No-Regret and Incentive-Compatible Prediction with Expert Advice
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The Main Question
In deployments of the prediction with expert advice problem experts’ reputation or financial compensation is often tied to the influence that they have on the prediction of the learner.

Experts might report differently from their true belief if that boosts their influence.

E.g., FiveThirtyEight ranks pollsters according to their accuracy:

<table>
<thead>
<tr>
<th>Pollster</th>
<th>MSE/ online/off</th>
<th>10/0/ -1</th>
<th>0/2/0.4</th>
<th>0/0.5/0.4</th>
<th>0/0.4/0.5</th>
<th>0/0.1/1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survey/AA</td>
<td>online/off</td>
<td>3.04</td>
<td>-0.10</td>
<td>0.80</td>
<td>0.50</td>
<td>0.10</td>
</tr>
<tr>
<td>Hannah &amp; Mills</td>
<td>online/off</td>
<td>1.11</td>
<td>0.57</td>
<td>0.40</td>
<td>0.50</td>
<td>0.05</td>
</tr>
<tr>
<td>Zippel</td>
<td>online/off</td>
<td>0.48</td>
<td>0.08</td>
<td>1.00</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>MSOE</td>
<td>online/off</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>YouGov</td>
<td>online/off</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Do there exist online learning algorithms that are simultaneously no-regret for the learner and incentivize the experts to report their true beliefs?

Model
Repeated Interaction Protocol
For round \( t \in [T] \):
1. Learner maintains a distribution \( \pi_t = (\pi_{t,1}, \ldots, \pi_{t,K}) \) over experts.
2. (a) Each expert \( i \in [K] \) has a private belief \( b_{t,i} \in [0,1] \) about the outcome.
   (b) Each expert \( i \in [K] \) reports prediction \( p_{t,i} \in [0,1] \) (potentially \( p_{t,i} \neq b_{t,i} \)) to the learner.
3. Learner chooses prediction \( \tilde{p}_t \in [0,1] \) according to \( \pi_t \).
4. Learner and experts observe event realization \( r_t \in [0,1] \).
5. Learner and experts incur losses \( \ell(p_t, r_t) \) and \( \ell(p_{t,i}, r_t) \), \( \forall i \in [K] \).
6. Learner updates \( \pi_{t+1} \).

Experts/Agents:
- Wish to increase leverage over the decisions of learner.
- Mathematically: \( p_{t,i} = \arg \max E_{r_t \sim \text{Bern}(b_{t,i})} \sum_{i \in [K]} \pi_{t,i} \cdot \ell(p_{t,i}, r_t) \)

Learner’s Goals

1. Incentive-Compatibility of Experts: \( \forall i \in [K] \) reporting their true belief maximizes their probability of being chosen, on expectation over \( r_t \sim \text{Bern}(b_{t,i}) \)

2. Learner’s Goal: Minimize Strategic Regret
\[
R(T) = \sum_{t=1}^{T} \ell(p_t, r_t) - \min_{i \in [K]} \sum_{t=1}^{T} \ell(b_{t,i}, r_t) \leq o(T)
\]

Main Result
Online Learning algorithm that is simultaneously incentive-compatible for the experts and has regret: \( O(\sqrt{T \log K}) \)

A Seemingly Unrelated Problem
Construction of incentive-compatible wagering mechanisms
Probability of winning WNBA championship?

Online Learning algorithms are Wagering Mechanisms!

WSWMs Made No Regret

Beyond Myopic Agents
- WWSM-type algorithms work only when agents care about their probability at the next round (i.e., myopic agents)
- Variant of ELF [Witkowski, Freeman, Vaughan, Pennock, Krause ‘18] performs well in simulations + incentive compatible for non-myopic agents

References
[Witkowski, Freeman, Vaughan, Pennock, Krause ‘18] Incentive Compatible Forecasting Competitions. AAAI’18.