From Model-free to Model-based AI: Representation Learning for Planning

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Outline

- Problem of **generality** in AI
- Model-free **learners**, model-based **solvers**
- **Learners and solvers** vs. Kahneman's **Systems 1 and 2**
- **Challenge** of integrating **Systems 1** and **System 2** inference
- **Learning representations (models)** from data for planning

AI Programming and Problem of Generality

There was a time (60s, 70s, 80s) when AI was done mostly by **programming**:

- pick up a challenging task and domain X (humor, story understanding, ...)
- analyze/introspect/find out how task is solved
- capture this reasoning in a program

Great ideas (and great books!) on programming and **AI programming** from this work, but a **methodological problem:**

- Programs written by hand were **not robust or general**

From Programs to Learners and Solvers

- This problem increasingly led to **methodological shift**:
  - from **programs for ill-defined problems** . . .
  - to **algorithms for well-defined mathematical tasks**

- New general programs **learners** and **solvers** have a **crisp functionality**: both can be seen as computing **functions** that map inputs into outputs

$$\textit{Input } x \Longrightarrow \boxed{\textsc{Function } f} \Longrightarrow \textit{Output } f(x)$$

- The algorithms are **general** in the sense that they are not tied to particular examples but to classes of **models** and **tasks** expressed in **mathematical form**

Learners (1)

$$\textit{Input } x \Longrightarrow \boxed{\textsc{Function } f} \Longrightarrow \textit{Output } f(x)$$

- In **deep learning (DL)** and **deep reinforcement learning (DRL)**, training results in function f_θ
- f_θ given by structure of **neural network** and adjustable parameters θ
  - ▷ In DL, **input** x may be an image and **output** $f_\theta(x)$ a classification label
  - ▷ In DRL, **input** x may be state of game, and **output** $f_\theta(x)$, value of state
- Parameters θ learned by **minimizing error function**
  - ▷ In DL, error depends on inputs and target outputs in training set
  - ▷ In DRL, error depends on value of states and successor states
- Most common **optimization algorithm** is **stochastic gradient descent**

Learners (2)

$$\textit{Input } x \Longrightarrow \boxed{\textsc{Function } f} \Longrightarrow \textit{Output } f(x)$$

- Excitement about AI due to **successes in DL and DRL**
  - ▷ Breakthroughs in image understanding, speech recognition, Go, . . .
  - ▷ Superhuman performance in Chess and Go from **self-play** alone
- The **basic ideas** underlying DL and DRL not new but from 80s and 90s
  - ▷ Recently, more CPU power, more data, deeper nets, attractive problems
- **Limitations:** black boxes, require (lots of) experience or data, no understanding

Solvers

$$\textit{Input } x \Longrightarrow \boxed{\textsc{Function } f} \Longrightarrow \textit{Output } f(x)$$

- **Solvers** derive output $f(x)$ for **given input** x from **model**:
  - **SAT:** x is a formula in CNF, $f(x) = 1$ if x satisfiable, else $f(x) = 0$
  - **Classical planner:** x is a planning problem P, and $f(x)$ is plan that solves P
  - **Bayesian net:** x is a query over Bayes Net and $f(x)$ is the answer
  - **Constraint satisfaction, Markov decision processes, POMDPs, . . .**

- **Generality:** Solvers not tailored to particular examples
- **Expressivity:** Some models very expressive, "AI-Complete" (POMDPs)
- **Learners are solvers too:** $\text{argmin}_w \sum_{x \in D} L(x, f_w(x))$ (Diff. programming)
- **Complexity:** Computation of $f(x)$ is (NP) hard; $|x|$ **not bounded**
- **Challenge:** Solvers shouldn't break just because x has many variables

Learners vs Solvers

$$\textit{Input } x \Longrightarrow \boxed{\textsc{Function } f} \Longrightarrow \textit{Output } f(x)$$

- **Learners** require **experience over related problems** x but then fast
  - ▷ They compute function f from training, then apply it
- **Solvers** deal with **completely new problems** x but **need to think**
  - ▷ They compute $f(x)$ for each input x from scratch

Thinking is hard but essential for dealing with new problems

Thinking can be done **effectively** with right computational ideas

Classical Planners: Finding Plans in Huge Mental Mazes

Challenge: find path to goal in graph with # nodes **exponential** in # variables

Old Idea: If you don't know how to solve P, **solve simpler problem** P', and use solution of P' for solving P (Polya, Minsky, Pearl)

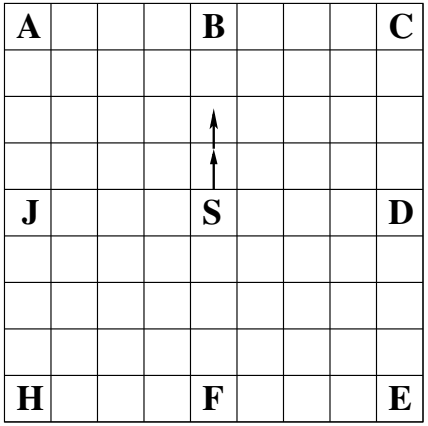
- In **monotonic relaxation** P', effects of actions on variables made **monotonic**
- Monotonicity makes relaxation P' **decomposable** and therefore **tractable**
- **Heuristic** $h(s)$ in P set to **cost of plan from** s **in relaxation** P'

Heuristic obtained and used to solve **any problem** P *from scratch*

No experience required *in problems related to* P

(McDermott 1996, Bonet, Loerincs, G. 1997, . . .)

Goal Recognition: Inferring hidden goal of observed agent



- **Task:** infer **agent goal** $G \in \mathcal{G}$ from **observations** O on behavior
- Bayes' rule: $P(G|O) = P(O|G)\,P(G)/P(O)$, priors $P(G)$ assumed given
- Likelihood $P(O|G)$ set as monotonic function f of **cost difference:**
  - ▷ $c^-(G)$: cost of reaching G with plan incompatible with observations
  - ▷ $c^+(G)$: cost of reaching G with plan compatible with observations

$P(G|O)$ *computed using* **Bayes' rule** *and* $2|\mathcal{G}|$ **calls to planner**

No experience required *in related problems*

(Ramirez and G. 2009, 2010)

Polynomial Algorithms for Exponential Spaces: Structure

- IW(1) is a **breadth-first search** that **prunes** states s that don't make a feature true for first time in the search, from given **set of boolean features** F
- IW(k) is IW(1) but over set F^k made up of conjunctions of k features from F
  - ▷ Most domains have **small width** $w \leq 2$ when **goals are single atoms**
  - ▷ **Any** such instances solved **optimally** by IW(w) in **low poly time**
- IW(k) can work with **simulators**. No PDDL or goal needed. **Variants:**
  - ▷ BFWS(R): SOTA planning algorithm which doesn't use **action structure**
  - ▷ Rollout IW(1): fast **on-line planner** that plays Atari from **screen pixels**

(Lipovetzky and G. 2012; Lipovetzky, Ramirez, G. 2015; Bandres, Bonet, G. 2018)

Learners vs. Solvers (2)

- Rollout IW(1) **planner** and DQN **learner** perform comparably well in Atari
- They illustrate **key difference between learners and solvers:**
  - ▷ DQN requires lots of training data and time, and then plays very fast
  - ▷ Rollout IW(1) plays out of the box but thinking a bit before each move

This is a general characteristic:

- **Learners** require **experience over related problems** x but then are fast
  - ▷ They compute function f from training, then apply it
- **Solvers** deal with **completely new problems** x but need **to think**
  - ▷ They compute $f(x)$ for each input x from scratch

Learners and Solvers: System 1 and System 2?

Dual process accounts of the human mind assume two processes (D. Kahneman: Thinking, Fast and Slow, 2011; K. Stanovich: The Robot's Rebellion, 2005)

System 1 (Intuitive Mind)	**System 2** (Analytical Mind)
fast	slow
associative	deliberative
unconscious	conscious
effortless	effortful
parallel	serial
specialized	general
. . .	. . .
Learners?	Solvers?

Learners and Solvers: Challenges

- **Top goal:** General **two-way integration** of System 1 and System 2 inference in AI systems; i.e. **learners** and **solvers**

- **Challenge:** **Learn representation of models used by solvers from data**
  - ▷ Learning symbols and state variables
  - ▷ Learning useful features and abstractions
  - ▷ Learning reusable, first-order predictive models

- **Two dimensions** in **representation learning for planning:**
  - ▷ Learning from what: symbolic, non-symbolic, or black-box states
  - ▷ Learning for what: model-free control, model-based control, generalized model

- We address next **two points** in this space . . .

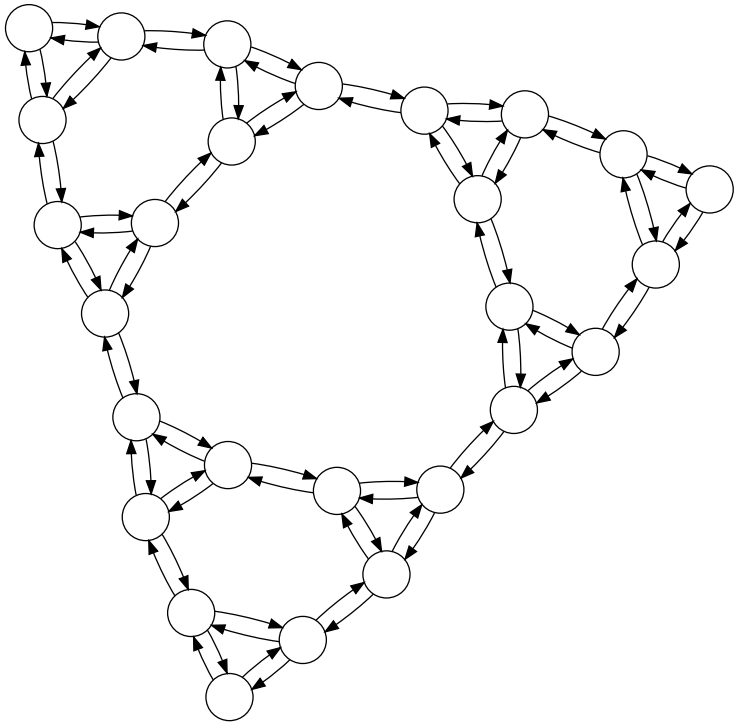
Learning first-order action model from black-box states

- Planning instance in PDDL is $P = \langle D, I \rangle$ where D is **first-order domain** (relations, action schemas) and I provides **instance information** (objects and relations they satisfy)
- **First-order** representation key for **reusability** and **compositionality**
- A planning instance P defines a **state graph** G. **Question:**

> ▷ Can we **learn** $P = \langle D, I \rangle$ back from the graph G?
>
> ▷ Can we **learn** $P_i = \langle D, I_i \rangle$, $i = 1, \ldots, k$ from graphs $G_1, \ldots, G_k$?
>
> (This means **learning action schemas and relations from graphs**)

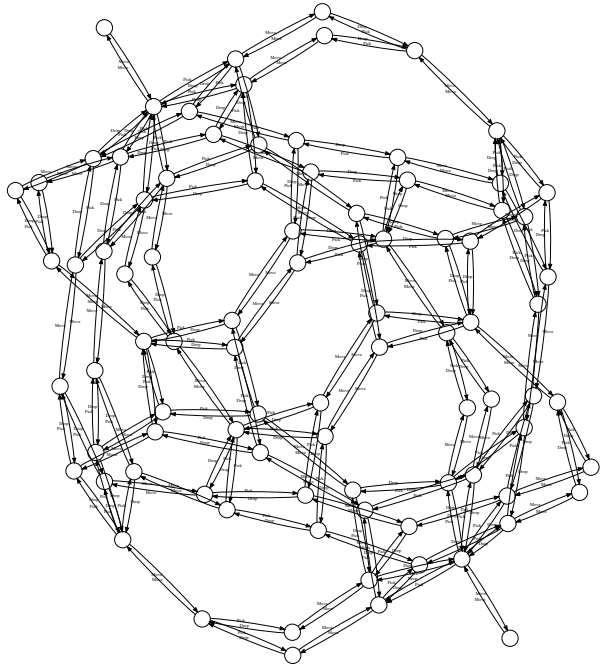
Learned domain D can be used to plan over **any** domain instances

Example: Hanoi. Input and Output



```
Move(fr,to,d):
 Static: BIGGER(fr,d),BIGGER(to,d) NEQ(fr,to)
 Pre: -clear(fr),clear(to),clear(d),Non(fr,d),-Non(d,fr),Non(d,to)
 Eff: clear(fr),-clear(to),Non(d,fr),-Non(d,to)
```

Example: Gripper. Input and Output



Move(from,to):

```
Static: CONN(from,to)
Pre: at(from),-at(to)
Eff: -at(from),at(to)
```

Drop(ball,room,gripper):

```
Static: PAIR(room,gripper)
Pre: at(room),Nfree(gripper),hold(gripper,ball),Nat(room,ball)
Eff: -Nfree(gripper),-hold(gripper,ball),-Nat(room,ball)
```

Pick(ball,room,gripper):

```
Static: PAIR(room,gripper)
Pre: at(room),-Nfree(gripper),-hold(gripper,ball),-Nat(room,ball)
Eff: Nfree(gripper),hold(gripper,ball),Nat(room,ball)
```

Formulation: From State Space Graph to First-Order STRIPS

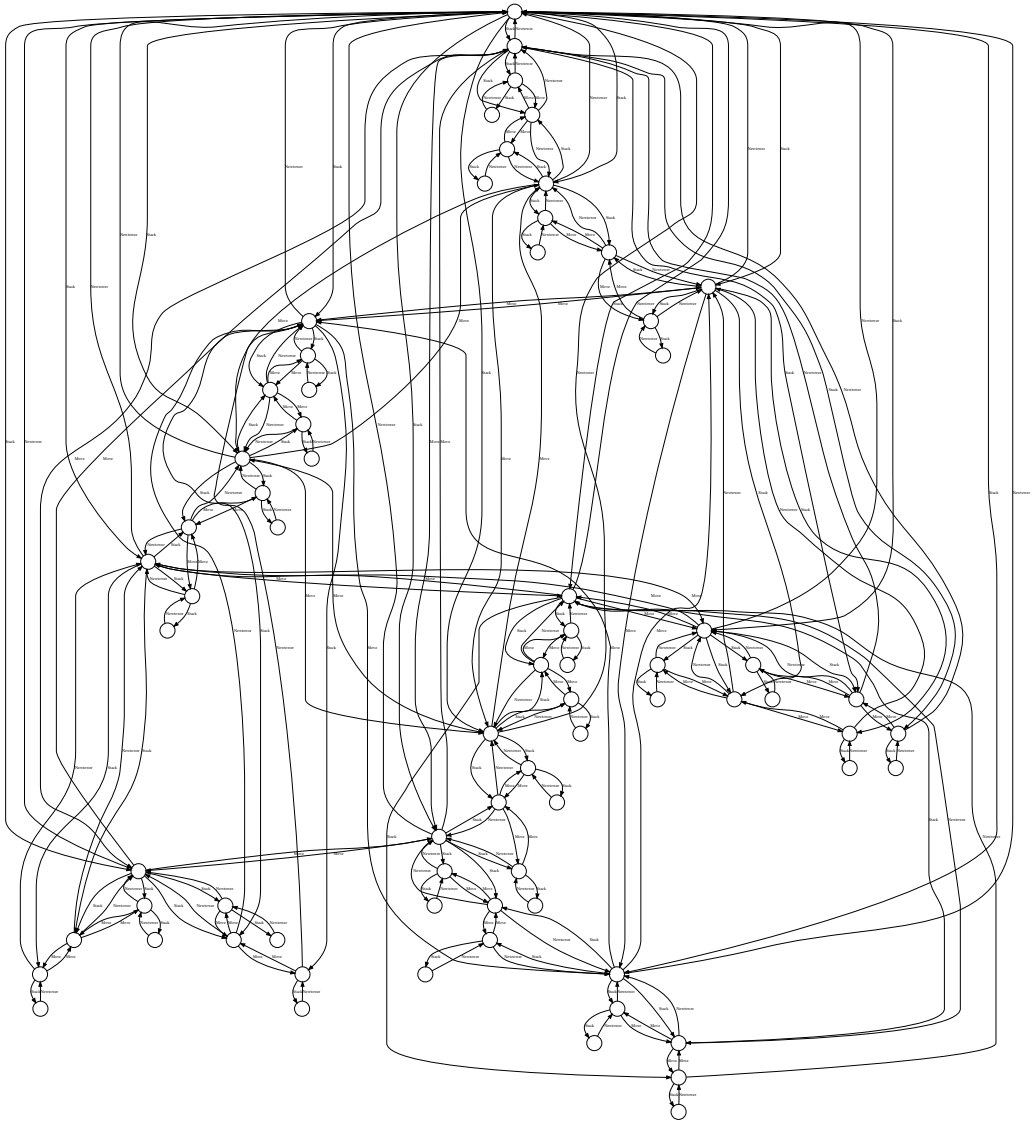
- **Task:** Find **simplest** instances $P_i = \langle D, I_i \rangle$ that account for **input** labeled graphs G_i, $i = 1, \ldots, k$, **without knowing anything about D or the I_i's**

- Space of possible domains D bounded by **small values** of a **small number of hyerparameters**: number of action schemas, predicates, arities.

- **Target language** and **bounds** provide **strong structural priors** and make task **combinatorial**, expressed and solved via **SAT**

Learning first-order symbolic representations from the structure of the state space, B. Bonet, H. G., ECAI 2020

Example: Blocks. Input



Example: Blocks. Output

```
MovetoTable(x,y):
 Static: NEQ(x,y)
 Pre: -Nclear(x),Nclear(y),-Ntable-OR-Non(x,y),Ntable-OR-Non(x,x)
 Eff: -Nclear(y),-Ntable-OR-Non(x,x),Ntable-OR-Non(x,y)

MoveFromTable(x,y,d):
 Static: NEQ(x,y),EQ(y,d)
 Pre: -Nclear(x),-Nclear(d),-Ntable-OR-Non(x,x),Ntable-OR-Non(x,y)
 Eff: Nclear(d),Ntable-OR-Non(x,x),-Ntable-OR-Non(x,y)

Move(x,z,y):
 Static: NEQ(x,z),NEQ(z,y),NEQ(x,y)
 Pre: -Nclear(x),Nclear(y),-Nclear(z),Ntable-OR-Non(x,x),
      Ntable-OR-Non(x,z),-Ntable-OR-Non(x,y)
 Eff: Nclear(z),-Nclear(y),Ntable-OR-Non(x,y),-Ntable-OR-Non(x,z)
```

A different representation: Generalized planning models

- **Generalized models** are for solving **multiple** planning instances at once
  - ▷ E.g., achieve $on(x, y)$ in **any instance** of BW with blocks x and y
- **Formulation** uses QNPs (Qualitative numerical planning problems)
  - ▷ **Learning generalized (QNP) model** from traces and action model
  - ▷ **Solving QNP model** to obtain general policy or plan
- Learning the **actions** and **variables (features)** in **abstract QNP** is key part

Learning generalized policies in planning using concept languages M. Martin and H. G. KR 2000
Learning features and abstract actions for generalized plans. B. Bonet, G. Francès, H. G. AAAI 2019
Qualitative numerical planning: reductions and complexity. B. Bonet, H. G. JAIR 2020 (to appear)

Example: General Policy for Achieving $on(x, y)$

- **Features** X (x held), H (other held), $on(x, y)$; counters $n(x)$, $n(y)$
- **Abstract (QNP) actions:** E abbreviates $\neg X \wedge \neg H$
  - Pick-x : $E, n(x) = 0 \mapsto X$,
  - Pick-above-x : $E, n(x) > 0 \mapsto H, n(x)\downarrow$,
  - Pick-above-y : $E, n(y) > 0 \mapsto H, n(y)\downarrow$,
  - Put-x-on-y : $X, n(y) = 0 \mapsto \neg X, on(x, y), n(y)\uparrow$,
  - Put-aside : $H \mapsto \neg H$.
- Policy that solves **all instances** found with off-the-shelf (FOND) planner
  - **If** $E, n(x) > 0, n(y) > 0$ **do** Pick-above-x,
  - **If** $H, \neg X, n(x) > 0, n(y) > 0$ **do** Put-aside,
  - **If** $H, \neg X, n(x) = 0, n(y) > 0$ **do** Put-aside,
  - **If** $E, n(x) = 0, n(y) > 0$ **do** Pick-above-y,
  - **If** $H, \neg X, n(x) = 0, n(y) = 0$ **do** Put-aside,
  - **If** $E, n(x) = 0, n(y) = 0$ **do** Pick-above-x,
  - **If** $X, \neg H, n(x) = 0, n(y) = 0$ **do** Put-x-on-y.

Features and abstract actions **learned** from action model and data (3 small STRIPS instances, 420 state transitions in $\mathcal{S}$, 657 features in $\mathcal{F}$)

Learning the features and abstract actions using SAT Solver

- **Inputs:**
  - **CNF formula** $T(\mathcal{S}, \mathcal{F})$ encoding requirements over desired **features**
  - $\mathcal{S}$: **sampled state transitions**
  - $\mathcal{F}$: **pool of features** computed from primitive predicates and general grammar
- **Variables:**
  - $selected(f)$ for each $f \in \mathcal{F}$, true iff $f \in F$, $F \subseteq \mathcal{F}$
  - $D_1(s, t)$ true iff selected features distinguish s from t; p or $n = 0$ true in one
  - $D_2(s, s', t, t')$ true iff selected features f distinguish transitions (s, s'), (t, t')
- **Formulas:**
  - $D_1(s, t) \Leftrightarrow \bigvee_f selected(f)$
  - $D_2(s, s', t, t') \Leftrightarrow \bigvee_f selected(f)$
  - $\neg D_1(s, t) \Rightarrow \bigvee_{t'} \neg D_2(s, s', t, t')$
  - $D_1(s, t)$, when one of s and t is a goal state

Theorem (Bonet, Frances, G. 2019) $T(\mathcal{S}, \mathcal{F})$ is SAT iff $\exists$ set of features $F \subseteq \mathcal{F}$ and actions A over F such that A is **sound and complete** relative to $\mathcal{S}$.

Wrap Up

- **Data-based learners** and **model-based solvers** like **Systems 1 and 2**
- **Deep (reinforcement) learning**, however, delivers **System 1** boxes only
- **Main challenge** is two-way integration of **learners** and **solvers**
- **Key problem** is learning representation of models used by solver from data
  - ▷ Learning **from** what: symbolic, non-symbolic, or black-box states
  - ▷ Learning **for** what: model-free control, model-based, generalized model
- We looked at two points in this space in context of **planning**

Ethical AI: In Defense of System 2 not just in AI Systems

- **System 2** not only necessary for AI systems; essential for people and **societies**
- **Ethical committees** and **AI principles** good but not sufficient
- **Markets and politics** play our **System 1**, focused on the **bottom line**
- If we want **good AI**, we need a **good and decent society** that appeals to our **System 2** and **cares about the common good**

"Need AI for social good 'cause natural intelligence is busy in other pursuits" :-)

An Ad

Doctoral and postdoc slots to work on **Representation Learning for Planning**:

- Linköping (funded by WASP)
- Barcelona (funded by ERC)