Developing Autonomous Systems in Artificial Intelligence: Solvers and Learners

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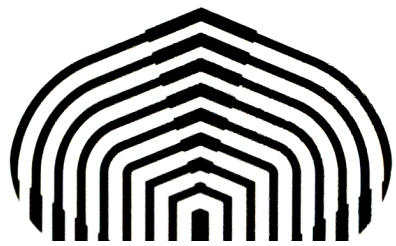


Challenge

How to develop agents that make decisions on their own?

Autonomous behaviour in AI

Control problem: at each decision time, select next **action to execute**

Three main approaches:

- **Programming-based:** specify control by hand in form of program

  Pros: domain-knowledge easy to express
  Cons: cannot deal with situations not anticipated by 'programmer'

- **Model-based (top-down):** synthesis of control from specification

  Pros: flexible, clear, and domain-independent
  Cons: need a model (specification), computationally intractable

- **Learning-based (bottom-up):** learn control from experience

  Pros: does not require much knowledge in principle
  Cons: right features needed, incomplete inf. is problematic, slow learning

Model-based approach: What's in the model?

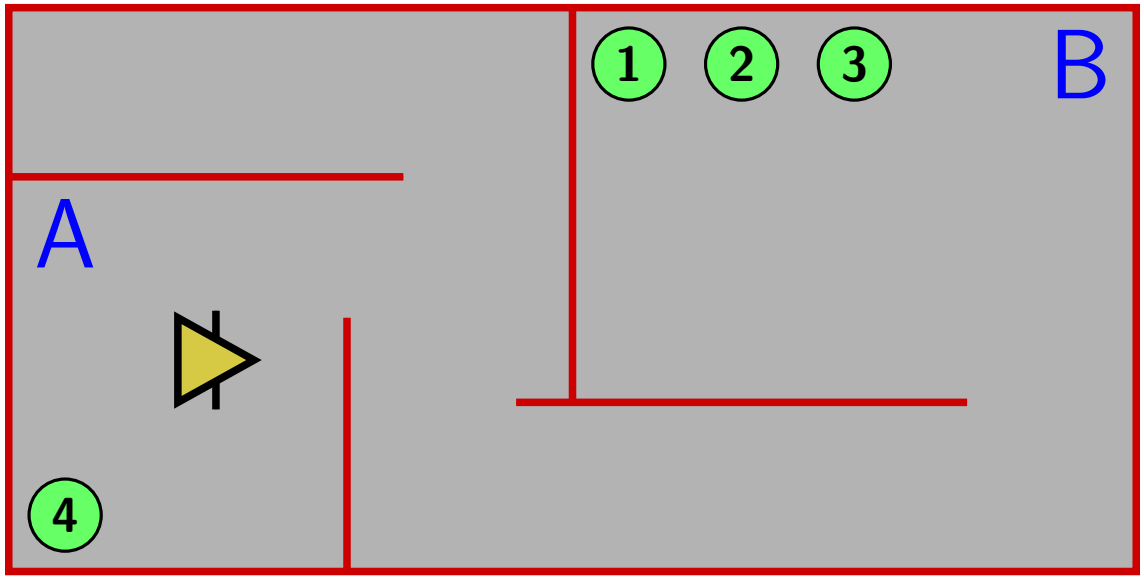
Model of the world (environment) captures:

- Variables make up states; e.g. position of agent(s) and objects, battery life, relations between objects, etc.
- Initial state of the system
- Goals of the agent
- Executable actions (may differ at each state)

It also captures **assumptions about the environment:**

- Deterministic vs. stochastic effects of actions
- Fully vs. partially observable variables
- Cost vs. reward setting
- ...

Example: Gripper



- Bunch of balls in room B
- Robot with left and right gripper, each one may hold a ball
- **Goal:** move all balls to room A

Robot may:

- move between rooms A and B; e.g. Move(A, B)
- use grippers to pick and drop balls from rooms; e.g. Pick(left, b_3, B)

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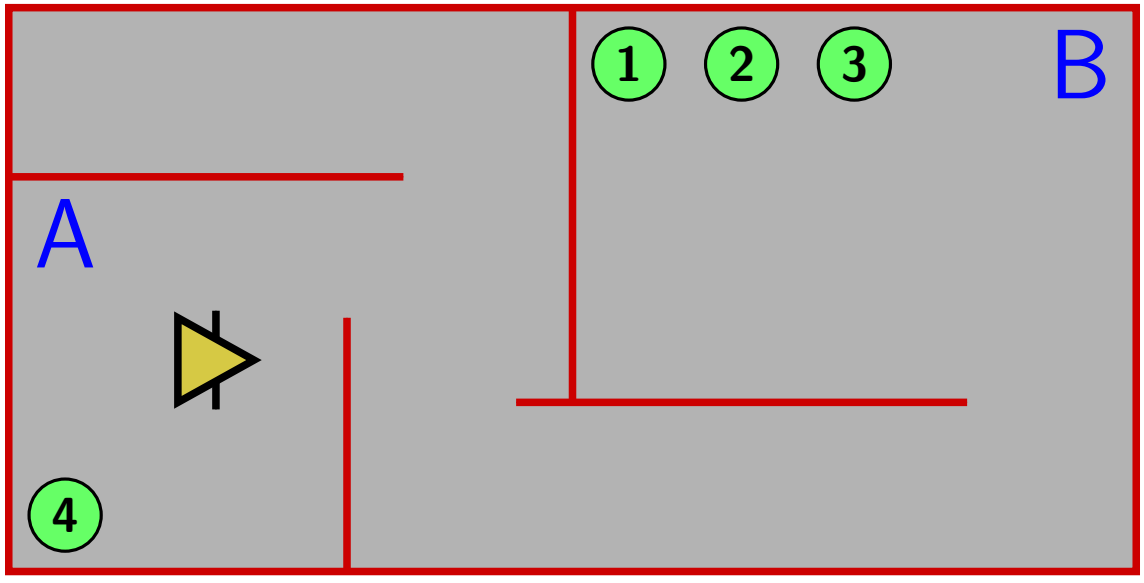


Variables:

– robot's position: room A or B

– position of each ball b_i: either room A or B, or left or right gripper

States: **valuation for vars** (#states $> 2^{n+1}$ for problem with n balls)

Actions:

– **deterministic transition function:** from state to next state

– may have preconditions; e.g. can drop ① in A only if at A and holding it

Classification of Models

Models classified depending on the assumptions:

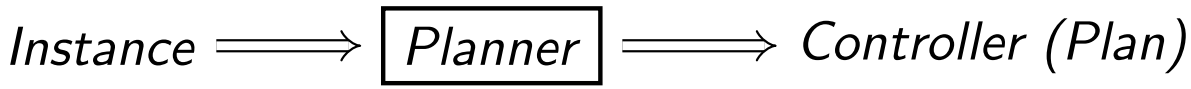
- **Classical planning:** one agent, full sensing (information), det actions
- **FOND/MDP (planning):** one agent, full sensing, non-det actions
- **POND/POMDP (planning):** one agent, partial sensing, non-det act.
- **DEC-POMDP:** multiple collaborative agents in non-det and partially observable setting: joint reward, decentralized partial sensing, and actions
- **Partially Observable Stochastic Games (POSG):** multiple (perhaps competing) agents with decentralized rewards, sensing, and actions

As model becomes more general, synthesis becomes harder!

Planners

A planner is a **solver** for a **class of models**

- input is specification of task (e.g. gripper)
- output is controller for task (e.g. sequence of steps in gripper)



Instance described with **specification language**

Class of models: models that can be described with language

The planner must solve **any task** in the class of models

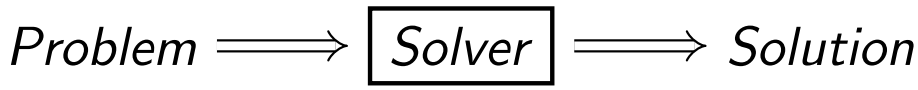
AI research today

Recent work published in top AI conferences and journals are on:

- Machine Learning
- Natural Language
- **Probabilistic Reasoning**
- Vision and Robotics
- **SAT and Constraints**
- **Search and Planning**
- Multi-Agent Systems
- ...

Highlighted often considered **techniques**, but often more convenient to think of them in terms of **models + solvers** (also applies to many things in ML)

Models + Solvers



Solver: program that solves input problems

Input: any problem that belongs to **well-defined class** of problems

Output: solution to input

- Input specified in some (fixed) **representation language**
- **Scope** of solver is class of all problems that can be specified in language

Example: Solver for linear equations

$$\textit{Problem} \Longrightarrow \boxed{\textit{Solver}} \Longrightarrow \textit{Solution}$$

Problem: the age of John is 3 times the age of Peter. In 10 years, it will be only 2 times. How old are John and Peter?

Expressed as: $J = 3P \ ; \ J + 10 = 2(P + 10)$

Solver: Gauss-Jordan (variable elimination)

Language: Sets of linear equations

Solution: $P = 10 \ ; \ J = 30$

Solver is **general** because it deals with **any instance** of the model

Model is **tractable** (solvable in **cubic time** as a function of number of variables and equations in the model); AI models are **intractable** ...

Example from AI: Solvers for SAT

SAT is the problem of determining whether there is a **truth assignment** that satisfies a **set of clauses** (disjunction of literals); e.g.

$$\underbrace{x \vee z}_{\text{clause}} \;;\; \underbrace{\neg y \vee \neg z \vee w}_{\text{clause}} \;;\; \underbrace{\neg x \vee z}_{\text{clause}} \;;\; \underbrace{\neg w \vee \neg z}_{\text{clause}}$$

Satisfying truth assignment: $w =$ false ; $y =$ false ; $z =$ true $\quad (x =$ any$)$

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SAT is **NP-Complete**: **worst-case** running time of SAT solvers is **exponential** in number of variables (100 vars: $2^{100} \approx 10^{30}$)

However, SAT solvers tackle problems with **thousands of variables and clauses**, and they are widely used (verification, CAD, etc)

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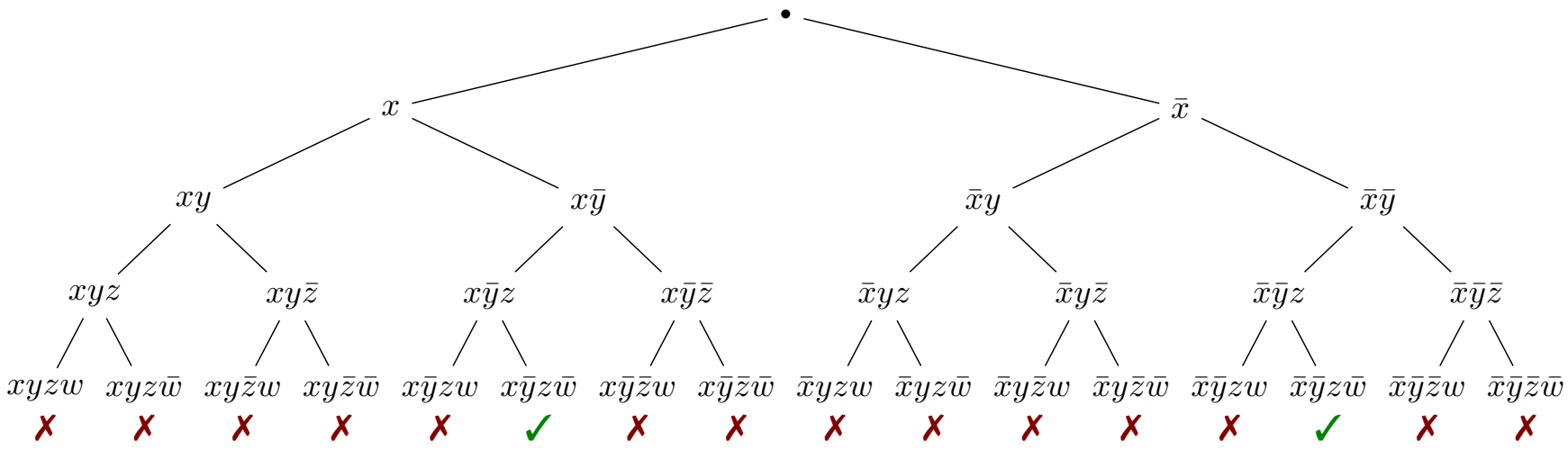
- **EXP** = exponential (deterministic) time **(provably intractable)**
- **NEXP** = non-deterministic exponential time **(provably intractable)**
- **EXPSPACE** = exp space (computer may run by double exp time) **(idem)**
- **EXP2** = doubly exponential (deterministic) time **(provably intractable)**
- ... hierarchy continues ...

How SAT solvers do it?

Formula in CNF: $\{ x \vee z,\ \neg y \vee \neg z \vee w,\ \neg x \vee z,\ \neg w \vee \neg z \}$

One approach: **Brute-force search**



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Another approach: **Inference (resolution)**

$$
\begin{aligned}
(x \vee z) \ \wedge\ (\neg x \vee z) &\implies z \\
z \ \wedge\ (\neg w \vee \neg z) &\implies \neg w \\
z \ \wedge\ \neg w \ \wedge\ (\neg y \vee \neg z \vee w) &\implies \neg y
\end{aligned}
$$

Brute-force search and inference are both correct, but don't scale up!

How SAT solvers do it?

Modern SAT solvers combine **search** with **inference**

Two types of **efficient inference** at every node in search tree:

- Unit propagation (UP)
- Conflict-based clause learning (CDCL) to implement **non-chronological backtracking** and **re-starts**

Main lesson: right thing isn't only about correctness; efficiency is crucial!

Specification of models

Models specified using **representation languages**

These languages are **factored languages**

They permit specifications of very large systems (i.e. very large number of states) using very few symbols (bytes)

Example: Gripper in PDDL

```
(define (domain gripper)
  (:predicates (room ?r) (ball ?b) (gripper ?g) (at-robby ?r) (at ?b ?r)
               (free ?g) (carry ?o ?g))

  (:action move
    :parameters (?from ?to)
    :precondition (and (room ?from) (room ?to) (at-robby ?from))
    :effect (and (at-robby ?to) (not (at-robby ?from))))

  (:action pick
    :parameters (?b ?r ?g)
    :precondition (and (ball ?b) (room ?r) (gripper ?g) (at ?b ?r) (at-robby ?r) (free ?g))
    :effect (and (carry ?b ?g) (not (at ?b ?r)) (not (free ?g))))

  (:action drop
    :parameters (?b ?r ?g)
    :precondition (and (ball ?b) (room ?r) (gripper ?g)
    (carry ?b ?g) (at-robby ?r))
    :effect (and (at ?b ?r) (free ?g) (not (carry ?b ?g))))
)

(define (problem p1)
  (:domain gripper)
  (:objects A B left right b1 b2 b3)
  (:init (room A) (room B) (gripper left) (gripper right) (ball b1) (ball b2) (ball b3)
         (at-robby A) (at b1 B) (at b2 B) (at b3 B) (free left) (free right))
  (:goal (and (at b1 A) (at b2 A) (at b3 A))))
```

Complexity of planning

Given problem represented in **factored form**, the task of checking whether there is a solution is:

- **Classical planning:** **PSPACE**
- **FOND planning / MDPs:** **EXP** for FOND / **P** for **explicit** MDPs
- **POND planning / POMDPs:** **EXP2** for POND / **PSPACE** for explicit and bounded horizon, **UNDECIDABLE** for unbounded horizon
- **DEC-POMDPs:** **NEXP** for explicit and bounded horizon, **UNDECIDABLE** for unbounded horizon
- **Partially Observable Stochastic Games (POSG):** at least as difficult as **NEXP(NP)** for explicit and bounded horizon

As model becomes more expressive, task becomes more difficult to solve!

Beyond classical planning

Classical planning works: solvers able to solve large problems

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Model is simple, but useful:

- actions may be non-primitive (e.g. abstractions of procedures)
- **closed-loop replanning** able to cope with some uncertainty and limitations

Beyond classical planning

Classical planning works: solvers able to solve large problems

Model is simple, but useful:

- actions may be non-primitive (e.g. abstractions of procedures)
- **closed-loop replanning** able to cope with some uncertainty and limitations

Inherent limitations:

- can't model **general uncertainty on outcome of actions**
- can't deal with **incomplete information** (partial sensing)

Two ways of handling limitations:

- **extend scope** of current solvers (replanning, translations, etc)
- develop **new solvers for more expressive models**

Online planning in reward-based video games

Methods and ideas from classical planning lifted to play Atari games:

- Collection of deterministic video games that share: screen of 160×210 pixels, each up to 128 colors, and 18 actions (joystick movements)
- In majority of games there is no fixed goal; goal is to max accrued reward
- Online game that runs at 60 fps: decisions must be taken at a rate of 4 decisions per second (at least)
- No explicit model, but **simulator is available**

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- Online game that runs at 60 fps: decisions must be taken at a rate of 4 decisions per second (at least)
- No explicit model, but **simulator is available**

Given **time budget** for choosing next action to apply:

- Use simulator to **explore search tree** of screens within time bound (tree grows exponentially fast: 18^d nodes at depth d)
- **Select** "best sequence of actions" in explored tree
- Apply **first action** in selected sequence, and **repeat**

Demo: Playing Atari games

- 60 frames per second, decision made every 15 frames
- Time budget of $1/2$ second per decision (almost real time)
- Play for at most 5 minutes or 18k frames
- Screen 160×210 pixels of 128 colors each:
  - split into 16×14 disjoint tiles
  - $\sim 28k$ features tell which colors contain each tile
  - $\sim 6.8m$ features for relative dist. between tiles with 2 given colors
  - $\sim 13.7m$ features for rel. dist. btw tiles with 2 col. at curr. and prev. screens
  - total of $\sim 20.5m$ features
- Games in demo:
  - Space invaders
  - Boxing
  - Breakout

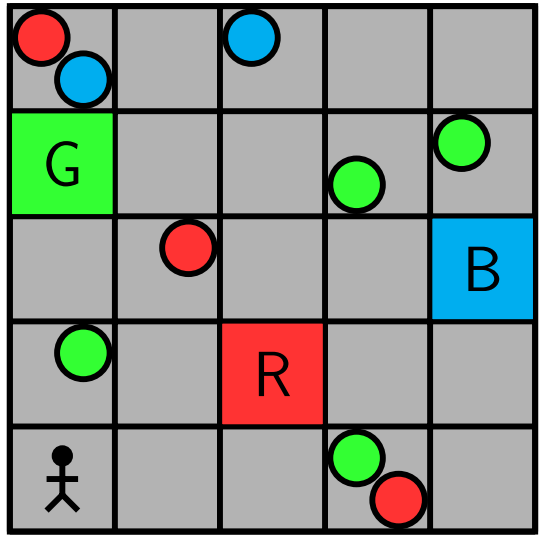
Agent with partial information

Agent has **partial information** when it doesn't see **full states**

General way to model such problems:

- finite set Ω of **observable tokens**
- **environment produces** a token after applying action
- agent **receives token** (it doesn't see state directly)
- token may depend on **current state** and **last applied action**

Example: Delivering colored balls



Agent knows its position and senses existence of balls in current cell

Observable tokens $\Omega = \{000, 001, 010, \ldots, 111\}$ (i.e. 3-bit word)

- 1st bit tells whether there is a **red ball** in current cell
- 2nd bit tells whether there is a **green ball** in current cell
- 3rd bit tells whether there is a **blue ball** in current cell

Belief states and information tracking

Agent keeps track of states that are possible given executed actions and observed tokens

Set of possible states is called **belief state**

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Afterwards,

– **belief after executing action a:**

$b_a = \{s' : s' \text{ is poss. successor after doing } a \text{ in } s \in b\}$ (progression)

– **belief after executing action a and receiving token $z \in \Omega$:**

$b_a^z = \{s' \in b_a : s' \text{ is compatible with token } z\}$ (filtering)

Solvers for problems with partial information

Solvers need to address two fundamental tasks (both intractable):

- information tracking (maintenance of belief states)
- action selection for achieving goal

First task is about how information is tracked, and the **form of solutions:**

- solution is mapping from belief states into actions

Second is about how beliefs, search and inference are combined to find solutions

Factored belief tracking

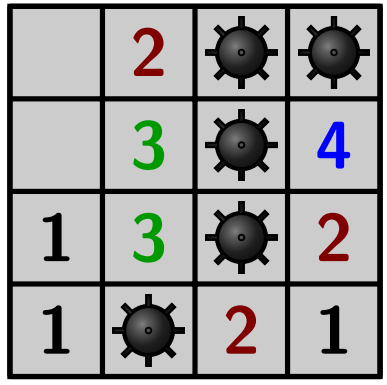
Number of system states is exponential in number of variables (e.g. with 9 balls, more than 9×10^{14} states)

Number of belief states is exponential in number of states; that is, **doubly exponential** in number of variables

Factored belief tracking (FBT) is algorithm for efficient **representation and update** of belief states (even at the expense of doing approximations)

FBT decomposes the task into **smaller subtasks** that are tracked **independently** while enforcing some degree of **consistency** among them

Example: FBT in Minesweeper



- In 4×4 board with 5 mines, there are 4,368 different configurations
- Number of belief states (i.e. non-empty subsets of states) is $2^{4,368} - 1$
- FBT tracks possible contents of 3×3 sub-grids **independently**
- Consistency among "local factors" is (approximately) enforced
- **Implemented in linear space + (amort.) const. time per decision**

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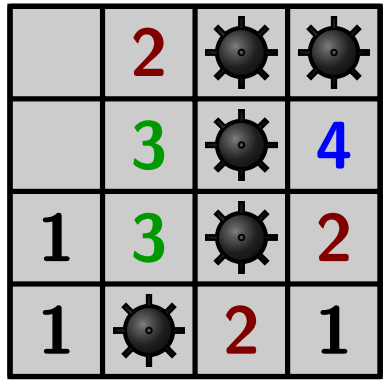

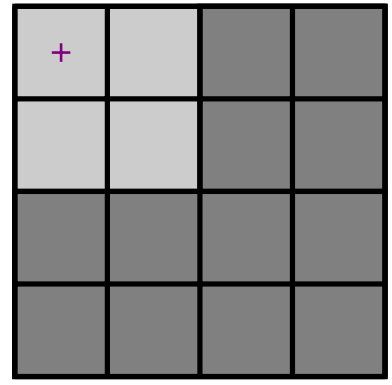

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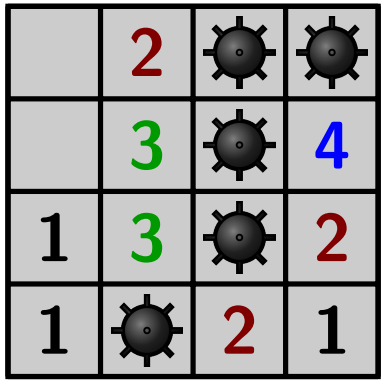

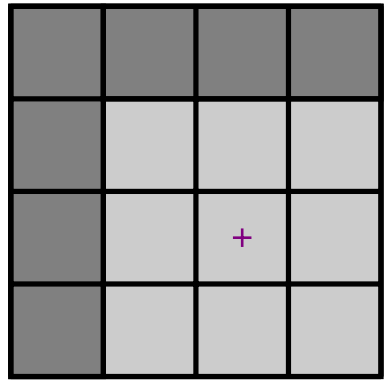

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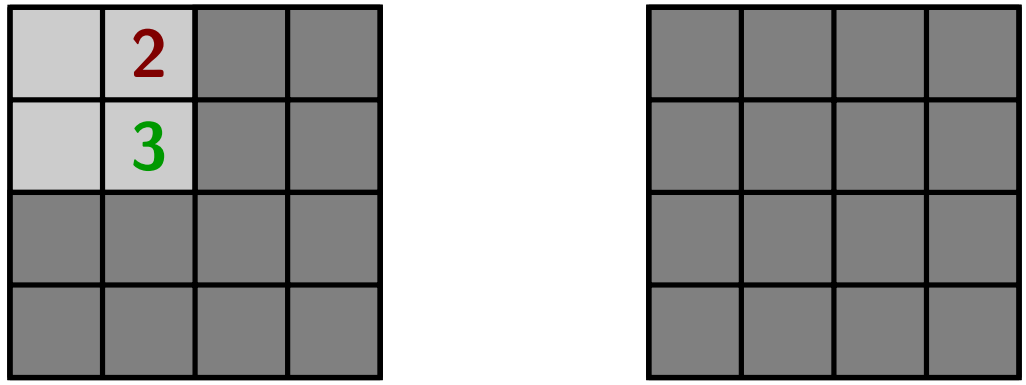

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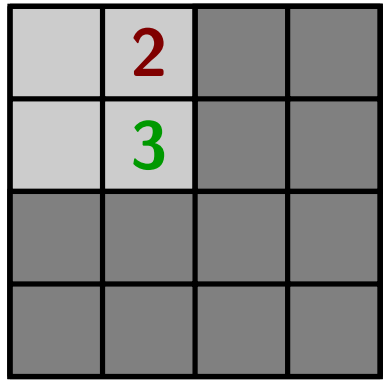

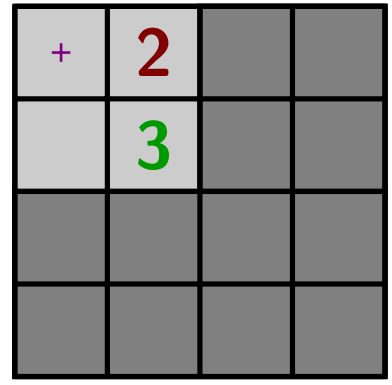

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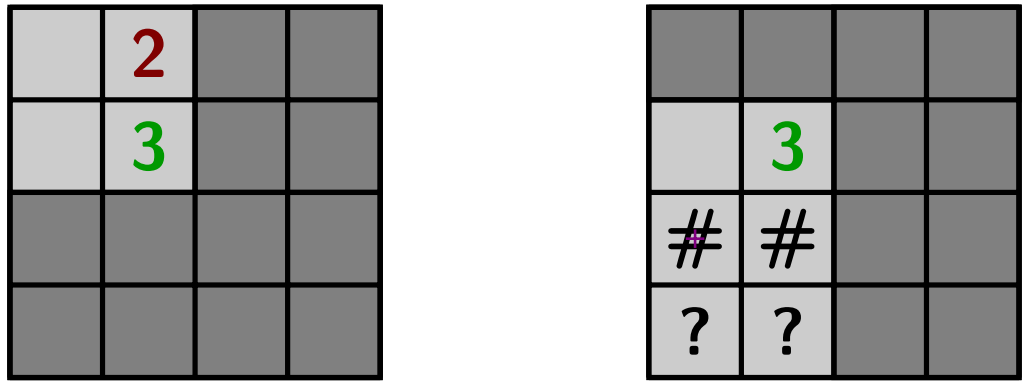

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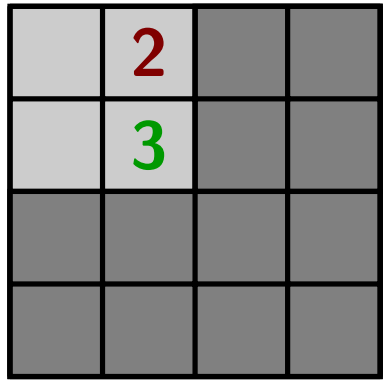

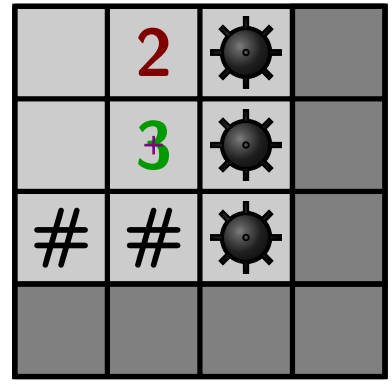

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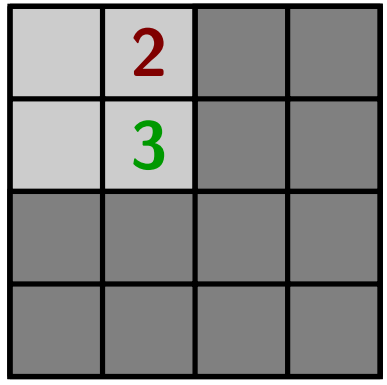

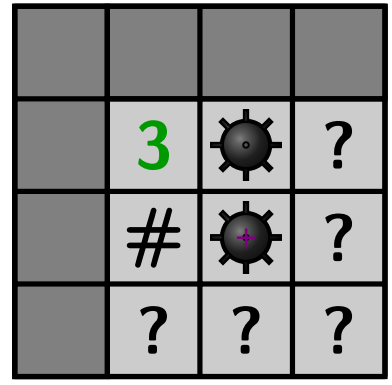

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Demo: Factored belief tracking

State-of-the-art agent for:

- Minesweeper
- Battleship

Both problems are difficult:

- Corresponding decision problems are **NP-Complete**
- Challenge for solvers is to do good belief tracking
- Once beliefs are correctly handled, decision making is trivial!
- Belief tracking done with FBT

Autonomous behaviour in AI

Control problem: at each decision time, select next **action to execute**

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- **Model-based (top-down):** synthesis of control from specification

  Pros: flexible, clear, and domain-independent
  Cons: need a model (specification), computationally intractable

- **Learning-based (bottom-up):** learn control from experience

  Pros: does not require much knowledge in principle
  Cons: right features needed, incomplete inf. is problematic, slow learning

(Supervised) Learners

$$x \Longrightarrow \boxed{\text{function } f_\theta(\cdot)} \Longrightarrow f_\theta(x)$$

- x is input; it may be a **high-dimensional vector**
- function f_θ has **fixed structure** but values determined by parameters in θ
- output $f_\theta(x)$ may be vector

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Supervised learning:

- Given **anotated** (i.i.d.) sample $(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)$
- Find parameter θ^* that is **"right fit":**
  - low "training error"; e.g., low $\frac{1}{2m} \sum_{i=1}^{m} (y_i - f_{\theta^*}(x_i))^2$
  - good "generalization"; e.g., low $\mathbb{E}_{(X,Y)\sim(x_i,y_i)} \left[(Y - f_{\theta^*}(X))^2 \right]$
- Standard algorithm: **Stochastic gradient descend** (SGD)

Deep Learning / Deep Reinforcement Learning

$$x \Longrightarrow \boxed{\text{function } f_\theta(\cdot)} \Longrightarrow f_\theta(x)$$

- f_θ is neural network with many **hidden layers**
- number of parameters in θ is often quite large
- **DL is about classification:** xs are objects, ys are class labels
- **DRL is about control:** xs are "state features", ys are actions (or state values)

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Training:

- Network trained with many examples during hours/days using SGD
- DL: training data often available (e.g. tagged images/videos from internet)
- DRL: often insufficient training data
- Once trained, evaluation is fast

Success and limitations of learners

Big success of deep nets in AI:

– Breakthroughs in image/video understanding, speech recognition, ...

– Superhuman performance in complex games like Chess and Go

Key limitation of trained nets is **fixed input size:**

– No problem for images, Chess or Go, as they correspond to "fixed-size inputs"

– Problematic in simpler domains; e.g. gripper with different # of balls or grippers (there is no deep net able to solve gripper with arbitrary # of balls)

Solvers vs. learners

Rollout IW **planner** and DeepMind's DQN **learner** perform well in Atari

They illustrate common characteristics of solvers and learners:

- Rollout IW works from scratch for any game without prior pre-processing. It calculates action to apply by doing exploration under given time budget.

  Solvers **"think before acting"** at each decision point

- DQN requires a lot of training over many data. Afterwards, DQN plays very fast as decision making is simply to "run network on given input".

  Learners require a lot of training and tuning. Then, decision making is fast

On the other hand:

- Solvers require models or, in some cases, simulators with given capabilities
- Learners require large training sets and pre-processing time

Integration of solvers and learners

Better agents by combining solvers and learners

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Better agents by combining solvers and learners

Training data for DRL can be automatically generated using solvers:

– Starting from sample $\mathcal{M}_i$ for $i = 0$:

- Train DRL function f_{θ_i} with sample $\mathcal{M}_i$
- Use **self-play** or **stochastic search** to generate new "interesting inputs" $\{x_k\}_k$
- Use solver (possibly enhanced by f_{θ_i}) to find labels $\{y_k\}_k$ for such inputs
- Make new sample $\mathcal{M}_{i+1} = \{(x_k, y_k)\}_k$, increase i, and **repeat**

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Models can be learned and then fed to solvers:

– From "observed behavior", use learner to build model

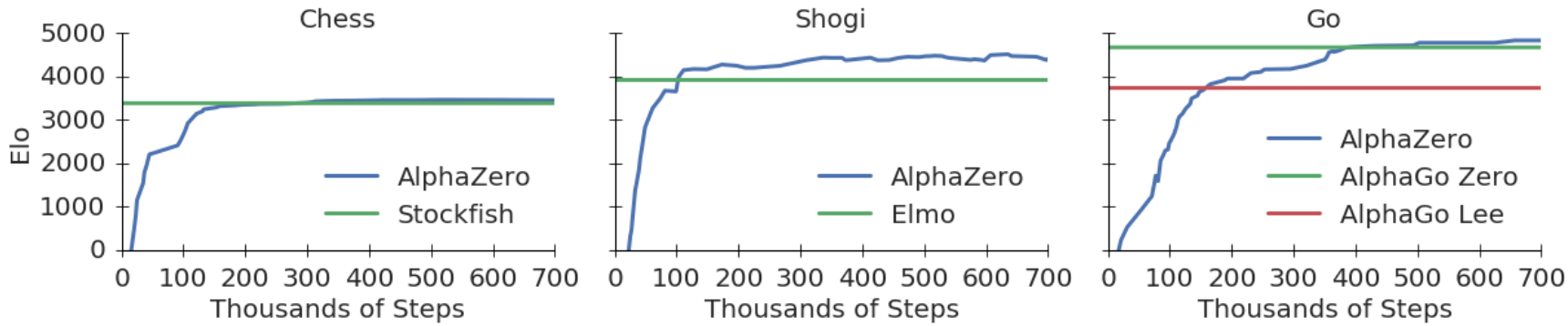
– Use solver to find controller for model

– Use controller to generated new behaviour, and **repeat**

Solvers + Learners: AlphaZero

DeepMind's AlphaZero:

- **Superhuman performance** in Chess, Shogi (Japanese Chess), and Go
- Learns how to play using only game rules and self play
- Combines DRL with Monte-Carlo Tree Search (MCTS)
- Deep net trained with SGD; it provides evaluation function f_θ for states
- Using f_θ and MCTS, AlphaZero does self-play to generate new training data



(∼300k steps in 4 hours) (∼110k steps in 2 hours) (∼165k steps in 8 hours)

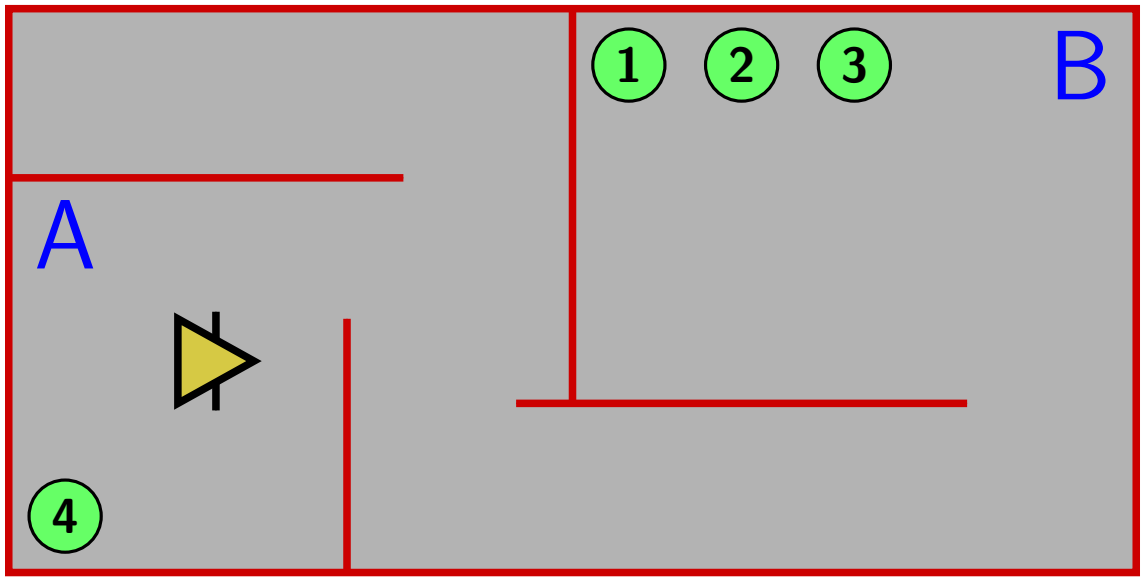
Silver et al. *Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm*. arXiv 2017.

Solvers + Learners: Generalized planning

Synthesis for **classes** of similar problems rather than for single instances

- **Learn** general abstraction for whole class
- **Solve** abstraction with solver (may need FOND solver)
- Obtained policy works for any instance in class

Example: General abstraction for Gripper



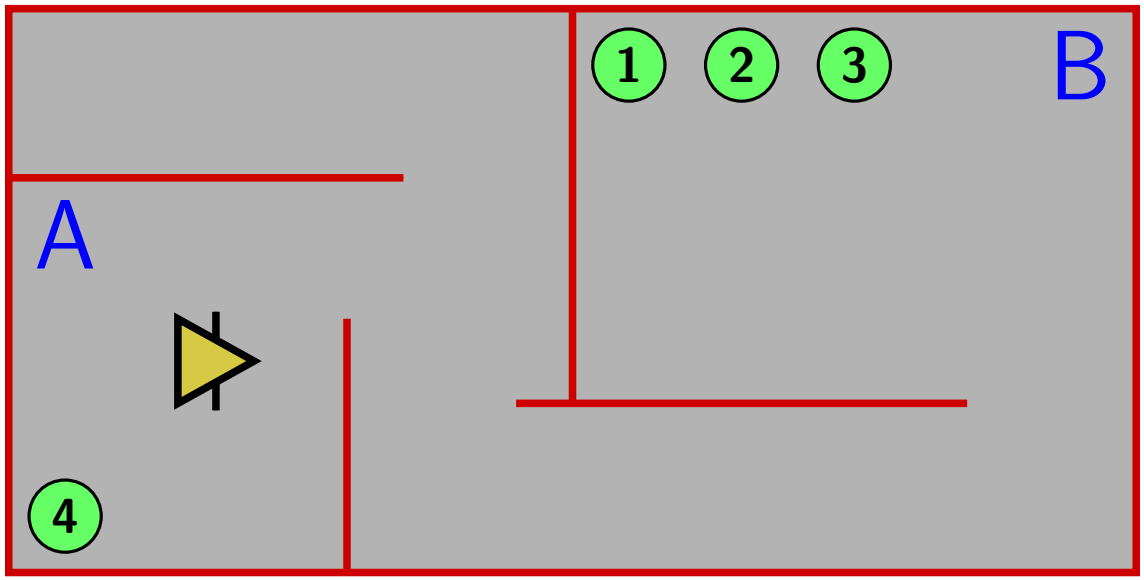
Features:

- $X =$ robot-at-destination-room, $B =$ #balls-in-other-room
- $C =$ #balls-being-carried, $G =$ #free-grippers

Abstract actions:

- **Pick** $= \{\neg X,\ B > 0,\ G > 0\} \mapsto \{B\downarrow,\ G\downarrow,\ C\uparrow\}$
- **Drop** $= \{X,\ C > 0\} \mapsto \{C\downarrow,\ G\uparrow\}$
- **Leave-destination-room** $= \{X,\ C = 0,\ G > 0\} \mapsto \{\neg X\}$
- **Go-destination-room-fully-loaded** $= \{\neg X,\ G = 0,\ C > 0\} \mapsto \{X\}$
- **Go-destination-room-half-loaded** $= \{\neg X,\ B = 0,\ G > 0,\ C > 0\} \mapsto \{X\}$

Example: General abstraction for Gripper



Features:

- $X =$ robot-at-destination-room, $B =$ #balls-in-other-room
- $C =$ #balls-being-carried, $G =$ #free-grippers

Starting with $X = true$:

While $B > 0 \vee C > 0$ **do:**

While $X \wedge C > 0$ **do:** **Drop**

If $X \wedge B > 0$ **then:** **Leave**

While $B > 0 \wedge G > 0$ **do:** **Pick**

If $C > 0 \wedge G = 0$ **then:** **Go-destination-room-fully-loaded**

Elsif $C > 0 \wedge G > 0$ **:** **Go-destination-room-half-loaded**

Current and future work

- Learners:
  - Learn states, variables and objects from traces
  - Learn abstractions from (learned) state representation
  - Learn abstractions from non-symbolic traces (images)
- Solvers:
  - Devise more efficient solvers
  - Identify tractable subclasses of interesting problems
- Combine learners and solvers into "full pipeline": from (symbolic or non-symbolic) traces to generalized controllers

(trace = interleaved sequence of actions and observations: $\langle a_0, z_0, a_1, z_1, \ldots \rangle$)

Learning state-transition diagrams from traces

ST-diagram: **Labeled directed graph**

– **vertices** are states

– **labeled arrows** are transitions triggered by actions

Learning done by solving **graph coloring** problem with SAT

Example: Learning ST-diagram in Gripper

Observable tokens: 3-bit strings with components for $B > 0$, $C > 0$, $G > 0$ denoted by b, c, and g

Action labels: `Move`, `Pick`, `Drop`

Traces (sample): 1,510 traces from single instance with 2 balls and 1 gripper

```
b-g Move b-g Move b-g Move b-g Move
b-g Move b-g Move b-g Move b-g Move b-g
b-g Move b-g Move b-g Move b-g Move b-g Move
b-g Move b-g Pick bc- Drop b-g Pick
b-g Move b-g Pick bc- Drop b-g Pick bc-
b-g Move b-g Pick bc- Drop b-g Pick bc- Drop
b-g Move b-g Pick bc- Drop b-g Pick bc-
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b-g Move b-g Pick bc- Move bc- Drop b-g Move
...
```
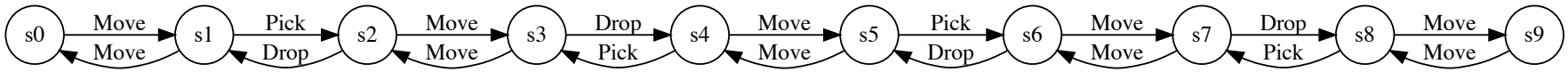
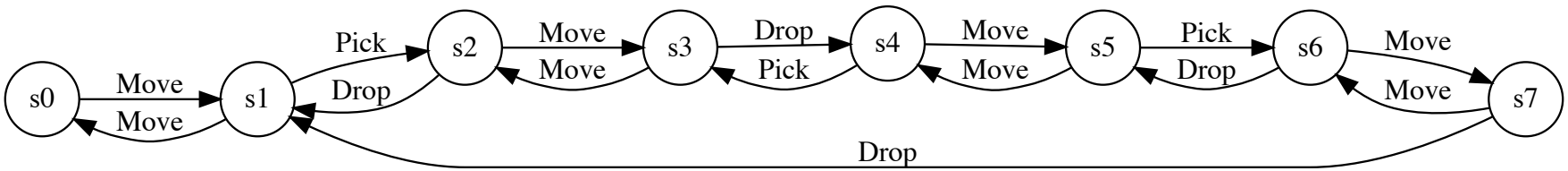

Example: Learning ST-diagram in Gripper

State space: 10 states, and 18 transitions; **"linear shape"**



With a smaller sample containing 422 traces only, get **incomplete diagram**:



Planning and learning at UC3M

Planning and Learning Group (PLG) at Departamento de Informática:

- **Head of group:** Daniel Borrajo Millán
- Carlos Linares López
- Fernando Fernández Rebollo
- Susana Fernández Arregui
- Raquel Fuentetaja Pizán
- Angel García Olaya
- Yolanda Escudero

Wrap up

- Two main approaches in AI for developing autonomous agents
- Solver-based approach:
  - Automatic synthesis of controller from model
  - Requires model and solver
  - Synthesis task is intractablee
  - Usually no pre-processing; at each decision point, the process of decision making requires time
- Learner-based approach:
  - Doesn't require model
  - Requires features and lots of training data
  - Controller is directly learned form data; afterwards, decision making is fast
- Combining the two approaches:
  - Intrinsic limitations of each approach can be overcomed
  - Very successful examples
  - Still requires some structure: states, action labels, and observation tokens
- Future work:
  - Learn state structure and control directly from traces