Reducing IMRT QA workload by 95% and keeping the same level of quality control

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2020 JULY 12–16 VIRTUAL EASTERN TIME [GMT-4] JOINT AAPM | COMP MEETING

Background:

Current machine learning methods for predicting IMRT quality assurance metrics minimize the average error over all plans. However, minimizing the maximum error possible over all plans is most important because one erroneous prediction for a single patient can result in a wrong decision regardless of low average error over the whole population [1]. Our objective is to introduce Chebyshev minimax loss function [2] as the natural selection for IMRT QA metrics that minimize the maximum error when predicting QA passing rate. Our proposed method will be compared to a typical linear model that use ordinary least-squares minimization [3,4].

Purpose:

To reduce the maximum possible error (max-error) in a quality assurance (QA) program by using a novel machine learning (ML) algorithm for predicting QA plan passing rate that minimizes the max-error.

Methods:

A total of 498 IMRT QA plans were delivered on 5 linear accelerators and Gamma passing rates were measured based on 3%/3mm. Plans were characterized by 78 features (Figure 1). Linear models were developed using minimax (MM) and ordinary least-squares (OLS) optimizations.

OLS minimization problem/solution are given below:

$$\text{minimize} \quad f_0(x) = \|Ax-b\|_2^2 = \textstyle\sum_{i=1}^{k}(a_i^T x - b_i)^2.$$

$$\begin{array}{ll} \text{minimize} & \|Ax-b\|_2^2 \\ \text{subject to} & l_i \le x_i \le u_i, \quad i=1,\ldots,n, \end{array}$$

Minimax problem and linear solution are given below:

$$\text{minimize} \quad \max_{i=1,\ldots,k} |a_i^T x - b_i|.$$

$$\begin{array}{ll} \text{minimize} & t \\ \text{subject to} & a_i^T x - t \le b_i, \quad i=1,\ldots,k \\ & -a_i^T x - t \le -b_i, \quad i=1,\ldots,k, \end{array}$$

where A is MxN matrix with M plans and N features values, x is an Nx1 matrix containing the coefficients of the linear model, and b is an Mx1 matrix containing passing rate of each plan's IMRT QA.

Results: Training performance

498 IMRT plans:
- Multiple sites (breast, CNS, GI, GU, Lung)
- Planned with Eclipse, mostly 6X beams
- Delivered with 5 TrueBeam LINACs
- QA measured with Mapcheck2 (3%/3mm)

78 features were extracted to characterize plans:
- MLC leaf transmission
- Leaf end leakage
- Transmission through jaws
- Tongue and groove effect
- Charge particle equilibrium failures

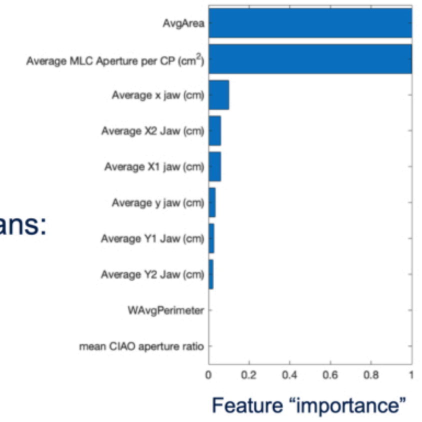

Figure 1 describes the IMRT QA dataset and model features (right).

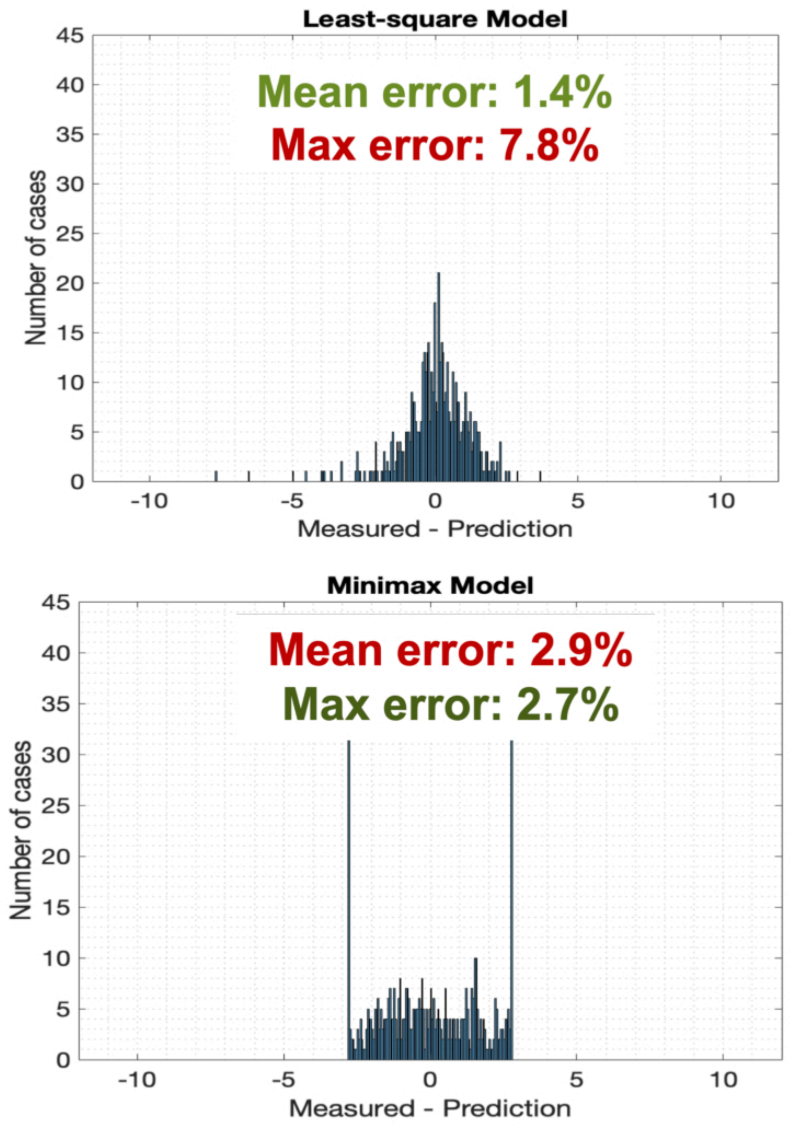

Figure 2 shows the distribution of plan passing rate differences for the OLS (top) and Minimax (bottom) models for training data. Reduction of max-error in the minimax model is due to optimization of data outliers.

Results: Testing performance

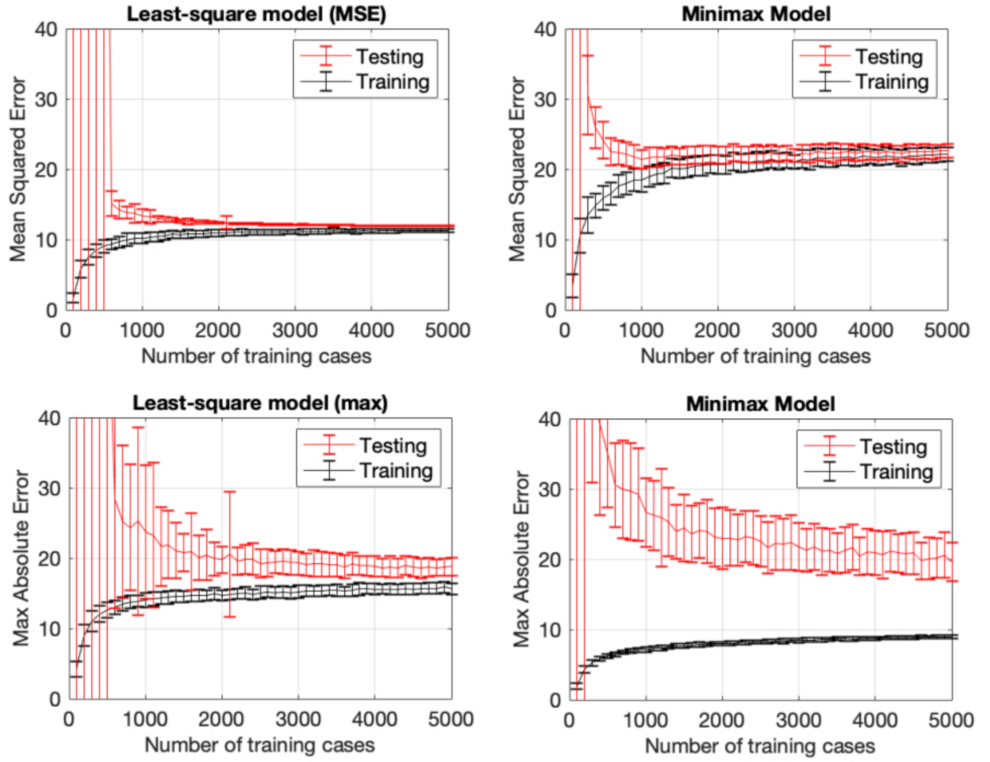

Figure 3 learning curves showing mean and max error for OLS (left) and Minimax (right) for training (black) and testing (red).

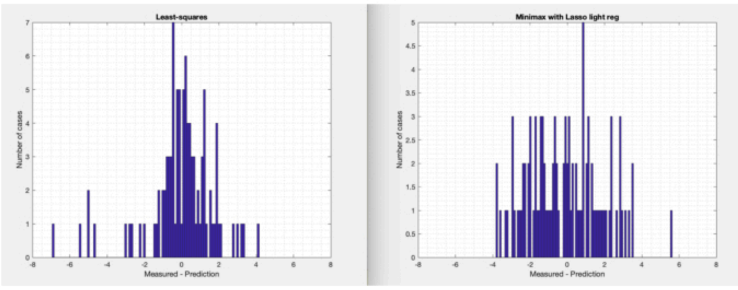

Figure 4 shows the results for test dataset with OLS max error for prediction is 7% (left), and minimax prediction error is 4% (right).

Results: Reducing QA workload

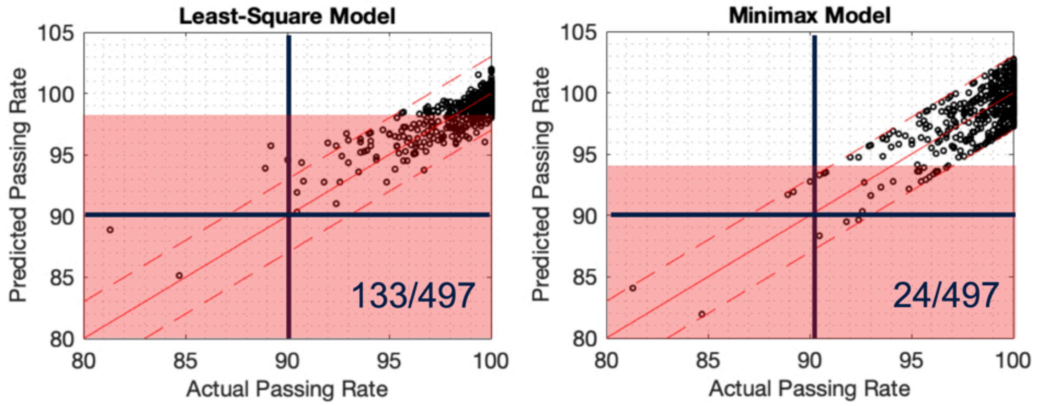

Figure 2 shows that to make sure all plans achieve a 90% passing rate, 133 plans would need testing with OLS versus 24 plans with Minimax.

Discussion:

Max-error of IMRT QA passing rate predictions was 7.6% for the OLS model and 3.0% for the MM model. The mean square error was, however, 1.4% and 2.8% for the OLS and MM models respectively. Following optimization and testing with hold-out sets (20% plans), the OLS and MM model max-errors were 7.0% and 3.8% respectively. To ensure that all plans have at least a 90% passing rate, all plans predicted to have 97.0% passing rate or lower (133 out of 498, 27.0%) would require QA using the OLS model. With the MM model, however, all plans predicted to be 93.8% or lower (24/498, 4.8%).

Conclusion:

Chebyshev's minimax optimization results in a reduction of the maximum error possible of machine learning algorithms. This algorithm can selectively choose plans that are more likely to fail QA for the physicist to prioritize resources according to TG 100. Efficient QA programs that ensure safe IMRT treatments require accurate identification of plans that are likely to fail QA criteria. Using a Minimax model, a 95% reduction of resources for IMRT QA can be achieved while meeting current passing criteria.

References:

1. Miften et. al., "Tolerance Limits and Methodologies for IMRT Measurement-Based Verification QA: Recommendations of AAPM Task Group", Med Phys, 2018
2. Boyd, Stephen, Stephen P. Boyd, and Lieven Vandenberghe. Convex optimization. Cambridge university press, 2004
3. Valdes et. al., "A Mathematical Framework for Virtual IMRT QA Using Machine Learning", Med Phys, 2016
4. Valdes et. al., "IMRT QA using machine learning: A multi-institutional validation", JACMP, 2017

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