CS 681 Fall 2008

Designing Expert Systems

7. Multistrategy Rule Learning

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Overview

Introduction

Multistartegy Rule Learning

Strategies for Explanation Generation

Demo and Hands-on

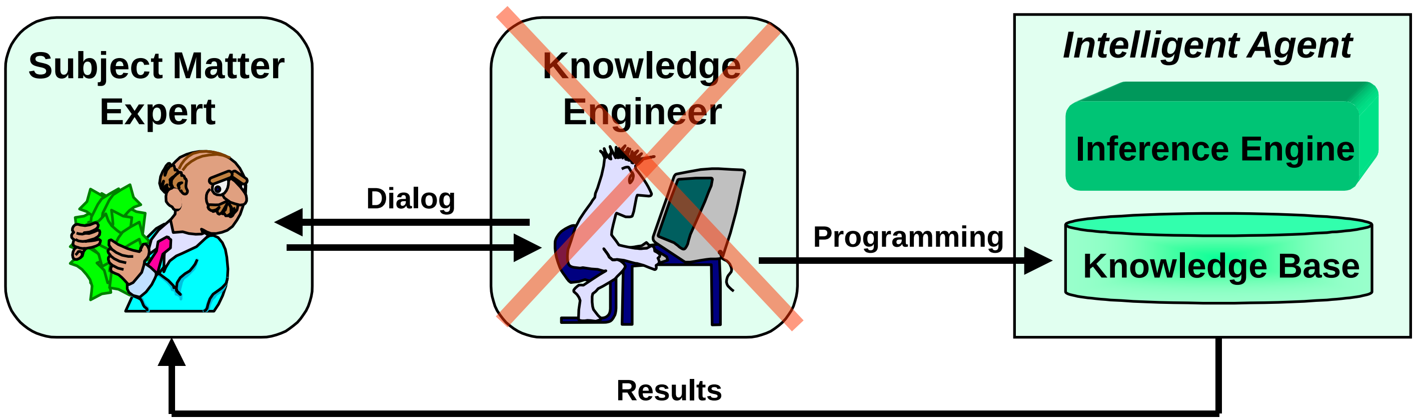
Explanations with Comparisons

Explanations with Functions

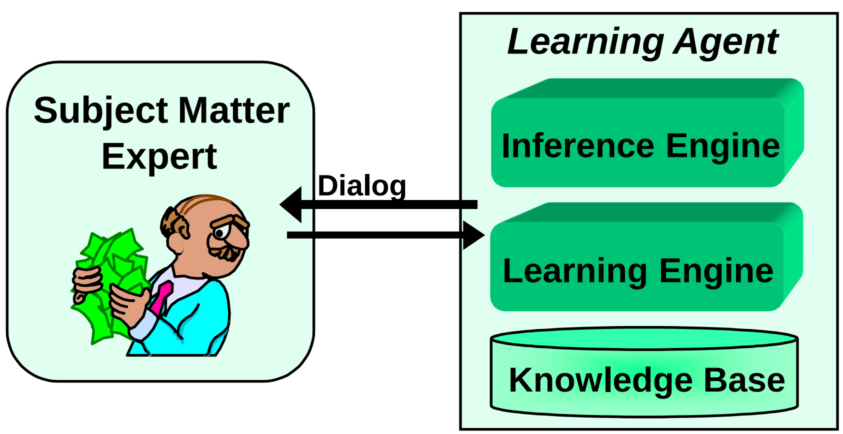
Reading

How Agents Are Built and Why It is Hard

Ed Feigenbaum (AAAI Address, 1993): *Rarely does a technology arise that offers such a wide range of important benefits of this magnitude. Yet as the technology moved through the phase of early adoption to general industry adoption, the response has been cautious, slow, and "linear" (rather than exponential).*



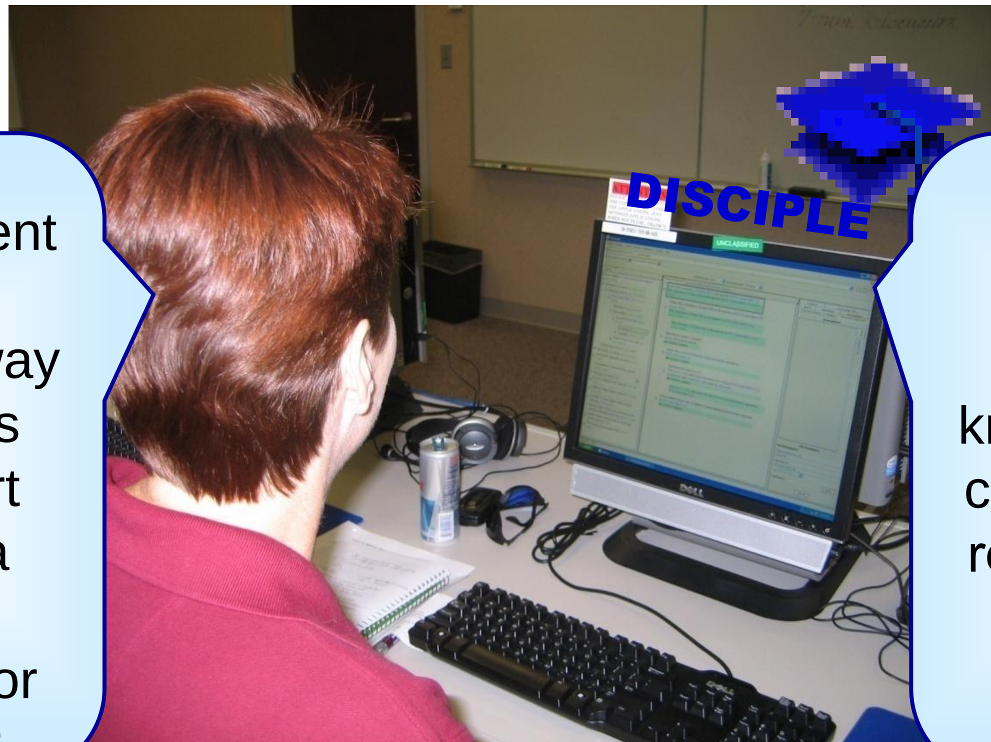
Another approach: Agent training directly by the subject matter expert



Bill Gates (NYT, 1 March 2004): *If you invent a breakthrough in artificial intelligence, so machines can learn, that is worth 10 Microsofts.*

Disciple Approach to Agent Development

Develop learning and problem solving agents that can be taught by subject matter experts to become knowledge-based assistants.



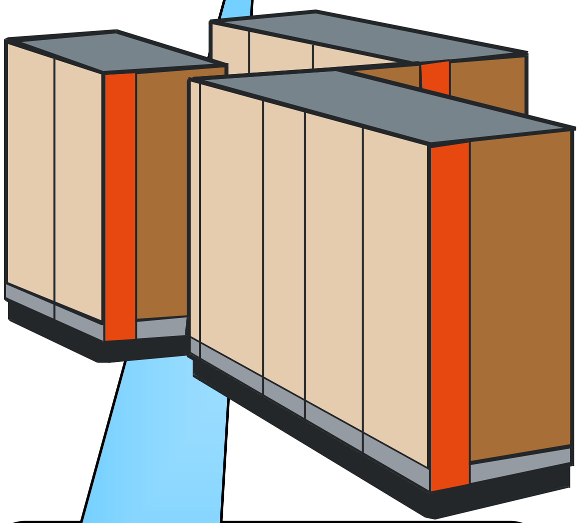
The expert teaches the agent how to solve problems in a way that resembles how the expert would teach a student, an apprentice or a collaborator.

The agent continuously develops and refines its knowledge base to capture and better represent expert's knowledge and problem solving strategies.

There is no longer a clear distinction between knowledge base development and its maintenance.

Vision: Evolution of Software Development and Use

Mainframe Computers

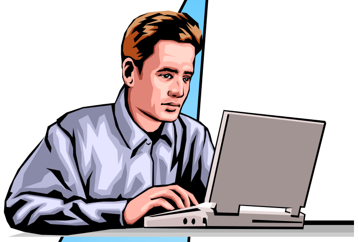


Software systems developed and used by computer experts

Personal Computers

Software systems developed by computer experts and used by persons who are not computer experts

Learning Assistants



Software systems developed and used by persons who are not computer experts

Multidisciplinarity and Integration in Disciple

Intelligence analysis, Center of gravity determination, Course of action critiquing, Emergency response planning, Workaround reasoning, PhD advisor selection, Teaching higher order thinking skills.

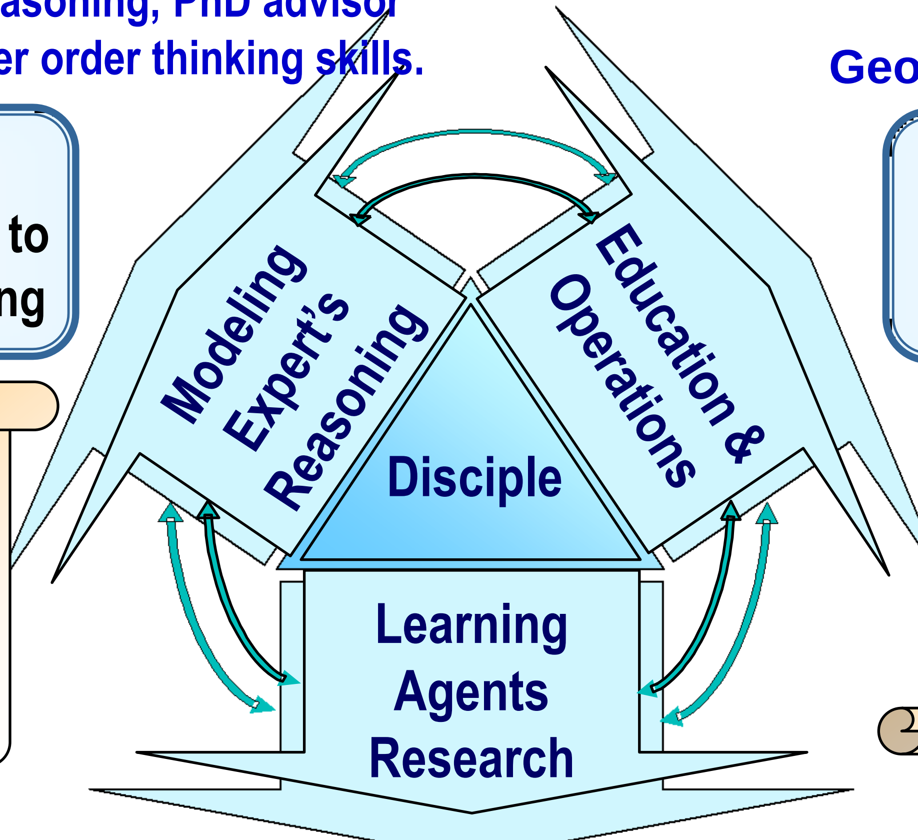
Army War College

Air War College

George Mason University

Development of systematic approach to expert problem solving

Development and application of Disciple agents

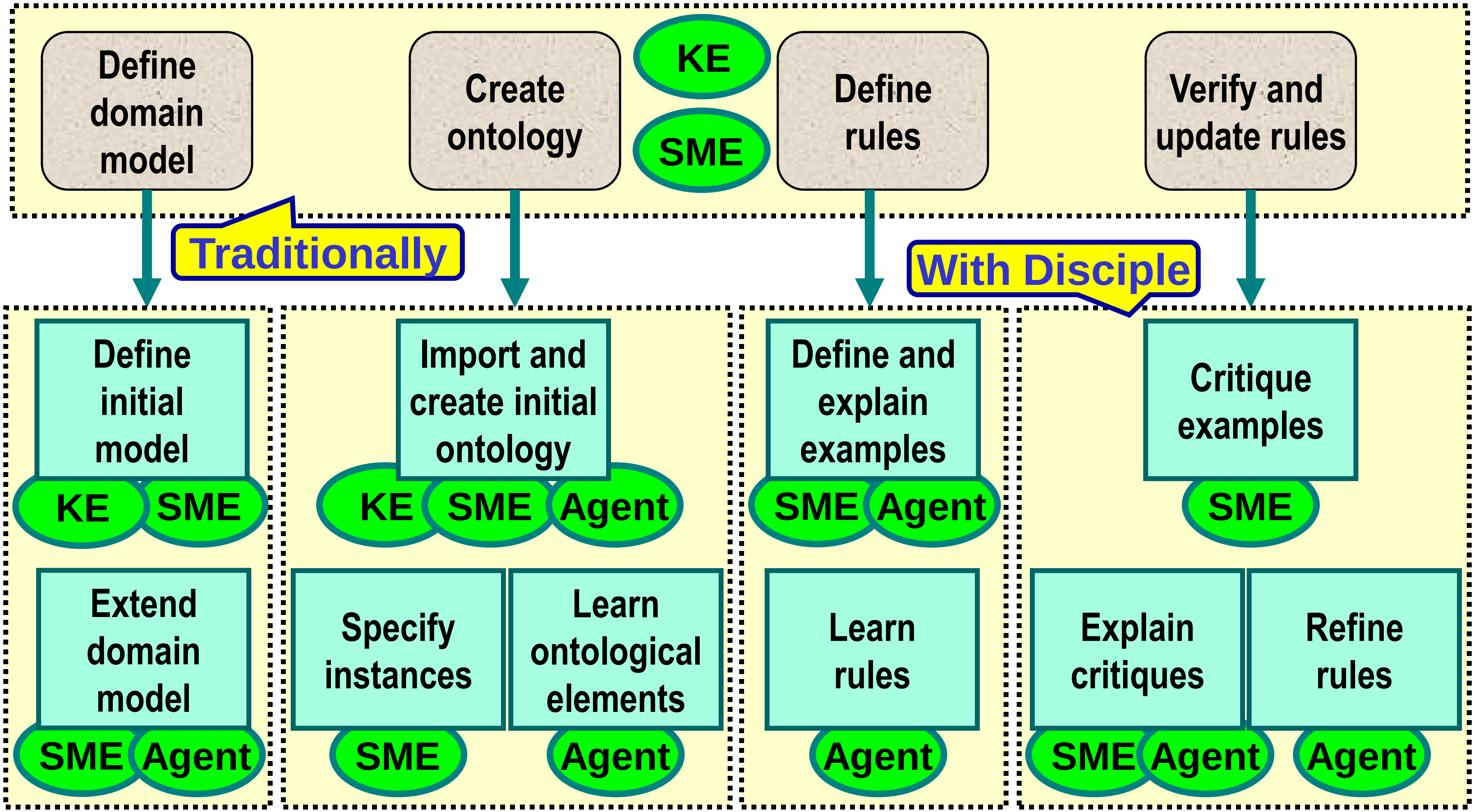


Working closely with subject matter experts to model their reasoning

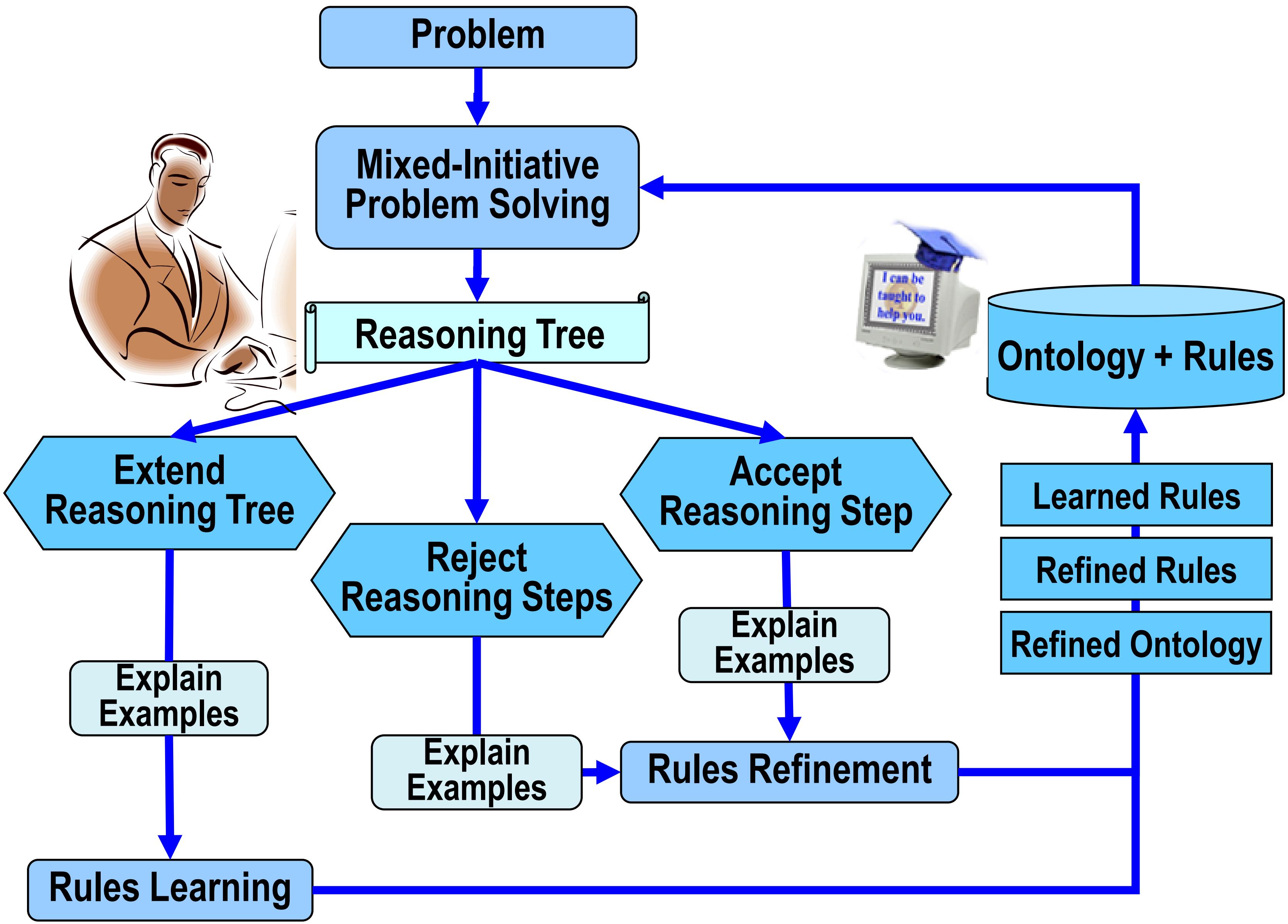
Working closely with end users to receive crucial and timely feedback

Development of the Disciple theory for agents teaching by non-computer experts

Knowledge Base Development Activities

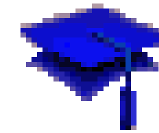


Control of Modeling, Learning and Problem Solving

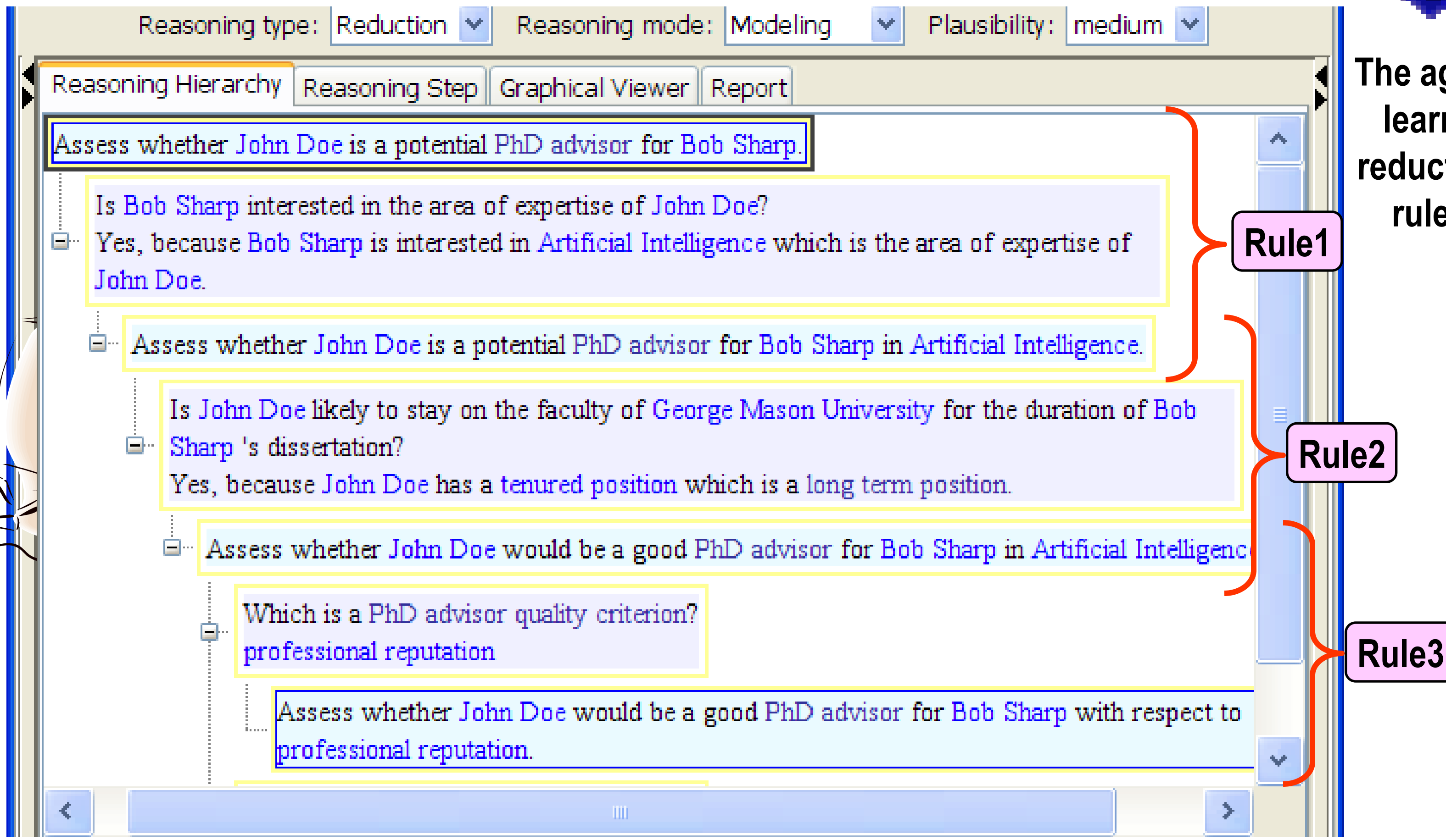


1. Modeling — **2. Learning**

The expert makes explicit how to solve a problem

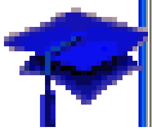


The agent learns reduction rules



Reasoning Hierarchy | Reasoning Step | Graphical Viewer | Report

3. Solving



Applies learned rules to solve new problems

Assess whether Bridget Jones is a potential PhD advisor for Bob Sharp.

Is Bob Sharp interested in the area of expertise of Bridget Jones?
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of Bridget Jones.

Assess whether Bridget Jones is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

Is Bridget Jones likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation?
Yes, because Bridget Jones has a tenured position which is a long term position.

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp in Artificial Intelligence.

Which is a PhD advisor quality criterion?
support for students

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to support for students.

Which is a PhD advisor quality criterion?
students learning experience

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to students learning exp

Which is a PhD advisor quality criterion?
responsiveness to students

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to responsiveness to stu

Which is a PhD advisor quality criterion?
quality of student results

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to quality of student res

Which is a PhD advisor quality criterion?
professional reputation

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to professional reputatio

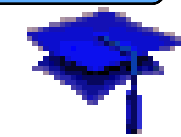
Which is a PhD advisor quality criterion?
personality and compatibility with student

Assess whether Bridget Jones would be a good PhD advisor for Bob Sharp with respect to personality and comp student.

4. Critiquing

Accepts or rejects individual reductions

5. Refining



Refines learned rules with the obtained positive and negative examples

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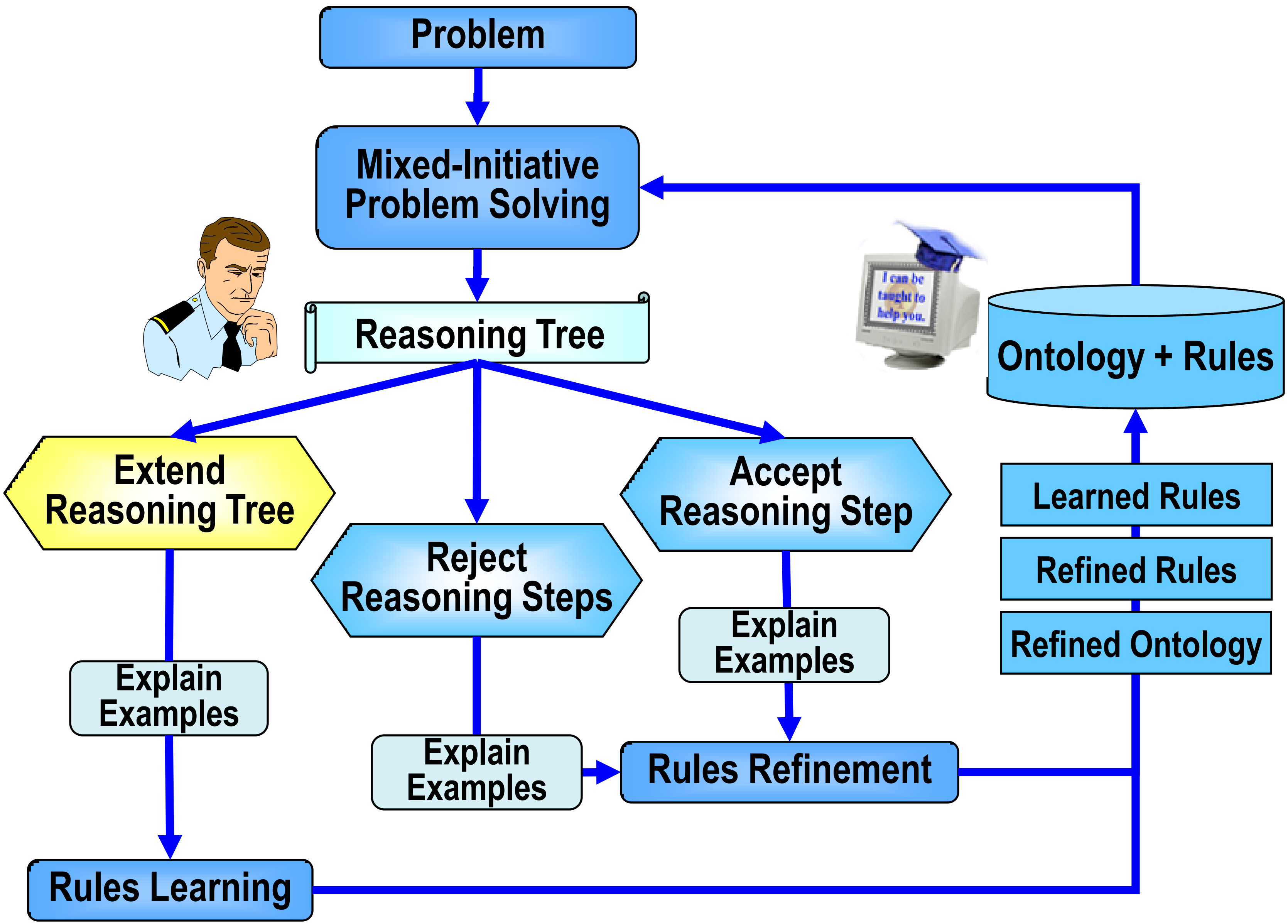


The Rule Learning Problem: Definition

GIVEN:

- an example of a problem reduction;
- a knowledge base that includes an object ontology and a set of problem reduction rules;
- an expert that understands why the given example is correct and may answer agent's questions.

DETERMINE:

- a plausible version space rule that is a plausible generalization of the specific problem reduction.

Rule Learning

LEARNED REDUCTION RULE

REDUCTION EXAMPLE

Task

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Question

Is Bob Sharp interested in the area of expertise of John Doe?

Answer

Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.

Sub-task (1)

Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

Rule Viewer

DECOMPOSITION RULE DDR.00000 FORMAL DESCRIPTION

IF:	Assess whether ?O1 is a potential PhD advisor for ?O2.

Q:	Is ?O2 interested in the area of expertise of ?O1?
A:	Yes, because ?O2 is interested in ?O3 which is the area of expertise of ?O1.

MAIN CONDITION

Var	Lower Bound	Upper Bound
?O1	(PhD advisor, associate professor)	(person)
?O2	(PhD student)	(person)
?O3	(computer science)	(PhD research area)

Var	Relationship	Var
?O2	is interested in	?O3
?O1	is expert in	?O3

THEN:	Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.

Basic Steps of the Rule Learning Method

1. Find a formal explanation of why the example is correct. This explanation is an approximation of the question and the answer, in the object ontology.

2. Generalize the example and the explanation into a plausible version space rule.

The Rule Learning Method: Details

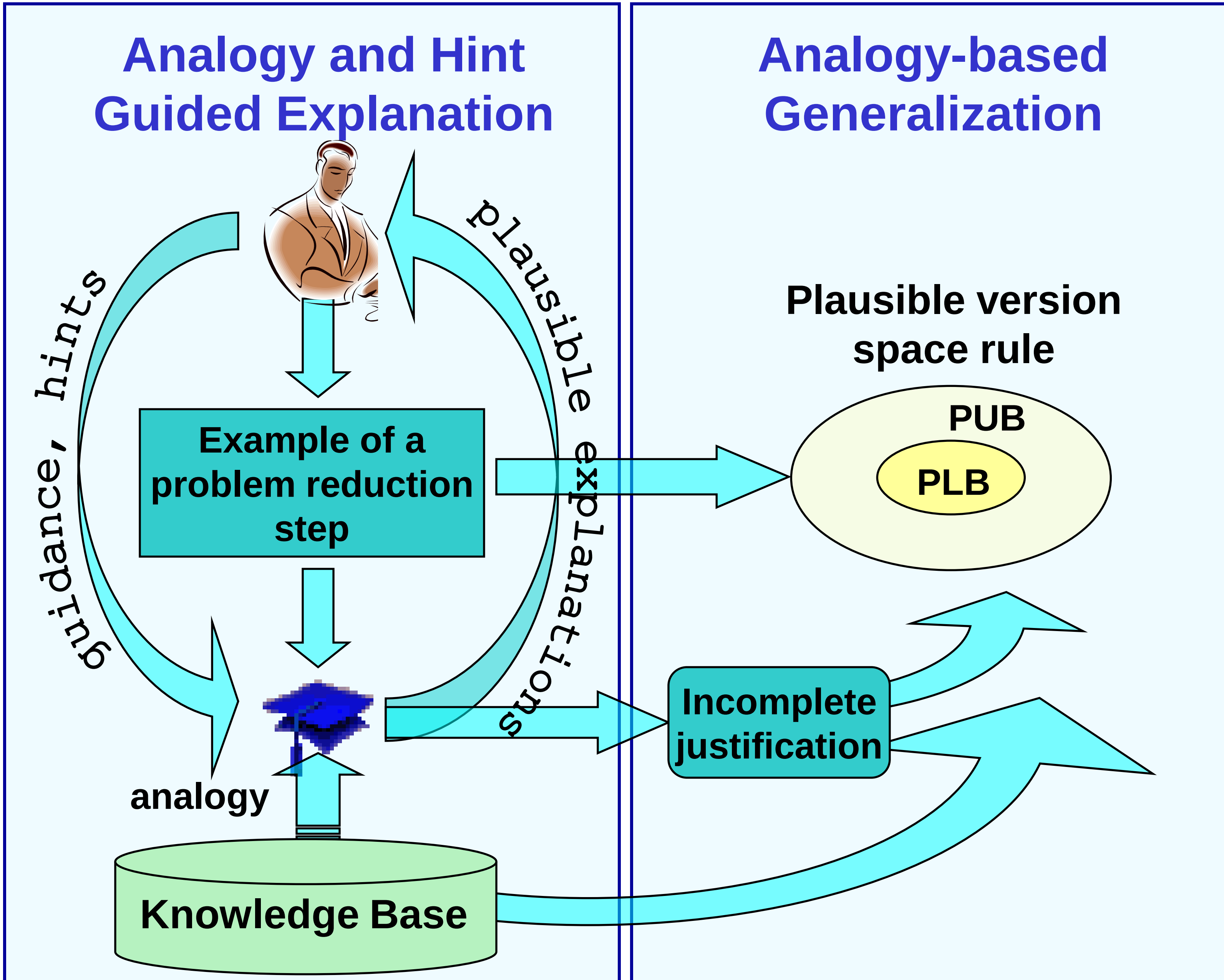
1. Identify a formal explanation EX of why the example E is correct, through mixed-initiative interaction with the subject matter expert. The explanation is an approximation of the meaning of the question and answer, expressed with the objects and the features from the object ontology. During the explanation generation process, new objects and features may be elicited from the expert and added to the object ontology.

2. Generate a variable for each instance, number and string that appears in the example and its explanation. Then use these variables, the example, and the explanation, to create an instance IC of the concept representing the applicability condition of the rule to be learned. This is the concept to be learned as part of rule learning.

3. Generate the problems, question, and answer of the rule by replacing each instance or constant from the example E with the corresponding variable generated in step 2. Then generate the plausible version space of the applicability condition of the rule. The concept represented by this condition is the set of instances and constants that produce correct instantiations of the rule. The plausible lower bound of this version space is the minimally general generalization of IC determined in step 2, generalization which does not contain any instance. The plausible upper bound of this version space is the set of the maximally general generalizations of IC.

5. If there is any variable from the THEN part of a rule which is not linked to some variable from the IF part of the rule, or if the rule has too many instances in the knowledge base, then interact with the expert to extend the explanation of the example and update the rule if new explanation pieces are found. Otherwise end the rule learning process.

The Rule Learning Method



Find an Explanation of Why the Example Is Correct

The explanation is an approximate representation of the question and its answer, in the object ontology.

Task

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Question

Is Bob Sharp interested in the area of expertise of John Doe?

Answer

Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.

Explanations

Bob Sharp —is interested in—> Artificial Intelligence

John Doe —is expert in—> Artificial Intelligence

Remove

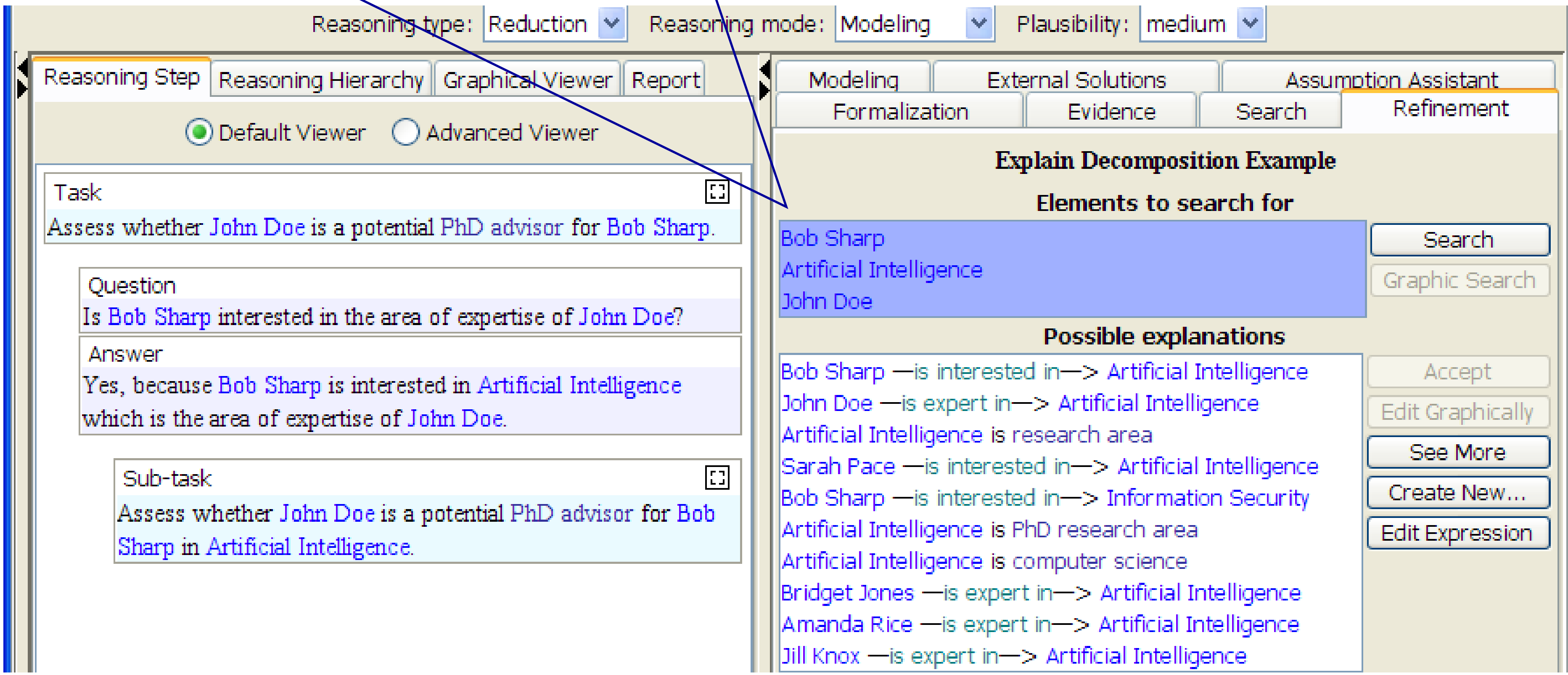
Sub-task

Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

Bob Sharp —is interested in→ Artificial Intelligence ← is expert in — John Doe

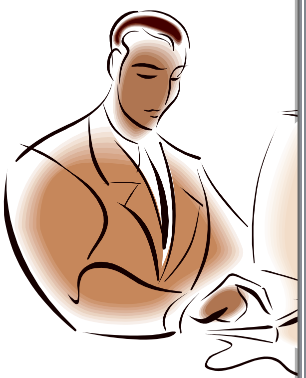
Explanation Generation

The expert can guide the agent in explanation generation by selecting the objects from the example for which explanation pieces will be proposed.



Plausible explanation pieces proposed by the agent.
The expert has to select the correct ones.

Generate Rule's Condition



Task
Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Question
Is Bob Sharp interested in the area of expertise of John Doe?

Answer
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.

Explanations
Bob Sharp —is interested in—> Artificial Intelligence
John Doe —is expert in—> Artificial Intelligence

Remove

Sub-task
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

Task
Assess whether ?O1 is a potential PhD advisor for ?O2.

Is ?O2 interested in the area of expertise of ?O1 ?

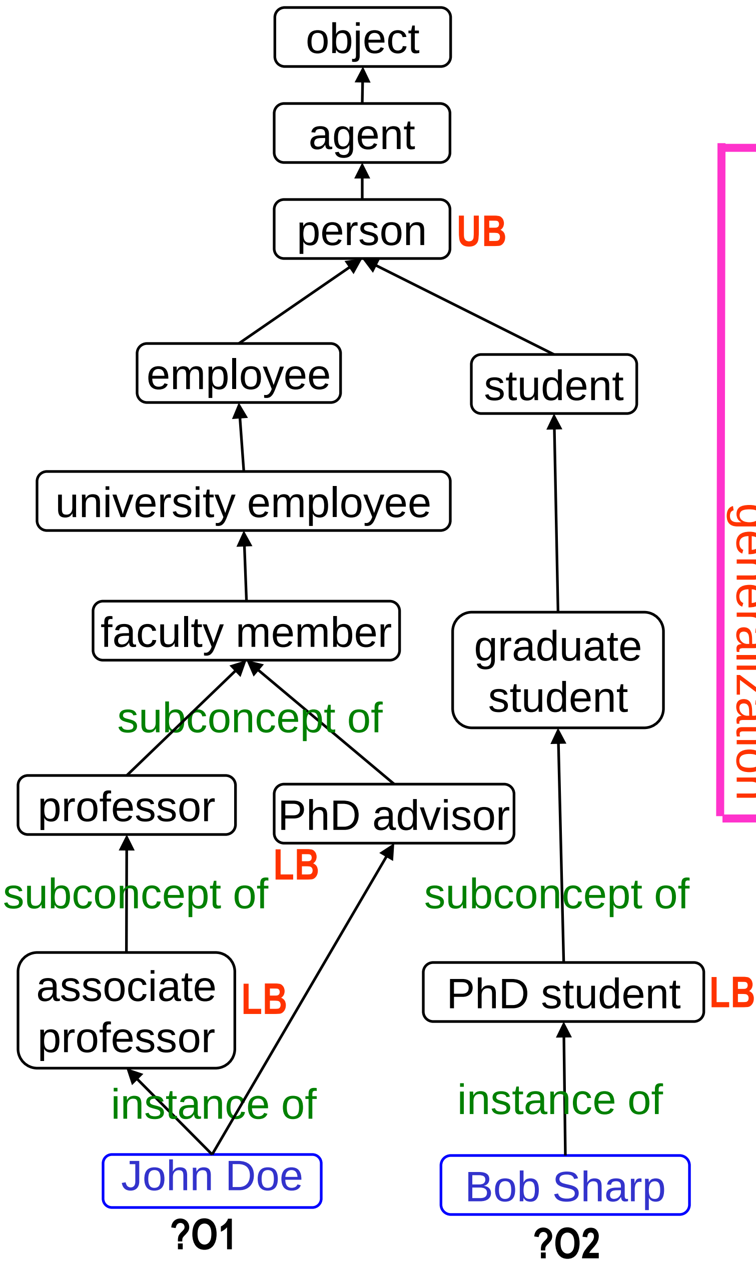
Yes, because ?O2 is interested in ?O3
which is the area of expertise of ?O1.

Sub-task
Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.

Rewrite the objects from the example as an applicability condition

?O1	is	John Doe	
	is expert in		?O3
?O2	is	Bob Sharp	
	is interested in		?O3
?O3	is	Artificial Intelligence	

Generate Rule's Condition



Var	Lower Bound	Upper Bound
?O1	(PhD advisor, associate professor)	(person)
?O2	(PhD student)	(person)
?O3	(computer science)	(PhD research area)

Var	Relationship	Var
?O2	is interested in	?O3
?O1	is expert in	?O3

Most specific generalization

Most general generalization

?O1 is John Doe
is expert in ?O3

?O2 is Bob Sharp
is interested in ?O3

?O3 is Artificial Intelligence

?O1 is expert in ?O3
person is expert in PhD research area

person is interested in PhD research area
?O2 is interested in ?O3

Explanation

Notice that the explanation is first re-written as a condition, and then two generalizations of this condition are created: a most conservative one (the plausible lower bound condition) and a most aggressive one (the plausible upper bound condition).

The plausible lower bound is the minimal generalization of the condition from the left hand side of the slide.
Similarly, the most general generalization of the condition is the plausible upper bound.

The agent uses various constraints from the knowledge base to restrict the values that the variables could take.

Rule Learned from an Example and its Explanation

LEARNED REDUCTION RULE

REDUCTION EXAMPLE

Task

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Question

Is Bob Sharp interested in the area of expertise of John Doe?

Answer

Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.

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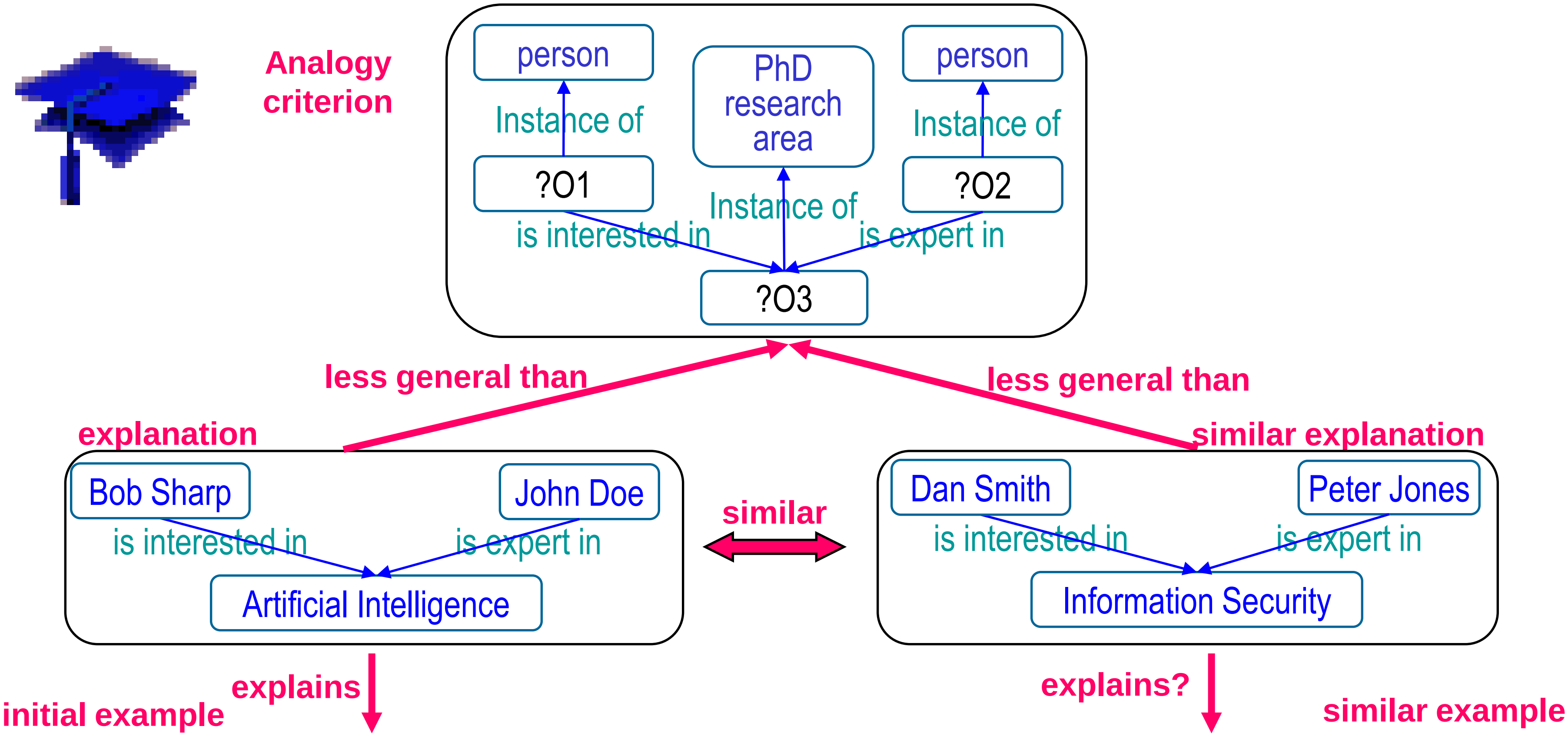
Var	Relationship	Var
?O2	is interested in	?O3
?O1	is expert in	?O3

THEN:	Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.

Bob Sharp — is interested in → Artificial Intelligence ← is expert in — John Doe

Analogical Reasoning



I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Therefore I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

similar

I need to

Assess whether Dan Smith is a potential PhD advisor for Peter Jones.

Therefore I need to

Assess whether Dan Smith is a potential PhD advisor for Peter Jones in Information Security.

Explanation

The agent uses analogical reasoning to generalize the example and its explanation into a plausible version space rule. This slide provides a justification for the generalization procedure used by the agent.

Let us consider that the expert has provided to the agent the problem reduction example from the bottom left of this slide. This reduction is correct because

Bob Sharp — is interested in → Artificial Intelligence ← is expert in — John Doe

Now let us consider

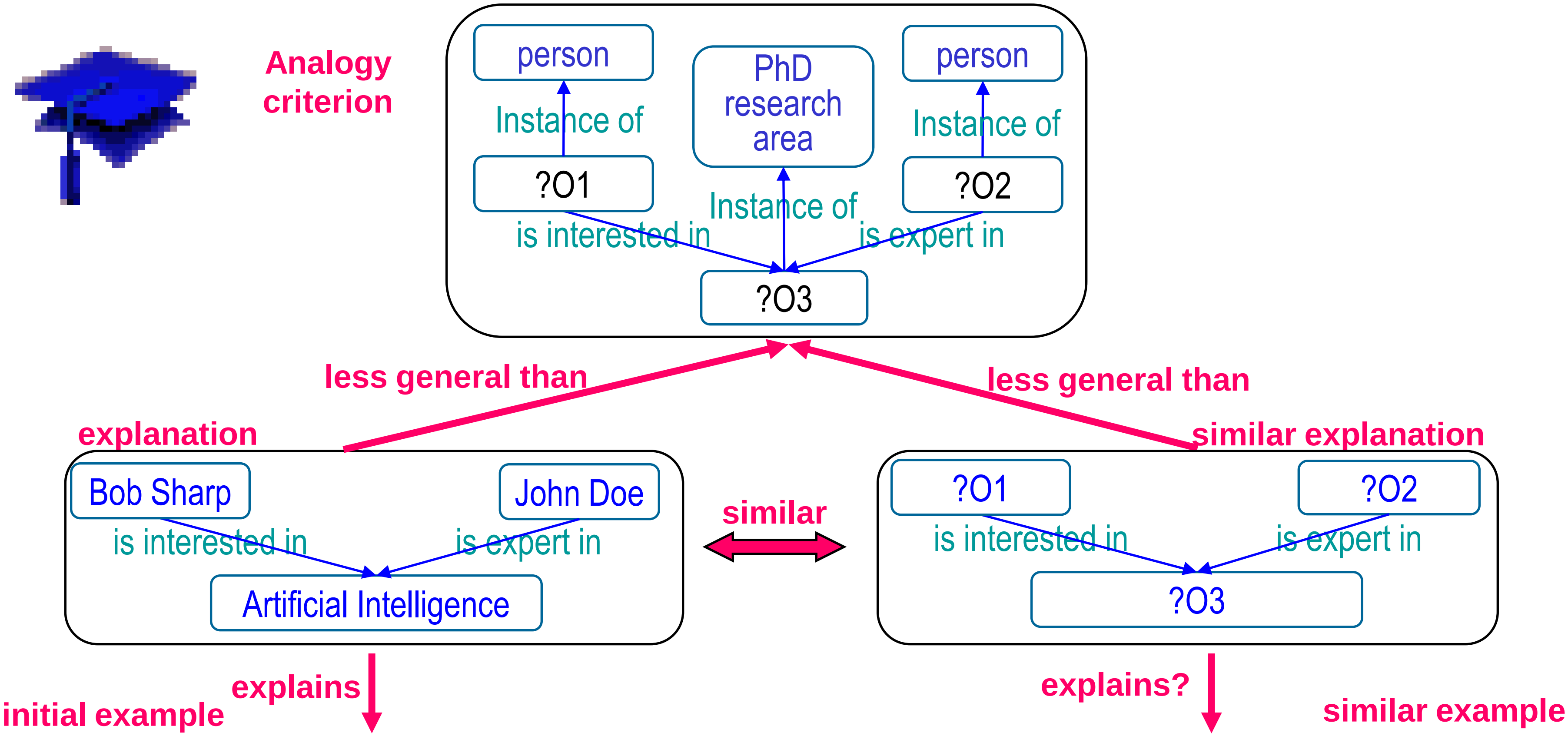
Dan Smith — is interested in → Information Security ← is expert in — Peter Jones

Using the same logic as above, one can create the problem reduction example from the bottom right of the slide.

This is a type of analogical reasoning that the agent performs. The explanation from the left hand side of this slide explains the problem reduction from the left hand side. This explanation is similar with the explanation from the right hand side of this slide (they have the same structure, being both less general than the analogy criterion from the top of this slide). Therefore one could expect that this explanation from the right hand side of the slide would explain an example that would be similar with the initial example. This example is the one from the right hand side of the slide.

To summarize: The expert provided the example from the left hand side of this slide and helped the agent to find its explanation. Using analogical reasoning the agent can perform by itself the reasoning from the bottom right hand side of the slide.

Analogical Reasoning



Initial example

I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Therefore I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

similar

Similar example

I need to

Assess whether ?O1 is a potential PhD advisor for ?O2.

Therefore I need to

Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.

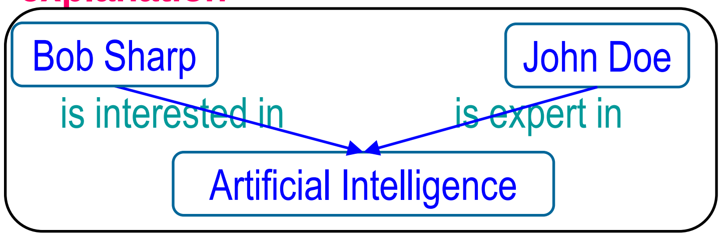
Explanation

Notice that in the previous illustration we could have used any other entities ?O1, ?O2 and ?O3 instead of Bob Sharp, Artificial Intelligence and John Doe. As long as ?O1 is interested in ?O3 and ?O2 is expert in ?O3, the agent would hypothesize that, in order to "Assess whether ?O1 is a potential PhD advisor for ?O2" then one would need to "Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3."

The agent uses various constraints from the knowledge base to restrict the values that the variables ?O1, ?O2 and ?O3 could take. For instance, ?O1 should have the feature "is interested in" and the domain of this feature (i.e. the set of objects that may have this feature) is person. Therefore ?O1 should be a person.
Using this kind of reasoning, the agent generalizes the example from the left hand side of this slide to the expression from the right hand side of this slide.

Generalization by Analogy

explanation



explains

initial example

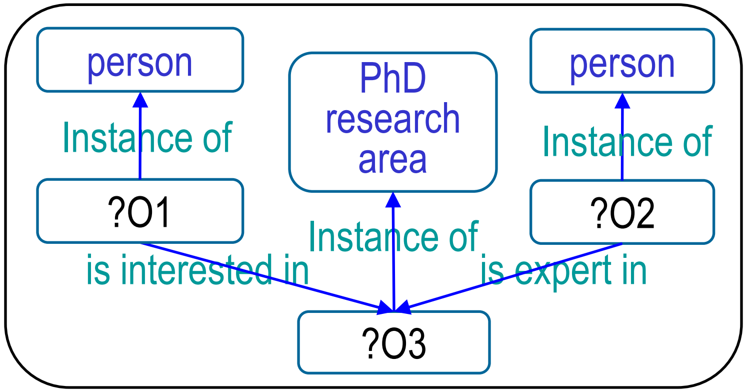
I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp.

Therefore I need to

Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.

generalization



explains

I need to

Assess whether ?O1 is a potential PhD advisor for ?O2.

Therefore I need to

Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.

Knowledge-base constraints on the generalization:

Any value of ?O1 should be an instance of:
DOMAIN(is interested in) = person

Any value of ?O3 should be an instance of:
RANGE(is interested in) = PhD research area

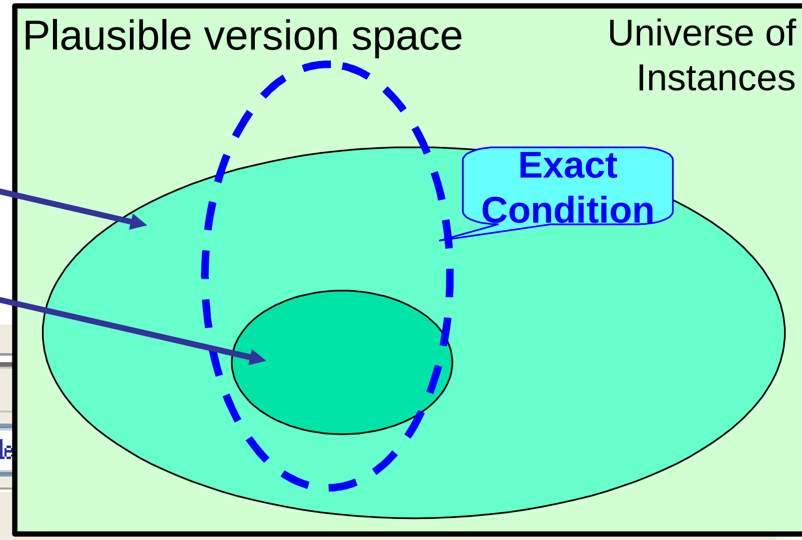
Learning with an Evolving Representation Language

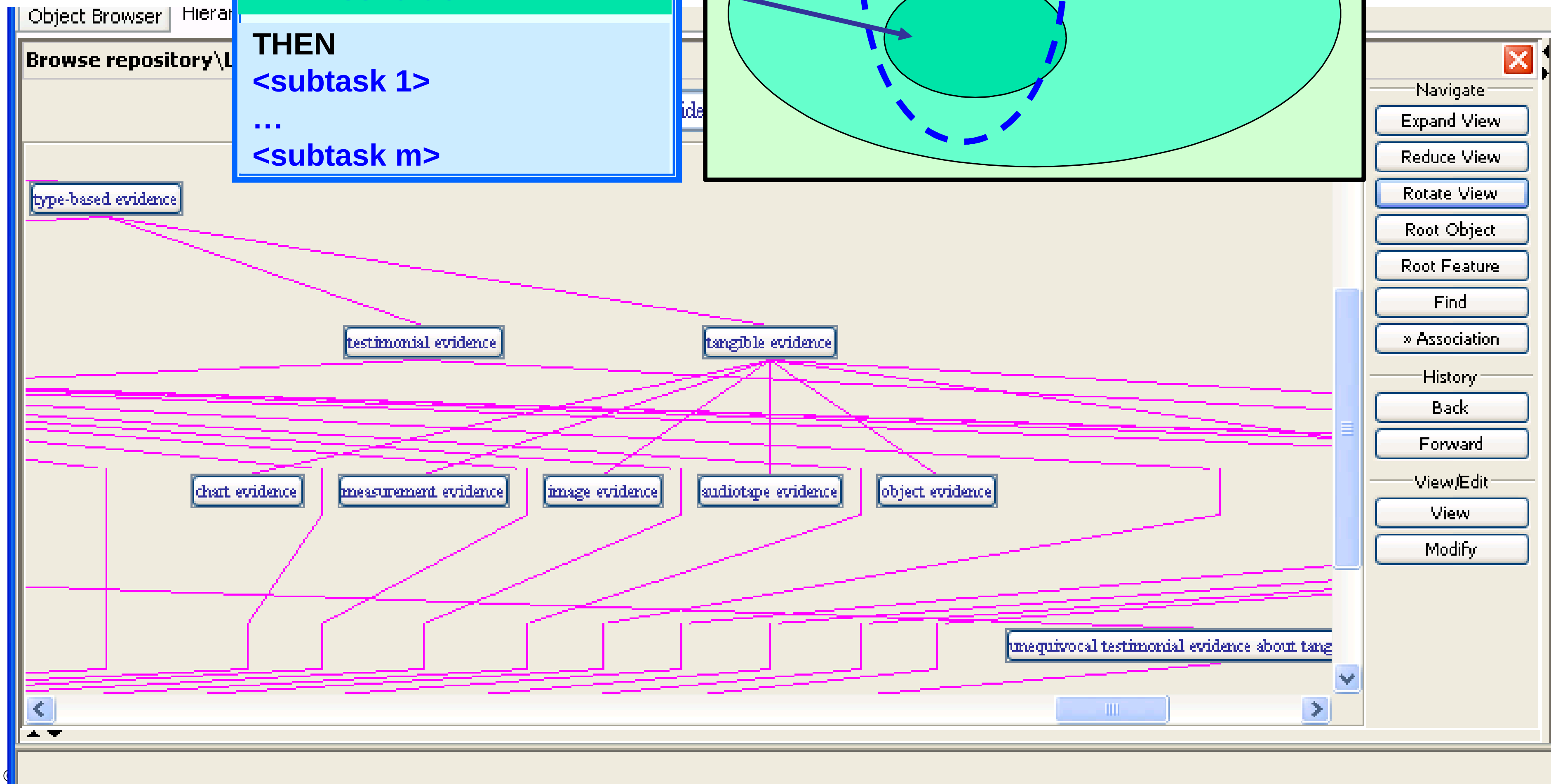
IF
<task>

Plausible Upper Bound Condition
<PUB condition>

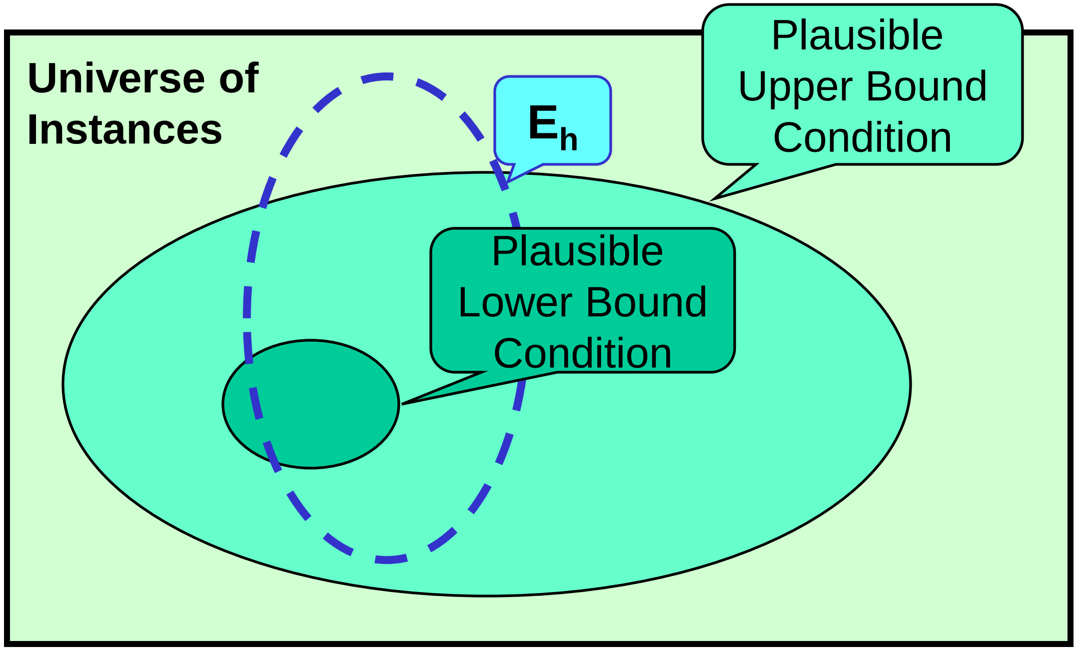
Plausible Lower Bound Condition
<PLB condition>

THEN
<subtask 1>
…
<subtask m>





Characterization of the Learned Rule



Explanation

The plausible upper bound condition of the learned rule is an analogy criterion that allows the agent to solve problems by analogy with the example from which the rule was learned. Because analogy is only a plausible reasoning process, some of the examples covered by the rule may be wrong. The plausible upper bound of the rule is therefore only an approximation of a hypothetical exact condition that will cover only positive examples of the rule. That is why it is called plausible upper bound.

The plausible lower bound condition of the rule covers the input example that is known to be correct. However, the bound is a minimal generalization performed in the context of an incomplete ontology (generalization hierarchy). Therefore it is also a plausible bound.

The previous slide shows the most likely relation between the plausible lower bound, the plausible upper bound and the hypothetical exact condition of the rule. Notice that there are instances of the plausible upper bound that are not instances of the hypothetical exact condition of the rule. This means that the learned rule could also generate wrong solutions to some problems, as already mentioned. Also, there are instances of the hypothetical exact condition that are not instances of the plausible upper bound. This means that the plausible upper bound does not cover all the cases in which the solution provided by the rule would be correct.

Similarly, there may be cases that are covered by the plausible lower bound, without being covered by the hypothetical exact condition. All these situations are a consequence of the fact that the explanation of the initial example might be incomplete, and that the representation language for learning (which is based on the object ontology) might also be incomplete. These results are consistent with what one would expect from an agent performing analogical reasoning.

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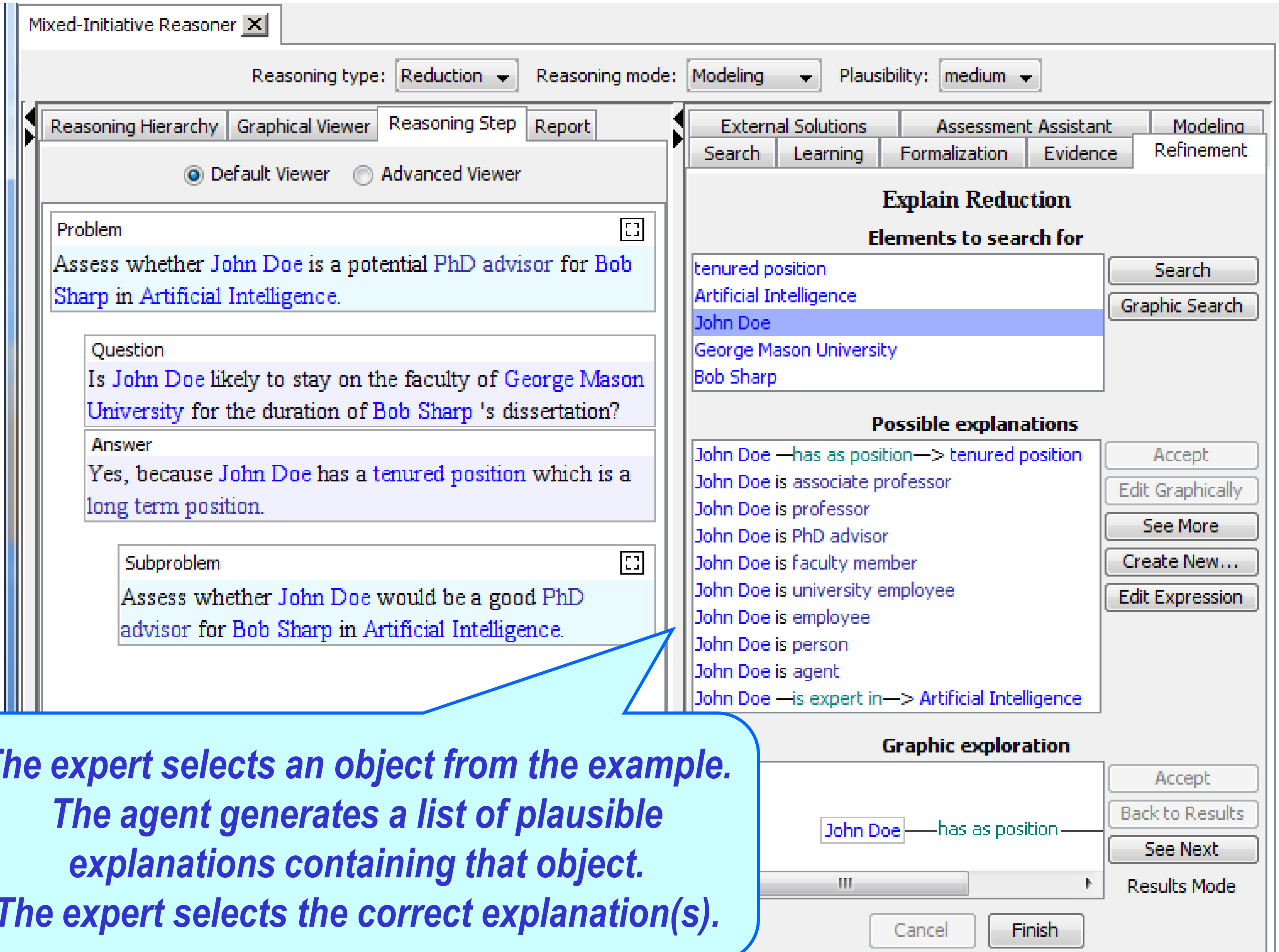
General Heuristics for Explanation Generation

Look for the relationships between the objects from the question and the answer.

Look for the relationships between an object from the IF problem and an object from the question or the answer.

User Hint: Selecting an Object from the Example



The expert selects an object from the example.
The agent generates a list of plausible explanations containing that object.
The expert selects the correct explanation(s).

Analogical Reasoning Heuristic

1. Look for a rule R_k that reduces the current problem P_1.
2. Extract the explanations E_g from the rule R_k.
3. Look for explanations of the current problem reduction that are similar with E_g.

Example to be explained:

IF the problem to solve is P_1
THEN solve $P_{1a}, \ldots P_{1d}$

Look for explanations that are similar with E_g

Previously learned rule R_k:

IF the problem to solve is P_{1g}

Explanation E_g

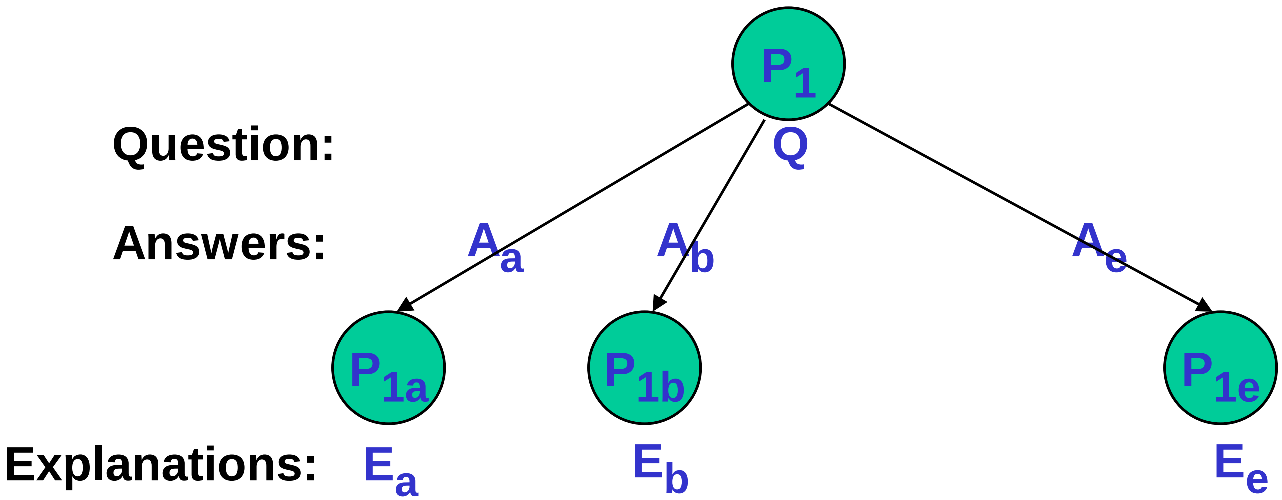
PUB condition

PLB condition

THEN accomplish $P_{11g} \ldots P_{1ng}$

Justification of the Heuristic

This heuristic is based on the observation that the explanations of the alternative reductions of a problem tend to have similar structures. The same factors are considered, but the relationships between them are different.



Another Analogical Reasoning Heuristic

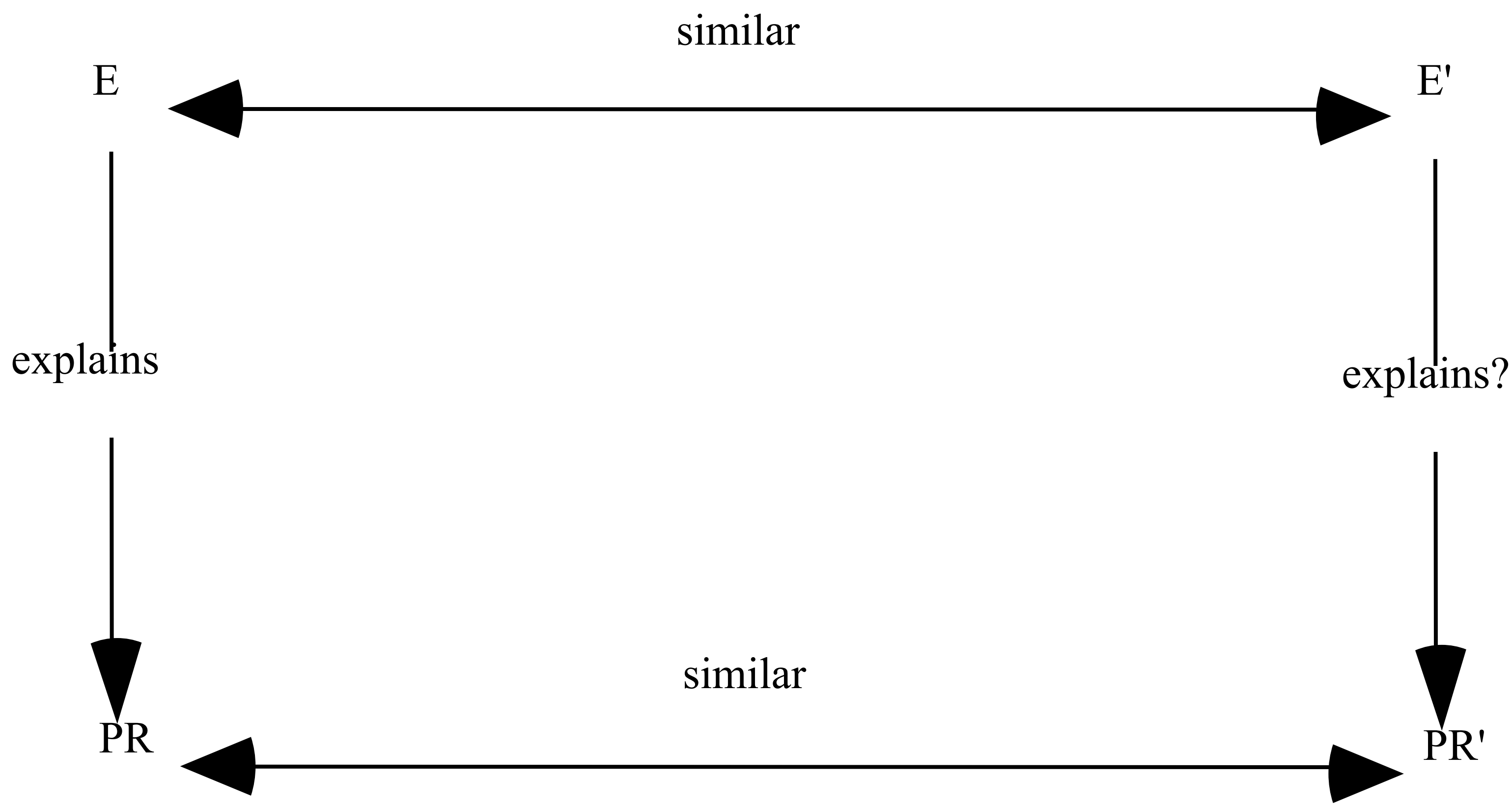
1. Look for a rule R_k that reduces a similar problem to similar subproblems.

2. Extract the explanations E_g from the rule R_k.

3. Look for explanations of the current problem reduction that are similar with E_g.

Justification of the Heuristic

This heuristic is based on the observation that similar problem solving episodes tend to have similar explanations:



Yet Another Analogical Reasoning Heuristic

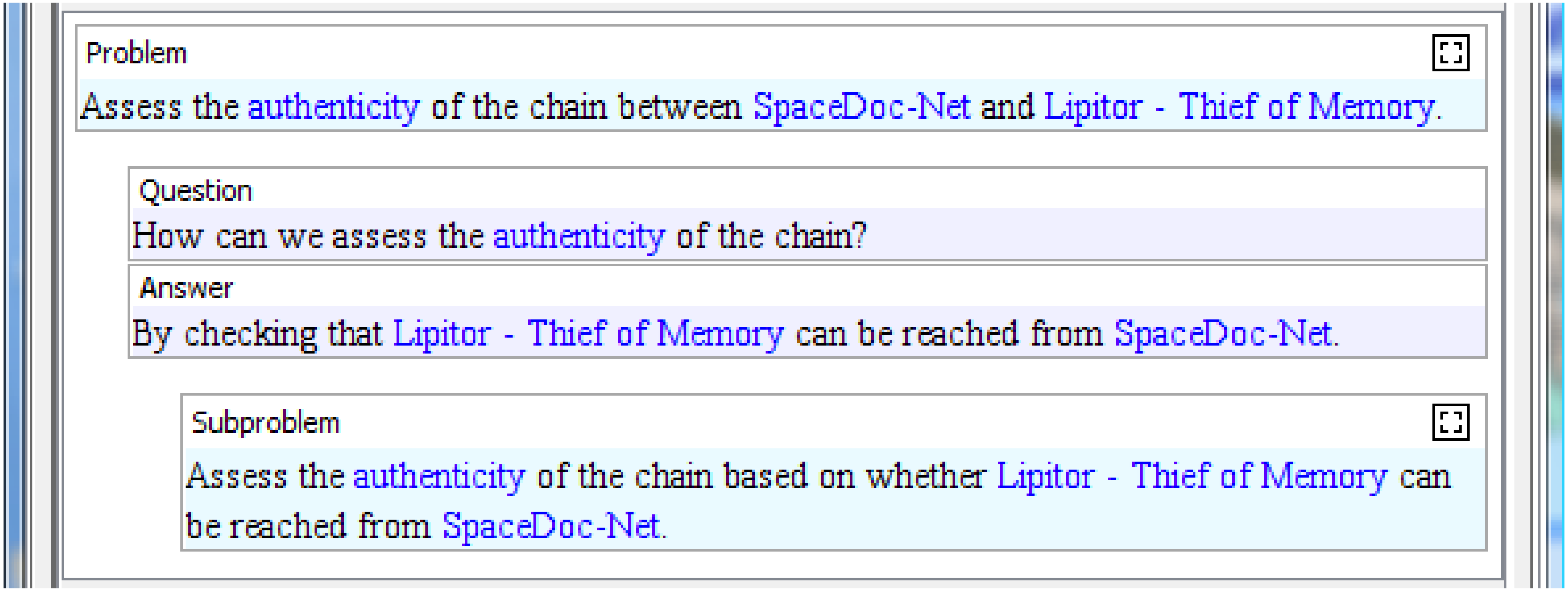
1. Look for a rule R_k that reduces a problem that is similar to the current problem even if the subproblems are not similar.

2. Extract the explanations E_g from the rule R_k.

3. Look for explanations of the current problem reduction that are similar with E_g.

The plausible explanations found by the agent can be ordered by their plausibility (based on the heuristics used).

No Explanation Necessary



Sometimes no formal explanation is necessary, as in the above example.

We need to invoke Rule Learning, but then quit it without selecting any explanation. The agent will generalize this example to a rule.

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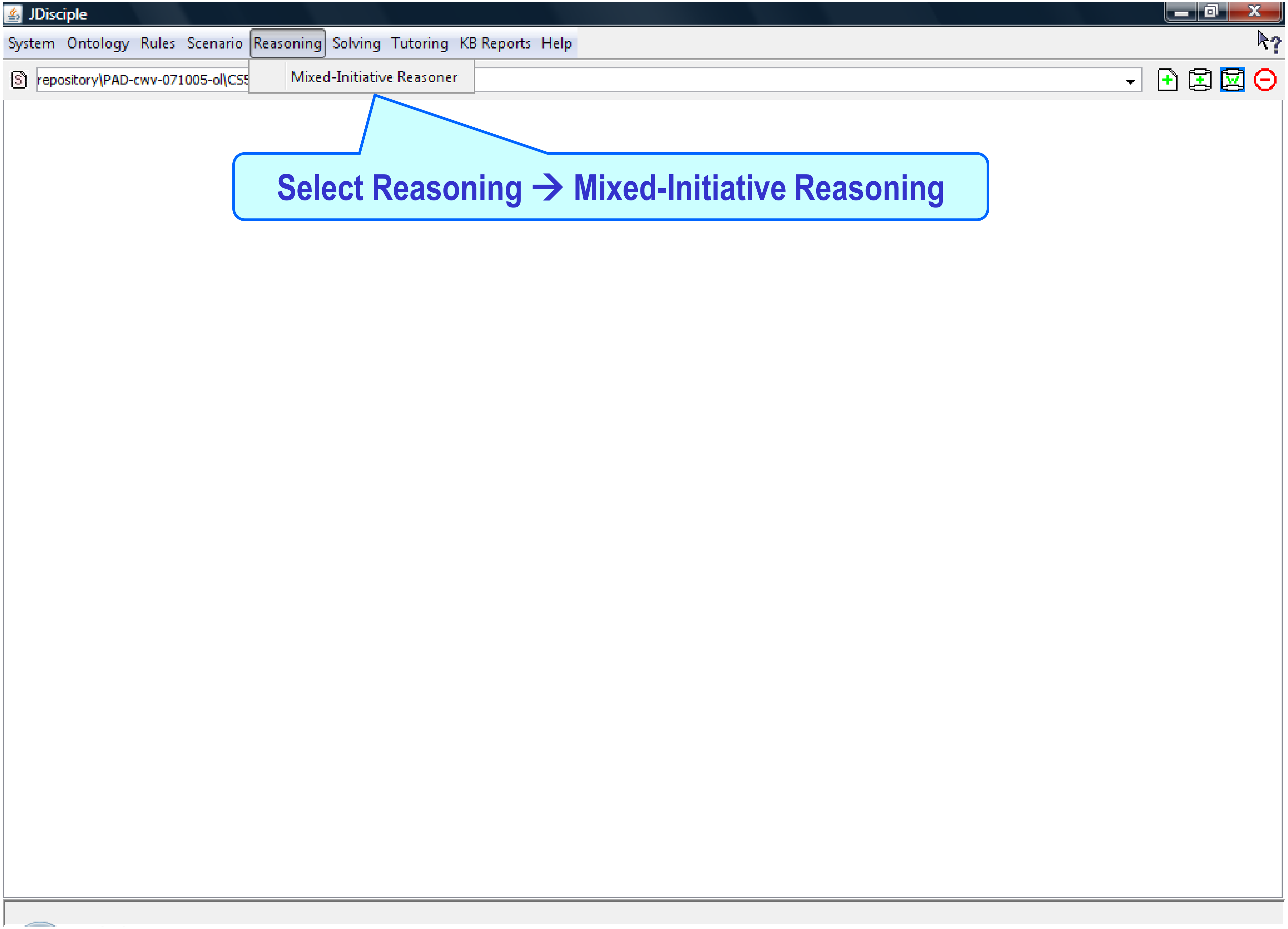
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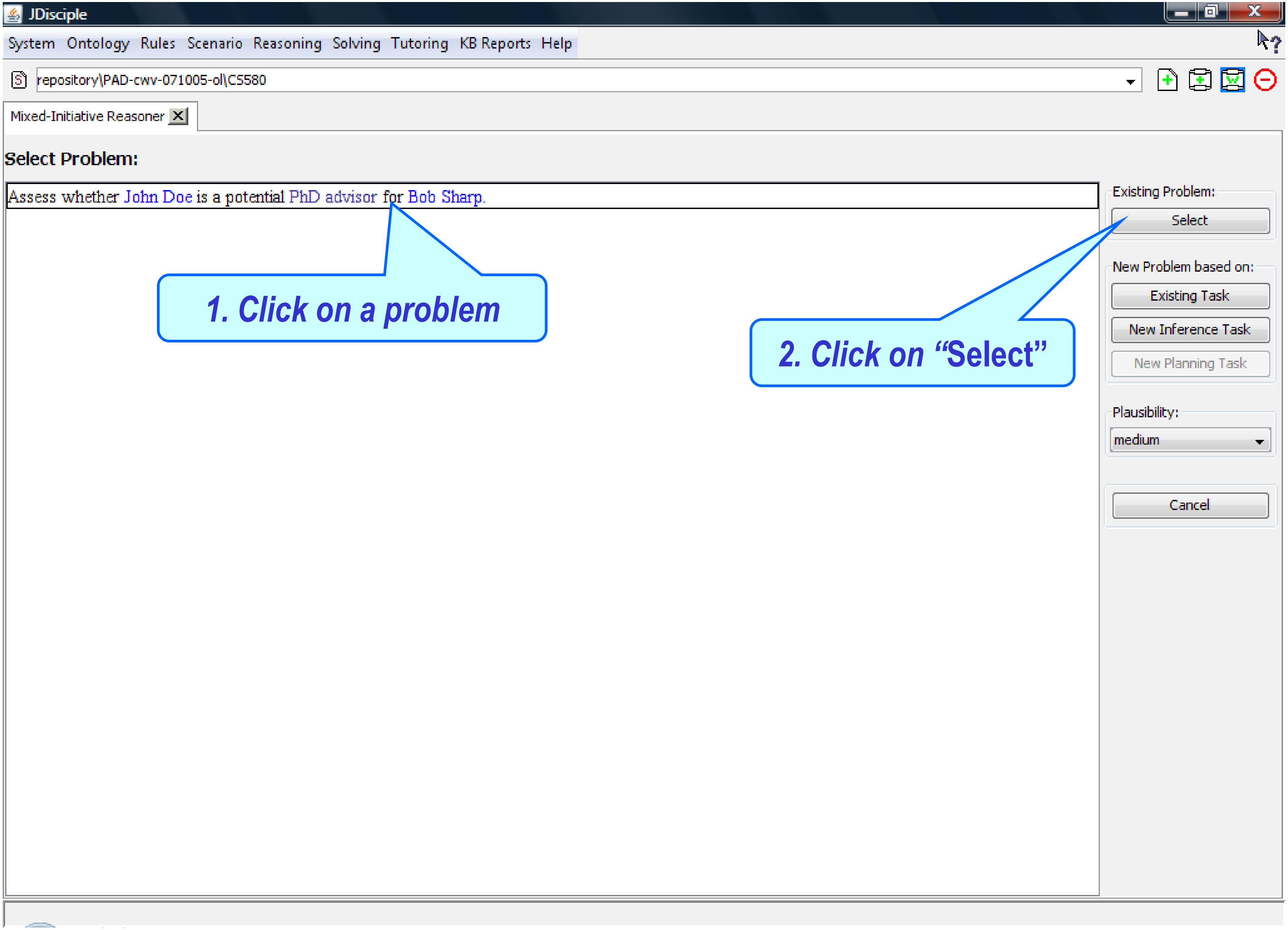
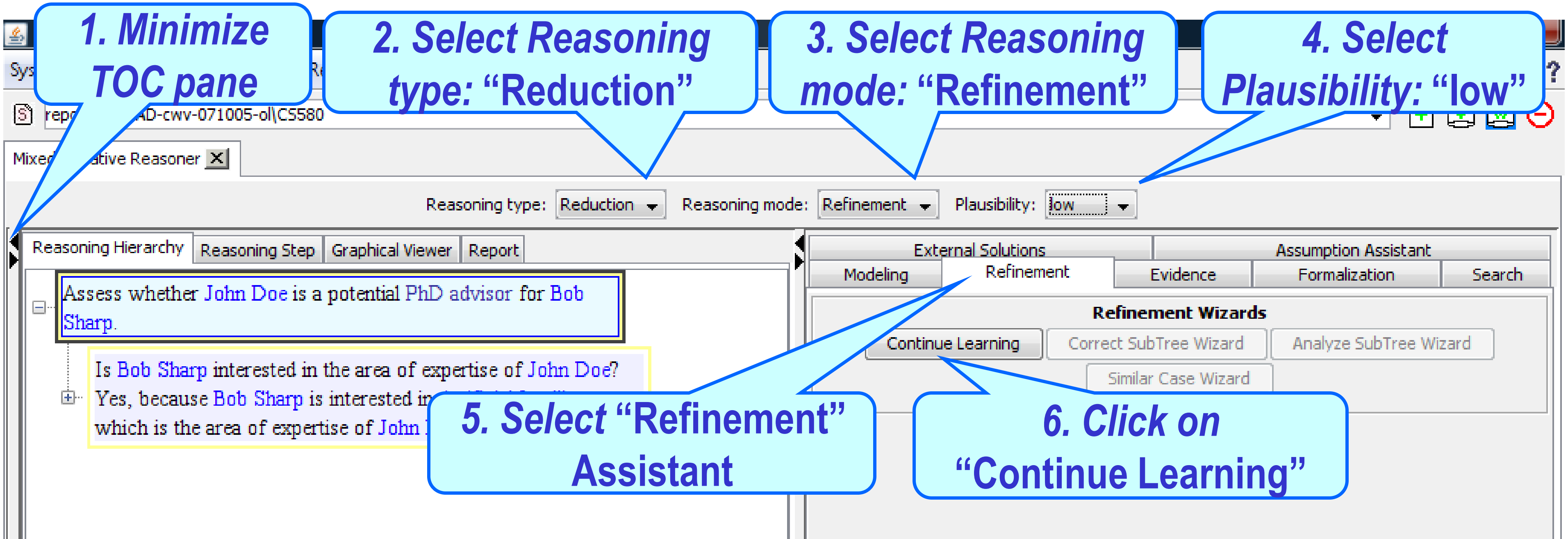
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS5
Mixed-Initiative Reasoner
Select Reasoning → Mixed-Initiative Reasoning



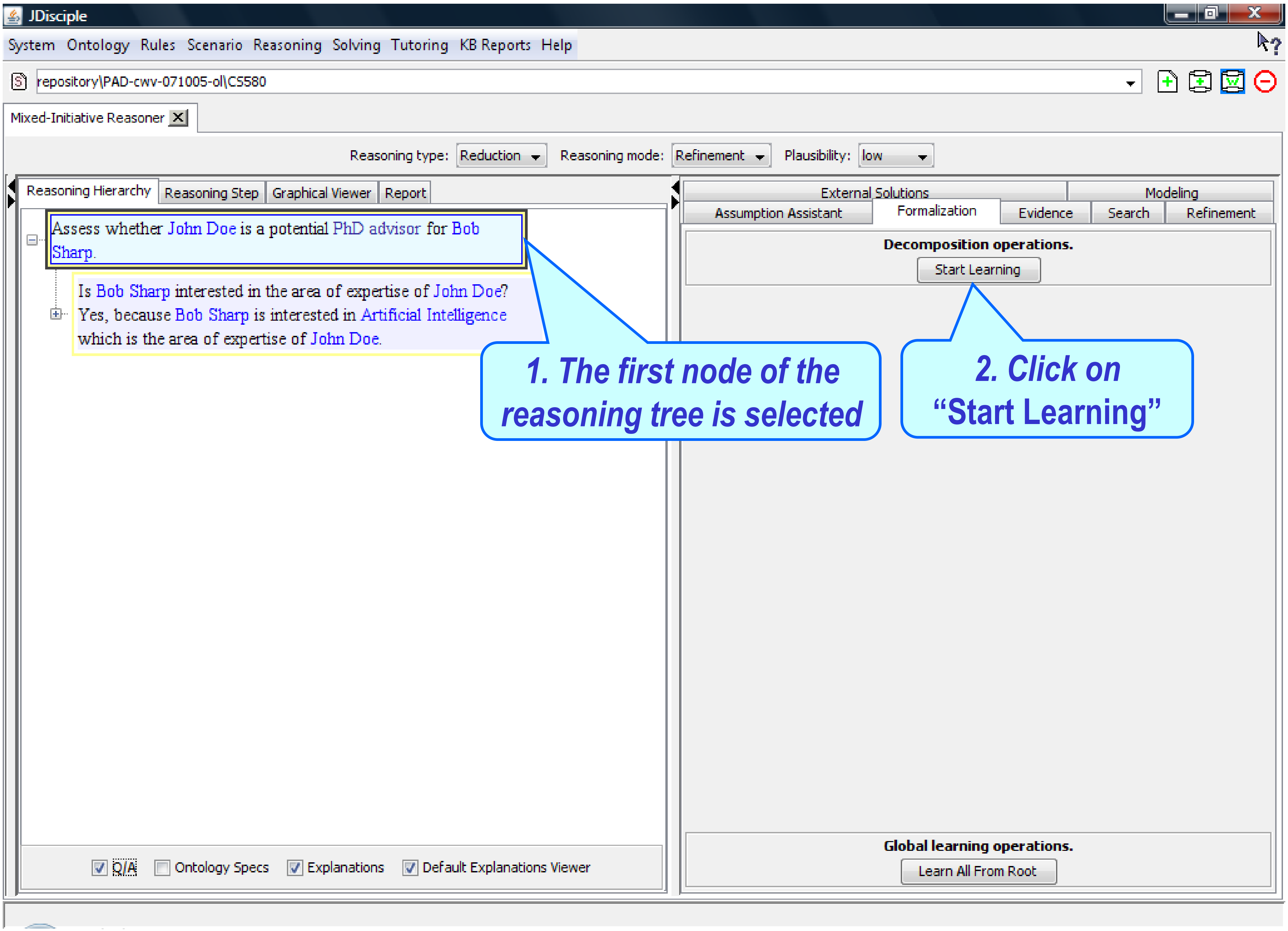
JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Select Problem:
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
1. Click on a problem
2. Click on "Select"
Existing Problem:
Select
New Problem based on:
Existing Task
New Inference Task
New Planning Task
Plausibility:
medium
Cancel



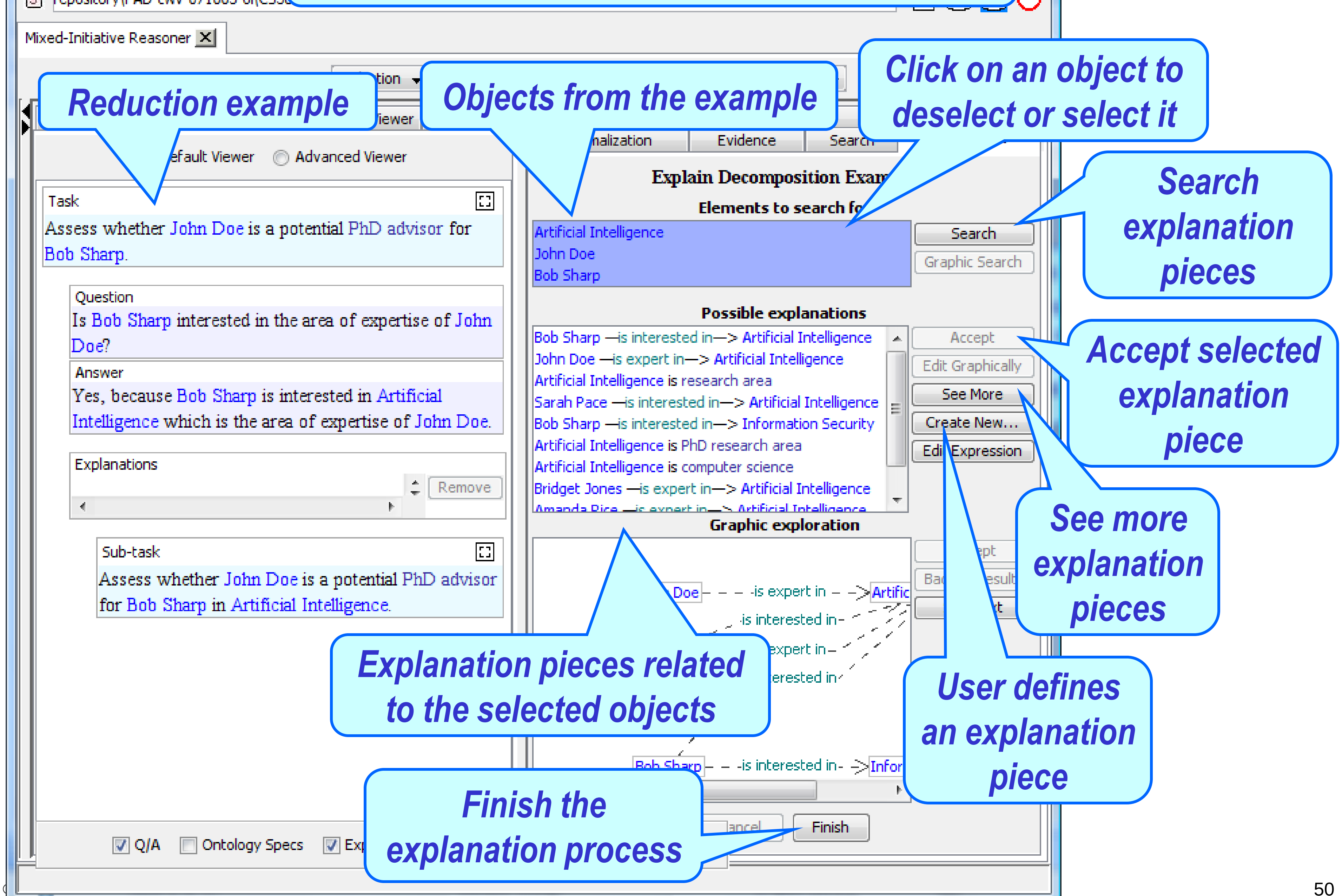
Disciple will select the first modeling node, in a depth-first search, to learn a rule from the corresponding reasoning step.

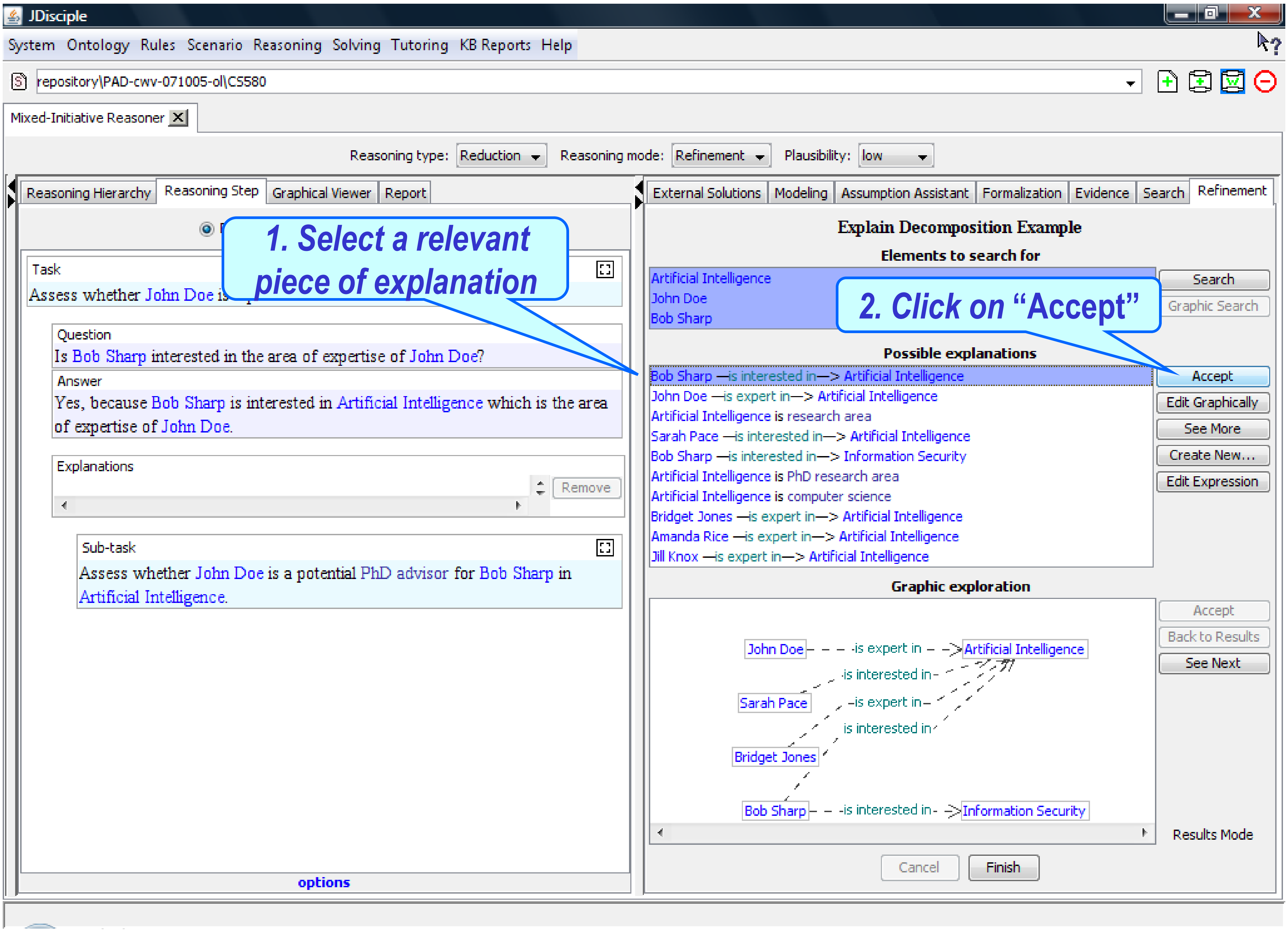
Alternatively, you can browse the reasoning tree, click on a modeling node (usually a question/answer node) of a modeling step, and then click on "Continue Learning" to learn a rule from that step.

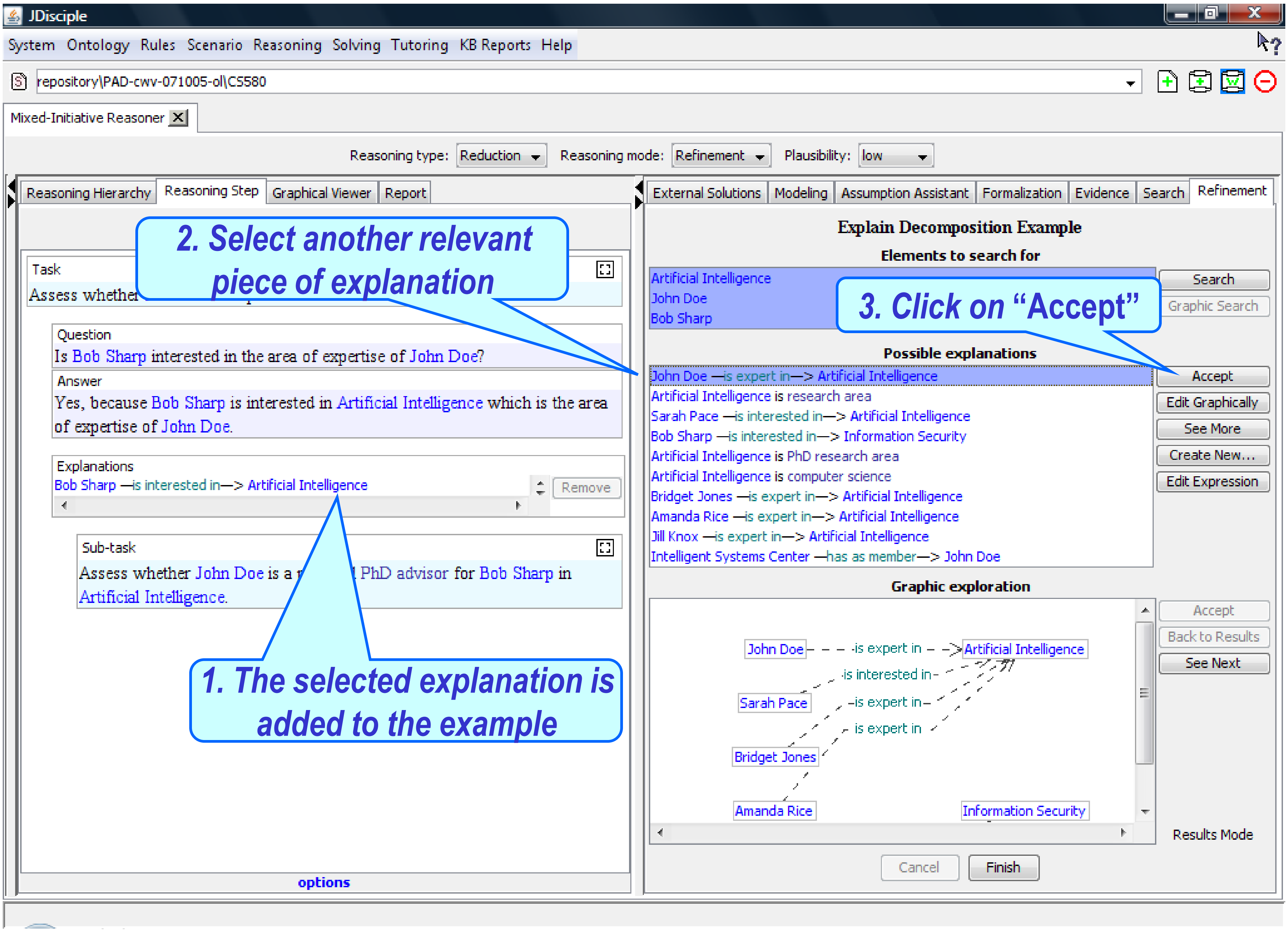
The modeling nodes have yellow borders to distinguish them from the nodes generated by learned rules, which have grey borders.

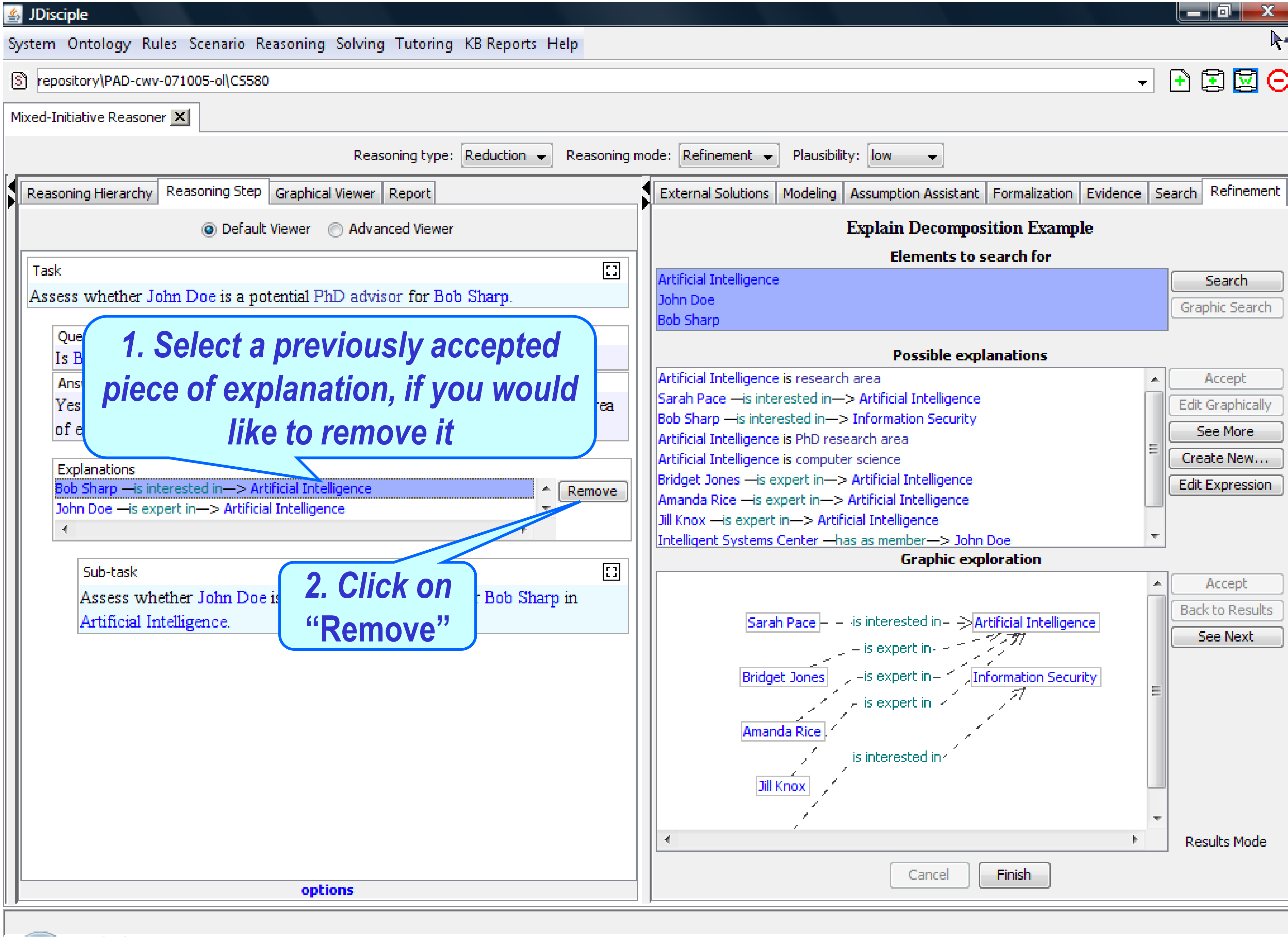

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Is Bob Sharp interested in the area of expertise of John Doe?
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Decomposition operations.
Start Learning
1. The first node of the reasoning tree is selected
2. Click on "Start Learning"
Global learning operations.
Learn All From Root
Q/A
Ontology Specs
Explanations
Default Explanations Viewer

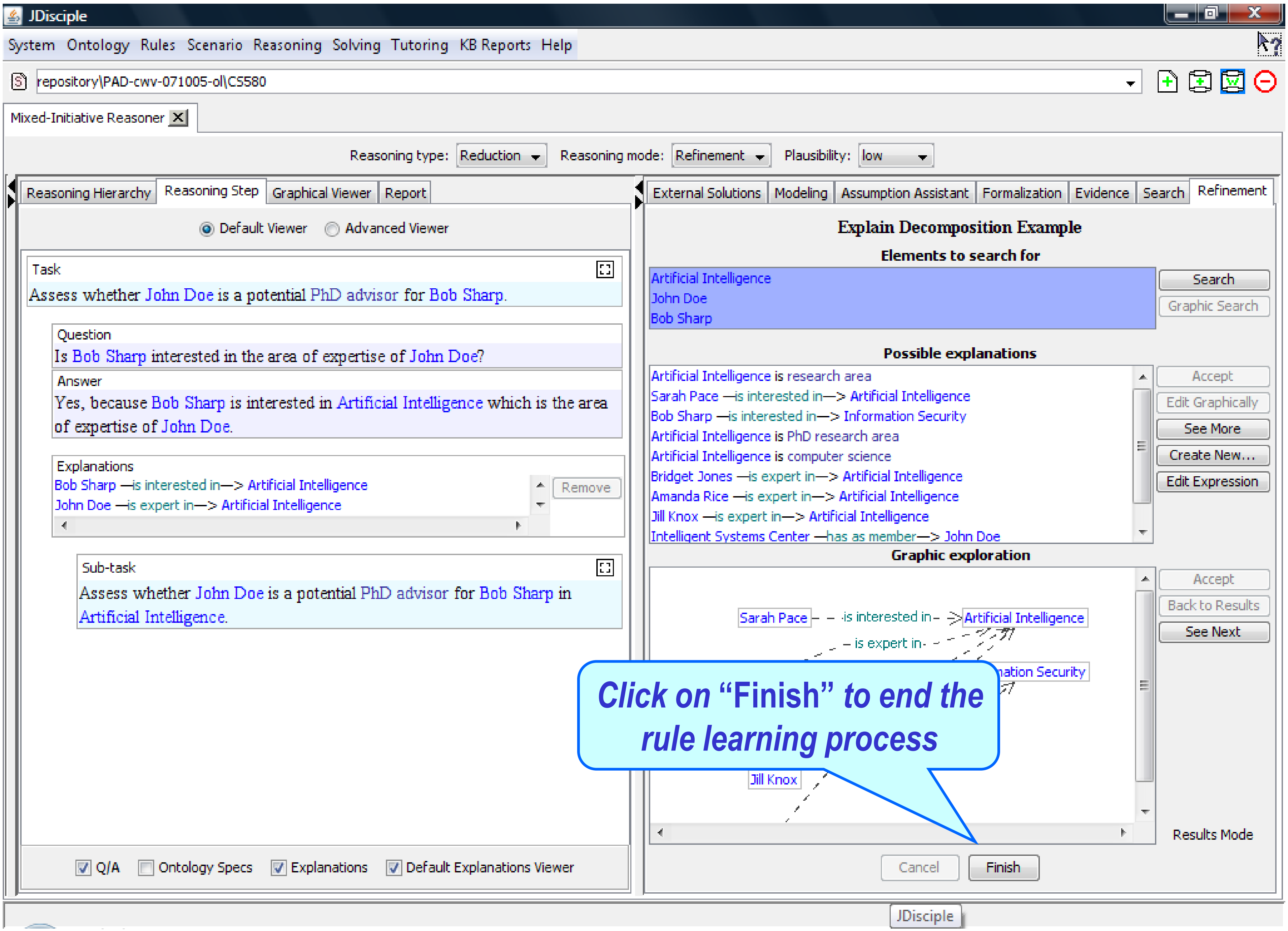
Example Explanation Interface

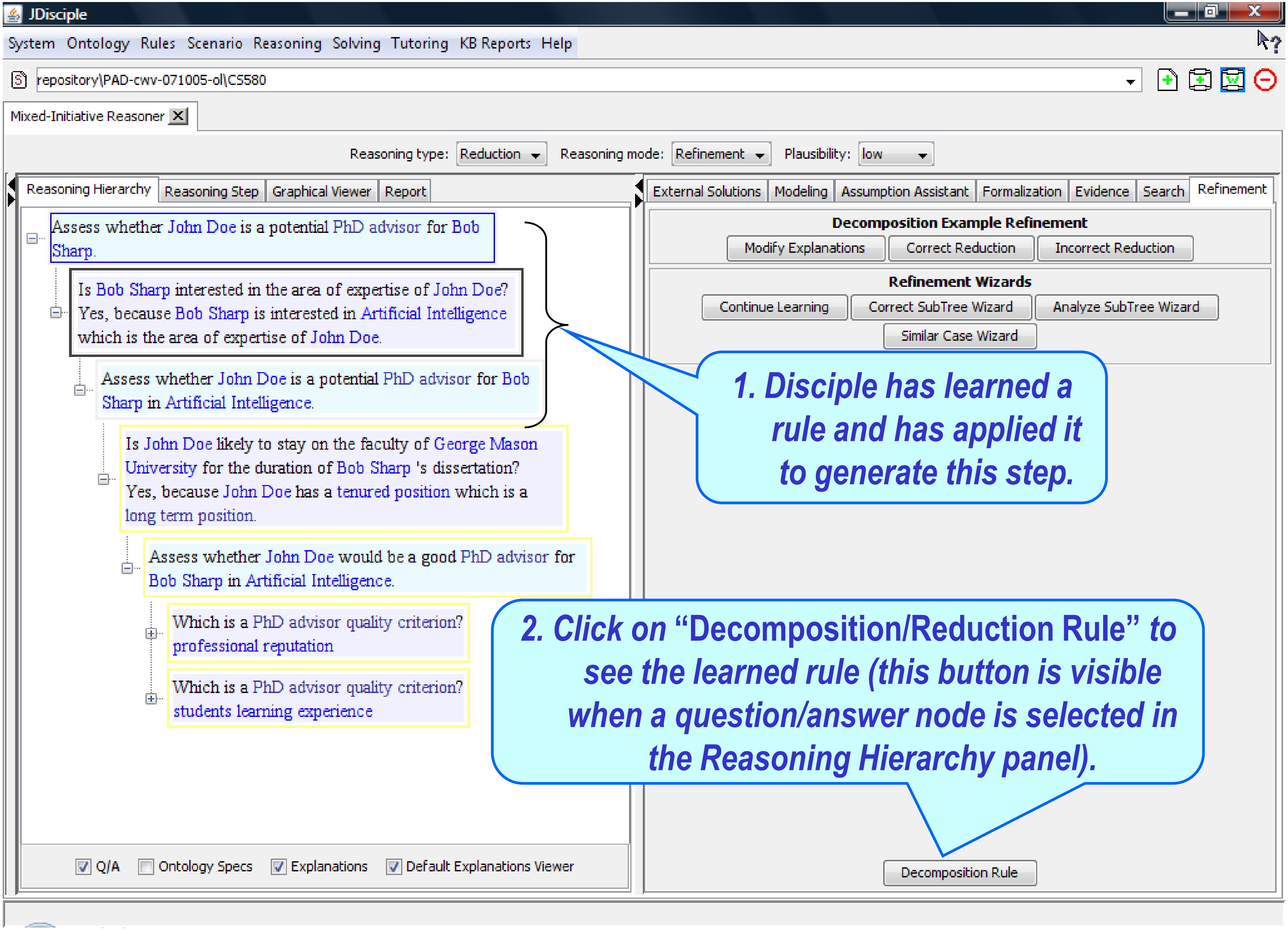


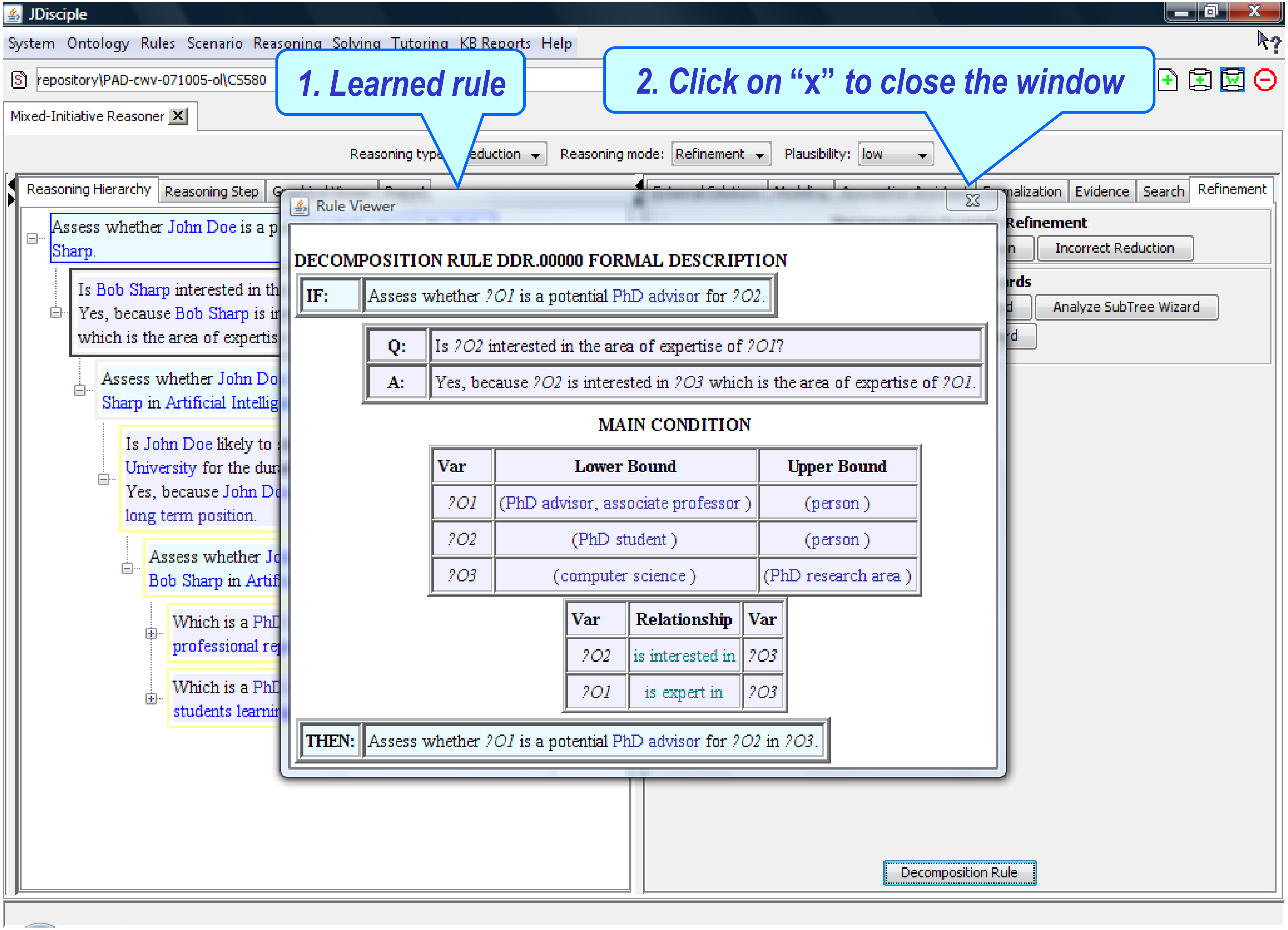

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
1. Select a relevant piece of explanation
Task
Assess whether John Doe is
Question
Is Bob Sharp interested in the area of expertise of John Doe?
Answer
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Explanations
Remove
Sub-task
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
options
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Explain Decomposition Example
Elements to search for
Artificial Intelligence
John Doe
Bob Sharp
Search
Graphic Search
2. Click on “Accept”
Possible explanations
Bob Sharp —is interested in—> Artificial Intelligence
John Doe —is expert in—> Artificial Intelligence
Artificial Intelligence is research area
Sarah Pace —is interested in—> Artificial Intelligence
Bob Sharp —is interested in—> Information Security
Artificial Intelligence is PhD research area
Artificial Intelligence is computer science
Bridget Jones —is expert in—> Artificial Intelligence
Amanda Rice —is expert in—> Artificial Intelligence
Jill Knox —is expert in—> Artificial Intelligence
Accept
Edit Graphically
See More
Create New…
Edit Expression
Graphic exploration
John Doe
is expert in
Artificial Intelligence
is interested in
Sarah Pace
is expert in
is interested in
Bridget Jones
Bob Sharp
is interested in
Information Security
Accept
Back to Results
See Next
Results Mode
Cancel
Finish


JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Task
Assess whether
Question
Is Bob Sharp interested in the area of expertise of John Doe?
Answer
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Explanations
Bob Sharp —is interested in—> Artificial Intelligence
Remove
Sub-task
Assess whether John Doe is a r PhD advisor for Bob Sharp in Artificial Intelligence.
options
2. Select another relevant piece of explanation
1. The selected explanation is added to the example
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Explain Decomposition Example
Elements to search for
Artificial Intelligence
John Doe
Bob Sharp
Search
Graphic Search
3. Click on "Accept"
Possible explanations
John Doe —is expert in—> Artificial Intelligence
Artificial Intelligence is research area
Sarah Pace —is interested in—> Artificial Intelligence
Bob Sharp —is interested in—> Information Security
Artificial Intelligence is PhD research area
Artificial Intelligence is computer science
Bridget Jones —is expert in—> Artificial Intelligence
Amanda Rice —is expert in—> Artificial Intelligence
Jill Knox —is expert in—> Artificial Intelligence
Intelligent Systems Center —has as member—> John Doe
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
John Doe
is expert in
Artificial Intelligence
is interested in
Sarah Pace
is expert in
is expert in
Bridget Jones
Amanda Rice
Information Security
Accept
Back to Results
See Next
Results Mode
Cancel
Finish

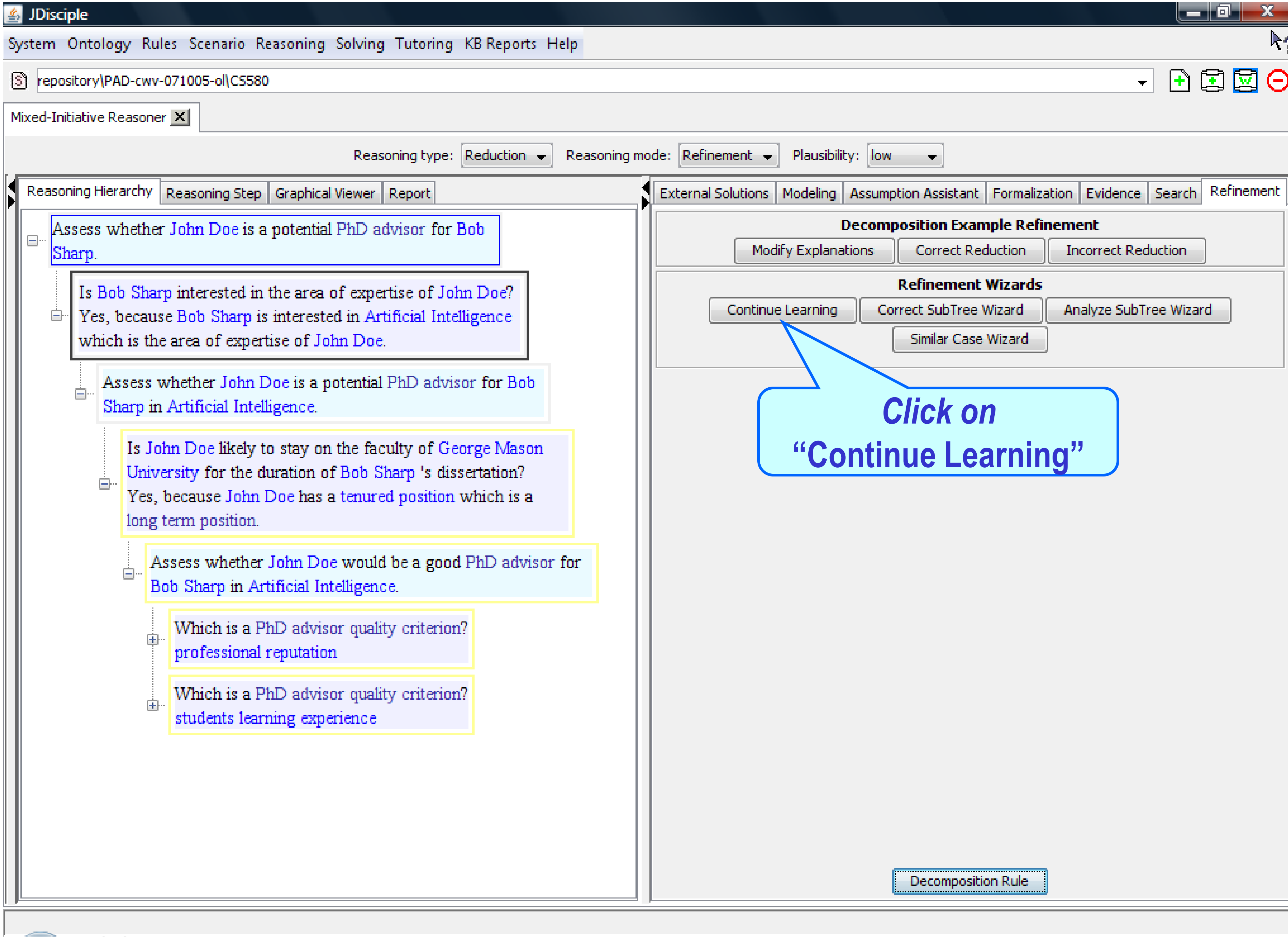

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Task
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
1. Select a previously accepted piece of explanation, if you would like to remove it
Explanations
Bob Sharp —is interested in—> Artificial Intelligence
John Doe —is expert in—> Artificial Intelligence
Remove
Sub-task
Assess whether John Doe is
Bob Sharp in
Artificial Intelligence.
2. Click on “Remove”
options
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Explain Decomposition Example
Elements to search for
Artificial Intelligence
John Doe
Bob Sharp
Search
Graphic Search
Possible explanations
Artificial Intelligence is research area
Sarah Pace —is interested in—> Artificial Intelligence
Bob Sharp —is interested in—> Information Security
Artificial Intelligence is PhD research area
Artificial Intelligence is computer science
Bridget Jones —is expert in—> Artificial Intelligence
Amanda Rice —is expert in—> Artificial Intelligence
Jill Knox —is expert in—> Artificial Intelligence
Intelligent Systems Center —has as member—> John Doe
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
Sarah Pace
is interested in
Artificial Intelligence
is expert in
Bridget Jones
is expert in
Information Security
is expert in
Amanda Rice
is interested in
Jill Knox
Accept
Back to Results
See Next
Results Mode
Cancel
Finish


JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Task
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Question
Is Bob Sharp interested in the area of expertise of John Doe?
Answer
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Explanations
Bob Sharp —is interested in—> Artificial Intelligence
John Doe —is expert in—> Artificial Intelligence
Remove
Sub-task
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
Q/A
Ontology Specs
Explanations
Default Explanations Viewer
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Explain Decomposition Example
Elements to search for
Artificial Intelligence
John Doe
Bob Sharp
Search
Graphic Search
Possible explanations
Artificial Intelligence is research area
Sarah Pace —is interested in—> Artificial Intelligence
Bob Sharp —is interested in—> Information Security
Artificial Intelligence is PhD research area
Artificial Intelligence is computer science
Bridget Jones —is expert in—> Artificial Intelligence
Amanda Rice —is expert in—> Artificial Intelligence
Jill Knox —is expert in—> Artificial Intelligence
Intelligent Systems Center —has as member—> John Doe
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
Sarah Pace
is interested in
Artificial Intelligence
is expert in
Jill Knox
Accept
Back to Results
See Next
Results Mode
Cancel
Finish
JDisciple
Click on "Finish" to end the rule learning process


JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Is Bob Sharp interested in the area of expertise of John Doe? Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
Is John Doe likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation? Yes, because John Doe has a tenured position which is a long term position.
Assess whether John Doe would be a good PhD advisor for Bob Sharp in Artificial Intelligence.
Which is a PhD advisor quality criterion? professional reputation
Which is a PhD advisor quality criterion? students learning experience
Q/A
Ontology Specs
Explanations
Default Explanations Viewer
Decomposition Example Refinement
Modify Explanations
Correct Reduction
Incorrect Reduction
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Analyze SubTree Wizard
Similar Case Wizard
1. Disciple has learned a rule and has applied it to generate this step.
2. Click on “Decomposition/Reduction Rule” to see the learned rule (this button is visible when a question/answer node is selected in the Reasoning Hierarchy panel).
Decomposition Rule



JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
1. Learned rule
2. Click on “x” to close the window
Mixed-Initiative Reasoner
Reasoning type
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Evidence
Search
Refinement
Incorrect Reduction
Analyze SubTree Wizard
Rule Viewer
DECOMPOSITION RULE DDR.00000 FORMAL DESCRIPTION
IF: Assess whether ?O1 is a potential PhD advisor for ?O2.
Q: Is ?O2 interested in the area of expertise of ?O1?
A: Yes, because ?O2 is interested in ?O3 which is the area of expertise of ?O1.
MAIN CONDITION
Var
Lower Bound
Upper Bound
?O1
(PhD advisor, associate professor)
(person)
?O2
(PhD student)
(person)
?O3
(computer science)
(PhD research area)
Var
Relationship
Var
?O2
is interested in
?O3
?O1
is expert in
?O3
THEN: Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.
Assess whether John Doe is a p
Sharp.
Is Bob Sharp interested in th
Yes, because Bob Sharp is i
which is the area of expertis
Assess whether John Do
Sharp in Artificial Intellig
Is John Doe likely to
University for the dur
Yes, because John D
long term position.
Assess whether J
Bob Sharp in Artif
Which is a PhD
professional re
Which is a PhD
students learni
Decomposition Rule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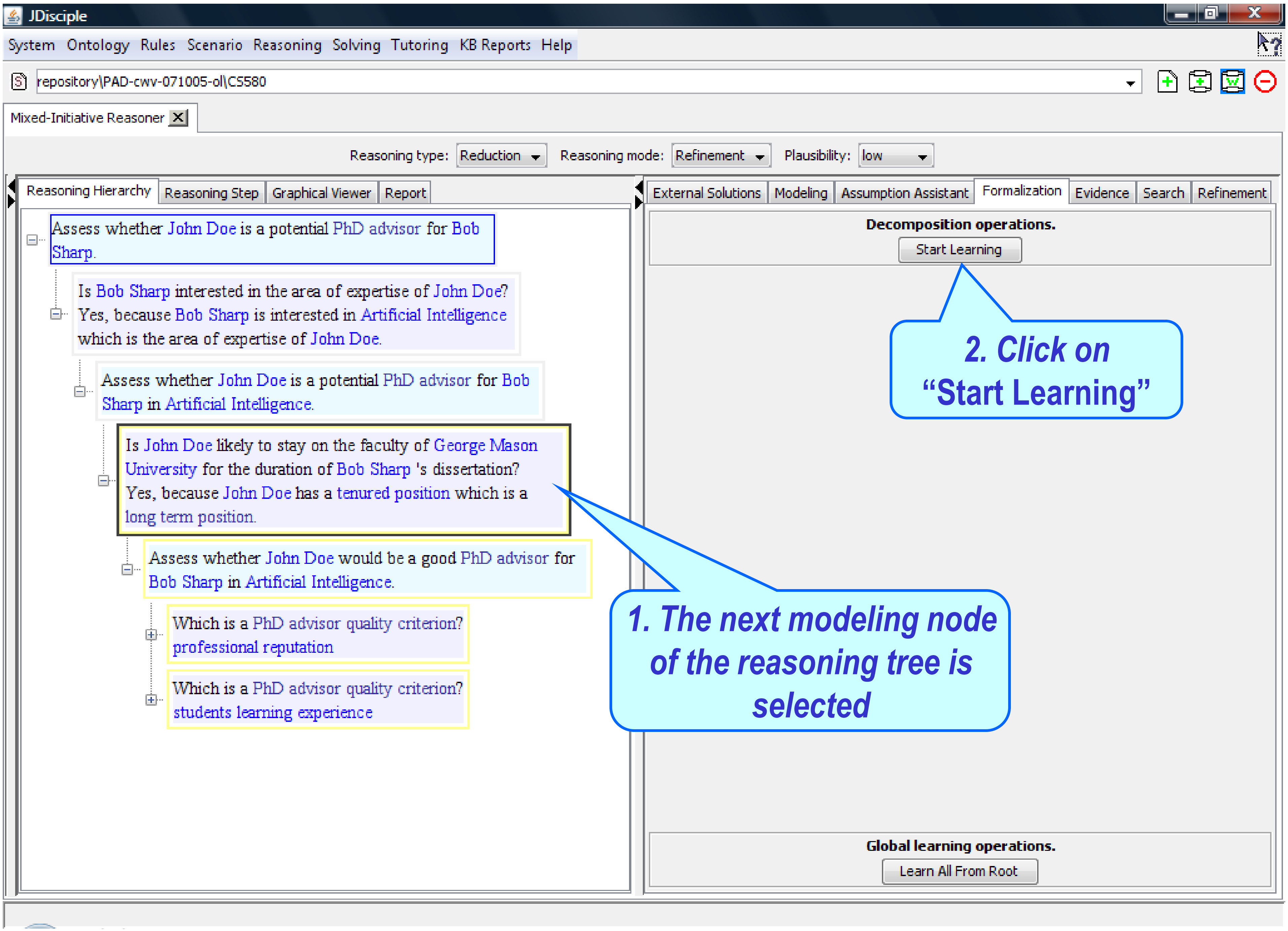
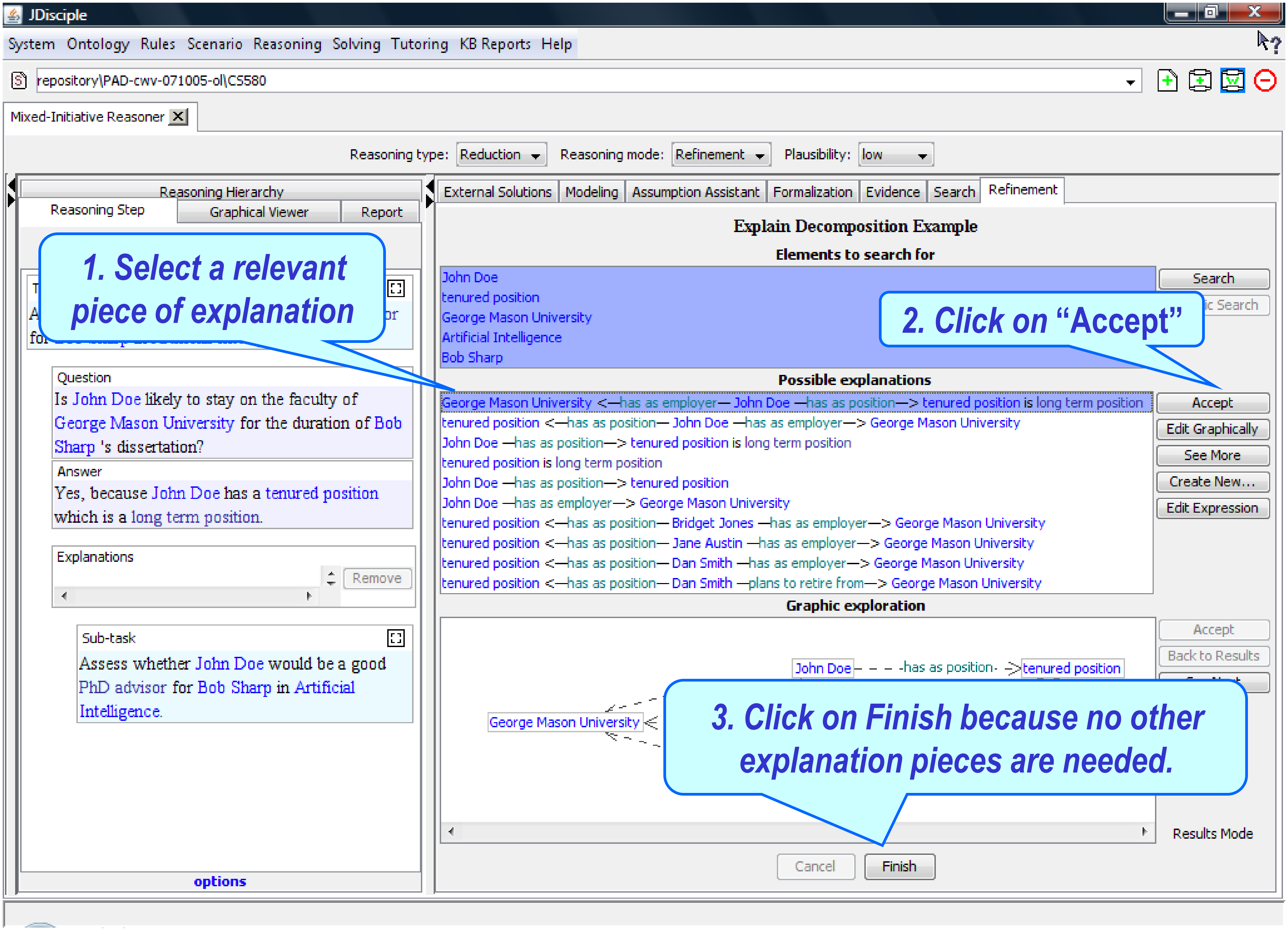
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Is Bob Sharp interested in the area of expertise of John Doe?
Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
Is John Doe likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation?
Yes, because John Doe has a tenured position which is a long term position.
Assess whether John Doe would be a good PhD advisor for Bob Sharp in Artificial Intelligence.
Which is a PhD advisor quality criterion?
professional reputation
Which is a PhD advisor quality criterion?
students learning experience
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Decomposition Example Refinement
Modify Explanations
Correct Reduction
Incorrect Reduction
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Analyze SubTree Wizard
Similar Case Wizard
Click on
“Continue Learning”
Decomposition Rule


JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Is Bob Sharp interested in the area of expertise of John Doe? Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
Is John Doe likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation? Yes, because John Doe has a tenured position which is a long term position.
Assess whether John Doe would be a good PhD advisor for Bob Sharp in Artificial Intelligence.
Which is a PhD advisor quality criterion? professional reputation
Which is a PhD advisor quality criterion? students learning experience
Decomposition operations.
Start Learning
2. Click on “Start Learning”
1. The next modeling node of the reasoning tree is selected
Global learning operations.
Learn All From Root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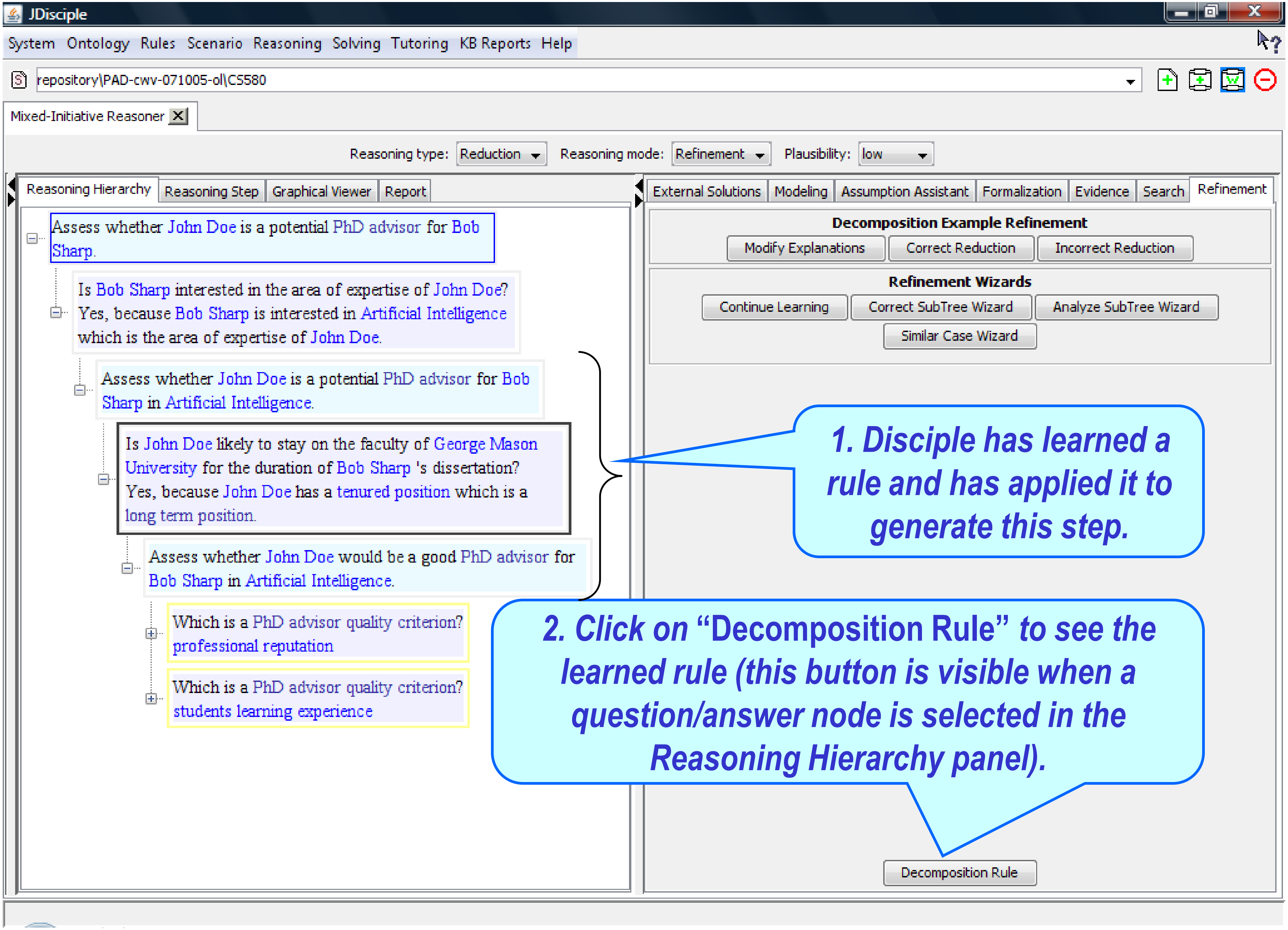
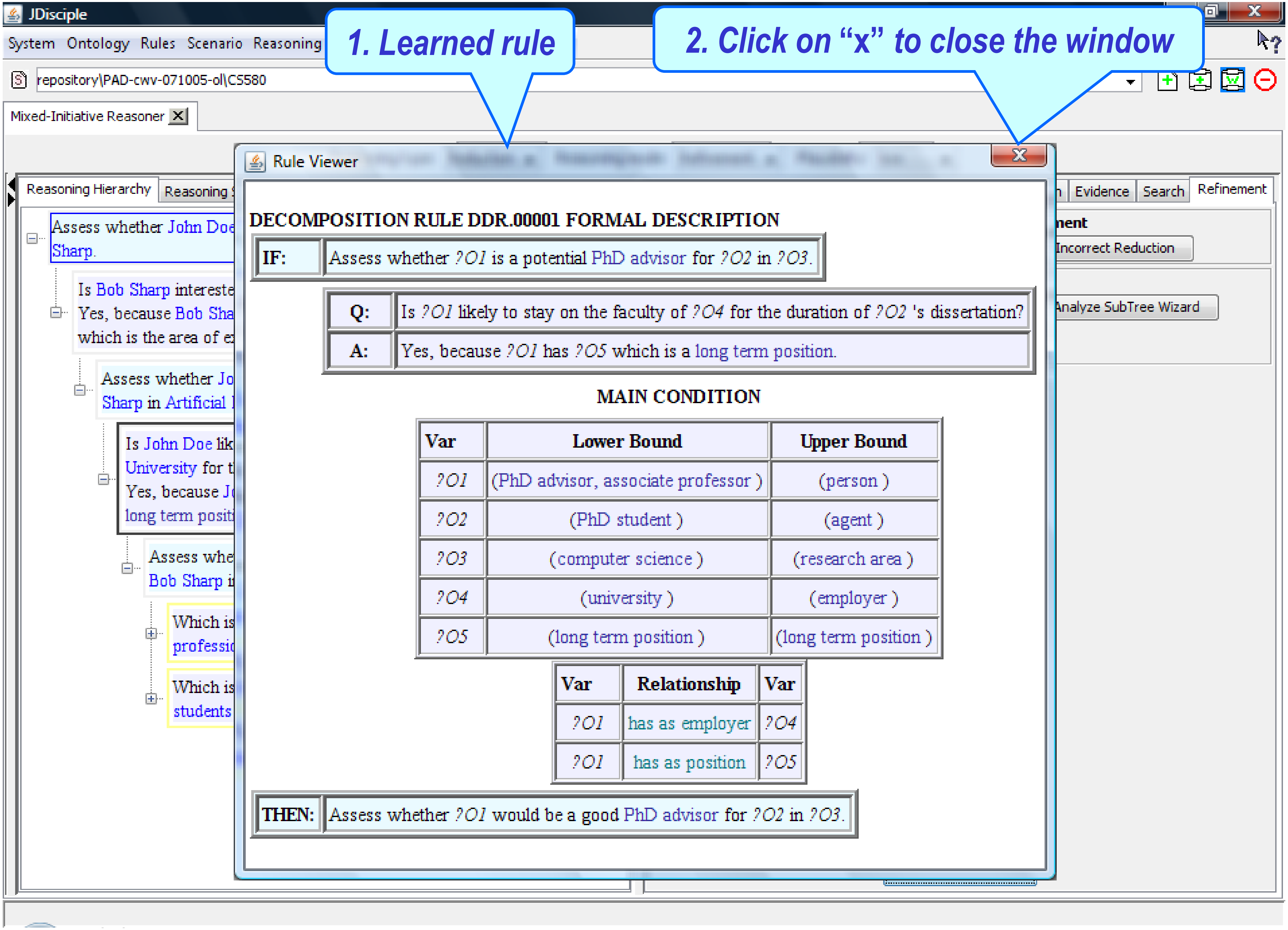
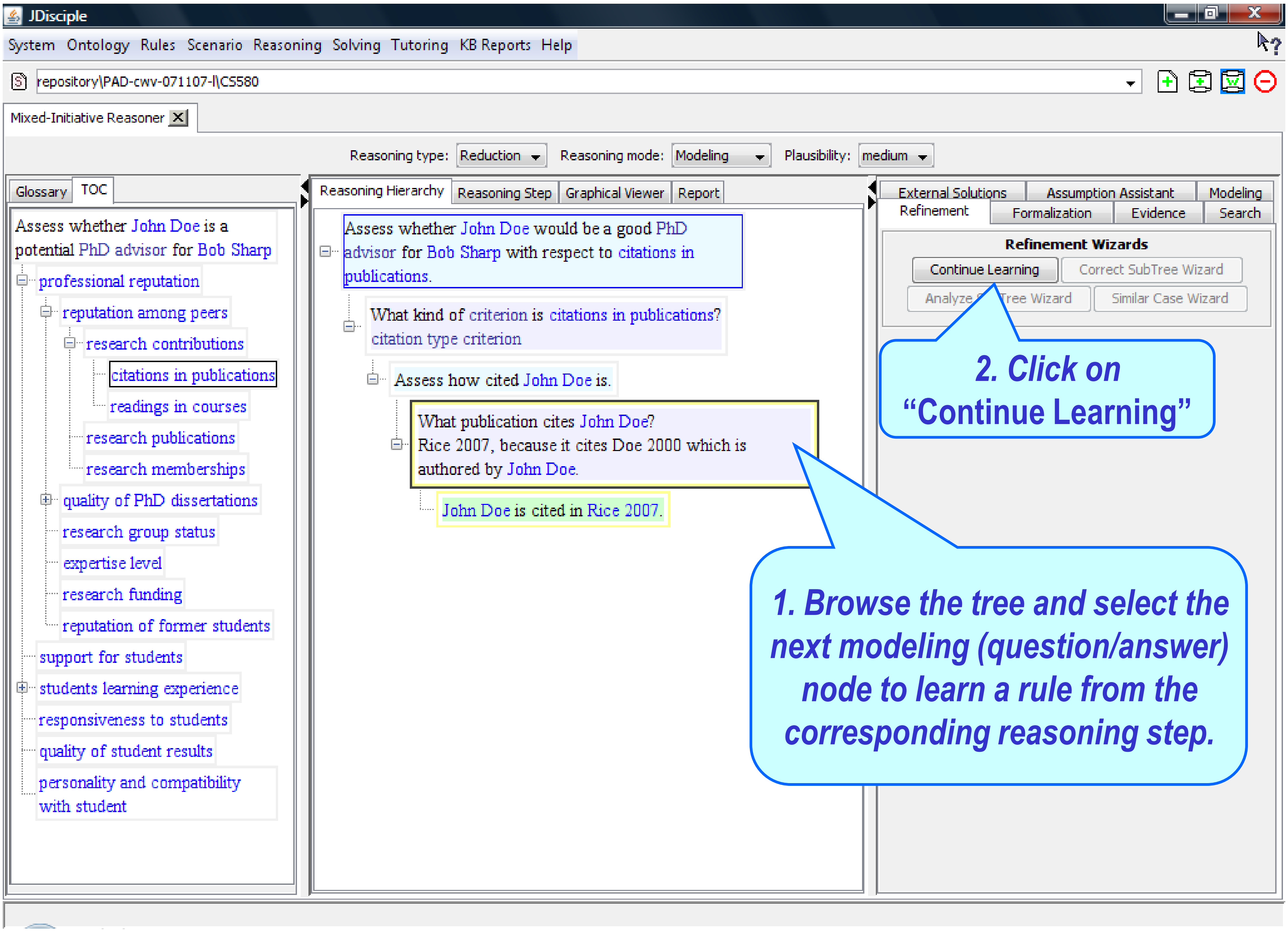
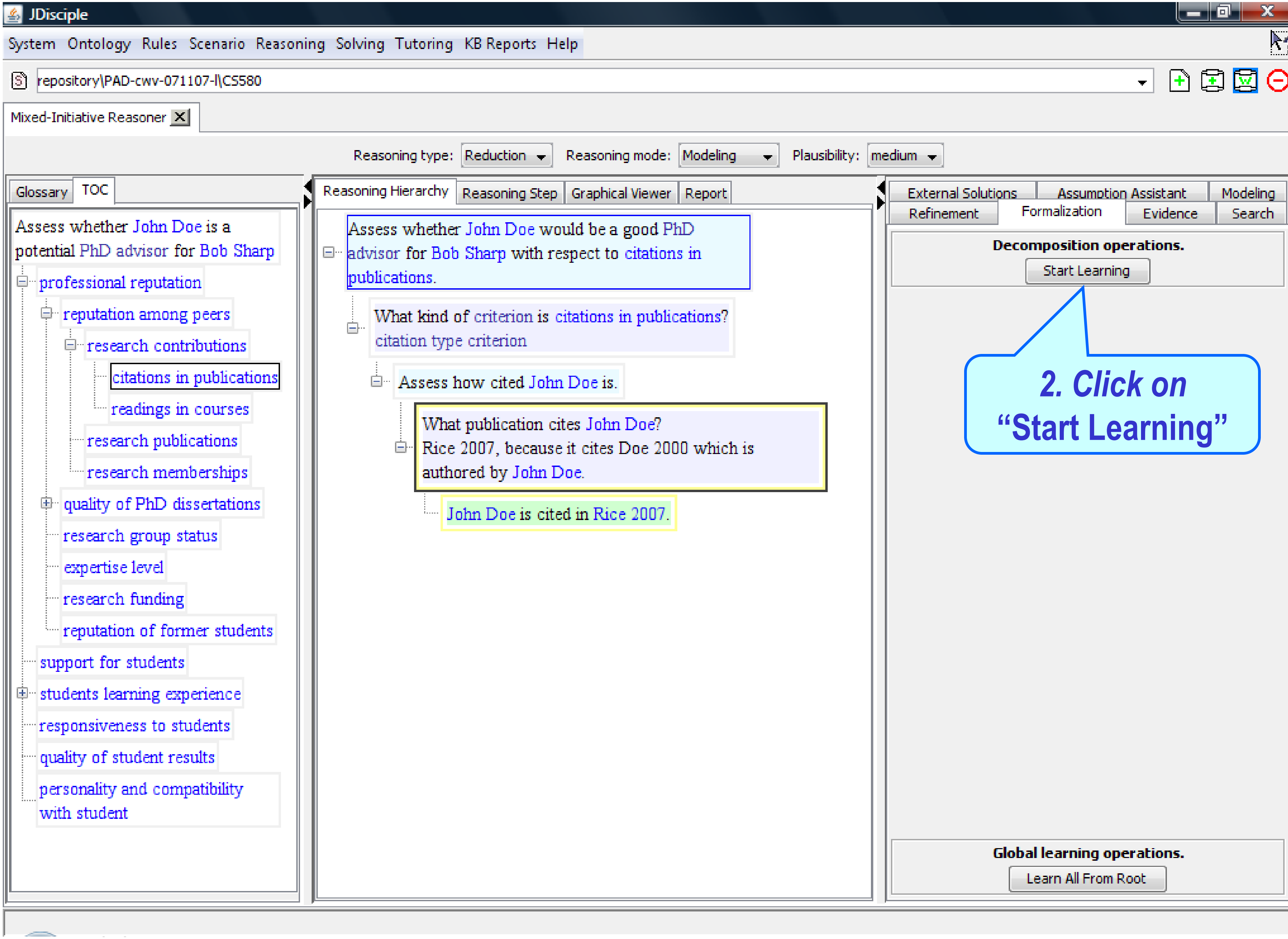
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Explain Decomposition Example
Elements to search for
John Doe
tenured position
George Mason University
Artificial Intelligence
Bob Sharp
Search
Possible explanations
George Mason University <—has as employer— John Doe —has as position—> tenured position is long term position
tenured position <—has as position— John Doe —has as employer—> George Mason University
John Doe —has as position—> tenured position is long term position
tenured position is long term position
John Doe —has as position—> tenured position
John Doe —has as employer—> George Mason University
tenured position <—has as position— Bridget Jones —has as employer—> George Mason University
tenured position <—has as position— Jane Austin —has as employer—> George Mason University
tenured position <—has as position— Dan Smith —has as employer—> George Mason University
tenured position <—has as position— Dan Smith —plans to retire from—> George Mason University
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
John Doe - - -has as position- -> tenured position
George Mason University
Accept
Back to Results
Results Mode
Cancel
Finish
Question
Is John Doe likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation?
Answer
Yes, because John Doe has a tenured position which is a long term position.
Explanations
Remove
Sub-task
Assess whether John Doe would be a good PhD advisor for Bob Sharp in Artificial Intelligence.
options
1. Select a relevant piece of explanation
2. Click on "Accept"
3. Click on Finish because no other explanation pieces are needed.

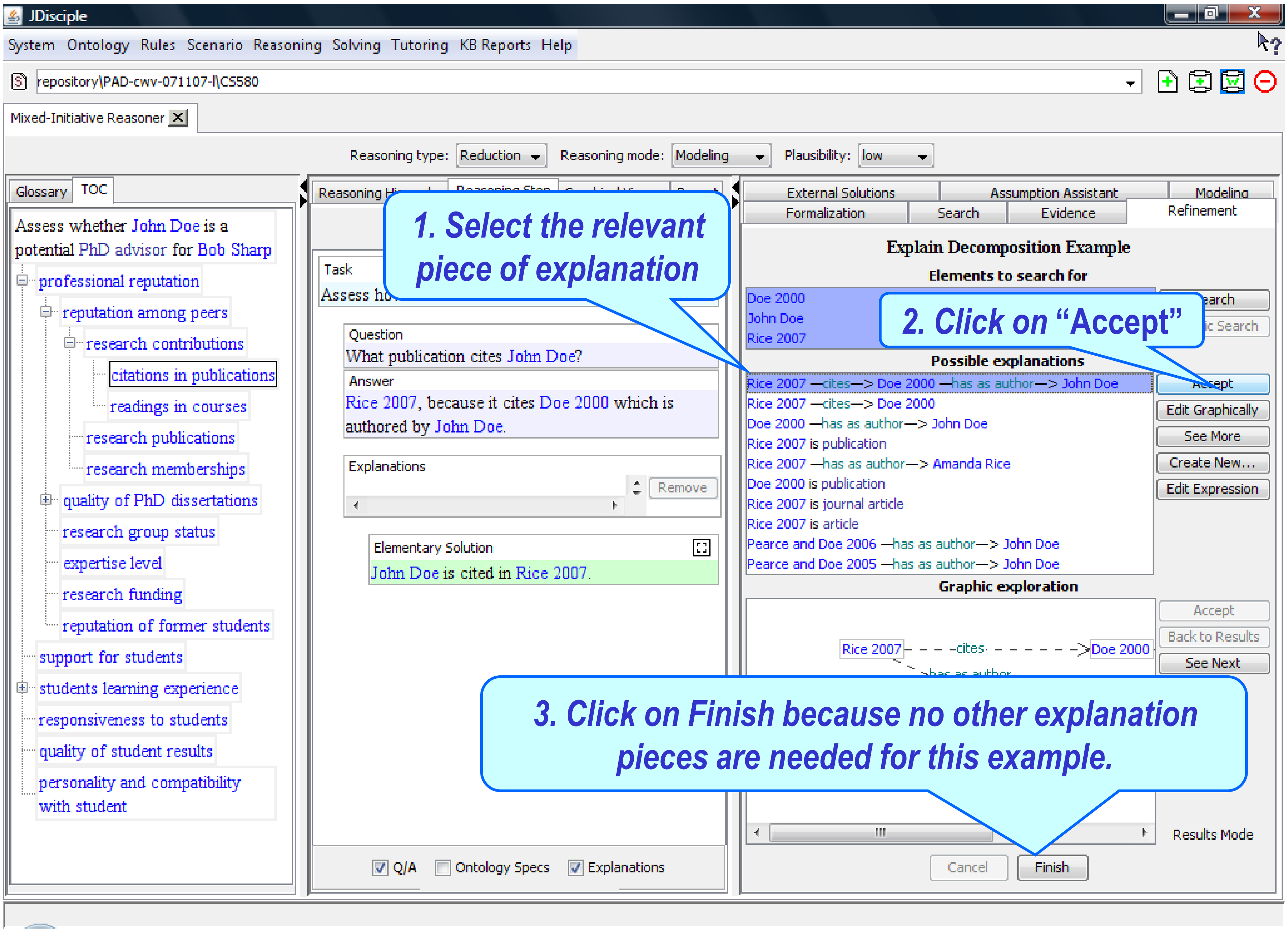

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Refinement
Plausibility: low
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe is a potential PhD advisor for Bob Sharp.
Is Bob Sharp interested in the area of expertise of John Doe? Yes, because Bob Sharp is interested in Artificial Intelligence which is the area of expertise of John Doe.
Assess whether John Doe is a potential PhD advisor for Bob Sharp in Artificial Intelligence.
Is John Doe likely to stay on the faculty of George Mason University for the duration of Bob Sharp 's dissertation? Yes, because John Doe has a tenured position which is a long term position.
Assess whether John Doe would be a good PhD advisor for Bob Sharp in Artificial Intelligence.
Which is a PhD advisor quality criterion? professional reputation
Which is a PhD advisor quality criterion? students learning experience
External Solutions
Modeling
Assumption Assistant
Formalization
Evidence
Search
Refinement
Decomposition Example Refinement
Modify Explanations
Correct Reduction
Incorrect Reduction
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Analyze SubTree Wizard
Similar Case Wizard
1. Disciple has learned a rule and has applied it to generate this step.
2. Click on "Decomposition Rule" to see the learned rule (this button is visible when a question/answer node is selected in the Reasoning Hierarchy panel).
Decomposition Rule

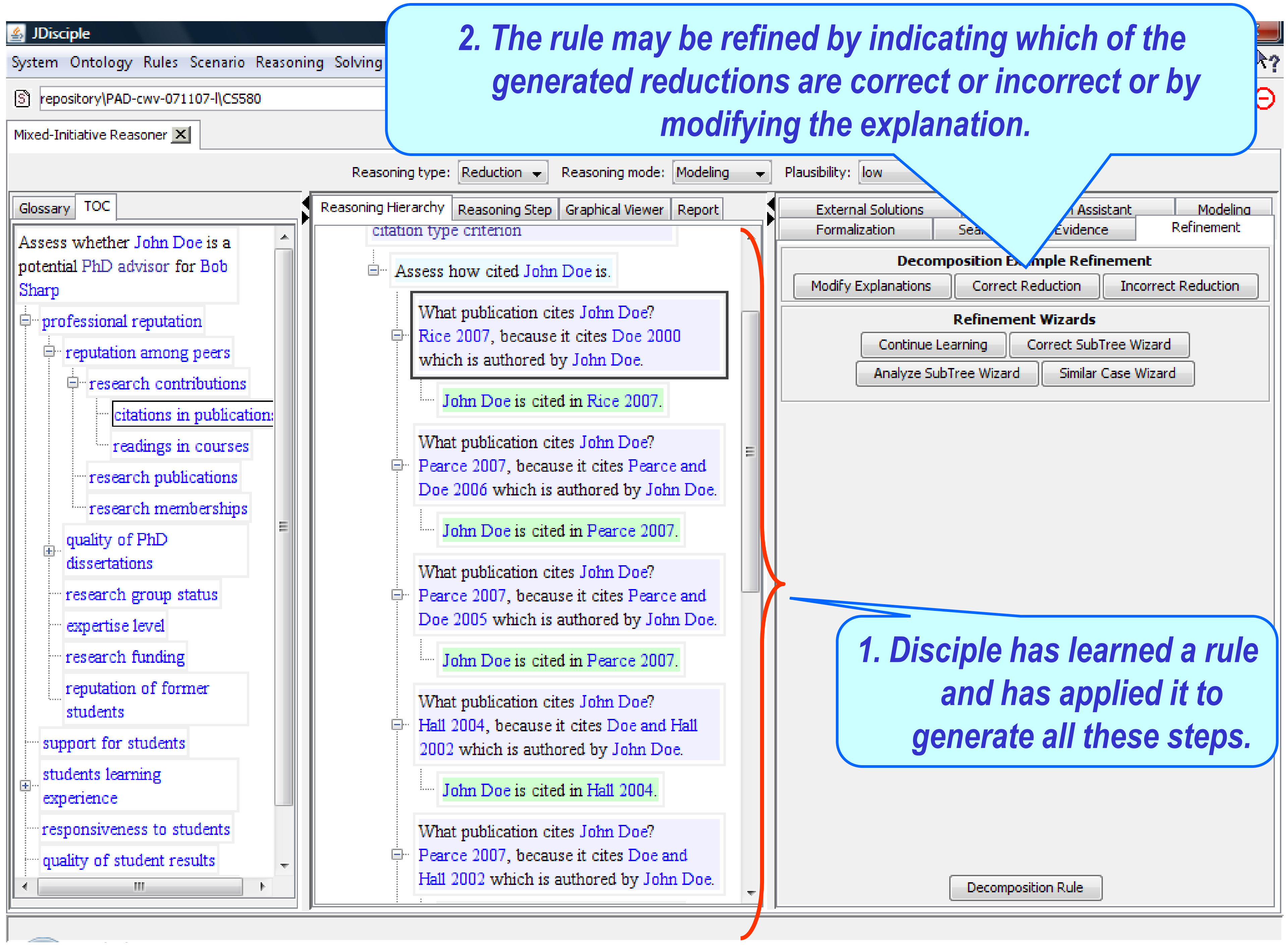

1. Learned rule
2. Click on "x" to close the window
JDisciple
System Ontology Rules Scenario Reasoning
repository\PAD-cwv-071005-ol\CS580
Mixed-Initiative Reasoner
Rule Viewer
DECOMPOSITION RULE DDR.00001 FORMAL DESCRIPTION
IF: Assess whether ?O1 is a potential PhD advisor for ?O2 in ?O3.
Q: Is ?O1 likely to stay on the faculty of ?O4 for the duration of ?O2 's dissertation?
A: Yes, because ?O1 has ?O5 which is a long term position.
MAIN CONDITION
Var | Lower Bound | Upper Bound
?O1 | (PhD advisor, associate professor) | (person)
?O2 | (PhD student) | (agent)
?O3 | (computer science) | (research area)
?O4 | (university) | (employer)
?O5 | (long term position) | (long term position)
Var | Relationship | Var
?O1 | has as employer | ?O4
?O1 | has as position | ?O5
THEN: Assess whether ?O1 would be a good PhD advisor for ?O2 in ?O3.
Evidence Search Refinement
Incorrect Reduction
Analyze SubTree Wizard
Reasoning Hierarchy
Assess whether John Doe
Sharp.
Is Bob Sharp intereste
Yes, because Bob Sha
which is the area of e
Assess whether Jo
Sharp in Artificial I
Is John Doe lik
University for t
Yes, because J
long term positi
Assess whe
Bob Sharp i
Which is
professi
Which is
students

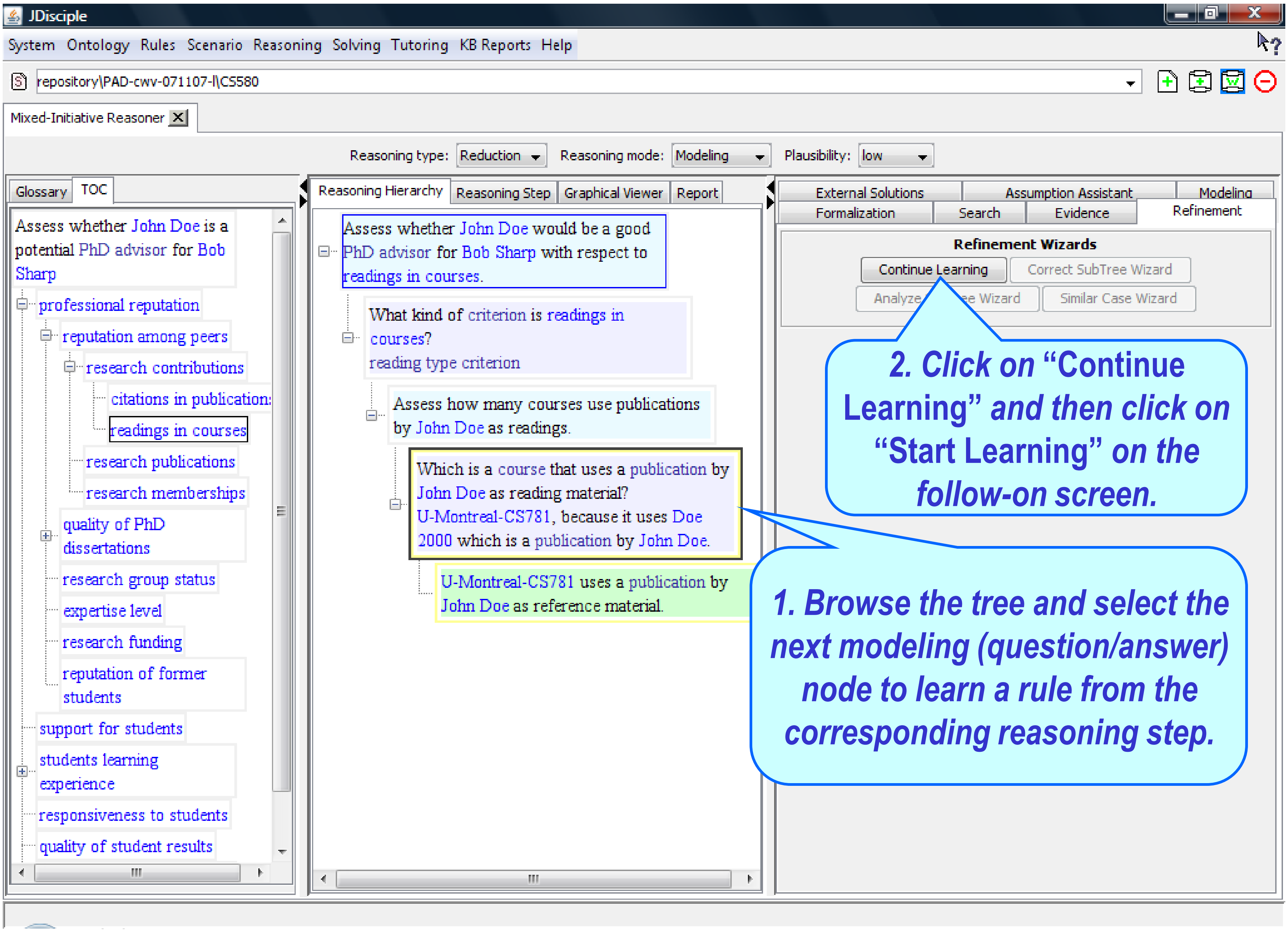

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071107-l\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: medium
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
personality and compatibility with student
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe would be a good PhD advisor for Bob Sharp with respect to citations in publications.
What kind of criterion is citations in publications?
citation type criterion
Assess how cited John Doe is.
What publication cites John Doe?
Rice 2007, because it cites Doe 2000 which is authored by John Doe.
John Doe is cited in Rice 2007.
External Solutions
Assumption Assistant
Modeling
Refinement
Formalization
Evidence
Search
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Tree Wizard
Similar Case Wizard
2. Click on "Continue Learning"
1. Browse the tree and select the next modeling (question/answer) node to learn a rule from the corresponding reasoning step.



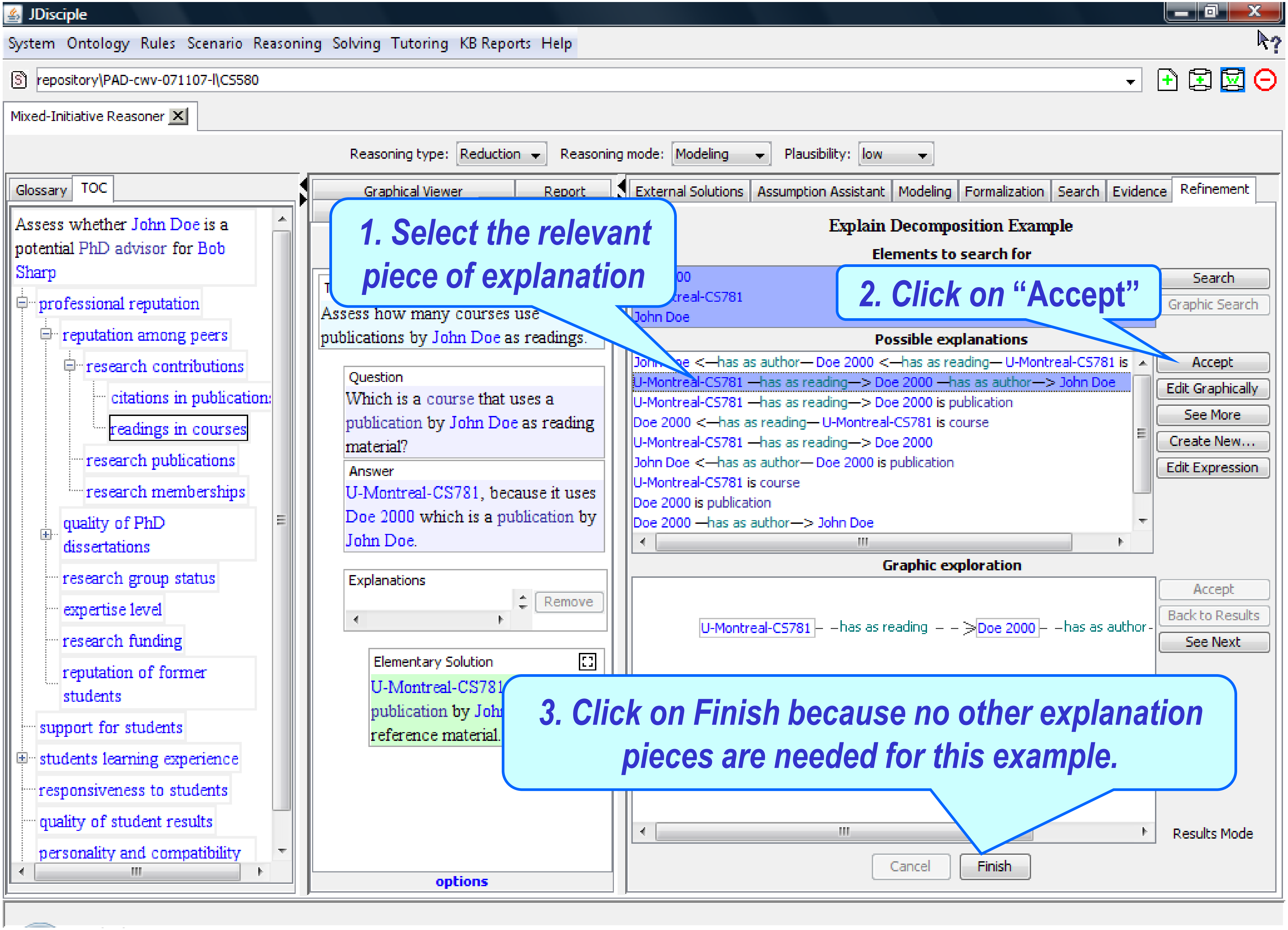
JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071107-I\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: medium
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
personality and compatibility with student
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe would be a good PhD advisor for Bob Sharp with respect to citations in publications.
What kind of criterion is citations in publications?
citation type criterion
Assess how cited John Doe is.
What publication cites John Doe?
Rice 2007, because it cites Doe 2000 which is authored by John Doe.
John Doe is cited in Rice 2007.
External Solutions
Assumption Assistant
Modeling
Refinement
Formalization
Evidence
Search
Decomposition operations.
Start Learning
2. Click on “Start Learning”
Global learning operations.
Learn All From Root

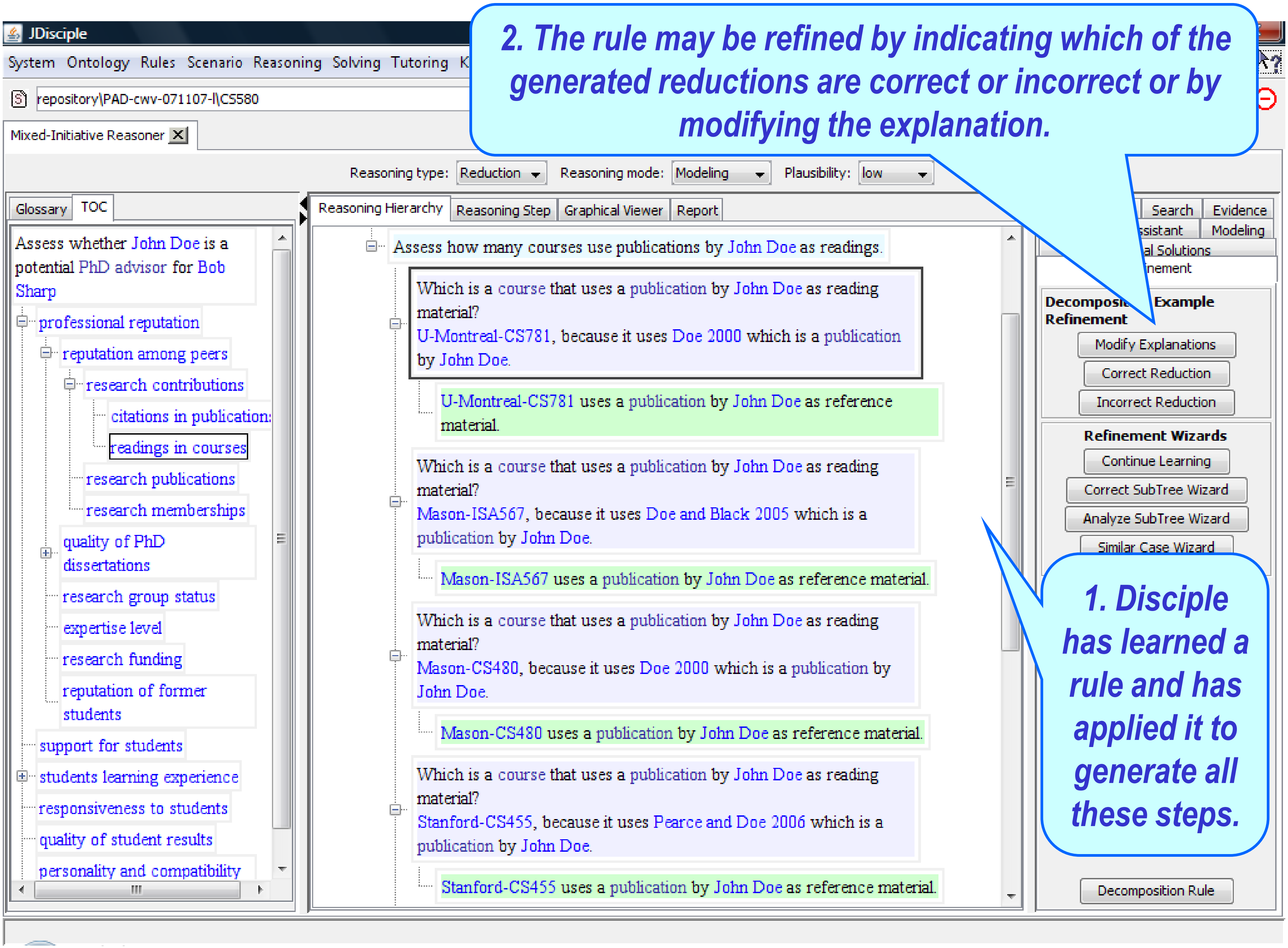

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071107-I\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: low
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
personality and compatibility with student
1. Select the relevant piece of explanation
Task
Question
What publication cites John Doe?
Answer
Rice 2007, because it cites Doe 2000 which is authored by John Doe.
Explanations
Remove
Elementary Solution
John Doe is cited in Rice 2007.
Q/A
Ontology Specs
Explanations
External Solutions
Assumption Assistant
Modeling
Formalization
Search
Evidence
Refinement
Explain Decomposition Example
Elements to search for
Doe 2000
John Doe
Rice 2007
2. Click on “Accept”
Possible explanations
Rice 2007 —cites—> Doe 2000 —has as author—> John Doe
Rice 2007 —cites—> Doe 2000
Doe 2000 —has as author—> John Doe
Rice 2007 is publication
Rice 2007 —has as author—> Amanda Rice
Doe 2000 is publication
Rice 2007 is journal article
Rice 2007 is article
Pearce and Doe 2006 —has as author—> John Doe
Pearce and Doe 2005 —has as author—> John Doe
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
Rice 2007
cites
Doe 2000
Accept
Back to Results
See Next
3. Click on Finish because no other explanation pieces are needed for this example.
Results Mode
Cancel
Finish


2. The rule may be refined by indicating which of the generated reductions are correct or incorrect or by modifying the explanation.
1. Disciple has learned a rule and has applied it to generate all these steps.
JDisciple
System Ontology Rules Scenario Reasoning Solving
repository\PAD-cwv-071107-I\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: low
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
citation type criterion
Assess how cited John Doe is.
What publication cites John Doe? Rice 2007, because it cites Doe 2000 which is authored by John Doe.
John Doe is cited in Rice 2007.
What publication cites John Doe? Pearce 2007, because it cites Pearce and Doe 2006 which is authored by John Doe.
John Doe is cited in Pearce 2007.
What publication cites John Doe? Pearce 2007, because it cites Pearce and Doe 2005 which is authored by John Doe.
John Doe is cited in Pearce 2007.
What publication cites John Doe? Hall 2004, because it cites Doe and Hall 2002 which is authored by John Doe.
John Doe is cited in Hall 2004.
What publication cites John Doe? Pearce 2007, because it cites Doe and Hall 2002 which is authored by John Doe.
External Solutions
Modeling
Formalization
Evidence
Refinement
Decomposition Example Refinement
Modify Explanations
Correct Reduction
Incorrect Reduction
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Analyze SubTree Wizard
Similar Case Wizard
Decomposition Rule

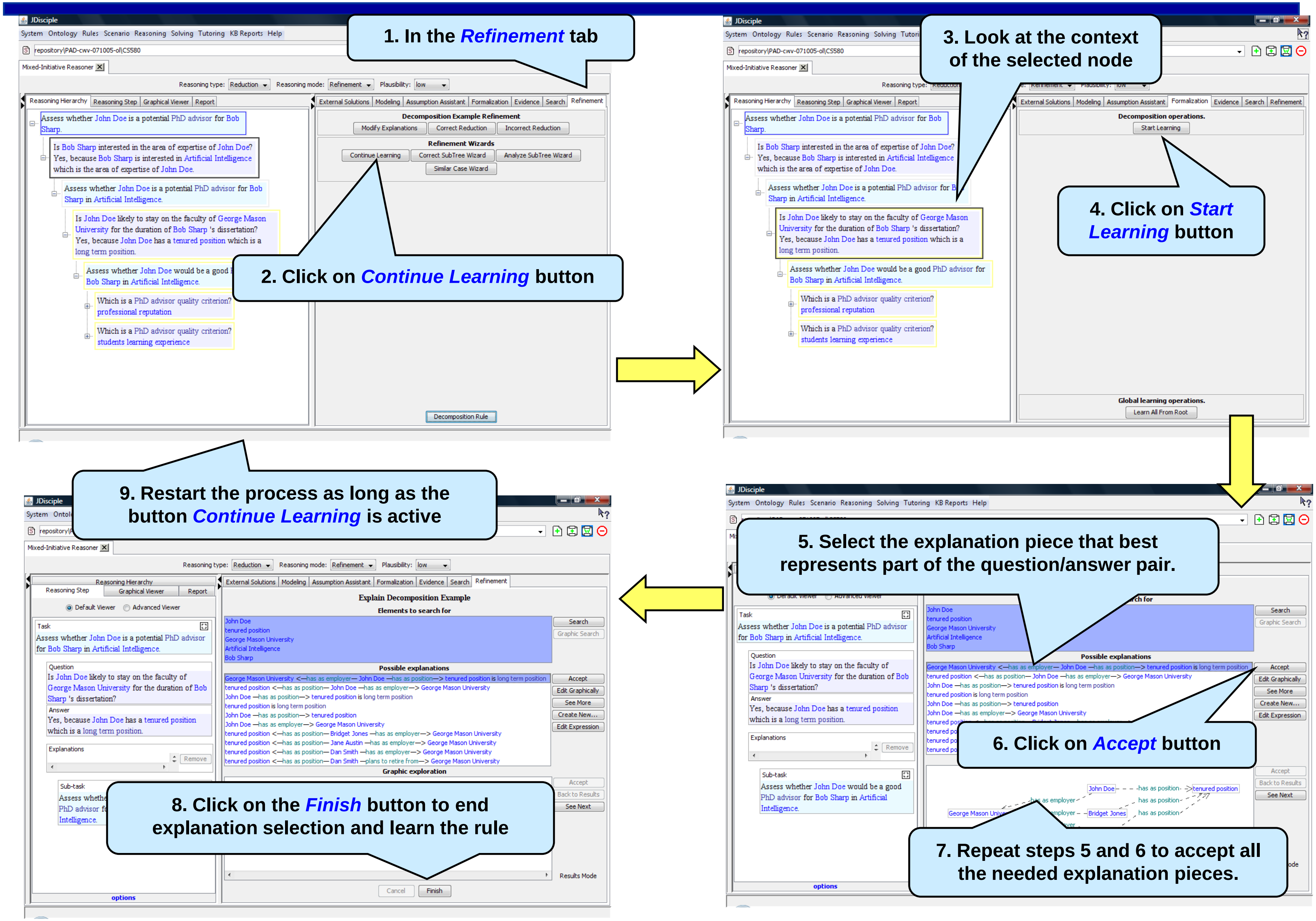


JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071107-l\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: low
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess whether John Doe would be a good PhD advisor for Bob Sharp with respect to readings in courses.
What kind of criterion is readings in courses?
reading type criterion
Assess how many courses use publications by John Doe as readings.
Which is a course that uses a publication by John Doe as reading material?
U-Montreal-CS781, because it uses Doe 2000 which is a publication by John Doe.
U-Montreal-CS781 uses a publication by John Doe as reference material.
External Solutions
Assumption Assistant
Modeling
Formalization
Search
Evidence
Refinement
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Similar Case Wizard
2. Click on “Continue Learning” and then click on “Start Learning” on the follow-on screen.
1. Browse the tree and select the next modeling (question/answer) node to learn a rule from the corresponding reasoning step.

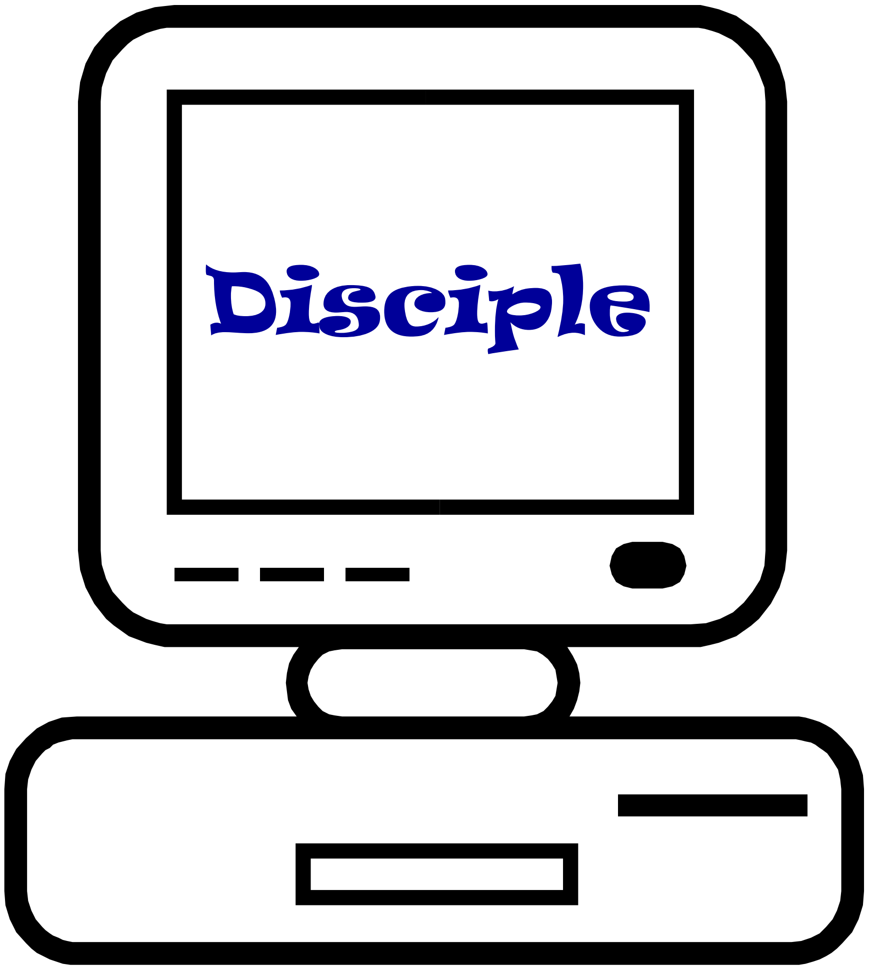

JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring KB Reports Help
repository\PAD-cwv-071107-I\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: low
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publications
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
personality and compatibility
Graphical Viewer
Report
Assess how many courses use publications by John Doe as readings.
Question
Which is a course that uses a publication by John Doe as reading material?
Answer
U-Montreal-CS781, because it uses Doe 2000 which is a publication by John Doe.
Explanations
Remove
Elementary Solution
options
External Solutions
Assumption Assistant
Modeling
Formalization
Search
Evidence
Refinement
Explain Decomposition Example
Elements to search for
John Doe
Search
Graphic Search
Possible explanations
Accept
Edit Graphically
See More
Create New...
Edit Expression
U-Montreal-CS781 —has as reading—> Doe 2000 —has as author—> John Doe
U-Montreal-CS781 —has as reading—> Doe 2000 is publication
Doe 2000 <—has as reading— U-Montreal-CS781 is course
U-Montreal-CS781 —has as reading—> Doe 2000
John Doe <—has as author— Doe 2000 is publication
U-Montreal-CS781 is course
Doe 2000 is publication
Doe 2000 —has as author—> John Doe
Graphic exploration
U-Montreal-CS781 —has as reading—> Doe 2000 —has as author
Back to Results
See Next
Results Mode
Cancel
Finish
1. Select the relevant piece of explanation
2. Click on "Accept"
3. Click on Finish because no other explanation pieces are needed for this example.


2. The rule may be refined by indicating which of the generated reductions are correct or incorrect or by modifying the explanation.
1. Disciple has learned a rule and has applied it to generate all these steps.
JDisciple
System Ontology Rules Scenario Reasoning Solving Tutoring
repository\PAD-cwv-071107-I\CS580
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Modeling
Plausibility: low
Glossary
TOC
Assess whether John Doe is a potential PhD advisor for Bob Sharp
professional reputation
reputation among peers
research contributions
citations in publication:
readings in courses
research publications
research memberships
quality of PhD dissertations
research group status
expertise level
research funding
reputation of former students
support for students
students learning experience
responsiveness to students
quality of student results
personality and compatibility
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Assess how many courses use publications by John Doe as readings.
Which is a course that uses a publication by John Doe as reading material?
U-Montreal-CS781, because it uses Doe 2000 which is a publication by John Doe.
U-Montreal-CS781 uses a publication by John Doe as reference material.
Which is a course that uses a publication by John Doe as reading material?
Mason-ISA567, because it uses Doe and Black 2005 which is a publication by John Doe.
Mason-ISA567 uses a publication by John Doe as reference material.
Which is a course that uses a publication by John Doe as reading material?
Mason-CS480, because it uses Doe 2000 which is a publication by John Doe.
Mason-CS480 uses a publication by John Doe as reference material.
Which is a course that uses a publication by John Doe as reading material?
Stanford-CS455, because it uses Pearce and Doe 2006 which is a publication by John Doe.
Stanford-CS455 uses a publication by John Doe as reference material.
Search
Evidence
Modeling
Decomposi Example Refinement
Modify Explanations
Correct Reduction
Incorrect Reduction
Refinement Wizards
Continue Learning
Correct SubTree Wizard
Analyze SubTree Wizard
Similar Case Wizard
Decomposition Rule

Rule Learning Summary



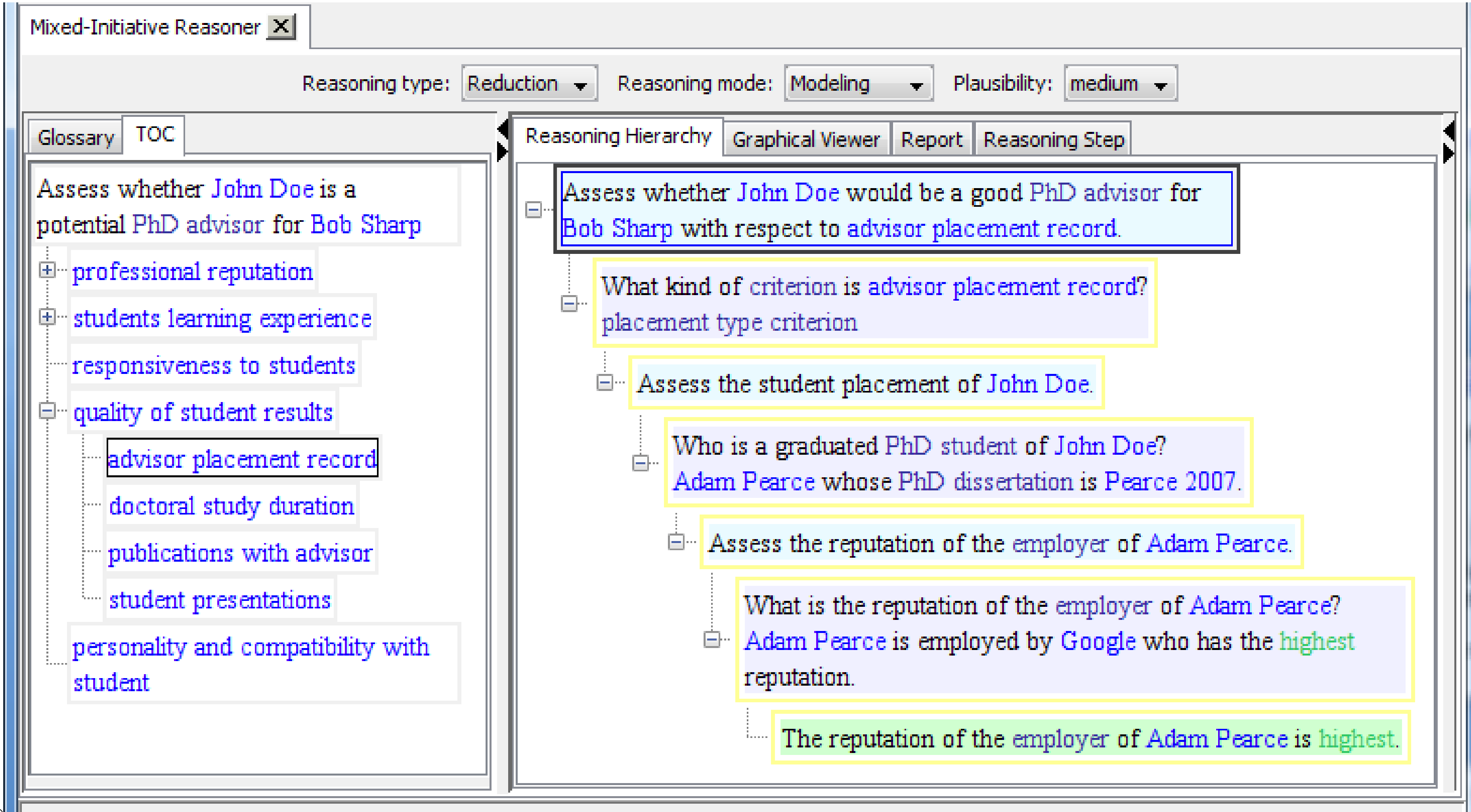
Hands-on: Rule Learning



Hands On: Rule Learning

Install the system from:
http://129.174.113.212/wba/jdisciplesetup-v2008.11a-WBA.exe

Load the “PAD-m2o\CS681” scenario KB.



Overview

Introduction

Multistartegy Rule Learning

Strategies for Explanation Generation

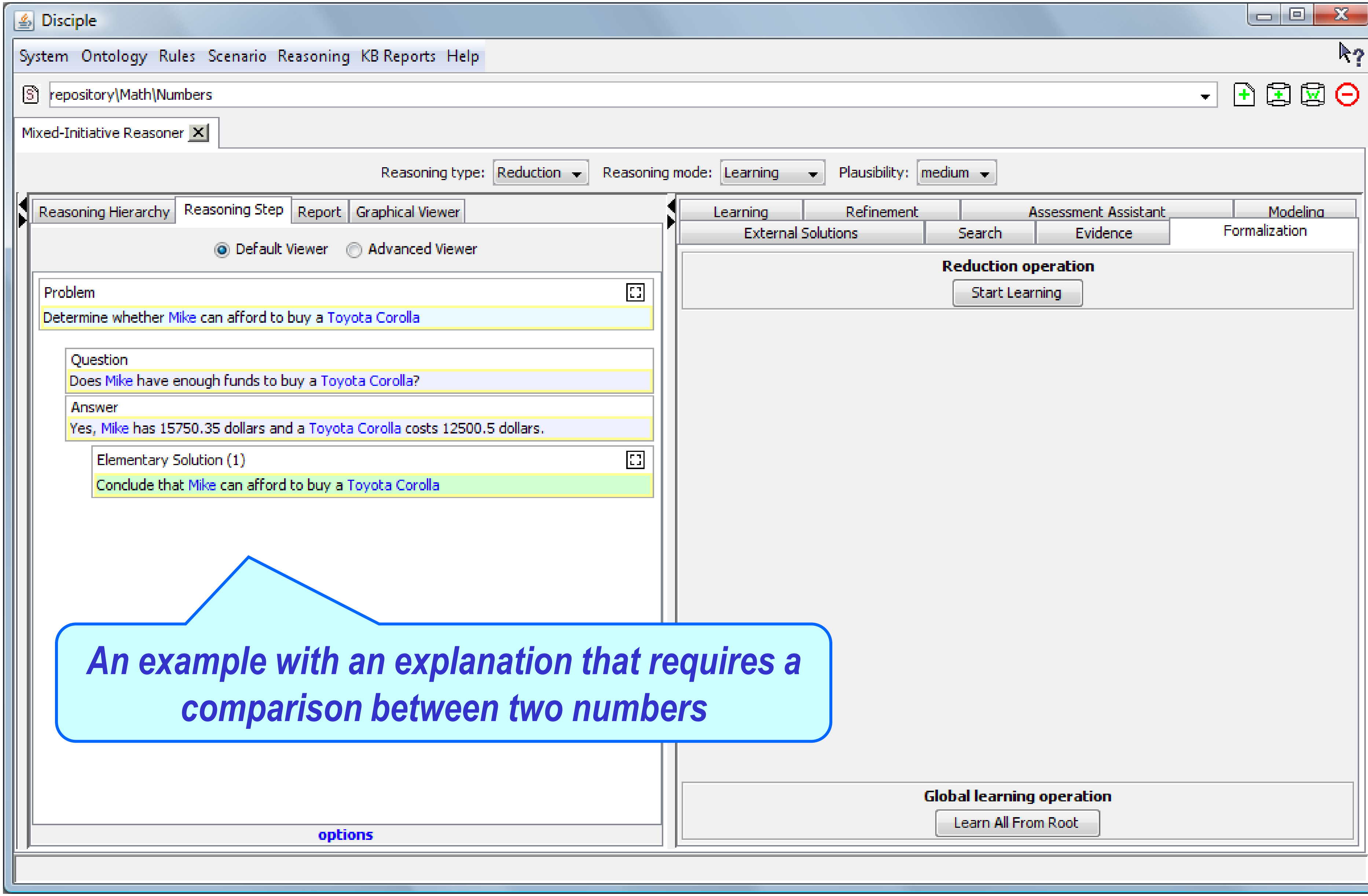
Demo and Hands-on

Explanations with Comparisons

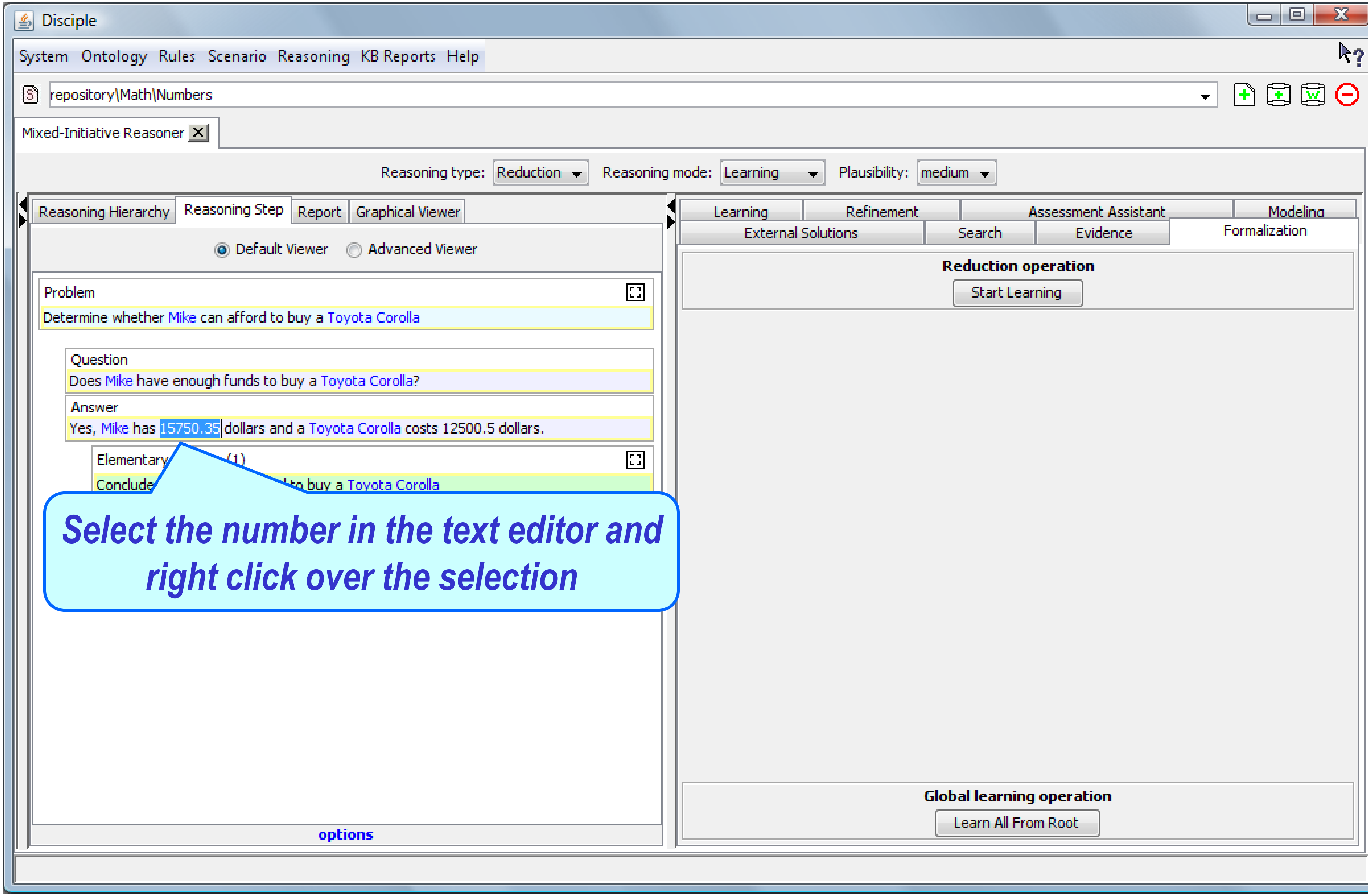
Explanations with Functions

Reading

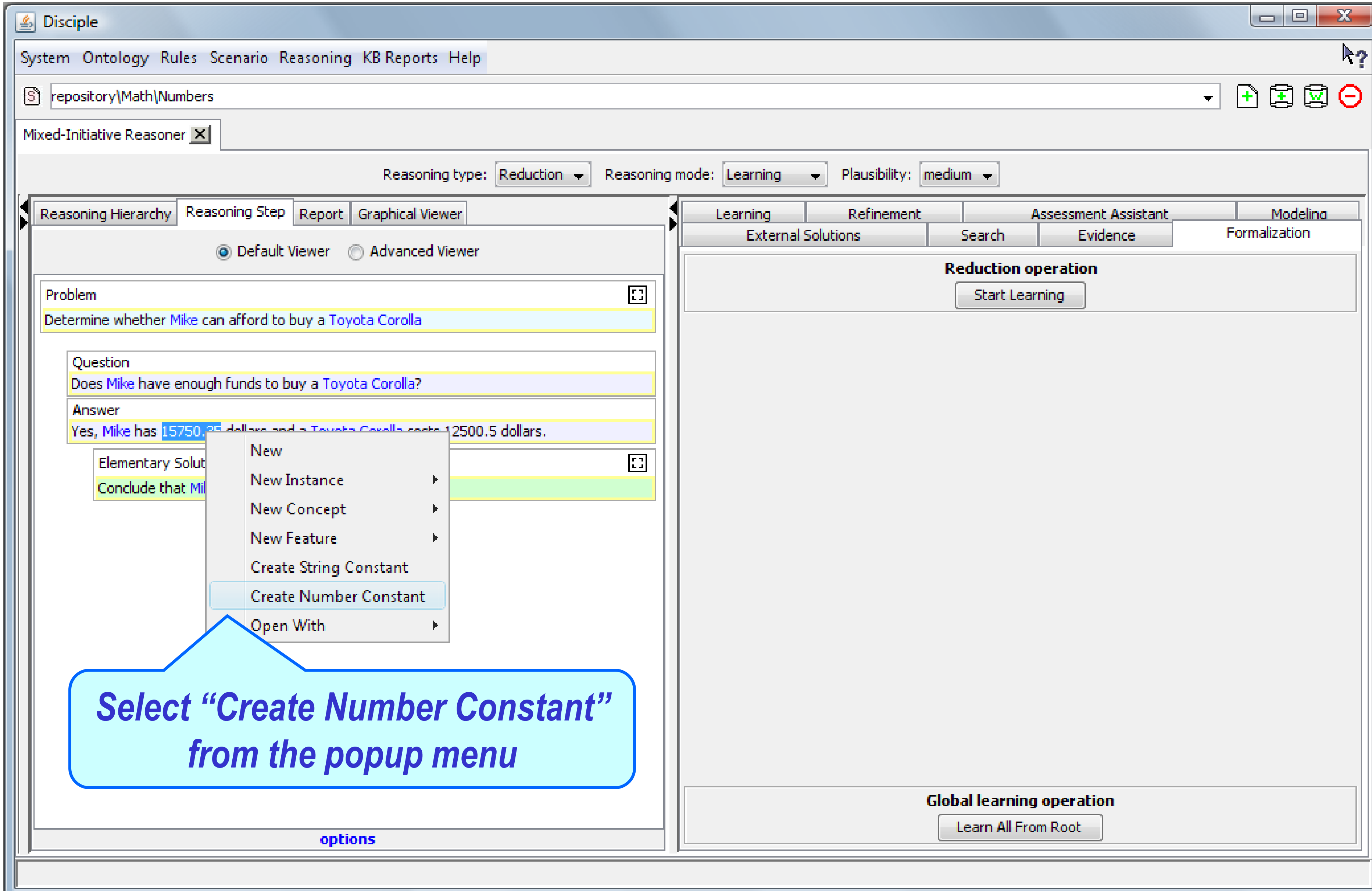
Explanations with Comparisons

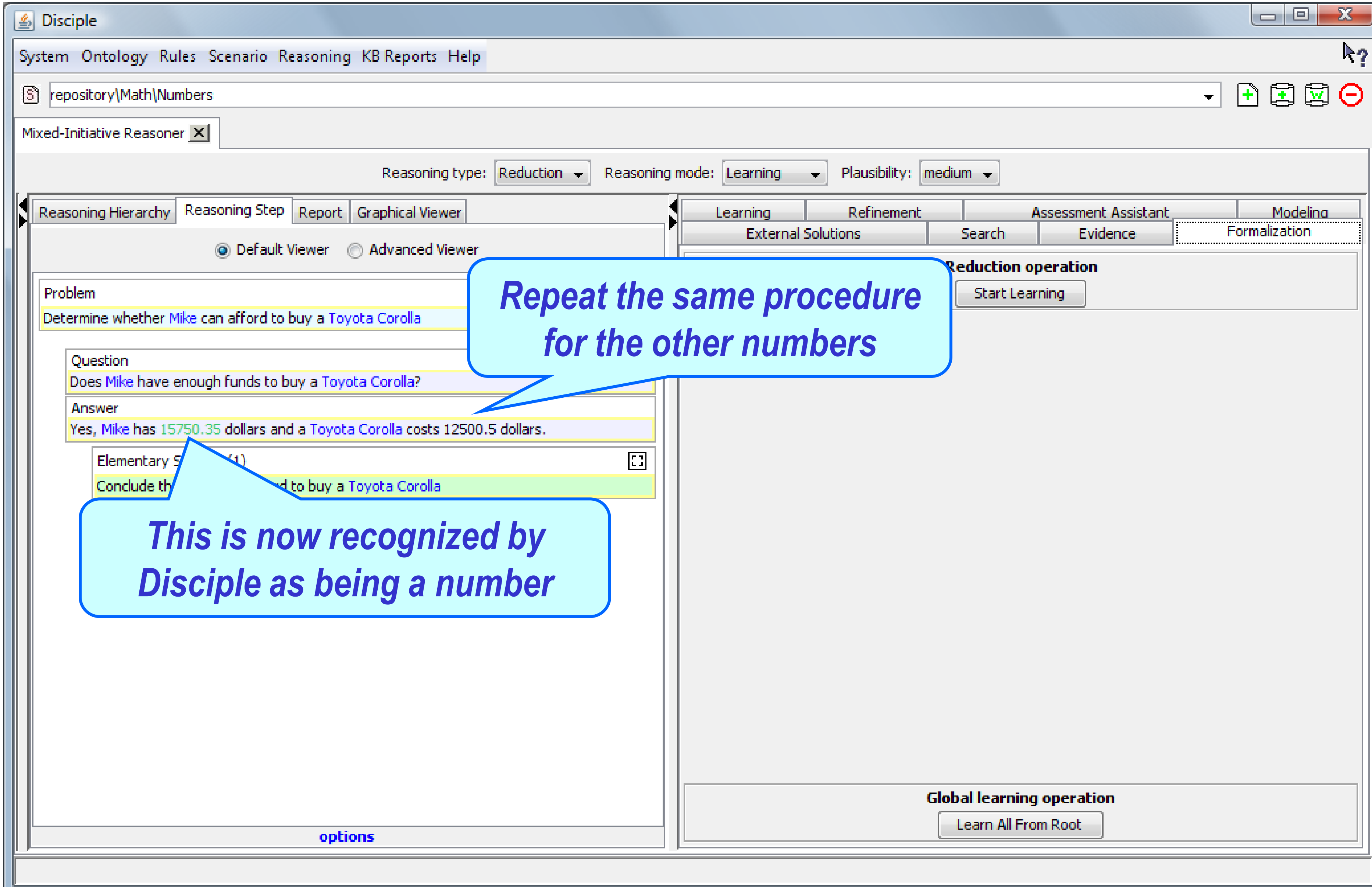


An example with an explanation that requires a comparison between two numbers

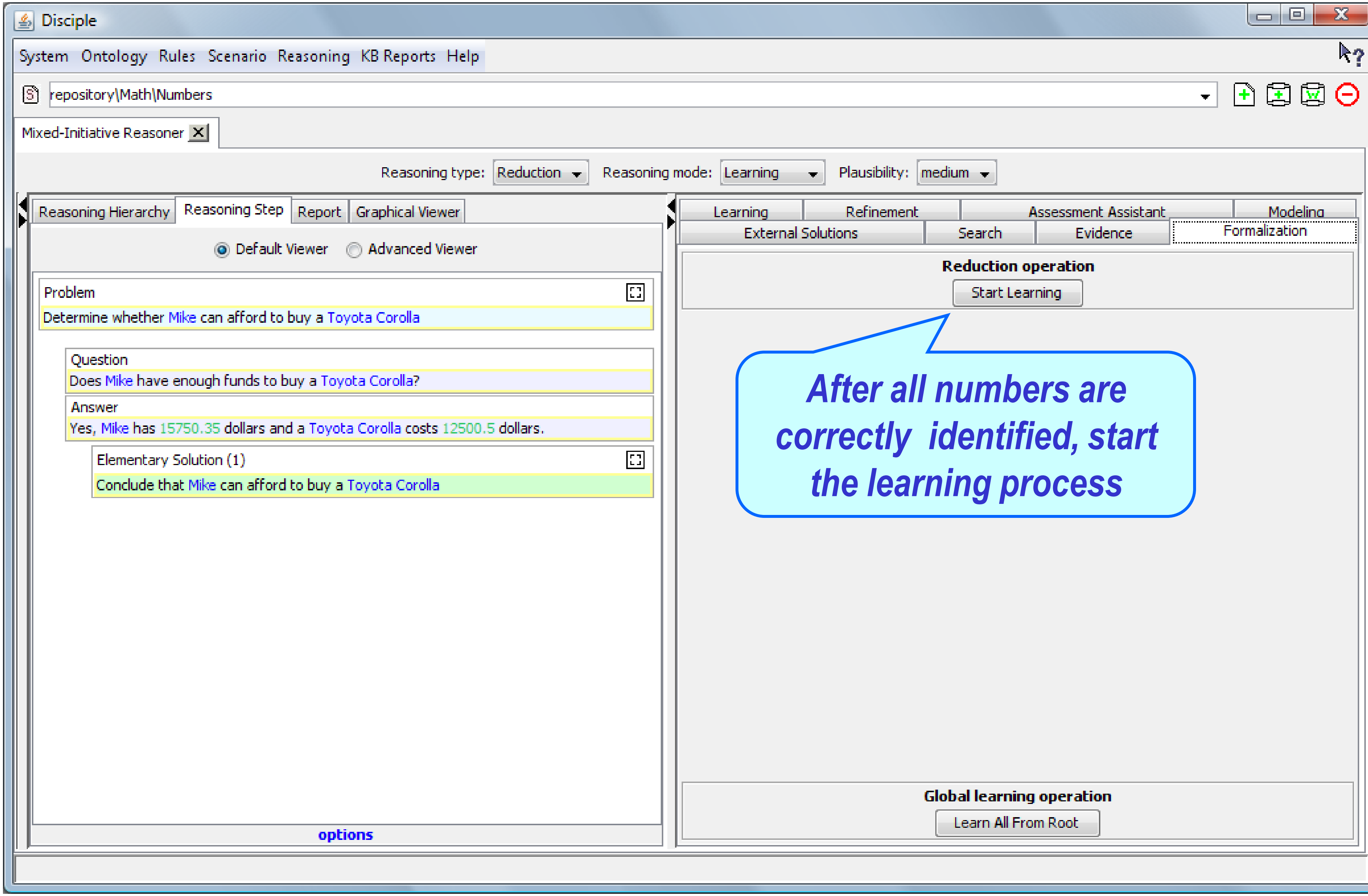


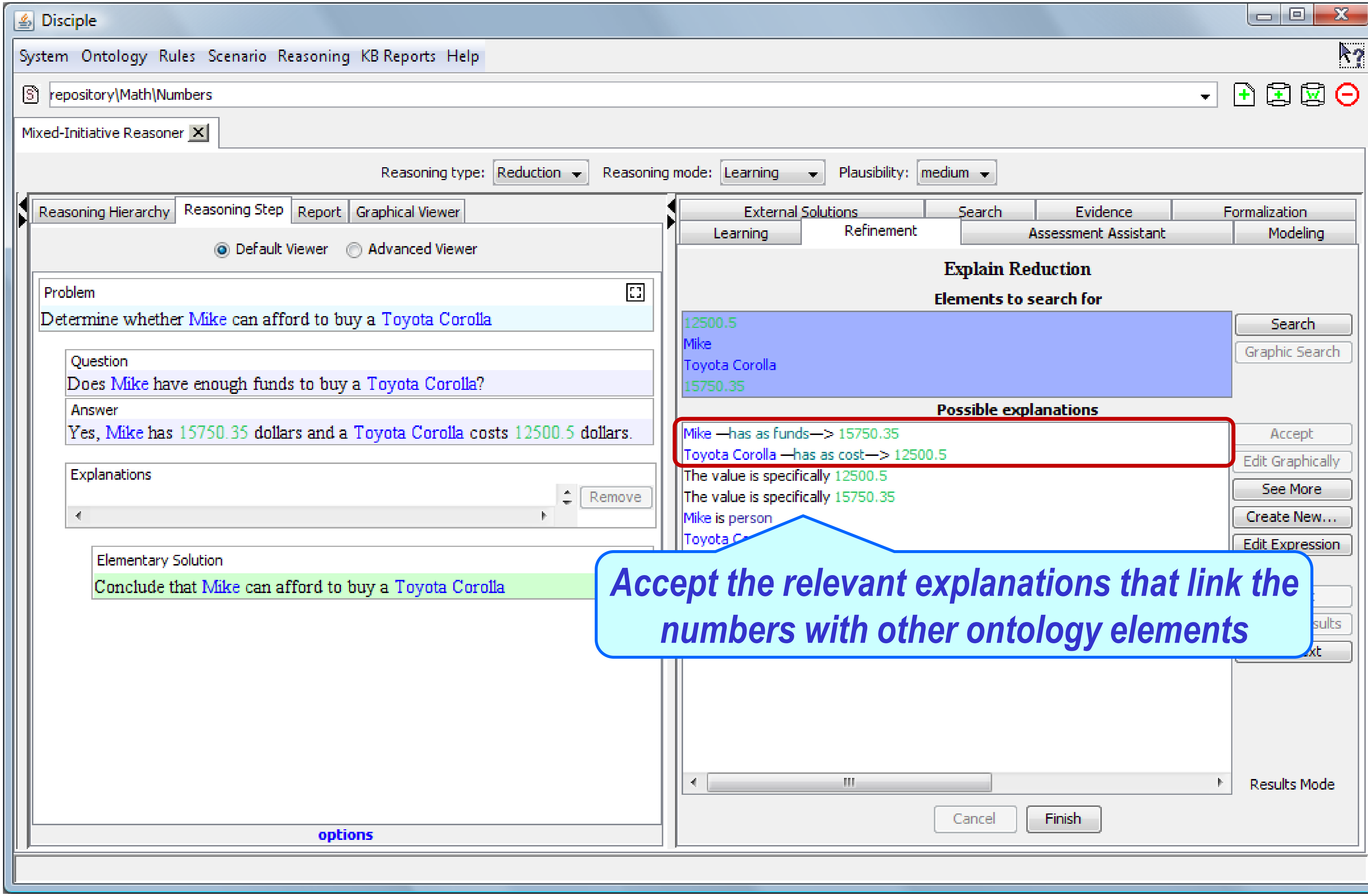
Select the number in the text editor and right click over the selection


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Default Viewer
Advanced Viewer
Problem
Determine whether Mike can afford to buy a Toyota Corolla
Question
Does Mike have enough funds to buy a Toyota Corolla?
Answer
Yes, Mike has 15750.
2500.5 dollars.
Elementary Solut
Conclude that Mi
New
New Instance
New Concept
New Feature
Create String Constant
Create Number Constant
Open With
Select "Create Number Constant" from the popup menu
options
Learning
Refinement
Assessment Assistant
Modeling
External Solutions
Search
Evidence
Formalization
Reduction operation
Start Learning
Global learning operation
Learn All From Root

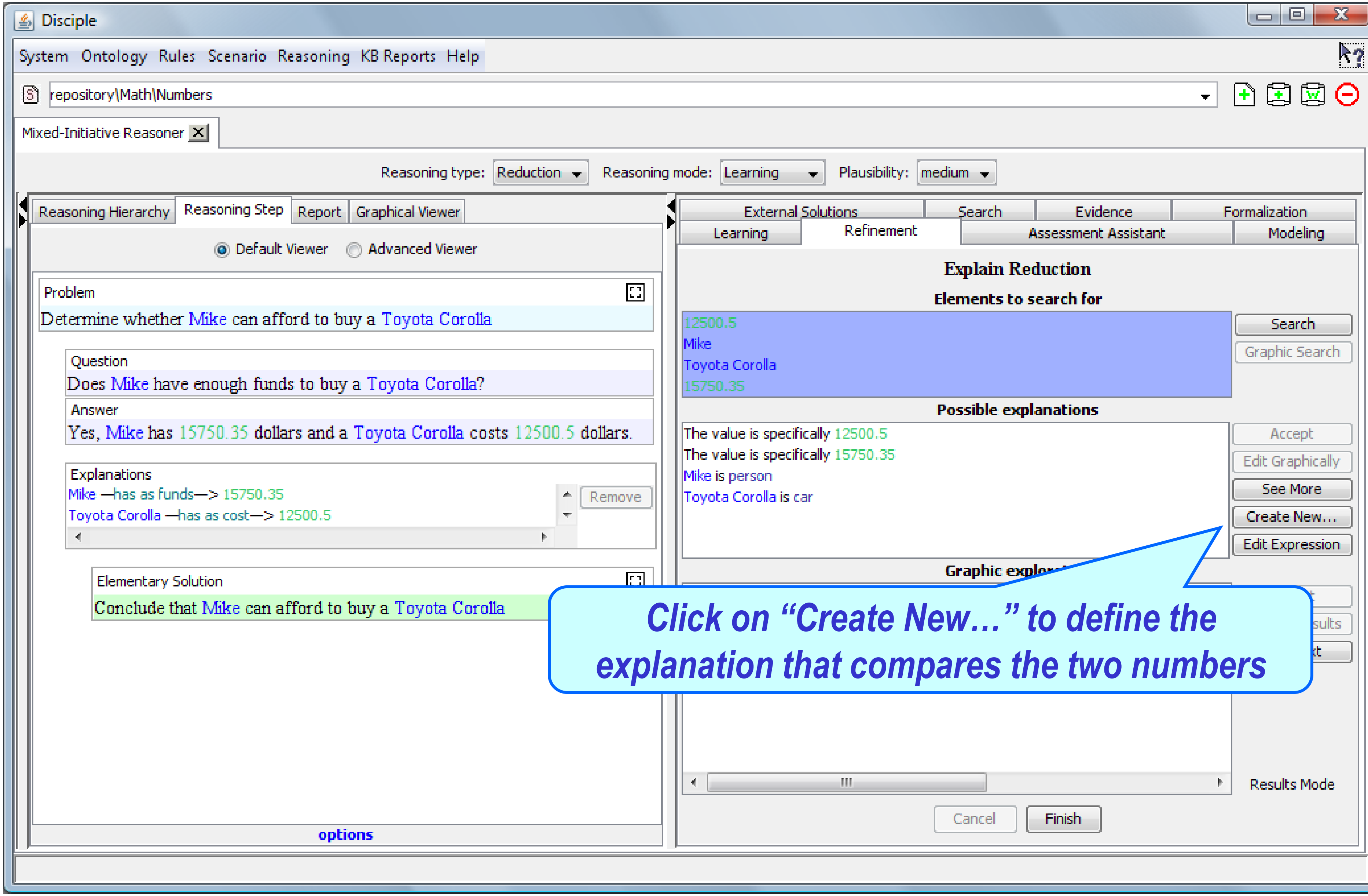


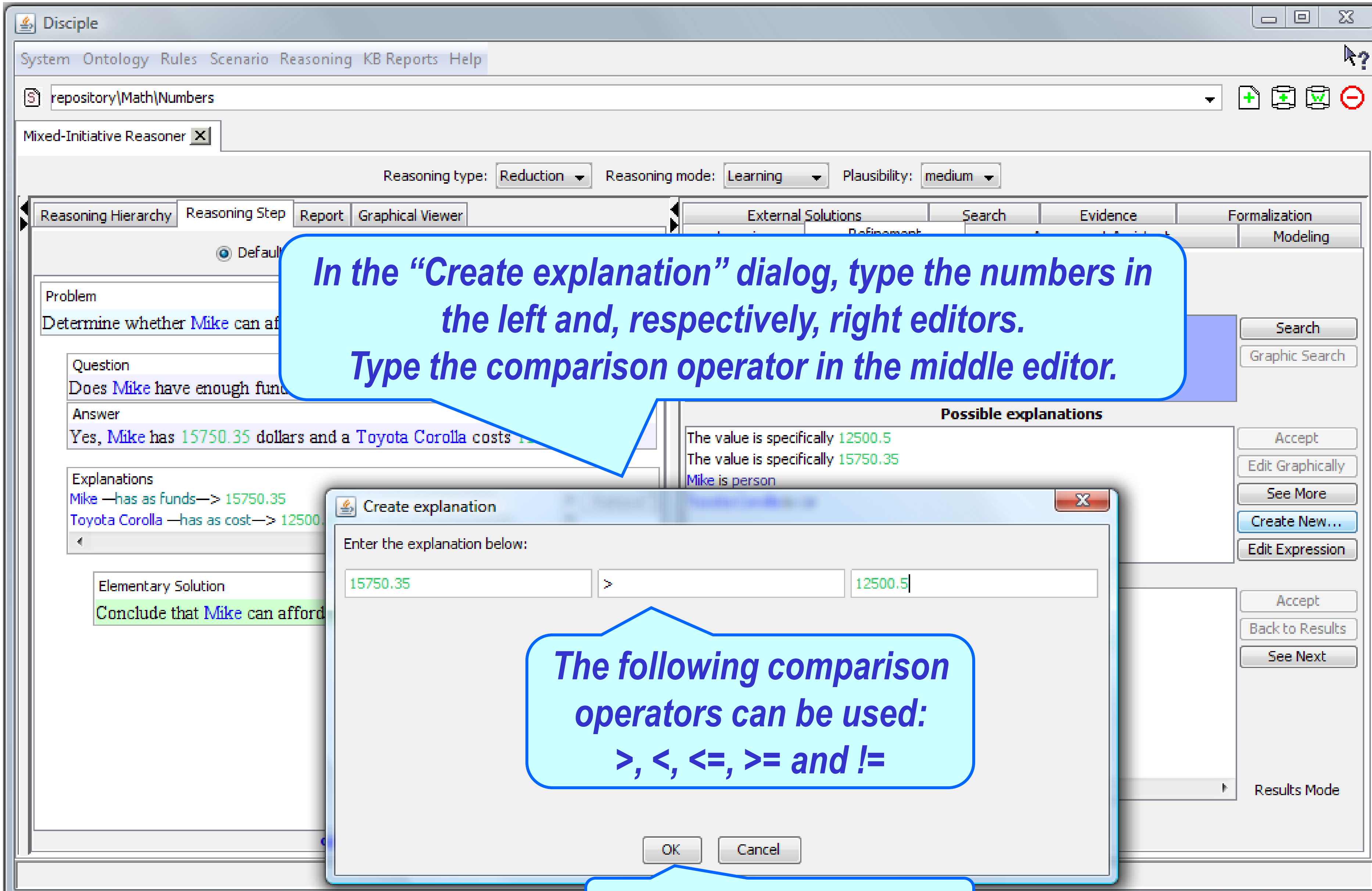
Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Default Viewer
Advanced Viewer
Problem
Determine whether Mike can afford to buy a Toyota Corolla
Question
Does Mike have enough funds to buy a Toyota Corolla?
Answer
Yes, Mike has 15750.35 dollars and a Toyota Corolla costs 12500.5 dollars.
Learning
Refinement
Assessment Assistant
Modeling
External Solutions
Search
Evidence
Formalization
Reduction operation
Start Learning
Global learning operation
Learn All From Root
options
Repeat the same procedure for the other numbers
This is now recognized by Disciple as being a number


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Default Viewer
Advanced Viewer
Problem
Determine whether Mike can afford to buy a Toyota Corolla
Question
Does Mike have enough funds to buy a Toyota Corolla?
Answer
Yes, Mike has 15750.35 dollars and a Toyota Corolla costs 12500.5 dollars.
Elementary Solution (1)
Conclude that Mike can afford to buy a Toyota Corolla
options
Learning
Refinement
Assessment Assistant
Modeling
External Solutions
Search
Evidence
Formalization
Reduction operation
Start Learning
After all numbers are correctly identified, start the learning process
Global learning operation
Learn All From Root



Accept the relevant explanations that link the numbers with other ontology elements

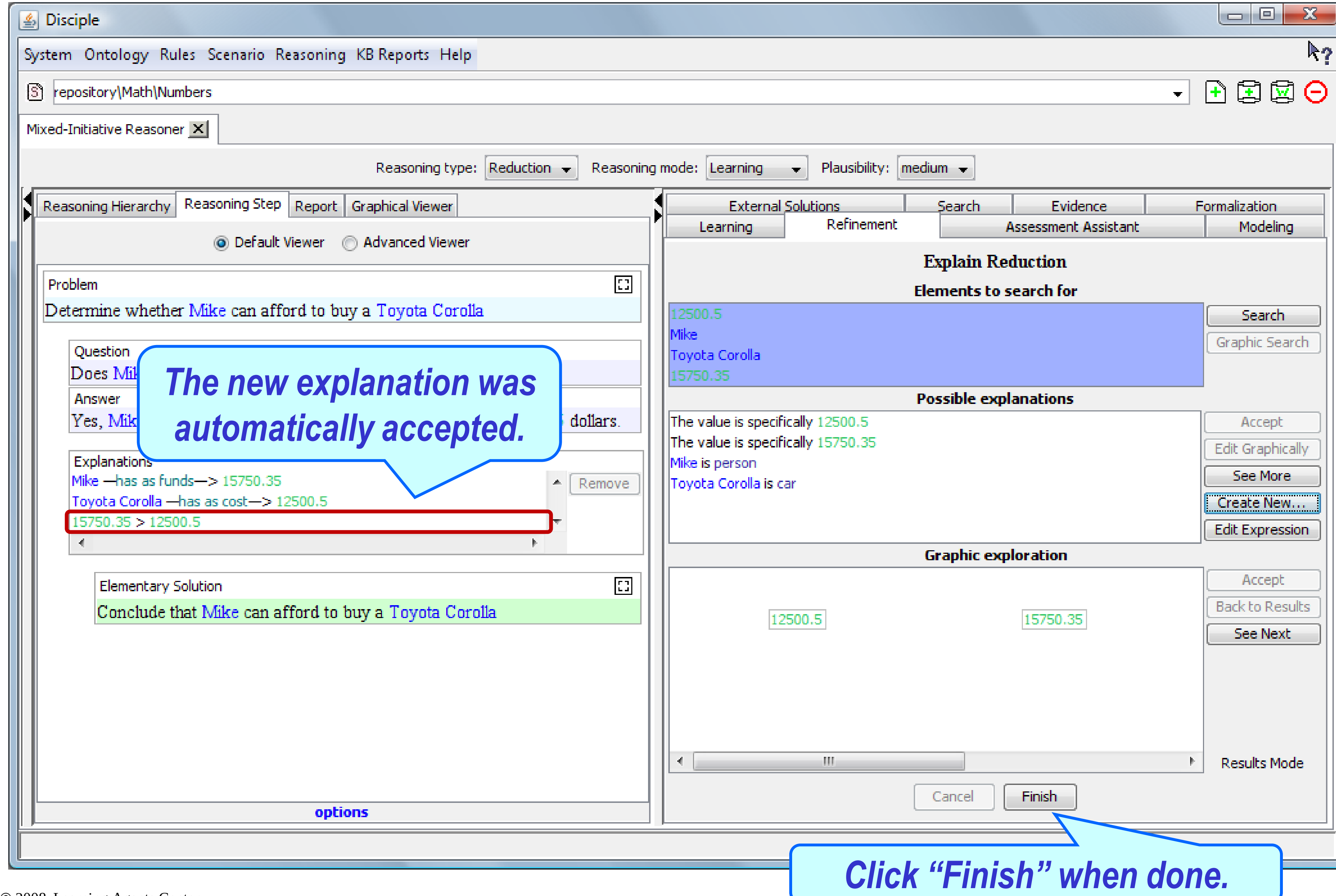

Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Default Viewer
Advanced Viewer
Problem
Determine whether Mike can afford to buy a Toyota Corolla
Question
Does Mike have enough funds to buy a Toyota Corolla?
Answer
Yes, Mike has 15750.35 dollars and a Toyota Corolla costs 12500.5 dollars.
Explanations
Mike —has as funds—> 15750.35
Toyota Corolla —has as cost—> 12500.5
Remove
Elementary Solution
Conclude that Mike can afford to buy a Toyota Corolla
options
External Solutions
Search
Evidence
Formalization
Learning
Refinement
Assessment Assistant
Modeling
Explain Reduction
Elements to search for
12500.5
Mike
Toyota Corolla
15750.35
Search
Graphic Search
Possible explanations
The value is specifically 12500.5
The value is specifically 15750.35
Mike is person
Toyota Corolla is car
Accept
Edit Graphically
See More
Create New...
Edit Expression
Results Mode
Cancel
Finish
Click on "Create New…" to define the explanation that compares the two numbers



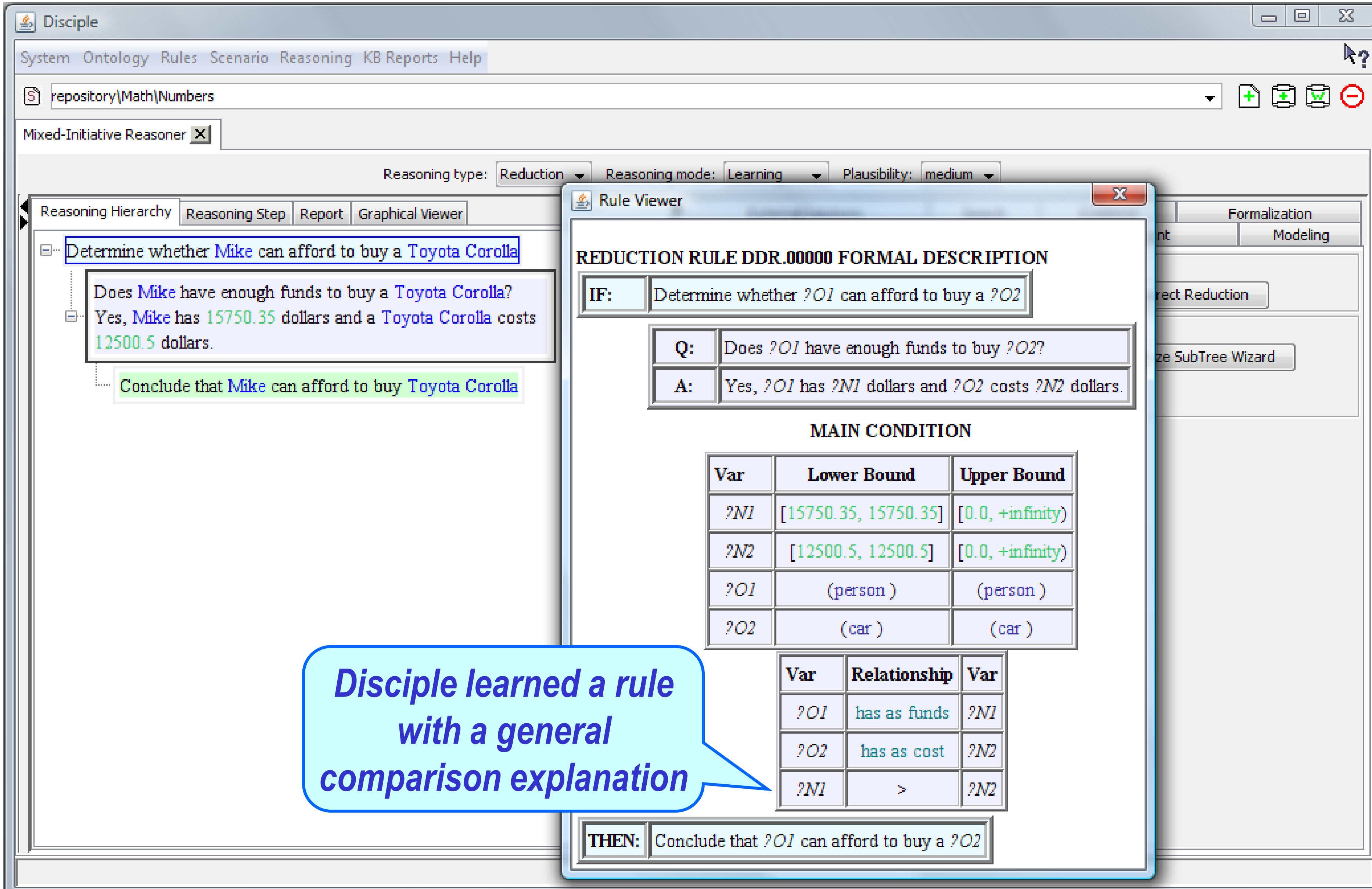
In the "Create explanation" dialog, type the numbers in the left and, respectively, right editors.
Type the comparison operator in the middle editor.

The following comparison operators can be used: >, <, <=, >= and !=

Click "OK" when done.



Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Default Viewer
Advanced Viewer
Problem
Determine whether Mike can afford to buy a Toyota Corolla
Question
Does Mik
Answer
Yes, Mik
dollars.
Explanations
Mike —has as funds—> 15750.35
Toyota Corolla —has as cost—> 12500.5
15750.35 > 12500.5
Remove
Elementary Solution
Conclude that Mike can afford to buy a Toyota Corolla
options
External Solutions
Search
Evidence
Formalization
Learning
Refinement
Assessment Assistant
Modeling
Explain Reduction
Elements to search for
12500.5
Mike
Toyota Corolla
15750.35
Search
Graphic Search
Possible explanations
The value is specifically 12500.5
The value is specifically 15750.35
Mike is person
Toyota Corolla is car
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
12500.5
15750.35
Accept
Back to Results
See Next
Results Mode
Cancel
Finish
The new explanation was automatically accepted.
Click "Finish" when done.


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Report
Graphical Viewer
Determine whether Mike can afford to buy a Toyota Corolla
Does Mike have enough funds to buy a Toyota Corolla?
Yes, Mike has 15750.35 dollars and a Toyota Corolla costs 12500.5 dollars.
Conclude that Mike can afford to buy Toyota Corolla
Formalization
Modeling
Rule Viewer
REDUCTION RULE DDR.00000 FORMAL DESCRIPTION
IF: Determine whether ?O1 can afford to buy a ?O2
Q: Does ?O1 have enough funds to buy ?O2?
A: Yes, ?O1 has ?N1 dollars and ?O2 costs ?N2 dollars.
MAIN CONDITION
Var | Lower Bound | Upper Bound
?N1 | [15750.35, 15750.35] | [0.0, +infinity)
?N2 | [12500.5, 12500.5] | [0.0, +infinity)
?O1 | (person) | (person)
?O2 | (car) | (car)
Var | Relationship | Var
?O1 | has as funds | ?N1
?O2 | has as cost | ?N2
?N1 | > | ?N2
THEN: Conclude that ?O1 can afford to buy a ?O2
Disciple learned a rule with a general comparison explanation

Overview

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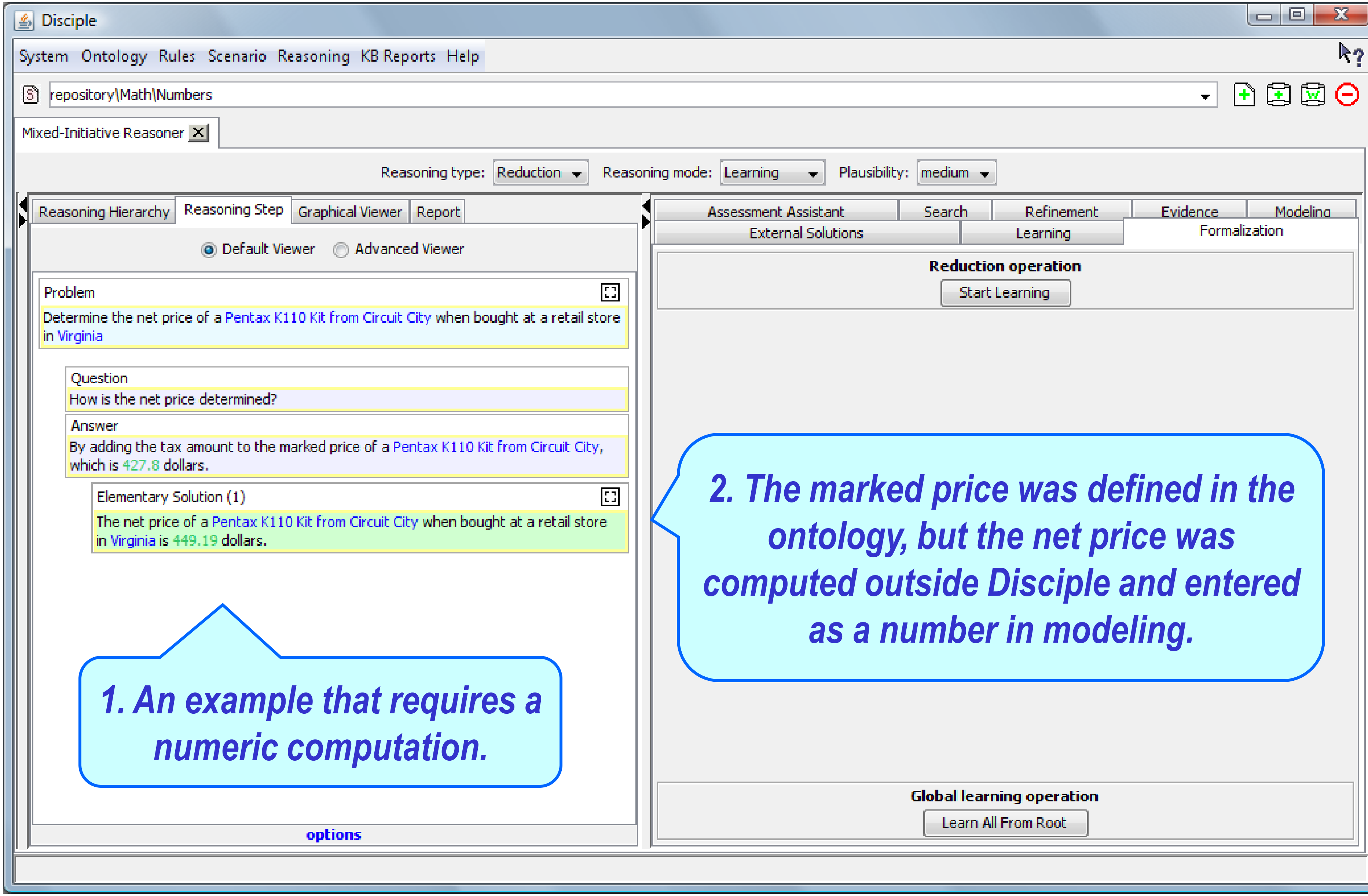
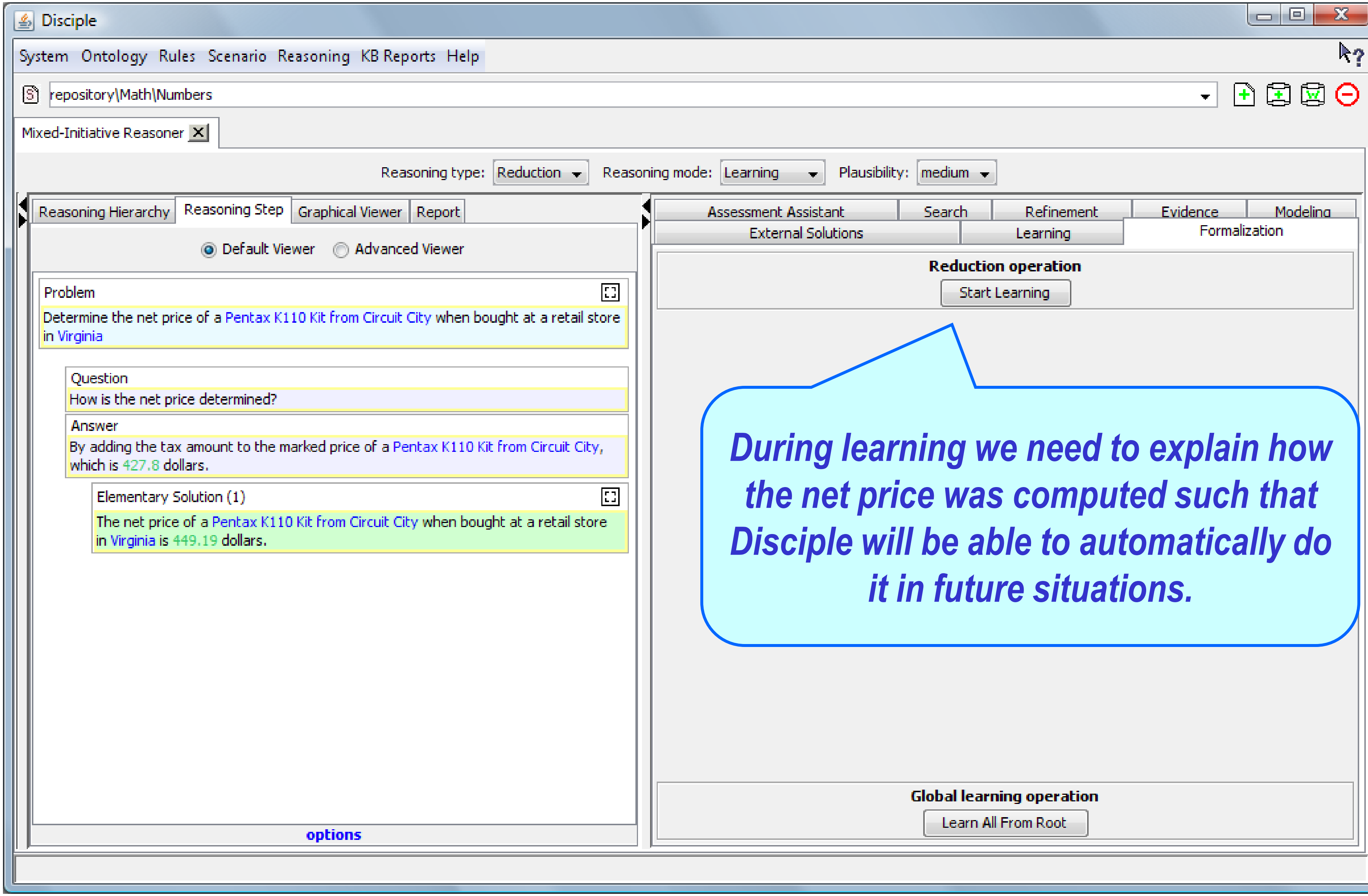
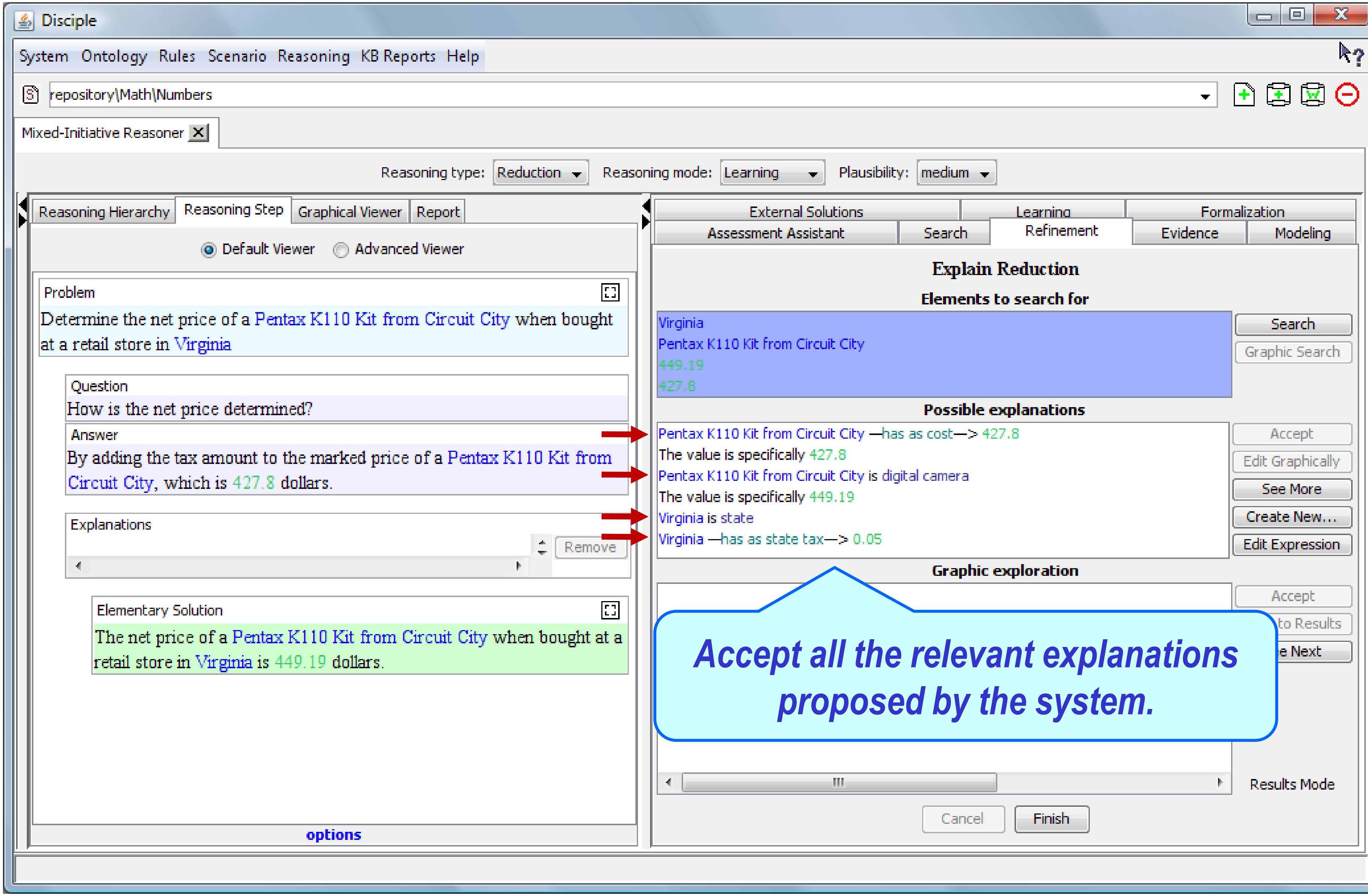
Explanations with Functions

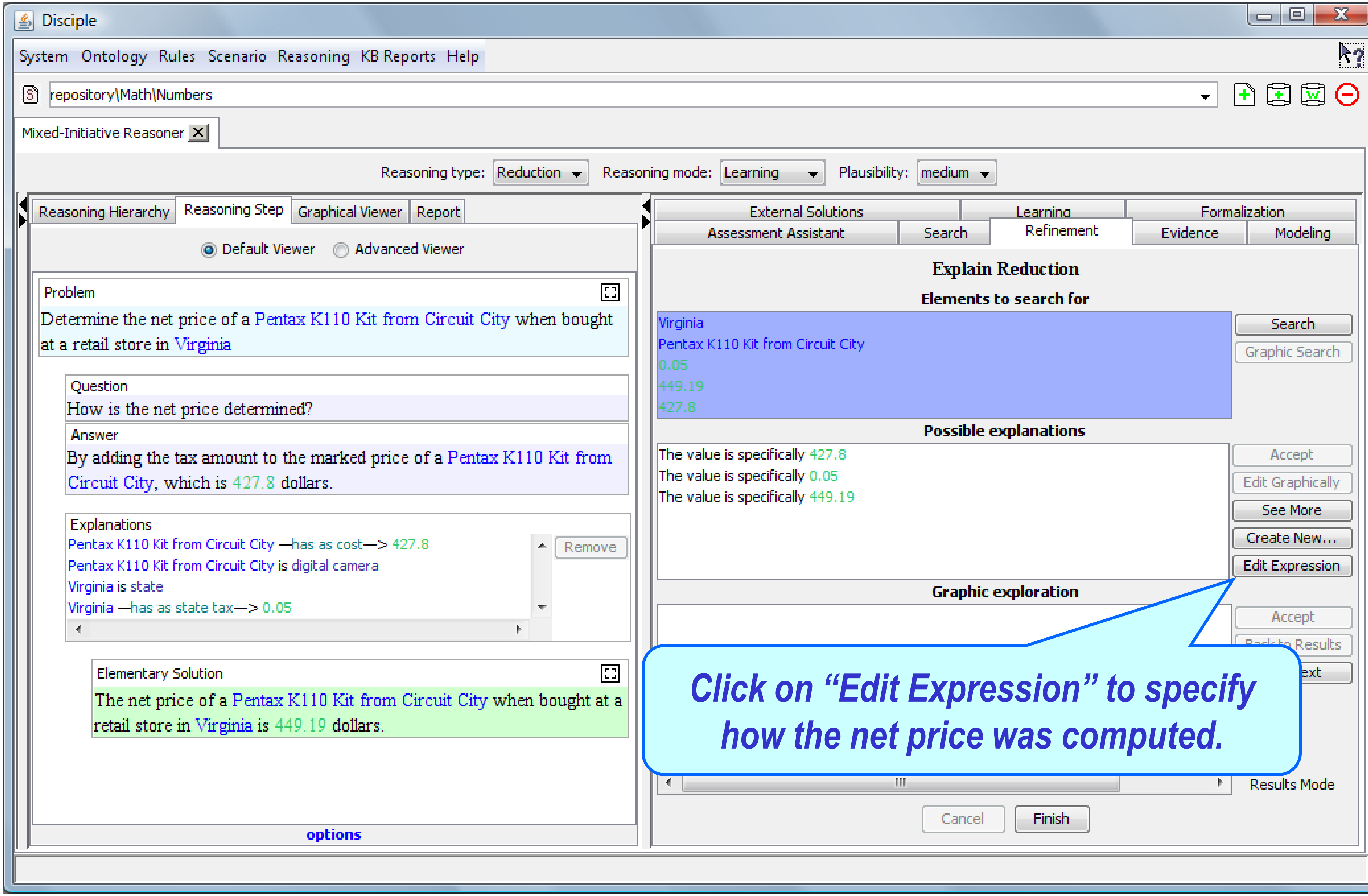
Reading

Explanations with functions

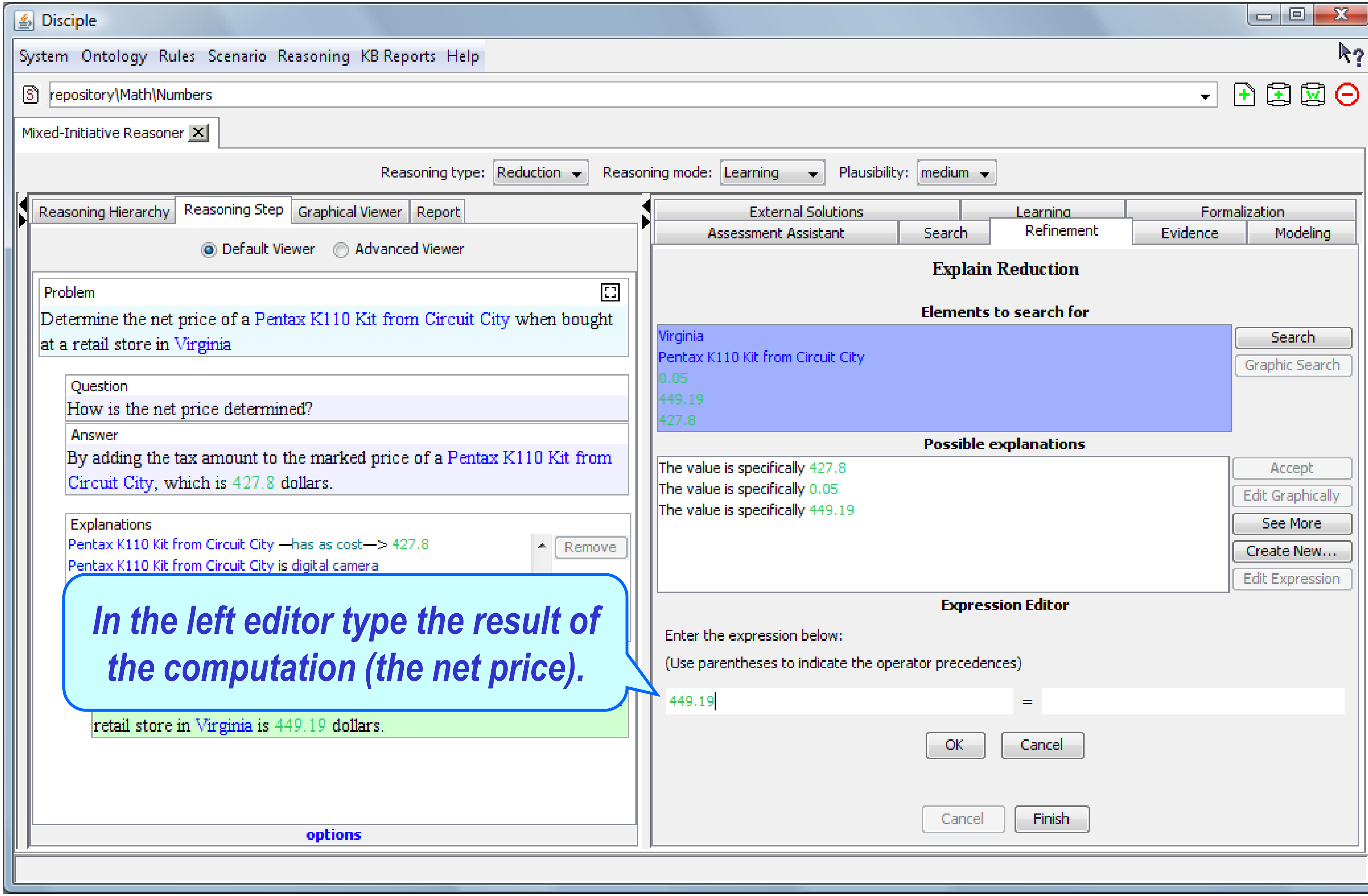


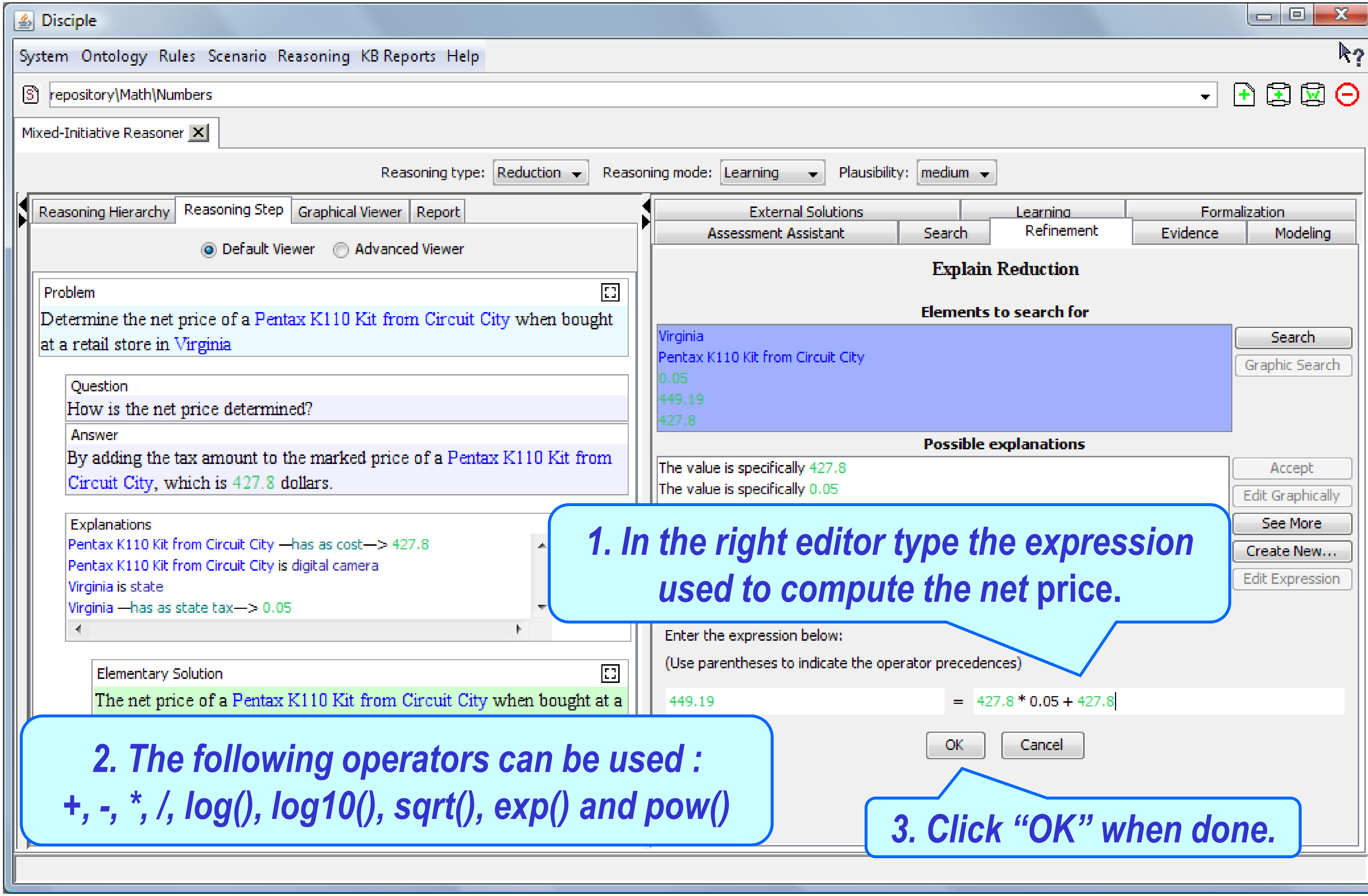

Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Problem
Determine the net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia
Question
How is the net price determined?
Answer
By adding the tax amount to the marked price of a Pentax K110 Kit from Circuit City, which is 427.8 dollars.
Elementary Solution (1)
The net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia is 449.19 dollars.
options
Assessment Assistant
Search
Refinement
Evidence
Modeling
External Solutions
Learning
Formalization
Reduction operation
Start Learning
During learning we need to explain how the net price was computed such that Disciple will be able to automatically do it in future situations.
Global learning operation
Learn All From Root


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Problem
Determine the net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia
Question
How is the net price determined?
Answer
By adding the tax amount to the marked price of a Pentax K110 Kit from Circuit City, which is 427.8 dollars.
Explanations
Remove
Elementary Solution
The net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia is 449.19 dollars.
options
External Solutions
Learning
Formalization
Assessment Assistant
Search
Refinement
Evidence
Modeling
Explain Reduction
Elements to search for
Virginia
Pentax K110 Kit from Circuit City
449.19
427.8
Search
Graphic Search
Possible explanations
Pentax K110 Kit from Circuit City —has as cost—> 427.8
The value is specifically 427.8
Pentax K110 Kit from Circuit City is digital camera
The value is specifically 449.19
Virginia is state
Virginia —has as state tax—> 0.05
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
Accept
to Results
e Next
Accept all the relevant explanations proposed by the system.
Results Mode
Cancel
Finish



Click on "Edit Expression" to specify how the net price was computed.

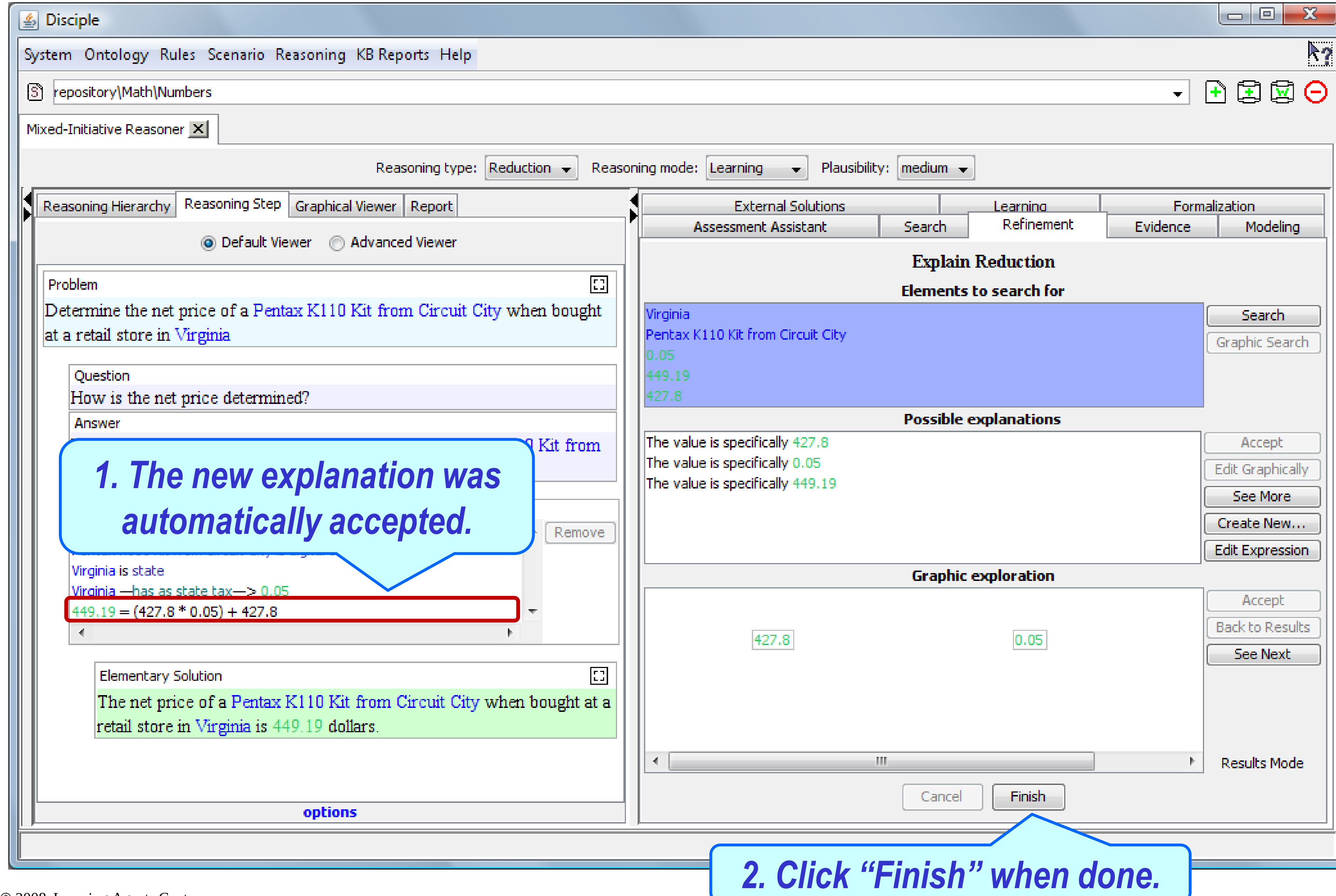

Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Problem
Determine the net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia
Question
How is the net price determined?
Answer
By adding the tax amount to the marked price of a Pentax K110 Kit from Circuit City, which is 427.8 dollars.
Explanations
Pentax K110 Kit from Circuit City —has as cost—> 427.8
Pentax K110 Kit from Circuit City is digital camera
Remove
retail store in Virginia is 449.19 dollars.
options
External Solutions
Learning
Formalization
Assessment Assistant
Search
Refinement
Evidence
Modeling
Explain Reduction
Elements to search for
Virginia
Pentax K110 Kit from Circuit City
0.05
449.19
427.8
Search
Graphic Search
Possible explanations
The value is specifically 427.8
The value is specifically 0.05
The value is specifically 449.19
Accept
Edit Graphically
See More
Create New...
Edit Expression
Expression Editor
Enter the expression below:
(Use parentheses to indicate the operator precedences)
449.19
=
OK
Cancel
Cancel
Finish
In the left editor type the result of the computation (the net price).

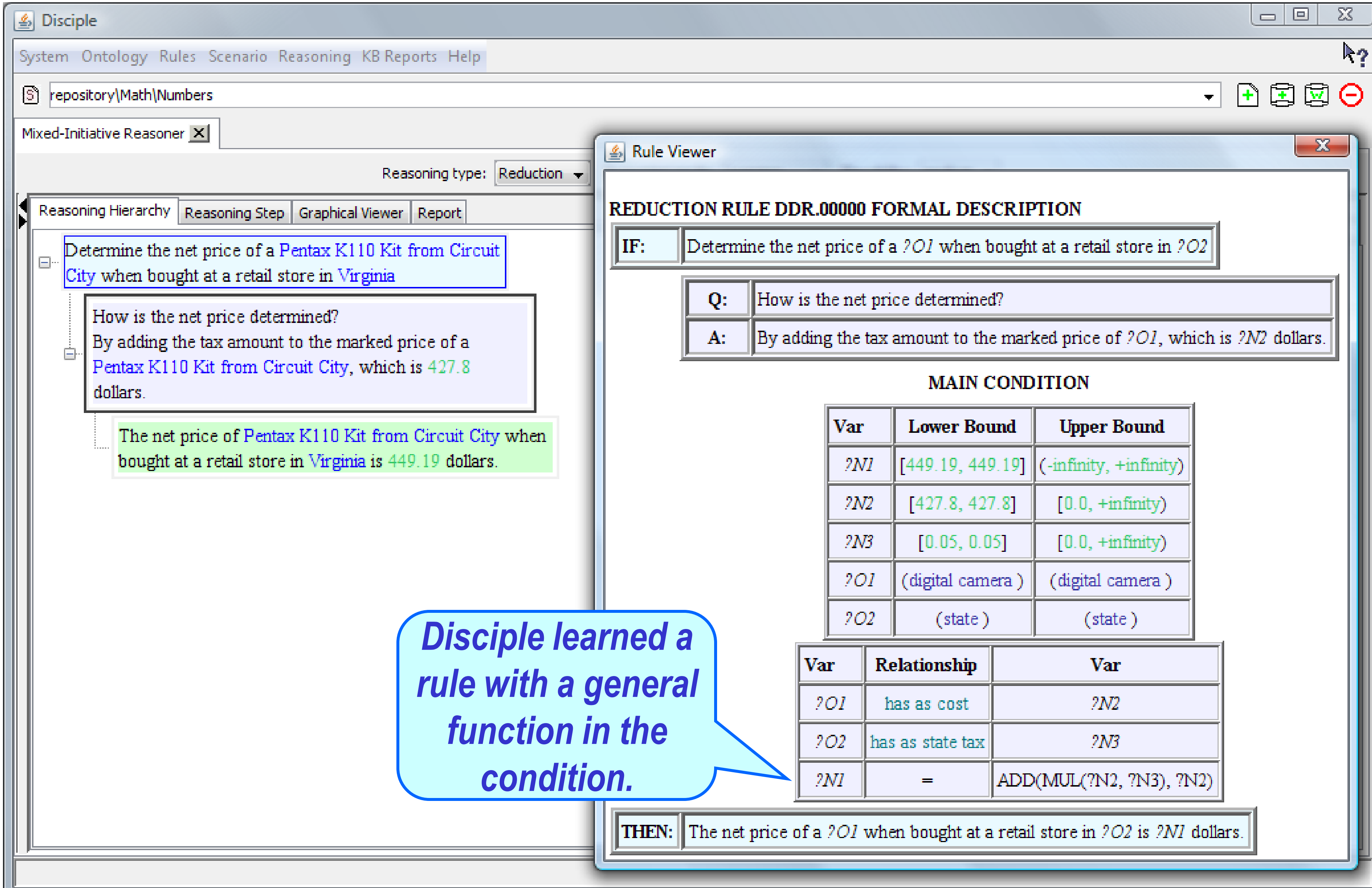


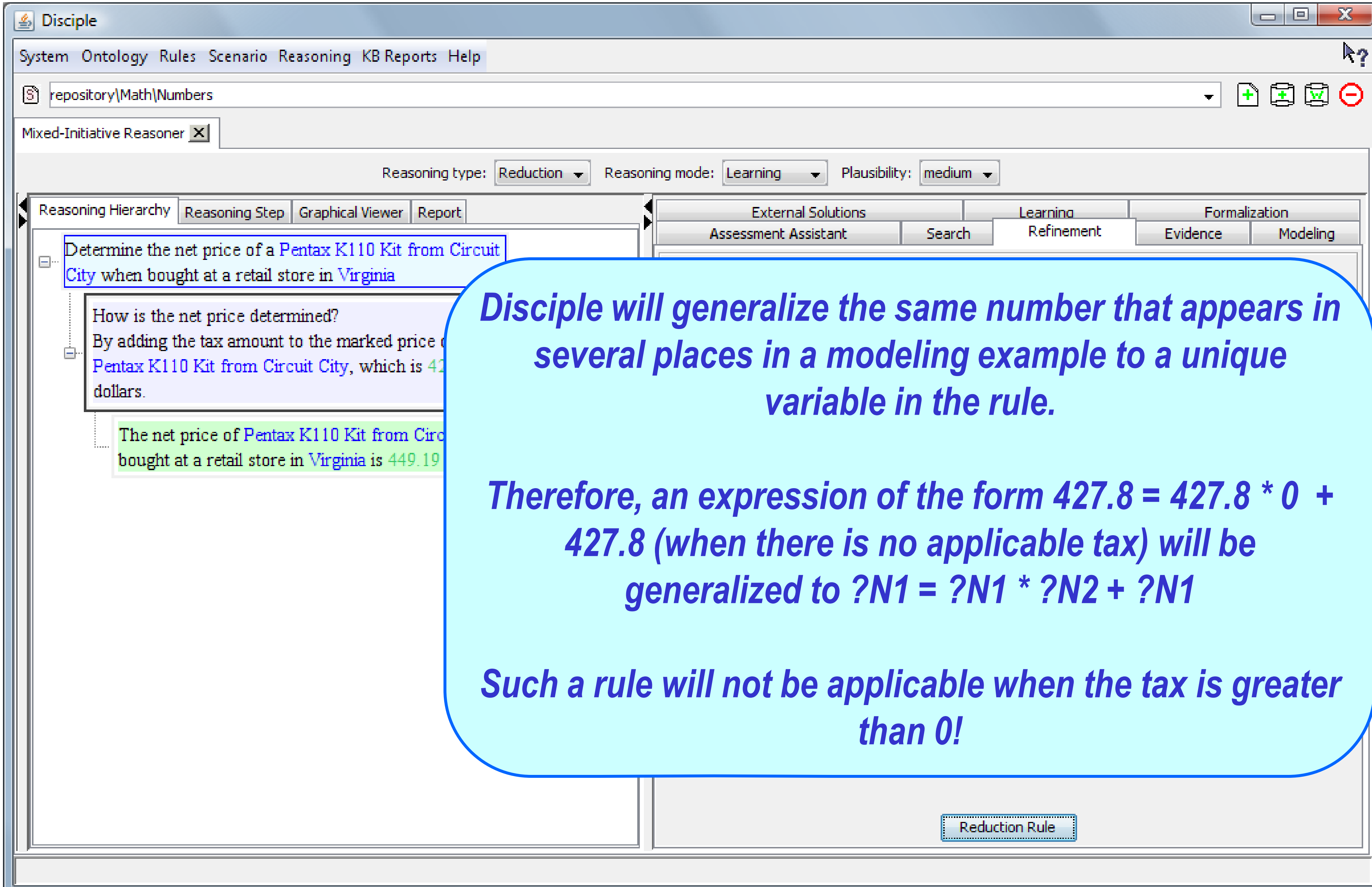
1. In the right editor type the expression used to compute the net price.

2. The following operators can be used : +, -, *, /, log(), log10(), sqrt(), exp() and pow()

3. Click "OK" when done.


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning mode: Learning
Plausibility: medium
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Default Viewer
Advanced Viewer
Problem
Determine the net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia
Question
How is the net price determined?
Answer
Remove
Virginia is state
Virginia —has as state tax—> 0.05
449.19 = (427.8 * 0.05) + 427.8
Elementary Solution
The net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia is 449.19 dollars.
options
External Solutions
Learning
Formalization
Assessment Assistant
Search
Refinement
Evidence
Modeling
Explain Reduction
Elements to search for
Virginia
Pentax K110 Kit from Circuit City
0.05
449.19
427.8
Search
Graphic Search
Possible explanations
The value is specifically 427.8
The value is specifically 0.05
The value is specifically 449.19
Accept
Edit Graphically
See More
Create New...
Edit Expression
Graphic exploration
427.8
0.05
Accept
Back to Results
See Next
Results Mode
Cancel
Finish
1. The new explanation was automatically accepted.
2. Click “Finish” when done.


Disciple
System Ontology Rules Scenario Reasoning KB Reports Help
repository\Math\Numbers
Mixed-Initiative Reasoner
Reasoning type: Reduction
Reasoning Hierarchy
Reasoning Step
Graphical Viewer
Report
Determine the net price of a Pentax K110 Kit from Circuit City when bought at a retail store in Virginia
How is the net price determined?
By adding the tax amount to the marked price of a Pentax K110 Kit from Circuit City, which is 427.8 dollars.
The net price of Pentax K110 Kit from Circuit City when bought at a retail store in Virginia is 449.19 dollars.
Rule Viewer
REDUCTION RULE DDR.00000 FORMAL DESCRIPTION
IF: Determine the net price of a ?O1 when bought at a retail store in ?O2
Q: How is the net price determined?
A: By adding the tax amount to the marked price of ?O1, which is ?N2 dollars.
MAIN CONDITION
Var | Lower Bound | Upper Bound
?N1 | [449.19, 449.19] | (-infinity, +infinity)
?N2 | [427.8, 427.8] | [0.0, +infinity)
?N3 | [0.05, 0.05] | [0.0, +infinity)
?O1 | (digital camera) | (digital camera)
?O2 | (state) | (state)
Var | Relationship | Var
?O1 | has as cost | ?N2
?O2 | has as state tax | ?N3
?N1 | = | ADD(MUL(?N2, ?N3), ?N2)
THEN: The net price of a ?O1 when bought at a retail store in ?O2 is ?N1 dollars.
Disciple learned a rule with a general function in the condition.



Disciple will generalize the same number that appears in several places in a modeling example to a unique variable in the rule.

Therefore, an expression of the form 427.8 = 427.8 * 0 + 427.8 (when there is no applicable tax) will be generalized to ?N1 = ?N1 * ?N2 + ?N1

Such a rule will not be applicable when the tax is greater than 0!

Reading

These Lecture Notes (required).

Tecuci G., Boicu M., Boicu C., Marcu D., Stanescu B., Barbulescu M., The Disciple-RKF Learning and Reasoning Agent, Computational Intelligence, Volume 21, Number 4, 2005, pp 1-15 (required).
http://lac.gmu.edu/publications/2005/TecuciG_Disciple_RKF_CI.pdf

Tecuci G., Boicu M., Boicu C., Marcu D., Boicu C., Barbulescu M., Ayers C., Cammons D., Cognitive Assistants for Analysts, 2007 (required).
http://lac.gmu.edu/publications/2007/TecuciG_Cognitive_Assistants.pdf

Tecuci, G., Boicu, M., Marcu, D., Stanescu, B., Boicu, C., Comello, J., Training and Using Disciple Agents: A Case Study in the Military Center of Gravity Analysis Domain, AI Magazine, 24, 4:51-68, AAAI Press, Menlo Park, California, 2002. Available at
http://lac.gmu.edu/publications/data/2002/2002_AI-Mag.pdf

Tecuci, Building Intelligent Agents, Ch. 4 pp. 79-100 (rule learning in Disciple).