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Federated Multi-armed Bandits for No-Sensing Spectrum Sharing

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Project Objectives and Significance

- **The goal of this SWIFT project is "*to develop a novel online learning based framework for distributed low-cost devices to efficiently and effectively access the shared spectrum without spectrum sensing.*"**

- **Main outcome of the project**
  - Federated multi-armed bandits (FMAB) extend the classical multi-armed bandit paradigm into a federated learning setting where multiple heterogeneous agents (e.g., wireless base stations or secondary users in spectrum sharing use cases) must explore and exploit spectrum opportunities under strict communication, privacy, and latency constraints

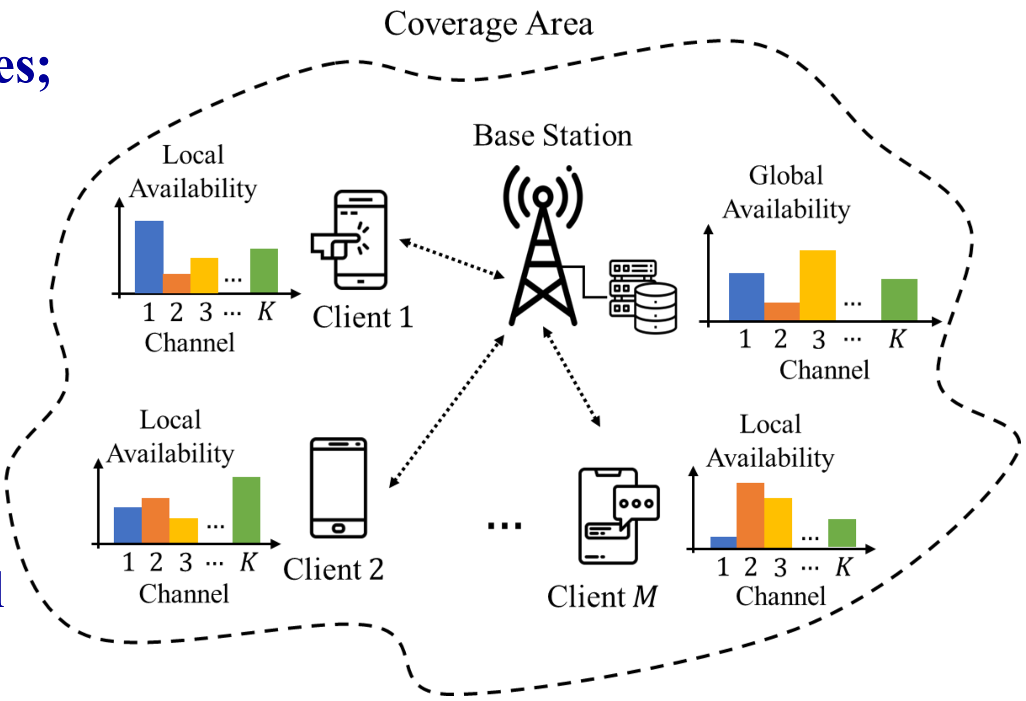
FMAB

- **In dynamic spectrum sharing, unlicensed (secondary) users must opportunistically access spectrum bands without causing harmful interference to licensed (primary) users**
- **Traditional approaches**
  - Centralized spectrum sensing: communication-heavy, slow
  - Independent local bandit learning: wastes data and ignores collaboration
- **Unique features of FMAB**
  - Collaborative spectrum learning: Multiple radios jointly learn the availability and quality of channels in real time without sharing raw I/Q data.
  - Adaptive exploitation: Radios dynamically select channels with higher availability and throughput while avoiding interference to primaries.
  - Scalability to dense networks: As the number of cognitive radios grows, FMAB ensures efficiency through federated coordination, rather than competition or over-sensing.

FMAB Application in Channel Selection

Server (base station):

- **Goal: the channel with best global availability;**
- **Fixed location → Cannot directly access global availabilities;**
- **Need to leverage the distributed clients**



Clients (mobiles):

- **Different locations → Heterogeneous local channel availabilities;**
- **Local observation: only a partial view of the overall global picture**

Server-clients coordination becomes crucial (just like FL!)

FMAB: How to Solve Global-Local Competition

FMAB: Global-Local Relationship [1]

Approximate model: views the local models as IID random variables from a latent global distribution

- Global model is a fixed ground truth, but is unknown:
  - K arms, arm $k \in [K]$ has mean reward μ_k
- Each local model is a random "sampling" of this unknown global model, based on a latent distribution
  - $\mu_{k,m}$ (client m, arm k) is an IID sample with mean μ_k

Challenge 1: average local models ≠ global model, i.e., $\hat{\mu}_k = \frac{1}{M}\sum_{m\in[M]} \mu_{k,m}$ may not match μ_k

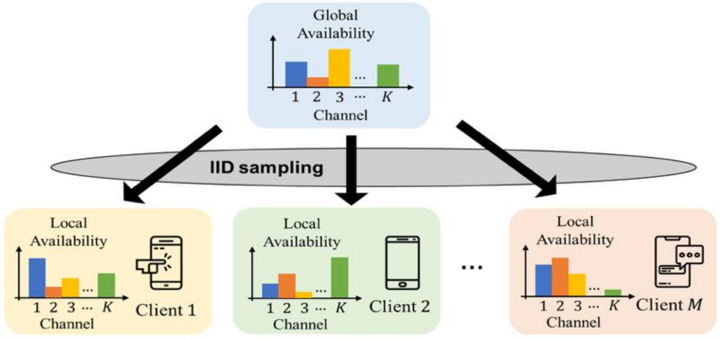
⇒ the optimal arms in both models may not be the same

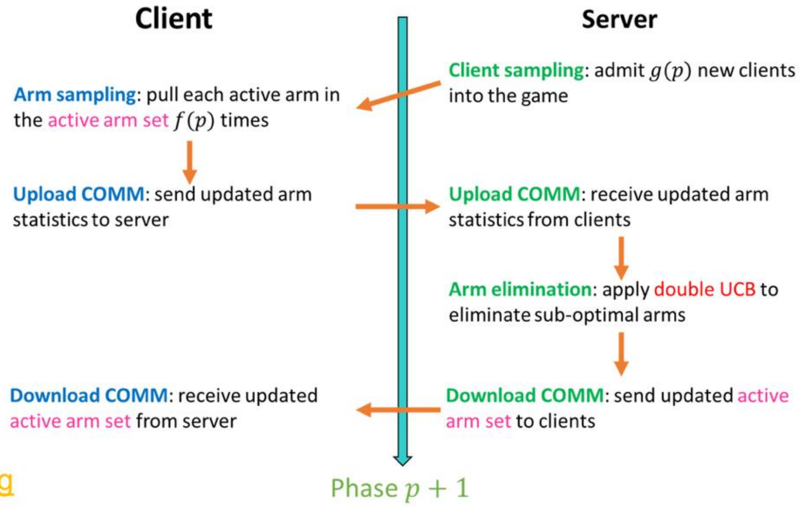
- How to ensure the same optimal arms? Sampling more clients
- Under-sampling: cannot guarantee matching optimal arms; Over-sampling: unnecessarily high comm. cost
- Need sufficient-but-not-excessive amount of clients

Challenge 2: balancing costly communication and necessary server-clients coordination (as in FL)

Key ideas: leading to an **order-optimal regret**

- Periodic communication, with period determined by the regret analysis to control its impact
- Gradually increase the number of of clients after each communication round
- A "double UCB" technique: overall uncertainty = uncertainty from client sampling + uncertainty from arm sampling





[1] Shi, C. and Shen, C. 2021. Federated multi-armed bandits. AAAI 2021

[2] Shi, C., Shen, C. and Yang, J., 2021. Federated multi-armed bandits with personalization. AISTATS 2021

Impact

- **The FMAB framework has significant implications for both wireless research and practice**
  - AI-Native Spectrum Management: It establishes a foundation for AI-native online decision-making in spectrum policy enforcement, beyond the static rule-based approaches used today.
  - Privacy-Preserving Collaboration: Because raw data never leaves devices, FMAB aligns with regulatory and security needs in defense, public safety, and commercial networks.
  - Resource-Efficient Learning: By reducing redundant sensing and communication, FMAB lowers energy consumption, which is critical for mobile and IoT devices.
  - Generalizable Framework: The principles extend beyond cognitive radio to edge computing, vehicular networks, and IoT ecosystems where distributed agents must make online sequential decisions under uncertainty.