Mining data to develop planning and treatment quality metrics

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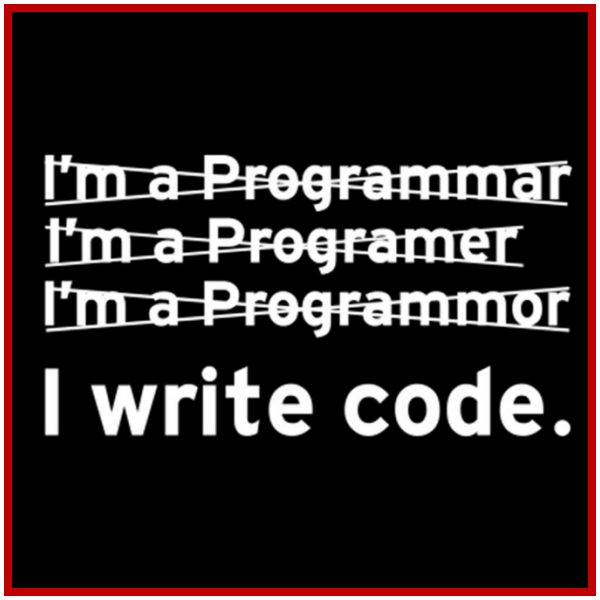
Research Disclaimer:

Author has an unrelated grant with Varian Medical Systems.

Spelling Disclaimer:



Mining data to develop planning and treatment quality metrics



Most of the work
Planting Ideas, Cultivating a data focused culture
Enabling technologies and clinical processes

Big Data

Metrics for Plan Quality

Int. J. Radiation Oncology Biol. Phys., Vol. 76, No. 3, Supplement, pp. S155–S160, 2010

0360-3016/10/$–see front matter

ELSEVIER

doi:10.1016/j.ijrobp.2009.08.074

QUANTEC: VISION PAPER

THE LESSONS OF QUANTEC: RECOMMENDATIONS FOR REPORTING AND GATHERING DATA ON DOSE–VOLUME DEPENDENCIES OF TREATMENT OUTCOME

Andrew Jackson, Ph.D.,* Lawrence B. Marks, M.D.,† Søren M. Bentzen, Ph.D., D.Sc.,‡ Avraham Eisbruch, M.D.,§ Ellen D. Yorke, Ph.D.,* Randal K. Ten Haken, Ph.D.,§ Louis S. Constine, M.D.,‖ and Joseph O. Deasy, Ph.D.¶

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Int. J. Radiation Oncology Biol. Phys., Vol. 76, No. 3, Supplement, pp. S151–S154, 2010

0360-3016/10/$–see front matter

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doi:10.1016/j.ijrobp.2009.06.094

QUANTEC: VISION PAPER

IMPROVING NORMAL TISSUE COMPLICATION PROBABILITY MODELS: THE NEED TO ADOPT A "DATA-POOLING" CULTURE

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We want to "follow the data" to make meaningful decisions on how to improve treatments to get better outcomes for our patients.

There is significant heterogeneity in treatment parameters that vary among clinics, providers, time, technology, etc. . To tease out details on what can be shown to matter, large , detailed, longitudinal datasets are needed.

It should be easier to show what treatment factors correlate with outcomes

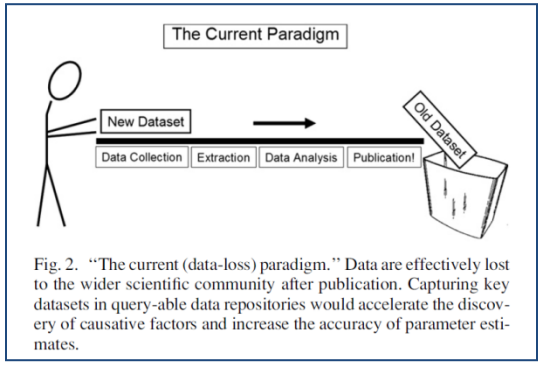

Fig. 2. "The current (data-loss) paradigm." Data are effectively lost to the wider scientific community after publication. Capturing key datasets in query-able data repositories would accelerate the discovery of causative factors and increase the accuracy of parameter estimates.

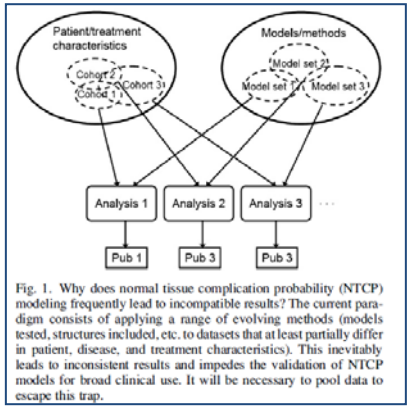

Fig. 1. Why does normal tissue complication probability (NTCP) modeling frequently lead to incompatible results? The current paradigm consists of applying a range of evolving methods (models tested, structures included, etc. to datasets that at least partially differ in patient, disease, and treatment characteristics). This inevitably leads to inconsistent results and impedes the validation of NTCP models for broad clinical use. It will be necessary to pool data to escape this trap.

Int. J. Radiation Oncology Biol. Phys., Vol. 76, No. 3, Supplement, pp. S28–S35, 2010

0360-3016/10/$–see front matter

ELSEVIER

doi:10.1016/j.ijrobp.2009.07.1753

QUANTEC: ORGAN-SPECIFIC PAPER **Central Nervous System: Optic Nerve/Chiasm**

RADIATION DOSE–VOLUME EFFECTS OF OPTIC NERVES AND CHIASM

Charles Mayo, Ph.D.,* Mary K. Martel, Ph.D.,† Lawrence B. Marks, M.D.,‡ John Flickinger, M.D.,§ Jhio Nam, M.D.,‡ and John Kirkpatrick, M.D., Ph.D.¶

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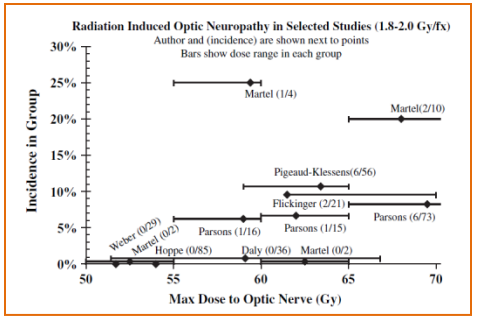
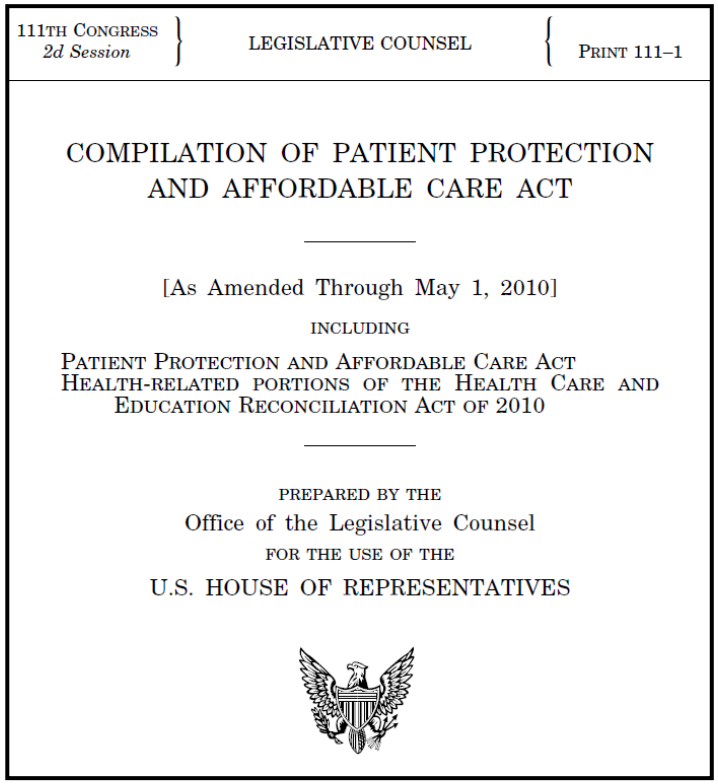


“The Coming Era of Big Data”

What is pushing health care there … Affordable Care Act



111TH CONGRESS *2d Session* | LEGISLATIVE COUNSEL | PRINT 111–1

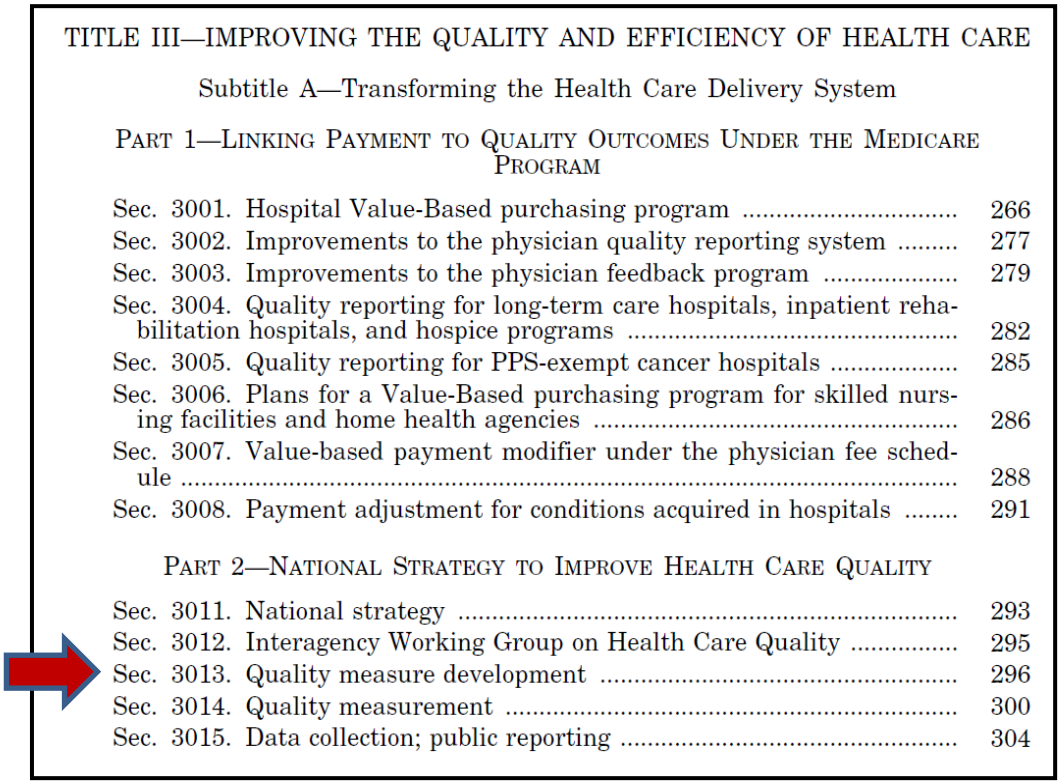
COMPILATION OF PATIENT PROTECTION AND AFFORDABLE CARE ACT

[As Amended Through May 1, 2010]

INCLUDING

PATIENT PROTECTION AND AFFORDABLE CARE ACT
HEALTH-RELATED PORTIONS OF THE HEALTH CARE AND EDUCATION RECONCILIATION ACT OF 2010

PREPARED BY THE
Office of the Legislative Counsel
FOR THE USE OF THE
U.S. HOUSE OF REPRESENTATIVES



TITLE III—IMPROVING THE QUALITY AND EFFICIENCY OF HEALTH CARE

Subtitle A—Transforming the Health Care Delivery System

PART 1—LINKING PAYMENT TO QUALITY OUTCOMES UNDER THE MEDICARE PROGRAM

PART 2—NATIONAL STRATEGY TO IMPROVE HEALTH CARE QUALITY

We need to define the metrics that are going to be used to define to quality measurement

Should be clinically useful, should be gettable from automated processes

Taussig Cancer Institute

Cleveland Clinic

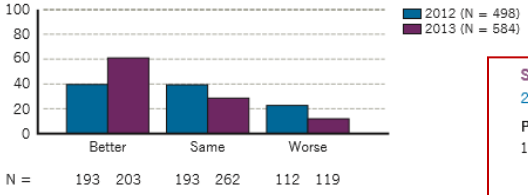
2013 Outcomes

Our commitment to transparent reporting of accurate, timely information about patient care reflects Cleveland Clinic's culture of continuous improvement and may help referring physicians make informed decisions.

Palliative Medicine

Fatigue Status at Discharge
2012 – 2013

Percent of Patients Reported

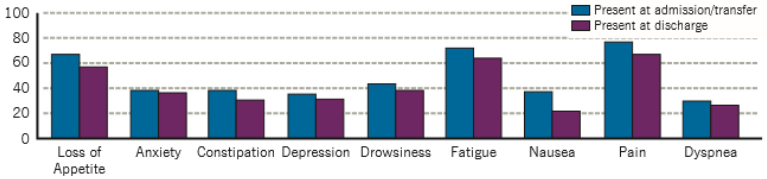


Status as reported by 584 patients with fatigue on admission/transfer or discharge in 2013; symptom assessed for 724 inpatients in 2013, inclu symptoms data for expired patients up to the time of death.

Palliative Medicine

Symptoms Present at Admission and Discharge
2013

Percent of Patients Reported

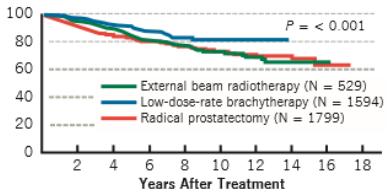


Symptoms assessed and reported for 1108 inpatients in 2013, including symptoms data for expired patients up to the time of death.

Measuring Outcomes Promotes Quality Improvement

Biochemical Relapse-Free Survival of Patients with *Intermediate-Risk* Prostate Cancer by Treatment Type (N = 3922)
1996 – 2013

Percent Biochemical Relapse-Free Survival

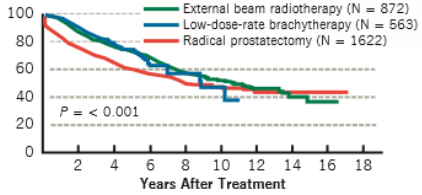


Percent Biochemical Relapse-Free Survival and (Number at Risk)

Treatment Type	5-Year	10-Year
External beam radiotherapy	85 (259)	72 (101)
Low-dose-rate brachytherapy	91 (286)	81 (25)
Radical prostatectomy	83 (337)	73 (108)

Biochemical Relapse-Free Survival of Patients with *High-Risk* Localized Prostate Cancer by Treatment Type (N = 3057)
1996 – 2013

Percent Biochemical Relapse-Free Survival



Percent Biochemical Relapse-Free Survival and (Number at Risk)

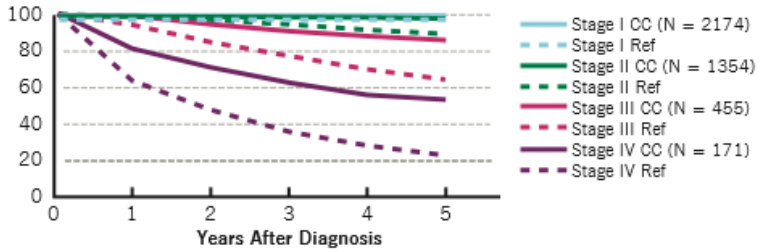
Treatment Type	5-Year	10-Year
External beam radiotherapy	74 (366)	52 (103)
Low-dose-rate brachytherapy	75 (69)	47 (5)
Radical prostatectomy	60 (172)	47 (44)

P value from log-rank test. Mantel N. Evaluation of survival data and two new rank order statistics arising in its consideration. *Cancer Chemother Rep*. 1966;50(3):163–170.

Low-, intermediate-, and high-risk stratification done per National Comprehensive Cancer Network (NCCN) criteria. NCCN Clinical Practice Guidelines in Oncology – Prostate Cancer. Version 2.2007, Apr. 9, 2007. National Comprehensive Cancer Network, Inc.

Five-Year Relative Survival of Patients with Breast Cancer by Stage at Diagnosis (N = 4154)
2006 – 2012

Percent Survival



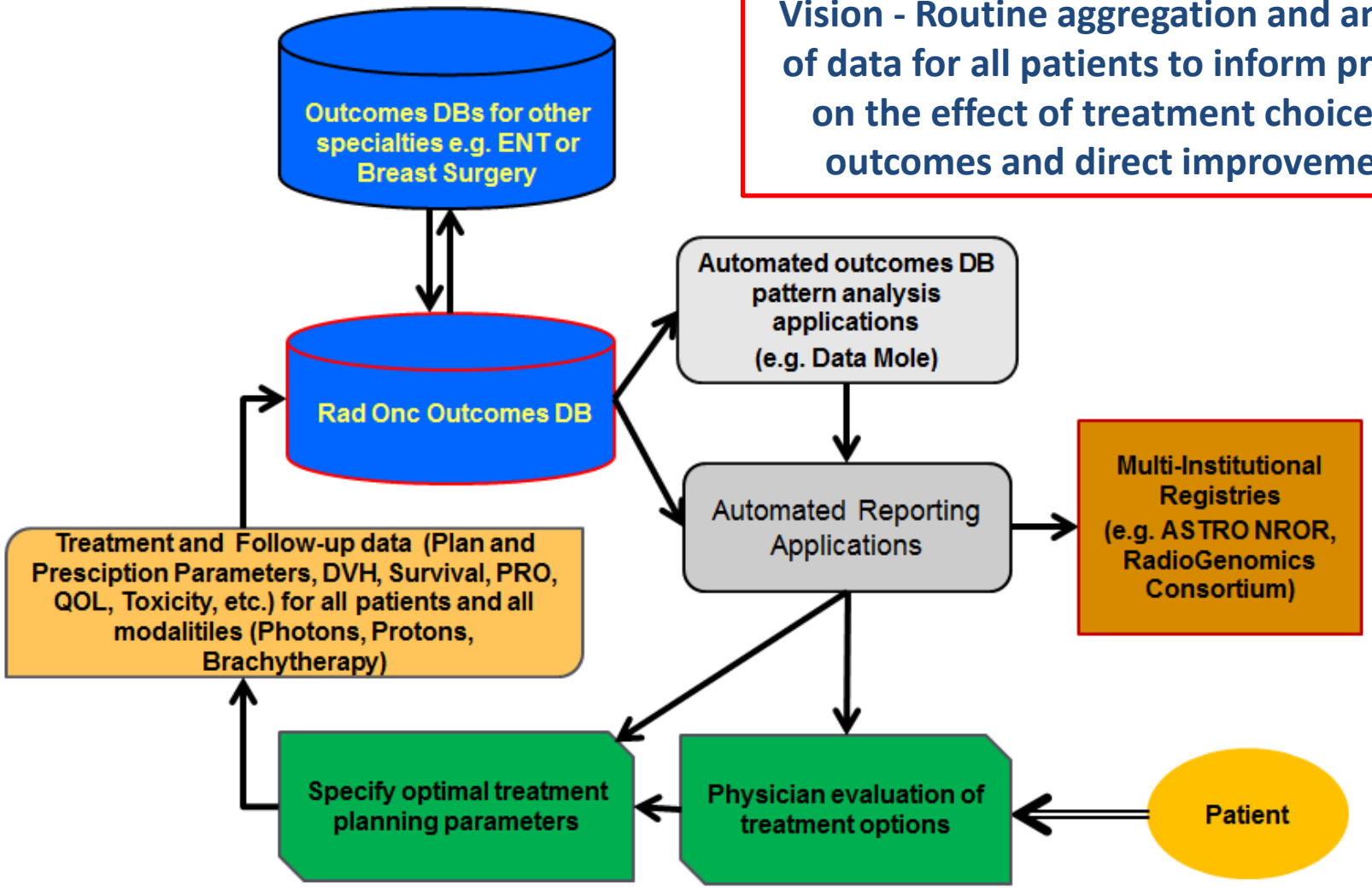
- Periodic Cleveland Clinic report (~83 pages) provided to physicians to give detailed data on outcomes for **all** disease sites.
- Example of how routine collection of data can be incorporated into clinician discussions of evidence based medicine and used as a baseline to better inform patients.
- Requires a commitment to "follow the data"

Courtesy of John Suh, MD

Knowledge Based Clinical Practice Improvement System (aka KPI or Kπ)

Mayo RadOnc System to routinely gather and analyze outcomes data for all patients

Vision - Routine aggregation and analysis of data for all patients to inform practice on the effect of treatment choices on outcomes and direct improvements



The basis of knowledge is information

Data Dictionary of KPI Dev Data Elements as of 10/10/2014

Enhanced Demographics: Name, ClinicID, DOB, DOD(i.e. survival), County, State, Country, Postal Code, Race, Ethnicity, Religion, Marital Status, Gender, E-Mail

Diagnosis and Staging: Date of Entry, Basis, T,N,M + G,H,N,P,R,S, etc, OverallStage, StagingSystem, Laterality, ICD9 (ICD10), ICD0,Ranking, Primary Site, DistantMets, Recurrence, ICD9 of Primary,Diagnosis Date, Diagnosis Method

Toxicity: Date, Grading System, Grade, Cause, Certainty

Patient Reported Outcomes: Date of PRO, Templates, Questions , Answers

Labs(Current): Height, Weight, BMI, Neutrophils, Platelet Count, Lymphocytes, Hemoglobin, Leukocytes, PSA (~ 3,000,000 rows of data ≥ 1/1/2011)

Treatment Course: CourseID, Course Start Date (based on treatment records), Course End Date (based on treatment records)

Treatment Rx: Number of course fractions, number of treatments per course fraction, dose to each target volume (i.e. all the data in the Rx in Planning Templates)

Treatment Delivery Details for Each Plan: Facility, Machine, NFractions Treated, NFractions Planned, Total Dose Delivered, Total Dose Planned, Number of Beams, Plan Name, Plan DicomUID, TotalMU, TotalBeamOnTime, TotalTreatmentDeliveryTime, TotalTreatmentSessionTime , IsProton, IsBrachy, IsSBRT, IsBreathHold, UsedStaticIMRT, UsedHybridIMRT, UsedVMATIMRT, UsedHybridVMAT, UsedWedges, UsedNonCoplanarBeams, UsedHalfBeamX, UsedHalfBeamY, UsedIGRT, UsedCBCT, UsedX06, UsedX06FFF, UsedX10, UsedX10FFF,UsedX18, UsedX18FFF, UsedE06, UsedE09, UsedE12, UsedE16,UsedE20,CouchVrt_Mean, CouchVrt_Stdev, CouchLng_Mean, CouchLng_Stdev, CouchLat_Mean, CouchLat_Stdev, CouchRotation_Mean, CouchRotation_Stdev, CouchPitch_Mean, CouchPitch_Stdev, CouchRoll_Mean,CouchRoll_Stdev, (Other Brachy and proton specific items to be added)

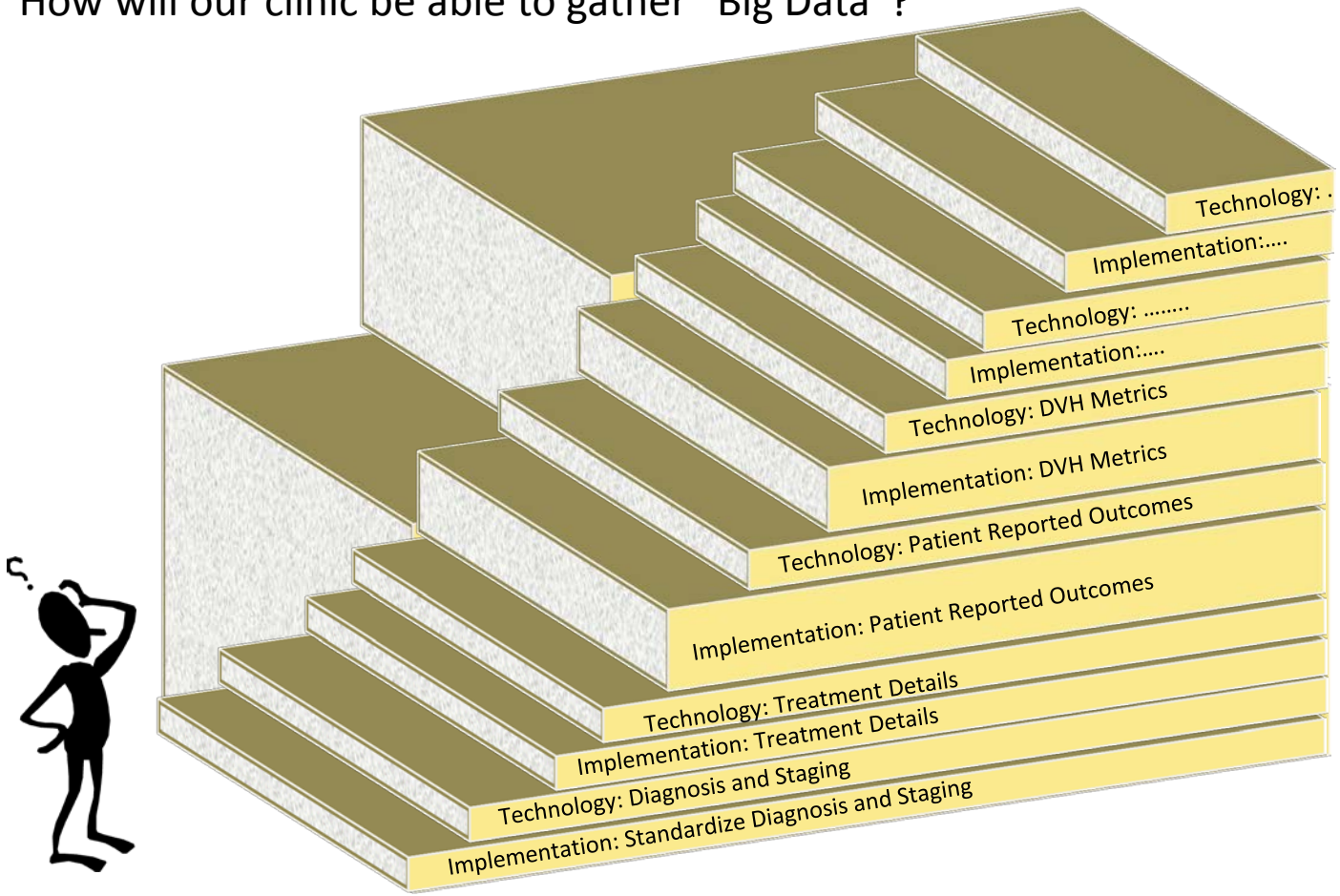
Treatment DVH Curves: Structure, Volume[cc], Max[Gy],Min[Gy], Mean[Gy], Median[Gy], Stdev[Gy], DVH curve (Percent Volume vs Absolute Dose as point pairs)

Treatment DVH Metrics: Values stored for course composite plans (e.g. 1st course + Boost), as in planning templates. This enables rapid identification of patient groups according to metrics that are most relevant to disease site groups, (i.e. find all esophagus patients with lung_total:V20Gy[%] > 20) The treatment DVH curves can be used to pull other values, but the searches based on DVH curves are slower than searches on DVH metrics.

Treatment Details Specific to Disease Site: e.g. Breast target details questionnaire, CU Androgen questionnaire, Head and Neck HPV status

Recurrence Status: HadLocalRelapse,Date of Local Relapse, HadRegionalLymphNodeRecurrence, Date of Regional LymphNodeRecurrence, HadDistant Relapse, Date of Distant Relapse, Site of Distant Relapse, Cause of Death (Cancer-Local, Cancer- Regional, Cancer-Distant, Treatment, Other, Unknown)

How will our clinic be able to gather “Big Data”?



- Demographics
- Diagnosis and Staging
- Survival/Recurrence
- Provider Reported Toxicity
- Patient Reported Outcomes
- Treatment Plan Details
- DVH Metrics
- DVH Curves
- Chemotherapy
- Surgery
- Labs
- Imaging
- Treatment Delivery Details
- Treatment Approach Details

- Technology is a much smaller step than culture changes needed for implementation: consensus (inter and intra institutional), process, changes in work duties, QA
- Can do a lot with existing treatment planning and radiation oncology information systems
- Think through what data elements you want /need in the long run, how they are related and then develop a strategy of small, manageable steps.

How to get there ?

Technology

- Software/database systems for aggregating information
- Software systems for analytics
- Integration with other systems

A few options here

- DIY – Use in house staff with expertise or train
- Use consultants to help build
- Purchase from current vendor (ROIS,TPS)
- Purchase from 3rd party vendor

Culture

- Need to shift thinking about data related to treating our patients.
- Thinking about the data not just for treatment of the patient before us , but for systematic aggregation to help all the patients yet to come.
- Implication is accepting limitations in options, standardizations
- Potentially more work to quantify data – "free text" is hard to use

This… only you can do

Assume you have the technology, what do you have to change about your practice to enable the technology to get the data?

- Consensus in your practice
- Standardize practice
- Change who does what

Baby Steps – a lot of them

To move a group you have to help them believe in the vision.
As you create working examples that show it is real and doable, then they will lead the way.

Pick working examples that can positively impact work flow in clinic and add value to current practice

Identify and tackle the "enabling" steps one by one. This positions you to grow your effort.

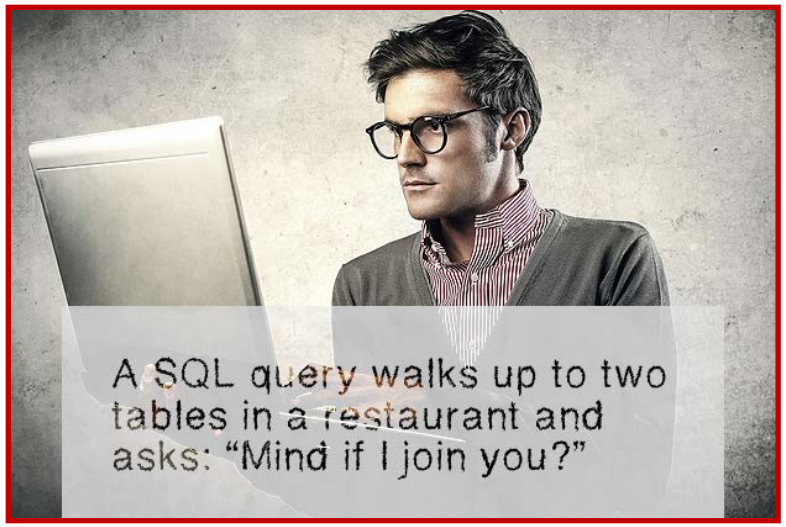
Standardization and nomenclatures are needed to enable the automation needed to handle Big Data

"Mind? I have no mind. I'm a computer."

A foolish consistency is the hobgoblin of little minds,
adored by little statesmen and philosophers and divines.

Ralph Waldo Emerson-Self Reliance

and database programmers



Manual effort is the enemy, free text is its cousin

Cost, FTE, Inconsistency, Speed

Standardize Diagnosis and Staging

This… only you can do

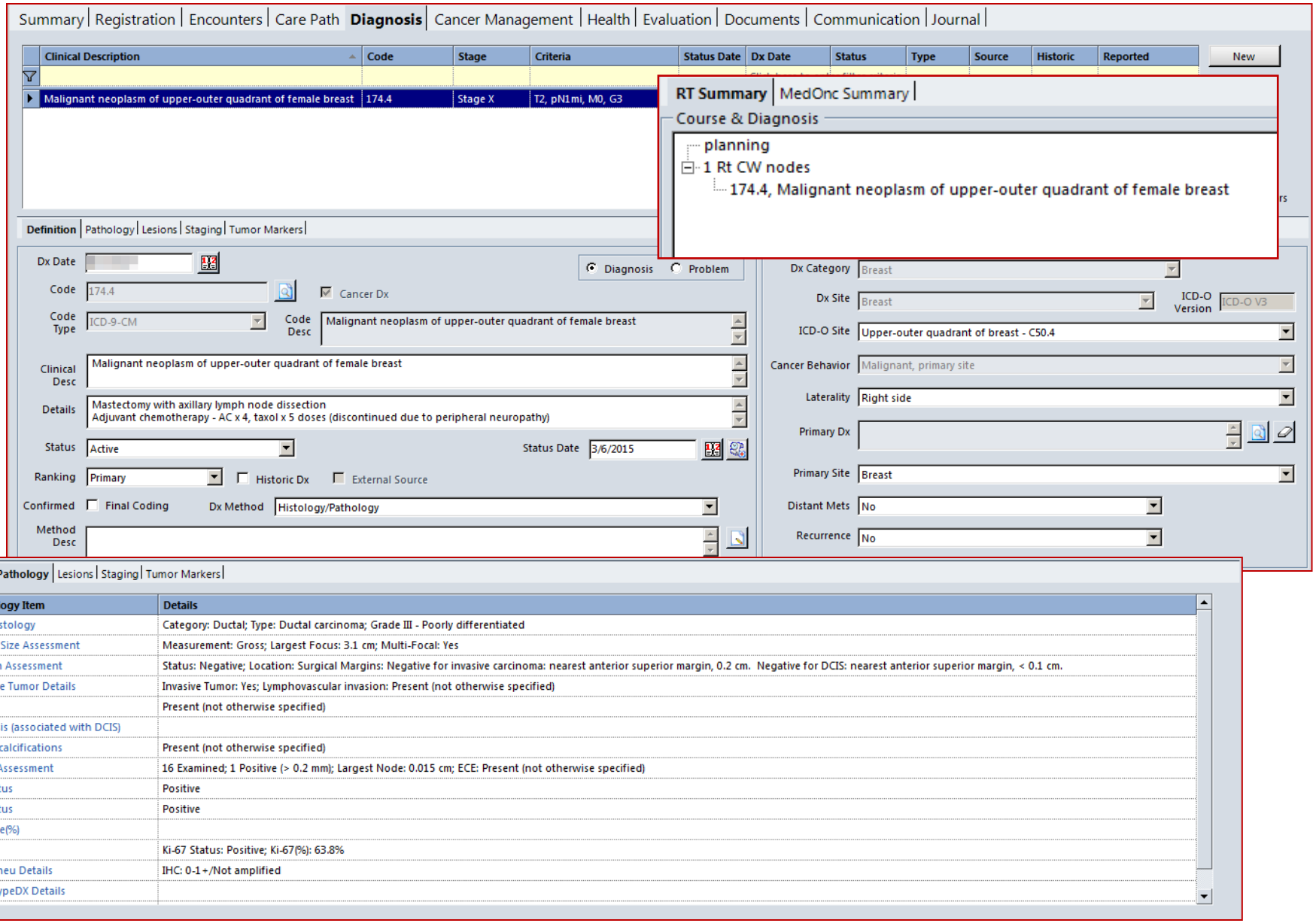
Assume you have the technology, what do you have to change about your practice to enable the technology to get the data?

- Consensus in your practice
- Standardize practice
- Change who does what

Assume you are going to use standard codes (ICD-9/10, ICD-0, TNM+, histology, etc) to filter your searches to find the patients of interest to you.

- What information is input for every patient?
- How do you handle metastatic sites?
  e.g. is metastatic prostate 198.5 with a secondary of 185?
- Is the diagnosis and staging linked to the course for easy, computer lookup?
- Are you inputting courses and diagnosis from outside institutions so that you have a complete record?
- Have you put in place a QA process/peer review to be sure you are not going to have doubts about the data when you look back?

ARIA Diagnosis and Staging Section

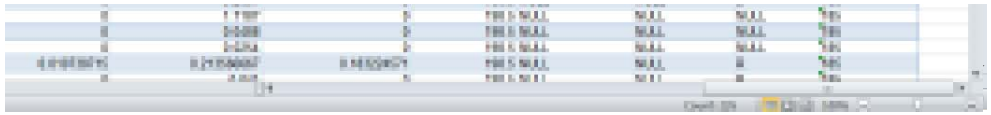


Once you standardize diagnosis and staging, you are in position to query your existing ROIS database to get a wealth of information on your practice. The tech is relatively easy.

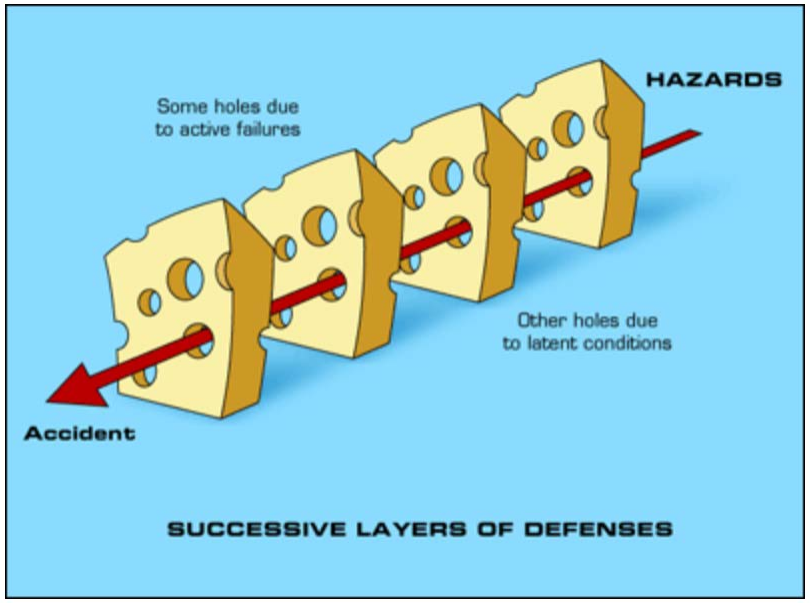
Patient ID	Used Static IMRT
Course ID	Used VMAT IMRT
Course Start Date	Used Hybrid IMRT
Course End Date	Used Hybrid VMAT
Treatment Facility	Used Wedges
Treatment Machine	Used Non-Coplanar Beams
Physician	Used Half Beam X
Plan ID	Used Half Beam Y
Plan Dicom UID	Couch Vrt Mean
Is Plan Sum	Couch Vrt Standard Deviation
Is Course Cummulative	Couch Lat Mean
N Fractions Planned	Couch Lat Standard Deviation
N Fractions Treated	Couch Lng Mean
Dose Per Fraction	Couch Lng Standard Deviation
Total Dose Planned	Couch Rotation Mean
Total Dose Delivered	Couch Rotation Standard Deviation
N Beams	Couch Pitch Mean
Primary Reference Point	Couch Pitch Standard Deviation
Total Plan MU	Couch Roll Mean
Is SBRT	Couch Roll Standard Deviation
Is Breath Hold	Couch Yaw Mean
Used X06	Couch Yaw Standard Deviation
Used X06 FFF	Diagnosis Ranking
Used X10	Diagnosis ICD9
Used X10 FFF	Overall Stage
Used X18	Staging Information
Used X18 FFF	Laterality
Used E06	Primary ICD9
Used E09	
Used E12	
Used E16	
Used E20	

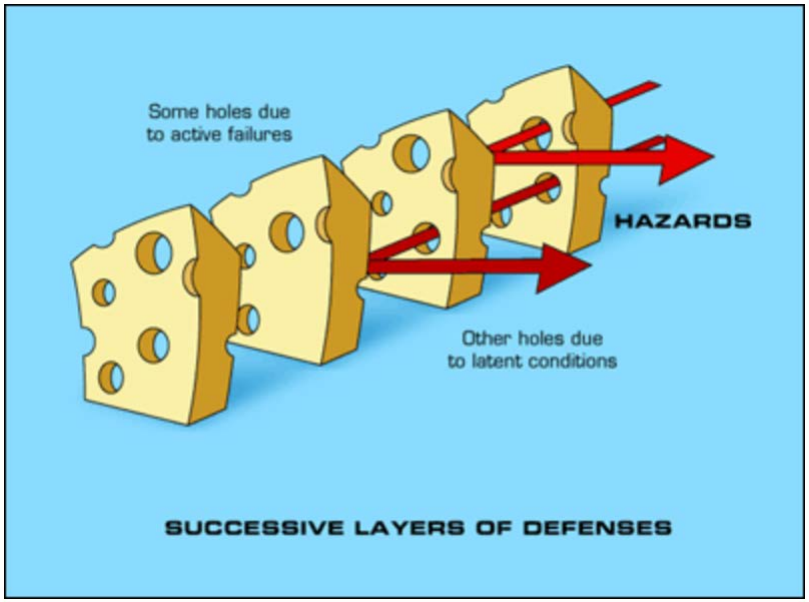
Once you standardize your inputs, you can pull large data sets from your existing ROIS system to answer many clinical questions

- *Find me all the patients treated for metastatic prostate cancer with SBRT at facility X in the last year.*
- *Find me all the breast patients treated with IMRT in the last 3 years for whom we used a couch kick.*
- *Find me all the left sided stage IA lung cancer patients for whom we used an 18MV beam.*
- *Calculate statistics on the range of couch variation for each of our treatment sites so that we can use it to set our couch tolerances.*
- *Calculate the last year's work load for machine X so that we can use it in the shielding calculation for our replacement machine.*
- *Find me all the breast patients we treated with breath hold.*
- *Find me all the SBRT liver plans that I treated last year using VMAT.*



How can big data fit into making our patient's more safe?





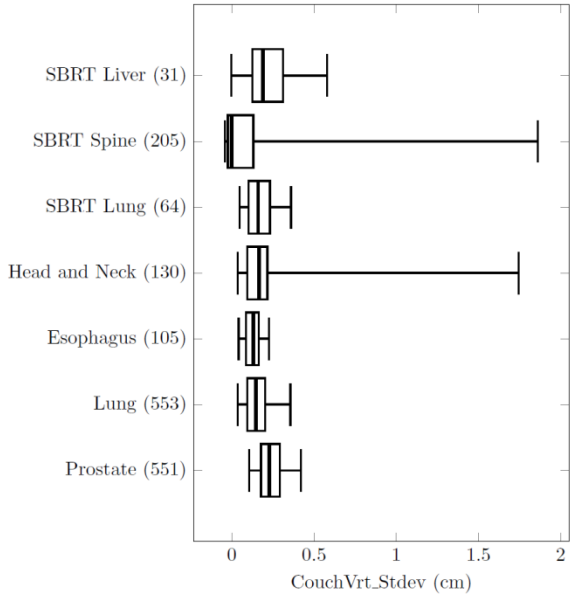
- Insert a statistical layer for consistency check of parameters with historical probability distributions for the parameters.
- Different doesn't mean wrong (not different doesn't mean right) but it does highlight attention for a closer look.

http://patientsafetyed.duhs.duke.edu/module_e/swiss_cheese.html

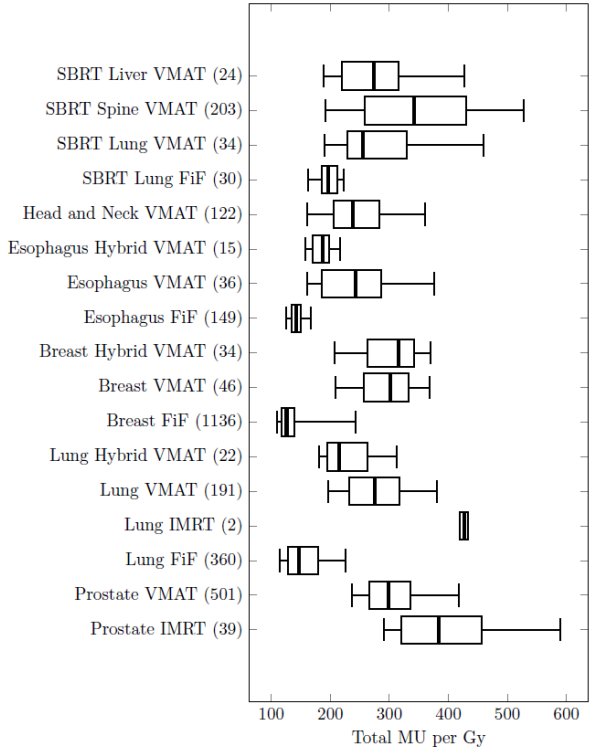
Using information from treatment records to define "expected" probability distributions

Retrospective statistics could be used in an automated plan check program to highlight sections for special attention

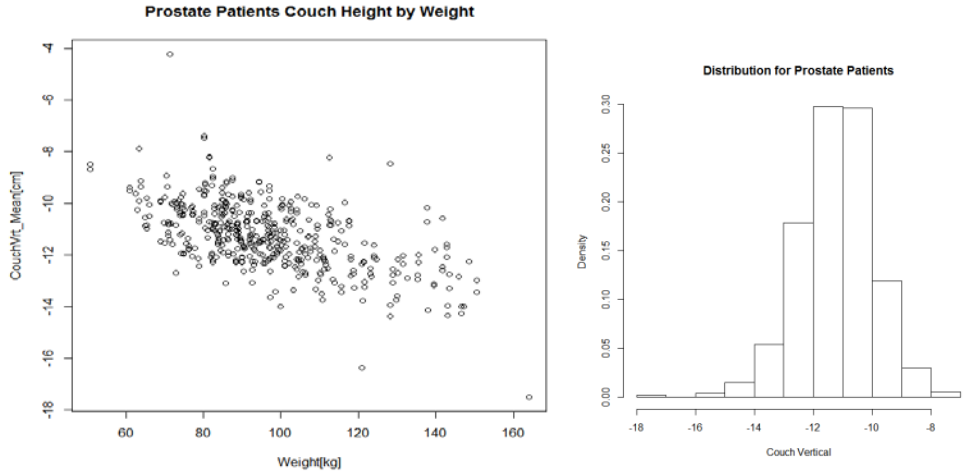
How should we set our tolerance tables base on our experience?



How many MU's is unusual?



Can we predict couch height by patient weight?



Build consensus with physician disease site groups define standard DVH metrics and objectives to use for all patient treatment plans ~ 18 months

- Supports physician lead initiative to develop and define standards of practice for treatment plans.

- Replace free text word documents with standardized tabular templates

- Critical point in dialog for building consensus is distinction between agreement on what metrics we measure vs. the the constraint value and priority

Agree on what to measure for all

lung_total V20Gy[%] < 25% Priority = 1

Enable per patient change from default of constraint/priority

- While defining vanilla (standard), must take an approach that allows for chocolate (per patient changes)

Planning Fraction	Number of Fractions	Dose to PTV_High (Gy)	Dose to PTV_Intermediate (Gy)	Dose to PTV_Low (Gy)
1st				
Boost 1				
Boost 2				
Total				

PTV_High contains	
PTV_Intermediate contains	
PTV_Low contains	

Bolus: None Additional Instructions:

A treatment plan should be constructed that covers targets with prescribed doses while reducing the magnitude and volume of hot (>108% x Rx Dose) spots. Doses to normal tissues and pins should be kept as low as reasonably achievable. In addition the following specific objectives or evaluation metrics are given.

Must: Plan must pass this constraint in order to be accepted

Consult: Stop planning process to consult with the physician if there are problems passing this constraint.

Desirable or Lower-Contra: Try to achieve, but do not stop planning process to consult with physician if there are problems passing this constraint. Plan will pass if constraint cannot be met. If plan is not done by a senior dosimetrist or physicist experienced with this plan type, confirm with one of these that the constraint cannot be met. Specification of Lower-Contra is used when there is more opportunity for sparing because disease at that level is ipsilateral

Structure	DVH Endpoint	Constraint Value	Planning Priority
pty_high	D95%(%)	> 100%	Must
	Mn_Dose (%)	> 95%	Consult
	Mn_Dose(Gy)		Report
	Mean_Dose (Gy)		Report
	Max_Dose(Gy)		Report
	Max_Dose (%)	< 115%	Must
	D1%(%)	< 110%	Consult
pty_intermediate	D95%(%)	> 100%	Must
	Mn_Dose (Gy)		Report
	Mean_Dose (Gy)		Report
	Max_Dose(Gy)		Report
pty_low	D95%(%)	> 100%	Consult
	Mn_Dose (Gy)		Report
	Mean_Dose (Gy)		Report
	Max_Dose(Gy)		Report
cty_high	V100%(%)	> 98%	Consult
	Mn_Dose(Gy)		Report
	Mean_Dose(Gy)		Report
	Max_Dose(Gy)		Report
cty_intermediate	V100%(%)	> 98%	Must
	Mn_Dose(Gy)		Report

Standardize structure and DVH Nomenclatures along with Rx and DVH metrics measured

Normal tissue naming schema is left to right: general to specific with laterality at the end.
Character string length, use of capitals, spaces, etc are guided by vended systems used in the clinic (simulator, planning system, information system, etc) constrain format

For targets (PTV, CTV, GTV, ITV)
take an approach
that allows a standard
name plus an alias in
the database
e.g. ptv_high = PTV7200

Using both a standard name and an alias, means when pulling data from the database we can identify the volume getting the highest dose for any plan or treatment site (ptv_high) independent of the specific name used in the plan (ptv6300).

Partial list of our structure nomenclature

Mayo Clinic Radiation Oncology Standard Structure Nomenclature version- 20130328

ptv_high	semi_cir_canal_l	parotid_total
ctv_high	semi_cir_canal_r	parotid-ptv_r
itv_high	ext_aud_canal_l	parotid-ptv_l
gtv_high	ext_aud_canal_r	parotid-ptv_total
ptv_intermediate	mastoid_l	sub_mandib_r

TemplateName	PlanName	Structure	DVHMetric	DVHMetric_Value	Alias_PTV_High	Alias_PTV_Low
Breast - Simple	R breast	ptv_high	D5%[%]	85.8196	ptv5256	ptv4256
Breast - Simple	R breast	ptv_high	Min[%]	76.75799	ptv5256	ptv4256
Breast - Simple	R breast	ptv_high	V110%[cc]	0	ptv5256	ptv4256
Breast - Simple	R breast	ptv_high	V115%[cc]	0	ptv5256	ptv4256
Breast - Simple	R breast	ptv_low	CV90%[%]	0.6428106	ptv5256	ptv4256
Breast - Simple	R breast	ptv_low	Mean[Gy]	43.728	ptv5256	ptv4256
Breast - Simple	R breast	ptv_low	Min[%]	31.97838	ptv5256	ptv4256

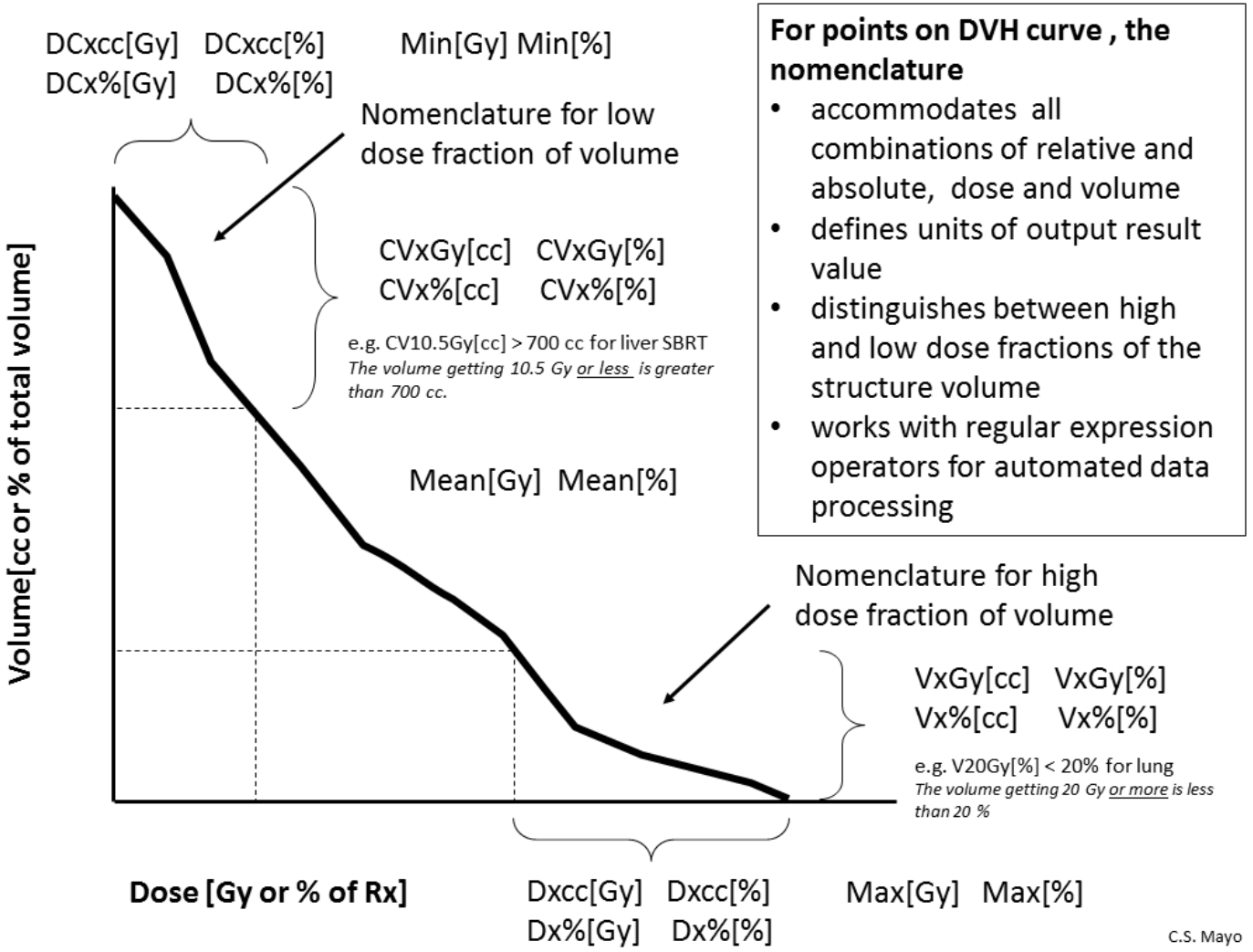
ptv_low	optic_nrv_r	oral_cavity

TemplateName	PlanName	Structure	DVHMetric	DVHMetric_Value	Alias_PTV_High	Alias_PTV_Low
Prostate - ConvFX	Pelvic region	ptv_high	Max[%]	108.2555	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_high	Mean[Gy]	64.72	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_high	V99%[%]	97.16188	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_high	V100%[%]	94.32925	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_high	V107%[%]	0.04317822	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_high	Volume[cc]	56.4	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_low	CV98%[%]	3.741312	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_low	D98%[%]	90.59662	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_low	Mean[Gy]	57.481	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_low	V98%[%]	96.25869	ptv6300	ptv5400
Prostate - ConvFX	Pelvic region	ptv_low	V99%[%]	95.51831	ptv6300	ptv5400

brain	eye_r	constrictors_p
brain-ptv	eye_l	constrictors_p-ptv

Define a DVH nomenclature schema that fully defines all parts of the curve and can be expanded upon to accommodate other DVH derived metrics as they evolve.

endpoint name(calculation parameters)[output units]



For points on DVH curve , the nomenclature

- accommodates all combinations of relative and absolute, dose and volume
- defines units of output result value
- distinguishes between high and low dose fractions of the structure volume
- works with regular expression operators for automated data processing

Example of use for radiobiological metrics: V35EQ2Gy(4)[%]

Several groups are coordinating efforts to address nomenclature for radiation oncology

NRG Oncology

International Journal of Radiation Oncology biology • physics
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BRIEF REPORT AND OPINION

Radiation Therapy Digital Data Submission Process for National Clinical Trials Network

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*IROC/NRG/Jefferson Medical College, Philadelphia, Pennsylvania; †IROC St. Louis, Department of Radiation Oncology, Washington University School of Medicine, St. Louis, Missouri; ‡Department of Radiation Oncology, Mayo Clinic, Rochester, Minnesota; §IROC Rhode Island, University of Massachusetts Medical School, Lincoln, Rhode Island; and ||IROC Houston, Department of Radiation Physics, University of Texas MD Anderson Cancer Center, Houston, Texas

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BrainStem_"exp"	"exp" can be a two digit number representing the uniform expansion of the Brain stem for a specific planning risk volume (PRV) margin in mm.
BrainStem_PRV	Brains Stem expanded with a non specific planning risk volume
BrainStemCore	core of the brains stem
BrainStemSurf	Surface of the brain stem
Breast_L	Left Breast
Breast_R	Right Breast
CaudaEquina	CaudaEquina
ChestWall	Chest Wall
Cochlea_L	Left Cochlea
Cochlea_R	Right Cochlea
Colon	Colon
CommonBileDuct	Common Bile Duct
Duodenum	Duodenum
Ear_External_L	External left Ear
Ear_External_R	External Right Ear
Ear_Middle_L	Left middle ear
Ear_Middle_R	Right middle ear
Esophagus	Esophagus
Esophagus_Lo	lower esophagus
Esophagus_Up	upper (cervical) esophagus
External	External patient contour encompassing all patient anatomy with a single contour on each slice
Eye_L	Left eye
Eye_R	right eye
Femur_L	Left Femur
Femur_R	Right Femur
Femurs	Both Femurs
GallBladder	Gall Bladder
GreatVessels	Great Vessels
Heart	Heart
Hippocampus_L	left Hippocampus
Hippocampus_R	right hippocampus
Hypothalamus	hypothalamus
IVC	Inferior Vena Cava
Jejunum_Ileum	Jejunum ileum
Kidney_L	Left Kidney
Kidney_R	Right Kidney
Kidneys	Both Kidneys

AAPM Task Group No. 263 - Standardizing Nomenclature for Radiation Therapy

Members represent multiplicity of stake holders – institutions, vendors, national regions and international, academic/non-academic, physicians, physics, AAPM/ASTRO

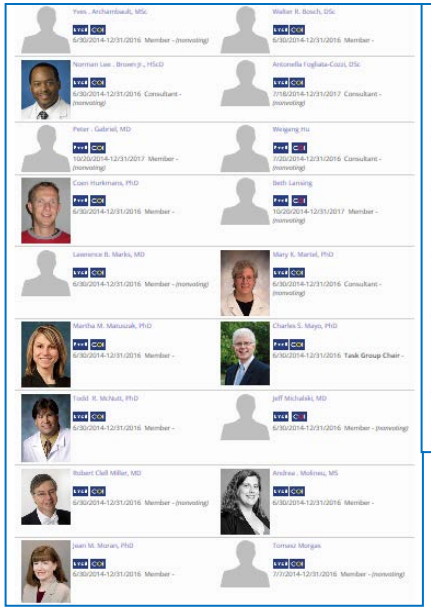
Left Optic Nerve(12): Lt Optic Nerve, OPTICN_L, OPTNRV_L, optic_nrv_l, L_optic_nerve, OPTIC_NRV_L, OpticNerve_L, LOPTIC, OpticNerve_L (3), Lef Optic Nerve

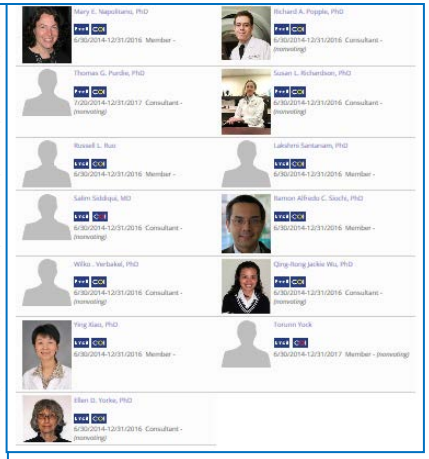
Left Lung(12): Lt Lung, Lung_L(4), LUNG_L(3), lung_l, L_lung, LLUNG, L Lung

Both Lungs(12): Lungs(2), LUNGs, LUNG_TOTAL, lung_total, combined_lung, LUNG, LUNGS(2), Lung BilatLung, Lung_Both

8th_cranial nerve(7): CN_VIII(5), cn_viii(2)

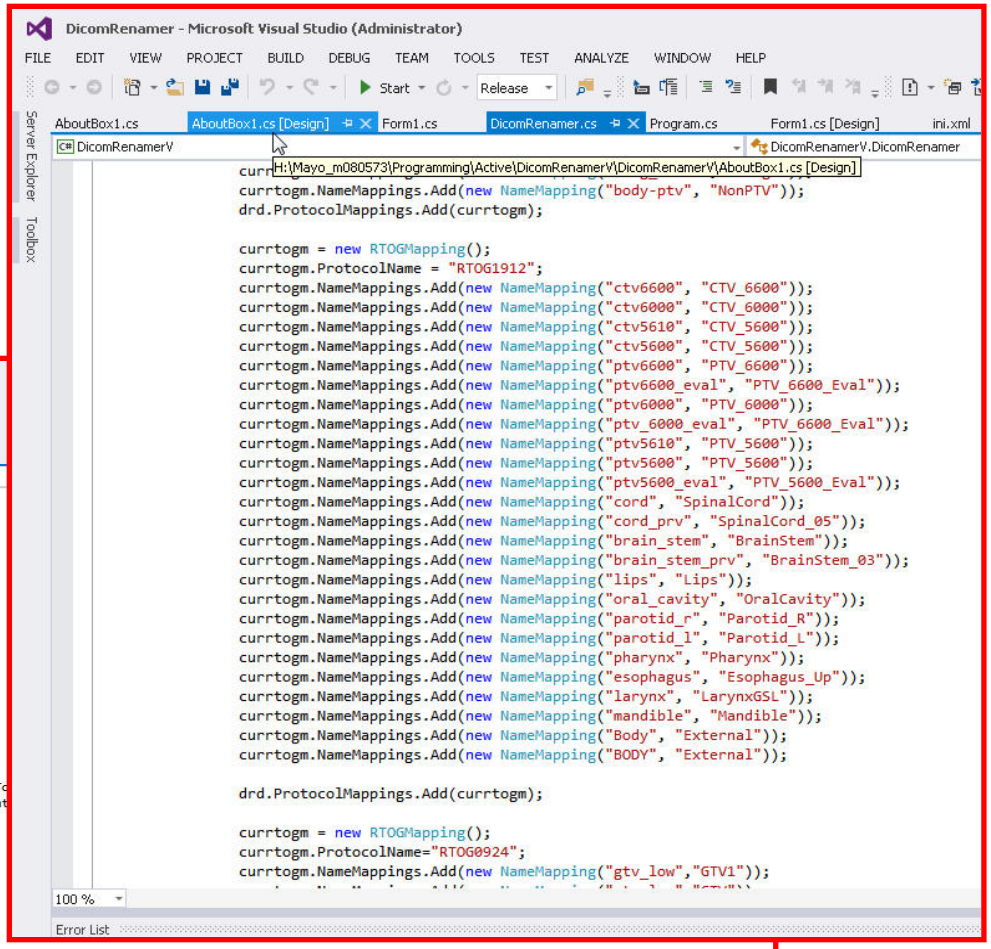
Right External Illiac Artery(2): A_ILLIAC_E_R, a_illiac_e_r

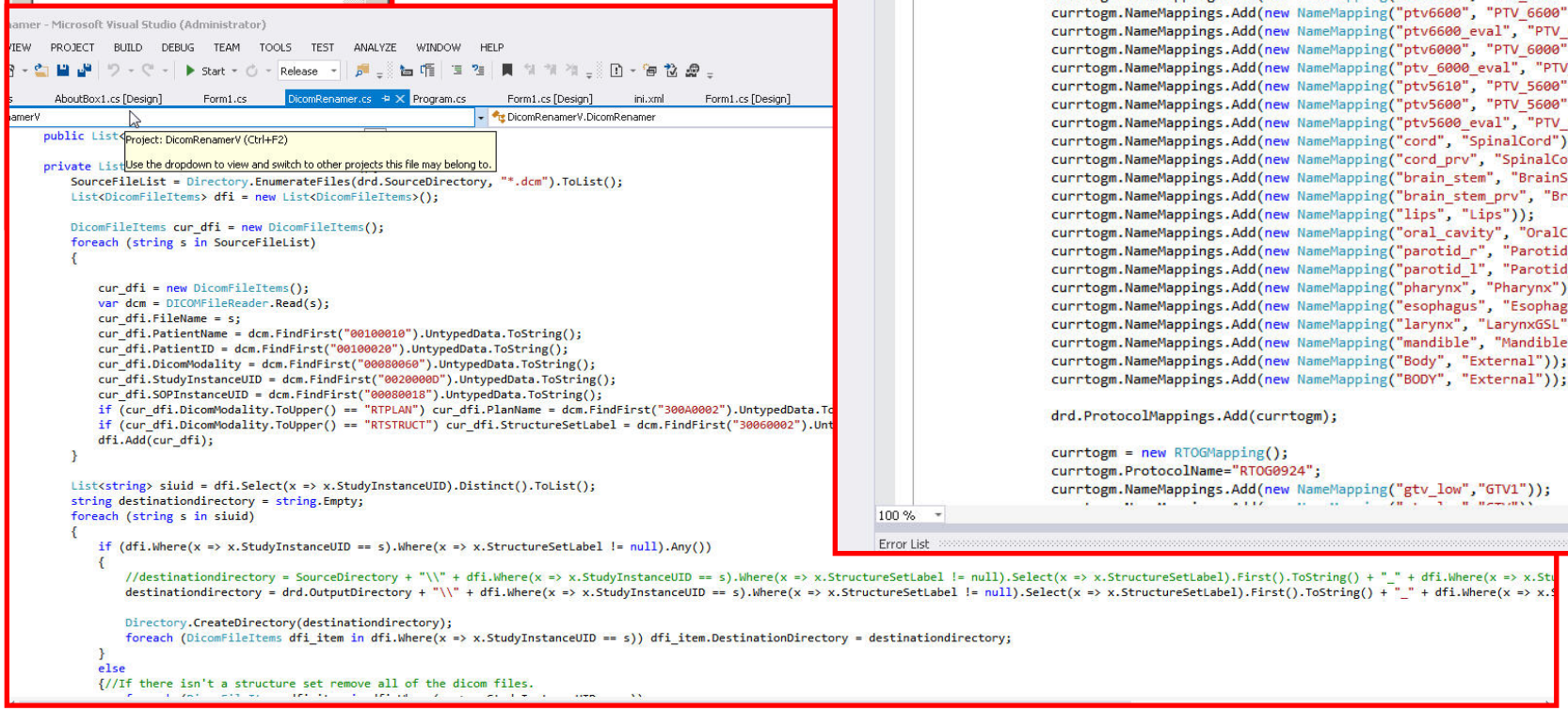




What do you do when your nomenclature differs from the nomenclature for a TRIAD submission of DICOM files?

Write a script using Evil Dicom (thanks Rex Cardan, UAB).





Iterative Process

Building consensus on the IT design and function.

Free text Word

Physician driven

Standardized formatted Word

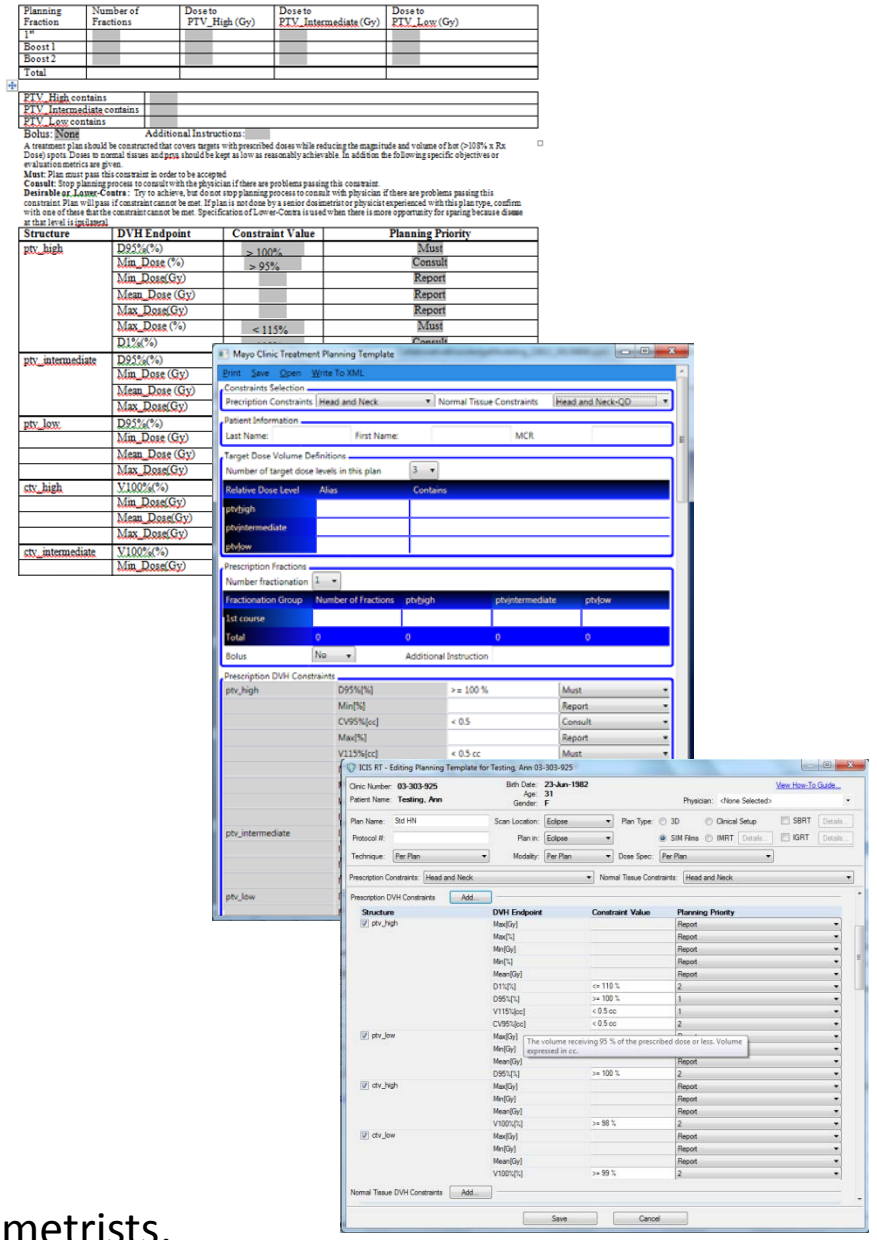
Physician + Physicist driven

Stand alone application that demonstrates automation and software driven templates

Physicist + Physician driven

Production application that uses database

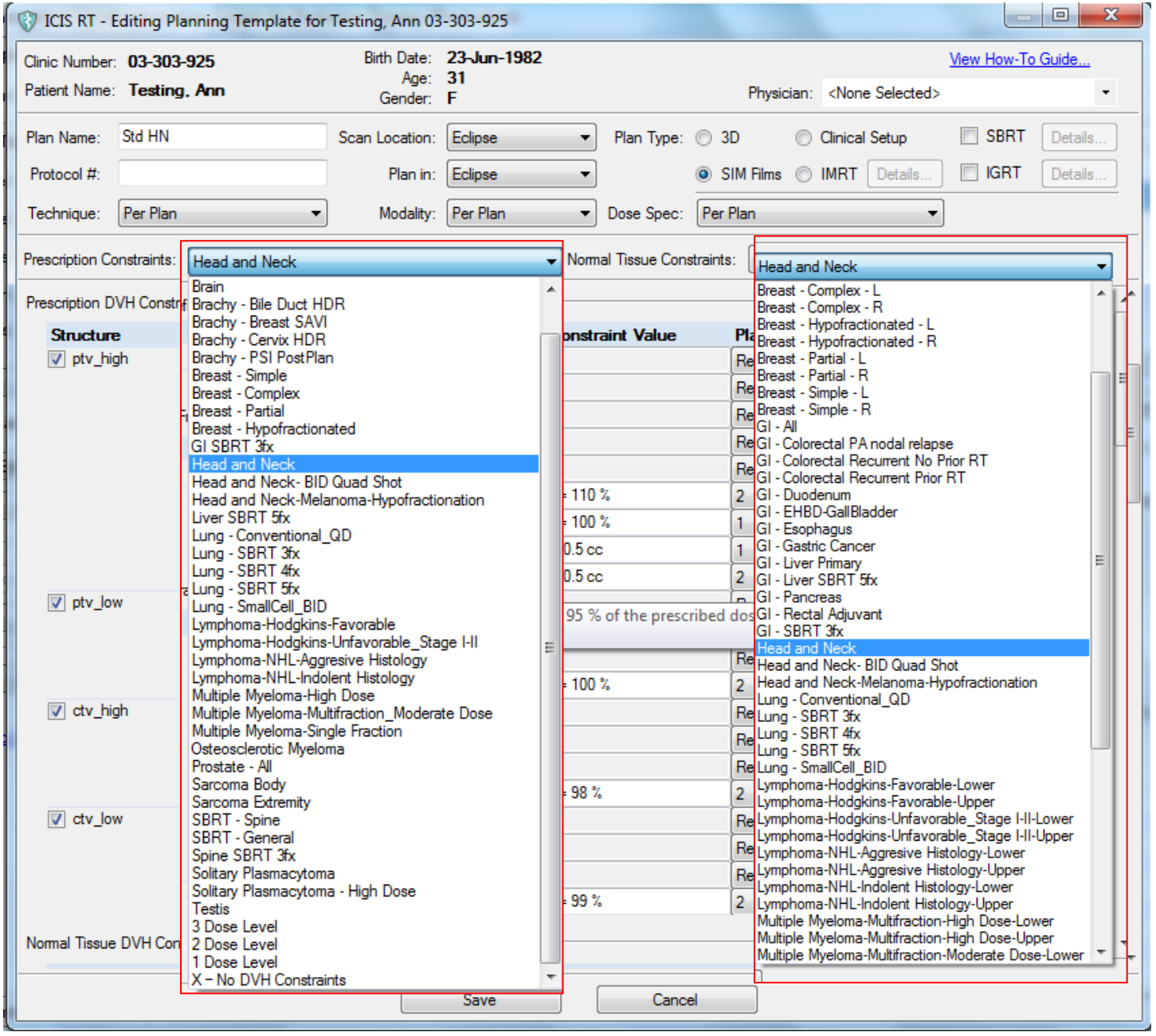
IT driven with multidisciplinary committee: physicians, dosimetrists, therapists, physicists



Application becomes our standard prescription.

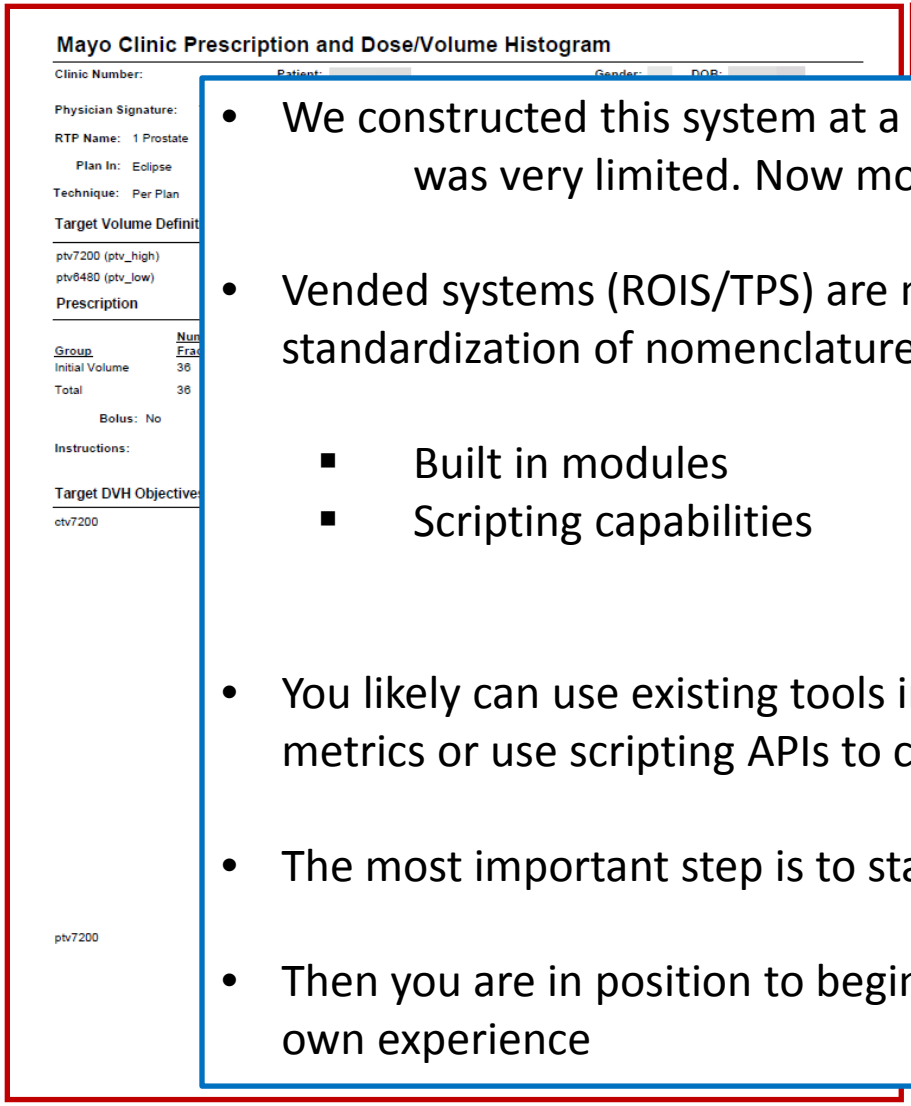
Also serves as documentation tool for image setup, notes, IMRT justification, etc.

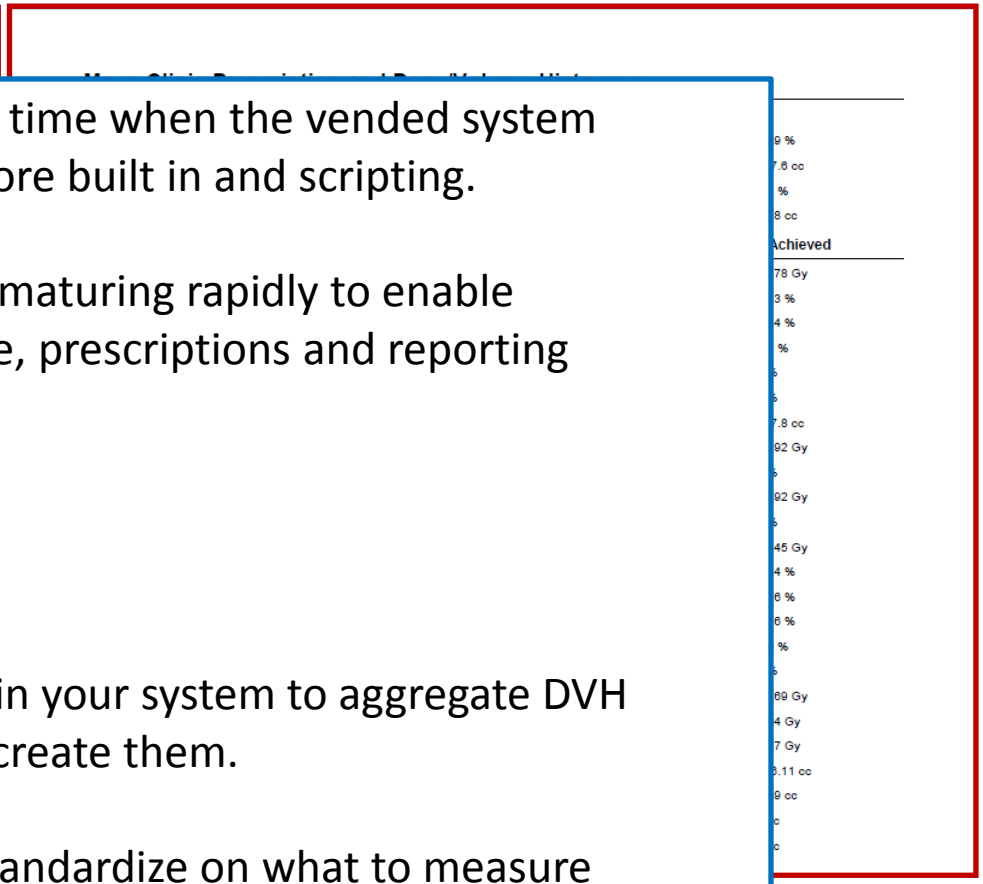
Physician groups define consensus for DVH metrics for all treatment sites; what to measure and default values for constraints and prioritizations.



Now generate a report as part of routine care that compares desired vs achieved DVH metrics for each patient . Use this in plan check to highlight areas for special attenuation.

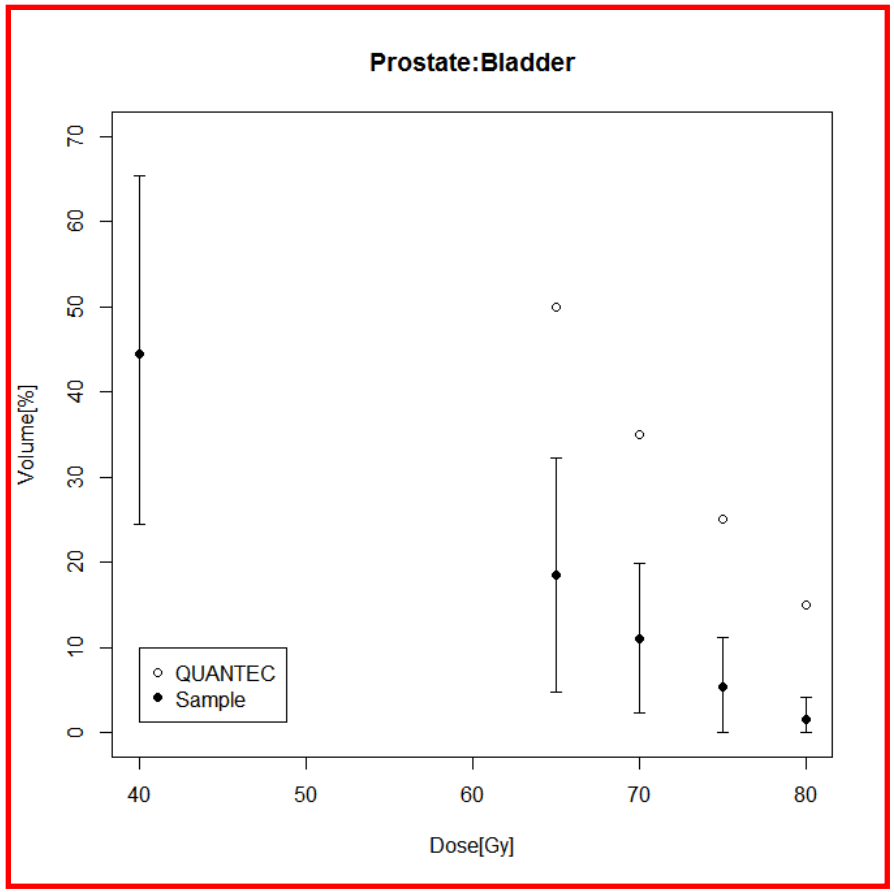
Save DVH metrics in database to mine results later

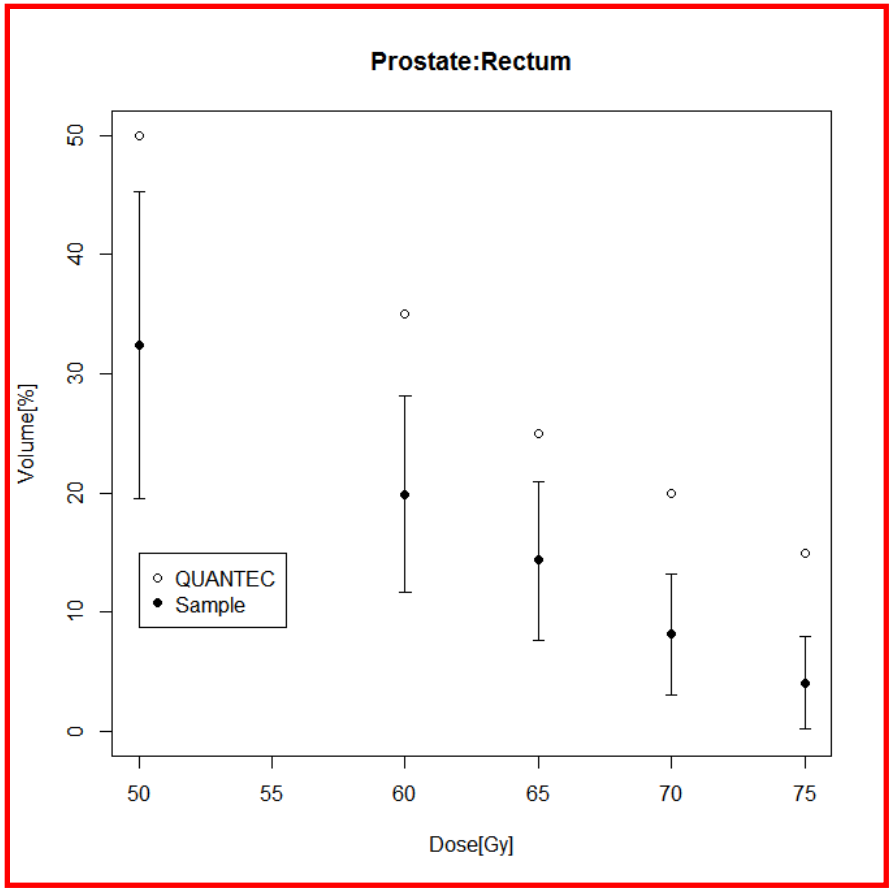




- We constructed this system at a time when the vended system was very limited. Now more built in and scripting.
- Vended systems (ROIS/TPS) are maturing rapidly to enable standardization of nomenclature, prescriptions and reporting
  - Built in modules
  - Scripting capabilities
- You likely can use existing tools in your system to aggregate DVH metrics or use scripting APIs to create them.
- The most important step is to standardize on what to measure
- Then you are in position to begin learning from the statistics on your own experience

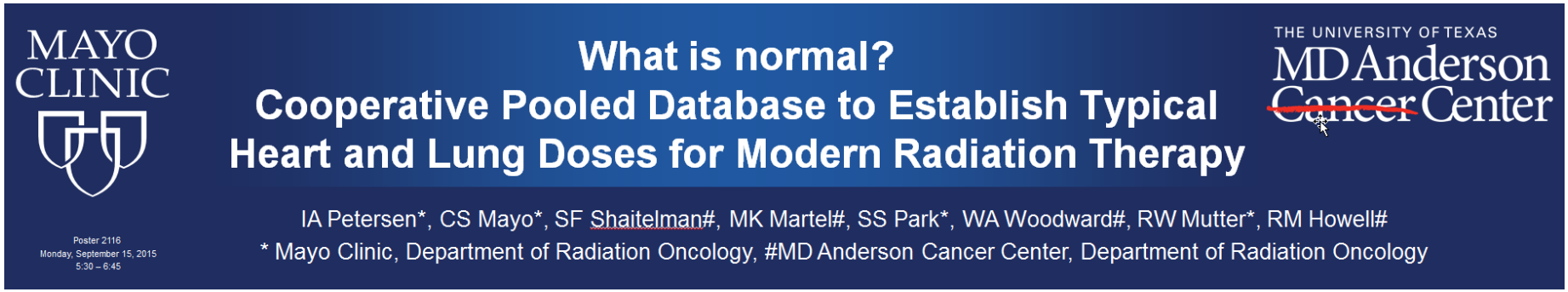
Using the data to improve our practice – gains for research and quality improvement





Sets the stage for constructing plan check software that uses recent retrospective data on distributions of values for DVH metrics , for highlighting values for a new plan that should get extra attention.

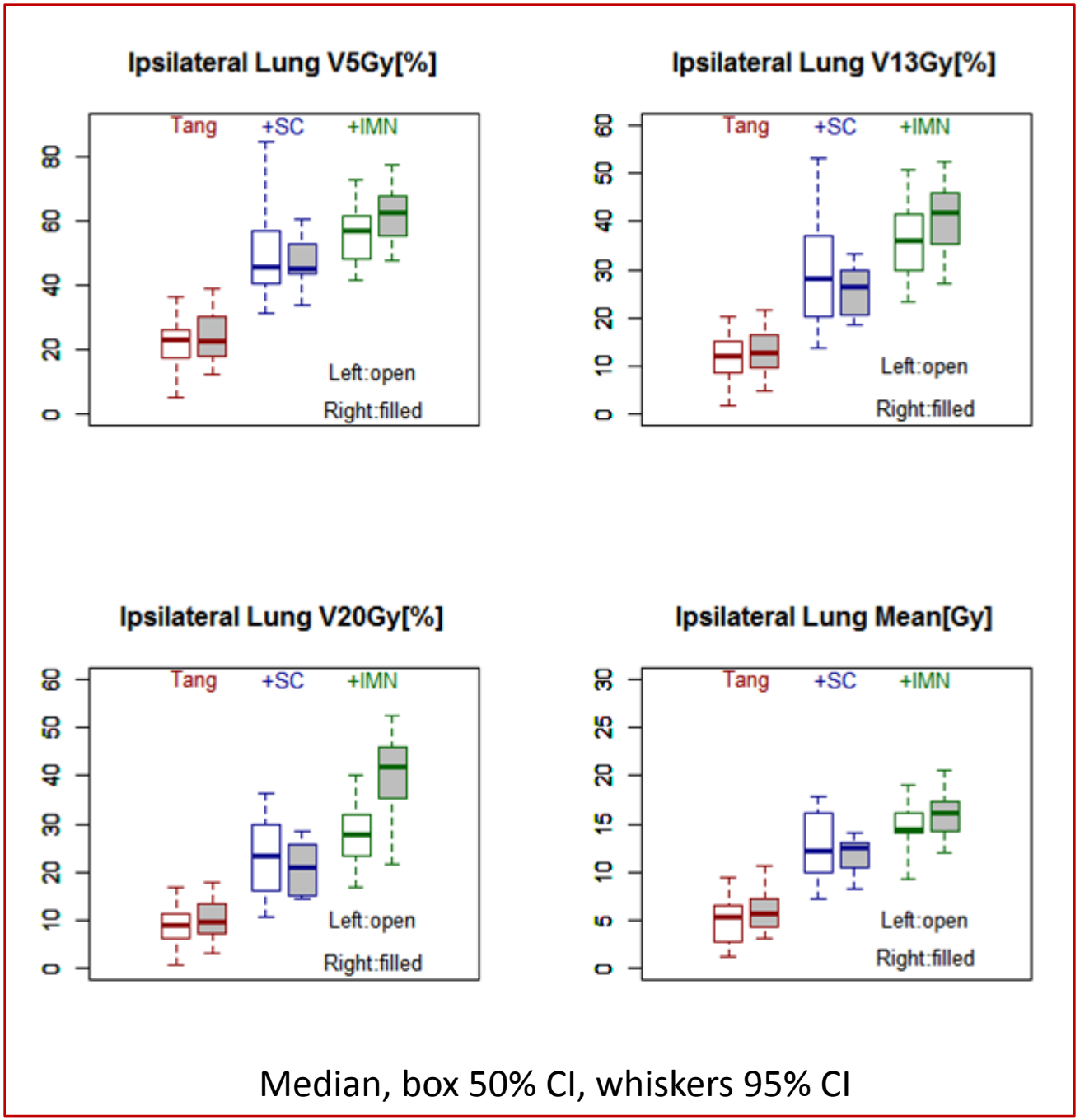
Look beyond our just our own experience and put the results in the context of other institutions.



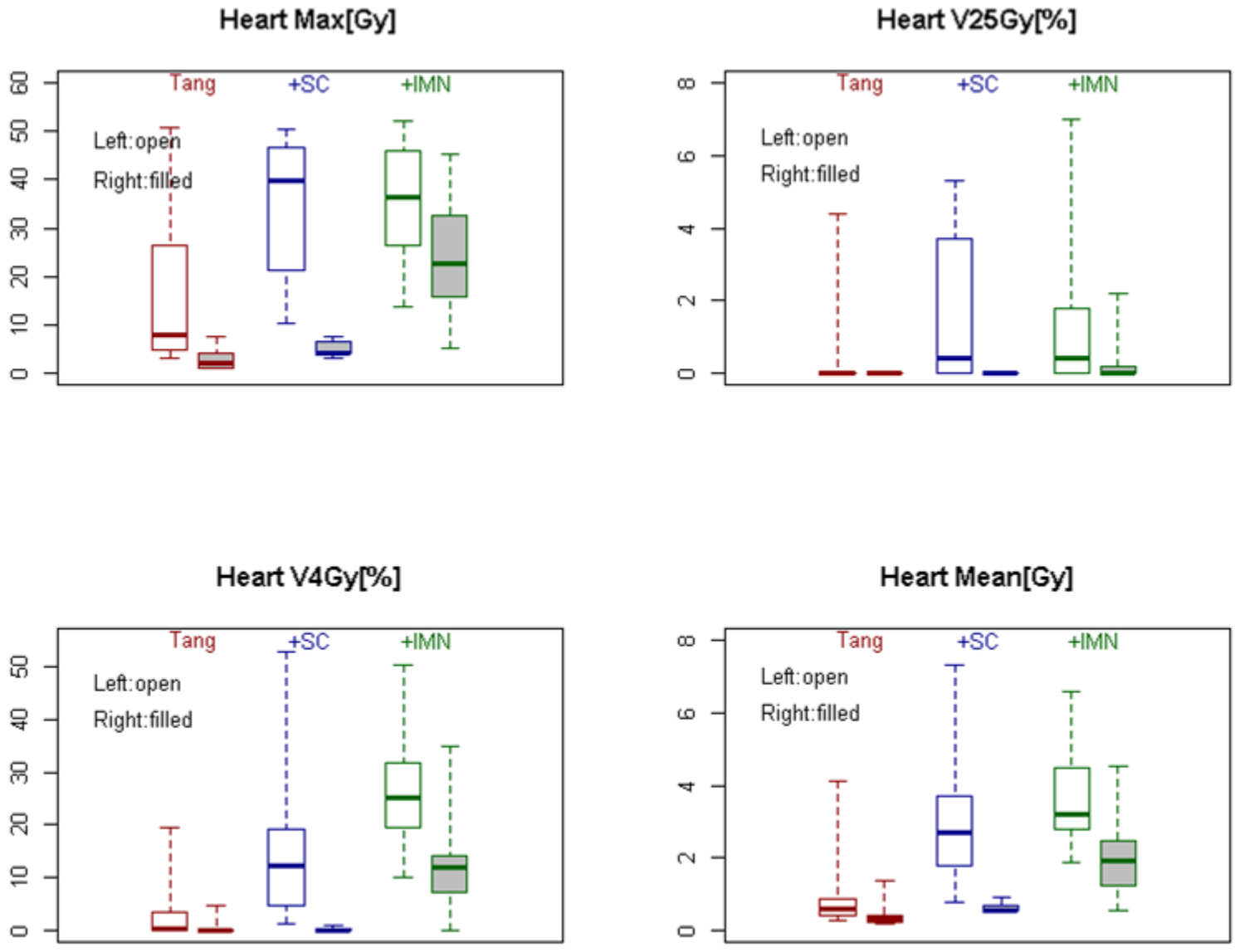
Pool data among institutions to define what is normal

Explore variations in treatment techniques and effects on DVH parameters

Together these efforts position us to evaluate individual plans in the context of the history of previous plans



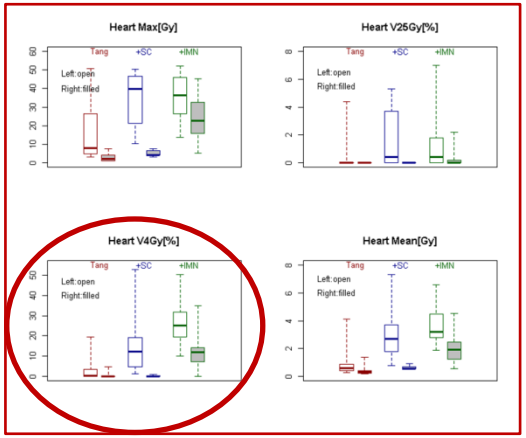
Median, box 50% CI, whiskers 95% CI

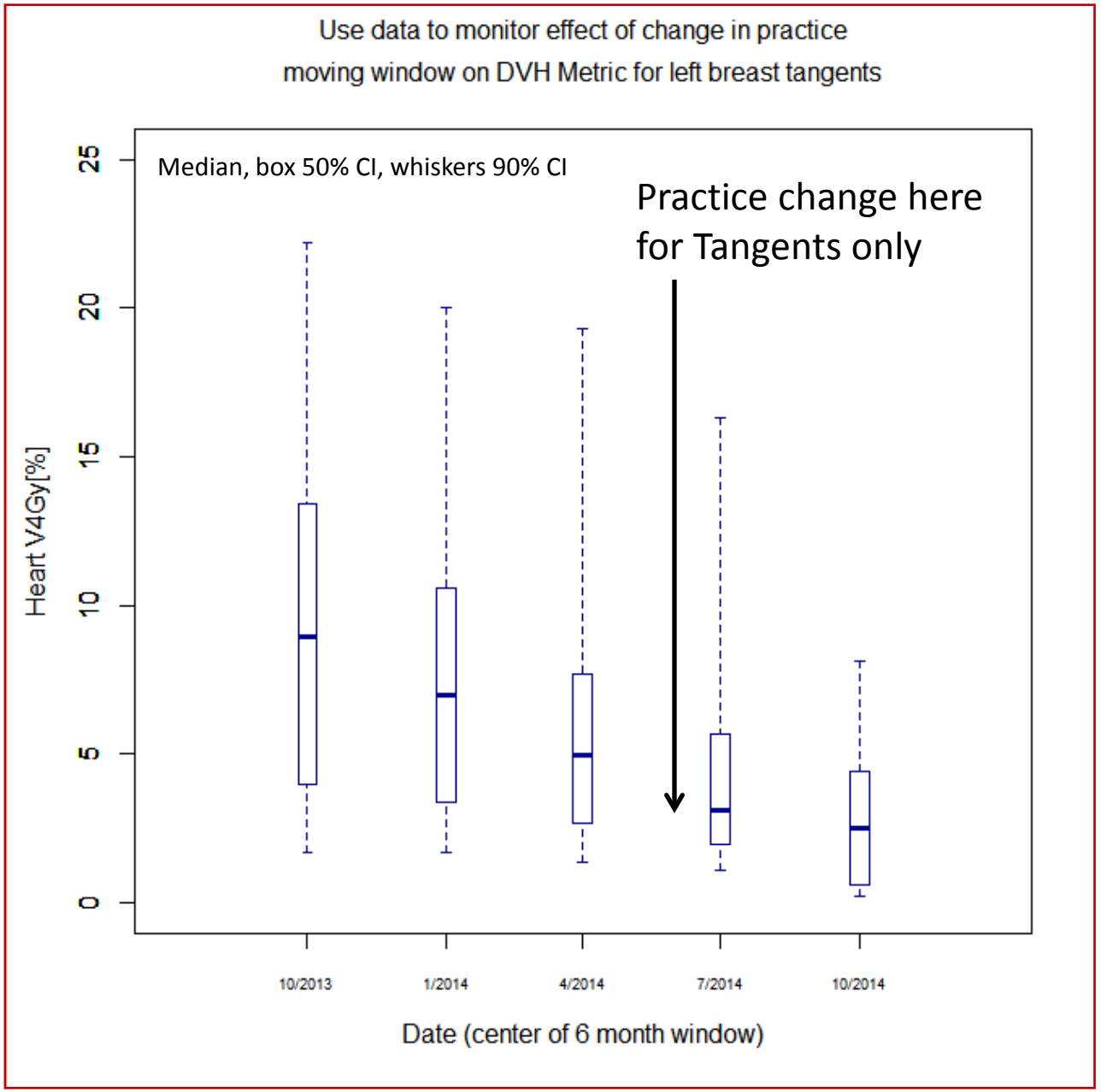


Median, box 50% CI, whiskers 95% CI

Considering the pooled data prompted, ideas about how to improve.

Systematically gathering the data enabled demonstrating the improvement.



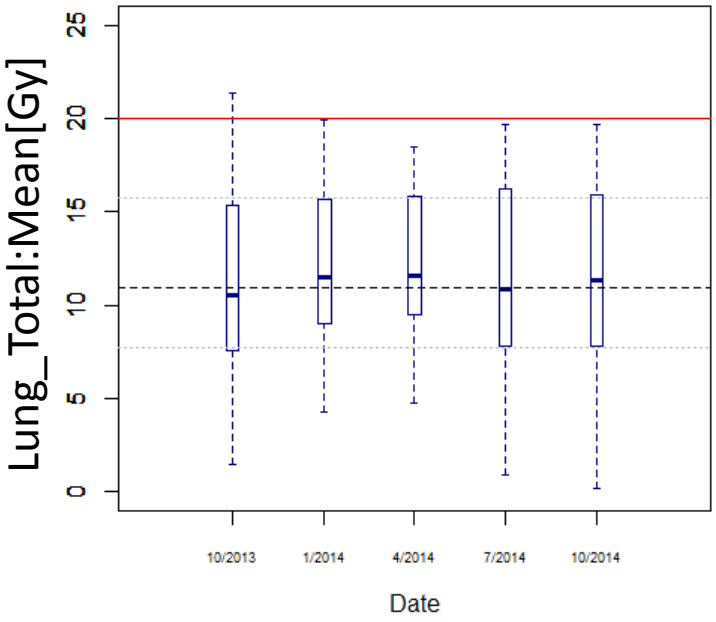


Completing the loop

Use data on what was achieved in DVH metrics
as basis to set new constraints to use as defaults for future plans in the planning templates.

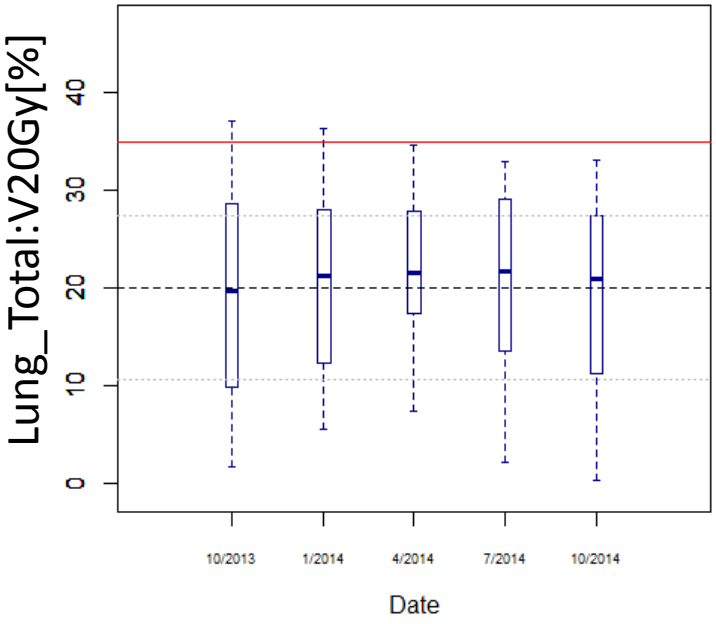
Suggested Mean Doses (range)	Mean heart dose (Gy)	Ipsilateral lung V20(%)	Total Lung V20 (%)
Tangential chest wall/breast			
Right	4 → 0.5 (0.2 – 1.6)	15 → 10.4 (2.7 – 18.6)	10 → 5.8 (1.6 – 11.1)
Left	4→1.1 (0.3 - 5.1)	15 → 8.9 (0 – 19.2)	10 → 4.4 (0.2 – 9.4)
Chest wall/breast + SCV			
Right	4 → 1.9 (0.5 – 8.0)	25 → 24.0 (14.3 – 36.3)	10 → 15.0 (7.9 – 28.3)
Left	4 → 3.2 (0.7 – 9.1)	25 → 23.9 (9.9 - 36.7)	10 → 10.9 (4.7 - 15.9)
Chest wall/breast + SCV + IM			
Right	4 → 2.1 (0.5 – 5.4)	25 → 32.1 (9.8 – 44.2)	10 → 18.2 (5.7 - 29.3)
Left	4 → 4.0 (1.4 – 9.2)	25 → 27.7 (8.9 – 43.4)	10 → 13.1 (7.7 – 20.2)

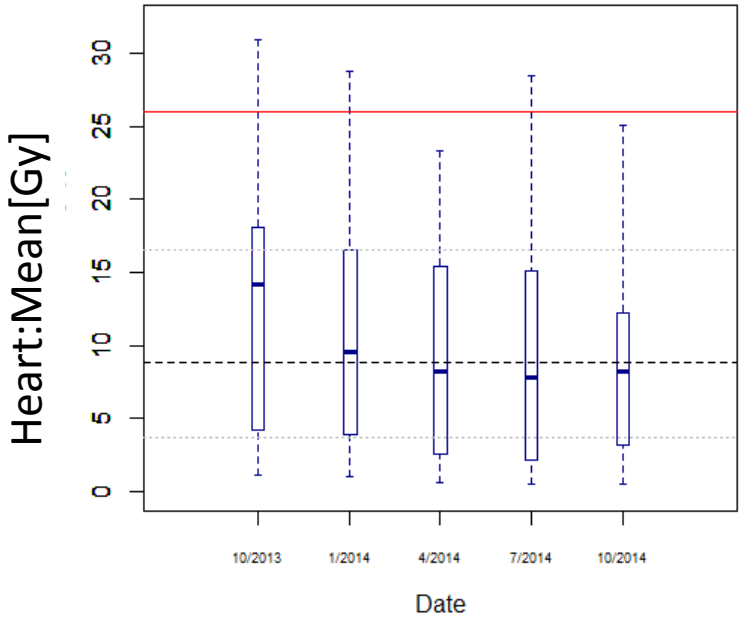
Conventional Lung Treatment DVH Metrics over 16 month period



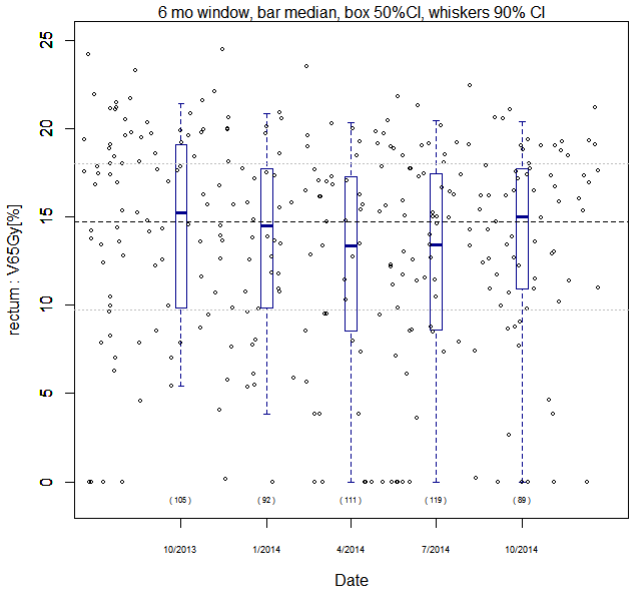
Benchmark objective (red),overall median (dark dashed line) and 50%CI (light dashed line) are compared to moving 6 month window box and whisker plots (median, 50%CI, 90%CI) spaced at 3 month intervals.

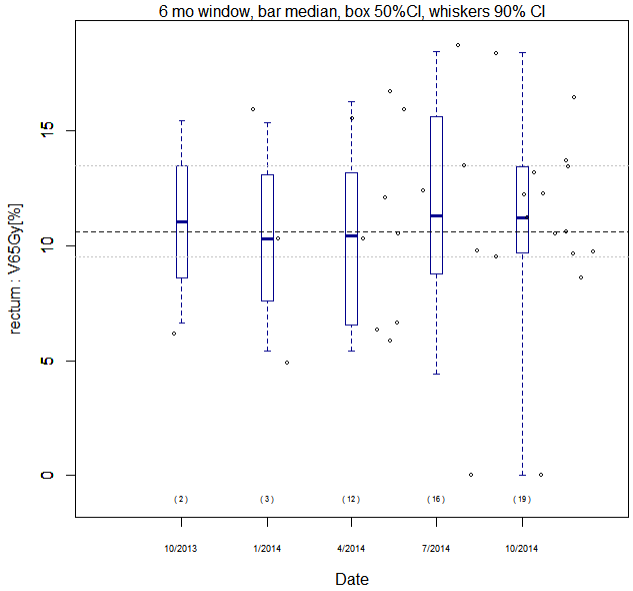
With routine collection of DVH metrics comes functionality for data pooling and one element for meaningful plan quality metrics that inform practice and address Affordable Care Act.

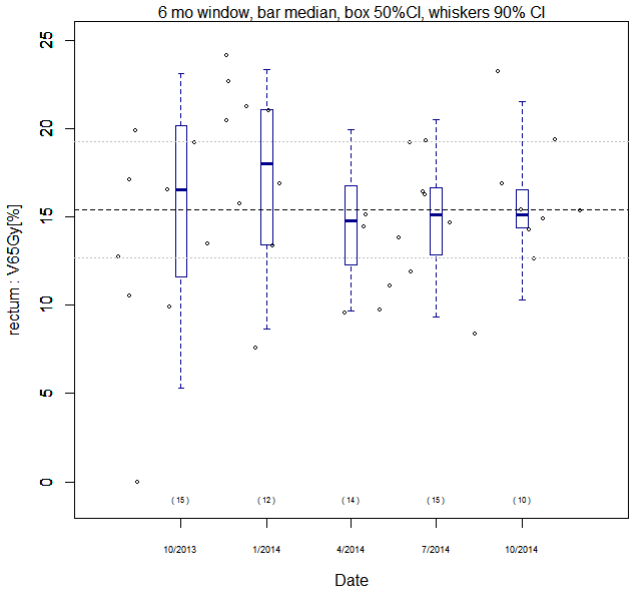


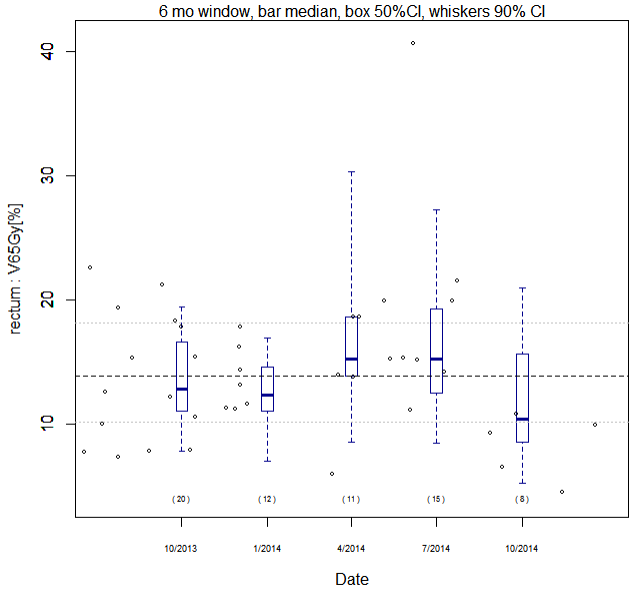


Using benchmarks to compare different practices
Example Rectum:V65Gy[%] for 4 groups

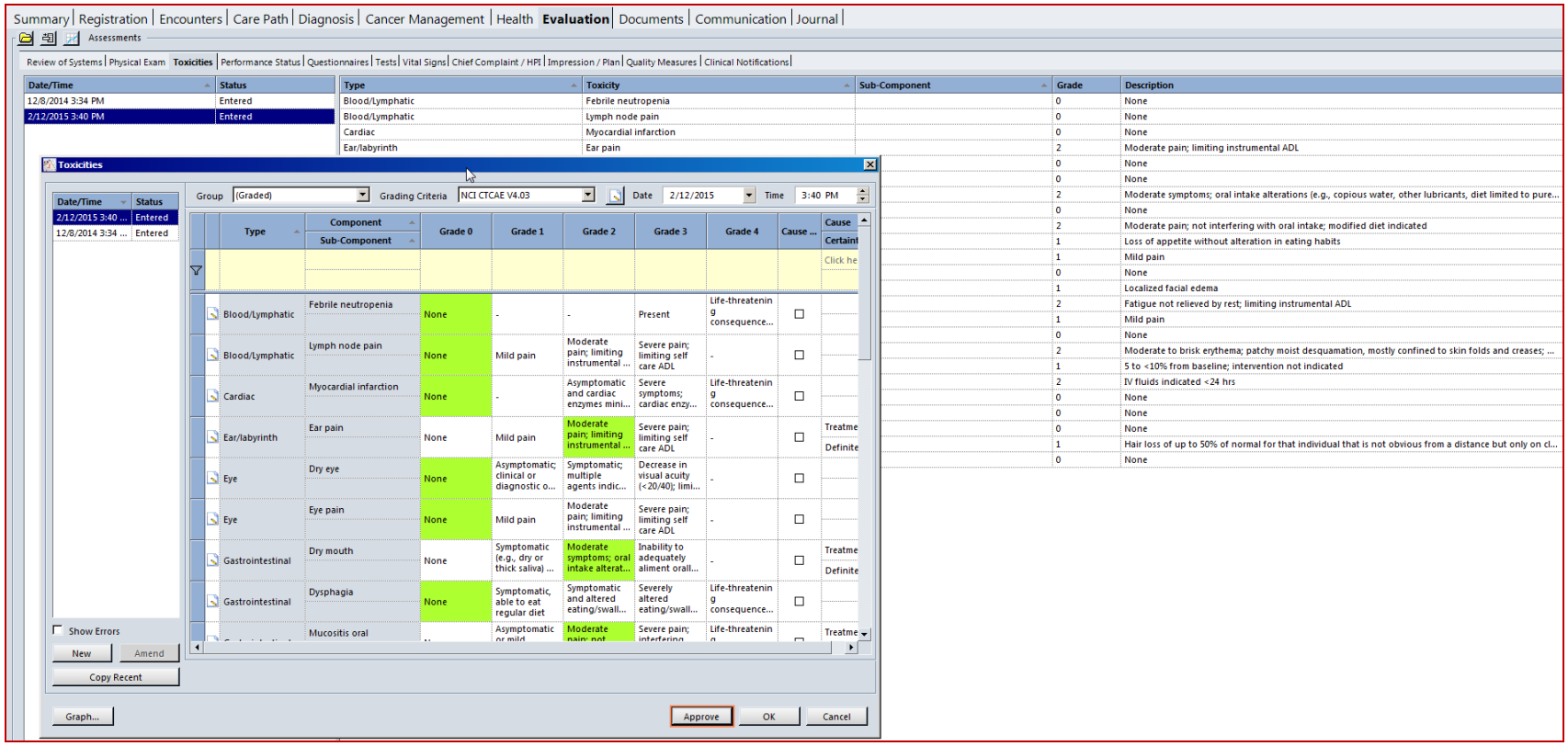


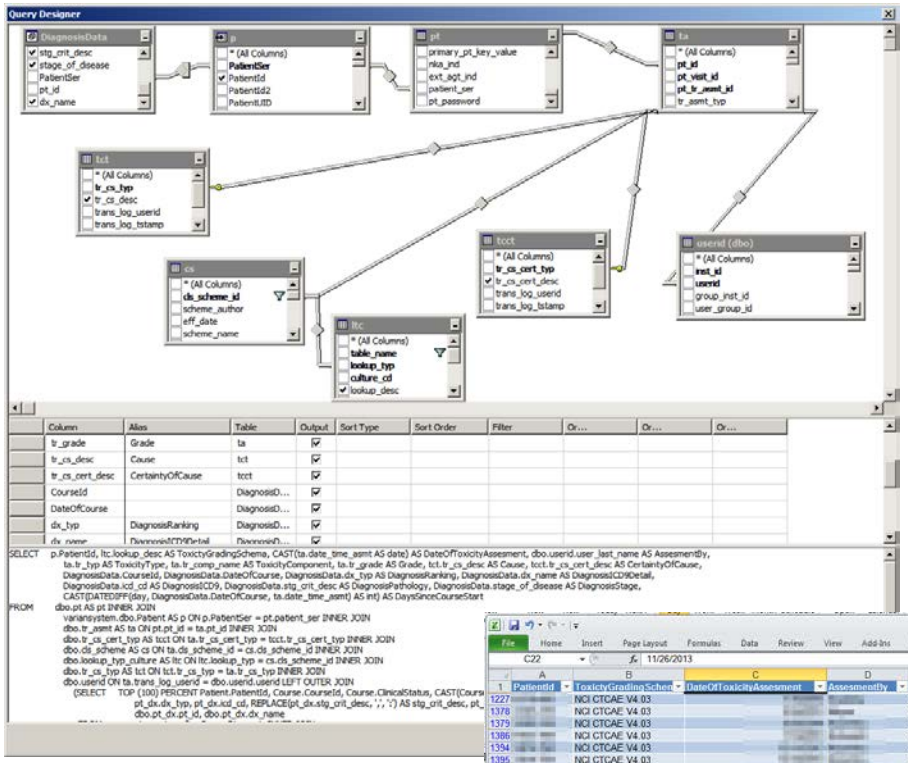


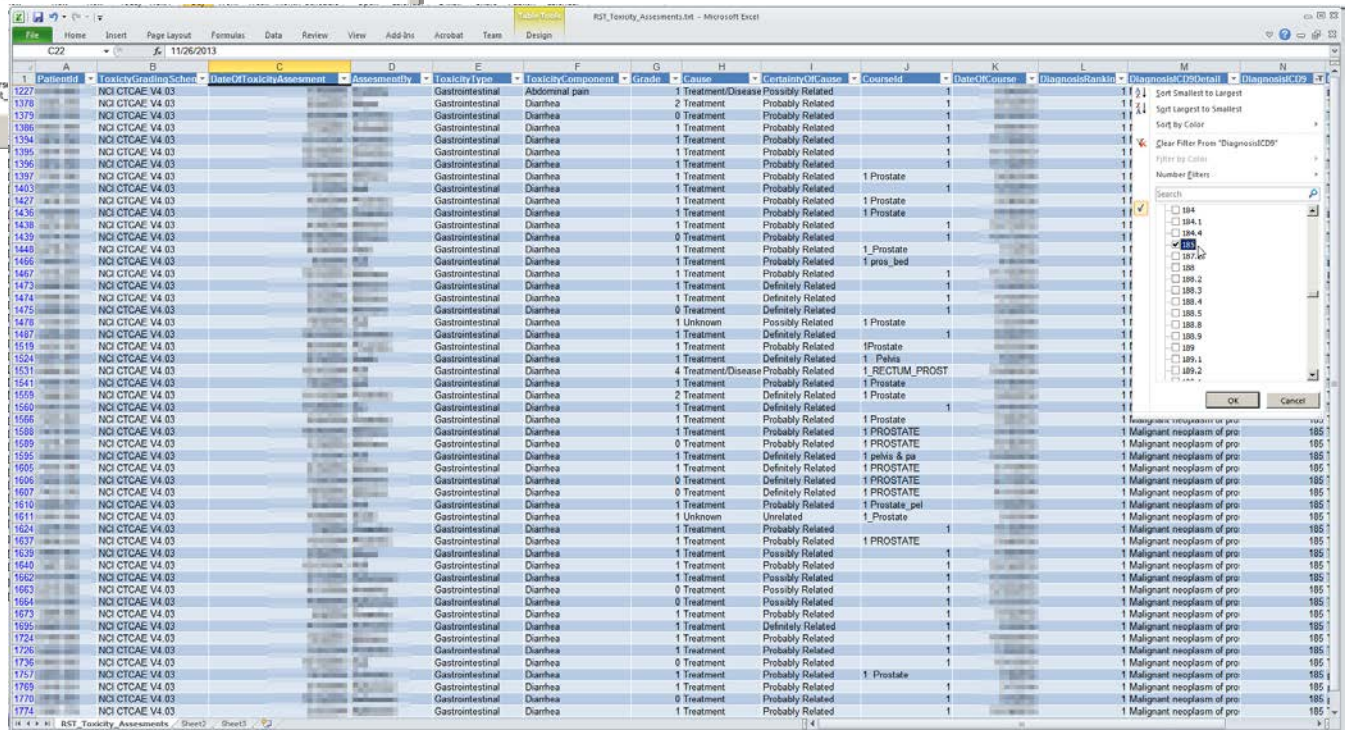




What about correlations of DVH metrics to toxicities?



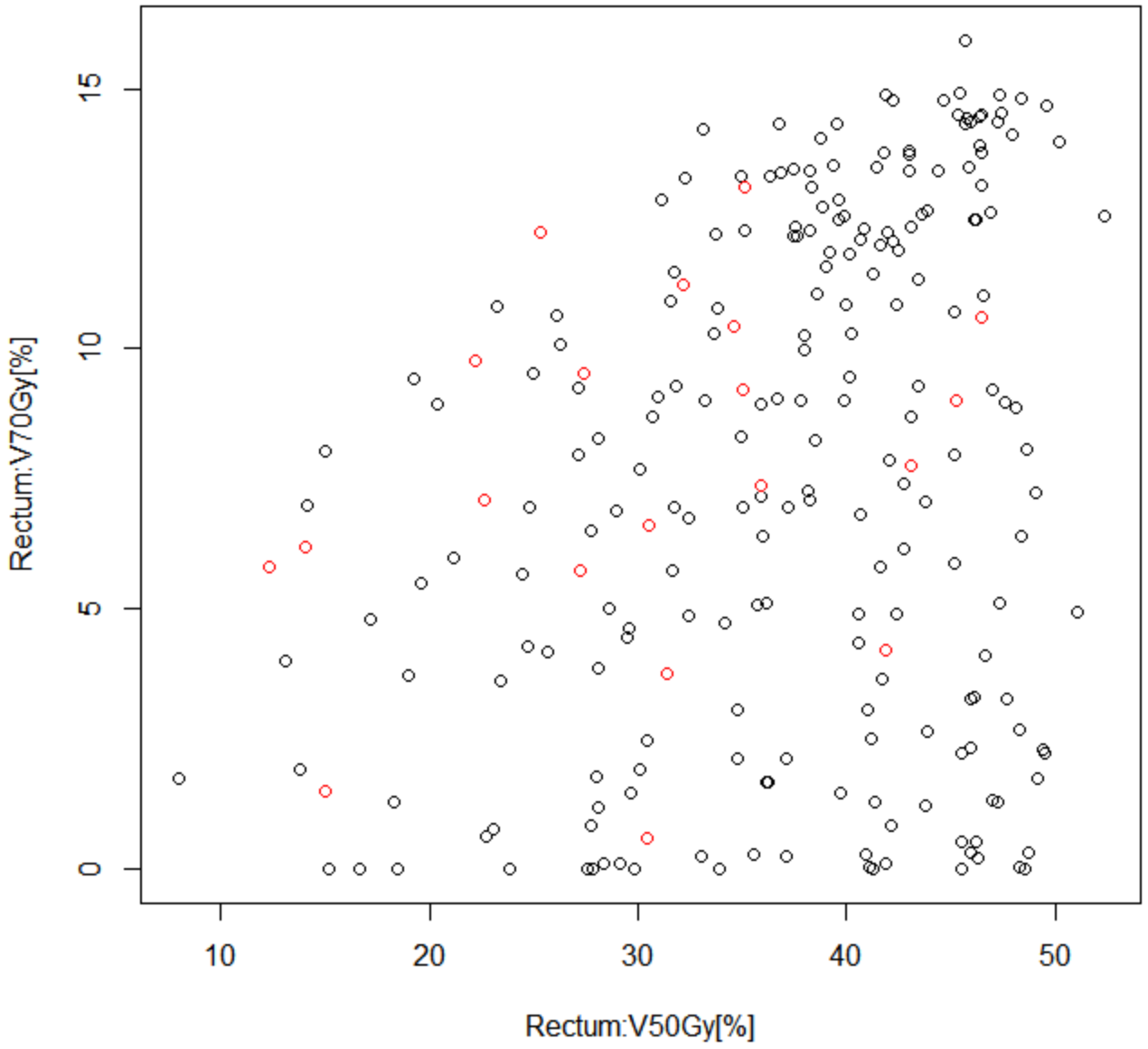




You can use your existing radiation oncology outcomes information system to query to pull toxicities

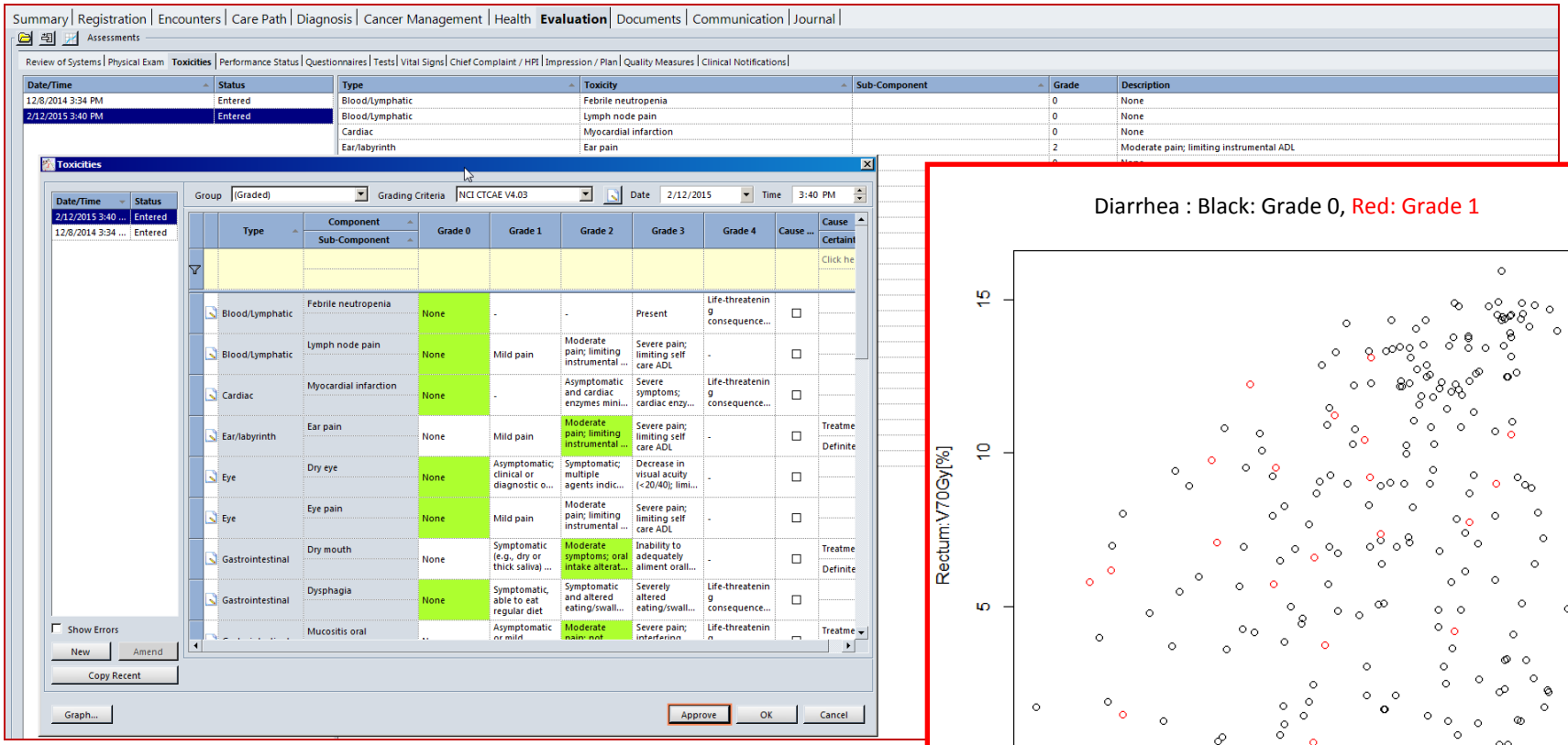
Remember to get the connection to diagnosis and staging right

Diarrhea : Black: Grade 0, Red: Grade 1

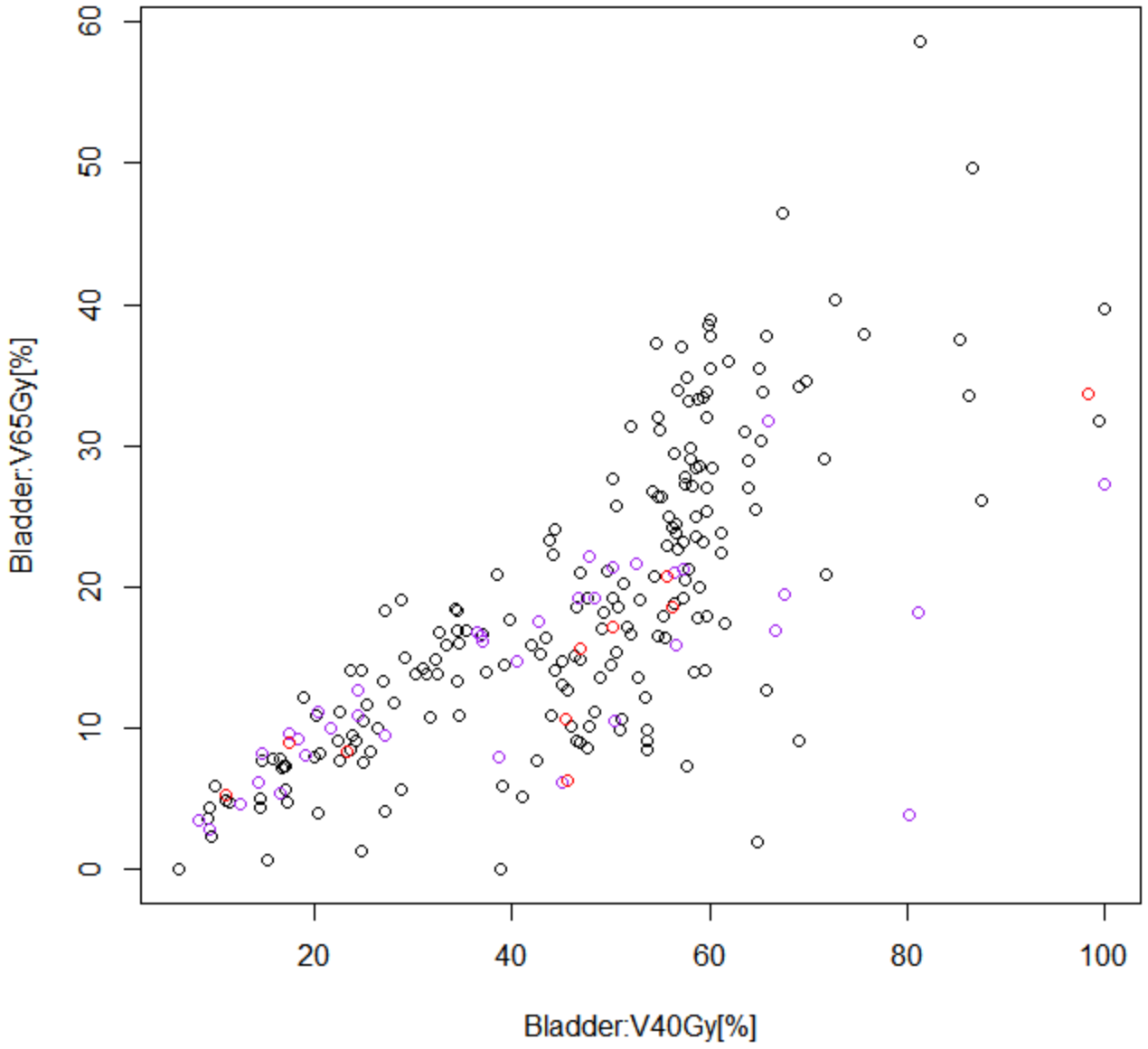


When is no data, data and when is it just no data?

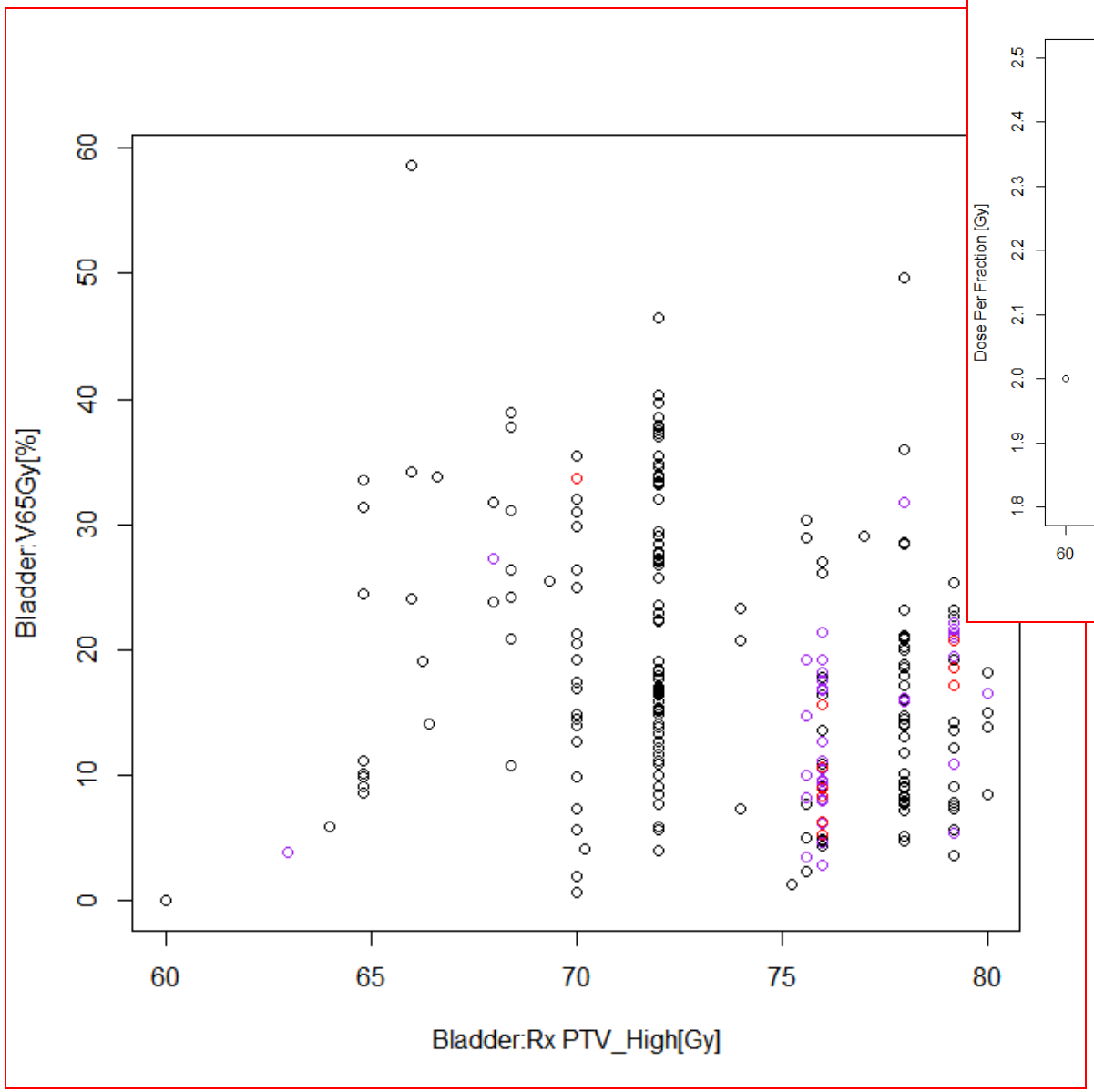
Another iteration on changing culture to think about treatment records as like a scientist as well as like a clinician.

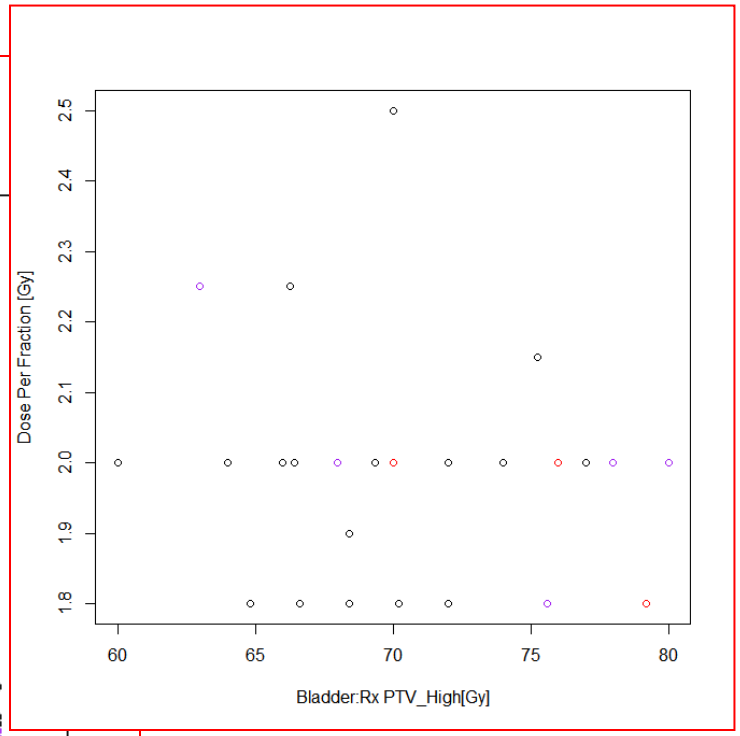


Urinary Frequency: Black-Grade 0, Purple- Grade 1, Red-Grade 2



Urinary Frequency: Black-Grade 0, Purple- Grade 1, Red-Grade 2





Summary

Standardize

- Make the input data consistent so that computer systems can automatically extract and reliably process it.
- Build in QA processes on your data so that you will believe it

Extract

- Use the capabilities of your current electronic systems
- The exercise of pulling large data sets from your existing ROIS and TPS systems will improve your understanding of connections and needed consistencies

Extend

- Train or get outside help if you need it
- Coordinate with other groups interested in data pooling to strengthen your processes and put the data to use
- This will work best if efforts are coordinated among institutions

Demonstrate

- Show use of data from your electronic systems to define your practice norms and demonstrate improvement
- Be prepared to iterate. Changing processes and changing minds takes sustained effort

Changing culture to think as a scientist as well as a clinician about data usage will require more effort than constructing the technology to use it.