Support For User Generated Evolutions Of Goal Models

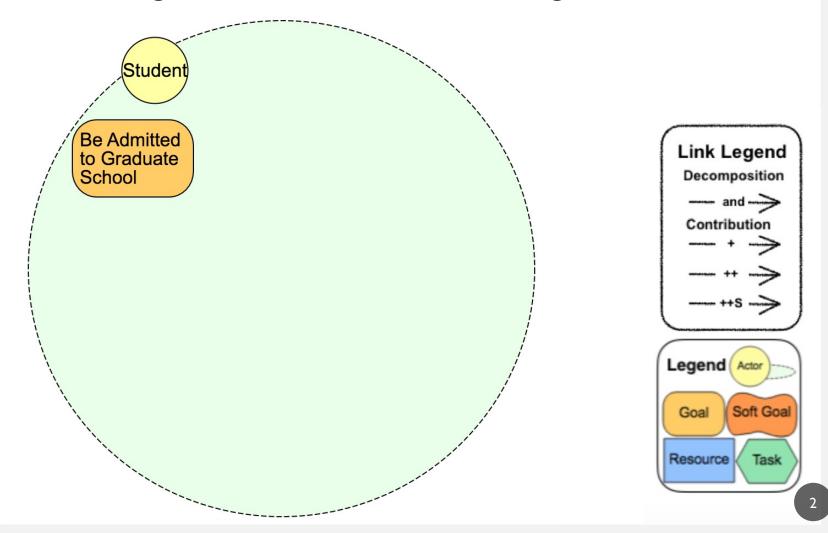
Boyue Caroline Hu

Alicia M. Grubb

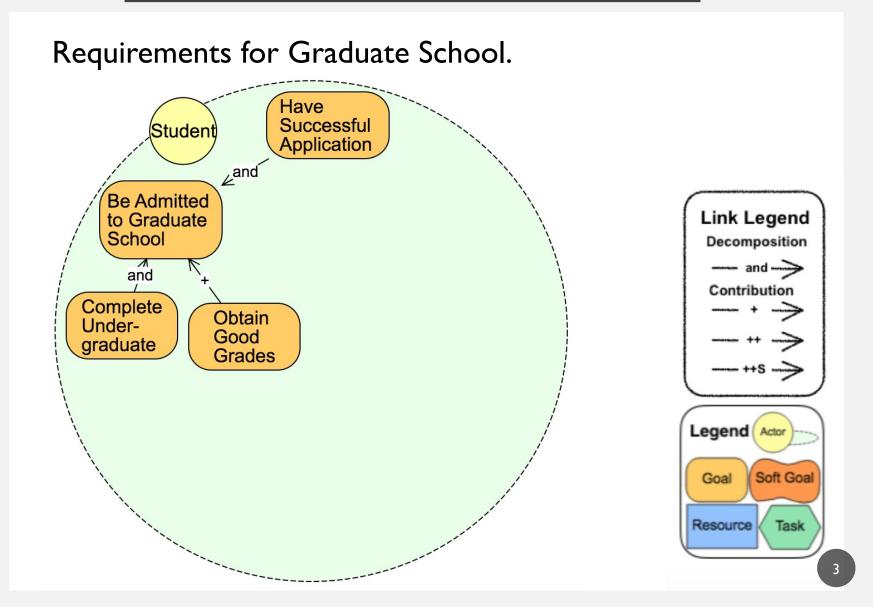


Motivating Example - GRAD

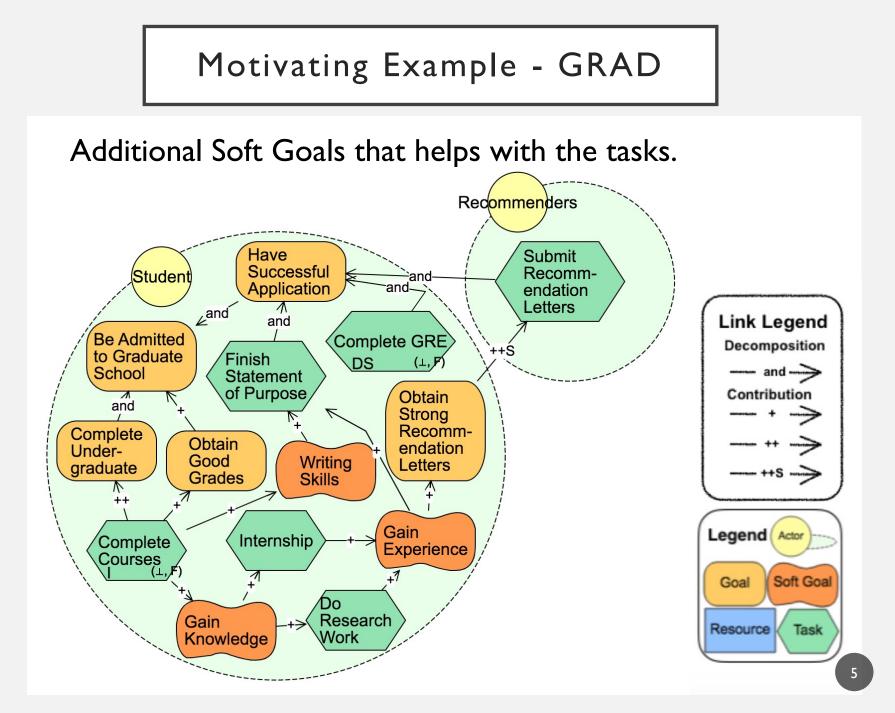
An undergraduate student interested in graduate school.

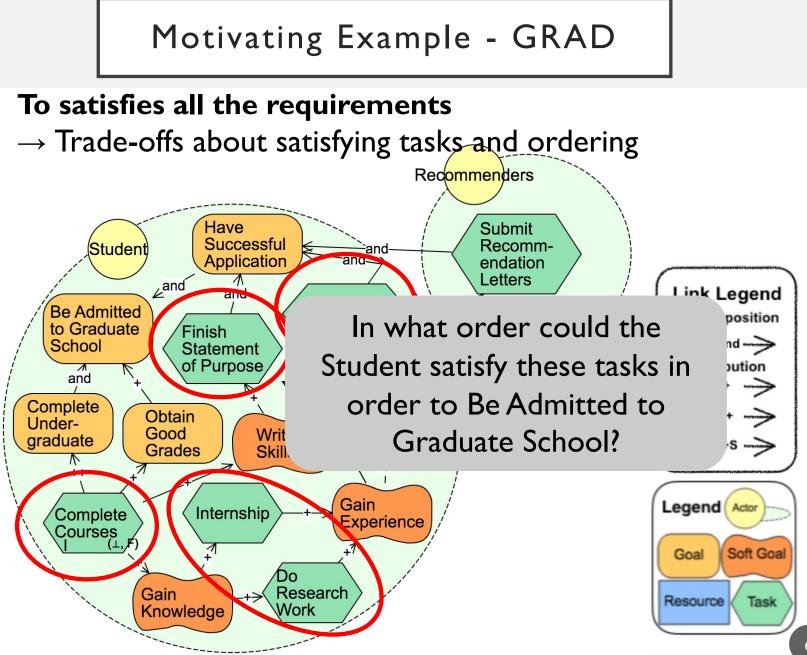


Motivating Example - GRAD



Motivating Example - GRAD Tasks/Goal to satisfy the requirements. Recommenders Have Submit Successful Recomm-Student and Application and endation Land Letters Link Legend $\overline{}$ and Decomposition Be Admitted Complete GRE to Graduate Finish DS ----- and ---> (⊥, J School Statement Contribution of Purpose and Complete Obtain Under-Good graduate Grades A ++ Legend Actor Internship Complete Courses Soft Goal Goal Do Resource Task Research Work





BloomingLeaf

Evolving Intentions Framework: Analysis of goal models when intention evaluations change over time

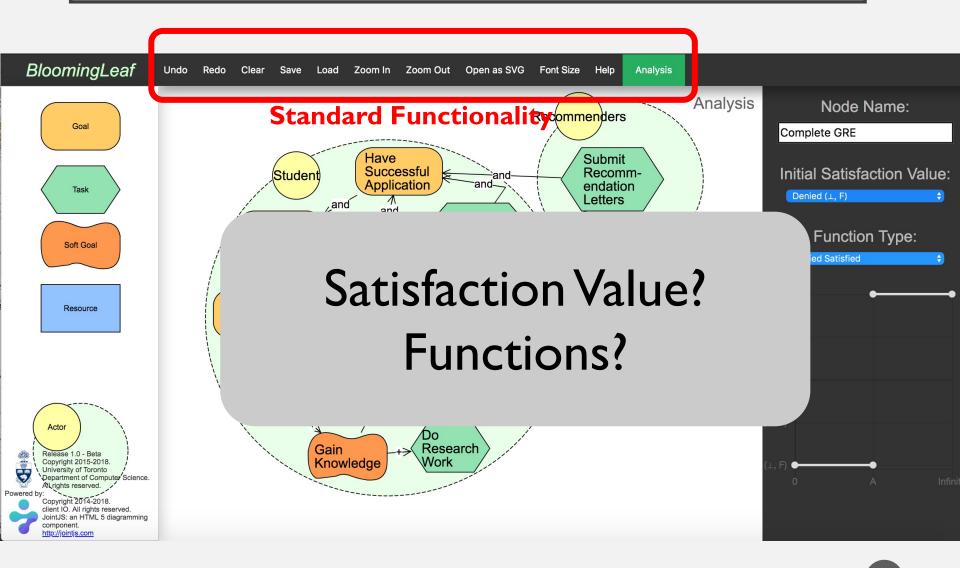


Will demonstrate through

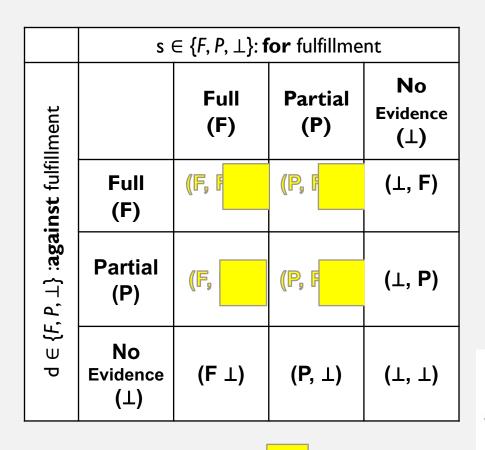
BloomingLeaf

BloomingLeaf

web-based goal modeling tool with automated formal analysis

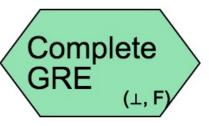


Evidence Pairs



: Conflict value

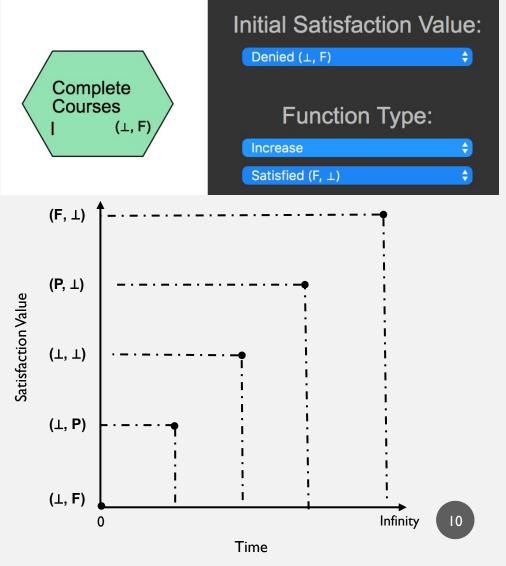
- evidence pairs (s, d)
- s evidence for the fulfillment of an intention (satisfaction)
- d evidence against the fulfillment of an intention (denial)



This goal is fully evidence against fulfillment (fully denied)

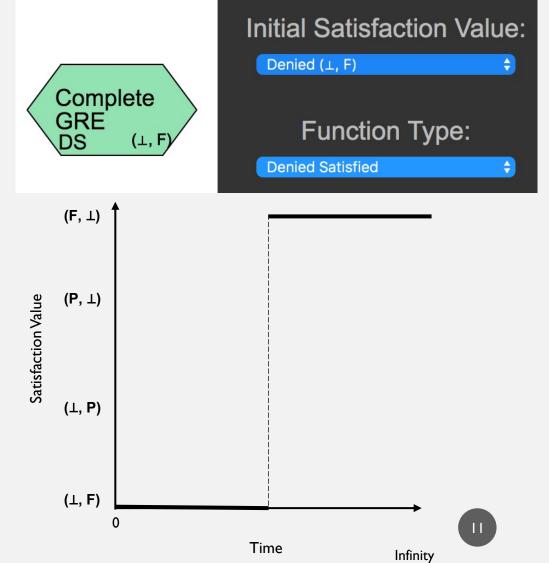
Evolving Intentions

- Fulfillment of intentions changes over time
- Intentions are assigned functions prior to analysis
- Four atomic functions: CONSTANT, INCREASE, DECREASE, and STOCHASTIC



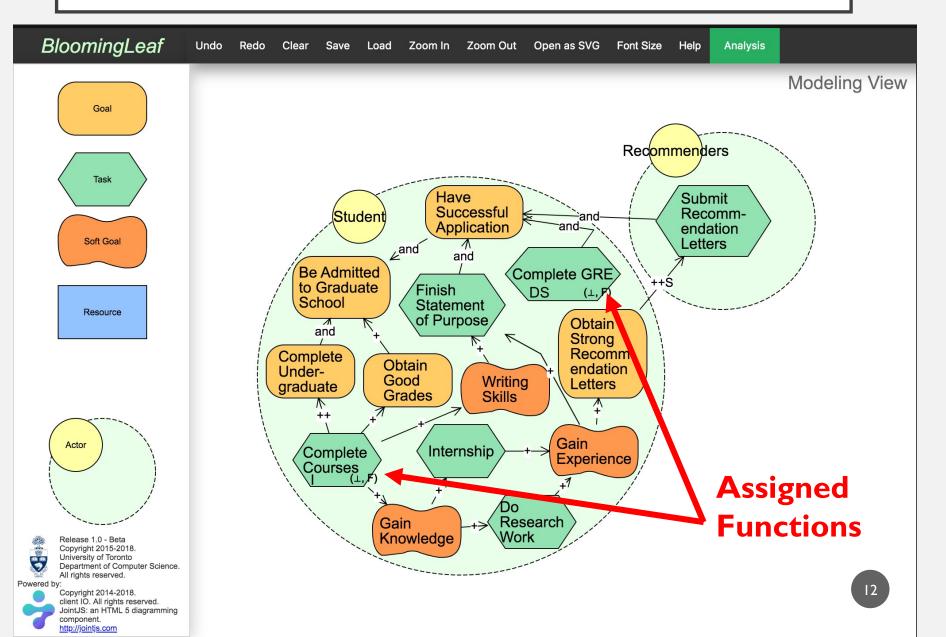
Evolving Intentions

- Fulfillment of intentions changes over time
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- Four atomic functions: CONSTANT, INCREASE, DECREASE, and STOCHASTIC



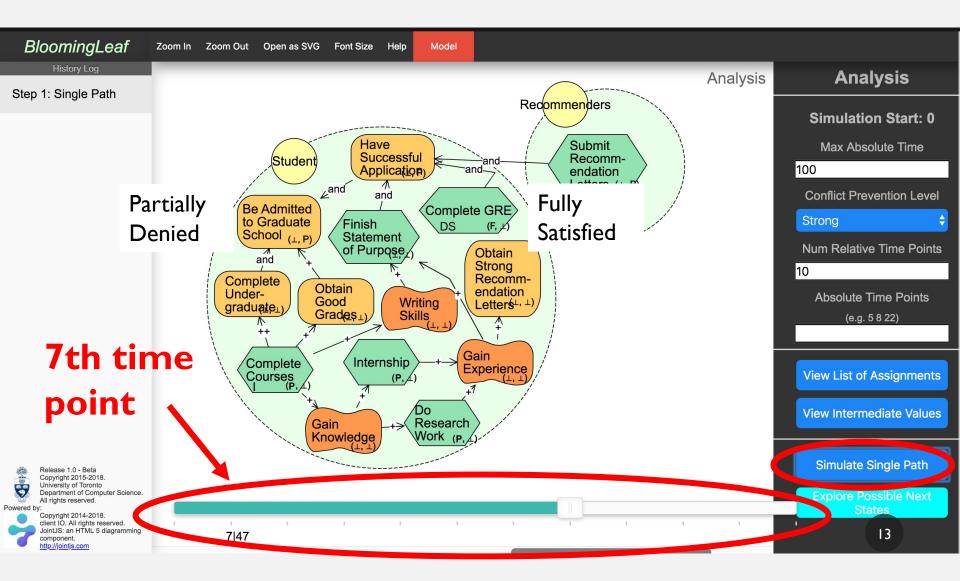
BloomingLeaf

web-based goal modeling tool with automated formal analysis

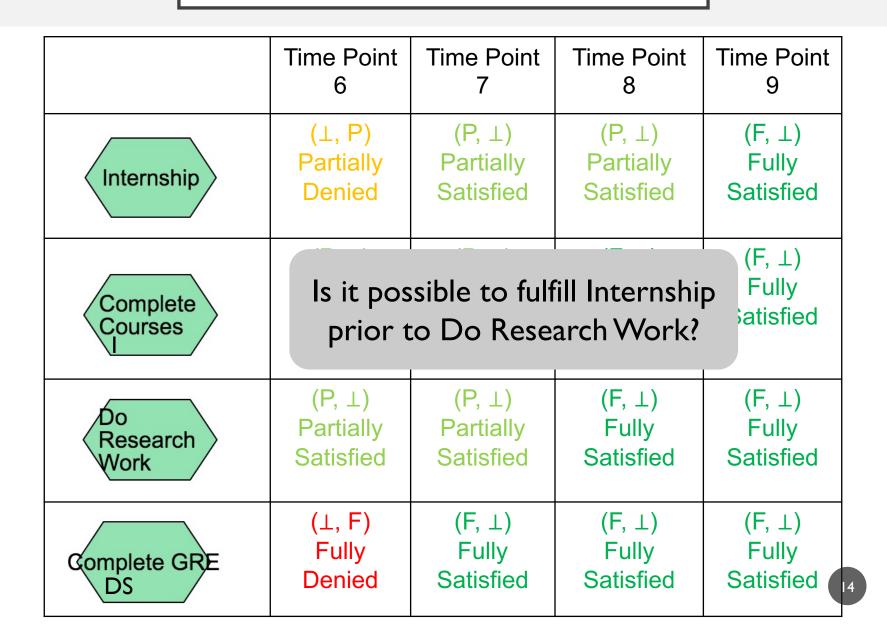


Single Path Analysis

one possible evolution of the model over a pre-specified number of time points.



Single Path For The Grad Model



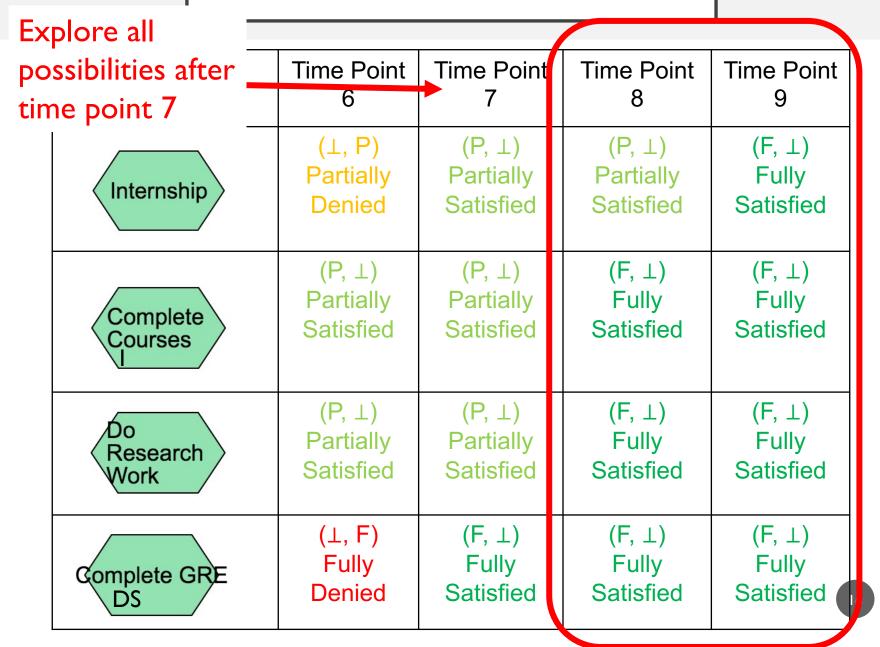
New Single Paths

Be Admitted	(⊥, P)	(⊥, ⊥)	(⊥, ⊥)	(⊥, ⊥)	(⊥, ⊥)
to Graduate	Partially	No	No	No	No
School	Denied	Information	Information	Information	Information

Be Admitted	(⊥, ⊥)	(P, P)	(P, F)	(F, F)	(F, F)
to Graduate	No	Conflict	Conflict	Conflict	Conflict
School	Information	Value	Value	Value	Value

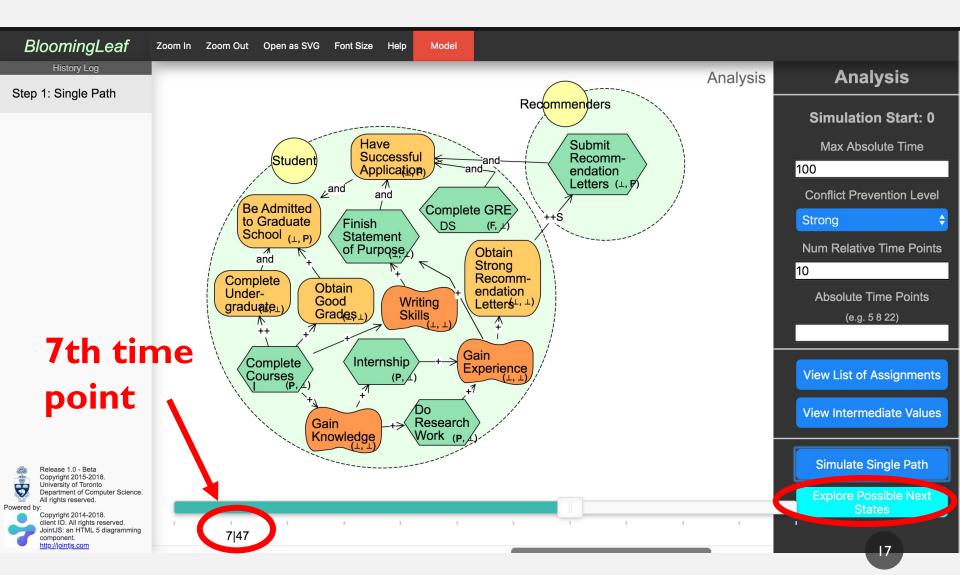
Be Admitted	(⊥, ⊥)	(F, P)	(F, F)	(P, P)	(P, F)
to Graduate	No	Conflict	Conflict	Conflict	Conflict
School	Information	Value	Value	Value	Value

Single Path For The Grad Model



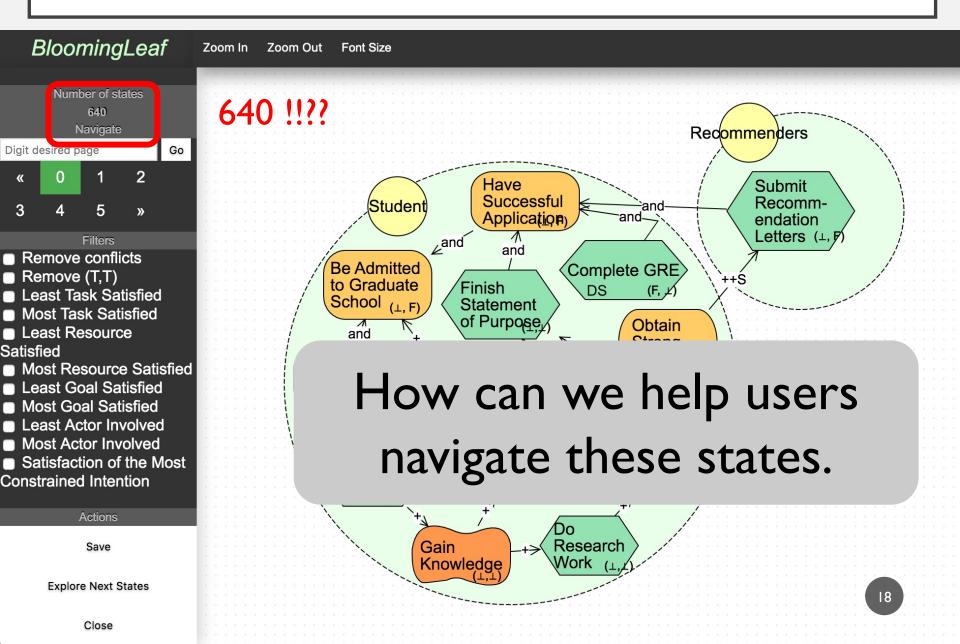
Single Path Analysis

one possible evolution of the model over a pre-specified number of time points.



Explore Next States At Time Point 7

allows users to step into any time point in the path and visualize all the possible next states



Overview

Background

- Evidence Pairs
- Evolving Intention
- BloomingLeaf Analysis

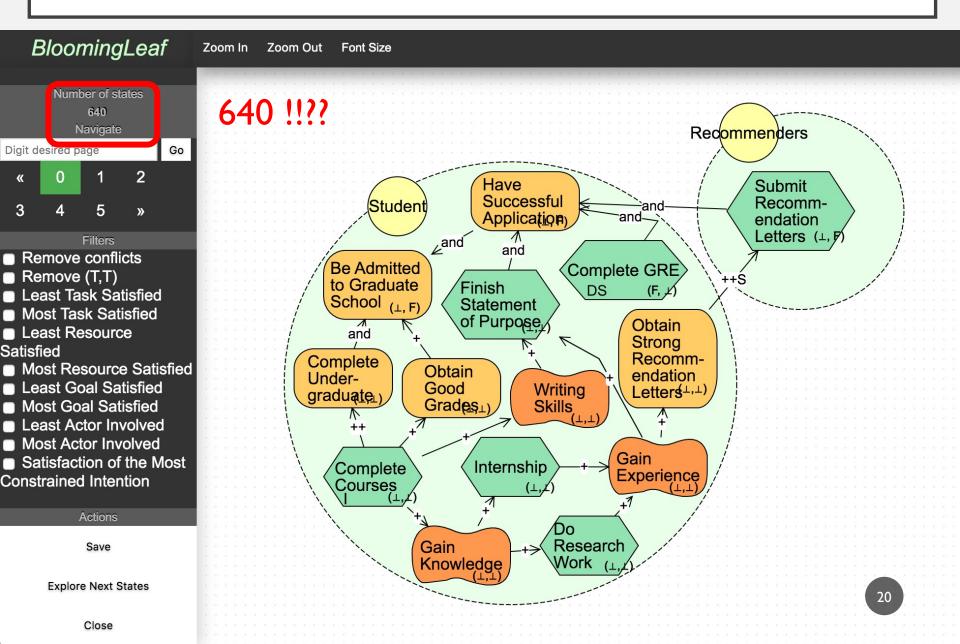
Problems

Proposed Solution

Initial Validation

Explore Next States At Time Point 7

allows users to step into any time point in the path and visualize all the possible next states



Solution Space Explosion Problem

- BloomingLeaf analysis uses Constraint Satisfaction Problems (CSPs)
 - CSPs often have high complexity

(Exhaustive Search -> NP-Hard)

- Domain for each intention: 9 possible evidence pairs
 - $(F, \bot), (P, \bot), (\bot, \bot), (F, P), (P, P), (\bot, P), (F, F), (P, F), (\bot, F)$
 - State space increases exponentially
- Explore all possible next states is looking for all solutions
- Result: Huge solution space

Solution Space Explosion Problem

Huge solution space:

- Difficult to review
- Hard to make choices

Goal: Reduce the number of next states

Overview

Background

- Evidence Pairs
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- BloomingLeaf Analysis

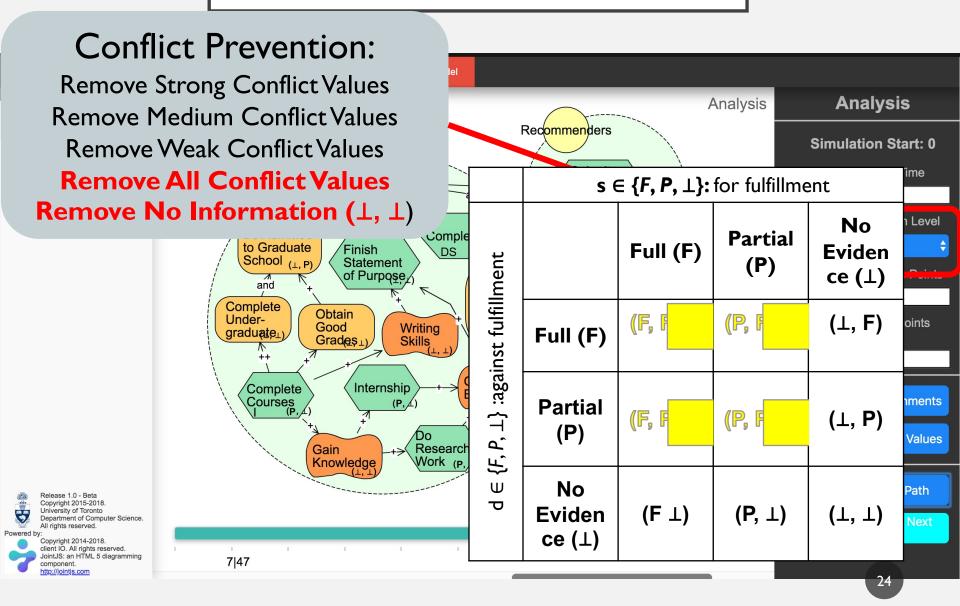
Problems

- Huge solution space
- Difficult for users to review and customize

Proposed Solution

Initial Validation

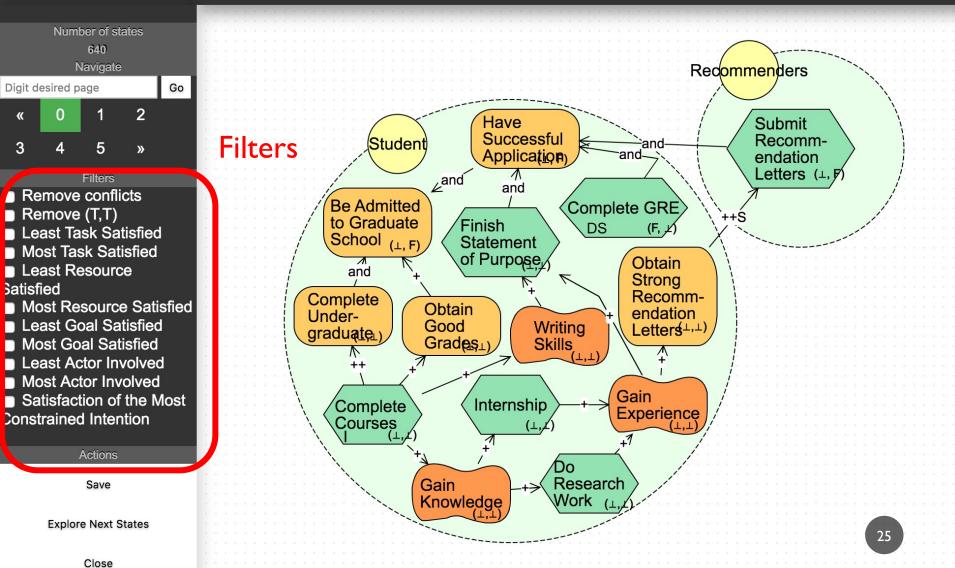
Domain Reduction



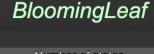
Solution Reduction



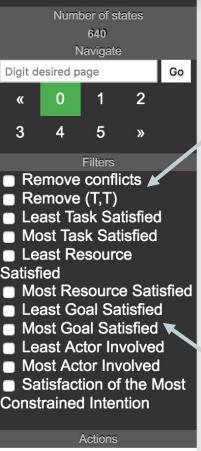
Zoom In Zoom Out Font Size



Filters

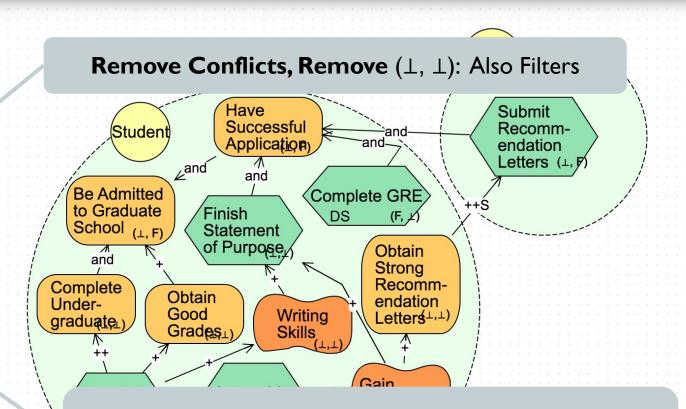






Save

Explore Next States



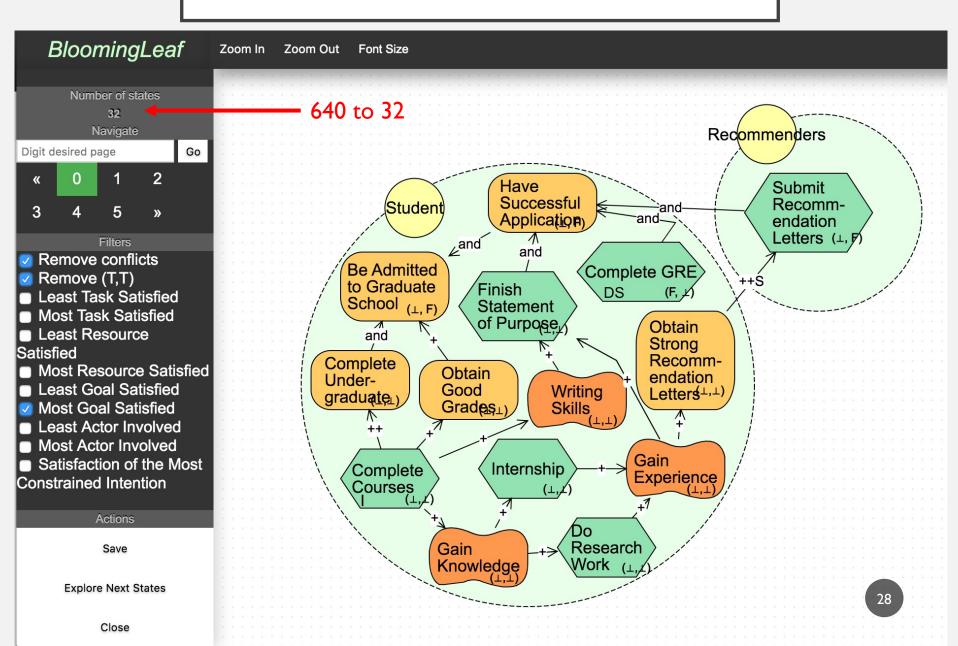
Least/Most Goal Satisfied: Keep only the solutions with the least/most number of goals that is fully satisfied.

26

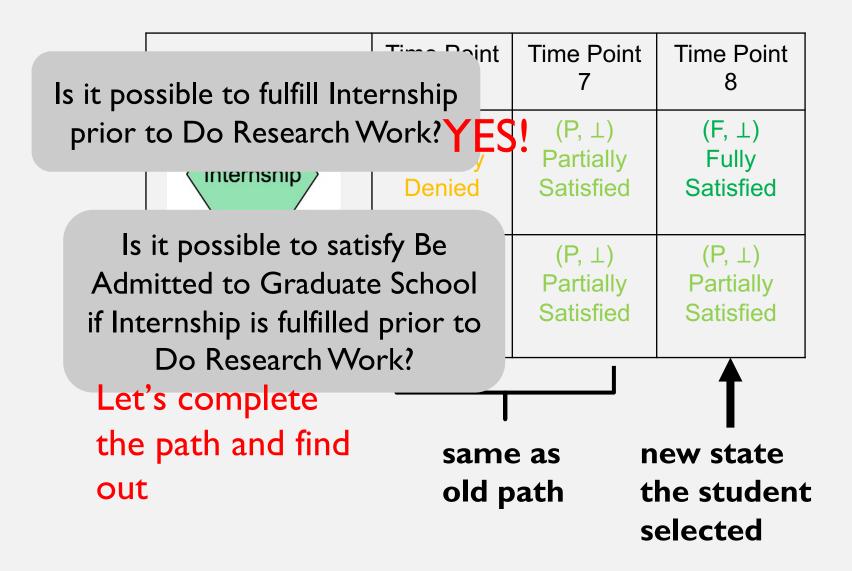
Filters

Name	Description	Example Usage			
Least/Most Tasks Satisfied	Keep only the solutions with the least/most number of tasks with the evaluation label satisfied (F , \perp).	In the GRAD example, if the student is looking for the minimum number of tasks he needs to complete to be admitted to graduate school.			
Least/Most Goals Satisfied	Keep only the solutions with the least/most number of goals with the evaluation label satisfied (F , \perp).	This would be useful for the student in the GRAD example to view the worst case and best case scenario.			
Least/Most Resources Satisfied	Keep only the solutions with the least/most number of resources with the evaluation label satisfied (F , \perp).	Consider a business person making budgets of all the resources he needs, <i>Least Resources Needed</i> would give a lower bound estimation and <i>Most Resources Needed</i> would give an upper bound.			
Least/Most Actors Involved	Keep only the solutions with the least/most number of actors involved. An actor is involved when at least one of their intentions is satisfied.	In the GRAD example, if the student were to ask whether he can finish the entire application process all by himself.			
Satisfaction of the Most Constrained Goal	Keep only the solutions with the status of the most con- strained goal being satisfied. Most constrained goals are goals with the smallest domain in the model.	This usually helps when users want to explore the satisfiability of some or all goals in the model.			

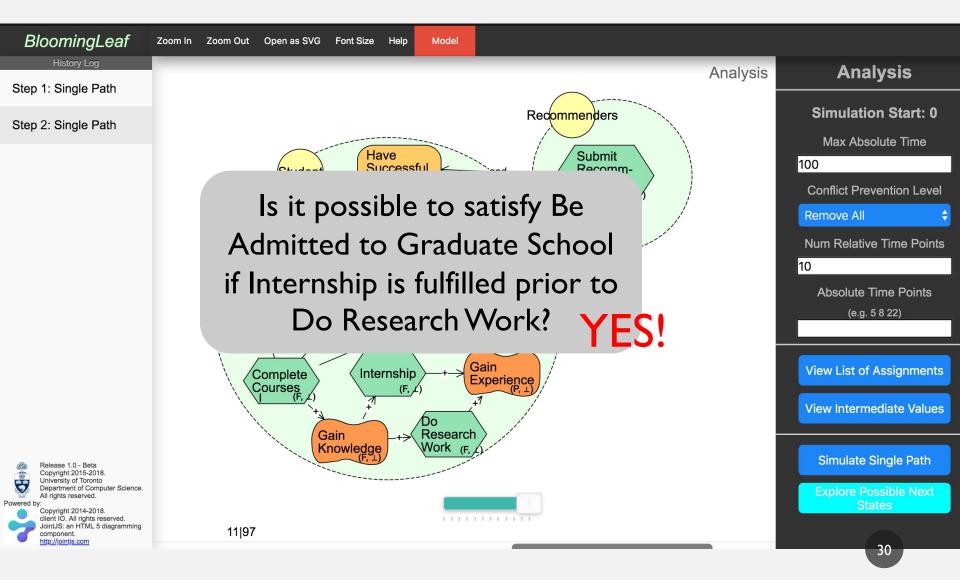
Filters



Select A State



Answering student question...



Overview

Background

- Evidence Pairs
- Evolving Intention
- BloomingLeaf Analysis

Problems

- Huge solution space
- Difficult for users to review and customize

Proposed Solution

- Domain Reduction
- Solution Reduction

Initial Validation

Research Questions

• (RQI) To what extent does the filters approach reduce computation time and the number of returned states?

• (RQ2) To what extent do users find this approach helpful?

(RQI) To What Extent Does The Filters Approach Reduce Computation Time And The Number Of Returned States?

> GRAD BLE [11] WME [11] Vote [11] Scheduler [14] Spadina Plan Spadina Plan Spadina Plan Spadina Pro Bike Lanes Full

30 37

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056

152

152

152 152

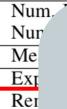
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448ء

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Model	Name



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Lea

Mo

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Mo

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Finding: The applicability of each filter varied based on the model structure, but
overall applying solution reduction filters
reduced the number of returned states
and computation time

Satisfac					_			51152
Measurement		(Computa	tion Time	in mi	llisecond	ds	
Explore Possible Next States - No Pref.	131	119	286	317	88	388	96	4141
Remove All Conflict Values	121	47	N/A	187	N/A	N/A	92	N/A
Remove No None	97	N/A	226	173	86	N/A	89	1444
N/A indicates that no measurement was collected because				the mode	was c	over-cons	straine	d. 33

(RQ2) To What Extent Do Users Find This Approach Helpful?

Participants:

Five volunteers at the University of Toronto Software Engineering group

Observations:

- I. Most time spent on selecting filters
- 2. All of the volunteers agreed that the filters saved them time and effort.

Findings:

- I. Strengthened our hypothesis that filters are useful
- 2. Volunteers suggested significant tool improvements

Further empirical research is required to validate the usefulness of filters.

Summary

- We presented **Filters**:
 - **Reduce the state space** of the Explore Possible Next States analysis
 - Help users review and customize their simulation path.

Future Work

- Guide users in selecting the most appropriate filters
- Allow users to update the evidence pair assignments to further prune the solution space
- Validate the effectiveness of our approach with goal model users

SUPPORT FOR USER GENERATED EVOLUTIONS OF GOAL MODELS

Thank you!

Tool:

http://www.cs.toronto.edu/~amgrubb/ dev/blooming/

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