Two Learning Operators for Clause Selection Guidance: An Experimental Evaluation

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Machine Learning Boosted Automated Theorem Proving

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- "selecting the proof clauses" intuition

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What are the differences? What is the same? Which one is better?

Outline

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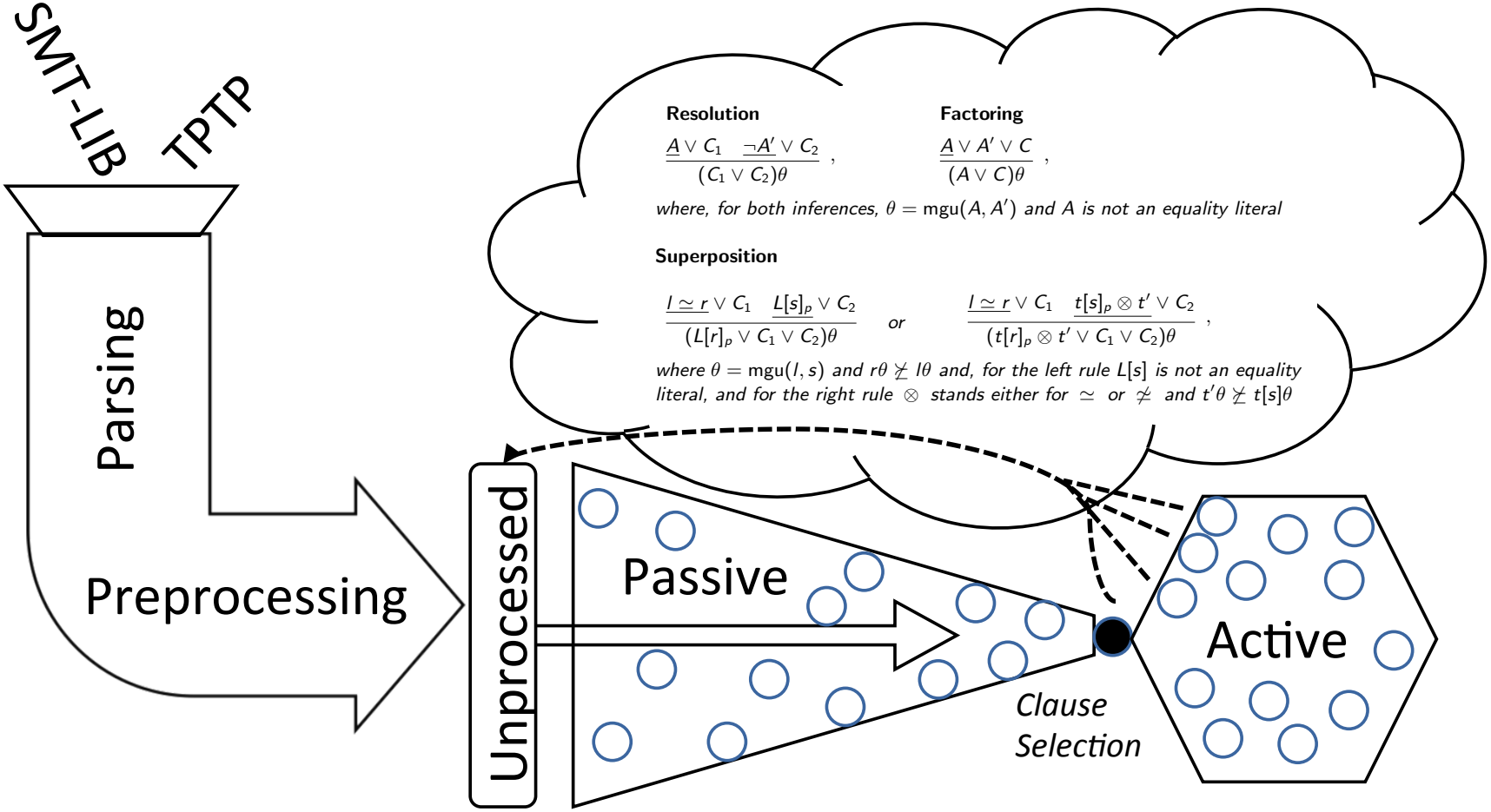
Saturation-based Theorem Proving



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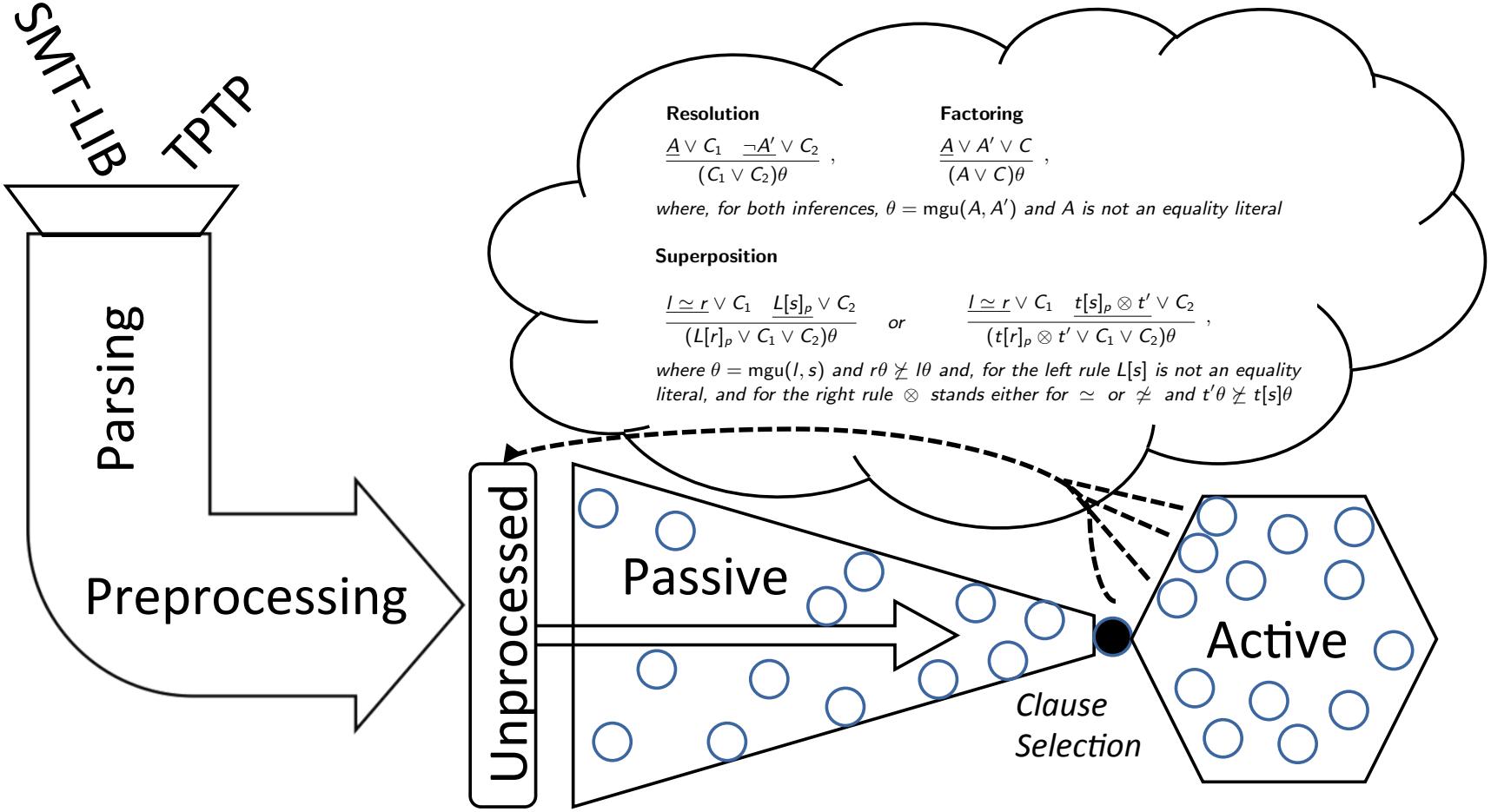

At a typical successful end: $|Passive| \gg |Active| \gg |Proof|$

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Take simple clause evaluation criteria:

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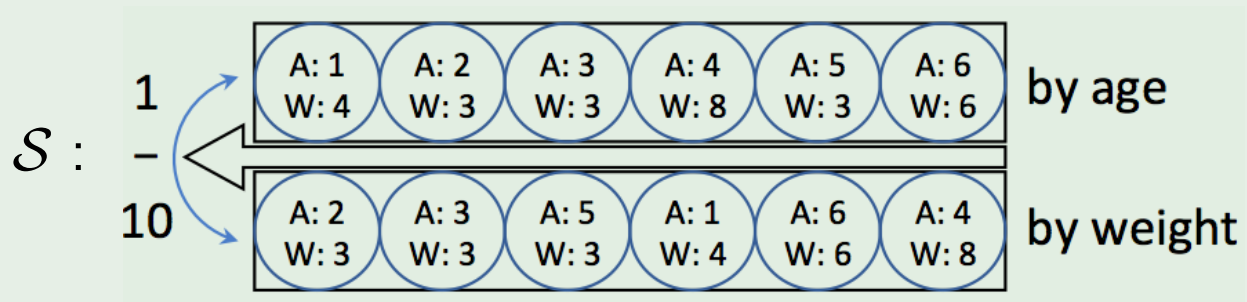
Example (Organizing *Passive* via two priority queues)



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ENIGMA-style

The core idea

Learn to recognize and prefer for selection clauses that look like those that contributed to a proof in past successful runs.

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- represent those clauses somehow (features, NNs, ...)
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Possible Ways of Integrating the Learnt Advice

Priority:

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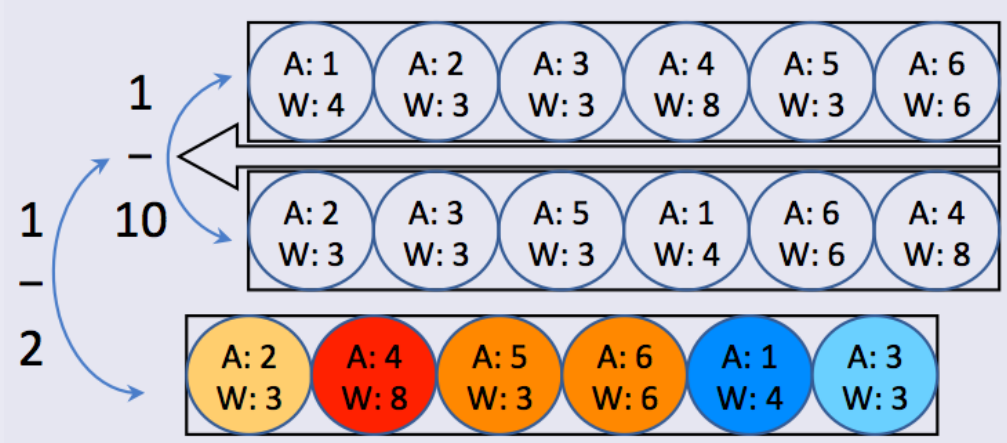
Combine with the original strategy

$\mathcal{S} \oplus \mathcal{M}^{1,0}$:



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➥ TRAIL [Crouse et al.'21], [McKeown'23], [Shminke'23], ...

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- for $q_\pi(s,C)$ we simply pick $\mathbb{I}_{\text{Did } C \text{ show up in the found proof?}}$

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Integrating the learned advice:

- ENIGMA-style: combine with your original heuristic
- RL-inspired: one queue sorted by the predicted scores

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Model:

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Iterative improvement:

- Both: yes (ENIGMA calls it "looping")

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Architecture

- simple clause features: age, weight, pos/neg-length, justEq/justNeq, varOcc, goalDist, numSplits
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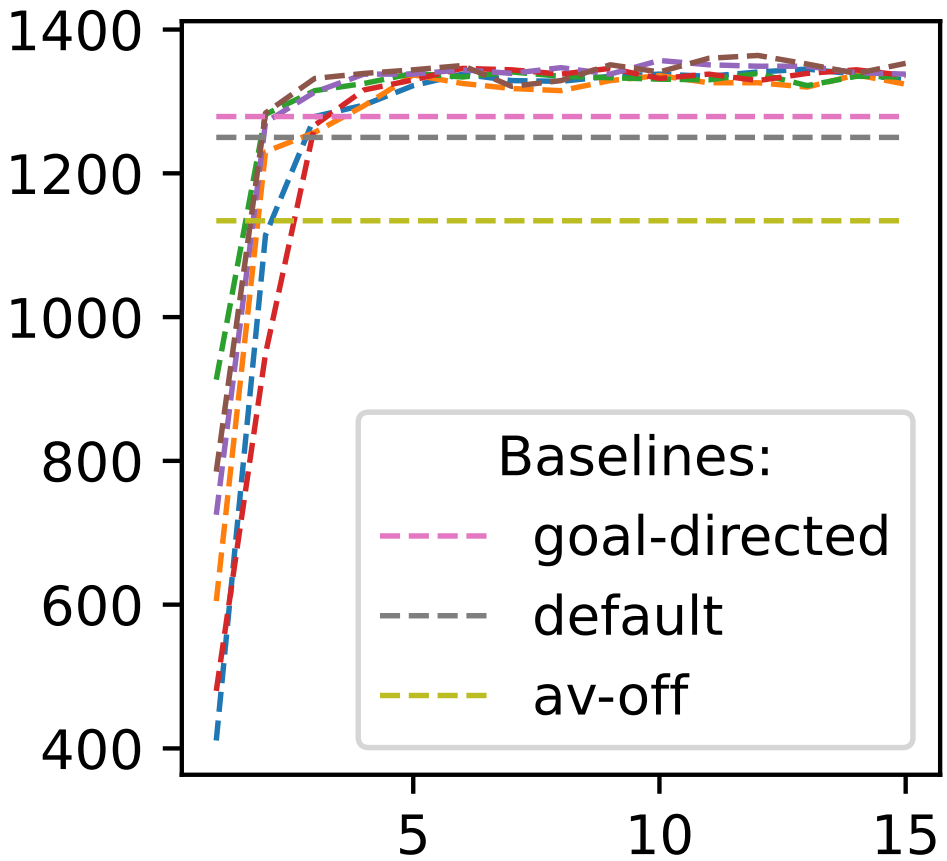
RL-inspired

- can beat the default strategy by 6%,
  (a good goal-directed strategy by 3.5%) on the test set

Training with the RL-inspired Operator



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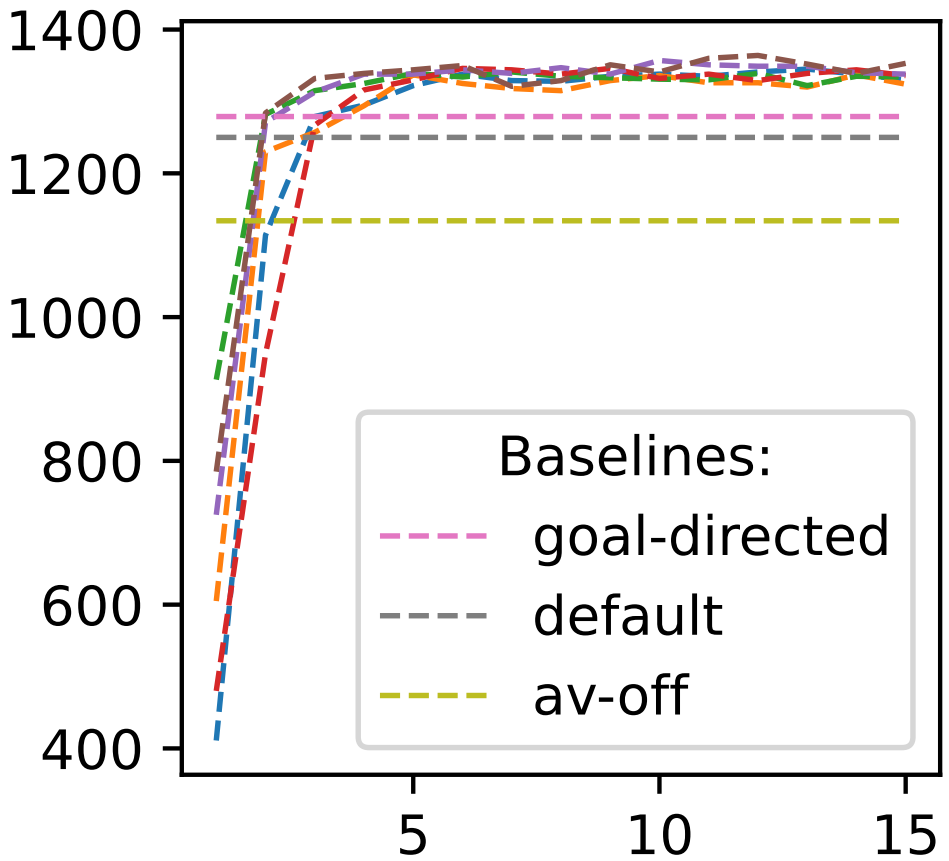

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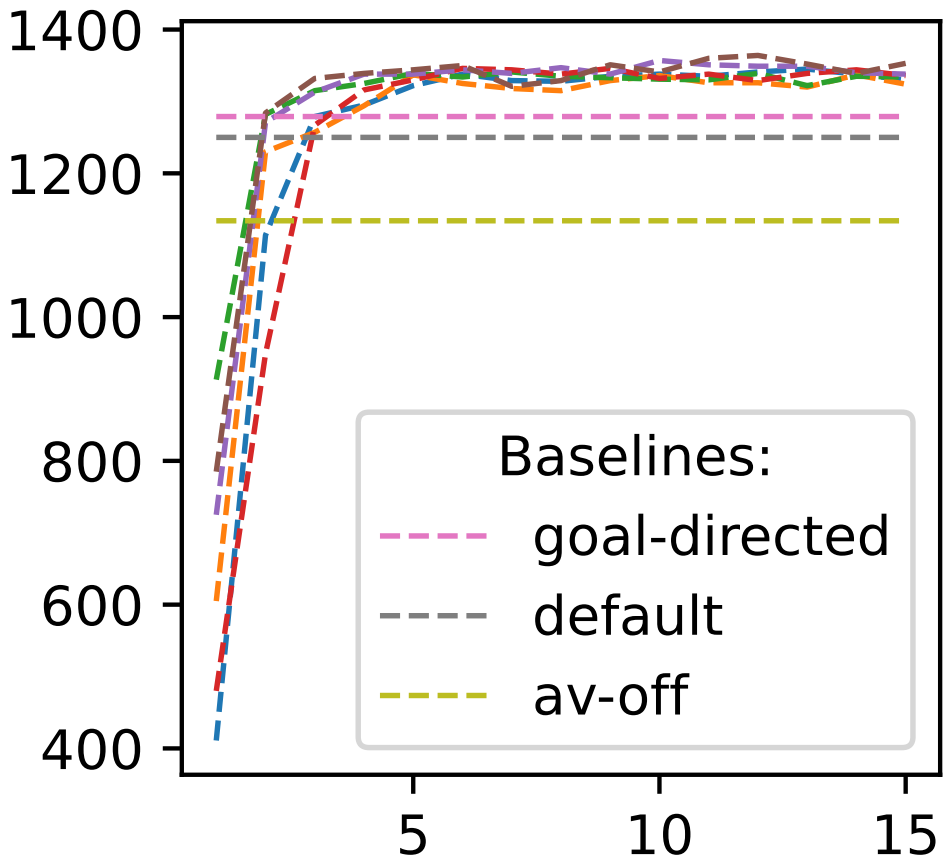

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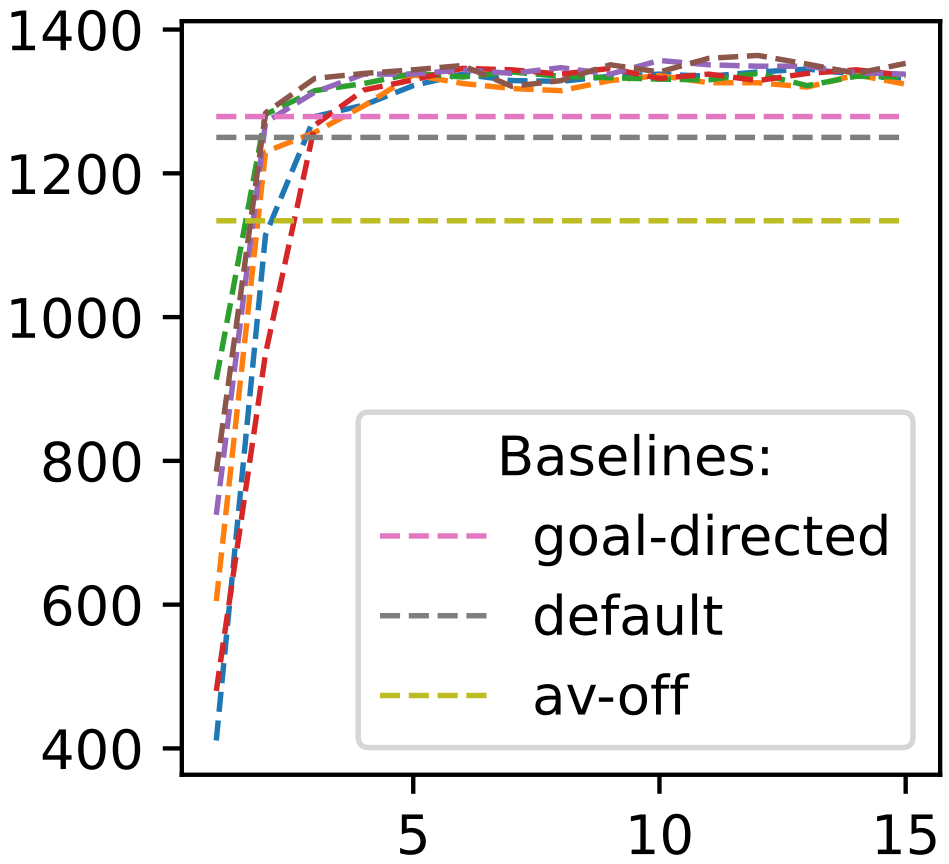

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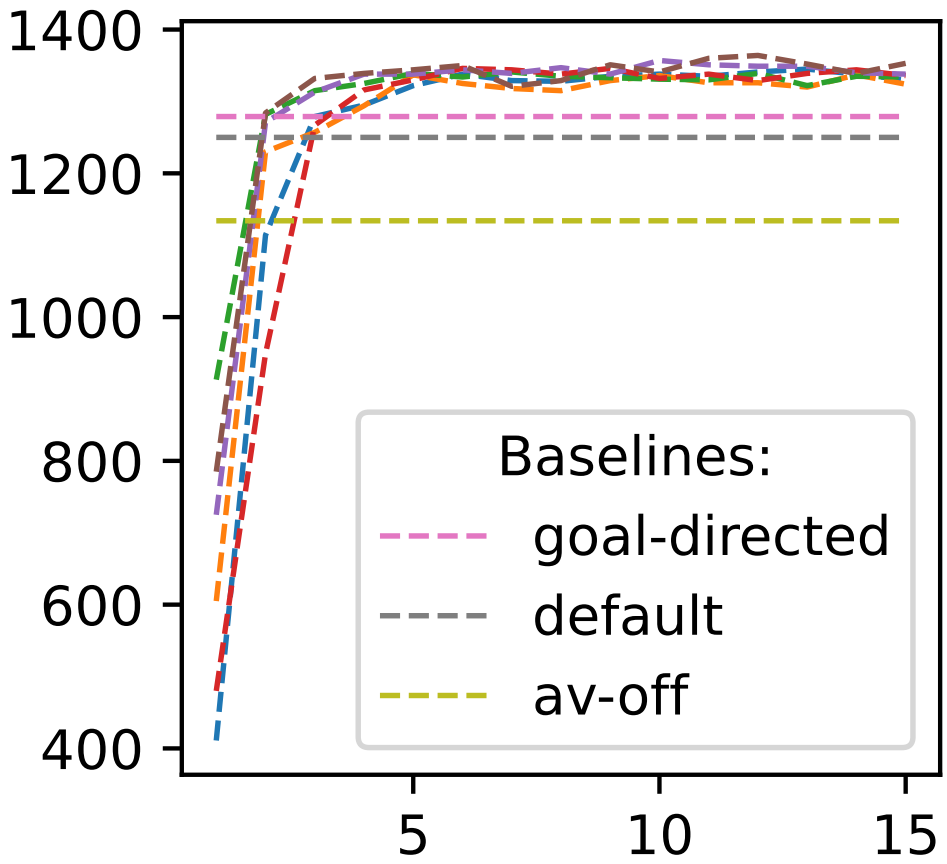

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