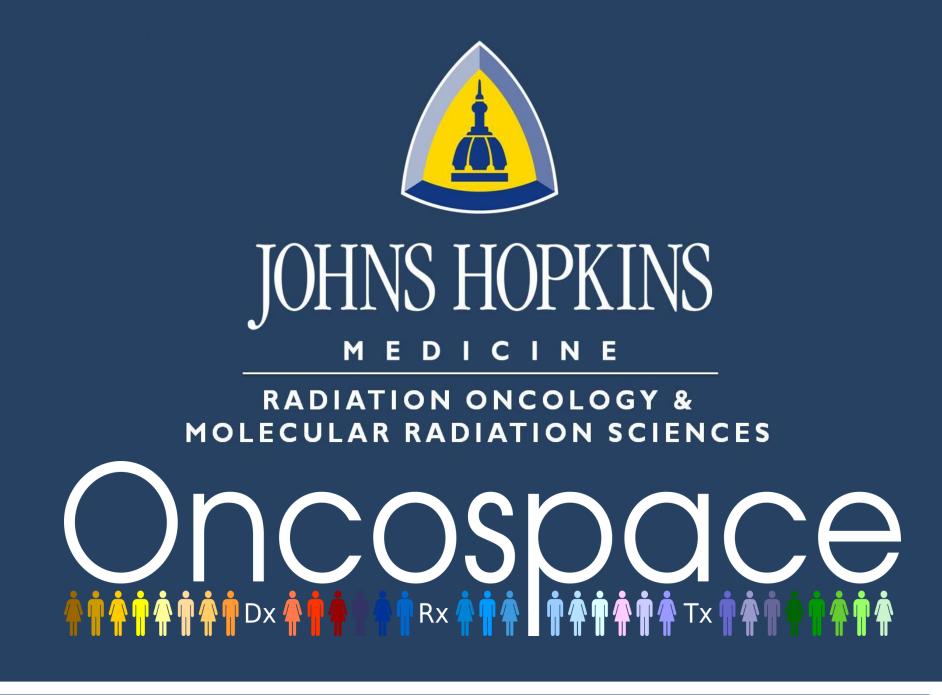


# The Role of a Decision Tree Model to Predict Weight Loss Following Radiotherapy in Head and Neck Cancer Patients

Z. Cheng<sup>1</sup>, M. Nakatsugawa<sup>1,2</sup>, A. P. Kiess<sup>1</sup>, S. P. Robertson<sup>1</sup>, J. Moore<sup>1</sup>, M. Allen<sup>1</sup>, S. Afonso<sup>1</sup>, A. Choflet<sup>1</sup>, K. Sakaue<sup>3</sup>, S. Sugiyama<sup>3</sup>, J. W. Wong<sup>1</sup>, T. R. McNutt<sup>1</sup>, and H. Quon<sup>1</sup>

<sup>1</sup>Johns Hopkins University, Baltimore, MD, <sup>2</sup>Toshiba America Research, Inc., Baltimore, MD, <sup>3</sup>Toshiba Medical Systems Corporation, Otawara, Japan



## Purpose/Objectives

- ➤ The QOL\*1 of the irradiated head and neck cancer (HNC) patient can be significantly affected by toxicities leading to **weight loss**
- To determine the predictors for weight loss based on the experience of similar previously treated patients
- To develop a real-time clinical decision support system to predict and reduce toxicities with a learning health system (LHS) model

#### Materials/Methods

- ➤ Oncospace: an integrated analytic relational database that systematically captures clinical outcome results and all aspects of a radiotherapy treatment plan.
- ➤ Retrospective analysis was undertaken using structured data elements (SDEs) that were prospectively acquired during routine clinical care
- > Data
  - 391 HNC patients from 2007 to 2014 (Table 1)
  - 3,015 clinical and dosimetric variables
    - diagnostic ICD-9 code
    - planned DVH\*2 at 1% volume increments
    - OVH (Overlap Volume Histogram): distance b/w PTV\*3 and OARs\*4 on CT Image
    - NCI-CTCAEv4.0 toxicity and QOL

Table. 1 – Demographic data (n=391)

5 3 3 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5	
Variable	N (%)
Onset Age, ≥60	169 (43%)
Male	306 (78%)
Caucasian	187 (48%)
Chemotherapy	261 (67%)
T stage, ≥T3	114 (29%)
N Stage, ≥N2	169 (43%)
Site, pharynx	126 (32%)

#### Materials/Methods (Cont.)

- Method
  - Weight loss of 5kg or more at 3 months post-RT was predicted by the Classification and Regression Trees (CART)
  - Two prediction models for incremental datasets (Fig. 1)
    - at RT planning without variables during RT
      at the end of RT with variables during RT

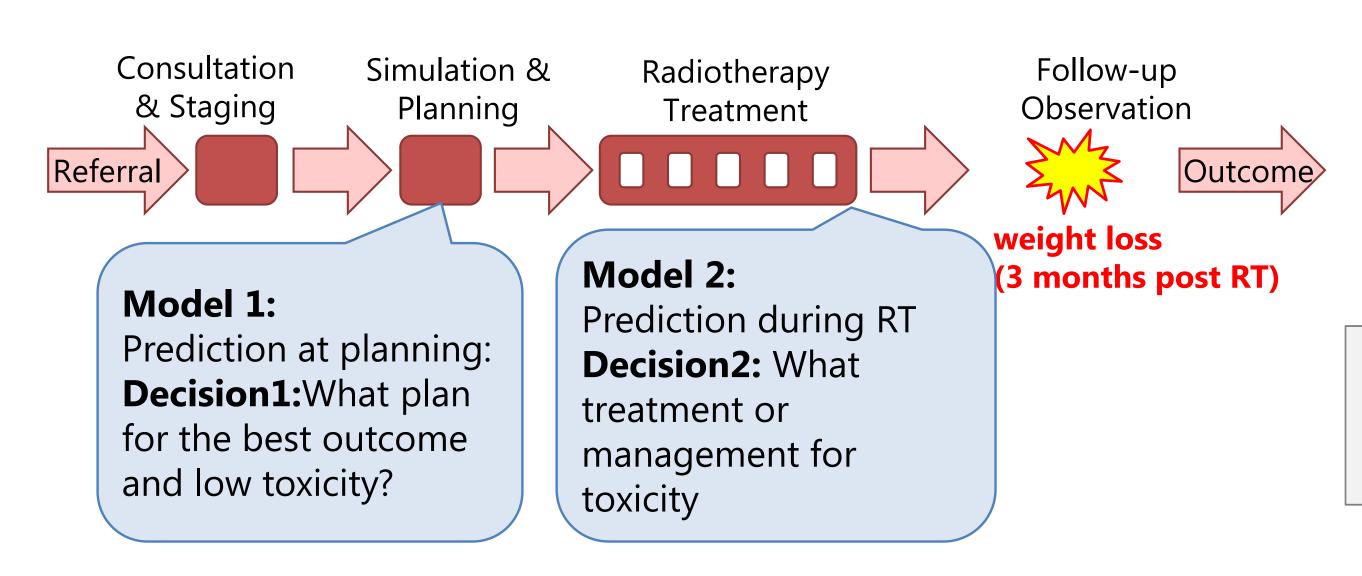


Fig. 1 – Two prediction models before/during treatment

# Results

- ➤ Weight loss predictors at RT planning (Fig. 2)
  - AUC\*5 0.773
  - Sensitivity 0.766, PPV\*6 0.426
  - Predictors:
    - (1: Dosimetry) dose to masticatory muscle, larynx, parotid
    - (2: Diagnosis) ICD-9 code
    - (3: Patient) age

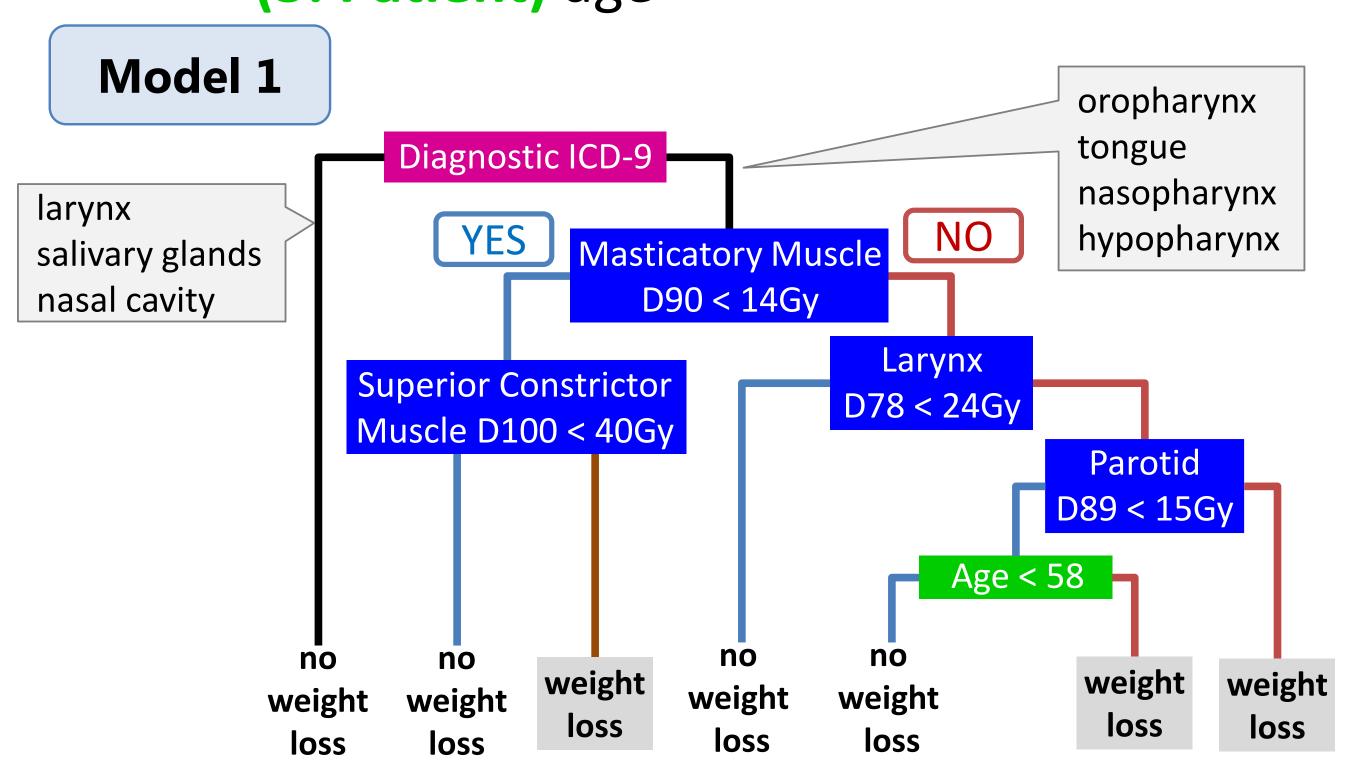


Fig. 2 – Weight loss prediction model at planning

- \*1 QOL: Quality of Life, \*2 DVH: Dose Volume Histogram,
- \*3 PTV: Planning Target Volume, \*40AR: Organ at Risk,
- \*5 AUC: Area Under Curve, \*5 PPV: Positive Predictive Value

## Results (Cont.)

- > Weight loss predictors <u>during treatment</u> (Fig. 3)
  - AUC 0.839
  - Sensitivity 0.988, PPV 0.467
  - Predictors:
    - (1: QOL) patient reported oral intake
    - (2: Diagnosis and staging) ICD-9, N stage
    - (3: Dosimetry) dose to larynx, parotid
    - (4: Toxicity) skin toxicity, nausea, pain
    - (5: Geometry) minimum distance between PTV and larynx

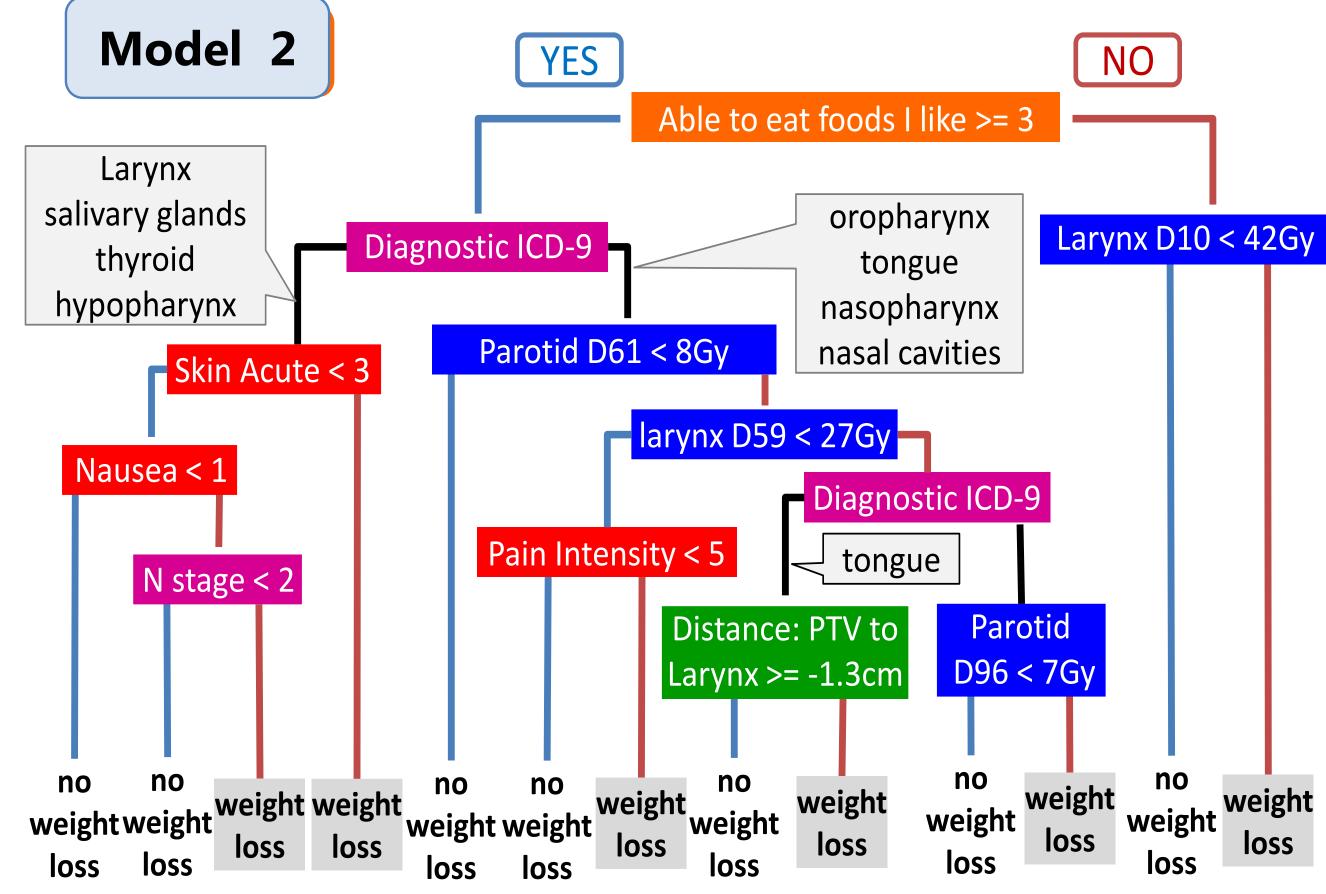


Fig. 3 – Weight loss prediction model during treatment

# Conclusion

- Systematic capture of SDEs and data-mining tools facilitated a decision-support analysis tool for weight loss based on past similarly treated patients
- The two prediction models at RT planning / treatment
  - identified the importance of Patient Reported Outcome
  - showed the potential for a real-time decision-support (e.g. prophylactic feeding tube placement)
- ➤ Future work: evaluating models in the clinical settings; imaging features might be helpful to improve PPV