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Research Trend of Causal Machine Learning Method: A Literature Review

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***Abstract*— Machine learning is commonly used to predict and implement pattern recognition and the relationship between variables. Causal machine learning combines approaches for analyzing the causal impact of intervention on the result, asumming a considerably ambigous variables. The combination technique of causality and machine learning is adequate for predicting and understanding the cause and effect of the results. The aim of this study is a systematic review to identify which causal machine learning approaches are generally used. This paper focuses on what data characteristics are applied to causal machine learning research and how to assess the output of algorithms used in the context of causal machine learning research. The review paper analyzes 20 papers with various approaches. This study categorizes data characteristics based on the type of data, attribute value, and the data dimension. The Bayesian Network (BN) commonly used in the context of causality. Meanwhile, the propensity score is the most extensively used in causality research. The variable value will affect algorithm performance. This review can be as a guide in the selection of a causal machine learning system.**

Keywords*— *causal inference, machine learning, causal machine learning,

1 INTRODUCTION

The development of causal machine learning has grown significantly in recent years. Causal machine learning combines approaches for analyzing the causative effect of treatment on the outcome considering a feasibly ambiguous variables (average treatment effect estimation) as well as techniques for grouping a sample within a population based on the sufficient effect of applying intervention rather than not utilizing it with relation to the results [1]. Most of the machine learning algorithms concern with the accuracy of predictions, but interpretability is not considered. The development of causal machine learning continues to be researched because of the primary factor.

A method is needed to extract the relationship between events based on the events' causal pattern [2]. Inference methods are applied to control the effect of a given treatment. Casual modeling can analyze and find a causal relationship between an event's treatment and outcome [3]. Interpretability is the understanding that humans can recognize the symptoms of strategic analysis, can persistently estimate the modeling approach, part of the rationalization, as the ability of human beings to realize in an understandable way [4]. Meanwhile, machine learning can solve two aspects of a problem with its algorithmic capabilities based on complex problems and adaptability [5].

A causal interpretation model is indispensable because the objective functions of machine learning models capture only correlations and not real causes. This model also can cause considerable decision-making difficulties, such as strategy [4]. Pearl [6] introduced different levels of interpretability and acknowledged that creating counter-actual hypotheses is the method to accomplish the highest level of interpretability. These are the levels of interpretability described by Pearl [6] and their concepts.

- Statistical (associational) interpretability: aims to discover statistical associations by providing feedback such as "How would x change my assumption in y? "
- Causal interventional interpretability: it is expected at "what if" questions.
- Counterfactual interpretability: it is the correct quality of interpretability that try to examine "why" questions.

Causal machine learning research has at least three procedures for implementing the experimental model. First, the relationships between variables are measured using an estimator variable by regression calculation. Furthermore, the relationships between the formed connection are evaluated using the machine learning model [1]. The combination technique of causality and machine learning is appropriate for predicting and understanding cause and effect from a result. The combination makes a causal machine learning model stronger, more precise, reduces bias, and reliable [7].

This paper leads to work that encourages machine learning researchers and practitioners to elaborate further study and development for causality. This paper's contributions focus on the causal machine learning model. The methodology includes the development algorithm, data characteristics, and performance measurement.

In the next section, this paper is prepared using Kitchenham's systematic literature review guide. Section 2 explains how systematic literature techniques are applied. Section 3 discusses the results and discussion. The last section, section 4, provides a conclusion.

2 METHOD

A systematic review of literature is a way to introduce and analyze the most relevant research required with a specific research question, a subject area, or a specific trend. The method used in this paper refers to Kitchenham's guide [8].

This paper aims to identify and elaborate on the latest research on developing a causal machine learning model. This literature review will not discuss the complexities of the model for developing these causal machine learning algorithms.

2.1 Identify The SLR Proces Flow

Based on Fig. 1, the review literature process flow is divided into three parts. The initial section is the planning section, where we identify the need for review article. We developed a research approach to constrain the context by identifying research questions, publication references, search techniques, evaluation process, techniques of retrieval of material, and analysis methods.

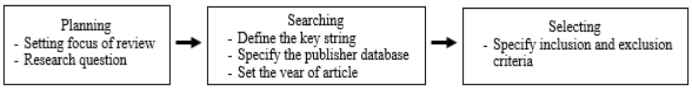

Figure 1. SLR Process Flow

2.2 Setting The Focus Of The Review

The extremely important element in a systematic literature review is the research question. The research questions regulate the investigation scope and the limitation criteria for the study. This paper review was assigned to answer the research questions in table 1.

TABLE 1: RESEARCH QUESTION

ID	Research Question	Objective
RQ1	What are the causal machine learning methods used?	Identify causal machine learning methods that are widely used or developed in causal research
RQ2	What are the data characteristics used?	Identify the characteristics of the data used in causal machine learning research, including the type of dataset, attribute value, and data dimension
RQ3	How does to measure the performance of the causal machine learning model?	Identify performance measures are applied in the causal machine learning algorithms

2.3 Searching Literature Database

We conducted a database search for literature reviews using the keywords "causal" and "machine learning."

We use three large databases, namely, IEEE, Science Direct, and Google Scholar. The use of different databases is intended to enhance literature sources. A more extensive database can be implemented as a comprehensive analysis. The database search was carried out manually on papers published from 2016 to 2020. We set the last five years as the paper's timeframe to be published, so the research trend for causal algorithms for machine learning is noticeable for further exploration.

2.4 Selecting Primary Studies

The main articles were selected using inclusion and exclusion criteria. The article proposes models for causality and machine learning research. The exclusion criteria for this study were as follows:

1. Paper with incomplete data information.

   The data information includes machine learning methods, data characteristics, measurement performance. Because of the focus of the researcher, papers with incomplete data information will not be used.

2. Review or survey paper.

   Researchers need to analyze a causal machine learning method from the research question. However, a review paper is used as part of the introduction to causal machine learning and the fundamental for the development of this paper.

3 RESULT AND DISCUSSION

This study's searching process results were carried out in IEEE, Science Direct, and Google Scholar databases from 2016 to 2020. The number of papers from the search results, screening results, and manual selection processes is selected 20 papers. For the relevant technical paper of this research, 70% of reference papers came from journal papers, and the rest came from proceeding papers. The conference paper used as a literature describes a feasibility that is commonly associated to causal machine learning. In addition, the type of data source used in the conference papers for causal search is an event log.

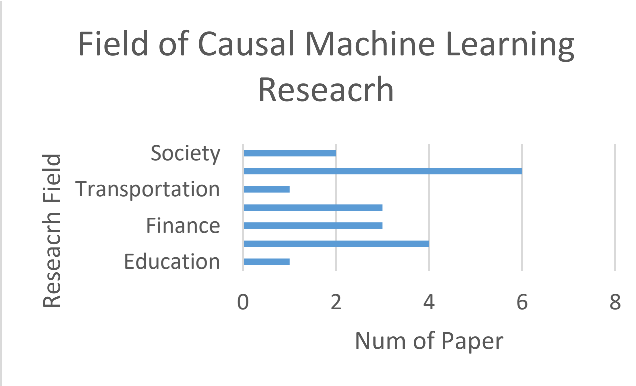

Figure 2. Field of Causal Machine Learning Research

Of the papers listed, causal machine learning applies in various fields. The health sector is generally involved in the development of this topic. Insignificant areas related to human life, such as the medical field, decision-making have been used as a reference. In decision making, humans have been making final decisions for the short term. In making decisions, it is essential to know why these decisions were made [9].

The aim of the causal machine learning algorithm is to recognize the linkage of the relation variables in the model. The variation between non-causal ML and causal ML is the integration of techniques and condition assessment for analysis of the effect among variable. The method commonly used in causal ml utilizes correlation to measure the importance of the relationship established and several metrics commonly being used causal inference work.

3.1 RQ1: What are the causal machine learning methods used?

Various models have been proposed in causal machine learning research to increase causality and make it more reliable. The reviewed papers' research results show that traditional machine learning methods were developed to understand the causal relationship between data, events, and time. Table 2 and Fig. 2 represent causal machine learning method based on how it works.

Table 2. The task of Causal Machine Learning

The Task of Causal Machine Learning Model	Paper Reference
Classification	Random Forest [3], [10], [11], XGBoost [9], Bayesian Network [12], [13], Support Vector Machine [2], [14]–[16], Optimal Discriminant Analysis (ODA) [17].
Clustering	K-Means clustering [18]
Regression	Logitic Regression [10], Linear Regression [9], [13], [19], Support Vector Regression [15], Ordinary Least Square [18], Lagrangian [3], Markov [1], [11], [12], [14], [17], [20]–[23],

Machine learning techniques have been used in classification, clustering, and regression. The difference between classification and clustering relates to their classifier and type of data. The task of clustering is grouping objects into several groups based on the similarities between each object. On the other side, regression is similar to classification. It requires labeled training data.

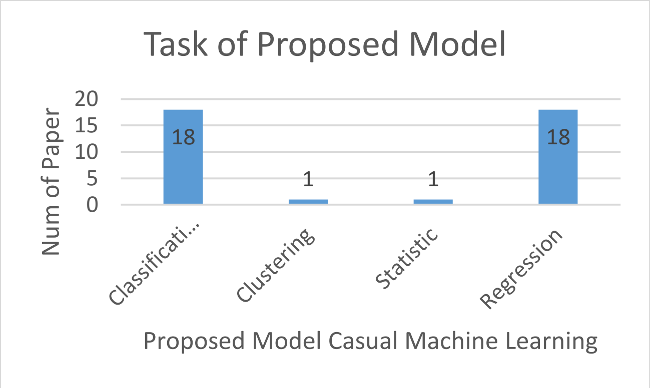

Figure 3. Task Models in Machine Learning

In the classification algorithm, the data used are in the type of data with a group or class label. So the final model was built begins from the previous data training model. Whereas with clustering techniques, data is grouped based on the similarity distance between an object and another object. There are 18 papers using the classification technique. The classification method most commonly used is based on a tree. The classification method most commonly used is based on a tree. This process utilizes a tree-structured framework in which each internal node evaluates whether an attribute requirement is met or not, while the final prediction is shown by leaf node (class label). A decision concludes an instance's label by initiating at the root and navigating the path until a leaf node is reached, which can be interpreted as if then rule[4].

The classification algorithms used in the literature read are Random Forest [3], [10], [11], XGBoost [9], *Bayesian Network* [12], [13], *Support Vector Machine* [2], [14]–[16], and *Optimal Discriminant Analysis* (ODA) [17]. Bayesian network and its development is the most frequently used model. One of the reasons is adopting the inference algorithm and the probability distribution value of the Bayesian Network conditions from the data collected. Bayesian Network finds the causal orientation related to the differentiated target variables' direct causes and effects [13], [20].

Apart from Bayesian networks, the random forest is also widely used in some causal machine learning research. The development of random forest (causal forest) when applied to the problem of prediction, the performance is generally impressive [24]. The causal forest takes a modified approach and focuses on the difference in mean yield between treated observations in each tree leaf. The causal forest is a non-parametric predictor in achieving consistency and probabilistic integration, a required distribution [10].

Meanwhile, Jansen *et al.* performed clustering using the development of the k-means clustering model. Clustering is applied to capture the movement of the data in a complex output model. Therefore, it is valuable to exchange information in groups of more linear actions and viable. The results of this cluster are influential on the implementation of the development executed by researchers using the AbACaD methodology [18].

Mostly classification or clustering technique is associated also with regression method in the causal machine learning model. This is designed to examine how far causal relationship between variables. Regression model design the linear relationship between dependent variable and the set of independent variable (features). The intensity of each feature represents the average adjustment in the estimate by measurements from one variable element. The features with more value would have more impact on the final effect [4].

3.2 RQ2: What is the data characteristic used?

This paper's data characteristics were analyzed based on three criteria, namely the type of data, the type of attribute value, and the number of datasets used. Fig. 3 shows a comparison of the use of datasets in the development of causal machine learning. Fifteen papers are using public datasets. The result indicates that causal machine learning development is fully open with prominent datasets. Data is the primary raw material for research to apply and develop algorithms. The better and easier data can be obtained, the smooth running of the algorithm development.

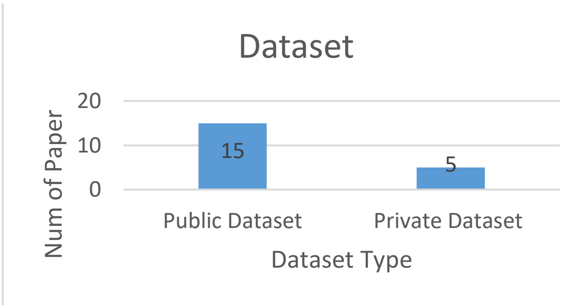

Figure 4. Dataset Category in Literature Reference

Data types are divided into static and dynamic data. Static data does not modify when processing, e.g., variable values in terms of identities. Furthermore, dynamic data refers to data changes during processing; the data changes based on the actual operation. Fig. 4, out of eleven articles using a dynamic dataset. An example of a dynamic set is a log activity. The event log will provide a record of the events that affect the process. The event log currently contains the event name, activity name, timestamp, and resources associated with the related activity.

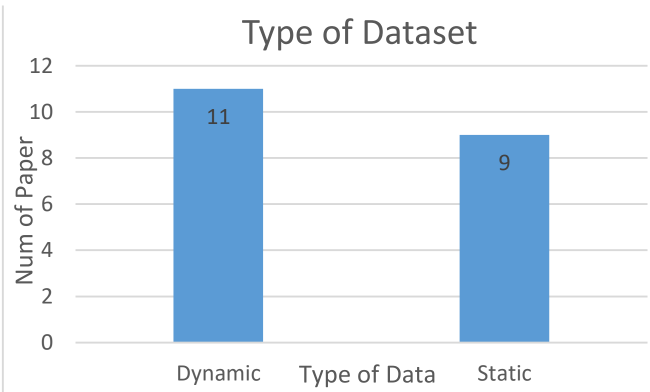

Figure 5. Type of Dataset in Literature Reference

Measurement can assume effect at varying levels, and the relationship among the assigned values represents the value of calculation. Four hierarchical levels of measurement identified are nominal, ordinal, interval, and the ratio [25]. Nominal - attribute whose value is in the form of a symbol, the value itself only functions as a label. Ordinal - variables whose values are symbols but can be sorted, cannot be measured by distances. Interval - a variable whose values can be ordered and measured in the same constant. Ratio – a variable with zero value and is treated as a real number with all of the mathematical operations.

Data dimensions in the dataset affect the performance of the causal machine learning model, both in terms of processing speed and accuracy of the method used. In Fig. 5, 16 papers are using one dataset. The rest used two or more datasets. Most researchers who use n-tiple datasets try to implement causal machine learning in various fields.

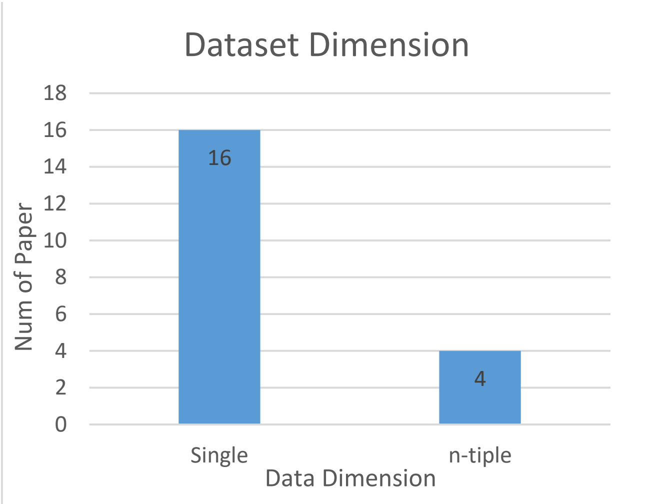

Figure 6. Dataset Dimension

Analysis of data characteristics is vital before developing causal relationships between variables in machine learning algorithms. Unfortunately, not all papers provide an in-depth analysis of the characteristics of the data.

3.3 RQ3: How does to measure the performance of a causal machine learning model?

The challenge in causal inference research is challenging to validate because possible results from counterfactual predictions will never be known. The causal model evaluation depends on what machine learning is being used. A causality prediction model must be able to efficiently and effectively to screen for potential independent variables. Moreover, the model must identify the most reliable and informative relationships and interactions.

The first point in the causal machine learning process is to define an estimator variable when capable of measuring the event relationships. There are not many articles detailing the explanations for taking a specific measure of performance. Causal machine learning research that applies intervention events to certain variables uses the Average Treatment Effect (ATE) and Conditional Average Treatment (CATE). The most broadly used estimator measure in the causal area is the propensity score.

A propensity score is almost used in this literature papers. A propensity score is a probability based on the relationship that occurs if it is formed. The propensity score method balances the covariates between the evaluated group and the control group using weighting. Then the trend fit estimator predicts the missing counterfactual for each actual observation [24]. Machine learning methods automatically estimate the results of the propensity score model [10].

Another performance measurement can be categorized into separate, either in terms of efficiency and effectiveness. Defining the efficiency of the model used is seen in how fast technology has completed mapping. We usually call as running time. Running time is used in papers [14], [15], [20]. The evaluation method referred to in this paper, is categorized in the context of the algorithm used.

Performance measurement uses accuracy in classification methods that are confusion matrix [2], [13], accuracy [15], [20], recall, precision and F1-measure [2], [14], ROC/AUC [9], [21], standard deviation [10], [11], [16], [19], [26]. Standard deviation is the narrowest measure of variability and is determined in cases involving outliers. Standard deviation can be interpreted as the typical distance between value and mean of a field, and the most current value would be within two means [27]. Several studies measure algorithm performance using error rate measurement [10], [17], [23], threshold [15], [18] and cross-validation [9], [12]. The k-fold cross-validation process determines a hyperparameter optimum solution and parameters for the machine learning algorithm [12]. Hyperparameter and parameter set to minimize errors in cross-validation [24].

TABLE 3: DESCRIPTION OF SELECTED STUDIES

	Title	Year	Ref.	Characteristic Dataset	Machine Learning Method	Performance Measurement
1	Random Forests Approach for Causal Inference with Clustered Observational	2020	[10]	Public Dataset	Causal Forest	Propensity Score, Standard Deviation, Mean Squared Error
2	Using Feature Selection for Local Causal Structure Learning	2020	[20]	Public Dataset	Markov Based	Precision, Recall
3	Markov Boundary Learning With Streaming Data for Supervised Classification Markov Boundary Learning With Streaming Data for Supervised Classification	2020	[14]	Public Dataset	SDMB and the combination method using KNN, NB, SVM	Precision, Recall, F1
4	Process Mining Meets Causal Machine Learning: Discovering Causal Rules from event logs	2020	[1]	Public Dataset	Uplift Modelling	Not Provide Validation
5	Modeling and learning cause-effect application in frost forecast	2020	[15]	Public Dataset	Support Vector Machine	Recall, Precision
6	Haze Pollution causality mining and prediction based on multi-dimensional time series with PS-FCM	2020	[21]	Public Dataset	Fuzzy Cognitive Maps	RMSE
7	Learning Causal Effect Using Machine Learning with Application to China's Typhoon	2020	[19]	Public Dataset	Logistic Regression, CART Tree, Random Forests, Support Vector Machine, Generalized Boosted Model	Propensity Score
8	Using causal discovery to analyze emergence in agent-based model	2019	[18]	Private Dataset	KNN	Spearman Correlation
9	Improve user retention with causal learning	2019	[3]	Private Dataset	Causal Forest, Lasso Regression	AAUC Using A/B Testing
10	Direct Causal Structure Extraction From Pairwise interaction patterns in NAT modeling Bayesian Networks	2019	[26]	Public Dataset	Bayesian Network	Propensity Score and Running Time
11	Causality measures and analysis: A rough set framework	2019	[28]	Public Dataset	Rough Set	Propensity Score
12	Causal Inference in Time Series via Supervised Learning	2018	[11]	Public Dataset	Granger Based	RCC
13	Interpretable Machine Learning Techniques for Causal Inference Using Balancing Scores As Meta-features	2018	[9]	Public Dataset	XGBoost	Cross-Validation 10 Fold, AUC
14	Challenges of Automated Machine Learning on Causal Impact Analytics for Policy Evaluation	2017	[12]	Public Dataset	Bayesian Network-Based	Hyperparameter Tuning
15	Causal data science for financial stress testing	2017	[13]	Public Dataset	Bayesian Network-Based	False Positive, False Negative

16	Dynamic causal modeling and machine learning for effective connectivity in auditory hallucination	2017	[16]	Public Dataset	Support Vector Machine	Standard Deviation
17	The causal effects of survivors' benefits on health status and poverty of widows in Turkey: evidence from Bayesian networks	2017	[22]	Public Dataset	Bayesian Network	Propensity Score
18	Capturing cognitive causal paths in human reliability analysis with Bayesian Network Models	2017	[23]	Private Dataset	Bayesian Network	Propensity Score
19	Causality patterns and machine learning for the extraction of problem action relations in discharge summaries	2016	[2]	Private Dataset	Support Vector Machine	Recall, Precision, F1
20	Combining machine learning and matching techniques to improve causal inference in program evaluation	2016	[17]	Private Dataset	Optimal Discriminant Analysis	Propensity Score

4 CONCLUSION

Currently, causal machine learning research is growing. Casual modeling can analyze and find a causal relationship between treatment and outcome in an event. In this review paper, 20 papers with various methods, fields of application, and types of data are studied. Bayesian Network (BN) are machine learning methods. BN is widely applied in the causality scope because this algorithm can adopt an inference and a network condition probability table from the data. BN also find the causal orientation related to the significant cause and effect of the specified control variables.

Meanwhile, the propensity score is the most frequently used in causality research. The probability value is formed based on the relationship that occurs in events. The machine learning method can automatically estimate the results of the propensity score model in the proposed model. For datasets, many causal machine learning studies use public datasets. A public dataset can be an opportunity for other researches in researching the field of causality using machine learning

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REFERENCES

[1] Zahra. Dasht. Bozorgi, Irene. Teinemaa, Marlon. Dumas, Marcello. La Rosa, and Artem Polyvyanyy, “Process Mining Meets Causal Machine Learning: Discovering Causal Rules from Event Logs,” in *International Conference on Process Mining (ICPM)*, 2020, no. 2, pp. 129–136, doi: 10.1109/icpm49681.2020.00028.

[2] Jae-Wook. Seol, Wangjin Yi, Jinwook. Choi, and Kyung. Soon. Lee, “Causality patterns and machine learning for the extraction of problem-action relations in discharge summaries,” *Int. J. Med. Inform.*, vol. 98, pp. 1–12, 2017, doi: 10.1016/j.ijmedinf.2016.10.021.

[3] Shuyang. Du , *James Lee, and Farzin Ghaffarizadeh*, “Improve User Retention with Causal Learning,” in *Proceedings of Machine Learning Research*, 2019, vol. 104, pp. 1–16, [Online]. Available: http://proceedings.mlr.press/v104/du19a/du19a.pdf.

[4] R. Moraffah, M. Karami, R. Guo, A. Raglin, and H. Liu, “Causal interpretability for machine learning - Problems, methods and evaluation,” *ACM SIKDD Explorations Newsletter*, vol. 22, no. 1, 2020.

[5] S. Shalev-Shwartz and S. Ben-David, *Understanding machine learning: From theory to algorithms*, 1st ed., vol. 9781107057. New York: Cambridge University Press, 2014.

[6] J. Pearl, “Theoretical Impediments to Machine Learning With Seven Sparks from the Causal Revolution,” *arXiv*, pp. 1–8, 2018, doi: 10.1145/3159652.3176182.

[7] B. Schölkopf, “Causality for Machine Learning,” pp. 1–20, 2019.

[8] B. Kitchenham, “Procedures for Performing Systematic Reviews,” 2004.

[9] Y. Nohara, K. Iihara, and N. Nakashima, “Interpretable Machine Learning Techniques for Causal Inference Using Balancing Scores as Meta-features,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2018, vol. 2018-July, pp. 4042–4045, doi:

10.1109/EMBC.2018.8513026.

[10] Y. Suk, H. Kang, and J. S. Kim, “Random Forests Approach for Causal Inference with Clustered Observational Data,” *Multivariate Behav. Res.*, vol. 0, no. 0, pp. 1–24, 2020, doi: 10.1080/00273171.2020.1808437.

[11] Y. Chikahara and A. Fujino, “Causal inference in time series via supervised learning,” in *International Joint Conference on Artificial Intelligence (IJCAI)*, 2018, vol. 27, pp. 2042–2048, doi: 10.24963/ijcai.2018/282.

[12] Y. J. Hu and S. W. Huang, “Challenges of automated machine learning on causal impact analytics for policy evaluation,” in *2nd International Conference on Telecommunication and Networks, TEL-NET 2017*, 2017, pp. 1–6, doi: 10.1109/TEL-NET.2017.8343571.

[13] G. Gao, B. Mishra, and D. Ramazzotti, “Causal data science for financial stress testing,” *J. Comput. Sci.*, vol. 26, pp. 294–304, 2018, doi: 10.1016/j.jocs.2018.04.003.

[14] C. Liu, S. Yang, and K. Yu, “Markov Boundary Learning with Streaming Data for Supervised Classification,” *IEEE Access*, vol. 8, pp. 102222–102234, 2020, doi: 10.1109/ACCESS.2020.2998482.

[15] L. Ding, K. Noborio, and K. Shibuya, “Modelling and learning cause-effect — application in frost forecast,” *Procedia Comput. Sci.*, vol. 176, pp. 2264–2273, 2020, doi: 10.1016/j.procs.2020.09.285.

[16] M. Graña, L. Ozaeta, and D. Chyzhyk, “Dynamic Causal Modeling and machine learning for effective connectivity in Auditory Hallucination,” *Neurocomputing*, vol. 326–327, pp. 61–68, 2019, doi: 10.1016/j.neucom.2016.08.157.

[17] A. Linden and P. R. Yarnold, “Combining machine learning and matching techniques to improve causal inference in program evaluation,” *J. Eval. Clin. Pract.*, vol. 22, no. 6, pp. 864–870, 2016, doi: 10.1111/jep.12592.

[18] S. Janssen, A. Sharpanskykh, R. Curran, and K. Langendoen, “Using causal discovery to analyze emergence in agent-based models,” *Simul. Model. Pract. Theory*, vol. 96, no. May, p. 101940, 2019, doi: 10.1016/j.simpat.2019.101940.

[19] P. Wu, Q. rui Hu, X. wei Tong, and M. Wu, “Learning Causal Effect Using Machine Learning with Application to China’s Typhoon,” *Acta Math. Appl. Sin.*, vol. 36, no. 3, pp. 702–713, 2020, doi: 10.1007/s10255-020-0960-1.

[20] Z. Ling, K. Yu, H. Wang, L. Li, and X. Wu, “Using Feature Selection for Local Causal Structure Learning,” *IEEE Trans. Emerg. Top. Comput. Intell.*, pp. 1–11, 2020.

[21] Z. Peng, W. Liu, and S. An, “Haze pollution causality mining and prediction based on multi-dimensional time series with PS-FCM,” *Inf. Sci. (Ny).*, vol. 523, pp. 307–317, 2020, doi: 10.1016/j.ins.2020.03.012.

[22] O. Ozdamar and E. Giovanis, “The causal effects of survivors’ benefits on health status and poverty of widows in Turkey: Evidence from Bayesian Networks,” *Econ. Anal. Policy*, vol. 53, pp. 46–61, 2017, doi: 10.1016/j.eap.2016.11.001.

[23] K. Zwirglmaier, D. Straub, and K. M. Groth, “Capturing cognitive causal paths in human reliability analysis with Bayesian network models,” *Reliab. Eng. Syst. Saf.*, vol. 158, no. January 2016, pp. 117–129, 2017, doi: 10.1016/j.ress.2016.10.010.

[24] A. Tiffin, “Machine Learning and Causality: The Impact of Financial Crises on Growth,” 2019. doi: 10.5089/9781513518305.001.

[25] N. L. Matthews, “Level of Measurement,” *Int. Encycl. Commun. Res. Methods*, 2017, doi: 10.1002/9781118901731.

[26] Y. Xiang, “Direct causal structure extraction from pairwise interaction patterns in NAT modeling Bayesian networks,” *Int. J. Approx. Reason.*, vol. 105, pp. 175–193, 2019, doi: 10.1016/j.ijar.2018.11.016.

[27] D. T. Larose and C. D. Larose, *Discovering Knowledge in Data: An Introduction to Data Mining: Second Edition*, vol. 9780470908. 2005.

[28] N. Yao, D. Miao, W. Pedrycz, H. Zhang, and Z. Zhang, “Causality measures and analysis: A rough set framework,” *Expert Syst. Appl.*, vol. 136, pp. 187–200, 2019, doi: 10.1016/j.eswa.2019.06.004.