

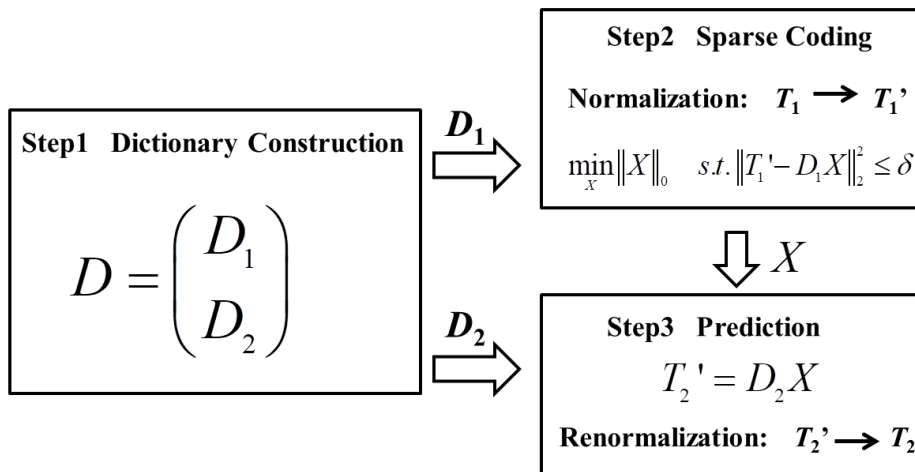
A framework based on sparse
representation model for time series
prediction in smart city

Zhiyong YU, Xiangping ZHENG, Fangwan HUANG,
Wenzhong GUO, Lin SUN, Zhiwen YU

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Problems & Ideas

- Problems of time series prediction in smart city
 - How to extract and represent discriminative features of sensing knowledge from the massive sequential data.
- Ideas: Sparse Representation Model
 - Proposes a systematic framework including eight variants of SRM based on different dictionary construction strategies.
 - Proposes a novel strategy for dictionary construction considering cross-domain dependencies.
 - Sparse Representation Model



• Eight variants of SRM

Abbr.	Generation of		Dictionary		Cross-Domain	
	Basic Dictionary		Learning		Dependencies	
	AA	DR	No	Yes	No	Yes
SRM-A	√		√		√	
SRM-D		√	√		√	
SRM-AL	√			√	√	
SRM-DL		√		√	√	
SRM-AC	√		√			√
SRM-DC		√	√			√
SRM-ALC	√			√		√
SRM-DLC		√		√		√

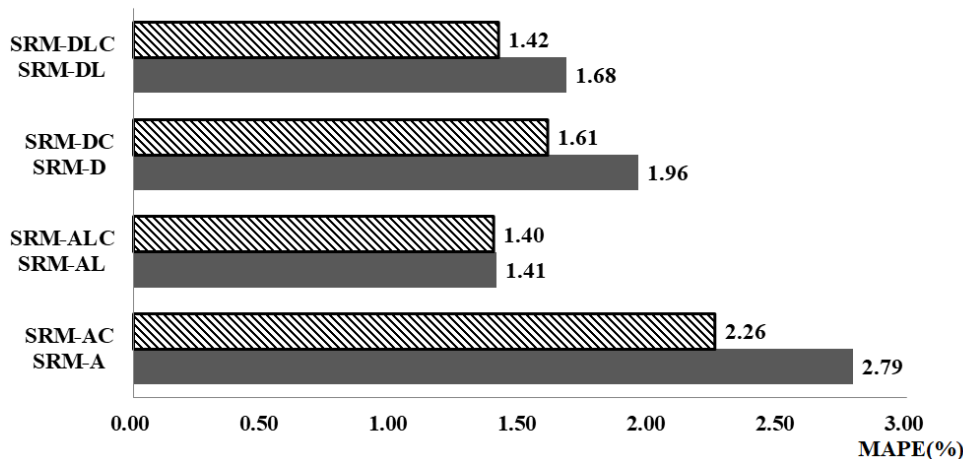
Note: AA and DR correspond to the abbreviations of analytic approach and data realization respectively.

Main Conclusions

- Conclusions

- SRM-D is more flexible and adaptable than SRM-A. However, SRM-A has the advantages of parameter-free and the lowest complexity.
- Dictionary learning can effectively improve the prediction performance of SRM, but it will increase the computational complexity.
- The prediction performance of SRM can be effectively improved by taking cross-domain influence factors into account, with the benefit of no additional computational complexity.

- Comparison of eight variants of SRM



- Comparison of different models

Model	MAPE (%)	Time (s)	Rank
ARIMA	4.08	42.5	10
RF	3.44	0.53	9
SVR	3.09	0.11	8
MLP	2.75	0.08	7
MGU	2.20	3986	6
GRU	1.91	2521	5
SRM-DC	1.61	0.27	4
LSTM	1.53	4949	3
SRM-DLC	1.42	0.47	2
SRM-ALC	1.40	1.01	1