## Methods for automatization of radiotherapy dosimetry

## PhD Summary

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This thesis explores innovative methodologies to enhance dosimetry, aiming to create a fully automated system adaptable to clinical constraints. While the presented solutions are promising, their practical applicability in real-world settings raises several challenges that must be addressed.

In the first phase, the thesis details the development of an efficient dosimetry engine, accompanied by a comprehensive evaluation of existing open-source optimization algorithms. The author creates a clinically meaningful distance between doses. These efforts identify both the limitations and opportunities for improving current systems.

A novel framework for multi-objective optimization and robust plan selection is introduced, leveraging graph theory to analyze the relationships between different dose levels. This framework simplifies the management of trade-offs among competing clinical objectives while ensuring the quality and safety of treatments. However, while innovative, reliance on graph theory could introduce computational complexity. Moreover, adopting this framework would necessitate a drastic change in the clinical workflow. Such changes may face resistance from doctors and dosimetrists, making their real-world clinical adoption uncertain.

The thesis explores reinforcement learning (RL) to advance the automation of dosimetry, presenting two main contributions. First, it proposes a system that leverages historical patient data to train an RL agent capable of optimizing treatment plans for new cases. While applying RL in dosimetry is not novel, the training metric is. The metric used for training the RL agent is the distance between the RL-generated and clinical doses. This metric minimizes biases inherent in metric selection, which could otherwise favor specific algorithms. The second contribution builds on this idea, demonstrating that the same RL algorithm can adapt to different clinical environments. Using different datasets, it is possible to reuse the same training algorithm to fit multiple centers. This adaptability highlights the method's potential for broader applicability. However, the approach relies heavily on the availability and quality of a large amount of historical data. It also assumes that past plans represent optimal solutions, a premise that may not hold universally. Furthermore, the extent to which the algorithm can produce clinically acceptable treatment plans across multiple clinics remains a critical area for further investigation.

The thesis also explores the application of deep learning for dose distribution prediction. The innovative idea examined involves using target Dose-Volume Histograms (DVHs) to guide dose prediction. This structured guidance indirectly incorporates clinical directives into the prediction process, enabling a single model to adapt to diverse clinical practices. Such innovation eliminates the need to develop bespoke models for each center, facilitating adoption across various

environments. However, using DVH targets simplifies complex anatomical and radiology factors into a single representation, potentially leading to a loss of detail. Furthermore, while this technique allows for developing template target DVHs tailored to each clinic, it remains unclear how dosimetrists might fine-tune the treatment plan if the "one-click" solution does not meet their expectations. Additionally, the robustness of the approach in scenarios with conflicting DVH targets has yet to be demonstrated.

This thesis presents non-cohesive approaches for creating an automated and intelligent dosimetry ecosystem in radiotherapy. It uses advanced computational techniques with clinical relevance, but its success depends on addressing challenges related to scalability, data dependency, computational efficiency, and validation in diverse clinical settings. Future work should focus on these areas to enable robust and widespread adoption.