M&M: Multi-level Markov Model for Wireless Link Simulations

Ankur Kamthe
Miguel Á. Carreira-Perpiñán
Alberto Cerpa

School of Engineering
University of California Merced
Merced, CA, 95343, USA

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Introduction
SimCity - The World of Simulation

- Computation and communication models
- Testing of novel ideas, CHEAPLY
- Design decisions
- Core Component: Wireless Communication
Why leave SimCity?

- Simulator Assumption [Kotz et al. MSWiM’04]
  1. The world is flat.
  2. A radios transmission area is circular
  3. All radios have equal range
  4. If I can hear you, you can hear me (symmetry)
  5. If I can hear you at all, I can hear you perfectly
  6. Signal strength is a simple function of distance
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- Simulation does not mimic reality.
Problem Statement

How can we model wireless links so that we can improve quality of simulation results?
Wireless Link Quality in Sensor Networks

**Good Link**

```
111111111100000000000001111
```

**Bad Link**

```
111111111110000011
00011111111111...
```

**Metrics**

- PRR (mean = 0.95)
- PRR (mean = 0.049)
Wireless Link Quality in Sensor Networks

Intermediate Links

Difficulty to Model
Goal

GOAL: Replicate multiscale structure present in wireless links.
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Wireless Link Modeling
Gilbert Model

- 2 State model
- Bernoulli output distribution.
Our Modeling Approach

- **Gilbert Model**
  - $p(1)=1$
  - $p(0)=0.6$

- **M&M Model**
  - $p(1111)=0.8$
  - $p(1100)=0.5$
  - $p(0111)=0.2$
  - $p(0011)=0.5$

Level 1: Hidden Markov Model (L1-HMM)

Level 2: Mixture of Multivariate Bernoulli (L2-MMB)

- M&M Model - Hierarchical in nature
M&M Model

- **L1–HMM**: models long term dynamics
- **L2-MMB**: models short term dynamics
- Trained using Expectation-Maximization (EM) algorithm for HMM with MMB output distribution (HMM-MMB).
Data Collection

- Packet reception traces
  - One transmitter and all others nodes act as receivers.
  - 64 26-byte packets per second for durations of 1/2, 1, 2, 6 and 12 hours.
  - Record **sequence number, received signal strength value (RSSI) and link quality indicator (LQI) value of each data packet.**

- Collected noise traces.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>802.15.4 Channel</td>
<td>26</td>
</tr>
<tr>
<td>Num. Noise Samples</td>
<td>196,608</td>
</tr>
<tr>
<td>Noise Sampling Period</td>
<td>1ms</td>
</tr>
</tbody>
</table>

*Table: Data collection parameters.*
Training Overview

- **Model Size:**
  - $Q$: HMM States ($=6$)
  - $M$: Number of Mixture Components ($=20$)
  - $W$: Window Size ($=128$)

- Get initial values for parameters.
  - HMM: Transition probability matrix
  - MMB: Mixture Proportions ($\pi_i$) and Bernoulli parameters ($\vec{p}_i$)

- Refine estimates using the EM algorithm for HMM-MMB.
Initializing the M&M Model

```
1 1 1 1 1 
1 1 1 1 1 
1 0 1 1 1 
1 1 1 1 1 
1 0 1 1 1 
1 1 1 1 1 
```

1.0

.75

1.0

.25

.50

1.0

1.0
Initializing the M&M Model

K-means Clustering with say 3 clusters
Initializing the M&M Model

K-means Clustering with say 3 clusters

\[
p(X|\mu_1, \sigma_1)
\]

\[
p(X|\mu_2, \sigma_2)
\]

\[
p(X|\mu_3, \sigma_3)
\]
Initializing the M&M Model

Trained L₁-HMM
Initializing the M&M Model

Trained L₁-HMM

Viterbi Algorithm

1.0 → \( S_1 \) → 1
..........0

.75 → \( S_1 \) → 1
..........1

1.0 → \( S_1 \) → 1
..........1

.25 → \( S_2 \) → 1
..........0

.50 → \( S_3 \) → 1
..........1

1.0 → \( S_1 \) → 1
..........1
Initializing the M&M Model

- **Trained L₁-HMM**

- **Viterbi Algorithm**
  - 1.0 → $S_1$ → \[ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \]
  - 0.75 → $S_1$ → \[ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \]
  - 0.25 → $S_2$ → \[ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \]
  - 0.50 → $S_3$ → \[ \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \]
  - 1.0 → $S_1$ → \[ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \]

- **Train Mixture of Multivariate Bernoulli L₂-MMB**
  - $S_1$: \[ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \]
  - $S_2$: \[ \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \]
  - $S_3$: \[ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \]
  - \[ \begin{bmatrix} \pi_s \\ p_{i1} \\ p_{i2} \\ p_{i3} \\ p_{i4} \end{bmatrix} \]
  - $S_1$: \[ \begin{bmatrix} 0.8 \rightarrow 0.9 \\ 0.9 \rightarrow 0.9 \\ 0.9 \rightarrow 0.9 \end{bmatrix} \]
  - $S_2$: \[ \begin{bmatrix} 0.2 \rightarrow 0.1 \\ 0.9 \rightarrow 0.9 \end{bmatrix} \]
Trained HMM-MMB: M&M Model

- Initialize HMM-MMB with:
  - \( L_1 \) HMM Transition Matrix
Trained HMM-MMB: M&M Model

- Initialize HMM-MMB with:
  1. \(L_1\) HMM Transition Matrix
  2. \(L_2\) MMB Parameters
Trained HMM-MMB: M&M Model

- Initialize HMM-MMB with:
  1. \( L_1 \) HMM Transition Matrix
  2. \( L_2 \) MMB Parameters

- Relatively fast convergence to local optima
Model Evaluation
Things of Interest

- Packet Reception Rate (PRR)
Things of Interest

- Packet Reception Rate (PRR)
- Run Length (RL) Distribution

![Graph showing weighted RL vs. run length of 1s]
Things of Interest

- Packet Reception Rate (PRR)
- Run Length (RL) Distribution
- Conditional Packet Delivery Function (CPDF) [Srinivasan et al. SenSys’08]
Comparing RL and CPDF Distributions - $L_1$ norm

Absence of rare cases of long runs does not affect the $L_1$ norm.
Comparing RL and CPDF Distributions - $L_1$ norm

$L_1$ norm unfairly penalizes run length distributions.
Comparing RL and CPDF Distributions - Nearest Neighbor Distance

\[ D(P, Q) = |P(1) - Q(1)| + |P(2) - Q(2)| + \\
|P(3) - Q(3)| + |P(4) - Q(4)| + \\
|P(5) - Q(5)| + |P(6) - Q(6)| + \\
|P(7) - Q(8)| + |7 - 8|/1000 \\
|P(100) - Q(8)| + |100 - 8|/1000 \]
Comparing RL and CPDF Distributions - Nearest Neighbor Distance

\[ D(P, Q) = |P(1) - Q(1)| + |P(2) - Q(2)| + |P(3) - Q(3)| + |P(4) - Q(4)| + |P(5) - Q(5)| + |P(6) - Q(6)| + |P(7) - Q(8)| + |7 - 8|/1000 + |P(100) - Q(8)| + |100 - 8|/1000 \]

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Nearest Neighbor Distance

\[ NND_{PQ} = \frac{D(P, Q) + D(Q, P)}{2} \]
M&M Simulator

- Simulate traces in TOSSIM.
- PRRs from 0% to 100%.

TOSSIM code: www.andes.ucmerced.edu/software
Comparison Methodology

1. Simulate traces for M&M as follows:
   - For a given model size, generate a sequence using the model parameters.

2. Simulate traces for TOSSIM as follows:
   - Use average RSSI of received packets as the gain value of the simulated trace.
   - Model noise using the CPM algorithm (Lee et al. IPSN’07).
Comparisons - Long Term Dynamics

Original PRR
28%
Comparisons - Long Term Dynamics

Original PRR: 28%

TOSSIM PRR: 49%
Comparisons - Long Term Dynamics

Original PRR = 28%

TOSSIM PRR = 49%

M&M PRR = 27%
Comparisons - Short Term Dynamics

Run Length of 0s

Original

10^0 10^5

546
Comparisons - Short Term Dynamics

Run Length of 0s

Original

M&M

546

276
Comparisons - Short Term Dynamics

Run Length of 0s

- Original
  - 546

- M&M
  - 276

- TOSSIM
  - 23
Comparisons - Short Term Dynamics

Run Length of 1s

![Graph showing run length of 1s](image)
Comparisons - Short Term Dynamics

Run Length of 1s

![Graph showing run length of 1s for Original and M&M models. The y-axis represents the number of occurrences, ranging from 10^0 to 10^5, with the x-axis showing percentages from 0 to 100. The Original model has a peak at 92%, while the M&M model has a peak at 65%.]
Comparisons - Short Term Dynamics

Run Length of 1s

Original: 92
M&M: 65
TOSSIM: 16

25 / 29
Sensitivity to Window Size $W$

<table>
<thead>
<tr>
<th>$W$</th>
<th>$NND$</th>
<th>Training Vectors per State (Trace Length = 230400)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>5.55</td>
<td>4800</td>
</tr>
<tr>
<td>64</td>
<td>2.45</td>
<td>600</td>
</tr>
<tr>
<td>128</td>
<td>1.45</td>
<td>300</td>
</tr>
<tr>
<td>192</td>
<td>1.25</td>
<td>200</td>
</tr>
</tbody>
</table>
Future Directions

- Model Adaptation
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  - Simulate different network conditions
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- **Extend to RSSI**
  - Better representation of link quality
    (Srinivasan and Levis EmNets’06)
Future Directions

- Model Adaptation
  - Simulate different network conditions
  - Minimal deployment and training data

- User Control
  - Length of burst of 1/0s
  - Qualitative factors

- Extend to RSSI
  - Better representation of link quality
    (Srinivasan and Levis EmNets’06)
  - Complement CPM
GOAL: Replicate multiscale structure in wireless links.

Long Term Dynamics

Short Term Dynamics

http://www.andes.ucmerced.edu/software

THANK YOU.
Conclusion

GOAL: Replicate multiscale structure in wireless links.

Long Term Dynamics ✓
Short Term Dynamics ✓

http://www.andes.ucmerced.edu/software

THANK YOU.
References for Slides

- David Kotz, Calvin Newport, Robert S. Gray, Jason Liu, Yougu Yuan, and Chip Elliott, “Experimental evaluation of wireless simulation assumptions”, in *MSWiM ’04*.
