Learning Counterfactual Representations for Estimating Individual Dose-Response Curves

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1 Introduction

Estimating what would be an **individual's potential response to varying levels of exposure to a treatment** is of high practical relevance for several important fields, such as healthcare, economics and public policy.

How can we train models to estimate counterfactual outcomes in settings **with any number of treatments and associated dosage parameters**?

2 Dose-response Networks (DRNet)

The core idea behind our approach is to leverage **conditional computation** in **Dose-Response Networks** (DRNets). To maintain a strong influence of treatment and dosage on the final prediction, DRNets provide **independent prediction paths** through a neural network for **each treatment** and for a **configurable number *E* of strata** of the range of possible dosage values. **Parameter sharing** across treatments and across dosage strata is handled through a **hierarchy of shared base layers.** The model is trained end-to-end on observed samples.

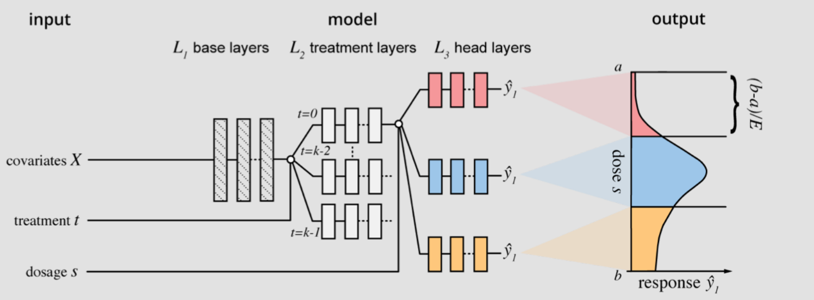
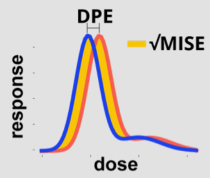


Figure 1. An overview of Dose-Response Networks (DRNets) with shared base layers, per-treatment layers and head networks for a configurable number *E* of dosage strata.

3 Metrics, regularisation and benchmarks

Estimating dose-response to multiple treatments with dosages poses challenges in terms of **model evaluation, model regularization,** and **method benchmarking.** To address these challenges, we introduce:

Performance metrics for estimating individual dose-response:
Mean Integrated Square Error (MISE), Dosage Policy Error (DPE)



Open benchmarks for counterfactual inference of dose-response:

News. Simulates reader's opinion on exposure to articles on different viewing devices. (n=5000, p=2870 features, T=2/4/8/16 treatments)

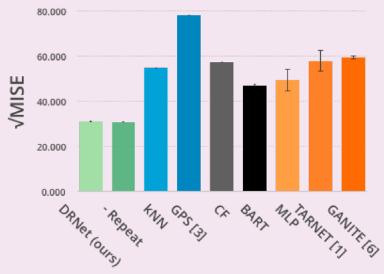
Mechanical Ventilation in the Intensive Care Unit (MVICU). Simulates patient response to mechanical ventilation. (n=8040, p=49, T=3)

The Cancer Genomic Atlas (TCGA). Simulates individual response to medication, surgery and chemotherapy. (n=9659, p=20531, T=3)

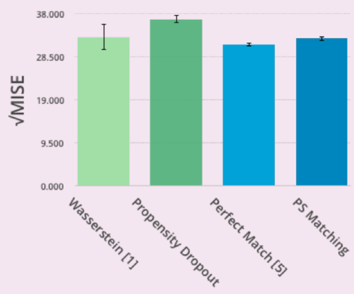
4 Results

DRNets **outperform** existing methods **across all three benchmarks**.

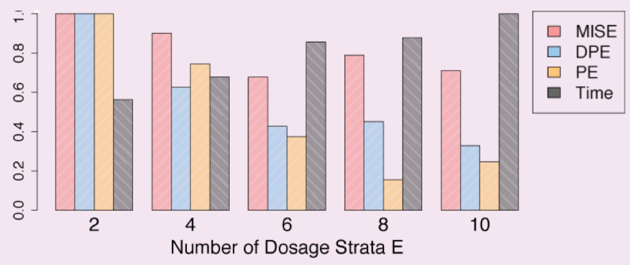
MVICU



Across benchmarks, Wasserstein [1] and Perfect Match [5] were slightly more effective than Propensity Score Matching and Propensity Dropout.



Tradeoff between computational and predictive performance: Experimentally, a higher number of dosage strata was associated with increases in predictive performance and computation time.



5 Conclusion

We present …

- an approach for estimating individual dose-response that works with **multiple treatment options with associated dosage parameters**
- extensions of several existing **regularization methods** for this setting
- **performance metrics** for evaluating dose-response estimators
- **open benchmarks** for comparing dose-response estimators

Source code is available at **https://github.com/d909b/drnet**

6 References

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