AI Empowered Networks

Predictive Maintenance for Mobile Networks and Services

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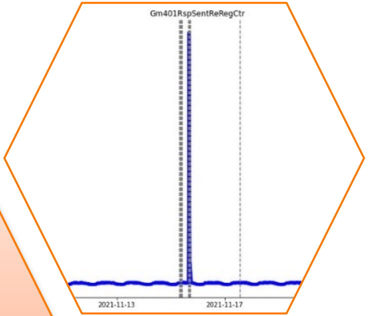
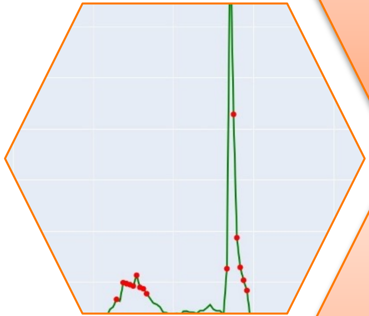
PhD, Tech Lead / AI Empowered networks

AMLD2022

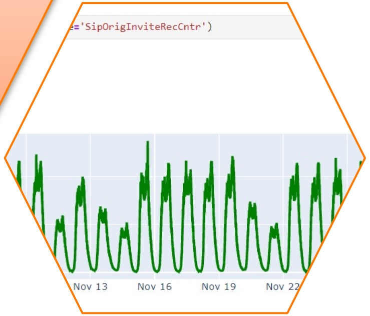
Outline

1-AI Empowered Networks : excerpt of use cases



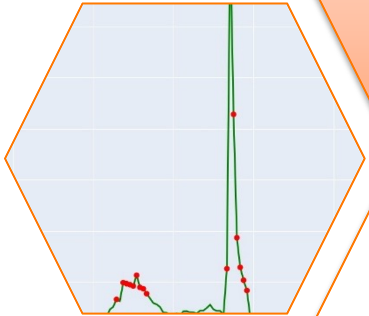


2- Focus on PNM for Mobile Networks



3- Zoom on Anomaly detection challenges and orientations

Outline



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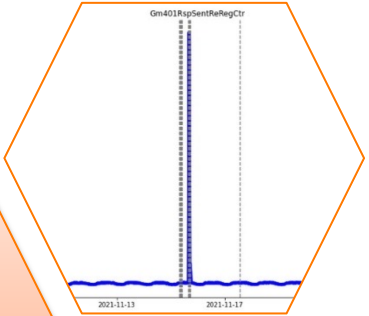

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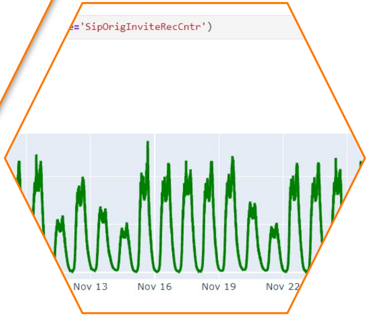
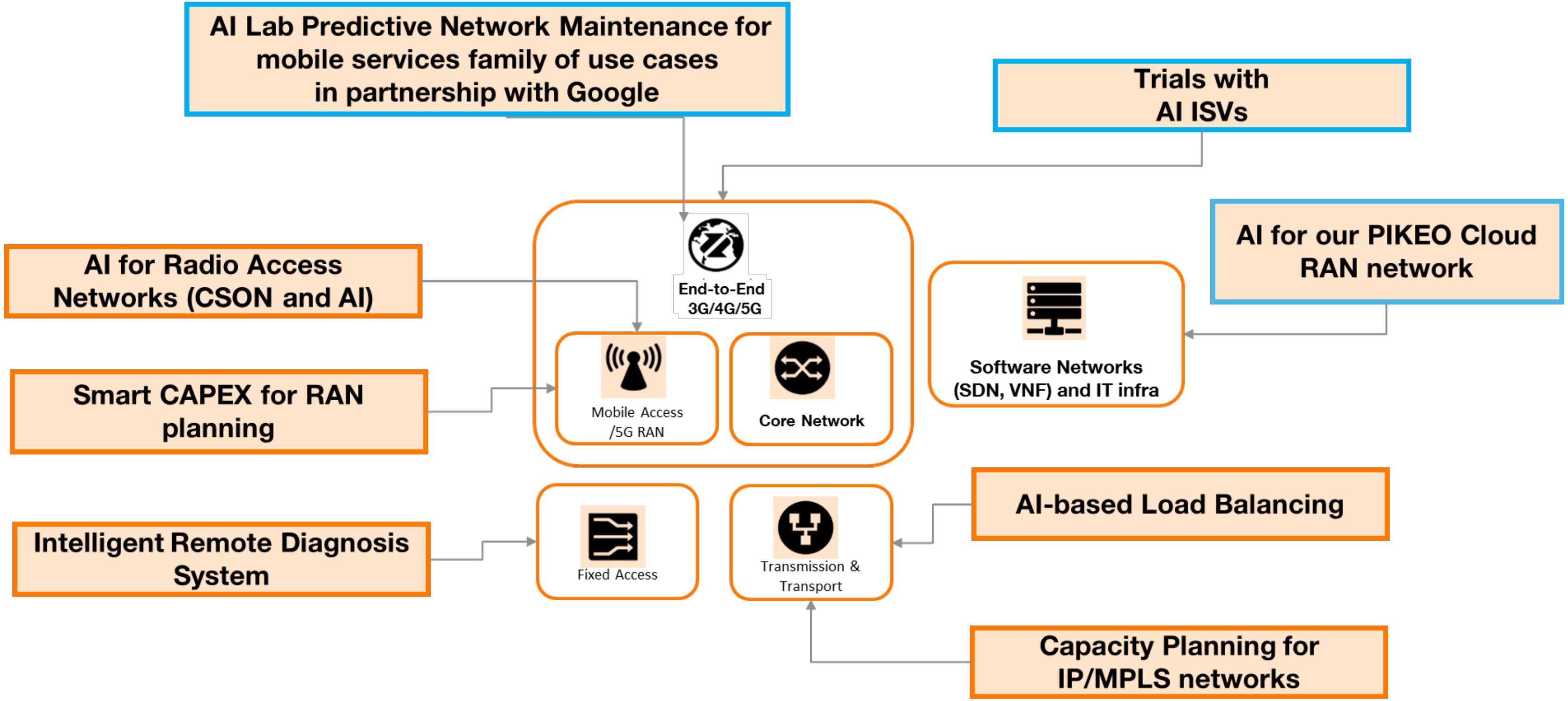


AI for Networks: Excerpt of current use cases



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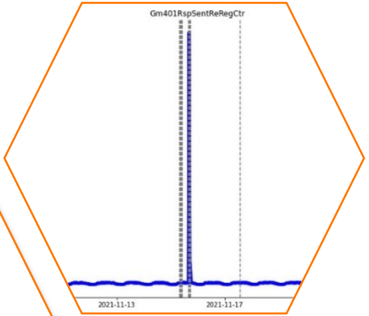

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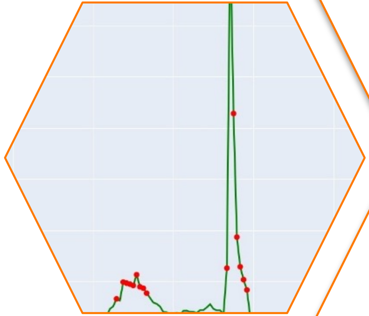

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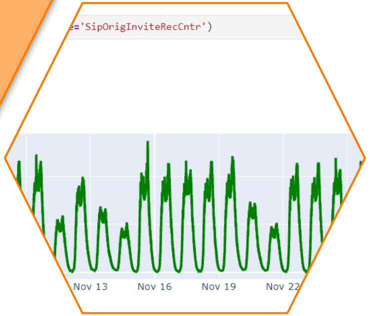

Zoom on Predictive Maintenance for Mobile Networks and Services

Pain Points

- **Several incidents not detected before, during and after the failures/degradations**
- Reactive network operations (e.g. upon customers complaints)
- Several thresholds to set, maintain and follow
- Static, noisy and non-informative alarms
- Slow manual root cause identification & Imprecise detection/identification of impacted customers

Empowering Network & Services with Predictive Maintenance

Functionalities

1. Multi-dimension network **data correlation / fusion**
2. **Anomalies Detection and prediction** of network events (e.g.failures, degradations,etc…)
3. Root cause identification / diagnosis
4. Operationalization & Automation : e.g. Mitigation and revovery actions; field intervention planning, etc.

Zoom on Predictive Maintenance for Mobile Networks and Services

Examples of PNM use cases & network data

	Example of PNM family of Use cases	Data
TMC/(GNOC)	Shortening root cause of Core networks routers based on syslog/events and KPIs	• Syslogs • KPIs (from routers) • Alerts
	Root cause analysis based on Error Code correlation with Eq counter-based KPIs for VoLTE	• KPIs (based on Eq. Counters data) • Error code • Alarms • TT
SMC/ & Customer	*PNM for VoIMS: (with Google teams)* Service Anomaly detection and Identification of Impacted Customers and a root cause analysis	• KPIs (based on Probes data) • KPIs (based on Eq. Counters data) • TT • Alarms
	Estimation of the per user QoS for mobile data services	• Mobile Internet KPIs based Probes data • Alarms, TT, etc. • Measurements campaign

e.g. AIEN TRIALS

1. *Data network labeling with Snorkel tool Trial*
2. *e2e Anomaly detection trial with Cardinality (Perception Platform)*

TMC: Technical Management center, SMC: Service Management Center

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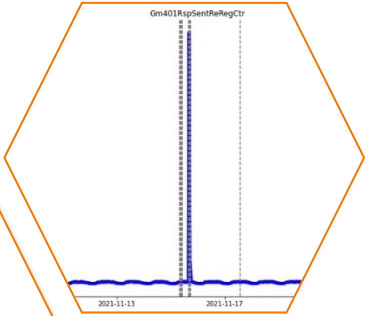

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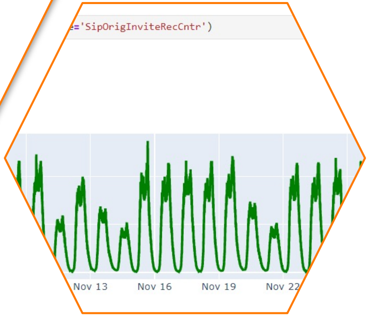
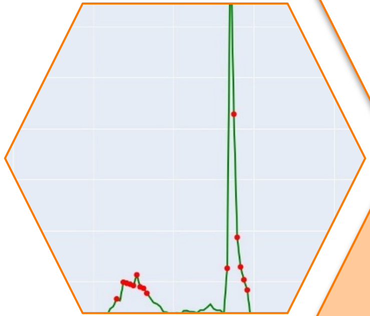
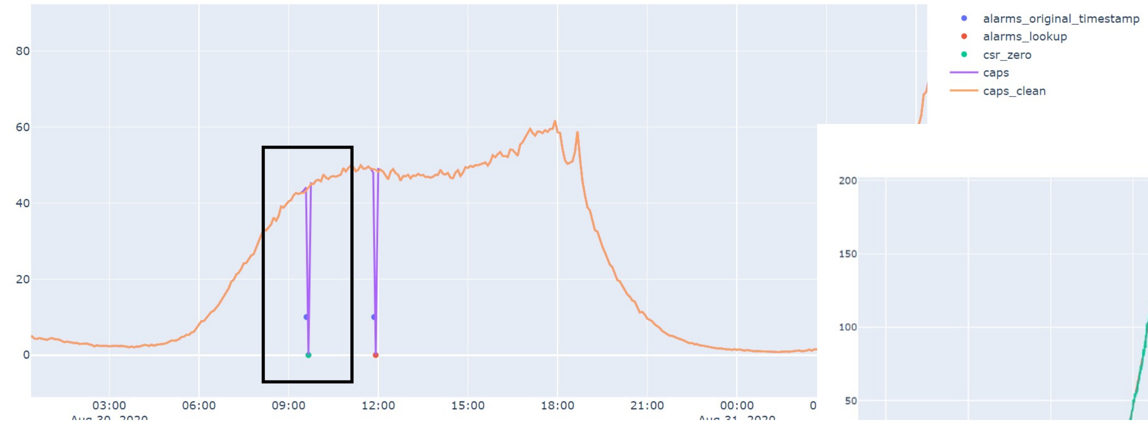
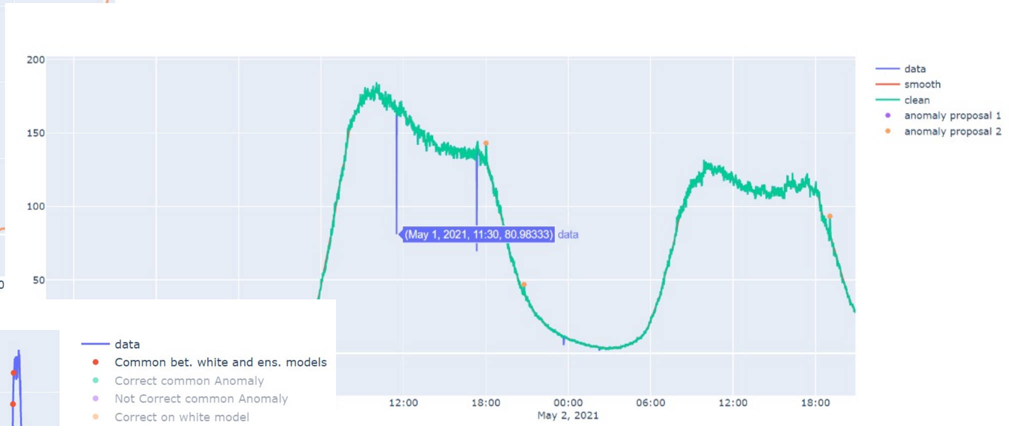


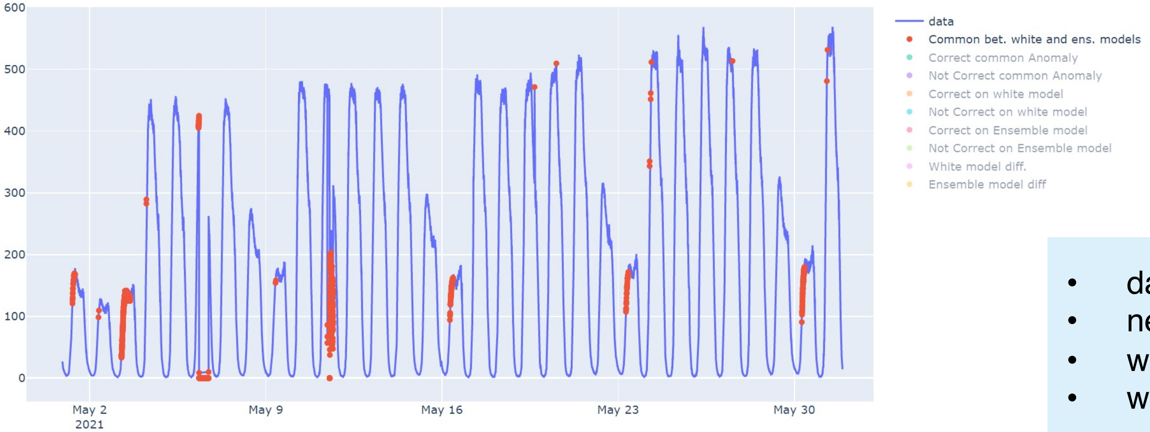


3- Zoom on Anomaly detection challenges and orientations

Network detected anomalies (but what is the root cause? which resolution is needed ? false detection?







- data quality anomalies
- network anomalies
- which ones are related to incidents
- which ones are related to events

Current approach for Anomaly detection in Predictive Network Maintenance

PNM Functionalities

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2. **Anomalies Detection and prediction** of network events (e.g.failures, degradations,etc…)
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Anomaly detecion 'classical' approach

2-Correlations between different KPIs
(service, customer and network level)

1-Multi-dimensional KPIs
(e.g. cell, call, country, reason code, etc.)

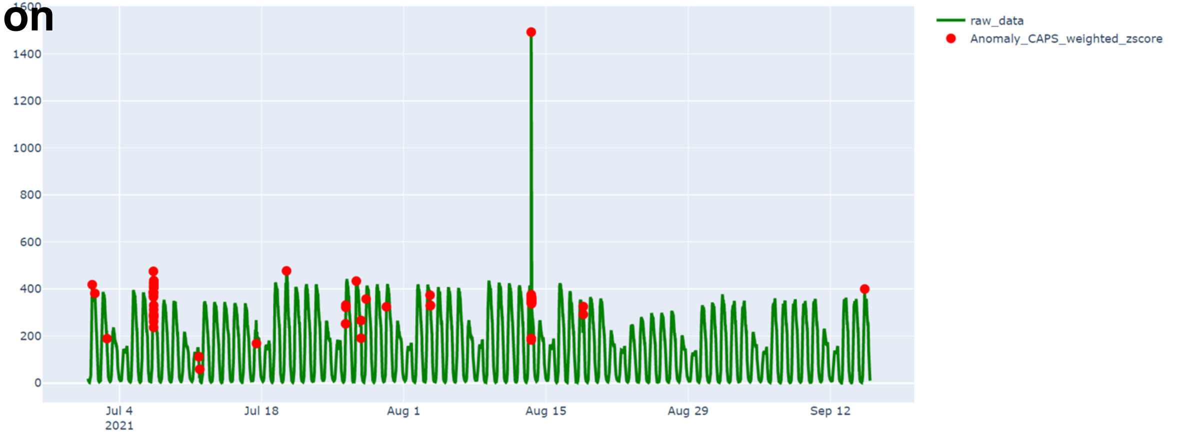
3-Rules, Statistics
(e.g. domain expert rules and thresolds, historical events, occurrences of error code, etc.

0-Network Raw data

Challenges of current anomaly detection approach for PNM (and beyond)

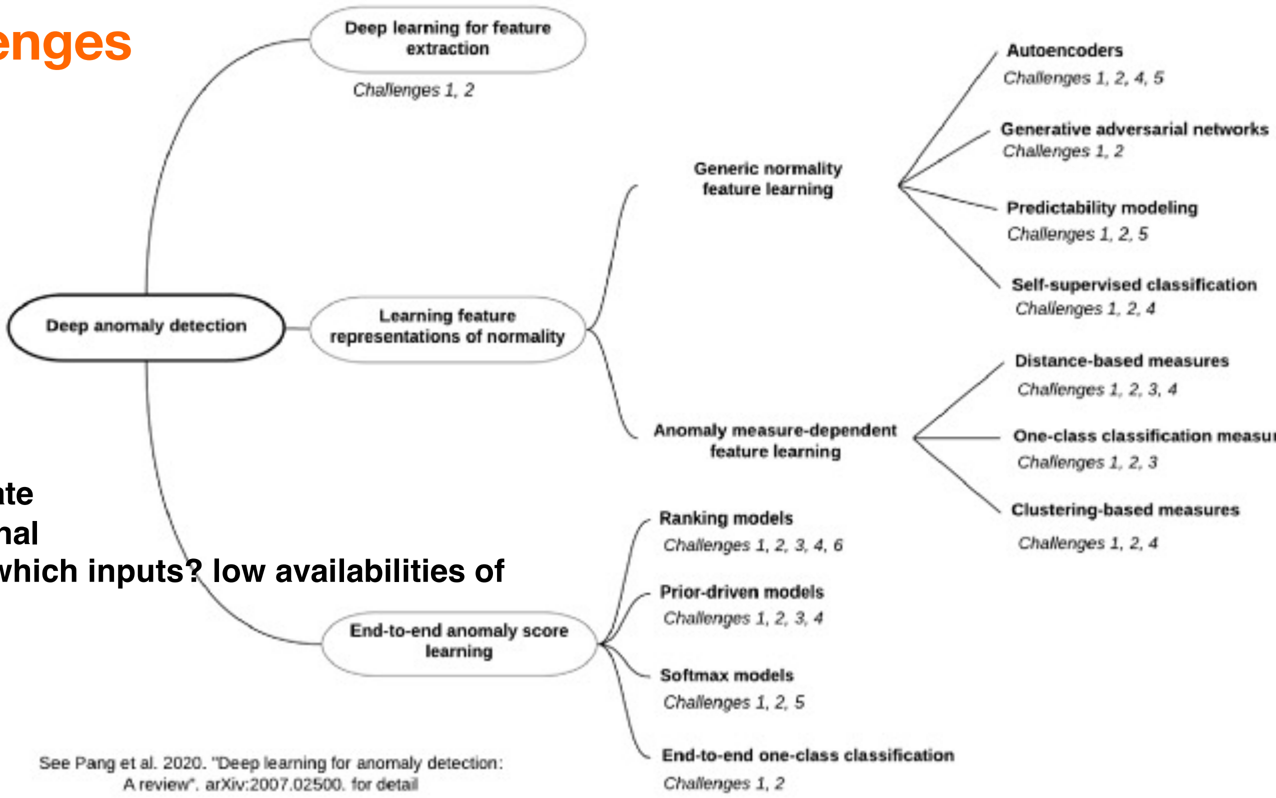
[1] Pang, Guansong, Chunhua Shen, Longbing Cao, and Anton Van Den Hengel. "Deep Learning for Anomaly Detection: A Review." *ACM Computing Surveys (CSUR)* 54, no. 2 (2021): 1–38.

1. **Anomaly explainability**
2. **High recall rate and high precision rate: difficult trade-off**
3. **Anomaly detection in high-dimensional data**
4. **Learning of normality/abnormality : which inputs? low availabilities of labels**
5. **noise-resilient anomaly detection**



Projection of the anomalies obtained from the weighted sum of Zscores of CAPS, Spikes, and Volatility (threshold = 2.5)
(known incident is shown in 7th of July 2021)

Deep learning & current anomaly detection challenges



See Pang et al. 2020. "Deep learning for anomaly detection: A review". arXiv:2007.02500. for detail

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Testing opensource explainability libraries on Network data

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2. High recall rate and high precision rate: difficult Trade of
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SHAP (SHapley Additive exPlanations) is a game theoretic approach to explain the output of any machine learning model. It connects optimal credit allocation with local explanations using the classic Shapley values from game theory and their related extensions (see papers for details and citations).

SHAP

DALEX

LIME	SHAP	ELI5	DALEX
Star 9.6k	Star 15.6k	Star 2.5k	Star 1k

Trial with Snorkel

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2. **High recall rate and high precision rate: difficult Trade of**
3. **Anomaly detection in high-dimensional : Noisy data**
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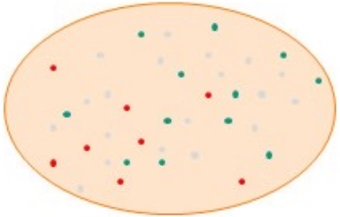
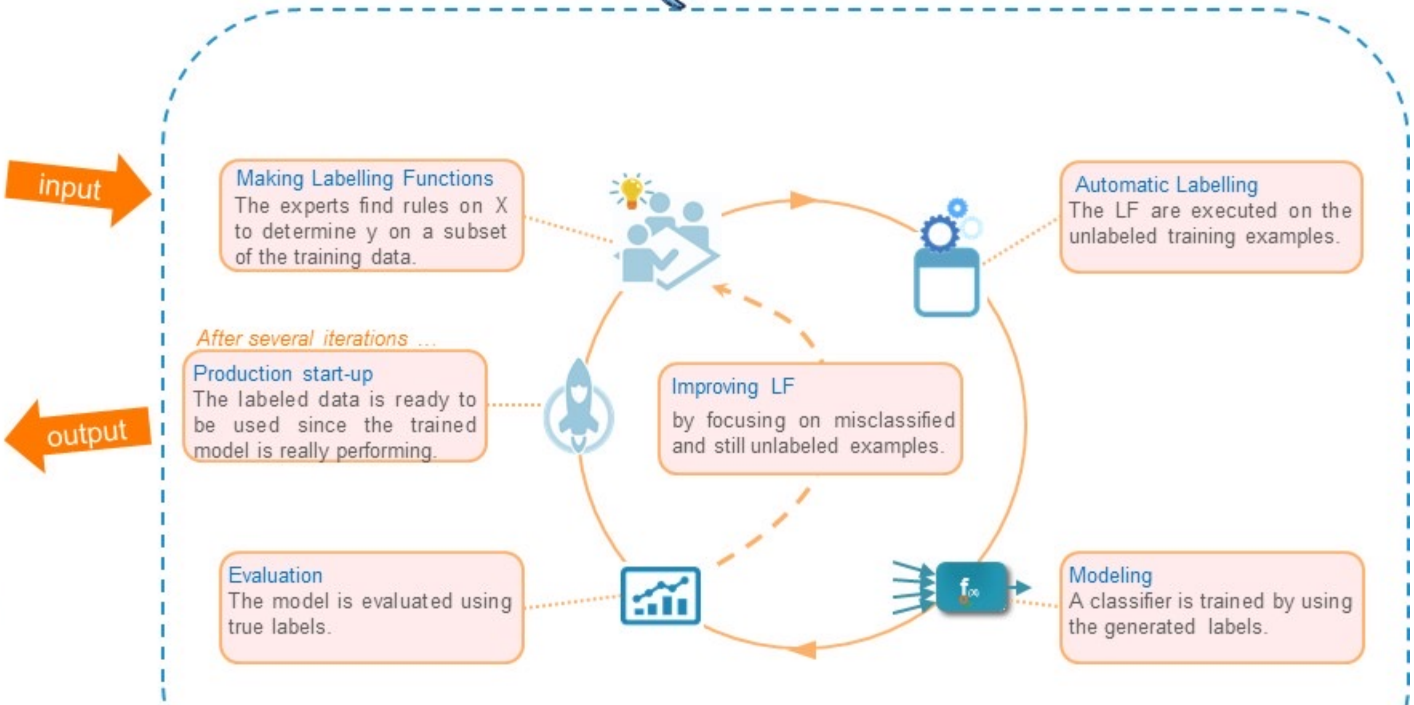
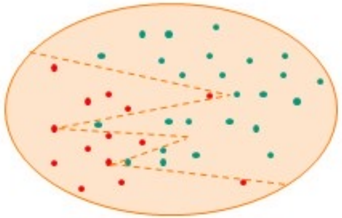
How it works



A partially labeled dataset

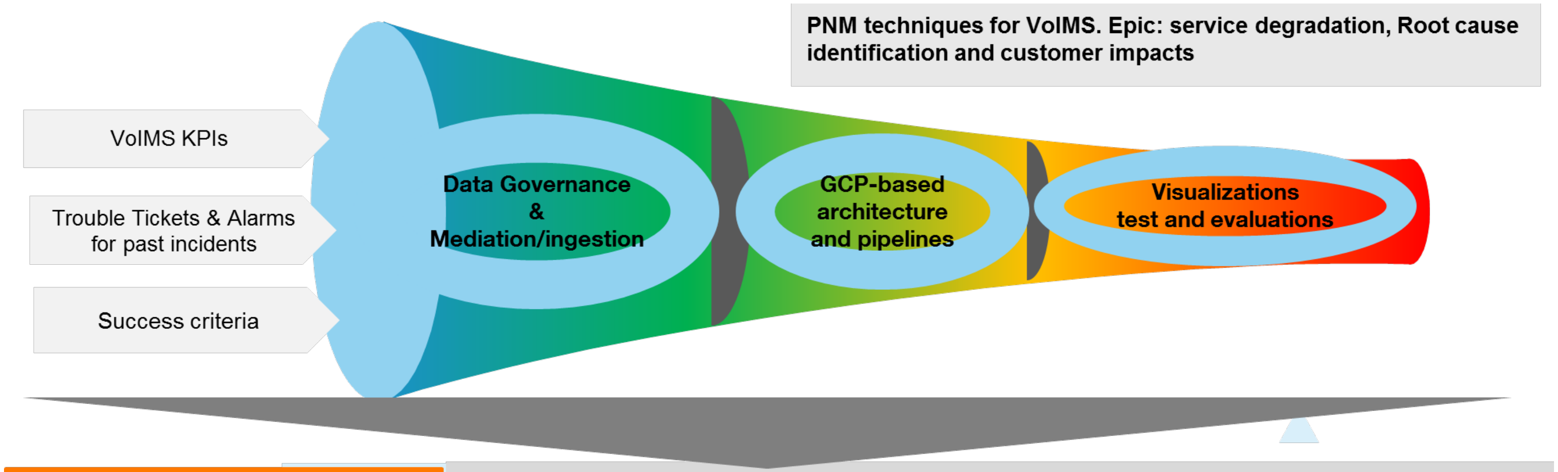




A fully (or almost) labeled dataset and the learned model

Key takeaways -1/2

from silo-ed use cases to replicable end to end approach



Common Journey

Ensuring replicability

Go Transform AI Lab Journey

common use case for PNM for mobile VoIMS

Multi-context agile development with central GCP platform + its common AI tools

Key takeaways -2/2

- Data-driven transformation with three pillars: AI, Automation and Cloudification of Network data
- Anomaly detection is a key functionality feeding the root cause and the resolution
- GCP as a reference platform for data pipeline development
- Building PNM pipelines for mobile network services with replicability by design (multi-countries context)
- Preparation of fundamentals towards AI for 5G and 5G SA, RIC, and cloud native networks

Orange Restricted

Thank you