One-Sided Feedback!

**Motivation**
- Loan approvals
- Hiring decisions
- Online advertising
- Predictive policing
- ...

**Fairness-Accuracy Trade-Off**

**Definition (-fair policy):** Fix a distribution \( D \). A policy \( \pi \in \Delta(\mathcal{H}) \) satisfies the \(-\)fairness assumption if \( \Delta(\mathcal{H}) \) contains the empirical distribution formed by the collected data.

**Question:** Why use a policy instead of a single hypothesis?
- Policies achieve better accuracy-fairness trade-off than single hypotheses.
- Optimal trade-off is always attained by policy of support size 2 at most.

**Example:**

\[
\begin{align*}
\mathcal{H} &= \{ \text{pos, neg}, h_1, h_2, h_3 \} \\
\text{pos} &:= \{ \text{class1, fair constant} \} \\
\text{neg} &:= \{ \text{class2, fair constant} \} \\
\Delta(\mathcal{H}) &\subseteq \mathbb{R}^{16} \\
\end{align*}
\]

**Objective**

\[
\text{sign} \text{Regret}(A) := \gamma - \text{fair policies in } \Delta(\mathcal{H}) \text{ w.r.t. } A \text{ or } \gamma \text{ fair online learning algorithm}
\]

**Partial Feedback to Contextual Bandits**

**Algorithm**

**Main Result**

**Theorem:** There exists an oracle-efficient algorithm that takes parameters \( \gamma \), \( \alpha \), \( \beta \), and \( \epsilon \) as input and satisfies, e.g., \( \epsilon = 5 \), \( \beta = \text{fairness and has an expected regret at most } \alpha (\mathcal{H}^{(\mathcal{H})}) \) with respect to the class of \( \gamma \)-fair policies, where \( \gamma \geq \gamma \text{ and } \epsilon (\mathcal{H}^{(\mathcal{H})}) \).

**Algorithm**

**Basic outline:**
1. For the first \( T_1 \) rounds, perform pure exploration by always predicting +1 to collect labeled data.
2. Use collected data to form empirical fairness constraints, construct a fair Cost Sensitive Classification oracle based on empirical constraints.
3. Run an oracle-efficient adaptive contextual bandit algorithm - “Mini-Monster” by Agarwal et al. 2014 - that minimizes cumulative regret, while satisfying the empirical fairness constraint on every round.

**Optimization Oracle**

1. We assume access to a Cost-Sensitive Classification oracle.
2. We adapt the reduction by Agarwal et al. 2018 to handle optimization with constraints defined only on the empirical distribution formed by the exploration data.
3. The result is an oracle that solves Cost-Sensitive Classification problems with empirical fairness constraints.

**Regret Analysis**

**Main challenge:** Unlike Agarwal et al. 2014, have to handle an infinite policy class.

**Useful fact:** The set of optimal fair policies is sparse.