



## Marketing Science

Publication details, including instructions for authors and subscription information:  
<http://pubsonline.informs.org>

### Editorial—Marketing Science and Big Data

Pradeep Chintagunta, Dominique M. Hanssens, John R. Hauser

To cite this article:

Pradeep Chintagunta, Dominique M. Hanssens, John R. Hauser (2016) Editorial—Marketing Science and Big Data. Marketing Science 35(3):341-342. <http://dx.doi.org/10.1287/mksc.2016.0996>

Full terms and conditions of use: <http://pubsonline.informs.org/page/terms-and-conditions>

This article may be used only for the purposes of research, teaching, and/or private study. Commercial use or systematic downloading (by robots or other automatic processes) is prohibited without explicit Publisher approval, unless otherwise noted. For more information, contact [permissions@informs.org](mailto:permissions@informs.org).

The Publisher does not warrant or guarantee the article's accuracy, completeness, merchantability, fitness for a particular purpose, or non-infringement. Descriptions of, or references to, products or publications, or inclusion of an advertisement in this article, neither constitutes nor implies a guarantee, endorsement, or support of claims made of that product, publication, or service.

Copyright © 2016, INFORMS

Please scroll down for article—it is on subsequent pages



INFORMS is the largest professional society in the world for professionals in the fields of operations research, management science, and analytics.

For more information on INFORMS, its publications, membership, or meetings visit <http://www.informs.org>

## Editorial

## Marketing Science and Big Data

Pradeep Chintagunta

Booth School of Business, University of Chicago, Chicago, Illinois 60637, [pradeep.chintagunta@chicagobooth.edu](mailto:pradeep.chintagunta@chicagobooth.edu)

Dominique M. Hanssens

UCLA Anderson School of Management, University of California Los Angeles,  
Los Angeles, California 90095, [dominique.hanssens@anderson.ucla.edu](mailto:dominique.hanssens@anderson.ucla.edu)

John R. Hauser

MIT Sloan School of Management, Massachusetts Institute of Technology,  
Cambridge, Massachusetts 02139, [hauser@mit.edu](mailto:hauser@mit.edu)*Keywords:* data science; computer science; big data; quantitative analysis; modeling; machine learning

Marketing science has a long tradition of embracing new challenges, new methods, and new disciplines. The field today is built upon the diverse efforts of researchers who, for almost 50 years, have synthesized solutions from a variety of disciplines to provide new insight to marketing problems. More often than not, the crucible of marketing science has given back to other disciplines, models, and methods that are better and more robust.

For example, in the early 1980s, consumer packaged goods firms experienced a data revolution. No longer dependent upon aggregate, time-delayed data such as warehouse withdrawals, the advent of scanner data enabled marketing scientists to observe the behavior of individual consumers making purchases over many shopping trips and for many product categories. Initial analyses were descriptive and led to new insights such as the type of consumers who would respond to coupons and deals. But soon researchers applied the logit model from transportation science and economics and used it in new and different ways. Loyalty, time-dependence, consumer perceptions, context dependence, and many other phenomena were first explored in marketing science and then made their way into other disciplines such as economics, operations management, and operations research.

We can cite many examples over the years where advanced econometrics, field experiments, optimization, and Bayesian methods were first used to solve marketing science problems and then developed further to give back to other disciplines. We can also cite many theoretical advances in game theory, strategic new product entry, and, especially, what are now called funnel measures, that have been driven by the

challenges of providing new insights to marketing managers. Many of these breakthroughs are documented by Winer and Neslin (2014).

In many ways, the big data revolution provides a parallel to the scanner data revolution. Big data are often defined by volume, velocity, and variety. Firms, and specialized data suppliers, now track and maintain extremely large databases on consumers' shopping and purchase behavior (volume). These data are often available on a real-time basis (velocity) enabling marketing science models that customize marketing instruments to consumers as consumers search for information, compare prices or make purchases. Big data comes in many formats beyond the simple numerical data with which we have dealt for many years (variety). These data include numerical data, text, audio, and video files which are increasingly interconnected.

To take advantage of big data, marketing science will need to embrace disciplines such as data science, machine learning, text-processing, audio-processing, and video-processing. For example, one paper in this special issue provides a fully-automated method to monitor brand-related messages on Twitter (Culotta and Cutler 2016). Another processes video data to make recommendations for new garment purchases (Lu et al. 2016). Still another uses active machine learning (fuzzy support vector machines) to provide a new method of preference elicitation for complex products (Huang and Luo 2016). Another combines methods from cloud computing, machine learning, and text mining to demonstrate how online social platforms such as Twitter can be used for sales forecasting

(Liu et al. 2016). A fifth paper that will appear in a subsequent issue, uses methods from multi-armed bandit problems to identify the banner-advertising characteristics that are most likely to appeal to consumers (Schwartz et al. 2016).

But the street runs both ways. For example, latent Dirichlet allocation (LDA) is normally used in text processing to identify “buckets of words.” Jacobs et al. (2016) turn LDA on its head to identify, from the consumer’s perspective, sets of products that tend to be purchased together. Their analyses have the potential to improve product recommendations and thus contribute to the recommendation system literature. Ringel and Skiera (2016) develop innovative mapping methods to help visualize complex market structures among more than 1,000 products. Trusov et al. (2016) develop and implement a targeting algorithm that reads consumers’ web-surfing behavior, profiles potential consumers, and enables improved behavioral targeting. Indeed, they demonstrate that their approach is superior to existing methods. Barajas et al. (2016) develop new methods that separate the target selection component and the campaign effect of online display ads for millions of users. Braun and Damien (2016) demonstrate how to scale rejection sampling for large hierarchical Bayes models.

While we are excited about the papers in this issue, we are equally excited about the potential of marketing science to learn from affiliated disciplines such as machine learning and large-data statistics, but at the same time provide new structures and theories that help firms understand and use big data. Many peer-reviewed solutions are already available and published in *Marketing Science*, others will be published in coming issues. The field of marketing science has developed a deep understanding of consumer choice

modeling, customer lifetime value, new product demand forecasting, marketing-instrument response modeling, customized communication and promotion, brand valuation, consumer-preference measurement, and consumer behavior modeling, among others. For each of these challenges, marketing science has models, structures, estimation, and theory. The combination of new affiliated disciplines, existing peer-reviewed methods, and proven theory heralds a bright future for marketing science and big data.

## References

- Barajas J, Akella R, Holtan M, Flores A (2016) Experimental designs and estimation for online display advertising attribution in marketplaces. *Marketing Sci.* 35(3):465–483.
- Braun M, Damien P (2016) Scalable rejection sampling for Bayesian hierarchical models. *Marketing Sci.* 35(3):427–444.
- Culotta A, Cutler J (2016) Mining brand perceptions from Twitter social networks. *Marketing Sci.* 35(3):343–362.
- Huang D, Luo L (2016) Consumer preference elicitation of complex products using fuzzy support vector machine active learning. *Marketing Sci.* 35(3):445–464.
- Jacobs BJD, Donkers B, Fok D (2016) Model-based purchase predictions for large assortments. *Marketing Sci.* 35(3):389–404.
- Liu X, Singh PV, Srinivasan K (2016) A structured analysis of unstructured big data by leveraging cloud computing. *Marketing Sci.* 35(3):363–388.
- Lu S, Xiao L, Ding M (2016) A video-based automated recommender (VAR) system for garments. *Marketing Sci.* 35(3):484–510.
- Ringel DM, Skiera B (2016) Visualizing asymmetric competition among more than 1,000 products using big search data. *Marketing Sci.* 35(3):511–534.
- Schwartz E, Bradlow E, Fader P (2016) Customer acquisition via display advertising using multi-armed bandit experiments. *Marketing Sci.* Forthcoming.
- Trusov M, Ma L, Jamal Z (2016) Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting. *Marketing Sci.* 35(3):405–426.
- Winer RS, Neslin SA (2014) *The History of Marketing Science* (World Scientific Publishing Co., Singapore).