



Figure 6. t-SNE plots of the features learned by SVDD (left), Geometric (center) and Imagenet pre-trained (right) on CIFAR10, where the normal class is Airplane (top), Automobile (bottom). We can see that Imagenet-pretrained features clearly separate the normal class (yellow) and anomalies (blue). Geometric learns poor features of Airplane and reasonable features on Automobile. Deep-SVDD does not learn features that allow clean separation.

time is using K-means clustering of the training features. This speeds up inference by a ratio of $\frac{N}{K}$. We therefore suggest speeding up DN2 by clustering the training features into K clusters and the performing kNN on the clusters rather than the original features. Tab. 6 presents a comparison of performance of DN2 and its K-means approximations with different numbers of means (we use the sum of the distances to the 2 nearest neighbors). We can see that for a small loss in accuracy, the retrieval speed can be reduced significantly.

5.2. Pretrained vs. self-supervised features

To understand the improvement in performance by pre-trained feature extractors, we provide t-SNE plots of normal and anomalous test features extracted by Deep-SVDD, Geometric and DN2 (Resnet50 pretrained on Imagenet). The top plots are of a normal class that achieves moderate detection accuracy, while the bottom plots are of a normal class that achieves high accuracy. We can immediately observe that the normal class in Deep-SVDD is scattered among the anomalous classes, explaining its lower performance. In Geometric the features of the normal class are a little more localized, however the density of the normal region is still only moderately concentrated. We believe that the

fairly good performance of Geometric is achieved by the massive ensembling that it performs (combination of 72 augmentations). We can see that Imagenet pretrained features preserve very strong locality. This explains the strong performance of DN2.

6. Discussion

A general paradigm for anomaly detection: Recent papers (e.g. Golan & El-Yaniv (2018)) advocated the paradigm of self-supervision, possibly with augmentation by an external dataset e.g. outlier exposure. The results in this paper, give strong evidence to an alternative paradigm: i) learn general features using all the available supervision on vaguely related datasets ii) the learned features are expected to be general enough to be able to use standard anomaly detection methods (e.g. kNN, k-means). The pretrained paradigm is much faster to deploy than self-supervised methods and has many other advantages investigated extensively in Sec. 4. We expect that for image data that has no similarity whatsoever to Imagenet, using pre-trained features may be less effective. That withstanding, in our experiments, we found that Imagenet-pretrained features were effective on aerial images as well as microscope images, while both settings