Supervised Learning to Control Energetic Reasoning : Feasibility Study

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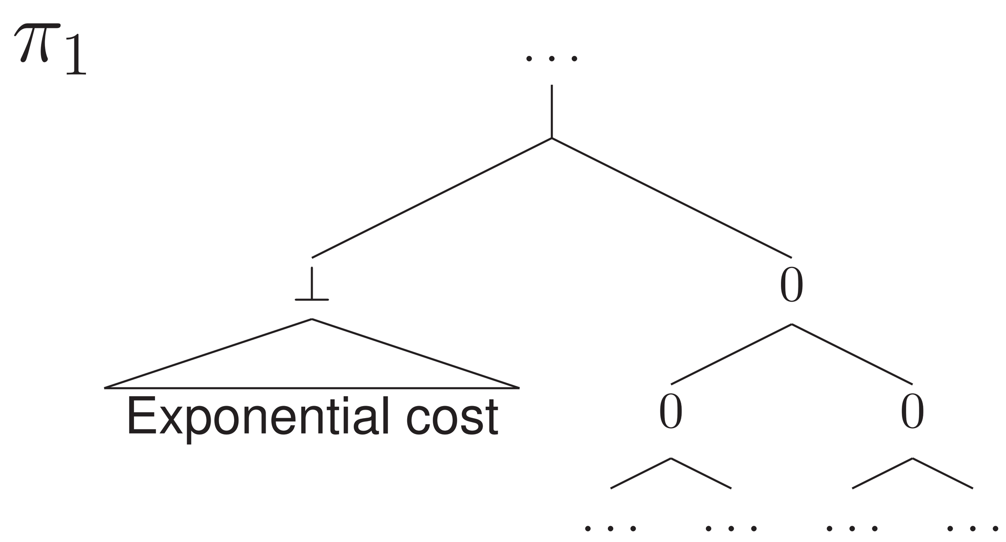
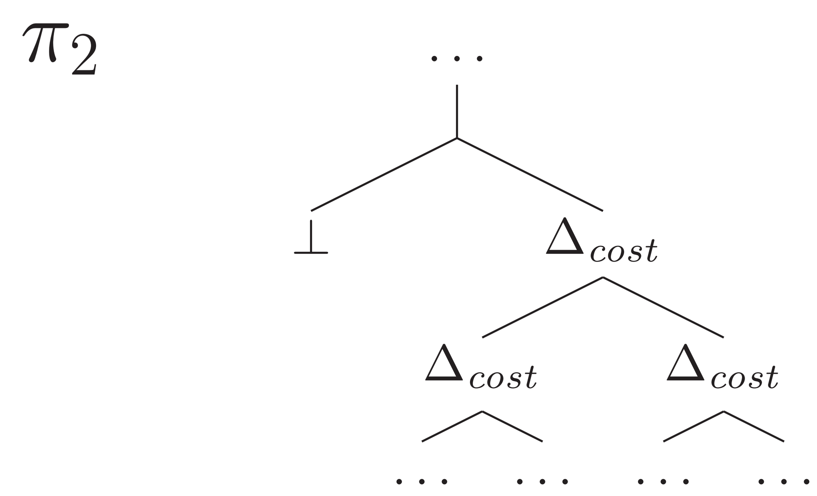
Motivation : Exponential gain from a smart use of costly and powerful propagators

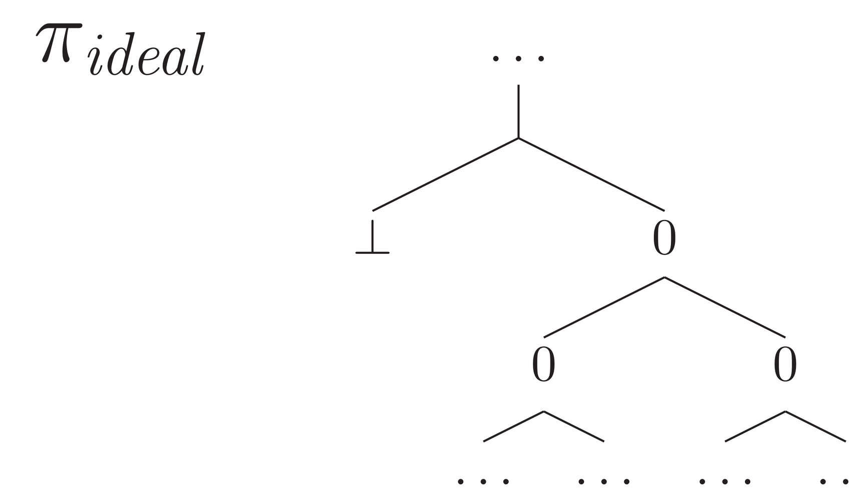
Propagators π_1 and π_2 with $cost_{\pi_2} >= cost_{\pi_1}$ and $inference_{\pi_2} >= inference_{\pi_1}$



Potential exponential gain with π_2 when $inference_{\pi_2} > inference_{\pi_1}$



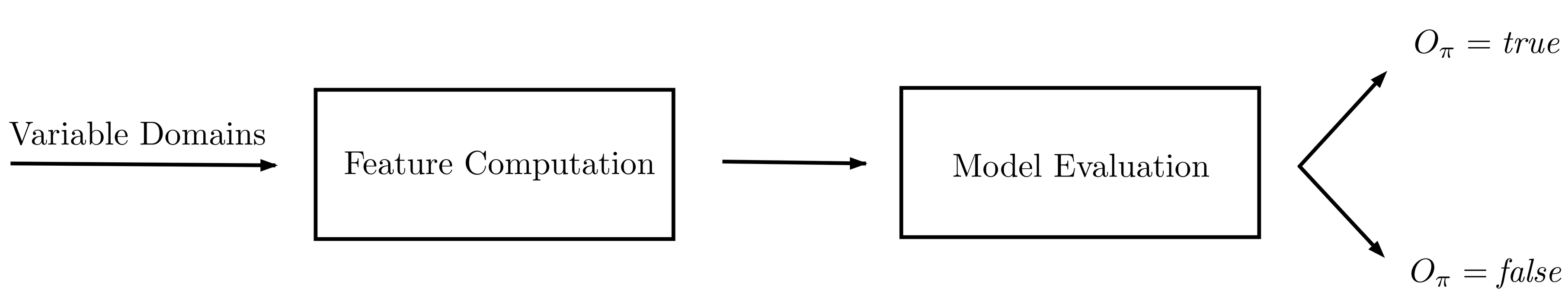
Overhead of Δ_{cost} on exponential number of nodes when $cost_{\pi_2} > cost_{\pi_1}$ and $inference_{\pi_2} = inference_{\pi_1}$



Avoid exponential cost from search exploration and cumulative overhead

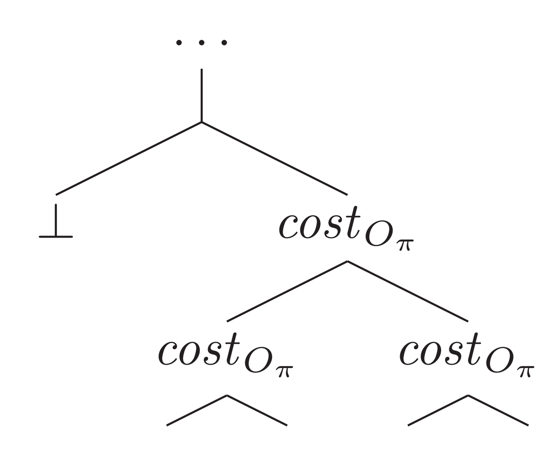
Oracle Estimator

$$O_{\pi_c}(D_i | x_i \in S(c)) = \begin{cases} true \text{ if some value will be pruned} \\ false \text{ otherwise} \end{cases}$$



- Oracle estimated using Machine Learning
- Feature computation and model evaluation must be cheap

Post Fix Point Prodecure



- $cost_{O_\pi} < \Delta_{cost}$
- After initial fix point, O_π is consulted until a new fix point is reached

Case Study : Energetic Reasoning

- Energetic Reasoning (ER) : propagator for the cumulative constraint.

$$\forall t = 0..eoh \sum_{s_i \le t < s_i + d_i} r_{ik} \le cap_k$$

- High time complexity ($\mathcal{O}(n^3)$) but more inferences than most other propagators.

  $\rightarrow$ used only if $O_{ER}(D_i) = true$ to keep higher inference and reduce time.

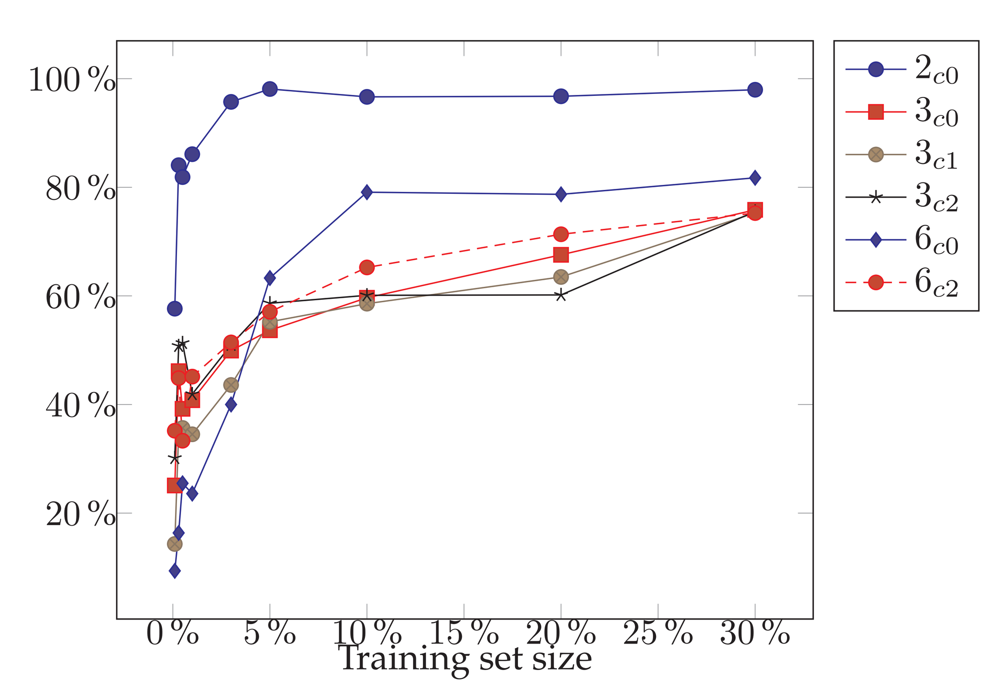
- π_1 : TimeTabling ($\mathcal{O}(n^2)$), π_2 : ER
- Feature example : *average domain tightness* ($\mathcal{O}(n)$)

$$\frac{1}{H.n} \sum_{i=1}^{n} lst_i - est_i$$

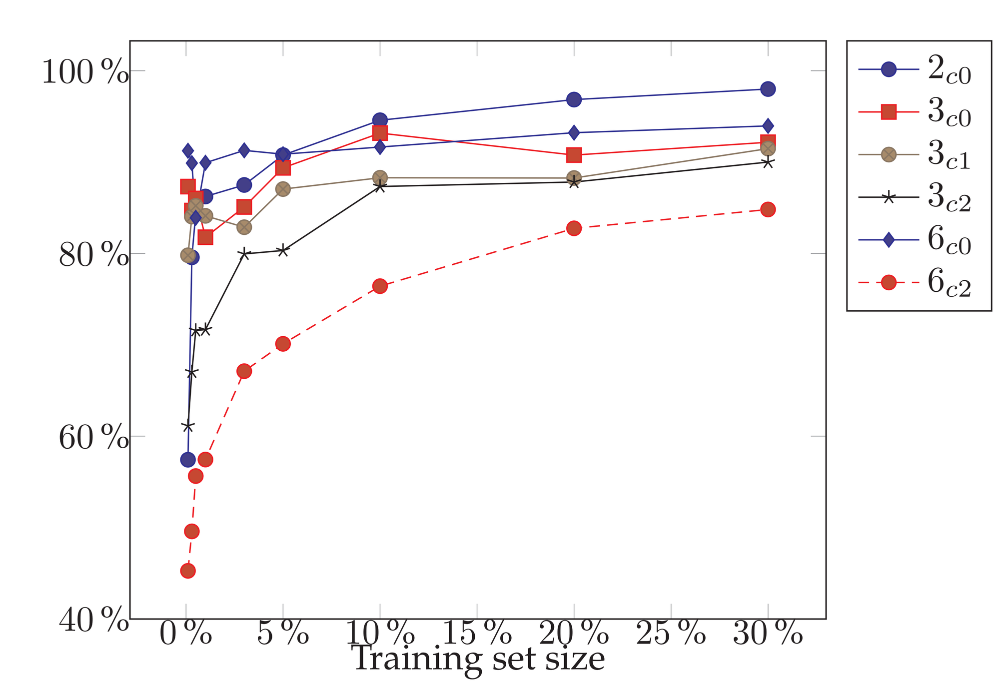
where H is the current horizon.

Good Prediction can be performed

- Training set : random subset of nodes in a search tree where
  - ER is applied with a probability 0.5
  - Binary lexicographic branching
- Test set : complete search tree where O_π are used
- BL instances (A_{cB} is cumulative number B of instance number A)



True Positive Rates



True Negative Rates

Current work

- Identify instances where the approach can be beneficial
  - π_2 must prune more at *"critical"* nodes
  - Cumulative Δ_{cost} must be significant
- Embed the approach to solve actual problems faster

Future work

- Prediction performances must take the *"benefit in time"* of a node into account
  - E.g., *depth* of a node.
- If a subtree can be explored faster with π_1 than with π_2 but still $O(\pi_2) = true$, we should use π_1 (other kind of prediction).

References

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