The Evolution Towards Autonomous Networks

A Comprehensive Overview of Frameworks and Applications of AIOps

A Technical Paper prepared for SCTE by

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Abstract

Artificial Intelligence (AI) and cloud computing are two factors (among others) that allow Communication Service Providers (CSPs) to become Digital Service Providers (DSPs). CSPs, through AI, have the possibility of transforming their networks, and the operation of services. The natural evolution of applying AI to our networks ("knowledge plane"), is what has been called Autonomous Networks. Networks that can be self-configured, self-healing, self-evolving and self-optimizing. In this paper we will present the journey that we have started in the data-driven operation of our networks and services (AIOps) and the use cases with which we seek to reach autonomous networks. Like also the discussion of some frameworks, the challenges and how long this evolution will take.

Content

1. Introduction

AI Operations (AIOps) is one of the most talked-about acronyms in the IT world these days. In the last year, the term AIOps has been introduced strongly in the Telecommunications industry and has become a special topic in the main conferences [1] [2].

The term AIOps was originally coined by Gartner in 2016 and have pushed the concept into the marketplace. “AIOps combines big data and machine learning to automate IT operations processes, including event correlation, anomaly detection and causality determination” [3].

This definition applies to AIOps in enterprise IT environments: CSP typically have bigger and more complex IT environments with multiple sets of IT challenges. For a long time at the SCTE Cable-Tech Expo and other conferences, data analytics and AI / ML applications have been presented that today we would call AIOps.

A first definition of AIOps in the telecommunications industry is the use of AI for the operation of networks and services. In some way the automation of many of the processes of the operation, being the long-term objective to reach what is called autonomous networks.

Certainly, there has been a lot of activity in trying to use AIOps to improve cable network operation and customer experience. On the other hand, future networks (full virtualization and containerization) and services will generate a volume of data with exponential growth, and this poses a great challenge.

In 2018, after the merger of Cablevision S.A. (MSO) and Grupo Telecom (Telco, MNO), Telecom Argentina began a process of digital transformation, which has accelerated since the COVID 19 pandemic. We are going from being an MSO and MNO, that is, a Communication Service Provider (CSP), to a Digital Service Provider (DSP). Telecom is going to a Multiservice Convergent Network and Multi devices approach, where the Client / User can consume their own and third-party services (platforms) from any device and connected to any of our access networks.

The DSP is not merely a dumb pipe offering shared access to a common utility; it is an online, real-time business that deals with countless transactions every day, managing high volumes of data traffic and multiple devices per user, and often multiple users per account. The mobile and fixed landscape has changed dramatically and CSP's are fine-tuning their businesses, and their network infrastructure, to cater for the digital needs of the data-hungry customer.

In our networks and services, AIOps has the potential to change, the way we operate, and to become the foundation of the transformation that leads to the fourth industrial revolution. But this requires hard work, a long-term commitment, and a deep cultural change. All Operations Support Systems (OSS) in our current and future networks generate a huge amount of data.

The final aim of all these efforts is to be able to offer our services in an adequate way for our next generations of clients. They are nowadays putting the requirements in the market and driving the evolution of technologies. Our clients do not buy technologies, they buy services. Operating, managing, and provisioning future services with automation processes becomes essential. If we want a complete automation, we will need AIOps.

This technical paper proposes a comprehensive overview of frameworks and applications of AIOps, and we will present the journey that we have started in the AI-driven operation of our networks and services (AIOps) and the use cases with which we seek to reach autonomous networks. This technical paper is organized as follows. Following this section, we introduce AIOps. In section 2, we expose AIOps Service Management Framework. In section 3, we present the state of the art in the evolution towards autonomous networks, the concept of the knowledge plane and our reference architecture. Section 4 we present the AIOps use cases in Telecom Argentina. The last section, which is section 5, outlines the key challenges in our digital transformation journey that we started in 2018.

1.1. AIOps Overview

While AIOps was developed to give scalability to the management of IT systems, given their increasing complexity, the associated platforms and the AIOps framework, we can extend its applications to Telecommunications operations. AIOps has 3 main parts: *observe*, *engage,* and *act*. (Figure 1).

AIOps brings together three different IT disciplines - Service Management, Performance Management, and Automation - to achieve your continuous improvement and information goals. AIOps is the recognition that in our new accelerated and hyper-scaled IT environments, there must be a new approach that takes advantage of advances in big data and machine learning to overcome legacy tools and human limitations.

Implementing an AIOps strategy goes beyond obtaining better analysis of existing data. To create the foundation of a machine learning system that provides continuous information, you need:

- Open access to data including multiple consumable sources of streaming and historical IT data
- Machine learning and algorithms that learn behavior patterns from data and generate automated information
- Automation to act on analytical information and collaborate with the ITSM customer service center

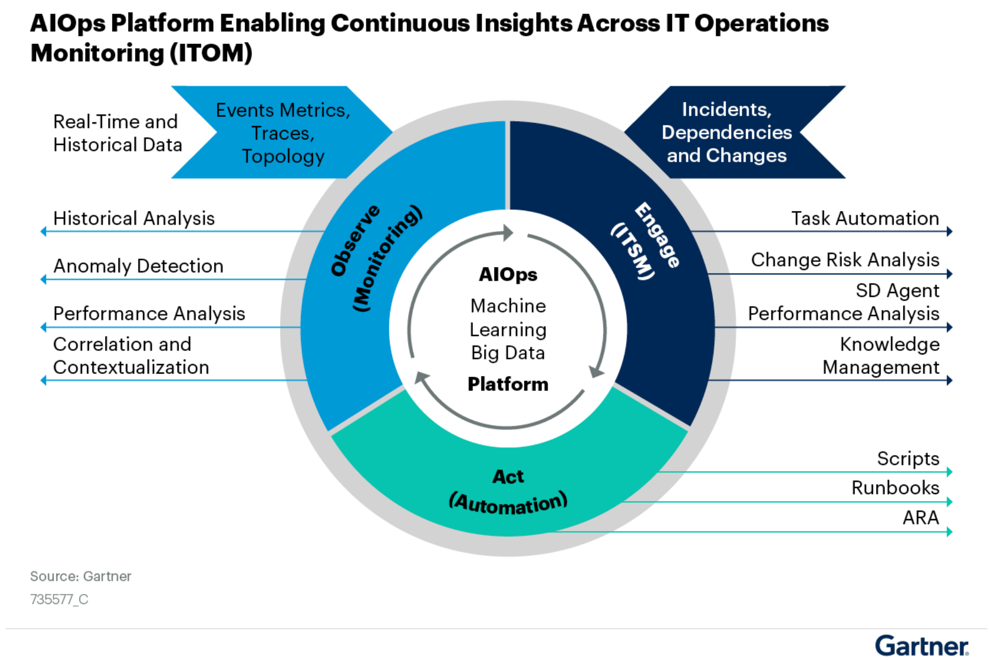

Figure 1 - AIOps for ITOM by Gartner

Various AIOps platforms have been developed in the IT world. “Nowhere is this more evident than in the world of DevOps, a data-rich, back-office practice that presents a perfect sandbox for exploring the power of artificial intelligence. The teams in charge of operations now have a burgeoning collection of labor-saving and efficiency-boosting tools and platforms on offer under the acronym AIOps, all of which promise to apply the best artificial intelligence algorithms to the work of maintaining IT infrastructure” [4].

AIOps platforms enhance decision making across I&O personas by contextualizing large volumes of operational data. I&O leaders should use AIOps platforms to improve analysis and insights across the application life cycle, in addition to augmenting IT service management and automation.

Enterprises are increasing their use of AIOps across various aspects of IT operations management (ITOM) and maturing their use cases across DevOps and SRE practices.

Enable continuous insights across ITOM by supporting these three aspects of AIOps platforms: observe, engage and act [5].

In Figure 2, we present where the AIOps platforms are in the Hype Cycle for Monitoring, Observability and Cloud Operations.

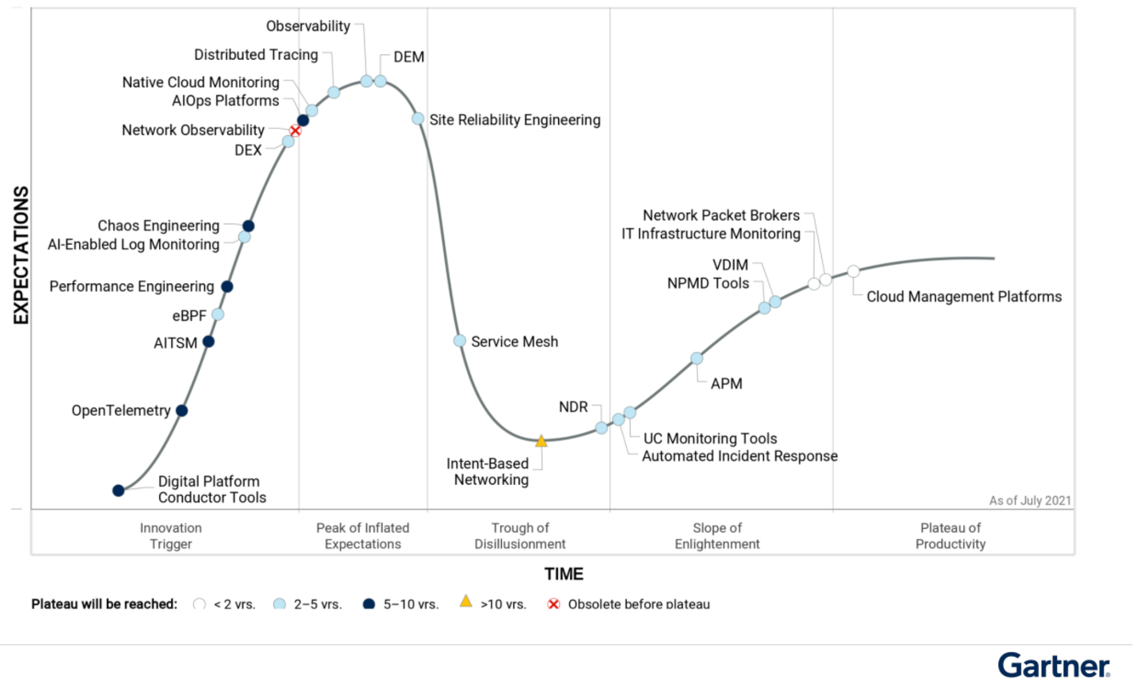

Figure 2 - Hype Cycle for Monitoring, Observability and Cloud Operations, 2021
Source: Gartner

1.2. AIOps and Cloud Native

We are building cloud native applications as a collection of smaller, self-contained microservices has helped organizations become more agile and deliver new features at higher velocity. In the Figure 3 we present the evolution in the IT world from a traditional architecture to one based on containers and the role of AIOps.

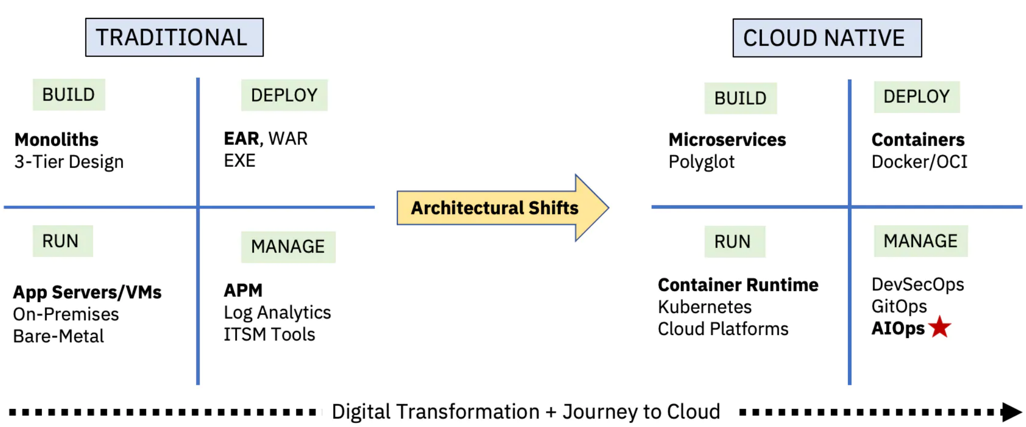

Figure 3 – Evolving IT landscape
Source: IBM[1]

[1] https://www.ibm.com/cloud/blog/aiops-a-path-to-reliability-at-cloud-scale

1.3. Future Networks and AIOps

According to the Ericsson Mobility Report [6] in 2026, 3.5 billion 5G subscriptions are forecast. The Massive IoT technologies NB-IoT and Cat-M1, in 2026, these technologies are forecast to make up 46 percent of all cellular IoT connections. Two-thirds of the world's data didn't exist five years ago, and the datasphere will grow more than 5X by 2025, according to IDC.

At Telecom Argentina our vision of 10 G and 5G is that it is not just an access technology, it is a *digital ecosystem* to create services tailored to our clients, end to end.

"5G promises to be revolutionary if CSPs, vendors, application developers and companies find how to co-create, manage and participate in a digital ecosystem" [7].

The 5G ecosystem is conceived with the technologies and architectures used by the "cloud natives[2]", its functions, services and attributes are controlled by software applications and can be exposed as an "API" or as a service adjusting to the measure of each need. Allowing to expose network capabilities and combine them with AI.

Figure 4 shows the journey towards a native cloud architecture and the level of automation, which was presented in "CableLabs Envision Vendor Forum 2021 Mobile and Convergence".

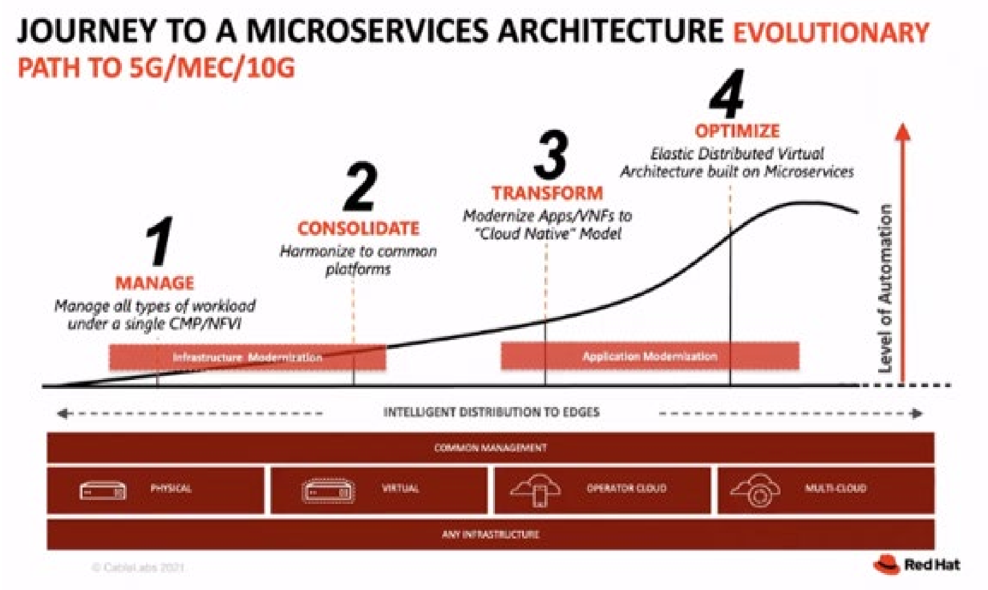

Figure 4 - Journey to a Microservices Architecture
Source: CableLabs[3]

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[2] When we deploy network functions in the cloud, we must distinguish between cloud ready, that is, network functions on virtual machines (Virtual network functions, VNFs) with deployment automation and cloud native where network functions are based on containers (cloud-native network functions, CNFs).

[3] https://community.cablelabs.com/wiki/display/COMMUNITY/Envision+2021 (members only)

The computing capacities necessary to generate the services are also distributed and can be located where it "makes the most sense" according to the need.

5G was born AIOps, since from its conception the so-called *plane of knowledge* has been included. That is, a layer within the architecture oriented to the operation and orchestration of networks and services.

1.3.1. Future Networks and AI

Although AI / ML is part of the architecture of future networks, it is important to highlight the combination of 5G, 10G and AI for the generation of new services. Future networks will provide the scalable bandwidth and remote computing power needed to collect and process the growing volumes of data that will drive the proliferation of artificial intelligence, distributing intelligence everywhere. Figure 5 shows the economic value generated by 5G and AI.

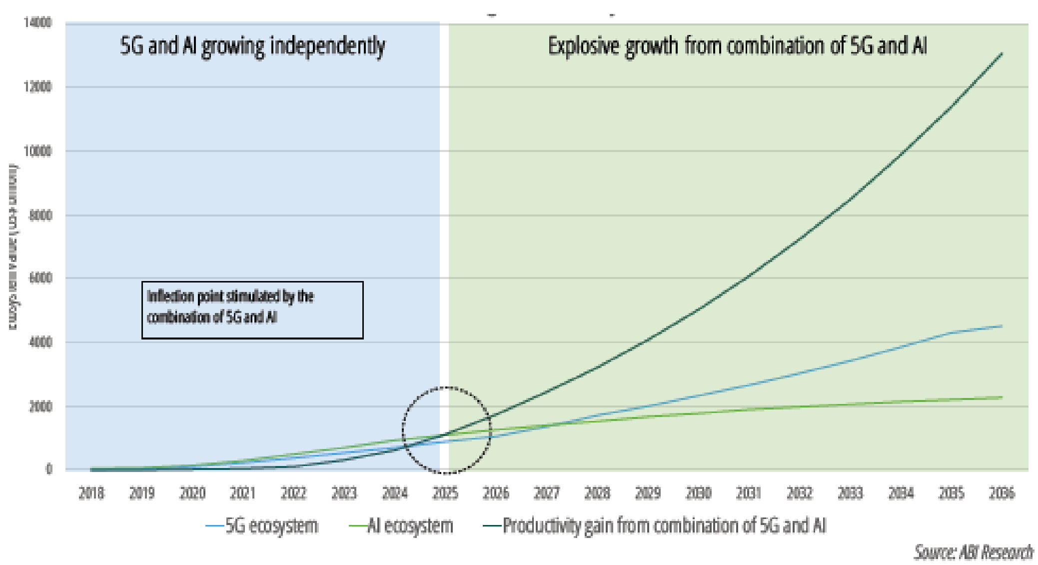

Figure 5 - Economic value generated by 5G and AI

Source: Intel[4]

2. AIOps Service Management Framework – TM Forum

The transformation affects all aspects of a CSP business, including operations that have undergone constant change since a few decades. CSP's role has shifted from offline records related to telephony services to processes that design, install, provision, activate, maintain, and manage inventory for each network-based service. AIOps, envisions a high level of AI-assisted or driven automation in IT and network operations [8].

In addition to the challenges faced by any large enterprise, CSPs include specific business and operations systems and processes, as well as new software-defined and controlled networks. Each of these environments is in flux, moving toward cloud-native architectures that can run on public, private, and hybrid (a mix of public and private) clouds. Automation of operations is the scope of AIOps for CSP,

[4] https://www.intel.la/content/www/xl/es/wireless-network/5g-ai-foundations-business-society-abi-report.html

although the teams working on AI and automation are largely separate today. Additionally, data tends to be disparate, processes can be semi-documented and inconsistently automated, and organizations tend to work in silos.

It is important to understand how different is working with AI from traditional operations. It is based on intention rather than procedure and employs non-deterministic logic and non-predictable outputs from specific inputs.

2.1. AIOps motivation

AIOps envisions a high level of AI-driven or assisted automation in IT and network operations. It's a radical leap, but critical if CSPs want to achieve their automation goals. How they get from here to there is the most important question that AIOps helps to answer.

While current technology (without AI) can automate nearly 75% of manual effort, AI is the best choice for processing extremely large data sets that combine heterogeneous data from multiple sources and where multi-domain, or cross-functional correlation is required.

In the context of our work, we adopt AIOps definition as in Figure 6, where Operations include:

1. Business processes enabled and driven by AI.
2. Service Management frameworks, processes, and tools that have been properly reengineered and adapted to support the operations management of AI-based applications and their components in Production. We call this layer *AIOps Service Management*.
3. AI-based applications that are actively running delivering business and operational services. In AIOps, we assume that key systems and their components in Production are deeply infused with AI capabilities forming a blend of AI and traditional software. In figure 1 we indicate these systems as AI-based BSS, AI-based OSS, AI-based Data Analytics, AI-based ERP, third-party AI platforms, other AI applications.
4. Infrastructure components where automation is driven by AI.

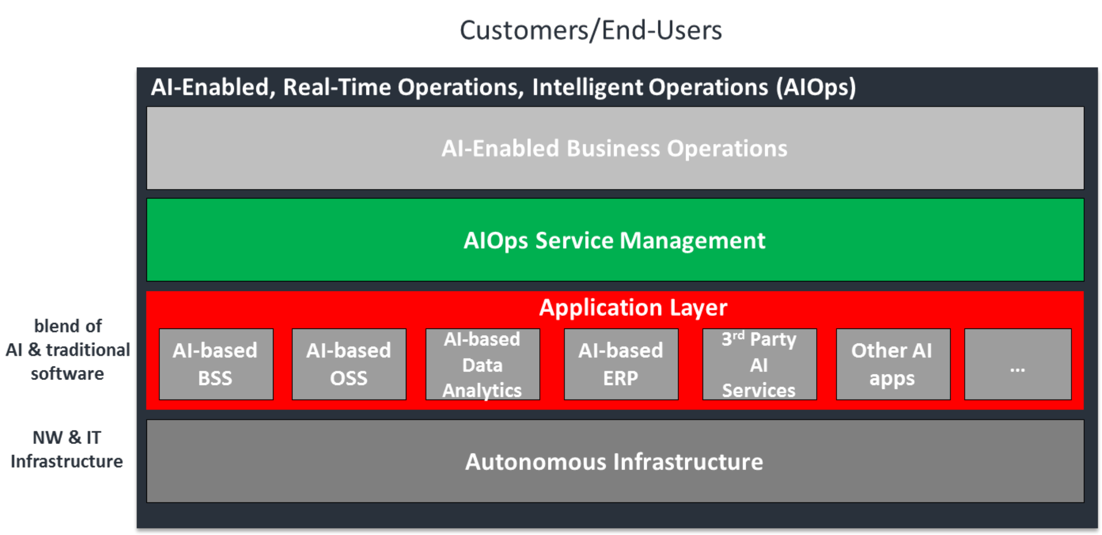

Figure 6 - AIOps and AIOps Service Management
Source: TM Forum

AI can also be a better fit than traditional software to automate responses to both repetitive analytical requirements and ever-changing network configuration and customer experience requirements.

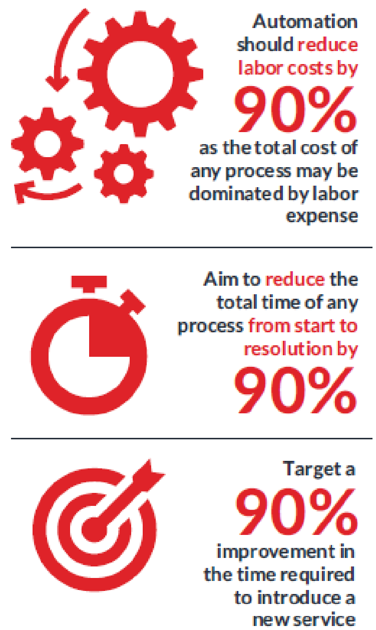

Figure 7 – Goals for AIOps
Source: TM Forum 2020, ACG Research

CSPs should take a few steps on the automation path to increase the degree of hands-on service they can deliver, regardless of the achievement of large-scale autonomous networks - many more milestones remain on that path.

2.2. AIOps Service Management processes

Within the life cycle of traditional software there are two stages: Implementation and Production.

- *Implementation*: it is the set of all the processes and activities that carry a given software and its corresponding components from the Development stage to the Production stage of the life cycle, making that software and its capabilities available to end users.

- *Production:* is the set of processes and activities that operate, monitor, support, maintain all applications and all their components in live production environments, and ensure that the capabilities and services provided by those applications are available and appropriately consumable by end users in accordance with SLA. Production is usually the stage where apps spend most of their life. We design and develop applications in days, weeks, or months. We then deploy them to Production in minutes or during an overnight rollout deployment. There, in production, applications can last for years and even decades.

In AIOps this segmentation is indistinguishable. The dynamic nature of AI software and its ability to learn and evolve autonomously while running in Production create a continuum between the Implementation and Production stages. AI components will permanently move from the deployment state to the live state and vice versa, challenging the distinguishable boundaries that currently exist between the deployment and production stages.

2.3. Real-world use cases

Some use cases based on the real-world business needs of CSPs have been developed. They are focused on customer experience, service quality, business performance, and efficiency.

These include:

- Prevention and prediction of poor customer experience
- Prediction of churn and proactive customer retention
- Accurate service level monitoring
- Proactive root cause identification, communication, and resolution in 5G networks
- Customer complaint prevention
- Preventive Maintenance
- Smart Operations and Maintenance (O&M) for Broadband Services in the Home
- Closed-loop service assurance

2.4. AIOps and Automation

The information provided by machine learning and analytics can drive automation to save time and reduce costs. An AIOps solution can provide functionality for high-value use cases, such as automated event remediation, closed-loop compliance processes, and event-driven automation. Smart ticketing can be particularly valuable as it automatically generates service tickets based on automatic anomaly detection and then optimally routes the tickets to the expert who can best fix the problem or fix the problem automatically. As a result, operators can manage a growing number of assets without increasing labor costs, freeing up staff for more valuable activities, and delivering better quality to customers.

2.5. How to start

AIOps continues an evolution in operations that began some decades ago, when teams focused primarily on offline record keeping, increasingly automated processes. This journey started with observability, moved to actionability, and now culminates in closed-loop automation. The solutions used to implement AIOps fall along similar lines.

- Analyze complex data sets to identify patterns in monitoring, capacity and automation data in hybrid on-premises and multi-cloud environments.
- Provide information that guides immediate actions to reduce costs, solve problems more quickly, and improve quality.
- Closed-loop automation: artificial intelligence and machine learning enable problems to be predicted, found, and solved without human intervention, often before they affect service quality, and to improve quality in a modern environment of software defined networks (SDN).

3. Autonomous Networks

Given the growing virtualization and cloudification (Telco-Cloud)[5] of our networks make possible the evolution towards autonomous networks. At Telecom we adopt the AIOps framework, understanding that it is the from automation path to autonomous networks (AN). "Autonomous networks, put simply, enable our engineers and technicians to go off and chase really interesting problems, leaving the less interesting problems to be operated by software systems" [9].

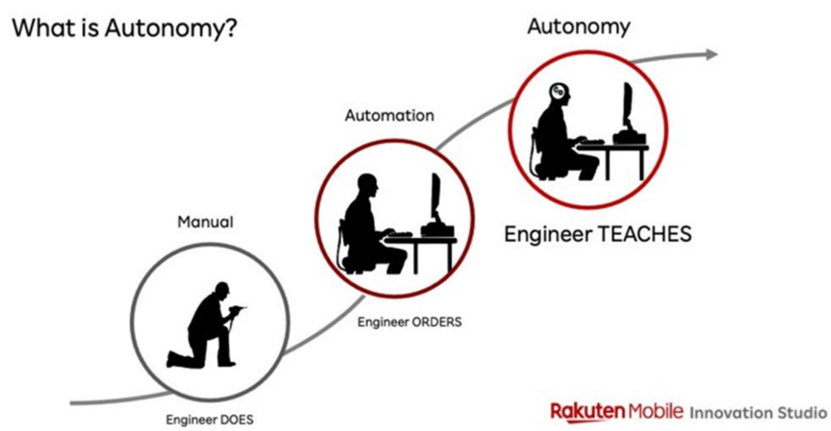

Figure 8 – What is Autonomy?
Source: Rakuten Mobile

We understand AIOps as the way to automate autonomous networks. Although today there are no autonomous networks (AN). Rakuten is the first fully virtualized network in the world, they have the privilege of being able to begin the journey of creating a truly autonomous network [10].

There are several organizations and working groups proposing frameworks, standards and how to apply the AI to automation in the networks. There are three main thrusts of AN: ETSI, ITU, and the TM Forum, which are driven by operators and vendor (Telecom Argentina is participating or is in consultation with them).

- TM Forum - Autonomous Networks Project [11].
- ITU Focus Group on Autonomous Networks (FG-AN) [12].
- ETSI Experiential Networked Intelligence Industry Specification Group (ENI ISG) [13].

3.1. Definitions

We have taken some definitions from those working groups and we started to build our own AIOps and AN framework.

- **Data Analytics**: monitoring data to look for patterns and anomalies (without applying intelligence) and applying those patterns towards effective decision making.

[5]Much of our core of the mobile network is virtualized, however the APIs are proprietary to the vendor.

- **Artificial Intelligence**: the development of computer systems capable of performing tasks that normally require human intelligence; this includes visual perception, speech recognition, decision-making, and translation between languages.

- **Machine learning**: a type of AI that gives machines the ability to learn automatically and improve from experience without being explicitly programmed.

- **Deep learning**: takes machine learning further by processing information in layers, where the result or output from one layer becomes the input for the next.

- **Automation:** within MSOs and MNOs, this means automation of processes that were previously carried out by people; AI is an enabling technology that may (or may not) help with the process of automation. Within MSOs and MNOs, this means automation of processes that were previously carried out by people like configuration, management, operation and testing of physical and virtual devices within the network. With growing costs and the daily emergence of bandwidth-hungry applications, networks cannot be managed manually. Increased levels of network automation help to reduce complexity and are essential for businesses to keep up in the digital world. AI is an enabling technology that may (or may not) help with the process of automation. What it culminates is a network that is highly predictable and highly available improving the business outcomes.

- **Cognitive computing:** like AI, cognitive computing is based on the ability of machines to sense, reason, act and adapt based on learned experience, but whereas AI acts on its analysis to complete a task, cognitive computing provides the information to help a person decide. Like AI, cognitive computing is based on the ability of machines to sense, reason, act and adapt based on learned experience. Cognitive computing refers to computing that focuses on reasoning and understanding at a higher level and in a manner that is analogous to human cognition, rationale, and judgement. Applications of cognitive computing include speech recognition, sentiment analysis, face detection, risk assessment and fraud detection. The difference between AI and cognitive computing lies in the way they approach the purpose of simplifying tasks. AI is used to augment human thinking and solve complex problems. Cognitive computing mimics human behavior and reasoning to solve complex problems like the way humans solve problems.

- **Autonomous networks:** are those that possess the ability to monitor, operate, recover, heal, protect, optimize, and reconfigure themselves; these are commonly known as the self-properties. The impact of autonomy on the network will be in all areas including planning, security, audit, inventory, optimization, orchestration, and quality of experience. At the same time, autonomy raises questions about accountability for non-human decision that affect customers" [14].

3.2. Intent-Based Networking

"Intent" is the keyword in this technology, which describes a network's business objective or an outcome.

Intent-based networking (IBN) is an emerging technology concept that aims to apply a deeper level of intelligence and intended state insights to networking. Ideally, these insights replace the manual processes of configuring networks and reacting to network issues. The goal is networking that uses machine learning and cognitive computing to enable more automation and less time spent on manual configuration and management. With intent-based networking, network administrators define the intent and the network's software finds how to achieve that goal using AI and ML by performing routine tasks, setting policies, responding to system events, and verifying that actions have been done.

These systems not only automate time-consuming tasks and provide real-time visibility into a network's activity to validate a given intent, but they also predict potential deviations to that intent, and prescribe the action required to ensure it. This greater intelligence makes the network faster and more agile and reduces errors [15].

3.3. Levels

Six levels of autonomous networks were defined by the members of the TM Forum. As shown in Figure 9.

Autonomous Levels	L0: Manual operation & maintenance	L1: Assisted operation & maintenance	L2: Partial Autonomous Networks	L3: Conditional Autonomous Networks	L4: High Autonomous Networks	L5: Full Autonomous Networks
AN services (Zero X)	N/A	Individual AN case	Individual AN case	Select AN cases	Select AN services	Any AN services
Execution	P	P/S	S	S	S	S
Awareness	P	P	P/S	S	S	S
Analysis/ Decision	P	P	P	P/S	S	S
Intent/ Experience	P	P	P	P	P/S	S

Personnel (manual) Systems (autonomous)

Figure 9 – Six Levels of Autonomous Driving Network

Source:TM Forum

Level 0 - manual management: The system delivers assisted monitoring capabilities, which means all dynamic tasks must be executed manually.

Level 1 - assisted management: The system executes a certain repetitive sub-task based on pre-configured to increase execution efficiency

Level 2 - partial autonomous networks: enables closed-loop O&M for certain units based on AI model under certain external environments, lowering the bar for personnel experience and skills.

Level 3 - conditional autonomous network: Building on L2 capabilities, the system with awareness can sense real-time environmental changes, and in certain network domains, optimize and adjust itself to the external environment to enable intent based, closed-loop management.

Level 4 - high autonomous network: Building on L3 capabilities, the system enables, in a more complicated cross-domain environment, analyze and make decision based on predictive or active closed-loop management of service and customer experience driven networks.

Level 5 - full autonomous network: This level is the goal for telecom network evolution. The system possesses closed-loop automation capabilities across multiple services, multiple domains (including partner's domains), and the entire lifecycle, achieving autonomous networks.

3.4. The Knowledge Plane

The research community has considered in the past the application of AI techniques to control and operate networks. In 2003 David Clark et. al propose the knowledge plane (KP) as a *pervasive system within the network that builds and maintains high level models of what the network is supposed to do, to provide services and advice to other elements of the network. The knowledge plane is novel in its reliance on the tools of AI and cognitive systems* [16].

The knowledge plane (Figure 10) paradigm proposes the evolution to a cognitive network, where the devices learn, decide, and act to achieve end-to-end goals. This emerging paradigm is clarifying a set of new cognitive-based protocols and algorithms that optimize network's performance.

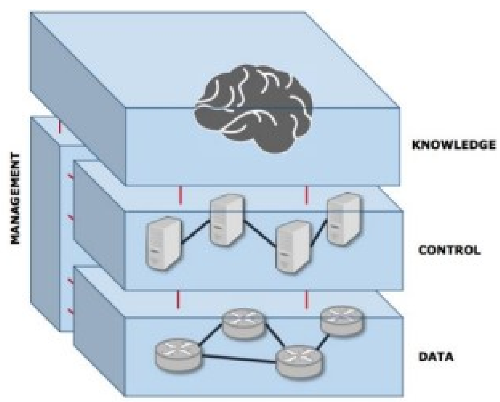

Figure 10 - The four planes in network architecture.
Source: TM Forum.

Several different KP based approaches have been proposed [17]. But it is not until the development of NFV and SDN that such proposal once again takes hold in communities such as the TM Forum, IETF, 3GPP, ETSI etc and the Industry.

In [18] progress is made in the definition of a new paradigm based on this plane. This is knowledge-defined network (KDN) operates by means of a control loop to provide automation, recommendation, optimization, validation, and estimation. The KDN paradigm is also taken by the TM Forum, ETSI and ONAP as a proposal to specify future architectures.

An example of the plane of knowledge in an SDN is presented in Figure 11 [19].

The introduction of AI and automation using AI, in short, seeks to ensure greater performance and efficiency of networks.

The paradigm shift that will be brought about by the introduction of these new technologies includes a substantial shift from a focus on network operations to a focus on the user experience.

We have conceptualized these AIOps tools that interact with the different types of networks as Knowledge Plane, a "place" where the massive amount of data obtained from the network is processed with the different

AI tools, either in real time or in a post-processing, and that, based on results, produces modifications in the network itself. This is called closed-loop automation[6].

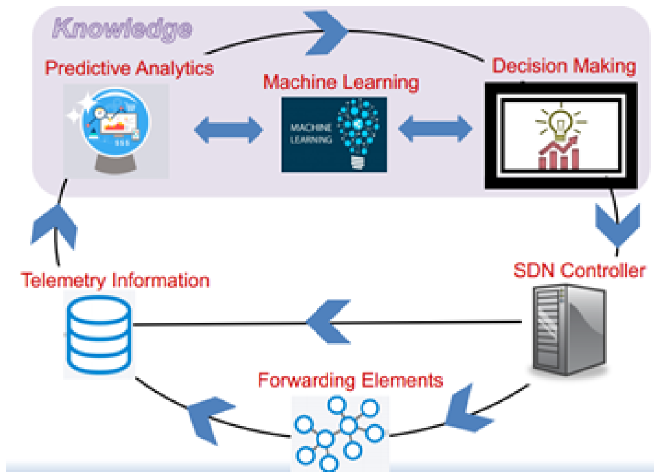

Figure 11 – Knowledge Plane in a SDN

3.5. The Knowledge Plane at Telecom

More than a decade has passed since the emergence of a paradigm of autonomous computing in the world of telecommunications. Back then, there was a gap between that paradigm and the capacities of the networks. However, a path has been taken in recent years with the adoption of cloud computing, NFV and SDN.

These technological advances have made available a more agile infrastructure, computing capacity and storage as resources more abundant than ever. Motivated by this evolution, together with the ever-growing need to improve the management and administration of networks and services, we present this first approach to the plane of KP. We adopt the knowledge plane paradigm for our Telco Cloud project.

We define a reference architecture (Figure 12) with the purpose of automating the services from end to end, with a holistic view of the network and services. It is based in the different WGs and other initiatives of other CSPs and vendors.

At the beginning, and to have a common language, a framework was defined in which the preponderance of the knowledge plane in the different layers of the network, both virtual and physical, is highlighted.

[6] Note: There are many different names for closed loop, cognitive loop, Monitor Analyze-Plan-Execute over a shared Knowledge (MAPE-K), observe–orient–decide–act (OODA), etc.

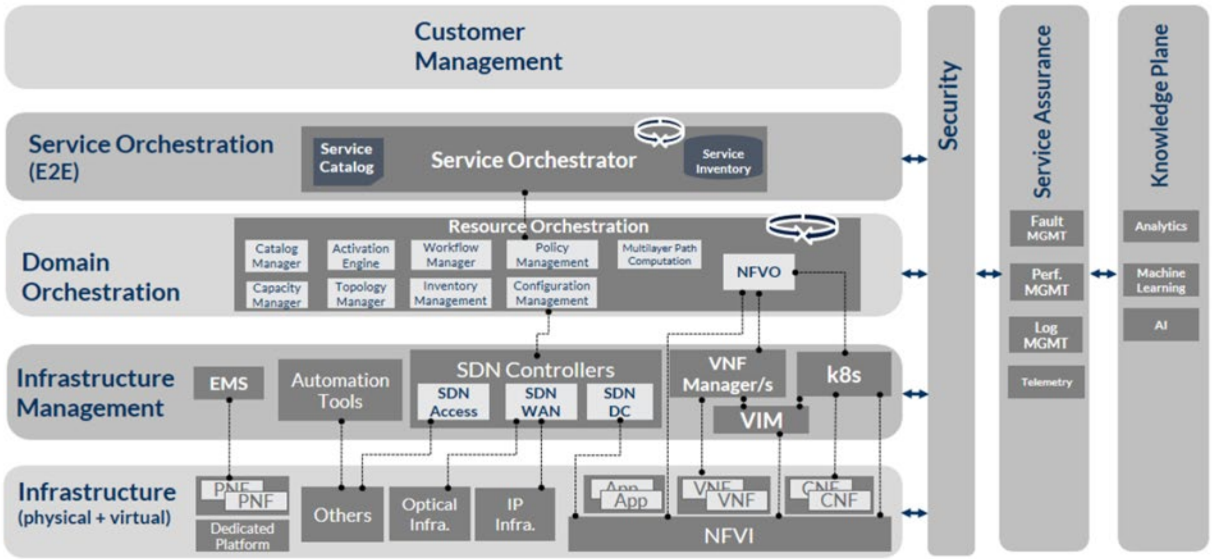

Figure 12 - Knowledge Plane Integration

There is no doubt that in the course of time this general vision will not only be modified but also specified. A result that only experience can provide.

3.6. An outline of Knowledge Plane architecture

Based on the different standards and our own experience in recent years, we can propose a conceptual architecture where two modalities of KP and Close Loops are distinguished.

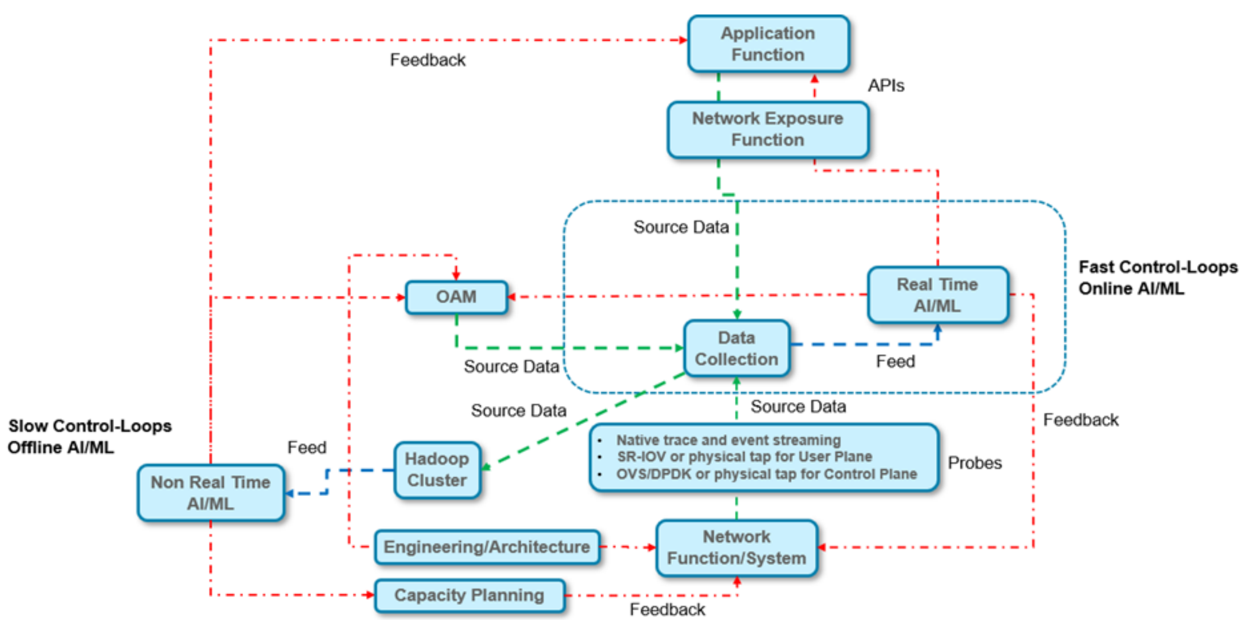

Figure 13 - Knowledge Plane architecture

Offline AI/ML (or Slow Control-Loops): based on a large amount of historical data, stored in a data lake, statistical models or other algorithms are applied (for example, time series) and the results obtained by data scientists lead to implement changes in the network, in OAM and in the long-term architecture.

Online AI/ML (or Fast Control-Loops): This instance is very dependent on:

- type of network to which it is applied
- if it is Access or Core

The information obtained from the network through probes, applications and OAM is stored in a Data Collection in real time. Then they could be combined in new tables to feed AI/ML algorithms (note that we are not putting training because it could be that the algorithm is a type of Clustering).

The Data Collection and Real Time AI/ML could be embedded in a network element or could be external to it.

As the algorithm works in real time, it would be necessary to prepare it, to test it with real data, making a pre-processing in laboratory before taking it to production, with a portable solution (for example Kubernete/KubeFlow) in a process of continuous improvement of the software. The result of the algorithm feeds back directly to the network elements, OAM, and applications. Obviously, the supervision of a human expert should be constantly validating the automated work of the algorithms ("He Teaches").

3.7. AI Techniques in Network Automation

Many techniques that can be used for decision making with each providing different cognitive capabilities. Many offer inference capabilities and only a few offer perceptive capabilities, so it is important to identify the problem requirements to choose the right technology. Figure 14 summarizes the comparative capabilities of the technologies [20].

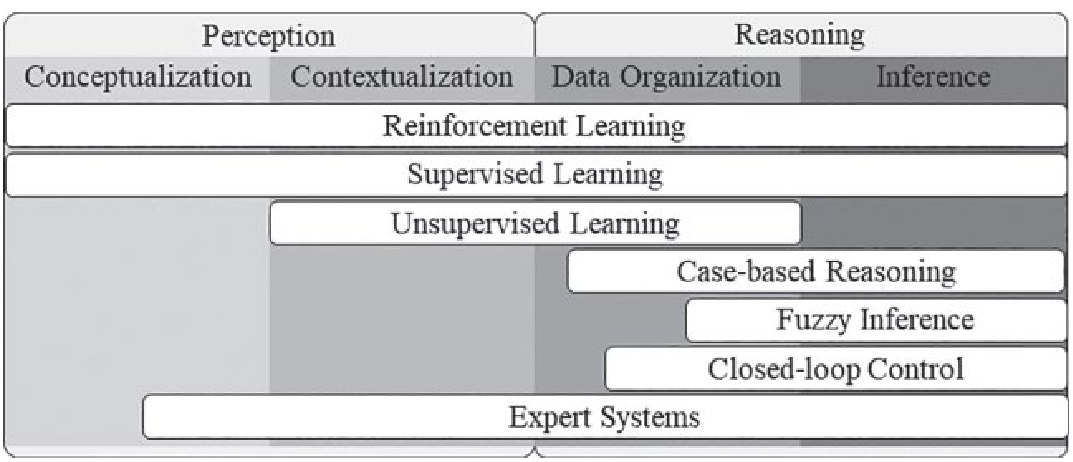

Figure 14 - Capabilities of the different automation techniques.

4. AIOps at Telecom Argentina

At Telecom, there are a few initiatives that we have considered within the AIOps framework. We believe that it is important that they are seen under the focus of Augmented Intelligence. Nowadays, as a STEM team one of our missions is to lead AIOps in our current and future networks. Our recipe within STEM team is diversity, work in cells, agile mindset, and self-learning. In the following sections we present two of the initiatives we have been working on.

4.1. Ada

At Telecom Argentina, we have been working on a tool for network dimensioning for some time now [21]. In 2017 we developed STEM-ML for Cablevisión, a tool that assisted the decision-making process for the dimensioning of the HFC network. Later, we decided to incorporate data from the radio-access network (RAN) and relaunched the project under the name Ada[7]. The goal is to have a tool that combines machine learning and SME input to assess decisions on CAPEX and OPEX investments.

Historical data is collected for every HFC node, as well as for every cell on the mobile network. The idea is that for decisions in the short term (up to a year from the present), ML-based forecasts are provided, and the role of experts is to set priorities and act based on them. For long-term decisions (5-10 years periods), on the other hand, ML-based forecasts would require a longitude of history that hasn't yet occurred. In our experience, however, it is possible to provide reasonable approximations if forecasts are supported not only by historical data but also by experts' knowledge. Hence, we are currently working on finding ways for the experts to pass input to ML algorithms.

In the past, planning engineers used to research on potential scenarios and make a series of calculations to approximate what they thought was going to happen in the long-term, based on their knowledge of the average client and use cases. Working together, we built profiles for the operating sectors, so they can refine on what would be expected from a variety of use cases. To better understand this, let's see that for example, the case of a group of households where the service is mostly used to check social media, and the income is low will not be the same as in another group of households where there are heavy streamers, and the income is higher. We are providing the planning teams with better information to start with.

As this paper is being written, we are working on how to enable engineers to pass information to a model about what they expect the CAGR would be at different kinds of operating sectors, in the next 5-10 years. This will involve a combination of simulation and forecasting techniques. Also, it will require a certain level of automation that would not be achievable outside a ML framework.

4.2. Customer claim prediction

Within the domain of AIOps one of the most popular use cases is customer claim or tickets prediction [22] [23]. The main idea is to use information derived from different elements of the network, such as: CMTS, cablemodems, electronic devices, etc. to estimate the probability of a customer to generate a complain.

Information is generally collected through OSS systems and ingested in a machine learning (ML) pipeline where preprocessing, analysis and ML model testing is performed. We are currently developing this kind of solution to ultimately increase customer satisfaction.

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[7] The Ada name of the AIOps tool for planning the mobile network and HFC, is in honor of who is considered the first programmer in history, Ada Lovelace (1815-1852)

Using hourly collected information from over 1.2 million DOCSIS 3.0 cablemodems we are trying to anticipate customer complains two days in advance. To handle this amount of data we have partnered with Google[8] to develop and deploy this project using Google Cloud Platform (GCP) services. Although we are in preliminary stages (MVM1), many steps have been given towards the final implementation.

Potentially relevant variables (e.g., signal to noise ratio, consumed bytes, average Rx, t3 and t4 time outs, etc.) have been identified and our Service Assurance team have been able to efficiently transfer these data, collected by our OSS systems, to GCP.

Daily, cablemodem and customer claims are transferred to a relational database mounted on GCP. After the data is successfully ingested, an automated data cleansing process is run using Big Query[9] to guarantee a proper information quality level. In addition, a Data Studio[10] dashboard has been created to double check this already curated information. We have found very useful to quickly visualize quality KPIs, such as: MAC Addresses count, percentage of missing values, customer claim evolution, etc.

Even though the data cleansing stage is run over the whole data set, we are using a different strategy to develop and test different ML models. Two random samples containing 10,000 and 50,000 cablemodems are being taken to accelerate the processes of feature engineering, hyper parameter tunning, model evaluation and model selection.

We are exploring different approaches to maximize precision and recall metrics[11].

At time this document is being written, we have tried a series of XGBoost models with different sets of hyperparameters[12] and feature engineering scenarios. We are also working on a different approach, reframing the whole task as a survival analysis problem. Furthermore, we are considering using recurrent neural networks to capitalize the sequential structure of the cablemodems metrics data.

Regarding technical challenges, two of the most difficult tasks have been dealing with an extremely unbalanced dataset and label noise. Although from a business perspective having a low proportion of customer claims is a good indicator, some ML models can struggle to learn from these kind of data sets. In our case, after filtering the target population (DOCSIS 3.0 residential customers), the positive class dropped to 0.1%, which added more complexity to the problem. To reduce the impact of this issue on model performance we applied hyperparameter tunning[13] and a technique called SMOTE [24] combined with an under sampling of the majority class. Both approaches led to improvements in model performance.
On the other hand, records are not always properly labeled. Some customers, for example, don´t make a complain, even when their cablemodem is not working adequately. This leads to label overlapping. Some cases that should have been labeled as positive get labeled as negative, hence, remaining in the same region in the feature space of the positive class with the opposite ground truth label. To handle this problem, we have used a Python package for confident learning called Cleanlab [25]. The main idea of this approach is to run a model and remove cases that have been confidently classified within a class when their ground truth label corresponds to another class.

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[8] Telecom Argentina adopted a multi-cloud strategy On-Premises, Amazon, Azure and Google.
[9] As stated from Google in their web page, Big Query is a: "Serverless, highly scalable, and cost-effective multicloud data warehouse designed for business agility"
[10] Google tool for data analysis and visualization.
[11] We found these two metrics to be the best way to measure model performance based on the characteristics of the data set (e.g., highly unbalanced) and business needs (maximize precision to avoid as many false positives as possible)
[12] We have performed random search, and we are currently changing to a Bayesian optimization approach.
[13] We searched for the best value of "scale_pos_weight", the hyperparameter used by XGboost to handle unbalanced classes.

We have been able to overcome many challenges and, although we are still in initial phases of this project, we hope to deploy a state-of-the-art ML system to give one more step towards AIOps goal: fully automated networks.

Finally, with the aim of showing a high-level view of our project, the Figure 15 below describe the data flow and the desired outcomes.

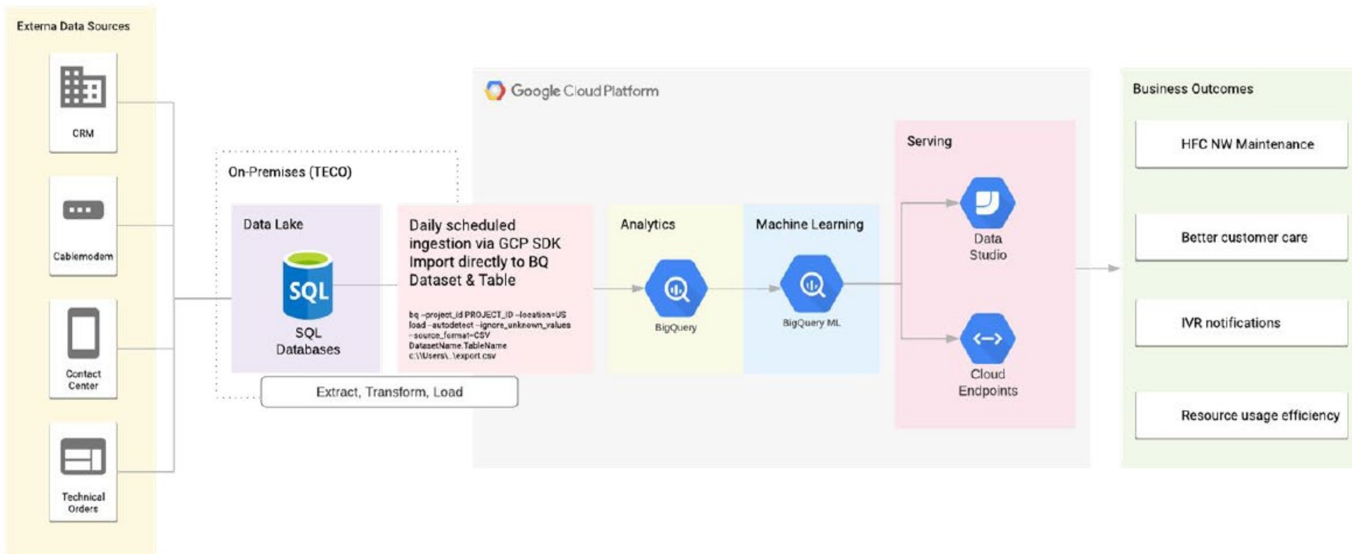

Figure 15 - Data Flow and outcomes

We are currently including DOCSIS 3.1 cablemodems in the first model (MVM 2) and starting field tests working with Service Quality, Field Service and Customer Experience teams.

On the other hand, we are beginning to define the MVM 3 related to a closed loop system to impact the QoE of some of our services. That is, with AIOps frameworks, starting our journey from automation to autonomous networks.

5. Conclusions

Throughout this technical paper we have seen the need to automate the operations of our current and future networks using artificial intelligence, presenting the AIOps framework that we have adopted in Telecom Argentina. This adoption was accelerated during the beginning of the pandemic that has produced an enormous change in our organization. However, we are still on the path of digital transformation and AIOps plays a fundamental role.

Within this transformation, however, there is something in which we cannot apply AIOps, it is in interpersonal skills that will not be able to be replaced. We must develop the empathy, collaboration, and autonomy of our work teams. On the other hand, although the path of AIOps is from automation to autonomous networks, we must not forget that we must see it from the perspective of Augmented Intelligence (AgI).

"While Artificial Intelligence is creating machines to work and react like humans, Augmented Intelligence is using those same machines with a different approach to improve human capabilities. In fact, AgI involves people and machines working together, leveraging their own strengths to achieve greater business value. In other words, the primary goal of AgI is to empower humans to work better and smarter" [26].

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Abbreviations

10G	10th generation
3GPP	3rd Generation Partnership Project
4G	4th generation
5G	5th generation
AgI	augmented intelligence
AI	artificial intelligence
AIOps	artificial intelligence operations
AN	autonomous networks
API	application programming interface
BSS	business support system
CMTS	cable modem termination system
CNF	cloud-native network function
CSP	communication service provider
DOCSIS	data over cable service interface specification
DSP	digital service provider
ENI ISG	experimental networked intelligence industry specification group
ERP	enterprise resource planning
ETSI	European Telecommunications Standards Institute
FG-AN	focus group on autonomous networks
GCP	Google Cloud Platform
HFC	hybrid fiber-coaxial
I&O	infrastructure and operations
IBN	intent-based networking
IETF	Internet Engineering Task Force
IoT	internet of things
IT	information technology
ITOM	IT operation management
ITSM	IT service management
ITU	International Telecommunication Union
KDN	knowledge-defined network

KP	knowledge plane
KPI	key performance indicator
MAC	media access control
MAPE-K	monitors analyze-plan-execute over a shared knowledge
ML	machine learning
MNO	mobile network operator
MSO	multiple system operator
MVM	minimum viable model
NB-IoT	narrow band IoT
O&M	operations and maintenance
OAM	operations, administration, and maintenance
OODA	observe–orient–decide–act
OSS	operations support systems
QoE	quality of experience
RAN	radio-access network
SCTE	Society of Cable Telecommunications Engineers
SDN	software defined networks
SLA	service level agreement
SMOTE	synthetic minority over-sampling technique
SRE	site reliability engineering
STEM	science, technology, engineering, and mathematics
VNF	virtual network function
WG	working group

Bibliography & References

[1] AIOPS 2020 International Workshop on Artificial Intelligence for IT Operations Available: https://aiopsworkshop.github.io/.

[2] AIOps Expo Florida 2021 Available: https://www.aiopsexpo.com/.

[3] Available: https://www.gartner.com/en/information-technology/glossary/aiops-artificial-intelligence-operations.

[4] Available: https://www.cio.com/article/3625580/top-aiops-platforms.html?upd=1626871907417.

[5] P. Prasad, P. Byrne, J. Chessman, Market Guide for AIOps Platforms, Published 6 April 2021 - ID G00735577 - 2021. Available: https://www.gartner.com/en/documents/4000217/market-guide-for-aiops-platforms.

[6] Available: https://www.ericsson.com/4a03c2/assets/local/mobility-report/documents/2021/june-2021-ericsson-mobility-report.pdf.

[7] T. McElligott, 5G future: Targeting the enterprise 9 2019. Available: https://inform.tmforum.org/research-reports/5g-future-targeting-the-enterprise/.

[8] E. Finegold, AIOps: From Automation to Autonomous Networks 12 2020. Available: https://inform.tmforum.org/research-reports/ai-ops-from-automation-to-autonomous-networks/.

[9] 6 2021. Available: https://rakuten.today/blog/rakuten-mobile-edge-computing-hub.html.

[10] R. Mobile, «Evolving Autonomous Networks,» Available: https://netlab.mobile.rakuten.co.jp/.

[11] T. Forum, «Autonomous Networks Project,» Available: https://www.tmforum.org/collaboration/autonomous-networks-project/.

[12] «ITU (FG-AN),» Available: https://www.itu.int/en/ITU-T/focusgroups/an/Pages/default.aspx.

[13] «ETSI - ENI,» Available: https://www.etsi.org/technologies/experiential-networked-intelligence.

[14] «ITU-T (FG-AN),» Available: https://www.itu.int/en/ITU-T/focusgroups/an/Documents/FG-AN_Terms_of_Reference.pdf.

[15] U. Gasser, V. A. F. Almeida, *A Layered Model for AI Governance,* IEEE Internet Computing 21 (6) (November): 58–62. doi:10.1109/mic.2017.4180835., 2017.

[16] D. D. Clark, C. Partridge, J. C. Ramming, J. T. Wroclawski, *A Knowledge Plane for The Internet,* New York: Conference on Applications, Technologies, Architectures and Protocols for Computer Communications (SIGCOMM), 2003.

[17] K. R. Sollins, «An Architecture for Network Management,» de *Workshop on Re-Architecting the Internet (ReArch)*, New York, NY, 2009.

[18] A. Mestres, A. Rodriguez-Natal, J. Carner, P. Barlet-Ros, et.al., *Knowledge-Defined Networking,* SIGCOMM Computer Communications, vol. 47, nº 3, pp. 2-10., 2017.

[19] Z. Zhu, *Knowledge-Defined Network Orchestration in a Hybrid Optical/Electrical Datacenter Network,* Dublin, Ireland: Conference on Optical Network Design and Modeling, 2018.

[20] S. S. Mwanje, C. Mannweiler, Towards Cognitive Autonomous Networks, Wiley, 2020.

[21] C. Righetti, M. Fiorenzo, E. Gibellini, et.al., *Network Capacity and Machine Learning,* SCTE Cable Tec Expo 2017, 2017.

[22] J. Hu, et.al., *CableMon: Improving the reliability of cable broadband networks via proactive network maintenance.,* 17th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 20), p. 619-632., 2020.

[23] J. Watson, R. Brooks, A. Colby, Christian, P. Kumar, A. Malhotra, M. Jain, *Predicting Service Impairments from Set-top Box Errors in Near Real-Time and What to Do About It,* SCTE Cable-Tec Expo 2018, 2018.

[24] N. V. Chawla, et.al., *SMOTE: synthetic minority over-sampling technique.,* Journal of artificial intelligence research, 2002, vol. 16, p. 321-357., 2002.

[25] C. NORTHCUTT, L. JIANG, I. CHUANG, *Confident learning: Estimating uncertainty in dataset labels.,* Journal of Artificial Intelligence Research, 2021, vol. 70, p. 1373-1411, 2021.

[26] C. Righetti, E. Gibellini, et.al., *Augmented Intelligence: Next Level Network and Services Intelligence,* SCTE NCTA CableLabs 2020 Fall Technical Forum, 2020.

