Abstract
Large-scale and multi-task learning remain difficult yet important problems in machine learning. In large-scale Gaussian processes the difficulty arises by the need to invert a potentially large covariance matrix during inference. For the multi-task learning problems the main challenge is the definition of valid kernels (covariance functions) able to capture the relationships between different tasks. In this talk I’ll address the complexity problem by constructing a stationary covariance function (Mercer kernel) that naturally provides a sparse covariance matrix. The sparseness of the matrix is defined by hyperparameters optimised during learning. This covariance function enables exact GP inference and performs comparatively to the squared-exponential one, at a lower computational cost.

The problem of multi-task learning will be addressed by presenting a novel methodology for constructing valid multi-task covariance functions for Gaussian processes allowing for a combination of kernels with different forms. The method is based on Fourier analysis and is general for arbitrary stationary covariance functions. Analytical solutions for cross covariance terms between popular forms are provided including Matern, squared exponential and sparse covariance functions.

I’ll also speak about our approach to classification of high dimensional hyperspectral datasets and application of machine learning to solution of differential and integral equations. Experimental results will be discussed for both artificial and real datasets demonstrating the benefits of the presented approaches.

Speaker Bio
Arman Melkumyan is a research fellow at the Australian Centre for Field Robotics (ACFR) at the University of Sydney. Arman got his PhD in 1995 in the field of Theoretical Mechanics and then worked as a postdoc at the Centre for Advanced Materials Technologies at the University of Sydney. In 2008 Arman joined the ACFR as a researcher in the field of large-scale multi-sensor machine learning modelling. Arman’s current work is mainly concentrated on development of mathematical machine learning techniques for probabilistic representations and information fusion for large scale environments.