

# Belief Aggregation and Trader Compensation in Infinite Outcome Prediction Markets

Blake Martin, Mithun Chakraborty, Sindhu Kutty Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI

#### Introduction

- Prediction markets are incentive-compatible mechanisms designed to elicit the personal beliefs of traders about a future uncertain event and aggregate those beliefs into the market price
- Prediction markets have been empirically observed to outperform polls as they have built-in financial incentives and timely responses
- We study the impact of traders' informativeness, budget, and the sequence in which they trade on aggregation properties and trader compensation under a new prediction market design

# Background

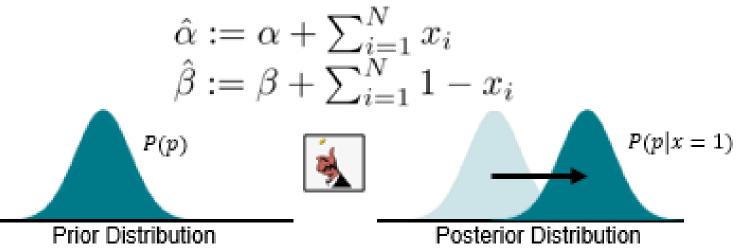
 The Bernoulli probability distribution models an uncertain binary event with success parameter p

$$f(x;p) = p^x (1-p)^{1-x}$$
, for  $x \in 0, 1$ 

 The Beta distribution is conjugate prior for the Bernoulli distribution success parameter and has pdf given by

$$f(p; \alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1} (1-p)^{\beta-1}$$

 Given a Beta prior over p and a sample of Bernoulli observations, the **Bayesian posterior update** is given by



 The gamma and digamma functions are used in computing statistics associated with the Beta distribution and are given below

$$\Gamma(n) = (n-1)!$$
  $\psi(n) = \frac{\mathrm{d}\Gamma(n)/\mathrm{d}n}{\Gamma(n)}$  for  $n \in Z^+$ 

#### **Trader Model**

- We assume traders are myopic, risk-neutral, and rational
- Trader informativeness is modeled by N, the size of their private sample of Bernoulli observations at each trade

$$x_1, \dots, x_N \stackrel{iid}{\sim} \text{Bern}(p)$$

 Traders may also have limiting budgets B, modeled by an additional constraint of using the largest observation sub-sequence of length k where worst-case losses do not exceed B

$$\max_{p} \left\{ C \left( \eta + \left[ \sum_{i=1}^{k} x_i, k - \sum_{i=1}^{k} x_i \right]^T \right) - C(\eta) - \left[ \sum_{i=1}^{k} x_i, k - \sum_{i=1}^{k} x_i \right] \cdot \left[ \ln p, \ln(1-p) \right] \right\} \le B$$

- Trades proceed as follows:
  - Trader samples from Bernoulli distribution according to their informativeness
  - $\hat{\alpha} := \alpha + \sum_{i=1}^{N} x_i$ - Trader updates Beta posterior beliefs according to
  - Trader purchases shares such that market posterior matches private beliefs

## Aggregation Mechanism: Beta-Bernoulli Market

- Securities and payoffs: The market has two securities with payoffs given by  $\ln p_{true}$  and  $\ln(1-p_{true})$  when  $p_{true} \in [0,1]$ , the true Beta forecast variable corresponding to the Bernoulli success parameter, is revealed
- Outstanding shares and aggregated belief: The market maintains and displays outstanding shares  $\eta = [\eta_1, \eta_2]$  which also corresponds to market belief given by BETA( $p; \alpha, \beta$ ) where  $\eta_1 = \alpha - 1, \eta_2 = \beta - 1$ . This gives us expectations of the Bernoulli parameter and payoffs

$$\mathbb{E}_{\eta}[p] = \frac{\eta_{1}+1}{\eta_{1}+\eta_{2}+2} \qquad \frac{\mathbb{E}_{\eta}[\ln p] = \psi(\alpha) - \psi(\alpha+\beta)}{\mathbb{E}_{\eta}[\ln(1-p)] = \psi(\beta) - \psi(\alpha+\beta)}$$

• Cost Function: This gives us the cost of a trade  $C(\eta_{new}) - C(\eta_{old})$ , the prices of each security  $\nabla_{n} C(\eta)$ , and is given by

$$C(\eta) = \ln \Gamma(\eta_1 + 1) + \ln \Gamma(\eta_2 + 1) - \ln \Gamma(\eta_1 + \eta_2 + 2)$$

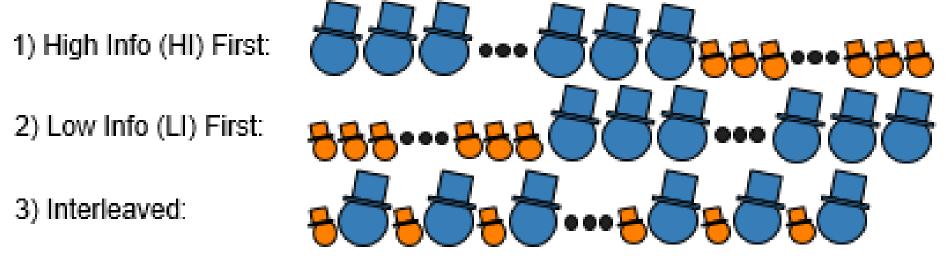
#### Informativeness and Sequence Results

Experimental Setup



6 Low Informativeness  $\leftrightarrow N = 1$ 

Three sequences are tested with 500 traders of each type with unlimited budgets



 We report market convergence (Fig. 1), overall belief aggregation (Fig. 2) and average compensation for each trade type (Table 1)

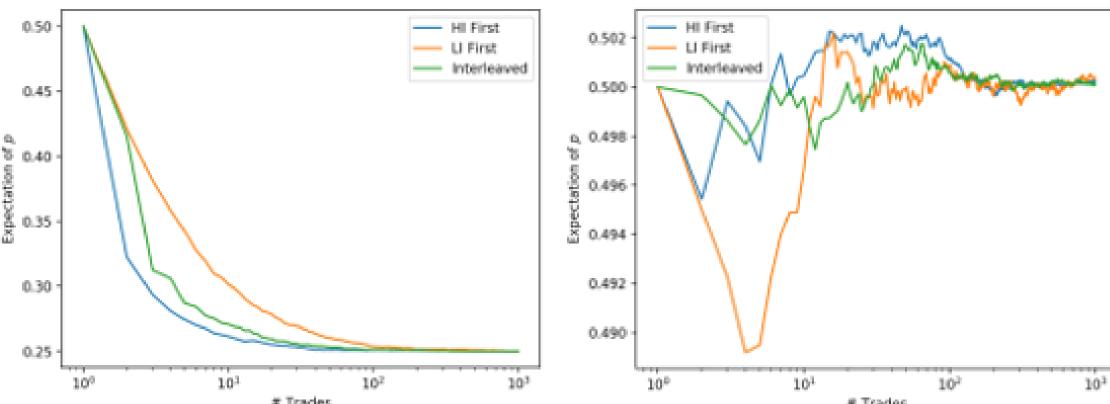
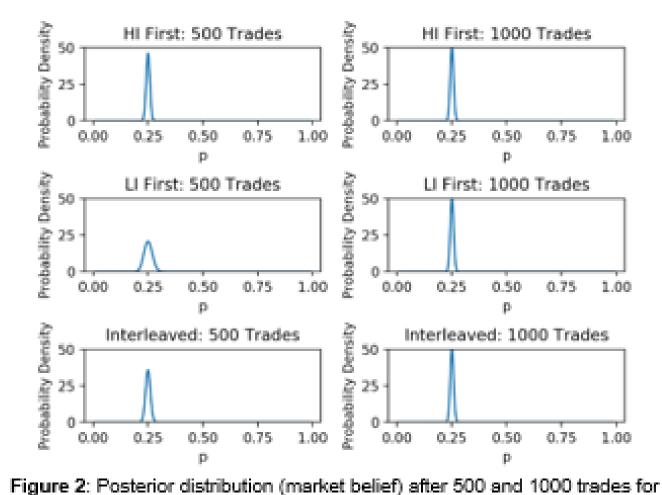


Figure 1: The market's expectation of the Bernoulli parameter as a function of the number of completed trades for different trader orderings, averaged over 1000 simulations with  $p_{true} = 0.25$  (left) and  $p_{true} = 0.5$  (right). Horizontal axis is logarithmic.



different trader orderings averaged across 1000 simulations with  $p_{true} = 0.25$ .

	0.50	HI First	$6.37 \pm 0.08$	$0.17 \pm 0.05$
		LI First	$1.75 \pm 0.11$	$4.78 \pm 0.09$
		Interleaved	$5.56 \pm 0.14$	$0.99 \pm 0.12$
	0.25	HI First	$6.70 \pm 0.08$	$0.21 \pm 0.05$
		LI First	$1.80 \pm 0.11$	$5.04 \pm 0.09$
		Interleaved	$5.52 \pm 0.14$	$1.26 \pm 0.12$
Table 1: Compensation of HI and LI traders for different trader ordering and press values. This table reports the compensation averaged over				
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Sequence

LI First

Interleaved

Avg HI (×10<sup>3</sup>)

 $6.66 \pm 0.09$ 

 $1.75 \pm 0.12$ 

 $5.51 \pm 0.15$ 

Avg LI (×10<sup>3</sup>)

 $0.18 \pm 0.05$ 

 $5.07 \pm 0.09$ 

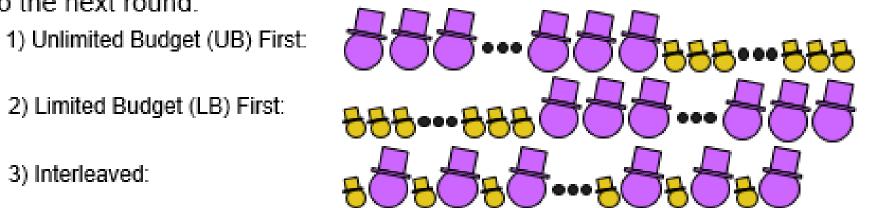
 $1.29 \pm 0.13$ 

1000 simulations with 95% confidence bounds.

## **Budget and Sequence Results**



Three sequences are tested with 500 traders of each type with constant informativeness (N=5 per trade) and initial budgets  $B_0$ . There are 25 successive market instances where agents trade, receive compensation, and update their budgets before proceeding to the next round.



· We report the change in average LB trader budget over market rounds

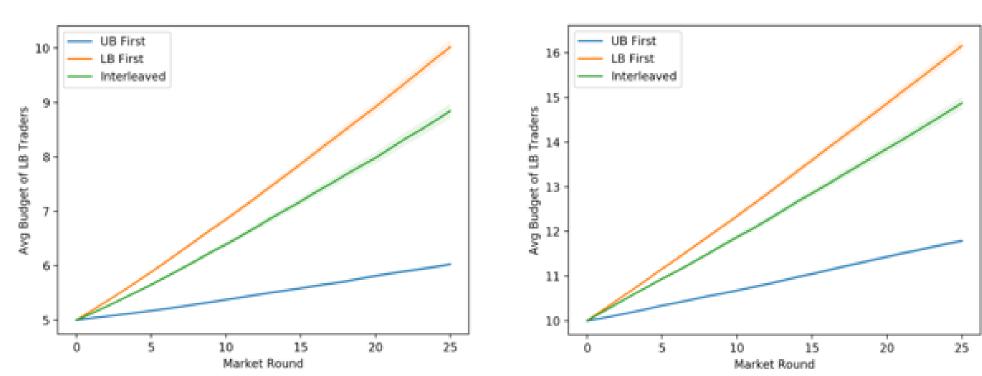


Figure 3: Change in budget of LB traders with an initial budget of  $B_0 = 5$  (left) and  $B_0 = 10$  (right) over rounds 1 – 25, averaged over 1000 simulations with  $p_{true} \sim U[0.05, 0.95]$  for different trader orderings

#### Conclusions

- . The expected compensation of a trader depends not only on her informativeness but also strongly on the sequence (Table 1)
- 2. Notably, LI traders receive higher compensation on average than HI traders when they trade first. This phenomenon underscores the advantage gained by injecting information into the market early as higher marginal value of information leads to higher compensation
- 3. Traders with the same overall informativeness induce the same aggregation characteristics at convergence regardless of sequence, but number of trades required to reach steady-state is largely impacted by trader ordering (Figs. 1-2)
- 4. All LB agents can trade on more information in round 25 than in the initial rounds due to increased budget regardless of sequence, though rate of change in budgets is affected by trader ordering (Fig. 3)
- 5. Future work includes further experiments with other trader models as well as theoretical analysis to quantify the impact of the sequencinginformativeness-budget interplay

# Significant References

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