

Machine-Learning Approaches to Identifying Error

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AAPM 2018, Nashville, TN. Thur 10:00-12:00 am. 35 min talk + 5 min for questions. TH-CD-KDBRA1-1 : **Errors and Data Mining in EMR**

Disclosures

- R18 HS022204-01
- NCI UG3 CA211310-01

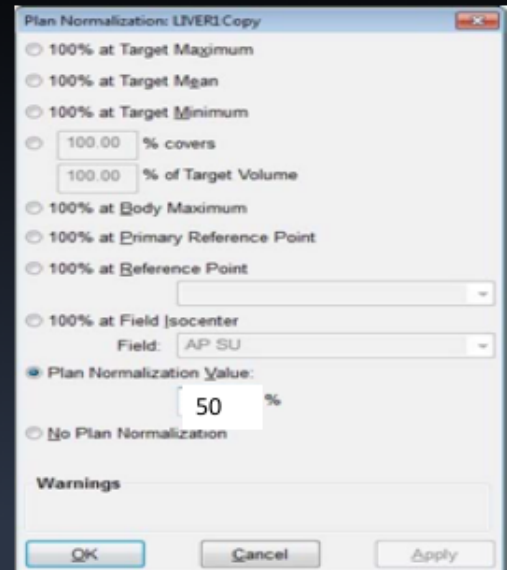
Learning Objectives

- Understand existing and emerging methods for analyzing electronic medical record (EMR) data to quantify gaps in the safety and quality of care.
- Understand how the EMR can be used to continuously monitor the status of patients for clinically important endpoints.
- Appreciate the role of the EMR and human-computer interaction in contributing to error.

Case Study

SBRT Planning Error: MU doubled

- 8 Gy x 5 liver plan
- Plan printed
- Planner is in a rush. Clicks “No plan normalization”
- Printed plan looks OK (% isodose lines)
- Plan QA. Not caught.
- Caught by RTT just prior to beam on



Existing Tools for Finding Errors and Hazards

FMEA



Incident
Learning



Failure Mode and Effects Analysis

References

The report of Task Group 100 of the AAPM: Application of risk analysis methods to radiation therapy quality management

M. Saiful Huq^{a)}

Department of Radiation Oncology, University of Pittsburgh Cancer Institute and UPMC CancerCenter, Pittsburgh, Pennsylvania 15232

Med. Phys. 43 (7), July 2016

Incident learning in radiation oncology: A review

Eric C. Ford^{a)}

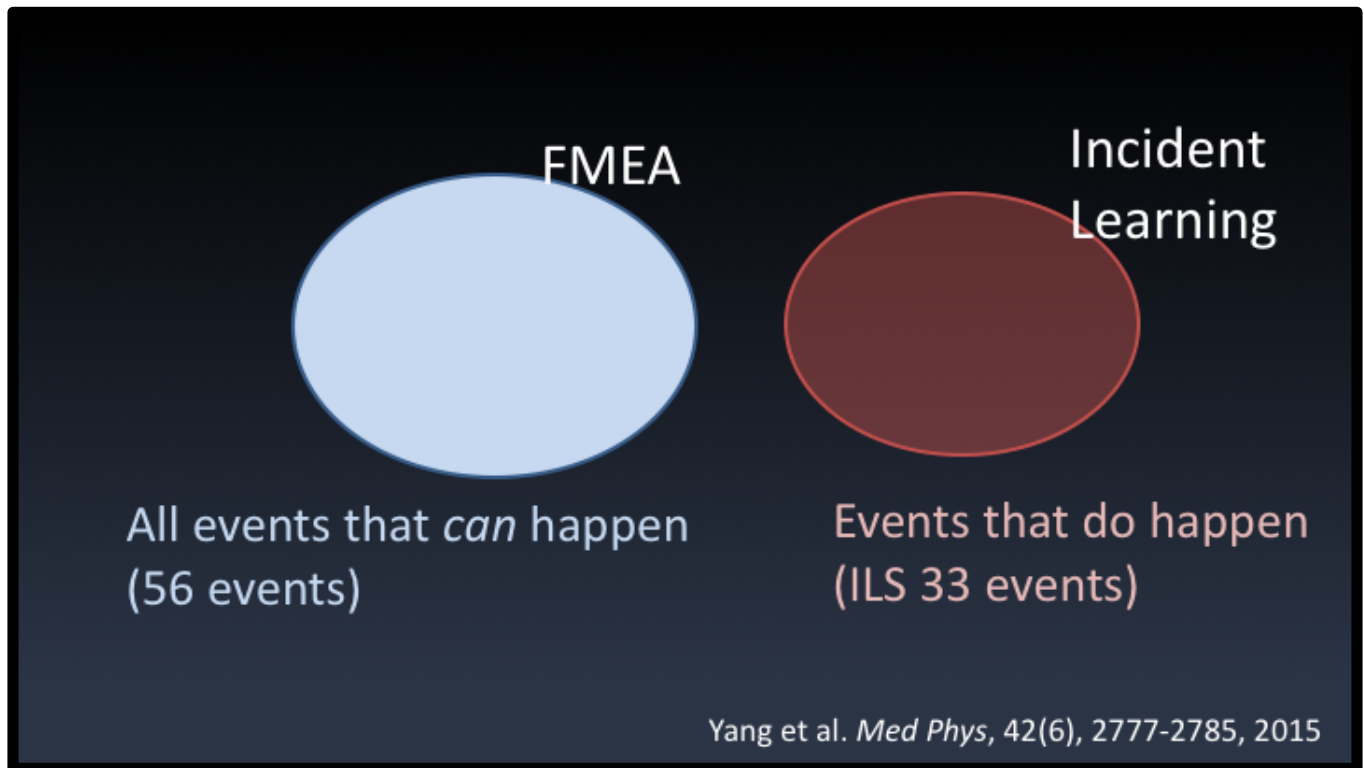
Department of Radiation Oncology, University of Washington, Seattle, WA 98195, USA

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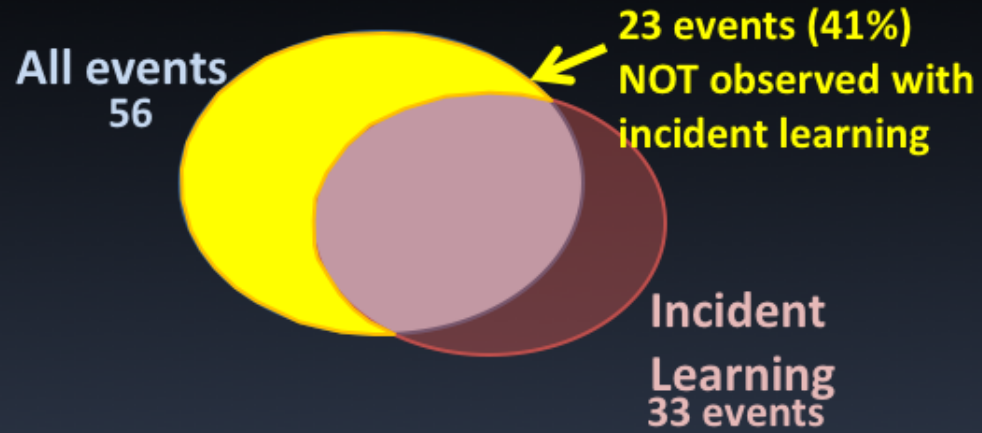
Med. Phys. 45 (5), May 2018

Assuming the audience is somewhat familiar with FMEA and ILS, but if not here are some references.



This is from a study in our group on SBRT which looked at all the events that can happen versus what was observed through incident learning.

Incident learning and Risk analysis are complementary



Yang et al. *Med Phys*, 42(6), 2777-2785, 2015

Link to FMEA and resident education

The Incident Reporting System Does Not Detect Adverse Drug Events: A Problem for Quality Improvement

DAVID J. CULLEN, MD, MS
DAVID W. BATES, MD
STEPHEN D. SMALL, MD
JEFFREY B. COOPER, PhD
A. ROBERTA NEMESKAL, RN
LUCIAN L. LEAPE, MD

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Audit: 54 Adverse Drug Events
3 incident reports (6%)

A different approach:
Mining the Health Record

Harvard Health Study

THE NATURE OF ADVERSE EVENTS IN HOSPITALIZED PATIENTS

Results of the Harvard Medical Practice Study II

LUCIAN L. LEAPE, M.D., TROYEN A. BRENNAN, M.D., J.D., M.P.H., NAN LAIRD, PH.D.,
ANN G. LAWTHERS, SC.D., A. RUSSELL LOCALIO, J.D., M.P.H., BENJAMIN A. BARNES, M.D.,
LIESI HEBERT, SC.D., JOSEPH P. NEWHOUSE, PH.D., PAUL C. WEILER, LL.M., AND HOWARD HIATT, M.D.

New England Journal of Medicine, 324(6), 377-384, 1991

Very expensive

Harvard Health Study

1984, 51 hospitals in NY

n=30,195 charts randomly sampled (in-patients)

Method:

- Screen for adverse events

- “unintended injury cause by medical management that resulted in measureable disability”

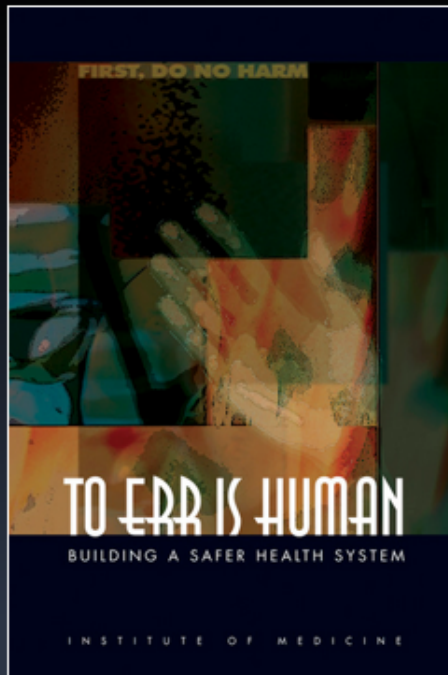
- RN screen (18 criteria)

- 2 MDs review & evaluate, rate disability

1,133 adverse events (3.7%)

Errors in management in 58% of these

Very expensive



Institute of Medicine (IOM)
1999

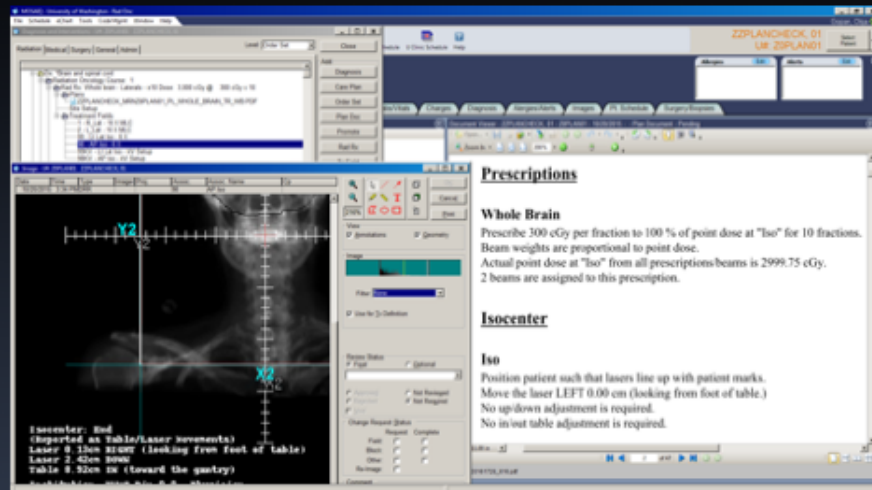
44,000 to 98,00 people die in US
hospitals each year due to
preventable errors

This led to the landmark IOM study. But note: the process used in the Harvard Health study relies on records and is extremely labor intensive and expensive.

Automatic Error Mining

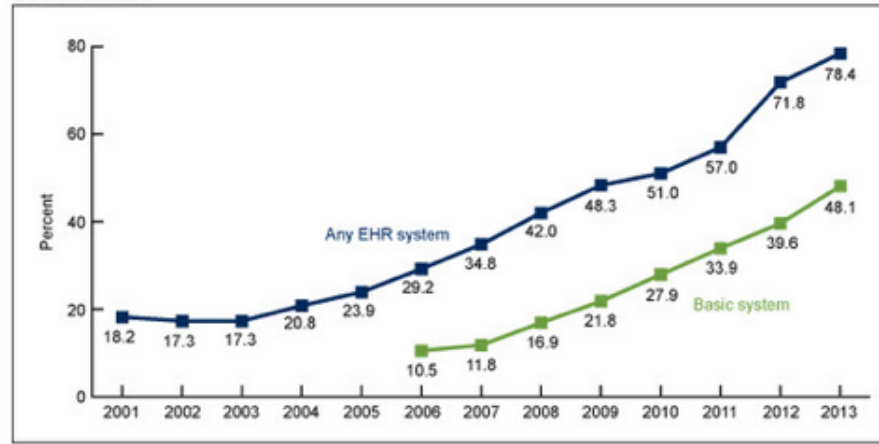
“Trigger Indicators”

Electronic Medical Record (EMR)



Key thing: the automatic mining relies on an HER. Our EMR(s) have a wealth of information, waiting to be extracted and used.

Figure 1. Percentage of office-based physicians with EHR systems: United States, 2001–2013



Growth of the EHR ... 97% of hospitals use an EHR now. Grew fast. How do you “mine” the EMR? One method is to randomly sample charts ...

Computerized Surveillance of Adverse Drug Events in Hospital Patients

David C. Classen, MD; Stanley L. Pestotnik, RPh; R. Scott Evans, PhD; John P. Burke, MD

JAMA, November 27, 1991 — Vol 266, No. 20

Audit: 54 Adverse Drug Events
3 incident reports (6%)

565 citations. Example automated signals: ordering known antidotes (e.g. naloxone hydrochloride Rx, vitamin K), lab tests for serum drug levels

Error indicators in the OIS

Diagnosis and Interventions -

Radiation [Medical] [Surgery] [General] [Admin]

Level: [Order Set] [Close]

Rad Rx: Left temple/parotid - Electrons - e12 Dose: 5,000 cGy @ 200 cGy x 25	A
Site Setup	A
Treatment Fields	H
2 - LT Temple - 12 E	A 5/ /2018 ECF
2A - LT Temple block chg - 12 E	

A field is "hidden"

Diagnosis and Interventions -

Radiation [Medical] [Surgery] [General] [Admin]

Level: [Order Set] [Close]

Rad Rx: lung_SF - AP/PA - Dose: 5,040 cGy @ 180 cGy x 28	A 5/30/2018 ECF
Rad Rx: lung_SF - AP/PA - Dose: 6,000 cGy @ 200 cGy x 30	A 5/30/2018 ECF
Treatment Fields	A 11/18/2014
L0 - S_noshift - 10 X MLC	

A prescription is changed

Diagnosis and Interventions -

Radiation [Medical] [Surgery] [General] [Admin]

Level: [Order Set] [Close]

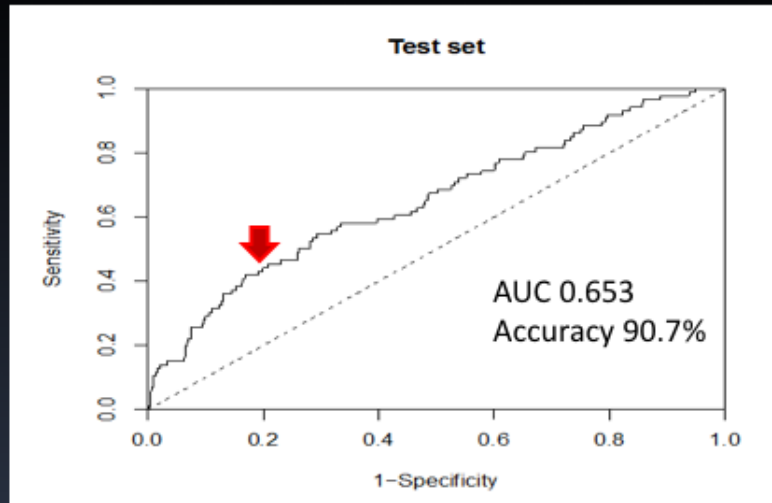
Rad Rx: lung_SF - AP/PA - Dose: 5,040 cGy @ 180 cGy x 28	A 5/30/2018 ECF
Rad Rx: lung_SF - AP/PA - Dose: 6,000 cGy @ 200 cGy x 30	A 5/30/2018 ECF
Treatment Fields	A 11/18/2014
L0 - S_noshift - 10 X MLC	

Voided

Document is voided

Training and Validation

- 15 potential indicators (MQ)
- Correlate: safety event per patient
- LR model



Hartvigson et al. pending 2018

train n=2210, test n=949

Can we predict for or identify error
before it happens?

“Correlates” Studies

- Treatment type “x” is more error prone

“Correlates” Studies

Study	Higher error rates for ...
Morganti et al. 2008	More complex treatments
Dominello et al. 2015	Weekend cases and “sim and treat”
Walker et al 2015	Time, # fractions, more Rx items, beam duration
Elnahal et al. 2016	Peds, H&N, breast, pts on protocol, IMRT/IGRT
Gensheimer et al. 2016	Peds
Judy et al. 2017	H&N, IMRT, daily IGRT

References in notes on handouts

Conclusion ... studies vary, institutional data, no one obvious predictor.

Morganti AG, Deodato F, Zizzari S, et al. Complexity index (COMIX) and not type of treatment predicts undetected errors in

radiotherapy planning and delivery. *Radiother Oncol.* Dec 2008;89(3):320-329.

Dominello MM, Paximadis PA, Zaki M, et al. Ten-Year Trends in Safe Radiation Therapy Delivery and Results of a Radiation

Therapy Quality Assurance Intervention. *International Journal of Radiation Oncology Biology Physics.* Nov 1 2015;93(3):E501-E502.

Walker GV, Johnson J, Edwards T, et al. Factors associated with radiation therapy incidents in a large academic institution. *Pract Radiat Oncol.* Jan-Feb 2015;5(1):21-27.

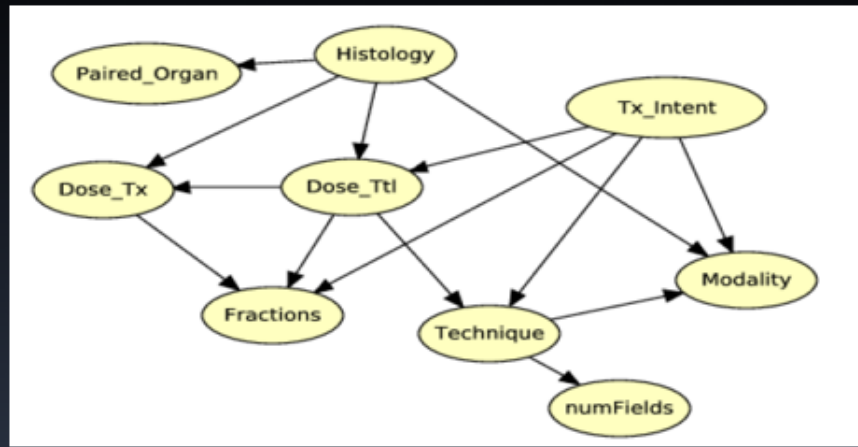
Elnahal SM, Blackford A, Smith K, et al. Identifying Predictive Factors for Incident Reports in Patients Receiving Radiation Therapy. *Int J Radiat Oncol Biol Phys.* Apr 1 2016;94(5):993-999.

Gensheimer MF, Zeng J, Carlson J, et al. Influence of planning time and treatment complexity on radiation therapy errors. *Pract Radiat Oncol.* May-Jun 2016;6(3):187-193.

Judy GD, Mosaly PR, Mazur LM, Tracton G, Marks LB, Chera BS. Identifying Factors and Root Causes Associated With Near-Miss or

Safety Incidents in Patients Treated With Radiotherapy: A Case-Control Analysis. *Journal of Oncology Practice.* 0(0):JOP.2017.021121.

Probabilistic Network for Error Detection

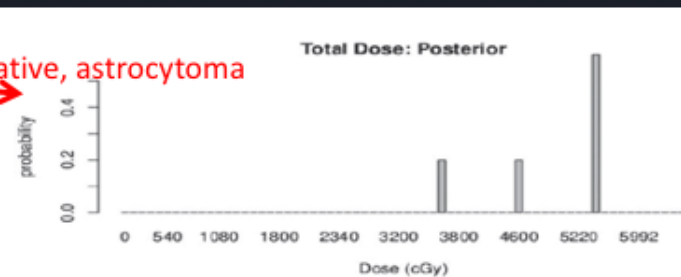
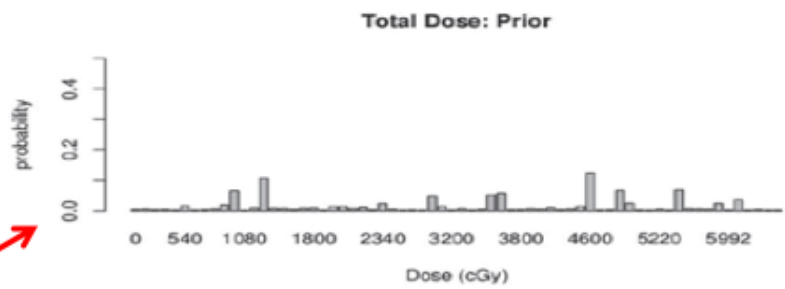


Kalet et al. Phys Med Bio, 60, 2735-2749, 2015

Bayesian Network

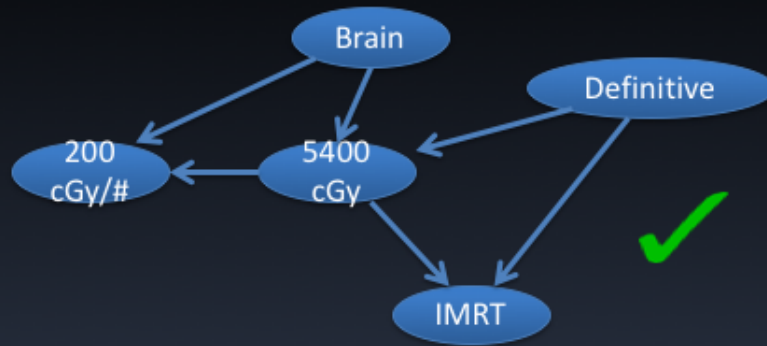


Curative, astrocytoma

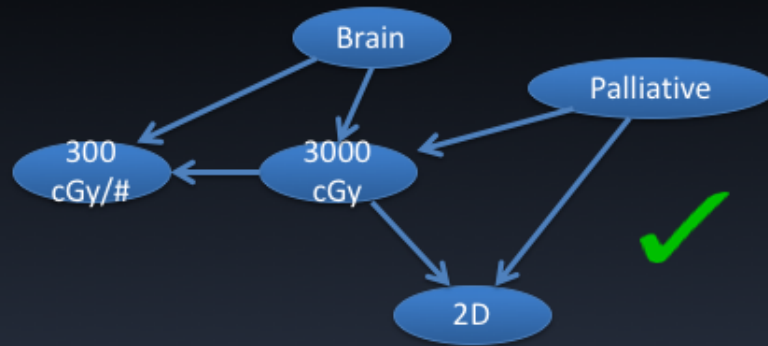


Kalet et al. Phys Med Bio, 60, 2735-2749, 2015

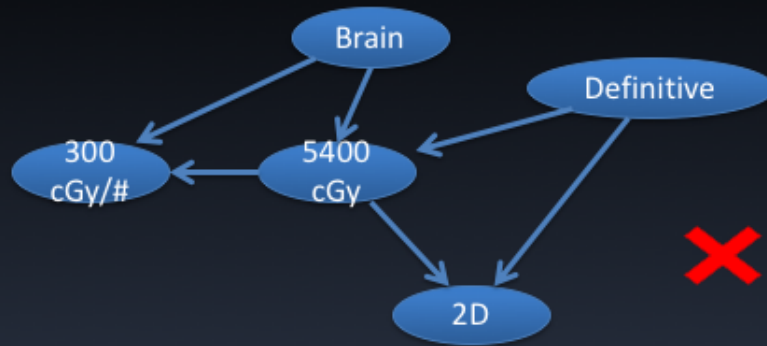
Probabilistic Network



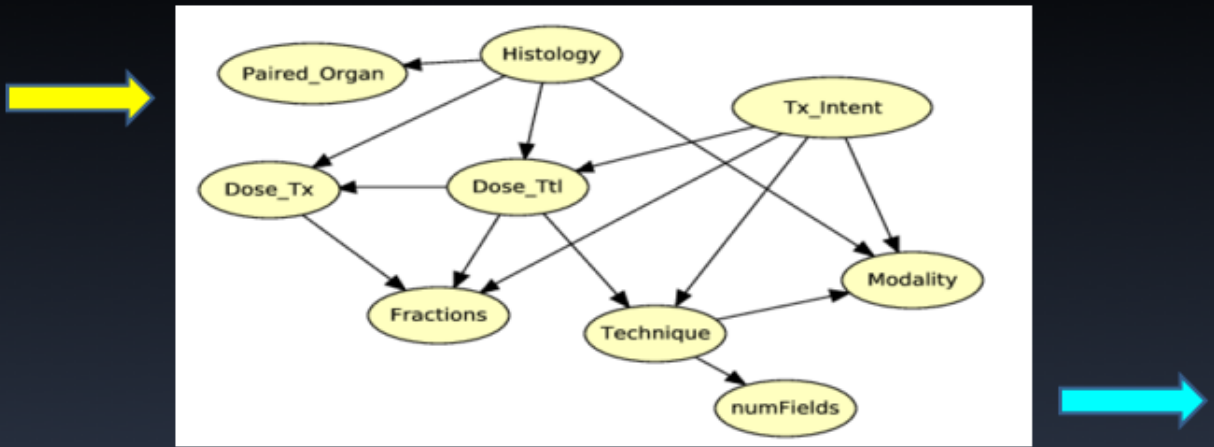
Probabilistic Network



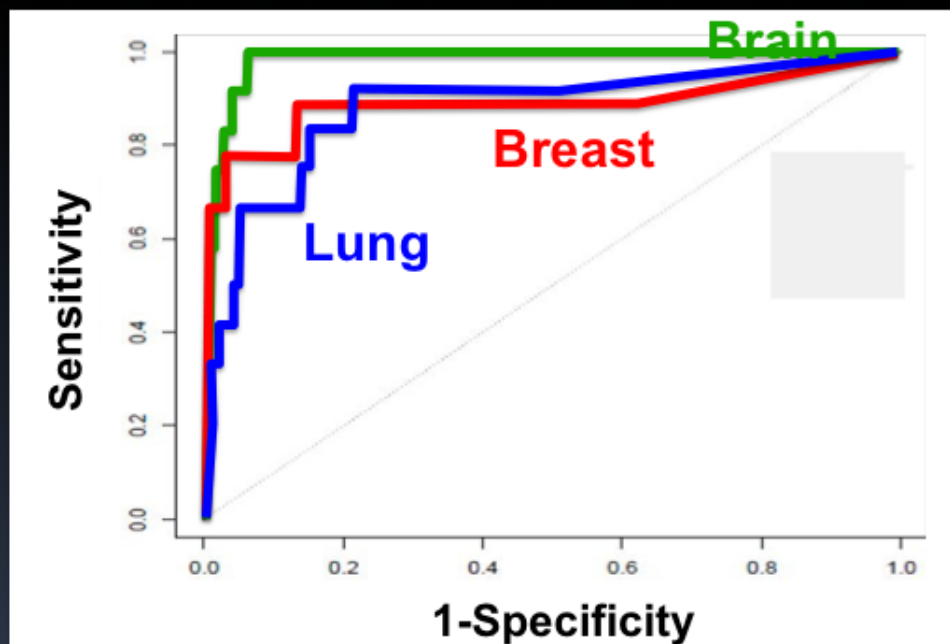
Probabilistic Network



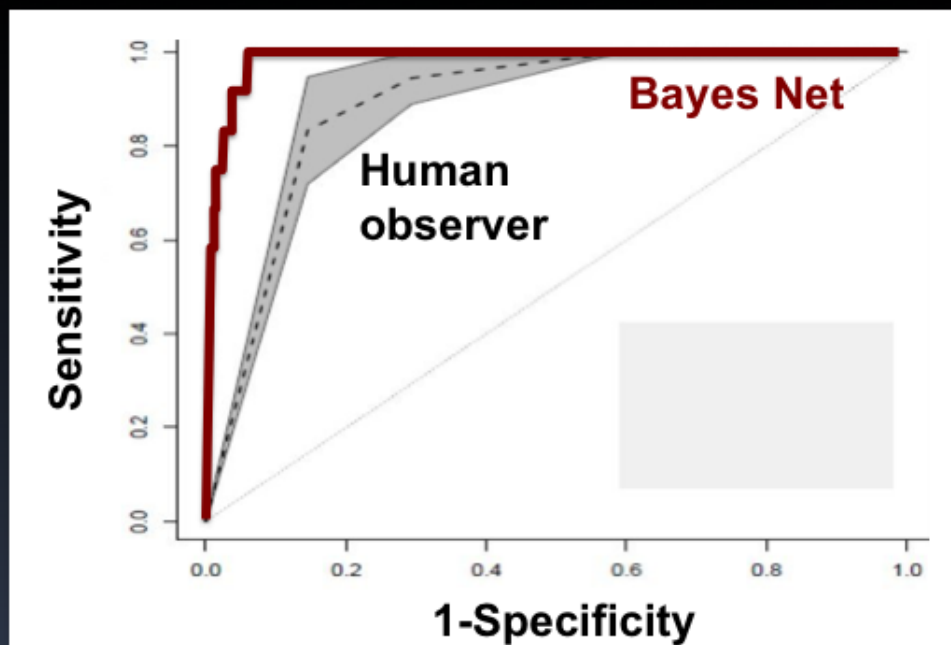
Validation Through Simulated Error



Kalet et al. Phys Med Bio, 60, 2735-2749, 2015

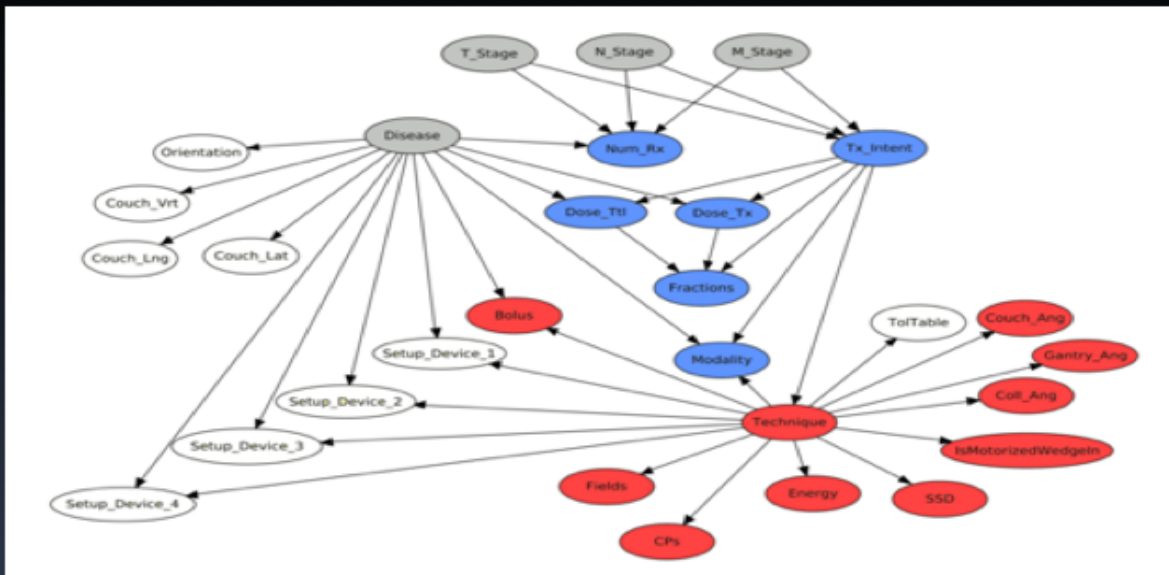


Kalet et al. Phys Med Bio, 60, 2735-2749, 2015



Kalet et al. Phys Med Bio, 60, 2735-2749, 2015

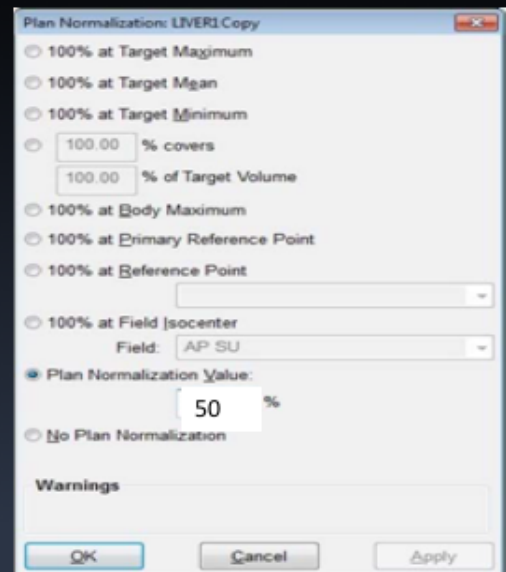
Expanded network



Kalet et al. in preparation 2018

SBRT Planning Error: MU doubled

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Of note here – this error might NOT have been reported to an ILS, but either the trigger indicator or the probabilistic network could pick it up

Conclusions

- EMR: automated identification of errors
- *Before* they reach the patient
- Complement to ILS and other tools

These tools could be used to probe your ILS and safety culture, e.g. identify problems and see if they are reported into the ILS. That gives some indicator of the 'health' of the clinical safety program, a "grade".

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UW RAD ONC QUALITY TEAM



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Thank You!
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