Big Data - How to Use the Past for the Future

AAPM Spring Clinical Meeting
Nomenclature and Big Data – TG263 and the future
3/31/2019 4:30 – 5:30

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Disclosures

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Acknowledgements *Big Data is a group effort*

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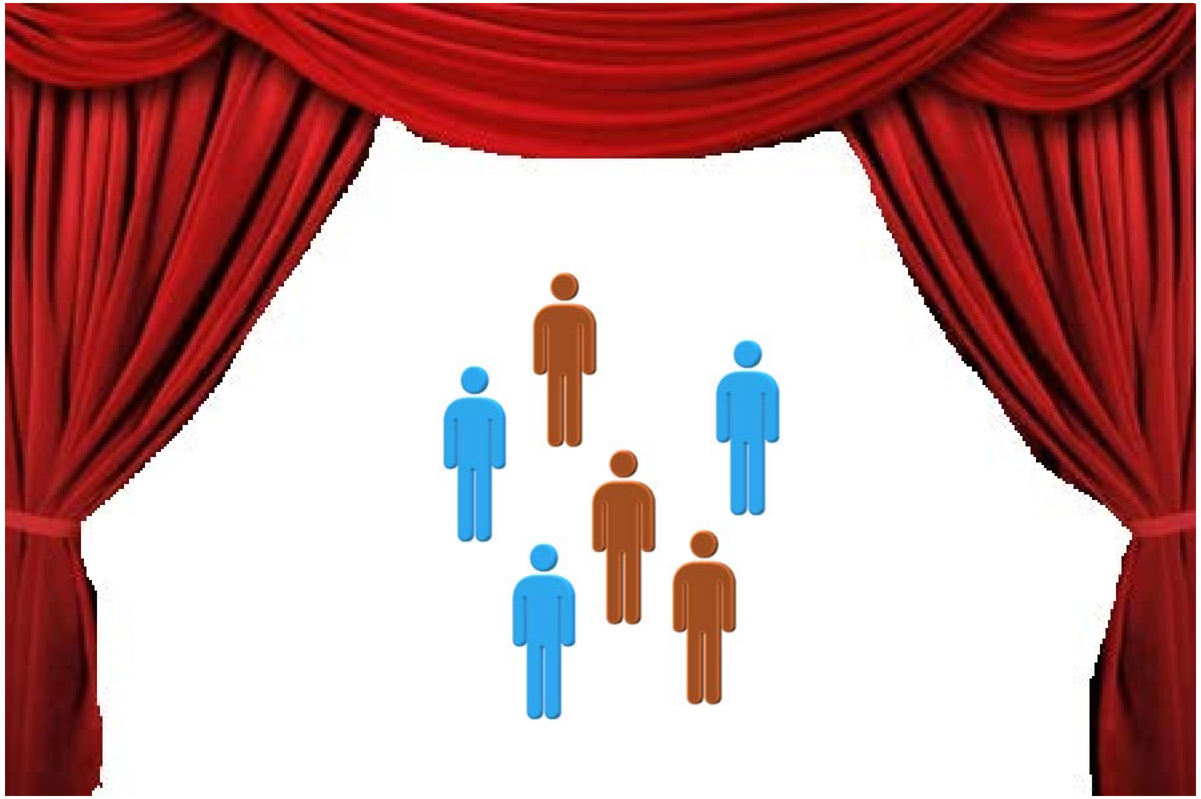
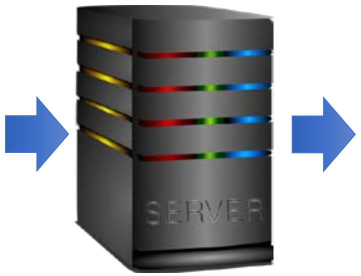
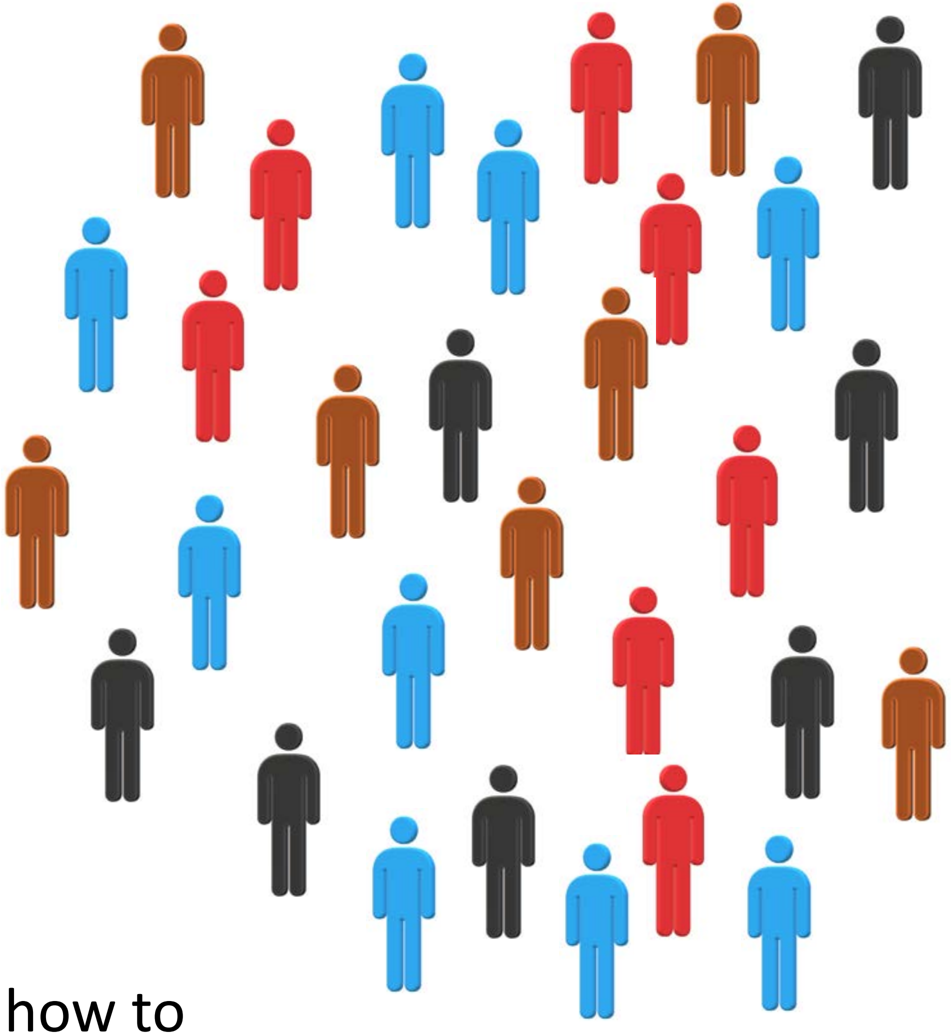
We know a lot about a few patients …

and apply knowledge gained to a much larger, more diverse set of patients



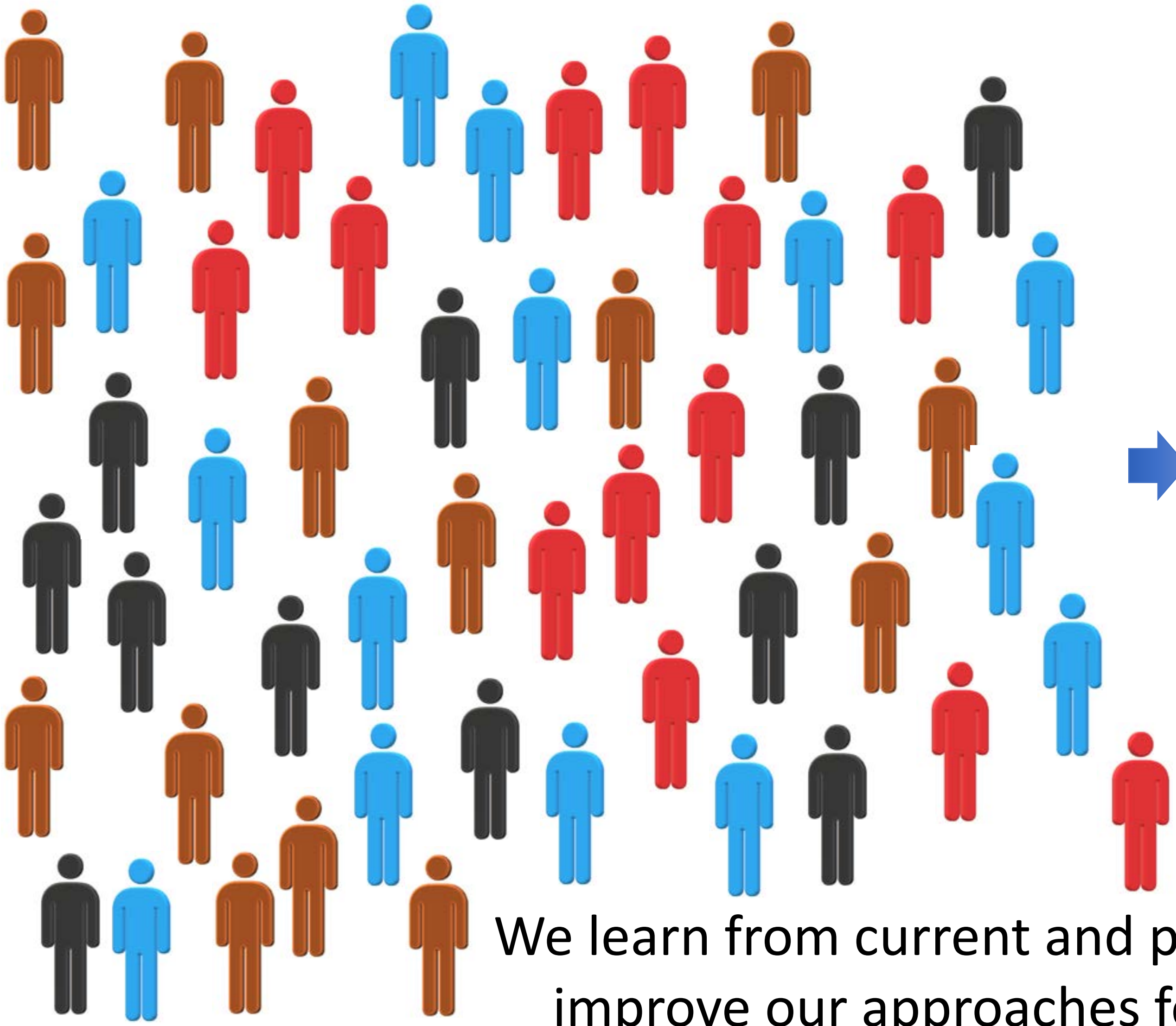


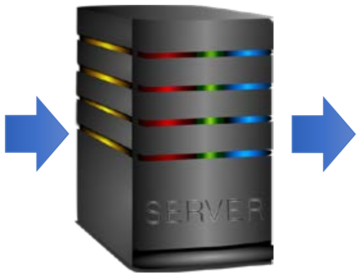


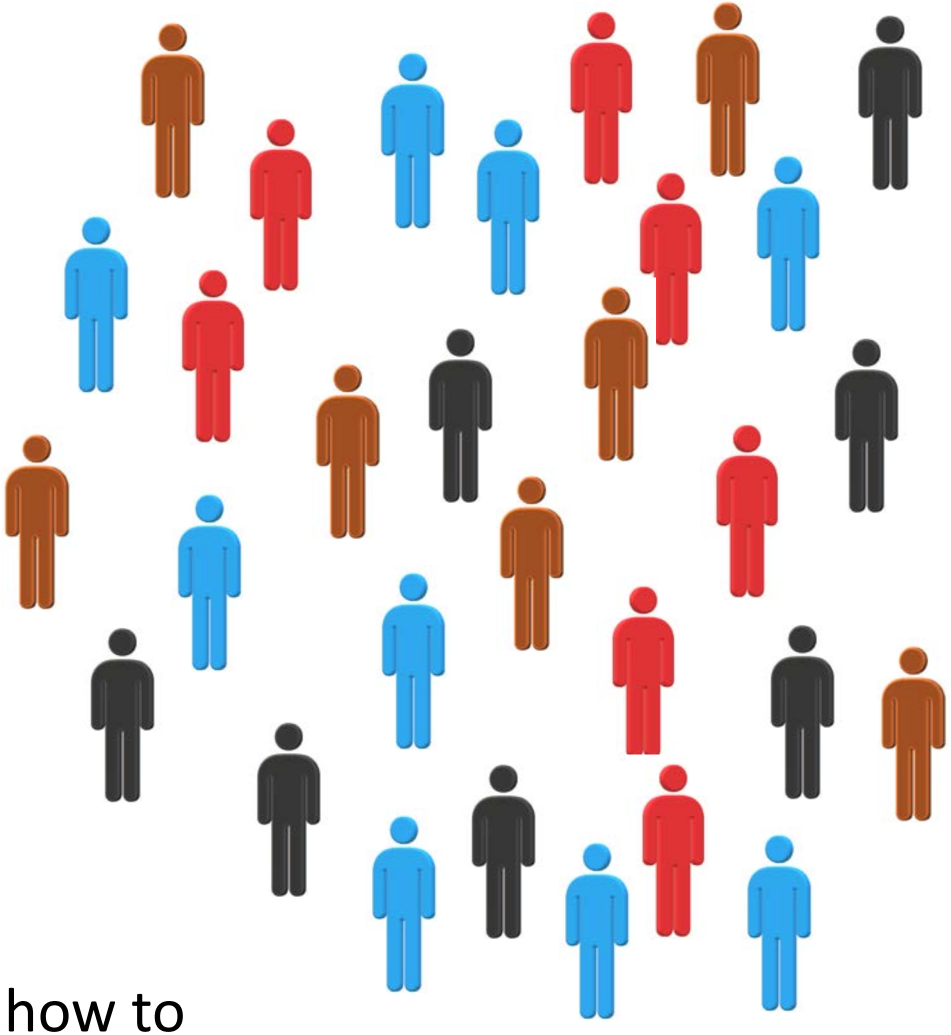
We learn from current and past patients how to improve our approaches for future patients

How can we improve so that we learn a lot about a lot of patients …

and apply knowledge gained to future patients ?

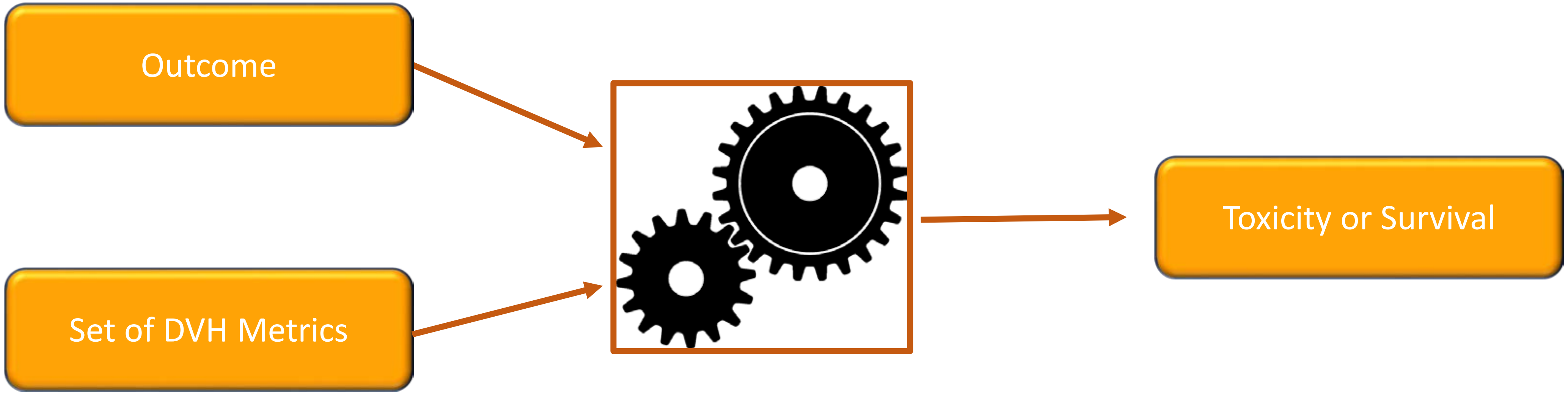




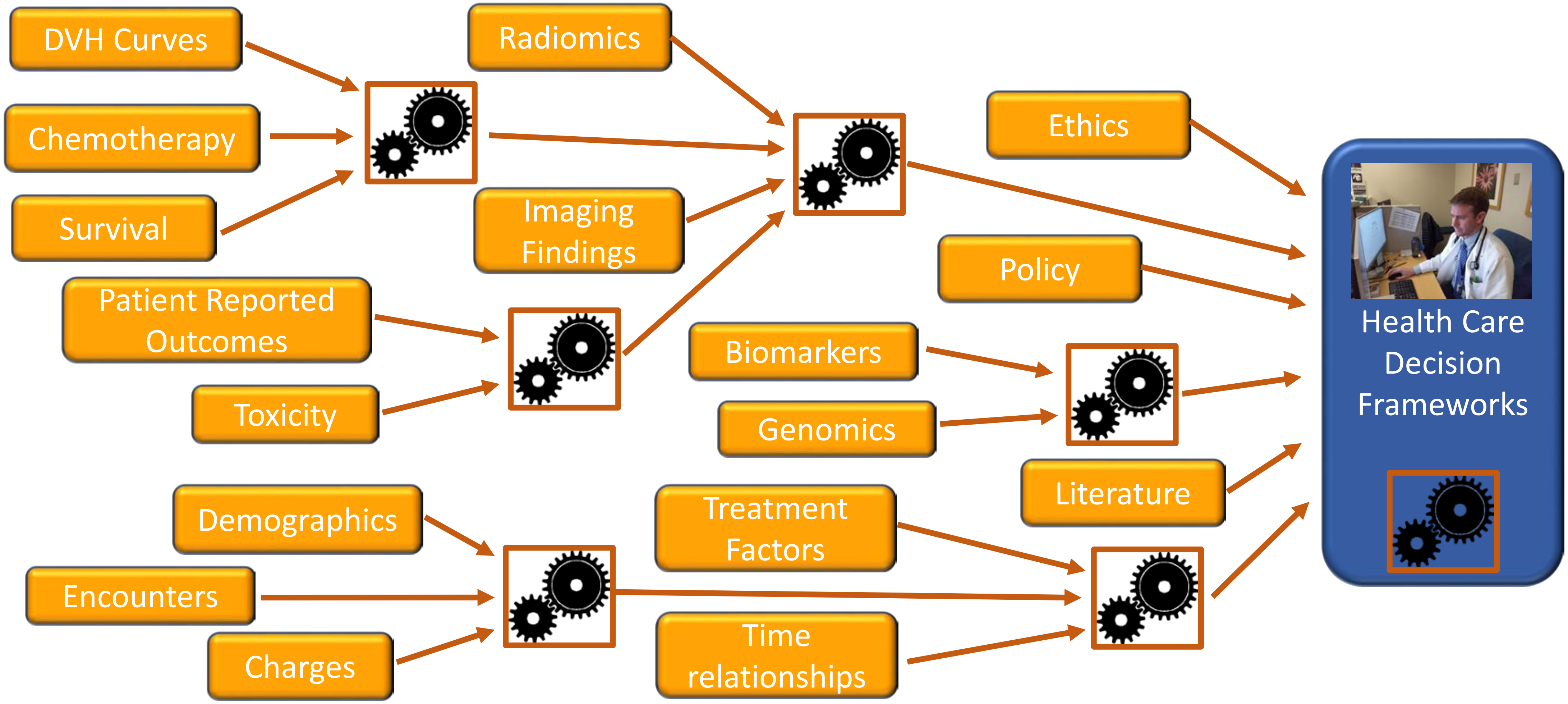


We learn from current and past patients how to improve our approaches for future patients

The models of today typically have narrow focus on limited types of inputs and outputs for low volume data

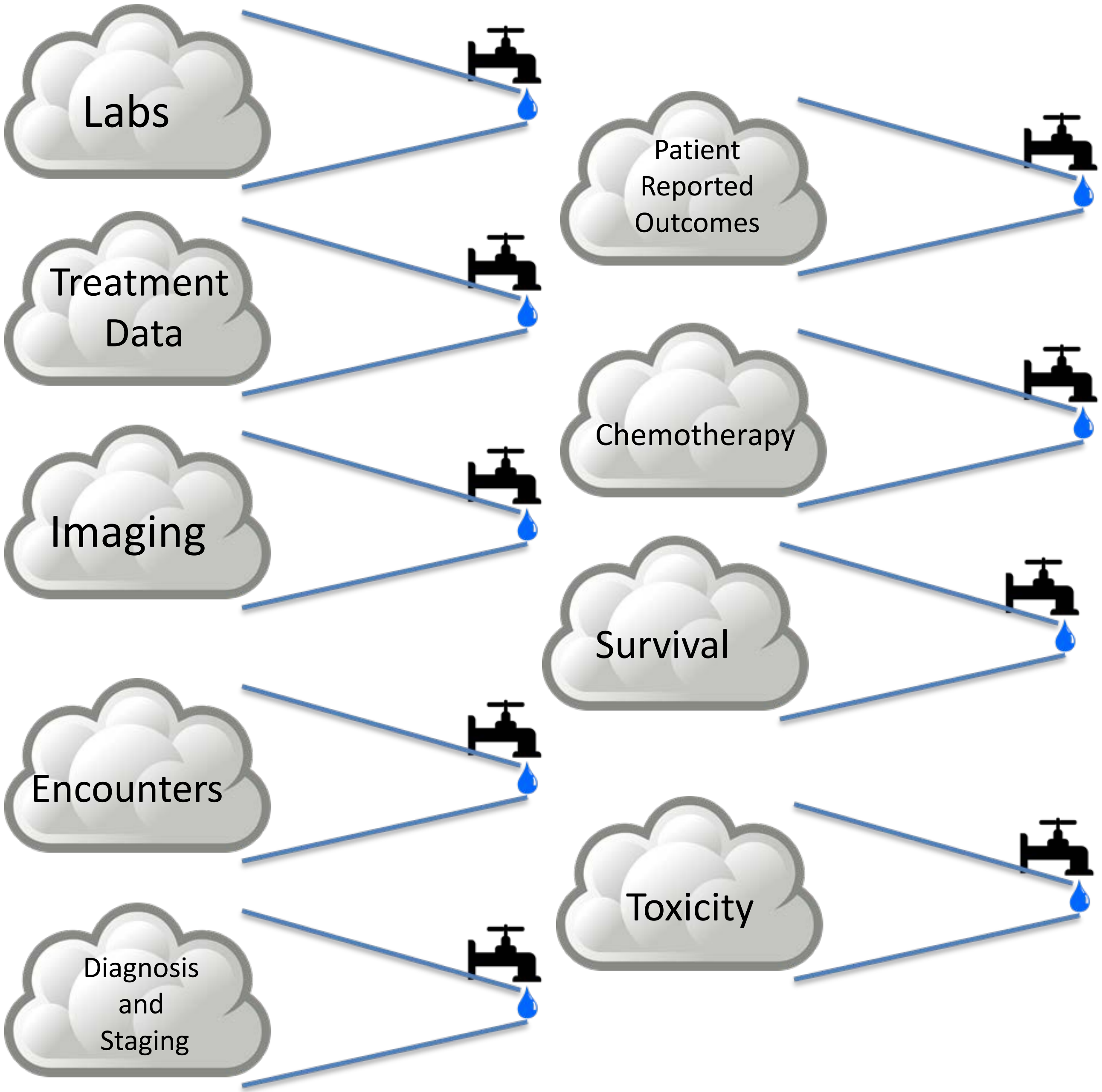


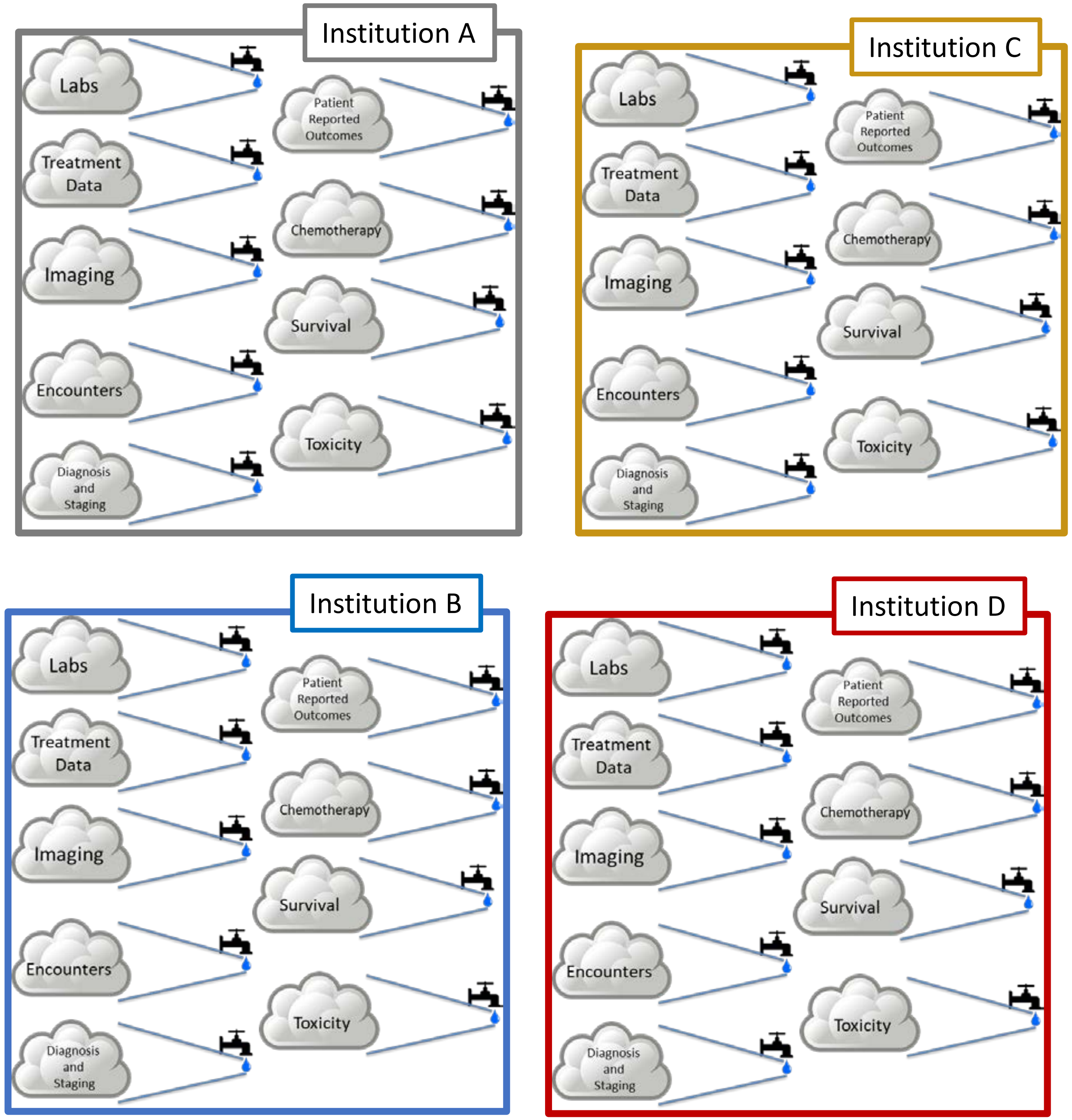
The models of tomorrow will integrate a wider range of input types using larger volumes of data and more complex interactions to inform decision frameworks



Condensing and collecting amorphous data from electronic record systems requires

- Technical Solutions
- Data Proactive Clinical Processes
- Professional Society Consensus Guidelines





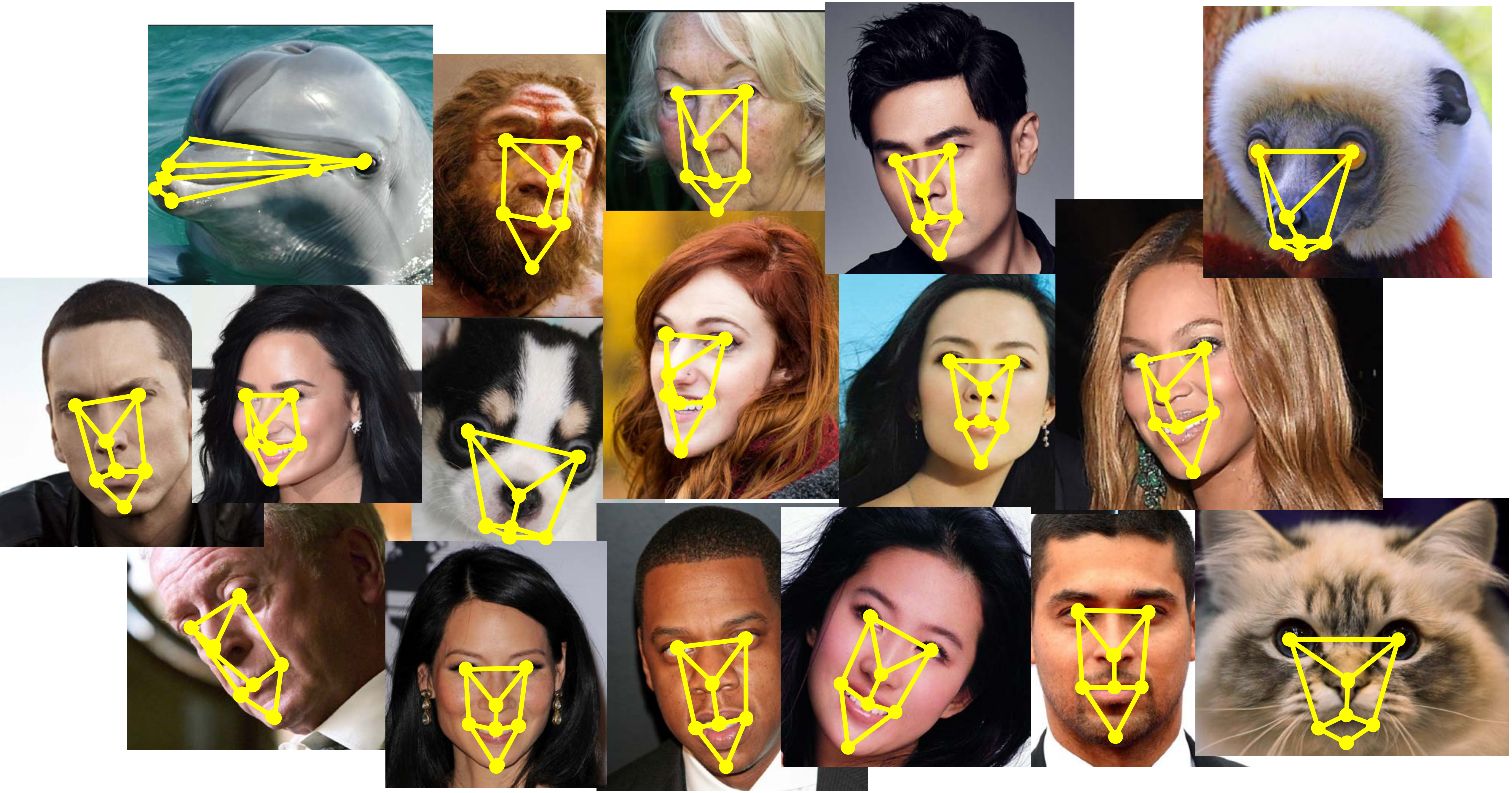
For truly big data
we need multi-institution,
multi-society, multi-stakeholder
collaboration on solutions

Standardization
is the foundation
for reaching the potential of

Big Data - AI

That can’t be right

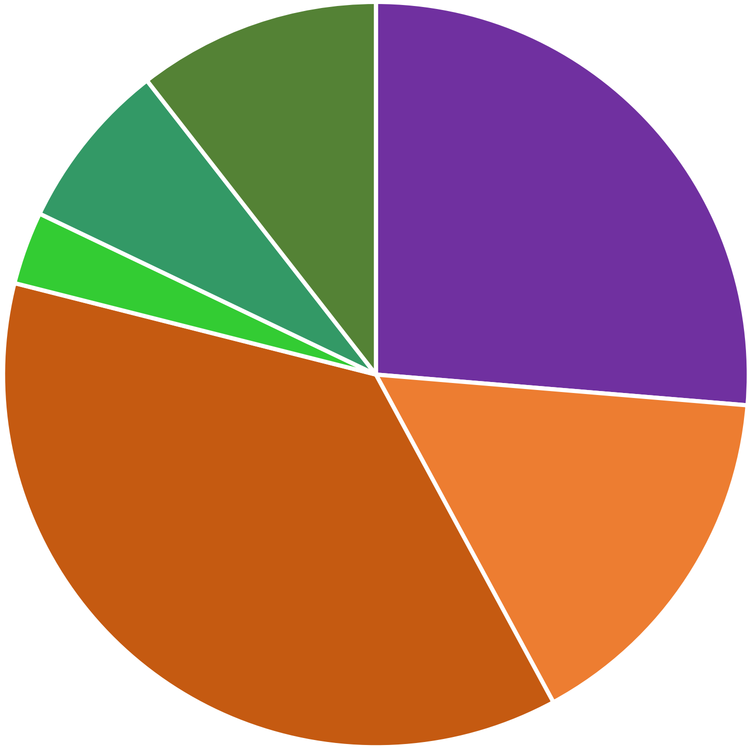
Example – All the amazing results from facial recognition using images “in the wild”



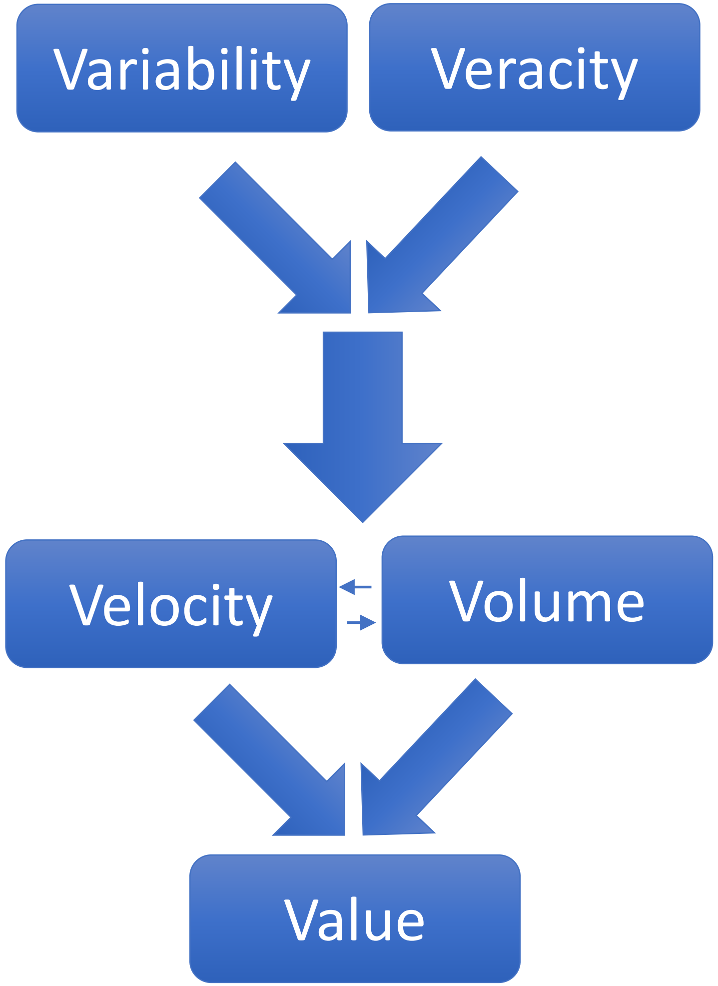
Standardization is built in by DNA

Medical Physicists combine the clinical and technical domain knowledge needed to operationalize Big Data – AI in the clinic

Big Data – AI: Where does the Medical Physicist's effort go?



- Technology (Volume, Velocity)
- Multi-Center/Society Collaborative Standardization (Variability)
- Data Centric Clinical Process Change (Variability, Veracity)
- Reporting and Dashboards (Value)
- Clinical Applications (Value)
- Machine Learning and AI (Value)



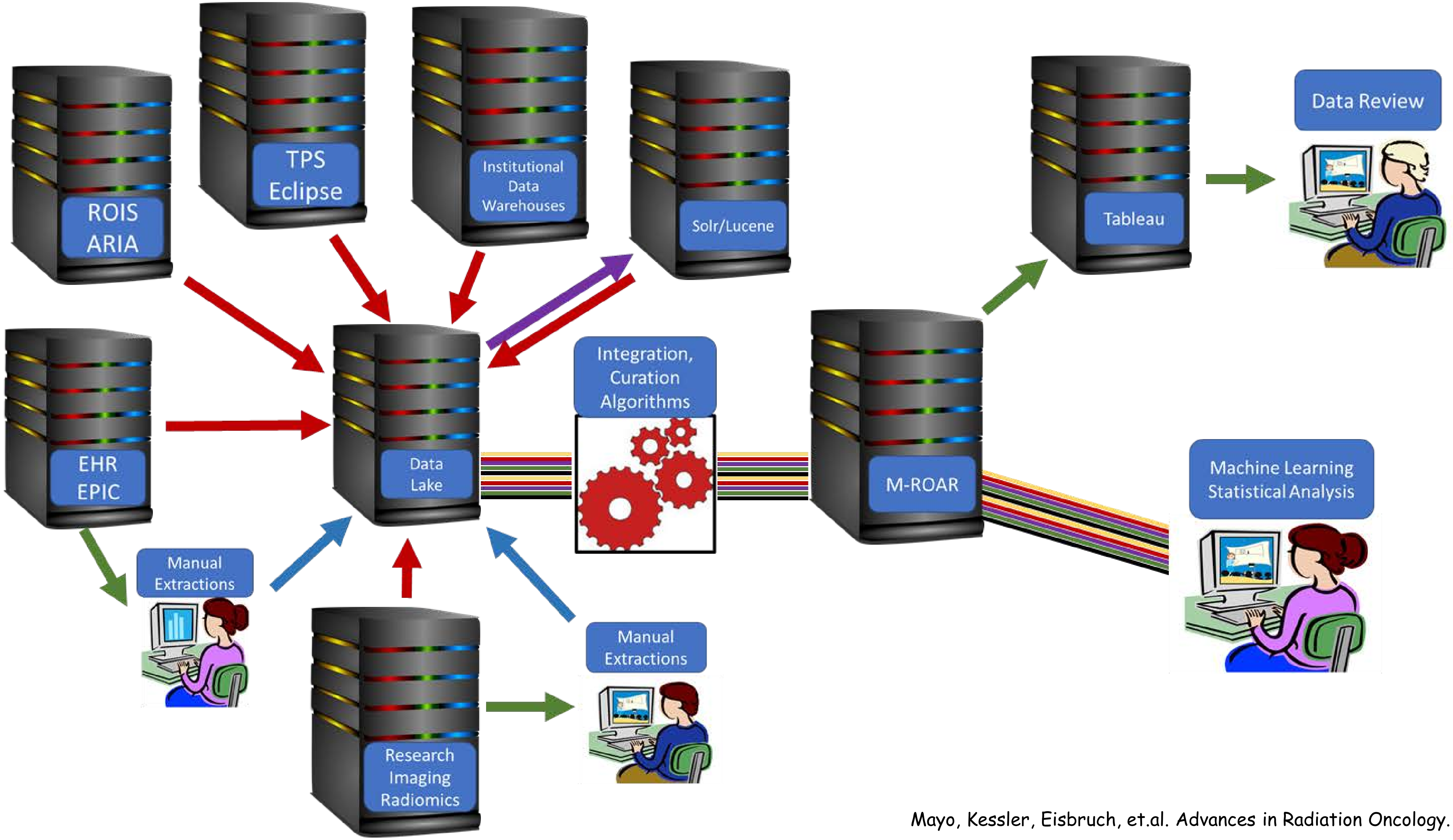
Data Base Technology

You can pay me now, or you can pay me later … but you're going to pay me

Factors to consider when selecting a technology stack (e.g. SQL vs No-SQL) and deciding when in the process to impose categorization of elements and relationships

- Speed for extracting/querying data
- Ability to interface with clinical systems
- Ability to integrate with production (clinical) level code and practices
- Hosting the technology on the institutional servers behind the firewall
- Density of people in the workforce with necessary to skills use the technology
- Operational barriers between you and the data needed - technology or clinical process

Michigan Radiation Oncology Analytics Resource (M-ROAR)



Mayo, Kessler, Eisbruch, et.al. Advances in Radiation Oncology. 2016 1(4): 260-271

Multi-Center/Society Collaborative Standardization

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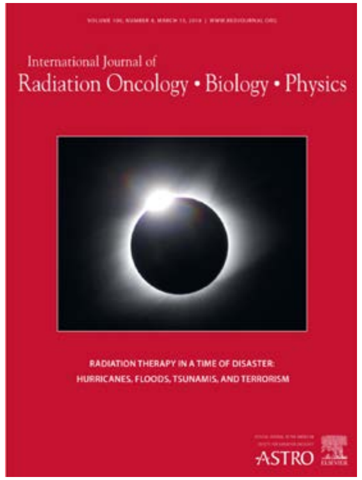
Standardizing Nomenclatures in Radiation Oncology

The Report of AAPM Task Group 263

Endorsed by:
AAPM, ASTRO
ESTRO, AAMD

- Target Structures
  - Standardized rule based approach (10)
  - Addresses primary issues and expandable
- Non-Target Structures
  - Rule based approach (15) with a few concessions
  - Specific listing of 756 defined structures
- DVH Nomenclature



https://www.aapm.org/pubs/reports/RPT_263.pdf

https://www.redjournal.org/article/S0360-3016(17)34232-3/pdf

Data Centric Clinical Process Change

StructureID	StructureID	StructureID	StructureID	StructureID	StructureID	StructureID
PTV 21.6	PTV 10-14-16	PTV_38RE_EVAL	PTV_FEMUR	PTV_R_Ax_70	PTV1_PTV2	PTV_2CM
PTV 2GY/FX_ALONE	PTV 1MM	PTV_44.8	PTV_High	PTV_R_CLAV	PTV1_SRS	PTV_30
PTV 30.6	PTV 61.2	PTV_47.6	PTV_High^66	PTV_R_Frontal	PTV1_SRS2	PTV_34
PTV 45Gy	PTV 75	PTV_48	PTV_High^70	PTV_R_Ilium	PTV1_SRS3	PTV_35
PTV 55Gy	PTV BACK	PTV_50_NM	PTV_High^NEW	PTV_R_Lung	PTV1_SUP	PTV_41.4
PTV BOOST	PTV bone met	PTV_50_OPT	PTV_High2	PTV_R_PUBIC	PTV1+2	PTV_45OPT
PTV BOOST OPT	PTV bone met bst	PTV_5412	PTV_Highdose	PTV_R_SHOULDER	PTV1R	PTV_50
PTV CHEST	PTV CLAV	PTV_58.8	PTV_HILUM	PTV_RCHEST	PTV1-RESIM	PTV_50.4
PTV GROSS NODE	PTV COMPROS	PTV_60	PTV_ILIAC/ING	PTV_RESIM2	PTV1-RESIMOPT	PTV_54EVAL
PTV L RIB	PTV dom tumors	PTV_60_NEW	PTV_IMN_L	PTV_RETX_OPT	PTV2 18GY	PTV_5600_Eval
PTV L&R	PTV electron	PTV_6000_Eval	PTV_INF	PTV_RGroin	PTV2 RCERE	PTV_56OPT
PTV LEG	PTV ESOPHAGUS	PTV_63OPT	PTV_interpolated	PTV_RHILUM	PTV2_2	PTV_5940
PTV LT BRAIN	PTV INITAL	PTV_72	PTV_JDNODE	PTV_RIB/TRACHEA	PTV2_2MM	PTV_60OPT
PTV MET1	PTV L PAR	PTV_8	PTV_KIDNEY	PTV_RIGHT	PTV2_Dome	PTV_64.8
PTV mid-chest	PTV LN-BOWEL	PTV_95IDL	PTV_L SHOULDER	PTV_RLEG	PTV2_L3	PTV_7
PTV N	PTV LNR	PTV_ABD	PTV_L1	PTV_RPLVS	PTV2_LOWER	PTV_79.2
PTV NODES	PTV LT LIV	PTV_abdomen	PTV_L2	PTV_RSacrum	PTV2_new	PTV_7920
PTV NODES OPT	PTV MRnodule	PTV_ABDWALL	PTV_L3_4	PTV_RT LUNG	PTV2_RIGHT	PTV_ADDDOSE
PTV OPT - CE	PTV NECK	PTV_anticube	PTV_L45	PTV_RT_SCAPULA	PTV2_SBRT	PTV_Adrenal
PTV OPT - ESOPH	PTV OPT 1	PTV_BACK	PTV_L5	PTV_RTHIGH	PTV2_SRS2	PTV_ALL
PTV OPT - S&E	PTV OPT HIP	PTV_BED	PTV_LCRBLM	PTV_RtIlium	PTV2_T10_49.2	PTV_AXILLA
PTV OPT BOWEL	PTV OPT-SIG	PTV_BOS	PTV_LFEMUR	PTV_RWRIST	PTV2_T6	PTV_BONE
PTV OPT R	PTV R PELVIC	PTV_BRAINSTEM	PTV_LHIP	ptv_sboverlap	PTV2+PTV3	PTV_BOOST_OPT1
PTV OPT R B	PTV R TEMP	PTV_BREAST	PTV_LHUM	PTV_SMALL	PTV20_OPT	PTV_BST_OPT1
PTV PROSTATE	PTV RIB	PTV_BST_OPT	PTV_LIVOPT	PTV_spine	PTV20160802	PTV_BST-MAND_O...
PTV R FRON	PTV RT LIV	PTV_BSTOPT	PTV_LN_OPT	PTV_SUP_LT	PTV21	PTV_C1_C3
PTV RESIM	PTV RT RIB	PTV_C3	PTV_LO	PTV_SUP_MID	PTV21_EVAL	PTV_C2_C3
PTV SACRUM	PTV SEMVES	PTV_C4_6_OPT	PTV_Low^54	PTV_SURG_BED	PTV220140513	PTV_CHESTL
PTV SCAPULA	ptv.3	PTV_C7	PTV_Low^59	PTV_T_OPT	PTV25_EVAL	PTV_CHESTR
PTV SKULL	PTV^LVRRTX	PTV_CALVARIUM	PTV_LS SPINE	PTV_T1_S2	PTV2-54_EVAL	PTV_Cspine
PTV TOTAL	PTV_1001	PTV_CENTRAL	PTV_LSUP	PTV_T10LRIB	PTV2-54_OPT	PTV_ELECTRON

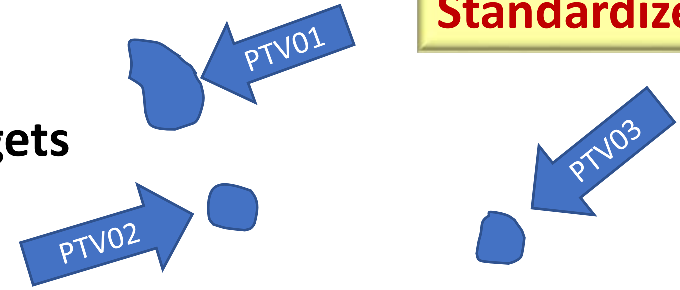
Variability in Target Structure Names is a Really Big Problem

Over 2600 different PTV names
in historic M-ROAR plans
(1400 CTVs, 1200 GTVs)

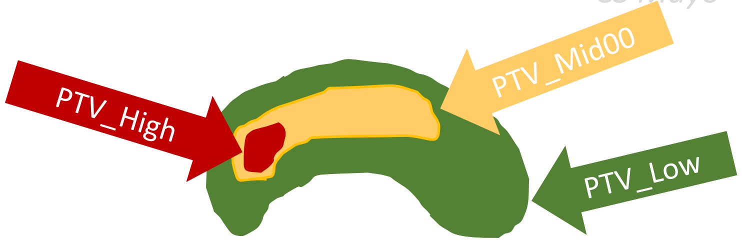
Standardize Target Naming

CS Mayo

Spatially Separate Targets



Embedded Targets



Standardized Brain SRS Directive

Target(s)	Priority	Drawn By	Dataset:	Instructions:	Locatior volume)
☐ GTV01 ______	______	MD	CT/MR	Choose	
☐ GTV02 ______	______	MD	CT/MR	Choose	
☐ GTV03 ______	______	MD	CT/MR	Choose	
☐ GTV04 ______	______	MD	CT/MR	Choose	
☐ GTV05 ______	______	MD	CT/MR	Choose	
☐ GTV06 ______	______	MD	CT/MR	Choose	
☐ GTV07 ______	______	MD	CT/MR	Choose	
☐ GTV08 ______	______	MD	CT/MR	Choose	
☐ GTV09 ______	______	MD	CT/MR	Choose	
☐ GTV 10 ______	______	MD	CT/MR	Choose	
Other notes:					

Standardized Head and Neck Directive

Targets (check all to be contoured)	Dataset:	Comments/Instructions
☐ CTV_High	☐CT ☐MR	
☐ CTV_ Mid00	☐CT ☐MR	
☐ CTV_ Mid01	☐CT ☐MR	
☐ CTV_ Low	☐CT ☐MR	
☐ PTV_High	CT	PTVs = CTVs + 0.3 cm or
☐ PTV_ Mid00		
☐ PTV_ Mid01		
☐ PTV_ Low		
☐ zSUBV_OVERLAP	CT	Overlapped volume between SUBV_PRE (from preRT MRI) an

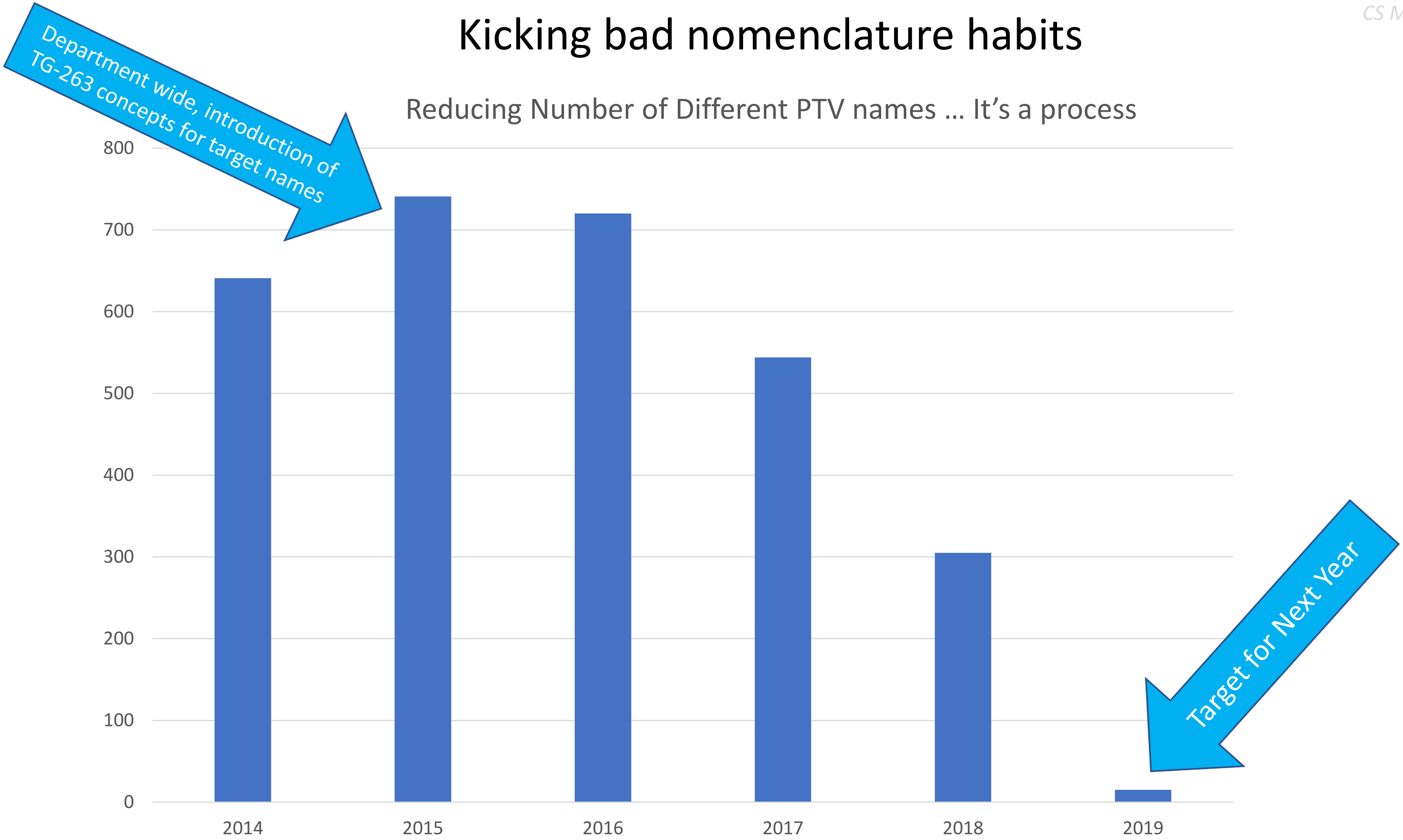
Standardized Liver SBRT Directive

Target(s):	Priority:	Dataset:	Comments / Instructions:
☐ GTV01 ("______")		☐ CT ☐ MRI	______
☐ GTV02 ("______")		☐ CT ☐ MRI	______
☐ GTV03 ("______")		☐ CT ☐ MRI	______
☐ ITV01 ☐ ITV02 ☐ ITV03		☒ CT	☐ Drawn By MD or ☐ Expansion of GTV by Physics
☐ PTV01 ☐ PTV02 ☐ PTV03	2 or ______	☒ CT	☐ SDX, Expand GTV(s) by 5mm axially, 8mm sup + ir ☐ Free breathing, Expand ITV(s) by 5mm axially, 8mm sup *If multiple tumors, consider additional margin for smaller PTV ba

Standardized Prostate Directive

Target(s)	Drawn by	Priority	Instructions
☐ CTV_High ☐ Prostate ☐ Sem Ves ☐ Prox Sem Ves ☐ Prostate Bed	MD	2	______
☐ CTV_Low (Nodes)	MD	2	______
☐ Other	MD	2	______
☐ PTV_Low (Initial)	Dosim	2	CTV_High+ 0.5cm or ______ + ☐CTV_Low + 0.7 cm or ______cm
☐ PTV_High (Boost)	Dosim	2	CTV_High + 0.5cm or ______
☐ Other	MD	______	______

Kicking bad nomenclature habits



Course

Name: 1 PELVIS (ACTIVE)

Add

New...

Plan

	Plan	Volume	Reference Point	Fractionation	Planned Dose [Gy]	Planned Dose Per Fraction [Gy]	No. Frac
☑	1.1v PELVIS	PTV_Low	1.1	F1	45.000	1.800	2
☑	1.2v PRSTBD	PTV_High	1.2	F1	30.800	2.200	1

Dose Contributions

☑ Show All Plans ☐ Hide Coefficient ☐ Hide Field Info ☐ Show All Ref Pts

Plan	Field	MU	Coefficient [MU/Gy]	1.1 Field Dose[Gy]	1.2 Field Dose[Gy]	C1 ICRU Dose Chk Field Dose[Gy]	C1 PTV_High Field Dose[Gy]	C1 PTV_Int Field Dose[Gy]	C1 PTV_Low Field Dose[Gy]
1.1v PELVIS	CW1	182	411.1347	0.444		0.625	0.450	0.450	0.450
	CCW1	180	411.1347	0.437		0.601	0.450	0.450	0.450
	CW2	166	411.1347	0.405		0.020	0.450	0.450	0.450
	CCW2	211	411.1347	0.514		0.624	0.450	0.450	0.450
	Planned Dose Per Fraction			1.800		1.870	1.800	1.800	1.800
	Planned Dose			**45.000**	**0.000**	**46.758**	**45.000**	**45.000**	**45.000**
1.2v PRSTBD	CW1	370	316.8905		1.167	1.132	1.100	0.900	0.000
	CCW1	327	316.8905		1.033	1.131	1.100	0.900	0.000
	Planned Dose Per Fraction				2.200	2.263	2.200	1.800	0.000
	Planned Dose			**0.000**	**30.800**	**31.687**	**30.800**	**25.200**	**0.000**
Dose Corrections				0.000	0.000	0.000	0.000	0.000	0.000
Delivered Dose from other plans				0.000	0.000	0.000	0.000	0.000	0.000
Sum				45.000	30.800	78.445	75.800	70.200	45.000
APPROVED DOSE SUMMARY									
Total Dose Limit				45.000	30.800	79.000	75.800	70.200	45.000
Daily Dose Limit				1.800	2.200	2.300	75.800	1.800	1.800
Session Dose Limit				1.800	2.200	2.300	2.200	1.800	1.800
Breakpoint									
Delivered Dose in Course (incl. dose corr)				0.000	0.000	0.000	0.000	0.000	0.000
Remaining Planned Dose in Course				45.000	0.000	46.758	45.000	45.000	45.000
Dose to be Recorded in Course				**45.000**	**0.000**	**46.758**	**45.000**	**45.000**	**45.000**
Dose to be Recorded from other Courses (excl. dose corr)				0.000	0.000	0.000	0.000	0.000	0.000
Total				**45.000**	**0.000**	**46.758**	**45.000**	**45.000**	**45.000**

Standardize Reference Points to mesh with Prescriptions

- Distinct Primary Reference Point for each plan
- ICRU dose check point located in PTV_High volume. Sanity check for safety
- Cummulative Rx tracking point matching each prescribed dose level in the plan

Now positioned to automate Prescription Cross checks and On Treatment Visit dose reporting

|> Disease SiteLocation = Oropharynx <|

|> Disease Site Status = No Evidence of Disease <|

|> Tobacco Use = Previous Smoker | PackYears = 1 packs per day x 20 years <|

Toxicities

{CTCAE_Fatigue_NoAttrib:34938}

|> Fatigue = 0 (None) <|
|> Fatigue = 1 (Fatigue relieved by rest) <|
|> Fatigue = 2 (Fatigue not relieved by rest; limiting instrumental ADL) <|
|> Fatigue = 3 (Fatigue not relieved by rest, limiting self care ADL) <|

|> Ear Pain = 1 (Mild pain) <|

|> Esophageal Pain = 0 (None) <|

|> Oral pain = 2 (Moderate pain; limiting instrumental ADL) <|

|> Pain = 2 (Moderate pain; limiting instrumental ADL) <|

|> Dehydration = 0 (None) <|

|> Dysphagia = 2 (Symptomatic and latered eating/swallowing) <|

|> Mucositis = 2 (Patchy ulcerations or pseudomembranes) <|

|> Dry Mouth = 0 (None) <|

|> Dysgeusia = 1 (Altered tasted but no change in diet) <|

|> Nausea = 0 (None) <|

|> Dermatitis Radiation = 0 (None) <|

|> Trismus = 0 (None) <|

|> Rash Acneiform = 1 (Papules and/or pustules covering < 10% BSA, which may orm ay not be associated with symptoms of pruritus or tenderness) <|

|>Xerostomia Dry Mouth - Day (dryness during the day) = 1 (Symptomatic [e.g., dry or

Standardize Collection and Data Dictionary For **Toxicity** **Disease Control Status** **Disease Site Location…**

Physician Adopter Hero's
for this Head and Neck project

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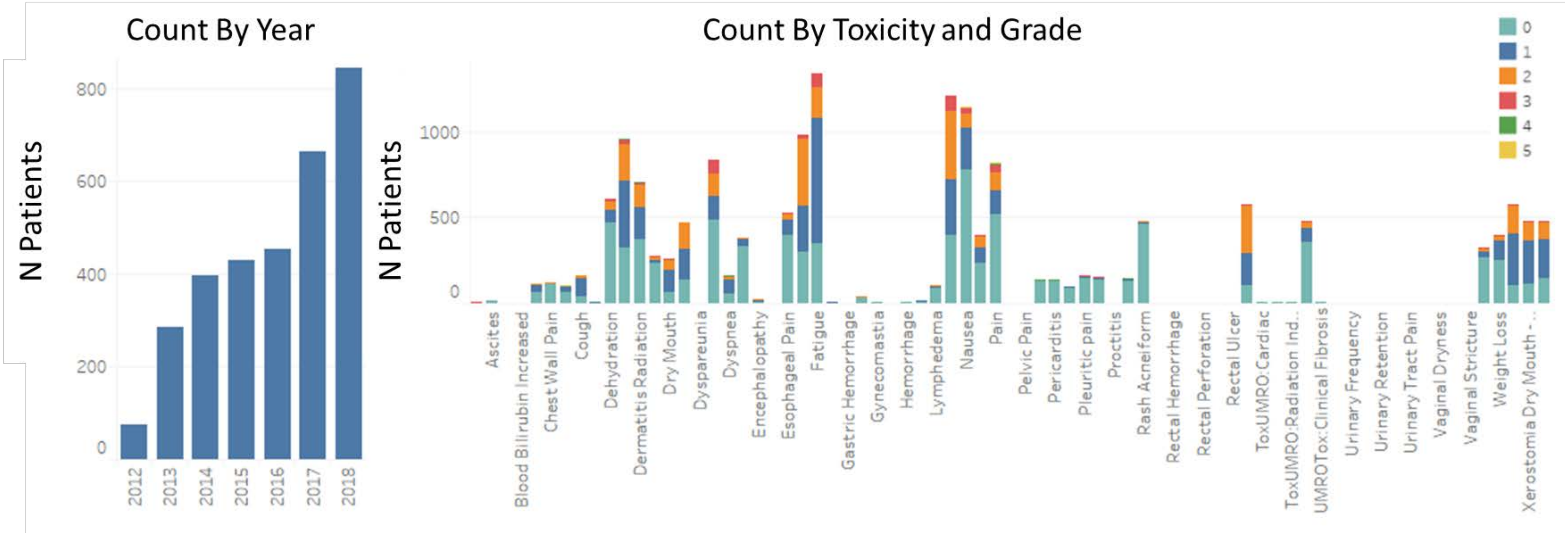
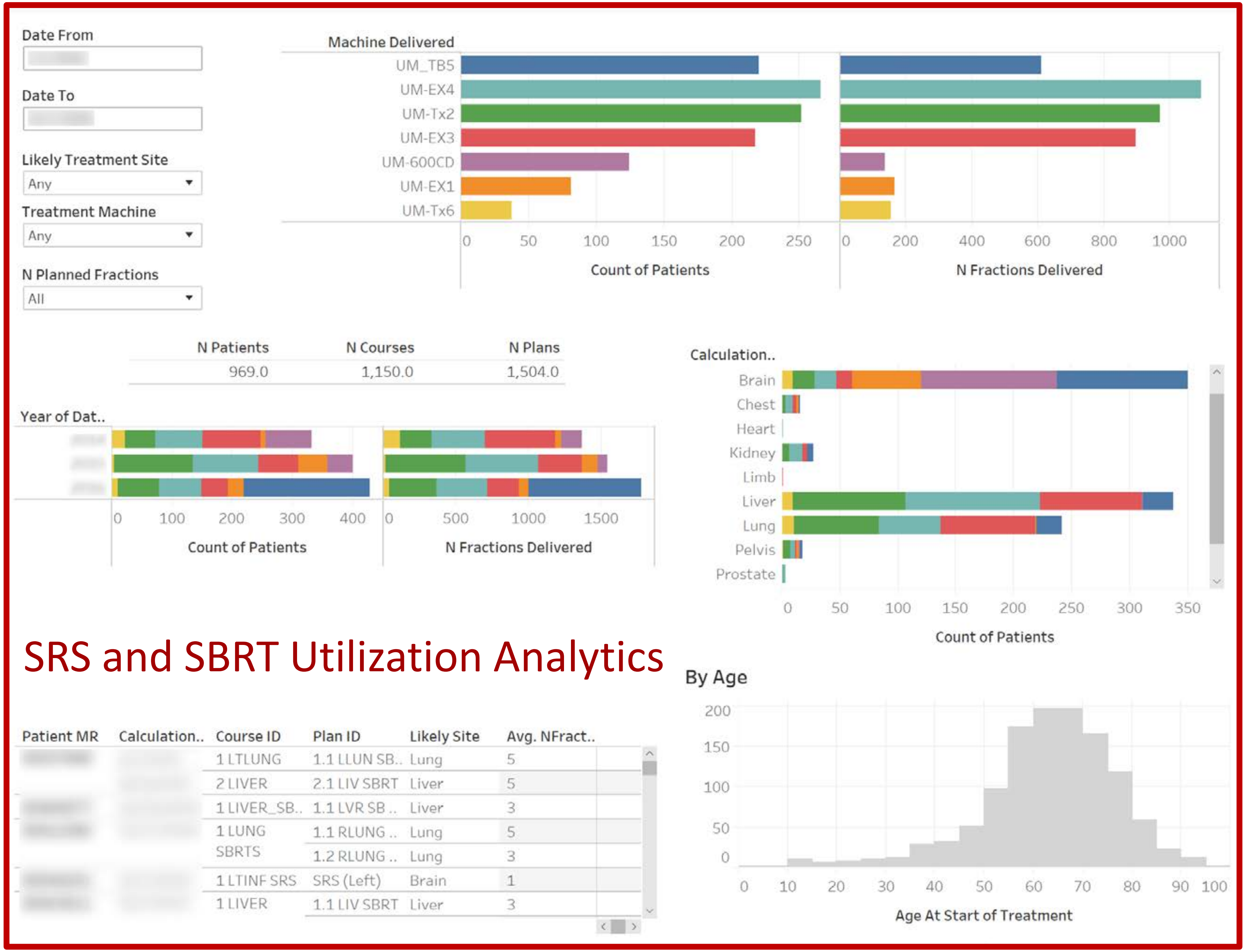
James Hayman, MD
Shruti Jolly, MD
Dawn Owen, MD

Mayo, Matuzak, Jolly, et al Big Data in Designing Clinical Trials: Opportunities and Challenges Frontiers in Oncology 7: 187, 2017.

Count of HN and Lung Patients with Toxicity Records



Reporting Dashboards



Dash boards to learn from Past patients how to best use resources for Future patients

Incorporating Statistical DVH Metrics (Past Patients) into Automated Planning (Future Patients)

Clinical Applications

```
StringBuilder sb = new StringBuilder();
// sb.AppendLine("Done with setting up course and VMAT plan");
// sb.AppendLine("Click OK to proceed with plan optimization");
// System.Windows.MessageBox.Show(sb.ToString());

Console.WriteLine("Starting Optimization");

double doseobjectivevalue_high = tsd.Where(x => x.StandardTargetName == "PTV
double doseobjectivevalue_low = tsd.Where(x => x.StandardTargetName == "PTV_

//cureps.OptimizationSetup.UseJawTracking = true;

cureps.OptimizationSetup.AddPointObjective(zoptptvlow, OptimizationObjective
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cureps.OptimizationSetup.AddNormalTissueObjective(80.0f, 0.0f, 100.0f, 40.0f


// Enter priority 1 constraints. Plan to switch over later to RxConstraints

// cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Single(
if(curstructset.Structures.Any(x => x.Id == "Brainstem"))
cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Single(x

if (curstructset.Structures.Any(x => x.Id == "SpinalCord"))
    cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Singl

if (curstructset.Structures.Any(x => x.Id == "Larynx"))
    cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Singl

if (curstructset.Structures.Any(x => x.Id == "Esophagus"))
    cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Singl

if (curstructset.Structures.Any(x => x.Id == "Musc_Constrict_I"))
    cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Singl

if (curstructset.Structures.Any(x => x.Id == "Musc_Constrict_S"))
    cureps.OptimizationSetup.AddPointObjective(curstructset.Structures.Singl

if (curstructset.Structures.Any(x => x.Id == "Musc_Constrict_S"))
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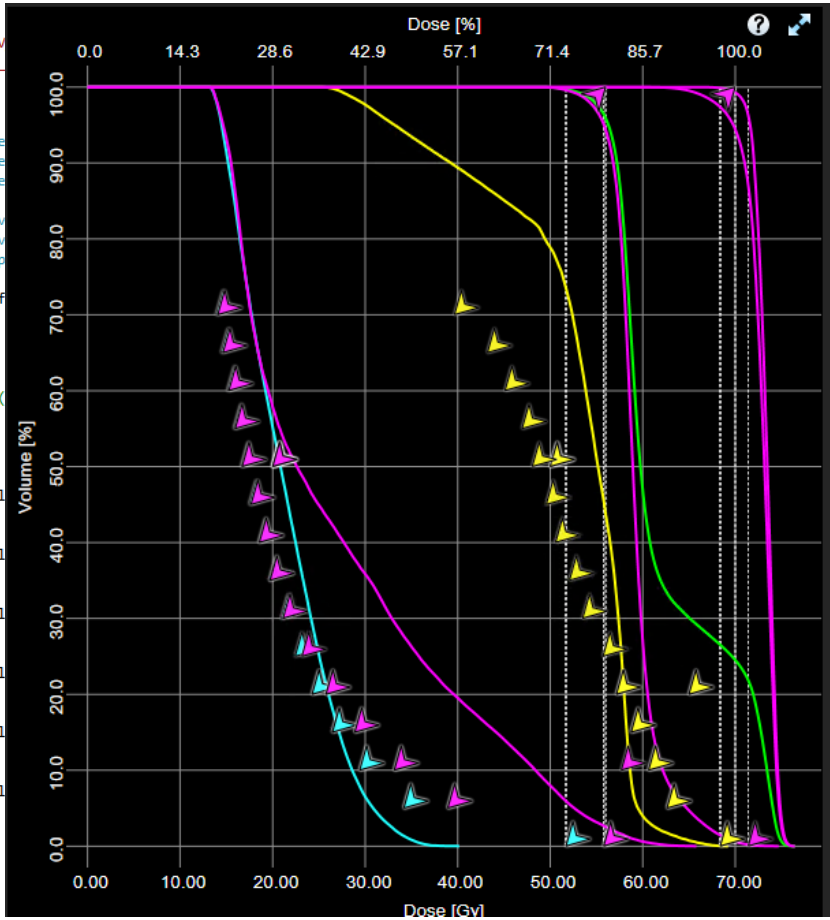
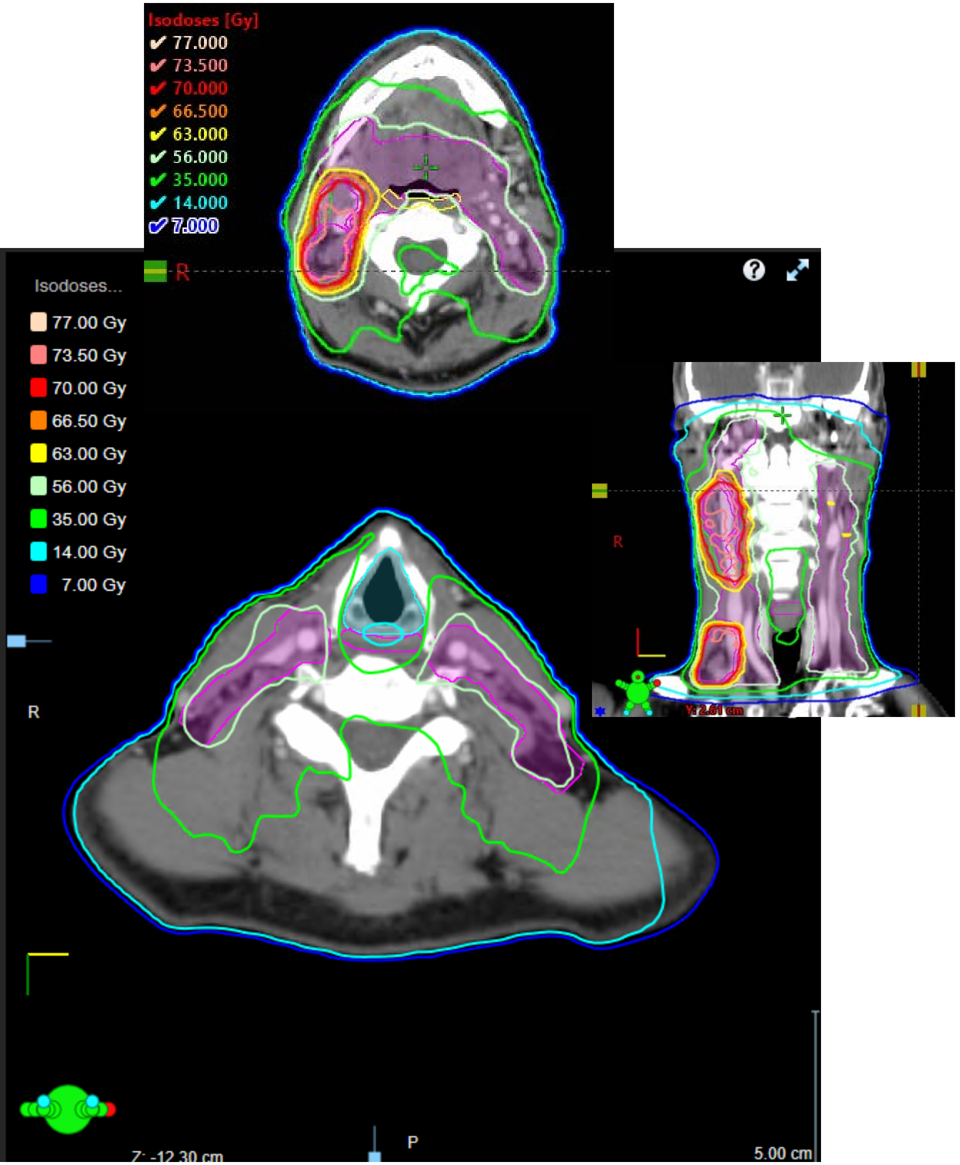




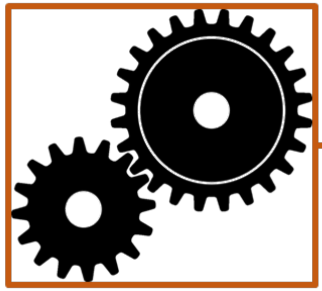
Learning from Past Patients What Constraints to Use for Future Patients

M-ROAR enables bringing large volume of data to the question

AI used to analyze large volume of data

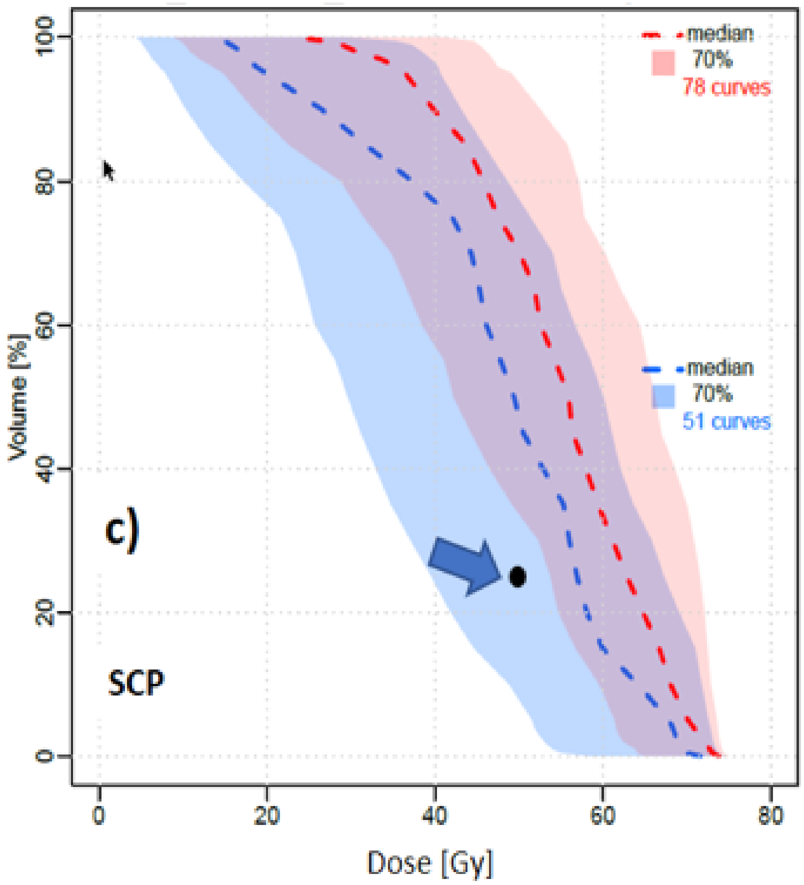
Toxicities

DVH Curves



Recommended Planning Constraints

Example for
Superior Constrictor Dx%[Gy]



439 Recent HN Patients
738 Metrics

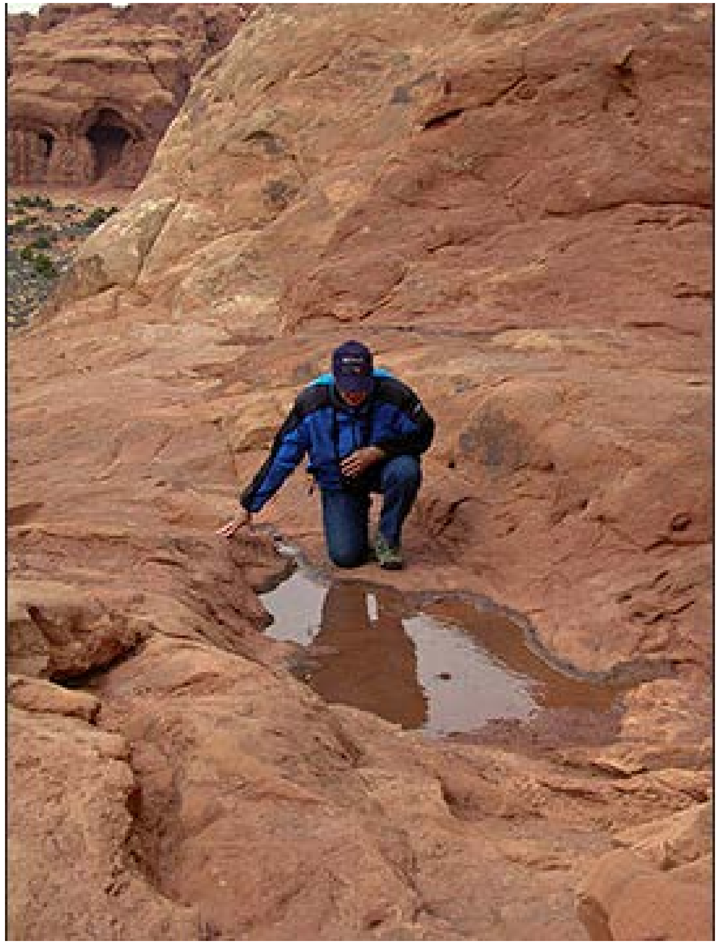
D25%[Gy]≤ 50.4

M-ROAR + Standardization gets us a lot more data to analyze

We need to develop different analytical methods

From Data Dessert

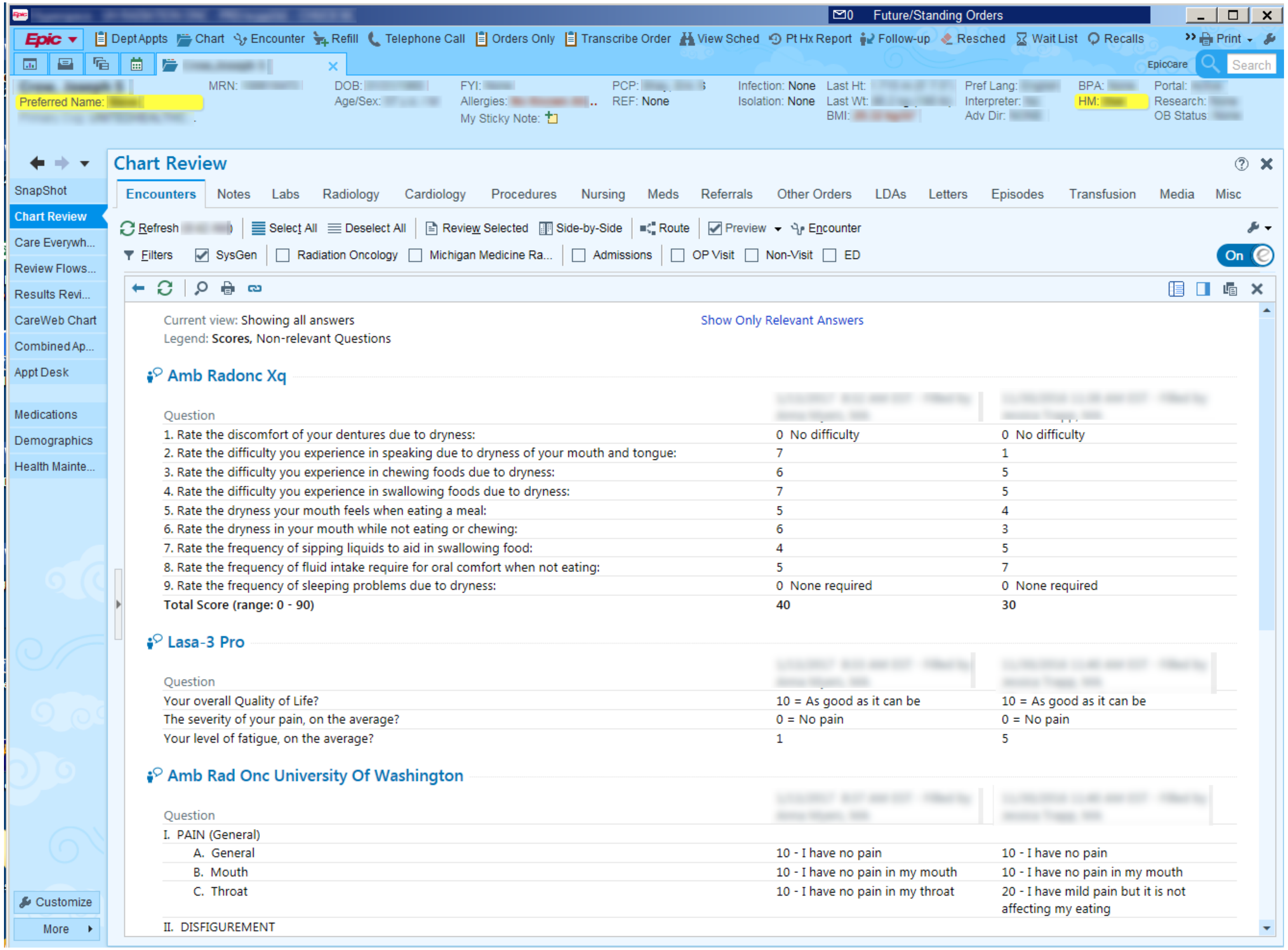
Conventional Manual Aggregations



To Data Ocean

Automated Aggregations with M-ROAR

Patient Reported Outcomes

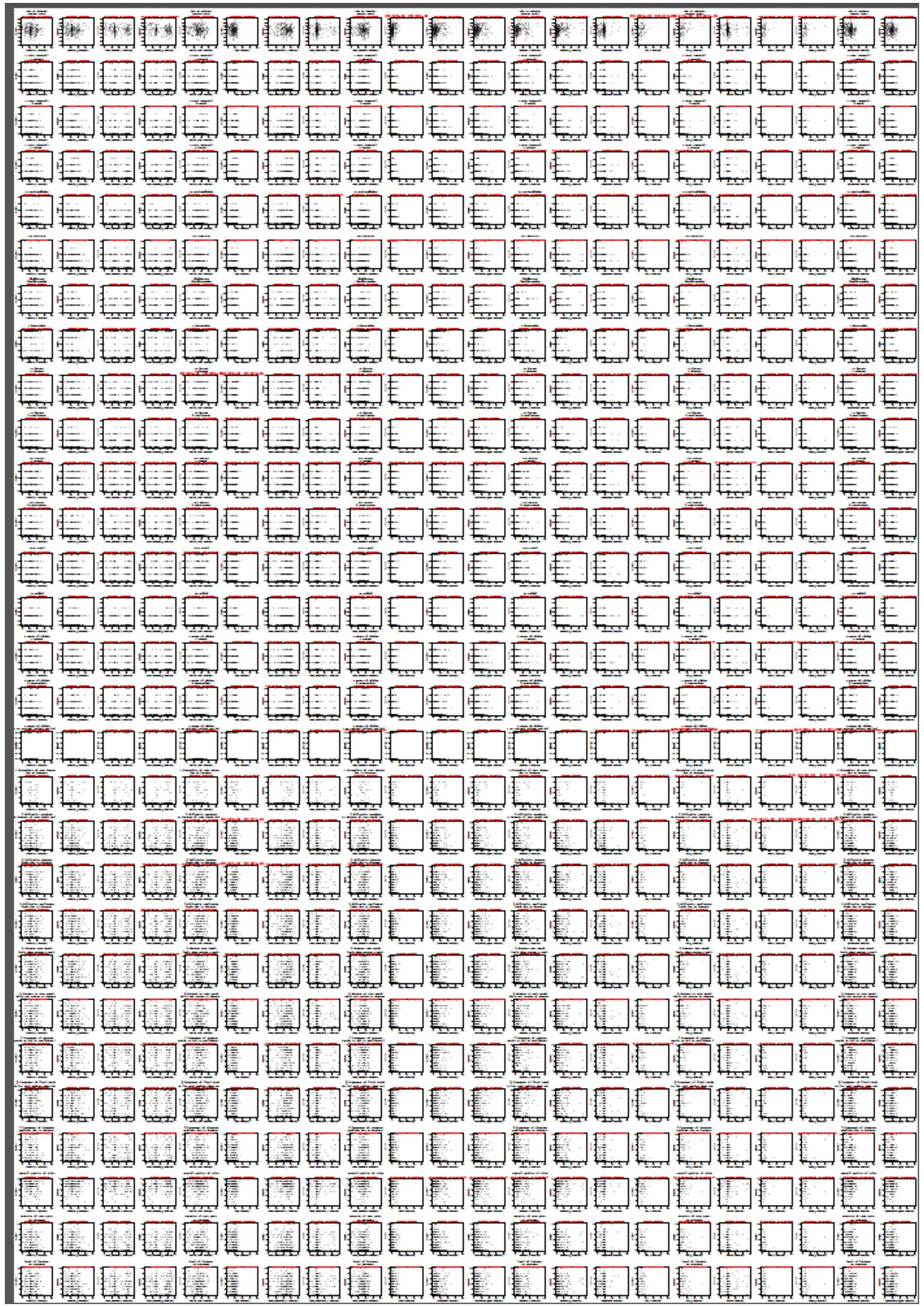


Courtesy of Joel Wilkie, MD and Michelle Mierzwa MD

Data Centric Clinical Process Change

Technology

Machine Learning and AI



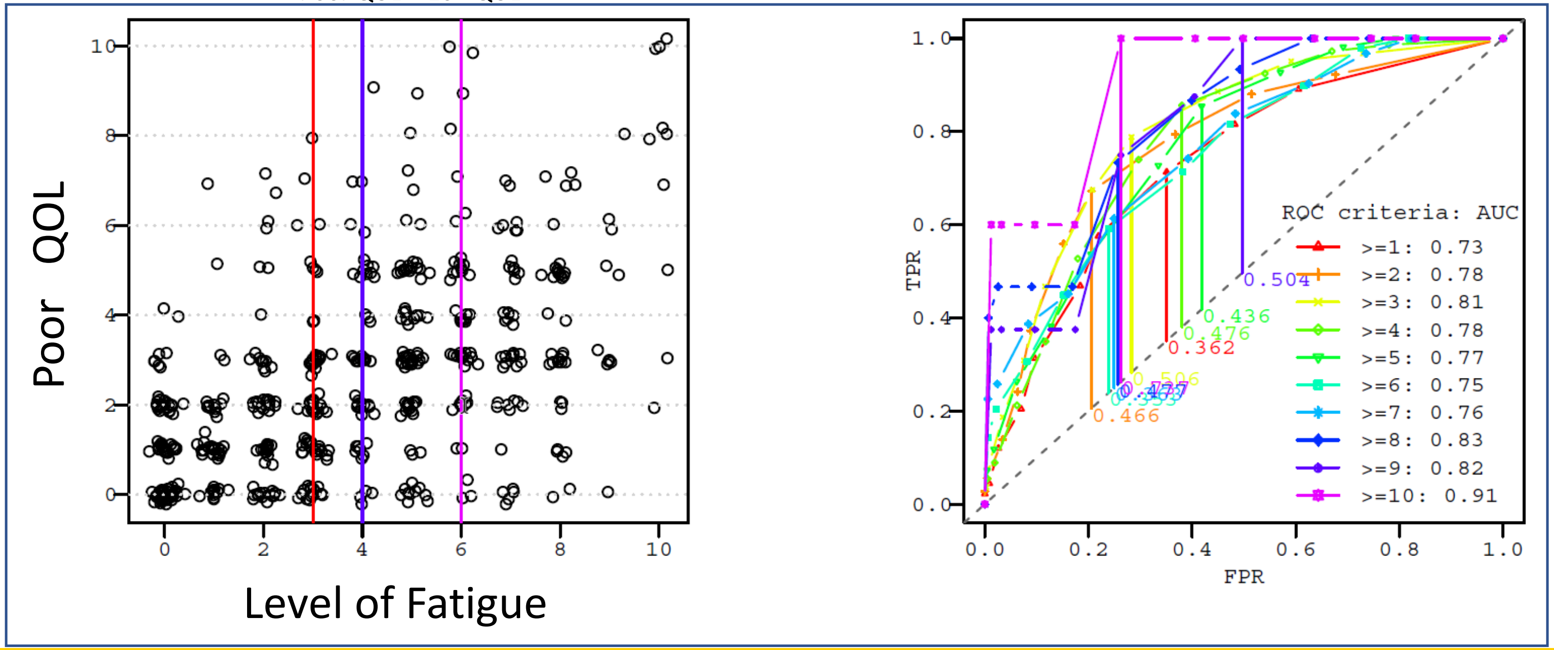
612 Patients, 1273 Office visits

33,100 PRO Question-Answer Pairs

- PRO vs PRO
- PRO vs Toxicity
- PRO vs DVH Metrics

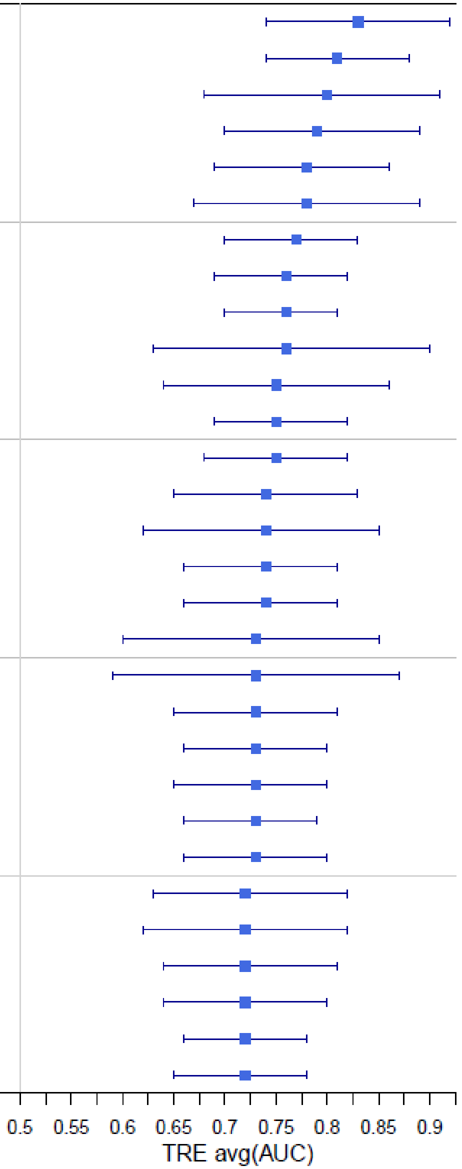
Part of the story is different approaches to analysis and modeling that we're taking

Poor QOL = 10 - QOL



Which PROs are predictive of provider reported toxicity?

Provider Reported	Patient Reported	avg(AUC)
Weight Loss	VI.EATING A.Chewing	0.83
Trismus	VI.EATING A.Chewing	0.81
Weight Loss	3.difficulty chewing foods due to dryness:	0.8
Weight Loss	XQ sum	0.79
Esophageal Pain	I.PAIN (General) C.Throat	0.78
Weight Loss	5.dryness your mouth feels when eating a meal:	0.78
Xerostomia Dry Mouth – Day	XQ sum	0.77
Dysphagia	VI.EATING B.Swallowing	0.76
Taste Changes	VIII.TASTE	0.76
Weight Loss	I.PAIN (General) B.Mouth	0.76
Weight Loss	7.frequency of sipping liquids to aid in swallowing food:	0.75
Xerostomia Dry Mouth – Day	VII.SALIVA A.Amount	0.75
Xerostomia Dry Mouth – Day	7.frequency of sipping liquids to aid in swallowing food:	0.75
Dysphagia	VI.EATING A.Chewing	0.74
Weight Loss	8.frequency of fluid intake require for oral comfort when not eating:	0.74
Xerostomia Dry Mouth – Day	5.dryness your mouth feels when eating a meal:	0.74
Xerostomia Dry Mouth – Day	6.dryness in your mouth while not eating or chewing:	0.74
Ear Pain	VII.SALIVA B.Consistency	0.73
Ear Pain	9.frequency of sleeping problems due to dryness:	0.73
Trismus	IX.SPEECH	0.73
Xerostomia Dry Mouth – Day	IV. RECREATION /ENTERTAINMENT	0.73
Xerostomia Dry Mouth – Day	4.difficulty swallowing foods due to dryness:	0.73
Xerostomia Dry Mouth – Night	VII.SALIVA A.Amount	0.73
Xerostomia Dry Mouth – Night	XQ sum	0.73
Dysphagia	IX.SPEECH	0.72
Fatigue	III.Activity	0.72
Oral pain	I.PAIN (General) A.General	0.72
Pain	I.PAIN (General) A.General	0.72
Taste Changes	4.difficulty swallowing foods due to dryness:	0.72
Xerostomia	VII.SALIVA A.Amount	0.72



Courtesy of Joel Wilkie, MD and Michelle Mierzwa MD

Professional societies need to establish more functional standardizations of key clinical concepts

- Disease Control Status
- Treatment Approach
  e.g. Prostate, Prostate+SV, Prostate+SV+Nodes
- Prescription
- Diagnosis, staging, pathology
- Imaging findings

Commercial Electronic Health Record (EHR), Radiation Oncology Information Systems (ROIS), and treatment planning systems (TPS) need to be much more focused on data aggregation and quality

- Better integration with clinical process workflow
- Efficient entry for standard core key data elements
  e.g. Diagnosis and staging
- Efficient entry / retrieval for other key data elements
  e.g. Treatment Details – breath-hold, fiducials, treating physician
- Linking ROIS to TPS to identify treated plans
- Disease Control Status
- Prescription

Combining Clinical and Technical Domain Knowledge Skill Sets

Medical Physicists are important to making Big Data – AI

a practical reality in clinical practice