Big Data Behaviour Modelling and Visual Analytics

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Certificate of Authorship/Originality

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I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

Big Data is composed of text, images, video, audio, mobile or other forms of data collected from multiple datasets, and is rapidly growing in both size and complexity. This has created a huge volume of multidimensional data within a very short time period. Big Data is therefore too big, too complex and moves too fast for us to analyze using traditional methods. Big Data behaviour is considered as a set of concepts and categories that descripts Big Data's acts towards others. The challenges facing Big Data analysis and visualization include: 1) how to classify Big Data across multiple datasets and different forms of data, 2) how to visualize structured and unstructured Big Data behaviour patterns for multidimensional data, 3) how to display Big Data behaviour patterns with very large volumes onto a normal-sized screen, 4) how to visualize Big Data behaviour patterns without the loss of information.

Big Data visualization normally requires optimized solutions through using different visual techniques for integrating display and exploration. To illustrate the huge amount of multidimensional data within a standard-size screen, visualization needs to find an efficient classification method for multiple datasets across any form of data. The current data interactive exploration has normally optimized data for visualization by excluding some pieces of information, resulting in missing information. Big Data visualization also suffers from visual cluttering and data overcrowding problems, whilst dealing with huge amounts of multidimensional data.

My approach includes two parts: Big Data behaviour modelling and Big Data visualization. I have firstly established the 5Ws dimensions for Big Data classification, based on data behaviour ontologies, that can be applied to multiple datasets and to any

form of data. Each data incident contains these 5Ws dimensions, which are posed as a set of concepts and categories that descripts Big Data acts for; When did the data occur, Where did the data come from, What did the data contain, How was the data transferred, Why did the data occur, and Who received the data. Secondly, I have introduced Pair-Density algorithms to measure Big Data behaviour patterns, which enables comparison and analysis between any two dimensions of behaviours. Two non-dimensional axes in parallel coordinates have then been created by using Pair-Density to measure and compare visual patterns for Big Data visualization. Finally, Shrunk Attributes has been deployed into Pair-Density parallel coordinates. This not only narrows down Big Data patterns for better understanding, but also dramatically reduces data cluttering and overcrowding in Big Data visualization.

Three different datasets with a combined total of more than 2.5 million data incidents have been implemented for measuring and visualizing different data patterns, including both numerical and non-numerical dimensions. The experimental results have shown that my new approach has significantly improved the accuracy of Big Data visualization, reduced data cluttering by more than 80% without the loss of information. The use of 5Ws dimensions and Pair-Density parallel coordinates therefore has large potential benefits and applications across both the business and research fields.

This thesis contains the research approach and implementation results obtained by the author during his Ph.D period. The majority of methods and results have been published in **Seventeen** research papers in journals and conference proceeding by May 2016.

Author's Seventeen published papers for PhD

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