Sequential Modeling of Dynamic Recognition Problems for the Medical Domain Using Graph Algorithms and Machine Learning Methods

1 Overview

1.1 Topic Relevance and Problem definition

Within the realm of imbalanced and recursive classification algorithms, there exists a practical need to create novel algorithms that can classify objects into predefined classes through successive transformations. We try to address and solve this task for the medical domain. In algorithmic research, we begin with graph theory and discrete optimization and then progress to stochastic modeling and reinforcement learning. Initially, we focus on graph theory, specifically examining simple models for problems with deterministic transition outcomes, then we obtain experimental results.

The defined problem of the thesis shares the most similarities with Hierarchical Reinforcement Learning (HRL) research area, so it is worth giving some background on the topic. Reinforcement Learning (RL) allows the agent to solve sequential decision-making problems by interacting with the environment. With large and complex environments, exploration requires unreasonable amount of interaction with the environment, and pure random exploration most often fails. HRL provides a divide-and-conquer approach for solving traditional RL problems by abstracting complex problems into smaller sub-problems.

It aims to achieve compositionality by learning reusable sub-behaviours; identify compositionality, the idea that representations can be constructed through the combination of primitives. Moreover, it can be seen as a way to facilitate lifelong learning by combining previously learned simple behaviours. HRL tries to achieve compositionality using two main mechanisms; temporal abstractions and state abstractions. Temporal abstraction divides the problem into temporally extended actions (sub-behaviours) consisting of a sequence of primitive actions for solving a more complex problem.

The second form of abstraction is the state abstraction. In high-dimensional spaces, it is extremely difficult to learn the best action in every possible state. For this reason, similar states in terms of transition dynamics and reward function, can be grouped to build state abstractions. Correctly constructed state abstractions have been shown to significantly increase the learning performance in RL problems. The idea is that instead of learning to control and navigate through the entire state space, a hierarchy of systems is able to control abstracted parts of the state space through temporally extended actions. Such abstractions also make it easier to transfer the learned skills to similar-problem domains. Abstractions can be achieved using a staged approach. Some examples of RL compositionality using graph partitioning are Q-Cut and L-Cut algorithms.

In this thesis we put compositionality and stage-based modeling on the bases of our experiments to come up with optimal medical procedures and treatment lines. We explore the problem not only from

the reinforcement learning perspective, but also from ensemble-iterative classification, combinatorial

optimization, graph search and pathfinding, utilizing statistical and machine learning methodologies,

where algorithms are proposed, and validation results are obtained. Problem formulation for target class allocation in a sequential procedure, data division in a stage-based format using tabular and graph based structures, algorithmic implementations and derived results may allow to:

• Improve healthcare delivery efficiency, provide timely and more personalized treatments to patients.

• To focus on specific aspects of the data and develop more accurate treatment plans. With more accurate treatment plans, patients can receive better care and have better outcomes.

• Propose algorithms and algorithmic variations to facilitate research advancements in the medical domain and beyond.

Currently, there is not much scientific literature which uses multi-stage approach for finding optimal treatments, especially for graph-based representations, which can be due to:

• The approach is new and has not yet been widely experimented.

• The problem of finding optimal treatment strategies is complex and can be approached from different

aspects, and people have taken other approaches to solve it.

The findings of the thesis have the potential to open up new research directions in this area, given that

in this work, in addition to other results, we provide a graph-theoretical analysis of target class classification (TCC) and connect these findings to ensemble classification and sequential searching with stages, and provide a novel link between multilayer graphs and reinforcement learning for solving medical treatment optimization tasks.

1.2 Thesis Aim

The thesis aims can be summarized as follows.

• To come up with a mathematical description and analysis of a medical problem and propose a mathematical model that can solve a dynamic treatment allocation task in terms of classification and target class transition logic.

• To connect obtained mathematical model to existing computer science and machine learning research directions, such as iterative classification, graph pathfinding, and reinforcement learning to enhance theoretical results with algorithmic evaluation.

• To conduct data processing and propose algorithmic approaches that can open new research directions in the medical domain regarding sequential treatment allocation and optimization.

1.3 Research Data and Methodologies

In the scope of the thesis, we obtained credentialed access to the MIMIC-III clinical database, which contains health-related information such as demographics, laboratory test results, procedures, medications, and various other medical statistics about forty thousand patients allowing to conduct numerous analytical studies. We processed this database in a stage-based approach and obtained data in tabular and graph (network) formats so that we could address the problems defined in the thesis. Besides, we also used eight publicly available medical datasets from UCI Machine Learning repository which have smaller dataset sizes and are more suitable to traditional regression and classification problems. In this thesis, we used graph modeling techniques and graph-search procedures, related to breadth-first and A\* search, used neural networks and reinforcement learning-based methods suitable for discrete and continuous learning tasks to come up with algorithms to solve medical optimization tasks in a sequential manner. We solved procedural and recursive programming tasks in Python programming language, used cloud computing services from AWS, and worked with libraries such as NetworkX, PyTorch, Django, OpeanAI Gym, scikit-learn, pandas, and NumPy for scientific computations.