Physics-informed machine learning for emulation of the systemic blood flow circulation

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Abstract:
There have been impressive advancements in the application of physics to the modelling of complex cardio-physiological systems. In principle this affords opportunities for deeper insight into the nature, cause and best treatment of cardio-physiological diseases. However, the corresponding mathematical models typically don't accommodate closed-form solutions and entirely rely on numerical simulation procedures instead. This becomes problematic in clinical applications, where model calibration and patient specific parameter estimation are indispensable, calling for repeated forward simulations from the model as part of an iterative optimization or sampling procedure at subsantial computational costs. In my talk, I will focus on a fluid dynamics model of the blood flow in a 17-vessel network connected to the human ascending aorta. I will discuss how physics-informed machine learning can be used to build effective and efficient emulators that allow accurate estimation of the physiologica l parameters at substantially reduced computational costs. In particular, I will focus on physics-informed neural networks (PINN). The key idea is to embed physical laws—such as conservation of mass, energy, momentum, or governing differential equations—into the training process of the neural network. This results in a machine learning surrogate model of the original fluid dynamics model that can make reliable predictions about blood flow and pressure time courses at a fraction of computational time that would be needed for a numerical integration of the original partial differential equations. The blood flow-pressure relation depends on the blood vessel geometry (the so-called vasculature), various boundary conditions and the physiological parameters, which act as inputs to the PINN. I will demonstrate how this provides a framework for compuationally efficient and accurate physiological parameter estimation and uncertainty quantification, which clearly outperforms more traditional methods.