Recent progress on Telco localization

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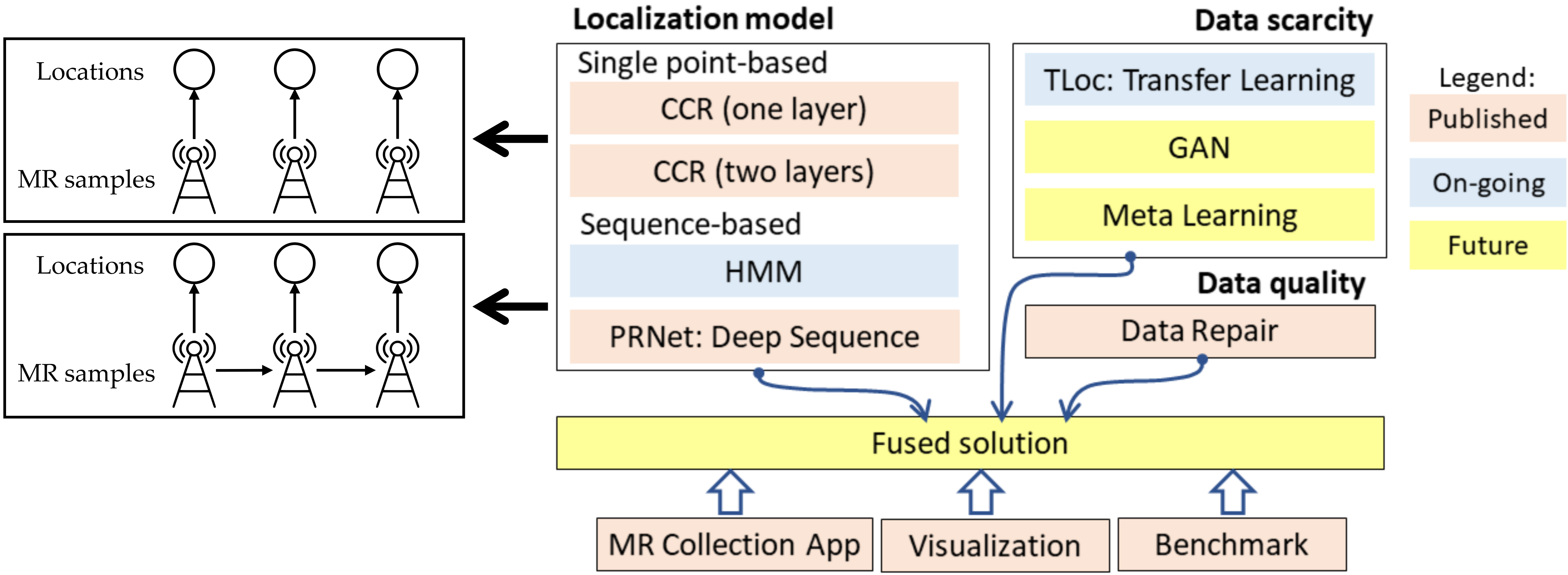
Agenda

- Framework Overview
- Telco Outdoor Localization
- Telco Indoor Localization

Framework Overview



PRNet: Outdoor Position Recovery for Heterogeneous Telco Data by Deep Neural Network

Yige Zhang, Kun Zhang, Weixiong Rao

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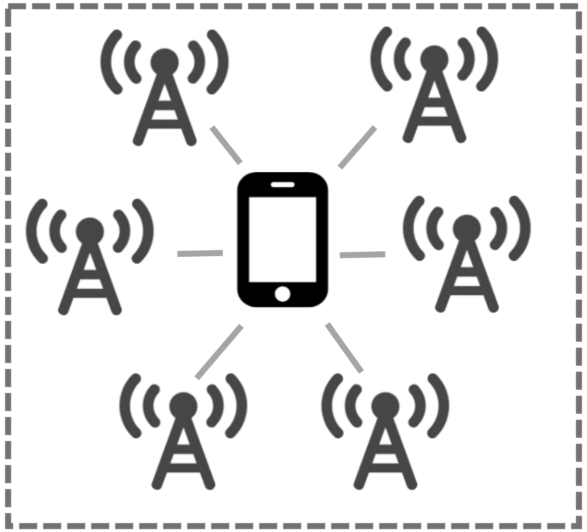
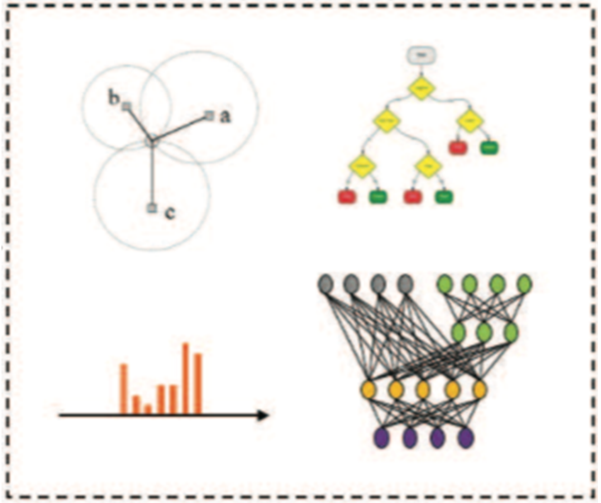
Telco Localization

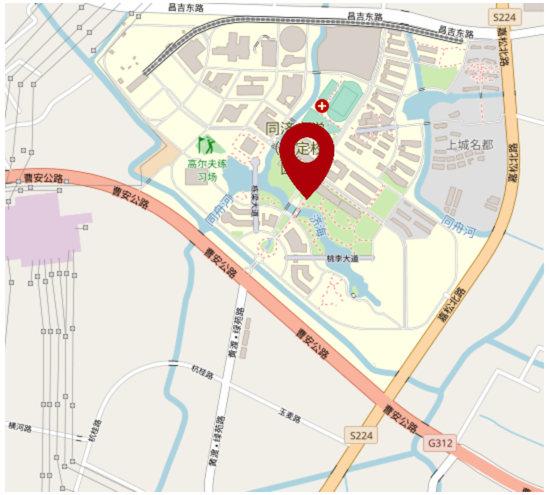
Working Flow



< 7 base stations



localization models



prediction result

MR data

MRTime	2018/4/23 9:20	IMSI	xxx	SRNCID	6188	BestCellID	26051	LCS BIT	300
RNCID_1	6188	CellID_1	26051	AsuLevel_1	27	SignalLevel_1	4	RSSI_1	-74.5
RNCID_2	6188	CellID_2	27394	AsuLevel_2	10	SignalLevel_2	3	RSSI_2	-84.88
RNCID_3	6188	CellID_3	27377	AsuLevel_3	18	SignalLevel_3	4	RSSI_3	-85.13
RNCID_4	6188	CellID_4	27378	AsuLevel_4	12	SignalLevel_4	4	RSSI_4	-85.87
RNCID_5	6182	CellID_5	41139	AsuLevel_5	8	SignalLevel_5	3	RSSI_5	-88.88
RNCID_6	6188	CellID_6	27393	AsuLevel_6	9	SignalLevel_6	3	RSSI_6	-90.22
RNCID_7	6182	CellID_7	44754	AsuLevel_7	9	SignalLevel_7	3	RSSI_7	-95

base stations

signal strength

Motivation

➢Why Telco Localization?

- Well-known GPS weaknesses.
- Telco data can be collected cheaply, frequently and on a global scale.
- Recovering outdoor locations for applications e.g., human mobility, urban planning and traffic forecasting.

➢Why sequential neural network model?

- The associated locations obviously exhibit spatiotemporal locality.
- Existing works using first-order sequence models (HMM) cannot precisely capture spatiotemporal locality.
- Deep neural network is used in learning spatial locality (CNN) and temporal locality (RNN).

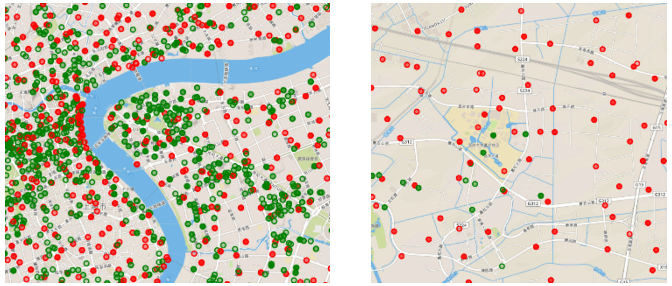
Challenges

- Mixed transportation mode (Fig 1)
  - walking, cycling, driving, etc.
  - higher speed -> weak dependency
- Irregular MR sampling rate (Fig 2)
  - 1s~120s
  - low battery, sensor anomaly, signal block
- Uneven density of base stations (Fig 3)
  - Urban > rural

Fig. 1

Fig. 2

urban



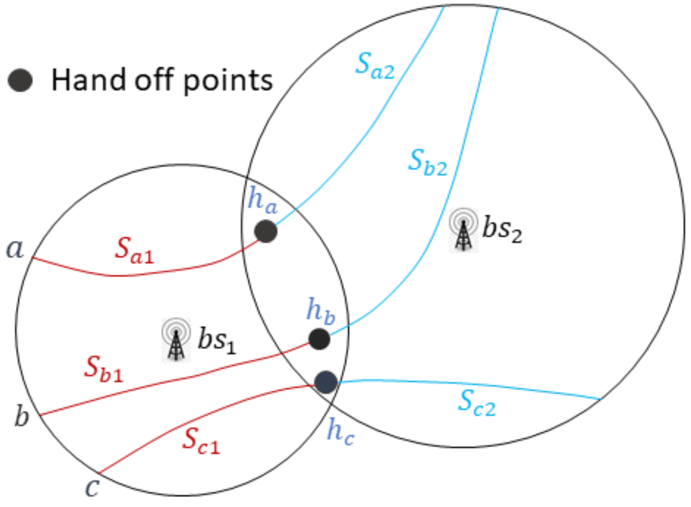
rural

Fig. 3

To address those issues, we propose **PRNet:**

1) allows variable-length windows of MR samples to capture spatial locality within each window
2) designs two attention mechanisms for time intervals and MR sequences to capture temporal locality
3) Develops a network structure consisting of local and global predictors to merge the spatiotemporal locality

MR (sub)sequence



[MR sequence]
– Definition: The MR samples with 1) same primary serving base station (RNCID_1 and CellID_1) and 2) IMSI
– Examples: $S_{a1,} S_{a2,} S_{b1,} S_{b2,} S_{c1,} S_{c2}$

[MR subsequence]
– Definition: The MR samples with 1) same primary serving base station, 2) IMSI, and 3) same non-serving base station (RNCID_2 and CellID_2)

Reason: the MR samples show tight dependency within (sub)sequences

-> solve challenge &3 (uneven density of base stations)

PRNet framework

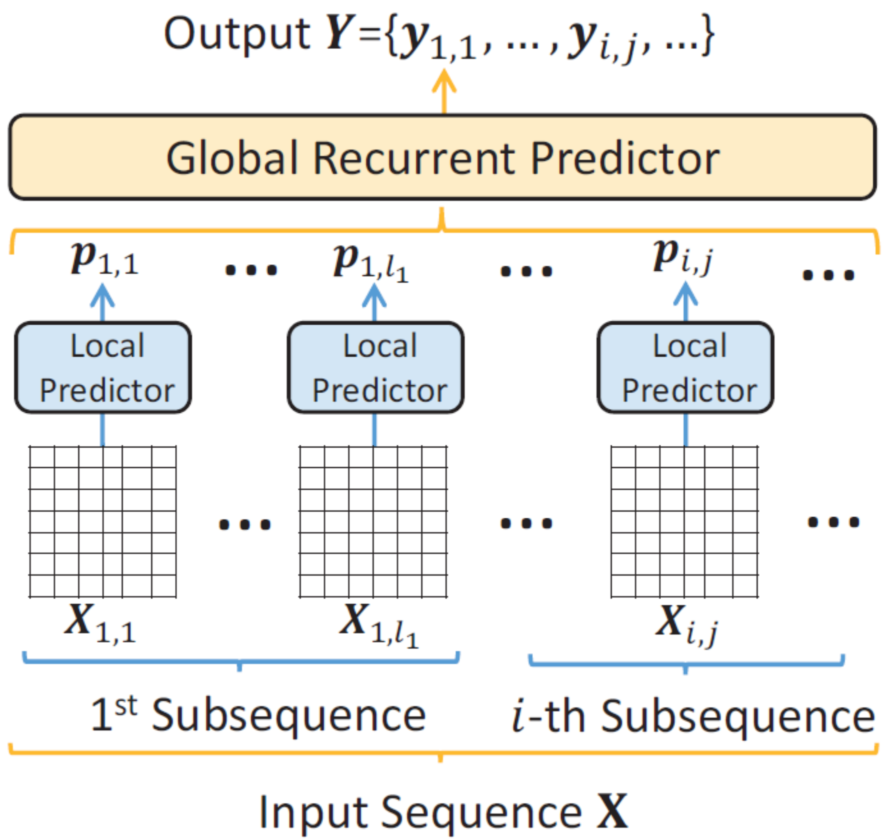
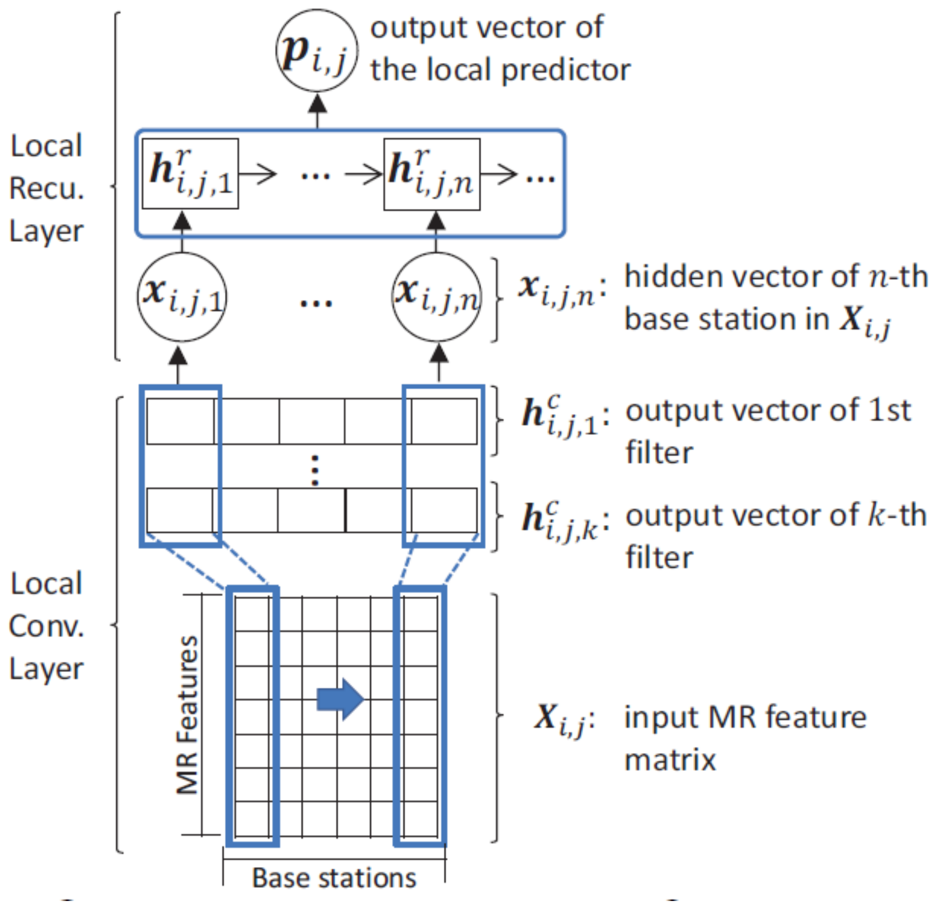


Figure 2: Framework overview of PRNet

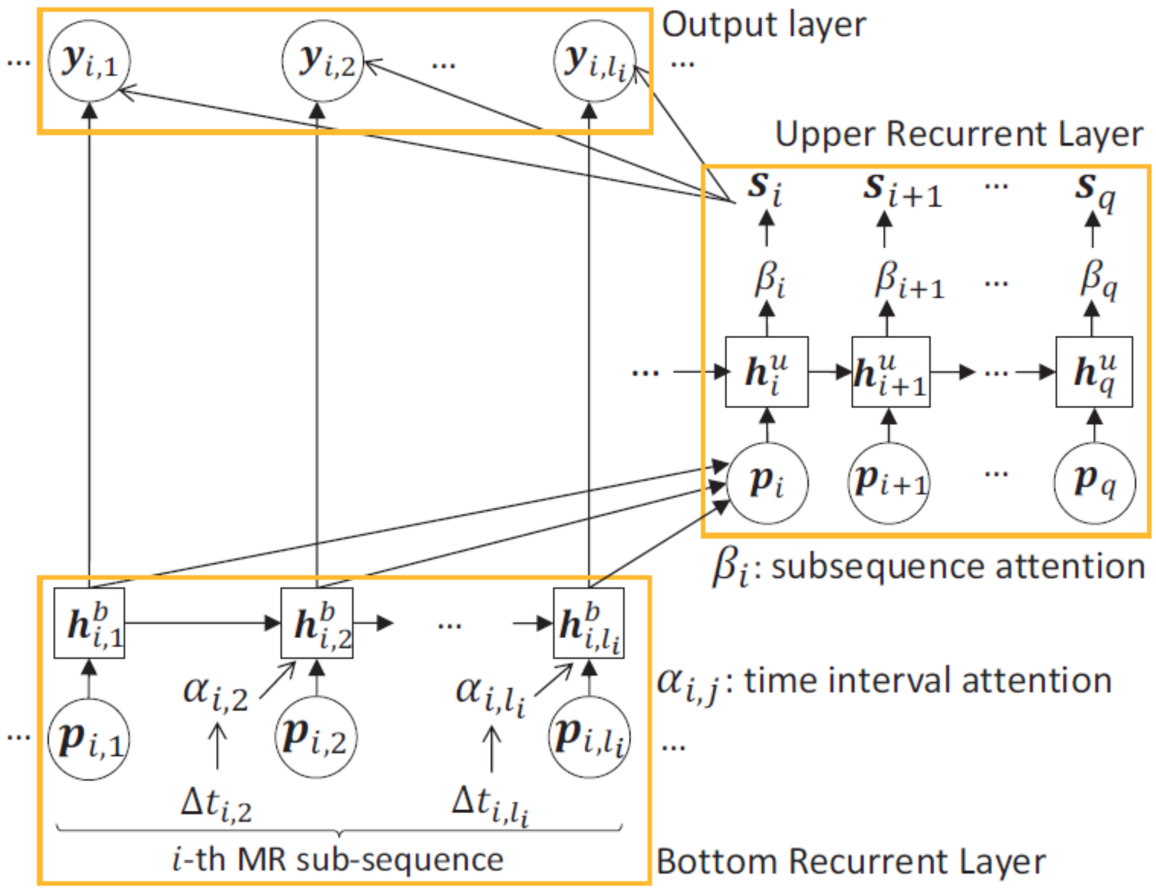
Local Predictor

Learn the correlations among base stations in MR sample

Learn local dependencies between MR features



Global Recurrent Predictor



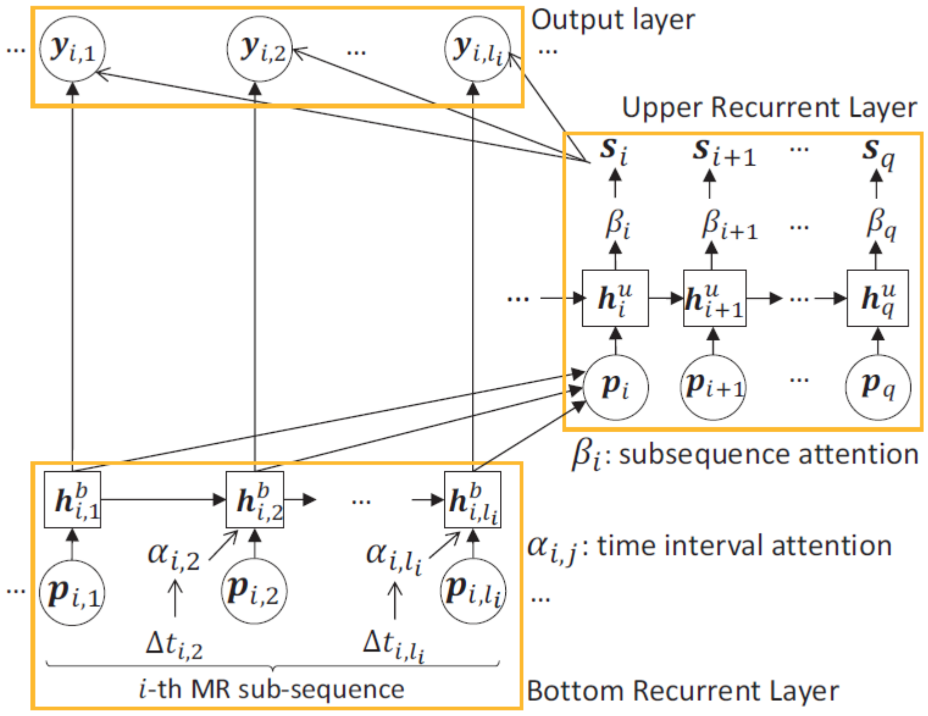
Concatenate hidden states to produce final output

Learn long-term dependencies / overall moving trend

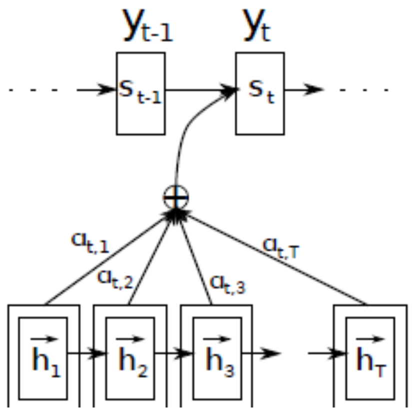
Learn short-term dependencies / local moving trend

-> solve challenge &1 &2 (transportation mode, irregular sampling rate)

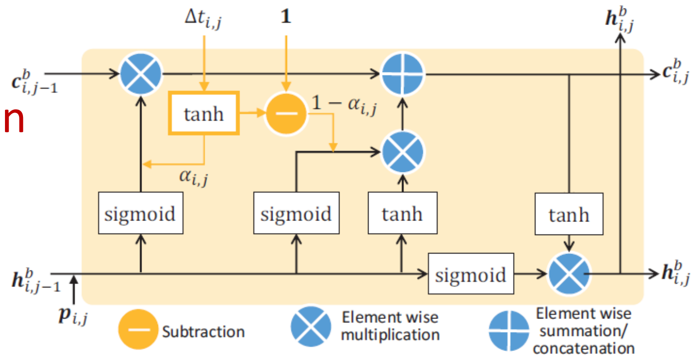
Global Recurrent Predictor



subsequence attention



time interval attention



Experiments

- Datasets

	Jiading	Siping	Xuhui
Num. of samples (2G/4G)	17354/12245	6723/4953	14680/10455
Route len (2G/4G) in km	96.5/60.3	24.6/15.5	29.3/15.9
Sampling rate (sec)	3	3	2
Area size (km^2)	1.67	0.862	0.57
% of MRs with walking/cycling/driving	64.7/25.2/14.1	63.8/36.2/0.0	58.5/0.0/41.5
Serving BSs density (2G/4G)	5.72/8.45	7.96/10.35	8.45/12.67

Table 2: Statistics of Used Data Sets

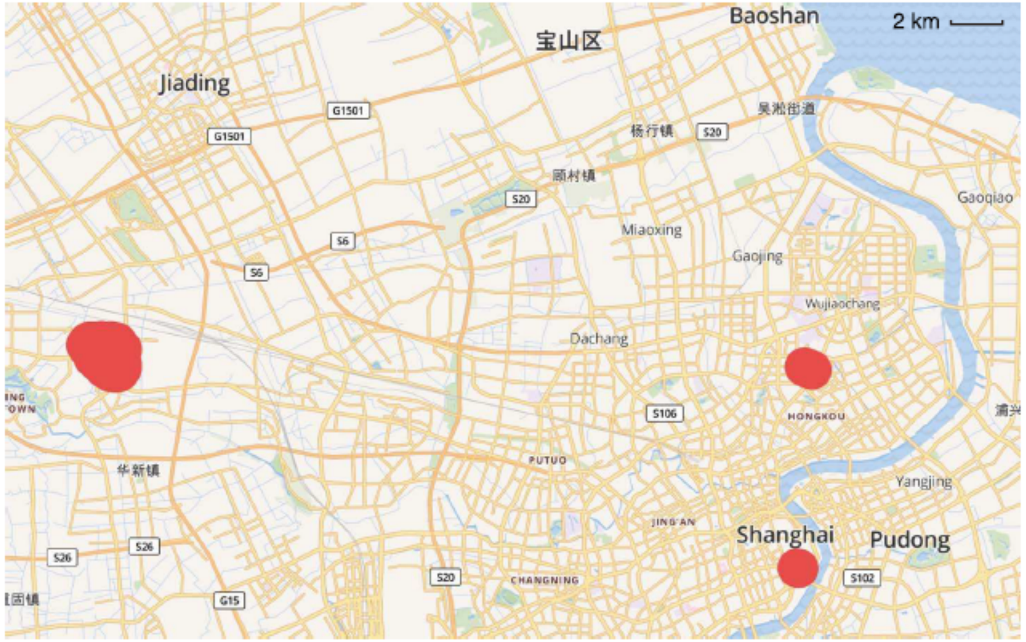


Fig. 9. Geographic locations of three testing areas in Shanghai

- Counterparts

Counterpart	Description	Approach
NBL	Recent fingerprinting method [13]	Single Point
DeepLoc	3-layer neural network [18]	Single Point
RaF	1-layer Random Forest regression [28]	Single Point
CCR	2-layer Random Forest regression [28]	Implicit Sequence
HMM	HMM + particle filtering [15]	Sequence
SeqtoSeq	a LSTM-based seq. to seq. model [19]	sequence
ConvLSTM	a convolutional LSTM [17]	Sequence
PRNet	proposed hierarchical neural network	Sequence

Table 3: Counterparts

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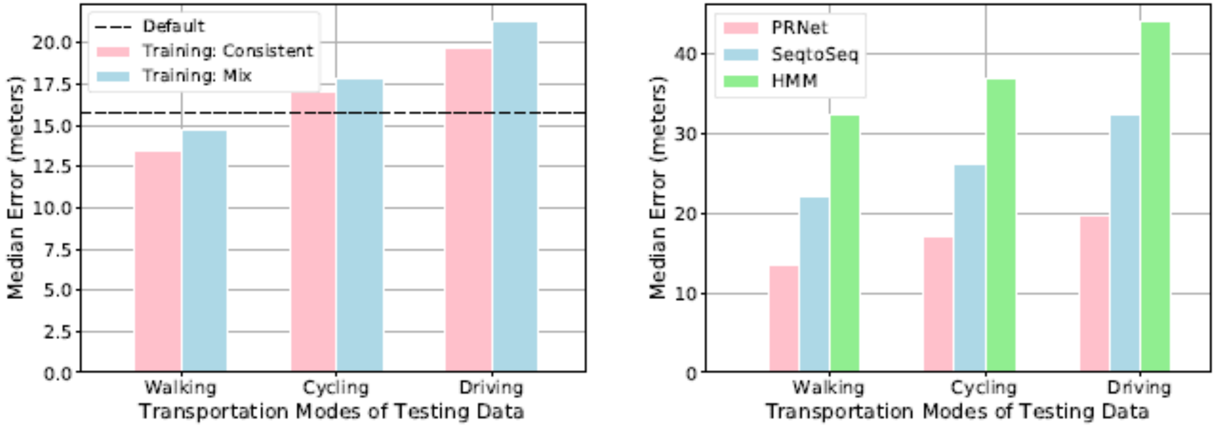
Baseline Results

Dataset	Jiading (2G)			Jiading (4G)		
	Median (m)	Mean (m)	90% (m)	Median (m)	Mean (m)	90% (m)
NBL	53.4	67.2	300.9	59.7	72.3	318.6
DeepLoc	35.1	47.6	250.3	40.2	53.9	280.6
RaF	38.3	48.3	168.9	38.5	47.2	158.9
CCR	34.1	43.2	142.3	30.2	44.5	145.9
HMM	36.5	52.3	172.8	42.1	53.6	188.4
SeqtoSeq	25.4	50.6	85.3	24.2	50.1	81.7
ConvLSTM	28.5	59.3	129.3	27.3	58.1	124.5
PRNet	**15.8**	**37.8**	**63.2**	**18.4**	**40.6**	**66.5**

Sensitivity Study

- ❑ Walking<Cycling<Driving (Errors)
  - The faster speed is, the higher errors are
- ❑ PRNet<SeqtoSeq<HMM (Errors)
- ❑ Short time intervals>Long time intervals
  - The denser, the better
- ❑ High base station density better



(a) Training/Testing Data (b) Sequence Model

Figure 6: Effect of Transportation Modes

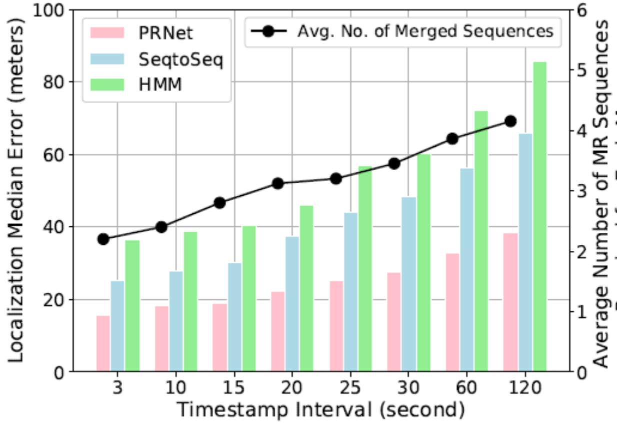


Figure 7: Timestamp Interval

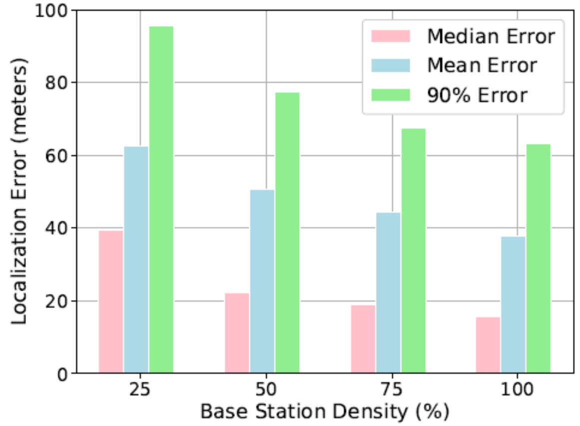
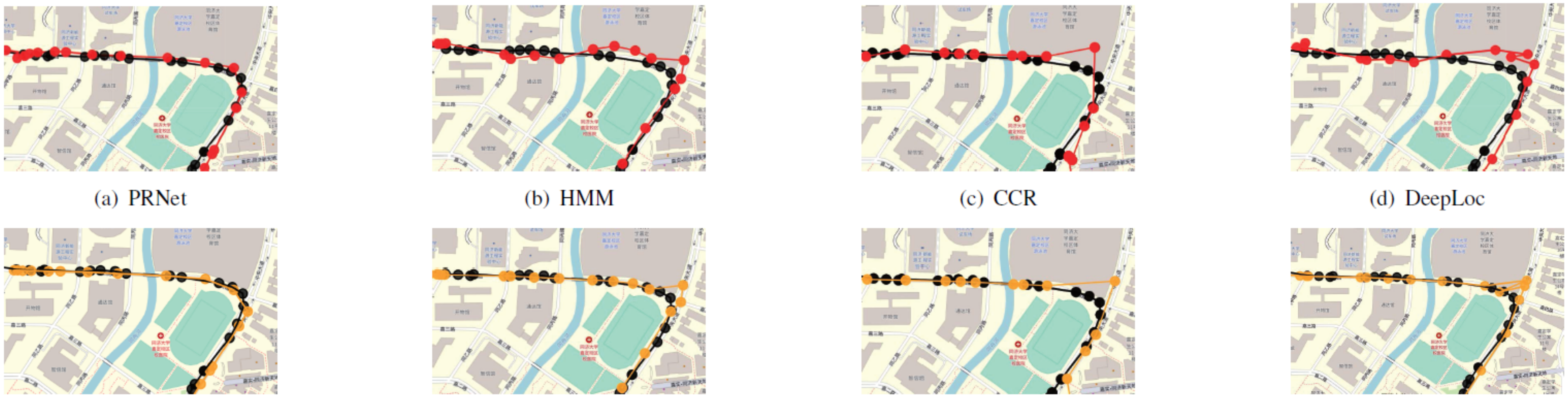


Figure 8: Base Station Density

Visualization

Black: Ground truth



(a) PRNet (b) HMM (c) CCR (d) DeepLoc

(e) PRNet_M (f) HMM_M (g) CCR_M (h) DeepLoc_M

Figure 11: Visualization (Map Scale 1.5:10000). Black: ground truth; Red: predicted location; Orange: Map-matching location.

Conclusion

- We are the first to leverage DNN model to learn spatiotemporal knowledge from heterogonous MR samples for accurate location recovery.

- The two components of PRNet: local predictor and global predictor is designed for learning local dependencies of individual MR sample and both short- and long-term dependencies from a series of MR samples.

- The evaluation by using six datasets collected on three areas in Shanghai (China) shows the inspiration results of PRNet.

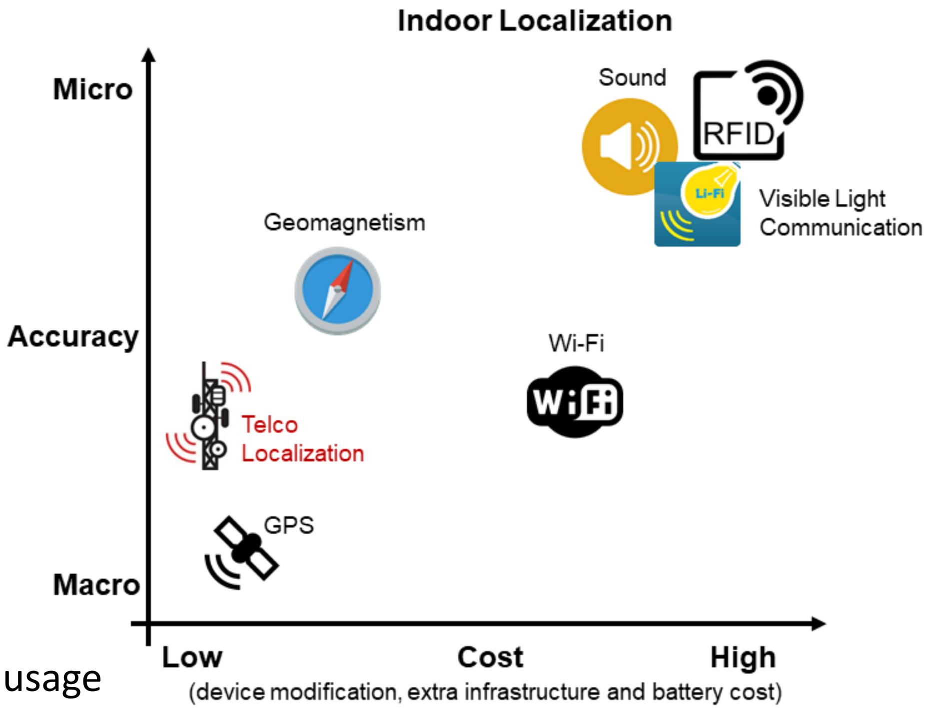
Telco 3D Indoor Localization

collaborate with Huawei by July, 1st

Background & Motivation

➢ Smartphone-based indoor localization has recently created significant commercial and social attraction by using various signals, such as WiFi, UWB, magnetic, visual light, etc.

- **Why Telco indoor localization?**
  - ✓ Cheap, frequent and large-scale Telco data
  - ✓ On-the-shelf infrastructure
  - ✓ Passive, silent localization without disturbing smartphone user
- **Why 3D localization?**
  - More and more tall buildings (>10f) are built for office and commercial usage
  - Accurate floor number is helpful for potential advertisement application



Challenges & Solutions

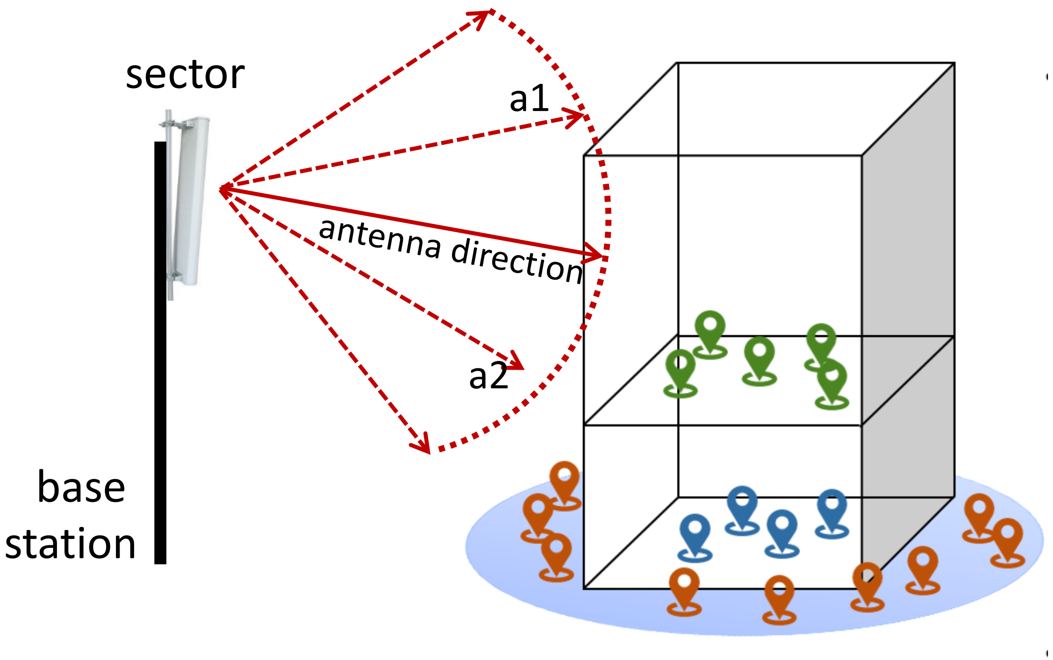
Challenges:

× No indoor map provided

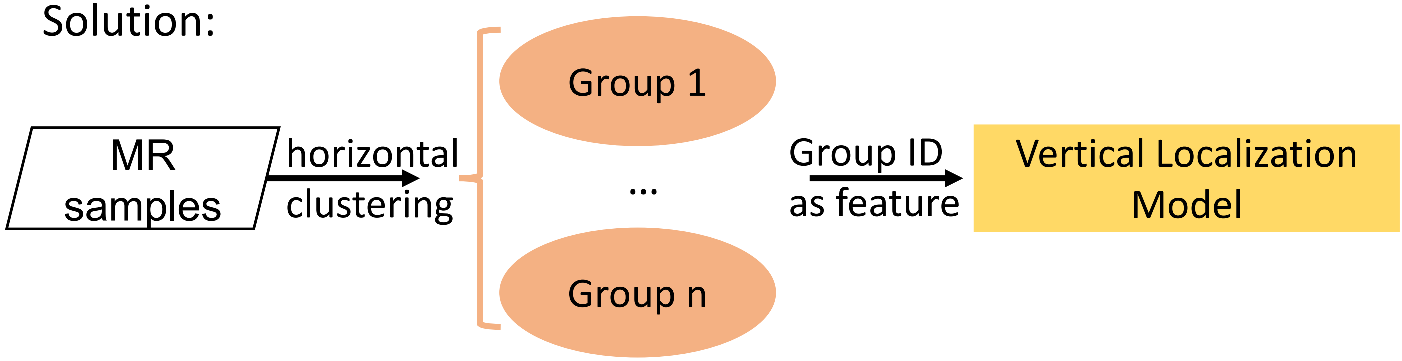
× Infrequent handoff between base stations

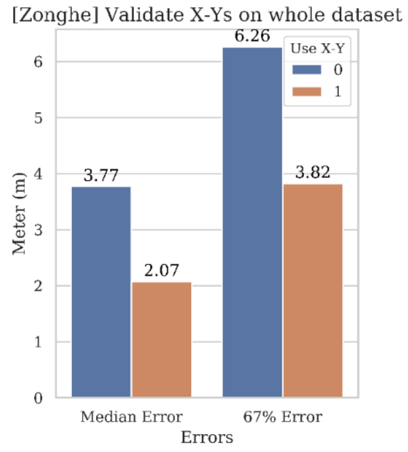
× Only primary serving base station is visible

Hard to differentiate those locations on different floors due to similar MR samples



Solution:





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Thanks !