

Observable Neural ODEs for Identifiable Causal Forecasting in Continuous Time

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The clinical decision problem

At each decision time, clinicians need to anticipate how a patient's condition would evolve under alternative treatment trajectories.

Observed history:
treatment a_t & outcome y_t

Decision time t_c : alternative futures

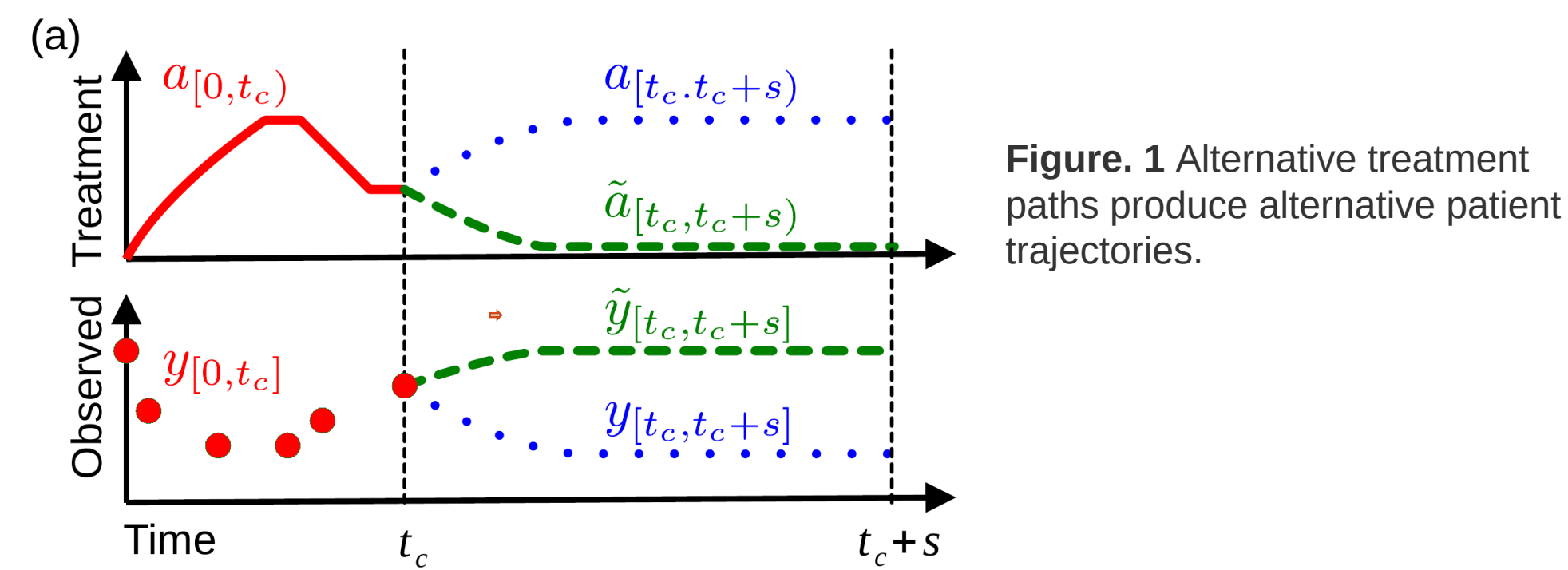


Figure. 1 Alternative treatment paths produce alternative patient trajectories.

Time-dependent confounding: the patient's evolving condition affects treatment decisions and outcomes -and is itself affected by past treatments.

→ Can bias treatment-effect estimates by conflating treatment effects with changes in the patient's condition.

Structural assumptions

Observed

- Treatment process A_t
- Observation process Y_t

Hidden:

- Latent disease state Z_t
- Disturbances/
- confounders ϵ_t

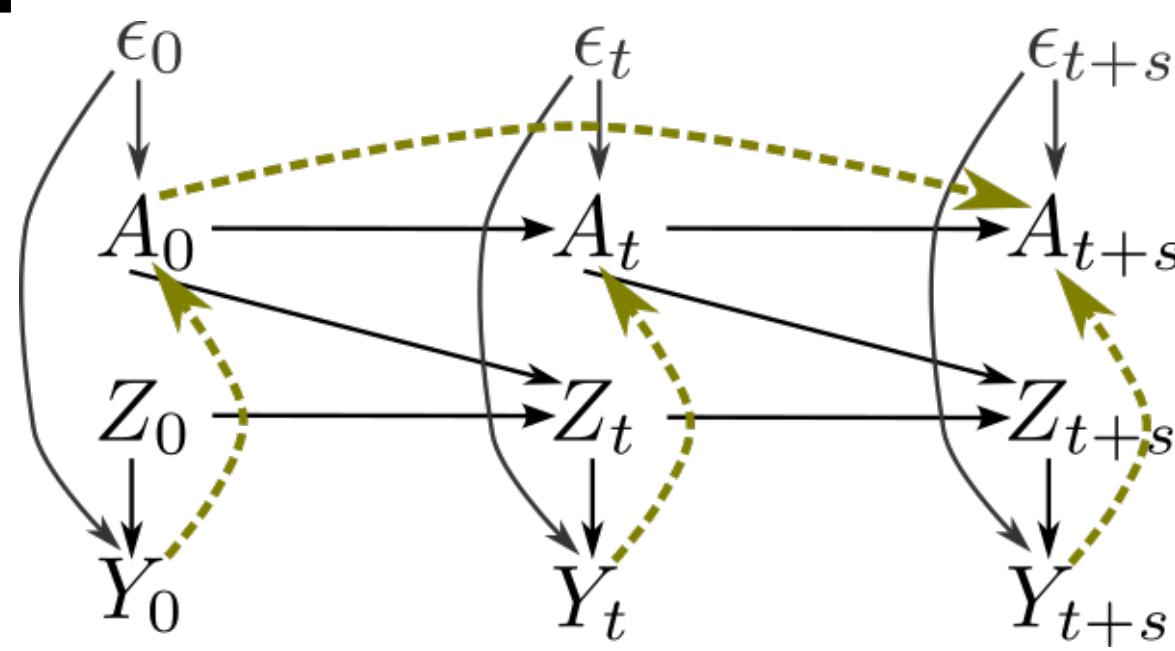


Figure. 2 Structural assumptions for observed and hidden processes at three consecutive time points. Green arrows: Dynamic treatment regime.

References

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Causal identifiability of the state space model

Latent Neural ODE:

$$\dot{z}_t = f_\theta(z_t, a_t). \quad y_t \sim q_\theta(\cdot | z_t)$$

Treatment acts on a continuous latent disease state; observations are generated from that state.

Observability: the latent state z_t can be reconstructed from observations y_t in some time interval.

- Depends on the vector field and the output map.
- Without observability, identical histories may correspond to states with different treatment responses.

Why observability matters

Theorem (informal): Under consistency, positivity, and the structural and independence assumptions of the latent state space model in Fig. 1, **observability of the latent dynamics enables identification of treatment effects** via a continuous-time adjustment formula for the conditional potential outcome distribution (CPOD):

$$P\left(y_{t_c+s} \mid \overbrace{a_{[t_c, t_c+s]}}^{\text{treatment history path}} \mid \mathcal{H}_{t_c}\right) = \int_{z_{t_c+s}} \int_{z_{t_c}} \left\{ \underbrace{p(z_{t_c} | \mathcal{H}_{t_c})}_{\text{infer current state}} \underbrace{p(z_{t_c+s} | z_{t_c}, a_{[t_c, t_c+s]})}_{\text{propagate under intervention}} \underbrace{p(y_{t_c+s} | z_{t_c+s})}_{\text{map state to outcome}} \right\}$$

$$\mathcal{H}_{t_c} = \{y_{[0, t_c]}, a_{[0, t_c]}\} = \{\text{current observation, previous observations and treatments}\}$$

- Remains valid under exogenous, temporally independent hidden confounders ϵ_t and can be generalized to serially correlated hidden confounders.

Method and implementation

- **Observable architecture:** We structure the latent Neural ODE in **observable normal form** (Bernard, 2019), ensuring that the latent state can be reconstructed from the observed history.
- **Self-supervised training:** From histories up to varying decision times, ObsNODE predicts future observations and minimizes a masked, normalized squared error at the observed time points.
- **Continuous updating:** ObsNODE assimilates new patient observations to update the latent-state estimate and forecasts under alternative treatment trajectories.

Experiments

Known counterfactuals: causal validation on semi-synthetic data

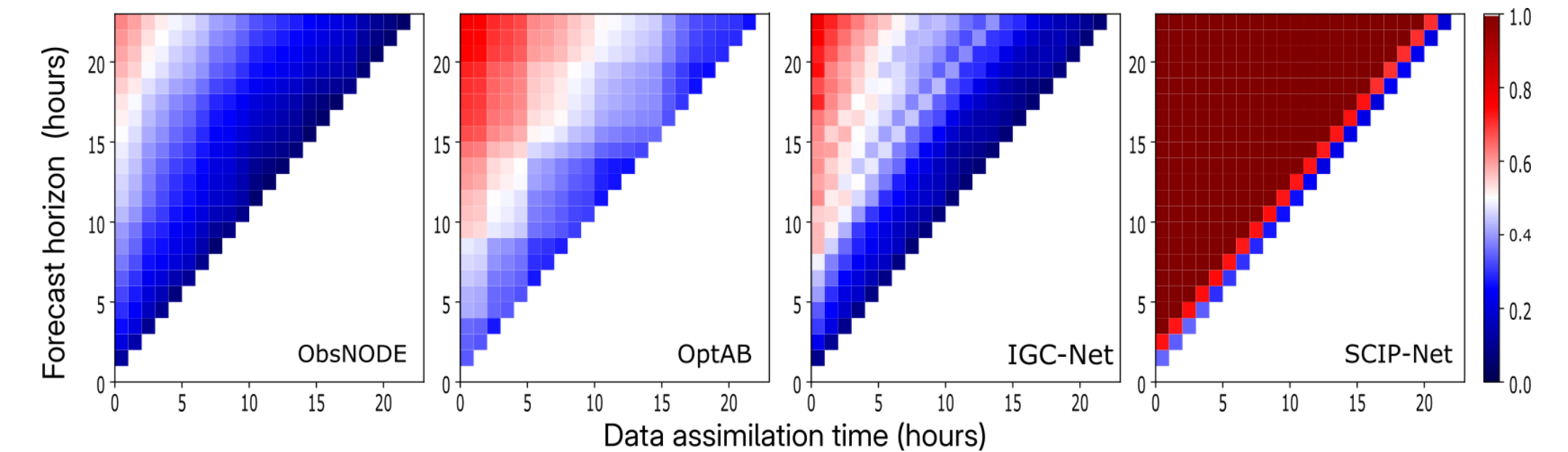


Figure 3: Semi-synthetic MIMIC-IV sepsis dataset. RMSE for ObsNODE and baseline models as a function of data assimilation time (observation time) and forecast horizon over a 24-hour horizon. Results are averaged over five runs and RMSE values larger than one were clipped at one.

Experiments with fully-synthetic data

Variable	Model/CF	1	2	3	4	5
Tumor Volume	ObsNODE	0.1738	0.1739	0.1724	0.1708	0.1708
Tumor Volume	NODE	-0.5152	-0.5288	-0.5364	-0.5321	-0.5321
Body Weight	ObsNODE	0.0952	0.0941	0.0924	0.0924	0.0926
Body Weight	NODE	-2.0229	-2.0272	-2.0313	-2.0315	-2.0315

Table 1: Counterfactual bias (CB) relative to the baseline treatment for five treatment regimes (CF1–CF5) in the synthetic cancer dataset (data assimilation time 5, confounding level $\gamma = 4$). CB were averaged over six prediction time points, and all results are averaged over five runs.

Real-world evaluation: antibiotic treatment of sepsis

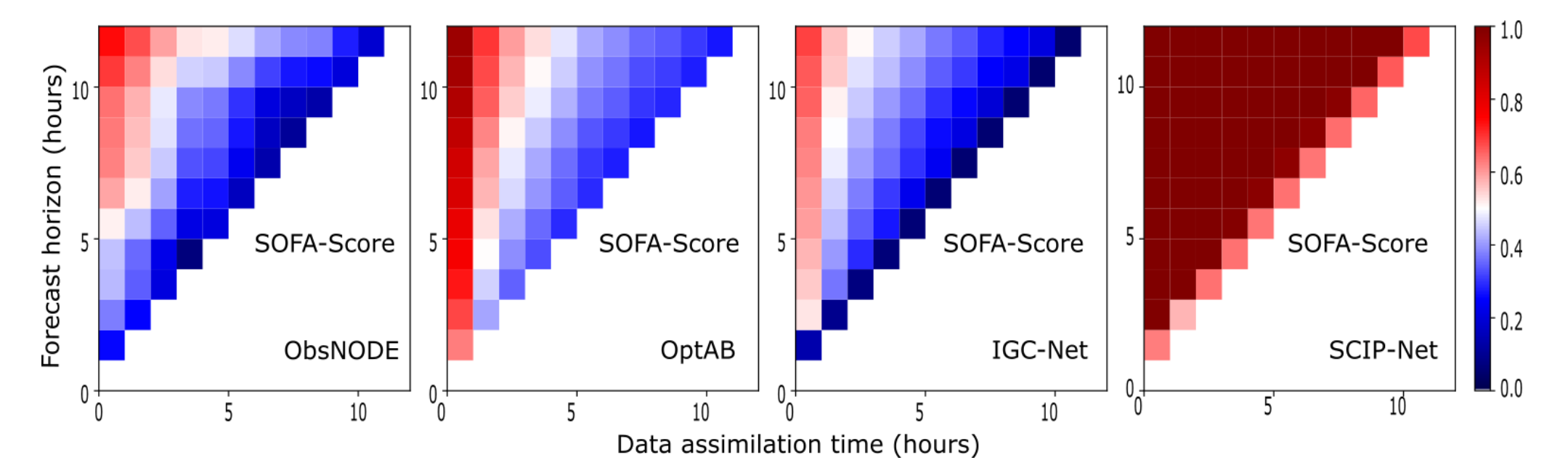


Figure 4: Forecasting results on the real-world sepsis dataset (MIMIC-IV). RMSE for different prediction horizons (in hours).

Data/time	1	2	3	4	5	6
MimicIV	0.24±0.00	0.32±0.01	0.37±0.01	0.42±0.02	0.47±0.03	0.50±0.04
AmsterdamUMCdb	0.26±0.00	0.37±0.01	0.43±0.02	0.44±0.02	0.51±0.02	0.59±0.03

Table 2: External validation. RMSE for ObsNODE, trained on MIMIC-IV sepsis data and tested on AmsterdamUMCdb.

Conclusion

Theory: Observability of latent states enables causal identification despite hidden confounding through a conditional front-door adjustment.

Method: ObsNODEs enforce reconstructible latent states by construction.

Results: Strong performance across synthetic and clinical settings.