Learning general policies and sketches

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Learning High-Level Representations: A Key Challenge in AI

- Learn representations that support **reasoning** and **planning**, that **generalize** and are **reusable**, . . .

- **Yoshua Bengio**'s challenges reflected in title of his IJCAI 2021 talk:
  - ▷ *System 2 Deep Learning: Higher-level cognition, agency, out-of-distribution generalization and causality*

- **Yann LeCun**'s three challenges, AAAI 2020:
  - ▷ AI must learn to represent the world
  - ▷ AI must think and plan in ways compatible with gradient-based learning
  - ▷ AI must learn hierarchical representation of action plans

Two Approaches to Learning High-Level Representations

- **Bottom-up approach**
  - ▷ Representations emerge from **architecture**, loss function, and "right" bias
  - ▷ Most common approach in deep (reinforcement) learning

- **Top-down approach**
  - ▷ Representations learned over **language** with "right" syntax and semantics
  - ▷ Reasoning, meaningful learning bias, transparency, **what** vs. **how**
  - ▷ Doesn't assume background knowledge; compatible with deep learning

Our focus: **top-down representation learning to act and plan**

Three concrete learning problems for acting and planning

- Learning **general models**
  - ▷ Language and semantics
  - ▷ Learning: **combinatorial approach**
- Learning **general policies**
  - ▷ Language and semantics
  - ▷ Learning: **combinatorial approach** and **DRL approach**
- Learning **general subgoal structures** (sketches)
  - ▷ Language, semantics, **width**
  - ▷ Learning: **combinatorial approach**

The setting is **classical planning**:

- ▷ factored deterministic MDPs; states given by atoms $p(c_1, \ldots, c_k)$
- ▷ fixed set of **domain predicates** p
- ▷ variable set of objects c_1 that depend on **domain instance**

Learning Problem #1: General Models

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

- E.g., DELIVERY problem where packages to be moved by robot to target cell in grid; **any** number of packages, **any** grid size, captured with domain with **three STRIPS action schemas**. Can they be **learned**, predicates included?

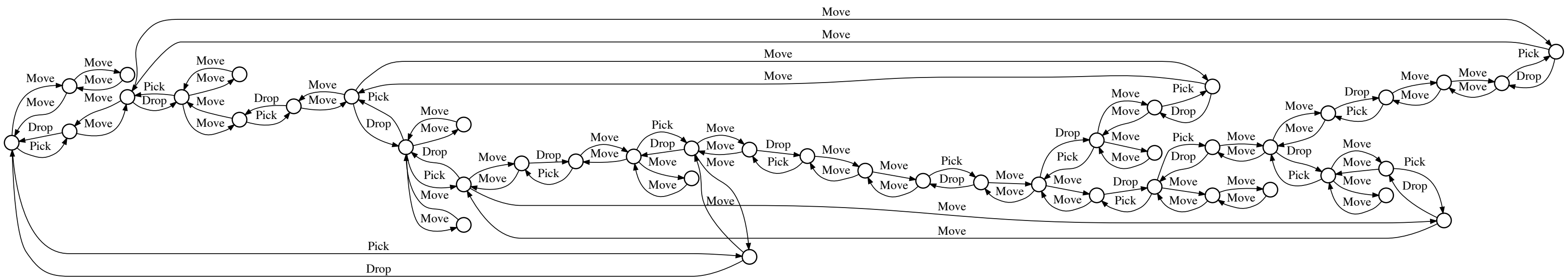
$move(c, c')$
Preconds: $atRobot(c)$, $adjacent(c, c')$
Effects: $atRobot(c')$, $\neg atRobot(c)$

$pick(o, c)$:
Preconds: $atRobot(c)$, $at(o, c)$, $emptyhand$
Effects: $held(o)$, $\neg at(o, c)$, $\neg emptyhand$

$drop(o, c)$:
Preconds: $atRobot(c)$, $held(o)$
Effects: $at(o, c)$, $\neg held(o)$, $emptyhand$

Example: Learning $P = \langle D, I \rangle$ from Single Graph G

Input: State graph G of agent in $1{\times}3$ grid, moving/picking/dropping 2 pkgs



Output: **Simplest** STRIPS representation $P = \langle D, I \rangle$ that **generates** G

```
Move(?to,?from):
  Pre: neq(?to,?from), p5(?to,?from)
  Pre:  p2(?from), -p2(?to)
  Eff: -p2(?from),  p2(?to)

Pick(?p,?x):
  Pre:  p2(?x),  p1, -p3(?p),  p4(?p,?x)
  Eff:          -p1,  p3(?p), -p4(?p,?x)

Drop(?p,?x):
  Pre:  p2(?x), -p1,  p3(?p), -p4(?p,?x)
  Eff:           p1, -p3(?p),  p4(?p,?x)
```

Interpretation of learned predicates:

– p_1: gripper empty
– $p_2(x)$: agent at cell x,
– $p_3(p)$: agent holds pkg p,
– $p_4(p, x)$: pkg p in cell x
– $p_5(x, y)$: cell x adj to y

- Domain D correct for **any** grid, **any** $\#$ of packages. Structure of nodes uncovered.

Learning Problem #1: General Models

- $P = \langle D, I \rangle$ defines unique **state graph** $G(P)$
- Learning as **inverse task:** from graphs $G_1, \ldots, G_k$, learn problems $P = \langle D, I_i \rangle$:

> 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/solved as **combinatorial optimization task** [Bonet and G., 2020]
- **Complexity** of P_i determined by # and arities of action schemas and predicates
- **Variations:** noisy graphs, gray-box states [Rodriguez *et al.*, 2021, Occhipinti *et al.*, 2022]

[**Open:** How to solve (a version of) this problem using **DL/gradient descent?**]

Learning Problem #2: General Policies [Bonet, G., 2018]

General policy for achieving $clear(x)$ in Blocks; **any instance**

- **Features** $\Phi = \{H, n\}$: 'holding' and 'number of blocks above x'
- **Policy** π for class $\mathcal{Q}_{clear}$ of 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**

- **Semantics of policy** π specified by rules $C_i \mapsto E_i$:
  - ▷ state transition (s, s') is π-**transition** iff $s \models C_i$, and $[s, s'] \models E_i$ for some i
  - ▷ π-**trajectories** made up of π-transitions, starting at s_0
  - ▷ π **solves** class of problems $\mathcal{Q}$ if, in every $P \in Q$, all π-trajectories end in goal

Example 2: Delivery

- **Domain:** Move packages in $n \times m$ grid, one by one, to target location
- **Features** $\Phi = \{H, p, t, n\}$: hold, dist. to nearest pkg & target, $\#$ undelivered
- **General policy** π: **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

Policy can be shown to be correct, solving **any instance**.

Learning Problem #2: Min-SAT Encoding $T(\mathcal{S},\mathcal{F})$

- **Inputs** to formula $T = T(\mathcal{S},\mathcal{F})$:
  - ▷ **Feature pool** $\mathcal{F}$ defined from domain predicates and **C2 logic**
  - ▷ **State transitions** $\mathcal{S}$ from the training instances $P_1,\ldots,P_k$
- **Variables** in T: $Good(s,s')$, $V(s,d)$, $Select(f)$: $(s,s')\in\mathcal{S}$, $f\in\mathcal{F}$, $d\leq d_{max}$
- **Formulas** in $T = T(\mathcal{S},\mathcal{F})$:

1. Policy **closed**: $\bigvee_{(s,s')\in\mathcal{T}} Good(s,s')$ *[non-goal, non dead-end s]*
2. Policy **acyclic**: $Good(s,s'), V(s,d), V(s',d') \supset d' < d$, *[non-goal, non-dead s]*
3. Policy **safe**: $\neg Good(s,s')$ *[non-dead-end, dead-end]*
4. **Exactly-1** $\{V(s,d) : d\leq d_{max}\}$ *[$V(s,d)$ iff $V(s)=d$, all s]*
5. Features **distinguishes** good from bad transitions: *[(s,s') and (t,t') in $\mathcal{S}$]*

$$Good(s,s')\wedge\neg Good(t,t')\rightarrow\bigvee_{f:\Delta_f(s,s')\neq\Delta_f(t,t')} Select(f)$$

Theorem: Theory $T(\mathcal{S},\mathcal{F})$ is SAT iff there is a policy π over features $\Phi\subseteq\mathcal{F}$ that solves $P_1,\ldots,P_n$. Policy rules from SAT assignment; capture feature changes in the transitions (s,s') labeled good.

Experimental Results over Classical Domains

	$\mathcal{S}$	$\mathcal{S}/\!\sim$	d_{max}	$\|\mathcal{F}\|$	$vars$	$clauses$	t_{all}	t_{SAT}	c_Φ	$\|\Phi\|$	k^*	$\|\pi_\Phi\|$
$\mathcal{Q}_{clear}$	1,161	55	7	532	7.9K	243.7K(242.3K)	6	1	8	3	4	3
$\mathcal{Q}_{on}$	1,852	329	10	1,412	17.3K	376.6K(281.5K)	231	153	13	5	5	7
$\mathcal{Q}_{grip}$	1,140	61	12	835	6.5K	102.6K(100.8K)	2	1	9	3	4	4
$\mathcal{Q}_{rew}$	432	361	15	514	5.5K	214.9K(98.9K)	8	1	7	2	6	2
$\mathcal{Q}_{deliv}$	42,473	5442	56	1,373	753.4K	38.2M(23.5M)	3071	2902	30	4	14	6
$\mathcal{Q}_{visit}$	2,396	310	8	188	13.9K	244.5K(160.6K)	3	1	7	2	5	1
$\mathcal{Q}_{span}$	10,777	96	19	764	85.0K	2.2M(2.2M)	46	2	9	3	6	2
$\mathcal{Q}_{micon}$	4,706	4,636	14	1,073	23.8K	23.6M(2.4M)	184	104	11	4	5	5
$\mathcal{Q}_{bw}$	2,136	2,136	7	1,766	10.9K	4.6M(180.1K)	252	64	10	3	6	1

Classes of problems $\mathcal{Q}_D$ for different planning domains D

Some theories $T(\mathcal{S}, \mathcal{F})$ are very large (38M clauses) but solved

Learned policies for each of the domains **can be proved to be correct**; but learning doesn't guarantee it

Learning Problem #3: Subgoal Structures [Bonet and G. 2021]

- **Sketch** of width=2 for Delivery:

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

- **Sketch** of width=1:

$$\begin{array}{ll} \{\neg H\} \mapsto \{H\} & \text{go and pick package} \\ \{H\} \mapsto \{\neg H, n\downarrow\} & \text{go and deliver package} \end{array}$$

- **Sketch** of width=0 (**full policy**)

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

- **Language** of sketches is **same language** of policies: rules $C_i \mapsto E_i$
- **Semantics** of sketches slightly different:
  - ▷ In state s_i where C_i holds, reach **subgoal** s_{i+1} s.t. $[s_i, s_{i+1}] \models E_i$
  - ▷ If sketch is **terminating** and **subproblems** have width $\leq k$, problems solvable by SIW_R algorithm in time $\exp(k)$

Learning Sketches [Drexler *et al.*, 2022]

- Given a **domain** D, training **instances** $P_1, \ldots, P_n$, a **pool** of features $\mathcal{F}$, and **bound** k, find **min-cost** sketch R over $\mathcal{F}$ such that
  - ▷ Subproblems induced by R on each P_i have all **width bounded** by k,
  - ▷ Sketch R is **terminating** (structurally acyclic)

- Learning task model and solved as combinatorial optimization problem in Clingo [Gebser, Kaufmann, Schaub 2012]

- E.g., sketch given by rules $\{\neg H\} \mapsto \{H\}$ and $\{H\} \mapsto \{\neg H, n\downarrow\}$ learned in this way

Last Twist: General policies via DRL and GNNs

- Can we learn general policies using **deep (reinforcement) learning**?

- Before, they were learned them by solving **Min-SAT problem** $T(\mathcal{S}, \mathcal{F})$:
  - ▷ $\mathcal{S}$: set of state transitions (s, s') over small instances
  - ▷ $\mathcal{F}$: **pool of features** derived from domain predicates and **C2 logic**

- **C2** is fragment of first-order logic that uses **two variables only**

- Interestingly, **tight correspondence** known between **C2** and **GNNs**

- **Idea:** Represent policy $\pi(s'|s; w)$ with GNN; learn w parameters with RL
  - ▷ **Before:** explicit pool of features; now, GNN takes care of features
  - ▷ **Before:** π constrained to solve training instances; now, penalize π if it doesn't

GNN + Actor-Critic for Gen Policies [Ståhlberg *et al.*, 2023]

Domain	Coverage (%)	Domain	Coverage (%)
Blocks	**100%**	Delivery	**100%**
Gripper	**100%**	Miconic	**100%**
Visitall	**100%**	Grid	70%
Logistics	36%	Spanner	68%

- Nearly **perfect general policies** obtained in several domains (100%)
- But the interesting part is the **failure** in three marked domains, as it has **nothing to do with RL algorithm:**
  - ▷ **C2/GNN expressivity not enough**: binary relations need to be composed
  - ▷ **Generality-optimality tradeoff**: can't have both in some domains
- By addressing these two problems, **100% coverage over all domains** obtained

(unlikely to get similar results without **understanding** these problems)

Summary: Top-down representation learning to act and plan

- **Three learning problems** in planning:
  - ▷ Learning general models
  - ▷ Learning general policies
  - ▷ Learning general subgoal structures (sketches)
- **Two methods**:
  - ▷ Combinatorial optimization: Min-SAT, Clingo
  - ▷ Continuous optimization: deep (reinforcement) learning
- **Potential benefits** of top-down approaches (vs. bottom-up):
  - ▷ Transparency, structural **generalization**; distinction what/how, **reuse**, . . .

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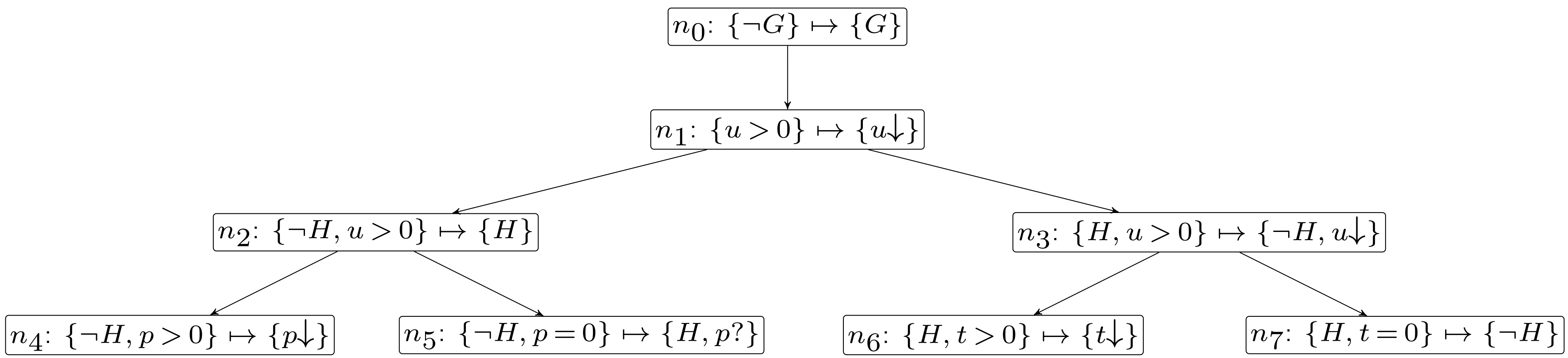
Pool of Features $\mathcal{F}$: From Domain predicates and C2 Logic

- **Fixed grammar** generates new **predicates** from **domain** and **goal** predicates p, p_G
- **Unary predicates** called concepts C; **binary predicates**, roles (description logics)
- **Denotation (extension)** of concept C in state s, $C(s)$: **objects** "in" C
- **Features** from concepts C: $n_C(s) = |C(s)|$; $p_C(s)=\top$ iff $|C(s)| > 0$
- **Complexity** of unary predicate ("concept") given by number of grammar rules used
- **Pool** $\mathcal{F}$ obtained from concepts of complexity bounded by a parameter
- **Grammar:** borrowed from "description logics", a **C2 logic**
  - ▷ Primitive: C_p given by domain predicates p and "goal predicates" p_G (p in goal)
  - ▷ Universal: C_u contains all objects
  - ▷ 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 (binary predicates): 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

Learning Hierarchical Policies [Drexler, Seipp, G. 2023]



Hierarchical policy for $\mathcal{Q} = \mathcal{Q}_{Delivery}$:

- Every **node** n has a **sketch rule** $r(n)$ and a **class** $\mathcal{Q}_n$ of subproblems
- $\mathcal{Q}_n$ determined by **rule** $r(n)$ and **parent** $\mathcal{Q}_{n'}$. For root, $\mathcal{Q}_n = \mathcal{Q}$.
  - ▷ $\mathcal{Q}_n$ forced to have **smaller width** than parent $\mathcal{Q}_{n'}$
  - ▷ $\mathcal{Q}_n$ has **width zero** iff n is a **leaf**

GNN-like net that maps STRIPS states s into $f^s(o) = f^s_L(o)$

1. **Input:** State s (set of atoms true in s), set of objects
2. **Output:** Embeddings $f_L(o)$ for each object o
3. $f_0(o) \sim \mathbf{0}^k$ for each object $o \in s$
4. For $i \in \{0, \ldots, L-1\}$
5. For each **atom** $q := p(o_1, \ldots, o_m)$ true in state s:
6. $m_{q,o} \;:=\; [\mathbf{MLP}_p(f_i(o_1), \ldots, f_i(o_m))]_j$
7. For each **object** o in state s:
8. $f_{i+1}(o) \;:=\; \mathbf{MLP}_U\big(f_i(o), agg(\{\!\{m_{q,o} | o \in q\}\!\})\big)$

- **Value** and **policy** learned from embeddings $f^s(o) = f_L(o)$ for each object o
- Objects o change from instance to instance but **domain predicates** p fixed
- One $\mathbf{MLP}_p$, for each **domain predicate** p; single $\mathbf{MLP}_U$
- **Relational** GNN-like architecture as **STRIPS states** not graphs but rel structures
- Messages exchanged among objects o through the atoms where they appear in s

From the Object Embeddings $f_L^s(o)$ to $V(s)$ and $\pi(s'|s)$

Value function $V(s)$ and policy $\pi(s'|s)$ from embeddings $f^s(o) = f_L(o)$:

- **Value function** $V(s) = V(s; w)$ outputs single scalar through $\mathbf{MLP}$ as:

$$V(s) \; = \; \mathbf{MLP}\big(\textstyle\sum_{o \in O} f^s(o)\big)$$

- **Stochastic policy** $\pi(s'|s) = \pi(s'|s; w)$ selects successor states s' by computing *logits* for pairs (s, s') and passing them through *softmax*:

$$\begin{aligned} \text{logit}(s'|s) &= \; \mathbf{MLP}_1\big(\textstyle\sum_{o \in O} \mathbf{MLP}_2(f^s(o), f^{s'}(o))\big)\,, \\ \pi(s'|s) &\propto \; \exp\big(\text{logit}(s'|s)\big) \end{aligned}$$

Training the General Policy Functions by DRL – Actor-Critic

Input: Training MDPs $\{M_i\}_i$, each with state priors p_i
Input: Value function $V(s)$ with parameter ω
Input: Policy $\pi(s'|s)$ with parameter θ
Input: Differentiable policy $\pi(s|s')$ with parameter θ
Input: Diff. value function $V(s)$ with parameter ω
Parameters: Step sizes $\alpha, \beta > 0$, discount factor γ

Initialize parameters θ and ω
Loop forever:
  Sample MDP index $i \in \{1, \ldots, N\}$
    Sample non-goal state S in M_i with probability p_i
    Sample successor state S' with probability $\pi(S'|S)$
    Let $\delta = 1 + \gamma V(S') - V(S)$
    $\omega \leftarrow \omega + \beta\delta\nabla V(S)$
    $\theta \leftarrow \theta - \alpha\delta\nabla \log \pi(S'|S)$
    If S' is a goal state, $\omega \leftarrow \omega - \beta V(S')\nabla V(S')$

Standard **Actor-Critic RL** algorithm, baseline $V(S)$, where policy does not select actions but **state transitions**, and **action costs** are all 1