Research Challenges in Artificial Intelligence for Network Management

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**Abstract**

To be completed

This document is intended to introduce the challenges to overcome when network management problems may require the use of AI solutions. There are many difficult problems in Network Management that to this date have no good solutions, or where any solutions come with significant limitations and constraints. Artificial Intelligence may help produce novel solutions to those problems.

To identify the right set of challenges, the document must define a method based on the evolution and nature of NM problems. This will be done in parallel with advances and the nature of existing solutions in AI in order to highlight where AI and NM have been already coupled together or could benefit from a higher integration. So, the method aims at evaluating the gap between NM problems and AI solutions. Challenges are derived accordingly assuming solving these challenges will help to reduce the gap between NM and AI.

Table of content

[1. Introduction 2](#_Toc98940103)

[2. Difficult problems in network management 3](#_Toc98940104)

[3. AI techniques for network management 5](#_Toc98940105)

[3.1. Problem type and mapping 5](#_Toc98940106)

[3.2. Performance of produced models 7](#_Toc98940107)

[3.3. Lightweight AI 8](#_Toc98940108)

[3.4. AI for planning of actions 9](#_Toc98940109)

[3.5. Distributed AI 11](#_Toc98940110)

[4. Data-driven AI 11](#_Toc98940111)

[4.1. Data for AI-based NM solutions 11](#_Toc98940112)

[4.2. Data collection 12](#_Toc98940113)

[4.3. Usable data 13](#_Toc98940114)

[5. Acceptability of AI 13](#_Toc98940115)

[5.1. Explainability of Network-AI products 14](#_Toc98940116)

[5.2. AI-based products and algorithms in production systems 14](#_Toc98940117)

[6. Definitions and Acronyms 15](#_Toc98940118)

[7. Conclusion 15](#_Toc98940119)

[8. References 15](#_Toc98940120)

## Introduction

*[This section must emphasize the unavoidable needs of AI technologies in future networks]*

NM scope is very large by nature ranging from monitoring to accountability by also security functions. The taxonomy defined in [Hoo18] extends the common FCAPS domains by considering additional functional areas but above all by promoting additional views. For instance, network management approaches can be classified according to the technologies, methods or paradigms they will rely on. Methods include common approaches as for example mathematical optimization or queuing theory but also techniques which have been widely applied in last decades like game theory, data analysis, data mining and machine learning. In management paradigms, autonomic and cognitive management are listed. As highlighted by this taxonomy, the definition of automated and more intelligent techniques have been promoted to support efficient network managements operations. Especially, research in NM and more generally in networking has been very active in the area of applied ML [Bou18].

However, for maintaining network operational in pre-defined safety bounds, NM still heavily rely on established procedures [CITE]. Even after several cycles of adding automation, those procedure are still mostly fixed in the sense that the exact control loop is and all possibilities are defined in advanced. Obviously, there have been a lot of proposition to make network smarter or intelligent with the use of ML but without large adoption for running real networks.

ML is a sub-area of AI that concentrates the focus nowadays but AI encompasses other areas including knowledge representation, inference rule engine, statistical methods or by extension the techniques that allows to observe and perform actions on a system.

It is thus legit to question if ML or AI in general could be helpful. This question is actually tight with the problems the NM aims to address. Independently of NM, ML solutions were introduced to solve in approximate way one type of problem which are very complex in nature when, i.e. finding an optimal solution is not possible. This is the case for NP-hard problems. In those cases, solutions typically rely on heuristics that may not yield optimal results, or algorithms that run into issues with scalability and the ability to produce timely results due to the exponential search space. In NM, those problems exists, for instance allocation of resources in case of service function chaining or network slicing among other are recent examples which have gained interest in our community with SDN. Many propositions consist into defining the problem as an ILP with some heuristics to reach a satisfactory of scalability. Hence, ML is well adapted to progress on this type of problem [Kaf19].

However, all problems of NM are not NP-hard. Due to real-time constraints, some involve very short control loops that require both rapid decisions and the ability to rapidly adapt to new situations and different contexts. So, even in that case, time is critical and approximate solutions are usually more acceptable. Again, it is where AI can be beneficial. Actually expert systems are AI systems [Ste92] but this kind of systems are not designed to scale with the volume and heterogeneity of data we can collect in network today for which the expert system must be built thanks to numerous inference rules. In contrast, ML is more efficient to automatically learn abstract representations of the rules, which can be eventually updated.

Finally, many problems also still rely on humans in the loop, from support issues such as dealing with trouble tickets to planning activities for the roll-out of new services. This creates operational bottlenecks and is often expensive and error prone. This kind of tasks could be either automated or guided by an AI system to avoid human bias. Indeed, the balance between human resources and problems to deal with is actually very imbalanced and this will continue to increase due to the size of network, heterogeneity of devices, services, etc. Hence, human-based procedures tend to be simple in comparison to the problem to solve or time-consuming. For example, they are not tailored to deal with a totally new problem. Notable examples are in security where the network operator must defend against potential unknow threat. As a result, services might be largely affected during hours

Actually, all the problems aforementioned are exacerbated by the situation of more complex network to operates on many dimensions (users, devices, services, connections, etc.). Therefore, AI is expected to enable or simplify the solving of those problems in real networks in a close future [CZB20,Yan20] because those would require to reach unprecedented levels of performances in terms of throughput, latency, mobility, security, etc.

*[Add here a short paragraph to explain how the document is organized]*

## Difficult problems in network management

[The goal of this section is to highlight what are the main criteria making NM problems hard which thus require AI and then classify some of them according to that. This is somehow a more “formal” representation of issues provided in introduction]

As mentioned in introduction, problems to be tackled in NM tends to be more complex in regards to different criteria:

 C1. A very large solution space, eventually infinite. All solutions cannot be usually tested (again NP-hard problems here)

 C2. Uncertainty and unpredictability of the context the solution will be applied on. Most of network are not anymore isolated, there are many external parameters affecting the efficiency of the solution to a problem and they cannot be known in advance: user activity, interconnected networks, etc.

 C3. The need to deliver a solution in a constrained or deterministic time.

 C4. Data-dependent solutions. To solve accurately a problem, it can be necessary to rely on data with all subsequent problems (collection and heterogeneity of data, large volume)

 C5. Need to be integrated with human processes

Many of problems are affected bu multiple criteria. Below is a non-exhaustive list of complex NM problems for which AI and/or non-AI solutions have been proposed:

* Computation of optimal paths: packet forwarding is not always based on traditional routing protocols with least cost routing, but on computation of paths that are optimized for certain criteria - for example, to meet certain level objectives, to result in greater resilience, to balance utilization, to optimize energy usage, etc. Many of those solutions can be found in SDN, where a controller or path computation element computes paths that are subsequently provisioned across the network. However, such solutions generally do not scale to millions of paths (C1), and cannot be recomputed in sub-second time scales (C3) to take into account dynamically changing network conditions (C2). To compute those paths, operations research techniques have been extensively used in literature along with AI methods as shown in [Lop20].
* Classification of network traffic: without loss of generality a common objective of network monitoring for operators is to know the type of traffic going through their networks (web, streaming, gaming, VoIP). By nature, this task analyzes data (C4) which can varies over time (C2) except in very particular scenarios like industrial isolated networks. However, the output of the classification technique is time-constrained only in specific cases where fast decisions must be made, for example to reroute traffic. Simple identification based on IANA-assigned TCP/UDP ports numbers were sufficient in the past. However with applications using dynamic port numbers, signatures techniques can be used to match packet payload [Sen04]. To handle applications now encapsulated in encrypted web or VPN traffic, machine-learning have been leveraged [Bri19].

[Feedback on the level of details above ?, agree on the criteria list ? If so, need volunteer to develop problems below with the same level of abstraction]

(Note: some hard problems have been identified in [CZB20])

Examples of difficult problems:

* Optimization of allocation of resources.
* Troubleshooting and diagnostics.
* Distributed network debugging
* Forecasting and anticipation of traffic, of resource utilization.
* Monitoring, diagnosing, preventing production traffic leakage - ability to provide users with control of what is happening with their data while in transit.
* Solutions that provide network providers with operational visibility into what is happening on their network while preserving at the same time user privacy.
* Security - recognition of novel attack vectors, including spoofing or DDOS amplification attacks
* Intent - having systems with the ability to automatically identify courses of actions for an outcome that is desired by the user
* Scheduling problems in wireless networks (MAC, user association, workload placement, etc.)
* Slicing and slice orchestration (intrinsically multi-objective and multi-domain).
* Deployment of service components (e.g., VNFs, microservices, …), including dynamic scaling (horizontal and vertical) and placement of component instances
* We all know that layers are useful, but I think one problem is that the community is mostly trying to split AI/ML problems into solutions to single or max cross-layer problems, creating what some call AI-silos. Those are useful too, but can we think beyond that? How do we integrate network management with AI/ML without getting stuck with the ISO/OSI 7 layers seems a good problem to me to ask the community.

As shown, AI techniques are good candidates for the difficult NM problems. There have been many propositions but still most of them remain at the level of prototypes or have been only evaluated with simulation and/or emulation. It is thus questionable why our community investigates many research in this direction but did not adopt those solutions to operate real networks. networks are already operated thanks to (semi-)automated procedures involving a large number of resources which are synchronized with management or orchestration tools. Adding AI supposes it would be seamlessly integrated within pre-existing processes Although, the goal of these procedures might be solely to provide relevant information to operators through alerts or dashboards in case of monitoring applications, many other applications rely on those procedures to trigger actions on the different resources, which can be local or remote.

In next sections, we identified three main types of obstacles. First, like in any other domain, our problems have their own specificities but few efforts have been made to NM-tailored AI algorithms, methods and techniques. Second, one frequent requirement of AI is to have data as input. Inherent challenges are related to techniques to acquire or create data and represent valuable knowledge. Third, because networks are critical infrastructures, lack of guarantees with AI and the pseudo-indeterminate nature of AI impacts its acceptability in real environments.

Hence, Network-specific AI, data-driven AI and acceptability and AI for actions are not new and not unique to NM research are. However, they constitute the major obstacles to consider to unleash the power of AI for network management. The next section lists more concrete problems characterized accordingly knowing that their categorization is not hermetic, i.e. addressing a single problem can help to overcome multiple obstacles.

## AI techniques for network management

AI advances have been historically driven by image and natural language processing and robotics for many decades. As a result, the most impressive applications are in this area including recently the generalization of home assistants or the large progress in autonomous vehicles. However, the network experts have been focused on building Internet especially building protocols to make the world interconnected and with always better performance and services. This continues today with the 5G in deployment and 6G under definition. Hence, AI was not our primarily focus. However, AI is not considered as a core enabler for the future 6G networks which are sometime qualified as AI-native networks.

While we can see major contributions in AI-based solutions for network over more than two decades, only a fraction of the community was concerned by AI at that time. Progress as a whole, from a community perspective, were so limited and compensated by relying the development of AI in the communities as mentioned earlier. Even if our problems some share commonalities, for example on the volume of data to analyze, there are many differences: data types are completely different, networks are by nature heavily distributed, etc. If problems are different, they should require distinct solutions. In a nutshell, a first set challenges is about the definition of NM-oriented AI.

### Problem type and mapping

In the last few years, an increasing number of different AI techniques have been proposed and applied successfully to a growing variety of different problems in different domains. Some of the more recently proposed AI approaches are clearly advancements of older approaches, which they supersede. Many other AI approaches are not predecessors or successors but simply complementary because they are useful for different problems or optimize different metrics.In fact, different AI approaches are useful for different kinds of problem inputs (e.g., tabular data vs. text vs. images vs. time series) and also for different kinds of desired outputs (e.g., a predicted value, a classification, or an action). Similarly, there may be trade-offs between multiple approaches that take the same kind of inputs and desired outputs (e.g., in terms of desired objective, computation complexity, constraints).

Overall, it is a key challenge of using AI for network management to properly understand and map which kind of problems with which inputs, outputs, and objectives are best solved with which kind of AI (or non-AI) approaches. Given the wealth of existing and newly released AI approaches, this is far from a trivial task.

Sub-challenge: Suitable Approach for Given Input

Different problems in network management come with widely different problem parameters. For example, security-related problems may have large amounts of text or encrypted data as input, whereas forecasting problems have historical time series data as input. They also vary in the amount of available data.

Both the type and amount of data influences which AI techniques could be useful. Generally, in scenarios with little data, classical machine learning techniques (e.g., SVM, tree-based approaches, etc.) are often sufficient and even superior to neural networks. On the other hand, neural networks have the advantage of learning complex models from large amounts of data without requiring feature engineering. Here, different neural network architectures are useful for different kinds of problems.The traditional and simplest architecture are (fully connected) multi-layer perceptrons (MLPs), which are useful for structured, tabular data. For images, videos, or other high-dimensional data with correlation between “close” features, convolutional neural networks (CNNs) are useful. On the other hand, recurrent neural networks (RNNs), especially LSTMs, and attention-based neural networks (transformers) are great for sequential data like time series or text. Finally, Graph Neural Networks (GNNs) can incorporate and consider the graph-structured input, which is very useful in network management, e.g., to represent the network topology.

The aforementioned rough guidelines can help identify a suitable AI approach and neural network architecture. Still, best results are often only achieved with sophisticated combinations of different approaches. For example, multiple elements can be combined into one architecture, e.g., with both CNNs and LSTMs, and multiple separate AI approaches can be used as an ensemble to combine their strengths. Here, simplifying the mapping from problem type and input to suitable AI approaches and architectures is clearly an open challenge. Future work should address this challenge by providing both clearer guidelines and striving for more general AI approaches that can easily be applied to a large variety of different problem inputs.

Sub-challenge: Suitable Approach for Desired Output

Similar to the challenge of identifying suitable AI approaches for a given problem input, the desired output for a given problem also affects which AI approach should be chosen. Here, the format of the desired output (single value, class, action, etc.), the frequency of these outputs and their meaning should be considered.

Again, there are rough guidelines for identifying a group of suitable AI approaches. For example, if a single value is required (e.g., the amount of resources to allocate to a service instance), then typical supervised regression approaches should be used. If classification (e.g., of malware) instead of a value is desired, supervised classification methods should be used. Alternatively, unsupervised machine learning can help to cluster given data into separate groups, which can be useful to analyze networking data, e.g., for better understanding different types of traffic or user segments.

In addition to these classical supervised and unsupervised methods, reinforcement learning approaches allow active, sequential decisions rather than simple predictions or classifications. Reinforcement learning agents autonomously select suitable actions in a given environment and are especially useful for self-learning network management. Related to model-free reinforcement learning, model-based planning approaches (e.g., Monte Carlo Tree Search (MCTS)) also allows choosing suitable actions in a given environment but requires full knowledge of the environment dynamics. In contrast, model-free reinforcement learning is ideal for scenarios with unknown environment dynamics, which is often the case in network management.

Similar to the previous sub-challenge, these are just rough guidelines that can help to select a suitable group of AI approaches. Identifying the most suitable approach within the group, e.g., the best out of the many existing reinforcement learning approaches, is still challenging. And, as before, different approaches could be combined to enable even more effective network management (e.g., heuristics + RL, LSTMs + RL, …). Here, further research should simplify the mapping from desired problem output to choosing or designing a suitable AI approach.

Sub-challenge: Trade-Offs

A third challenge concerns trade-offs between multiple equivalent approaches. With the aforementioned rough guidelines, a suitable field of AI approaches (e.g., reinforcement learning) may be identified. Still, there are many available approaches within the field, which are all suitable choices but have different strengths and weaknesses. For example, in reinforcement learning, off policy approaches enable learning from pre-recorded experience (e.g., from human operators) and are often more sample-efficient, whereas on policy approaches are often more robust and time-efficient. Consequently, there are important trade-offs between available amount of data, available time for training and for online inference, required solution quality and stability.

Here, future work should further explore these trade-offs and provide clearer guidelines on how to navigate these trade-offs, e.g., for different network management tasks.

Current State of the Art

A Survey of Machine Learning Techniques Applied to Software Defined Networking (SDN): Research Issues and Challenges

An Overview on Application of Machine Learning Techniques in Optical Networks

Comparison of Machine Learning algorithms performance in detecting network intrusion

### Performance of produced models

From a general point of view, any AI technique will produce results with a certain level of quality. This leads to two inherent questions: (1) what is the definition of the performance in a context of a NM application? (2) How to measure it? and (3) How to ensure/improve the quality of produced results?

Many metrics have been already defined to evaluate the performance of an AI-based techniques in regards to its NM-level objectives. For example, QoS metrics (throughput, latency) can serve to measure the performance of a routing algorithms. Number of true/false positives/negatives are most basic metrics for network attack detection functions. Although the first two questions are thus already answered, question (3) refers to the integration of metrics into AI algorithms. Its objective is to obtain the best results which must be quantified with these metrics. Depending on the type of algorithm, these metrics are either evaluating in an online manner with feedback loop (for example with reinforcement learning) or in batch to test optimize a model based on a particular context (for example described by a dataset for machine learning).

The problem is two-fold. First, the performance can be measured through multiple metrics of different types (numerical or ordinal for example) and some can be constrained by fixed boundaries (like a maximum latency), making their joint use challenging when creating an AI model to resolve a NM problem. Second, the scale metrics differ from each other in terms of importance or impact and can eventually varies on their domains. It can be hard to precisely say what is a good or bad values (as it might depend on multiple other ones) and it is even more difficult to integrate in an AI technique, especially for learning algorithms adjust their models based on the performance of the produced outputs. Indeed, learning algorithms goes through multiple iterations and rely on internal metric (MAE for neural network, gini index or entropy for decision trees, distance to an hyperplane for SVMs, etc) which are not strongly correlated to the final metrics of the application. For instance, a decision tree algorithm for classification purposes aims at being able to create branches with a maximum of data from the same classes and so avoid mixing classes. It is done thanks to a criterion like the entropy index but this kind of Index does not assume any difference between mixing class A and B or A and C. Assuming now that from an operational point of view, if A and B are mixed in the predictions is not critical, the algorithm should have preferred to mix and A and B rather than A and C even if in the first case it will produce more errors.

Therefore, the internal functioning of the AI algorithms should be refined, here by defining a particular criterion to replace the entropy as a quality measure when separating two branches. It assumes that the final NM objectives must be integrated at this stage.

Another concrete example is traffic predictors which aim at forecasting traffic demands. They only produce an input that is not necessarily simple to be interpreted and used by, e.g., capacity allocation strategies/policies. A traditional traffic prediction that tries to minimize (perfectly symmetric) MAE/MSE treats positive and negative errors in identical ways, hence is agnostic of the diverse meaning (and costs) of under- and over-provisioning. And, such a prediction does not provide any information on, e.g., how to dimension resources/capacity to accommodate the future demand avoiding all underprovisioning (which entails service disruption) while minimizing overprovisioning (i.e., wasting resources). In other words, it forces the operator to guess the overprovisioning by taking (non-informed) safety margins. A more sensible approach here is instead forecasting directly the needed capacity, rather than the traffic [Beg19].

While the one above is just an example, the high-level challenge is devising forecasting models that minimize the correct objective/loss function for the specific NM task at hand (instead of generic MAE/MSE). In this way, the prediction phase becomes an integral part of the NM, and not just a (limited and hard-to-use) input to it. In ML terms, this maps to solving the loss-metric mismatch in the context of anticipatory NM [Hua19].

Another issue for statistical learning (from examples/observations) is mainly about extracting an estimator from a finite set of input-output samples drawn from an unknown probability distribution that should be descriptive enough for unseen/new input data. In this context online monitoring and error control of the quality/properties of these point estimators (bias, variance, mean squared error, etc.) is critical for dynamic/uncertain network environments. Similar reasoning/challenge applies for interval estimates, i.e., confidence intervals (frequentist) and credible intervals (Bayesian).

### Lightweight AI

Network management and operations often need to be performed under strict time constraints, i.e. at line rate, in particular in the context of autonomic or self-driven networks. Locating NM functions as close as possible where forwarding is achieved is thus an interesting option to avoid additional delays when these operations are performed remotely, for example in a centralized controller. Besides, forwarding devices may offer available resources to supplement or replace edge resources. In case of AI coupled with network management, AI tasks can be offloaded in network devices, or more generally embedded within the network. Obviously, time-critical tasks are the best candidates to be offloaded within the network. Costly learning tasks should be processed in high-end servers but created models can be deployed, configured, modified and tuned in switches.

Recent advances in network programmability ease the programming of specific tasks at data-plane level. P4 [Bos14] is widely used today for many tasks including firewalling [Dat18] or bandwidth management [Che19]. P4 is prone to be agnostic to a specific hardware. Switches actually have particular architectures and the RMT (Reconfigurable Match Table) [Bos13] model is generally accepted to be enough generic to represent limited but essential switch architecture components and functionalities. P4 is inspired by this architecture. The RMT model allows to reconfigure match-action tables where actions can be usual ones (rewrite some headers, forward, drop...). Actions are thus applied on the packets when they are forwarded. Actions can be also more complex programs with some safeguards: no loop, resistivity… The impact on the program development is huge. For example, real number operations are not available by default while they are primordial in many AI algorithms.

In a nutshell, the first challenge to overcome of embedding AI in network is the capacity of the hardware to support AI operations (architectural limitation). Considering software equipment such as a virtual switch simplifies the problem but does not totally resolve it as, even in that case, strong line-rate requirement limits the type of programs to be executed. For example, BPF (Berkley Packet Filter) programs provides a higher control on packet processing in OVS [Cha18] but still have some limitations, as the execution time of these programs are bounded by nature to ensure their termination, an essential requirement assuming the run-to-completion model which permits high throughput.

The second challenge (resource limitation) of network-embedded AI in the network is to allocate enough resources for AI tasks with a limited impact on other tasks of network devices such as forwarding, monitoring, filtering… Approximation and/or optimization of AI tasks are potential directions to help in this area. For instance, many network monitoring proposals rely on sketches and with a proposed  well-tuned implementation for data-plane [Liu16, Yan18]. However, no general optimized AI-programmable abstraction exists to fit all cases and proposals are mostly use-case centric.  Research direction in NM regarding this issue can benefit from propositions in the field of embedded systems that face the same issues. Binarization of neural networks is one example [Lia18]. Besides, distributed processing is a common technique to distribute the load of a single task between multiple entities. AI task decomposition between network elements, edge servers or controllers has been also proposed [Gup18].

### AI for planning of actions

Many tasks in network management revolve around the planning of actions with the purpose of optimizing a network and facilitating the delivery of communication services, as for example:

* Paths need to be planned and set up in ways that minimize wasted network resources (to optimize cost) while facilitating high network utilization (avoiding bottlenecks and the formation of congestion hotspots) and ensuring resiliency (by making sure that backup paths are not congruent with primary paths).
* Virtual Network Functions need to be placed on physical resources and Service Function Chains designed in optimized manner to avoid use of networking resources and minimize energy usage.
* Admission control needs to be set up and performed in ways that ensure service levels are optimized in a manner that is fair and aligned with application needs, congestion avoided or its effects mitigated.

The need for planning only increases with the rise of centralized control planes. The promise of central control is that decisions can be optimized when made with complete knowledge of relevant context, as opposed to distributed control that needs to rely on local decisions being made with incomplete knowledge while incurring higher overhead to replicate relevant state across multiple systems. However, as the scale of networks and interconnected systems continues to grow, so does the size of the planning task. Many problems are NP-hard. As a result, solutions typically need to rely on heuristics and algorithms that often result in suboptimal outcomes and that are challenging to deploy in a scalable manner.

The emergence of Intent-Based Networking emphasizes the need for automated planning even further. The concept underlying “intent” is that it should allow users (network operators, not end users of communication services) to articulate desired outcomes without the need to specify how to achieve those outcomes. An Intent-Based System is responsible for translating the intent into courses of action that achieve the desired outcomes and that continue to maintain the outcomes over time. How the necessary courses of action are derived and what planning needs to take place is left open but where the real challenge lies. Solutions that rely on clever algorithms devised by human developers face the same challenges as any other network management tasks.

These properties (problems with a clearly defined need, whose solution is faced with exploding search spaces and that today rely on algorithms and heuristics that in many cases result only suboptimal outcomes and significant limitations in scale) make automated planning of actions an ideal candidate for the application of AI-based solutions.

AI applications in network management in the past have been largely focusing on classification problems. Examples include analysis by Intrusion Protection Systems of traffic flow patterns to detect suspicious traffic, classification of encrypted traffic for improved QoS treatment based on suspected application type, and prediction of performance parameters based on observations. In addition, AI has been used for troubleshooting and diagnostics, as well as for automated help and customer support systems. However, AI-based solutions for the automated planning of actions, including the automated identification of courses of action, have to this point not been explored much.

A much-publicized leap in AI has been the development of Alpha Go. Instead of using AI to merely solve classification problems, Alpha Go has been successful in automatically deriving winning strategy for board games, specifically the game of Go which features a prohibitively large search space that was long thought to put the ability to play Go at a world class level beyond the reach of problems that AI could solve. Among the remarkable aspects of Alpha Go is that it is able to identify winning strategies completely on its own, without needing to be taught or learn by observation.

The challenge for AI in network management is hence, where is the equivalent of an Alpha Go that can be applied to network management (and networking) problems? Specifically, better solutions are needed for solutions that automatically derive plans and courses of actions for network optimization and similar NP-hard problems, such as provided today with only limited effectiveness by controllers and management applications.

Also, the evaluation of AI algorithms to derive courses of actions is more complex than more common regression or classification tasks. Actions needs to be applied in order to observe the results it leads to. However, contrary to game playing, solutions need to be applied in the real world, where actions have real effects and consequences. Different orientations can be envisioned. First, incremental application of AI decisions with small steps can allow to carefully observe and detect unexpected effects. This can be complemented with roll-back techniques. Second, formal verification techniques can be leveraged to that verify decisions made by AI is maintained in safety bounds. Third, sandbox environments can be used but they must be representative enough of the real world. After progress in simulation and emulation, recent research advances lead to the definition of digital twins which implies a tight coupling between a real system and its digital twin to ensure a parallel but synchronized execution. Alternatively, transfer learning techniques in another promising area to be able to capitalize on ML models applicable on a real word system in on more generic sandbox environment to be then. It is actually also an open problem to make the use of AI more acceptable as highlighted in the dedicated section.

Some of the related research questions to be asked include:

* How can network management and networking problems be articulated as a “game” to allow the application of systems analogous to Alpha Go to identify optimal solution strategies?
* How can solutions be deployed in real-world deployments? Contrary to game playing, solutions need to be applied in the real world, where actions have real effects and consequence. How can planning strategies be allowed to evolve in environments where sandbox environments that are representative of the real world may not be easy to come by or not exist at all?
* What are proper architectures to deploy this? To what extent can concepts help such as transfer learning, collaborative learning, distributed AI involving computing at the edge?
* What foundational advances are needed to AI techniques themselves to make them better applicable to networking problems?

### Distributed AI

## Data-driven AI

Many application of AI is based on data. Data is in the core of ML. The quality of the outputs of ML-based techniques are highly dependent on the quality and quantity of data used for learning but also on other parameters. For example, as modern network infrastructures move towards higher speed and scale, they aim to support increasingly more demanding services with strict performance guarantees. These often require resource reconfigurations at run time, in response to emerging network events, so that they can ensure reliable delivery at the expected performance level. Timely observation detection of events is also of paramount importance for security purposes, and can allow faster execution of remedy actions thus leading to reduced service downtime.

Thus, the challenge of data management is multifaceted as detailed in next subsections.

### Data for AI-based NM solutions

Assuming a network management application, the first problem to address is to define the data to be collected which will be appropriate to obtain accurate results. This data selection can require defining problem-specific data or features (feature engineering).

Firstly, NM have already produced a lot of methods and technologies to acquire data. However, in most of case, the goal was not support AI problems and leads so to a mismatch. Indeed, machine learning algorithms only work as desired when data to be analyzed respects properties. Many methods rely on vector-based distances which so supposes that the data encoded into the vector respects the underlying distance semantic. Taking the first n bytes of a packet as vectors and computing distances accordingly is possible but does not embed the semantic of the information carried out in the headers. For example, (deep) learning techniques mostly rely on vectors of (real) numbers as input which fits some metrics (packet/byte counts, latency, delays, etc) but needs some adjustment for categorical (IP addresses, port numbers, etc) or topological features. Conversions are usually applied using common techniques like one-hot encoding or by coarse-grained representations [Sco11]. However, more advanced techniques have been recently propose to embed representation of network entities rather than pure encoding [Rin17,Evr19,Sol20]. Data to handle can be in a schema-free or eventually text-based format. One example could the automated annotation of management intents provided in an unstructured textual format (policies descriptions, specifications,) to extract from them management entities and operations. For that purposes, suitable annotation models must be built existing NER (Named Entity Recognition) techniques usually applied for NLP. However, this must carefully crafted or specialized for network management (intent) language which indirectly bounces back to the challenges of AI techniques for NM specified earlier.

Secondly, The behavior of any network is not just derived from the events that can be directly observed, such as network traffic overload, but also from events occurring outside the environment of the network. The information provided by the detectors of such kinds of events, e.g. a natural incident (earthquake, storm), can be used to determine the adaptation of the network to avoid potential problems derived from such events. Those can be provided by BigData sources as well as sensors of many kinds. The AI challenge related to this task is to process so large amounts of data and associate it with the effects that those events have on the network. It is hard to determine the static and dynamic relation between the data provided by external sources and the specific implications it has in networks. For instance, the effect of a “flash crowd” detected in an external source depends on the relation of a particular network to such an event. This must be addressed by AI and its particular application to network management. The objective is to complement a control-loop, as shown in [Mar18], by including the specific AI engines into the decision components as well as the processes that close the loop, so the AI engine can receive feedback from the network in order to improve its own behavior. Similar challenges are addressed in other domains, image processing and computer vision, by using artifacts for anticipating movements in object location and identification.

### Data collection

Once defined, the second problem to address is the collection of data. Monitoring frameworks have been developed for many years such as IPFIX [Cla13] and more recently with SDN-based monitoring solutions [add some citations here]. However, going towards more AI for actions in network management supposes also to retrieve more than traffic related information. Actually, configuration information such as topologies, routing tables or security policies have been proven to be relevant in specific scenarios. As a result, many different technologies can be used to retrieve meaningful data. To support improved QoE, monitoring of the application layer is helpful but far from being easy with the heterogeneity of end-user application and the wide use of encrypted channels. Monitoring techniques must be reinvented through the definition of new techniques to extract knowledge from raw measurement [Bri19] or by involving end-users with crowd-sourcing [Hir15] and distributed monitoring.

The collecting process requirements depend on the kind of processing. We can distinguish two major classes: batch/offline vs real-time/online processing. In particular, real-time monitoring tools are key in enabling dynamic resource management functions to operate on short reconfiguration cycles. However, maintaining an accurate view of the network state requires a vast amount of information to be collected and processed. While efficient mechanisms that extract raw measurement data at line rate have been recently developed, the processing of collected data is still a costly operation. This involves evaluating and aggregating a vast amount of state information as a response to a diverse set of monitoring queries, before generating accurate reports. Machine learning methods, e.g. based on regression, can be used to intelligently filter the raw measurements and thus reduce the volume of data to process. For example, in [Tan20] the authors proposed an approach in which the classifiers derived for this purpose (according to measurements on traffic properties) can achieve a threefold improvement in the query processing capability. A residual question is the storage of raw measurements. In fact, predicting the lifetime of data is challenging because their analysis may not be planned and triggered by a particular event (for example, an anomaly or attack). As a result, the provisioning of storage capacity can be hard.

In parallel to the continuously increasing dynamicity of networks and complexity of traffic, there is a trend towards more user traffic processing customization [Fil21,Li19]. As a result, fine grained information about network element states is expected and new propositions have emerged to collect on-path data or in-band network telemetry information [Tan20b]. These new approaches have been designed by introducing much flexibility and customization and could be helpful to be used in conjunction with AI applications. However, the seamless coupling of telemetry processes with packet forwarding requires careful definition of solutions to limit the overhead and the impact of the throughput while providing the necessary level of details. This shares commonalities with lightweight AI challenge.

### Usable data

Although all agree on the necessity to have more shared datasets, it is quite uncommon in practice. Data contains private or sensitive information and may not be shared because of the criticality of data (which can be used by ill-intentioned adversaries) or due to laws or regulations, even within the same company. To solve this issue, anonymization techniques must be enhanced to optimize the trade-off between valuable data vs sensitive information (potential) leakage or reconstruction.

Whatever the final user of data, regulations and laws impose rules on data management with potentially costly impact if they are not respected voluntarily or not. Defining a new monitoring framework should always consider security and privacy aspects, for example to let any user/customer or access/remove its own data with General Data Protection Regulation (GDPR) in EU. The challenge resides here in the capacity of qualifying what is critical or private information and the capacity for an adversary to reconstruct it from other sources of data. Hence AI/ML based solutions will require more data but also more administrative, legal and ethical procedures. Those can last long and so slow down the deployment of a new solution. In addition, this requires interaction with experts from different domains (e.g. AI engineer and a lawyer). The integration of these non-technical constraints should be considered when defining new data to be collected or a new technique to collect data. However, knowing the final use of data is most of the time necessary for ethical and legal assessment which means that those considerations must be integrated from the early design of new AI-based solutions.

For supervised or semi-supervised training, having a labelled dataset is a prerequisite. It constitutes a major challenge as well. One one hand, collectors are able to retrieve data. On the other hand, trough network data are typically unlabeled. This limits application of ML to unsupervised learning tasks (learning from data). Because manual labelling is a tedious task. one option is to leverage AI to guide humans. This may also support a better generalization of a learnt model. Indeed, an underlying challenge is the genericity or coverage of the datasets. Labels encode values of an objective function, the challenge posed by the design of such tools is tremendous since for involving a M:N relationship: 1 data type may be associated to M objective function values and N data types may be associated to 1 objective function. As a result, most datasets used for research encodes a single label for a particular application like attack label for datasets to be used in the context of intrusion detection or application type for network traffic used for classification where the value of a single dataset could be capitalized in several applications.

Again, researchers need empirical (or at least realistic) datasets to validate their solutions. Unfortunately, as highlighted above, having such data from real deployments for various reasons (business secrets, privacy concerns, concerns that vulnerabilities are revealed by accident, raw unlabeled data, etc.) is tough. Even if such a dataset is available it might not be enough to convincingly validate a new algorithm.

Instead of falling back to artificial testbed experiments or simulation, it would be useful to have the capability to generate datasets with characteristics that are not 100% identical but similar to the characteristics of one or more real datasets. Such synthetic networks can be used to validate new management algorithms, intrusion detection systems, etc.

The usage of AI (for example GANs) in this area is not yet widespread and there are still many concerns that deter researchers, e.g. the fear of leaking sensitive information from the original dataset into the synthetic dataset.

### Acceptability of AI

Networks are critical infrastructures. On one hand, they should be operated without interruption and must be interoperable. Networks, except in lab, are not isolated which slow down innovation in general. For example, changing Internet routing protocols must be accepted by all. The same applies for protocol. Even if there have been several version of major protocols in use like TCP or DNS, there are still some security issues which cannot be patched with 100% guarantee. On other hand, results provided by AI solutions are uncertain by nature. The same technique applied in different environments can produce different results. AI techniques need so some effort (time and human) to be properly configured or to be stabilized. For instance, reinforcement learning needs several iterations before being able to produce acceptable results. These properties of AI techniques are thus a bit antagonist with the criticality of network infrastructures. With that in mind, acceptability of AI by network operators is clearly an obstacle for its larger adoption

### Explainability of Network-AI products

A common issue across all Machine Learning (ML) applications is that they are black boxes. This means that, after training, the knowledge acquired by ML models is unintelligible to humans. As a result, offering hard guarantees on performance is a very challenging issue. In addition, complex ML models like neural networks -that often have more than hundreds of thousands of parameters- are very hard to debug or troubleshoot in case of failure.

While this is a common issue for all applications of AI, many areas work well with uncertainty and the black-box behavior of AI-based solutions. For instance, users accept an inherent error in recommender systems or computer vision solutions.

The networking field has already produced a set of well-established network management algorithms and methods, with clear performance guarantees and troubleshooting mechanisms [Rex06][Kr14]. As such, improving debugging, troubleshooting and guarantees on AI-based solutions for networking is a must.

AI researchers and practitioners are devoting large research efforts to improve this aspect of ML models, which is commonly known as Explainability [XAI]. This set of techniques provides insights and, in some cases, guarantees on the performance and behavior of ML-based solutions. Understanding such techniques, researching and applying them to network AI is critical for the success of the field.

There exist several ML-based methods that are human-understandable, although not widely used today. For instance, [Mar20] shows a method for building anticipation models (prediction) that provide explanations while determining some actions for tuning some parameters of the network. There are other challenges that must be addressed, such as providing explanations for other ML methods that are quite extended. For instance, xNN/SVM models can be accompanied by Digital Twins of the network that are reversely explored to explain some output from the ML model (e.g., xNN/SVM). In this context, there already exist several methods [Zil20][Puj21] that produce human-readable interpretations of trained NN models, by analyzing their neural activations on different inputs.

### AI-based products and algorithms in production systems

AI-based network management and optimization algorithms are first trained, then the resulting model is used to produce relevant inferences in operation, either in management or optimization scenarios. A relevant question for the success of AI-based solutions is: where does this training occur?

Traditionally, AI-based models have been trained in the same scenario where they operate[Val17][Xu18], this is the customer network. However this presents critical drawbacks. First, training an AI model for management and operation typically requires generating network configurations and scenarios that can break the network. This is because training requires seeing a broad spectrum of scenarios. Thus, it is not feasible in production networks. Second, customer networks may not be equipped with the monitoring infrastructure required to collect the data used in the training process (e.g., performance metrics).

A more sensible approach is to train the AI-based product in a lab, for instance in the vendor’s premises. In the lab, AI models can be trained in a controlled testbed, with any configuration, even ones that break the network. However, the main challenge here arises from the fundamental differences between the lab’s network and the customer networks. For instance, the topology of the lab’s network might be smaller, etc. As a result, there is a need for models that are able to generalize. In this context, generalization means that models should be able to operate in other scenarios not seen during training, with different topologies, routing configurations, scheduling policies, etc.

In order to address this generalization problem, two main approaches are possible: The first one is Transfer Learning [TL1]. With this technique, the knowledge gained in the lab’s training is used to operate in the customer network. Transfer Learning still requires that some data from the customer is used to re-train the model (e.g., accurate performance measurements). This means that, for each customer network, re-training is required. This presents important drawbacks, since this represents an added cost and access to customer data might be problematic.

A different approach is to use Graph Neural Networks (GNN) [GNN1, GNN2]). GNNs are a novel type of neural network able to operate and generalize over graphs. Indeed, networks are fundamentally represented as graphs: topology, routing, etc. With GNN, vendors can train the AI model in a lab and then use the resulting model, as is, in different customer networks, without additional re-training using customer data.

*[One important challenge below we should describe and integrate]*

|  |  |  |
| --- | --- | --- |
| 4 | **Human in/on the loop when using AI**: what is the necessary level of inputs to be given by the user (e.g. to tune the algorithms) | **Lisandro (TBC)**Stenio FernandesStefan (TBC) |

**III. Illustrating Use cases**

*[To be removed]*

 a. UC#1

 b. UC#2

***IV. Directions and Recommendations,***

*[To be removed]*

+ Roadmap, + promising/emerging approaches/techniques/technologies/enablers

## Definitions and Acronyms

## Conclusion

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