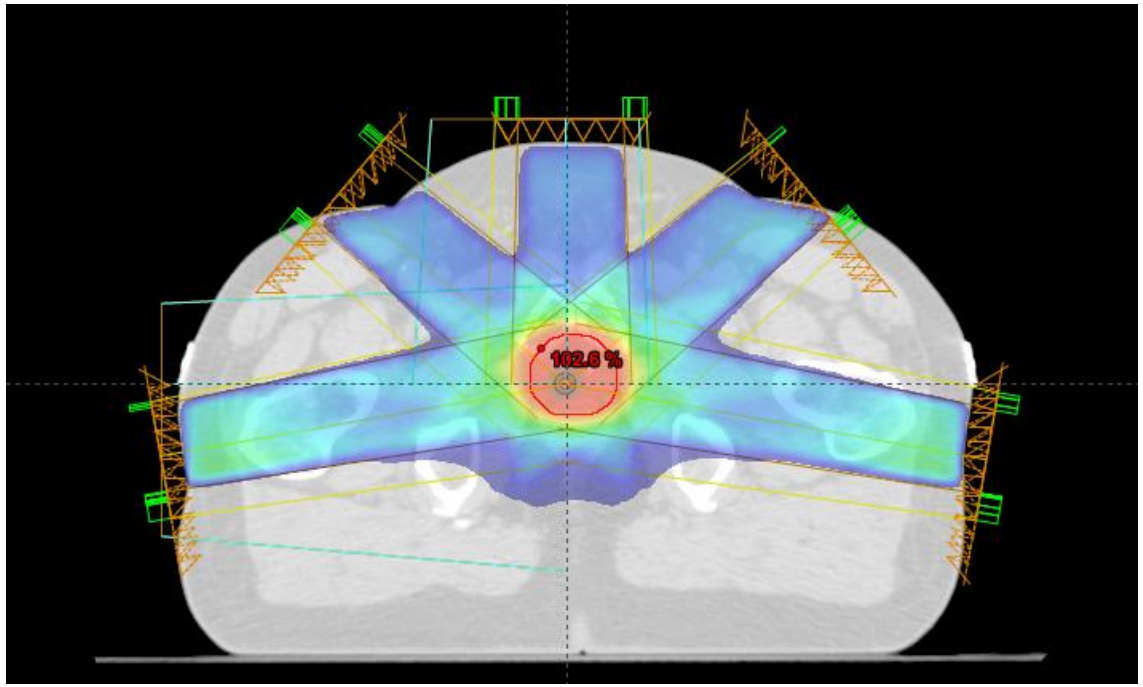
Towards Personalized PTV Margins for External Beam Radiation Therapy of the Prostate

ANDREW COATHUP

MSC ORAL EXAMINATION

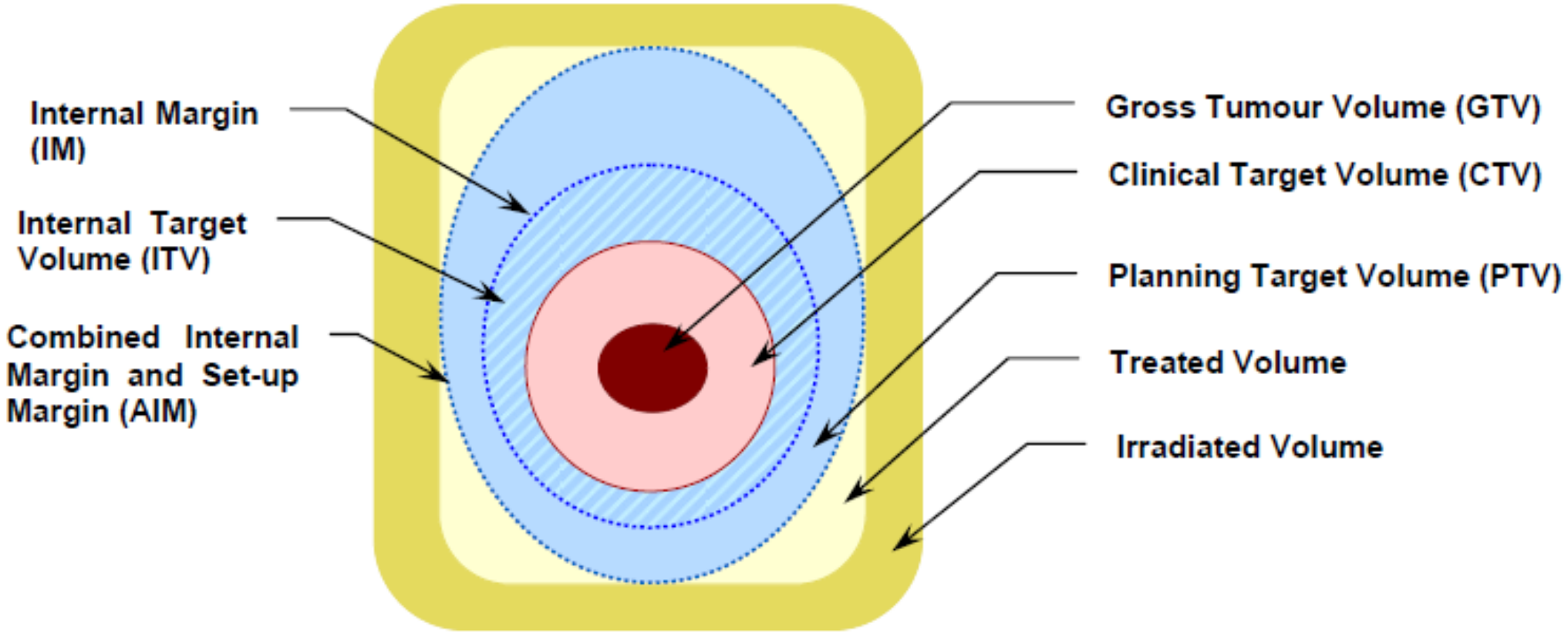
AUGUST 22, 2017

Introduction: External Beam Radiation Therapy

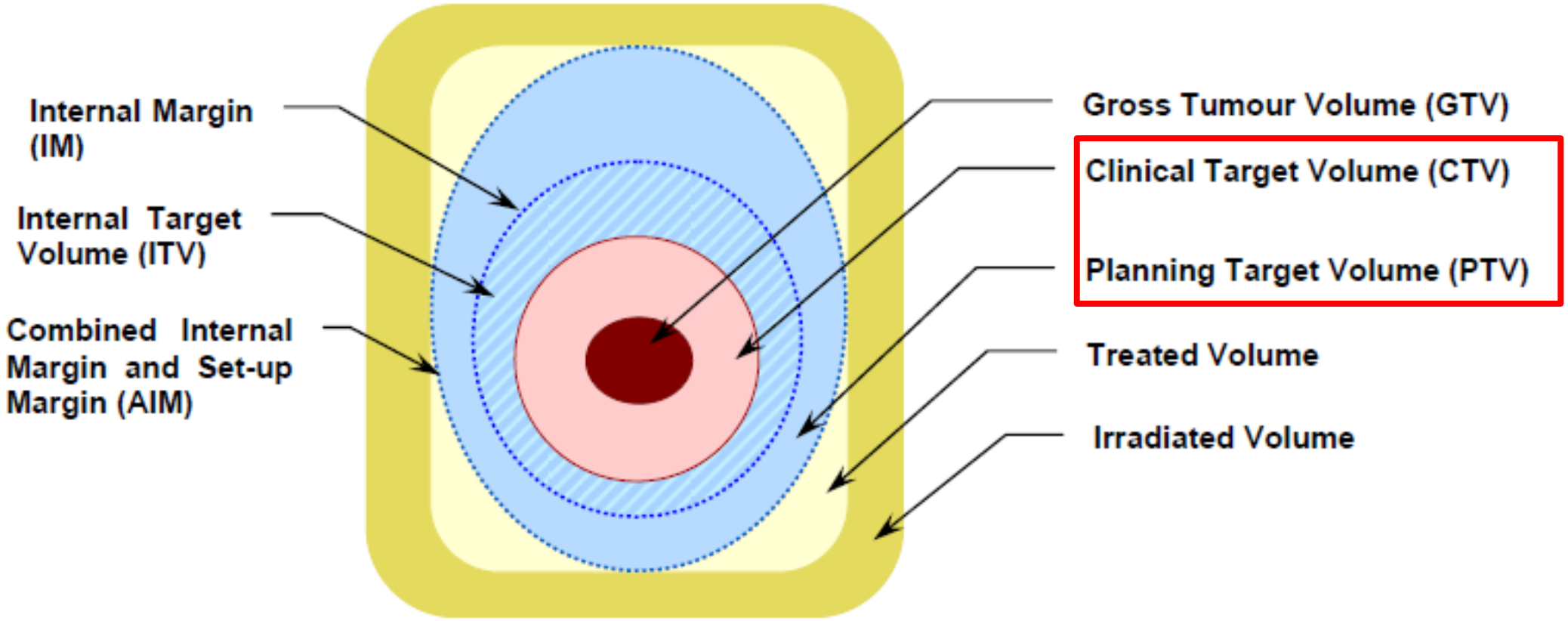


- Uses radiation originating from outside the patient to irradiate and kill cancer cells
- External beam radiation therapy is a common treatment option for prostate cancer patients

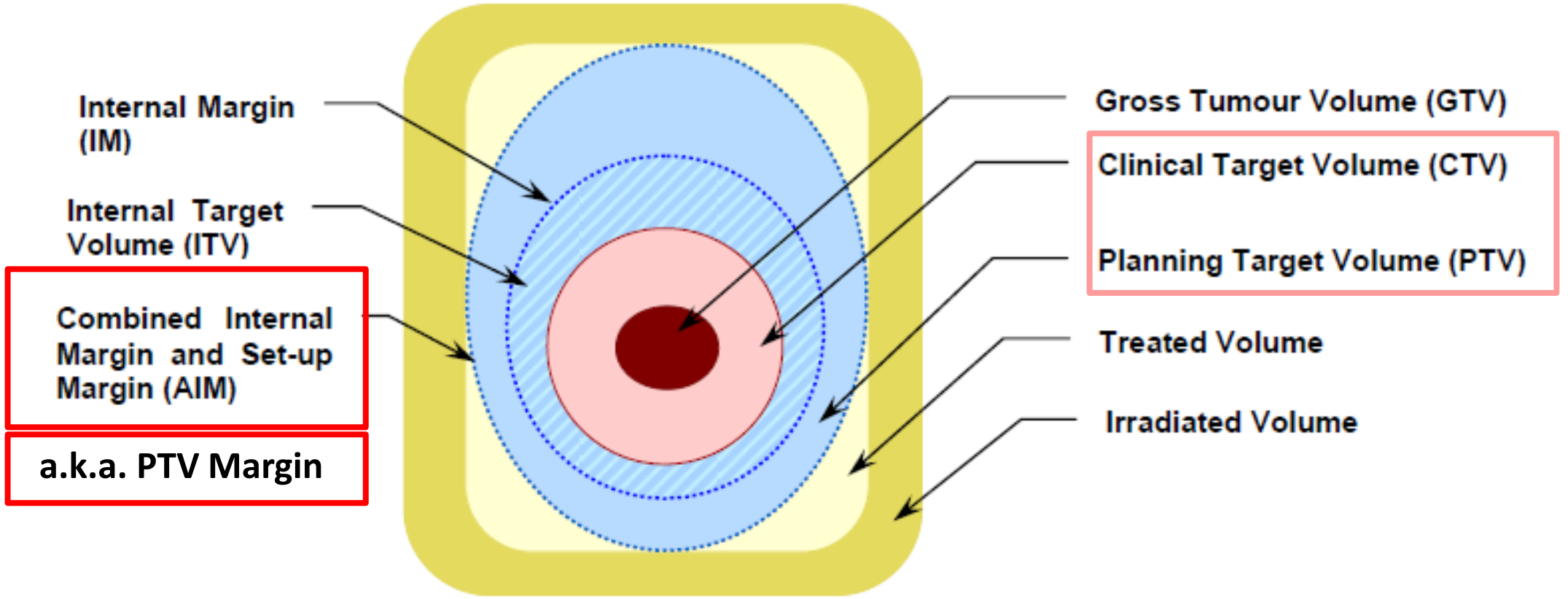
Introduction: Volumes and Margins in Radiation Therapy



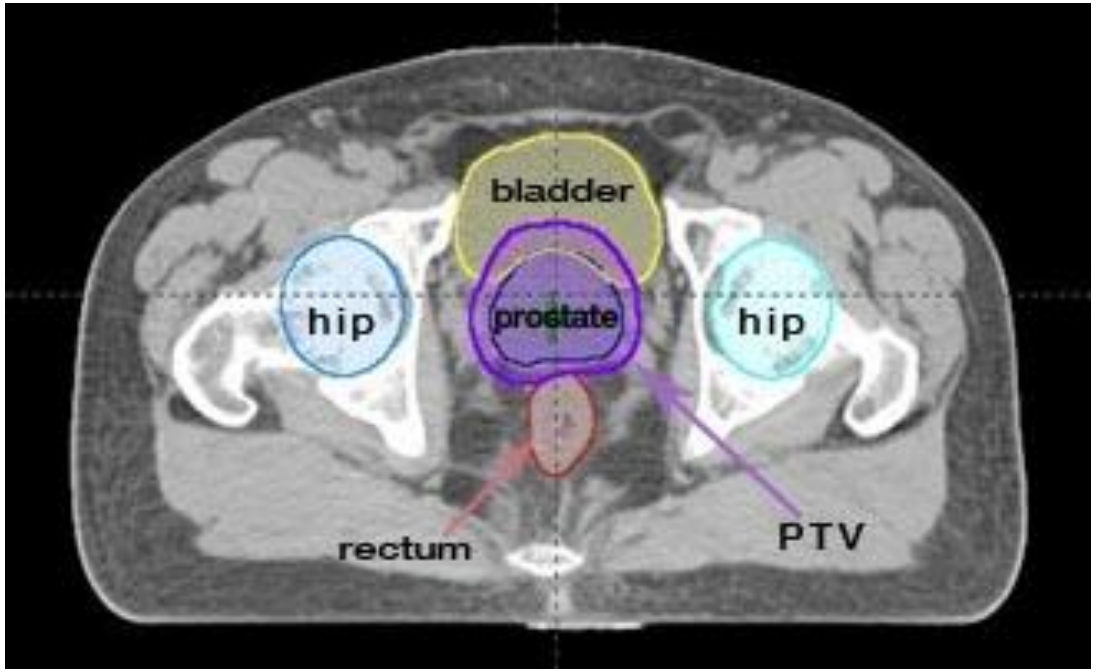
Introduction: Volumes and Margins in Radiation Therapy



Introduction: Volumes and Margins in Radiation Therapy



Introduction: PTV Margins for Prostate Cancer Treatment

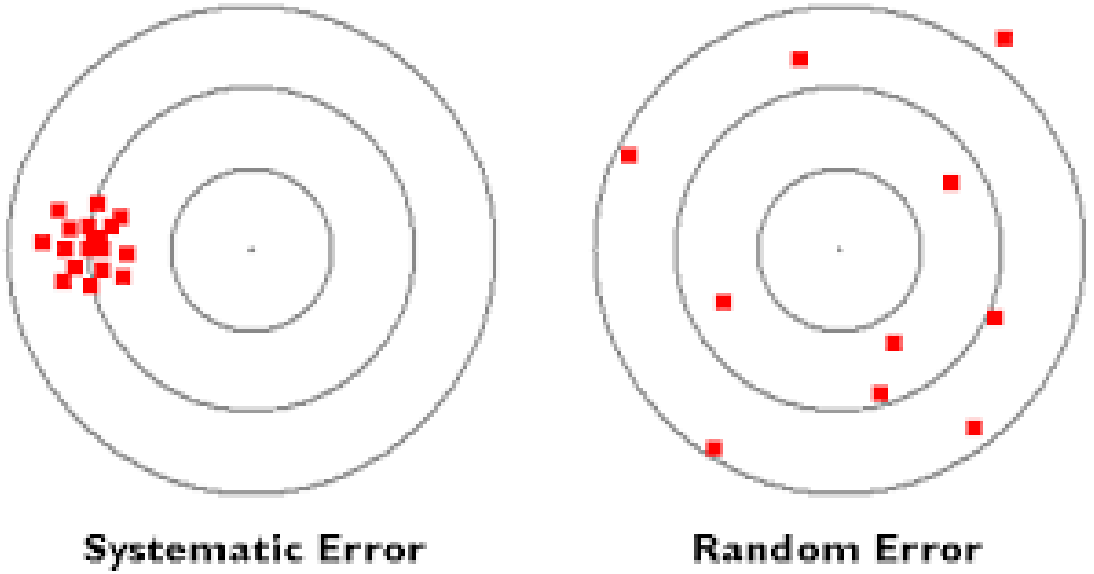


- Prostate, bladder, and rectum are all close together
- Bladder and rectum are going to receive high dose
- Want to limit dose to bladder and rectum, while maintaining acceptable dose to prostate

Introduction: Estimating the PTV Margin – van Herk Approach

What influences the size of margin?

- Errors in treatment planning and delivery (systematic & random errors)
- Systematic errors affect all fractions similarly (the mean position of dose distribution)
- Random errors affect fractions about mean location (the spread of the dose distribution)



Introduction: Estimating the PTV Margin – van Herk Approach

$$PTV\ Margin = 2.5\,\Sigma_{pop} + 0.7\,\sigma_{pop}$$

$$\Sigma_{\mathrm{pop}}^2 = \Sigma_m^2 + \Sigma_s^2 + \Sigma_d^2$$

$$\sigma_{pop}^2 = \sigma_m^2 + \sigma_s^2$$

Errors:

- *Target delineation (systematic)*
- *Patient Set-up (systematic & random)*
- *Target Motion (systematic & random)*

These errors (especially motion errors) may be related to various 'patient specific factors' (PSFs)

Introduction: Research Questions

- Can the PTV margin be personalized based on *patient specific factors* describing the individual patient (and relating to their intra-fraction motion)?

- Is there a benefit to using personalized PTV margins over a population-based PTV margin?

Methodology: Data Collection & Organization

Time Dependent Data

- Motion data
- Treatment time data
- Rectal Distension data

Time Independent Data

- Patient Specific Factors

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Time Independent Data

- Patient Specific Factors

Methodology: Predictive Algorithms

- Several algorithms were chosen based on the problem to be solved and properties of the available dataset

Problem: Regression

Data Properties
- Labelled Data
- Small number of samples
- Small number of features

Algorithms
- Linear
- Ridge
- LASSO
- SVR
- kNN
- MLP

Methodology: Predictive Algorithms on Simulated Data

- Generated clinically relevant intra-fraction motion data from randomly sampled, clinical relevant PSFs (Table 2 in thesis, pg.51)

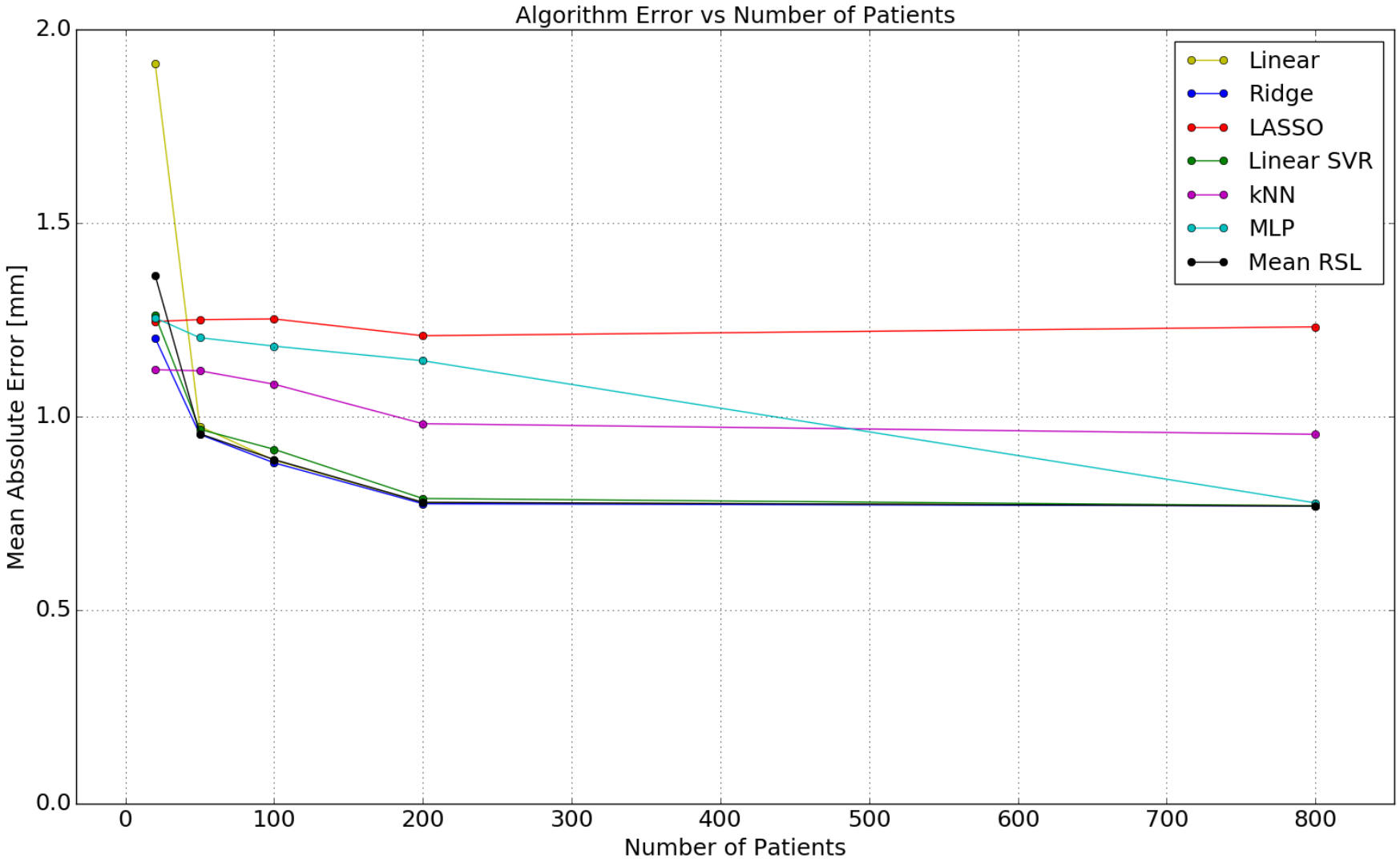
Three principal simulations were performed:

- Effect of sample size
- Algorithm evaluation
- Effect of noise in the data

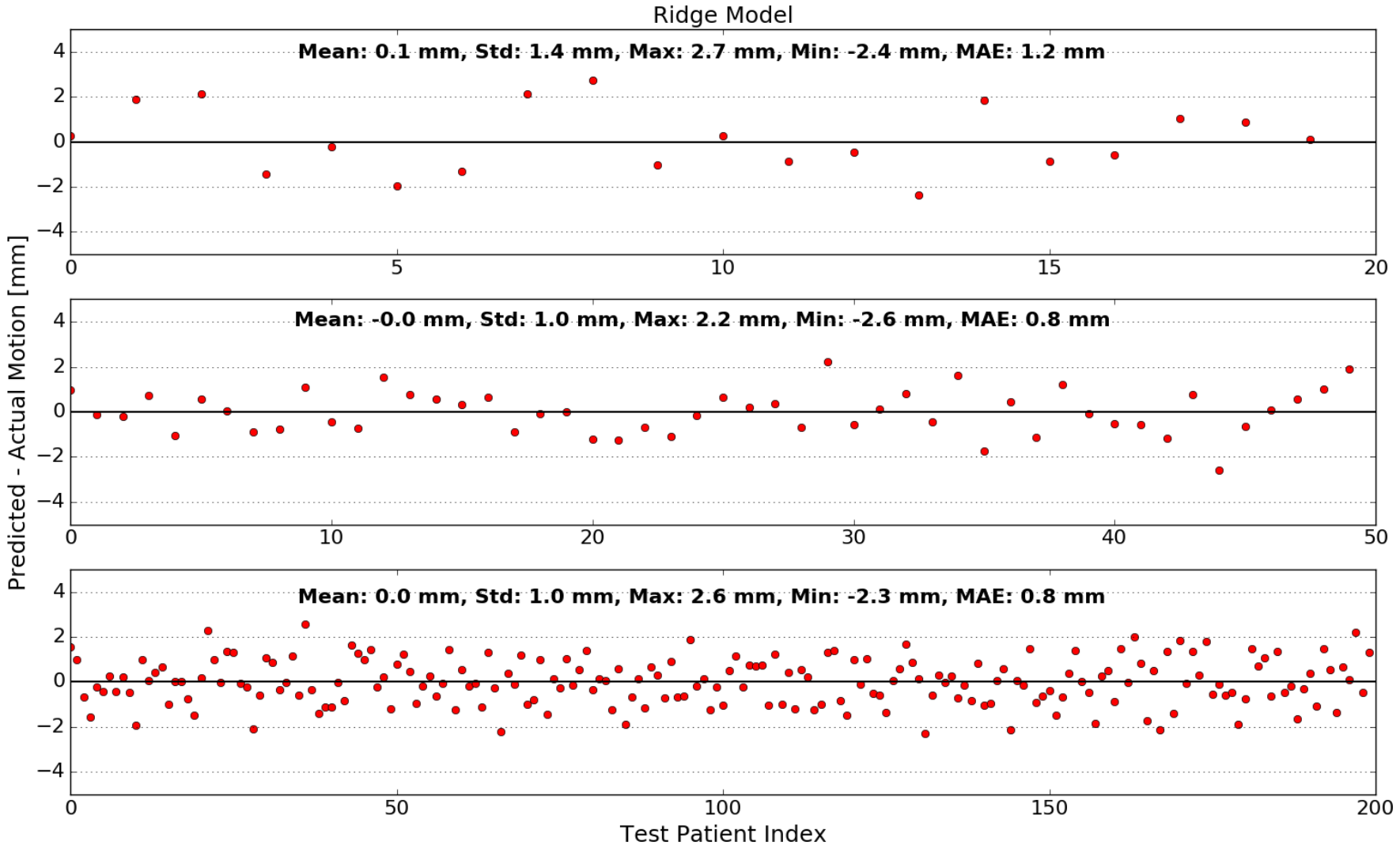
PSF	Range Sampled (inclusive)
PSA Score	*0 – 15*
Primary Gleason Score (pGleason)	*1 – 5*
Secondary Gleason Score (sGleason)	*1 – 5*
Total Gleason Score	*pGleason + sGleason*
Total Cores Sampled	*6 – 25*
Total Cores Positive	*0 – Total Cores Sampled*
ECOG Status	*1 – 5*
Stage	*1 – 4*
Age	*40 – 95*
Weight [kg]	*65 – 125*
Height [cm]	*150 – 200*
BMI [kg/m^2]	*Weight / (Height/100)^2*
Diabetes	*Boolean*
IBS	*Boolean*
COPD	*Boolean*
Implants	*Boolean*

Table 2: Sampling range for each PSF

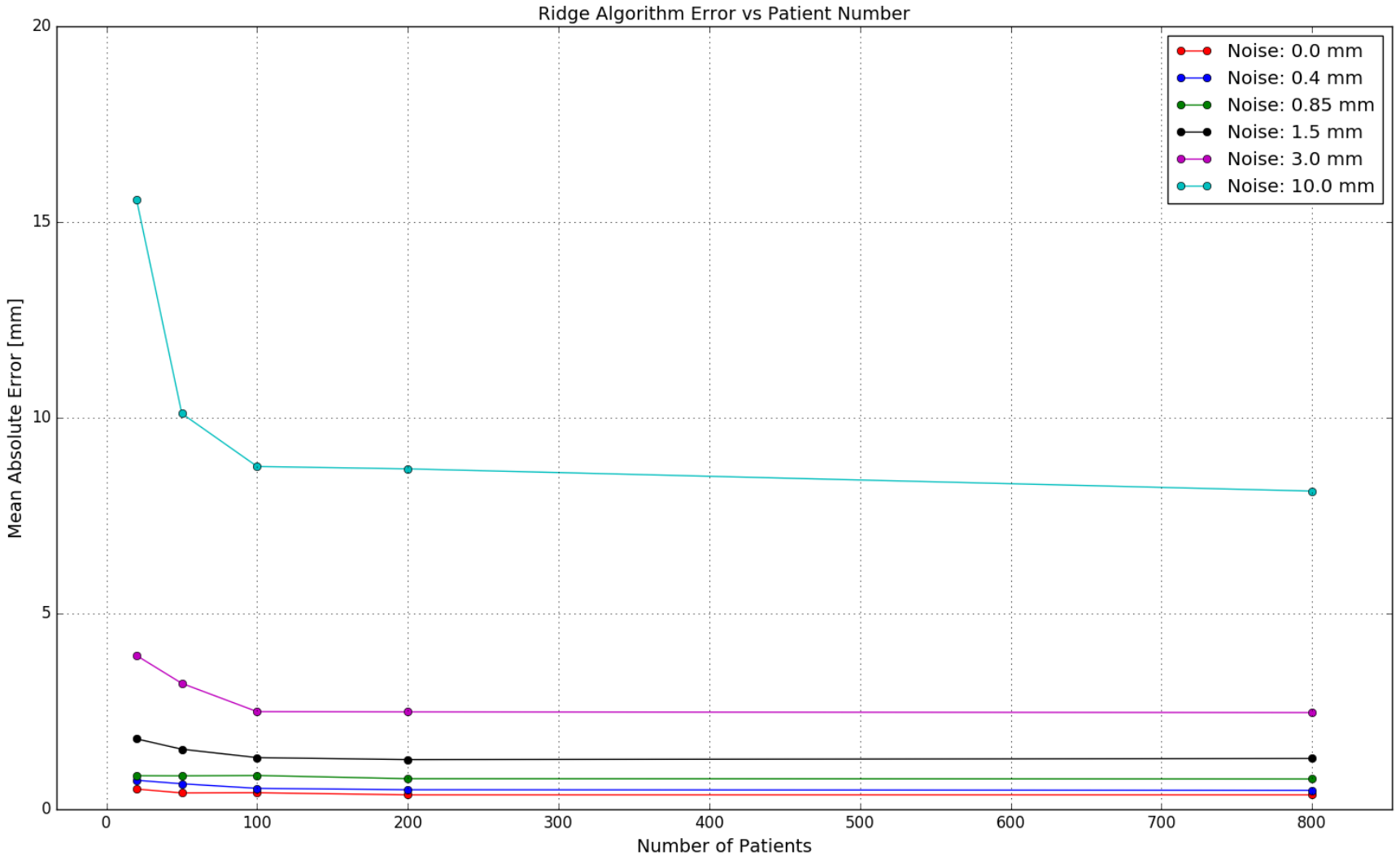
Results: Number of Patient Requirements (Simulated Data)



Results: Algorithm Evaluation (Simulated Data)



Results: Effect of Noise (Simulated Data)



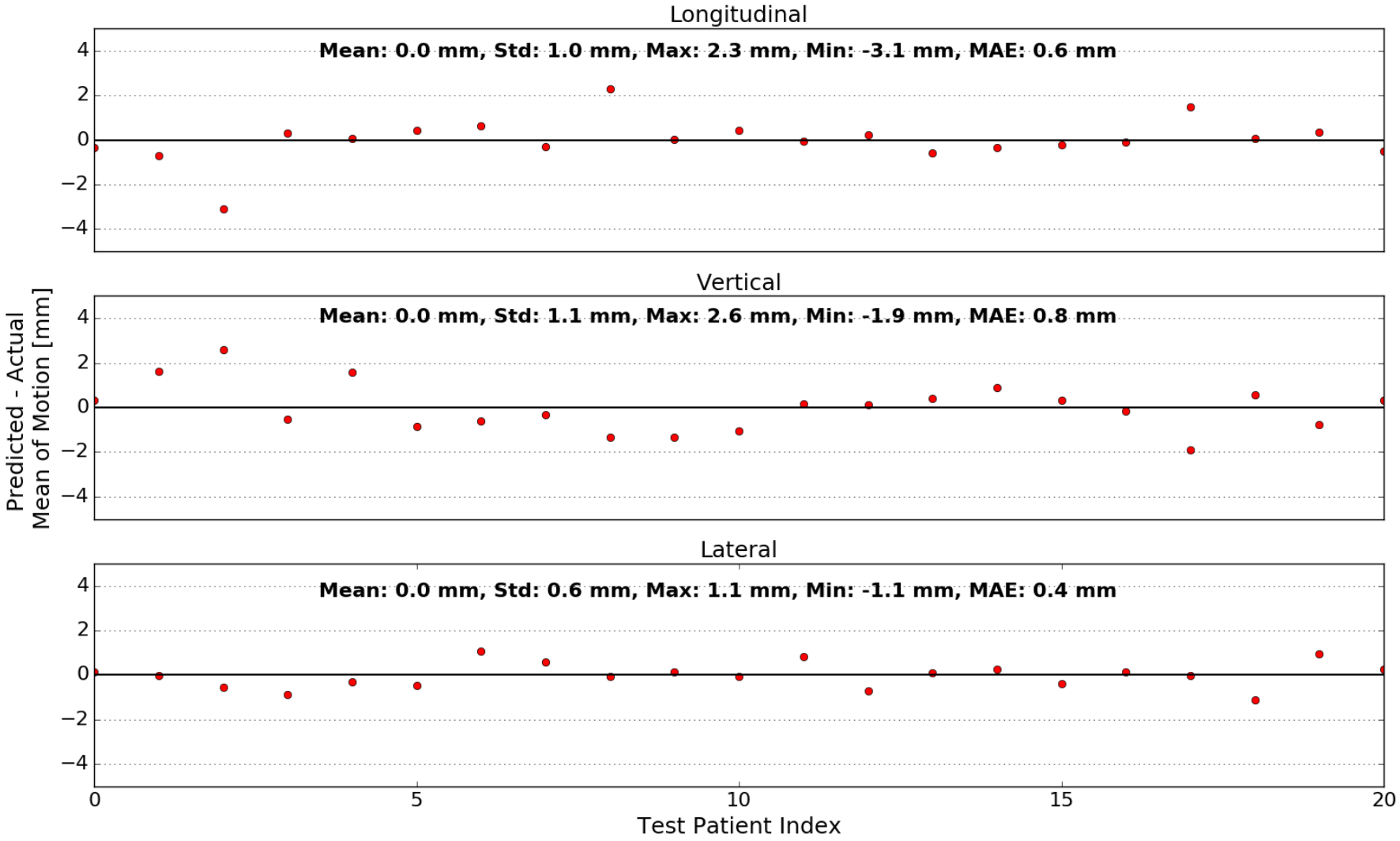
Methodology: Predictive Algorithms on Real Patient Data

- 21 patients were used for training and validation
- Each patient had 16 PSFs and intra-fraction motion data along three spatial directions

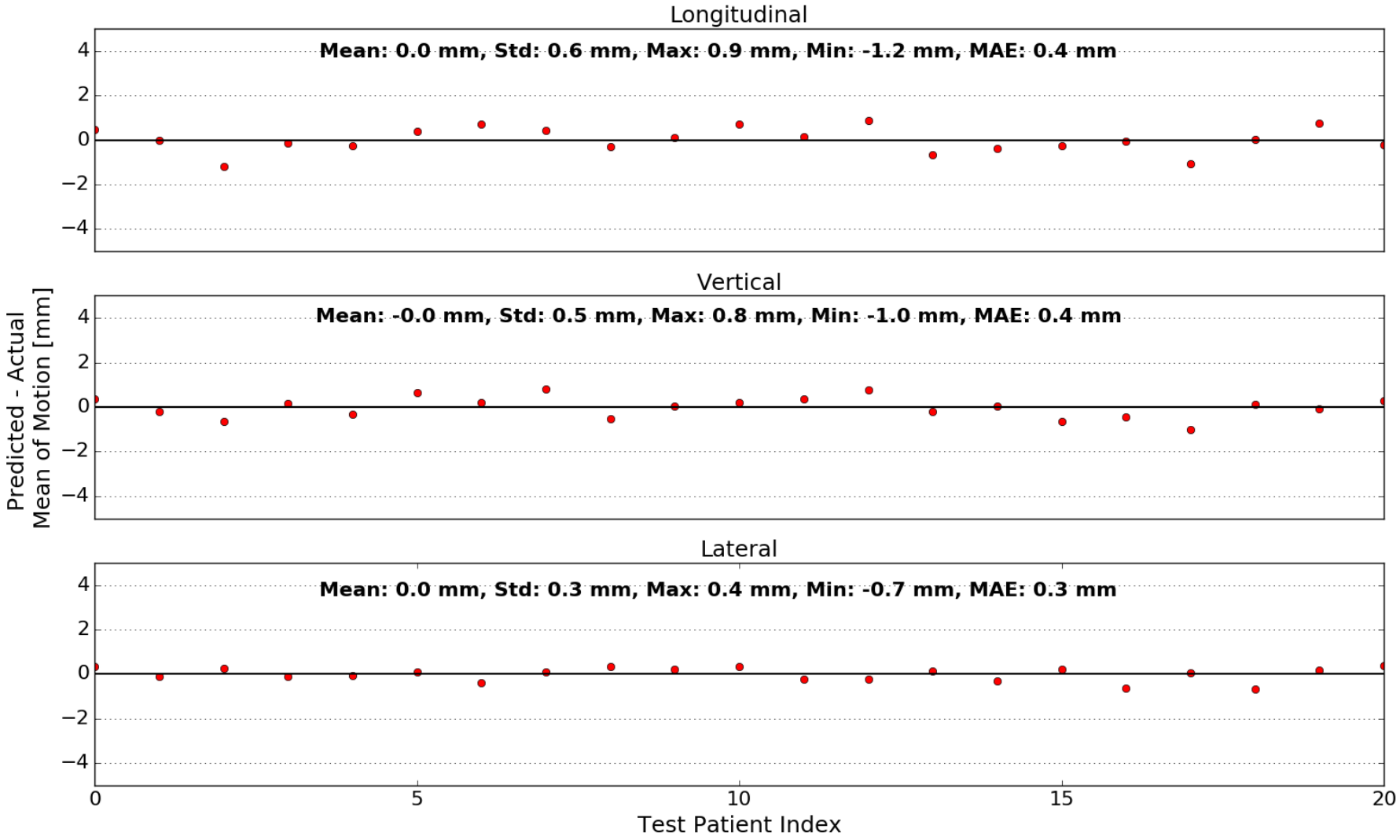
Input:
- PSF profile

Output:
- Patient mean intra-fraction motion (M)
- Patient standard deviation of intra-fraction motion (σ)

Results: Algorithms for Real Patient Data (Mean)



Results: Algorithms for Real Patient Data (Std Dev)



Methodology: Personalized PTV Margin

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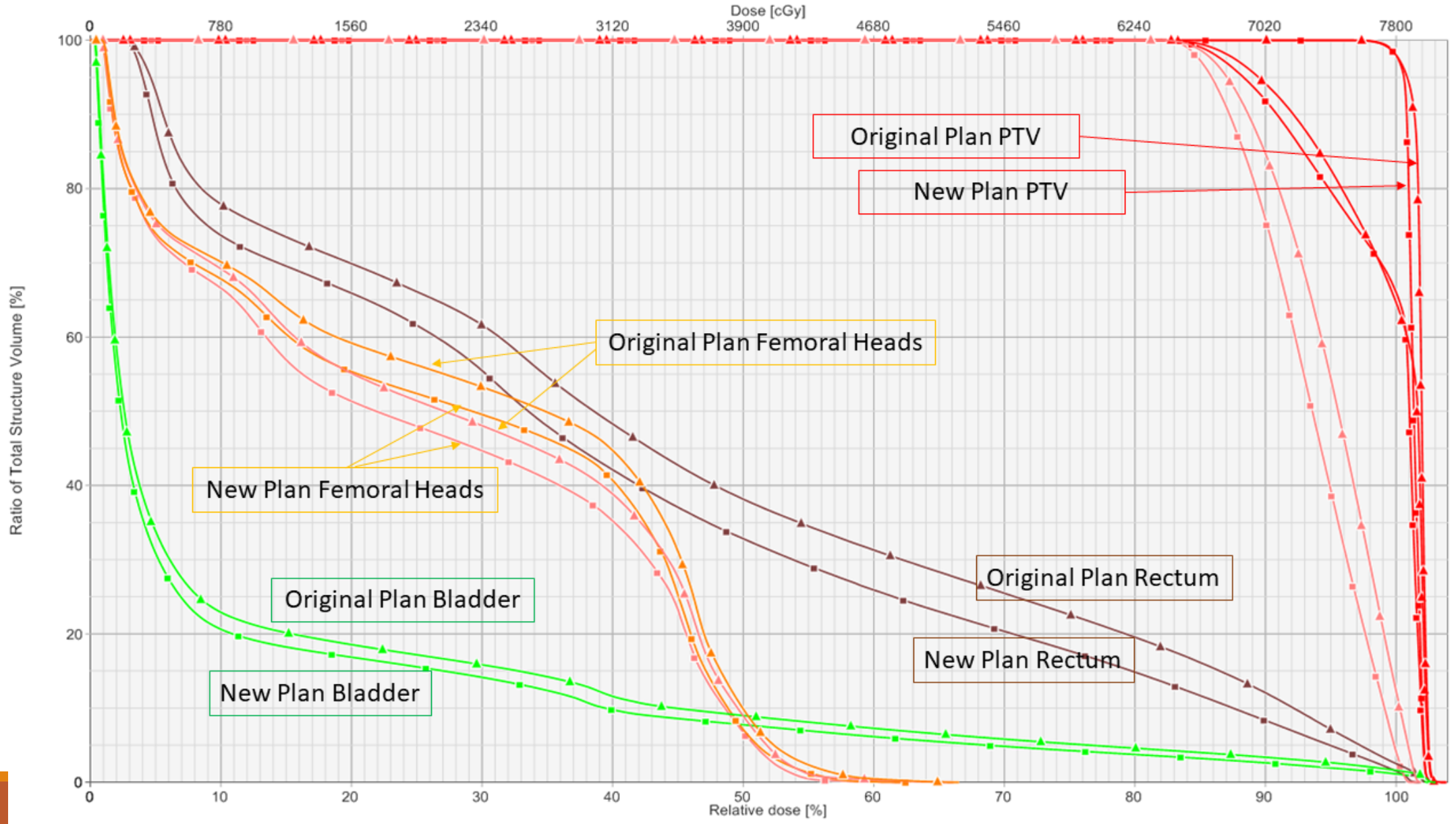
Results: Personalized PTV Margin

Error Source	Vertical [mm]	Longitudinal [mm]	Lateral [mm]
Systematic Error	**1.3**	**1.7**	**1.0**
Target Delineation	0.7	1.3	0.7
Setup	0.5	0.5	0.5
Inter-fraction motion	0.0	0.0	0.0
Intra-fraction motion	1.0	0.9	0.5
Random Error	**1.9**	**1.8**	**1.2**
Setup	0.9	0.9	0.9
Inter-fraction motion	0.0	0.0	0.0
Intra-fraction motion	1.7	1.5	0.8
Personalized PTV Margin			
Systematic PTV Component	3.3	4.2	2.5
Random PTV Component	1.4	1.2	0.8
PTV Margin	4.7	5.4	3.3
Treatment Planning PTV	5	6	4

Results: Personalized PTV Margin



Conclusions

- Predictive algorithms are a tool that can be used to predict patient motion and help to personalize the PTV margin
- Ridge regression appears to be a good candidate for future work based on simulation results
- Prediction performance is expected to improve dramatically within the first 50 to 100 patients
- Currently, the LASSO regression performed the best on real patient data, but unfortunately did so by disregarding the input PSFs

Future Work

- Explore the time dependence of prostate motion (real time) and how this time dependence relates to a patient's PSF profile
- In particular, look into the drift of the prostate and how the drift rate is influenced by the PSFs
- Identify patients at high risk for systematic prostate motion based on PSFs and put more resources into managing that motion

Thank you!