Gluformer: Transformer-Based Personalized Glucose Forecasting with Uncertainty Quantification

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Continuous glucose monitors

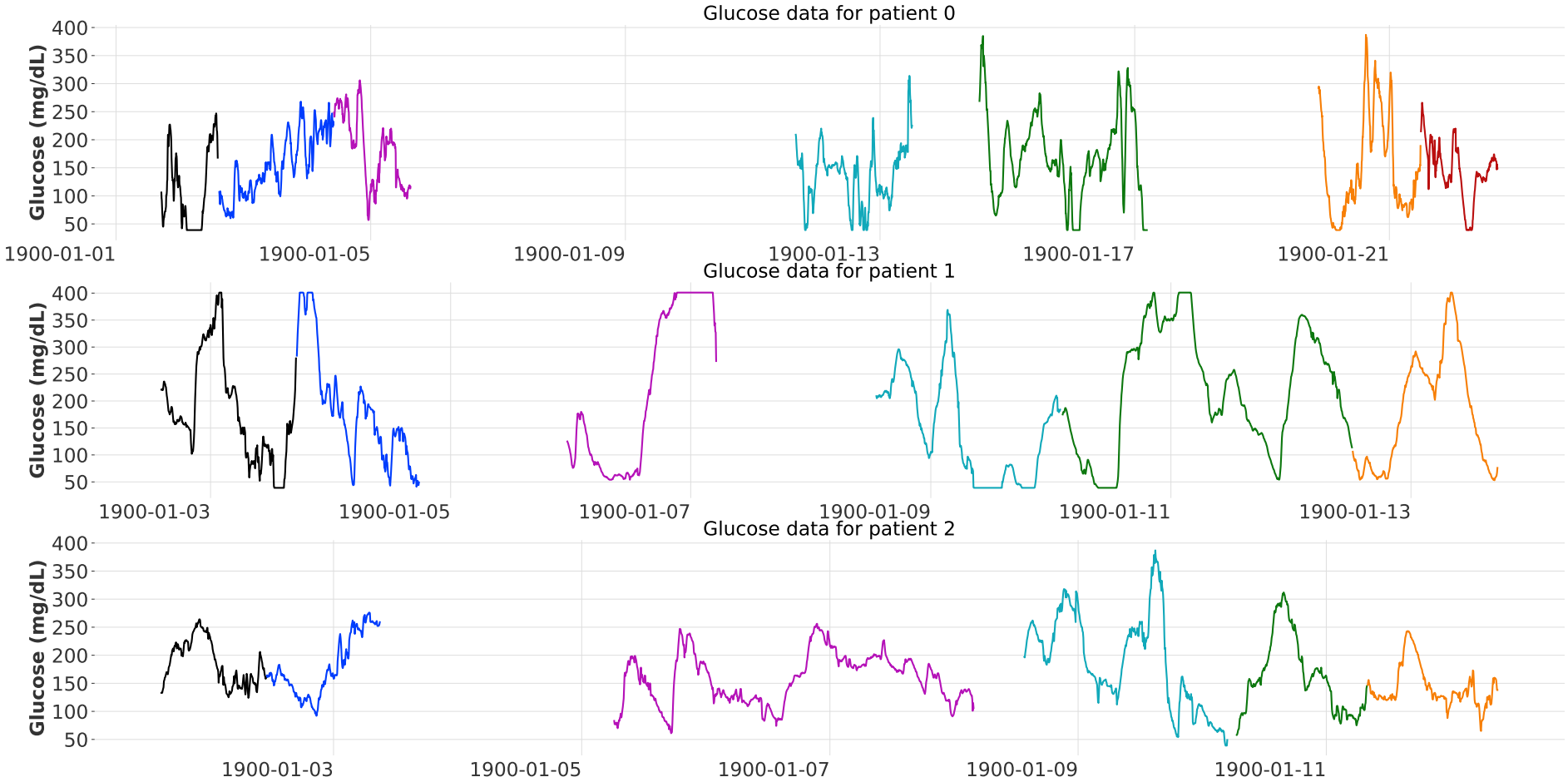
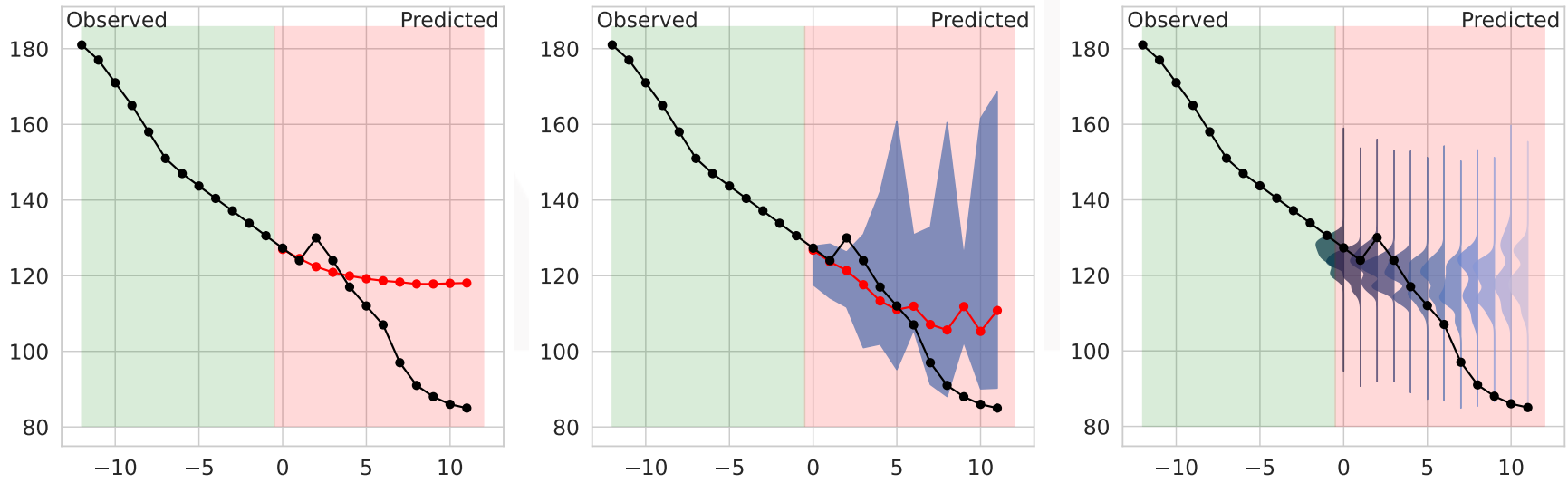


Figure: Example of continuous glucose monitor (CGM) data [2].

Setup and notation

Having observed data, $y_i(t)$ for $t \leq T$, for patient i, we would like to predict:

1. (Forecasting) Future trajectory, $y_i(t)$ for $t \in [T, T + L]$,
2. (Probabilistic forecasting) Distribution of future trajectory p_i.

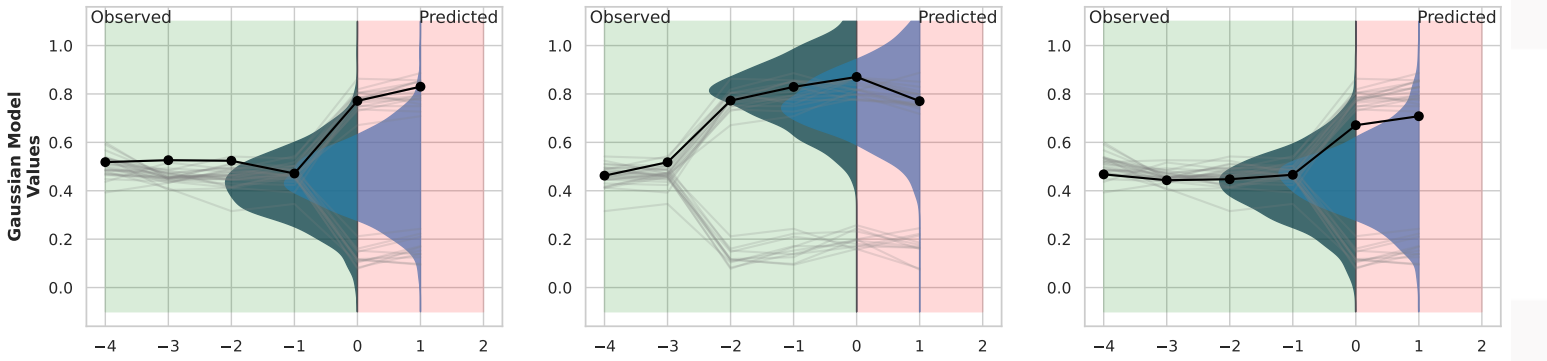


Simulation

Data generation: consider a **toy example**, where the **data is generated** following:

$$\mathbf{y} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma)$$

$$\boldsymbol{\mu}_{1:n} \sim \mathcal{N}(\mathbf{0}, I_n) \qquad \boldsymbol{\mu}_{n:2n} \sim \frac{1}{2}\mathcal{N}(\mathbf{0}, I_n) + \frac{1}{2}\mathcal{N}(\mathbf{1}, I_n).$$



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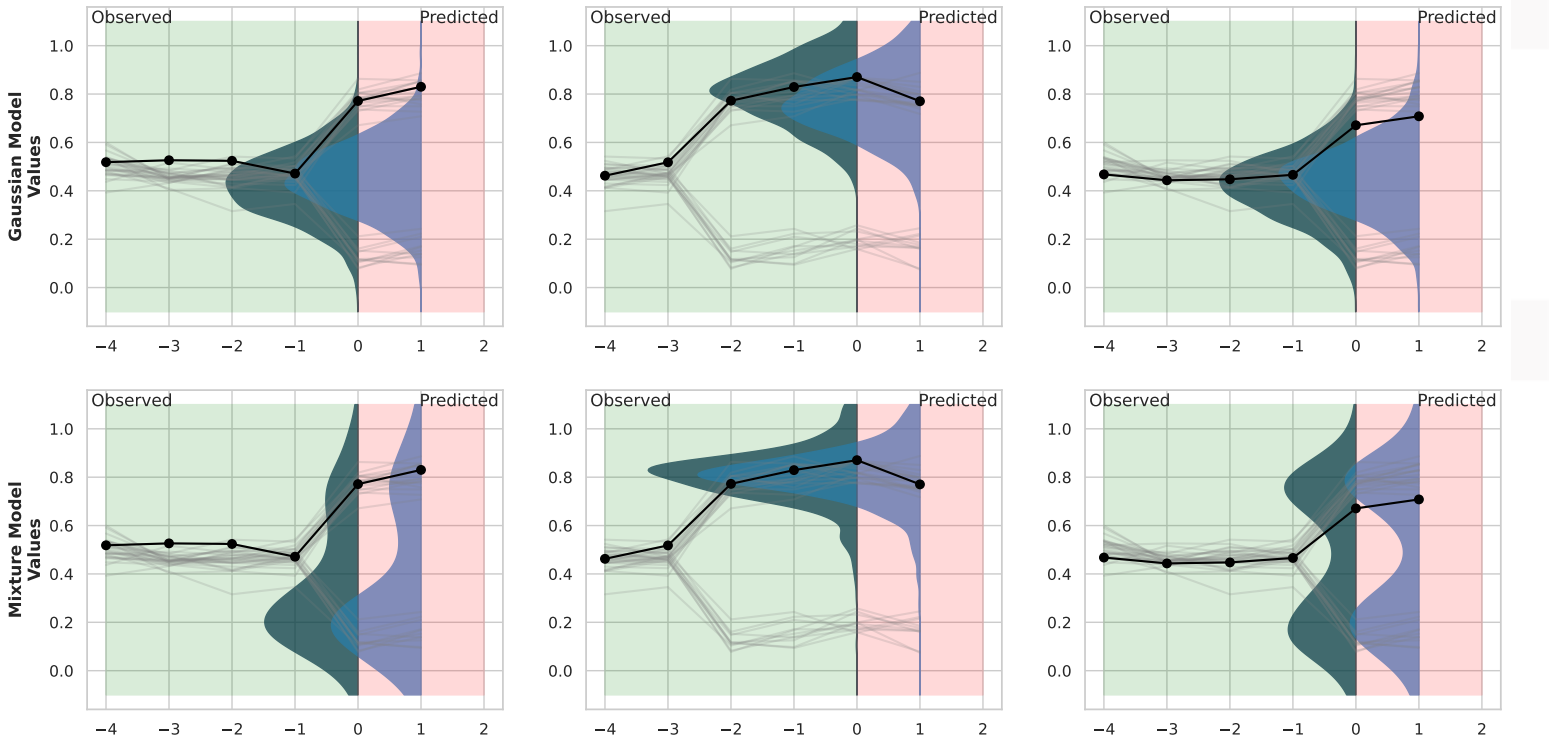


Approach

We change model loss by conditioning on latent variables $\boldsymbol{z}$:

$$\boldsymbol{y}_{t:t+l}|\boldsymbol{y}_{1:t}, \boldsymbol{z} \sim \mathcal{N}(\hat{\boldsymbol{\mu}}, \hat{\sigma}^2 I_l) \qquad (\hat{\boldsymbol{\mu}}, \hat{\sigma}^2) = f_\theta(y_{1:t}|z) \qquad \boldsymbol{z} \sim p_{\boldsymbol{z}}.$$

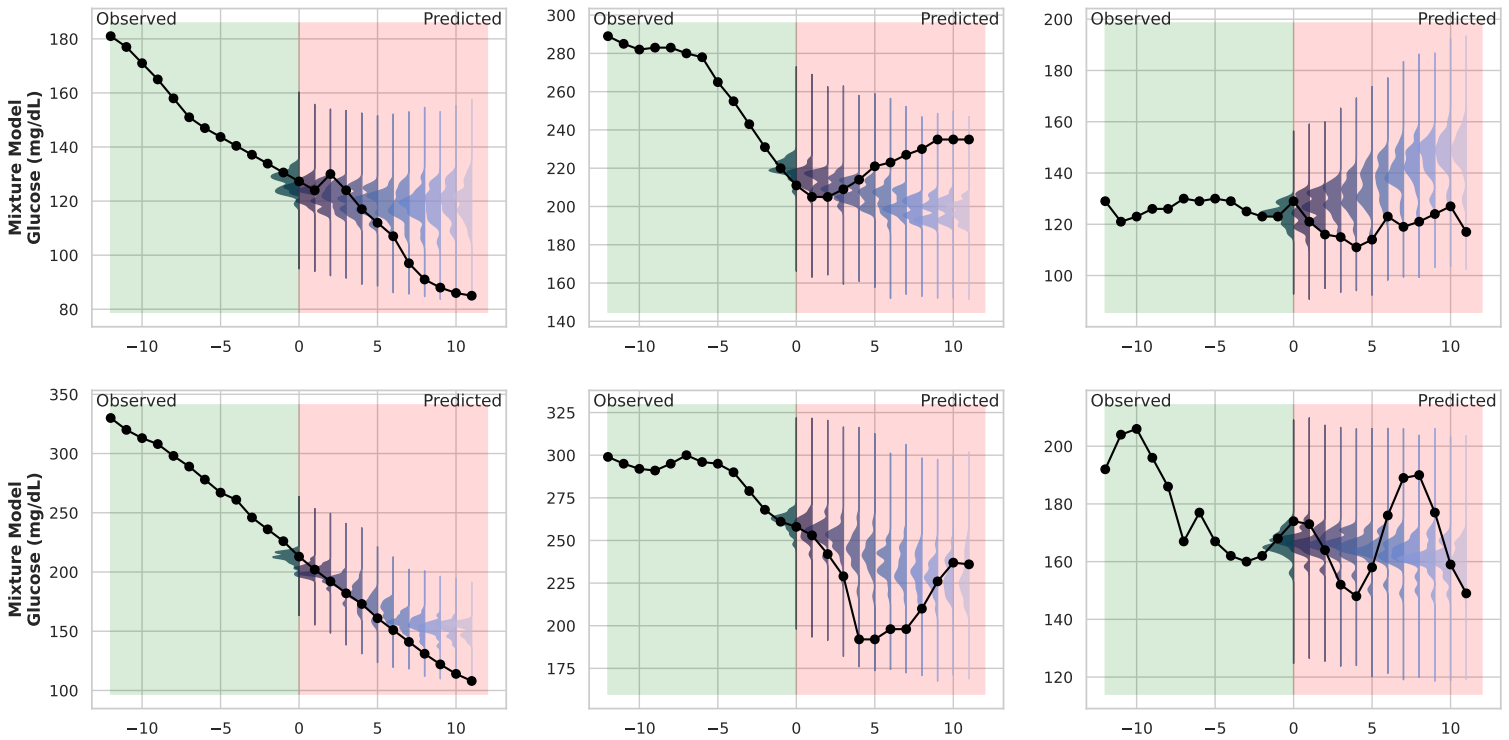
We optimize model parameters θ to minimize negative log-likelihood:

$$\theta^\star = \arg\min \left(-\log \int p(\boldsymbol{y}_{t:t+l}|\boldsymbol{y}_{1:t}, \boldsymbol{z}) p(z) d\boldsymbol{z} \right).$$

During training, we approximate the integral using Monte Carlo, which amount to several **stochastic passes through the network**.
During inference, we form the predictive distribution as a finite mixture using the stochastic passes:

$$p(\boldsymbol{y}_{t:t+l}|\boldsymbol{y}_{1:t}) \approx \frac{1}{n} \sum_1^n \mathcal{N}(\hat{\boldsymbol{\mu}}_{\boldsymbol{i}}, \hat{\sigma}_i^2 I_l) \qquad (\hat{\boldsymbol{\mu}}_i, \hat{\sigma}_i^2) = f_\theta(\boldsymbol{y}_{1:t}|z_i) \qquad z_i \sim p_{\boldsymbol{z}}.$$

CGM Data



Results

Model	Full	Event	Hypo	Hyper	Likelihood
ARIMA [4]	9.85 / 17.65	8.91 / 19.86	19.94 / 14.53	8.51 / 22.17	-14.93
RF:Rec [5]	9.04 / 17.15	8.97 / 20.36	18.84 / **12.43**	8.68 / 23.41	-14.58
RF:MO [5]	10.22 / 18.27	8.61 / 19.90	21.64 / 17.36	7.99 / 21.58	-15.34
PolySeqMO [2]	8.55 / 15.68	8.27 / 18.81	22.86 / 21.87	**6.77 / 18.30**	-15.61
RNN [1]	8.17 / 15.67	8.29 / 19.37	18.72 / 16.26	6.99 / 19.22	-13.50
TFT [3]	7.80 / 15.78	8.03 / 18.23	16.23 / 14.62	6.87 / 18.98	–
(Our)	**7.78** / **15.40**	**7.89 / 17.85**	**15.75** / 14.03	7.08 / 19.58	**-2.67**

Table: APE/RMSE for 60-minute prediction window (Full), hypoglycemia, hyperglycemia, and event (hypo-or hyperglycemia), and model log-likelihood on test data.

References

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[3] B. Lim, S. Ö. Arık, N. Loeff, and T. Pfister. Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4):1748–1764, 2021.

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Thank You!