are very different from Imagenet. We therefore expect DN2-like methods to be very broadly applicable.

External supervision: The key enabler for DN2's success is the availability of a high quality external feature extractor. The ResNet extractor that we used was previously trained on Imagenet. Using supervision is typically seen as being more expensive and laborious than self-supervised methods. In this case however, we do not see it as a disadvantage at all. We used networks that have already been trained and are as commoditized as free open-source software libraries. They are available completely free, no new supervision at all is required for using such networks for any new dataset, as well as minimal time or storage costs for training. The whole process consists of merely a single PyTorch line, we therefore believe that in this case, the discussion of whether these methods can be considered supervised is purely philosophical.

Scaling up to very large datasets: Nearest neighbors are famously slow for large datasets, as the runtime increases linearly with the amount of training data. The complexity is less severe for parametric classifiers such as neural networks. As this is a well known issue with nearest neighbors classification, much work was performed at circumventing it. One solution is fast kNN retrieval e.g. by kd-trees. Another solution used in Sec. 5, proposed to speed up kNN by reducing the training set through computing its k-means and computing kNN on them. This is generalized further by an established technique that approximates NN by a recursive K-means algorithm (Fukunaga & Narendra, 1975). We expect that in practice, most of the runtime will be a result of the neural network inference on the test image, rather than on nearest neighbor retrieval.

Non-image data: Our investigation established a very strong baseline for image anomaly detection. This result, however, does not necessarily mean that all anomaly detection tasks can be performed this way. Generic feature extractors are very successful on images, and are emerging in other tasks e.g. natural language processing (BERT (Devlin et al., 2018)). This is however not the case in some of the most important areas for anomaly detection i.e. tabular data and time series. In those cases, general feature extractors do not exist, and due to the very high variance between datasets, there is no obvious path towards creating such feature extractors. Note however that as deep methods are generally less successful on tabular data, the baseline of kNN on raw data is a very strong one. That withstanding, we believe that these data modalities present the most promising area for self-supervised anomaly detection. Bergman & Hoshen (2020) proposed a method along these lines.

7. Conclusion

We compare a simple method, kNN on deep image features, to current approaches for semi-supervised and unsupervised anomaly detection. Despite its simplicity, the simple method was shown to outperform the state-of-the-art methods in terms of accuracy, training time, robustness to input impurities, robustness to dataset type and sample complexity. Although, we believe that more complex approaches will eventually outperform this simple approach, we think that DN2 is an excellent starting point for practitioners of anomaly detection as well as an important baseline for future research.

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