Fighting Fire with Fire: Survey of Strategies for Counteracting The Complexity of Future Networks Management

Anne-Marie Bosneag*, Sidath Handurukande* and MingXue Wang*
*Network Management Lab, Ericsson Ireland
Email:anne.marie.cristina.bosneag@ericsson.com, sidath.handurukande@ericsson.com, mingxue.wang@ericsson.com

***Abstract*—The evolution of telecommunications systems towards complex 5G networks implies changes on many levels. In this paper, we concentrate on the management landscape of current and future networks, unfolding a vision of advanced analytics and machine learning approaches to mitigate the unavoidable complexity of future networks. We explore proficient Deep Learning mechanisms and Cognitive Frameworks in the context of future management system needs, looking at techniques that can deliver automated feature engineering, integrating more knowledge into the system and paving the road towards heavily data driven and automated decision making. With this perspective, we analyse techniques such as deep learning, active learning, hybrid learning, and their relevance to the future telecommunications systems.**

***Index Terms*—5G network management, big data, deep learning, hybrid learning, active learning, advanced analytics and machine learning**

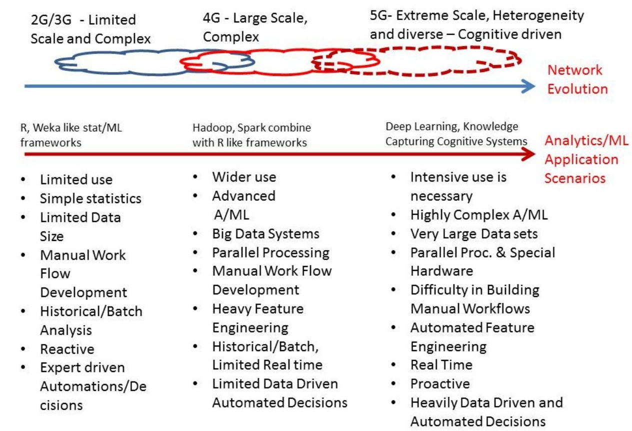

Fig. 1. Parallel Changes in Network Technology Environments and Analytics/Machine Learning Application Scenario for Network Management

I. Introduction

In telecommunication network management, statistical approaches, analytics and machine learning techniques have been used in various forms for more than a decade now. These various forms include network problems detection, network optimizations, customer and quality of experience management, churn prediction and reduction. Telecommunication network technologies have evolved over the years from 1st generation (1G) to 4th generation (4G) as of now. Plans are underway for 5G already. From 1G telecom network technology to 4G technology, a significant evolution has happened in terms of features, functionalities, customer expectations, and operations and management paradigms.

One important observation is that, in parallel to this telecom network system evolution, the application scenarios of statistics, machine learning and analytics have also evolved with significant changes. This parallel evolution in network technologies and analytics/machine learning is depicted in Figure 1 considering 2G/3G to 5G network technologies, together with the corresponding data analytics and machine learning techniques.

The network evolution was accompanied by increasing complexity and scale. As a result, in parallel, the application needs and scenarios of analytics and machine learning also increased in complexity. In 2G/3G networks, the focus was on statistics performed on relatively small data sets, with manual work flow engineering. In 4G networks, we witness analytics at increasing scale with parallel executions of machine learning workflows in clusters, and mostly historical/batch processing and heavy feature engineering.

However, in 5G, and also in complex/large 4G telecom networks, due to their complexities and scale, a significant paradigm change is necessary in terms of application of analytics/machine learning. Management in these systems includes virtual, as well as physical resources, a huge number of different types of services, and many radio access technologies. Under these circumstances, to match the complexity and scale of these networks, new and proficient analytics/machine learning frameworks are compulsory to drive network management in a data driven and automated way. More specifically, analytics/machine learning work flows should be built not only relying on human experts, but also by analytics/machine learning programs themselves. In other terms, tasks like feature engineering should be done by machine learning frameworks themselves with limited direction from experts. Furthermore, given the complexity and nature of the 4G and 5G telecom networks, there is a huge knowledge base within human experts. The analytics and machine learning systems should be designed in a way that they become capable of extracting this knowledge by working in tandem with experts who manage the network. In addition to automation, adaptibility and scalability become of paramount importance.

In our paper, we match these types of requirements for the management of future telecom networks with advanced analytics and machine learning technologies, such as deep learning, active and hybrid learning. We take a look at existing tools and propose a vision of a future management system based on proficient learning and cognitive frameworks, in the context of 5G management use cases.

In our paper, Section II takes a deeper look at the network evolution and the existing analytics / machine learning applied todate in telecom. Section III presents our vision, exposing requirements for future management systems. Section IV looks at advanced analytics / machine learning technologies. Section V shows how to match the requirements for future management systems to the features provided by advanced machine learning. Section VI presents our conclusion.

II. Existing Data Analytics / Machine Learning Techniques in the Telecom Landscape

Given the relatively limited complexity of 2G & 3G telecom systems, the application scenarios of analytics/machine learning frameworks were limited and mainly using basic statistics on relatively smaller data sets. The machine learning workflows (i.e., a sequence of tasks in the form of programs) were predominantly developed by expert programmers based on careful feature engineering in 2G, 3G and 4G network technologies [1]. We witnessed here the use of R, RapidMiner, KNIME, and Weka- like statistics and learning frameworks. Examples of such applications of analytics and machine learning in 2G/3G networks include enabling machine learning techniques for customer and quality of experience management [2], [3].

In most currently deployed systems in 3G and 4G networks, analytics/machine learning processes are historical/batch processing and reactive systems. Similarly, in these telecom network generations, although network management tasks are sometimes automated in very specific circumstances (e.g., cell neighbour relationships are automatically generated in LTE), in general, decisions are taken by experts. These observations are based on main application scenarios, though there are exceptional application scenarios with advanced use cases. For example, adopting big data technologies such as Hadoop/STORM for network analytics is becoming common in 4G network management [4], [5], [6]. Additionally, data driven features with complex analytics for automatic network management are fundamental to complex 4G network settings as well as for emerging 5G network management [7], [8], [9].

As well as solutions built into existing telecom management systems, many general third party tools for data analytics have appeared. Examples of such tools are many, including Emcien [10], BeyondCore [11], BigML [12], Datameer Smart Analytics [13], IBM SPSS Analytic Catalyst [14], Data Hero [15], Unomaly [16], Automated Insights [17], and Narrative Science [18]. Most of these tools focus on minimizing the need to understand how the different data analytics methods work, improving usability for non-data scientists. In order to be able to provide a simple view to the user, each of these tools addresses a certain sub-domain in the analytics space. For example, they focus on predictive analytics ([10], [11], [12], [14]), identifying anomalies in data trends([16]), identifying patterns in the data ([13], [15]), or translating these patterns into natural language ([17], [18]).

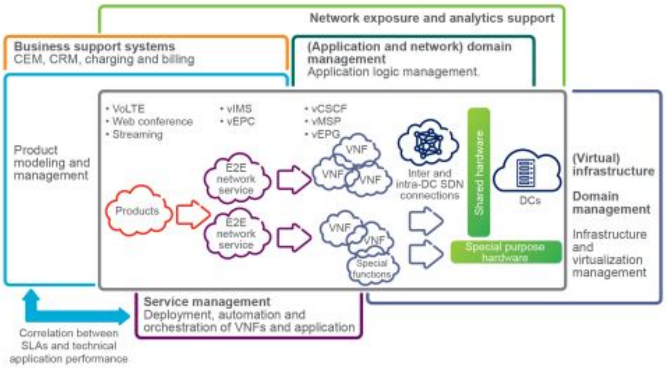

Fig. 2. The management landscape for 5G networks [19]

The use of such tools in the telecommunications domain is restricted. While they can give some insights into the data, they can only be used as point solutions, focusing on pre-defined classes of problems. Moreover, such tools would have to be highly customized to deal with telecom problem domains, while at the same time they are commercial tools, mostly closed to specific domain knowledge incorporation. Their focus is also on trying to make data science more available to non-data scientists and bringing quick results in plain view – their use can therefore be satisfying for quick development of easy analytics applications (usually focusing on the ”low hanging fruit”). For all these reasons, these existing tools do not provide all the features needed within a coherent solution that can cover a wide range of issues in future network management systems.

III. Automation of Analytics and Management at scale for 5G management systems

Future 5G telecom systems come with features that enable unprecedented connectivity, targeted towards services that combine many areas of expertise in a new non-traditional way of conducting business. 5G networks will be designed in a way that enables logical network slicing to provide adequate connectivity demands for a wide-range of targeted applications. In this context, virtual resources must be managed in addition to physical ones, adding to the complexity of the system. The system will be designed to be adaptable and therefore the need for automation becomes of prime importance. To handle these demanding requirements, automated feature engineering, heavily data-driven and automated decision making must become de facto approaches in 5G management systems.

The 5G Systems Ericsson white paper [19] shows the different management planes in a future 5G network (Figure 2). It is also outlined that advanced analytics and machine learning techniques must be part of the management of future telecom networks, especially in the area of improving the performance, operation and automation of the 5G system. Use cases include enhancement of RAN features based on data analytics, automation and analytics features for OSS and NMS, automation and data analytics technologies for NOCs, etc.

Because of the high degree of change and automacity already built into 5G systems, the management of these networks must adapt to include machine learning frameworks with automated feature engineering, and also become real time, proactive, and be able to provide heavily data driven and automated decisions. Since manual building of work flows will become prohibitive, the analytics / machine learning systems must come with automated feature engineering characteristics, designed in such a way that they can automate tasks such as capturing of human expert knowledge. Additionally, they must be able to adapt to changes in the environment, automatically provide new insights from data and cope with the unprecedented scale.

Based on the complexity, scale and automation needs of future networks, we identify the following directions for extended research and development in the context of 5G network and service management:

1) Minimizing the need for data analytics/machine learning knowledge by embedding more options into the tools
2) Automating expert knowledge capturing
3) Providing new insights from data and driving decisions from these insights (keeping the human expert in the loop where neccessary)
4) Adaptability of algorithms
5) Scalability of complex learning algorithms

Although these features are defined at different conceptual levels, they are key to enabling future management systems for 5G networks. To provide such features, we envision systems built on Deep Learning technologies and knowledge-capturing Cognitive Systems, which can address the needs of 5G networks. In the next Section, we provide insights into these types of technologies, while in Section V we explain how we match the above requirements to the described advanced analytics / machine learning technologies.

IV. Advanced data analytics and their relevance to the telecom domain

Data analytics and machine learning has been a very active domain in the past years, and advanced methods have shown great results in certain areas. For example, deep learning is actively used by big technology companies (such as Google, IBM) and has shown impressive results in a broad area of applications such as speech recognition, computer vision, and natural language processing. They have also been applied to a few use cases in mobile networks, such as using deep learning to predict customer churn [20], but deployment has been finite todate. Similarly, active learing is being used by companies such as Google, IBM, Microsoft, Siemens, CiteSeer, in some of their machine learning solutions, but this technology is not traditionally used in telecom solutions/products. Also, different hybrid learning approaches have been proposed and used with various degrees of success. We are going to present each of these 3 areas in the next sub-sections, looking into what they can offer in the context of next-generation telecom systems.

A. Deep Learning

Deep learning [21], [22], [23] represents a set of algorithms in machine learning that attempt to learn on multiple levels, each of these levels corresponding to different levels of abstraction, with higher-level concepts being defined from lower-level ones. Also, the same lower level concepts can help to define several higher-level concepts. Deep learning tries to improve existing machine learning algorithms (i.e., their accuracy) rather than targeting specific types of applications. They are therefore candidates for telecom applications in which we need to process massive amounts of complex data.

The following are key principles of Deep Architectures [22]:

1) Unsupervised learning of representations are used to (pre-)train each layer.
2) Unsupervised training is done for one layer at a time, on top of the previously trained ones. The representation learned at each level is the input for the next layer.
3) Supervised training is used to fine-tune all the layers (in addition to one or more additional layers that are dedicated to producing predictions).

Like processing of scientific algorithms, the extensive computations required to train and use deep neural networks naturally lend themselves to parallel computing implementations and GPU technology is ideally suited for parallel computing tasks. GPUs differ from CPUs in that they are optimized for throughput instead of latency, as throughput is more important for massive computations. In general, large operations like matrix multiplication, or element-wise operations with large inputs, will be significantly faster. Taking advantage of existing GPU hardware for computationally intensive deep learning implementations will generate performance acceleration. As a result, much current research in this area focuses on GPU-accelerated deep learning. There are already some machine learning toolkits utilizing GPU direct programming, mainly for neural networks and SVM. For example, the Deeplearning4j project [24] actually integrates with the CUDA kernels to perform operations in the GPUs' underlying storage. CUDA is a software layer providing APIs that gives direct access to the GPU's virtual instruction set and parallel computational element. Another tool, apart from Deeplearning4j, that allows developers to directly introduce deep learning algorithms into their systems is the R package Deepnet [25].

Because deep learning algorithms are capable of processing and performing machine learning on large data sets efficiently, this technique can be applied to mine the very large data sets that are generated in large operators networks and future 5G networks, and to find insights and other useful discoveries. Existing results show that deep learning algorithms are efficient in cathegorisation problems where the data space is extremely large (such as image recognition). In such situations, other machine learning mechanisms would be less efficient. Deep learning also improves the automation aspect, in that results are obtained with less supervision by the developer/data-scientist. At the same time, the intrinsic layered structure of telecom networks, with higher level concepts and data being built from lower level ones, is also a natural fit for deep learning concepts. All of these features show that deep learning is a technique that helps in handling complex problems with large data sets, which lends itself well to being applied to future telecom management systems.

B. Active Learning

Active learning [26] is a sub-field of machine learning in which the goal is to allow the algorithm to choose the samples that it will use for its training. In doing so, the algorithm will learn faster, i.e., not use (to reach a certain accuracy threshold) an entire training set in which some of the samples might provide little learning benefits. It is still a form of supervised learning in that a human annotator must give the expected value corresponding to the examples that the algorithm asks about. It is beneficial in situations where there is a large pool of unlabelled data, but labels are scarce and it is expensive to annotate samples. There are different strategies with respect to how the algorithm chooses the training examples, as shown in [26]:

- Membership query synthesis refers to the method where the learning algorithm asks for annotations on any example from the input space, including queries generated by the learning algorithm itself. In practice, it was shown that this method was not very effective as the automated system generates a significant number of queries that do not exist in the real space.
- Stream based selective sampling refers to the method whereby the learning algorithm gets unlabeled instances to very little cost and then decides whether to query the annotator in relation to an instance or discard the instance. The decision is based either on a query strategy where an informativeness measure is a-priori defined, or on approximating a region of uncertainty that the learning algorithm will query from. This sampling method might be more suitable to applications with limited memory or processing power.
- Pool-based sampling refers to the method in which the active learner has at its disposal a pool of instances. This pool of instances will be classified according to an informativeness measure and then instances will be greedily queried in the order of the classification. Most applications of active learning use this method.

It has been shown that active learning is efficient when the human annotator has very good domain knowledge; for novice annotators, the method does not work that well and passive learning is recommended. The use of a human annotator seems to detract from the suitability of these methods for automation. However, the use of active learning as part of a hybrid learning system, as shown in the next sub-section, shows promising results. One example of such system is workfusion [27], which is creating automation through active learning and crowd-sourced resources to re-train algorithms for data collection and cleaning.

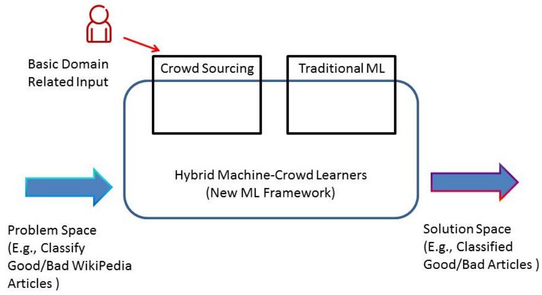

Fig. 3. Basic Idea of a Hybrid Learning System that Combines Crowd-Sourcing with Machine Learning

Active learning has mainly been used todate in image retrieval and recognition [28], [29], [30] and natural language processing applications [31], [32]. More recently, active learning techniques have also been applied in an adversarial context, e.g., for detecting malicious ads or phishing pages [33], [34], [35].

Since Active Learning helps to capture domain experts knowledge and optimize the learning of the machine learning system, it is useful for incorporating domain knowledge into a learning system for network management. In the network management domain, a lot of knowledge exists within the human domain expert, based on his/her historical expertise and because of the lack of completely automated tools for network management tasks. For a machine learning system, it is non-trivial to capture all this knowledge and train itself just using the historical data analysis. In that sense, using Active Learning, a domain expert can provide, as input, good learning samples and instances. We will further take a look at active learning in the context of hybrid learning, as we believe that the real value of active learning in the context of future network management would show best in a hybrid learning situation.

C. Hybrid Learning

Among new machine learning technologies, certain approaches combine two different solutions to formulate a better machine learning methodology. Such hybrid mechanisms try to overcome short-comings of individual approaches. In this sub-section, we present three hybrid mechanisms geared towards integration of knowledge into automated machine learning-based solutions.

Hybrid Learning with Crowd Sourcing

Machine Learning algorithms can be combined with crowd-sourcing for solving complex problems. For example, machine learning systems find it difficult to automatically extract complex features to solve a given problem, e.g., in applications such as differentiation of images of foxes vs. dogs, identifying bad WikiPedia articles, or shortlisting badly performing urban micro radio cells. Here, the learning process can iterate with crowd-sourced input, not just providing examples of good /

bad cases but actively helping during the learning process by providing features to look for and also augmenting the model (e.g., including additional nodes in a decision tree that was built by the machine learning system). In the recent past such systems [36], [37], [38], [39] have been proposed.

As described in Figure 3, Crowd sourcing is a system design methodology focusing on taking crowd information as input, such as feature selection, training data and model parameters to improve traditional ML algorithms (e.g., decision trees, regression and recommender systems, etc.) For example, the Amazon book recommendation feature takes users ratings of books as input data and recommends books for a targeted user using a recommender algorithm. Another example is the Flock system [39] system, where an underperforming decision tree model that classifies WiKiPedia documents is optimized by crowdsourced-based features. The user is given an option to examine the underperforming model and then add features/nodes to improve the classification. Examples of such features are, for example, "strong introduction" to the article or "attractive images". Based on the crowd-sourced inputs, the Flock system automatically adds further subtrees to the introduced nodes/features, improving the final accuracy of the classification from 58% to 80%.

Such hybrid systems are capable of formulating questions for the user/domain expert (e.g., asking to classify two examples), asking users/domain experts to provide differentiating features for two examples, asking for labels for examples/samples, etc. This transforms the machine learning process into a more agile process, where programing (machine learning) and usage scenarios are overlapped in a given period. Another example in this sense is the one already mentioned under Active Learning [27].

As mentioned before, in the telecom domain there is a large accumulated knowledge among the domain experts. Experts such as network troubleshooters actively use their knowledge gathered overtime for solving problems in the network. In general, it is impossible to learn this information in its complete form by automated tools. Crowd-sourcing can be used in conjunction with machine learning to extract and embed the expert knowledge, at least partially, within the machine learning framework. A gradual incorporation of expert knowledge into the tools is vital for future generation management systems, for automation reasons and also because domain experts (e.g., engineers, consultants, network auditors, performance optimizers, etc.) are becoming a hard to find resource, while the networks are getting larger in all dimensions (number of users, of equipment types, coverage areas, data usage, etc.) It is therefore crucial to capture the domain expertise within the intelligent network management systems. By doing so, complex scenarios that machine learning frameworks find difficult to learn today can be circumvented and hence the performance of the machine learning based system can be improved.

Hybrid Learning with Analytical Modelling

Classical machine learning based prediction/estimations are completely data driven and "black-box" type of approaches. This means that they do not analyse and dissect the internal behaviour of the system they model. For example, if one is modelling a radio network to identify performance issues, the approach does not necessarily dissect the internals of the radio network configuration/operation, etc., but instead uses a data-driven approach. The accuracy of such black-box approaches strongly relates to the quality of the data set, which includes sample size, feature space completeness and sample representative level (i.e., does the sample data cover various types of data). Due to technical and non-technical limitations in the real world, obtaining such complete sets of sample data to cover various situations is difficult and sometimes even impossible.

On the other hand, one can think of analytical modelling, for example, considering radio network internals such as spectrum usage, scheduling, queuing, SINR (Signal-to-Interference-plus-Noise-Ratio) levels etc. Such approaches are called "white-box" approaches. Simulations, emulations, mathematical modelling etc. are used in such approaches. Such analytical modelling requires no or minimal training using sample data. However, such analytical modelling or white-box approaches requires very good understanding of the internal operations, and typically they must use simplified assumptions of the operations and conditions that relate to complex dynamic systems. They also require significant amount of effort in modelling a given system and lack of flexibility is a problem. These issues make it hard to entirely rely on analytical modelling for performance estimations, for example.

New hybrid approaches are being devised and used. They combine these two distinctively different approaches to overcome the shortcomings of both. For example, in [40], [41] these approaches are used in modelling complex distributed systems. Sometimes known as "gray-box" techniques, these approaches make modelling more reliable in complex scenarios. By combining, two main advantages are gained:

1) Relying on an analytical model to bootstrap a machine learning system with lower training time and indirectly providing valuable input to the machine learning system (such as relevant features)
2) Using the machine learning system to improve the system's performance over time, as more and more data is made available.

Analytical modelling is useful to augment machine learning systems with additional domain knowledge. This analytical modelling needs knowledge about how the systems work, perform and react. In the telecom sector, the knowledge and understanding that exists today within developers and operations engineers is useful for analytical modelling. For example, it is understood that the CQI (Channel Quality Index) distribution of a macro cell forms a bell curve with highest values roughly in the middle of the curve; such knowledge can form the basis as an analytical model describing how a cell behaves. In that sense, when devising machine learning based systems in the telecom domain, analytical modelling can be used in conjunction with machine learning to improve the

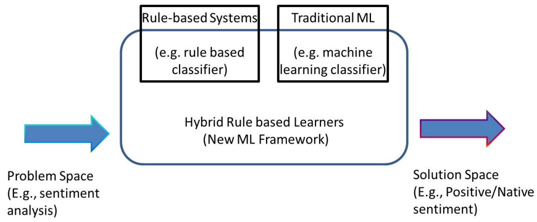

Fig. 4. Rule-based Systems used in combination with Machine Learning

performance of the resulting system. Such approaches can be very valuable in the context of managing highly complex and dynamic networks.

Hybrid Systems with Machine Learning and Rule-based Systems

Another technique to improve the performance of machine learning based systems are hybrid methods that combine machine learning approaches with rule-based systems (Figure 4). Examples include [42], [43], where the rule based systems are used at various stages in the data analytical flow. The rule based system in [42] is used after the data analytics data flow, in order to handle any underperforming outputs of the machine learning module and/or augment the output. In contrast, in [43], the rule based classifier is used before the machine learning phase to generate output that would be consumed by the machine learning system.

In general, machine learning based systems and rule-based systems are driven by different motivations, where rule-based systems use pre-generated rules to drive the system, while machine learning- based systems derive rules to form the functionality of the system. However, traditionally, in telecom and network management, a lot of rule driven systems are used. For example, in the early days, cell neighbourhood was preconfigured; routing and similar tables are also preconfigured by rules. Various call/service related policies are coded in to policy systems as rules. As a result, traditionally, there is a lot of knowledge in the form of rules based systems. However, going forward towards increasingly complex systems, rule-based systems will not be able to cover all possibilities. In this sense, the knowledge from rule-based modelling could potentially be reused within newer machine learning based systems.

To conclude this section, our review of existing advanced analytics and machine learning technologies shows that there are a few common trends:

1) Improving accuracy and speed of learning by new methodologies such as deep learning and active learning
2) Improving capabilities and adaptability of algorithms by using hybrid techniques
3) Improving ease of use and automation by embedding analytics knowledge into the systems, providing non-expert-readable reports, automatically taking care of aspects of scalability, programmability, etc.

The next section explains how these features can help develop future telecom management systems.

V. Analytics trends for next-generation telecom network management systems

Advanced analytics are essential for the development of future 5G network management systems [19]. New complex use cases must be addressed, such as auto-configuration of virtualised resources for efficient resource usage [44], [45]), efficient spectrum usage in 5G [46], rectifying interferences coming from different types of cells (pico, macro, etc.), advanced automated troubleshooting in the context of complex 5G networks, emerging SON [47], etc. The following recommendations are a first step in tackling the new, more complex 5G network management space. Since the recommendations address general requirements that span across the use cases mentioned, they can apply to all of these use cases.

A. Minimizing the need for data analytics knowledge

The adoption of advanced analytics is often being hindered by expert knowledge requirements in statistics, data science, etc. Traditional advanced and expert analytics frameworks, such as R and SAS are not suitable to most business users that do not have any fundamental data science knowledge. From the study of existing commercial products, we can observe that one constant goal is minimizing the domain knowledge barriers for advanced analytics applications and tools. As a result, the application can automatically find insights for users without requiring statistical know-how.

Common ideas that keep on coming up in existing tools are:

1) Providing summarized information of data to give insights
2) Suggesting questions that need to be asked from users to drive the analysis
3) Applying all common techniques such as correlation, prediction and let the users pick the results they need
4) Wrapping common techniques such as prediction in simple one click or wizard features

The implementation of such system can come with very complex design. For example, the system must automatically understand the data to enable the system to ask questions from the users. The algorithms might also need an ability of tuning themselves, since they want no expert interventions in the data analytics steps. Research based tools, such as Spark-based tools or the Automated Statistician [48] focus on veiling the complexities exposed to the user. They provide a limited range of machine learning algorithms which can fit certain problems well, and also make it easier for a user to program the application, while taking care of aspects such as scalability, performance, etc.

Trying to minimize the need for expert knowledge is one area of major importance for future generation management systems, as a neccessary step in improving the automation of the system. This direction must be considered in conjunction with incorporating domain knowledge into the system.

B. Automating the expert knowledge capturing

In telecommunications network management, a lot of domain knowledge and expertise is confined to a set of human domain experts. For example, a typical performance assurance system processes hundreds of millions of counters/Key Performance Indicators (KPIs) in a collection period. These counters and KPIs correspond to various faults, metrics and configurations. A good domain expert in a particular area would know what configurations yield which types of behaviours in the network, as well as the exact meaning of counters, events, KPIs and combinations in a given context. A good expert essentially knows which parameters drive desired behaviour and knows which counters/events/KPIs to look for when identifying problems. For example, an expert in radio optimization would know the acceptable types of SINR distributions within the range of an urban micro cell. The expert would also know how these distributions can change during the seasons of the year due to foliage-related changes.

For the next several years, a gradual incorporation of more and more human expert knowledge into the automated management systems is foreseeable, as discussed in Section IV. In theory, this knowledge can be captured within the system at different stages. For example, it can happen at the development stage of the tool, either on the development site or at the field, or it can happen while the tool is being used (in the first stages of usage, at least by a small set of selected users/experts). As we have realized over time, it is not practical to capture all the instances and knowledge at the development stage. On the other hand, capturing knowledge on the field while the system is being used is much more effective because of a number of reasons, one of the most important ones being exposure to real world scenarios. As a result, automating expert knowledge capturing at the field by the machine learning based system is crucial in building better performing, effective network management systems. In fact this is also a hot area in the research world now and there are various methodologies developed both within academia and industry. These methodologies include: (a) Crowd Sourced Machine Learning to automate expert knowledge gathering; (b) Active Learning; (c) Interactive Learning and Refinements for Machine Learning ([49], [50]).

As they exist today, these approaches are not developed enough to a level where they can be used in an industrial setting in the telecom network management domain. However, these approaches are very valuable for the telecom network management domain, where a lot of expertise is engrained within human domain experts. Their use will pave the road towards improved automation. Implications such as changes in the role of the network operator, degree of control over the system, etc. must also be considered.

C. Providing new insights to drive business decisions

Providing insights that are hidden in the input data is a major goal of analytics and machine learning. This is usually achieved by combining complex data coming from different types of systems and using advanced analytics algorithms. This trend of handling the complexities in the input data is seen in the most advanced machine learning techniques, such as deep learning and active learning. These techniques are not traditionally being used in telecom systems. Providing new insights can also be achieved by new specialized analytics techniques [51].

For future network management systems, the new insights generated must be valuable in the aspect of automatically driving business decions in the adaptable environment provided by 5G networks.

D. Adaptability of algorithms

Aspects of extending the capabilities and adaptability of learning systems can be implemented by using hybrid techniques. Understanding which aspects apply most to telecom network management is an important area for study. For example, active learning has been used mostly in natural language processing and image recognition problems. The technique can be used for speeding up the training phase of a machine learning algorithm, by asking an expert to provide labels for input points chosen by the algorithm itself. It can also be used as part of a hybrid technique, by combining active learning with semi-supervised learning methods. Or it can be used in combination with crowdsourcing for automating part of the input of knowledge into the system. Used appropriately, the technique could be valuable under well-defined circumstances in telecom applications. Most probably, it will be used in conjunction with other machine learning techniques. The challenges here will include identifying the type of telecom situations that are fit for active learning and also understanding which type of hybrid model would work best for the identified scenarios.

It is also worth noting that there is a tradeoff between having a general tool which might miss some insights in the data but is quicker to provide results of a general analysis, and going towards a specialized technique, which might prove to be extremely valuable in specific situations but requires a lot of expert knowledge and it can't be easily ported to other situations. The challenge here is to understand the aspects that are critical for the system and then picking the right tradeoff when moving towards automating learning in telecom management systems. This direction should be investigated in conjunction with automating the capturing of expert knowledge, to understand which are the limits of each direction and how they push the boundaries when used together.

E. Scalability of complex learning algorithms

In the Deep Learning area, we see a focus on handling the scale and complexity of data. As a consequence, efficiently scaling complex deep learning algorithms becomes important.

One of challenges of deep learning is handling the scale and complexity of big data [52]. Telecom data comes in all types of formats from a variety of sources at high speed, with different distributions and high dimensionality. This trend will be exacerbated in 5G systems. Efficiently scaling or parallelizing complex deep learning algorithms for big data is a defined challenge.

VI. Conclusion

Based on our survey, we propose a vision of future telecom management systems partly fuelled by deep learning and cognitive methods. This vision caters to demands of heavy automation and integrates overtime-evolved experts knowledge, while at the same time minimizing the need for analytics knowledge, and providing new insights through adaptable and scalable algorithms. Our proposal is presented in the context of the telecom systems historical evolution with a view towards 5G systems, where new complex use cases emerge. Future work includes applied research to specific areas within 5G.

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