Departmemt of Mathematics and Statistics

CAPSTONE PAPER REVIEW WEEK 2 (PAPER 2)

Literature Review on A Different Approach for Casual Impact Analysis on Python with Bayesian Structural Time-Series and Bidirectional LSTM Models

Gianyce Michelle Gesualdo Ortiz

Supervisor: **Dr. Shushen Pu**

Contents

CHAPTER 1

Background/Motivation

Describe the context in which the research was conducted.

Fotia and Ferrara, in their article "A Different Approach for Causal Impact Analysis on Python with Bayesian Structural Time-Series and Bidirectional LSTM Models," propose combining the CausalImpact model with a Bidirectional LSTM model, while also incorporating the pre-existing Incremental Difference-in-Differences (IDiD) model. By integrating these methods, they aim to infer information and analyze the causal impact of an event.

Their goal is to evaluate the impact of therapy by comparing placebo (sham) therapy with real therapy, assessing the effects of these sessions over time. They note that RCTs, PSM, and DiD are commonly used for causal effect analysis. While RCTs are considered the gold standard, they are not always practical or ethical, making alternatives like DiD more suitable in certain contexts. DiD allows researchers to compare changes in outcomes over time between groups, such as those exposed to the therapy in this study.

The study combines concepts from Bayesian inference and causal impact analysis to estimate the causal influence of an intervention or policy on a specific outcome. Additionally, it employs the Bidirectional LSTM model to forecast the intervention's causal effect on time series data, further enhancing its ability to predict and analyze the outcomes.

As addressed earlier, the key standard for casual impact analysis is RTCs, yet they have flaws, as they are not always practical or ethical. This paper attempts to address different ways that are not RTCs and can be as effective. It also shows the inherent

limitations of DiDs and PSMs since they do not capture the full complexity of the data. This paper does add the use of the Bidirectional LSTM model, which is both for estimation and for future forecasting of data.

CHAPTER 2

Methods Used

To begin with, the authors utilized fictitious data based on the assumption that the policy in question has a substantial positive effect on the real therapy sessions. Then, they utilized an Incremental Difference in Difference model to exam the data. They applied it to compare the pre-intervention and post-intervention periods for their analysis on the policy's impact. Then they use a Google-developed Bayesian structured causal effect model and applied it during the whole study period. This model employs Bayesian Structural Time Series approach, and finally after the tuning phase the Bi-LSTM model was executed.

Within the code, they utilized Python libraries pandas and numpy for the data structure, machine learning, and data tools. TensorFlow and keras for deep learning as well. Then, they used matplotlib for visualization and casualimpact library to the actual data to estimate the causal impact of a treatment or intervention. All these methods are well suited for the question as these libraries are commonly used in data science, statistical modeling, machine learning, and deep learning projects

Noteworthy is the method of combining the Bayesian structural time series and bidirectional LSTM model. They integrate the Bayesian model using CasualImpact with LSTM neural networks. Bayesian provides a way to estimate placebo therapy, while the LSTM model captures the complex model patterns in time-series data by processing the data in forward propagation and back propagation through time.

CHAPTER 3

Significance of the Work

Throughout the use of the three models (DiD, CasualImpact, and Bidirectional LSTM), the values appeared to be steadily increasing over time, meaning that the treatment group was exerting a greater influence with time. After 100 periods, a change point was shown in the data at which the treatment's effect began to rise. Using the DiD as a benchmark for the other two techniques to measure the efficacy of the model's impact, the other two models did provide a low p-value. Therefore, this strategy did offer valuable insights into the effects of the treatments. Nonetheless, locating an appropriate control group for the research is one of the obstacles to using real-world data that this paper has not achieved. Overall these results are important in this field as they provided insights on the efficacy of various methodologies for evaluating the impact of interventions on a particular system.

CHAPTER 4

Connection to Other Work

This paper does reference important works that inspired them. Notably for the Bi-LSTM model, they mention the development of LSTM and what makes them different for learning. Traditionally, recurrent neural networks are not optimal for learning long-term dependencies due to vanishing/exploding gradient concerns, as cited in *Neural Networks and Deep Learning* by Nielsen. LSTMs and GRUs are types of RNNs that work with time series data since it can capture long-term dependencies that Fotia and Ferrara try to capture. Due to the multifacited objective, that is what makes the difference between Nielsen's work and Fotia's work.

CHAPTER 5

Relevance to Capstone Projects

This paper demonstrates how to use Python to implement a Bi-LSTM procedure for forecasting data, which aligns with my interest in incorporating forecasting techniques into time series analysis for my project. One of my goals is to potentially utilize Bi-LSTM and Bayesian Structural Time Series within Python to enhance my analysis. Additionally, learning about different methods in the data science field, such as those presented in this paper, is valuable as they can further aid the development and refinement of my project.

Bibliography

[1] Fotia, Pasquale, and Massimiliano Ferrara. "A Different Approach for Causal Impact Analysis on Python with Bayesian Structural Time-Series and Bidirectional LSTM Models." *Atti della Accademia Peloritana dei Pericolanti - Classe di Scienze Fisiche, Matematiche e Naturali, vol. 101, no. 2*, 2023.

[2] Nielsen, Michael. *Neural Networks and Deep Learning*. Determination Press, 2015.