Project AI - PID27: AI for Intermittent Demand Forecasting

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1 Introduction

Demand forecasting is crucial to support an efficient supply chain in retail. However, many products sold by retailers show intermittent demand: periods of low to zero demand interspersed with periods of high demand. In this project the goal is to build a model that can accurately forecast demand for products that show intermittent demand. A dataset with products that show intermittent demand on which the models can be evaluated will be provided. The students are encouraged to think about topics such as which model structure to use (e.g. LSTMs, GRUs, a Transformer), which metrics to consider to evaluate performance and which baseline to compare with. The result of the project should include (i) a model that can forecast demand for products with intermittent demand for the given dataset, (ii) insights into the performance of the model, (iii) a high level analysis of the supply chain impact of using the proposed model and (iv) recommendations for future research.

2 Background

Intermittent demand Forecasting methods have been reviewed by [5, 7] and could serve as a basis to start from to understand the problem. Recent work on intermittent demand forecasting is, e.g. [6] which provides a Bayesian method for intermittent demand forecasting in the context of large-scale e-commerce.

Sequence-to-sequence Models such as encoder-decoder models based on LSTMs, GRUs or the more recent Transformer [8] naturally lend itself to use in sequence modelling tasks a.o. due to their ability to retain knowledge of distant past observations.

Baseline models Based on the above related work the naïve forecasting method [4], Croston's method [2] and XGBoost [1] seem appropriate baselines to compare against the developed model.

Error metric To evaluate the accuracy of an intermittent demand forecast the *mean absolute scaled error* (MASE) [3] is suggested.

Supply chain impact To evaluate the quality of the forecast in terms of the supply chain an inventory cost measure or a measure for loss of sales could be used.

3 Problem definition

Denote a time series a sequence of time-ordered measurements $\{Y_1, Y_2, \dots\}$. We are interested in finding a model $f(\cdot)$ to estimate future values of the time series based on past observations and/or additional attributes:

$$\{\hat{Y}\}_{t+1}^{t+p} = f\left(Y_t, Y_{t-1}, \dots, Y_{t-T}, X_{t+1}, X_t, \dots, X_{t-T}\right) \quad (1)$$

with X_t the additional attributes, for example a day-of-week indicator. Let $X \in \mathbb{R}^{m\times n}$ and $Y \in \mathbb{R}^{m\times k}$. We denote t the time indicator (e.g. hour, day or week) which scale is assumed to be constant, T the number of past observations included in the model to estimate $\hat{Y}$, k the number of time series to be forecast, p the number of time steps to be forecast, n the number of additional attributes and m the number of samples. It is advised to (first) restrict the analysis to the case where $k = 1$ and $p = 1$ (*one-step ahead univariate forecasting*). The problem of intermittent demand is that many observations in the sequence $\{Y_1, Y_2, \dots, Y_T\}$ may be zero yet we still want to be able to produce an accurate forecast for $\hat{Y}_{t+1}$.

4 Dataset

We will use the `predict future sales` Kaggle public dataset that is part of the final project for the Coursera course 'How to win a datascience competition'. The dataset consists of daily historical sales data per item per store. We are interested in creating an accurate forecast on a per product per store level on the test set.

5 Research questions

Questions that the project aims to answer are:

- How can we apply modern sequence-to-sequence techniques such as an LSTM encoder-decoder to an intermittent demand forecasting problem?

- What are problems encountered when applying such methods? What are benefits?
- How do these techniques compare to baselines in terms of accuracy and ease of implementation/tuning?
- What are next steps to improve intermittent demand forecasting using modern machine learning techniques?
- What are considerations to take into account when choosing a method for intermittent demand forecasting?

6 Timeline

The following project timeline is proposed:

- Week 1: Introduction; understanding the problem; understanding the data; formulating questions and approach; restricting scope.
- Week 2: Building model and baselines;
- Week 3: Evaluating model against baselines; writing report;
- Week 4: Further evaluation; creating poster.

References

[1] Tianqi Chen and Carlos Guestrin. "XGBoost: A Scalable Tree Boosting System". In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16*. ACM Press, 2016, pp. 785–794. ISBN: 978-1-4503-4232-2. DOI: `10.1145/2939672.2939785`. URL: `http://dl.acm.org/citation.cfm?doid=2939672.2939785` (visited on 04/15/2019).

[2] J. D. Croston. "Forecasting and Stock Control for Intermittent Demands". In: *Operational Research Quarterly (1970-1977)* 23.3 (1972), pp. 289–303. ISSN: 0030-3623. DOI: `10.2307/3007885`. URL: `https://www.jstor.org/stable/3007885` (visited on 04/17/2019).

[3] Rob J Hyndman. "ANOTHER LOOK AT FORECAST-ACCURACY METRICS FOR INTERMITTENT DEMAND". In: (), p. 4.

[4] Rob J Hyndman. *Forecasting: Principles and Practice*. 2018. URL: `https://Otexts.com/fpp2/` (visited on 04/15/2019).

[5] Fotios Petropoulos, Nikolaos Kourentzes, and Konstantinos Nikolopoulos. "Another Look at Estimators for Intermittent Demand". In: *International Journal of Production Economics*. SI: ISIR 2014 181 (Nov. 1, 2016), pp. 154–161. ISSN: 0925-5273. DOI: `10.1016/j.ijpe.2016.04.017`. URL: `http://www.sciencedirect.com/science/article/pii/S092552731630041X` (visited on 06/03/2019).

[6] Matthias W Seeger, David Salinas, and Valentin Flunkert. "Bayesian Intermittent Demand Forecasting for Large Inventories". In: *Advances in Neural Information Processing Systems 29*. Ed. by D. D. Lee et al. Curran Associates, Inc., 2016, pp. 4646–4654. URL: `http://papers.nips.cc/paper/6313-bayesian-intermittent-demand-forecasting-for-large-inventories.pdf` (visited on 04/24/2019).

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[8] Ashish Vaswani et al. "Attention Is All You Need". In: (June 12, 2017). arXiv: `1706.03762 [cs]`. URL: `http://arxiv.org/abs/1706.03762` (visited on 04/11/2019).