06 Forecasting future data for unobserved locations

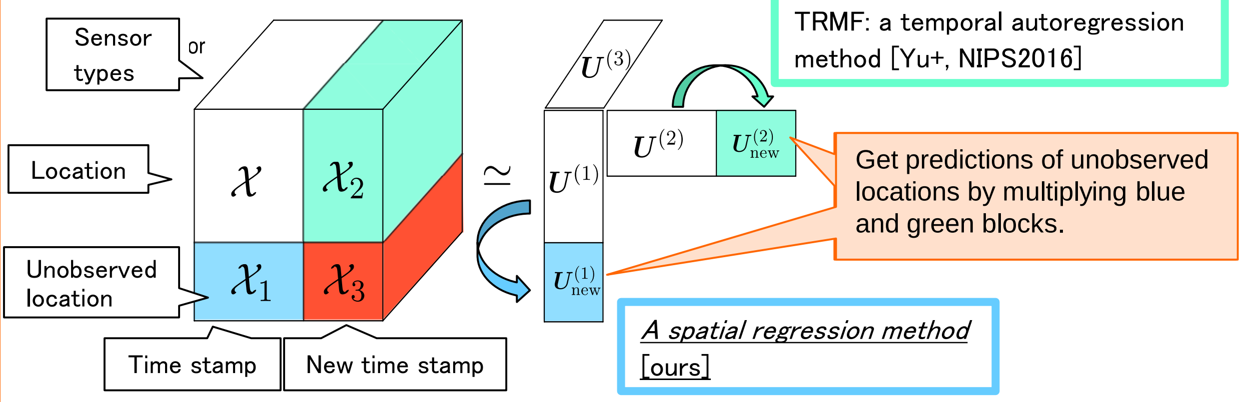
- Tensor factorization for spatio-temporal data analysis -

Abstract

Analysis of spatio-temporal data is a common research topic that requires the interpolations of unobserved locations and the predictions of feature observations by utilizing information about where and when the data were observed. One of the most difficult problems is to make future predictions of unobserved locations. Tensor factorization methods are popular in this field because of their capability of handling multiple types of spatio-temporal data, dealing with missing values, and providing computationally efficient parameter estimation procedures. We propose a new tensor factorization method that estimates low-rank latent factors by simultaneously learning the spatial and temporal correlations. We introduce new spatial autoregressive regularizers based on existing spatial autoregressive models and provide an efficient estimation procedure.

Spatio-Temporal Regression Problem

Our tensor factorization method estimates factors of unobserved locations (blue) with a spatial regression and employ it as a spatial regularizer. By combining it with future actors (green) obtained from an autoregression model, we enable to get predictions of unobserved locations (red).



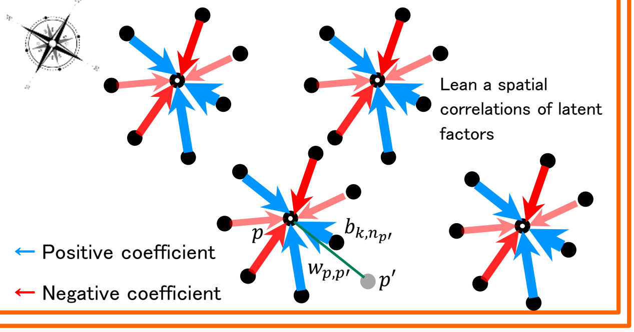
Our spatial regression method can deal with both grid and non-grid sensor locations by assigning the same coefficients based on the angle between a source and a target sensor locations.

Our angle dependent coefficient learning enables to get factors of unobserved locations $u^{(1)}_{p,k}$.

Spatial regression regularizer

$$\sum_{k=1}^{K}\sum_{p=1}^{P}\left(u^{(1)}_{p,k} - \sum_{p'\in E_p} \boxed{b_{k,n_{p'}}} w_{p,p'} u^{(1)}_{p',k}\right)^2 + \frac{\eta}{2}\|\boldsymbol{u}^{(1)}_k\|_2^2,$$

A regression coefficient $b_{k,n_{p'}}$ is assigned by the angle between p and p' (red and blue arrows)



References

[1] K. Takeuchi, H. Kashima and N. Ueda, "Autoregressive Tensor Factorization for Spatio-Temporal Predictions," in *Proc. of 2017 IEEE International Conference on Data Mining (ICDM)*, 2017.

[2] 竹内孝, 鹿島久嗣, 上田修功, "自己回帰テンソル分解による時空間データ予測," *2018年度人工知能学会全国大会(第32回)*, 2018.

Contact

Koh Takeuchi Email: cs-liaison-ml at hco.ntt.co.jp
Ueda Research Laboratory

Innovative R&D by NTT
Open House 2019