

**Ph.D. in Information Technology  
Thesis Defense**

**June 19<sup>th</sup>, 2026**

**at 1:00 pm**

**Room 1B – building 20A**

**Federico GIANNINI – XXXVIII Cycle**

**A First Step Towards Streaming Continual Learning in Dynamic Environments**

Supervisor: Prof. Emanuele Della Valle

**Abstract:**

*Learning from data streams poses significant challenges due to the dynamic and non-stationary nature of data, where the data distribution may evolve over time. Models are therefore required to continuously learn from incoming data, detect changes (i.e., concept drifts), and adapt to new distributions.*

*This work introduces a specific scenario (named Evolving Streaming Time Series) posing additional challenges. It assumes that past knowledge remains relevant or is similar to future knowledge. This situation requires avoiding forgetting previously acquired knowledge. Moreover, the data points are temporally dependent, further complicating the analysis. The present work identifies a critical gap in the literature: existing solutions in the literature largely neglect the interplay between concept drift types, learning continuously, avoiding forgetting, and temporal dependence. To bridge this gap, it introduces a novel paradigm called Streaming Continual Learning (SCL), extended to Temporal SCL (TSCL) to explicitly incorporate temporal dynamics. This unified framework integrates the adaptability of Streaming Machine Learning, the knowledge preservation of Continual Learning, and the temporal modeling capabilities of Time Series Analysis.*

*To concretely embody this vision, the thesis presents a comprehensive benchmarking methodology tailored for ESTS scenarios. This benchmark includes both synthetic and real-world data sources with different types of concept drifts and temporal dependencies. It also introduces specific evaluation protocols that assess online performance, forgetting, and resource usage.*

*Building on this benchmark, several TSCL embodiments are proposed: (i) Continuous Recurrent Neural Networks (cRNN), which model temporal sequences while learning continuously; (ii) Continuous Progressive Neural Networks (cPNNs) and their dynamic variant (DYNcPNN), which start from cRNN and add methodologies for drift-triggered architectural growth with knowledge transfer and forgetting mitigation; (iii) Continuous Piggyback (cPB), which applies a strategy to cRNN to leverage pretrained models via*

*adaptive masking in streaming contexts; and (iv) MAGIC Net, a self-growing model balancing flexibility and compactness by combining the rationales of cPNN and cPB. Furthermore, the Mutual Assisted Learning (MAL) paradigm and its practical instantiation, the Mutual Assisted cPNN (MAcPNN), enable decentralized, collaborative adaptation across multiple agents facing distinct yet related streaming environments in the context of edge computing in Internet of Things scenarios.*

*Extensive experimental results confirm that, since conventional SML models are meant to address rapid adaptation with independent data points, they fail in environments characterized by significant temporal dependence and forgetting challenges. In contrast, the proposed TSCL solutions successfully integrate temporal dependence management with continuous adaptation and knowledge preservation. Overall, this thesis makes a compelling case for the SCL paradigm as a necessary new approach for real-world data streams, delivering both a conceptual framework and concrete, benchmark-validated architectures that address long-standing limitations in the literature and pave the way for robust, real-world continuous learning systems.*

**Giacomo ZIFFER – XXXVII Cycle**

## **Beyond IID: Online Learning for Temporal and Evolving Data Streams**

Supervisor: Prof. Emanuele Della Valle

### **Abstract:**

*Data stream mining has gained increasing attention in Machine Learning (ML), especially with the widespread adoption of sensor networks and the Internet of Things. Traditionally, such data were stored as time series and analyzed offline in batches, but modern applications demand real-time processing. This raises a fundamental question about the relationship between data streams and time series: on one hand, time series can naturally appear in streaming form; on the other, many streams exhibit temporal correlations that align them with time series. Empirical studies have confirmed that widely used benchmarks in the data stream literature already contain sequential structures, yet most approaches operate under the assumption that individual observations are independent and identically distributed (IID). Streaming Machine Learning (SML) and Time Series Analysis (TSA) each address part of this challenge. SML algorithms update their models continuously as new data arrive, processing streams in real time and adapting to changes in the data distribution, commonly referred to as concept drift, but still assume that observations are independent. TSA, in contrast, explicitly models temporal dependencies through autoregressive and structural decomposition methods, yet requires stationarity as a precondition. When temporal dependence and non-stationarity coexist, as is common in real-world streams, both paradigms face fundamental limitations that neither can resolve in isolation. This raises a central research question: Can we develop unified learning frameworks that simultaneously adapt to distributional shifts while exploiting temporal dependencies in non-IID streaming environments?*

*This dissertation addresses this question through a progression from theoretical unification to algorithmic design and experimental validation. A unified taxonomy of temporal data evolution and a formal framework of design principles for non-IID streaming systems are proposed, establishing the conceptual foundation of the work. These principles are then instantiated through a series of contributions spanning benchmarking environments, adaptive neural and probabilistic learners for structured streams, and diagnostic and classification pipelines for unstructured data, specifically image streams. The results demonstrate that bridging the structural depth of TSA with the adaptive efficiency of SML is not only feasible but necessary to effectively address the challenges posed by temporal and evolving data streams.*

## **PhD Committee**

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