

Quantitative Imaging in Radiomics and Machine Learning

AI in Radiation Oncology – Now and in the Future

Charles Mayo, Ph.D.
University of Michigan

TU-GH-D888-0
Tuesday July 31 1:45-3:45



Disclosures

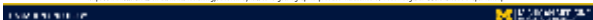
Grants from Varian Medical Systems



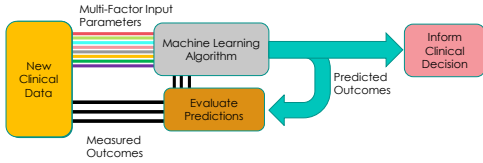
Artificial Intelligence is poised to soon be a
routine part of our reality



<https://www.msn.com/en-us/news/technology/boston-dynamics-is-gearing-up-to-produce-thousands-of-robots-designed-for-industrial-design/ar-BBQNEChcolrger?hpid=hp>



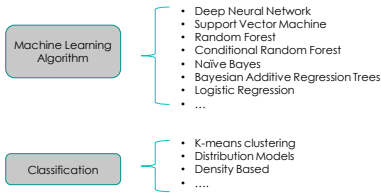
Machine Learning



Pattern Matching
Fact Finding
Typically, Black Box Predictions



Machine Learning

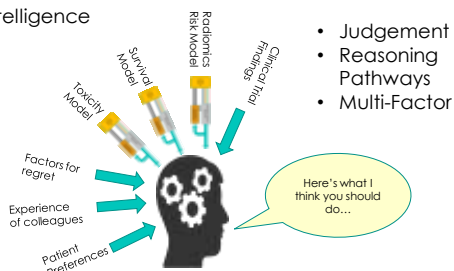


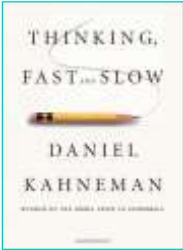
Algorithms are widely available (R,Python, C#.Net, ...), but can have issues:

- Susceptibility to overfitting
- Interpretability
- Accuracy



Artificial Intelligence





- All physicians would like to learn from experience
- We don't want to treat according to the "last error" or "last success"
- But our memories are very selective
- "In my experience..."

TS Lawrence, PBDW2018

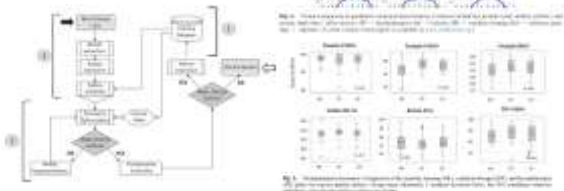


We are seeing ML increasingly applied across a wide range of Radiation Oncology tasks



Evaluation of a Machine Learning Algorithm for Treatment Planning in Prostate Low-Dose-Rate Brachytherapy
 Alexander Brink, PhD^{1,2}, David Harter, MD, Alan Hsing, MD, Michael Lujan, MD, Anand Srin, MD, PhD, Paul Sigmund, MD, PhD, Li Lu, MD, Justin Wang, MD, Phyllis K. Tenenbaum, PhD, Holly Heath, PhD, and Anand Srin, PhD

IJROBP. 2017; 97(4): 822-829



A Novel Methodology using CT Imaging Biomarkers to Quantify Radiation Sensitivity in the Esophagus with Application to Clinical Trials

Scientific Reports, 2017; 7:4034 | DOI:10.1038/s41598-017-00034-4

Study Size	Population	Intervention	Outcome
1000	1000	1000	1000
1000	1000	1000	1000
1000	1000	1000	1000

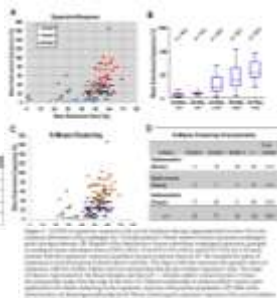


FIGURE 1. Biomarker values for CT imaging biomarkers. A: Heatmap of biomarker values. B: Box plot of biomarker values. C: Scatter plot of biomarker values. D: Table of biomarker values.

Support Vector Machines Model of Computed Tomography for Assessing Lymph Node Metastasis in Esophageal Cancer with Neoadjuvant Chemotherapy

Int J Comput Assist Tomogr 2017; 41:455-460

Indicator	ROC	SE	NPV
Thickness on pCT	0.820	0.0090	0.811 to 0.791
LSL N on pCT	0.865	0.0052	0.878 to 0.746
SSL N on pCT	0.705	0.0446	0.619 to 0.782
Number of LN on pCT	0.609	0.0424	0.590 to 0.709
Number of LN on nCT	0.816	0.0020	0.847 to 0.718
Thickness change	0.814	0.0096	0.845 to 0.716

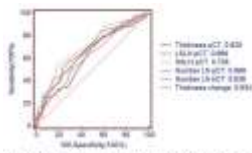


FIGURE 2. Receiver operating characteristic (ROC) curve for lymph node metastasis with an CT indicator. The highest AUC of these six CT indicators was 0.705 which was performed by the mean and size of metastases lymph node CT indicator of preoperative CT. Figure 2 can be viewed online at <http://dx.doi.org/10.1007/s12018-017-0003-4>.

Deep Learning Algorithms for Auto-Delineation of High-Risk Oropharyngeal Clinical Target Volumes With Built-In Dice Similarity Coefficient Parameter Optimization Function

Study Size	Population	Intervention	Outcome
1000	1000	1000	1000
1000	1000	1000	1000
1000	1000	1000	1000

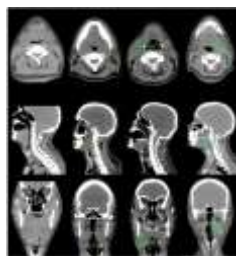


FIGURE 3. Auto-delineation of high-risk oropharyngeal clinical target volumes. The images show the results of the deep learning algorithm for auto-delineation of high-risk oropharyngeal clinical target volumes.

FIGURE 3. Auto-delineation of high-risk oropharyngeal clinical target volumes. The images show the results of the deep learning algorithm for auto-delineation of high-risk oropharyngeal clinical target volumes.

Big Data and Predictive Analytics - Recalibrating Expectations

Thoughtful Identification of Risk-Sensitive Decisions

- "Prediction modelers frequently give scant attention to the formal properties of clinical decisions that might make them risk sensitive"
- "It is surprising how rarely good predictions are brought to bear on difficult clinical decisions in a way that affects clinical outcomes"

Shah ND, Steyerberg EW, Kent DM. Big Data and Predictive Analytics Recalibrating Expectations. JAMA. 2018;320(1):27-28. doi:10.1001/jama.2018.5602



Big Data and Predictive Analytics - Recalibrating Expectations

Calibration: The Achilles Heel of Prediction

- Benchmarking
- Test stability with variations with populations
- Test sensitivity to unmeasured cofactors
- Test reliability to correctly give the known answer
- Clinically interpretable

Shah ND, Steyerberg EW, Kent DM. Big Data and Predictive Analytics Recalibrating Expectations. JAMA. 2018;320(1):27-28. doi:10.1001/jama.2018.5602



Annals of Internal Medicine RESEARCH AND REPORTING METHODS

Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD): Explanation and Elaboration

Royston P, Moons P, Schemper D, et al. *Ann Intern Med*. 2015;162:W1-W73



Big Data and Predictive Analytics - Recalibrating Expectations

User Trust, Transparency, and Commercial Interests

- Hype or reality
- What's really going on in the ML black box?
- Influence of commercial, or other, gain

Shah ND, Steyerberg EW, Kent DM. Big Data and Predictive Analytics Recalibrating Expectations. JAMA. 2018;320(1):27-28. doi:10.1001/jama.2018.5602



Big Data and Predictive Analytics - Recalibrating Expectations

Data Quality and Heterogeneity

- Volume and quality of data used in models
- Inconsistent coding practices
- Who is entering the data?
- Lack of standardization of data extracted from EHR

Shah ND, Steyerberg EW, Kent DM. Big Data and Predictive Analytics Recalibrating Expectations. JAMA. 2018;320(1):27-28. doi:10.1001/jama.2018.5602

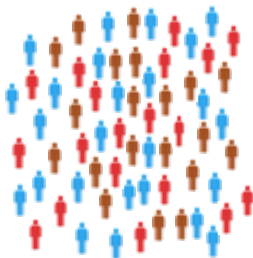


Challenge for ML viability

Model developed for relatively small cohort



Much larger more diverse population



There are challenges for AI to match the sophistication of humans



<https://www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk>



The report of Task Group 150 of the AAPM: Application of risk analysis methods to radiation therapy quality management

- Dr. David Hall***
Department of Radiation Oncology, University of Toronto, Toronto, Ontario and (2016) Visiting Professor, Pennsylvania State University, University Park, PA, USA
- Dr. David A. J. Phipps**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Peter B. Sturgis**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. John P. Gibbins, Jr.**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Stephen G. Meade**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Anne J. Hagan**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Todd Hinkle**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Jennifer E. Phipps**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Frank Pugh**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Steven B. Thomopoulos**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Jeffrey F. Williamson**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada
- Dr. Alan D. Kirk**
Department of Radiation Oncology, University of Toronto, Toronto, Ontario, Canada



Let's place scripting in automation in the context of Failure Mode and Effects Analysis (FMEA)

- What could go wrong that would impact a patient?
- How likely is it that this will happen?
- How bad would it be if this happened?

Working Group on Treatment Planning – Sponsoring a new task group for scripting (R. Pople et al)



"The computer is magic, I can disconnect my brain"

Importance of building in sanity checks

- **Set plan dose to correct dose, but automate optimization to incorrect dose**
- Plan only has a prescribed dose (DPV) point so it looks like everything is OK.
- If physical dose point in high dose target were added, there would be a cross checkable sanity check



"The computer is magic, I can disconnect my brain"

Importance of building in sanity checks

- **Automated plan OAR metrics look OK, but structure (e.g. brain stem) is incorrectly drawn.**
- Automatically generated plan check says everything is OK
- Dig deeper on algorithms to automate checking algorithms, still need people for visual checks



- Special Issue of Medical Physics covering papers from Practical Big Data Workshop 2017 will be out soon
- **Includes recommendations for standards and best practices for ML and AI (I El Naqa et al.)**





Summary

- Medical physicists are exceptionally good at
 - rising to the occasion to create new Tools with new technologies
 - extracting knowledge and understanding about systems from data
 - creating standardizations and guidelines to ensure safety and efficacy

- Machine learning solutions are developing rapidly for use in Radiation Oncology
- True AI to execute decision frameworks are also emerging

- Initiation of task group to promote safety and commissioning guidelines for automation is underway (WGTP)

- Is it is a good time to initiate similar task group efforts for AI and ML?
 - Safety
 - Commissioning
 - Communication
 - Standards

