The Institute for Collider Particle Physics

UNIVERSITY OF ZULULAND

UNIVERSITY OF LIMPOPO

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

NRF National Research Foundation

iThemba LABS Laboratory for Accelerator Based Sciences

INSTITUTE FOR COLLIDER PARTICLE PHYSICS
UNIVERSITY OF THE WITWATERSRAND

First ASFAP Particle Physics Day, 19/11/21

Outline

- ❑ Overview
  - ❑ Current membership and scope
- ❑ Data analysis and Phenomenology
  - ❑ The world of anomalies
  - ❑ Role of Artificial Intelligence
- ❑ Instrumentation at ATLAS
  - ❑ Maintenance, operations, upgrade
- ❑ Human capacity development
  - ❑ Pipeline of future academics
- ❑ Technology transfer

Current graduate students: (19 PhD + 23 MSc + 6 honors, 48 students)

Lawrence Christopher, PhD
Sukanya Sinha, PhD
Mvelo Dhlamini, MSc
Danielle Wilson, MSc
Karien du Plessis, MSc
Hannah Van Der Schyf, MSc
Roy Gusinow, MSc
Benjamin Lieberman, PhD
Joshua Choma, MSc
Hirmans Tabaharizato, PhD
Thuso Mathaha, MSc
Thabang Lebese, PhD
Phuti Rapheeha, PhD
Gaogalalwe Mokgatitswane, PhD
Edward Nkadimeng, PhD

Ryan McKenzie, MSc → PhD
Nkosiphendule Njara, MSc
Thabo Lepota, MSc
Humphry Tlou, PhD
Abdualazem Fadol, PhD
Onesimo Mtintsilana, PhD
Esra Shrif, PhD
Elias Malwa, MSc
Lerato Baloyi, PhD
Talemwa Kaheru, MSc
Malipalema Khang, MSc
Meghan Malaatjie, MSc
Nidhi Tripathi, PhD
Innocent McHechesi, MSc
Tshegofatso Sekgobela, MSc
Lungisani Phakakthi, MSc

Nathan Boyles, PhD
Kentaro Hayasi, MSc
Finn Stevenson, MSc
Ralekete Temo, MSc
Mpho Gololo, PhD
Ronewa Nemalili, MSc
Ayanda Thwala, MSc
Othmane Mouane, PhD
Tshepo Mahafa, PhD
Nicholas Perikli, MSc
Sanele Gumede, MSc

+ 6 honors students

Over 30 prizes and awards

Post-doctoral fellows:
Tashnuva Choudri, Salah Dahbi, Abhaya Swain + 3 new fellows

Engineers and technical staff: Fernando Carrio, Roger van Rensburg

Academics:
Deepak Kar, Betty Kibirige, Mukesh Kumar, Xifeng Ruan, Bruce Mellado

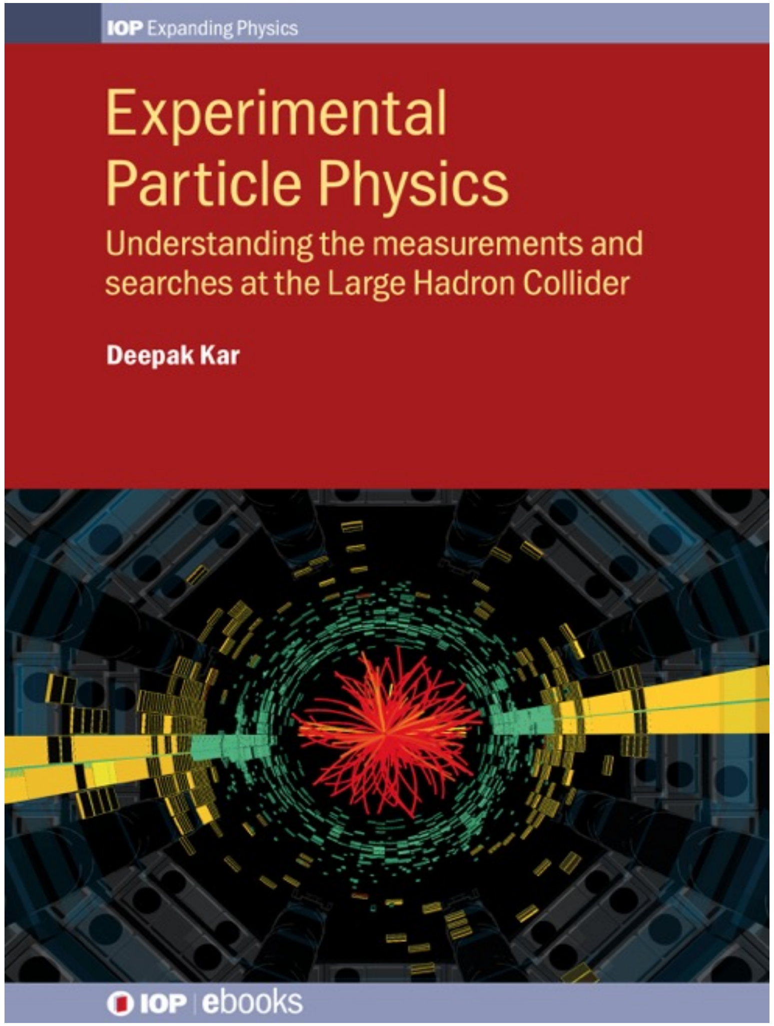
Positions of Leadership at ATLAS (past two years)

Name	Position	Area
Edward Nkadimeng	Convenor of LVPS working group	Instrumentation
Humphry Tlou	TileCal run coordinator	Instrumentation
Ryan McKenzie	TileCal run coordinator	Instrumentation
Bruce Mellado	Chairperson of the Institutional Board of the Tile Calorimeter, TileCal management	Instrumentation
Bruce Mellado	Level 2 Manager of the TileCal Phase II upgrade	Instrumentation
Xifeng Ruan	Lead contact of analysis group	Data analysis
Sukanya Sinha	Lead contact of analysis group	Data analysis
Yesenia Hernandez	Lead contact of analysis group	Data analysis

Strive at having a strong presence at the ATLAS experiment

The book!

Prof. Deepak Kar



First book to focus on experimental data analysis techniques.

An one stop resource for beginning students in the field, downloaded many times and acclaimed by readers!

Scope of Research

Physics through data analysis

Analysis of ATLAS Data
Experimental HEP,
experimental techniques,
Big Data

Artificial Intelligence
Machine Learning,
Data analytics,
Statistics

Particle Physics Phenomenology
HEP Theory,
Connection with SKA and future facilities

Radiation studies
Nuclear Physics,
Material sciences,
Chemistry, NECSA,
iThemba LABS,
SASOL etc..

Analog and Fast Digital Electronics.
Electrical engineering,
industry

Theory

Instrumentation

Physics, Data Analysis and Phenomenology

The world of anomalies, a major driver
Looking for new physics at the TeV scale with new methods
Looking for new physics at the EW scale
The role of Machine Learning

Unveiling hidden Physics Beyond the Standard Model at the LHC

1-3 March 2021

Europe/Zurich timezone

Nicole Bell (University of Melbourne)
Eduard Boos (Moscow State University)
Kingman Cheung (National Tsing Hua University)
Andreas Crivellin (Paul Scherrer Institute)
Bhupal Dev (Washington University in St. Louis)
Belen Gavela (Autonomous University of Madrid)
Rohini Godbole (Indian Institute of Science, Bangalore)
Tao Han (University of Pittsburgh)
Rabindra Mohapatra (University of Maryland)
Biswarup Mukhopadhyaya (IISER Kolkata)
Tilman Plehn (Heidelberg University)
Yifang Wang (Institute of High Energy Physics, Beijing)

Oliver Fischer (University of Liverpool), co-chair
Bruce Mellado (University of the Witwatersrand and iThemba LABS), co-chair

Starts 1 Mar 2021, 13:30
Ends 3 Mar 2021, 17:30
Europe/Zurich

This workshop is fully

Oliver Fischer
Bruce Mellado

Registration
Registration for this event is currently open.

573 **Register now ›**

White paper under review by EPJC

arXiv:2109.06065v1 [hep-ph] 13 Sep 2021

Unveiling Hidden Physics at the LHC

Oliver Fischer[†,1], Bruce Mellado[†,2,3], Stefan Antusch[4], Emanuele Bagnaschi[5], Shankha Banerjee[6], Geoff Beck[2], Benedetta Belfatto[7,8], Matthew Bellis[9], Zurab Berezhiani[10,11], Monika Blanke[12,13], Bernat Capdevila[14,15], Kingman Cheung[16], Andreas Crivellin[5,6,17], Nishita Desai[18], Bhupal Dev[19], Rohini Godbole[20], Tao Han[21], Philip Harris[22, 23], Martin Hoferichter[24], Matthew Kirk[25,26], Suchita Kulkarni[27], Clemens Lange[28], Kati Lassila-Perini[29], Zhen Liu[30], Farvah Mahmoudi[6,31], Claudio Andrea Manzari[5,17], David Marzocca[32], Biswarup Mukhopadhyaya[33], Antonio Pich[34], Xifeng Ruan[2], Luc Schnell[35, 36], Jesse Thaler[22, 23], and Susanne Westhoff[37]

[1] *Department of Mathematical Sciences, University of Liverpool, Liverpool, L69 7ZL, UK*
[2] *School of Physics and Institute for Collider Particle Physics, University of the Witwatersrand, Johannesburg, Wits 2050, South Africa.*
[3] *iThemba LABS, National Research Foundation, PO Box 722, Somerset West 7129, South Africa.*
[4] *Department of Physics, University of Basel, Klingelbergstr. 82, CH-4056 Basel, Switzerland*
[5] *Paul Scherrer Institut, CH–5232 Villigen PSI, Switzerland*
[6] *CERN Theory Division, CH–1211 Geneva 23, Switzerland*
[7] *Dipartimendto di Fisica "E. Fermi", Università di Pisa, Largo Bruno Pontecorvo 3, I-56127 Pisa, Italy*
[8] *INFN Sezione di Pisa, Largo Bruno Pontecorvo 3, I-56127 Pisa, Italy*
[9] *Siena College, 515 Loudon Road, Loudonville, NY 12211-1462, United States*
[10] *Dipartimendto di Fisica e Chimica, Università di L'Aquila, 67100 Coppito, L'Aquila, Italy*
[11] *INFN, Laboratori Nazionali del Gran Sasso, 67100 Assergi, L'Aquila, Italy*
[12] *Institute for Astroparticle Physics (IAP), Karlsruhe Institute of Technology, Hermann-von-Helmholtz-Platz 1, D-76344 Eggenstein-Leopoldshafen, Germany*
[13] *Institute for Theoretical Particle Physics (TTP), Karlsruhe Institute of Technology, Engesserstrasse 7, D-76128 Karlsruhe, Germany*
[14] *Dipartimento di Fisica, Università di Torino, Via P. Giuria 1, Torino I-10125, Italy*
[15] *INFN Sezione di Torino, Via P. Giuria 1, Torino I-10125, Italy*
[16] *Department of Physics, National Tsing Hua University, Hsinchu 300, Taiwan*
[17] *Physik-Institut, Universität Zürich, Winterthurerstrasse 190, CH-8057 Zürich, Switzerland*
[18] *Tata Institute of Fundamental Research, 1 Homi Bhabha Road, Mumbai 400005, India*
[19] *Department of Physics and McDonnell Center for the Space Sciences, Washington University, St. Louis, MO 63130, USA*
[20] *Indian Institute of Science (IISc), Bangalore 560012, Karnataka, India*
[21] *Pittsburgh Particle Physics, Astrophysics, and Cosmology Center, Department of Physics and Astronomy, University of Pittsburgh, Pittsburgh, PA 15206, USA*
[22] *Center for Theoretical Physics, Massachusetts Institute of Technology, Cambridge, MA 02139, USA*
[23] *The NSF AI Institute for Artificial Intelligence and Fundamental Interactions*
[24] *Albert Einstein Center for Fundamental Physics, Institute for Theoretical Physics, University of Bern, Sidlerstrasse 5, 3012 Bern, Switzerland*
[25] *Dipartimento di Fisica, Università di Roma "La Sapienza", Piazzale Aldo Moro 2, 00185 Roma,*

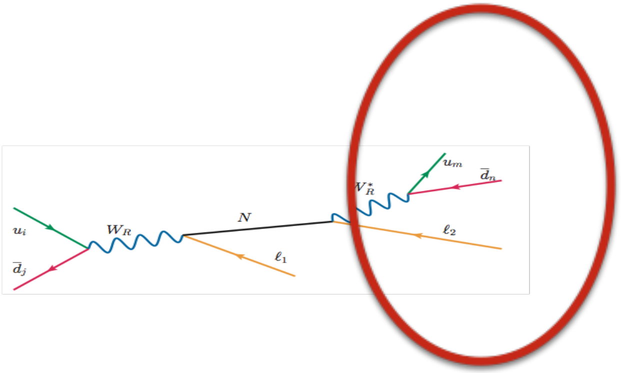
Condensed version to be submitted to Snowmass

We are in the business of discovery; existing anomalies are a very important driver

Boosted Heavy Neutrino Search: electrons in jets

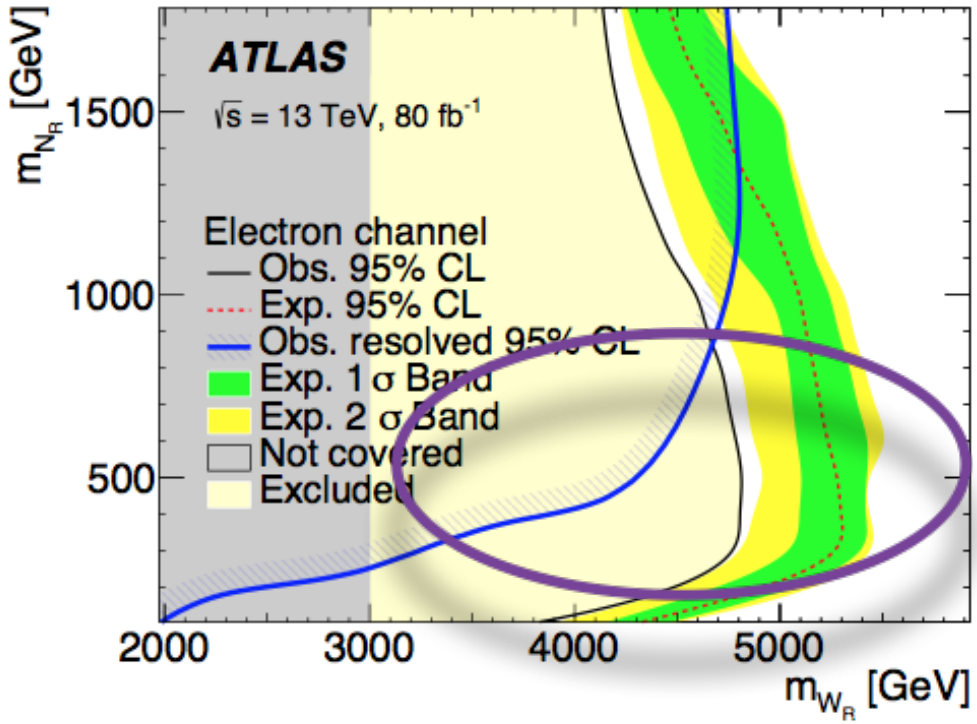
Debarati Roy, Former postdoc

Lawrence Davou PhD student

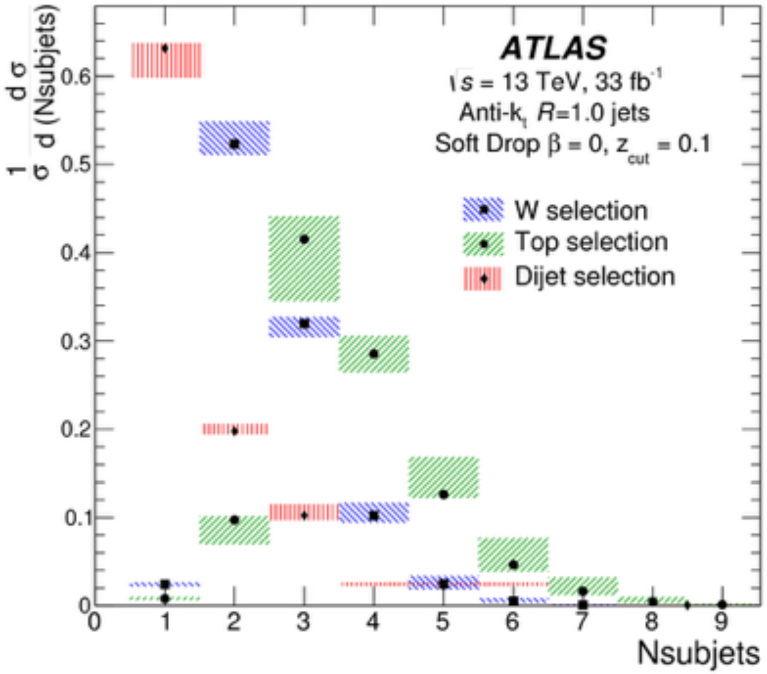


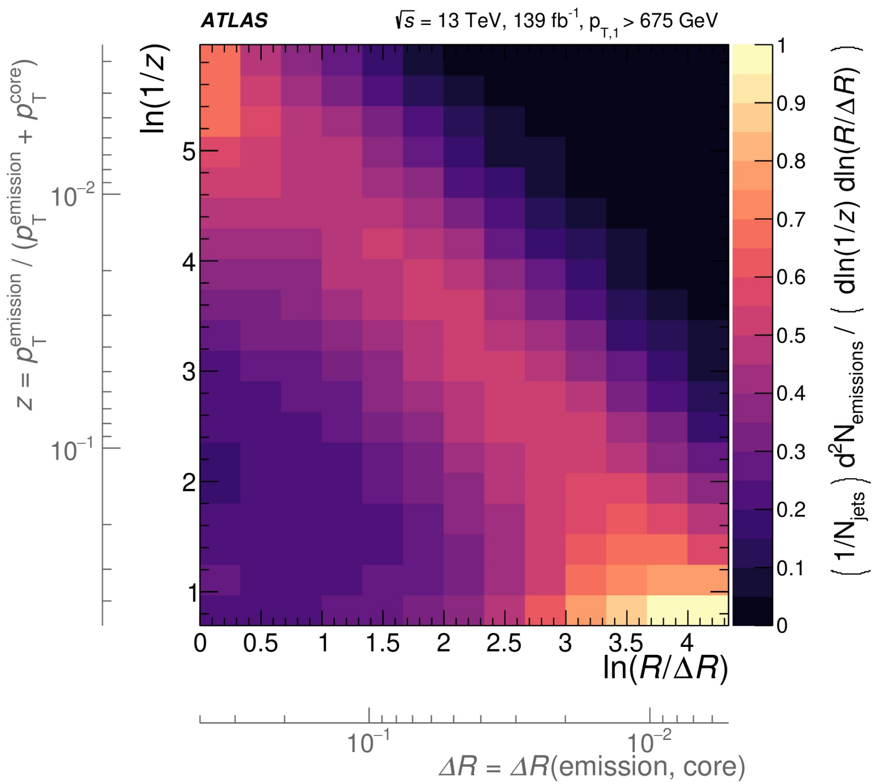
In ATLAS, electrons close to jets are typically overlap-removed, so this was a challenging analysis to look at this unusual topology.

Complementary strength from existing analyses



Zooming in on Jet Substructure

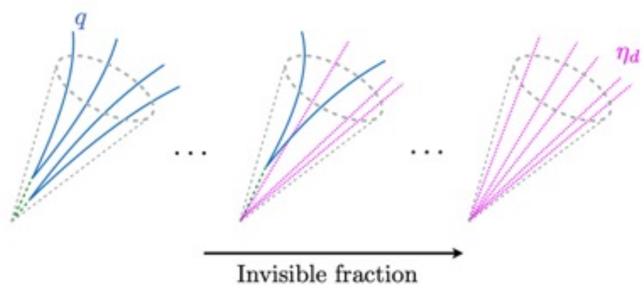




Most comprehensive jet substructure
measurement using a bottom-up
Derivation of experimental uncertainties

First measurement of jet Lund plane!

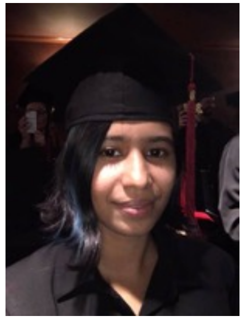
Dark and Semivisible jets: unusual signatures emanating from strongly interacting dark sector



Collaborating with Lund/Manchester/UCL/Glasgow on these projects

CONTUR to probe the parameter space of these models

Sukanya Sinha,
Current PhD student



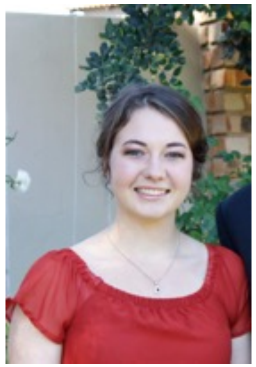
Tasnuva Chowdhury,
Current postdoc

Results in jets-close-to-met, another typically uncovered topology in ATLAS. First search in progress a

Machine learning methods are being used!

Pheno paper (Kar and Sinha) on the subject published (with Scipost referee comment): "... the research explores a new research direction and, if successful, could lead to many measurements from the ATLAS and CMS"

Roy Gusinow,
MSc student



Danielle Wilson
MSc student

Multi-lepton anomalies: Methodology

(to avoid biases and look-else-where effects)

Based Higgs p_T, hh, tth, VV in Run 1
Eur. Phys. J. C (2016) 76:580

Model defined and predictions made for multilepton excesses

Multi-lepton excesses in Run 1 and few Run 2 results available in 2017

J.Phys.G 45 (2018) 11, 115003

Model parameters fixed in 2017 with m_H=270 GeV, m_S=150 GeV, S treated as SM Higgs-like, dominance of H→Sh,SS

Fixed final states and phase-space defined by fixed model parameters.
NO tuning, NO scanning

Update same final states with more data in Run 2

Study new final states where excesses predicted and data available in Run 1 and Run 2 (e.g., SS0b, 3l0b, ZW0b)

J.Phys. G46 (2019) no.11, 115001
JHEP 1910 (2019) 157
Chin.Phys.C 44 (2020) 6, 063103
Physics Letters B 811 (2020) 135964
Eur.Phys.J.C 81 (2021) 365

Combination of fit results (2019)

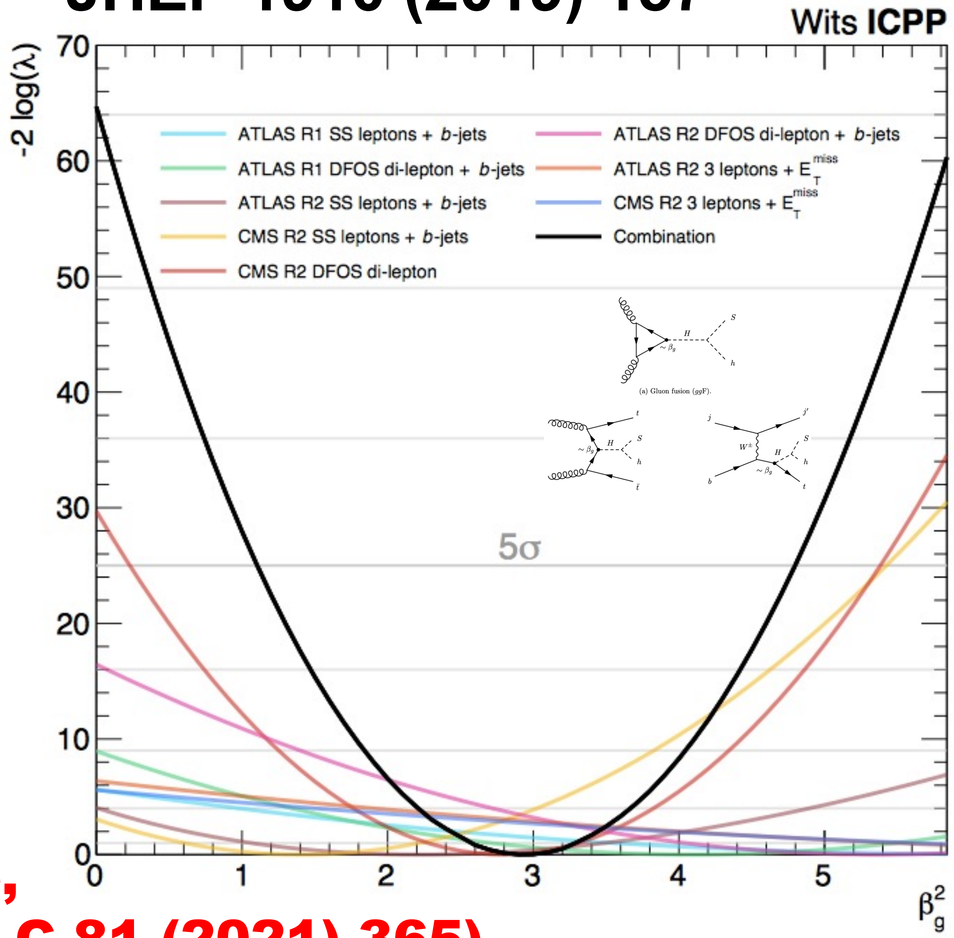
- **Simultaneous fit for all measurements:**
- **To the right: (-2 log) profile likelihood ratio for each individual result and the combination of them all**
- **The significance for each fit is calculated as**

$$\sqrt{-2\log\lambda(0)}$$

- **Best-fit: $\beta_g^2 = 2.92 \pm 0.35$**
- **Corresponds to 8.04σ**

Excesses have been growing since, and new have emerged (Eur.Phys.J.C 81 (2021) 365)

JHEP 1910 (2019) 157



Interpretation: Measure of the inability of current MC tools to describe multiple-lepton data and how a simplified model with H→Sh is able to capture the effect with one parameter

Anatomy of the multi-lepton anomalies

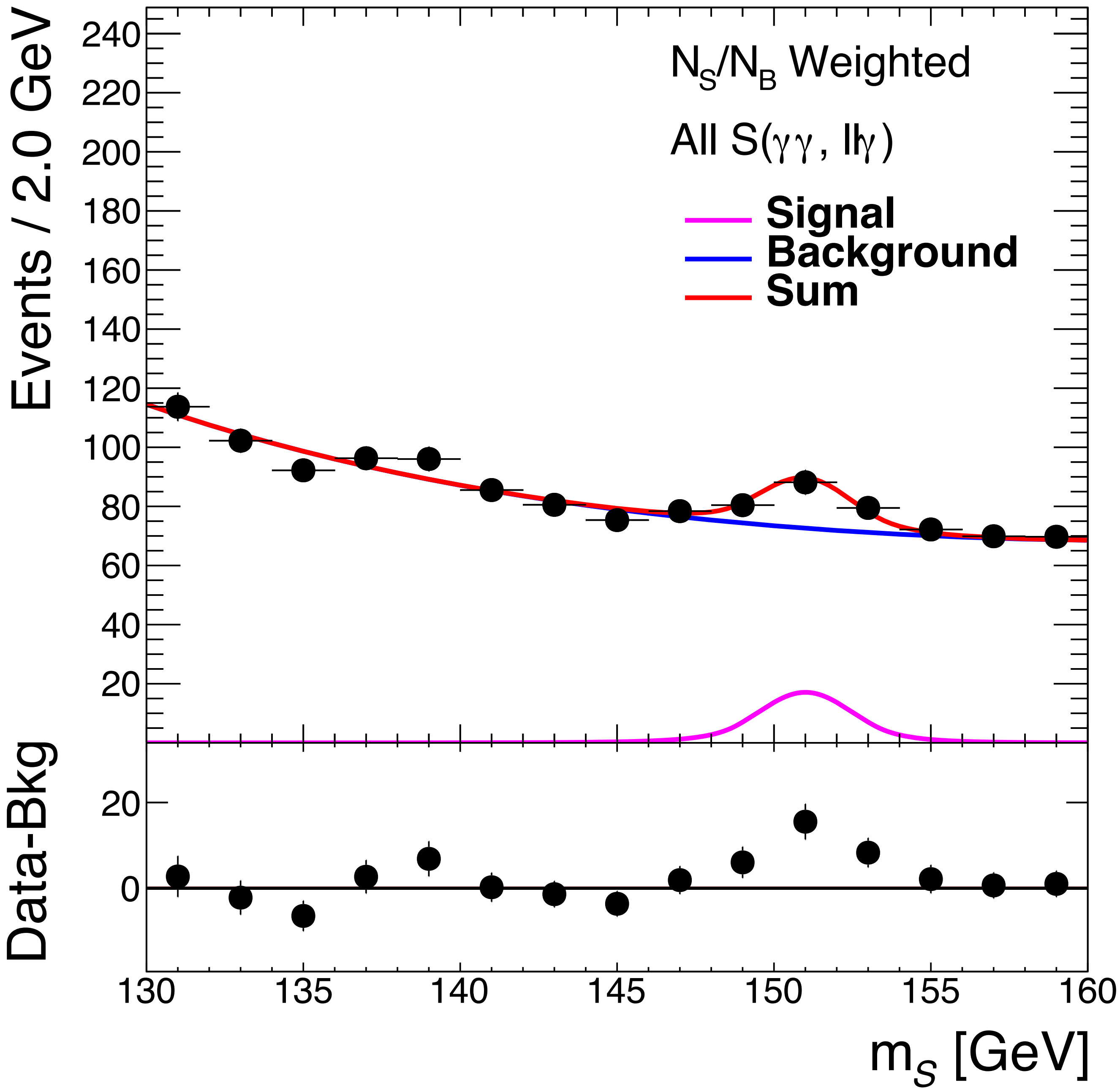
Final state	Characteristic	Dominant SM process	Significance
l^+l^- + jets, b-jets	m_{ll}<100 GeV, dominated by 0b-jet and 1b-jet	tt+Wt	>5σ
l^+l^- + full-jet veto	m_{ll}<100 GeV	WW	~3σ
$l^\pm l^\pm$ & $l^\pm l^\pm l$ + b-jets	Moderate H_T	ttW, 4t	>3σ
$l^\pm l^\pm$ & $l^\pm l^\pm l$ et al., no b-jets	In association with h	Wh, WWW	~4.5σ
$Z(\rightarrow l^+l^-)+l$	p_{TZ}<100 GeV	ZW	>3σ

Anomalies cannot be explained by mismodelling of a particular process, e.g. ttbar production alone. In both ATLAS and CMS.

https://arxiv.org/abs/2109.02650 under review

Analysis of publicly available di-photon and $Z\gamma$ spectra in associated production gives global 4.8σ excess around 151 GeV. Fiducial yields consistent with H→SS* hypothesis with m_H=270 GeV (see above)

Excess not seen in $S \to ZZ \to 4\ell, \ell = e, \mu$



P.Harris

How does Semi/Weak-supervision work in anomaly detection

Sample A

VS

Sample B

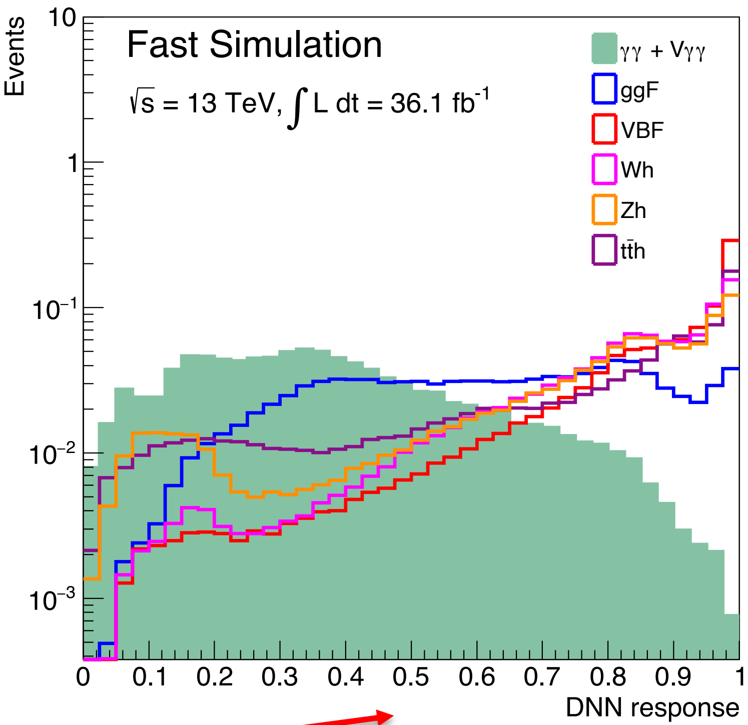
Difference: 

Strategy: Train the data in A agains B

Challenge:  Must all be same in A and B

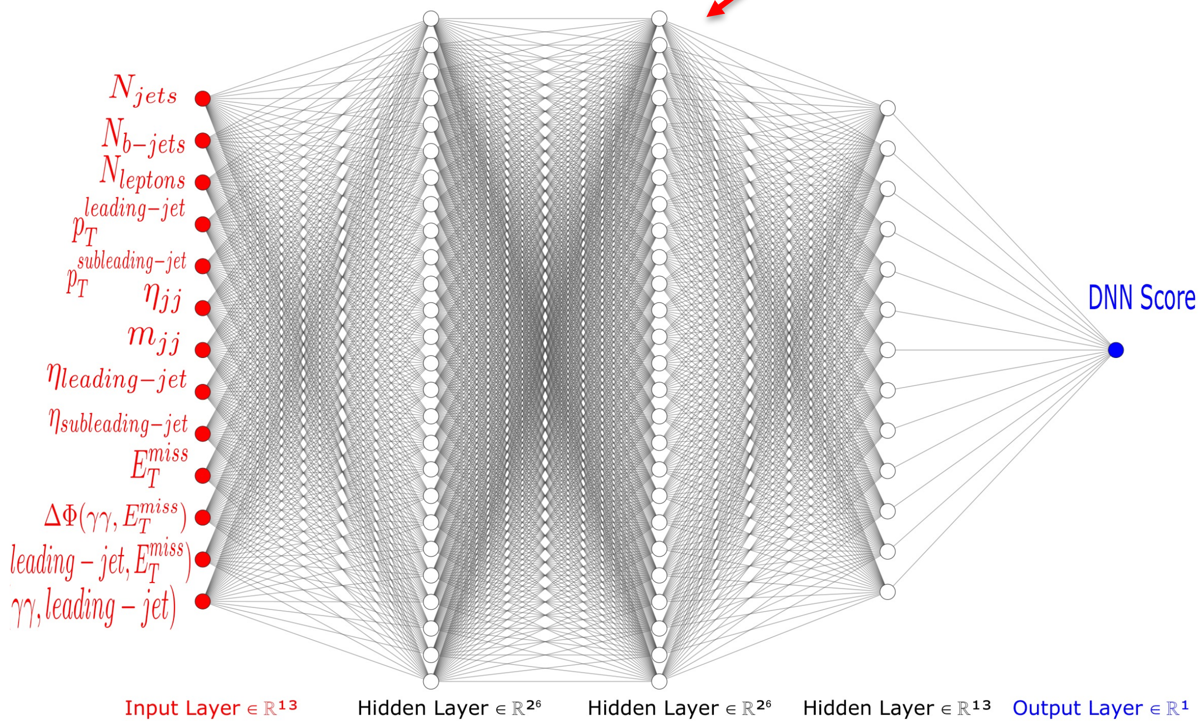
Machine learning approach for the search of resonances with topological features at the Large Hadron Collider

- ML may play a significant role in the deeper exploration of new physics BSM at LHC.
- We introduce a search for any resonances in Data with Weak Supervised learning.
- Higgs production is used as benchmark



DNN response distributions for the SM Higgs boson associated production with unlabelled signals.

DNN architecture and features



Link to publication:
https://arxiv.org/abs/2011.09863

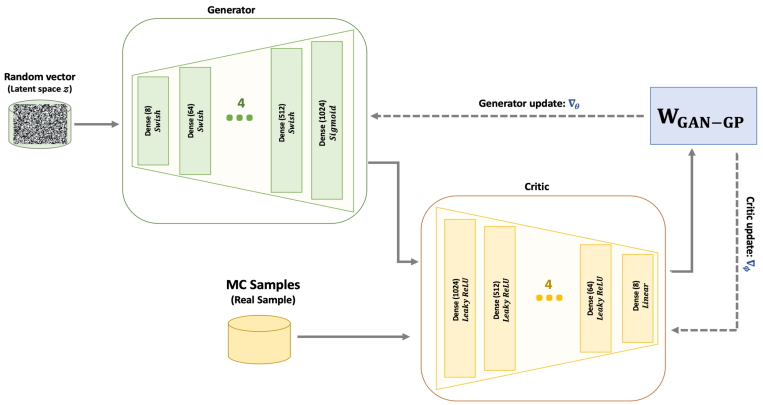
Generative Models in High Energy Physics

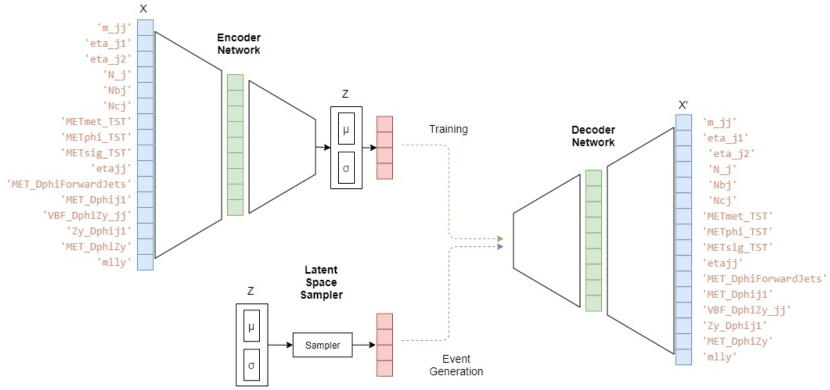
Exploration and evaluation of various generative AI methods to simulate datasets.

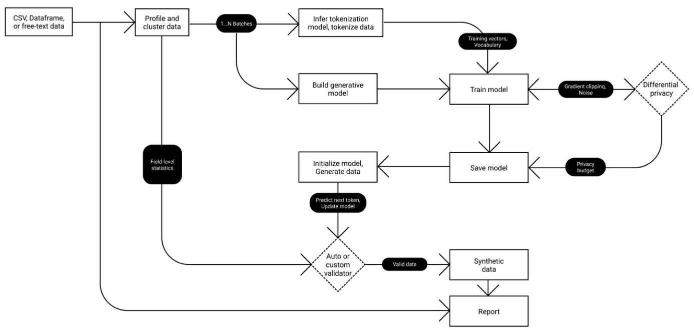
Monte Carlo Data → Generative Model → Generated Data

<u>Methods</u>

1. Kernel Density Model
2. Long-Short Term Memory (LSTM) Neural Network Model
3. Variational Autoencoders (VAE) Model
4. Wasserstein Generative Adversarial Networks (WGAN)

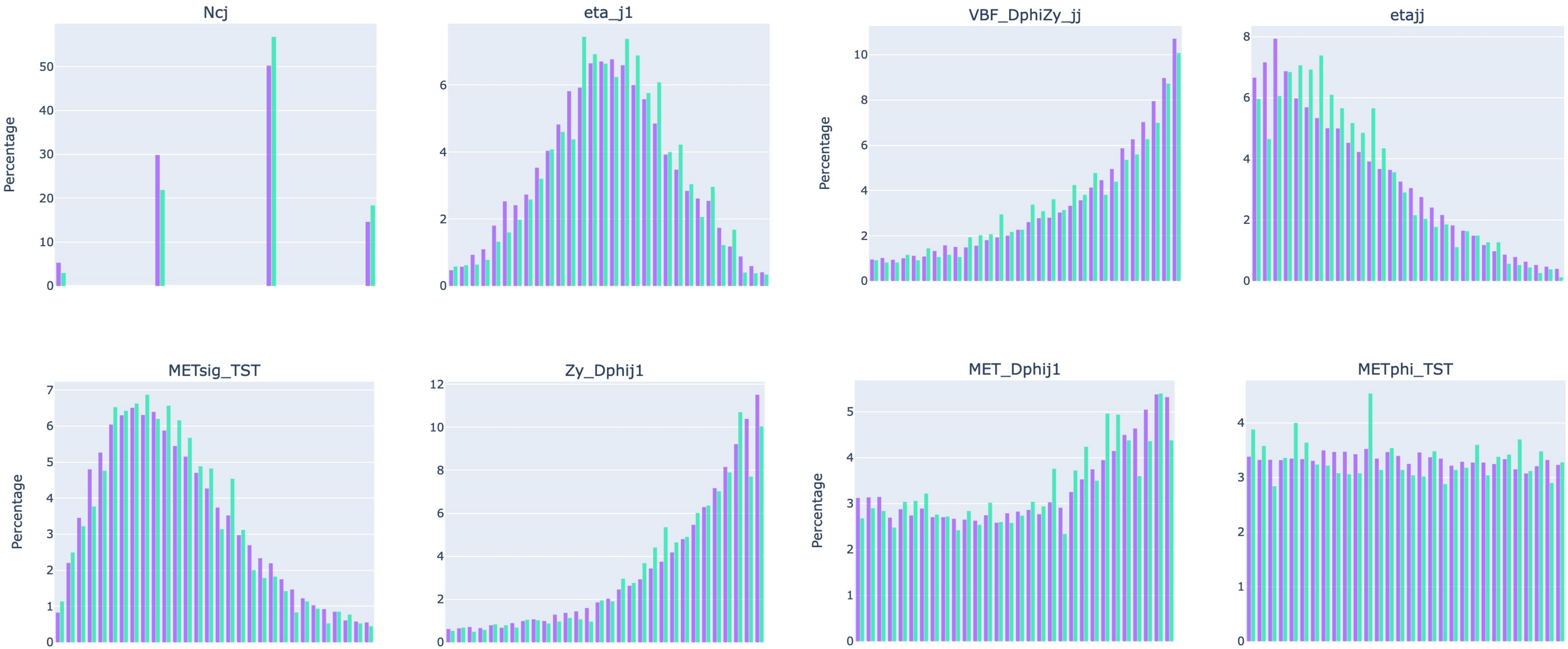






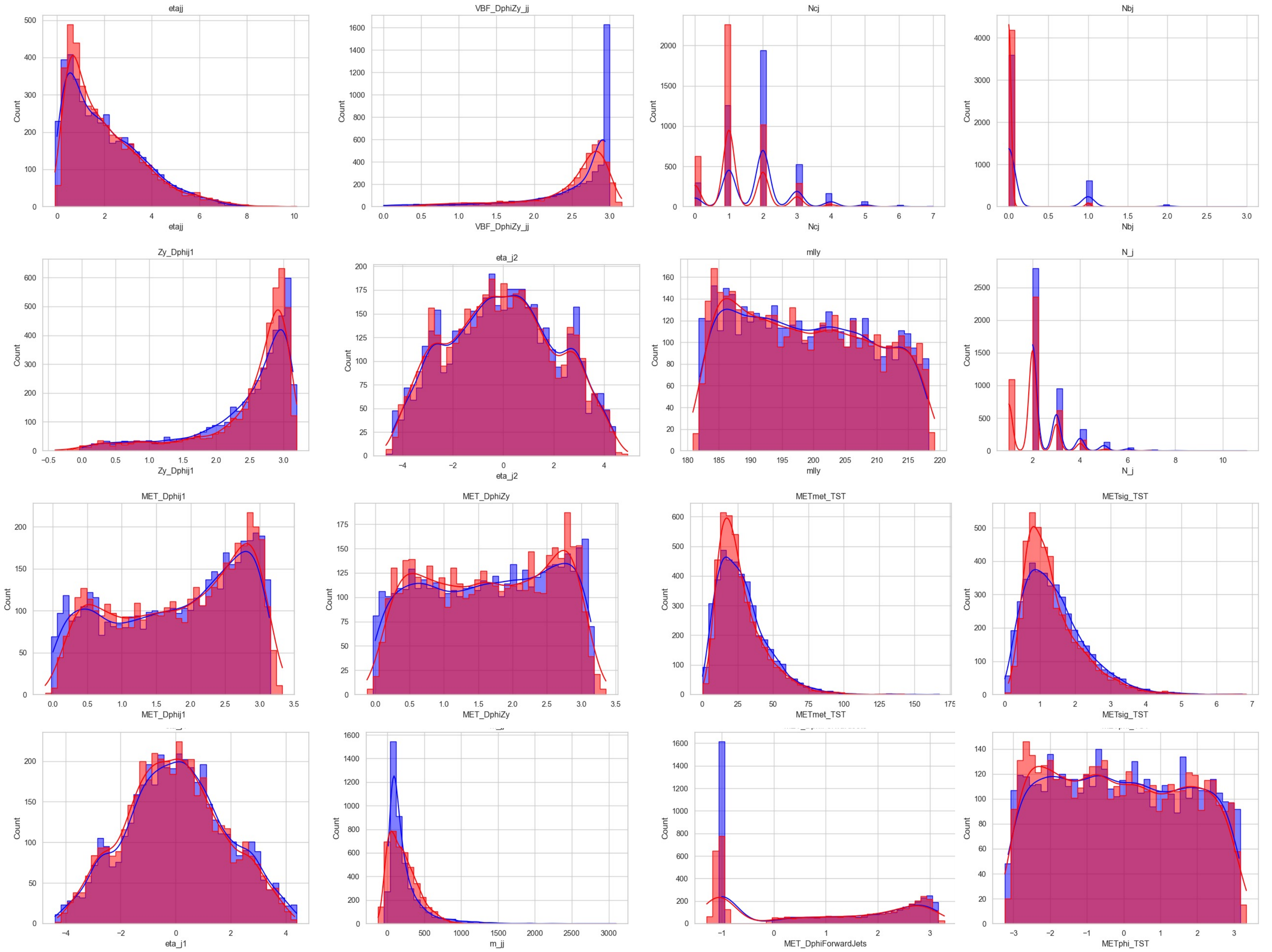
Long-Short Term Memory (LSTM) Neural Network Model

Training Data   Synthetic Data

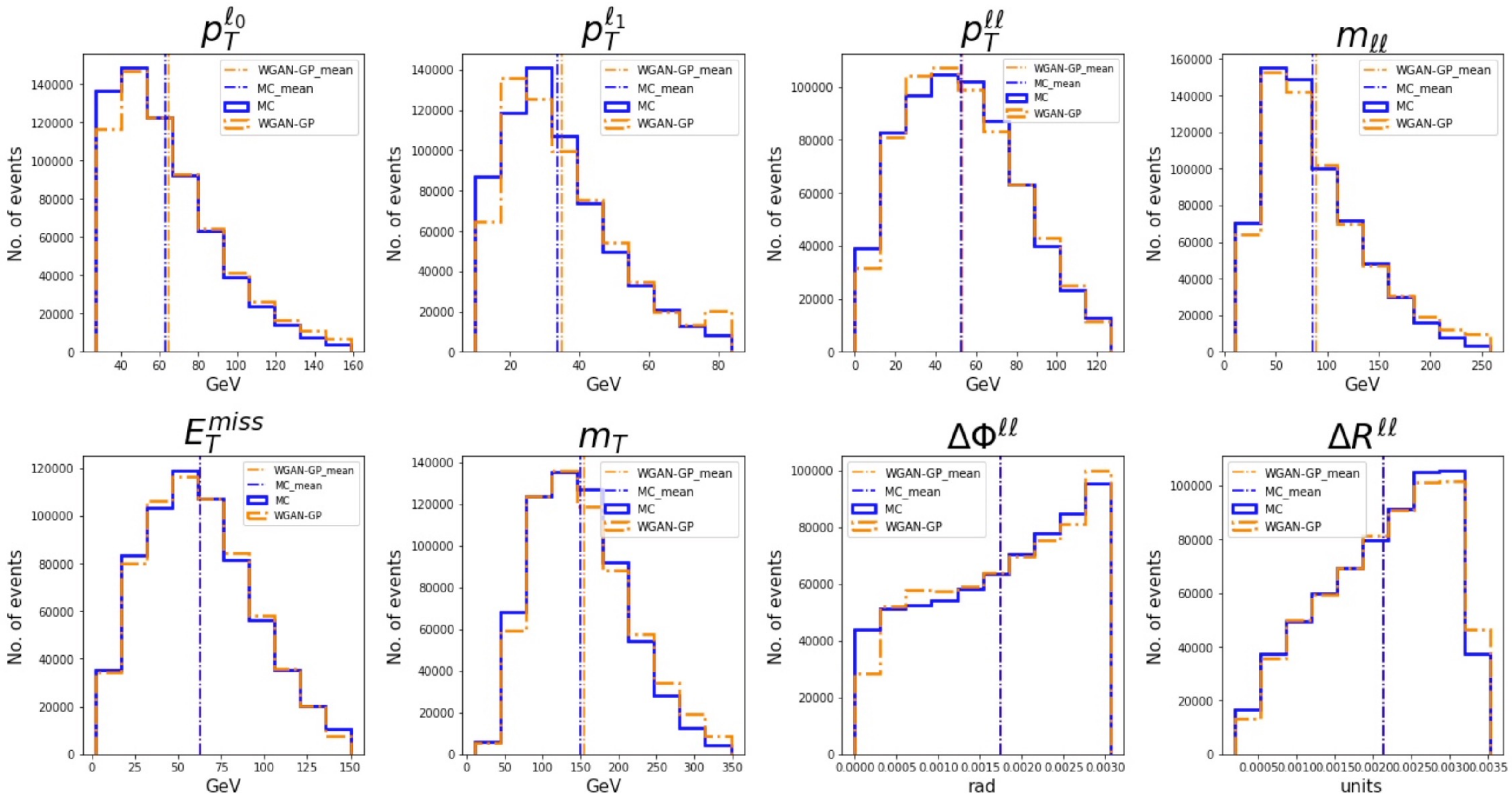


Preliminary Results of VAE based **Event Generation**

Red - Input Event Distributions, Blue - Event Reconstruction



WGAN-gp: Output Distributions

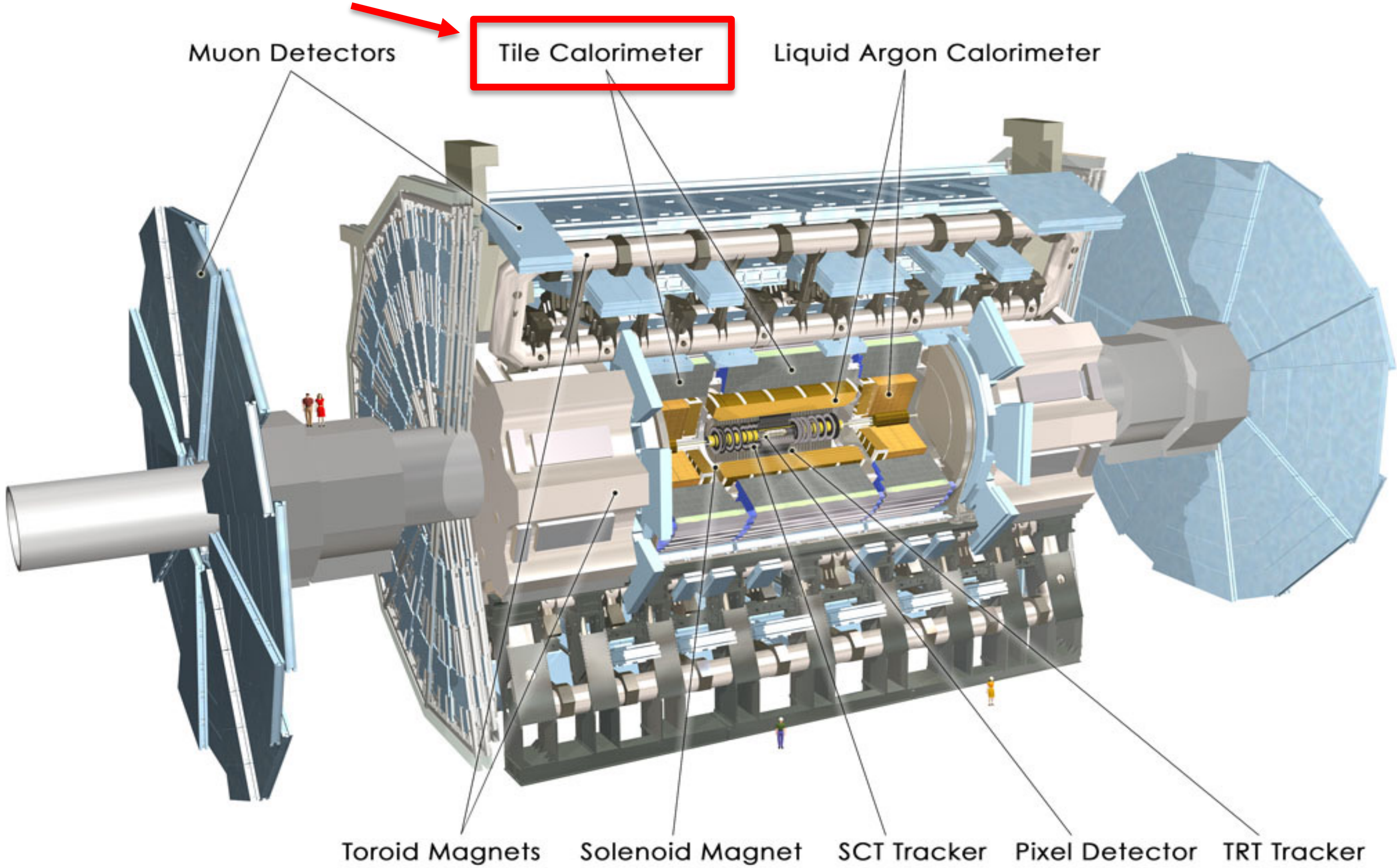


Instrumentation

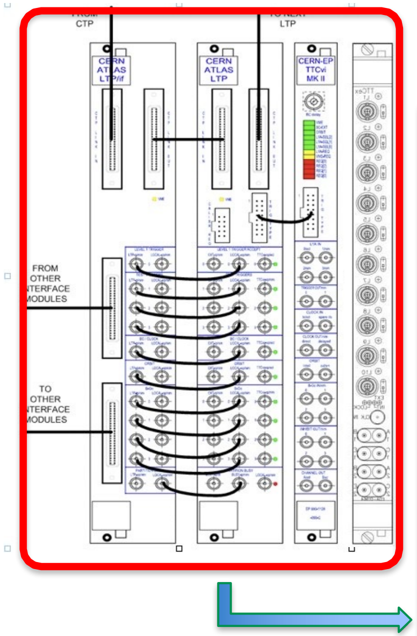
Maintenance and Operations
Phase-I upgrade
Phase-II upgrade

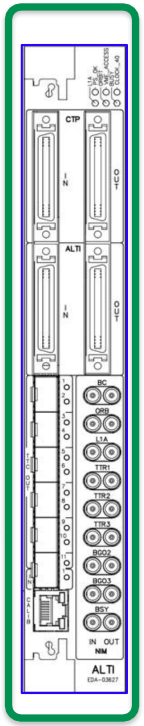
The ATLAS Detector

ICPP contribution



Phase-I upgrade





ATLAS Local Trigger Interface (ALTI)

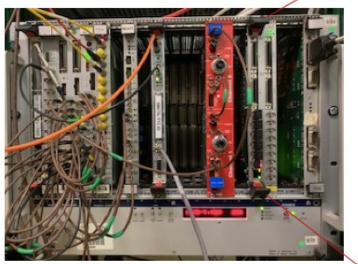
Set of local trigger processor boards (LTPi, LTP, TTCvi, TTCex) replaced by a single ALTI board

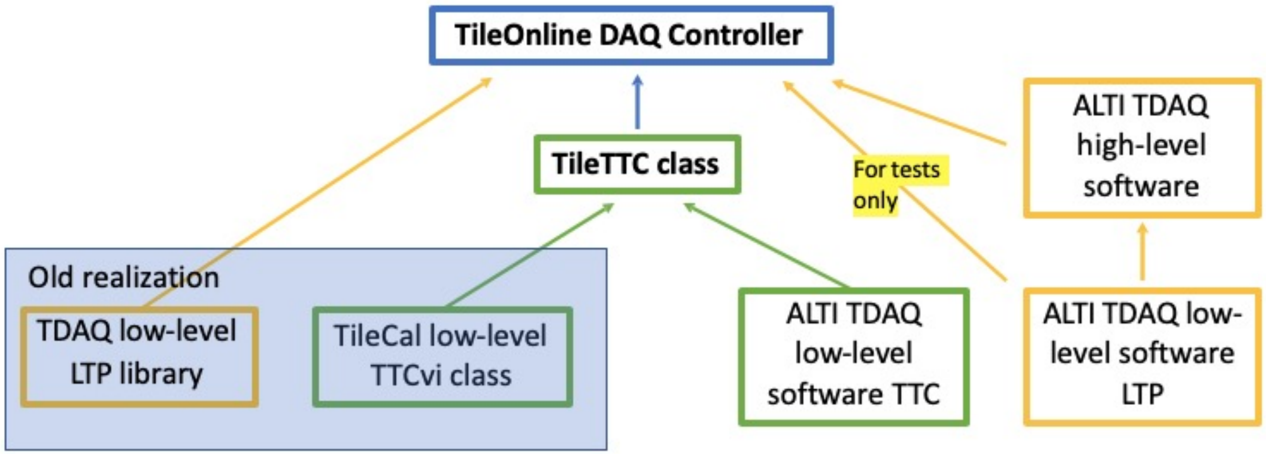
- ❑ Aging legacy modules, spares (obsolete components)
- ❑ New sub-systems in Run-3 need new TTC modules

TileCal Online software now incorporates new TileTTC class functionalities, compatible with the ALTI and TTCvi systems

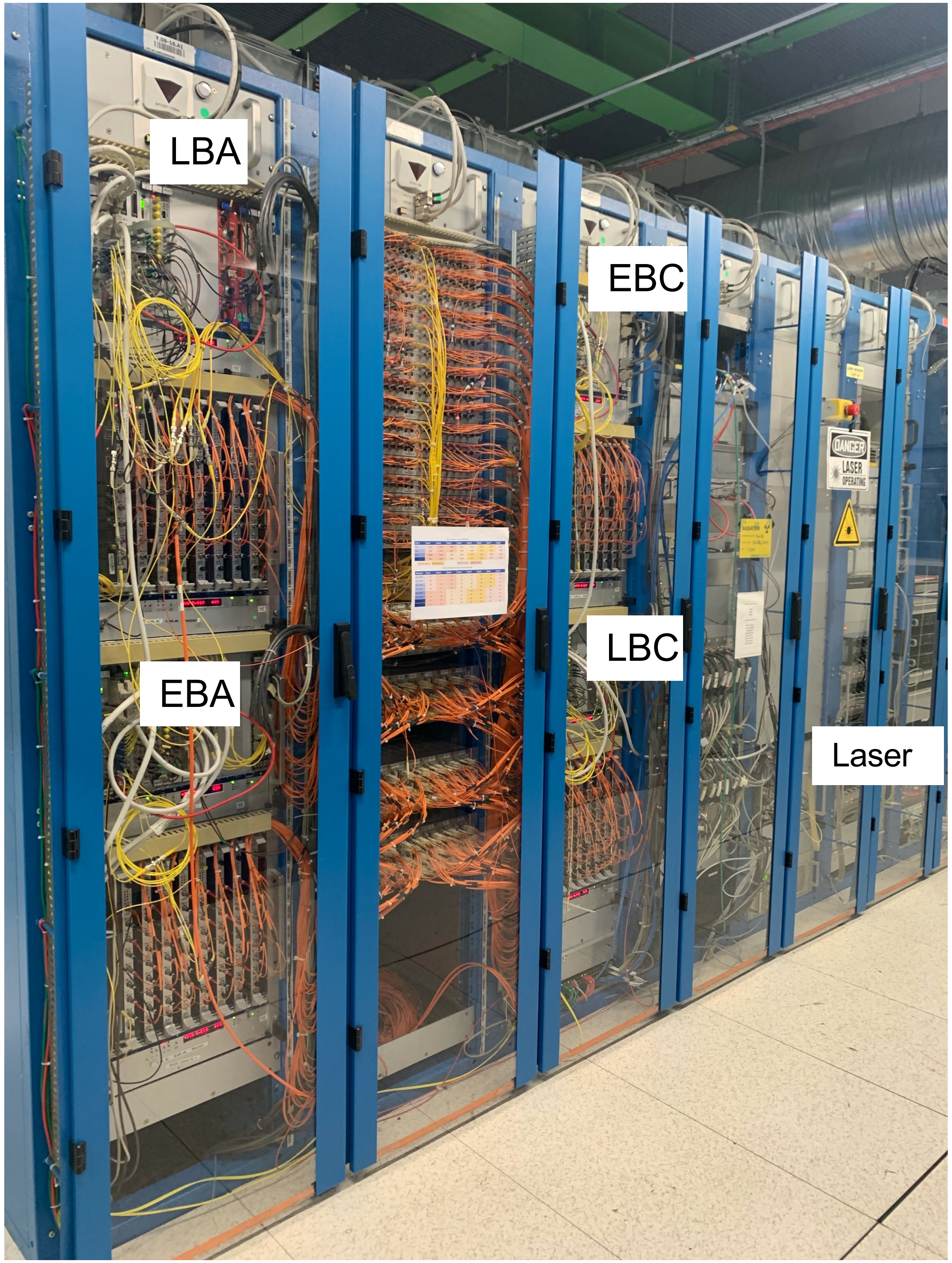
- ❑ Tested and installed in P1 in July 2021

CERN test bench



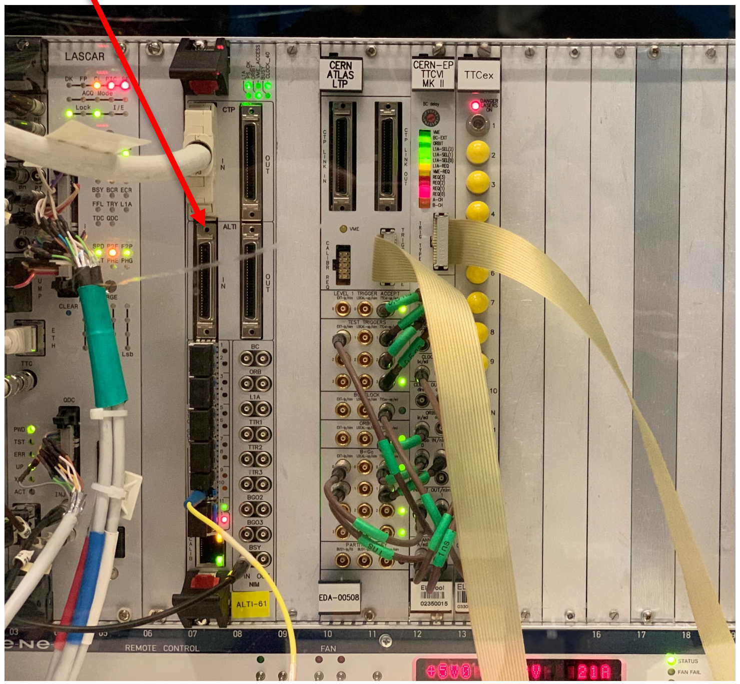


Installation of ALTI boards in the USA15 cavern

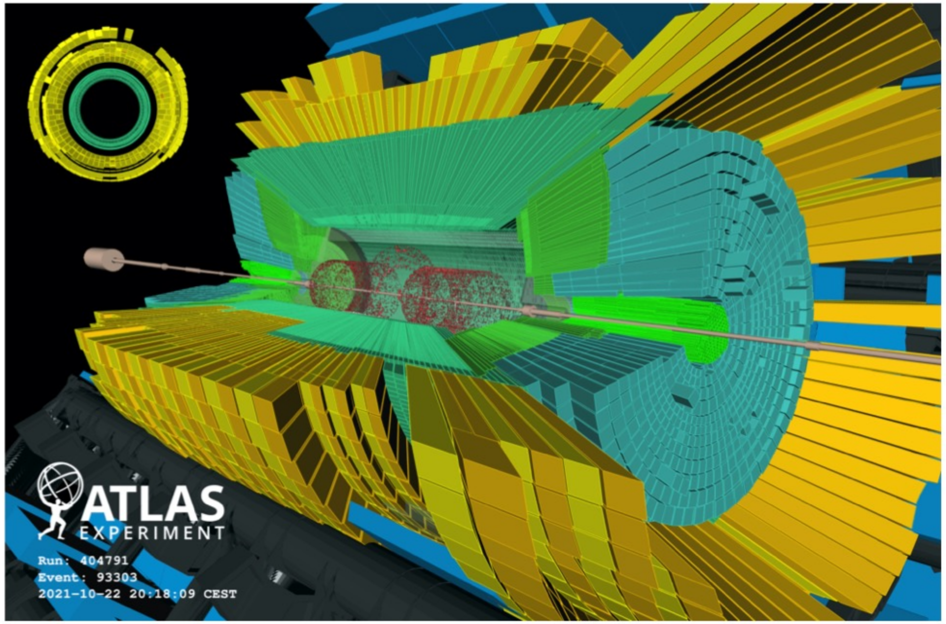


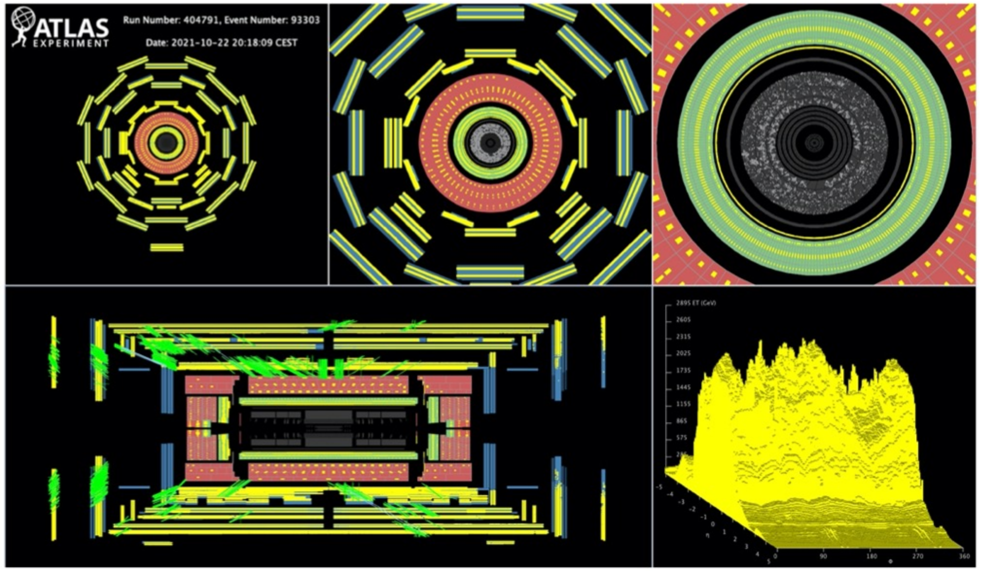
Started on the 29th of July to the end of the first week of August ALTI boards were installed in the TTC crates of LBA, LBC, EBA, EBC and the Laser crate.

ALTI board in Laser crate



The TileCal ALTI system tested during Run 3 pilot run





- The TileCal subsystem was included in the ATLAS combined run
- ATLAS successfully recorded 25-30 beam splashes from each beam on the 22nd of October 2021
- a view of a few event displays from the run is shown on the ATLANTIS display
- the TileCal ALTI system has been fully validated and is now ready for Run 3 data-taking

Phase-I Upgrade activities: Assembly, quality checks and instalation of the gap scintillator counters on the ATLAS detector

During Run-2 (2015-2018) data-taking period of the LHC, Crack and MBTS scintillators were degraded by radiation and had to be replaced with more radiation-hard scintillators as part of the phase-I upgrade.

Upgrade activities consisted:

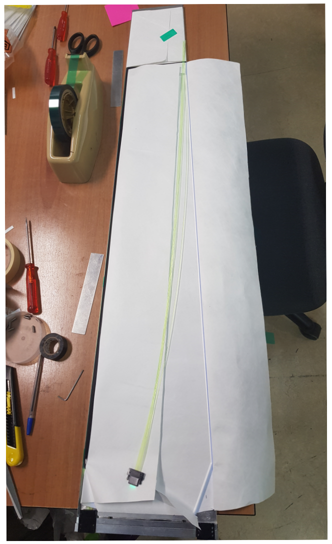
- Re-design of the crack and MBTS counters
- Assembly of detector modules
- Qualification and characterization using radioactive sources (Strontium-90 and Cesium-137)
- Installation on the ATLAS detector

ASSEMBLY (Crack and MBTS)

E3 Scintillator slab

Slab wrapping

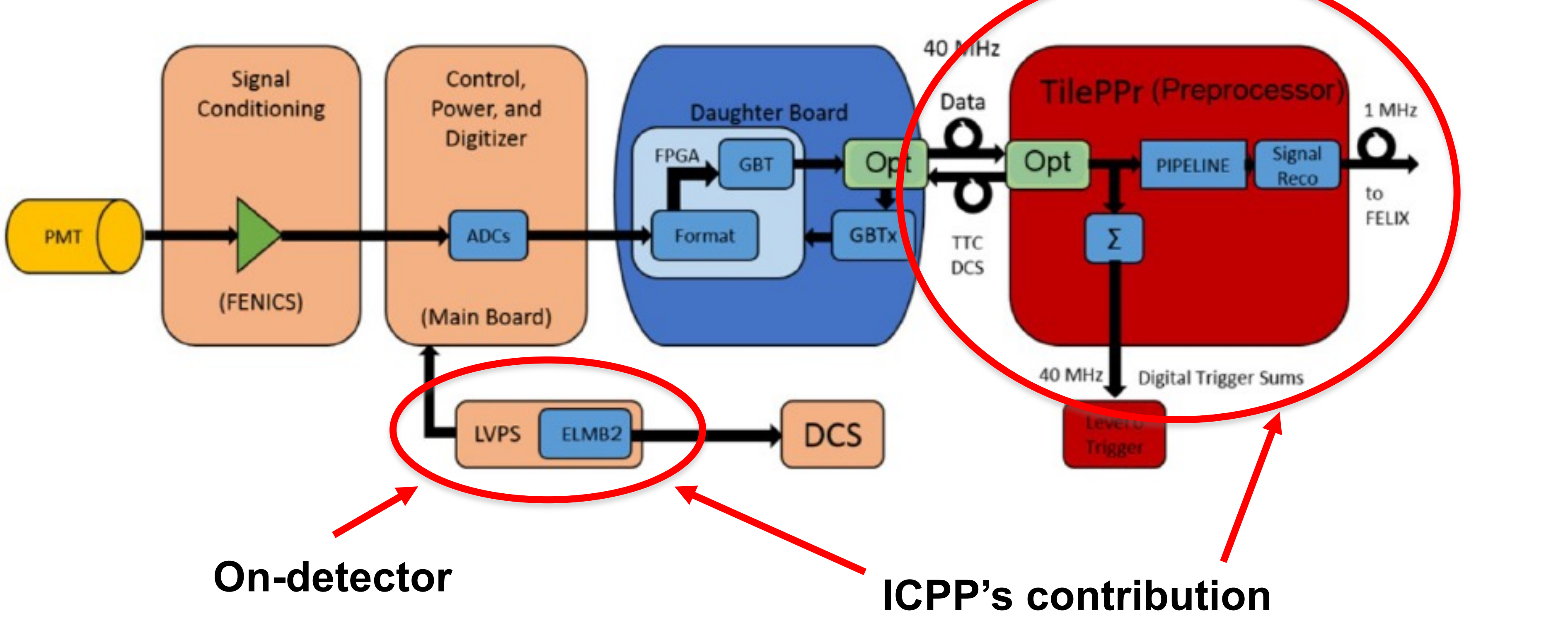
Fibre placement



Encapsulation with Al

Assembled modules

Phase-II upgrade of the Tile Calorimeter



South Africa's contribution to the TileCal Phase-II Upgrade is

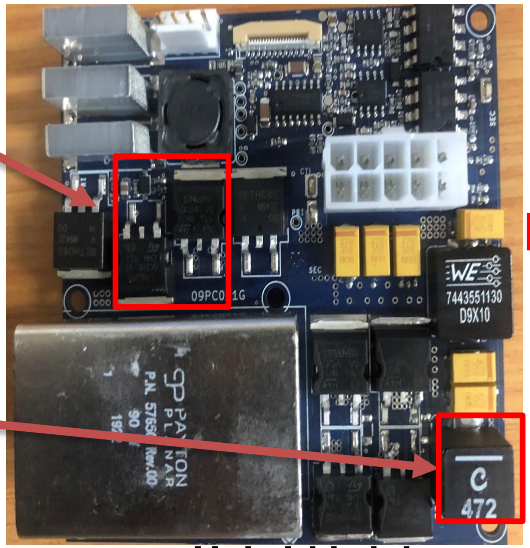
1. 50% of the production of the Low Voltage Power Supplies (LVPS)
   - Fully manufactured in South Africa
   - Fully tested in South Africa
2. 24% of the production of the Tile Preprocessor (PPr)
   - Two of the boards within the PPr fully manufactured in SA
   - Contribute to fare-share share of FPGAs and Back-ends

Brick production in South Africa

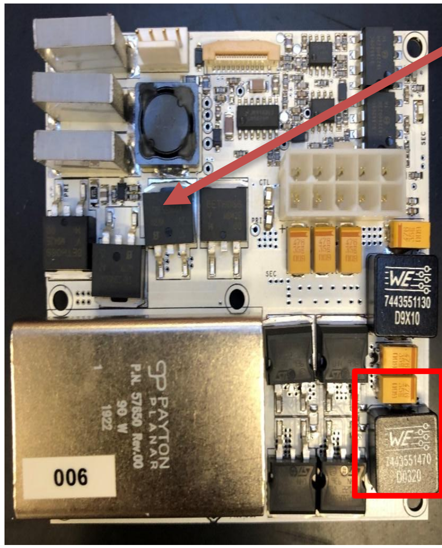
- Latest round of eight (8) bricks were populated in May 2021
- All 8 of these bricks were shipped to CERN to be used in several vertical slice tests
- Test performed on all bricks showed expected behaviour as per specification requirements
- Changes made on for the hybrid to the latest high efficiency bricks shown on labels

MOSFETS:
STB57N65M5

Inductor: XAL1010-472MEB



Hybrid brick



MOSFETS:
IRFS9N60APBF

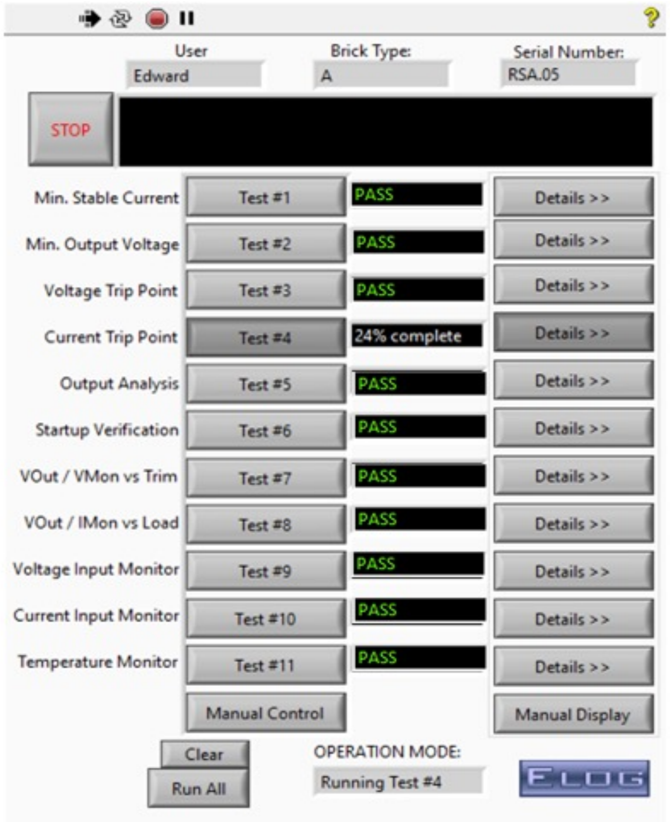
Inductor:
7443551470

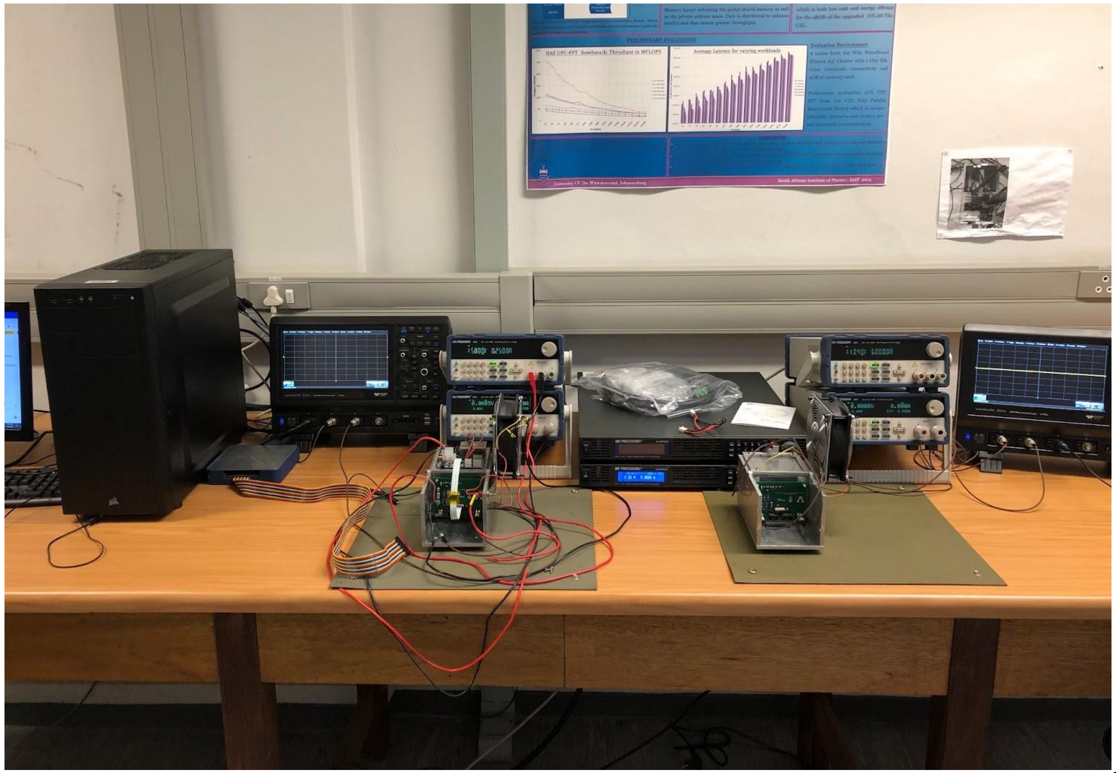
High Efficiency brick

Individual brick test bench

- ❑ Two test benches are being commissioned with the LabVIEW control software being modified to include some new tests and remove the obsolete tests

- ❑ Test setup comprises of a single brick running on a mechanical fixture. Test bench based on computer controlling and reading out equipment which perform the tests in LabVIEW



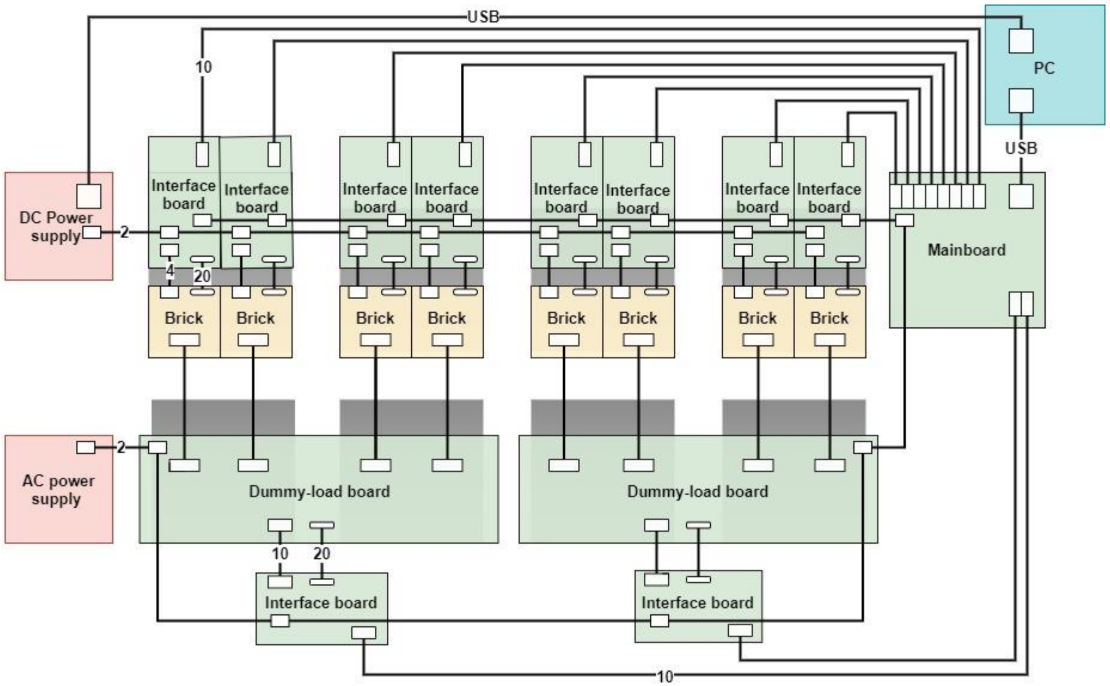


Burn-in station - Hardware

There are four PCB types within the Burn-in station:

- Main board - A demultiplexer responsible for communicating to the brick and load interface boards through control
- Brick Interface board - Provides Tri-state signal to Bricks to switch them on \ off. Provides on\off control of 200 VDC input to Bricks. Performs analog to digital conversion of the Bricks performance measurements such as output current and operating temperature.
- Load Interface board - Interface boards provide control, digitization, and transmission functions to their associated Dummy-load board. The applied load of a Brick can be set and the actual current drawn at the Dummy-load can be monitored.
- Dummy-load board - Applies a separate load to each of the 4 Bricks and facilitates the conversion of electrical power received from Bricks into heat which is removed by the cooling system.

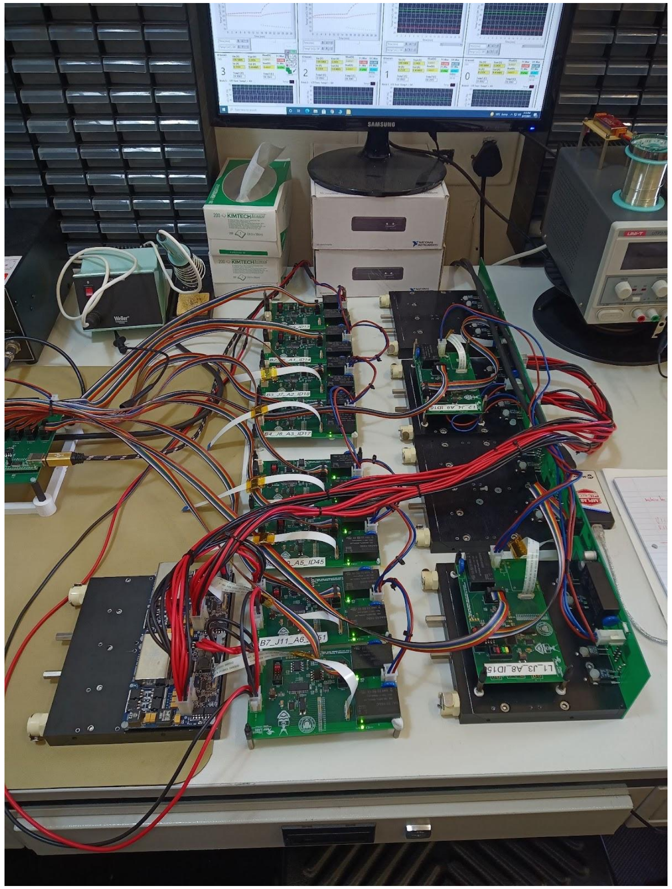
<u>A simplified block diagram of the Burn-in station hardware</u>



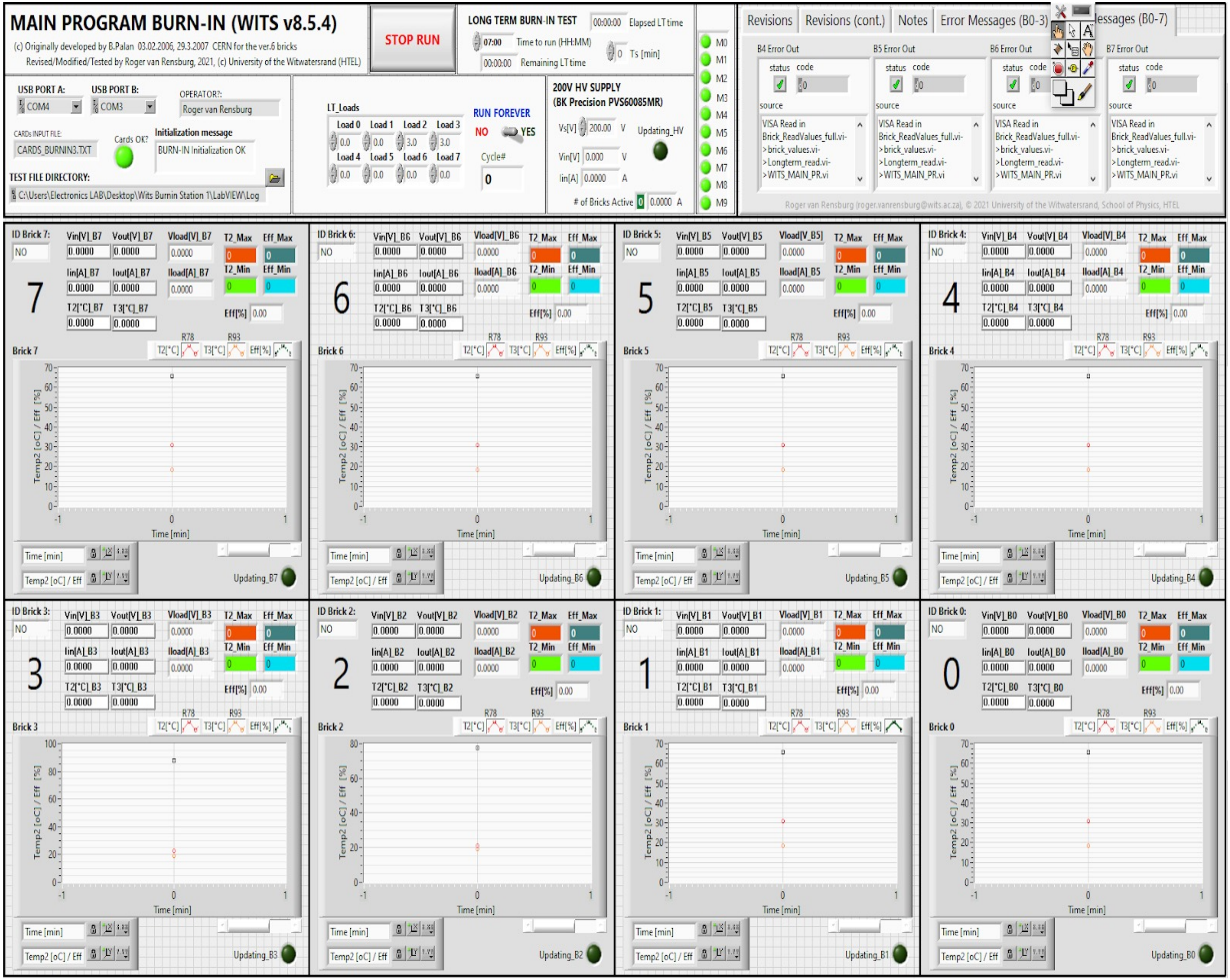
Burn-in station hardware testing

Testing of serial communication between PC and all Interface boards

Testing of Brick Interface board amd Dummy-load board with Bricks



Burn-in station - LabVIEW control application



- Custom LabVIEW application refactored by R. Van Rensburg.
- Allows for the fully automated Burn-in of 8 Bricks per test cycle.
- Burn-in parameters fully customizable.
- Automated data logging function.
- Real time graphical display of temperature and efficiency.

Burn-in station - Final integration

Final integration is ongoing.

The Cooling plate mounting brackets are being designed and manufactured.

The custom made Wiring is being produced.

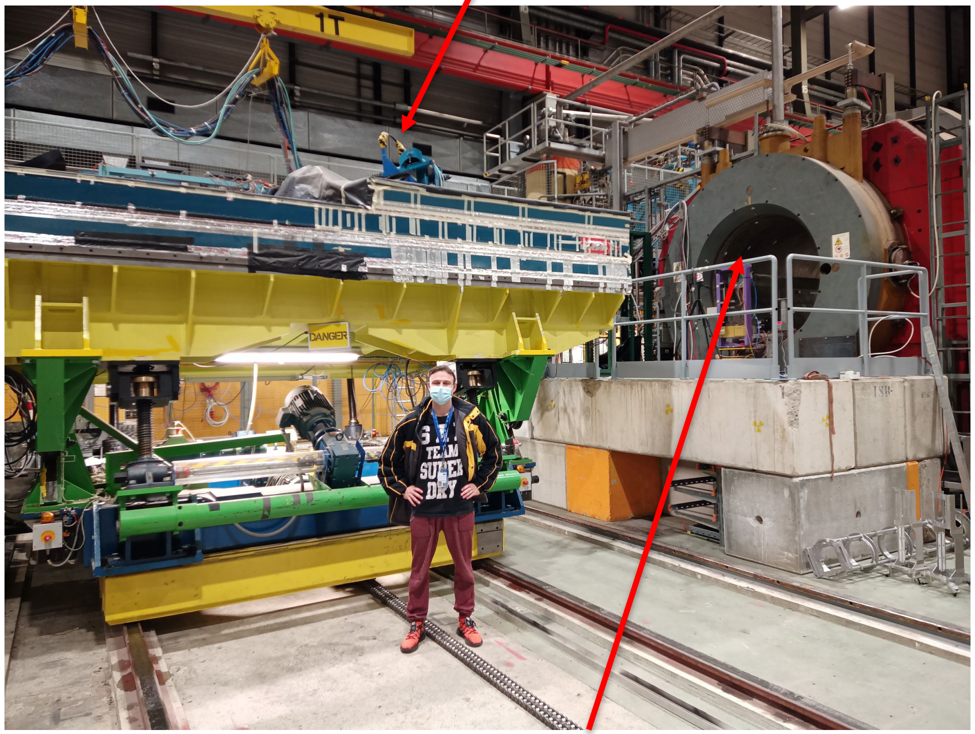
The perspex lid and top panel are to be produced in the coming month.

<u>Testing of a complete Burn-in station is expected to occur in early December of 2021.</u>

ATLAS TileCal November 2021 Test-beam

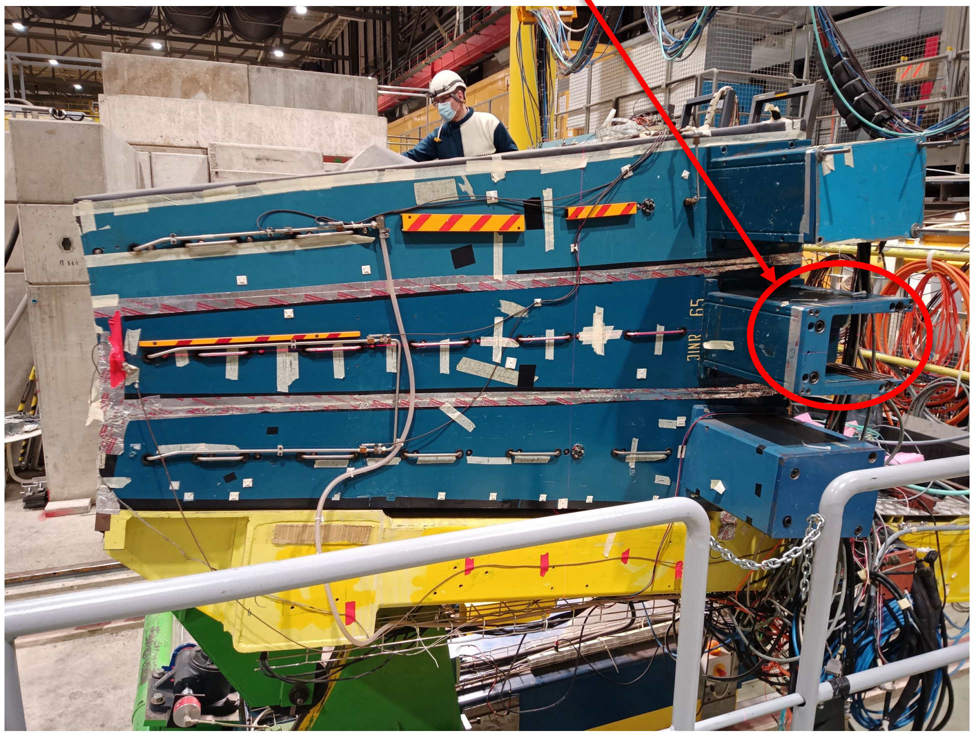
- The latest Test-beam campaign took place from 3/11/2021 to 14/11/2021 at the CERN H8 beam line located in Prevessin, France.
- The latest iterations of the Phase-II upgrade electronics were tested; these included 8 high efficiency LVPS Bricks produced in South Africa.
- The LVPS Bricks operation was successful with all performance metrics being met.
- The team from the University of the Witwatersrand contributed to both test beam preparation and experimental activities.

Three TileCal modules



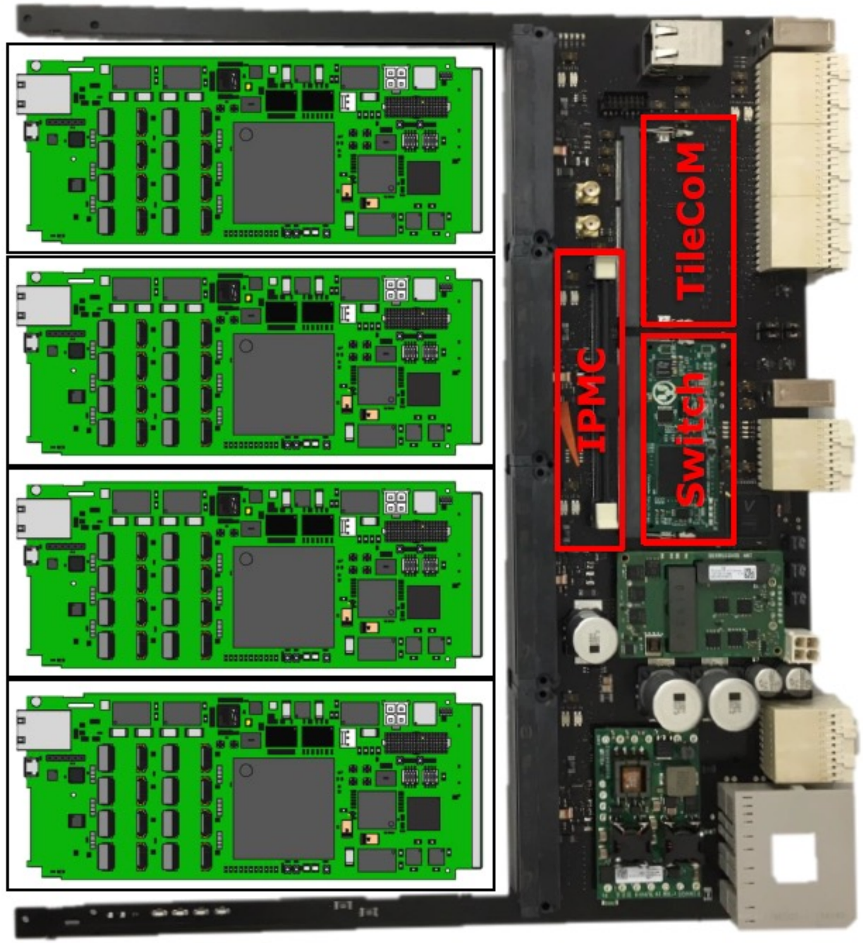
The H8 beam line

The new LVPS being inserted



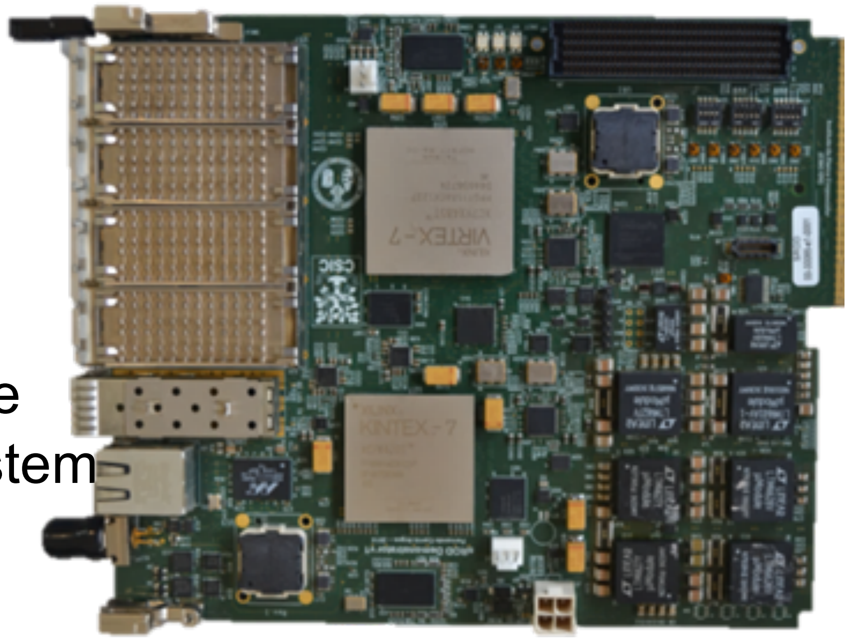
The TilePPr for Tile Phase II upgrades

- S.A Contributes 24 % of the Tile PPr
  - Production of boards in S.A.
  - Current production focus on the TileCoM and the Tile GbE Switch
- Developments and testing
  - TileCoM standalone developments
  - Testing of the boards after production
  - Integration of boards produced in S.A with Tile-PPr boards

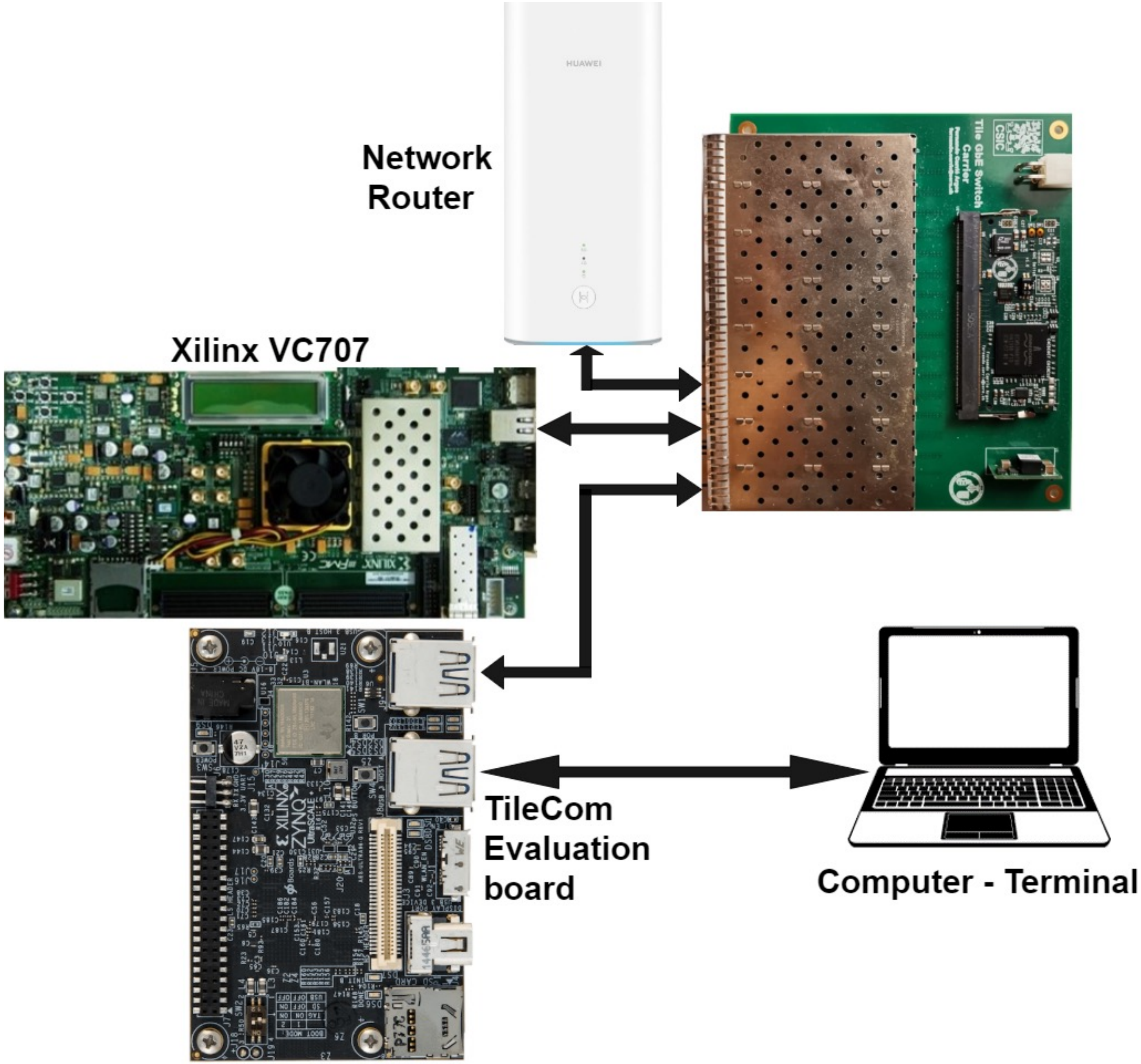


The TilePPr boards produced in SA

- First **PPr demonstrator** board produced in South Africa (**Similar to CPM**)
  - Successfully tested in the demonstrator project
  - Currently used for data acquisition in the Tile Cal Phase II upgrade electronic system
- Tile GbE Switch produced in South Africa
  - Successfully tested with the TileCoM firmware and software developments
- The next board to be produced by South African companies is the TileCoM
  - Production of this board will start soon
  - This board will host all the developments developed by University of the Witwatersrand



The TilePPr testbench in SA



New electronics research lab to benefit students in Physics department

TIP@UNIZULU

NALEDI HLEFANE

THE University of Zululand's (UNIZULU) Department of Physics has officially launched its newly established electronics research laboratory, which is set to expose its students to ground-breaking research involving particle physics.

The laboratory is funded by the South African branch of the European Centre for Nuclear Research (CERN). CERN investigates the fundamental structure of particles that make up all matter by using the world's largest, most complex scientific instruments. Through its scientific findings, the laboratory has, over the years, helped bridge the particle physics knowledge gap while also facilitating technological advancements in various industries.

As part of its knowledge-transfer mission, CERN ensures the training of the future generation of scientists and uniting of nations through its technologies and expertise. The main aim of the SA-CERN programme is to make the facilities at the laboratory in Geneva, Switzerland available to South African researchers, engineers, technicians and students. These facilities include the Large Hadron Collider (LHC), the world's largest and most powerful particle accelerator through which four experiments are currently being run.

Dr Betty Kibirige, a lecturer in the Department of Physics, explained that the department has, since early 2015, collaborated with the University of the Witwatersrand at the level of the Tile

Sanele Gumede and Lungisani Phakathi, Master's students in the Department of Physics, using coding language to operate an electronic object in the newly established SA-CERN funded electronics research laboratory.

Calorimeter of ATLAS, one of the four experiments at CERN's LHC.

"Currently, two full-time Master's students are working on tasks related to the maintenance and operations of the Tile Calorimeter. These students are working towards ma
Calorimete
she added.

The UN
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SA-CERN C
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integrate in world-class global research facilities.

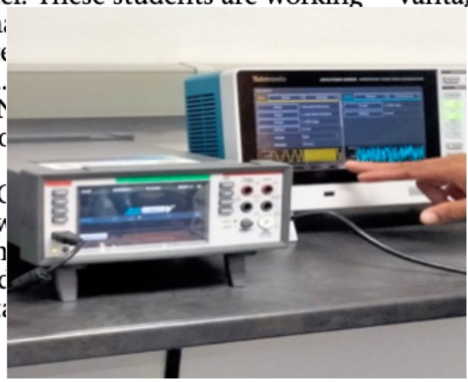
"The main goal of establishing the laboratory is to afford students from different walks of life, especially the disadvantaged, access to a skillset that would

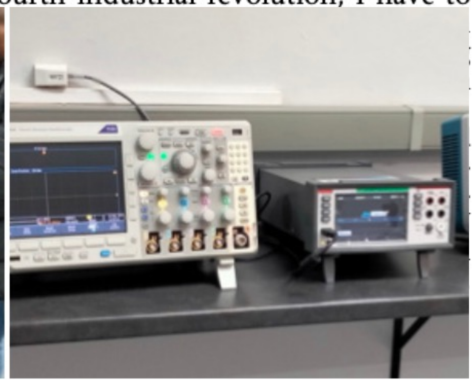
and prototyping of electronics. There will also be spin-offs into instrumentation involved in other physics disciplines, especially Materials Science, Nuclear Physics and Astrophysics—a discipline that is currently being introduced in the Physics Department.

The laboratory hosts state-of-the-art test equipment that provides resources with capacity above the undergraduate test equipment. This allows for proper packaging of prototypes, with a soldering station and 3-D printer also available.

Sanele Gumede, a Master's student in the Physics Department, said that taking part in the CERN initiative has been an eye-opener for him as he has learned how to use coding languages in conjunction with electronics in order to collect adequate data for his research.

For Lungisani Phakathi, also a Master's student in the Physics Department, the most fascinating yet challenging part of being a part of the CERN project is the interpretation of big data. "Coding is so essential. Even the banks use it. With the world moving into the fourth industrial revolution, I have to





UNIZULU already contributed routinely to the ATLAS experiment

ATLAS Tile-in-One DCS Plugin

Tile-in-One (TiO) is a collection of small sized independent web tools called plugins.

UNIZULU Team is working on TIO-0016, a plugin that is a precursor to updating the Detector Control Systems (DCS) user interface at ATLAS Tile Calorimeter.

The Team has updated the **d3.js to plotly.js** as indicated for the number of Analogue to Digital Converters shown in Figure 1 and 2 respectively.

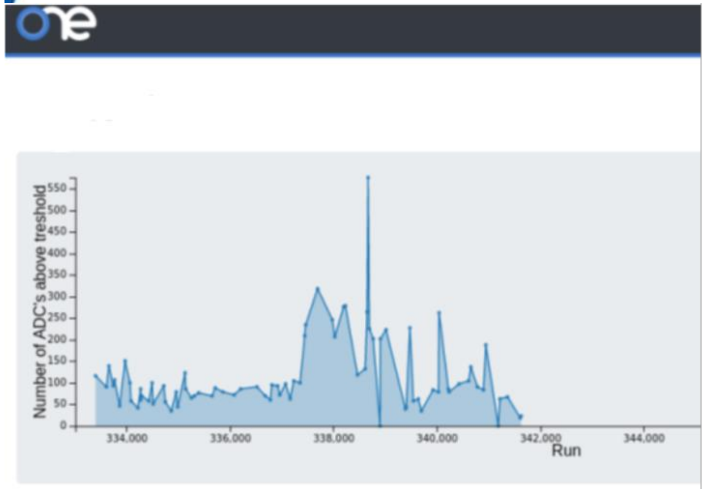


Figure 1: d3.js plot

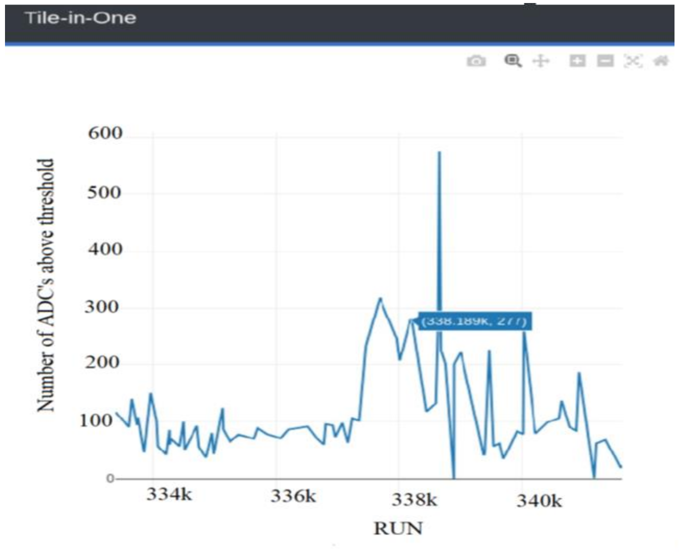


Figure 2: Plotly.js plot

Plotly has better functionality: capturing data at a point where the curser is placed (see Figure 2), zooming in and out of the plot, downloading .png file for use in reports and much more.

UNIVERSITY OF ZULULAND

UNIZULU officially a full-fledged member of SA-ATLAS in October 2021

Human Capacity Development

Training future academics

Three of former team members have become academics, more in the pipeline

Our students receive world-class training at the European Laboratory CERN

Working together with top scientist from Europe, the US and other countries

Humphry Tlou, PhD student

ATLAS PhD thesis grant award 2020 and SA-CERN excellence fellowship

Appointed Run Coordinator of the Tile Calorimeter of the ATLAS detector at CERN in 2019

Edward Nkadimeng, PhD student

SAINTS Fellowship 2019

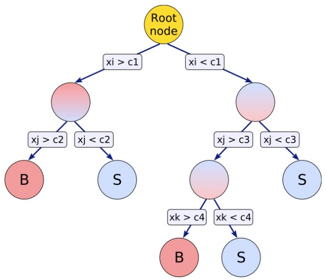
Appointed co-Chair of the Low Voltage Working Group of the Tile Calorimeter of the ATLAS detector in February 2020 https://www.dst.gov.za/index.php/media-room/latest-news/3109-wits-students-showcase-south-african-electronics-research-at-top-international-conference

https://www.nrf.ac.za/media-room/news/wits-students-showcase-south-african-electronics-research-top-international-workshop

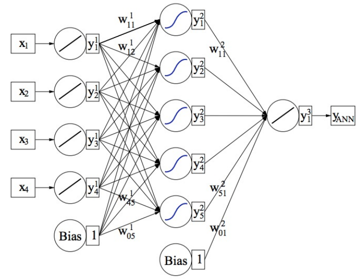
Our graduates and former researchers in industry

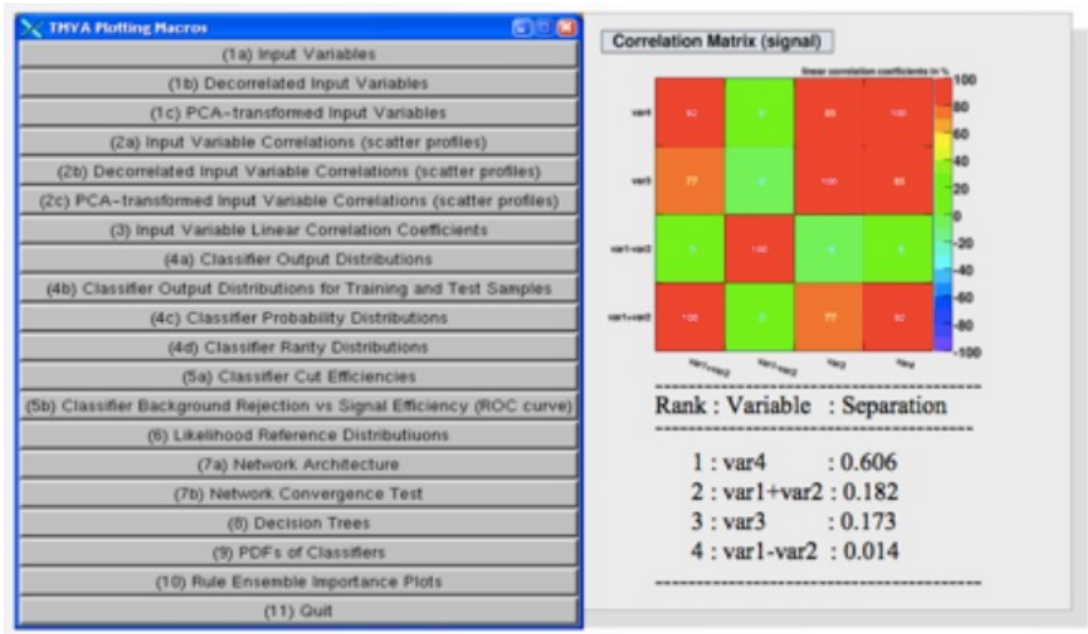
Increasing number of our graduates choose employment outside academia.

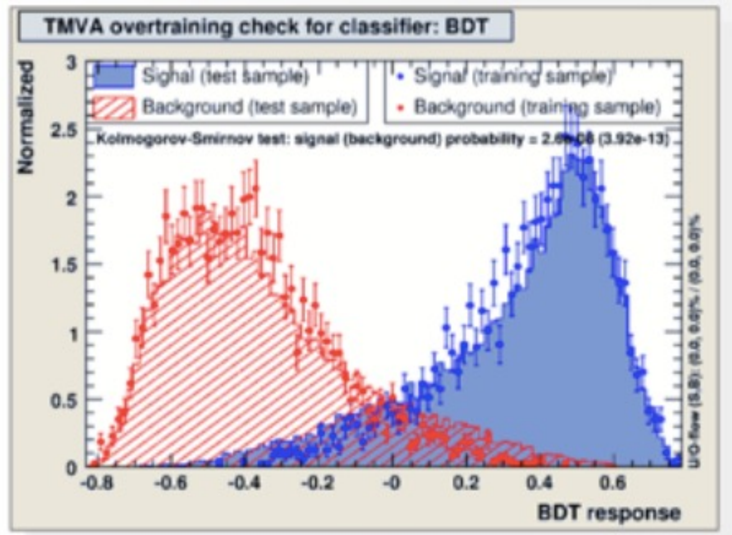
Most of graduates and former researchers leaving academia work in Big Data and Artificial Intelligence

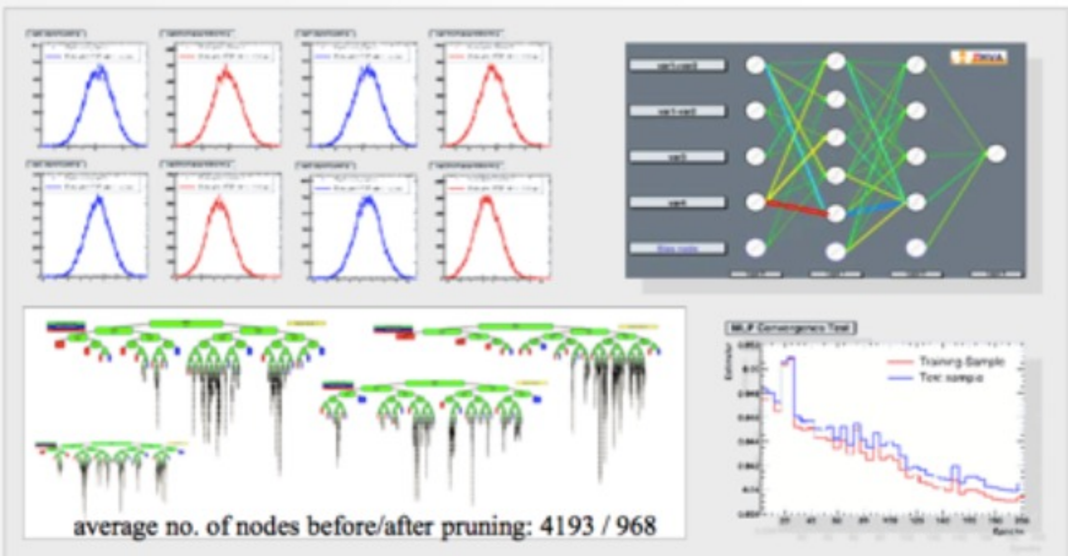


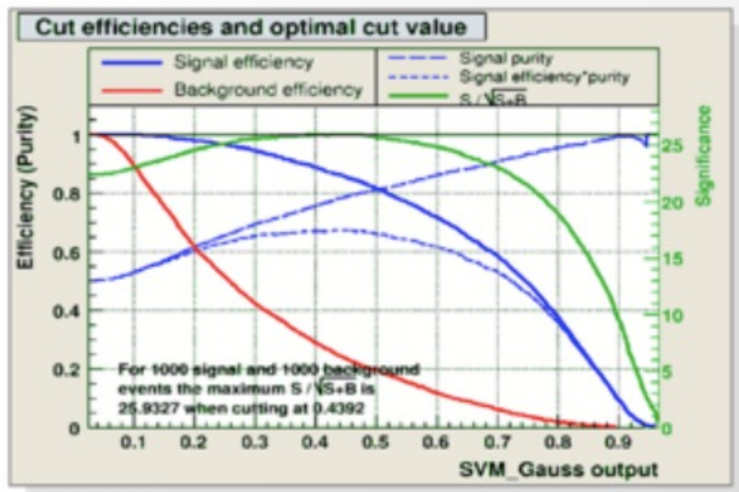
Modern Machine Learning at CERN







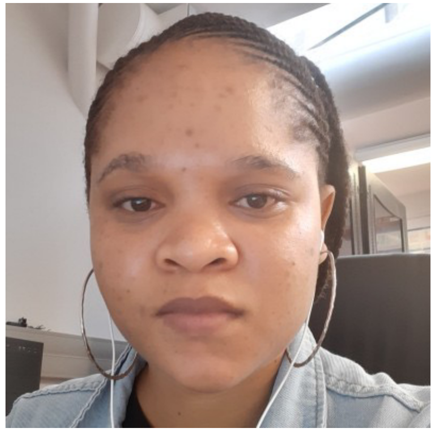




Nkateko Baloyi, MSc 2020, Data Scientist FNB

Theodore Gaelwjwe, MSc 2020, Data Scientist IBM

Nthabiseng Lekalakala, Software Engineer at Luno



Lehumo Mashishi, MSc 2020, Data Scientist at OLSPS Analytics

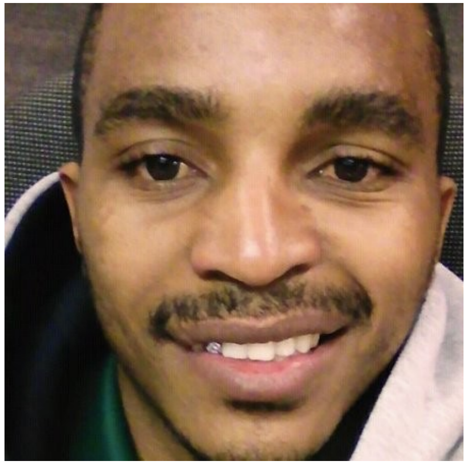
Kgomotso Monnakgotla, MSc 2020, Junior Software Developer at SARAO

Stefan Von Buddenbrock, PhD 2020, Associate Consultant at True North Partners LLP

Kehinde Tomiwa, PhD 2019
Data Engineer at Wipro Limited, Zurich, Switzerland

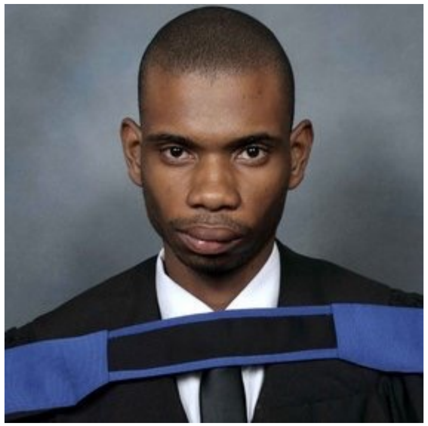
Dimbiniaina Rafanoharana, MSc 2019, Data Analyst Axian Group

Chuene Mosomane
MSc 2018, Data Scientist at Modernising Management



Skhathisomusa Mthembu, MSc 2018
Analyst at Pivot Sciences

Tshidiso Molupe, MSc 2018
Developer at Fusebox Online



Robert Reed, PhD 2017
Big Data Consultant at Bain Consulting

Dingane Hlaluku, MSc 2017
Cloud Engineer at IBM

Marc Sacks, MSc 2017
Data Scientist at Pivot Sciences

Xolane Ngcobo, MSc 2017
Market Risk Analyst at RMB

Amanda Kruse, PhD 2014
Data Scientist at Allstate, USA

Roman Hartmann, Intern 2014
Data Scientist at Discourse AI

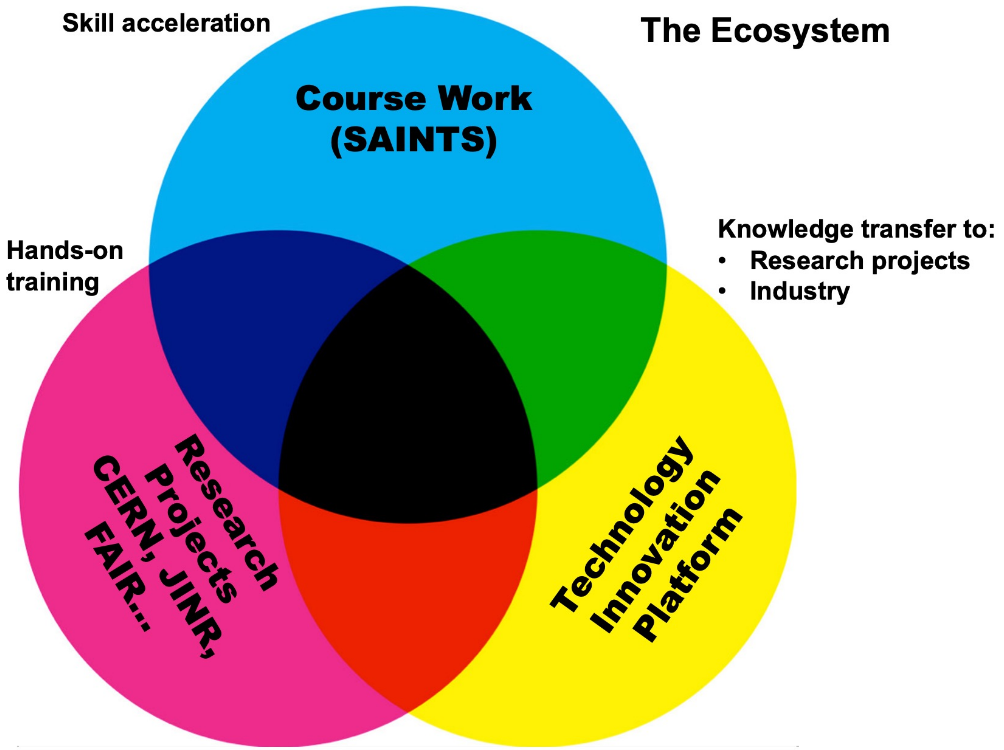
German Carrillo, Dr. Fellow 2013-2015
Machine Learning at Alpiq, Switzerland

Luis March, Dr. Fellow 2014-2015
Data Scientist at Inmarsat, Switzerland

Gilad Amar, Intern 2013
Data Scientist at DataProphet

Kieran Bristow, MSc 2013
Software Engineer at
Standard Bank Group

Tim Bristow, MSc 2011
Data Scientist at
Discovery Limited

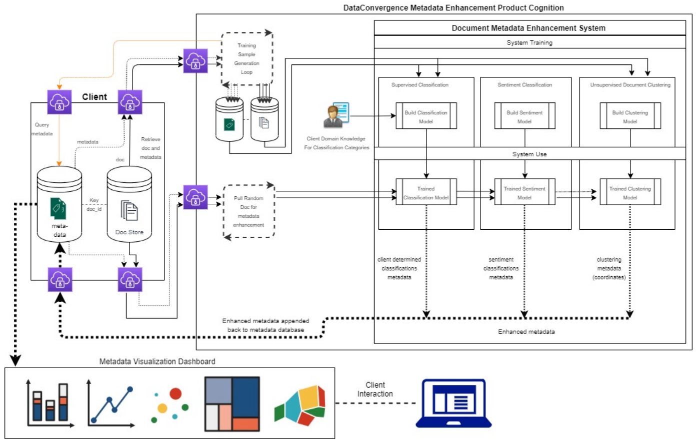


Technology Transfer

Work within the Technology Innovation Platform, pfficially supported by the National Research Foundation and the Department of Science and Innovation

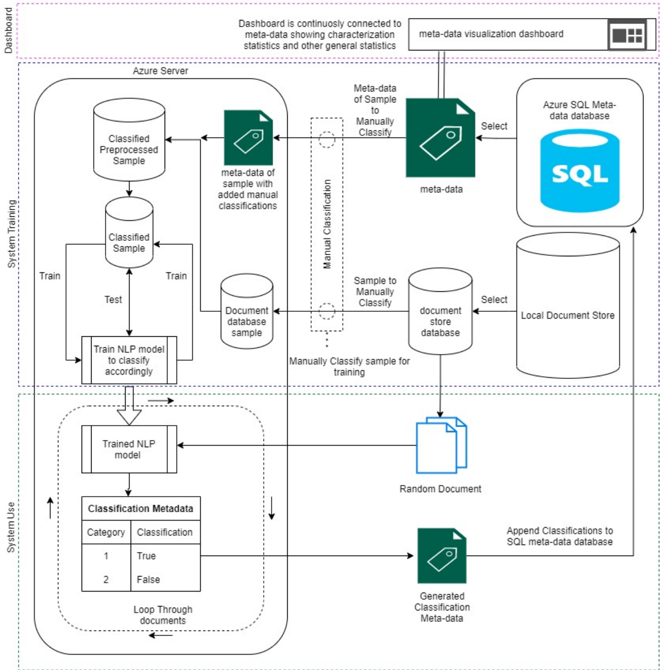
Current portfolio of contracts concluded, in progress or in process of being signed

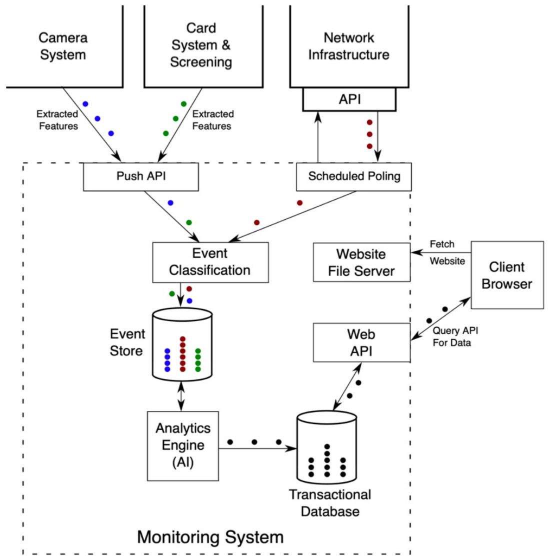
TIP@AI: Product and Solution Development



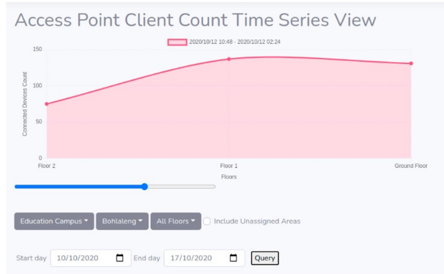
Draft Document Classification System Flow Diagram

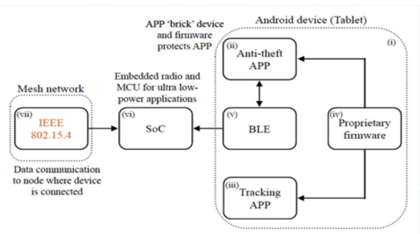
The flow diagram below shows a draft of the training phase and the use phase of a document classification system. Training Phase: meta-data from a SQL database and documents from a local document store are selected. A sample of the meta-data and documents are further selected for manual classification. Classification categories are chosen and manual classification of the sample is completed. This manually classified sample is then used as the training dataset for the NLP model. Use Phase: Documents are randomly pulled from the document store, classified using the trained NLP model and classification meta-data is generated and appended back to the main meta-data SQL database for the specific document. This will happen continuously until all documents are classified. Lastly, the diagram shows a dashboard for displaying key metadata statistics.

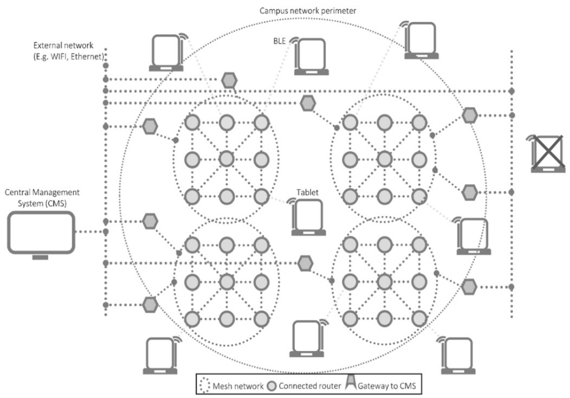




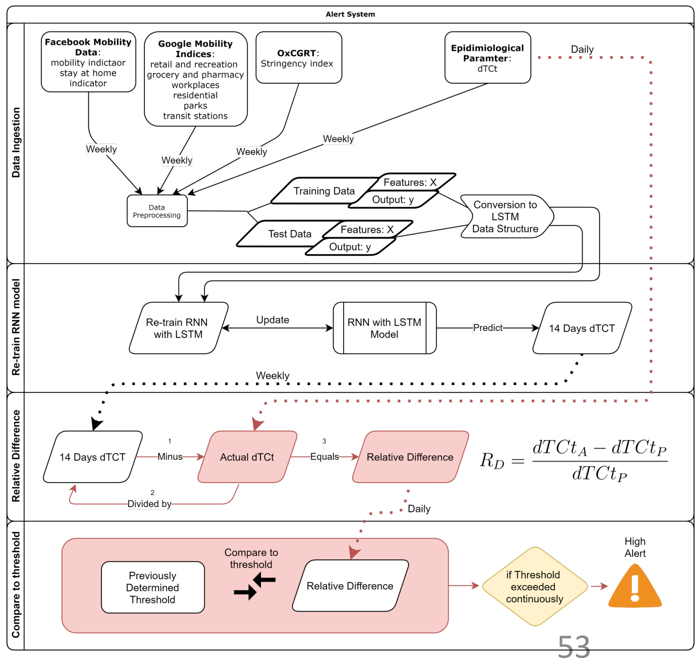
WEB BASED GRAPHICAL INTERFACE







The block diagram of a mesh network prototype



AREAS OF APPLICATION

CURRENT AND EMERGING APPLICATIONS OF AI IN LAW

- Augmenting Research and Contract Review
- Drafting Legal Documents
- Due Diligence
- Data Analysis
- Predict Future Outcomes
- Automate Case Procedures
- The Automation of Basic Tasks
- Automating Intellectual Property
- Digitilizing Payment Processes

"LEGAL ANALYTICS"

- **"Legal Analytics":** Applying AI and ML tools to sift quickly and accurately through masses of legal data and information to recognize patterns, draw conclusions, make predictions, evaluate the riskiness of cases and predict court outcomes;
- Using Machine Learning (ML) and Natural Language Processing (NLP), AI platforms can undertake mass review of contracts;
- **Areas of application of "Legal Analytics":** e.g., legal research (e.g., implicit references, cases of precedence), recognition of decision patterns (administrative authorities, courts, judges), prediction of decisions, assistance in legal writing, classification, evaluation, or generation of legal documents (e.g., contracts);

DATACONVERGENCE

OUR PORTFOLIO OF RECENT PROJECTS INCLUDES:

A VISUALISATION DASHBOARD: LINKAGES BETWEEN COURT CASE DATA AND DEMOGRAPHICS DATA

The DataConvergence team has been tasked to build a visualisation dashboard for a legal client that easily extracts, processes and displays relationships between different data from multiple data sources; and that allows for easier interaction with this data. This involves an automated process comprising of scheduled checks of new files, the extraction of relevant data, and the consolidation of findings (trends, patterns, disparities), which are then visualised on a dashboard for quick and meaningful interaction. The system allows the user to upload new data (for example on new court cases), that is automatically connected to the main data source and visualised on the visualisation platform chosen.

AN AI-BASED LEGAL CLASSIFICATION AND ANALYTICS SYSTEM

Law firms collects annually terabytes of data of which a very small percentage is structured and having very limited search and classification capabilities to work through these massive datasets. Therefore, it currently takes days for a lawyer to search for similar cases. DataConvergence is in the process of building an AI-based legal classification and analytics system for a legal client to address these challenges. The system will involve the application of Natural Language Processing (NLP) to extract and contextualize insights from the documents, to assist with the classification of documents, and make predictions.

NLP makes it possible for computers to read text, hear speech, interpret it, measure sentiment and determine which parts are important.

DATACONVERGENCE
AI SPECIALISTS

Inputs

Problem statement
Problem statement descibed clearly to DC

Client data architecture overview
Client data structure and storage overview

Client Azure server for DC
Azure server used for project

Data Access Protocols
All Data Access, firewall and VPN protocols explained to DC

Classification Categories Chosen
Knowledge and Learning choose categories for classification

Outputs

Prototype solution
Draft solution provided to client based on problem statement

NLP Doc Classification preliminary results
Initial results of NLP classification model shared with client

Optimized NLP Model
Final NLP model classification results shared

Enhanced metadata output
Feed client documents to model to enhance metadata

Metadata Dashboard
Visualization of metadata classification and general stats

System Report
DC to provide client with detailed report on solution completion

Key Input Outputs Diagram: Shows the basic inputs and outputs of the solution.

DATACONVERGENCE
AI SPECIALISTS

Document Topic Classification Using NLP

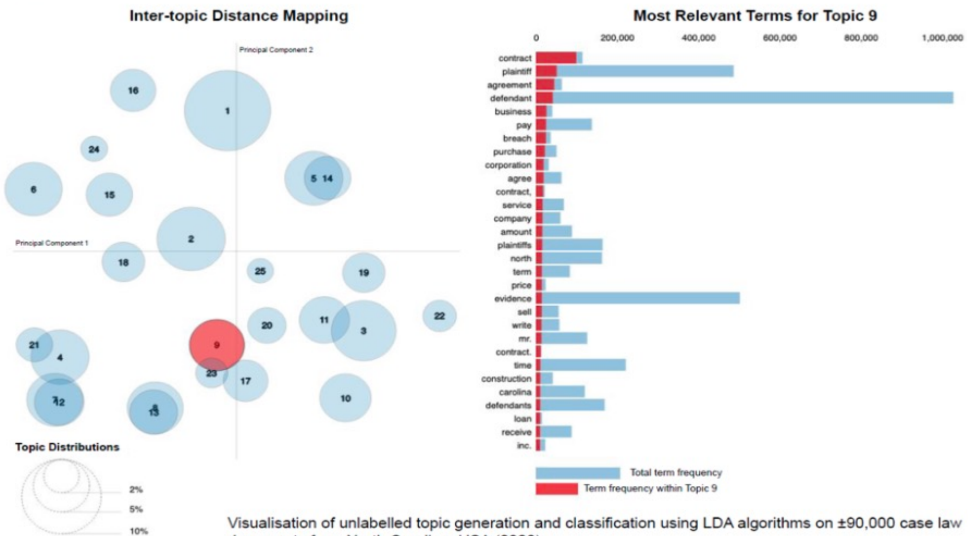
The visualisation on the right shows an example of a topic classification of case law documents. This snapshot of an interactive dashboard allows the user to perform an in depth analyses of the document topics.

In this example, the Latent Dirichlet Allocation (LDA) machine learning method is used to categorise more than 90,000 case law documents from North Carolina, USA. The LDA method is a generative statistical model that enables document text to be analysed and attributed to a given topics. Topics can be provided by the user or determined independently by the model.

The trained LDA model, such as the model shown in the example, is able to take either a new document or a document already stored in the database and categorise the document into a topic. It also is able to connect the user to similar/relevant documents to a given document.

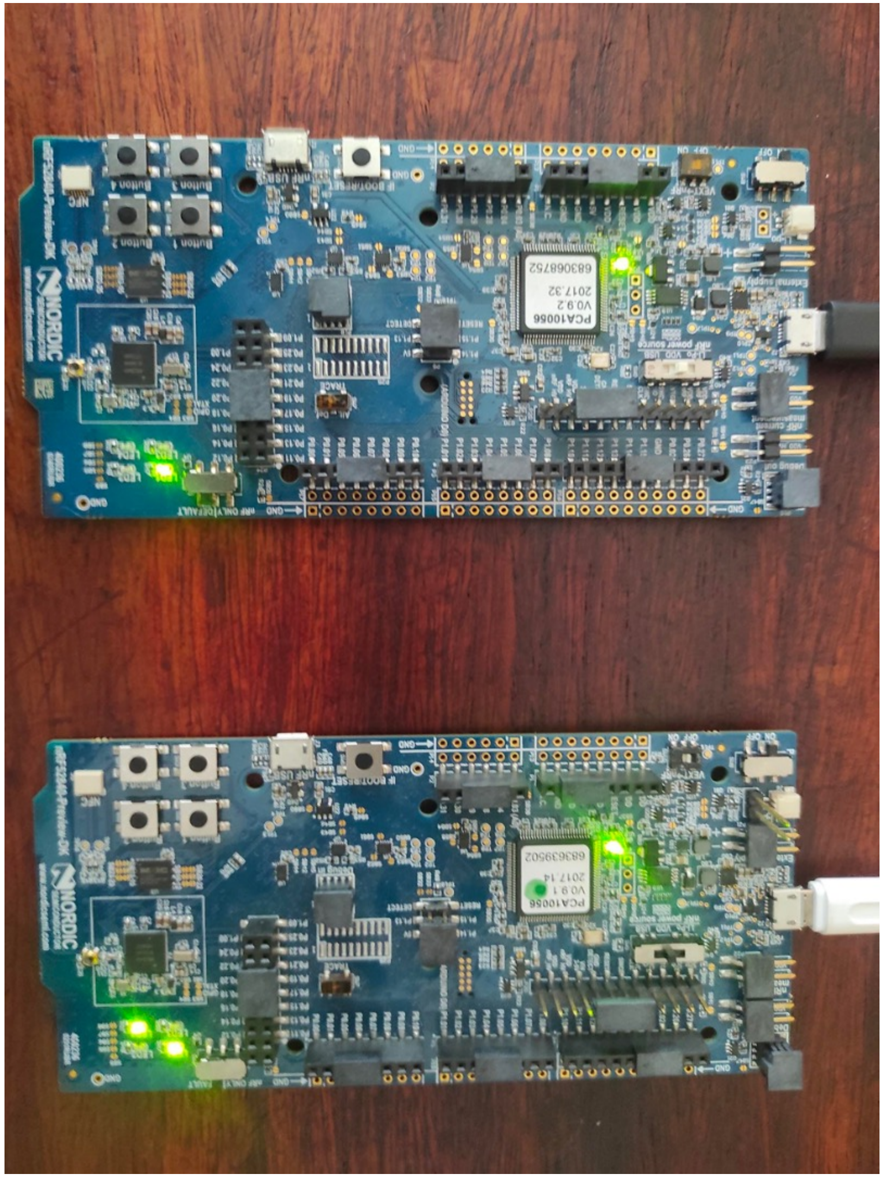
DATACONVERGENCE
AI SPECIALISTS

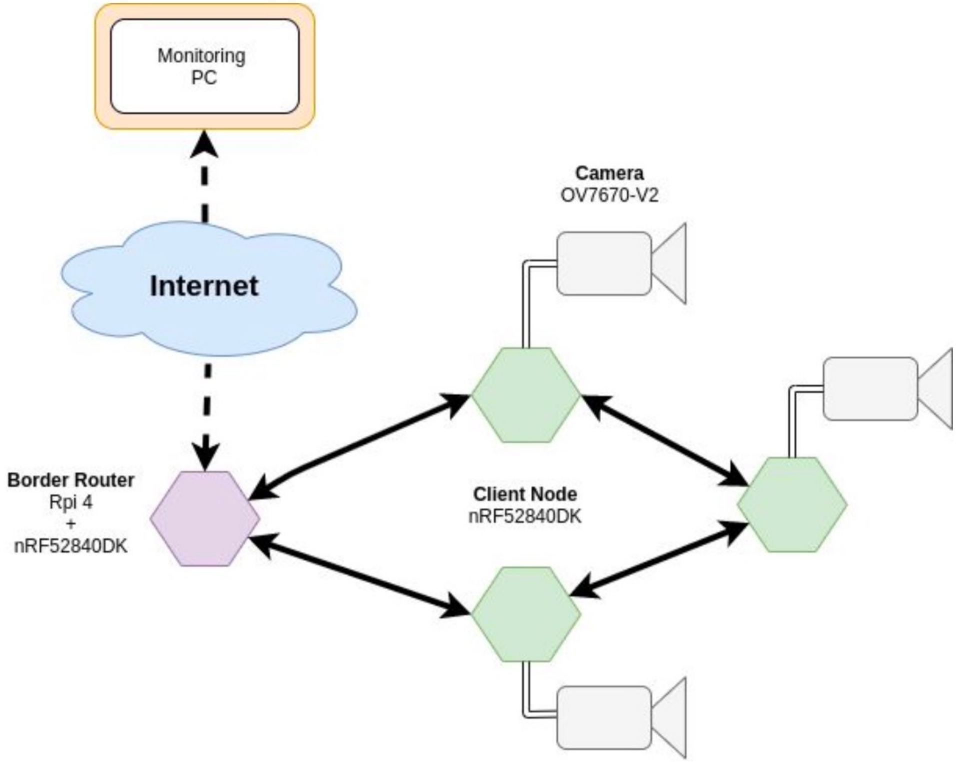
USA Law Document Visualisation of Topic Generation and Categorization



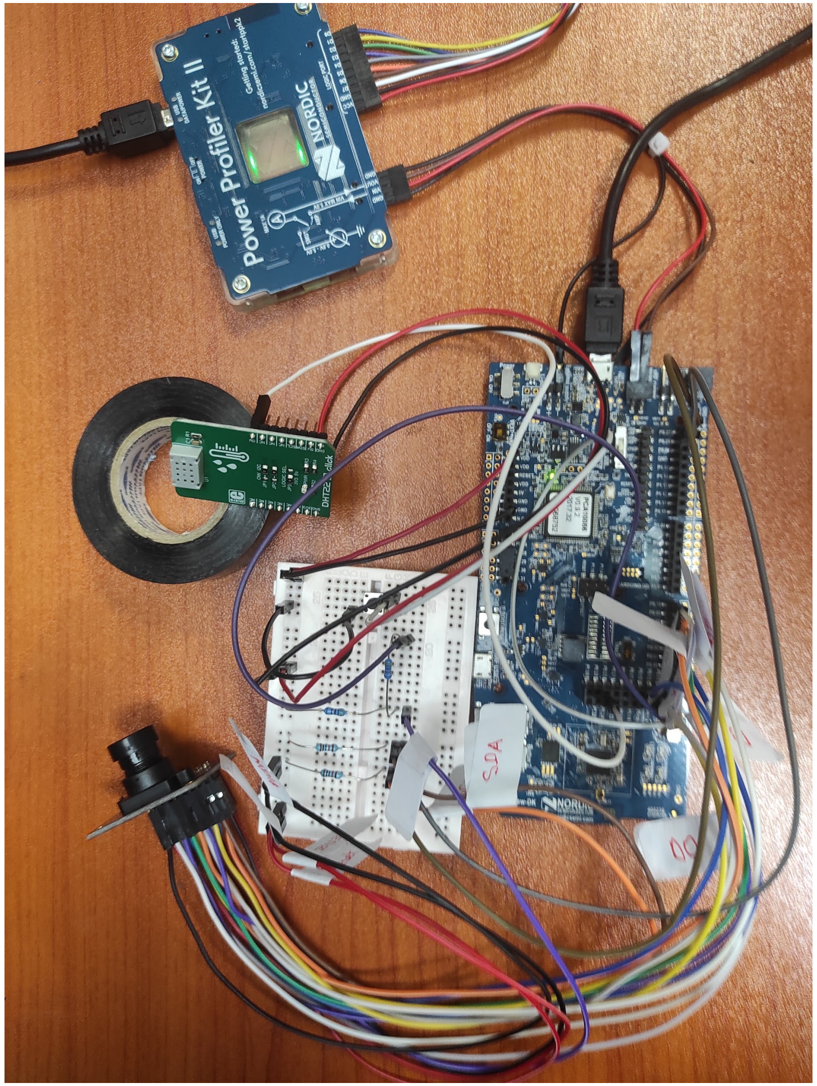
Visualisation of unlabelled topic generation and classification using LDA algorithms on ±90,000 case law documents from North Carolina, USA (2020).

IoT product development for smart economies using WiFi and RF signals.
<u>Optimised for farming and mining</u>





Sensor + Board Integration



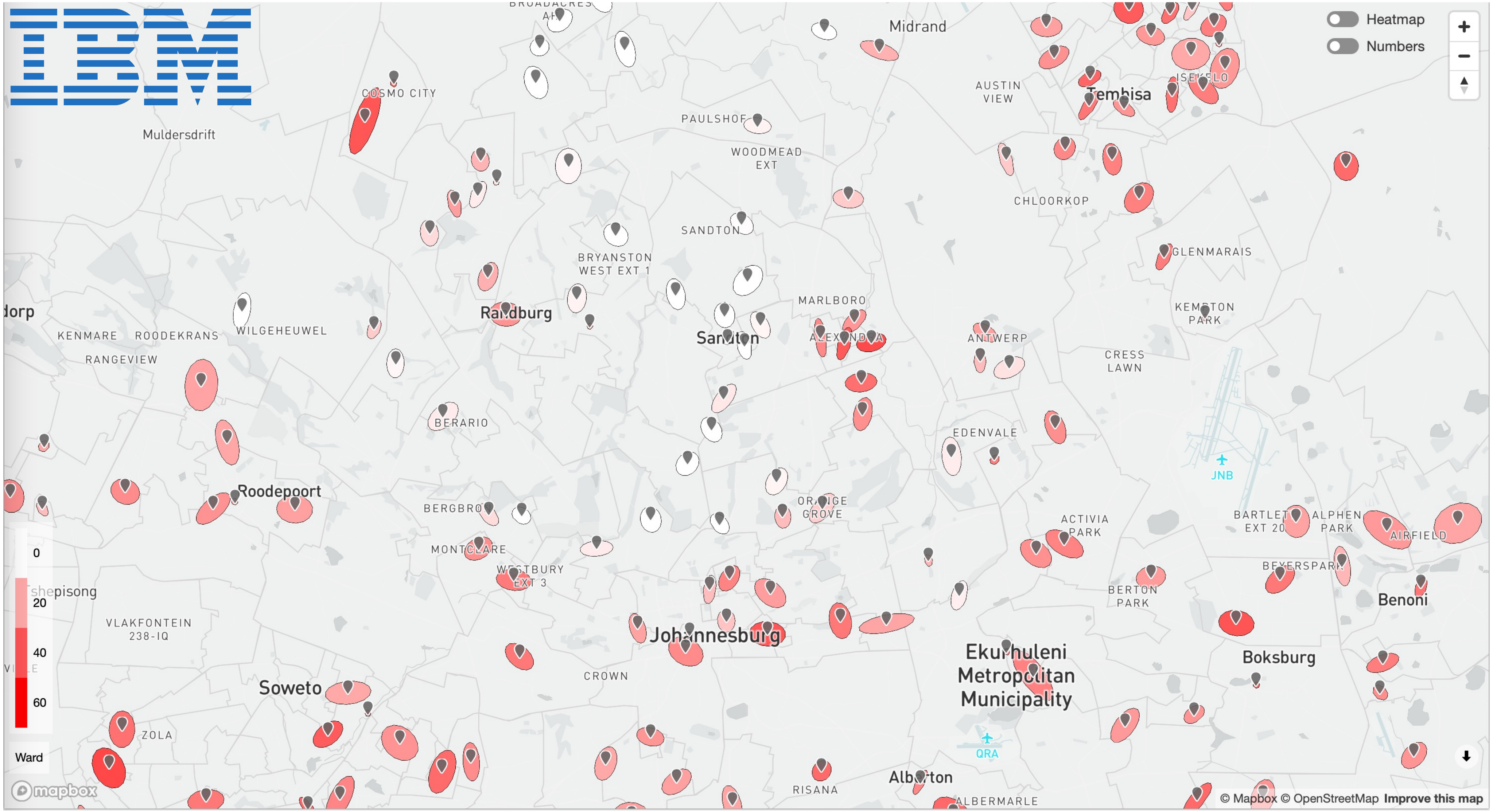
The current system under development is the integration of sensors with the nRF52840-DK board as well as power consumption analysis.

The development system consists of a

- DHT22 temperature and humidity sensor
- OV7670-V2 camera
- A temporary push button to simulate a motion sensor
- nRF52840 Development Kit
- A Power Profiler Kit II for precision power analysis

Picture displays geolocation and severity of hot-spots in Johannesburg Partnership with IBM, where we developed the AI.

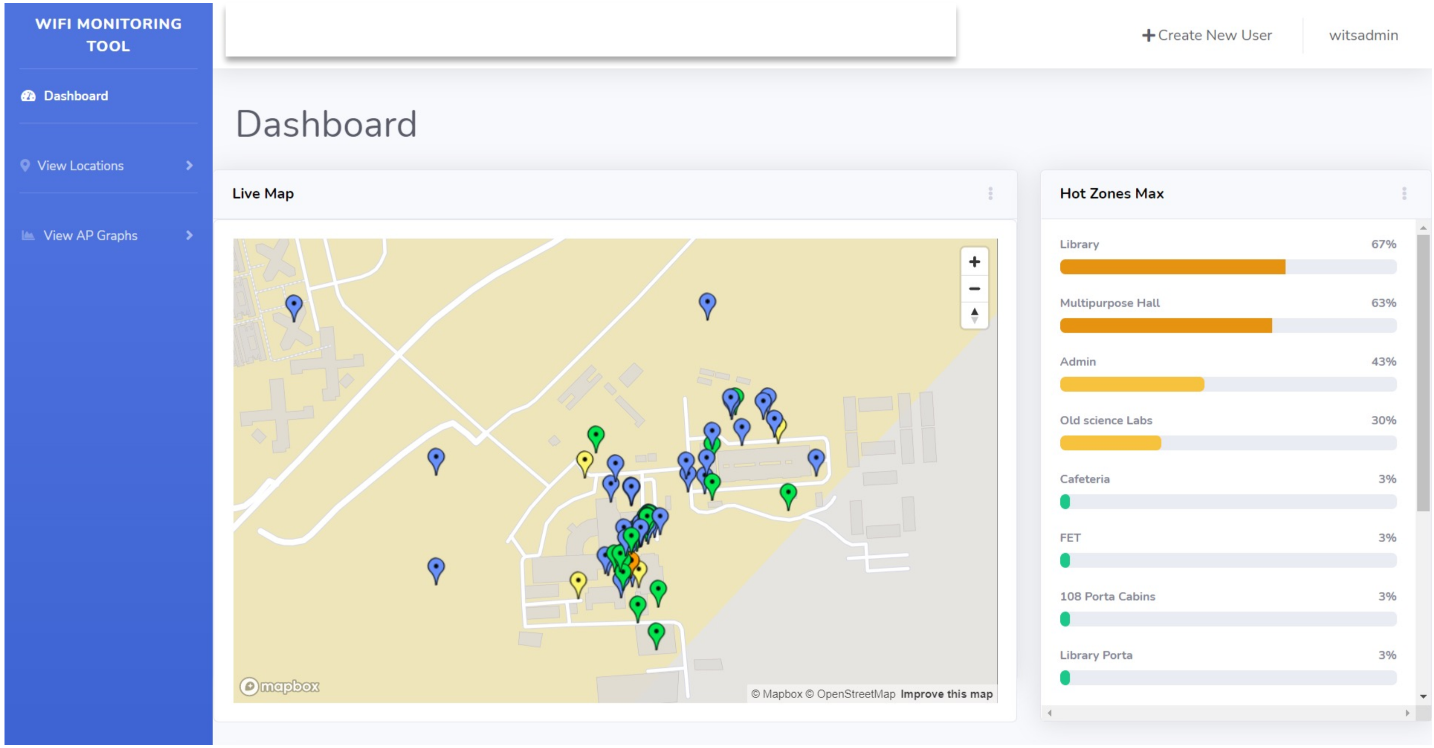
Hot-spots in Gauteng during the second wave

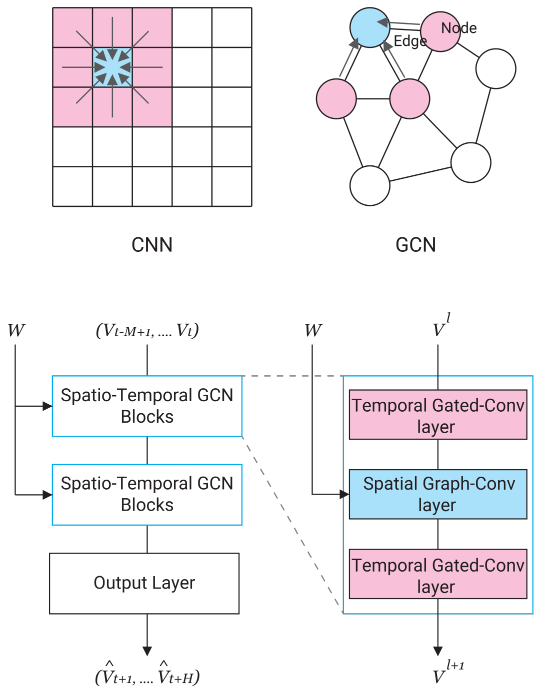


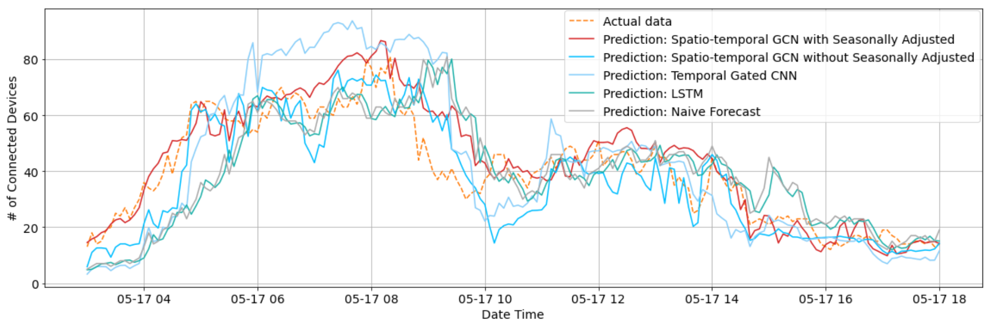
Product developed for the Provincial Government

Monitoring system with Wifi signals

Wits built a monitoring tool to show the number of connected mobile devices to each AP to monitor social distancing.
In order to enhance this system, we added the predicted values of each AP after one hour with Graph Neural Network.







Winning Prospector final pitch
11th November 2021

DATACONVERGENCE
AI SPECIALISTS

AI Enabled Wi-Fi tracking solution for shopping malls

- Join us in congratulating **Dominique Adams**: **AI Enabled Wi-Fi tracking solution for shopping malls**, and his team in presenting the winning pitch.

- The winning pitch met all the requirements of the pitch presentation as they demonstrated the engagement with industry and articulated the value proposition very well.

Wi-Fi tracking combined with AI-enabled solutions and data analytics can be used as a new method for obtaining intelligent foot count and hence data for strategic planning and evidence-based decision-making by SA mall and retail managements.

Additional Slides

With Hon. Minister Naledi Pandor, October 2016

Hon. Minister Mmamoloko Kubayi-Ngubane visits us at CERN, May 2018

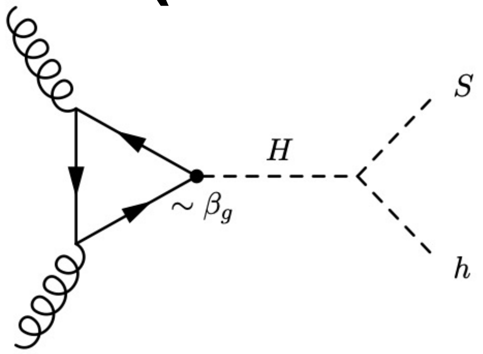
Visit of Dr. Clifford Nxomani, Deputy CEO of the National Research Foundation, on September 11th 2019. NRF is showing interest about how to bridge the gap between research and industry in the light of our contribution in this area.

Prof. Habib's visit of our team at CERN, October 2019

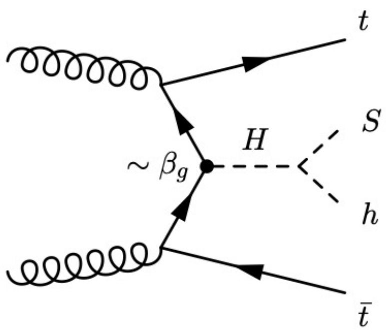
Eur. Phys. J. C (2016) 76:580

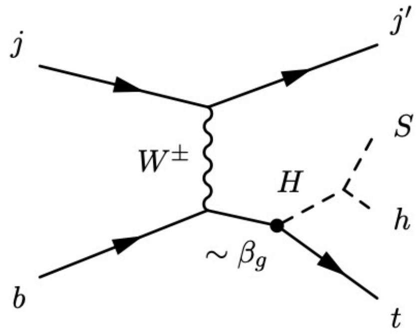
The simplified Model (from Run I)

1. The starting point of the hypothesis is the existence of a boson, H, that contains Higgs-like interactions, with a mass in the range 250-280 GeV
2. In order to avoid large quartic couplings, incorporate a mediator scalar, S, that interacts with the SM and Dark Matter.
3. Dominance of



(a) Gluon fusion (ggF).





$$\mathcal{L}_{\text{int}} \supset -\beta_g \frac{m_t}{v} t\bar{t}H + \beta_V \frac{m_V^2}{v} g_{\mu\nu}\, V^\mu V^\nu H$$

$$\mathcal{L}_{HhS} = -\frac{1}{2}\, v\Big[\lambda_{hhS} hhS + \lambda_{hSS} hSS + \lambda_{HHS} HHS + \lambda_{HSS} HSS + \lambda_{HhS} HhS\Big],$$

The Decays of H

- In the general case, H can have couplings as those displayed by a Higgs boson in addition to decays involving the intermediate scalar and Dark Matter

$$H \to WW, ZZ, q\bar{q}, gg, Z\gamma, \gamma\gamma, \chi\chi$$

$$+ \quad H \to SS, Sh, hh$$

Dominant decays

Diboson decay

$$\boxed{H \to h(+X), S(+X)}$$

The 2HDM+S

Eur. Phys. J. C (2016) 76:580

Introduce singlet real scalar, S.

2HDM potential, $\mathscr{V}\left(\Phi_1, \Phi_2\right)$

$$= m_1^2 \Phi_1^\dagger \Phi_1 + m_2^2 \Phi_2^\dagger \Phi_2 - m_{12}^2 \left(\Phi_1^\dagger \Phi_2 + \text{h.c.}\right)$$
$$+ \frac{1}{2}\lambda_1 \left(\Phi_1^\dagger \Phi_1\right)^2 + \frac{1}{2}\lambda_2 \left(\Phi_2^\dagger \Phi_2\right)^2$$
$$+ \lambda_3 \left(\Phi_1^\dagger \Phi_1\right)\left(\Phi_2^\dagger \Phi_2\right) + \lambda_4 \left|\Phi_1^\dagger \Phi_2\right|^2$$
$$+ \frac{1}{2}\lambda_5 \left[\left(\Phi_1^\dagger \Phi_2\right)^2 + \text{h.c.}\right]$$
$$+ \left\{\left[\lambda_6 \left(\Phi_1^\dagger \Phi_1\right) + \lambda_7 \left(\Phi_2^\dagger \Phi_2\right)\right] \Phi_1^\dagger \Phi_2 + \text{h.c.}\right\}$$

2HDM+S potential

$$\mathscr{V}\left(\Phi_1, \Phi_2\right) + \frac{1}{2} m_{S_0}^2 S^2 + \frac{\lambda_{S_1}}{2} \Phi_1^\dagger \Phi_1 S^2$$
$$+ \frac{\lambda_{S_2}}{2} \Phi_2^\dagger \Phi_2 S^2 + \frac{\lambda_{S_3}}{4} (\Phi_1^\dagger \Phi_2 + \text{h.c}) S^2$$
$$+ \frac{\lambda_{S_4}}{4!} S^4 + \mu_1 \Phi_1^\dagger \Phi_1 S + \mu_2 \Phi_2^\dagger \Phi_2 S$$
$$+ \mu_3 \left[\Phi_1^\dagger \Phi_2 + \text{h.c}\right] S + \mu_S S^3 .$$

Out of considerations of simplicity, assume S to be Higgs-like.
See backup slides for more details on model parameters.

The model leads to rich phenomenology. ***Of particular interest are multilepton signatures***

S. No.	Scalars	Decay modes
D.1	h	$b\bar{b}$, $\tau^+\tau^-$, $\mu^+\mu^-$, $s\bar{s}$, $c\bar{c}$, gg, $\gamma\gamma$, $Z\gamma$, W^+W^-, ZZ
D.2	H	D.1, hh, SS, Sh
D.3	A	D.1, $t\bar{t}$, Zh, ZH, ZS, $W^{\pm}H^{\mp}$
D.4	$H^{\pm}$	$W^{\pm}h$, $W^{\pm}H$, $W^{\pm}S$
D.5	S	D.1, $\chi\chi$

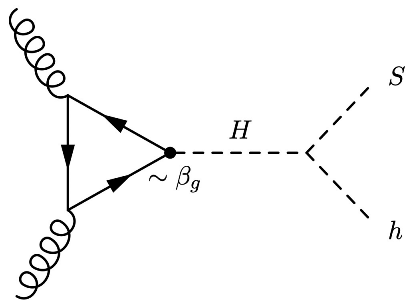
Eur. Phys. J. C (2016) 76:580

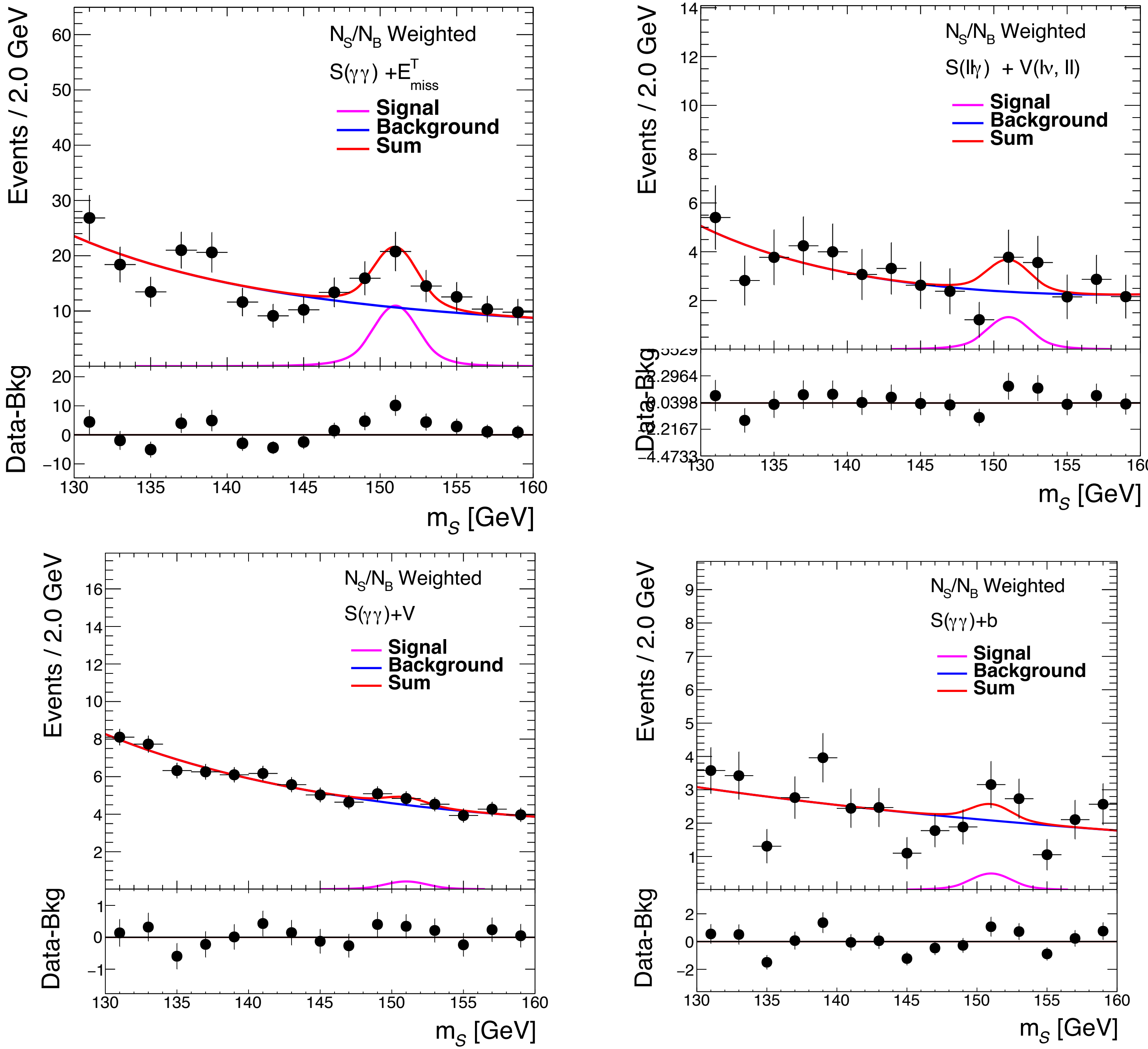
Scalar	Production mode	Search channels
H	$gg \to H, Hjj$ (ggF and VBF)	Direct SM decays as in Table 1 $\to SS/Sh \to 4W \to 4\ell + E_T^{miss}$ $\to hh \to \gamma\gamma b\bar{b}$, $b\bar{b}\tau\tau$, $4b$, $\gamma\gamma WW$ etc. $\to Sh$ where $S \to \chi\chi \implies \gamma\gamma$, $b\bar{b}$, $4\ell + E_T^{miss}$
	$pp \to Z(W^{\pm})H$ $(H \to SS/Sh)$	$\to 6(5)l + E_T^{miss}$ $\to 4(3)l + 2j + E_T^{miss}$ $\to 2(1)l + 4j + E_T^{miss}$
	$pp \to t\bar{t}H, (t+\bar{t})H$ $(H \to SS/Sh)$	$\to 2W + 2Z + E_T^{miss}$ and b-jets $\to 6W \to$ 3 same sign leptons + jets and E_T^{miss}
$H^{\pm}$	$pp \to tH^{\pm}$ $(H^{\pm} \to W^{\pm}H)$	$\to 6W \to$ 3 same sign leptons + jets and E_T^{miss}
	$pp \to tbH^{\pm}$ $(H^{\pm} \to W^{\pm}H)$	Same as above with extra b-jet
	$pp \to H^{\pm}H^{\mp}$ $(H^{\pm} \to HW^{\pm})$	$\to 6W \to$ 3 same sign leptons + jets and E_T^{miss}
	$pp \to H^{\pm}W^{\pm}$ $(H^{\pm} \to HW^{\pm})$	$\to 6W \to$ 3 same sign leptons + jets and E_T^{miss}
A	$gg \to A$ (ggF)	$\to t\bar{t}$ $\to \gamma\gamma$
	$gg \to A \to ZH$ $(H \to SS/Sh)$	Same as $pp \to ZH$ above, but with resonance structure over final state objects
	$gg \to A \to W^{\pm}H^{\mp}(H^{\mp} \to W^{\mp}H)$	$6W$ signature with resonance structure over final state objects

Procedure

(avoiding “cherry picking”)

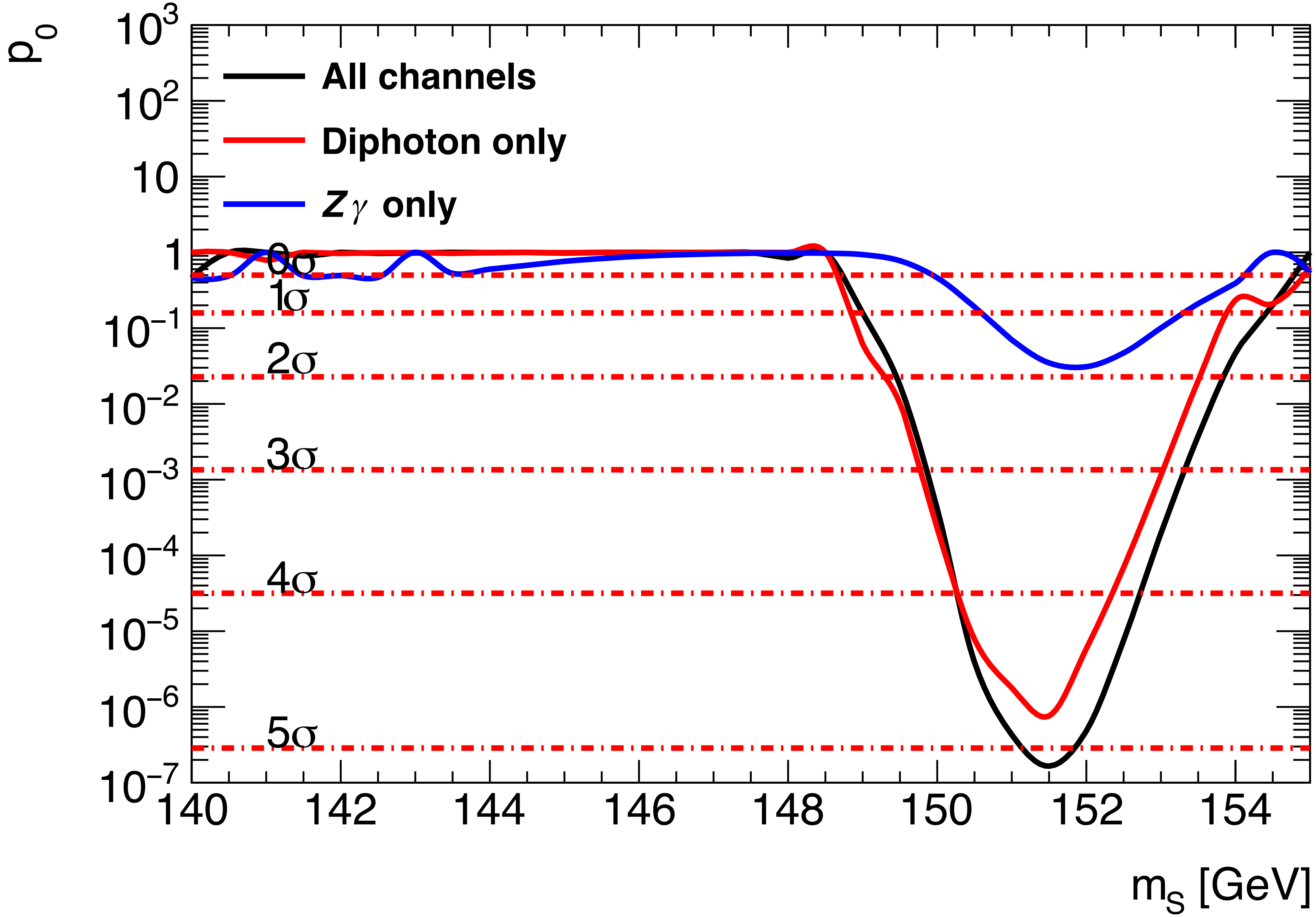
- ❑ **Setting a well-defined procedure is essential to the integrity of a search. Scanning nullifies significance**
- ❑ **From the di-lepton anomalies: $m_h < m_s < 170$ GeV**
  - ❑ **It is critical that search be localized and motivated**
- ❑ **Focus on $\gamma\gamma$ and $Z\gamma$ decays**
- ❑ **As per the model that described the multi-lepton anomalies, we select final state according to di-boson signatures. S is produced via the decay of something heavier and not directly**
  - ❑ **Re-use Higgs boson data**
  - ❑ **Remove VBF and boosted topologies**
    - **Related to direct production**



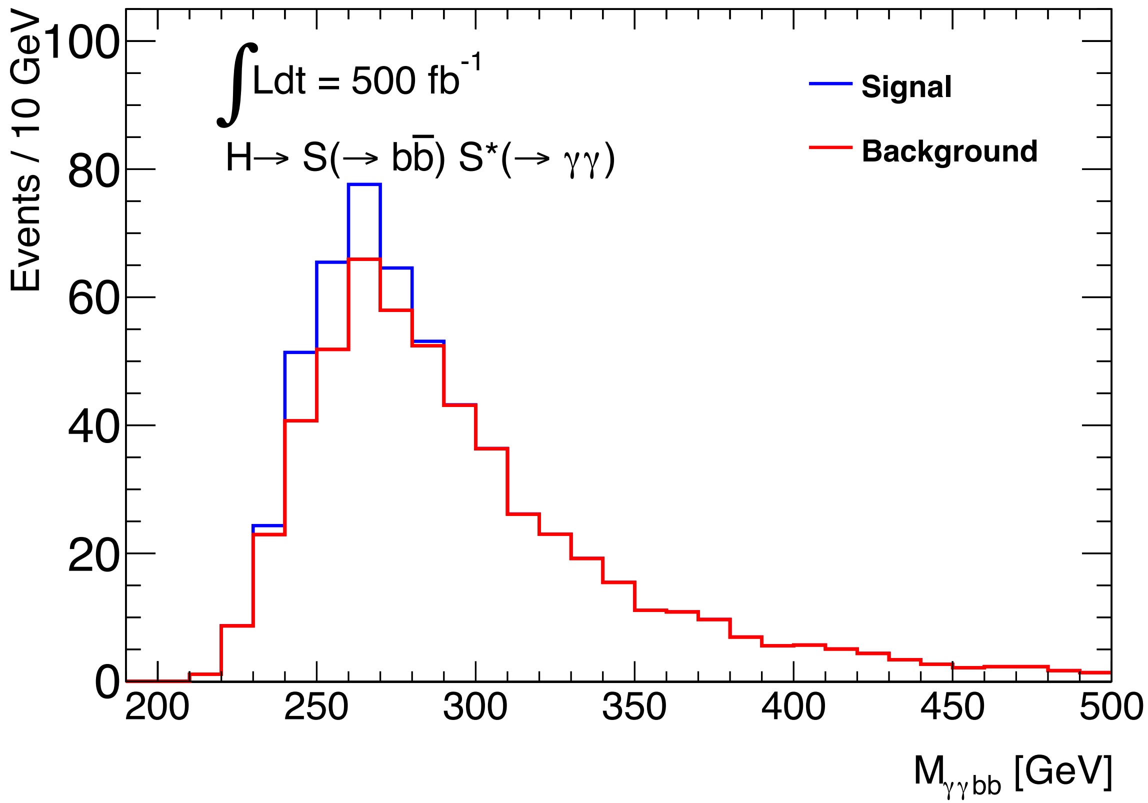


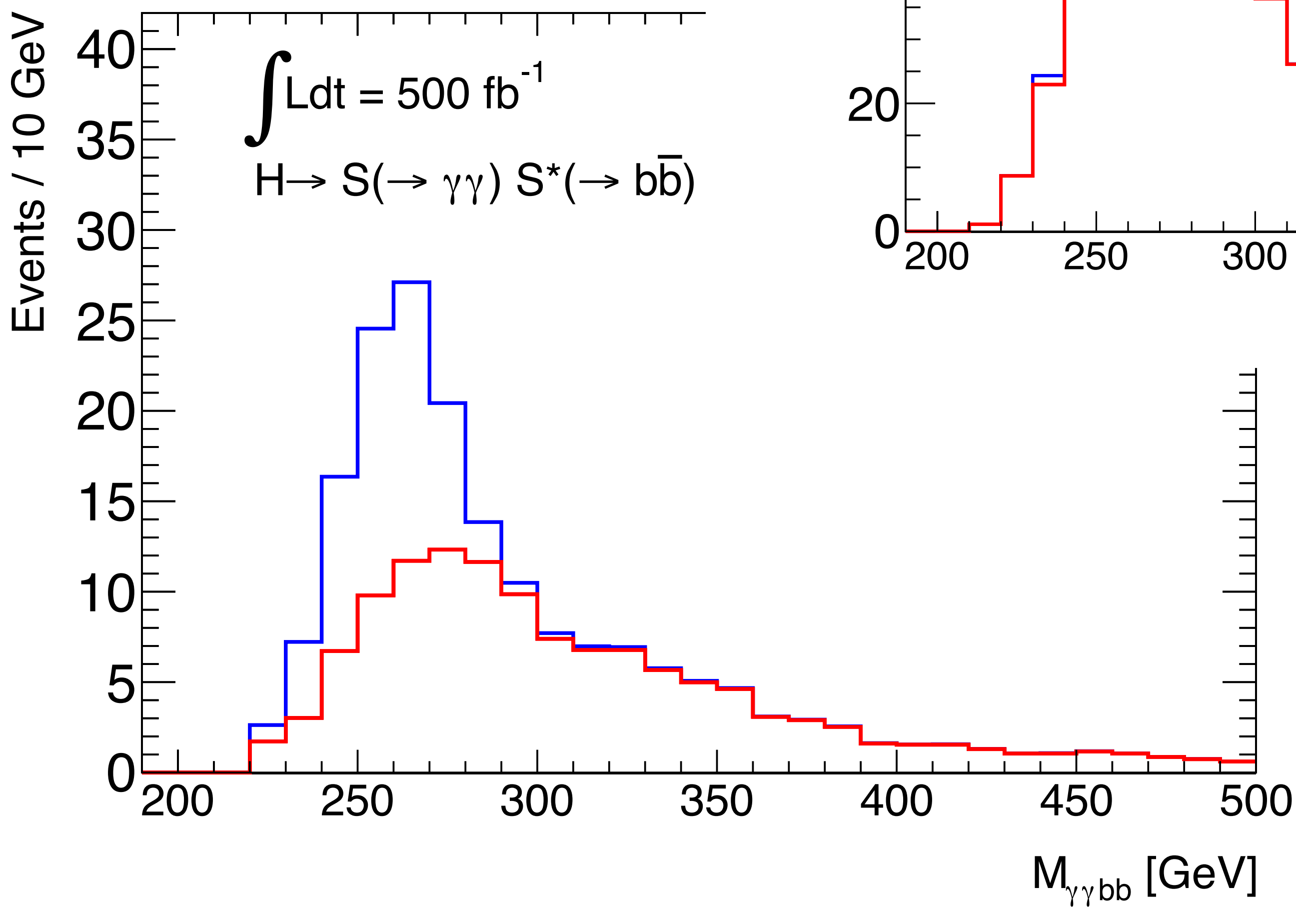
Events / 2.0 GeV
Data-Bkg
m_S [GeV]
N_S/N_B Weighted
$S(\gamma\gamma)$ +E^T_{miss}
Signal
Background
Sum
N_S/N_B Weighted
$S(ll\gamma)$ + $V(l\nu, ll)$
Signal
Background
Sum
N_S/N_B Weighted
$S(\gamma\gamma)$+V
Signal
Background
Sum
N_S/N_B Weighted
$S(\gamma\gamma)$+b
Signal
Background
Sum

Result is obtained with public results from the LHC experiments



Abovementioned excess further motivates searches for bosons in asymmetric $\gamma\gamma$bb configurations not performed before at the LHC





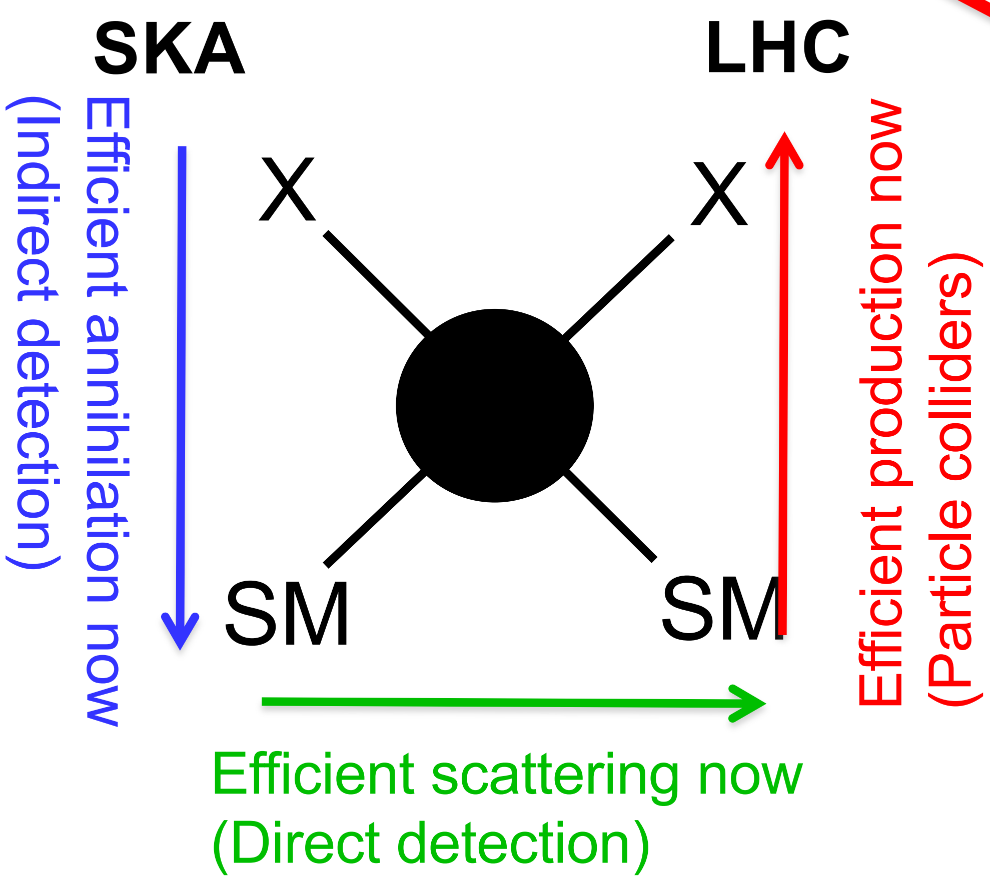
Expect more than 7σ significance for one experiment with the Run 2 + Run 3 data sets.

G.Beck, E.Malwa, M.Kumar, R.Temo and B.M., 2102.10596

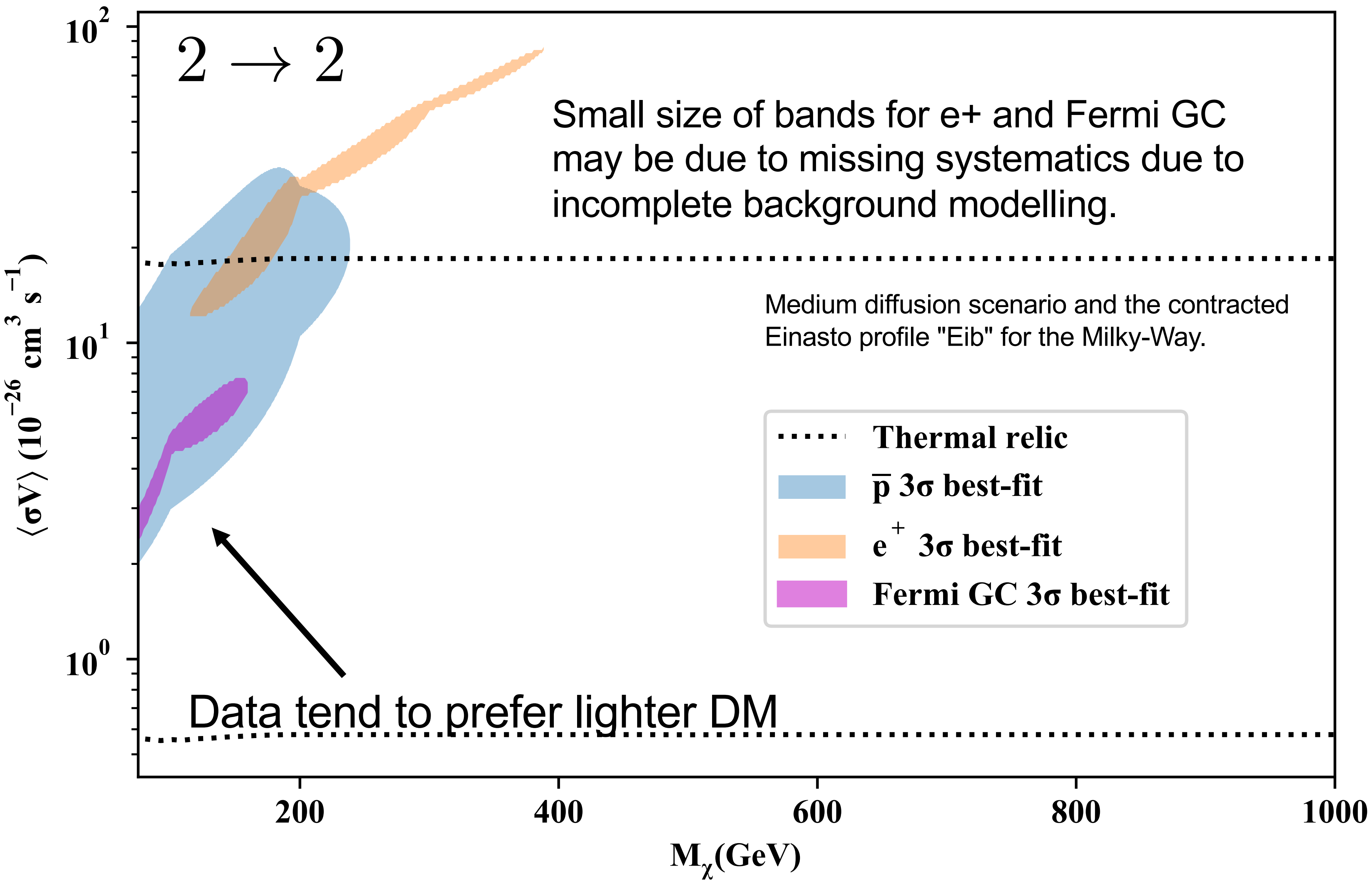
The multi-lepton anomalies and excesses in astrophysics

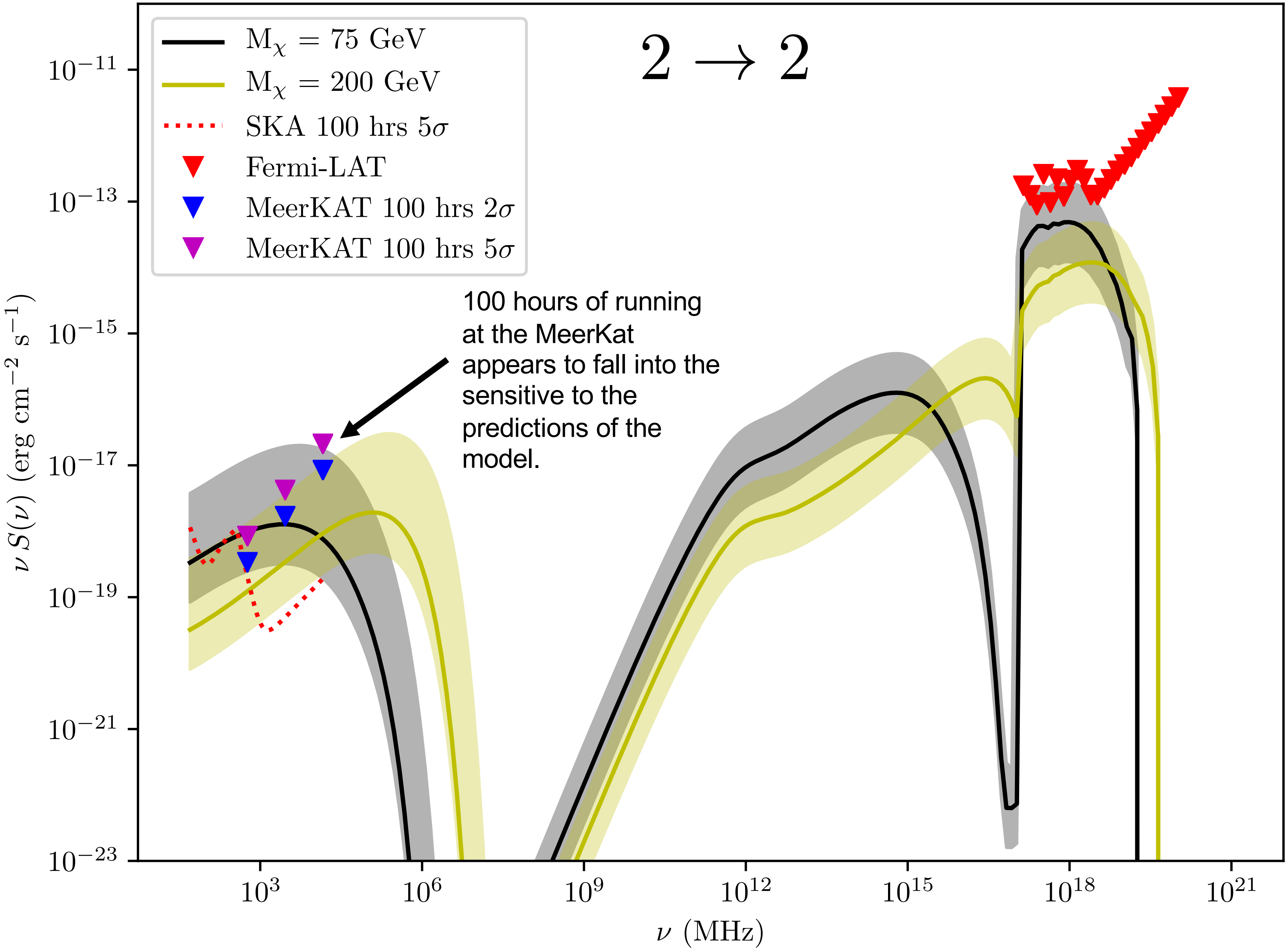
LHC-SKA connection

Effective theory for Weakly Interacting Massive Particles (WIMPs)



Name	Operator	Coefficient
D1	$\bar{\chi}\chi\bar{q}q$	m_q/M_*^3
D2	$\bar{\chi}\gamma^5\chi\bar{q}q$	im_q/M_*^3
D3	$\bar{\chi}\chi\bar{q}\gamma^5 q$	im_q/M_*^3
D4	$\bar{\chi}\gamma^5\chi\bar{q}\gamma^5 q$	m_q/M_*^3
D5	$\bar{\chi}\gamma^\mu\chi\bar{q}\gamma_\mu q$	$1/M_*^2$
D6	$\bar{\chi}\gamma^\mu\gamma^5\chi\bar{q}\gamma_\mu q$	$1/M_*^2$
D7	$\bar{\chi}\gamma^\mu\chi\bar{q}\gamma_\mu\gamma^5 q$	$1/M_*^2$
D8	$\bar{\chi}\gamma^\mu\gamma^5\chi\bar{q}\gamma_\mu\gamma^5 q$	$1/M_*^2$
D9	$\bar{\chi}\sigma^{\mu\nu}\chi\bar{q}\sigma_{\mu\nu}q$	$1/M_*^2$
D10	$\bar{\chi}\sigma_{\mu\nu}\gamma^5\chi\bar{q}\sigma_{\alpha\beta}q$	i/M_*^2
D11	$\bar{\chi}\chi G_{\mu\nu}G^{\mu\nu}$	$\alpha_s/4M_*^3$
D12	$\bar{\chi}\gamma^5\chi G_{\mu\nu}G^{\mu\nu}$	$i\alpha_s/4M_*^3$
D13	$\bar{\chi}\chi G_{\mu\nu}\tilde{G}^{\mu\nu}$	$i\alpha_s/4M_*^3$
D14	$\bar{\chi}\gamma^5\chi G_{\mu\nu}\tilde{G}^{\mu\nu}$	$\alpha_s/4M_*^3$

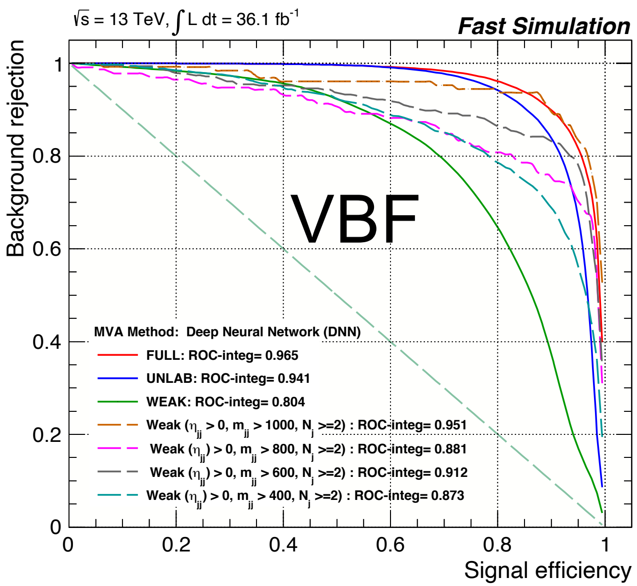

$2 \to 2$
Small size of bands for e+ and Fermi GC may be due to missing systematics due to incomplete background modelling.
Medium diffusion scenario and the contracted Einasto profile "Eib" for the Milky-Way.
Thermal relic
$\bar{p}$ 3σ best-fit
e^+ 3σ best-fit
Fermi GC 3σ best-fit
Data tend to prefer lighter DM
$\langle \sigma V \rangle$ $(10^{-26}$ cm^3 s$^{-1})$
10^2
10^1
10^0
200
400
600
800
1000
M_χ(GeV)

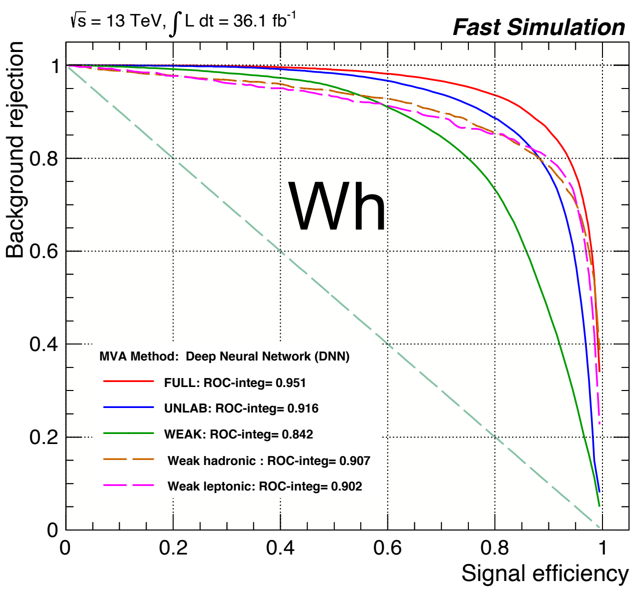


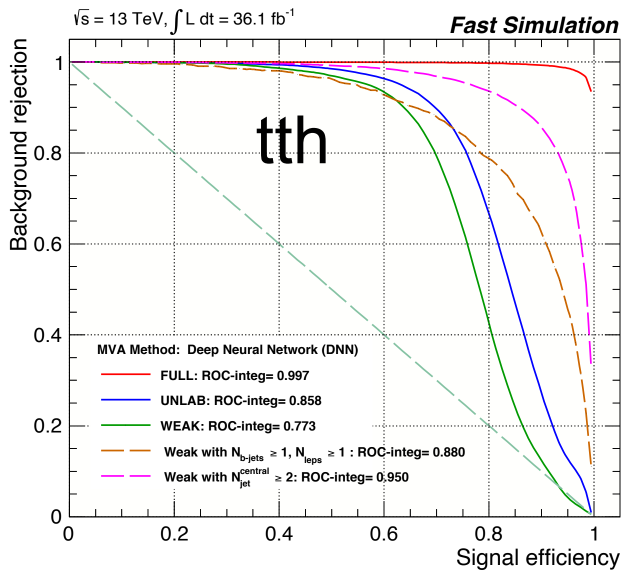
M_χ = 75 GeV
M_χ = 200 GeV
SKA 100 hrs 5σ
Fermi-LAT
MeerKAT 100 hrs 2σ
MeerKAT 100 hrs 5σ
$2 \rightarrow 2$
100 hours of running at the MeerKat appears to fall into the sensitive to the predictions of the model.
$\nu S(\nu)$ (erg cm^{-2} s^{-1})
ν (MHz)
10^{-11}
10^{-13}
10^{-15}
10^{-17}
10^{-19}
10^{-21}
10^{-23}
10^{3}
10^{6}
10^{9}
10^{12}
10^{15}
10^{18}
10^{21}

Machine learning approach for the search of resonances with topological features at the Large Hadron Collider

- Results demonstrate the ability of the Weak supervised learning to extract subtle signals in data.
- The mythology is introduced to the ATLAS collaboration.
- We started the search for any resonances in the Zγ final states using ATLAS data.







Link to the paper: https://arxiv.org/abs/2011.09863

Kernel Density Estimation

- Kernel density estimation in scikit-learn is implemented in the KernelDensity() function, which uses the Ball Tree or KD Tree for efficient queries.
- Given a sample of $(x_1, x_2, \ldots, x_n)$ the kernel density estimate, is given by:

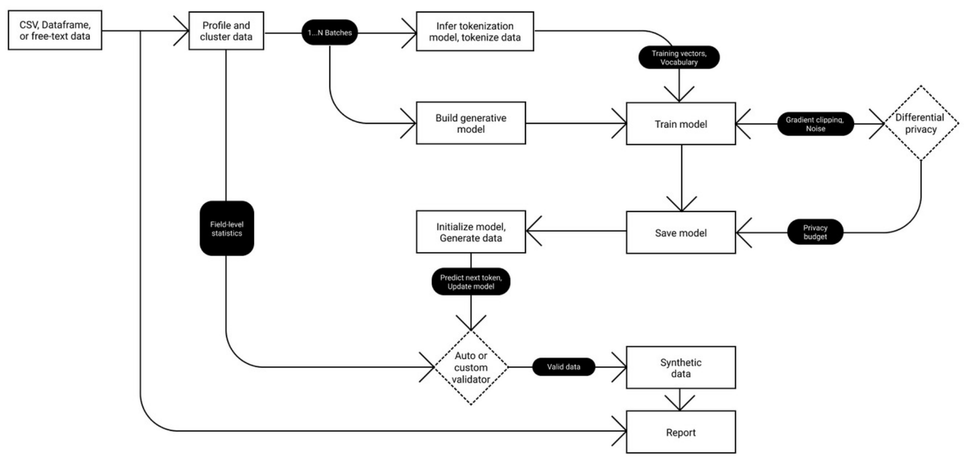
$$p(x)=\frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x-xj}{h}\right)$$

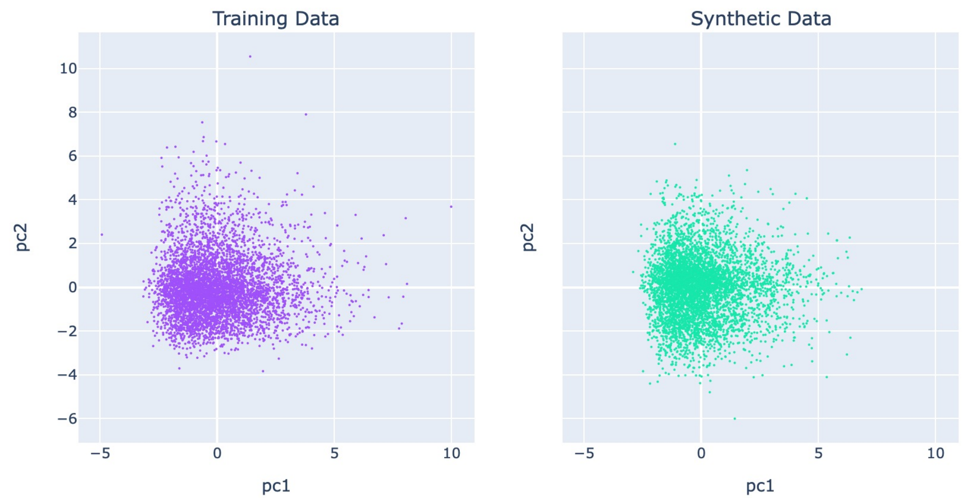
where K(a) is the kernel function and h is the smoothing parameter, also called the bandwidth.

Tuning Bandwidth Parameter:

- The scikit-learn library allows the tuning of the bandwidth parameter via cross-validation and returns the parameter value that maximizes the log-likelihood of data. The function we can use to achieve this is GridSearchCV(), which requires different values of the bandwidth parameter.

Long-Short Term Memory (LSTM) Neural Network Model





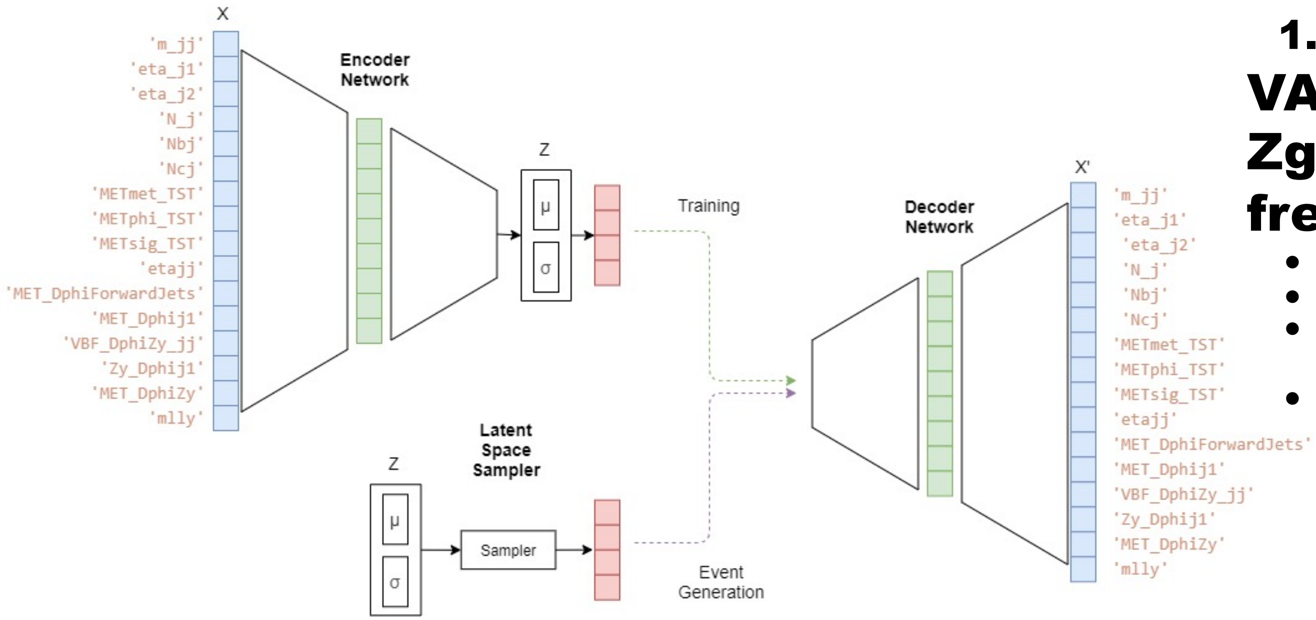
Gretel-synthetics utilizes a sequence-to-sequence architecture to train on a text dataset and learn to predict the next characters in the sequence. Gretel-synthetics uses a Long-Short Term Memory (LSTM) artificial neural network to learn and create new synthetic examples from any kind of text or structured data.

Long-Short Term Memory (LSTM) Neural Network Model

The Use of Variational Autoencoders (VAE) in HEP

Dual purpose use:

1. Event Generation **2. Classification and Anomaly Detection**



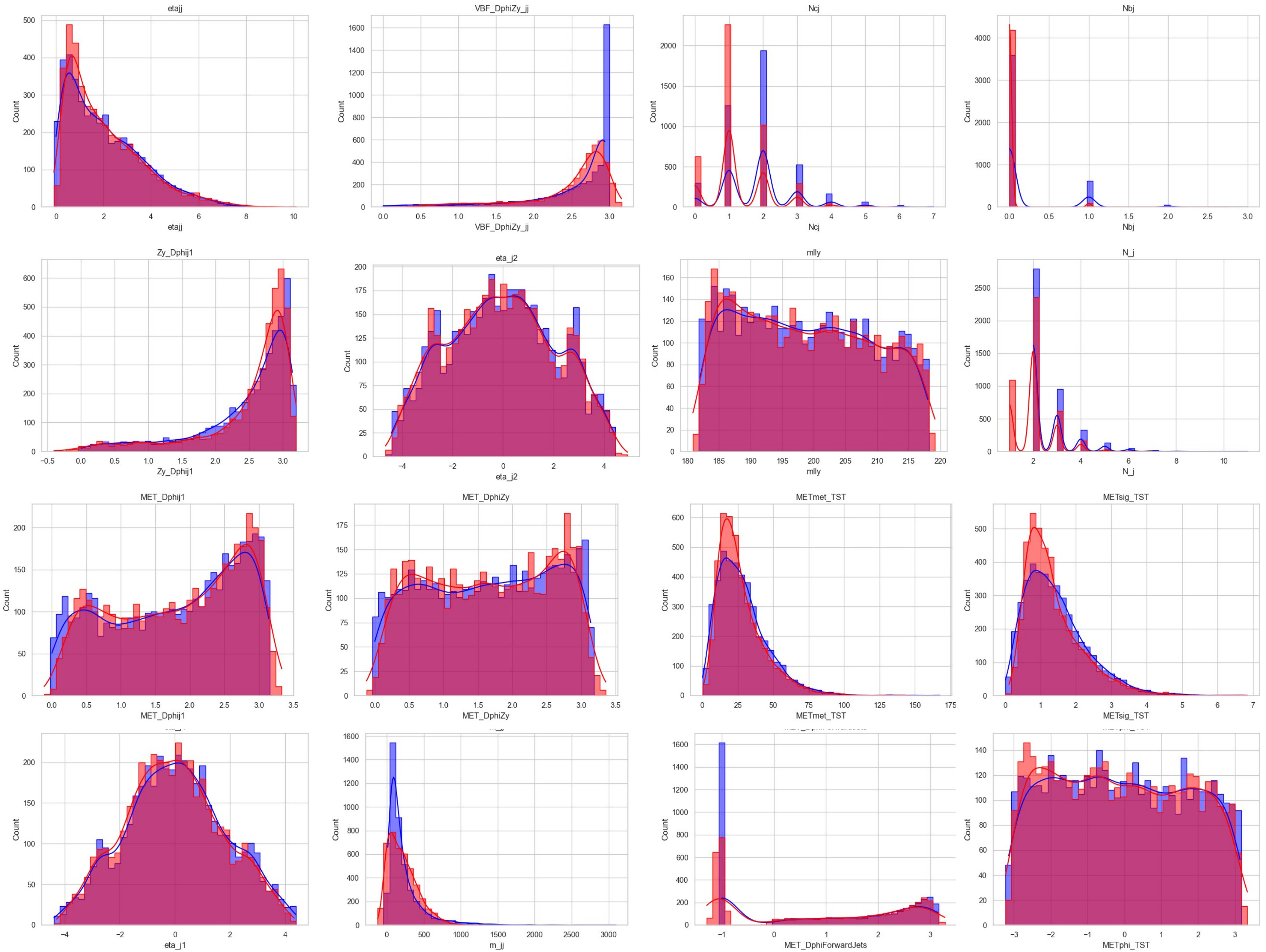
1. Event Generation:
VAE used to generate Zgamma data used in frequentist study:

- **182 < mlly < 218**
- **16 features**
- **'event_weight' incorporated into loss function during training**
- **VAE learns to generate two vectors that represent the parameters (mean and variance) of a distribution from which the latent vector is sampled, and which the decoder function can transform back to the original input vector**
- **Events can then be created by sampling randomly from the latent dimension and feeding into the decoder network**

2. Classification and Anomaly Detection:
Once trained on specific background data, VAE can be used as a signal classifier by monitoring the reconstruction loss and latent representation of an inputted event which could be either signal or background.

Preliminary Results of VAE based Event Generation

Red - Input Event Distributions, Blue - Event Reconstruction

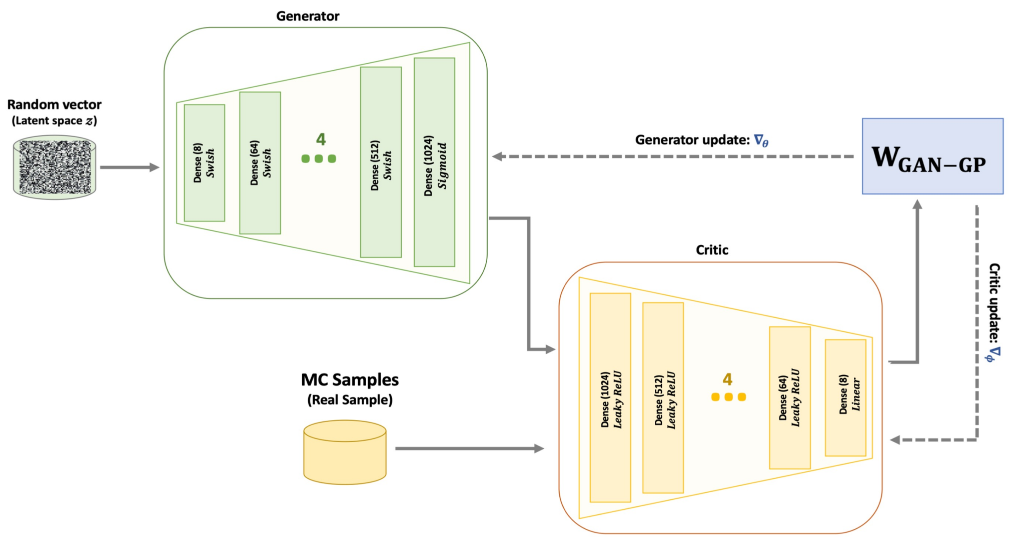


High Energy Physics Event Generation Using WGANs

Generative Adversarial Networks, GANs, are an attractive solution and a potential alternative to address the inverse problem in HEP. This is due to the fact that with GANs we can synthesize fake MC samples at scale with high accuracy and speed.

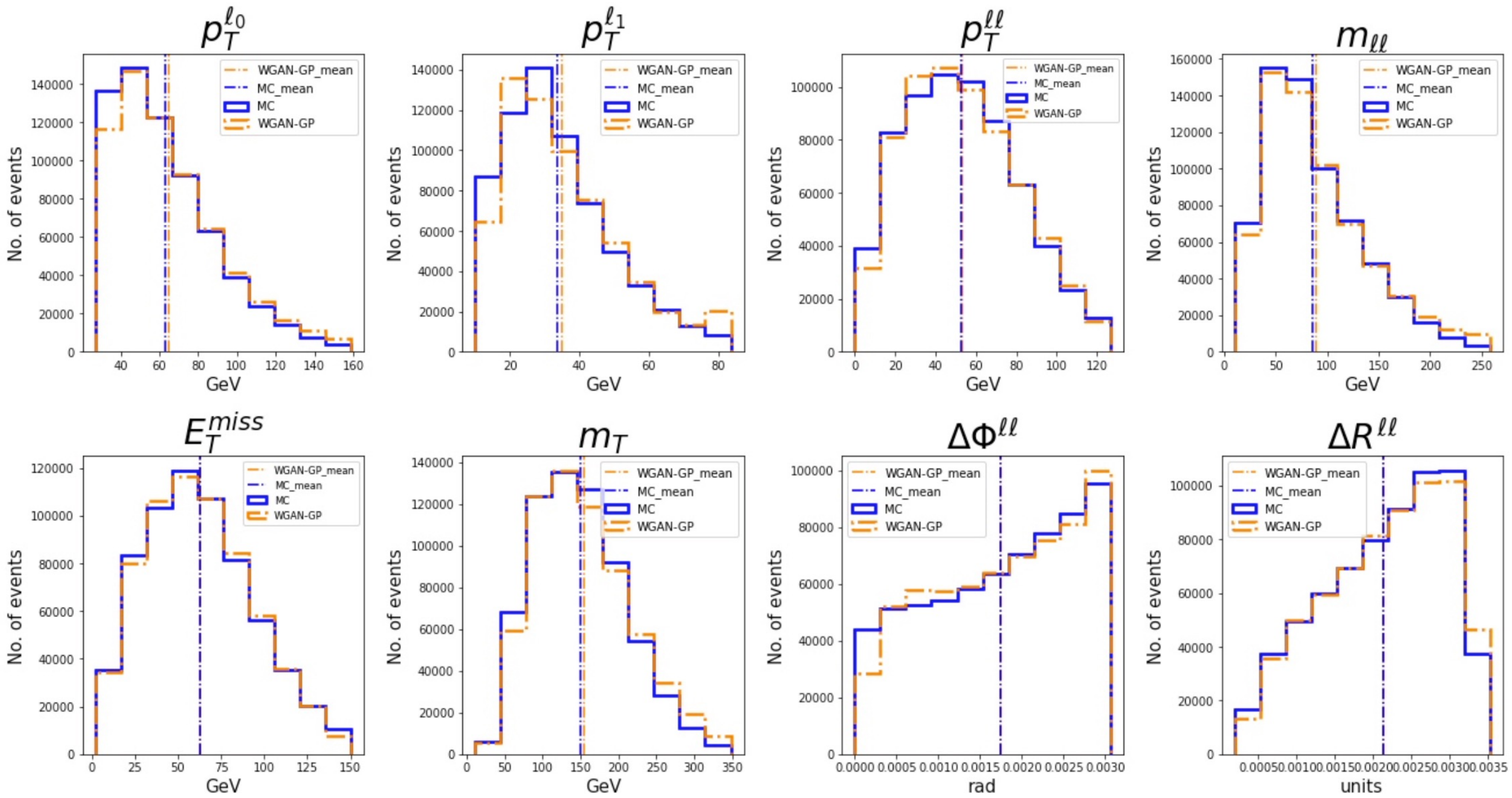
Wasserstein GAN using gradient penalty on the loss function is found to be the ideal methodology in simulating high energy physics data.

$$V_{\text{WGAN-GP}} = V_{\text{WGAN}} + \lambda \mathbb{E}_{\hat{\mathbf{x}} \sim \mathbb{P}_{\mathbf{d}}(\hat{\mathbf{x}})}\left[(\|\nabla_{\hat{\mathbf{x}}} D_{\phi}(\hat{\mathbf{x}})\|_2 - 1)^2\right]$$



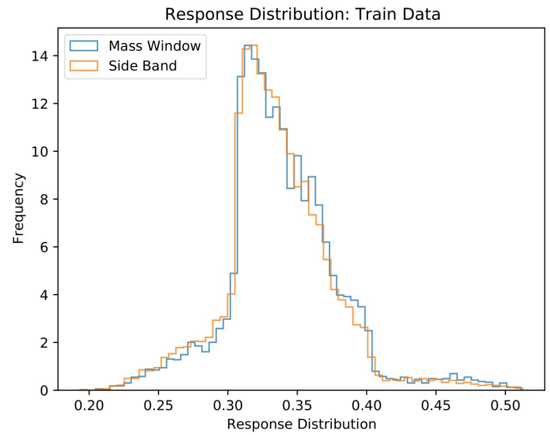
The WGAN-GP Network architecture with a generator (G) and a critic (C). This network is build via a connection of outputs of (G) to inputs of critic (C) whilst penalizing gradient weights with values above 1.

WGAN-gp Preliminary Output Distributions



INVESTIGATION OF OVERTRAINING WITHIN SEMI-SUPERVISED MACHINE LEARNING DNN MODELS

Using a DNN and semi-supervised methodology described above, pure Zy toy MC samples are used to quantify the overtraining of the semi-supervised technique at a benchmark center of mass of 200GeV.



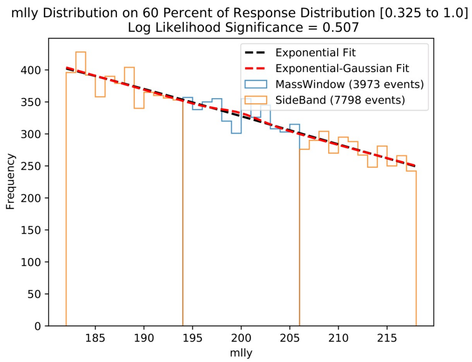
Methodology

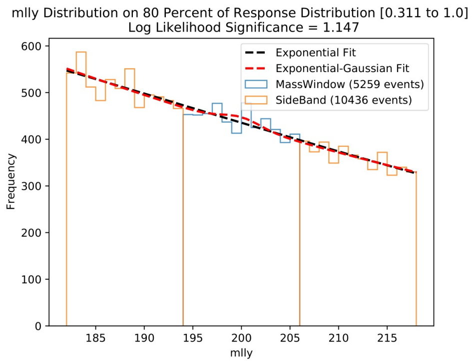
1. The response distribution is divided into batches containing 50, 60, 70, 80 and 90% of the events.
2. An exponential, f(x), and exponential + gaussian function, g(x), is applied to each mlly distribution.

$$f(x) = n_0 \cdot e^{ax+bx^2},$$

$$g(x) = n_0 \cdot e^{ax+bx^2} + n_1 \cdot e^{\frac{(x-\mu)^2}{2\sigma}},$$

3. The significance of fake signals generated in the mass-window can than be quantified as the difference between the log-likelihoods of the two functions



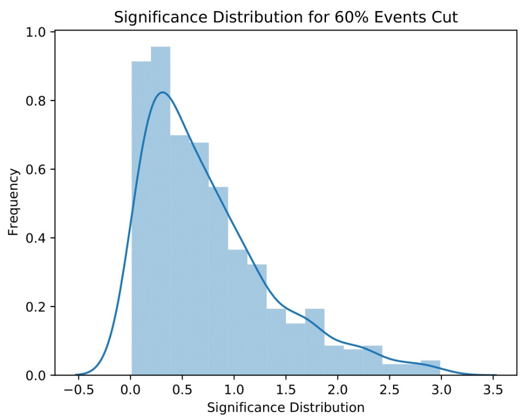


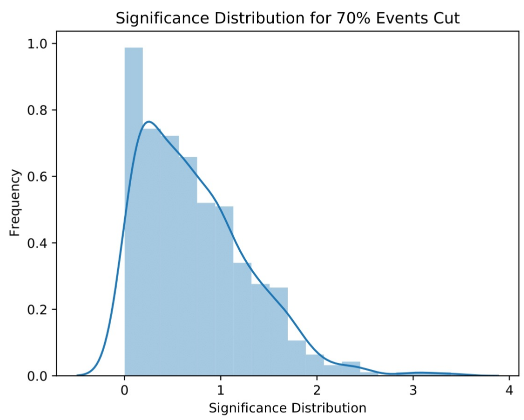
Example Output of a single run (using one toy MC sample)

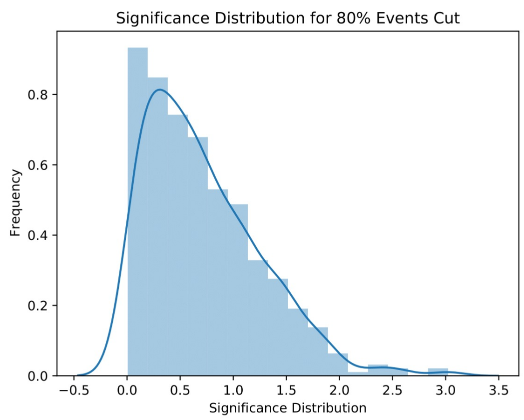
Results

In order to evaluate the uncertainty generated in the training of semi-supervised methods, the process must be repeated a sufficient number of times on samples with unique statistics. The results below demonstrate the significance distributions produced when the model is run on 500 toy MC generated samples.

% Events	Mass-Window Events	Side-Band Events	Significance
50	3358	6451	0.5675
60	3973	7798	0.5073
70	4632	9101	0.8714
80	5259	10436	1.1471
90	5869	11788	0.6078





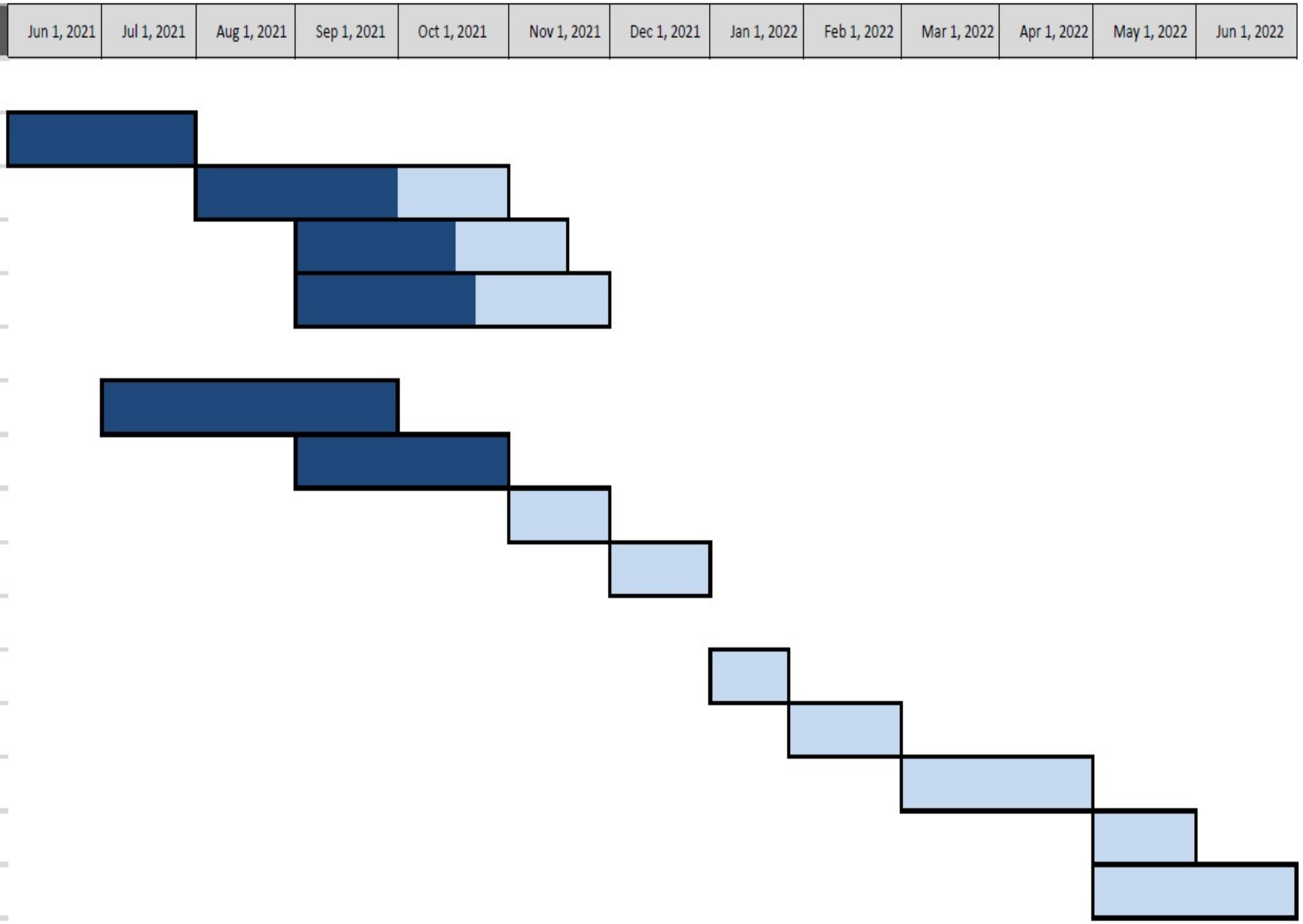


2021 / 2022 progress for the SA TilePPr contribution

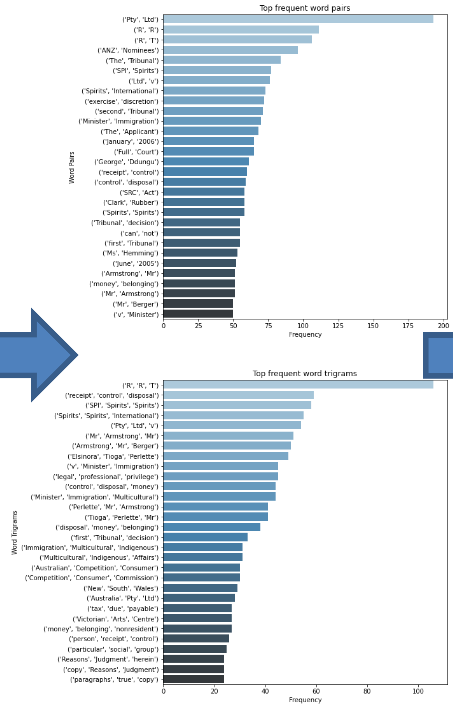
Task Completed

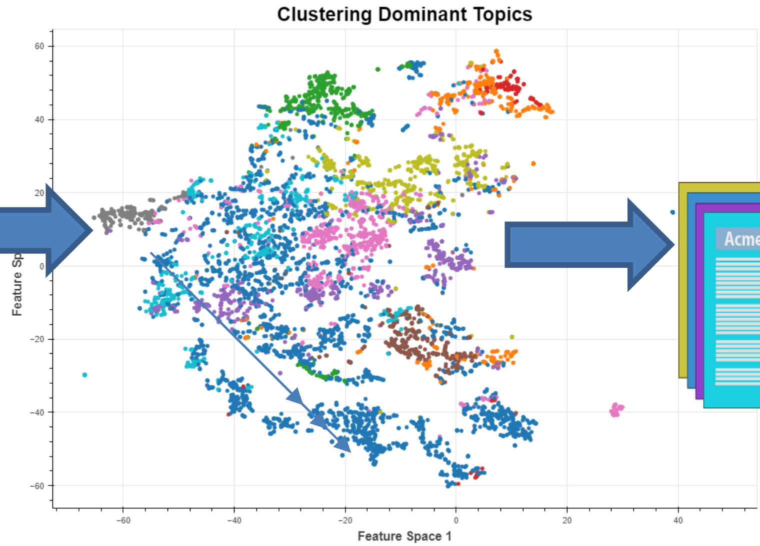
Task to complete

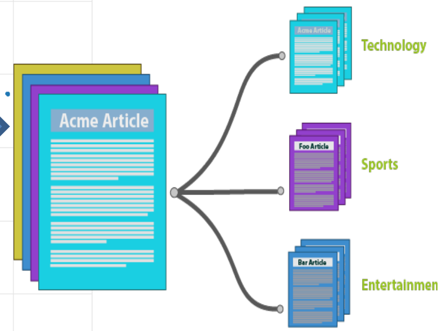
TASK	PROGRESS	START	END
OPC-UA TileCal Software developments			
First Project: OpcUaTileXADC	100%	6/1/21	7/30/21
Second Project: OpcUaTileCoM	60%	8/1/21	10/31/21
Integration tests of OpcUA	50%	10/1/21	11/30/21
Deployment of both projects	50%	11/30/21	11/30/21
ATLAS TileCal TileCoM Note			
Document preparation	100%	7/1/21	9/31/2021
Document internal review	90%	9/31/2021	11/1/21
Document ATLAS TileCal review	0%	11/1/21	11/30/21
Document ATLAS review	0%	11/30/21	12/31/21
Production of TileCoM in SA			
Request for Quotation	0%	1/1/22	1/15/22
PCB manufacturing	0%	1/16/22	2/28/22
PCB population	0%	2/28/22	4/30/22
PCB electrical test at WITS	0%	4/30/22	5/1/22
Integration tests with TilePPr	0%	5/1/22	6/31/2022



UNSUPERVISED TEXT CLASSIFICATION







Collection of documents

Bag of words(NGrams)

Cluster of dominant topics

Classified documents

Predictive method

This project used Spatio-temporal GCN.
The model can make predictions for all access points with a single model.
Graph Convolutional Network(GCN): Neural networks with graph networks.
They use the information of the edges to predict the information of the nodes.
Spatio-temporal GCN: It has the structure of GCN sandwiched between CNNs.

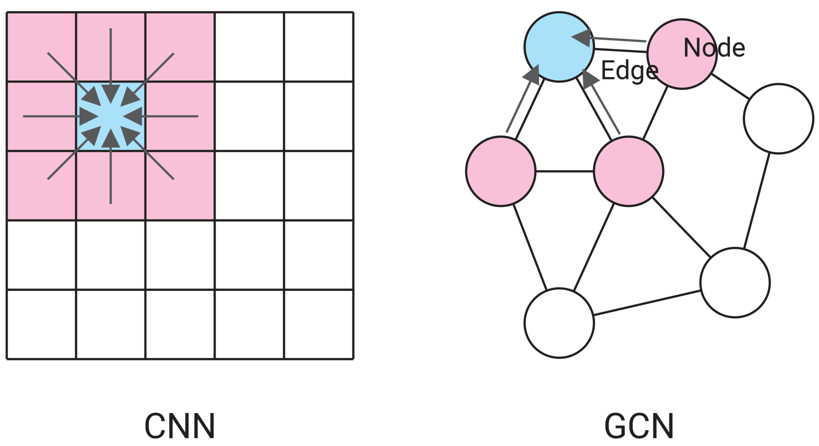


Fig. Images of the CNN and GCN

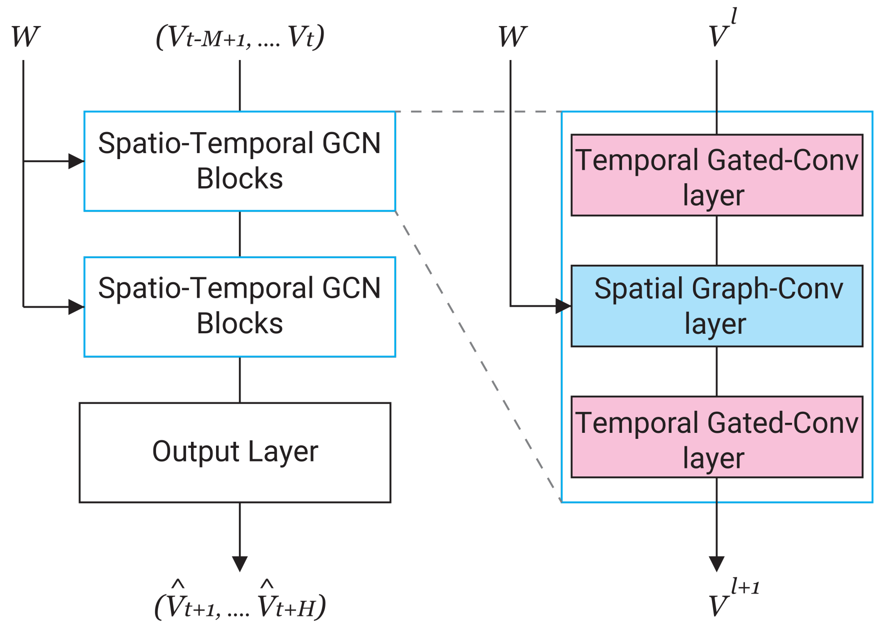


Fig. Spatio-temporal GCN Structure

Results

Spatio-temporal GCN with weekly seasonally adjusted is the most accurate model and can make a predictive model very quickly compared to existing models.

	Minutes
Spatio-temporal GCN	5.82
LSTM RNN	173.99

Table Time to Make Predictions

Predictive Model	The highest frequency APs			Middle frequency APs			The lowest frequency APs		
	AP29	AP52	AP33	AP31	AP49	AP1	AP74	AP189	AP173
Spatio-temporal GCN with weekly seasonally adjusted	8.78	15.50	6.78	1.81	4.91	1.85	2.20	1.18	6.36
Spatio-temporal GCN without seasonally adjusted	9.95	21.91	7.24	2.64	5.74	2.29	3.46	1.33	6.72
Temporal Gated CNN	12.92	24.50	11.92	3.64	6.26	3.41	3.83	1.59	6.74
LSTM RNN	10.55	25.26	7.21	2.28	5.79	2.15	2.40	0.84	6.54
Naive Forecast	10.42	24.86	7.20	2.20	5.82	2.10	2.34	0.84	3.62

Table Comparison of accuracies (RMSE) between Predictive Models

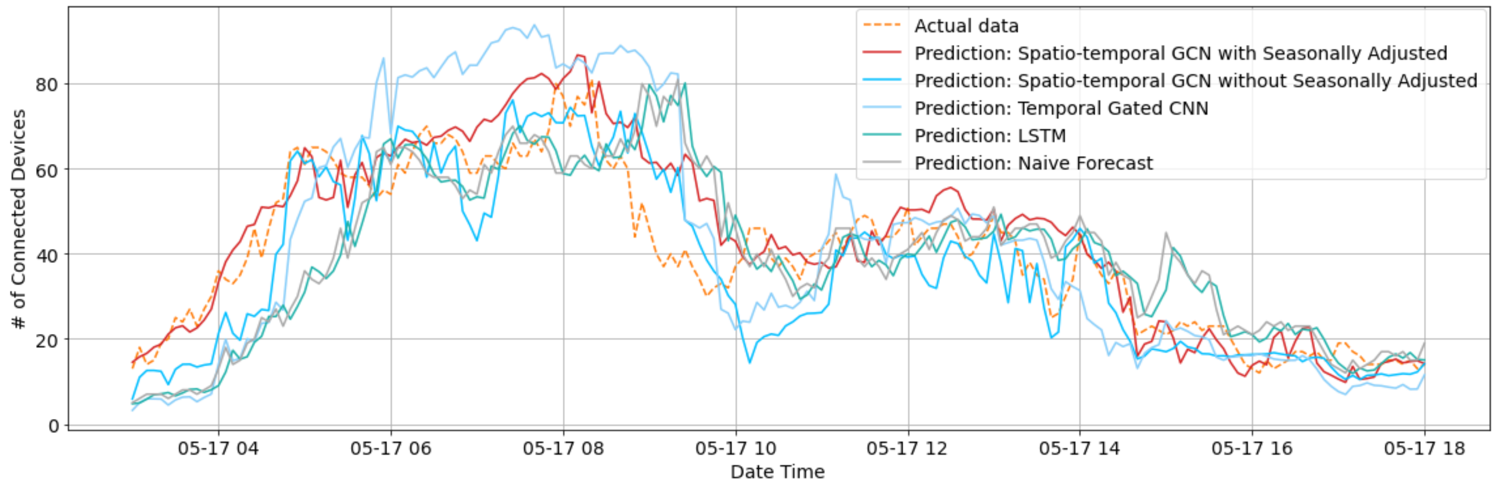


Fig. Comparison between Predictive Models for the most frequent AP

Objectives

1. Gather South African tweets with COVID19 and vaccine related keywords.

2. Clean and use NLP techniques to transform the Twitter dataset (Tokenization. Lemmatization, Cleaning the dataset by removing stop word, URL links, punctuations).

3. Create a sentiment analysis model, - negative neutral, positive. This project attempts to analyze how South Africans have responded and coped with the coronavirus in the country.

Methodology - models

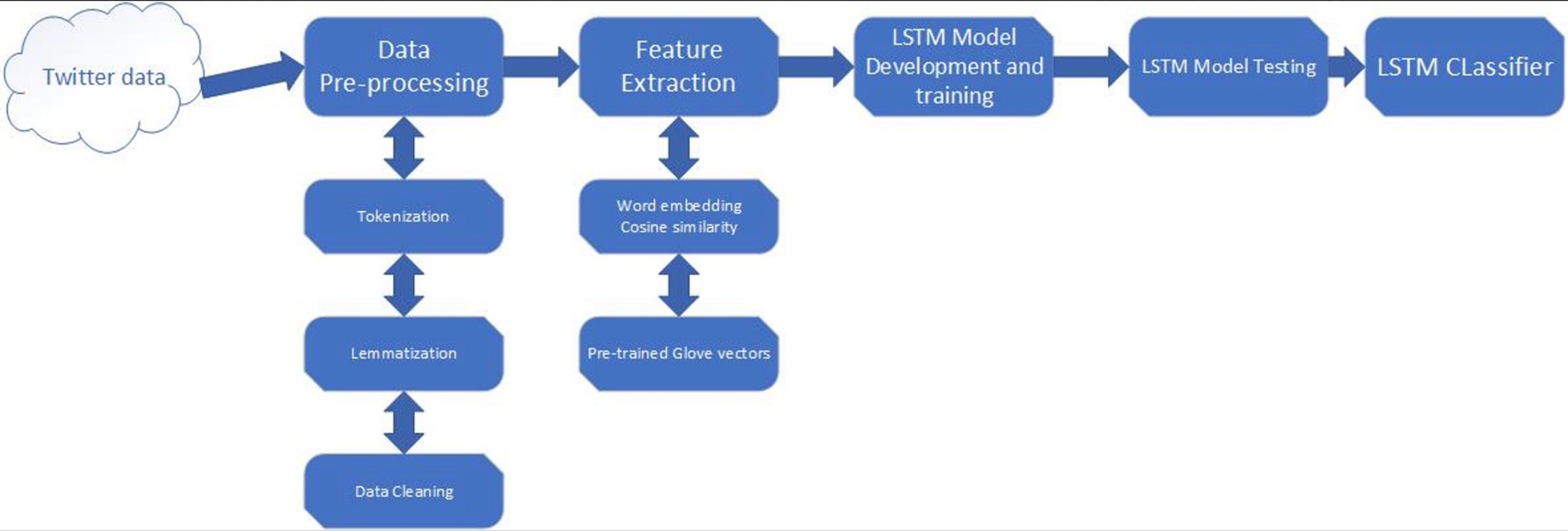
LSTM – excellent for temporal sequences.

Bidirectional LSTM - Bidirectional LSTM models process information in two directions, rather than making use of only previous context state for determining the next states which are based on bidirectional RNNs.

BERT - A transformer is an extended LSTM model that adopts the mechanism of attention which mimics cognitive attention to enhance important parts of the data while fading the rest.

Distell BERT - DistilBERT is a small, fast, cheap and light Transformer model trained by distilling BERT base. It has 40% less parameters than *bert-base-uncased*, runs 60% faster while preserving over 95% of BERT's.

Methodology - LSTM



RESULTS

TABLE 3.1: Training performance for BD-LSTM, LSTM and BERT and Distell-Bert model using 10 thousand South African COVID-19 labeled Twitter dataset

Metric	RNN-LSTM	BD-LSTM	BERT	DISTELL-BERT
Accuracy	0.49	0.52	0.59	0.59
Precision-Negative	0.53	0.52	0.63	0.70
Precision-Neutral	0.45	0.50	0.56	0.57
Precision-Positive	0.48	0.59	0.57	0.52
Recall-Negative	0.57	0.72	0.69	0.55
Recall-Neutral	0.58	0.44	0.47	0.47
Recall-Positive	0.23	0.36	0.60	0.77
F1 score-Negative	0.55	0.60	0.66	0.62
F1 score-Neutral	0.51	0.46	0.51	0.52
F1 score-Positive	0.51	0.44	0.58	0.62

Aim of Research:

Covid is a devastating disease that has the whole world in a state of panic, but vaccines seem to be our best attack against the virus.

Unfortunately, several people are against mass vaccination schemes, mainly due to misinformation and a lack of knowledge.

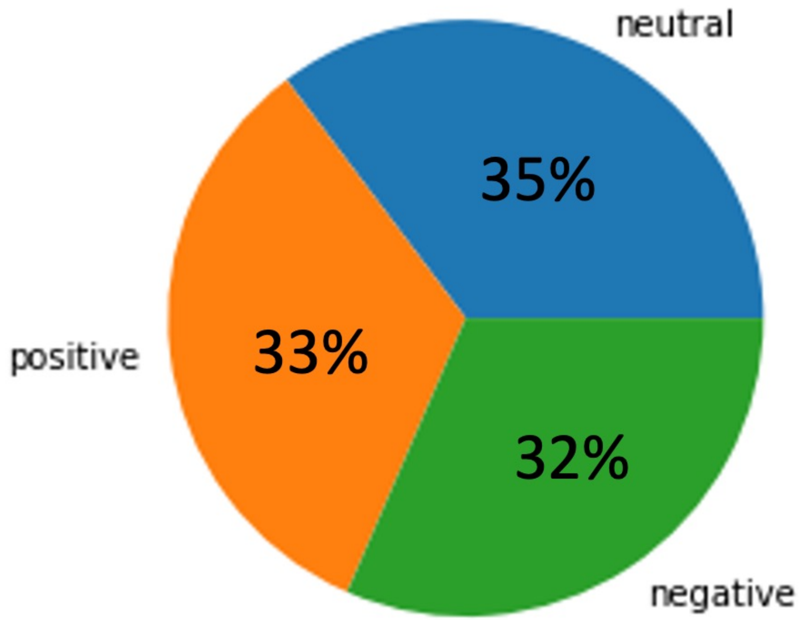
The aim of this study is, thus, to investigate the public's response to these vaccination schemes in order to help policy makers implement new strategies in the promotion and acceleration of vaccine rollout.

In this study, 10-000 tweets from South African over the months of August, September and October of this year were analysed.

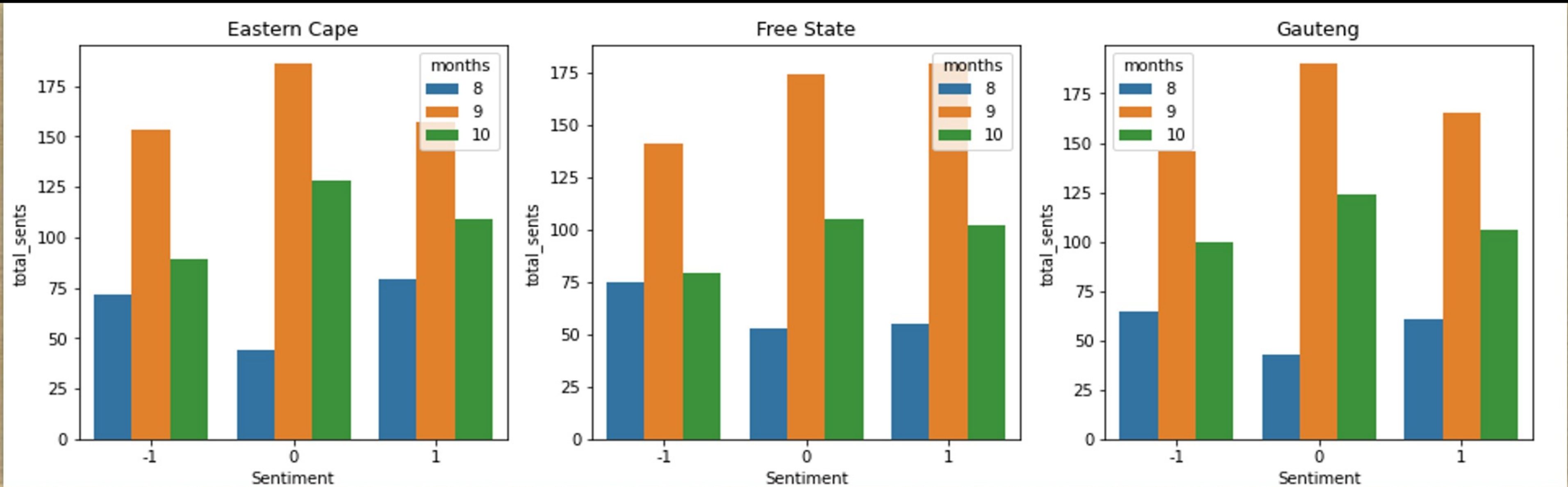
These tweets were classified into one of three sentiment types and the distribution of these sentiment types were plotted per province.

Distribution of Sentiments

From the analysis of my labelled dataset, it was determined that the three sentiment types are almost equally distributed.



Visualizations of Findings



- Aug: 38% neg/ 22% neu/ 40% pos
- Sep: 31% neg / 38% neu / 31% pos
- Oct: 27% neg / 39% neu / 34% pos

- *(51% → 49% → 56%) positive*
- *(49% → 51% → 44%) negative*

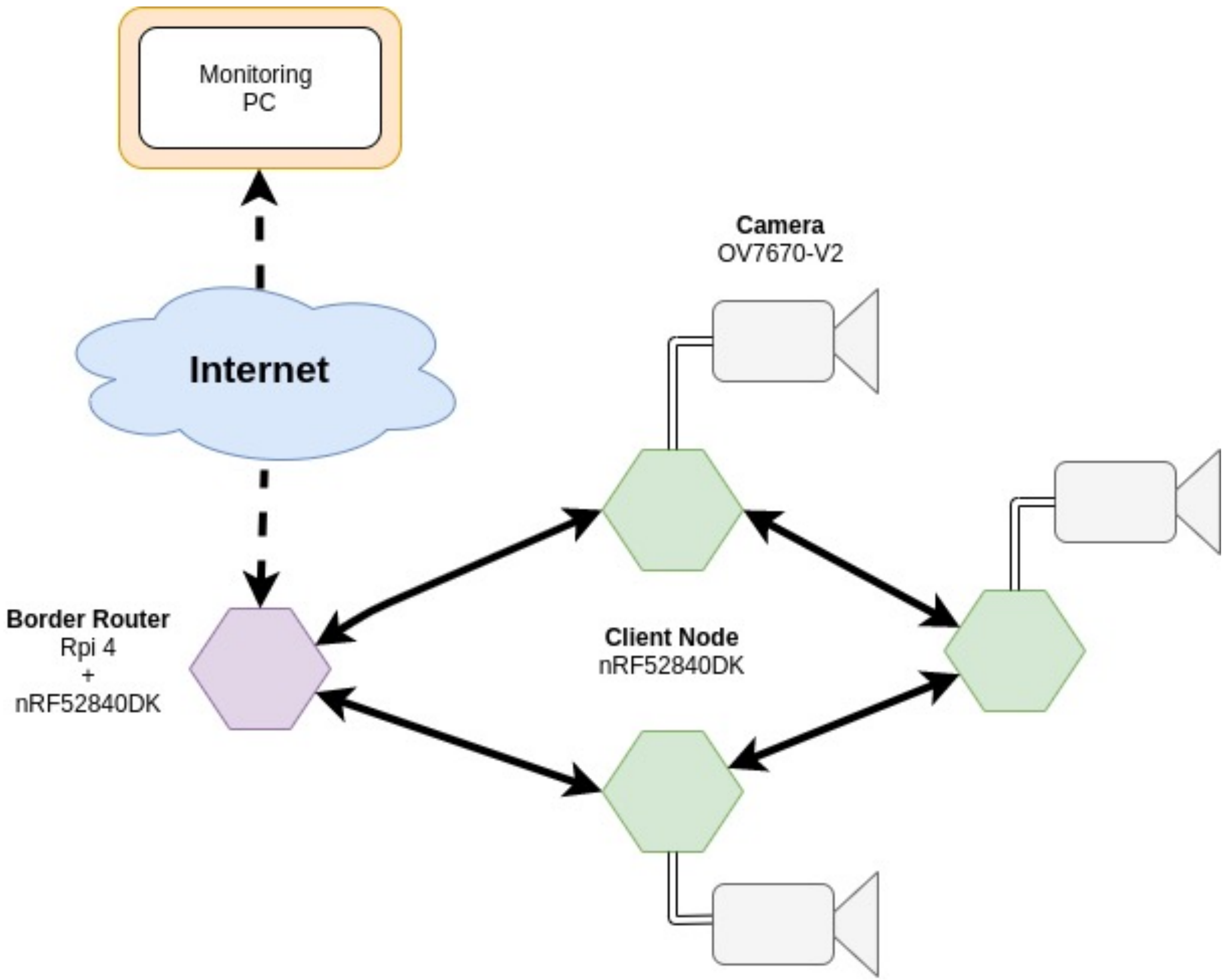
- Aug: 38% neg/ 31%neu / 31% pos
- Sep: 28% neg/ 35% neu/ 37% pos
- Oct: 28% neg/ 37% neu/ 35% pos

- (46% → 54% → 54%) positive
- (54% → 44% →44%) negative

- Aug: 38% neg/ 27% neu/ 35% pos
- Sep: 30% neg/ 37% neu/ 33% pos
- Oct: 30% neg/ 38% neu/ 32% pos

- (52% → 47% → 48%) positive
- (48% → 53% → 52%) negative

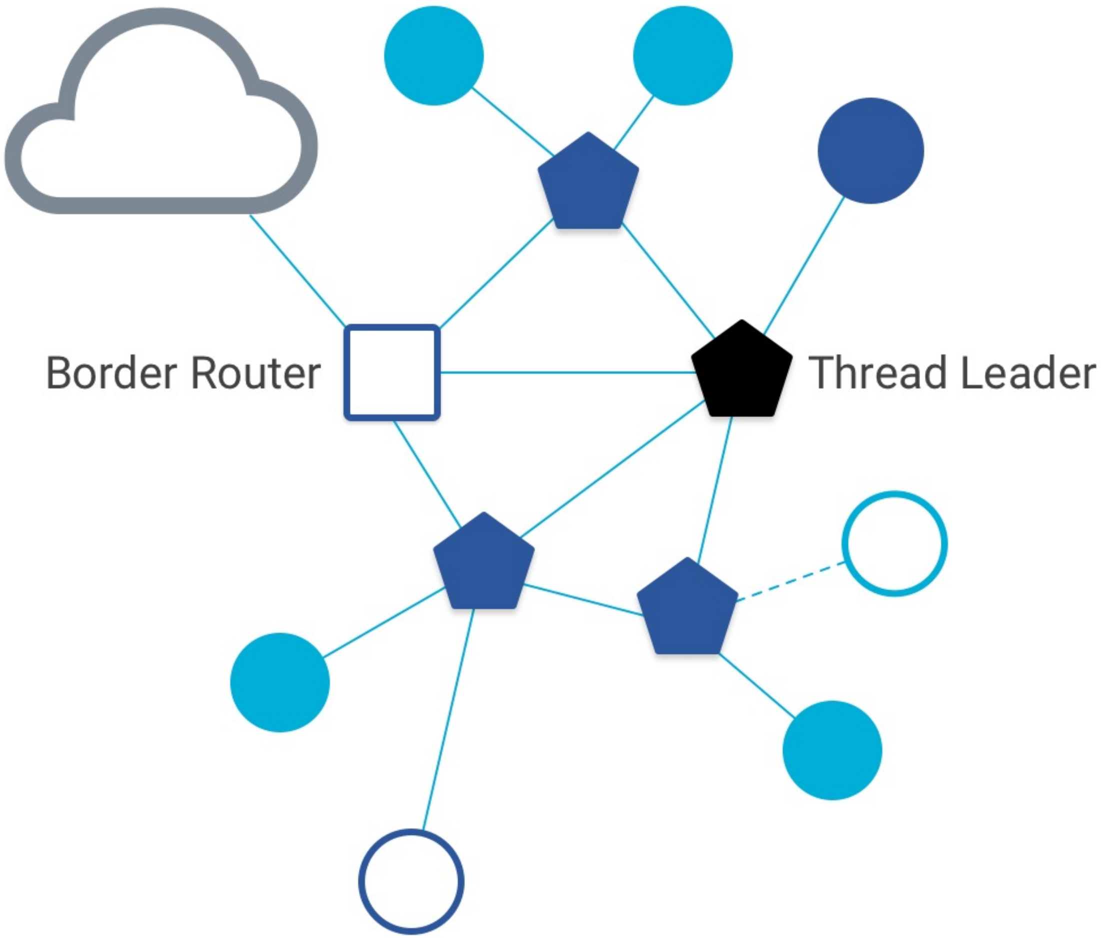
AI-Powered IoT Solution



Networked Sensors

- nRF52840DK
- OV7670-V2
  - The OV7670 image sensor is a small size, low voltage, single-chip VGA camera and CMOS image processor for all functions. It provides full-frame, sub-sampled or windowed 8-bit images in various formats, controlled through the Serial Camera Control Bus (SCCB) interface.
  - The camera module is powered from a single +3.3V power supply, and external clock source for camera module XCLK pin. The OV7670 camera module built-in onboard LDO regulator only requires single 3.3V power and can be used in Arduino, STM32, Chipkit, ARM, DSP,FPGA and etc.
- Temperature Sensor
- Humidity Sensor
- Motion Sensor

Node Roles and Types

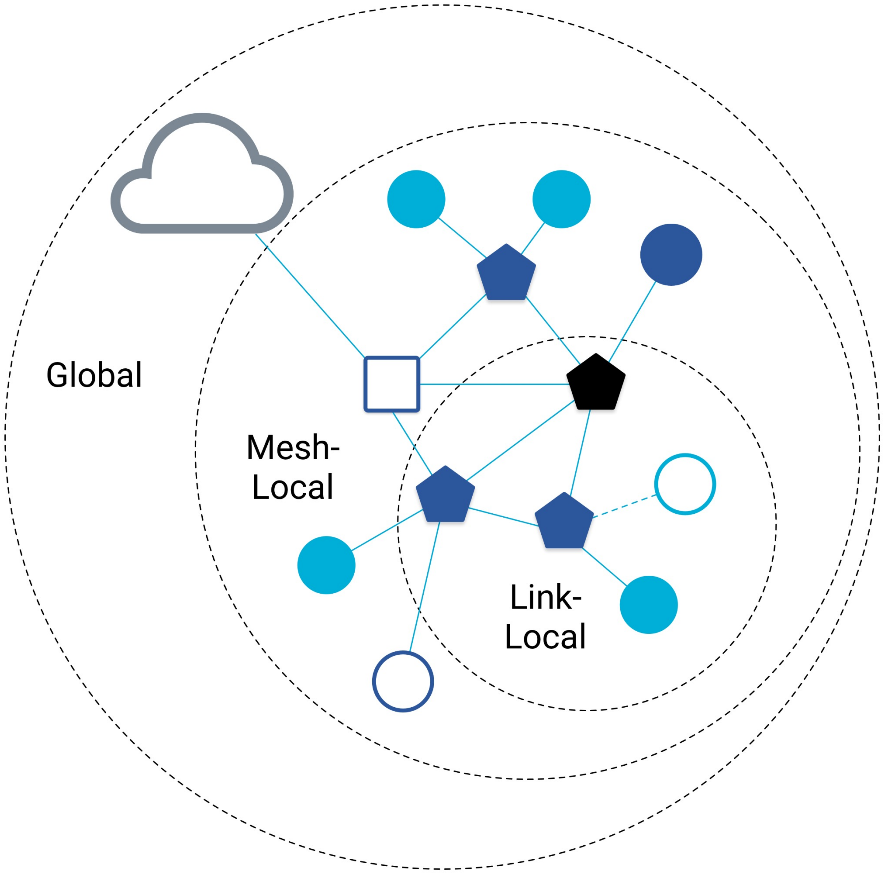


Role	Limit
Leader	1
Router	32
End Device	511 per router

Network Scope

There are three scropes in a Thread network for unicast addressing:

- Link-Local - all interfaces reachable by a single radio transmission
- Mesh-Local - all interfaces reachable within the same Thread network
- Global - all interfaces reachable from outside a Thread network



The first two scopes correspond to prefixes designated by a Thread network. Link-Local have prefixes of *fe80::/16*, while Mesh-Local have prefixes of *fd00::/8*