Error Discovery in Radiotherapy Plan Verification: An Advanced Probabilistic Approach

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Science of Safety - AAPM, 2019

Disclosures

NIH support
- award 1R41CA217452-01A1
(STTR partnership with Sun Nuclear)

Outline

Plan verification and expert knowledge
Development methods
Testing/validation
Results
The role of probabilistic models in QA
Challenges and future directions

Pre-treatment plan verification process

- Consult
- Investigate
- Evaluate
- Decide

Pre-treatment plan verification process

- Consult with multiple people:
  Physicians, Dosimetrists, Physics, Sim/Therapy staff, nursing...
- Investigate multiple software systems:
  Data transfer, plan technicals, MU 2nd check, imaging, tracking, motion control systems...
- Evaluate multiple results:
  Coverages, setup devices, protocols, policies, billing...
- Decide:
  - Based on Experience, Expert knowledge, Guidelines and recommendations (ASTRO, AAPM)

There are no established standards for how to do this! (TG 100, TG 275 begins to address)

So what's the issue?

We know the Physics pre-Tx review:

- Potentially catch between 50-80% of errors
- But in practice only catches about 30-40% [1]

We spend a lot of time and effort **Searching** for and **Evaluating** information

automation and tools can have high impact!

[1] Gopan, Olga, et al. "The effectiveness of pretreatment physics plan review for detecting errors in radiation therapy." *Medical Physics* 43.9 (2016): 5181-5187

Bayesian Network approach

- Address points where 'judgment' is required
- Leverage clinical data - adapts to local practice
- Investigative potential - shows you where to look

Collection of data over the years (**big data**) largely enables the use of complex probabilistic models

- Record and Verify systems
- Hospital EMRs and local database systems
- Treatment Planning

Bayesian Network vs. rules-system

	Bayes net	Rules
Errors of judgment	✓	X
Maintenance/Updating	✓	X
Complex relationships	✓	✓
Transparency	✓	✓
Speed	X	✓
Static Errors (protocols)	X	✓

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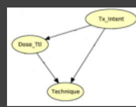
Model building

1. **Topology**
   - Network structure
   - Holds underlying dependency semantics



Directed acyclic graph

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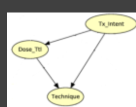


2. **Probability Tables**
   - Experiential
   - From clinical OIS

0.333	1.333	0.667	1.000	0.333	0.333
0.417	1.667	0.833	1.250	0.417	0.417
0.167	0.667	0.333	0.500	0.167	0.167
0.083	0.333	0.167	0.250	0.083	0.083

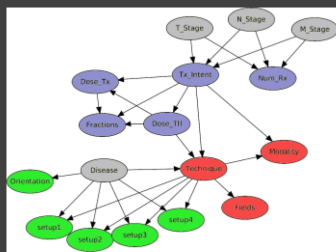
Ex: given Palliative Intent and Total Dose of 10Gy, what is the probability of using VMAT Technique?

1. Topology

- Identify concepts important to the radiotherapy plan check
- In-house software derives structure according to direction of dependency

1. **Topology**

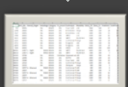
- Identify concepts important to the radiotherapy plan check
- In-house software derives structure according to direction of dependency
  - Based on ontological formalism
- Causality flows downhill: Diagnosis -> Rx -> Plan -> Setup



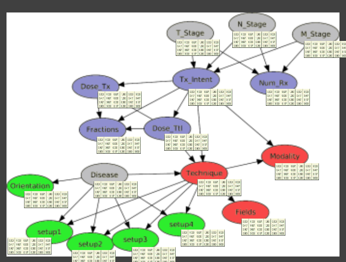
2. Probability tables

Mosaiq RDB

SQL



Machine Learning (EM algorithm)



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What do we want to catch?

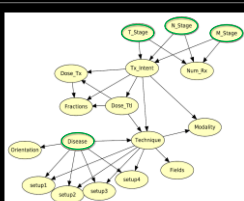
Prescription level errors:
540cGy Total dose prescribed for 28 fraction curative esophagus
18MV Modality prescribed for brain VMAT

Plan/Beam level errors:
180 Gantry angle for VMAT prostate (treat through couch rails)
Wrong SSD for 4 field box bladder plan (misplaced iso)
18MV Energy selected for brain VMAT

Setup level errors:
Breast board setup device used for T-Spine plan
Headrest setup device selected for prostate case

Derived from both incident learning systems and expert knowledge

Propagation



Instantiate clinical findings ("ground truth")

Changes propagate downstream

check probability, and decide if error

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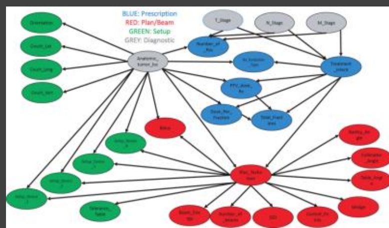
Practical considerations for commercial implementation:

1. What diversity of data is needed?
2. Robustness of performance over time?
3. How to handle missing data?
4. Differentiation of error class?



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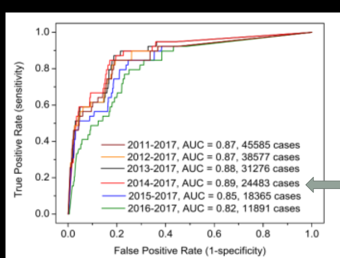
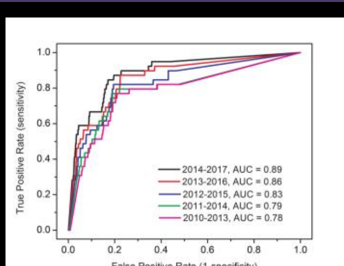


Expanding Window

3 year window

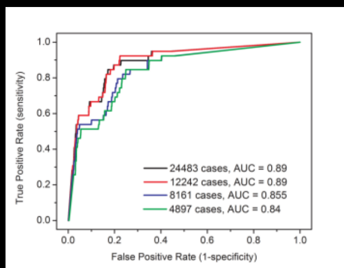
2. Robustness of performance over time?



Sliding Window

lose ~ 3% per year

3. Impact of missing data



Half the data is ok

4. Differentiation by error class

What accounts for most of the loss?

Time-frame	2014-2017	2010-2013
All error types	0.89	0.78
Prescription	0.92	0.84
Beam/Plan	0.86	0.73
Setup	0.95	0.93

← More rapid change in planning and delivery methods

Result Summary

Good discerning ability (AUC = 0.89) Vs. Human experts (AUC = 0.9)

Practical considerations:

1. 3 years of data to cover good range of possibilities
2. Even half the data within the 3 year window is sufficient
3. Updates needed annually to avoid performance loss

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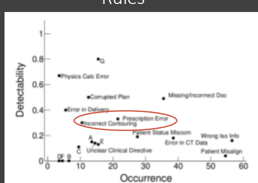
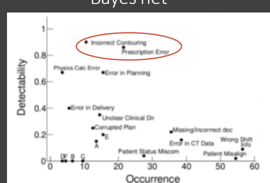
Rules



Bayes net



Detectability = fraction of detectable incidents
Occurrence = number of events in incident learning database

Challenges and future work

1. Understand how to translate to different clinical profiles
2. Different EMR usage and data requirements
3. Account for varying practice patterns
4. Ways to trace error sources – not just flag values
5. Planned multisite evaluation and testing

Main Takeaways

- Demonstrated successful BN approach to error detection
- Combine with other methods to form best defense
- High potential component of assistive QA tools

Thank you!

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Acknowledgements

Sam Luk, PhD, MP Resident, UWMC
Mark Phillips, PhD, Professor, UWMC
Eric Ford, PhD FAAPM, Professor, UWMC
Jeff Kapatoes, Senior Director, Research & Regulatory, Sun Nuclear Corporation