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Learning Insulin-Glucose Dynamics in the Wild

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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

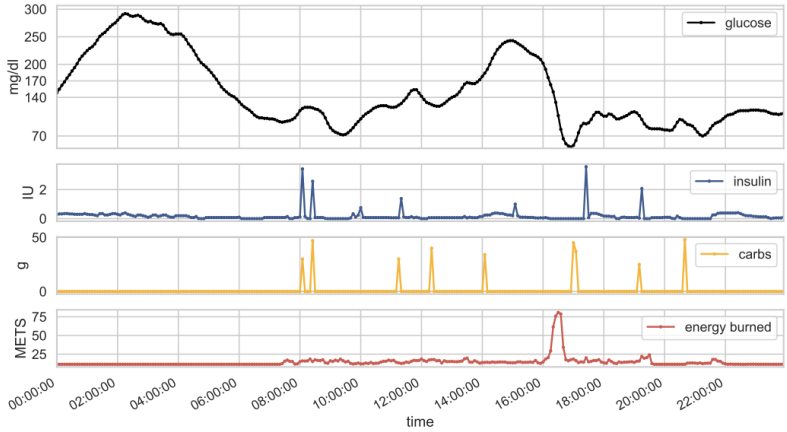

Figure 1: Data for a single day: blood glucose as measured by CGM, insulin delivered by pump, user carbohydrate log, and energy use captured every five minutes by HealthKit.

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

Model

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

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

$$\boldsymbol{d}_t = \texttt{NN}_\phi(\boldsymbol{z}_t) \qquad \text{dynamic simulator params.} \qquad (3)$$

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

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

where $\boldsymbol{z}_t \in \mathbb{R}^D$, $\boldsymbol{d}_t \in \mathbb{R}^K$, $\boldsymbol{x}_t \in \mathbb{R}^{13}$, $\boldsymbol{u}_t \in \mathbb{R}^J$, and $\boldsymbol{s} \in \mathbb{R}^J$. The dimensionality of the latent space D can be tuned. The physiological state $\boldsymbol{x}_t$ 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.

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

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

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

$$\triangleq \texttt{UVA-step}(\boldsymbol{x}_t, \boldsymbol{u}_t, \boldsymbol{p})\,. \tag{8}$$

Results

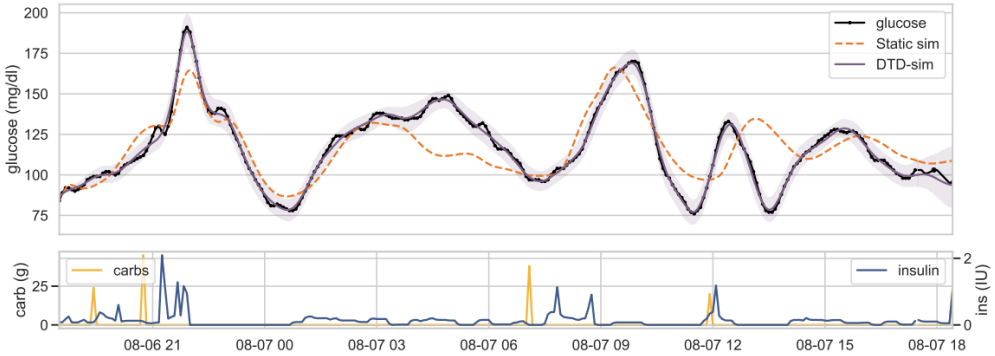

Figure 3: *Static* UVA/Padova lacks the capacity to describe real CGM data. *Top*: model fit comparison of *static* UVA/Padova simulator and *dynamic* `DTD-sim` model for a full day of CGM data. *Bottom*: corresponding insulin and carbohydrate data. Without varying parameters in time and accounting for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