Wireless Optimisation via Convex Bandits

Unlicensed LTE/WiFi Coexistence

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Unlicensed LTE/WiFi Coexistence
Unlicensed LTE

- Mobile traffic demands are exponentially increasing.

- General consensus:
  - Aggregate data rate needs to increase by 1000x!

- This increase may be achieved mainly through gains in:
  - Densification (small cells).
  - Advances in MIMO.
  - Wide spectrum: mmWave and the unlicensed 5GHz band.
  - Offloading using other technologies vs. LTE access.

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Coexistence of Unlicensed LTE and WiFi

- LTE and WiFi channel accesses are very different in nature:
  - LTE uses a scheduled-based approach.
  - WiFi abides to polite rules (random access).

- Along with unmodified LTE WiFi networks can starve.

- Concerns have been raised from the WiFi Alliance and FCC.

- Coexistence mechanisms are required.
Fair Sharing
Fairness guarantees

- How to divide resources to be fair to both networks?
- What does fairness even mean?
- We take a **proportional fair** approach:\(^2\)
  - Intuitively, give more resources to more efficient devices...
  - ...as far as no other is too penalised from that.
  - Popular due to its analytical tractability as well.

Proportional fair allocation

- Convex optimisation problem:

\[
\max_{\tilde{s}_{\text{wifi},j}, \tilde{s}_{\text{LTE}}, \tilde{z}} \tilde{s}_{\text{LTE}} + \sum_{j=1}^{n} \tilde{s}_{\text{wifi},j}
\]

s.t. \[
\tilde{s}_{\text{wifi},j} - \log s_j - \tilde{z} + \log(T_{\text{on}} + c_1 + e^{\tilde{z}}) \leq 0, \quad j = 1, \ldots, n
\]

\[
\tilde{s}_{\text{LTE}} - \log q + \log(T_{\text{on}} + c_1 + e^{\tilde{z}}) \leq 0,
\]

where \( z = \bar{T}_{\text{off}} - c_1 \), \( q := r(T_{\text{on}} - c_2) \) and \( c_1 \) and \( c_2 \) are constants that capture the heterogeneity cost.
Applying Bandits
Change of traditional paradigm

- Move from **characterising** the network behaviour.
  - Which requires assumptions and inferring parameters.

- To **learn** the fair configuration by **interacting** with the environment.

- Can we benefit from the problem being **convex**?
  - Many wireless optimisation problems are formulated as convex.
Bandit convex optimisation

- General idea:
  - Repeated game in which the adversary is constrained to select convex cost functions.
  - Interested in guaranteeing that the cumulative sum of the incurred losses is as small as possible (low regret).

- Benefits:
  - Intrinsically handles network dynamics.
  - Only the variable to optimize is needed as input.
BCO State-of-the-art

- Algorithms use gradient descent **without a gradient**:
  - Feed gradient descent with an estimation of the gradient.
  - Pioneered by Flaxman.\(^3\)
  - Followed by many refined versions.\(^4\)

- None of these are practical:
  - Single-point estimations have **high variance** in practice.
  - Multi-point estimations require sampling the function **multiple times per round**.

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Sequential BCO

- We use multi-point estimation ideas by Agarwal.\(^5\)
  - But combine queries from **two consecutive rounds**.

- Results:
  - If the functions change arbitrarily:
    - Matches best single-point known results: \(O\left(\frac{T^{3/4}}{4}\right)\).
  - If the function changes *infrequently*:\(^6\)
    - Same regret bound as Agarwal: \(O\left(\sqrt{T}\right)\).

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6. At most \(N\) times in \(T\) with \(N < < T\).
Formulation of our Example as a BCO Problem

Repeated Game

- In each round $t = 1, 2, \ldots, T$:
  - The player chooses a point $\tilde{z}_t \in \mathcal{K}$.
  - The adversary independently chooses $f_t \in \mathcal{F}$.
  - The player observes $f_t(\tilde{z}_t)$.

- The decision set $\mathcal{K}$ is convex.

- All functions in $\mathcal{F}$ are convex in $\tilde{z}_t$. 

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Experimental Results
Convergence and sensitivity to learning parameters

Figure: $\omega = 0.01$. 

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Convergence and sensitivity to learning parameters

Figure: $\omega = 1$. 

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Adaptability to network dynamics

Figure: \( n \) increases in 1.
Noisy estimates

- Cost function vs. simulator evaluations.
Final Remarks

- Many network problems are **formulated as convex**.

- Bandit Convex Optimisation can **ease implementation**.
  - Only the variable to optimise is needed as input.
  - Handles network dynamics intrinsically.

- Still much research **ahead**.
  - Explore single-point estimation further.
  - Methods to deal with noisy estimates.
  - Higher dimension problems.