

**Investigating the Impact of Different Representations of Data on Neural
Network and Regression**

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By

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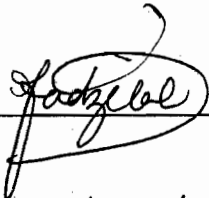
INVESTIGATING THE IMPACT OF DIFFERENT REPRESENTATION
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ABSTRACT

In this research the impact of different data representation on the performance of neural network and regression was investigated on different datasets that has binary or Boolean class target. In addition, the performance of particular predictive data mining model could be affected with the change of data representation. The seven data representations that have been used in this research are As_Is, Min Max normalization, standard deviation normalization, sigmoidal normalization, thermometer representation, flag representation and simple binary representation. Moreover, all data representations have been applied on two datasets which are Wisconsin breast cancer and German credit dataset. As a result, the neural network performance is better than logistic regression on both datasets if we exclude the thermometer and flag representations. For datasets having a binary or Boolean target class, flag or thermometer binary representation is recommended to be used if logistic regression analysis is performed. Meanwhile, As_is representation, min max normalization, standard deviation normalization or sigmoidal normalization is recommended for neural network analysis on datasets having binary or Boolean target class.

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CHAPTER 1

INTRODUCTION

1.0 Background

Data mining has been used widely in many different areas and domains to extract useful information from large amounts of data (Leung *et al.*, 2001). Instead of being its own field, data mining is a combination of several fields such as computer science, artificial intelligence and statistics (Remondino & Correndo, 2005). In addition, data mining is a crucial step in the Knowledge Discovery in Databases (KDD) process which comprises of data cleaning, data consolidation, data selection, data transformation, data mining, pattern analysis and knowledge presentation (Ozekes & Osman, 2003). There are two types of data mining models, namely the predictive and the descriptive (Kusiak, 2006; Remondino & Correndo, 2005; Ozekes & Osman, 2003). Descriptive data mining aims to summarize data and extract interesting properties from the data, while predictive data mining aims to build models and predict future behaviours. Data mining tasks can be grouped into four categories which are association, summarization, classification, clustering and trend analysis (Luo, 2008). There are many different methods of predictive data mining, for example, prediction, classification, regression, and time series.

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