LAB MEETING 24/03/25

Optimal Task Selection in Meta Curriculum Learning

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Theoretical basis

What is learning?

Learning is the **acquisition of knowledge** through **experience**, in an uncertain **environment**

(Silver et al., 2021)

How do we learn?

Guidance of a **teacher**

Complex sequences are **broken down** into simpler tasks

Meaningful order

Based on **feedback**

In humans: **Internal teacher** (autonomous organisation)

(Bengio et al., 2009; Tong et al., 2023)

Why do we learn this way?

REWARD

→ Efficient learning

Reinforcement learning agent : learns how to maximise reward through trial and error exploration

Curiosity and spontaneous exploration

(Forestier et al., 2022; Silver et al., 2021; Sutton & Barto, 1998; Ten et al., 2021)

The curriculum strategy

Curriculum: handpicked tasks

The **teacher learns** how to maximise learning by exploring the values of actions

Curriculum learning

Filtering

Chaining

1 → 2 → 3

(Bengio et al., 2009; Tong et al., 2023)

The curriculum strategy

Curriculum: handpicked tasks

The **teacher learns** how to maximise learning by exploring the values of actions

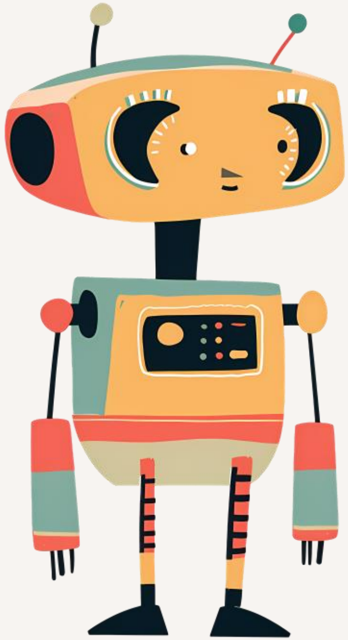
Curriculum learning

Which principles/criteria?

Meta curriculum learning

(Bengio et al., 2009; Tong et al., 2023)

Benefits of a curriculum on machine learning



Faster convergence

Higher **quality** local minima

(Bengio et al., 2009)

Study by Bengio and colleagues (2009):

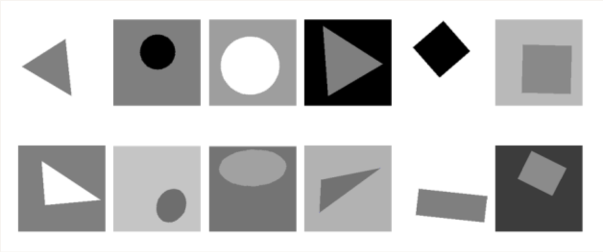


Fig. 1 Basicshapes (top) and Geomshapes (bottom) datasets example

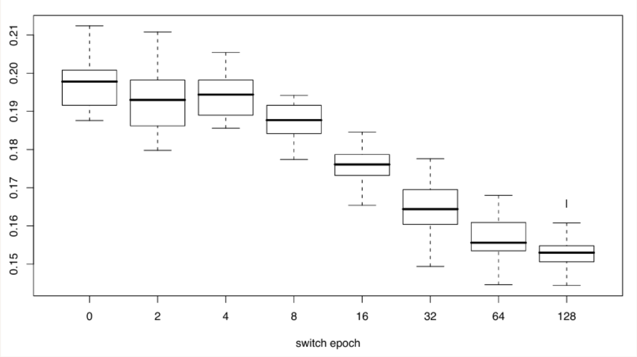


Fig. 2 Test classification error distribution as a function of the switch epoch

Benefits in machines

A comparison by Wu and colleagues (2021):

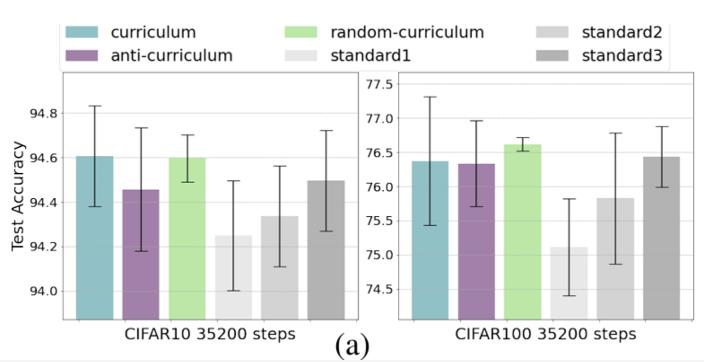


Fig. 1 Curriculum shows little benefit for standard machine learning

(Wu et al., 2021)

Benefits in machines

A comparison by Wu and colleagues (2021):

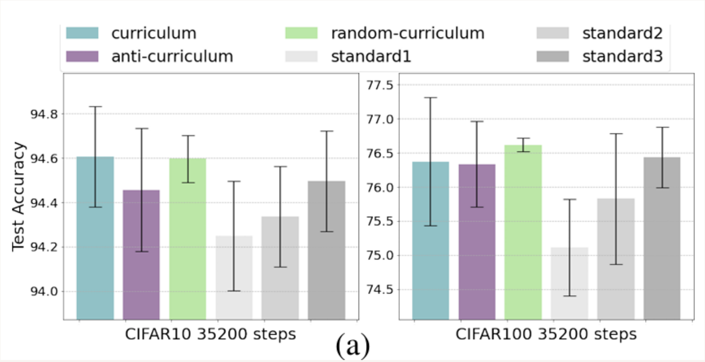


Fig. 1 Curriculum shows little benefit for standard machine learning

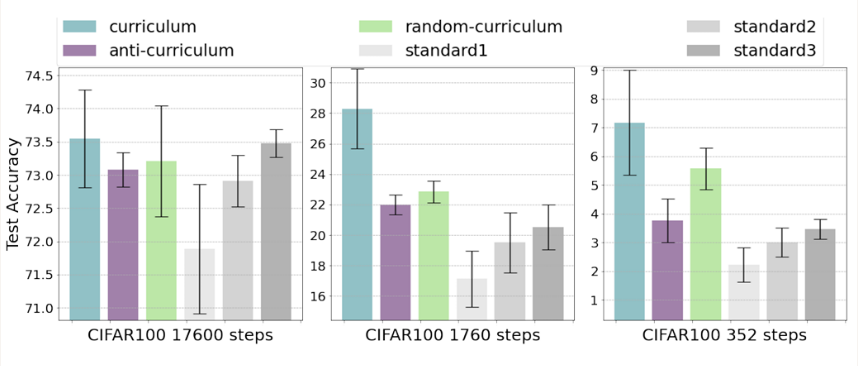


Fig. 2 Curriculum helps when the time budget for training is limited

(Wu et al., 2021)

Benefits in machines

A comparison by Wu and colleagues (2021):

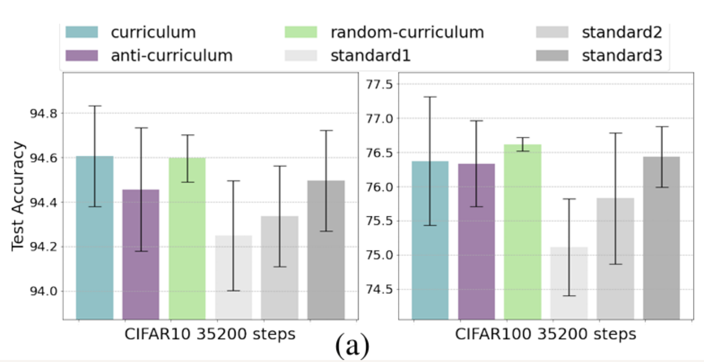


Fig. 1 Curriculum shows little benefit for standard machine learning

Curriculum **benefits are situational!**

(Wu et al., 2021)

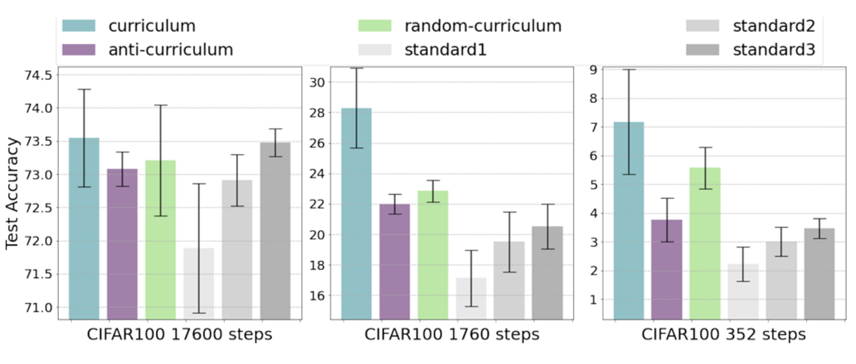


Fig. 2 Curriculum helps when the time budget for training is limited

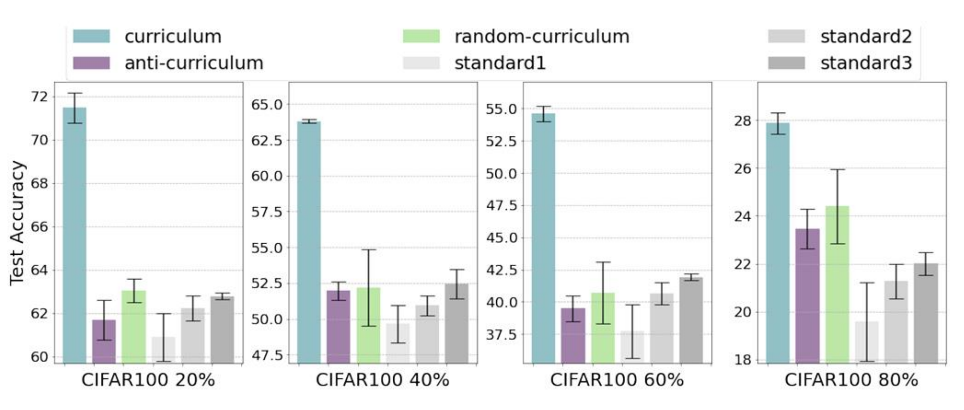


Fig. 3 Curriculum helps when training with noisy data (% of label noise)

Goals of the project

Goals of the project

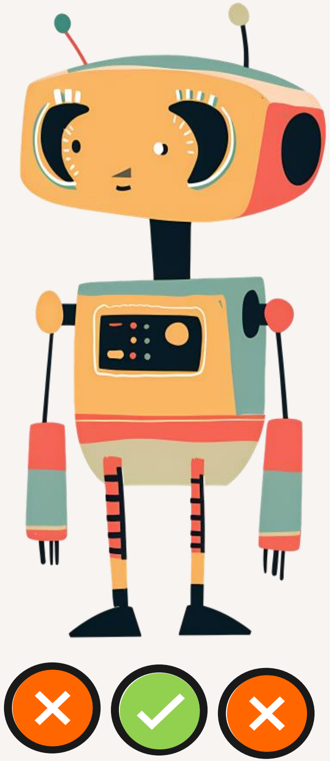
A multi-level computational model

Which task selection strategy allows for optimal learning?

- Reinforcement learning computational model
- Meta-curriculum learning

In the future:

Which task selection strategy do humans use for learning?



Methods

Three Tasks

Name	AND	XOR (Exclusive OR)	Random mapping
Characteristics	Linear logical relationship	Non-linear logical relationship	No relationship
Difficulty	Easy	Hard	Impossible

Three Tasks

AND

x1	x2	y
0	0	0
1	0	0
0	1	0
1	1	1

	0	1
0	0	0
1	0	1

XOR

x1	x2	y
0	0	0
1	0	1
0	1	1
1	1	0

	0	1
0	0	1
1	1	0

Three Tasks

RANDOM

x1	x2	y
0	0	?
1	0	?
0	1	?
1	1	?

	0	1
0	?	?
1	?	?

A multi-level computational model

LEVEL I: The Student

LEVEL II: The Teacher

LEVEL III: The Coordinator

Level 1: The Student

A multi-level computational model

ROLE: Learns the tasks

OBJECTIVE: Minimise loss

MODEL: Supervised learning model

Level 1: The Student

A multi-level computational model

TASK

0	0
1	0
0	1
1	1

CONTEXT

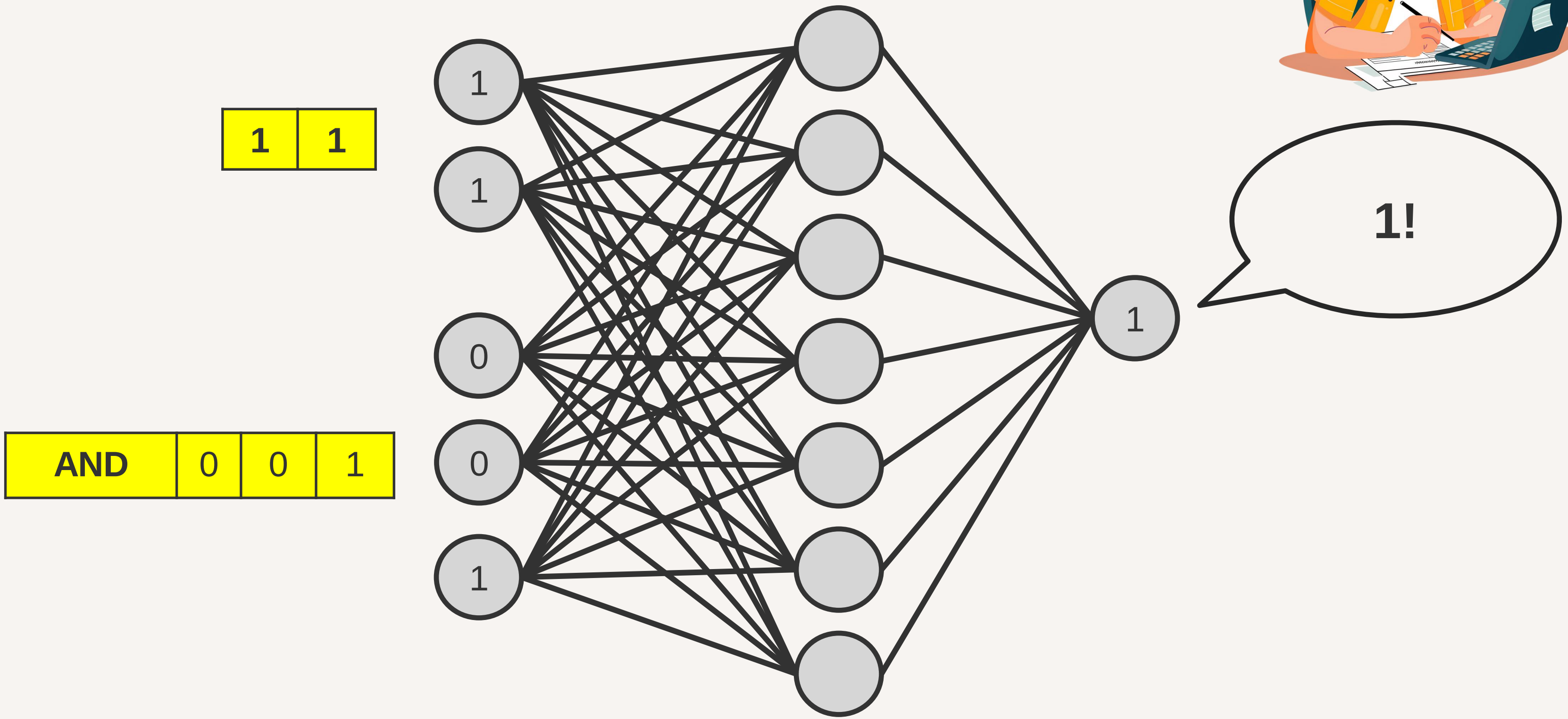
AND	0	0	1
XOR	1	0	0
RANDOM	0	1	0

OUTPUT

1!

Level 1: The Student

A multi-level computational model



Level II: the Teacher(s)

A multi-level computational model

ROLE: Choose and administer the tasks

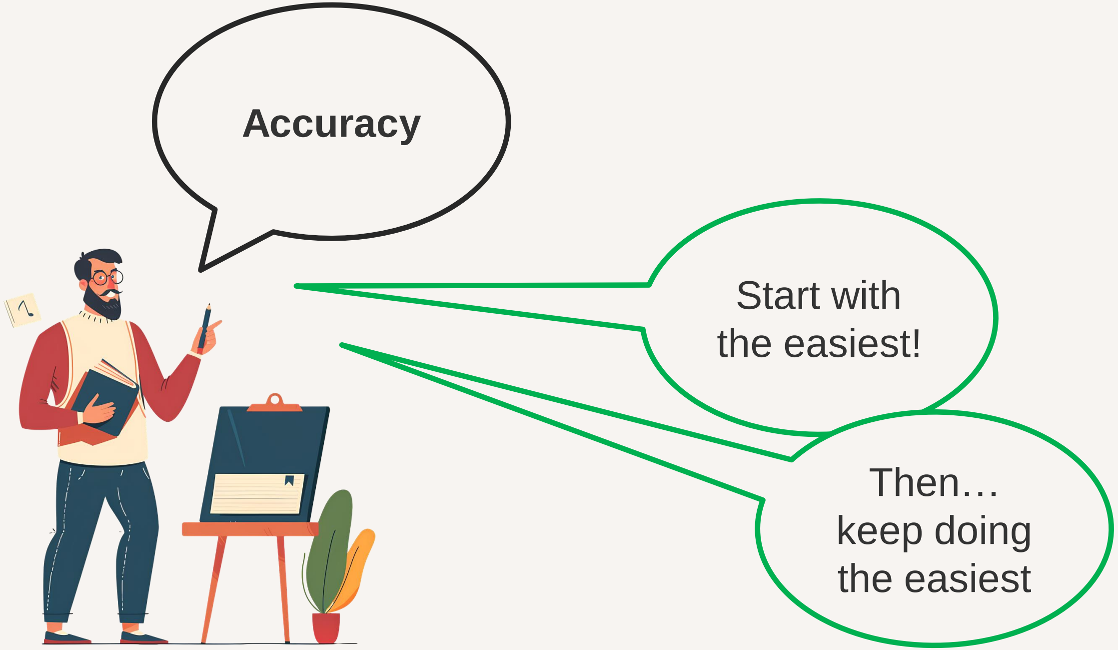
OBJECTIVE: Maximise the criterion

MODEL: Reinforcement learning model

Level II: the Teacher(s)

A multi-level computational model

The **criterion** can be different things:



(Poli et al., 2022; Ten et al., 2021)

Level II: the Teacher(s)

A multi-level computational model

The **criterion** can be different things:

Accuracy

Novelty

Explore what you don't know!

(Poli et al., 2022; Ten et al., 2021)

Level II: the Teacher(s)

A multi-level computational model

The **criterion** can be different things:

Accuracy

Novelty

Signed Learning progress

Keep improving!

(Poli et al., 2022; Ten et al., 2021)

Level II: the Teacher(s)

A multi-level computational model

The **criterion** can be different things:

Accuracy

Novelty

Signed Learning progress

Unsigned Learning progress

Don't forget anything…

(Poli et al., 2022; Ten et al., 2021)

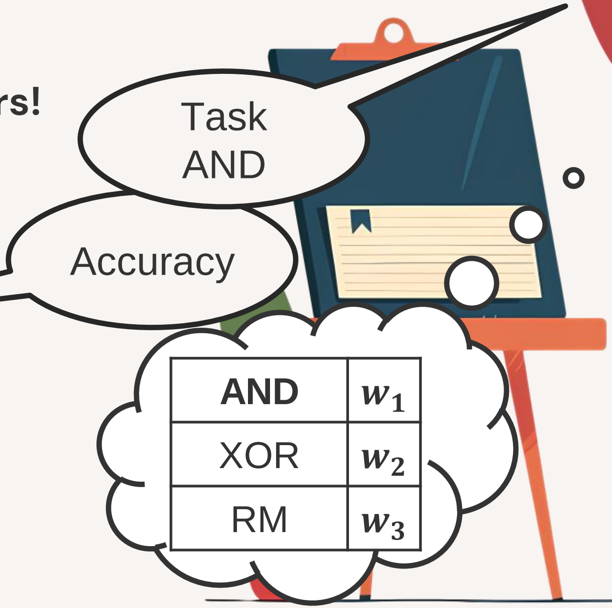
Level II: the Teacher(s)

A multi-level computational model

Uses the Rescorla–Wagner Rule:

$$V_{t\,[option]} = V_{t-1\,[option]} + \alpha\,(R_{t-1} - V_{t-1\,[option]})$$

→ This applies to **all teachers!**



Level III: the Coordinator

A multi-level computational model

ROLE: Gives weights to the teachers (LVL II)

OBJECTIVE: Maximise reward

MODEL: Reinforcement learning model

LVL II:

$$V_{t\,[option]} = \beta_1 G_t + \beta_2 B_t + \beta_3 A_t + \beta_4 H_t$$

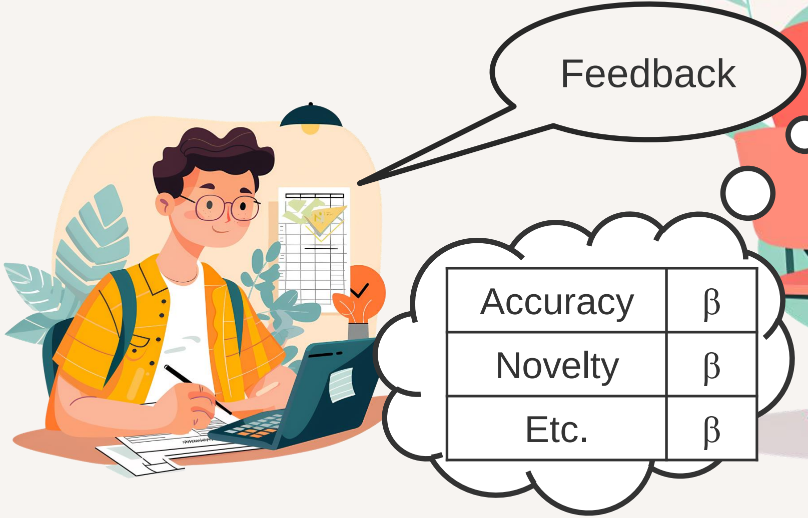
Level III: the Coordinator

A multi-level computational model

LVL III:

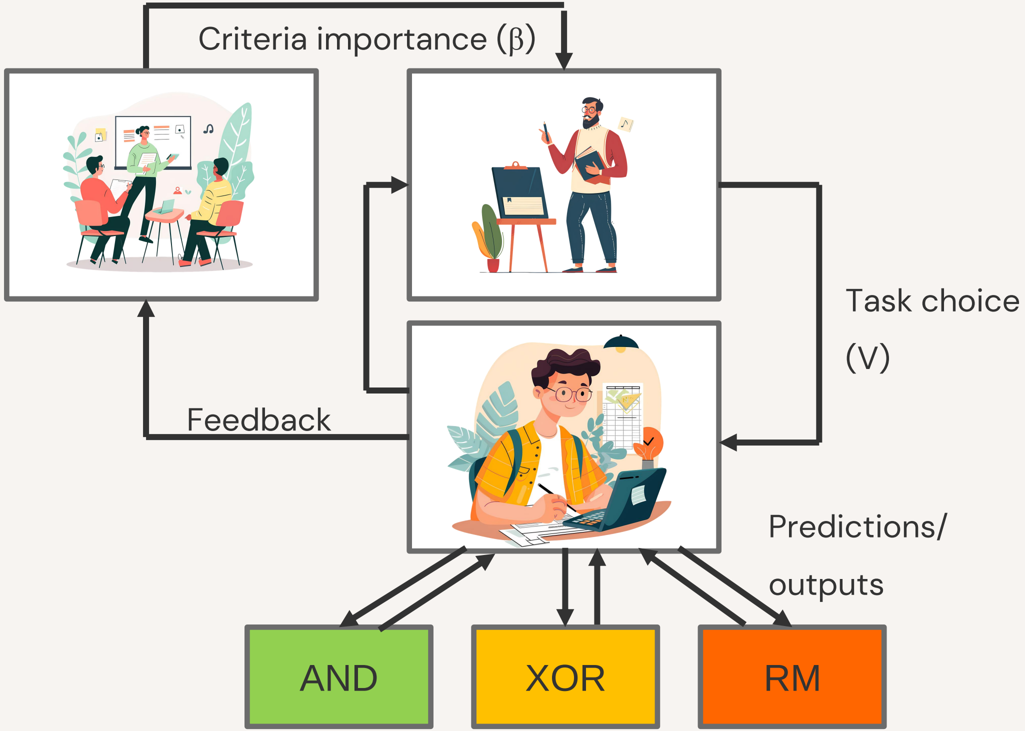
Receives feedback from student

Update each criteria weight (β)



A multi-level computational model

Structure of the levels



Hypotheses

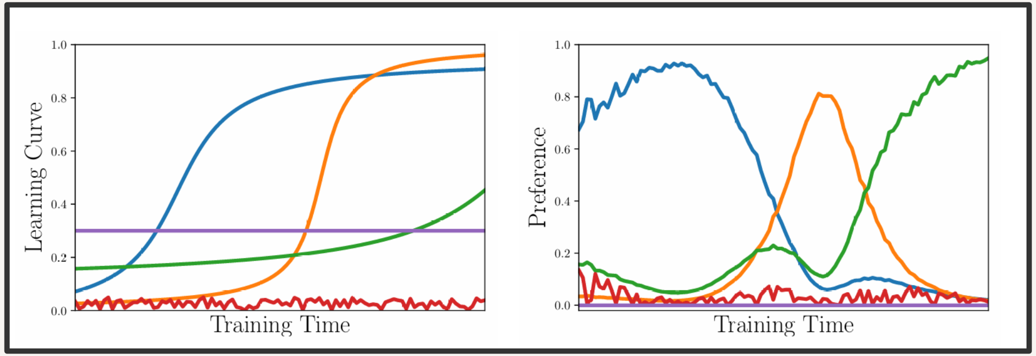
The curriculum model:

- **first** focus on the **easy task**
- then **hard task**
- **disregard** the **impossible task**

→ **faster learning** of both easy and hard task.

The random sampling model:

– **slowed down** by the **noisy task** (RM).



(Forestier et al., 2022)

Results

Results overview

LVL2 progress:

- **Accuracy OK**
- **Signed LP in progress**
- **Unsigned LP in progress**

→ Early testing for each criterion is done separately

General parameters of the models:

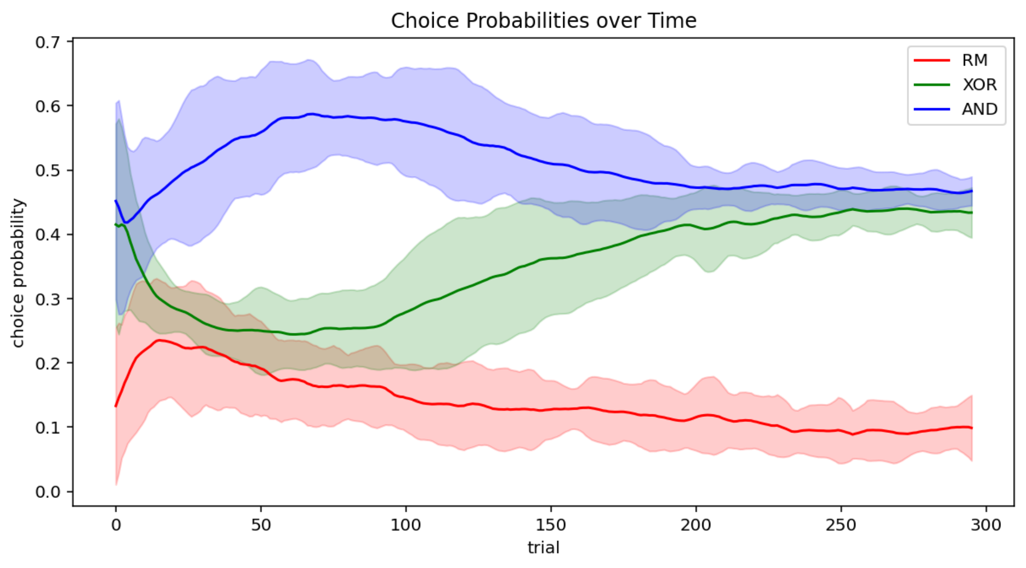
Learning rate of level 1: **0,05**

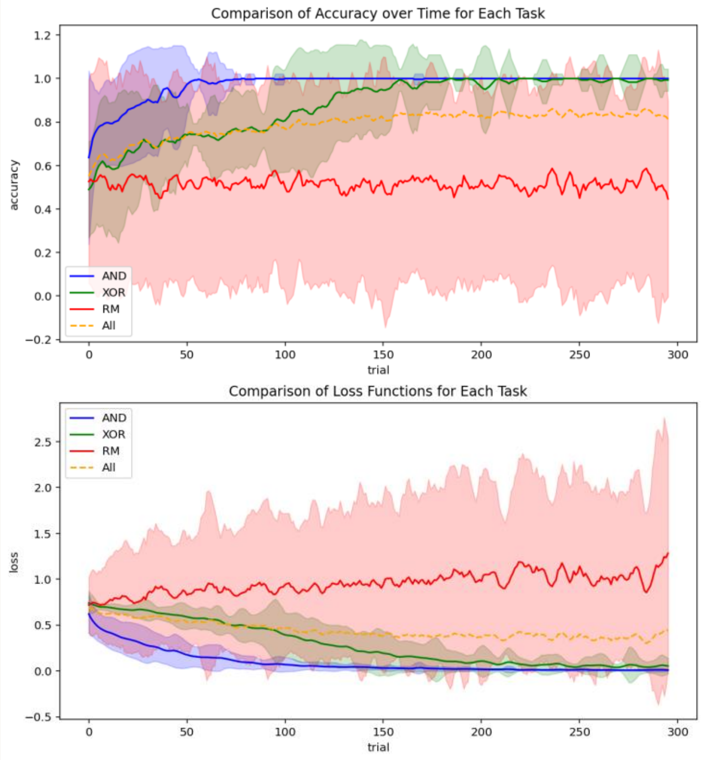
Learning rate of level 2: **0,3**

Inverse temperature: **2**

Number of runs: **15**

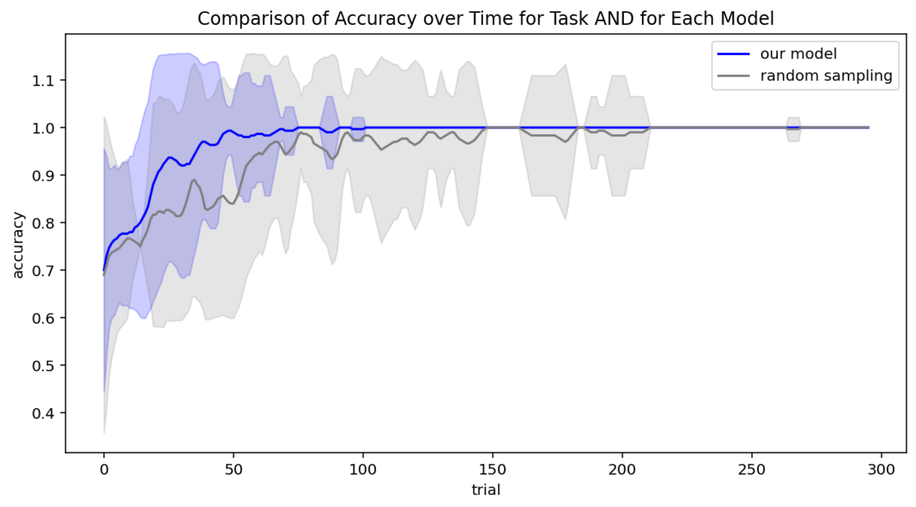
Criterion 1: Accuracy

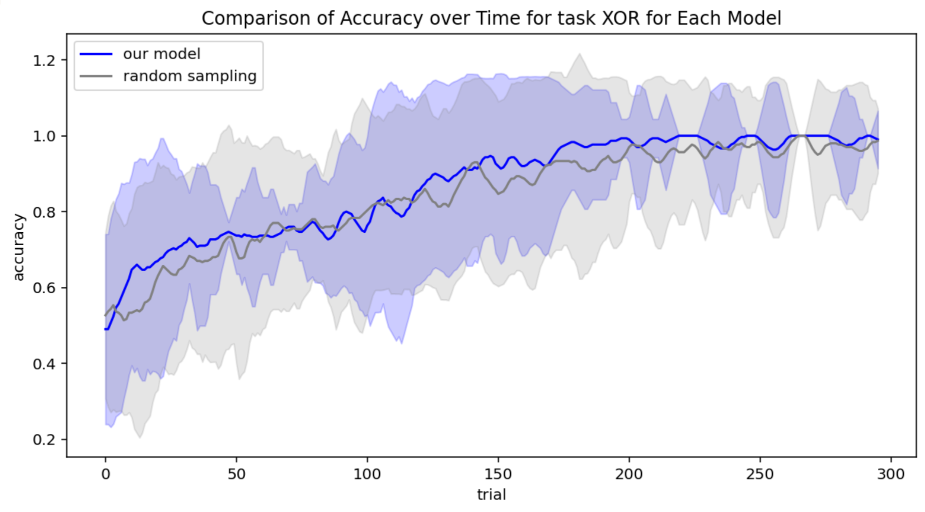




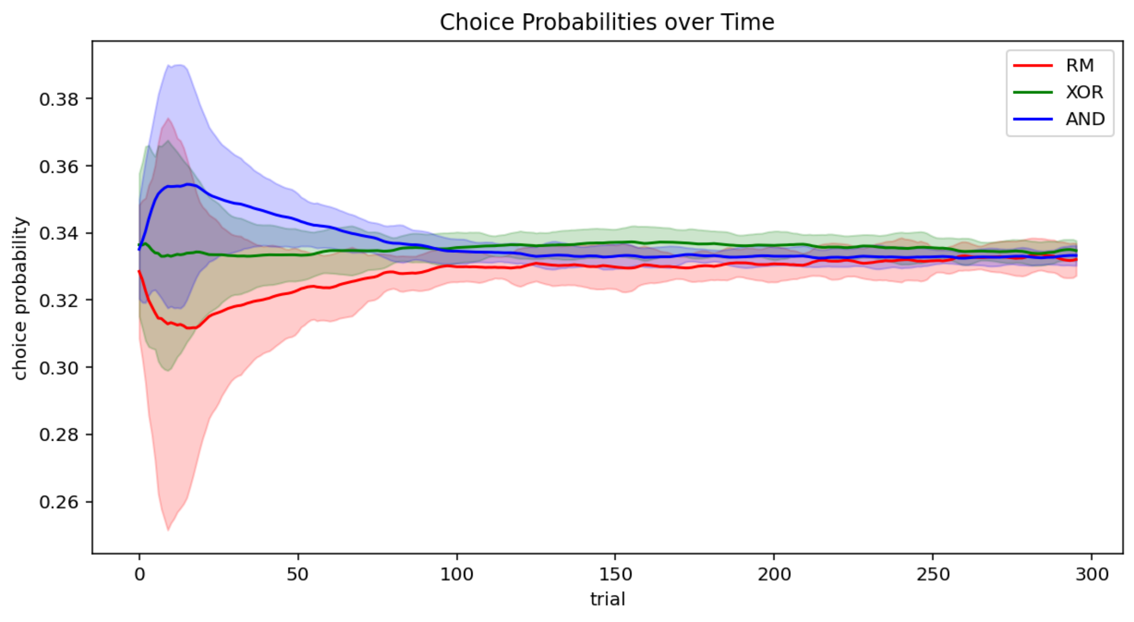
Criterion 1: Accuracy

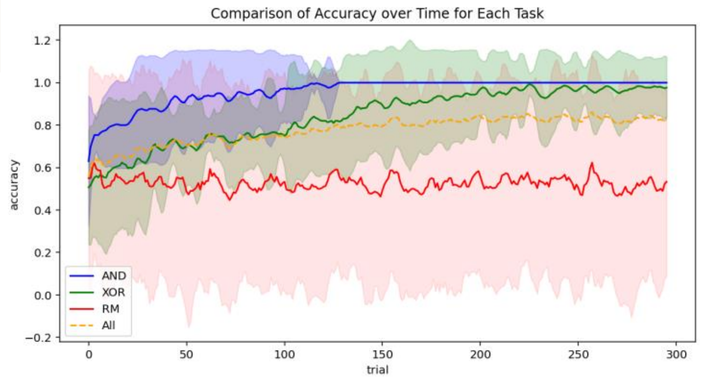
Performance

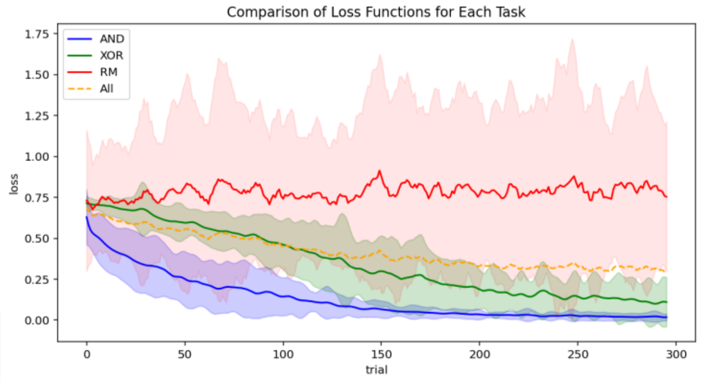




Criterion 2: Signed Learning Progress

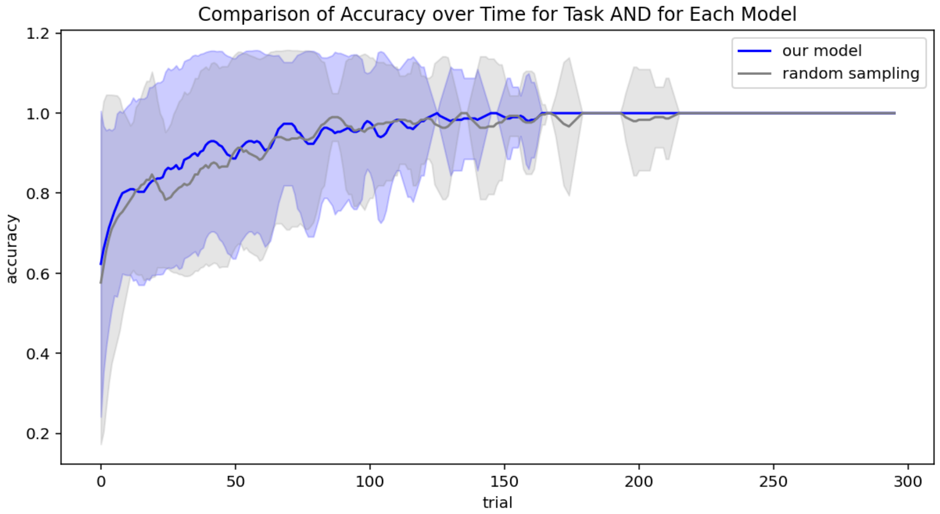


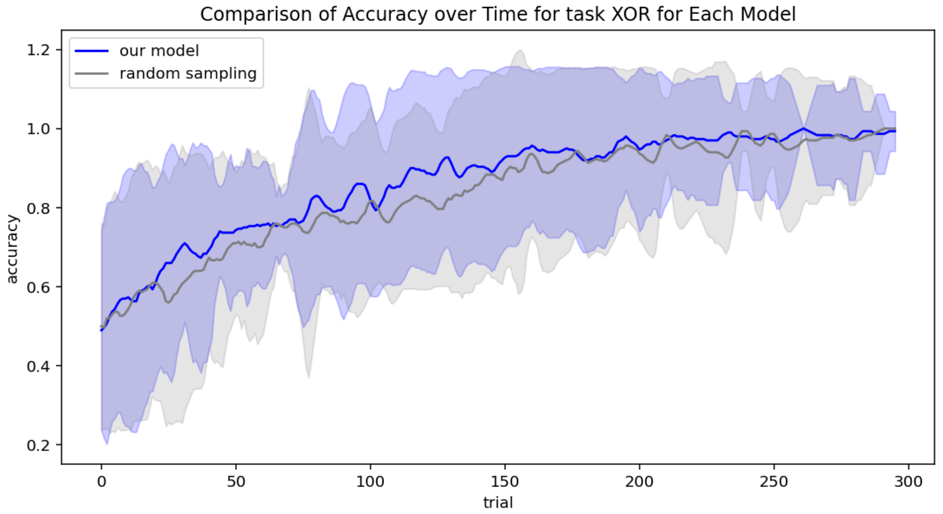




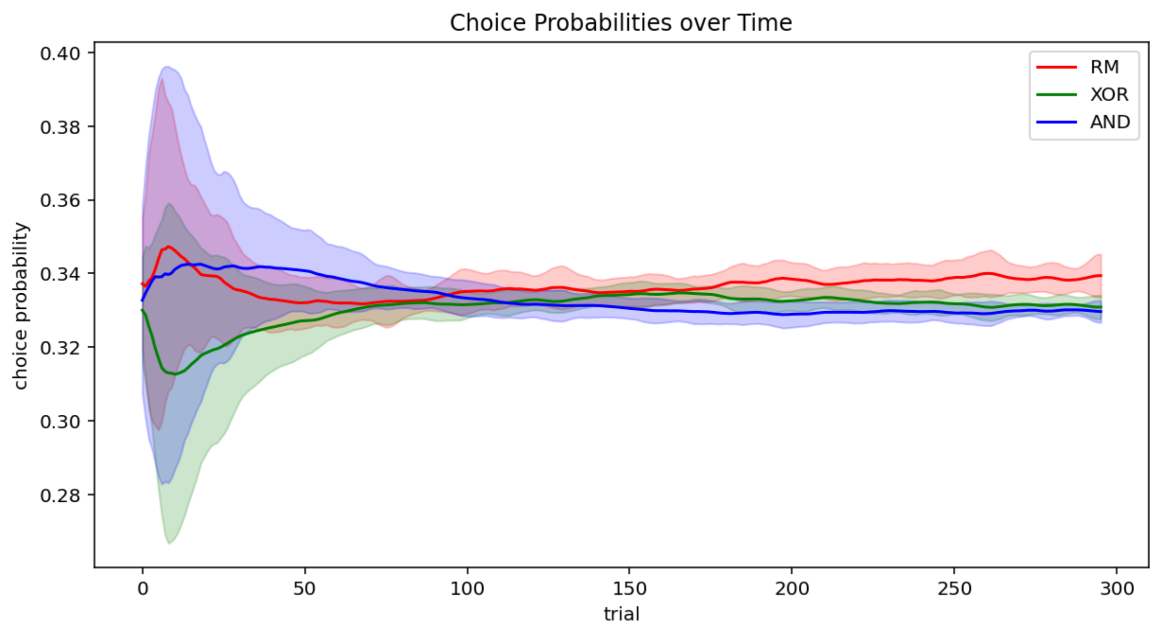
Criterion 2: Signed Learning Progress

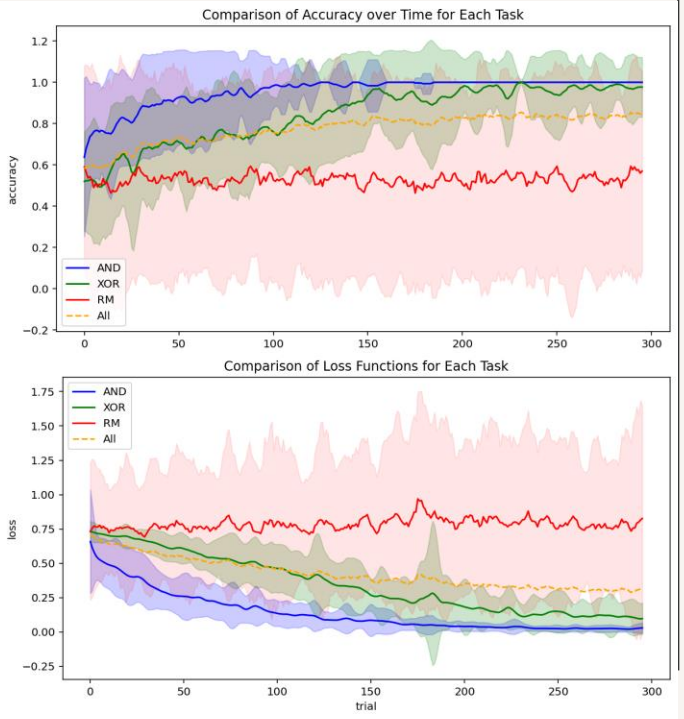
Performance





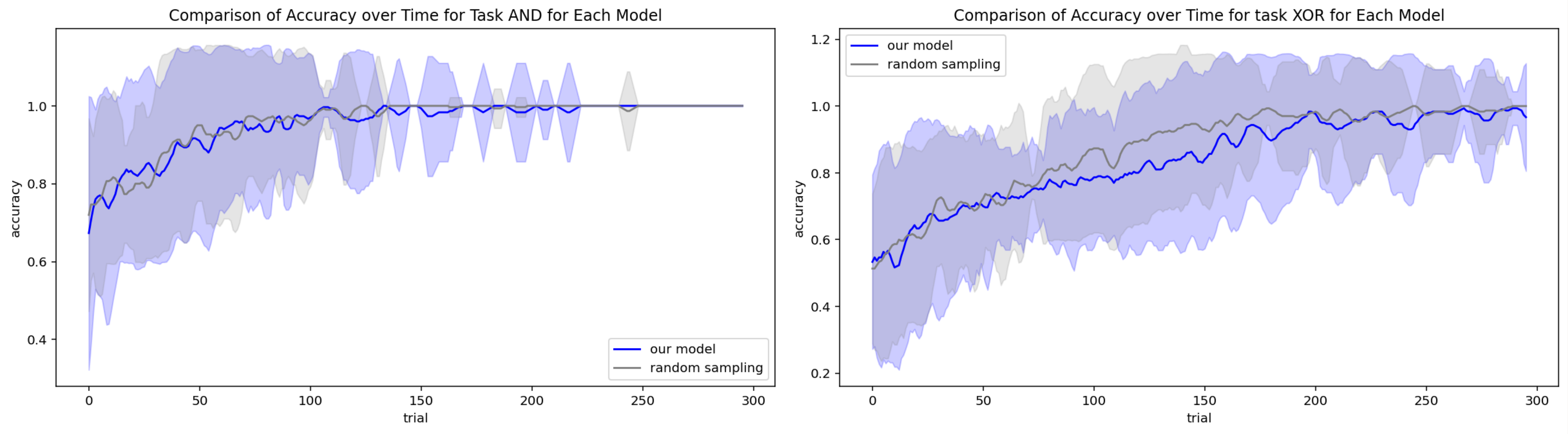
Criterion 3: Unsigned Learning Progress





Criterion 3: Unsigned Learning Progress

Performance



Results Conclusion

Not as sequential as we thought

Some effects are **still too small**

But:

Good **task differentiation**

Slightly **faster learning speed** for the **accuracy teacher.**

Next objectives

Next objective

- Add Novelty
- Set up LVL3, Coordinator

Thank you for listening

References

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