Efficient Competitions and

Online Learning with Strategic Forecasters



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Classic online learning from expert advice

On rounds $t = 1, \ldots, T$:

- Expert i predicts $p_{it} \in [0, 1]$
- Algorithm chooses an expert
- Outcome $\omega \in \{0,1\}$; *i*'s loss is $(\omega p_{it})^2$
- Algorithm's goal: low regret to the best expert

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Multiplicative weights (MW):

choose i w.prob. $\propto e^{-\eta({\rm total \; loss})}.$

Guarantees: Regret $O(\sqrt{T})$.

Strategic experts

Changes to model:

- Experts report some r_{it} , potentially $\neq p_{it}$
- Experts want to be chosen, e.g. max $\mathbb{E}[\# \text{ times chosen}]$
- Strategic regret: to the best expert's knowledge still according to p_{it}'s

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Question: what is the cost of strategic behavior in online learning?

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- Myopic experts: $O(\sqrt{T})$ regret truthful algorithm
- Forward-looking experts: open problem (truthful algorithm, but no regret guarantee)

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But: we don't know how.

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Theorem $\label{eq:main} \mbox{MW achieves } O(\sqrt{T}) \mbox{ strategic regret.}$

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Solution concept? In equilibrium?

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Theorem

MW achieves $O(\sqrt{T})$ strategic regret when experts play undominated strategies.

(more discussion at the end)

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 $(1) + (2) \implies$ MW has \sqrt{T} regret to beliefs.

(Also enables better forecasting competitions.)

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But: Report Noisy Min is also approximately truthful:

- **1** Let $Y_i = (\text{total loss of } i) + \text{Laplace}(\gamma)$
- **2** Choose $\arg \min_i Y_i$.

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$$Y_i = (\text{total loss of } i) + \text{Laplace}(\gamma)$$

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But but: not true for Gaussian noise!

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Model of strategic behavior

Our model: immutable beliefs

- Participant has beliefs p_{it} , unchanging
- Strategy is a plan of reports r_{i1}, \ldots, r_{iT}
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Extensions / questions: Bayesian models, sequential equilibrium, ...

Conjecture

MW achieves strategic regret $O(\sqrt{T})$ in any of the above models.

Conclusion

Setting:

- **1** Online learning from strategic experts
- 2 Experts try to maximize expected # times chosen
- 3 Immutable belief model

Results:

- **1** MW has strategic regret $O(\sqrt{T})$ in undominated strategies.
- 2 exponentially more efficient forecasting competitions (not covered)

Open problems:

- 1 Truthful no-regret algorithm?
- 2 Bayesian settings

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Thanks!