The SMARTHEP European Training Network

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Abstract. **S**ynergies between **MA**chine learning, **R**eal-**T**ime analysis and **H**ybrid architectures for efficient **E**vent **P**rocessing and decision-making (SMARTHEP) is a European Training Network, training a new generation of Early Stage Researchers (ESRs) to advance real-time decision-making, driving data-collection and analysis towards synonymity.
SMARTHEP brings together scientists from major LHC collaborations at the frontiers of real-time analysis (RTA) and key specialists from computer science and industry. By solving concrete problems as a community, SMARTHEP will further the adoption of RTA techniques, enabling future HEP discoveries and generating impact in industry.
ESRs will contribute to European growth, leveraging their hands-on experience in machine learning and accelerators towards commercial deliverables in fields that can profit most from RTA, e.g. transport, manufacturing, and finance.
This contribution presents the training and outreach plan for the network, and is intended as an opportunity for further collaboration and feedback from the CHEP community.

1 Introduction

The **S**ynergies between **MA**chine learning, **R**eal-**T**ime analysis and **H**ybrid architectures for efficient **E**vent **P**rocessing and decision making (SMARTHEP) European Training Network is an EU Horizon-funded training network, with a focus on the development of expertise in real-time analysis (RTA) techniques through applications to high energy physics (HEP) research and industry. The network centres around the training of 12 Early Stage Researchers (ESRs) between September 2021 and September 2025.

2 SMARTHEP as a European Training Network

As a European Training Network (ETN), the primary aim of the network is in training ESRs, whilst deepening synergies between HEP and industry. The network takes a novel approach to building such synergies, structuring each ESR position (a 3 year period of doctoral study) around academic and industrial secondments. To achieve this, the network is formed of a series of partnerships between universities, research institutes and organisations in industry, as listed in Table 1.

The network is formally structured as 7 Work Packages (WPs), laid out in Figure 1. WP1 “Management”, covers the management of the network by the Project Manager/Project

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Category	Partners
Universities	Lund University, Sorbonne University (LPNHE & LIP), Technische Universität Dortmund, University of Bologna, University of Geneva, University of Heidelberg, University of Helsinki, University of Manchester, Universidade Santiago de Compostela (IGFAE), Vrije Universiteit Amsterdam
Research institutes	CERN, CNRS, NIKHEF
Industry partners	IBM France, Lightbox, Point 6, Uni.versity of Manchester Institute for Data Science and AI, Verizon Connect, Ximantis

Table 1. The 18 organisations which form the SMARTHEP network.

Coordinator/Executive Board. WP2 "Training", sets out training and development of participants, by both network partners and external training providers. WP3 "Machine learning & advanced data analysis", develops machine learning (ML) techniques for use in real-time environments. WP4 "Hybrid architectures" focuses upon the deployment of non-CPU computing architectures in acceleration of data processing. WP5 "Decision-making in research and industry", applies WP3 and WP4 to develop RTA-based decision-making technologies. WP6 "Monitoring and discoveries", also applies WP3 and WP4 to RTA approaches in data analysis. WP7 "Dissemination and communication of results", publishes and propagates the results produced in WP6 and WP7.

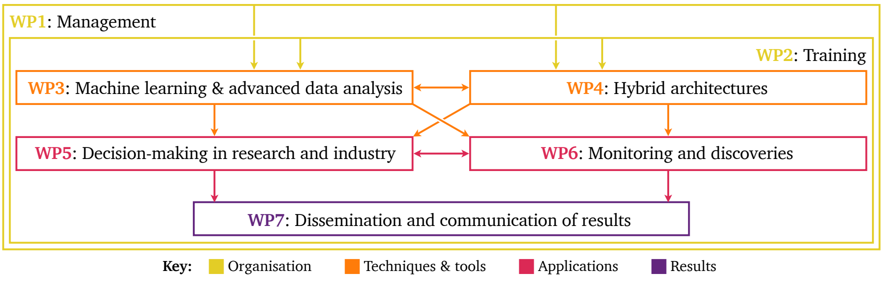

Figure 1. The structure of WPs within the SMARTHEP network. WP1 and WP2 define the organisation of the network; WP3 and WP4 introduce the techniques and tools of real-time analysis to the network; WP5 and WP6 use said techniques and tools to produce results for HEP and industry; WP7 makes these results available and promotes their wider use and adoption.

The network has a particular focus on physics at the Large Hadron Collider (LHC). Each ESR is thus affiliated to one of the four major experiments based at the LHC: ALICE, ATLAS, CMS and LHCb. The network duration coincides with Run 3 of the LHC, 2022-2025. As such, ESR projects and outcomes have an emphasis upon delivering required work for said experiments in the wider Run 3 context.

A unique feature of the network is the extensive cooperation between HEP and industry across all ESR positions. RTA approaches have seen significant adoption in industry in recent years, with many organisations turning to RTA as a means to handle "big data".

3 Real-time analysis

The challenge of rapidly processing large quantities of data is common to both HEP and industry, and remains a significant hurdle to progress in both areas. [1] Recent advances in computing have enabled the possibility of processing data in real-time, i.e. as data is collected (also commonly referred to as “online” processing). [2] Real-time analysis (RTA) is thus an umbrella term for such approaches, encompassing a number of state-of-the-art data processing techniques. By processing data online, resources (computing power, storage space, energy, etc.) can be saved and new insights can be obtained from the data recorded, as shown in Figure 2.

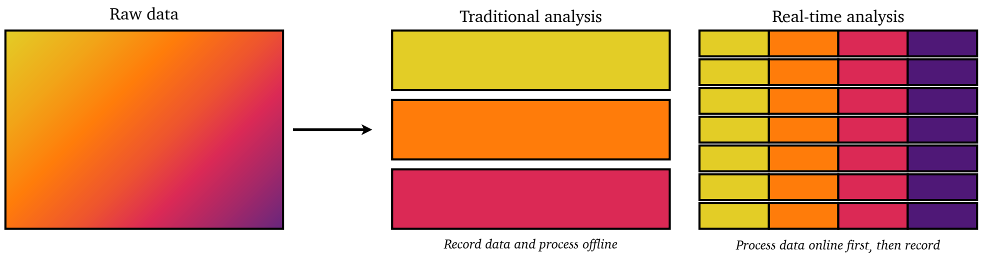

Figure 2. The traditional and real-time analysis approaches to processing raw data. Traditional approaches rely on recording all data and processing this offilne. Real-time analysis reverses this, processing data as it is produced and recording only the relevant processed information, enabling larger volumes of processed data to be stored.

RTA techniques have seen widespread adoption across HEP, in particular amongst trigger and data acquisition (TDAQ) systems. Since it is not possible to record the detector output and carry out event reconstruction at the LHC collision rate of 40MHz, a trigger must be devised to select only those events which are relevant to the physics goals of a given experiment. Such a trigger conventionally consists of a hardware trigger acting directly on parts of the detector output, and a staged software trigger, applying gradually more fine-tuned selections with increasing amounts of reconstructed event detail.

In industry, the limitations of the scale of “big data” looms over many applications of computing. However,

Successful implementation of RTA approaches rests upon the . In particular, in the areas of machine learning and hybrid architectures, which are summarised in Sections 3.1 & 3.2.

3.1 Machine learning

Machine learning (ML), a catch-all for a number of techniques and technologies wherein algorithms are trained to analyse data, enables rapid decision making and pattern recognition across a broad range of use cases. [3] Whilst general consumer access to ML models is a relatively recent phenomenon, ML already has an extensive history, with the foundations being laid in the 1950s and 1960s. [4, 5] In HEP, this history begins in the 1990s with the use of classifiers in offline physics analysis, and has since developed to a variety of classification on pattern recognition/anomaly detection techniques for both online and offline use. [6, 7]

Leading with the firs of these tools, ML classifiers are algorithms classed with classification. Many such algorithms exist, with Boosted Decision Trees (BDTs) and Neural Networks (NNs) amongst those employed across the field. The use of BDTs in signal selection for offline physics analysis has become standard practice, e.g. in suppresion of combinatorial background in the LHCb experiment measurement of the $B^0_s - \bar{B}^0_s$ oscillation frequency. [8] However, classifiers are also used to aid event reconstruction, e.g. in the CMS boosted event shape tagger, a NN trained to discriminate between possible t, $W^{\pm}$, Z^0 and H candidates within an event. [9] In industry, ML classifiers are used frequently in content deliver

Machine learning techniques can also be applied to pattern recognition and anomaly detection—tasks which cannot be realistically carried out on the scales of data presently being analysed. In industry, this is applied intuitively to fraud detection, wherein subtle details in data such as the transactions of a customer. In HEP [10]

3.2 Hybrid architectures

Typical computational resources consist of Central Processing Units (CPUs), processors which are designed for general purpose computation (i.e. varied tasks with significant variety in computing/memory resources), with large on-board memory and often multiple processing cores. Alternative architectures, such as those shown in Figure 3, can be applied in conjunction or in place of CPU architectures to accelerate processing where tasks are not well-suited are to CPU architectures alones.

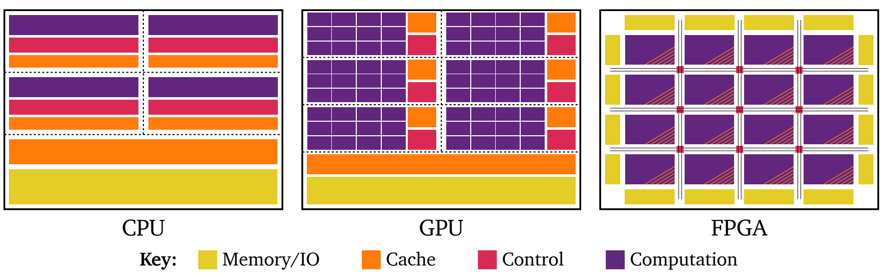

Figure 3. Comparison of CPU, GPU and FPGA architectures. A CPU is typically formed of several cores, each containing computational, control and cache resources, and a centralized cache, memory and input/output (IO) interface. GPUs are formed similarly, with centralized cache, memory and IO, and many multiprocessors; however, each multiprocessor contains a greater proportion of computational resources, which are themselves partitioned to perform tasks in parallel. FPGAs are structured in a radically different way, with memory and IO connected to many interlinked control blocks, each primarily formed of simpler logic gate arrangements and often accompanied by a small cache.

Field-programmable gate arrays (FPGAs) are integrated circuits which can be programmed by the user for specific tasks. [11] An FPGA consists of many simple logic circuits with a small amount of on-board memory, formed into logic blocks, each of which are connected via switch matrices. [12] FPGAs are thus well-suited to bespoke, computationally light but highly parallelisable tasks, such as low-level trigger decisions, wherein simple selections must be made rapidly. [13] In industry, FPGAs have seen adoption . However; a lack of on-board memory limits the deployment of FPGAs to more intensive tasks.

Graphical Processing Units (GPUs) can also be employed to . [14] Historically, the use of GPUs has been

4 Early stage researchers

The 12 ESRs form the core of the network, with the training and partnerships providing a scaffold for the completion of their respective outcomes. These ESRs work with HEP and industry partners throughout the 3 years of their doctoral study.

4.1 Structure of ESR positions

Each ESR is enrolled as a doctoral student at a partner university for 3 years. This university is typically also the primary institution of the ESR (2 industry-centred ESR positions are enrolled at a university near to the respective industry partner). At the end of the period of doctoral study, each ESR will receive a doctorate in particle physics from their university of enrollment.

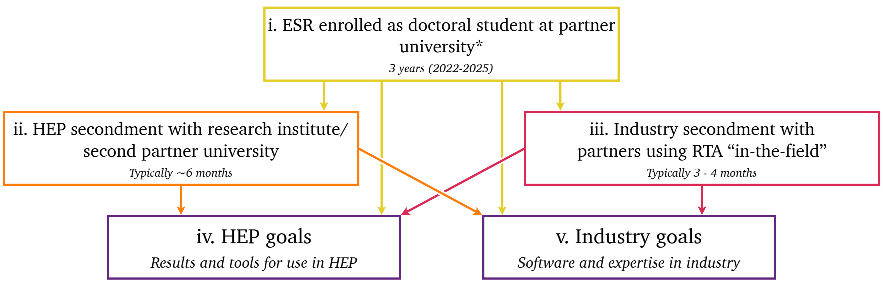

Figure 4. Diagram of the structure of a SMARTHEP ESR position. Each ESR is enrolled (i.). During the course of their enrolment, they will undertake secondments with network partners in HEP (ii.) and industry (iii.). Through the combination of their primary and secondment work, each ESR will achieve several goals in HEP (iv.) and industry (v.), as discussed in further detail in Section 5.1.

Each ESR will undertake a secondment in HEP during their studies, either at another partner university or a partner research institute. This is generally organised to last for 6 months, though this varies from project to project.

In addition to their time working in HEP, each ESR will also spend time working in industry, typically as a secondment of 3-4 months (though this is again flexible to the specific programme of each ESR position).

To paint a clearer picture of how the positions take shape, a few examples are given. Jamie Gooding (ESR7) is based at Technische Universität Dortmund, working on real-time event selection at the LHCb Experiment, with a HEP secondment of ≈ 6 months at CERN to support this work and a 3-4 month industry secondment with Ximantis, working on real-time traffic monitoring. Laura Boggia (ESR2)

5 Network outcomes

As an obligation to the European Union, intended network outcomes were laid out as a set of deliverables. These deliverables act to a guide the progression of the network and its participants. Key outcomes of the network are discussed in the following sections.

5.1 Goals of HEP and industry

The core outcomes of the network are a set of goals, which are completed on behalf of the network partners by the network participants. These goals vary, with the majority associated to a specific ESR position, for example, the goal of "calibration of ALICE TPC for heavy-ion physics" associated to ESR10, Joachim Hansen.

5.2 RTA whitepapers

As a deliverable of the network, the participants will write a series of whitepapers reviewing the current RTA state-of-the-art. The four whitepaper topics are listed in the following subsections and an overview is given for each. At time of writing, these whitepapers are expected to be submmited for publication by the end of 2023.

The first network whitepaper provides a review of current ML applications to HEP in RTA contexts and corresponding best practices. Examples of such applications range from data-taking, e.g. in particle identification at the ALICE experiment, to offline analysis, e.g. anomaly detection for diject resonance searches at the ATLAS experiment. [15, 16]

The use of hybrid architectures by LHC experiments is reviewed in the second SMARTHEP whitepaper. Acceleration of tasks such as selection and reconstruction by hybrid archetictures was developed significantly during Run 2 of the LHC (2015-2018). Run 3 deployments of hybird architectures capitalise on this progress, e.g. in the use of FPGAs in the ALICE Central Trigger System and the use of GPUs in the ATLAS High Level Trigger farm. [17, 18]

In the third whitepaper, the TDAQ systems of LHC experiments are reviewed, with a focus upon best practices for both TDAQ hardware and software. As such, this whitepaper reviews topics ranging from upgrades to the ATLAS TDAQ system, to the Allen framework of the LHCb experiment enabling software trigger operation at a 30 MHz readout rate. [19, 20]

5.3 Training of ESRs

Funding is allocated within the network for participants to attend relevant training activities. In the case of ESRs, training and career devlopment is discussed in writing their respective PCDP, providing a clear overview of their intended and requested training activities. Examples of such activities include attendance of specialist industrial training sessions and academic schools. Training is also provided within the network, between participants, for example in the First SMARTHEP School on Collider Physics and Machine Learning discussed in Section 6.2.

5.4 Software and digital assets

The work of the ESRs will generate a number of digital assets (e.g. software packages, data processing tools), with many being applicable beyond narrow academic/industrial applications. The network is committed to producing making any produced digital assets **F**indable, **A**ccessible, **I**nteroperable, and **R**eusable (FAIR). [21] Under these guiding principles our assets and results should be open and accessible to the wider community. To implement these commitments, a project on GitHub has been created to host such assets, https://github.com/SMARTHEP. Other assets and resources will be made available on the network website, https://smarthep.org.

6 Network events

Network events form the backbone of the SMARTHEP network, giving participants unique opportunities to meet, exchange ideas and develop. Whilst the events of the network are focused on an ESR audience, SMARTHEP has made many events available to additional interested early career scientists working/studying at SMARTHEP institutes.

6.1 SMARTHEP Kick-off Meeting

To commence ESR particpation in the network, a kick-off meeting was held at the University of Manchester from 21st to 25th November 2022, formally introducing the ESRs, and discussing objectives and organisation of the network. The meeting also served as an opportunity for participants from all sides of SMARTHEP to meet in person, network and discuss ideas. To facilitate this, a visit to the Jodrell Bank Centre for Astrophysics was held, and a review paper-writing course was provided by Scriptoria to train ESRs ahead of the writing of the 4 RTA whitepapers.

6.2 First SMARTHEP School on Collider Physics and Machine Learning

The First SMARTHEP School on Collider Physics and Machine Learning was hosted by the University of Geneva from 10th to 13th January 2023. The school provided a varied programme, including lectures on experimental physics at collider experiments by Anna Sfyrla and on theoretical physics & Monte Carlo event generators by Torbjörn Sjöstrand. Additionally, hands-on lessons in machine learning were led by Maurizio Pierini, with seminars also given on multimessenger astronomy by Teresa Montaruli and the CERN experimental programme by Jamie Boyd.

6.3 Upcoming events

At time of writing, the network still has two years ahead of it, in which further network events are planned. These will guide the governance of the network, develop ESR expertise and deepen collaborations with industry.

The network assembly sits as a cornerstone of network policy and governance.

Accelerator bootcamps in specific aspects of RTA . These are likely to take place in the summer of 2024. An industry applications school will round off the collaboration with industry, by which time it is expected that ESRs will have completed their industry secondments.

7 Conclusion

The network will provide valuable contributions in HEP, particularly to the commisioning and operation of LHC experiments throughout Run 3 of the LHC. Additionally, the network serves to further the adoption of RTA approaches in industry and do demonstrate the value of collaboration between HEP and industry.

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