



Chapter XII

**Cluster Analysis of
Marketing Data Examining
On-line Shopping
Orientation: A Comparison
of k -means and Rough
Clustering Approaches**

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Cluster analysis is a common market segmentation technique, usually using k -means clustering. Techniques based on developments in computational intelligence are increasingly being used. One such technique is the theory of rough sets. However, previous applications have used rough sets techniques in classification problems, where prior group membership is known. This chapter introduces rough clustering, a technique based on a simple extension of rough sets theory to cluster analysis, and applicable where group membership is unknown. Rough clustering solutions allow multiple cluster membership of objects. The technique is demonstrated through the analysis of a data set containing scores on psychographic variables, obtained from a survey of shopping orientation and Web purchase intentions. The analysis compares k -means and rough clustering approaches. It is suggested that rough clustering can be

considered to be extracting concepts from the data. These concepts can be valuable to marketers attempting to identify different segments of consumers.

INTRODUCTION

Cluster analysis has been a fundamental technique in marketing research for many decades, both as a general data reduction technique and as the basis for market segmentation (Arabie & Hubert, 1994; Punj & Stewart, 1983). While there are numerous ways to undertake market segmentation, the grouping of similar objects through cluster analysis remains one of the fundamental starting points. In marketing research, objects are usually the measured demographic or psychographic characteristics of consumers. Forming groups that are homogenous with respect to these measured characteristics segments the market. One psychographic measure often used in segmentation studies is shopping orientation.

Consumers go shopping for a variety of reasons, not just for the procurement of goods (Tauber, 1972). Reasons may include social interaction, sensory stimulation, role enactment, and physical exercise, to name a few (Tauber, 1972). The psychographic characteristic of shopping orientation refers to the general predisposition of consumers toward the act of shopping and has been used to partially explain retail shopping behaviour (Dholakia, Pedersen & Hikmet, 1995). Six core shopping orientations have been identified in the published marketing literature: economic, recreational, apathetic, convenience-oriented, ethical, and personalising (Brown, 1999).

Economic shoppers are essentially concerned with buying products at the lowest price or getting the best value for the money they spend (Bellenger & Korgaonkar, 1980; Shim & Mahoney, 1992). *Recreational* shoppers enjoy the act of shopping regardless of whether a purchase is made or not (Bellenger & Korgaonkar, 1980). *Apathetic* or inactive shoppers are mostly interested in minimizing shopping effort (Darden & Reynolds, 1971). *Convenience-oriented* shoppers are those under time constraints and possibly also under space and effort constraints (Gehrt, Yale & Lawson, 1996). *Ethical* shoppers can be distinguished by their loyalty, with studies investigating store loyalty, brand loyalty, or both (Darden & Reynolds, 1971). *Personalizing* shoppers demonstrate a propensity to value relationships with suppliers (Darden & Reynolds, 1971; Peppers & Rogers, 1997).

The starting point for many of these market segmentation studies has been cluster analysis. Many clustering methods have been identified, including partitioning, hierarchical, nonhierarchical, overlapping, and mixture models (Arabie & Hubert, 1994; Hair, Anderson, Tatham & Black, 1998). One of the most commonly used nonhierarchical methods is the *k*-means approach. This approach will be considered in more detail in the following section.

In the last few decades many new techniques based on developments in computational intelligence have started to be more widely used as clustering

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