



Data Driven Automation and Practice Quality Evaluation

Todd McNutt PhD
Associate Professor
Radiation Oncology
Johns Hopkins University





Disclosures

This work has been partially funded with collaborations from:

Radiation Oncology Institute
Canon Medical Systems
Philips Radiation Oncology Systems

Todd McNutt is a Co-Founder of Oncospace Inc.

2

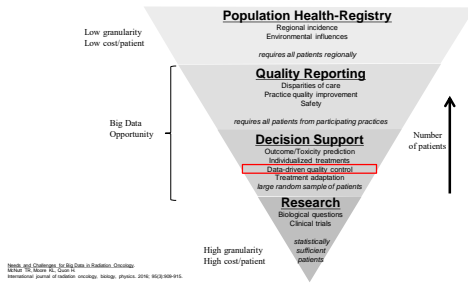


July 15, 2019

<https://globalcompliance.com/quality-management-systems/>

3

Levels of Big Data



Data for quality control



- Indications
 - Diagnosis, staging and histology
 - Guidelines
- Radiation
 - Prescription
 - Regions of interest
 - Dosimetry
 - Beam delivery (logs)
 - Imaging
- Patient outcomes
 - Clinician assessed toxicity
 - Patient reported
 - Disease response

7/15/2019

5

Measures for quality control

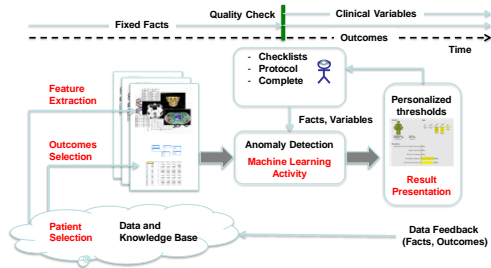


- Dose goals (DVH)
- Dose measurement (IMRT QA, diode)
- Delivery complexity (IMRT modulation)
- Region of interest features (volume)
- Patient localization (imaging and couch)
- Patient toxicity (modeled and measured)
- . . .

July 15, 2019

6

Learning health system – Quality Check



What does it mean to be data driven?

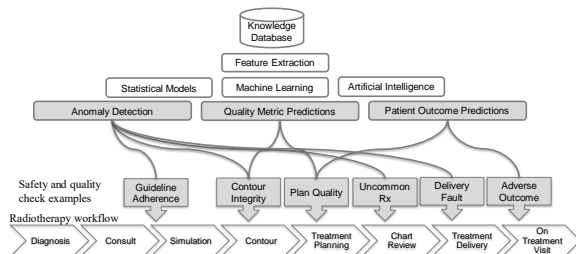


- Protocols are population based
- Each patient is different
- Data can provide personalization within population based guidelines
- Prediction models and refined cohort selection provide patient-specific guidelines

July 15, 2019

8

Learning health system to support quality and safety



Potential data driven checks



- Region of interest anomalies
- Dose goals
- NTCP, TCP
- Treatment plan complexity
- Rx appropriateness

July 15, 2019

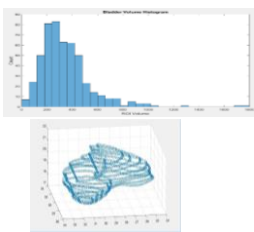
10

Contour integrity

Veera Shah

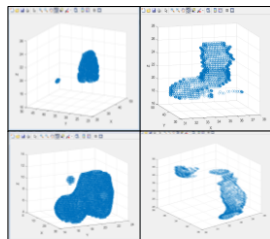


Data-driven

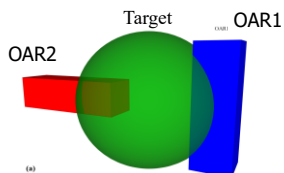


July 15, 2019

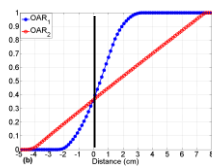
Contiguousness



OVH: serial vs parallel



(a)



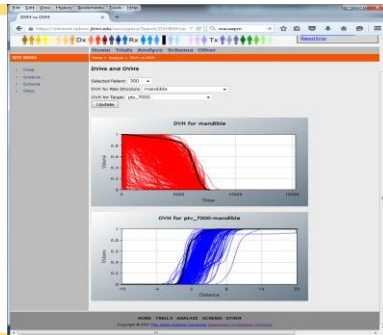
(b)

For parallel organs, **OAR2** is more easily spared.
For serial organs, **OAR1** is more easily spared.

**Mandible
vs
PTV_7000**

pt: 300

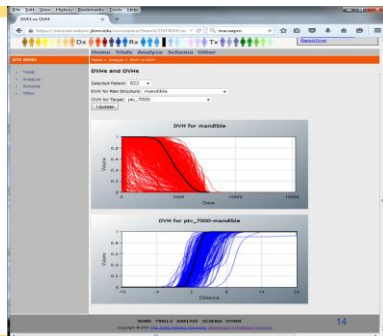
7/15/2019



**Mandible
vs
PTV_7000**

pt: 822

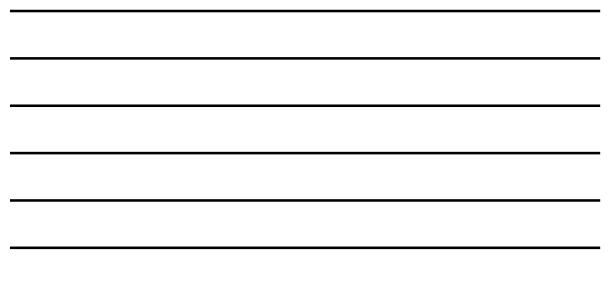
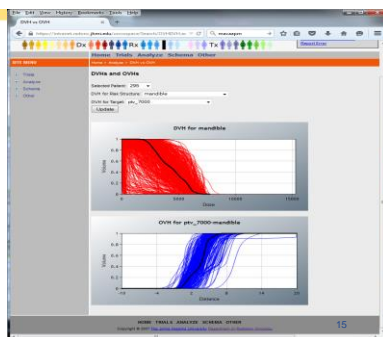
7/15/2019



**Mandible
vs
PTV_7000**

pt: 295

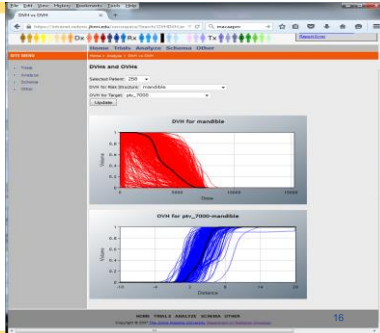
7/15/2019



Mandible vs PTV_7000

pt: 258

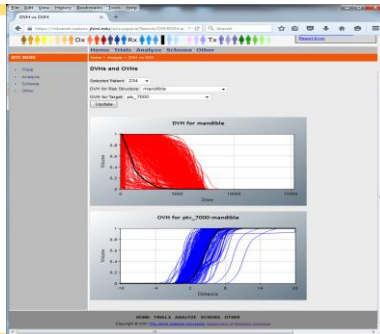
7/15/2019



Mandible vs PTV_7000

pt: 234

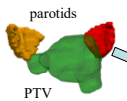
7/15/2019



Shape-dose relationship for radiation plan quality



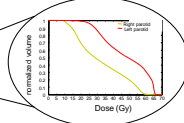
Shape relationship



DB of prior patients



Dose prediction



Decisions:

- Plan quality assessment
- Automated planning
 - IMRT objective selection
- Dosimetric trade-offs

For a selected Organ at Risk and % V, find the lowest dose achieved from all patients whose % V is closer to the selected target volume?

Radiation prescription safety



ID	ICD9	Morphology	Site	Px	Dose	Freq	Count	Total
1191 Brain: MN		Glioblastoma, NOS (T-191_)	Right pariet-occ GBM	23	200	35.97%	100	278
1191 Brain: MN		Glioblastoma, NOS (T-191_)	CD Right par-occ GBM	7	200	37.77%	105	278
1154 Rectum, Rectosigmoid Junction		Adenocarcinoma, NOS	rectal CD	3	180	29.28%	98	130
1154 Rectum, Rectosigmoid Junction		Adenocarcinoma, NOS	whole pelvis PTV	25	180	43.68%	56	130
1150 Esophagus: MN		Adenocarcinoma, NOS	Esophagus	23	180	65.71%	46	70
1191 Brain: MN		Medulloblastoma, NOS	Craniospinal	23	180	0%	0	27
1191 Brain: MN		Medulloblastoma, NOS	Left cerebellar CD	7	180	0%	0	27
1157 Pancreas: MN		Adenocarcinoma, NOS	Left Retroperitoneum	11	250	0.56%	1	252
1174 Female Breast: MN		Infiltrating duct carcinoma	L CMV-Low ax	20	180	5.54%	34	624
1174 Female Breast: MN		Infiltrating duct carcinoma	LTPAB	25	50	0.49%	3	624
1174 Female Breast: MN		Infiltrating duct carcinoma	LTH Ax+Sc	25	200	18.97%	124	624
1141 Tongue: MN		Squamous cell carcinoma, NOS	PTV left neck, L BOT	40	130	0.69%	1	151
1162 Trachea, Bronchus, Lung: MN		Adenocarcinoma, NOS	Left parietal PTV	1	2000	0.51%	1	197
1162 Trachea, Bronchus, Lung: MN		Adenocarcinoma, NOS	Rt lung & SCV node	6	200	1.52%	3	197
1162 Trachea, Bronchus, Lung: MN		Adenocarcinoma, NOS	Rt lung tumor c/GABC	6	200	1.52%	3	197
1162 Trachea, Bronchus, Lung: MN		Adenocarcinoma, NOS	Rt lung/SVC nodeABC	21	200	1.02%	2	197
1140, C41 Bones and joints		Malignant melanoma, NOS	Right T10 Paraspinal	5	500	0.0%	0	50
1162 Trachea, Bronchus, Lung: MN		Adenocarcinoma, NOS	Rt lung mass	4	1200	4.14%	36	902
1102 Lymphoid/Histiocytic Tiss		Malignant lymphoma, large cell	boost ptx	3	180	0%	0	27
1102 Lymphoid/Histiocytic Tiss		Malignant lymphoma, large cell	whole brain	10	300	11.11%	3	27

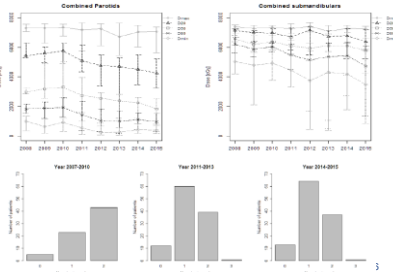
Importance of model update

Minuro Nakatsugawa



Table 1: Patient Characteristics

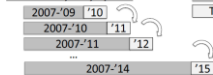
Characteristic	N	%
Age		
Median	57	28.4
Age Range		
18-24 years	10	5.0
25-34 years	10	5.0
35-44 years	10	5.0
45-54 years	10	5.0
55-64 years	10	5.0
65-74 years	10	5.0
75-84 years	10	5.0
85-94 years	10	5.0
95-104 years	10	5.0
105-114 years	10	5.0
115-124 years	10	5.0
125-134 years	10	5.0
135-144 years	10	5.0
145-154 years	10	5.0
155-164 years	10	5.0
165-174 years	10	5.0
175-184 years	10	5.0
185-194 years	10	5.0
195-204 years	10	5.0
205-214 years	10	5.0
215-224 years	10	5.0
225-234 years	10	5.0
235-244 years	10	5.0
245-254 years	10	5.0
255-264 years	10	5.0
265-274 years	10	5.0
275-284 years	10	5.0
285-294 years	10	5.0
295-304 years	10	5.0
305-314 years	10	5.0
315-324 years	10	5.0
325-334 years	10	5.0
335-344 years	10	5.0
345-354 years	10	5.0
355-364 years	10	5.0
365-374 years	10	5.0
375-384 years	10	5.0
385-394 years	10	5.0
395-404 years	10	5.0
405-414 years	10	5.0
415-424 years	10	5.0
425-434 years	10	5.0
435-444 years	10	5.0
445-454 years	10	5.0
455-464 years	10	5.0
465-474 years	10	5.0
475-484 years	10	5.0
485-494 years	10	5.0
495-504 years	10	5.0
505-514 years	10	5.0
515-524 years	10	5.0
525-534 years	10	5.0
535-544 years	10	5.0
545-554 years	10	5.0
555-564 years	10	5.0
565-574 years	10	5.0
575-584 years	10	5.0
585-594 years	10	5.0
595-604 years	10	5.0
605-614 years	10	5.0
615-624 years	10	5.0
625-634 years	10	5.0
635-644 years	10	5.0
645-654 years	10	5.0
655-664 years	10	5.0
665-674 years	10	5.0
675-684 years	10	5.0
685-694 years	10	5.0
695-704 years	10	5.0
705-714 years	10	5.0
715-724 years	10	5.0
725-734 years	10	5.0
735-744 years	10	5.0
745-754 years	10	5.0
755-764 years	10	5.0
765-774 years	10	5.0
775-784 years	10	5.0
785-794 years	10	5.0
795-804 years	10	5.0
805-814 years	10	5.0
815-824 years	10	5.0
825-834 years	10	5.0
835-844 years	10	5.0
845-854 years	10	5.0
855-864 years	10	5.0
865-874 years	10	5.0
875-884 years	10	5.0
885-894 years	10	5.0
895-904 years	10	5.0
905-914 years	10	5.0
915-924 years	10	5.0
925-934 years	10	5.0
935-944 years	10	5.0
945-954 years	10	5.0
955-964 years	10	5.0
965-974 years	10	5.0
975-984 years	10	5.0
985-994 years	10	5.0
995-1004 years	10	5.0



Importance of model update



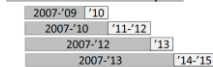
Method A: yearly update



Training data

Test data

Method B: condition-based update



Method C: no update

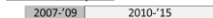


Table 3: Comparison of AUC for grade 2-3 sarcoma prediction in three model updating methods

	Model updating	Training data	Test data	AUC (2008-2015)
A	Every year (6 times)	2007 - year 6 (2008 - 2012) (5 years)	year 6-1	0.683
B	Condition-based updates (update if AUC < 0.6, 3 times)	2007 - year 7 (year 6-10) (4 years)	year 6-1	0.604
C	No updates (Baseline model)	2007 - 2009	2010 - 2015	0.489

How to stay safe and maintain quality?



- Data is not always the highest quality – must make sure methods/models don't assume it is
- Data does not contain all knowledge. Existing knowledge is often absent
 - If all patients in database meet a dose goal, then there is no knowledge outside of that goal contained in the data.
 - Be wary of situations where you may be outside of the available data bounds
- Data gets old
 - How to keep models current?
 - Do we want to be treated the way patients were treated a 2 decades ago?
 - The Rx anomaly may be using an old Rx that has been superseded.

July 15, 2019

28

Summary



- Quality follows a system of checks
- Predefined checklists and scorecards provide population level quality
- Data driven methods can personalize the measures of quality
- The learning health system concept offers the opportunity to include data driven quality systems into clinical practice

July 15, 2019

29

Thank You

July 15, 2019

30

Acknowledgments



- **JHU-RO**
 - Sierra Cheng MD
 - Peijin Han MD
 - Michael Bowers BS
 - Joseph Moore PhD
 - Scott Robertson PhD
 - Pranav Lakshminarayanan MS
 - Xuan Hu MD
 - Junghoon Lee PhD
 - John Wong PhD
 - Theodore DeWeese MD
- **GI Team**
 - Joseph Herman MD
 - Amy Hacker-Prietz PA
- **H&N Team**
 - Harry Quon MD
 - Ana Keiss MD
 - Brandi Page MD
- **Thoracic Team**
 - Russ Hales MD
 - Ranth Voong MD
 - Lori Anderson, Kristy Ford
- **JHU - CS**
 - Russ Taylor PhD
 - Misha Kazhdan PhD
 - Ilya Shpilner PhD
 - Siddiqui Saleh PhD
 - Wei Jiang PhD (6/18)
- **Philips PROS**
 - Karl Bzdusek BS
- **Toshiba/Canon**
 - Minoru Nakatsugawa PhD
 - John Haller
- **University of Washington**
 - Kim Evans MS
 - Mark Phillips PhD
 - Kristi Hendrickson PhD

Manufacturing Quality



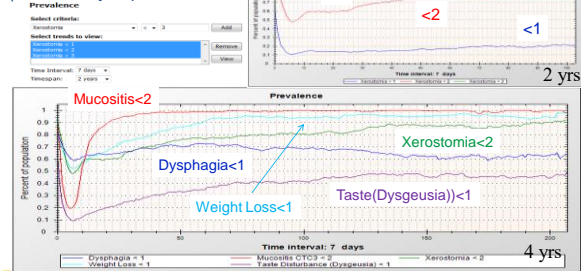
- Do things the same way every time
- Control of process
- Testing samples
- Feedback from measures
- But each patient is different

July 15, 2019

32

Toxicity Prevalence

(P. Lakshminarayanan)



Which patient will do better?



69-year-old man with Stage Squamous cell carcinoma, NOS of the Right Malignant neoplasm of tonsil

63-year-old man with T3 N2b M0 Stage IVA Squamous cell carcinoma, NOS of the Malignant neoplasm of larynx