QA Automation and Machine Learning

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Learning objectives

- Understand the general workflow of automated physics QA / QC tools
- Understand that machine learning methods can be applied for detecting clinical data errors that are difficult to detect using conventional rule-based checks
- Understand the machine learning methods can be applied to predict patient IMRT QA passing rates.

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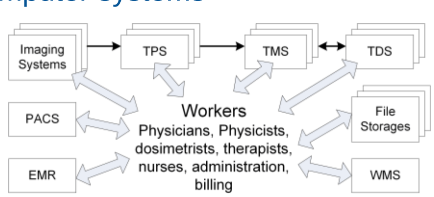
Computer systems



TPS = Treatment Planning System, TMS = Treatment Management System (Mosaiq, ARIA, etc.)
TDS = Treatment Delivery System (LINACs, HDRs), WMS = Workflow Management System (Whiteboard)
EMR = Electronic Medical Records, PACS = DICOM File Archive System

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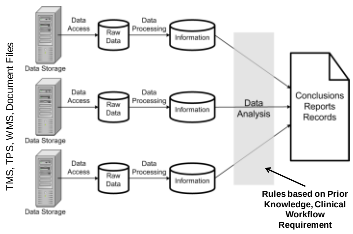
General workflow of QA/QC Automation



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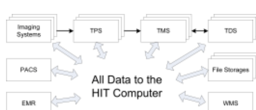
Error detection methods

- **Rule-based methods**
  - Simple comparison
    - To data from different source
    - To standard reference values
  - More complicated comparison
    - Data comparison with dependencies
    - Reference values are based on other conditions
- **Knowledge-based methods**
  - Mean, standard deviations
  - Machine learning methods

TPS – treatment plan parameters, images
TDS – log files, treatment records
TMS – treatment plan parameters, configuration, delivery records, documents
WMS – treatment intent (MD order), QA results
Files storages – documents, QA results
EMR – patient medical records, lab results, diagnostic notes



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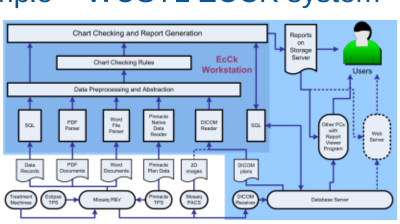
Example – WUSTL ECCK system



*ECCK = Electronic Chart Checking

Deshan Yang et al,, *Electronic chart checks in a paperless radiation therapy clinic*, Medical Physics, 2012, 39(8), pp 4726-4732

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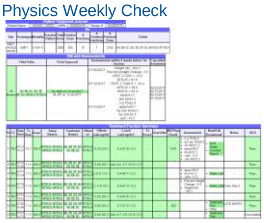
Usages and statistics (2013 to 2017)

Items	2013-2017	2015 only	2016 only
Usage	55204	15221	16753
# Patients Checked	10360	2882	2847
Errors in Prescription	3601	1173	712
Errors in Site Setup	2840	645	783
Errors in Plan	7299	2080	1901
Errors in Assessment	6395	1654	1822
Errors in DRR/DCT	2175	783	706
Errors in Prescription	1292	372	405
Errors in Beam Schedule	1774	578	344
Errors in Documents	2312	726	715

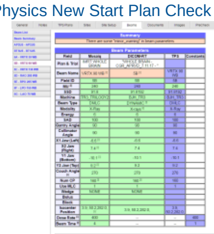
- Used clinically since 2013
- Most frequently detected errors
  - Beam name and ID
  - Incorrect scheduling
  - Wrong beam angles and incorrect scheduling for setup beams
  - Inconsistencies among prescription, beam energies and treatment calendar
  - Minor beam parameter errors, e.g. incorrect dose rates.

ECCK examples

Physics Weekly Check

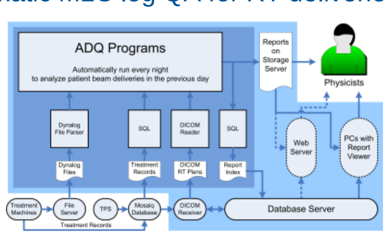


Physics New Start Plan Check



Deshan Yang et al., *Electronic chart checks in a paperless radiation therapy clinic*, Medical Physics, 2012, 39(8), pp 4726-4732

Automatic MLC log QA for RT deliveries



Y Wu, Deshan Yang, et al, *ADQ - a Software Tool That Automatically, Autonomously, Intelligently and Instantly Verify Patient Radiation Therapy Beam Deliveries*, AAPM 2011

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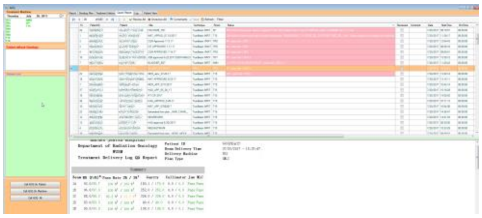
Automatic log QA for treatment deliveries



Y Wu, Deshan Yang, et al, *ADQ - a Software Tool That Automatically, Autonomously, Intelligently and Instantly Verify Patient Radiation Therapy Beam Deliveries*, AAPM 2011

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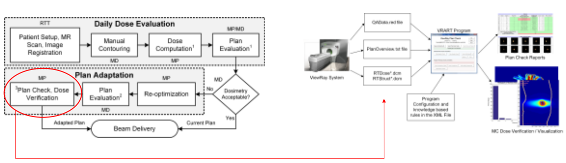
Example - Viewray online plan adaptation



Deshan Yang, et al, A computer software tool to perform physics QA for MRI guided online radiation therapy treatment adaptation, under review at JACMP

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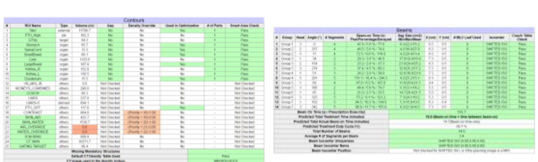
Online adaptation plan integrity check



Deshan Yang, et al, A computer software tool to perform physics QA for MRI guided online radiation therapy treatment adaptation, under review at JACMP

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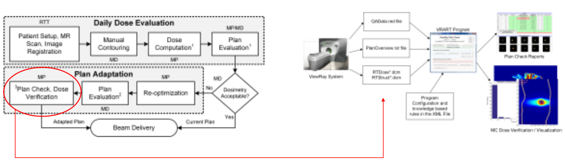
Online adaptation plan consistency check

Deshan Yang, et al, A computer software tool to perform physics QA for MRI guided online radiation therapy treatment adaptation, under review at JACMP

Example - Viewray online plan adaptation



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Error detection methods

- Rule-based methods
  - Simple comparison
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- Knowledge-based methods
  - Mean, standard deviations
  - Machine learning methods

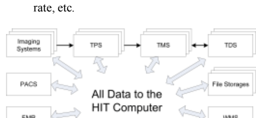
To support dependencies and probabilities, and to detect advanced errors that cannot be quantitatively defined as rules.

Examples of complex errors:

- Incorrect prescription dose, incorrect patient arm positions, etc.

Examples of simple errors:

- Wrong plan parameter transfer, wrong dose rate, etc.



1D cluster analysis - MU/cGy ratio

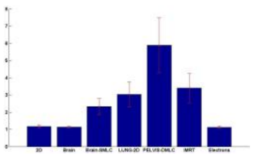


Figure 1, An error bar graph of selected MU/cGy ratio for various input parameters. Bar represents the mean values for corresponding parameters, and the red error line represents the corresponding standard deviations.

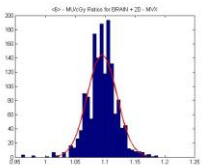


Figure 2. An example histogram of the MU/cGy radio for whole brain treatment (Brain + 2D). Mean value is 1.1, and the standard deviation is 0.02.

S Liu, Y Wu , X Chang , H Li , Deshan Yang*, Automatic Pre-Delivery Verification Using Statistical Analysis of Consistencies in Treatment Plan Parameters by the Treatment Site and Modality, AAPM 2016

2D cluster analysis

Plan data is more complicated. Cluster analysis not enough

MU/cGy ratio + averaged SSD:

- **Chi-Square distribution**: sum of squared Gaussian data points

$$\left(\frac{x}{a}\right)^2 + \left(\frac{y}{b}\right)^2 = s$$

- **For 95% confidence level:**

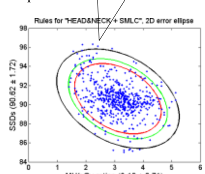
$$P(s < 5.991) = 1 - 0.05 = 0.95$$

$$\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2 = 5.991$$

- **2D quadratic rules:** in the form of [*a, b, c, d, e, f*]

$$Error(x, y|95\%) = ax^2 + bxy + cy^2 + dx + ey + f = 0$$

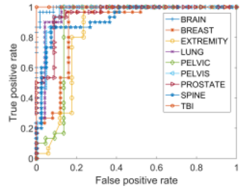
- **90%, 95%, or 99% confidence levels**



S Liu, Y Wu , X Chang , H Li , Deshan Yang*, Automatic Pre-Delivery Verification Using Statistical Analysis of Consistencies in Treatment Plan Parameters by the Treatment Site and Modality, AAPM 2016

Bayesian network for error detection in prescriptions

X Chang , H Li , Deshan Yang*, A Method to Detect Radiation Therapy Physician Order Errors Using Bayesian Networks, AAPM 2017



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Examples of extracted association rules

Extracted association rule	Support (%)	Confidence (%)	# of parameters
Prostate → Technique = IMRT	8	99.8	2
TBI → Technique = 2D	4	100	2
PELVIC , Dose >= 401 and <=799 → Technique = 2D	0.7	100	3
PELVIS , Dose = 5000 → Technique = IMRT	0.1	100	3
LUNG , Tumor stage = T3 , Metastatic stage = M0 , Dose = 4500 → Technique = IMRT	0.1	100	5
LUNG , Tumor stage = T1 , Previous Treatment = Yes, Laterality = right → Technique = 3D	0.3	100	5
Tumor stage = T1 , Nodal stage = N2 , Metastatic stage = M0 → Simulation= CT	0.9	100	4

Xiao Chang, Harold Li, Deshan Yang, A method to detect errors in radiation therapy physician orders using association rules, AAPM 2018

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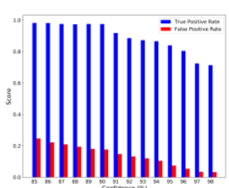
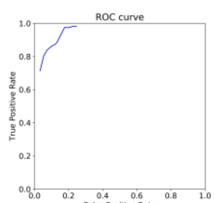
Prescription error detection with association rules





Xiao Chang, Harold Li, Deshan Yang, A method to detect errors in radiation therapy physician orders using association rules, AAPM 2018

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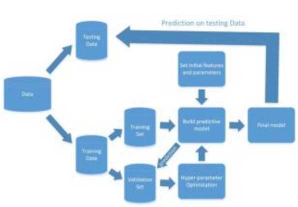
QA passing rate prediction using machine-learning



Total 168 patients with 1447 fields. Energy: 6MV and 10 MV. Machines: 2 Trilogy and 3 TrueBeams

- Machine characteristics:
  Machine name, imager type, et al
- Beam parameters:
  MU, beam energy, jaw positions, et al
- Beam complexity:
  Beam irregularity, aperture area and perimeter, leaf gap, MU per segment, etc

Dao, Sun, A Stacking Method for Predicting Patient QA Passing Rates Using Machine Learning, AAPM 2018

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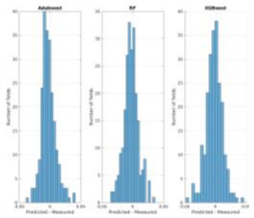
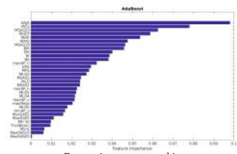
Results of QA passing rate prediction





Feature importance ranking

AAJA – Ratio of the average area of an aperture over the area defined by jaws
MCS – Modulation complexity score.
MSAS20 – Mean of fraction of aperture smaller than 20 mm.
MUCP – Mean of Mus per control point in a beam.

Dao, Sun, Predicting gamma passing rates for portal dosimetry based IMRT QA using machine learning, under review at Med Phys, June. 2019

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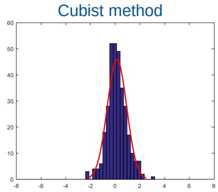
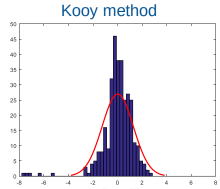
Results of proton MU prediction

Cubist method



Kooy method



Sun, Lam, Yang, Grantham, Zhang, Mutic, Zhao, Predicting gamma passing rates for portal dosimetry based IMRT QA using machine learning, Med Phys, May. 2018

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Conclusions and discussion

- Many physics QA / QC tasks can be automated
- Machine learning methods can be applied for detecting clinical errors that are difficult to detect using conventional rule-based checks
- Machine learning methods can be applied to predict QA passing rates.

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