

Quantitative Imaging in Radiomics and Machine Learning

AI in Radiation Oncology – Now and in the Future

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Disclosures

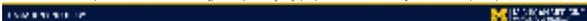
Grants from Varian Medical Systems



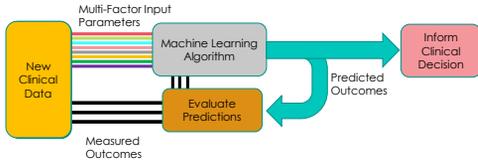
Artificial Intelligence is poised to soon be a
routine part of our reality



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



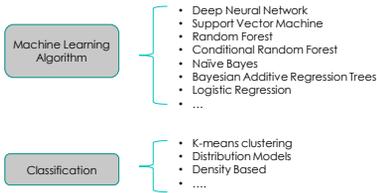
Machine Learning



Pattern Matching
 Fact Finding
 Typically, Black Box Predictions



Machine Learning

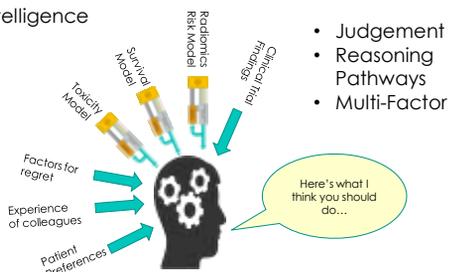


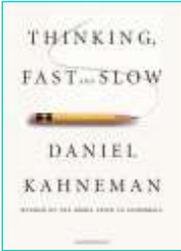
Algorithms are widely available (R,Python, C#.Net, ...), but can have issues:

- 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

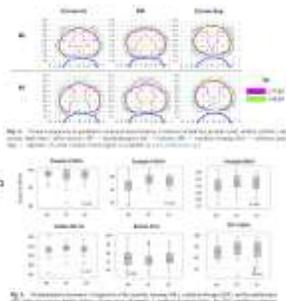
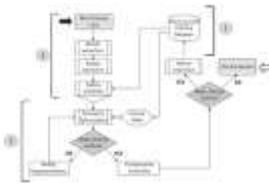


We are seeing ML increasingly applied across a wide range of Radiation Oncology tasks



Evaluation of a Machine Learning Algorithm for Treatment Planning in Prostate Low-Dose-Rate Brachytherapy
 Alexander Brachler, PhD^{1,2}, David Harter, MD, Alan Hsing, MD, Michael Lujan, MD, Anand Sahni, MD, PhD, Paul Sigmund, MD, PhD, Li Lu, MD, Justin Wang, MD, Phyllis K. Tenover, PhD, Kelly Smith, PhD, and Anand Veni, 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/s41598-017-02023-4

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

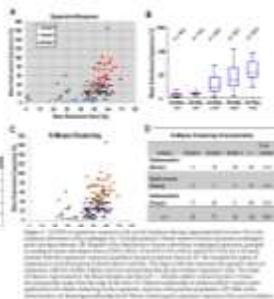


FIGURE 1. Biomarker distributions and correlations. (A) Heatmap of biomarker values. (B) Box plots of biomarker distributions. (C) Scatter plot of biomarker values. (D) Table of biomarker values.

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

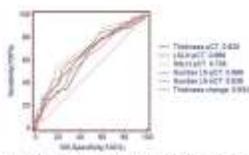
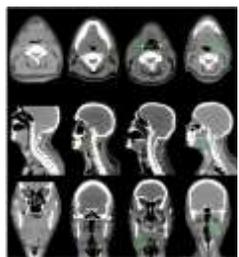


FIGURE 2. Receiver operating characteristic (ROC) curve for lymph node metastasis with an CT indicator. The highest AUC of these six CT indicators was 0.705 which was performed by the mean and size of metastases from the nodes. AUC of preoperative CT. Figure 2 can be viewed online at <http://dx.doi.org/10.1007/s12020-017-02023-4>.

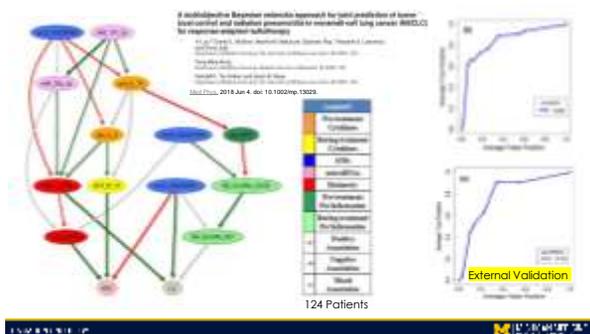
Deep Learning Algorithm for Auto-Delineation of High-Risk Oropharyngeal Clinical Target Volumes With Built-In Dice Similarity Coefficient Parameter Optimization Function

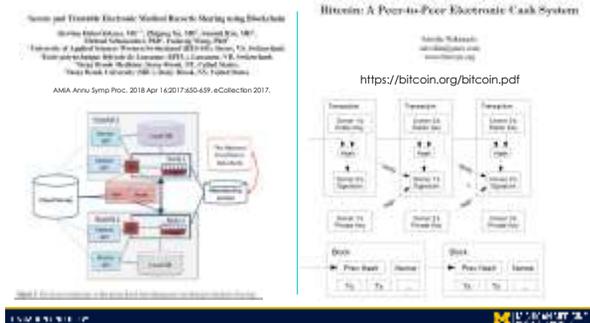
Case	Volume	Volume	Volume	Volume
1	1.00	0.98	0.95	0.92
2	1.00	0.99	0.96	0.93
3	1.00	0.97	0.94	0.91
4	1.00	0.96	0.93	0.90
5	1.00	0.95	0.92	0.89
6	1.00	0.94	0.91	0.88
7	1.00	0.93	0.90	0.87
8	1.00	0.92	0.89	0.86
9	1.00	0.91	0.88	0.85
10	1.00	0.90	0.87	0.84
11	1.00	0.89	0.86	0.83
12	1.00	0.88	0.85	0.82
13	1.00	0.87	0.84	0.81
14	1.00	0.86	0.83	0.80
15	1.00	0.85	0.82	0.79
16	1.00	0.84	0.81	0.78
17	1.00	0.83	0.80	0.77
18	1.00	0.82	0.79	0.76
19	1.00	0.81	0.78	0.75
20	1.00	0.80	0.77	0.74



Int J Radiation Oncol Biol Phys, 2018; 101(2):468-478

FIGURE 3. Axial and sagittal CT scans showing oropharyngeal target volumes. The volumes are delineated in red and compared against ground truth delineations in green.





Areas where ML/AI are looking like they may become viable parts of radiation oncology clinical processes

- Auto-contouring
- Auto-planning and plan evaluation
- Diagnosis and planning approach recommendation
- Radiomics predictors for risk factors

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

Franklin D, Moons P, Altman DG, et al. (2015) *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

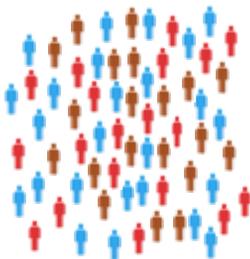


Challenge for ML viability

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 RSPM: Application of risk analysis methods to radiation therapy quality management

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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. Poppo 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

