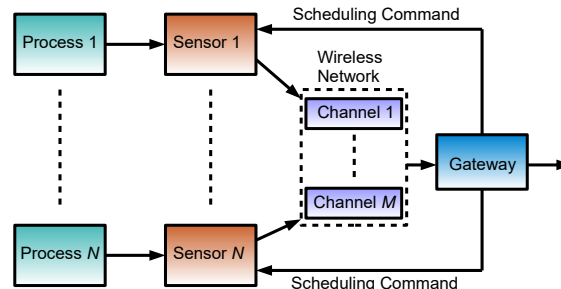


Project Title: Large Scale Sensor Scheduling Using Deep Reinforcement Learning

Background: A general wireless sensor scheduling problem can be posed as follows: Suppose N sensors want to transmit information wirelessly to a central gateway, but only $M < N$ transmission channels are available. The problem is to dynamically allocate the channels to the sensors in such a way that some performance criterion is optimized. Such allocation problems have applications in areas such as wireless communications and networked control [1, 2]. In general these problems are very difficult to solve, with large state and action spaces, where each state corresponds to the state of the overall system, and each action corresponds to a particular allocation of channels to the sensors.

In [3], we have studied a sensor scheduling problem for allocating wireless channels to sensors for the purpose of remote state estimation of dynamical systems. Each sensor measures the state of a different dynamical process, with the central gateway estimating the states of each of the N processes. The channel allocation aims to optimize the estimation performance at the gateway, averaged over all processes and all times. With the goal of providing a scalable method which can handle larger state spaces than previous work, we proposed an approach to the sensor scheduling problem based on the deep reinforcement learning algorithm of [4]. The resulting scheduling algorithm can be run online, and does not require knowledge about the channel parameters.

Project: While the method of [3] works well for small to medium sized systems (with the number of actions perhaps in the thousands), systems with larger action spaces cannot be efficiently handled using the deep reinforcement learning algorithm of [4]. The purpose of the current project is to implement an alternative algorithm, proposed in [5], for handling large action spaces, so that this deep reinforcement learning approach to sensor scheduling can be made “large-scale”. Eventual implementation of the code on a GPU will also be highly desirable.



Prerequisites: Knowledge of control theory and stochastic processes. Expertise in Python programming, and experience with deep learning libraries such as Tensorflow and Keras.

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