Dynamic Treatment Plan Optimization for Chronic Disease Management Using Restless Multi-Armed Bandit Algorithms

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Outline

Introduction

- Chronic diseases, such as diabetes and heart disease, require long-term management and personalized treatment plans.
- Traditional treatment methods may not always adapt to the changing condition of the patient, leading to suboptimal outcomes.
- This project leverages Restless Multi-Armed Bandit (RMAB) algorithms to optimize treatment plans dynamically, considering patient health progression over time.
- Aim to maximize long-term health outcomes through AI-powered decision-making.

Motivation

- **Limitations in Conventional Healthcare**: Standard treatment plans are often static and don't adapt to changes in a patient's health, leading to inefficiencies and inconsistent outcomes.
- **Need for Personalized Care**: There is a growing demand for personalized treatment strategies that can adapt to patient-specific responses and evolving health conditions.
- **Potential of RMAB**: Restless Multi-Armed Bandit (RMAB) algorithms provide a structured way to optimize decision-making in uncertain and evolving environments, making them ideal for dynamic healthcare applications.
- **Successful Applications Elsewhere**: Similar techniques have been used in domains like digital marketing (e.g., ad placement optimization) with proven success, highlighting their potential in healthcare.

Problem Statement

Challenges in Traditional Healthcare

Conventional treatment plans are often rigid and fail to adjust in real-time to changes in patient health, leading to less effective and generalized care.

Limitations in Adaptive Treatment Systems

Current adaptive models in healthcare care struggle to incorporate diverse patient data and do not dynamically personalize treatment, resulting in missed opportunities for optimized patient outcomes.

Research Objective

This project aims to design a robust adaptive treatment framework based on RMAB that continuously learns from patient responses, allowing personalized data-driven care for better health outcomes.

Objective

AI-Driven Treatment Optimization

- Apply RMAB algorithms to dynamically personalize treatment strategies based on patient health states.
- Leverage the MIMIC-III dataset to validate the approach.

Outcome

- Maximize long-term patient health improvements.
- Efficiently utilize healthcare resources.

Jiang (2024): Optimizing Online Advertising with MAB [1]
Techniques Used:

- Applies Multi-Armed Bandit strategies to allocate ads effectively in real-time.
- Balances exploration (testing new ads) and exploitation (showing successful ads).
- Illustrates fundamental bandit principles that can be adapted to healthcare resource allocation.

Limitations:

- Focuses on advertising; direct application to healthcare requires additional modeling of patient states.
- Less complex state space compared to chronic disease management.

Literature Review - 2

Puterman (1994): Markov Decision Processes [2]
Techniques Used:

- Formalizes decision-making under uncertainty using states, actions, and rewards.
- Provides mathematical foundations for both finite and infinite horizon problems.
- Widely applied in operations research and serves as a basis for modeling patient health transitions.

Limitations:

- Computational complexity increases with large state and action spaces.
- Real-world healthcare scenarios often require approximation methods to handle high-dimensional data.

Literature Review - 3

Mate et al. (2022): Finite Horizon & Streaming RMAB [3]
Techniques Used:

- Proposes efficient algorithms for finite horizon and streaming Restless Multi-Armed Bandit problems.
- Addresses dynamic arrival of "arms," which is analogous to continuously arriving patients in healthcare.
- Emphasizes real-time decision-making under uncertain conditions.

Limitations:

- May not incorporate fairness constraints explicitly.
- Scalability can become challenging for large-scale, high-frequency data.

Literature Review - 4

Killian et al. (2023): Equitable RMAB in Digital Health [4]
Techniques Used:

- Introduces an equitable framework for RMAB to ensure fair resource allocation in digital health.
- Balances patient outcomes and fairness by embedding equity constraints into the bandit mechanism.
- Demonstrates improved health outcomes while maintaining equitable treatment distribution.

Limitations:

- Additional computational overhead when integrating fairness objectives.
- Applicability to large patient cohorts may require further optimization.

Literature Review - 5

Johnson et al. (2016): MIMIC-III Critical Care Database [5]
Techniques Used:

- Provides a rich dataset of ICU patient records, enabling large-scale predictive modeling.
- Includes demographic, vital signs, laboratory results, and treatment data for thousands of patients.
- Widely used for machine learning research in clinical settings.

Limitations:

- Data originates from a single hospital system, potentially limiting generalizability.
- Contains missing or noisy data, which require thorough cleaning and pre-processing.

Research Gaps Identified

Personalization at the Individual Level

- Existing RMAB approaches often focus on population-level interventions (e.g., monitoring vital signs for large groups).
- Few studies explore dynamic, personalized treatment plans that adapt over time for each patient.

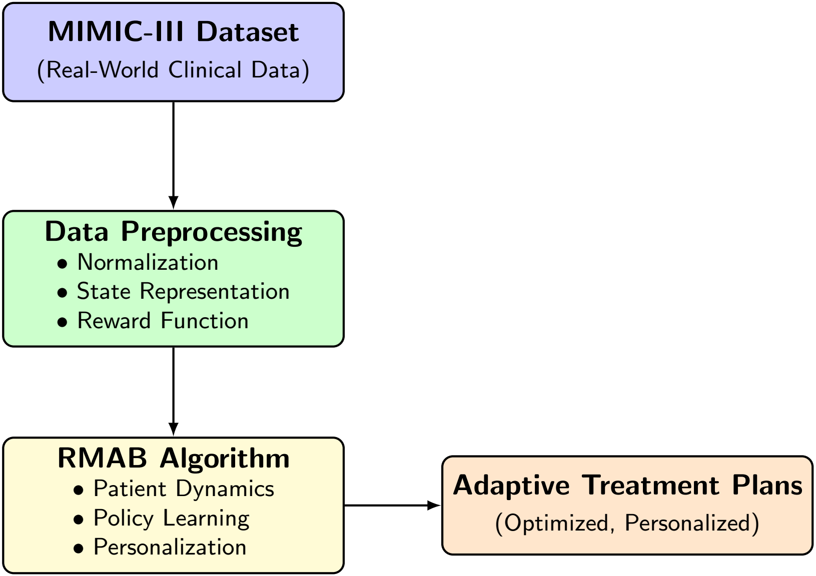
Continuous Adaptation of Chronic Diseases

- Most RMAB healthcare applications emphasize resource allocation or fairness.
- They rarely address the evolving nature of chronic diseases, which require ongoing updates to treatment strategies.

Real-World Dataset Integration

- Comprehensive studies leveraging real-world datasets (e.g., MIMIC-III) are limited.

Proposed Work-Flow Diagram



Conclusion

- **RMAB Algorithms** can transform chronic disease management by enabling adaptive, patient-specific treatment plans.
- **Balancing Exploration & Exploitation** improves both resource efficiency and long-term health outcomes.
- **Real-World Validation** using datasets such as MIMIC-III bridges the gap between theoretical models and clinical practice.
- **Future Directions** include expanding fairness constraints, handling multi-comorbidity scenarios, and refining real-time adaptation in large-scale clinical settings.

References

1. **Jiang, C. (2024).** *Optimizing online advertising with multi-armed bandit algorithms. Applied and Computational Engineering*, 83:52-61.
2. **Puterman, M. L. (1994).** *Markov Decision Processes: Discrete Stochastic Dynamic Programming.* Wiley-Interscience, New York.
3. **Mate, A., Biswas, A., Siebenbrunner, C., Ghosh, S., & Tambe, M. (2022).** *Efficient algorithms for finite horizon and streaming restless multi-armed bandit problems.*
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Thank You!