Universiteit Leiden

Human Environment and Transport Inspectorate
Ministry of Infrastructure and Water Management

THE eXPOSE APPROACH TO CROSSLIER DETECTION

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SUMMARY

Transit of wasteful materials within the European Union is highly regulated through a system of permits. Waste processing costs vary greatly depending on the waste category of a permit. Therefore, companies may have a financial incentive to allege transporting waste with erroneous categorisation. Our goal is to assist inspectors in selecting potentially manipulated permits for further investigation, making their task more effective and efficient. For this purpose we (1) introduce the concept of crosslier: an anomalous instance of a category which lies across other categories; (2) propose eXPose: a novel approach to crosslier detection based on supervised category modelling; and (3) present the crosslier diagram: a visualisation tool specifically designed for domain experts to easily assess crossliers. We compare eXPose against traditional outlier detection methods in various benchmark datasets with synthetic crossliers and show the superior performance of our method in targeting these instances.

Method

1. From a pool of candidate models, measure ROC AUC performance (cross-validated) of the classification task towards each category $z \in Z$;

2. Select surrogate model with highest performance;

3. Re-learn the selected classifier, but this time with a probability-calibration wrapper (Platt scaling) trained over each validation fold;

4. Given a category z, the crosslier score of a sample x is given by $f_z(x) = -\log_2 P(y|x)$ in which the posterior probability is computed as the output of the Platt-scaled learned classifier previously selected.

CONCEPT

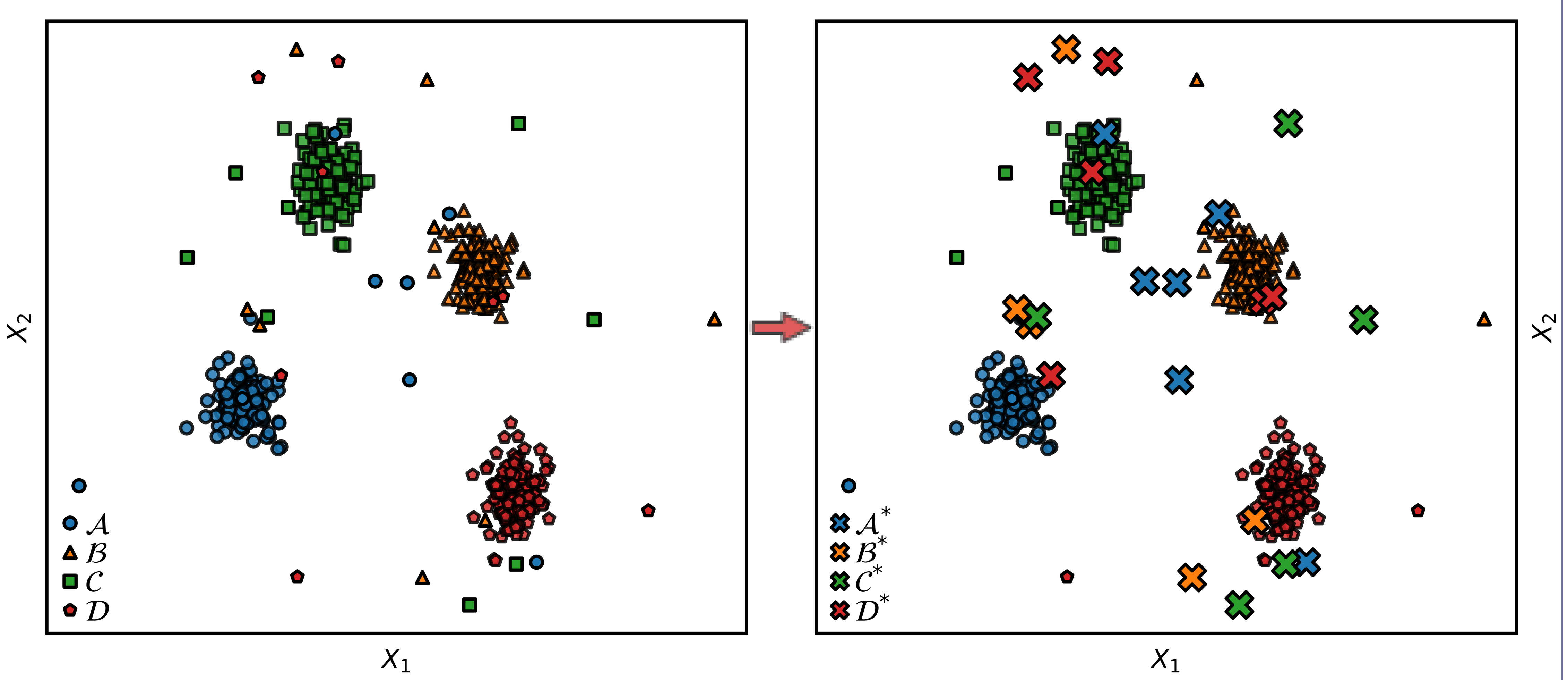

Fig. 1. **Crosslier detection**. Samples with features X1 and X2, pertaining to either category A, B, C, or D (left). Crossliers are marked as crosses (right).

WASTE TRANSPORTATION RESULTS

Table. 1. **Surrogate model performance (ROC AUC) per waste category.** XGBoost (XGB) was used to generate crosslier scores, over Logistic Regression (LR).

Category	LR	XGB
1	0.983 ± 0.008	$\mathbf{0.985 \pm 0.010}$
2	0.868 ± 0.044	$\mathbf{0.919 \pm 0.037}$
3	0.868 ± 0.020	$\mathbf{0.908 \pm 0.027}$
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5	0.672 ± 0.092	$\mathbf{0.755 \pm 0.082}$
6	0.740 ± 0.038	$\mathbf{0.794 \pm 0.037}$
7	0.776 ± 0.016	$\mathbf{0.821 \pm 0.015}$
8	0.798 ± 0.026	$\mathbf{0.856 \pm 0.025}$
9	0.867 ± 0.047	$\mathbf{0.915 \pm 0.047}$
10	0.737 ± 0.032	$\mathbf{0.788 \pm 0.035}$
11	0.815 ± 0.021	$\mathbf{0.896 \pm 0.016}$
12	0.860 ± 0.032	$\mathbf{0.897 \pm 0.031}$
13	0.609 ± 0.063	$\mathbf{0.720 \pm 0.062}$
14	0.776 ± 0.034	$\mathbf{0.817 \pm 0.024}$
15	0.841 ± 0.019	$\mathbf{0.883 \pm 0.016}$
16	0.695 ± 0.016	$\mathbf{0.753 \pm 0.019}$
17	0.845 ± 0.023	$\mathbf{0.889 \pm 0.022}$
18	0.894 ± 0.015	$\mathbf{0.921 \pm 0.015}$
19	0.806 ± 0.014	$\mathbf{0.851 \pm 0.013}$
20	0.719 ± 0.024	$\mathbf{0.779 \pm 0.027}$

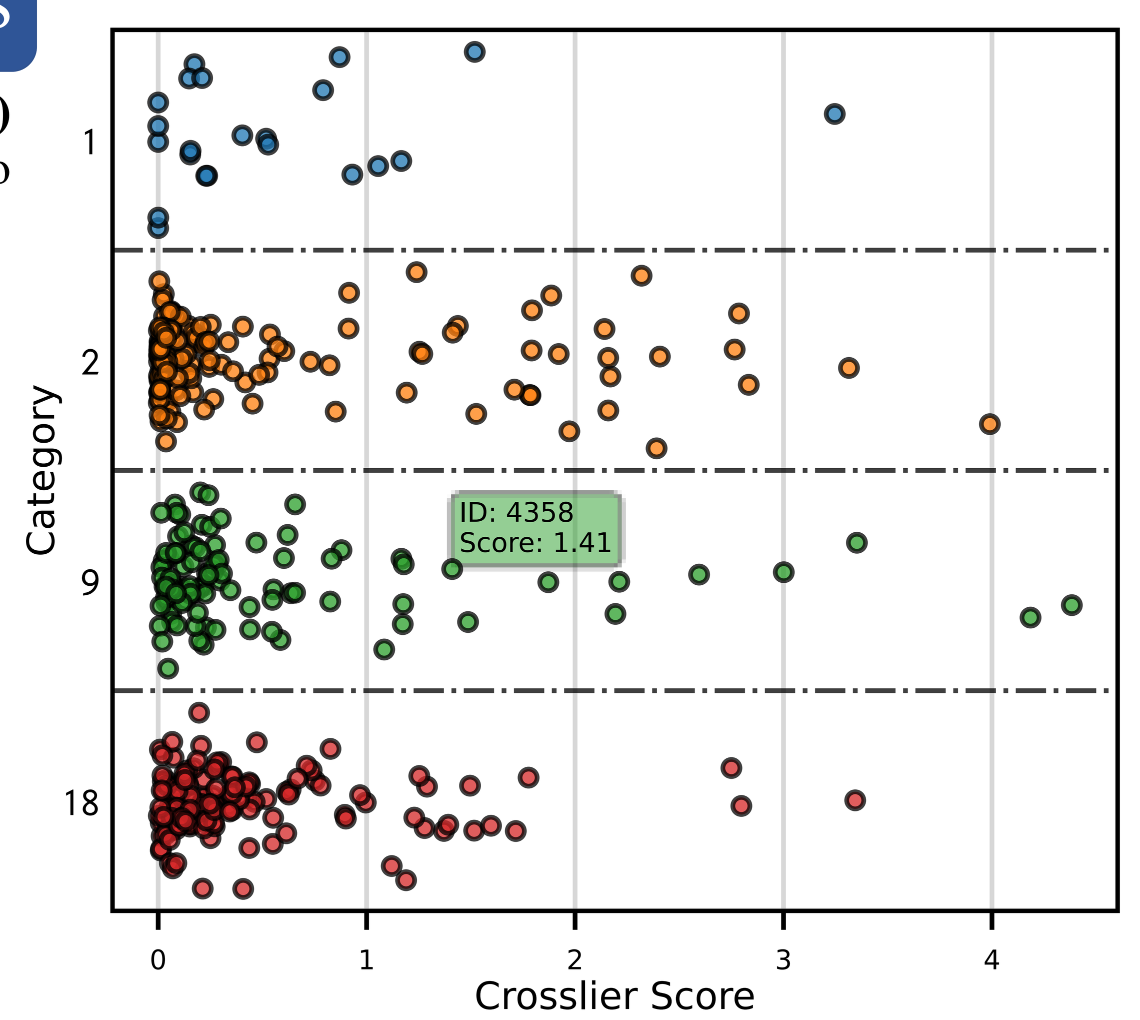

Fig. 2. **Crosslier diagrams of four waste categories.** Hovering over an instance highlights its identifier (4358) and crosslier score (1.41).

BENCHMARK RESULTS

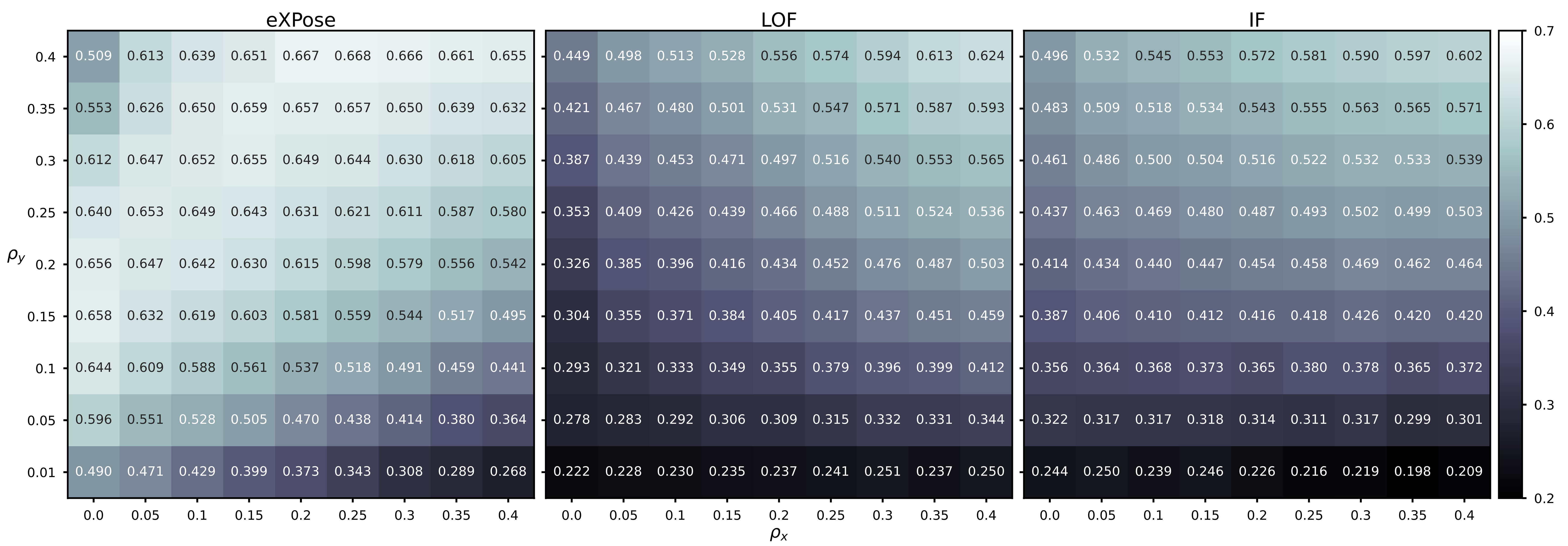

Fig. 3. **Crosslier detection performance across different methods**. Heatmaps depict the average precision (AP) scores for our method (eXPose), local outlier factor (LOF), and isolation forest (IF). Performance values were averaged across datasets and random initialisations. In the vertical axis, y is the proportion of samples which have been category-swapped. In the horizontal axis, x denotes the proportion of features (in category-swapped samples) of which the values were replaced to further mimic the swapped label instances.