Automated Planning - Technical Considerations for Ensuing Safety and Quality

Automated Planning and Data-driven Plan Quality Control

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Toronto Western
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Disclosures

Method and System for Automated Planning of Radiation Therapy technology patented in PCT/CA2011/001130

Automated Quality Assurance (QA) and Planning technology patented in WO2014197994 A1

Receive royalties from RaySearch Laboratories for license of technology for Automated Breast Treatment Planning and Machine Learning-based Automated Treatment Planning

Have an equity interest in bridge7, licensee of technology for Machine Learning-based for Automated Quality Assurance in Radiation Oncology

Outline

Responsible Machine Learning (ML)
Regulatory Process with AI/ML
Risks of Automated Planning
Open Knowledge Based Planning (KBP) Challenge

Are We Ready to Use Deep Neural Networks Clinically?

LETTER

doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1]*, Brett Kuprel[1]*, Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

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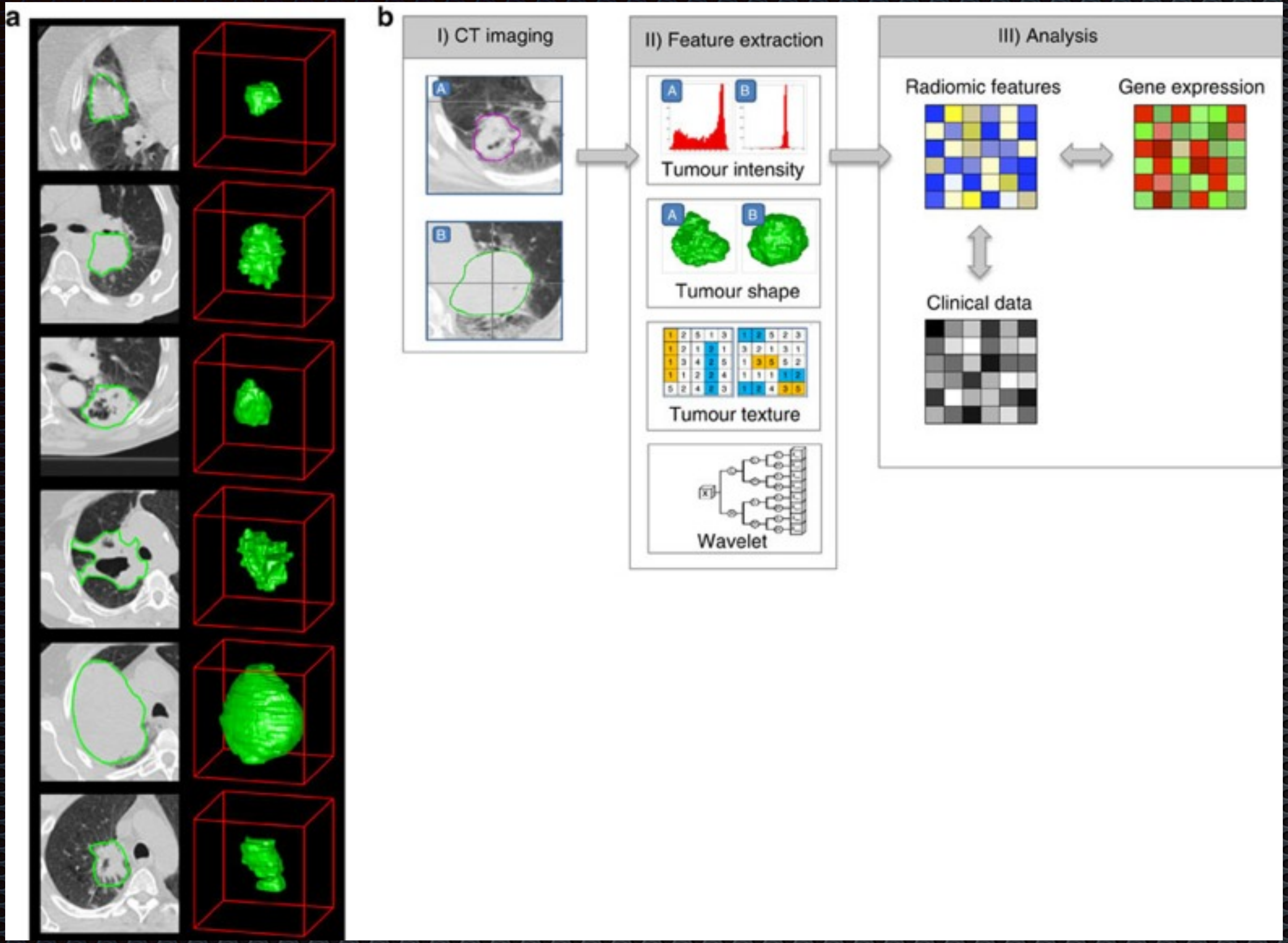
2 FEBRUARY 2017 | VOL 542 | NATURE | 115

Deep neural network tested for diagnosing skin lesions representing the most common and deadliest skin cancers with 21 board-certified dermatologists used as control

Bottom line:

- Algorithm matched the performance of dermatologists

Promise | Potential for AI to Infer New Knowledge



- AI recognizes complex data in images and can give quantitative metrics
- Radiomics → High throughput extraction of quantitative image features (non-human detectable) for biomarker discovery

Aerts et al. Nat Commun 2014

Are we Inferring New Knowledge?

Radiotherapy and Oncology
Volume 130, January 2019, Pages 2-9

Original article

Vulnerabilities of radiomic signature development: The need for safeguards

Mattea L. Welch[a, f, i], Chris McIntosh[e, f, i], Benjamin Haibe-Kains[a, c, i, j], Michael F. Milosevic[b, e, i], Leonard Wee[g], Andre Dekker[g], Shao Hui Huang[b, i], Thomas G. Purdie[b, e, f, i], Brian O'Sullivan[b, i], Hugo J.W.L. Aerts[h], David A. Jaffray[a, b, d, e, f, i]

Responsible Use of Machine Learning

nature medicine

PERSPECTIVE

https://doi.org/10.1038/s41591-019-0548-6

Corrected: Author Correction

Do no harm: a roadmap for responsible machine learning for health care

Jenna Wiens[1,20*], Suchi Saria[2,3,4,20], Mark Sendak[5], Marzyeh Ghassemi[6,7,8], Vincent X. Liu[9], Finale Doshi-Velez[10], Kenneth Jung[11], Katherine Heller[12,13], David Kale[14], Mohammed Saeed[15], Pilar N. Ossorio[16], Sonoo Thadaney-Israni[17] and Anna Goldenberg[6,8,18,19,20*]

Interest in machine-learning applications within medicine has been growing, but few studies have progressed to deployment in patient care. We present a framework, context and ultimately guidelines for accelerating the translation of machine-learning-based interventions in health care. To be successful, translation will require a team of engaged stakeholders and a systematic process from beginning (problem formulation) to end (widespread deployment).

New Regulatory Approach for AI/ML Needed

AI/ML-Based SaMD are highly iterative, autonomous, and adaptive

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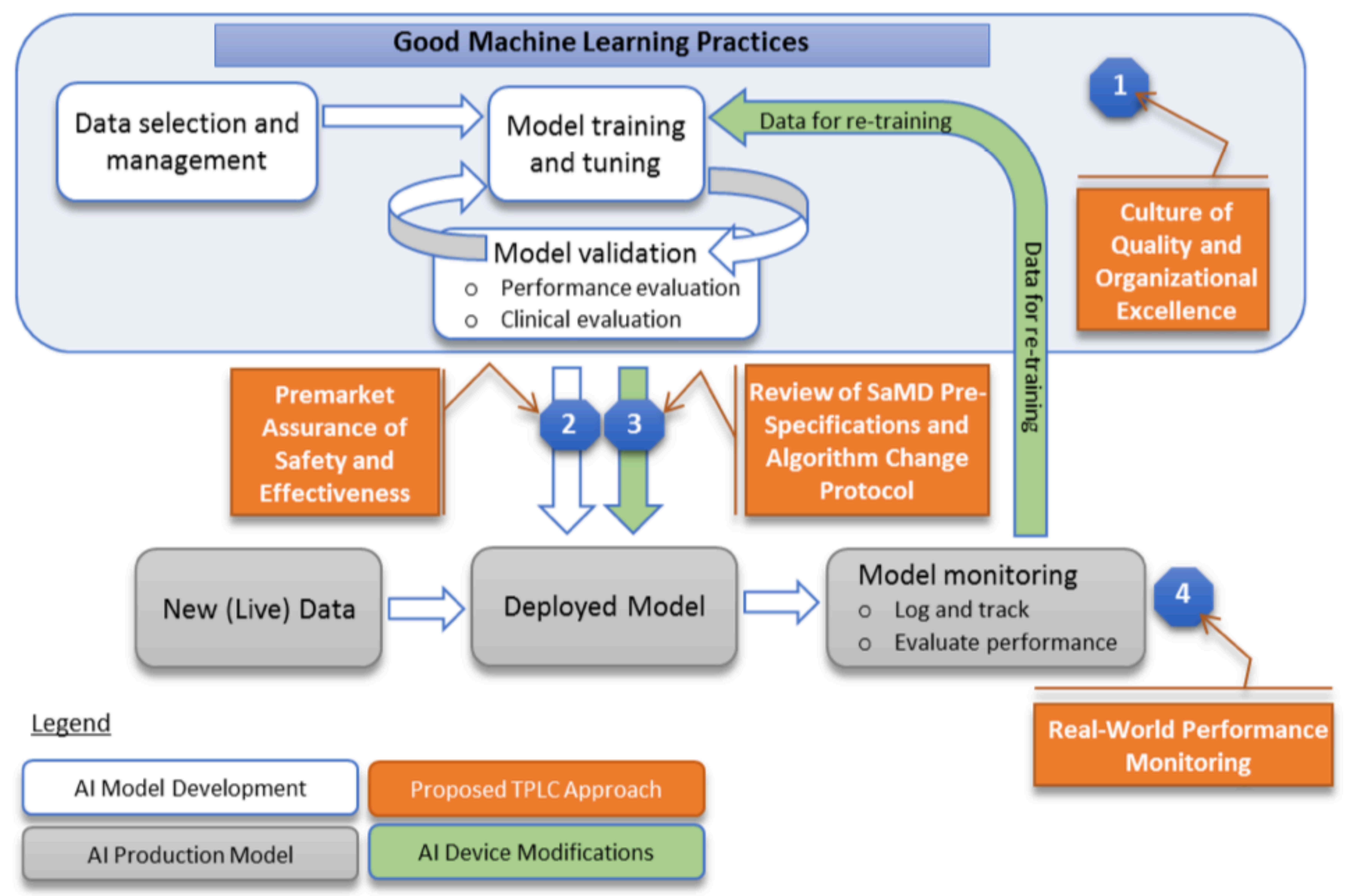
Need to facilitate rapid cycle of constant improvement while providing effective safeguards

New Regulatory Approach for AI/ML Needed



Where do Medical Physicists fit in?

Physicists are technical experts with clinical domain expertise

We are uniquely positioned to shape the future of AI in Medical Physics

- Data: governance, collection, curation
- Problem definition
- Model development, testing, and tuning
- Workflow design, validation, and implementation
- Supervision, maintenance
- Development and execution of routine QA

What does a QA program for AI look like?

We are no longer testing for constancy

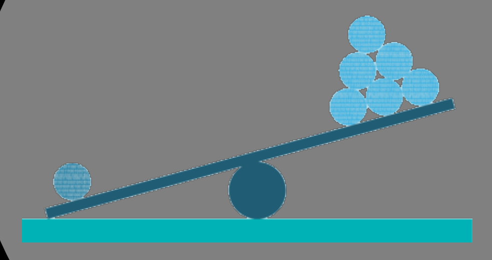
Courtesy of Leigh Conroy

Metrics to Evaluate Machine Learning Models

- Classification Accuracy ➔ Number of correct predictions
- Logarithmic Loss ➔ Penalize false classifications
- Confusion Matrix ➔ Complete performance of model
- Area Under the Curve ➔ Probability of ranking +data higher than −data
- F1 Score ➔ Precision of model based on precision and recall
- Mean Absolute Error ➔ Prediction minus truth | No direction
- Mean Squared Error ➔ Prediction minus truth | Penalize larger errors

https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234

Sources of Error in AI-based Error Detection



Class Imbalance

There are many more examples of non-errors than errors

Bias & Underfitting

Lots of historical data… not collected for this purpose

Inaccurate assumptions/simplifications of the model

Variance & Overfitting

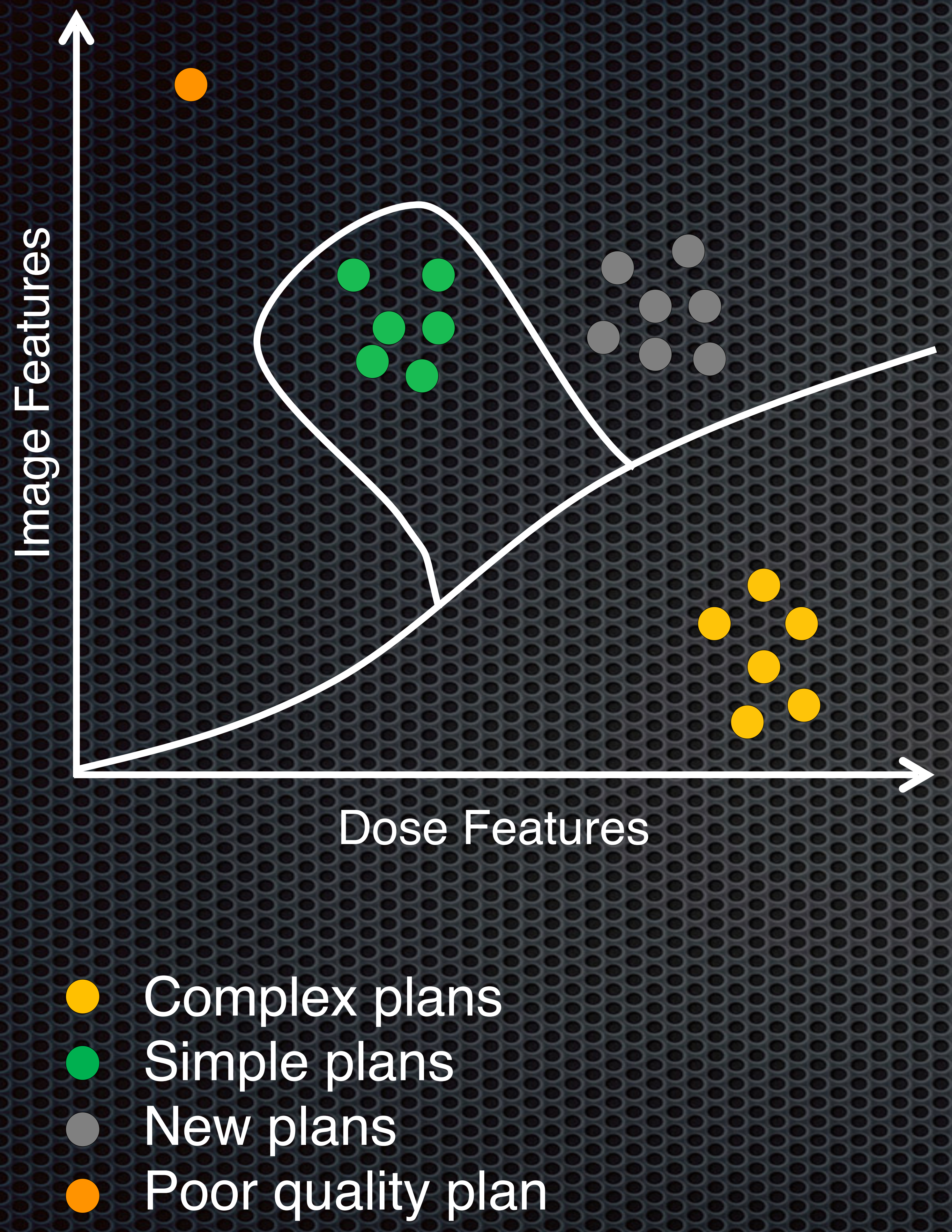
Detect the signal, not the noise!

Inter-institutional applicability

Courtesy of Leigh Conroy

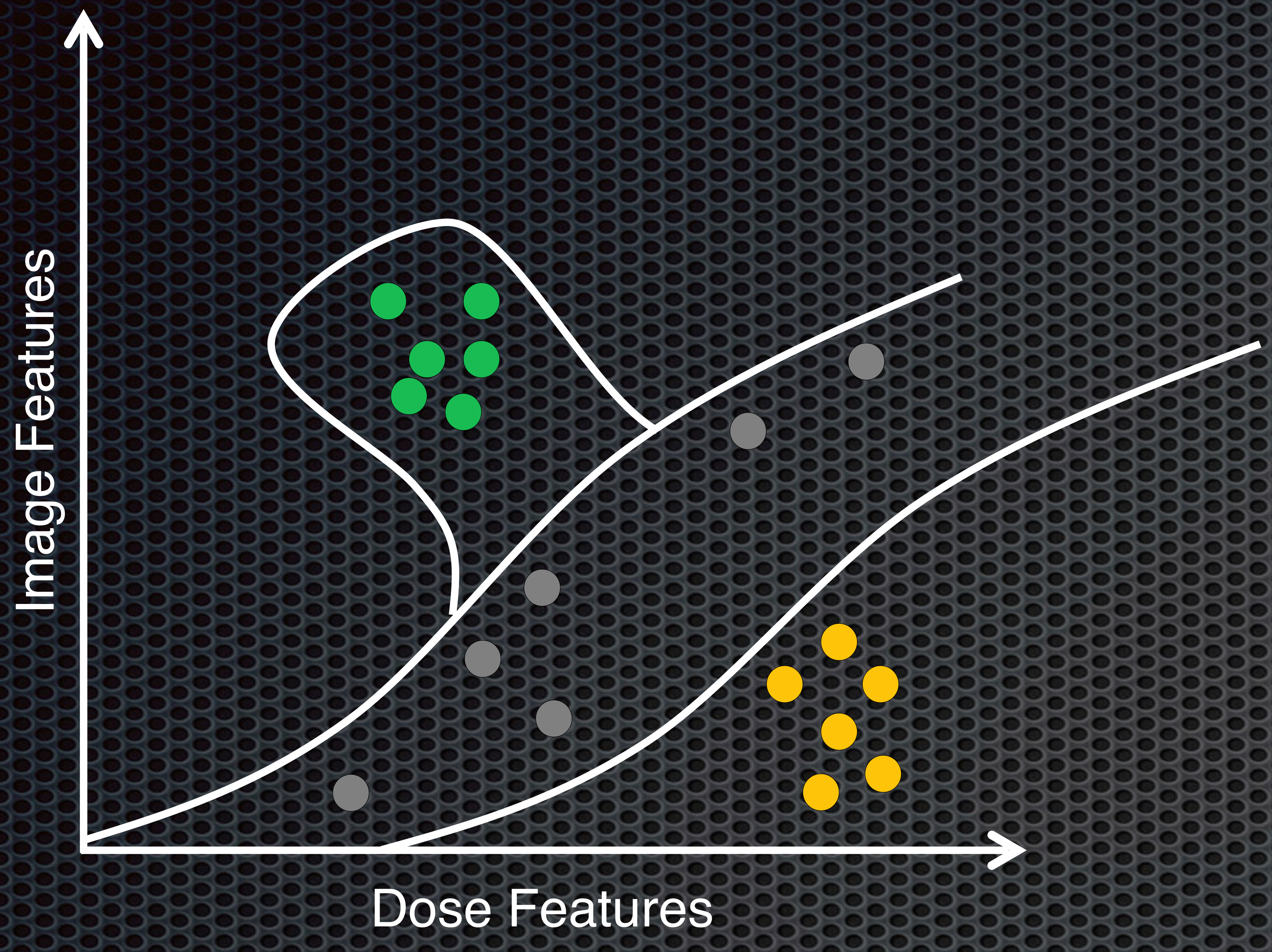
Risks of Automated Planning

Poor Model ➔ Include Sub-Optimal Plans in Training



Risks of Automated Planning

Model Error ➔ Over-fitting resulting in lack of generalization for new patients



- Plans of type A with standardized planning
- Plans of type B with standardized planning
- Plans of type C with standardized planning

Risks of Automated Planning

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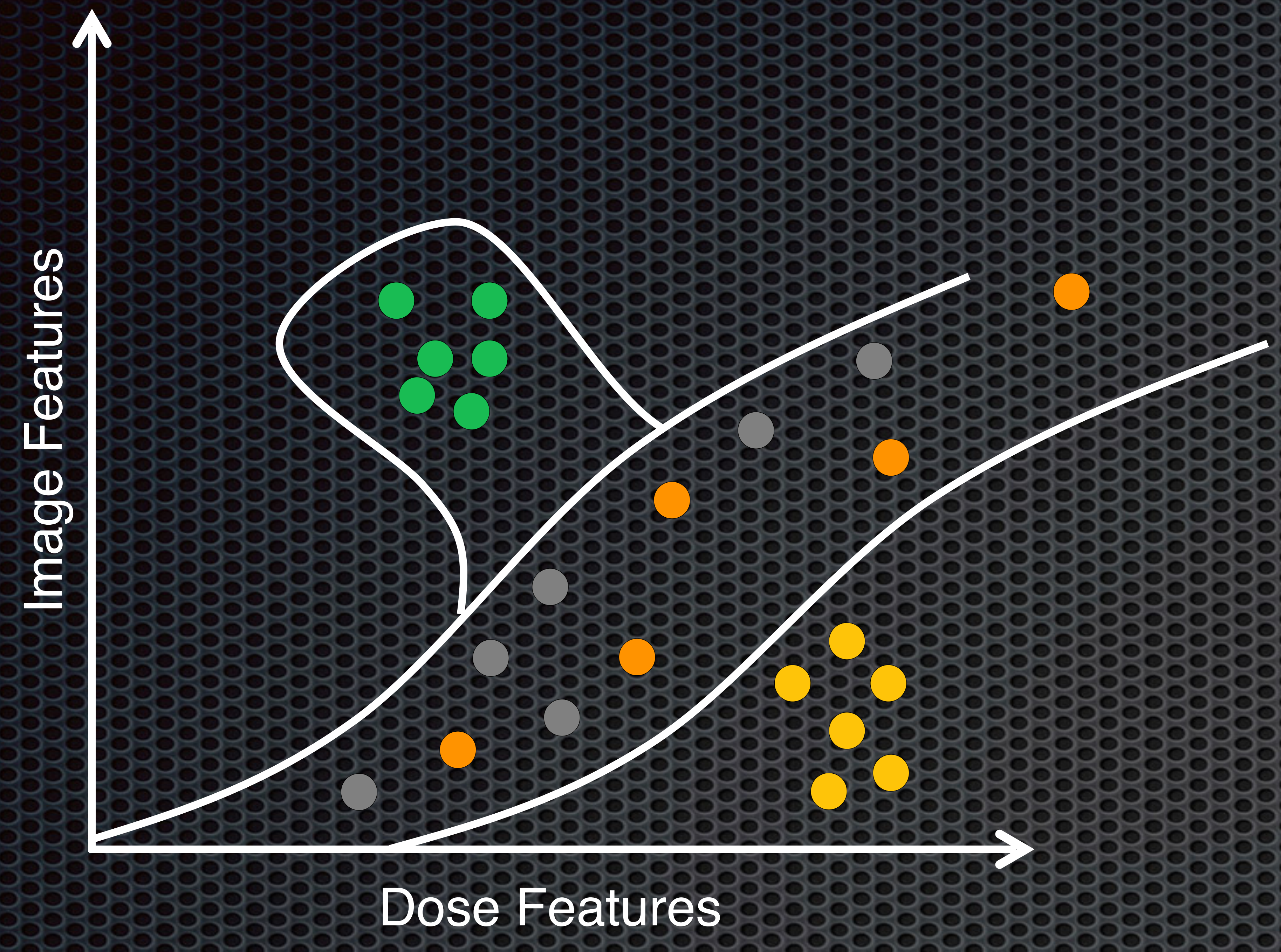

- Plans of type A with standardized planning
- Plans of type B with standardized planning
- Plans of type C with standardized planning
- Plans of type D with inconsistent planning

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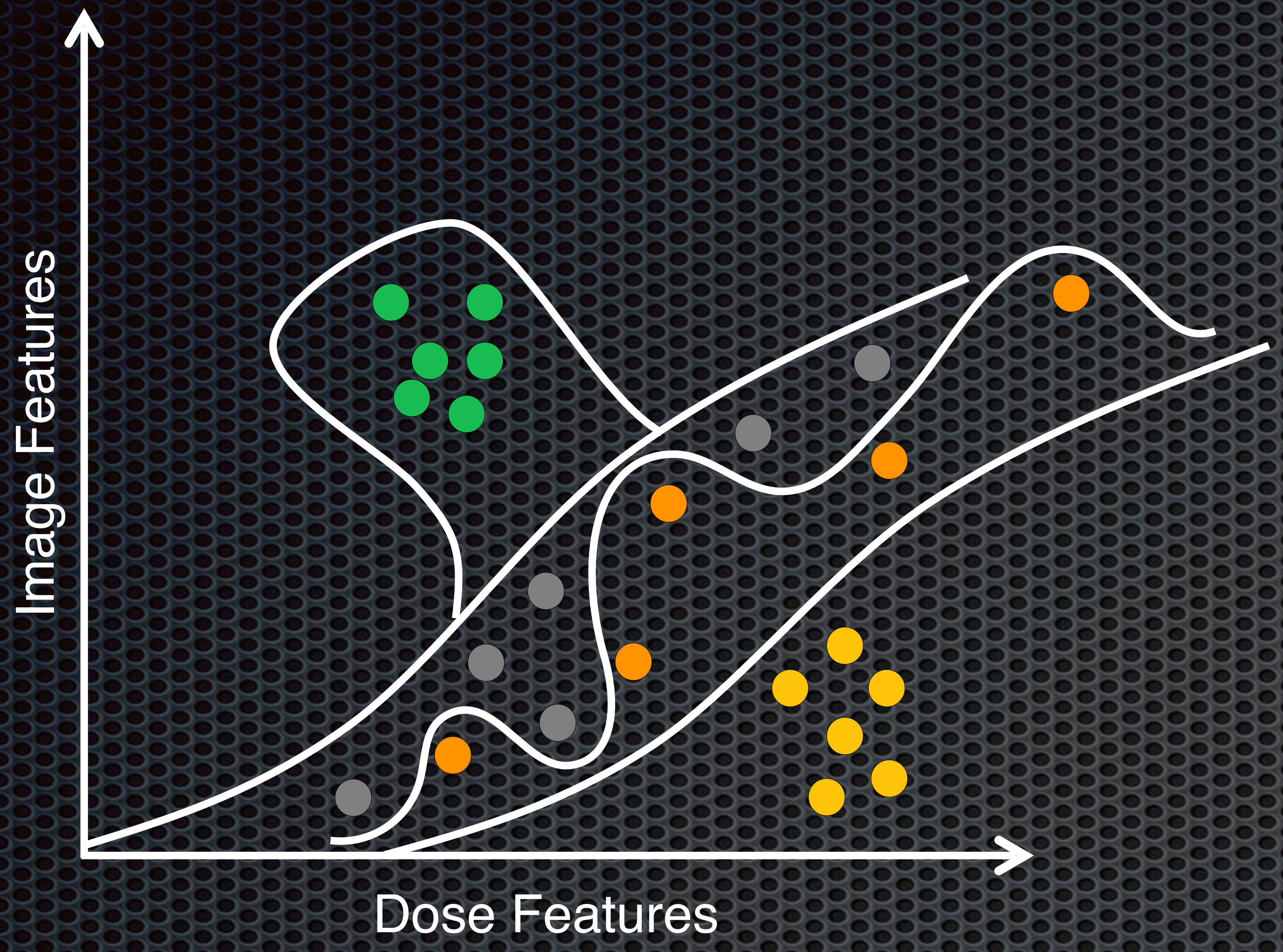

- Plans of type A with standardized planning
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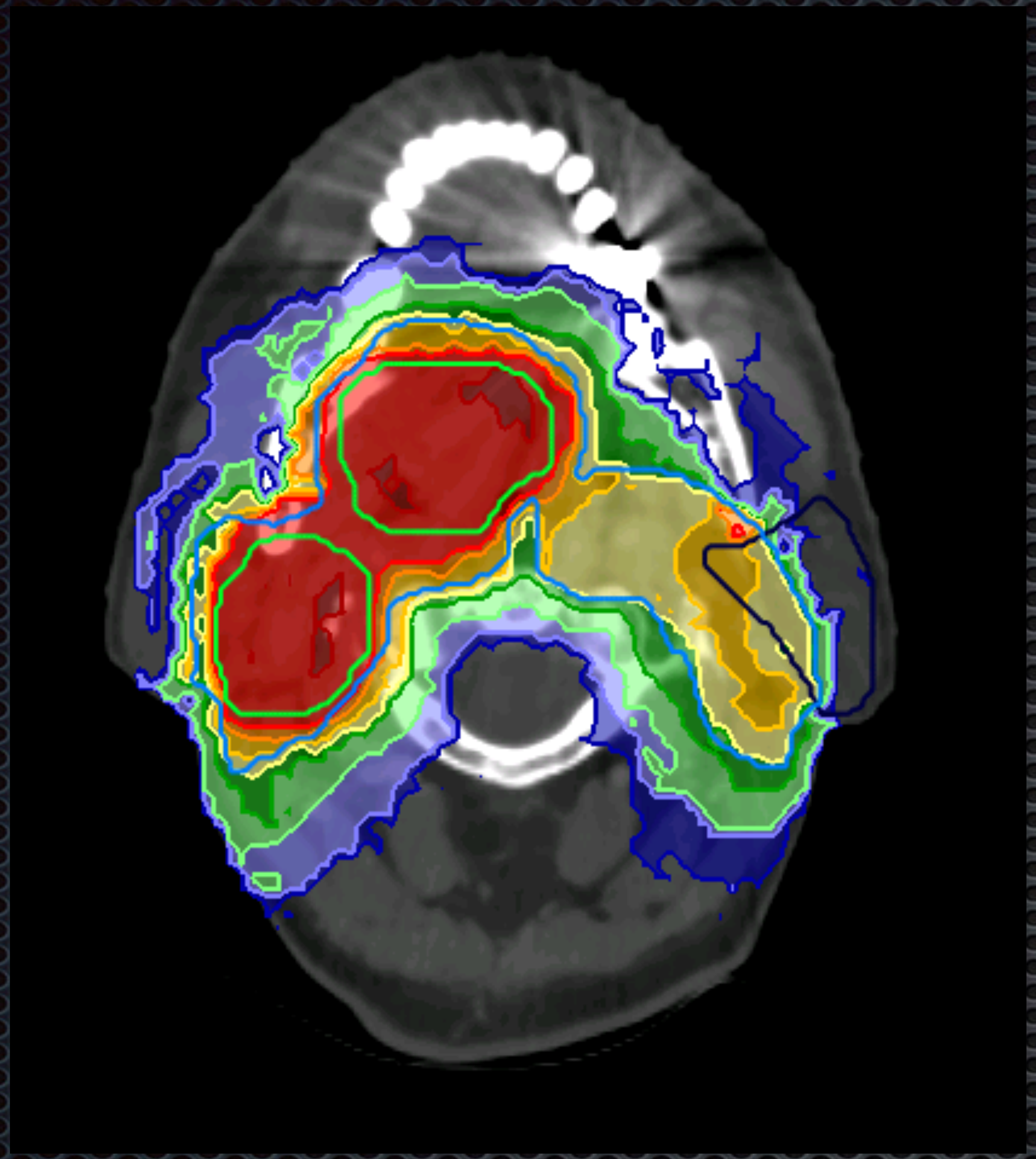
Risks of Automated Planning

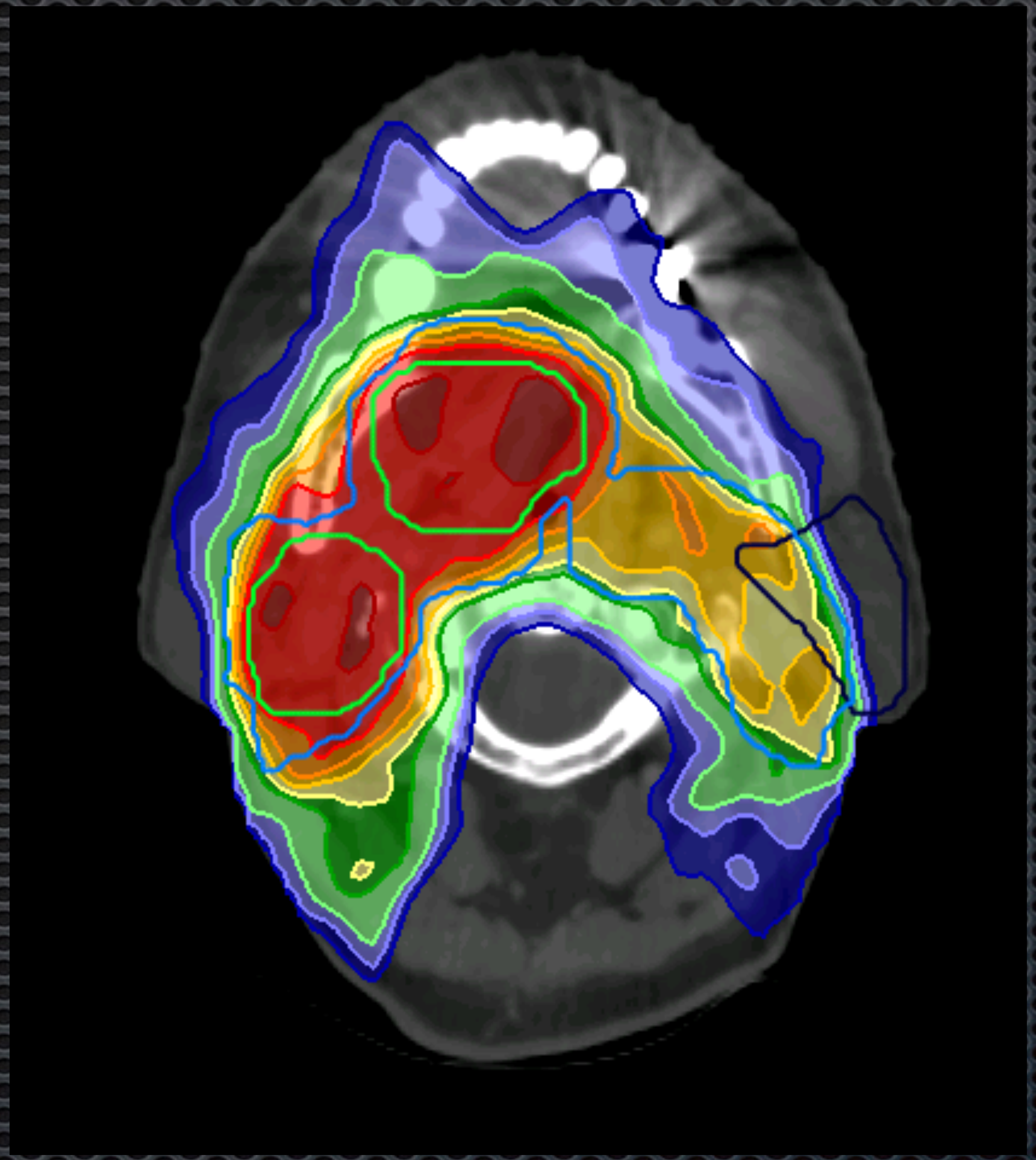
Unrealistic Dose Prediction ➔ Optimization Loop Cannot Achieve Predicted Dose

ML Predicted Dose



Dose Mimicking Optimization

Deliverable Dose



Risks of Automated Planning

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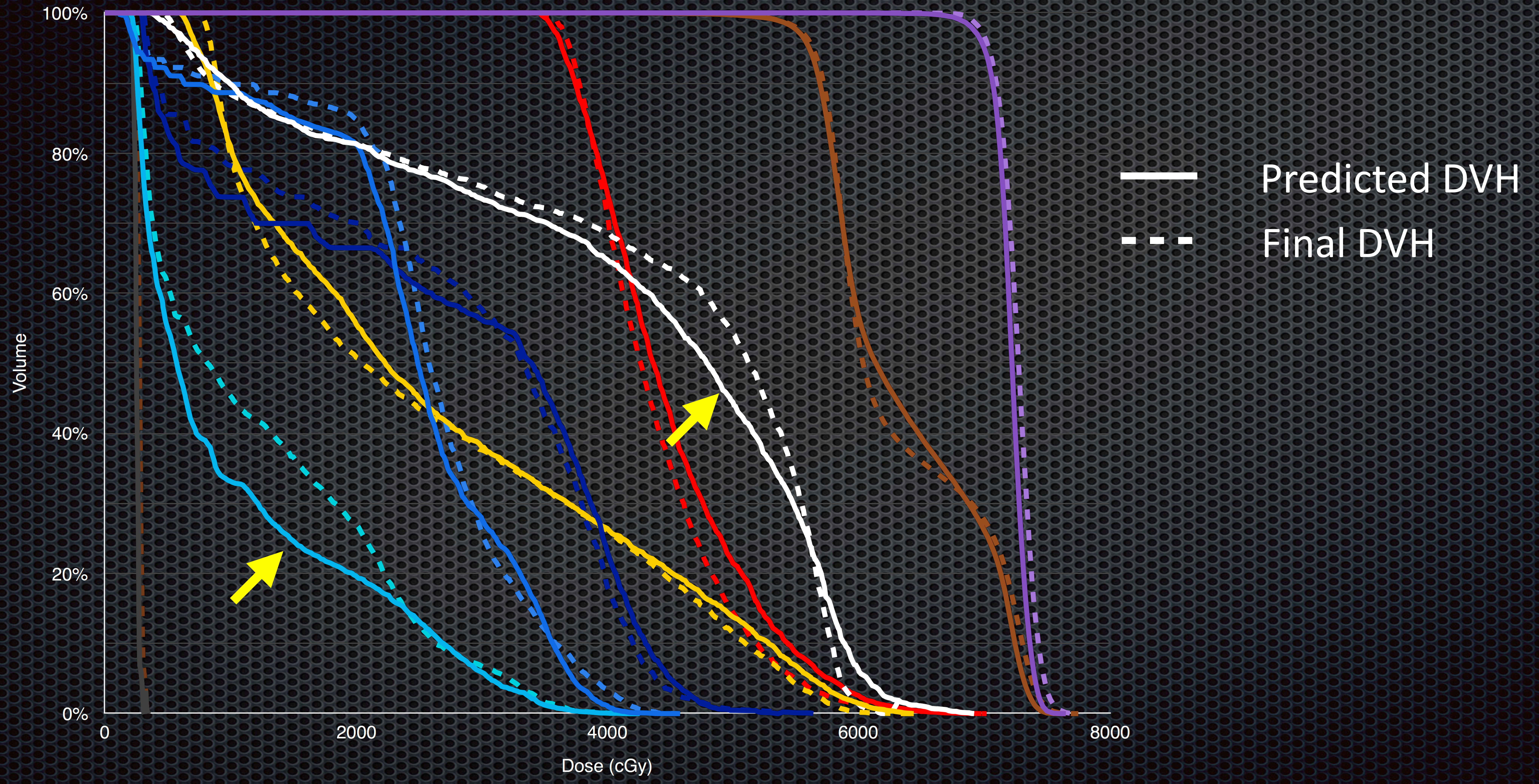
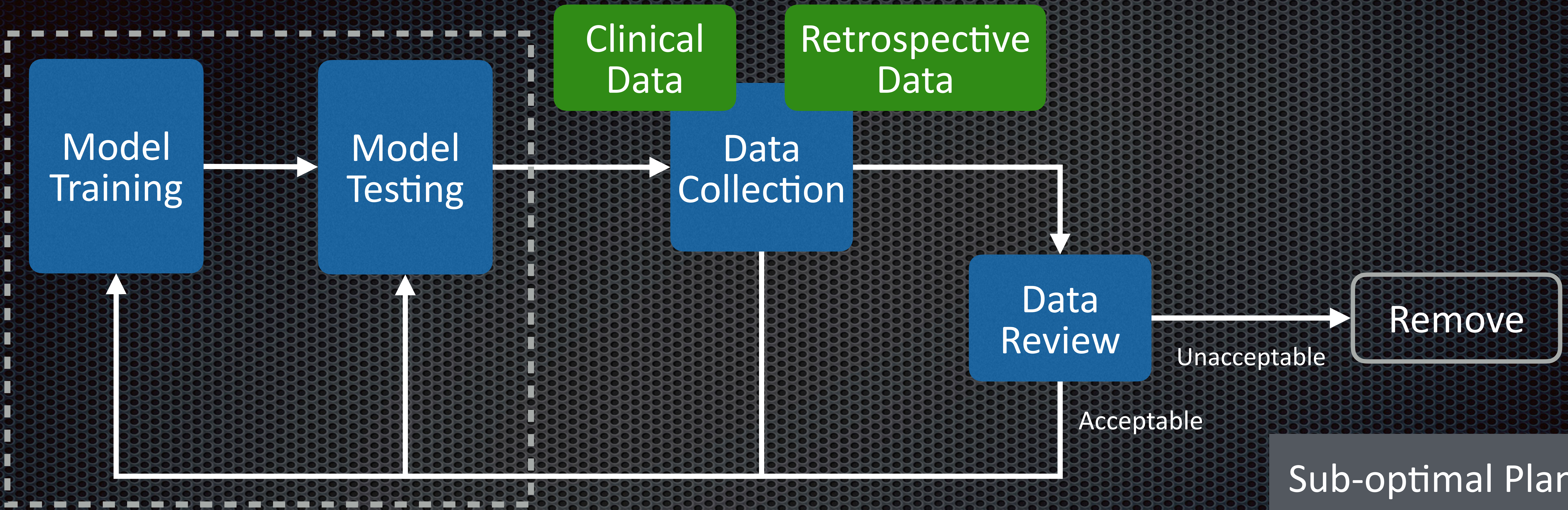


Risks of Automated Planning

Outlier Data



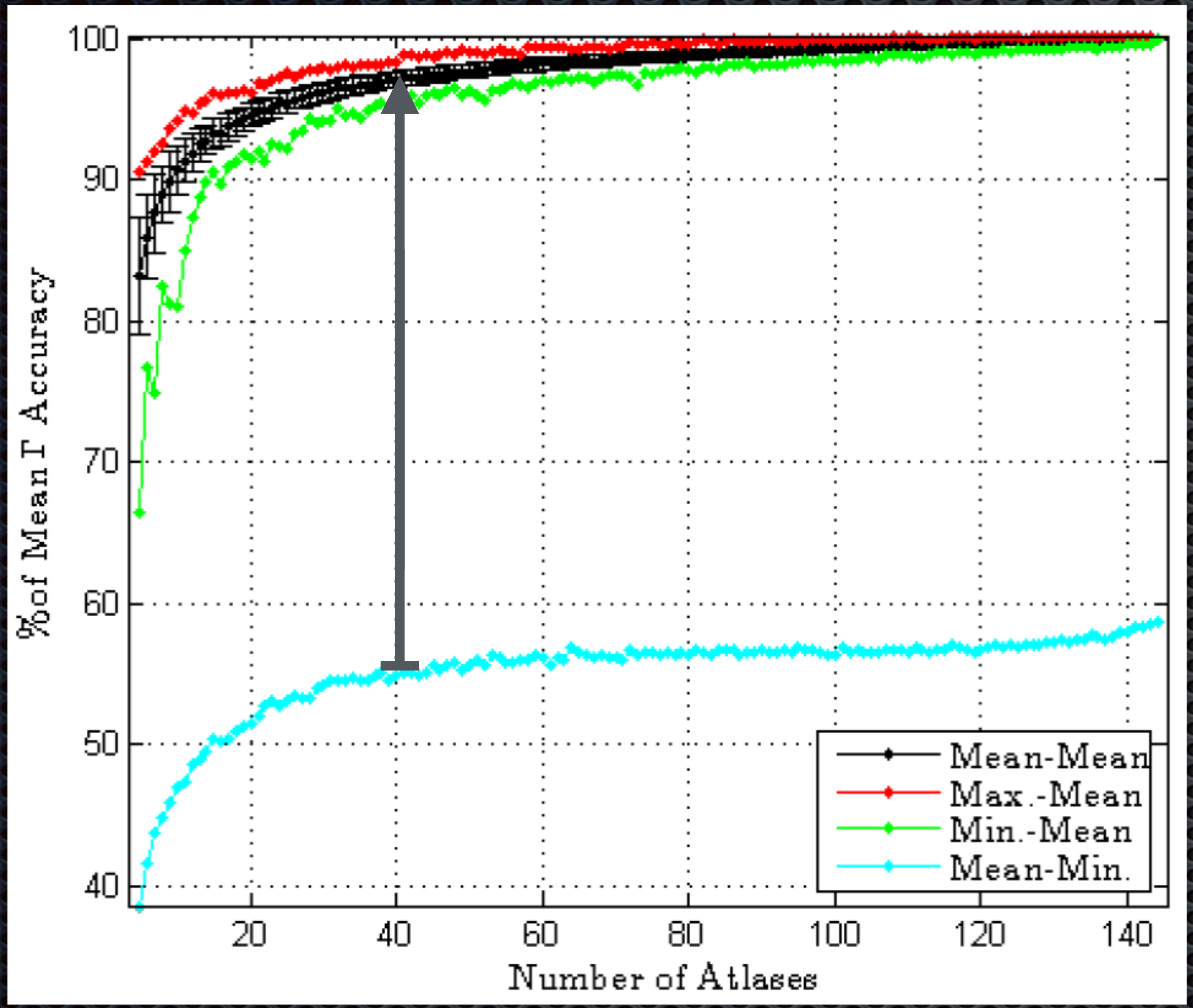
Sub-optimal Plans

Bias Stability → Data Half-Life

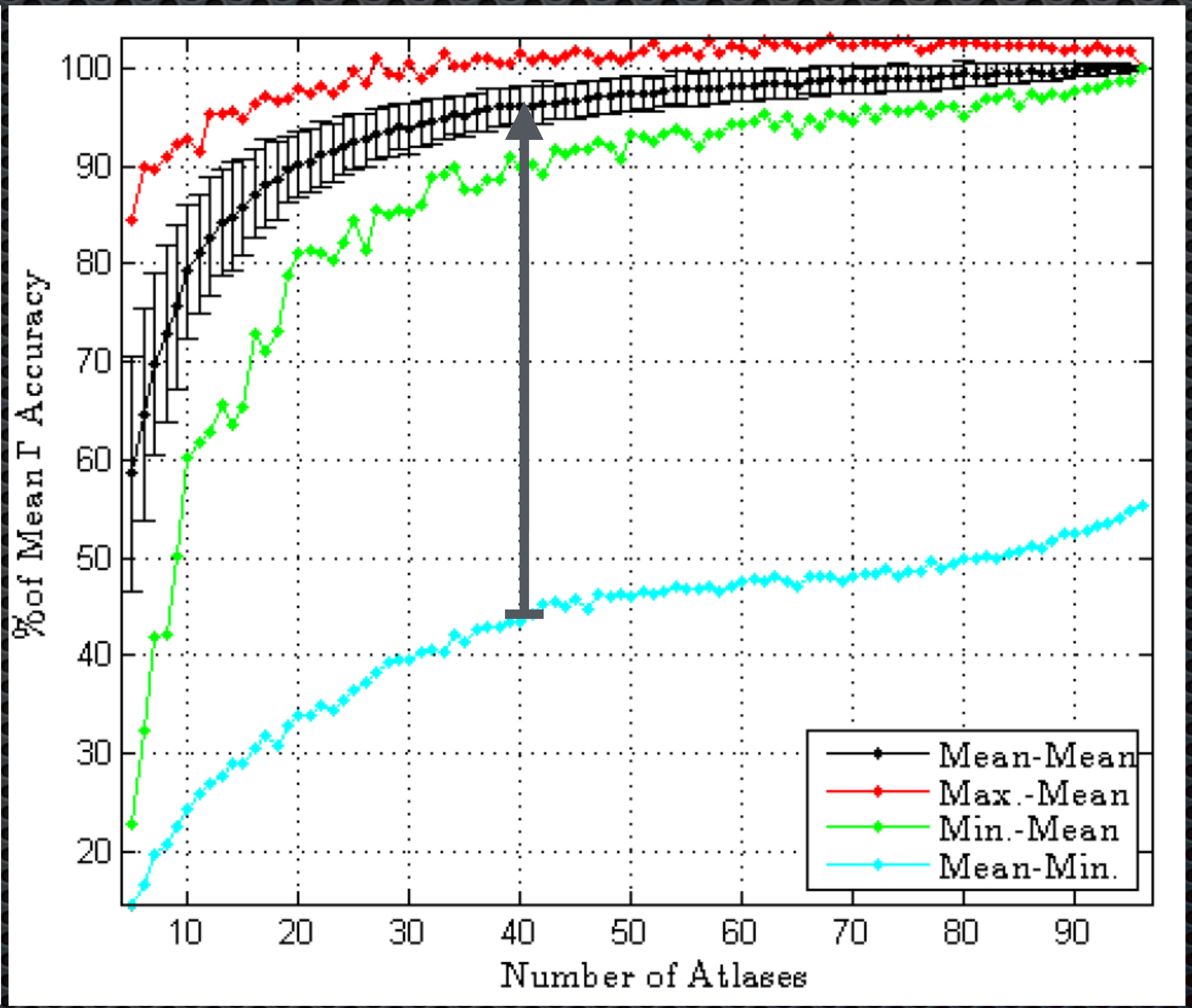
How many samples do I need in my training dataset?

Accuracy | Number of Training Atlases

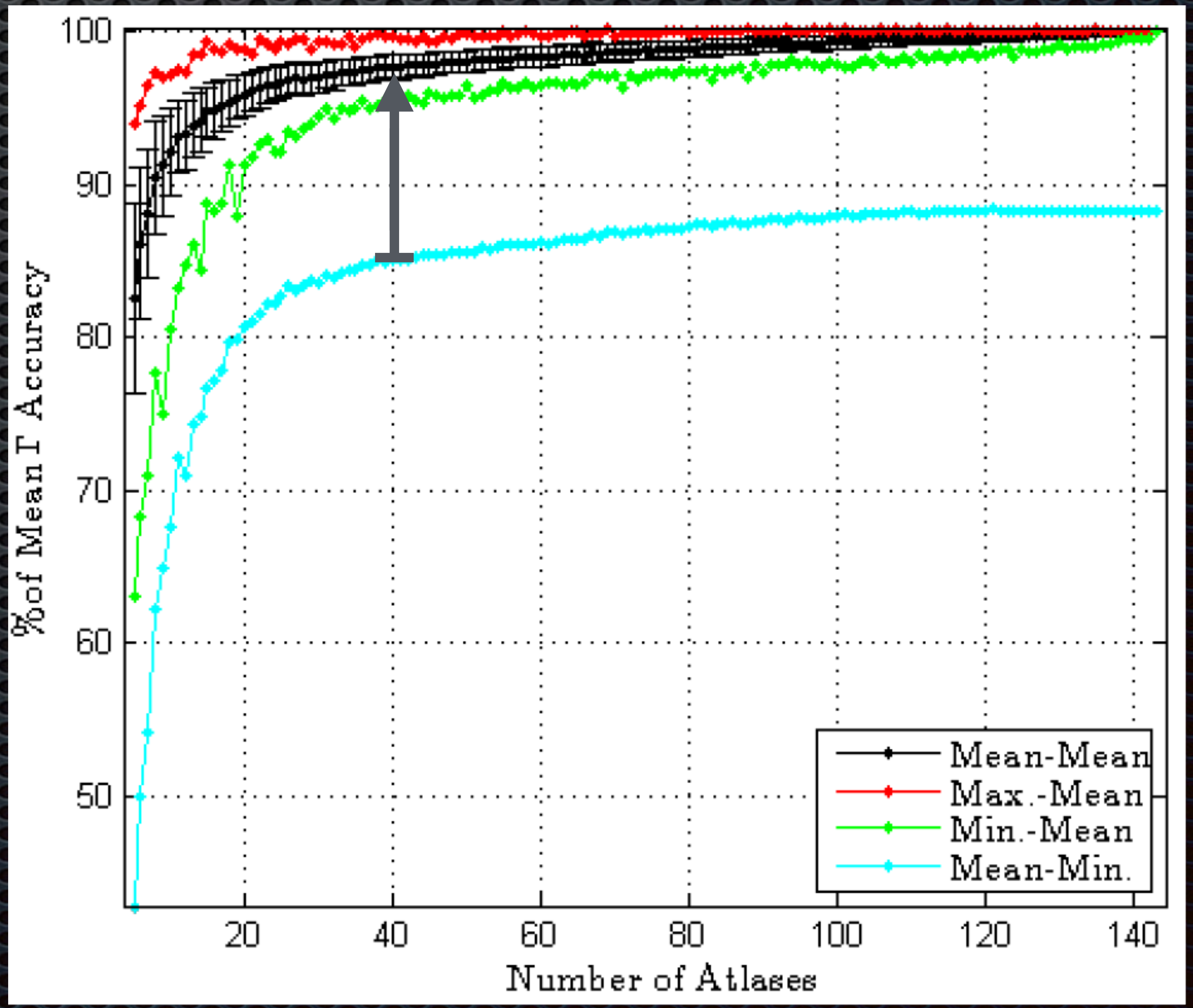
Accuracy is the % of voxels with similar radiation dose to ground truth



Whole Breast



Breast Cavity (Boost)



Prostate

Courtesy of Chris McIntosh

AMERICAN ASSOCIATION of PHYSICISTS IN MEDICINE

The Open Knowledge-Based Planning Challenge (OpenKBP)

An AAPM Grand Challenge

The aim of the OpenKBP Challenge is to advance fair and consistent comparisons of dose prediction methods for knowledge-based planning (KBP). Participants of the challenge will use a large dataset to train, test, and compare their prediction methods, using a set of standardized metrics, with those of other participants.

AAPM Grand Challenge 2020

Open Knowledge-Based Planning (KBP)

Objective
Implement the most accurate KBP dose prediction method on a large open-access dataset

Evaluation
All models are trained on the same data, and evaluated with standard metrics

Mechanical & Industrial Engineering
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Courtesy of Aaron Babier and Tim Chan

AAPM Grand Challenge 2020

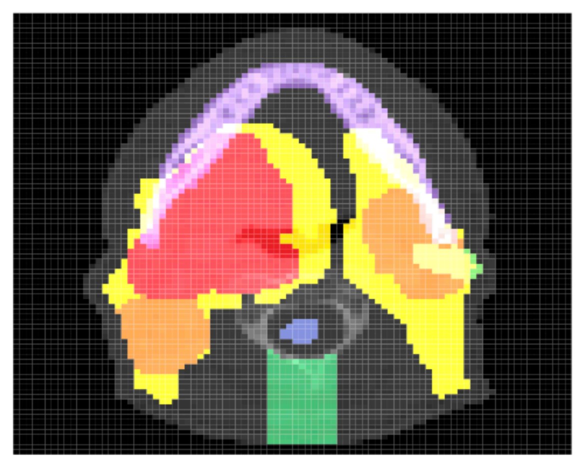
Open Knowledge-Based Planning (KBP)

March 1 → April 30

Prize (Top 2):
Free registration to the 2020 AAPM/COMP Annual Meeting in Vancouver

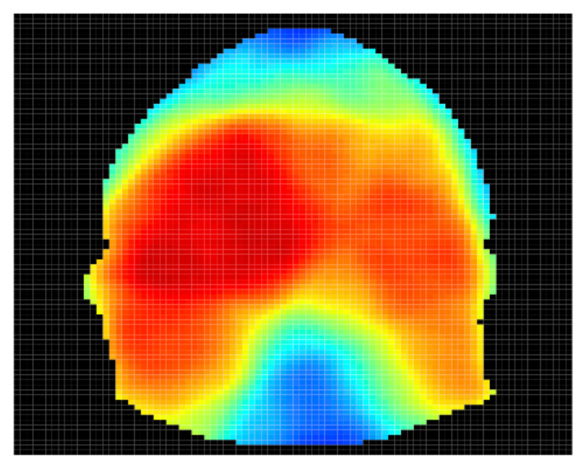
Courtesy of Aaron Babier and Tim Chan

The Competition



Planning CT + ROIs

Dose Prediction Method



Predicted Dose

Objective
Predict Dose using CT images

3D
Predict Full 3D Dose Distributions

DVH
Predict DVH Curves

Courtesy of Aaron Babier and Tim Chan

DVH Error Metric

Average difference between ground truth and predictions were evaluated at two and three DVH metrics for OARs and targets, respectively:

OAR DVH metrics

- $D_{0.1cc}$: Highest dose received by any 0.1cc of OAR volume
- D_{mean}: Mean dose to OAR

Targets DVH metrics

- $D_{1\%}$: Highest dose received by any 1% of target volume
- $D_{95\%}$: Highest dose received by any 95% of target volume
- $D_{99\%}$: Highest dose received by any 99% of target volume

Courtesy of Aaron Babier and Tim Chan

Leaderboard Streams

	3D Leaderboard	DVH Leaderboard
Ranking	Lowest average error	
Ground truth	Plan dose distribution	Plan DVH
Error measure	Voxel-by-voxel mean absolute error	Mean absolute error at dose volume metrics
3D stream	(✔)	(✔)
DVH stream	(✘)	(✔)

Courtesy of Aaron Babier and Tim Chan

Leaderboard Phases

Validation phase

Each team's best validation submission was displayed on a public leaderboard

Testing Phase

Each team made one submission to the testing phase, which was used to determine winners

Scores were blinded until competition closed

Courtesy of Aaron Babier and Tim Chan

Summary of Participation

	Registration	Active in Validation	Active in Testing
Total participants	195	73	54
Total teams	129	44	28
Number of submissions	---	1750	28

New interest to research community

57% say primary research is Not "Medical Physics"

62% say NEVER done KBP research before

Courtesy of Aaron Babier and Tim Chan

Thanks for your attention