

System 1.5

Designing Metacognition in AI

System-2 Reasoning at Scale Workshop @ NeurIPS 2024





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System 1

System 2



System 1.5





Three key components:

- Monitor (M), assessing "familiarity" score f
 - where *f* = *problem-type* and *solution-pattern*
- 2. **Generator** (**G**), producing potential *k* solutions
 - where k = C(1 f) and C = hyperparameter
- **3. Evaluator** (**V**), verifying the quality of those solutions
 - Optimisation problem

NOTE: The paper prioritises **theoretical** description grounded in psychological and cognitive insights over mathematical formalisations (e.g., Direct Preference Optimisation) **Initialization:** Let $\mathcal{M}_{\text{BASE}}$ be a pretrained base model and $\mathcal{D}_{\text{SFT}} = \{(x_i, y_i)\}_{i=1}^N$ be an initial dataset where x_i represents problem description and y_i represents corresponding solution. We obtain:

 $\mathcal{M}_{SFT} = finetune(\mathcal{M}_{BASE}, \mathcal{D}_{SFT})$

Iterative Process (for iterations t = 1, ..., T):

1. For each problem x_i , generate k candidate solutions (Cobbe et al., 2022):

$$\{\hat{y}_{ij} \sim \mathcal{M}_t(y|x_i)\}_{j=1}^k$$

2. Construct three datasets:

$$\mathcal{D}_{\text{GENERATE}_t} = \{(x_i, \hat{y}_i) | z_{ij} = \text{preferred}\}$$

where z_{ij} indicates preference

$$\mathcal{D}_{ ext{EVALUATE}_t} = \{(x_i, \hat{y}_{ij}, z_{ij})\}$$

containing all solutions with preferences

$$\mathcal{D}_{\text{MONITOR}_t} = \{(x_i, \hat{y}_{ij}, f_{ij})\}$$

where f_{ij} captures "familiarity".

3. Update model:

 $\mathcal{M}_t = \text{finetune}(\mathcal{M}_{\text{BASE}}, \mathcal{D}_{\text{GENERATE}_{t-1}})$

At final iteration T, we obtain three specialised functions:

$\mathcal{G}_T = ext{train}(\mathcal{D}_{ ext{GENERATE}_{T-1}})$	(Generator)
$\mathcal{V}_T = \text{train}(\mathcal{D}_{\text{EVALUATE}_{T-1}}, \text{preference optimisation})$	(Evaluator)
$\mathcal{M}_T = \operatorname{train}(\mathcal{D}_{\operatorname{MONITOR}_{T-1}}, \operatorname{familiarity} \operatorname{assessment})$	(Monitor)

Inference (for input *x*): At inference time, we adapt our strategy based on how familiar the problem is:

1. Compute familiarity: $f = \mathcal{M}_T(x)$

2. Determine strategy based on familiarity:

$$\mathsf{out}(x) = \begin{cases} \mathcal{G}_T(x) & \text{if } f > \theta_h \\ \arg\max_{y \in \{\mathcal{G}_T(x)_j\}_{j=1}^k} \mathcal{V}_T(x, y) & \text{if } \theta_l < f \le \theta_h \\ \arg\max_{y \in \mathcal{Y}} \mathcal{V}_T(x, y) & \text{if } f \le \theta_l \end{cases}$$

where $k = \lceil C(1-f) \rceil$ and $\mathcal{Y} = \{\mathcal{G}_T(x)_j\}_{j=1}^{k_{\max}} \cup \{\mathcal{G}_T(x|h) : h \in \text{System-2}(x)\}$

Chess, as an Intuitive Explanation



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- 2. Determine strategy based on familiarity:

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Letter Chess, **as an Intuitive Explanation**





f > 9_h

Letter Chess, **as an Intuitive Explanation**





$$\operatorname{argmax}_{y \in \{\mathcal{G}_T(x)_j\}_{j=1}^k} \mathcal{V}_T(x,y)$$

Chess, as an Intuitive Explanation







(the first half) Finding theoretical consensus on System-1

(the second half) Revisiting cognitive science theories and derive architectural principles for AI systems.



Non-technical nature

"familiarty" formalisation

System-2 discussion

Thank You!

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