AI at 50: From Programs to Solvers
Models and Techniques for General Intelligence

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Goals

• Address some changes that have taken place in Al research in last 20 years

▷ Changes that have to do with move from programs to solvers

\[ \text{Problem} \implies \text{Solver} \implies \text{Solution} \]

▷ Solvers are general programs whose scope defined in terms of a model

▷ Challenge is computational: how to make the solvers scale up

• Explain its relevance to the old AI goals concerning general intelligence and human cognition
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  - Many of the debates surrounding AI (GOFAI, Situated AI, Symbolic vs. Non-Symbolic) date back to the 80’s and not revised since

- I aim to show that this impression is wrong
Outline

• Some AI history

• The problem of generality in AI

• Models and Solvers:
  - Graphical Models: logical and probabilistic (SAT, CSPs, Bayesian Nets)
  - Planning Models: logical and probabilistic (Strips, POMDPs, Contingent)

• Lessons learned and why they matter

• Summary
"The proposal (for the meeting) is to proceed on the basis of the conjecture that every aspect of . . . intelligence can in principle be so precisely described that a machine can be made to simulate it"
An early collection of AI papers and programs for playing chess and checkers, proving theorems in logic and geometry, planning, etc.
Importance of Programs in Early AI Work

In preface of 1963 edition of *Computers and Thought*

We have tried to focus on papers that report results. In this collection, the papers . . . describe actual working computer programs . . . Because of the limited space, we chose to avoid the more speculative . . . pieces.

In preface of 1995 AAAI edition

A critical selection criterion was that the paper had to describe . . . a running computer program . . . All else was talk, philosophy not science . . . (L)ittle has come out of the “talk”.
Many of the key AI contributions in 60’s, 70’s, and early 80’s had to do with \textit{programming} and the \textit{representation of knowledge} in programs:

- Lisp (Functional Programming)
- Prolog (Logic Programming)
- Rule-based Programming
- Interactive Programming Environments and Lisp Machines
- Frame, Scripts, Semantic Networks
- ‘Expert Systems’ Shells and Architectures
AI methodology: Theories as Programs

- For writing an AI dissertation in the 60’s, 70’s and 80’s, it was common to:
  - pick up a task and domain $X$
  - analyze/introspect/find out how task is solved
  - capture this reasoning in a program

- The dissertation was then
  - a **theory** about $X$ (scientific discovery, circuit analysis, computational humor, story understanding, etc), and
  - a **program** implementing the theory, **tested** over a few examples.

Many great ideas came out of this work . . . but there was a problem . . .
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Theories expressed as programs cannot be proved wrong: when a program fails, it can always be blamed on ‘missing knowledge’
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  - problem: limited scientific value
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AI in the 80’s

The knowledge-based approach reached an impasse in the 80’s, a time also of debates and controversies:

- **Good Old Fashioned AI** is "rule application" but intelligence is not (Haugeland)
- **Situated AI**: representation not needed and gets in the way (Brooks)
- **Neural Networks**: inference needed is not logical but probabilistic (PDP Group)
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**How valid are they now?**
AI Research in 2007

Recent issues of AIJ, JAIR, AAAI or IJCAI shows papers on:

1. **SAT and Constraints**
2. **Search and Planning**
3. **Probabilistic Reasoning**
4. **Probabilistic Planning**
5. Inference in First-Order Logic
6. Machine Learning
7. Natural Language
8. Vision and Robotics
9. Multi-Agent Systems

I’ll focus on 1–4: these areas often deemed about **techniques**, but more accurate to regard them as **models** and **solvers**.
Example: Solver for Linear Equations

\[ \text{Problem} \Rightarrow \boxed{\text{Solver}} \Rightarrow \text{Solution} \]
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\[ \text{Problem} \implies \boxed{\text{Solver}} \implies \text{Solution} \]

- **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?
Example: Solver for Linear Equations

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

- **Solver:** Gauss-Jordan (Variable Elimination)

- **Solution:** \( P = 10 \); \( J = 30 \)
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Solver is **general** as deals with any problem expressed as an instance of **model**

Linear Equations Model, however, is **tractable**, AI models are not . . .
AI Solvers

\[ \text{Problem} \implies \text{Solver} \implies \text{Solution} \]

- The basic models and task we will consider are
  - **Constraint Satisfaction/SAT**: find state that satisfies constraints
  - **Bayesian Networks**: find probability over variable given observations
  - **Planning Problems**: find actions that map given state into a final state
  - **Planning with Feedback**: find strategy for mapping state into final state

- All of these models are **intractable**, and some extremely powerful (POMDPs)
- The challenge is computational: **how to scale up**
- For this, solvers must **recognize and exploit structure** of the problems
- Methodology is **empirical**: benchmarks and competitions
- Significant progress in recent years
SAT and CSPs

- **SAT**: determine if there is a truth assignment that satisfies a set of clauses

\[ x \lor \neg y \lor z \lor \neg w \lor \cdots \]

- Problem is NP-Complete, which in practice means worst-case behavior of SAT algorithms is exponential in number of variables

- Yet current SAT solvers manage to solve problems with thousands of variables and clauses, and used widely (circuit design, verification, planning, etc)

- Key is efficient (poly-time) inference in every node of search tree: unit resolution, conflict-based learning, . . .

- Many other ideas logically possible, but do not work (don’t scale up).

- Same for Constraint Satisfaction Problems (CSPs)
Related Tasks: From SAT to Bayesian Networks

- **Weighted MAX-SAT**: find assignment \( \sigma \) that minimizes total cost \( w(C) \) of violated clauses

\[
\sum_{C: \sigma \not\models C} w(C)
\]

- **Weighted Model Counting**: Adds up 'weights' of satisfying assignments:

\[
\sum_{\sigma: \sigma \models T} \prod_{L \in \sigma} w(L)
\]

SAT methods extended to these other tasks, closely connected to *probabilistic* reasoning tasks over **Bayesian Networks**:

- **Most Probable Explanation (MPE)** easily cast as Weighted MAX-SAT
- **Probability Assessment** \( P(X|Obs) \) easily cast as Weighted Model Counting

Current best BN solvers built over this formulation (ACE, Weighted Cachet)
The underlying structure of SAT, CSPs, and BNets can be expressed by graph $G$

A parameter called the (induced) treewidth $w(G)$ measures then how 'close' is $G$ to a Tree, $w(G) = 2$ for $G$ above, and $w(G) = 1$ if $G$ is a tree.

All SAT, CSP, and BN tasks are exponential in $w(G')$, and thus solvable in polynomial time for bounded $w(G)$ (e.g., trees)

These models often referred to as graphical models (Dechter 03)
Action Selection in Planning Models

• (Classical) Planning concerned with finding a sequence of actions that transforms an initial state into a goal state. This is called a plan.

• States are truth assignments as before, represented by the atoms that are true.

• Actions add certain atoms and delete others, provided their preconditions hold.

• A planner is a solver that takes a planning problem (initial and goal states, and actions) and outputs a plan.

• The cost of a plan given by the number of actions.

\[
\text{Init, Actions, Goals} \rightarrow \text{Planner} \rightarrow \text{Plan}
\]
Given the **actions** that move a 'clear' block to the table or onto another 'clear' block, **find a plan** to achieve the goal.

Problem becomes **finding a path** in a **directed graph**.
How planning problems are solved?

- How do we find a route in a map from Barcelona to Madrid?

- Need **sense of direction**: whether an action takes us towards the goal or not

- In AI, this is captured by **heuristic functions**: functions $h(s)$ that provide an **estimate of the cost** (number of actions) from any state $s$ to the goal.
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• In AI, this is captured by **heuristic functions**: functions \( h(s) \) that provide an estimate of the cost (number of actions) from any state \( s \) to the goal

• Key new idea in planning is that useful heuristics \( h(s) \) can be obtained automatically from the problem encoding

• **How?** Solving a **relaxed problem** where **deletes** are dropped

• Heuristic \( h(s) \) is cost of solution found for **relaxed problem** in **poly-time**
How is our problem solved?

- Provided with the **heuristic** $h$, plan found without search by **hill-climbing**
- Actually, only the states reached by the actions in **blue** evaluated in FF
The appraisals $h(s)$ from a cognitive point of view

- they are **opaque** and thus cannot be **conscious**

  *meaning of symbols in the relaxation is not the normal meaning; e.g., objects can be at many places at the same time as old locations not deleted*

- they are **fast and frugal** (linear-time), but unlike the ’fast and frugal heuristics’ of Gigerenzer et al. are **general**

  *they apply to all problems fitting the model (planning problems)*

- they play the role of ’**gut feelings**’ or ’**emotions**’ according to De Sousa 87, Damasio 94, Evans 2002, Gigerenzer 2007

  *providing a guide to action while avoiding infinite regresses in the decision process*
Status of Classical Planning

- The good news: **Classical planning works!**
  - *Large problems solved very fast (non-optimally)*

- **Model simple but useful**
  - *Operators not primitive; can be policies themselves*
  - *Fast closed-loop replanning able to cope with uncertainty sometimes*

- Not so good; **limitations:**
  - *Does not model Uncertainty (no probabilities)*
  - *Does not deal with Incomplete Information (no sensing)*
  - . . .
Beyond Classical Planning: Two Strategies

1. **Top-down**: Develop solver for more general class of models; e.g., Markov Decision Processes (MDPs), Partial Observable MDPs (POMDPs), . . .
   
   +: generality  
   -: complexity

2. **Bottom-up**: Extend the scope of current 'classical' solvers
   
   +: efficiency  
   -: generality
The Trouble with Incomplete State Information

Problem: A robot must move from an uncertain $I$ into $G$ with certainty, one cell at a time, in a grid $n \times n$. No sensing is available.

- Conformant and classical planning look similar except for uncertain $I$
- Plans, however, may be quite different: best conformant plan above must move robot to a corner first! (to localize)
**Wumpus World PEAS description**

Performance measure
- gold +1000, death -1000
- -1 per step, -10 for using the arrow

Environment
- Squares adjacent to wumpus are smelly
- Squares adjacent to pit are breezy
- Glitter iff gold is in the same square
- Shooting kills wumpus if you are facing it
- Shooting uses up the only arrow
- Grabbing picks up gold if in same square
- Releasing drops the gold in same square

Actuators Left turn, Right turn,
- Forward, Grab, Release, Shoot

Sensors Breeze, Glitter, Smell
How to solve planning problems with incomplete information?

- Action selection problem in classical planning (full state info, deterministic actions) solved by automatic extraction of informative heuristic functions \( h(s) \) that estimate cost to goal

- Action selection problem \( P \) in planning with sensing pursued in two ways:
  - extract informative heuristics \( h(b) \) automatically over beliefs \( b \)
  - convert automatically into problem \( K(P) \) with no incomplete information

- Both approaches optimal for optimal heuristic \( h(b) \) and complete translation \( K(P) \); although fast approximations used instead

- A number of planning competitions exist to evaluate ideas and push the state of the art . . .
Summary

- A **research agenda** that has emerged in last 20 years: **solvers** for a range of **intractable models**

- **Solvers** unlike other programs are **general** as they do not target individual problems but families of problems (**models**)

- The challenge is **computational** and the methodology **empirical**

- Consistent **progress**:
  - efficient but effective inference methods (derivation of $h$, conflict-learning)
  - islands of tractability (treewidth methods and relaxations)
  - transformations (compiling away incomplete info, extended goals, . . . )

- While the agenda is technical, resulting ideas likely to be **relevant** for understanding general intelligence and human cognition
How people solve this problem?

- Blocks looks too easy; psychologists preferred puzzles like Tower of Hanoi. Yet
  - Blocks is not trivial for a general solver, and indeed
  - Language and Perception easy for people but not computationally

- Are these problems solved using 'domain-knowledge'?
  - not clear: easy to introduce variations where knowledge does not apply
  - not necessary: can be solved provided 'right inferences' are captured
Bayesian Networks

A Bayesian Network (Pearl 1988) is a compact representation of a joint probability distribution over a set of variables $X_1, \ldots, X_n$ made up of:

- a DAG where the nodes are the variables $X_1, \ldots, X_n$

- Conditional probability tables $prob(X_i|pa(X_i)), i = 1, \ldots, n$, where $pa(X_i)$ refers to the parents of $X_i$ in the DAG

The DAG implicitly defines a set of independenteses that result in joint distrib.

\[
P(X_1, \ldots, X_n) = \prod_{i=1,n} P(X_i|pa(X_i))
\]

A Hidden Markov Model is a Bayesian Tree solvable in linear-time.
Executing Policies vs Finding the Policies

- Solutions to planning problems (Strips, MDPs, POMDPs, . . . ) can be expressed as stimulus-action rules (and many other ways)

- Yet, expressing solutions (to Strips, MDPs, . . . , ..) is different than finding solutions

- In Situated-AI (Brooks 90), it is assumed that the programmer solves the problem in his/her head, and the robot just executes this solution

- In Model-based AI, solutions computed by solver.
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  Is this necessary?
  
  ▶ in lower animals, solutions **hardwired** by evolution
  ▶ in humans, evolution and culture have produced **solution methods** as well

- **Learning** is the third approach to get solutions, different than **Model-based Solver** or **Programming/Evolution**