Predicting the Future: Machine Learning and Marketing

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ABSTRACT

This research reviews the use of machine learning in marketing. We define machine learning, explaining the field's origins and its potential as a powerful tool for academics as well as practicing marketers. Many of the benefits of machine learning are similar for academics and managers but perspectives differ, and we note the key area of divergence. Highlighting contributions made in major marketing journals, we classify research as primarily methodological or applied. We note how both types of contributions are valuable and may apply to either structured or unstructured data.

We extend the field of machine learning in marketing by integrating current knowledge, examining new developments, and advancing ideas for future research. Marketing research can be transformed by machine learning and we note wider implications for academia. For example, that machine learning can change the way we look at the search for results and has potential to unify some behavioral and quantitative research.

Keywords: Machine Learning, Prediction, Deep Learning, Literature Review, Science, Trends, Future Directions

INTRODUCTION: WHAT IS MACHINE LEARNING?

In the late 1950's, the field of machine learning emerged from its parent fields of artificial intelligence (AI) and cognitive science. The field focused on learning-related issues and the role of knowledge in intelligence, regardless of its origin. The field tackled the challenge of developing learning mechanisms covering the full range of human abilities (Langley 2011). Early research largely focused on attempting to replicate human thinking but increasing influence from the fields of pattern recognition and statistics during the 1990s led to decreased interest in mapping human thinking. The new and prevailing interest is to use data to better predict outcomes, but not necessary ape the way humans think. "The current wave of advances in artificial intelligence doesn't actually bring us intelligence but instead a critical component of intelligence: prediction" (Agrawal et al. 2018, page 4). In the last twenty or so years, machine learning has delivered impressive achievements. Indeed, machine learning is clearly having a considerable impact on the way marketing practitioners act. For example:

- Machine learning is already being used to determine product price elasticity (Columbus 2018). Assessments of elasticity can be made for numerous segments, various channels, and different time periods. Companies' pricing strategies have been transformed by machine learning as can academics' assessments of elasticity.
- Supply chains are being radically improved as companies gain better predictions of what goods will be needed and when they will be needed (McKinsey Global Institute 2017).
- The way advertising is being displayed has been significantly changed by the use of programmatic advertising driven by machine learning (Gilliland 2018).

However, the marketplace adoption of machine learning beyond early adopters remains nascent (Wladawsky-Berger 2018). Stéphane Bérubé, chief marketing officer for Western Europe at L'Oréal SA suggests that while many marketers think that the technology is the hardest aspect of artificial intelligence, "the tough part is finding the purpose" (Ives 2018). We believe that marketing scholars are also facing this challenge. Accordingly, the 2018-20 research priorities outlined by the Marketing Science Institute (MSI) describe a tier 1 research priority under *approaches to ingesting and analyzing data to drive marketing insights* as; "What are the current best practices in machine learning and large data to inform marketing decision making?" (Marketing Science Institute 2018).

In response, this paper provides an overview of machine learning in marketing academia. We argue that machine learning can be transformative not only for business practitioners, but also for marketing *researchers*. Machine learning has the potential to change how science is conducted (Mjolsness and DeCoste 2001). Marketing academics are not unique in facing a radically shifting research frontier and lessons can be learned from other research fields. Machine learning has already transformed fields such as astronomy, physics, and medical science, and is making inroads in economics, but there will not be a simple mapping; how machine learning has impacted physics need not be the same as how it impacts marketing. To aid our thinking about what the impact on marketing research will be, this paper provides a review of the marketing ML literature, develops a framework for understanding machine learning, and offers suggestions for the future.

After clarifying the important definitions related to machine learning (ML), we discuss the conceptual differences for academics in approaching data from a traditional theoretical and a ML perspective. We argue that the two approaches are not mutually exclusive and that the rigour of marketing research can only benefit from both. We then discuss the strengths and challenges of using machine learning and the types of data that have been studied with various ML tools. We list and describe statistical software packages that are “off-the-shelf” available for future researchers. Finally, we derive what this all means for the future of research in marketing. The new approaches being developed have great potential to radically change, and mostly improve, academic research but, critically, there are significant challenges that researchers (and reviewers) must be aware. Without understanding these challenges academic research will not realize the potential benefits machine learning has to offer.

DEEPER INTO MACHINE LEARNING

Defining the Terms

Recent achievements in both machine learning and artificial intelligence have been impressive and well-publicized (see Figure 1 for a timeline). A challenge that arises in the communication of machine learning related research with various stakeholders is that both popular and technical terms enter the zeitgeist and get used excessively and loosely. For example, artificial intelligence and machine learning are often spoken of interchangeably in the media. To clarify these terms, we conceptualize machine learning as a subset of artificial intelligence as noted below.

<Insert Figure 1 about here>

Artificial intelligence (AI) is a broad area of computer science that focuses on “intelligent agents”, or machines that can perceive their environment and perform tasks that human intelligence can tackle (Poole, Mackworth, and Goebel 1998). As the marketing common language dictionary states, “AI systems exhibit the characteristics generally associated with intelligence in human learning, reasoning, and solving problems" (MASB 2018). AI branches out into closely related but distinct fields of computer vision (i.e. detection of images), natural language processing (i.e. understanding written language), speech recognition (i.e. interpreting spoken language), and machine learning.

The term *machine learning* was first coined by Arthur Samuel in 1959 as he described a program to play checkers (Samuel 1959). 'Machine learning' referred to a process whereby heuristics pruned possibilities. (Such heuristic processes never guarantee that the best approach is found; a heuristic that optimizes locally is computationally efficient but need not find the global optimum). "Machine Learning is now the field of scientific study that concentrates on induction algorithms and on other algorithms that can be said to 'learn'" (Kohavi and Provost 1998). A modern marketing definition of machine learning suggests it uses "methods or algorithms designed to learn the underlying patterns in the data and make predictions based on these patterns." (Dzyabura and Yoganarasimhan 2018). For example, a marketer might want to learn what predicts the likelihood of a credit card customer defaulting on their debt. The machine can aid this by learning what inputs are associated with credit card default.

Consider that learning is through a *training experience* with respect to some class of *tasks* and the success of the learning is judged using a *performance measure* (Mitchell 1997). For example, consider how machine learning can predict who will be the "best" students for an MBA program (Agrawal, Gans, and Goldfarb 2018). We can break down the task, training experience, and the performance measure.

- *Task*: Classifying MBA applicants to decide whether to give them an offer.

- *Training experience*: The algorithm can be given a set of past MBA students with each student's characteristics and the outcomes observed. The algorithm learns the statistical relationship between observed characteristics and observed outcomes.
- *Performance measure*: Learning's success can be judged against how well the algorithm predicts an outcome of interest. There are two key predictions; on 1) the training set and 2) on new data. How the algorithm predicts with new data is typically what matters most.

The broadest categorization of machine learning methods is between supervised learning and unsupervised learning (Murphy 2012). The above is an example of a supervised learning problem, in which an algorithm learns the mappings given a labeled dataset of input-output pairs and predicts some output. Unsupervised learning is concerned with *knowledge discovery*. in which the goal is to find interesting patterns and improve our understanding of the input data. Semi-supervised learning is a halfway point between supervised and unsupervised learning. Algorithms of this approach do use labelled data but a relatively limited amount, which minimizes the amount of human intervention in the learning performance and is practically efficient. Deep learning is a specific branch of machine learning that goes beyond task-specific algorithms to focus on learning data representations. We present a taxonomy of Machine Learning in Figure 2.

<Insert Figure 2 about here>

A Machine Learning Approach to Data Analysis

Machine learning covers a wide variety of tasks, but we note that the methods per se are not what defines the conceptual approach of machine learning. For example, ordinary least squares (OLS) regression is one of the primary tools used by researchers for statistical inference, but it is also used in machine learning to predict a continuous outcome variable. We believe that a more useful conceptualization of machine learning is related to the objectives of causation and prediction. Traditionally for some observed phenomena marketing scholars were primarily interested in some approach to theory-building by causal inference (we henceforth refer to this as the theoretical approach). The appropriateness of a different machine learning approach depends on the user's objectives, but prediction, not necessarily causal inference, is often the key function.

Machine learning approaches the bias-variance trade-off from a novel angle. A traditional goal for academics might be to minimize bias in description, i.e. errors in the model, to really understand the data. When developing practical applications, we aren't always especially interested in really understanding the training data. Instead we want a model that better predicts on similar data. Machine learning algorithms sacrifice some bias in the given data set in return aiming for less variance across datasets. Indeed, to predict one need not necessarily understand the causal process. Consumer characteristics fed into an algorithm may allow an accurate prediction of purchasing but not what drives the purchasing choice. That said causal issues remain important, even for some pragmatic decisions, which we discuss more later.

This distinction between the theoretical approach and machine learning is highlighted by the example of instrumental variable regression. If an independent variable is endogenous, the regression model will not accurately capture the data generating process and its parameter estimates will be biased (Rossi 2014). One option available to researchers attempting to rectify the model and identify the causal effect of the independent variable is to use an instrument. This instrument should be correlated with the endogenous variable, but uncorrelated with the idiosyncratic error term. The endogenous variable is regressed on the instrument to capture only the exogenous component of the endogenous variable's variance. However, this procedure decreases the goodness-of-fit of the overall model, thereby reducing its predictive accuracy on a testing dataset (Wedel and Kannan 2016). This loss of predictive accuracy is implicitly accepted by scholars because it is primarily the identification of a causal effect in the data that drives theory building.

Endogeneity is not the central concern for machine learning because identifying causal relationships between variables is not of primary interest. Proper data collection procedures remain important because the principle of "garbage-in, garbage-out" does not change; poor quality data will yield poor results, regardless of the complexity of the algorithm. However, machine learning may not necessarily require an understanding of the causal process for prediction. As such, machine learning may be popular in the industry because practitioners are not always interested in understanding the training data per se but using the learning to improve prediction.

These outlined differences in theoretical and machine learning approaches might lead researchers to erroneously conclude for the mutually exclusive use of either one or the other. However, we argue for the case that machine learning can benefit marketing researchers, regardless of their approach to research. We identify three key areas in the general scientific research process where we expect the greatest impact from machine learning: *data exploration, variable creation,* and *estimation.*

Machine Learning in the Research Process

Data Exploration: Marketing research, similar to other scientific disciplines, starts with the development of hypotheses, often by observing the real world (Mjolsness and DeCoste 2001).

Thought-provoking phenomena give rise to often managerially relevant and interesting research questions (Lynch Jr. et al. 2012). However, the advancement in technology and the subsequent rise of big data has increased the number of variables and noise in the data. For example, the individual-level longitudinal data maintained by firms can be massive, and the sheer number of feature variables collected from each of the individuals can obscure what is truly deserving of attention. In addition, the growth of unstructured data (e.g., text, images, and video, see Balducci and Marinova 2018) makes observing all relevant data on consumers expensive and time-consuming; a near Sisyphean task for researchers. As such, some modern marketing phenomena are much more difficult for capacity constrained humans to fully observe.

Unsupervised learning can provide an efficient and effective method for researchers to observe and explore data. For example, Wang et al. (2015) use latent Dirichlet allocation (LDA), which is an unsupervised algorithm, to summarize 40 years worth of *Journal of Consumer Research* article abstracts. Manual reading and coding of these abstracts would be a complex and arduous task. Instead, the authors use LDA to uncover a set of 16 topics that summarizes the article abstracts and visualize how the topics evolve over time to yield new insights for researchers. More recently, a working paper by Novak and Hoffman (2018) develops a framework that leverages clustering and word2vec, which is a lingiuistic algorithm that uses an unsupervised neural network, to visualize the structure of a massive Internet-of-Things dataset.

Often, the exploration and visualization of the data itself can lead to new and managerially relevant insights. Pilot studies that serve to captivate the readers' interest and motivate the paper's main research questions are commonly observed in marketing research papers. With the larger volume and variety of data that marketers frequently encounter today, we expect an increasing number of marketing researchers to either develop new unsupervised frameworks for data exploration or incorporate unsupervised learning early in their research paper to motivate their hypothesis development.

Variable Creation: Machine learning methods introduce new capabilities to study unstructured data. An important form of unstructured data for marketing researchers is text, which was studied long before machine learning methods became popular. For example, marketing researchers have traditionally used human coders to measure valence in text, such as customer reviews (Liu 2006). A variety of commercial software, such as LIWC, have become available for researchers (Humphreys and Wang 2017). Futhermore, the accuracy of supervised learning algorithms used for text analysis, such as measuring valence and sentiment, are improving at a rapid pace. Given this in the future we will likely see researchers applying off-the-shelf machine learning tools catered to their own training dataset, which can now be labeled efficiently using Amazon Mechanical Turk. The reduction in measurement error by using these machine learning algorithms will benefit researchers by increasing the power of their statistical tests.

Machine learning allows researchers to study many forms of unstructured data beyond text. A working paper by Liu, Dzyabura, and Mizik (2018) collects images labeled by users on Flickr to train a Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) to predict brand attributes from images posted by users on Instagram. Moreover, Li, Shi, and Wang (2019) uses CNN to analyze video contents while providing new metrics for future marketing researchers. Wedel and Kannan (2016) list the transformation of unstructured to structured data as one of the priorities for researchers. Indeed, we expect to see an increasing number of novel methods and metrics for analyzing unstructured data, allowing researchers the freedom to pursue new research questions in marketing.

Estimation: There is a growing stream of literature in econometrics that aims to improve causal effect estimation methods using machine learning. Athey and Imbens (2017) conceptually divides this research stream into two categories: average causal effects and heterogeneous causal effects. Research related to average causal effects involves versatile methods that control a large number of covariates that belong to both the treated and control group to better estimate the average treatment effect. For example, a working paper by Athey, Imbens, and Wager (2016) presents an estimator that reduces the amount of extrapolation required from the control group when predicting outcomes for the treated group in the absence of the treatment by balancing the covariates and applying regression adjustment. Research related to heterogeneous causal effects involves methods to study how treatment effects vary by different settings and subgroups. There exist machine learning methods that extend regression trees, using sample splitting to estimate different treatment effects within the leaves (Athey and Imbens 2016). This is especially relevant to marketing researchers wishing to conduct supplementary analyses of how treatments, for example the effectiveness of advertising, vary across subgroups of consumers. We expect that these machine learning methods will transition from applied economics into the field of marketing in the near future.

Model specification are important considerations for researchers. For example, it is common for researchers to assume a priori a linear functional form of the relationship between variables (Rossi 2014). Thereafter, the researcher will include in the model the dependent variable, the focal independent variable, and a set of control variables for hypothesis testing. A potential issue that arises from this procedure is that an incorrect specification can lead to large variance that is resistant to reduction from an increase in sample size (Leamer 1983). Additionally, the sensitivity of the model's results to control variables may not be transparent (Spector and Brannick 2011).

Worryingly, there is increasing evidence across a number of research fields that science may be abused or, at a minimum, not working as intended (Gelman and Loken 2014; Ioannidis 2005; Meyer, Witteloostuijn, and Beugelsdijk 2017; Simmons, Nelson, and Simonsohn 2011). We believe that the increase in the size and the variety of data may exacerbate this problem. Traditional solutions to mitigate these concerns include model-free evidence and robustness checks in the form of alternative model specifications. We expect that machine learning methods, the strength of which are grounded in its data-driven nature, will promote a systematic framework for robustness checks (Athey and Imbens 2015).

Table 1 offers a sample of tools and techniques used in machine learning research.

<Insert Table 1 About here>

INVESTIGATING MACHINE LEARNING IN MARKETING RESEARCH

Scope and Overview

In this section we outline the current state of machine learning in top level academic marketing research. To focus on leading scholarly marketing outlets, we chose four relevant journals from the UT Dallas list: *Marketing Science, Journal of Marketing, Journal of Marketing Research,* and the *Journal of Consumer Research*. To this list we added the *International Journal of Research in*

Marketing given this journal has important contributions in the field. Using this list, we searched for machine learning articles on Google Scholar and categorized these articles using a 2*x*2 framework. One dimension was whether the paper was primarily making a *methodological* or an *applied* research contribution. We define methodological-oriented papers as those in which the ML method is part of the paper's contribution. Applied papers are those in which the ML method is not the novel contribution. (Papers in top journals often make both methodological and applied contributions so we classified them according to their key contributions). The second dimension was whether the data used was structured or unstructured. A brief summary of the papers reviewed is given in Table 2 and highlights described below.

<Insert Table 2 about here>

Methodologically Orientated Research

There is a reasonably large number of papers making primarily a methodological contribution in the area of structured data. Cui and Curry (2005) brought Support Vector Machine (SVM) into marketing. Their paper illustrates the use of SVM for cases where there is a non-linear relationship between predictors and outcome. Evgeniou et al. (2005) proposed a nonlinear method for conjoint estimation. Both papers introduce ***non-linear*** methods, the ability to cope with non-linear data being a particular strength of machine learning. Following these papers, there was a significant stream of research making methodological contributions in the area of conjoint analysis (Chen, Iyengar, and Iyengar 2017; Dzyabura and Hauser 2011; Evgeniou, Pontil, and Toubia 2007; Hauser et al. 2010; Huang and Luo 2016). More recent papers have tended to move away from non-linear optimization and noise filtering to active-learning, which are algorithms designed to learn interactively in their environment to predict outputs to new data points.

Recently, methodologically-oriented machine learning research focuses on domains other than conjoint analysis. Trusov et al. (2016) extends the method of Correlated Topic Modeling (CTM) to model online user profiles, while Yoganarasimhan (2018) makes a contribution towards optimizing search engine results. In addition, recent methodologically-oriented research focuses on unstructured data. Advances have been made employing text in market structure analysis (Lee and Bradlow 2011). Tirunillai and Tellis (2014) use a supervised form of LDA to study market structure, while Liu and Toubia (2018) use unsupervised dual LDA to measure consumer preferences. Timoshenko and Hauser (2018) use deep learning and word embeddings to develop an efficient framework that identifies consumer needs from online reviews. These published papers focus on text leaving considerable possibilities for future research to develop methods to analyze other forms of unstructured data, such as images and videos. Such work would be extremely relevant for both marketing researchers and practitioners.

Applied Marketing/Machine Learning Research

There are numerous areas of marketing where contributions can be made by applying machine learning to marketing problems. There are already a notable number of papers doing so using structured data. This started thirty years ago when Currim et al. (1988) introduced the “concept learning system”, publishing marketing’s first machine learning paper. The authors highlighted concerns about the interpretability of machine learning; they warned readers that although such algorithms can describe the data the best, they cannot describe consumer behavior.

A promising approach is the use of machine learning classifiers to predict customer churn, the level of consumers failing to renew subscriptions (Ascarza 2018; Bloemer et al. 2003; Lemmens and Croux 2006; Neslin et al. 2006). Ascarza (2018) echoes the sentiment of Currim et al. (1988) in raising a note of caution about machine learning. Specifically, she suggests being careful when interpreting results from machine learning methods in respect of retention. The challenge is that those predicted to be most likely to churn are not the most sensitive to targeted firm promotions. Just because someone is most likely to churn it does not automatically follow targeting them is the best use of retention resources. The ML model gives a prediction but not necessarily a recommendation for action.

Further research has extended applied research with structured data. Schwartz et al. (2014) examines how to select the optimal method for prediction given a specific dataset while Schwartz et al. (2017) applies a *reinforcement learning* method in a field experiment setting.

While many marketing questions are suited to structured data – e.g., we want to predict whether offers influence sales the details of which are all recorded in the company database – there exists considerable potential to use machine learning techniques for data exploration and visualization. Examining the use of unstructured data in the literature there are a large number papers that use machine learning to make an applied contribution. There is a broad array of research that primarily focuses on analyzing *text* to create variables to be included in empirical models (e.g. sentiment analysis, LDA, etc.). Given the power of machine learning with text it is not surprising that reviews have proved a key area where our understanding has been improved by the new methods (Hartmann et al. 2018; Homburg, Ehm, and Artz 2015; Lee and Bradlow 2011; Timoshenko and Hauser 2018; Tirunillai and Tellis 2012, 2017; Zhang and Godes 2018).

Other work has focused on how machine learning can help understand the impact of images (Ghose, Ipeirotis, and Li 2012; Klostermann et al. 2018; Xiao and Ding 2014). An interdisciplinary neuroimaging paper in *JMR* uses machine learning for analysis (Chen, Nelson, and Hsu 2015) while Lu et al. (2016) analyzes faces in video data. Given the power of machine learning techniques to help address applied questions, and the profusion of unstructured data becoming available, there seems little doubt that considerably more research can be done using machine learning to analyze other forms of unstructured data. Indeed, the *Journal of Consumer Research* recently accepted its first machine learning paper (Ordenes et al. 2018) and other research has combined machine learning with the cloud in order to reveal the promise of big data (Liu, Singh, and Srinivasan 2016).

Summary

Machine learning remains in its early stages of adoption and there is plenty of opportunity for further machine learning research in marketing. With marketing being at the frontline of where firms meet consumers, machine learning introduces opportunities for further "home-grown" research that is unique to marketing as a discipline and directly relevant to practitioners. This would include such areas as conjoint analysis, market structure analysis, and new product development. In addition, Wedel and Kannan (2016) suggests analytics research on the efficiency of machine learning algorithms. Critically, there is a sizable opportunity for ML approaches to be applied to a wide variety of data. ML learning techniques can take us beyond text to include images and video data. This review has examined where we are, and it is against this background that we will suggest new directions for marketing research. We will build on the cautions of earlier scholars while maintaining an overall positive view of the possibilities for the marketing discipline.

FUTURE DIRECTIONS FOR RESEARCH IN MARKETING

With the increasing prominence of machine learning methods in both industry and academia, we predict the rise of many new research questions for the field of marketing. In this section, we attempt to outline research questions that are especially pertinent for marketing scholars. We organize the research questions into three broad categories: *uses*, *adoption*, and *implementation*. Research contributions will stem from more than just methodological and quantitative research. As we will note we expect that a wide spectrum of marketing scholars, from consumer behavior to quantitative researchers, will need to collaborate and work closely with managers to answer these questions. Given its externally facing role we envision marketing as the management discipline to lead the research on firms machine learning adoption and implementation.

Uses

The evolving landscape of businesses and technology presents novel challenges for managers to handle both effectively and efficiently. We expect many traditional methods used by marketers will either become obsolete or see radical changes in the future. We found in our overview of machine learning research in marketing that much of the innovative methodologically oriented research has focused in this area. However, we note that some managerial tasks, such as conjoint analysis and churn prediction, have received disproportionately more attention from scholars. We believe that there remains much more work to be done.

We build on the issues for further research regarding marketing analytics provided by Wedel and Kannan (2016). Specifically, “marketing academia will need to develop analytical methods with a keen eye for data volume and variety as well as speed of computation.” To complement the work by Wedel and Kannan, we outline some specific uses relevant to academic marketing researchers that can be addressed by further research using machine learning.

Prediction and Causation: Machine learning is not well-suited to isolating a single cause; we need a new way of thinking about how to understand 'black box' results. A simple machine learning algorithm might note that higher frequency mailings to a customer tend to presage churn, but this should not be interpreted as suggesting that higher frequency mailings cause churn. (The firm is likely targeting those thought to be at risk of churning). We must understand the precise business conditions to interpret findings; algorithms cannot learn important information that is not contained in the data. Yet it would be wrong to issue a blanket declaration that machine learning cannot address causation (Athey 2018). ML techniques can move in a causal direction yet, we argue, that it is not necessary to mimic prior methods and look for single issue causation to be useful. Single issue causation is merely a fiction employed to make life manageable and machine learning can review more complex interactions of causes. The need for theory is still there – it just looks a little different having more caveats and forks in the road. Rather than boundary effects we look for a region where one relationship holds and another region where a different relationship holds. ML's contextualized output is not necessarily better -- it rarely permits powerful universal pronouncements that can often be very useful -- but it allows more nuance. We can check ML's black box predictions against simple models and traditional models to increase our confidence in our understanding of the world.

Competitor Identification and Marketing Metrics: With ML we can hope to better understand market structure and competitor identification improving our analysis by using algorithms to understand consumer choice sets. With a more nuanced view of markets traditional marketing metrics, especially market share, will be increasingly challenged. If a market is really a myriad of sub markets what does an overall market share mean and what use can we make of market share (Armstrong and Collopy 1996)? Customer Lifetime Value (CLV) should remain relevant but our understanding will change. What will an increase in the accuracy of churn and retention prediction mean for the estimation of CLV models? Combining ML insights with current marketing thinking presents ample opportunity for future research to improve theoretical understanding or drive the practical aim of revisiting models to incorporate ML approaches directly into them.

Basic and Applied Research: We might expect to see research that shifts the balance somewhat from basic towards applied research, a theme we will return to. Modern marketers may learn from prior generations, resurrecting a new wave of research in the spirit of decision support systems (Little 1979). If practical goals matter how can academics hope to produce work that is directly usable by managers in their roles? Critically how should academia reward those doing such work? Should we expect to see greater personal stories of real-world implementation in academic papers?

Tasks best suited to ML are often those with large volumes of data and a myriad of interactions. Indeed, one potential boon from ML is the better description of the results of field experiments when managerial action has lots of different levels and levers. Here setting up experiments with randomized treatments and controls becomes very expensive -- managers must make numerous offers they do not believe will be optimally effective. Rather than lament that field experiments lack the control of a laboratory investigation we can use ML methods to visualize different dimensions that are uncontrolled, allowing the researcher to detect patterns. Do consumers of different ages appear to react similarly or not? The researcher can report more varied results, allowing the reader to understand the strengths and weakness of the approach.

This ability to delve into the data allows for contextual questions to be answered. Will a consumer react better to a specific type of display in a specific type of store at a particular time of the year? The researchers need not have a strong prior but can let the data speak. As we note later this is not the same as secretive data mining given the researcher reveals the approach. All know what was done and so all can take this into account when judging the findings.

Changing Marketing Research Streams: Machine Learning might suggest greater prominence for those able to develop algorithms. This sounds plausible but will quantitative marketers outperform computer scientists and statisticians at this? Technically superior researchers will thrive but that is true at present. We suggest a greater number of researchers will rely on developments from outside marketing; the researcher's value-add being finding interesting question to address. More interestingly, ML can be applied to understand human behavior which might somewhat reduce the prominence of laboratory experiments. As machine learning techniques become more widespread, and accessible we might expect consumer behavior scholars will apply their psychological knowledge to investigate how behavior changes within a specific context. CB scholars might be able to note what behaviors can be expected to persist in which markets (Bendle and Vandenbosch 2014). ML techniques gain some benefits of field experiments at a fraction of the cost to the researcher given the availability of online data. Laboratory experiments will retain value but some of the best behavioral scholars will use newly developed ML approaches to investigate real-world behavior. As context matters we might see a resurgence of unfashionable marketing sub-disciplines, e.g., 'marketing strategy' and 'qualitative research' given ML will allow such scholars to leverage their contextual knowledge to interpret the findings of the models.

Perhaps the idea of marketing sub-discipline performance will become a misnomer as machine learning may help bridge the gap between marketers of different training. For example, machine learning models can study human cognitive constraints and bring these out in findings. We anticipate lots of potential for fruitful collaboration between those who use non-laboratory quantitative methods with those whose primary contribution is insight into human behavior. At our most optimistic we see ML as a boon to interdisciplinary research with the future of marketing seeing less methodological balkanization.

Adoption

Interpretation: Machine learning algorithms are likened to a “black box”, in which we observe only the input and the output of the algorithm but not its internal workings. This departs from traditional econometric models, in which the researcher can assess the effect size and confidence interval for each individual parameter. This can pose problems for managers when persuading others in the organization to adopt machine learning methods and act on certain predictions. Rather than see this as the death of theory we argue that the burden placed on theory will increase. Its role will be to provide convincing explanations behind empirical predictions.

One currently used approach to try and unravel the black box nature of machine learning methods, or at least make the results more interpretable, is to simultaneously run a simple and a complex model. For example, Liu, Dzyabura, and Mizik (2018) applies both SVM and convolutional neural network in their work to predict the same set of images, using the latter for prediction and the former for only examining the weights, or the importance of the different predictors. We expect the continuing development of *interpretable* machine learning methods.

Firm Behavior: As the barriers to entry in machine learning rapidly decrease, we expect an increasing number of firms will adopt machine learning in accordance with standard competitive theory from economics (Demsetz 1982). This raises questions related to which departments of a firm are the most likely to adopt and resist the adoption of machine learning. Any differential in the adoption will create tensions. Most obviously, tensions may arise between experienced marketers and algorithm users over how to best serve customers when tried and tested ways are overturned by ML prescribed methods. This is especially problematic as the shelf life of ML results are limited. The solution to the shelf life problem is typically to rerun the ML analysis to make sure it is up to date but where does this leave the role of marketer experience and the sort of heuristics learned over a career in the field? Marketers adopting machine learning techniques may find it increasing challenging to explain what they are doing to their line managers. Who will want to adopt a plan that may be better but might still fail and can't be easily explained? Or will managers rely on the machines and aim to claim immunity from mistakes as they were merely following the instructions of the algorithms? This seems like a prescription for bad marketing.

To develop value from the sort of contextual analysis that ML can provide will need massive datasets of company information. We expect strategy research to pursue data from well beyond the S&P 500. The exciting prospect is of work that better understands small and medium size firms but this will remain reliant on public data. This should see calls for greater disclosure of company information presenting challenges for accounting regulators to remain relevant. When interpreting the findings from public data as ML skills become more abundant and cheaper the shortage in academia will be in understanding firm behavior. This might see the greater success of scholars with prior work experience, or those able to take sabbaticals to learn deep industry details.

Furthermore, we expect that the behaviors of firms at the aggregate level will change in the long-term. As firms delegate an increasing amount of decisions to machine learning methods, researchers are likely to observe less human and more machine decisions in the firm-level data (Athey 2018). More extensive theories as to how humans and machines interact to form managerial decisions will be required.

A Changing Field: It will become increasingly easy for marketing researchers to apply machine learning. As the skills necessary are available to many who have trained on R, or similar programs, most quantitative researchers will adopt some of these techniques. The methods will also become increasingly available as pre-packaged tools, usable by those without an in-depth quantative expertise.

Currently research often occurs in a university. This might be working in a laboratory with student subjects, writing surveys for online paid panels, or a lone researcher sequestered in an office interrogating secondary data. A new venue might increasing be the workplace of practising managers. (Academics need not be literally seated at companies – the academic may still physically be at a university while being virtually in marketers' workplaces). Working closely with managers will allow for testing models on up-to-date data hoping to deliver immediately useful outcomes for practicing managers.

To be successful such interaction will require more attention to be given to aligning the incentives of managers and academics. Academics will need a guarantee of being able to publish whereas managers will want to ensure confidentiality and timeliness. The conflicts inherent in this are likely to be somewhat mitigated by the nature of machine learning. Managers need not worry quite so much about publication given ML results are contextual and somewhat time limited. Furthermore, limited shelf lives suggest an increased academic incentive for speed. This might also recommend that publication venues consider how to maintain standards while working on swifter publication schedules.

Improving Marketing Practice: The adoption of ML by researchers and managers has potential to better connect industry and academia. The challenge at present is that many methods used by academic researchers, e.g., laboratory experiments, econometric analysis of public accounting data, are not the same approaches as used by managers. More constructive collaboration can occur if both researchers and managers speak the same ML language. This will also allow for a shift in academic questions from understanding broad effects in industries to understanding the specifics facing any given firm. This greatly increases the possibility of collaboration with firms and academics researchers making a direct impact on practice.

Black Box Best Practice: A great advantage of supervised ML is that one must specify in advance what one considers success which forces clairty about strategy (Agrawal, Gans, and Goldfarb 2018). ML is often associated with searching for the best model which contrasts with specifying a-priori what the model should be. This sounds like ML gives the researcher extra chances of a successful result – a worrying idea in this era of replication crisis (Honig et al. 2018). Academics must indeed develop clearer black box best practice, how we describe our work. That said we take a relatively benign view of ML’s influence as many problems pre-date the new methods that we focus on. Indeed, machine learning is well suited to cope with the era of dubious results and retractions because the upfront nature of its methodology provides a safeguard against academic mal-practice. Consider an algorithm that searches for the best model to represent a relationship between A and B through many potential models and picking the best.

This 'model mining' is upfront; all readers know what is happening and can factor that into the findings. This feels an odd approach to some as traditional statistical approaches require an a-priori specification. Yet already experience suggests that academic behavior on this front may be less ideal (Gelman and Loken 2014; Ioannidis 2005; Meyer, Witteloostuijn, and Beugelsdijk 2017; Simmons, Nelson, and Simonsohn 2011). Strong incentives to find publishable results can mean if researchers do not find these with their first model they may rarely abandon the project. Perhaps they 'learn' and change their model. Current marketing academic research practice rarely sees scholars explicitly adjusting their statistical approaches for this or detailing the models they tried and failed before settling on the published version. ML formalizes the search for models – adding clarity about its method which seems like a major advance in research transparency.

Implementation

Intervention: As calls for responsible business research increase (Responsible Research in Business and Management 2018), machine learning has potential to develop research that fills this need. We would suggest single issue causation is rarely high on manager's priorities. (By single issue causation we mean targeting the impact of changing a specific variable in a controlled circumstance rather than, for example, better predicting the effect of an offer that contains a package of elements). In practice managers need to know, for example, how to draft offers that will appeal to their customers. For this that a specific construct is linked with a specific outcome is useful background information, but no appeal features a single non-contextualized construct. Managers must work with massive interactions between operationalisations. Furthermore, managers tend not to pursue options that do not look good. We rarely check what seems to be a bad idea because our view of the world, formed by research or gut feeling, told us not to. Given patchy testing even with massive amounts of data captured we might not have sufficient data to examine what we want to know meaning claims must be modest. Yet this problem of imperfect data is independent of the technique used. Advice from research that seeks to zero in on a single cause is not perfect data for theory to apply in the messy real-world. We might be interested in how construal level, interacts with communication length, which interacts with communication media, which is turn is moderated by the prior interactions of the customer with the firm, and a multitude of other potential features. No program of research drilling into specific details can ever hope to document all the main effects that matter to managers never mind all the interactions and interactions of interactions.

Machine learning techniques can consider such a multiple of potential details. The techniques can even, with sufficient data, produce trees highlighting what is beneficial in any given context. As noted, this is not a replacement for single issue cause focused research, but it may prove more useful for managers in their everyday decisions.

Bridging the Practitioner Divide: Traditional marketing research is seen as more important if it posits a near universal causal connection, e.g., innovation leads to higher profits. Boundary conditions are usually specified but the researcher has an incentive to downplay the caveats and these caveats are critical to managers. This leads to failure to adequately engage with managers (Reibstein, Day, and Wind 2009). ML generates weaker assertions about underpinning relationships. Positing fewer theories of universal relationships may be more intellectually honest and marketing academics, especially in their role as editors and reviewers, may learn to come to terms with more modest, context dependent assertions in research papers.

More modest assertions can be more persuasive to managers. Rather than expecting to speak to all managers ML research may take a page from marketing 101 and target who they speak to. Speaking more powerfully to some, e.g., those working on recommendation agents, may be more impactful than aiming to influence all marketers at Alphabet through Omega. ML techniques can, with sufficient data, highlight what is beneficial in any given context supporting responsible business research (Responsible Research in Business and Management 2018). Managers may often use the term proof when, we argue, they are only looking for ideas to test in their workplace. As ML generates research situated in specific context it is easier for managers to see how ideas can be applied. This more modest view of research is a major departure for academics yet if academia's universal, context free findings continue to be questioned as methodologically suspect, challenging to replicate, and lacking in relevance maybe there is room for more modest, but more useful, assertions.

Manipulability: One question that arises is how manipulable is machine learning by those being observed? ML models open the possibility that consumer behavior will change; we will start observing not natural human behavior but attempts to manage the process. If the algorithm suggests those that travel a lot are receptive to discounts consumers will manage the signals they send to gain discounts. They are already tools designed to beat the algorithms. A consumer 'VPN' might actively manage the data that goes to the marketer on the consumer's behalf. The challenges for managers are obvious but academics should also be concerned. There is an ever increasing adverse selection problem, a Red Queen scenario (Ridley 2003) where ML experts representing firms and consumers each innovate, neither gaining a decisive advantage. Even if consumers never defeat the algorithms still attempts to beat the machine cause problems as economic style research leans heavily on the notion of revealed preference. What represents the consumer's true preference given multiple layers of obfuscation? Social desirability infects survey data but will this become more of an issue for "observed" behaviors. Will marketing theory have to develop a set of primitives increasingly diverging from revealed preference? Though challenging this increases the possibility of marketing becoming its own discipline relatively free from the shadow of economics.

ML Prediction's Shelf life: Machine learning's contextualized advice highlights a fascinating problem. Findings hold as long as the context holds but everything constantly changes. Machine learning might accurately predict, for example, recommendation behavior but for how long does this hold? Is today's prediction valid for activity next year? What is the shelf-life of predictions?

Without universal statements of relationships you only really know that a relationship held (not that it currently holds). How would you know the relationship still holds without running the model again? This leads to a fundamental conflict between managerial and academic use of machine learning. The manager is often seeking advice on how to act now. Even if the results of a ML model hold only temporarily it is relatively safe to act on it now. Furthermore, the manager has the data to run the ML algorithm again. A manager may never know when a model becomes out of date but refreshing the model regularly makes this less of a problem. Any worries? Then run the model again and get a fresh look. Academic research is generally not content with being so ephemeral. Academics want to publish "facts" that will still have influence a generation later; a classic paper's influence may outlive its author. Academics may uncover a genuine relationship but it is a problem if they suggest that the relationship may well not hold by the time the paper winds its way through a tortuous publication process. Academic and review timelines may need to shorten. Perhaps to aid this, with a brave editor, machine learning could take on the role of triage editor, giving a speedy desk reject to those papers not meeting certain pre-set objectives.

Research as Exploration: ML's approach means that we might rethink our analogies of the whole academic process. Currently academic studies may be seen as a mountain climbing expedition. Scholars know where they are going, building on prior achievements to gain a little more altitude. ML uses a different logic. The algorithms are powerful enough to fly the researcher from one peak to another. Research becomes not a search for a specific mountain top but a desire to investigate mountain tops across a whole region, jumping to a new area of knowledge. This has obvious upsides in encouraging novel thinking and generating new perspectives. We still won't know that any peak crested is the globally highest point but that is always the case. The unique challenge with ML is that we will visit more mountaintops than we know how to describe. It will not be always obvious which are the most important mountains to climb. This will present challenges for academics in positioning their findings and create additional work for reviewers. The review team can expect to face many more results outside their area of expertise, how does one faithfully review this? Conscientious reviewers will aim to help the researchers position their work but we can expect increasing disputes as reviewers disagree what exactly is a contribution.

Ethics: What managers do with the prediction, and how consumers react to the perceived unfairness, is an active subject of research. For example, firms have the potential to customize their product offerings at the individual level by predicting customer spending, excluding some customers from their best offers (Ariely 2010). Furthermore, the predictive accuracy demonstrated by machine learning algorithms raises the issue of *ethical prediction* for firms. Kosinski, Stillwell, and Graepel (2013) find that sensitive personal traits of individuals -- such as intelligence, sexual orientation, use of addictive substances, and political affiliation -- can be predicted accurately using Facebook 'likes'. As such, simply deciding not to provide personal information to firms may not be enough for consumers to protect their privacy. If ML allows a marketer to access more data, this exacerbates questions of whether it is ethically permissible to do so. This also provides opportunities; for example, the current work on methods of cloaking individuals in such contexts (Chen et al. 2017).

Discrimination: There are widespread concerns about the use of machine learning in managerial and policy decisions. These have emerged in popular writing (O'Neil 2016) where the argument is made that introducing machine learning can lead to some being discriminated against. An illustrative case is the launch, and withdrawal less than 24 hours later, of Microsoft's Tay. Tay, a bot, was designed to interact with others on Twitter and learn from human interactions. The bot would repeat information received from Twitter users with little filter for accuracy or appropriateness. Tay soon "learned" to be bigoted but in an inconsistent way; holding strident pro- and anti-views on charged topics. Tay predicted Twitter behavior well enough to engage with humans but who wants machines to learn humanity's worst qualities?

Some of the arguments that discrimination is *rising* because of the implementation of ML seem hard to justify. People discriminated long before they had computers never mind machine learning and limited evidence is often provided to suggest that society is being made more discriminatory by ML than it was in the past. That said, the story of the Tay bot is a salutatory lesson of how an unprejudiced machine can adopt human bias quickly. We do not want to bake society's evils into machine algorithms that can be opaque making it be hard to see whether any specific decision is impacted by prejudice. The challenges have similarities to those faced in psychology. We can work to remove explicit human and machine bias but prejudice may be deeply hidden (Banaji and Greenwald 2013). It is often relatively easy to illustrate that prejudice exists, for example highlighting bias in general hiring decisions through showing some groups fare worse than should be expected. Yet it can be harder to incontrovertibly demonstrate bias in any given decision, given any single decision is likely impacted by a whole host of idiosyncratic factors.

It is worth noting however that, as with any technology, machine learning does not necessitate a lack of human involvement. Unsupervised methods may be relatively undirected, but they still are initiated by a human and ultimately a human chooses whether to use the output in a specific way. Supervised methods involve human beings setting some sort of objective for the machine. By its nature this means we can, and we would argue should, impose societal objectives on ML. There is no reason why lack of prejudicial outputs, for example no differences between races, cannot be an objective fed into machine learning. Of course, this does not mean managers will do so, but prejudice isn't an inevitable consequence of using a model. Instead prejudice arises through the use of a model when those using the model do not care enough to tackle the problem. It is disappointing that people do not always tackle prejudice, but it seems an abdication of managerial responsibility to merely say that the machine made me do it.

New Technology (Cloud Computing and Quantum Computing): Given the size of modern datasets, machine learning methods can be very resource-intensive with algorithms taking a very long time to converge. In addition to methodological research that aims to be more computationally efficient, we expect future work to integrate new technology with machine learning methods to increase their efficiency for managerial use. For example, LDA is a topic modeling algorithm that is computationally expensive and difficult to use with very large datasets. To bypass this problem, Liu, Singh, and Srinivasan (2016) use Amazon's cloud computing service to analyze their dataset. New technology, such as quantum computing, will further decrease the cost of computation and open new opportunities for research.

The possibilities of cloud computing are truly stunning. With sufficient data and ingenuity researchers will be able to dig into real world interactions and zero in on small level phenomenon. While each finding may have a modest effect the proliferation of findings each generating a small improvement give the possibility of a significant boost in marketing effectiveness. Technology advances aligned with ML methods should improve the return on marketing spend. Ideally, this will raise the status of marketers and reduce the constant threat of firing (Whitler and Morgan 2017).See Table 3 for a summary of the implications for future research.

<Insert Table 3 about here>

CONCLUSION

Machine learning is already making a significant impact on academic marketing research and through this, managers. We expect this to continue and, although challenges certainly arise, the changes can have significantly positive elements. It is important to understand that ML brings a altereed way of thinking to research but that this has potential to solve many of the problems plaguing research, from model mining, through an inability to connect with managers, to balkanization of the discipline. Machine learning is here to stay and the trials it brings are real, but the benefits are likely to be greater.

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TABLES

Table 1. *Tools and Techniques for Machine Learning*

Tools	**Key Uses**	**R Packages**	**Python Packages**
Cluster Analysis	Uncover groups in the data that are more like each other than others.	‘stats’	‘scikit-learn’
Factor Analysis	Reduce many variables into fewer number of factors.		
Topic Modeling	Uncover word distributions, or ‘topics’ that summarize documents.	‘topicmodels’; ‘lda’; ‘stm’	‘gensim’
Word2vec	Produce word embeddings, or vector representation of words.	‘text2vec’	
Classification and Regression Trees (CART)	Uses a decision tree to predict target values (classification if discrete, regression trees if continuous).	‘rpart’; ‘caret’	‘scikit-learn’
Boosting or MART (multiple additive regression trees)	Iteratively learning weak classifiers and adding them to a final strong classifier.	‘gbm’; ‘caret’	
Naïve Bayes Classifier	Classifier based on Bayes’ theorem with strong independence assumption between predictors.	‘e1071’; ‘caret’	
Support vector machine (SVM)	Classifier that uses the kernel trick to predict outcome.		
Random Forest	Constructs a multitude of decision trees for purposes of either classification or regression.	‘caret’; ‘randomForest’	
Convolutional Neural Network (CNN)	Uses a variation of multilayer perceptrons that require relatively little pre-processing (deep learning).	‘keras’	‘TensorFlow’

Table 2. *Summary of Marketing Research on Machine Learning*

Authors	Journal	Marketing Research Question	Marketing Domain	Machine Learning Contribution to the Problem
Methodological Research With Structured Data				
Cui and Curry (2005)	MKSC	How is prediction useful for marketing researchers, and what can SVM contribute if that is the case?	Prediction/Forecasting	Performance of SVM and its kernel method in non-linear and complex settings, such as non-compensatory structures.
Evgeniou, Boussios and Zacharia (2005)	MKSC	Can preference modeling be done without assuming a probabilistic model of the data?	Conjoint Analysis	Preference modeling as an optimization problem, extending optimization mechanics of SVM.
Evgeniou, Pontil and Toubia (2007)	MKSC	How can we better account for consumer heterogeneity in a conjoint analysis setting?	Conjoint Analysis	A data-driven ML approach (i.e. cross-validation) to endogenously model heterogeneity, which outperforms hierarchical Bayes (which uses priors for heterogeneity).
Hauser, Toubia, Evgeniou, Befurt and Dzyabura (2010)	JMR	Can a method be developed for non-compensatory decision rules (in a conjoint setting) that can account for many possible disjunctions-of-conjunctions rules?	Conjoint Analysis	Conceptual link between *cognitive simplicity* and *complexity control* (i.e. modeling and controlling for cognitive simplicity enhances prediction). The exogenous parameters are determined using cross-validation.
Dzyabura and Hauser (2011)	MKSC	Can an active-machine-learning algorithm (adaptive question selection) be developed that can	Conjoint Analysis	Errors (from incorrect answers) in an adaptive conjoint analysis setting are framed as tuning parameters, which the

		account for errors in non-compensatory decision heuristics?		algorithm learns after data collection.
Huang and Luo (2016)	MKSC	Can a method of preference elicitation for complex products (that is computationally efficient and can account for errors on the fly) be developed?	Conjoint Analysis	Fuzzy SVM that can assign different weights to data points in customizing questions to refine customer-specific preference estimate.
Trusov, Ma and Jamal (2016)	MKSC	Can a method that can predict user profiles (summaries of interests and preferences) from online activity data (e.g. visitation intensity and dynamics) be developed, which is efficient and scalable?	Consumer Profiling	Topics that are generated from a correlated topic model reflect “roles” that consumers play while visiting various websites.
Chen, Iyengar and Iyengar (2017)	MKSC	Can multimodal continuous heterogeneity (MCH) distribution be modeled in a conjoint setting, given across-segment and within-segment heterogeneity? How should individual-level partworths be recovered?	Conjoint Analysis	Cross-validation used to determine the amount of shrinkage to recover individual-level partworths.
Yoganarashimhan (Accepted)	MKSC	How can results on search engines (in response to a query) be optimally ranked for consumers, while accounting for heterogeneity? What are the benefits (in terms of clicks) to firms from personalization?	Search Engine	Multiple adaptive regression trees (gradient boosting) used for variable selection and inferring optimal functional form and parameters from the data.
Methodological Research With Unstructured Data				
Lee and Bradlow (2011)	JMR	Can market structure be validly analyzed and visualized using customer reviews?	Market Structure	K-means clustering to group extracted phrases from customer reviews.

Tirunillai and Tellis (2014)	JMR	Can a method be developed to extract dimensions of customer satisfaction from customer reviews?	Market Structure	Extend the LDA framework to also capture dimensions of products, along with their corresponding valence from customer reviews.
Liu and Toubia (Forthcoming)	MKSC	Can a method be developed to uncover consumer preferences from the topics of search queries and webpages (for purposes of search engine optimization)?	Search Engine Consumer Profiling	A dual-LDA framework to extract a common set of topics from webpages and search queries.
Timoshenko and Hauser (Accepted)	MKSC	Can customer reviews be used to identify customer needs in a more efficient way (relative to traditional methods such as interviews) to develop new products?	Product Development	Supervised CNN used to extract sentences that contain customer needs from those that do not.
Applied Research With Structured Data				
Currim, Meyer and Le (1988)	JMR	Can individual-level heterogeneity be estimated in models of customer choice, without making hierarchical assumptions?	Choice Modeling	Decision trees used to build a system of disaggregate models.
Bloemer, Brijs, Vanhoof and Swinnen (2003)	IJRM	Can managers identify specific segments of customers that are most likely to churn?	Churn	Classification Trees, and Classification and Regression trees.
Lemmens and Croux (2006)	JMR	Can we improve the prediction of customer churn over the standard binary logit model?	Churn	Bagging and boosting to improve the performance of the predictive model.
Neslin, Gupta, Kamakura, Lu and Mason (2006)	JMR	Which predictive model predicts churn the best?	Churn	A comparison of various classifiers using a ‘tournament’ that is open to both academics and practitioners.
Schwartz, Bradlow and Fader (2014)	MKSC	How can one (managers) determine (in a data-driven way) which model to use given a certain dataset?	Prediction/Forecasting	Classification & Regression Trees test model performance,

				and Random Forest to test the classification tree itself.
Schwartz, Bradlow and Fader (2017)	MKSC	How can managers find the best online banner advertisement out in the field in real-time (i.e. "Earning while Learning")?	Advertising	Thomson sampling as a solution to the presented multi-armed bandit problem.
Ascarza (2018)	JMR	Are people predicted to churn (using classification models) the most sensitive to firm intervention?	Churn	Random forest to estimate which individuals respond more favorably to intervention.
Applied Research With Unstructured Data				
Tirunillai and Tellis (2012)	MKSC	Does user-generated content affect stock performance?	Marketing-Finance	Naïve Bayes and SVM to classify valence.
Ghose, Ipeirotis and Li (2012)	MKSC	How can hotel ranking system be designed to incorporate the economic value of different locations and service-based characteristics of hotels?	Demand Estimation	SVM to classify images of cities to categories.
Xiao and Ding (2014)	MKSC	Do faces of print advertisements affect consumers?	Visual Marketing Advertising	CART to examine heterogeneity in response to facial features.
Chen, Nelson and Hsu (2015)	JMR	Are mental processes related to brands' personality traits connected with specific brain areas?	Neuroimaging	Cross-validation to predict neural response/brain activity in fMRI images.
Homburg, Ehm and Artz (2015)	JMR	How does firm engagement with consumers online affect consumer sentiment?	Online WOM	SVM used for sentiment analysis of user-generated content.
Liu, Singh and Srinivasan (2016)	MKSC	Can TV ratings be predicted using user-generated content?	Big Data Online WOM	Singular value decomposition for dimension reduction of data, LDA used to analyze content on Amazon Cloud computing.
Lu, Xiao and Ding (2016)	MKSC	Can the service process of providing customer recommendations in-store be automated?	Personalization Recommendation	Pre-trained classifier and collaborative filtering on real-

				time, in-store video data to calculate a “preference score”.
Tirunillai and Tellis (2017)	MKSC	Do TV ads affect online chatter?	Advertising Online WOM	SVM and Naïve Bayes to classify valence of reviews.
Zhang and Godes (2018)	MKSC	Do social ties (strong and weak) impact purchase decision quality?	Online WOM Social Network	Classify whether the text in reviews are either informative or non-informative.
Ordenes, Grewal, Ludwig, Ruyter, Mahr and Wetzels (2018)	JCR	What are the characteristics of content on social media platforms (Twitter and Facebook) and those that are most likely to be shared?	Online WOM	SVM to classify brand-generated messages as either assertive, expressive, or directive.
Klostermann, Plumeyer, Boger and Decker (2018)	IJMR	How can various brand information and their associative networks be extracted from social media platforms?	Market Structure	Cluster Analysis (to group images), and Google Cloud Vision API (service that tags Instagram images).
Hartmann, Huppertz, Schamp and Heitmann (2018)	IJRM	Which methods perform the best in analyzing sentiment and content of unstructured text?	Online WOM	An ensemble of classifiers (e.g. SVM, Naïve Bayes, and Random Forest) is used to classify sentiment and content.

Table 3. *Implications for Future Research*

Prediction	Implication
Falling Entry Barriers To Machine Learning Research	More ML applied to marketing problems. Most quantitative marketers will use some ML techniques and as packages become more available scholars from all approaches will use ML techniques.
Changing Marketing Models	There will be plenty of opportunity to revisit marketing models to better align them with novel findings both in theoretical work and practical application.
Improving Marketing Best Practice	Problems with malpractice will be somewhat mitigated by the 'honesty' of ML algorithms. Research will make it clear when model mining is occurring allowing more accurate assessment of the contributions of a paper.
Change in Venues for Research	We expect academic marketers to find themselves more connected to practitioners in their workplace with a concomitant decline in the importance of the laboratory research and even panels.
More Modest but More Useful Research	Claims made by academic research will be more modest. The quest for universal single issue causation will be lessened. More credit will be given for work with clear implications in a specific context
Bridging The Practitioner Divide	More modest research that applies in specific contexts will be more useful for managers, helping to bridge the academic-practitioner divide
Change in Prominence of Research Streams within Marketing	We expect a fall in the prominence of laboratory experiments and more interest in marketing sub-disciplines that concentrate on specific market details such as marketing strategy work and "qualitative" research.
Merging Marketing Research Streams	Great incentive and opportunity for scholars of diverse methodological backgrounds within marketing to collaborate.

FIGURES

Figure 1. History of Machine Learning

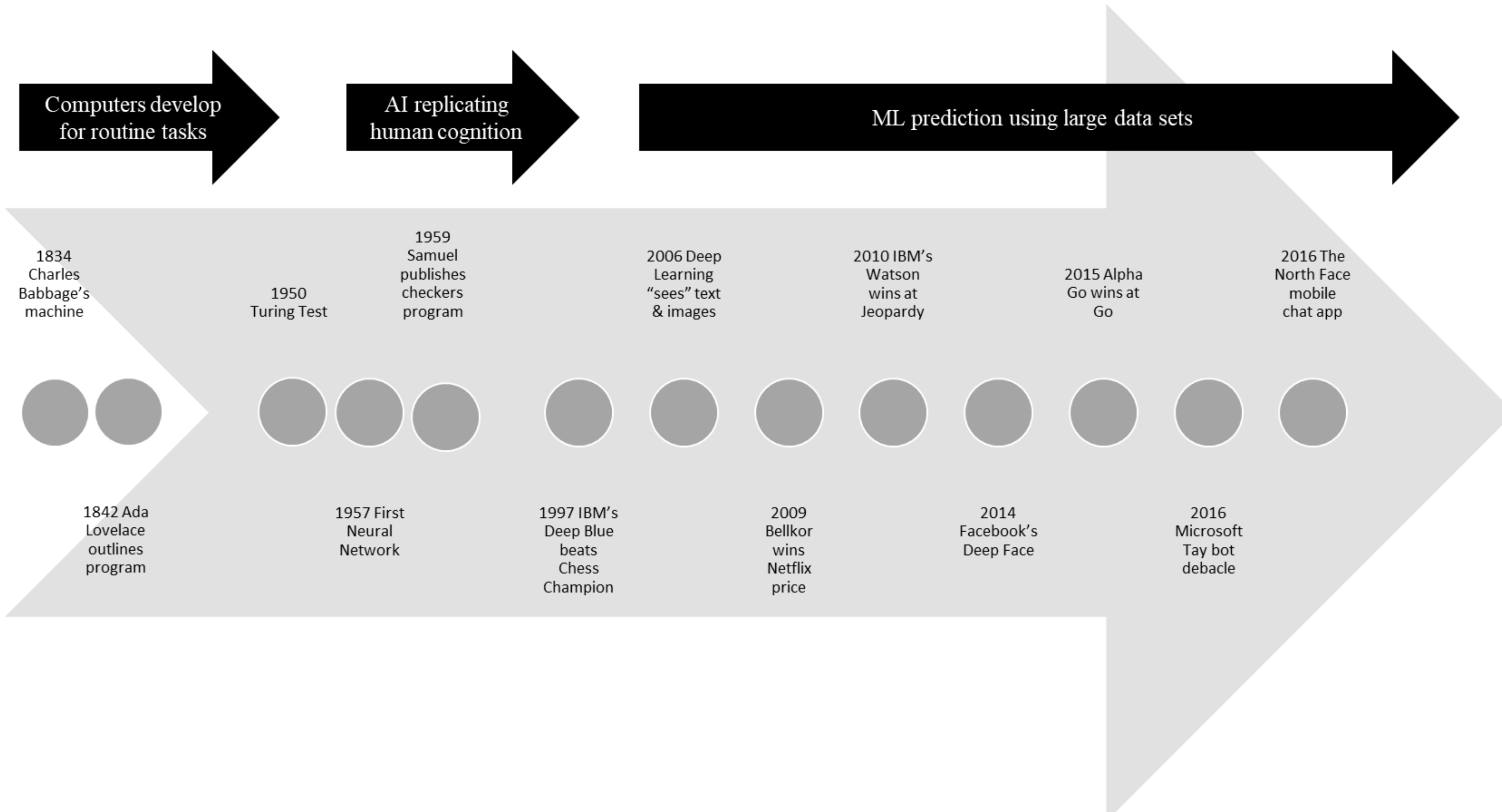

Figure 2. A Taxonomy of Machine Learning