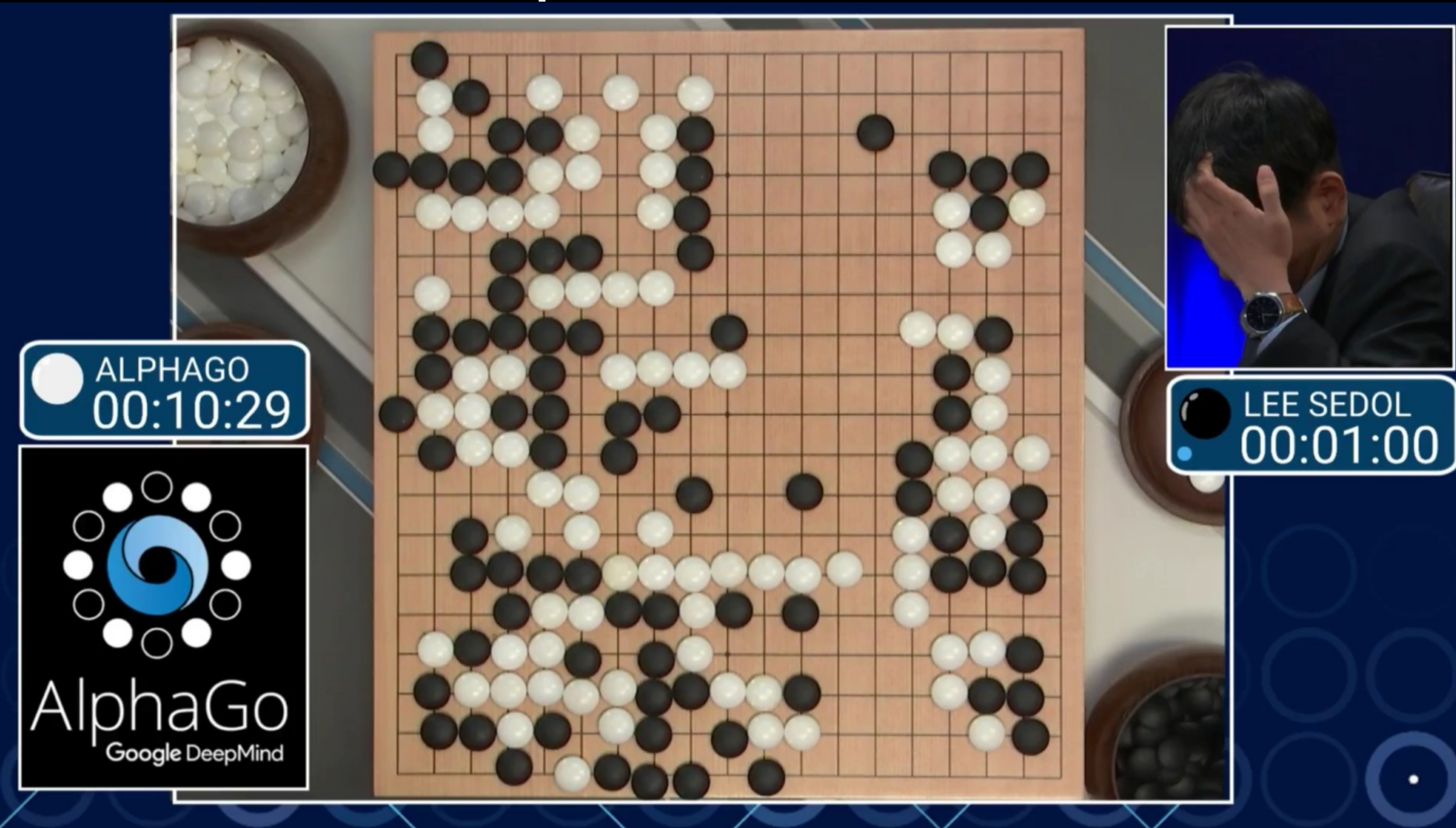
Aristo: Allen AI Challenge

Jeroen Craps
Jorik De Waen

1996: Deep Blue

VS

2016: AlphaGo



https://www.engadget.com/2016/03/12/watch-alphago-vs-lee-sedol-round-3-live-right-now/

Are these computers
smarter than humans?

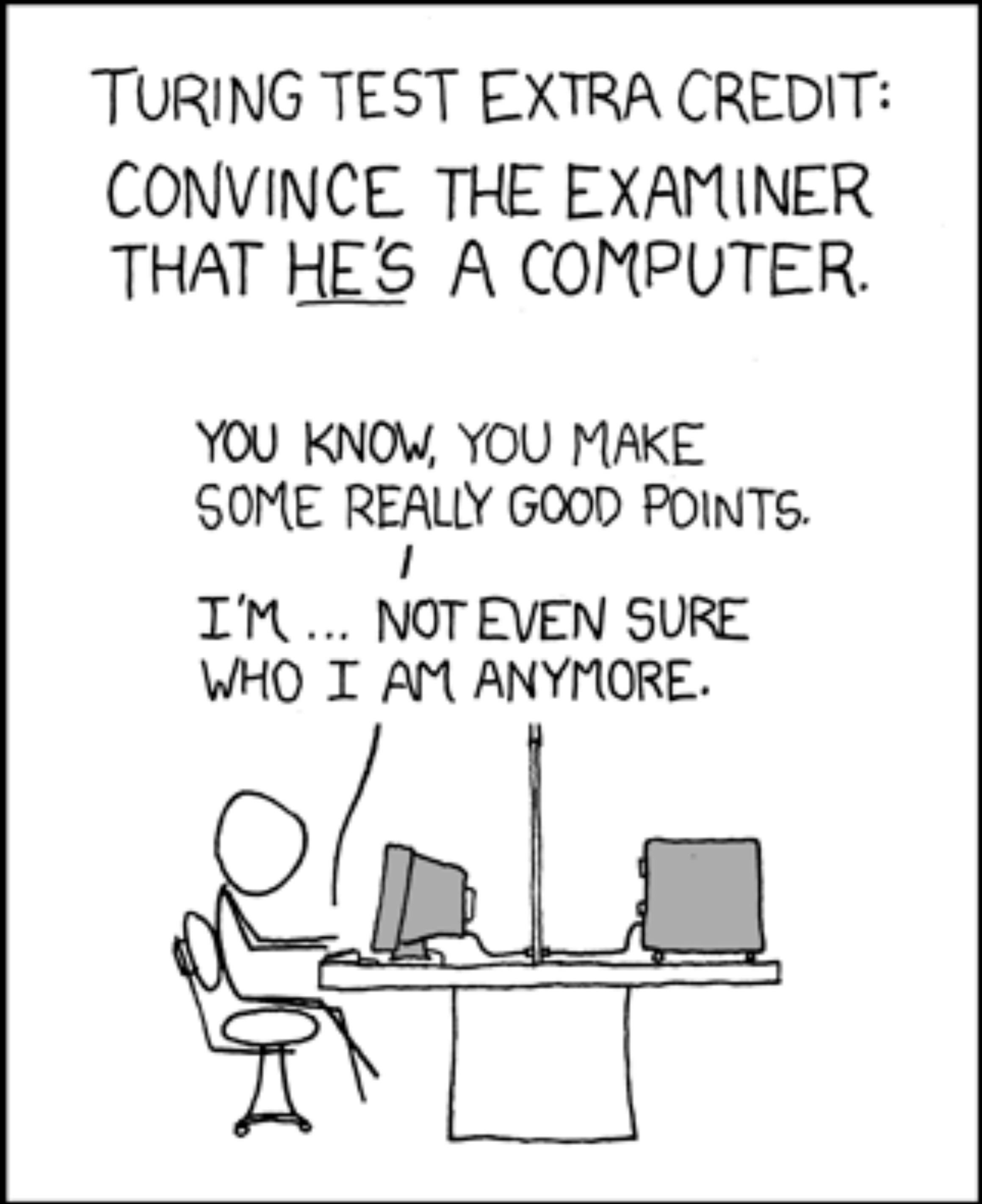
Are these computers
INTELLIGENT?

Turing test

Inventor: Alan Turing

Year: 1950

Test: Convince a human that it is chatting with another human instead of a computer



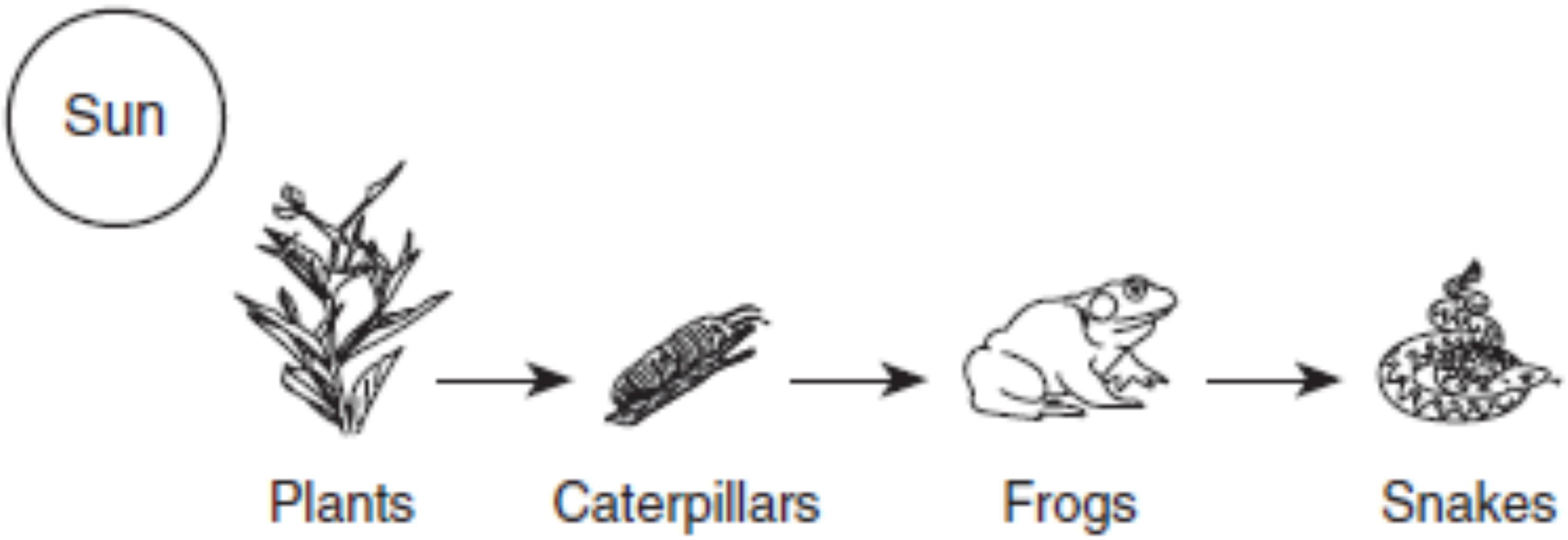
https://xkcd.com/329/

If a computer can
solve the Turing test,
is it truly intelligent?

If a computer can
solve the Turing test,
is it truly intelligent?

No.

An example



(Not drawn to scale)

If the population of snakes increases, the population of frogs will most likely

(A) decrease
(B) increase
(C) remain the same

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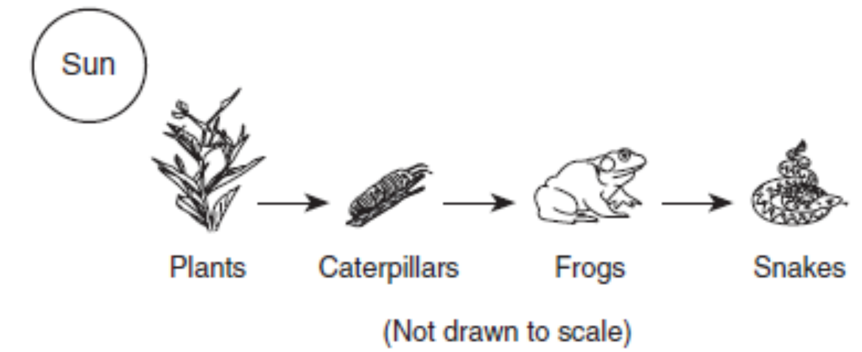
An example

Target: 4th grader

Goal: Interpreting a figure and world modelling

Problem: Not factoid questions and requires language understanding



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New pillars

VARIETY

COMPLEX

COMMONSENSE

SCALABLE

Why 4th grade tests?

Measurable ✓

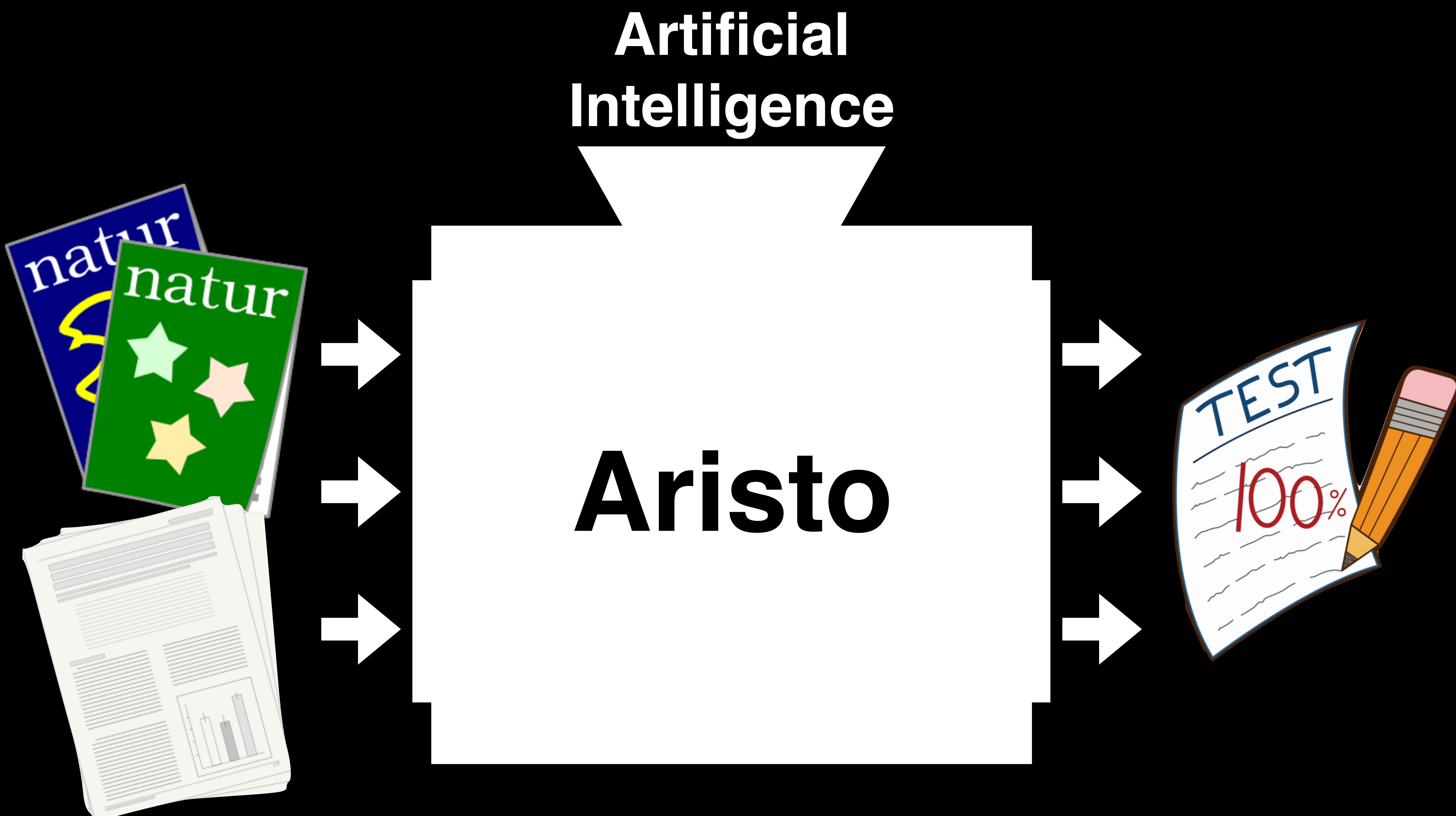
Graduated ✓

Not game-able ✓

**Ambitious
but realistic ✓**

Motivating ✓

Tackling the problem



1.
IMAGE
RETRIEVAL

2.
LEXICAL
ANALYSIS

PDFFigures2.0

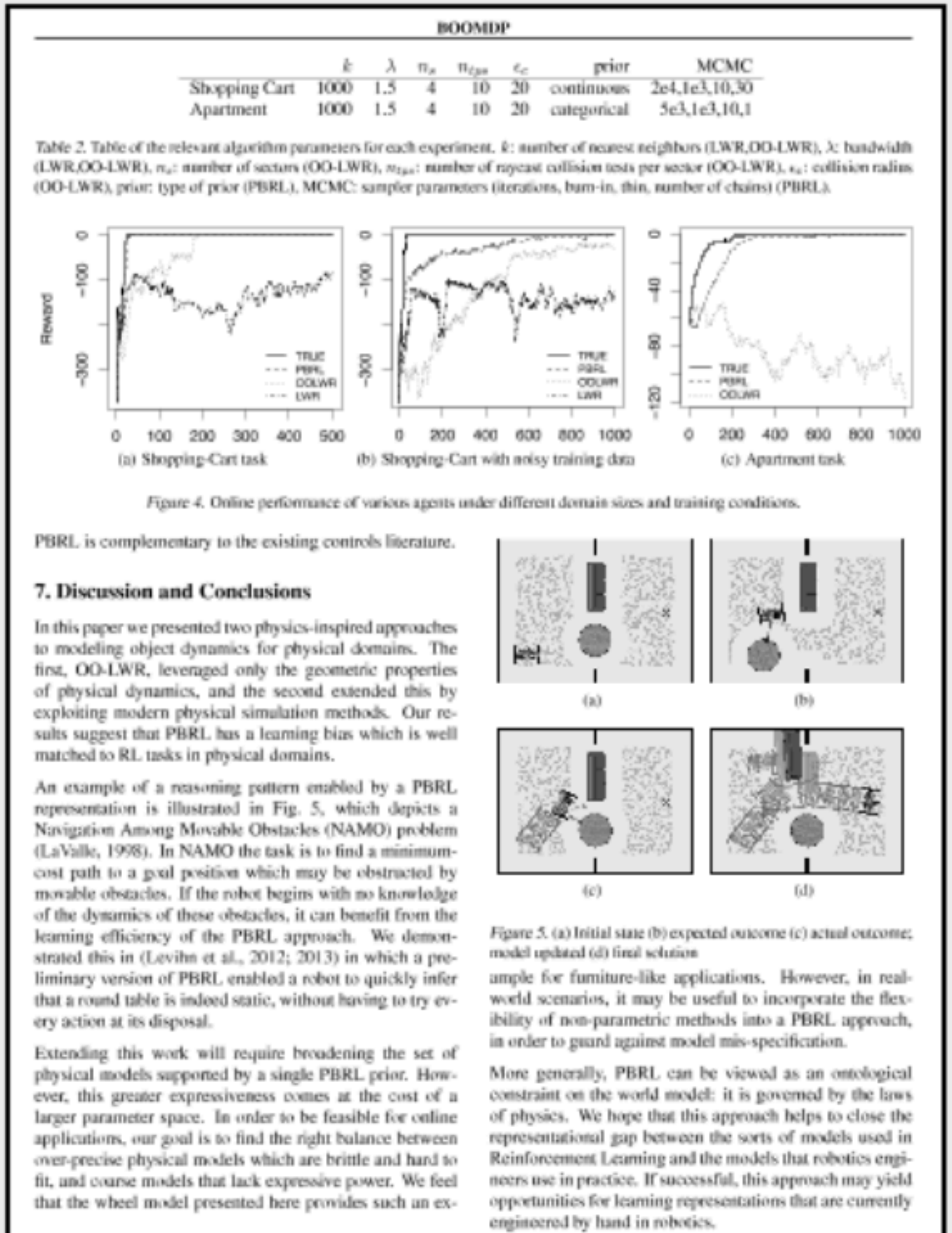
Input: Scientific papers

Step 1: Find the caption (keywords)
↳Removing false positives (filters)

Step 2: Classify regions and text

Step 3: Assign captions with titles
through clustering

PDFFigures2.0 (Result)



BOOMDP

	k	λ	n_s	n_{tps}	ϵ_c	prior	MCMC
Shopping Cart	1000	1.5	4	10	20	continuous	2e4,1e3,10,30
Apartment	1000	1.5	4	10	20	categorical	5e3,1e3,10,1

Table 2. Table of the relevant algorithm parameters for each experiment. k: number of nearest neighbors (LWR,OO-LWR), λ: bandwidth (LWR,OO-LWR), n_s: number of sectors (OO-LWR), n_{tps}: number of raycast collision tests per sector (OO-LWR), ϵ_c: collision radius (OO-LWR), prior: type of prior (PBRL), MCMC: sampler parameters (iterations, burn-in, thin, number of chains) (PBRL).

(a) Shopping-Cart task (b) Shopping-Cart with noisy training data (c) Apartment task

Figure 4. Online performance of various agents under different domain sizes and training conditions.

PBRL is complementary to the existing controls literature.

7. Discussion and Conclusions

In this paper we presented two physics-inspired approaches to modeling object dynamics for physical domains. The first, OO-LWR, leveraged only the geometric properties of physical dynamics, and the second extended this by exploiting modern physical simulation methods. Our results suggest that PBRL has a learning bias which is well matched to RL tasks in physical domains.

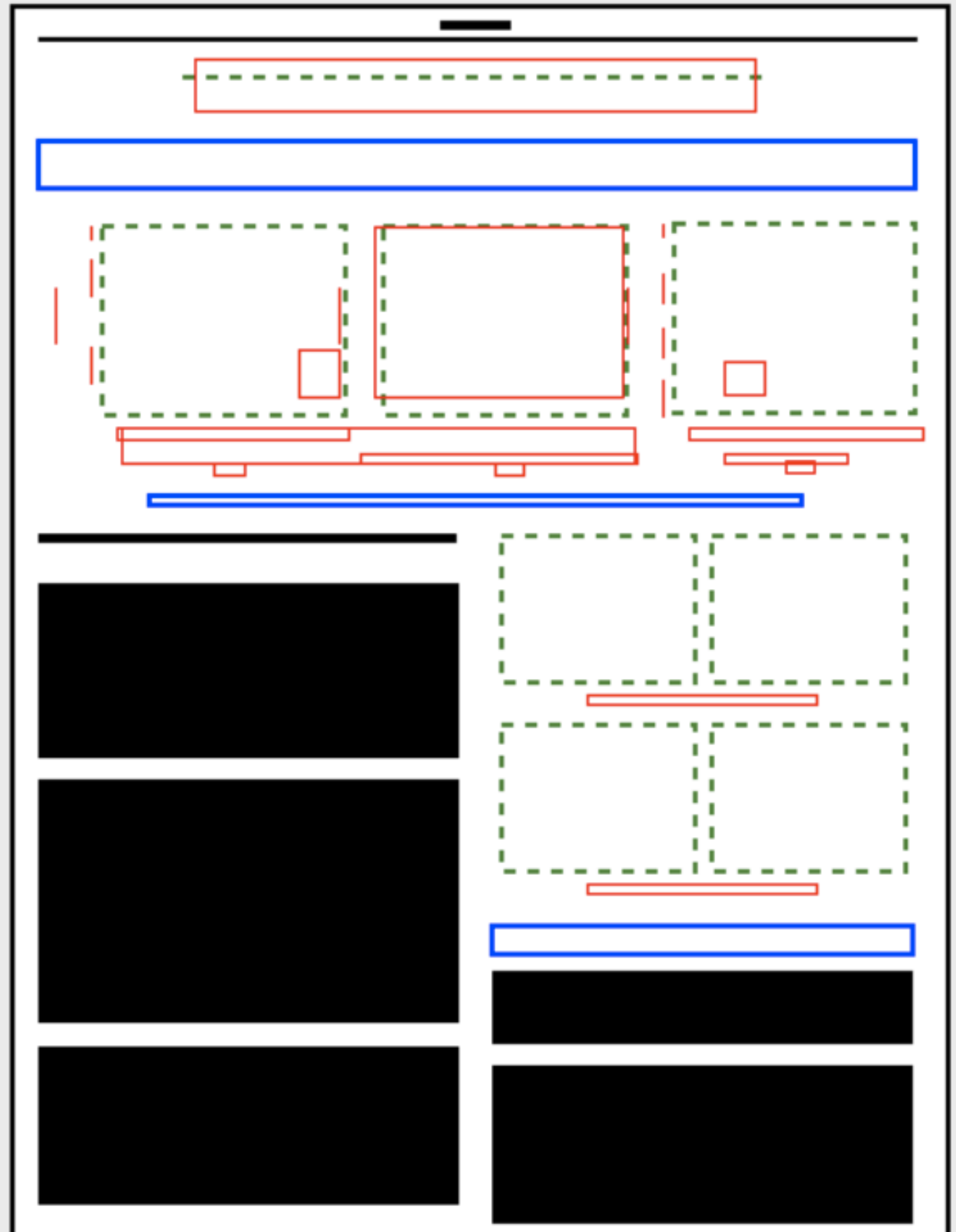
An example of a reasoning pattern enabled by a PBRL representation is illustrated in Fig. 5, which depicts a Navigation Among Movable Obstacles (NAMO) problem (LaValle, 1998). In NAMO the task is to find a minimum-cost path to a goal position which may be obstructed by movable obstacles. If the robot begins with no knowledge of the dynamics of these obstacles, it can benefit from the learning efficiency of the PBRL approach. We demonstrated this in (Levihn et al., 2012; 2013) in which a preliminary version of PBRL enabled a robot to quickly infer that a round table is indeed static, without having to try every action at its disposal.

Extending this work will require broadening the set of physical models supported by a single PBRL prior. However, this greater expressiveness comes at the cost of a larger parameter space. In order to be feasible for online applications, our goal is to find the right balance between over-precise physical models which are brittle and hard to fit, and course models that lack expressive power. We feel that the wheel model presented here provides such an example for furniture-like applications. However, in real-world scenarios, it may be useful to incorporate the flexibility of non-parametric methods into a PBRL approach, in order to guard against model mis-specification.

(a) (b) (c) (d)

Figure 5. (a) Initial state (b) expected outcome (c) actual outcome; model updated (d) final solution

More generally, PBRL can be viewed as an ontological constraint on the world model: it is governed by the laws of physics. We hope that this approach helps to close the representational gap between the sorts of models used in Reinforcement Learning and the models that robotics engineers use in practice. If successful, this approach may yield opportunities for learning representations that are currently engineered by hand in robotics.



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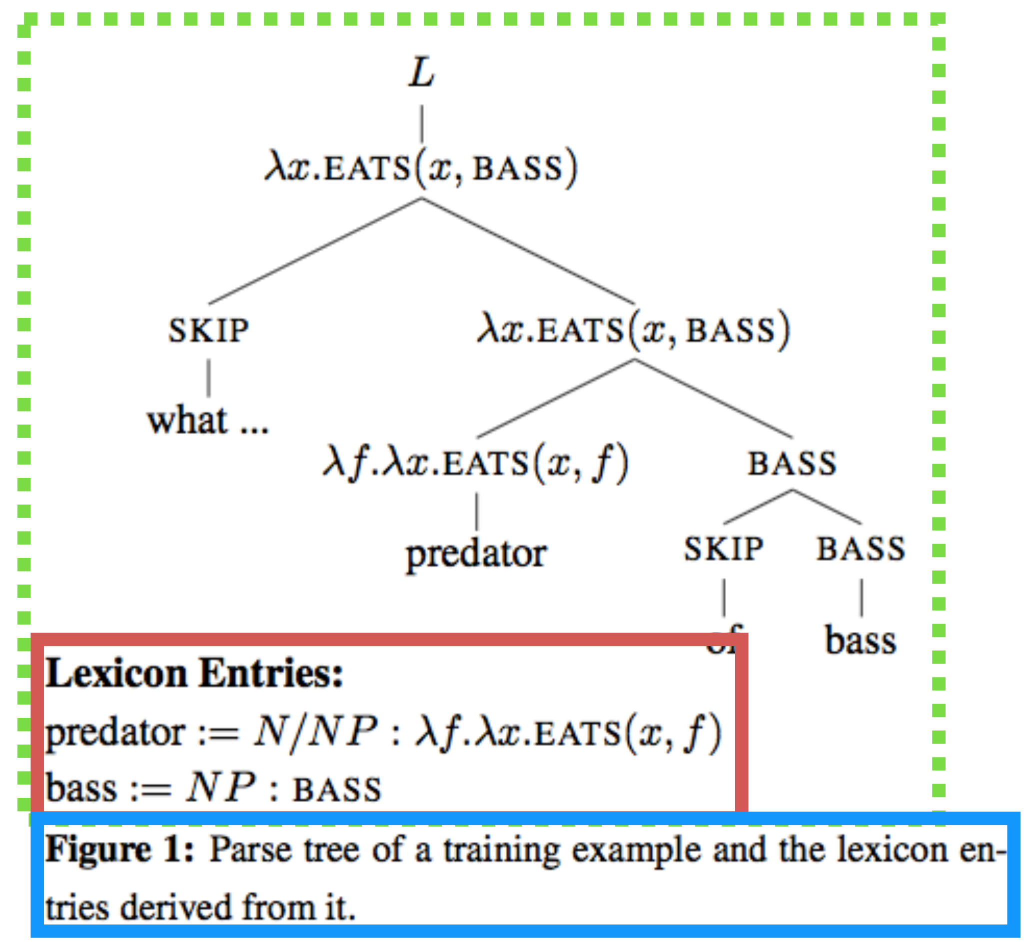
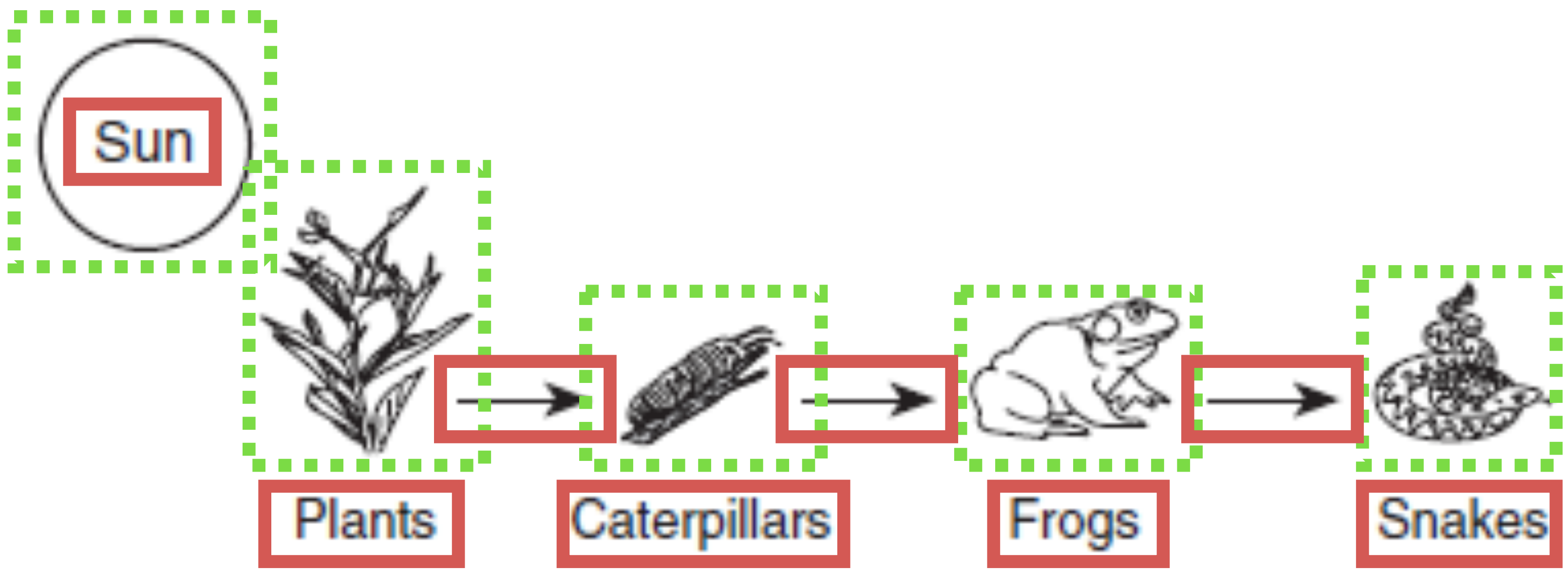


[redacted]

An example (Cont'd)



(Not drawn to scale)

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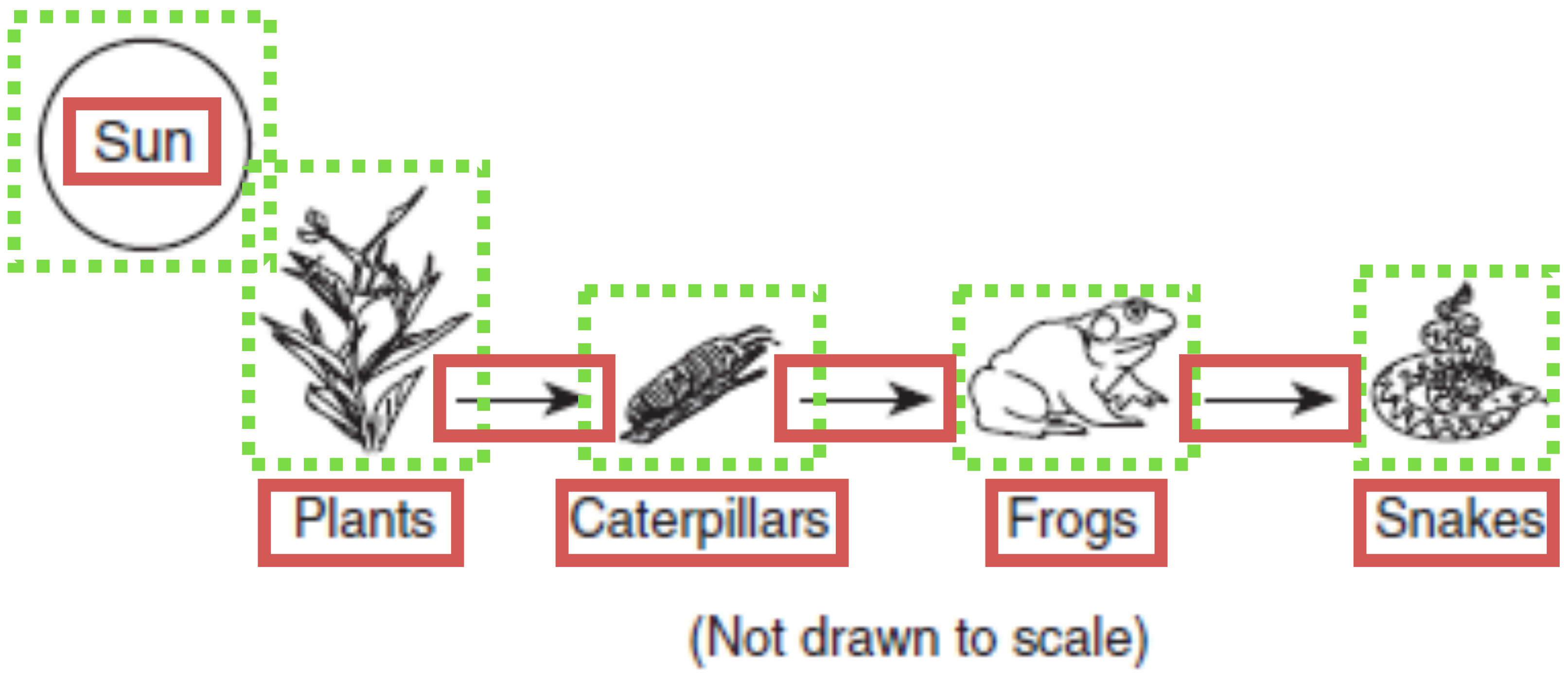
Lexical analysis

An example (Cont'd)



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DEMO

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