# Course on Automated Planning: Introduction

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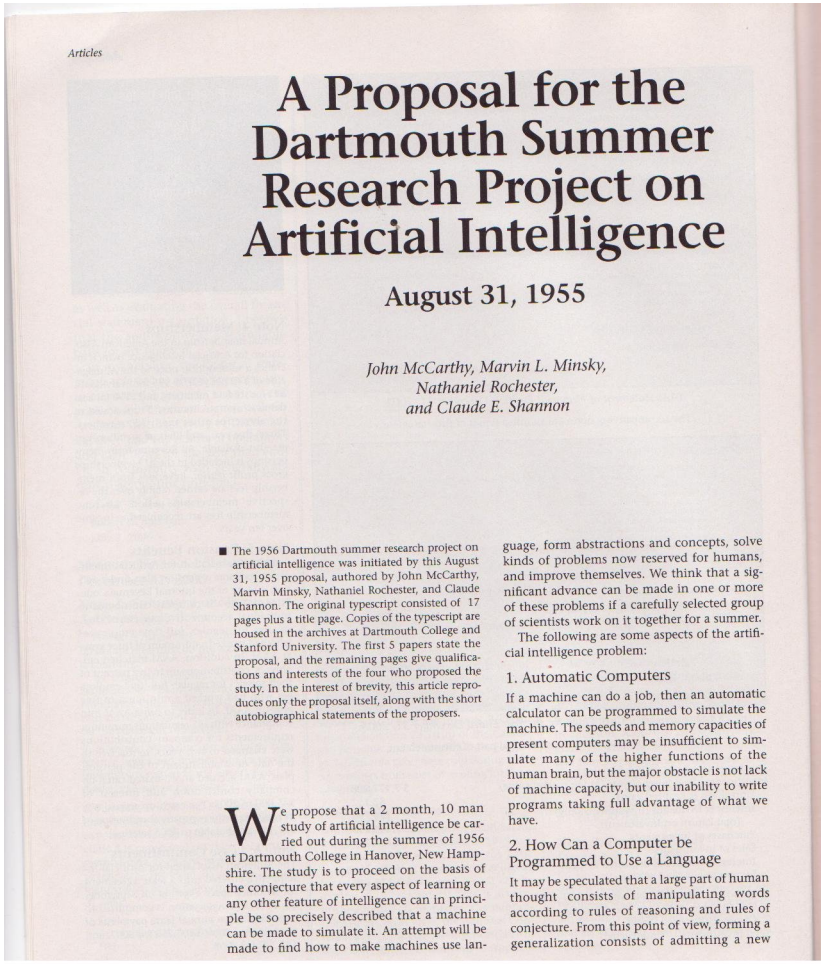
# Plan for the Course (6 days)

1. Intro to AI and Automated Problem Solving
2. Classical Planning as Heuristic Search and SAT
3. Beyond Classical Planning: Transformations
   - ▷ *Soft goals, Conformant Planning, Finite State Controllers, Plan Recognition*
4. Planning with Uncertainty: Markov Decision Processes (MDPs)
5. Planning with Incomplete Information: Partially Observable MDPs (POMDPs)
6. Open Challenges in the field; Wrap up

# First Lecture

- Some AI history
- The Problem of Generality in AI
- Models and Solvers
- Planning

# Darmouth 1956



Articles

## A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence

August 31, 1955

*John McCarthy, Marvin L. Minsky, Nathaniel Rochester, and Claude E. Shannon*

■ The 1956 Dartmouth summer research project on artificial intelligence was initiated by this August 31, 1955 proposal, authored by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon. The original typescript consisted of 17 pages plus a title page. Copies of the typescript are housed in the archives at Dartmouth College and Stanford University. The first 5 papers state the proposal, and the remaining pages give qualifications and interests of the four who proposed the study. In the interest of brevity, this article reproduces only the proposal itself, along with the short autobiographical statements of the proposers.

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

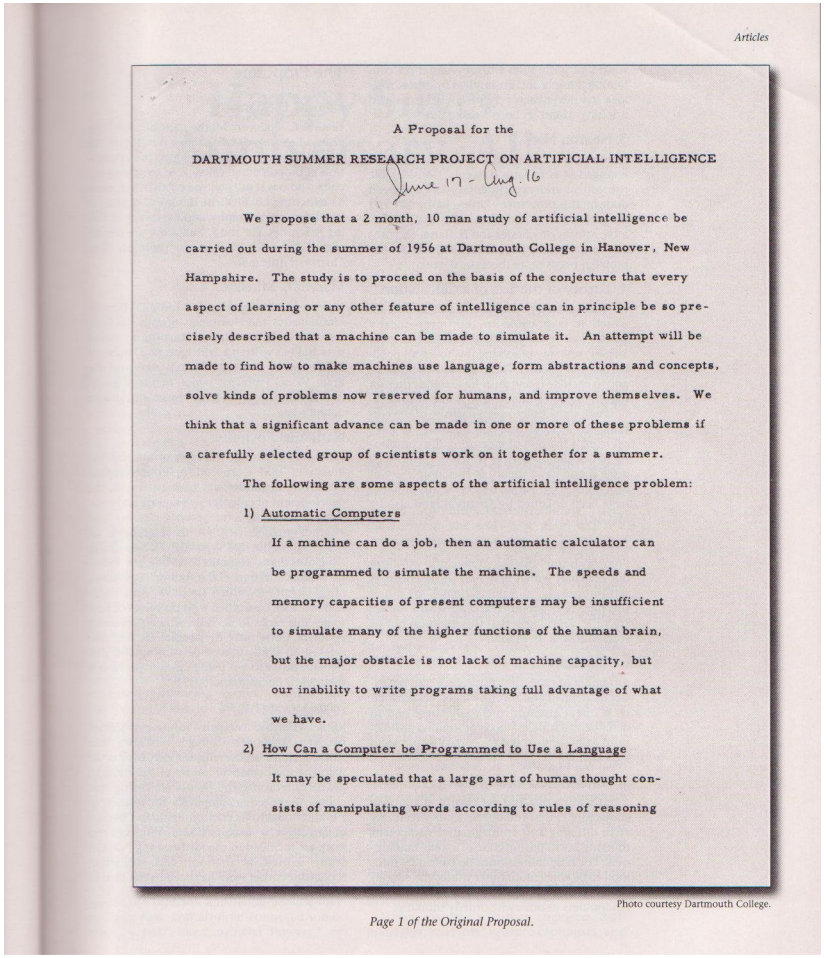
The following are some aspects of the artificial intelligence problem:

### 1. Automatic Computers

If a machine can do a job, then an automatic calculator can be programmed to simulate the machine. The speeds and memory capacities of present computers may be insufficient to simulate many of the higher functions of the human brain, but the major obstacle is not lack of machine capacity, but our inability to write programs taking full advantage of what we have.

### 2. How Can a Computer be Programmed to Use a Language

It may be speculated that a large part of human thought consists of manipulating words according to rules of reasoning and rules of conjecture. From this point of view, forming a generalization consists of admitting a new



Articles

A Proposal for the

DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

June 17 - Aug. 16

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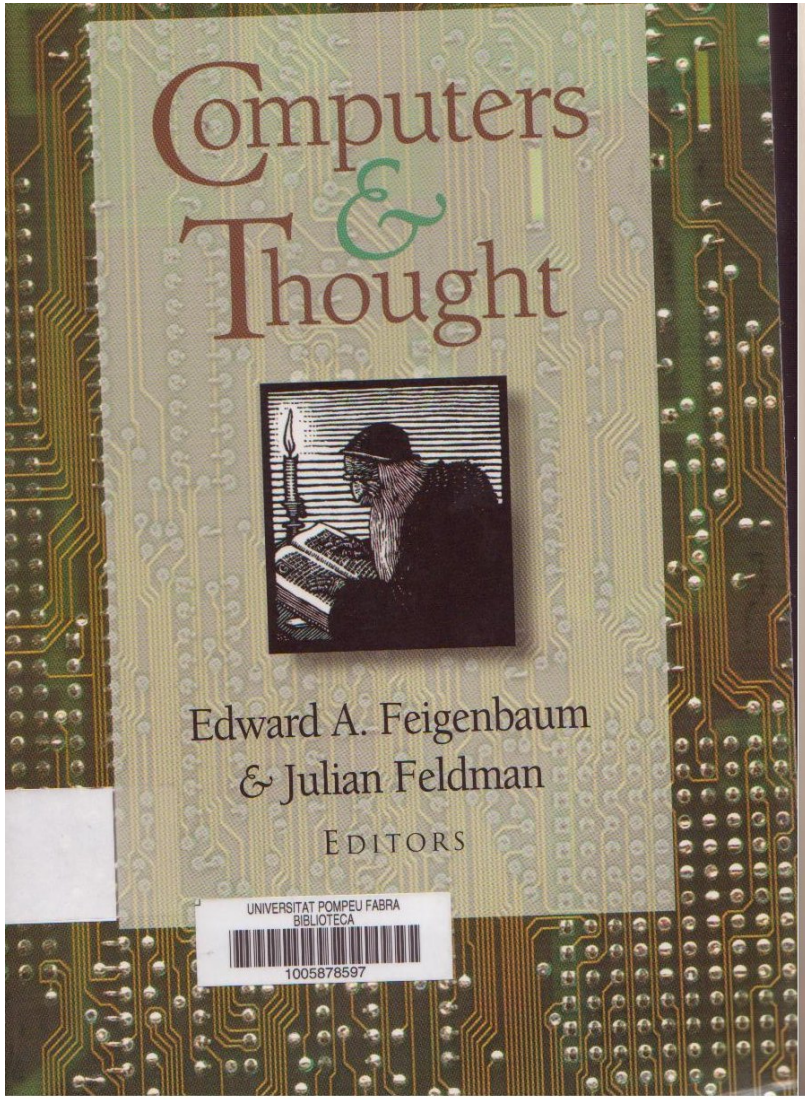
Photo courtesy Dartmouth College.

*Page 1 of the Original Proposal.*

"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"

# Computers and Thought 1963




Contents




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".*

# AI, Programming, and AI Programming

Many of the key AI contributions in 60's, 70's, and early 80's had to to with **programming** and the **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 . . .

# Methodological Problem:

**Theories expressed as programs cannot be proved wrong: when a program fails, it can always be blamed on 'missing knowledge'**

Three approaches to this problem

- narrow the domain (expert systems)
  - ▷ problem: lack of generality
- accept the program is just an illustration, a demo
  - ▷ problem: limited scientific value
- fill up the missing knowledge (intuition, commonsense)
  - ▷ problem: not successful so far

# 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)

Many of these criticisms of mainstream AI partially valid then; less valid now.

# AI Research in 2010

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

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

- **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)
- **Solution:** $P = 10 \;\; ; \;\; J = 30$

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

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

- The basic models and tasks include
  - **Constraint Satisfaction/SAT**: find state that satisfies constraints
  - **Bayesian Networks:** find probability over variable given observations
  - **Planning Problems:** find action sequence that produces desired state
  - **Planning with Feedback:** find strategy for producing desired 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

$$x \vee \neg y \vee z \vee \neg w \vee \cdots$$

- 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:

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

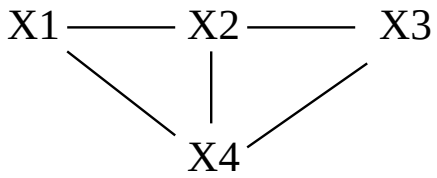
SAT methods extended to these other tasks, closely connected to **probabilistic** reasoning tasks over **Bayesian Networks** (and Neural Networks):

- **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)

# Further ties between Deductive and Probabilistic Inference

- 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)

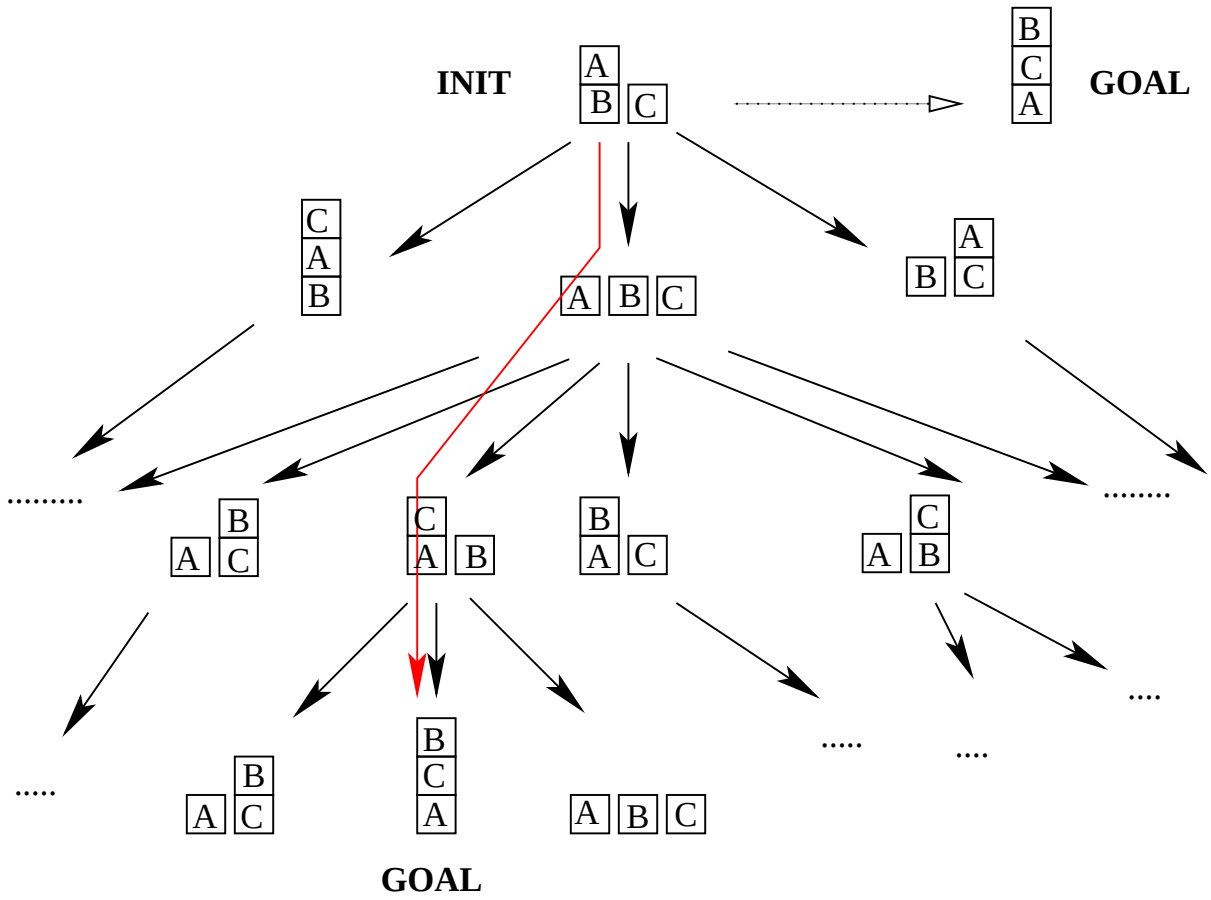
- Resolution methods for all these models closely related

# Planning Models: Producing States by Applying Actions

- **(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 is given by the **number of actions**

$$\textit{Init, Actions, Goals} \Longrightarrow \boxed{\textit{Planner}} \Longrightarrow \textit{Plan}$$

# Example

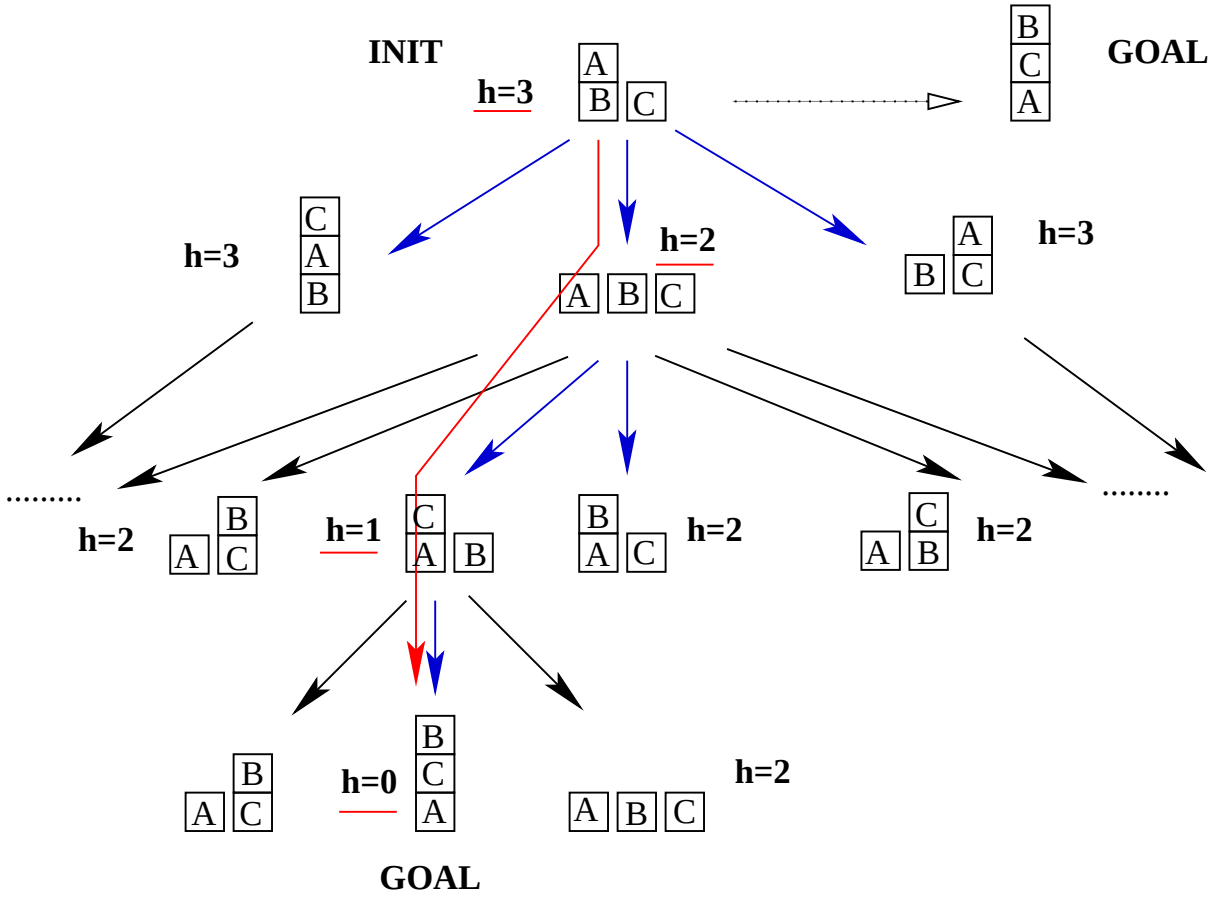



- Given the **actions** that move a 'clear' block to the table or onto a another 'clear' block, **find a plan** to achieve the goal
- Problem becomes **finding a path** in a **directed graph**

# 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
- **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 states reached by actions in blue need to be evaluated

# Summary: AI and Automated Problem Solving

- 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**: how to scale up
- Sheer **size of problem** shouldn't be impediment to meaningful solution
- **Structure** of given problem must recognized and **exploited**
- Lots of room for **ideas** but 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, . . . )