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In the first edition, we have been fortunate to train more than 1,000 participants in the Applied Data Analytics classes, resulting in increased data analytics capacity, in terms of both human and technical resources. What we have learned in delivering these classes has greatly influenced the second edition. We also have added a new chapter on Bias and Fairness in Machine Learning as well as reorganized some of the chapters.

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