Dynamic Content Updates in Heterogeneous Wireless Networks

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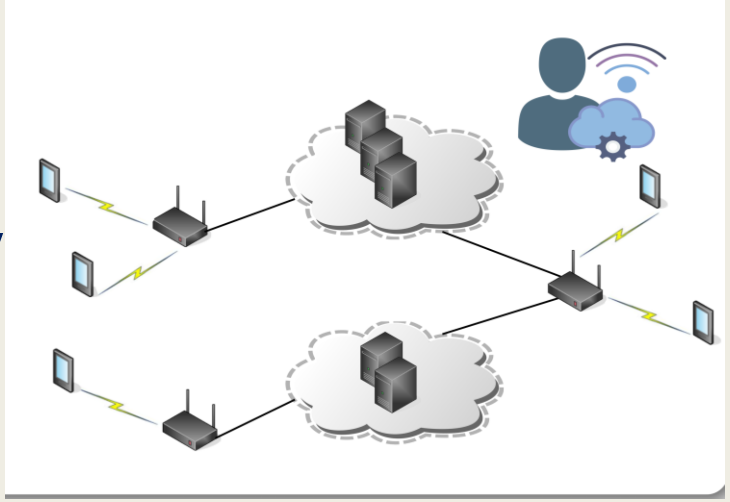
Edge Caching



- ❑ Caching at edge nodes help improve user quality
  - o Popular contents stored and served from small cell base stations (SBSs).
  - o Reduces backhaul cost and delay.

- ❑ Many solutions exists:
  - o Uncoded vs. coded caching
    - o K. Shanmugam et al., “FemtoCaching: Wireless content delivery through distributed caching helpers”, IEEE Transactions on Information Theory, 2013.
    - o K. Poularakis, “Approximation Algorithms for Mobile Data Caching in Small Cell Networks”, IEEE Transactions on Communications, 2014
  - o Known vs. unknown content popularity
    - o A. Sadeghi et al., “Optimal and scalable caching for 5g using reinforcement learning of space-time popularities”, IEEE Journal of Selected Topics in Signal Processing, 2018
    - o P. Yang et al., “Content popularity prediction towards location-aware mobile edge caching”, IEEE Transactions on Multimedia, 2018

Dynamic content edge caching

Most Internet content is dynamic.

- E.g., news, weather forecast, social networking videos, virtual reality games.
    - Providing personalized experience for users based on the time dependent events.
    - Event driven gaming experience in MMORPG games.
- Stale content reduces user satisfaction.
- Dynamic content in caches should be updated frequently.
- Updating edge caches frequently burdens backhaul!

Motivation

- ❑ Dynamic contents makes the ***age*** of contents important for the users:
  - *Refreshing the contents frequently will maximize the QoE of the users but would also increase the backhaul cost.*
  - *Refreshing the contents rarely, will reduce the backhaul cost but would degrade the user QoE.*
- ❑ A smart content refreshment strategy is required for striking a balance between the QoE of users and the backhaul cost.

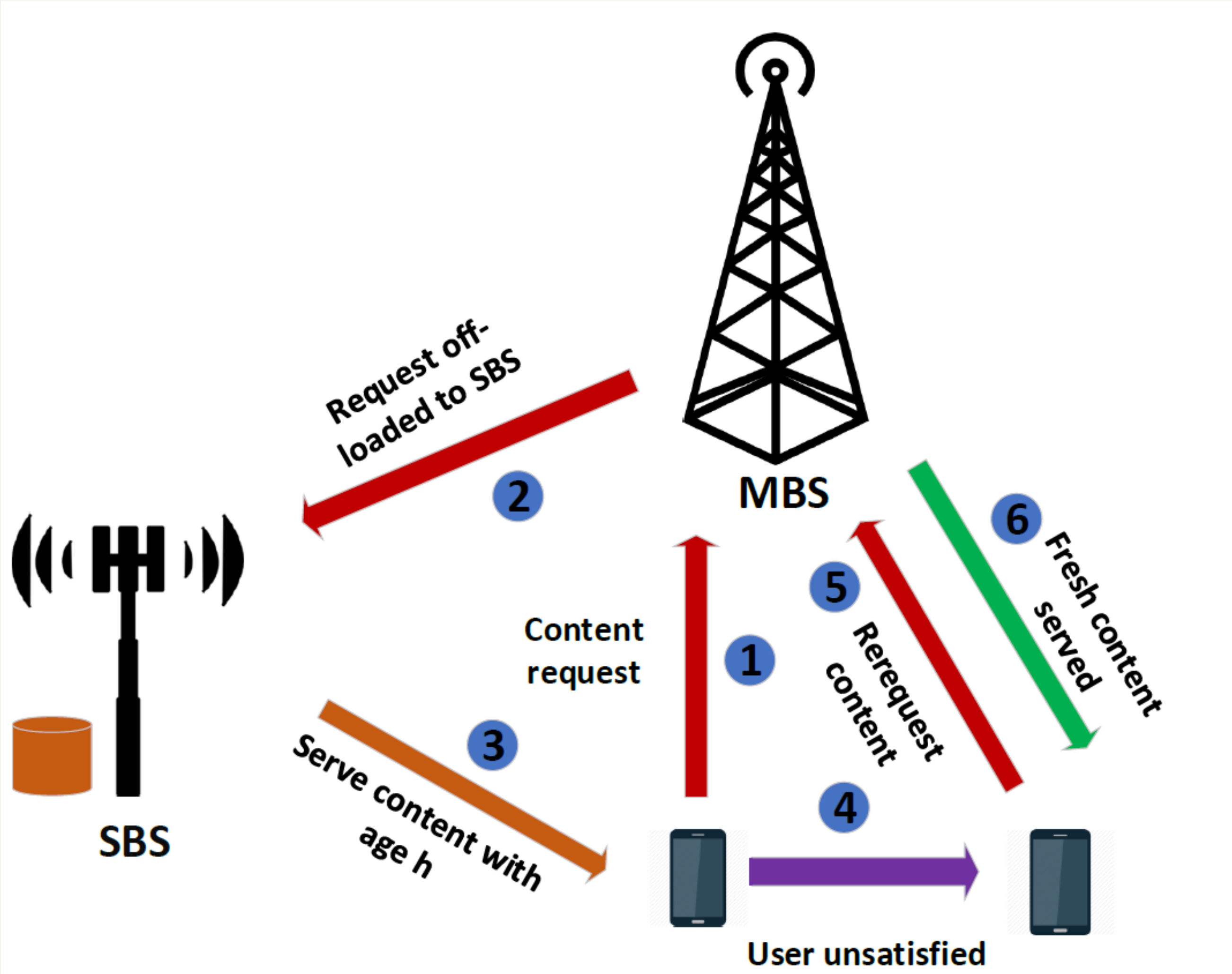
- ❑ User preference for varying age of content is different.
- ❑ Updating contents requires accessing costly backhaul link.
- ❑ User preference is UNKNOWN.

Approach

- We formulate the problem as an infinite-horizon Markov decision process (MDP)
- Show that MDP is separable to reduce the exponentially large state space.
- *Show that the optimal policy has threshold structure on the age of the contents.*
- We formulate and solve the problem of finding the optimal thresholds by a multi armed bandit problem.

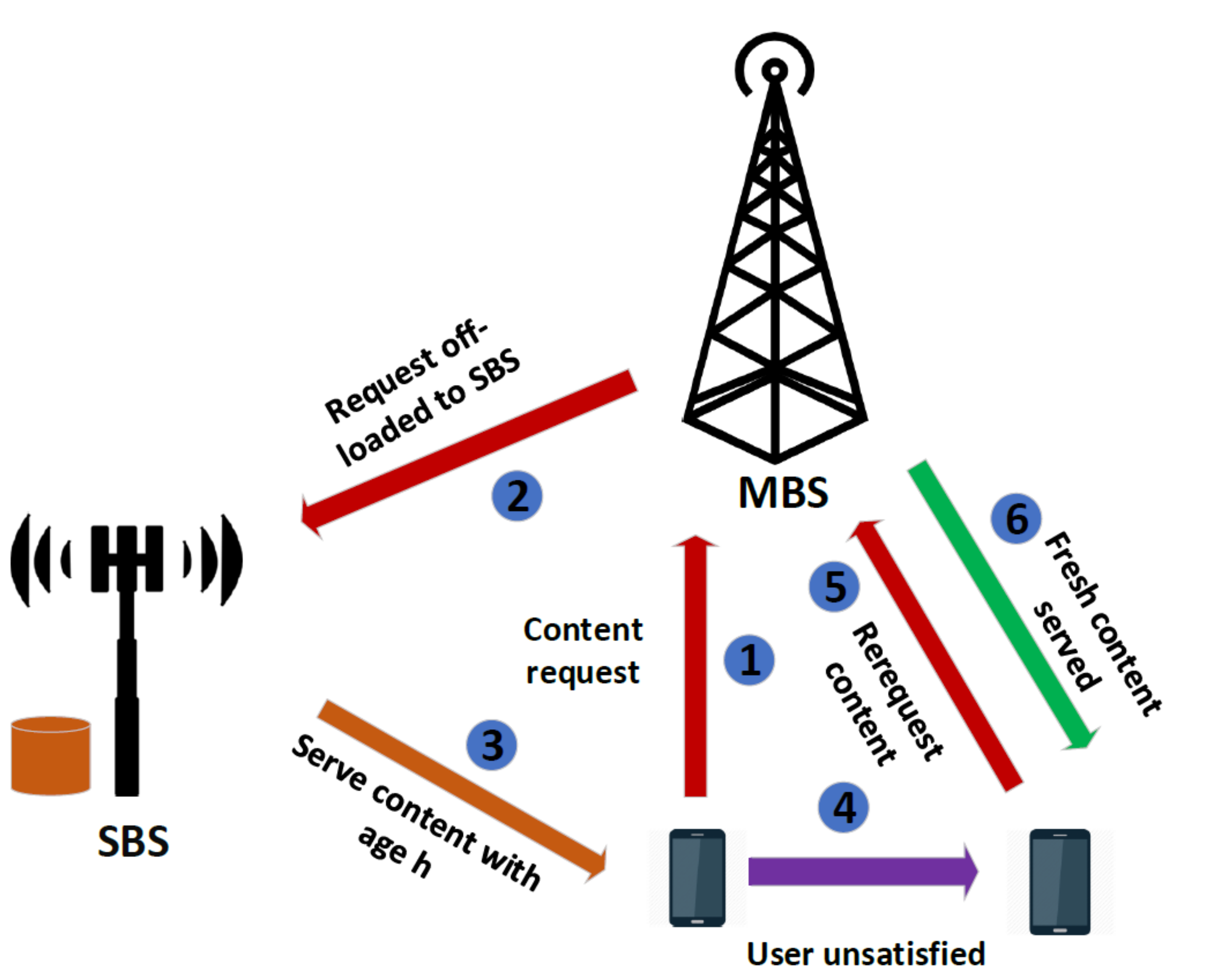
System model

- Consider N popular contents
- **Parameters:**
  - p_n: popularity of content n.
  - $P^n_{redirect}(h_n)$: probability of redirecting content n, when its age is h_n.
- **State:**
  - $h_n(t)$: age of content n at time t
- **Action:**
  - $\boldsymbol{d}(t) = \left(d_1(t), \ldots, d_N(t)\right)$: decision vector at time t
    - $d_n(t) = 1$: update content n
    - $d_n(t) = 0$: do not update content n



Users’ request model

1. User request a content from macro base station (MBS)
2. MBS offloads user’s request to SBS for service
3. SBS serves the requested content with age of h
4. The service process is finished *if* user is satisfied with the age of content; *else:*
5. *User makes another request from SBS*
6. *MBS serves the user with fresh content*



Problem Formulation

- $\lambda(t)$: Total number of users arriving to network at time t
- $\lambda_{rn}(t)$: number of requests for content n, redirected to MBS
  - $\lambda_{rn}(t)$ is governed by the age $h_n(t)$ as well as popularity
- $C\left(\lambda_{r1}(t), \dots, \lambda_{rN}(t), \boldsymbol{d}(t)\right)$: cost of serving redirected requests when action is $\boldsymbol{d}(t)$ and age is $\boldsymbol{h}(t)$
  - Linear backhaul cost:

$$C\left(\lambda_{r1}(t), \dots, \lambda_{rN}(t), \boldsymbol{d}(t)\right) = \sum_{n=1}^{N} C_{\mathrm{n}}(\lambda_{rn}(t), d_{\mathrm{n}}(t))$$

  - $C_n(\lambda_{rn}(t), d_n(t)) = C_n(\lambda_{rn}(t), 0) + d_n(t) C_{BH}$
    - $C_n(\lambda_{rn}(t), 0)$: cost of $\lambda_{rn}(t)$ number of users redirected to MBS.
    - C_{BH}: Backhaul cost associated with updating a content
- We aim at minimizing the expected cost over infinite horizon by optimizing the decision vector $\boldsymbol{d}(t)$:

$$\min_{\boldsymbol{d}(t)} \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} C\left(\lambda_{r1}(t), \dots, \lambda_{rN}(t), \boldsymbol{d}(t)\right)$$

Optimal policy

- $\boldsymbol{h}(t) = \big(h_1(t), \cdots, h_N(t)\big)$: state of the system at time t

$$h_n(t+1) = \min\{\big(1 - d_n(t)\big)(h_n(t) + 1), h_{max}\}$$

- h_{max}: Corresponds to an age when the content becomes stale.
- $P(\boldsymbol{\acute{h}}|\boldsymbol{h}, \boldsymbol{d})$: transition probability, $\boldsymbol{\acute{h}} \to \boldsymbol{h}$ when action $\boldsymbol{d}$ is taken at state $\boldsymbol{h}$
- $V(\boldsymbol{h})$: value function at state $\boldsymbol{h}$

  $V_{\boldsymbol{d}}(\boldsymbol{h})$: action-value function at state $\boldsymbol{h}$ when action $\boldsymbol{d}$ is taken
- Bellman equations:
  - $V_{\boldsymbol{d}}(\boldsymbol{h}) = \bar{C}(\boldsymbol{h}, \boldsymbol{d}) + P(\boldsymbol{\acute{h}}|\boldsymbol{h}, \boldsymbol{d})\ V(\boldsymbol{\acute{h}})$
  - $\bar{C}(\boldsymbol{h}, \boldsymbol{d}) = \boldsymbol{E}\big(C(\lambda_{r1}, \ldots, \lambda_{rN}, \boldsymbol{d})\big)$
- Expectation is w.r.t PDF of λ_{rn}

Bellman optimality criteria dictates:

$$d^*(t) = \mathrm{arg}min_{\boldsymbol{d}} V_{\boldsymbol{d}}(\boldsymbol{h}(t))$$

Discussion

- State space of the MDP:
  - *Number of states increase exponentially with N*
  - *There are h_{max}^{N} number of states. h_{max} is the maximum age of a content.*
- Action space of the MDP:
  - *Number of actions is also exponential in N*
  - *There are 2^{N} number of actions*

MDP suffers from the curse of dimensionality!

Convergence becomes slow

Implementation requires a look-up table with a large size

Structure of the optimal policy

- Value function separable

$$V(\boldsymbol{h}) = V^{(1)}(h_1) + \cdots + V^{(N)}(h_N)$$

- $V^{(n)}(h_n)$: *value function for content* n
- *Follows from the linearity of cost function*
- Hence, each content can be considered separately
- *Bellman equations for content* n *becomes*
- $V_{d_n}^{(n)}(h_n) = \bar{C}_n(h_n, d_n) + d_n V^{(n)}(0) + (1 - d_n)V^{(n)}(h + 1)$

Theorem: There exists a threshold H_n on the age of each stored content at which it is optimal to update content n.

Separability of value function

$+$

optimality of threshold policy

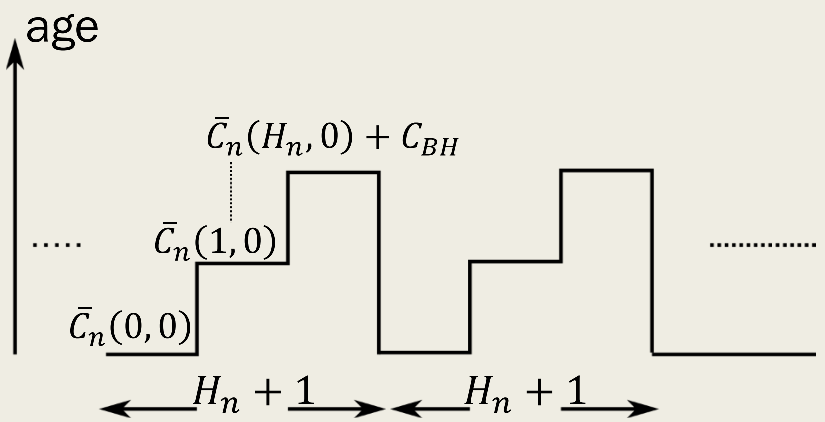
$\downarrow$

considerably simplify the procedure to find optimal decisions

Objective under threshold structure

- Objective function for each content n becomes

$$\min_{H_n} \frac{\sum_{h=0}^{H_n} \bar{C}_n(h,0)+C_{BH}}{H_n+1}$$



Need for a learning framework

Redirection probabilities are unknown

$\bar{C}_n(h,0)$ cannot be analytically computed.

Even if every other statistics is known

Even if cost function is calculated, the objective function is hard to solve

Learning optimal thresholds: Multi armed bandit (MAB) formulation

- MAB: For each content n, there is an agent:
  - *Agent chooses an arm (age update threshold, H_n)*
  - *Observes the random cost,* $\hat{C}(H_n) = \frac{\sum_{h_n=0}^{H_n} C_n(\lambda_{rn}(h_n),0)+C_{BH}}{H_n+1}$
  - Repeats the process until optimal arm, H_n^* is found

MAB agent

- $a_n \in \{0, \dots, h_{max}\}$: action of agent n
- $q^{(n)}(a_n)$: how favorable is to select threshold a_n for content n

ϵ-greedy algorithm

- Optimal action is chosen according to

$$a_n^* = \arg\min_{a_n} q^{(n)}(a_n)$$

  – *First, we need to determine the values of $q^{(n)}(a_n)$*

ϵ-greedy

With probability ϵ

chose a random arm

exploration improves the estimates of non-greedy actions' values

With probability $1-\epsilon$

Choose $\arg\min_{a_n} q^{(n)}(a_n)$

exploitation is favorable when we reach sufficiently reliable estimates of action values

take action a_n

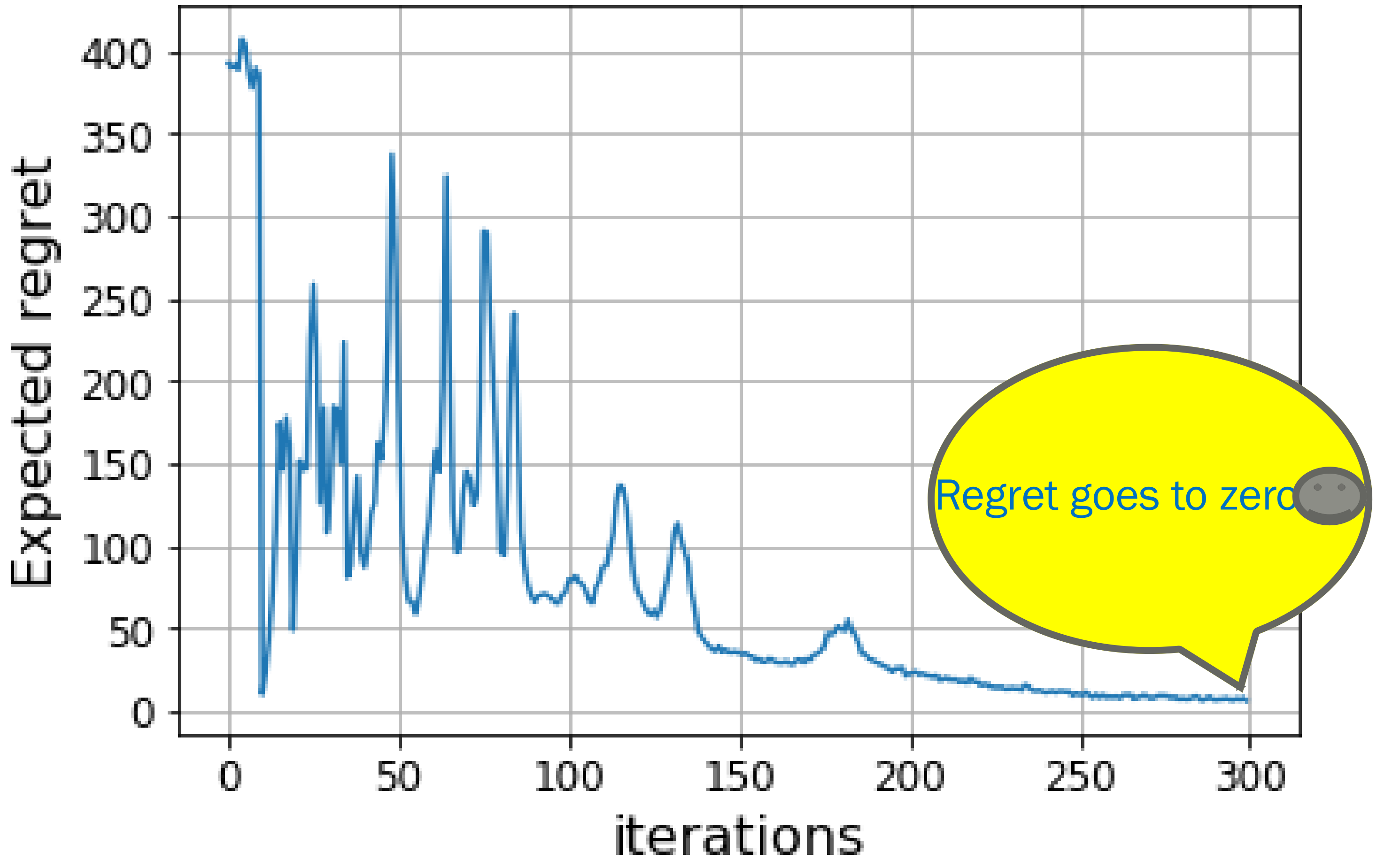
Observe sample mean $\hat{C}(a_n)$

$$q^{(n)}(a_n) \leftarrow q^{(n)}(a_n) + \alpha\left(\hat{C}(a_n) - q^{(n)}(a_n)\right)$$

α is the learning rate

Numerical Results

- $\lambda(t) \sim Poisson(100)$
- Popularity profile; $p \sim Zipf(2)$
- 5 applications
- $h_{max} = 9$
- $P_r(h) = 1 - e^{-0.2h}$,
- $C(x) = 10x$
- $C_{BH} = 500$



Expected regret: cost of the policy learned by MAB agent – optimal cost

Conclusions and future work

- Balancing user QoE and backhaul cost of updating dynamic content caches
  - Updating frequently results in higher backhaul cost
- Showed that the MDP is separable: reduced the state and action spaces
- Showed the optimal policy is of threshold type in age
  - Used multi-armed bandit framework to find efficient learning algorithms
- Future work
  - Non-linear cost functions
  - Random backhaul condition and constraint
  - Energy harvesting SBS