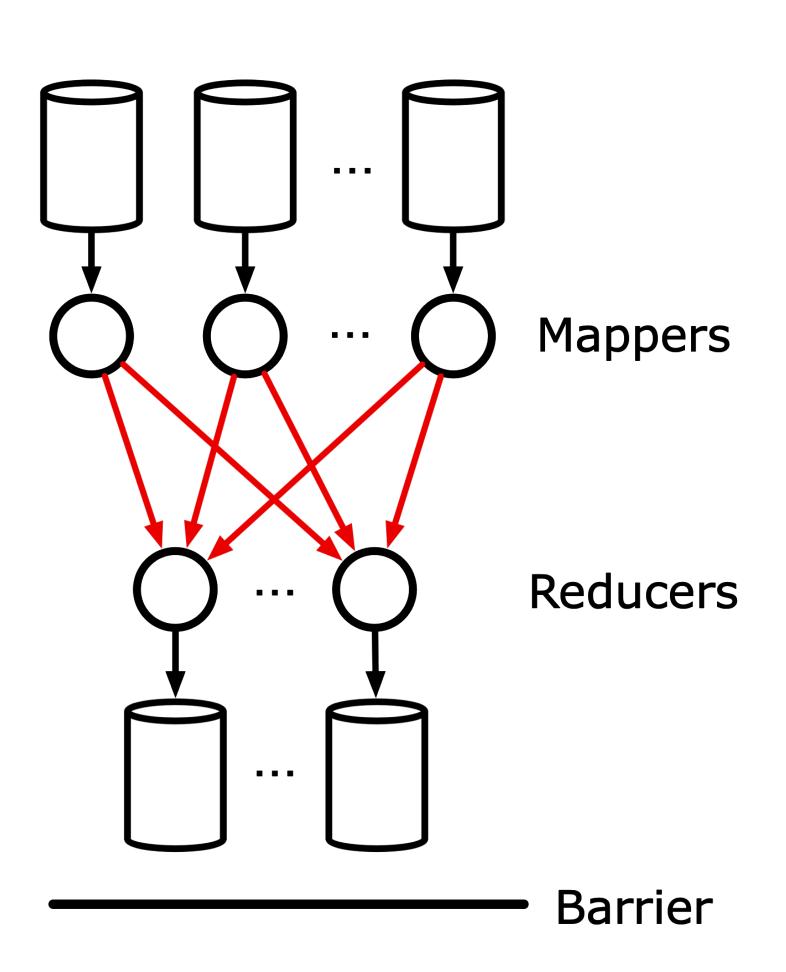
CoFlow: network abstraction for flow scheduling

- CoFlow: network abstraction for flow scheduling
- A group of semantically-related flows, optimized to finish at the same time

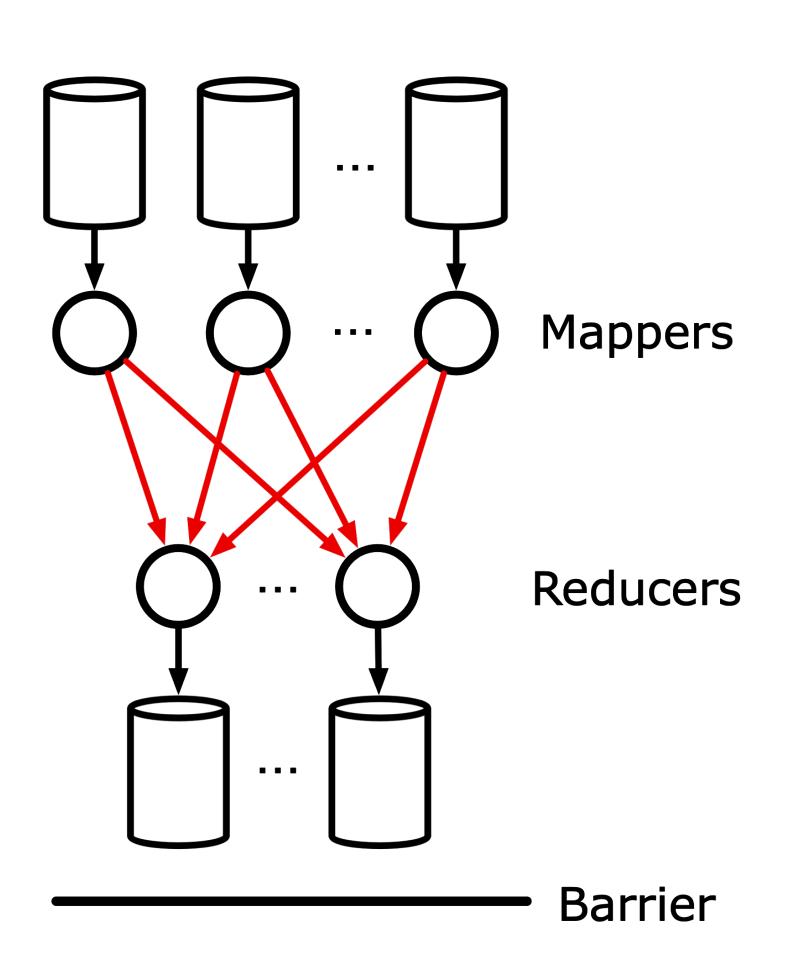


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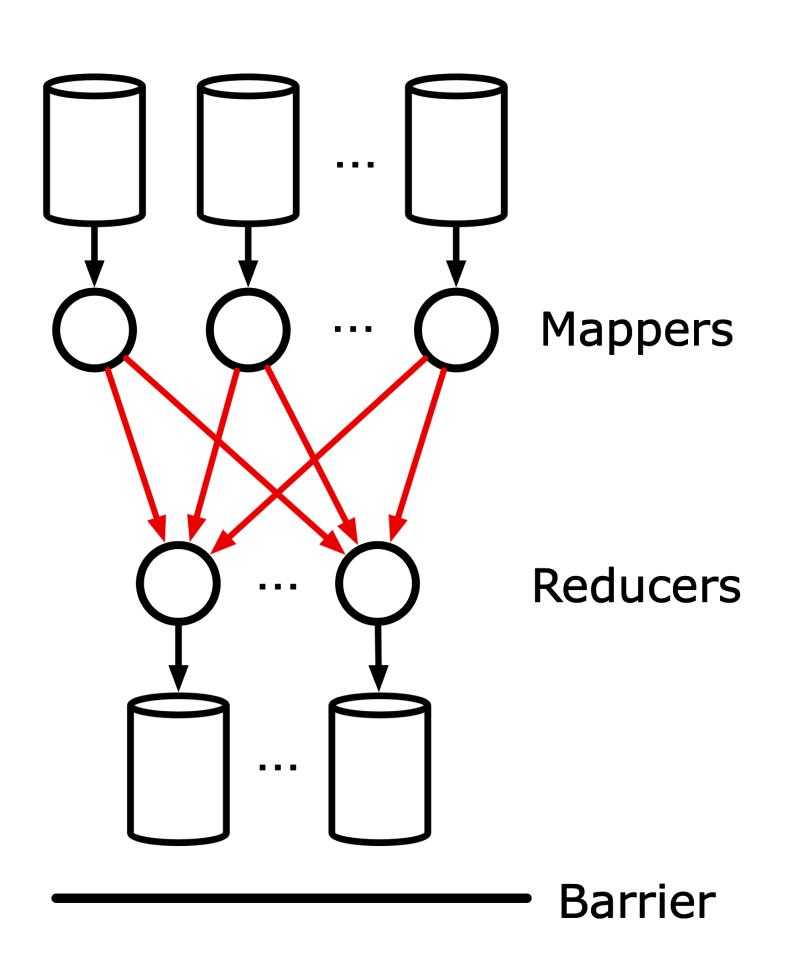




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 - Big data frameworks
 - ML training paradigms

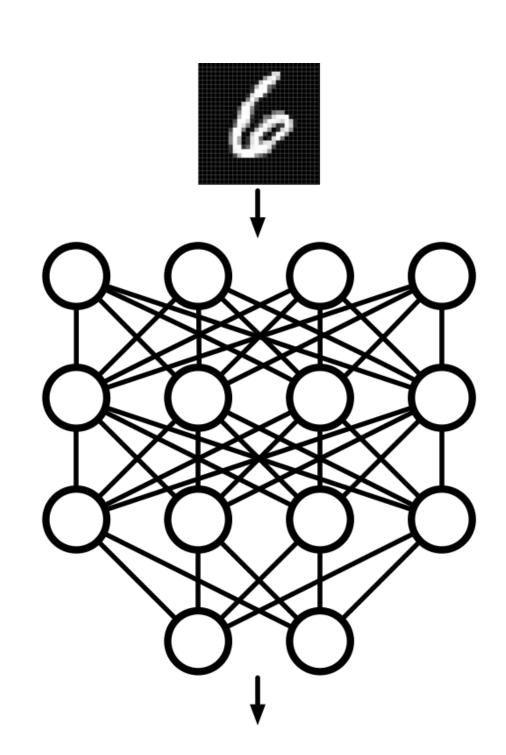
Training paradigm	Examples
Data Parallelism	AllReduce, Parameter Server
Pipeline Parallelism	GPipe, PipeDream
Tensor Parallelism	Megatron-LM
Fully Sharded Data Parallelism	ZeRO, FairScale

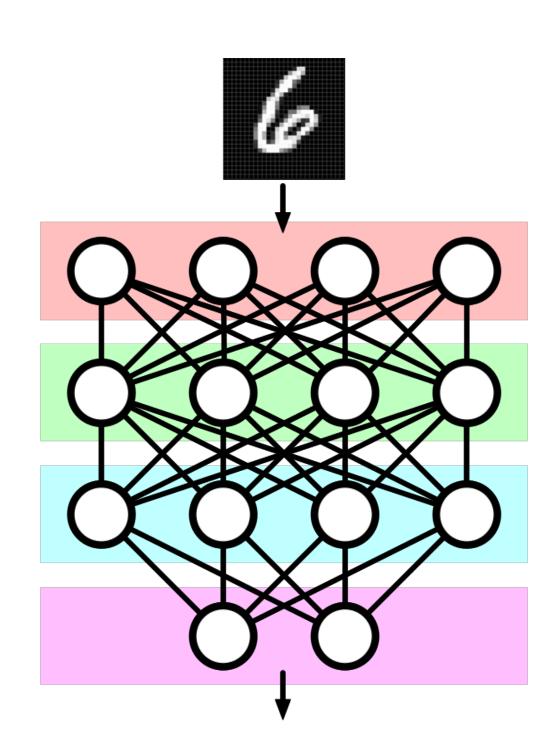
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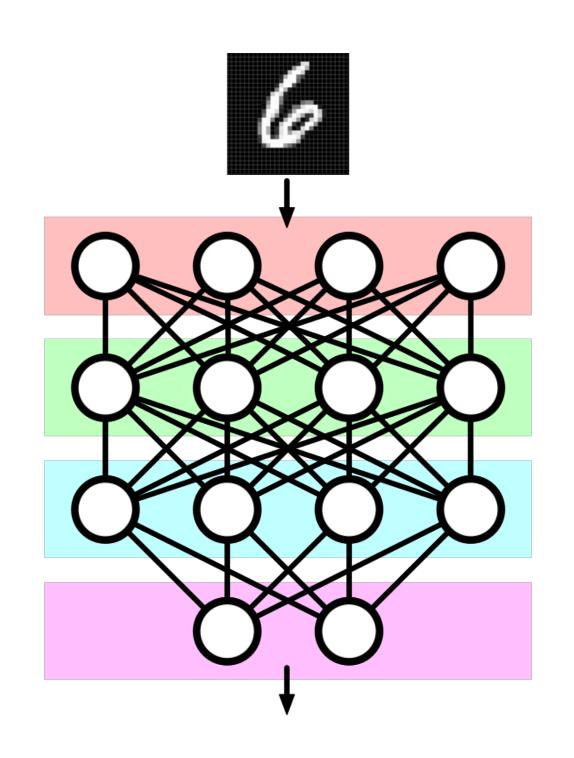
 Parallelization paradigms have different communication patterns

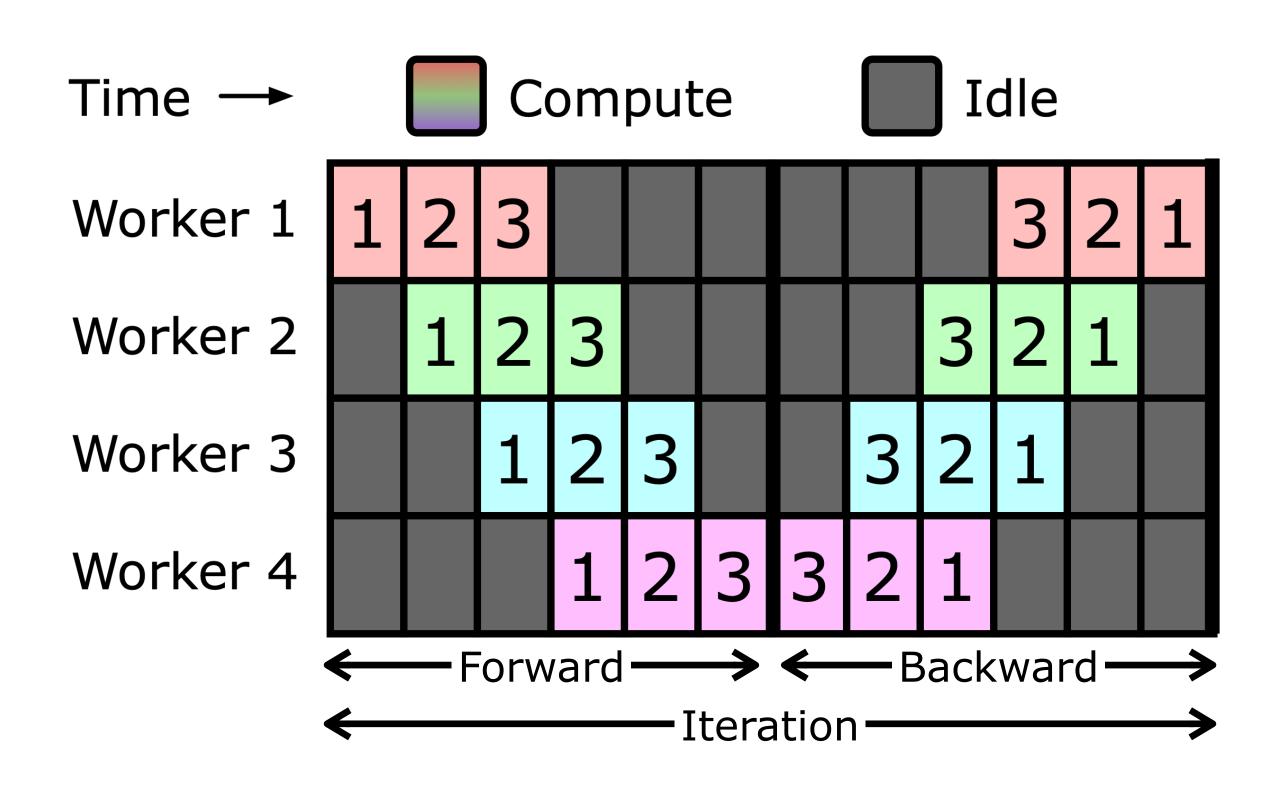
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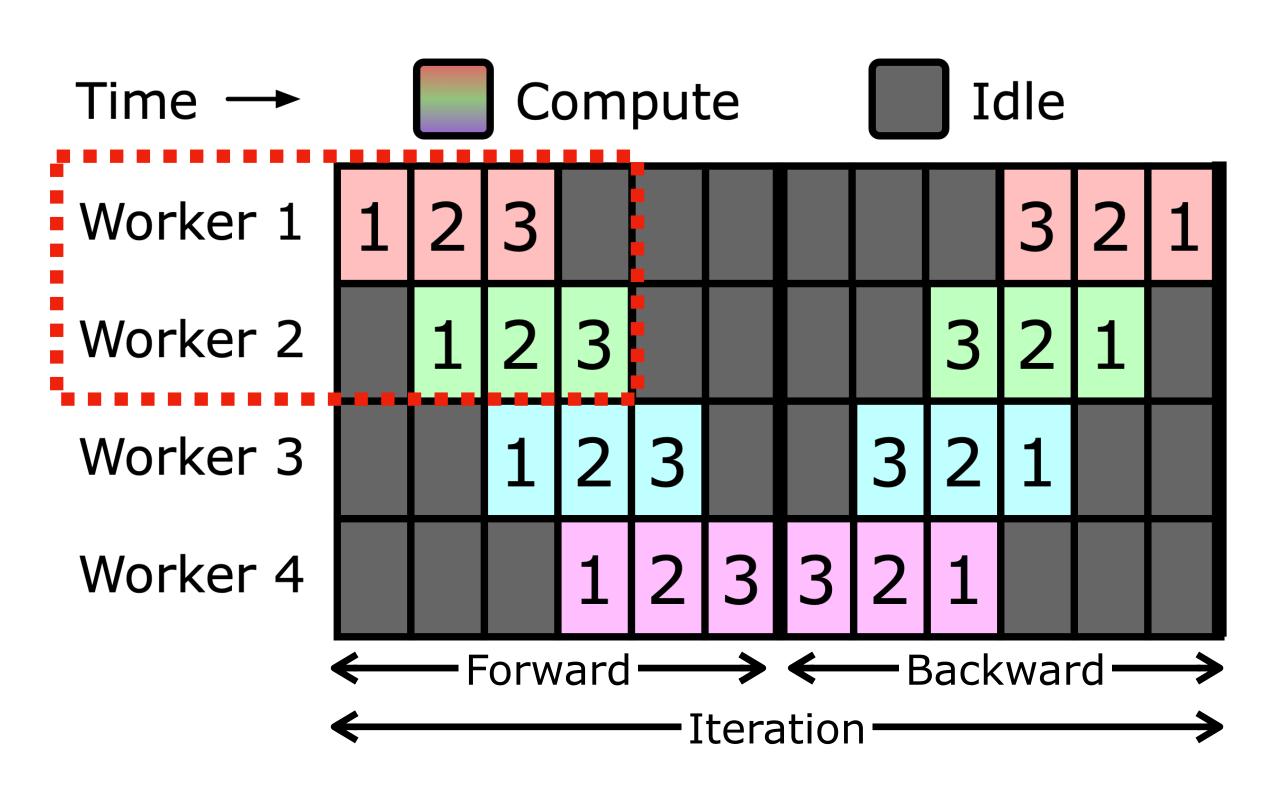
- Parallelization paradigms have different communication patterns
- Lack of good network abstraction

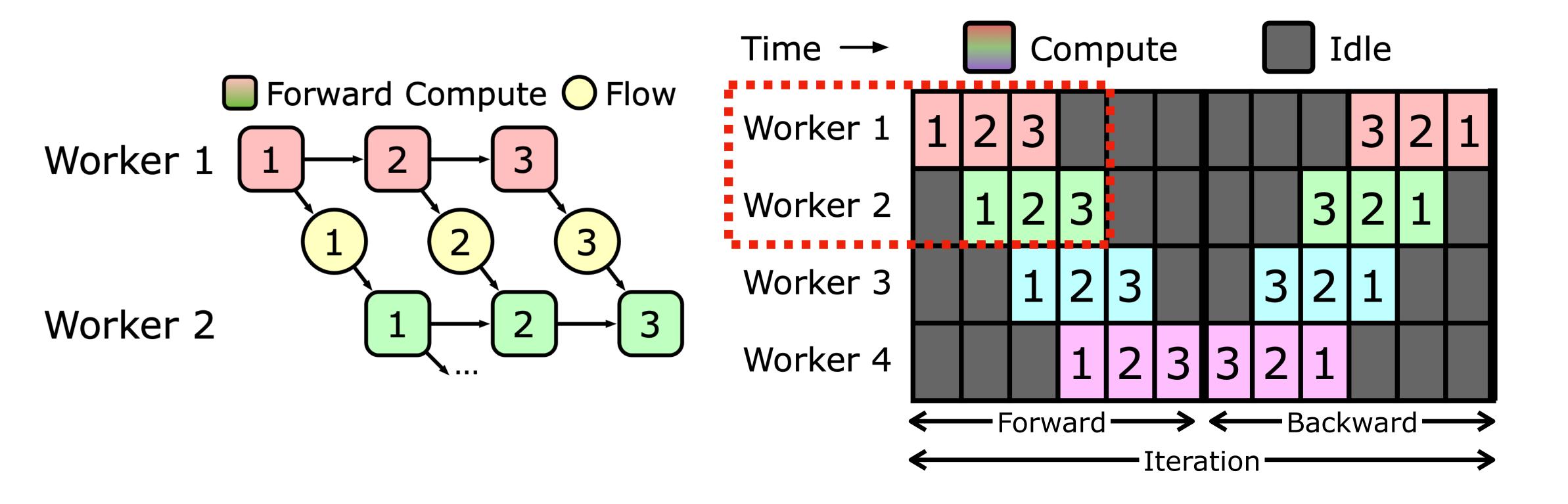


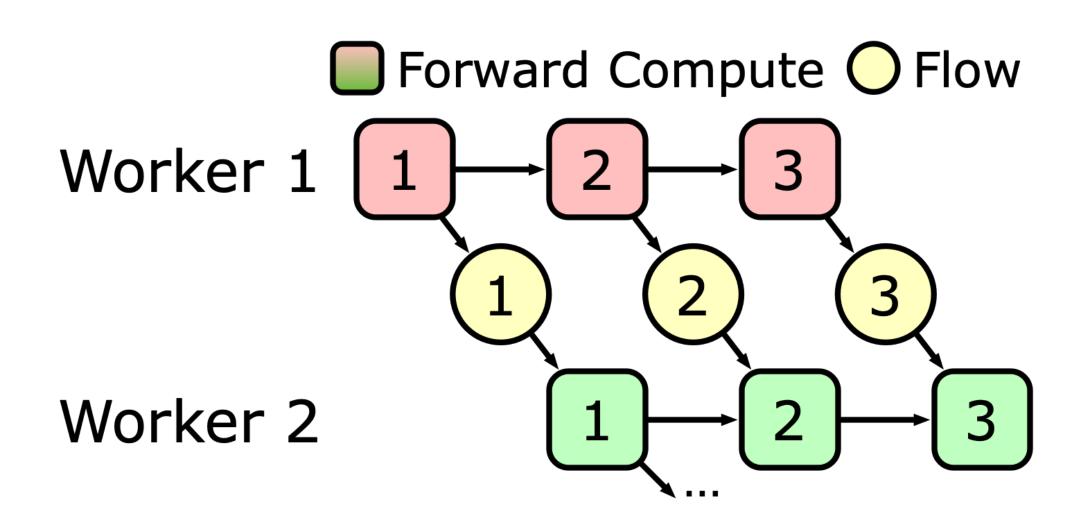


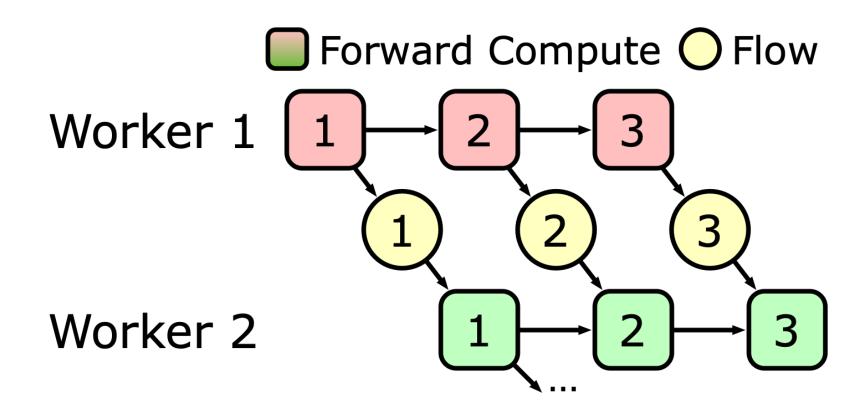


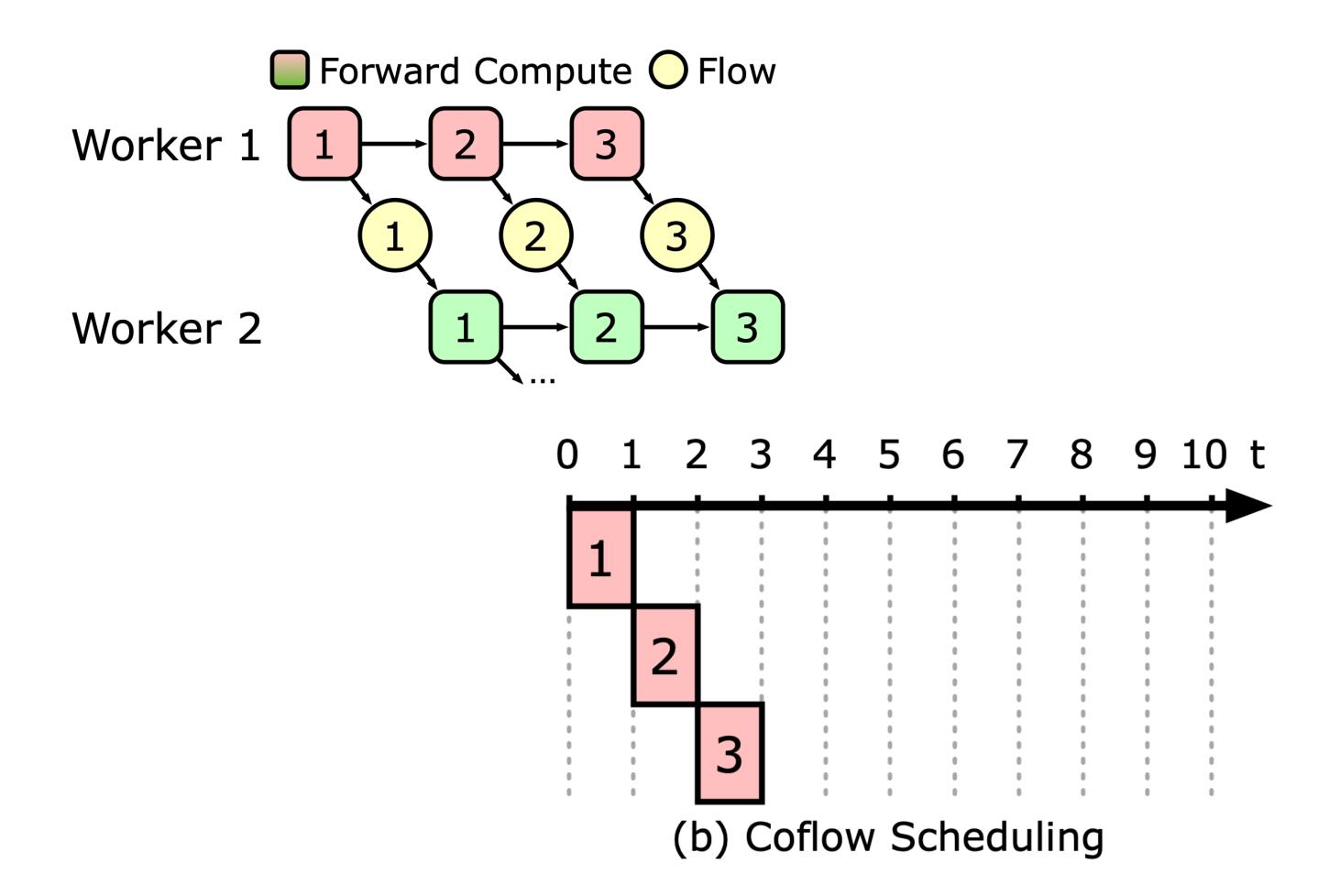


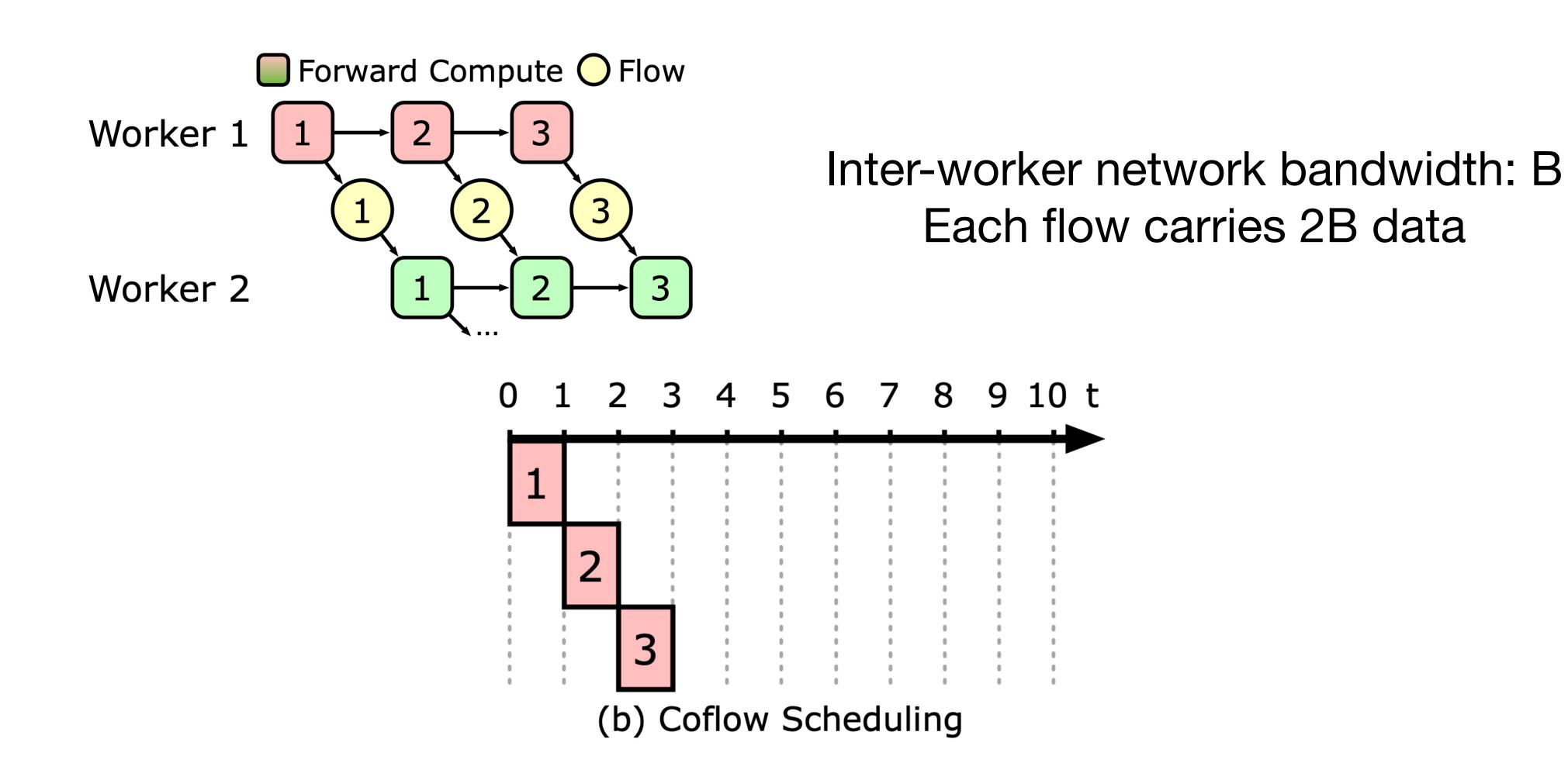


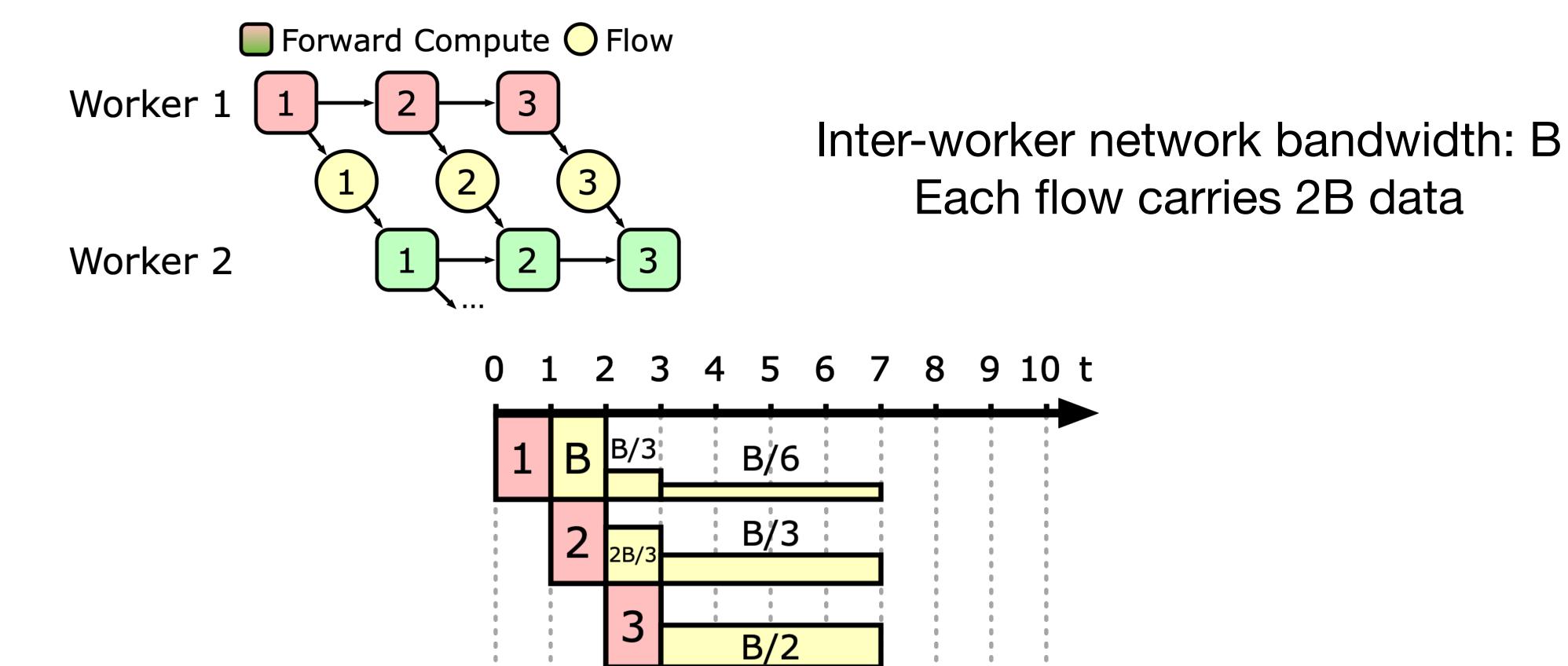




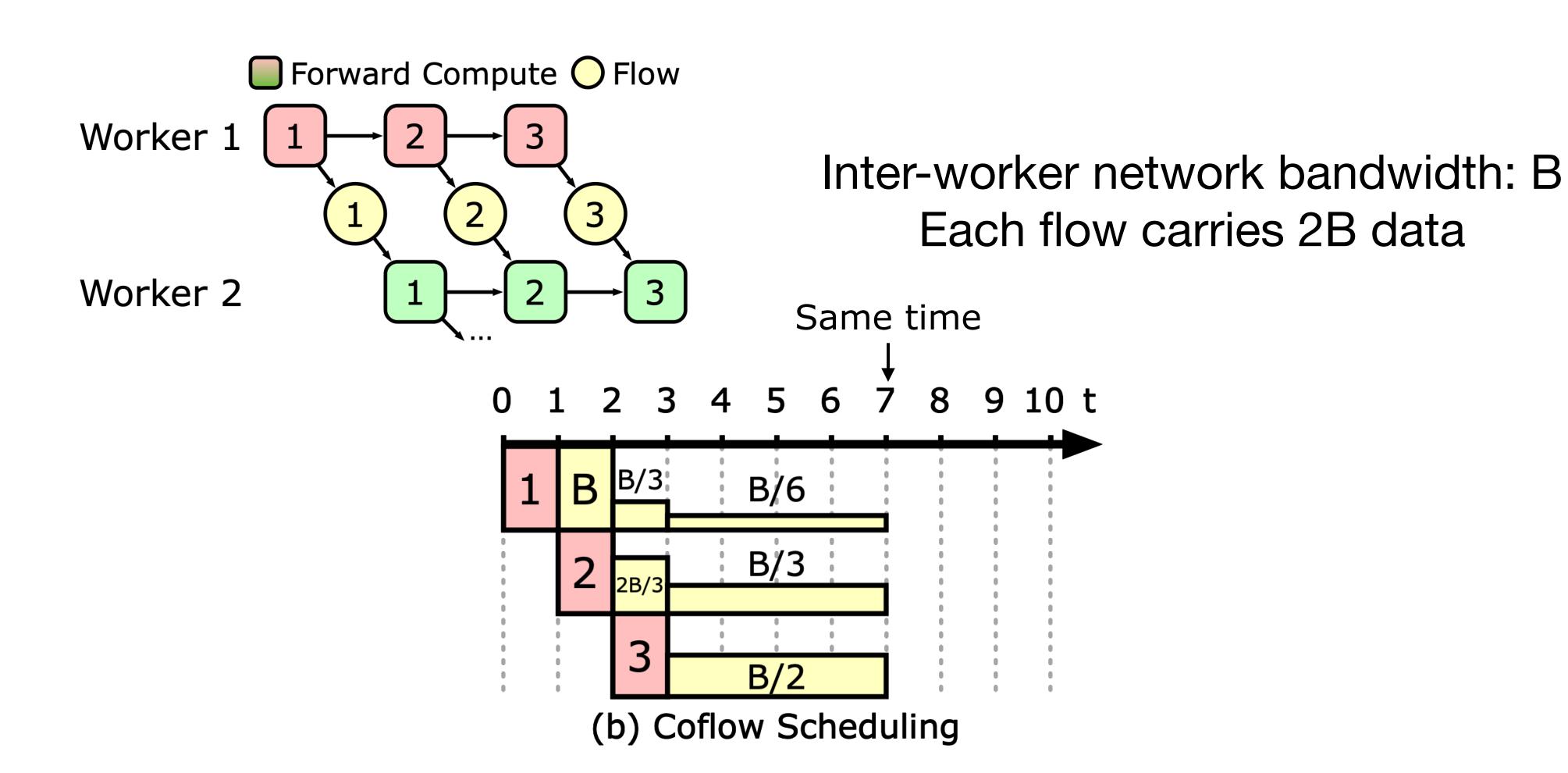


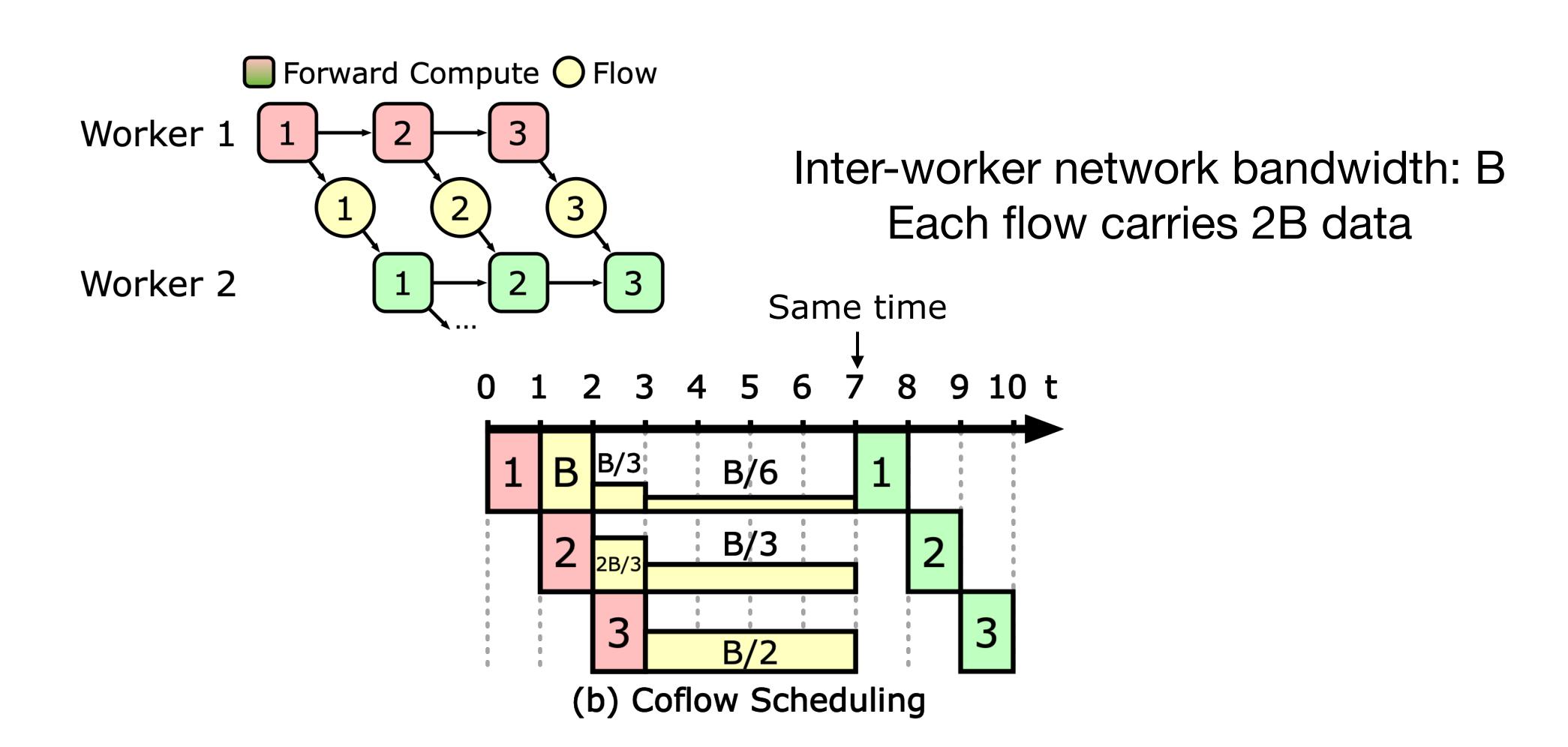


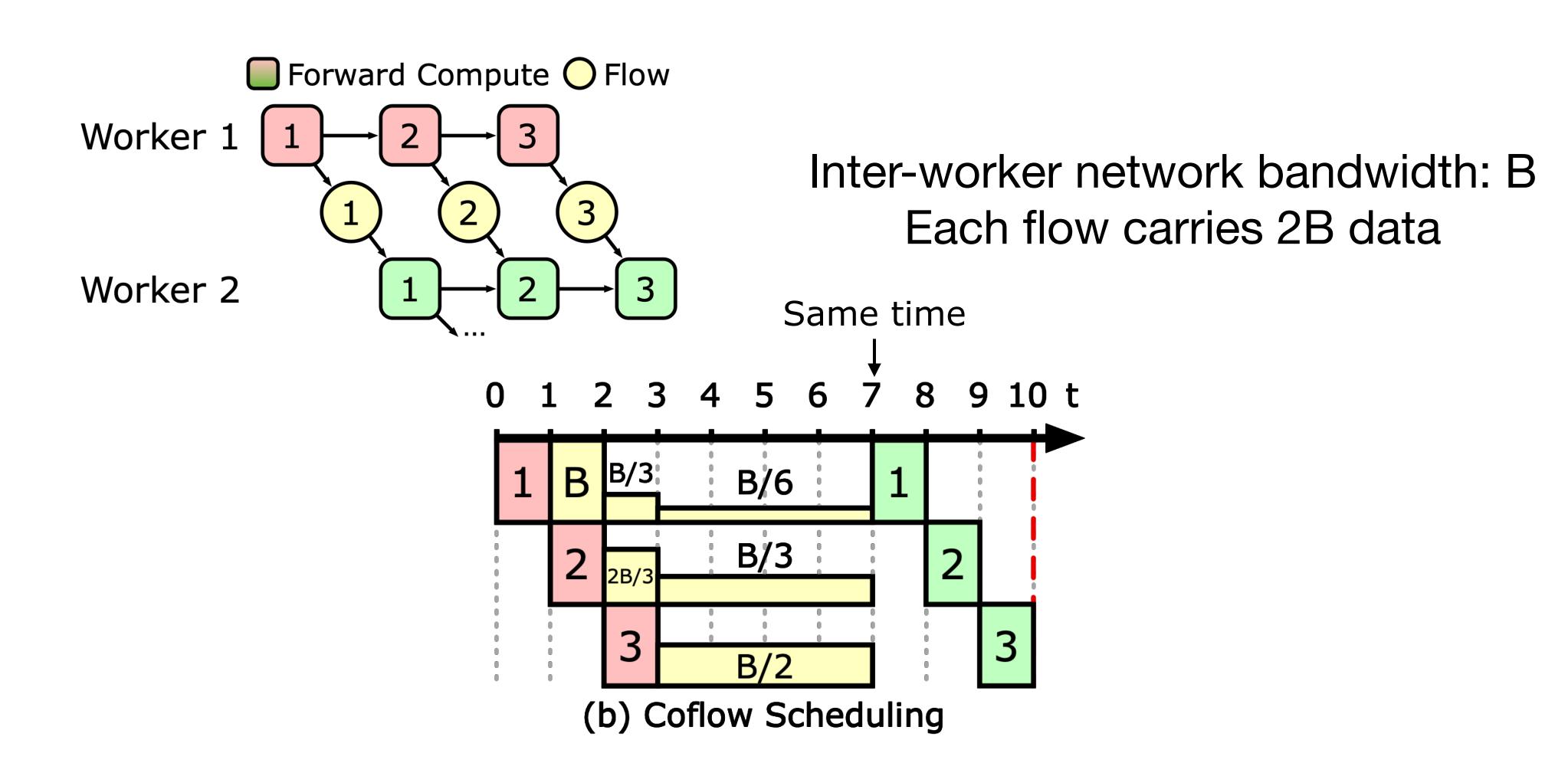


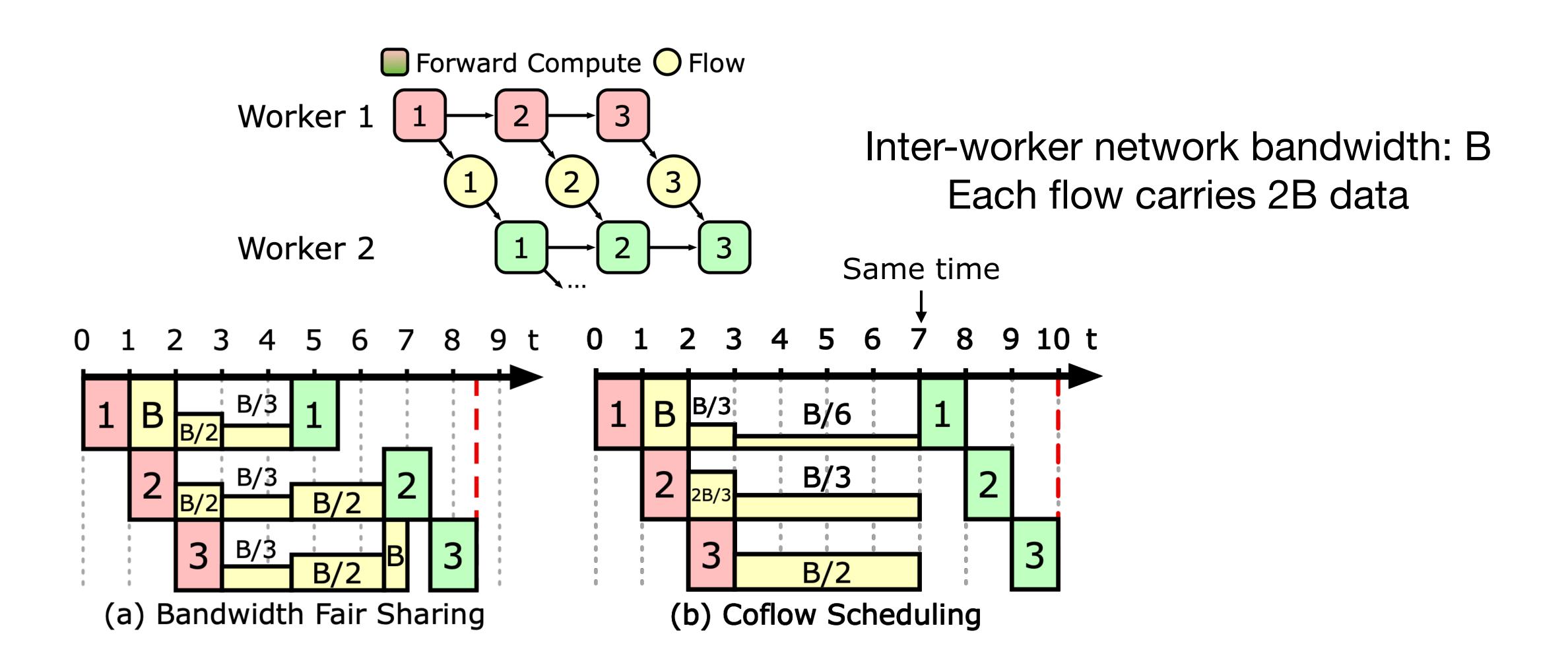


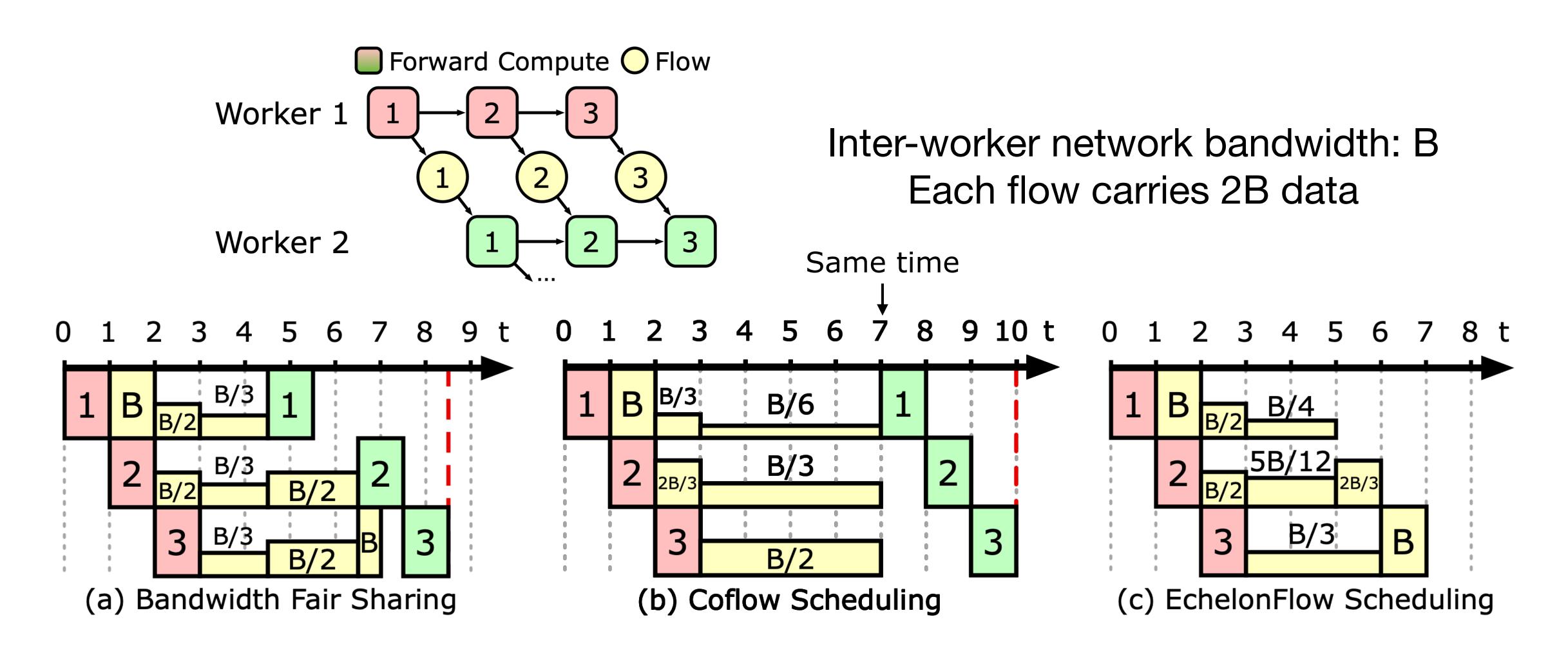
(b) Coflow Scheduling

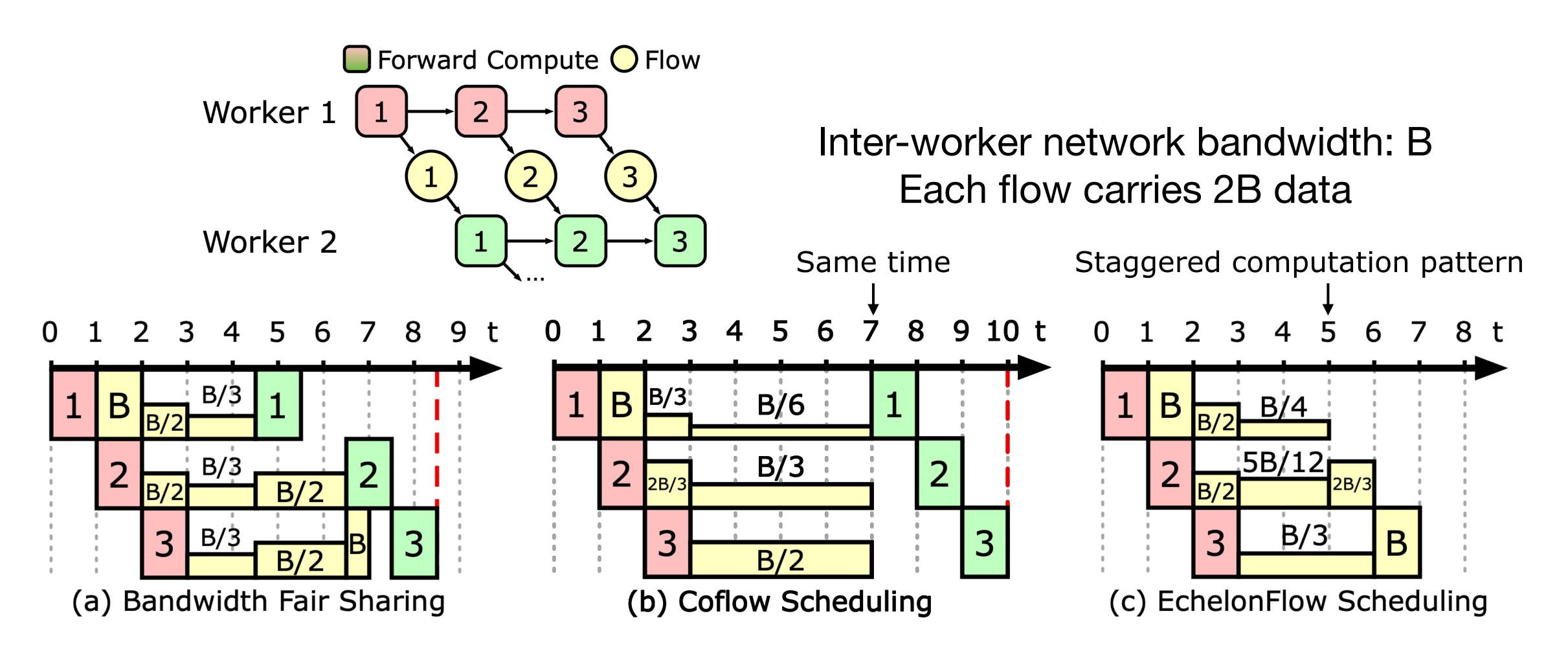


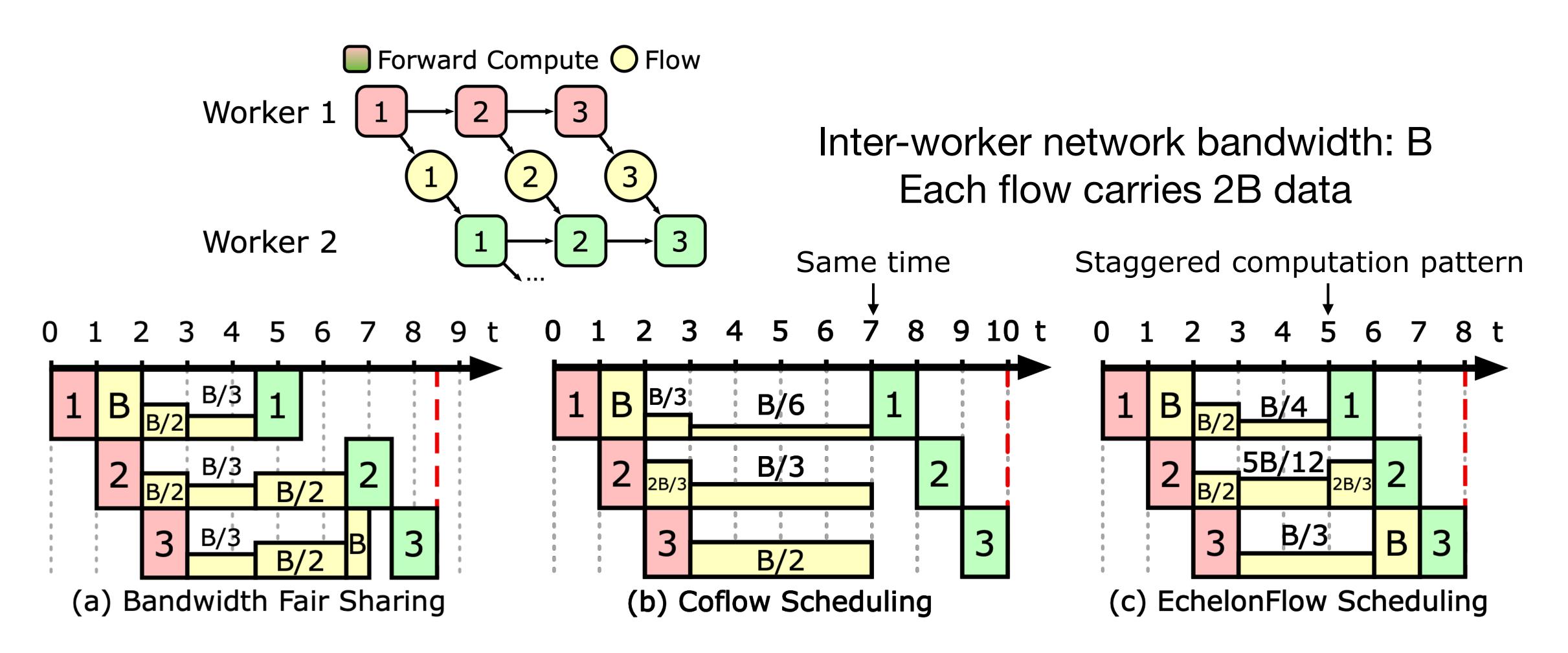


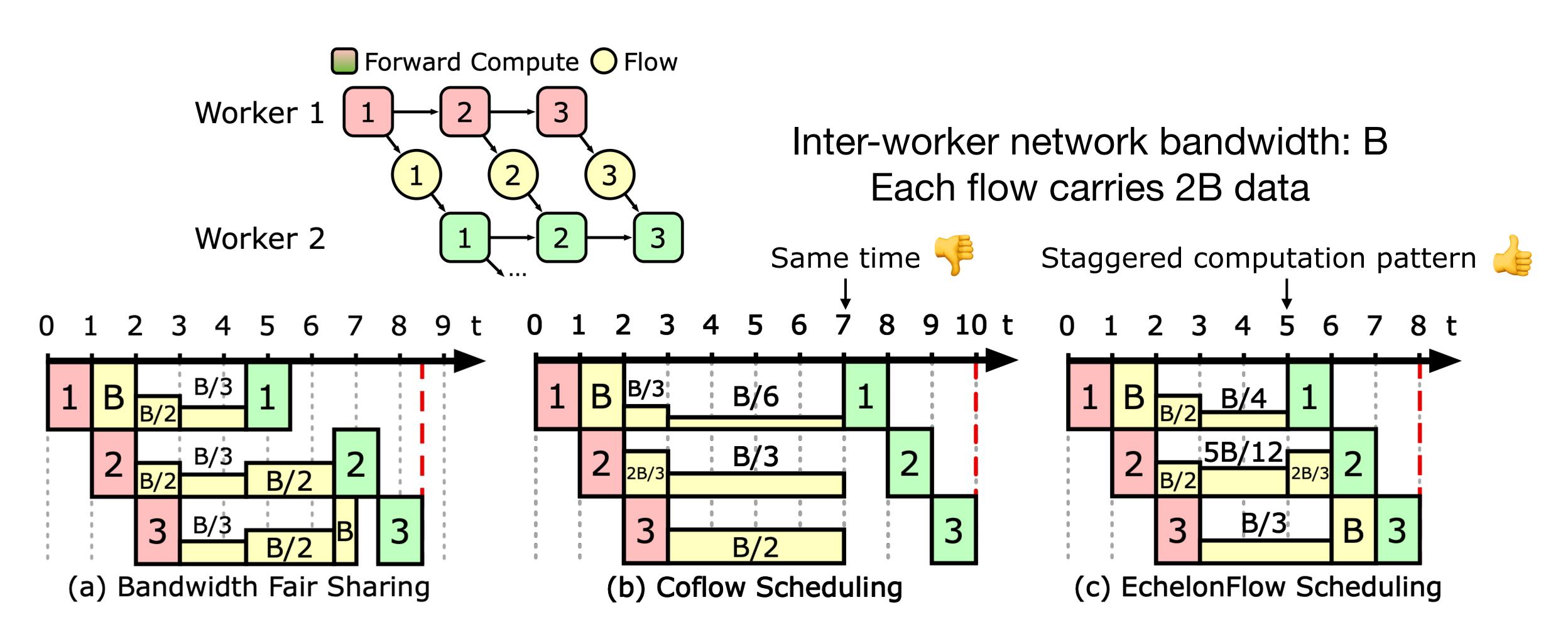










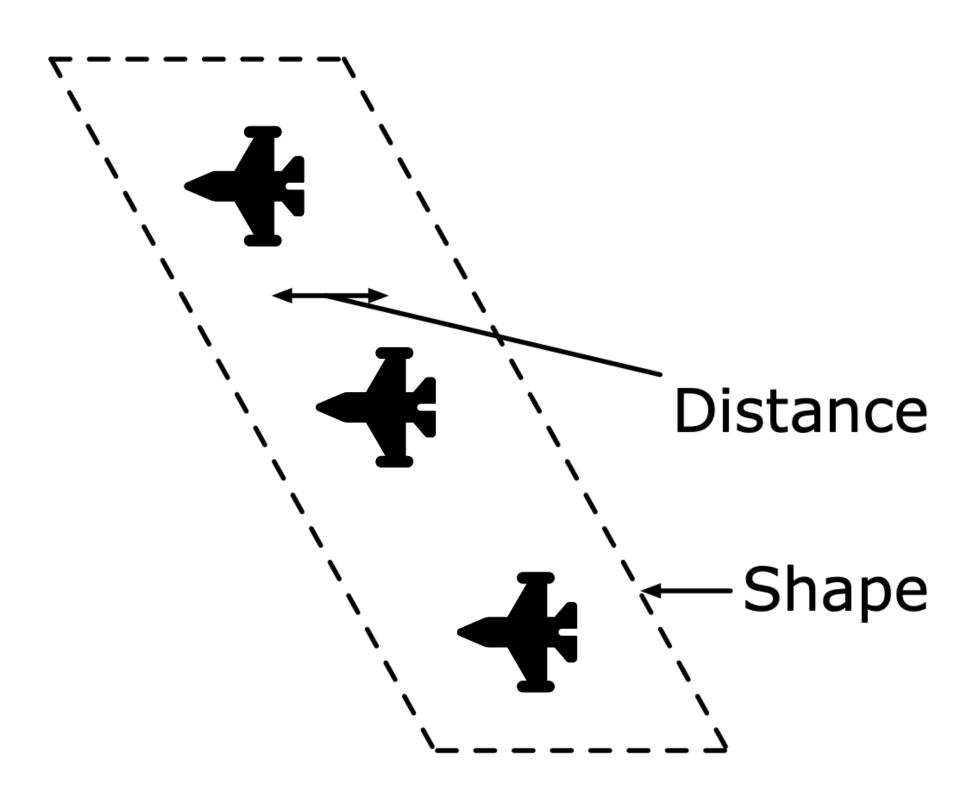


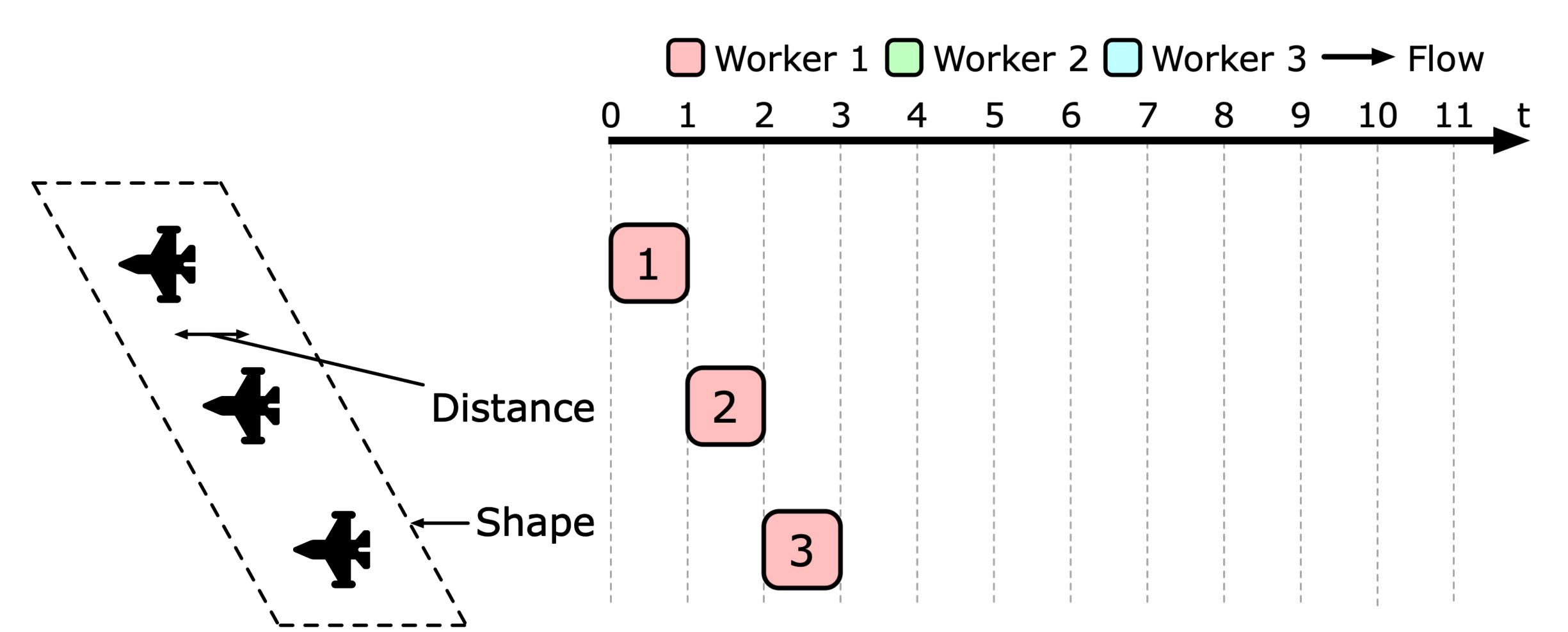


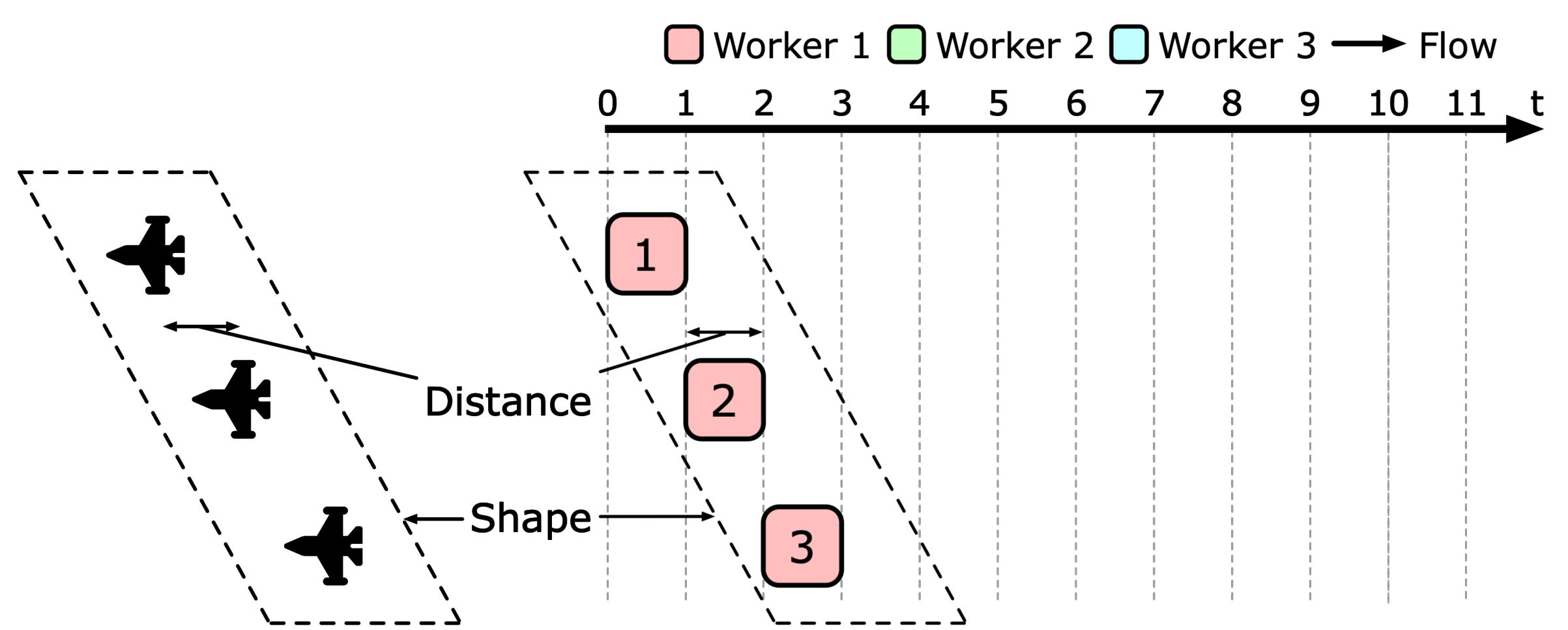


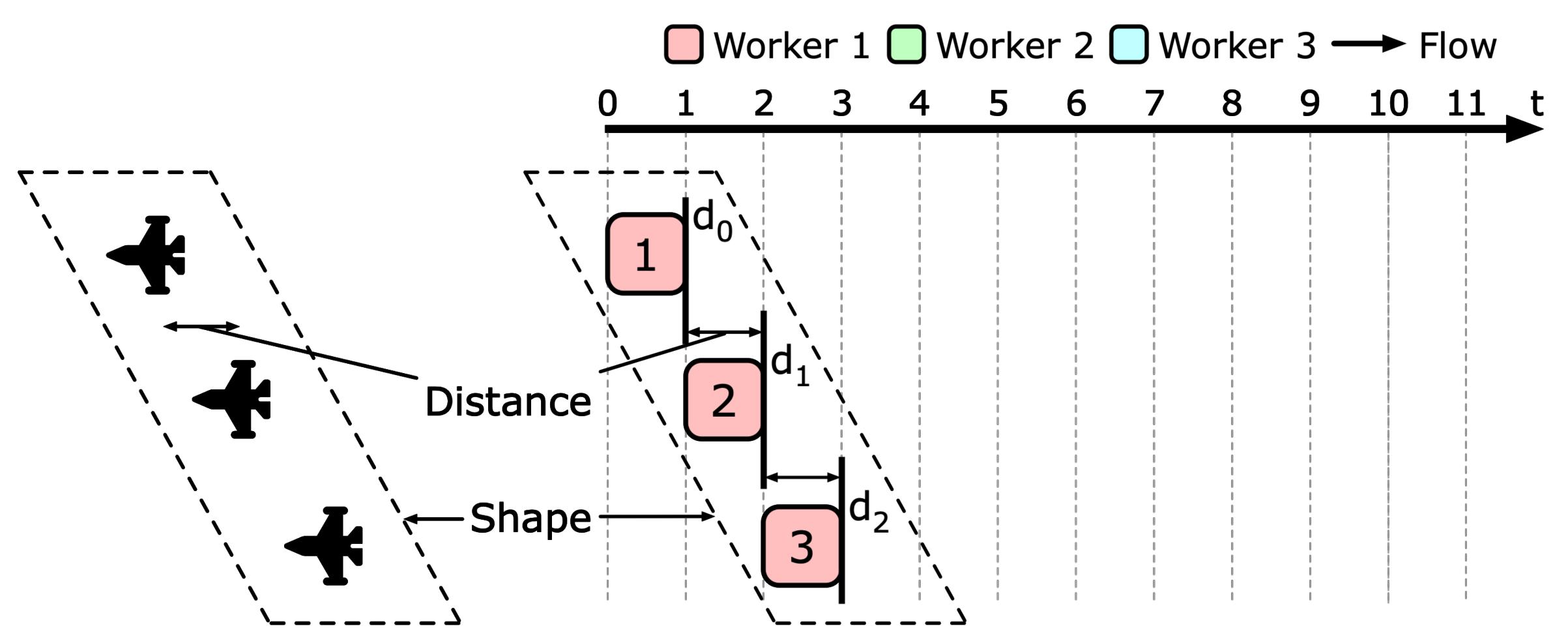


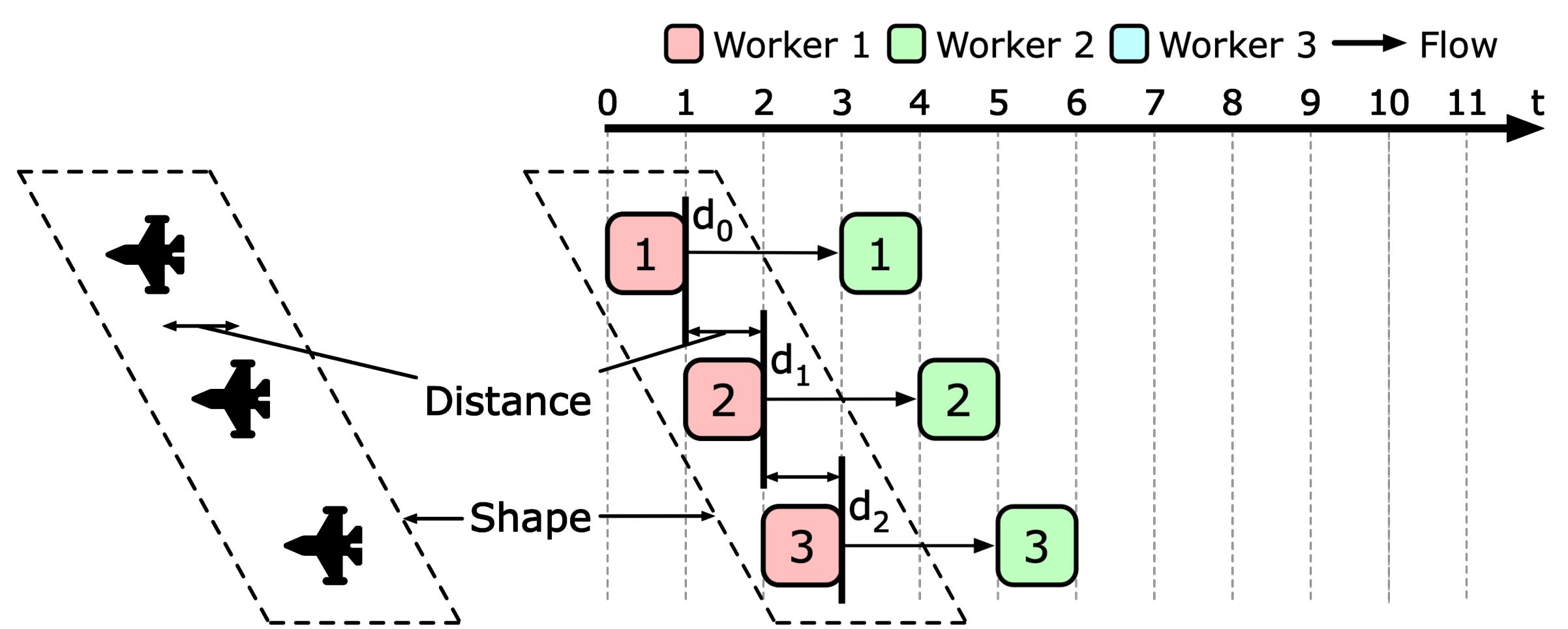


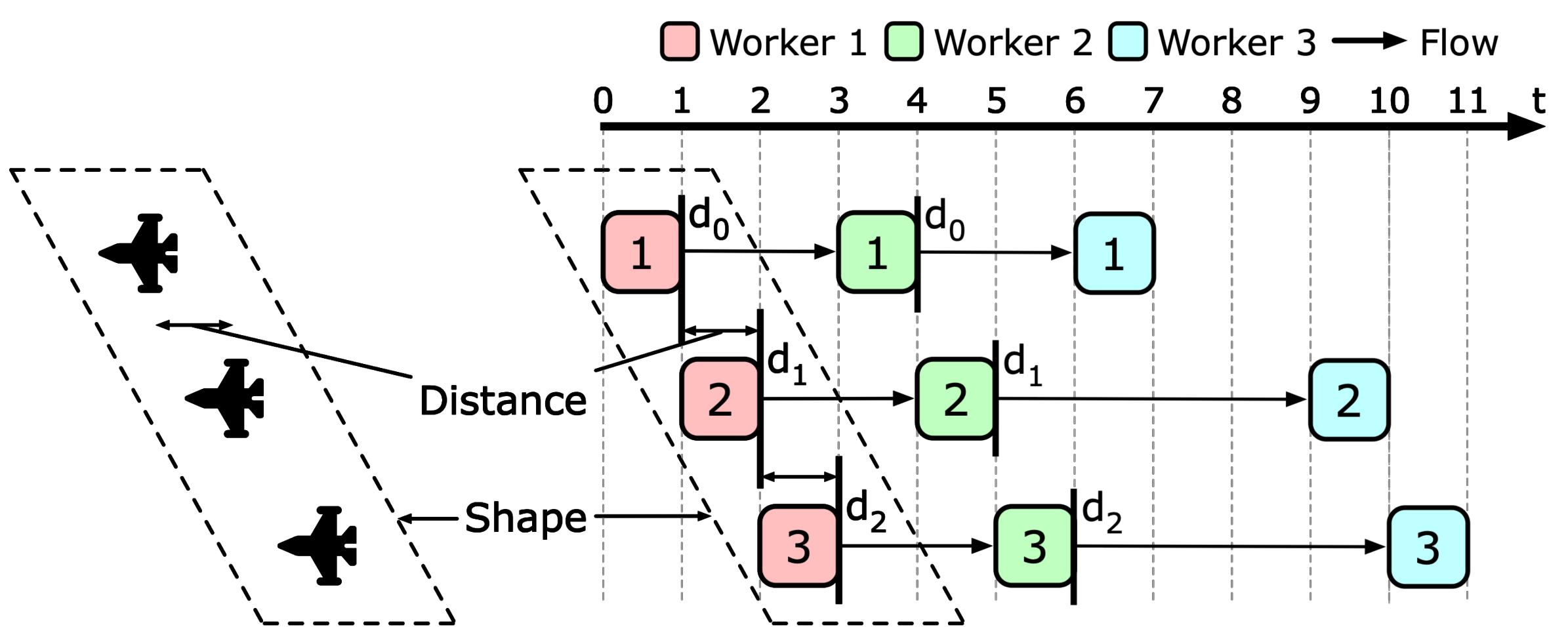


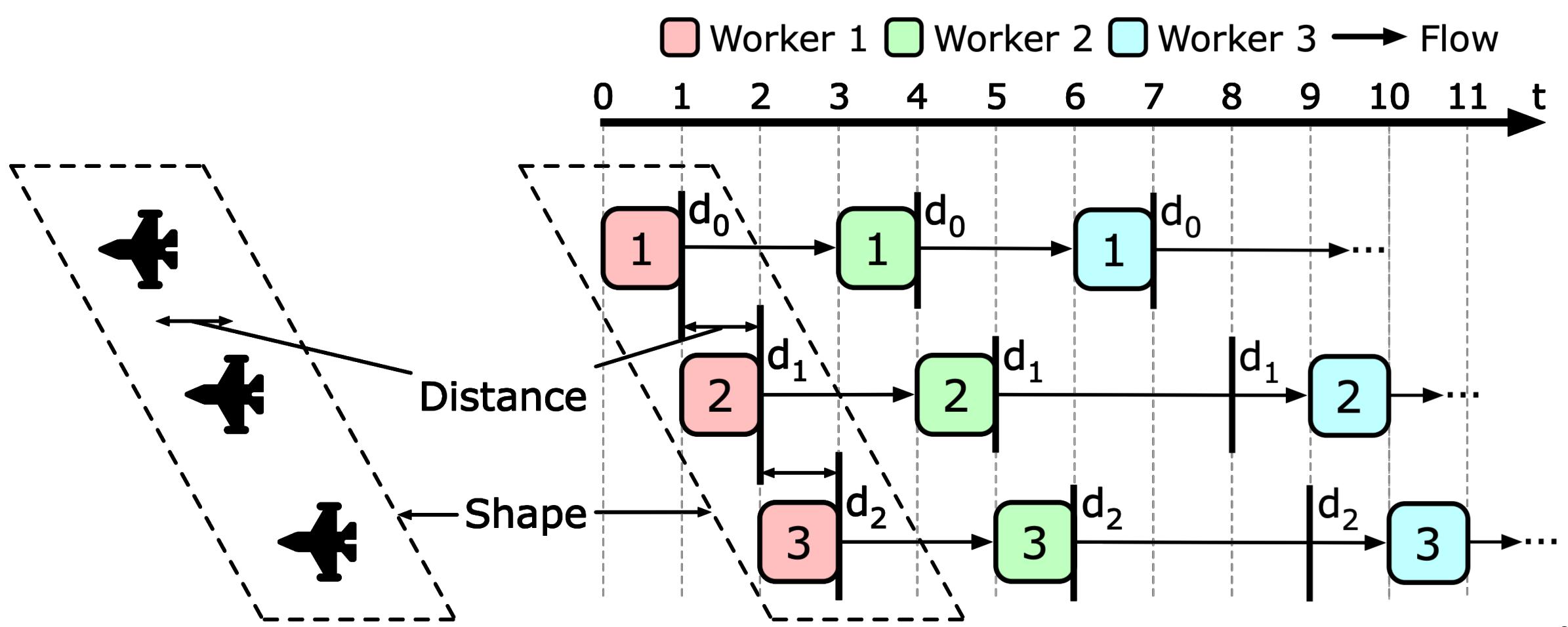












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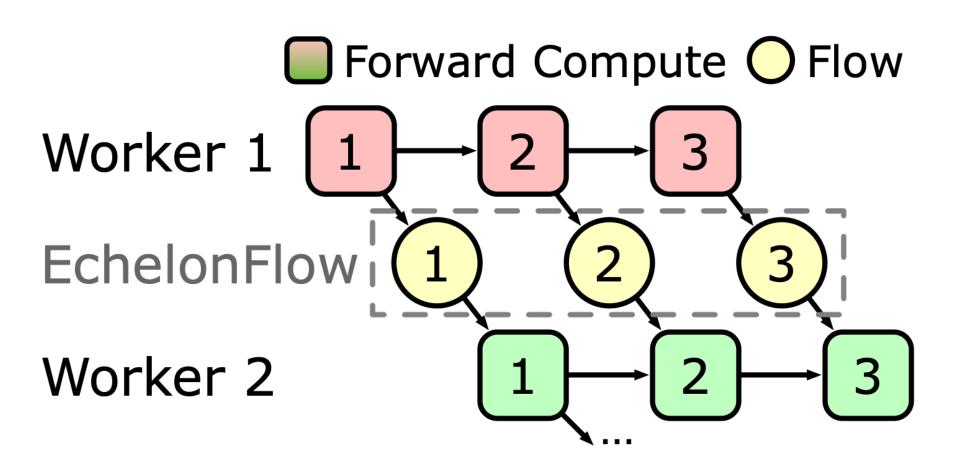
Definition

- EchelonFlow: a set of flows whose ideal finish times are related
 - Not necessarily equal
 - Can be represented by an arrangement function

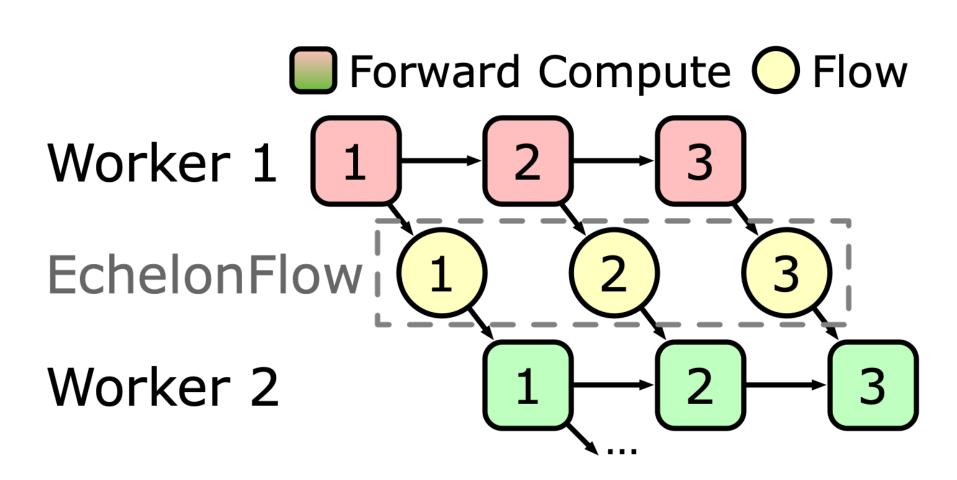
Expressiveness

Training paradigm	Examples	CoFlow compliance	EchelonFlow compliance
Data Parallelism	AllReduce, Parameter Server		
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Case study: pipeline parallelism



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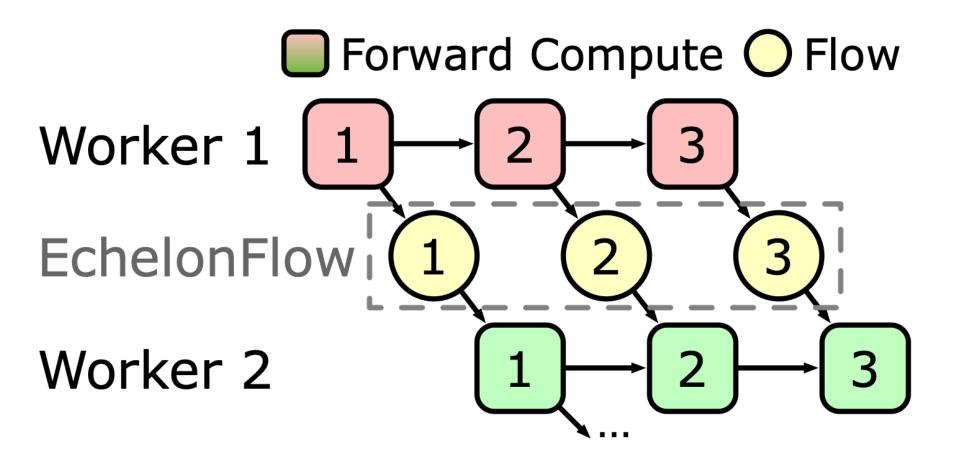


Arrangement function:

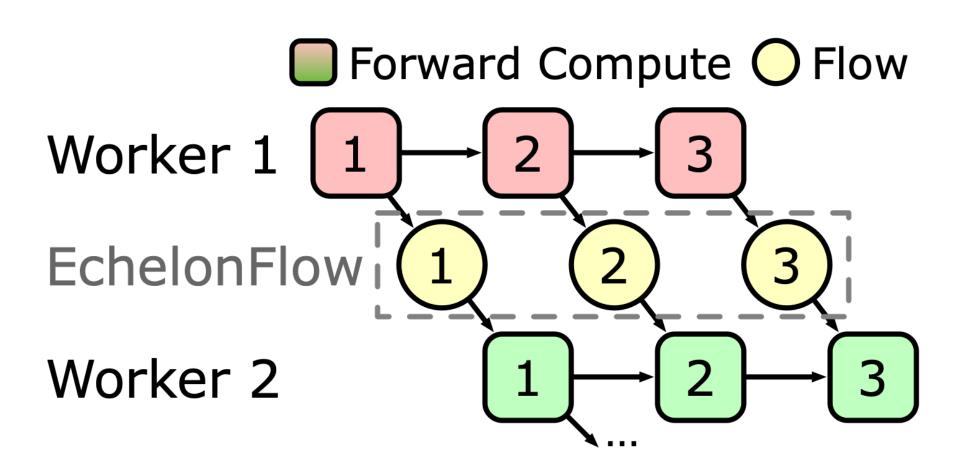
$$d_j = d_{j-1} + T$$

d_j: ideal finish time of flow j T: time of one forward pass of one micro-batch

Properties

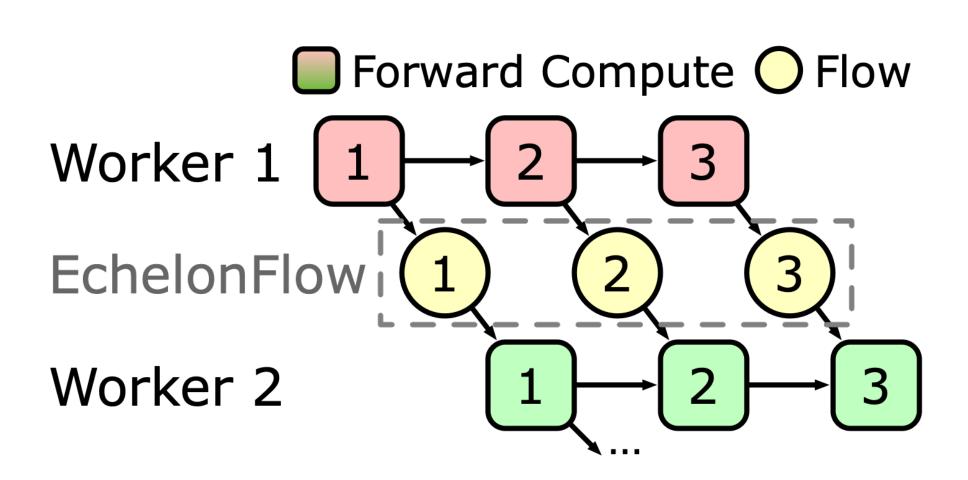


Properties



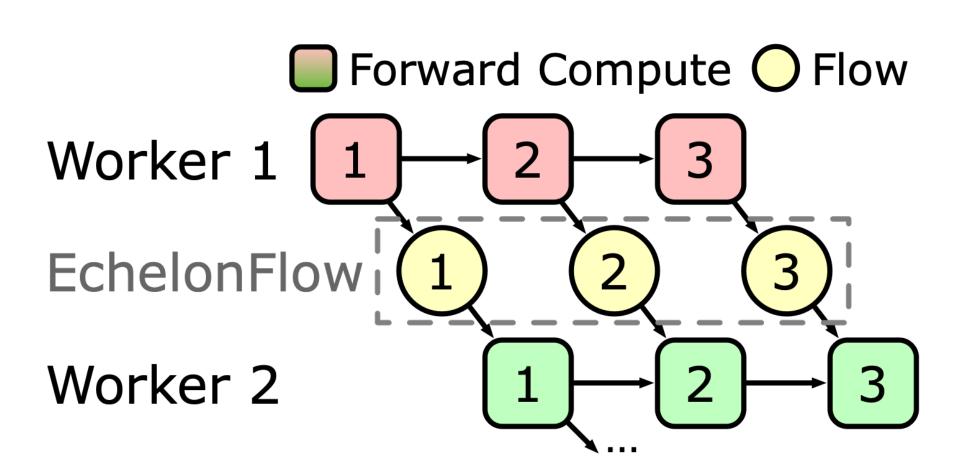
General to diverse distributed training paradigms

Properties



- General to diverse distributed training paradigms
- A superset of CoFlow

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- General to diverse distributed training paradigms
- A superset of CoFlow
- Same complexity as CoFlow scheduling

EchelonFlow Implementation

Implementation

 We know: flow size, computation time, and computationcommunication dependencies

Implementation

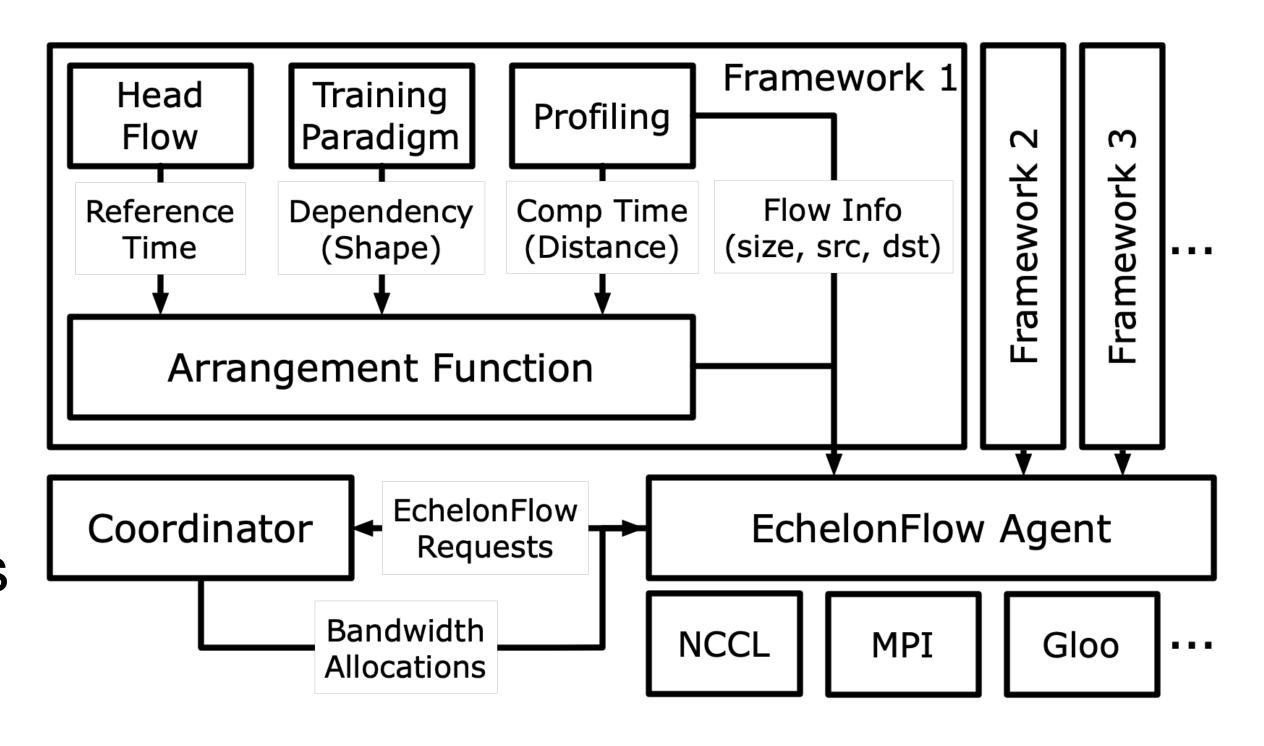
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 - Flow finish times are not necessarily the same, but follow a pattern
 - Arrangement function for high training throughput