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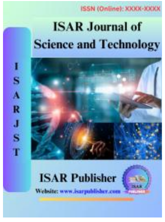

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Causal Inference in Machine Learning for Accurate Prediction in Dynamic Pricing Models

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Abstract: In recent years, there has been a noticeable increase in the use of Machine Learning (ML) methods in a wide range of domains, including recommendation systems, text categorisation, picture analysis, and predictive credit scoring. It begins by providing an overview of the conventional asset pricing models and analysing how well they represent the intricacies of financial markets. Furthermore, the Granger causality test—which is inappropriate for non-stationary and non-linear stock factors—is a major determinant of causal link inference. Furthermore, the majority of current research does not take into account the influence of confounding factors or further confirmation of causal linkages. Unfortunately, correlation does not imply causation, because causality—rather than merely correlation—drives the actual world. For example, recommender systems may suggest a battery charger to a user after they purchase a phone, even if the latter may be the source of the former; this kind of causal relationship is irreversible. This was accomplished by incorporating causal diagrams from the structural causal model (SCM) into the stock data analysis. The possible values of closing prices were then predicted using a sliding window method in conjunction with Gated Recurrent Units (GRUs), and confounding factors were controlled using a grouped architecture modelled after the Potential Outcomes Framework (POF). Using the non-linear Granger causality test, the architecture was used to identify causal links between closing price and pertinent parameters. Lastly, comparative experimental findings show that adding causative elements to the prediction model significantly improved the performance and accuracy of closing price forecasts.

Keywords: Prediction Model, Prediction Model, Causal Relationships, Machine Learning (ML), Structural Causal Model (SCM), Gated Recurrent Units (Grus), Stock Data, Battery Charger, Causation, Granger Causality Test, Experimental Results.

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I. Introduction

Recommender systems (RecSys) have become the essential service for enabling users to obtain information in the age of information overload. The methods and models of recommender systems are evolving quickly, starting with the first shallow models and continuing with the latest deep learning-based models and the most recent models based on graph neural networks [1]. By combining past behaviours with gathered user profiles, item features, or other contextual data, recommender systems generally seek to understand user preferences [1, 2]. In this case, the recommendation policy has a significant impact on the interaction, which is mostly caused by the prior recommender system [2]. Recommender systems then choose products that fit users' individual needs and tastes after filtering through the item-candidate pools. Following deployment, the system gathers fresh interactions to update the model [2, 3], creating a feedback loop across the whole framework. In general, recommender systems fall into two categories: content-based recommendation, often known as click-through rate (CTR) prediction or simply CTR prediction, and collaborative filtering (CF) [3. 4].

The emphasis of collaborative filtering is on users' past actions, such clicking, buying, etc. [5]. Collaborative filtering is based on the fundamental premise that users who exhibit comparable past behaviours are likely to exhibit similar future behaviours [4, 5]. The most representative matrix factorisation model (MF), for instance, represents users and things using vectors and then computes the relevance scores between users and items using the inner product. Recent research uses deep neural networks to match users with goods in order to increase the model's capacity. One such method is neural collaborative filtering, which uses multi-

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layer perceptron's to replace the inner product in the MF model [6, 7]. The timestamp of each behaviour in sequential suggestions, the user social network in social recommendation, the multi-type behaviours in multi-behaviour recommendation, and other additional information are also taken into account when modelling the relevance of collaborative filtering from a broad perspective [6, 7].

For investors, fund managers, and regulators, empirical asset pricing models are essential [6, 7], since they seek to clarify the intricate connections between financial assets and their anticipated returns [8]. Conventional models such as the Fama-French models and the Capital Asset Pricing Model (CAPM) have been fundamental since The complex and nonlinear dynamics of financial markets are sometimes difficult to represent [8, 9]. Traditional models' less flexible functional forms, challenging variable selection, and worse prediction accuracy have all been well reported in the literature [6, 8]. Using machine learning to asset pricing in order to address these problems. Better prediction power and greater flexibility in modelling intricate non-linear interactions are two benefits of machine learning models [6, 7]. Additionally, they make it possible to include non-traditional data sources, such as text, picture, video, and audio data, which enhances decision-making. Furthermore, real-time decision-making is made possible by continuous learning based on fresh data thanks to fine-tuning and parameter optimisation techniques [6, 7]. As a consequence, machine learning is being used more and more in the banking industry, particularly to estimate asset price complexity. In this study, we provide a thorough analysis of machine learning (ML)-based empirical asset pricing [7].

We look at how classic models have been changed by ML-based techniques, offering a fresh viewpoint on asset pricing difficulties [7, 8]. In contrast to some earlier works that only addressed Finance or those that described the taxonomy of financial-risk tasks associated with machine learning techniques, our method examines recent research contributions from both computer science and finance, providing a thorough understanding of the interdisciplinary developments [8]. Additionally, we critically assess the present obstacles to using machine learning for empirical asset pricing [8], pointing out areas in need of further study and offering suggestions for future lines of inquiry. Because of this, [8], this study is a useful tool for scholars in the future, providing a foundation for understanding the latest developments in this multidisciplinary field [8, 10]. Our investigation is ground-breaking in its extent and the first to cover a significant gap in the literature by offering a thorough focus on the ML algorithm development viewpoint particularly for asset pricing [10, 11].

If we consider a function that controls a product's demand, the price elasticity of demand is just the derivative of this function in relation to the price [11, 12]. Since the demand function cannot be determined in advance, techniques that can provide the most accurate estimate of the elasticity must be used. The method utilised determines the quality of the estimate, and each approach may be used in a variety of situations or under certain circumstances [11, 12]. The techniques used for elasticity estimate originate from the topic of causal inference, which is a broader area of study. Determining the independent, real impact of a specific phenomenon that is a part of a broader system is the aim of the study topic known as causal inference [12]. It examines a dependent variable's reaction in relation to the phenomenon's realisation [11]. One specific challenge of causal inference is elasticity estimation, which involves estimating the independent impact of a change in an item's price on the amount requested for that commodity [11].

But because the price is only one of the variables affecting demand, its impact must be separated. Numerous algorithms for causal inference exist [11, 12]; they all operate under various assumptions and make use of various statistical and mathematical theories. The majority of them have a lengthy literary history that demonstrates their effectiveness in both simulated and real-world settings [12]. By examining the use of two causal inference algorithms in the crucial domain of elasticity assessment for the e-commerce industry, we provide our contribution to this field of study [11, 12]. We have been able to examine the elasticity values computed on real-data pertaining to two e-commerce businesses that operate in the same market and offer comparable items because of the data supplied by the Canadian firm Coveo [11, 12].

1.1 Pricing decisions

In order to determine the value of a product or service, a corporation must make decisions about pricing [13]. An efficient price is one that transfers the majority of the consumer's economic surplus to the producer and is very near to the utmost that consumers are prepared to pay [13, 14]. The price that is chosen throughout the process should fall between the price floor, which is the price below which the firm loses money, and the price ceiling, which is the price at which there is no demand for the product [14]. A number of criteria must be considered in the pricing process; here, we highlight the most important ones:

- **Costs:** Business expenses should be taken into account initially [14, 15]. This category covers variable costs, which are the expenditures incurred by the firm in the process of creating and delivering its goods and services, as well as fixed costs, which are expenses that a business must pay regardless of sales or production level [15]. To properly price a product, all of these expenses must be computed and taken into consideration [15].
- **Competitors:** To adjust the pricing of its products, a business must consider its rivals. Customers are more inclined to purchase from a rival if, for instance, they provide the same product at a cheaper cost [15, 16]. This is generally accurate, however there could be more factors to consider, such client loyalty, service quality, and so on. The existence of viable alternatives that might divert customers' attention from the analysed product's pricing must also be examined [16].
- **Laws and regulations:** Price controls are often used by certain governments to safeguard consumers and promote competition [16, 17]. Avoiding the practice of price fixing, which happens when businesses band together and decide to charge the same rates, is one of the primary objectives of regulations [17]. In order to force customers to spend large amounts regardless of where they buy an item, it often entails establishing high pricing. Government laws sometimes try to stop big companies from offering goods at a discount in order to draw people to their establishments; this is often accomplished by establishing a minimum selling price [18].

- **Economy:** Price adjustments must take into consideration the overall development of the economy. Prices should be reduced appropriately when the economy is poor [18], but they may also be higher during times of robust economic growth [20].
- **Customers:** Perhaps the most crucial factor to take into account when setting a product's price is the consumer. The total number of prospective clients and their response to price adjustments are the two primary considerations. The price elasticity of demand, which is a crucial component of the majority of pricing schemes, is a direct measure of the second factor [20].

The main goal of current techniques like logistic regression, gradient boosting models, deep learning, etc [20, 21] is to fit observed data in order to find correlation information between variables. Variables that have strong correlations with the target variable are then chosen as prediction input variables. Prediction accuracy may be impacted, however, if correlations are the only thing taken into account and causation is not taken into account when selecting predictors [20, 21]. Although correlations may result from causal linkages, they are not the same as causation and are also impacted by confounding factors. Confounding factors cause correlations between the treatment and goal variables by concurrently affecting both of them [21].

Financial time series causal links are often inferred using the Granger causality test. Vector Auto regression (VAR), the Vector Error Correction Model (VECM), and their corresponding variations are the primary traditional techniques for determining Granger causation [22, 23].

Expanding on the ideas discussed above, a novel causal decomposition approach and further applied it to investigate information flow between two financial time series on different time scales. The causal decomposition method has three main steps: decomposition, [22, 23], reconstruction, and causality testing. By tracking the driving factors of causal relationships from the perspective of information frequency, the causal decomposition method re-evaluates the causal relationship between stock prices and trading volume from the time-frequency perspective [21, 22].

This research is innovative because it uses causal diagrams and uses deep learning networks to create a grouped architecture [23]. The following is a summary of the main contributions of the suggested approaches:

- The stock data analysis uses causal diagrams to examine the links between confounding factors, treatment variables, [23], and target variables in order to better understand how confounding variables affect causal linkages. Confounding variables may be controlled and the link between closing prices and pertinent elements can be accurately inferred with the use of front-door and backdoor modifications [23].
- The GRU model incorporates a sliding window method to provide accurate closing price prediction, using the computational power of deep learning networks and mitigating the shortcomings of the Granger test [23]. By extending the Granger test's use beyond linear stationary data, GTU's improved capacity makes it easier to directly evaluate causal relationships in non-linear time series data [23].
- Inspired by the POF, a grouped architectural structure is constructed utilising GRUs in conjunction with a sliding window technique to account for confounding factors [23]. Furthermore, a deep learning-based causal inference framework and algorithm are implemented by using the non-linear Granger test to infer the causal links between specific stock closing prices and pertinent components [24].
- Various sets of input data, including individual closing prices, all associated factors, and causative factors, are utilised to forecast stock closing prices in order to further verify the correctness of the inferred causal links [11, 12]. The findings demonstrate that prediction accuracy is much increased when causative factors are included as input variables. These results provide further proof of the suggested algorithm's dependability and efficacy [12].

II. Method

2.1 Causal Diagrams

Judea Pearl developed causal diagrams, which use directed acyclic graphs (DAGs) [12, 13], to illustrate the causal links between variables. By using conditional distributions, causal diagrams may assist remove estimate bias. This method's basic concept is to minimise bias caused by other factors when estimating and testing distributions. Three different paths—cause, backdoor, and front-door paths—arise in causal inference as a result of confounding factors [13, 14]. These three routes are shown in Figure 1. In this case, X stands for the treatment variable, Y for the target variable, and Z for the confounding variable [14].

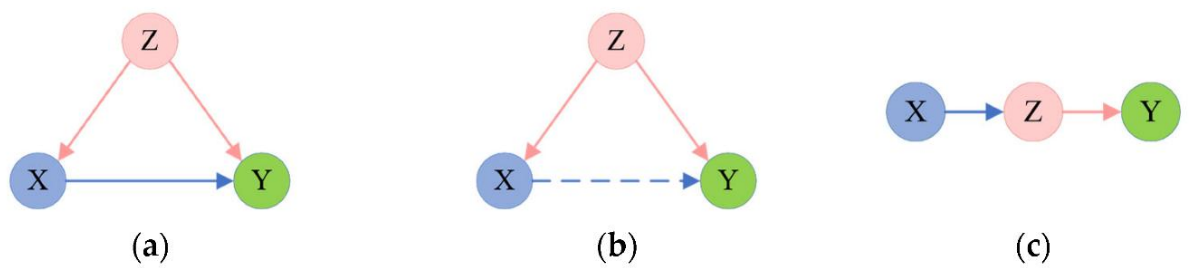

Fig. 1 A causal diagram's paths. (a) Causal path: the treatment variable X and the goal variable Y are directly causally related, however there could be a confounding variable Z. The confounding variable Z influences both the treatment variable X and the target variable Y (not between X → Y, and both). This is known as the backdoor route. (c) Front-door route: X → Y is directly impacted by the confounding variable Z, which also influences the path from X to Y. [15]

2.2 Granger Causality Test

The Granger causality test examines the causal relationship between economic variables using statistical methods [20]. The evaluation of the importance of the corresponding previous period indicators, as represented by the lagged variables of the economic variables, establishes the presence and direction of causal linkages between variables [20, 21].

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \cdots + \alpha_p Y_{t-p} + \beta_p X_{t-p} + \varepsilon_t \text{ ....1}$$

$$H_0 . \beta_1 \beta_2 = \cdots . = \beta_p = 0 \text{ ....2}$$

$$F = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T-2p-1)} \text{ ....3}$$

2.3 Temporal Causal Network

Time-series data includes the closing price of the stock and the variables that affect it. The causal linkages between these temporal data are shown in Figure 1 [20, 21]. In this figure, X_i Refers to the treatment variable, Z_i represents the potential confounding variable, and Y denotes the target variable. The figure's arrows show the way the variables impact one another [22].

2.4 Deep Learning-Based Causal Inference Network Architecture and Algorithms

Figure 2 shows the deep learning-based causal inference architecture [23, 24]. In order to extract feature representations and identify temporal correlations in sequence data, this architecture uses GRU networks [23, 24]. The problems of gradient vanishing, gradients explosion, and long-term dependencies in a conventional RNN are all addressed by LSTM and GRUs. GRUs, on the other hand, have a more condensed structure than LSTM, [24, 25], which speeds up computation and makes them appropriate for handling big datasets. In the meanwhile, GRUs use memory more efficiently, which lessens the strain on computation and storage [25].

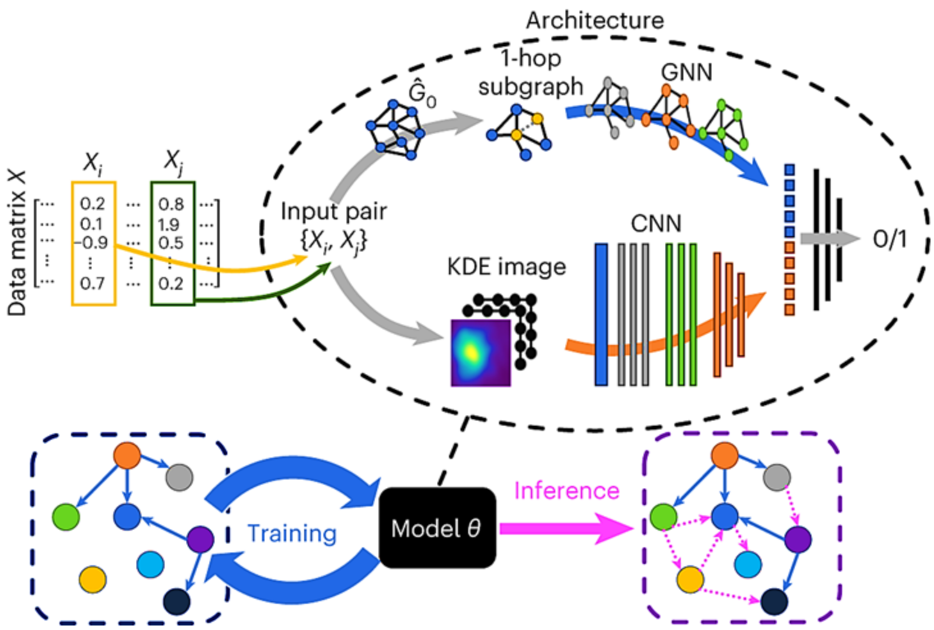

Fig. 2 Deep learning-based network design for causal inference. [22, 23]

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} y_i - y_i'^2} \text{ ....4}$$

$$MAE = \frac{i}{N}\sum_{i=1}^{N} y_i - y_i' \text{ ......5}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} \frac{y_i - y_i}{y_i} \text{ ......6}$$

$$R_2 = \frac{\sum_i^N y_i - y_i^{-2}}{\sum_i^N y_i' - y_t^{-2}} \text{ ....7}$$

III. Result

3.1 Experimental Hardware and Software Environment

The Tensor Flow framework, which is based on Python, was used to construct a deep learning network for the experiment. The graphics card was an Nvidia GeForce GTX1650 with 4 GB of RAM, while the central CPU was an Intel® Core™ i7-9750H [23]. The optimiser Adam's learning rate was set to 0.001, the batch training size was set at 64, [25], and there were 80 training epochs in total. The causal inference studies initialised weights using a fixed seed in order to precisely investigate causation. Data analysis was conducted using Pycharm version 2022 [23].

3.2 Data Pre-processing and Normalization

We verified that there were no missing numbers in the stock data after obtaining it from Bao Stock [25] and, if so, we filled them up using the data from the day before. Equation (8), which is stated as follows, was used to standardise the data format after the processing of the missing values [23, 26]:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \text{ ....8}$$

3.3 Causal Inference Experiment

The dataset has a length of 1215, which is known as sample size T. The lag length p is 5 in the GRU model, which uses a sliding window approach with a window size of 5 [27]. By referring to the F distribution table, the critical value F_a corresponding to the values T = 1124 and p = 5 was determined to be 3.501. The factor passed the Granger test if the computed F value was more than 3.501 [28, 29]. The average of the outcomes from 10 trials was computed to increase the findings' dependability, and it is shown in Table 1 [30, 31] with a 95% confidence interval [31].

Table 1 F-test results for every variable in the Shanghai Stock Exchange datasets (values that pass the Granger test are bolded). [31, 32]

	Sh.059634	**Sh.051952**	**Sh.078491**	**Sh.054986**	**Sh.098658**	**Sh.097849**
Opening Price	9.549	0.059	31.529	36.591	31.659	14.596
Highest Price	9.548	0.541	2.599	5.544	2.536	21.541
Lowest Price	9.658	6.219	2.418	9.541	2.216	2.549
Trading Volume	7.964	2.418	2.549	2.694	2.415	2.059
Trading Amount	9.518	0.548	2.219	2.549	2.965	0.549
Turnover Rate	6.205	2.514	65.259	11.249	2.548	0.649
Percentage change	5.296	2.968	2.148	2.188	2.596	0.514
P/E Ratio	9.658	9.589	2.541	1.287	2.598	5.659
P/B Ratio	2.259	6.489	2.595	2.215	5.968	6.958
P/S Ratio	4.149	5.489	4.149	3.659	41.596	5.489
P/CF Ratio	2.549	6.879	51.259	2.146	2.218	5.519
SHCOMP	6.548	5.418	2.895	5.491	2.696	2.959

IV. Discussion

To ascertain the causality of components in sectors that are both substantially and somewhat impacted by the SHCOMP, the causal inference experiment uses the Granger causality test. The findings indicate that the open price, high price, low price, trading volume, trading amount, turnover rate, percentage change, P/E ratio, P/B ratio, and the associated index itself were all causative elements in highly impacted sectors [33, 34]. The causal association between the closing price and the other elements, with the exception of the associated index, is more substantial in less prominent sectors, according to [35]. These results imply that index components have a greater impact on closing stock prices in highly prominent sectors [36]. In contrast, less significant industries have a stronger causal link between specific stock components.

Using identical input data, the performance of many models was examined, and Table 2 shows the percentage increase in performance of the best model over the others. It is clear from the data in the table that the GRU model performed better in terms of predicted accuracy than the RNN and LSTM models [32, 36]. This result demonstrates that using GRUs to calculate the target variable's potential value is a sensible and suitable decision made by the suggested method and framework.

Table 2 The ideal model's performance increase as a percentage of other models. [33]

Input Variables	**Optimal Models**	**Comparative Models**	**Stock**	**Percentage %**			
				RMSE	**MAE**	**MAPE**	**R2**
Potential Factors	**GRU**	**RNN**	Sh.604955	21.59	21.54	69.59	21.45
			Sh.604959	26.59	63.59	21.54	21.59
			Sh.627496	22.51	32.51	21.49	64.52
			Sh.654985	26.96	65.59	24.99	52.59
			Sh.694189	54.59	26.96	14.59	24.58
			Sh.607496	68.92	54.59	25.99	21.51
		LSTM	Sh.640989	21.51	68.92	25.96	25.99
			Sh.610595	26.96	21.51	64.59	25.96
			Sh.650896	21.59	26.96	25.99	64.59
			Sh.698749	63.69	21.59	25.96	21.54
			Sh.614896	67.96	63.69	64.59	96.89
			Sh.632926	21.59	25.96	21.54	21.54

Casual Factors	**GRU**	**RNN**	Sh.604955	21.59	21.54	96.89	54.29
			Sh.604959	26.59	63.59	21.54	69.59
			Sh.627496	26.96	32.51	54.29	64.52
			Sh.654985	54.59	65.59	69.59	52.59
			Sh.694189	68.92	36.54	64.59	24.58
			Sh.607496	21.51	65.96	21.54	65.59
		LSTM	Sh.640989	26.96	32.59	96.89	26.96
			Sh.610595	21.59	63.59	21.54	54.59
			Sh.650896	63.69	36.96	54.29	21.48
			Sh.698749	63.69	49.59	69.59	52.96
			Sh.614896	67.96	21.54	21.54	21.54
			Sh.632926	21.59	25.96	54.29	21.96

By focussing on the most relevant knowledge as well as reducing the quantity of noisy data the model must process, the application of causal factors enhances the model's predictive capabilities [37, 38]. While the benchmark model with all potential factors input performed worse in terms of prediction accuracy and prediction performance than the model with causal factors inputs, the causal factors concluded by the method provided in this paper as inputs to the closing price prediction GRU model performed better than the models using closing price as inputs [39, 40]. These findings strengthen the validity and dependability of the approach suggested in this work and further test the causal inference of correctness.

V. Conclusion

The Granger causality test and the GRU model were used in this study's causal inference approach to achieve the causality analysis based on stock data. We might identify significant components and ascertain the extent to which index factors impact the closing prices of individual stocks by implementing Granger causality tests. The accuracy of causal inference was further confirmed by the experimental outcomes of adding causal components to the prediction model.

In conclusion, the algorithms and deep learning-based causal inference architecture presented in this work provide encouraging outcomes when it comes to understanding causal linkages in stock data. The use of causal inference techniques in the examination of more financial time series data may be investigated in future studies. The use of causal inference techniques in the study of other financial time series data may be further investigated in future studies. Furthermore, further model performance optimisation and application scope expansion are possible.

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