# Machine Learning Write-Up

## Related Works

While we aim to see how Machine Learning algorithms are affected over time, traditionally time has been only considered in seeking to predict the preference a user would have to an item, i.e. recommender-system research. Time is considered important in this case in marking the changes in user preference over time. Lee et al (2008) for example use a time-based approach to effective recommender systems using implicit feedback [4]. Their focus lies on adjusting algorithms to make them consider time and improve the effectiveness of the algorithms in accordance with the users wishes [3]. An example of a temporal feature as such is seasonality. Seasonality is something that is often considered as an important contextual feature, i.e it is something to be considered that one should use a different algorithm in winter than in summer. However, it seems from our study that all of the research work in concern to time is trying to use time to improve machine learning algorithms as opposed to a comparison study for machine learning models for regression, which we aimed to conduct. To the best of our knowledge, most of the works that relate to our studies is focused on the effectiveness of particular a ML algorithm over a predictive time-series. Kyoung-jae Kim et al (2002) tries to evaluate the feasibility of using Support Vector Machines in order to predict a financial time series [2]. This study examines the feasibility of applying SVM in financial forecasting by comparing it with back-propagation neural networks and case-based reasoning. Another study conducts time-series forecasting focusing on using SES, one of the models we observe in our study [5]. The work we found most closely related to ours, Atiya and Ahmed et al(2010), utilises a similar method to ours aiming to answer a similar question, as they present present a large scale comparison study for the major machine learning models for time series forecasting. The models that they use differ from ours using ‘multilayer perceptron, Bayesian neural networks, radial basis functions, generalized regression neural networks, K-nearest neighbor regression, CART regression trees, support vector regression, and Gaussian processes’. They also apply the models to monthly time series data however on a larger scale, with ‘around a thousand time series’[1].

## Results & Discussion, Limitations & Outlook

Overall my experience with the Simple Exponential Smoothing (SES) model was relatively positive. It was overall fairly easy to apply as only three pieces of data are required for exponential smoothing methods. One, it needs the forecast for the most recent time period. Two, it needs the actual value for that time period. And three, it needs the value of the smoothing constant, a weighting factor that reflects the weight given to the most recent data values. Exponential smoothing is best used for forecasts that are short-term and are not affected by seasonal variation. As a result, forecasts aren’t accurate when data with cyclical variations are present and won’t work well with trends.

The results that I obtained from trying to evaluate the SES model in a time series forecast gave me a root mean square error of 70.48 the RSME, when using 1/12th of the data to test and the rest to train. The RSME being relatively high indicated that this model was not the best approach. Given a shorter period of time, 4 years of data as opposed to 13 years from the data the RSME decreased to 58.168, indicating it has quite a short range. The procedure gives heaviest weight to more recent observations and smaller weight to observations in the more distant past. The accuracy of the SES method strongly depends on the optimal value of the smoothing constant a.

I felt that we were limited by how small our dataset was as it left for a wide margin of error and wasn’t very representative.

## References

[1] Ahmed, N., Atiya, A., Gayar, N. and El-Shishiny, H. (2010). An Empirical Comparison of Machine Learning Models for Time Series Forecasting. Econometric Reviews, 29(5-6), pp.594-621.

[2] Kim, K. (2003). Financial time series forecasting using support vector machines. Neurocomputing, 55(1-2), pp.307-319.

[3] Koren, Y. (2010). Collaborative filtering with temporal dynamics. Communications of the ACM, 53(4), p.89.

[4] Lee, T., Park, Y. and Park, Y. (2008). A time-based approach to effective recommender systems using implicit feedback. Expert Systems with Applications, 34(4), pp.3055-3062.

[5] Ostertagová, E. and Ostertag, O. (2012). Forecasting using simple exponential smoothing method. Acta Electrotechnica et Informatica, 12(3).