

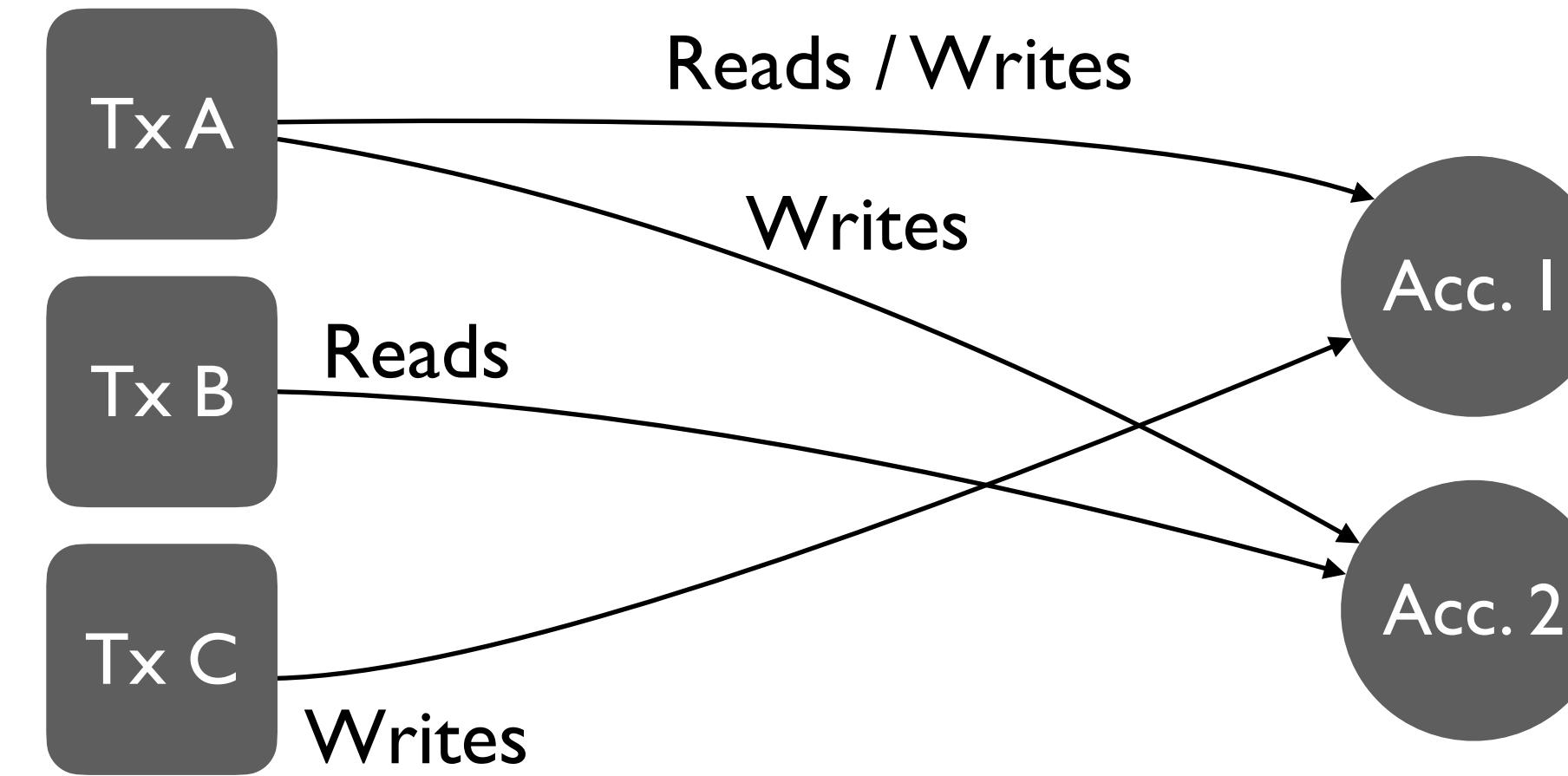
A Lagrangian Approach to Conflict-aware Transaction Packing

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Block building

- Block builders decide which transactions get selected for inclusion.
- Extracted fees and throughput are directly linked to:
 - ▶ validator incentives.
 - ▶ economic security.
- Block building is a security primitive:
 - ▶ revenue & throughput \iff security.
- As execution becomes parallel, selection quality matters more.

Why conflicts matter



- Conflicts cause failures, wasted blockspace and hinder parallel execution \Rightarrow cannot be ignored.
- Outright prohibition would leave money on the table.
- Greedy or overly conservative selection ignores this tradeoff.

Existing approaches and their limits

- Greedy:
 - ▶ packs the block sorting transactions by fee over cost.
 - ▶ ignores conflicts.
- Greedy conflict-aware:
 - ▶ packs the block sorting transactions by fee over cost but only packs non-conflicting ones.
 - ▶ hard exclusions.

Key idea: soft conflicts

- Conflicts are priced, not forbidden.
 - ▶ profit = revenue – conflict penalty.
- Kernelization.
 - ▶ Let $y_i, y_j \in \mathbb{R}^d$ be feature vectors representing transaction i and j with fees q_i and q_j .
 - ▶ Let $\phi(\cdot, \cdot) \rightarrow [0,1]$ be a PSD kernel and let $\phi(y_i, y_j) = \Phi_{ij}$ be the pairwise conflict likelihood.
 - ▶ We define the penalty incurred when including both i and j as $Q_{ij} = \Phi_{ij} \min\{q_i, q_j\}$.

Kernel instantiations

- Several PSD kernels may be employed:

- ▶ linear, polynomial, Gaussian, etc...

- Weighted variants:

- ▶ $W = \begin{bmatrix} W_{rr} & W_{rw} \\ W_{wr} & W_{ww} \end{bmatrix} \succeq 0.$

- ▶
$$\phi(y_i, y_j) = \frac{y_i^T W y_j}{\sqrt{y_i^T W y_i} \sqrt{y_j^T W y_j}}, \quad \phi(y_i, y_j) = \exp\left(-\frac{1}{2\sigma}(y_i - y_j)^T W (y_i - y_j)\right).$$

- ▶ weights can be learned from historical failure data.

Modeling as a quadratic knapsack

- Compact formulation:

$$\begin{array}{ll}\text{maximize} & q^T x - \frac{\gamma}{2} x^T Q x \\ \text{subject to} & c^T x \leq M, \quad x \in \{0,1\}^n.\end{array}$$

- ▶ $q \in \mathbb{R}_+^n$ fees.
- ▶ $c \in \mathbb{R}_+^n$ costs.
- ▶ $M > 0$ block capacity.
- ▶ $Q \in \mathbb{S}_+^n$ conflict penalties.
- ▶ $\gamma \in [0,1]$ risk-revenue tradeoff parameter.

Quadratic term proxies expected loss

- Let F_{ij} let the binary RV indicating that transaction i fails due to a conflict with j .
- Let $F_i = \bigvee_j F_{ij}$ be the binary RV indicating whether transaction i fails.
- Let $F = \{F_i\}_{i=1}^n$ and the total loss $L(x; F) = \sum_{i=1}^n q_i x_i F_i$.
- Applying the union bound and linearity of expectation we get:
 - ▶ $\mathbb{E}_F[L(x; F)] \leq \frac{1}{2} \sum_{1 \leq i, j \leq n} \Phi_{ij} \min\{q_i, q_j\} x_i x_j = \frac{1}{2} x^T Q x$.
 - ▶ we assume only the lower fee transaction fails in a conflict.

Continuous relaxation

- Quadratic knapsack is NP-hard:
 - ▶ finding an exact solution is computationally difficult.
- If we relax the integrality constraint we obtain a tractable formulation:

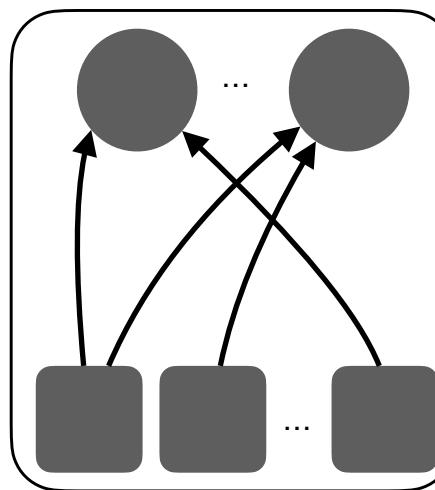
- ▶ Substitute $x \in \{0,1\}^n$ with $x \in [0,1]^n$,

$$\begin{aligned} & \text{maximize} && q^T x - \frac{\gamma}{2} x^T Q x \\ & \text{subject to} && c^T x \leq M, \quad x \in [0,1]^n. \end{aligned}$$

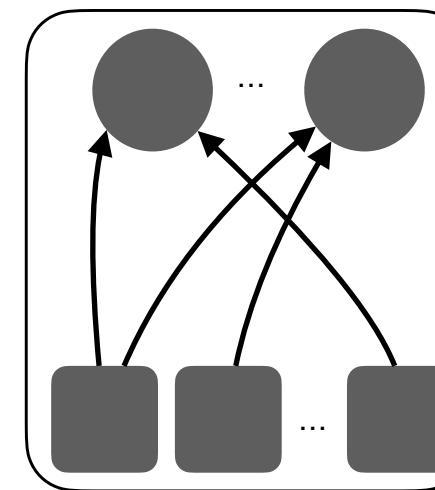
- ▶ concave objective and convex feasible region \Rightarrow polynomial time solution.

Conflict graph and decomposition

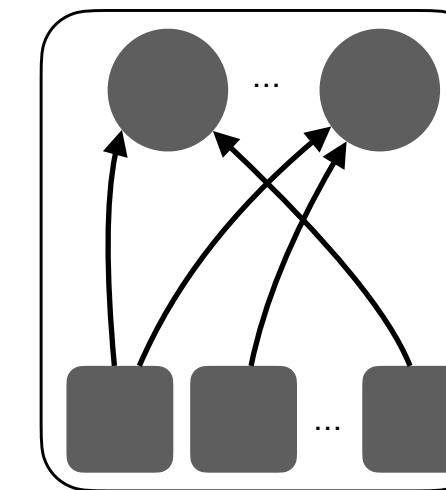
- Conflicts induce a graph structure.
- Each transaction interacts with a limited number of accounts.
- Access patterns form connected components.



DApp 1

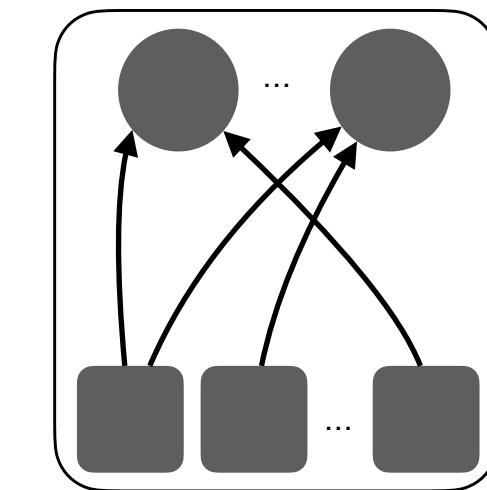


DApp 2



DApp 3

...



DApp K

Lagrangian relaxation

- Dualize the capacity constraint.
 - ▶ $c^T x \leq M \rightarrow \lambda(c^T x - M), \quad \lambda \geq 0.$
- The original problem decomposes into K independent sub-problems, one for each connected component.
- The dual function is defined as:

$$g(\lambda) = \sum_{k=1}^K \max_{x_{\mathcal{C}_k} \in [0,1]^{|\mathcal{C}_k|}} [(q_{\mathcal{C}_k} - \lambda c_{\mathcal{C}_k})^T x_{\mathcal{C}_k} - \frac{\gamma}{2} x_{\mathcal{C}_k}^T Q_{\mathcal{C}_k} x_{\mathcal{C}_k}] + \lambda M.$$

Dual variable as price

- The dual variable λ has a clear economic interpretation.
 - ▶ λ = shadow price of compute.
 - ▶ $q_i - \lambda c_i \leq 0 \implies$ transaction i is not included.
- Transactions compete on fee to cost adjusted for conflict penalties.

Dual root finding

- Solving the dual reduces to the following root finding problem
 - ▶ $g'(\lambda) = M - c^T x^*(\lambda) = 0.$
- The dual derivative $g'(\lambda)$ is increasing and the root can be efficiently bracketed in $O(\log(1/\varepsilon))$ iterations.
- Cool, but what about integrality?

Rounding: from fractional to integer

- Steps: $x^{\text{frac}} \rightarrow x^{\text{int}} \rightarrow x^{\text{feas}}$. Cost is $O(n \log n)$.

1. Bernoulli rounding

- $x^{\text{frac}} \rightarrow x^{\text{int}}$.
- $x_i^{\text{int}} \sim \text{Bernoulli}(x_i^{\text{frac}})$, $i = 1, \dots, n$.

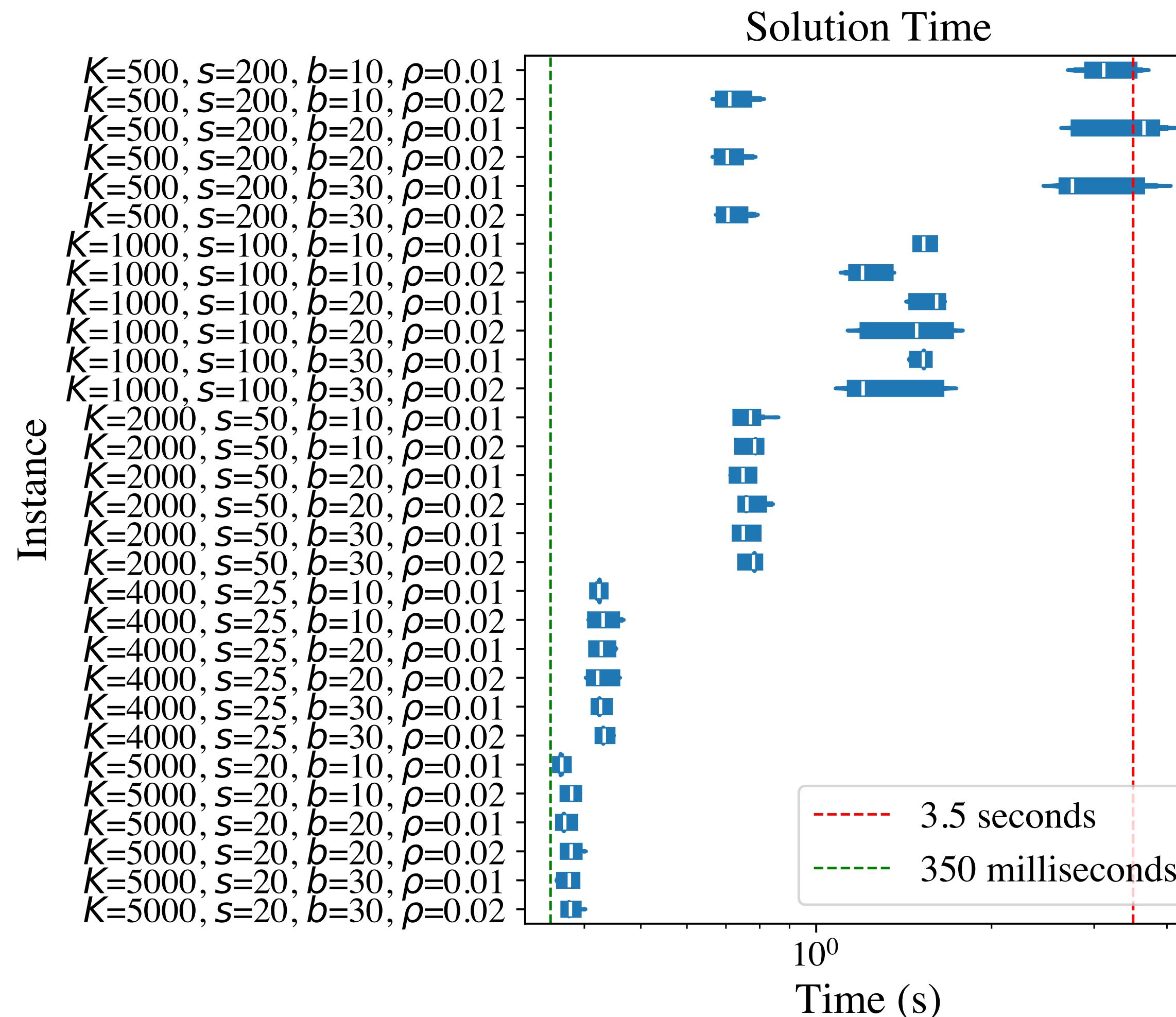
2. Greedy pruning for feasibility ($c^T x \leq M$).

- $x^{\text{int}} \rightarrow x^{\text{feas}}$.
- Removes selected transactions with smallest fee-to-cost ratios until capacity is met.

Guarantees

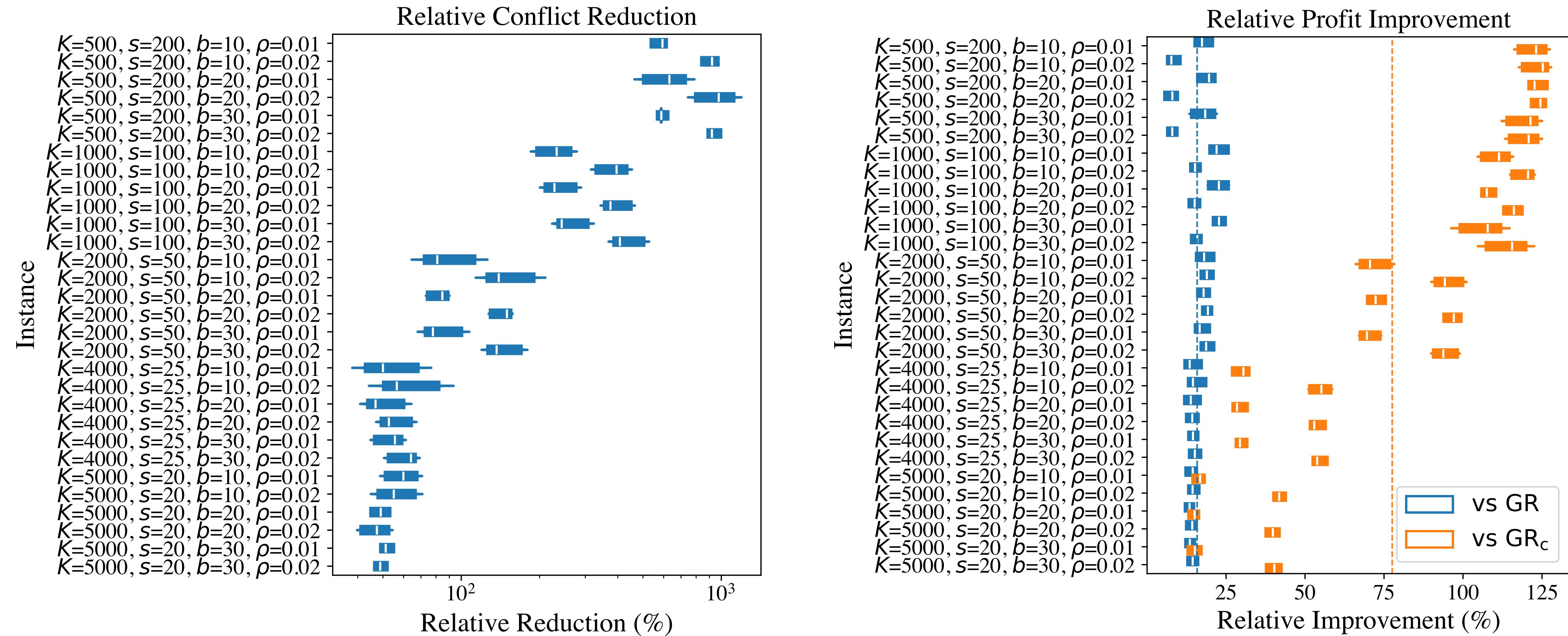
- High probability error bound. For any $\delta, \eta \in (0,1)$:
 - ▶
$$\Pr \left[f(x^{\text{feas}}) \geq f(x^{\text{frac}}) - \sqrt{\frac{U}{2} \ln \frac{1}{\delta}} - R \sqrt{\frac{V}{2} \ln \frac{1}{\eta}} \right] \geq 1 - \delta - \eta.$$
- The loss depends on:
 - ▶ Conflict intensity U .
 - ▶ Cost variability V .
 - ▶ The largest fee-to-cost ratio R .
- Rounded solutions retain at least 90% of the fractional optimum in tested instances.
- Repeating the rounding procedure in parallel boosts odds exponentially.

Scalability



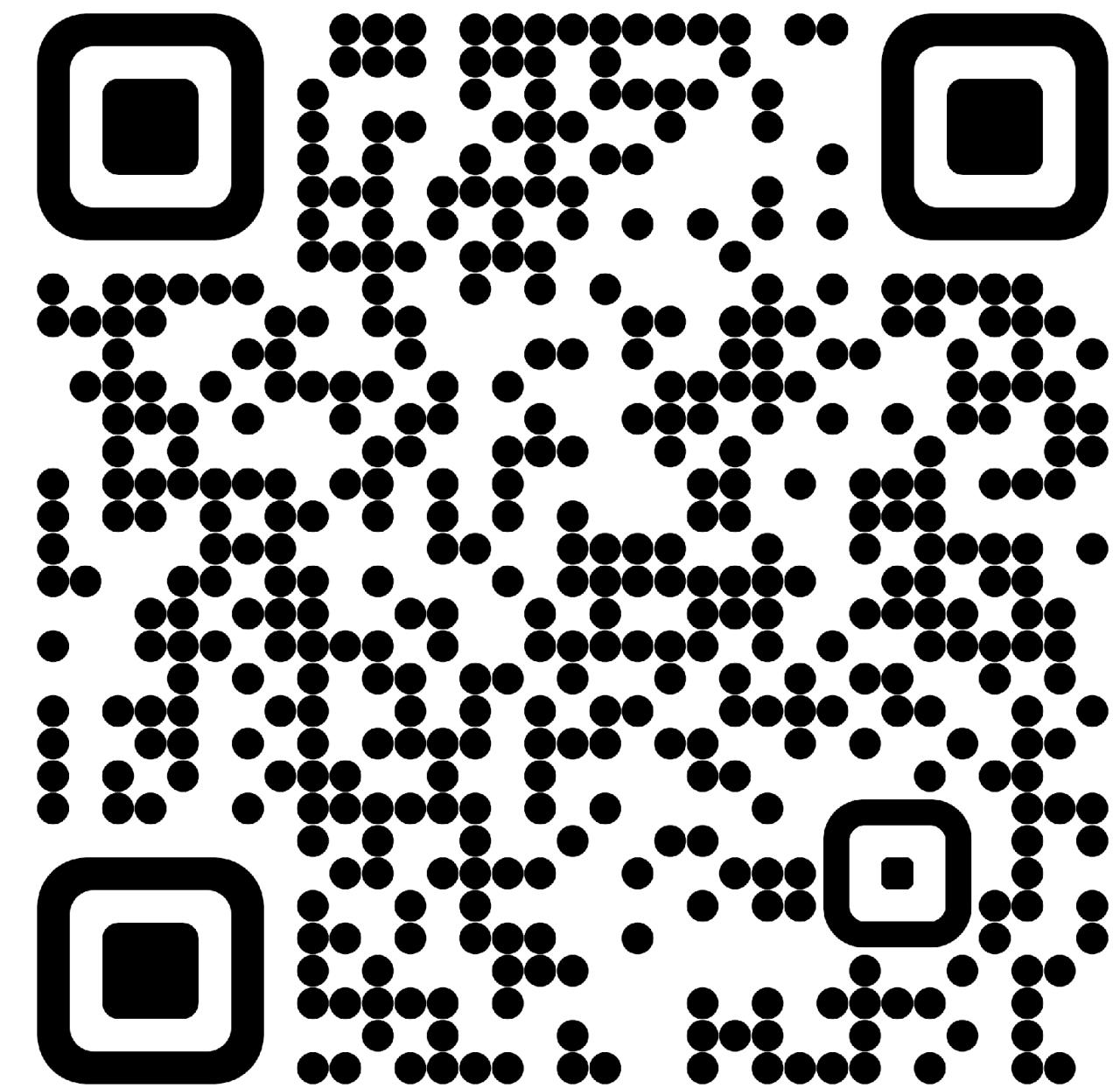
- The total number of TXs is approximately $K \times s$.
 - ▶ K controls the number of connected components.
 - ▶ s controls their sizes.
- b controls the conflict intensity.
- ρ controls capacity.
- 100k+ TXs are packed in seconds on consumer grade hardware.

Quality vs. baselines



Takeaways

- Soft conflicts beat naive methods:
 - naive greedy.
 - greedy with hard exclusions.
- Our method is principled:
 - scales by exploiting the problem's structure.
 - leverages modern multicore hardware.
- Practical for real block builders.



[Link to preprint](#)