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DATA SCIENCE FOR REAL-TIME DECISION-MAKING

Mila

IVADO

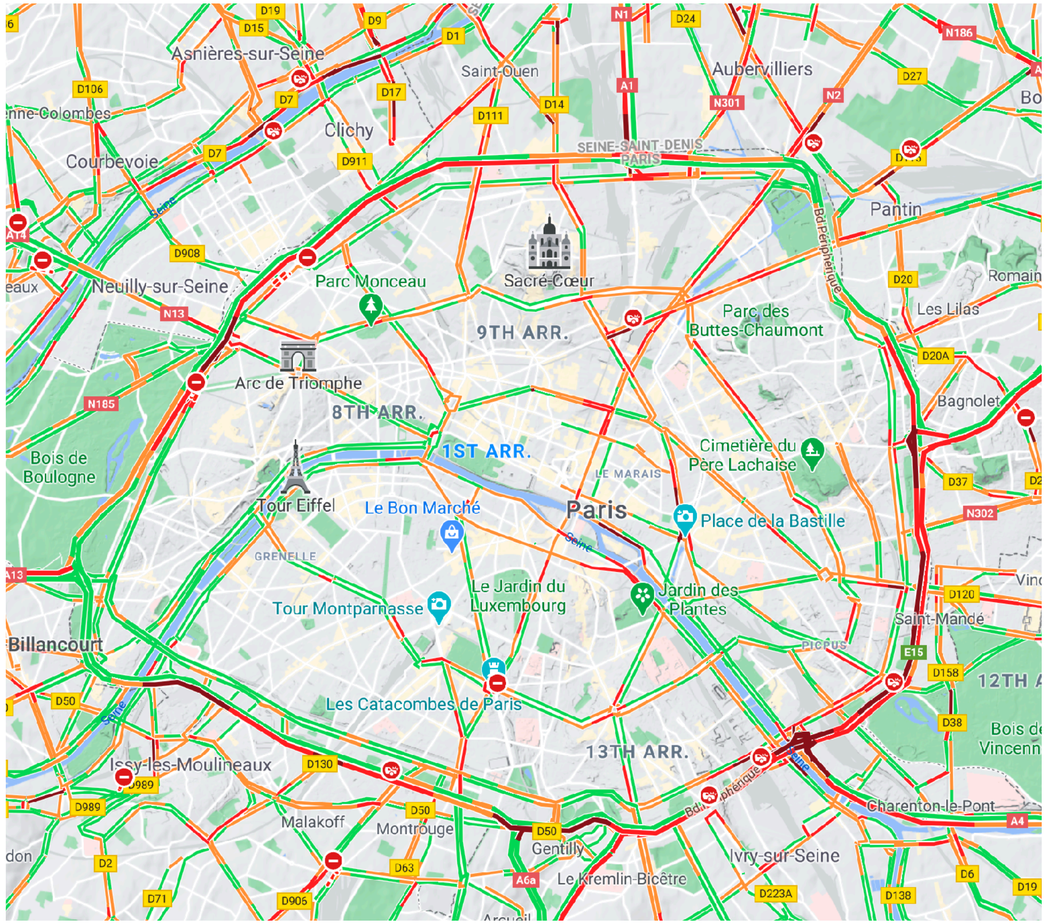
POLYTECHNIQUE MONTRÉAL
UNIVERSITÉ D'INGÉNIERIE

How MILP get solved

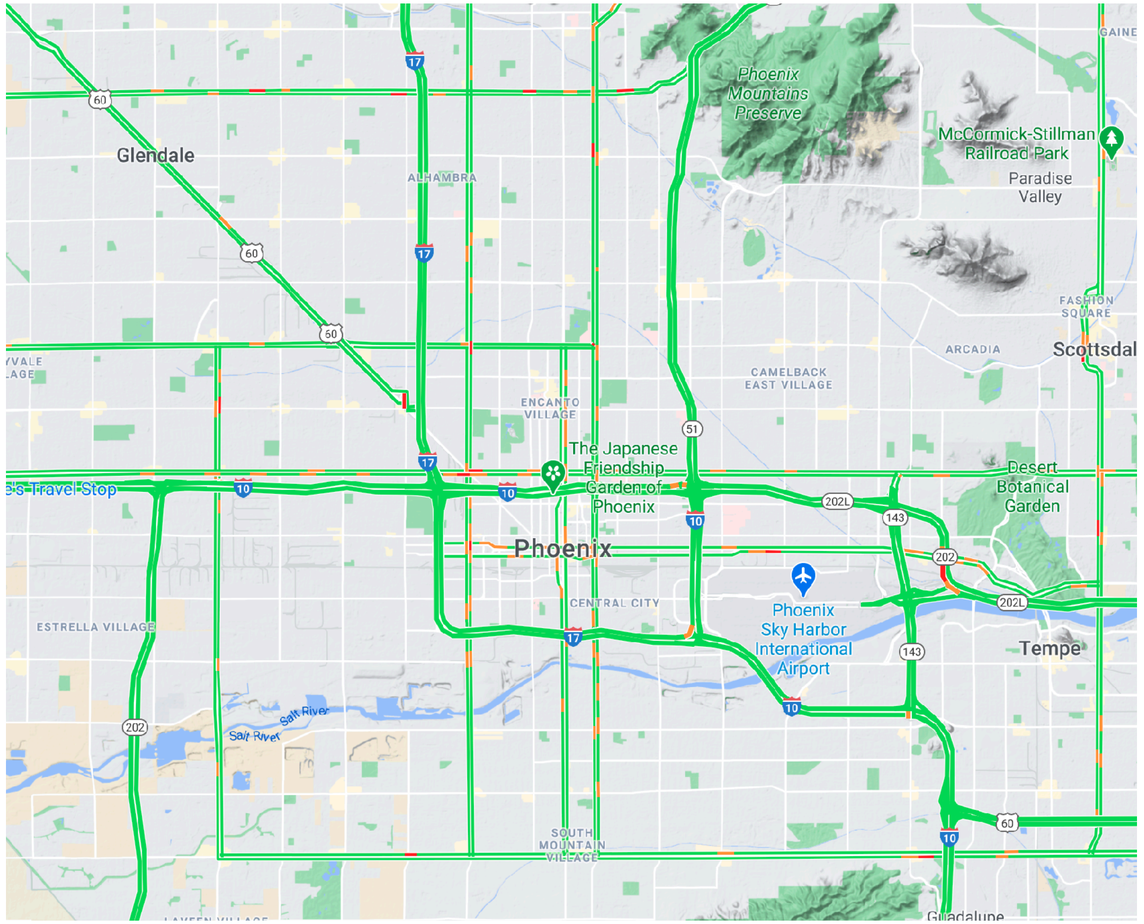
Handcrafted Heuristics

- Not focusing on all problems to beat $\mathcal{NP}$-hardness
- Weak form of **learning**
- Trained through researchers **trials and errors**
- On datasets such as MipLib

Problem Distribution



Paris



Phoenix

Learned Heuristics

- **Automatically** can be **specialized**
- Scale to more complex tasks (unlike rule based systems)
- Can span a large heuristic space

Bengio, Lodi, Prouvost. "*Machine learning for combinatorial optimization: a methodological tour d'horizon*." European Journal of Operational Research (2020).

Why Ecole?

Research Code

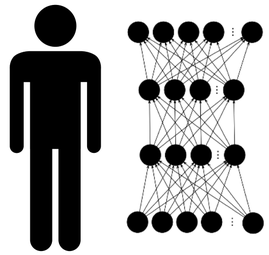
- Need to iterate fast
- Not tested
- Not optimized for speed
- Not modular
- Hard to install
- Often not reproducible

Introducing Ecole

- Intuitive API
- Python and C++
- Fast
- Well tested
- Easy to install
- Good defaults
- Extensible (through SCIP and PySCIPOpt)
- Ease comparison

Learning Environments

OpenAI Gym



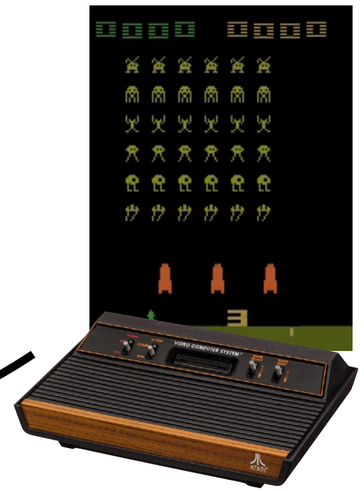
Agent
$\pi(a|s)$

State
S_{t+1}

Reward
R_{t+1}

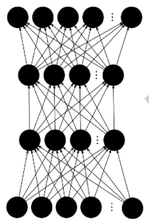
Action
A_t

Environment
$p(s', r|a, s)$

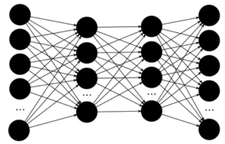


OpenAI Gym

```
import gym


env = gym.make("SpaceInvaders-v0")

for episode in range(1000):
    observation, done = env.reset(), False

    while not done:
        action = policy(observation)
        observation, reward, done, info = env.step(action)
```



Branching with Ecole



Agent
$\pi(a|s)$

Solver statistics

State
S_{t+1}

Reward
R_{t+1}

Action
A_t

Branching variable

Number of nodes

Environment
$p(s', r|a, s)$

Solver

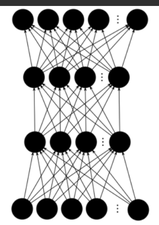
Branching with Ecole

```python
import ecole


env = ecole.environment.Branching()

for episode in range(1000):
    obs, action_set, reward, done = env.reset("path/to/problem")

    while not done:
        action = policy(observation, action_set)
        obs, action_set, reward, done, info = env.step(action)
```

Solved multiple times

Solver statistics

Branching candidates



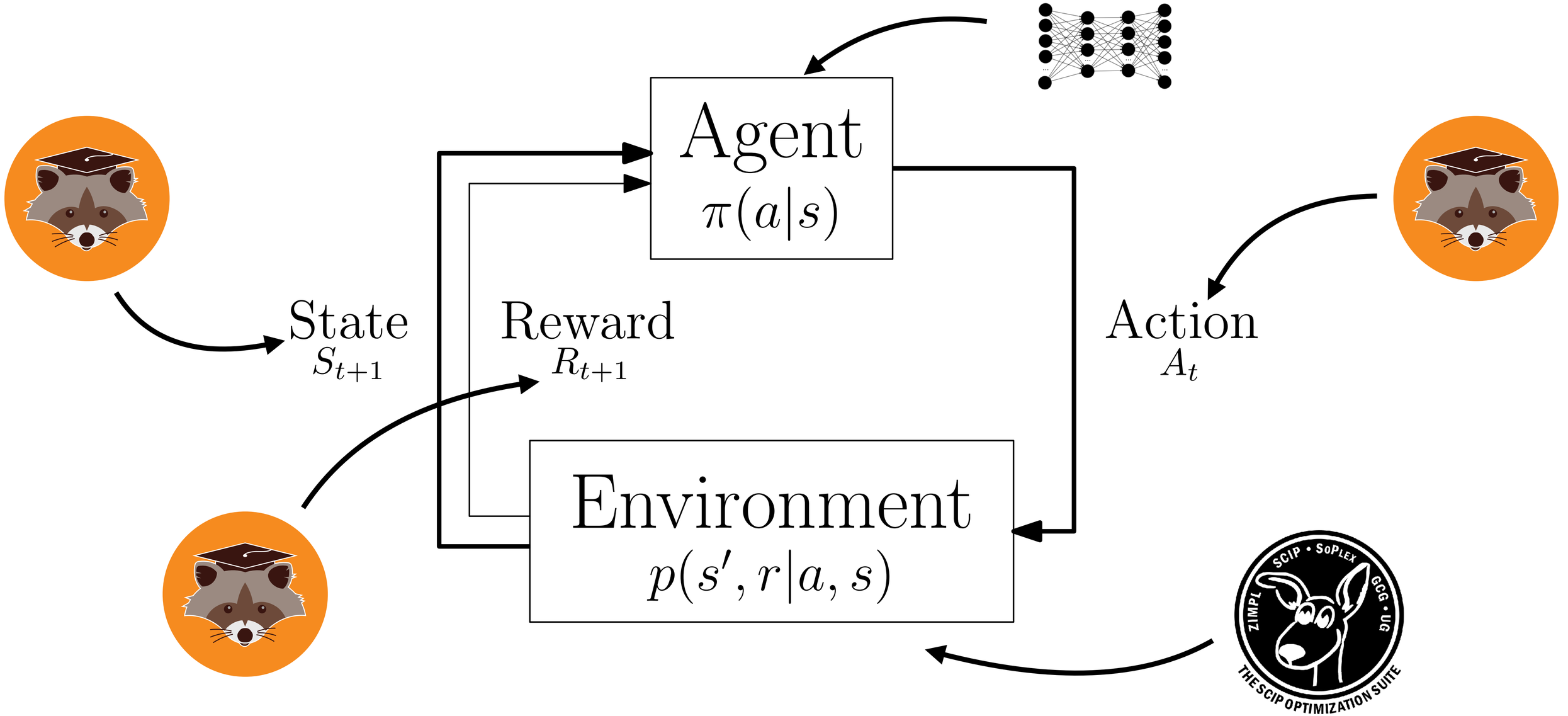
Number of nodes

Instance solved

Branching variable

Extensibility

Highly configurable



Easily swap and define

- Rewards
  - LP Iterations
  - Number of Nodes
  - Solving Time
  - Primal / Dual Integral
- Observation (States)
  - Milp Bipartite
  - Gasse et al. “Exact combinatorial optimization with graph convolutional neural networks”, 2019
  - Hutter et al. “Sequential model-based optimization for general algorithm configuration.”, 2011
  - Khalil et al. “Learning to branch in mixed integer programming.”, 2016
- Any additional information
- Environments
  - Branching variable selection
  - Parameter selection
  - Primal search

Composition

```
env = ecole.environment.Branching(
    reward_function=(LpIterations()**2 - 3* NNodes()),
    observation_function=NodeBipartite(),
    scip_params={"presolving/maxrestarts": 2},
)
```

New Reward Function

```
class NNodeInitLPIterations:

    def before_reset(self, model):
        self.last_iterations = 0.0

    def extract(self, model, done):
        new_iterations = model.as_pyscipopt().getNNodeInitLPIterations()
        diff_iterations = new_iterations - self.last_iterations
        self.last_iterations = new_iterations
        return diff_iterations
```

New Environment Dynamics

```
class SimpleBranchingDynamics(BranchingDynamics):

    def reset_dynamics(self, model):
        # Share memory with Ecole model
        pyscipopt_model = model.as_pyscipopt()

        pyscipopt_model.setPresolve(PY_SCIP_PARAMSETTING.OFF)
        pyscipopt_model.setSeparating(PY_SCIP_PARAMSETTING.OFF)

        # Let the parent class do the rest
        return super().reset_dynamics(model)

    def step_dynamics(self, model):
        ...
```

Instance Generators

```
from ecole.instance import SetCoverGenerator

generator = SetCoverGenerator(n_rows=100, n_cols=200)

for i in range(50):
    instance = next(generator)

    instance.write_problem("some-folder/set-cover-{i:04}.lp")
```

- Set Cover
- Capacitated Facility Location
- Independent Set
- Combinatorial Auction

Ecole In Math

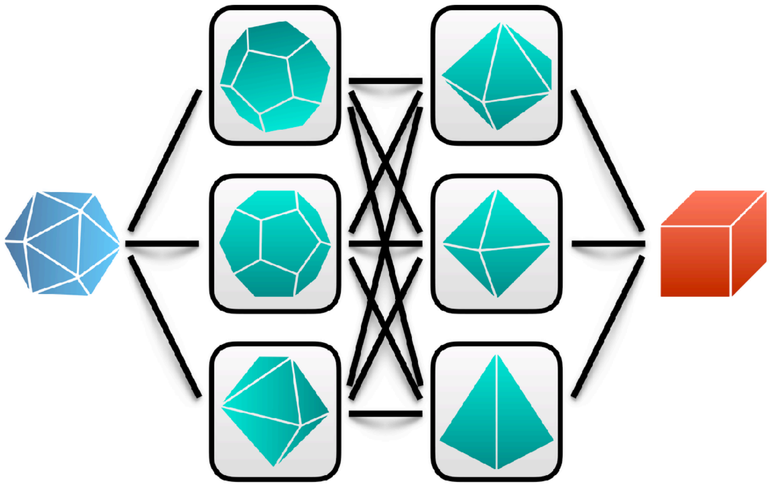
- Instance space $\mathscr{I}$
- State space $\mathscr{S}$ and action space $\mathscr{A}$
- Instance distribution $p_{inst} : \mathscr{I} \to \mathbb{R}_{\geq 0}$
- Conditional initial state distribution $p_{init} : \mathscr{S} \times \mathscr{I} \to \mathbb{R}_{\geq 0}$
- State transition distribution $p_{trans} : \mathscr{S} \times \mathscr{A} \times \mathscr{S} \to \mathbb{R}_{\geq 0}$
- Reward function $R : \mathscr{S} \to \mathbb{R}$
- Observation space $\mathscr{O}$ and function $O : \mathscr{S} \to \mathscr{O}$ (POMDP)
- User policy π

$$\tau \sim \underbrace{p_{inst}(i)}_{\text{instance distribution}} \underbrace{p_{init}(s_0 \mid i)}_{\text{initial state}} \prod_{t=0}^{\infty} \underbrace{\pi(a_t \mid O(s_t))}_{\text{next action}} \underbrace{p_{trans}(s_{t+1} \mid a_t, s_t)}_{\text{next state}}.$$

NEURAL INFORMATION PROCESSING SYSTEMS

Machine Learning for Combinatorial Optimization

——COMPETITION 2021——



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https://www.ecole.ai/2021/ml4co-competition/

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