Application of science-informed AI in experimental particle physics and neuroscience (Poster #85)

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Hungarian Research Network (HUN-REN)
EuCAIFCon, Amsterdam, 30 April 2024

Department of High Energy Physics:
CERN LHC CMS, ALICE and CERN FCC
LVK (LIGO/VIRGO/KAGRA) and Einstein Telescope (ET)
Department of Computational Science:
Natural and Artificial Intelligence, Neuroscience
Brain Research, AI/ML/Deep Learning
Wigner Datacenter: CERN Grid, GPU, HPC, Quantum comp.

KFKI Budapest → KFKI RMKI →
→ HUN-REN Wigner RCP
Institute for Particle and
and Nuclear Physics (1952)
Particle and nuclear physics, gravity,
Detectors/accelerators, neutron stars
Functional materials, space science
ML/AI/Brain res. & IT (GPU, HPC)
Quantum comp., QTech/Qcommun.

Basic problem of neuroscience and brain research:

--- Brain sciences lack a unifying mathematical theory of brain function, theories for individual faculties are not available either.

Innovative answers from neuroscientists:

--- Generative modelling framework has been widely adopted to explore mathematical principles in a data-driven manner: generative models are probabilistic models that assume that observations are a result of a (nonlinear) combination of latent factors that correspond to relevant quantities (e.g. physical measures);

--- Neuroscience has adopted an open-ended approach to learn about the mathematical principles by constraining them with an ever-more-complex approach to data: instead of constraining data to more-and-more controlled settings, rich and little-constrained data is flexibly interpreted with AI-borrowed deep generative models;

--- Diffusion models, variational autoencoders, contrastive learning methods provide a spectrum of opportunities to integrate complex nonlinear generative models with physical intuitions as inductive biases, or generalize interpretations across existing experiments, as well as to new experiments.

Basic problem of HEP research:

--- A unified mathematical theory (Standard Model) describes experimental data with high precision, but we do not understand the origin of the „free parameters" and do not see hints for Beyond SM phenomena – although numerous candidates exist to become the winner mathematical model.

Basic problems of Nuclear Physics research:

--- The World of strongly interacting many-body systems is very rich, no unified mathematical theory describes experimental data with reasonable precision;

--- Numerous phenomenological description has been invented, but the connection between these models are weak in many cases.

Basic problems of Astroparticle (and Astro)Physics:

--- Enormous amount of data arrive from the new instruments (telescopes, detectors) and the understanding of these data is focusing into a very narrow target direction;

--- On the other hand the usual expectation is to understand the multimessenger data in a unified frame, answering basic questions about the investigated objects;

--- Numerous phenomenological description has been invented, but the connection between these models and connection to HEP is not well established (see e.g. the problem of „dark matter" and „dark energy").

How does Artificial Intelligence and Machine Learning could help?
(What could we learn from neuroscientists?)

--- Probabilistic approaches already receive wider support in HEP
(see e.g. the separation of gluon-jets and quark-jets during their study and detection)

--- ML applications became part of the usual routine protocol in data analyses,
self-improving cycles are capable to increase the precision
(altough the request of CPU-time is enormous, it is limiting the applications)

--- Generative model applications are widely adopted to explore mathematical principles in a data-driven manner: the identification and exploration of latent factors and their non-linear combination is in the focus of recent analysis to discover new knowledge element hiding behind the phenomenological descriptions;

--- During the analyses of huge and complex datasets (including high-resolution pictures and time evolution with small timesteps --- see e.g. multimessenger astrophysics) the application of diffusion models, variational autoencoders, contrastive learning methods could provide a spectrum of opportunities to integrate complex nonlinear generative models with physical intuitions as inductive biases, and improve the interpretations and understanding of existing date (see e.g. LSST mission).

Cross-fertilization between different fields and disciplines could become very useful !

Useful Links:

HUN-REN Wigner Research Centre for Physics:

https://wigner.hun-ren.hu/en/

14. GPU Days: Meeting on Massive Parallel Computing

Date: 30-31 May 2024, Budapest, Hungary

https://gpuday.com/

6. HEPTECH AIME on AI/ML and Quantum Computing

Date: 18-19 November 2024, Budapest, Hungary

5. AIME: https://indico.wigner.hu/event/1523/

Wigner Datacenter at Wigner RCP

https://wignerdc.wigner.hu/home

Increasing the Model Agnosticity of Weakly Supervised Anomaly Detection

Thorben Finke [1] Joep Geuskens [1] **Marie Hein** [1] Gregor Kasieczka [2, 3] Michael Krämer [1] Alexander Mück [1] Parada Prangchaikul [2] Tobias Quadfasel [2] David Shih [4] Manuel Sommerhalder [2]

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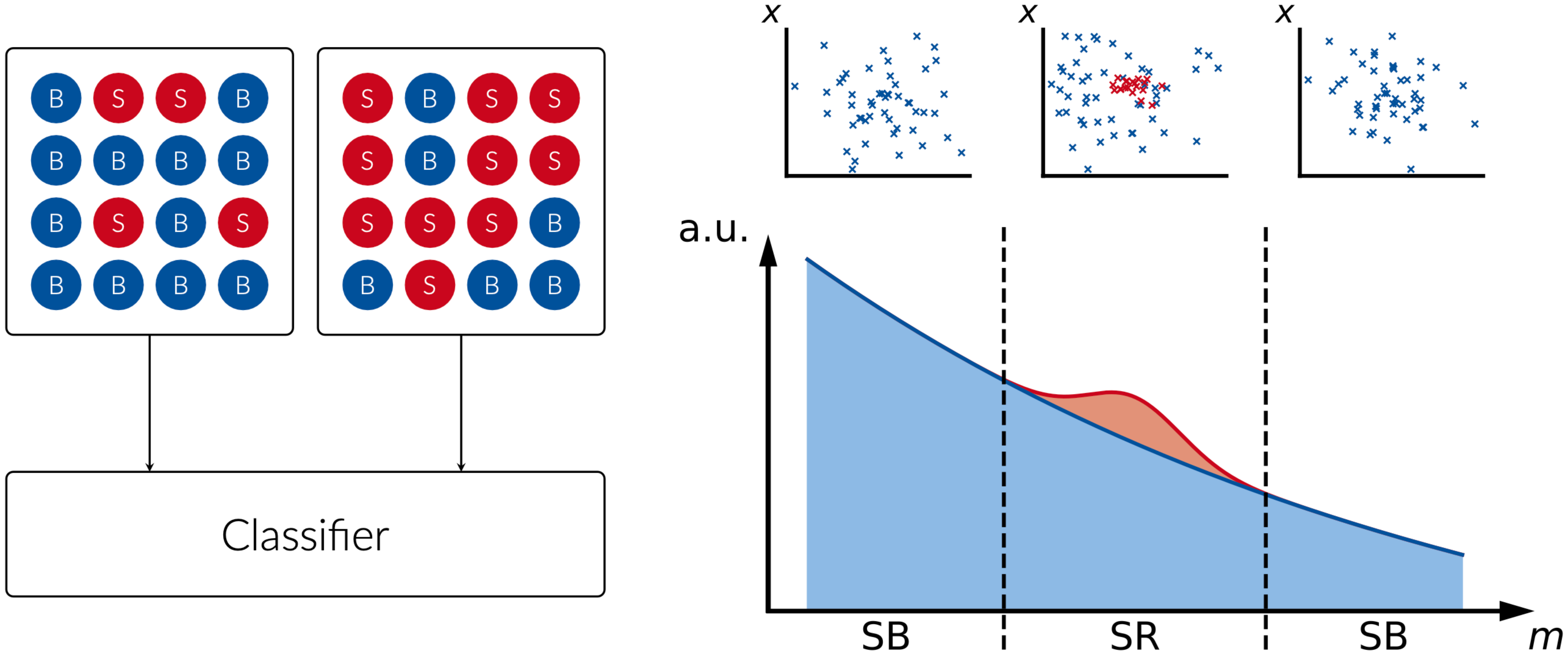
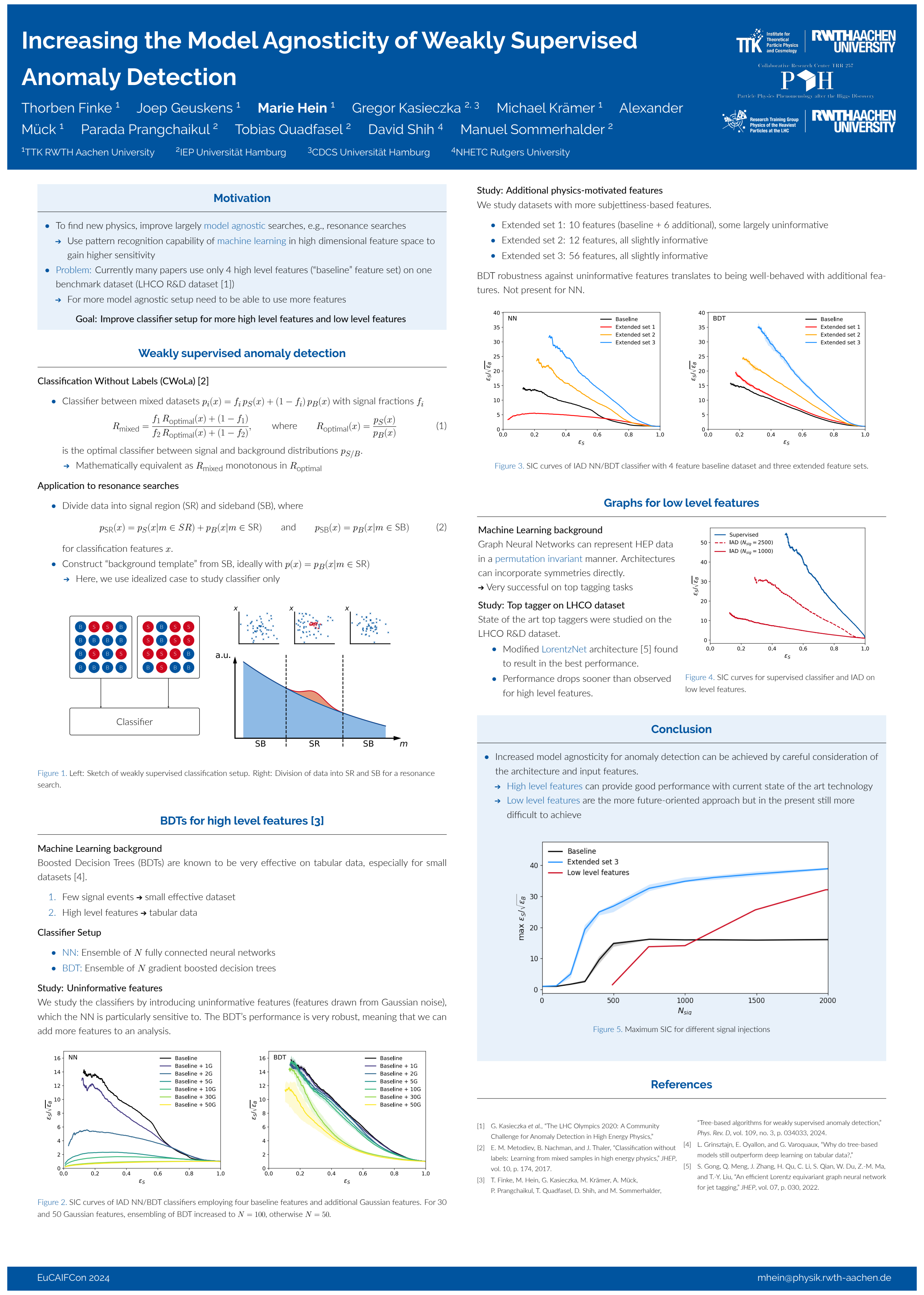
Institute for Theoretical Particle Physics and Cosmology · RWTH AACHEN UNIVERSITY · Collaborative Research Center TRR 257 P3H Particle Physics Phenomenology after the Higgs Discovery · Research Training Group Physics of the Heaviest Particles at the LHC · RWTH AACHEN UNIVERSITY





Weakly supervised anomaly detection can be applied to resonance searches to find BSM physics.

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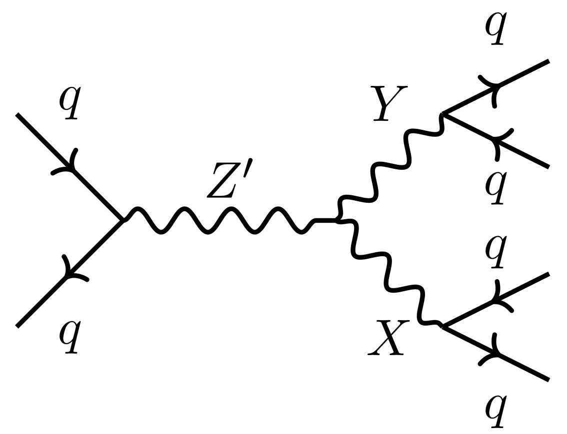
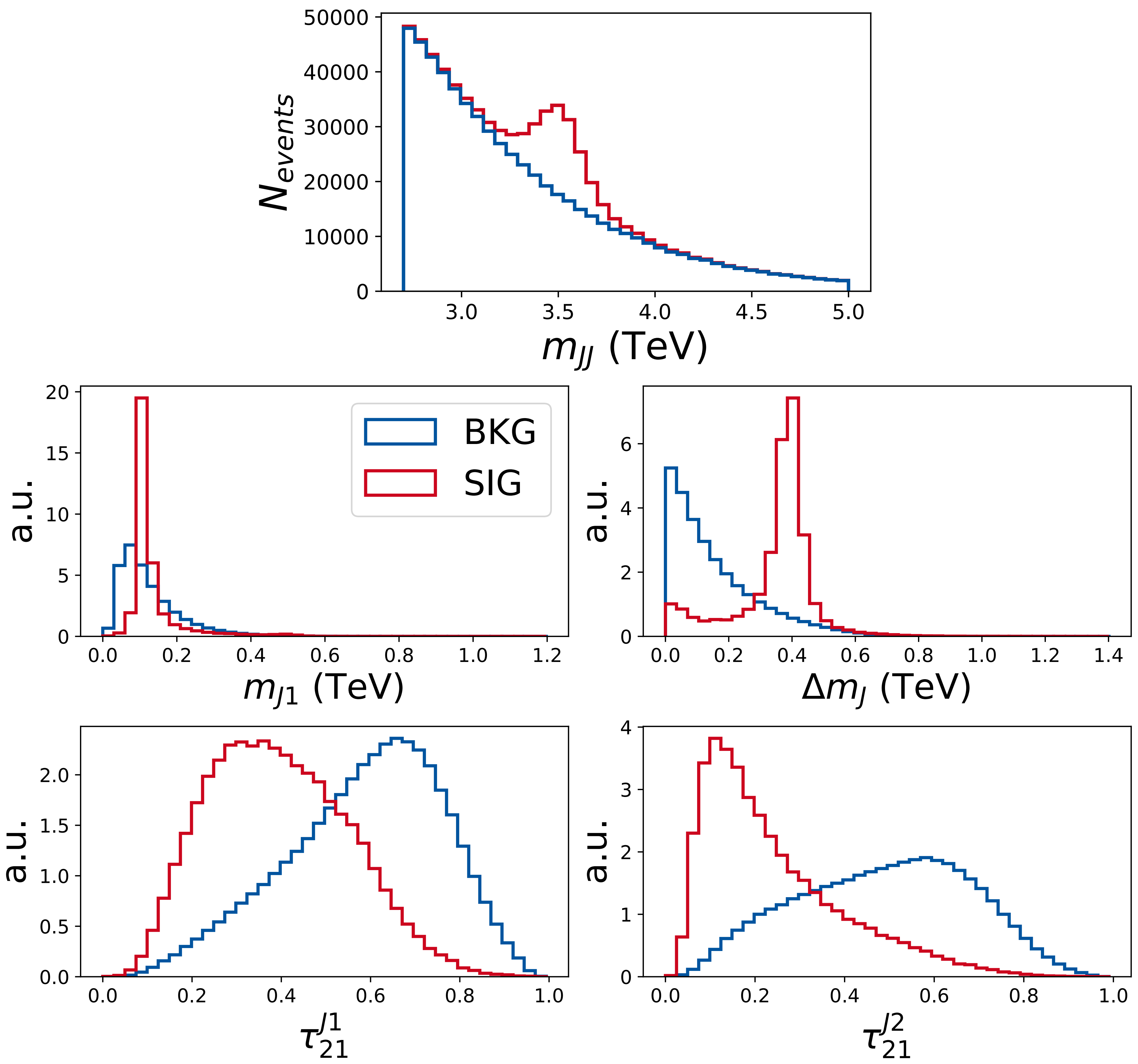
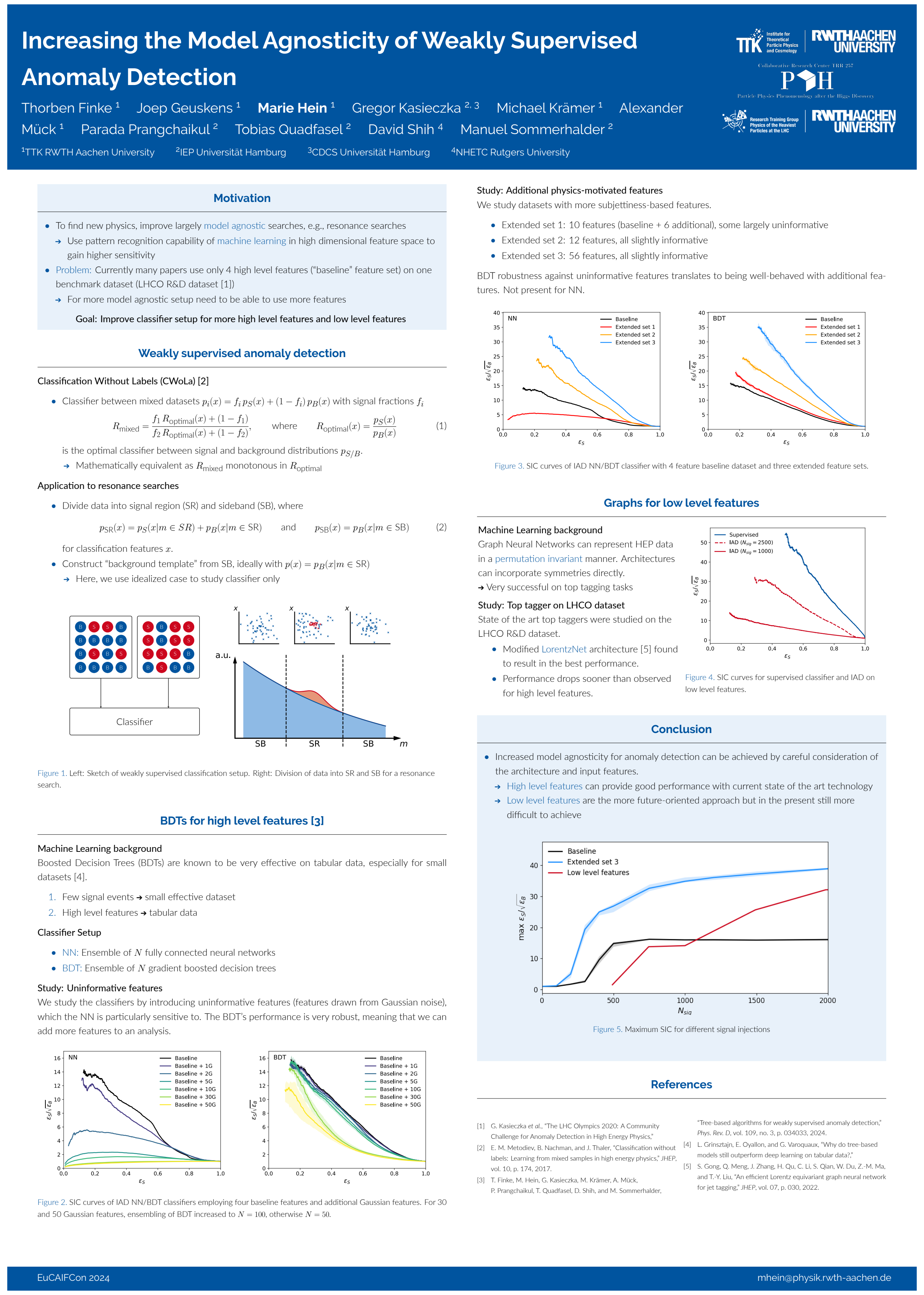
LHCO R&D dataset

Background: QCD dijets
Signal:



Usual features for weak supervision papers
⇒ not very model agnostic





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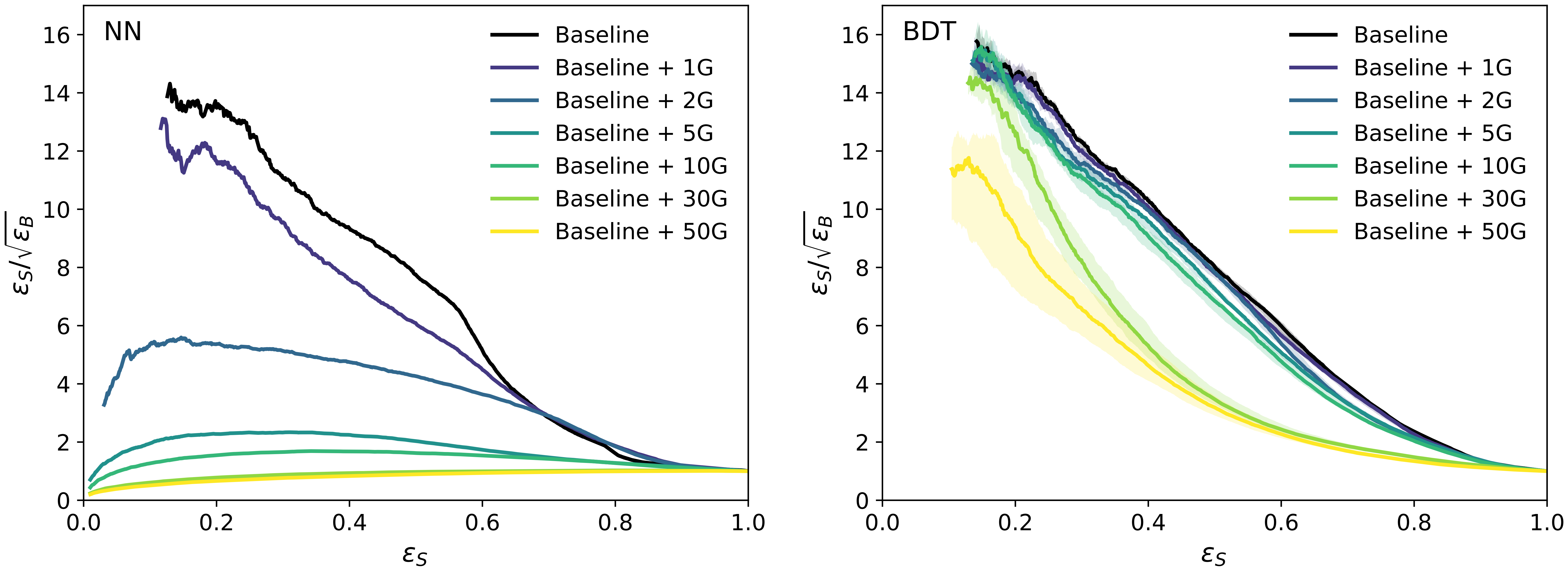
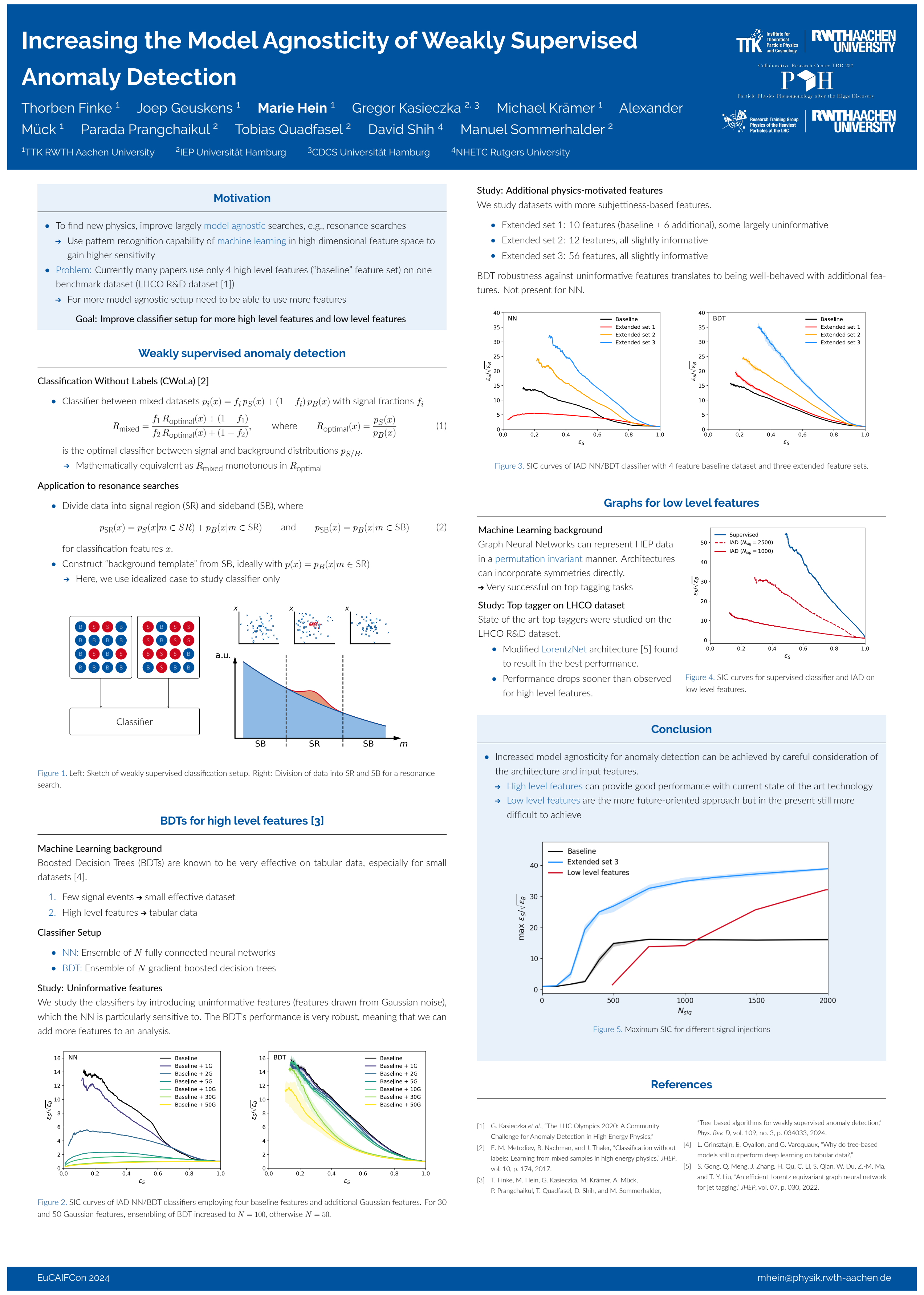


To include more features, robustness against uninformative features is necessary, which is not present for NNs.



Galaxy redshift estimations with transfer and multi-task learning

M. Eriksen [eriksen@pic.es], L.Cabayol, H.Guo - IFAE-PIC, Barcelona

- Cosmology requires redshift estimations for large number of galaxies.
- Image galaxies in different bands and determine redshift as an inverse problem.
- Challenge: Inferring galaxy distances with small and biased training samples.

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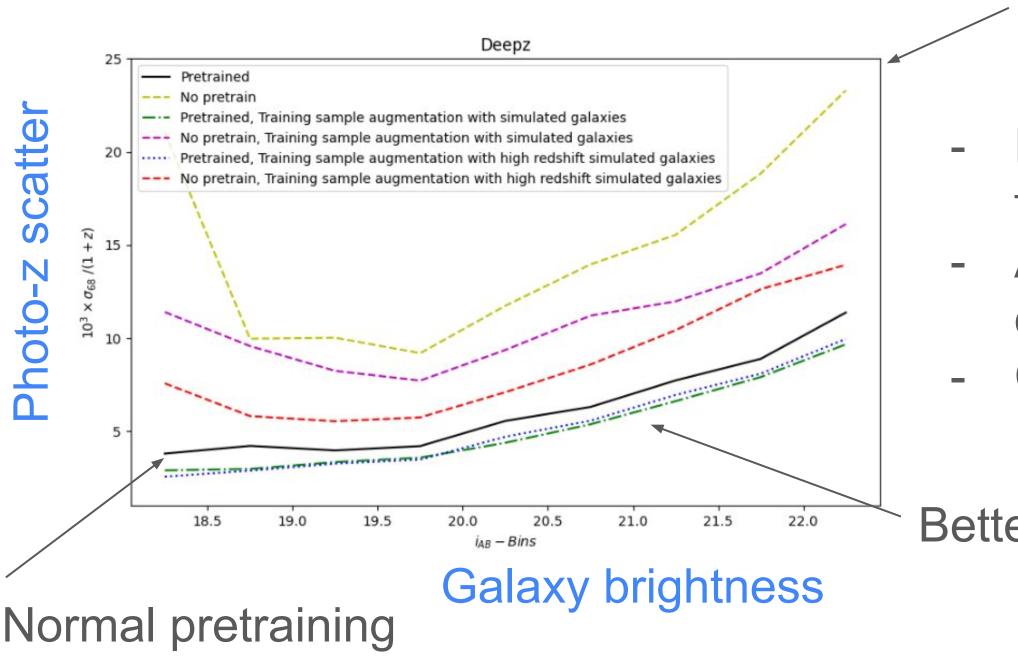
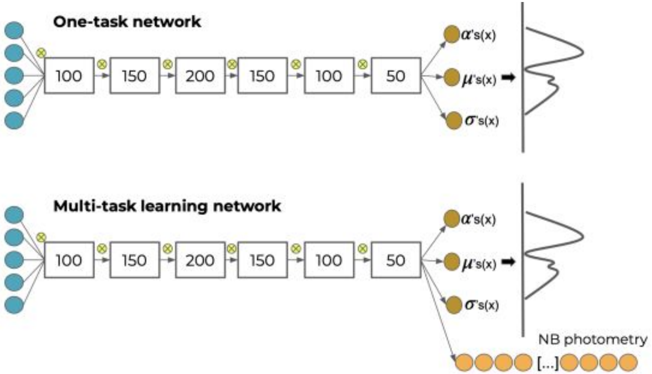
Transfer learning from simulations

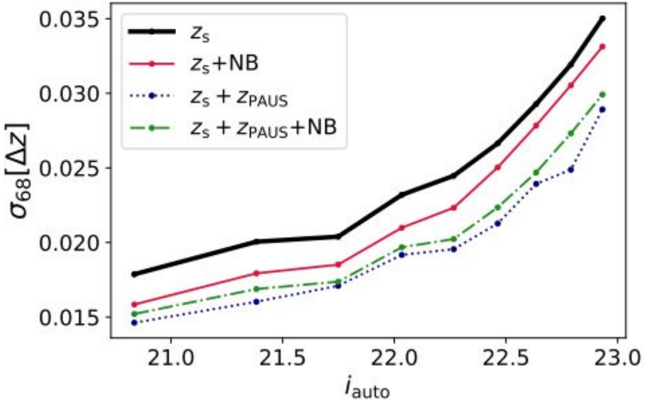


- Deepz is a deep neural network for photo-z estimation.
- Achieved state-of the art results on narrow-band photometry.
- Combining simulated data is key.

arXiv: 2004.07979

Multi-task learning





Problem: How to benefit from PAUS NB, which only covers 0.3% sky-area of *Euclid*.

Solution: Multi-task learning, predicting PAUS narrow bands (top plot).

Result: Reduces the photo-z scatter for all galaxies (bottom plot).

arXiv: 2209.10161

Gradient-Annihilated PINNs for Solving Riemann Problems: Application to Relativistic Hydrodynamics

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valgrAI Valencian Graduate School and Research Network of Artificial Intelligence

30/04/2024

Keywords

- Riemann problem → Problems with discontinuous initial conditions
- Neural networks → Physics-Informed Neural Networks
- Euler equations, Relativistic hydrodynamics → Problems in Astrophysics: New application

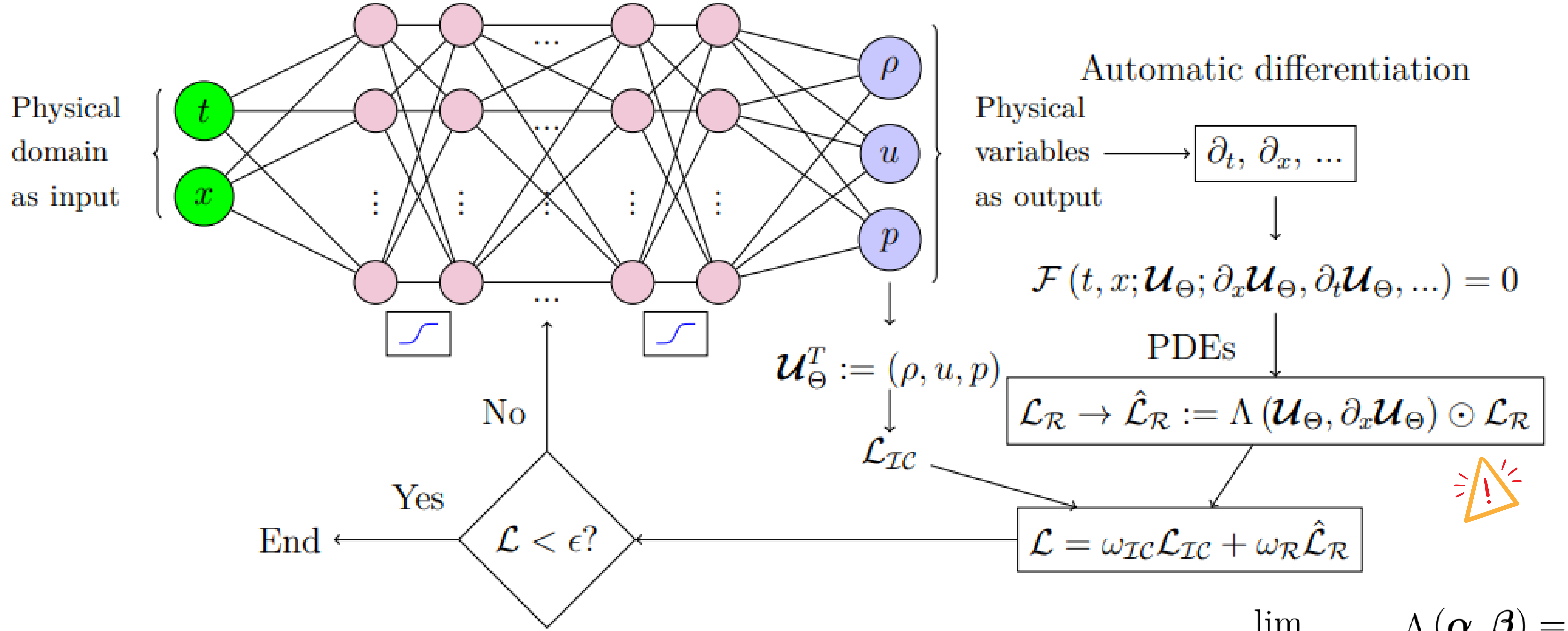
$$\frac{\partial \boldsymbol{\mathcal{U}}}{\partial t} + \nabla \cdot f(\boldsymbol{\mathcal{U}}) = \mathcal{S}(\boldsymbol{\mathcal{U}}) \longrightarrow \frac{\partial}{\partial t}\begin{pmatrix} D \\ S \\ \tau \end{pmatrix} + \frac{\partial}{\partial x}\begin{pmatrix} Du \\ Su + p \\ S - Du \end{pmatrix} = 0 \quad \Bigg\} \; \rho\,,u\,,p$$

D, S, τ: Relativistic densities of mass, momentum and energy, respectively.

ρ, u, p: Density, velocity and pressure of the fluid: primitive variables.

METHOLOGY PROPOSED

Diagram and algorithm



$$\lim_{|\partial_x \rho|,|\partial_x u|,|\partial_x p|\to\infty} \Lambda\left(\boldsymbol{\alpha},\boldsymbol{\beta}\right) = 0$$

Antonio Ferrer-Sánchez, José D. Martín-Guerrero, Roberto Ruiz de Austri, Alejandro Torres-Forné, and José A. Font. Gradient-annihilated pinns for solving riemann problems: Application to relativistic hydrodynamics, 2023.

SOME RESULTS

Riemann problems in Relativistic Hydrodynamics

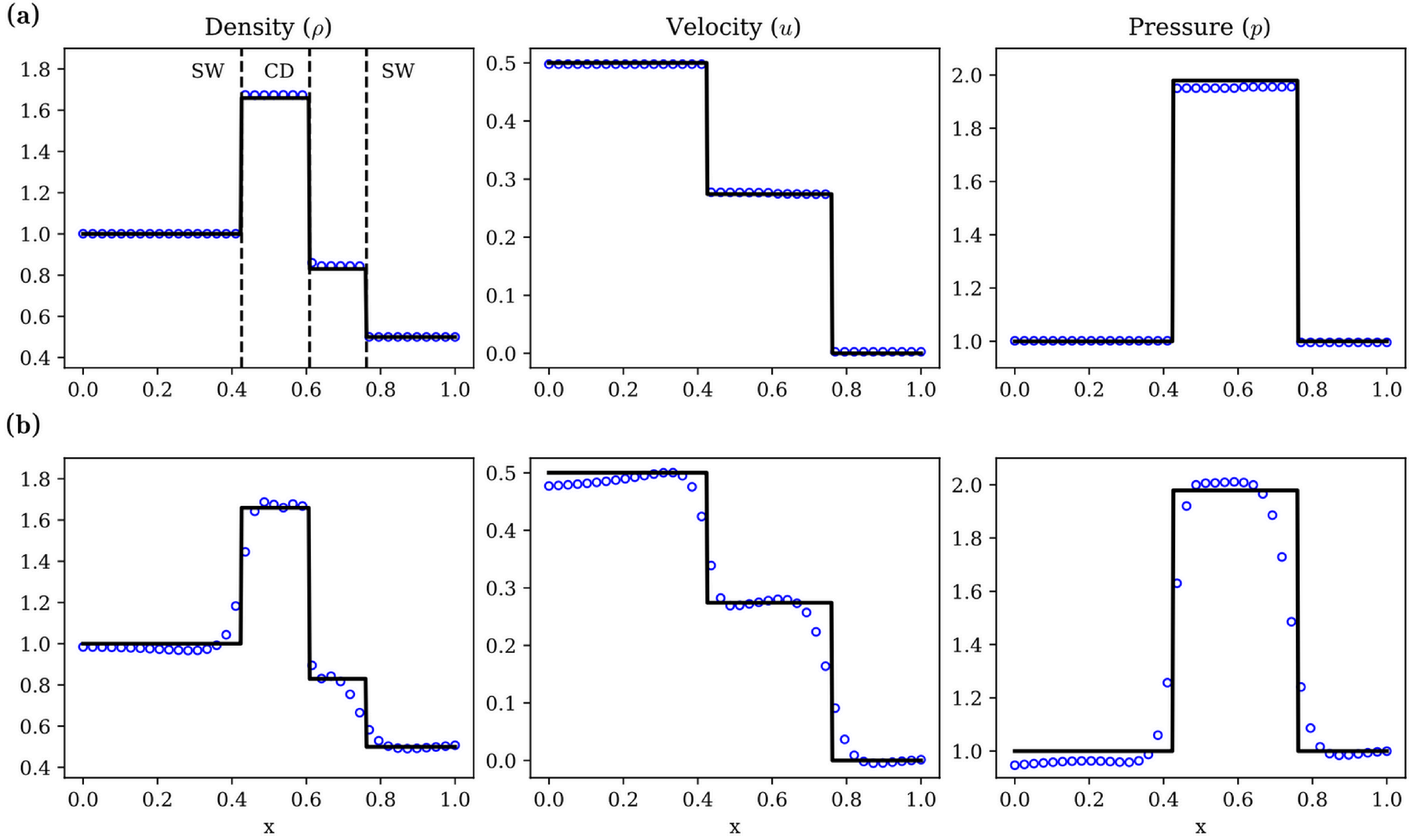


Figure 2: Final profiles for the primitive variables (density, velocity and pressure) with respect to the analytical solution (black solid line) obtained by the GA-PINN in **(a)** and by a vanilla PINN model in **(b)**.