Finding Meaningful Gaps to Guide Data Acquisition for a Radiation Adjudication System

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Motivation
- Machine learning methodologies for radiation threat detection.
- Training data generated synthetically because too few true threats are observed in the field.
- High dimensional data is prone to omissions of meaningful information.
- We aim to provide a framework which presents insufficiencies of training data in a user-friendly manner, allowing data engineers to inject data needed to fill gaps in the feature space.

Data
- 114 Features
- Semi-Synthetic
- Over 50K Samples
- Multiple Folds

Classes include:
1. Non-Emitting sources
2. Emitting sources posing a threat
3. Emitting sources explainable by naturally occurring radioactive materials

Iterative Build Process

Training Samples
- Generate Data
- Train a Model
- Evaluate Testing Samples
- Obtain Diagnostics
- Learning System

Expert Analysis
- Decide Course of Action
- Visualize Gaps
- Obtain Gaps in Low-D Projection
- Evaluate Loss Function
- Gap Retrieval

Learning System
Contains a learner and an evaluation procedure which characterizes performance diagnostics on the test data.

Gap Retrieval System
Finds low-dimensional projections where the testing and training data differ significantly, or where the performance diagnostics indicate considerable loss of accuracy.

Expert Analysis of Training Data
Experts gain intuition for what data may be missing from the training set and decide which parts of the feature space would most benefit from additional samples. The training samples in the next iteration will reflect these changes.

Model – Random Forest
Build random forest using k-fold cross validation which admits diagnostics

Experiment Results
Non-Parametric, Direct Gap Finding
- Distribution of testing samples are shifted from training samples
- Due to changing a single coefficient between successive data builds

Non-Parametric, Diagnostic Gap Finding
- Most confident predictions reside in T-shape while less confident predictions reside outside this region
- Recovered irregular shaped gap in data

Parametric, Diagnostic Gap Finding
- Less confident predictions cluster to a small region where confident predictions are spread.
- This region is easy to interpret by data engineers

Effect of Filling Gaps on Model Accuracy
Baseline With Gap | Add Data | Fill the Gap
75.0% | 75.2% | 75.7%

Conclusions
- Visualizations allow engineers to make changes necessary to improve synthetic data generation.
- By resolving gaps in training data, model classification performance improves.
- Nonparametric loss function finds irregular gaps.
- Parametric loss function reveals structured gaps in data, allowing users to identify adjustments in data generation that will improve accuracy.

References