Time Series and Machine Learning Reading Group 2023
Spring/Summer

We will read following references on deep nerual networks theories and nonparametric/quantile regression:

References

Schmidt-Hieber, J. (2020). Nonparametric regression using deep neural networks with ReLU activation function. *The Annals of Statistics*, **48**, 1875–1897.

Farrell, M. H., Liang, T., and Misra, S. (2021). Deep neural networks for estimation and inference. *Econometrica*, **89**, 181–213

Yarotsky, D. (2017). Error bounds for approximations with deep ReLU networks. *Neural Networks* **94**, 103–114.

Yarotsky, D. (2018). Optimal approximation of continuous functions by very deep ReLU networks. In *Conference on Learning Theory*, PMLR, 639–649.

Bauer, B., and Kohler, M. (2019). On deep learning as a remedy for the curse of dimensionality in nonparametric regression. *The Annals of Statistics*, **47**, 2261-2285.

Kohler, M., and Langer, S. (2021). On the rate of convergence of fully connected deep neural network regression estimates. *The Annals of Statistics*, **49**, 2231–2249.

Jia, Y., and Jeong, J. H. (2022). Deep learning for quantile regression under right censoring: DeepQuantreg. *Computational Statistics and Data Analysis*, **165**, 107323.

Shen, G., Jiao, Y., Lin, Y., Horowitz, J. L., and Huang, J. (2021). Deep quantile regression: Mitigating the curse of dimensionality through composition. *arXiv preprint*, arXiv:2107.04907.

Shen, G., Jiao, Y., Lin, Y., and Huang, J. (2021). Robust nonparametric regression with deep neural networks. *arXiv preprint*, arXiv:2107.10343.

He, X., Pan, X., Tan, K. M., and Zhou, W. X. (2021). Smoothed quantile regression with large-scale inference. *Journal of Econometrics.*, **232**, 367–388.

Padilla, O. H. M., Tansey, W., and Chen, Y. (2022). Quantile regression with ReLU Networks: Estimators and minimax rates. *Journal of Machine Learning Research*, **23**, 1–42.

We will also read following non-techinical papers on state-of-the-art time series forecasting:

References

Grigsby, J., Wang, Z., and Qi, Y. (2021). Long-range transformers for dynamic spatiotemporal forecasting. *arXiv preprint*, arXiv:2109.12218.

Lim, B., Arık, S. Ö., Loeff, N., and Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, **37**, 1748–1764.

Oreshkin, B. N., Carpov, D., Chapados, N., and Bengio, Y. (2019). N-BEATS: Neural basis expansion analysis for interpretable time series forecasting. In *International Conference on Learning Representations.*

Yu, H. F., Rao, N., and Dhillon, I. S. (2016). Temporal regularized matrix factorization for high-dimensional time series prediction. In *Advances in Neural Information Processing Systems.*

Rangapuram, S. S., Seeger, M. W., Gasthaus, J., Stella, L., Wang, Y., and Januschowski, T. (2018). Deep state space models for time series forecasting In *Advances in Neural Information Processing Systems.*

Menchetti, F., Cipollini, F., and Mealli, F. (2023). Combining counterfactual outcomes and ARIMA models for policy evaluation. *The Econometrics Journal*, **26**, 1–24.

Hartford, J., Lewis, G., Leyton-Brown, K., and Taddy, M. (2017). Deep IV: A flexible approach for counterfactual prediction. In *International Conference on Machine Learning.*