ILP-based Reasoning for Weighted Abduction

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Introduction

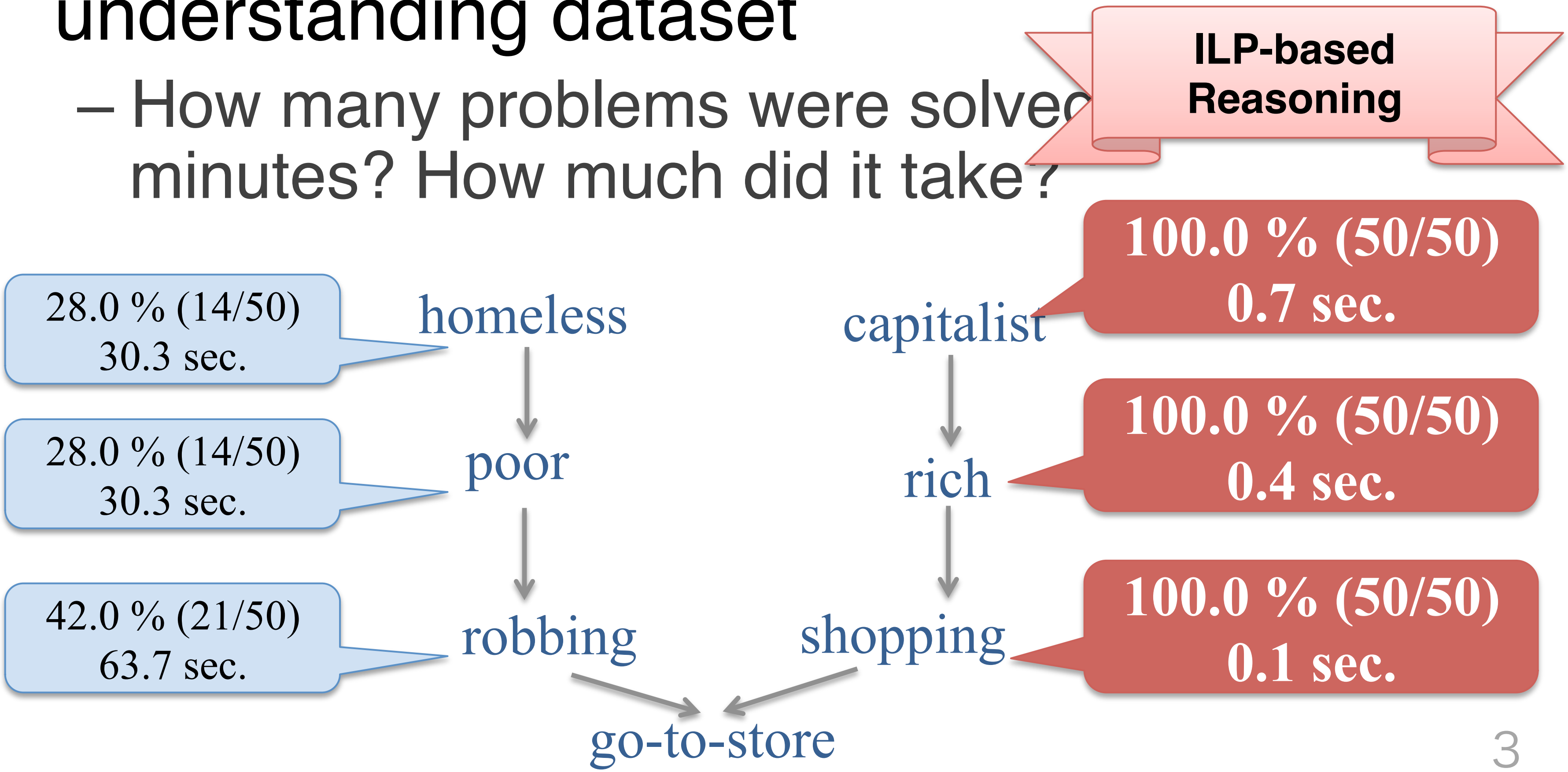
- **Goal:** Plan recognition from natural language texts

- Adopt abduction-based framework
  - Hobbs et al. (93)'s Weighted abduction

- No tools available for large-scale problem

Scalability Problem

- Experiments with Mini-TACITUS (Mulkar-Mehta 07) on Ng & Mooney (92)'s story understanding dataset
  - How many problems were solved in 2 minutes? How much did it take?



☑Introduction

☐Weighted Abduction

☐ILP-based Reasoning

☐Evaluation

Hobbs+ (93)'s Weighted Abduction

- Abduction-based framework of natural language understanding
- "Interpreting sentences is to prove the logical forms of the sentences."
  - Merging redundancies where possible
  - Making assumptions where necessary
- Important features
  - Best explanation is selected by assumability costs
  - Evaluating both likelihood and specificity appropriateness of the best explanation

Abduction

- Inference to the best explanation

robbing ⇒ go-to-store
shopping ⇒ go-to-store

shopping robbing

It's necessary to quantify
(i) likelihood of H
(ii) appropriateness of specificity of H

"go-to-store" is observed.

- Formally,

Given

Background knowledge: B
Observations: O

Find

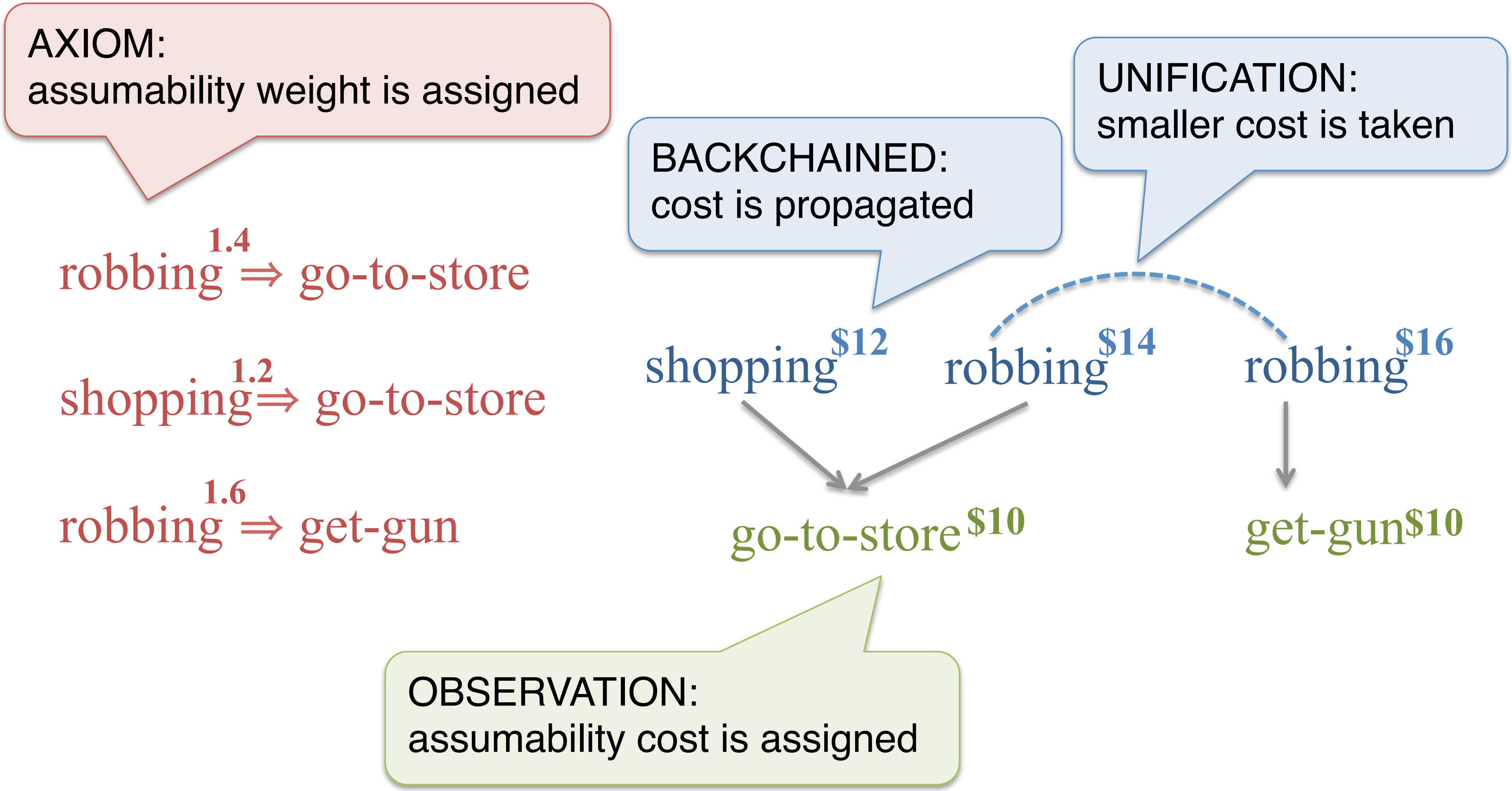
Hypothesis: H such that

$$H \cup B \models O$$

$$H \cup B \not\models \perp$$

B, O, H: sets of logical formulae

Scheme of Weighted Abduction



Background knowledge: B

robbing$^{1.2}$ $\rightarrow$ get-gun

robbing$^{1.5}$ $\rightarrow$ go-to-store

hunting$^{1.1}$ $\rightarrow$ get-gun

shopping$^{1.4}$ $\rightarrow$ go-to-store

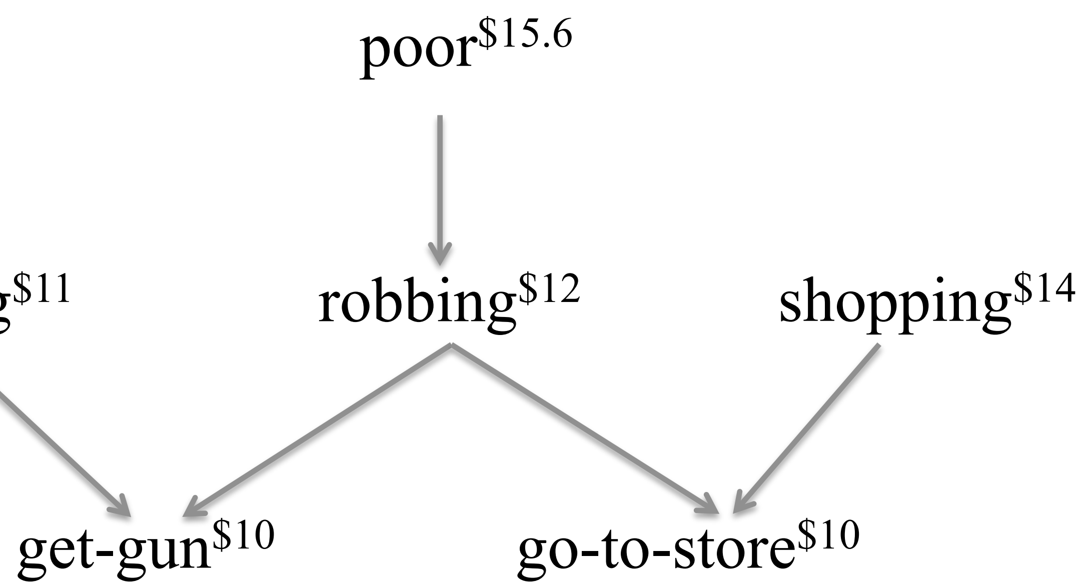
poor$^{1.3}$ $\rightarrow$ robbing

Hypothesis: H

{hunting$^{\$11}$, shopping$^{\$14}$}

{robbing$^{\$12}$}

{poor$^{\$15.6}$}



Observations: O

Background knowledge: B

$\text{robbing}^{1.2} \rightarrow \text{get-gun}$

$\text{robbing}^{1.5} \rightarrow \text{go-to-store}$

$\text{hunting}^{1.1} \rightarrow \text{get-gun}$

$\text{shopping}^{1.4} \rightarrow \text{go-to-store}$

$\text{poor}^{1.3} \rightarrow \text{robbing}$

Hypothesis: H

$\{\text{hunting}^{\$11}, \text{shopping}^{\$14}\}$

$\{\textbf{robbing}^{\$12}\}$

$\{\text{poor}^{\$15.6}\}$

:

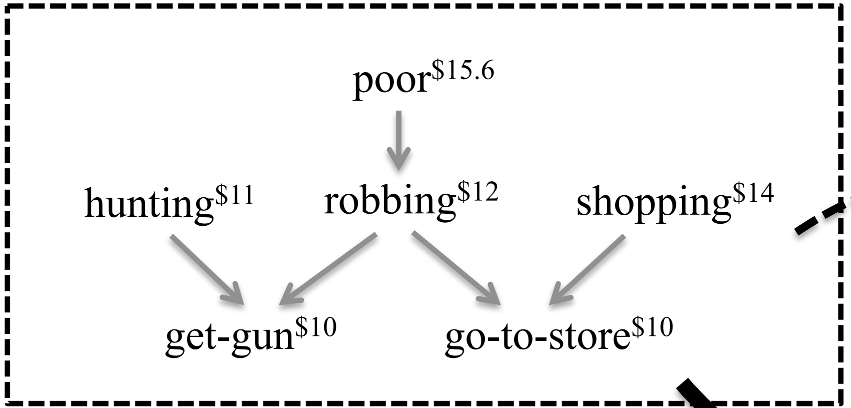
lanation is least-cost explanation

te specificity is selected

Implementation Issue:

The combinatorial explosion of candidate hypotheses.

Observations: O $\text{get-gun}^{\$10}$ $\text{go-to-store}^{\$10}$



Naive approach

H_1 = {robbing$^{\$12}$}
H_2 = {poor$^{\$15.6}$}
H_3 = {hunting$^{\$11}$, shopping$^{\$14}$}
⋮

$$\arg\min_i C(H_i)$$

$$C(H_i) = \sum_{h \in H_i} c(h)$$

Our solution: ILP-based Reasoning

Key ideas:

- Assign 0-1 ILP variables over all literals potentially included in the best hypothesis for representing candidate hypotheses

$$h_{get\text{-}gun}\ \ h_{hunting}\ \ h_{robbing}, \cdots$$
$$r_{get\text{-}gun}\ \ r_{hunting}\ \ r_{robbing}, \cdots$$
$$u_{robbing1,robbing2} \cdots$$

- Cost of hypothesis is represented as the sum of variables

$$C(H) = 10 \cdot h_{get\text{-}gun} + 11 \cdot h_{hunting}, \cdots$$

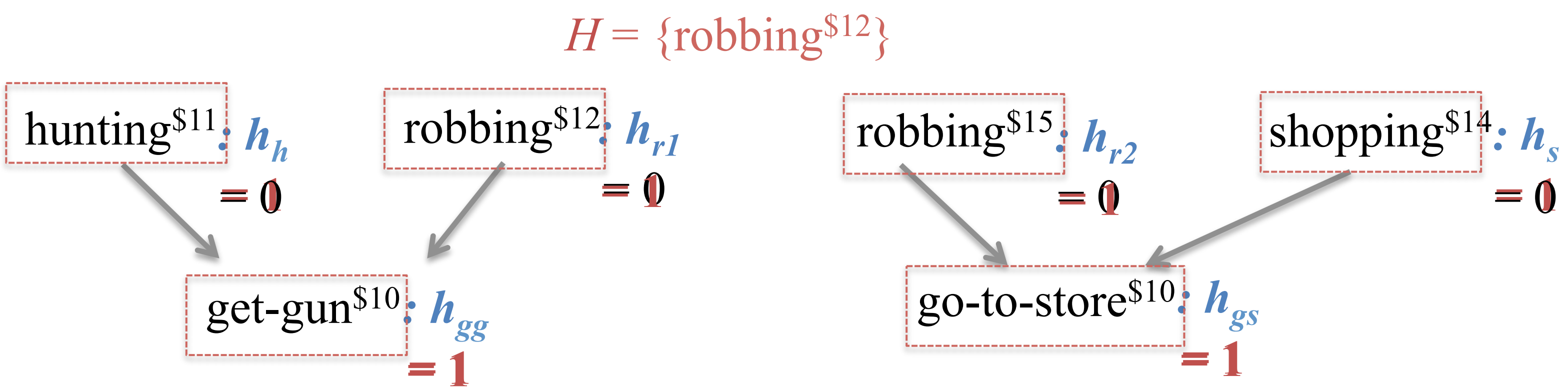
- There is efficient algorithms to find the optimal assignment of variables

$$\arg\min_{h_{get-gun}, h_{hunting}, \cdots} C(H)$$

ILP formulation (h → r → u)

$$\arg\min_{h} \sum_{p \in \{p | p \in P, h_p = 1\}} c(p)$$

- P: set of literals potentially included in hypothesis
- h_p: 1 if literal p is included in hypothesis

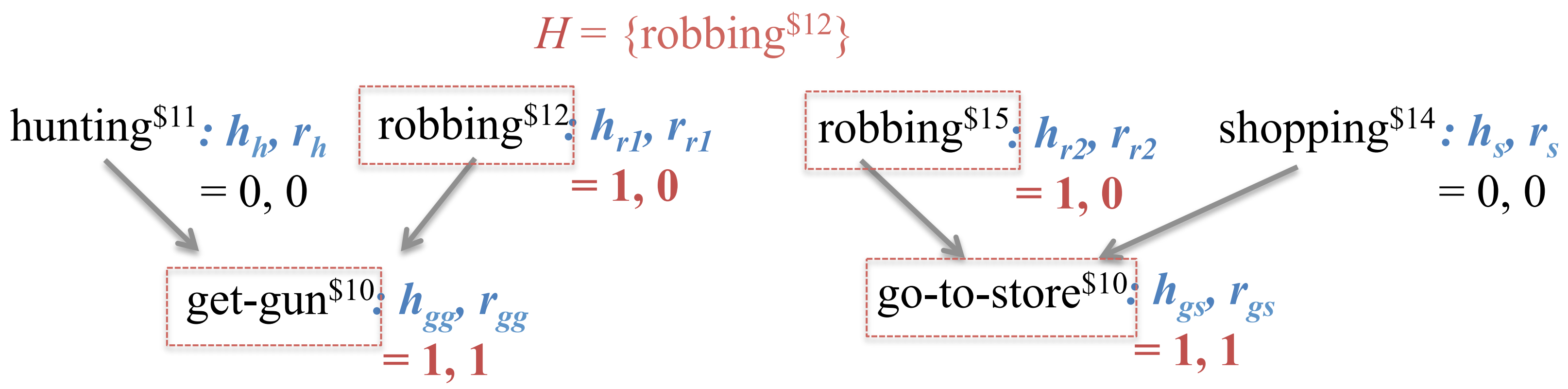


P = {get-gun, go-to-store, hunting, robbing1, ...}

ILP formulation (h → r → u)

$$\arg\min_{h,r} \sum_{p\in\{p|p\in P, h_p=1, \underline{r_p=0}\}} c(p)$$

- P: set of literals potentially included in hypothesis
- h_p: 1 if literal p is included in hypothesis
- r_p: 1 if literal p doesn't pay its cost



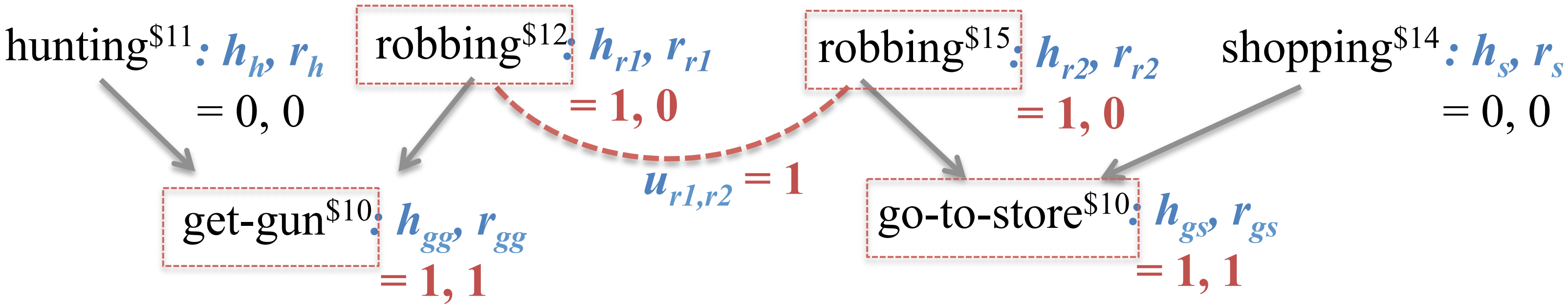
P = {get-gun, go-to-store, hunting, robbing1, ...}

ILP formulation (h → r → u)

$$\arg\min_{h,r} \sum_{p \in \{p | p \in P, h_p = 1, r_p = 0\}} c(p)$$

- P: set of literals potentially included in hypothesis
- h_p: 1 if literal p is included in hypothesis
- r_p: 1 if literal p doesn't pay its cost
- $u_{p,q}$: 1 if literal p is unified with literal q

$H = \{\text{robbing}^{\$12}\}$



$P = \{\text{get-gun, go-to-store, hunting, robbing1, ...}\}$

ILP Constraints

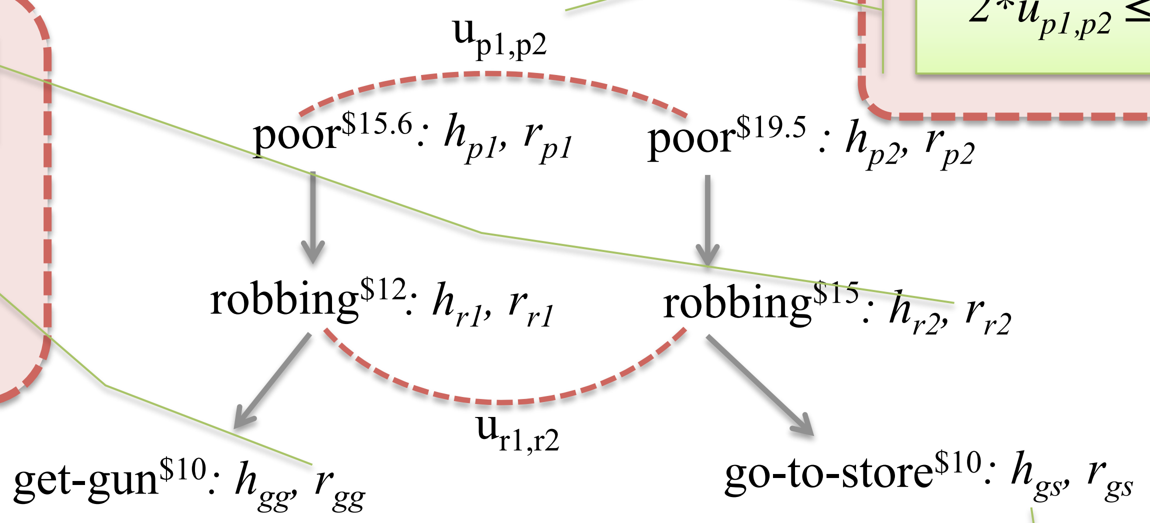
Literals do not pay cost (r=1) only if they are
(i) explained by another literal (h=1), or
(ii) unified with another literal (u=1) of lesser cost

$r_{r2} \leq h_{p2} + u_{r1,r2}$

$r_{gg} \leq h_{r1}$

Literals can be unified (u=1) only if they are hypothesized (h=1)

$2 * u_{p1,p2} \leq h_{p1} + h_{p2}$



Literals in observations must be included in a hypothesis

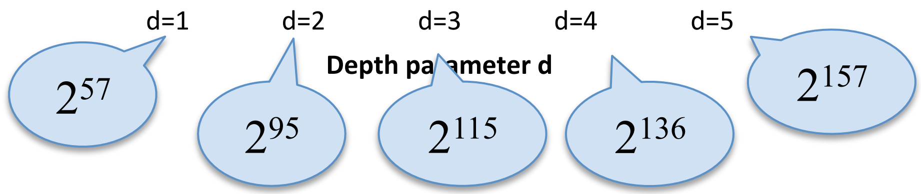
$h_{gs} = 1$

Evaluation

- How scalable is our approach?
  - Plotted (depth, inference time)
    - The depth limit of back-chaining
    - Inference time averaged for all problems

- Dataset
  - 50 problems in Ng & Mooney (92)'s story understanding corpus

Results



- The increase of inference time is not exponential to the number of candidate hypotheses
- ➢ Indicates the efficiency of our approach!

Summary

- Addressed the issue of scalability for abductive reasoning
- Proposed ILP-based approach to Hobbs et al. (93)'s weighted abduction
- Results of our experiments showed that:
  - our approach efficiently finds the best explanation
- Future work
  - Exploring the semantics of weights, costs
  - To handle negation in ILP-based approach

THANK YOU!