Research Statement

My general research interests encircle in the methodologies and applications of artificial intelligence. More specifically, my research interests are in areas of deep learning, recurrent neural networks, neuroevolution, time series analysis, and Bayesian methods with applications to mineral exploration, solid Earth evolution, and geo-coastal and reef modelling.

Technology Development

1. ***Neural networks and learning algorithms:*** Neural networks are loosely modelled after biological neural systems and have a wide range of data-driven applications that include time series prediction and pattern recognition. Opposed to gradient-based methods, neuro-evolution features evolutionary algorithms that provide a black-box approach to learning in neural networks. Hence, the learning algorithm is not constrained to the architecture of the network and does not face the limitations of gradient descent such as local minima and vanishing gradients. I have been developing novel neural network learning algorithms using neuro-evolution with motivations from transfer learning, multi-task learning and reinforcement learning. I have been using feedforward and recurrent neural networks with application to a wide range of time series problems that include multidimensional and multi-step-ahead prediction with applications that include predicting the behaviour of extreme events such as cyclones. The challenge is in problems that have missing information, noise and inconsistencies in the organisation of data. Collaboration: Prof. Yew-Soon Ong, School of Computer Science and Engineering, Nanyang Technological University; Prof. Junbin Gao, Business School, University of Sydney; Prof. Christian Omlin, University of Agder, Norway.

2. ***Evolutionary optimisation:*** Evolutionary algorithms used for optimisation are inspired by the theory of evolution. The major feature of these algorithms is their applicability in large-scale problems, particularly that do not have the feature to use gradient information to form new proposals. I have contributed to the field of cooperative coevolution and problem decomposition for neuro-evolution and large-scale global optimisation problems. I would like to extend this field further with Bayesian methods that have a natural way for uncertainty quantification which could address the limitation of convergence in evolutionary optimization and related stochastic and metaheuristic algorithms. Collaboration: Prof. Mengie Zhang, Victoria University of Wellington, New Zealand; Prof. Yew-Soon Ong, School of Computer Science and Engineering, Nanyang Technological University, Singapore.

3. ***Bayesian neural networks:*** Markov Chain Monte Carlo (MCMC) methods provide a probabilistic approach for estimation of the free parameters in a wide range of models. Parallel tempering is an MCMC method that features parallelism with enhanced exploration capabilities. It features a number of replicas with slight variations in the acceptance criteria. More recently, I have been developing algorithms for Bayesian neural networks that feature parallel tempering and parallel computing in order to address computationally expensive problems. The challenge is in the inference for deep learning network architectures that features millions of parameters. Collaboration: Prof. Sally Cripps, School of Mathematics and Statistics, University of Sydney.

4. ***Surrogate-assisted inference and optimisation:*** Surrogate-assisted optimization considers the estimation of an objective function for models given computational inefficiency or difficulty to obtain clear results. Surrogate-assistance inference addresses inefficiency of parallel tempering for large-scale problems by combining parallel computing features with surrogate assisted estimation of likelihood function that describes the plausibility of a model parameter value, given specific observed data. I have been developing these methods for large-scale

Bayesian neural networks and also for computationally expensive Geoscientific models such as landscape evolution models. The challenge is to have a good estimation by the surrogates when the actual model features hundreds of free parameters. Collaboration: Prof. Dietmar Muller, School of Geosciences, University of Sydney; Prof. Yew-Soon Ong, School of Computer Science and Engineering, Nanyang Technological University, Singapore

Technology Applications

1. ***Solid Earth evolution:*** Bayesian inference has been a popular methodology for the estimation and uncertainty quantification of parameters in geological and geophysical forward models. Badlands is a basin and landscape evolution forward model for simulating topography evolution at a large range of spatial and time scales. Our solid Earth evolution projects consider Bayesian inference for parameter estimation and uncertainty quantification for landscape dynamics model (Bayeslands). The challenge is in parameter estimation for computationally expensive models which are being addressed by high-performance computing and surrogate-assisted Bayesian inversion. Collaboration: Prof. Dietmar Muller and Dr. Tristan Salles, School of Geosciences, University of Sydney.

2. ***Reef and geo-coastal modelling:*** Geological reef models such as Py-Reef-Core provides insights into the flux of carbon by analysing carbonate platform growth and demise through time, and modelling their evolution using landscape dynamics and reef modelling. We provide uncertainty quantification estimation of free parameters using Bayesian inference for reef modelling (BayesReef). Bayesian inference via MCMC and parallel tempering is used with Py-Reef-Core model to understand reef evolution on a geological timescale that can help in predicting the future evolution of coral reefs. The challenge here is an estimation of the parameters which involves highly non-separable and constrained optimisation. Collaboration: A/Prof. Jody Webster and Dr. Tristan Salles, School of Geosciences, University of Sydney.

3. ***Mineral exploration:*** The extraction of geological lineaments from digital satellite data is a fundamental application in remote sensing. The location of geological lineaments such as faults and dykes are of interest in terms of mineralization. Although a wide range of applications has utilized computer vision techniques, a standard workflow for application of these techniques to mineral exploration is lacking. We use computer vision techniques for extracting geological lineaments using optical remote sensing data. Furthermore, in another research direction, we provide a synergy of geophysical forward models, and Bayesian inference for 3D joint inversion for mineral prospecting and exploration. Collaboration: Prof. Dietmar Muller, Ehsan Farahbakhsh, and Prof. Gregory Houseman, School of Geosciences, University of Sydney. Dr. Hugo Olierook, Prof. Chris Clark, and Prof. Steven Reddy, Curtin University. Dr. Richard Scalzo and Prof. Sally Cripps, Centre for Translational Data Science, University of Sydney.

4. ***Paleoclimate reconstruction:*** The reconstruction of paleoclimate precipitation can provide light to Earth's climate history of millions of years in the past. Although global circulation models have been used with success for reconstruction of precipitation in the Miocene period, their application to an era back in time is a major challenge due to limited data. We use an alternate approach that features machine learning methods to predict precipitation that defines paleoclimate that spans up to 400 millions of year in the past. The data features a range of geological indicators including sedimentary deposits (coal, evaporates, glacial deposits). The challenge has been in addressing missing values in the dataset and providing rigorous uncertainty quantification in order to develop paleo-maps of forests and vegetation. Collaboration: Prof. Dietmar Muller, School of Geosciences, and Prof. Sally Cripps, Centre for Translational Data Science, University of Sydney.

Future work

1. Most of the literature considered surrogate assisted optimization, whereas my work recently considered inference for machine learning problems. This opens the road to use surrogate models for machine learning. Surrogates could be helpful in case of big data problems and cases where there are inconsistencies in the data stream or noisy data. Furthermore, other optimization methods could be used in conjunction with surrogates for big data problems rather than parallel tempering.

2. Although parallel tempering in a high-performance computing environment has shown to be a powerful technique for addressing some of the challenges of Bayesian neural learning and Geo-scientific models such as Badlands, the need for effective proposals remains open issue which will be addressed with evolutionary algorithms. Hence, a synergy of neuro-evolution and Bayesian neural learning by using evolutionary algorithms for forming efficient proposals in parallel tempering which could be used for Geoscience models and Bayesian neural learning.

3. The paleoclimate project would be focusing on vegetation soil datasets to further improve the framework. Also, we will try to develop fine-grained reconstructed paleo-maps of the vegetation of up to 400 millions years.

4. In the case of reef modelling, although we have addressed parameter estimation and uncertainty quantification in a geological reef evolution model, there are other areas of interest which can facilitate data-driven methods. I would like to use computer vision and machine learning methods for automatically documenting assemblage formation in images taken from drilled reef cores.

5. Due to multi-disciplinary nature, the industry has yet to take full advantage of the application of machine learning and computer vision methods in mineral exploration. Future work will consider a wide range of data that includes gravity, radiometric and magnetics. Bayesian uncertainty quantification in edge detection would also be developed. Furthermore, there is scope to develop novel methods for extraction and reconstruction of underground mineral structures based on 3D structures and topological information. This also opens the road to use deep learning methods for reconstruction of mineral structures.