The 3rd International Joint Conference on Learning & Reasoning (IJCLR), Bari, Italy

TAILOR

Explanatory machine learning for sequential human teaching

Lun Ai[1], Johannes Langer[2], Stephen Muggleton[1], Ute Schmid[2]

[1]Department of Computing, Imperial College London, UK
[2]Faculty of Information Systems and Applied Computer Sciences, University of Bamberg, Germany

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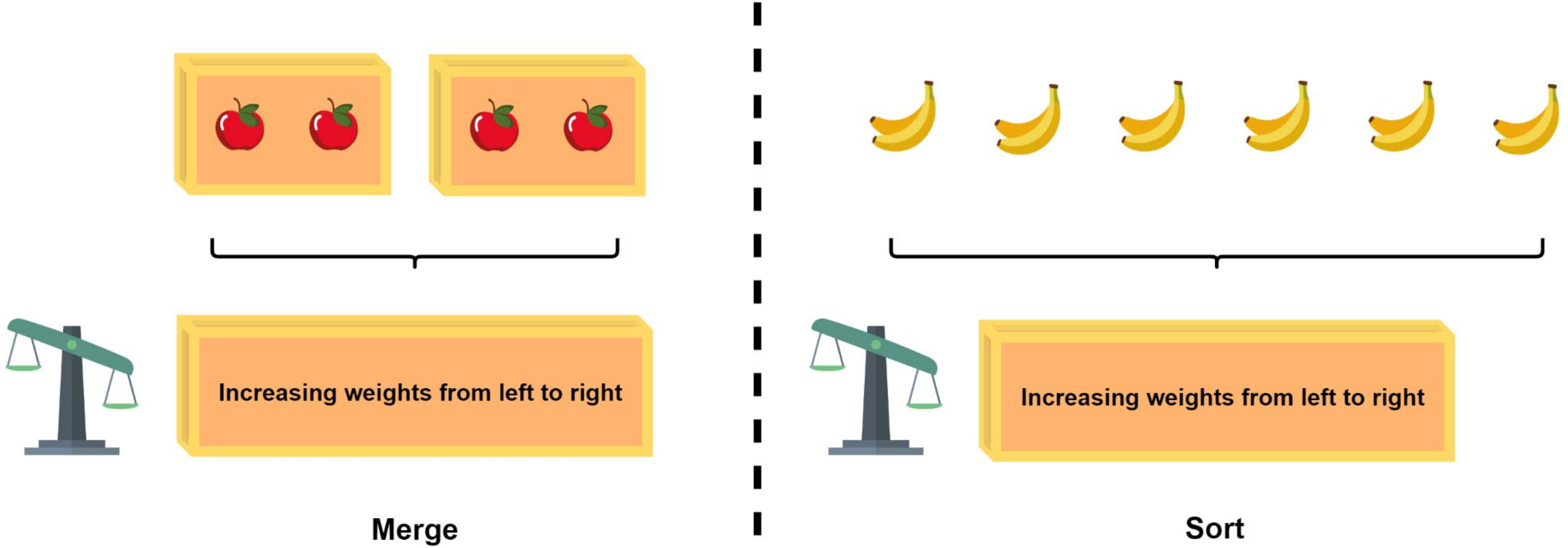
Which task would you first select to teach children?

Arrange fruits of different weights by merge sort



Using machine learned output for **knowledge transfer**

Ultra-Strong Machine Learning (USML) [Michie, 1988]

- ML outputs in **symbolic** representation
- The output can be **taught** to humans whose **performance can increase** to a level beyond learning from training examples

USML and Inductive Logic Programming (ILP)

Background BK: { father(john,susan). parent(susan,sam). }

Examples E+: { grandfather(john,sam). }

Hypothesis H: { $\underbrace{\text{grandfather(X,Y) :- father(X,Z), parent(Z,Y).}}_{\text{BK U H should cover E+ and none of E-}}$ }

*The world's **1st demonstration** of USML is in ILP [Muggleton et al., 2018]*

Are logic programs from ML suitable for knowledge transfer?

Minimal guidance **curriculum**

No guidance *Full guidance*

- <u>Learning merge sort via ILP</u>
- Teaching merge sort
- Comprehension assessment
- Empirical results
- Remarks

ILP: Meta-Interpretive Learning

Background BK:	{ father(john,susan). parent(susan,sam). }
Example E+:	{ grandfather(john,sam). }
Higher-order Meta-rule M:	{ **P(X,Y) :- Q(X,Z), R(Z,Y).** }
Hypothesis H:	{ grandfather(X,Y) :- father(X,Z), parent(Z,Y). }

BK U H should cover E+ and none of E-

and **instantiate M**

Can learn *recursive logic programs* and invent *new predicates*!

A variant of **bottom-up** merge sort [Goldstine & Neumann, 1963]

```
merger(A,B):-parse_exprs(A,C),merger_1(C,B).

merger_1(A,B):- compare_nums(A,C),merger_1(C,B).

merger_1(A,B):-compare_nums(A,C),drop_bag_remaining(C,B).

sorter(A,B):-merger(A,C),sorter(C,B).

sorter(A,B):-recycle_memory(A,C), sorter(C,B).

sorter(A,B):-single_expr(A,C), single_expr(C,B).
```

Produced by a Meta-Interpretive Learning system *Metagol*

Input:

[4, 6, 5, 2, 3, 1]

After Iteration 1

[4 < 6, 2 < 5, 1 < 3]

After Iteration 2

[2 < 4 < 5 < 6, 1 < 3]

After Iteration 3

[1 < 2 < 3 < 4 < 5 < 6]

- Learning merge sort via ILP
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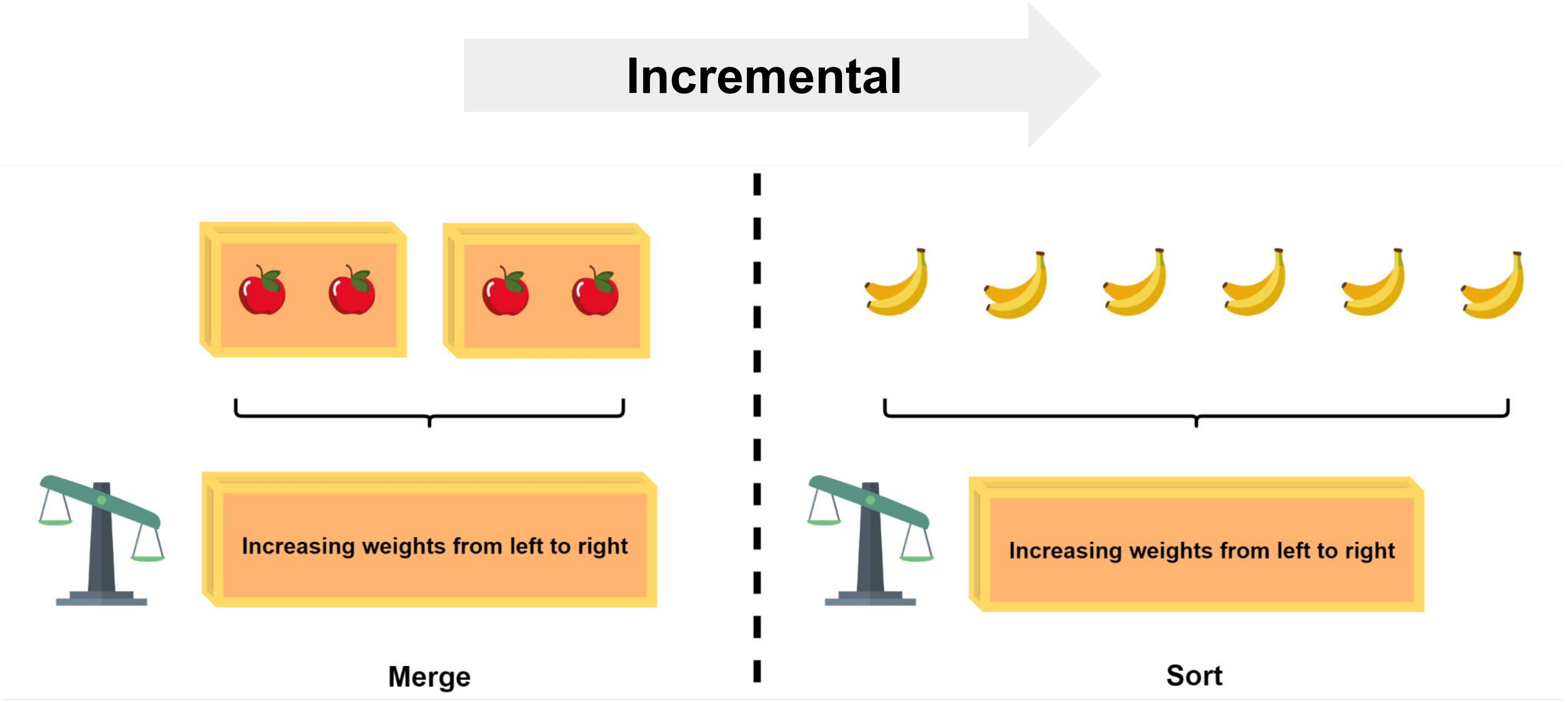
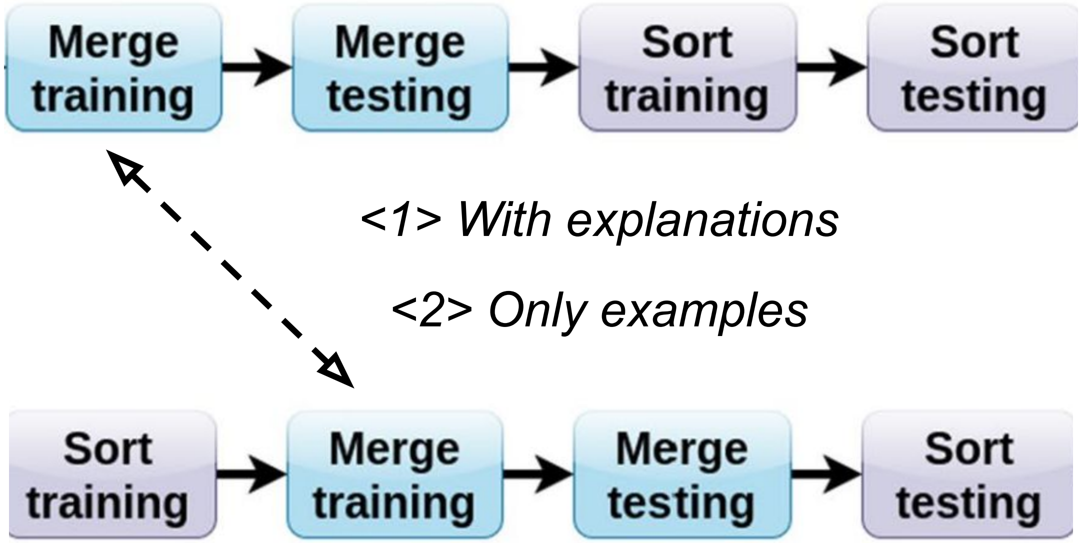
A case study: teach **Merge Sort** to human novices



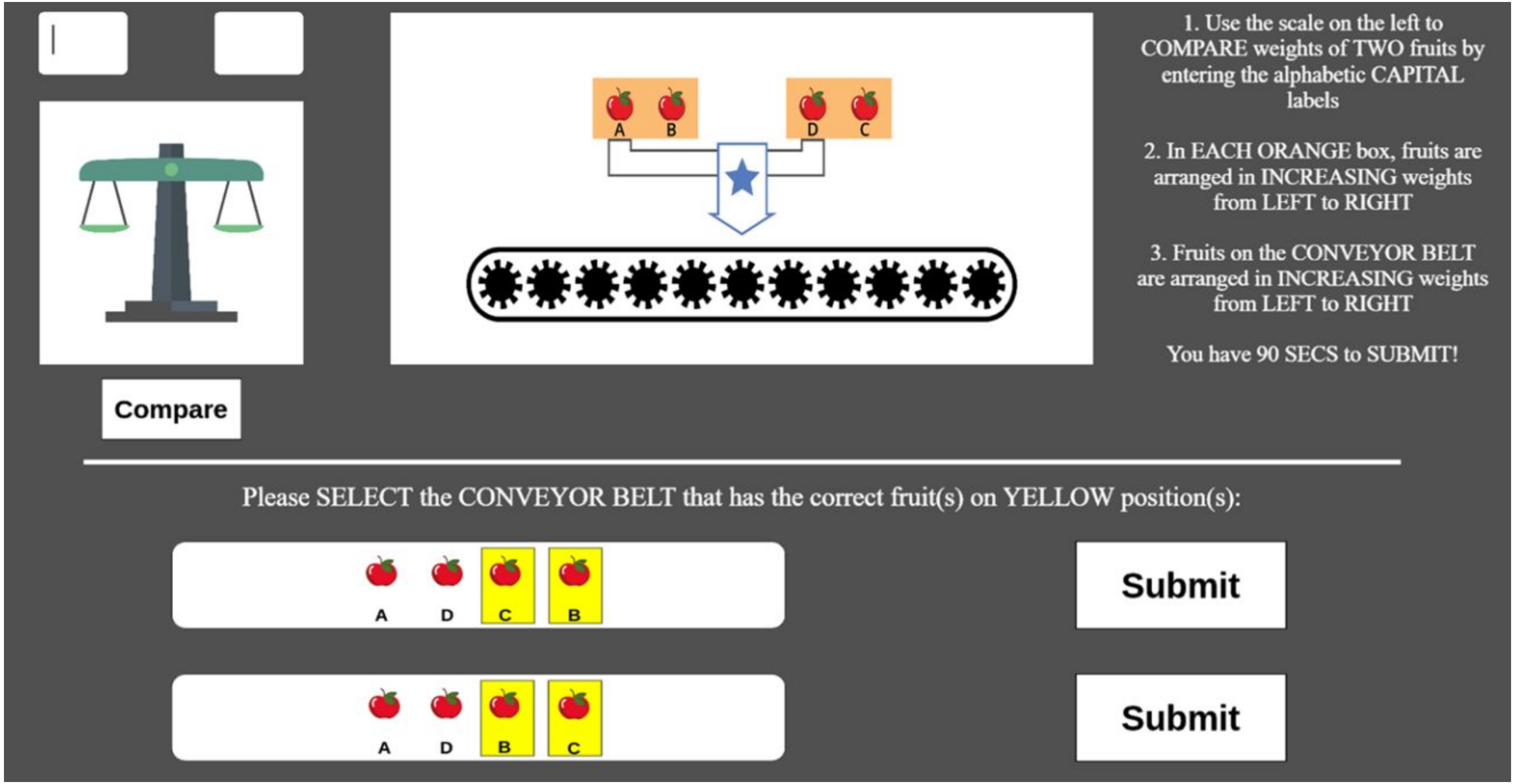
2x2 Experimental design

(a) Merge-then-sort

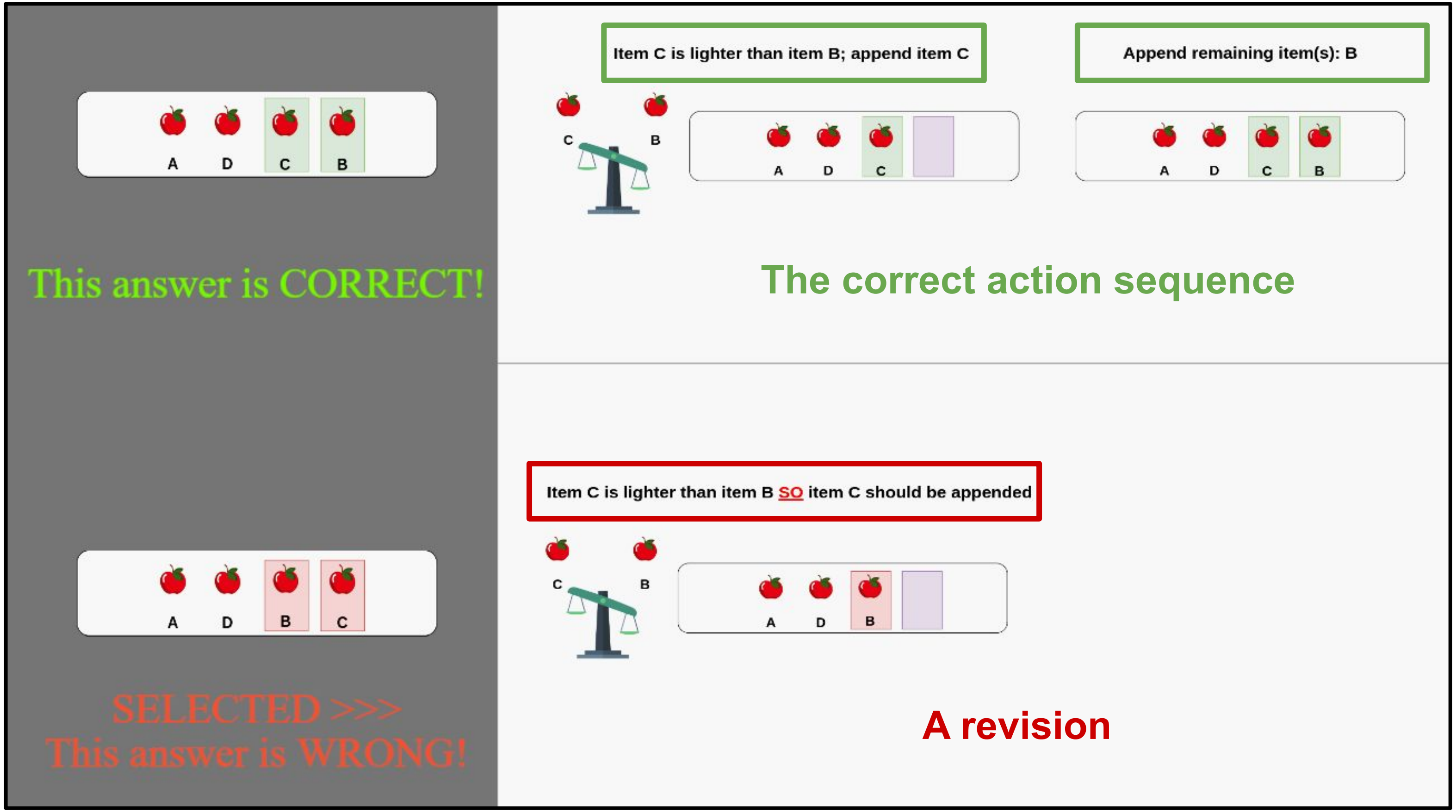
(b) Sort-then-merge



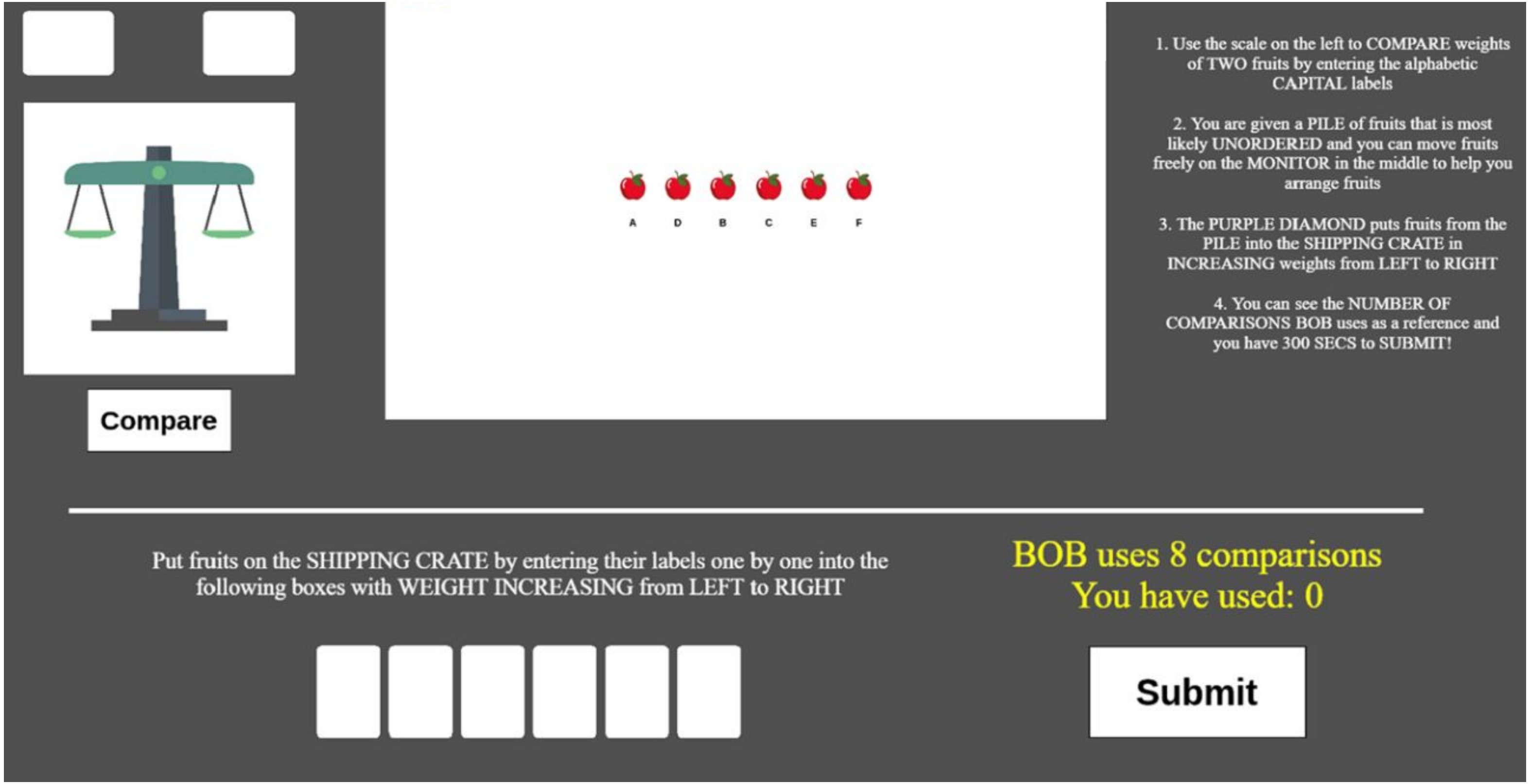
Learning to merge via **multiple-choice** questions



Explanations: why is/isn’t an action optimal?



Learning to sort through **explorations**



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Ultra-strong ML -> human behavioural change

Explanatory effect =

machine-aided task performance - self-learning task performance

Machine-aided: with explanations (e.g. generated from LP)

Self-learning: with only training examples

Performance: predictive accuracy on unseen tests

[Ai et al., 2021]

Evaluating human sorting performance

Spearman rank correlation coefficient [Spearman, 1904]:

Non-parametric test of the **monotonicity** between the **rank values** of two variables ***X**, **Y***

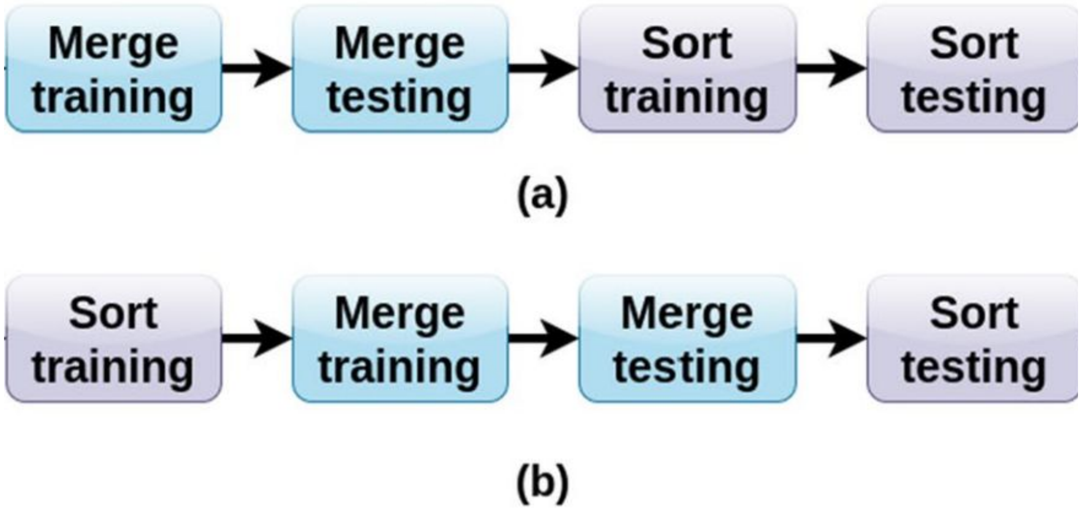
$$\frac{\mathrm{cov}(\mathrm{R}(X), \mathrm{R}(Y))}{\sigma_{\mathrm{R}(X)}\sigma_{\mathrm{R}(Y)}}$$

E.g. ***X***: [1, 2, 3, 4, 5, 6]

Y1: [<u>4</u>, 6, 5, <u>2</u>, 3, 1] ***Y2***: [1, 2, <u>6</u>, 3, 4, 5]

$$\varrho(\boldsymbol{X},\boldsymbol{Y1}) < \varrho(\boldsymbol{X},\boldsymbol{Y2})$$

Comparing between different curriculum order



Effect of curriculum on task T =

Performance of T in (a) - Performance of T in (b)

Can we identify human **sorting strategy**?

Sequence [4, 6, 5, 2, 3, 1]

Human trace:

[(6, 4), (5, 2), (3, 1), (4, 2), (5, 4), (6, 5), (2, 1), (3, 2), (4, 3)]

Machine trace (24 algorithms, 6 categories):

[(4, 6), (5, 2), (2, 4), (4, 5), (5, 6), (3, 1), (1, 2), (2, 3), (3, 4)]

There are <u>21</u> possible pairs (symmetric pairs are considered identical).

An example of **trace-based** evaluation

Step 1: Identify common/different pairs via $\boldsymbol{\chi}^2$

	Not in human trace	In human trace
Not in machine trace	13	1
In machine trace	1	10

(Added 1s to avoid zero cells)

$\boldsymbol{\chi}^2 = 14.3$ with $p < .001$

Step 2: Rank algorithms via spearman rank correlation

Spearman rank correlation $\boldsymbol{\rho} = .9$ and $p < .001$

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Cognitive window for a machine-learned logic program P

Axiom 1: Hypothesis space to necessarily learn P must be small

Humans have limited search ability in the hypothesis space

Axiom 2: P has “shortcuts” to reduce grounding cost

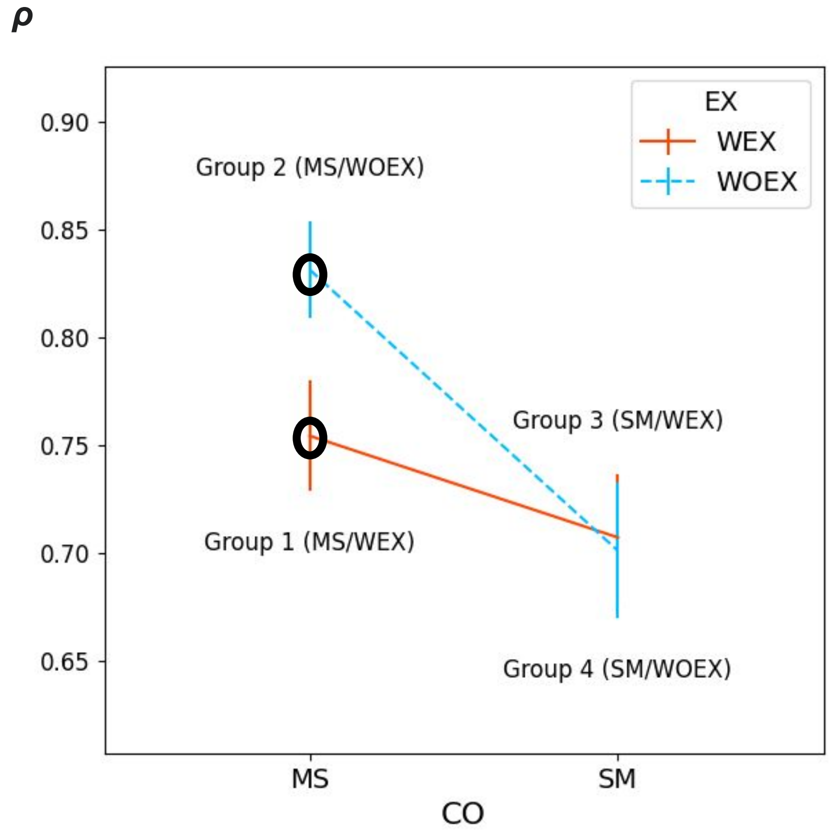
Humans have limited capacity for mental computations

[Ai et al., 2021]

Merge-then-sort learning **reduces total hypothesis space size**

Improved performance

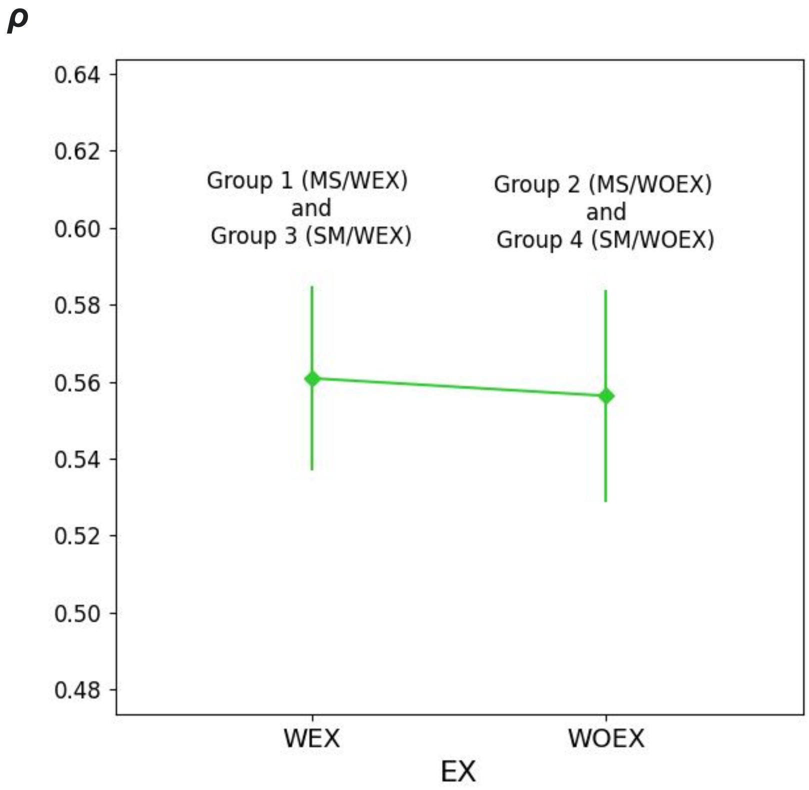
(**supports Axiom 1**)



Explanations contain **no “shortcuts”** to merging

No performance differences

(**supports Axiom 2**)



Effects of **Incremental** learning with **explanations**

Group	Algorithm adapted	Is adaptation significant	Is performance improvement significant
Group 1 (**MS/WEX**)	QS	✓	✓
Group 2 (**MS/WOEX**)	MS	✓	*X*
Group 3 (**SM/WEX**)	DS	*X*	✓
Group 4 (**SM/WOEX**)	IS	✓	✓

Increased application of **quick sort like** algorithms

=> **higher performance** than other approaches

Impact of explanations on **performance**

Group	Algorithm adapted	Is adaptation significant	Is performance improvement significant
Group 1 (**MS/WEX**)	QS	✓	$\boxed{✓}$
Group 2 (**MS/WOEX**)	MS	✓	*X*
Group 3 (**SM/WEX**)	DS	*X*	$\boxed{✓}$
Group 4 (**SM/WOEX**)	IS	✓	✓

Explanations **contextualise the binary selection** concept

(quick sort, dictionary sort)

Impact of incremental curriculum on **strategy adaptation**

Group	Algorithm adapted	Is adaptation significant	Is performance improvement significant
Group 1 (**MS/WEX**)	QS	✓	✓
Group 2 (**MS/WOEX**)	MS	✓	X
Group 3 (**SM/WEX**)	DS	X	✓
Group 4 (**SM/WOEX**)	IS	✓	✓

Incremental curriculum helps **reduce hypothesis size** for learning

divide-and-conquer algorithms (quick sort, merge sort)

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Learning merge sort is a **challenging** task

Concluding remarks

While we took a **minimalist** approach,

- teaching logic programs can lead to **remarkable re-discoveries**
- incremental learning and explanations had a **USML potential**
- results supported the **cognitive window**

Future work

- Beyond **ILP** and **noise-free** framework
- Two-way learning via **behavioural cloning**
- Curricula and optimisations for **human discovery**

Imperial College London

Lun Ai

Email: lun.ai15@imperial.ac.uk

Website: https://lai1997.github.io/

Linkedin: https://www.linkedin.com/in/lun-ai-46481a128/