

A Convex Optimization Approach to Radiation Treatment Planning with Dose Constraints

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Problem Description

Convex Formulation

Refinements

Clinical Example

Outline

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Radiation Therapy

- ▶ Patient is scanned to obtain 3D image of anatomy, delineated into structures consisting of discrete voxels
- ▶ Clinician identifies planning target volumes (PTVs) and organs-at-risk (OARs)
- ▶ Clinician prescribes radiation dose for each PTV
- ▶ Patient is placed on couch, and radiation beams are delivered via a linear accelerator

Medical Linear Accelerator



Figure: Varian Linear Accelerator at Central Vermont Medical Center

Treatment Planning

- ▶ Radiation traveling through body damages both diseased and healthy tissue
- ▶ Trade-off between irradiating PTVs and sparing OARs

Treatment Planning

- ▶ Radiation traveling through body damages both diseased and healthy tissue
- ▶ Trade-off between irradiating PTVs and sparing OARs

Given beam positions and shapes, what beam intensities

- ▶ Deliver “close” to the prescribed dose for each PTV, and
- ▶ Minimize radiation to OARs and healthy tissue?

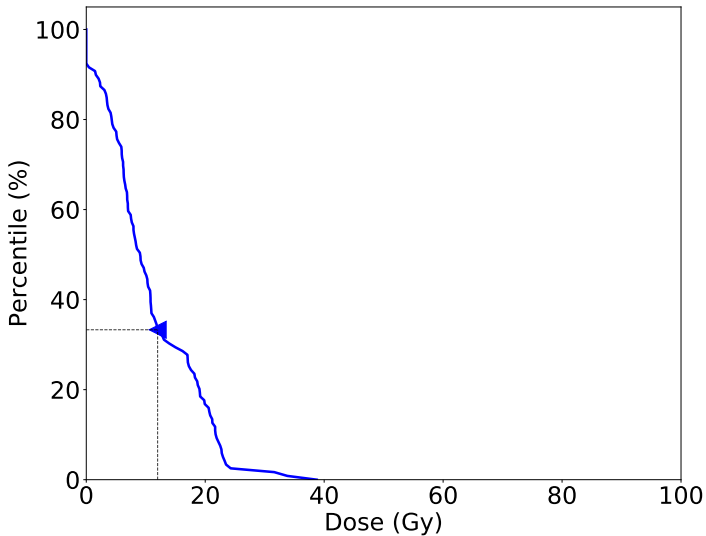
Dose-Volume Histogram (DVH) Constraints

- ▶ Different anatomical structures react differently to radiation
- ▶ Need to control **dose distribution** over a structure
- ▶ We do this by imposing a DVH constraint:

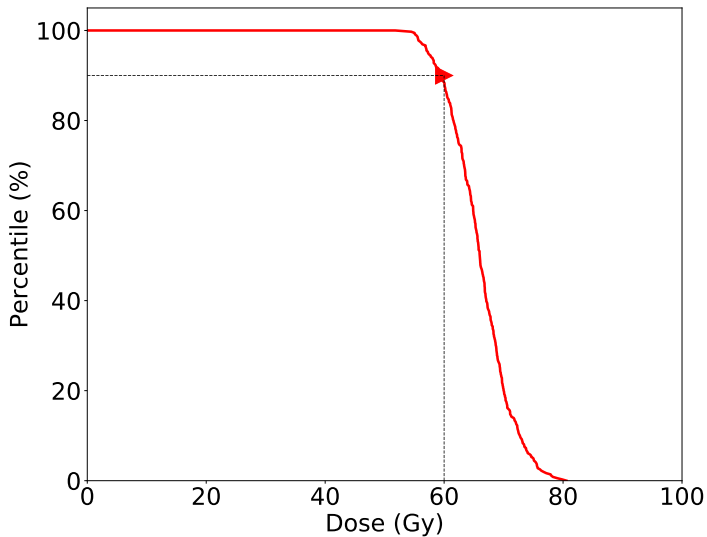
At most (least) $p\%$ of structure receives over b Gy

- ▶ Ex: $D(33) \leq 12$ on an OAR means at most 33% of the organ receives over 12 Gy.

Upper DVH Constraint: $D(33) \leq 12$



Lower DVH Constraint: $D(90) \geq 60$



Previous Work

- ▶ Linear and quadratic programming (Shepard et al, 1999)
- ▶ Multi-objective optimization (Hamacher & Küfer, 2002)
- ▶ Volumetric dose penalty with local search (Ehrgott et al, 2008)
- ▶ Mixed-integer programming (Lee, Fox & Crocker, 2000)
- ▶ CVaR approximation (Rockafellar & Uryasev, 2000)
- ▶ Constraints on dose moments (Zarepisheh et al, 2013)

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Convex Model

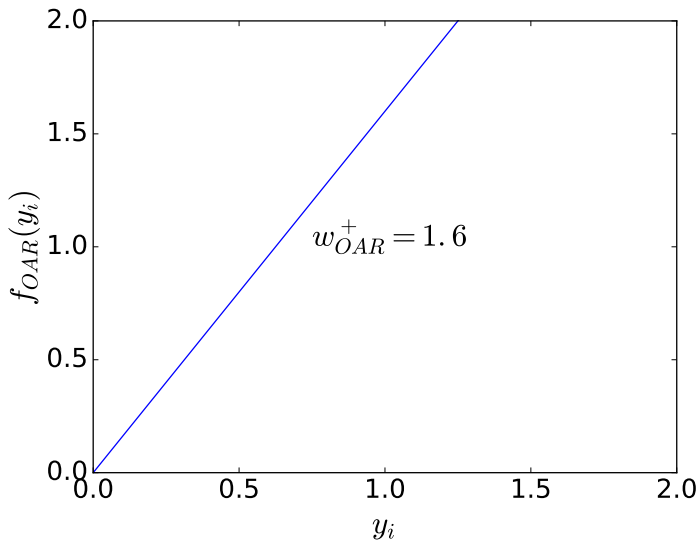
$$\begin{aligned} & \underset{x,y}{\text{minimize}} && f(y) \\ & \text{subject to} && Ax = y, \quad x \geq 0 \end{aligned}$$

- ▶ $x \in \mathbf{R}_+^n$ beam intensities, $y \in \mathbf{R}_+^m$ voxel doses
- ▶ A is $(m \text{ voxels}) \times (n \text{ beams})$ dose influence matrix
- ▶ $f : \mathbf{R}^n \rightarrow \mathbf{R}$ is sum of piecewise linear functions

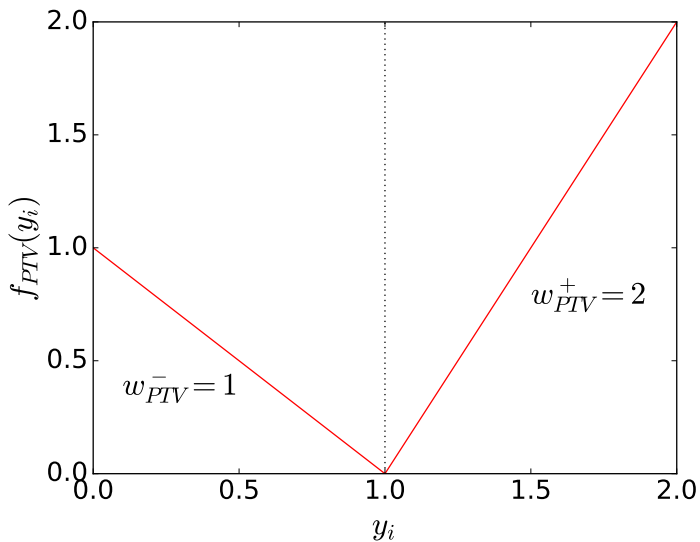
$$f_s(y_i) = w_s^- \underbrace{(y_i - d_s)_-}_{\text{underdose}} + w_s^+ \underbrace{(y_i - d_s)_+}_{\text{overdose}},$$

where d_s is prescribed dose and (w_s^-, w_s^+) are penalty weights for structure s

Penalty Function (OAR)



Penalty Function (PTV)



DVH Constraint Model

- ▶ Recall the (upper) DVH constraint $D_s(p, y) \leq b$:

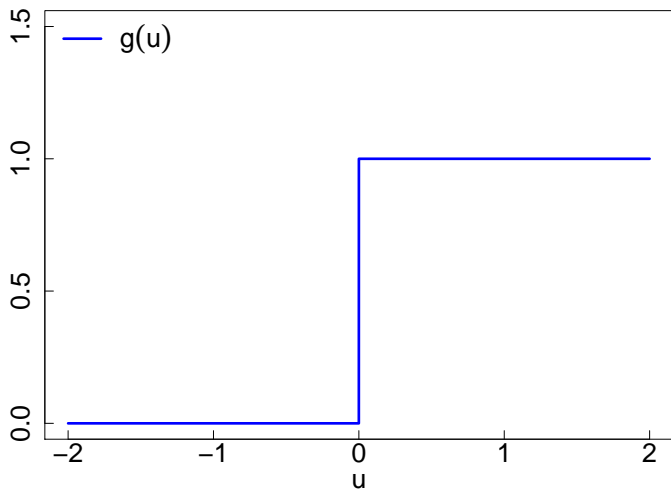
At most $p\%$ of structure s receives over b Gy

- ▶ Let \mathcal{V}_s be the set of voxels for structure s
- ▶ If $\phi_s(p) = (p\%$ of voxels in s), we can write this as

$$v_s(y, b) := \sum_{i \in \mathcal{V}_s} \mathbf{1}\{y_i \geq b\} = \sum_{i \in \mathcal{V}_s} g(y_i - b) \leq \phi_s(p),$$

where $g(u) = \mathbf{1}\{u \geq 0\}$

Indicator Function

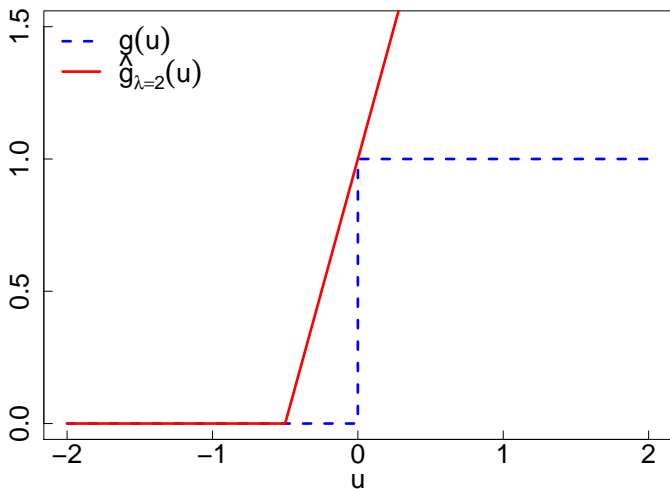


Convex Restriction

- ▶ DVH constraints are **not** convex!
- ▶ Replace $g(\cdot)$ with convex hinge loss

$$\hat{g}_\lambda(u) = \max(1 + \lambda u, 0) \quad \text{for } \lambda > 0$$

Hinge Loss vs. Indicator



Convex Restriction

- ▶ DVH constraints are **not** convex!
- ▶ Replace $g(\cdot)$ with convex hinge loss

$$\hat{g}_\lambda(u) = \max(1 + \lambda u, 0) \quad \text{for } \lambda > 0$$

- ▶ Since $g(u) \leq \hat{g}_\lambda(u)$, this provides restriction

$$\sum_{i \in \mathcal{V}_s} g(y_i - b) \leq \sum_{i \in \mathcal{V}_s} \hat{g}_\lambda(y_i - u) \leq \phi_s(p)$$

Restricted Problem

- ▶ By defining $\alpha := \frac{1}{\lambda} > 0$, restriction can be written as

$$\hat{D}_s(p, y, b, \alpha) = \sum_{i \in \mathcal{V}_s} (\alpha + (y_i - b))_+ - \alpha \phi_s(p) \leq 0$$

- ▶ Convex restricted problem is

$$\begin{array}{ll} \underset{x, y, \alpha}{\text{minimize}} & f(y) \\ \text{subject to} & Ax = y, \quad x \geq 0, \quad \alpha \geq 0 \\ & \hat{D}_s(p, y, b, \alpha) \leq 0 \end{array}$$

with variables $x \in \mathbf{R}_+^n, y \in \mathbf{R}_+^m$, and $\alpha \in \mathbf{R}_+$

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Two-Pass Refinement

- ▶ $D_s(p, y) \leq b$ iff $y_i \leq b$ for at least $(100 - p)\%$ of voxels in s
- ▶ Refinement selects voxels to precisely bound using heuristic
- ▶ Solution with precise bound always satisfies DVH constraint

Two-Pass Refinement

- ▶ **First pass:** Solve convex restricted problem for (x^*, y^*, α^*)
- ▶ Compute underdose margins $\xi_i^* = b - y_i^*$
- ▶ Identify $\lceil \phi_s(100 - \rho) \rceil$ largest margins and include their indices in Q
- ▶ **Second pass:** Solve for (x^{**}, y^{**}) in

$$\begin{aligned} & \underset{x,y}{\text{minimize}} && f(y) \\ & \text{subject to} && y = Ax, \quad x \geq 0 \\ & && y_i \leq b, \quad \forall i \in Q \end{aligned}$$

using (x^*, y^*) as a warm start

DVH Constraints with Slack

- ▶ Convex restricted problem may be infeasible even if original problem is feasible
- ▶ Add slack variable $\delta \in \mathbf{R}_+$ so restriction always feasible

$$\begin{array}{ll} \underset{x,y,\alpha,\delta}{\text{minimize}} & f(y) \\ \text{subject to} & y = Ax, \quad x \geq 0, \quad \alpha \geq 0, \quad \delta \geq 0 \\ & \hat{D}_s(p, y, b + \delta, \alpha) \leq 0 \end{array}$$

- ▶ For second pass, use slack margins $\xi_i^* = b + \delta^* - y_i$

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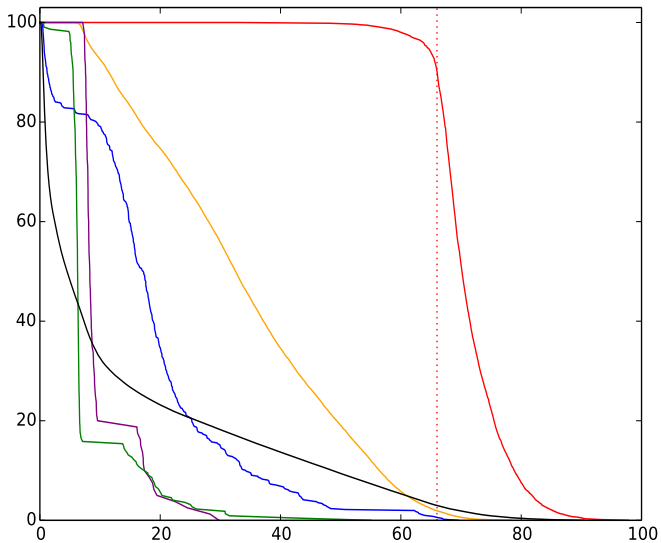
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Head and Neck Case

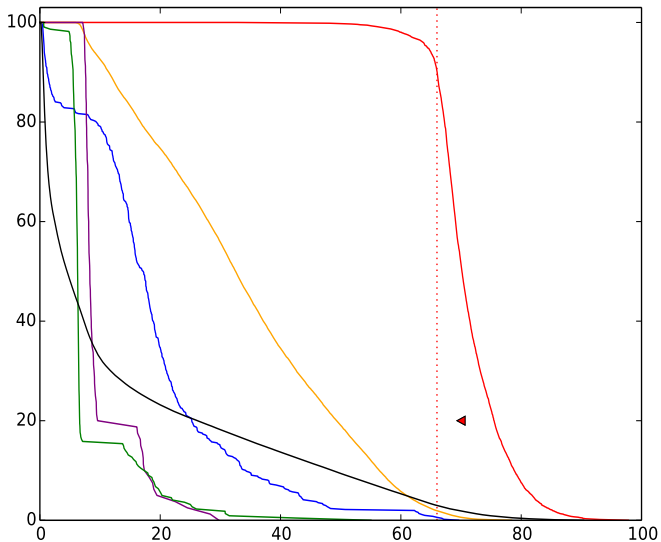
- ▶ 4-arc VMAT aperture re-weighting case
- ▶ 270,000 voxels \times 360 beams
- ▶ 17 structures: PTV (66 Gy), OARs, generic body voxels

Unconstrained Plan



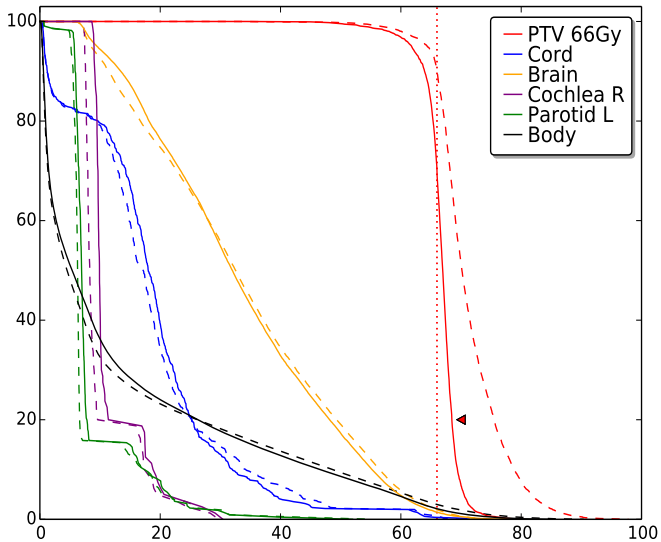
Clinical Example

Add $D(20) \leq 70$ Gy on PTV



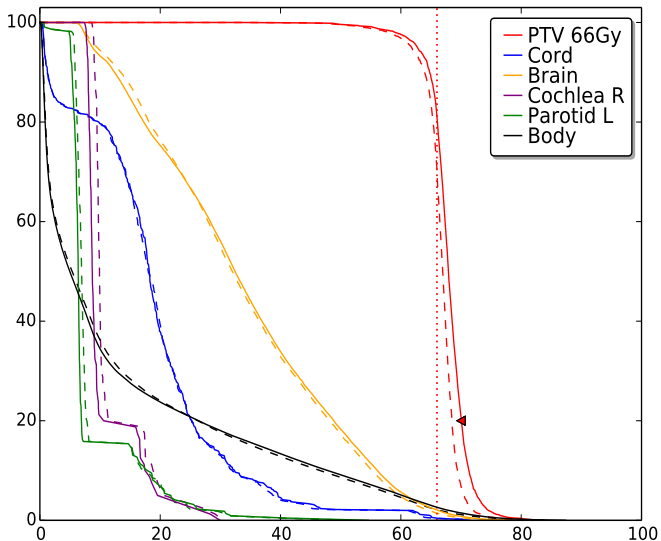
Clinical Example

First Pass



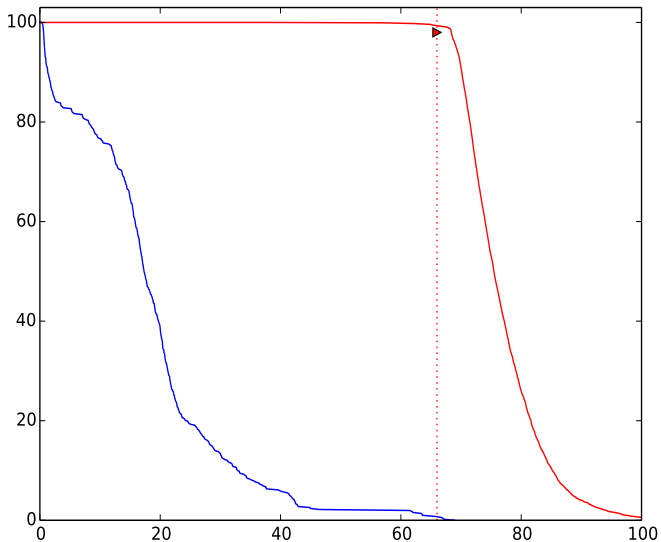
Clinical Example

Second Pass



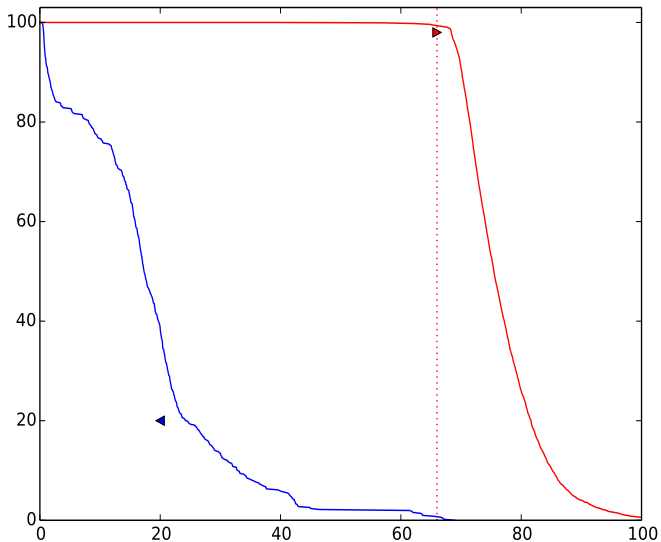
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$D(98) \geq 66$ Gy on PTV, No Slack



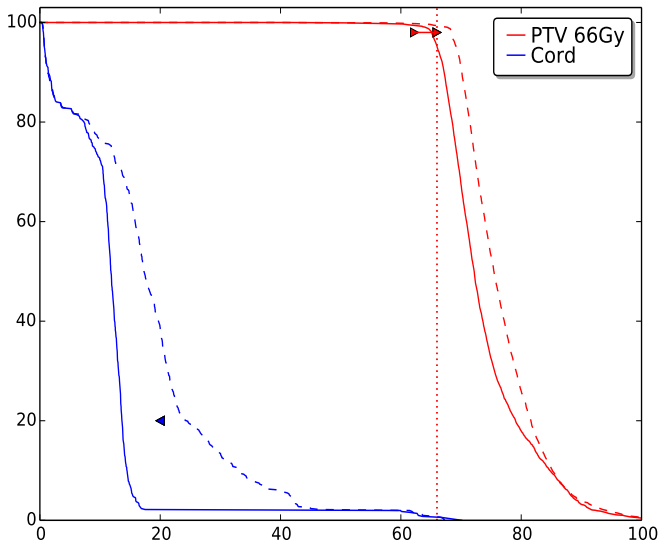
Clinical Example

Add $D(20) \leq 20$ Gy on OAR



Clinical Example

Plan with Slackened PTV Constraint



Clinical Example

Conclusion

- ▶ First principled method for handling DVH constraints
- ▶ Python library ConRad with intuitive interface
- ▶ <http://stanford.edu/~boyd/papers/conrad.html>