Cost-effective Signal Map Crowdsourcing with Auto-Encoder based Active Matrix Completion

$C@IBTJIB -DP, :<I>C<J ;C<J, ,PI ;CP, 4C@IB ;C<IB <I? +D@ 8P

/<IEDIB 6IDQ@MNDOT JA "@MJI<POD>N <I? "NOMJI<POD>N

/<IEDIB 6IDQ@MNDOT

5@H KG@ 6IDQ@MNDOT

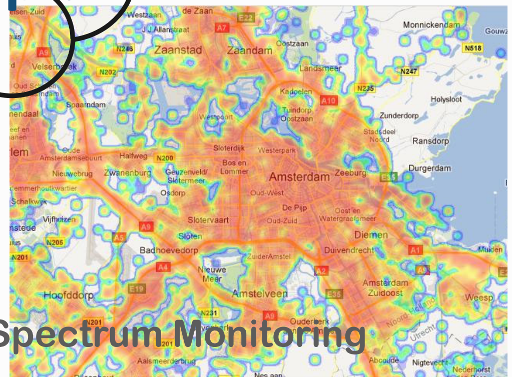
Reporter： Chengyong Liu

Outline

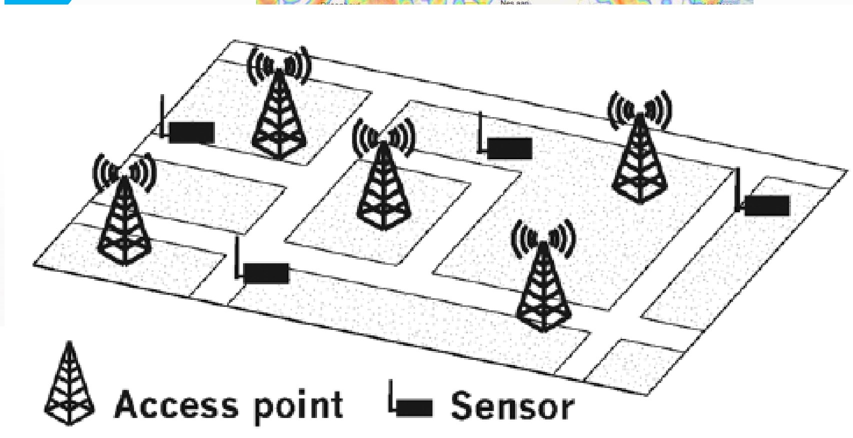
Signal map ?

Signal map con
strength at diff

Location-Based Se
(LBS)

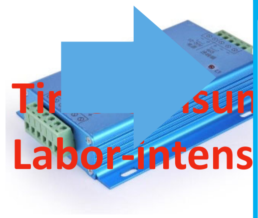


Spectrum Monitoring



Zhou X , Zhang Z , Wang G , et al. Practical conflict graphs in the wild[J]. IEEE/ACM Transactions on Networking, 2015, 23(3):824-835.

Traditional signal map constructio
Full site survey



Professionals
Professional equipments

Interpolation reconstruction based on a small number of signals

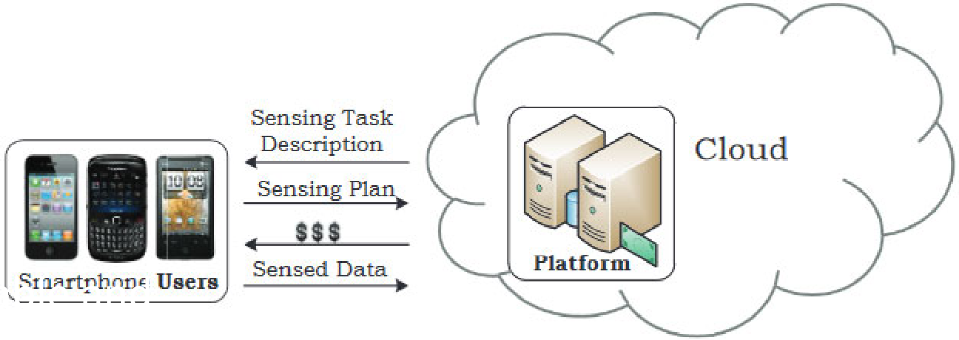
Related Works

- KNN — Low accuracy
- Gaussian Processes — Complex model
- Compressive Sensing — Sparse property
- Matrix completion — Prior knowledge

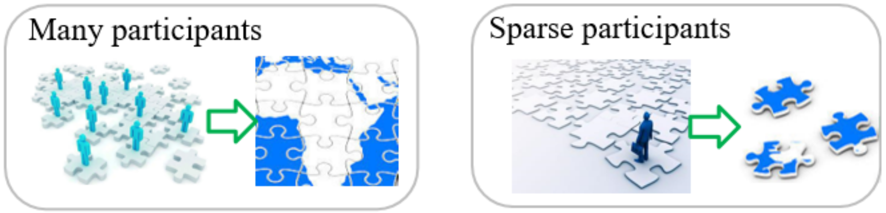
…

Crowdsourcing method to collect signals

- Smartphones are program… equipped with a set of che… powerful embedded sensors
- Mobile phones are quite pervasive



Yang D , Xue G , Fang X , et al. Crowdsourcing to Smartphones : Incentive Mechanism Design for Mobile Phone Sensing[C]// International Conference on Mobile Computing & Networking. ACM, 2012.

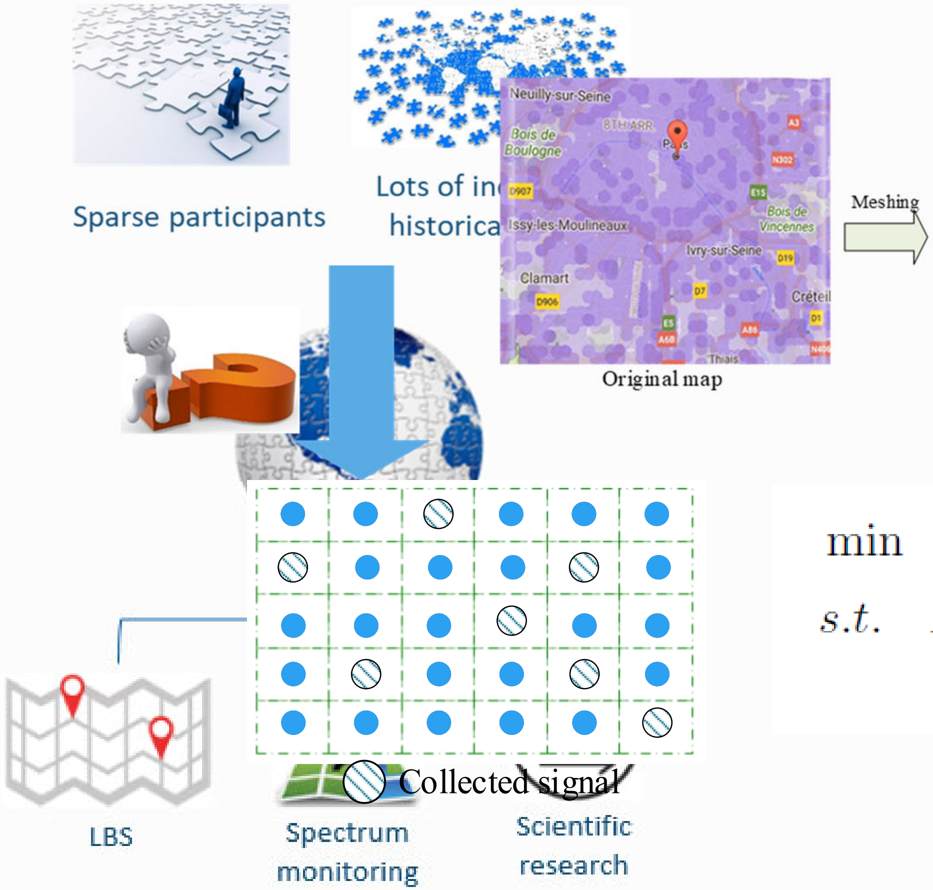


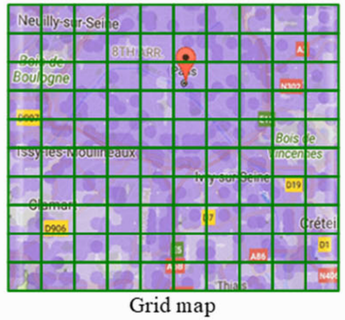
Unevenly distributed participants

Sensorly : https://www.sensorly.com/
OpenSignal : https://www.opensignal.com/

Outline

- Background
- **System Model**
- Algorithms
- Experiments
- Conclusions



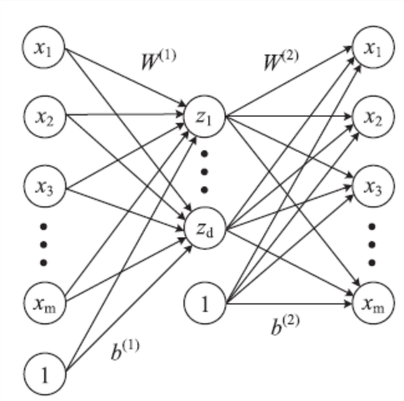


$$
\begin{aligned}
\min \quad & \varepsilon = error(\widetilde{M}, M) \\
s.t. \quad & \widetilde{M} = \Psi_{old}(O_{m \times n}) \\
& O = \Omega \bullet M
\end{aligned}
$$

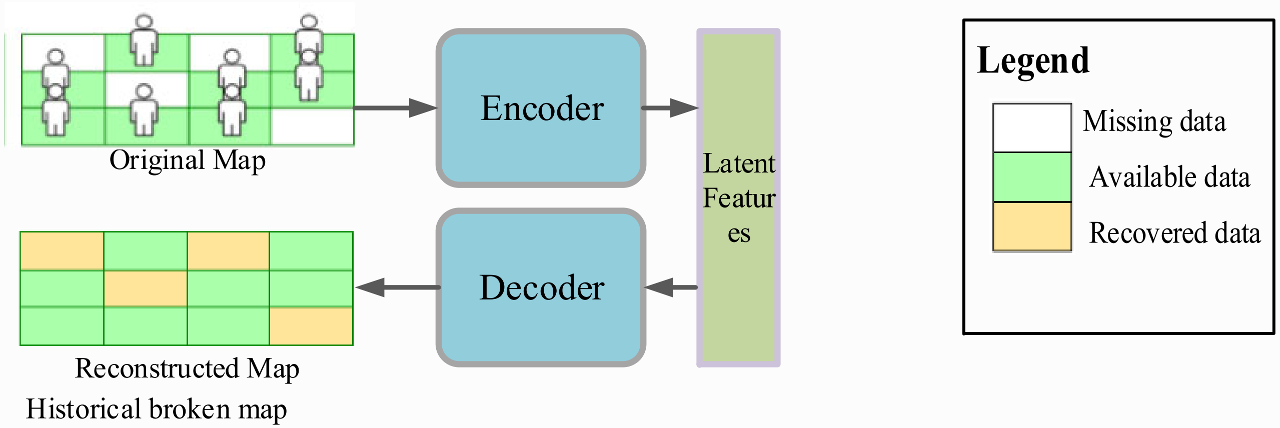
Outline

- Background
- System Model
- **Algorithms**
- Experiments
- Conclusions

Signals fluctuate significantly during different times of day, and this fluctuation is non-linear

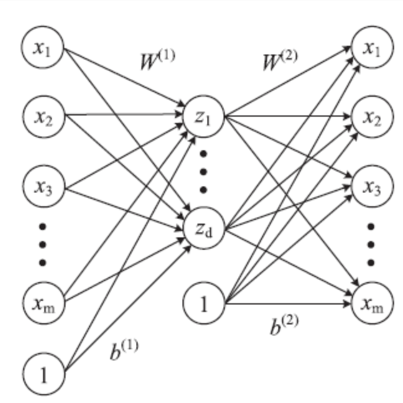


Auto-encoder can learn nonlinear features in matrices

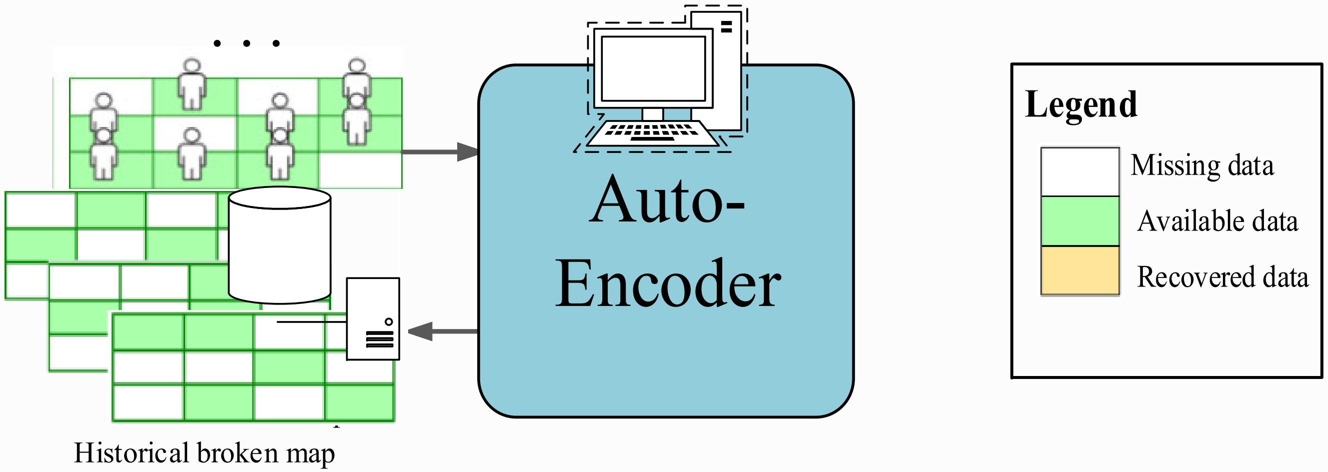


Fan J , Chow T . Deep learning based matrix completion[J]. Neurocomputing, 2017:S0925231217309621.

Signals fluctuate significantly during different times of day, and this fluctuation is non-linear

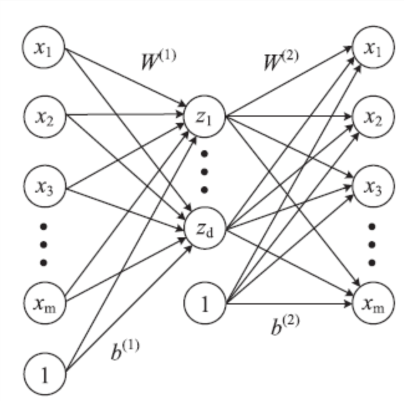


Auto-encoder can learn nonlinear features in matrices

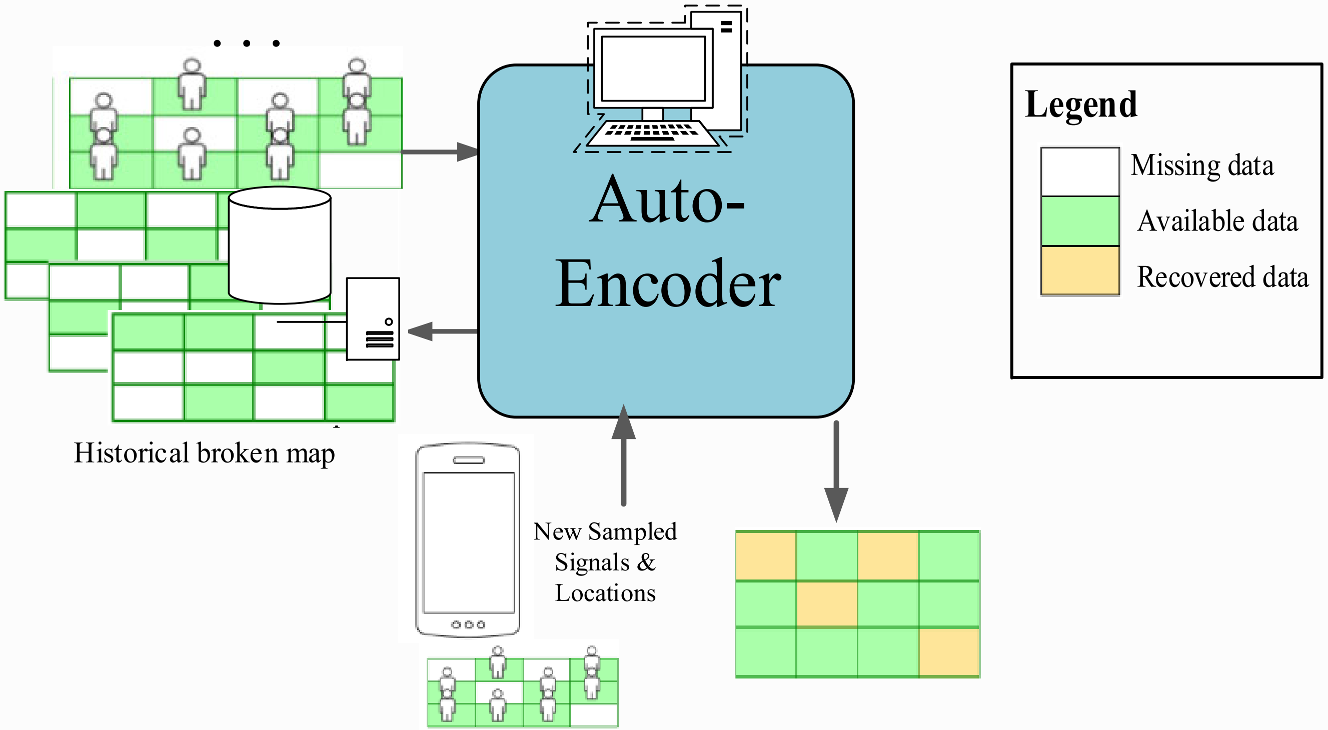


Fan J , Chow T . Deep learning based matrix completion[J]. Neurocomputing, 2017:S0925231217309621.

Signals fluctuate significantly during different times of day, and this fluctuation is non-linear

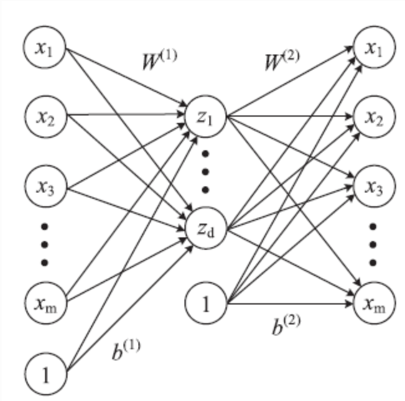


Auto-encoder can learn nonlinear features in matrices

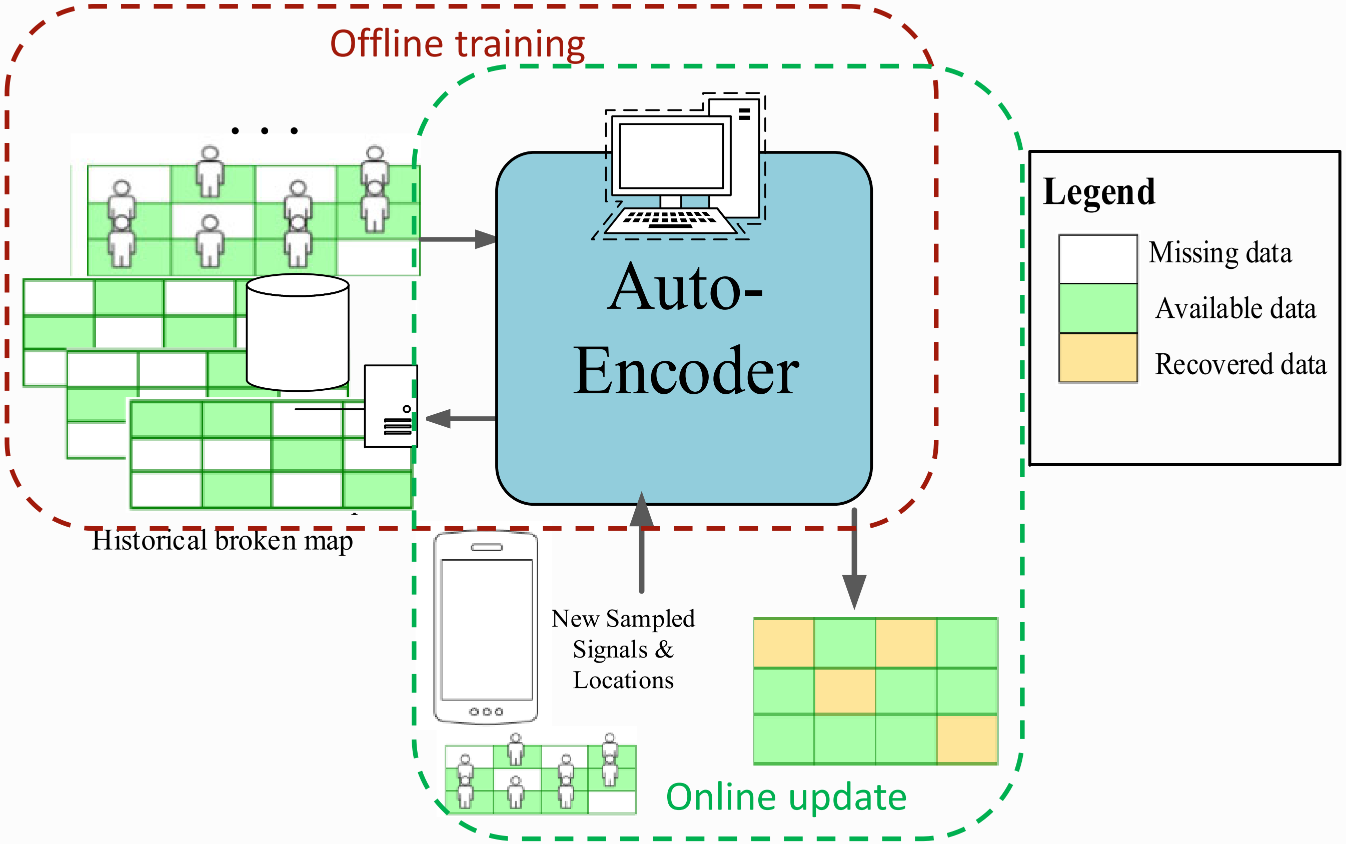


Fan J , Chow T . Deep learning based matrix completion[J]. Neurocomputing, 2017:S0925231217309621.

Signals fluctuate significantly during different times of day, and this fluctuation is non-linear



Auto-encoder can learn nonlinear features in matrices



Fan J , Chow T . Deep learning based matrix completion[J]. Neurocomputing, 2017:S0925231217309621.

The original image

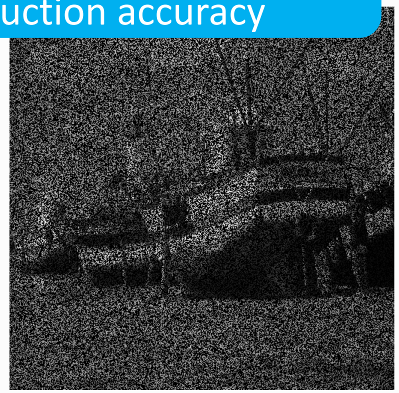
The 30% sampling rate

For reconstruction algorithms, the signals at different locations have different effects on the reconstruction accuracy

The 40%(30%+10%) sampling rate

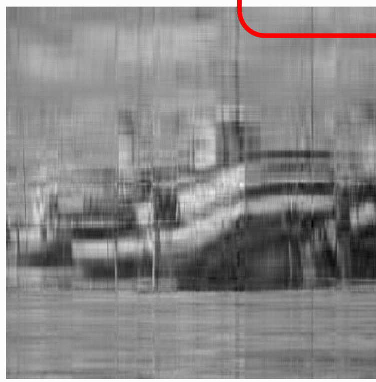
Relative error 41%

The reconstructed image



The 40%(30%+10%) sampling rate

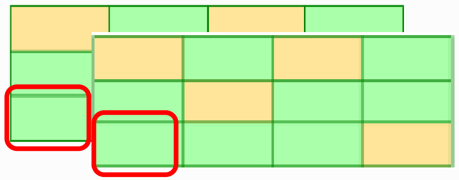
Relative error 39%



The reconstructed image

Active Crowdsouring Scheme

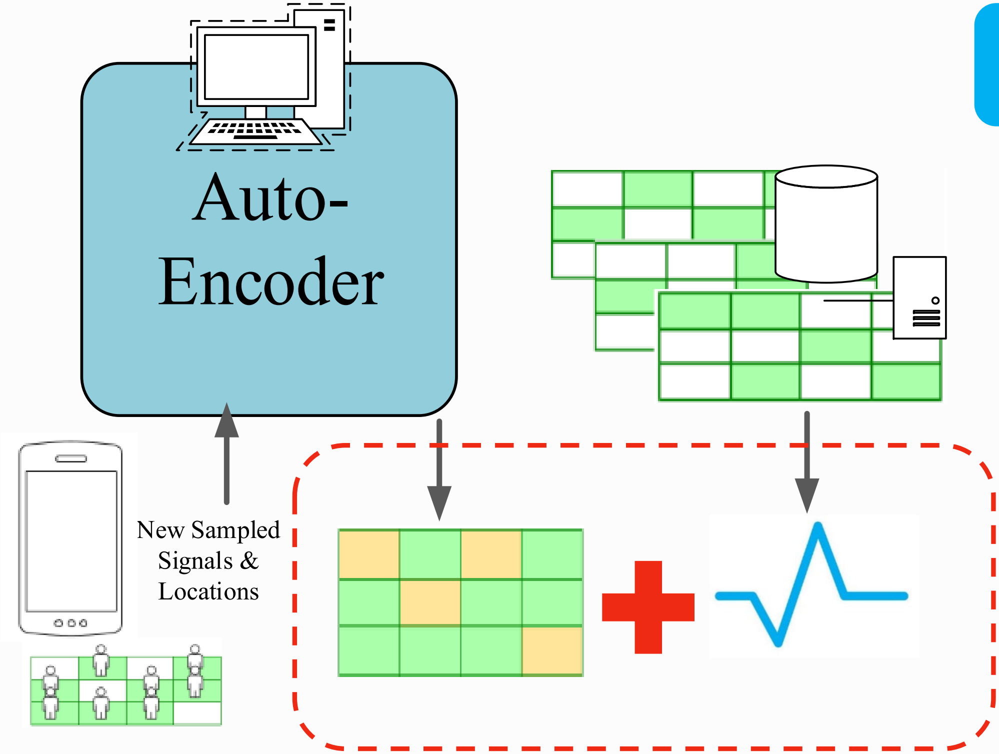
Difference in reconstructed signal maps in different batches



$$I^{i,j} = abs(x_{t-1}^{i,j} - x_t^{i,j})$$

$$I_{initial} = abs(\widetilde{M}_0 - mean(M_{his}))$$

The degree of changes in signals



The Signal Dynamics

$$s_x^2 = \frac{1}{k-1} \sum_{i=1}^{k} \frac{\Omega_t \bullet ||X_t - \chi||_F^2}{|\Omega_t|}$$

$$(M - s_x, M + s_x)$$

Sample relationship with the population

Outline

- Background
- System Model
- Algorithms
- **Experiments**
- Conclusions

Experiment Setup

- The simulated WiFi indoor positioning dataset

 -- The ray tracing technology generates 5000 signal maps with random changes of channel as historical signal maps
 -- 50% missing rate
 -- signal maps from the same channel random variation as test data

- Baseline algorithms

 -- BCS Model signal map reconstruction as a compressive sensing model
 -- LmaFit A popular alternating least-squares method for matrix completion

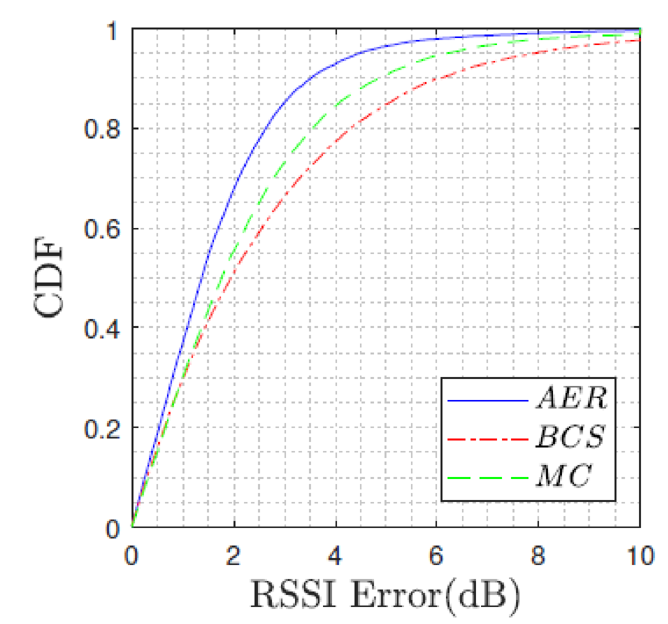
Experiment Results

AER can achieve lower errors with higher probability

	5%	6%	7%	8%
AER	**0.0530±0.0011**	**0.0523±0.0000**	**0.0517±0.0011**	**0.0510±0.0013**
BCS	0.0716±0.0000	0.0716±0.0000	0.0715±0.0000	0.0716±0.0000
MC	0.0908±0.0024	0.0859±0.0017	0.0831±0.0015	0.0810±0.0013

9%	10%	15%	20%	25%
0.0507±0.0015	**0.0502±0.0015**	**0.0489±0.0020**	**0.0486±0.0022**	**0.0484±0.0020**
0.0716±0.0000	0.0716±0.0000	0.0715±0.0000	0.0715±0.0000	0.0715±0.0000
0.0797±0.0000	0.0786±0.0000	0.0752±0.0000	0.0714±0.0124	0.0611±0.0000

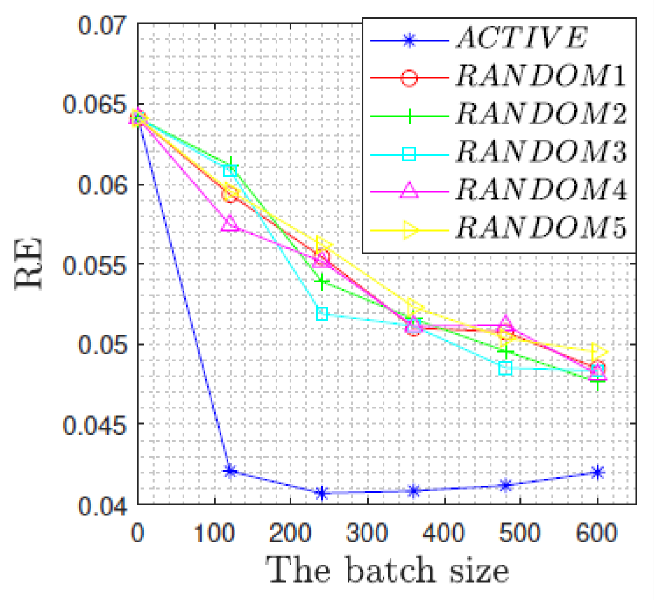
$$RMSE = \frac{||\hat{\Omega} \bullet (\widetilde{M} - M)||_F}{||\hat{\Omega} \bullet M||_F}$$

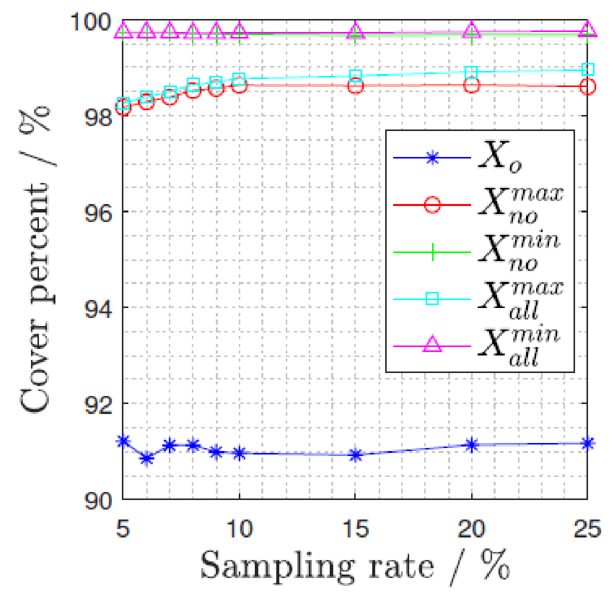


The relative error of AER is at least 2% lower than the other two algorithms

Experiment Results

The proposed method can achieve more than 90% coverage





Under the same number of acquisitions, the active method is far superior to other methods

Outline

- Background
- System Model
- Algorithms
- Experiments
- **Conclusions**

Conclusions

A comprehensive solution for signal map construction

- The offline training phase
- The online reconstruct phase

An active crowdsourcing scheme for better performance

A more realistic signal map model with the description of the signal dynamics

Future Works

- Impact of different types of collection equipment on signal collection
- How to accurately determine the signal collection location of historical signals
- How to design an active mechanism more reasonably

Thanks for coming

Have a nice day!