Kernel Null Space Methods for Novelty Detection

Code Available

CVPR 2013 Portland, Oregon June 23-28

since 1558

INTERNATIONAL COMPUTER SCIENCE INSTITUTE

Paul Bodesheim[1], Alexander Freytag[1], Erik Rodner[1,2], Michael Kemmler[1], and Joachim Denzler[1]

[1]Computer Vision Group, Friedrich Schiller University Jena, Germany

[2]ICSI Vision Group, UC Berkeley, California

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

Friedrich Schiller University Jena

Computer Vision Group

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

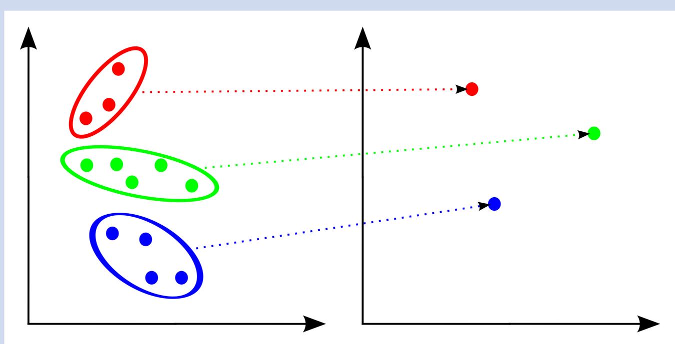
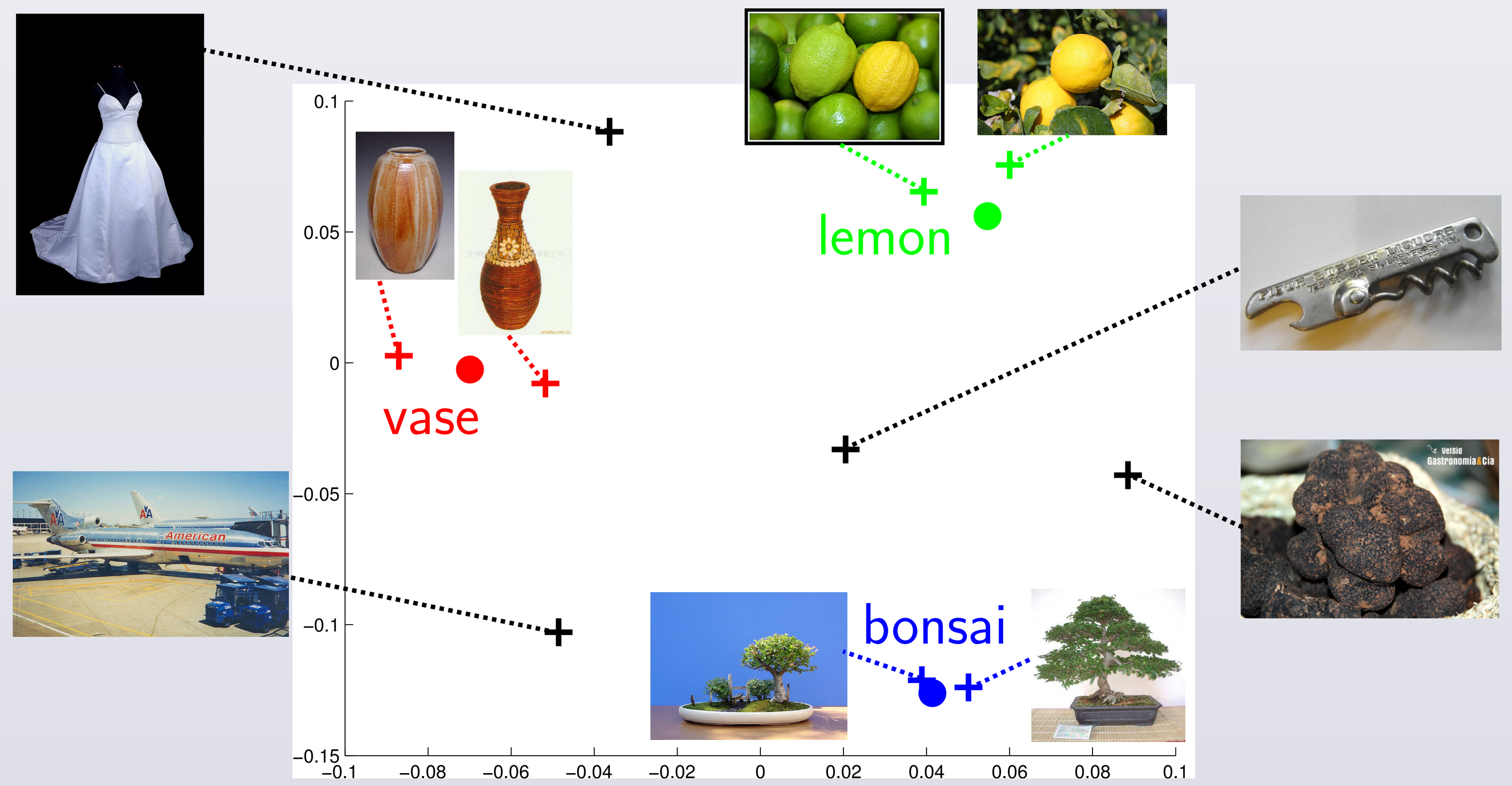


Illustration of null space embedding

- Find transformation such that:
  1. samples of **same class** are mapped to **same point** and
  2. 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) [2]
- Solution: embedding in high dimensional feature space using kernels! ⇒ **Kernel-NFST (KNFST)** [5]
- For C classes, the null space has **dimension** $\mathrm{C}-1$

References

[1] Bishop: *Pattern Recognition and Machine Learning*. Springer, 2006.
[2] Guo et al.: Null foley-sammon transform. *Pat. Recog.*, 39(11):2248–2251, 2006.
[3] Kemmler et al.: One-class classification with gaussian processes. In *Proc. ACCV*, pp. 489–500, 2010.
[4] Landgrebe et al.: Optimising two-stage recognition systems. In *Multiple Classifier Systems*, pp. 206–215, 2005.
[5] Lin et al.: Kernel null foley-sammon transform. In *Proc. Int. Conf. Comput. Sci. Software Eng.*, pp. 981–984, 2008.
[6] Schölkopf et al.: Estimating the support of a high-dimensional distribution. *Neur. Computation*, 13(7):1443–1471, 2001.
[7] Tax and Duin: Support vector data description. *Machine Learning*, 54(1):45–66, 2004.
[8] Tax and Duin: Growing a multi-class classifier with a reject option. *Pat. Recog. Lett.*, 29(10):1565–1570, 2008.



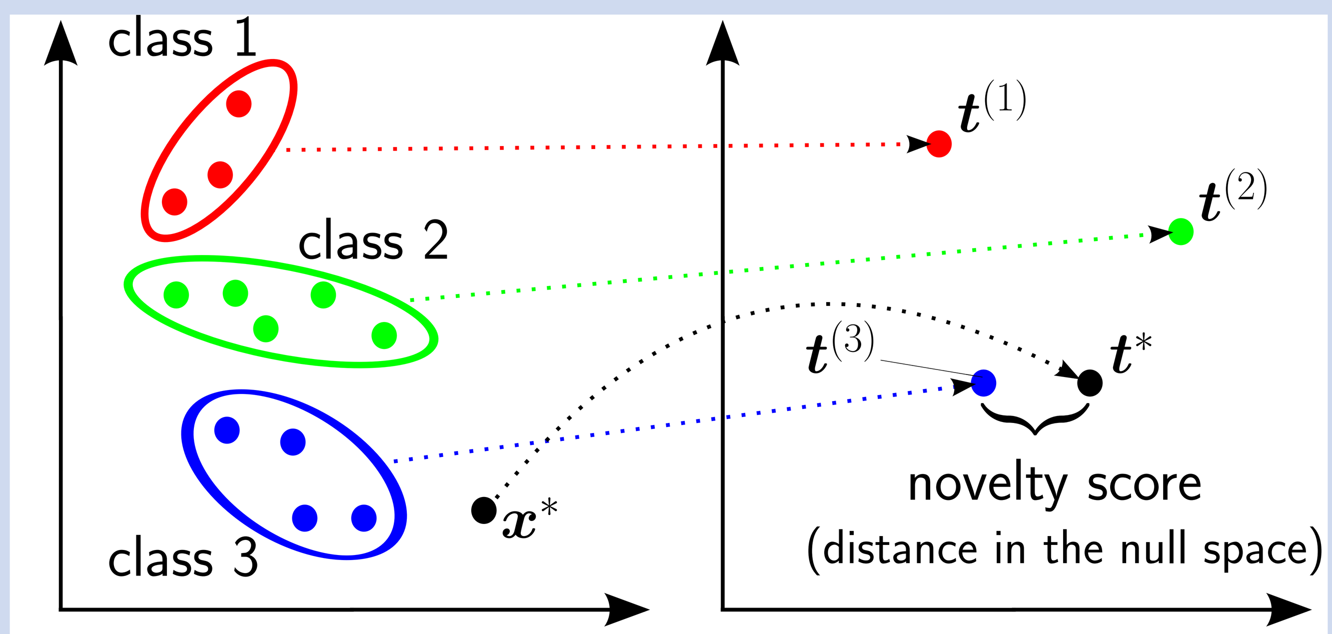
Real null space example with three categories of the ImageNet dataset

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 $\boldsymbol{t}$
2. Project test sample $\boldsymbol{x}^*$ into the null space to obtain $\boldsymbol{t}^*$
3. Compute minimum distance to target points in the null space

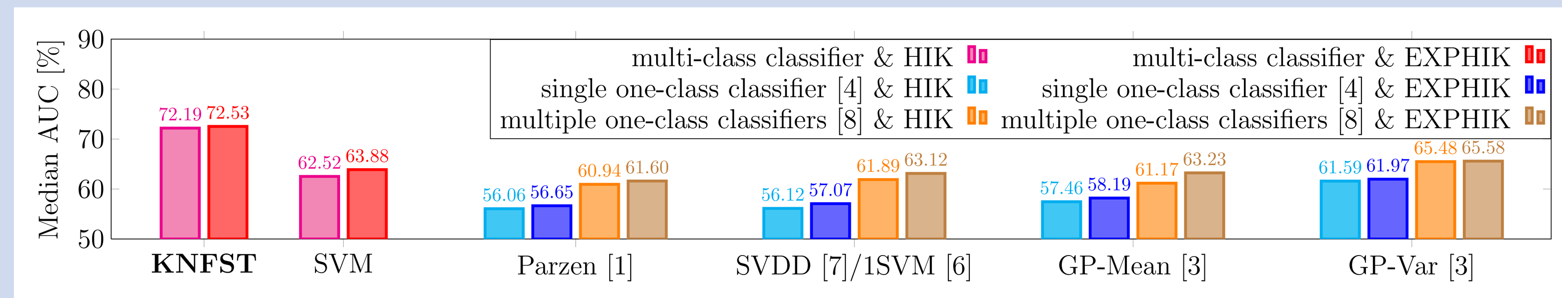


Calculating novelty scores in the joint null space of multiple classes

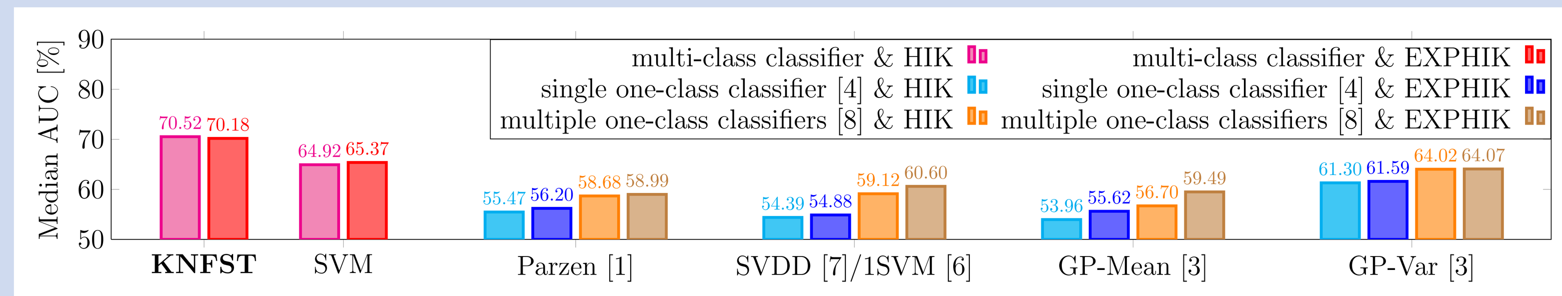
Experimental setup

- Datasets: Caltech-256 and ImageNet ($1{,}000$ categories of the **I**mageNet **L**arge **S**cale **V**isual **R**ecognition **C**hallenge 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

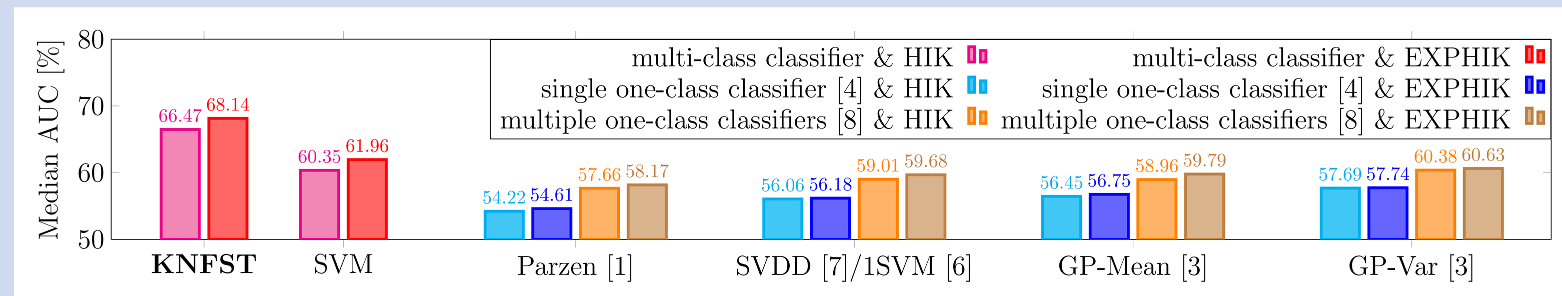
Experimental results



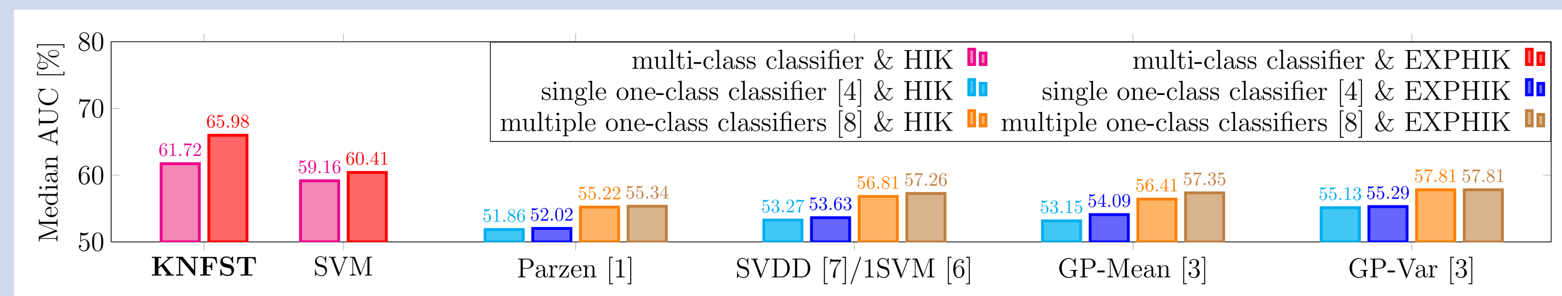
Five object categories known during training (Caltech-256 dataset)



Ten object categories known during training (Caltech-256 dataset)



Five object categories known during training (ImageNet dataset)



Ten object categories known during training (ImageNet dataset)