Mobility-based Proactive Multicast for Seamless Mobility Support in Cellular Network Environments

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Problem & motivation: Post-handover delay

- Resubmit subscriptions
- Wait for resolution

- Delay-sensitive mobile applications
- Applications with certain/strict QoS requirements
- Video streaming
MPM : Mobility-based Proactive Multicast scheme

✓ Autonomous, local resource allocation decisions
  ✓ Per requested object
  ✓ Prior to mobile handovers

✓ Semi-Markov mobility prediction model
  • Next-cell transitions
  • Duration between mobile transitions

Heterogeneous cellular N/Ws:
  • Micro, small, pico or femto cells
  • Wi-Fi hotspots
BACKGROUND
Background

• ICN is intrinsically multicast
  • Pub/Sub
  • Wide distribution of data around N/W “areas”

• Past: Multicast for handling large mobile populations
  ❌ Blind/naïve multicast in all possible N/W regions is resource-wasting

✔ Proactive caching in Pub/Sub N/W based on mobility prediction

❖ MPM: proactive multicast based on mobility prediction
  ❖ Restricted resource: backhaul connection
MPM MODEL
Optimization problem

\[
\min_{b_s^l} \sum_{s \in S_l} D_s
\]

\[
s.t: \sum_{s \in S_l} o \cdot b_s^l \leq B_l, \quad \forall l \in L,
\]

- Minimize average delay for obtaining content \(s\) in next cell \(l\)
- \(b_s^l\) is 1 (resp. 0) if \(s\) is (resp. not) proactively multicast
Semi-Markov prediction model

- User mobility history: A list of successive cells and residence times
  - Both offline and online learning

- Model assumes arbitrary distribution of residence times
  - Common assumption of exponentially distributed residence times
Semi-Markov prediction model

- \( p_{i,l} = \frac{|H_{i,l}|}{|H_i|} \)
- \( \psi_{i,l}(\tau) = \frac{|H_{i,l,\tau}|}{|H_{i,l}|} \)
- Define the kernel
  \[ \phi_{i,l}(t) = p_{i,l}\psi_{i,l}(t) \]

- **Predicted future destination:**
  Cell with highest \( \phi_{i,l}(\tau) \) probability when the time spent in cell i falls within time interval \( \tau \)

- \( q_s^l \equiv \phi_{i,l}(\tau) \)
MPM decisions: *basic model*

**Basic decision model**

\[ Q_s^l = \sum q_s^l , \]

\[ D_\text{hit}, \ D_\text{miss} , \]

\[ b_s^l = \begin{cases} 1 & \text{if } Q_s^l (D_\text{miss} - D_\text{hit}) \geq p_l , \\ 0 & \text{Otherwise} , \end{cases} \]

**Congestion price**

\[ p_l = \left[ p_l' + \gamma \left( \sum_{s \in S_l} o \cdot b_s^l - B_l \right) \right]^+ \]
MPM model extensions

- **MPM-R**: Replacements
  - Proactive multicast of highest Gain objects
  - Goal: improve temporal locality
  - Update decisions upon all changes on $Q_s^I$
    - $(2 + o(1))n$ actions, i.e. $O(n) >> O(1)$

- Knapsack combinatorial optimization problem
  - Maximize the total gain of multicast objects given their different individual gain values $G(s)$:
    \[
    \sum_{e} G(e) / \sum o_e < G(s)/o_s, \\
    G(e) = Q_s^I \cdot (D_{miss} - D_{hit}).
    \]
PERFORMANCE EVALUATION

Preliminary performance evaluation
Simulation setup

- City of Cologne
  - Realistic car traffic mobility trace
  - Realistic cell distribution trace
    - Range ~ 500m
    - Backhaul = 20 Mbps
  - 6 sampled sub-areas: 2.5 km × 2.5 km

- Video file requests
  - Synthetic traces of produced with the Globe-Traff
  - Zipfian distr., z=0.9
  - 5 traces, 440 files each, 10 requests per mobile
CONCLUSIONS
Mobility-based Proactive Multicast model for cellular networks using semi-Markov mobility prediction

- Reduce transfer cost after attaching to a new cell
  - Pub/Sub-implied delay
  - Over regular TCP/IP => reduce client-server connection time establishment

- Preliminary performance evaluation indicates
  - Adapt well to temporal locality: fresh user demand & mobility info.
  - Higher gains against popularity-based multicast.
Questions ?
SEMI-MARKOV PREDICTION MODEL FOR MOBILITY

• Mobility history of a user is represented as the list of successive visited cells and time spent in each cell during the user’s trip.

• Each cell records the number of handovers made to neighboring cells, as well as the residence time.

• This allows for the computation of the cell-transition probabilities and the distribution of cell residence times.

• User mobility is thus modelled by a semi-Markov process with arbitrary distributed residence times.
• This is a convenient departure from the common assumption of exponentially distributed residence times.

• The state transition probability matrix and the residence time distribution matrix are initialized by utilizing the past handover history of a user as a tuple <attachment time, cell ID>.

• This prediction process can be used for both offline and online learning.

• We use an offline prediction model as operators are usually aware of their transition statistics.
Bibliography