Poster: Towards Explainable Artificial Intelligence for Network Function Virtualization

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ABSTRACT

Network Function Virtualization (NFV) refers to the process of running network functions in virtualized IT infrastructures as softwarized Virtual Network Functions (VNFs). Several telecom service providers are currently benefiting from this concept, as it enables a faster introduction of new network services, thereby meeting changing requirements. Following a trend initially adopted by cloud service providers, telecom service providers are also adopting deaggregation of the VNFs into microservices (μservices). However, a μservice-based architecture that can manage a large set of diverse and sensitive network functions requires new Artificial Intelligence (AI)-based methodologies to cope with the complexity of the μservice-based NFV paradigm. This paper focuses on the use of explainable AI (XAI) for gradually migrating towards a μservices-based architecture in NFV. The paper first establishes the need for XAI to transform the NFV architecture to a µservice-based architecture and then describes some of our research objectives. Afterwards, our preliminary approach and long-term visions are provided.

CCS CONCEPTS

• **CCS->Networks->Network architectures->Network design principles** ;

KEYWORDS

Network Function Virtualization, explainable AI, Microservices

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1 INTRODUCTION

Future telecom networks will be software-defined [1], with most network functions virtualized and deployed as software running on virtual machines in cloud data centres [4]. These Virtual Network Functions (VNFs) in the current mode of operation are deployed as a single piece of software code capturing all functionalities of the network function, and are known as 'monoliths'. Further, some telecom service providers e.g., BT and Telefonica are now looking forward to the μservices-based architecture for their VNFs[1]. The μservices-based architecture de-aggregates a large application into its sub-components (i.e., μservices) and deploys them in a network. This facilitates a more flexible, lightweight system, as smaller components are easier to process.

The several μservices de-aggregated from a VNF (or a VNF service chain) have complex mesh-like inter-dependencies among them [3, 5] i.e., they may require to call each other several times to set up a network service. Hence, catering to these inter-dependencies, which are typically governed by strict network requirements in terms of traffic volume, latency, quality of service, etc., makes the μservices management unprecedentedly complex. Therefore, we need an Artificial Intelligence (AI) framework to solve the above problems where such inter-dependencies can be modelled using the data generated from the network. Furthermore, the users of these models (e.g., network operators, cloud providers, etc.) need to know why a specific AI model arrived at a specific decision in a specific scenario, and this requires novel techniques from the explainable AI (XAI) field. This paper focuses on XAI for μservices in NFV (a new field of study for NFV). It presents the next steps in the field of XAI in NFV, describes our envisioned XAI-based μservices de-aggregation framework (mapped with the NFV-MANO standard) and gives our long-term vision.

2 XAI-BASED μSERVICES DE-AGGREGATION

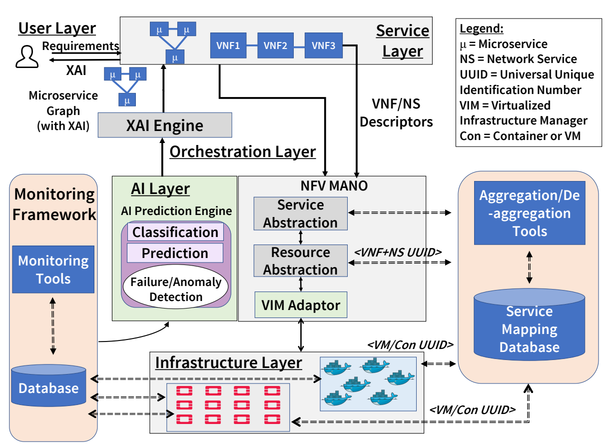

Figure 1: Proposed XAI-based μservices De-aggregation Framework

[1] https://www.sdxcentral.com/networking/nfv/definitions/microservices-architecture-telco-cloud

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Fig. 1 shows integration of XAI in NFV MANO architecture (our proposed XAI-based μservices de-aggregation framework). In Fig. 1, we have user, service, orchestration and infrastructure layers. There is also a monitoring framework (to collect data and monitor the network) and service-mapping framework (to store the mapping of VMs). The AI layer will run in parallel to NFV-MANO and the XAI part will be on top of it. The AI layer will provide the decisions of μservices de-aggregation and the XAI part will provide explainability.

First and foremost, to effectively apply AI to any problem, data availability is crucial. The above issue is even more important in applying AI techniques to solve telecom-network problems. This is because data from real operational networks are difficult to obtain but may lead to inaccurate results in terms of training the AI algorithms. A sub-optimal arrangement can be the usage of data generated from publicly available testbeds like Fed4Fire+https://www.fed4fire.eu/. Starting with these data, known XAI frameworks such as, e.g., LIME [2] (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) can be applied to develop intelligent XAI approaches tailored to our problem. The adoption of a specific XAI framework depends on the considered surrogate AI model (i.e., the main AI algorithm for the decision-making process).

As the number of XAI frameworks is very limited with their own drawbacks, existing XAI tools needs to be adapted to suit the proposed research problem and address specific requirements not fully addressed by current models. To highlight the added value that explainability caters, a comparison of the performance of the proposed XAI algorithms to that of non-explainable AI algorithms is essential. This comparison will allow us to quantify the benefits of explainability in our problem and, more importantly, highlight the effectiveness of XAI in communication networks. Moreover, linear and non-linear optimization techniques will also be employed. Such optimization techniques serve as ground truth to validate proposed XAI algorithms, such as in the problem of decomposition and placement of μservices, and can also be used along with the XAI algorithms.

3 NEXT STEPS AND CHALLENGES

Starting directly with a μservices architecture is not always pragmatic and at times can be risky too[2]. In fact, VNFs should be deployed as monoliths and only when the system complexity increases, one should start 'peeling off' μservices from the monoliths. The decision about system complexity and μservices de-aggregation can be taken by an AI framework. Furthermore, considering the fundamental roles that μservices-based applications will play in our future society (e.g., orchestrating a connection establishment for a self-driving car or for a remote surgery), the AI models for μservices management should be explainable, reproducible, and trustworthy. New XAI-based solutions for μservices de-aggregation require research breakthroughs that go well beyond the current state-of-the-art in this area.

The followings are the next steps of the XAI work: (1) Analyse use cases, requirements and complexity of the μservices de-aggregation problem, (2) Devise XAI algorithms for μservice decomposition by: a) identifying and eliminating biases (data collection, training, results, evaluation); and considering social and ethical aspects too, b) Introducing explainability in the AI lifecycle, c) Validating and evaluating explainability; i.e., the capability to answer questions as: are models and outcomes explained effectively to all stakeholders? Are transparency and trust enhanced?, (3) Measuring effectiveness of the explanations, e.g., transparency, trust, and usability, Ensuring interpretability of the models and (4) Getting results in real settings using testbed evaluations to mimic the settings of practical networks.

As the number of state-of-art XAI frameworks is very limited (e.g., for measuring transparency and trust), these frameworks need to be adapted substantially to meet above objectives.

4 LONG TERM VISION

AI systems are mainly composed of machine learning, deep learning and statistical tools. Although AI is already used in network industry, it is not typically used in real time operations. In order to move to real-time operations, network operators need systems that are capable of learning automatically. This might be possible with AI somehow integrated with the next-generation μservices-based NFV. Network automation platforms, such as the Open Networking Automation Platform (ONAP), may add AI techniques to support such visions.

As was also pointed out by a number of executives from the Telecom industry at the 2019 AI Telco Summit[3], there is serious concern about AI being a "black box" or the lack of explainability. The development of novel scientific methods to understand how or why an AI-enabled telecommunication system has provided a specific output can advance and accelerate the vision of a completely autonomous network. XAI is not only a key requirement for network operators to ensure that their automated systems are working as expected, but it might also be necessary to meet requirements, or it might be important in changing environment where the requirements change very quickly. There can also be challenges involved in creating explainable AI in telecommunication system: there may be concerns about user/organization privacy or to put in-place controls to ensure that the explanations provided are according to organization/user privacy. Further, the explanations should be correct and reliable. XAI-based μservices-deaggregation framework will ensure accountability across the full analytics pipeline – from data collection to decision and also take into account the needs of different people working with the system, considering what differnt types of explanation might be useful and for what purpose.

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[3]https://tmt.knect365.com/software-driven-operations/