

A Family Review of Parameter–Learning Models and Algorithms for Making Actionable Decisions

Chun-Kit Ngan

The Pennsylvania State University, USA

INTRODUCTION

Learning optimal decision parameters over time series (Bisgaard & Kulahci, 2011; Chatfield, 2001) to make actionable recommendations is an important topic which has gained significant interest in the past decade. In financial markets, stock investors analyze economic indicators to predict the occurrence of a bear market bottom or a bull market top to determine when they should buy or sell their stocks in order to gain the maximal profit. In medical diagnosis, physicians measure diabetes patients' blood-glucose-level (BGL) threshold to detect when the patients suffer hypo- and hyperglycemia. In energy industry, microgrid engineers investigate electricity peak demands to decide when the load shedding of electric power within the microgrid should be executed in order to minimize energy costs and maximize customers' savings while preserving the desired quality of service (QoS) in terms of power interruption. The goal of these time-series data analyses is to enable domain experts to understand the problems and lead them into a better decision-making and actionable recommendation.

Consider one particular example above that the stock investors are interested in determining when a bear market bottom will occur so that they can buy the stocks in the lowest price and then sell the stocks in the future to gain the maximal profits. To achieve this purpose, financial specialists suggest that a bear market bottom (Stack, 2009) has occurred if some changes of the financial indexes, such as the S&P 500 falls at least 20% and the Consumer Confidence Index declines at

least 30 points, are detected. Note that these decision parameters, e.g., 20% and 30 points, may be given by the domain experts or learned from the formal mathematical computations. To support such a decision-making event, it is important for domain experts to develop a data analytical methodology that is reliable and useful for their decision-making. The main challenge in such a methodology is how accurately, expressively, and effectively to model, analyze, and compute those time series data such that domain experts can analytically learn the optimal parameters to make a better decision. This is exactly the focus of this chapter.

BACKGROUND

To support the above decision-making events, there are two approaches, i.e., qualitative and quantitative, that data analysts often use to help domain experts learn optimal decision parameters. A qualitative analysis is a domain-knowledge-based approach that requires domain experts to base upon their past experience and observation to analyze scenarios, from which the experts determine the decision parameters. For example, in the stock market, financial specialists have identified a set of stock indicators that can be used to determine the bear market bottom. The indicators include the S&P 500 percentage decline (SPD), Coppock Guide (CG), Consumer Confidence Index drop (CCD), ISM Manufacturing Survey (ISM), and Negative Leadership Composite "Distribution" (NLCD). If these indicators satisfy the

DOI: 10.4018/978-1-5225-2255-3.ch186

pre-defined, parameterized conditions, e.g., $SPD < -20\%$, $CG < 0$, etc., it signals that the best period for the investors to buy the stocks, e.g., the S&P 500 Index Fund, is approaching. Often these parameters may reflect some realities since they are set by the domain experts based on their past experiences, observations, intuition, and domain knowledge. However, the suggested parameters may not always be accurate because those parameters are static, but the scenarios that the experts deal with are always dynamic in nature. Thus data analysts need to develop a class of mathematical models and algorithms that can be used to help the domain experts learn the decision parameters dynamically to fit the need of these scenarios.

A quantitative analysis is a machine-learning-based approach (Bell, 2014) that enables data analysts to apply mathematical models and algorithms to learn parameters on a large amount of datasets for decision making. For instance, the logistic regression models (Bierens, 2008; Cook, et. al., 2000; Dougherty, 2011; Hansen, 2014; Heij, et. al., 2004; Rawlings, et. al., 2012; SL, et. al., 2014) are often used to predict the occurrence of an event (0 or 1) by learning parametric coefficients of the logistic distribution function of the explanatory variables. This is done based upon the historical data by applying nonlinear regression models and the Maximum Likelihood Estimation (MLE) (Myung, 2003). However, using the machine-learning-based approach to learn parameters is computationally complicated and time consuming because each dataset has a large number of attributes (i.e., the curse of dimensionality) (Bellman, 2003 and 2015) that require the data analysts to take a long time to select the significant ones before they can do the parameter learning. Hence domain experts' knowledge is necessary to help the analysts identify and select the significant attributes to avoid the curse of dimensionality before learning the parameters.

Thus this chapter addresses the approach to close the above research gaps. More specifically, the chapter addresses the following two research questions:

1. How to develop the “time-point-based” mathematical models and learning algorithms that combine the strengths of both qualitative and quantitative approaches to learn optimal decision parameters to make actionable recommendations.
2. How to implement the experimental case studies that evaluates the performance of these developed hybrid-based parameter-learning models and algorithms.

HYBRID-BASED PARAMETER-LEARNING MODELS AND ALGORITHMS

To answer the above research questions, the authors have developed a family of parameter-learning models and algorithms, i.e., Expert Query Parametric Estimation (EQPE) models and Checkpoint algorithms (Ngan, et. al., 2010, 2011, 2012 & 2013), which combines the strength of both qualitative and quantitative methodologies to complement each other to learn optimal decision parameters in an efficient manner. This family of models and algorithms relies on domain expertise to select attributes and conditions against the data, from which the family of EQPE models and Checkpoint algorithms can learn decision parameters efficiently. This class of models and algorithms can be divided into two categories: Single-Event (SE) and Multi-Event (ME). The SE-EQPE model, using the Checkpoint algorithm, learns one decision parameter to detect the occurrence of a single event, e.g., the bear market bottom or the bull market top. The ME-EQPE model is the further extension of the SE-EQPE model, using the (Multidimensional) M- or (Relaxed) R-Checkpoint algorithm, to learn multiple decision parameters simultaneously to detect the occurrence of multiple events in sequence, e.g., the bear market bottom and then the bull market top. More specifically, the M-Checkpoint algorithm is a brute-force approach that learns multiple decision parameters optimally at their inter-related time points for multi-events.

10 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

www.igi-global.com/chapter/a-family-review-of-parameter-learning-models-and-algorithms-for-making-actionable-decisions/183927

Related Content

Evaluating the Effectiveness of Multi-Web Services in Load Balancing Cluster-Based Web Server

Abhijit Bora and Tulshi Bezboruah (2021). *Encyclopedia of Information Science and Technology, Fifth Edition* (pp. 1037-1050).

www.irma-international.org/chapter/evaluating-the-effectiveness-of-multi-web-services-in-load-balancing-cluster-based-web-server/260247

Mathematical Representation of Quality of Service (QoS) Parameters for Internet of Things (IoT)

Sandesh Mahamure, Poonam N. Raikar and Parikshit N. Mahalle (2017). *International Journal of Rough Sets and Data Analysis* (pp. 96-107).

www.irma-international.org/article/mathematical-representation-of-quality-of-service-qos-parameters-for-internet-of-things-iot/182294

Theoretical Analysis of Different Classifiers under Reduction Rough Data Set: A Brief Proposal

Shamim H. Ripon, Sarwar Kamal, Saddam Hossain and Nilanjan Dey (2016). *International Journal of Rough Sets and Data Analysis* (pp. 1-20).

www.irma-international.org/article/theoretical-analysis-of-different-classifiers-under-reduction-rough-data-set/156475

The Contribution of ERP Systems to the Maturity of Internal Audits

Ana Patrícia Silva and Rui Pedro Marques (2022). *International Journal of Information Technologies and Systems Approach* (pp. 1-25).

www.irma-international.org/article/the-contribution-of-erp-systems-to-the-maturity-of-internal-audits/311501

Autonomic Cooperative Networking

Micha Wódczak (2015). *Encyclopedia of Information Science and Technology, Third Edition* (pp. 6132-6142).

www.irma-international.org/chapter/autonomic-cooperative-networking/113070