INCLUSION OF DATA-DRIVEN RISK PREDICTIONS IN RADIATION TREATMENT PLANNING IN THE CONTEXT OF A LOCAL LEVEL LEARNING HEALTH SYSTEM

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Disclosures

This work has been partially funded with collaborations from:

Philips Radiation Oncology Systems
Elekta Oncology Systems
Toshiba Medical Systems

as well as

Commonwealth Foundation
Maritz Foundation

Learning health system
Mandible vs PTV_7000
pt: 258

Mandible vs PTV_7000
pt: 234

Shape-dose relationship for radiation plan quality

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

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

Sample automated radiation planning result

Original plan

Automated plan

Current dose based auto-planning

- Has demonstrated improved quality
- Removed human variability for standard cases
- Now advancing commercially
That was all DVH based

- Dose is not what matters to the patient
- Quantify the patient experience?

Should we just apply existing NTCP and TCP models to dose predictions?

…or should we try to expand the knowledge based approach using clinical data?

Mucositis data collected at JHU

GRADE 1
GRADE 2
GRADE 3
GRADE 4

At what time point do we have enough data to make decisions based on future predictions?

Input Variables => Prediction?
Data Collection in Clinic

Clinical Assessment | Quality of life | Disease Status

FACT HN
SSQ
SHIM
IPSS
PAN26

Head and Neck Inventory
~800 pts up to 6 yr follow up

Head and Neck Inventory
Organs at risk with full 3D dosimetry

Prostate Inventory
~1700 pts - ~650 with dose

DVH, Toxicities and Grade distributions
Bad DVH!

- DVH assumes that every sub-region of an OAR has the same radiosensitivity and functional importance to the related toxicity
- DVH assumes that each OAR is uniquely responsible for the overall human function related to the toxicity

Spatially dependent features of dose in the structures (F. Marungo et al.)

<table>
<thead>
<tr>
<th>Method</th>
<th>Voice dysfunction n=99, n+91, n-91</th>
<th>Xerostomia n=364, n+271, n-89</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bagged Naive Bayes (1000 iterations)</td>
<td>0.915 0.743</td>
<td></td>
</tr>
<tr>
<td>Bagged Linear Regression (1000 iterations)</td>
<td>0.905 0.737</td>
<td></td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.900 0.734</td>
<td></td>
</tr>
<tr>
<td>Linear Regression</td>
<td>0.896 0.731</td>
<td></td>
</tr>
<tr>
<td>Random Forest (1000 trees)</td>
<td>0.724 0.683</td>
<td></td>
</tr>
<tr>
<td>NTCP_PMC</td>
<td>0.596 0.700</td>
<td></td>
</tr>
</tbody>
</table>

Weight loss prediction
(N. Minoru, S. Cheng et al…)

Endpoint: > 5kg loss at 3 months post RT

At planning

At end of RT
Pancreas Resectability
(S. Cheng et al.)

<table>
<thead>
<tr>
<th>Variable &amp; metric</th>
<th>LA (n=76)</th>
<th>BR (n=20)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance_SMA_0%</td>
<td>0.8302</td>
<td>0.3216</td>
<td>0.0764*</td>
</tr>
<tr>
<td>Distance_SMA_25%</td>
<td>0.3739</td>
<td>0.1231</td>
<td>0.0922</td>
</tr>
<tr>
<td>Distance_SMA_50%</td>
<td>0.0362</td>
<td>0.4849</td>
<td>0.0882</td>
</tr>
<tr>
<td>Distance_SMA_75%</td>
<td>0.4101</td>
<td>0.9975</td>
<td>0.0805</td>
</tr>
<tr>
<td>Distance_ClosestVessel_0%</td>
<td>1.0421</td>
<td>0.4121</td>
<td>0.0361*</td>
</tr>
<tr>
<td>Distance_ClosestVessel_25%</td>
<td>0.6513</td>
<td>0.0427</td>
<td>0.0454*</td>
</tr>
<tr>
<td>Distance_ClosestVessel_50%</td>
<td>0.3894</td>
<td>0.2739</td>
<td>0.0373*</td>
</tr>
<tr>
<td>Distance_ClosestVessel_75%</td>
<td>0.08</td>
<td>0.5603</td>
<td>0.0238*</td>
</tr>
<tr>
<td>PTV volume</td>
<td>89.2791</td>
<td>66.7585</td>
<td>0.0065*</td>
</tr>
</tbody>
</table>

Summary

- We can quantify the patient experience and are improving our capabilities rapidly
- It is possible to collect and house RT data/knowledge in a clinical setting
- Current dose based auto-planning utilizes a learning health system
- Data science models are maturing that can convert the knowledge to clinical predictions
- Incorporation of these predictions into the planning process would make Leonard "Bones" McCoy proud
- The potential to have clinical impact is evident... we have work to do which requires real partnership with our clinicians

Acknowledgments

- **JHU-BIO**
  - Sierra Cheng MD
  - Michael Bowers BS
  - Joseph More PhD
  - Scott Roberson PhD
  - Praveen Lakhotia PhD
  - Jinks Wang PhD
  - Theodore DeWese MD
  - GI Team
  - Joseph Herman MD
  - Amy Hacker-Printz PA
  - HAN Team
  - Harry Quon MD
  - Ana Kao MD
  - Myshu Alks RN
  - Sara Altena RN
  - Toronto Sunnybrook
  - William Song PhD
  - Patrick

- **JHU - CS**
  - Russ Taylor PhD
  - Meha Kachhbin PhD
  - Forteys Murango BS

- **Philips PROS**
  - Karl Bodianski BS

- **Toshiba**
  - Minoru Nakatsugu PhD
  - Bobby Omary PhD
  - Rachael Louise Koktava
  - John Haller

- **Elekta**
  - Bob Hubbel

- **University of Washington**
  - Kim Evans MS
  - Mark Philips PhD
  - Kristi Hendrickson PhD
For parallel organs, **OAR2** is more easily spared. For serial organs, **OAR1** is more easily spared.

**Problem**

Ability to advance radiotherapy is limited by our knowledge of which patients are at risk of high grade toxicity or of limited ability to cure.

Knowledge from clinical trials is quite coarse and fails to consider all of the aspects of the individual patient.

‘Big Data’ offers an opportunity to better predict treatment outcome and provide improved clinical decisions for individual patients.
Toxicity trends during and after treatment – detect outliers

<table>
<thead>
<tr>
<th>Toxicity</th>
<th>Trends during and after treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dysphagia</td>
<td>Swallowing</td>
</tr>
<tr>
<td>Mucositis</td>
<td>Inflammation</td>
</tr>
<tr>
<td>Xerostomia</td>
<td>Dry Mouth</td>
</tr>
</tbody>
</table>

- **Swallowing**: Worsens after Tx for many patients, then improves long term.
- **Mucositis Inflammation**: Heals after Tx for most patients.
- **Dry Mouth**: Tends to be permanent.

Oncospace Consortium Repository
(It’s all about the data)

- Johns Hopkins
- U. Washington
- U. Toronto
- Sunnybrook
- U. Virginia
- Johns Hopkins

What can we do with the data?

- **Shape based auto-planning**
  - Clinical (prostate, pancreas)
  - Efficient high quality plan
- **Weight loss prediction**
  - Improved symptom management
- **Toxicity Risk**
  - DVH based
  - Spatial dose based
- **Disease response prediction**
  - Pancreas resectability
  - Head and neck HPV dose de-escalation