Recent advances in sensors, cloud computing, and related technologies are making wearables a powerful component of Cyber-Physical Systems (CPSs). These advances promise to provide wearables with the ability to observe patients or users remotely and take actions or give feedback regardless of their locations. Wearables rely on computation and communication deeply embedded in and interacting with the human body and the environment. Because of the need for integration into the everyday life of users, wearables need to meet higher reliability, usability and predictability standards than general-purpose computing systems. But, utilization of wearables is currently limited to controlled environments, laboratory settings, and predefined protocols. This limitation creates major obstacles in scaling these systems up and advancing their utility in real-world environments. Therefore, there is a growing need for designing autonomous wearables that withstand uncontrolled and unexpected conditions and deliver an acceptable level of accuracy to users. Computational methods, including machine learning and signal processing algorithms, are used as the core intelligence of wearables for real-time extraction of clinically important information from sensor-collected data. Current approaches employing such methods, however, suffer from several deficiencies: 1) the accuracy of the computational algorithms decreases as the configuration of the system changes (e.g., due to sensor misplacement). 2) Computational algorithms for such tasks as classification and template matching typically need training data for building processing models for each configuration. In order to re-train the computational algorithms across configurations, there is a need to collect sufficient amount of labeled training data, a process that is known to be time-consuming and expensive. 3) Data collected for a specific type or a sensor brand may not be accurate enough in a new setting. In this ongoing work, our goal is to devise effective transfer learning methods (at the signal level) for adapting a computational model of wearables developed in one domain to a different but related domain. The target domain for the system could arise as a result of user-specific uncertainty, sensor variation, environmental changes, etc. Our main focus is on motion sensors (e.g., accelerometer) We developed network analysis methods to map signal patterns from the source domain to the target domain. In particular, we build a suitable graph model for the sensor data and use community detection methods on the graph to cluster the sensor data based on signal similarity. Our results show that by using the community detection methods, data can be better clustered into a similar set of signals for different domains (e.g., different smartphones). In a subsequent step of our method, the similar communities are used to transfer knowledge from the source to the target domain. This is a joint work with Assefaw Gebremedhin, Seyed Ali Rokni and Hassan Ghasemzadeh, all at Washington State University.