AI FOR DEMAND PLANNING - A USE CASE APPLYING HISTORICAL CONSISTENT NEURAL NETWORKS

MASTER'S THESIS

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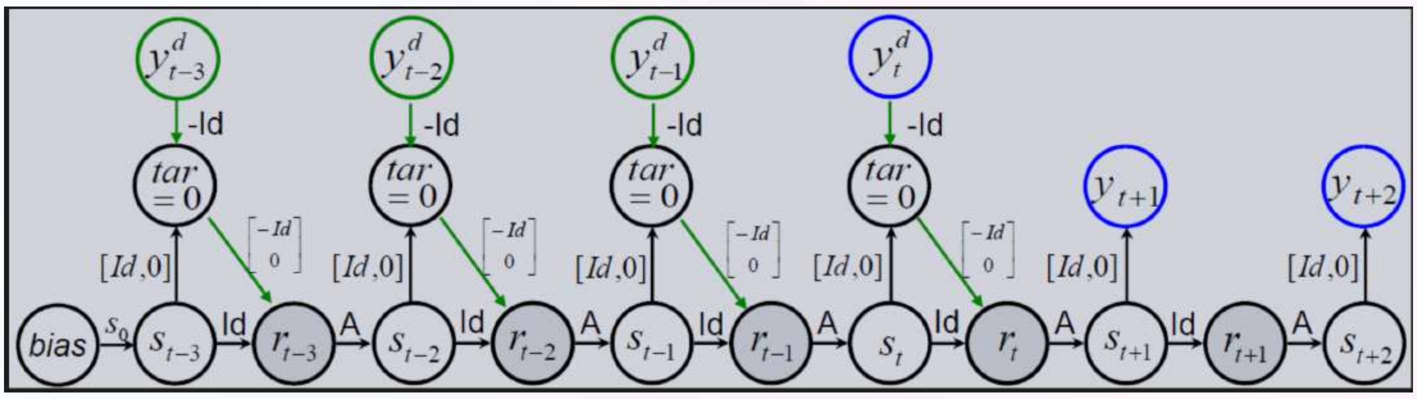
INTRODUCTION

Forecasting plays a critical role in supply chain management of wholesale and retail industry. The prediction of future demand forms the basis for production planning and inventory management. For the estimation of the future demand, one of the approaches is to make use of artificial intelligence and machine learning. There are a wide variety of models and algorithms that are available for forecasting. This thesis, in particular, investigates performance of the newly proposed deep learning models in comparison to the existing statistical, machine learning and deep learning models.

METHOD

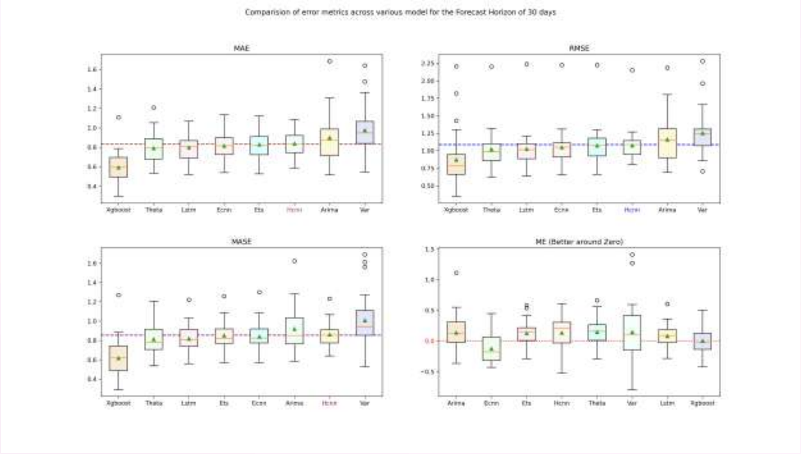
To facilitate this, a raw dataset from a wholesale supply chain company is taken and then transformed using the standard and customized data preprocessing techniques in order to be used with the existing models. With the help of the algorithms and the dataset - the target variable i.e., quantity demand has been forecasted across three different forecast horizons. After obtaining the forecast across three different forecast horizons, errors are calculated with the help of actual values in testset, the distributions of errors are recorded. With the help of these recorded distributions of errors, evaluation of the performance of each model is conducted using four different forecast metrics. Taking into the consideration of time, computational complexity and data availability limitations, the scope of this thesis is limited to primarily evaluate whether these novel deep learning models could be considered while making a decision in forecasting scenarios.

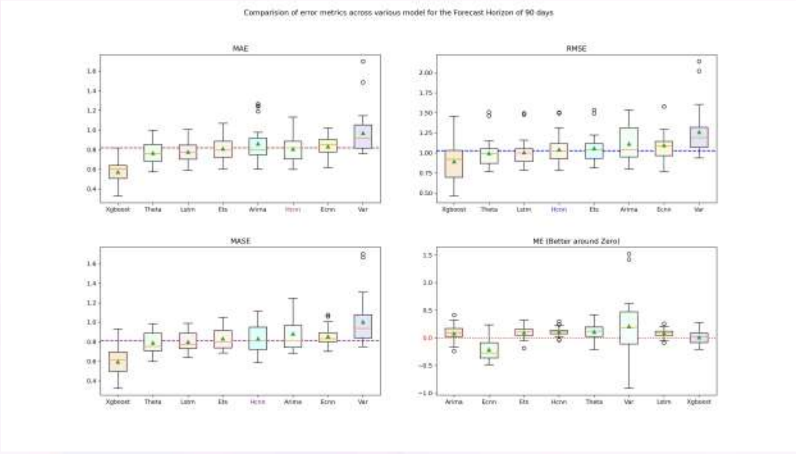
HCNN NEURAL NETWORK ARCHITECTURE

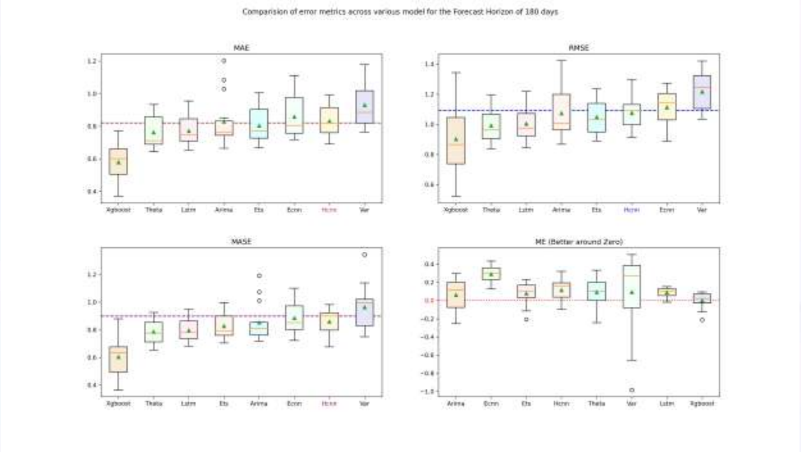


This architecture was first proposed by Dr. Hans Gerog Zimmermann, and further developed using PyTorch library by Department of Data Science in the working group of Supply Chain Services at Fraunhofer IIS. (Picture Source: Zimmermann's HCNN lecture slides.

VARIOUS MODELS IN FORECAST HORIZONS







ANALYSIS

The plot is the summary of median and standard deviation value of each model against the three forecast horizons across all the four errors. This plot shows the sensitivity of the model as the forecast horizon is varied from 30 days to 180 days. It is evident from measuring the median of errors, XGBoost model minimizes the error. But the model HCNN has median of MAE at 0.82 for both forecast horizon of 90 Days, 180 Days. This is a significant performance of an algorithm, as the error usually tends to increase with the increase of forecast horizon. When considering the standard deviation of error of MAE HCNN with forecast horizon of 180 days has the lowest deviation one reason for this could be availability of fewer observations as I have same test set for both 30 days and 180 days windows, this is further support by both MASE and RMSE that HCNN performance is much better, as it gives reliable forecast across the various forecasting windows. Though from MASE error metric the median of HCNN is lowest for 90 days when compared to 30 days and 180 days it could be because MASE measures seasonal effect and for 180 days the seasonal component could lead to increase in median value of error.

NOVEL DEEP LEARNING NEURAL NETWORKS LIKE HCNN PROVIDE RELIABLE RESULTS WHEN COMPARED TO EXISTING STATISTICAL AND MACHINE LEARNING MODELS, ALTHOUGH THEY NEED TO BE TUNED OPTIMALLY TO DECREASE THE ERROR.

CONCLUSION

On a final note, from my findings Deep Learning models HCNN and ECNN are good at forecasting for long forecast horizons across multiple windows as it has lowest standard deviation, and XGBOOST is having a lowest median of error. Depending on the objective of whether if the user is interested in point forecast then XGBOOST would be the model of use, if the user is looking for a tight range of values to have a better risk mitigation strategy, then HCNN or ECNN would be the model. I would suggest to use the information from both algorithms