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Machine Learning in Marketing

Overview, Learning Strategies, Applications, and Future Developments

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Machine Learning in Marketing

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ABSTRACT

The widespread impacts of artificial intelligence (AI) and machine learning (ML) in many segments of society have not yet been felt strongly in the marketing field. Despite such shortfall, ML offers a variety of potential benefits, including the opportunity to apply more robust methods for the generalization of scientific discoveries. Trying to reduce this shortfall, this monograph has four goals. First, to provide marketing with an overview of ML, including a review of its major types (supervised, unsupervised, and reinforcement learning) and algorithms, relevance to marketing, and general workflow. Second, to analyze two potential learning strategies for marketing researchers to learn ML: the bottom-up (that requires a strong background in general math and calculus, statistics, and programming languages) and the top-down (focused on the implementation of ML algorithms to improve explanations and/or predictions given within the domain of the researcher's knowledge). The third goal is to analyze the ML applications published in top-tier marketing and management journals, books, book chapters, as well as recent working papers on a few promising marketing research sub-fields. Finally, the last goal of the monograph is to discuss possible impacts of trends and future developments of ML to the field of marketing.

1

Introduction

The widespread impacts of artificial intelligence (AI) and machine learning (ML) in all segments of society have driven researchers to term the present day as the “AI Revolution” (Makridakis, 2017). This AI revolution has sparked multidisciplinary research. In the business world, such processes have been impactful as a significant source of innovation (Huang and Rust, 2018). Despite their relevance, for many marketing researchers and practitioners, terms such as artificial intelligence and machine learning may seem akin to terms of a foreign language (Conick, 2017). This monograph attempts to change this scenario by discussing the central role that AI and, more specifically, ML can play as a research method in the marketing field.

Why should ML be applied to marketing? There are many possible answers to this question rooted both in academic and applied practices of the discipline. For practitioners, for example, ML is disrupting many industries with new business models, products, and services. In academia, the impact appears to equally substantial. For example, the lack of generalization of scientific discoveries is at the center of the so-called “replication crisis,” which has affected many of the life and social sciences, including the fields of management and marketing. This

crisis has occurred because researchers have found that many of the most important scientific studies are difficult or impossible to replicate or reproduce (see, for example, Camerer *et al.*, 2018). As this monograph will discuss, the fundamental goal of machine learning is to generalize beyond the examples provided by training data, looking for generalizability (Domingos, 2012). Thus, one of the potential contributions of ML to marketing (and to management in general) lies in its robustness for the generation, testing, and generalization of scientific discoveries. With these different academic and practical perspectives in mind, the goal of this monograph is to provide marketing with an overview of ML and to analyze required learning, applications, and future developments involved in applying ML to marketing.

This monograph progresses as follows. The following section provides an overview of ML, including a review of its most relevant types, algorithms, and relevance to marketing. The following section presents a typical ML workflow, followed by a section that proposes two different learning strategies that can be used by management/marketing researchers interested in ML. That section is followed by a descriptive analysis of applications of ML published in top-tier marketing and management journals, books, book chapters, and recent working papers that explore a few of the most promising marketing research sub-fields. The following section discusses how trends and future developments of ML can impact the field of marketing. The last section summarizes the monograph's contributions, limitations, and suggestions for future research.

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