Matthews (1985) has carried out many further computations in his Stanford Ph.D. thesis. He works in the context of a random walk on a group and derives the distribution until the walk hits (or is suitably close to) every point. This relates to projection pursuit via Asimov's scheme for the "grand tour." Asimov considers projections that "wiggle around" by small random rotations. His results agree with those reported by Huber in the following sense, it takes a long time to get close to most projections in high dimensions. Therefore, some form of projection pursuit is needed. On the other hand, once an interesting projection has been located, it seems useful to have some kind of grand tour to "wiggle around" in a neighborhood, to try to explore the features of the interesting projection.

REFERENCES

ASIMOV, D. (1985). The Grand Tour. *SIAM J. Sci. Statist. Comput.* **6** 128–143.

DIACONIS, P. (1983). Projection pursuit for discrete data. Stanford University Technical Report #198.

DIACONIS, P. and FREEDMAN, D. (1984). Some asymptotics for graphical projection pursuit. *Ann. Statist.* **12** 793–815.

DIACONIS, P. and GRAHAM, R. L. (1983). The Radon transform on Z_2^k. Stanford University Technical Report #206. To appear in *Pacific J. Math.*

DIACONIS, P. and SHAHSHAHANI, M. (1984). Some theory for projection pursuit regression. *SIAM J. Sci. Statist. Comput.* **5** 175–191.

MATTHEWS, P. (1985). Covering problems for random walks on spheres and finite groups. Doctoral dissertation, Dept. of Statist., Stanford University.

SUDAKOV, V. N. (1980). Typical distributions of linear functionals chosen at random. Colloques Internationaux Du Centre National de la Recherche Scientifique No. 307, pp. 501–511.

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In our discussion of this very stimulating paper, we will mostly confine our remarks to some of the general issues Huber raises in the introductory paragraphs.

1. The curse of dimensionality. In paragraph four of the introduction, Huber writes "· · · the most exciting feature of PP is that it is one of the very few multivariate methods able to bypass the 'curse of dimensionality' · · · "

Actually, Huber gives no precise definition of the "curse." Perhaps this is best, because there are several curses of dimensionality. Adverse effects of increasing dimension can include: less robustness, greater computational costs, worse mean squared error, and slower convergence to limiting distributions.

In this instance, Huber is concerned with the effects of increasing dimension on the mean-squared-error of smoothers. He points out that kernel and related