Learning the ‘Match’ Manifold to Accelerate Template Bank Generation

Introducing LearningMatch and TemplateGeNN…

Susanna Green, Andrew Lundgren, Xan Morice-Atkinson

LearningMatch: The Aim

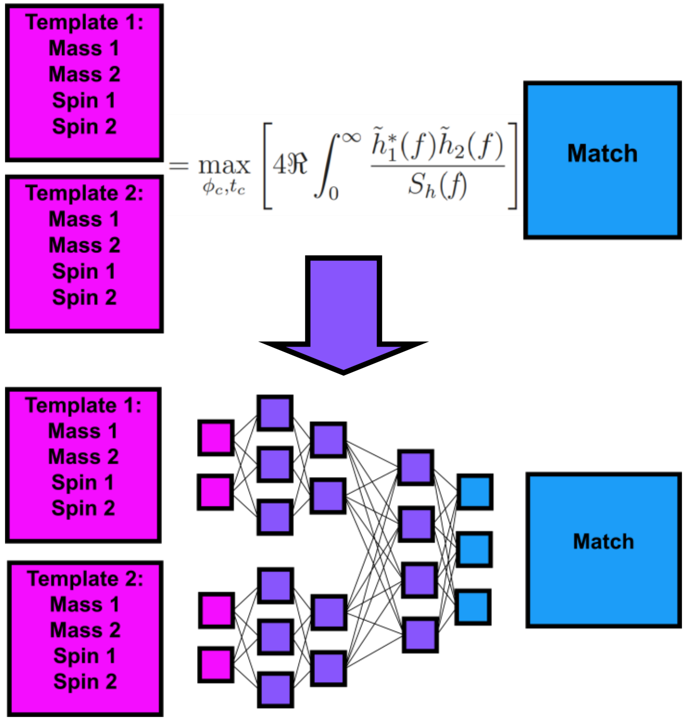


Figure 1: The aim of LearningMatch is to learn the mathematical relationship between the template parameters (specifically the mass and aligned spin of the black holes) and the ‘match’.

TemplateGeNN: The Results

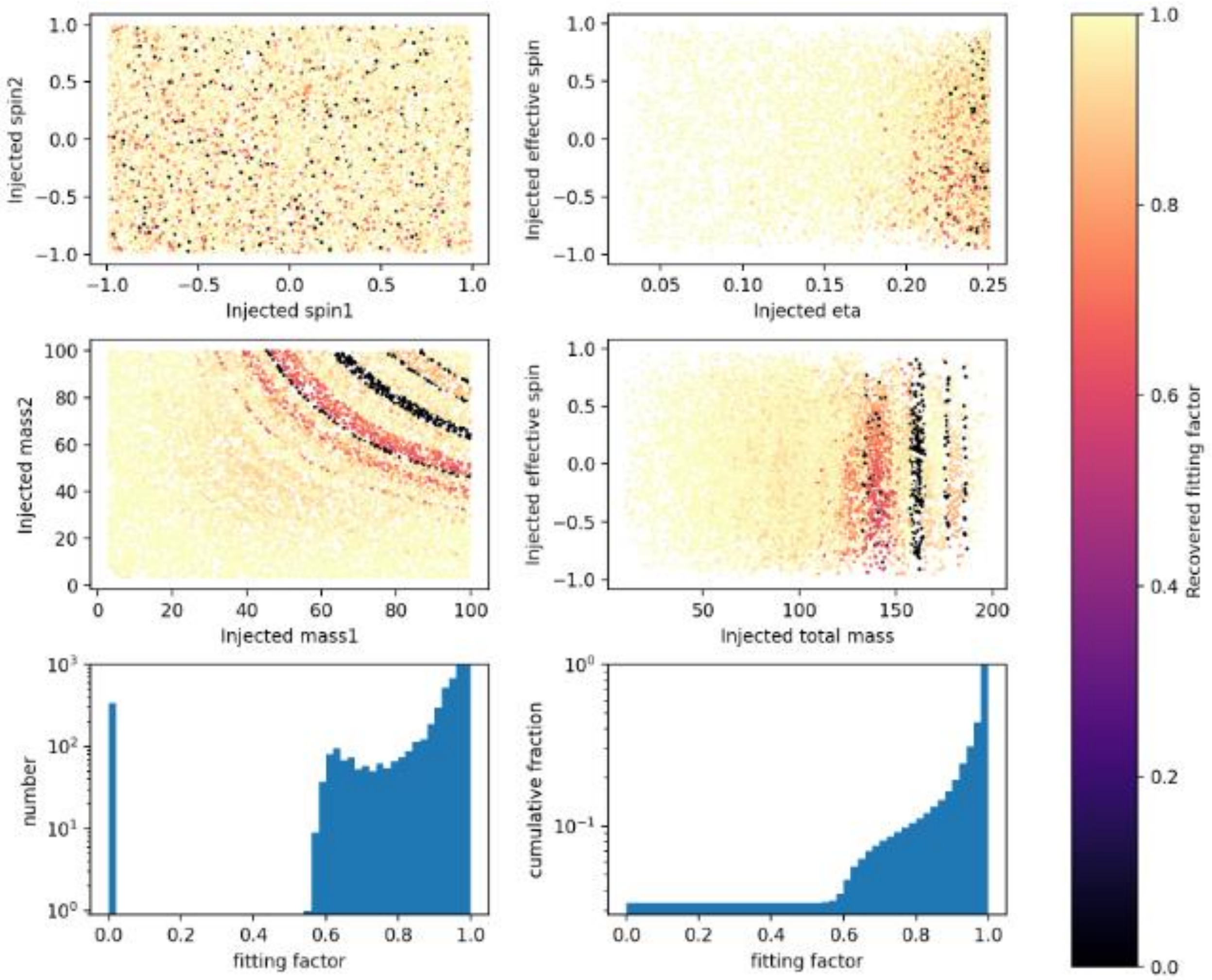


Figure 2: Results from PyCBC template bank verifier.

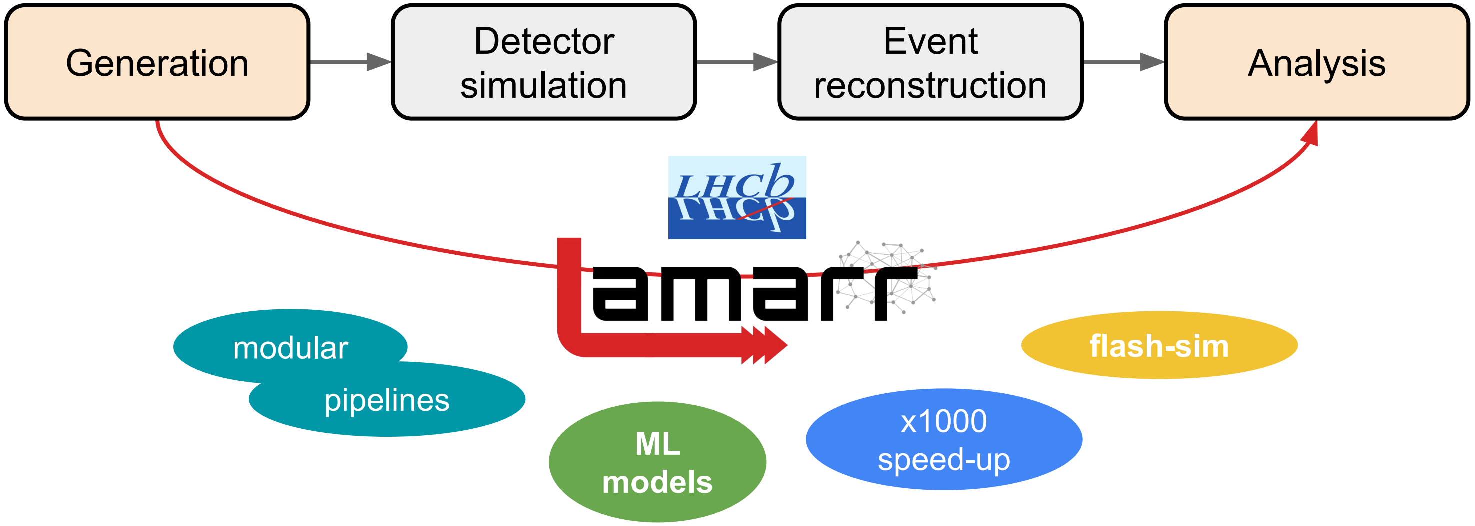
Image by pikisuperstar on Freepik

Please feel free to drop me an email at: susanna.green@port.ac.uk

- ☑ Simulations are **crucial** for High Energy Physics experiments
- ☑ Detailed Simulation is computationally **very expensive**
- ☑ Detailed Simulation **not scale** for the future experiment demands

Viable solutions?

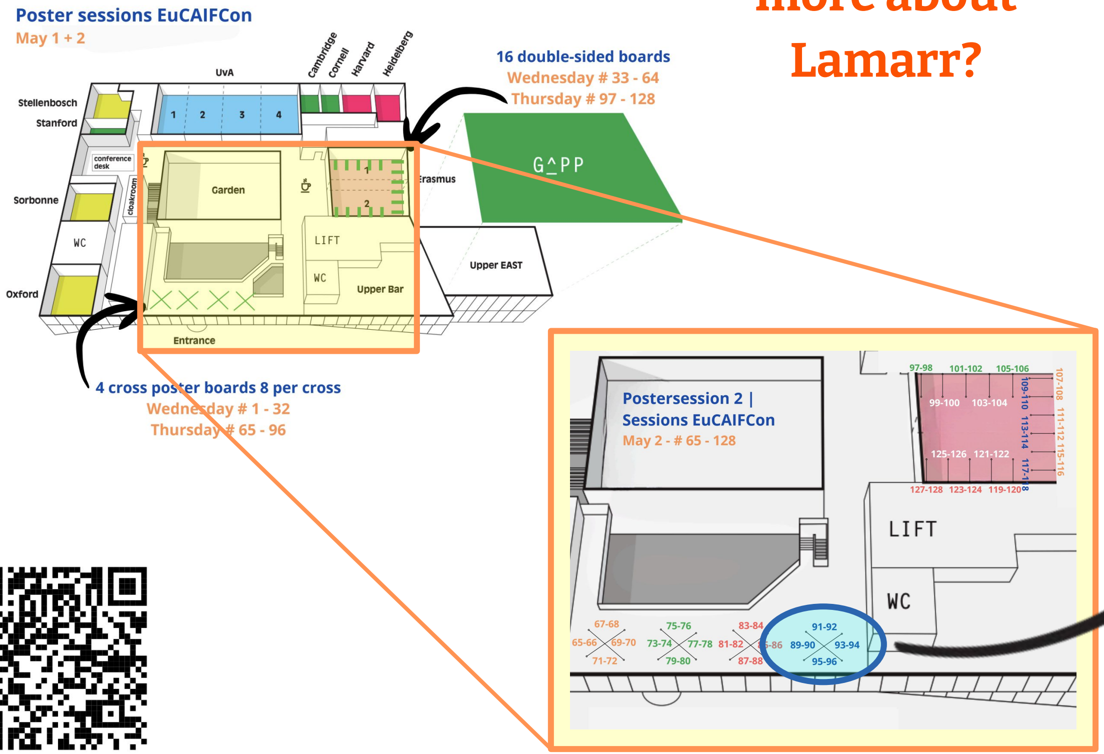
- ☒ Renouncing to increase statistics → **lower demand**
- ☑ Developing **faster options** for simulation → at LHCb, ***Lamarr***

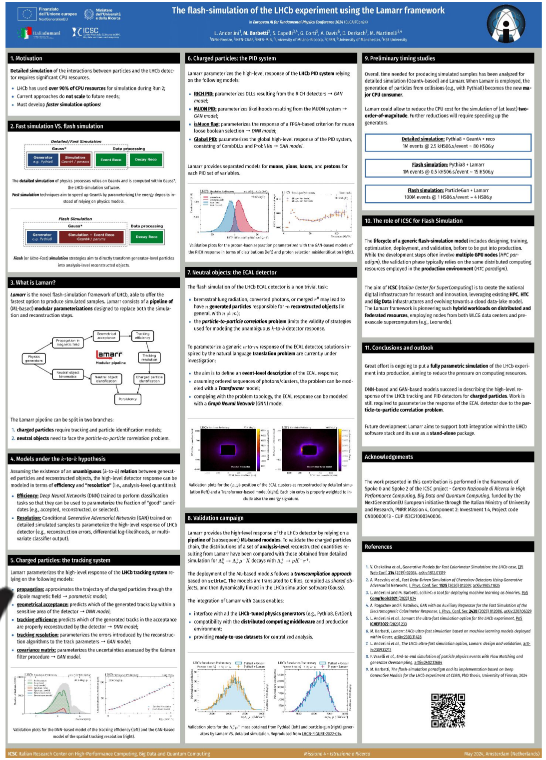


EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE
EuCAIFCon 2024

Poster loc: **#93**

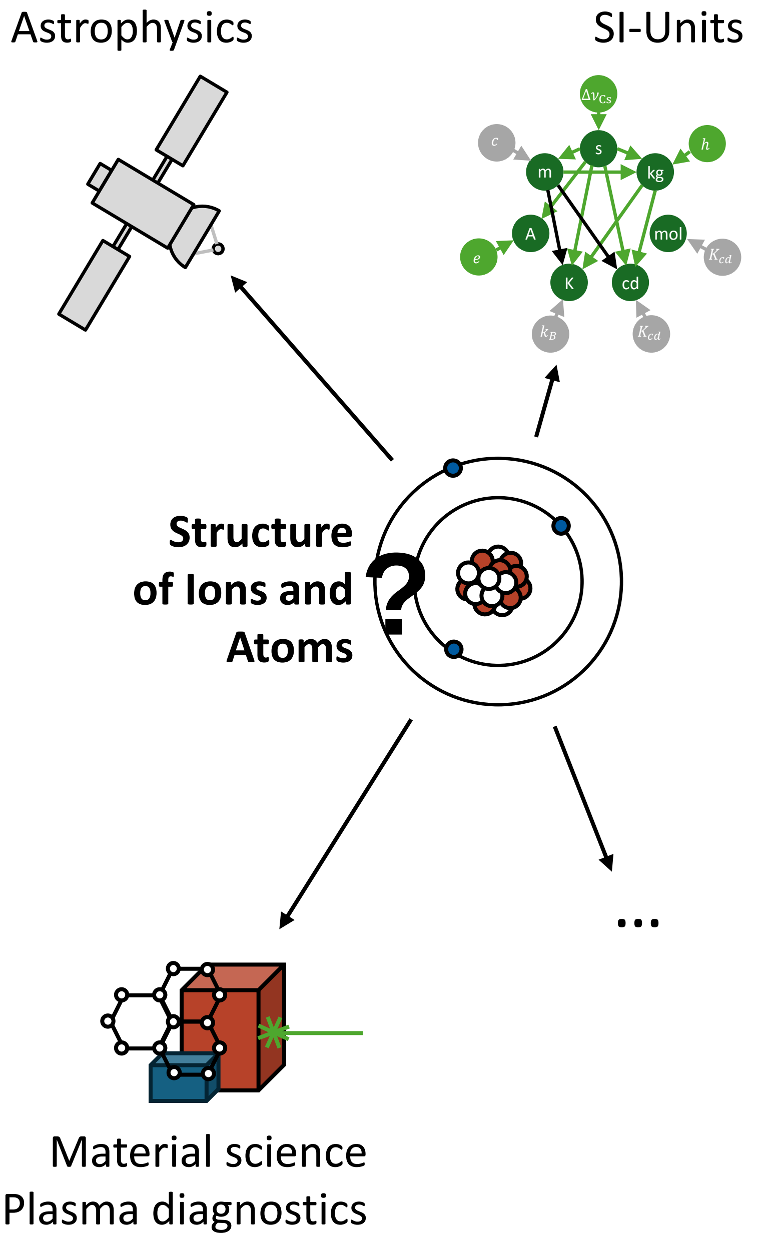
Do you want to know more about Lamarr?





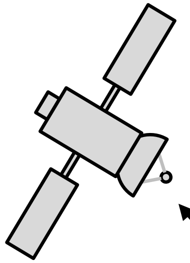
M. Barbetti *et al.*

30.05.2024

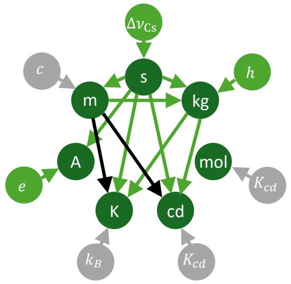


Astrophysics
SI-Units
Δν_Cs
c
h
s
m
kg
A
mol
e
K_cd
K
cd
k_B
K_cd
Structure
of Ions and
Atoms
?
...
Material science
Plasma diagnostics

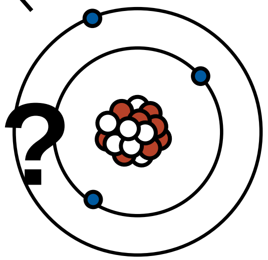
Astrophysics

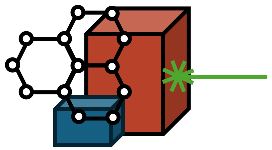


SI-Units



Structure of Ions and Atoms

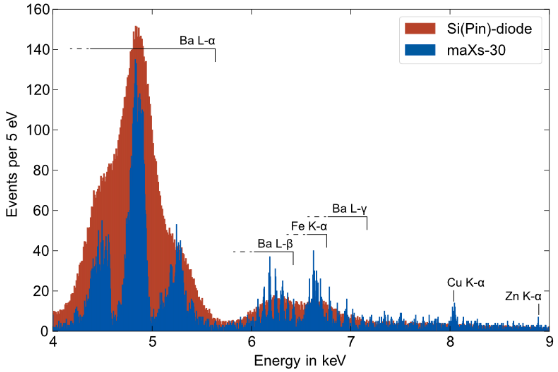




Material science
Plasma diagnostics

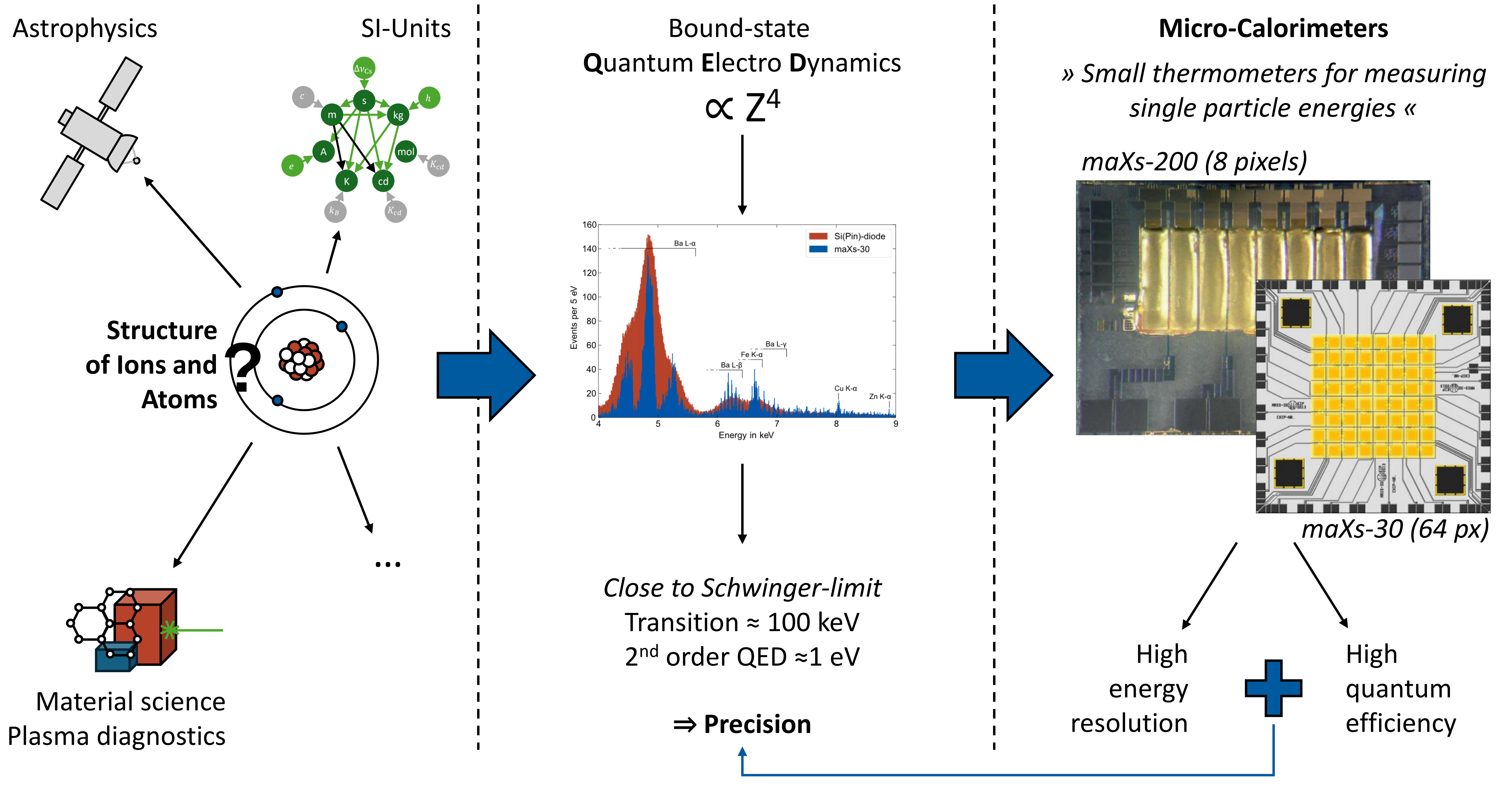
...

Bound-state
Quantum **E**lectro **D**ynamics
$\propto Z^4$

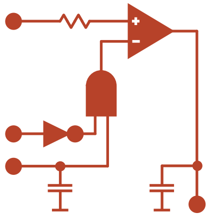


Close to Schwinger-limit
Transition ≈ 100 keV
2^{nd} order QED ≈1 eV

⇒ **Precision**


Astrophysics
SI-Units
c
Δν_Cs
h
s
m
kg
A
mol
e
K
cd
K_cd
k_B
K_cd
Structure
of Ions and
Atoms
?
Material science
Plasma diagnostics
...
Bound-state
Quantum Electro Dynamics
∝ Z^4
Events per 5 eV
Energy in keV
Si(Pin)-diode
maXs-30
Ba L-α
Ba L-β
Fe K-α
Ba L-γ
Cu K-α
Zn K-α
Close to Schwinger-limit
Transition ≈ 100 keV
2nd order QED ≈1 eV
⇒ Precision
Micro-Calorimeters
» Small thermometers for measuring
single particle energies «
maXs-200 (8 pixels)
maXs-30 (64 px)
High
energy
resolution
High
quantum
efficiency

High sensitivity…
… also to **noise**



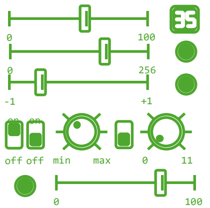
Signal processing:

Analog

```
float get_e
{
  uint32_t
  for ( uin
  {
    float v
    mwd_maf
```

Digital

Compensate artifacts

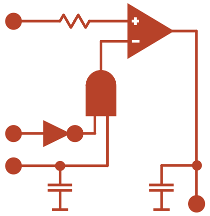


Optimization of many parameters / pixel

⇒ **Future: More Pixels**

> 1000 px

High sensitivity…
… also to **noise**



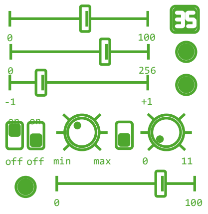
Signal processing:

Analog

```
float get_e
{
  uint32_t
  for ( uin
  {
    float v
    mwd_maf
```

Digital

Compensate artifacts



Optimization of many parameters / pixel

⇒ **Future: More Pixels**

> 1000 px

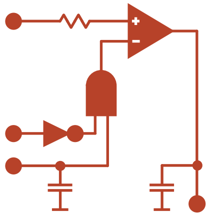
Solution:
Artificial Intelligence?

Parameter optimization
Signal characterization
1D temporal analysis

…

⇒ **Lots of potential!**

High sensitivity…
… also to **noise**



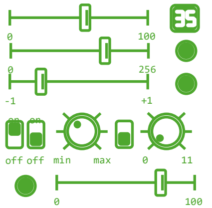
Signal processing:

Analog

```
float get_e
{
  uint32_t
  for ( uin
  {
    float v
    mwd_maf
```

Digital

Compensate artifacts



Optimization of many parameters / pixel

⇒ **Future: More Pixels**

> 1000 px

Solution:

Artificial Intelligence?

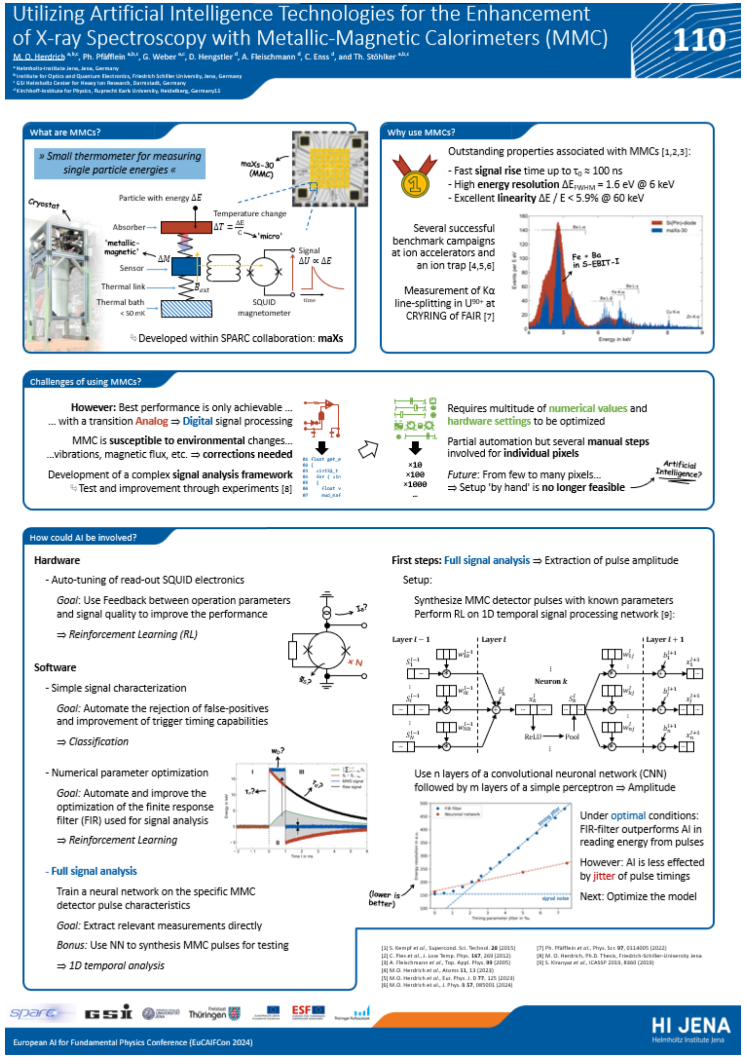
Parameter optimization

Signal characterization

1D temporal analysis

…

⇒ **Lots of potential!**



Marc Oliver Herdrich

Helmholtz-Institute Jena

Poster **#110**

Quark/Gluon Discrimination and Top Tagging with Dual Attention Transformer

— EuCAIFCon24 —

Daohan Wang

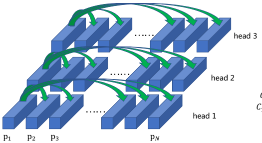
Institute of High Energy Physics (HEPHY), Austrian Academy of Sciences (OeAW)

April 30, 2024

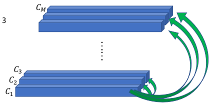
Dual Attention Mechanism

$$\mathcal{A}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \mathrm{Concat}(\mathrm{head}_1,\ldots,\mathrm{head}_{N_h})$$

$$\text{where } \mathrm{head}_i = \mathrm{softmax}\left[\frac{\mathbf{Q}_i(\mathbf{K}_i)^{\mathrm{T}}}{\sqrt{C_h}} + \mathbf{U_1}\right]\mathbf{V}_i$$



Particle Attention Map $P\times P$

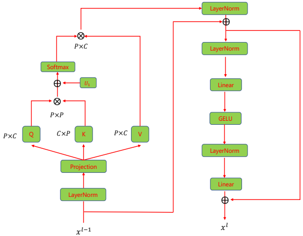


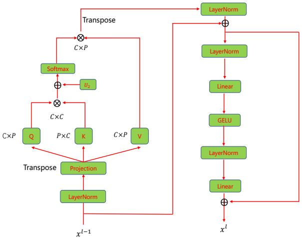
Particle Feature Attention Map $C\times C$

$$\mathcal{A}(\mathbf{Q}_i,\mathbf{K}_i,\mathbf{V}_i) = \mathrm{softmax}\left[\frac{\mathbf{Q}_i^{\mathrm{T}}\mathbf{K}_i}{\sqrt{C}} + \mathbf{U_2}\right]\mathbf{V}_i^T$$

Particle interaction matrix $\mathbf{U_1}$:

$$\Delta R = \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},$$
$$k_{\mathrm{T}} = \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})\Delta,$$
$$z = \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})/(p_{\mathrm{T},a} + p_{\mathrm{T},b}),$$
$$m^2 = (E_a + E_b)^2 - \|\mathbf{p}_a + \mathbf{p}_b\|^2,$$
$$\Delta p_{\mathrm{T}} = |p_{\mathrm{T},a} - p_{\mathrm{T},b}|$$



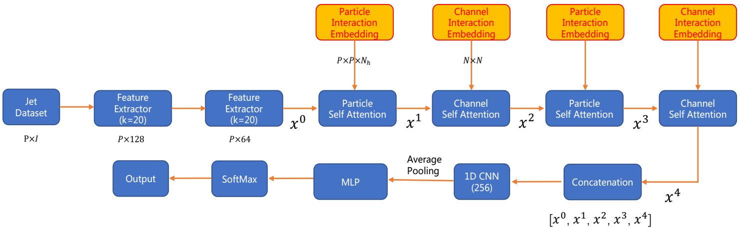


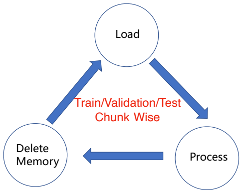
Channel interaction matrix $\mathbf{U_2}$:

Straightforward ratios of $\{E_{\mathrm{J}}, p_{\mathrm{T_J}}, \sum p_{\mathrm{T}f}, \sum E_f, \overline{\Delta\eta}, \overline{\Delta\phi}, \overline{\Delta R}, \mathrm{PID}\}$ where $\overline{\Delta\eta}$, $\overline{\Delta\phi}$ and $\overline{\Delta R}$ correspond to the transverse momentum weighted sum of the $\Delta\eta$, $\Delta\phi$, ΔR of all the constituent particles inside the input jet, respectively. Here $\Delta\eta$, $\Delta\phi$ and ΔR refer to the distances in the $\eta - \phi$ space between each constituent particle and the input jet.

Model Architecture

- Input features: $\log E$, $\log p_{\mathrm{T}}$, $\frac{p_{\mathrm{T}}}{p_{\mathrm{TJ}}}$, $\frac{E}{E_J}$, $\Delta\eta$ $\Delta\phi$, ΔR, PID of leading 100 particles.
- The particle attention module ($P \times P$ attention map) and the channel attention module ($C \times C$ attention map) are stacked while maintaining a consistent feature dimension of $N = 64$ and they can complement each other.
- Particle - Dual Attention Transformer: 2 Feature Extractor (1 EdgeConv + 3 Conv2D + 1 AvgPool) + 2 Particle Attention modules + 2 Channel Attention modules + 1D CNN + MLP.





Chunk Loading Strategy