OptalCP

Constraint Programming with Parallel Search and Reinforcement Learning-Based Acceleration

Petr Vilím · ScheduleOpt

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Scheduling Seminar · schedulingseminar.com

What is OptalCP?

- **Constraint Programming solver for scheduling problems.**
- From the outside similar to *IBM ILOG CP Optimizer*.
  - Similar modeling language and concepts.
  - Interval variables, sequences, cumulative resources.
- From the inside, completely different.
  - Modern architecture, designed for **parallel search**.
  - Written in **C++20**, APIs in **TypeScript**/JavaScript and **Python**.

> **Today's focus:** How does the solver work inside?

What makes OptalCP Different?

I've built CP solvers before. **Now I'm free to rethink EVERYTHING.**
In particular the **internals**.

Architecture:

- Built for speed from the ground up.
- True parallelism.
- Heterogeneous workers.
- External heuristic hybridization.

Modeling & API:

- Native **Python** and **TypeScript** APIs.
- **Async** event-driven solving.
- Integers with **optional presence**.
- New modeling constructs.

It's not "just faster" — it's a different architecture that enables new capabilities.

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For **academic licenses**, send me your GitHub username.

Inside the Solver

Propagation
Remove infeasibilities

LNS
Large Neighborhood Search

FDS
Failure-Directed Search

FDS Dual
Failure-Directed Search Dual

Every algorithm has **strengths** and **weaknesses**.

Propagation

Propagation

Always in the Party

Role: Support

Action: Remove impossible values

Produces: Smaller domains

✓ Prunes domains | Detects infeasibility

✗ Can't solve alone

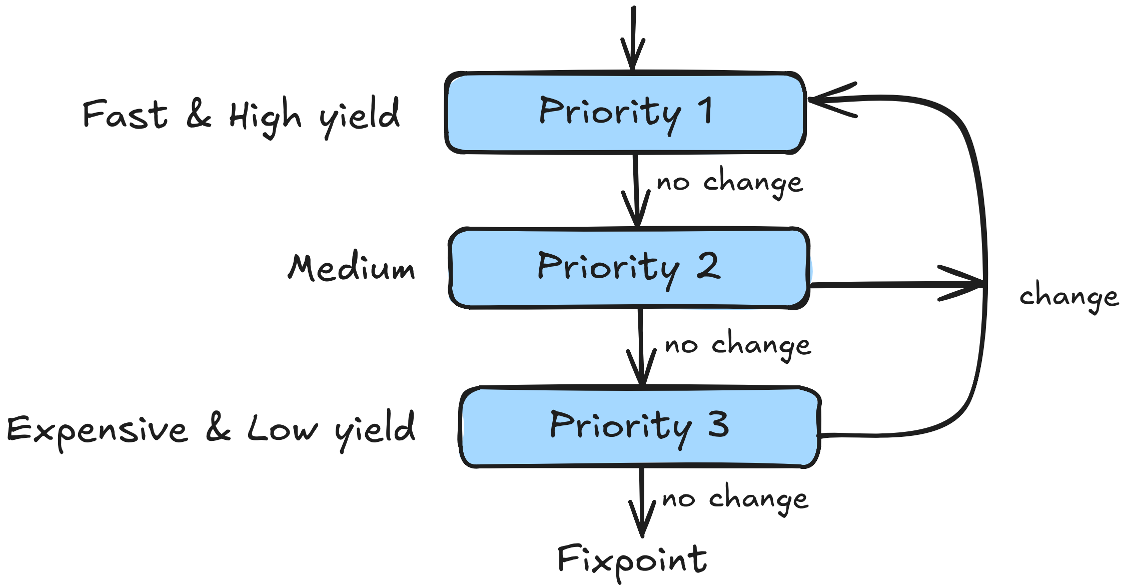
Propagation Algorithms for Scheduling

Algorithms for resource constraints in OptalCP:

- Detectable Precedences
- Edge-finding
- Not-first / Not-last
- Timetabling
- Timetable Edge-Finding

Propagation

In every search node, **propagation** removes impossible values until fixpoint or infeasibility.



Large Neighborhood Search (LNS)

LNS

Large Neighborhood Search

Type: Local search with CP repair

Assumes: Better solution exists nearby

Strategy: Destroy part, repair with CP

Produces: Better solutions

✓ Fast solutions | Exploits structure

✗ Requires initial solution

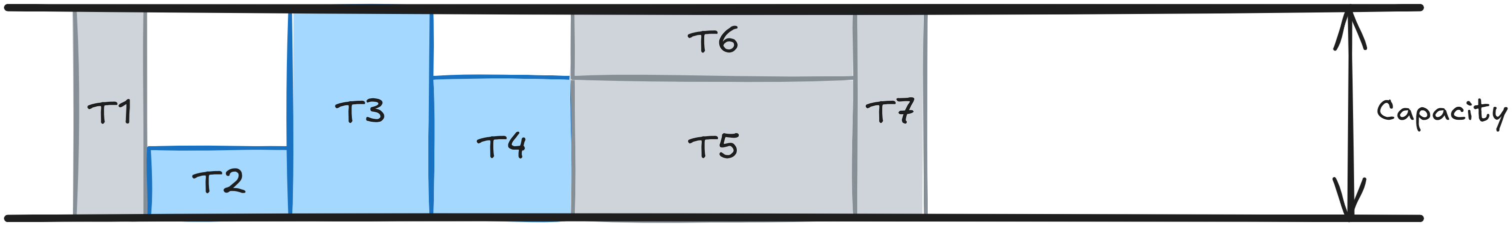
✗ Local optima | No optimality proof

How *Standard* LNS Works

Suppose the following solution:

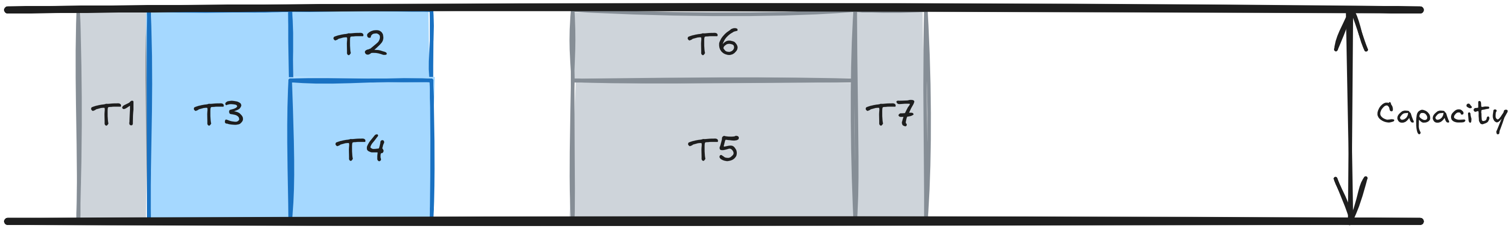
How *Standard* LNS Works

We relax part of it:



How *Standard* LNS Works

We solve the relaxed problem:



The problem: Standard LNS fixes the ***values*** of non-relaxed variables.
Since these are ***times***, we can't improve the makespan unless we relax more variables.

> Keeping variable **values** fixed is too restrictive.

How *Standard* LNS Works

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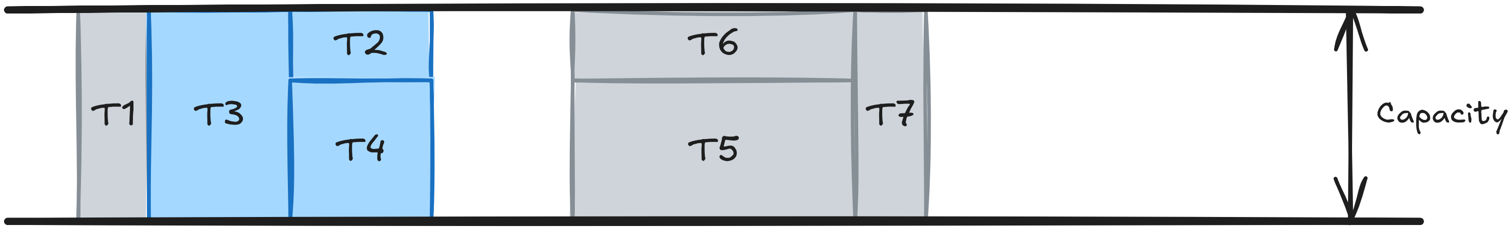


The problem: Standard LNS fixes the ***values*** of non-relaxed variables.
Since these are ***times***, we can't improve the makespan unless we relax more variables.

> Keeping variable **values** fixed is too restrictive.

> **Idea:** Modify relaxation to capture the ***structure*** of the solution instead.

Philippe Laborie, Daniel Godard:
Self-adapting large neighborhood search: Application to single-mode scheduling problems

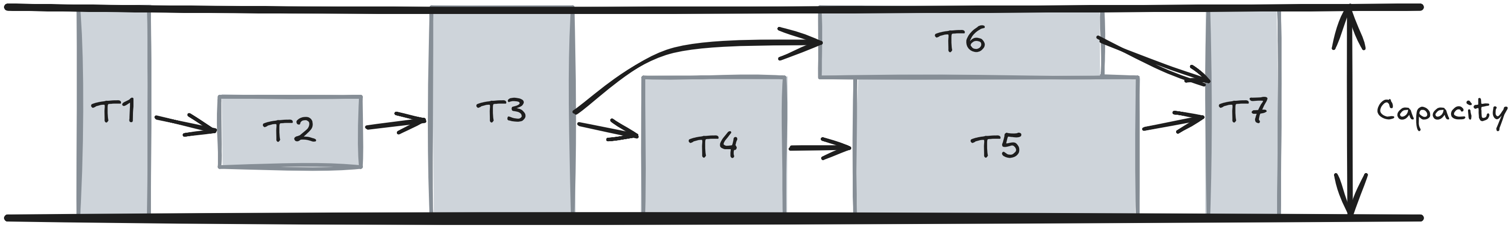
Partial Order Schedule (POS)

Suppose we have the following solution:

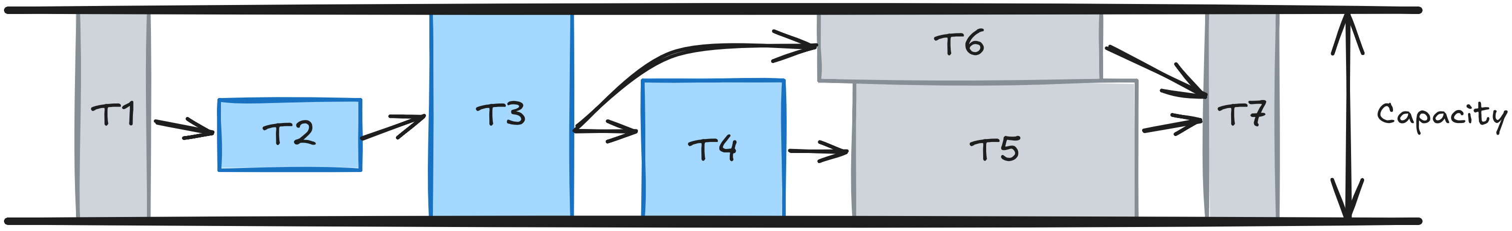
Partial Order Schedule (POS)

Suppose we have the following solution:

POS = **structure of the solution** = a set of precedences between tasks.
If the variables respect the precedences, resource constraints are automatically satisfied.

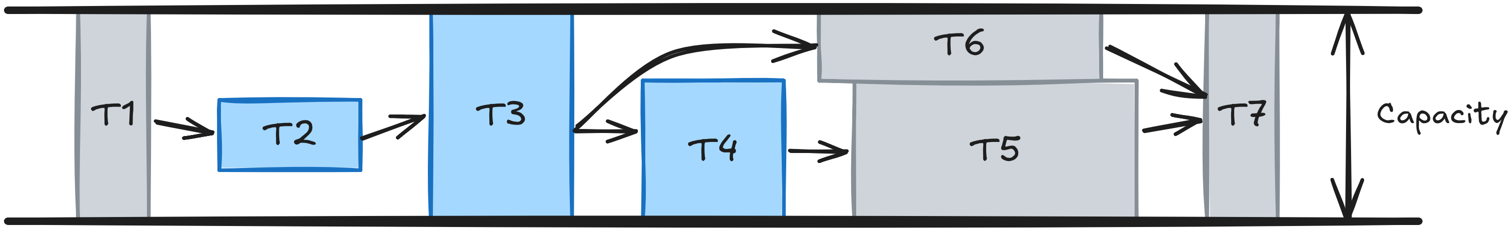


Relaxing with POS



To relax a task, we remove all its precedences.
Transitive precedences between the remaining tasks are added instead.

Relaxing with POS



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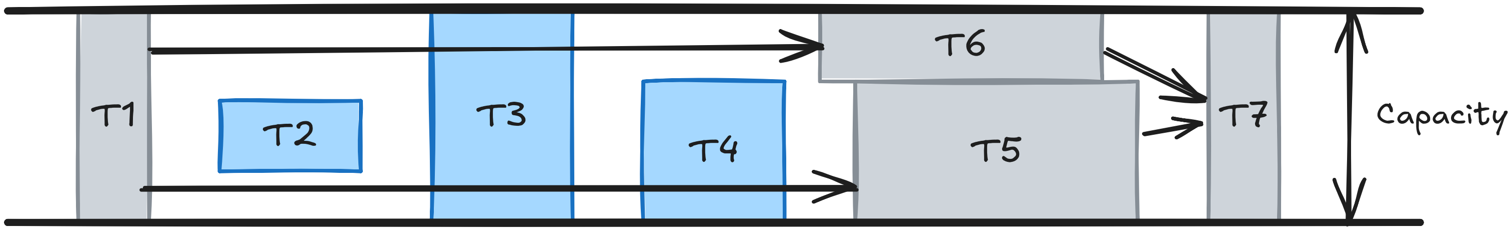
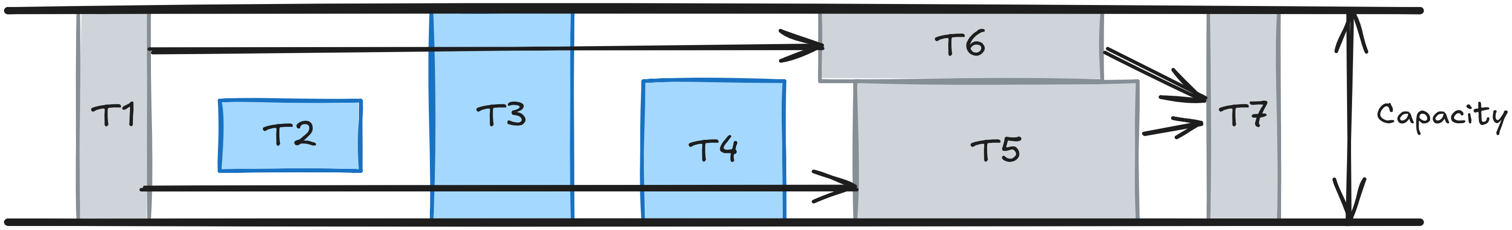


Solving with POS

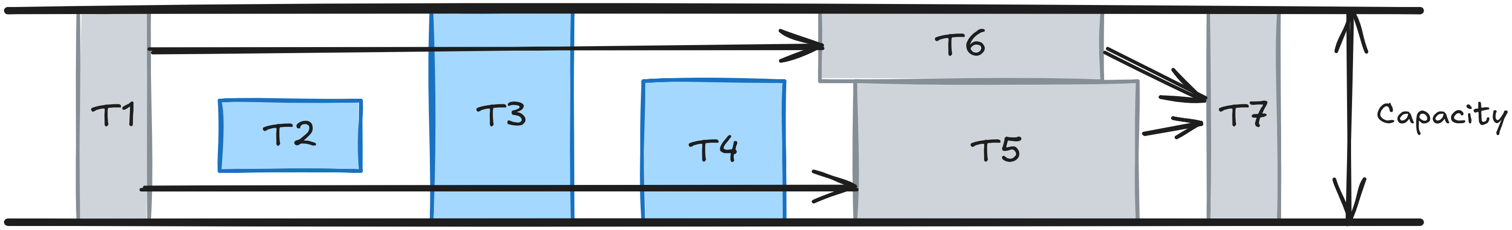


LNS **sub-problem**:

- Has the same variables (and domains).
- But **more constraints** (precedences from relaxed POS).

Sub-problem solution:

Solving with POS



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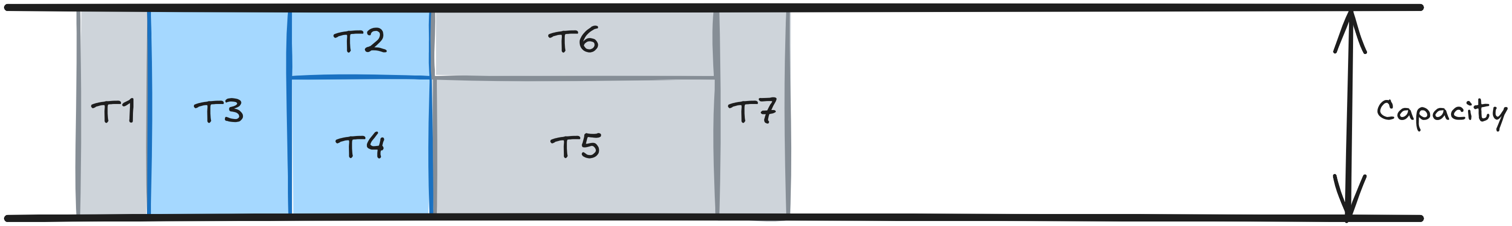
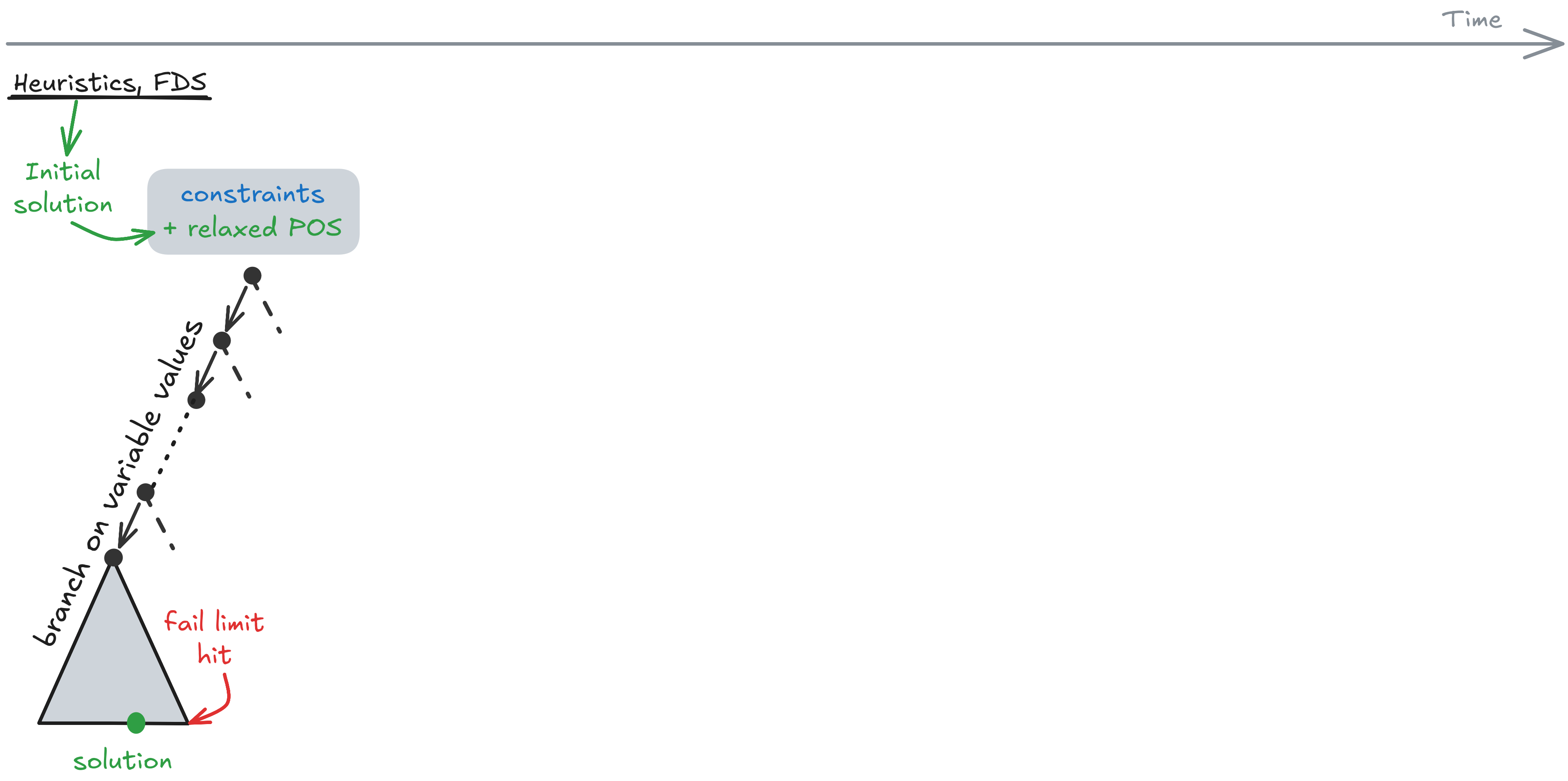


LNS Iterations



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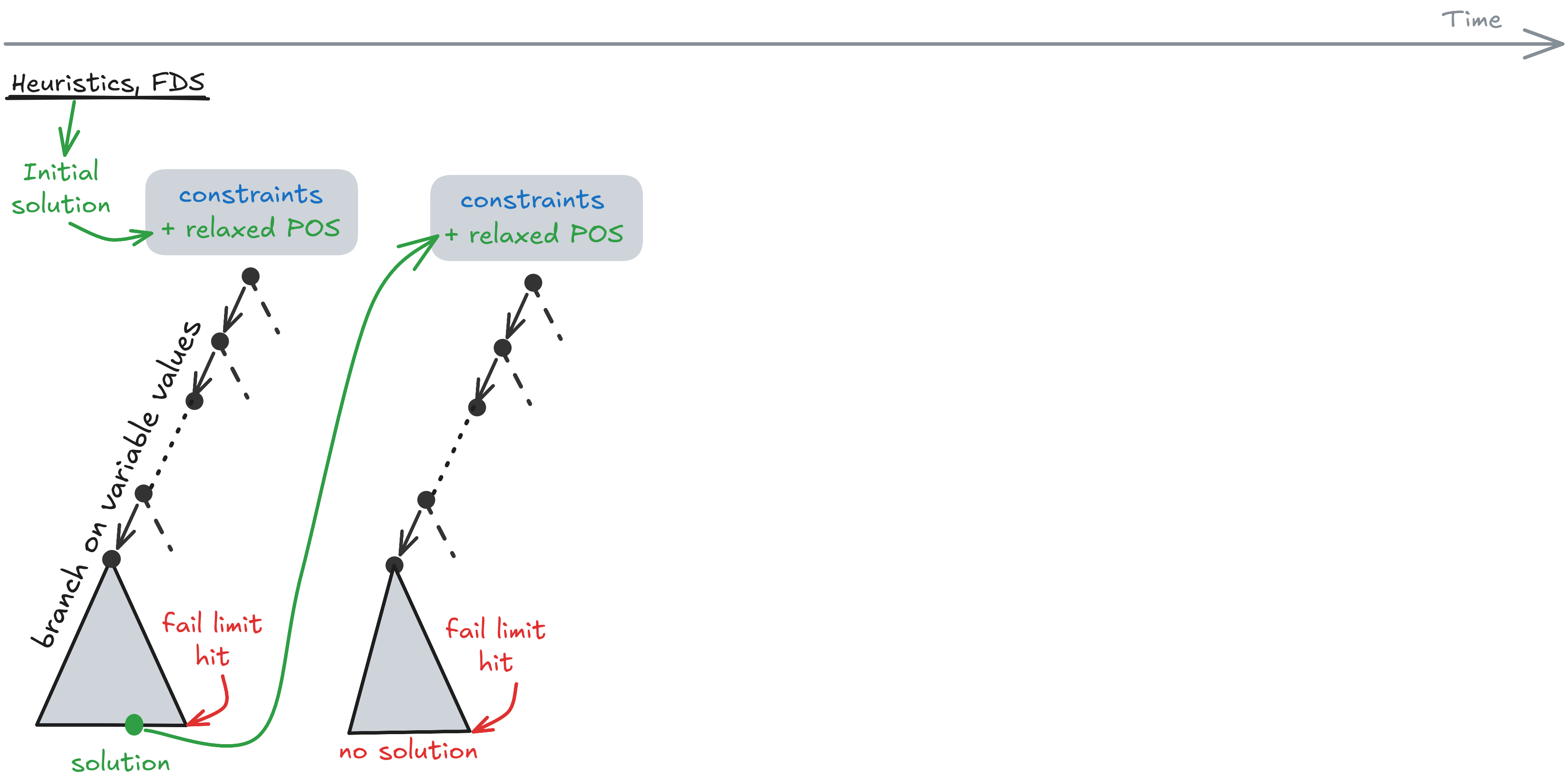

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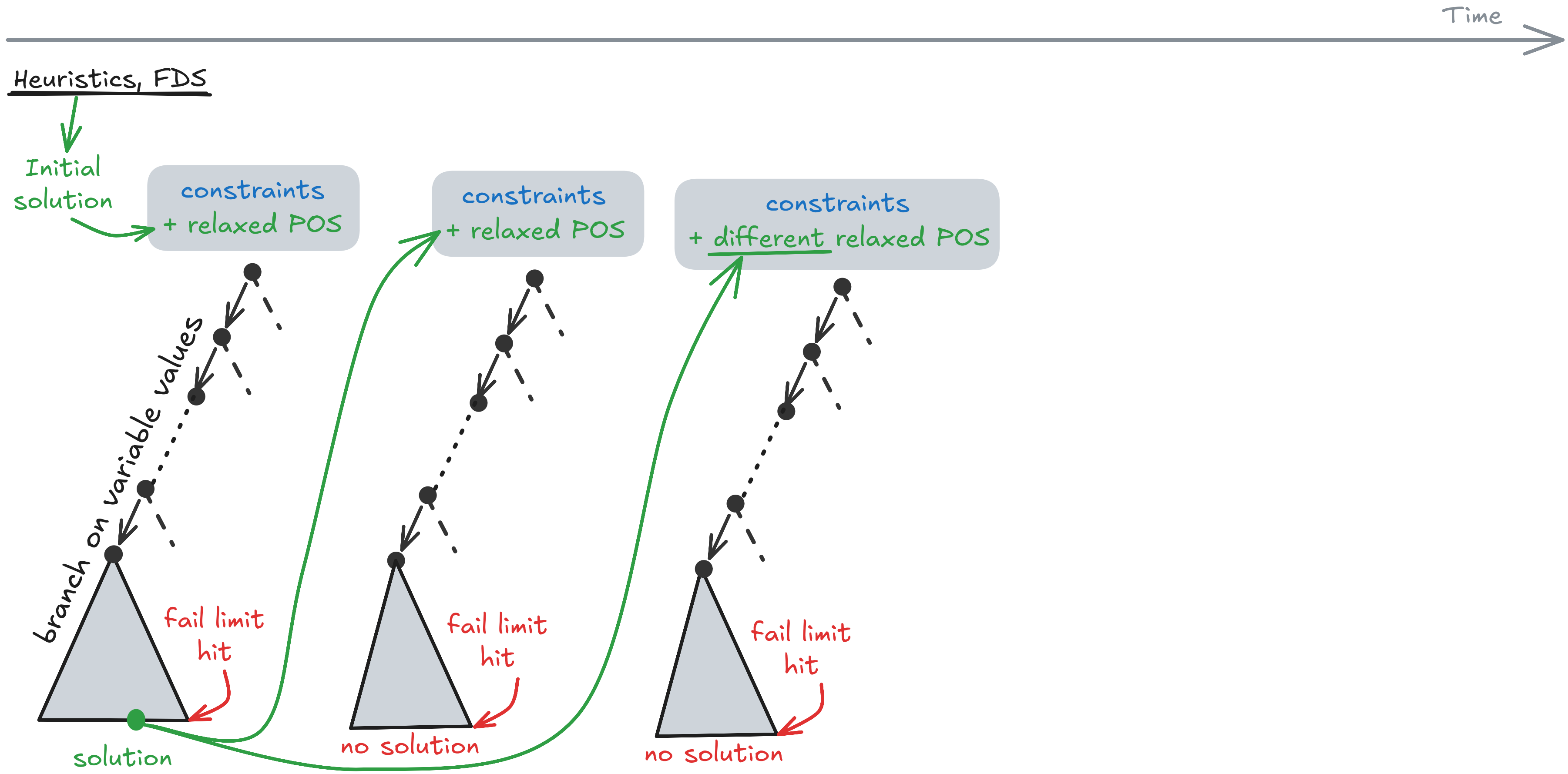

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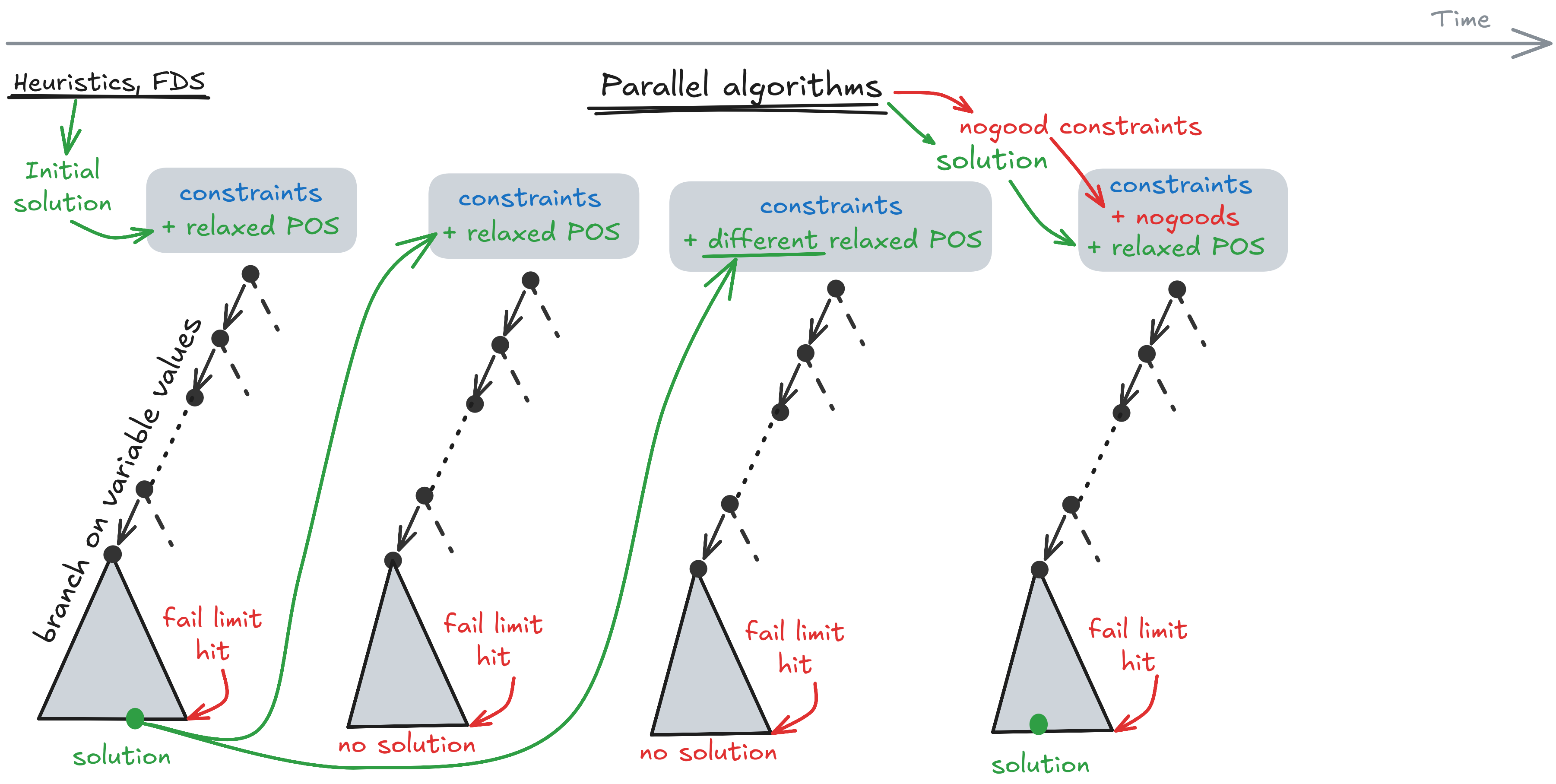

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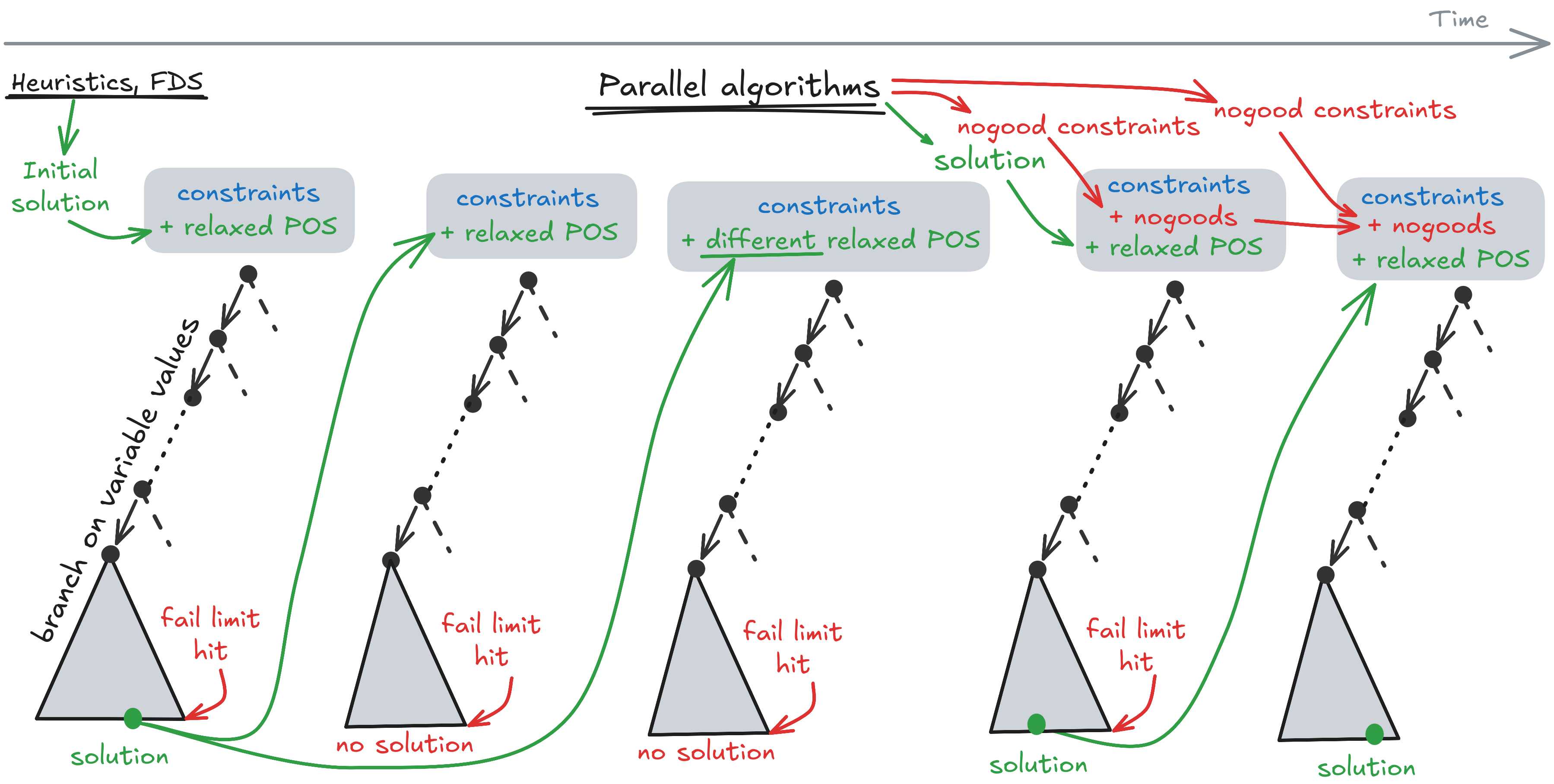


Failure-Directed Search (FDS)

FDS

Failure-Directed Search

Type: Systematic tree search

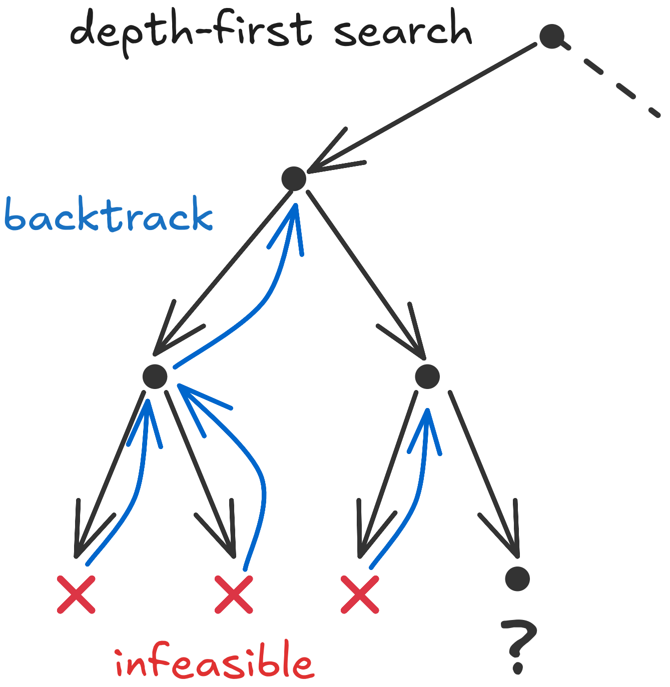
Assumes: Problem is infeasible/hard

Strategy: Learn from failures, restart

Produces: Solutions, proofs, nogoods

✓ Optimality proofs | Lower bounds

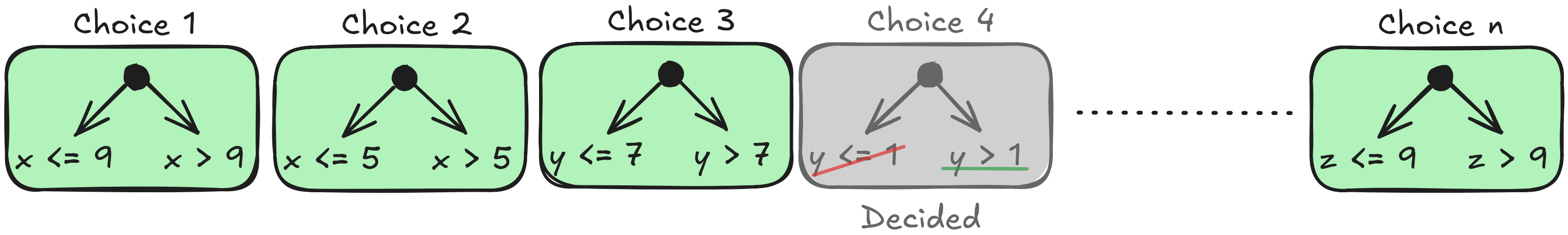
✗ Slow | Solutions are a byproduct



Vilém Heinz, Petr Vilím, Zdeněk Hanzálek:
Reinforcement Learning for Search Tree Size Minimization in Constraint Programming: New Results on Scheduling Benchmarks

Simplified FDS

FDS maintains **ratings** on *choices*:



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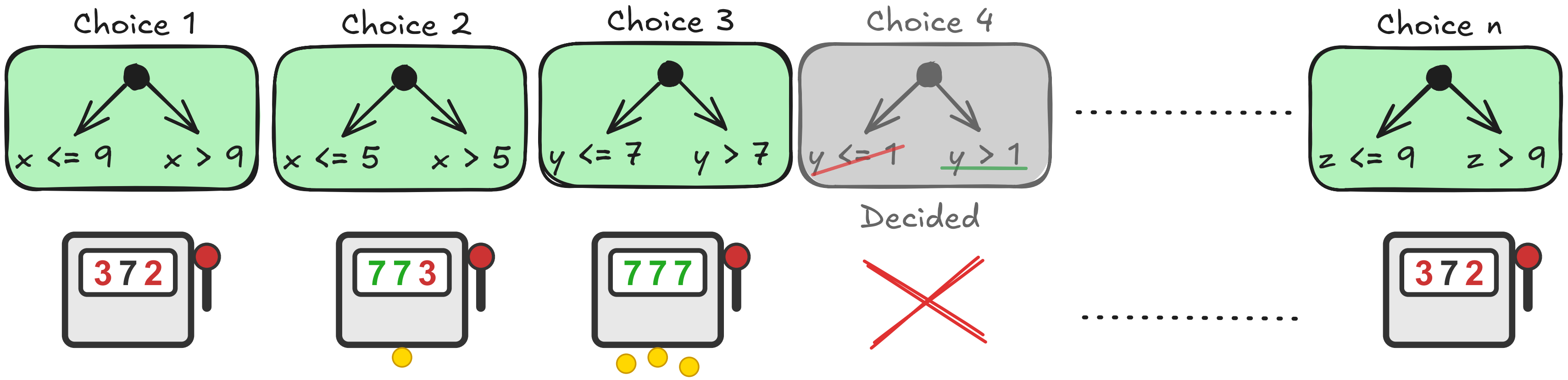

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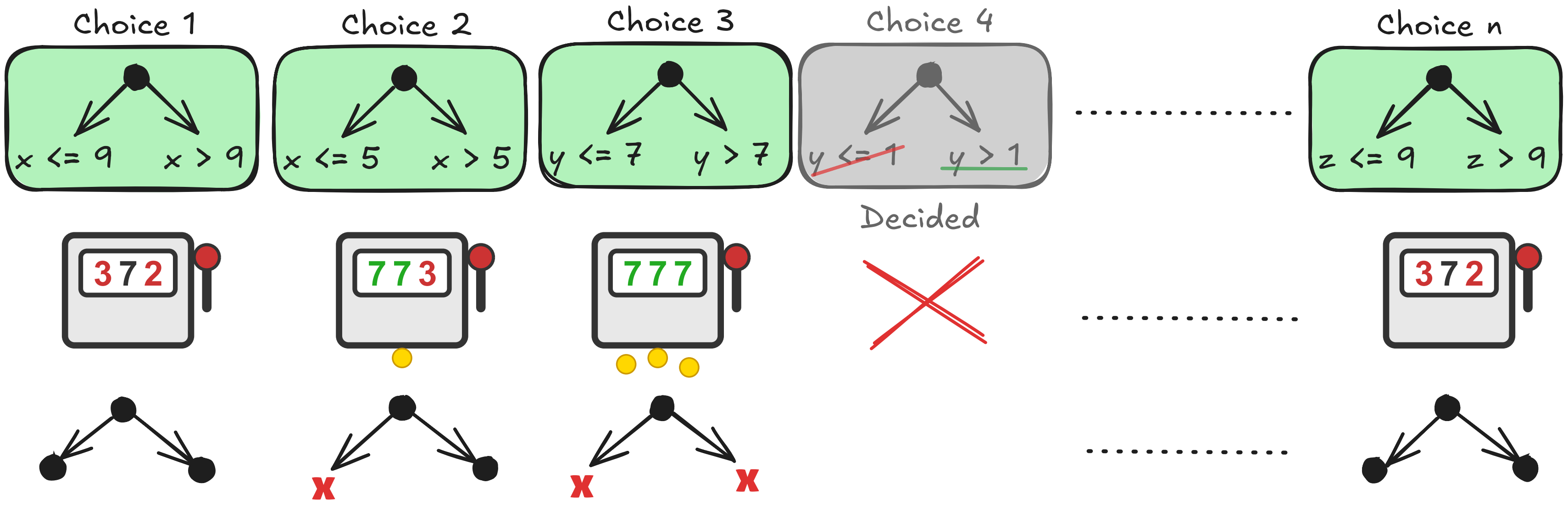

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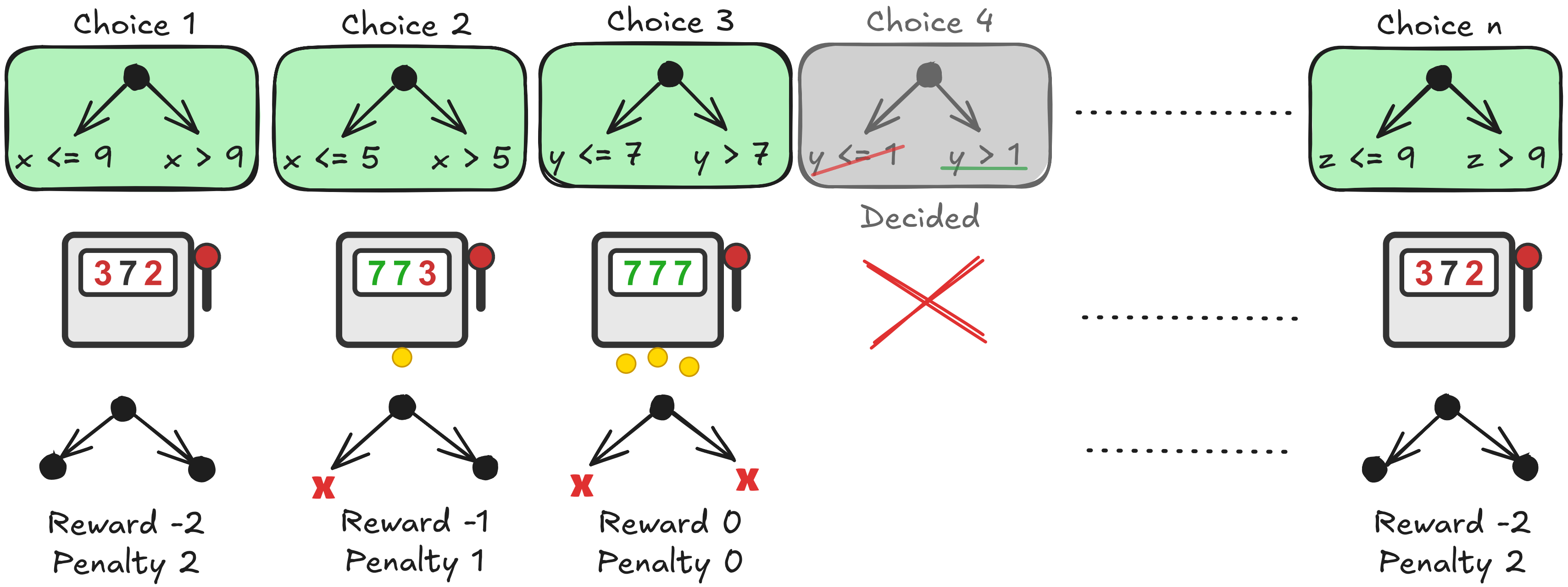


$$\mathbf{rating}(\text{choice}) \;:=\; \alpha \cdot \mathbf{rating}(\text{choice}) + (1-\alpha) \cdot \text{penalty}$$

The FDS - MAB Connection

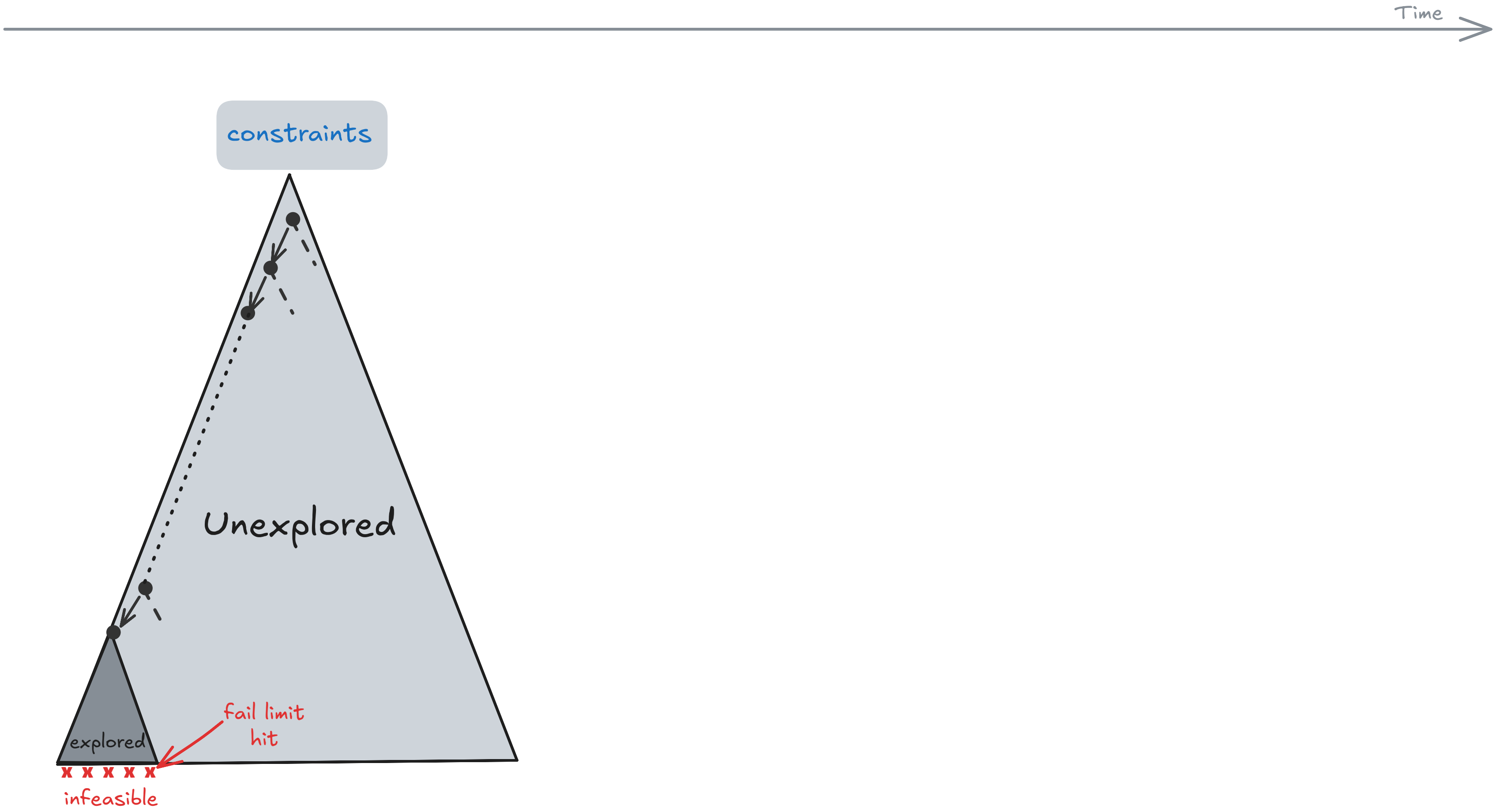
- MAB algorithms minimize sum of penalties.
- In (simplified) FDS, sum of penalties **is the tree size!**

FDS learns to minimize tree size. By design.

I didn't know this when we designed FDS. But it makes sense now.

Vilém will explore the MAB perspective in more depth.

FDS Restarts



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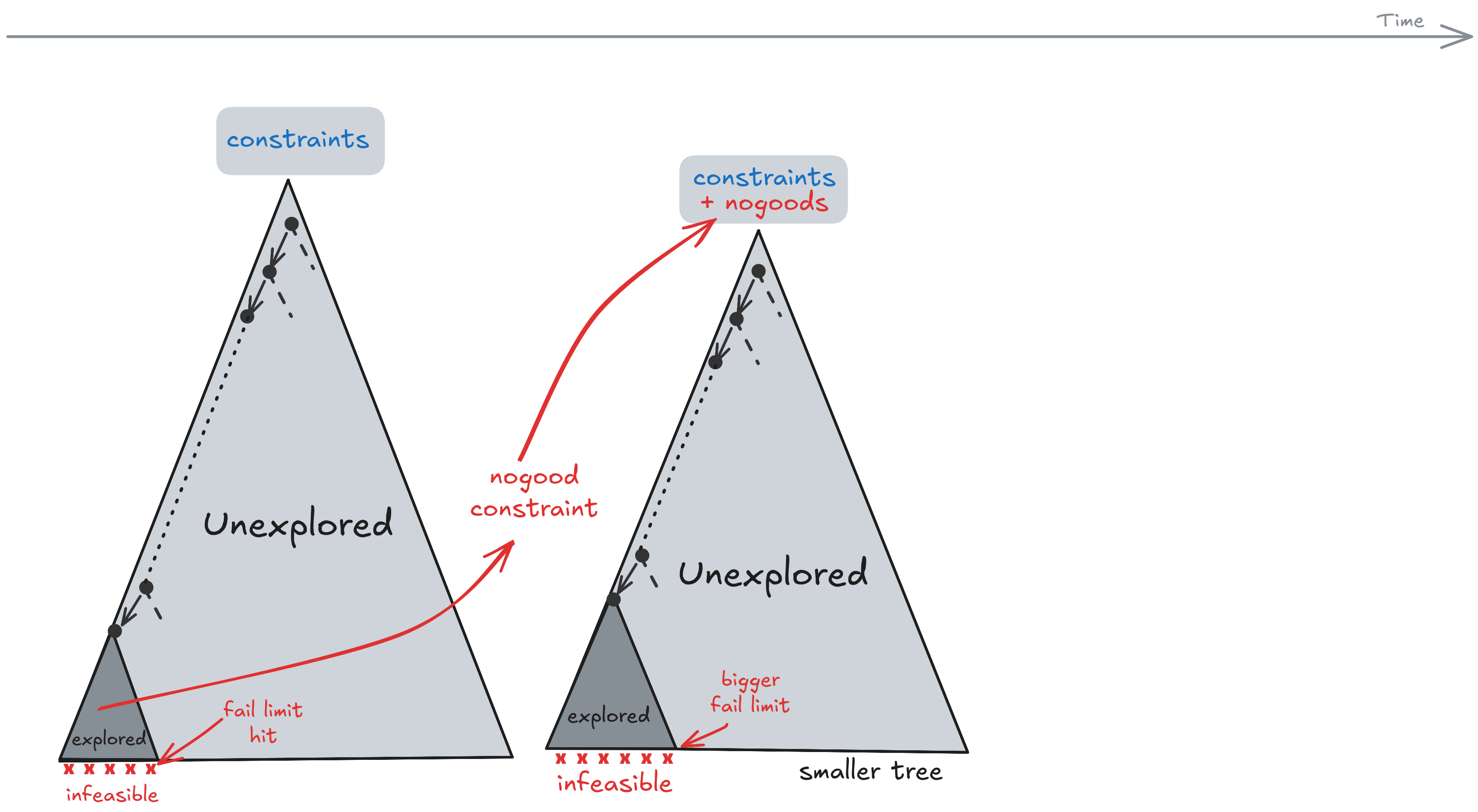
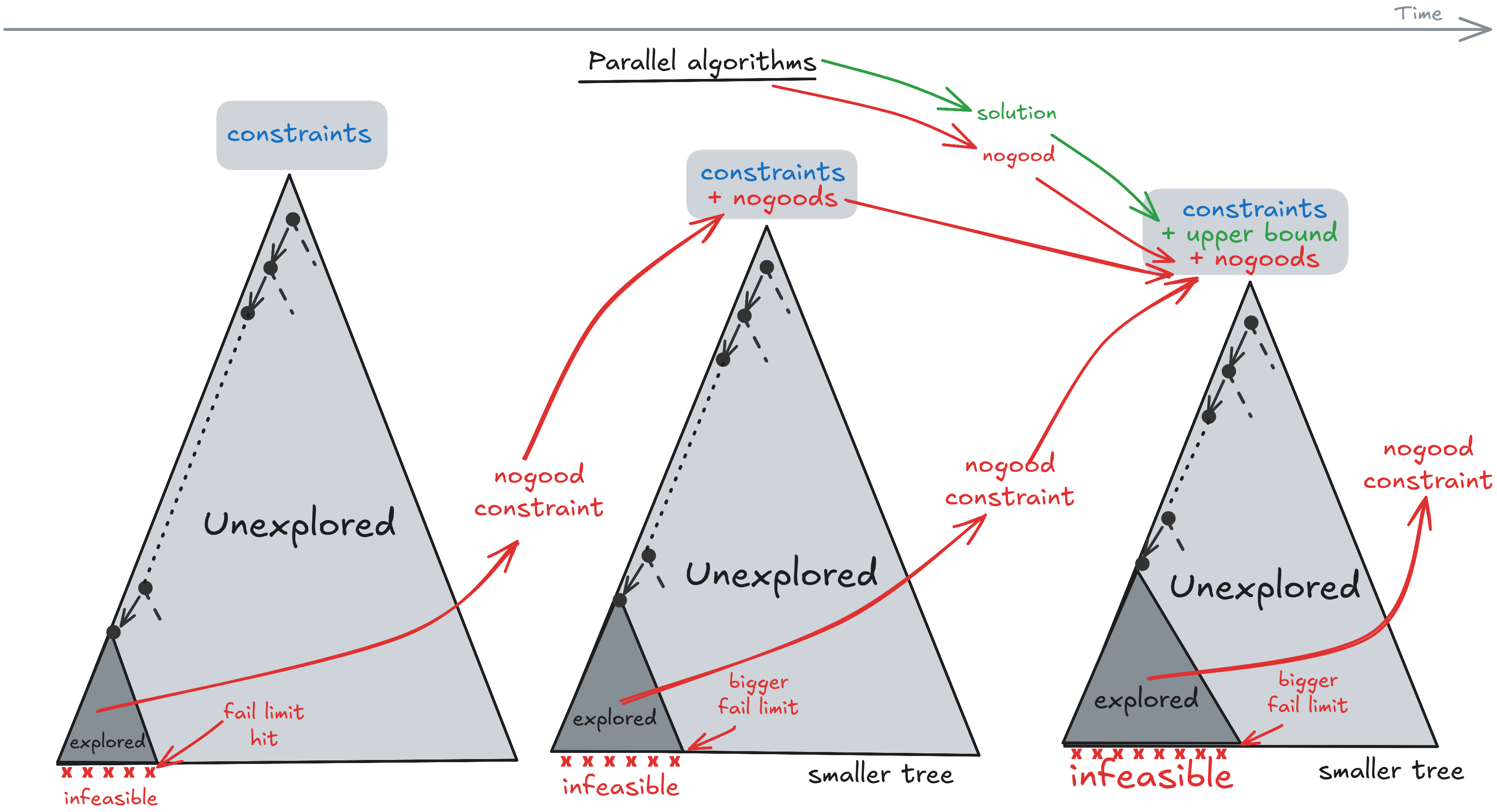


Underlying trees get smaller due to better choices and accumulated nogoods.
Explored subtrees get bigger due to increased fail limits.

FDS Restarts



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FDS Dual

FDS Dual

Lower Bound Prover

Type: Bound-focused search

Assumes: Lower bound can be improved

Strategy: Prove infeasible, increment

Produces: Tighter lower bound, nogoods

✓ Fast bound proofs | Efficient for LB

✗ No solutions | Not good team player

Smarter version of **destructive lower bounds**.

FDS Dual Search

Efficient lower bound proving

Start with a tight bound, prove it infeasible, then relax.

```
bound = current_LB
while solve(objective <= bound) == INFEASIBLE:
  reportLB(bound + 1)              # Assuming integer
  bound += new_bound_to_try(..)  # by parameter FDSDualStrategy
```

FDS Dual workers focus specifically on tightening the lower bound.

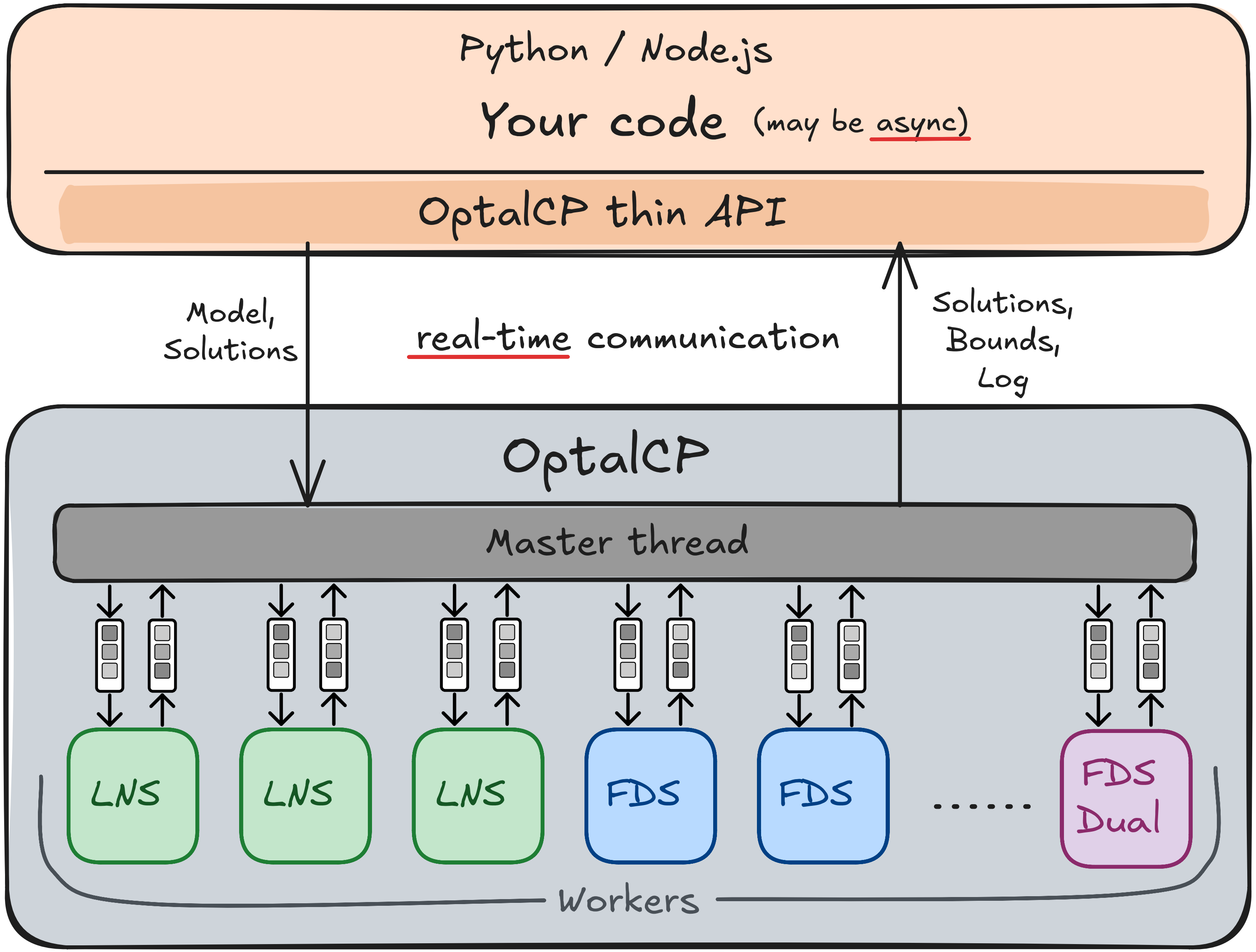
The Perfect Combo

LNS	FDS	FDS Dual
Fast solutions	Proves optimality	Tightens bounds

They complement each other:

- LNS finds solutions → FDS has a better bound
- FDS finds solutions → LNS escapes local optima
- FDS Dual proves bounds → Gap shrinks from below
- FDS FDS Dual restarts → Generate nogoods for LNS FDS FDS Dual
- LNS FDS FDS Dual prove optimality together → Search ends

Parallel Architecture



Heterogeneous Workers

Each worker can be configured independently:

```
model.solve({
  nbWorkers: 4,
  workers: [
    // Fast exploration:
    { searchType: "LNS", noOverlapPropagationLevel: 2 },
    // Stronger reasoning:
    { searchType: "LNS", noOverlapPropagationLevel: 4 },
    // Optimality focus, escape local optima:
    { searchType: "FDS", noOverlapPropagationLevel: 4 },
    // Prove lower bounds:
    { searchType: "FDSDual", noOverlapPropagationLevel: 4 }
  ]});
```

Or you can just let OptalCP to decide.

Hybrid Solution Using Your Algorithm

Your Algorithm

Your Secret Weapon

Type: Revolutionary

Solutions: Always the best

Speed: Blazing fast

Code: Beautiful and bug-free

✓ Perfect for the problem

✓ Scales effortlessly

✗ Not in OptalCP No lower bounds

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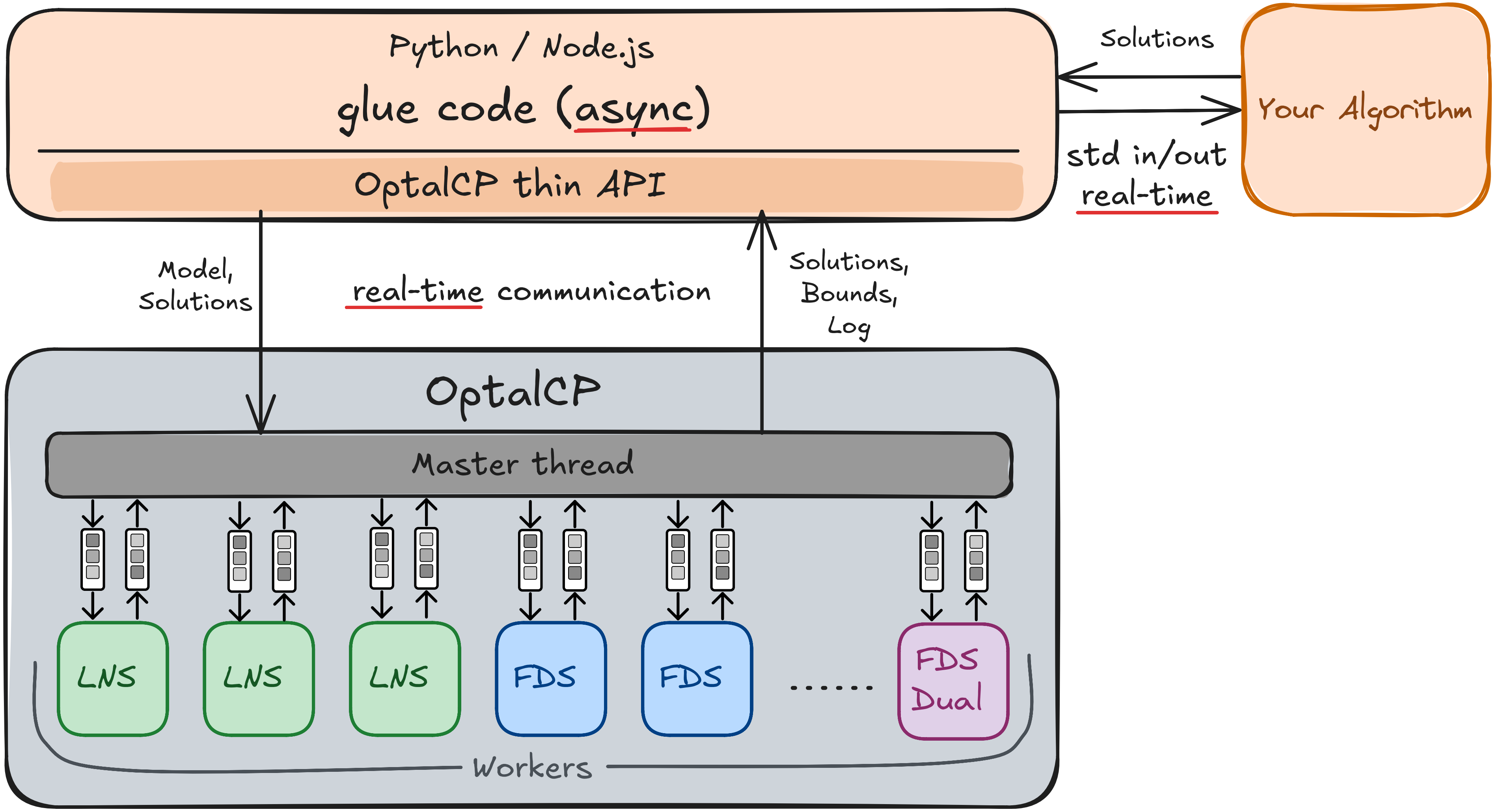
Why hybridize?

- Solution exchange both ways
- Improved robustness
- Escape local optima
- Better than parallel alone
- Adds optimality gap, stops at optimum

How to plug in:

- Your algorithm in any language
- Communicates via stdin/stdout
- Short glue code in Python/*TypeScript*
- Example on GitHub

Architecture Enabling Hybrid Solution



Plugging In Your Algorithm

```python
your_algorithm = await asyncio.create_subprocess_exec(...)
solver = cp.Solver()

def on_optalcp_solution(event: cp.SolutionEvent) -> None:
    serialized = your_solution_format(event.solution)
    your_algorithm.stdin.write(serialized + b'\n')

async def read_your_solutions() -> None:
    while True:
        line = await your_algorithm.stdout.readline()
        solution = to_optalcp_solution(line)
        await solver.send_solution(solution)

solver.on_solution = on_optalcp_solution
asyncio.create_task(read_your_solutions())
await solver.solve(model, parameters)
your_algorithm.kill()
```

Live Demo demo

Research Results

- **Hybridization with (Meta)heuristics**
- **Search Acceleration using Reinforcement Learning**

Vilém Heinz

Hybridization with (Meta)heuristics

Experiments on Scheduling and Routing Problems

Research

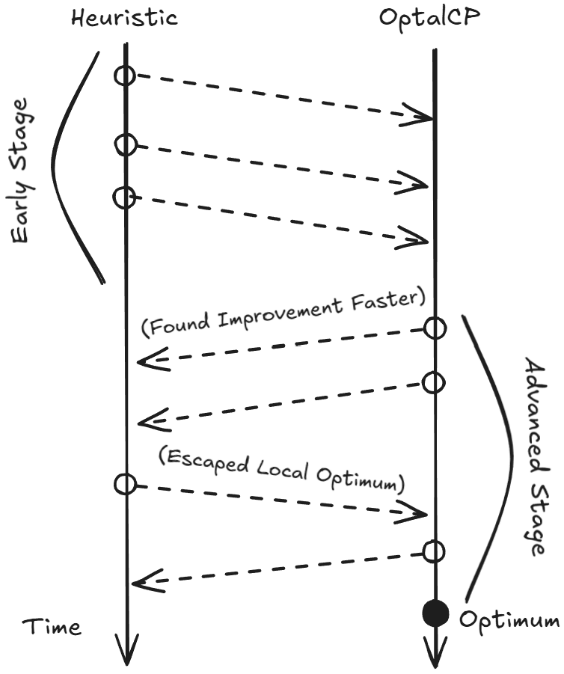
Motivation

Capability	CP Solver	(Meta)heuristics
Bounds and optimality proofs	✓	
Systematic and complete search	✓	
Can prove infeasibility	✓	
Scales to large instances	(✓)	✓
Good anytime behavior		✓
Problem-aware search		(✓)

Question: Can we benefit from their complementary nature?

Goals

- **Early search stage:**
  - Heuristics provide good feasible solutions
  - **Heuristics guide solver's search to promising regions early**
- **Advanced search stage:**
  - Solver incrementally improves and provides bounds
  - **Solver helps heuristics to escape local optima**
- **Overall robustness:**
  - Adversarial instances to one method solved by others

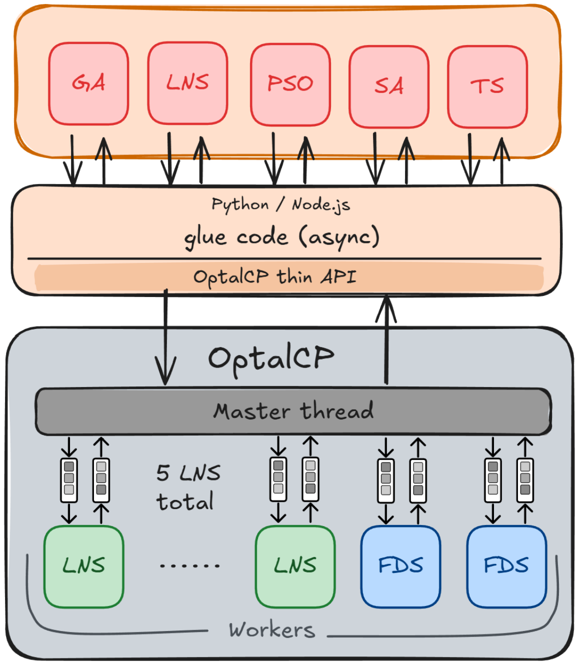


Benchmark Problem Classes

- Two application domains
- Scheduling
  - Flow Shop (FSSP)
  - Job Shop (JSSP)
  - Resource-Constrained Project Scheduling Problem (RCPSP)
- Routing
  - Travelling Salesman Problem (TSP)
  - Capacitated Vehicle Routing Problem (CVRP)
  - Vehicle Routing Problem with Time Windows (VRP-TW)

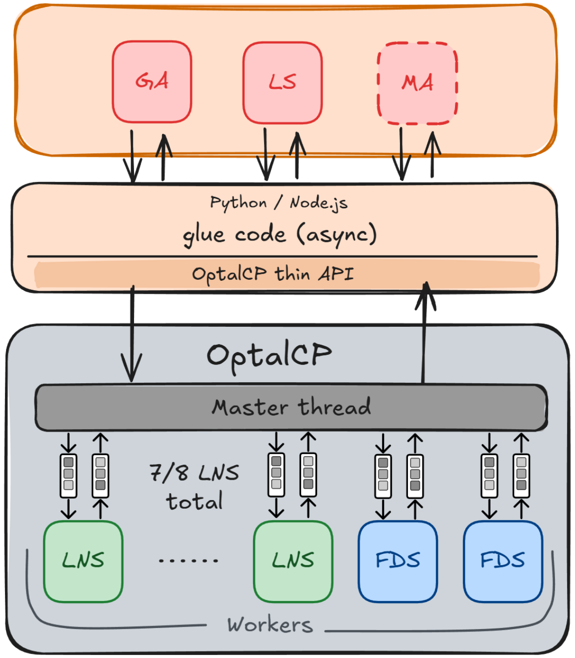
Configuration Scheduling

- 5 different metaheuristics for scheduling problems
  - Genetic Algorithm (GA)
  - Large Neighborhood Search (LNS)
  - Particle Swarm Optimization (PSO)
  - Simulated Annealing (SA)
  - Tabu Search (TS)
- 12 threads
  - one thread for each heuristic (5 threads total)
  - rest for solver (5 LNS workers + 2 FDS workers)
- 120s runtime



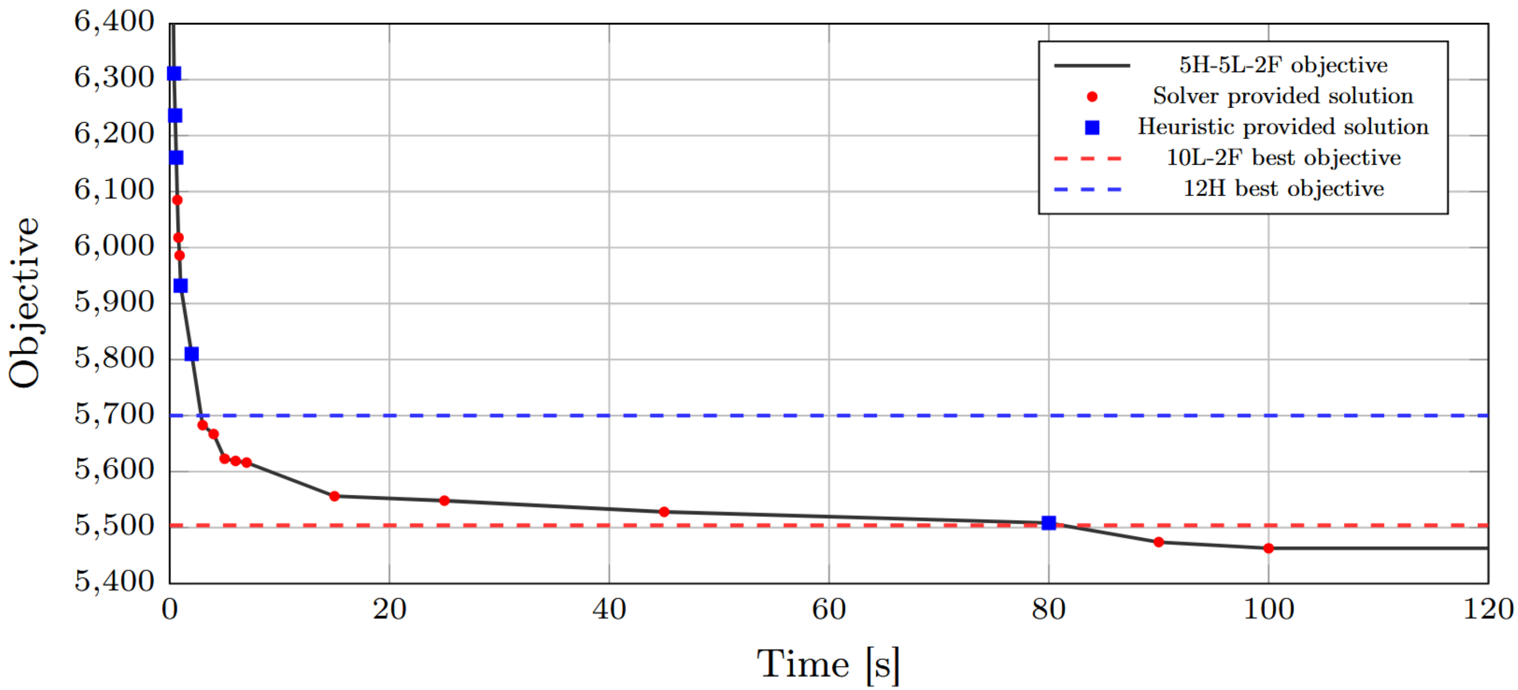
Configuration Routing

- 2/3 different (meta)heuristics for routing problems
  - Genetic Algorithm (GA)
  - Local Search (LS)
  - Memetic Algorithm (MA) - only for VRP-TW
- 12 threads
  - one thread for each heuristic (2/3 threads total)
  - rest for solver (7/8 LNS workers + 2 FDS workers)
- 120s runtime



Practical Example

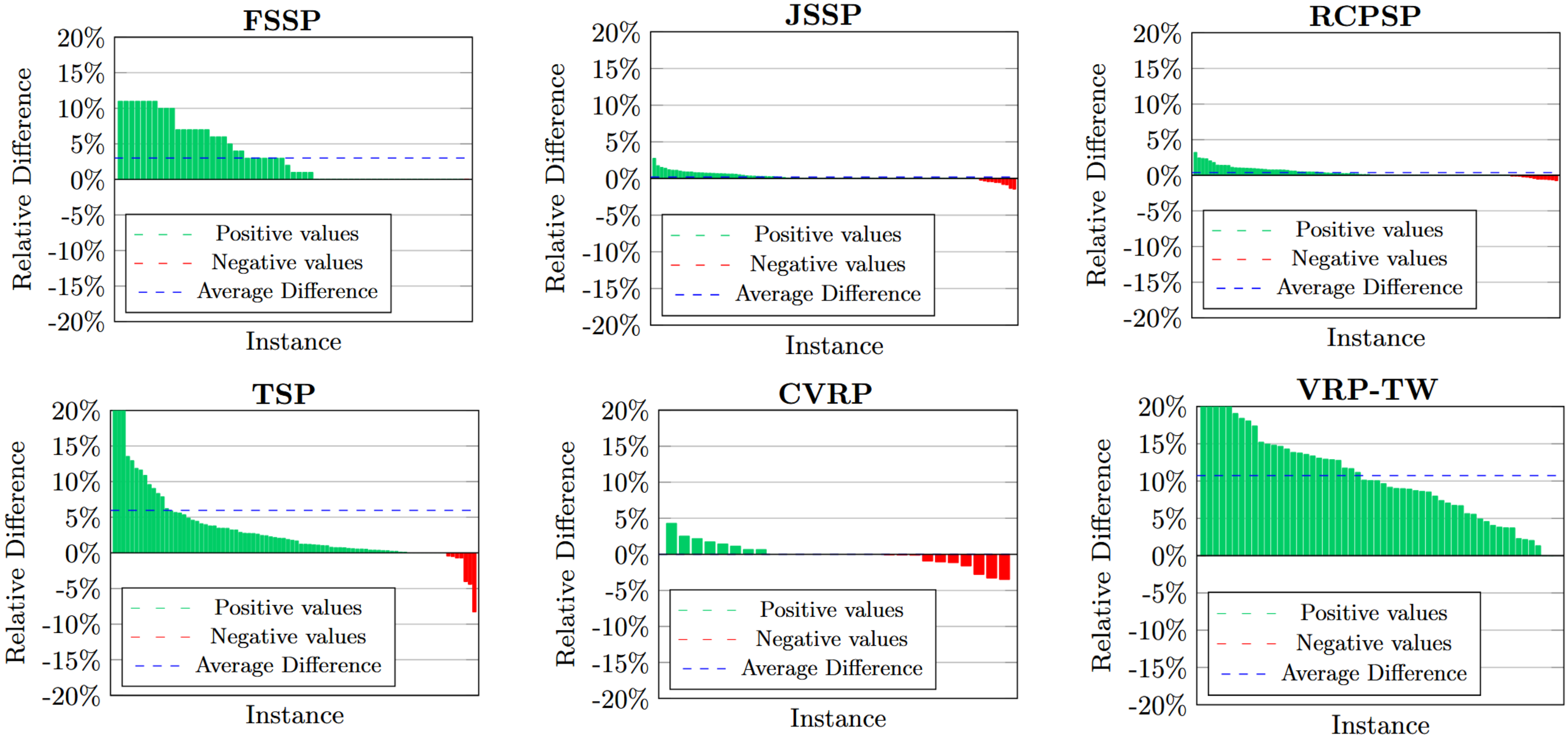
- Job Shop instance cscmax_40_15_7



- Produces better solution than solver or heuristic portfolio alone
  - Different methods clearly profit from real-time exchange
  - Heuristics are useful again once local optima is escaped

Results: Instance Solutions

- Green bars denote instances where hybrid outperformed solver, red denote the opposite



Conclusion

Hybridization improves overall solution quality, anytime behavior and robustness.

- Clear improvements on 3 problem classes
- Overall **60%** of solutions **improved**, only **10% worsened** (mostly slightly) **using same resources**
- Improved overall robustness
  - A few instances unsolved by OptalCP alone were solved by heuristics
- (Meta)heuristics used were not state-of-the-art
  - Still potential for improvements in problems where solver is strong (JSSP, RCPSP)

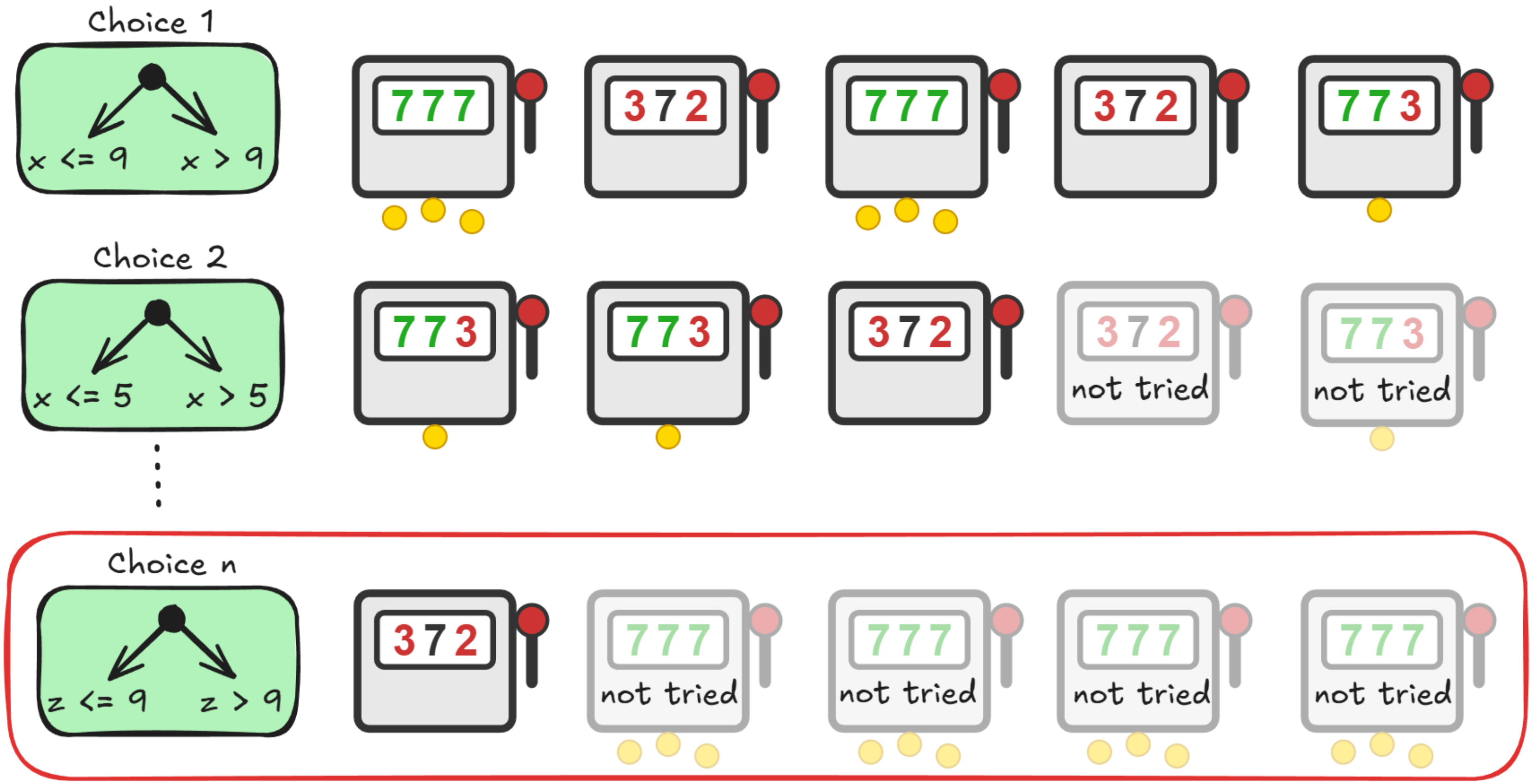
Problem	Improvement
FSSP	+3% average
JSSP	marginal
RCPSP	marginal
TSP	+6% average
CVRP	marginal
VRP-TW	+11% average

Accelerating FDS with Reinforcement Learning

Application of Multi-Armed Bandit Algorithms

Research

Motivation



- FDS always picks (undecided) choice with best rating
- Good choices with bad initial/recent performance are ignored
  - Choice success can depend on current search state (previous choices)

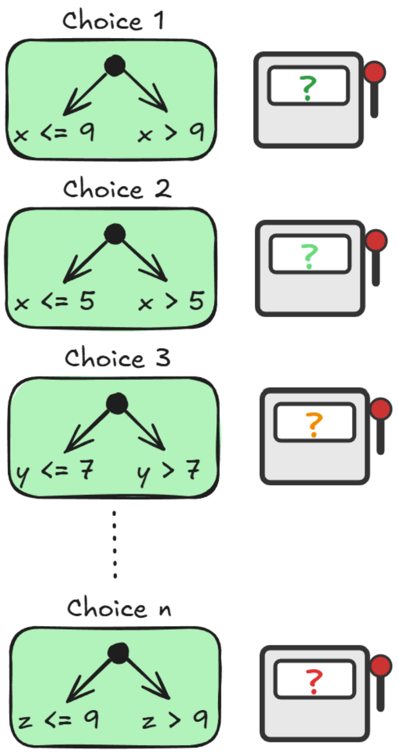
Question: How to prevent missing such good choices?

Goals

- We need to sufficiently test all choices to get an accurate assessment
  - Test all choices initially
  - Revisit bad choices occasionally
- **Enforcing initial choice exploration**
  - Initialize all choices with good rating (optimistic initialization)
- **Reassess choice quality efficiently**
  - FDS choice selection problem ≈ MAB problem

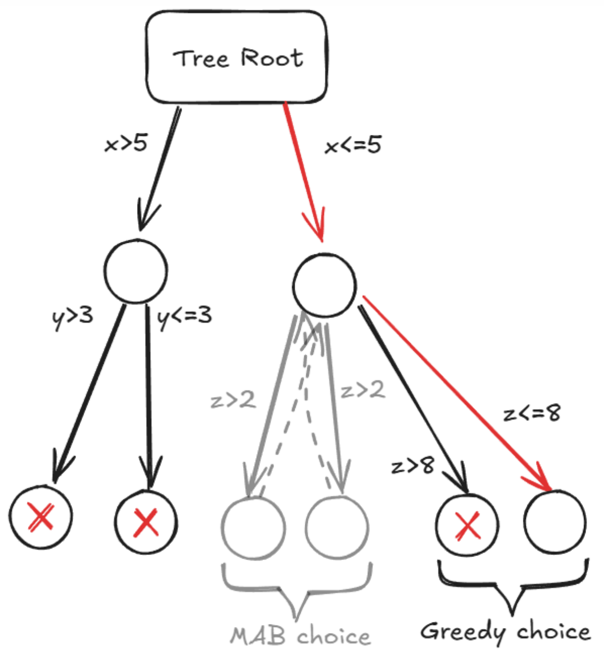
Reinforcement Learning: MAB Problem

- Exploration-Exploitation dilemma (the problem we have)
  - When to pick the best-known action (exploit)
  - When to test new/under-used actions (explore)
- **Multi-Armed Bandit problem**
  - Framework solving exploration-exploitation dilemma
  - Different algorithms/ways to handle exploration
  - Epsilon-greedy (ε), UCB-1 (U), Boltzmann exploration (B), Thompson sampling (T)
  - MAB reward maximization → Search tree size minimization

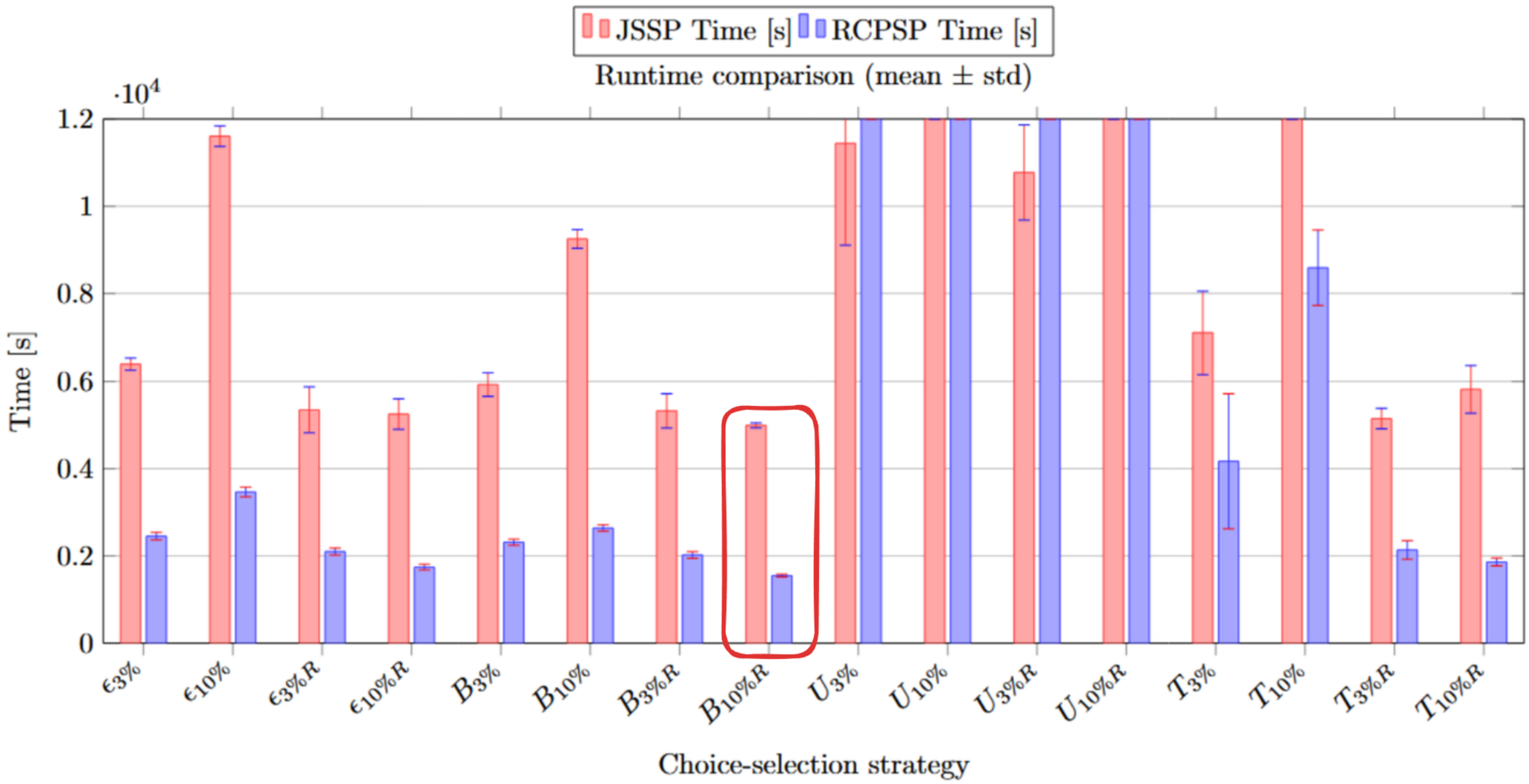


Exploration in FDS Setting

- **MAB-based exploration can be costly in FDS**
  - Bad exploratory choice = doubling the tree size
- **Switch between pure exploitation and MAB strategy**
  - In most cases, we exploit
- **MAB-based choice rollback**
  - “Test run” to evaluate effect and update rating (exploration)
  - Choice is used if it does not increase search tree size, else best-rated choice is used (exploitation)



Results: Selection Strategies

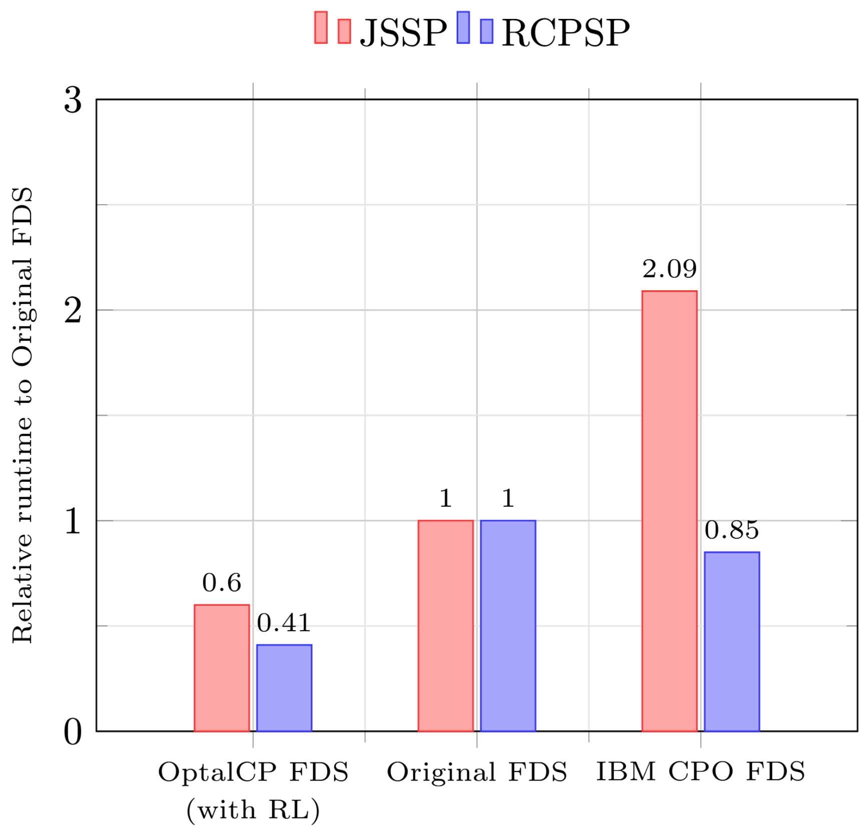


- Measurements on JSSP and RCPSP (percentage denotes MAB choice probability)
- **10% of Boltzmann exploration with Choice rollback performs the best**
- UCB-1 and Thompson embed exploration in action values (actions regain priority)
  - Degrades performance in FDS exploitation-heavy setting

Conclusion

Application of extended MAB algorithm with optimistic initialization roughly halved the computation time required by FDS in JSSP and RCPSP instances.

- Improved a large number of lower bounds for both problems
  - 78/84 of open standard JobShop (JSSP) instances
  - 226/393 of open standard RCPSP instances
  - A few instances for both problems were closed
  - 900s time limit per instance



Heinz, S., Vilím, P., & Hanzálek, Z. (2025). *Reinforcement learning for search tree size minimization in constraint programming.*

Thank You!

Questions?

Website: https://optalcp.com

Benchmarks GitHub: https://github.com/scheduleopt/optalcp-benchmarks

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