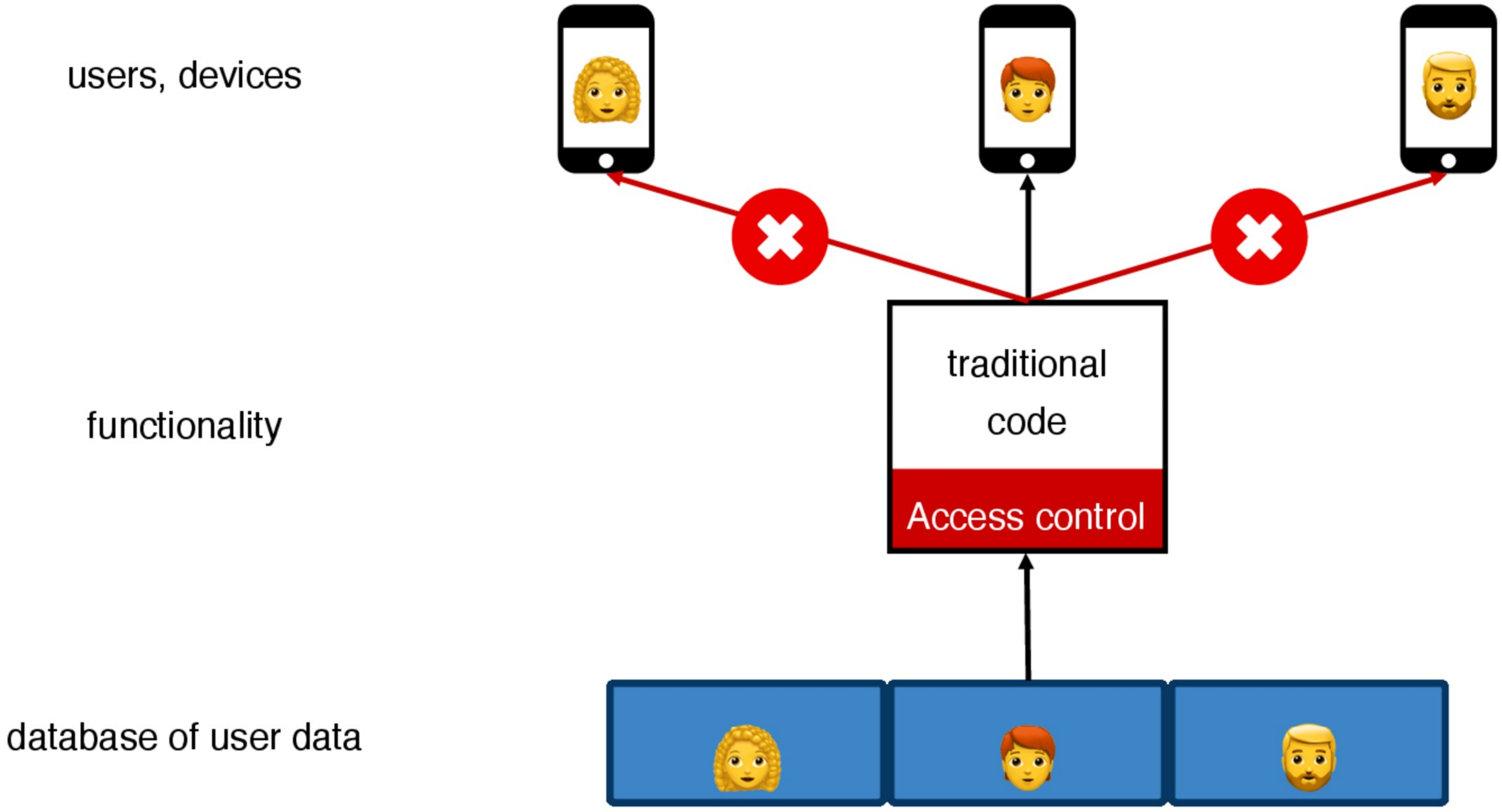
Privacy Budget Scheduling

Tao Luo*, Mingen Pan*, **Pierre Tholoniat***
Asaf Cidon*, Roxana Geambasu*, Mathias Lécuyer†

**Columbia University* †*Microsoft Research*

Example: Messaging App



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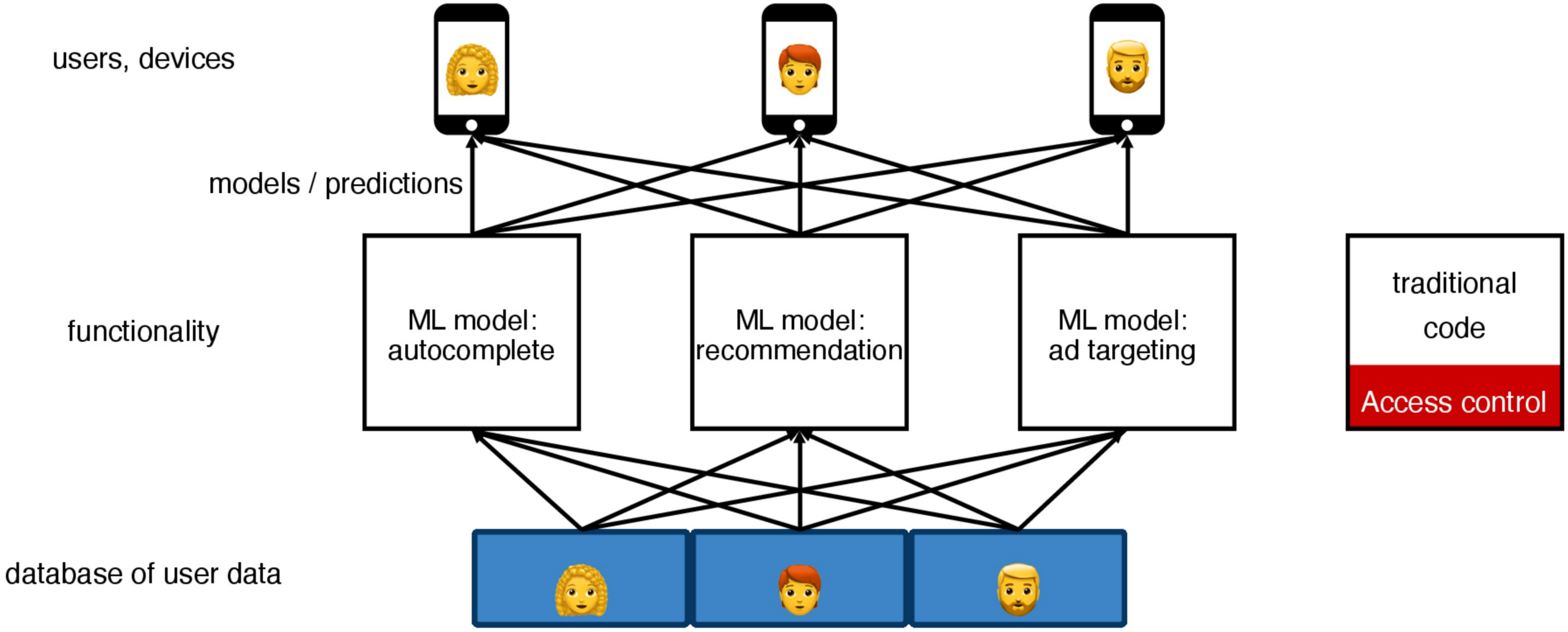
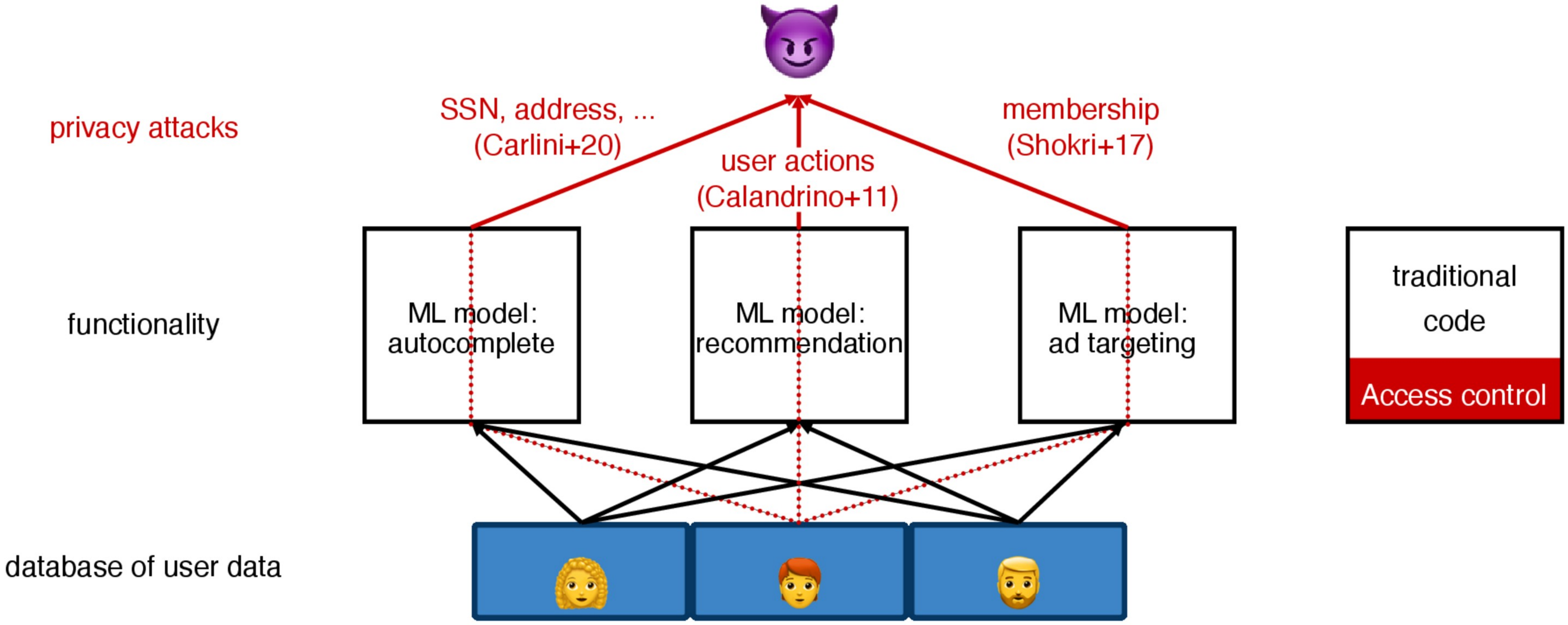
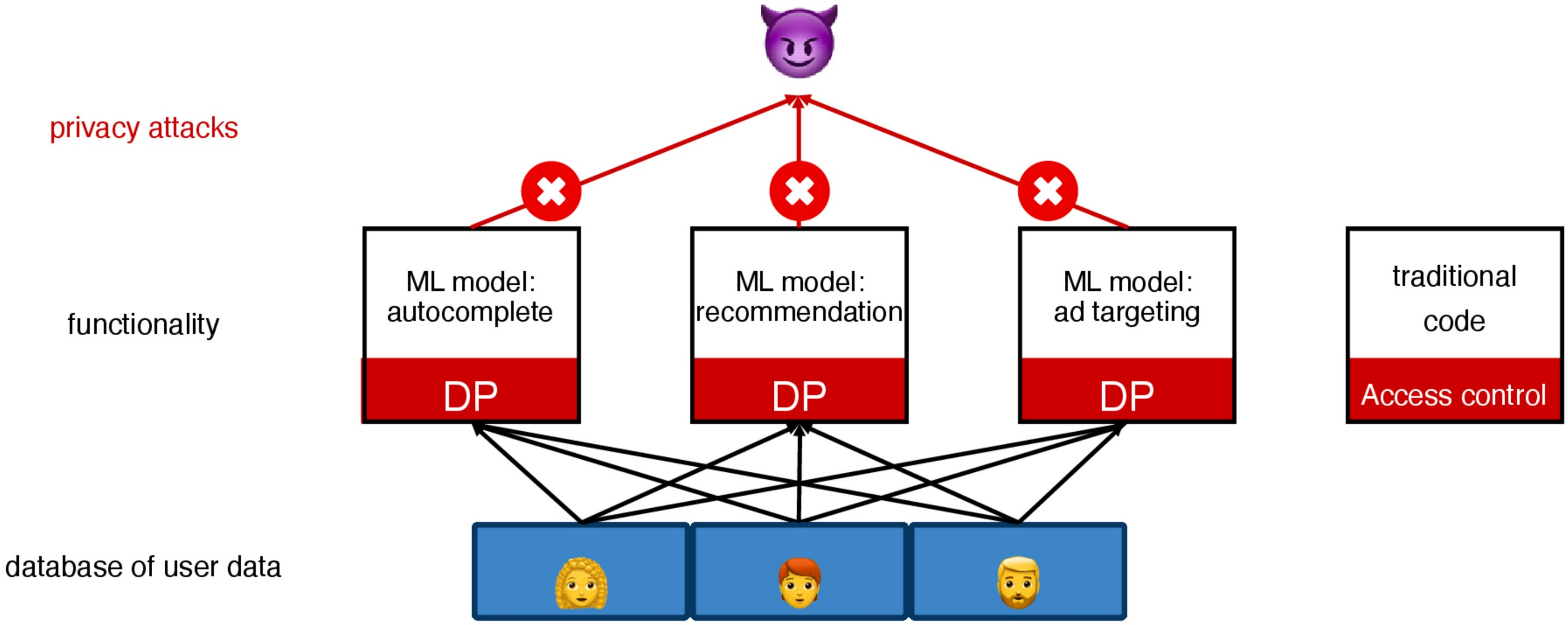


What Can Leak?

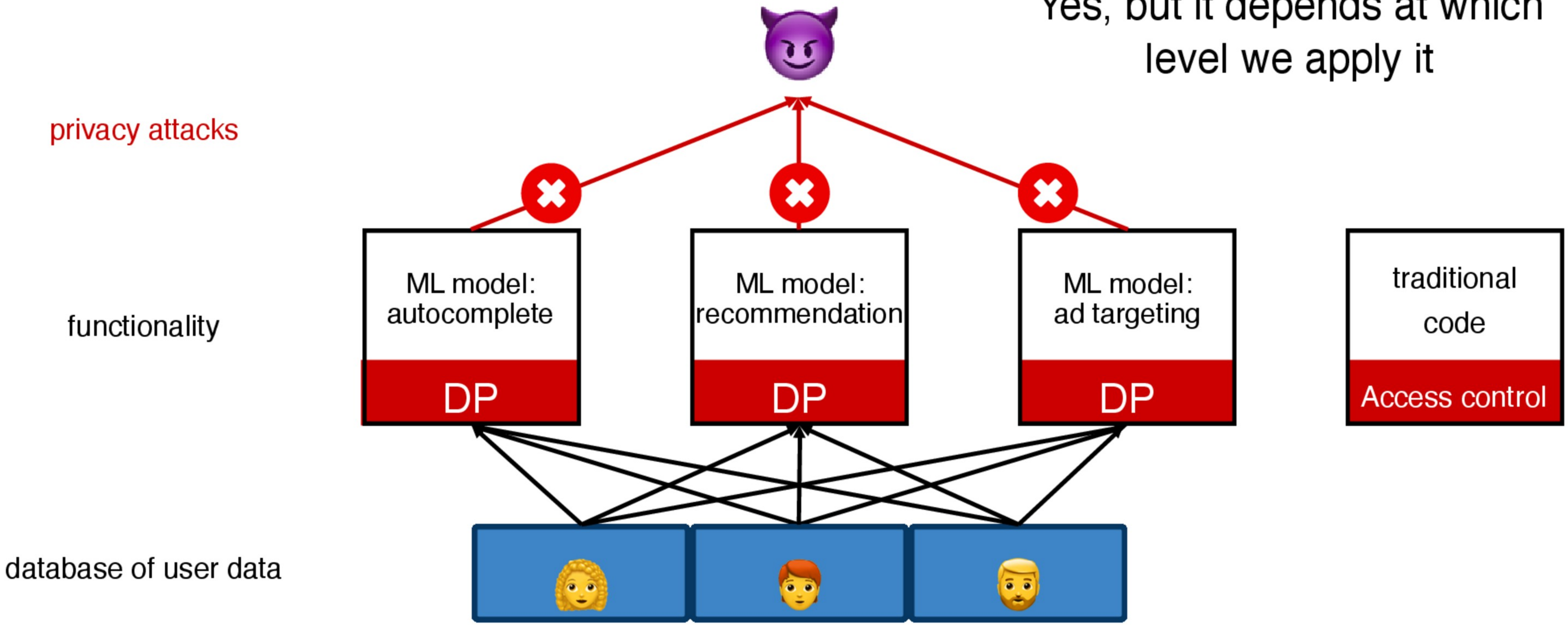


Is Differential Privacy (DP) the Solution?



Is Differential Privacy (DP) the Solution?

Yes, but it depends at which level we apply it



DP at Individual Model Level

- Privacy attacks find data points that make a given observed model more likely

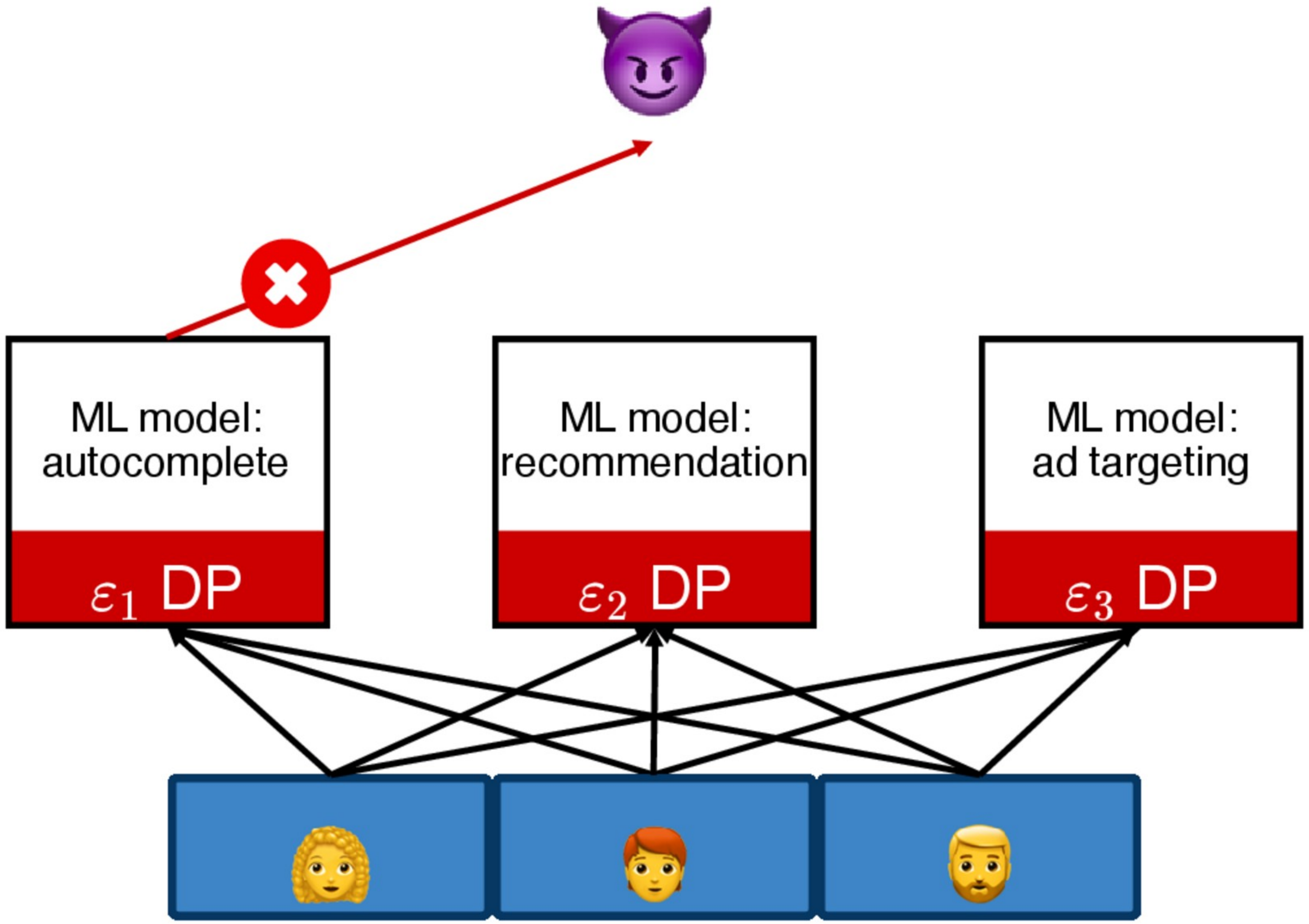
- DP randomizes the training procedure of a model (e.g., SGD) to guarantee that no data point **drastically increases** the likelihood of the outputted model.

- The increase in likelihood of the outputted model is controlled by the **privacy loss** $\varepsilon > 0$

Definition. A randomized procedure $f : D \to O$ over databases is (ε, δ)-**differentially private** if for all databases $d_1, d_2 \in D$ that differ in one data point, and for all output sets $S \subseteq O$:

$$\Pr[f(d_1) \in S] \leq e^{\varepsilon} \Pr[f(d_2) \in S] + \delta$$

Problem: Privacy Loss Accumulates



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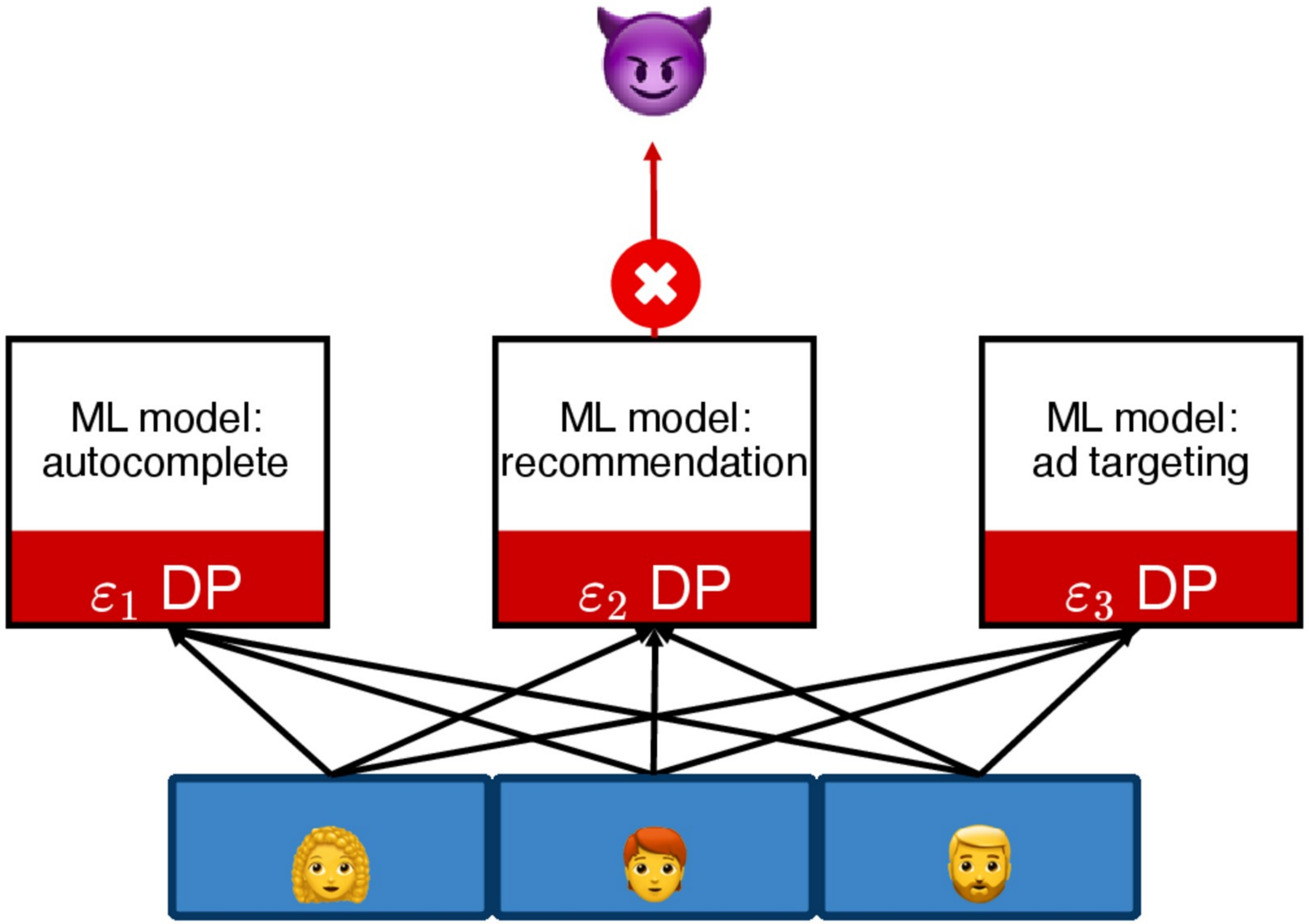

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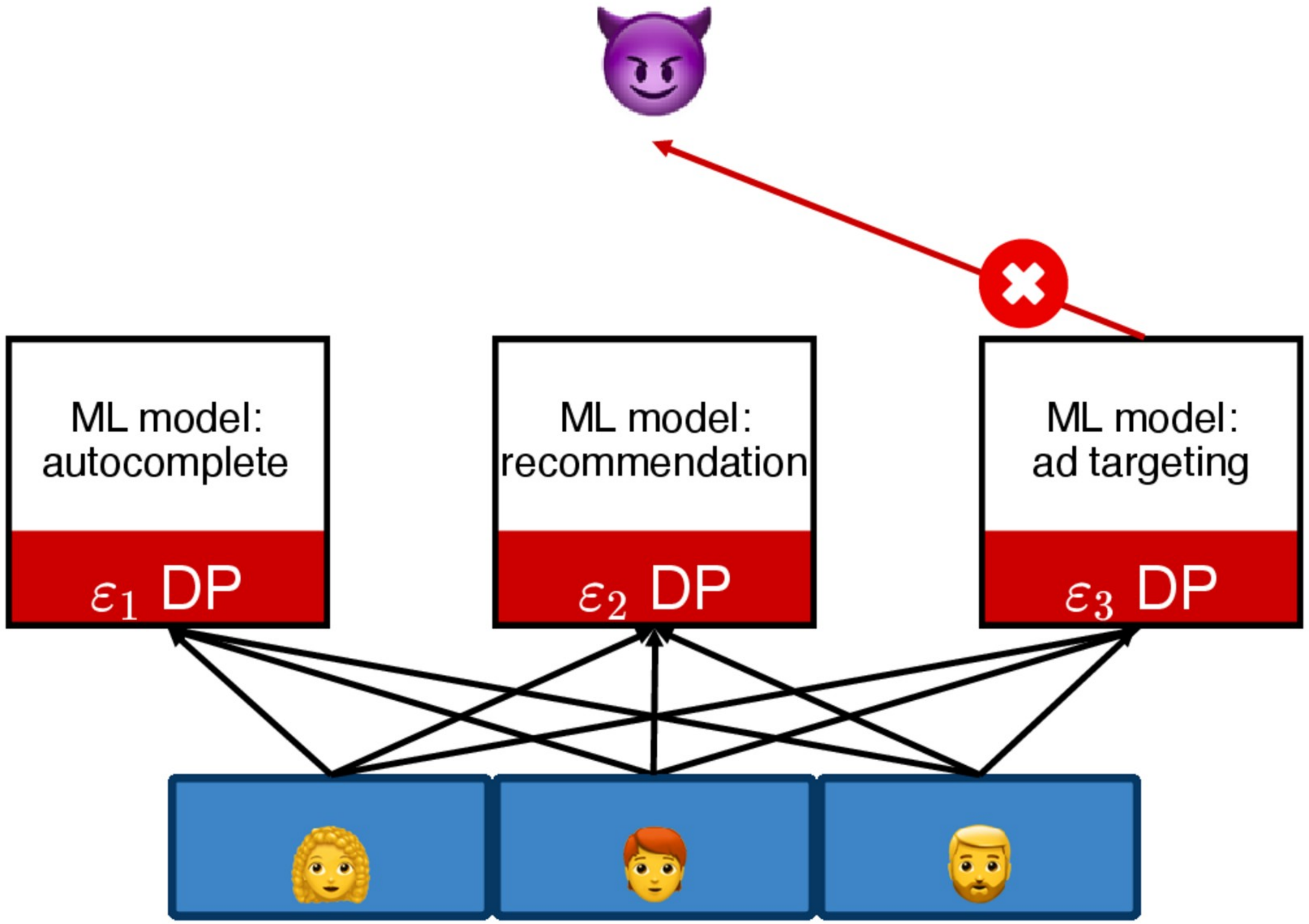
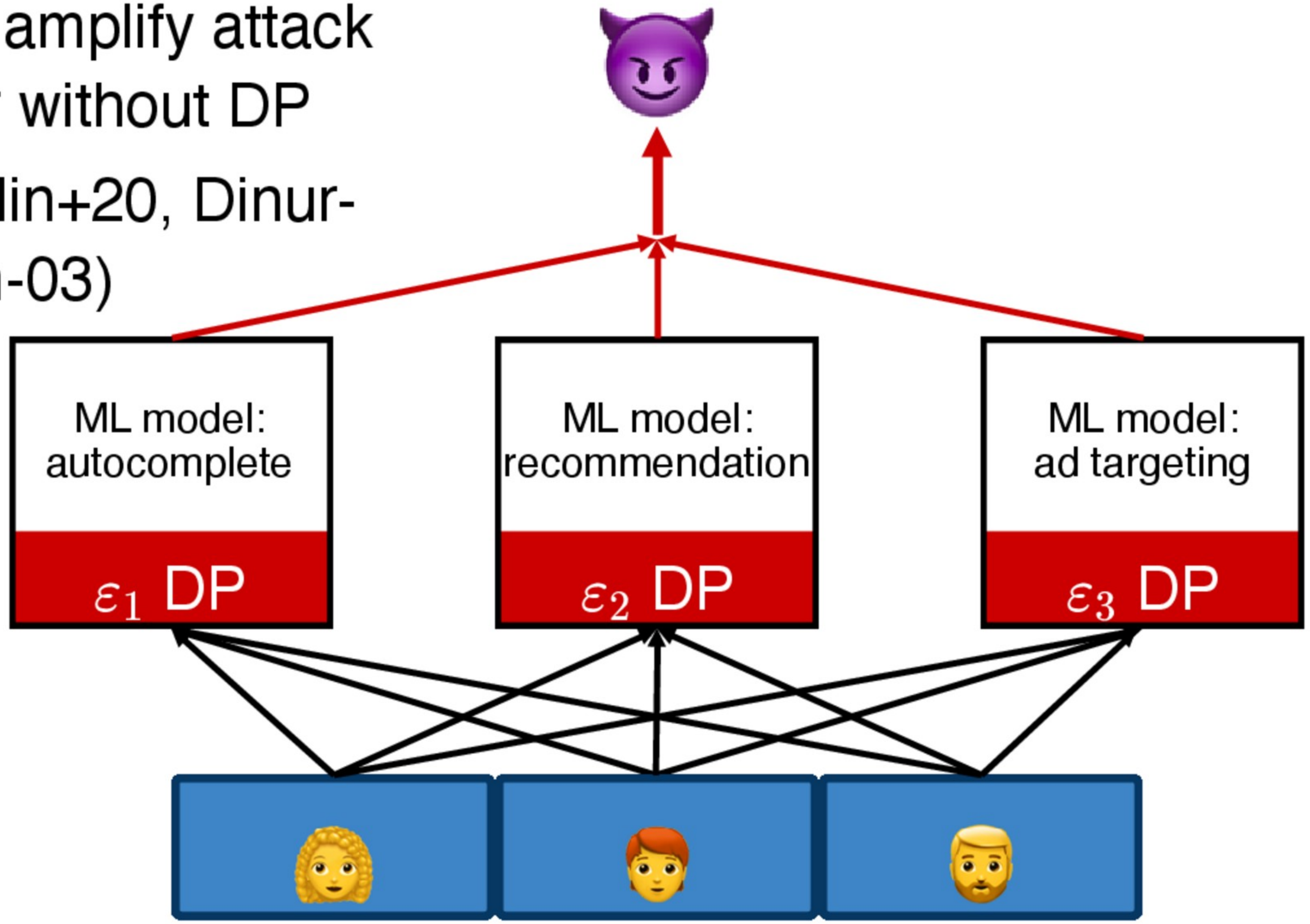


Problem: Privacy Loss Accumulates

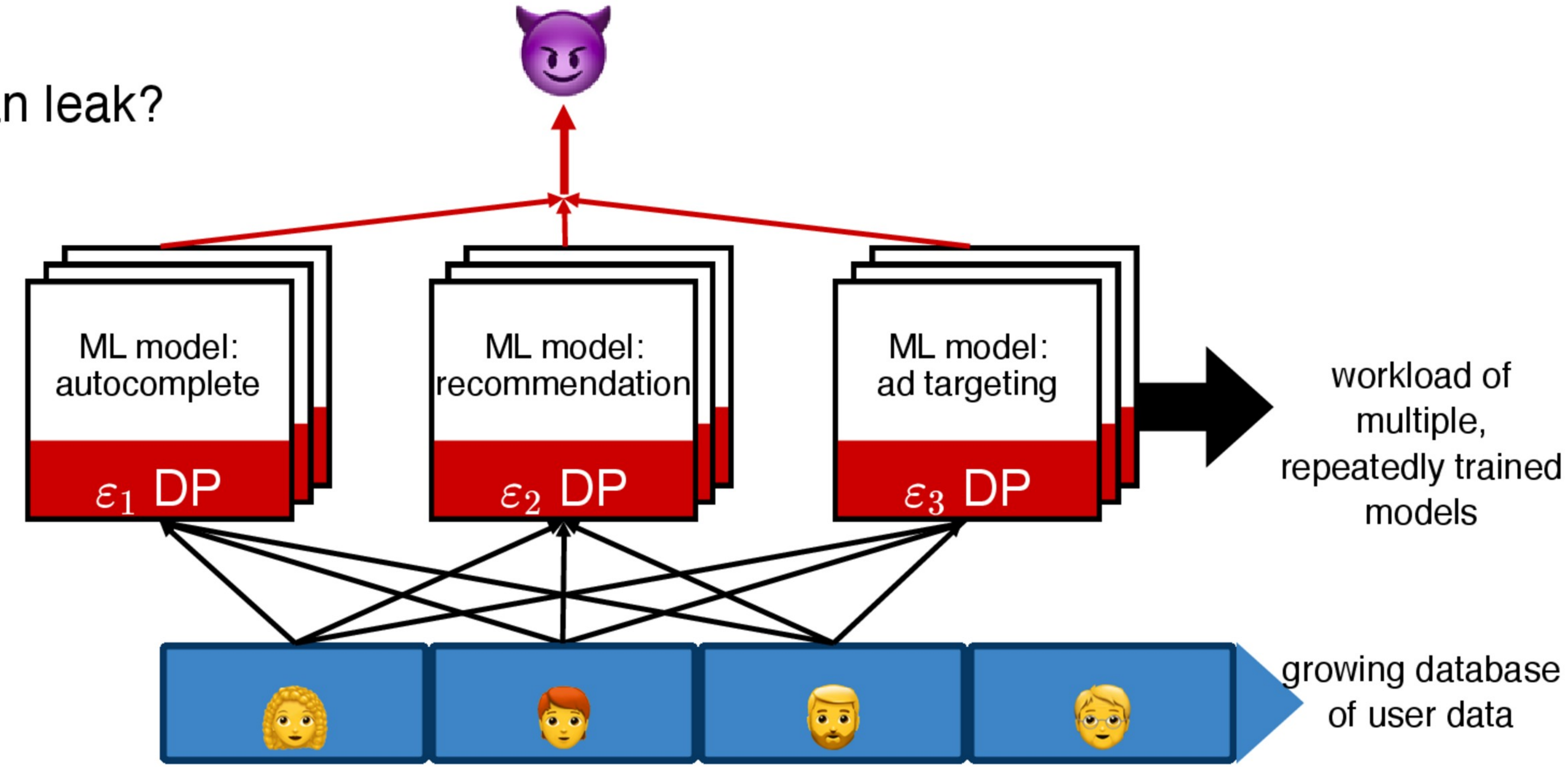
Multiple models amplify attack power, with or without DP

(Zanella-Béguelin+20, Dinur-Nissim-03)



Problem: Privacy Loss Accumulates

What can leak?



Problem: Privacy Loss Accumulates

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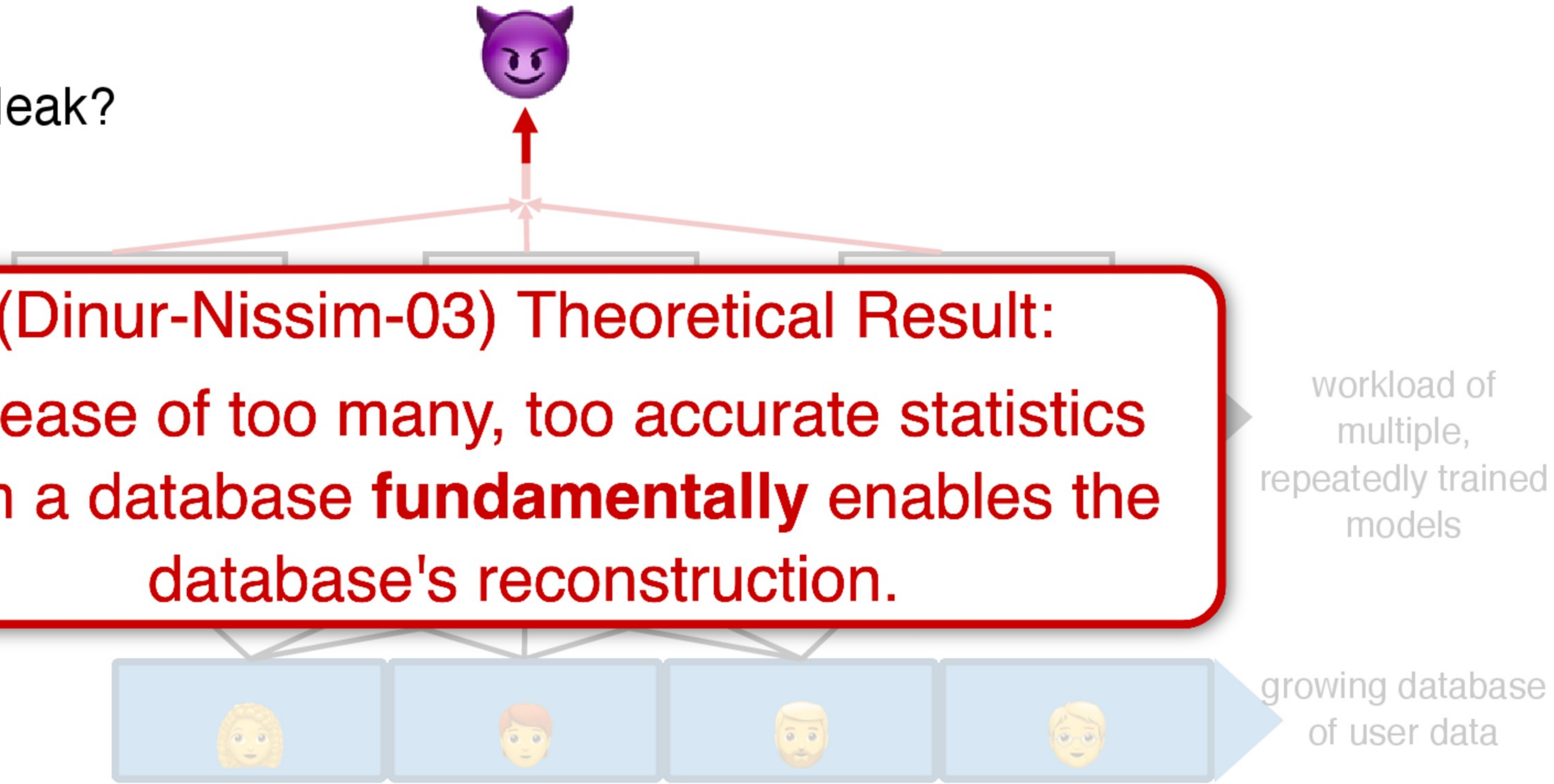
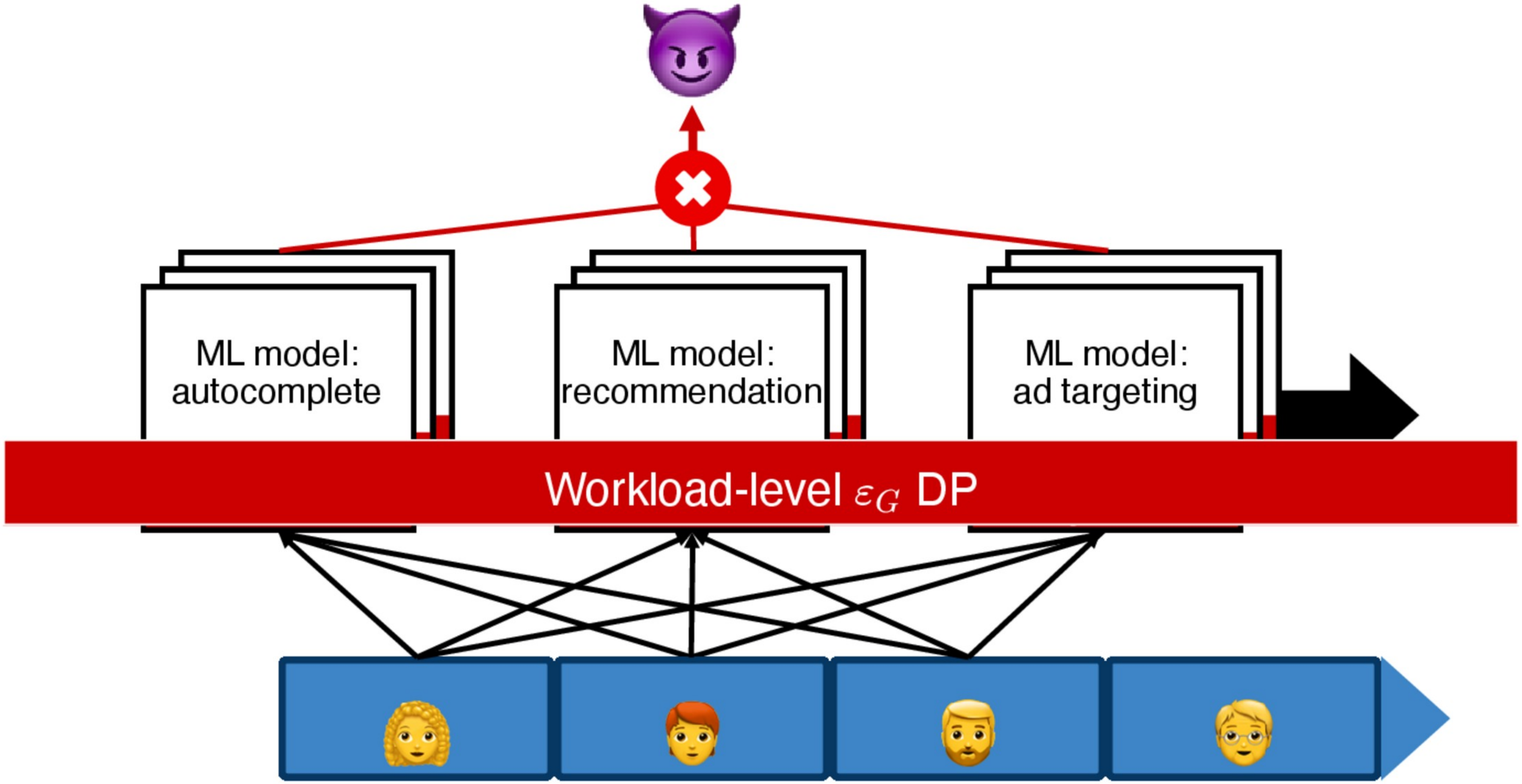


(Dinur-Nissim-03) Theoretical Result:

Release of too many, too accurate statistics from a database **fundamentally** enables the database's reconstruction.

Solution: DP at Workload Level



Our Vision:
Privacy as a Compute Resource

- DP composes, so ML training tasks consume a **global privacy budget** ε_G :

$$\sum_{task\ i} \varepsilon_i \leq \varepsilon_G.$$

- Privacy should be a **compute resource**, alongside CPU, GPU, RAM

- We must **schedule privacy efficiently and fairly**:
  - Can we use existing schedulers? Which ones?
  - Which fairness/efficiency properties?

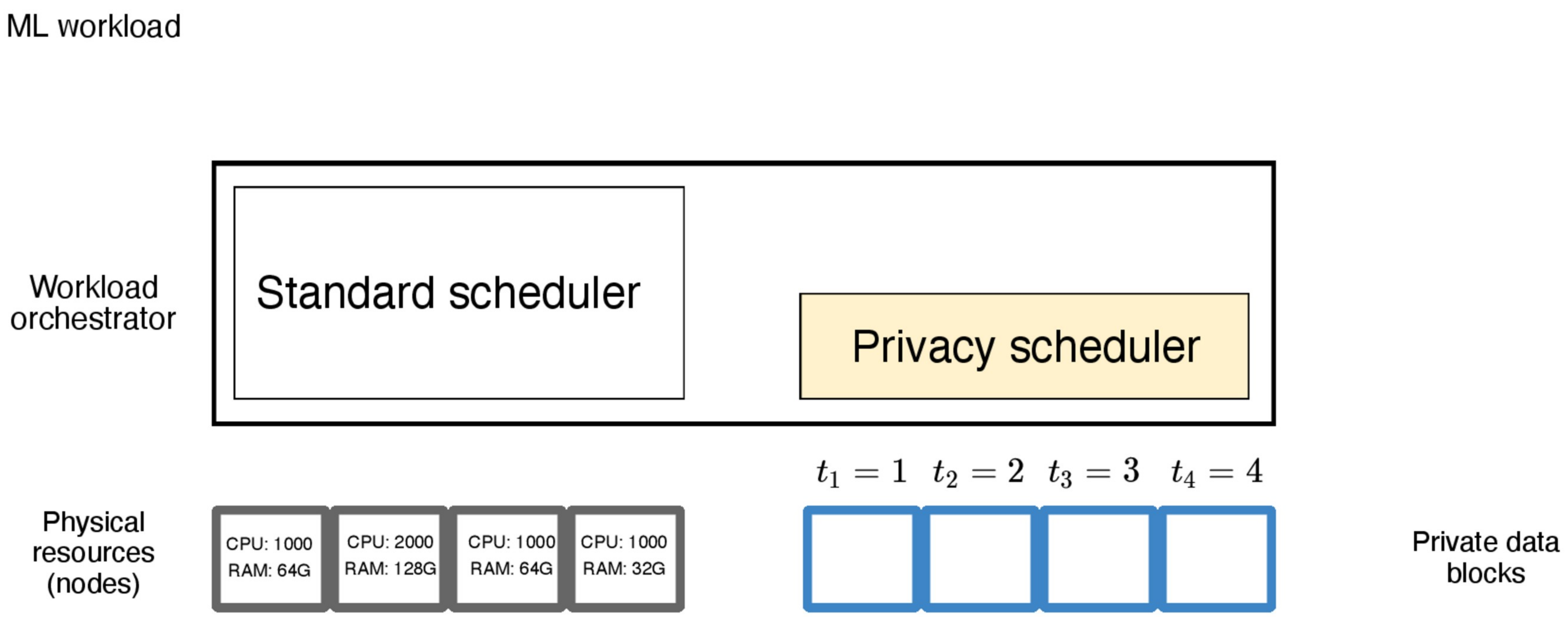
PrivateKube

- Extension for Kubernetes that adds privacy as a **new resource** alongside traditional compute resources
- New scheduler: **Dominant Privacy Fairness (DPF)**, a variant of Dominant Resource Fairness (DRF)
- DPF enjoys similar **fairness properties** as DRF, with some definitional changes to account for privacy characteristics

Outline

1. Motivation
2. **Architecture**
3. DPF scheduler
4. Evaluation

Architecture



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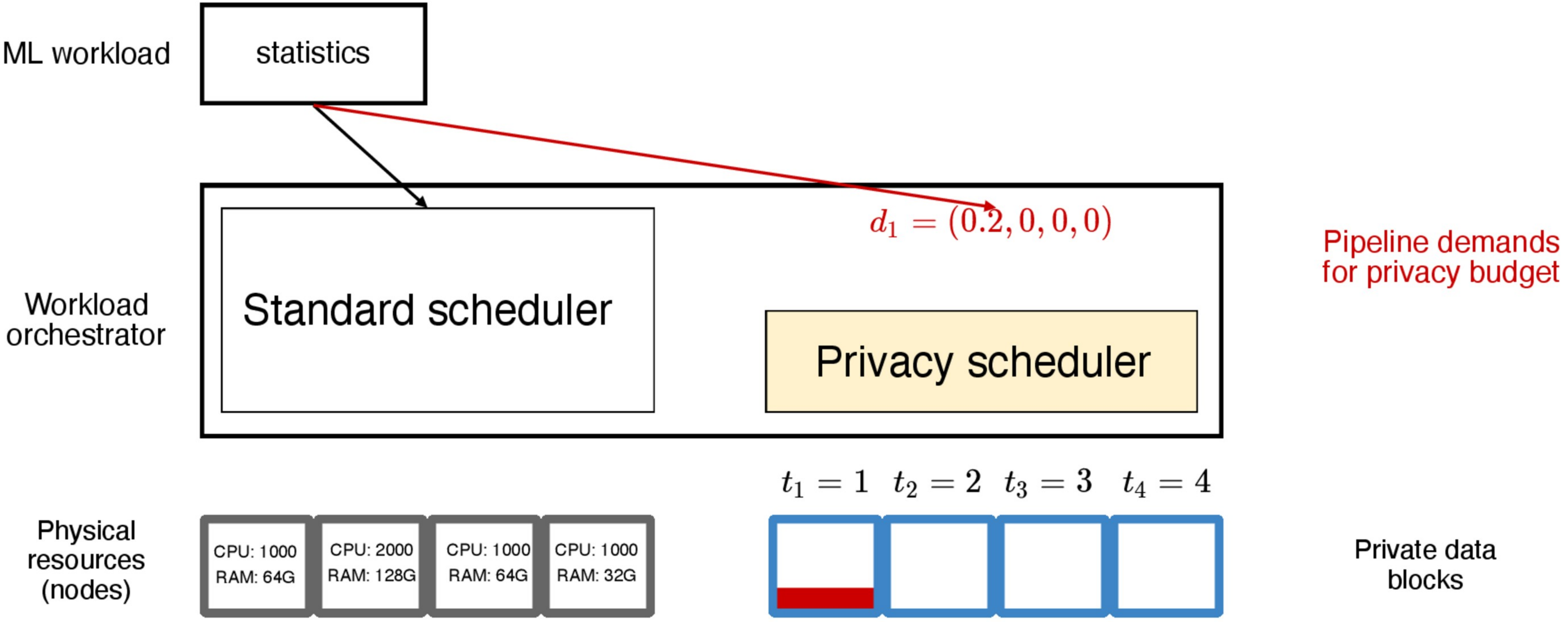

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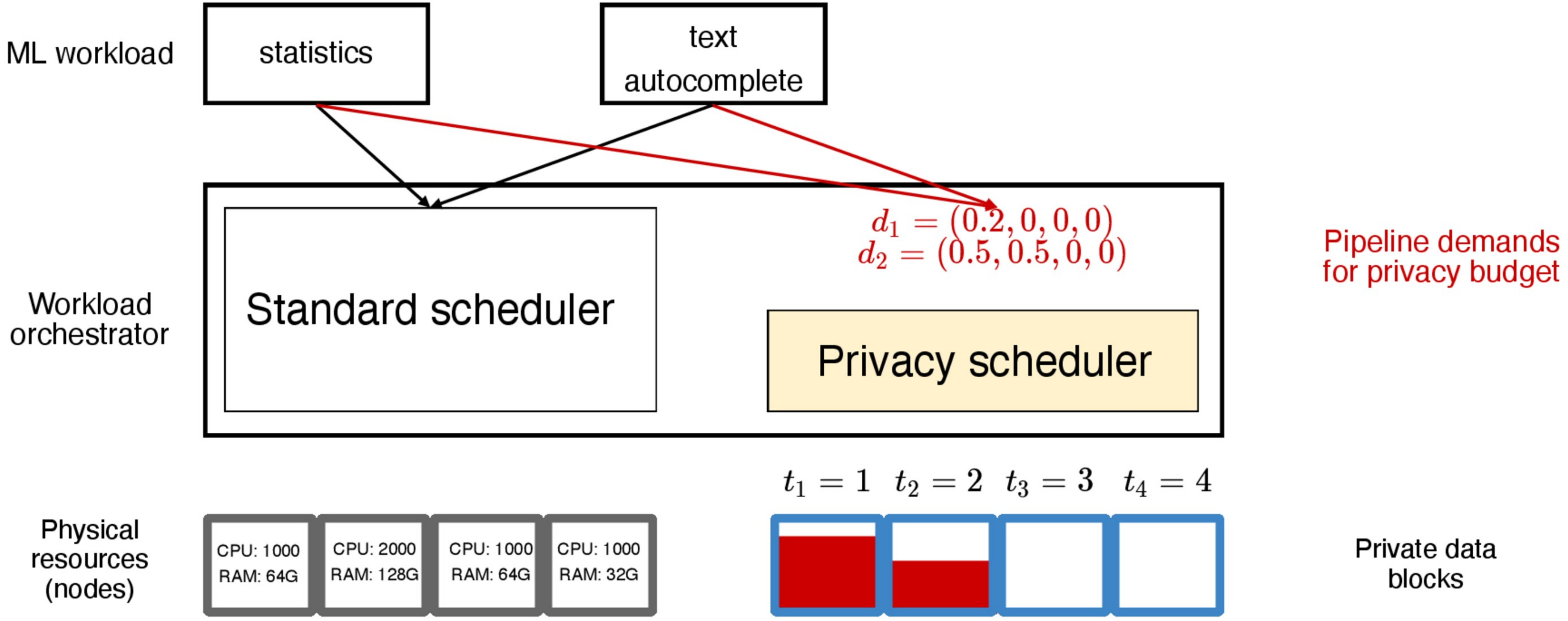

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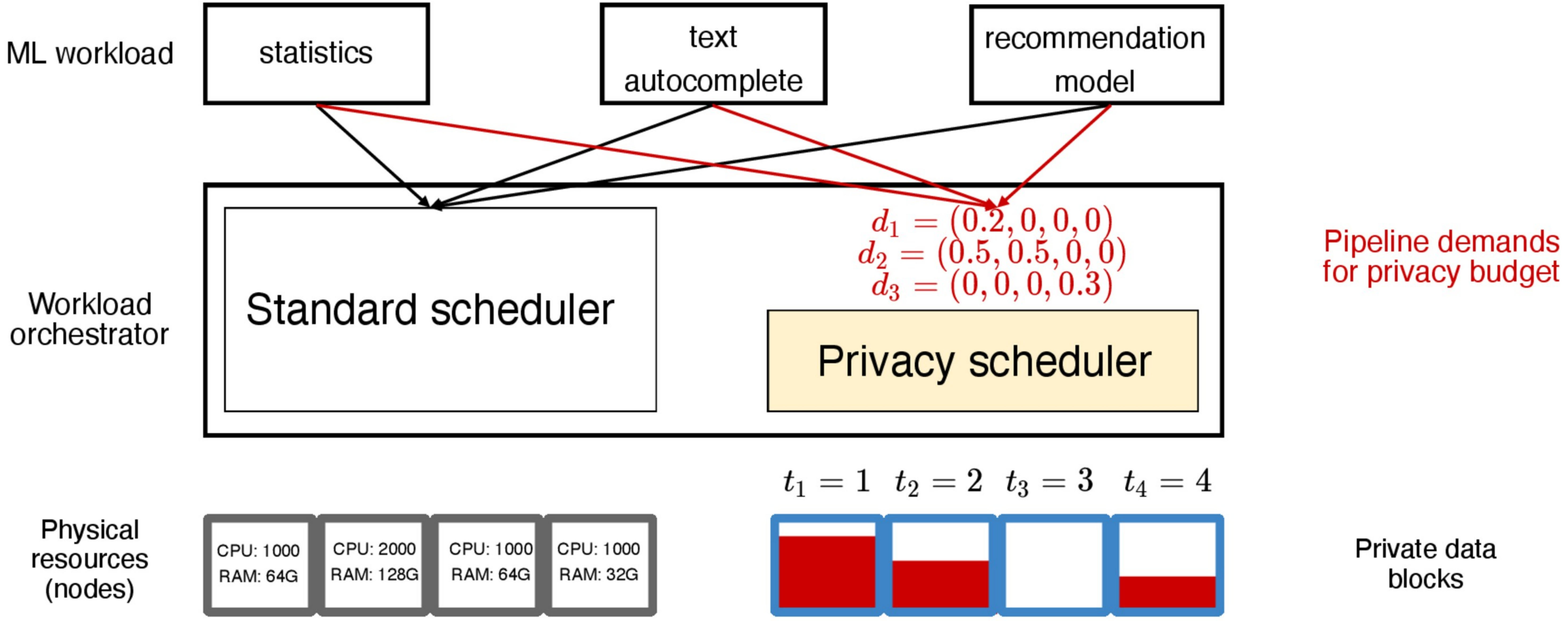

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DRF as a Basis

- Dominant Resource Fairness (DRF) to allocate **multiple resources** (Ghodsi+11)

- Popular for datacenters (CPU, GPU, RAM)

- For compute, it gives **max-min fairness** over m resources

Algorithm 1. DRF

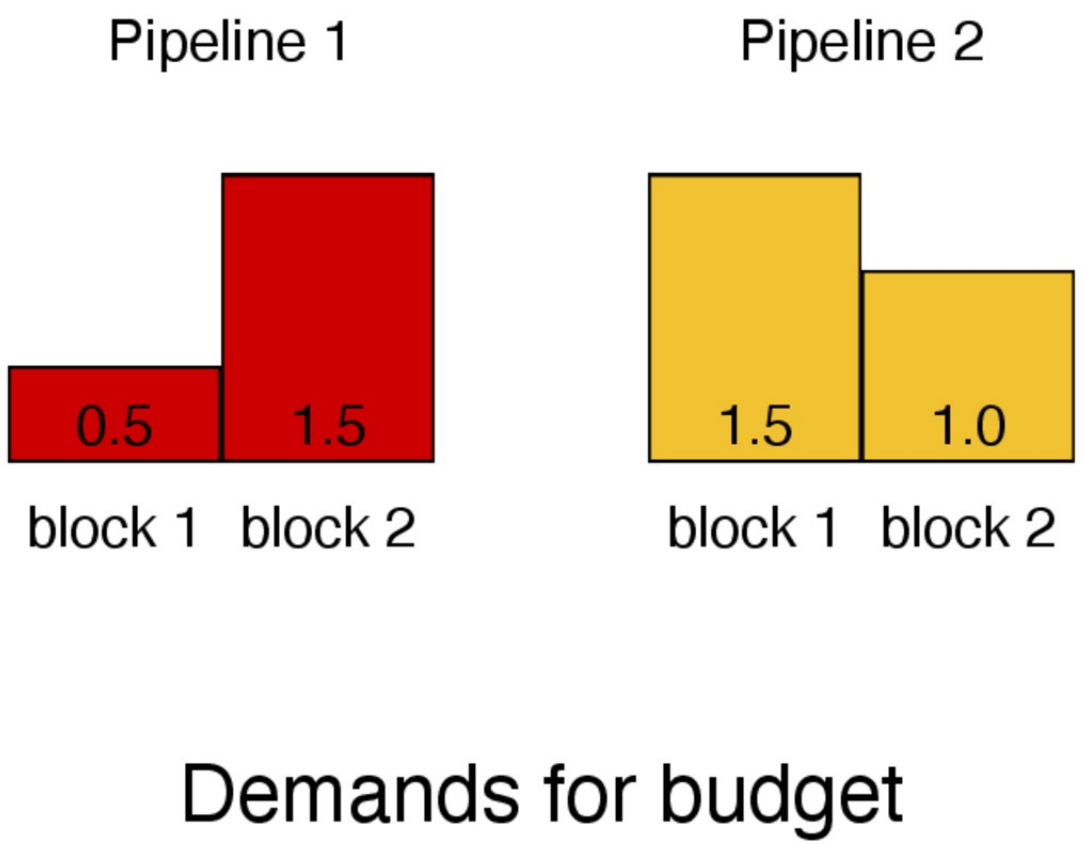
$R = \langle R_1, \ldots, R_m \rangle$ resource capacities
$C = \langle C_1, \ldots, C_m \rangle$ consumed resources

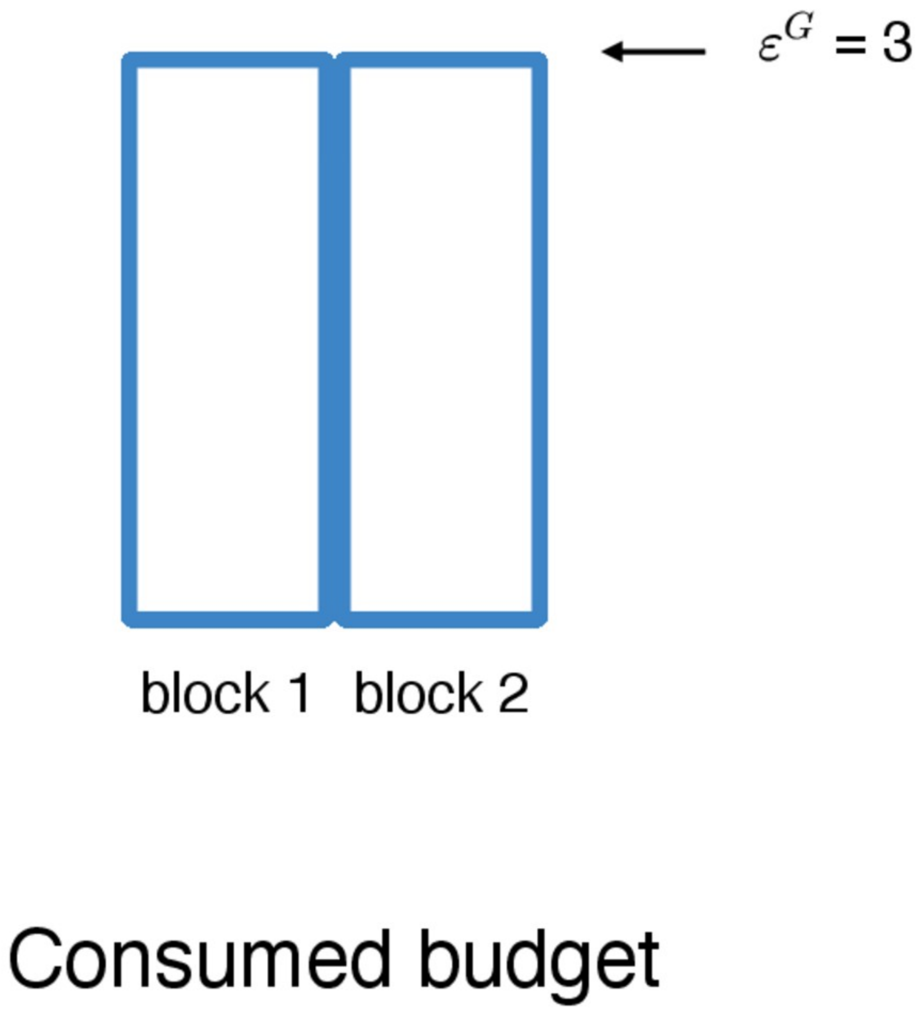
$\text{DominantShare}(d_i) := \max_j \frac{d_{i,j}}{R_j}$

$\text{OnSchedulerTimer}(WaitingJobs):$
$\quad SortedJobs \leftarrow \text{sortBy}(\text{DominantShare}, WaitingJobs)$
$\quad \text{for } i \in SortedJobs:$
$\quad\quad \text{if } C + d_i \leq R:$
$\quad\quad\quad C \leftarrow C + d_i$

Problem: Privacy is not Replenishable

$$t = 1$$





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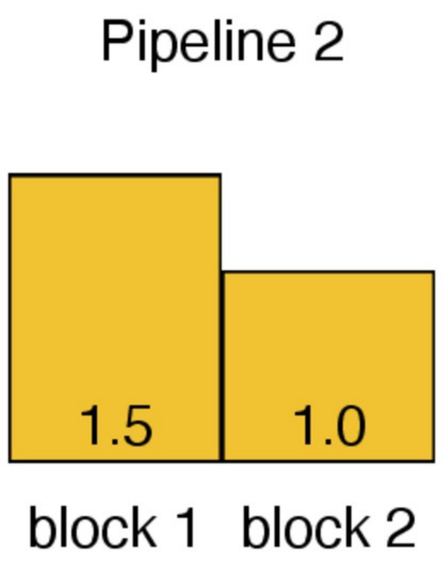
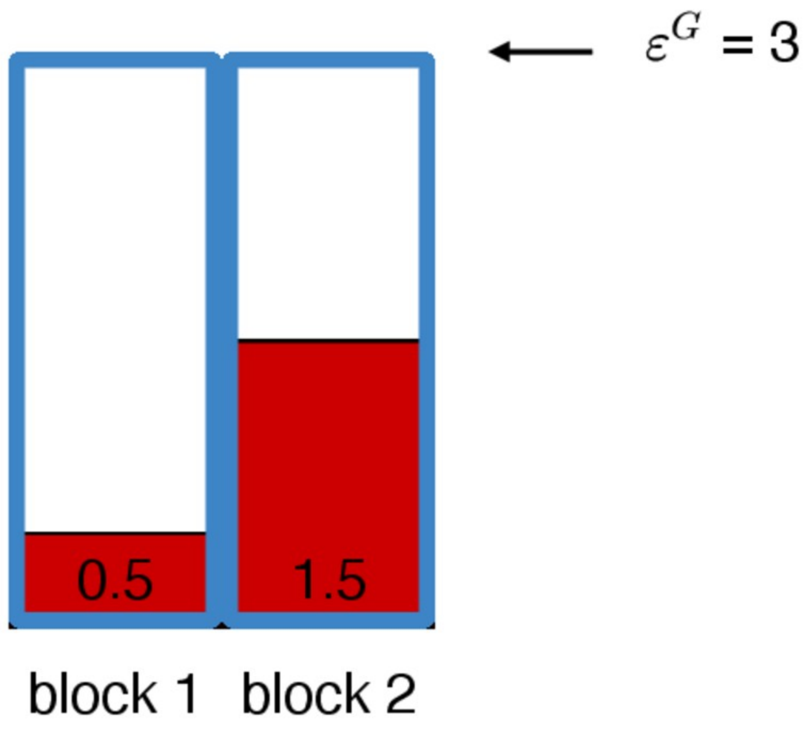


Demands for budget



Consumed budget

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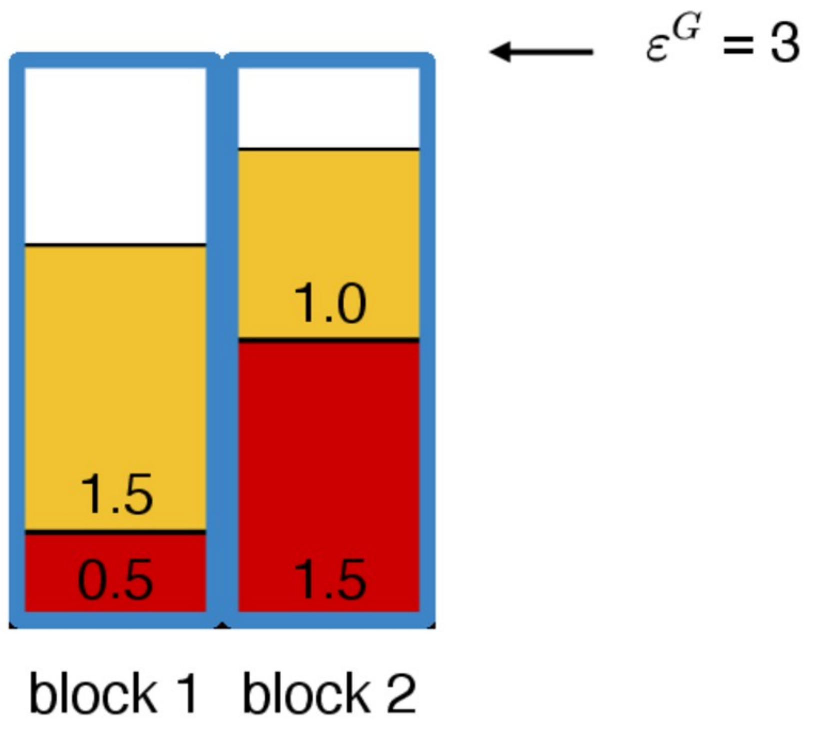

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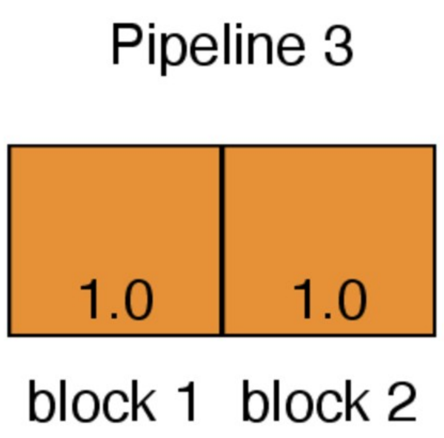

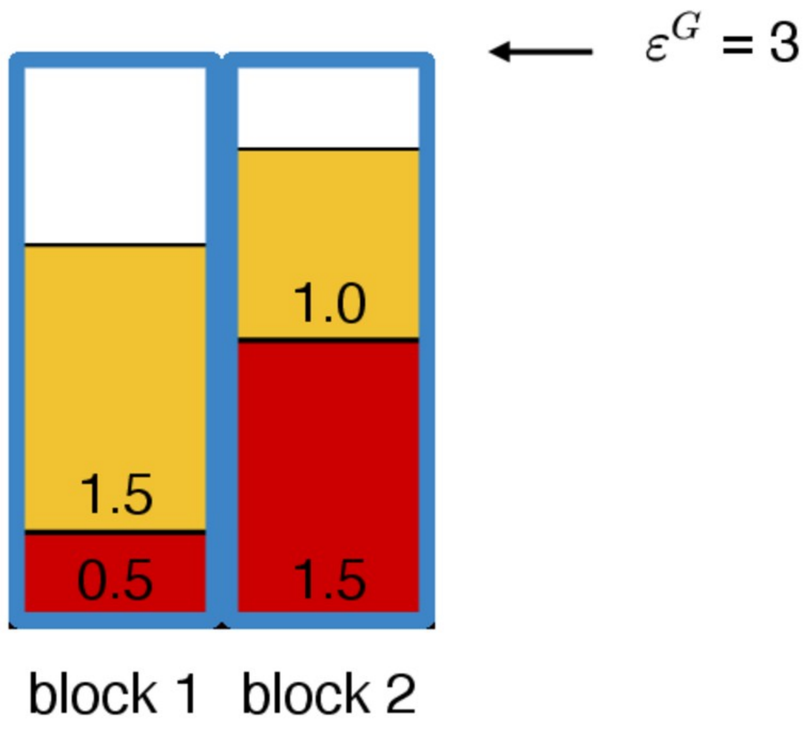

Demands for budget

Consumed budget

Problem: Privacy is not Replenishable

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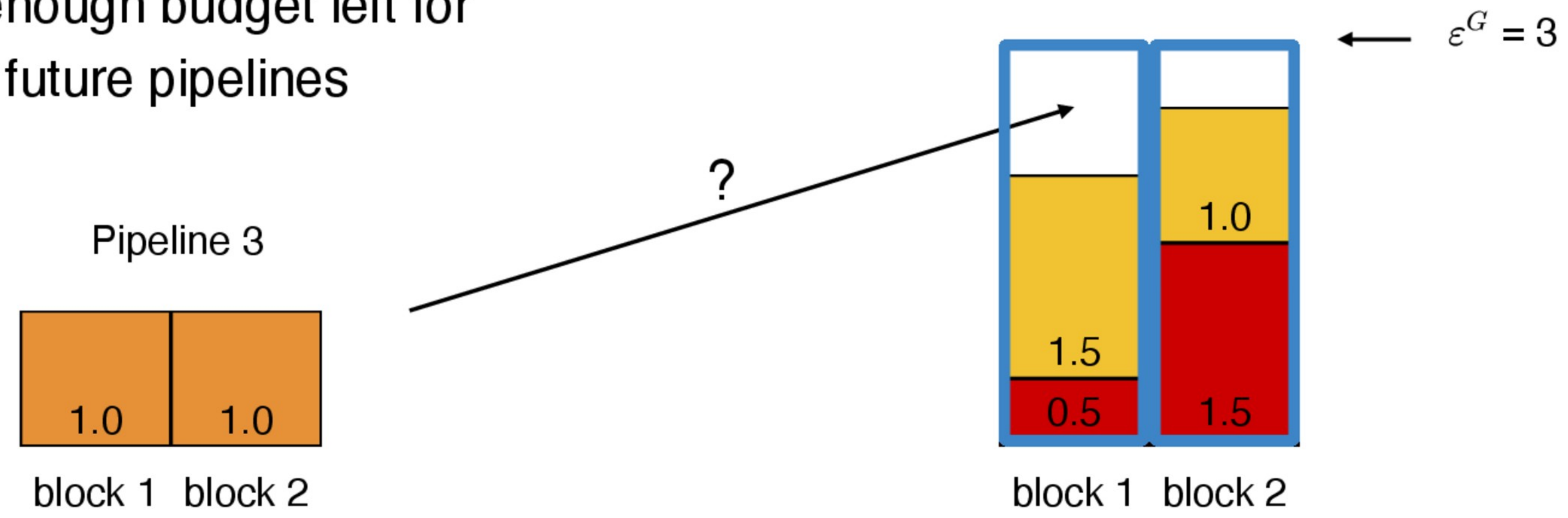
Not enough budget left for future pipelines



Demands for budget

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Dominant Privacy Fairness (DPF)

- Idea: **unlock privacy budget** for each block progressively, so budget remains for the future

- Like DRF but only for the first N pipelines for each block, and best-effort scheduling for the others

Algorithm 2. DPF-N

$R = \langle R_1, \ldots, R_m \rangle$ private block capacities (aka ε^G)
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DPF Example

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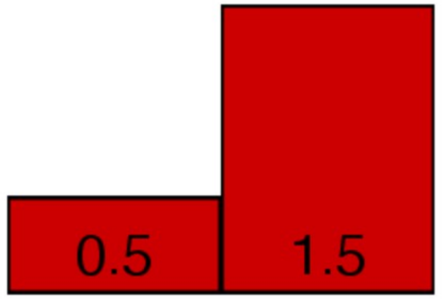
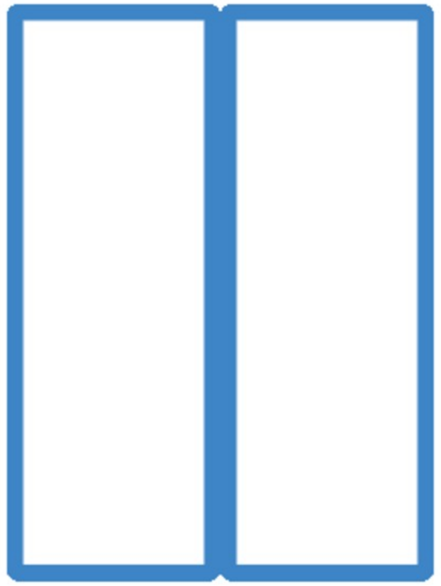
Pipeline 1



block 1 block 2



block 1 block 2

Incoming pipelines

DPF queue

Allocated budget

DPF Example

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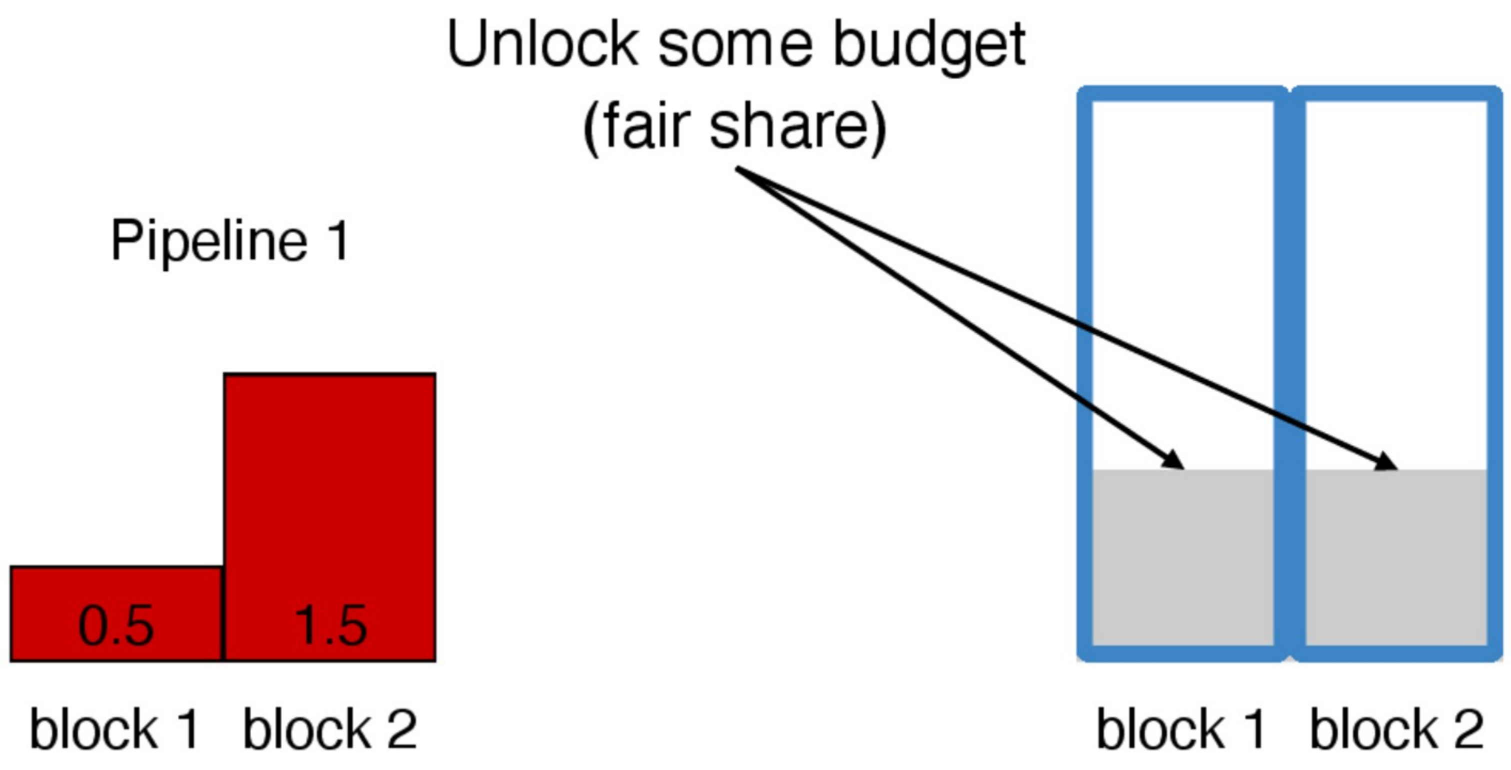

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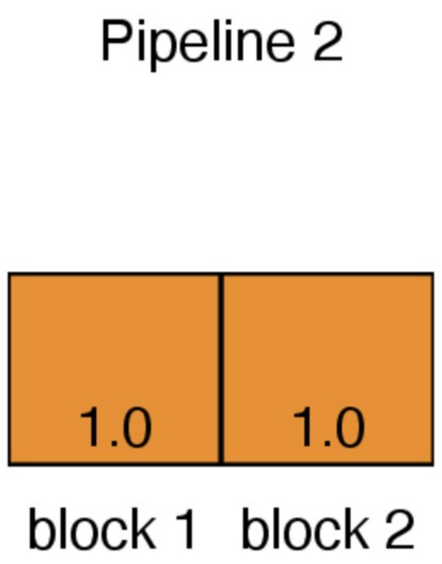
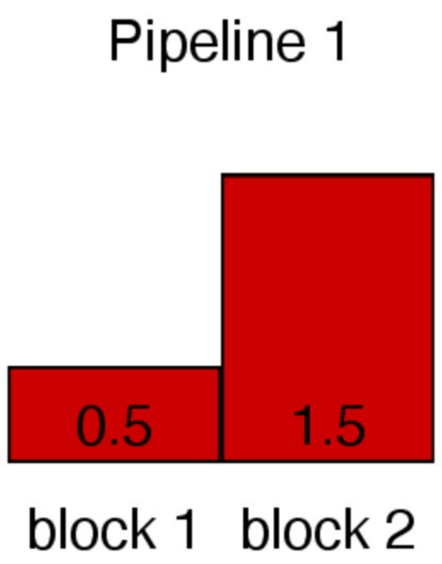
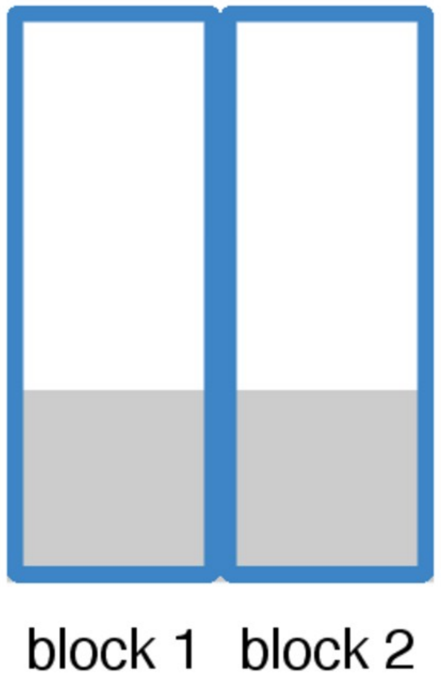


Incoming pipelines



DPF queue



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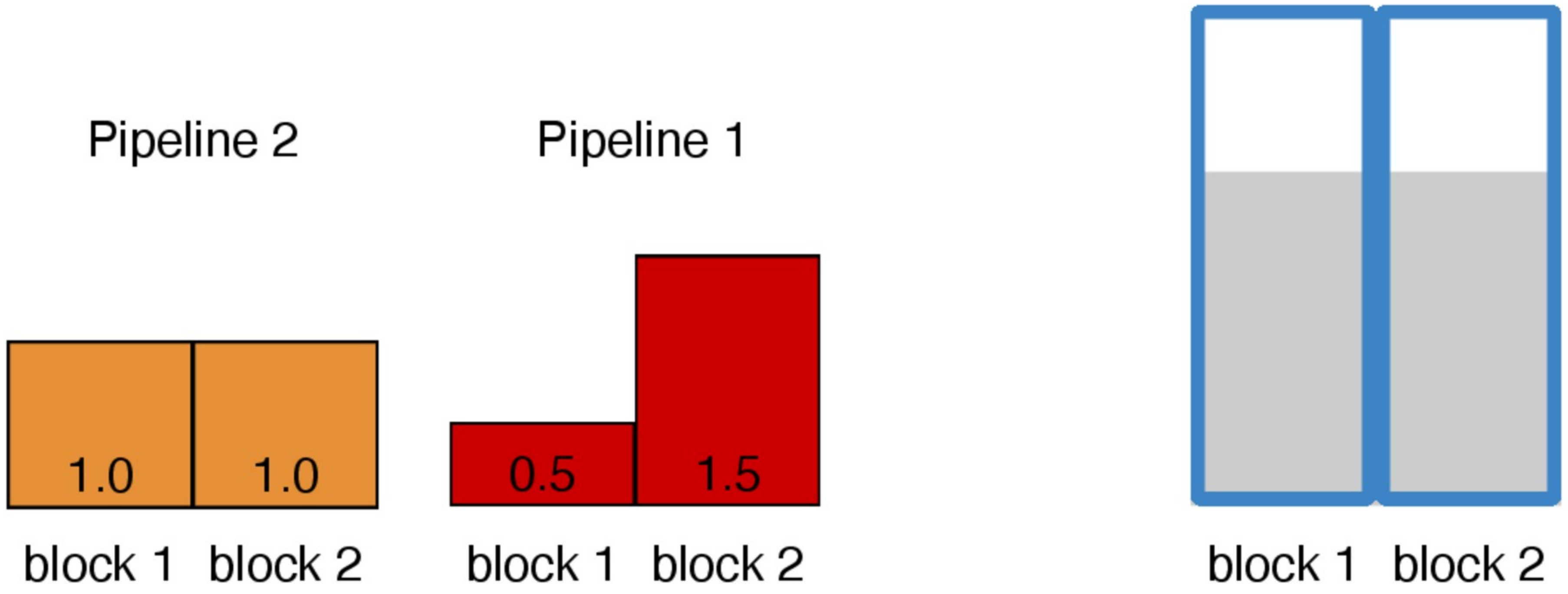

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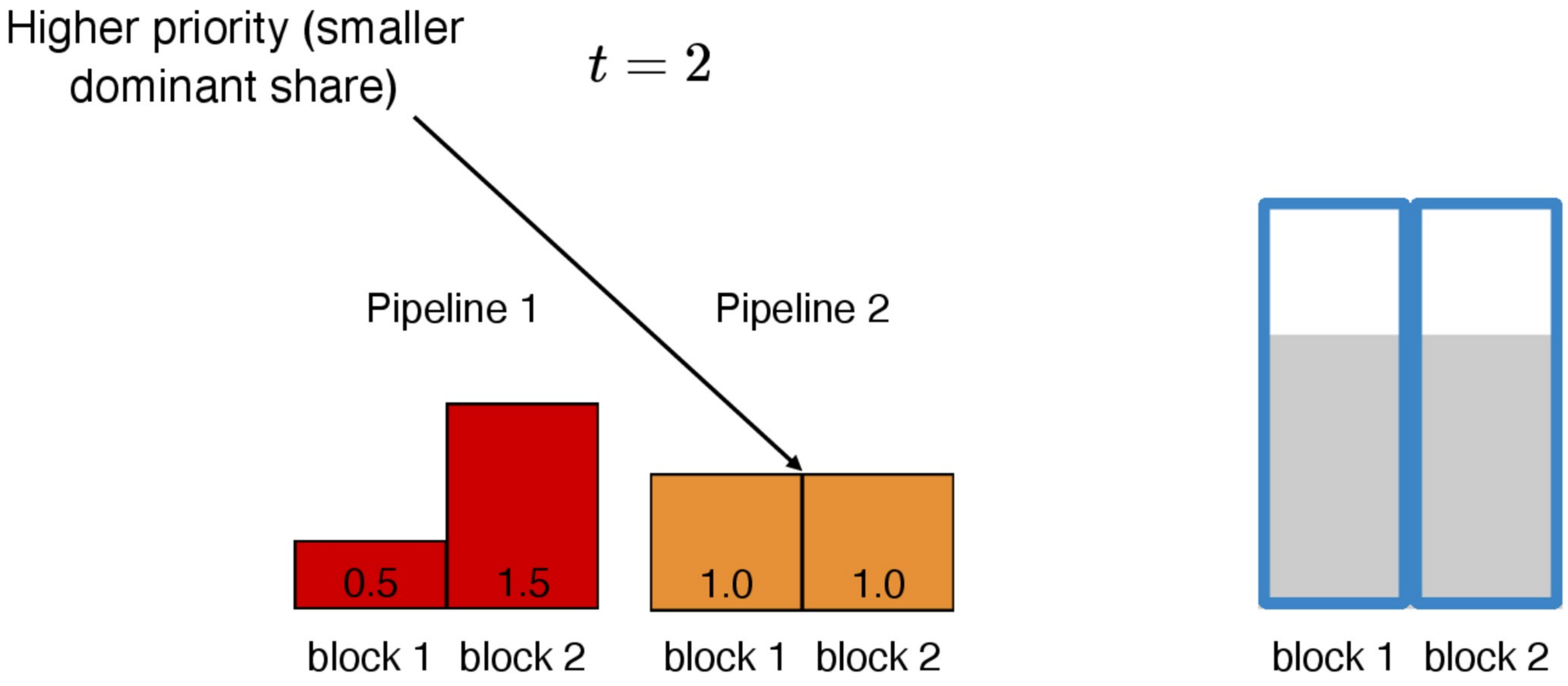

Incoming pipelines DPF queue Allocated budget

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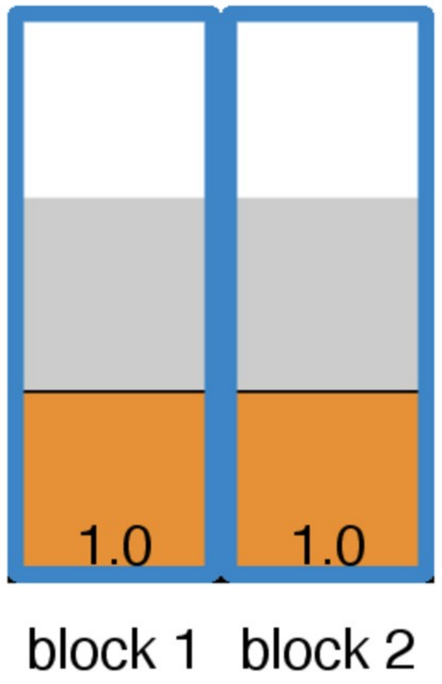


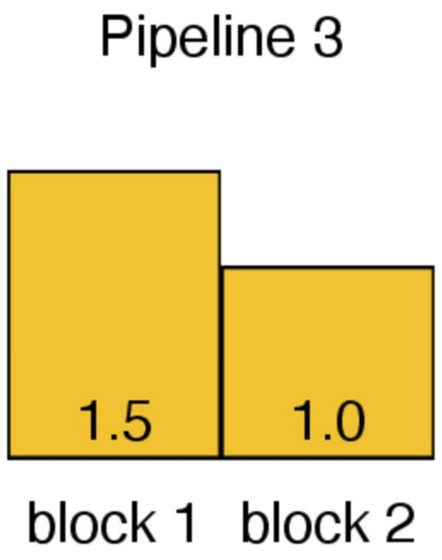
Incoming pipelines

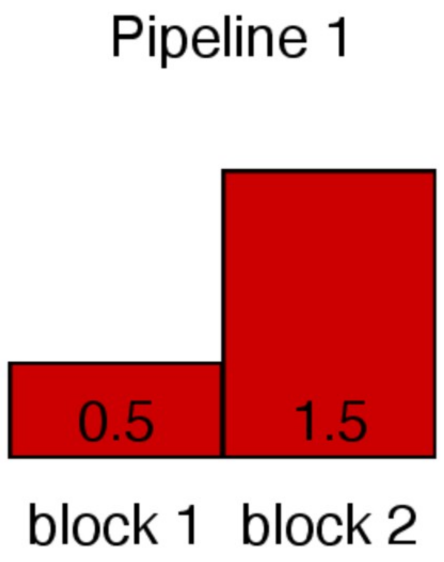
DPF queue

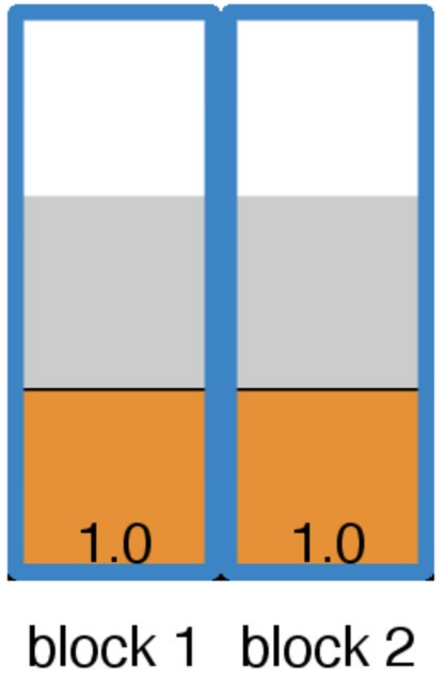
Allocated budget

DPF Example

$$t = 3$$







Incoming pipelines

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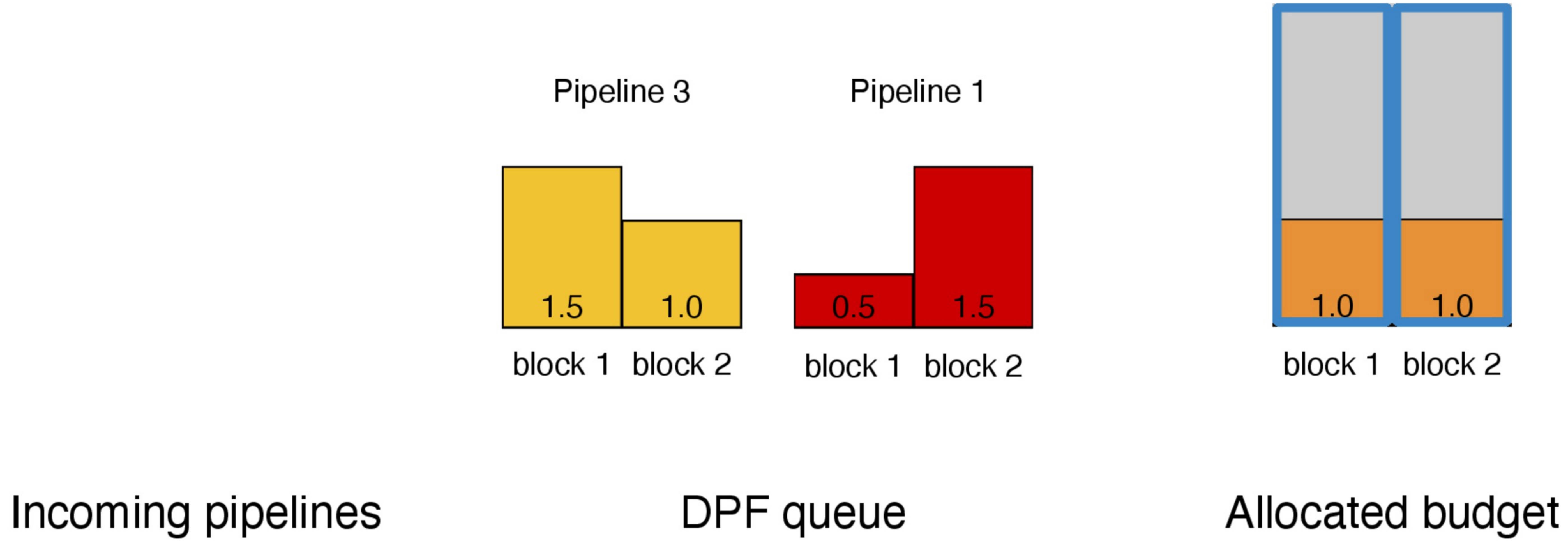

DPF Example

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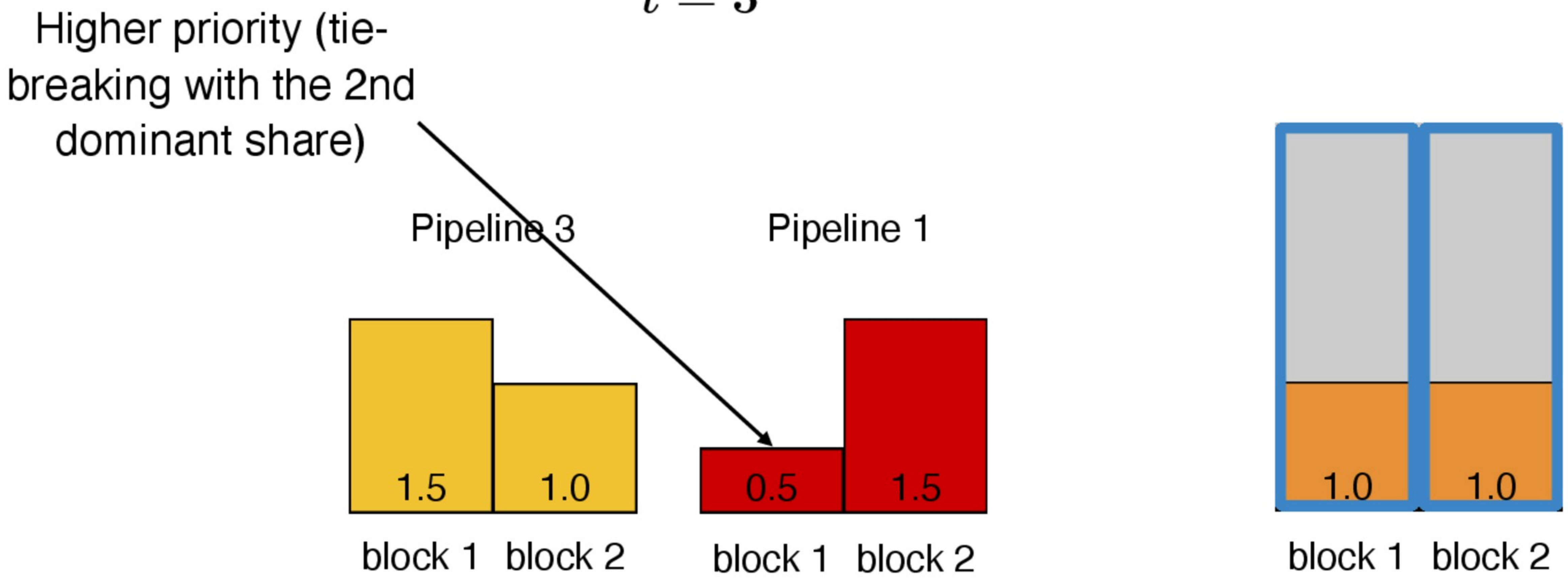

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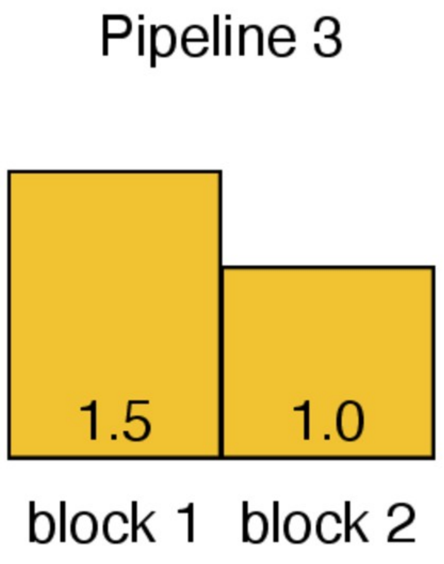

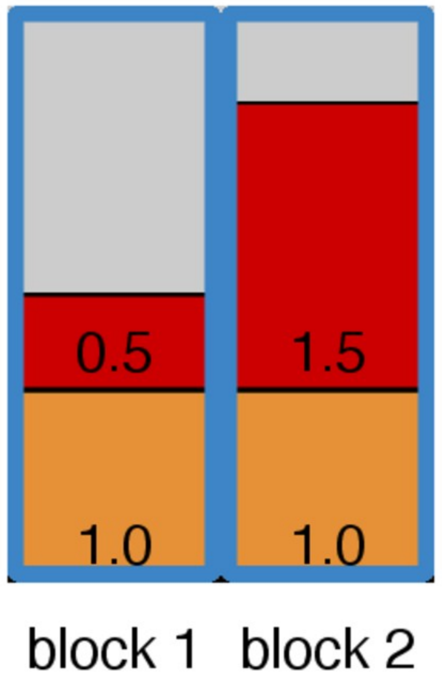

Incoming pipelines

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DPF Properties

Max-min fairness **only for the first N pipelines** over any block

Game theoretic properties:

- sharing incentive
- strategy-proofness
- dynamic envy-freeness
- Pareto-efficiency

Definition. A pipeline is a *fair demand pipeline* if:

a) its demand for each one of the blocks is smaller than the fair share ϵ_j^G/N and

b) it is within the first N pipelines that requested some budget for all its requested blocks

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4. **Evaluation**

Methodology

Questions

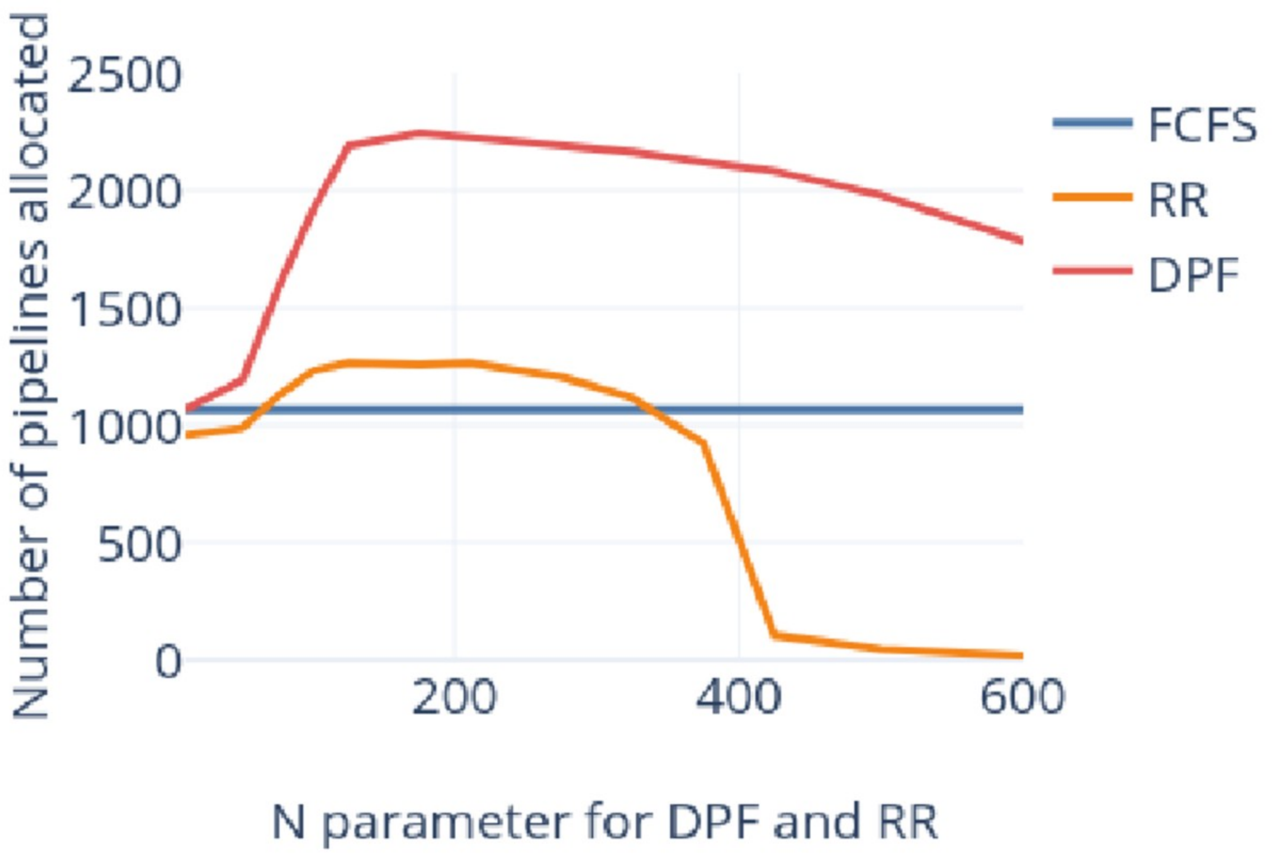
- **How does DPF compare to baseline schedulers?**
- How do workload characteristics impact DPF?
- How does the DP semantic impact DPF?

Workloads

- **Microbenchmark**: $\varepsilon \in \{0.01\varepsilon^G, 0.1\varepsilon^G\}$, either the last block or the 10 last blocks
- Macrobenchmark: NLP pipelines and summary statistics over the Amazon Reviews dataset with various demands

How does DPF compare to baseline schedulers?

Allocation



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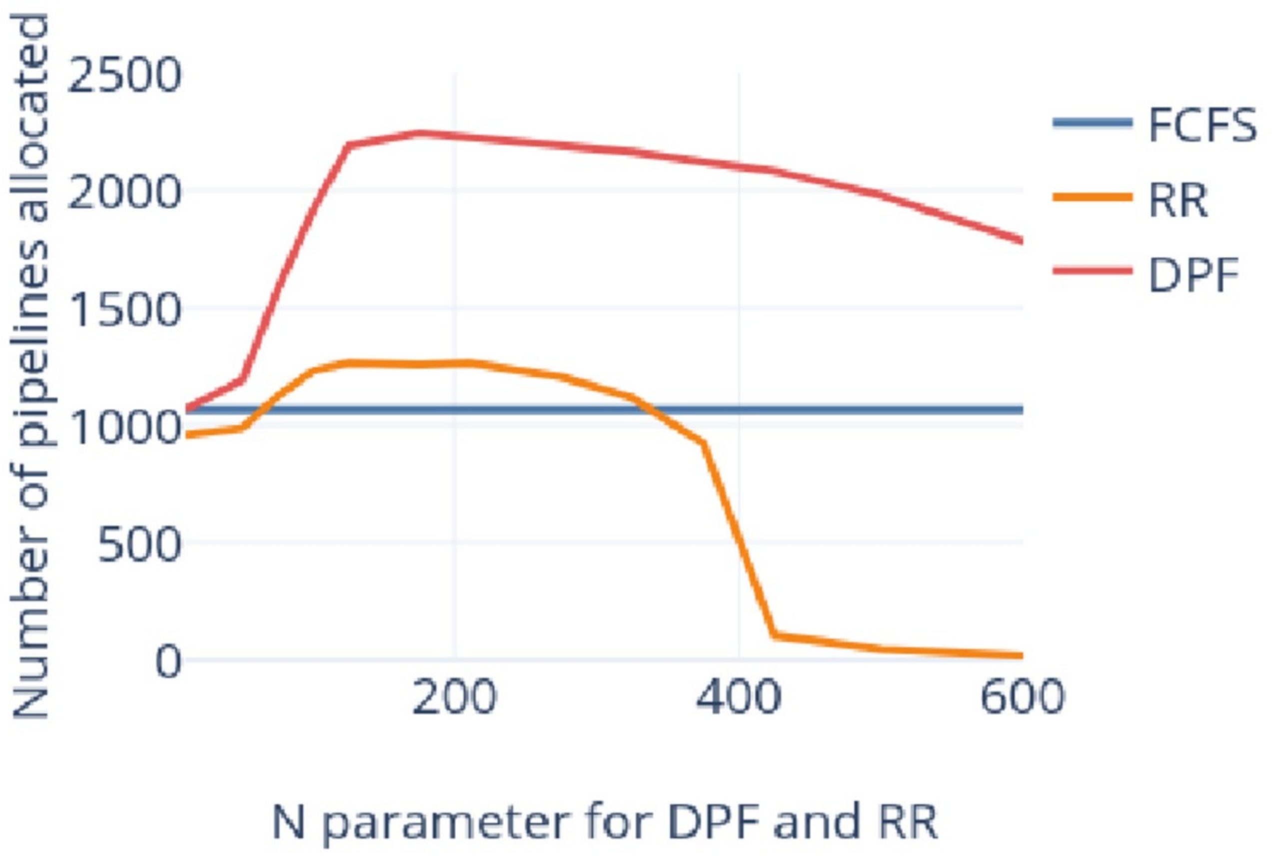
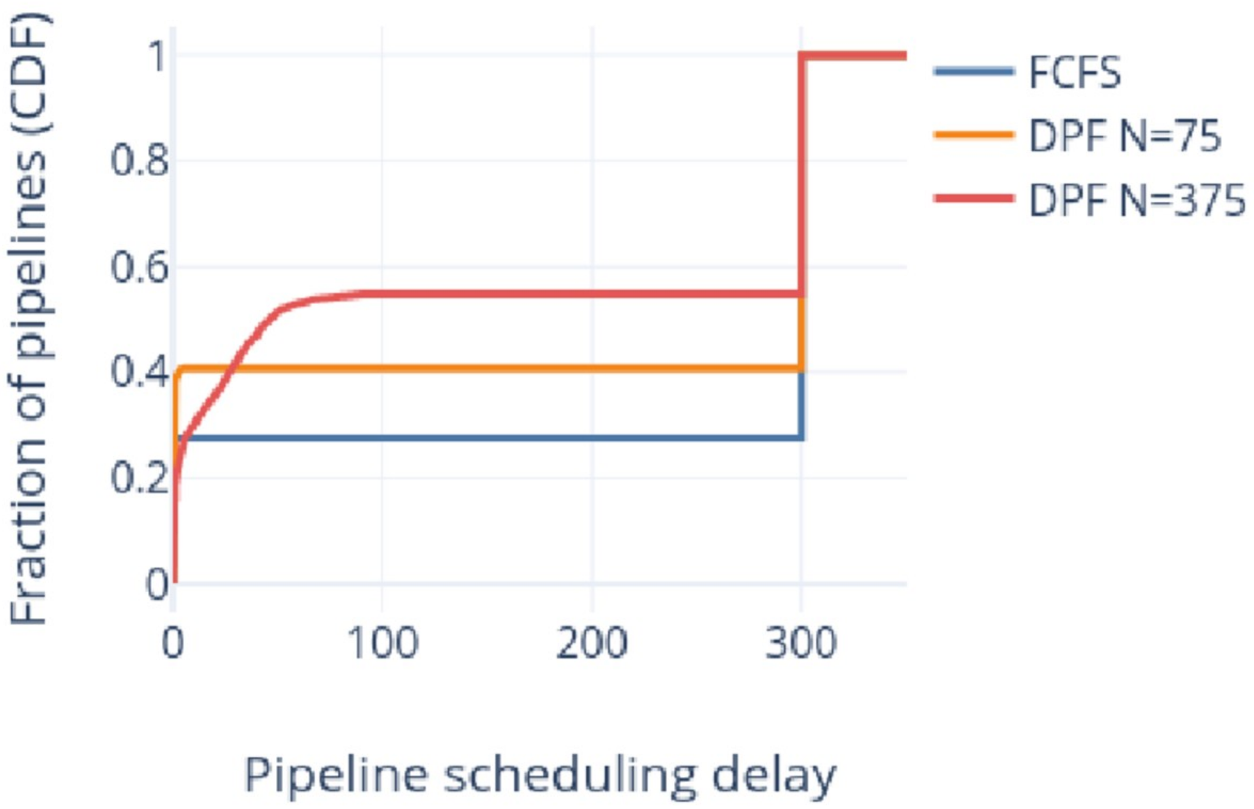


Latency



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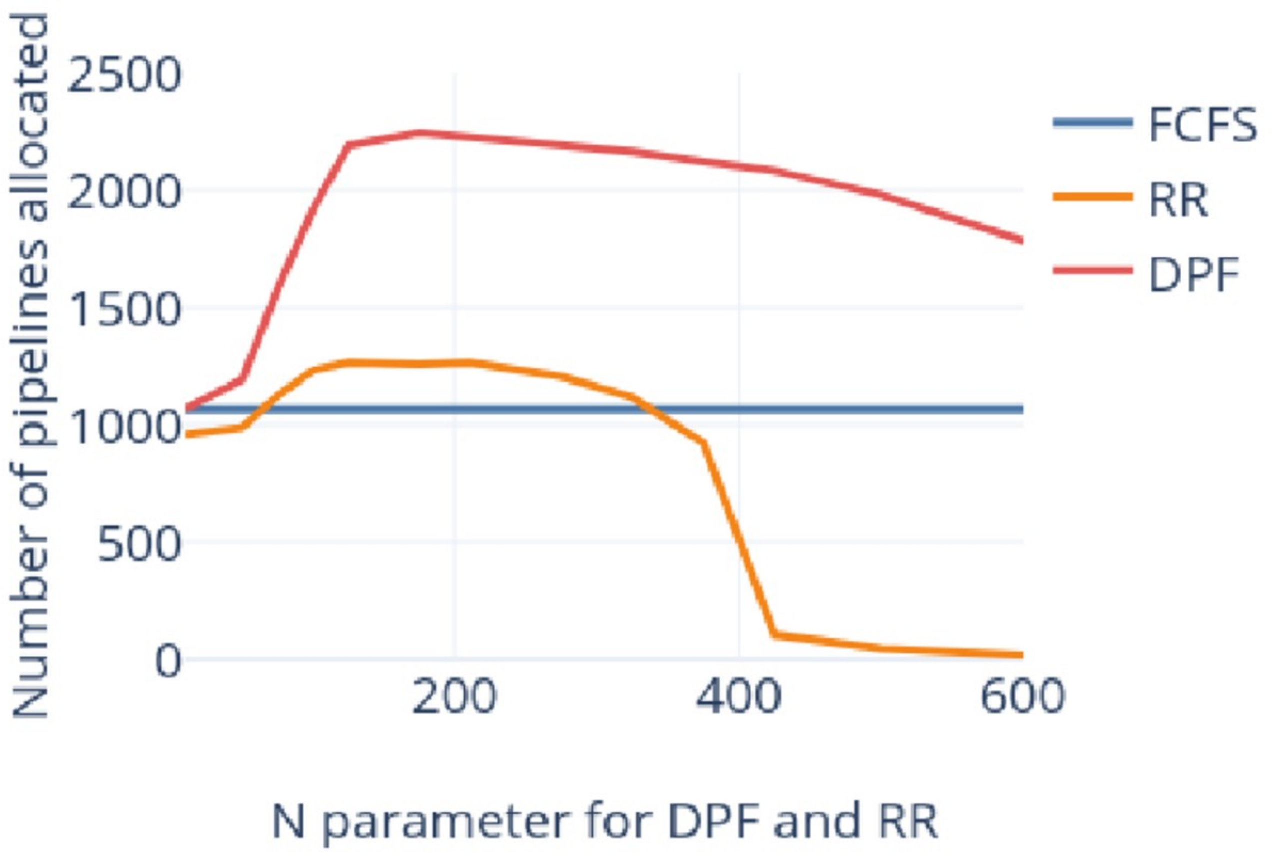

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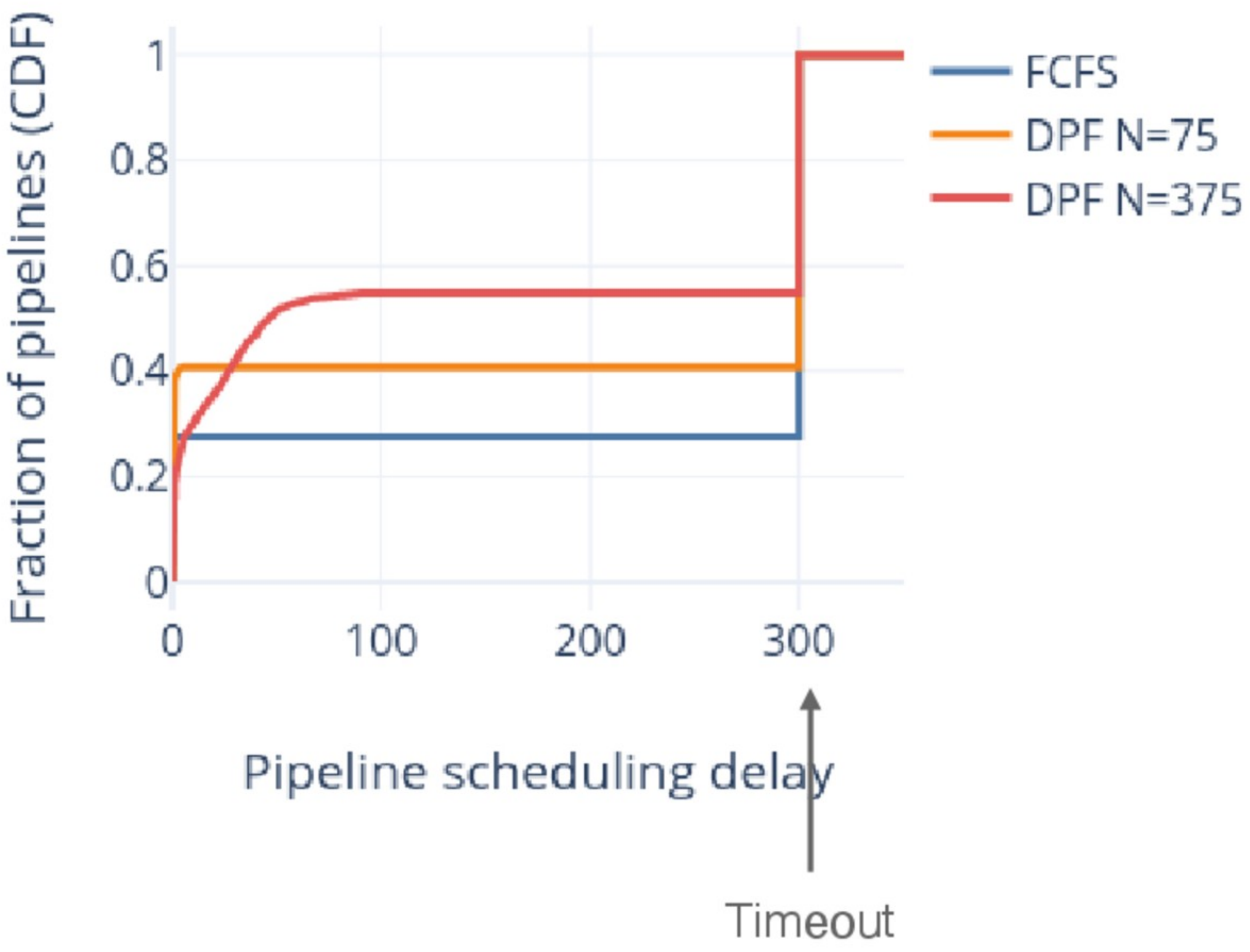

Conclusion

- **Privacy as a resource** that should be tracked and scheduled

- PrivateKube incorporates privacy as a new resource into Kubernetes and provides **Dominant Privacy Fairness (DPF)**, the first scheduling algorithm suitable for this non-replenishable resource.

- Changes to the algorithm and fairness definitions show that **scheduling privacy is a new problem**, for which more work is needed.

Code and paper: https://columbia.github.io/PrivateKube

Contact: pierre@cs.columbia.edu

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