Online Learning in Monkeys

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Abstract

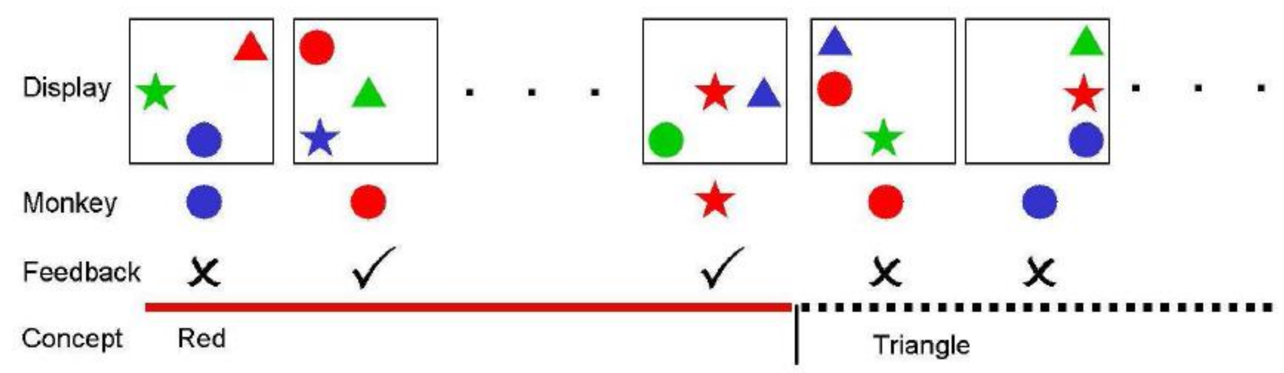
Online learning assumes that an adversary provides data sequentially to a learner, and can change the target concept at any time (called a *concept drift)* unbeknownst to the learner. This study is the first to address the connection between online learning in primates and learning algorithms.

We examine online learning in the context of the Wisconsin Card Sorting Task (WCST), a task for which the concept acquisition strategies for human and other primates are well documented. We describe a new WCST experiment in rhesus monkeys, comparing the monkeys' behaviors to that of online learning algorithms. Our expectation is that insights gained from this work and future research can lead to improved artificial learning systems.

It appears that the monkeys are bad learners for this task. We suspect the primary cause for the "inefficiency" in the monkeys' responses is due to the fact that they must first acquire the hypothesis space for the game, whereas the computer algorithm's search space is predefined. The monkeys may not yet be actually playing the WCST as we understand it.

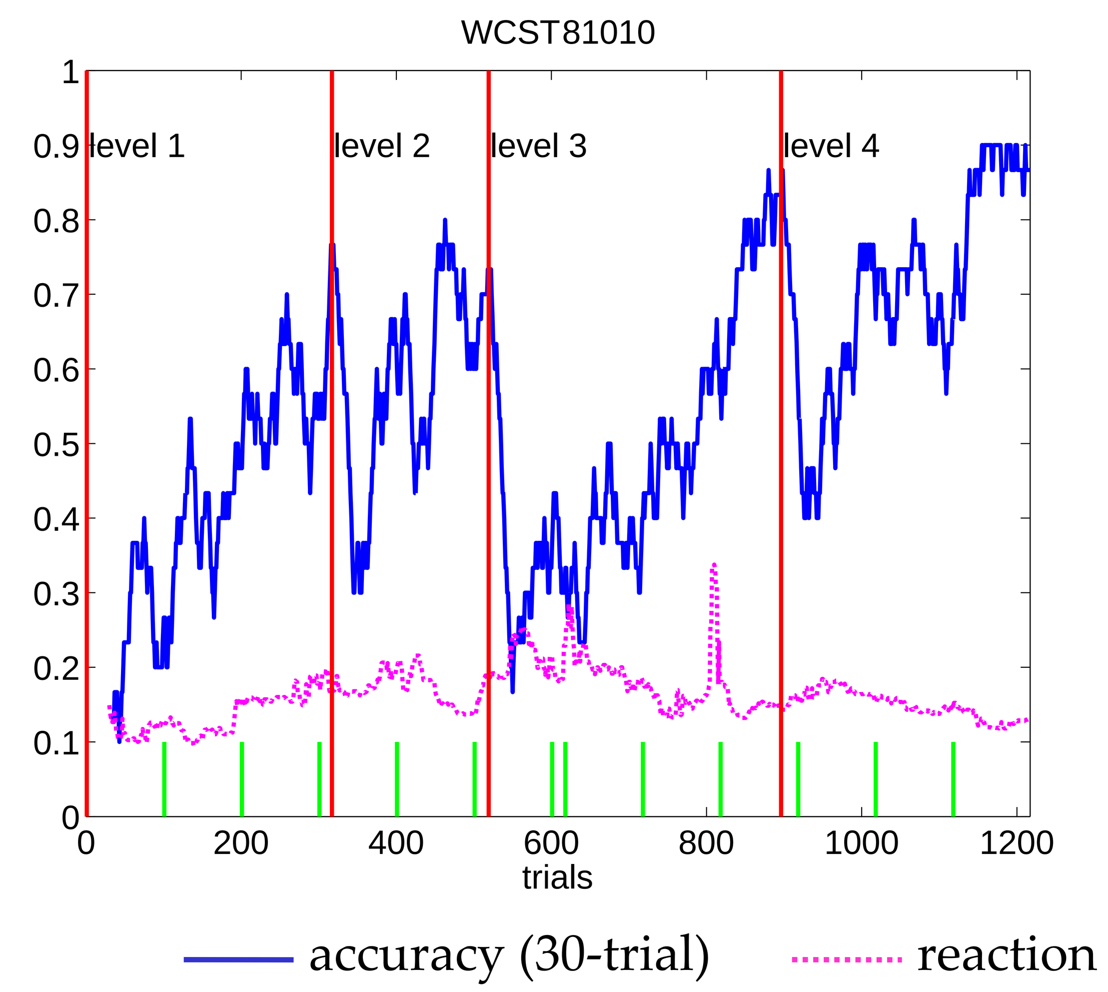
Acknowledgement We thank Timothy Rogers for WCST discussions. Research supported in part by the Wisconsin Alumni Research Foundation, NIA grant P01 AG11915, NCRR grant P51 RR000167, and the University of Wisconsin School of Medicine and Public Health.

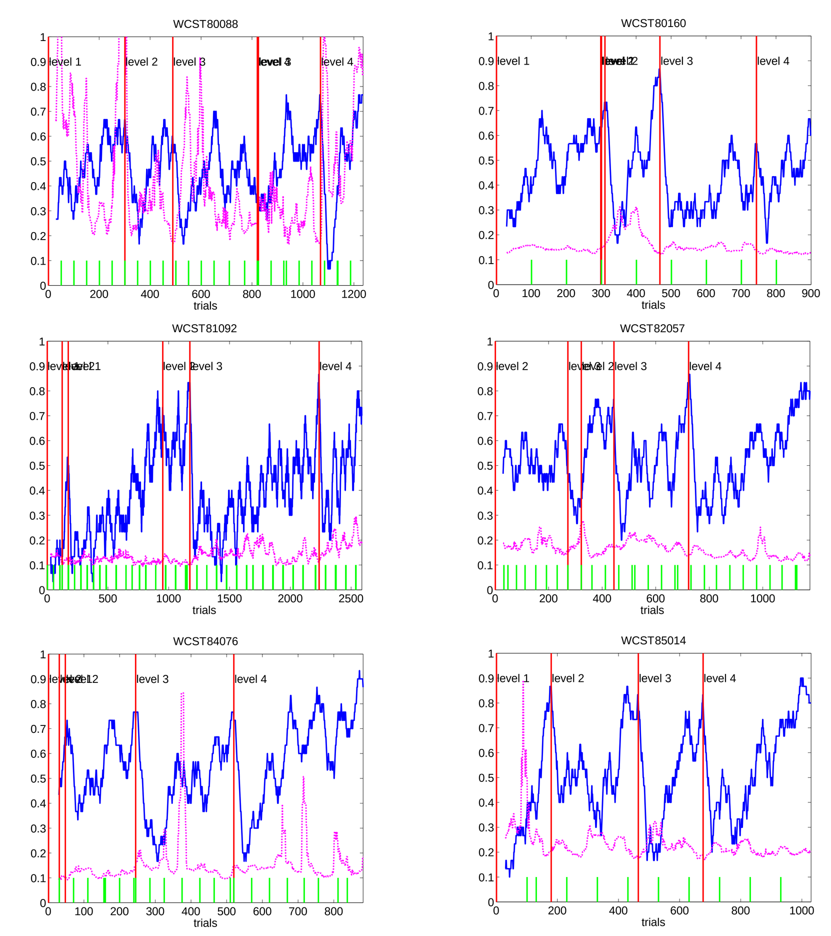
The Wisconsin Card Sorting Task (WCST)



In each trial, three shapes appear simultaneously on screen, each randomly combined with a different color. The target concept is initially Red. The monkey is rewarded with a food pellet for touching the red object regardless of its shape. Once the monkey has had 10 consecutive correct trials, a *concept drift* happens where the target concept is changed to Triangle without warning. The concept later shifts to Blue and then Star in a similar way.

Monkeys (*Macaca mulatta*)





1. Monkeys adapt to concept drifts slowly – on average around 300 trials.
2. Perseverative error dominates at 75%: A perseverative error is a mistake which would have been correct under the immediately preceding concept.
3. The monkeys do not slow down after a concept drift: Do they realize the change?

	trials	errors	persv
Red	425	242	-
Triangle	249	113	89
Blue	437	247	186
Star	279	132	94

Computers

Online disjunction learning algorithm

- Each object x has d=6 Boolean features (R,G,B,C,S,T).
- Adversary presents $d/2$ objects, learner picks one, adversary says yes/no
- Adversary can change the concept, i.e., concept drift.
- Want the number of mistakes not too larger than the number of concept drifts.

1. Initially $h = (1 \ldots 1)$ (d ones). Repeat 2–4:
2. Randomly pick $x \in \{x_1 \ldots x_{d/2}\}$ for which $h \wedge x \neq 0$
3. If x is correct, $h = h \wedge x$.
4. If x is wrong, $h = h \wedge \neg x$. If $h = 0$, reset $h = (1 \ldots 1)$.

Theorem: For any input sequence with m concept drifts, the algorithm makes at most $(2m+1)(d-1)$ mistakes.

Specifically, the bound is 35 (m=3, d=6). Very different from monkey behaviors.

	errors	persv
Red	4	-
Triangle	4	3
Blue	3	2
Star	2	1

An algorithm closer to monkey behaviors

- "slow": skip learning (steps 3, 4) with probability a.
- "stubborn": when h=0 in step 4, retain the old incorrect h with probability b.

When a=0.93, b=0.96, this algorithm makes on average 563 errors, with 312 perservative errors (67%) out of 469 in T,B,S.

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