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Machine Learning in Radiotherapy QA

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Disclosure

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- NIH/NCI Cancer Center Support Grant P30 CA008748
- Ashland Inc. Research Grant #SKI-1069

Relevant financial interests

- None

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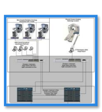
Outline


Machine Learning


Applications in QA


Clinical Implication

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Types of Learning

1. **Unsupervised learning**
   - Training data without labeled responses
   - Clustering, probability distribution, etc.

2. **Supervised learning**
   - Training data with labels or desired outputs
   - Prediction, classification, etc.

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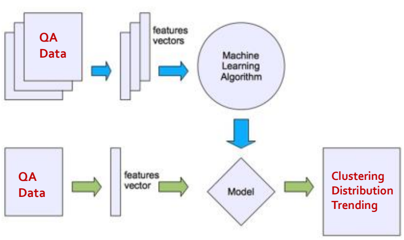
Unsupervised Learning



Picture credit: Chang & Ding

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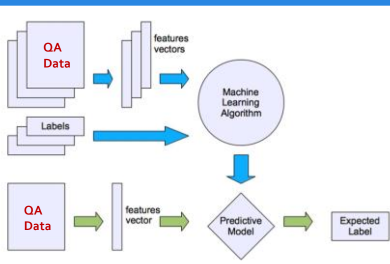
Supervised Learning



Picture credit: Chang & Ding

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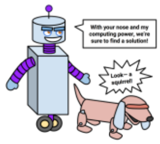
Validation of a ML Model

- Use different ML algorithms (same data) to compare the results
- Use a hold-out sample (in-sample testing)
- Compare with well-established models
- Validate using a sample not from the training period (out-of-time)
- Validate using a sample that is selected from a different population than that used to build the model (out-of-sample)



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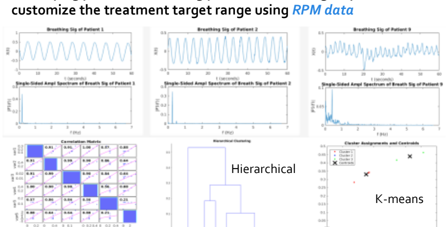
Unsupervised Learning Example (Clustering)

Classifying patients' breathing patterns into sub-groups to customize the treatment target range using *RPM data*



Q Li, MF Chan, C Shi 2017 Ann Machine Learning Symposium, NY

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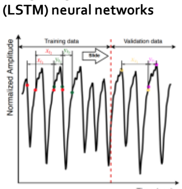
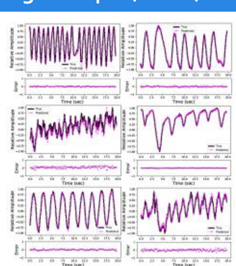
Supervised Learning Example (LSTM)

Real-time respiratory signal prediction with same *RPM data* using Long Short-Term Memory (LSTM) neural networks





Six patients w/ different breathing frequencies, amplitudes:

Truth: ---
Predicted: ---

Exhaustive grid search to optimize hyper-parameters of the LSTM model

H Lin, C Shi, B Wang, MF Chan et al 2019 Phys. Med. Biol. 64 085010 doi:10.1088/1361-6560/ab13fa

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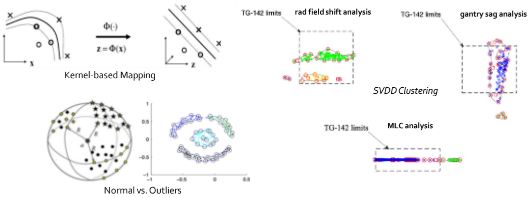
Semi-supervised Learning Example (SVDD)

Machine learning for automated quality assurance in radiotherapy: A proof of principle using EPID data description



IE Naqa, J Irrer, TA Ritter et al 2019 Med Phys, 46(4):1914-1921, DOI: (10.1002/mp.13433)

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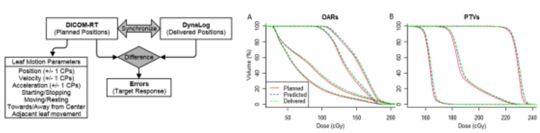
Prediction of MLC Positional Errors using Machine Learning

A machine learning approach to the accurate prediction of MLC positional errors – Cubist model outperformed linear regression and random forest



Workflow of the extraction of errors between DICOM-RT and Dynalog files and the extraction of leaf motion parameters from planned positions

In all cases the DVH curves calculated using the predicted positions are in closer agreement with the delivered curves than are the planned curves.

JNK Carlson, JM Park, SY Park et al 2016 Phys. Med. Biol. 61 2514 doi:10.1088/0031-9155/61/6/2514

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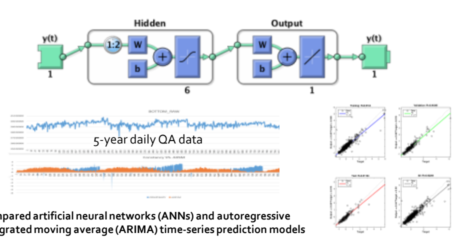
Predictive Time-series Modeling using ANN for Linac Beam Symmetry



Compared artificial neural networks (ANNs) and autoregressive integrated moving average (ARIMA) time-series prediction models

Q Li and MF Chan 2017 Annals of the New York Academy of Sciences, 1387(1):84-94, DOI: (10.1111/nyas.13215)

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IMRT QA using Machine Learning

Predicting IMRT QA gamma passing rates for a risk-based QA program and adaptive planning

Training process: IMRT Plan → Features Extraction → Calculation Complexity Metrics → Passing Rates (Any Detector)

Testing: IMRT Plan → Features Extraction → Calculation Complexity Metrics → *Prediction* Passing Rates

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Virtual IMRT QA

Penn Data (80 features extracted):

- 498 clinical IMRT plans were planned in Eclipse. Clinacs (M120) or TrueBeam (HD MLC) using ***MapCHECK***

MSKCC Data (90 features extracted):

- 203 clinical IMRT beams were planned in Eclipse. Trilogy (M120) using ***Portal Dosimetry (100MU = 0.907CU)***

Poisson regression with Lasso regularization was trained to learn the relation between the plan characteristics and each pass rate

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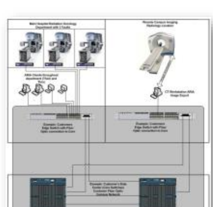
Features extraction from the Eclipse database using SQL queries

MapCHECK:

- ✓ Fraction of area delivered outside a circle with 20 cm radius
- ✓ MU factor (MU/Gy)
- ✓ Fraction of opposed MLCs with aperture smaller than 5 mm
- ✓ (DLG, dose algorithm)

Portal Dosimetry:

- ✓ Complete irradiated area outline (CIAO)
- ✓ Fraction of MLC leaves with gaps smaller than 20 mm or 5 mm
- ✓ Fraction of area receiving less than 50% of the total CU area



G Valdes, MF Chan et al 2017 J Applied Clinic Med Phys, 18(5):279-284, DOI: (10.1002/acm2.12161)

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Virtual IMRT QA: Modeling

$$Passing\ Rate = 100 - e^{-\mu} = 100 - e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 ... + \beta_{80} X_{80})}$$

- x is a 80 dimensional vector, $(1, x_1, x_2, \ldots x_{79})$; each represents one of the features (complexity metrics)
- β^T is the transpose of a constant vector with the same dimensions as x
- β is estimated as the constant vector maximizing the conditional probability of obtaining β giving our dataset of failing rates and complexity metrics

$$argmin_{\beta} Loss(\beta|D) = argmin_{\beta} [- \Sigma_{j=1,n} (y_j x_j \beta^T - e^{x j \beta T)} + \lambda|\beta|]$$

- D represents dataset: the pair of all features of a given plan $j(x_j)$ and the failing rate given by y_j
- λ is a constant governing complexity

G Valdes, R Scheuermann et al 2016 Med Phys, 43(7):4323-4334, DOI: (10.1118/1.4953835)

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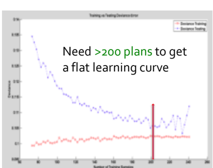
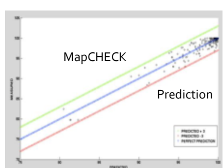
Virtual IMRT QA (Composite Field - MC)



Learning Curve



Correlation

G Valdes, R Scheuermann et al 2016 Med Phys, 43(7):4323-4334, DOI: (10.1118/1.4953835)

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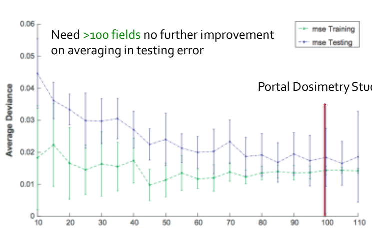
Virtual IMRT QA (Individual Field - PD)



G Valdes, MF Chan et al 2017 J Applied Clinic Med Phys, 18(5):279-284, DOI: (10.1002/acm2.12161)

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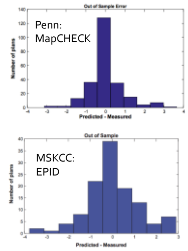
Multi-Institutional Validation

Table 1 Sample variables in Virtual IMRT QA modeling (continuous variables >90).

Number	Variable	Possible value
1	QA device	MapCHECK2, Portal dosimetry
2	Energy	6 MV, 15 MV
3	Machine type	TrueBeam, Trilogy, 21IX, 21EX, 6EX
4	Collimator angle	Mean value averaged over all control points
5	CIAO area (i.e., 5->5 × 5)	<5, 5–10, 10–15, 15–20, 20–25, 25–30, >30
6	Jaw position	<5, 5–10, 10–15, 15–20, 20–25, >25
7	Small aperture score	Fraction of MLC gaps <2, 5, 10, 20 mm
8	Fraction of area receiving at least x% of CU	10, 20, 30, 40, 50
9	Irregularity factor	Fraction of area outside Radius = 5, 10, 20 cm
10	MLC leaf transmission	HD, M120-pre-2007, M120-post-2007
11	Perimeter	<10, 10–30, 30–50, 50–70, 70–90, 90–110, >110
12	Duty cycle (Total MU/Dose)	<2, 3–3, 3–4, 4–5, 5–6, >6
13	Modulation factor	Overall complexity (1, 2, 3)



G Valdes, MF Chan et al 2017 J Applied Clinic Med Phys, 18(5):279-284, DOI: (10.1002/acm2.12161)

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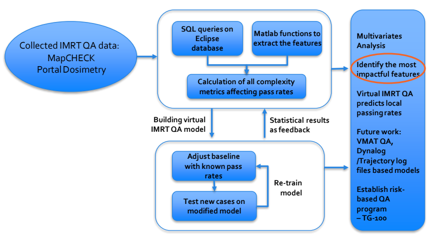
Virtual IMRT QA Workflow



G Valdes, MF Chan et al 2017 J Applied Clinic Med Phys, 18(5):279-284, DOI: (10.1002/acm2.12161)

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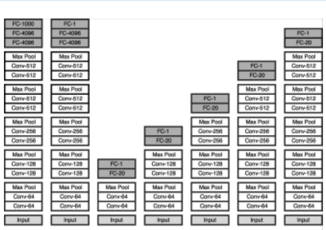
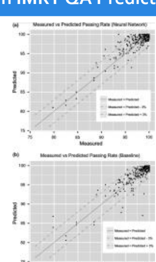
Deep Nets vs. Expert Designed Features in IMRT QA Prediction



Architecture of each network



Y Interian, V Rideout et al 2018 Med Phys, 45(6): 2672-2680, DOI: (10.1002/mp.12890)

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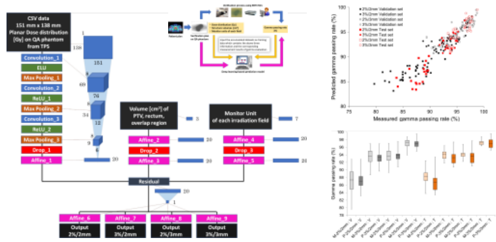
Deep Learning-based Prediction Model for IMRT QA



S Tomori, N Kadoya et al 2018 Med Phys, 45(9): 4055-4065, DOI: (10.1002/mp.13112)

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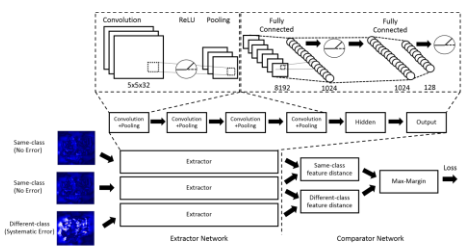
Identifying Errors in Delivery by Radiomic Analysis of Gamma Images with CNN



MJ Nyflot 2019 Med Phys, 46(2): 456-464, DOI: (10.1002/mp.13338)

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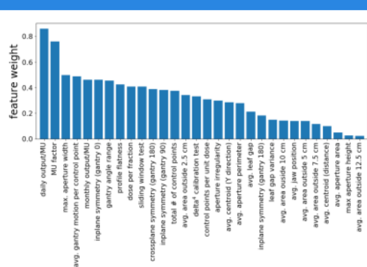
Predictive VMAT QA Model with VMAT Plan Characteristics and Linac QC Metrics



D Granville et al 2019 Phys Med Biol, 64 095017 doi:10.1088/1361-6560/ab142e

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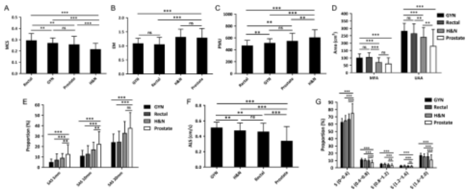
Impact of Delivery Characteristics on VMAT for Different Treatment Sites

MCS = modulation complexity score; EM = edge metric; PMU = plan-normalized MU; SAS = small aperture score; MFA = mean field area; UAA = union aperture area; ALS = average leaf speed; S (a–b) = proportion of leaf speed ranging from a to b cm s−1.



J Li, X Zhang, J Li, R Jiang, J Sui, MF Chan, R Yang 2019 J Radiation Research, doi:10.1093/jrr/rrz033

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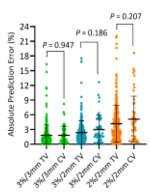
Virtual VMAT QA: Prediction and Classification



TV: Technical Validation (n=255)
CV: Clinical Validation (n=48)

J Li, L Wang, X Zhang, L Liu, J Li, MF Chan, J Sui, R Yang 2019 Int J Rad Onc Biol Phys

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Machine QA using Machine Learning

Group	QA Source	Data Set	ML Model	Research Highlight
Carlson et al., *PMB, 2016*	DICOM_RT & Dynalog Files	74 VMAT plans	Regression, Random Forest, Cubist	MLC Position Errors Detection
Li & Chan, *AMLS, 2017*	Daily QA Device	5-year daily QA data	ANN time-series, ARIMA models	Symmetry Prediction
Naqa et al. *Med Phys, 2019*	EPID	119 images from 8 Linacs	Support Vector Data Description (SVDD), Clustering	Gantry sag, Radiation field shift, MLC offset

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Patient-Specific QA using Machine Learning

Group	TPS/Delivery	QA Tool	Data Source	ML Model	Research Highlight
Valdes et al. *Med Phys, 2016*	Eclipse/Varian	MapCHECK2	498 IMRT Plans	Poisson Regression	Founding Paper
Valdes, Chan et al. *JACMP, 2017*	Eclipse/Varian	Portal Dosimetry	203 IMRT Beams	Poisson Regression	Multi-sites Validation
Interian, Rideout et al. *Med Phys, 2018*	Eclipse/Varian	MapCHECK2	498 IMRT Plans	Convolutional Neural Network	Fluence Map as Input
Tomori et al. *Med Phys, 2018*	iPlan/Varian	EBT3 film	60 IMRT Plans	Convolutional Neural Network	Planar Dose, Volumes, MU
Nyflot et al. *Med Phys, 2019*	Pinnacle/Elekta	EPID	186 IMRT Beams	Convolutional Neural Network, etc.	Image features, Radiomic QA
Granville et al. *PMB, 2019*	Monaco/Elekta	Delta4	1620 VMAT Beams	Support Vector Classifier	1st VMAT model, w/ QC Metrics
Li, et al. *Red Journal, 2019*	Eclipse/Varian	MatriXX	248 VMAT Beams	Poisson Lasso & Random Forest	Specificity, Sensitivity, Clinical

Machine Learning Models Could Predict Radiotherapy QA Results

- Machine learning enables machine QA data to be more intuitive, leading towards automated QA.
- Prediction of QA results could have profound implications on the current IMRT process.

Questions?

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