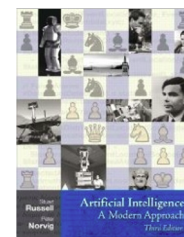


Planning

- Introduction
 - Planning vs. Problem-Solving
 - Representation in Planning Systems
- Situation Calculus
 - The Frame Problem
- STRIPS representation language
 - Blocks World
- Planning with State-Space Search
 - Progression Algorithms
 - Regression Algorithms
- Planning with Plan-Space Search
 - Partial-Order Planning
 - The Plan Graph and GraphPlan
 - SatPlan

Material from
Russell & Norvig,
chapters 7.7. and 10



Many slides based on
Russell & Norvig's slides
[Artificial Intelligence:
A Modern Approach](#)

Some based on Slides by
Lise Getoor and Tom Lenaerts

Planning

https://www.youtube.com/watch?v=_U21fT8VLp0



Planning problem

- Planning is the task of coming up with a sequence of actions that will achieve a goal starting from an initial state
 - many search-based problem-solving agents are special cases
- **Given:**
 - a set of **action descriptions** (defining the possible primitive actions by the agent),
 - an initial **state description**, and
 - a **goal state description** or predicate,
- **Find** a plan, which is
 - a **sequence of action** instances, such that executing them in the initial state will change the world to a state satisfying the goal-state description.
- Goals are usually specified as a conjunction of subgoals to be achieved

Key Novelty:
Actions and States are described with properties

Application Scenario

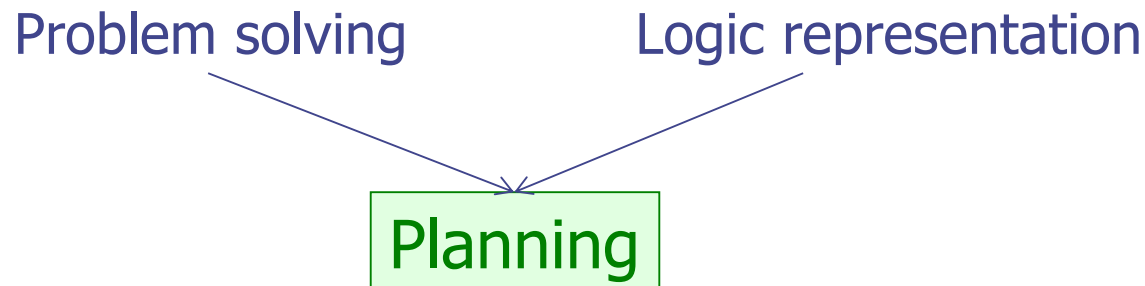
- Classical planning environment
 - fully observable, deterministic, finite, static, discrete
- Some practical Applications
 - design and manufacturing
 - airports
 - military operations
 - games
 - space exploration
 - transportation
 - enterprise
 - ...

Planning vs. Problem Solving

- Planning and problem solving methods can often solve the same sorts of problems
- Planning is more powerful because of the representations and methods used
 - States, goals, and actions are decomposed into sets of sentences (usually in first-order/relational logic)
- Planning can **analyze** the **effects of actions**
 - The **successor function** is a kind of **black box**: it must be “applied” to a state to know which actions are possible in that state and what are the effects of each one
 - An explicit representation of the possible actions and their effects would help the problem solver
- **Subgoals** can often be planned independently, reducing the complexity of the planning problem
- Search may be through **plan space** rather than **state space**

Representation in Planning

- In **Problem Solving**, actions, states, and goals are **black boxes**
 - each problem has its own representation
 - agent does not understand the representations of actions, states, and goals
 - cannot exploit relations between them
- **Planning** works with **explicit representations** of actions, states, and goals
 - typically in some form of logical calculus



Key Problems

- Which actions are relevant?
 - Example: Goal is **have (milk)**
 - the agent may have billions of possible actions
 - e.g., one **buy**-action for each possible product in a store
 - an intelligent planner will know that **buy (X)** will cause **have (X)** , and only consider the action **buy (milk)**
- What is a good heuristic functions?
 - Problem:
 - states are domain-specific data structures, and new heuristics must be supplied for each new problem
 - Example: Goal is buying n different items
 - Number of plans grows exponentially with n
 - Problem-independent heuristics are needed
 - e.g., number of subgoals that have already been reached
- How to decompose a problem?

Decomposable Problems

- **Goals** are often given as a **conjunction of subgoals**
 - e.g., **have(milk) & have(bread)**
 - In this example, each subgoal can be solved independently

Other problems can be **decomposed** into subproblems:

- Example: overnight delivery of a set of packages
 - Planning a complete route for all packages at once is very expensive ($O(n!)$ different routes)
→ Better decompose the problem:
 - First distribute the packages to the airports nearest to the respective destinations
 - Then plan separate routes from each airport to the final destinations
→ $O(k \cdot (n/k)!)$ different routes if we have k airports
 - much less than $O(n!)$

Nearly Decomposable Problems

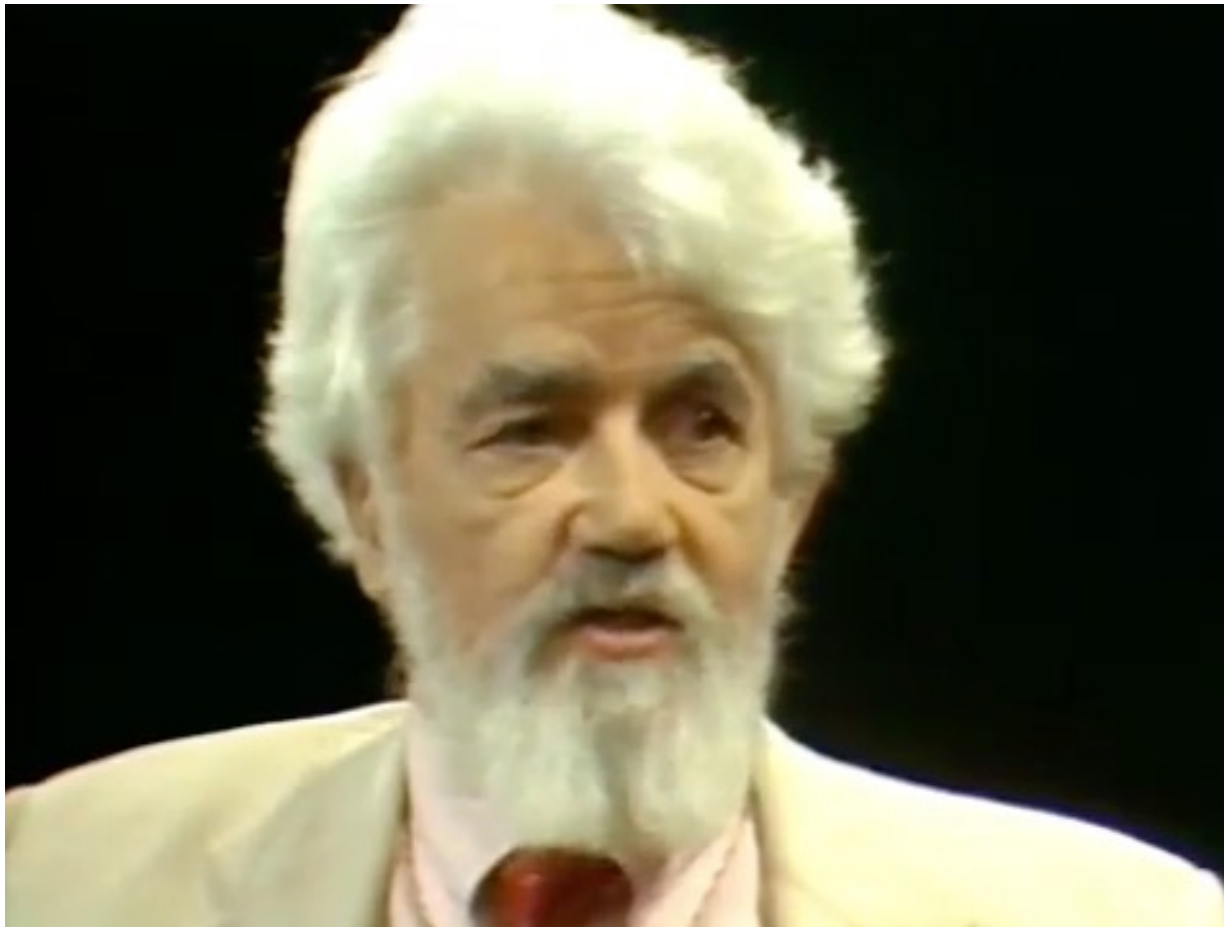
- Completely decomposable problems are rare
 - typically there are interactions between subgoals
- Nearly decomposable problems
 - planning for subgoals is possible
 - but additional work may be required to bring the partial results together
- Example:
 - Independent plans for **have (milk)** and **have (bread)** may have the result that two different super-markets are visited

Major Approaches to Planning

- Situation calculus
- State space planning
- Partial order planning
- Planning graphs
- Planning with Propositional Logic
- Hierarchical decomposition (HTN planning)
- Reactive planning

Logic for Intelligent Behaviour

<https://www.youtube.com/watch?v=Ozipf13jRr4&t=773s>



John McCarthy

Planning in First-Order Logic

Principal Idea:

- Formulate planning problem in First-Order Logic (FOL)
 - states (and goals) are conjunctions of literals
 - actions are logical rules
- Use theorem prover to find a proof for the goal
 - the actions used in this proof are the plan
 - e.g., use PROLOG

Key Problem:


- How to represent change?
 - a) add and delete sentences from the Knowledge Base (KB) to reflect changes
 - b) all facts are indexed by a situation variable → situation calculus

PROLOG-like Logical Notation

- **Constant:** represents some objects
 - starts with a number or a lower-case letter
 - e.g., `pam`, `bob`, `liz`, `1`, `pi`, `true`, etc.
 - functions are like constants, but complex expressions
- **Variable:** denotes some unknown object/constant
 - starts with an upper-case letter or an underscore
 - e.g. `X`, `Person`, `Nummer`, `_42`, etc.
 - within a conjunction of literals, same variables refer to same objects
 - but may be different objects in different conjunctions / rules
- **Predicate:** denotes a relation between two objects
 - starts with a lower-case letter
 - e.g., `parent`, `male`, `female`
- **Literal:** a predicate symbol with some arguments
 - e.g., `parent(pam,bob)`, `at(pam,X)`, `airport(X)`
- **Rule:** an implication, typically written `Head :- Cond1, Cond2,`
 - e.g., `grandparent(X,Y) :- parent(X,Z), parent(Z,Y).`

Situation Calculus

- A **situation** is a snapshot of the world at some instant in time
- Every true or false statement is made with respect to a particular situation
 - Add **situation variables** to every predicate.
 - $\text{at}(\text{agent}, 1, 1)$ becomes $\text{at}(\text{agent}, 1, 1, \mathbf{s0})$, i.e., $\text{at}(\text{agent}, 1, 1)$ is true in situation (i.e., state) **s0**.
- Add a new function, **result(a, s)**, that maps a situation s into a new situation as a result of performing action a .
 - For example, $\text{result}(\text{forward}, s)$ is a function that returns the successor state (situation) to s after performing action `forward`
 - Note that this is just notation!
 - Logical functions are not implemented or evaluated!
 - They are used in pattern matching



John McCarthy, Turing Awardee and inventor of the situation calculus, also coined the term “Artificial Intelligence”

Situation Calculus

- **Actions** can be represented as logical rules that describe which states can be valid. Example:
 - The action *agent-walks-to-location-y* could be represented by the PROLOG rule

`at(A, Y, result(walk(Y), S)) :- at(A, X, S) .`

agent A is now at location Y in state `result(walk(Y), S)`
if it was at location X in state S and performed action `walk(Y)`

- **Action sequences** result in nested function expressions
 - `at(home, result(go(home),
 result(go(grocery),
 result(go(hardwarestore), s0))))`
 - In the state that results from the application of `go(home)` to the state that results from the application of `go(grocery)` to the state that results from the application of `go(hardwarestore)` to the state `s0` the proposition `at(home)` holds.

Situation Calculus

- **Actions** can be represented as logical rules that describe which states can be valid. Example
 - The action *agent-walks-to-location-y* could be represented by the PROLOG rule

`at(A, Y, result(walk(Y), S)) :- at(A, X, S) .`

agent A is now at location Y in state `result(walk(Y), S)`
if it was at location X in state S and performed action `walk(Y)`

- **Action sequences** are also useful: `results(l, s)` is the result of executing the list of actions `l` starting in `s`:
 - corresponding rules could be included as **short-hand notation** into inference engine

`results([], S) = S`

`results([A|P], S) = results(P, result(A, S))`

Situation Calculus Planning

- **Initial state**

- a logical sentence that describes current situation S_0

`at(home, s0), not(have(milk, s0)), not(have(bread, s0)),
not(have(drill, s0))`

- **Goal state**

- a logical sentence that describes the goal state

`at(home, G), have(milk, G), have(bread, G), have(drill, G)`

- **Actions (Operators)**

- logical rules that describe the effects of actions

`have(milk, result(A, S)) :- at(grocery, S),
 A = buy(milk).`

`have(milk, result(A, S)) :- have(milk, S),
 A != drop(milk).`

etc.

Situation Calculus Planning

Solution

A sequence of actions P (a plan) that, when applied to the initial state, yields a situation satisfying the goal query

$\text{at}(\text{home}, G), \text{have}(\text{milk}, G), \text{have}(\text{bread}, G), \text{have}(\text{drill}, G)$

with $G = \text{results}(P, s_0)$

- P could, for example, be something like

$$P = [\text{go}(\text{grocery}), \text{buy}(\text{milk}), \text{buy}(\text{bread}), \\ \text{go}(\text{hardwareStore}), \text{buy}(\text{drill}), \text{go}(\text{home})]$$

- **Projection**
 - determine the effect of a sequence of actions
- **Planning**
 - find the sequence of action with the desired effect

The Frame Problem

- The action rules only specify what aspects change when an action is performed

```
have(milk, result(A, S)) :- at(grocery, S),  
                             A = buy(milk).
```

- But we also need rules that describe what does **not** change!

```
at(grocery, result(A, S)) :- at(grocery, S),  
                             A = buy(milk).
```

If we are in a grocery store and buy milk, we remain in the grocery store.

- Such **frame axioms** are necessary for all possible combination of state predicates and actions
- **representational frame problem:**
 - we do not want to represent each such possible combination
- **inferential frame problem:**
 - most of the work will be spent in deriving that nothing changes

Situation Calculus (SC) Planning: More Problems

- **Qualification problem:**
 - difficulty in specifying all the conditions that must hold in order for an action to work
 - e.g., `go` action might fail for various reasons (locked doors, hit by a truck while crossing the street, ...)
- **Ramification problem:**
 - difficulty in specifying all of the effects that will hold after an action is taken
 - e.g., if the agent carries something, a `go` action will move that thing too...
- **Complexity:**
 - problem solving (search) is exponential in the worst case
- **Optimality:**
 - resolution theorem proving can only find *a* proof (plan), not necessarily a *good* plan

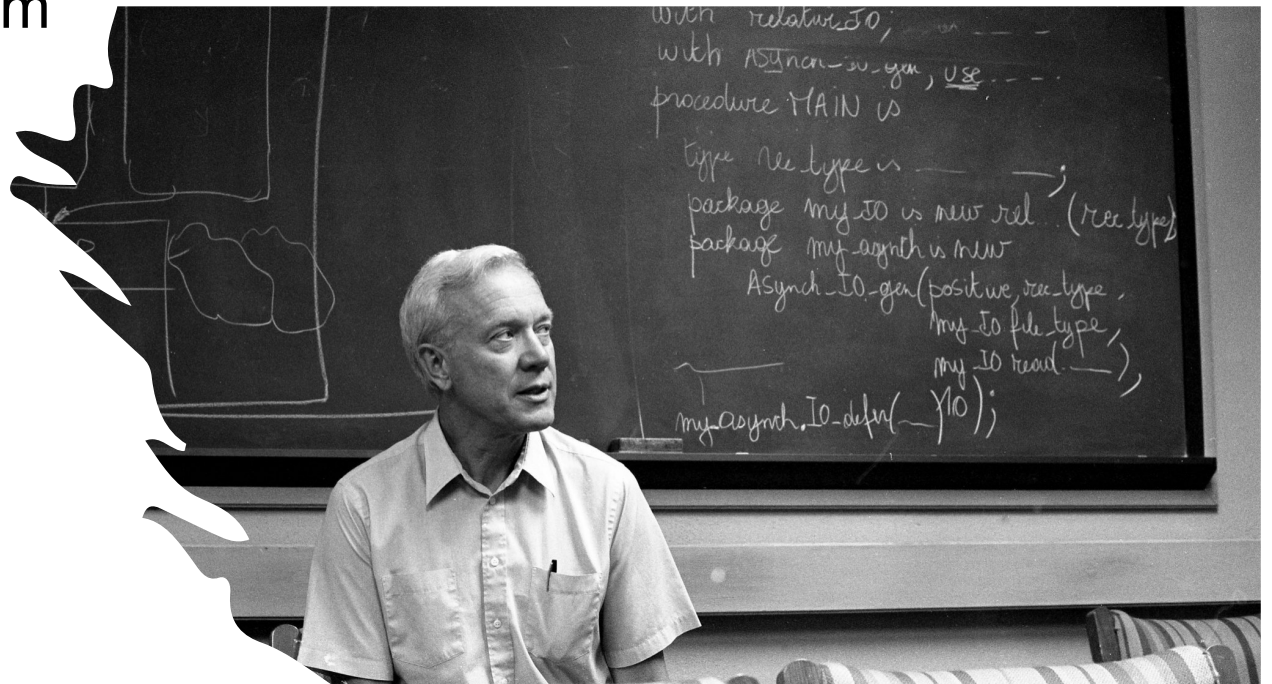
Representation Languages for Planning

- Some of the afore-mentioned problems can be solved by better knowledge representation
 - some of them will necessarily remain (e.g., qualification and ramification problems)
- **Alternative approach**
 - we restrict the language
 - use a special-purpose algorithm (a planner) rather than general theorem prover
- Criteria for a **good representation language**
 - **Expressive** enough to describe a wide variety of problems
 - Restrictive enough to allow **efficient** algorithm
 - Planning algorithm should be able to take advantage of the logical **structure** of the problem.

The STRIPS Language

STRIPS (STanford Research Institute Problem Solver)

- classical planning system (Fikes & Nilsson, 1971)
- representation of states and actions quite influential



On (A* and) STRIPS Planning

<https://www.youtube.com/watch?v=mQ7M-zhiu7U>



STRIPS: Representation of States

- Decompose the world in logical conditions and represent a state as a conjunction of positive literals.
 - Propositional literals
 - e.g., `poor` \wedge `unknown`
 - First-Order literals
 - e.g., `at(plane1, melbourne)` \wedge `at(plane2, sydney)`
 - grounded (contain no variables)
 - function-free (contain no function symbols)
- Closed world assumption (CWA)
 - what is not known to be true, is assumed to be false

STRIPS: Representation of Goals

- like any other state, a **goal** is a **conjunction of positive ground literals**, e.g., `rich \wedge famous`
- may be partially instantiated:
 - e.g., `at(P,paris) \wedge plane(P)`
(some plane should be in Paris)
- A **goal is satisfied** if the state contains all literals in goal
 - e.g. `rich \wedge famous \wedge miserable` satisfies goal
- In the case of partially instantiated first-order predicates, the state must contain some instantiation of the literals
 - e.g., `at(spirit_of_st_louis,paris) \wedge plane(spirit_of_st_louis)`
satisfies the goal with the substitution
 $\theta = \{P/\text{spirit_of_st_louis}\}$

STRIPS: Representation of Actions

Preconditions: determine the applicability of an action

- conjunction of function-free literals
- the action is applicable if the preconditions match the current state (similar to goals)

Effects: describe the state change after executing an action

- conjunction of function-free literals
- typically divided into:
 - **ADD**-list: facts that become true after executing the action
 - **DELETE**-list: facts that become false after executing the action

```
Action( fly(P, From, To) ,  
  PRECOND: at(P,From) ,  
           plane(P) ,  
           airport(From) ,  
           airport(To)  
  ADD:      at(P,To)  
  DELETE:   at(P,From)  
)
```

Semantics of the STRIPS Language

- **What actions are applicable in a state?**
 - An action is applicable in any state that satisfies the precondition.
 - For First-Order action schema applicability involves a substitution θ for the variables in the **PRECOND**.

- **Example:**

`at(p1,jfk), at(p2,sfo), plane(p1), plane(p2),
airport(jfk), airport(sfo)`

satisfies

`at(P,From), plane(P), airport(From), airport(To)`

with

$\theta = \{P/p1, From/jfk, To/sfo\}$

- Thus the action `fly(P, From, To)` is applicable.

Semantics of the STRIPS Language

- **What effects do the actions have?**
 - The result of executing action a in state s is the state t
 - t is same as s except
 - Any literal P in the **ADD**-list is added
 - Any literal P in the **DELETE**-list is removed

- **Example**

ADD: $\text{at}(P, \text{To})$
DELETE: $\text{at}(P, \text{From})$

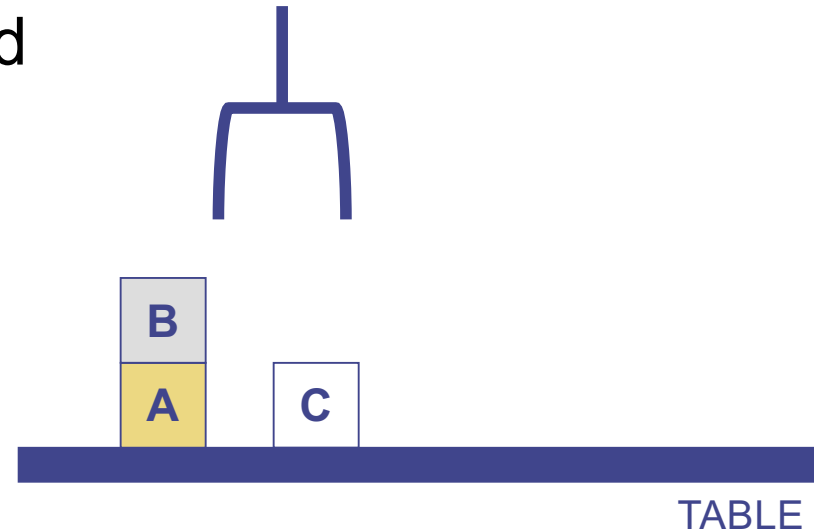
with substitution $\theta = \{P/p1, \text{From}/\text{jfk}, \text{To}/\text{sfo}\}$ results in state

~~$\text{at}(p1, \text{jfk})$~~ , $\text{at}(p2, \text{sfo})$, $\text{plane}(p1)$, $\text{plane}(p2)$,
 $\text{airport}(\text{jfk})$, $\text{airport}(\text{sfo})$, **$\text{at}(p1, \text{sfo})$** ,

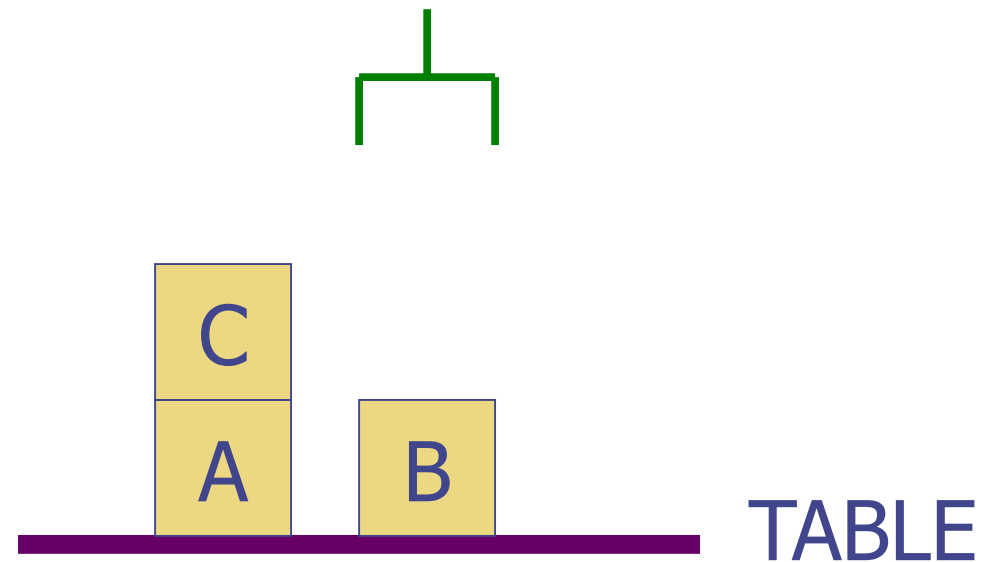
- **STRIPS assumption**
 - every literal **NOT** in the effect remains **unchanged**
 - avoids representational frame problem

Example: Blocks World

- Very famous AI toy domain
- The blocks world is a micro-world that consists of
 - a table
 - a set of blocks
 - a robot hand
- Operation
 - The robot hand can grasp a single block
 - The robot hand can move over the table (with or without a block)
 - The robot hand can release a block it is holding
 - Blocks can be stacked on top of each other if the top is clear
 - Any number of blocks can be on the table
 - The hand can only hold one block

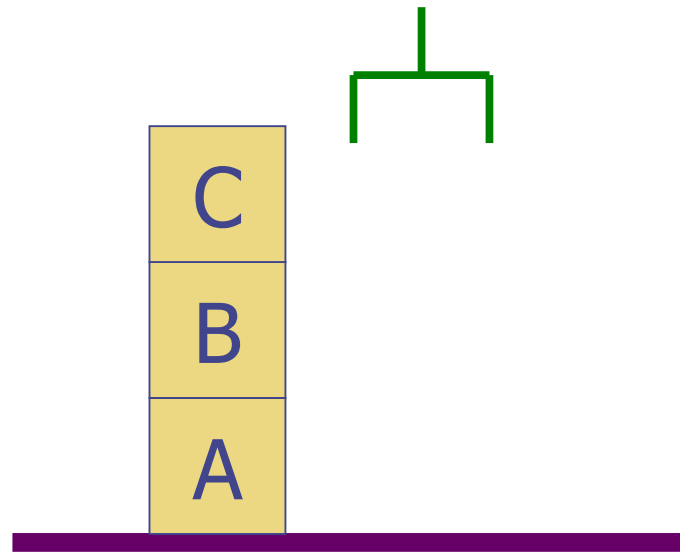


State Representation



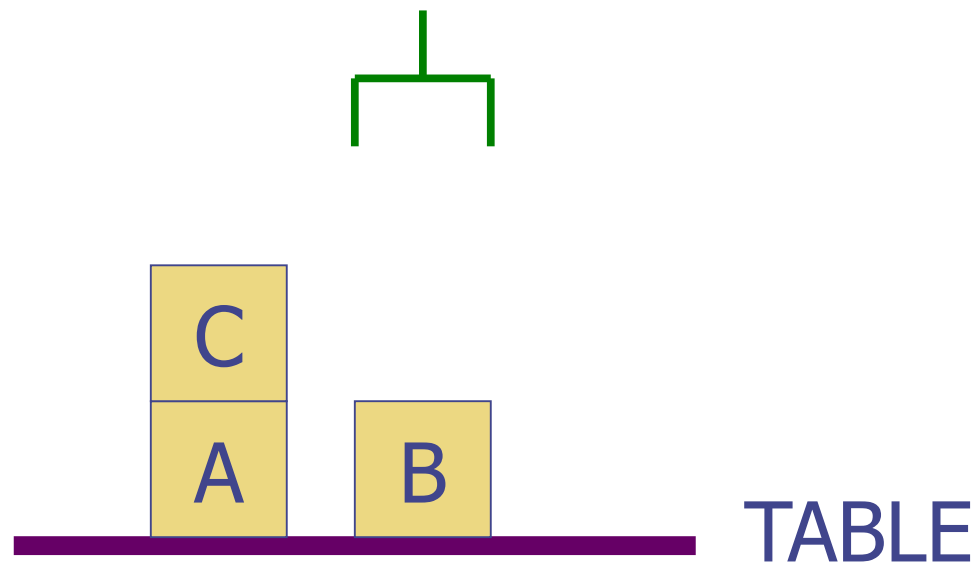
```
block(a), block(b), block(c),  
on(a,table), on(b,table), on(c,a),  
clear(b), clear(c), handempty
```

Goal Representation



`on(a, table), on(b, a), on(c, b)`

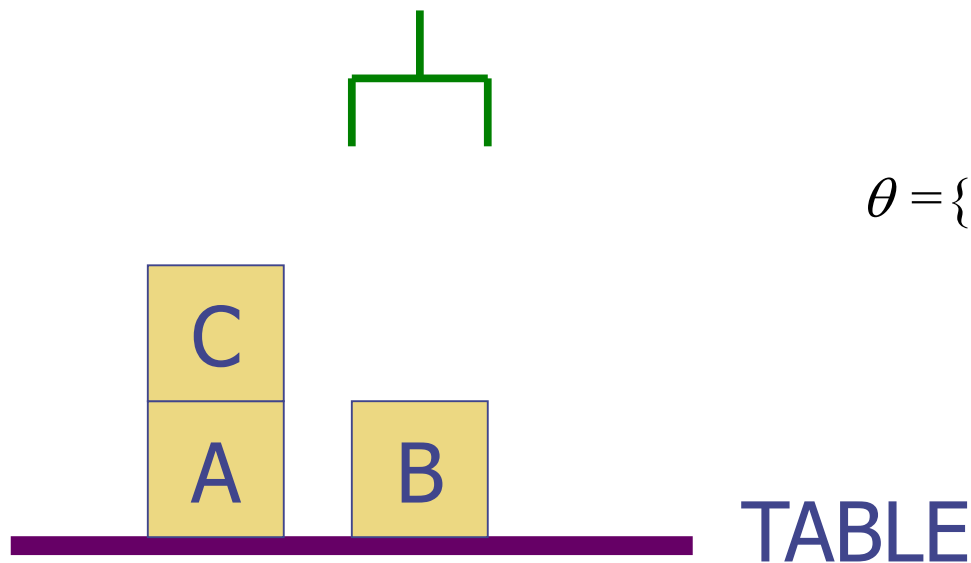
Action Application



```
Action( unstack(X,Y) ,  
PRECOND: handempty,  
         block(X) ,  
         block(Y) ,  
         clear(X) ,  
         on(X,Y) ,  
ADD:     holding(X) ,  
         clear(Y) ,  
DELETE:  handempty,  
         clear(X) ,  
         on(X,Y)  
)
```

```
block(a) , block(b) , block(c) ,  
on(a,table) , on(b,table) , on(c,a) ,  
clear(b) , clear(c) , handempty ,
```


Action Application



$$\theta = \{X/c, Y/a\}$$

```

Action( unstack(X,Y) ,
  PRECOND: handempty,
          block(X) ,
          block(Y) ,
          clear(X) ,
          on(X,Y) ,
  ADD:    holding(X) ,
          clear(Y) ,
  DELETE: handempty,
          clear(X) ,
          on(X,Y)
)

```

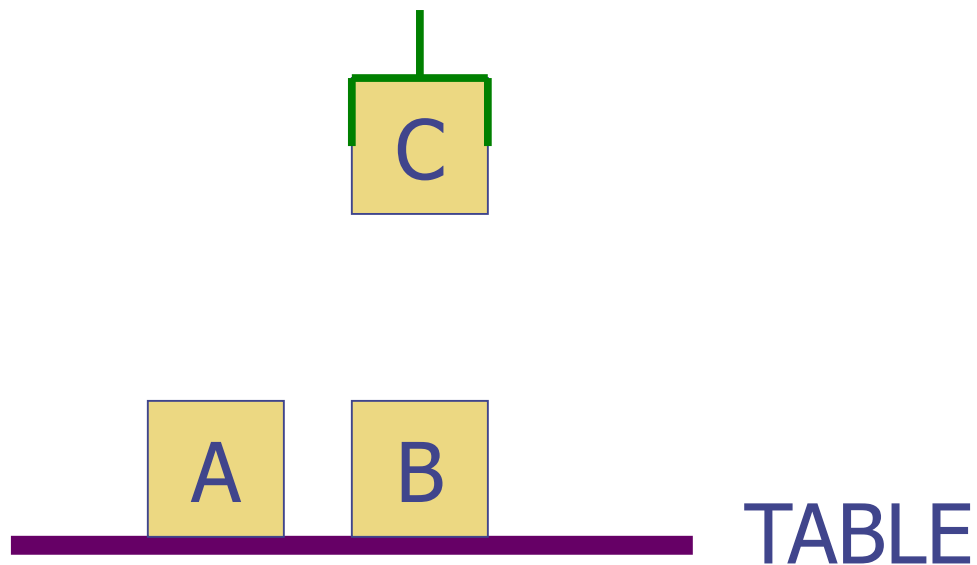
```

block(a) , block(b) , block(c) ,
on(a,table) , on(b,table) , on(c,a) ,
clear(b) , clear(c) , handempty ,
holding(c) , clear(a)

```

unstack(c,a)

Action Application



```

Action( unstack(X,Y) ,
PRECOND: handempty,
        block(X) ,
        block(Y) ,
        clear(X) ,
        on(X,Y) ,
ADD:    holding(X) ,
        clear(Y) ,
DELETE: handempty,
        clear(X) ,
        on(X,Y)
)
  
```

```

block(a) , block(b) , block(c) ,
on(a,table) , on(b,table) ,
clear(b) ,
holding(c) , clear(a)
  
```

unstack(c,a)

More Blocks-World Actions

```

Action( stack(X,Y) ,
PRECOND: holding(X) ,
        block(X) ,
        block(Y) ,
        clear(Y)
ADD:    handempty,
        clear(X) ,
        on(X,Y) ,
DELETE: holding(X) ,
        clear(Y)
)

```

```

Action( pickup(X) ,
PRECOND: handempty,
        block(X) ,
        clear(X) ,
        on(X,table) ,
ADD:    holding(X) ,
DELETE: handempty,
        clear(X) ,
        on(X,table)
)

```

```

Action( putdown(X) ,
PRECOND: holding(X)
ADD:    handempty,
        clear(X) ,
        on(X,table)
DELETE: holding(X)
)

```

Example: Air Cargo Transport

- Initial state:

```
at(c1,sfo), at(c2,jfk), at(p1,sfo),
  at(p2,sfo), cargo(c1), cargo(c2),
  plane(p1), plane(p2),
  airport(jfk), airport(sfo)
```

- Goal state:

```
at(c1,jfk), at(c2,sfo)
```

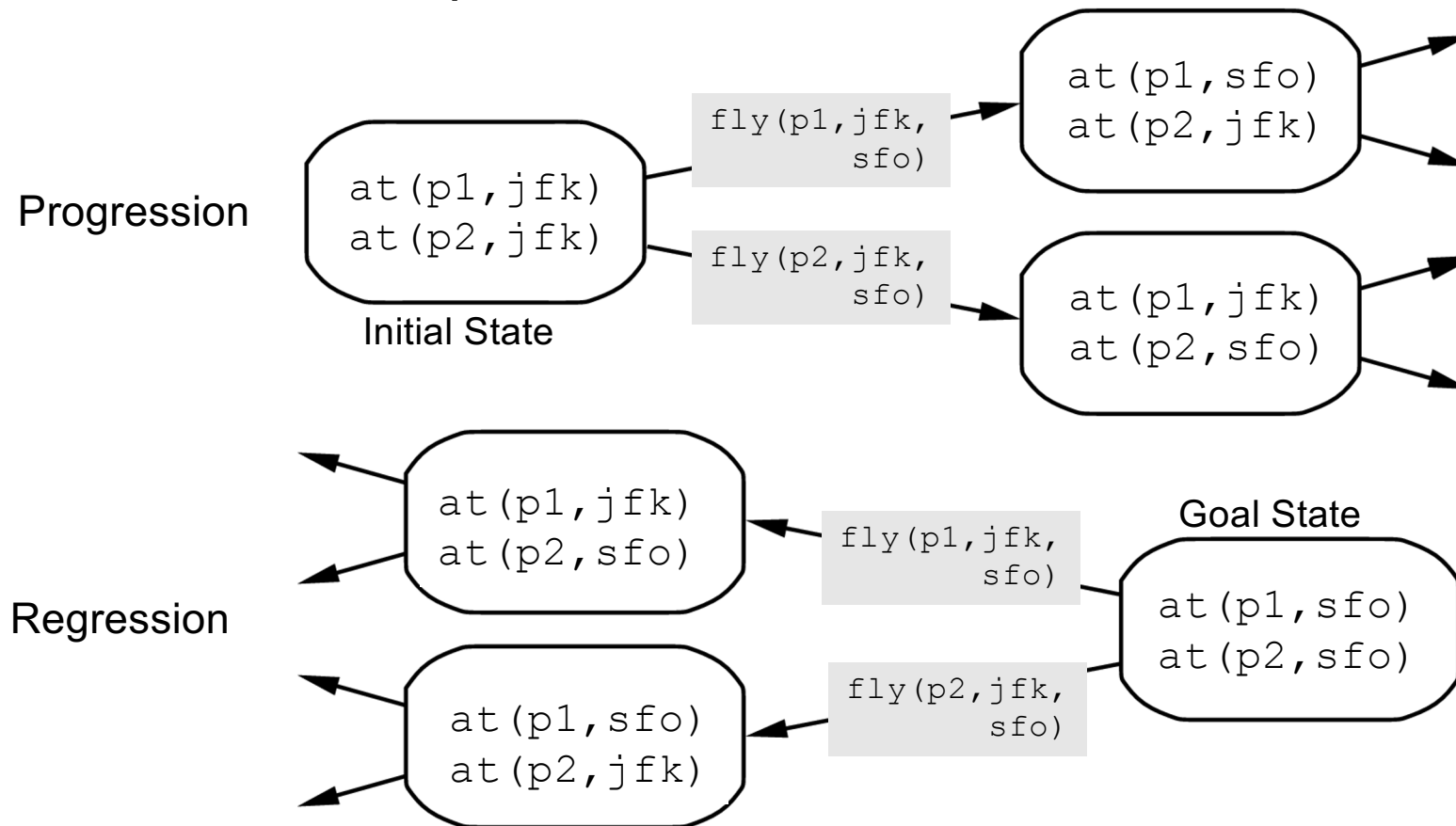
```
Action(unload(C,P,A) ,
  PRECOND: in(C,P) ,
           at(P,A) ,
           cargo(C) ,
           plane(P) ,
           airport(A)
  ADD:      at(C,A)
  DELETE:   in(C,P)
)
```

```
Action( fly(P,From,To) ,
  PRECOND: at(P,From) ,
           plane(P) ,
           airport(From) ,
           airport(To)
  ADD:      at(P,To)
  DELETE:   at(P,From)
)
```

```
Action( load(C,P,A) ,
  PRECOND: at(C,A) ,
           at(P,A) ,
           cargo(C) ,
           plane(P) ,
           airport(A)
  ADD:      in(C,P)
  DELETE:   at(C,A)
)
```

Planning with State-Space Search

- Progression planners
 - forward state-space search
- Regression planners
 - backward state-space search



Progression Algorithm

Formulation as state-space search problem:

- **Initial state** = initial state of the planning problem
 - Literals not appearing are false
- **Actions** = those whose preconditions are satisfied
 - Add positive effects, delete negative
- **Goal test** = does the state satisfy the goal
- **Step cost** = each action costs 1
 - could be changed if necessary

Search Algorithms

- function-free \rightarrow finite \rightarrow any complete graph search algorithm will yield a complete planner
- Efficiency is a problem
 - irrelevant action problem
 - good heuristic required for efficient search

Regression Algorithm

- In order to be able to use a backward search, we must be able to apply the STRIPS operators backwards
 - **Relevant actions**
 - actions that achieve one of the subgoals
 - i.e., the subgoal is on the actions' ADD-list
 - Example:
 - Goal state:
 $\text{at}(c1, a), \text{at}(c2, a), \dots, \text{at}(c20, a)$
 - Relevant action for first conjunct: $\text{unload}(c1, P, a)$
 - **Consistent actions**
 - Actions must not undo subgoals that are already achieved
 - Example:
 - $\text{load}(c1, P)$ will never appear in a plan for the above task because it will delete the subgoal $\text{at}(c1, a)$ which has been achieved with the first action
- How can an action be applied backwards?

Inverse Action Application

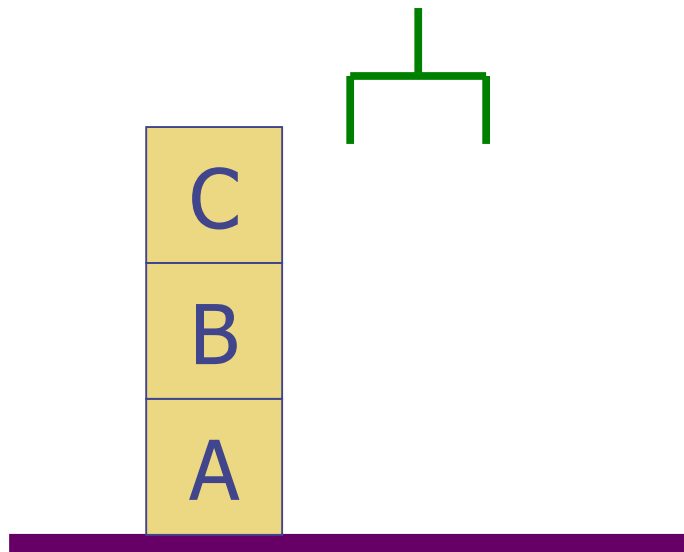
General process for predecessor construction

- Given a goal description G
- Let A be an action that is relevant and consistent
- The predecessor state is determined as follows:
 - **Positive effects** of A that appear in G are **deleted**.
 - because they are assumed to have been added by A (otherwise we do not need A in the plan)
 - **Each precondition literal** of A is **added** (unless it already appears)
 - because in order to apply A, we must now make find actions that enable the preconditions.

→ $\text{New Goal} = \text{Old Goal} - \text{ADD}(A) + \text{PRECOND}(A)$

Inverse Action Application

- Goal:

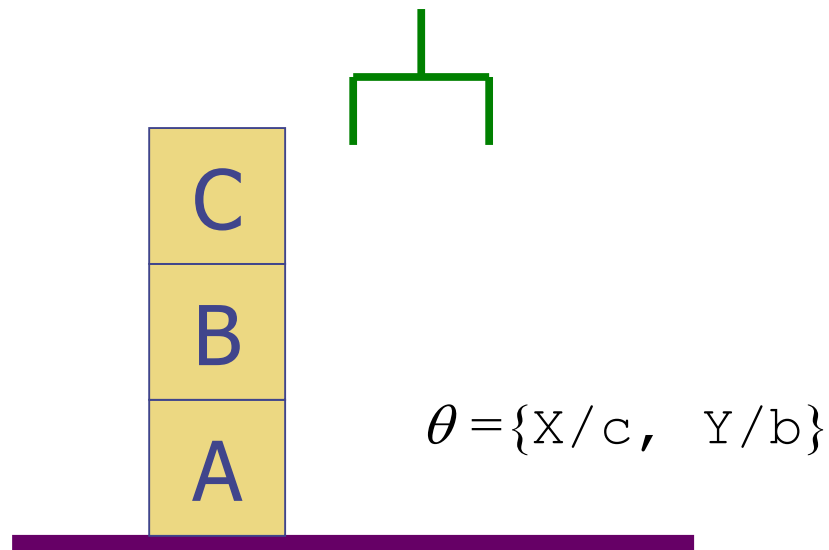


```
Action( stack(X,Y) ,  
  PRECOND: holding(X) ,  
           block(X) ,  
           block(Y) ,  
           clear(Y)  
  ADD:    handempty ,  
           clear(X) ,  
           on(X,Y) ,  
  DELETE: holding(X) ,  
           clear(Y)  
)
```

`on(a, table) , on(b, a) , on(c, b)`

Inverse Action Application

- Goal:



```

Action( stack(X,Y) ,
PRECOND: holding(X) ,
          block(X) ,
          block(Y) ,
          clear(Y)

ADD:      handempty ,
          clear(X) ,
          on(X,Y) ,

DELETE:   holding(X) ,
          clear(Y)

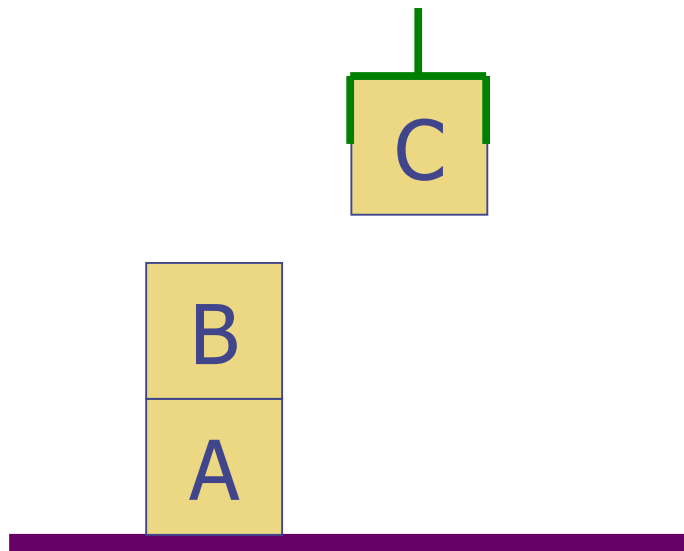
)
  
```

`on(a,table) , on(b,a) , on(c,b) stack(c,b)`

`holding(c) , block(c) , block(b) , clear(b)`

Inverse Action Application

- New Goal:



```
Action( stack(X,Y) ,  
PRECOND: holding(X) ,  
          block(X) ,  
          block(Y) ,  
          clear(Y)  
ADD:      handempty ,  
          clear(X) ,  
          on(X,Y) ,  
DELETE:   holding(X) ,  
          clear(Y)  
)
```

`on(a,table) , on(b,a) ,`

`holding(c) , block(c) , block(b) , clear(b)`

Regression Algorithm

Formulation as state-space search problem:

- **Initial state** = goal state of the planning problem
 - Literals not appearing may be true or false
- **Actions** = those whose add-list satisfy the current state
 - delete positive effects, add preconditions
- **Goal test** = is the current state satisfied in the initial state of the planning problem?
- **Step cost** = each action costs 1
 - could be changed if necessary

Search algorithm

- again, any standard algorithm can perform the search
- **Main Advantage of Regression Planning**
 - only relevant actions are considered
 - often much lower branching factor than for forward search

Heuristics for State-Space Search

- Even for regression **we need good heuristics**
 - How many actions are needed to achieve the goal?
 - Exact solution is NP hard, find a good estimate

Two approaches to find an admissible search heuristic:

(1) The optimal solution to a **relaxed problem**

- remove all preconditions from actions
 - almost identical to the number of open subgoals
- remove only the delete-list and find a (minimal) set of actions that collectively achieve the goals
 - problem: finding a minimal set cover is NP-hard, and relaxing the constraint loses admissibility of heuristic

Heuristics for State-Space Search

- Even for regression **we need good heuristics**
 - How many actions are needed to achieve the goal?
 - Exact solution is NP hard, find a good estimate

Two approaches to find an admissible search heuristic:

(2) The **subgoal independence** assumption:

- The cost of solving a conjunction of subgoals is approximated by the sum of the costs of solving them independently
- is only admissible if co-ordination causes additional complexity
- (not admissible for the `have(milk) & have(bread) plan`)

Heuristics for State-Space Search

<https://www.youtube.com/watch?v=kyCjEsFpzbA&t=603s>

Why
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What?
○○

How
○○○○○○○○○○

Theory
○

Practice
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And Now?
○○

References

Artificial Intelligence Planning
Heuristic Search Planning
A Tiny (But Tasty) Appetizer

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