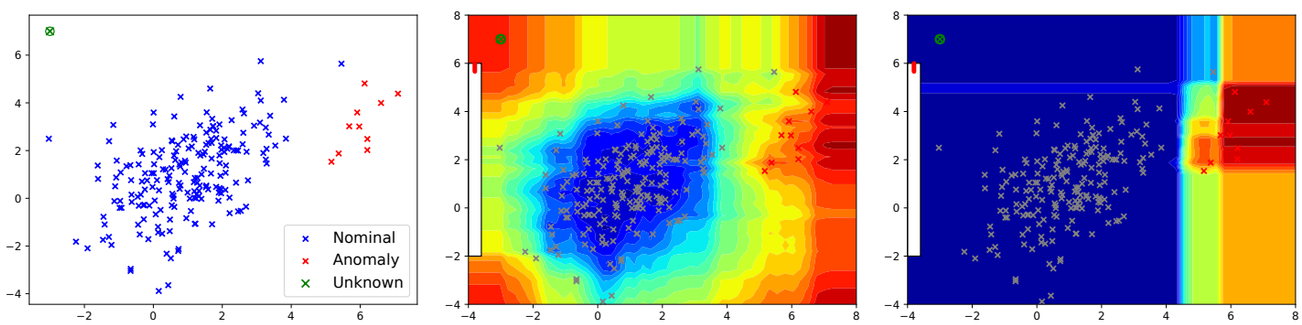

(a) Dataset with labeled examples (b) Score contours for anomaly detector (c) Score contours for classifier

Anomaly detector (AAD) vs. Classifier (Random Forest) when labeled data is available. **(a)** Shows the labeled dataset. Only the point marked in green at the top left is unlabeled. **(b)** Shows the anomaly score contours when the anomaly detector (AAD) was trained with the labeled instances (i.e., **ensemble weights were tuned to take the labels into account**). **(c)** Shows the probability contours for the anomaly class when a classifier was employed. In both (b) and (c), **red** corresponds to *more anomalous*, and **blue** corresponds to *more nominal*. Although we employed a *Random Forest* (RF) classifier, it learned an almost linear classifier. All points to the left of $x = 4.5$ (approx.) will be classified as **nominal** by the classifier, including the unlabeled point marked in **green**. In contrast, the **green** point will be classified as **anomaly** by the anomaly detector. Since the classifier learns a *decision boundary* between the two classes, it only checks which side of the boundary the instance is on before classifying it. On the other hand, most i.i.d point-based anomaly detectors (like in this example) are sensitive to the *data density*; instances which are in sparse regions are more likely be flagged as anomalies by default. **Whether to choose an anomaly detector or a classifier is application dependent since there are likely use cases for both of the types of behaviors.**