Kernel Null Space Methods for Novelty Detection

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http://www.inf-cv.uni-jena.de/novelty_detection.html

Contribution
We provide a method based on null space projections that allows for multi-class novelty detection with a single model using true multi-class labels of training samples.

Problem formulation
- Given: samples from a fixed number of known categories
- Task: decide for each test sample whether it belongs to one of the known categories or to a new/unseen category
- Usual approach: apply one-class classification methods like one-class SVM (treats all training samples as a single class)

Null space methods
- Find transformation such that:
  - samples of same class are mapped to same point and
  - samples of different classes are mapped to different points

Transformed feature space is called null space

Problem: transformation only exists in small sample size case
⇒ Null Foley-Sammon transform (NFST) \cite{2}

Solution: embedding in high dimensional feature space using kernels! ⇒ Kernel-NFST (KNFST) \cite{5}

For \( C \) classes, the null space has dimension \( C - 1 \)

Our novelty detection approach...
- ... has no method-specific parameters!
- ... does not rely on complex density estimation!
- ... clearly outperforms other methods in all our experiments!

Multi-class novelty detection
1. Compute KNFST from training data and obtain target points \( t \)
2. Project test sample \( z^* \) into the null space to obtain \( t^* \)
3. Compute minimum distance to target points in the null space

Calculating novelty scores in the joint null space of multiple classes

Experimental setup
- Datasets: Caltech-256 and ImageNet (1,000 categories of the ImageNet Large Scale Visual Recognition Challenge 2010)
- Features: bag-of-visual-words histograms (1,000 dimensions) of densely sampled SIFT descriptors
- Kernels: histogram intersection kernel (HIK) and exponential generalization (EXPHIK)
- Results: for five and ten known categories, median AUC scores over 50 (Caltech) and 100 (ImageNet) randomly selected training sets

References