CHAPTER 1. INTRODUCTION

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Geometrical analyses of parametric inference problems have developed from two appealing ideas: that a local measure of distance between members of a family of distributions could be based on Fisher information, and that the special place of exponential families in statistical theory could be understood as being intimately connected with their loglinear structure. The first led Jeffreys (1946) and Rao (1945) to introduce a Riemannian metric defined by Fisher information, while the second led Efron (1975) to quantify departures from exponentiality by defining the curvature of a statistical model. The papers collected in this volume summarize subsequent research carried out by Professors Amari, Barndorff-Nielsen, Lauritzen, and Rao together with their coworkers, and by other authors as well, which has substantially extended both the applicability of differential geometry and our understanding of the role it plays in statistical theory.**

The most basic success of the geometrical method remains its concise summary of information loss, Fisher's fundamental quantification of departure from sufficiency, and information recovery, his justification for conditioning. Fisher claimed, but never showed, that the MLE minimized the loss of information among efficient estimators, and that successive portions of the loss could be

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