Dynamic Information Extraction and Provenance Ledger for Edge AI

Ryan Coffee (PI), Audrey Corbeil Therrien, Angelo Dragone, Ryan Herbst,
Omar Quijano, and Jana Thayer – SLAC National Accelerator Laboratory
Matt Feldman – Stanford University
Ben Taylor – LedgerDomain, LLC

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The Linac Coherent Light Source II (LCLS-II) holds great promise to answer critical questions regarding ultra-fast materials dynamics, the molecular motion responsible for light harvesting, and the first trigger events in catalysis. The corresponding newly enabled experimental techniques such as femtosecond x-ray Fourier holography [2], time-domain ghost imaging [3], time-domain phonon dynamics [4, 5] and femtosecond resolved dark field x-ray microscopy [6] extract valuable information only after sorting or otherwise statistically treating signal dependence on stochastic source parameters, e.g. time-delay, spectral content, or spatial mode. The need to identify both very weak and/or very rare events in overwhelmingly cluttered and noisy data requires extreme data rate detectors that could be capable of one million readout frames per second either as next-generation commercial visible cameras or SLAC's own ePix family of x-ray imaging detectors. The raw data volume for such rates (TB/s) would be equivalent to producing 100 years worth of Ultra-HD video [7] every day which would require nearly $1M in new storage for each day of operation [8]. [1] Although the scale of the data for the complementary facilities LCLS-II and the upcoming Advanced Photon Source Upgrade (APS-U) pose extreme scale challenges, the evolution of 5G networked sensors driving autonomous industrial decision portends a critical need for data handling at the point of generation, at the sensor [9, 10]—conventional data center hosted mining is not a viable option for DOE labs and for Industry 4.0 alike. Similar to the multi-threading paradigm shift of the mid-2000s (Fig. 1), the Edge AI paradigm shift is upon us now.

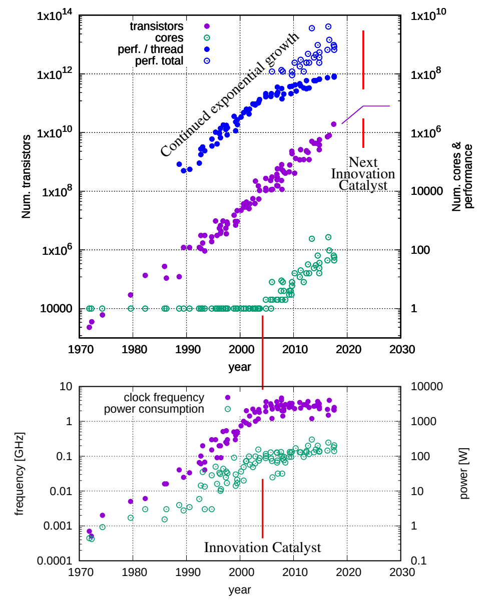

Figure 1: Adapted from Ref. [1]. Note that the limitations in the mid-2000s triggered the multi-threading paradigm.

A significant portion of human sensory processing occurs in the sensory organs themselves such as the edge detection in the retinal ganglion cells and rapid eye stabilization. We propose a similar function for our scientific sensors; a processing unit at the detector–Edge AI–that can analyze incoming data in real-time and provide actionable information back to the detector, out to the source, and forward to the downstream analysis networks. These inference engines will host dynamically adaptive algorithms based on user-trained machine learned inference models that are unique to the particular scientific question and extract contextually relevant information before passage down the analysis chain. This Edge AI system will be hosted on sensor-based Field Programmable Gate Arrays (FPGAs) and emerging flexible "batch size=1" inference accelerators [11, 12, 13, 14, 15] that will minimize latency to alleviate the need for inappropriately large memory buffers.

The streaming information extraction must flexibly handle the weekly re-definition of actionable information since new users mount experiments with vastly different objectives every week; this precludes a static data acquisition system. We therefore require user trained real-time streaming inference that can dynamically route data flow through the entire acquisition chain. The path of the data flow will typically depend on the particulars of the stochastically varying source parameters. For instance, in the case of time-domain phonon dynamics [4], diffuse scattering images would be sorted into time ordered bins until each bin holds sufficient statistics. At this point the time axis would be Fourier transformed to obtain a phonon-frequency map relevant for the experiment. Since only narrow regions in the frequency domain need to be sent from

[1]This only considers hardware costs. Actual costs including power, space and personnel are much higher (estimated at $30 per GB per month) and accumulate over time.

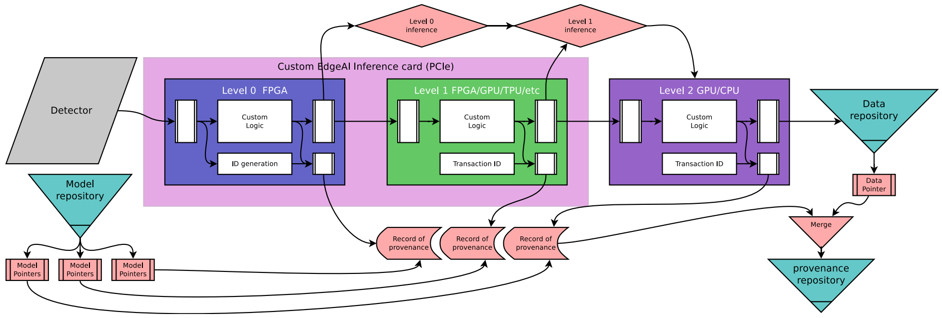

Figure 2: Schematic of information flow through heterogeneous hardware with ID generation and provenance tracking.

the Edge node to permanent storage, the desirable information can be as small as 10^{-3} compressed relative to the millions of individual images that were produce that information. In the case of time-domain ghost imaging [3], the spectroscopic information comes from the batch covariance of measured signal with incoming x-ray pulse time-energy distribution, itself the result of a trained inference model [16]. Since each group will train its own data processing and diagnostic inference models, these models will change weekly with each new arriving user group. This weekly re-definition requires that an Edge AI system fundamentally records both data and model provenance into a transaction ledger.

The transaction ledger will log the precise actions taken on the particular data event into a unique data provenance record (see Fig. 2). The ledger then will continue to track and update a quantifiable metric according to the derived scientific value of both data and algorithm. This "value aware" ledger can then be used for an automated dynamic retention policy whereby lifetime in archive would scale proportionally with the evolving scientific value. In other words, the more that data individuals or ML models are used for publications and even training subsequent inference models or the higher the impact of resulting products, the longer the data or model will remain active and discoverable in a data sharing marketplace. Aggregation would reveal the integrated value for scientific facilities, experimental techniques, and sensor technologies based on this quantifiable impact. The transaction ledger can also be used to track data individuals and models given the possibility for changing levels of sensitivity and privacy that are sure to arise in any future data marketplace. This ability to handle varying levels of sensitivity concern is why we target a blockchain solution to data and model identification and provenance ledger.

The immediacy of our need for ultra-low latency and dynamic handling data coupled with our long history of detector development–from sensor to readout electronics to complex data pipeline design–makes SLAC a unique environment with the necessary infrastructure to develop Edge AI infrastructure. SLAC has experts in scientific instrumentation, data analysis, FPGA development, and machine learning all on-site to create, implement, and deploy the Edge AI system. The PI will leverage his collaboration with blockchain industry partner LedgerDomain [17, 18] as well as his inter-lab and inter-agency collaborations to ensure that the developed infrastructure is compatible with an emerging data marketplace and can adapt to varying levels of open or restricted access and data redaction. Furthermore, the PIs has existing collaboration with emerging Edge AI inference chip makers in the private sector and therefore is well positioned to develop a broadly compatible framework across DOE and Industry 4.0 at large.

Deliverables Ultra-low latency streaming analysis provides actionable information for autonomous feedback control of both the light source and the detector, thus enabling an fully adaptive instrument, source, and analysis pipeline. The primary objective of this project is therefore the deployment of an extremely low latency, real-time Edge AI system that maximizes data reduction while also maximizing user-defined domain-specific information preservation. The system will create a state-identifying transaction ledger that serves as a continual provenance ledger and enables dynamic access and retention control. This data and algorithm provenance ledger will imbue respective data and algorithms with quantitative metrics that perpetually track derived scientific value. We will target ultra-high frame rate imaging detectors, including the ePix family of x-ray imaging detectors as well as commercial waveform digitizers and image capture cards. We will help formulate interface standards for emerging commercial on-detector inference acceleration microchips.

Ryan Coffee (PI): Sr. Staff Scientist, LCLS/PULSE, SLAC National Accelerator Laboratory, coffee@slac.stanford.edu, 650-387-0981. Graduate and Postdoctoral Advisors: G. Gibson (University of Connecticut), P.H. Bucksbaum (PULSE/Stanford) **Graduate Advisees:** Kareem Hegazy (Stanford), Katie Fotion (Cruise Automation), Abdullah Ahmed-Rashed (Brown), Nick Hartmann (Coherent Inc), Mina Bionta (MIT), Doug French (Bettis Atomic Power Laboratory) **Postdoctoral Advisees:** Wolfram Helml (U. Dortmund), Markus Ilchen (XFEL), Anton Lindahl (Qamcom), Averell Gatton (SLAC), Audrey Corbeil Therrien (SLAC) **Collaborators:** Ani Aprahamian (Notre Dame), Nora Berrah (U Connecticut), Christoph Bostedt (PSI), Phil Bucksbaum (SLAC), Adrian L Cavalieri (PSI), Martin Centurion (U Nebraska), John Costello (U Dublin), James Cryan (SLAC), Franz-Josef Decker (SLAC), Philip Demekhin (U Kassel), Lou DiMauro (Ohio State U), Hermann A Dürr (Uppsala Univ.), Amir Farbin (UT Arlington), William Fawley (SLAC), Raimund Feifel (U Gothenburg), Thomas Feurer (U Bern), Leszek Frasinski (Imperial College), Alan Fry (SLAC), Andreas Galler (XFEL), Tais Gorkhover (SLAC), Grzhimailo (Lomonosov Moscow State Univ), Jan Grunert (XFEL), Markus Gühr (U Potsdam), Gregor Hartmann (U Kassel), Tony Heinz (SLAC), Wolfram Helml (U. Dortmund), Andrew Hock (Cerebras), Zhirong Huang (SLAC), Markus Ilchen (Euro XFEL), Andreas Junge (Penguin Computing), Nikolai Kabachnik (Lomonosov Moscow State Univ.), Daniel Kane (Mesa Photonics), Reinhard Keinberger (TU Munich), Adam Kirrander (U. Edinburgh), Jeff Koller (Apple), Craig Levin (Stanford), Anton Lindahl (Qamcom), Aaron M Lindenberg (SLAC), Alberto Lutman (SLAC), Jon Marangos (Imperial College), Todd Martínez (Stanford), Serguei Molodtsov (XFEL), Scott Murphy (AMD), Ajay K Nair (Google), Anders Nilsson (U Stockholm), Kunle Olukotun (Stanford), Timor Osipov (NOVA Instruments), Rob Parrish (QCWare), Gregory Penn (LBNL), Rishiraj Pravahan (INQNET), Mohan Rajagopalan (Curious-AI), Daniel Ratner (SLAC), Tor Raubenheimer (SLAC), Dipanwita Ray (KLA-Tencor), Nina Rohringer (U Hamburg), Daniel Rolles (KSU), Arnaud Rouzee (MBI-Berlin), Jan Eric Rubensson (Uppsala U), Artem Rudenko (KSU), Alvaro Sanchez-Gonzalez (DeepMind), Robert Schoenlein (SLAC), Sharon Shwartz (Bar-Ilan U), Klaus Sokolowski-Tinten (Essen Univ.), Mike Styer (Google), Conny Såthe (MAX4 Lund), Ben Taylor (LedgerDomain), Olivier Temam (DeepMind), Thomas Tschentscher (XFEL), Jens Viefhaus (DESY), Xijie Wang (SLAC), Peter Weber (Brown), Chris White (Google)

Audrey Corbeil Therrien, Banting Research Fellow & Linac Coherent Light Source (LCLS) Data Systems. Postdoctoral advisors: Ryan N. Coffee (SLAC), Jana B. Thayer (SLAC) **Graduate advisors:** Serge A. Charlebois (Sherbrooke), Réjean Fontaine (Sherbrooke), Roger Lecomte (Sherbrooke), Paul Lecoq (CERN), Jean-Francois Pratte (Sherbrooke) **Collaborators:** Averell Gatton (SLAC), Stefan Gundacker (CERN), William Lemaire (Sherbrooke), Samuel Parent (Sherbrooke), Omar Quijano (SLAC), Marc-Andeé Tétrault (Sherbrooke, now Harvard Medical School).

Ryan Herbst: Department Head, Electronics Systems, Technology & Innovation Directorate, Advanced Instrumentation For Research Division. Collaborators: Shiva Abbasazadeh (University of Illinois), David Abbot (Jefferson Laboratory), Babek Abi (University of Oxford), Nathan Baltzell (JLAB), Giles Barr (University of Oxford), Marco Battaglieri (INFN Genova), Kurt Biery (Fermilab), Mariangela Bondi (INFN Catania), Sergey Boyarinov (JLAB), Stephen Bueltmann (ODU), Volker Burkert (JLAB), Daniela Calvo INFN (Torino), Gabriella Carini (Brookhaven), Massimo Carpinelli (INFN Sassari), Andrea Celentano (INFN Genova), Gabriel Charles (ORSAY), William Cooper (FNAL), Chris Cuevas (JLAB), Annalisa D'Angelo (INFN U. Rome), Natalia Dashyan (YerPhI), Marzio De Napoli (INFN Catania), Alexandre Deur (JLAB), Raffaella DeVita (INFN Genova), Raphaël Dupre (ORSAY), Hovanes Egiyan (JLAB), Latifa Elouadrhiri (JLAB), Rouven Essig (Stony Brook U.), Vitaliy Fadeyev (UCSC), Alessandra Filippi (INFN Torino), Arne Freyberger (JLAB), Michel Garçon (CEA-Saclay), Nerses Gevorgyan (YerPhI), Francois-Xavier (Girod JLAB), Keith Griffioen (W&M), Michel Guidal (ORSAY), Maurik Holtrop (UNH), Greg Kalicy (ODU), Mahbub Khandaker (Idaho U.), Emanuele Leonora (INFN Catania), Luca Marsicano (INFN Genova), Kyle McCarty (UNH), Bryan McKinnon (Glasgow U.), Carlos Munoz-Camacho (ORSAY), Silvia Niccolai (ORSAY), Kurtis Nishimura (University Of Hawaii), Michail Osipenko (INFN Genova), Rafayel Paremuzyan (UNH), Nunzio Randazzo (INFN Catania), Ben Raydo (JLAB), Alessandro Rizzo (INFN U. Rome), Youri Sharabian (JLAB), Gabriele Simi (INFN Padova), Valeria Sipala (INFN Sassari), Stepan Stepanyan (JLAB), David Strom (University Of Oregon), Lauren Thompkins (Stanford), Sho Uemura (Los Alamos), Maurizio Ungaro (JLAB), Holly Vance (JLAB), Gary Varner (University Of Hawaii), Hakop Voskanyan (YerPhI), Andrew White (University Of Texas, Arlington), Bradley Yale (UNH)

Ben Taylor, Founder and CEO, LedgerDomain, LLC. Graduate advisor: William H Orme-Johnson. **Collaborators:** Perry Shieh (UCLA), Josenor deJesus (UCLA) and William Chien (UCLA).

Omar Quijano, Department Head, Linac Coherent Light Source (LCLS) IT/Networking. Graduate Advisor: Nikos Mourtos **Collaborators:** Patrick H Reisenthal, Daniel J. Lesieutre, Michael R. Mendenhall, Harrison S. Y. Chou, Joel Tambaoan, Ivan Tan, Namgyal Tesur, Ian Dupzyk, Linda Contreras, Sean Montgomery.

Matt Feldman, Graduate Fellow, Stanford Computer Science & Developer SambaNova Systems. Graduate advisor: Kunle Olukotun.

Angelo Dragone (not funded), Department Head, Integrated Circuits, Technology & Innovation Directorate, Advanced Instrumentation For Research Division.

Jana Thayer (not funded), Department Head, Linac Coherent Light Source (LCLS) Data Systems.

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