Predictive Modeling of Exercise-Induced Glycemic Outcomes Using Generative Deep Learning

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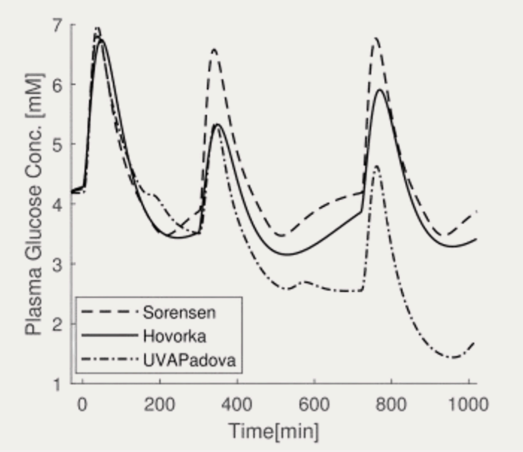
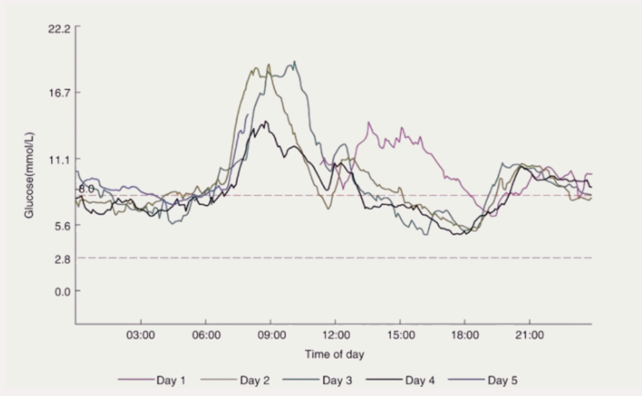
Modeling & Intelligent Control Engineering

Motivation

- **Physiological models cannot fully capture** glucose homeostasis **complexity**
- Data-driven models learn from real-life data, including lifestyle factors



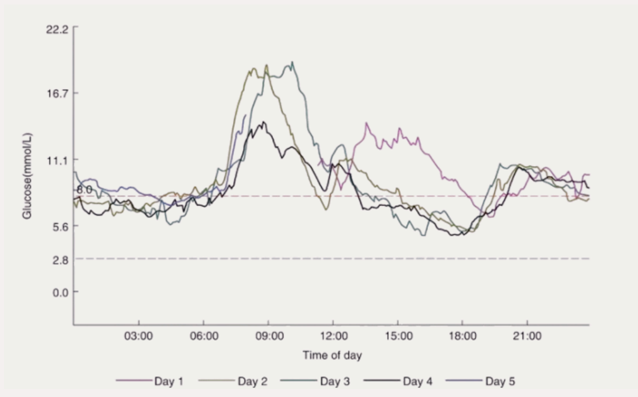
Blood glucose simulations using the three common physiological models [1].



Overlay of multiple days of CGM for a newly diagnosed diabetic patient [2].

Data-driven virtual patients

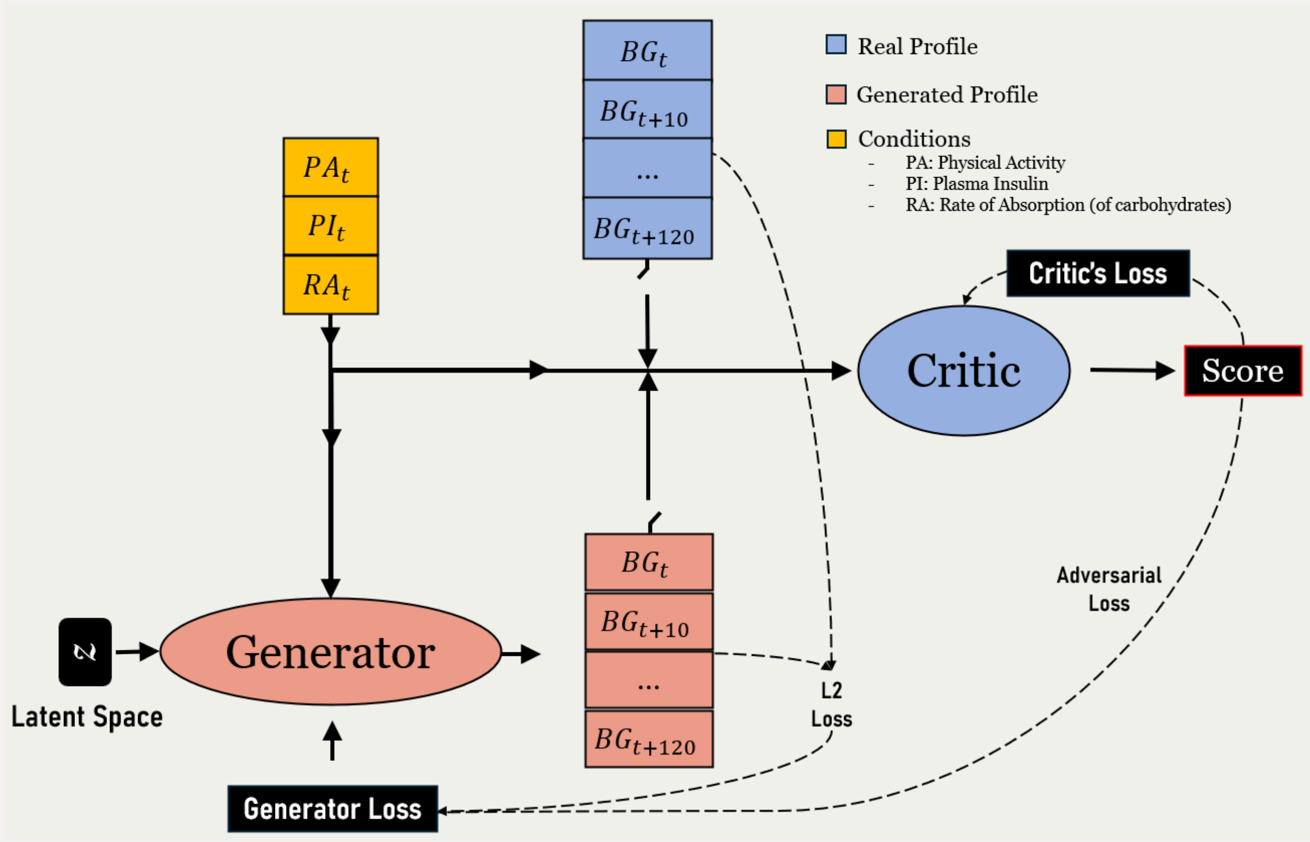
- Generative Adversarial Networks (GANs) are able to replicate the unpredictable **stochasticity** seen in real patients
- In previous works, we implemented GANs with two conditions: insulin and meals. [3]
- Objective: extend our simulator to also **include exercise activities**



24-hour blood glucose profiles: Demonstrating simulator stochasticity under identical inputs [3]

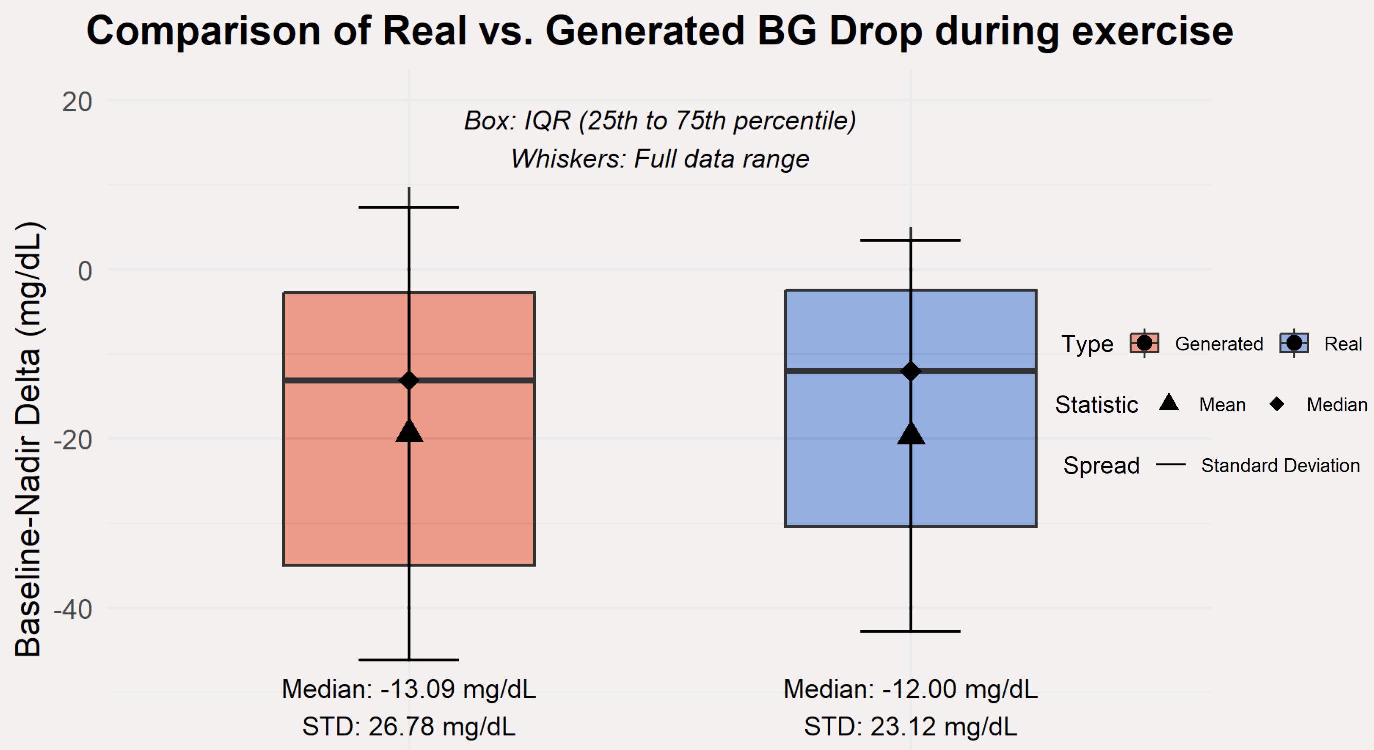
Methods

- Implementation of a Deep Convolutional, Conditional, Wasserstein Generative Adversarial Network in 1 dimension
- Generator produces shifted sequences with 120 min. prediction horizon (PH)
- **Inputs**: delivered insulin, carbohydrates intake, exercise intensity
- **Data**: 60 standard insulin pump patients from **T1DEXI** dataset who were assigned **aerobic exercise**
- Physical Activity dynamics are modeled through intensity data



GAN architecture for training.

Results

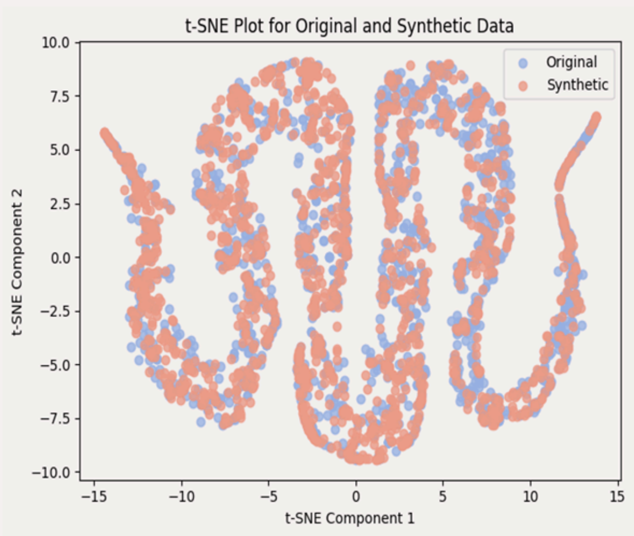


Boxplot of the drop in blood glucose concentration during exercise activity from baseline to nadir (minima during the activity).

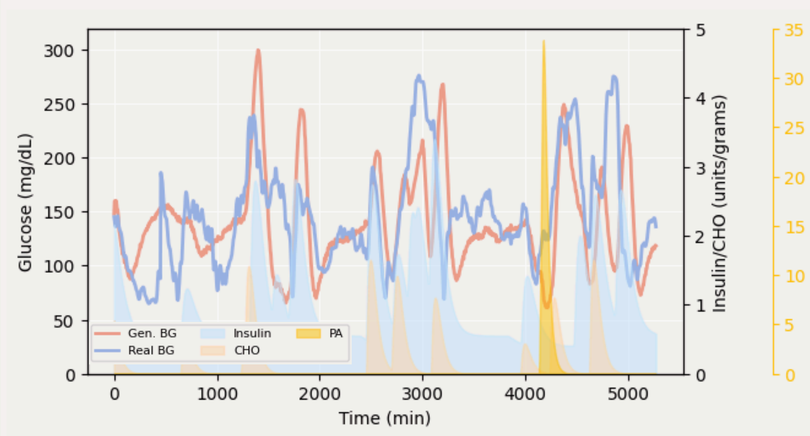
Generated Real

Type		Mean Glucose	Std Glucose	Coef. Variation	Time < 70 (%)	Time in Range (%)	Time > 180 (%)	T. in Tight Range (%)
Sedentary	Generated	149.33	49.57	32.70	0.00	77.43	21.18	51.22
	Real	141.46	41.18	29.95	2.78	77.26	18.40	54.17
Active	Generated	145.60	40.75	31.00	1.39	79.17	20.14	48.96
	Real	142.10	39.56	28.95	0.00	81.25	17.36	52.43

Comparative table of glycemic outcomes for generated vs. real patients on sedentary and active days



t-SNE analysis of real vs. synthetic BG values for patient 50



Real vs. synthetic glucose profiles for patient 50

Conclusions

- Data based virtual patients show potential in **predicting** exercise-induced **glycemic outcomes**
- Model realistically replicates glucose-insulin dynamics
- We are working on adding other exercise types included in T1DEXI

References:
[1] Pompa, Marcello, et al. "A comparison among three maximal mathematical models of the glucose-insulin system." PloS one 16.9 (2021)
[2] Li, M., and Y. Bao. "Methods for Interpreting Continuous Glucose Monitoring Graphs." Continuous Glucose Monitoring (2018):
[3] Mujahid, O., et al. "Generative deep learning for the development of a type 1 diabetes simulator". Communications Medicine, (51), (2024)

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