MobiSensing: Exploiting Human Mobility for Multi-Application Mobile Data Sensing with Low User Intervention*

> Kang Chen¹ and Haiying Shen² ¹Dept. of ECE, Southern Illinois University, IL, USA ²Dept. of ECE, Clemson University, SC, USA

* Work was done when at Clemson

Outline

- Introduction
- System Design
- Performance Evaluation
- Conclusion

- Explosive growth of mobile devices
 - Smart phones, tablets, and wearable devices
 - Around 2 billion smart phone users now
- Rich sensing & computing capability on those mobile devices
 - GHz level CPUs
 - Various sensors: GPS/Microphone/Accelerometer

- Inspires mobile device based sensing systems
 - Exploit otherwise underutilized resources
 - Does not need dedicated infrastructure
 - A bunch of existing endeavors
 - Bus arrival time prediction (MobiSys'12)
 - Red light advisory (MobiSys'11)
 - Remote sensing (MobiSys'10)
 - Road status sensing and mobitoring (SenSys'08)
 - etc.

- Mobile devices holders are not dedicated
 - Do not want to move or operate purposely for sensing
 - Want to be interrupted as few as possible
 - A major barrier for such distributed sensing systems

- The passive mode appears to be more attractive
 - Collect data without explicit user interruption
 - Can exploit more resources

- How to realize passive data sensing effectively?
 - Accurate mobility prediction
 - Understand where mobile devices are going
 - Efficient task assignment
 - Send the task to the device that is most likely to finish it
 - Reduce explicit user participation as much as possible
 - Enhance the accuracy of the above two steps "silently"

- MobiSensing is proposed in this direction
 - Exploit the heterogeneous semi-markov model for mobility modeling
 - Mobility model based task assignment
 - A task is always assigned to devices that are most likely to complete them
 - Exploit mobile device's intermittent connection to server for
 - Mobility model refinement
 - Task assignment and data collection

Outline

- Introduction
- System Design
- Performance Evaluation
- Conclusion

- Treat device mobility as transition between landmarks
 - $\mathcal{L} = \{L_1, L_2, L_3, \dots, L_m\}$: landmark space consisting of m landmarks
- Using semi-markov process (SMP) to model those transitions
 - X_n : the status (i.e., which landmark) after the *n*-th transition
 - T_n : the time when the node changes to X_n
 - Kernel:

$$Q_{ij}(t) = P[X_{n+1} = L_j, T_{n+1} - T_n \le t | X_n = L_i]$$

• It means the probability of transiting to L_j after staying at L_i for less than t time slots

• How to obtain $Q_{ij}(t)$?

$$\begin{aligned} Q_{ij}(t) &= P \big[X_{n+1} = L_j, T_{n+1} - T_n \leq t \big| X_n = L_i \big] \\ &= P \big[X_{n+1} = L_j \big| X_n = L_i \big] * P \big[T_{n+1} - T_n \leq t \big| X_{n+1} = L_j, X_n = L_i \big] \\ &= p_{ij} U_{ij}(t) \end{aligned}$$

• p_{ij} : the probability of transiting to L_j after staying at L_i

$$p_{ij} = V_{ij}/V_i$$

- V_{ij} : the number of transits from L_i to L_j
- V_i : the number of transits leaving L_i

• How to obtain $Q_{ij}(t)$?

$$Q_{ij}(t) = P[X_{n+1} = L_j, T_{n+1} - T_n \le t | X_n = L_i]$$

= $P[X_{n+1} = L_j | X_n = L_i] * P[T_{n+1} - T_n \le t | X_{n+1} = L_j, X_n = L_i]$
= $p_{ij}U_{ij}(t)$

• $U_{ij}(t)$: the probability that the sojourn time at L_i is no more than t on the condition that the node transits to L_j after staying at L_i

$$U_{ij}(t) = V_{ij}(t)/V_{ij}$$

- $V_{ij}(t)$: the number of transits from L_i to L_j with the sojourn time at L_i less than t
- V_{ij} : the number of transits from L_i to L_j

- Usage of $Q_{ij}(t)$
 - Deduce $\Phi_{ij}(t)$: the probability of at status L_j after t time slots if the node is at status L_i at time 0.
 - Refer to the paper for the detail of getting $\Phi_{ij}(t)$
- Usage of $\Phi_{ij}(t)$
 - If a node is at L_i now, it has a probability of $\Phi_{ij}(t)$ to be at L_j after t time slots
 - Use it to determine what tasks can be assigned to the node

System Design : Sensing Task

• A sensing task is a tuple with four elements

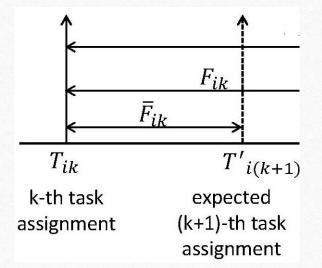
{DataType, Location, Date, TimeSlot}

- The *DataType* must be supported by mobile devices
- The *Location* refers to landmarks
- Time is slotted
- A job that spanning a longer period of time is divided into consecutive sensing tasks

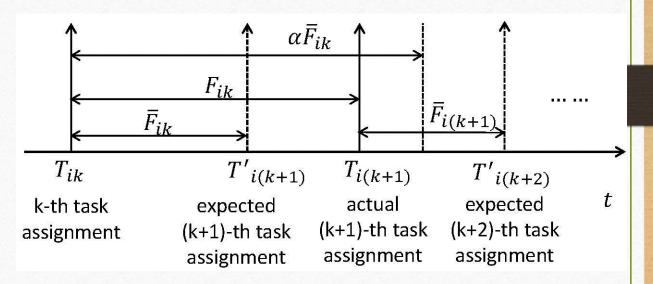
- Mobility prediction based task assignment
 - Predict future mobility
- How long we need to look into the future?
 - User mobility has uncertainty
 - The longer we look, the low prediction accuracy we have
 - The prediction for the next hour is more accurate that for 1 day later

- How long we need to look into the future?
 - Exploit user's intermittent connection to the network (WiFi or LTE)
 - Conduct a task assignment at each connection
 - Only need to predict the mobility between this connection and the next connection
 - Between T_{ik} and $T_{i(k+1)}$, where T_{ik} denotes the k-th connection to the server
 - Can refine the accuracy of mobility prediction
 - Can reduce the overhead, as we only need to consider sensing tasks in this period of time

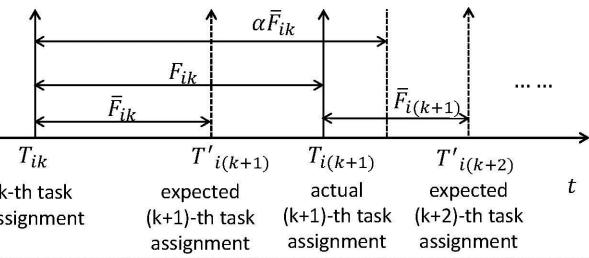
- When is the next connection?
 - It is unknown as we do not require user participation
 - To reduce user interruption
 - Predict it with historical data
 - Using the average interval between two task assignments
 - \overline{F}_{ik} in the figure



- Incorrectly predicted next task assignment may miss tasks
 - When actual next task assignment happens after the predicted one, i.e., T_{i(k+1)} is after T'_{i(k+1)}
 - As we only consider tasks between T_{ik} and $T'_{i(k+1)}$, tasks between $T'_{i(k+1)}$ and $T_{i(k+1)}$ will not be assigned to any node



- Solve the problem with a redundancy factor *α*
 - Consider tasks in the period of $\alpha \overline{F}_{ik}$
 - Can effectively reducing the chance of missing tasks
 - Duplicate period of time is fine as it k-th task only indicates a little more overhead assignment



- Summary of task assignment
 - When a node connects to the server, determine the period of future time slots to consider, i.e., $\alpha \overline{F}_{ik}$
 - Calculate the node's probability of appearing at each landmark, i.e., $\Phi_{ij}(t)$ at time slots 1,2,3, ..., $\alpha \overline{F}_{ik}$ for landmarks L_j , j = 1,2,3,...,m,
 - Tasks corresponding to $\Phi_{ij}(t)$ that is larger than a threshold is assigned to the node

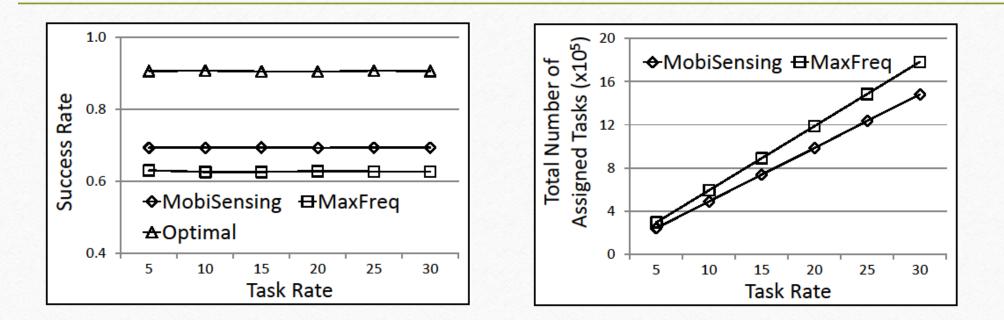
Outline

- Introduction
- System Design
- Performance Evaluation
- Conclusion

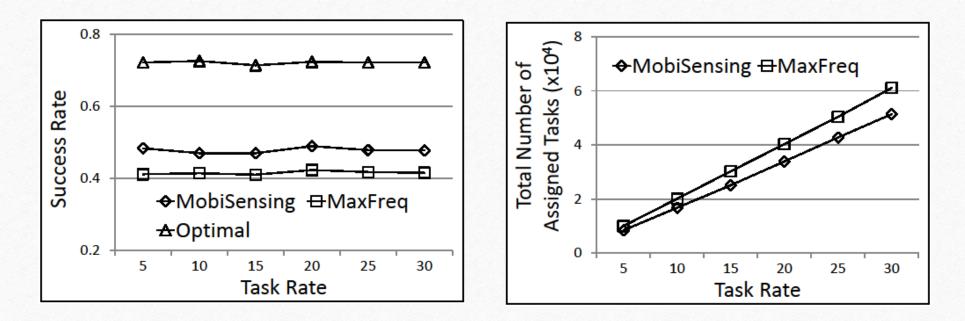
Evaluation

- Traces
 - MIT Reality: encountering of mobile devices on a campus
 - DieselNet: encountering of buses in a community
- Metrics
 - Success rate: percentage of successfully completed sensing tasks
 - Overhead: total # of assigned tasks
- Methods
 - Optimal: assign a copy of a task to every node
 - MaxFreq: assign a task to nodes most frequently visit the target landmark

Evaluation : MIT Reality Trace



Evaluation : DieselNet



• MobiSensing leads to a high success rate and low overhead compared to MaxFreq

Conclusion

- The popularity of mobile devices leads to rich sensing capability
- Ideally to exploit such capability passively with a low interruption to users
- Solution:
 - Assign tasks to mobile devices during their intermittent connection to the network
 - Modeling user mobility with semi-markov process for efficient task assignment
- Future work:
 - Privacy protection: not all users are willing to share their locations
 - Social properties: mobility patterns reflected in social structures



Thank you! Questions & Comments?