Automated treatment planning for radiotherapy

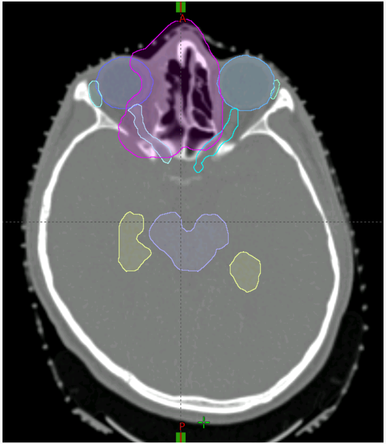
Renato Bellotti

2021-06-15

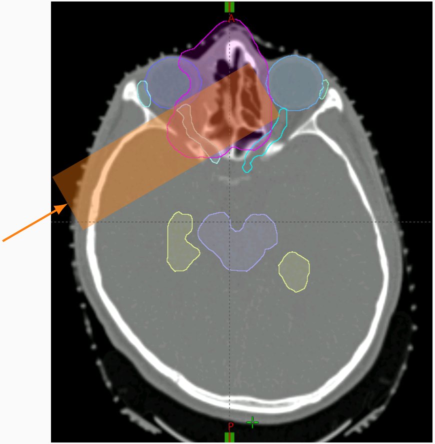
Kill tumour, spare healthy tissue

How?

Step 1: Beam arrangement



Step 1: Beam arrangement



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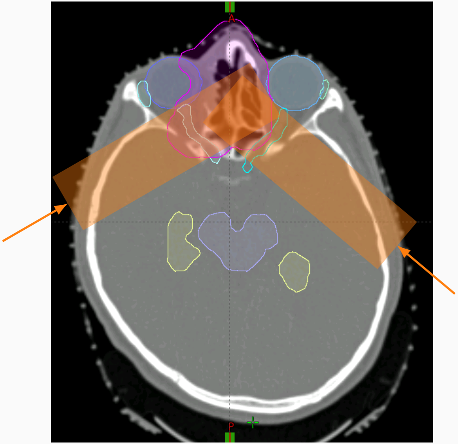
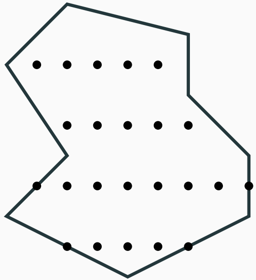


Step 1: Beam arrangement

Beam Arrangement

$$\{\nearrow, \nwarrow, \searrow, \swarrow\}$$

Step 2: Spots I



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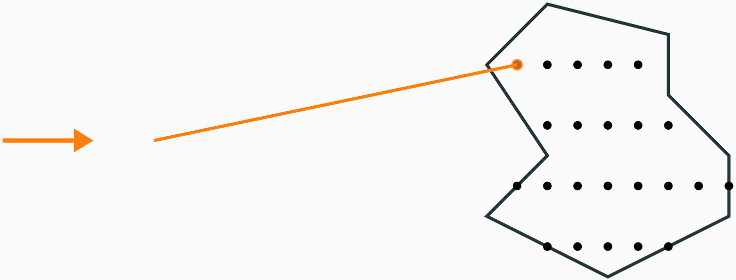

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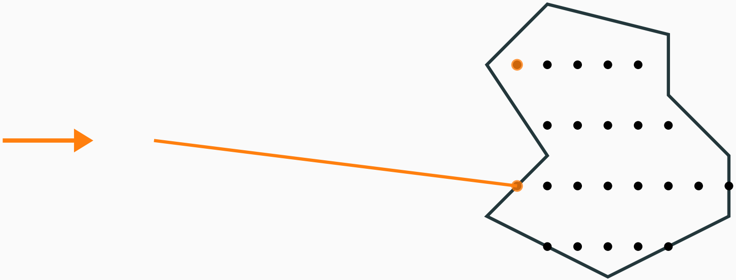

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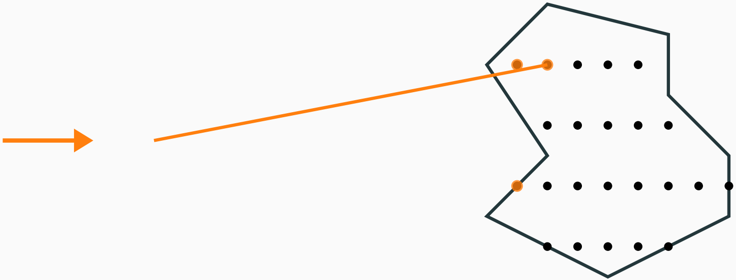

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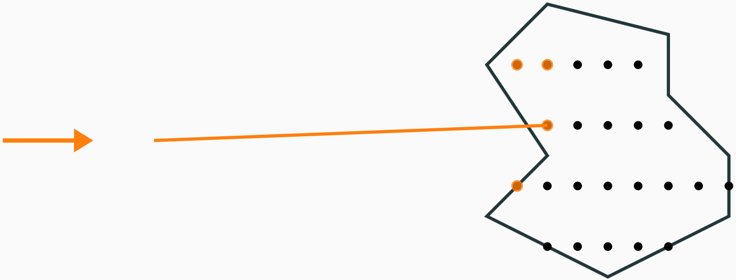

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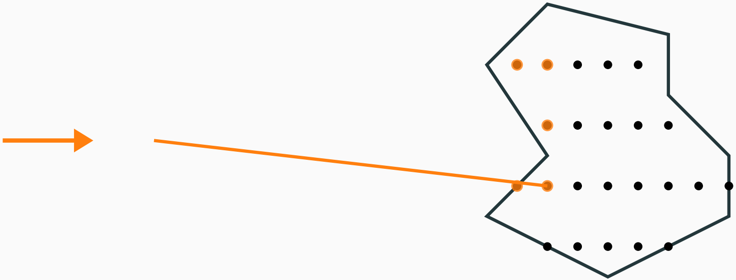

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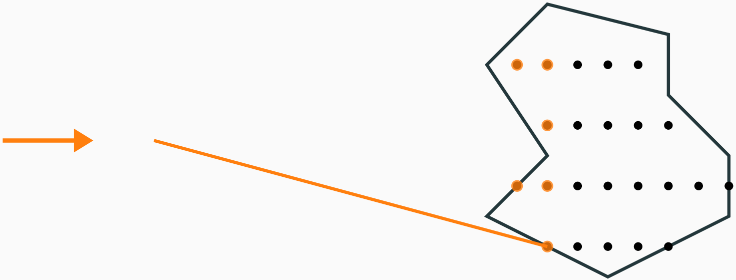

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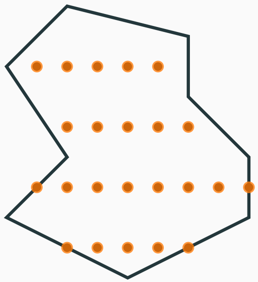

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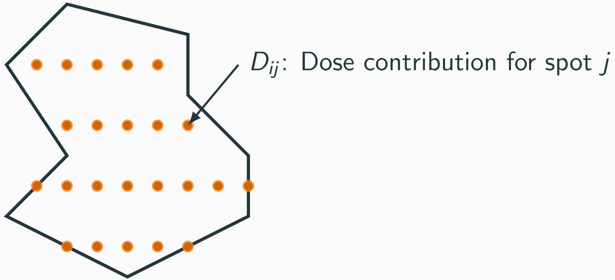

Dose distribution from field i:

$$D_i(\vec{x}) = \sum_j D_{ij}(\vec{x}) w_j$$

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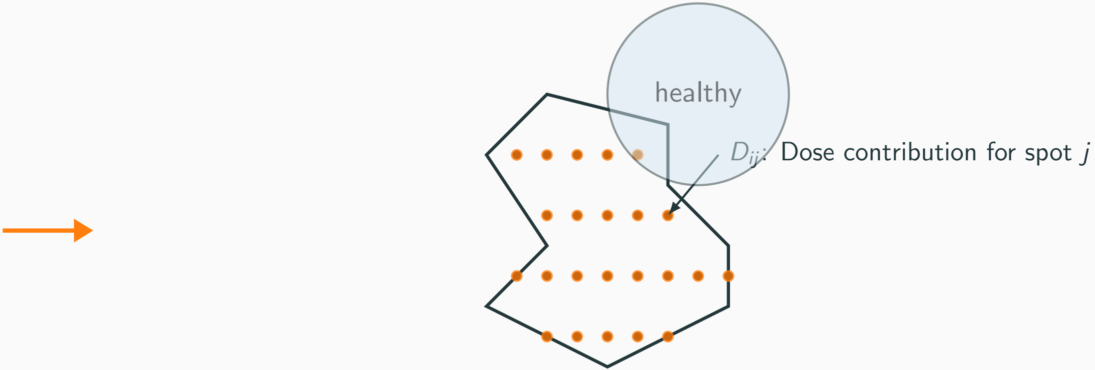

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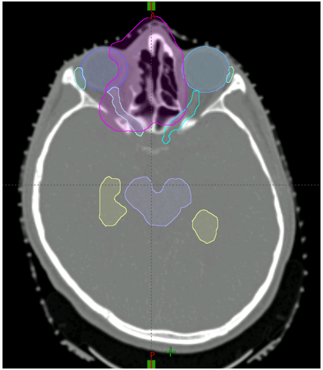
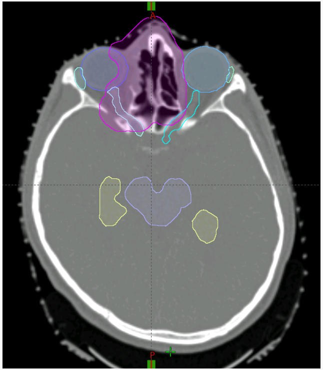
Step 2: Spots II



Structure	Constraint
Target	$= 45\,\mathrm{Gy}$
Eye	$D_2 \leq 60\,\mathrm{Gy}$
Hippocampus	$D_{40} \leq 50.4\,\mathrm{Gy}$
$\vdots$	$\vdots$

Approx. 15 – 30 constraints per patient.

Step 2: Spots II



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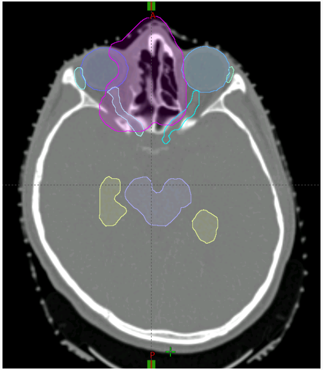

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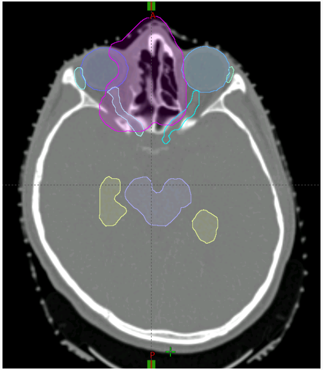

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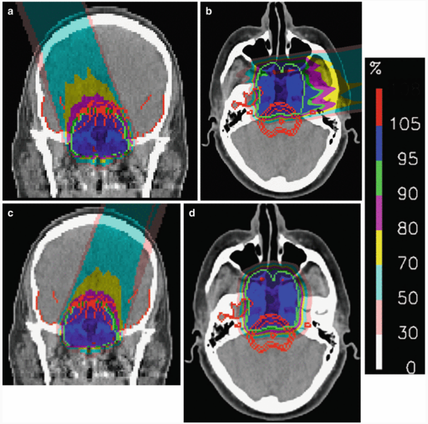
$$D = D(\omega, \mathrm{o})$$

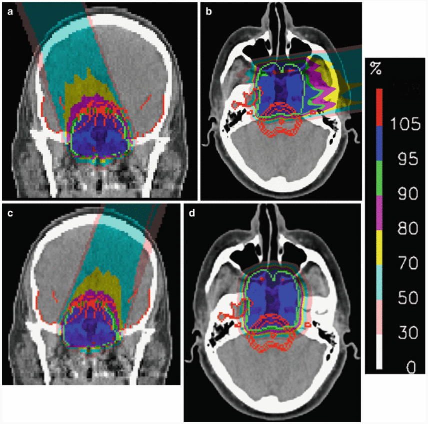
Step 2: Spots III



Single-Field

Uniform Dose

Step 2: Spots III



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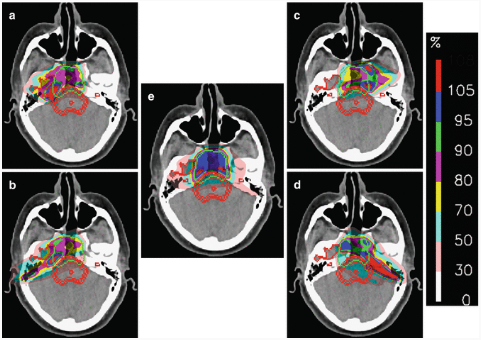
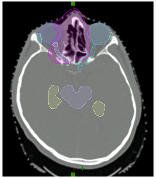


Multi-Field

Uniform Dose

Planning workflow



+

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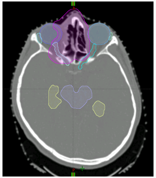

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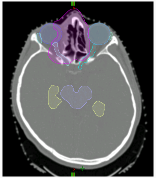
→ **Beam arrangement**

Planning workflow



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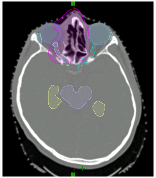
$\longrightarrow$ **Beam arrangement** $\{\ ,\ ,\ ,\ \}$ $\longrightarrow$ **Obj. weights** o

Planning workflow



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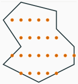
→ **Beam arrangement**

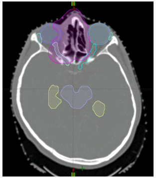
→ **Obj. weights** o →

Optimise spots



$$\min_{\mathrm{w}} L\left(D(\omega, \mathrm{w}, \mathrm{o})\right)$$

Planning workflow



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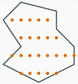
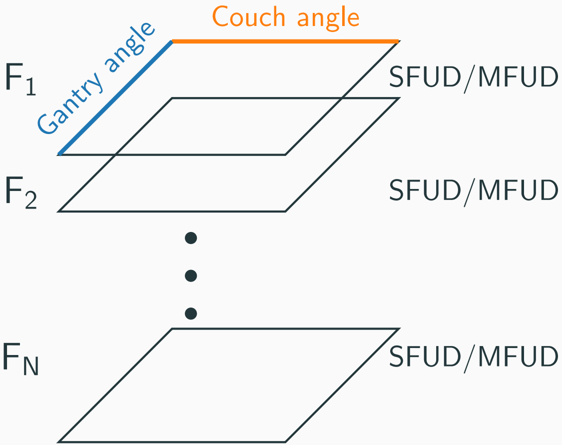


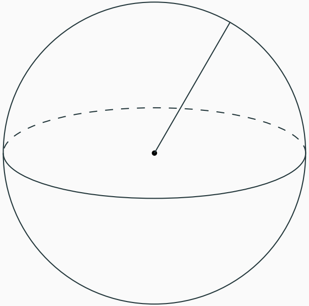
$$\min_{w} L\left(D(\omega, w, o)\right)$$

Plan space

Beam arrangement ω

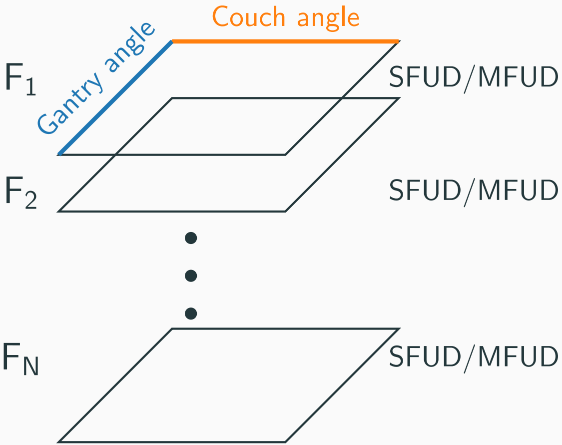


Objective weights o



(# Constr. - 1)-dim sphere

Beam arrangement ω



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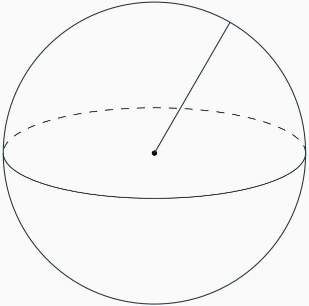
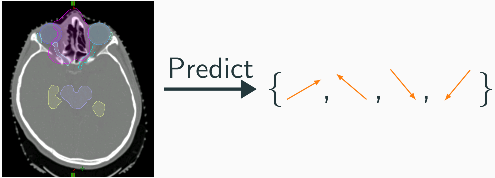


(# Constr. - 1)-dim sphere

Total dimension: 30-45

My Plans

Learn from historic plans to predict beam arrangement.



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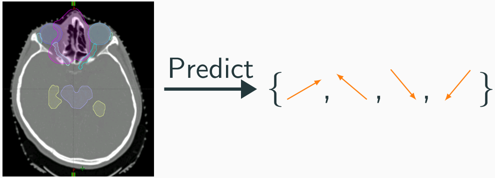
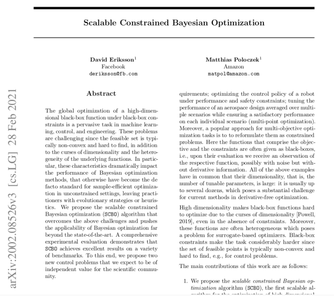


Efficiently explore the plan space.

Use the predicted plans as starting point.



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Scalable Constrained Bayesian Optimization

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Abstract

The global optimization of a high-dimensional black-box function under black-box constraints is a pervasive task in machine learning, control, and engineering. These problems are challenging since the feasible set is typically non-convex and hard to find, in addition to the curses of dimensionality and the heterogeneity of the underlying functions. In particular, these characteristics dramatically impact the performance of Bayesian optimization methods, that otherwise have become the de facto standard for sample-efficient optimization in unconstrained settings, leaving practitioners with evolutionary strategies or heuristics. We propose the scalable constrained Bayesian optimization (SCBO) algorithm that overcomes the above challenges and pushes the applicability of Bayesian optimization far beyond the state-of-the-art. A comprehensive experimental evaluation demonstrates that SCBO achieves excellent results on a variety of benchmarks. To this end, we propose two new control problems that we expect to be of independent value for the scientific community.

quirements; optimizing the control policy of a robot under performance and safety constraints; tuning the performance of an aerospace design averaged over multiple scenarios while ensuring a satisfactory performance on each individual scenario (multi-point optimization). Moreover, a popular approach for multi-objective optimization tasks is to to reformulate them as constrained problems. Here the functions that comprise the objective and the constraints are often given as black-boxes, i.e., upon their evaluation we receive an observation of the respective function, possibly with noise but without derivative information. All of the above examples have in common that their dimensionality, that is, the number of tunable parameters, is large: it is usually up to several dozens, which poses a substantial challenge for current methods in derivative-free optimization.

High dimensionality makes black-box functions hard to optimize due to the curses of dimensionality [Powell, 2019], even in the absence of constraints. Moreover, these functions are often heterogeneous which poses a problem for surrogate-based optimizers. Black-box constraints make the task considerably harder since the set of feasible points is typically non-convex and hard to find, e.g., for control problems.

The main contributions of this work are as follows:

1. We propose the *scalable constrained Bayesian optimization* algorithm (SCBO), the first scalable al-

Open for your ideas!

Available tools & data

- Available as standalone program:
  - Spot placement
  - Spot optimisation (GPU accelerated)
  - Dose calculation (GPU accelerated)

  Source code is available (Java). Developed at PSI by a professional development team.
- Data:
  - 151 intracranial patients
  - For each patient:
    CT, contours, historic plan, prescription
- HPC cluster (NVIDIA DGX A100)

Questions?