**Anomaly Segmentation**

Given set of **inlier classes** and **image**, segment regions that semantically not belong to any of the inlier classes.

Datasets for autonomous driving consider anomalous what is not a class in **CityScapes**.

Only the wooden pallet is marked red because it is not a class in CityScapes.

**MDM – Maximal Detection Margin**

- Designing method around AP is not practical (only requires existence of a good threshold)
- Need for metric that captures robustness regarding threshold choice

Columns: dense prediction, thresholded at 0.3, 0.5, 0.8 Lower column is more desirable, but AP is close (95.5% vs. 98.9%)

\[ \text{MDM}_{\text{low}}(A, B) = \max_{0 \leq x \leq 1} (y-x) \cdot \mathbb{E}_{z \in [x, 1]} \cdot d(A > z, B) > T_{\text{margin}}. \]

**Results**

- No missing patches inside segmented anomaly
- High accuracy around borders
- No predictions in non-anomalous areas
- Visualization threshold by optimizing F1

---

**Maskomaly**

- **Pure Post-processing: no training**
- Builds up on **Mask-based Segmentation Networks**
- Combines idea of **rejecting inlier areas and accepting anomalous regions**
- Deals with **border regions explicitly**

- **Key Insight:** Mask-based Segmentation Networks learn **fixed queries** that predict masks for anomalies which are discarded by the segmentation algorithm

---

**Experimental configuration:**

- **Backbone:** Mask2Former/Swin-L trained on **Cityscapes** for segmentation
- **Validation set:** SMIYC Validation
- **Evaluated on:** SMIYC, FishyScapes, RoadAnomaly, StreetHazards

**Quantitative Results:**

- Maskomaly achieves **state-of-the-art** performance
- **MDM** is more informative than AP

**Ablations:**

---

**Maskomaly: Zero-shot Mask Anomaly Segmentation**

Jan Ackermann, Christos Sakaridis, Fisher Yu

https://github.com/jan-ackermann/maskomaly