Representation Learning for Acting and Planning: A Top Down Approach

Tutorial IJCAI 2022

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Slides at https://www.dtic.upf.edu/~hgeffner/tutorial-2022.pdf

Bottom-up vs. Top-Down Representation Learning (1)

- Deep learning (DL) and Deep Reinforcement Learning (DRL) have **revolutionised** the landscape of AI, exploiting power of stochastic gradient descent

- Yet DL and DRL struggle with OOD/structural **generalization**
  - ▷ Inductive biases in neural architectures assumed to help but vague, informal

- **Alternative:** **Language-based representation learning**
  - ▷ Don't choose low-level arch and expect "right representation" to **emerge**
  - ▷ Choose high-level language instead, and learn **representations over language**

- Separation between **what** is to be learned and **how**

Bottom-up vs. Top-down Representation Learning (2)

- Yoshua Bengio at IJCAI 2021: *System 2 Deep Learning: Higher-Level Cognition, Agency, Out-of-Distribution Generalization and Causality:*

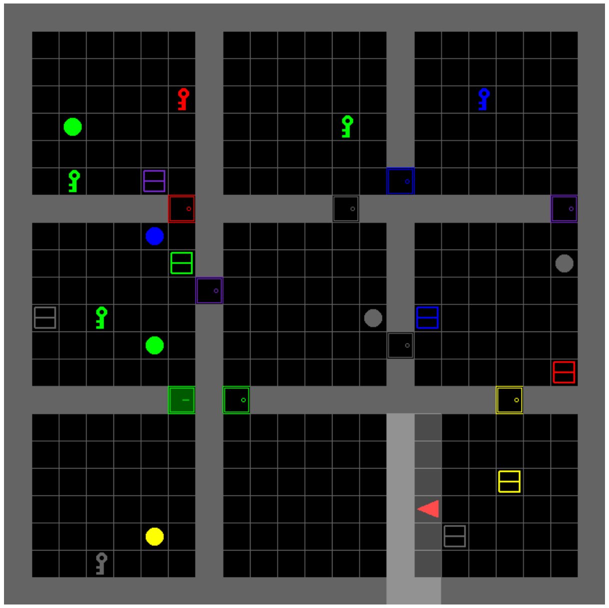
> ". . . **Systematic generalization** hypothesized to arise from efficient factorization of knowledge into **recomposable pieces** corresponding to reusable factors . . . "

- Language-based representation learning:
  - ▷ learn the "recomposable pieces" in a **language**
  - ▷ recombinations and generalization will follow **semantics**

- Very much in line with **traditional AI:** just *learn from data the representations that have traditionally been crafted by hand*

- **Potential benefits:** meaningful learning bias, semantics, transparency, reasoning

Example: Minigrid/BabyAI [Chevalier-Boisvert et al., 2019]



- **Task:** *Pick up grey box behind you, then go to grey key and open door*
- Red triangle is agent at bottom right. Light-grey is field of view
- Learn **controller** that accepts **goals** and **obs**, and outputs **action** to do
- Like a "classical planning problem" **but** state representation **not known**, and goals to be achieved **reactively** (not by planning) with policies that **generalize**

DRL vs. Language-based Representation Learning

- Surprise is not that DL and DRL methods struggle in Minigrid, but that they manage to generate meaningful behavior at all, given **so little prior knowledge**

- Yet **methodology** largely **ad hoc:** from intuitions to **architectures** and **experiments** using baselines . . .

- From perspective of language-based representation learning, **key questions** are:
  - ▷ What are the **domain-independent languages** for representing *dynamics*?
  - ▷ What the **languages** for representing *general reactive policies*, *subgoals*?
  - ▷ How can **representations** over such languages be **learned**?

Outline of the Tutorial

- **Background 1:** Classical planning, planning **width**
- **Languages** for
  - ▷ representing general **dynamics**
  - ▷ representing general **policies**
  - ▷ representing general **subgoal structures** (sketches; 'intrinsic rewards")
- **Background 2:** Qualitative numerical planning problems (**QNPs**)
- **Learning** representations over these languages:
  - ▷ learning general **dynamics**
  - ▷ learning general **policies**
  - ▷ learning general **subgoal structures**
- **Wrap up; Challenges**

Copy of these slides at https://www.dtic.upf.edu/∼hgeffner/tutorial-2022.pdf

Outline of the Tutorial (2)

- Tutorial is **not a survey** on learning to act and plan; too much for us; too much for 1:30h
- Focus is on a **coherent** research thread that covers a lot of ground:
  - ▷ **Crisp** and **simple** ideas and formulations for **stating**, **understanding**, and **addressing** key problems
- Many **open problems**; many opportunities for research

Background 1:

Classical Planning and Planning Width

Background: Model for Classical AI Planning

A (classical) **state model** is a tuple $\mathcal{S} = \langle S, s_0, S_G, Act, A, f, c \rangle$:

- finite and discrete **state space** S
- a known **initial state** $s_0 \in S$
- a set $S_G \subseteq S$ of **goal states**
- **actions** $A(s) \subseteq Act$ **applicable** in each $s \in S$
- a **deterministic state-transition function** $s' = f(a, s)$ for $a \in A(s)$
- positive **action costs** $c(a, s)$, assumed 1 by default

A **solution** to the model or **plan** is a sequence of applicable actions $a_0, \ldots, a_n$ that maps s_0 into S_G

i.e. there must be state sequence $s_0, \ldots, s_{n+1}$ such that $a_i \in A(s_i)$, $s_{i+1} = f(a_i, s_i)$, and $s_{n+1} \in S_G$

A Language for Classical Planning: STRIPS

- A (grounded) **problem** in STRIPS is a tuple $P = \langle F, O, I, G \rangle$:
  - ▷ F is set of (ground) **atoms**
  - ▷ O is set of (ground) **actions**
  - ▷ $I \subseteq F$ stands for **initial situation**
  - ▷ $G \subseteq F$ stands for **goal situation**

- Actions $o \in O$ **represented** by
  - ▷ **Add** list $Add(o) \subseteq F$
  - ▷ **Delete** list $Del(o) \subseteq F$
  - ▷ **Precondition** list $Pre(o) \subseteq F$

A **problem** P in STRIPS defines **state model** $S(P)$ in compact form . . .

From Language to Models

STRIPS problem $P = \langle F, O, I, G \rangle$ determines **state model** $\mathcal{S}(P)$ where

- the states $s \in S$ are collections of atoms from F
- the initial state s_0 is I
- the goal states s_G are such that $G \subseteq s_G$
- the actions a in $A(s)$ are ops in O s.t. $Prec(a) \subseteq s$
- the next state is $s' = [s \setminus Del(a)] \cup Add(a)$
- action costs $c(a, s)$ are all 1

Common approach for solving P is using **path-finding/heuristic search** algorithms over **graph** defined by $\mathcal{S}(P)$ where nodes are the states s, and edges (s, s') are state transitions caused by an action a; i.e., $s' = f(a, s)$ and $a \in A(s)$

The **source** node is the initial state s_0, and the **targets** are the goal states s_G

Background: Width and Width-based Algorithms

- IW(1) is a **breadth-first search** that **prunes** states s that don't make a **feature** true for first time in the search, given **set of Boolean features** F
  - ▷ In **classical planning**, F is the set of (ground) atoms in problem
- IW(k) is IW(1) but over set F^k made up of conjunctions of k features from F
- **Alternatively**, IW(k) is a breadth-first search that prunes s if **novelty**$(s) > k$

- **IW** runs IW(1), IW(2), . . . , IW(k) sequentially until problem solved or $k = N$
- IW is blind like DFS and BFS but diff **enumeration**; uses **state structure**
- IW(k) expands up to N^k nodes and runs in **polytime** $\exp(2k - 1)$

Planning for *Atomic Goals* with IW(1) and IW(2)

#	Domain	I	IW(1)	IW(2)	Neither
1.	8puzzle	400	55%	45%	0%
2.	Barman	232	9%	0%	91%
3.	Blocks World	598	26%	74%	0%
4.	Cybersecure	86	65%	0%	35%
...	...	...	...	...	...
22.	Pegsol	964	92%	8%	0%
23.	Pipes-NonTan	259	44%	56%	0%
24.	Pipes-Tan	369	59%	37%	3%
25.	PSRsmall	316	92%	0%	8%
26.	Rovers	488	47%	53%	0%
27.	Satellite	308	11%	89%	0%
28.	Scanalyzer	624	100%	0%	0%
...	...	...	...	...	...
33.	Transport	330	0%	100%	0%
34.	Trucks	345	0%	100%	0%
35.	Visitall	21,859	100%	0%	0%
36.	Woodworking	1659	100%	0%	0%
37.	Zeno	219	21%	79%	0%
Total/Avgs		**37,921**	**37.0%**	**51.3%**	**11.7%**

88.3% of the 37,921 instances solved by IW(1) or IW(2) [Lipovetzky and G., 2012]

Performance of IW is No Accident: Theory

- **Width** of P, $w(P)$, is min k for which there is a sequence of **subgoals** (atom tuples) $t_0, t_1, \ldots, t_n$, $|t_i| \leq k$ such that:
  - ▷ t_0 is true in the initial situation
  - ▷ the optimal plans for t_n are optimal plans for P
  - ▷ all **optimal plans for** t_i **can be extended into optimal plans for** t_{i+1} by adding a **single action**

- Also $w(P) = 0$ if goal reachable in 0 or 1 step; $w(P) = N + 1$ if no solution, where N is number of atoms in P.

- **Theorem:** If $w(P) = k$, then IW(k) solves P optimally in $\exp(2k - 1)$ time

- **Theorem:** Domains like Blocks, Logistics, Gripper, . . . have all **width 2** independent of problem **size** provided that goals are **single atoms**

Practical Variations of IW

SIW: Serialized iterated width [Lipovetzky and G., 2012]

- Use IW greedily to decrease **number of unachieved goals** $\#g$; assumes conjunctive top goal (simple goal serialization)

BFWS: Best-first guided by **novelty measure** $w_{\langle \#g, \#c \rangle}$ and $\#g$

- BFWS(f_5): back-end of state-of-the-art Dual-BFWS, $\#c$ from relaxed plans
- k-BFWS(f_5): **poltytime** variant of BFWS(f_5) used as front-end of Dual-BFWS
- BFWS(R): version that does not use **action structure**; just **PDDL simulator**

[Lipovetzky and G., 2017; Francès *et al.*, 2017]

Understanding Width: Test Your Knowledge!

How to **prove** in standard encodings that:

- Blocks world instances with goal $clear(x)$ or $hold(x)$ have **width 1**
- Delivery instances with goal $hold(x)$ or $AgentAt(y)$ have **width 1**
- Blocks world instances with goal $on(x, y)$ have **width 2**
- Delivery instances with goal $PkgAt(x, y)$ have **width 2**
- Blocks and Delivery with **arbitrary conjunctive goals** have **no bounded width**

Delivery is simplified LOGISTICS: agent in grid, picking up and dropping pkgs

For **proving** $w(G) \leq k$:

- **Necessary 1:** If $a_1, \ldots, a_n$ is optimal plan for goal G, each **prefix** $a_1, \ldots, a_i$ must be optimal plan for some t_i, $|t_i| \leq k$
- **Necessary 2:** For these t_i's, **all** optimal plans for t_i **extend** into optimal plans for t_{i+1}.

Part II: Languages

- Language for expressing **dynamics**
- Language for expressing **general policies**
- Language for expressing **general subgoal structures**

Language for Expressing Dynamics: First-Order STRIPS

Problems specified as **instances** $P = \langle D, I \rangle$ of **general** planning domain:

- **Domain** D specified in terms of **action schemas** and **predicates**
- **Instance** is $P = \langle D, I \rangle$ where I details **objects**, **init**, **goal**

Distinction between **general** domain D and **specific** instance $P = \langle D, I \rangle$ important for **reusing** action models, and also for **learning** them:

- Learning $P_i = \langle D, I_i \rangle$ implies learning D that **generalizes** to other instances

In RL and DRL, there is no notion of **domain:** generalization to other "instances" analyzed **experimentally**; closest things are "procedurally generated instances," and "probability distribution over tasks"

Example: 2-Gripper Problem $P = \langle D, I \rangle$ in PDDL

```
(define (domain gripper)
   (:requirements :typing)
   (:types room ball gripper)
   (:constants left right - gripper)
   (:predicates (at-robot ?r - room)(at ?b - ball ?r - room)(free ?g - gripper)
        (carry ?o - ball ?g - gripper))
   (:action move
       :parameters  (?from ?to - room)
       :precondition (at-robot ?from)
       :effect (and  (at-robot ?to) (not (at-robot ?from))))
   (:action pick
       :parameters (?obj - ball ?room - room ?gripper - gripper)
       :precondition  (and  (at ?obj ?room) (at-robot ?room) (free ?gripper))
       :effect (and (carry ?obj ?gripper) (not (at ?obj ?room)) (not (free ?gripper))))
   (:action drop
       :parameters  (?obj - ball ?room - room ?gripper - gripper)
       :precondition  (and  (carry ?obj ?gripper) (at-robot ?room))
       :effect (and (at ?obj ?room) (free ?gripper) (not (carry ?obj ?gripper)))))

(define (problem gripper2)
    (:domain gripper)
    (:objects roomA roomB - room Ball1 Ball2 - ball)
    (:init  (at-robot roomA) (free left) (free right)  (at Ball1 roomA)(at Ball2 roomA))
    (:goal (and (at Ball1 roomB) (at Ball2 roomB))))
```

Preview: Learning Dynamics in Lifted STRIPS

- Planning problem $P_i = \langle D, I_i \rangle$ defines unique **state graph** $G(P_i)$
- Learning as **inverse problem:** from graphs $G_1, \ldots, G_k$, learn D, I_i:

> Given graphs $G_1, \ldots, G_k$, find **simplest** instances $P_i = \langle D, I_i \rangle$ such that graphs G_i and $G(P_i)$ are isomorphic, $i = 1, \ldots, k$.

- Problem cast and solved as combinatorial optimization task [B. and G., 2020]
- **Complexity** of D determined by $\#$ and arities of action schemas and predicates
- **Variations:** missing edges, noisy observations [Rodriguez *et al.*, 2021a]
- **Related**
  - ▷ Learning schemas from **ground traces** [Cresswell *et al.*, 2013]
  - ▷ Deep learning of action schemas from images via **autoencoders** [Asai, 2019]
  - ▷ Learning prop. action models from **options** [Konidaris *et al.*, 2018]
  - ▷ Most work on **learning action models** assumes **domain predicates** known

Second Task: General Policies

- **General policy** represents strategy for solving **multiple** domain instances **reactively**; i.e., without having to search or plan
    - ▷ E.g., policy for achieving $on(x, y)$; **any** # of blocks, **any** configuration
- What are good **languages** for expressing such policies?
- Number of works have addressed the problem [Khardon 1999; Martin and G., 2004; Fern *et al.*, 2006; Srivastava *et al.*, 2011; Hu and De Giacomo, 2011]
- **Subtlety:** set of (ground) actions change from instance to instance with objects

Learning general policies also a key goal in (Deep) RL

General Policies: A Language [B. and G., 2018]

- **General policies** are given by **rules** $C \mapsto E$ over set Φ of **features**

- **Features** f are state functions that have a well-defined value $f(s)$ on every reachable state of any instance of the domain
  - ▷ **Boolean** features p: $p(s)$ is true or false
  - ▷ **Numerical** features n: $n(s)$ is non-negative integer

Computation of feature values assumed to be "cheap": features assumed to have **linear** number of values at most, computable in **linear** time (in $|P|$).

Example: General Policy for $clear(x)$

- **Features** $\Phi = \{H, n\}$: 'holding' and 'number of blocks above x'
- **Policy** π for class $\mathcal{Q}$ of Block problems with goal $clear(x)$ given by two rules:

$$\{\neg H, n > 0\} \mapsto \{H, n\downarrow\} \qquad ; \qquad \{H, n > 0\} \mapsto \{\neg H\}$$

Meaning:

– if $\neg H$ & $n > 0$, move to successor state where H holds and n **decreases**

– if H & $n > 0$, move to successor state where $\neg H$ holds, n **doesn't change**

Language and Semantics of General Policies: Definitions

- **Policy rules** $C \mapsto E$ over set Φ of Boolean and numerical **features** p, n:
  - ▷ *Boolean conditions* in C: p, $\neg p$, $n = 0$, $n > 0$
  - ▷ *qualitative effects* in E: p, $\neg p$, $p?$, $n\downarrow$, $n\uparrow$, $n?$
- **State transition** (s, s') **satisfies** rule $C \mapsto E$ if
  - ▷ $f(s)$ makes body C true
  - ▷ change from $f(s)$ to $f(s')$ satisfies E
- A **policy** π for class $\mathcal{Q}$ of problems P is given by policy rules $C \mapsto E$
  - ▷ *Transition* (s, s') in P compatible with π if (s, s') satisfies a policy rule
  - ▷ *Trajectory* $s_0, s_1, \ldots$ compatible if s_0 of P and transitions compatible with π
- π **solves** P if all max trajectories compatible with π reach goal of P
- π **solves** collection of problems $\mathcal{Q}$ if it solves each $P \in \mathcal{Q}$

Example: Delivery

- Pick packages spread in $n \times m$ grid, one by one, to target location
- **Features** $\Phi = \{H, p, t, n\}$: hold, dist. to nearest pkg & target, $\#$ undelivered
- Policy π that solves class $\mathcal{Q}_D$: **any** $\#$ of pkgs and distribution, **any** grid size

$\{\neg H, p > 0\} \mapsto \{p\downarrow, t?\}$	go to nearest package
$\{\neg H, p = 0\} \mapsto \{H, p?\}$	pick it up
$\{H, t > 0\} \mapsto \{t\downarrow, p?\}$	go to target cell
$\{H, t = 0\} \mapsto \{\neg H, n\downarrow, p?\}$	drop package

General Policies: Three Questions

1. How to **prove** that general policy solves potentially infinite class of instances $\mathcal{Q}$?
2. How to **learn** policies (and the features involved) to solve $\mathcal{Q}$?
3. How to **learn** policies that are **guaranteed** to solve infinite $\mathcal{Q}$?

We consider idea of **learning** first and move then to 1. Not much to say about 3.

Preview: Learning General Policies

Given a known domain D, training instances $P_1, \ldots, P_k$, over D, and a **finite pool of domain features** $\mathcal{F}$, each with a cost, find the cheapest policy π over $\mathcal{F}$ such that π solves all P_i, $i = 1, \ldots, k$

- Problem cast and solved as **combinatorial opt. task** [Francès *et al.*, 2021]
- Pool of **features** $\mathcal{F}$ generated from domain predicates using **2-variable** (description) logic grammar; feature cost given by syntax tree size
- **Deep learning** approaches [Toyer *et al.*, 2018; Garg *et al.*, 2020] do not need $\mathcal{F}$ but not 100% correct in general
- Recent DL approach also avoids $\mathcal{F}$ and nearly 100% correct when **2-variable logic** features suffice; exploits relation between **GNNs** and 2-variable logic [Ståhlberg *et al.*, 2022a and 2022b]

Proving that a General Policy Solves Class of Instances $\mathcal{Q}$

How to **prove** that this policy π achieves $clear(x)$ in all Block problems?

$$\{\neg H, n > 0\} \mapsto \{H, n\!\downarrow\} \qquad ; \qquad \{H, n > 0\} \mapsto \{\neg H\}$$

- **Soundness:** policy π applies in every **non-goal** state s
  - ▷ for any such s, there is (s, s') compatible with π
- **Acyclicity:** no sequence of transitions (s_i, s_{i+1}) compatible with π **cycle**

Theorem: If π is sound and acyclic in $\mathcal{Q}$, and no dead-ends, π solves $\mathcal{Q}$

Exercise: *Show that policy for $clear(x)$ is* **sound** *and* **acyclic** *in Blocks*

Acyclicity, Termination, and QNPs

- **Termination:** criterion that ensures that policy is **acyclic** over **any** domain

- A policy π is **terminating** if for all infinite trajectories $s_0, \ldots, s_i, \ldots$ compatible with π, there is a **numerical feature** n such that:
    - ▷ n is **decremented** in some recurrent transition (s, s'); i.e., $n(s') < n(s)$
    - ▷ n is **not incremented** in any recurrent transition (s, s'); i.e., $n(s') \not> n(s)$

- Every such trajectory deemed **impossible** or **unfair** (n can't decrement below 0), thus if π terminates, π-trajectories **terminate**

- **Termination** notion is from **QNPs**; verifiable in time $O(2^{|\Phi|})$ by SIEVE algorithm [Srivastava *et al.*, 2011], where Φ is set of features involved in the policy

More about QNPs later on . . .

Third Task: Subgoal Structure

Subgoal structure important in planning and RL ("intrinsic rewards", hierarchies)

Sketches powerful language for expressing subgoal structure [B. and G., 2021]

- **Goal serialization** and **full policies** expressible as sketches
- **Semantics** in terms of **subgoals to be achieved**; not so with HTNs, LTL
- Sketches **split** problems into **subproblems**

If **subproblems** have a **bounded width**, problems solved in **polytime**

Example: Sketches for Delivery

- **Width=0** Sketch (full policy)

$\{\neg H, p > 0\} \mapsto \{p\downarrow, t?\}$	go to nearest package
$\{\neg H, p = 0\} \mapsto \{H, p?\}$	pick it up
$\{H, t > 0\} \mapsto \{t\downarrow, p?\}$	go to target cell
$\{H, t = 0\} \mapsto \{\neg H, n\downarrow, p?\}$	drop package

- **Width=2** Sketch:

$\{n > 0\} \mapsto \{n\downarrow\}$	deliver package

- **Width=1** Sketch:

$\{\neg H\} \mapsto \{H\}$	go and pick package
$\{H\} \mapsto \{\neg H, n\downarrow\}$	go and deliver package

Features: Holding (H); Dist. to nearest Pkg (p), Target (t); $\#$ Undeliv Pkgs (n)

Syntax and Semantics of Sketch Rules

- **Syntax:** For Boolean and numerical **features** p and n:
  - ▷ p, $\neg p$, $n > 0$, $n = 0$ can appear in C
  - ▷ p, $\neg p$, $n\uparrow$, $n\downarrow$, $n?$ can appear in E

- **Semantics: State pair** (s, s') **satisfies** sketch rule $C \mapsto E$ if
  - ▷ $f(s)$ satisfies C
  - ▷ $(f(s), f(s'))$ satisfies E

Syntax of sketches and policies the **same**, and so with semantics, **except** that (s, s') is not a **1-step state transition** necessarily

Interpretation: When in state s, the **set of subgoal states** $G_R(s)$ to aim at is:

$$G_R(s) \;=\; \{\, s' \,|\, (s, s') \text{ satisfies sketch rule or } s' \text{ is goal} \,\}$$

Sketch Width

- Sketch R **splits** problems P in $\mathcal{Q}$ into collection of **subproblems** $P[s, G_R(s)]$:
  - ▷ **Initial state** s: reachable state s in P
  - ▷ **(Sub) goal states** $G_R(s) = \{ \, s' \, | \, (s, s') \text{ satisfies sketch rule or } s' \text{ is goal } \}$
- **Width of sketch** R over $\mathcal{Q} = \max_{s, P \in \mathcal{Q}}$ width$(P[s, G_R(s)])$
  - ▷ *for definition in presence of* **dead-ends**, *see refs*

Theorem: Any P in $\mathcal{Q}$ is **solvable** in $O(b \cdot N^{|\Phi|+2k-1})$ time by $\mathsf{SIW_R}$ algorithm if sketch R is **terminating** and has **width** over $\mathcal{Q}$ bounded by k [B. and G., 2021]

- ▷ N: *Number of atoms in problem* P ; Φ: *Set of features in sketch*

$\mathsf{SIW_R}$ is like SIW but **subgoal** to achieve next given by sketch

▷ SIW is $\mathsf{SIW_R}$ with sketch R with **single rule:** $\{\#g > 0\} \mapsto \{\#g\!\downarrow\}$

Another Example: IPC Grid [Drexler et al., 2021]

This sketch is **terminating** and has **width** 1 for IPC domain Grid (pick and deliver keys spread in grid where cells can be locked and opened with other keys):

- **Sketch:**
  - ▷ $r_1 : \{l > 0\} \mapsto \{l\downarrow, k?, o?, t?\}$ (if locked cells, unlock them)
  - ▷ $r_2 : \{l = 0, k > 0\} \mapsto \{k\downarrow, o?, t?\}$ (else, place keys in targets)
  - ▷ $r_3 : \{l > 0, \neg o\} \mapsto \{o, t?\}$ (if locked cells, pick key to open locked cell)
  - ▷ $r_4 : \{l = 0, \neg t\} \mapsto \{o?, t\}$ (if all locks open and misplaced keys, pick up such key)
- **Features:**
  - ▷ l is the number of unlocked grid cells
  - ▷ k is the number of misplaced keys
  - ▷ o is true iff robot holds key for which there is a closed lock
  - ▷ t is true iff robot holds key that must be placed at some target grid cell

Preview: Learning Sketches [Drexler et al., 2022]

Given a known domain D, training instances $P_1, \ldots, P_n$, and non-negative integer k, find simplest sketch R over a pool of features $\mathcal{F}$ such that

- Subproblems induced by R on each P_i have all **width bounded** by k,
- Sketch R is **terminating**

Possibly first approach for **learning subgoal structure** based on crisp **principles**

Many threads that come together:

- Planning **width**
- Language of **general policies**
- Termination notion from **QNPs**
- Semantics of **sketches**

Exercise: Test Your Knowledge! (Not trivial)

In the 1985 AIJ paper, *Macro-Operators: A Weak Method for Learning*, Rich Korf provides **macro-tables** for puzzles like Rubik Cube, 8-puzzle, and other hard puzzles that encode **policies** $\pi(s)$ for solving them from any initial state

- Can these compact policies be replaced by even more compact **sketches** of **bounded width**?
- Can these sketches be **general**? That is, applicable to Rubik cubes and n-sliding puzzles of **different sizes**?
- Can such sketches be **learned** with current method? Expressivity? Scalability? Other methods?

Background 2:

Qualitative Numerical Planning Problems (QNPs)

Language for QNPs

- Language for planning involving **propositional** and **numerical variables**

- QNPs [Srivastava *et al.* 2011] different than **numerical planning:**
  - ▷ Numerical vars in QNPs are non-negative, **real-valued**
  - ▷ **Effects** on numerical variables: just **qualitative** increments/decrements
  - ▷ **Numerical literals:** whether variable is **zero** or **positive** only

- These differences make plan-existence for QNPs **decidable**

- QNPs provide language for **general policies and sketches:**
  - ▷ QNP actions similar to policy/sketch rules but **features** replaced by **variables**

- We follow [B. and G., 2020b]

Syntax for QNPs

A **qualitative numerical problem (QNP)** is tuple $Q = \langle F, V, I, O, G\rangle$:

- F and V are sets of propositional and numerical **variables** (not features!)
- I and G denote initial and goal states
- O: actions a with precs, and prop. and numeric effects $Pre(a)$, $Eff(a)$, $N(a)$:
  - ▷ F-literals may appear in I, G, $Pre(a)$ and $Eff(a)$
  - ▷ V-literals may appear in I, G and $Pre(a)$
  - ▷ $N(a)$ can only have expressions of the form $X\!\uparrow$ and $X\!\downarrow$ for var X in V
- V-literal is either $X = 0$ or $X > 0$ for variable X in V
- **Example:** QNP $Q_{clear} = \langle \{H\}, \{n\}, I, O, G\rangle$
  - ▷ $I = \{n > 0, \neg H\}$
  - ▷ $G = \{n = 0\}$
  - ▷ $O = \{a, b\}$ where $a = \{\neg H, n > 0\} \mapsto \{H, n\!\downarrow\}$ and $b = \{H\} \mapsto \{\neg H\}$
- QNP actions like policy rules above but H and n not features but **variables**

Semantics and Solutions of QNPs

- Policy π for a QNP is partial map from state s into actions such that:
  - ▷ $\pi(s) = \pi(s')$ if s and s' **qualitatively similar:** same F and V true literals

- π **solves** QNP if all maximal **QNP-fair** π-trajectories reach the goal
  - ▷ **QNP fairness:** trajectory **unfair** if numerical variable **decremented** infinite number of times and **incremented** finite number of times.

Theorem [Srivastava *et al.*, 2011]: π solves QNP Q iff π is **strong cyclic solution** of the **FOND** problem $T_D(Q)$ obtained from Q that **terminates**

- $T_D(Q)$ replaces **numerical** X by **Boolean** variable "$X{>}0$" ("$X{=}0$" is negative literal)
- **Qualitative effects** $X\uparrow$ replaced by **effect** $X{>}0$
- **Qualitative effects** $X\downarrow$ replaced by **non-deterministic effect** "$X{>}0 \mid X{=}0$"
- **Strong-cyclic:** every reachable state is connected to goal state by π

Polytime reduction from QNPs to FOND, but more complex than T_D [B. and G.,2020b]

Termination, Sieve Algorithm [Srivastava et al., 2011]

Policy for QNP Q **terminates** if no infinite **QNP-fair** π-trajectories

SIEVE provides **sound** and **complete** polynomial termination test

- State s **terminates** if either
  - ▷ there is no cycle on state s, or
  - ▷ every cycle on s contains a state s' that terminates, or
  - ▷ $\pi(s)$ decrements a variable X, and every cycle on s that contains a state s' such that $\pi(s')$ increments X, contains another state s'' that terminates
- Policy π terminates iff every state reached by π terminates

Recent FOND$^+$ planner handles strong FOND, strong cyclic FOND, QNPs, and hybrids by stating **fairness assumptions** explicitly [Rodriguez *et al.* 2021b]

Part III: Learning Dynamics, Policies, Sketches

- Learning **action models:**

Given graphs $G_1, \ldots, G_k$, find **simplest** instances $P_i = \langle D, I_i \rangle$ such that graphs G_i and $G(P_i)$ are isomorphic, $i = 1, \ldots, k$.

- Learning **general policies:**

Given known domain D, training instances $P_1, \ldots, P_k$, over D, and **finite pool of domain features** $\mathcal{F}$, each with a cost, find the cheapest policy π over $\mathcal{F}$ such that π solves all P_i, $i = 1, \ldots, k$

- Learning **sketches:**

Given known domain D, training instances $P_1, \ldots, P_n$, and non-negative integer k, find simplest sketch R over a pool of features $\mathcal{F}$ such that

- ▷ Subproblems induced by R on each P_i have all **width bounded** by k,
- ▷ Sketch R is **terminating**

Learning Action Models: Encoding [Rodriguez et al., 2021a]

- Construct **answer set program**, bounding number of objects, preds, and action/pred. arities:
  - ▷ **Given** $G_1, \ldots, G_n$ as input graphs over **black-box states**, with edge labels,
  - ▷ **Check** whether there is STRIPS model D and instances $I_1, \ldots, I_n$ such that graphs $G(P_i)$ and G_i are **isomorphic**, $i = 1, \ldots, n$, where $P_i = \langle D, I_i \rangle$
  - ▷ **Optimize:** sum of action and predicate arities, etc

- **(Basic) choice variables:**
  - ▷ Lifted atom is pair `(P,T)` where `P` is int and `T` is tuple of ints
  - ▷ `prec(A,(P,T),V)` and `eff(A,(P,T),V)` (lifted atoms in precs/effects)
  - ▷ `p_arity(P,N)` and `a_arity(A,N)` (arities for predicate and action)
  - ▷ `val(S,(P,O),V)` where `O` is tuple of objs and `V` is 0/1 (value of ground atoms at states)
  - ▷ `next(A,O,S,T)` (ground action `A(O)` assigned to `(S,T)`)

- **(Basic) constraints**:
  - ▷ `{ next(A,O,S,T) : label((S,T),A) } = 1 :- appl(A,O,S).` (assign edges to actions)
  - ▷ `:- state(S), state(T), S < T, val(T,(P,O),V) : val(S,(P,O),V).` (diff. states)
  - ▷ `:- state(S), action(A), N = { label((S,T),A) }, { appl(A,O,S) } != N.` (matching)
  - ▷ Compliance of precs/effects of assigned grounded actions to edges

- Clingo program ~ 400 lines [Rodriguez *et al.* 2021a]; more complex in SAT [B. and G., 2020a]

Learning General Policies: Encoding [Francès et al., 2021]

- **Input** is set of transitions $\mathcal{S}$ from small instances, pool of features $\mathcal{F}$, **parameter** (int) δ
- **Output** is policy: rules obtained from **selected features** and ("good") **transitions**
- **Combinatorial opt. task** $T(\mathcal{S}, \mathcal{F}, \delta)$: Solve constraints minimizing **feature complexity**
- **Choice variables:**
  - ▷ `select(F)` (features that define rules)
  - ▷ `good(S,T)` (transition `(S,T)` is "compatible" with policy)
  - ▷ `V(S,N)` (distance from `S` to goal is `N`)
- **Constraints:**
  - ▷ $1\ \{$ `good(S,T)` $\}$ `:- state(S), not terminal(S).` (good transitions at non-terminals)
  - ▷ `:- good(S,T).` (no good reach dead-end `T`)
  - ▷ $1\ \{$ `select(F)` : `diff(F,S,T)` $\}$ `:- goal(S), not goal(T).` (distinguish goals)
  - ▷ $\{$ `V(S,D)` : $V^*(\texttt{S}) \leq \texttt{D} \leq \delta V^*(\texttt{S})$ $\}$ `= 1 :- state(S).` (set distances)
  - ▷ `:- good(S,T), V(S,D1), V(T,D2), D2 <= D1.` (distances avoid cycles)
  - ▷ $1\ \{$ `select(F)` : `diff(F,S1,T1,S2,T2)` $\}$ `:- good(S1,T1), not good(S2,T2).` (distinguish good/bad transitions)

where `diff/3` and `diff/5` computed from pool at **pre-processing**

Learning General Sketches: Encoding [Drexler et al., 2022]

- **Input:** transitions $\mathcal{S}$ in small instances, pool $\mathcal{F}$, width bound k, max $\#$ sketch rules m
- **Output:** sketch of **width** $\leq k$, **acyclic** in given instances, with up to m rules
- **Combinatorial opt. task** $T(\mathcal{S}, \mathcal{F}, k, m)$: solve constraints min **complexity** of selected features
- **(Basic) variables:**
  - `rule(I)` (sketch rule `I`)
  - `select(F)` (features that define sketch rules)
  - `cond(I,F,V)` and `eff(I,F,E)` (conditions and effects for rule `I`)
  - `subgoal(S,T)` (tuple `T` of width k is subgoal for `S`)
  - **(Implied)** `subgoal(S1,T,S2)` (subgoal `T` for `S1` may lead to `S2`)
  - **(Implied)** `satis(S1,S2,I)` (pair `(S1,S2)` satisfies rule `I`)
- **(Basic) constraints:**
  - **Well formed rules:** atoms `cond/3` and `eff/3` are consistent and imply `select(F)`
  - `1 { subgoal(S,T) : tuple(T) } :- state(S), not goal(S).` (width k subgoal for `S`)
  - `subgoal(S1,T,S2) :- subgoal(S1,T), found(S1,T,S2).` (subgoal `T` may lead to `S2`)
  - `:- subgoal(S1,T,S2), not satis(S1,S2,I) : rule(I).` ((`S1,S2`) satisfies some rule)
  - `:- satis(S1,S2,I), not subgoal(S1,T) :` $d(\texttt{S1},\texttt{T}) < d(\texttt{S1},\texttt{S2})$. (dead-end S2 is farther)
  - `:- satis(S1,S2,I), not subgoal(S1,T) :` $d(\texttt{S1},\texttt{T}) \leq d(\texttt{S1},\texttt{S2})$. (subgoals optimal)
  - Collection of rules is **terminating** (approx'ed by testing acyclicity)

About the Pool of Features $\mathcal{F}$ [B. et al., 2019]

- **Description logic grammar** allows generation of **concepts** and **roles** from **domain predicates**
- Complexity of concept/role given by **size of its syntax tree**
- Pool $\mathcal{F}$ obtained from concepts of complexity bounded by parameter
- Denotation of concept C in state s is **subset of objects**
- Each concept C defines num and Bool features $n_C(s) = |C(s)|$; $p_C(s)=\top$ iff $|C(s)| > 0$
- Grammar:
  - Primitive: C_p given by unary predicates p and unary "goal predicates" p_G
  - Universal: C_u contains all objects
  - Nominals: $C_a = \{a\}$ for constants/parameter a
  - Negation: $\neg C$ contains $C_u \setminus C$
  - Intersection: $C \sqcap C'$
  - Quantified: $\exists R.C=\{x : \exists y[R(x,y) \wedge C(y)]\}$ and $\forall R.C=\{x : \forall y[R(x,y) \wedge C(y)]\}$
  - Roles (for binary predicate p): R_p, R_p^{-1}, R_p^+, and $[R_p^{-1}]^+$
- Additional **distance features** $dist(C_1, R, C_2)$ for concepts C_1 and C_2 and role R that evaluates to d in state s iff minimum R-distance between object in C_1 to object in C_2 is d

General Policies By Deep Learning [Ståhlberg et al., 2022a,b]

- Exploits correspondence between **graph neural networks (GNNs)** and **two-variable logic** $\mathcal{C}_2$ to learn policy **without requiring** pool of $\mathcal{C}_2$ features $\mathcal{F}$
- **Value function** V learned that yields general policy π_V **greedy** in V
- For **generalization**, based on GNN arch. for MaxCSP(Γ) [Toenshoff *et al.*, 2021]
  - ▷ **Input** given by the states s extended with "goal predicates" p_G
  - ▷ **Output** $V(s)$ is non-linear aggregation of object embeddings
  - ▷ **Min Loss:** $|V^*(s) - V(s)|$ for supervised learning of optimal policies
  - ▷ **Min Loss:** $\max\{0, [1 + \min_{s' \in N(s)} V(s')] - V(s)\}$ unsupervised/non-optimal
- Nearly **as good as** policies based on **explicit pool $\mathcal{F}$ of $\mathcal{C}_2$ features**
- Complexity of "latent features" not explicitly bounded

GNN Architecture [Ståhlberg et al., 2022a,b]

Algorithm 1: GNN maps state s into scalar $V(s)$

```
Input: State $s$: set of atoms true in $s$, set of objects
Output: V(s)
$f_0(o) \sim \mathbf{0}^{k/2}\mathcal{N}(0,1)^{k/2}$ for each object $o \in s$;
for $i \in \{0, \ldots, L-1\}$ do
    for each atom $q := p(o_1, \ldots, o_m)$ true in $s$ do
        // Msgs $q \to o$ for each $o = o_j$ in $q$
        $m_{q,o} := [\mathbf{MLP}_p(f_i(o_1), \ldots, f_i(o_m))]_j$;
    for each $o$ in $s$ do
        // Aggregate, update embeddings
        $f_{i+1}(o) := \mathbf{MLP}_U\big(f_i(o), agg(\{\!\!\{m_{q,o} | o \in q\}\!\!\})\big)$;
// Final Readout
$V := \mathbf{MLP}_2\big(\sum_{o \in s} \mathbf{MLP}_1(f_L(o))\big)$
```

Wrap Up: Representation Learning for Acting and Planning

- **Background 1:** Classical planning, planning **width**
- **Languages** for
  - ▷ representing general dynamics
  - ▷ representing general policies
  - ▷ representing general subgoal structures (sketches; ‘intrinsic rewards”)
- **Background 2:** Qualitative numerical planning problems (**QNPs**)
- **Learning** representations over these languages:
  - ▷ learning general dynamics
  - ▷ learning general policies
  - ▷ learning general subgoal structures
- **Wrap up; Challenges**

Wrap Up

- To learn representations that generalize due to structure, don't play with low-level neural architecture; choose suitable (domain-independent) **target language** and learn representations over it:
  - ▷ generalization
  - ▷ transparency
  - ▷ powerful, meaningful bias
  - ▷ distinction between **what** and **how**

- Examples of learning language-based representations to **act** and **plan:**
  - ▷ general action **dynamics**
  - ▷ general **policies**
  - ▷ general **subgoal structures** (sketches)

Challenges: Language-based Representation Learning

- Scalability of combinatorial optimization approaches
- Use of deep learning (learning lifted dynamics, policies, sketches).
- Alternative target languages for learning (e.g., vs lifted STRIPS)
- Continuous domains, space, time
- Stochastic and non-deterministic domains
- States in the input: black-box, parsed images, images, videos
- Grounded vs. ungrounded representations
- Learning and reusing "skills", hierarchies
- . . .

Plenty to do; if seriously interested, reach us

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