Artificial Intelligence for Treatment Planning

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Introduction

AI Is Changing The World

AI Is Going to Transform Healthcare

Machines Treating Patients? It's Already Happening

TIME   BY ALICE PARK   MARCH 21, 2019

http://time.com/5556339/artificial-intelligence-robots-medicine/

Medical Artificial Intelligence and Automation Lab

AI for Treatment Planning

- Big Picture

Potential Applications of AI in Treatment Planning

Ultimate Goal
(Outcome, Patient preference, Practicality, etc)

- Variation among physicians
- Art part of tx planning

- Outcome based planning
- Functional imaging and true dose painting

Physician Goal
(Physician's perception based on experience, training, etc)

- Iterations between physician and dosimetrist
- Inefficiency

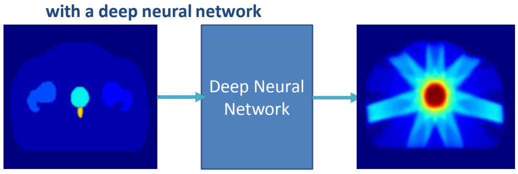
- Dose/DVH prediction
- Pareto surface navigation
- DRL for parameter tuning

Planning Objectives
(Overly simplified mathematical modeling via dose)

AI for Treatment Planning
- Dose Distribution Prediction

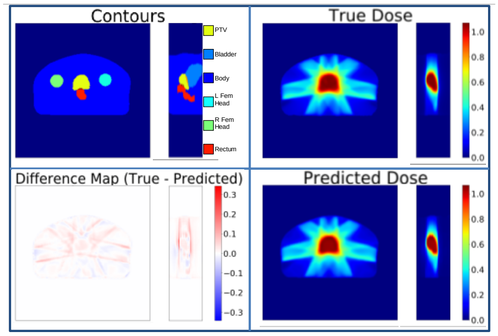
3D Dose Prediction Using Deep Learning

- Predict 3D radiation dose distribution based on
  - Patient's anatomy and physician's prescription
- Hypothesis: Patients of similar medical conditions should have a similar relationship between optimal radiation dose and patient anatomy and this relationship can be learned with a deep neural network

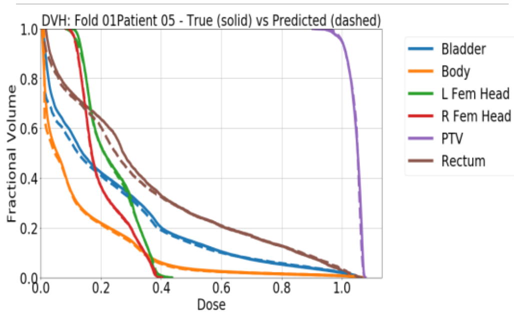


Nguyen, …, Jiang, (2017) arXiv:1709.09233; *Sci Rep*. 9(1):1076, 2019.

Test Results for A Prostate Case (IMRT)



Test Results for A Prostate Case (IMRT)



Prostate IMRT Dose Prediction w/ Different Losses

- **Tested 4 types of losses**
  - MSE
  - MSE + DVH
  - MSE + ADV (adversarial loss)
  - MSE + DVH + ADV
- **DVH loss**

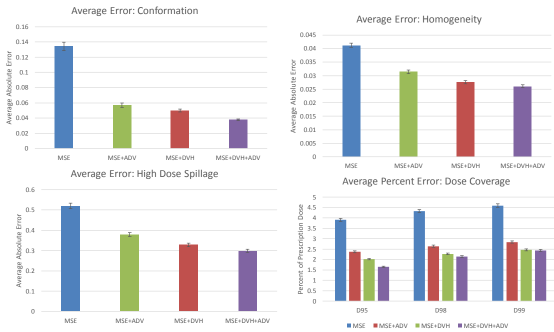
$$Loss_{DVH}\left(D_{true}, D_{pred}, M\right) = \frac{1}{n_s}\sum_s \frac{1}{n_b}\left\|\widetilde{DVH}_s(D_{true}, M_s) - \widetilde{DVH}_s\left(D_{pred}, M_s\right)\right\|_2^2$$

- **ADV loss w/ LSGAN formulation**

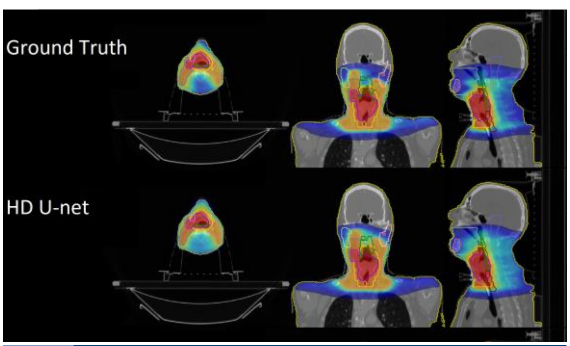
$$\underset{N_D}{\text{minimize}}\ \frac{1}{2}\|N_D(y_{true}) - b\|_2^2 + \frac{1}{2}\|N_D(N_G(x)) - a\|_2^2$$

$$\underset{N_G}{\text{minimize}}\ \frac{1}{2}\|N_D(N_G(x)) - c\|_2^2$$

Results for Different Losses

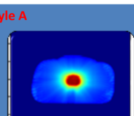
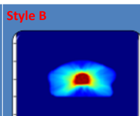


H&N VMAT Dose Prediction w/ HD U-NET



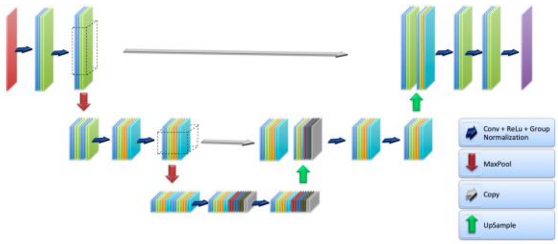
Dose Prediction w/ Different Planner Styles

- Style A (Dose Conformality Oriented)
  - balance between dose conformity and OAR sparing
- Style B (OAR Sparing Oriented)
  - utilize tuning structures and hard constraints to pull dose away from specific OARs

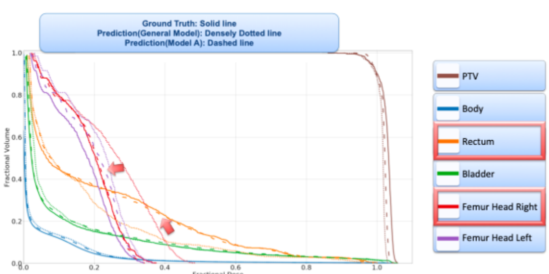
	Style A 	Style B 
Training dataset	65 cases	132 cases
Cross validation	60 cases	123 cases
Test cases	5 cases	9 cases

Model Training

- U-Net with group normalization
- Train a general model using all training dataset
- Adapt the trained general model to each sub-dataset (A/B)



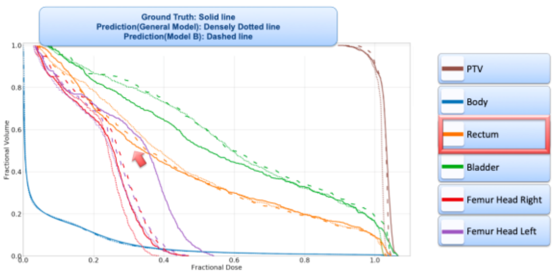
Result w/ Dataset A: General model vs Model A



Result w/ Dataset A: General model vs Model A

Prediction Error (normalized to prescription dose)		General Model	Model A
PTV Coverage	D98	%1	%0.0
	D99	%0.8	%0.4
Mean Dose Error	PTV	%2	%1
	Body	%0.4	%0.4
	Bladder	%0.8	%0.6
	Rectum	% 1.2	%1.6
	Left Femur	%1.4	%0
	Right Femur	%2.2	%0.8

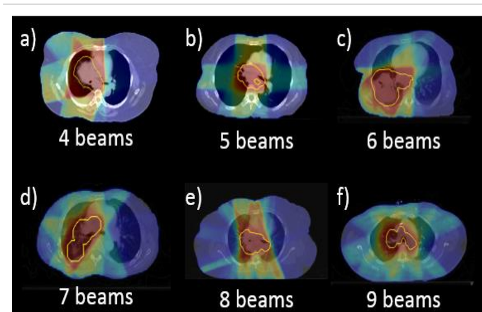
Result w/ Dataset B: General model vs Model B



Result w/ Dataset B: General model vs Model B

Prediction Error (normalized to prescription dose)		General Model	Model B
PTV Coverage	D98	%0.2	%1.4
	D99	%0.2	%1.2
Mean Dose Error	PTV	%1	%0.5
	Body	%0.04	%0.15
	Bladder	%1.03	%0.92
	Rectum	%3.7	%2.1
	Left Femur	%2	%0.8
	Right Femur	%1.4	%1.2

Dose Prediction w/ Variable Beam Angles



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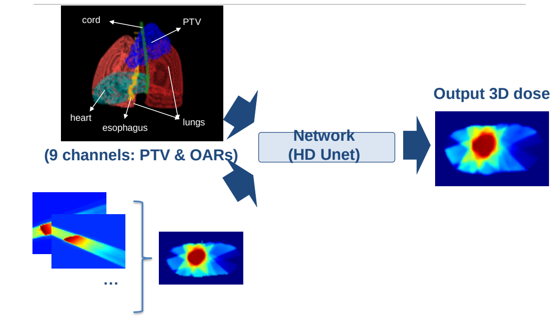
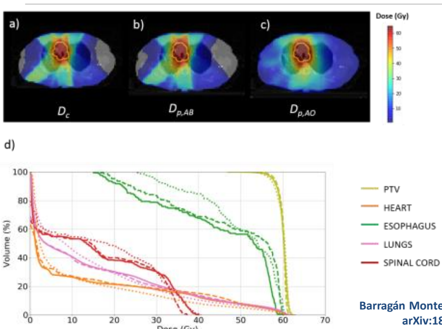


Dose Prediction w/ Variable Beam Angles

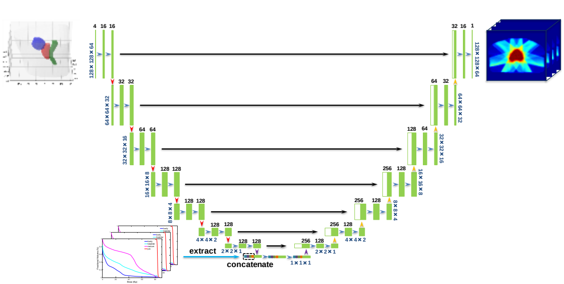


AB = Anatomy Beam Model

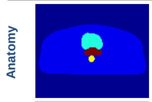
AO = Anatomy Only Model

Barragán Montero,..., Jiang (2018), arXiv:1812.06934.

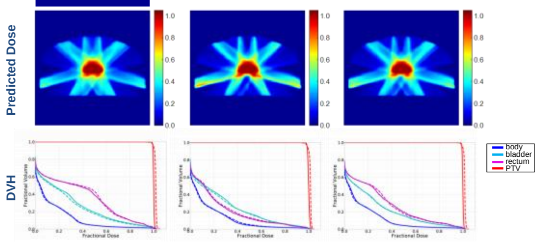
Dose Prediction w/ Variable Desired Tradeoffs



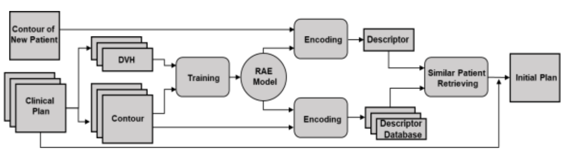
Dose Prediction w/ Variable Desired Tradeoffs

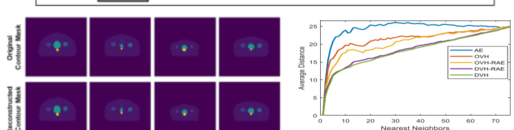


- Solid lines - desired DVH curves
- Dashed lines - DVH curves of the predicted dose distributions



Relational Autoencoder for Similar Patient Retrieval





Average Dice: 0.8682

Average PLCC to DVH: 0.9847

	DVH	DVH-RAE	OVH-RAE	OVH	AE
PLCC	1	0.9847	0.9536	0.9488	0.892

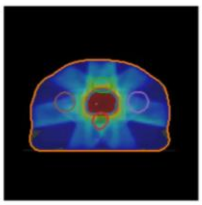
AI for Treatment Planning

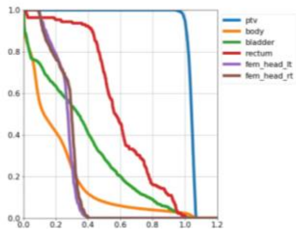
- Pareto Surface Navigation

Real Time Inference on Pareto Surface

Capable of predicting plans with 3% mean and max dose error (compared to optimized plan)

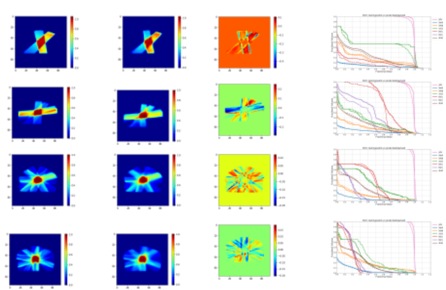
Prediction time: 0.6 seconds



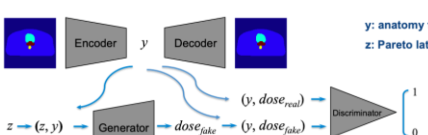


Nguyen,..., Jiang (2019), arXiv:1906.04778.

Pareto Surface Modeling w/ Various Beam Angles

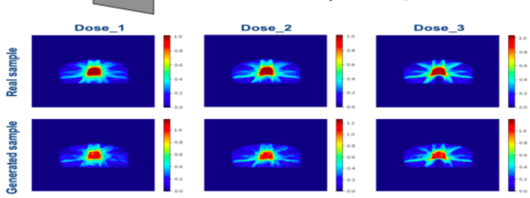


Generating Pareto Front Using Conditional GAN



y: anatomy feature

z: Pareto latent space, ∈ N(0,1)

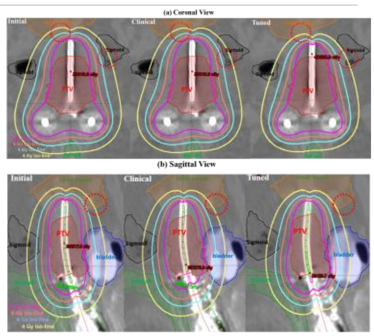


AI for Treatment Planning

- Hyper-parameter Tuning w/ DRL

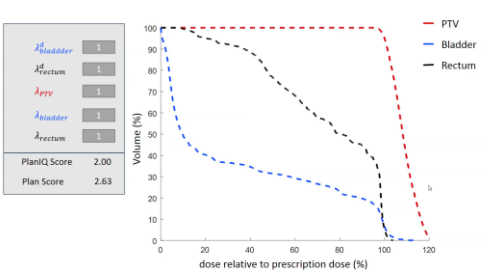
HDR Planning w/ DRL Based Organ Weight Tuning

- Testing case 4
- Same PTV coverage
- OARs are spared better in auto-tuned plan



Shen,..., Jia (2018), arXiv:1811.10102

IMRT Planning w/ DRL Based Hyper-Parameter Tuning

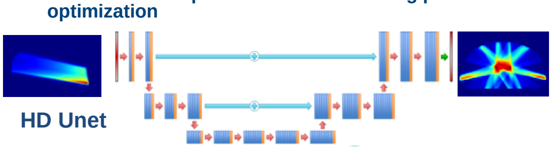


AI for Treatment Planning

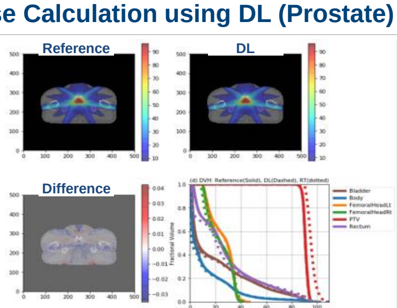
- Dose Calculation

Dose Calculation using Deep Learning

- Dose calculation using deep learning directly from fluence maps requires a complicated DNN and a large dataset for training
- Combining 1st order approximation (ray tracing) with deep learning can greatly reduce the complexity
- A completely different system so it is good for secondary dose check
- If accurate and fast, can also be used for intermediate step dose calculation during plan optimization

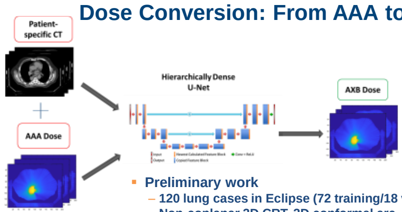


Dose Calculation using DL (Prostate)



Patient		1	2	3	4	5	6	7	8	Mean	SD
Gamma Index	1mm/1%	99.1%	99.9%	97.6%	99.8%	99.9%	99.9%	95.7%	96.3%	98.5%	1.6%
	2mm/2%	100%	100%	100%	100%	100%	100%	99.7%	99.8%	99.9%	0.1%

Dose Conversion: From AAA to Acuros XB



- Preliminary work
  - 120 lung cases in Eclipse (72 training/18 validation/30 testing)
  - Non-coplanar 3D CRT, 3D conformal arc, IMRT, and VMAT plans
  - Rx dose: 24 Gy to 60 Gy
  - Energy: 6 MV, 10 MV, 6xFFF, and 10xFFF

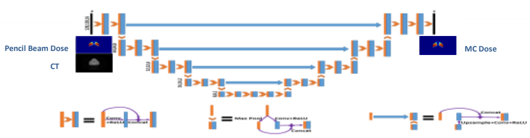
Dose Maps	Gamma Pass rates 2mm/2%	Gamma Pass rates 1mm/1%	MSE	% of voxels over 3% dose diff of Rx dose
Original AAA dose	(97.7±2.1)%	(86.0±9.8)%	0.52±0.26	(2.01±1.19)%
Converted AXB dose	(99.9±0.4)%	(98.3±1.7)%	0.16±0.10	(0.46±0.46)%

Convert PB Dose to MC Dose for Proton RT

- All Patient Data from MGH Proton Center
  - PB dose calculated with XiO, MC dose calculated with TOPAS

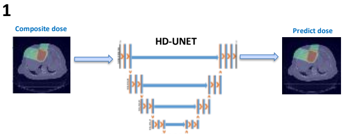
	Head &Neck	Liver	Prostate	Lung	Total
Number of patients	90	93	75	32	290
Training & Validation	72	75	62	26	235
Testing	18	18	13	6	55

Hierarchically Dense U-Net (HD U-net) w/ patch-based training

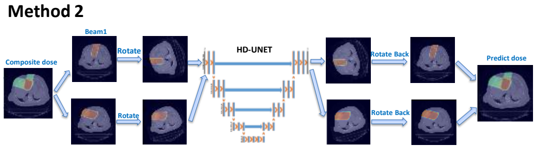


Two Methods

Method 1

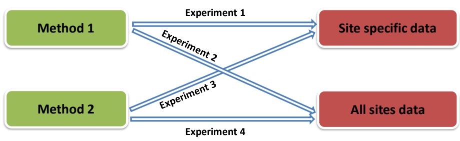


Method 2



Four Experiments

	HN	Liver	Prostate	Lung	Total
Number of patients	90	93	75	32	290
Number of beams	726	218	260	91	1294



Results: Gamma Index and MSE

Head & Neck	Gamma Index (1mm/1%)	MSE
Pencil beam dose	(72.8±5.8)%	5.05±3.89
Experiment 1 (Method 1 + Site specific data)	(83.3±3.8)%	2.07±1.50
Experiment 2 (Method 1 + All sites data)	(83.9±4.1)%	2.11±1.59
Experiment 3 (Method 2 + Site specific data)	(92.2±2.6)%	0.83±0.68
Experiment 4 (Method 2 + All sites data)	(92.3±2.8)%	0.77±0.61

Liver	Gamma Index (1mm/1%)	MSE
Pencil beam dose	(78.6±5.4)%	1.74±0.53
Experiment 1 (Method 1 + Site specific data)	(88.3±5.0)%	0.61±0.42
Experiment 2 (Method 1 + All sites data)	(88.9±4.0)%	0.63±0.39
Experiment 3 (Method 2 + Site specific data)	(92.2±3.5)%	0.38±0.20
Experiment 4 (Method 2 + All sites data)	(92.2±3.3)%	0.32±0.17

Results: Gamma Index and MSE

Lung	Gamma Index (1mm/1%)	MSE
Pencil beam dose	(65.5±5.3)%	2.94±1.70
Experiment 1 (Method 1 + Site specific data)	(73.2±5.5)%	2.02±1.80
Experiment 2 (Method 1 + All sites data)	(76.3±6.3)%	1.88±1.93
Experiment 3 (Method 2 + Site specific data)	(85.5±3.6)%	0.68±0.55
Experiment 4 (Method 2 + All sites data)	(88.6±3.6)%	0.50±0.39

Prostate	Gamma Index (1mm/1%)	MSE
Pencil beam dose	(73.6±2.5)%	2.17±1.03
Experiment 1 (Method 1 + Site specific data)	(99.0±0.5)%	0.19±0.11
Experiment 2 (Method 1 + All sites data)	(98.4±1.0)%	0.20±0.12
Experiment 3 (Method 2 + Site specific data)	(99.4±1.0)%	0.11±0.05
Experiment 4 (Method 2 + All sites data)	(99.3±0.6)%	0.13±0.10

AI for Treatment Planning
- Beam Angle Optimization

AI for Beam Orientation Optimization (BOO)

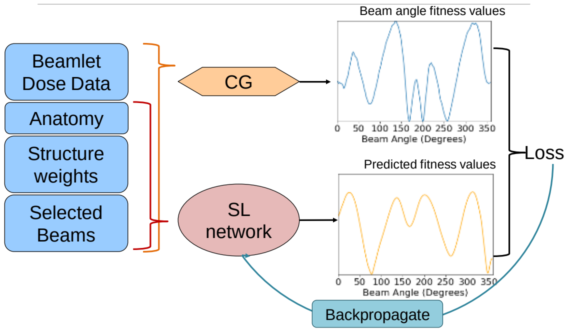
- **Develop an AlphaGo type of DL algorithm**
  - reinforcement learning (RL) policy network
  - Monte Carlo Tree Search (MCTS)
- **Go movements → CyberKnife robot sequence**

Ogunmolu, ..., Jiang, AAPM, 2018.

Deep BOO for 4Pi/CK Optimization

- **Traditional BOO algorithms**
  - requires pre-dose calculation for a large number of candidate beams
  - Difficulty to explore the huge solution space
- **Deep BOO (v1)**
  - Use column generation (CG) to train a supervised learning (SL) policy network
  - Perform guided Monte Carlo Tree Search with pre-trained SL policy network

Training a SL Network using CG



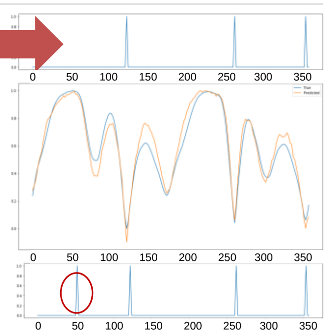
Example prediction: selecting the 4th beam

Input: previously selected beams
(and anatomy)

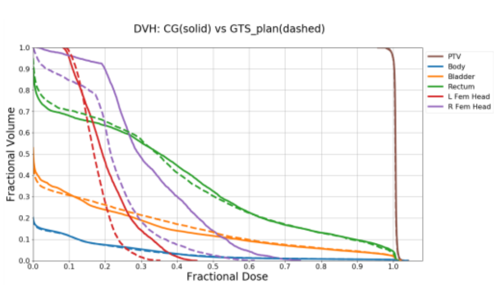
Network predicts fitness values for angles 0° through 358° (2° separation).

Orange: prediction
Blue: CG output

Select beam with best fitness and add to current pool



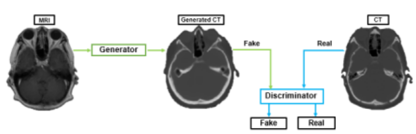
Deep BOO vs Column Generation



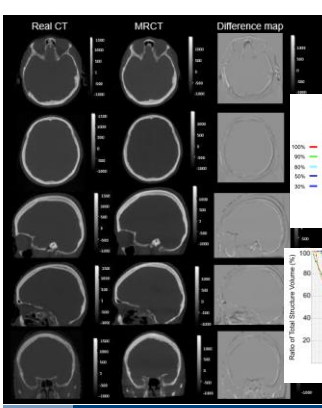
AI for Treatment Planning
- Direct MR based Planning

CT Synthetization from MRI

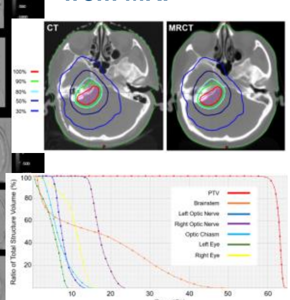
- Unpaired CT and MR images from 77 brain patients who underwent brain tumor radiotherapy
- CT images were acquired with a 512x512 matrix and voxel size 0.68mm×0.68mm×1.50mm
- MR images were acquired at 1.5T using a post-gadolinium 2D T1-weighted spin echo sequence with TE/TR = 15/3500 ms



DCGAN - Deep convolutional generative adversarial network



CT Synthetization from MRI

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Thank
You
https://www.utsouthwestern.edu/labs/maia/
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