

Modelling search
and
evaluating strategies
in
theorem proving

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MARIA PAOLA BONACINA
DEPT. OF COMPUTER SCIENCE
THE UNIVERSITY OF IOWA

What is theorem proving
and how does it relate
to software technology?

Theorem proving

H: assumptions

What follows from H ?

φ : conjecture

Does φ follow from H ?

$$(H \stackrel{?}{\models} \varphi)$$

H may be:

- mathematical theory
(e.g., algebra
geometry
analysis)
- system specification
(e.g., message-passing)

Refutational theorem proving

$$H \cup \{\neg \varphi\}$$

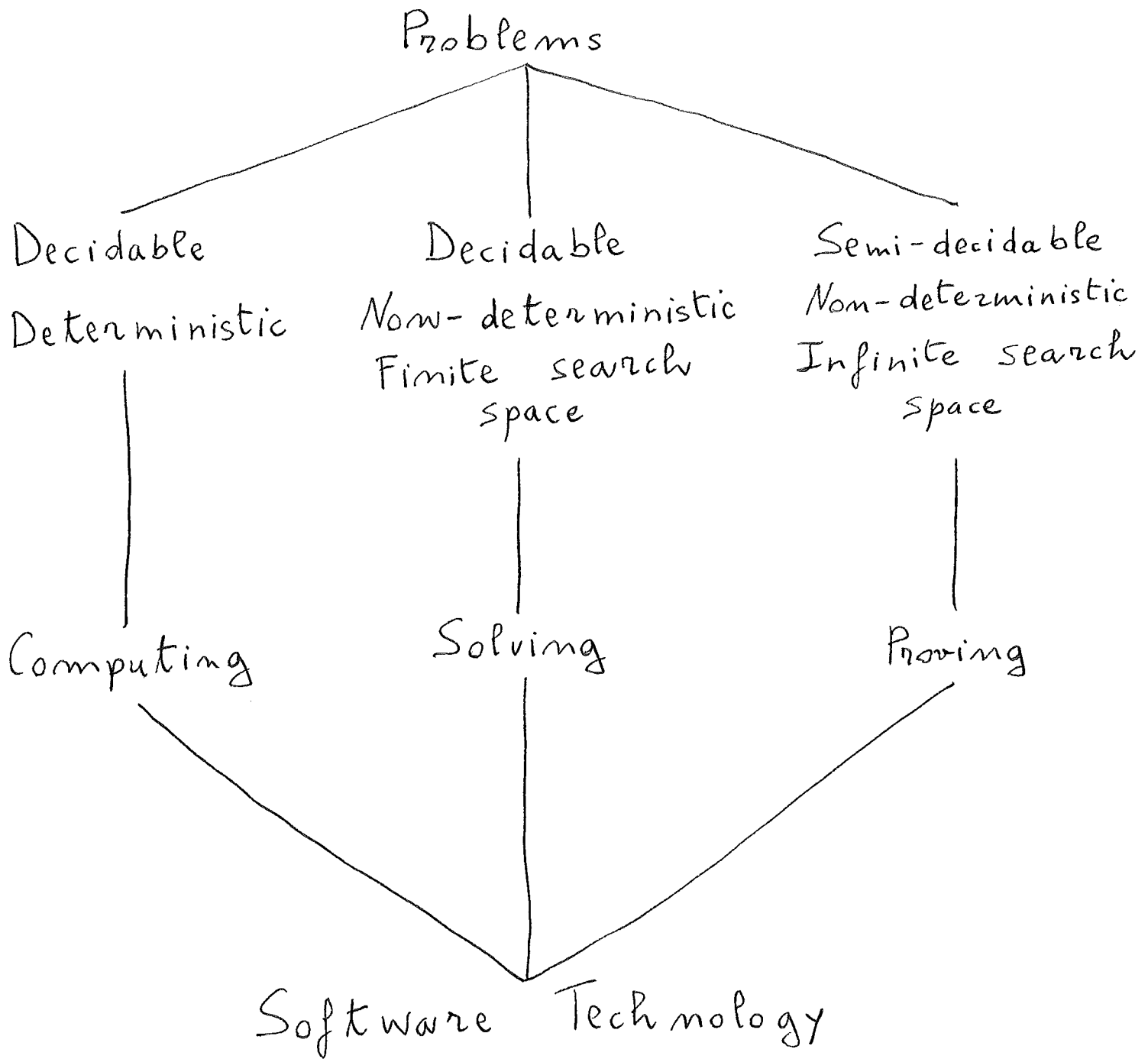
either prove φ by generating
a refutation of $H \cup \{\neg \varphi\}$

$$H \cup \{\neg \varphi\} \vdash \perp$$

or disprove φ by generating
a counterexample

(a model of $H \cup \{\neg \varphi\}$)

T.P. and S.T.:



T.P. and S.T.:

Proving helps computing:

Formal Methods

Verification / Synthesis

Computing helps proving:

Algorithms

Human - Computer Interfaces

T.P. and S.T.:

Solving helps proving:

Constraint solving (e.g., SAT)

Symbolic Computation
(e.g., Computer Algebra)

Proving helps solving:

Deductive proofs

Inductive proofs

Models to work in

Different axiomatizations

Problems in proving

Refutationally complete method

Exhaustive search

Done !?

NO!

Too much redundant information

Brute-force search not adequate

Remedies:

Inference systems with less redundancy

Better search techniques

My research program

Common theme: control of deduction

Research directions:

- Combination of forward and backward reasoning

Target-oriented equational reasoning

Lemmatization in semantic strategies

- Distributed deduction

Clause-Diffusion (Aquarius, Peers)

Modified Clause-Diffusion (Peers-mcd)

Distributed search: criteria to partition search space

- Analysis of strategies

(both inference system and search plan)

Search space reduction by contraction

Distributed-search contraction-based strategies

Why modelling

search and evaluating

strategies in T.P. ?

Theorem proving is difficult

Semi-decidable problem

Infinite search space

Finite resources

but:

it works!

In mathematics, e.g.:

- Moufang identities in rings
S. Anantharaman, J. Hsiang
SBR 2 1990
- Axiomatizations of Łukasiewicz
many-valued logic
S. Anantharaman, M.P. Bonacina
SBR 3 1989-91
- Single axioms for groups
W. McCune OTTER 1993
- Robbins algebras are Boolean
W. McCune EQP 1996

And not only in math:

- Deductive composition of SW
from subroutine libraries
(M.E. Stickel et al.
SNARK 1994)
- Verification of cryptographic
protocols
(J. Schumann SETHEO 1997)
(C. Weidenbach SPASS 1999)
- Modelling + verification of
message-passing systems
(W. McCune IVY 1999)
O. Shumsky

These systems implement
many different strategies:

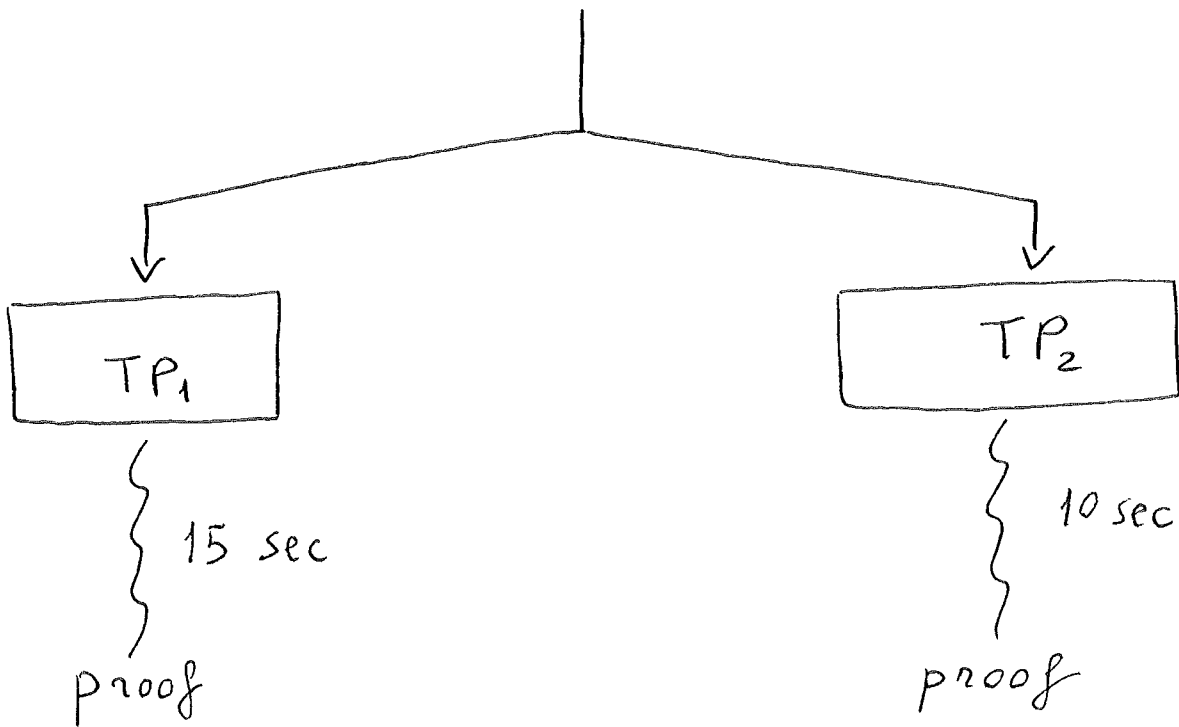
inference	rules	I
search	plans	Σ
<hr/>		
T.P.	strategy	$\mathcal{L} = \langle I; \Sigma \rangle$

Why do they work?

How to evaluate them?

Traditional approach:

implement φ_1 in TP_1
implement φ_2 in TP_2



φ_2 is better!

Clearly not satisfactory.

Conventional complexity analysis
does not apply

- infinite search space
- undecidable problem domain

Can't do worst-case nor average-case analysis.

- complexity not proportional to input (e.g., input length)
- complexity not proportional to output (e.g., proof length)

Need a way to analyze the process
of finding a proof.

A key feature of today

T.P. strategies:

contraction

Assume forward reasoning:
generate (e.g., resolution)
and keep clauses.

Contraction:

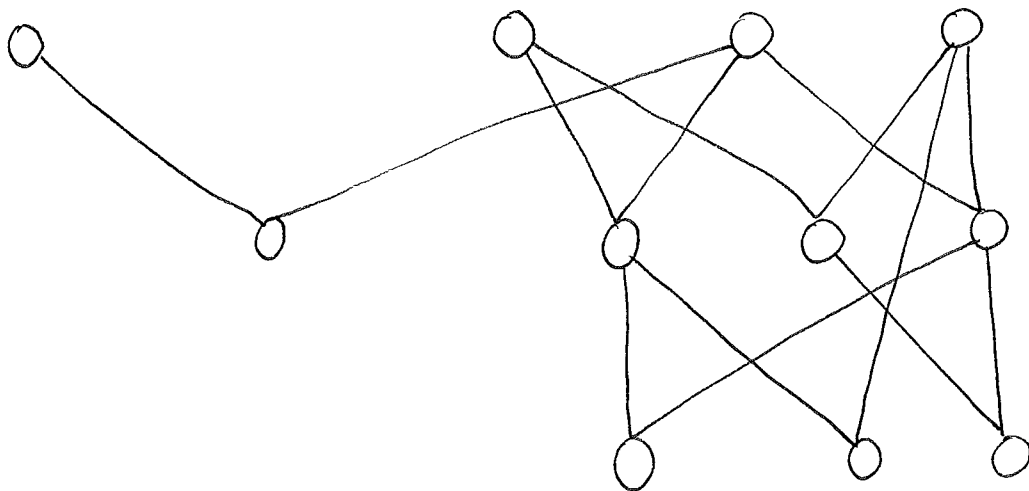
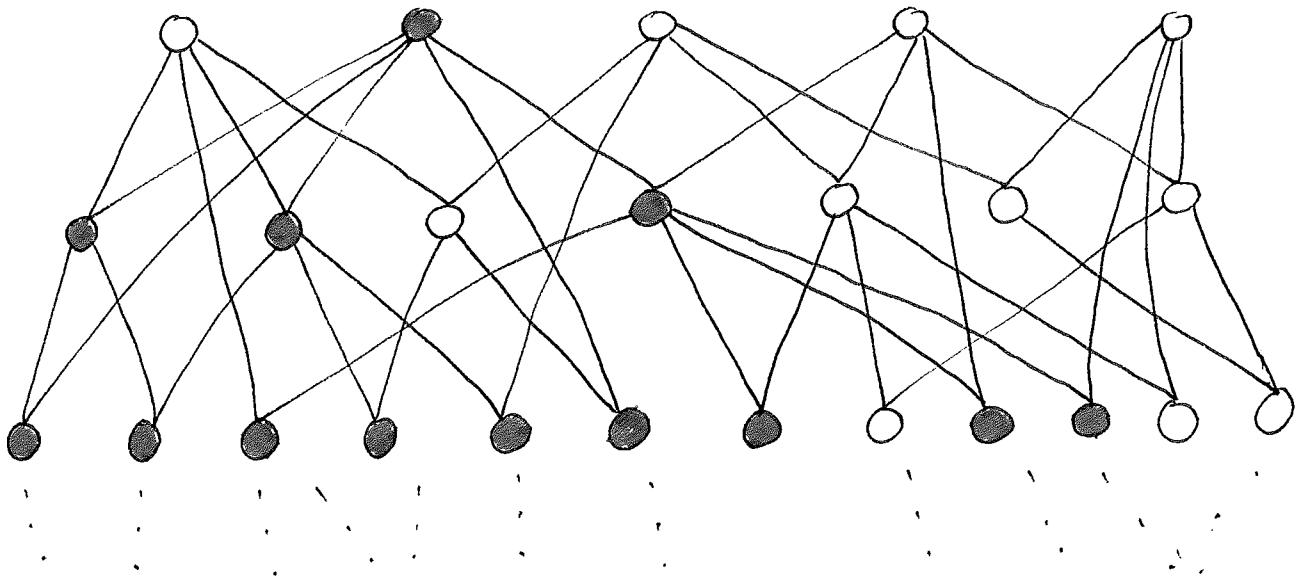
deletion / replacement rules,

e.g., subsumption

simplification

(term rewriting)

Contraction reduces search space

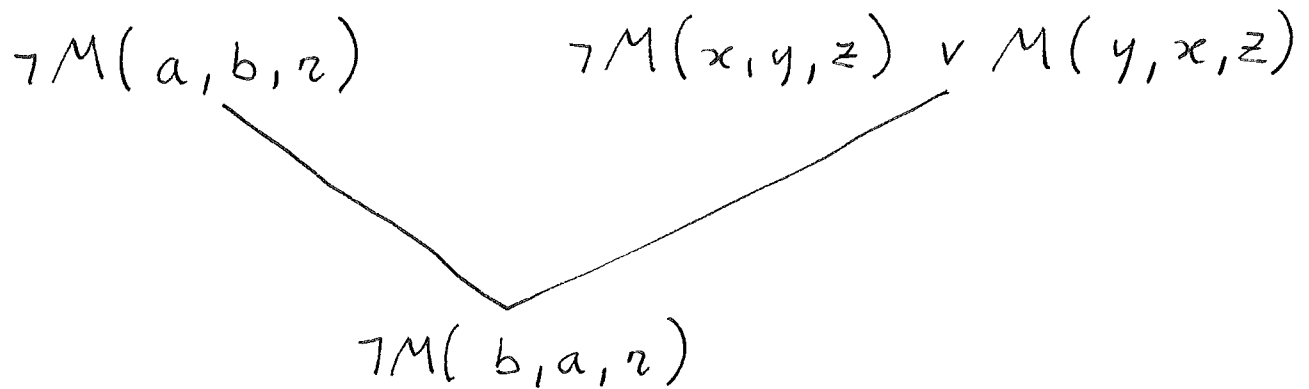


But how do we compare two
infinite graphs?

T.P. strategy: $\mathcal{E} = \langle I, \Sigma \rangle$

I: set of inference rules

Expansion (e.g., resolution)



Contraction (e.g., simplification)

$P(ffffo)$

$\vee \downarrow^*$

$P(fo)$

$ffx \xrightarrow{\triangleright} fx$

\triangleright : well-founded ordering

Search plan and derivation

Σ : search plan

reduce the non-determinism of I

• state: multiset of clauses

• $\Sigma = \langle \xi, \zeta \rangle$

ξ : $\text{States}^* \longrightarrow I$ (decides next rule)

ζ : $\text{States}^* \longrightarrow \mathcal{L}^*$ (decides next premises)

Derivation: $S_0 \vdash S_1 \vdash \dots \vdash S_i \vdash \dots$

Eager-contraction search plan

Contraction-based strategy

Second part :

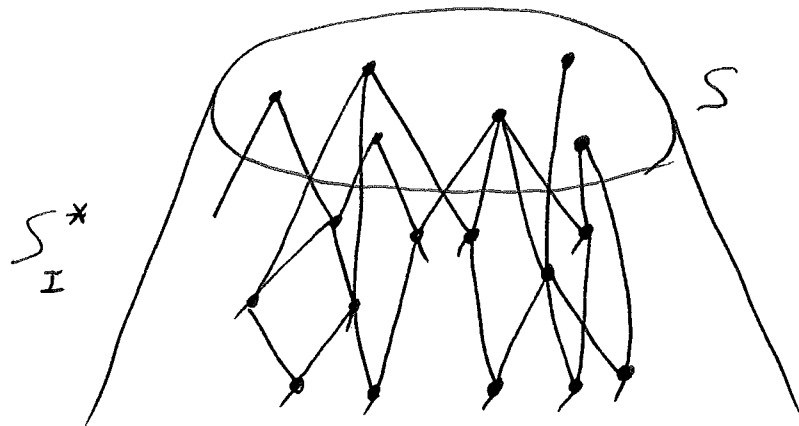
modelling search

Representation of search space

I : inference system

S : input clauses

S_I^* : closure of S w.r.t. I



Search graph: $G(S_I^*) = (V, E, \ell, h)$

Vertices V : clauses

$\ell: V \longrightarrow \mathcal{L} / \doteq$

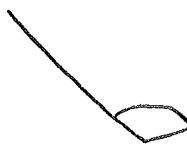
Hyperarcs E : inferences

$h: E \longrightarrow I$

Examples:

$M(a, a, b)$

$\neg M(x, y, z) \vee M(z, y, x \cdot y)$



$M(b, a, a \cdot a)$

$x \cdot x \rightarrow x$



$M(b, a, a)$

$M(x, y, y)$

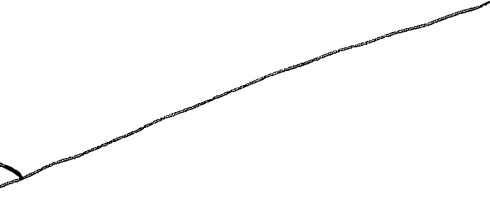


T

$\neg A(x) \vee \neg B(y) \vee R(x, y)$

$A(t)$

$B(s)$



$R(t, s)$

How to represent the evolution of the search space?

- Markings:

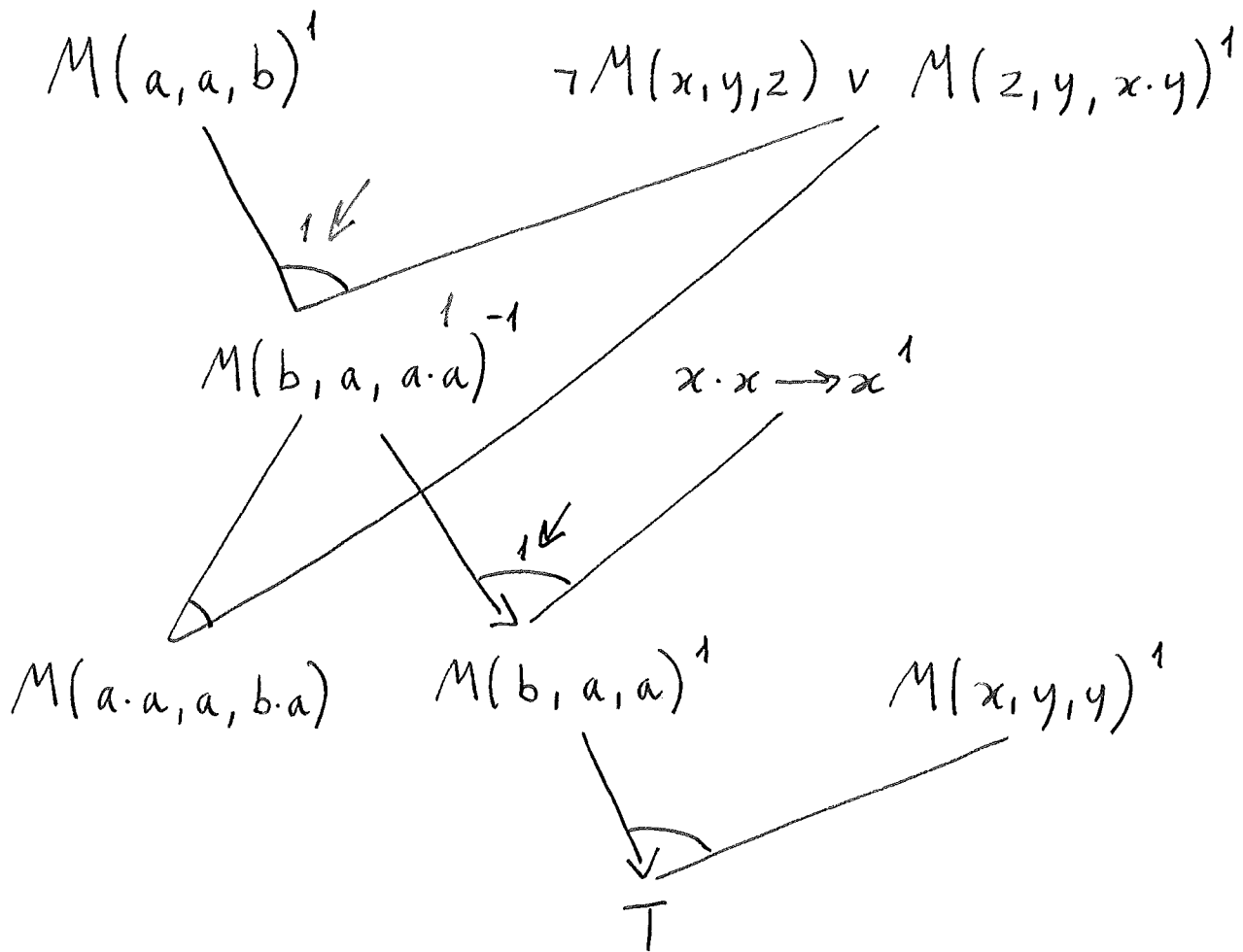
marked graph $G = (V, E, l, h, s, c)$

- s : # 'copies' (variants) of a clause

$$s(\varphi) = \begin{cases} m & \text{if } m \text{ variants } (m > 0) \\ & \text{of } \varphi \text{ are present} \\ -1 & \text{if all variants of } \varphi \\ & \text{are deleted} \\ 0 & \text{otherwise} \end{cases}$$

- $c(e) =$ # of times arc e
has been executed

Example:



Evolution of search space

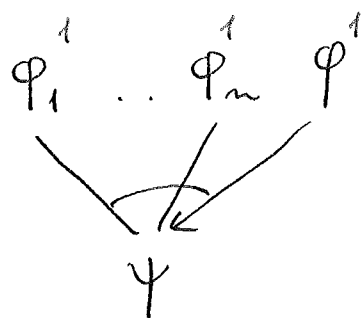
$S_0 \vdash S_1 \vdash \dots \quad S_i \vdash S_{i+1} \vdash \dots$

$G_0 \quad G_1 \quad \quad G_i \quad G_{i+1}$

At stage 0:

$$S_0(\varphi) = \begin{cases} 1 & \text{if } \varphi \in S_0 \\ 0 & \text{otherwise} \end{cases}$$

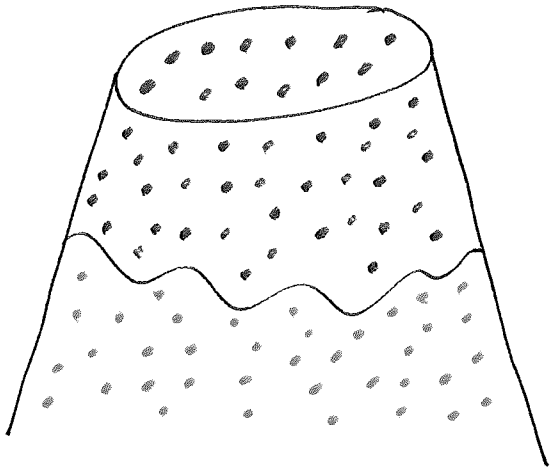
At stage i:
select hyperarc e :



$$S_{i+1}(x) = \begin{cases} S_i(x) + 1 & \text{if } x = \psi \wedge S_i(x) \geq 0 \\ 1 & \text{if } x = \psi \wedge S_i(x) < 0 \\ S_i(x) - 1 & \text{if } x = \varphi \wedge S_i(x) > 1 \\ -1 & \text{if } x = \varphi \wedge S_i(x) = 1 \\ S_i(x) & \text{otherwise} \end{cases}$$

$$C_{i+1}(e) = C_i(e) + 1$$

Marked search graph



- Active: $s(\varphi) > 0$
- Generated: $s(\varphi) \neq 0$

Advantages:

- Graph does not change
marking does
- Easy to represent contraction
- Also extended to parallel search
(one marking per process)

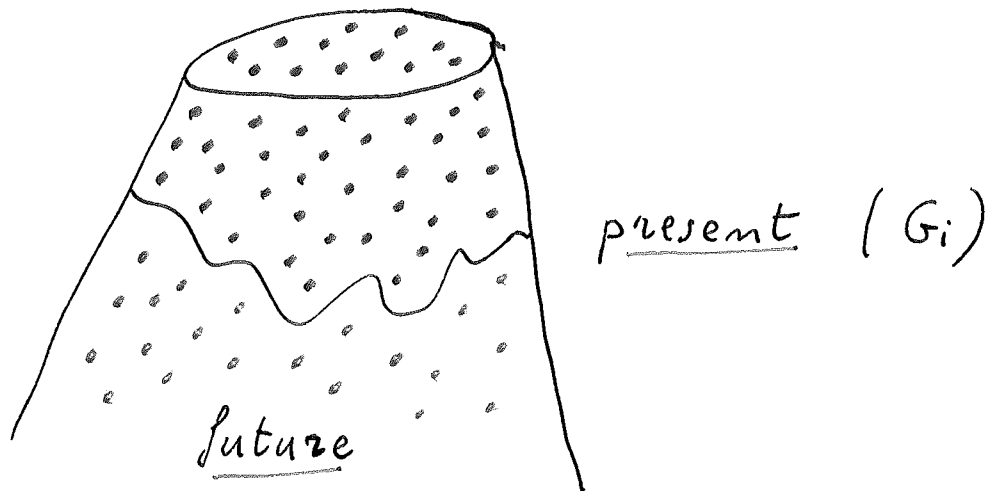
Third part:

evaluating strategies

Analysis of strategy behaviour

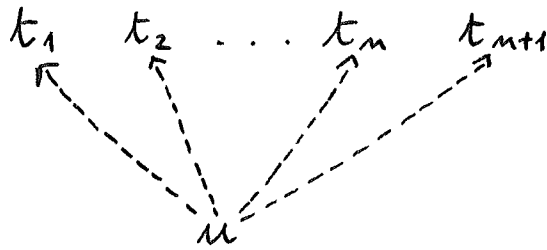
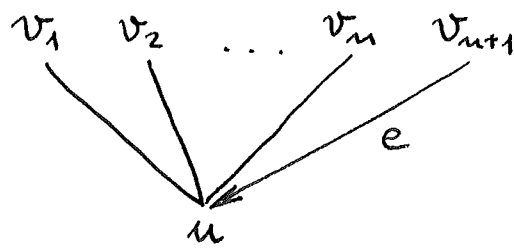
How to capture the effect of the steps performed up to stage i on the search space including the part that remains to be explored after stage i ?

G:



The future is infinite but we have something finite if we look back.

Ancestor-graph



An ancestor-graph of u is

$$t = (u; e; (t_1 \dots t_{n+1}))$$

where t_i is an ancestor-graph of v_i .

$at_G(u)$ or $at_G(\varphi)$: set of ancestor-graphs of u
/* $\varphi = l(u)$ */

Remark: an ancestor-graph of u represents
a generation-path that generates φ from S_0 .

Relevance

The nodes relevant to the generation of φ

Given $u \in V$

$$t = (u; e; (t_1 \dots t_{n+1}))$$

$$e = (v_1 \dots v_n; v_{n+1}; u)$$

$w \in t$ is relevant to v in t

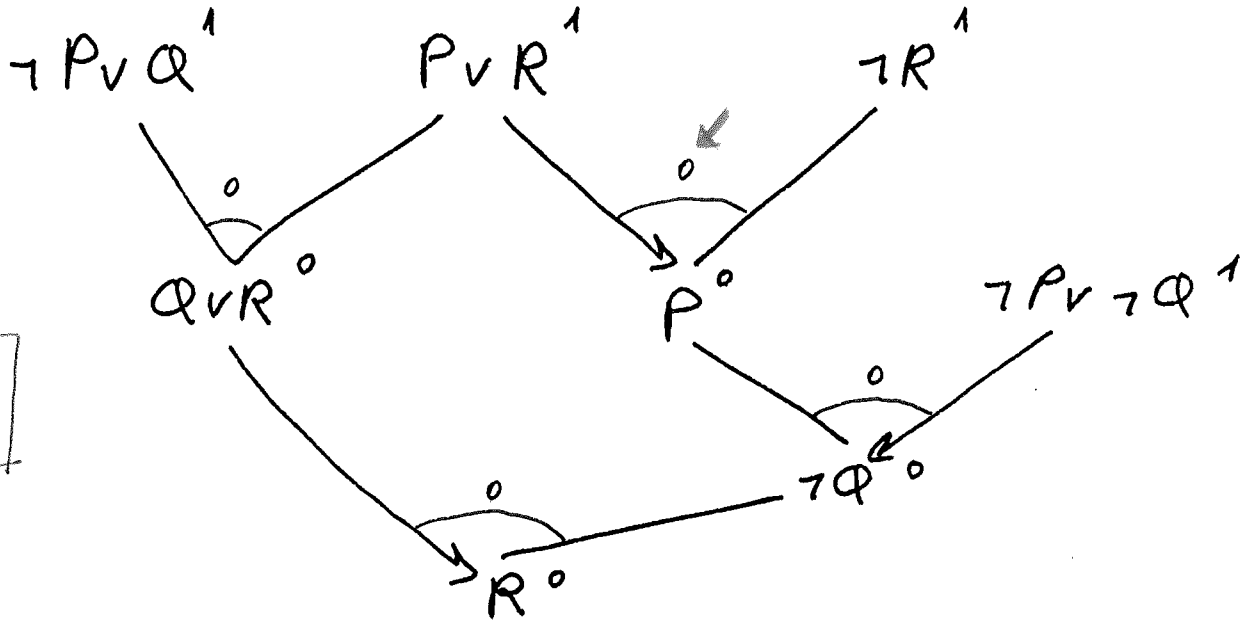
if

- $w \in \{v_1 \dots v_{n+1}\}$ and $c(e) = 0$ or
- w is relevant to v_i in t_i for some i .

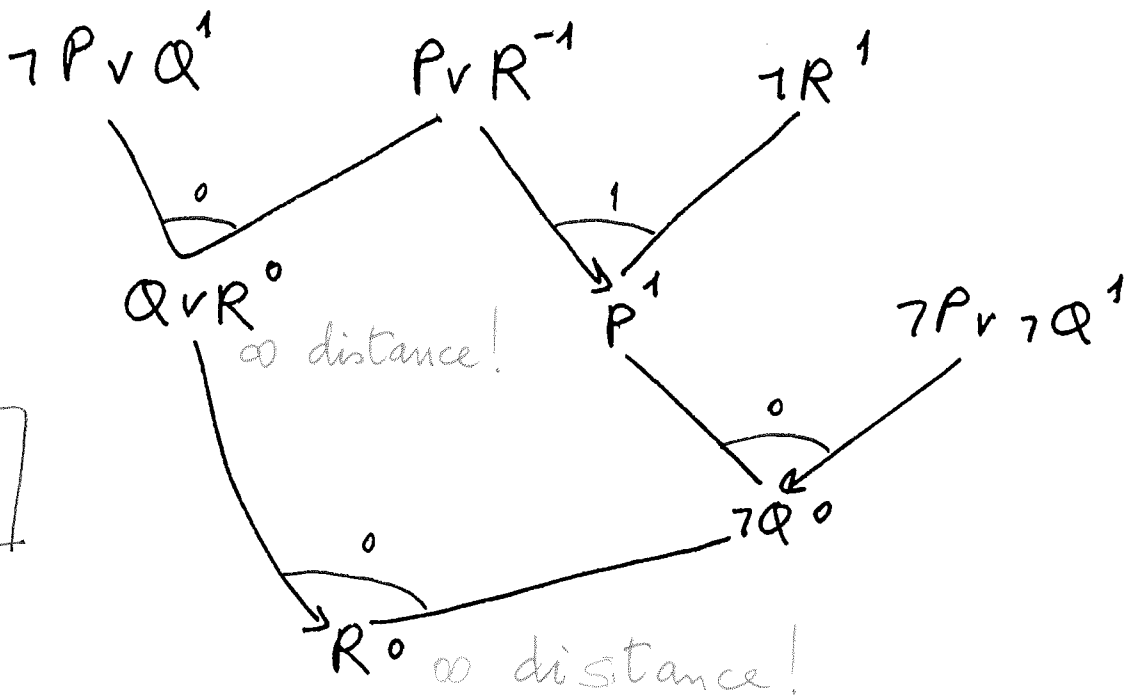
$Rev_G(t)$: set of relevant nodes in t .

Example:

S_i



S_{i+1}



A notion of distance

Given $G, \varphi, t \in \text{at}_G(\varphi)$

- Past distance of φ in t :

$$\text{pdist}_G(t) = |\{w \mid w \in t, s(w) \neq 0\}|$$

- Future distance of φ in t :

$$\text{fdist}_G(t) = \begin{cases} \infty & \text{if } s(\varphi) < 0 \text{ or} \\ & \exists w \in \text{Rev}_G(t) \text{ } s(w) < 0 \\ |\{w \mid w \in t, s(w) = 0\}| & \text{o/w} \end{cases}$$

- Global distance of φ in t :

$$\text{gdist}_G(t) = \text{pdist}_G(t) + \text{fdist}_G(t)$$

- f-distance of φ : $\text{fdist}_G(\varphi) = \min_{t \in \text{at}_G(\varphi)} \text{fdist}_G(t)$

- g-distance of φ : $\text{gdist}_G(\varphi) = \min_{t \in \text{at}_G(\varphi)} \text{gdist}_G(t)$

Remarks:

(1) Dynamic distance:

if ∞ then unreachable!

($\infty \Rightarrow$ redundant)

(2) $f_{\text{dist}_G}(t)$ measures the portion of t that needs to be traversed in order to reach φ

(3) Alternative definitions:

use multisets instead of cardinalities.

Bounded search spaces

Slice infinite graph G into sequence of finite layers:

at stage i ($\forall i$) of derivation,
define the bounded search space
reachable within distance j ($j > 0$)
(from the beginning):

$$\text{space}(G, j) = \sum_{\substack{v \in V \\ v \neq T}} \text{mul}_G(v, j) \cdot P(v)$$

where

$$\text{mul}_G(v, j) = \left| \left\{ t : t \in \text{at}_G(v), \right. \right. \\ \left. \left. 0 < \text{gdist}_G(t) \leq j \right\} \right|$$

space (G_i, j) is dynamic

Expansion inferences visit the search space:

if $S_i \vdash S_i \cup \{\psi\}$ then

$$\text{space}(G_{i+1}, j) = \text{space}(G_i, j) \quad \forall j$$

Contraction inferences visit and modify (prune) the search space:

if $S_i \cup \{\varphi\} \vdash S_i \cup \{\psi\}$ then

$$\bullet \text{space}(G_{i+1}, j) \leq_{\text{mul}} \text{space}(G_i, j) \quad \forall j$$

• if $s_i(\varphi) = 1$ and $D_{i+1}(\varphi) \neq \emptyset$

$$\exists k > 0 \quad \forall j \geq k$$

$$\text{space}(G_{i+1}, j) <_{\text{mul}} \text{space}(G_i, j)$$

where:

$$D_{i+1}(\varphi) = \left\{ \varphi' \mid \exists t \in \text{at}_s(\varphi'), \varphi \in \text{Rev}_{G_{i+1}}(t) \right\}$$

Analysis of search space reduction
by contraction:
compare strategies of different
contraction power

Given $\mathcal{L}_1 = \langle I_1, \Sigma_1 \rangle$ $\mathcal{L}_2 = \langle I_2, \Sigma_2 \rangle$
input set S_0

Assume same expansion rules:

$$G^1 \neq G^2$$

$$\text{space}(G_0^1, j) \neq \text{space}(G_0^2, j)$$

because of different contraction rules.

What can we compare?

Compare the variations

Given derivation

$$S_0 \xrightarrow{e} S_1 \xrightarrow{e} \dots S_i \xrightarrow{e} S_{i+1} \xrightarrow{e} \dots$$

$$G_i = (V, E, P, R, s_i, c_i)$$

$$\Delta \text{mul}_{G_i}(v, j) = \text{mul}_{G_0}(v, j) - \text{mul}_{G_i}(v, j) \quad (\geq 0)$$

$$\bullet \Delta \text{space}(G_{i,j}) = \sum_{\substack{v \in V \\ v \neq T}} \Delta \text{mul}_{G_i}(v, j) \cdot P(v)$$

the portion of space $(G_{i,j})$ that is pruned up to stage i of the derivation.

Use $\Delta \text{space}(G_{i,j})$ as measure to compare contraction-based strategies.

• I_1 and I_2 are equipollent if $S_{I_1}^* = S_{I_2}^* \forall S$

• Consider $\mathcal{C}_1 = \langle I_e \cup I_{R_1}; \Sigma \rangle$

$\mathcal{C}_2 = \langle I_e \cup I_{R_2}; \Sigma \rangle$

where (i) I_1 and I_2 are equipollent

(ii) Σ is eager-contraction + fair

(iii) \mathcal{C}_2 has more contraction power than \mathcal{C}_1 ($R_1(S) \subseteq R_2(S) \forall S$)

Use $S_0^1 \xrightarrow{e_1} S_1^1 \xrightarrow{e_1} S_2^1 \xrightarrow{e_1} \dots S_i^1 \xrightarrow{e_1} S_{i+1}^1 \dots$

G_i^1

$S_0^2 \xrightarrow{e_2} S_1^2 \xrightarrow{e_2} S_2^2 \xrightarrow{e_2} \dots S_i^2 \xrightarrow{e_2} S_{i+1}^2 \dots$

G_i^2

Note: the (unmarked) search graphs $G^1 \neq G^2$

Lemmas:

- $\forall i \geq 0 \quad \forall \varphi \in S_i^1 \quad \exists \kappa \geq 0$ s.t. $\varphi \in S_\kappa^2$ or $\varphi \in R_2(S_\kappa^2)$
and vice versa
- $\forall i \geq 0 \quad \forall \varphi \in R_1(S_i^1) \quad \exists \kappa \geq 0$ s.t. $\varphi \in R_2(S_\kappa^2)$
(but not vice versa)
- $\forall i \geq 0 \quad \forall \varphi \in G^1$ if $S_i^1(\varphi) = -1$ then
 - $\exists \kappa \geq 0$
 - $\cdot S_\kappa^2(\varphi) = -1$ or
 - $\cdot S_\kappa^2(\varphi) = 0$ and $f \text{dist}_{G_\kappa^1}(\varphi) = \infty$
- $\forall i \geq 0 \quad \forall \varphi \in G^1 \quad \forall t \in at_{G^1}(\varphi)$,
if $f \text{dist}_{G^1}(t) = \infty$ then $\exists \kappa \geq 0 \quad f \text{dist}_{G_\kappa^1}(t) = \infty$

- More contractions eventually prunes more space

Thm : $\forall i > 0 \exists k > 0 \forall j > 0$

$$\Delta_{\text{space}}(G_{k,i,j}^2) \geq_{\text{mul}} \Delta_{\text{space}}(G_{i,j}^1).$$

- More contraction eventually causes fewer things to be generated

$at_G^e(v)$ = ancestor-graphs of v made of only expansion steps

$$emul_G(v,i,j) = |\{t : t \in at_G^e(v), 0 \leq gdist_G(t) \leq j\}|$$

$$espace(G,i,j) = \sum_{\substack{v \in V \\ v \neq T}} emul_G(v,i,j) \cdot l(v)$$

Thm : $\forall i > 0 \exists k > 0 \forall j > 0 \quad espace(G_{k,i,j}^2) \leq_{\text{mul}} espace(G_{i,j}^1)$

- If all rules in $I_2 - I_1$ are deletion rules

Thm: $\forall i > 0 \quad \exists k > 0 \quad \forall j > 0$
 $\text{space}(G_{k,j}^2) \leq_{\text{mul}} \text{space}(G_{i,j}^1).$

Summary

Stronger contraction ($R_1(S) \subseteq R_2(S)$)

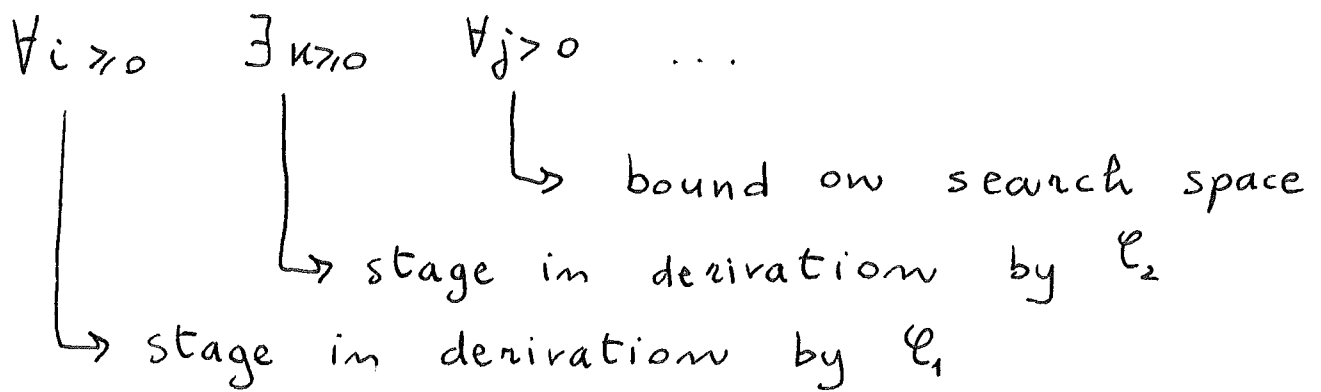
induces more reduction of the

bounded search spaces, thus

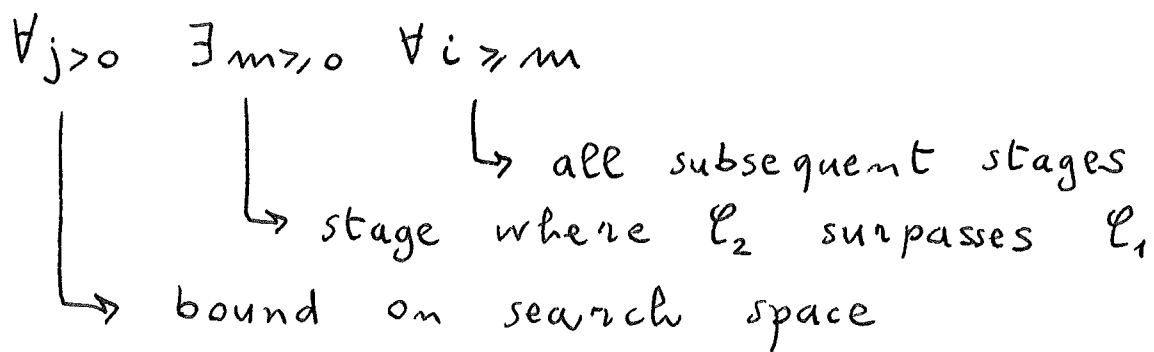
higher reduction of search

complexity.

All theorems so far in the form



Further results in the form



- $\forall j > 0 \quad \exists m \geq 0 \quad \forall i \geq m$

$$\text{espace}(G_{i,j}^2) \leq_{\text{mue}} \text{espace}(G_{i,j}^1).$$

- $\forall j > 0 \quad \exists m \geq 0 \quad \forall i \geq m$

$\text{space}(G_{i,j}^2) \leq_{\text{mue}} \text{space}(G_{i,j}^1)$ if all rules
 in $I_2 - I_1$ are deletion rules.

Discussion

- Lack of ways to analyze / compare strategies ("strategy analysis") has hampered T.P. (A.I.).
- Main difficulty: infinite search space.
- Representation of search space
 - all possible inferences form a static infinite graph
 - dynamics of the search described by marking, essential for contraction.

Discussion

- Slice infinite search graph into sequence of (now-static) finite search graphs.
- Notion of complexity based on WFO (e.g., multiset orderings) not only linear ordering ($\mathbb{N}, >$).
- Comparison of contraction-based strategies:
give a formal justification of why contraction is effective.

Future work

- The beginning of the journey ...
 - stimulate interest
 - more concepts
 - more notions
- Apply to other strategies
(e.g., subgoal-reduction)
- Comparison of search plans
- Already extended to parallel deduction
(distributed-search contraction-based strategies)
- Asymptotic analysis ?

Related work

- Search space representation
[Kowalski 1969]
-

- Proof complexity

$NP \neq co-NP$ iff no p -bounded proof system

$f(x) = y$ for propositional tautologies

[Cook-Reckhow 1979, Urquhart 1995]

- Lower bounds based on Herbrand Theorem

[Statman 1979, Orevkov 1982, Goubault 1994]

- Search complexity

[Plaisted 1994, Plaisted-Zhu 1997]

[Leitsch 1997]