Develop Explainable AI Services on Cloud Computing and Open Source Models

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***Abstract*—The objective of this tutorial is to introduce systematic methods with supplementary tools and computing models for developing explainable AI. As AI increasingly penetrates various application domains, practitioners need more comprehensive approaches for model quality assessments and explainability. This tutorial bridges the gap between theoretical XAI techniques and their practical implementation in cloud services and open-source models. We explore a range of XAI methodologies, from model-agnostic to model-specific approaches, examining their applicability across diverse AI models and deployment scenarios. The tutorial introduces design principles for integrating XAI into AI services and facilitating early adoption in MLOps lifecycles. Through experimental evaluations and case studies on both cloud AI services and open-source models, we demonstrate the effectiveness of these approaches in real-world scenarios. We discuss strategies for pipeline automation, provenance data management, and optimizing the operational overhead of XAI integration. Additionally, we explore the robustness of XAI methods under adversarial conditions. This comprehensive exploration equips participants with insights into XAI's role in AI systems, practical implementation skills, and critical perspectives on future research directions, ultimately benefiting the development of explainable and robust AI systems.**

***Index Terms*—explainable AI, cloud computing, open source model, software quality, robustness**

I. Tutorial Goals and Relevance

As AI increasingly influences software systems, the demand for explainability has become essential, particularly in sensitive domains [1]. We address this challenge by providing an automatic solution for implementing and evaluating XAI methods across diverse AI models and services [2]–[4].

The goals of this tutorial are:

1) To provide an understanding of state-of-the-art XAI methods and their theoretical foundations.
2) To demonstrate practical implementation of XAI techniques for both cloud services and open-source models.
3) To explore strategies for integrating XAI into the MLOps lifecycle and assess its impact on model development.
4) To analyze the computational costs and performance implications of XAI in production environments.
5) To investigate the robustness of XAI methods under adversarial conditions.

The tutorial covers a range of XAI techniques, including model-agnostic and model-specific explanation methods [5]. We review the mathematical foundations of these methods, discussing their strengths, limitations, and appropriate use cases. Particular attention is given to the challenges of applying these techniques to black-box cloud AI services versus transparent, open-source models.

The tutorial is dedicated to the practical aspects of XAI implementation. Participants gain hands-on experience in applying XAI methods to real-world AI systems. The tutorial also includes the evaluation of XAI methods. We introduce and discuss various quality attributes for assessing the model with explanations. An important aspect of the quality attributes is the examination of model robustness and XAI resilience under adversarial conditions. We provide insights into developing more resilient XAI.

The relevance of this tutorial to the CASCON community is multifaceted. For researchers, it offers insights into the recent XAI techniques and their theoretical underpinnings, potentially inspiring new research directions in AI transparency. Practitioners gain knowledge for implementing XAI in real-world systems, enhancing their ability to develop more trustworthy AI solutions. The tutorial's focus on both cloud services and open-source models makes it particularly valuable for attendees working across different AI systems.

In conclusion, this tutorial aims to bridge the gap between theoretical XAI research and their practical implementation, addressing the XAI need in the AI community.

II. Tutorial Structure

Here, we introduce the segments of the half-day tutorial.

A. Segment 1: Theoretical Foundations (45 minutes)

1) Introduction to XAI: XAI methods response to the increasing complexity and opacity of AI systems [1]. As detailed in study [2], the AI service, particularly through cloud platforms, has intensified the need for explainable. XAI aims to make AI decisions by providing explanations for feature contributions.

2) AI Quality Requirements and the Role of XAI: Our study has uncovered inconsistencies and risks in cloud AI services. XAI addresses quality concerns in cloud AI services by providing explanations and evaluations.

3) Challenges of XAI: There is operational complexity in adapting XAI techniques to diverse model architectures. Implementing XAI faces several significant challenges.

4) XAI Tools and Frameworks: Our research provides a comprehensive comparison of existing XAI frameworks including IBM's Explainability 360 [6], Microsoft's InterpretML [7], Vertex XAI [8], and OmniXAI [9]. We analyze their strengths, limitations, and suitability for different platforms. We offer integration with both cloud AI services and open-source models, support parallel XAI pipelines, and incorporate other XAI frameworks as well as evaluation metrics for assessing explanation.

B. Segment 2: XAI Service Operation (45 minutes)

1) Essential Components: We introduces a service-oriented approach to XAI. The core components, as outlined in our methodology section, include:

- Data Processing Microservice: Ensures correct data formatting and applies adversarial attack conditions.
- AI Model Microservice: Encapsulates and deploys pre-trained AI models.
- XAI Method Microservice: Offers various XAI algorithms for generating explanations.
- Evaluation Microservice: Aggregates results and evaluates defined quality attributes.

These components work in concert to provide a comprehensive XAI solution adaptable to various AI deployment scenarios.

2) Parallel XAI Pipelines: Our framework supports parallel XAI pipelines to address XAI's computational challenges. This allows for efficient processing of multiple XAI tasks simultaneously, significantly reducing overall computation time for complex AI systems.

3) Deployment and SDK: We offers a streamlined deployment process and a comprehensive SDK. The SDK provides a high-level interface for configuring and executing XAI tasks, making it accessible to both researchers and practitioners. Our deployment strategy leverages containerization for easy scaling and cross-platform compatibility.

C. Segment 3: XAI Application Scenarios and Future Directions (45 minutes)

1) XAI Application Scenarios: This segment explores practical applications of XAI across various domains.

a) Cloud AI Service Evaluation and Discoveries: This work integrates XAI with Azure AI services [10]. Our findings demonstrate that XAI techniques can uncover inconsistencies in model predictions across different cloud platforms.

b) Adversary Perturbation for Open Model AI Services: We conduct comprehensive experiments apply various adversarial perturbations [11] at different severity levels. We observe that certain models, such as Vision Transformers [12], exhibited higher robustness.

2) Future Directions - XAI 2.0: We propose a roadmap for XAI's future, aligned with XAI 2.0 principles: Extending XAI to new AI types, including cloud services and complex models like Vision Transformers. Introducing metrics for explanation consistency and stability across models and datasets. Enabling flexible adjustment of models and XAI methods in microservices. This simplified version reduces the word count while maintaining the key points of the future directions for XAI.

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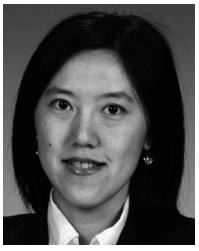

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