AI in Treatment Planning

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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/sub-optimal

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

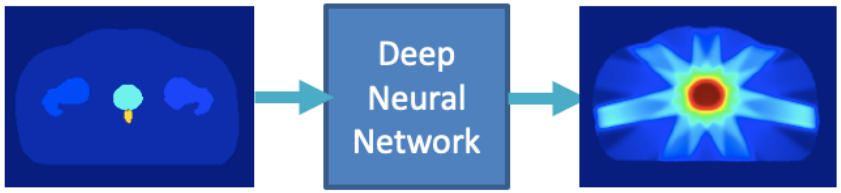
Planning Objectives
(Overly simplified mathematical modeling via dose)

AI for Treatment Planning

- Dose Distribution Prediction

3D Dose Prediction Using Deep Learning

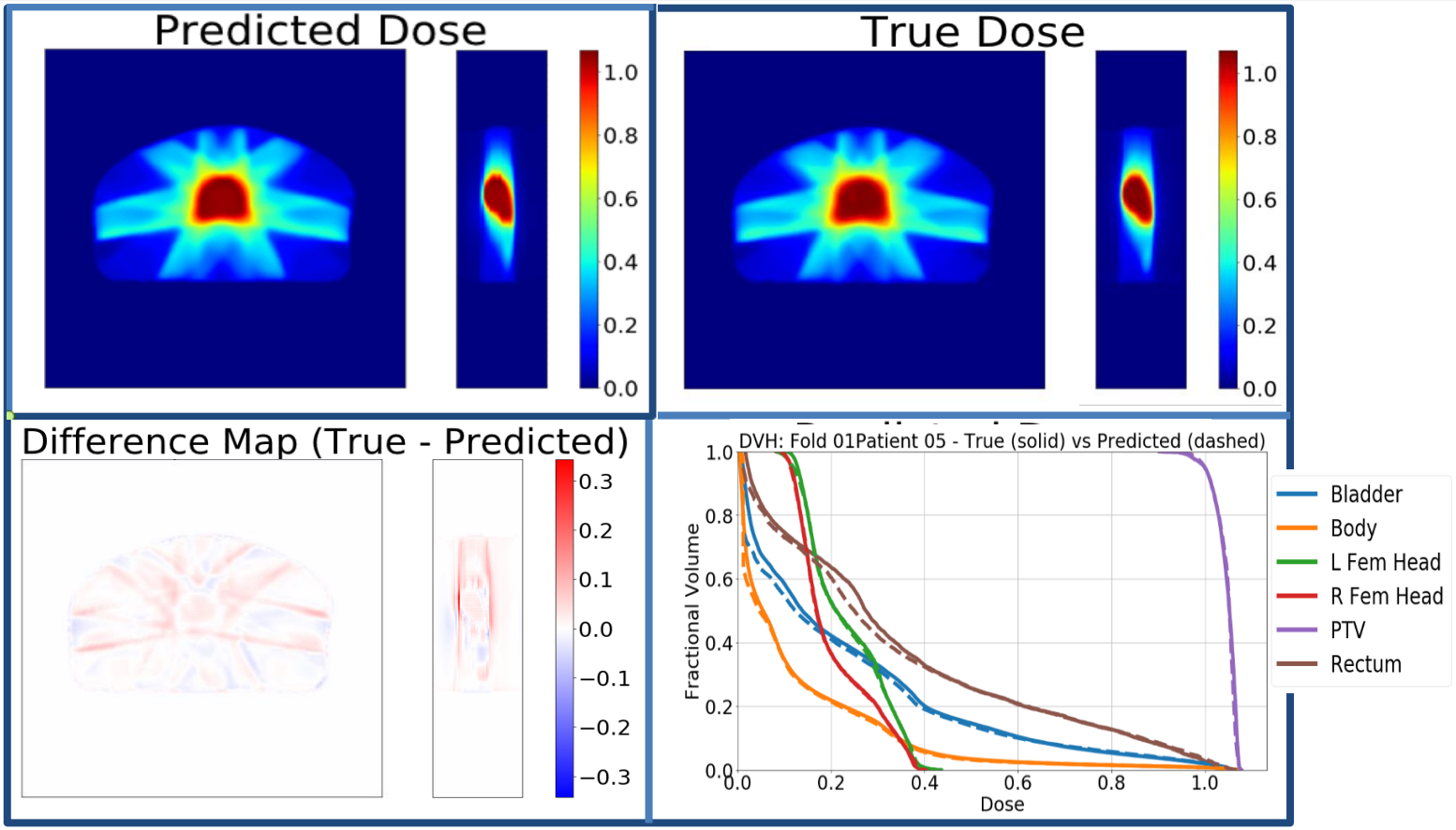
- **Hypothesis**
  - Patients of similar medical conditions should have a similar relationship between optimal radiation dose and patient anatomy
  - This relationship can be learned with a deep neural network



- **Potential applications**
  - Treatment planning guidance
  - Automated treatment planning
  - Tradeoff navigation
  - Modality comparison
  - Patient consultation
  - Insurance approval

- **Technical barriers**
  - Different tumor sites, treatment protocols, treatment modalities, treatment machines, beam setups, energies, etc.
  - Different institutions, different physician/planner styles, etc.
  - General model versus model commissioning

Dose Prediction – Feasibility Study (9/2017)



arXiv.org > physics > arXiv:1709.09233

Nguyen, …, Jiang, *Sci Rep*. 9(1):1076, 2019.

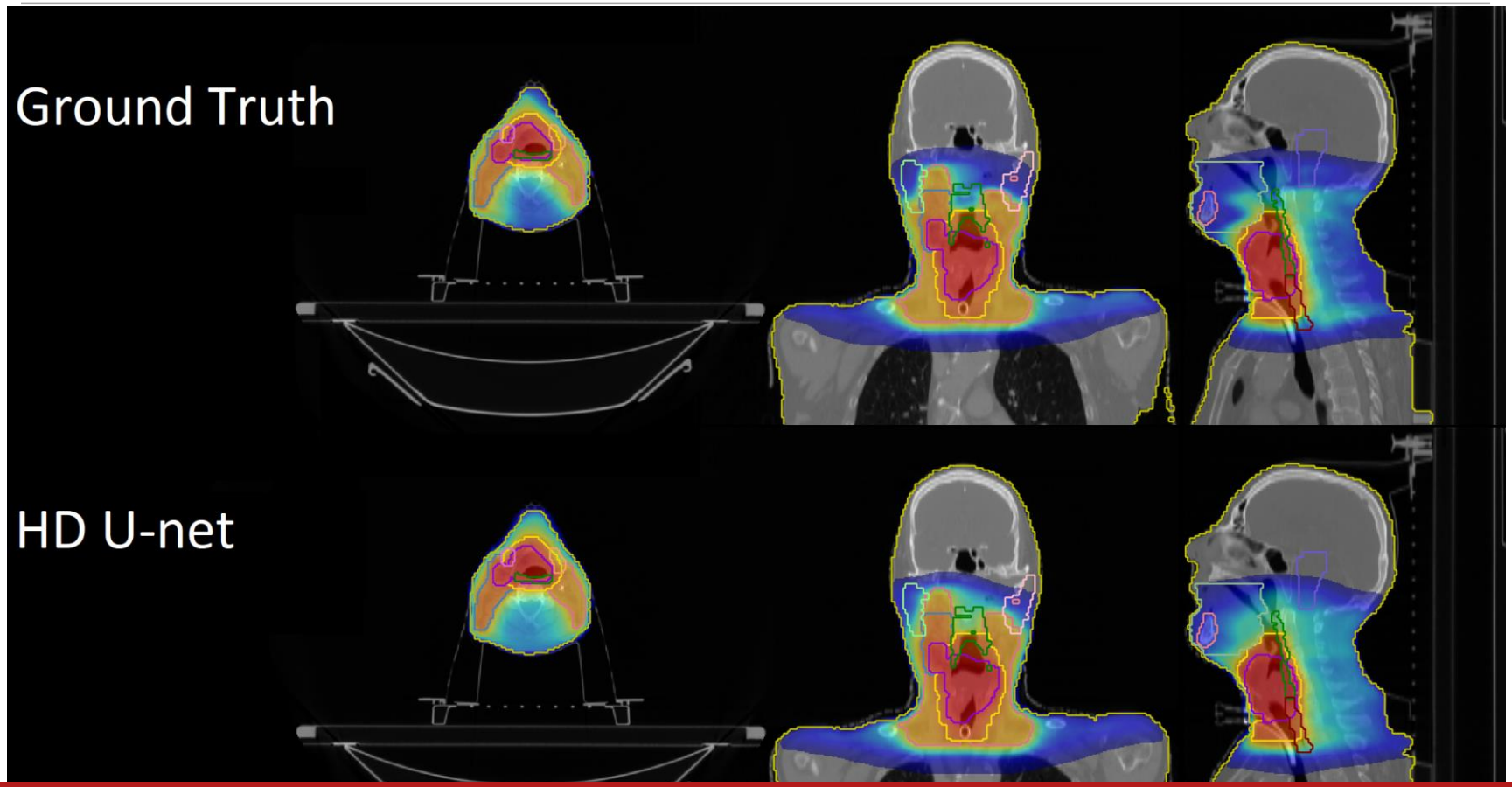
Physics > Medical Physics

[Submitted on 26 Sep 2017 (v1), last revised 29 Nov 2018 (this version, v4)]

A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning

Dan Nguyen, Troy Long, Xun Jia, Weiguo Lu, Xuejun Gu, Zohaib Iqbal, Steve Jiang

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



arXiv.org > physics > arXiv:1805.10397

Nguyen, …, Jiang, *Phys Med Biol.* 64(6):065020, 2019.

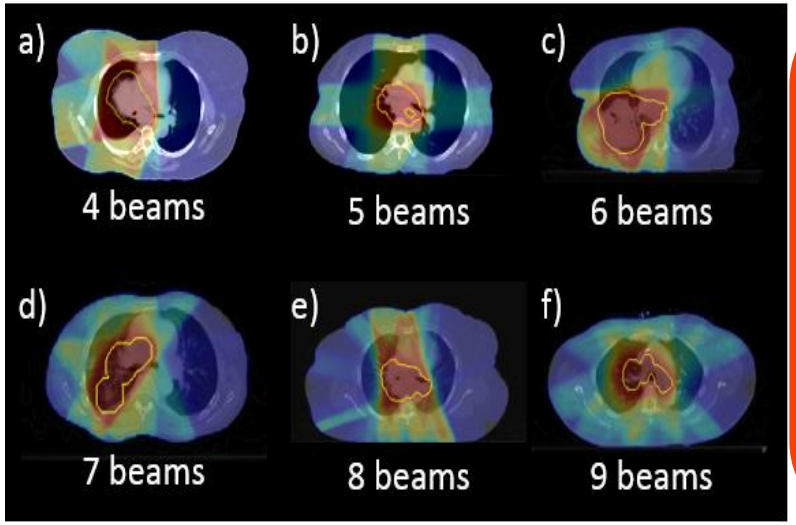
Physics > Medical Physics

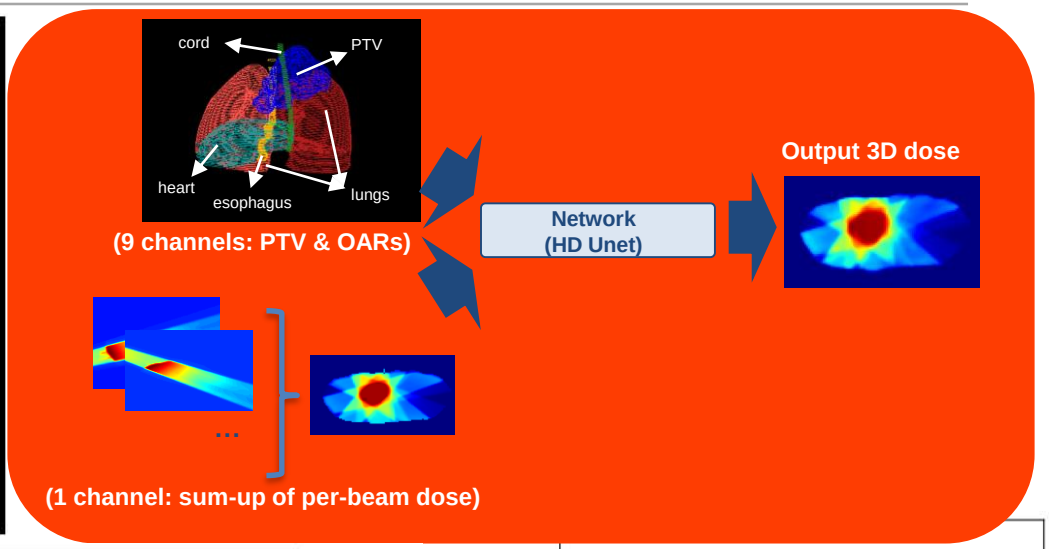
[Submitted on 25 May 2018 (v1), last revised 4 Feb 2019 (this version, v3)]

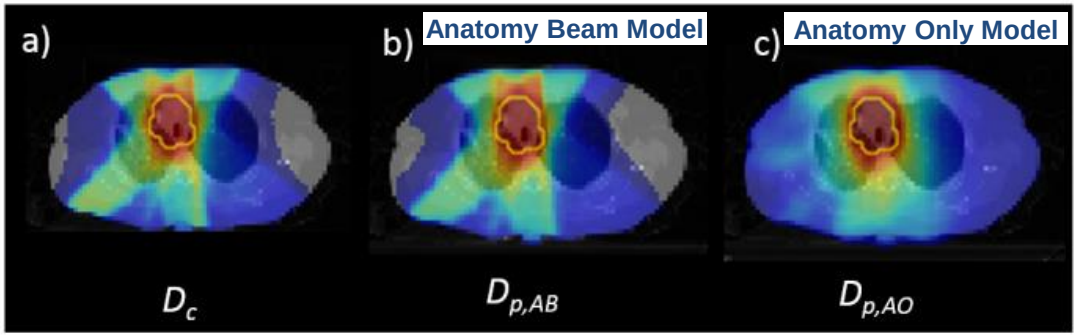
Three-Dimensional Radiotherapy Dose Prediction on Head and Neck Cancer Patients with a Hierarchically Densely Connected U-net Deep Learning Architecture

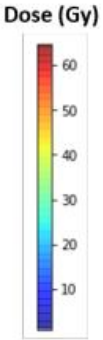
Dan Nguyen, Xun Jia, David Sher, Mu-Han Lin, Zohaib Iqbal, Hui Liu, Steve Jiang

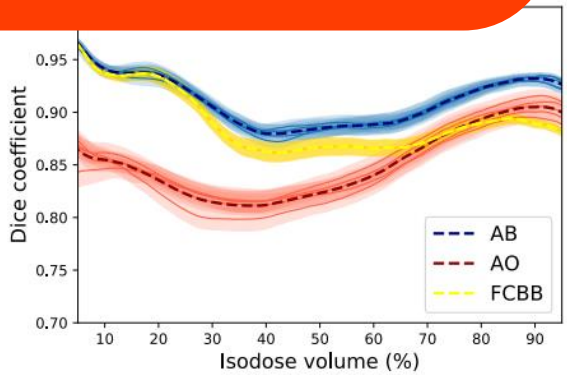
Dose Prediction - Variable Beam Angles











arXiv.org > physics > arXiv:1812.06934

Barragán Montero,..., Jiang, *Med Phys* 46(8)3679-3691, 2019.

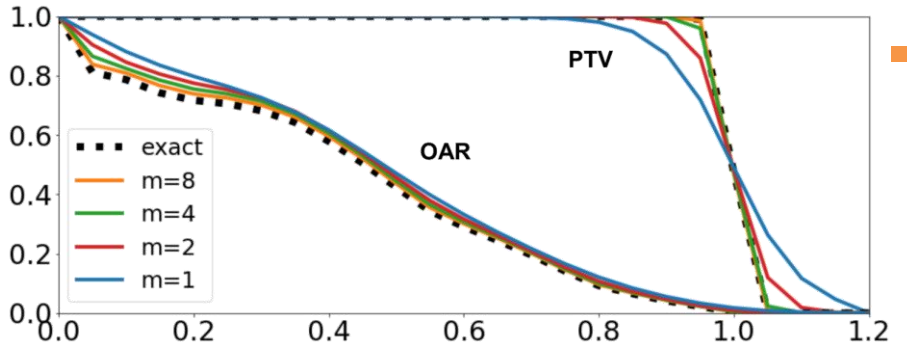
Physics > Medical Physics

[Submitted on 17 Dec 2018 (v1), last revised 11 Apr 2019 (this version, v2)]

Three-Dimensional Dose Prediction for Lung IMRT Patients with Deep Neural Networks: Robust Learning from Heterogeneous Beam Configurations

Ana M. Barragan-Montero, Dan Nguyen, Weiguo Lu, Mu-Han Lin, Xavier Geets, Edmond Sterpin, Steve Jiang

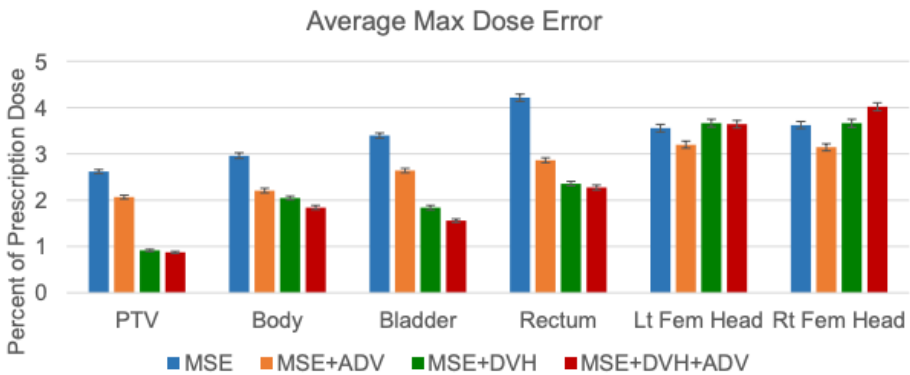
Dose Prediction - Differentiable DVH Approximation



- **Human Domain Knowledge**

$$Loss_{DVH}(D_{true}, D_{pred}, M)$$

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



- **Learned Domain Knowledge**

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

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

arXiv.org > physics > arXiv:1908.05874

Nguyen, …, Jiang, *Med Phys* 47(3):837-849, 2020.

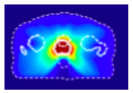
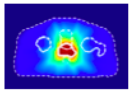
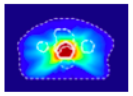
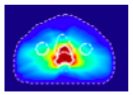
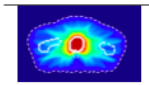
Physics > Medical Physics

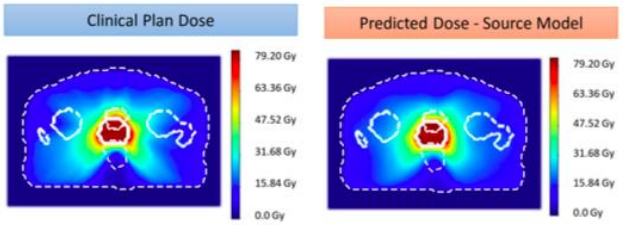
[Submitted on 16 Aug 2019 (v1), last revised 7 Dec 2019 (this version, v2)]

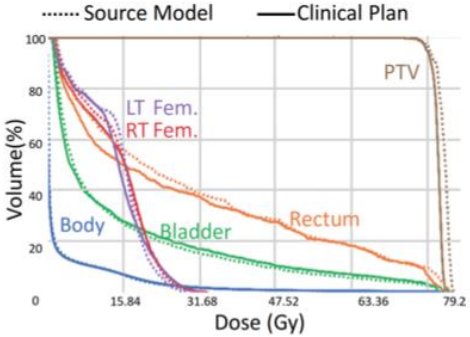
Incorporating human and learned domain knowledge into training deep neural networks: A differentiable dose volume histogram and adversarial inspired framework for generating Pareto optimal dose distributions in radiation therapy

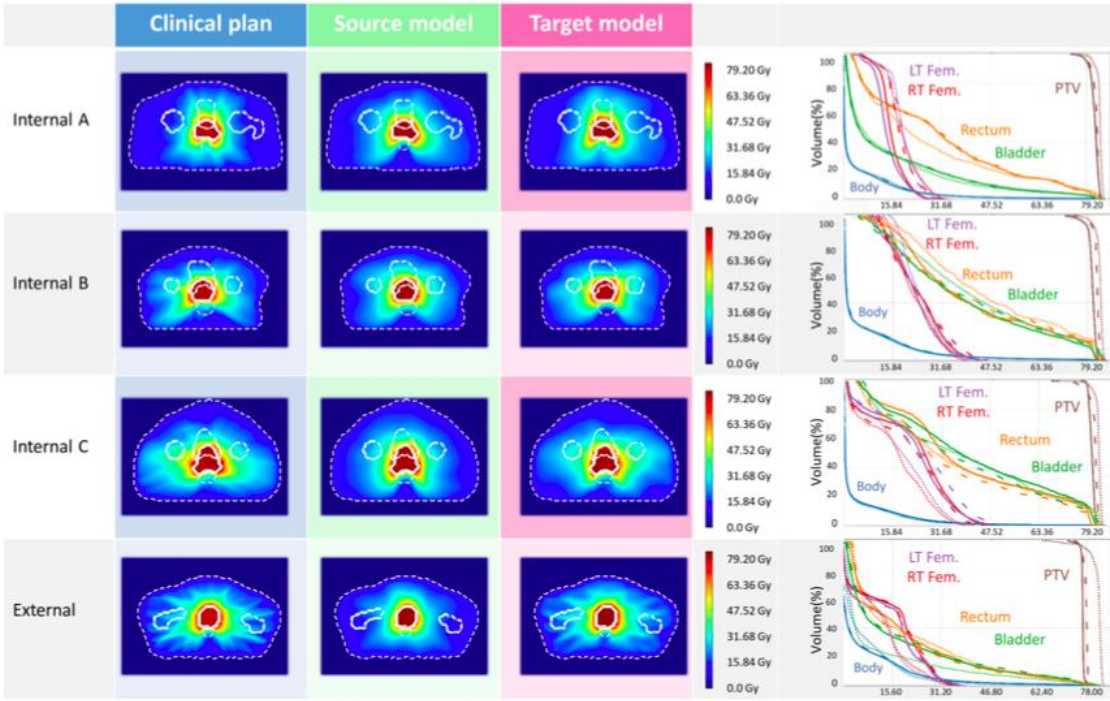
Dan Nguyen, Rafe McBeth, Azar Sadeghnejad Barkousaraie, Gyanendra Bohara, Chenyang Shen, Xun Jia, Steve Jiang

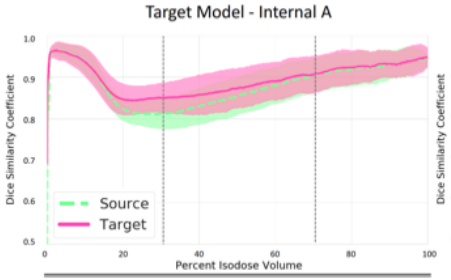
Dose Prediction - Different Planner Styles

Dose Style	Name	Dataset	Training	Testing
	Source	118	108	10
	Internal-A	34	29	5
	Internal-B	16	14	2
	Internal-C	20	17	3
	External	60	20	40

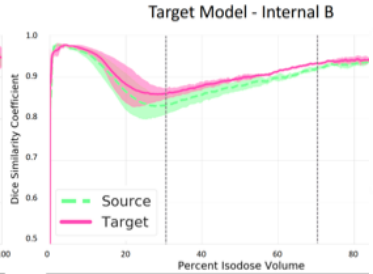




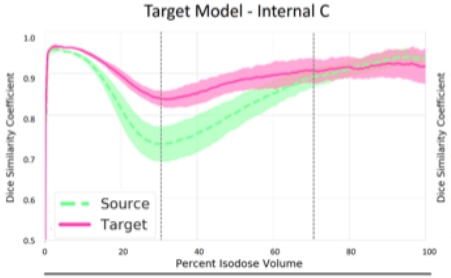




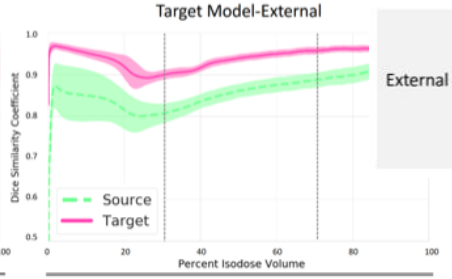
Model	Low Dose	Intermediate Dose	High Dose
Source	0.85 (0.78-0.97)	0.86 (0.78-0.95)	0.93 (0.86-0.98)
Target	0.87 (0.79-0.98)	0.88 (0.82-0.96)	0.93 (0.85-0.98)



Model	Low Dose	Intermediate Dose	High Do
Source	0.88 (0.81-0.96)	0.88 (0.82-0.92)	0.94 (0
Target	0.90 (0.84-0.97)	0.90 (0.85-0.93)	0.95 (0



Model	Low Dose	Intermediate Dose	High Dose
Source	0.82 (0.70-0.94)	0.81 (0.69-0.91)	0.92 (0.86-0.96)
Target	0.90 (0.82-0.96)	0.88 (0.81-0.94)	0.92 (0.88-0.97)

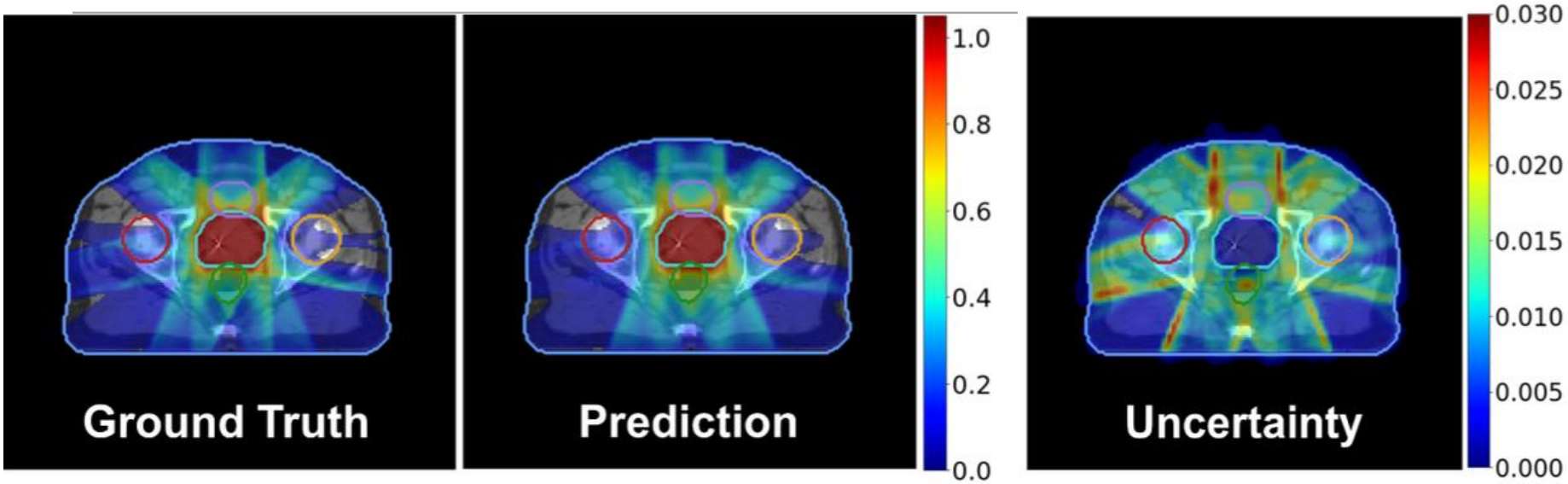


Model	Low Dose	Intermediate Dose	High Dose
Source	0.82 (0.69-0.95)	0.86 (0.76-0.92)	0.91 (0.84-0.97)
Target	0.92 (0.81-0.97)	0.93 (0.87-0.97)	0.96 (0.89-0.98)

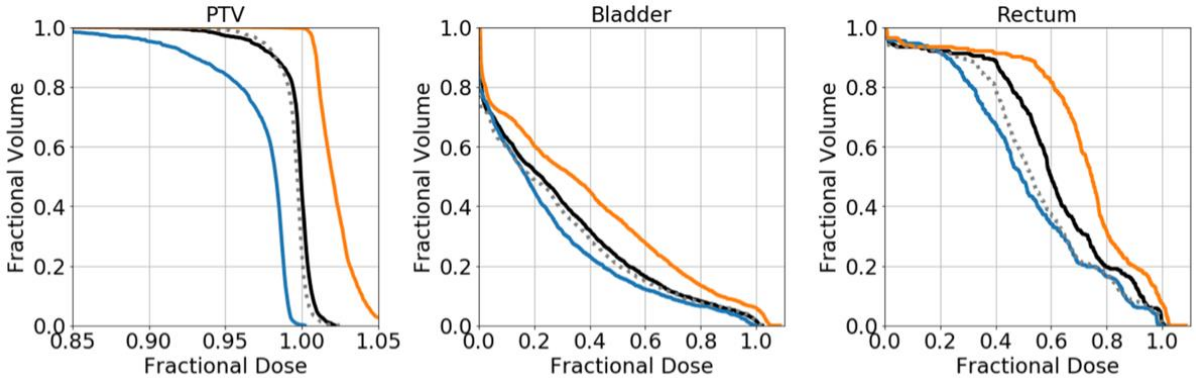
Dose Prediction with Deep Learning for Prostate Cancer Radiation Therapy: Adapting a Model to Different Treatment Planning Practices

Roya Norouzi Kandalan[a,b], Dan Nguyen[a], Nima Hassan Rezaeian[a], Ana M. Barragán-Montero[c], Sebastiaan Breedveld[d], Kamesh Namuduri[b], Steve Jiang[a,1], Mu-Han Lin[a,1]

Dose Prediction – Uncertainty Estimation



- **Monte Carlo Dropout**
  - Use dropout during training AND inference
  - Effective performs variational inference from a Bernoulli distribution

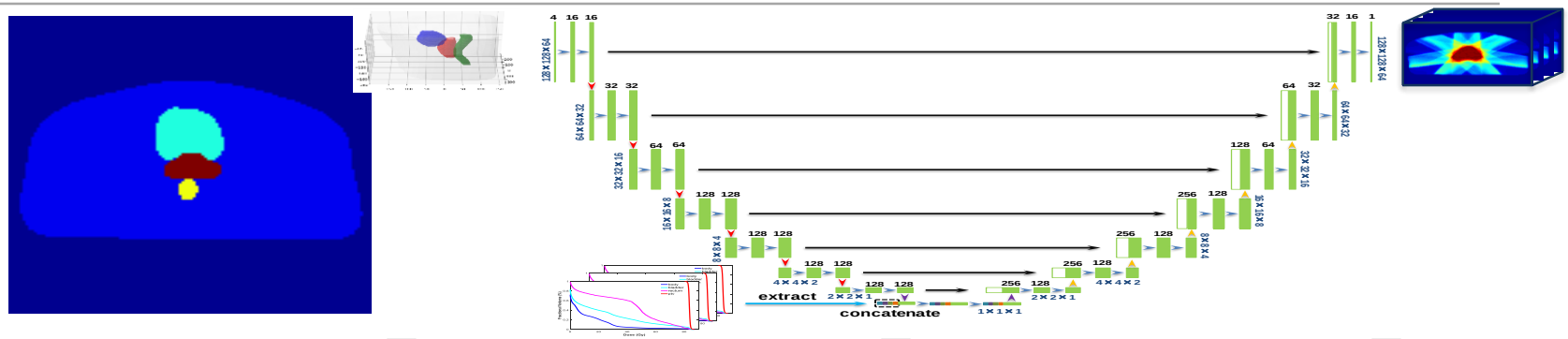


Towards Safer Artificial Intelligence-Based Radiation Therapy Treatment Planning: Adding Uncertainty Estimation to Volumetric Dose Prediction Using An Approximate Bayesian Method On Deep Neural Networks

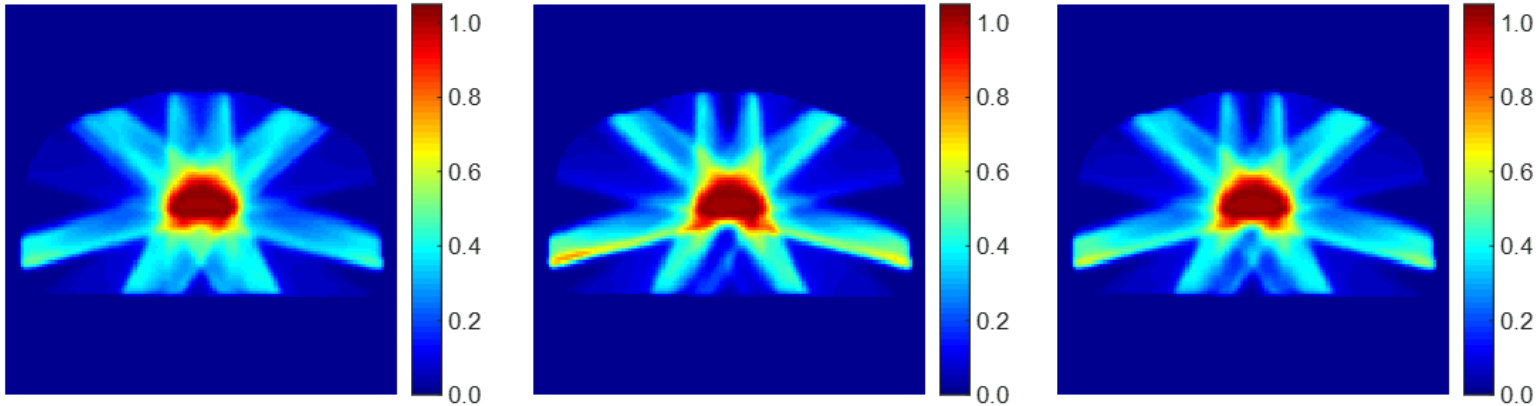
D Nguyen*, A Balagopal, A Sadeghnejad Barkousaraie, R McBeth, S Jiang, Medical Artificial Intelligence and Automation (MAIA) Laboratory, UT Southwestern Medical Center, Dallas, TX

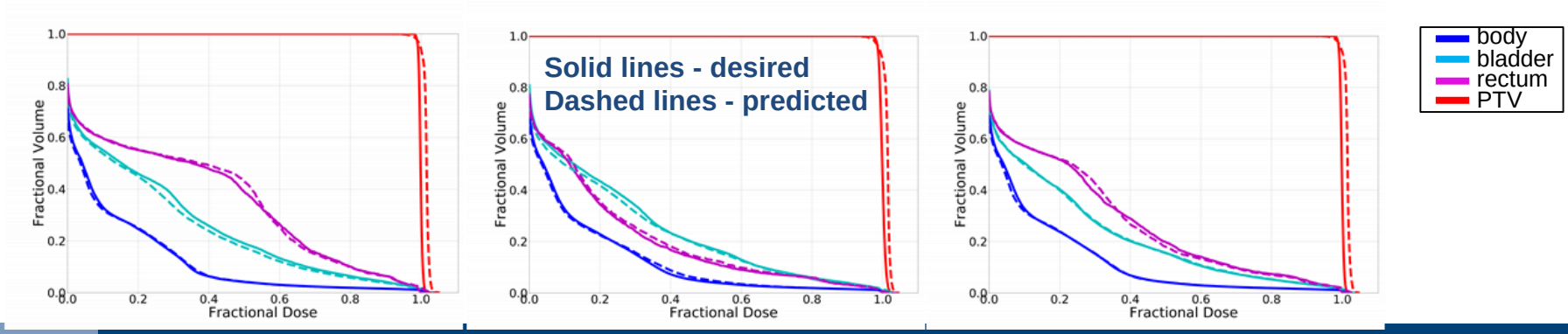
Dose Prediction - Variable Desired Tradeoffs

Anatomy

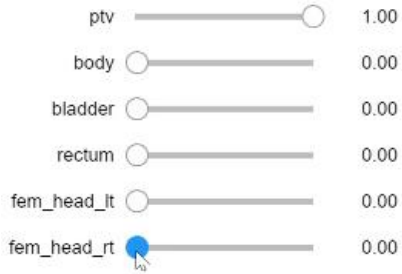


Predicted Dose



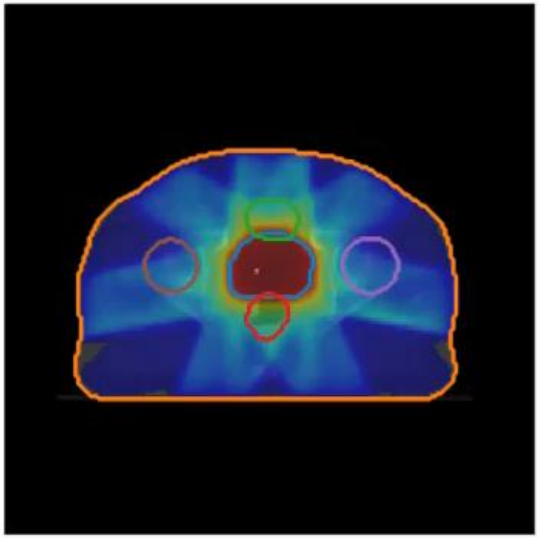


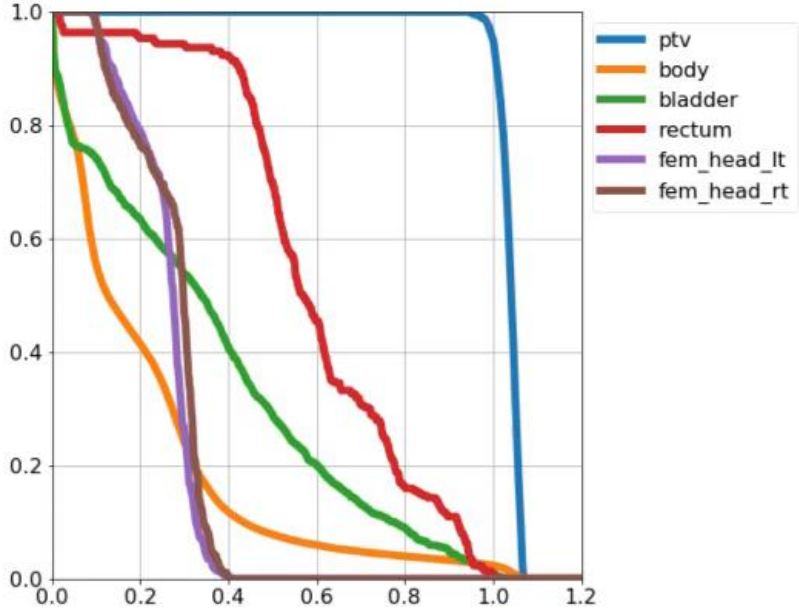
Dose Prediction - Real Time Pareto Surface Navigation



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

Prediction time: 0.6 seconds





arXiv.org > physics > arXiv:1906.04778

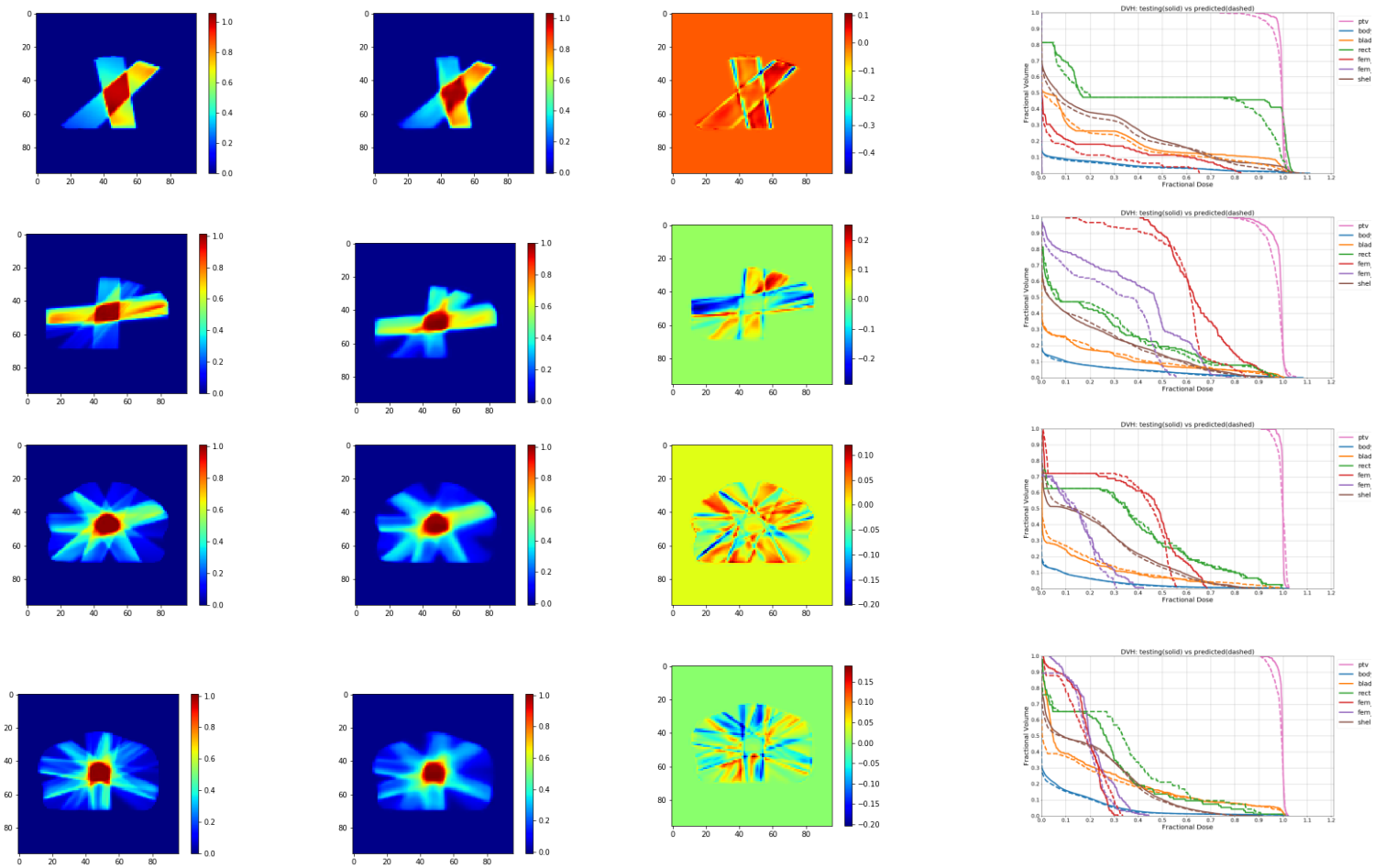
Physics > Medical Physics

[Submitted on 11 Jun 2019 (v1), last revised 31 Jul 2019 (this version, v2)]

Generating Pareto optimal dose distributions for radiation therapy treatment planning

Dan Nguyen, Azar Sadeghnejad Barkousaraie, Chenyang Shen, Xun Jia, Steve Jiang

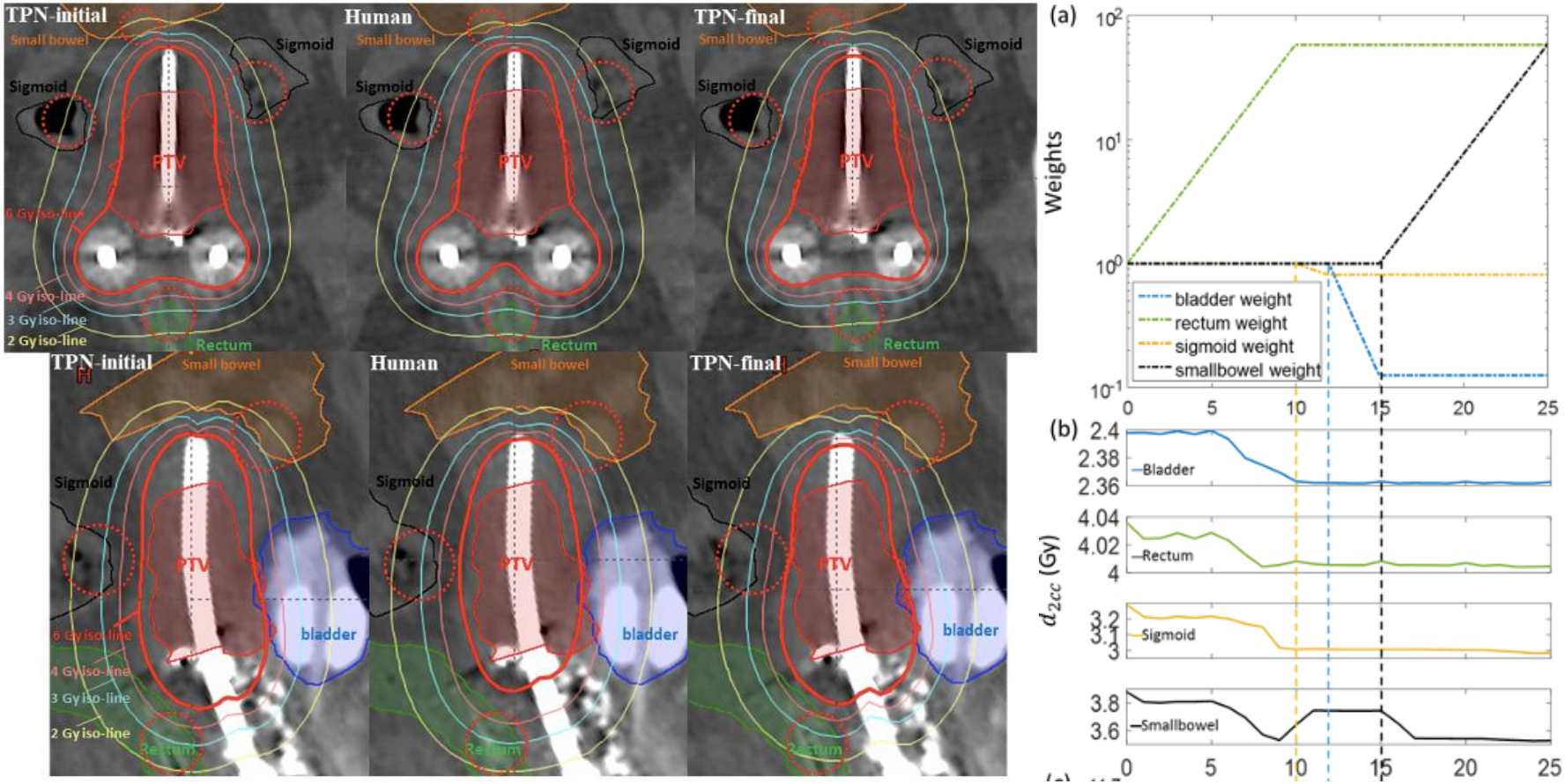
Dose Prediction - Navigation w/ Beam Angles



AI for Treatment Planning

- Hyper-parameter Tuning w/ DRL

HDR Planning w/ DRL Based Organ Weight Tuning



arXiv.org > physics > arXiv:1811.10102

Shen,..., Jia, *Phys Med Biol.* 64(11):115013, 2019.

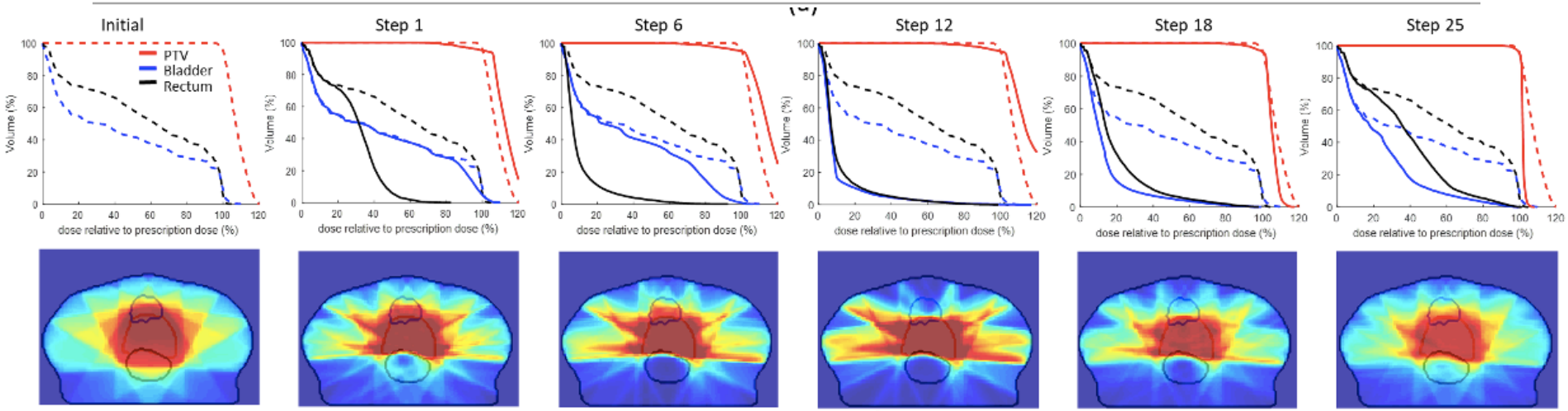
Physics > Medical Physics

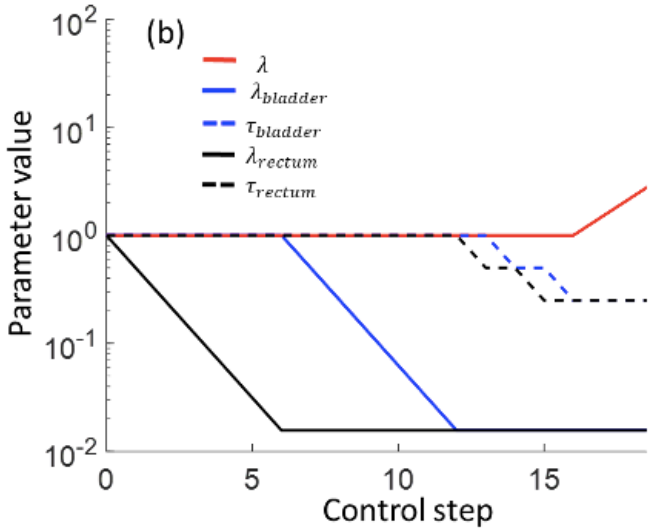
[Submitted on 25 Nov 2018]

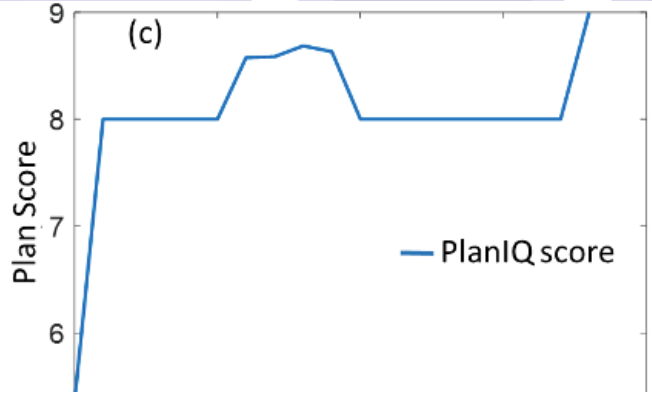
Intelligent Inverse Treatment Planning via Deep Reinforcement Learning, a Proof-of-Principle Study in High Dose-rate Brachytherapy for Cervical Cancer

Chenyang Shen, Yesenia Gonzalez, Peter Klages, Nan Qin, Hyunuk Jung, Liyuan Chen, Dan Nguyen, Steve B. Jiang, Xun Jia

IMRT Planning w/ DRL Based Hyper-Parameter Tuning







Medical Physics Letters | Free Access

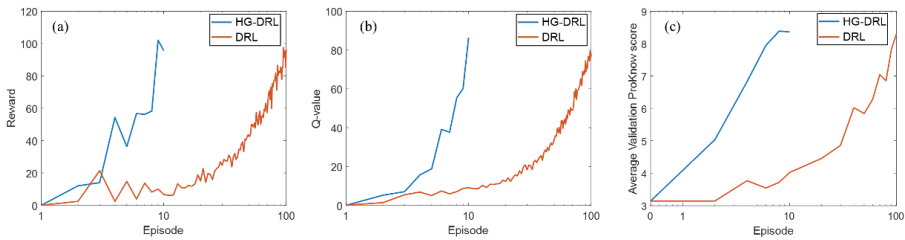
Operating a treatment planning system using a deep-reinforcement learning-based virtual treatment planner for prostate cancer intensity-modulated radiation therapy treatment planning

Chenyang Shen, Dan Nguyen, Liyuan Chen, Yesenia Gonzalez, Rafe McBeth, Nan Qin, Steve B. Jiang, Xun Jia

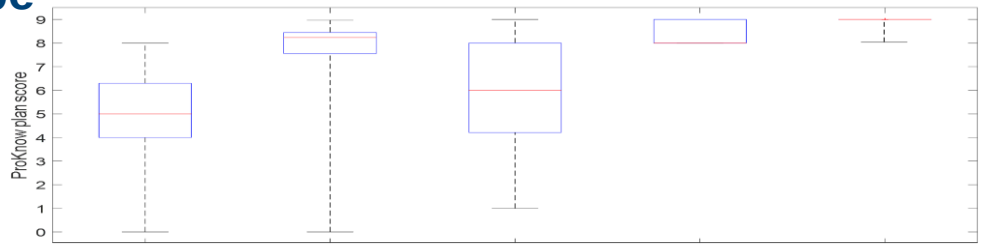
First published:05 March 2020 | https://doi.org/10.1002/mp.14114

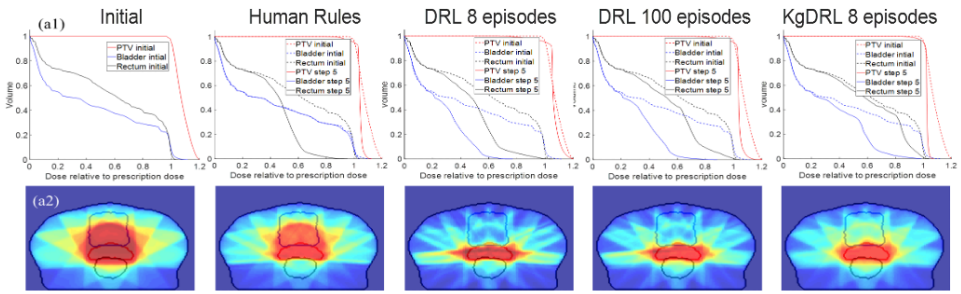
Hyper-Parameter Tuning w/ Human-Knowledge Guided DRL

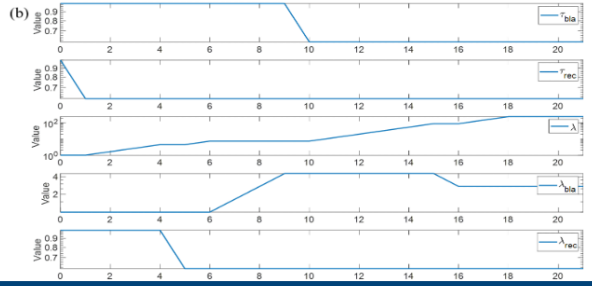
- **Standard DRL is inefficient in training because of searching for optimal policy randomly**
- **Human planner's rule in operating a TPS generally works, but may not be optimal**
- **Human-knowledge guided DRL**
  - **Sample actions based on human knowledge**
  - **Allow random search to explore new policy**
  - **Substantial improvement in training efficiency**
  - **Better performance in treatment planning**

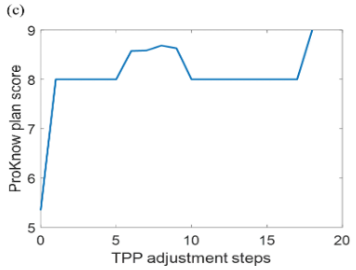


Training time of KgTPN is only 8% of TPN



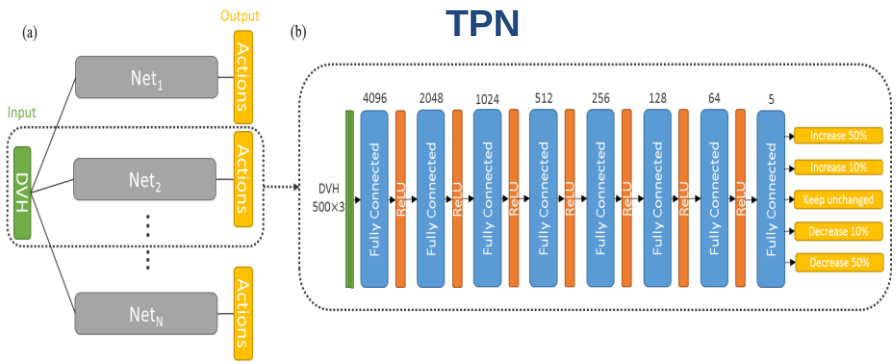




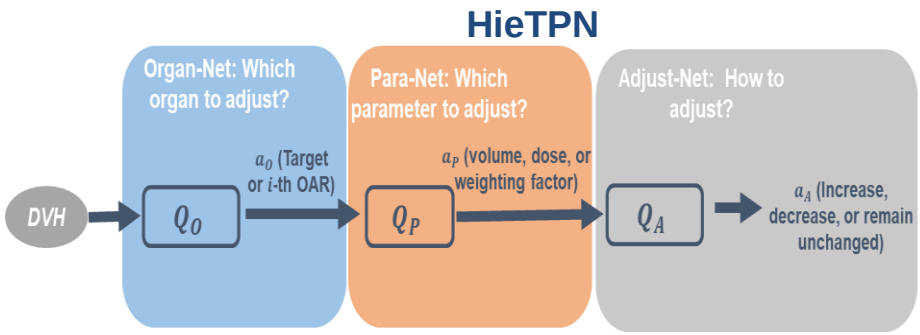


Hyper-Parameter Tuning w/ Hierarchical TP Network

- **Standard DRL does not scale to actual planning cases**
  - Network size of TPN grows with number of actions for a TPS linearly



- **Hierarchical TPN (HieTPN)**
  - A **mathematically rigorous Hierarchical DRL framework** to train HieTPN
  - Sequential decision making similar to a human
  - Network size does not grow with number of TPS actions



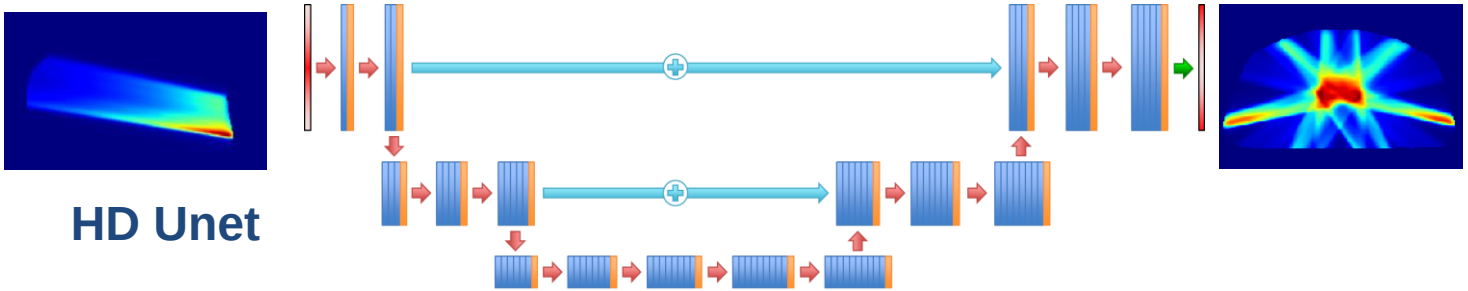
Planning Performance of TPN and HieTPN		
	PlanIQ score (TPN initial)	PlanIQ score (TPN-final)
TPN	4.84 ($\pm$2.02)	8.44 ($\pm$0.48)
HieTPN	4.84 ($\pm$2.02)	8.62 ($\pm$0.83)

AI for Treatment Planning

- Dose Calculation

Dose Calculation using Deep Learning

- **Deep learning can learn the difference between a simple and a sophisticated dose calculation method**
  - scatter dose and inhomogeneity effort
- **A completely different system is good for secondary dose check**
- **It can be used when real-time efficiency and reasonable accuracy are needed**
  - Intermediate step dose calculation during plan optimization
  - Plan casting for online ART



HD Unet

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%

arXiv.org > physics > arXiv:1908.03159

Xing, ..., Jiang, *Med Phys* 47(2)753-758, 2020

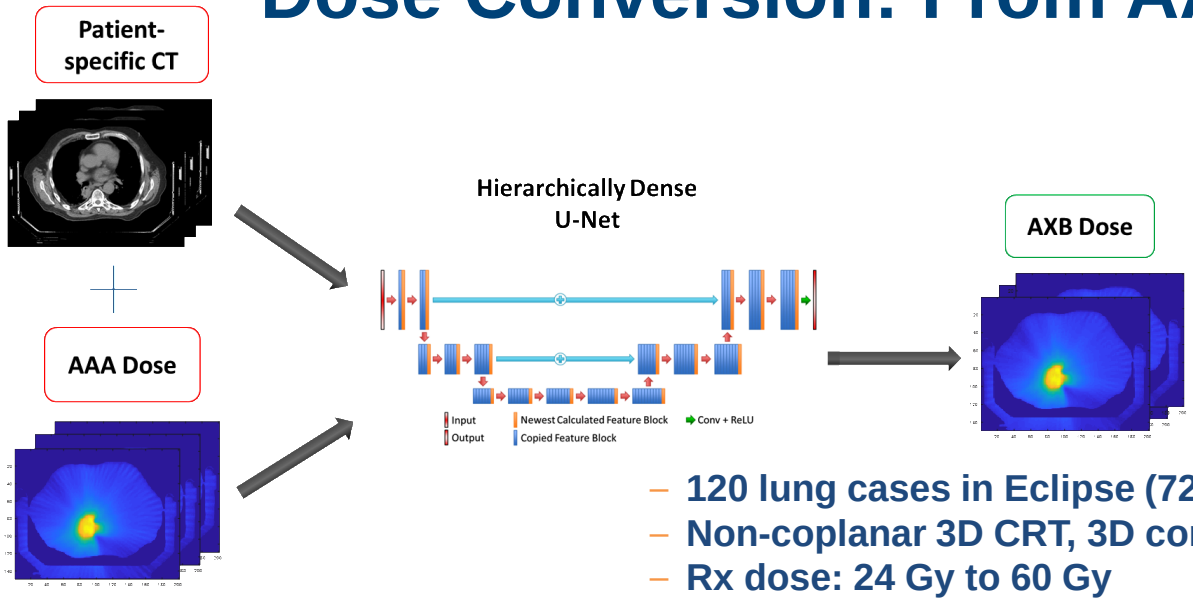
Physics > Medical Physics

[Submitted on 8 Aug 2019]

A Feasibility Study on Deep Learning-Based Radiotherapy Dose Calculation

Yixun Xing, Dan Nguyen, Weiguo Lu, Ming Yang, Steve Jiang

Dose Conversion: From AAA to Acuros XB



- 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		MSE	% of voxels over 3% dose diff of Rx dose
	2mm/2%	1mm/1%		
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)%

arXiv.org > physics > arXiv:2005.03065

Xing, Zhang, …, Jiang, *JACMP* DOI: 10.1002/acm2.12937, 2020

Physics > Medical Physics

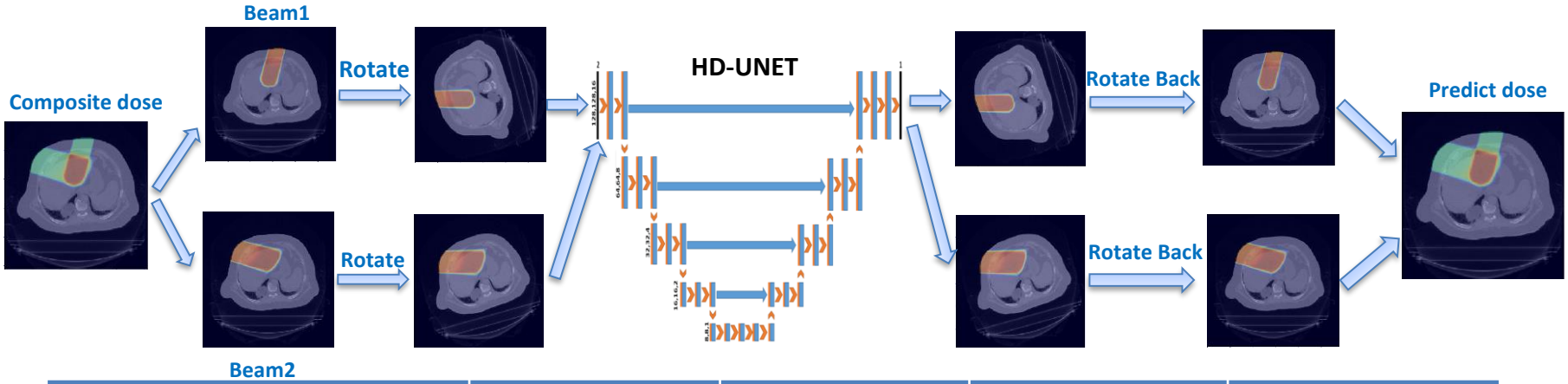
[Submitted on 6 May 2020 (v1), last revised 15 May 2020 (this version, v2)]

Boosting radiotherapy dose calculation accuracy with deep learning

Yixun Xing, Ph.D., You Zhang, Ph.D., Dan Nguyen, Ph.D., Mu-Han Lin, Ph.D., Weiguo Lu, Ph.D., Steve Jiang, Ph.D

Convert PB Dose to MC Dose for Proton RT

- **MGH Data: Pencil Beam (XiO) → Monte Carlo (TOPAS)**



	HN	Liver	Prostate	Lung
Number of patients	90	93	75	32
Number of beams	726	218	260	91
Pencil Beam vs MC	(73.3±6.3) %	(79.2±5.1) %	(73.3±2.7) %	(65.4±5.3) %
Predicted vs MC	(92.8±2.9) %	(92.7±2.9) %	(99.6±0.3) %	(89.7±3.8) %

Gamma index (1%/1 mm)

arXiv.org > physics > arXiv:2004.02924

Physics > Medical Physics

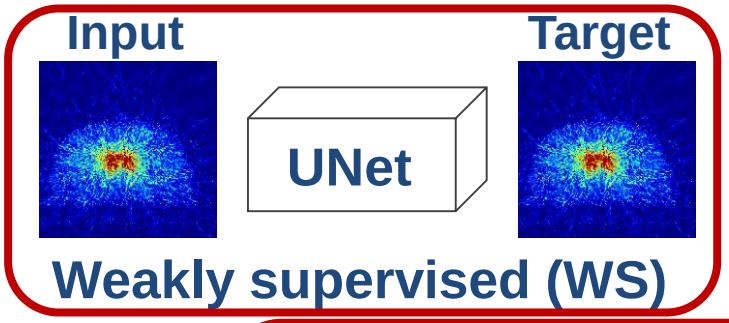
[Submitted on 6 Apr 2020]

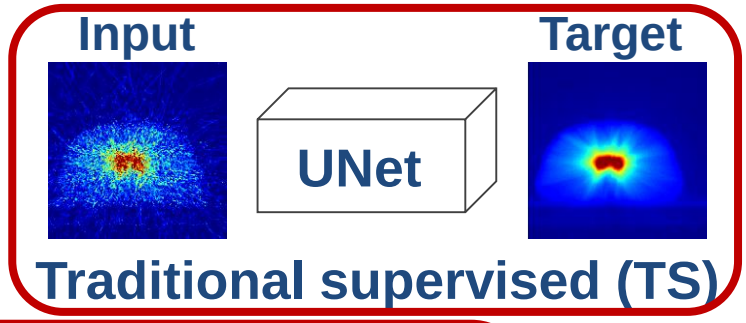
Improving Proton Dose Calculation Accuracy by Using Deep Learning

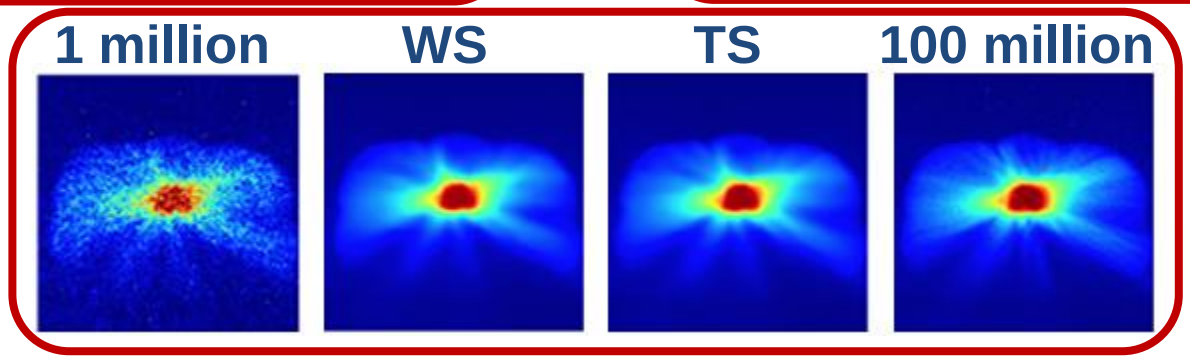
Chao Wu, Dan Nguyen, Yixun Xing, Ana Barragan Montero, Jan Schuemann, Haijiao Shang, Yuehu Pu, Steve Jiang

MC Denoising w/ Weakly SL and Lightweight CNN

- **Goal**
  - A DL denoising plugin to facilitate real-time MC dose calculation
  - ~100X efficiency improvement
- **Methods**
  - Weakly supervised learning for high training efficiency
  - A lightweight CNN for high inference efficiency







- **Relative MSE: 1.9% (WS); 1.8%(TS)**
- **Inference speed: ~80ms on one Tesla K80 GPU**

AI for Treatment Planning

- Beam Angle Optimization

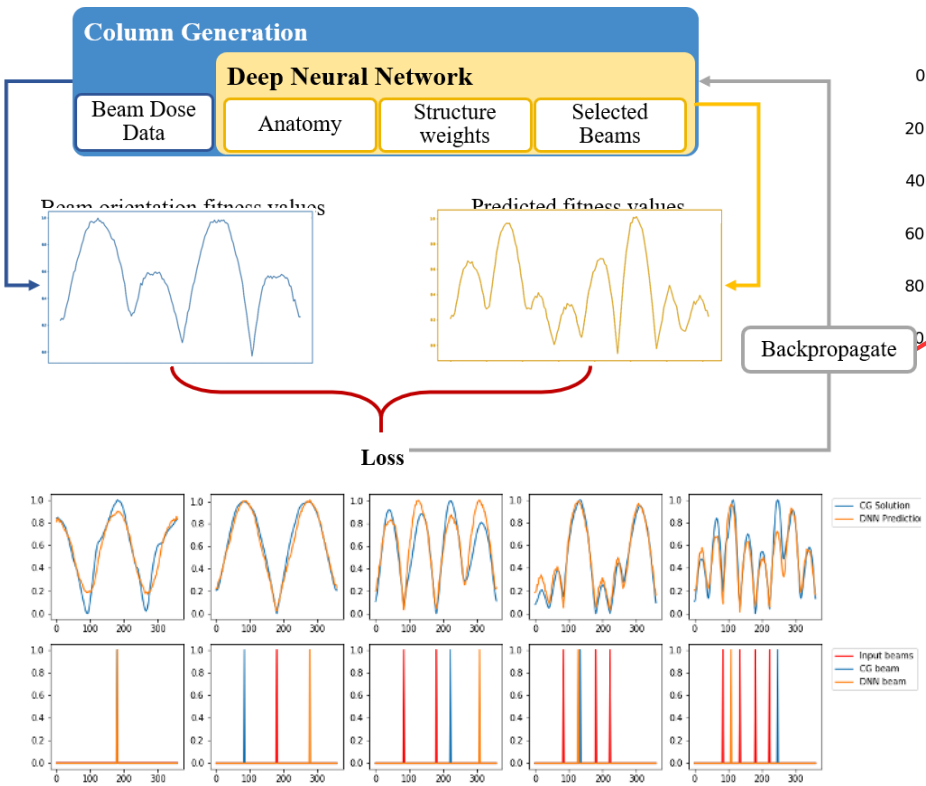
AI for Beam Orientation Optimization (BOO)

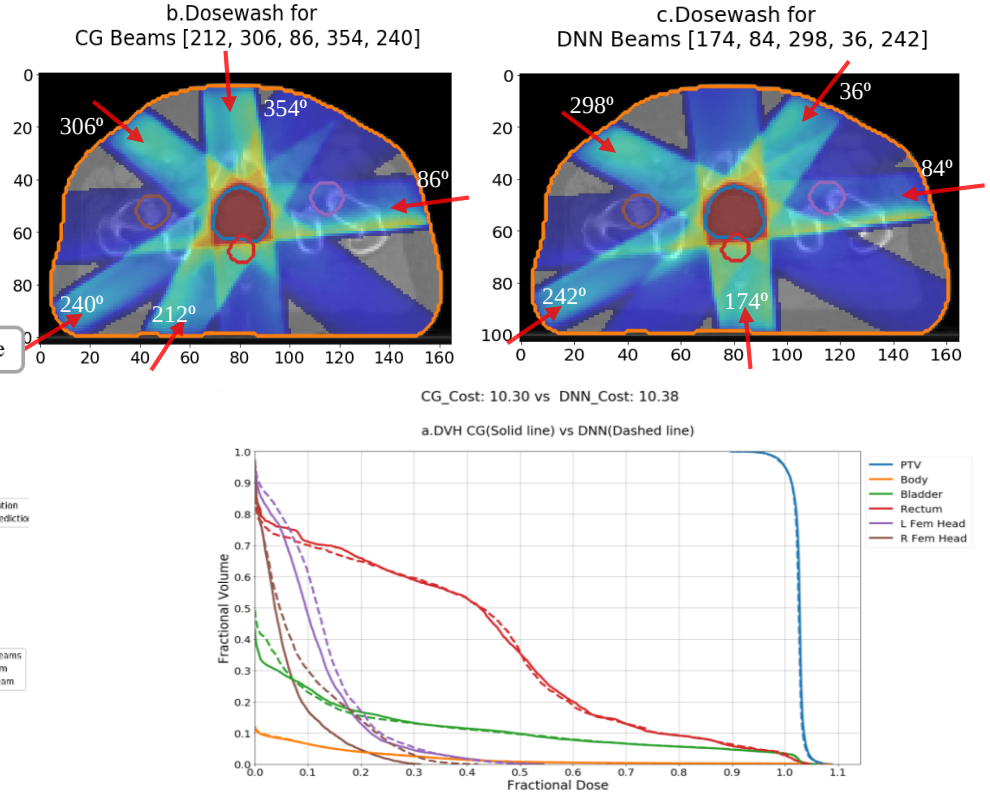
- **Develop an AlphaGo type of DL algorithm**
  - reinforcement learning (RL) policy network
  - Monte Carlo Tree Search (MCTS)
- **Go movements → CyberKnife robot sequence**

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

DeepBOO V1: Policy Network Trained w/ Column Generation

Use column generation (CG) to train a supervised learning (SL) policy network





arXiv.org > physics > arXiv:1905.00523

Sadeghnejad Barkousaraie, …, Nguyen, *Med Phys* 47(3)880-897, 2020.

Physics > Medical Physics

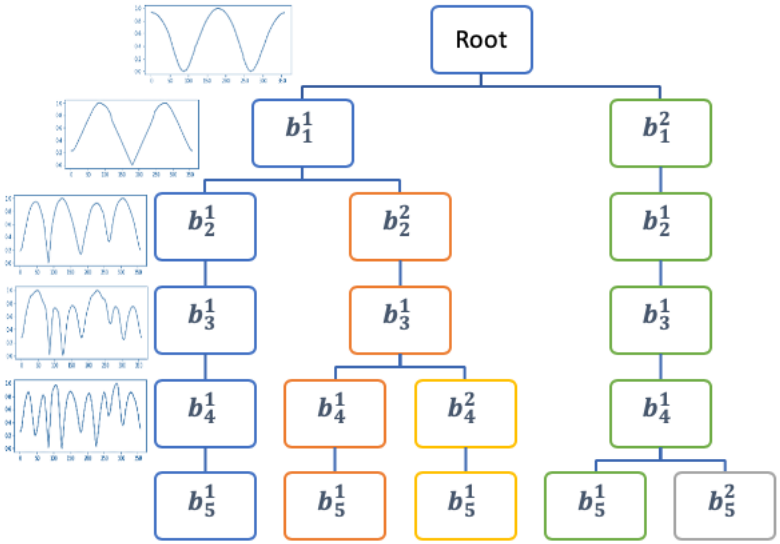
[Submitted on 1 May 2019 (v1), last revised 19 Dec 2019 (this version, v2)]

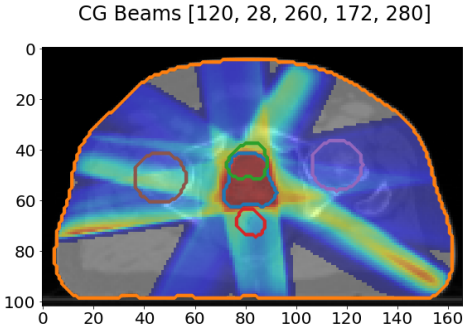
A Fast Deep Learning Approach for Beam Orientation Optimization for Prostate Cancer IMRT Treatments

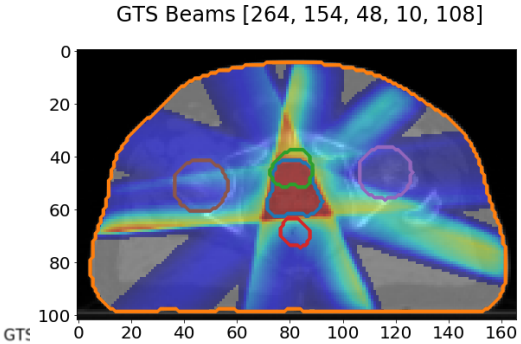
Azar Sadeghnejad Barkousaraie, Olalekan Ogunmolu, Steve Jiang, Dan Nguyen

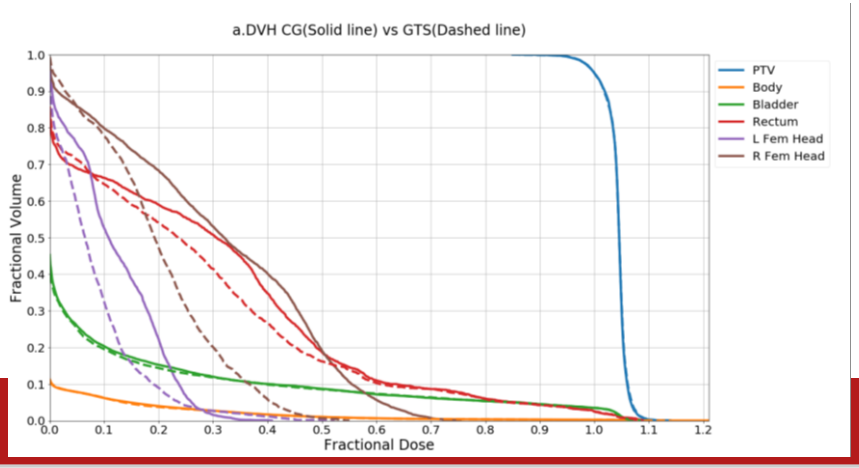
DeepBoo V2: Guided Monte Carlo Tree Search

- **Policy network quickly generates a sampling probability at each level**
- **Tree builds its own policy over time**
  - Search policy is updated as a weighted sum of NN policy and tree policy









arXiv.org > physics > arXiv:2004.06244

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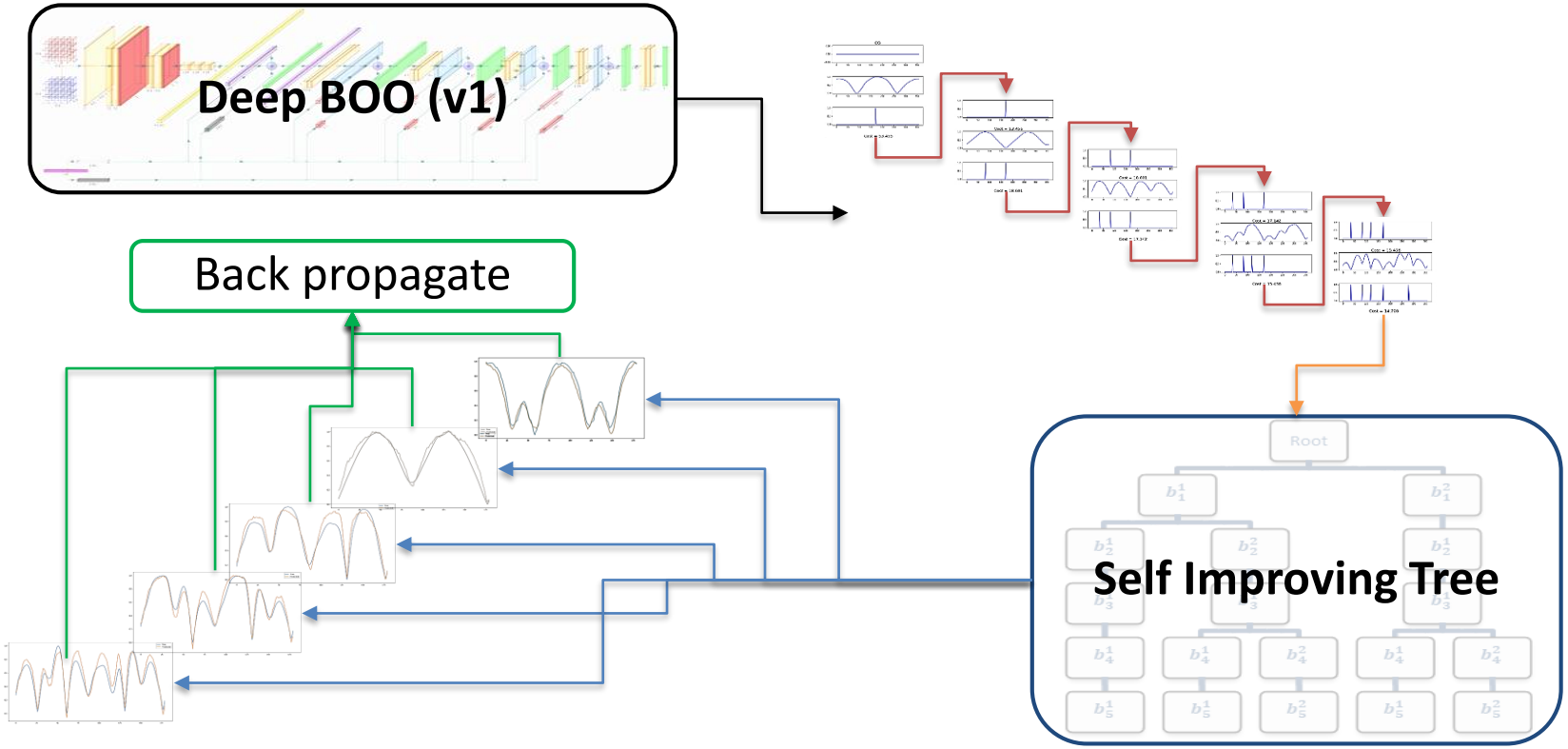
[Submitted on 14 Apr 2020]

A reinforcement learning application of guided Monte Carlo Tree Search algorithm for beam orientation selection in radiation therapy

Azar Sadeghnejad-Barkousaraie, Gyanendra Bohara, Steve Jiang, Dan Nguyen

DeepBoo V3: w/o the need of pre-dose calculation

- **DNN is updating during the tree search after exploring each leaf**
- **No prior dose calculation is needed:**
  - Using a pre-trained network to measure the quality of the treatment plan



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