## MSc Project: *ε*-Best Mixture Identification

**Supervisor:** Wouter M. Koolen **Keywords:** Sequential Decision Making, Bandits, Pure Exploration, Sample Complexity, Mixture Policy Identification

**Background:** Pure Exploration is an active area of Machine Learning and Statistics. Its central problem of Best Arm Identification has been studied intensively since (Even-Dar, Mannor, and Mansour, 2002), and worst-case optimal methods have been developed for the fixed confidence, fixed budget and simple regret settings (Bubeck, Munos, and Stoltz, 2011). After a long and respectable series of papers establishing worst-case optimality, a revolutionary new approach called Track-and-Stop was pioneered by Garivier and Kaufmann (2016) that delivers instance-optimal methods. Since then, several aspects of Track-and-Stop have been generalised and refined: tighter stopping thresholds were constructed by Kaufmann and Koolen (2021), computational efficiency was improved using saddle-point methods by Degenne, Koolen, and M'enard (2019), and problems with multiple answers were analysed by Degenne and Koolen (2019). A recent extension with subpopulations was proposed by Russac et al. (2021).

Academic Content: The typical pure exploration task is identification of the best arm from samples. Letting  $\mu k$  denote the mean of arm k, the task is to identify arg  $\max_k \mu k$ . The sample complexity for this problem is well studied. One may reduce the sample complexity — at the cost of incurring some approximation error  $\epsilon$  — by asking for identification of any  $\epsilon$ -best arm  $k \in \{k \mid \mu k \ge \max k \mu k - \epsilon\}$ .

The starting point of this project is the realisation that for many applications it is enough to identify an  $\epsilon$ -optimal mixture policy. That is, we are happy with any probability distribution p

$$\left\{ p \in \triangle_K \left| \sum_{k=1}^K p_k \mu_k \ge \max_k \mu_k - \epsilon \right\} \right\}.$$

One may think of p as a randomised policy that is close to optimal. This could find application e.g. when applying bandit techniques to reinforcement learning problems, in particular near-optimal policy identification in MDPs.

This project will investigate these questions: Is the sample complexity of  $\epsilon$ -best mixture identification strictly lower than that of  $\epsilon$ -best arm identification? If so, what is the sample complexity of  $\epsilon$ -best mixture identification? And how can one design efficient algorithms for  $\epsilon$ -best mixture identification? Possible algorithms include elimination methods based on confidence-intervals, Track-and-Stop and Bayesian-flavoured approaches (Kaufmann, Koolen, and Garivier, 2018).

The project is envisaged to consist of mostly theoretical work, with only minor computational and empirical components.

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