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Business analytics has become profound. Ten years ago, when I was able to recruit my first class of MBA students to my new statistical learning elective, my colleagues were astonished because our department struggled to fill most electives. Today, we offer a Masters in Business Analytics, which is the largest specialized master's program in the school and has application volume rivaling those of our MBA programs. Our department's faculty size and course offerings have increased dramatically, yet the MBA students are still complaining that the classes are all full. Google's chief economist, Hal Varian, was indeed correct in 2009 when he stated that "the sexy job in the next 10 years will be statisticians."

This demand is driven by a simple, but undeniable, fact. Business analytics solutions have produced significant and measurable improvements in business performance, on multiple dimensions and in numerous settings, and as a result, there is a tremendous demand for individuals with the requisite skill set. However, training students in these skills is challenging given that, in addition to the obvious required knowledge of statistical methods, they need to understand business-related issues, possess strong communication skills, and be comfortable dealing with multiple computational packages. Most statistics texts concentrate on abstract training in classical methods, without much emphasis on practical, let alone business, applications.

This book has by far the most comprehensive review of business analytics methods that I have ever seen, covering everything from classical approaches such as linear and logistic regression, through to modern methods like neural