A Contextual Bi-armed Bandit Approach for MPTCP Path Management in Heterogeneous LTE and WiFi Edge Networks

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* slides taken from authors and modified

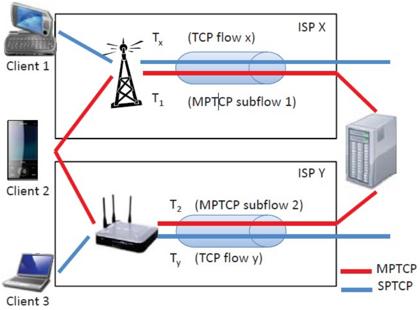
Background

- Optimize transmissions at last mile within wireless edge network
- Multihomed smartphones, laptops, tablets
- MPTCP Benefits:
  - Higher Throughput
  - Failover from one path to another
  - Seamless mobility

Multi-path TCP (MPTCP)

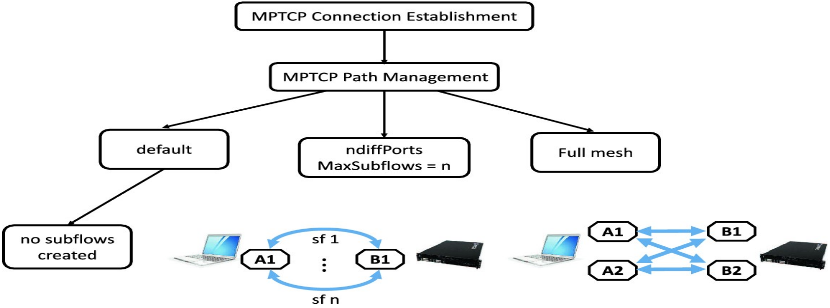
Forms multiple TCP flows over all available network interfaces to simultaneously utilize them.

- Split single data stream transmission across multiple paths.
- concurrent transmissions to increase connectivity resilience and maximizes network resources usage.



MPTCP Path Manager

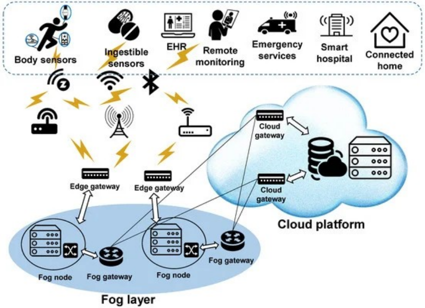
The throughput of MPTCP relies extensively on its path management mechanism and path characteristics.



Motivation: Dynamic Online Multi Path Transmission

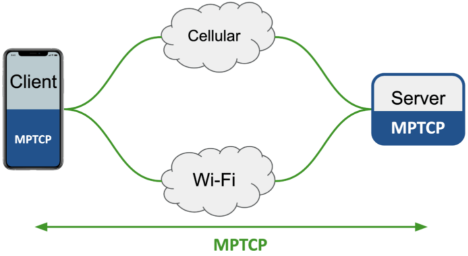
Online machine learning algorithms helps to make precise and effective decisions

1. Explore multiple paths for multiple access technologies (Wifi, LTE, etc).
2. Establish new subflows of multiple paths.
3. Uses online learning theory to take optimal decisions under unpredictable traffic environment.



Gap: Existing Transmission Protocols are Suboptimal

- Do not fit into dynamic and distributed environment.
- Missing adaptability and autonomy for heterogeneous networks.
- Rely on static and predefined rules
- Employ fullmesh to setup subflows between all available pair of interfaces.



Need for Real Time Automation

Automate decision process according to real time system learned rules.

Objective: MPTCP Path Manager via Bi-Armed Bandit

- Design new MPTCP path manager
  - Use machine learning to generate optimal path decision rules under uncertain network conditions.
- Adopt contextual bandit (online active learner) to find MPTCP primary path in heterogeneous networks.

Recent Studies

- In edge cloud systems (adding reliability to MPTCP)
- Utilize LTE and NR channels
- Improve video streaming sessions
- Energy-aware telecommunications
- ★ Dynamic MPTCP path configuration with SDN
- ★ MPTCP with path-aware information
- ★ Ndiffport subflow manager for data centers
- ★ Fullmesh path manager

Contextual Multi Armed Bandits (C-MAB)

Introduced by William R Thompson in 1993:

ON THE LIKELIHOOD THAT ONE UNKNOWN PROBABILITY EXCEEDS ANOTHER IN VIEW OF THE EVIDENCE OF TWO SAMPLES

(Thompson 1933), From the Department of Pathology at Yale University

- Machine learning in a streaming data setting by training a model in consecutive rounds.
  - At each round, the algorithm perform prediction on some input sample.
  - The algorithm verifies prediction correctness and feeds it back to the model.

C-MAB Model Settings

Basic C-MAB Model

- At each round T, the algorithm selects an action and collects a reward for that chosen arm.
- For each round $t \in [T]$, the algorithm observes a context x_t, picks an arm a_t from $k = \{1, .., k\}$, and experience a reward $r_t \in [0, 1]$, whose value depends on the context x_t and the chosen arm a_t.

Notations

1. A set of contexts $x_k^t \in X$: $t = \ rounds, \ k = \ arms$
2. Policy $\pi : \ (context\ x) \mapsto (action\ a)$
3. Action / Arm a_t
4. Reward r_k^t

C-MAB Model Settings (cont'd)

Exploration Vs. Exploitation dilemma.

- Use what is already learnt (exploit), but also learn about actions that look inferior (explore).
- Balance to get good statistical performance.

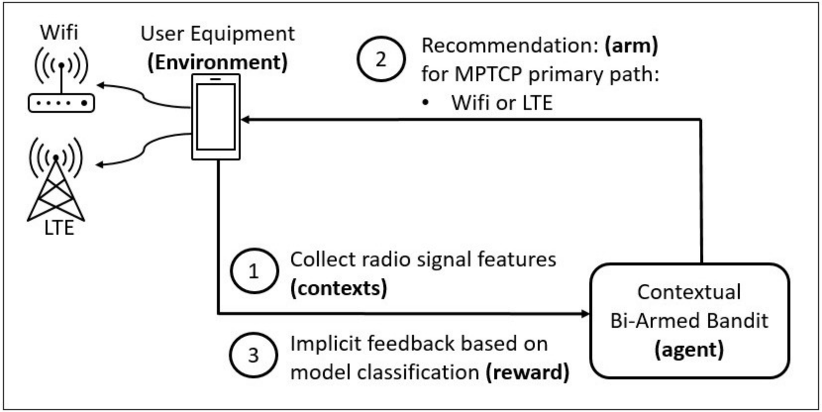
Contextual Bandit Policies

Active Explorer:

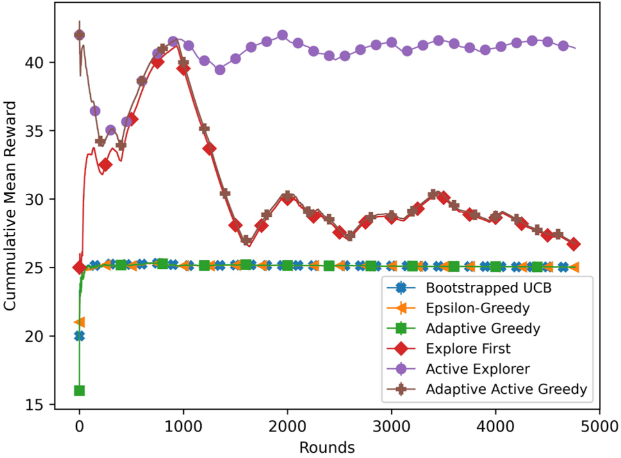
With probability p:
Select action $a = \ argmax\ \hat{f}(x^t)$
Otherwise:
for arm q, Set $w_q = \ (1 - \hat{f}_q(x^t)||g_q(x^t, 0)|| + \hat{f}_q(x^t)||g_q(x^t, 1)||$
Select action $argmax\ w$

- Predictions are made according to an active learning heuristic:
  - The gradient that the observation would produce on each model predicting a class

Our Solution: MPTCP Path Manager via Bi-Armed Bandit

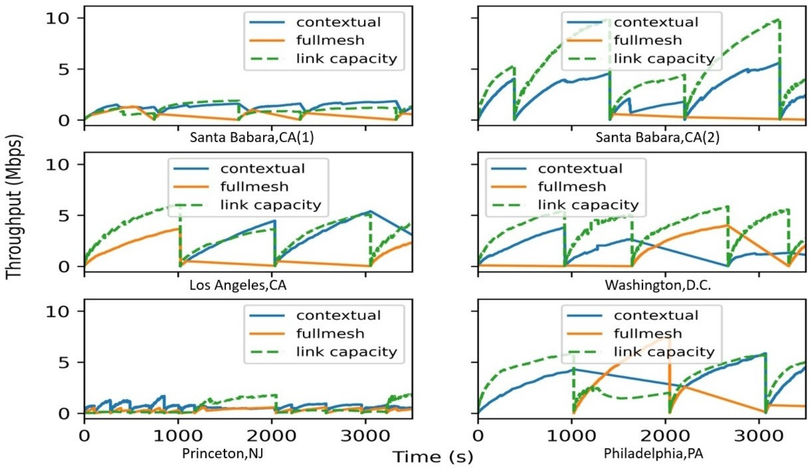


C-MAB MPTCP Results and Evaluation



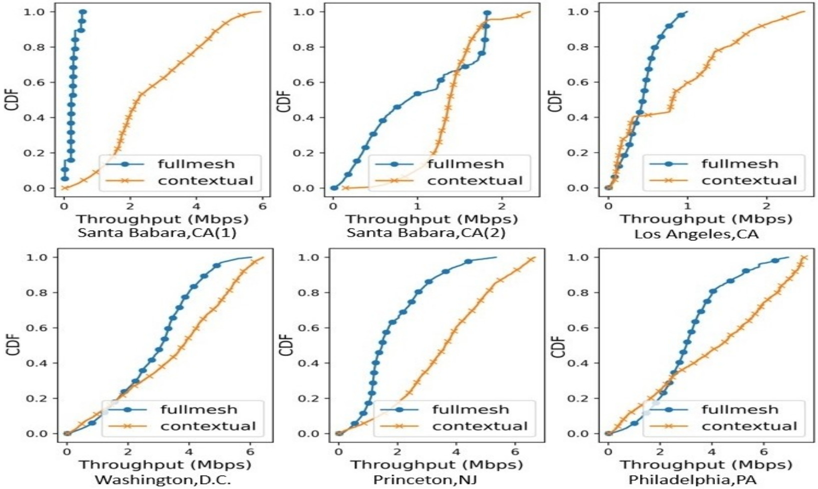
The mean cumulative reward (and its error upto 95% confidence level) is calculated for each policy over its 50 batch online simulations.

C-MAB MPTCP Results and Evaluation (cont'd)



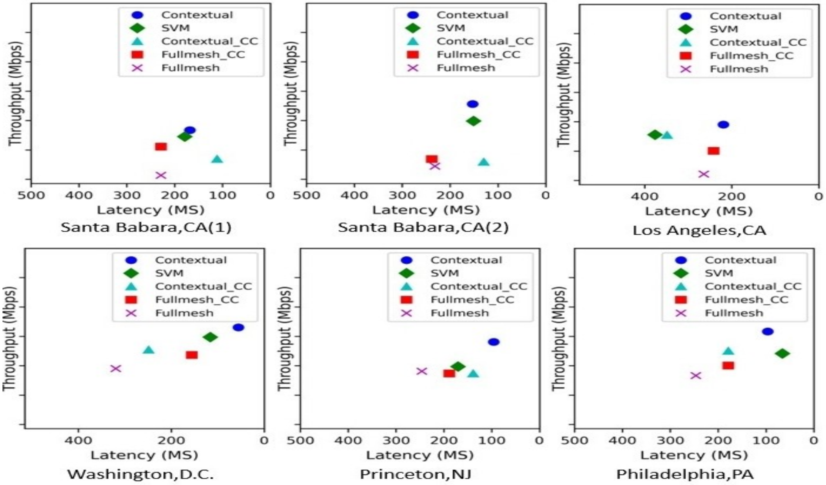
Contextual bandit path manager maximize utilization of available resource within given capacity limit.

C-MAB MPTCP Results and Evaluation (cont'd)



The throughput of contextual bandit approach is higher at a rate of around 50% of the times in average for all locations.

C-MAB MPTCP Results and Evaluation (cont'd)



The Top-right part of the graph indicate better performance.

Conclusion

- Designed MPTCP path manager selection strategy to decide primary path under rapid wireless signal fluctuations in heterogeneous edge networks.
  1. Online contextual bandit algorithm using Stochastic Gradient Descend classification as an oracle to decide the optimal primary MPTCP path for each new connection.
  2. A patch to the MPTCP protocol that allows overwrites to the path manager module.

Discussion

- Reward function is binary (1 if throughput and latency above a threshold)
- Feature list is incomplete e.g., band information for LTE is key
- Doesn’t adapt to link capacity efficiently
- Experimental evaluation is weak (NS3-based, data from 2013)
- Problem statement is vague too (path mgmt. vs. scheduling)
- What about fairness, utilization, tail-latencies?