# Internal Regret and Calibration

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## Outline

External and Internal Regret

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Using an external regret algorithm to minimize internal regret

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- ► For log loss we have  $\max_i R_i^n = O(\ln N)$

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# Internal regret

- R<sub>(i,j),n</sub> regret for not taking action j instead of each action i during iterations 1...n
- ▶ We want an algorithm such that  $\max_{(i,j)} R_{(i,j),n} = o(n)$

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- Use a prediction algorithm that minimizes internal regret.
- ▶ If the prediction is not  $\epsilon$  calibrated, then the internal regret has to be large.

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- We solve the fixed point equation

$$\mathbf{p}_t = \sum_{i \neq j} \Delta_{(i,j),t} \mathbf{p}_t^{i \to j}$$