User(s) Mobility Predictin in Mobile Networks to Enhance Location Based Services(LBS).

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24.07.2017

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Agenda

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- Introduction
- Problem Statement
- Approach
- Results
- Future Works
- Colaboration project

Introduction

- Different type of information (history about user movements trajectories, BTSs location map, city map…) could be used to estimate the next location of users(s).

- Information about next location of user(s), could be applied to improve various performance metrics.

- Location Based Services (LBS).

Problem Statement

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- In this research, one key issue is predicting the future location of mobile users based on current context, such as current location (*Place ID*), time stamp of visiting each place, duration of staying at a place, etc.
- MDC data set:
  - Launched in early October-2011 and closed after one year.
  - The campaign population reaches 185 participants.
  - Includes Temporal and spatial features (*Place_ID*, *Network_ID*, *Time_stamp*).
- Crowd Signal data set:
  - Launched in early November-2016 and closed after two month.
  - The campaign population reaches 30 participants.
  - Granularity of data set is 1 minutes.
  - Includes Temporal and spatial features of users profiles.

User Classification(1/2)

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> User Trace Quality:
  - Very good: more than 1500 instances
  - Good: 1200-1500 instances
  - OK: 1000-1200 instances
  - Bad: 800-1000 instances
  - Very bad: less than 800 instances

> User Movement Patterns:
  - Homogenous movement: mobility pattern is quite regular and repeatable.
  - Heterogeneous movement: mobility pattern is rather random and non-repeatable.

User Classification (2/2)

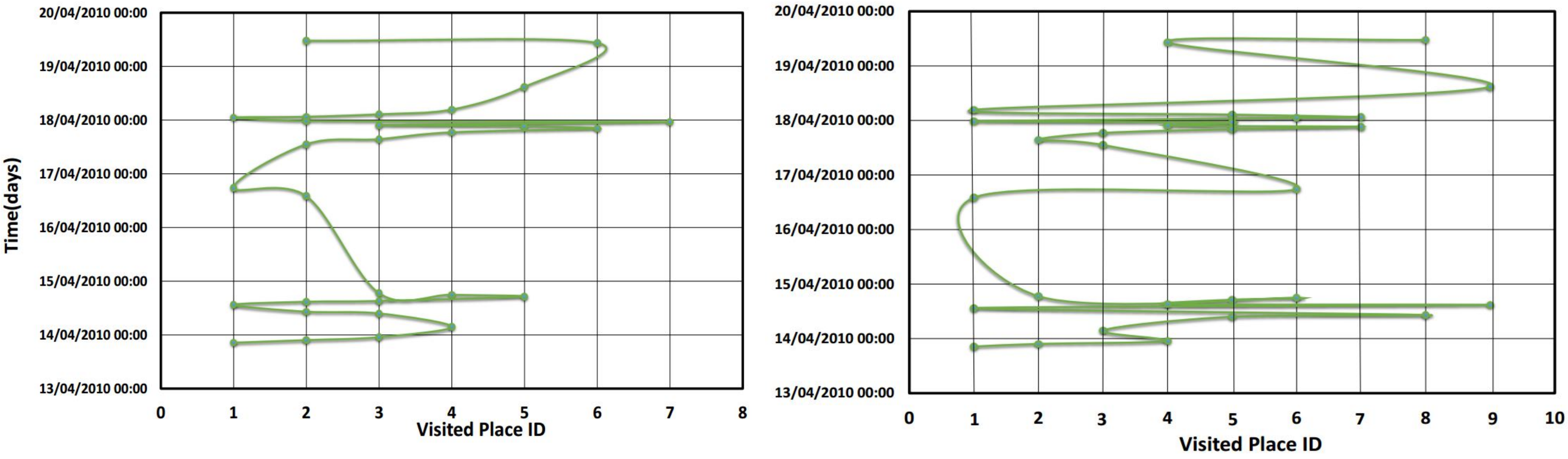

Figure 1: Homogeneous and Heterogeneous movements

Features(1/2)

> Temporal and spatial Features:
- Weekday: to indicate which weekday is the visit
- Leaving time: the ending time of the visit. We defined 6 time intervals, and each time period could be mapped to a specific place.
- Duration: time duration of the visit.
- Visiting frequency: how often to re-visit a place during data collection period.

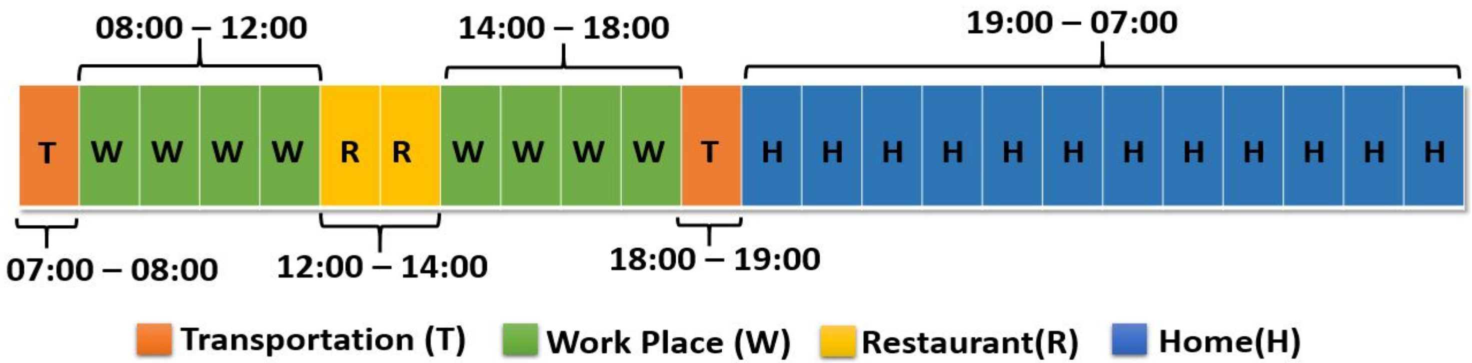

Figure 2: Day time decomposition

Features(2/2)

- System Features:
  - WiFi connection: number of detected WiFi networks.
    - Home, work place, city center.
  - Acceleration variation: movement speed variation, which can be derived from smartphone’s embedded motion sensors.
    - Transportation location, gym
  - Running application: the type of running application
    - Indoor or outdoor

Approach

- Individual Predictors:
  - Decision Tree
    - J48
    - Random Forest
  - Bayes
    - Bayes Network
    - Naïve Bayes
  - Neural Networks
    - Multilayer perceptron (MLP)

- Ensemble Predictors:
  - Boosting
  - Bagging
  - Stacking

Individual Predictors-Decision Tree

— Hierarchical structure for classifying.

— Root node contains all the visits of the training data, while child nodes contain those visits that match the dividing criteria along the path from root to the node.

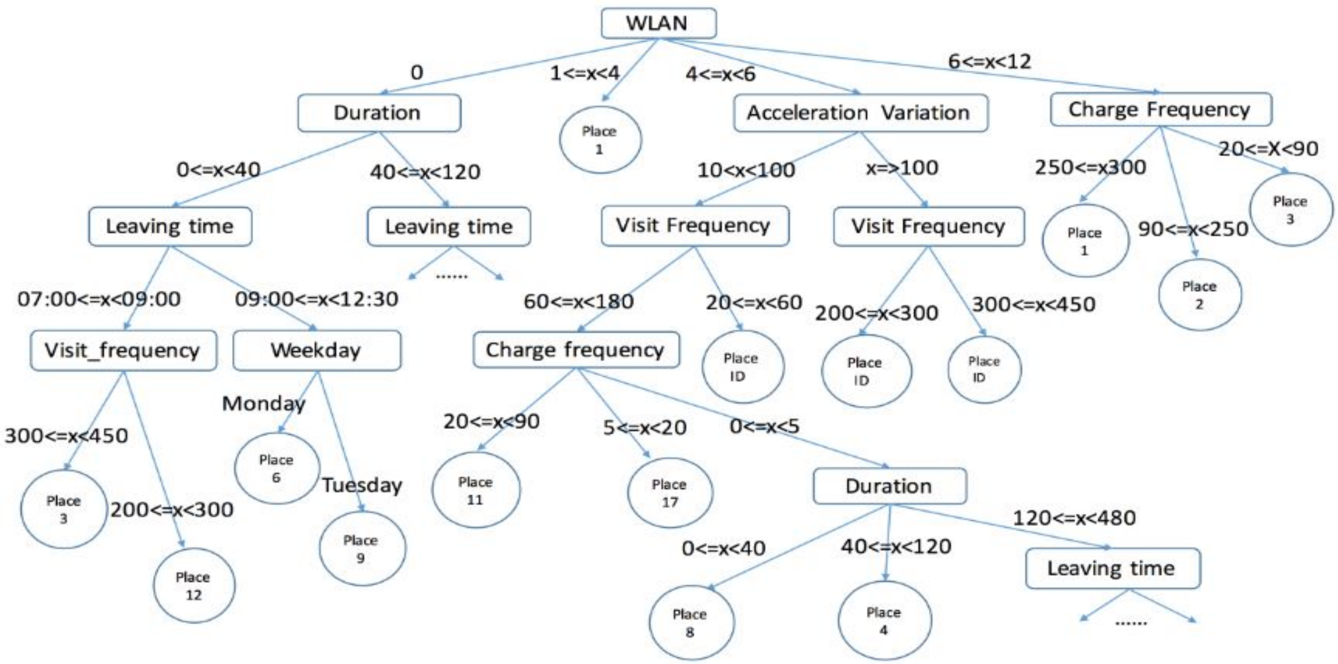

Figure 3: A decision tree structure

Individual Predictors-Bayes Networks

> Bayesian Networks are class of statistical models to define conditional dependencies between features and parent node.

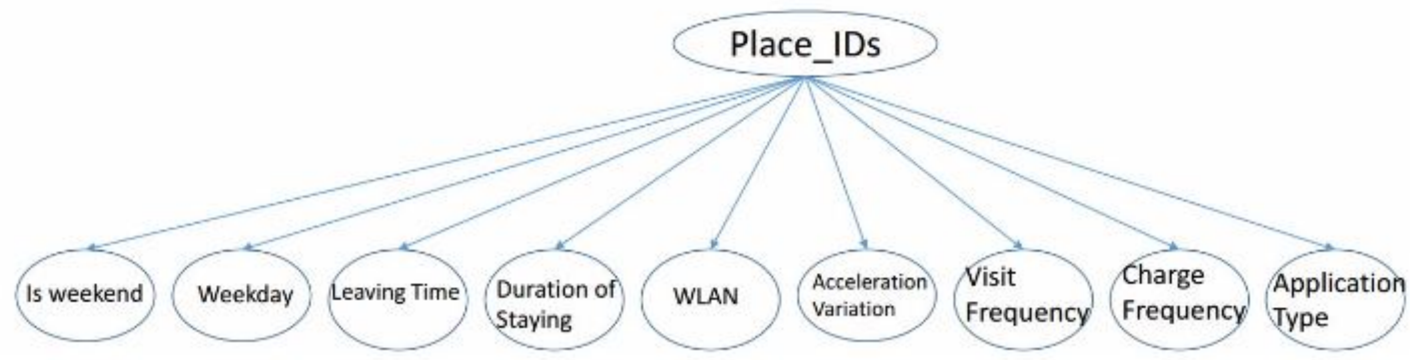

Figure 4: A Directed Acyclic Graph (DAG) of Bayesian networks

Ensemble Predictors – Boosting

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- Boosting, starts with Base classifier (*Individual Predictors*), then a meta classifier (*AdaBoostM1*) focus on the instances that the first classifier got wrong.

$$w_t^{h+1} = \frac{w_t^h \beta_h^{(1-l_h^t)}}{\Sigma_{i=1}^N w_i^h \beta_h^{(1-l_h^t)}}, \quad w_t^1 \in [0,1], \quad \Sigma_{t=1}^N w_t^1 = 1$$

- Bagging, divides the training data set to several different sets with the same size (called subsets). Then, individual predictor is doing training and testing on each subset. The final decision are calculated by getting average.

$$Pr_{Bagging} = \frac{1}{N} \Sigma_{j=1}^N e_j \quad j = 1, ..., N$$

Ensemble Predictors-Stacking

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- Stacking, refers to integration of different kinds of individual predictors to improve prediction accuracy.

$$L_{Level-1} = \{(y_n, z_{1,n}, ..., z_{k,n}), n = 1, ..., N\}$$

- In stacking we are using *weighted Majority* , as a meta learner, this is a method to decide weights of each algorithm based on their individual prediction performances.

Results

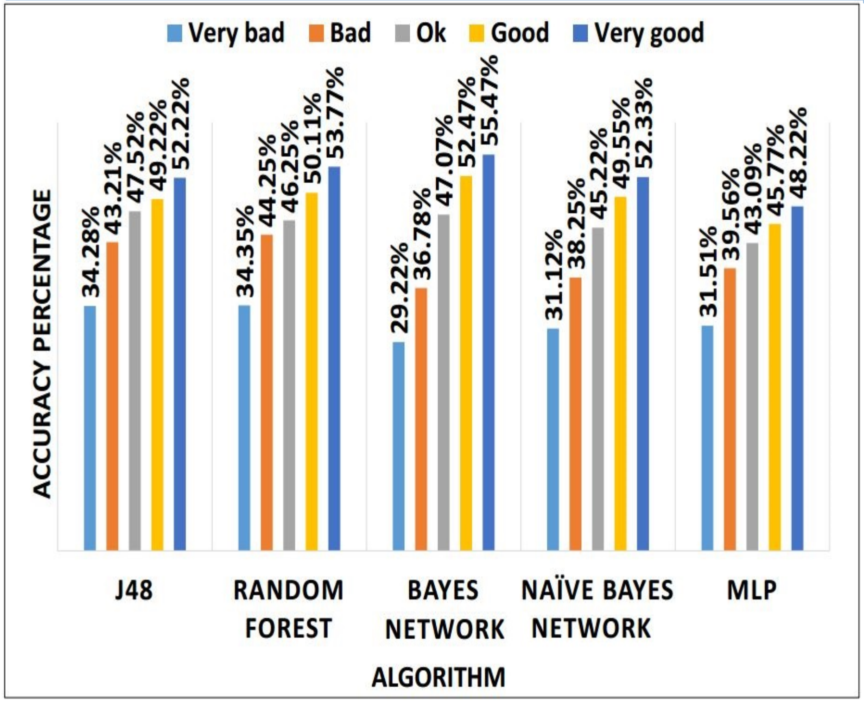

Figure 5: Prediction accuracy of individual algorithms using Temporal+Spatial features.

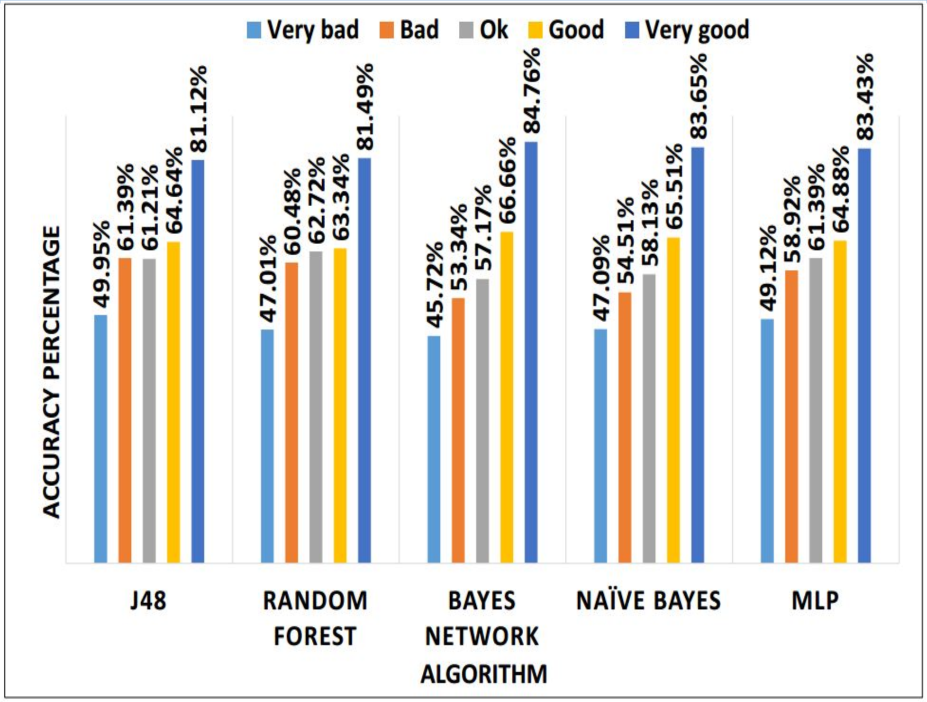

Figure 6: Prediction accuracy of individual algorithms using Hybrid features.

Results

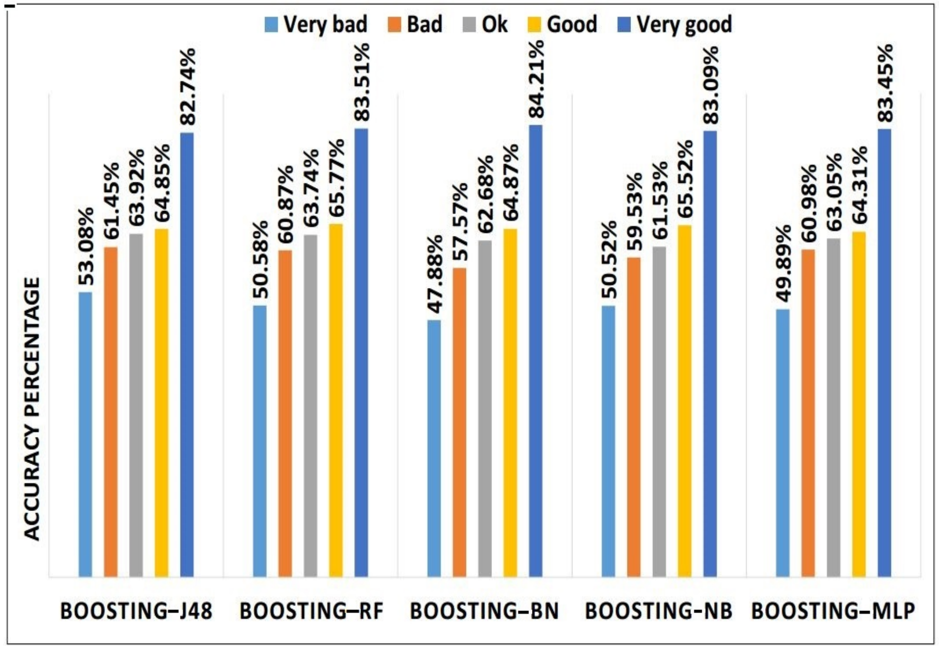

Figure 7: Prediction accuracy of Boosting

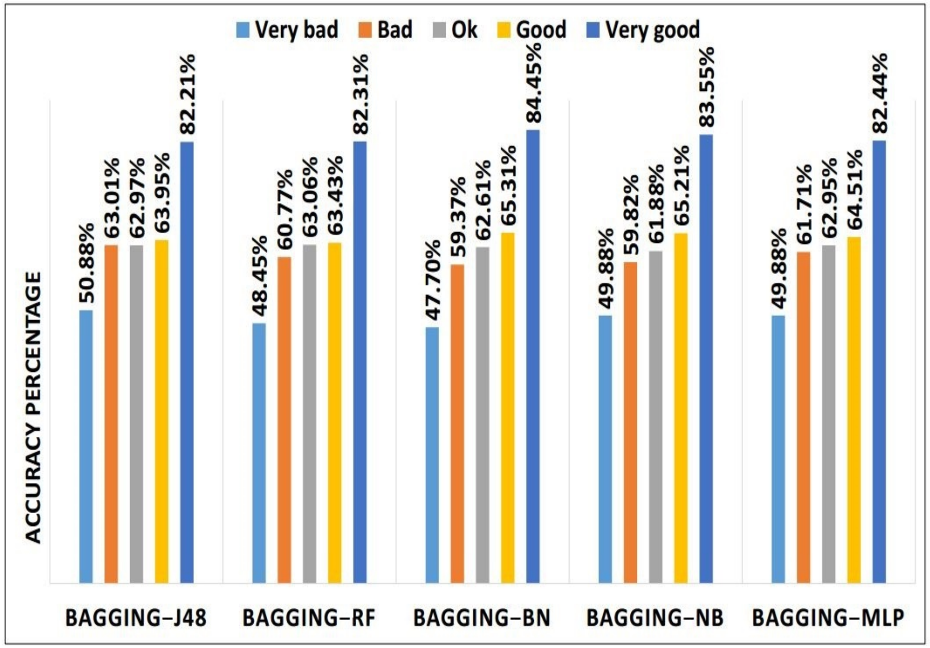

Figure 8: Prediction accuracy of Bagging

Results

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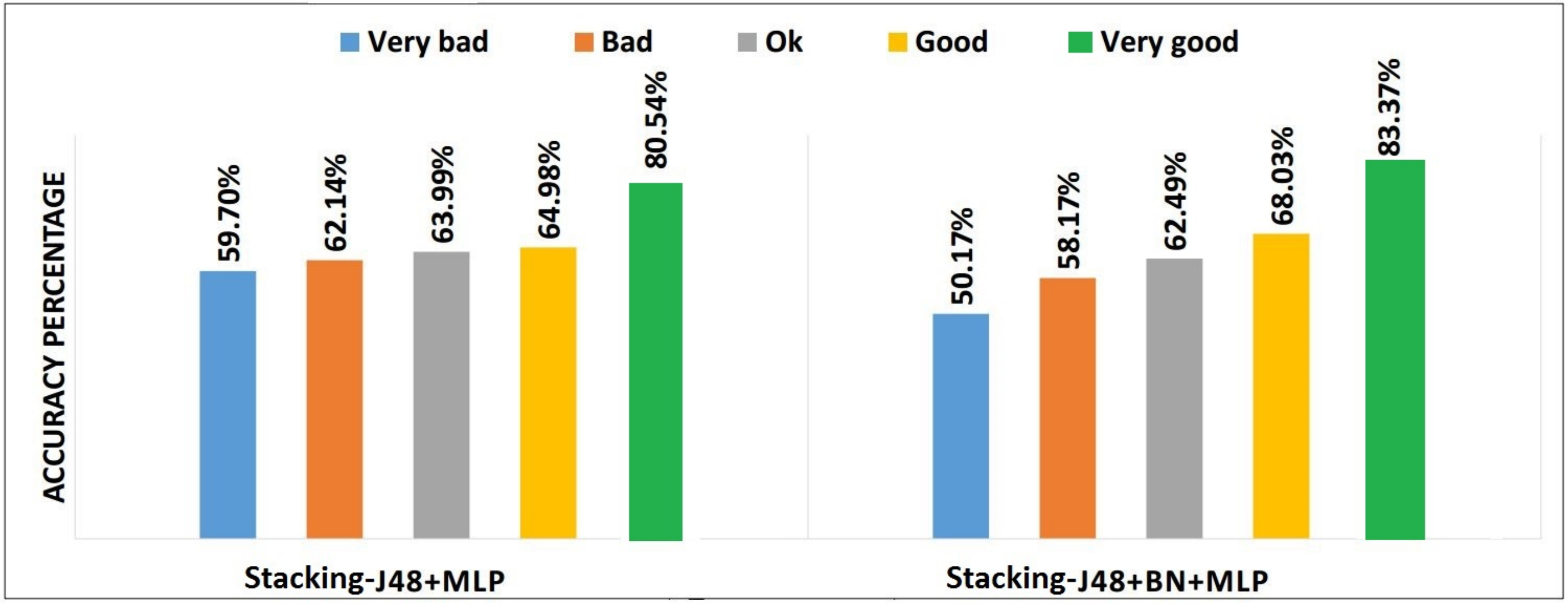


Figure 9: Prediction accuracy of stacking

Results

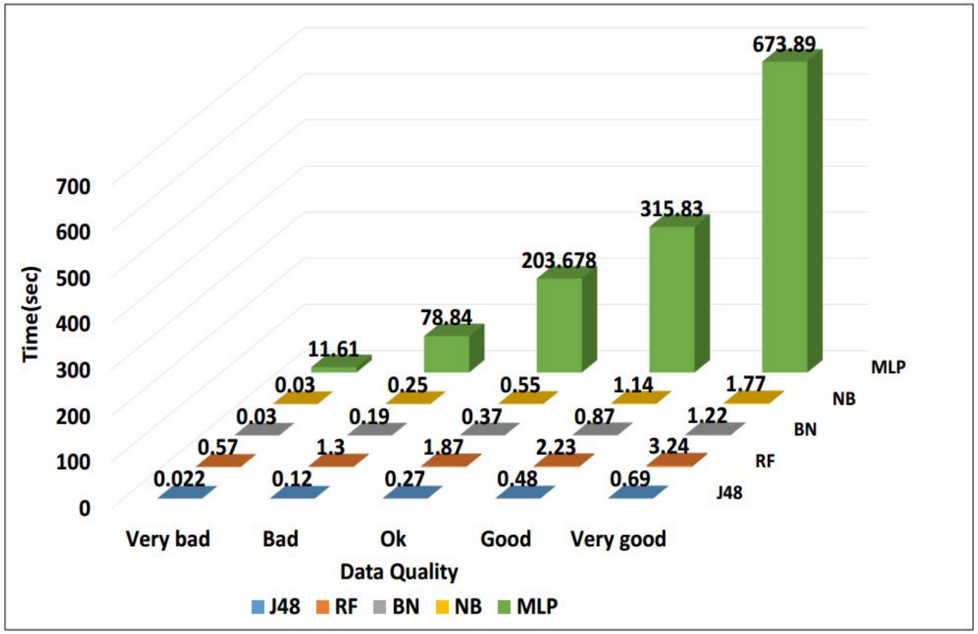


Figure 10: Average execution time of individual algorithms using Hybrid features.

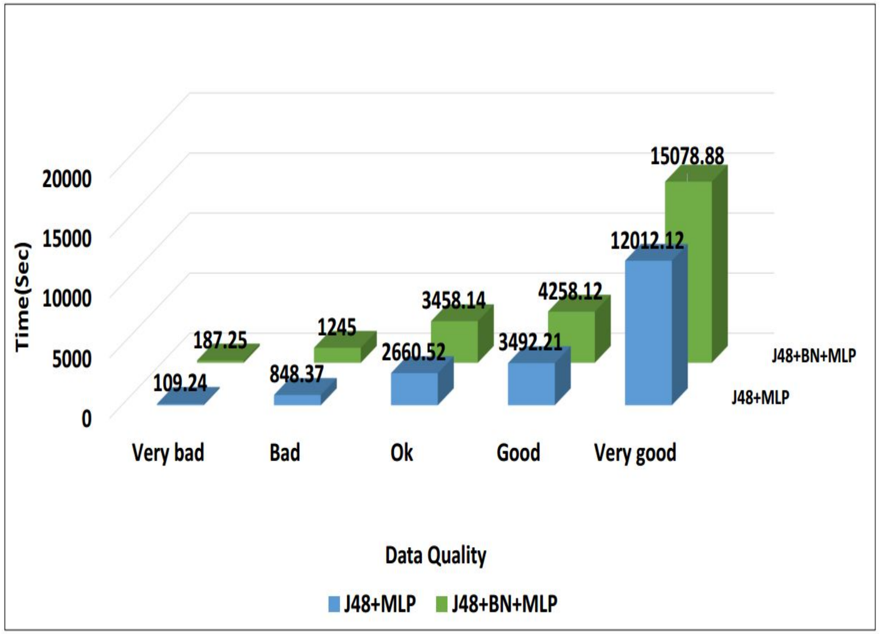


Figure 11: Average execution time of stacking with Hybrid features.

Approach- my current work (1/2)

> Mobility prediction algorithm is Markov Chain model that benefits from Bayesian Networks, the next location (*cell*) visited by user depends on:
  - It's current location.
  - Current time.
  - Day of the week that the user is in the movement .

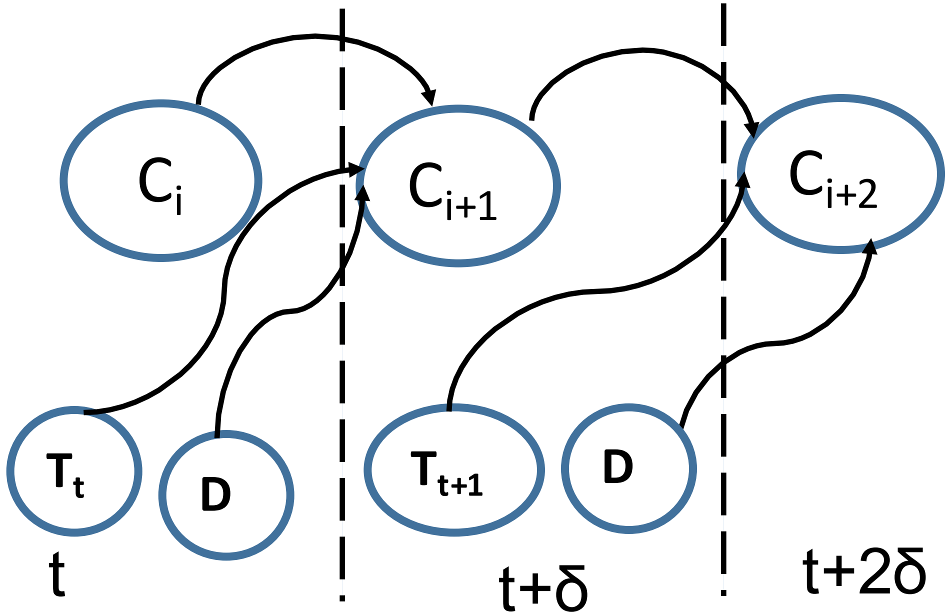
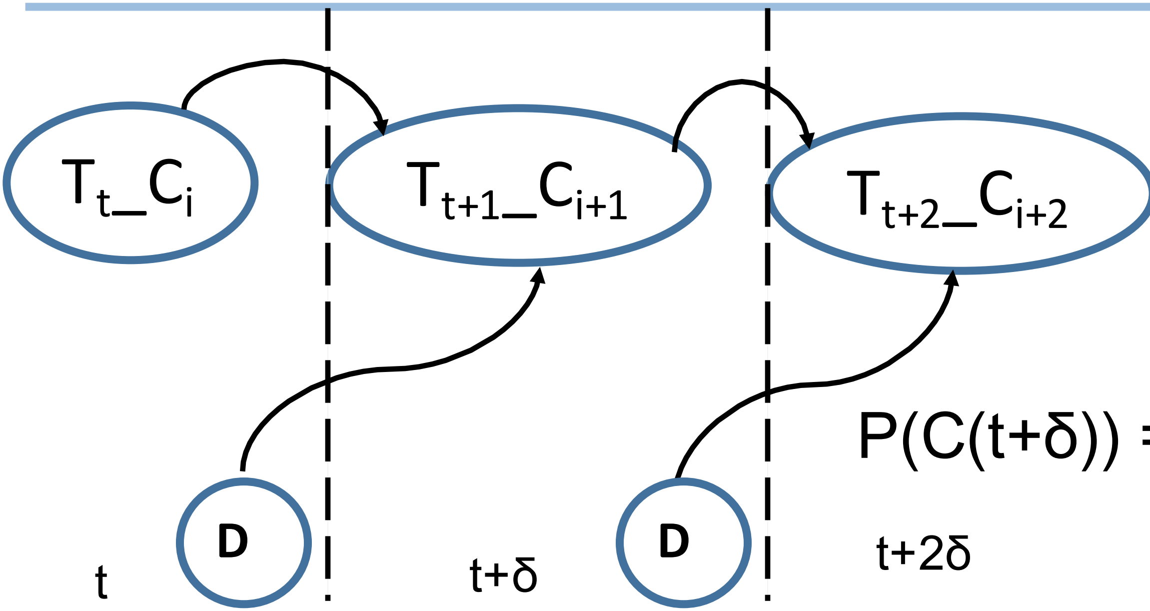


Figure 12: Basic Bayesian Networks Model

Approach(2/2)



$$P(C(t+\delta)) = C_i \mid C\,(t) = C_i,\, T(t) = T_i,\, D)$$

Figure 13: Modified Bayesian Networks model, as First Order Markov Chain*

User Movement Type:

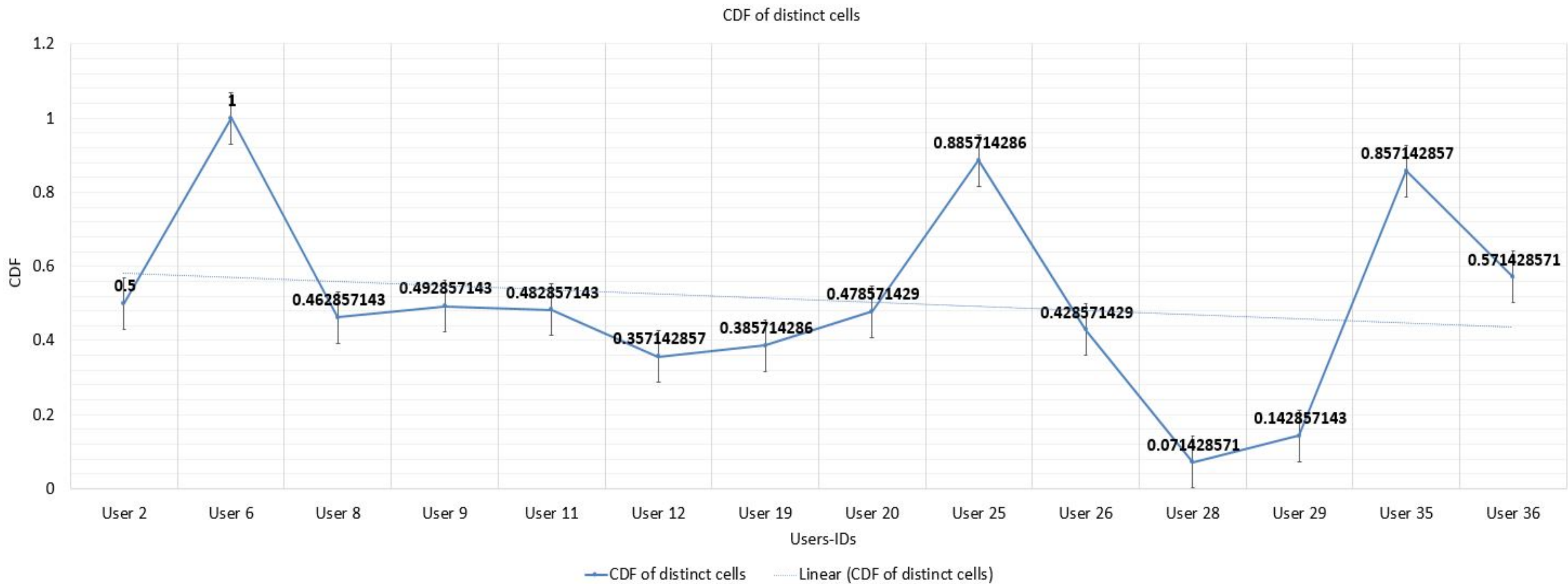
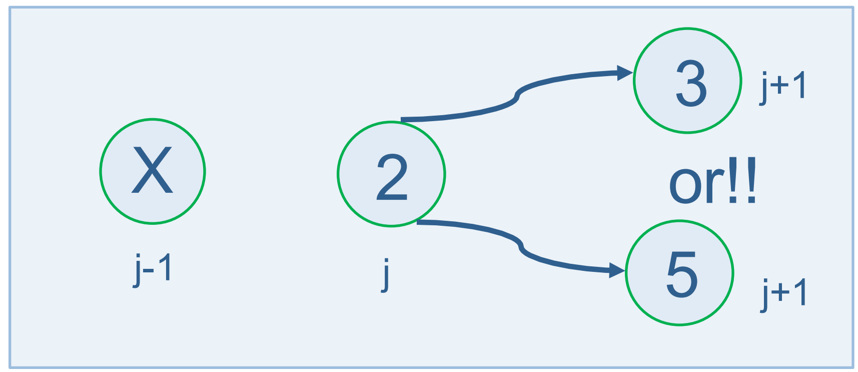


Figure 14: Cumulative Distribution Function of distinct visited cells during data collecting.

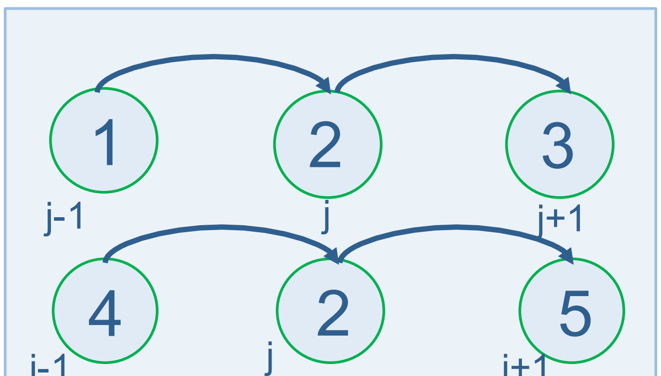
First Order Markov Chain Model:

> First order Markov chain model is not good for Heterogeneous movement type, because:

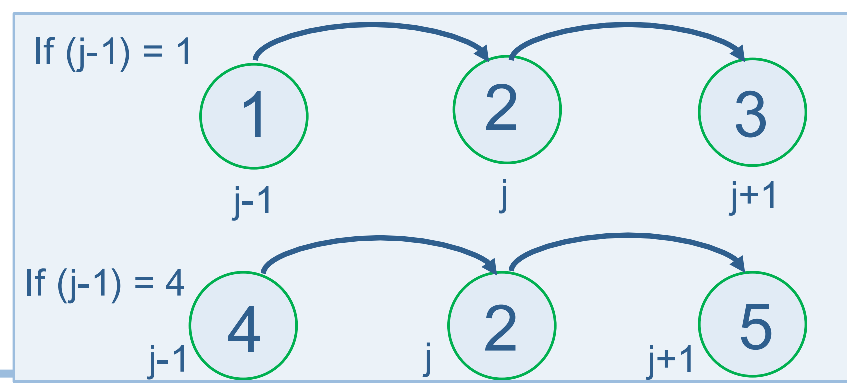
Estimation by 1-MC



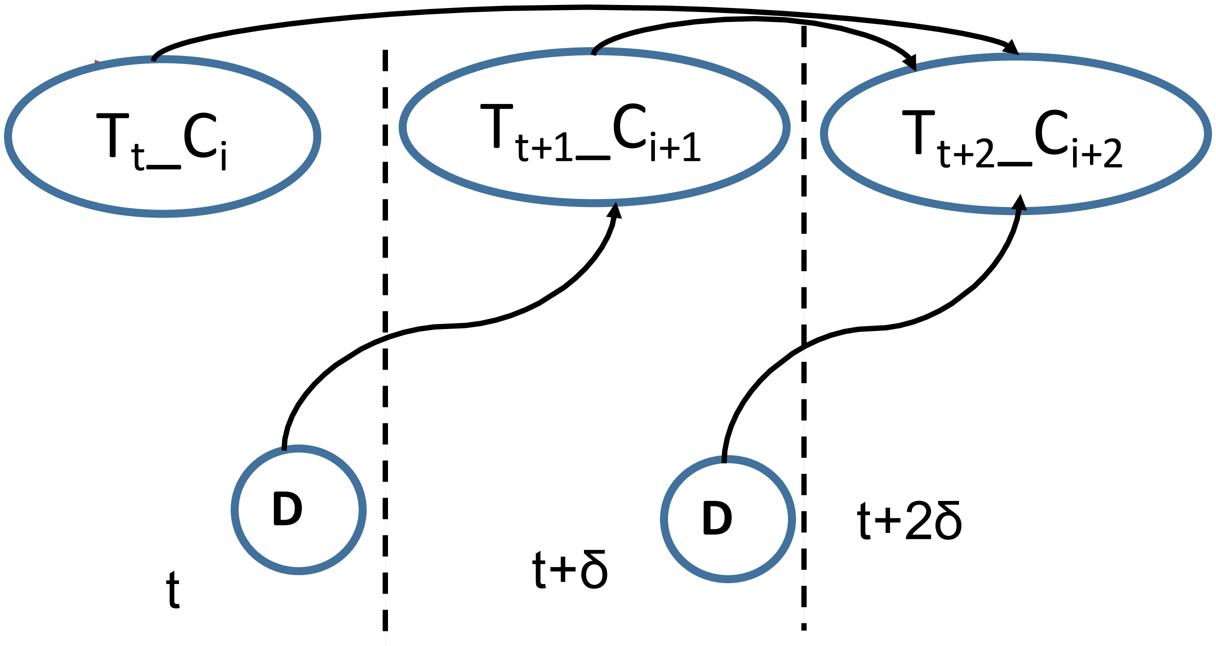
Training



Estimation by 2-MC



Second Order Markov Chain:



$P(C(t+2\delta)) = C_{i+2} \mid C\ (t+1) = C_{i+1},\ C\ (t) = C_i,\ T(t+1) = T_{i+1},\ D,\ T(t+1) = T_{i+1},\ D)$

Figure 15: Modified First Order Markov chain model, as Second Order Markov Chain

Second Order Markov Chain Model-poor quality:

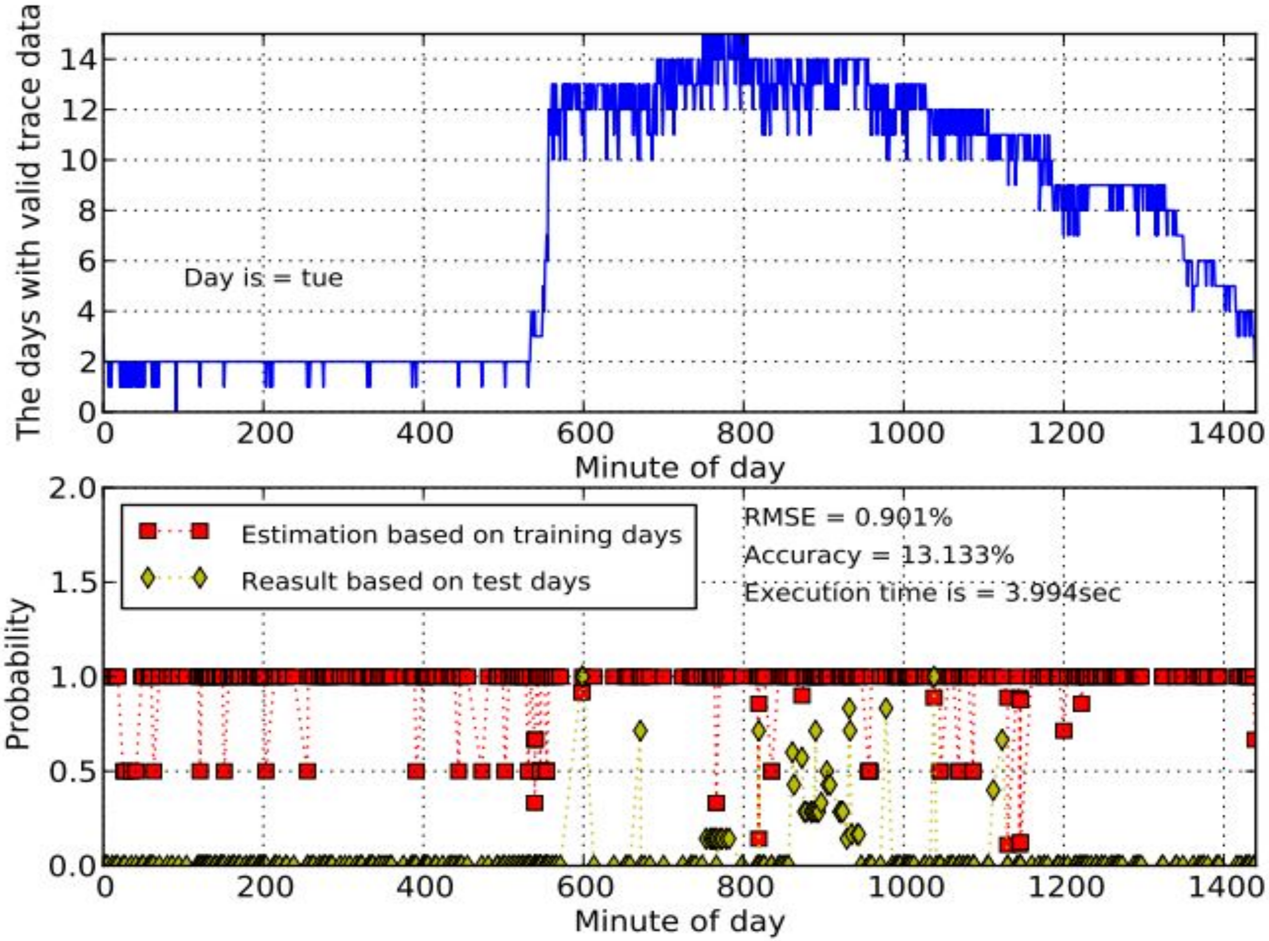


Figure 16: Performance of second order Markov chain with poor quality.

First Order Markov Chain Model-poor quality:

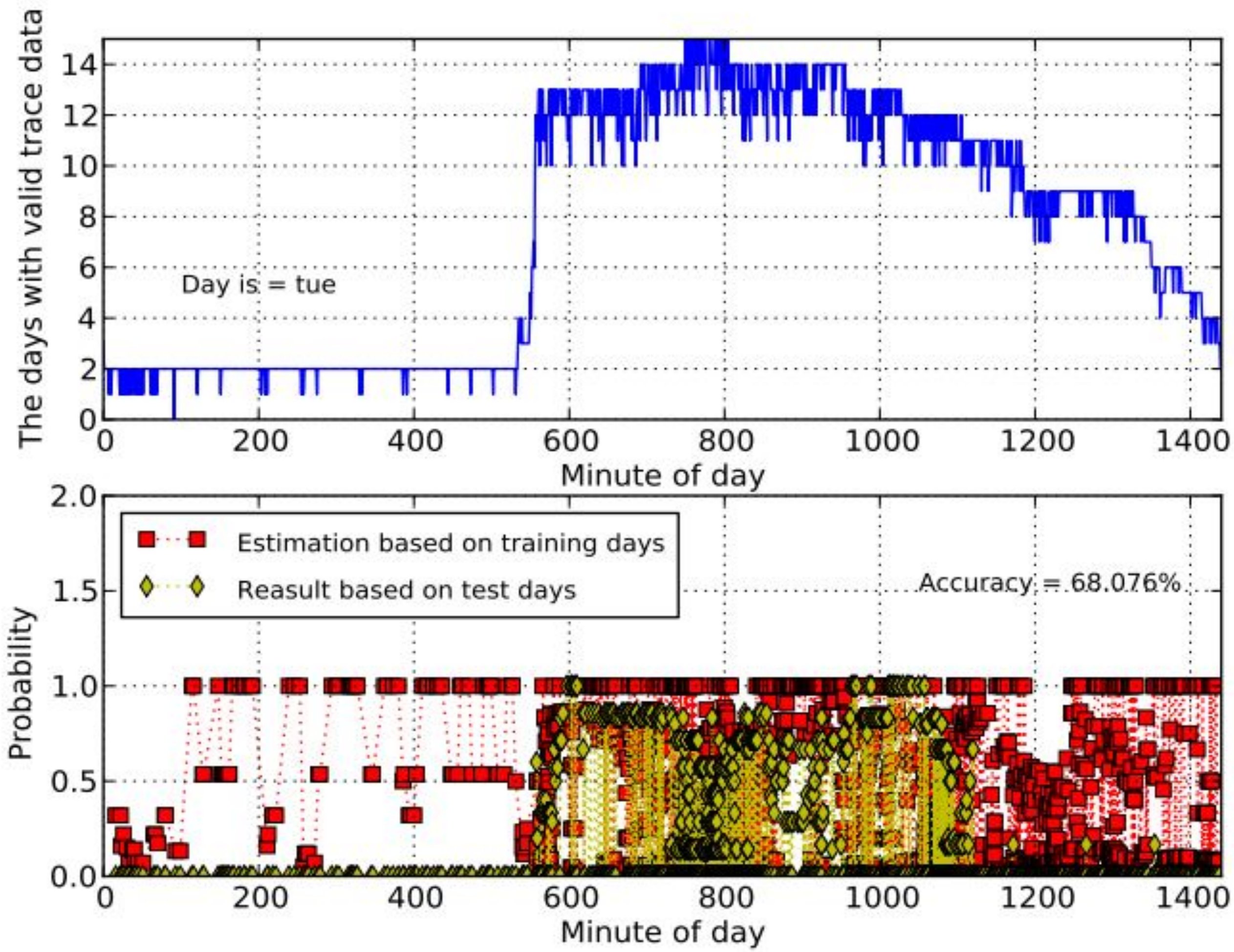


Figure 17: Performance First order Markov chain with poor quality.

Second Order Markov Chain Model-high quality:

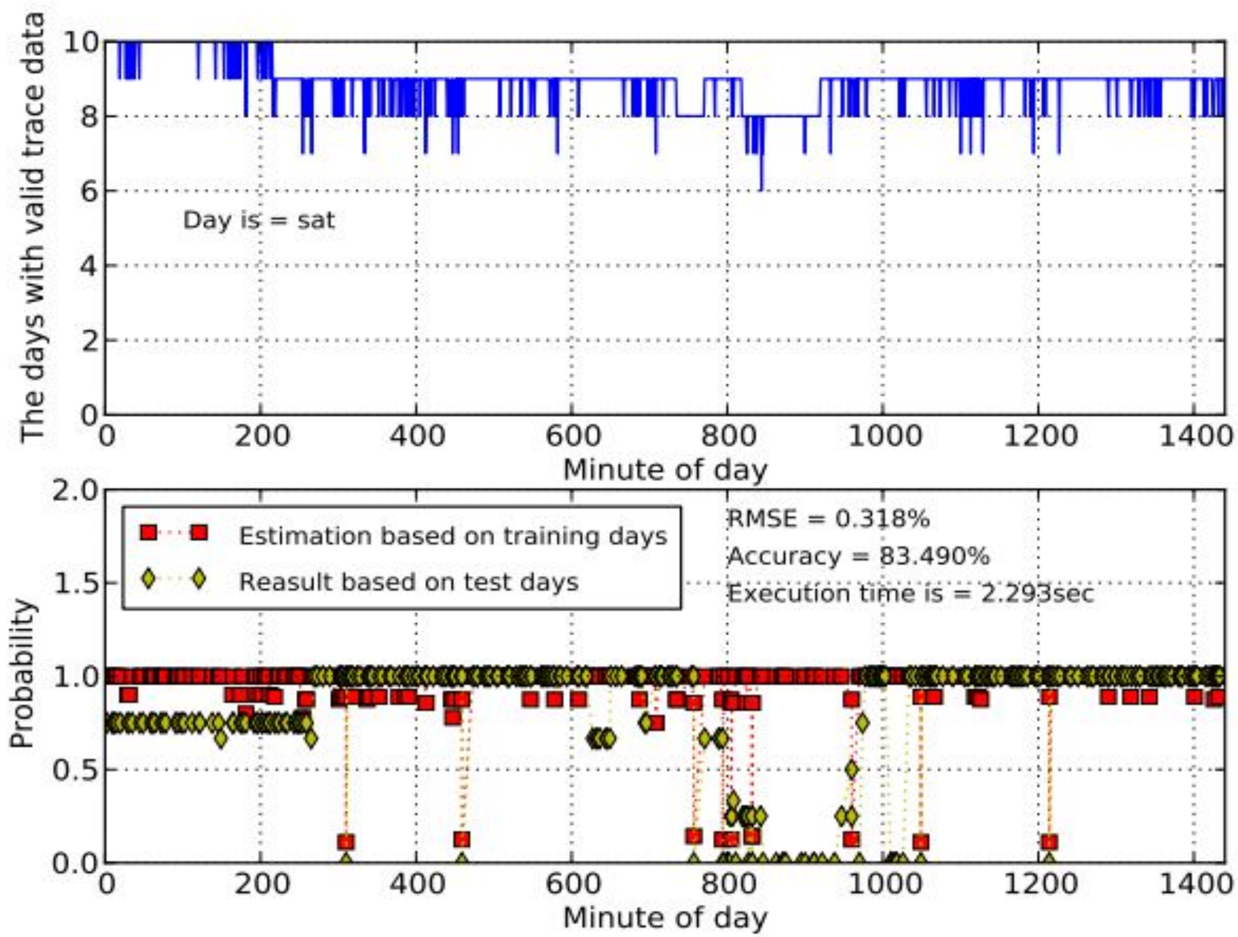


Figure 18: Performance of second order Markov chain with high quality.

First Order Markov Chain Model-high quality:

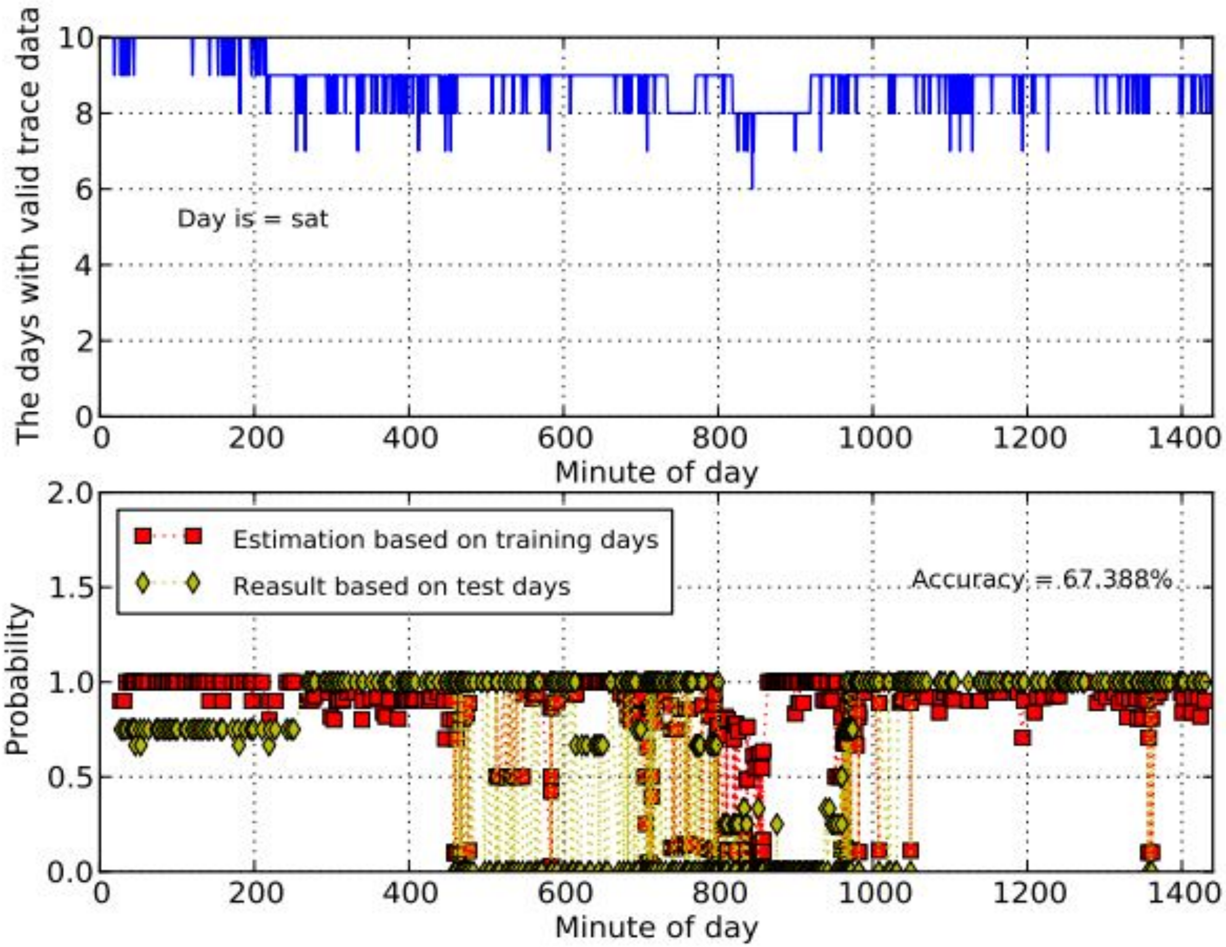
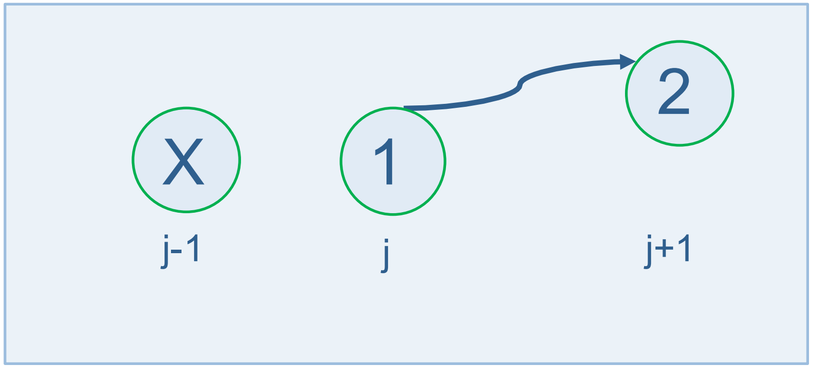


Figure 19: Performance of First order Markov chain with high quality.

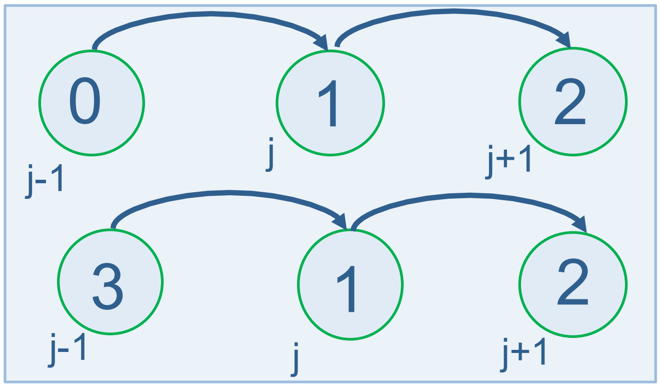
Second Order Markov Chain Model:

- Second order Markov chain model is not good for poor quality data, because:

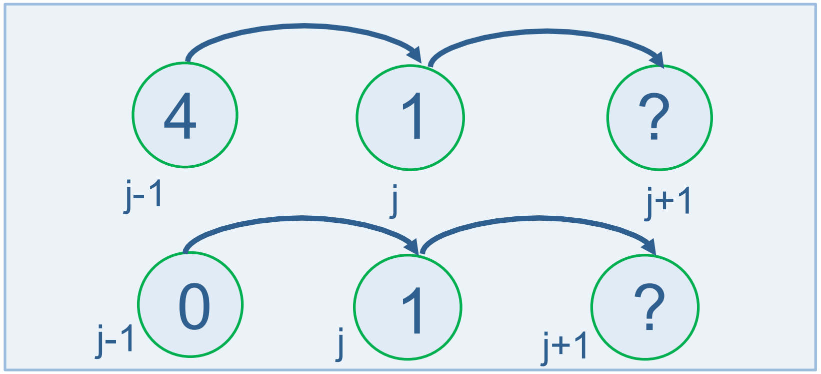
Estimation by 1-MC



Training



Estimation by 2-MC



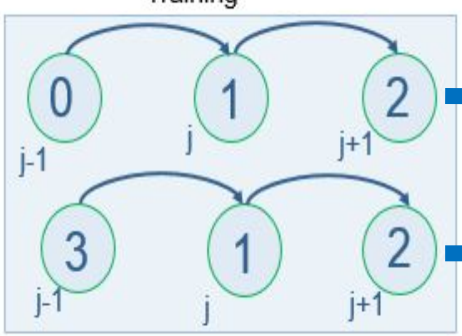
Proposed Model:

> Hybrid Markov Chain Model: Integration of 1-MC and 2-MC to solve user movement type(Hetro&Homo) and traced data with poor quality:

Hybrid Markov Chain Model

$$P(C(t+\delta)) = C_i \mid C\,(t) = C_i,\ T(t) = T_i,\ D)$$
$$P(C(t+2\delta)) = C_{i+2} \mid C\,(t+1) = C_{i+1,}\ C\,(t) = C_i,\ T(t+1) = T_{i+1},\ D,\ T(t+1) = T_{i+1},\ D)$$

Training



$$P(C(t+\delta)) = C_i \mid C\,(t) = C_i,\ T(t) = T_i,\ D)$$

$$P(C(t+2\delta)) = C_{i+2} \mid C\,(t+1) = C_{i+1,}\ C\,(t) = C_i,\ T(t+1) = T_{i+1},\ D,\ T(t+1) = T_{i+1},\ D)$$

Results

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1MC Vs 2MC-MDC

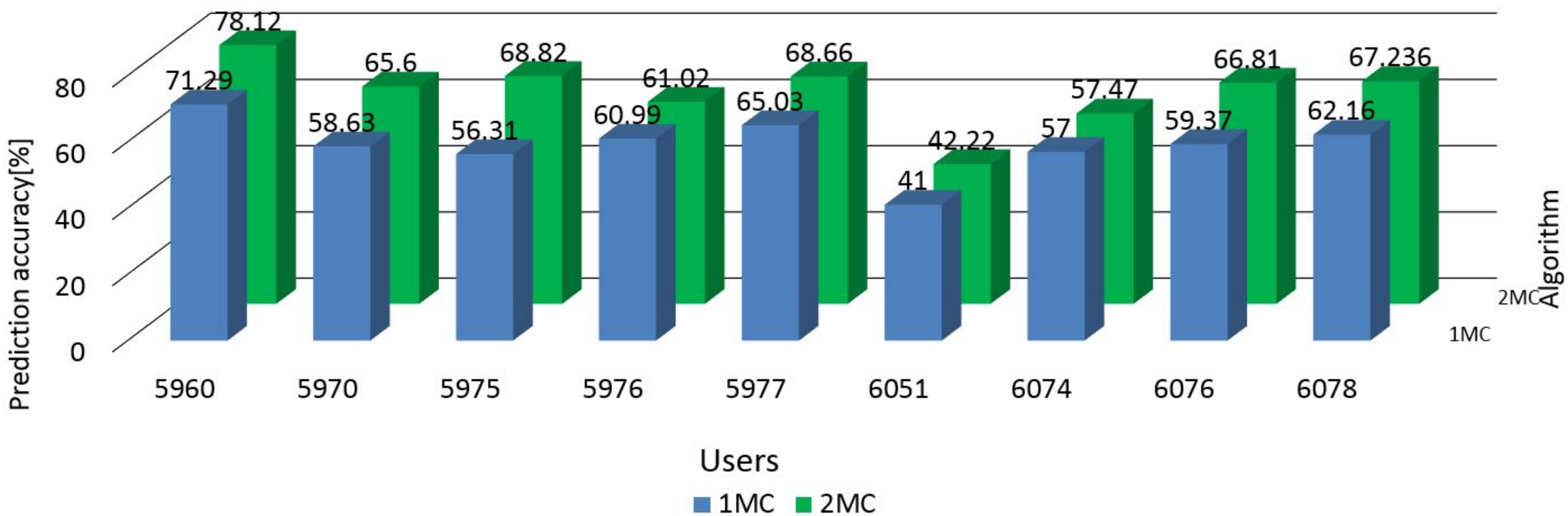

Figure 20: Prediction accuracy for MDC users.

Results

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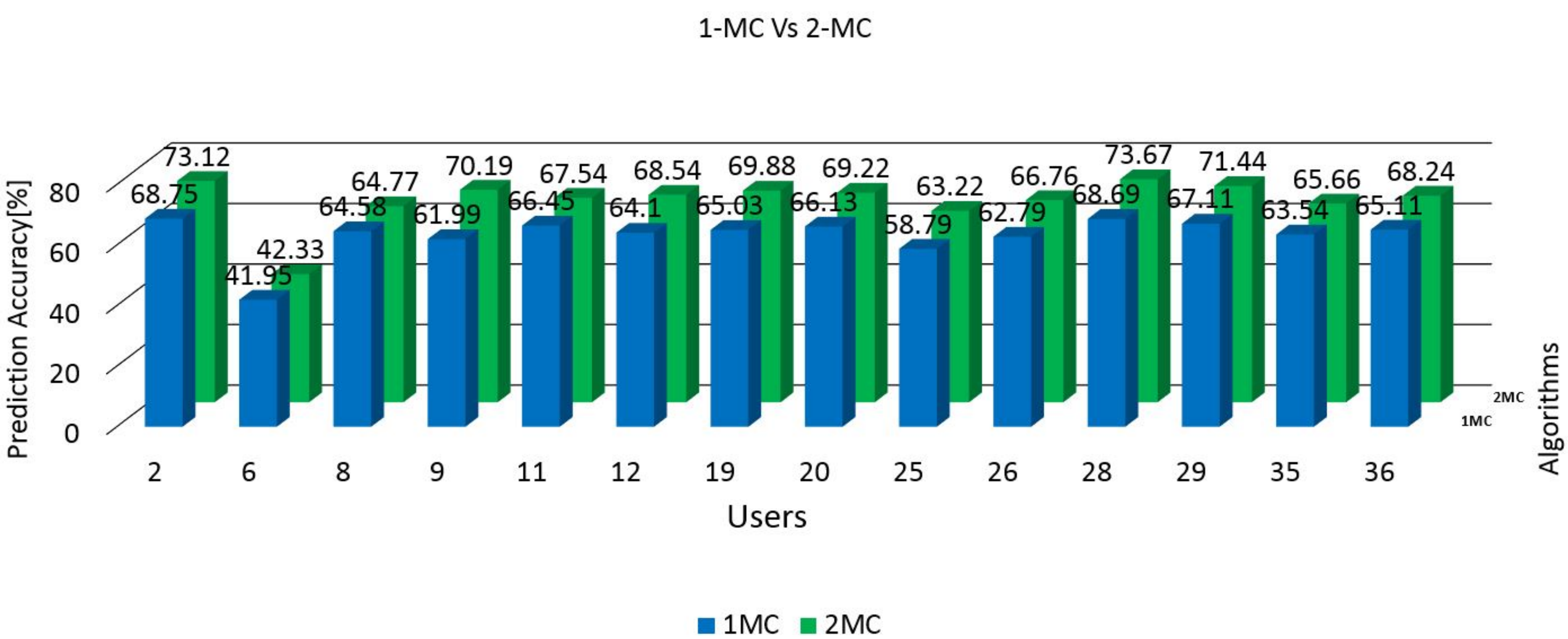

Figure 21: Prediction accuracy for crowd Signal users.

Results

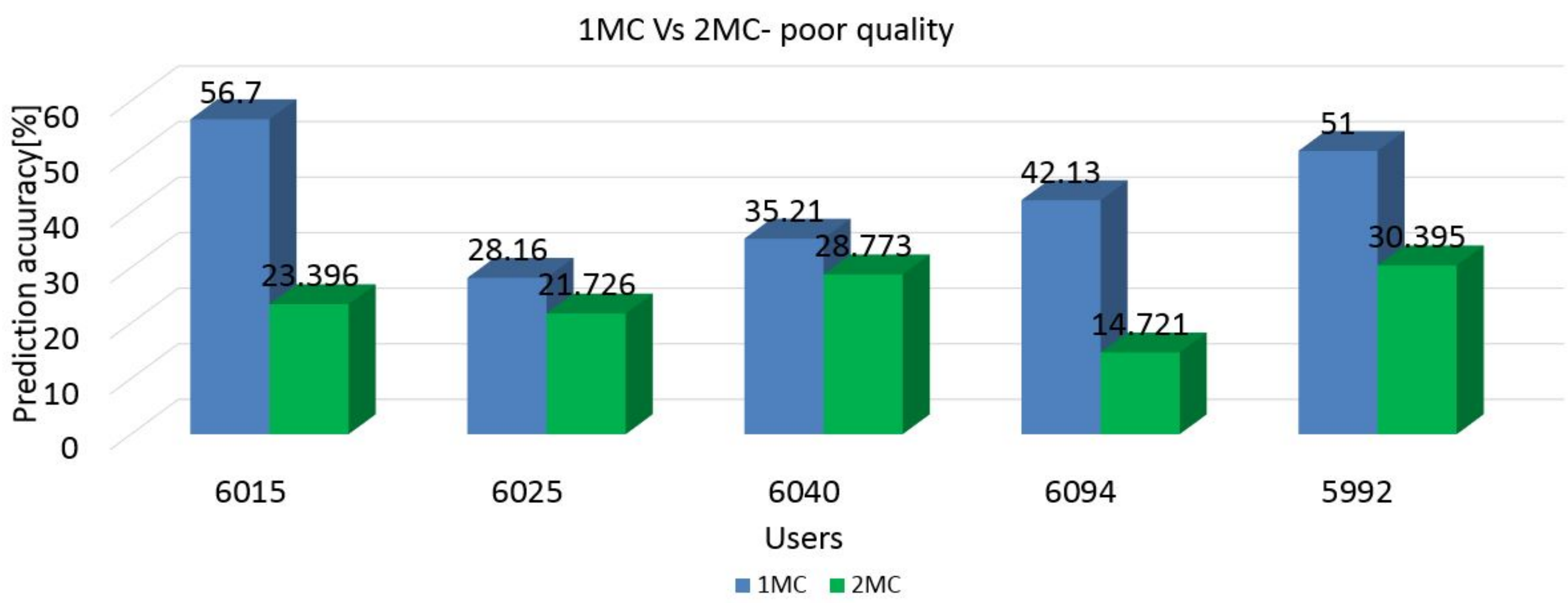

Figure 22: Prediction accuracy for MDC users with poor quality.

Future Works

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- Implementing Hybrid Markov model.
- Semantic meaning part of Crowd Signal data set.
- Using Markov model to predict next place(Home, Work place…)

Collaboration project (Traffic Estimation)

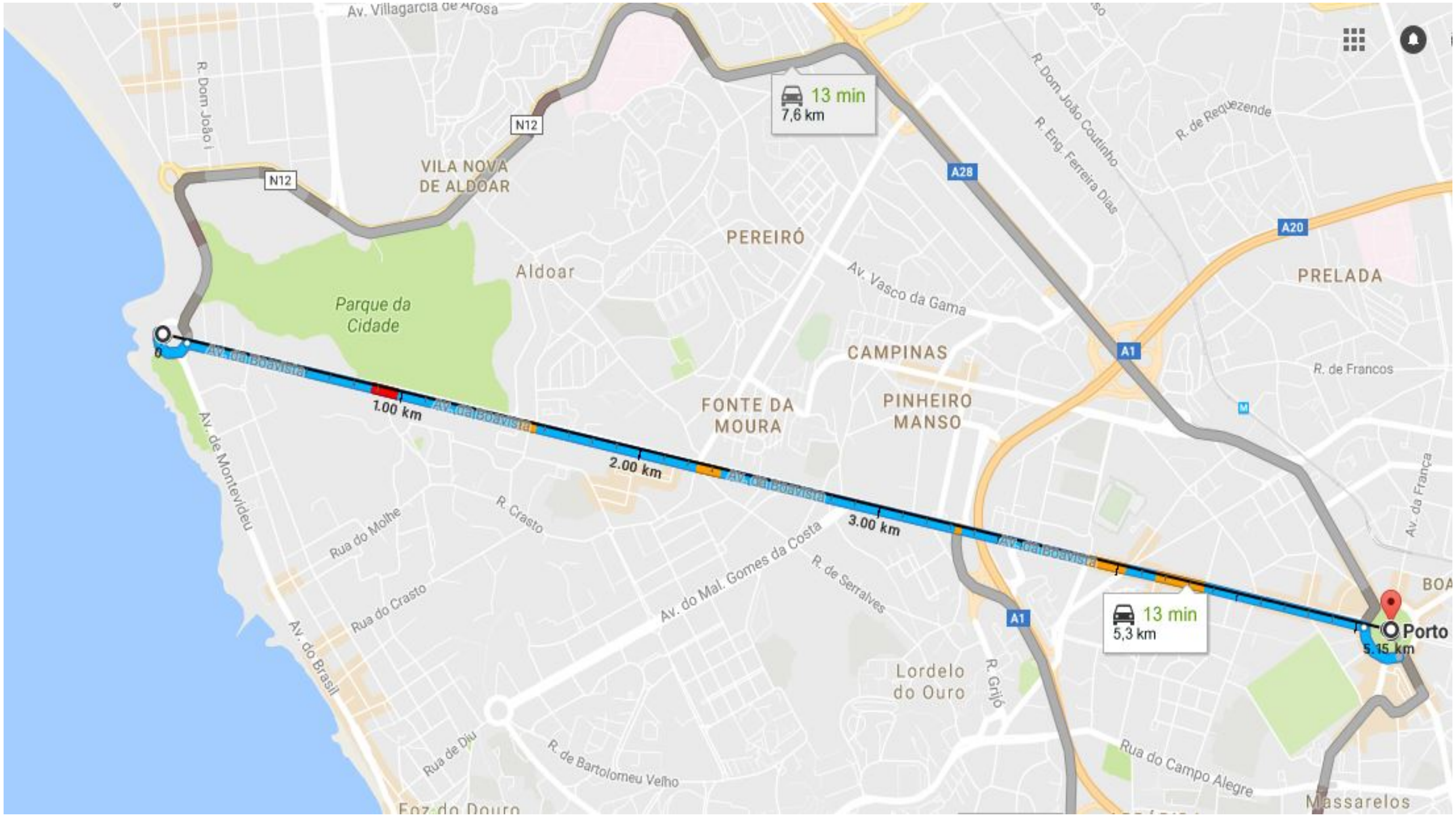
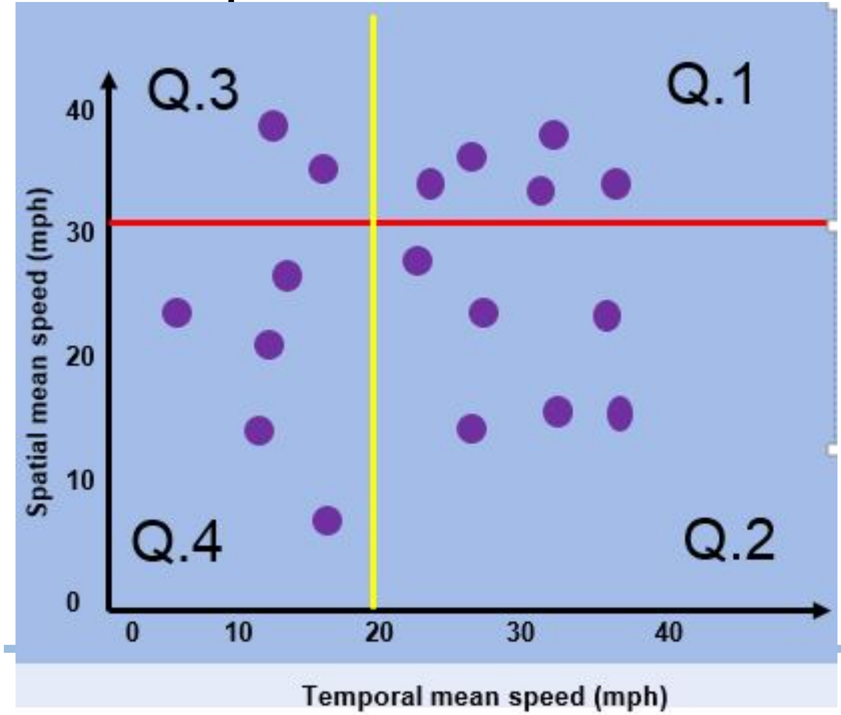


Figure 23: Street for segmentation and traffic estimation.

Proposed Model:

- Spatial – Temporal traffic speed plot:
  - Temporal mean speed (X) : Average speed over time : The length of road segment divided by traversal time.
  - Spatial mean speed (Y) : Mean of instantaneous vehicles speed.



Quadrant - 1 : High speed of traversal on road segment less stop&Go or Slow&Go **Very Good**

Quadrant - 2 : High speed of traversal on road segment Middle Stop&Go or Slow&GO **Good**

Quadrant - 3 : Slow speed of traversal on road segment Middle Stop&Go or Slow&Go **OK**

Quadrant - 4 : Slow speed of traversal on road segment High Stop&Go or Slow&GO **Bad**

Traffic Estimation- Preliminary results(1/2)

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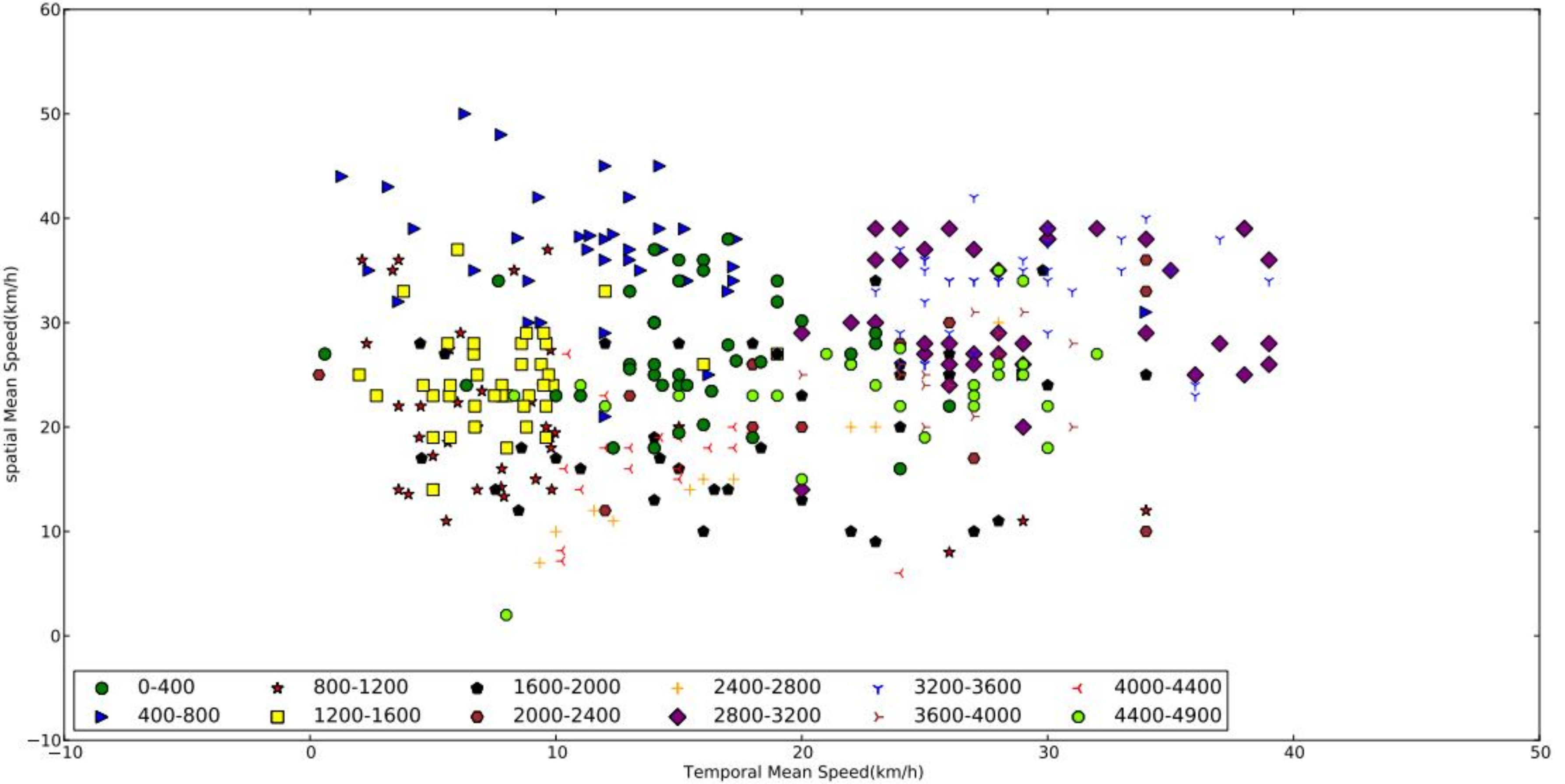

Figure 24: Traffic estimation for weekdays-rush time.

Traffic Estimation- Preliminary results(2/2)

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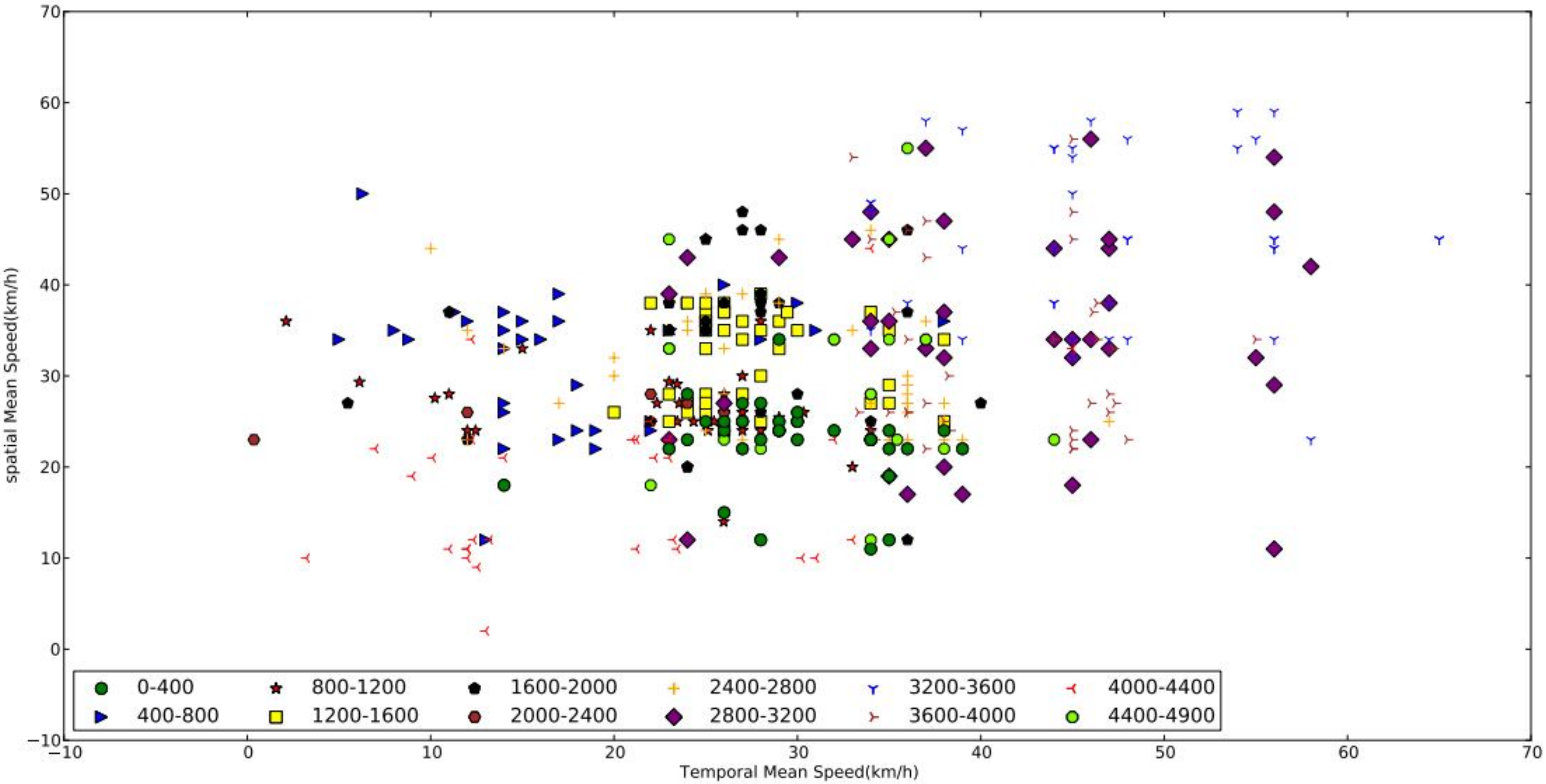

Figure 25: Traffic estimation for weekdays-non rush time.

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Thank you for your attention!