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Intelligent structuration: Machine learning forecasting

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Abstract

Artificial Intelligence and machine learning have contributed to today's business domain in areas including operational efficiency, smart decision making in cost savings, revenue maximization and customer satisfaction. However, there are missing links when machine learning algorithms are adopted in business environments. There is no rigorous and systematic explanation on data manipulation and machine learning algorithm selection processes. This research adopts the social construction perspective where the process of structuration is in the reciprocal interactions of data and algorithms using Structuration Theory. Intelligent Structuration for machine learning forecasting is proposed where three layers of structures – inference layer for signifying data, reference layer for dominating algorithms, and meta layer for legitimating insights - interact. The suggested intelligent structuration is demonstrated with hotel rate predictions. The empirical results indicate that the machine learning blending in the meta layer can significantly improve the prediction accuracy.

Keywords: structuration, artificial intelligence, machine learning, forecasting, neural network, support vector machine, nearest neighbor, regression

Introduction

Modern computing has advanced with faster processing, larger data storage, massive data transfer and even interoperability among all smart devices. This phenomenon leads to a data explosion today where we have more data than we can analyze. Big data analytical platforms such as Hadoop and Spark have enabled the utilization of data sitting in organizations (Reece and Hong, 2021). The best scenario is that commodity computing contributes to this bigger scheme of data analytics. Artificial Intelligence (AI), on the other hand, may become a perfect solution for the majority of use cases in data analytics, giving the power of predictability from the abundant data. We can claim that descriptive analytics using statistical power has been shifted into predictive analytics with more adaptive machine learning algorithms.

Machine learning plays a key role with big data today in business use cases (Christozov and Mitreva, 2020) while AI has been revived and regained its fame from the 1950's in various fields. As the name implies, machine learning involves the ability to automate analytical model building (Gulcu and Sanli 2017). However, there are missing links when we adopt machine learning algorithms in business environments. The limitations come from the fact that machine learning algorithms are limited to narrow scopes of its data in specific business cases. How we adopt a specific machine learning algorithm is often very subject to human analysis and it requires iterative manual pilot tests. Also, there are many grey areas where human analysts opt to manipulate parameters of algorithms to get better insights. The whole process is not very scientific as data must be manipulated while we are anticipating a rigorous and systematic explanation

(Canonico et al., 2018). This discrepancy stems from the lack of understanding where the social construction nature of human knowledge grows gradually in interactions with environmental variables (Giddens 1984). Unless you are a computer scientist who is making machine learning algorithms more effective or efficient, business use cases are required to build agile application development. This entails adopting and applying machine learning algorithms from public programming libraries such as scikit learn and tensorflow in Python examples. Relying on machine learning algorithms, however, is the optimal solution for organizations, because they are often guaranteed opportunities to crunch the vast data they have collected. The data is turned insightful which enhances business operations in cost savings, revenue maximization, improved customer satisfaction, and so on.

Social Structuration in Machine Learning

Social construction has been heavily investigated and has established profound traditions. The process of structuration in societal settings is the *reciprocal interaction of human players and institutional properties of organizations* (Giddens 1984; Orlikowski 1993; Orlikowski and Robey1991). The theory of structuration recognizes that human actions are enabled and constrained by structures, yet these structures are the result of previous actions (Orlikowski 1993; Orlikowski and Robey1991). Though run by machines in AI applications, social structuration in machine learning business use cases adopt the structuration process: *the reciprocal interactions of data and algorithms*. This research is theorizing possible structuration on data (human players) and machine learning algorithms (institutional properties) (Carroll and Swatman 2000; Glaser and Strauss 1967; Miles and Huberman 1984; Strauss and Corbin 1998).

Machine learning algorithms are purely logical ways of thinking, providing institutional properties, which have been built by numerous scientists and developers. Choosing a right algorithm is crucial in machine learning applications as it is often apparent that one algorithm is dominating other similar algorithms when applied to the same dataset. Yet, there are various informal ways of applying algorithms to data sources. Each analyst is trained to create their own methods to interpret, clean and manipulate data sources to fit into machine learning algorithms. In other words, this informal process of *signification of data interpretation* is key to successful machine learning projects (Giddens 1984). As a result, multiple views of data interpretation are created and the best scenario on *dominating algorithms* is elected (Giddens 1984). Therefore, *legitimating machine learning* is gradually constructed by inter-reciprocal refinement between the data and machine learning algorithm in an iterative manner (Giddens 1984). **Intelligent Structuration**, hence, is proposed where business insights are constructed by the structuration process of legitimating business activities influenced by significating data manipulation and choosing dominating machine learning algorithms.

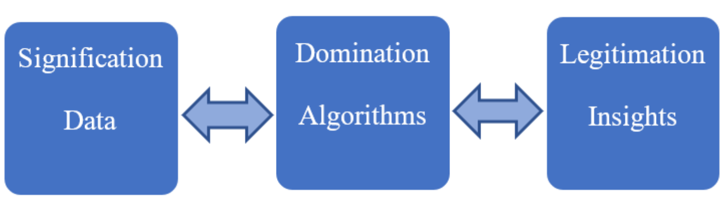

Figure 1: Intelligent Structuration

Intelligent Structuration in Machine Learning Forecasting

Inspired by the social structuration theory, we propose intelligent structuration for machine learning forecasting. This structuration is implemented through three layers – (1) Inference layer for signifying data, (2) Reference layer for dominating algorithms, and (3) Meta layer for legitimating insights.

Inference Layer - Signification of Data

Data plays a central role in any machine learning model development. Data needs to be retrieved, cleaned, and often manipulated before it is fed into machine learning models. As the quality and the choice of data determine the performance of machine learning forecasting, the traditional machine learning forecasting process requires substantial human involvement and manual programming especially for parameter selection. The focus on selecting potential relevant parameters is, in part, due to the fact that a single best model will be chosen and applied to the data to get final forecasts. In the inference layer, multiple models of different approaches and parameters are considered and forecast values from those multiple models are combined to create the final forecast later in the meta layer. As the final forecasts are based on various models, they are relatively more robust to the choice of features. Hence, by allowing almost all potential features into the inference layer, human intervention for parameter selection can be minimized.

Reference Layer - Selecting Dominating Algorithms

Various supervised machine learning models including neural network, support vector machine, nearest neighbor, and regression and its variants are used for forecasting. Different machine learning models may have different behaviors and characteristics. Some models may produce more stable and conservative forecasts. Other models may be more responsive to recent trends and offer more aggressive forecasts. On the other hand, some models may tend to overforecast, producing the forecast greater than the actual while others may tend to underforecast, offering the forecast smaller than the actual. Traditional forecasting process requires selecting a single best model out of multiple models with different performance and characteristics in the hope that the patterns and behaviors of the selected model will repeat in the future data. However, the behavior of actual data is often more complicated than what a single model can handle. In reference layer, we suggest that multiple dominating algorithms can be selected and fed into the next layer in the intelligent structuration. By developing multiple dominating models of different characteristics and approaches, we may not only reduce human modeler's intervention for selecting and tuning a single best model but also improve forecasting accuracy through the next step – the meta layer.

Meta Layer - Legitimating Insights

The meta layer of the intelligent structuration forecasting framework uses machine learning algorithms to combine multiple forecasts generated in the reference layer. The basic idea of blending forecasts has been adopted by previous research including (Gavahi et al., 2021; Lee et al., 2020; Nasios and Vogklis, 2022; Rajopadhye et al., 2001; Tang et al., 2019; Zhang et al.,2021). Early studies on combined models use either regression or a weighted average of two or more forecasts that are computed from different models, typically traditional time-series and/or domain-specific models (Rajopadhye et al., 2001). Recent studies such as (Gavahi et al., 2021; Lee et al., 2020; Nasios and Vogklis, 2022; Tang et al., 2019; Zhang et al.,2021) blend forecasts obtained from more advanced machine learning approaches. However, most of the blending structures are either simple ensemble approach (Nasios and Vogklis, 2022) or serial combining of sequentially divided models (Gavahi et al., 2021; Zhang et al.,2021). Work by (Lee et al., 2020) and (Tang et al., 2019) suggest neural network models for combining multiple forecasting approaches, but the blending structure is limited to a specific neural network model for blending two pre-developed models.

In this research, we suggest more general machine-learning layers (meta layer) for legitimating the dominating models obtained from the reference layer. Using machine-learning blending, we re-train the multiple dominating models of different characteristics and approaches selected in the reference layer. Through the meta layer, we can recreate new types of models that can handle more complex shapes and characteristics. Figure 2 illustrates how a machine-learning blended model can better fit the actual data. Model 1 and Model 2 in Figure 2 show very different patterns and behavior. Model 1 overestimates the upward trend while Model 2 overly projects the downward trend. By combining these two different forecasts, we may create more realistic forecasts as illustrated in the left side of Figure 2. In this example, a blended model does not simply choose the better forecast from two individual models. Machine learning blending restructures characteristics of individual models to better fit data.

An important issue regarding blending is which machine learning algorithm should be used for blending forecasts. Theoretically any supervised learning algorithm such as neural network, genetic algorithms, support vector machine, and regression can be adopted in the meta layer. On the one hand, the performance of final forecasts may depend on the choice of the machine learning algorithm that is used for blending. Machine learning models capable of capturing complicated relationships such as neural network may be more suitable for blending various shapes of forecasts. For example, linear regression is one of widely used supervised learning algorithms and offers a convenient way for forecasting and blending. However, if the actual data shows complex patterns, linear regression blending may not offer flexible modeling capability enough to combine various patterns of forecasts.

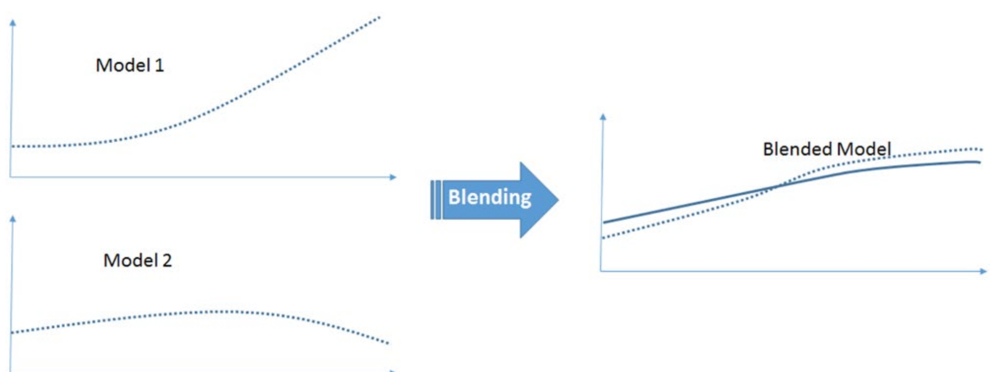

Figure 2: Illustration of a Blended Model - Meta Layer

Empirical Results – Application to Hotel Rate Prediction

We further discuss and demonstrate the intelligent structuration by applying the suggested framework to hotel rate prediction. When purchasing a perishable product with dynamic pricing such as airline tickets and hotel rooms, consumers consider whether the price will drop in the future. In formal terms, consumers face an optimal stopping problem: when to buy. Under price volatility and uncertainty, minimum price forecasts for the remaining days in the booking horizon are useful information for customers. Online services and OTAs (Online Travel Agencies) such as Google Flights provide price forecasts to help consumers' decisions for purchase timing. This case study shows how intelligent structuration can be implemented for forecasting by providing three layers; inference, reference, and meta layers. Several different forecasting models including traditional time-series models and machine learning models are examined for the reference layer, and neural network blending architecture for the meta layer is developed.

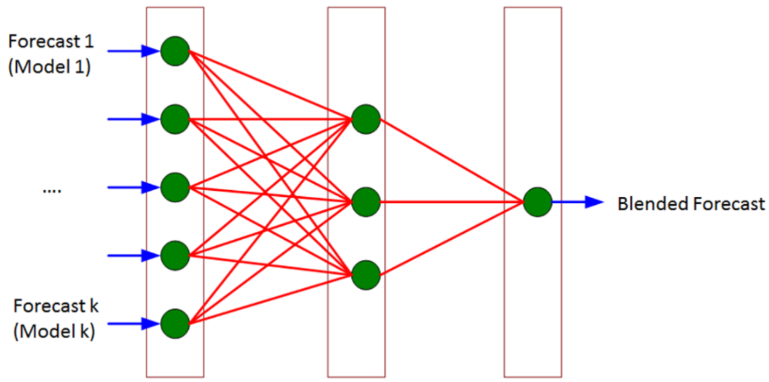

Figure 3: Neural Network Blending Structure

For validation, we have collected daily price data of three hotels covering two years' arrival dates for a booking window of 0-60 days. The last two months' data is reserved for model validation. We trained three individual machine learning models – KNN (k-nearest neighbor), support vector machines, and neural network – in the reference layer. Then, the forecast values obtained from these individual models are fed into the blending model in the meta layer. While any supervised learning algorithm such as genetic algorithm, neural network, and support vector machine can be used for blending, we have used a neural network as a blending structure as illustrated in Figure 3. Offering highly flexible modeling capability, neural network can capture complicated relationships between inputs and output and thus is suitable for combining various forecasts of different shapes and characteristics (Bengio, et al., 2021).

We apply the forecasting models in the reference layer and meta layer to the validation data of daily hotel rates obtained from three hotels. We have considered a booking window of 1-60 days for 60 arrival dates. For each forecasting date (forecasting run) out of 60 forecasting dates, the system generates forecasts of minimum rates for the next 60 days.

To evaluate the forecasting performance, we use Mean Absolute Scaled Error (MASE):

$$MASE = \frac{\sum_t |F_t - A_t|}{\sum_t |F'_t - A_t|}$$

where A_t denotes the actual value for period t, F_t the forecast value, and F_t' the naïve forecast.

MASE is a scale-independent measure and relatively robust to outliers (Hyndman 2006). As indicated in the equation, MASE is the ratio of the forecast error to the error obtained using a naïve forecasting model. For naïve forecasts, we use the current hotel rate. Intuitively, MASE measures relative improvement of the forecasting model. For example, if MASE is 0.6, the absolute error of the forecasting model is 60% of that of the naïve model, reducing the forecasting error by 40%.

Table 1 presents the average MASE of 60 forecasting runs of machine learning blended models in the meta layer along with individual machine learning models in the reference layer. The empirical result in Table 1 confirms that machine learning blended models in the meta layer significantly improve forecasting accuracy across all three hotels. Moreover, machine learning blending produces robust forecasts. The MASE values of the blended model have smaller variation compared to those of each individual forecasting model. In addition, the performance of the blended forecasts in the meta layer is robust to the performance of individual models that are used for blending. For example, the empirical results in Table 1 show that the support vector machine reports relatively higher error rates compared to other models. However, including the inferior model does not increase the number of errors in the final blended model.

Table 1: Average MASE

Models	Hotel 1	Hotel 2	Hotel 3	Average
Meta Layer (Machine Learning Blended)	**0.072**	**0.125**	**0.089**	**0.095**
Reference Layer – Neural Network	0.124	0.177	0.142	0.148
Reference Layer - KNN	0.121	0.193	0.173	0.162
Reference Layer – Support Vector Machine	0.184	0.531	0.479	0.398

Discussion

Within the big datasets we have with data explosion we quickly realized that there is something machines can learn from data. This opens up prescriptive analytics that tells descriptive future events with predictive insights not backed just by theories but by data we have collected. The social construction approach in machine learning is a new theory in data and algorithms. Though data does not have consciousness, it is transcendent from data analysts who clean, interpret, then manipulate data to fit into algorithms.

Inspired by the social structuration theory, we propose intelligent structuration for machine learning forecasting that consists of the three layers - the inference layer is for signifying data, the reference layer for dominating algorithms, and the meta layer for legitimating algorithms. In the suggested structuration, multiple models of different approaches and parameters are developed in the reference layer and blended in the meta layer. This makes models relatively more robust to the choice of features in the inference layer. In the reference layer, multiple dominating algorithms can be developed and fed into the meta layer. By selecting multiple dominating models of different characteristics and approaches, we may not only reduce the human modeler's intervention for selecting and tuning a single best model but also improve forecasting accuracy through the next step – the meta layer. The machine learning meta layer leverages complementary characteristics of distinctive models to produce optimal forecasts.

We demonstrate the proposed intelligent structuration on hotel rate prediction application. We apply three different machine learning models in the reference layer and neural network blended model in the meta layer to the validation data of daily hotel rates obtained from three hotels. The empirical results indicate that the machine learning blending in the meta layer can significantly improve the prediction accuracy of hotel minimum rates.

References

Bengio, Y., Lecun, Y., and Hinton, G. (2021). “Deep Learning for AI”, Communications of the ACM, 64(7), 58-65

Canonico, L. B., McNeese, N. J. and Duncan, C. (2018). “Machine Learning as Grounded Theory: Human-Centered Interfaces for Social Network Research through Artificial Intelligence”, Proceedings of the Human Factors and Ergonomics Society 2018, 1252-1256.

Carroll, J. M. and Swatman, P. A. (2000). “Structured-case: A methodological framework for building theory in information systems research”, *European Journal of Information Systems*, 9, 235-242.

Christozov, D. and Mitreva, M. (2020). "Big data analytics for smart sports using apache spark", *Issues in Information Systems*, 21(1), 147-152.

Gavahi, K., Abbaszadeh, P. and Moradkhani H. (2021). DeepYield: A combined convolutional neural network with long short-term memory for crop yield forecasting, *Expert Systems with Applications*, 184, 115511

Giddens, A. (1984). The constitution of society. University of California Press, Berkeley, CA.

Glaser, B. G. and Strauss, A. L. (1967). *The discovery of grounded theory: strategies for qualitative research*, Aldine Publishing Company, New York, NY.

Gulcu, A. and Sanli, T. (2017). What's Old is New Again: Machine Learning in Revenue Management Technology, *IDEAS White Paper*.

Hyndman, R. J. (2006). Another look at forecast accuracy metrics for intermittent demand. Foresight: The *International Journal of Applied Forecasting*, 1(4), 43-46.

Lee, M., Mu, X. and Zhang, Y. (2020). A Machine Learning Approach to Improving Forecasting Accuracy of Hotel Demand: A Comparative Analysis of Neural Networks and Traditional Models, *Issues in Information Systems*, 21 (1), 12-21.

Miles, M. B. and Huberman, A. M. (1984). *Qualitative Data Analysis: A Sourcebook of New Methods*, Sage Publications, Newbury Park, CA.

Nasios I. and Vogklis K. (2022). Blending gradient boosted trees and neural networks for point and probabilistic forecasting of hierarchical time series, *International Journal of Forecasting*, Forthcoming.

Orlikowski, W. J. (1993). Case Tools as Organizational Change: Investigating Incremental and Radical Changes in Systems Development, *MIS Quarterly* 17 (3), 209-338

Orlikowski, W. J. and Robey, D. (1991). Information technology and the structuring of organizations. Information Systems Research 2 (2), 143-169.

Rajopadhye, M., Ghalia, M. B.,Wang, P. P., Baker, T., and Eister, C. V. (2001). Forecasting uncertain hotel room demand. Information Sciences, 132(14), 1e11.

Reece, J. and Hong, S. (2021). "Big data analytics for smart sports using apache spark", *Issues in Information Systems*, 22(3), 1-13.

Strauss, A. and Corbin, J. (1998). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, Sage Publications, Thousand Oaks, CA.

Tang, X., Gao, S. and Jiang, Z. (2019). A Blending Model Combined DNN and LightGBM for Forecasting the Sales of Airline Tickets. *2019 3rd International Conference on Computer Science and Artificial Intelligence*, 150-154.

Zhang, H., Yang, Y., Zhang, Y. et al. (2021). A combined model based on SSA, neural networks, and LSSVM for short-term electric load and price forecasting. Neural Comput & Applic 33, 773–788.