

Improving Virtual Diabetes Patient Simulations with Bayesian Networks

Video Link: <https://youtu.be/evUZOl8BPg>

Even though commercially-available simulators exist to model the physiology of patients with types 1 and 2 diabetes, such as the [UVA-Padova Simulator](#) and the [Tidepool Metabolism Simulator](#), these simulators fail to incorporate the variability of human behavior into their simulations. A disease like diabetes is exhausting, requiring frequent dose adjustments and management of blood glucose levels, and often patients will forget to make adjustments or keep all of their medical devices connected together. This is problematic when studying hybrid closed-loop insulin dosing algorithms, which require some user intervention in order to function properly; simulators that do not model patient behavior will return overly positive results and may not catch dangerous ‘edge’ situations.

I created a Bayesian Network-inspired approach that can create a unique behavioral profile for each simulated patient. I chose Bayesian Networks to model this variability because many of these behavioral attributes, such as the probability of dosing insulin to cover a meal, are affected by other attributes, like age and whether the person entered carbohydrates into the system. In the future, I would like to use Markov Decision Processes to incorporate the element of time into these behavioral models, but I wasn’t able to start that aspect due to how long it took to find reasonable probabilities for my Bayesian Network. From reading the literature and examining user experiences with automated insulin dosing systems, I chose to incorporate the three most significant behavioral ‘aspects’ that affect the performance of closed-loop systems: signal loss (and its duration), carbohydrate entry, and bolusing.

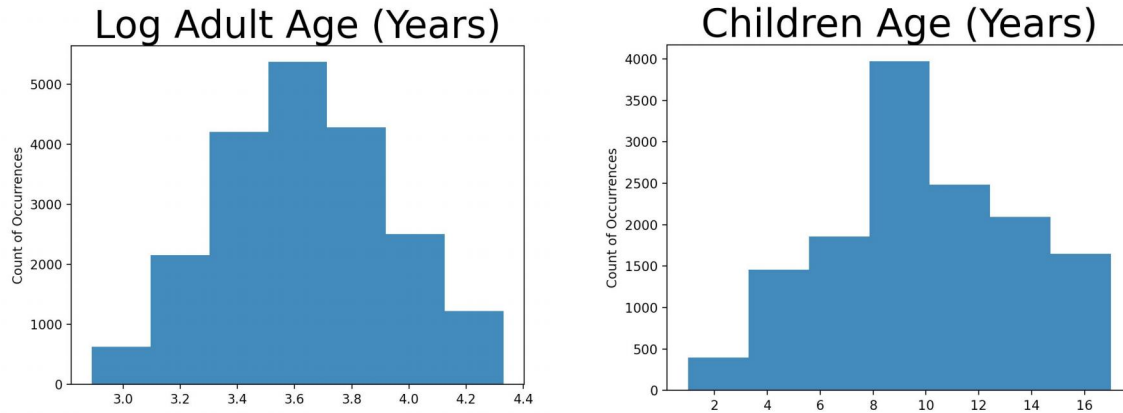
Signal loss is when the various components of the closed-loop system (insulin pump and continuous glucose monitor) become disconnected from the controller (typically a mobile device). This is almost entirely due to either walking away from the controller or experiencing signal interference from the environment. In order to determine probabilities, I examined reports from the Looped Facebook group, which provides support and information for patients using closed-loop systems. I identified that signal loss occurred consistently for all patients, anecdotally around 2% of the time, but that the likelihood of walking away from the controller was affected by activity level, occurring around 1% of the time. As a result, I made connectivity dependent on these two factors and modeled them with Bernoulli random variables (RVs); I modeled the duration of signal loss as a Poisson RV in order for the simulator to correctly ‘disconnect’ the devices for the appropriate amount of time.

However, I needed to also determine if a patient was active in order to determine how often they’d experience signal loss. I found statistics from Statista, a consumer data firm, that indicated that activity was affected by both age and gender. Since type 1 diabetes is equally prevalent in males and females, I modeled it as a Bernoulli RV with probability of 0.5; unfortunately, the statistics did not include information on gender non-conforming individuals, so I was unable to include it in my analysis.

Modeling age was one of my largest challenges, since its overall distribution doesn’t follow any distributions we studied in class. I used data from one of the largest studies on

automated insulin dosing (the Jaeb Observational Study) to determine age distribution in closed-loop users.

I identified that the distribution depended on whether the patient was an adult or a child; for adults, age is log-normally distributed, but for children it's normally distributed.



I used maximum likelihood estimation for the normal distribution to find the mean and standard deviation of age for the children and log-transformed adult age data.

After I had determined how to model signal loss, I turned to modeling carbohydrate entry and mealtime bolusing behavior, which are closely linked. ‘Carbohydrate entry’ is defined as when the patient enters the number of carbohydrates consumed into the system so it can recommend the appropriate insulin dose, and ‘mealtime bolusing’ is the delivery of insulin to cover carbohydrates consumed during meals.

I thought that age and gender would affect the likelihood that a user enters carbs and boluses, but interestingly, researchers have found that gender has no influence and that only age influences this behavior when the patient is less than 18 years old. I used the probabilities from two clinical trials I found that studied mealtime insulin dosing behaviors. I had to adapt the probabilities slightly due to the fact closed-loop systems are slightly different compared to manual therapy; in closed-loop systems, it's possible to enter carbs but forget to bolus, which isn't possible when dosing manually. I treated carbohydrate entry and bolusing as being two separate but closely-linked events, with the mealtime dosing probabilities from the studies as the probabilities for carbohydrate entry and there being a 95% chance the patient bolused, given that carbohydrates were entered. I found the 95% probability of bolusing (given carbohydrate entry) by examining reports in the Looped Facebook group.

Once I had this ‘patient behavior’ class that could probabilistically generate a unique patient behavior profile, I incorporated it into the Tidepool Metabolism Simulator as a proof of concept, a demonstration of which is present in my video. In the future, especially once I modify my profile generator to use Markov Decision Processes, I'm hopeful that this work can be contributed back to the Tidepool Metabolism Simulator in order to improve its simulations, which are currently being used to demonstrate the safety of Tidepool's hybrid closed-loop insulin dosing system to the FDA.