Individualized treatment effect prediction for Mechanical Ventilation

Using Causal Multi-task Gaussian Process to estimate the individualized treatment effect of a low vs high PEEP regime on ICU patients

1 – Background

- Mechanical ventilation in the ICU has a positive end-expiratory pressure (PEEP) setting
- Unknown if a high vs low PEEP regime is more beneficial [1]
- Randomised Control Test not always viable so confounding features that influence treatment and outcome occur in data
- Try to determine the Conditional Average Treatment Effect (CATE) (*formula 1*)
- CATE estimators help understand treatment effects on specific populations, considering individual characteristics

How can Causal Multi-task Gaussian Process be used to estimate the individualized treatment effect of a low vs high PEEP regime on ICU patients?

2 – Method

Implement CATE estimators:

- Meta Learners: S and T [2]
- Causal Multi-task Gaussian Process [3]
- S and T Learner with Gradient Boosting and Gaussian Process Regression as base learners
- Gaussian Processes with a simplistic Radial Basis Function Kernel

- Validate estimators using simulated data
- Perform CATE estimation on real-world ICU patient data, MIMIC-IV [4] and external RCT dataset
- Preprocess dataset with imputing and normalization
- Identify possible confounding features
- Performance measured using Cumulative Gain Curve, where Larger area indicates better performance

3 – Results

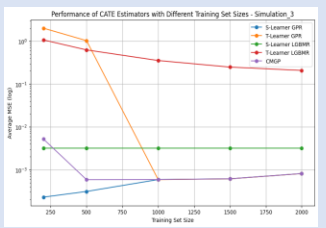

Fig 1. Mean MSE - simulation

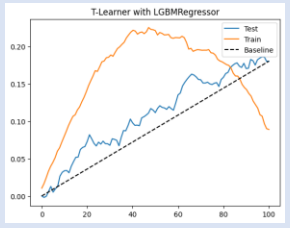

Fig 3. T-Learner LGBMR - MIMIC-IV

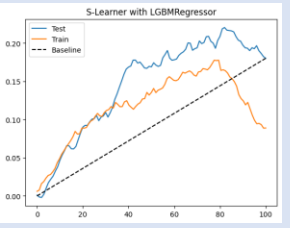

Fig 5. S-Learner LGBMR - MIMIC-IV

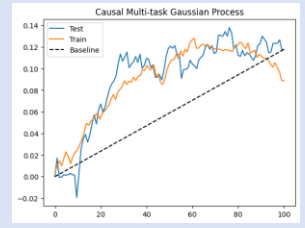

Fig 7. CMGP - MIMIC-IV

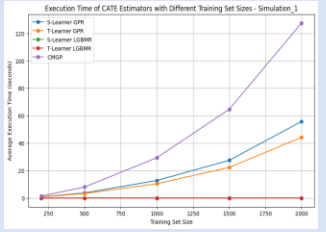

Fig 2. Mean execution time - simulation

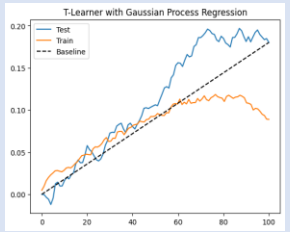

Fig 4. T-Learner GPR - MIMIC-IV

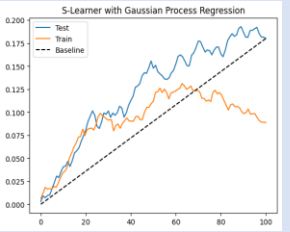

Fig 6. S-Learner LGBMR - MIMIC-IV

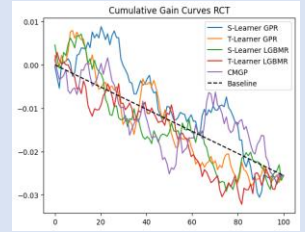

Fig 8. Gain Curves - RCT dataset

4 – Conclusions

- Significant execution time degradation for CATE estimators using Gaussian Processes
- CMGP and S-Learners perform equally well. T-Learners perform the worst
- Cumulative gain curves for MIMIC-IV and RCT dataset give different conclusions. Overall conclusion is therefore inconclusive and requires further research

5 – Future Work

- More robust research into possible confounders
- Analyse more complex kernels for Gaussian Processes
- Investigate Sparse Gaussian Processes to combat execution time degradation

References

[1] Walkey, A. J. et al. Higher PEEP versus lower PEEP strategies for patients with acute respiratory distress syndrome: A systematic review and meta-analysis. Ann. Am. Thorac. Soc. 14, S297–S303 (2017)

[2] Künzel, Sören R., et al. "Metalearners for estimating heterogeneous treatment effects using machine learning." Proceedings of the national academy of sciences 116.10 (2019): 4156-4165

[3] Ahmed M. Alaa and Mihaela van der Schaar. Bayesian Inference of Individualized Treatment
Effects using Multi-task Gaussian Processes. 2017. arXiv: 1704.02801 [cs.LG]

[4] Johnson, A. E. W. et al. MIMIC-IV, a freely accessible electronic health record dataset. Sci. Data 10, 1–9 (2023)

$$\tau(X) = \mathrm{E}[\, Y^{high} - Y^{low} \mid X \,]$$

Formula 1: CATE formula

Author Kieran McAlpine k.t.mcalpine@student.tudelft.nl **Supervisors** Jim Smit & Rickard Karlsson **Responsible Professor** Jesse Krijthe

TU Delft