

Learning Insulin-Glucose Dynamics in the Wild

Andrew C. Miller

*Apple
Seattle, WA, USA*

ACMILLER@APPLE.COM

Nicholas J. Foti

*Apple
Seattle, WA, USA*

NICHOLAS_FOTI@APPLE.COM

Emily Fox

*Apple
Seattle, WA, USA*

EMILY_FOX@APPLE.COM

Summary

- new model of carbs-insulin-glucose dynamics for type 1 diabetes
- fully learned models like LSTM yield implausible predictions
- this work combines mechanistic knowledge and prob. models
- glucose levels are noisy measurement of latent state, which evolves wrt a diff eq.

Data Collected

- two T1D participants using a continuous glucose monitor (CGM) and an insulin pump
- instantaneous continuous blood glucose measurements
- other measurements using Apple Healthkit: estimated carb ingestion + active energy burned.

Cohort + Validation

- management of T1D highly personalized.
- here, study two individuals
- data: 150 days, train/valid on 120 days, test prediction on 30 days
- one sample every 5 min., each participant has over 40k points recorded

Data Example

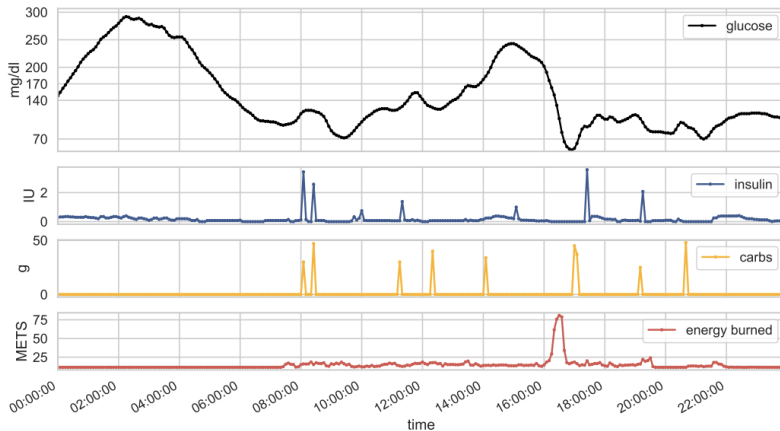


Figure 1: Data for a single day: blood glucose as measured by CGM, insulin delivered by pump, user carbohydrate log, and energy use captured every five minutes by HealthKit.

Existing Methods

- prob. models:
 - can predict glucose change from carbs, insulin
 - unstable for long term predictions (why?)
- physiological models
 - predict over long periods in controlled settings
 - UVA/Padova simulator: interaction of glucose, insulin, and orally ingested carbohydrates (Dalla Man et al., 2014)
 - not robust to noise and missing data, doesn't account for fluctuations in insulin sensitivity, meal absorption

$$\mathbf{z}_0 \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \quad \text{initial latent state} \quad (1)$$

$$\mathbf{z}_t \sim A\mathbf{z}_{t-1} + B\mathbf{a}_t + Q^{1/2}\boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, I) \quad \text{latent temporal dynamics} \quad (2)$$

$$\mathbf{d}_t = \text{NN}_\phi(\mathbf{z}_t) \quad \text{dynamic simulator params.} \quad (3)$$

$$\mathbf{x}_t = \text{UVA-step}(\mathbf{x}_{t-1}, \mathbf{d}_t, \mathbf{u}_t, \mathbf{s}, \Delta_t) \quad \text{T1D simulator} \quad (4)$$

$$y_t \sim \mathcal{N}(\text{CGM}(\mathbf{x}_t, \mathbf{s}), \sigma^2) \quad \text{CGM observation} \quad (5)$$

where $\mathbf{z}_t \in \mathbb{R}^D$, $\mathbf{d}_t \in \mathbb{R}^K$, $\mathbf{x}_t \in \mathbb{R}^{13}$, $\mathbf{u}_t \in \mathbb{R}^J$, and $\mathbf{s} \in \mathbb{R}^J$. The dimensionality of the latent space D can be tuned. The physiological state \mathbf{x}_t size is fixed by the simulator definition. The simulator parameters chosen to be dynamic, K , and static, J , is a hyperparameter setting, which we fix for this work and describe in [Appendix A](#).

$$\frac{d\mathbf{x}_t}{dt} = f^{(uva)}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{p}), \quad (6)$$

where the dynamics are a function of the current state, time-varying inputs, and static parameters, respectively.⁵ The evolution from state \mathbf{x}_{t-1} to \mathbf{x}_t involves integrating these dynamics over the time increment Δ_t , which in this work we assume is always one so that:

$$\mathbf{x}_{t+1} = \int_t^{t+1} f^{(uva)}(\mathbf{x}_{t'}, \mathbf{u}_t, \mathbf{p}) dt' \quad (7)$$

$$\triangleq \text{UVA-step}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{p}). \quad (8)$$

Results

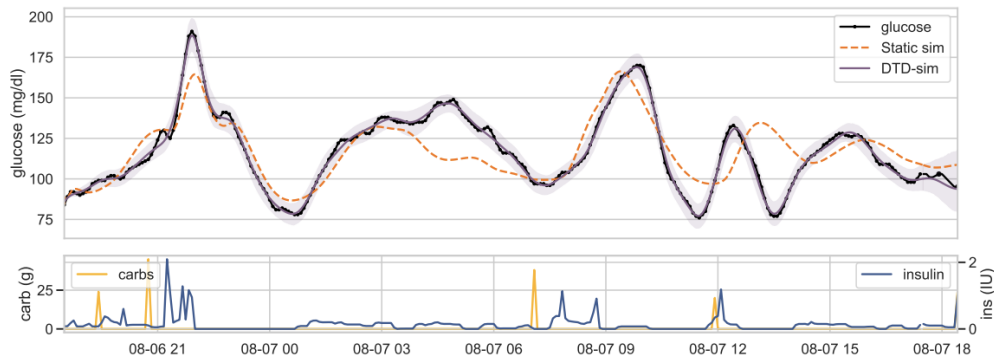


Figure 3: *Static* UVA/Padova lacks the capacity to describe real CGM data. *Top*: model fit comparison of *static* UVA/Padova simulator and *dynamic* DTD-sim model for a full day of CGM data. *Bottom*: corresponding insulin and carbohydrate data. Without varying parameters in time and accounting for data noise, the T1D simulator model does not describe observed data.