Applying Markov Logics for Controlling Abox Abduction

Dissertation Presentation

Anahita Nafissi

Chairman: Prof. Gollmann

Reviewers: Prof. Möller, Prof. Neumann

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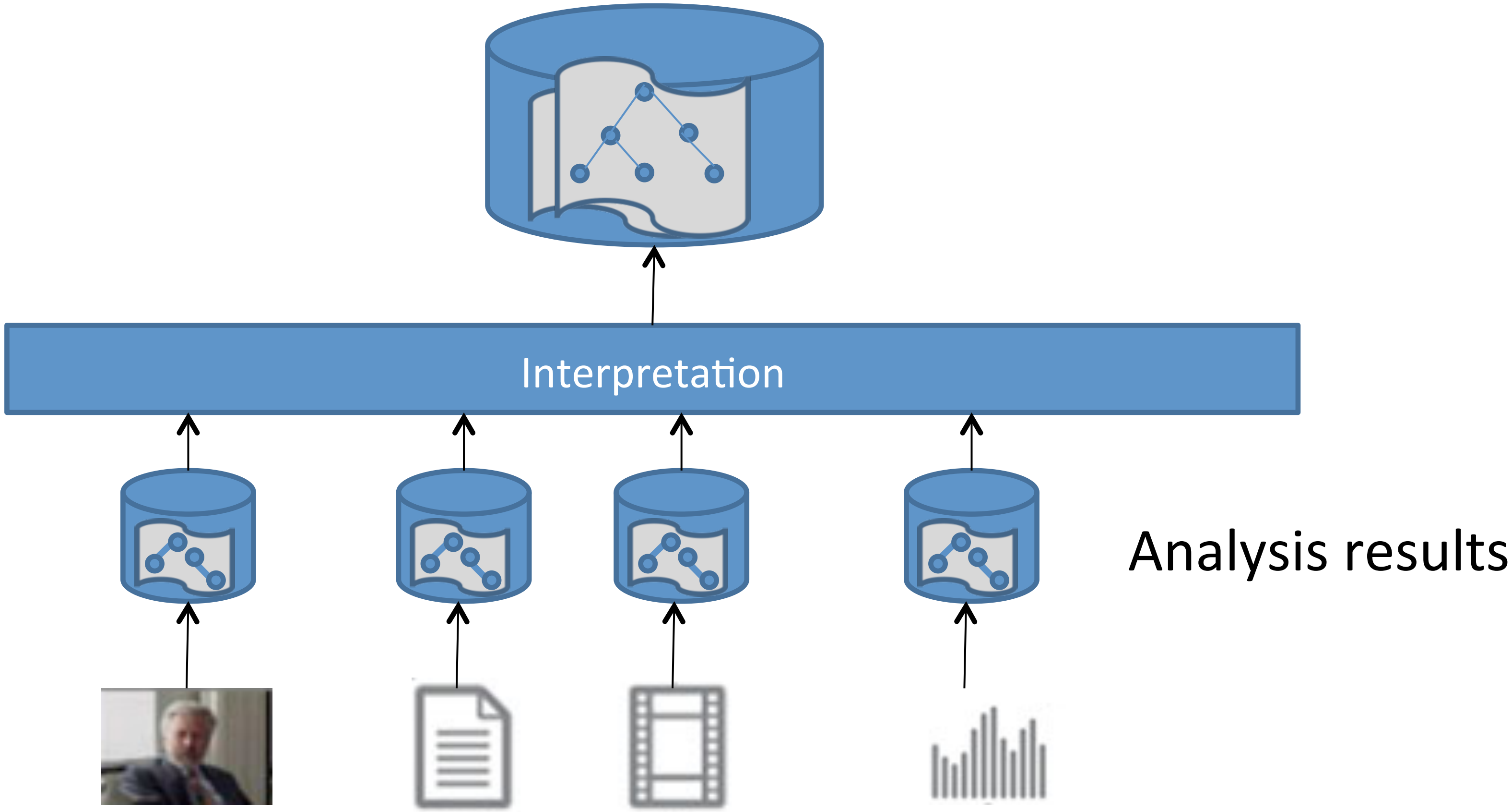
Symbolic Descriptions of Multimedia Documents



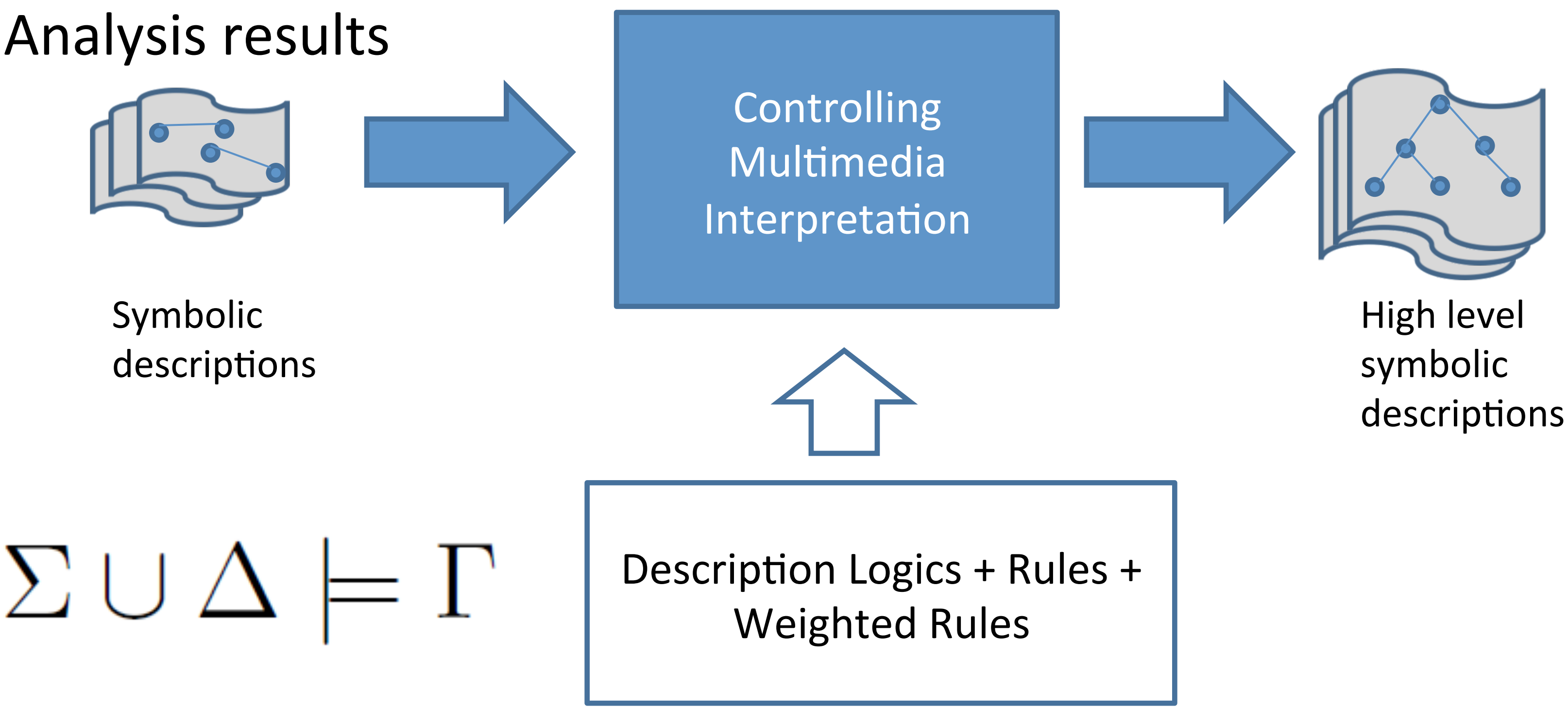
Agenda

- Motivation, research objectives, advances
- My approach in detail
- Evaluation
- Summary and outlook

State of the Art

- Kowalski
  - Abductive logic programming
- Espinosa, Kaya, Möller
  - Abduction as a formalization of interpretation
- Bohlken, Neumann
  - Interpretation operators, beam search, probabilistic ranking

Contribution

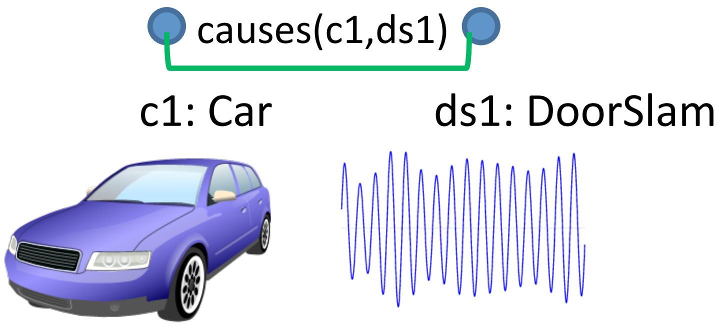


$$\Sigma \cup \Delta \models \Gamma$$

- Abduction: Resoning from observations to explanations
- **Controlling the abduction process in terms of branching and depth**

Interpretation Example

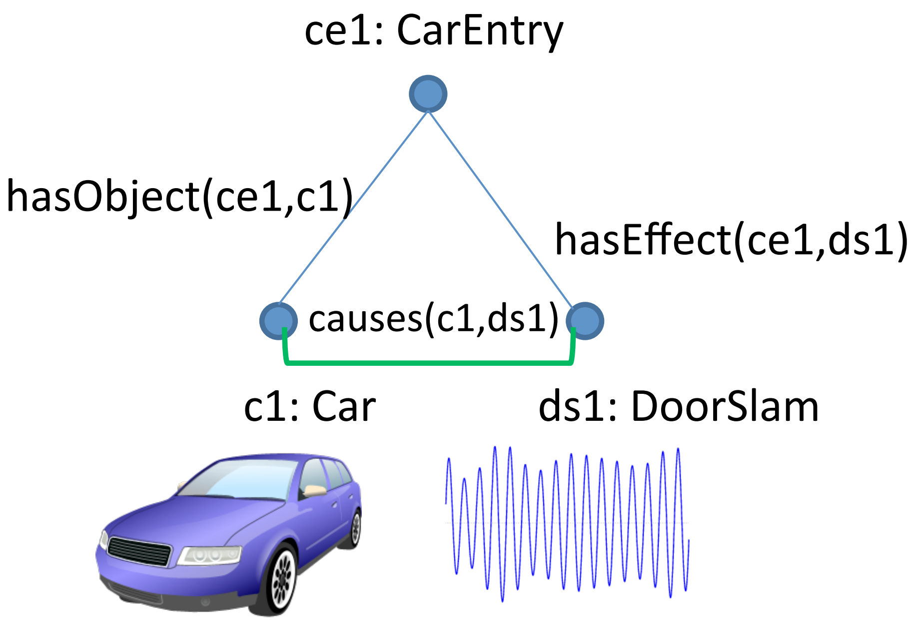
$$\forall x, y \; causes(x,y) \;\leftarrow\; \exists z \; CarEntry(z), hasObject(z,x), hasEffect(z,y), Car(x), DoorSlam(y)$$

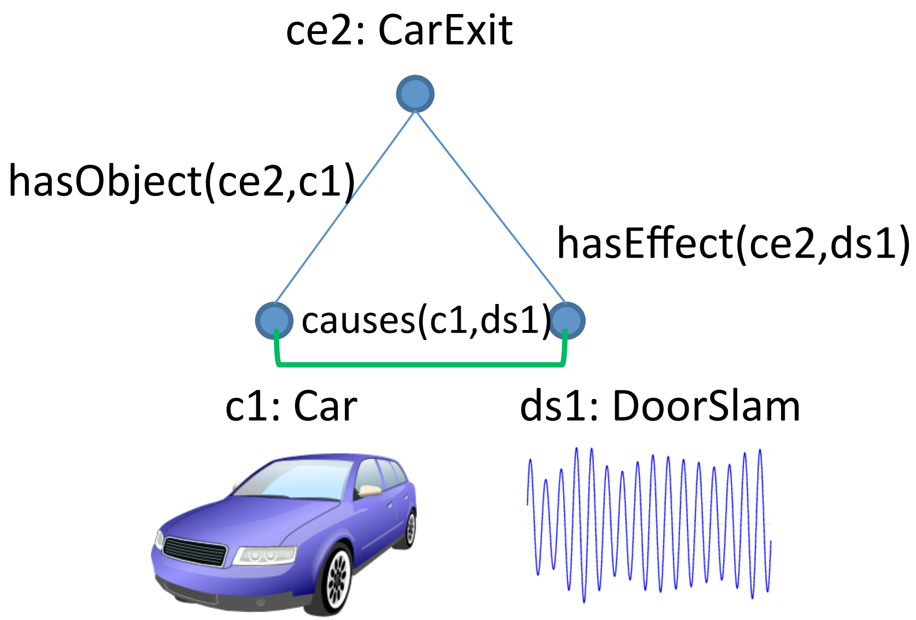


Interpretation Example Continued

$$\forall x, y\ causes(x,y) \ \leftarrow\ \exists z\ CarEntry(z), hasObject(z,x),\ hasEffect(z,y), Car(x), DoorSlam(y)$$

$$\forall x, y\ causes(x,y) \ \leftarrow\ \exists z\ CarExit(z), hasObject(z,x),\ hasEffect(z,y), Car(x), DoorSlam(y)$$





Consequence: Branching!

Markov Logic Network

A Markov Logic network $MLN = (\mathcal{F}_{MLN}, \mathcal{W}_{MLN})$ consists of a sequence of first order formulas $\mathcal{F}_{MLN} = \langle F_1, ..., F_m \rangle$ and a sequence of weights $\mathcal{W}_{MLN} = \langle w_1, ..., w_m \rangle$

$$0.5 \ \forall x \ \ CityWithTrafficJam(x) \Rightarrow CityWithAirPollution(x)$$
$$0.5 \ \forall x \ \ CityWithIndustry(x) \Rightarrow CityWithAirPollution(x)$$

$$P(\vec{X} = \vec{x}) = \frac{1}{Z} exp\left(\sum_{i=1}^{|\mathcal{F}_{MLN}|} w_i n_i(\vec{x}) \right)$$

$$Z = \sum_{\vec{x} \in \vec{X}} \exp\left(\sum_{i=1}^{|\mathcal{F}_{MLN}|} w_i n_i(\vec{x}) \right)$$

Example for MLN

$$0.5\ \forall x\ CityWithTrafficJam(x) \Rightarrow CityWithAirPollution(x)$$
$$0.5\ \forall x\ CityWithIndustry(x) \Rightarrow CityWithAirPollution(x)$$

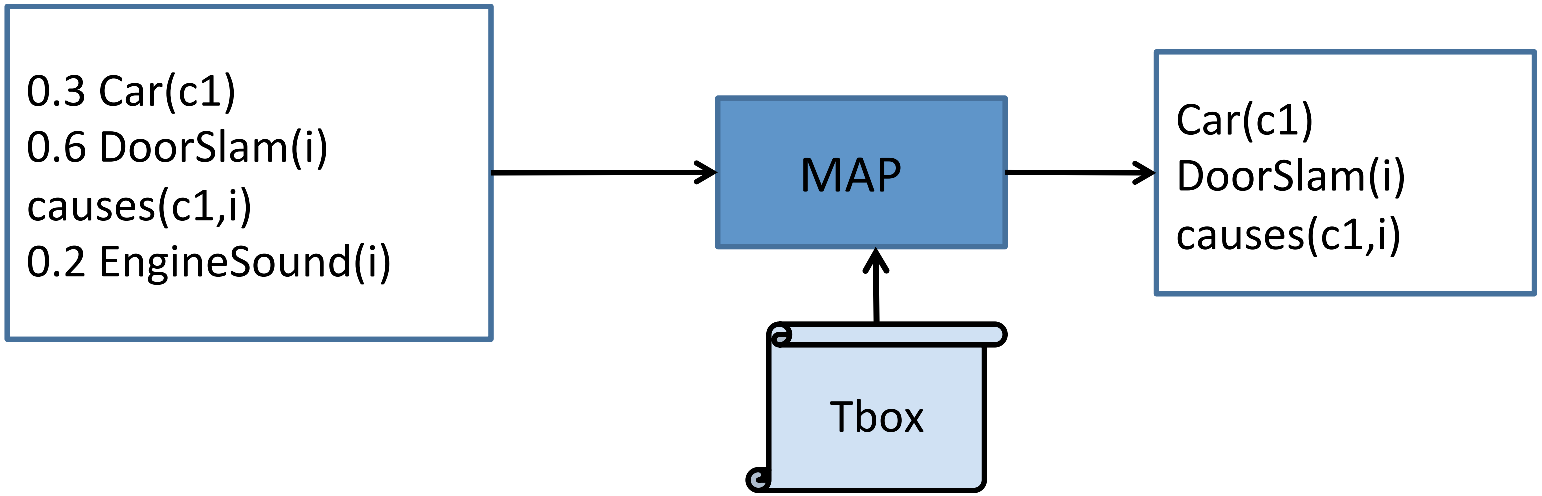
Assume: *CityWithIndustry(h)=true*
Constant: *h*

$Worlds\ W_i$	$CWTJ(h)$	$CWAP(h)$	$CWI(h)$	$P(W_i)$
W_1	0	0	1	$\exp(0.5)/Z = 0.20$
W_2	0	1	1	$\exp(1)/Z = 0.34$
W_3	1	0	1	$1/Z = 0.12$
W_4	1	1	1	$\exp(1)/Z = 0.34$

Alchemy System

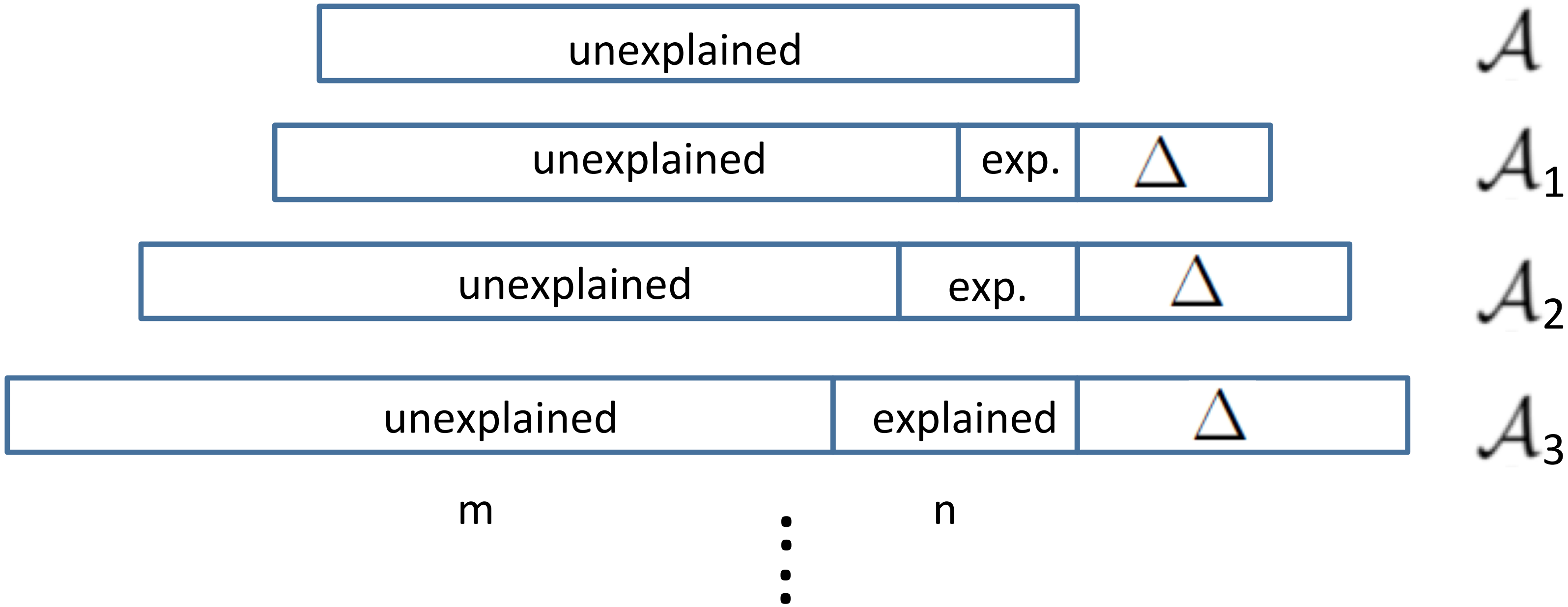
$$Z = 1 + 2 \times \exp(1) + \exp(0.5)$$

Handling Uncertain Data



Consequence: Branching!

Controlling the Interpretation Process

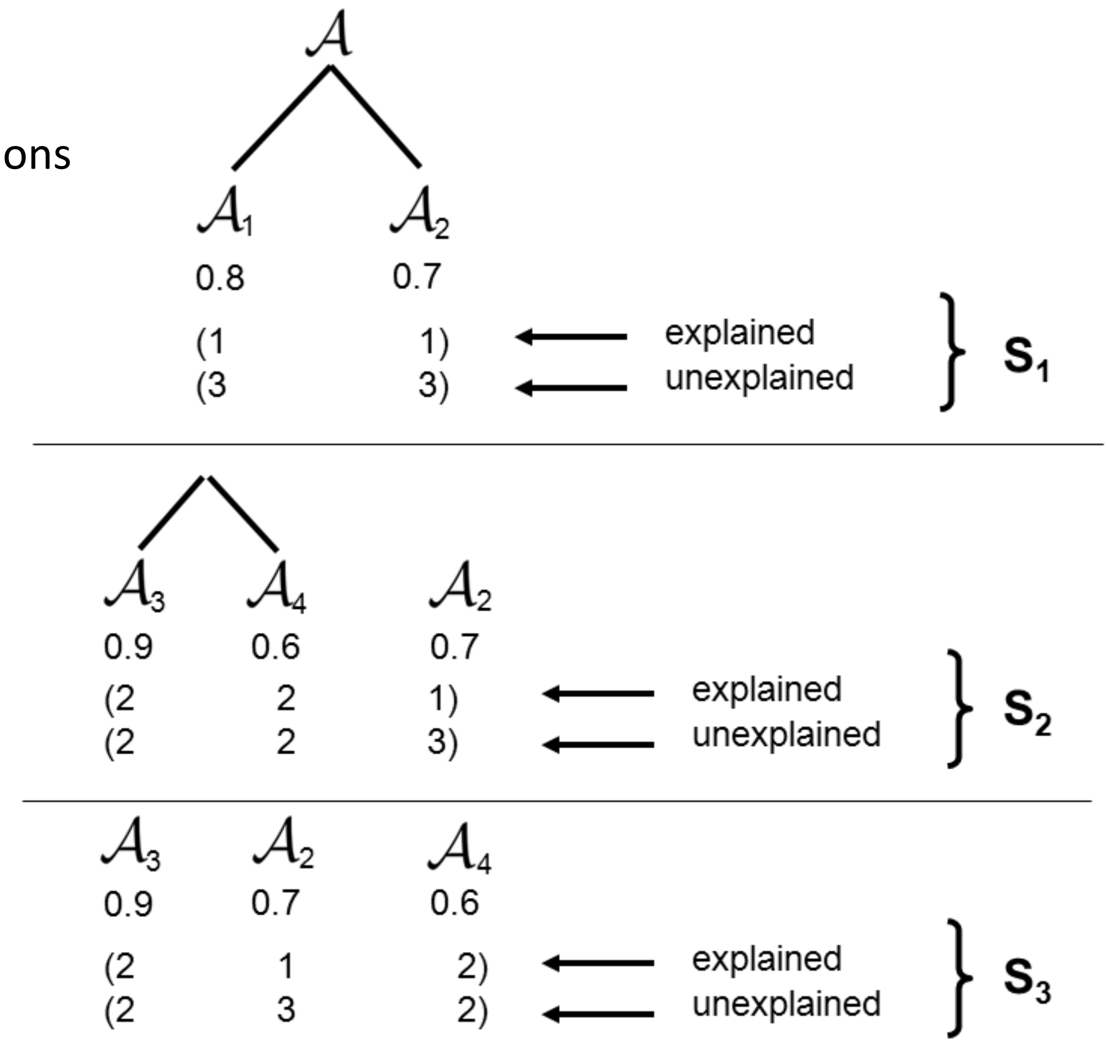


$$P(\mathcal{A}, \mathcal{WR}) = \frac{1}{n+m}\left(m \times 0.5 + \sum_{i=1}^{n} P_{MLN(\mathcal{A},\mathcal{WR})}(Q_i(\mathcal{A}) \mid \vec{e}(\mathcal{A}))\right)$$

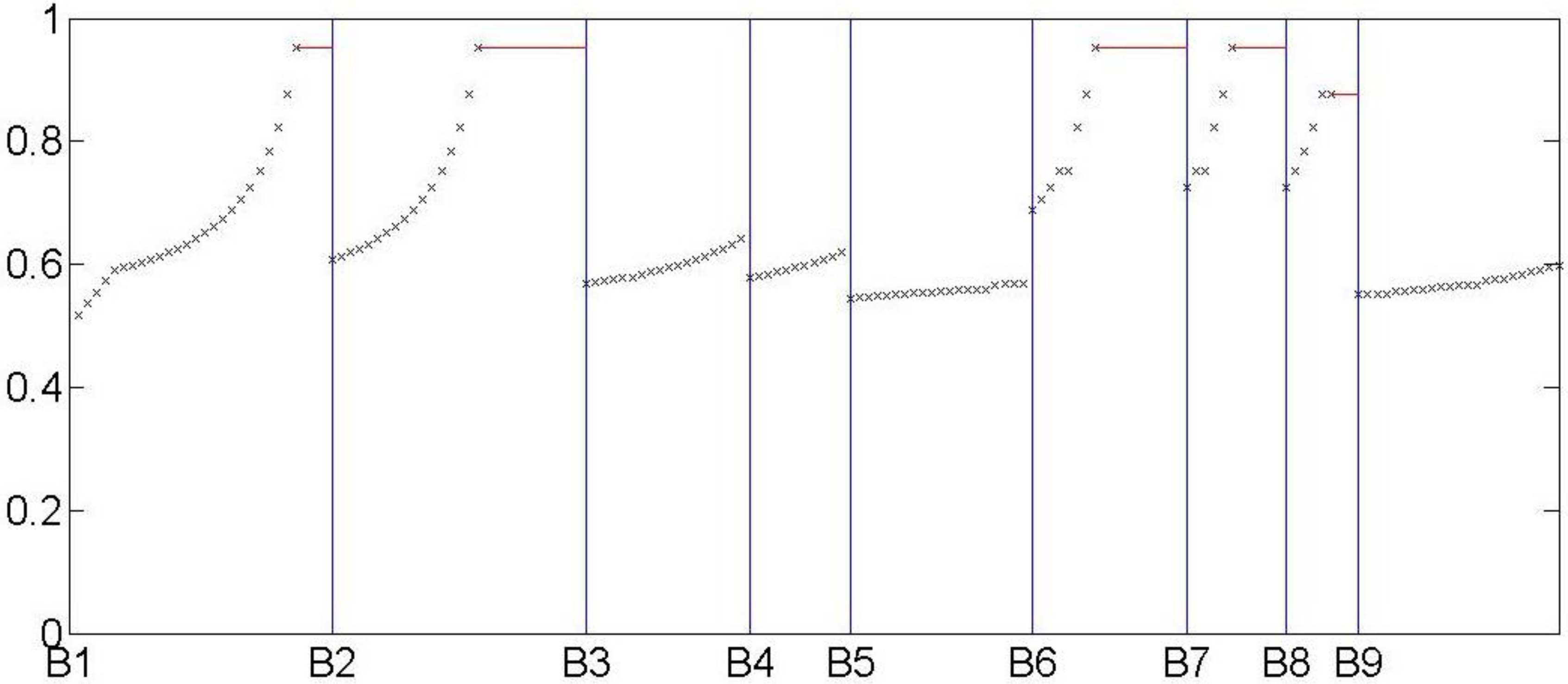
m = Number of unexplained observations
n = Number of explained observations

Interpretation Controlling Example

Assume 4 observations
Depth = 2



Development of the P-Score

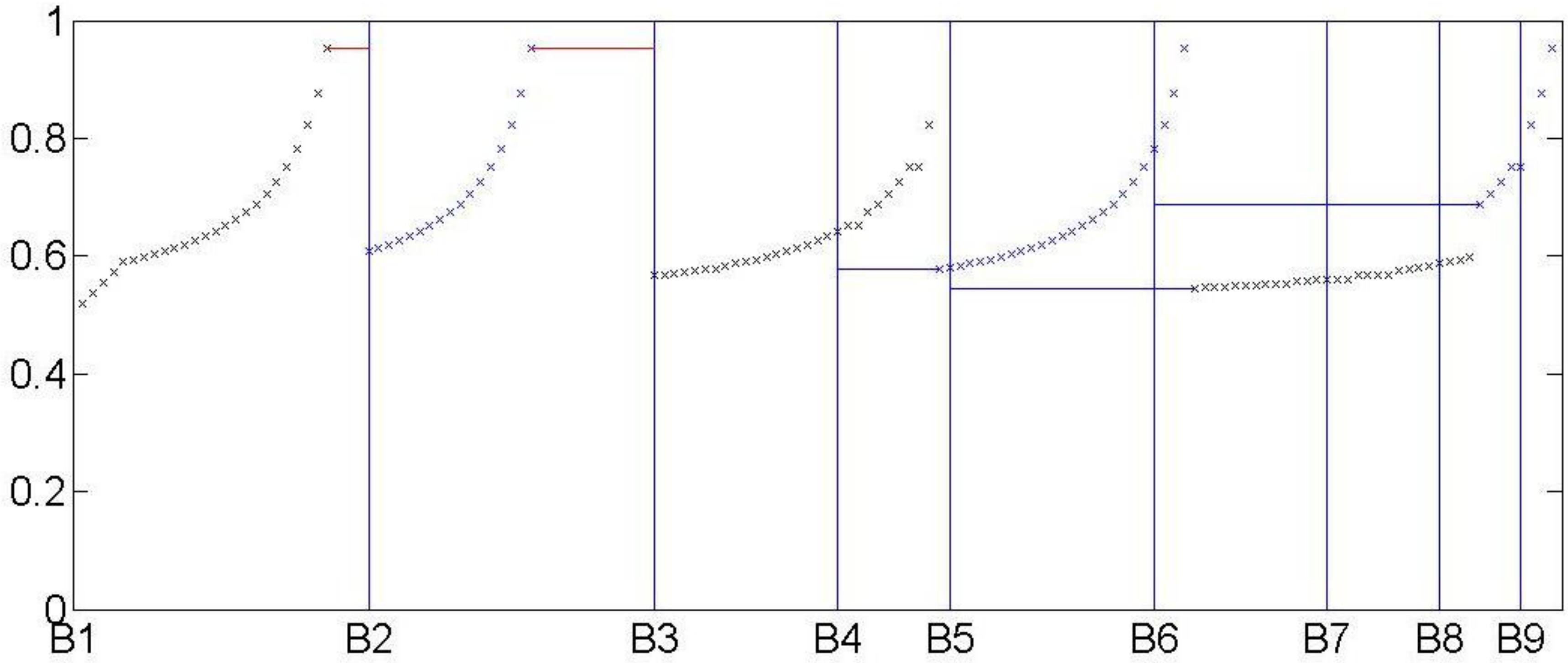


x = time axis indicated with arrival time of bunches
y = scoring value of the interpretation Abox
(Strategy : Stop-Processing)

Controlling the Interpretation Process

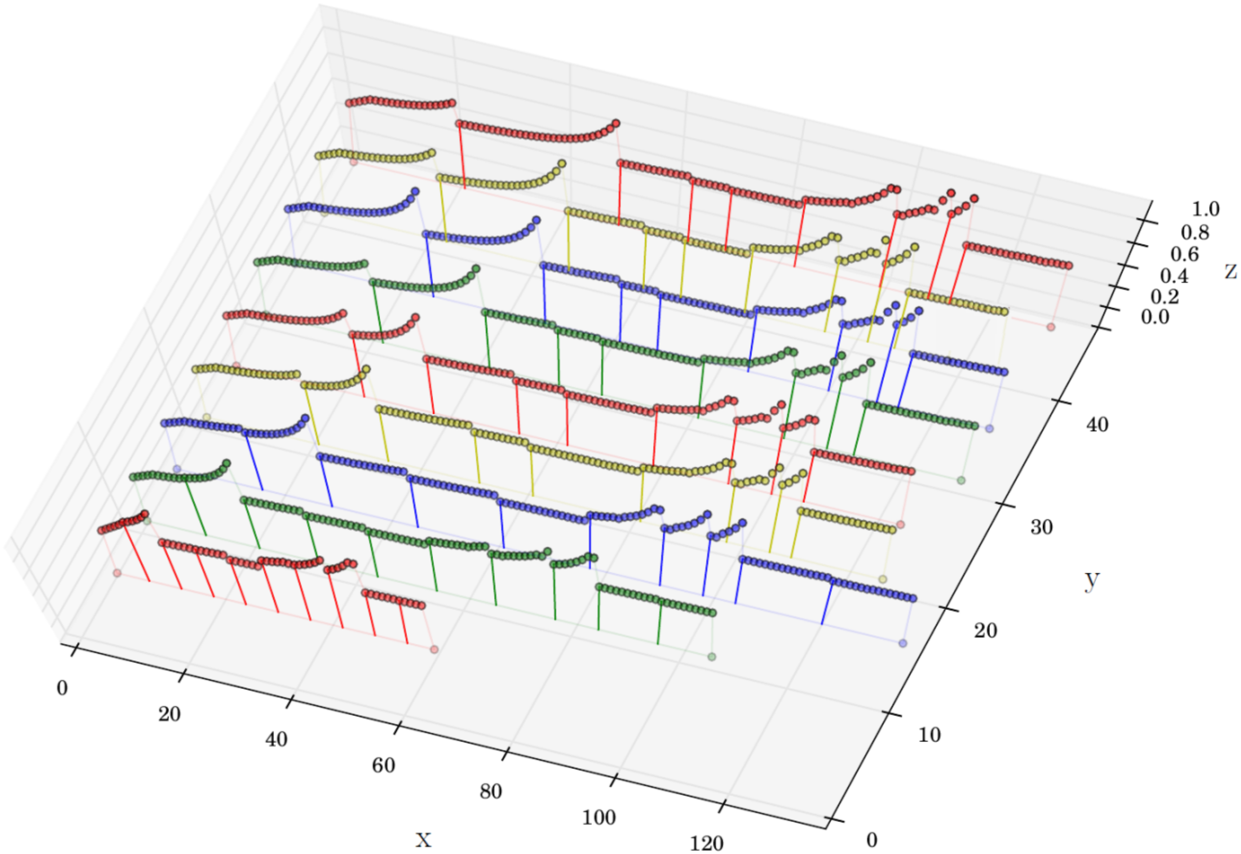
- Controlling branching (beam Search)
- Controlling abduction depth
- Controlling reactivity

Increasing the Score by Explaining Observations



x = time axis indicated with arrival time of bunches
y = scoring value of the interpretation Abox
(Strategy : Non-Stop-Processing)

Increasing the Score by Explaining Observations



x = time spent for explaining observations

y = number of observations to be explained in a bunch

z = scoring value

Summary

- Deal with uncertain and inconsistent observations
- Rank interpretation alternatives probabilistically
- Control the abduction process in terms of branching and depth
- Incrementally process the input data
- Increase the rank of interpretation alternatives monotonically by successively explaining observations.

Outlook

- Determine the maximum depth adaptively
- Learn the weights of the weighted rules
- Fuse interpretations of segments

Publications

Conference Papers

- O. Gries, R. Möller, A. Nafissi, M. Rosenfeld, K. Sokolski, and M. Wessel. A Probabilistic Abduction Engine for Media Interpretation based on Ontologies. *In Proceedings of 4th International Conference on Web Reasoning and Rule Systems (RR-2010),* September 2010.

Workshop Papers

- O. Gries, R. Möller, A. Nafissi, M. Rosenfeld, K. Sokolski, and M. Wessel. A Probabilistic Abduction Engine for Media Interpretation based on Ontologies. *In Proceedings of the International Workshop on Uncertainty in Description Logics (UnIDL-2010),* 2010.