Ong Yew Soon, IEEE Fellow (2024 – 2026)

School of Computer Science and Engineering,

Nanyang Technological University

Block N4, 2a-28, Nanyang Avenue, Singapore 639798

Center for Frontier AI Research

Agency for Science, Technology and Research

1 Fusionopolis Way, #16-16, Connexis North Tower, Singapore 138632

Email: asysong@ntu.edu.sg, Ong_Yew_Soon@hq.a-star.edu.sg

Lecture Topic 1: Artificial Intelligence for Global Good

Abstract: With the rapid development of AI technologies witnessed over the past decade, such as large language models and foundation models, there is consensus that the field is indeed primed to have a significant impact on society. Distilling from historical definitions, AI can be seen as the science and engineering of intelligent machines. The long-term goal is therefore to develop machines that can think, act and learn by themselves, targeting the greater good of countries, economies, and societies. Being cognizant of the challenges and opportunities in present AI research, it is important to set guidance to those who are developing the technologies to realize those intelligent machines and to create positive impact as a result. To provide such guidance, in this talk, foundation capabilities that form the basis of long-term endeavours to realize the full potential of AI shall be presented. These foundation capabilities which have been conceived with a strategy of balancing AI risks and growth including Responsible AI, Sustainable AI, Rationalizable AI and Synergistic AI, shall be discussed.

Lecture Topic 2: Towards General Optimization Intelligence

Abstract: Traditional Optimization tends to start the search from scratch by assuming zero prior knowledge about the task at hand. Generally speaking, the capabilities of classical optimization solvers do not automatically grow with experience. In contrast however, humans routinely make use of a pool of knowledge drawn from past experiences whenever faced with a new task. This is often an effective approach in practice as real-world problems seldom exist in isolation. Similarly, practically useful artificial

systems are expected to face a large number of problems in their lifetime, many of which will either be repetitive or share domain-specific similarities. This view naturally motivates advanced optimizers that can replicate human cognitive capabilities, leveraging on lessons learned from the past to accelerate the search towards optimal solutions of never before seen tasks. With the above in mind, this talk aims to shed light on recent research advances in the field of global black-box optimization that champion the general theme of ‘General Optimization Intelligence’.

Lecture Topic 3: Insights on Multifactorial Evolution: Towards Multitasking Optimization
Abstract: The human mind possesses the most remarkable ability to perform multiple tasks with apparent simultaneity. In fact, with the present-day explosion in the variety and volume of incoming information streams that must be absorbed and appropriately processed, the opportunity, tendency, and (even) the need to multitask is unprecedented. Thus, it comes as little surprise that the pursuit of intelligent optimization algorithms that are capable of efficient multitasking is rapidly gaining importance among contemporary scientists who are faced with the increasing complexity of real-world problems. The design of population-based search algorithms of evolutionary computation (EC) has traditionally been focused on efficiently solving a single optimization task at a time. Multifactorial optimization (MFO) is a new paradigm in EC that was recently introduced to explore the potential of evolutionary multitasking. The nomenclature signifies a multitasking search involving multiple optimization tasks at once, with each task contributing a unique factor influencing the evolution of a single population of individuals. MFO leverages the scope for implicit genetic transfer offered by the population in a simple and elegant manner, by exploiting underlying synergies between related tasks. In this talk, the formalization of the concept of MFO is introduced. Novel evolutionary multitasking algorithms including the Multifactorial Optimization (MFEA) and its Multi-Objective variants (MO-MFEA, MO-MFEA-II, and others) that are inspired by bio-cultural models of multifactorial inheritance, so as to best harness the genetic complementarity between tasks will be presented.

Lecture Topic 4: Jack and Masters of all Trades: One-Pass Learning Sets of Model Sets from Large Pre-Trained Models with Neuroevolutionary Multitasking
Abstract: For deep learning, size is power. Massive neural nets trained on broad data for a spectrum of tasks are at the forefront of artificial intelligence. These foundation models or ’Jacks of All Trades’ (JATs), when fine-tuned for downstream tasks, are gaining importance in driving deep learning advancements. However, environments with tight resource constraints, changing objectives and intentions, or varied task requirements, could limit the real-world utility of a singular JAT. Hence, in tandem with current trends towards building increasingly large JATs, this talk presents exploratory insights into concepts underlying the creation of a diverse set of compact machine learning model sets. Composed of many smaller and specialized models, the concept of Set of Sets AI models to simultaneously fulfil many task settings and environmental conditions is discussed. A means to arrive at such a set tractably in one pass of a neuroevolutionary multitasking algorithm is then presented for the first time, bringing us closer to models that are collectively ’Masters of All Trades’.

Lecture Topic 5: From Gradient-Based to Gradient-Free Deep Learning of Physics
Abstract: In the past decade, artificial intelligence (AI) has entered wide range of research and application domains in science and engineering and completely changed their frontier. AI, especially the deep learning methods, thrive in tasks where data is abundant. At the same time, the use of AI models in science and engineering gives rise to concern and doubt, mainly regarding their veracity. They can generate physically inconsistent or implausible results, especially when there may be insufficient data to learn from. These concerns motivate an emerging and evolving research frontier in physics-augmented AI, with the aim of integrating a priori physics knowledge into AI reasoning process, hence aiding the AI models in becoming consistent with fundamental physics laws without the need for increased labelled data. This talk focuses on a specific branch of physics-augmented AI—namely the physics-informed neural networks (PINNs)—focuses on learning physics with deep neural network models through infusing the governing equations,

i.e., typically in the form of ordinary and partial differential equations (ODEs & PDEs), into the training loss function. The goal of this research work is to advance our understanding of the theoretical aspects of PINNs, and to develop effective and efficient learning algorithms and methodologies for the deep learning of physics. With that in mind, novel and computationally efficient transfer neuroevolution algorithms to exploit relevant experiential priors when solving the PINN optimization problem shall be discussed. The work establishes gradient-free methods as a noteworthy approach for optimizing PINNs and seek to further advance both gradient-based and gradient-free learning algorithms for PINNs.