

# Using weighted constraints to build a tutoring system for logic programming

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# Agenda

1. Motivation: Tutoring systems for programming
2. Existing approaches
3. Approach proposal
4. Evaluation
5. Conclusions

# Tutoring Systems

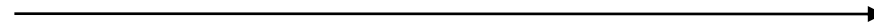
System



Student



Problem tasks



Solution attempts



Feedback & correction hints



Corrected solutions



# The Domain of Programming

- Requirements:
  - Design a program in free form
  - Refine a program iteratively
  - The solution space is large.

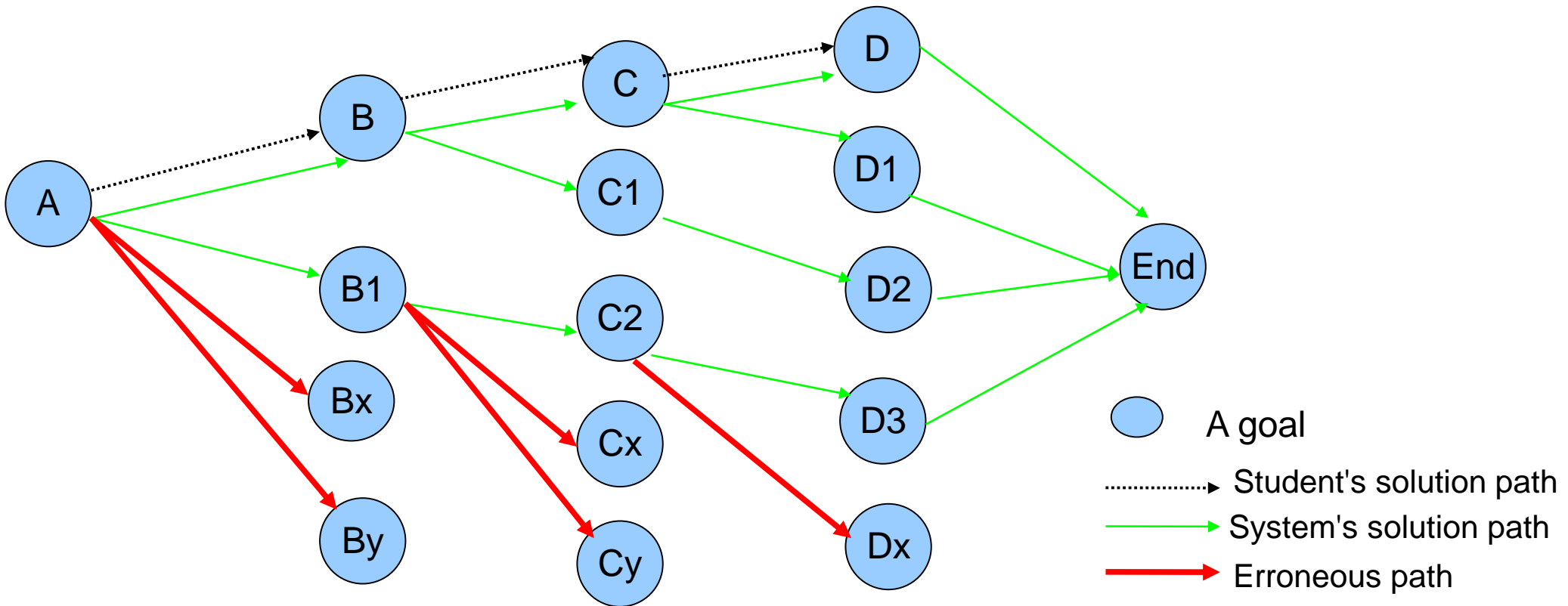
# Problems

- How can a student solution be interpreted by the system correctly?
  - How can the system be able to generate comprehensive feedback to the student solution?
- => The system must be modelled with sufficient domain knowledge.

# Cognitive Modeling Approaches

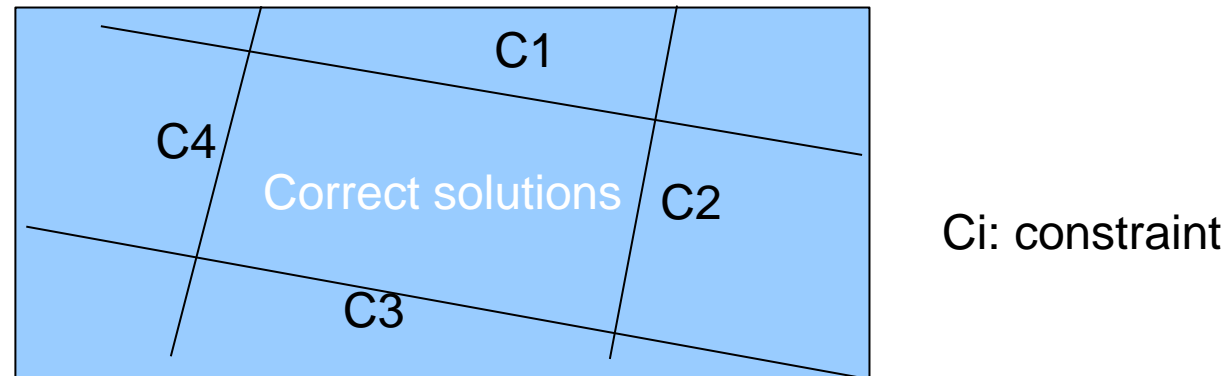
- Model tracing:
  - learning from the process of solving a problem
  - process-oriented
- Constraint-based:
  - learning from performance errors
  - product-oriented

# Model-Tracing



- A solution path is represented by a sequence of problem solving steps.
- An error occurs if the student's solution path deviates from the system's solution path or matches an erroneous path.
- This approach tends to model linear problem solving process.

# Constraint-based Modeling (CBM)



- A constraint represents a domain principle or a property of correct solutions.
- Constraints span the space of correct solutions.
- A constraint violation indicates an error in the solution.
- Advantages:
  1. No enumeration of the correct solutions
  2. No anticipation of the students' erroneous behaviours
  3. Iterative problem solving process can be modelled



# Research Question

- Is the constraint-based approach applicable to build a tutoring system for the domain of logic programming?

# The Solution Space

For a problem, the solution space is created on 2 levels:

## 1. **Solution strategy**

- Experts have some kinds of knowledge about problem categories and solution strategies(Hoc88).

## 2. **Implementation**

- Based on the available constructs of a particular domain

# Alternative Solution Strategies

- Task sample: *"Write a predicate to compute the return of investment after a period for a fixed interest rate"*

Strategy	Normal form implementation
Analytic	<code>inv(Sum, Rate, Period, Return) :- Return is Sum*(Rate+1)^Period.</code>
Recursive & Arithmetic_Before	<code>inv(Sum, _, Period, Sum) :- Period=0. inv(Sum, Rate, Period, Return) :- Period&gt;0, NewPeriod is Period-1, inv(Sum, Rate, NewPeriod, NewSum), Return is NewSum + Rate*NewSum.</code>
Recursive & Arithmetic_After	<code>inv(Sum, _, Period, Sum) :- Period=0. inv(Sum, Rate, Period, Return) :- inv(Sum, Rate, NewPeriod, NewSum), Period is NewPeriod +1, Return is NewSum + Rate*NewSum.</code>
Tail recursive	<code>inv(Sum, _, Period, Sum):-Period=0. inv(Sum, Rate, Period, Return) :-Period&gt;0, NewSum is Sum*Rate + Sum, NewPeriod is Period-1, inv(NewSum, Rate, NewPeriod, Return).</code>

# Alternative Implementation Variants

- Syntactic reformulations
  - Explicit or implicit unifications
  - $S \text{ is } M * X + N * X \Rightarrow S \text{ is } (M + N) * X$ , or  $S \text{ is } X * N + M * X$
- Alternative sequential orders
  - Clause order, subgoal order
- Defining helper predicates/functions
  - To modularize a program
- The option of introducing identifiers

# Proposal 1: Semantic Table

- Goal: model alternative solution strategies
- Each solution strategy is represented by a generalised solution description (GSD).
- Arbitrary entry order => Alternative sequential orders are covered.

Str	Clause	Head	Subgoals	Description
S1	C1	$p(S,R,P,Ret)$	Ret is $S^*(R+1)^P$	Use an analytic formula
S2	C1	$p(S,_,P,S)$	$P=0$	Recursion ends
S2	C2	$p(S,R,P,Ret)$	$P>0$	Check investment period
S2	C2	$p(S,R,P,Ret)$	NS is $S^*R+S$	Calculate new sum
S2	C2	$p(S,R,P,Ret)$	NP is $P-1$	Update period
S2	C2	$p(S,R,P,Ret)$	$p(NS,R,NP,Ret)$	Calculate sum with new period

- S1 is a GSD for the analytic strategy; S2 is a GSD for the tail recursive strategy.

# Proposal 2: Transformation rules

- Goal: cover variants of arithmetic expressions and helper predicates
- Rule 1:  $A^0 X \pm B^0 X \Rightarrow (A \pm B)^0 X \mid ^0 \in \{*, /\}$
- Rule 2:  $A^0 B \Rightarrow B^0 A$
- Rule 3: transform user-defined helper predicates
  - Using folding/unfolding techniques
  - Limitation: not for all helper predicates

# Proposal 3: Weighted Constraints

- Constraints serve the purposes:
  1. Modelling general principles of the domain, e.g.,  
**IF** An arithmetic test subgoal comparing two variables  $X$ ,  $Y$  exists  
**THEN** Both  $X$  and  $Y$  have the instantiation state instantiated
  2. Establishing a mapping between the student solution and components of the semantic table  
**IF** in the semantic table, a component  $X$  exists and satisfies condition  $C$   
**THEN** in the student solution, a corresponding component must exist and satisfy condition  $C$ .

# Proposal 3: Weighted Constraints

- Constraint weight represents the importance of a constraint.
- Constraint weights serve three purposes:
  1. Decide for the most plausible error explanation. E.g., an arithmetic test checking whether a person is adult:

Expected solution:  $X \geq 18$  and student's input:  $X \geq 17$

Possible error explanations:

- The operator is not correct. The corrective proposal is  $X > 17$
- The operand is not correct. The corrective proposal is  $X \geq 18$

Constraints checking operands are more important than the ones checking operators.  $\Rightarrow$  The 2nd corrective proposal is more plausible.

2. Hypothesize the student's applied solution strategy
3. Ranking the severity of feedback messages



# Error Diagnosis

- Hypothesis generation:
  - $H(S1) = \text{Student solution} \langle \text{matching} \rangle \text{ gsd (Strategy 1)}$
  - $H(S2) = \text{Student solution} \langle \text{matching} \rangle \text{ gsd (Strategy 2)}$
  - ...
- Hypothesis evaluation: for each  $H$ , computing the plausibility  $\mathbf{P}$  by evaluating relevant constraints.
  - $P(H) = W_1 * \dots * W_n$  |  $W_i$  is the weight of the  $i$ -th violated constraint
  - $\text{Max}(P(H(S))) \Rightarrow H$  is the best hypothesis,  $S$  is the applied solution strategy
  - Error diagnosis is derived from constraint violations of the best hypothesis  $H$ .

# Diagnostic Accuracy

- Design:
  - 221 student solutions from past written examinations
  - System's diagnosis was compared against a gold standard.

System	Pro. Language	Intention Analysis	Diagnosis Accuracy
INCOM	Prolog	87.9%	92.7%
PROUST	Pascal	81%	87%
PITS	Prolog	80%	95.8%

# Learning Effects - Design

- Pre/Post test: 10 minutes
- Experiment session: 60 minutes
- Exercises are normal homework tasks not seen before.
- Questionnaire: 10 minutes
- Two studies:
  - 2009: Control (17 participants) vs. experimental group (18 participants)
  - 2010: Control (16 participants) vs. experimental group (16 participants)

# Learning Effects - Results (1)

Group	Study	Learning gain (s.d.)	P-value (significant)
Control	1	0.74 (2.64)	0.27 (No)
Experimental	1	1.25 (1.81)	0.01 (Yes)
Control	2	1.28 (1.45)	0.003 (Yes)
Experimental	2	1.81 (1.79)	0.001 (Yes)

1. Groups are balanced:  $\text{score}(\text{Pre, con}) = \text{score}(\text{Pre, exp})$ 
  - $p=0.07$  (Study 1),  $p=0.48$  (Study 2),  $\text{sig-level}=0.05$
2. The learning gains:  $\text{LG} = \text{score}(\text{Post}) - \text{score}(\text{Pre})$ 
  - Experimental groups did made significant gains in both Studies
  - Only control group of Study 2 did made significant gains

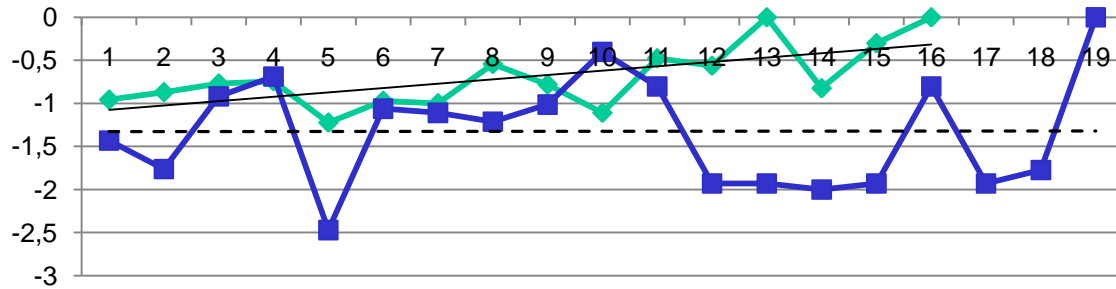
# Learning Effects - Results (2)

Study	Learning gain (control)	Learning gain (experimental)	p-value (significant)	Cohen's d
1	0.74 (2.64)	1.25 (1.81)	0.5 (No)	0.23
2	1.28 (1.45)	1.81 (1.79)	0.36 (No)	0.33

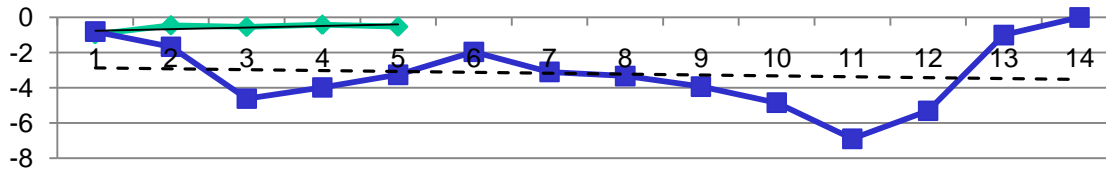
3. Is LG(exp) significantly better than LG(con)? No
4. How much is the LG(exp) better than LG(con)?  
 $d=[0.23; 0.33] \Rightarrow$  INCOM contributed a small learning effect

# Learning Effects – Results (3)

## 5. Learning curves based on weighted error rates



◆ Analysis      ■ Implementation  
— Linear (Analysis)      - - - Linear (Implementation)



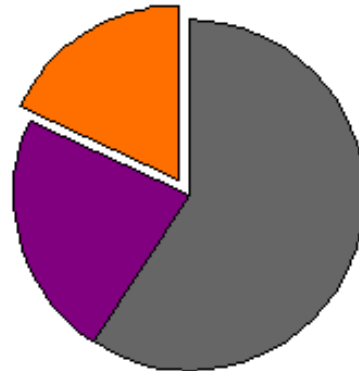
◆ Analysis      ■ Implementation  
— Linear (Analysis)      - - - Linear (Implementation)

# Student's Attitudes - Results

Error location



Motivation



Transferability to exercises of the same type



Students confirmed

- high diagnostic accuracy
- high motivation
- confident to solve similar exercises

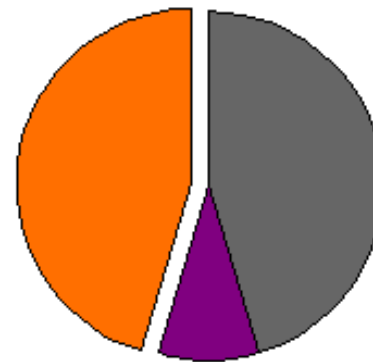
Feedback



System's help

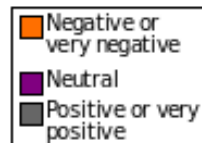


Usage of the system for homework



No clear positive answer for

- feedback
- system's helpfulness
- the usage of the system for homework



# Conclusions

- Constraint weights are useful to
  - hypothesize the student intention,
  - choose the most plausible error explanation among several alternatives
  - Prioritise the severity of feedback messages
- Semantic table composes two ideas:
  - Covers alternative solution strategies
  - Represent a class of implementations in generalized form.
- Limitations:
  - A number of solution strategies need to be anticipated.
  - Not all helper predicates can be transformed.



Thank you for your attention