Rodrigo López Portillo Alcocer
Contact: rodrigo.lopez-portillo-alcocer@ipvs.uni-stuttgart.de

Anomaly Detection

Under the supervision of **Prof. Dr. Staab, Dr. Boutalbi** and **Amin Totounferoush**

“Persistent anomalies drive scientific revolutions.”[1]

Introduction

Anomalies, also called outliers or novelties, are observations that **deviate considerably** from some **concept of normality**.[2]

Because of the inherently low probability of these events, a common strategy in Anomaly Detection is to learn a model of normality in an unsupervised manner, so that anomalies become detectable through deviations from the model.

Formal Definition

$$\mathscr{A} = \{ \boldsymbol{x} \in \mathscr{X} \mid p^+(\boldsymbol{x}) \leq \tau \}, \quad \tau \geq 0$$

$\mathscr{A}$: set of anomalies.
$\mathscr{X}$: data space given by some task.
p^+: pdf corresponding to the distribution $\mathscr{P}^+$ on $\mathscr{X}$ that is the ground-truth law of normal behaviour for the given task.
τ: threshold such that the probability of $\mathscr{A}$ under $\mathscr{P}^+$ is “sufficiently small”.

Approaches

Most approaches in the field can be classified into one of the following categories:

- Density estimation and probabilistic models.
- One-class classification.
- Reconstruction models.

Challenges

The (mostly) unsupervised nature of the problem requires assumptions to be made about the specific application, the domain, and the given data.
Some critical characteristics and questions to explore for every application are:

- The relevant types of anomalies.
- The possible **prior assumptions** about the anomaly distribution.
- The challenge of how to **incorporate labeled data** (if available) instances in a generalizing way.
- How to derive an anomaly score or threshold for this task.
- Which tradeoff between false alarms and missed anomalies is reasonable?
- Is the data-generating process assumed to be non-stationary?
- Are distributional shifts expected at test time?
- How to **explain and interpret** the detected anomalies?

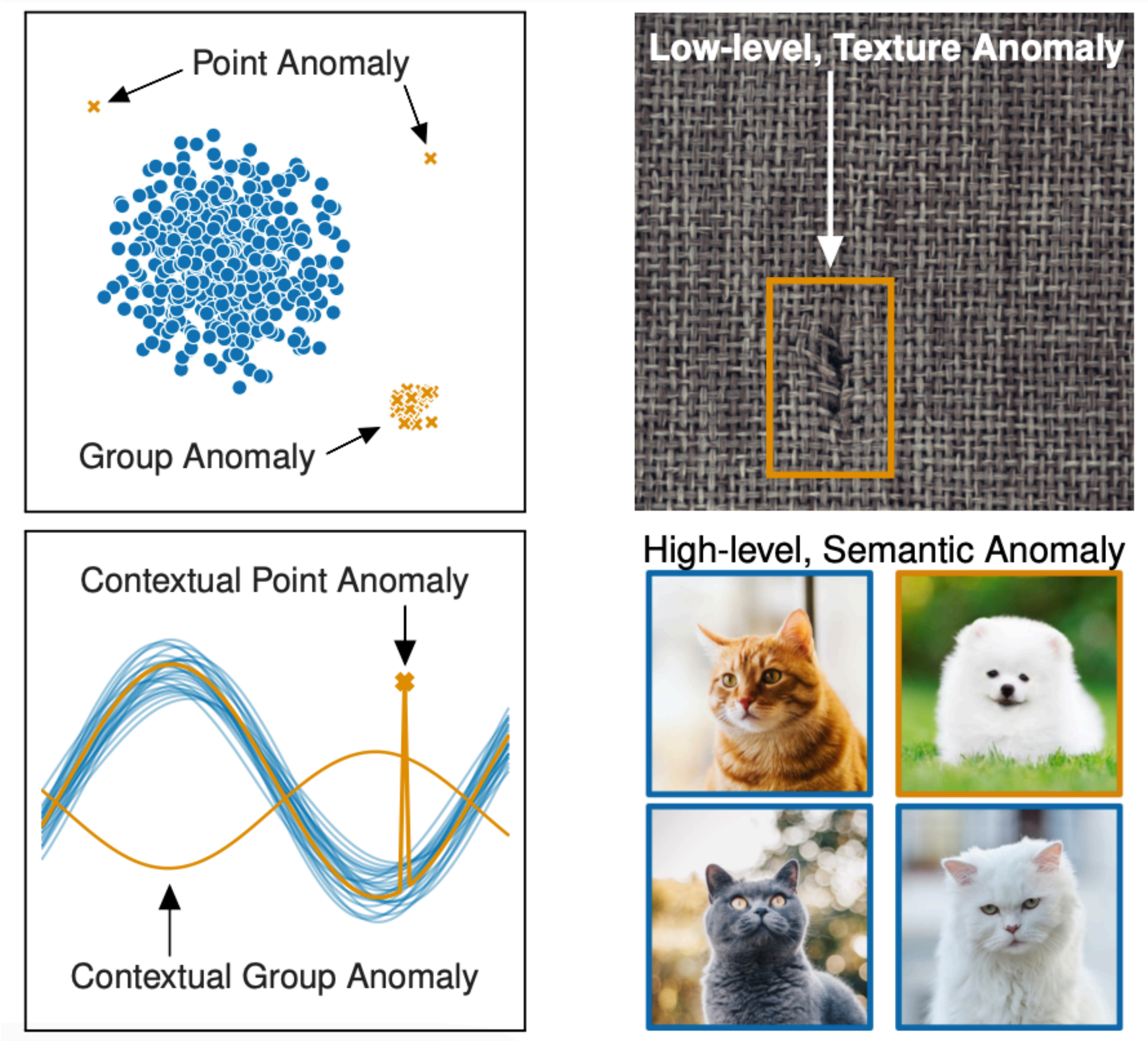

Figure 1. An illustration of the types of anomalies. [2]

Our research directions

- Local Neural Transformations for Anomaly Detection in Time Series. [3]

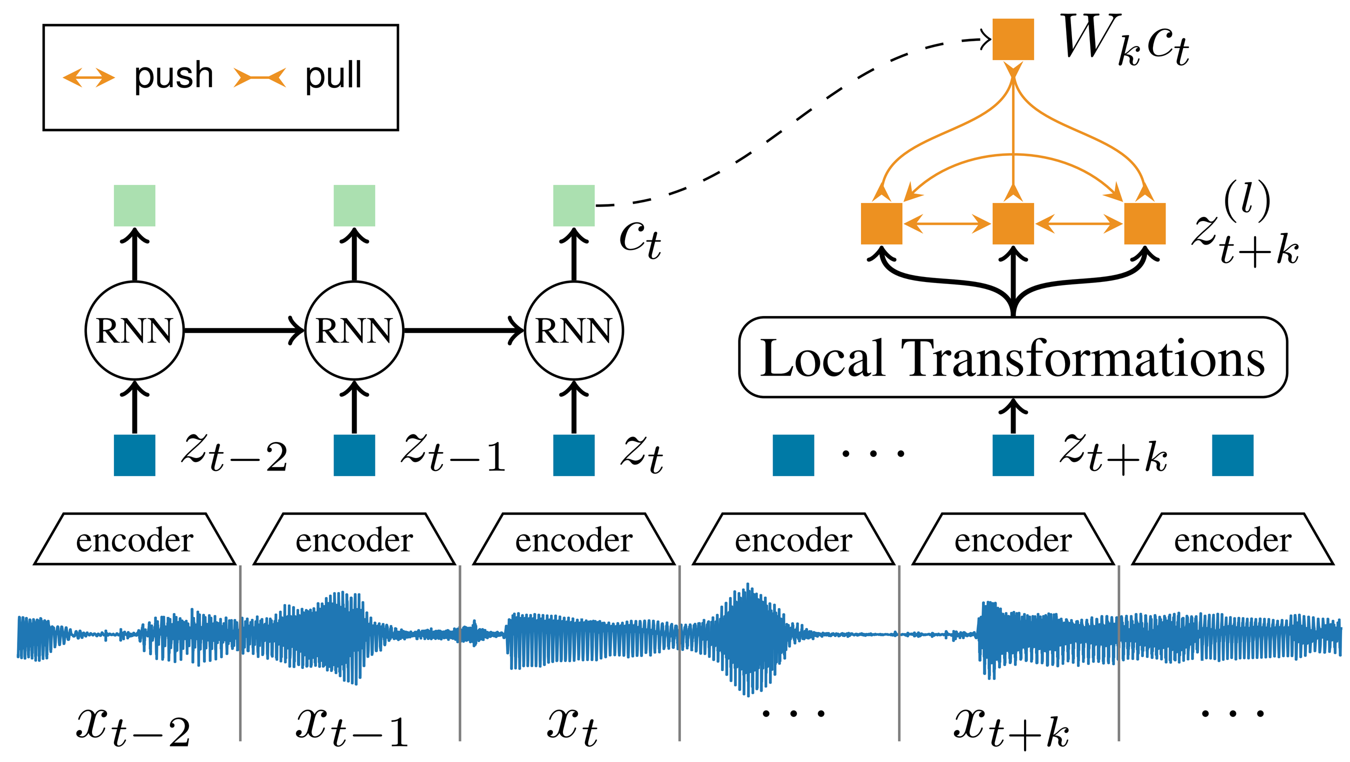

Figure 2. Diagram of the Local Neural Transformations technique. [3]

- Specialized benchmark dataset for testing contextual Anomaly Detection techniques.

References
[1] T.S. Kuhn, 1970. *The Structure of Scientific Revolutions*. Univ. of Chicago Press.
[2] Ruff et al., 2021. *A Unifying Review of Deep and Shallow Anomaly Detection*. Proceedings of the IEEE 2021, p.1-40.
[3] Schneider et al., 2022. *Detecting Anomalies within Time Series using Local Neural Transformations,* arXiv:2202.03944v2 [cs.LG].