Induce Pedagogical Strategy Using Reinforcement Learning

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591/791: ML for User Adaptive System

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Reinforcement Learning in practice

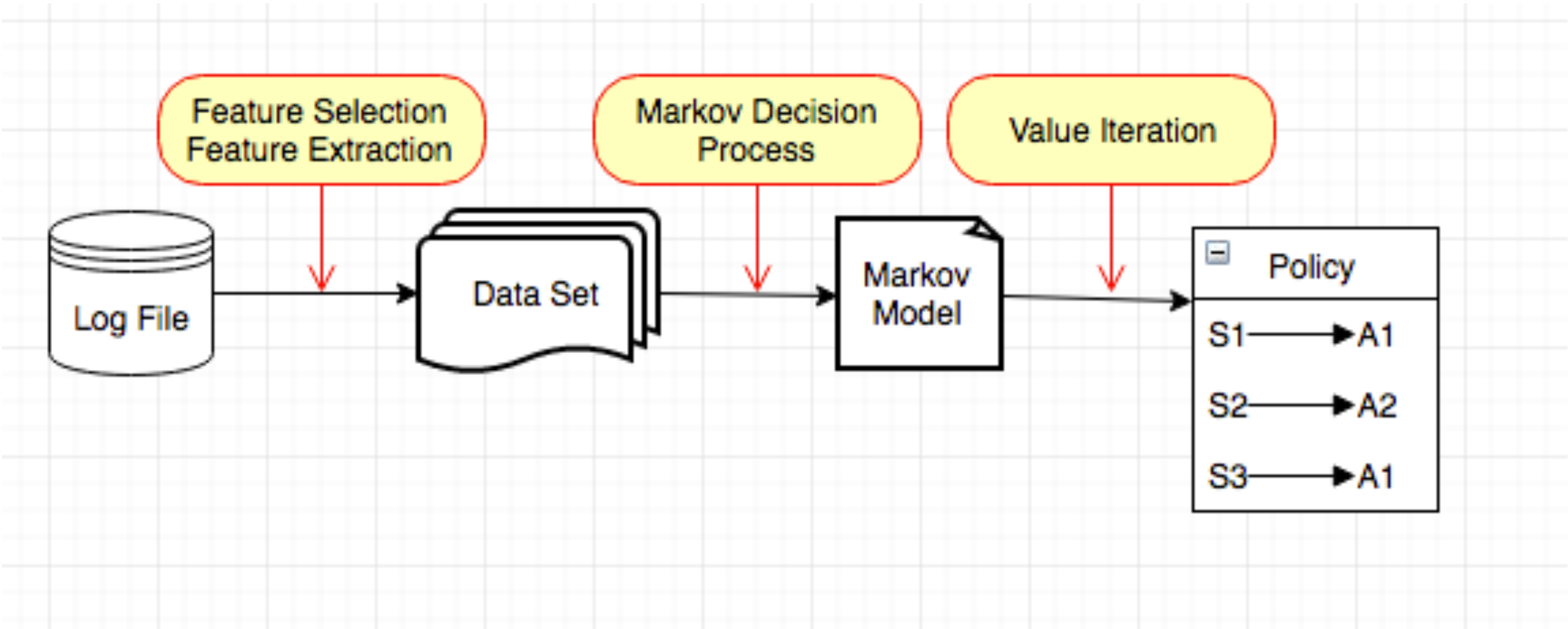
- Induce policy to make Intelligent Tutoring Systems:
  - Adaptive
  - Effective

- Reinforcement Learning in practice:

What is the best **action** for the **agent** ***(tutor)***
to take in any **state** ***(learning context)***
in order to maximize **reward** ***(student learning)***

  - Real dataset
  - Including all the necessary steps for RL project

Process


Feature Selection
Feature Extraction
Markov Decision
Process
Value Iteration
Log File
Data Set
Markov
Model
Policy
S1 → A1
S2 → A2
S3 → A1

Markov Decision Processes (MDPs)

$S = \{S_1, \ldots, S_n\}$ state space;

Student Competence, Concept Difficulty

$A = \{A_1, \ldots, A_m\}$ action space;

{Elicit, Tell}

R : reward

Student Learning Gain

T : is a set of transition probabilities between states.

Output:

$\pi: S \rightarrow A$ is defined as a policy.

An Example Log File

Pretest =0

t1	**T: Which principle** will help you calculate the KE of the rock?
t2	**S: Definition of energy.**
t3	T: **No, we should apply the Definition of Kinetic Energy**
t4	**T:** Please write the equation….
t5	S: **KE=0.5*m*v1^2**
t6	T: Go ahead calculate the equation.
t7	S: **0.5*0.6kg*2.0 m/s^2 = 1.2 J**
…	
t423	**T:** SInce the kinetic energy…

Posttest =0.8

NC

State:

Action: *{Elicit, Tell}*

Reward:

t1	**T: Which principle** will help you calculate the KE of the rock?	**Elicit**
t2	S: Definition of energy.	
t3	T: **No, we should apply the Definition of Kinetic Energy**	
t4	**T:** Please write the equation….	**Elicit**
t5	S: **KE=0.5*m*v1^2**	
t6	T: Go ahead calculate the equation.	**Elicit**
t7	S: **0.5*0.6kg*2.0 m/s^2 = 1.2** J	
	…	
t423	**T:** SInce the kinetic energy…	**Tell**

Posttest =0.8

State feature:

Student Competence

Pretest =0

t1	T: **Which principle** will help you calculate the KE of the rock?	Elicit
t2	**S: Definition of energy.**	✗
t3	T: **No, we should apply the Definition of Kinetic Energy**	
t4	T: Please write the equation….	Elicit
t5	S: **KE=0.5*m*v1^2**	✓
t6	T: Go ahead calculate the equation.	Elicit
t7	S: **0.5*0.6kg*2.0 m/s^2 = 1.2 J**	✓
…		
t423	T: SInce the kinetic energy…	Tell

Posttest =0.8

Pretest =0

t1	T: Which principle will help you calculate the KE of the rock?	**Elicit**
t2	S: Definition of energy.	✗
t3	T: No, we should apply the Definition of Kinetic Energy	
t4	T: Please write the equation….	**Elicit**
t5	S: KE=0.5*m*v1^2	✓
t6	T: Go ahead calculate the equation.	**Elicit**
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J	✓
	…	
t423	T: SInce the kinetic energy…	**Tell**

Posttest =0.8

NC STATE UNIVERSITY

Number of Correct

Pretest =0

			Number of Correct
t1	**T: Which principle** will help you calculate the KE of the rock?	**Elicit**	0
t2	**S: Definition of energy.**	✗	
t3	T: **No, we should apply the Definition of Kinetic Energy**		0
t4	**T:** Please write the equation....	**Elicit**	
t5	S: **KE=0.5*m*v1^2**	✓	1
t6	T: Go ahead calculate the equation.	**Elicit**	
t7	S: **0.5*0.6kg*2.0 m/s^2 = 1.2 J**	✓	
	…		…
t423	**T:** SInce the kinetic energy…	**Tell**	55

Posttest =0.8

Number Correct → Student Competence

if ≤ 40, *Low*; otherwise, *High*

t1	T: Which principle will help you calculate the KE of the rock?	Elicit	0	*Low*
t2	S: Definition of energy.			
t3	T: No, we should apply the Definition of Kinetic Energy		0	*Low*
t4	T: Please write the equation....	Elicit		
t5	S: KE=0.5*m*v1^2		1	*Low*
t6	T: Go ahead calculate the equation.	Elicit		
t7	S: 0.5*0.6kg*2.0 m/sˆ2 = 1.2 J			
	…		…	…
t423	T: SInce the kinetic energy…	Tell	55	*High*

Posttest =0.8

State: Student Competence {*Low, High*}

t1	T: Which principle will help you calculate the KE of the rock?	Elicit	*Low*
t2	S: Definition of energy.		
t3	T: No, we should apply the Definition of Kinetic Energy		*Low*
t4	T: Please write the equation....	Elicit	
t5	S: KE=0.5*m*v1^2		*Low*
t6	T: Go ahead calculate the equation.	Elicit	
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J		
...			...
t423	T: SInce the kinetic energy...	Tell	*High*

Posttest =0.8

State: Student Competence {*Low, High*}

Action: {*Elicit, Tell*}

Reward:

t1	T: Which principle will help you calculate the KE of the rock?	Elicit
t2	S: Definition of energy.	
t3	T: No, we should apply the Definition of Kinetic Energy	
t4	T: Please write the equation....	Elicit
t5	S: KE=0.5*m*v1^2	
t6	T: Go ahead calculate the equation.	Elicit
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J	
...		
t423	T: SInce the kinetic energy...	Tell

Posttest =0.8

Low

↓ Elicit

Low

↓ Elicit

Low

↓ Elicit

...

High

⊥ Tell

Reward: Normalized Learning Gain (NLG) X100

Pretest =0

t1	T: Which principle will help you calculate the KE of the rock?	Elicit
t2	S: Definition of energy.	
t3	T: No, we should apply the Definition of Kinetic Energy	
t4	T: Please write the equation….	Elicit
t5	S: KE=0.5*m*v1^2	
t6	T: Go ahead calculate the equation.	Elicit
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J	
	…	
t423	T: SInce the kinetic energy…	Tell

Posttest =0.8

$$NLG = \frac{\text{Posttest} - \text{Pretest}}{1 - \text{Pretest}}$$

$$NLG \times 100$$

$$= \frac{0.8 - 0}{1 - 0} \times 100 = 80$$

State: Student Competence {*Low, High*}

Action: {*Elicit, Tell*}

Reward: NLG × 100

t1	T: Which principle will help you calculate the KE of the rock?	Elicit
t2	S: Definition of energy.	
t3	T: No, we should apply the Definition of Kinetic Energy	
t4	T: Please write the equation....	Elicit
t5	S: KE=0.5*m*v1^2	
t6	T: Go ahead calculate the equation.	Elicit
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J	
...		
t423	T: SInce the kinetic energy...	Tell

Posttest =0.8

Low

$\downarrow$ Elicit,0

Low

$\downarrow$ Elicit,0

Low

$\downarrow$ Elicit,0

...

High

$\perp$ Tell,80

One student's Log File ➔ One Trajectory

$$\textbf{\textit{Low}} \xrightarrow{\text{Elicit, 0}} \textbf{\textit{Low}} \xrightarrow{\text{Elicit, 0}} \textbf{\textit{Low}} \xrightarrow{\text{Elicit, 0}} \textbf{\textit{High}} \xrightarrow{\text{Tell,80}} \bullet$$

Training Dataset → Trajectories

$\textit{Low} \xrightarrow{\text{Elicit, 0}} \textit{Low} \xrightarrow{\text{Elicit, 0}} \textit{Low} \xrightarrow{\text{Elicit, 0}} \textit{High} \xrightarrow{\text{Tell,80}} \bullet$

$\textit{High} \xrightarrow{\text{Elicit, 0}} \textit{Low} \xrightarrow{\text{Elicit, 0}} \textit{Low} \xrightarrow{\text{Tell, 0}} \textit{Low} \xrightarrow{\text{Elicit, 60}} \bullet$

$\textit{Low} \xrightarrow{\text{Tell, 0}} \textit{Low} \xrightarrow{\text{Elicit, 0}} \textit{High} \xrightarrow{\text{Elicit, 0}} \textit{High} \xrightarrow{\text{Tell, 20}} \bullet$

…

$\textit{High} \xrightarrow{\text{Elicit, 0}} \textit{High} \xrightarrow{\text{Tell, 0}} \textit{High} \xrightarrow{\text{Elicit, 0}} \textit{High} \xrightarrow{\text{Elicit, -30}} \bullet$

Training Dataset → Trajectories

Low $\xrightarrow{\text{Elicit, 0}}$ ***Low*** $\xrightarrow{\text{Elicit, 0}}$ ***Low*** $\xrightarrow{\text{Elicit, 0}}$ ***High*** $\xrightarrow{\text{Tell,80}} \bullet$

High $\xrightarrow{\text{Elicit, 0}}$ ***Low*** $\xrightarrow{\text{Elicit, 0}}$ ***Low*** $\xrightarrow{\text{Tell, 0}}$ ***Low*** $\xrightarrow{\text{Elicit, 60}} \bullet$

Low $\xrightarrow{\text{Tell, 0}}$ ***Low*** $\xrightarrow{\text{Elicit, 0}}$ ***High*** $\xrightarrow{\text{Elicit, 0}}$ ***High*** $\xrightarrow{\text{Tell, 20}} \bullet$

…

High $\xrightarrow{\text{Elicit, 0}}$ ***High*** $\xrightarrow{\text{Tell, 0}}$ ***High*** $\xrightarrow{\text{Elicit, 0}}$ ***High*** $\xrightarrow{\text{Elicit, -30}} \bullet$

Transition Probabilities T estimated from Training Dataset.

An Example of *P*(*Low*|*High, Elicit*)

$$Low \xrightarrow{\text{Elicit, 0}} Low \xrightarrow{\text{Elicit, 0}} Low \xrightarrow{\text{Elicit, 0}} High \xrightarrow{\text{Tell, 80}} \bullet$$

$$\boxed{High \xrightarrow{\text{Elicit, 0}} Low} \xrightarrow{\text{Elicit, 0}} Low \xrightarrow{\text{Tell, 0}} Low \xrightarrow{\text{Elicit, 60}} \bullet$$

$$Low \xrightarrow{\text{Tell, 0}} Low \xrightarrow{\text{Elicit, 0}} \boxed{High \xrightarrow{\text{Elicit, 0}} High} \xrightarrow{\text{Tell, 20}} \bullet$$

$$\boxed{High \xrightarrow{\text{Elicit, 0}} High} \xrightarrow{\text{Tell, 0}} \boxed{High \xrightarrow{\text{Elicit, 0}} High} \xrightarrow{\text{Elicit, -30}} \bullet$$

$$P(Low \mid High, Elicit) = \frac{\# High \xrightarrow{Elicit} Low}{\# \mathrm{High} \xrightarrow{\mathrm{Elicit}} \mathrm{Low} + \# \mathrm{High} \xrightarrow{Elicit} High} = \frac{1}{4}$$

An Example **Single-feature** Policy

$$
\begin{aligned}
<Low> \quad &\rightarrow \quad Tell \\
<High> \quad &\rightarrow \quad Elicit
\end{aligned}
$$

Two state features:

Competence; Difficulty

4 states:

{<*Low*, *Easy*>, <*Low*, *Difficult*>,
<*High*, *Easy*>, <*High*, *Difficult*>}

t3	T: No, we should apply the Definition of Kinetic Energy	
t4	T: Please write the equation....	Elicit
t5	S: KE=0.5*m*v1^2	
t6	T: Go ahead calculate the equation.	Elicit
t7	S: 0.5*0.6kg*2.0 m/s^2 = 1.2 J	
...		
t423	T: SInce the kinetic energy...	Tell

Posttest =0.8

<*Low*, *Easy*>

$\downarrow$ Elicit, 0

<*Low*, *Difficult*>

$\downarrow$ Elicit, 0

<*Low*, *Easy*>

$\downarrow$ Elicit, 0

<*High*, *Difficult*>

$\perp$ Tell, 80

A Two-Feature Policy Example

$$
\begin{aligned}
< Low, Easy > \quad &\rightarrow \quad Elicit \\
< High, Difficult > \quad &\rightarrow \quad Elicit \\
< High, Easy > \quad &\rightarrow \quad Tell \\
< Low, Difficult > \quad &\rightarrow \quad Tell
\end{aligned}
$$

Value Iteration

1. Initial value of each state: $V(s)$

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1. Initial value of each state: $V(s)$
2. Update each state's $V(s)$ using neighboring $V(s')s$:

$$V(s) = \max_a \sum_{s'} P(s'|s,a) \; [R(s,a,s') \; + \; \gamma \cdot \; V(s')]$$

Probability of landing on a neighboring state.

Reward/Cost of going to the neighboring state.

Value of the neighboring state

Value Iteration

1. Initial value of each state: $V(s)$
2. Update each state's $V(s)$ using neighboring $V(s')s$:

$$V(s) = \max_a \sum_{s'} P(s'|s,a) \;\; [R(s,a,s') \;\; + \;\; \gamma \cdot \quad V(s')]$$

Probability of landing on a neighboring state.

Reward/Cost of going to the neighboring state.

Value of the neighboring state

3. Induce the policy:

$$\pi(s) = \operatorname*{argmax}_a \sum_{s'} P(s'|s,a)\,[R(s,a,s') \;\; + \;\; \gamma \cdot \; V(s')]$$

For any state s, take an action to the neighboring s' with highest V(s')

γ :: Discount factor 0.9.

Adapted from: Sutton & Barto (1998)

Purpose

- Induce policy to make Intelligent Tutoring System:
  - Adaptive: **Feature Discretization/Selection/Extraction**
  - Effective: **ECR**

- Reinforcement Learning in practice:

  What is the best **action** for the **agent** *(tutor)*

  to take in any **state** *(learning context)*

  in order to maximize **reward** *(student learning)*
  - Real dataset
  - Including all the necessary steps for RL project.

Policy Evaluation

- Expected Cumulative Reward (Tetreault, 2006)

$$ECR = \sum_{i=1}^{m} \frac{N_i}{N_1 + N_2 + \cdots + N_m} \times V^{\pi}(S_i)$$

Where S_i is the starting state, N_i is the times that S_i exists as starting state

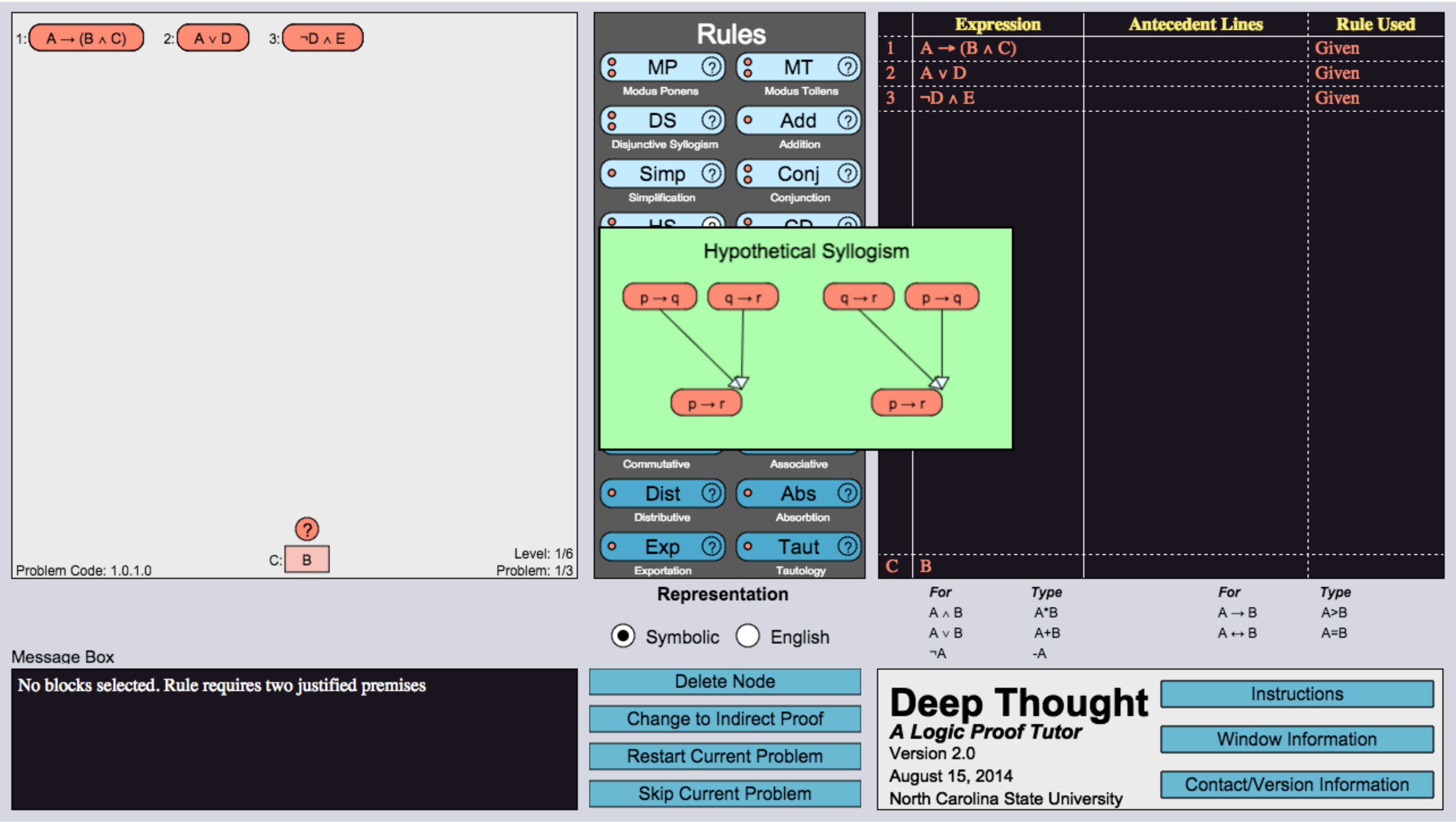
- The higher ECR of the policy means the better policy

Shitian's Work

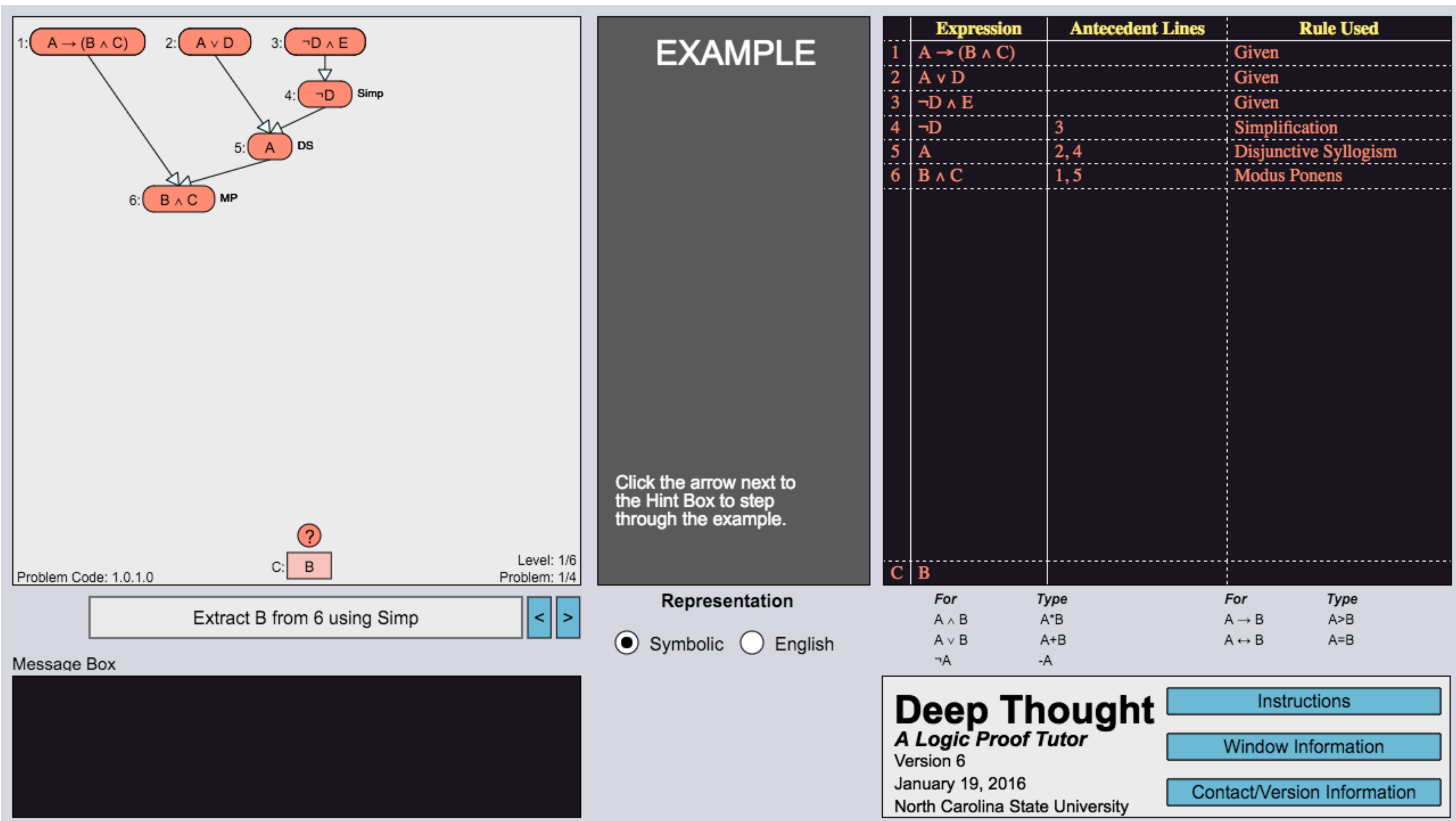
Deep Thought (Dr. Barnes, 2015)

- A rule-based tutoring system for teaching logic proof problems
- Student solves 1-3 problems per level (Total 6 levels)
- Level score ($LevelScore_i, i \in [1,6]$) is given for each student based on his/her performance on the last problem in the level i

Problem Solving



Work Example



Deep Thought Data Sets

- Total 303 students
- Average time spend in tutor is 416.60 minutes
- Total 4 categories and 124 features
- Action set
  – should it ask student to solve the next problem (PS)
  – should it provide an example to show the student how to solve the next problem (WE)

Four categories: 124 State Features

- Autonomy: the amount of work done by the student
  - PSCount,
  - PercPS
- Temporal Situation: the time related information about the work process
  - TotalTime,
  - avgPSTime,
- Student Action:the statistical measurement of student's behavior
  - AppCount,
  - hintCount
- Performance: Students' performance on current problem
  - ruleScore,
  - wrongApp

Feature Discretization

- Median split

TotalTime	[0: <=172.34, 1: >172.34]
avgTime	[0: <=6.25, 1: >6.25]
hint	[0: <=0.04, 1: >0.04]

- Kmeans
  - Data points didn’t uniformly distribute
  - Particular data points may group together
  - Avoid unbalanced clustering

  CurrPro_NumProbRule [0: close to 4.1, 1: close to 6.4]

Feature-Selection: Correlation Metrics

Given labeled data, we can compute some simple score S(i) that measures how informative each feature X is about class labels Y.

- Chi-square (CHI) (Zibran, 2007)

$$\chi^2 = \sum_i \frac{(X_i - Y_i)^2}{Y_i}$$

- Information Gain (IG) (C. Lee, 2010)

$$IG(X,Y) = H(Y) - H(Y|X)$$

Feature-Selection: Correlation Metrics

- Information Gain Ratio (IGR) (J. T. Kent, 1983)

$$IGR(X,Y) = \frac{H(Y) - H(Y|X)}{H(X)}$$

- Symmetric Uncertainty (SU) (L. Yu, H. Liu, 2003)

$$SU(X,Y) = \frac{H(Y) - H(Y|X)}{H(X) + H(Y)}$$

- Weighted Information Gain (WIG) (We proposed)

$$WIG(X,Y) = \frac{H(Y) - H(Y|X)}{(H(X) + H(Y))H(X)}$$

Correlation-based Feature Selection Methods

- Feature Selection for model-based RL
- Apply correlation between current optimal feature set and potential feature as the feature selection criteria
- Forward feature selection strategy

10 Correlation-based Methods

- Explore both high and low correlation
- Obtain 10 correlation-based feature selection methods (5 correlation metrics $\times$ 2 correlation types)

	High	**Low**
CHI	CHI-High	CHI-Low
IG	IG-High	IG-Low
IGR	IGR-High	IGR-Low
SU	SU-High	SU-Low
WIG	WIG-High	WIG-Low

Correlation-based Methods: Algorithm

Algorithm

Require: Ω: $Feature\ Space$; $\mathcal{D}$: $Training\ Data$;
$\mathcal{N}$: $Maximun\ Number\ of\ Selected\ Features$;

Ensure: $\mathcal{S}^*$: $Optimal\ Feature\ Set$

```
for f_i in Ω do
    ECR_i ← CalculateECR(D, f_i)
end for
Add f* with highest ECR to S*
while SIZE(S*) < N do
    for f_i in Ω − S* do
        C_i ← CalculateCORRELATION(S*, f_i, m)
    end for
    F ← SelectTop(C, 5, reverse)
    for f_i in F do
        ECR_i ← CalculateECR(D, S* + f_i)
    end for
    Replace S* by S* + f_i with highest ECR
end while
```

Initialization

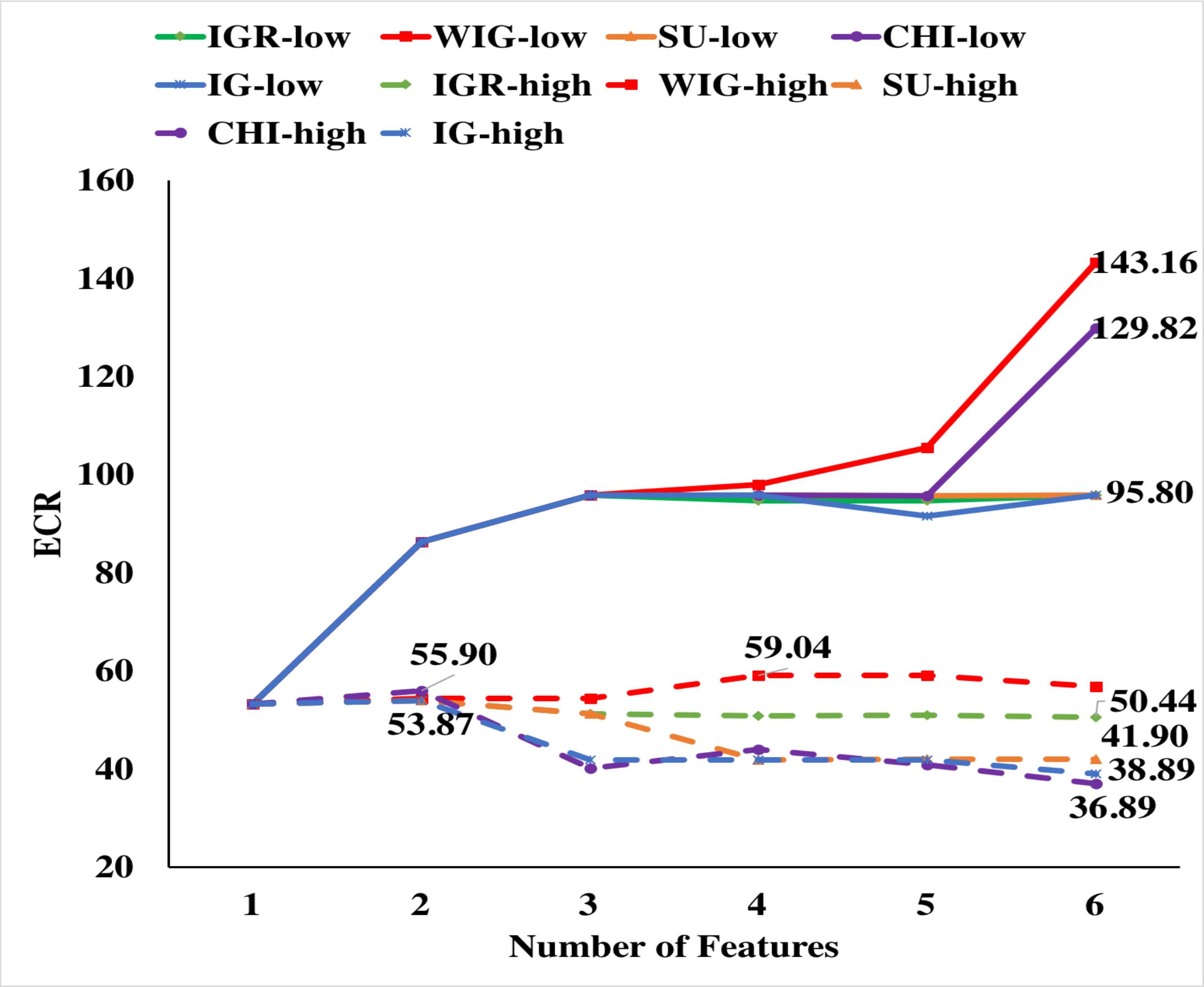
Feature Selection

Updating Feature Set

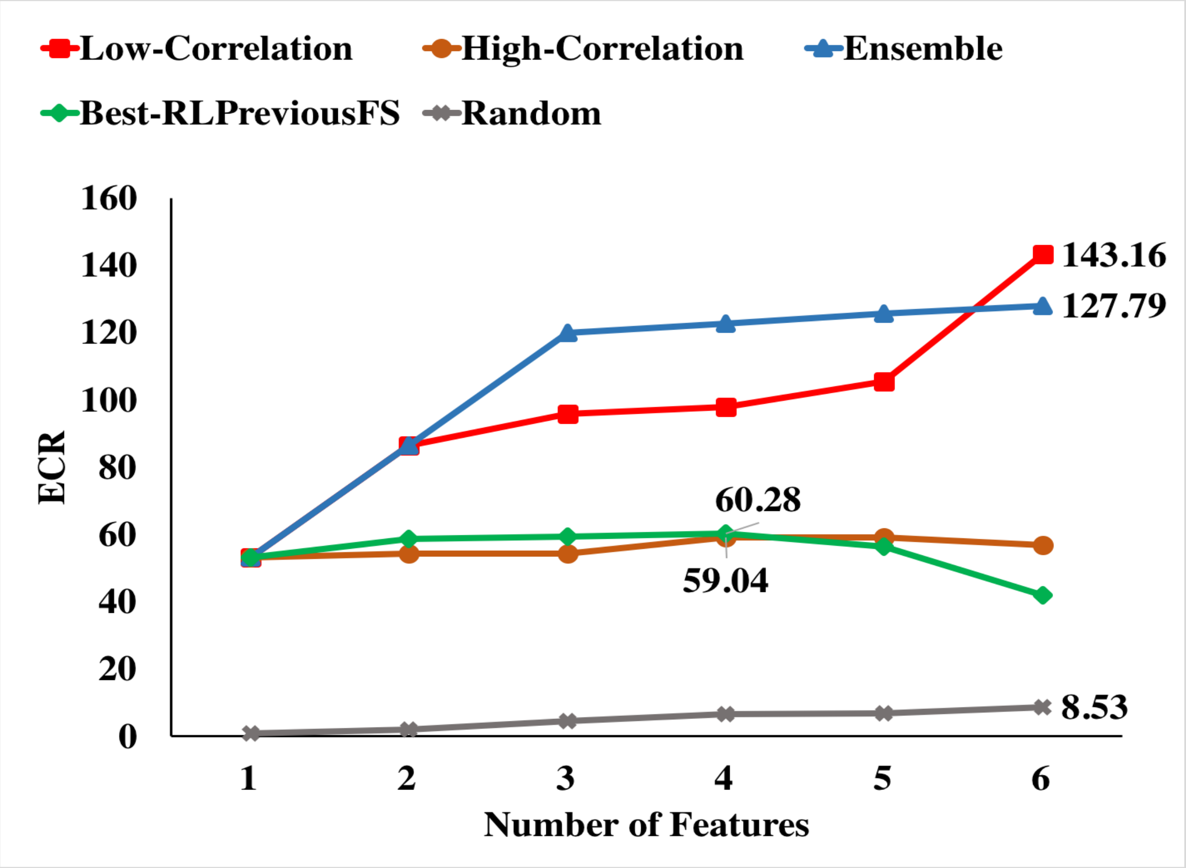
Ensemble Methods

- Integrate multiple selection methods
- 10 correlation-based methods
- 4 other RL based methods

Result: High vs Low correlation

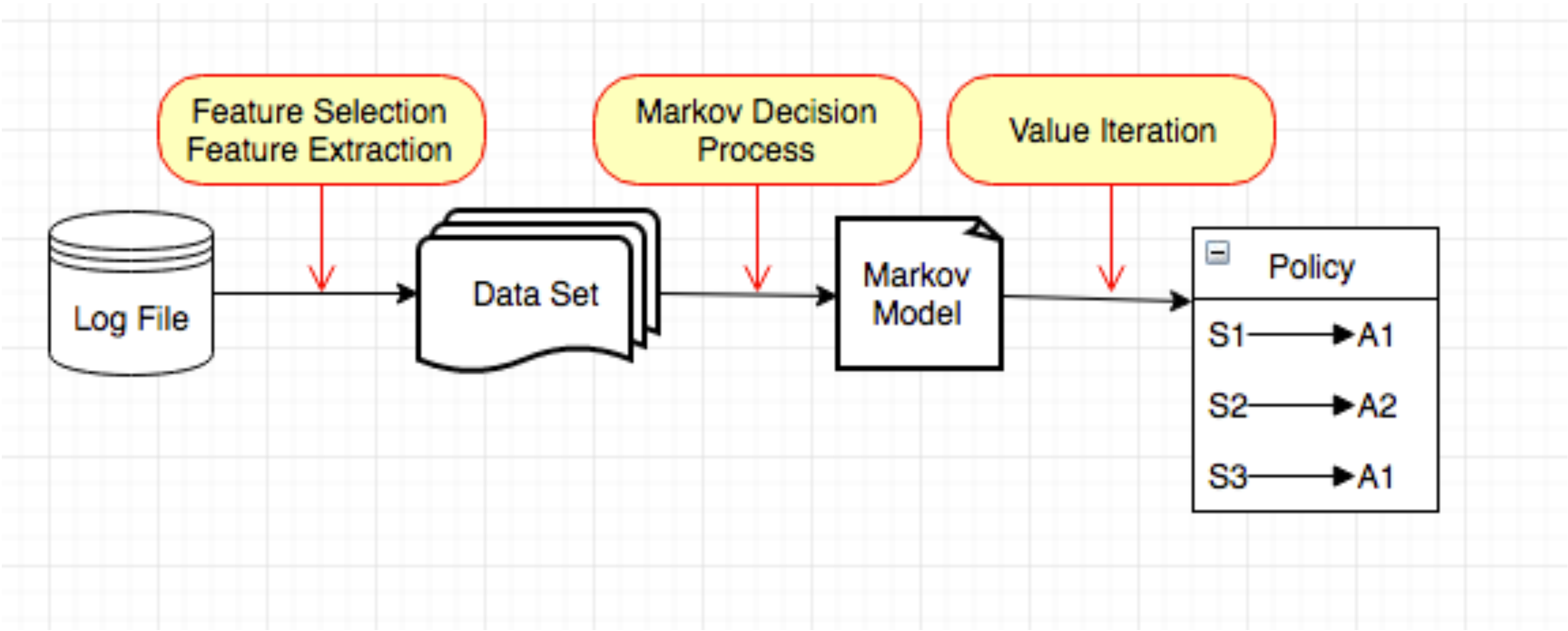


Results: Overall Evaluation



The Assigned Project:

Process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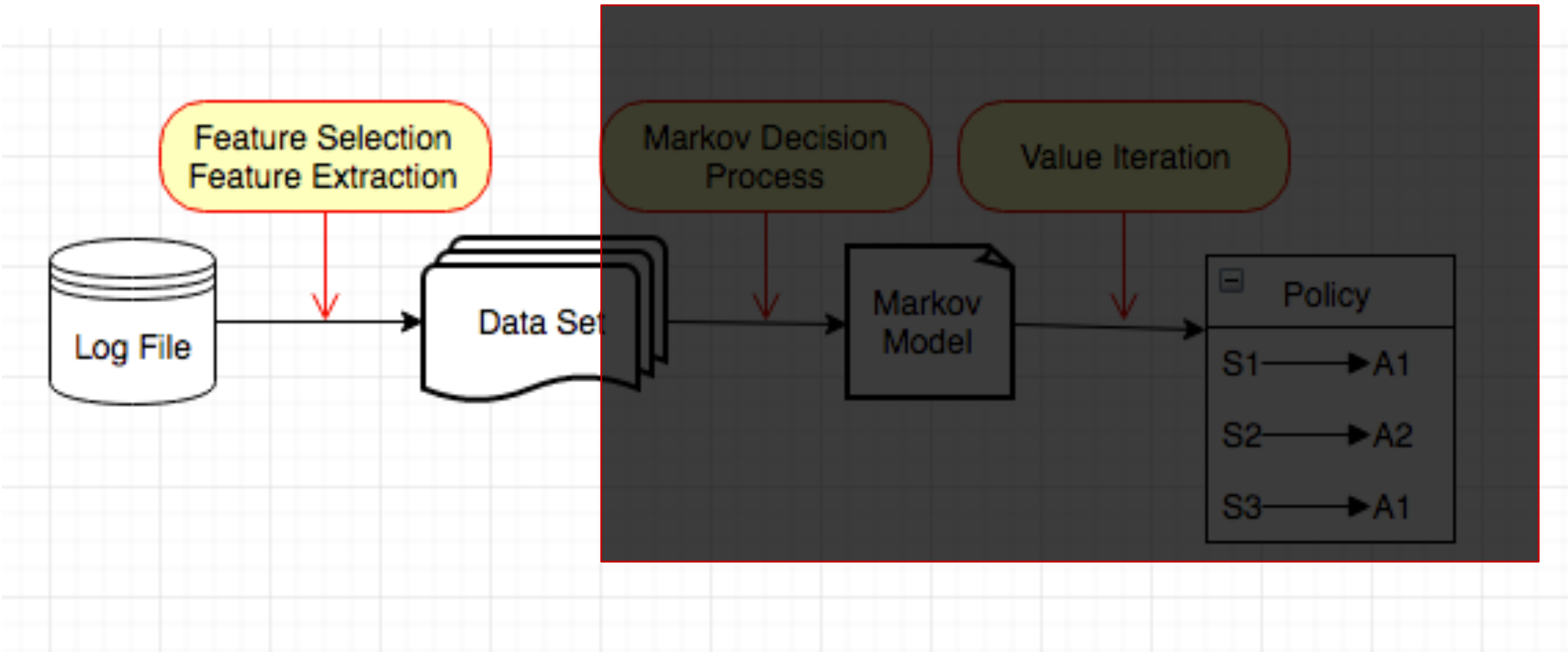
Process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A1
S2
A2
S3
A1

Goals for Feature Selection or Extraction

- Representing interactive environment effectively (Maximize ECR)
- Please Note:
  - Discrete features
  - Maximum feature size is 8

Suggestion: Discretization Procedure

- Feature Selection
  - Discretize features first
  - Explain how to discretize features in report
  - Keep the original names of selected features

- Feature Extraction
  - Not necessary to discretize features first
  - Explain how to extract features in report
  - Get a new name the extracted features: f1, f2….

To run MDP package, all features must be discretized.

Suggested: Feature Selection

- Discrete features (median split, distribution)
- Filtering approach
  - Design a ranking function and select top n features
  - ECR of each single-feature policy
- Forward feature selection
  - Good selection strategy
    - Use ECR as a selection standard
  - Maintain a limited search space
    - Apply correlation, mutual information gain as the condition

Try other methods.

Additional points for exploring novel methods.

Suggested: Feature Extraction

- PCA
  - How to deal with discrete features
  - Factor analysis of mixed data (FAMD)
- Fuzzy Clustering
  - Data point can belong to multiple clusters
  - Specify distance function, handing continuous and discrete features
- Autoencoder
  - Do Not recommend
- Output Discrete Features
  - Explain how to extract features in report
  - Transfer extracted features into discrete ones

Suggested: Feature Extraction

- Unsupervised feature extraction
- Construct connection between feature extraction with reinforcement learning
- Apply ECR as the condition in the feature extraction process

Markov Decision Process

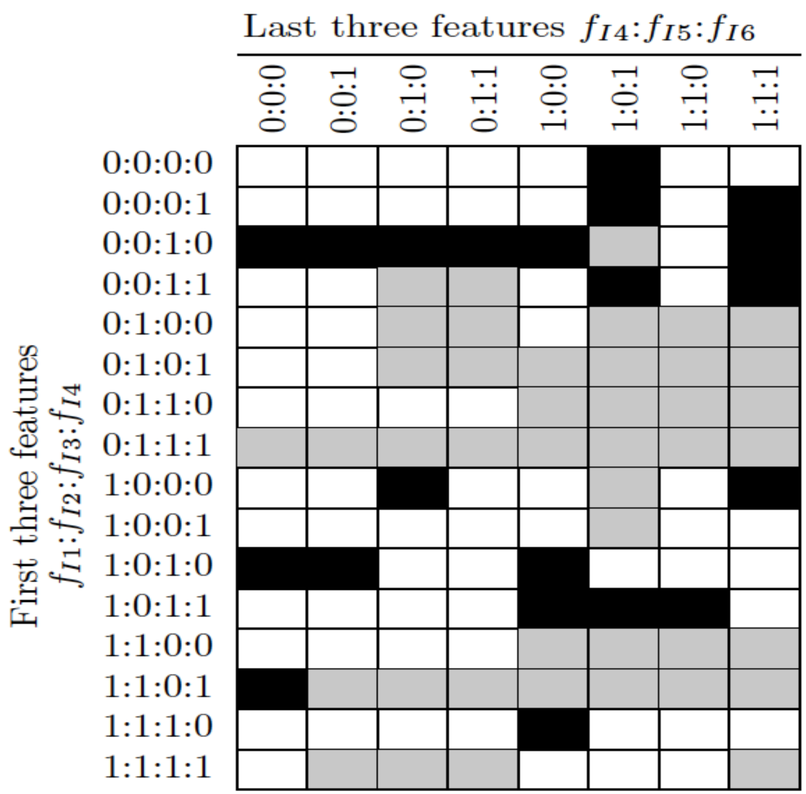
1	student	currProb	course	session	priorTutorAc	reward	Level	probDiff
2	0006-F14	1.0.1.0	226-001-BAR	1	PS	0	1	0
3	0006-F14	1.0.2.0	226-001-BAR	1	WE	0	1	0
4	0006-F14	1.0.3.0	226-001-BAR	1	WE	0	1	0
5	0006-F14	1.0.4.0	226-001-BAR	1	PS	-94.078947	1	0
6	0006-F14	2.1.1.0	226-001-BAR	1	PS	0	2	1
7	0006-F14	2.1.2.0	226-001-BAR	1	WE	0	2	1
8	0006-F14	2.1.3.0	226-001-BAR	1	PS	161.81004	2	1
9	0006-F14	3.1.1.0	226-001-BAR	1	WE	0	3	1
10	0006-F14	3.1.2.0	226-001-BAR	1	WE	0	3	1
11	0006-F14	3.1.3.0	226-001-BAR	1	PS	-43.265073	3	1

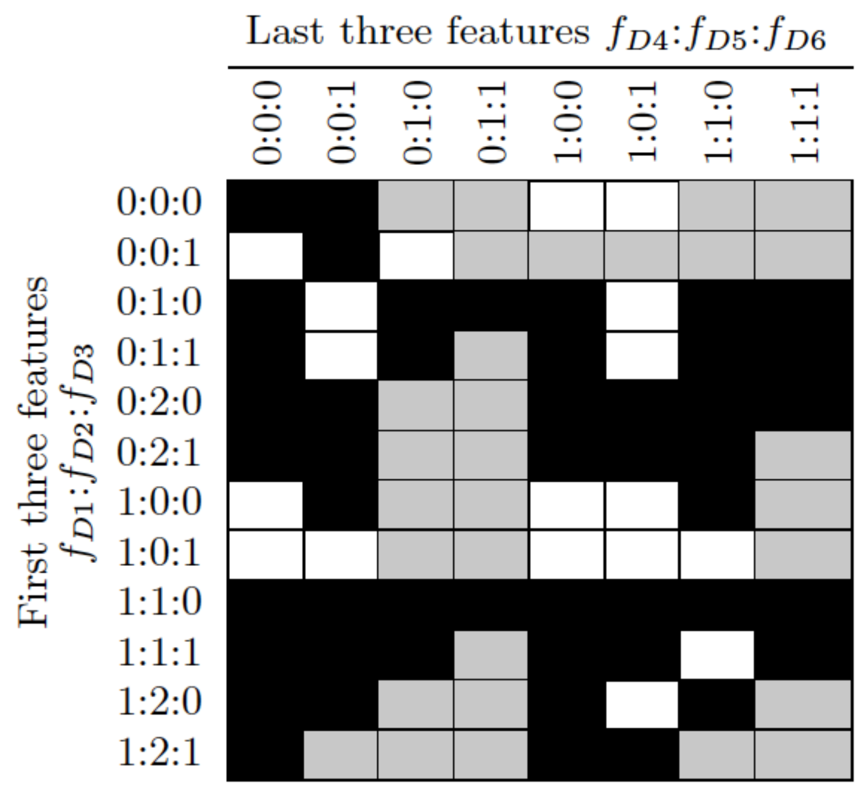
- States:
  - Level=1, probDiff=0, then state = ‘1:0’,
  - Level=2, probDiff=1, then state = ‘2:1’,
  - Level=3, probDiff=1, then state = ‘3:1’

Policy Example

```
Policy:
state -> action, value-function
1:0 -> WE, 36.2980141792
2:1 -> PS, 50.6234894691
3:-1 -> WE, 30.7327270058
4:1 -> PS, 38.0276536834
5:1 -> PS, 31.1271670497
6:1 -> PS, 38.7017874912
3:1 -> PS, 37.5870989962
2:-1 -> WE, 28.4686139413
4:-1 -> WE, 26.6276418488
5:-1 -> WE, 26.4065388562
6:-1 -> WE, 0.0
ECR value: 36.2980141792
```

Policy Visualization- For your Presentation





Policy 1

64 rules associated with WE (White)

21 rules associated with PS (Black)

43 no rules (Gray)

Policy 2

18 rules associated with WE

48 rules associated with PS

30 no rules

Demo

Q & A

Thank you !