Deep Learning - Term Project

P1 - Project Proposal

Richard Hoehn*

Middle Tennessee State University

CSCI 7850

Prof. Dr. Joshua L. Phillips

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*Electronic address: rhoehn@mtmail.mtsu.edu; corresponding author

1 Introduction

In this term project I plan on focusing my research and student learning on demand forecasting using Deep Learning recurrent neural networks (RNNs) in specific the Long Short Term Memory (LSTM) and Gate Recurrent Units (GRU) architectures. Both the LSTM and GRU models can capture complex temporal dependencies over longer ranges of time and patterns in historical sales data[1, 3, 5], making them a very good option for demand forecasting tasks.

My motivation for the this project is two fold. **Firstly**, a time-series problem is very interesting for me personally since I often question how one can predict the future based on past data; additionally how the future might change if the input of data is changed - a type scenario forecasting. **Secondly**, a better understanding of RNN in specific LSTM and GRU networks will really help me better understand and learn for my future endeavors in Computation & Data Sciences.

In order to complete this term project I plan on using data from Kaggle's Demand Forecasting challenge[2] released in 2018. The dataset is comprised of five (5) years of store sales data based on 50 different items at 10 different stores. Each data point is on a daily basis; with this being said the training dataset is comprised of 912,500 rows in a `csv` file.

2 Specific Aims

For this term project in deep learning I have four (4) main goals.

- Build, Train, and Validate the LSTM & GRU RNN models
- Using Plots display the actual and forecast-ed data in graphical forms
- Expand the dataset with Seasons, Weekdays, and other information related to sales data
- Finally, submit my model to Kaggle for evaluation

2.1 Build, Train & Validate LSTM and GRU

Long Short-Term Memory (LSTM) networks and Gate Recurrent Units (GRU) networks are two widely accepted variations of recurrent neural networks (RNNs), which are known for their proficiency in capturing long-term dependencies within sequential / temporal data[1]. In the scope of this term project, I intend to construct both LSTM and GRU models and conduct a solid comparative analysis of their performance to each other. The objective is to discern the relative strengths and possible weaknesses of these neural network architectures when applied to this specific[2] demand forecasting dataset.

The comparison process will adhere closely to the evaluation methodology presented in a paper by Shudong Yang et al.[5], which primarily centered around the analysis of comparing LSTM and GRU architectures. By following a similar evaluation framework as presented in Shudong Yang et al. paper[5], I hope to ensure consistency and facilitate a meaningful assessment of the two models to each other in a similar fashion to the before mentioned paper, however using the Kaggle[2] dataset.

2.2 Plotting of Actual and Predicted Values

In the realm of demand forecasting, the significance of managerial forecasting using graphics, as highlighted in Arnab Mitra et al.'s research[4, Section 4.3], is important. Their emphasis in the section on visual representations is particularly noteworthy. To this end, I aim to employ straightforward and informative plots that go beyond mere numerical assessments of the validated models. These visualizations will serve as a valuable means of encapsulating the performance of forecasting models comprehensively.

Through these graphical / visual representations, my aim is: **first**, offer a holistic view of how well the demand forecasting models perform, and **second**, to facilitate a direct comparison between the different models (LSTM vs GRU) employed. This approach not only supports me in the clear communication of results but also could in the real-world empower decision-makers with intuitive insights, making it easier for a business to interpret and act upon the demand forecasting predictions more effectively.

2.3 Expand the Dataset with Seasons, Weekdays, and Other Information

Based on the description from Kaggle[2] of the data it's evident that it is derived from real-world sources, suggesting its inherent complexity. In order to enhance the demand forecasting capabilities of my models, I intend to explore the extraction of additional contextual information related to the timestamps, such as seasons, weekdays, holidays, or any other relevant time-based factors. By incorporating these additional features into the dataset, I aim to provide the LSTM and GRU models with a richer contextual understanding of the underlying data, which can lead to more accurate predictions.

The strategy here involves augmenting the dataset with these extracted features and subsequently comparing the performance of the LSTM and GRU models with that of the previous non-expanded dataset. This comparative analysis will shed light on the extent to which the inclusion of more temporal information influences forecasting accuracy.

2.4 Submit my model to Kaggle for evaluation

By participating in the Kaggle[2] challenge as a data scientist provides numerous advantages, primarily an environment allowing me to benchmark my model with the data science community. I plan on learning on how to build and submit my model for the Kaggle kernel to evaluate and glean some insight on how I performed versus other's on the demand forecasting challenge.

3 Proposed Methods

With the demand forecasting I will need to initially work on the **data pre-processing**, this will entail creating a tokenization / embedding for the different store IDs, the sales volumes (normalized) and dates. Once the data is ready both the LSTM and GRU can be designed and **hyper-parameters** assigned to them. The focus will be on the **learning rate**, **regularization** (dropout and L2), in addition to **batch size**. I plan on using the first four (4) years from training and the last year for validation, which will be an 80% - 20% split. In this project's case I believe the **F1-Score** and **Accuracy** will be key to determining the models' performance. In addition to numerical scores I feel **plotting** predicted vs. actual values over time can provide qualitative insights into how well the model captures trends and patterns in the data.

4 Expected Results

Overall, my hope is that both the LSTM and GRU models should demonstrate the ability to predict demand well compared to the validation data. In other words, the models should perform adequately on the validation dataset that were not used during training.

In addition to the performance I expect that as I add more features that will capture and replicate underlying trends such seasonality and the week days; I would witness performance improvements. This addition to the vanilla data is of importance since I plan on basing my future work on forecasting models and the insight into expanding features to gain improvements interests me a great deal.

And finally, by visualizing the forecasting in plots and graphics I will provide an even more insightful view of demand forecasting since a visual representation of the predictions can lead to true managerial business value, which ultimately adds trust in a model's accuracy.

References

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