Reproducing "Multi-Task Adversarial Learning for Treatment Effect Estimation in Basket Trials"

Causal inference plays a crucial role in healthcare by enabling reliable estimation of treatment effects from observational data. Traditional clinical trials are often constrained by high costs, time limitations, and challenges in recruiting sufficient sample sizes—particularly for rare subpopulations. Basket trials offer an innovative alternative in which patients with various types of cancer but sharing the same genetic mutation receive a common treatment. However, this approach introduces new complexities for treatment effect estimation due to the absence of a control group and the presence of confounding factors introduced by tumor heterogeneity.
The selected paper, Multi-Task Adversarial Learning for Treatment Effect Estimation in Basket Trials by Chu, Rathbun, and Li (2022), proposes a novel deep learning framework—Multi-Task Adversarial Learning (MTAL)—to address these challenges. The objective of my project is to reproduce and validate the results from this study to assess the robustness and generalizability of MTAL in the context of causal inference within healthcare applications.

The MTAL framework comprises two major components: an outcome generator and a true-or-false (TF) discriminator. The outcome generator predicts potential outcomes across various tumor types using a multi-head deep neural network enriched with a deep feature selection mechanism. This design ensures that relevant features are emphasized for each specific tumor type. In parallel, the TF discriminator functions as a binary classifier, adversarially trained to distinguish between factual and counterfactual outcomes. Through adversarial learning, the generator improves its ability to create realistic counterfactuals, effectively reducing selection bias caused by tumor heterogeneity. The authors evaluate MTAL on synthetic basket trial data and two well-known benchmarks, IHDP and News, using standard causal inference metrics such as the Precision in Estimation of Heterogeneous Effects (PEHE) and Average Treatment Effect (ATE).

What sets MTAL apart is its design specifically tailored for basket trial data—a setting that traditional causal inference models are not well-equipped to handle. The novelty of MTAL lies in its integration of adversarial learning with multi-task feature selection to estimate treatment effects without relying on control groups. This approach allows for more accurate inference of counterfactual outcomes and subgroup-specific treatment effects. The authors hypothesize that MTAL not only generalizes well across multiple tumor types but also enables better performance in estimating group-level treatment effects, particularly in scenarios with limited or imbalanced data.

To further explore the method's capabilities, I plan to investigate potential extensions such as incorporating real-world basket trial datasets, adding interpretability tools for feature importance analysis, and experimenting with different regularization strategies beyond elastic net. Additionally, I am interested in examining the model's adaptability to umbrella trials, which involve multiple treatments for different subgroups—a setup that shares some characteristics with basket trials but introduces further complexity.

For implementation, I will use the IHDP and News datasets, both of which are publicly available via GitHub and the UCI Machine Learning Repository. The synthetic basket trial dataset described in the paper can be generated based on the provided simulation protocol. Furthermore, the IHDP benchmark is supported by the NPCI codebase (https://github.com/vdorie/npci), which will facilitate initial validation.

Given the moderate model complexity, MTAL can be implemented using frameworks such as PyTorch or TensorFlow and trained using widely available computing resources, such as a local machine with a GPU or cloud services like Google Colab or AWS EC2 instances. The reproducibility of the simulation-based data, coupled with accessible benchmarks, makes the project computationally feasible within the scope of this course.

While I will partially leverage existing code for data preprocessing and benchmark validation, the MTAL architecture itself will be re-implemented from scratch to ensure a faithful reproduction of the original study. This will allow me to critically assess the claims made in the paper and test the model under controlled variations.

Overall, this project will provide an opportunity to explore advanced causal inference techniques tailored to non-traditional clinical trial designs and will contribute to a deeper understanding of how machine learning can enhance healthcare research.