Spatial-Temporal Data Modelling and Processing for Personalised Decision Support

Muhaini Othman

A thesis submitted to Auckland University of Technology
in fulfilment of the requirement for
the degree of Doctor of Philosophy

Supervisors:
Prof. Nikola Kasabov
Assoc. Prof. Russel Pears
Assoc. Prof. Dave Parry

Consultants:
Dr. Rita Krishnamurthi
Prof. Valery Feigin
Assoc. Prof. Sue Worner

prepared at The Knowledge Engineering and Discovery Research Institute, KEDRI

submitted on May, 2015

School of Computer and Mathematical Sciences

Abstract

Introduction

Capturing the nature of spatio/spectro-temporal data (SSTD) is not an easy task nor is understanding the relationships between the different data dimensions such as between temporal and spatial, temporal and static, and between temporal variables themselves. In the past it has been normal to separate the SSTD dimensions and only take one dimension of the data and convert it into a static representation and model from there. While other dimensions are either ignored or modelled separately. Although this practice has had significant outcomes, the relationships between data dimensions and the meaning of that relationship defined be the data is lost and can result in inaccurate solutions. Any relationship between the static and dynamic or temporal data has been under analysed, if analysed at all, dependent upon the field of study.

Purpose of the research

The purpose of this research is to undertake the modelling of dynamic data without losing any of the temporal relationships, and to be able to predict likelihood of outcome as far in advance of actual occurrence as possible. To this end a novel computational architecture for personalised (individualised) modelling of SSTD based on spiking neural network methods (PMeSNNr), with a three dimensional visualisation of relationships between variables is proposed. The main architecture consists of a spike time encoding module; a recurrent or evolving 3D spiking neural network reservoir (eSNNr); an output module for either classification or prediction based around another evolving spiking neural network; and a parameter optimisation module. In brief, the architecture is able to transfer spatio-temporal data patterns from a multidimensional input stream into internal patterns in the eSNNr. These patterns are then analysed to produce a personalised model for either classification or prediction dependent on the specific needs of the situation.

Method

The architecture described above was constructed using MatLab in several individual modules linked together to form NeuCube (M1). This is the first iteration of the NeuCube architecture and as such remains relatively basic in its operations. The value of results obtained have also been analysed against the backdrop of the limitations of existing global and personalised methods with respect to SSTD. The following list briefly outlines the constituent components of the current version of NeuCube (M1) that was developed by our team.

- An encoding method employing Address Event Representation (AER) algorithm.
- A recurrent 3D SNN reservoir based on the Liquid-State Machine (LSM) concept and implementation of Spike Time Dependent Plasticity (STDP) as a learning rule.
- Innovative input variables mapping techniques utilizing Factor Graph Matching (FGM) algorithm.
- A predictive personalised modelling method for early event prediction.
- Various selections of evolving spiking neural network classifiers including a novel extended dynamic evolving spiking neural network method for multi-NN classification and regression problems called deSNNs_wkNN.
- A grid-search optimisation module and visualisation of the spiking network activities specifically on a group and personalised level.

This methodology has been applied to two real world case studies. Firstly, it has been applied to data for the prediction of stroke occurrences on an individual basis. This data consists of static variables (personal and geographic), and dynamic variables (climate, pollution and geomagnetic daily readings). Secondly, it has been applied to ecological data on aphid pest abundance prediction. The aphid data consists of only dynamic climate and geomagnetic variables. Two main objectives for this research when judging outcomes of the modelling are accurate prediction and to have this at the earliest possible time point. These two objectives are applied to both case studies. Decisions of accuracy and dependability of the prediction are dependent upon the data available and the desired precision of the prediction.

Product

This study has found a number of interesting results.

- Firstly that using spiking neural networks for personalised modelling is more suitable for analysing and modelling SSTD dynamically compared with conventional machine learning methods that use global modelling, thus verifying the validity of this approach and that this methodology has also achieved a better results in terms of prediction accuracy.

- Secondly, using this approach early event prediction is possible where the time length of the training data (samples, collected in the past) and the test data (samples used for prediction) can be differentiate. Early event prediction is very crucial when solving important ecological and social tasks and disease risk prediction described by temporal-and/or spatial-temporal data, such as stroke risk prediction, pest population burst prevention, natural disaster warning, and financial crisis prediction.

- Thirdly, that these methods take all features without the need to filter noise and still produce good results.

- Fourthly, the innovative input variables mapping techniques enable dynamics mapping of SSTD variables and assist in revealing unknown spatio-temporal patterns and its associations.

- Lastly, the visualisation of spiking network activities enables deep network learning of the spiking patterns. This assists us in understanding the spiking neurons connection and relationships. Furthermore this visualisation reveals new knowledge about the SSTD that deserves to be investigated further.

Conclusions

The implications of these findings are not insignificant in terms of health care management and environmental control. As the case studies utilised here represent vastly different application fields, it reveals more of the potential and usefulness of NeuCube for modelling data in an integrated manner. This in turn can identify previously unknown (or less understood) interactions thus both increasing the level of reliance that can be placed on the model created, and enhancing our human understanding of the complexities of the world around us without the need for over simplification. The visualisation of the cube inside NeuCube enables the researcher to gain valuable insight into not just the connectedness of variables but how this change dynamically as new data is presented. A simulation of what the real situation is more likely to be like in its construction, connection and the nature of the interaction between variables, i.e. does the current neuron promote the next neuron or inhibit it. The findings were published in five (5) papers and two (2) more have been recently submitted.

Acknowledgement

Alhamdullillah to Allah for giving me strength and perseverance to finish the journey that started almost 4 years ago. There are so many people that have helped me and I am very thankful to have been blessed to meet such good people. First of all, I would like to express my deepest gratitude to my supervisor, Professor Nikola Kasabov, whose guidance and support from the very beginning to the final stage of my journey has helped me learn and deepen my understanding of the research area. Nikola, who has the attitude and the substance of a genius; has continually and convincingly conveyed a spirit of adventure in regard to research. He is a great supervisor with a pleasant personality, enthusiasm and wisdom.

I would also like to thank Dr. Yingjie Hu, who although supervised me briefly, advised and encouraged me and gave me strength to continue with my work. My thanks also go to Associate Professor Russel Pears for his insight and support in my research. I thank Associate Professor Dave Parry for giving me advice in the area of ontology.

I am heartily thankful to Dr. Rita Krishnamurthi and Professor Valery Feigin from The National Institute for Stroke and Applied Neurosciences (NISAN), for their advice, knowledge sharing and cooperation in my research. Without their case study, this research would be incomplete. My sincere thanks go to Associate Professor Sue Worner from Lincoln University for her advice.

During my study, I have had the opportunity to learn and work with a lot of people in the Knowledge Engineering and Discovery Research Institute (KEDRI). I would like to express my gratitude to the past and present members of KEDRI for their support and encouragement that had eased my PhD journey tremendously. Dr. Yixiong Chen and Dr. Jin Hu from Chinese Academy of Science, along with Dr. Enmei Tu from Shanghai Jiao Tong University deserves a special acknowledgement for their advice, guidance and for providing technical support, especially in system design and development during their brief stay at KEDRI. Without their genius mind, this research would be incomplete. Their kindness and friendship will forever be etched in my memory. I thank Vivienne Breen for her friendship and assistance in proof reading my writing and always being there for helpful discussions, especially in understanding mathematical algorithms. My thanks goes to Reggio Hartono who helped in providing technical support whenever I needed it. My gratitude also goes to Dr. Yuxiao Li for her assistance in the case study of aphid pest abundance prediction. Thanks also to all the staff of KEDRI, Nathan Scott, Neelava Sengupta, Elisa Capecci, Maryam Gholami Doborjeh and Fahad Alvi. Not to forget the past staff of KEDRI, I thank Dr. Stefan Schliebs, Dr. Ammar Mohemmed, Dr. Haza Nuzly, Dr. Linda Liang, Dr. Kshitij Dhoble and Dr. Nuttapod Nuntalid for their support. I also like to thanks Nurdiana Nordin and Norhanifah Murli for their utmost sincere friendship and support.

To Joyce D'Mello, I am totally grateful for her assistance and support. She is always been there to advise and encourage me to pursue my dream and finish my study. She is the backbone of KEDRI. I am grateful for her friendship that will forever have a special place in my heart.

Thanks also to the Ministry of Education of Malaysia and University Tun Hussein Onn Malaysia (UTHM) for the financial support through the SLAB/SLAI Scholarship.

On a personal level, I would like to express my gratitude to my loving husband Kardi Sebli for his support, patience and encouragement. Without him by my side, I would not be able to finish this journey. To my sons Haziq, Syafiq and Taufiq, thanks for being such wonderful and supportive sons. You are my pillar of strength and I am doing this for you. My thanks also go to my beloved parents Othman Ismail and Sarah Awang who definitely cannot be thanked enough. Thank you for your support and prayers.

Lastly, I would like to offer my sincere appreciation to all of those who have helped me in any respect during my PhD journey.

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List of Abbreviations

NO_2	Nitrogen Dioxide
O_3	Ozone
SO_2	Sulfur Dioxide
kNN	k-Nearest Neighbour
AER	Address Event Representation
Alate	Winged aphid
Anholocyclic	Parthenogenetics - reproduction without fertilization
ANN	Artificial Neural Network
Apterae	Non-winged aphid
ARCOS	Auckland Regional Community Stroke
BSA	Ben's Spike Algorithm
CNNs	Convolutional Neural Networks
CNS	Central Nervous System
CSVM	Cluster Support Vector Machine
DBNs	Deep Belief Networks
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System
deSNN	Dynamic Evolving SNN
deSNNs_wkNN	A novel algorithm for classification and regression
ECF	Evolving Classification Function
ECOS	Evolving Connectionist System

EEG	Electroencephalography - a test that measures and records the electrical activity of the brain
eeSNN	Extended Evolving SNN
EFuNN	Evolving Fuzzy Neural Network
eSNN	Evolving Spiking Neural Network
FGM	Factor Graph Matching
FMRI	Functional magnetic resonance imaging - is a functional neuroimaging procedure using MRI technology that measures brain activity by detecting associated changes in blood flow, page 58
GRN	Gene Regulatory Network
HMM	Hidden Markov Models
Holocycly	Combination of sexual and asexual reproduction
HSA	Hough Spiker Algorithm
IMPM	Integrated Method for Personalised Modelling
LibSVM	A library for SVM
LIFM	Leaky Integrate-and-Fire Models
LOOCV	Leave-One-Out Cross Validation
LSM	Liquid-State Machine
LSSVM	Least Square Support Vector Machine
PMeSNNr	An evolving personalised modelling and spiking neural network framework and system
POC	Population Rank Order Coding
PSP	Post-synaptic Potential

QEA	Genetic Algorithm and Quantum-Inspired Evolutionary Algorithm
reSNN	Recurrent Evolving SNN
RO	Rank Order
ROC	Rank Order Coding
SNN	Spiking Neural Networks
SPAN	Spike Pattern Association Neuron
SRM	Spike Response Models
SSTD	Spectro, spatio-temporal data
SSVM	Smooth Support Vector Machine
STDP	Spike-Time Dependent Plasticity
STOS	Spatio-Temporal Ontology-based System
SVM	Support Vector Machine
TIA	Transient Ischaemic Attack
TWNFI	Transductive Neural Fuzzy Inference System with Weighted Data Normalization
TWRBF	Transductive RBF Neural Network with Weighted Data Normalization
wkNN	Weighted k-Nearest Neighbour
ww$k$NN	Weighted-weighted k-Nearest Neighbour
YDV	Yellow Dwarf Viruses

Chapter 1

INTRODUCTION

"All our knowledge has its origins in our perceptions."

- Leonardo da Vinci

1.1 Background

Spectro, spatio-temporal data (SSTD) is collected daily in many domains and is challenging to analyze because there are spatial and temporal connections amongst the data that need to be addressed accordingly. In them reside hidden patterns and new undiscovered knowledge that may solve numerous problems. Processing SSTD increases the data mining task complexity because it includes both temporal and spatial dimensions [Andrienko 2006].

In the domain area of bioinformatics, the concerns of manipulating SSTD to represent knowledge is crucial because it could lead to the notion of improving and saving lives either for humans, animals or the environment. In health related problems such as predicting stroke and heart attack occurrences, the analysis of SSTD will help in predicting the risk of these diseases by learning the temporal relations in the data for prevention purposes.

Analyzing SSTD related to ecological problems could help in restoration of the ecological balance that is sometimes disturbed or changed due to environmental factors. In the geological domain, SSTD pattern learning could assist in disaster management and may save lives.

1.2 Motivation

The development of personalised decision support systems has the potential to be the tool for better understanding health related problems like chronic disease including stroke, cardiovascular disease, cancer and countless unsolved medical problems. For instance, health related problems like chronic diseases are the major cause of death in almost all countries and it is projected that 41 million people will die of a chronic disease by 2015 unless urgent action is taken [Organization 2005]. Various initiatives have been taken to control the progression of symptoms in chronic disease patients such as clinical prevention using combination of drug therapy and calculation of a person's risk by referring to an existing risk chart which takes into account several risk factors. Additional initiatives involve the use of statistical methods to generate a survival model and to investigate several risk factors associated with chronic disease, such as the Cox Proportional Hazards Model [Lumley 2002], [Wolf 1991], [Yusuf 1998]. There are also several machine learning applications that used global models for prediction of a person's risk or the outcome of a certain diseases [Khosla 2010], [Das 2003], [Anderson 2006], [Levey 1999]. According to [Shabo 2007] there is evidence that prediction and treatment based on global models are only effective for some patients (about 70% average) leaving the remaining 30% of patients without proper treatment which could worsen their condition and possibly lead to their death. A global model is derived from all available data for the target and then applied to any new patient anywhere at any time. While it may give 70% to 80% average accuracy over the whole population, it still may not be suitable for many individuals [Kasabov 2010b]. Hence, using global models for prediction of a person‘s risk is inadequate, based on the assumption that every person or individual has their own unique characteristics.

Personal human health is defined by many factors such as the food they eat, their lifestyle, life stage, ethnic origin, previous growth and development, gender, environment influences, genetic differences, allergies, diseases and many other important factors [Lange 2007], including information regarding space (such as region and distance) and temporal constraint (for a period of time before the event) and relations between them. An example of stroke related studies, a simplified framework of the causal relations between climate-related factors and stroke was developed to clarify the relations between environmental factors, lifestyle and a clinical risk factor with stroke occurrences.

Consequently, the emerging approach utilized to solve the problem is personalised modelling, where a model is created for every single new input vector of the problem space based on its nearest neighbours using a transductive reasoning approach [Kasabov 2007a]. However, there are very few efficient methods for the analysis of such complex data and discovery of complex spatio-temporal patterns, especially for on-line and real time applications.

1.3 Research Objectives, Research Questions and Hypothesis

Global modelling applied in most conventional machine learning methods has proven its effectiveness in the past, however it has a limited capability in producing models that fit each person or each case in the problem space since global modelling takes all available data in a problem space and produce a single general function [Kasabov 2007b]. The produced model is applied to a new individual regardless of their unique personal features. Common global modelling algorithms include Support Vector Machine (SVM) [Vapnik 1963] and Multilayer Perceptron (MLP) [Hornik 1989]. Therefore, in the case of stroke or any medical condition, personalized modelling methods are preferred for the reason that they can produce a model for each individual based on their personal features.

In numerous incidents, unforeseen events occur when triggered by the cascading effect of specific spatio, spectro temporal pattern interaction amongst multiple features over a period of time such as in the case of stroke [Feigin 1997], [Low 2006], ecological problems [Lankin 2001], geological disaster, financial crisis and many more. Such events can be avoided or the aftermath minimized if the risk is predicted early enough. However classical personalized modelling methods such as k-Nearest Neighbour (kNN) [Fix 1951] and weighted k-NN (wkNN) [Dudani 1976] are only suitable when classifying static vector based data, not SSTD.

The concept of spiking neural networks (SNN) has been considered as an emerging computational technique for the analysis of spatio-temporal datasets. This is because SNN has the potential to represent and integrate different aspects of information dimensionality such as time and space; and has the ability to deal with large volumes of data using trains of spikes [Kasabov 2013]. SNN models such as Spike Response Models (SRM) [Gerstner 1995], Leaky Integrate-and-Fire Models (LIFM) [Gerstner 2002], Evolving Spiking Neural Network (eSNN) [Wysoski 2006] and Izhikevich models [Izhikevich 2004] have been successfully utilized in several classification tasks. They process input data streams as a sequence of static data vectors, ignoring the potential of SNN to simultaneously consider space and time dimensions in the input patterns. It can be viewed that SNN has more potential and is more suitable for SSTD pattern recognition utilizing emerging new methods such as reservoir computing [Maass 2002], Probabilistic Spiking Neuron Model [Kasabov 2010a], Extended Evolving SNN (eeSNN) [Hamed 2011], Recurrent Evolving SNN (reSNN) [Schliebs 2010], Spike Pattern Association Neuron (SPAN) [Mohemmed 2011] and Dynamic Evolving SNN (deSNN) [Dhoble 2012].

The main goal of this research is to develop a novel framework of an information method and system to analyse SSTD for personalised knowledge interpretation and prognosis. The main objective is to develop a generic modelling environment to analyse SSTD (medical, brain, financial, geological or ecological data, etc.) using personalised modelling and spiking neural network methods. Accordingly, the personalised modelling method called the Integrated Method for Personalised Modelling (IMPM) introduced by [Kasabov 2010b] will be incorporated into the system. The proposed framework will be applied to case studies related to stroke occurrences and ecological problems.

1.3.1 Research Objectives

Based from the above considerations, the research will achieve the following objectives:

1. To review the literature concerning how personalised modelling based on spiking neural networks method can best predict possible outcomes for a new person/event using historical SSTD.

2. To design a framework that can analyse and learn from SSTD and produce a

model that facilitates new knowledge discovery and provides better decision support.

3. To develop software systems that analyse, learn and visualise the pattern residing in SSTD.

4. To verify the proposed method and system for personalised decision support utilising case studies related to a chronic disease and an ecological problem.

1.3.2 Research Questions

The main research question here is:

Can personalised modelling based on spiking neural networks methods be developed to learn SSTD and produce a better personalised knowledge representation and risk prognosis for a person/event?

More specifically, several sub questions can be derived from this:

1. How to select an optimal set of features, neighbourhood, model and parameters for SSTD using spiking neural network methods?

2. How to encode the real value continuous SSTD into a train of spikes?

3. How to develop a recurrent 3D spiking neural networks reservoir for learning the continuous train of spikes?

4. How to utilise spiking neural networks modeling for improved classification accuracy without filtering any noise?

5. How to visualise complex SSTD feature correlation and interaction patterns for better interpretation of knowledge?

6. How to obtain the earliest time point for best prediction of the risk of an event occurring in the future for an individual?

7. How to improve the spiking neural networks method for regression problems?

1.3.3 Hypothesis

We hypothesise that the new method for a given complex problem,

1. utilising an individualised (personalised) modelling approach, where an individual model is created for every new individual, will be more accurate than a global modelling approach, where a single model is derived from all existing data to predict at earliest time a future event can be accurately predicted for any individual regardless of their specific static variable values.

2. that analysing all data collectively without data pre-processing or filtering proves that NeuCube is robust to noise.

3. the visualisation of interaction patterns amongst the features will assist in the learning process. The network of connections created during the learning process can be visualised and the relationship between features can be comprehended through the understanding of changes in the connection weights of neurons.

1.4 Thesis Structure

- Part 1 - Literature Review
  - Chapter 2 outlines the fundamentals of data modelling and pattern recognition approaches, including comparison between inductive modeling and transductive modeling approaches. This is followed by a more detailed discussion of global, local and personalized modeling approaches including conventional methods related to these approaches.
  - Chapter 3 introduces the Spiking Neural Networks as the new paradigm to process SSTD. Similarity between biological neurons and artificial neurons is reviewed. This chapter also outlines a brief history of SNN and its components including neuron models, data encoding, learning algorithms, working memories, reservoir computing and is followed by a review of several types of new SNN model and applications for spatio-temporal pattern recognition such as eSNN, eeSNN, reSNN and deSNN. This chapter also reviews a new paradigm of integrated system for brain data modelling.

- Part 2 - Proposed Novel PMeSNNr for SSTD and Applications
  - Chapter 4 discusses the motivation behind the development of this novel evolving personalised modelling and spiking neural network framework and system (PMeSNNr). Each component of the framework will be outlined; the encoding module, the unsupervised learning module, the supervised learning module and optimization module. New method that combines deSNNs with the wkNN method for Multi-NN classification and regression are proposed in this chapter.
  - Chapter 5 discusses the implementation of the PMeSNNr framework called NeuCube M1 and demonstrates the system's capability for predictive modelling; and added functionality to assist in deep learning and knowledge discoveries.
  - Chapter 6 reviews on the stroke disease including modifiable factors and external factors that influence the stroke occurrences. This chapter will also review previous studies regarding the influence of environmental factors that may cause brain stroke in humans. For application purposes, the New Zealand stroke occurrences case study will be used to evaluate the feasibility of the PMeSNNr in analysing and modelling real-value SSTD. This proposed method is used to do predictive personalised modelling for stroke risk prediction using temporal environmental data. The experimental study aims to produce an individual model for each subject and obtain the earliest time point to best predict the risk of a stroke event occurring in the future for an individual. Several groups of individuals are chosen according to season and personal information. Comparative experiments with conventional machine learning methods are also carried out. Discovery on new personalised knowledge will be further discussed based on visualisation generated during the modelling process.
  - Chapter 7 reviews the ecological problem relating to aphids pest infestation in certain areas of New Zealand. The case study will used for classification application using NeuCube. Comparative experiments with conventional machine learning methods are also carried out.

- Part 3 - Conclusion and future direction
  - Chapter 8 summarizes the findings and contributions of this research proposed further future developments. For example; combining ontology-based systems for more organized and systematic modelling of SSTD, to enhance NeuCube M1's optimisation strategies, dealing with variability in data and multiple type of data.

1.5 Thesis Contribution

This is the first comprehensive study of utilising personalised modelling based on spiking neural network methods resulting in several contributions to the areas of both information science and bioinformatics.

During the course of this study, several novel contributions have been applied including analysing the problems related to global modelling and conventional personalised modelling for SSTD and their respective potential solutions; development of a prototype system based on the PMeSNNr framework called NeuCube M1 which comprises an encoding method employing Address Event Representation (AER) algorithm; a recurrent 3D SNN reservoir based on the Liquid-State Machine (LSM) concept and implementation of Spike Time Dependent Plasticity (STDP) as a learning rules; an innovative input variables mapping techniques utilizing Factor Graph Matching (FGM) algorithm; a predictive personalised modelling method for early event prediction; various selections of evolving spiking neural network classifiers including a novel extended dynamic evolving spiking neural network method called deSNNs_wkNN for multi-NN classification and regression problems; a grid-search optimisation module and visualisation of the spiking network activities specifically on a group and personalised level. All these contributions are described and applied in Chapters 4, 5, 6 and 7. The methods have been applied to two real world case studies which are stroke occurrences prediction and aphid pest population prediction.

This study has found a number of interesting results. Firstly is that using spiking neural networks for personalised modelling is more suitable for analysing and modelling SSTD dynamically compared with conventional machine learning methods that use global modelling, thus verifying the validity of this approach and that this methodology has also achieved a better results in terms of prediction accuracy. Secondly, using this approach, early event prediction is possible where the time length of the training data (samples, collected in the past) and the test data (samples used for prediction) can be differentiate. Early event prediction is very crucial when solving important ecological and social tasks and disease risk prediction described by temporal-and/or spatio-temporal data, such as stroke risk prediction, pest population burst prevention, natural disaster warning, financial crisis prediction. Thirdly, that these methods take all features without the need to filter noise and still produce good results. Fourthly, the innovative input variables mapping techniques enable dynamics mapping of SSTD variables and assist in revealing unknown spatio-temporal patterns and its associations. Lastly, the visualisation of spiking network activities enables deep network learning of the spiking patterns. This assists us in understanding the spiking neurons connection and relationships. Furthermore this visualisation reveals new knowledge about the SSTD that deserves to be investigated further.

NeuCube revealed hidden associations amongst environmental features in stroke prediction case study where the associations of environmental factors suggest there is influence on stroke occurrences. We also discovered that there is a cascading effect, unique to each individual depending on their exposure to certain environmental factors within a specific time window. This study has also successfully and accurately predicted the risk of stroke occurrences at an earlier time point then produces models and demonstrates that analysing all the features collectively can accurately predict stroke risk. The second case study on ecological data in aphid pest abundance prediction, verified NeuCube's capability in modelling any type of SSTD. The result has been an earlier prediction of aphid pest abundance to assist in timely agricultural management.

This study gives light to future research directions for personalised modelling based on SNN with the improvements in the NeuCube architecture for SSTD processing and personalised profiling. The main results of this study emphasise the new discoveries that have been published as conference papers and will further published as journal papers.

1.6 Publication List

- **Journal**

1. Kasabov, N., Feigin, V., Hou, Z.G., Chen Y., Liang, L., Krishnamurthi, R., Othman, M., Parmar, P. (2014). Evolving spiking neural network method and systems for fast spatio-temporal pattern learning and classification and for early event prediction with a case study on stroke. Neurocomputing, Volume 134, 25 June 2014, Pages 269-279.
2. Nikola Kasabov, Nathan Scott, Enmei Tu, Stefan Marks, Neelava Sengupta, Elisa Capecci, Muhaini Othman, Maryam Doborjeh, Norhanifah Murli, Reggio Hartono, Josafath Israel Espinosa-Ramos, Lei Zhoua,Fahad Alvi, Grace Wang, Denise Taylor, Valery Feigin, Sergei Gulyaeh, Mahmoud Mahmoud, Zeng-Guang Hou,Jie Yang. Evolving Spatio-Temporal Data Machines Based on the NeuCube Neuromorphic Framework: Design Methodology and Selected Applications, Neural Networks, Preliminary Accepted 2015.
3. Kasabov, N., Othman, M., Tu, E., Krishnamurthi, R., Feigin, V. Personalised Predictive Modelling with Spiking Neural Networks: Predicting Stroke Risk, Nature Reviews Neurosciences, submitted 2015.

- **Conference**

1. Othman, M., Kasabov, N., Hu, Y. (2012), Spatial-Temporal Data Representation in Ontology System for Personalized Decision Support, Talent Management Symposium 2012, Northern Melbourne Institute of TAFE, Australia, UTHM Publisher.
2. Othman M, Kasabov N, Tu E, Feigin V, Krishnamurthi R, Hou Z, et al (2014). Improved predictive personalized modelling with the use of Spiking Neural Network system and a case study on stroke occurrences data. Neural Networks (IJCNN), 2014 International Joint Conference on; 2014: IEEE; 2014. p. 3197-3204.
3. Tu E, Kasabov N, Othman M, Li Y, Worner S, Yang J, et al. (2014). NeuCube (ST) for spatio-temporal data predictive modelling with a case

study on ecological data. Neural Networks (IJCNN), 2014 International Joint Conference on; 2014: IEEE; 2014. p. 638-645.

4. Keynote Speaker on behalf of Prof Nikola Kasabov at New Zealand Applied Neuroscience Conference (NZANC), Auckland University of Technology, New Zealand on 19th September 2014 on a paper titled Personalised Predictive Data Modelling Methods and Case Study Applications.

5. Othman, M., Kasabov, N., Tu, E., Feigin, V., Krishnamurthi, R.(2015), Using NeuCube, 13th International Conference on Neuro-Computing and Evolving Intelligence 2015, Knowledge Engineering and Discovery Research Institute, Auckland University of Technology, New Zealand.

- **Abstract**

1. Othman, M., Breen, V., Kasabov, N. (2014), Personalised Predictive Data Modelling Methods and Case Study Applications, New Zealand Applied Neuroscience Conference (NZANC), Auckland University of Technology, New Zealand.

2. Othman, M., Kasabov, N., Tu, E., Feigin, V., Krishnamurthi, R.(2015), Using NeuCube, 13th International Conference on Neuro-Computing and Evolving Intelligence 2015, Knowledge Engineering and Discovery Research Institute, Auckland University of Technology, New Zealand.

3. Othman, M., Kasabov, N. (2015). Extended Dynamic Evolving Spiking Neural Network for Spectro-Spatio Temporal Pattern Multi-NN Classification, Evolving System.

- **Poster**

1. Othman, M., Kasabov, N., Hu, Y. (2012), Spatial-Temporal Data Representation in Ontology System for Personalized Decision Support, 12th International Conference of Neuro-Computing and Evolving Intelligence 2012 (NCEI'12) , Knowledge Engineering and Discovery Institute, Auckland University of Technology, New Zealand.
2. Othman, M., and Kasabov, N. (2013), Spatial-Temporal Data Representation and Processing in Ontology-based System for Personalized Decision Support, 26th Australasian Joint Conference on Artificial Intelligence 2013, University of Otago, Dunedin, New Zealand.
3. Othman, M., Kasabov, N., Tu, E., Feigin, V., Krishnamurthi, R. (2015), Evolving Spiking Neural Networks for Predictive Data Modelling, 13th International Conference of Neuro-Computing and Evolving Intelligence 2015 (NCEI'15), Knowledge Engineering and Discovery Institute, Auckland University of Technology, New Zealand.

Chapter 2

PERSONALISED MODELLING: A REVIEW

"The measure of intelligence is the ability to change."

- Albert Einstein

2.1 Introduction

This chapter reviews the concept of the personalised modelling method. However before the personalised modelling method can be discussed in detail, the basis of data modelling and pattern recognition approaches need to be addressed briefly. Inductive and transductive inference approaches are two of the most basic theories for data modelling and the main idea behind global, local and personalised modelling methods.

2.2 Inductive and Transductive Inference Approaches

Inductive and transductive inference approaches are commonly used to build models and systems for data analysis and pattern recognition [Kasabov 2009b]. Inductive inference approaches will create a single function (a model) based on historical data to predict a future event [Levey 1999]. In the inductive inference approach the model is created based on the analysis of the entire problem space (global space) without taking into account the information related to the new data vector. Neglecting information from the new data vector raises an issue about the relevance of global modelling to produce an accurate model or solution to a specific problem. Figure 2.1 illustrates the inductive inference approach. The engine will train on historical data and create a global function to model incoming new data. Popular inductive inference approaches are Support Vector Machine (SVM) [Cortes 1995], Multi-Layer Perceptron [Hornik 1989] and Linear Regression.

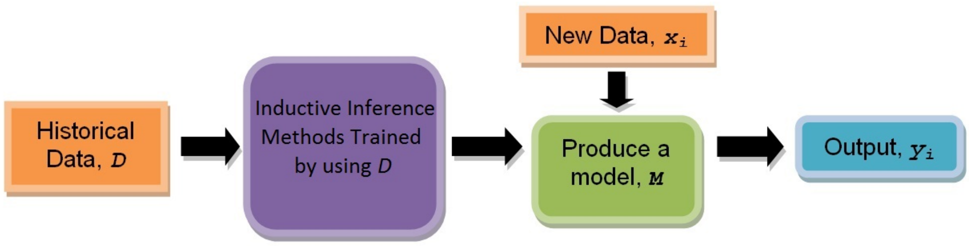

Figure 2.1: Inductive inference approach.

The transductive inference was introduced by [Vapnik 1998] as a solution to solve the issue raised by the inductive inference engine. This approach creates a model based on observations of a specific group of data vectors and only focuses on one point in the space (local space). Transductive inference takes into account the additional information of the new data vector to find relevant information for analysis purposes. This in the end will create many different specific models (functions), to test every new data vector. Figure 2.2, illustrates a basic process of transductive inference.

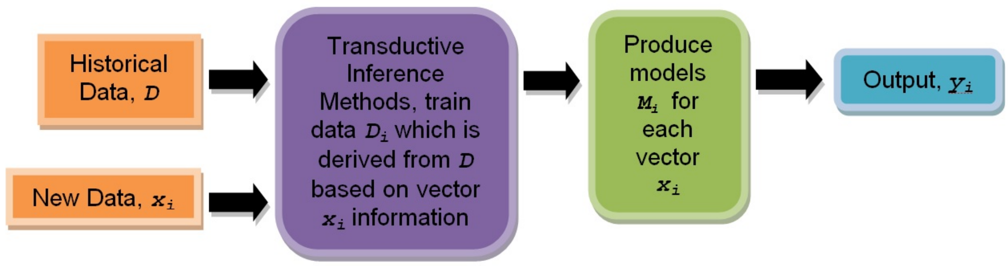

Figure 2.2: Transductive inference approach.

Several types of advanced transductive inference model have been build such as Transductive RBF Neural Network with Weighted Data Normalization - TWRBF [Song 2004] and Transductive Neural Fuzzy Inference System with Weighted Data

Normalization - TWNFI [Song 2006] and successfully applied for medical decision support and time series prediction. As a result the transductive inference approach is considered the most suitable approach toward building a learning model for the application of personalised decision support, especially in medical application or event prediction. Since individual personal features of a patient or event are important to consider for future prediction or treatment decision.

2.3 Global, Local and Personalised Modelling

2.3.1 Introduction

In computational intelligence modelling and learning, the main techniques are global, local or personalised modelling which are derived from inductive and transductive inference approaches. Global modelling produces a model from the data for the whole problem space. The model represents the data by a single function whereas local modelling creates a set of models from data where each model represents a cluster of the whole problem space. These models can be a set of functions or set of rules. Personalised modelling on the other hand utilises transductive reasoning to create a specific model for each data point (a patient, an event) within a localised problem space.

2.3.2 Global Modelling

Support vector machine (SVM) also called support vector networks is one of the most popular algorithm used for global modelling. It is very efficient in classifying static and vector-based data using few training samples. However, SVM is not suitable to analyse high-dimensional dataset like SSTD.

2.3.2.1 Support Vector Machine

Support vector machine is widely used for classification and regression problems. Originally the SVM algorithm was created by Vladimir Vapnik in 1963 [Vapnik 1963] then new SVM with ‘soft margin’ approach was introduced by Vladimir Vapnik and colleagues in 1995 [Cortes 1995]. After that, several other extended versions has been developed such as Least Square SVM (LSSVM) [Suykens 1999], Linear Proximal SVM [Fung 2001], Wavelet SVM [Zhang 2004], Smooth SVM (SSVM) [Lee 2001] and the robustness of SVM still inspired researchers to extend the algorithm, current examples like SVM-Wavelet Transform [Mohammadi 2015], Cluster SVM (CSVM) [Harris 2015] and many more. Since the active development of the SVM algorithms, a group of researcher developed a library for SVM called LibSVM [Chang 2011] to support users in implementing their application using SVM.

Fundamentally SVM is based on the concept of decision planes that define decision boundaries. The decision planes (hyperplanes) are like clear gaps that separate a set of objects that belong to different classes, the distance from the hyperplane to the data is maximized (also known as the maximum margin hyperplane). For example for a linear SVM (illustrated in Figure 2.3), the set of objects either belong to class RED or BLUE. The line represents the linear decision surface that separates between RED and BLUE class. When a new object (black circle) is added to the problem space, it will be mapped to the features space of these two planes either in RED or BLUE. Depending on where it is mapped, it will be classified as RED when it falls in the left plane and BLUE if it falls in the right plane.

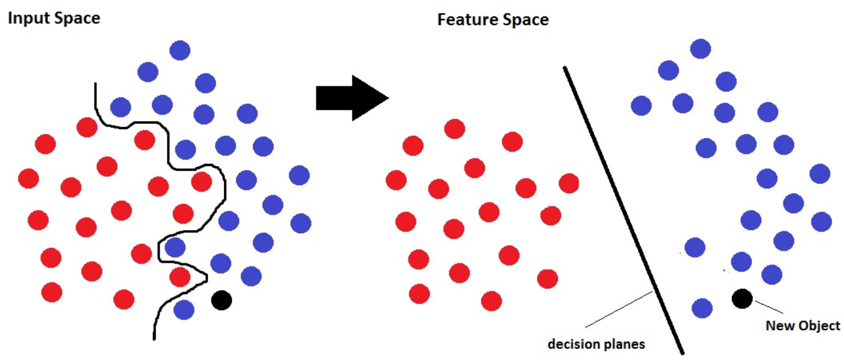

Figure 2.3: Overview of simple SVM transformation (mapping).

In mathematical terms, linear SVM can be defined as follows. Given a set of data that can be linearly separated:

$$D = \{x_i, y_i \mid x \in R^p, y \in \{-1, 1\}\}_{i=1}^{n} = size \tag{2.1}$$

where D is the training data, x_i is a p-dimensional vector, n is a set of data points, and y_i is either -1 or 1, indicating which class x_i belongs to.

Maximum margin hyperplane is found using Equation 2.2, to separate the two classes.

$$w.x - b = 0 \tag{2.2}$$

where w the normal vector to the hyperplane, b is a scalar and . denotes the dot product.

Two hyperplanes can be selected to separate the data, where there no data points lies between them and try to maximize their distance. The region bounded by the hyperplanes is called the margin and is described by the following equations.

$$w.x - b = 1 \tag{2.3}$$

and

$$w.x - b = -1 \tag{2.4}$$

Constraints must be added to keep the data point from falling inside the margin and to classify each sample into a specific class. The constraints are:

$$w.x_i - b <= -1 \tag{2.5}$$

where x_i belong to first class, and

$$w.x_i - b >= 1 \tag{2.6}$$

where x_i belong to second class.

Figure 2.4 shows the overview of linear SVM.

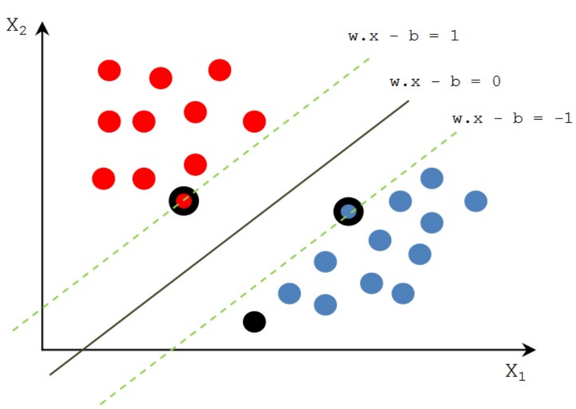

Figure 2.4: Overview of simple linear SVM. The samples on the margin are called support vectors.

To overcome the issue of inseparable data where some data cannot be linearly separated, nonlinear SVM is introduced by applying kernel approach to find maximum margin hyperplanes. The data is initially transformed into high dimensional space a using nonlinear kernel function, then the standard algorithm is used to find the maximum margin hyperplanes [Boser 1992]. Several types of kernel can be utilized in SVM which include linear, polynomial, radial basis function (RBF) and sigmoid.

- Linear: $K(x_i, x_j) = x_i.x_j$
- Polynomial: $K(x_i, x_j) = (\gamma x_i.x_j + C)^d$
- Radial Basis Function:$K(x_i, x_j) = exp(-\gamma \mid x_i.x_j \mid^2)$
- Sigmoid: $K(x_i, x_j) = tanh(\gamma x_i.x_j + C)$

where $K(x_i, x_j) = \delta(x_i).\delta(x_j)$. The kernel function represents a dot product of input data points mapped into the higher dimensional feature space by transformation δ. Gamma (γ) is an adjustable parameter of certain kernel function.

One of the disadvantages of SVM is that it has a high computational burden because of the quadratic programming, making it slow in the training phase [Horváth 2003]. Another drawback is the choice of kernels and kernel parameter determination suitable for the data under investigation. Kernel models are sensitive to over-fitting the model selection criterion [Cawley 2010]. Domain knowledge is also hard to incorporate in SVM, especially new information about the new sample.

2.3.3 Local Modelling

The local modelling approach was created to overcome the drawbacks of global modelling where it is more adaptable to the new data vector, and to create a model to represent the cluster within which the new data vector resides. This has made local modelling methods more suitable to analyse individual samples than global modelling. Evolving Classification Function (ECF) is one example of local modelling methods and is built based on the concept of Evolving Connectionist System (ECOS) [Kasabov 2002].

2.3.3.1 Evolving Classification Function (ECF)

ECOS are systems that evolve in time through interaction with the environment; it is adaptable to changes in the system through new incoming information [Kasabov 1998b]. Evolving Classification Function (ECF) was developed based on ECOS principles has four layers of neurons (nodes) which represent input variables, fuzzy memberships functions, a set of data centers in input spaces and classes [Kasabov 2002]. ECF methods exhibit fast incremental on-line and off-line learning and have dynamic environments that allocate rule nodes to help users understand and verify the model's functionality. Figure 2.5 illustrates clusters of nodes in the ECF environment, based on the information of new input vector (n_i) ECF will produce clusters of rule nodes that are identified by its center (o_j), radius (r_j) and class (C).

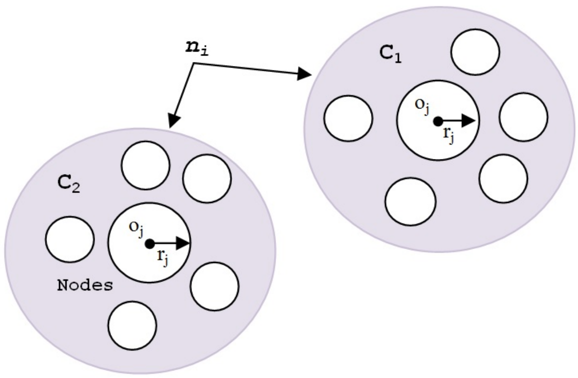

Figure 2.5: An example of evolving clusters in ECF.

2.3.4 Personalised Modelling

Personalised modelling is different from global modelling because it will create a specified model for each new data vector based on the samples that are closest to the new data vector in the dataset. Other than advance transductive methods listed above, methods that can be categorised as personalised modelling are k-Nearest Neighbour (kNN), weighted k-Nearest Neighbour (wkNN) and weighted-weighted k-Nearest Neighbour (ww$k$NN).

2.3.4.1 *k*-Nearest Neighbour(*k*NN)

The k-Nearest Neighbour (kNN) method is a supervised learning algorithm that has been successfully used for classifying sets of samples based on nearest training samples in a multi-dimensional feature space, and was originally proposed by [Fix 1951]. The basic idea behind the kNN algorithm is depicted in Figure 2.6:

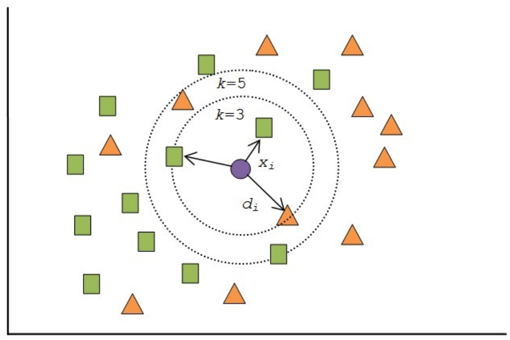

Figure 2.6: kNN modelling.

The kNN modelling:

- Firstly, a set of pairs features (e.g. (x_1, y_1),...(x_n, y_n)) are defined to specify each data point, and each of those data points are identified by the class labels $C = c_1, ...c_n$.
- Secondly, a distance measure (d_i) is chosen (e.g. Euclidean distance, or Manhattan distance) to measure the similarity of those data points based on all their features.
- Finally, the k-nearest neighbours are found for a target data point by analyzing similarity and using the majority voting rule to determine which class the target data point belongs to.

2.3.4.2 Weighted *k*-Nearest Neighbour (w*k*NN)

The weighted k-Nearest Neighbour (wkNN) is designed based on the transductive reasoning approach, which has been widely used to evaluate the output of a model focusing solely on an individual point of a problem space using information related to the individual [Vapnik 1998]. In the wkNN algorithm, each single vector requires a local model that is able to best fit each new input vector rather than a global model, thus each those new input vectors can be matched to an individual model without taking into account any specific information about existing vectors. In contrast to the kNN algorithm, the output values of a new input vector (y_i), is not only dependent upon its output values of k-nearest neighbour vectors (y_j), but also upon the weight (w_j) that is decided by the distance between existing vectors and the new input vector. This is the basic idea behind the wkNN algorithm. Mathematically wkNN can be described as:

$$y_i = \sum_{j=1}^{k} \frac{w_j y_j}{w_j} \tag{2.7}$$

where weight (w_j) is calculated based on the distance of k-nearest neighbour vectors to new vector using the following equation:

$$w_j = [max(d) - (d_j - min(d))]/max(d) \tag{2.8}$$

The vector $d = [d_1, d_2, ...d_{N_i}]$ is defined as the distances between input vector (x_i) and the k nearest neighbour (x_1, y_1) for $j = 1$ to k. The Euclidean distance measured between new vector (x_i) and neighbouring vector (x_j) is calculated based on:

$$d_j = sqrt[\sum_{l=1}^{V}(x_{i,l} - x_{j,l})^2] \tag{2.9}$$

where V is the number of the input variables, $x_{i,l}$ and $x_{j,l}$ are the values of the variables in vector x_i and x_j, respectively. An example of wkNN implementation in a classification problem that consists of two classes, represented by 0 (class 1) and 1 (class 2) as output class labels. If the new vector (x_1) belongs to class 2, this means it has "personalised probability". To classify the new vector (x_1) into classes, there has to be probability threshold selected P_{thr}, so if the output value $y_i \geq P_{thr}$ then the new vector (x_1) will be classified into class 2. For example the probability threshold value is set to 0.5 and if the output value is 0.75 which is more than the probablity threshold, the new vector will be classified into class 2 not class 1 where the output value should fall within the range of $0 \leq y_i \leq 0.5$.

2.3.4.3 Weighted-Weighted k-Nearest Neighbour (ww$k$NN)

The weighted-weighted k-Nearest Neighbour (ww$k$NN) is a novel personalised modelling algorithm which was proposed by [Kasabov 2007b]. The basic idea behind this algorithm is the output of each new input vector is measured dependent upon its k-nearest neighbours and also upon the distance between the existing vectors and the new input vectors, and the power of each vector which is weighted according to its importance within the sub-space (local space) to which the new input vector belongs. The new Euclidean distance measure is calculated using this equation:

$$d_j = sqrt[\sum_{l=1}^{V}(c_{i,l}(x_{i,l} - x_{j,l}))^2] \tag{2.10}$$

where $c_{i,l}$ is the coefficient weighing variables x_l in the neighbourhood of x_i. The coefficient value is calculated using the Signal-to-Noise Ratio (SNR) procedure that ranks each variables across all vectors in the neighbourhood set D_i of N_i vectors.

$$C_i = (c_{i,1}, c_{i,2}, ..., c_{i,V}) \tag{2.11}$$

$$c_{i,l} = S_l / sum(S_l) \qquad \text{for} \quad l = 1, 2, \cdots, V \quad \text{where} \tag{2.12}$$

$$S_l = abs(M_l^{(class1)} - M_l^{(class2)}/(Std_l^{(class1)} + Std_l^{(class2)}) \tag{2.13}$$

$M_l^{(class1)}$ and $Std_l^{(class1)}$ is the mean value and standard deviation of variable x_l for all vectors in D_i that belong to class 1. The new distance measurement that assigned weight to all variables according to its importance is the new feature in ww$k$NN that differentiates it from wkNN. Weighting variables in personalised models is also used in TWNFI models [Kasabov 2007b], [Song 2006].

2.4 Integrated Method for Personalised Modelling

Personalised modelling framework for gene data analysis and biomedical applications was proposed by [Kasabov 2010b]. The framework is called Integrated Method for

Personalised Modelling (IMPM) (refer to Figure 2.7). The methodology of IMPM is described in Table 2.1 below:

Table 2.1: The IMPM Methodology

1:	Collect, filter and store data D .
2:	Compile new input vector x of a new person.
3:	Select a subset of relevant variables, V_x of the the new input vector x from a global variables set V.
4:	Select k-nearest neighbour vectors K_x from the global data set D and forming a neighbourhoodD_x of similar samples to x using the variables from V_x to define the similarity.
5:	Rank the V_x variables within the local neighbourhood D_x in order of importance to the outcome, obtaining a weight vector W_x.
6:	Train and optimise a local prognostic/ classification model M_x, that has a set of model parameters P_x, a set of variables V_x and local train/test data set D_x.
7:	Generate a functional profile F_x for the person x using the selected set V_x of variables, along with the average profiles of the samples from D_x that belong to different outcome classes, e.g., F_i and F_j.

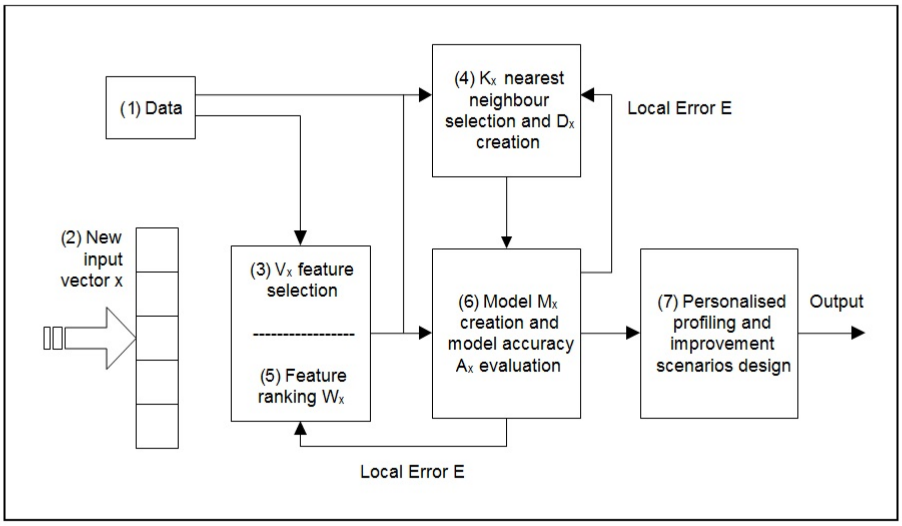

Figure 2.7: Functional block diagram of IMPM [Kasabov 2010b].

2.5 Chapter Summary

Global modelling applied in most conventional machine learning methods has proven its effectiveness in the past, however it has a limited capability in producing models that fit each person or each case in the problem space since global modelling takes all available data in a problem space and produces a single general function [Kasabov 2007a]. The produced model is applied to a new individual regardless of their unique personal features. Therefore, in the case of specific medical condition e.g. stroke, heart attack and environmental events e.g. earthquake, volcano eruption; personalised modelling methods are preferred for the reason that they can produce a model for each individual/event based on their personal features.

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