Automatic root cause (anomaly) detection – 3GPP ETSI 4G LTE RAN KPIs

Machine learning model

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Agenda

1. Motivation

- Context: “Why optimize 4G networks?”
- Automation: “Why AI/*machine learning*?”
- Objective

2. Case study

- Network performance metrics and evaluation criteria
- 4G LTE 3GPP solution
- Anomaly and network issues

3. Development

- 4G solution
- Data strategy
- Machine learning algorithm selection
- Proof of concept (*PoC*)

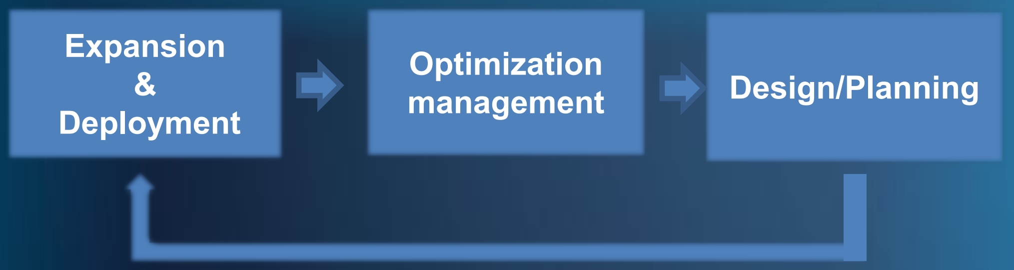
4. Results

- *Cell I example*
- *Cell II example*

1. Motivation

Why optimization?

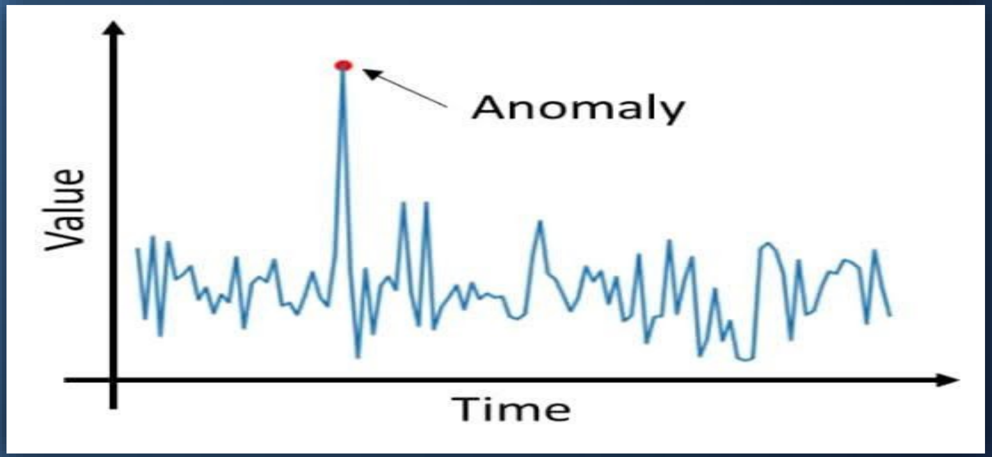
- Maximize MNO OPEX and CAPEX
  - Seasonality
  - Traffic behavior and user type
  - Network engineering resource strategy
- QoS improvement and user live network experience



Source: GSMA Mobile Economy – Global June 2020

Why automate?

- Human error→ Process loop impact
- Complexity → Heave amount of data and parameters to analyze and improve
- Autonomous network concept → Digital transformation
- Increase cost efficiency and resource productivity
- **Automatic anomaly detection/root cause → AI/*Machine Learning***



Source: How Machine Learning Can Enable Anomaly Detection, 2020

1. Motivation

Objective

ML model for 4G 3GPP Radio Network Performance management (automatic anomaly detection)

- **Identify network performance anomalies**
- **Identify potential root cause (diagnostics)**
- **Automate the process (digital transformation)**
- **Increase efficiency (time reduction per activity)**

→ ICT (Telco) + IA

2. Study case

Network performance metrics and evaluation criteria for 3GPP 4G LTE Radio Acces Network (RAN)

- 3GPP ETSI TS 132 451 → *"User experience and QoS based on Key Performance Indicators"*
  - Accessibility
  - Retention capacity
  - Integrity
  - Traffic
  - Utilization

Name	*Average Uplink Interference*
Object	4G Cell
KPI Formula	*UL.Interference.Avg* (unique counter)
Unit	Power (dBm)

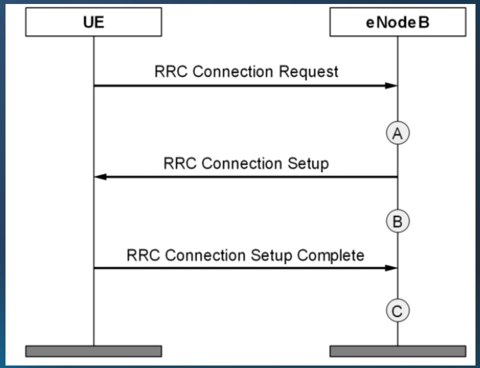
KPI – Uplink interference

Name	*Max User Number*
Object	4G Cell
KPI Formula	*Max.User.Number (unique counter)*
Unit	N/A

KPI – User traffic

Name	*RRC Setup Success Rate*
Object	4G Cell
KPI Formula	*RRC_SSR = RRC.Connection.Success/RRC.Connection.Attempt x 100%*
Unit	Percentage (%)

KPI - Accessibility



2. Case study

Counters aggregation (formula) and commercial network acceptance based on technical performance metrics

Counters of different categories (e.g. network failure, external events, etc)

Traffic behavior(seasonality)

Time (mm/dd/yyyy) hh:mm	4G Cell	Counter1	Counter2	...	Counter or KPI formula of interest
6/01/2021 12:00	Cell1	1424	422	...	0
6/01/2021 12:00	Cell2	533	328	...	6
...	...	...	...	...	...
8/14/2021 21:00	Cell1	1621	457	...	7
8/14/2021 21:00	Cell2	1111	127	...	9

Global standard 3GPP → Time series, extracted by hour

2. Case study

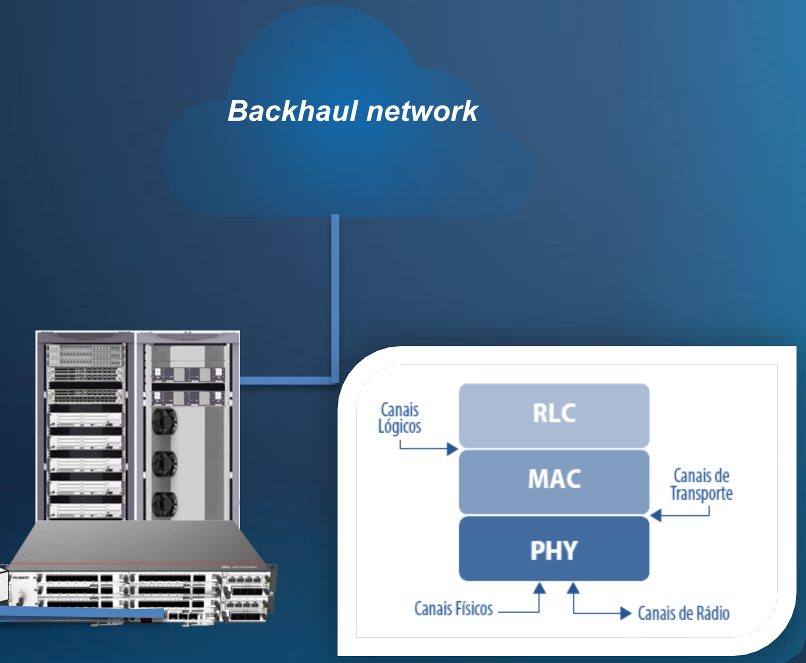
4G common anomalies and network issues

- Hardware malfunction on live network (site to backhaul-core)
- Human error → Network parameterization
- External interference, decreasing the performance of 4G active carrier
- 4G network traffic congestion

3. Development

4G Solution – Access Network:

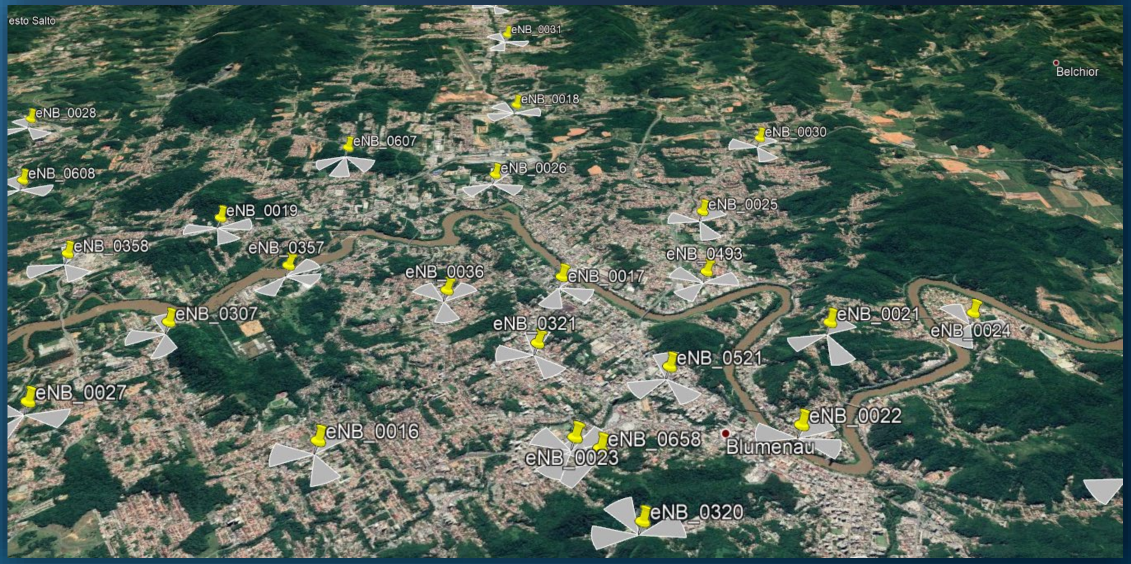
- *LTE 1800MHz – 3GPP Band 3 FDD*
- *BW = 10MHz*
- *1 antenna per sector*
- *1 LTE cell per sector*
- *3 antennas per eNodeB*
- *256QAM algorithm switch downlink feature*
- *64QAM uplink*



eNodeB (4G site)

Scenario:

- Blumenau city – SC (South Brazil)
- 2020/H2
- Total of 95 performance indicator counters → KPI formula of interest is *RRC Setup Succcess Rate (97.5% acceptance metric)*
- Collected for two 4G cells *(Cell1* e *Cell2*), different sites (06/1/2022 to 8/18/2022)
- 1785 samples (rows) for each 4G cell (*dataset.csv*)



3. Development

Acceptance metric and KPI evaluation criteria for RRC Setup Success Rate (%)

- 3GPP → 97.5% for network acceptance

Data strategy → Anomaly identification

- Automatic metric labeling (by hour)

Time (mm/dd/yyyy) hh:mm	4G cell	Counter1	Counter2	…	RRC Setup Success Rate (%)	KPI anomaly?
6/01/2021 12:00	Cell1	1424	422	...	97	1
6/01/2021 12:00	Cell2	533	328	...	99	0
…	...	…	…	…	…	…
8/14/2021 21:00	Cell1	1621	457	...	100	0
8/14/2021 21:00	Cell2	1111	127	...	75	1

3. Development

Machine learning model selection → Supervised classification (binary)

- *Naive Bayes*
- *Decision tree*

- *Python (scikit-learn)*
- *Feature importance extraction*

dataset.csv → *Input* → *ML model* → *Output* → *Anomaly (0 or 1) and feature Importance extraction*

Time (mm/dd/yyyy) hh:mm	4G Cell	Contador1	Contador2	...	RRC Setup Success Rate (%)	KPI anomaly?
6/01/2021 12:00	Cell1	1424	422	...	97	1
6/01/2021 12:00	Cell2	533	328	...	99	0
...	...	...	...	...	...	...
8/14/2021 21:00	Cell1	1621	457	...	100	0
8/14/2021 21:00	Cell2	1111	127	...	75	1

Input **Output**

4. Results

Proof of concept (*PoC*) → RRC Setup Success Rate (%) for new data (*Cell1 e Cell2*)

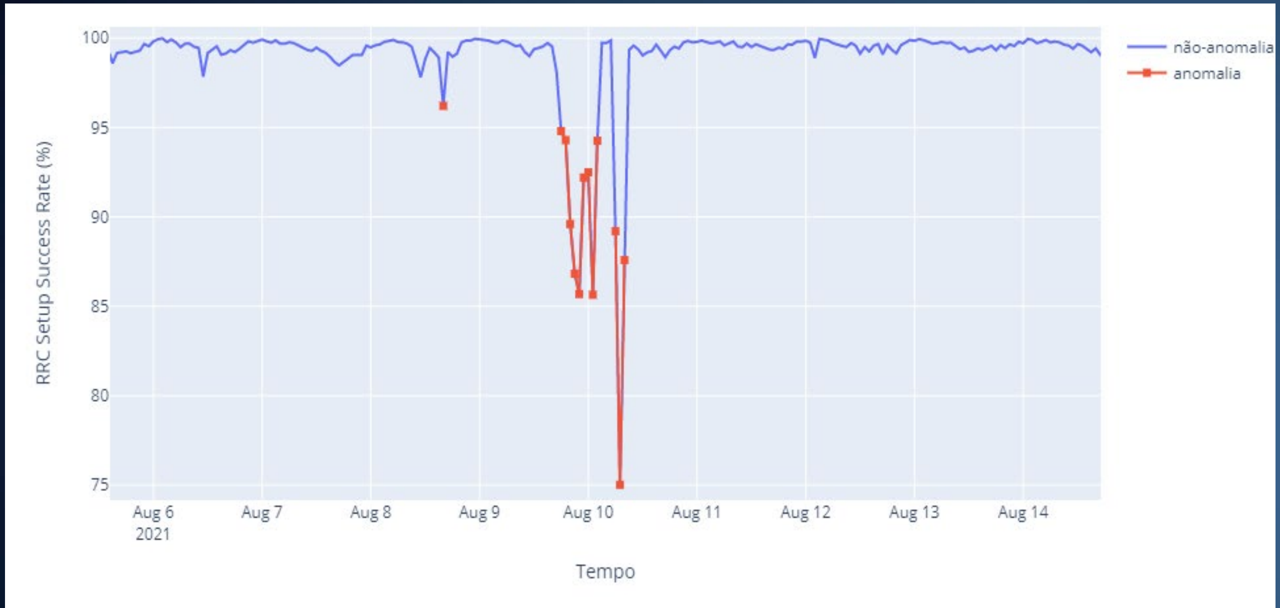
Modelo	Accuracy	Precision
Decision Tree Classifier	99.64%	96.67%
Naive Bayes	82.42%	18.58%

Notes:

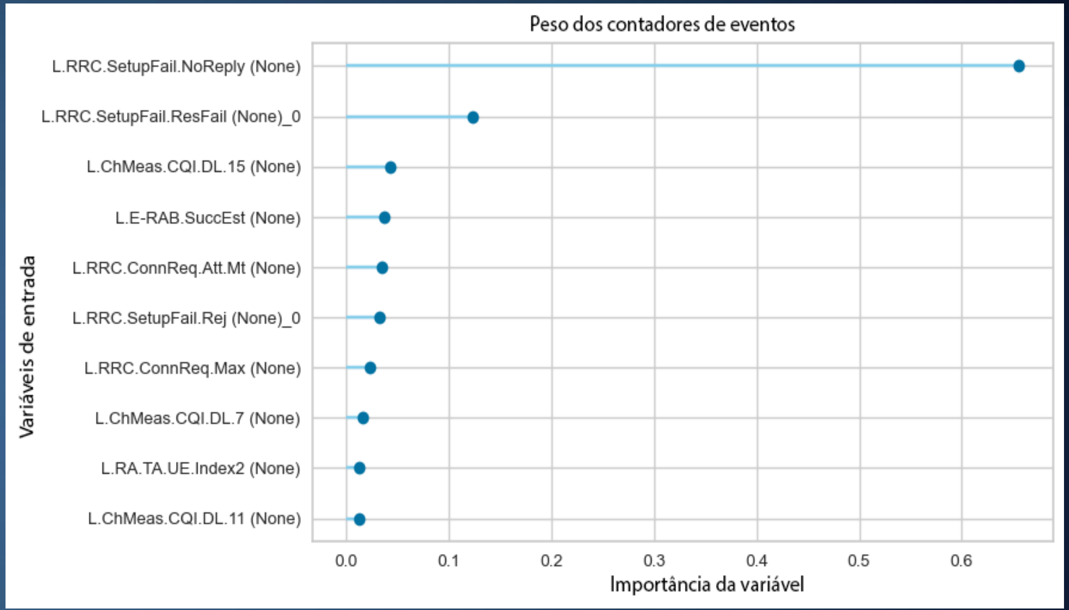
- *Decision Tree* → Better performance (correlated features)
- *Feature importance* extraction as the most correlated root cause

4. Results

Proof of concept (*PoC*) → RRC Setup Success Rate (%) for *Cell1*



KPI identified as anomaly



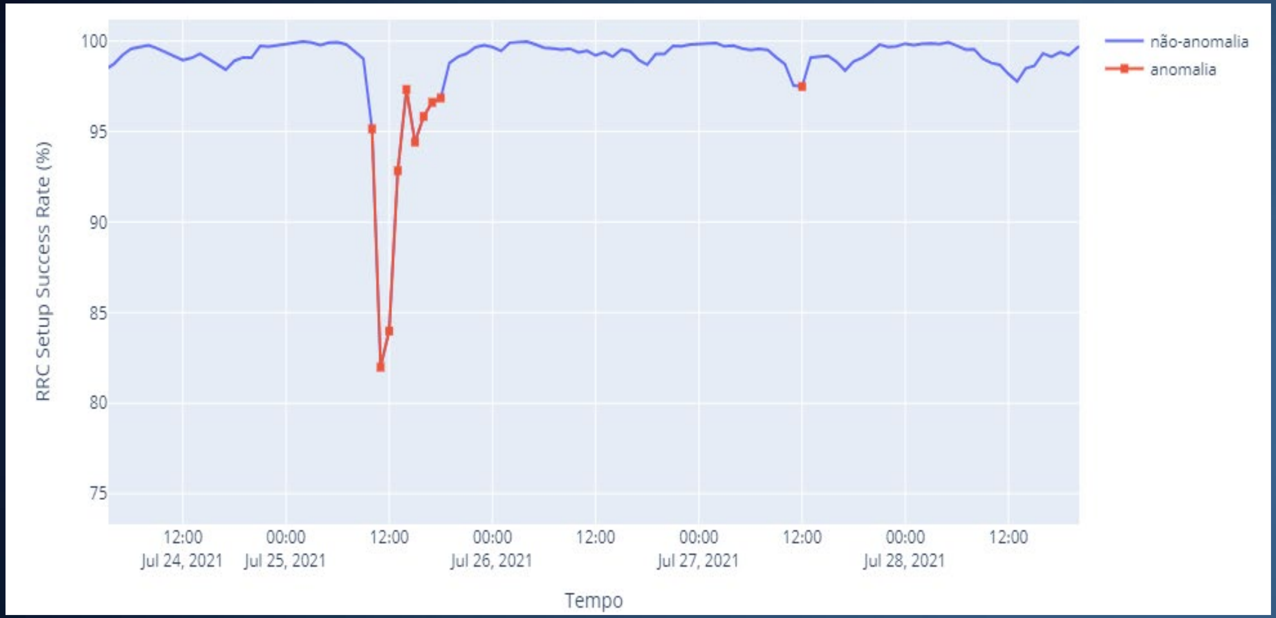
Feature importance

Notes:

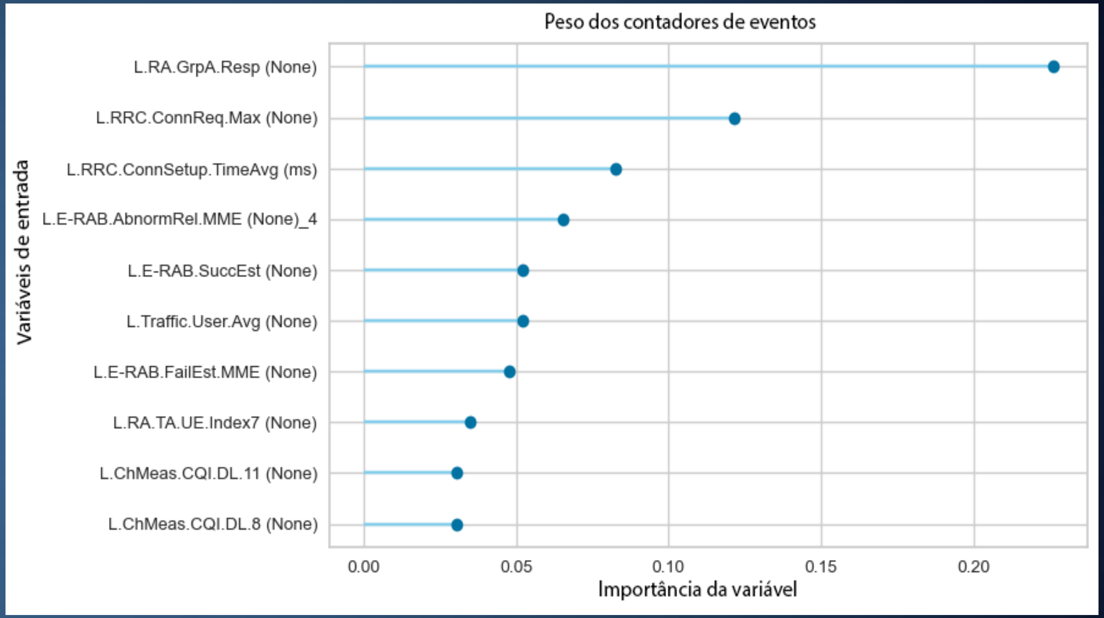
- Possible to identify anomaly and its root cause
- 3GPP → *L.RRC.SetupFailNoReply counter indicator*

4. Results

Proof of concept (*PoC*) → RRC Setup Success Rate (%) for *Cell2*



KPI identified as anomaly



Feature importance

Notes:

- Possible to identify anomaly and its root cause
- 3GPP → *L.RA.GrpA.Resp counter indicator*

Thank you