Attention Allocation is Adapted to Context: Evidence from a Naturalistic Discrimination Task

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Motivation

Attention is a crucial for elite human performance, particularly in high-paced, high-stakes situations. Attentional effort is a finite cognitive resource that is intentionally allocated. We adapt our decision-making strategies and learning processes in response to the evolving context. Inference of the underlying context can provide insights into how attentional resources are distributed and tailored to specific situations

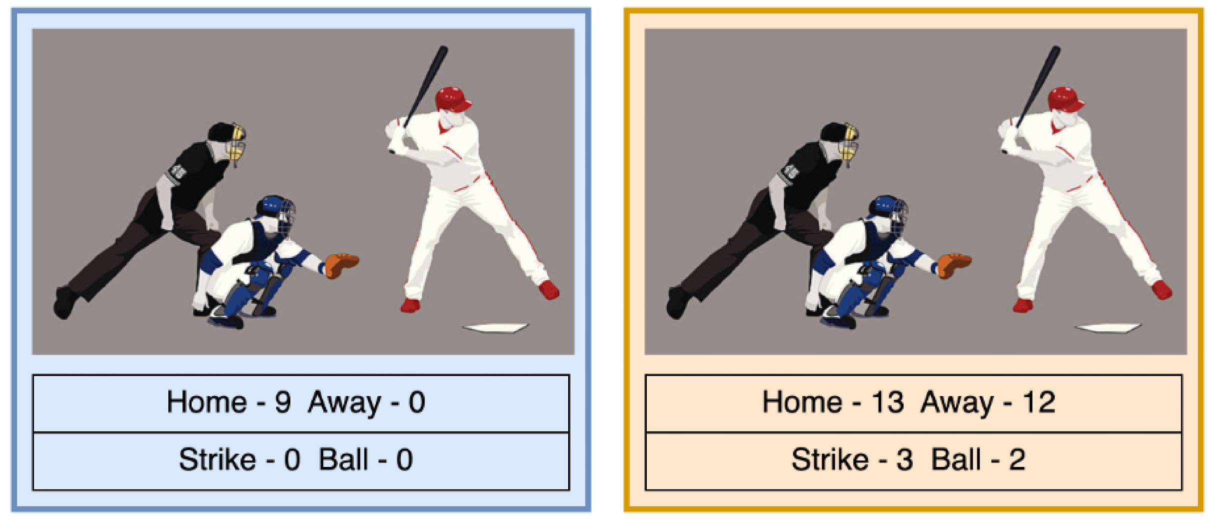


Figure 1. An example of two different game contexts

Contribution

- **Contextual inference** Using Bayesian principles, we model context as a latent variable that changes over time.
- **Attention allocation policy** The optimal policy is formalized using Discrete choice model and a mixture policy approach to account for uncertainty about the current context.

We present a model of attentional effort allocation in relation to time-varying, subjective perceptions of task-relevant context.

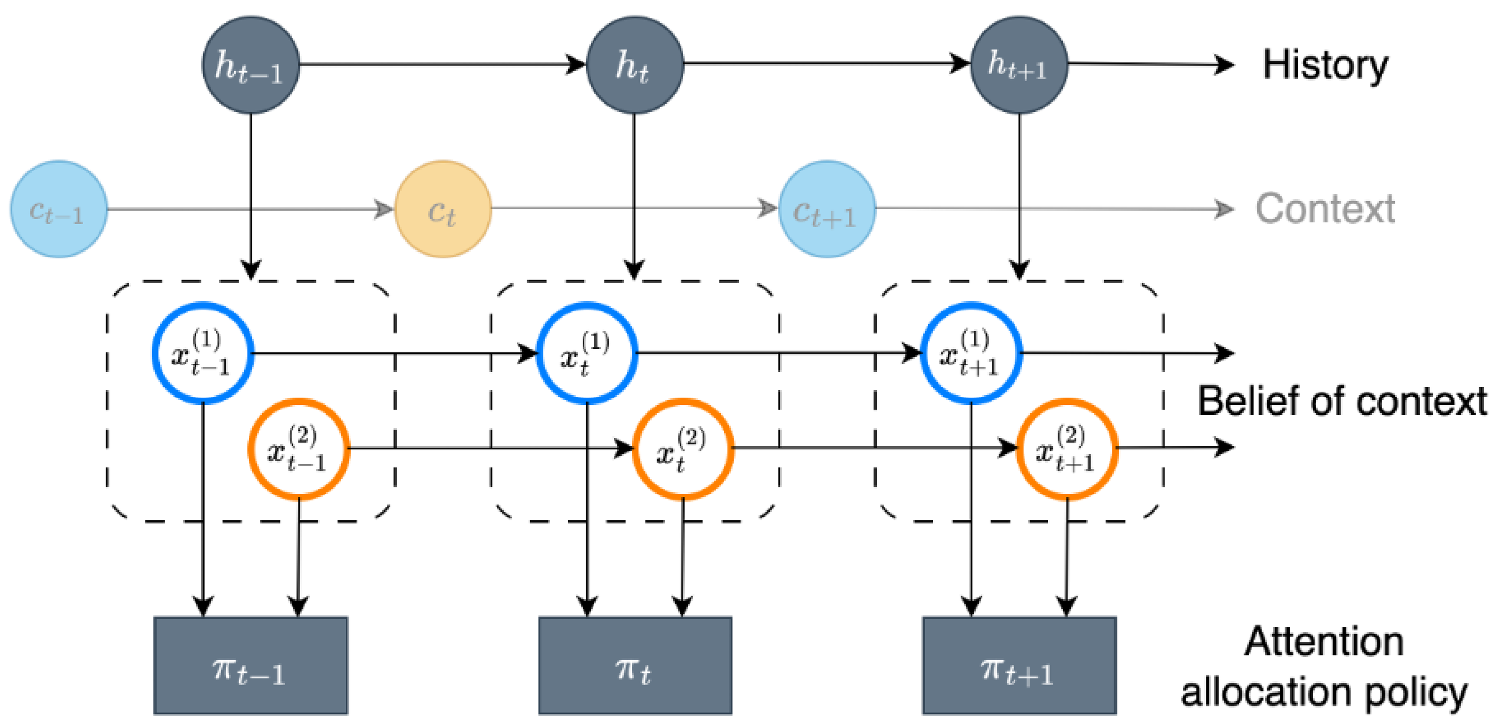


Figure 2. Graphical Model of Contextual Inference & Attention Allocation

A Model of Context-Adapted Attention

Given a data set of N trajectories, each sequence of T periods of observations (z_t) and actions (a_t) : $h_t = \{z_0, a_0, z_1, a_1, \ldots, z_t, a_t\}$. The estimation process involves two stages:

Phase 1 Estimation

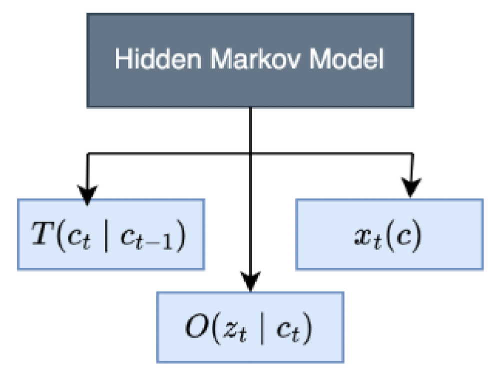


Figure 3. Estimating Transition Probabilities, Observation Probabilities, and Belief contexts

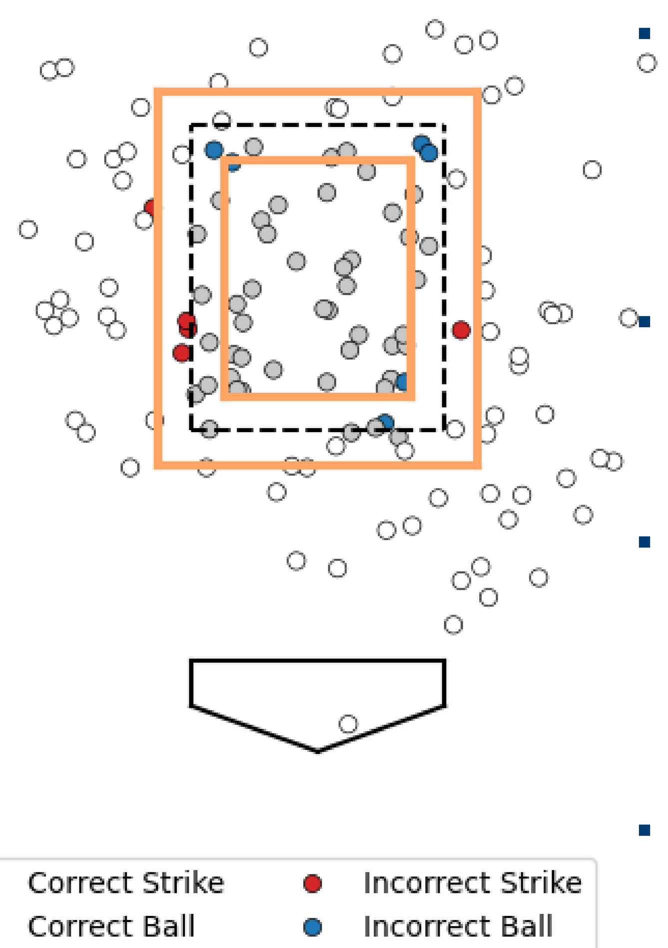
Phase 2 Estimation

$$\pi(a \mid c, z) = \mathbb{P}\Big(a \in \arg\max_{a'} \{r(s, z, a') + \varepsilon(a')\}\Big)$$

$$l(r) = \sum^{N}\sum^{T} \log\Big(\sum^{C} \pi(a_t \mid c, z_t) \cdot x_t(c)\Big)$$

Figure 4. Estimating optimal attention policy using Maximum likelihood estimation

Umpire's Decision-making in Major League Baseball



- The primary factor in evaluating an umpire's performance is the frequency of errors in his calls : incorrect ball, incorrect strike.
- **Observation data**: number of strikes z_s, number of balls z_b, home team indicator z_h, status of the pitcher z_p
- **Action data** : Greater attention devoted to a decision increases the probability of making a correct call. $a_t = 1$, high attention effort
- We focus on borderline pitches or areas where umpires can employ maximum subjectivity

Way forward

By employing a semi-Markov framework, we investigate attention allocation in forward-looking environments, where decision-makers consider both immediate outcomes and future consequences.

References

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Results: Umpire context profile

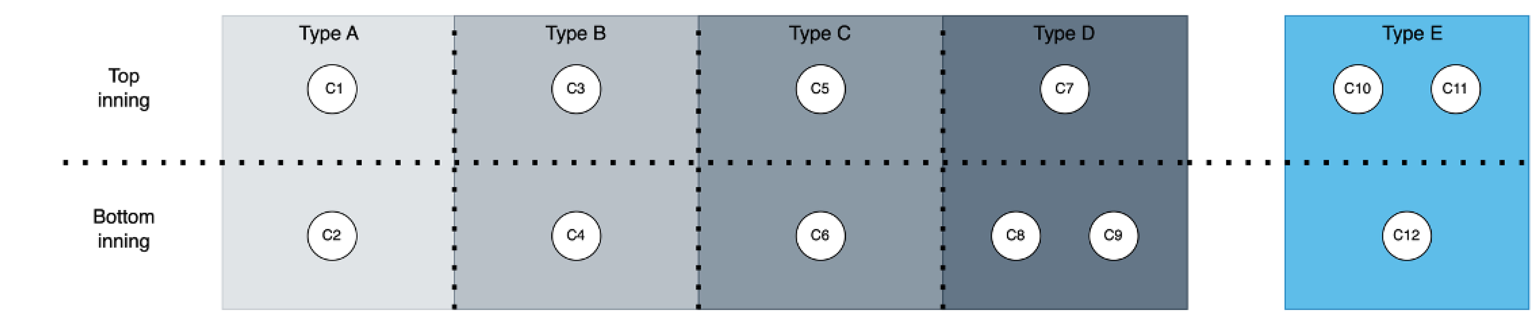

Figure 5. 12 contexts were identified using HMM. These states are grouped into 5 types

Context reflects the progression of the game.Terminal pitches (which can end a batter's plate appearance) are subject to higher scrutiny and can significantly alter umpire behavior. For high-status pitchers, the distinction between longer at-bats and the start of an at-bat disappears

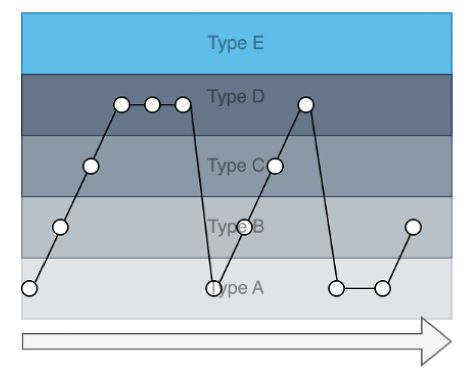

Figure 6. Example of top inning pitches with low status pitcher

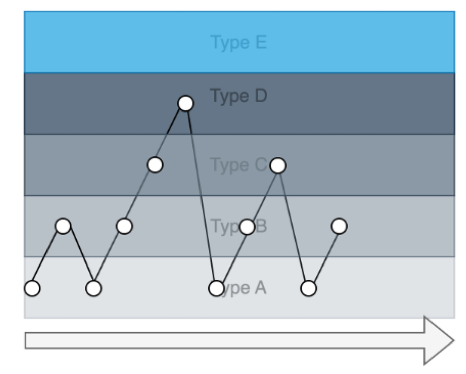

Figure 7. Example of Bottom inning with low status pitcher

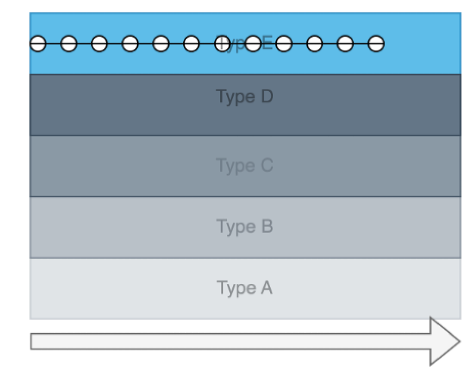

Figure 8. Example of top inning with high-status pitcher

Results: Umpire attention allocation

Utility is modelled as a function of the leverage index of the current game situation and the umpire's decision:
$r(s, z, a) = \theta_s \cdot z_l$

			Context											
			Type A		Type B		Type C		Type D			Type E		
Umpire	Accuracy	Pitches Called	1	2	3	4	5	6	7	8	9	10	11	12
B	90.9%	$32.1k$	0.80	0.68	0.85	0.77	0.86	0.85	1.12	0.88	1.08	0.70	0.83	0.68
A	91.4%	$35.1k$	0.75	0.69	0.92	0.77	0.98	0.91	1.14	1.07	1.14	0.78	0.78	0.90
C	91.8%	$35.6k$	0.92	0.86	0.97	0.90	1.02	0.88	1.35	1.21	1.43	0.89	1.03	0.72
D	93.0%	$30.9k$	1.05	1.11	1.15	1.32	1.60	1.32	1.42	1.33	0.85	1.01	1.32	1.17
E	94.1%	$32.3k$	1.27	1.27	1.47	1.26	1.43	1.34	1.74	1.83	1.54	1.23	1.22	1.22
F	95.0%	$18.6k$	1.27	1.29	1.14	1.70	1.35	1.85	1.47	1.55	1.46	1.43	1.34	1.33

Table 1. Utility estimates θ_s across different contexts for 6 Umpires ordered by their call accuracy. In each case, three highest utility values are highlighted.

(1) Umpires demonstrate fewer errors, implying increased allocation of attention in **context type D** (states 7,8,9). In contrast, **context type A and E** shows relatively low estimated utilities. (2) Positive correlation between umpire accuracy and the magnitude of the estimated utility, indicating that more accurate umpires tend to have higher utility values. (3) The variations highlight that while there are common patterns there are also unique tendencies that may be influenced by personal experience or decision-making styles.