Deep Multi-modal Glucose Level Prediction

Julia Gomes and Nick Lane

Mobile health and medical sensor data is becoming increasingly common and accessible to data scientists and researchers. I propose leveraging this data to build online learning systems that can provide actionable insights and improve type one diabetes management in real-time.

The main goal in type one diabetes management is to artificially maintain stable blood glucose levels in a narrow (healthy) range of values, since the body of a diabetic patient is unable to regulate blood glucose levels itself. Severe low blood glucose levels (hypoglycemia) can cause immediate death or mental impairment, while high blood glucose levels (hyperglycemia) is responsible for long-term health complications, such as neuropathy and heart disease. Today many patients use the CGM to view and record blood glucose values from a medical sensor in continuous five minute intervals. The sensor is calibrated with "ground truth" values from a blood draw every twelve hours to increase accuracy and adjust the sensor smoothing algorithm. Additionally, patients record a logbook of daily activity and events which are known to affect blood glucose values, including carbohydrate intake, protein intake, exercise, walking, weather, sleep, and other variables. With so many variables affecting blood glucose, it is also unrealistic for patients to accurately record all the relevant information in daily life.

In this research project, I am applying machine learning techniques to mobile health data in order to achieve three related goals: 1) Use an online multi-modal recurrent neural network to predict blood glucose values in advance so that patients can both fill in gaps in sensor data and take preventive measures, 2) Automate the process of data collection by integrating data from wearable and smart-phone devices, and 3) Use outlier detection techniques to identify when the sensor is malfunctioning and providing erroneous values.