A Unified Brand-name-Free Introduction to Planning

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Planning is hot...

New people. Conferences. Workshops. Competitions. Inter-planetary explorations. So, Why the increased interest?

- **Significant scale-up in the last 4-5 years**
  - **Before we could synthesize about 5-6 action plans in minutes**
  - **Now, we can synthesize 100-action plans in minutes**
    - » **Further scale-up with domain-specific control**
- **Significant strides in our understanding**
  - **Rich connections between planning and CSP(SAT) OR (ILP)**
    - » **Vanishing separation between planning & Scheduling**
  - **New ideas for heuristic control of planners**
  - **Wide array of approaches for customizing planners with domain-specific knowledge**

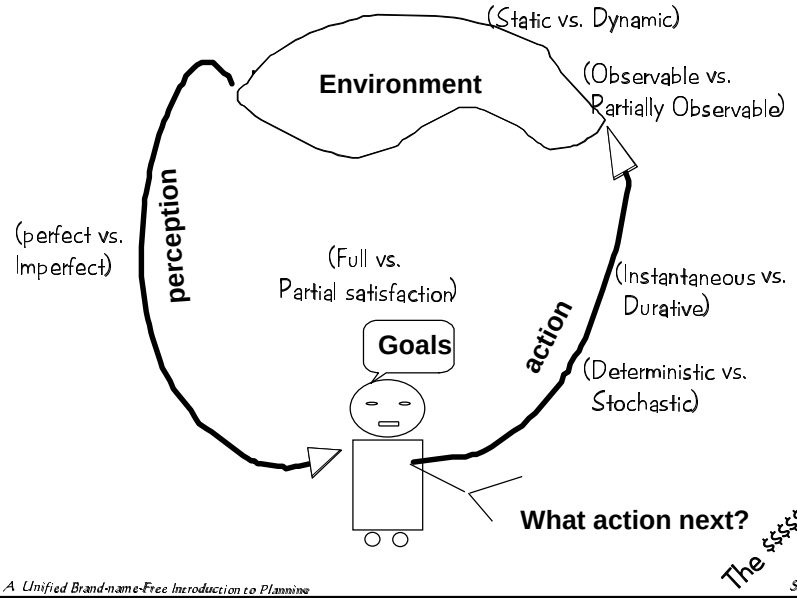
Overview

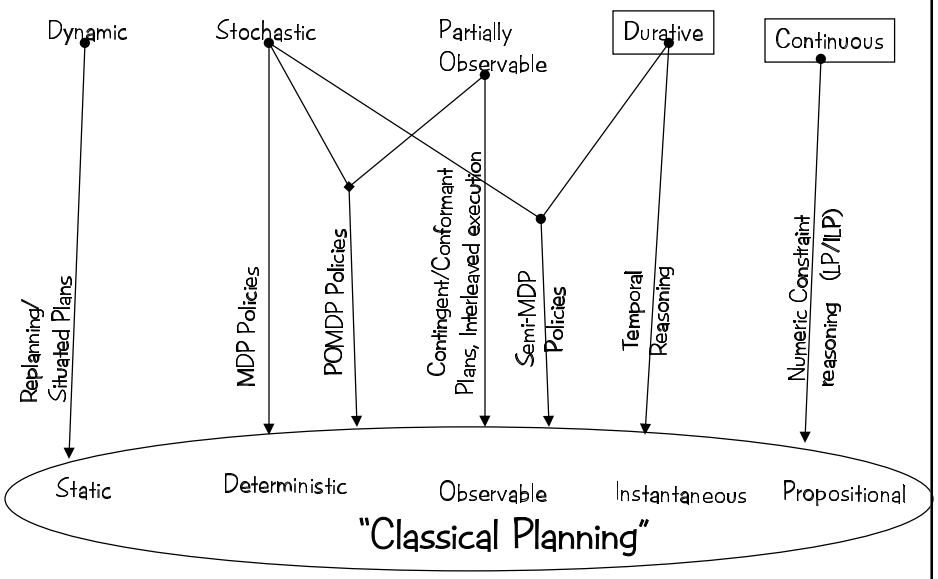
- The Planning problem
  - Our focus
  - Modeling, Proving correctness
- Refinement Planning: Formal Framework
- Conjunctive refinement planners
- Disjunctive refinement planners
  - Refinement of disjunctive plans
  - Solution extraction from disjunctive plans
    - » Direct, Compiled (SAT, CSP, ILP,BDD)
- Heuristics/Optimizations
- Customizing Planners
  - User-assisted Customization
  - Automated customization
- Support for non-classical worlds

Planning : The big picture

- **Synthesizing goal-directed behavior**
- **Planning involves**
  - **Action selection; Handling causal dependencies**
  - **Action sequencing and handling resource allocation**
    - **» typically called SCHEDULING**
  - **Depending on the problem, plans can be**
    - **» action sequences**
    - **» or "policies" (action trees, state-action mappings etc.)**

The Many Complexities of Planning





Broad Aims & Biases of the Tutorial

AIM: We will concentrate on planning in <u>deterministic, quasi-static and fully observable worlds</u>

Neo-Classical Planning

Will start with "classical" domains; but discuss handling durative actions and numeric constraints, as well as replanning

BIAS: To the extent possible, we shall shun brand-names and concentrate on unifying themes

- **Better understanding of existing planners**
  - **Normalized comparisons between planners**
  - **Evaluation of trade-offs provided by various design choices**
- **Better understanding of inter-connections**
  - **Hybrid planners using multiple refinements**
  - **Explication of the connections between planning, CSP, SAT and ILP**

Why Care about "neo-classical" Planning?

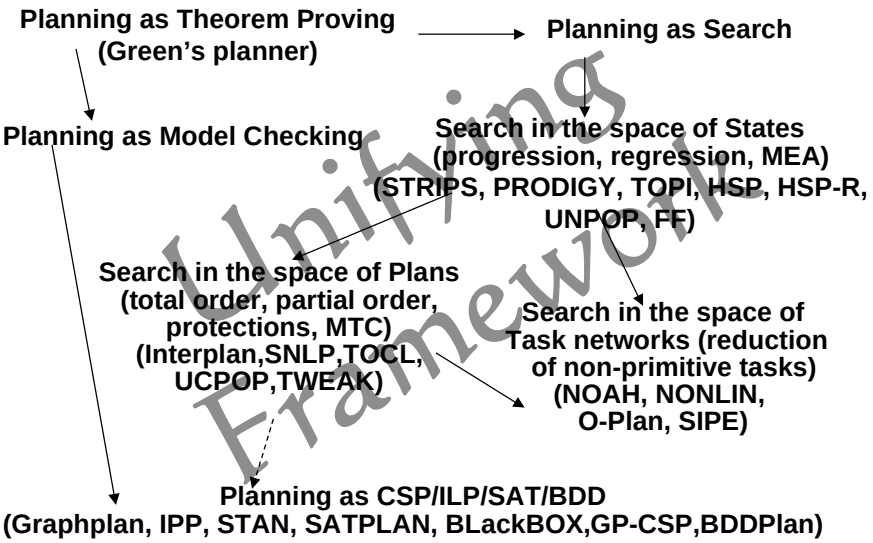
- **Most of the recent advances occurred in neo-classical planning**
- **Many stabilized environments satisfy neo-classical assumptions**
  - **It is possible to handle minor assumption violations through replanning and execution monitoring**

  "This form of solution has the advantage of relying on widely-used (and often very efficient) classical planning technology" Boutilier, 2000
- **Techniques developed for neo-classical planning often shed light on effective ways of handling non-classical planning worlds**
  - **Currently, most of the efficient techniques for handling non-classical scenarios are still based on ideas/advances in classical planning**

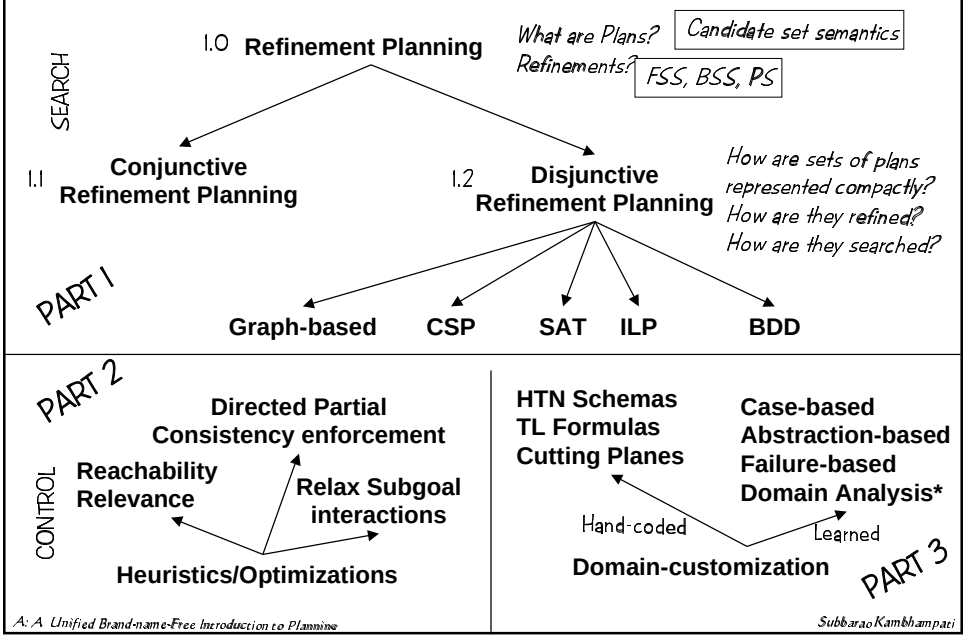
Applications (Current & Potential)

- Scheduling problems with action choices as well as resource handling requirements
  - Problems in supply chain management
  - HSTS (Hubble Space Telescope scheduler)
  - Workflow management
- Autonomous agents
  - RAX/PS (The NASA Deep Space planning agent)
- Software module integrators
  - VICAR (JPL image enhancing system); CELWARE (CELCorp)
  - Test case generation (Pittsburgh)
- Interactive decision support
  - Monitoring subgoal interactions
    - » Optimum AIV system
- Plan-based interfaces

The (too) many brands of classical planners



A Unifying View



Overlap with other courses

- Hector will talk more o
- Dana & D ic kno
- P ing
- Mal temporal planning
- Bernha will talk more on the formal stuff

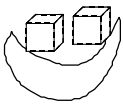
I want to know God's thoughts
The rest is mere details.
Albert Einstein

PART I.0

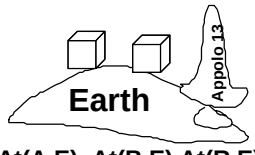
Modeling Planning Problems: Actions, States, Correctness

Modeling Classical Planning

- States are modeled in terms of (binary) state-variables
  - -- Complete initial state, partial goal state
- Actions are modeled as state transformation functions
  - -- Syntax: ADL language (Pednault)
  - -- Apply(A,S) = (S \ eff(A)) + eff(A) (If Precond(A) hold in S)



At(A,M),At(B,M)
¬In(A), ¬In(B)



At(A,E), At(B,E),At(R,E)

Effects

$In(o_1)$ $\neg In(o_1)$

$\forall_x In(x) \Rightarrow At(x,M)$ & $\neg At(x, E)$

Load(o_1) Unload(o_1) Fly()

Prec.

$At(o_1,l_1)$, $At(R,l_1)$ $In(o_1)$ At(R,E)

At(R,M), ¬At(R,E)

Some notes on action representation

- **STRIPS Assumption: Actions must specify all the state variables whose values they change...**
- **No disjunction allowed in effects**
  - **Conditional effects are NOT disjunctive**
    - **» (antecedent refers to the previous state & consequent refers to the next state)**
- **Quantification is over finite universes**
  - **essentially syntactic sugaring**
- **All actions can be compiled down to a canonical representation where preconditions and effects are propositional**
  - **Exponential blow-up may occur (e.g removing conditional effects)**
    - » *We will assume the canonical representation*

Action A

Eff: If P then R
If Q then W

Action A1
Prec: P, Q
Eff: R, W

Action A2
Prec: P, ~Q
Eff: R, ~W

Action A3
Prec: ~P, Q
Eff: ~R, W

Action A4
Prec: ~P,~Q
Eff:

Actions with Resources and Duration

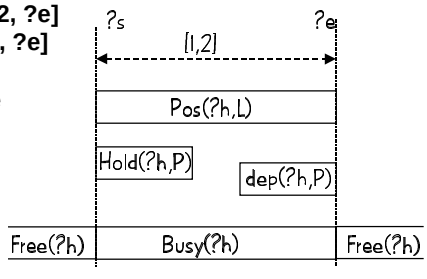
Load(P:package, R:rocket, L:location)

Resources: **?h : robot hand**
Preconditions: **Position(?h,L)** **[?s, ?e]**
Free(?h) **?s**
Charge(?h) > 5 **?s**

Effects: **holding(?h, P)** **[?s, ?t1]**
depositing(?h,P,R) **[?t2, ?e]**
Busy(?h) **[?s, ?e]**
Free(?h) **?e**
Charge - = .03*(?e - ?s) **?e**

Constraints: **?t1 < ?t2**
?e - ?s in [1.0, 2.0]

Capacity(robot) = 3



Planning vs. Scheduling

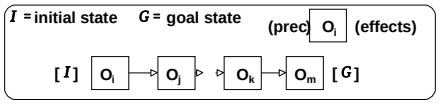
A Continuum

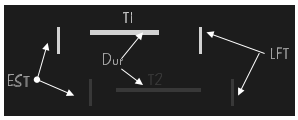
Planning
- Initial state & a set of Goals,
- A library of actions
  - » Preconditions/effects
    - Discrete/Continuous
  - » Resource requirements

Synthesize a sequence of actions capable of satisfying goals

Scheduling
- Set of jobs (may have of tasks in some (partial) order)
- Temporal constraints on jobs
  - » EST, LFT, Duration
- Contention constraints
  - » Each task can be done on a subset of machines

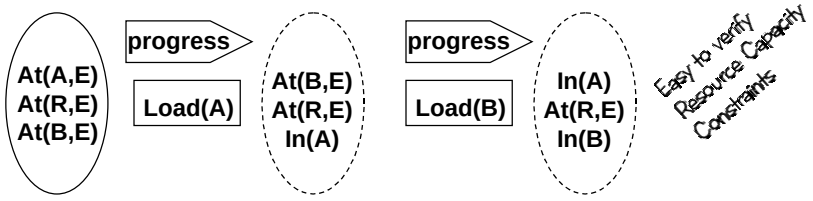
Find start times for jobs that are optimal (wrt make-spans, resource consumption etc)



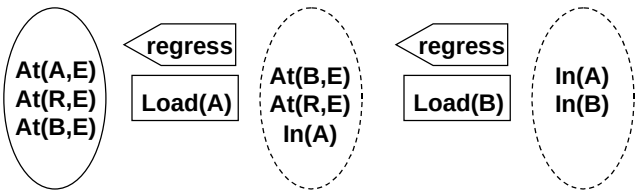


Checking correctness of a plan: The State-based approaches

- **Progression Proof: Progress the initial state over the action sequence, and see if the goals are present in the result**



- **Regression Proof: Regress the goal state over the action sequence, and see if the initial state subsumes the result**



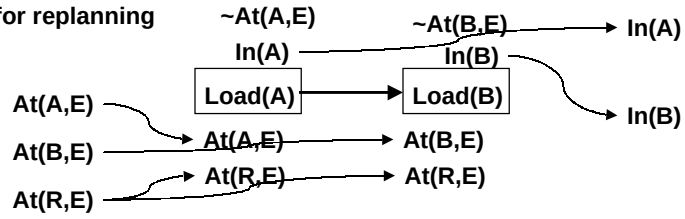
Checking correctness of a plan: The Causal Approach

Contd..

- **Causal Proof: Check if each of the goals and preconditions of the action are**
  - » **"established" : There is a preceding step that gives it**
  - » **"unclobbered": No possibly intervening step deletes it**
    - **Or for every preceding step that deletes it, there exists another step that precedes the conditions and follows the deleter adds it back.**

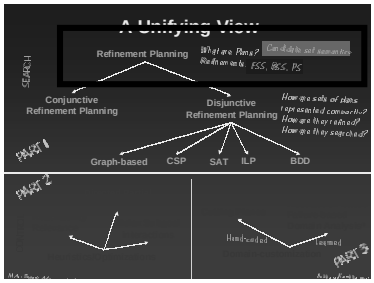
Causal proof is

- **"local" (checks correctness one condition at a time)**
- **"state-less" (does not need to know the states preceding actions)**
  - » **Easy to extend to *durative* actions**
- **"incremental" with respect to action insertion**
  - » **Great for replanning**

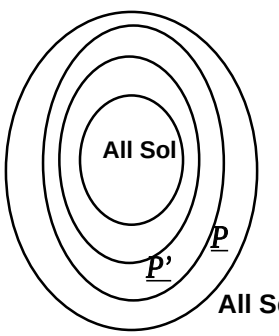


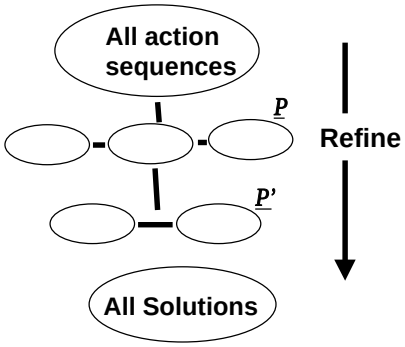
The Refinement Planning Framework:

1. Syntax & Semantics of partial plans
2. Refinement strategies & their properties
3. The generic Refinement planning template



Refinement Planning:Overview





Refinements

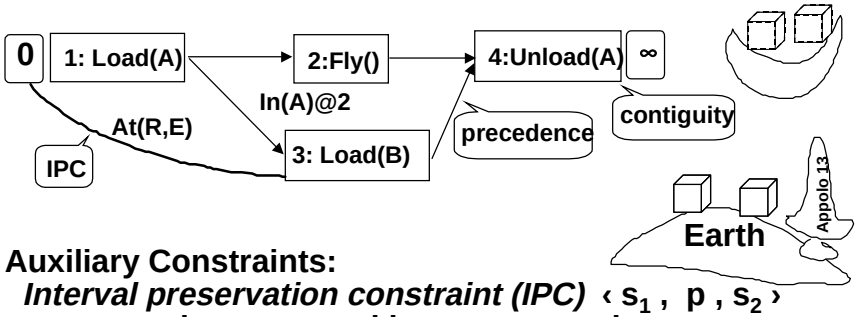
Partial plans

Narrowing *sets of action sequences* to progress towards solutions

Remove non-solutions

Partial Plans: Syntax

Partial plan = ⟨Steps, Orderings, Aux. Constraints ⟩



Auxiliary Constraints:

Interval preservation constraint (IPC) **‹ s_1 , p , s_2 ›**

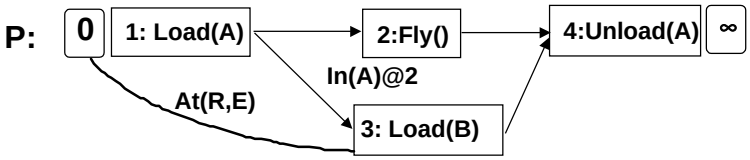
p must be preserved between s_1 and s_2

Point truth Constraint (PTC) **p@s**

p must hold in the state before s

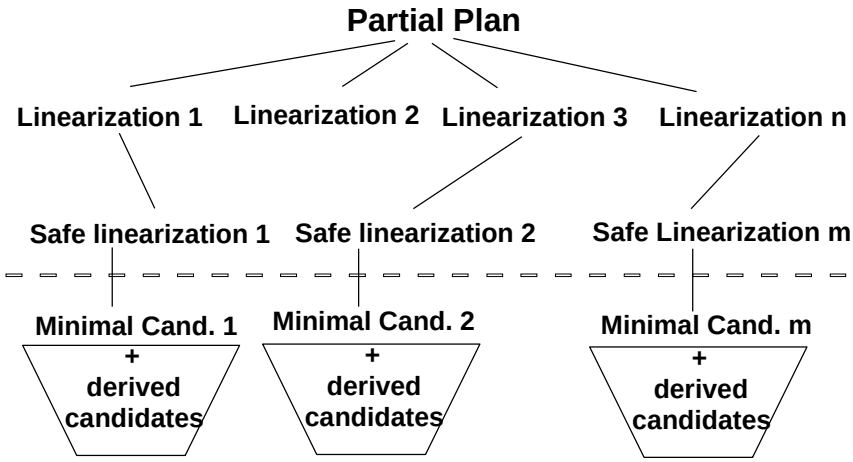
Partial Plans: Semantics

Candidate is any action sequence that
-- contains actions corresponding to all the steps,
-- satisfies all the ordering and auxiliary constraints



Candidates ($\in$ «P»)	Non-Candidates ($\notin$ «P»)
[Load(A),Load(B),Fly(),Unload(A)]	[Load(A),Fly(),Load(B),Unload(B)]
Minimal candidate. Corresponds to safe linearization [01324 ∞]	Corresponds to unsafe linearization [01234 ∞]
[Load(A),Load(B),Fly(), Unload(B),Unload(A)]	[Load(A),Fly(),Load(B), Fly(),Unload(A)]

Linking Syntax and Semantics



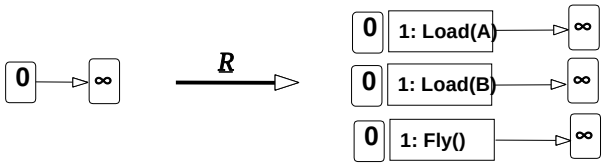
Refinements
- **Reduce candidate set size**
- **Increase length of minimal candidates**

Refinement (pruning) Strategies

"Canned" inference procedures — actions & their inter-relations

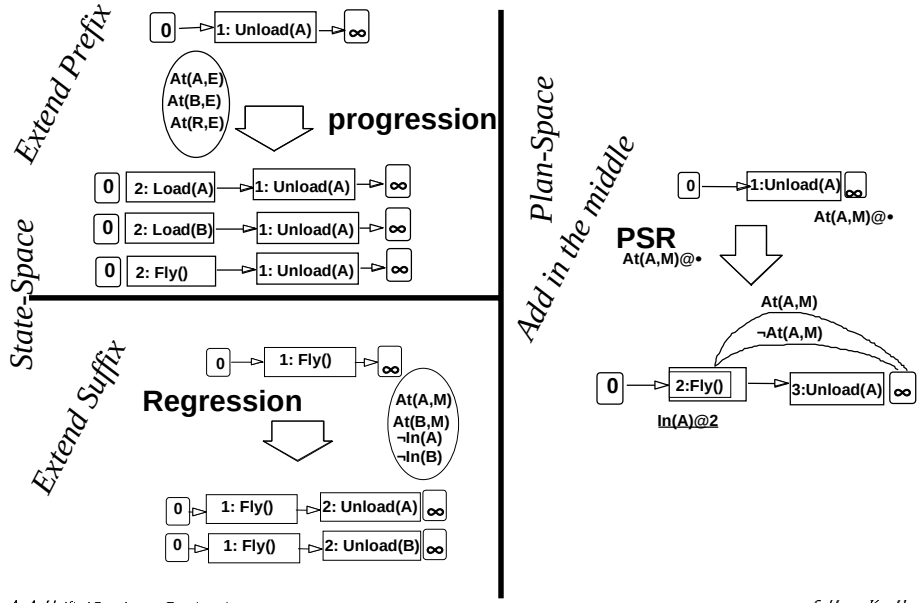
-- Prune by propagating the consequences of domain theory and meta-theory of planning onto the partial plan

- A refinement strategy $R : P \rightarrowtail P'$ («P' » a subset of «P »)
  - R is complete if «P' » contains all the solutions of «P »
  - R is monotonic if «P' » has longer minimal candidates than «P »
  - R is progressive if «P' » is a proper subset of «P »
  - R is systematic if components of P' don't share candidates

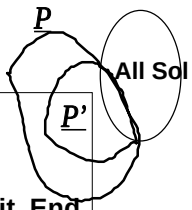


§ A plan set P is a set of partial plans $\{P_1, P_2 \ldots P_m\}$

Existing Refinement Strategies



The Refinement Planning Template



Refineplan(P : Plan set)

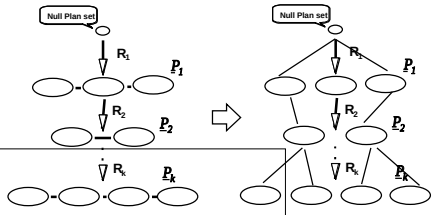
Use proofs of correctness

0*. If «P » is empty, Fail.
1. If a minimal candidate of P is a solution, return it. End
2. Select a refinement strategy R
Apply R to P to get a new plan set P'
3. Call Refine(P')

-- Termination ensured if R is complete **and** monotonic
-- Solution check done using one of the proofs of correctness

Issues:
1. Representation of plan sets (Conjunctive vs. Disjunctive)
2. Search vs. solution extraction
3. Affinity between refinement and proof used for solution check

A flexible Split&Prune search for refinement planning



Refineplan(P : Plan)

0*. If «P » is empty, Fail.
1. If a minimal candidate of P is a solution, terminate.
2. Select a refinement strategy R .
Appply R to P to get a new plan set P'
3. Split P' into k plansets
4. Non-deterministically select one of the plansets P'_i
Call Refine(P'_i)

Two classes of refinement planners

Conjunctive planners

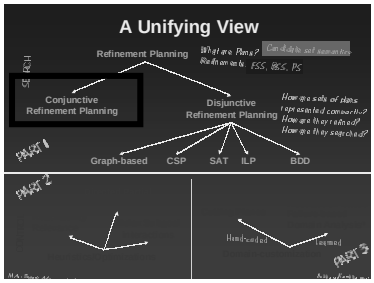
- **Search in the space of conjunctive partial plans**
  - **Disjunction split into the search space**
    - » **search guidance is nontrivial**
  - **Solution extraction is trivial**
- **Examples:**
  - **STRIPS & Prodigy**
  - **SNLP & UCPOP**
  - **NONLIN & SIPE**
  - **UNPOP & HSP**

Disjunctive planners

- **Search in the space of disjunctive partial plans**
  - **Disjunction handled explicitly**
  - **Solution extraction is non-trivial**
    - » **CSP/SAT/ILP/BDD methods**
- **Examples:**
  - **Graphplan,IPP,STAN**
  - **SATPLAN**
  - **GP-CSP**
  - **BDDPlan, PropPlan**

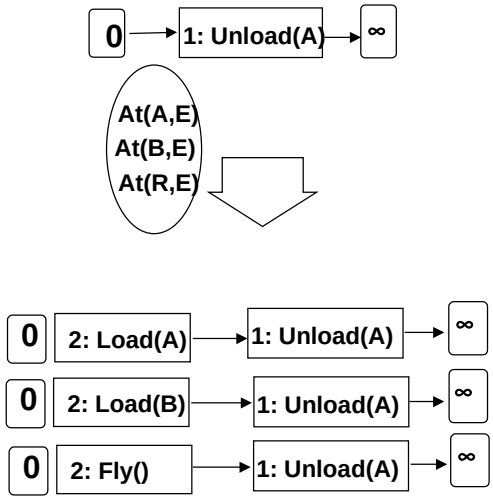
CONJUNCTIVE REFINEMENT PLANNING

Part I.I



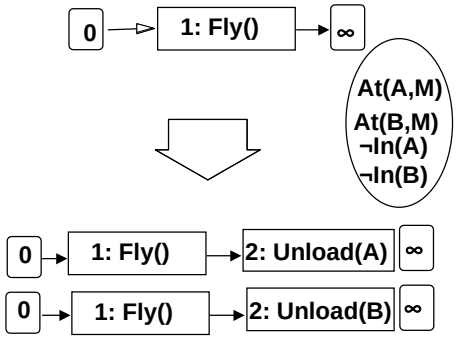
Forward State-space Refinement

- Grow plan prefix by adding applicable actions
  - Complete, Monotonic
    - » *consideration of all executable prefixes*
  - Progressive
    - » *elimination of unexecutable prefixes*
  - Systematic
    - » *each component has a different prefix*
  - ✚ Completely specified state
    - » Easier to control?
  - Higher branching factor



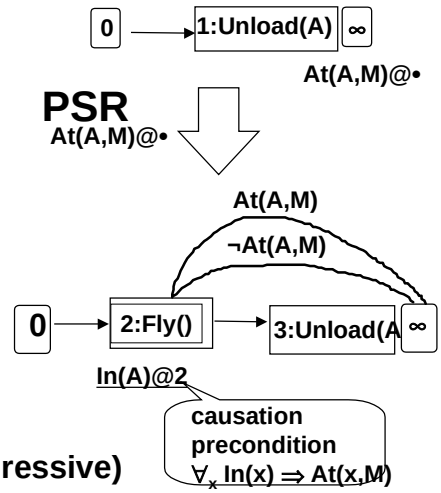
Backward State-space Refinement

- Grow plan suffix by adding relevant actions
  - Complete, Monotonic
    - » *consideration of all relevant suffixes*
  - Progressive
    - » *elimination of irrelevant suffixes*
  - Systematic
    - » *each component has a different suffix*
  - ✚ Goal directed
    - » Lower branching
  - Partial state
    - » Harder to detect inconsistency



Plan-space Refinement

Goal selection:
Select a precondition
Establishment:
Select a step (new or existing) and make it give the condition
De-clobbering:
Force intervening steps to preserve the condition
Book-keeping: (Optional)
Add IPCs to preserve the establishment
⇒ Systematicity



(PSR is complete, and progressive)

(Sacerdoti, 1972; Pednault, 1988; McAllester, 1991)

Tradeoffs among Refinements

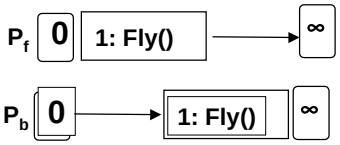
The Tastes great/ Less Filling holy wars

FSR and BSR must commit to both position and relevance of actions

+ Give state information (Easier plan validation)

- Leads to premature commitment

- Too many states when actions have durations



Plan-space refinement (PSR) avoids constraining position

+ Reduces commitment (large candidate set /branch)

- Increases plan-validation costs

+ Easily extendible to actions with duration

Issues in instantiating Refineplan

- Although a planner can use multiple different refinements, most implementations stick to a single refinement
- Although refinement can be used along with any type of correctness check, there is affinity between specific refinements and proof technqiues (support finite differencing)
  - FSR and Progression based proof
  - BSR and Regression based proof
  - PSR and Causal proof
- Although it is enough to check if *any one* of the safe linearizations are solutions, most planners refine a partial plan until all its linearizations are safe
  - Tractability refinements (pre-order, pre-satisfy)

With these changes, an instantiated and simplified planner may "*look*" considerably different from the general template

Generating Conjunctive Refinement Planners

Refineplan ($\underline{P}$: Plan)

0*. If «$\underline{P}$ » is empty, Fail.
1. If a minimal candidate of $\underline{P}$ is a solution, terminate.
2. Select a refinement strategy $\underline{R}$.
Appply $\underline{R}$ to $\underline{P}$ to get a set of new plans $\underline{P1…Pj}$
Add all plans to the search queue.
4. Non-deterministically select one of the plans P_i
Call Refine($\underline{P}_i$)

Keep all linearizations safe (Tractability refinements)
Select the proof strategy so it becomes incremental with respect to the refinement
Stick to a single refinement strategy

Case Study: UCPOP

Refineplan ($\underline{P}$: Plan)

0*. If P is order inconsistent, FAIL.
1. If no open conditions and no unsafe IPCs, SUCCESS.
2. Generate new plans using either 2' or 2''
Add the plans to the search queue
2'. Remove an open condition c@s in P.
2.1. For each step s' in P that gives c, make a new plan
P' = P + (s' < s) + IPC s'-c-s
2.2. For each action A in the domain that gives c, make a new plan P' = P + sn:A + (sn <s) + IPC sn-c-s.
2.2.1. For each precondition c' of A, add c'@sn to the list of open conditions of P'.
2.2.2. For each IPC s'-p-s'', if sn deletes p, add [s'-p-s''; sn] to the list of unsafe IPCs of P'.
2''. Remove an unsafe IPC [s'-p-s''; s'''] from P.
Make two plans: P' = P + s'''< s' P'' = P + s'' < s'''
3. Non-deterministically select one of the plans P_I from the search queue and Call Refine($\underline{P}_i$)

Incrmental Soln. check

Finite-differencing structures

Tractability refinement

Many variations on the theme..

Planner	*Termination*	*Goal Sel.*	*Bookkeeping*	*Tractability refinements*
TWEAK	**MTC**	**MTC**	***-none-***	***-none-***
UA	**MTC**	**MTC**	***-none-***	**pre-order**
SNLP / UCPOP	**Causal proof**	**arbitrary**	**Contrib. Prot**	**pre-satisfaction**
TOCL	**Causal proof**	**arbitrary**	**Contrib. Prot.**	**pre-order**
McNonlin/ Pedestal	**Causal proof**	**arbitrary**	**Interval Prot.**	**pre-satisfaction**
SNLP-UA	**MTC**	**MTC**	**Contrib. Prot.**	**unambig. ord.**

(Kambhampati, Knoblock & Yang, 1995)

Some implemented conjunctive planners

	Refinement	Heuristics
UCPOP, SNLP [Weld et. al.]	Plan-space	Fail-first Flaw selection
UNPOP [McDermott] HSP [Geffner & Bonet] FF [Hoffman]	Forward state space	Distance heuristics
IxTET [Ghallab et al] RAX [Muscettola et al]	Plan-space	Hand-coded search control
Prodigy [Carbonell et. al.]	Forward state space	Means-ends analysis

Conjunctive planners: The State of the Art

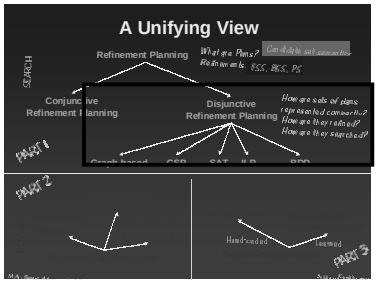
- ***Vanilla*** **state-space (FSR/BSR) planners were known to be less efficient than vanilla plan-space planners**
  - **Several research efforts concentrated on extending plan-space approaches to non-classical scenarios**
- **However, State-space planners seem to have better heuristic support than plan-space planners at this time**
  - **Distance-based heuristics seem particularly useful for state-space planners**
- **But, plan-space planners are alleged to provide better support for incremental planning, durative actions etc.**
  - **replanning, reuse and plan modification, temporal reasoning**
    - » **IXTET, HSTS, RAX….**

Charge: ***Either develop effective approaches for replanning etc. in state-space planners or develop good heuristics for plan-space planners***

Part 1.2

DISJUNCTIVE REFINEMENT PLANNING

1. Refining disjunctive plans
2. Solution Extraction
   --Direct
   --Compilation
      CSP/SAT/ILP/BDD

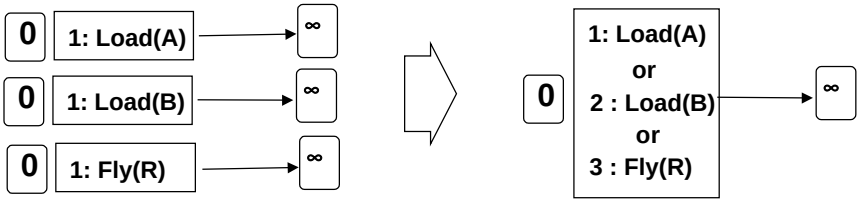


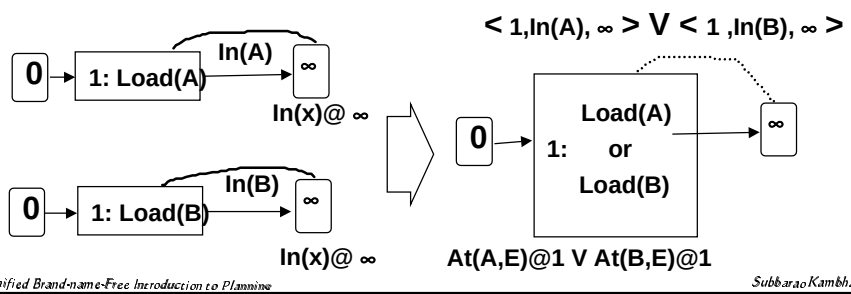
Disjunctive Planning

- **Idea: Consider Partial plans with disjunctive step, ordering, and auxiliary constraints**
- **Motivation: Provides a lifted search space, avoids re-generating the same failures multiple times (also, rich connections to combinatorial problems)**
- **Issues:**
  - **Refining disjunctive plans**
    - **» Graphplan (Blum & Furst, 95)**
  - **Solution extraction in disjunctive plans**
    - **» Direct combinatorial search**
    - **» Compilation to CSP/SAT/ILP**

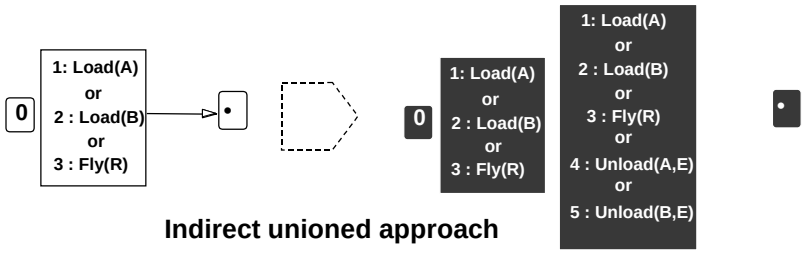
Disjunctive Representations

--Allow disjunctive step, ordering and auxiliary constraints in partial plans





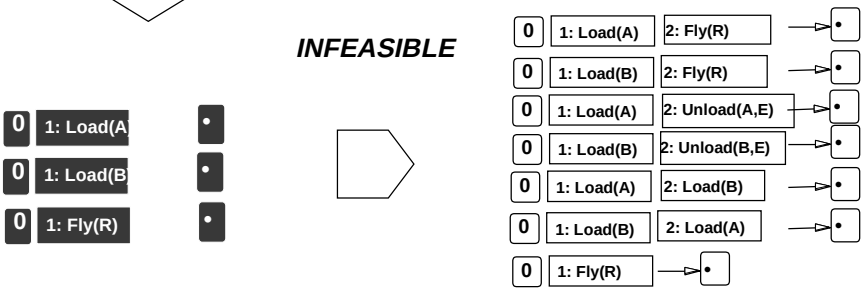
Refining Disjunctive Plans (1)



Indirect unioned approach

+ Maximum pruning power
- Exponential refinement cost

INFEASIBLE



Refining Disjunctive plans (2)

Direct naive approach

Put all actions at all levels

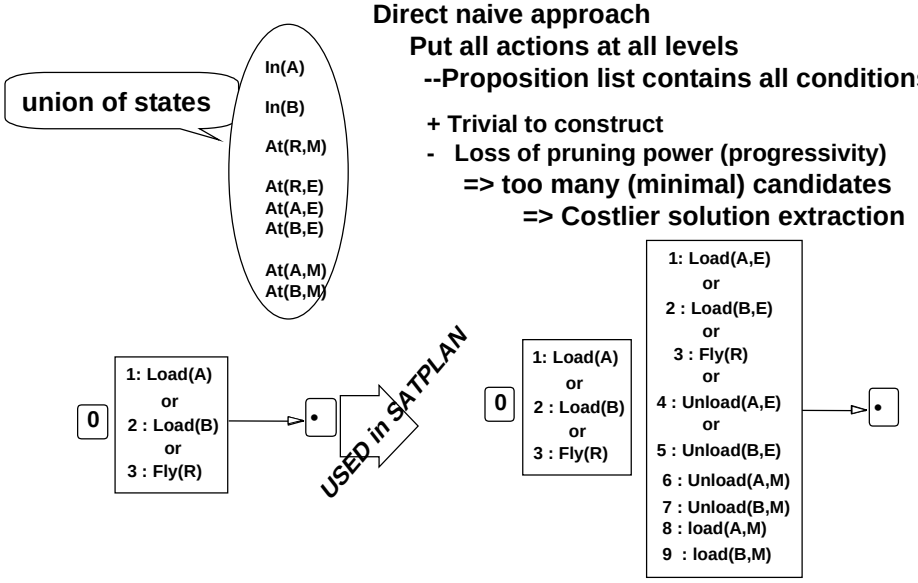
--Proposition list contains all conditions

+ Trivial to construct

- Loss of pruning power (progressivity)

=> too many (minimal) candidates

=> Costlier solution extraction



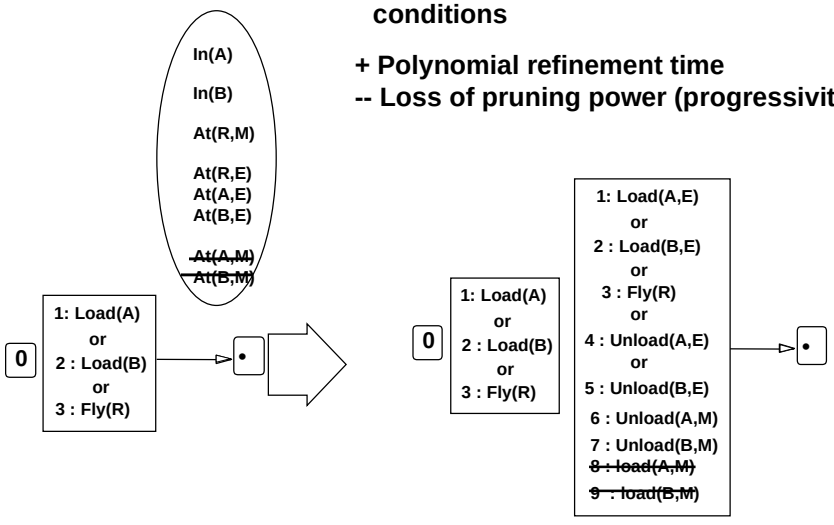
Refining Disjunctive plans (3)

Enforce partial 1-consistency

Proposition list avoids unsupported conditions

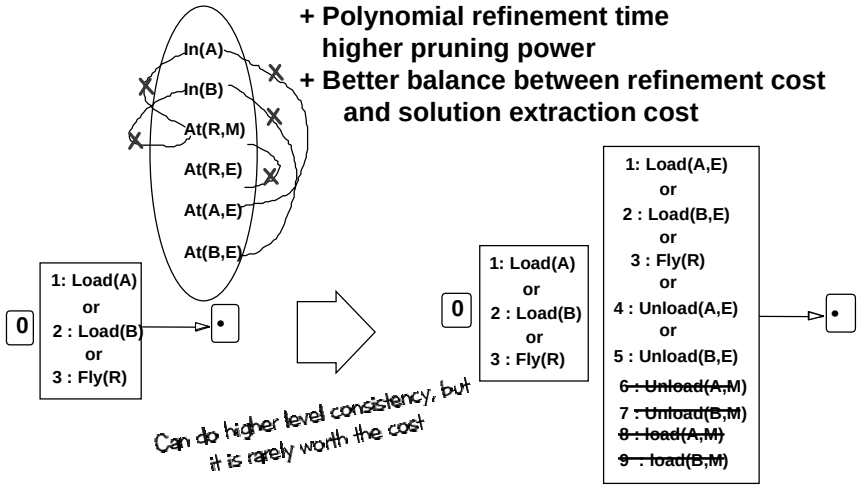
+ Polynomial refinement time

-- Loss of pruning power (progressivity)



Refining Disjunctive plans (4)

Enforce (partial) 2-consistency
Proposition list maintains interactions between pairs of conditions
+ Polynomial refinement time
higher pruning power
+ Better balance between refinement cost and solution extraction cost



Open issues in disjunctive refinement

- **Directed partial consistency**
  - **Mutex propagation is a form of reachability analysis**
    - » **Relevance analysis?**
  - **Higher levels of directional consistency?**
    - » **Typically not cost effective**
- **Supporting refinements other than FSR**
  - **Direct naïve refinements are easy to support; enforcing an appropriate level of consistency is harder**
  - **Some "relevance" based approaches exist for BSR**
    - » **Inseperability, backward mutex [**
      - **Kambhampati et. al. ECP, 1997**
    - » **Can be used in conjunction with reachability analysis**
  - **Enforcing effective consistency for PSR is still virgin territory…**

Solution Extraction in Disjunctive Plans

- **Verify if some minimal candidate of the disjunctive plan is a solution ("Model Finding")**
  - » **Involves (implicit or explicit) use of proof strategies**
- **Direct methods: Can be solved using special techniques customized to the disjunctive structure**
  - » **Graphplan backward search; Graphplan local search**
- **Compilation methods: Generate a set of constraints, whose satisfaction ensures that a substructure of the disjunctive structure is a solution. Find a model for the constraints.**
  - » **Constraints will correspond to lines of proof**
    - **Progression proof, regression proof, causal proof**
  - » **Constraints can be in any standard form**
    - **e.g. CSP, SAT, ILP, BDD**

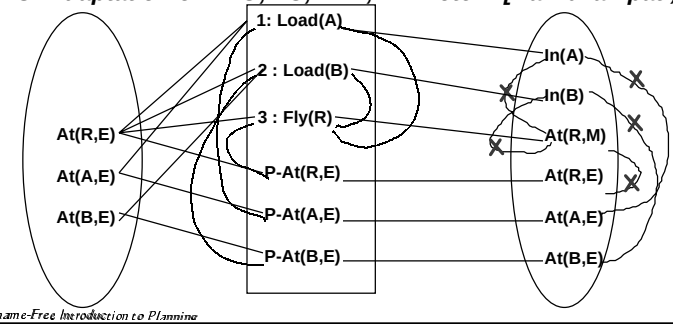
Graphplan Backward Search

(Direct Search I)

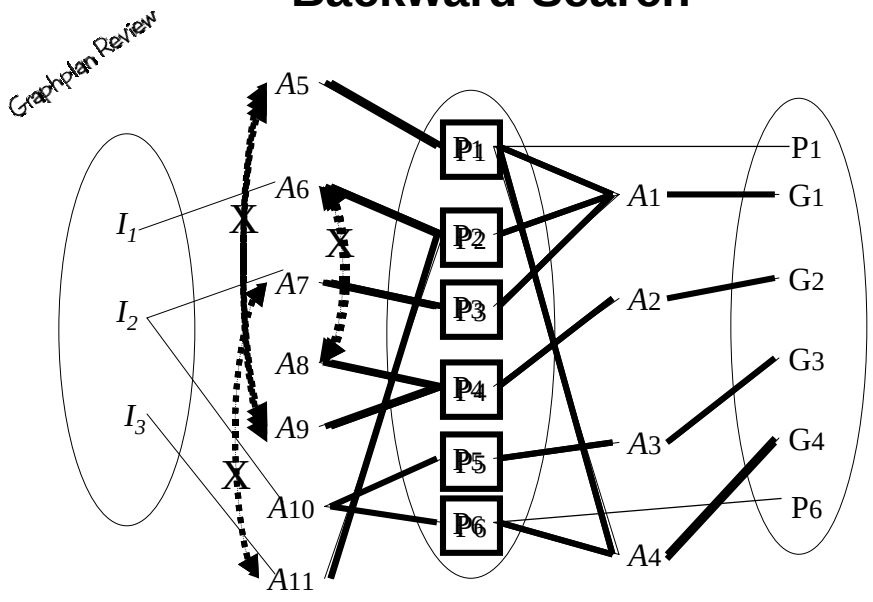
Objective: Find a sub-graph of the plangraph that corresponds to a valid plan.

Method: Start from the goal propositions at the last level
Select actions to support the goals so that no two are *mutex (choice)*
Recurse on the preconditions of the selected actions
(recursion ends at the initial state)
(When backtracking over the goals at a level, memoize them)

Optimizations: Adaptation of DVO, FC, EBL, DDB etc… [Kambhampati, JAIR 2000]

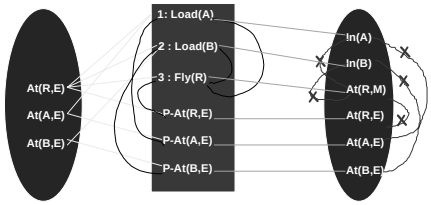


Backward Search



Other Direct Extraction Strategies

- **Motivation: No compelling reason for making the search for a valid subgraph backward, or systematic...**
- **Alternatives:**
  - **Forward Search (dynamic programming) [Parker & Kambhampati; 98,99; Blum & Langford 98]**
  - **Systematic Undirectional search [Rintanen, 98]**
    - » *Select an action anywhere in the plan-graph for inclusion in the solution; Propagate consequences (adapts normal CSP Search to plan-graph)*
  - **Local Search [Gerevini et. al., 99]**

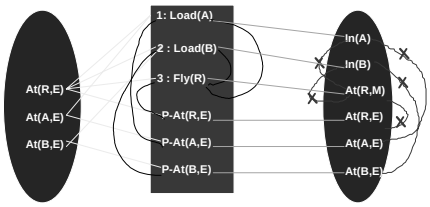


Compilation to CSP

[Do & Kambhampati, 2000]

Goals: In(A),In(B)

CSP: Given a set of discrete variables, the domains of the variables, and constraints on the specific values a set of variables can take in combination, FIND an assignment of values to all the variables which respects all constraints



Variables: Propositions (In-A-1, In-B-1, ..At-R-E-0 …)
Domains: Actions supporting that proposition in the plan
In-A-1 : { Load-A-1, #} At-R-E-1: {P-At-R-E-1, #}

[Corresponds to a regression-based proof]

Constraints: Mutual exclusion
~[(In-A-1 = Load-A-1) & (At-R-M-1 = Fly-R-1)] ; etc..

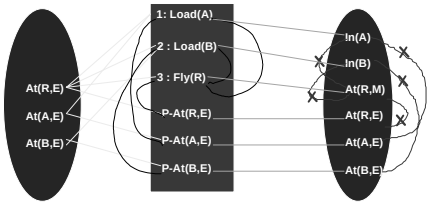
Activation
In-A-1 != # & In-B-1 != # (Goals must have action assignments)
In-A-1 = Load-A-1 => At-R-E-0 != # , At-A-E-0 != #
(subgoal activation constraints)

Compilation to SAT

[Kautz & Selman]

Goals: In(A),In(B)

SAT is CSP with Boolean Variables



Init: At-R-E-0 & At-A-E-0 & At-B-E-0
Goal: In-A-1 & In-B-1

Graph: ***"cond at k => one of the supporting actions at k-1"***
In-A-1 => Load-A-1 In-B-1 => Load-B-1
At-R-M-1 => Fly-R-1 At-R-E-1 => P-At-R-E-1

Load-A-1 => At-R-E-0 & At-A-E-0 ***"Actions => preconds"***
Load-B-1 => At-R-E-0 & At-B-E-0
P-At-R-E-1 => At-R-E-0h

~In-A-1 V ~ At-R-M-1 ~In-B-1 V ~At-R-M-1 ***"Mutexes"***

Compilation to Integer Linear Programming

ILP: Given a set of real valued variables, a linear objective function on the variables, a set of linear inequalities on the variables, *and a set of integrality restrictions on the variables,* Find the values of the feasible variables for which the objective function attains the maximum value
-- o/1 integer programming corresponds closely to SAT problem

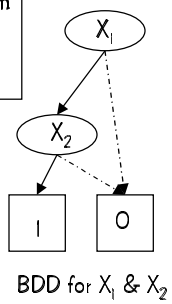
- **Motivations**
  - **Ability to handle numeric quantities, and do optimization**
  - **Heuristic value of the LP relaxation of ILP problems**
- **Conversion**
  - **Convert a SAT/CSP encoding to ILP inequalities**
    - » **E.g. X v ~Y v Z => x + (1 - y) + z >= 1**
  - **Explicitly set up tighter ILP inequalities (Cutting constraints)**
    - » **If X,Y,Z are pairwise mutex, we can write x+y+z <= 1 (instead of x+y <=1 ; y+z <=1 ; z +x <= 1)**

[Walser & Kautz, Vossen et. al, Bockmayr & Dimopoulos]

Compilation to Binary Decision Diagrams (BDDs)

[Cimatti et. al., Fourman, Hans-Peter]

BDDs support compact representation *and* direct manipulation of boolean formulae on a finite set of propositions. [Popular in CAD community]
Standard algorithms for converting a boolean formulae into BDDs and for supporting standard boolean operations on them [Bryant et. al.]



BDD for X_1 & X_2

- **Idea: Represent disjunctive plans as BDDs and plan extension as BDD operations**
  - **Proposition list at level *k* is an approximation to the set of states reachable in *k* steps.**
    - » **The set can be represented compactly as BDDs**
    - » **Plan growth can be modeled as direct manipulations on BDD**
      - **Operations such as "action projection" need to be modeled as BDD modifications**

Relative Tradeoffs Offered by the various compilation substrates

- CSP encodings support implicit representations
  - More compact encodings [Do & Kambhampati, 2000]
  - Easier integration with Scheduling techniques
- ILP encodings support numeric quantities
  - Seamless integration of numeric resource constraints [Walser & Kautz, 1999]
  - Not competitive with CSP/SAT for problems without numeric constraints
- SAT encodings support axioms in propositional logic form
  - May be more natural to add (for whom ;-)
- BDDs are very popular in CAD community
  - Commercial interest may spur faster algorithms (which we can use)

CSP Encodings can be more compact: GP-CSP

	Graphplan		Satz		Relsat		GP-CSP	
Problem	time (s)	mem	time(s)	mem	time (s)	mem	time (s)	mem
bw-12steps	0.42	1 M	8.17	64 M	3.06	70 M	1.96	3M
bw-large-a	1.39	3 M	47.63	88 M	29.87	87 M	1.2	11M
rocket-a	68	61 M	8.88	70 M	8.98	73 M	4.01	3M
rocket-b	130	95 M	11.74	70 M	17.86	71 M	6.19	4 M
log-a	1771	177 M	7.05	72 M	4.40	76 M	3.34	4M
log-b	787	80 M	16.13	79 M	46.24	80 M	110	4.5M
hsp-bw-02	0.86	1 M	7.15	68 M	2.47	66 M	.89	4.5 M
hsp-bw-03	5.06	24 M	> 8 hs	-	194	121 M	4.47	13 M
hsp-bw-04	19.26	83 M	> 8 hs	-	1682	154 M	39.57	64 M

Do & Kambhampati, 2000

Advantages of CSP encodings over SAT encodings: GP-CSP

	Size-based EBL		Rel-based EBL		Speedup/Mem-ratio for Rel-10 EBL			
Problems	time (s)	mem	time	mem	GP-CSP	GP	SATZ	Relsat
bw-12steps	1.31	11 M	1.46	10 M	1.34x/0.30x	0.28x/0.1x	5.60x/6.40x	2.10x/7.00x
bw-large-a	259	24 M	134	26 M	9.21x/0.42x	0.01x/0.12x	0.36x/3.38x	0.22x/3.34x
rocket-a	2.08	8 M	2.39	11 M	1.68x/0.27x	28.45x/5.54x	3.72x/6.36x	3.76x/6.63x
rocket-b	3.55	9 M	4.00	10 M	1.55/0.40x	32.50x/9.50x	2.94x/7.00x	4.47x/7.10x
log-a	2.37	18 M	2.30	18 M	1.45x/0.22x	770x/9.83x	3.07x/4.00x	1.91x/4.22x
log-b	39.55	19 M	35.13	19 M	3.13x/0.29x	22.40x/4.21x	0.46x/4.16x	1.32x/4.21x
log-c	61	24 M	48.72	25 M	10.47x/0.88x	> 220x	24.42x/3.36x	2.61x/3.56x
hsp-bw-02	1.03	12 M	1.09	12 M	0.82x/0.37x	0.79x/0.08x	6.56x/5.67x	2.27x/5.50x
hsp-bw-03	5.04	26 M	5.17	41 M	0.86x/0.32x	0.98x/0.59x	> 5570x	37.52x/2.95x
hsp-bw-04	38.01	86 M	23.89	86 M	1.65x/0.75x	0.81x/0.97x	> 1205x	70.41x1.79x

Size of learning: k = 10 for both size-based and relevance-based

→ Speedup over GP-CSP up to 10x

→ Faster than SAT in most cases, up to 70x over Blackbox

Direct vs. compiled solution extraction

DIRECT

- ✗ Need to adapt CSP/SAT techniques
- ✓ Can exploit approaches for compacting the plan
- ✓ Can make the search incremental across iterations

Compiled

- ✓ Can exploit the latest advances in SAT/CSP solvers
- ✗ Compilation stage can be time consuming, leads to memory blow-up
- ✗ Makes it harder to exploit search from previous iterations
- ✓ Makes it easier to add declarative control knowledge

Disjunctive planners based on BSS and PS refinements?

Graphplan can be seen as a disjunctive planner based on state-space refinement.

- **How about planners based on other refinements?**

- **Chief difficulty lies in generalizing the refinements to disjunctive plans, while retaining their progressivity**
  - **The mutex propagation step of Graphplan is what makes it progressive**
- **Generalization is however quite easy *If* we sacrifice "progressiveness" of refinements**

Basic idea:

- **Set up bounded length disjunctive structure**
- **Search for a substructure that satisfies solution properties**
  - » **Use lines of proofs**

[Mali & Kambhampati, 1999]

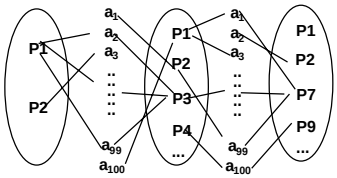
Lines of Proof as basis for (*naïve*) encodings

- **Loop from k=1, until a solution is found**
  - **Set up k-length sequence of disjunctive actions (a1 V a2 V ….V an)**
    - » **In effect, a direct naïve refinement is used (monotonic, complete, but not progressive)**
  - **Impose constraints, satisfaction of which ensures that some sub-sequence of the disjunctive sequence is a solution**
    - » **The constraints set up lines of proof**
      - **State-space proofs**
        - **Graphplan's backward search can be thought of as setting up backward proof**
      - **Causal proofs**
  - **Convert the constraints into your favorite combinatorial substrate and solve**

a1	a1	a1	a1
a2	a2	a2	a2
a3	a3	a3	a3
….	….	….	….
an	an	an	an
1	2		k

Encodings based on state-based proofs

Propositions corresponding to initial conditions and goals are true at their respective levels
P1-0 & P2-0 & P7-k & P9-k
At least one of the actions at each level will occur
a1-j V a2-J V … V an-j
Actions imply their preconditions and effects
ai-k => $prec_{ai}$-k-1 & Eff_{ai}-k



[Corresponds to Graphplan Backward Search]

Forward proof (classical Frame)

A proposition P at j remains true if no action occuring at j+1 deletes P
Pi-j & Ak-(j+1) => Pi-j
forall Ak that don't affect Pi
No more than one action occurs at each step
~aj-k V ~am-k forall j,m,k

Backward proof (explanatory frame)

A proposition P changes values between j and j+1 only if an action occurs that makes it so
~Pi-j & Pi-(j+1) => al-j V am-j ..
Where al, am… add Pi
No pair of interacting actions must occur together
~aj-k V ~am-k forall k
forall aj,am that interfere

Encodings based on Causal proofs

S0	S1	S2	S3	Sk	S∞
	a1	a1	a1	a1	
Needs(S0, I1)	a2	a2	a2	a2	Needs(S∞, G1)
Needs(S0, I2)	a3	a3	a3	a3	Needs(S∞, G2)
	….	….	….	….	
Needs(S0, In)	an	an	an	an	

Each step is mapped to exactly one action
Si = A1 V Si = A2 … ; ~(Si = Ai & Si = Aj)
A step inherits the needs, adds and deletes of the action it is mapped to
Si = Aj => Adds(Si, Pa) & Needs(Si, Pp) & Deletes(Si, Pd)
A Step get needs, adds and deletes only through mapped actions
Adds(Si, Pa) => Si = Aj V Si = Ak … (Ai, Ak add Pa)
Every need is established by some step
Needs(Si,Pj) => Estab(S1, Pj, Si) V Estab(S2, Pj, Si) … V Estab(Sk, Pj, Si)

Establishment with causal links
Estab(S1,Pj,Si) => Link(S1,Pj,Si)
Link implies addition & precedence
Link(Si,Pj,Sk) => Adds(Si,Pj) & Precedes(Si,Pj)
Link implies preservation by intervening steps
Link(Si,Pj,Sk) & Deletes(Sm,Pj) => Precedes(Sm, Si) V Precedes(Sk, Si)

Precedence is irreflexive, asymmetric and transitive...

[Mali & Kambhampati, AAAI-99]

Alternative causal encodings

Whiteknight based establishment

Some preceding step adds
Estab(S1,Pj,Si) => Adds(S1, Pj)
& Precedes (S1, Sj)
For every preceding step deleting a needed condition, there is a white-knight that adds it back
Needs(Sj, Pj) & Deletes(Sd, Pj) & Precedes(Sd,Sj)
=> Wknight(S1, Sj, Sd, Pj) V
Wknight(S2,Sj,Sd,Pj) V ….

Wknight(Sw,Sj,Sd,Pj) => Precedes(Sw, Sj) &
Precedes(Sd, Sw) & Adds(Sw, Pj)

Contiguity based precedence

Step Sj is in position j

Precedes(S1,S2)
Precedes(S1, S3)
…….
Precedes(Sj,Sj+k)

Eliminates the need for $O(k^3)$ Transitivity clauses

Eliminates the need for $O(k^2)$ causal link variables

Tradeoffs between encodings based on different proof strategies

- **Progression (classical frame) encodings lead to higher number of clauses, and allow only serial plans**
  - **O(#prop * #actions * #levels)**
  - **To allow parallel plans, we need to look at frame axioms with sets of actions, increasing the clauses exponentially**
- **Regression (explanatory frame) encodings reduce clauses, and allow parallel plans**
  - **O(#prop * #levels)**
- **Empirical results validate dominance of regression over progression encodings**
  - **The SAT compilation of Graphplan plan-graph corresponds to a form of regression-proof based encoding**

Tradeoffs between encodings based on different proof strategies

- **Causal encodings in general have more clauses than state-space encodings**
  - **O(#actions x #actions x #fluents) for causal link variables**
    - » **Could be reduced by using white-knight based proofs**
  - **O(#actions x #actions x #actions) clauses for partial ordering**
    - » **Could be reduced by using contiguous ordering**
  - **However, the best causal encodings will still be dominated by the backward state-space encodings [Mali & Kambhampati, 99]**
- **Paradoxical given the success of partial order planners in conjunctive planning?**
  - **Not really! We are using causal proof which is typically longer than state-based proofs, and are not using the flexibility of step insertion.**
    - » **Can be helpful in incremental planning & Plan reuse**
    - » **Are helpful in using causal domain specific knowledge (e.g. HTN schemas)**

Some implemented disjunctive planners

	Refinement	Solution Extraction
Graphplan (Blum/Furst) **IPP (Koehler)** **STAN (Fox/Long)** **GP-EBL (Kambhampati)**	***Direct Partially 2-consistent refinement* with FSR**	**Direct search on the disjunctive plan**
SATPLAN (Kautz/Selman)	***Naïve direct refinement* with FSR, BSR, PSR**	**Compilation to SAT**
Blackbox (Kautz/Selman)	***Same as Graphplan***	
GP-CSP (Do/Kambhampati)	***Same as Graphplan***	**Compilation to CSP**
IPP Plan (Walser/Kautz)	***Naïve direct refinement* with FSR**	**Compilation to ILP**
BDDPlan (Hans-Peter) **PROPPlan (Stoerr)**	***Naïve direct refinement* with FSR**	**Compilation to BDDs**

Conjunctive vs. Disjunctive planners

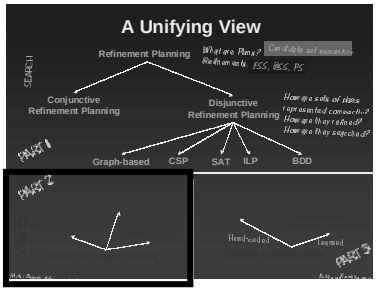
- Progress depends on the effectiveness of the heuristics for judging the goodness of a partial plan
- Space consumption can be regulated
- Better fit with mixed-initiative, incremental planning scenarios(?)

- Space consumption is a big issue
  - Creation and storage of disjunctive structures
    - » CSPs do better by supporting implicit representations
- Connection to combinatorial substrate
- Better integration with non-propositional reasoners (?)

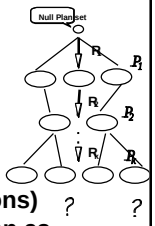
Hybrid planners--Controlled splitting & Search in the space of disjunctive plans

PART 2

HEURISTICS & OPTIMIZATIONS



Distance Heuristics from Relaxed Problems



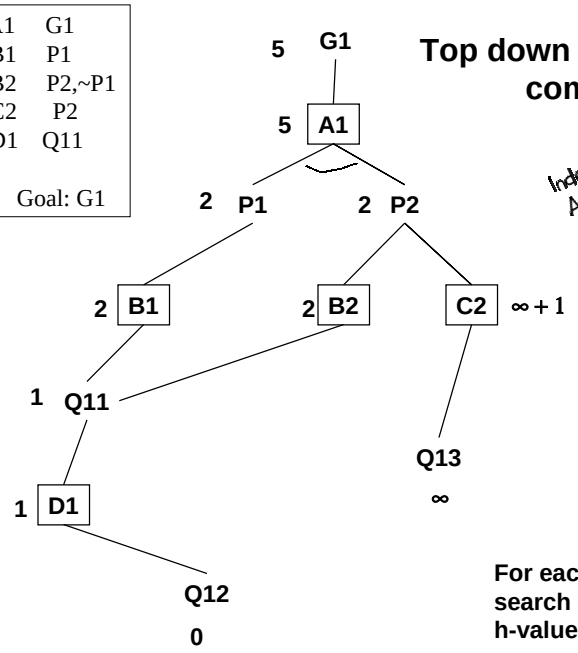
Problem: Estimating the distance of a (partial) state from the initial (or goal) state

Solution: Relax the problem by assuming that all subgoals are independent (ignore +ve / -ve interactions between actions)
Solve the relaxed problem and use the length of the solution as part of the heuristic

Properties: The heuristic is neither a lower bound (-ve interactions) nor an upper-bound (+ve interactions).
--leads to inoptimal solutions (in terms of plan length)
>>Possible to reduce inoptimality by considering interactions

History: First used in IxTET [Ghallab et. al. 1995]
hinted at by Smith's Operator Graphs [Smith et. al., 1995]
independently re-discovered in UNPOP [McDermott, 1996]
independently re-re-discovered in HSP [Bonet & Geffner, 1997]

P1,P2	A1	G1
Q11	B1	P1
Q11	B2	P2,~P1
Q13	C2	P2
Q12	D1	Q11
Init: Q12	Goal: G1	



Top down greedy distance computation

Independence Assumption

+ve as well as -ve interactions between P1 and P2 are ignored….

TOP DOWN Demand-Driven

For each partial plan in the search queue, estimate its h-value using this procedure

Bottom-up Distance computation

- Each condition (state-variable & value combo) has a distance
  - Initialized to 0 for all conditions in the initial state
  - ∞ for everything else
- Repeat until reaching fix-point (until no distances change)
  - Select an action A to be applied. Let P_1 …P_m be its preconditions and E_1 …E_n be the conditions it adds.
  - Reset the distance values of E_i as follows

Bottom-up

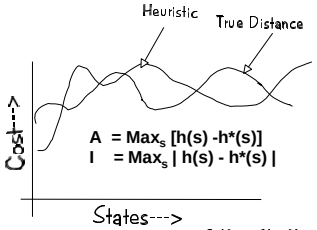
$$Dist(E_i) = Min\left(\underbrace{Dist(E_i)}_{Old\ Dist}, Dist(\{P_1..P_i\}) + 1\right)$$

$$Dist(\{P_1..P_i\}) = \sum_i Dist(P_i)$$

Independence assumption

Improving the Heuristic

- Subgoal independence assumption leads to
  - Inadmissibility (when subgoals interact positively; A is +ve)
  - Un-informedness (when subgals interact negatively; I is large)
- Informedness improved by accounting for -ve interactions
  - Use information about infeasible subgoal sets ("Mutexes")
    - » No plan of length k can achieve p and q
    - » No plan can ever achieve p and q
- Admissibility can be improved by accounting for +ve interactions
  - Solve the planning problems ignoring -ve interactions between actions to get lower bound on plan length (distance)



[Long & Kambhampati, AAAI 2000]

Using the Planning Graph to account for +ve/-ve Interactions

- **Mutex relations can help account for -ve interactions**
  - **Grow the PG until *level-off* (Polynomial operation)**
  - **Distance of a set {P_1 P_2 …P_n} is the *index* of the first level of the PG where P_1…P_n are present without any mutexes**
    - » **Easy to generalize to n-ary mutexes**
    - » **Informedness can be improved by partitioning P_1…P_n into some *k* partitions, S_1…S_k and *summing* the distances of S_i**
- **+ve interactions can be accounted for by extracting a plan from the PG *ignoring* mutex relations**
  - **Run Graphplan algorithm, but do not do any mutex propagation.**

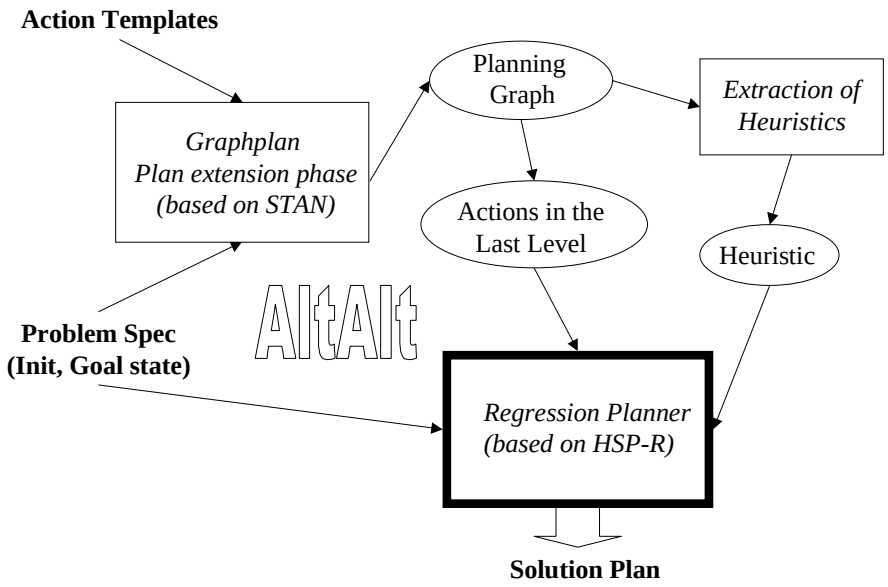
Insight: Ideas of disjunctive planning help in generating heuristics for conjunctive planners!!

Plan Graph produces a large spectrum of effective heuristics with differing tradeoffs

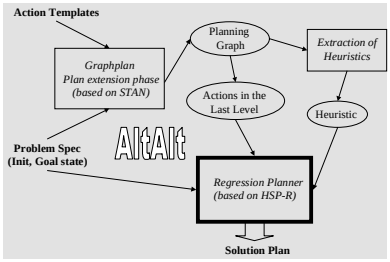
Problem	Graphplan	Sum-mutex	set-lev	partition-1	partition-2	adj-sum	combo	adj-sum2
bw-large-b	18/ 379.25	18/ 132.50	18/ 10735.48	-	18/ 79.18	22/ 65.62	22/ 63.57	18/ 87.11
bw-large-c	-	-	-	-	-	30/ 724.63	30/ 444.79	28/ 738.00
bw-large-d	-	-	-	-	-	-	-	36/ 2350.71
rocket-ext-a	-	36/ 40.08	-	32/ 4.04	32/ 10.24	40/ 6.10	34/ 4.72	40/ 43.63
rocket-ext-b	-	34/ 39.61	-	32/ 4.93	32/ 10.73	36/ 14.13	32/ 7.38	36/ 554.78
att-log-a	-	69/ 42.16	-	65/ 10.13	-	63/ 16.97	65/ 11.96	56/36.71
att-log-b	-	67/ 56.08	-	69/ 20.05	-	67/ 32.73	67/ 19.04	61/53.28
gripper-20	-	59/ 90.68	-	59/ 39.17	-	59/ 20.54	59/ 20.92	59/38.18
8-puzzle1	31/ 2444.22	33/ 196.73	31/ 4658.87	35/ 80.05	47/ 172.87	39/ 78.36	39/ 119.54	31/ 143.559
8-puzzle2	30/ 1545.66	42/224.15	30/ 2411.21	38/ 96.50	38/ 105.40	42/ 103.70	48/ 50.45	30/ 348.27
8-puzzle3	20/ 50.56	20/ 202.54	20/ 68.32	20/ 45.50	20/ 54.10	24/ 77.39	20/ 63.23	20/ 62.56
travel-1	9/ 0.32	9/ 5.24	9/ 0.48	9/ 0.53	9/ 0.62	9/ 0.42	9/ 0.44	9/ 0.53
grid3	16/ 3.74	-	16/ 14.09	16/ 55.40	16/ 46.79	18/ 21.45	19/ 18.82	16/ 15.12
grid4	18/ 21.30	-	18/ 32.26	18/ 86.17	18/ 126.94	18/ 37.01	18/ 37.12	18/ 30.47
aips-grid1	14/ 311.97	-	14/ 659.81	14/ 870.02	14/ 1010.80	14/ 679.36	14/ 640.47	14/ 739.43
mprime-1	4/ 17.48	-	4/ 743.66	4/ 78.730	4/ 622.67	4/ 76.98	4/ 79.55	4/ 722.55

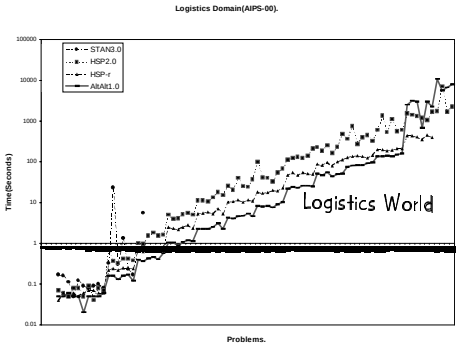
Table 2: Number of actions/ Total CPU Time in seconds. The dash (-) indicates that no solution was found in 3 hours or 250MB.

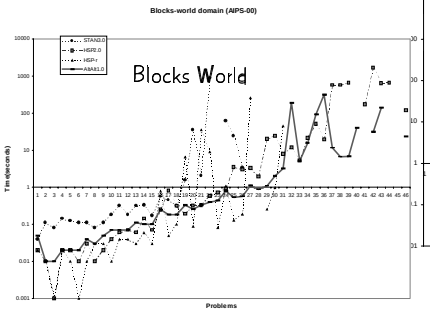
[Long & Kambhampati, AAAI 2000]

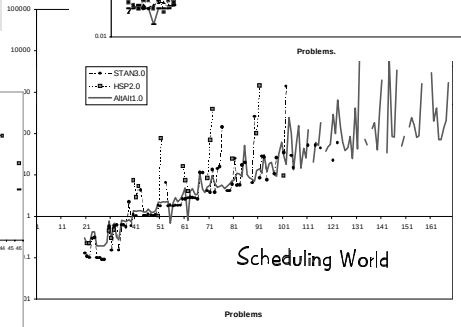


AltAlt shows quite impressive performance

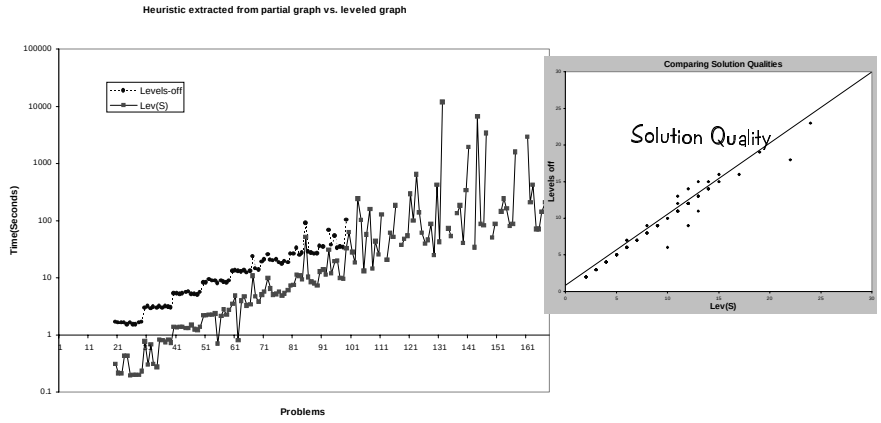








The cost of heuristic computation can be controlled...



Distance based heuristics help CSP Search too!

Kambhampati & Sanchez AIPS-2000

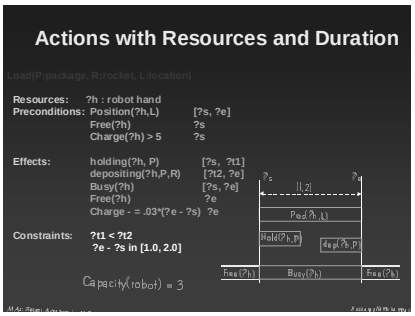
- Variable ordering: Pick the goal with the highest level first
- Value ordering: Pick the action whose precondition literals appear unmutexed at the lowest level.

Can give huge speedups
(5000x on rocket-world, 100x on gripper problems)

Is insensitive to the length of the planning graph
--Can start search in planning graphs of lengths higher than the minimal solution bearing planning graph
Rocket-ext-b goes from 29 to 32 steps and 0.03 to 0.01sec when searching on a planning graph of length 17 instead of 7
--Avoids exhaustive search in failing levels

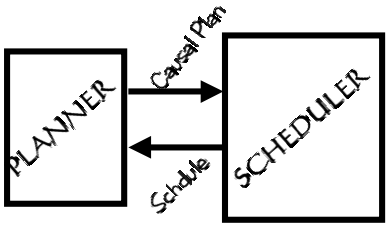
Using Distance Heuristics

- Conjunctive FSS planners need to recompute the heuristic as the init state changes
  - UNPOP [McDermott], HSP [Bonet & Geffner], FF [Hoffman]
    - » GRT [Refanidis & Vlahavas] elaborates the goal state and computes heuristic in the reverse direction
- Conjunctive BSS planners can get by with a single computation of the heuristic
  - HSP-R [Bonet & Geffner], AltAlt [Long & Kambhampati &..]
- Conjunctive PS planners can use distance heuristics and mutex information to rank partial plans and flaw resolution choices
  - IxTET [Ghallab et. al.]; AltAlt-UC [Long & Kambhampati]
- Disjunctive planners can use distance heuristics as the basis for variable and value ordering heuristics
  - GP-HSP [Kambhampati & Nigenda], GP-CSP [Do & Kambhampati]



Handling Resources, Metric and Temporal Contraints

Adapting to Metric/Temporal Planning



Schedulers already routinely handle resources and metric/temporal constraints.

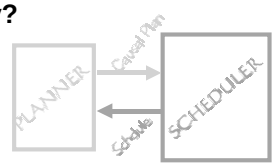
- **Let the "planner"concentrate on causal reasoning**
- **Let the "scheduler" concentrate on resource allocation, sequencing and numeric constraints for the generated causal plan**

Need better coupling to avoid inter-module thrashing....

Issues in handling time and resources

- **Monolithic or loosely-coupled?**
- **How can the Planner keep track of consistency?**
  - **Low level constraint propagation**
    - **» Loose path consistency on TCSPs**
    - **» Bounds on resource consumption,**
    - **» LP relaxations of metric constraints**
  - **Pre-emptive conflict resolution**

  The more aggressive you do this, the less need for a scheduler..
- **How do the modules interact?**
  - **Failure explanations; Partial results**
- **Which Planners are best suited for time and resources?****



RealPlan--Master/Slave

[Srivastava & Kambhampati ECP'99; AAAI, 2000]

Master-Slave (RealPlan-MS)

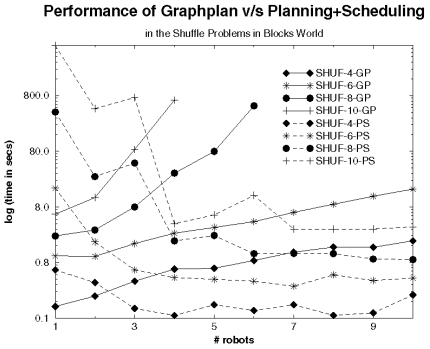
P

S

Planner does causal reasoning.

Scheduler attempts resource allocation

If scheduler fails, planner has to restart



RealPlan: Peer-to-Peer

Explanation-directed backtracking between Planner and Scheduler

Peer-Peer (RealPlan-PP)

P T S

Rakapedi.eas.asu.edu/realplan.html

Problem	RealPlan-PP			BTPWF Time	RealPlan-MS		Speedup (x)	
	Class	Time	#bk		Class	Time	BTPWF	RealPlan-MS
Shuf_b8r4	INFRES	2.52	4	>3 hr	SAMELEN	9373	**>4170**	**3619**
Shuf_b8r4	FIX	8.74	1	>3 hr	SAMELEN	9373	**>1236**	**1072**
Huge_r6	***INFRES***	***4.53***	***4***	***976***	***INCRLEN***	***11056***	***215***	***2441***
Huge_r6	FIX	17.48	3	991	INCRLEN	11056	**56.7**	**632**
Huge_r6	SAMELEN	20.59	2	983	INCRLEN	11056	**47.7**	**537**

What planners are good for handling resources and time?

- **State-space approaches have an edge in terms of ease of monitoring resource usage**
  - ***Time-point based representations are known to be better for multi-capacity resource constraints in scheduling***
- **Plan-space approaches have an edge in terms of durative actions and continuous change**
  - **Notion of state not well defined in such cases (Too many states)**
  - ***PCP representations are known to be better for scheduling with single-capacity resources***
- **Disjunctive compilation approaches may provide better basis for interacting with schedulers and other external constraint reasoners**
  - **Conjunctive approaches better for *monolithic* architectures (disjunctive ones may lead to very large encodings)**

[Adapted from David Smith's Invited Talk at AIPS-2000]

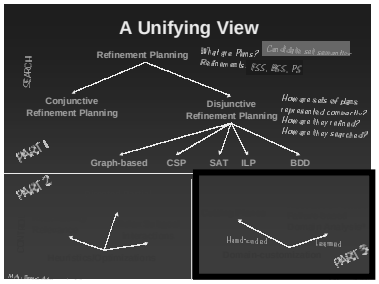
Tradeoffs in the current implementations

	Multi-capacity Resources	Metric Quantities	Optimization	Continuous Time	Speed
Graphplan	hard?	hard IPP	hard?	hard TGP	good
SAT Compilation	moderate?	moderate LPSAT	moderate?	very hard?	good
ILP Compilation	easy?	easy ILP-plan	easy ILP-plan	very hard?	fair?
Conjunctive PS	moderate IxTeT	moderate Zeno	moderate?	easy HSTS	fair?

Work on loosely-coupled architectures is just starting… [Srivastava, 2000]

PART 3 CUSTOMIZING PLANNERS WITH DOMAIN SPECIFIC KNOWLEDGE

1. **User-assisted customization**
2. **Automated customization**



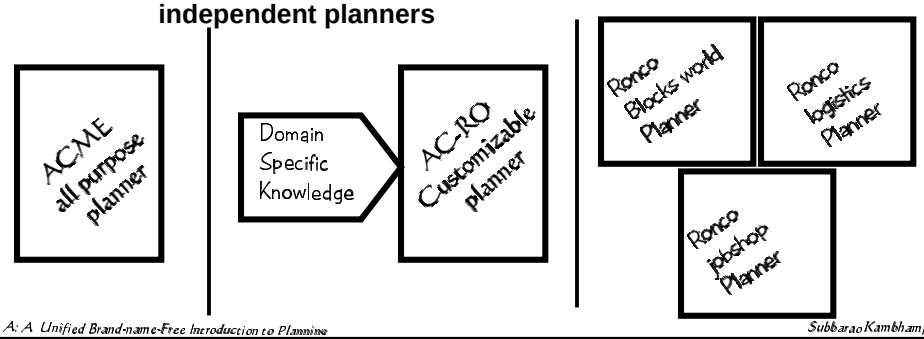
Improving Performance through Customization

- **Biasing the search with control knowledge acquired from experts**
  - **Non-primitive actions and reduction schemas**
  - **Automated synthesis of customized planners**
    - » **Combine formal theory of refinement planning and domain-specific control knowledge**
- **Use of learning techniques**
  - **Search control rule learning**
  - **Plan reuse**

User-Assisted Customization (using domain-specific Knowledge)

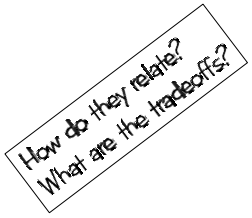
- Domain independent planners tend to miss the regularities in the domain
- Domain specific planners have to be built from scratch for every domain

An ***"Any-Expertise"*** Solution: Try adding domain specific control knowledge to the domain-independent planners



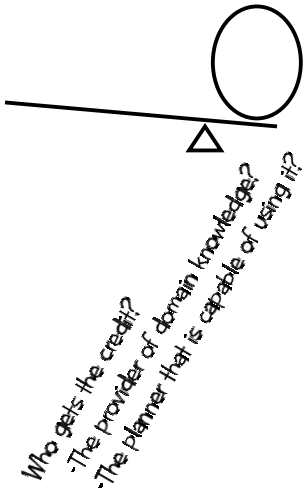
Many User-Customizable Planners

- Conjunctive planners
  - HTN planners
    - » SIPE [Wilkins, 85-]
    - » NONLIN/O-Plan [Tate et. al., 77-]
    - » NOAH [Sacerdoti, 75]
    - » Also SHOP (Nau et. al., IJCAI-99)
  - State-space planners
    - » TLPlan [Bacchus & Kabanza, 95; 99]
    - » TALPlan [Kvarnstrom & Doherty, 2000]
  - Customization frameworks
    - » CLAY [Srivastava & Kambhampati, 97]
- Disjunctive planners
  - HTN SAT [Mali & Kambhampati, 98]
  - SATPLAN+Dom [Kautz & Selman, 98]



With right domain knowledge any level of performance can be achieved...

- **HTN-SAT, SATPLAN+DOM beat SATPLAN…**
  - **Expect reduction schemas, declarative knowledge about inoptimal plans**
- **TLPLAN beats SATPLAN, GRAPHPLAN**
  - **But uses quite detailed domain knowledge**
- **SHOP beats TLPLAN…(but not TALPlan)**
  - **Expects user to write a "program" for the domain in its language**
    - » **Explicit instructions on the order in which schemas are considered and concatenated**



Types of Guidance

- **Declarative knowledge about desirable or undesirable solutions and partial solutions (SATPLAN+DOM; Cutting Planes)**
- **Declarative knowledge about desirable/undesirable search paths (TLPlan & TALPlan)**
- **A declarative grammar of desirable solutions (HTN)**

(largely) independent of the details of the specific planner
(affinities do exist between specific types of guidance and planners)

Planner specific. Expert needs to understand the specific details of the planner's search space

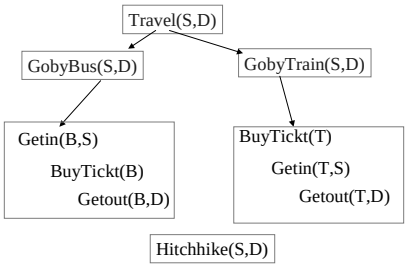
- **Procedural knowledge about how the search for the solution should be organized (SHOP)**
- **Search control rules for guiding choice points in the planner's search (NASA RAX)**

Ways of using the Domain Knowledge

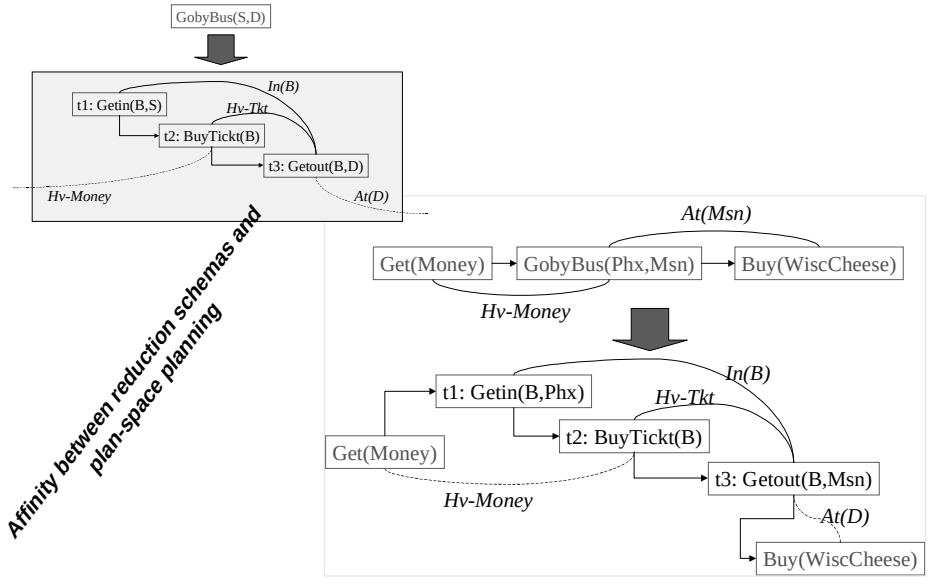
- As search control
  - HTN schemas, TLPlan rules, SHOP procedures
  - *Issues of Efficient Matching*
- To prune unpromising partial solutions
  - HTN schemas, TLPlan rules, SHOP procedures
  - *Issues of maintaining multiple parses*
- As declartative axioms that are used along with other knowledge
  - SATPlan+Domain specific knowledge
  - Cutting Planes (for ILP encodings)
  - *Issues of domain-knowledge driven simplification*
- Folded into the domain-independent algorithm to generate a new domain-customized planner
  - CLAY
  - *Issues of Program synthesis*

Task Decomposition (HTN) Planning

- The OLDEST approach for providing domain-specific knowledge
  - Most of the fielded applications use HTN planning
- Domain model contains non-primitive actions, and schemas for reducing them
- Reduction schemas are given by the designer
  - Can be seen as encoding user-intent
    - » *Popularity of HTN approaches a testament of ease with which these schemas are available?*
- Two notions of completeness:
  - Schema completeness
    - » (Partial Hierarchicalization)
  - Planner completeness



Modeling Action Reduction



Dual views of HTN planning

- **Capturing hierarchical structure of the domain**
  - **Motivates top-down planning**
    - » **Start with abstract plans, and reduce them**
- **Many technical headaches**
  - **Respecting user-intent, maintaining systematicity and minimality**
    [Kambhampati et. al. AAAI-98]
    - » **Phantomization, filters, promiscuity, downward-unlinearizability..**

- **Capturing expert advice about desirable solutions**
  - **Motivates bottom-up planning**
    - » **Ensure that each partial plan being considered is "legal" with respect to the reduction schemas**
    - » **Directly usable with disjunctive planning approaches**
      [Mali & Kambhampati, 98]
- **Connection to efficiency is not obvious**

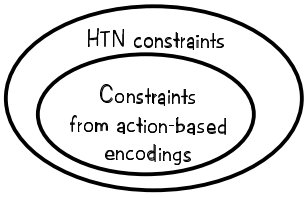
Relative advantages are still unclear...

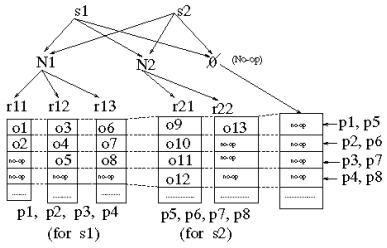
[Barrett, 97]

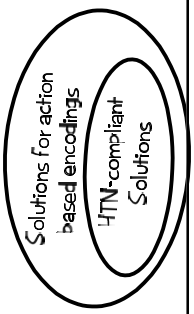
[Mali & Kambampati, AIPS-98]

SAT encodings of HTN planning

- **Abstract actions can be seen as disjunctive constraints**
  - **K-step encoding has each of the steps mapped to a disjunction of the non-primitive tasks**
  - **If a step s is mapped to a task N, then one of the reductions of N must hold (**The heart of encoding setup**)**
  - **+ The normal constraints of primitive action-based encoding**
    - » **Causal encodings seem to be a natural fit (given the causal dependencies encoded in reduction schemas)**



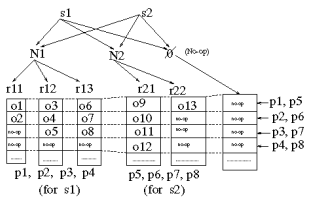


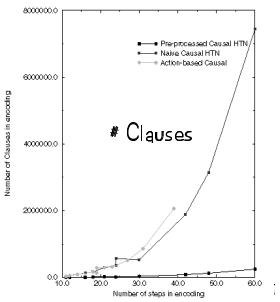


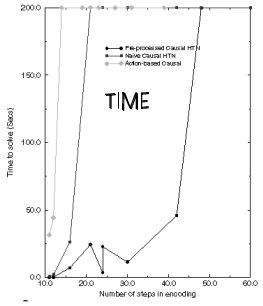
Solving HTN Encodings

Puzzle: How can increasing encoding sizes lead to efficient planning?
Abstract actions and their reductions put restrictions on the amount of step-action disjunction at the primitive level.
--Reduction in step-action disjunction propagates
e.g. Fewer causal-link variables, Fewer exclusion clauses…

Savings won't hold if each non-primitive task has MANY reductions







[Nau et. al., 99]

Full procedural control: The SHOP way

Shop provides a "high-level" programming language in which the user can code his/her domain specific planner

-- Similarities to HTN planning
-- Not declarative (?)

The SHOP engine can be seen as an interpreter for this language

```
(:method (travel-to ?y)
    (:first (at ?x)
     (at-taxi-stand ?t ?x)
     (distance ?x ?y ?d)
     (have-taxi-fare ?d))
   `((!hail ?t ?x) (!ride ?t ?x ?y)
     (pay-driver ,(+ 1.50 ?d)))
    ((at ?x) (bus-route ?bus ?x ?y))
   `(((!wait-for ?bus ?x)
     (pay-driver 1.00)
     (!ride ?bus ?x ?y)))
```

Travel by bus only if going by taxi doesn't work out

Blurs the domain-specific/domain-independent divide
How often does one have this level of knowledge about a domain?

[Kautz & Selman, AIPS-98]

Non-HTN Declarative Guidance

Invariants: *A truck is at only one location*
at(truck, loc1, I) & loc1 != loc2 => ~at(truck, loc2, I)

Optimality: *Do not return a package to the same location*
at(pkg, loc, I) & ~at(pkg,loc,I+1) & I<J => ~at(pkg,loc,j)

Simplifying: *Once a truck is loaded, it should immediately move*
~in(pkg,truck,I) & in(pkg,truck,I+1) & at(truck, loc, I+1) =>
~at(truck, loc, I+2)

Once again, additional clauses first increase the encoding size but make them easier to solve after simplification (unit-propagation etc).

Rules on desirable State Sequences: TLPlan approach

TLPlan [Bacchus & Kabanza, 95/98] controls a forward state-space planner

Rules are written on state sequences using the linear temporal logic (LTL)

LTL is an extension of prop logic with temporal modalities

U	**until**	**[]**	**always**
O	**next**	**<>**	**eventually**

Example:

If you achieve on(B,A), then preserve it until On(C,B) is achieved:

[] (on(B,A) => on(B,A) U on(C,B))

TLPLAN Rules can get quite baroque

Good towers are those that do not violate any goal conditions

$$goodtower(x) \triangleq clear(x) \wedge goodtowerbelow(x)$$

$$\begin{aligned} goodtowerbelow(x) \triangleq\ & (ontable(x) \wedge \neg \mathrm{GOAL}(\exists [y{:}on(x,y)] \vee holding(x))) \\ & \vee \exists [y{:}on(x,y)]\, \neg \mathrm{GOAL}(ontable(x) \vee holding(x)) \wedge \neg \mathrm{GOAL}(clear(y)) \\ & \wedge \forall [z{:}\mathrm{GOAL}(on(x,z))]\, z = y \wedge \forall [z{:}\mathrm{GOAL}(on(z,y))]\, z = x \\ & \wedge goodtowerbelow(y) \end{aligned}$$

Keep growing "good" towers, and avoid "bad" towers

$$\begin{aligned} \Box \Big(& \forall [x{:}clear(x)]\, goodtower(x) \Rightarrow \bigcirc goodtowerabove(x) \\ & \wedge badtower(x) \Rightarrow \bigcirc(\neg \exists [y{:}on(y,x)]\ ) \\ & \wedge (ontable(x) \wedge \exists [y{:}\mathrm{GOAL}(on(x,y))]\, \neg goodtower(y)) \\ & \quad \Rightarrow \bigcirc(\neg holding(x)) \Big) \end{aligned}$$

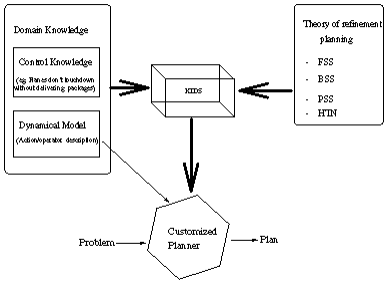
How "Obvious" are these rules?

The heart of TLPlan is the ability to *incrementally* and *effectively* evaluate the truth of LTL formulas.

Srivastava & Kambhampati, JAIR 97

Folding the Control Knowledge into the planner: CLAY approach

- Control knowledge similar to TLPlan's
- Knowledge is folded using KIDS semi-automated software synthesis tool into a generic refinement planning template
  - Use of program optimizations such as
    - » Finite differencing
    - » Context-dependent & independent simplification
- Empirical results demonstrate that folding can be better than interpreting rules



Caveat: Current automated software synthesis tools have a very steep learning curve

Conundrums of user-assisted cutomization

- Which planners are easier to control?
  - Conjunctive planners are better if you have search control knowledge
    - » Forward State Space (according to TLPlan)
    - » Plan-space planners (according to HTN approaches)
  - Disjunctive planners are better if your knowledge can be posed as additional constraints on the valid plans
    - » Which SAT encoding?
      - HTN knowledge is easier to add on top of causal encodings
- Which approach provides the best language for expressing domain knowledge for the lay user?
  - *(Mine--no, no, Mine!)*
- What type of domain knowledge is easier to validate?
- When does it become "cheating"/ "wishful-thinking"
  - Foolish not to be able to use available knowledge
  - Wishful to expect deep procedural knowledge...

Automated Customization of Planners

- **Domain pre-processing**
  - **Invariant detection; Relevance detection; Choice elimination, Type analysis**
    - » **STAN/TIM, DISCOPLAN etc.**
    - » **RIFO; ONLP**
- **Abstraction**
  - » **ALPINE; ABSTRIPS, STAN/TIM etc.**
- **Learning Search Control rules**
  - » **UCPOP+EBL,**
  - » **PRODIGY+EBL, (Graphplan+EBL)**
- **Case-based planning (plan reuse)**
  - » **DerSNLP, Prodigy/Analogy**

Most of the work has been done in the context of Conjunctive Refinement Planners

Symmetry & Invariant Detection

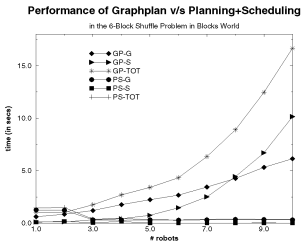
- **Generate potential invariants and test them**
  - **DISCOPLAN [Gerevini et. al.]**
    - » **Allows detection of higher-order mutexes**
  - **Rintanen's planner**
    - » **Uses model-verification techniques**
  - **STAN/TIM**
    - » **Type analysis of the domain is used to generate invariants**
  - **ONLP (Peot & Smith)**
    - » **Use operator graph analysis to eliminate non-viable choices**

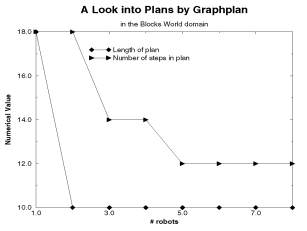
Abstraction

- **Idea**
  - **Abstract some details of the problem or actions.**
  - **Solve the abstracted version.**
  - **Extend the solution to the detailed version**
- **Precondition Abstraction**
  - **Work on satisfying *important* preconditions first**
    - » **Importance judged by:**
      - **Length of plans for subgoals [ABSTRIPS, PABLO]**
      - **Inter-goal relations [ALPINE]**
      - **Distribution-based [HighPoint]**
  - **Strong abstractions (with downward refinement property) are rare**
  - **Effectiveness is planner-dependent**
    - » **Clashes with other heuristics such as *"most constrained first"***

Example: Abstracting Resources

- **Most planners thrash by addressing planning and scheduling considerations together**
  - **Eg. Blocks world, with multiple robot hands**
- **Idea: Abstract resources away during planning**
  - **Plan assuming infinite resources**
  - **Do a post-planning resource allocation phase**
  - **Re-plan if needed**





(with Biplav Srivastava)

Learning Search Control Rules with EBL

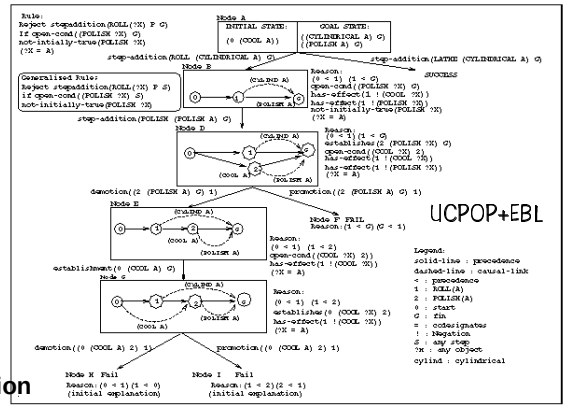
Explain leaf level failures

Regress the explanations to compute interior node failure explanations

Use failure explanations to set up control rules

Problems:

- **-- Most branches end in depth-limits**
  - **>No analytical explanation**
  - **>Use preference rules?**
- **-- THE Utility problem**
  - **>Learn general rules**
  - **>Keep usage statistics & prune useless rules**



If Polished(x)@S &
~Initially-True(Polished(x))
Then
REJECT
Stepadd(Roll(x),Cylindrical(x)@s)

(Kambhampati, Katukam, Qu, 95)

Example Rules (Learned)

UCPOP

If Polished(x)@S &
~Initially-True(Polished(x))
Then
REJECT
Stepadd(Roll(x),Cylindrical(x)@s)

Pruning rule

Prodigy

If (and (current-node *node*)
(candidate-goal *node*
(shape *obj* Cyl))
(candidate-goal node
(surface-condition *obj*
polished)))
Then: Prefer (shape *obj* cyl) to
(surface-condition *obj* polished)

Preference rule

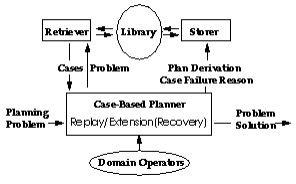
Case-based Planning
Macrops, Reuse, Replay

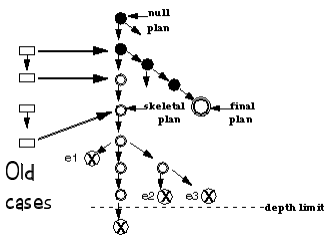
- Structures being reused
  - Opaque vs. Modifiable
  - Solution vs. Solving process (derivation)
- Acquisition of structures to be reused
  - Human given vs. Automatically acquired
- Mechanics of reuse
  - Phased vs. simultaneous
- Costs
  - Storage & Retrieval costs; Solution quality

(Ihrig & Kambhampati, JAIR 97)

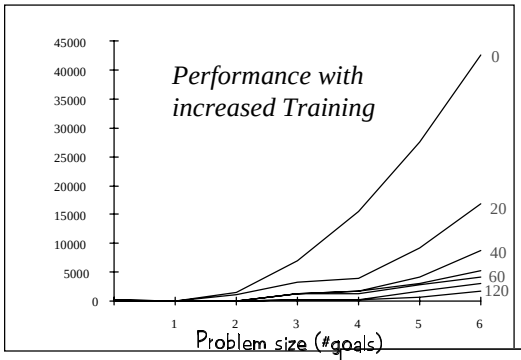
Case-study: DerSNLP

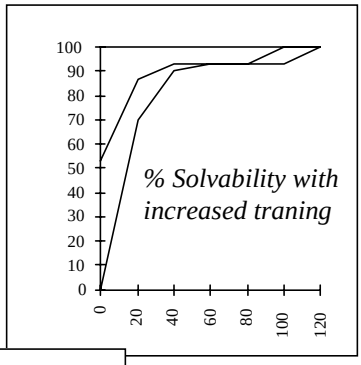
- Modifiable derivational traces are reused
- Traces are automatically acquired during problem solving
  - Analyze the interactions among the parts of a plan, and store plans for *non-interacting* subgoals separately
    - » Reduces retrieval cost
  - Use of EBL failure analysis to detect interactions
- All relevant trace fragments are retrieved and replayed before the control is given to from-scratch planner
  - Extension failures are traced to individual replayed traces, and their storage indices are modified appropriately
    - » Improves retrieval accuracy

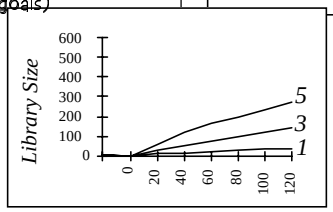




DerSNLP: Results







(JAIR, 97)

Reuse in Disjunctive Planning

- **Harder to make a disjunctive planner commit to extending a specific plan first**
- **Options:**
  - **Support opaque macros along with primitive actions**
    - » **Increases the size of k-step disjunctive plan**
    - » **But a solution may be found at smaller k**
  - **Modify the problem/domain specification so the old plan's constraints will be respected in any solution (Bailotti et. al.)**
  - **MAX-SAT formulations of reuse problem**
    - » **Constrain the encoding so that certain steps may have smaller step-action mapping and ordering choices**
    - » **Causal encodings provide better support**

[with Amol Mali]

Summary

- Focus on "Neo-classical" planning
  - Refinement planning provides a unifying view
  - – Conjunctive Refinement Planners
  - – Disjunctive Refinement Planners
    - » Refinement
    - » Solution Extraction
      - Direct vs. compilation to CSP/SAT
- Heuristics/Optimizations
  - – Relaxed Problem heuristics
  - – Consistency enforcement
- Customization of planners
  - – User-assisted
  - – Automated
- Related approaches to non-classical planning

But who is winning???
(Using AIPS-2000 Competition as a benchmark)

- 15 planners took part in AIPS-2000 competition
  - – Representatives from all types of planners we discussed
- Competition focussed on pure classical problems
  - – Separate tracks for domain-independent and user-customized planners
- Domain independent:
  - – FF (Forward state-space planning; Heuristics based on planning graphs, local search)
- Customized:
  - – TALPlan (control knowledge about good and bad state sequences, applied to a forward state-space planner)
- Million Dollar question: Will the line-up be same for neo-classical planning (durative actions, continuous change etc?)

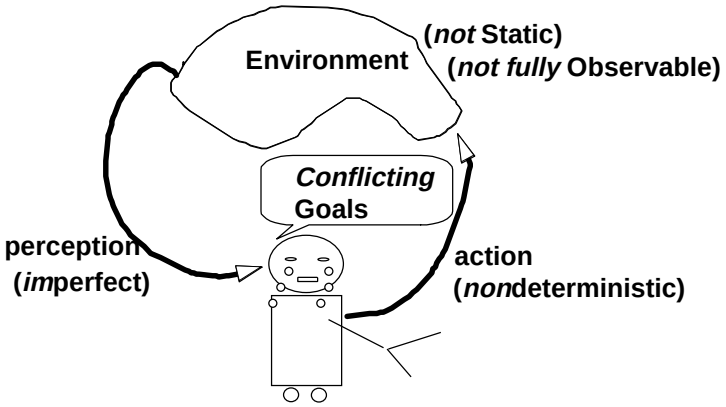
Status

- Exciting times…
  - Many approaches with superior scale-up capabilities
    - » Broadened views of planning
  - Many influences (CSP; OR; MDP; SCM)
- Ripe for serious applications
  - VICAR [JPL]; DeepSpace monitoring [NASA/AMES]
  - Plant monitoring [Ayslett et. al.]
  - Manufacturing Process Planning [Nau et. al.; Kambhampati et. al]
  - Supply chain management/ Logistics
    - » Industrial "Planning" does not have to the optimal scheduling of an inoptimal action selection!

Resources

- Mailing Lists
  - Planning list digest
    - » http://rakaposhi.eas.asu.edu/planning-list-digest
  - U.K. P & S List
    - » http://www.salford.ac.uk/planning/home.html
- Special Conferences
  - Intl. Conf. on AI Planning & Scheduling
    - » http://www.isi.edu/aips (April 2000, Breckenrdige, CO)
  - European Conference on Planning
    - » http://www.informatik.uni-ulm.de/ki/ecp-99.html
  - Also, AAAI, IJCAI, ECAI, Spring/Fall Symposia
- Courses
  - ASU Planning Seminar Online Notes (2000,1999, 1997, 1995,1993)
    - » http://rakaposhi.eas.asu.edu/planning-class.html

Adapting to Incompleteness, Uncertainity and Dynamism



The most efficient approaches to all these *ills* are sti

Incomplete Information

- **PROBLEM: Values of some state variables are unknown; There are actions capable of sensing (some) of them.**
  - **If k boolean state variables are unknown, then we are in one of 2^k initial states**
  - **Two naïve approaches**
    - » **PLAN/SENSE/EXECUTE : Solve each of the 2^k problems separately; At the execution time sense the appropriate variables, and execute the appropriate plan**
    - » **SENSE/PLAN/EXECUTE: First sense the values of the variables. Solve the problem corresponding to the sensed values**
  - **Problems with naïve approaches**
    - » **Solving the 2^k problems separately is wasteful**
      - **Shared structure (Tree structured plans)**
    - » **Not all variables may be observable (or worth observing)**
      - **Conformant planning**
        - **(Find non-sensing plans that work in all worlds)**
      - **Irrelevant variables (Goal directed planning)**

Incomplete Information: Some Implemented Approaches

- **Conjunctive planners**
  - **CNLP [Peot & Smith; 92] CASSANDRA [Pryor & Collins, 96] add sensing actions to UCPOP; support tree-shaped plans**
  - **SADL/PUCCINI [Golden & Weld; 96-98] integrates planning and sensing in the context of a UCPOP-like planner**
- **Disjunctive planners**
  - **CGP [Smith & Weld, 98] supports conformant planning on Graphplan**
  - **SGP [Weld et. al., 98] supports conditional planning on Graphplan**
    - » **One plan-graph per possible world/ Interactions among plangraphs captured through induced mutexes**
  - **[Rintanen, 99] converts conditional planning to QBF encodings**

Dynamic Environments

- **PROBLEM: The world doesn't sit still. Blind execution of a "correct" plan may not reach goals**
- **APPROACHES:**
  - **PLAN/MONITOR/REPLAN: Monitor the execution; when the observed state differs from the expected one, REPLAN**
    - » **Replanning is like reuse except there is added incentive for minimal modification**
      - **Easy to support with conjunctive plan-space planners**
        - **PRIAR [Kambhampati; 92]; DerSNLP [Ihrig & Kambhampati, 97]**
      - **Possible to support with disjunctive causal encodings**
        - **[Mali, 1999]**
  - **MONITOR/REACT/LEARN:**
    - » **Policy construction (Universal plans)…**
  - **MODEL OTHER AGENTS CAUSING CHANGE:**
    - » **Collaborative/Distributed planning**

Stochastic Actions

- **PROBLEM: Action effects are stochastic**
  - **Actions transform *state-distributions* to state-distributions**
  - **Maximize "probability" of goal satisfaction**
  - **Plan assessment itself is hard**
- **APPROACHES:**
  - **Conjunctive planners**
    - » **BURIDAN [Hanks et. al., 95] uses UCPOP techniques to put candidate plans together and assesses them**
      - ***Multiple /redundant supports***
  - **Disjunctive planners**
    - » **Pgraphplan [Blum & Langford, 98] modifies Graphplan to support some forms of stochastic planning**
      - **Forward search; value propagation; Envelope extension**
    - » **Maxplan [Majercik & Littman, 98] uses EMAJSAT encodings to solve stochastic planning problems**
      - **Chance variables & Choice variables. Equivalence classes of models that have the same values of choice variables. Find the equivalence class with maximum probability mass.**

Complex & Conflicting Goals

- **Problems & Solutions:**
  - **Goals that have temporal extent (stay alive)**
    - » **UCPOP, TLPlan, TGP [Smith& Weld, 99]**
  - **Goals that have mutual conflicts (Sky-dive & Stay Alive)**
  - **Goals that take cost of achievement into account**
  - **Goals that admit degrees of satisfaction (Get rich)**
    - » **Branch & Bound approaches; MAXSAT approaches**
      - **Pyrrhus [Williamson & Hanks; 92]**

Decision Theoretic Approaches:
Model goals in terms of factored reward functions
for Markov Decision Processes
--Can utilize tricks and insights from classical planning
[Boutilier, Hanks, Dean; JAIR 99]

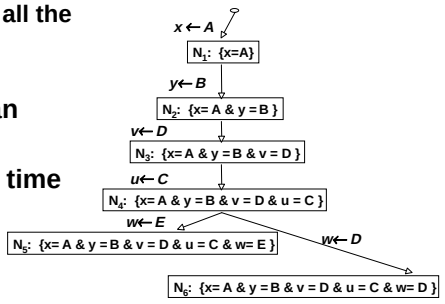
CSP/SAT/TCSP Review

(very) Quick overview of CSP/SAT concepts

- **Constraint Satisfaction Problem (CSP)**
  - **Given**
    - » **A set of discrete variables**
    - » **Legal domains for each of the variables**
    - » **A set of constraints on values groups of variables can take**
  - **Find an assignment of values to all the variables so that none of the constraints are violated**
- **SAT Problem = CSP with boolean variables**
- **TCSP = CSP where variables are time points and constraints describe allowed distances**

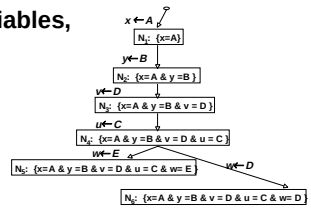
x,y,u,v: {A,B,C,D,E}
w: {D,E} l : {A,B}
x=A ⇒ w≠E
y=B ⇒ u≠D
u=C ⇒ l≠A
v=D ⇒ l≠B

A solution:
x=B, y=C, u=D, v=E, w=D, l=B



Important ideas in solving CSPs

Variable order heuristics:
Pick the most constrained variable
--Smallest domain, connected to most other variables,
causes most unit propagation,
causes most resource contention,
has the most distance etc…



Value ordering heuristics
Pick the least constraining value

Consistency enforcement
k-consistency; adaptive consistency. (pre-processing)
Forward Checking, unit propagation during search (dynamic)

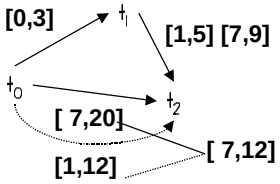
x,y,u,v: {A,B,C,D,E}
w: {D,E} I : {A,B}
x=A ⇒ w≠E
y=B ⇒ u≠D
u=C ⇒ I≠A
v=D ⇒ I≠B

Search/Backtracking
DDB/EBL: Remember and use interior node failure explanations
Randomized search

[Dechter, Schwalb, AIJ 1997]

Temporal Constraint Satisfaction Problem (TCSP)

- **Variables correspond to time points**
- **Constraints retrict allowable distances between time points**
- **Constraints can be represented as sets of intervals**
  - **Simple temporal problem (STP)**
    - » **All constraints have at most one interval (TRACTABLE!!!)**
- **Solution of general TCSP involves enforcing *path-consistency***
  - **Approximations such as loose path consistency can be used to detect inconsistencies**

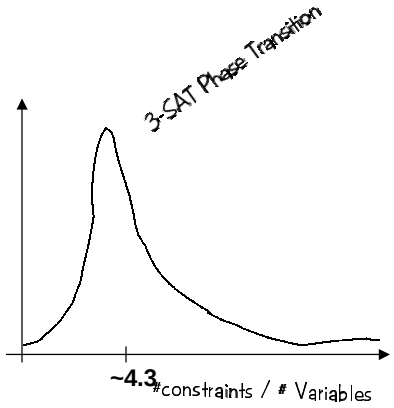


$$(0 \le t_1 - t_0 \le 3)$$
$$(1 \le t_2 - t_1 \le 5) \vee (7 \le t_2 - t_1 \le 9)$$

$$c_{02} = (t_0 t_1) \circ (t_1 t_2) = [1,8][7,12] = [1,12]$$
$$c_{02} \cap (t_0 t_2) = [7,20] \cap [1,12] = [7,12]$$

What makes CSP problems hard?

- **Asignments to individual variables that seem locally consistent are often globally infeasible, causing costly backtracking.**
- **The difficulty of a CSP/SAT problem depends on**
  - **Number of variables (propositions)**
  - **Number of constraints (clauses)**
  - **Arity of constraints**
  - **Degree of local consistency**



Hardness & Local Consistency

- **An n-variable CSP problem is said to be k-consistent iff every consistent assignment for (k-1) of the n variables can be extended to include any k-th variable**
  - **» Directional consistency: Assignment to first k-1 variables can be extended to the k-th variable**
  - **» Strongly k-consistent if it is j-consistent for all j from 1 to k**
- **Higher the level of (strong) consistency of problem, the lesser the amount of backtracking required to solve the problem**
  - **A CSP with strong n-consistency can be solved without any backtracking**
- **We can improve the level of consistency of a problem by explicating implicit constraints**
  - **Enforcing k-consistency is of $O(n^k)$ complexity**
    - **» Break-even seems to be around k=2 ("arc consistency") or 3 ("path consistency")**
    - **» Use of directional and partial consistency enforcement techniques**