Anomaly detection in Telecommunications

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Anomaly detection
Anomalies in the data.

- Anomaly represents the type of behaviour in the data that differs significantly from some expected behaviour.

- Anomaly ≠ Outlier

- Types of anomalies:
  1. Point anomalies
  2. Contextual anomalies
  3. Collective anomalies
Point anomaly

Point anomaly is an instance that could be considered as anomalous among other instances in the dataset. Point anomalies often represent some extremum, irregularity or deviation that happens randomly and have no particular meaning.
Contextual anomaly

**Contextual anomaly** is an instance that could be considered as anomalous in some specific context.

The contextual anomaly is determined by combining contextual and behavioural features, like space and/or time with some quantitative measurement (total money spent, average temperature, average end user throughput,...)
Collective anomaly is often represented as a group of correlated, interconnected or sequential instances.

While each particular instance of this group doesn’t have to be anomalous itself, their collective occurrence is anomalous.
Anomaly detection techniques

- Supervised anomaly detection.
- Unsupervised anomaly detection.
- Semi-supervised anomaly detection.
The process of anomaly detection

**Domain understanding**
- Mastering basic concepts of the domain
- Consultations with the domain expert
- Define the term "anomaly"

**Choosing a technique**
- Supervised approach
- Unsupervised approach
- Semi-supervised approach

**Evaluating a model**
- Check if model assumptions are satisfied
- Set up initial parameters
- Run a model

**Data understanding**
- Descriptive analysis
- Exploratory analysis

**Applying a model**
- Check if model assumptions are satisfied
- Set up initial parameters
- Run a model

**Drawing conclusions**
- Present root causes if possible
- Define some actions based on a given insight

**Interpreting identified anomalies**
- Drill down/drill through analysis
- Root cause analysis
- Correlation analysis

**Choosing a model**
- Choose a model from given approach
- Determine model assumptions
- Prepare input data

**Evaluating a model**
- Evaluate the model with some performance measure if possible
- Consult the domain expert
Telecommunication network
Telecommunication network.
Problem definition
Problem definition.

“Understanding the **project objectives** and **requirements** from a domain perspective and then converting this knowledge into a **data mining problem** definition with a **preliminary plan** designed to achieve the objective.” (CRISP-DM)

- Site behaviour through time (100+ KPIs)
  - packet loss
  - packet delay
  - transmission success rate
  - ...
- Labels not available
- Based on the available KPIs, **automatically identify anomalous sites** in a given period of time

Technique to be used: **unsupervised anomaly detection**

Available models: **Isolation Forest / Autoencoders**
Benefits
24/7
Health checks
Enables continuous checks over the network parameters, and fires a signal when anomalous behaviour is detected.

Efficient
Problem diagnosis
Contains information which KPIs have been flagged as anomalous, and in which point of time.

Process
Automation
Helps in process automation, 100+ KPIs are simultaneously analysed, to automatically detect and report anomalous behaviour.
Isolation Forest
Isolation Forest algorithm.

- tries to “isolate” an instance
- the isolation is performed by building an ensemble of trees
- trees are built by recursively selecting a random feature and performing random partitioning, until an instance is positioned in a terminal node, which means it is isolated
- a smaller number of partitions needed to isolate an instance indicates higher chances of anomaly
- Anomaly score is determined by the average path length to the terminal node a given instance has been placed into.

Xo is more likely to be an anomaly than Xi
Isolation Forest - example.

[43, 45, 50, 50, 53, 53, 56, 82]
Autoencoders
Autoencoders.

Autoencoder is a unsupervised neural network. In most cases, the main goal of training an autoencoder is to provide an output that is the same as input.

They work by compressing the input into a latent-space representation, and then reconstructing the output from this representation. It is consisted of two parts: encoder and decoder.

**Encoder** is used for mapping from the original space to another space, of possibly higher or lower dimensionality.

**Decoder** is used for mapping back from this new space to the original one.

**Anomaly score** is determined by the error a decoder made in reconstruction phase.
Autoencoder - characteristics.

Compression and decompression functions are:
- Data-specific
- Lossy
- Automatically-learned

... which makes it pretty convenient for:
- Data denoising
- Dimensionality reduction
- Anomaly detection
Comparative analysis
## Comparative analysis

<table>
<thead>
<tr>
<th></th>
<th>Isolation Forest</th>
<th>Autoencoder</th>
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<tbody>
<tr>
<td><strong>1</strong></td>
<td><strong>Accuracy</strong></td>
<td><strong>Pros</strong></td>
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</table>
| **2** | 72% | - Very fast  
- Good performances with redundant data  
- Can work in both supervised and unsupervised mode | - Possible to extract error per each dimension  
- Good for catching nonlinear dependencies  
- Convenient for noise reduction | - Not possible to extract path lengths for individual dimensions  
- Not possible to visualize i-trees  
- Could have low performance when working with non or slightly deviant features |
| **3** | | - Takes too much time with high-dimensional data  
- Learns to capture as much information as possible rather than as much relevant information as possible |