Clustering Items through Bandit Feedback Finding the Right Feature out of Many

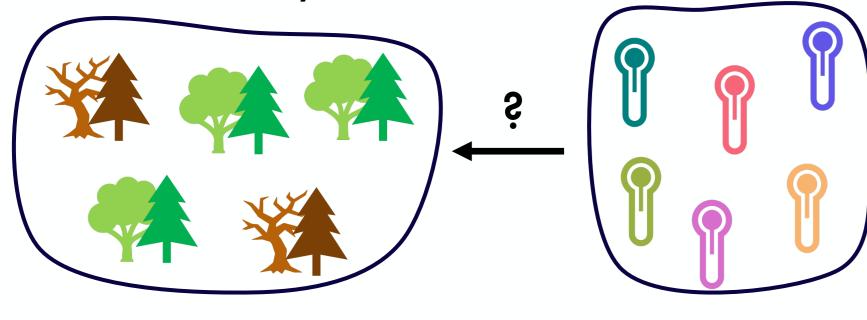
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Motivation

- forest patches, divided into two unknown groups
- want to use biodiversity sensors to recover groups
- which sensors are informative? how can we allocate them efficiently?



Main Results

Distribution-dependent control of the budget: Let

$$\mathbf{H} \coloneqq \frac{\mathbf{d}}{\mathbf{\theta}} \frac{\mathbf{1}}{\|\mathbf{\Delta}\|^2} + \min_{s \in [\mathbf{d}]} \left[\left(\frac{\mathbf{d}}{\mathbf{s}} + \mathbf{n} \right) \frac{\mathbf{1}}{\Delta_{(s)}^2} \right]$$

with $|\Delta_{(1)}| \ge |\Delta_{(2)}| \ge \cdots$. With probability $\ge 1 - \delta$, BanditClustering recovers the true partition after

 $T \lesssim \log\left(\frac{1}{\delta}\right) \cdot H$ steps.

Matching minimax lower bound: For any δ -PAC algorithm \mathcal{A} , we find a modification M'

of M such that

$$\mathbb{P}_{\mathsf{M}',\mathcal{A}}\left(\mathsf{T} \geq \frac{2\mathsf{d}}{\theta \parallel \Delta \parallel^2} \log\left(\frac{1}{6\delta}\right) \vee \frac{2(\mathsf{n}-2)}{\parallel \Delta \parallel_{\infty}^2} \log\left(\frac{1}{4.8\delta}\right)\right) \geq \delta$$

Some references:

ARIU, Kaito, et al. Optimal clustering from noisy binary feedback. Machine Learning, 2024 CASTRO, Rui M. Adaptive sensing performance lower bounds for sparse signal detection and support estimation. Bernoulli, 2014

Mathematical Model

- n items, d features
- mean value of j-th feature on i-th item as matrix entry M_{i.i}
- Assumption: rows M_{i} either equal μ_0 or μ_1
- gap vector $\Delta \coloneqq \mu_1 \mu_0 \in \mathbb{R}^d \setminus \{0\}$
- minimal group proportion

$$\theta = \frac{\left|\left\{i: M_{i, \cdot} = \mu_0\right\}\right| \wedge \left|\left\{i: M_{i, \cdot} = \mu_1\right\}\right|}{n}$$

Goal: cluster items ($M_{i,\cdot} = \mu_0 \text{ vs } M_{i,\cdot} = \mu_1$)

	P	P	P	P	P	P
*	0	0	0	0	0	0
	0	1	0	0.5	0.05	0
	0	1	0	0.5	0.05	0
*	0	0	0	0	0	0
	0	1	0	0.5	0.05	0

Example: Two Values

 Δ being h > 0 in s entries, 0 in all others with probability $\geq 1 - \delta$, BanditClustering recovers true partition in $T \leq \log\left(\frac{1}{s}\right) \cdot H$ steps with

$$\mathbf{H} = \frac{1}{\theta} \frac{\mathbf{d}}{\parallel \Delta \parallel^2} + \frac{\mathbf{n}}{\mathbf{h}^2}$$

SAAD, El Mehdi, et al. Active ranking of experts based on their performances in many tasks. In: International Conference on Machine Learning. PMLR, 2023 ZHAO, Yao, et al. Revisiting simple regret: Fast rates for returning a good arm. In: International Conference on Machine Learning. PMLR, 2023





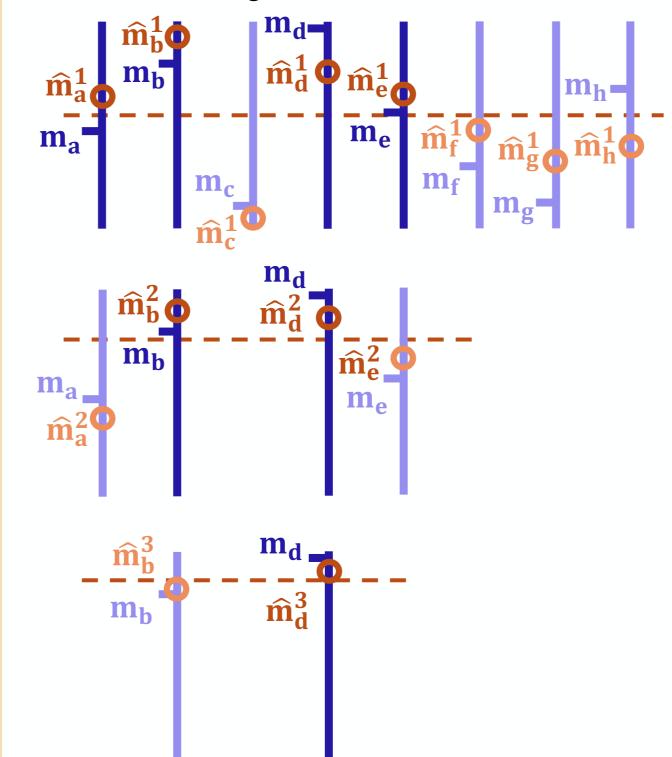


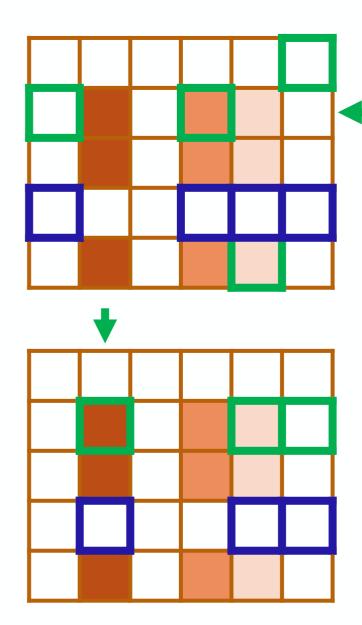
Recovering the Groups through Sequential Sampling

generating samples sequentially:

- can choose Indices $I_t \in [n]$, $J_t \in [d]$ at time t = 1, 2, ...
- observe feedback $X_t = M_{I_t,J_t}$ + random noise

Goal: given $\delta > 0$, want adaptive sampling strategy to recover partitions with probability $\geq 1 - \delta$ → δ-PAC algorithm BanditClustering

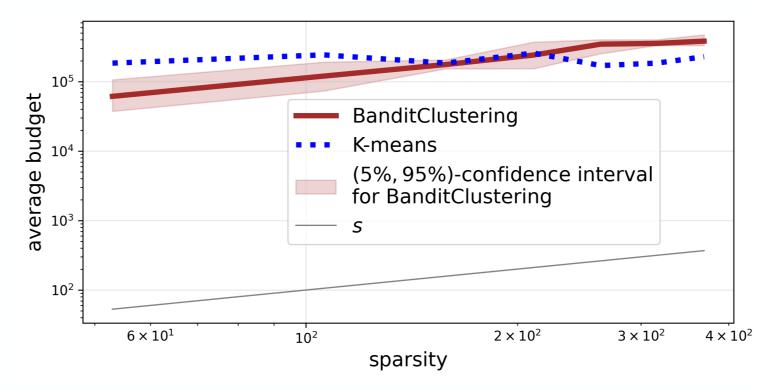


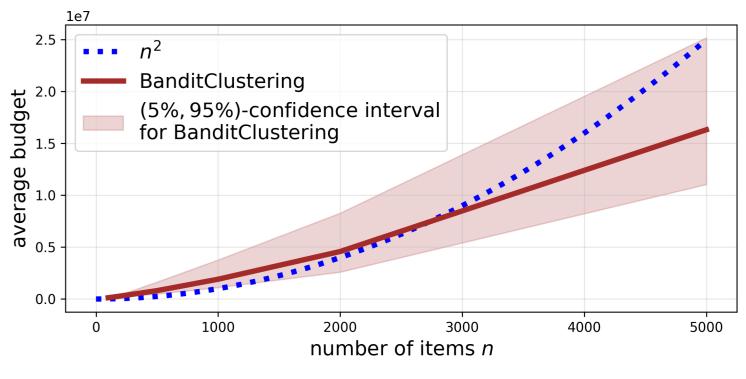


inspired by Sequential Halving for Best Arm Identification

subsample indices to find discriminative items/features

Numerical Experiments

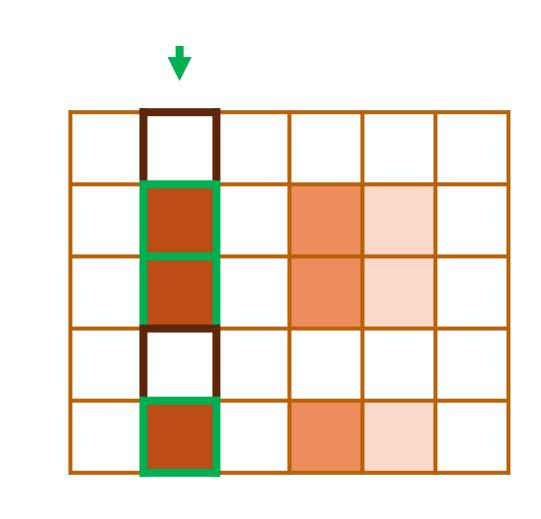




performance of BanditClustering for varying n, d = 10 \cdot n and fix s, h, δ and θ

comparing BanditClustering and KMeans for varying s and fix $|| \Delta ||^2$, n, d, δ and θ





use informative feature for clustering step