COMET: Constrained Counterfactual Explanations for Patient Glucose Multivariate Forecasting

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Outline

- Background
- Proposed COMET method
- Empirical evaluation
- Conclusions

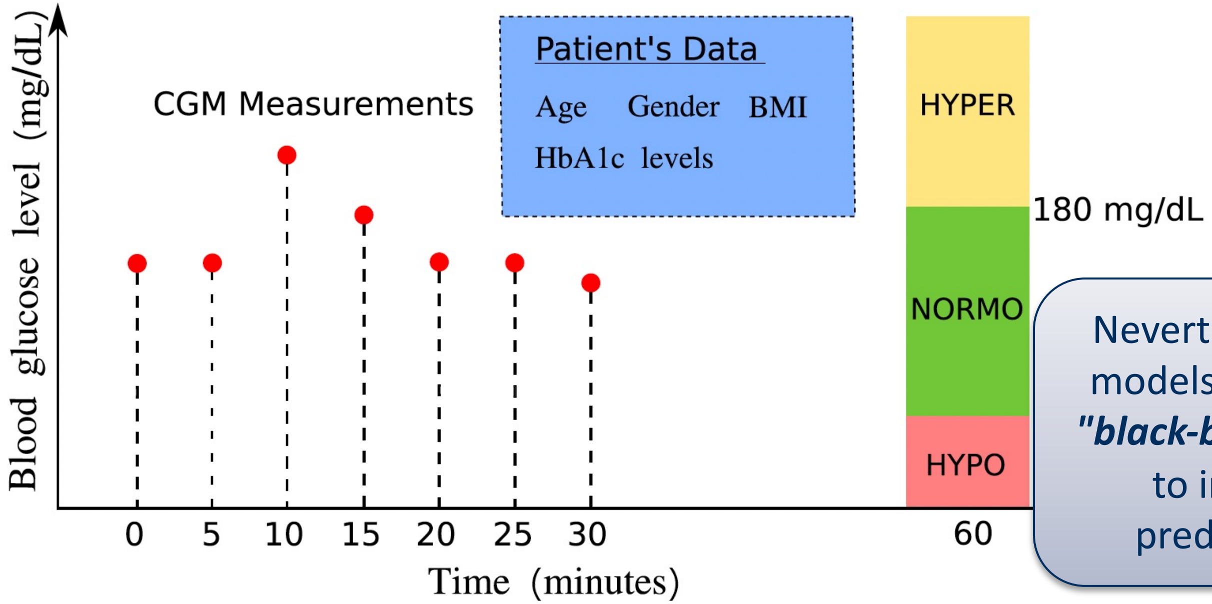
Forecasting in healthcare

- Deep learning (DL) models can assist medical decision--making process in forecasting
  - E.g., Daily patient arrivals and length of stays in the ICU

- For type 1 diabetes mellitus (T1DM) patients, closely tracking glucose levels is a crucial task
  - *RNN-based* models and *transfer learning* have been applied to accurately predict patients' glucose
  - Incorporated additional covariate variables, e.g., insulin dosages and daily carbohydrates

[Deng et al., 2021]
[Cui et al. 2021]

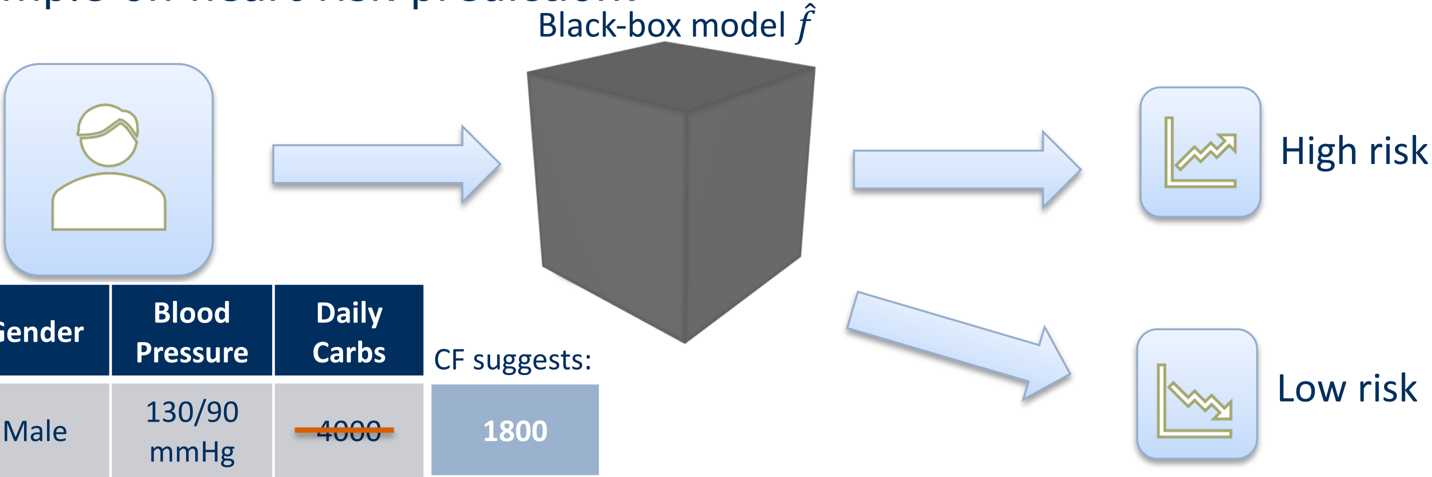
DL forecasting of diabetic blood glucose (30 mins -> 5 mins)



Nevertheless, most DL models are considered ***"black-box"*** and difficult to interpret the prediction results

Counterfactual (CF) explanations

- Show modifications required to change a prediction from an **undesired** (e.g., unhealthy) to a **desired** outcome (e.g., healthy)
- Example on heart risk prediction:



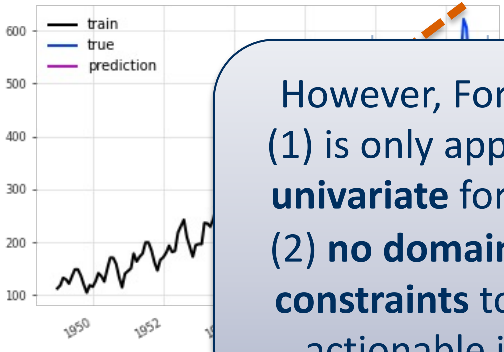
Age	Gender	Blood Pressure	Daily Carbs
43	Male	130/90 mmHg	~~4000~~

CF suggests: **1800**

[Wachter et al., 2017]

Counterfactuals for forecasting

- Recent study proposed to provide counterfactuals for time series forecasting: **ForecastCF**
  - Define desired outcome: *upper* and *lower* bounds that forecasted values are desired to fall into
- Desired bounds for sales forecasting:



Example of Fore

However, ForecastCF:
(1) is only applicable to **univariate** forecasting;
(2) **no domain-specific constraints** to provide actionable insights

 [Wang et al., 2023]

Pseudo-code for proposed COMET

Algorithm 1: COMET counterfactual search

input : Time series $\boldsymbol{X}$, differentiable forecaster $f(\cdot)$, lower and upper bounds $[\boldsymbol{\alpha}, \boldsymbol{\beta}]$, clipping ranges $[\boldsymbol{\rho}, \boldsymbol{\phi}]$, historical value set $\boldsymbol{\mathcal{G}}$, forecast margin weight w, learning rate η, maximum iteration max_iter

output: Counterfactual $\boldsymbol{X}'$ with desired outcome

$\boldsymbol{X}^* \leftarrow \boldsymbol{X}$

$\hat{\boldsymbol{y}}^* \leftarrow f(\boldsymbol{X}^*)$

$\boldsymbol{C} \leftarrow ActivityTemporalConstriant(\boldsymbol{X}^*)$

$loss \leftarrow L(\boldsymbol{X}^*, w, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{C})$

$t \leftarrow 0$

while $(\hat{\boldsymbol{y}}^* > \boldsymbol{\beta} \vee \hat{\boldsymbol{y}}^* < \boldsymbol{\alpha}) \wedge (t < max\_iter)$ **do**

- $\boldsymbol{X}^* \leftarrow AdamOptimize(\boldsymbol{X}^*, loss, \eta)$
- $\boldsymbol{X}^* \leftarrow Clip(\boldsymbol{X}^*, \boldsymbol{\rho}, \boldsymbol{\phi})$
- $\hat{\boldsymbol{y}}^* \leftarrow f(\boldsymbol{X}^*)$
- $\boldsymbol{C} \leftarrow HistValueConstraint(\boldsymbol{X}^*, \boldsymbol{\mathcal{G}})$
- $loss \leftarrow L(\boldsymbol{X}^*, w, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{C})$
- $t \leftarrow t + 1$

$\boldsymbol{X}' \leftarrow \boldsymbol{X}^*$

return $\boldsymbol{X}'$

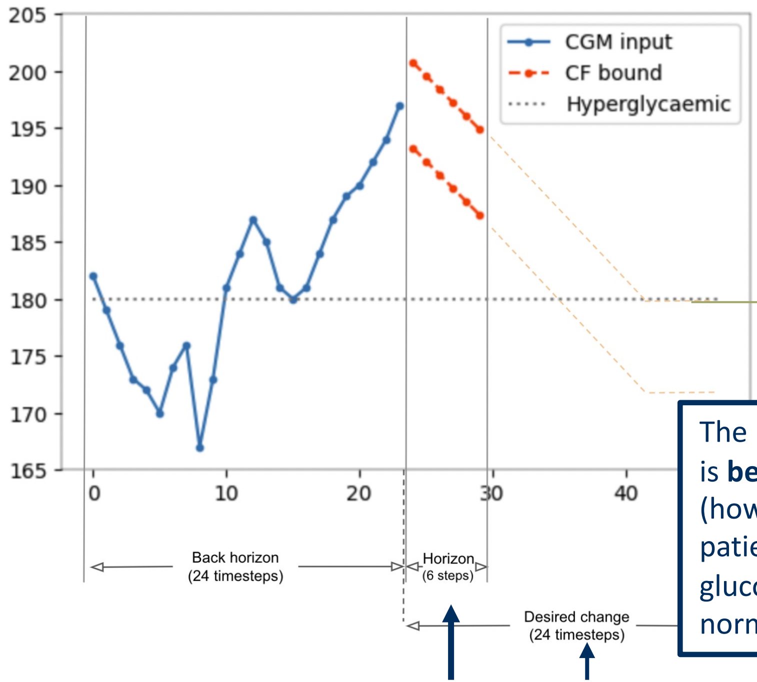
COMET considers three domain-specific constraints for T1DM patients:

1. Activity temporal constraint (-**A**): incorporates constraint **c** to encourage counterfactual changes at specific period with any planned activity (e.g., meal and exercise)

2. Clipping constraint (-**C**): ensures each value at timestep of the CF sample are within the minimum and maximum range

3. Historical values constraint (-**H**): imposes constraints on the CF samples to be closer to the historical values for each patient

Define desired bounds in COMET



The normal glucose range is **between 70 and 180** (however, many T1DM patients often have glucose levels outside the normal range)

…erate constraint …ing a trend to reach the **…ange in 2 hours** (e.g., …teps) and **trim it to the …on** (e.g., 6 steps)

Experimental set-up

- Multivariate forecasting setup:
  - Using 5 clinical features from previous 2 hours to predict CGM measurements in the next 30 mins
  - 2 DL models: GRU and WaveNet
- 2 datasets of diabetes patients
  - *OhioT1DM*: a real-world type 1 diabetes patient dataset
  - *SimGlucose*: simulated from FDA-approved UVA/PADOVA simulator
  - Divide patients in 2 groups: hyper-/hypo-glycemia

- 3 variants of COMET
  - COMET-**C**: included the clipping constraint
  - COMET-**A**: both clipping and activity temporal constraints
  - COMET-**H**: included all three mechanisms (i.e., with historical values constraint)

Empirical evaluation

Stockholm University

Baseline: ForecastCF

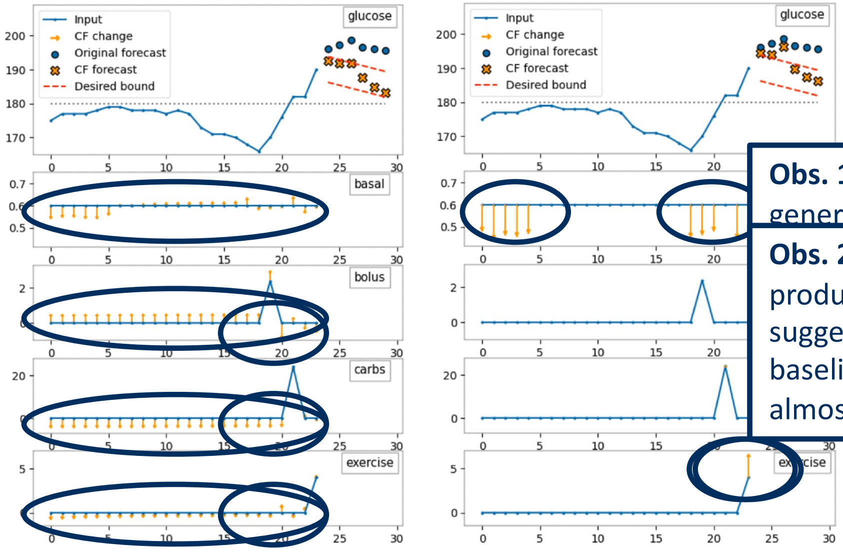
Dataset	Patient group	CF model	GRU *Valid.*	GRU *Proxi.*	GRU *Compa.*	GRU *Step AUC*	WaveNet *Valid.*	WaveNet *Proxi.*	WaveNet *Compa.*	WaveNet *Step AUC*
OhioT1DM	Hyperglycemia	ForecastCF	**0.945**	0.193	0.264	**0.783**	**0.955**	0.159	0.758	**0.790**
		COMET-C	0.867	0.349	0.558	0.706	0.900	0.251	0.844	0.746
		COMET-A	0.675	0.347	0.808	0.526	0.718	0.192	0.935	0.569
		COMET-H	0.585	**0.173**	**0.910**	0.459	0.658	**0.150**	**0.955**	0.521
	Hypoglycemia	ForecastCF	**0.497**	0.284	0.049	**0.188**	0.525	0.162	0.721	**0.196**
		COMET-C	0.490	0.345	0.247	0.175	**0.530**	0.189	0.829	0.171
		COMET-A	0.207	0.396	0.775	0.066	0.238	0.111	0.937	0.074
		COMET-H	0.165	**0.173**	**0.909**	0.046	0.145	**0.042**	**0.973**	0.055
SimGlucose	Hyperglycemia	ForecastCF	**0.984**	**0.056**	0.368	**0.853**	**0.964**	0.117	0.889	**0.823**
		COMET-C	0.858	0.108	0.776	0.758	0.873	0.095	0.935	0.720
		COMET-A	0.732	0.117	0.935	0.624	0.727	0.009	**0.999**	0.457
		COMET-H	0.726	0.116	**0.935**	0.618	0.727	**0.008**	**0.999**	0.457
	Hypoglycemia	ForecastCF	0.115	0.143	0.213	0.041	**0.163**	0.285	0.856	**0.019**
		COMET-C	**0.215**	0.065	0.928	**0.062**	0.094	0.171	0.955	0.009
		COMET-A	0.155	0.031	0.998	0.052	0.103	0.020	**0.999**	0.004
		COMET-H	0.155	**0.031**	**0.998**	0.052	0.103	**0.018**	**0.999**	0.004

Metrics:

- *Validity Ratio* (proportion of valid timesteps)
- *Proximity* (Euclidean distance)
- *Compactness* (unchanged proportion)
- *Stepwise AUC* (consecutive validity)

Qualitative analysis: a T1DM patient

- Forecasting for the next 30 mins (*blue dots*), with upper and lower bounds (*red-dotted lines*)
- Original sample illustrated in *blue*, CF suggestions in *orange arrows*
- Baseline: ForecastCF



(a) Baseline (b) COMET

Obs. 1: Baseline generated out-of-

Obs. 2: COMET produced sparser suggestions while baseline changed almost every step

Conclusions

- Summary of the paper:
  - Proposed COMET generated counterfactual explanations for **multivariate forecasting**, with three **domain-specific constraints** for glucose forecasting
  - Experiments with 2 diabetes datasets outperformed the baseline ForecastCF in proximity and compactness, while maintaining reasonable validity
- Future work:
  - Incorporating clinical experts in assessing counterfactuals' effectiveness and medical relevance
  - Extending into other forecasting applications by involving domain-specific constraints

Github link

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References

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Many thanks
for your attention!