**Classifier-Adjusted Density Estimation for Anomaly Detection and One-Class Classification**

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**Method Overview**

- Classifier-adjusted density estimation (CADE) detects anomalies by identifying low-probability instances in large, multivariate data sets.
- CADE estimates the joint probability density function of its training data by using a classifier to "correct" a naive density estimate.

1. Start with unlabeled data.
2. Label original data positive (non-anomalous). Construct a naive density estimate of the positives \( P(X | A) \).
3. Generate pseudo-negatives (pseudo-anomalies) from \( P(X | A) \).
4. Train a classifier to distinguish the positives from the pseudo-negatives.
5. Combine classifier’s prediction with initial density estimate to compute a final density estimate \( P(X | T) \).
6. Apply final density estimator \( P(X | T) \) to unlabeled data to identify anomalies.

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**Summary**

- High-quality anomaly detection is possible in multivariate data with a relatively simple method that estimates a joint probability function.
- Experimental evidence across a range of data sets shows CADE to be competitive and scalable.
- Within CADE, simple components often work well:
  - Marginally independent initial density estimates
  - Adjusted by random forest or k-nearest neighbor classifier
- Probability density estimators are more robust than local outlier factor methods to the challenge of irrelevant attributes.

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**Algorithm Components and Performance**

Many density estimate/classifier combinations perform well.

![Graph showing performance of different density estimates and classifiers](image)

**Comparer with Local Outlier Factor**

[Breunig, Kriegel, Ng, Sander. SIGMOD 2000]

CADE performs competitively with LOF (varies by data set).

Robustness to irrelevant attributes: when uniform noise attributes are added, LOF degrades quickly. CADE is much more resistant.

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**Unsupervised Runs on Large Data Sets**

**Data Set** Employee

- **Source**: Collected for DARPA
- **ADAMS** project on insider threat detection. Describes computer activities of ~5500 employees of a real company.
- **# features**: 88
- **# instances**: 108,215 to 133,770 (6 separate months)
- **# anomalies**: 8 to 98
- **Avg. runtime**: 368.1 sec

**Density Estimate**

- **Uniform**
- **Gaussian**
- **KDE**
- **Bayes Net**
- **LOF**

**Classifier**

- None
- **KNN**
- **RF**
- **Bagged LOF**

![Graph showing performance of different density estimates and classifiers](image)

**Unsupervised Runs on Large Data Sets**

**Data Set** Shuttle

- **Source**: UCI
- **# features**: 9
- **# instances**: 45,596 to 54,489
- **# anomalies**: 10 to 8903
- **Avg. runtime**: 104.3 sec

**Density Estimate**

- **Uniform**
- **Gaussian**
- **KDE**
- **Bayes Net**
- **LOF**

**Classifier**

- None
- **KNN**
- **RF**
- **Bagged LOF**

![Graph showing performance of different density estimates and classifiers](image)

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