

Introduction to Artificial Intelligence Queen's Diagnostic Radiology

A summary of learning objectives for the artificial intelligence training workshop with Bloom's taxonomic levels in parentheses. The learning objectives focus on developing foundational literacy, hence, more emphasis and higher taxonomic levels were assigned to initial two sessions and more advanced topics, like neural networks, were presented to develop simple familiarity. Bloom's taxonomic levels are defined as 1 = remembering, 2 = understanding, 3 = applying, 4 = analyzing, 5 = evaluating, 6 = creating.

| Session | Learning Objectives (Bloom's Taxonomic Level) |
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| 1 | <p>1.1: To compare and contrast the differences between AI, machine learning, and deep learning (2).</p> <p>1.2: To define a feature, sample, ground truth, model, and task in the context of AI (2).</p> <p>1.3: To understand the strengths and limitations of classical statistics in predictive analysis (2).</p> <p>1.4: To distinguish supervised, unsupervised, and semi-supervised learning (2).</p> <p>1.5: To assess the performance of AI classifiers when compared to radiologists in diagnostic tasks (5).</p> <p>1.6: To apply exploratory data analysis in software (3)</p> |
| 2 | <p>2.1: To understand the process of machine learning (problem definition, data preprocessing, model selection, optimizing, training, validation) (2).</p> <p>2.2: To present a clinical problem as an AI task with defined input and output (3).</p> <p>2.3 To understand how dimensionality reduction reduces overfitting (2).</p> <p>2.4 To recognize preprocessing techniques of first order statistic filters, principal component analysis, and collinearity filtering (1).</p> <p>2.5: To recognize machine learning models of classification rules, logistic regression, decision trees, support vector machines, k-nearest neighbors, random forests, and neural networks (1).</p> <p>2.6: To select a compatible validation metric for classification, regression, and segmentation problems (3).</p> <p>2.7: To assess risk of bias for machine learning model performance (3).</p> |

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| | <p>2.8: To contrast learning parameters and hyperparameters (2).</p> <p>2.9: To apply preprocessing to train an ML model in software (3).</p> |
| 3 | <p>3.1: To outline the input and output data types to convolutional neural networks and generative adversarial networks (1).</p> <p>3.2: To recognize increase of complexity in neural networks (1).</p> <p>3.3: To understand the sensitivity of neural networks to perturbations of training data (2).</p> <p>3.4: To recognize when a modern neural network is present in literature (1).</p> <p>3.5: To recognize interpretability techniques for neural networks (1).</p> <p>3.6: To evaluate performance of neural networks in literature (4).</p> <p>3.7: To understand the role of interpretability for clinical utility (2).</p> <p>3.8: To apply cross validation and generate confidence intervals for machine learning models (3).</p> |
| General | <p>4.1: To assess the potential role of AI in medicine (5)</p> <p>4.2: To evaluate if AI can address a clinical problem (5)</p> <p>4.3: To locate resources for standard guidelines for predictive analysis and assessing risk of bias (1)</p> |

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A summary of the curriculum delivered with associated learning objectives in parentheses. AI = artificial intelligence. ML = machine learning. DL = deep learning. TRIPOD = transparent reporting of a multivariable prediction model for individual prognosis or diagnosis. PROBAST = prediction model risk of bias assessment tool. CNN = convolutional neural network. gradCAM = gradient class activation map. LIME = local interpretable model-agnostic explanations. MedNIST = medical national institute of standards and technology.

| Lecture Topic (Learning Objective) | Case Studies (Learning Objective) | Programming Example (Learning Objective) |
|--|--|---|
| Session 1: Defining AI, ML, and DL (1.1) Defining features, samples, ground truths, models, and tasks (1.2) Descriptive vs. inferential vs. predictive analysis (1.3) Classical clinical prediction models vs. machine learning models (1.3) Supervised vs. unsupervised learning (1.4) | Traumatic brain injury decision tree [Kuppermann] (1.3, 4.1, 4.2) Comparison of predictions of 101 radiologists vs. machine learning models [Rodriguez-Ruiz] (1.5, 4.1) FDA-approved AI devices in healthcare and level of invasiveness [Leeuwen] (1.5, 4.1) | Importing and formatting features, outcome and sample (1.3, 1.6, 2.1) Displaying input data as a dataframe (1.6) Generating descriptive statistics for the dataset (1.3, 1.6) Visualizing Pearson correlation ratios (1.3, 1.6) |
| Session 2: The machine learning pipeline (problem definition, preprocessing, model selection, training, optimizing, validation) (2.1, 2.2) Classification vs. regression vs. segmentation (2.1) Dimensionality reduction techniques (2.3) Machine learning models: classification rule, logistic regression, SVM, kNN, decision trees, random forests, neural | Survival prediction with radiomic feature extraction and a logistic regression classifier [Bogowicz] (2.2, 2.3, 2.4, 2.5, 2.6, 4.2) COVID-19 diagnostic prediction from acoustic analysis of cough [Laguarta] (2.2, 2.6, 2.7, 4.2) | Dimensionality reduction with PCA (2.3, 2.9) Training a logistic regression classifier and a decision tree classifier on the Wisconsin Breast Cancer Dataset (2.5, 2.9) Visualizing training and testing classification accuracies (2.6, 2.9) Hyperparameter optimization of decision trees (2.8, 2.9) |

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| <p>networks (2.5)</p> <p>Resampling techniques: cross-validation and bootstrapping Evaluation metrics for different AI tasks (2.6, 2.7)</p> <p>Complexity vs. interpretability of ML models (2.6)</p> <p>Optimization: parameters vs. hyperparameters (2.8)</p> | | <p>Cross-validation and confidence intervals for model performance (2.6, 2.7, 2.9)</p> |
| <p>Session 3: Input and output data types to neural networks and CNNs (3.1, 3.4)</p> <p>Complexity of scaling neural networks (3.2)</p> <p>Sensitivity of neural networks to changes in input data (3.2, 3.3)</p> <p>Data augmentation for CNNs (3.3)</p> <p>Saliency maps, gradCAMs, and LIME for interpretability (3.5, 3.7)</p> <p>Evaluating performance of CNNs (3.6)</p> <p>Risk of bias for ML models (3.7)</p> <p>Selecting CNN vs point-data models (2.2, 2.5, 3.7)</p> | <p>Predicting COVID-19 diagnosis from CT with a CNN [Li] (2.2, 3.1, 3.2, 3.4, 3.5, 3.6, 3.7, 4.2)</p> <p>Predicting thoracic pathologies from chest x-rays with a CNN [Rajpurkar] (2.2, 3.1, 3.2, 3.4, 3.5, 3.6, 3.7, 4.2)</p> | <p>Training neural network classifier on the Wisconsin Breast Cancer Dataset (3.1, 3.4)</p> <p>Evaluating classification performance of neural network (3.6)</p> <p>Adjust hyperparameters and kernels of neural network (3.2, 3.3)</p> <p>CNN for classification of MedNIST images (3.2, 3.3, 3.4)</p> <p>Confusion matrices of neural network and CNN performance (3.6, 3.8)</p> |
| <p>Reference Material: List of common AI models and tradeoffs between complexity and interpretability</p> <p>Neural network kernels and activation functions</p> <p>Optimization of neural networks with backpropagation</p> | <p>TRIPOD checklist for predictive analysis models [Collins] (2.6, 2.7, 4.2, 4.3)</p> <p>PROBAST checklist for assessing risk of bias [Wolff] (2.6, 2.7, 4.2, 4.3)</p> <p>Review of performance difference in external validation of DL models [Yu] (1.5, 4.1, 4.2)</p> | <p>Tutorial on running software in the jupyter environment</p> <p>Computation requirements for deep learning</p> |