unimpeded: A universal parameter estimation, model comparison and tension quantification distributed over every dataset

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DiRAC

Simple and straightforward pip installable package gives you access across models and datasets!
Your choice of samplers! MCMC or Nested Sampling

```
pip install unimpeded
```

```
samples = unimpeded.get(data='planck_2018_CamSpec', model='lcdm',
method='ns')
```

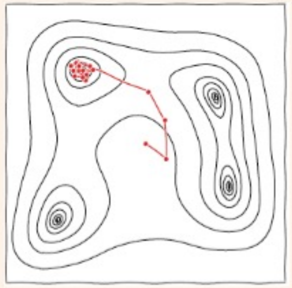
Cosmological datasets

- CMB:(Plik, Camspec, NPIPE, BICEP) $\pm$ CMB lensing
- BAO:SDSS, BOSS, eBOSS, Lyα
- SNe: Pantheon, SH0ES
- WL: DESY1

Cosmological models

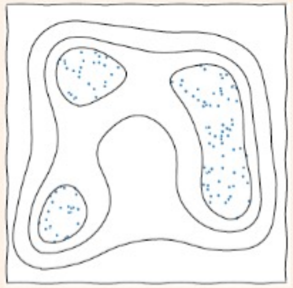
- ΛCDM : H_0, $\tau_{\rm reio}$, $\Omega_b h^2$, $\Omega_c h^2$, A_s, n_s
- $K\Lambda$CDM : ΛCDM + Ω_K (varying curvature)
- $N\Lambda$CDM : Varying $N_{\rm eff}$ and total mass of 3 degenerate ν's
- $n\Lambda$CDM : Varying total mass of 3 degenerate ν's with $N_{\rm eff}$=3.044
- $m\Lambda$CDM : Varying $N_{\rm eff}$ with two massless ν and one with m=0.06
- $n_{\rm run}\Lambda$CDM : ΛCDM + $n_{\rm run}$ (running of spectral index $dn_s/d\ln k$)
- wCDM : ΛCDM + w (constant cosmological equation of state)
- $w_0w_a\Lambda$CDM : ΛCDM + w_0 + w_a (varying dark energy equation of state, CLP)
- $r\Lambda$CDM : ΛCDM + r (varying scalar-to-tensor ratio)

Metropolis–Hastings MCMC



- Single "walker"
- Explores posterior
- Fast, if proposal matrix is tuned
- Parameter estimation, suspiciousness calculation
- Channel capacity optimised for generating posterior samples

Nested Sampling



- Ensemble of "live points"
- Scans from prior to peak of likelihood
- Slower, no tuning required
- Parameter estimation, model comparison, tension quantification
- Channel capacity optimised for computing partition function

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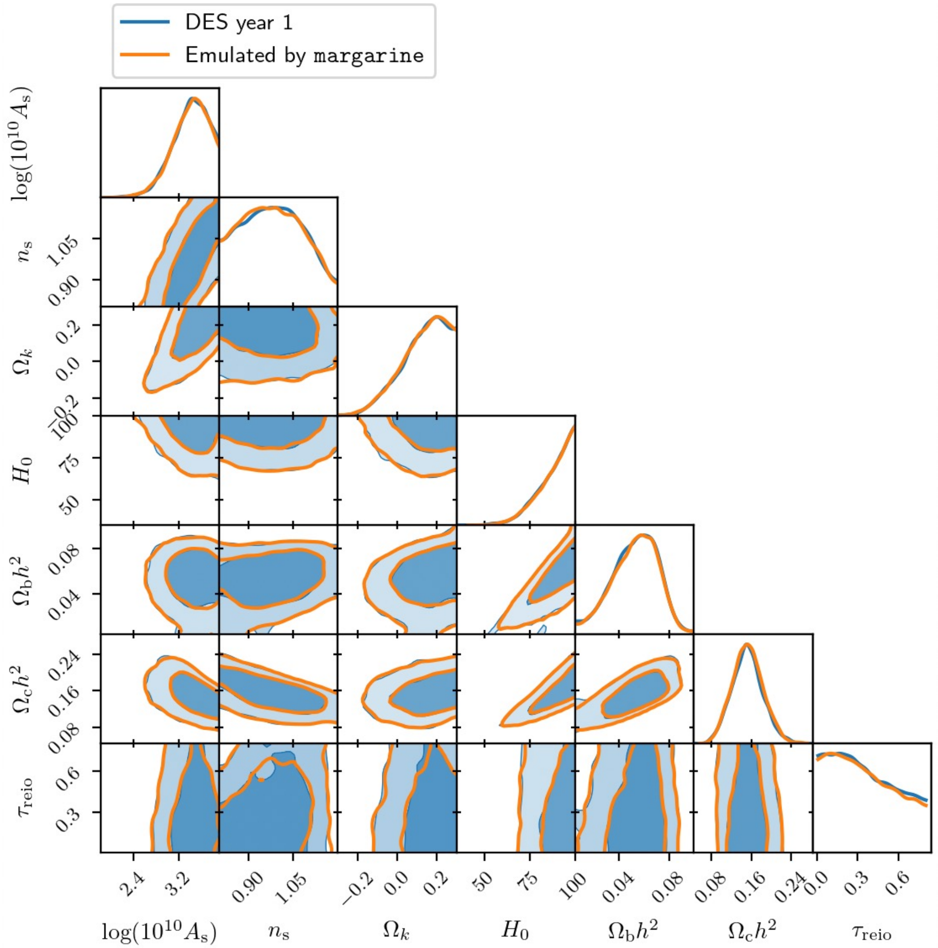
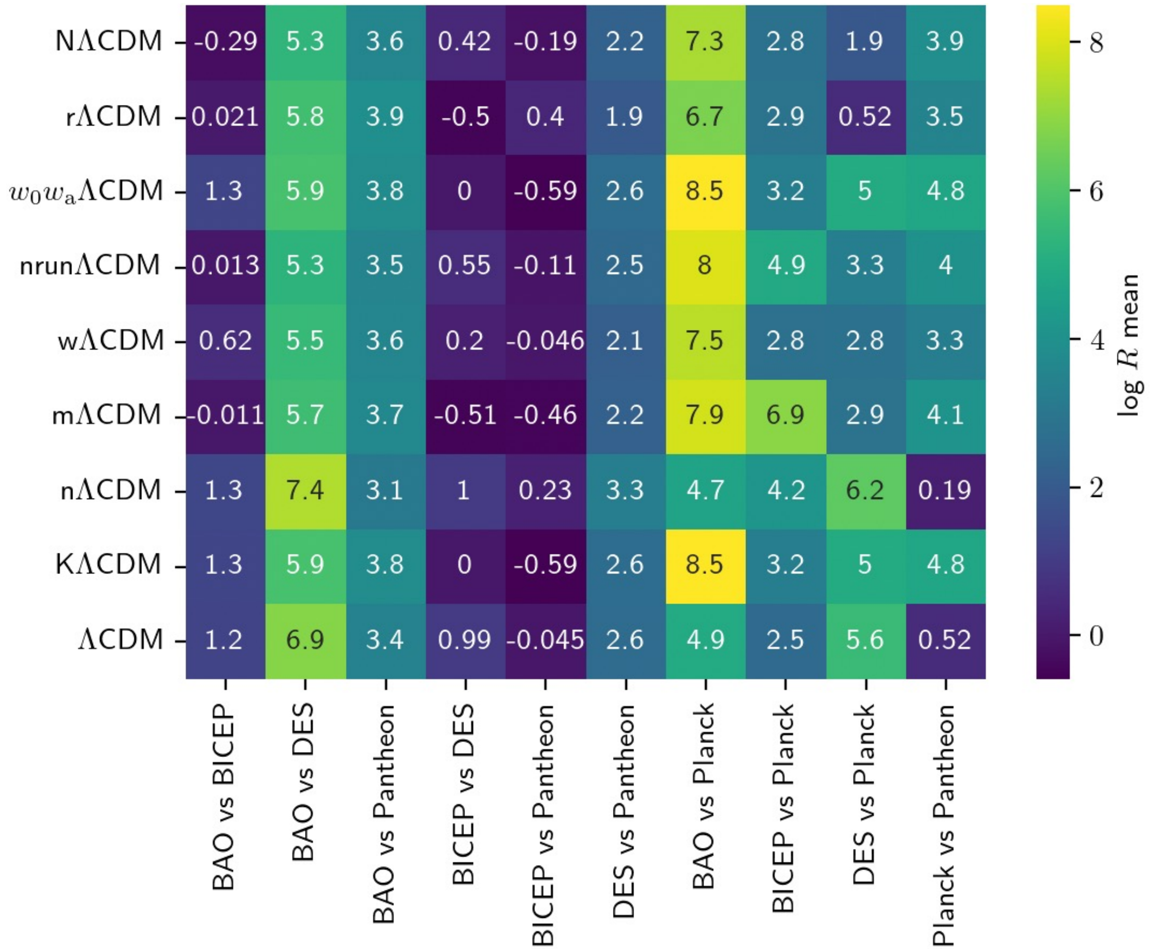
DiRAC

- A re-usable library of machine learning emulators, implemented with piecewise normalising flows



- Rapid tension statistics comparisons across models and datasets



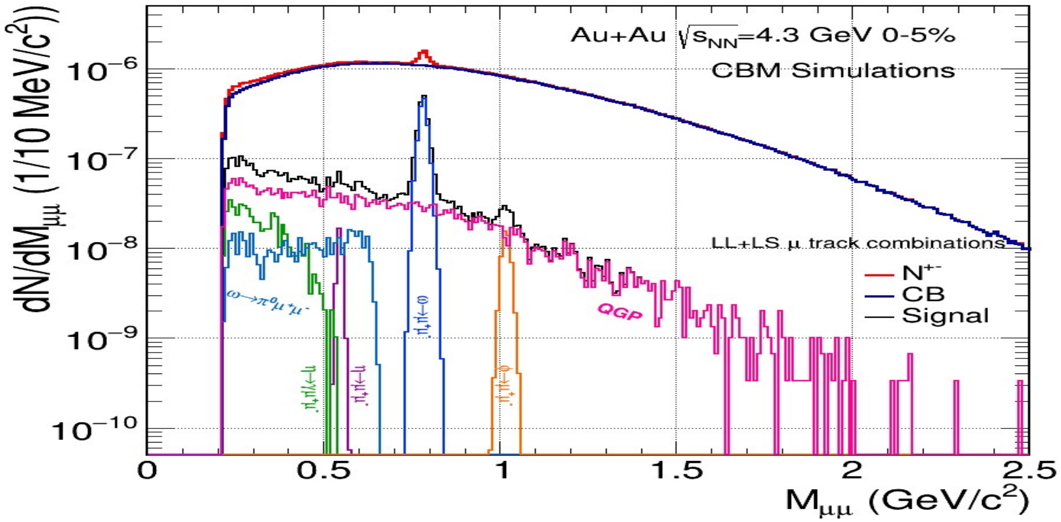
EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE
EuCAIFCon 2024

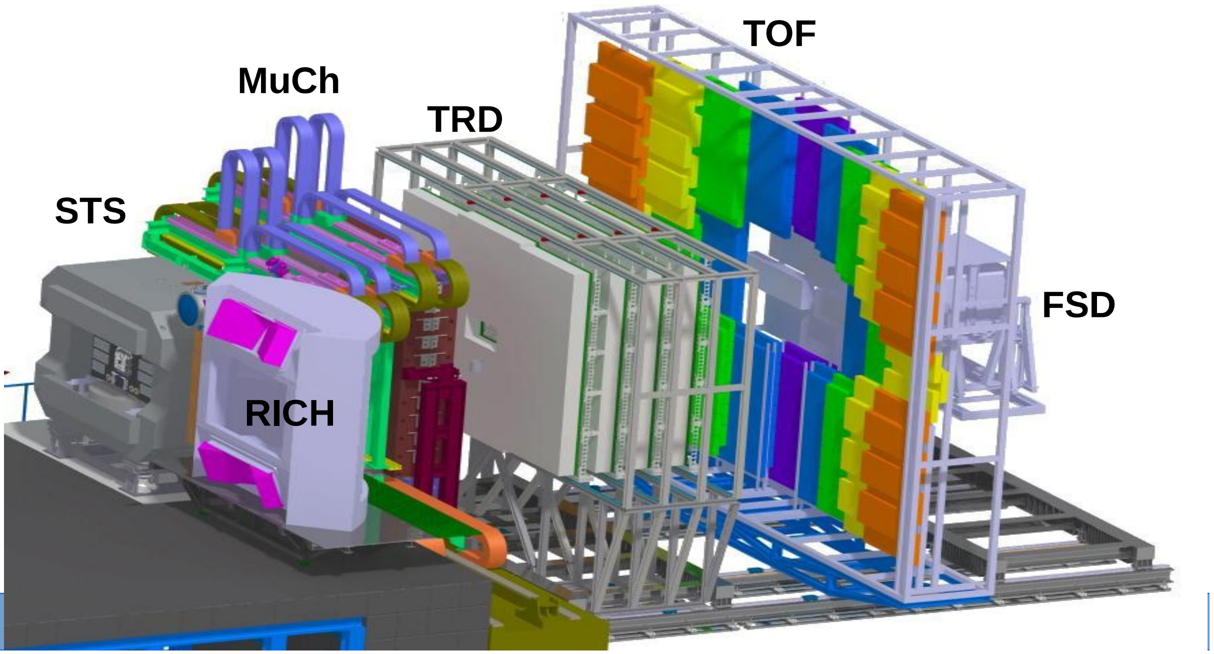
Reconstruction of Low Mass Vector Mesons(LMVM) using machine learning techniques for CBM Experiment at FAIR SIS100

Presented by: Abhishek Kumar Sharma
Collaborators: Raktim Mukherjee, Pawan Sharma, Partha Partim Bhaduri, Apar Agarwal, Anand Kumar Dubey, Anna Senger, Subhashish Chattopadhyay

CBM Experiment at FAIR

- The Compressed Baryonic Matter Experiment is situated within the accelerator facility known as Facility for Anti Proton Ion Research (FAIR) in Darmstadt, Germany
- The goal of the CBM experiment is to investigate the phase diagram of strongly interacting matter under conditions characterized by high net baryon densities and moderate temperatures.
- In-medium modification of light vector mesons, hyper-nuclei, charm production and their propagation inside the nuclear matter.
- The particle multiplicity of the particle like ω, η, ϕ, ρ is quite low.
- The precision and rare probes need high statistics with greater efficiency. The signal efficiency obtained through traditional uni-variate cut method is low.
- Therefore the need for multivariate analysis for the dimuon detection is required.

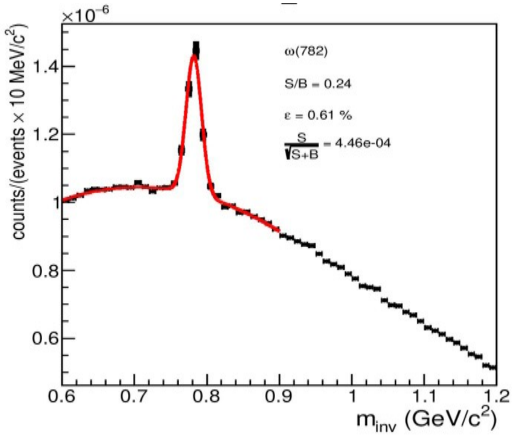




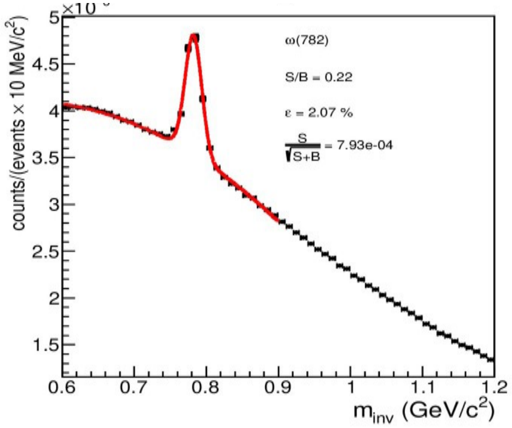
Physics Observables

ω ⟶ $\mu^+ \mu^-$ η ⟶ $\mu^+ \mu^-$ ϕ ⟶ $\mu^+ \mu^-$

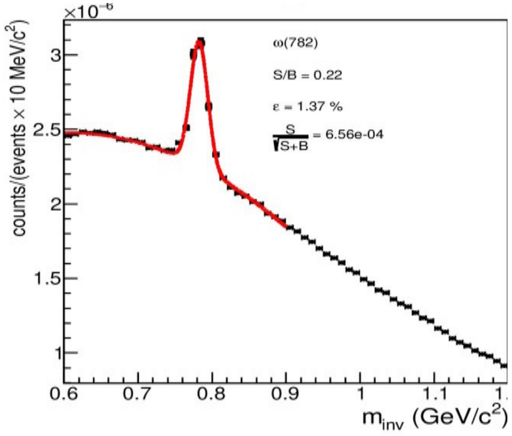
ω meson using manual cuts with efficiency 0.61



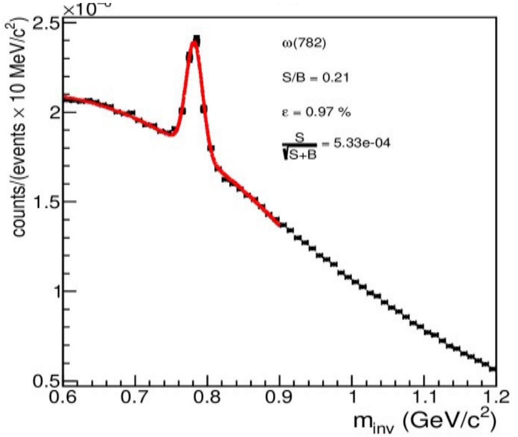
ω meson BDTG @ 0.7 with efficiency increase of 3.39 with same S/B



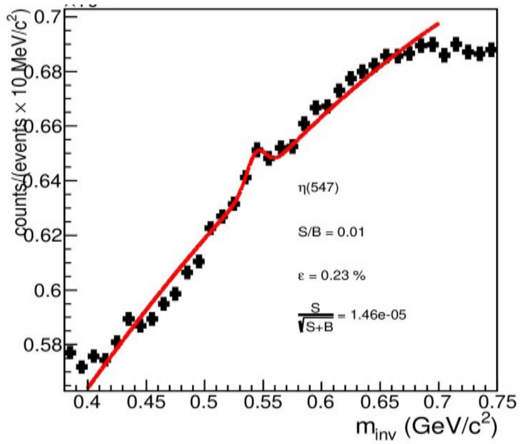
ω meson kNN @ 0.88 with efficiency increase of 2.24 with same S/B



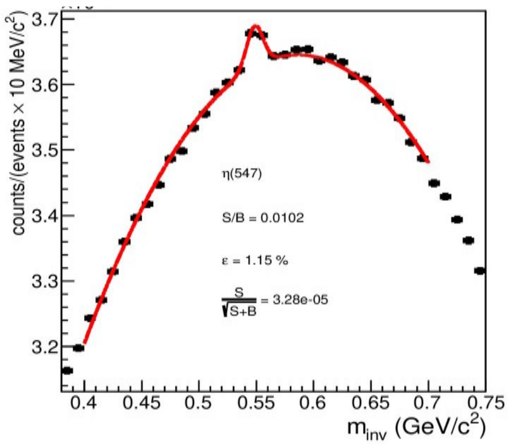
ω meson HMatrix @ 0.18 with efficiency increase of 3.39 with same S/B



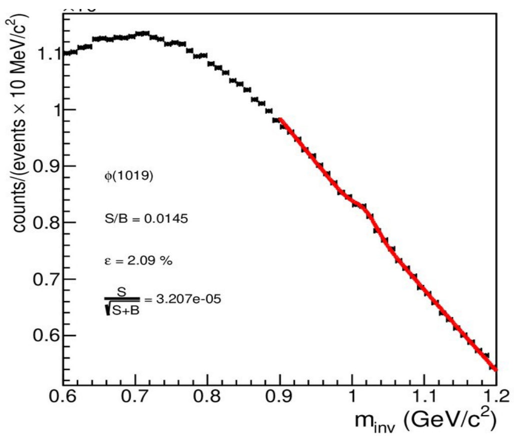
η meson using manual cuts with efficiency 0.23



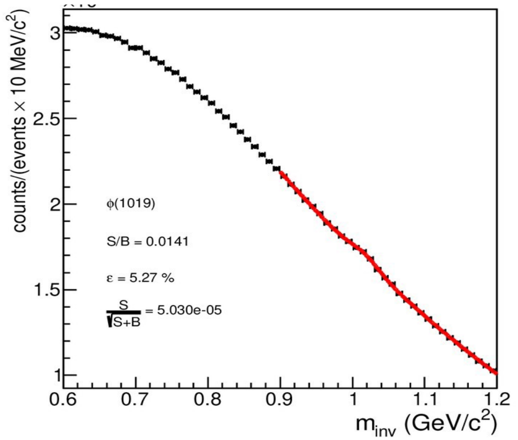
η meson BDTG @ 0.7 with efficiency increase of 5.00 with same S/B



ϕ meson using manual cuts with efficiency 2.09



ϕ meson BDTG @ 0.71 with efficiency increase of 2.52 with same S/B



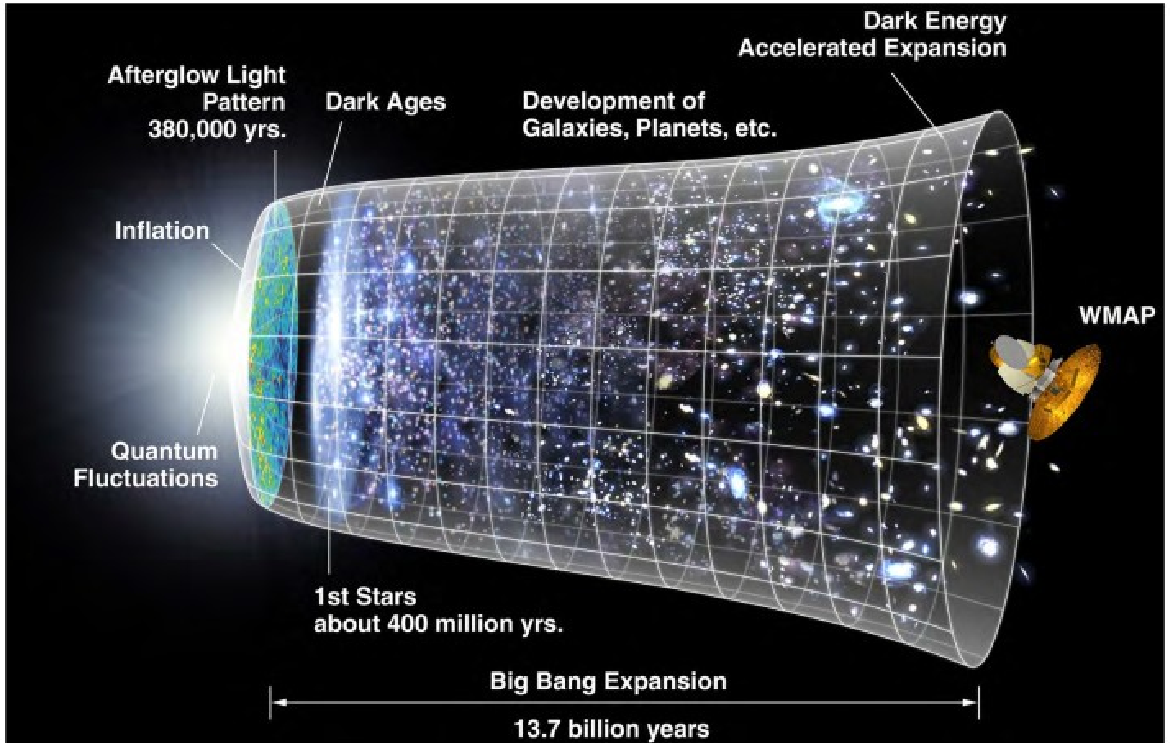
Comparison Table for Physics Observables

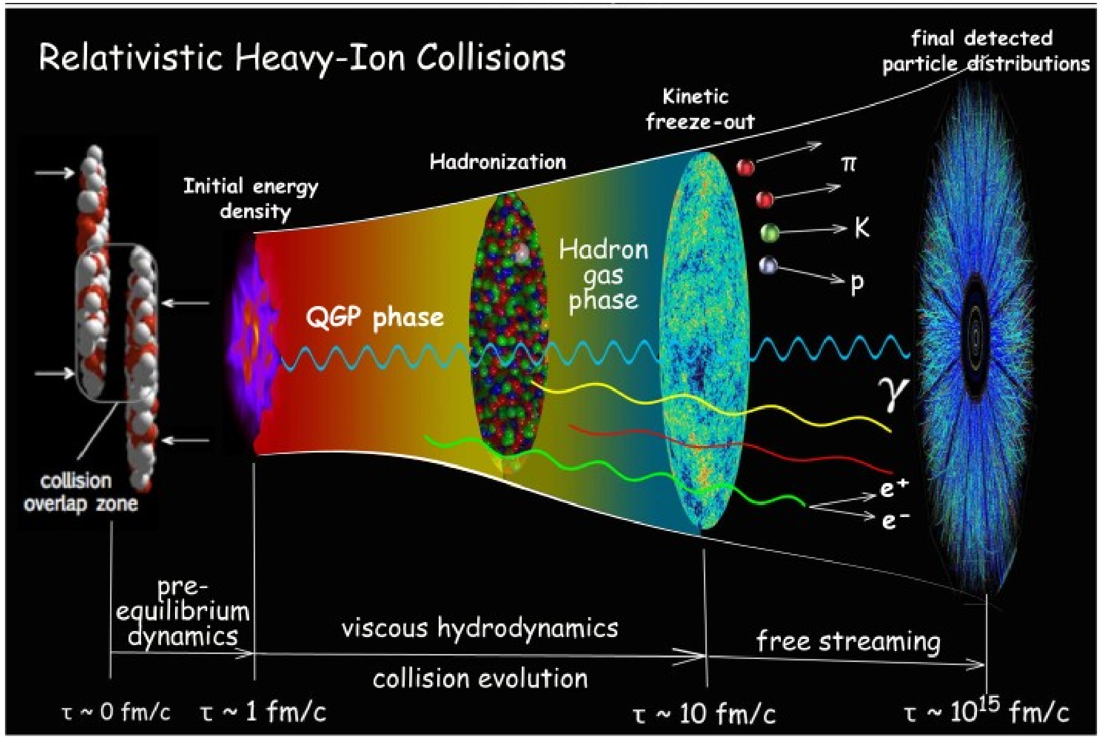
meson	method	S/B ratio	Efficiency(%)	Normalised Significance
$\omega \rightarrow \mu^+ \mu^-$	Manual cuts	0.24	0.61	1.00
$\omega \rightarrow \mu^+ \mu^-$	BDTG @ 0.65	0.22	2.07	1.77
$\omega \rightarrow \mu^+ \mu^-$	kNN @ 0.88	0.22	1.37	1.47
$\omega \rightarrow \mu^+ \mu^-$	HMatrix @ 0.18	0.21	0.97	1.19
$\eta \rightarrow \mu^+ \mu^-$	Manual cuts	0.01	0.23	1.00
$\eta \rightarrow \mu^+ \mu^-$	BDTG @ 0.7	0.01	1.15	2.24
$\phi \rightarrow \mu^+ \mu^-$	Manual cuts	0.014	2.09	1.00
$\phi \rightarrow \mu^+ \mu^-$	BDTG @ 0.71	0.014	5.27	1.57

- Further investigation of complete dimuon cocktail production and for high mass region for J/ψ production is under progress.
- These ML algorithms can also be used to at the digitization and reconstruction level as well for improving the detector efficiency.

Thank you very much for your Kind Attention !

G.G. Barnaföldi *et al*: Deep learning predicted elliptic flow of identified particles at the RHIC & LHC energies





EuCAIFCon 2024, JENAA
Amsterdam, The Netherlands, 28th April 2024

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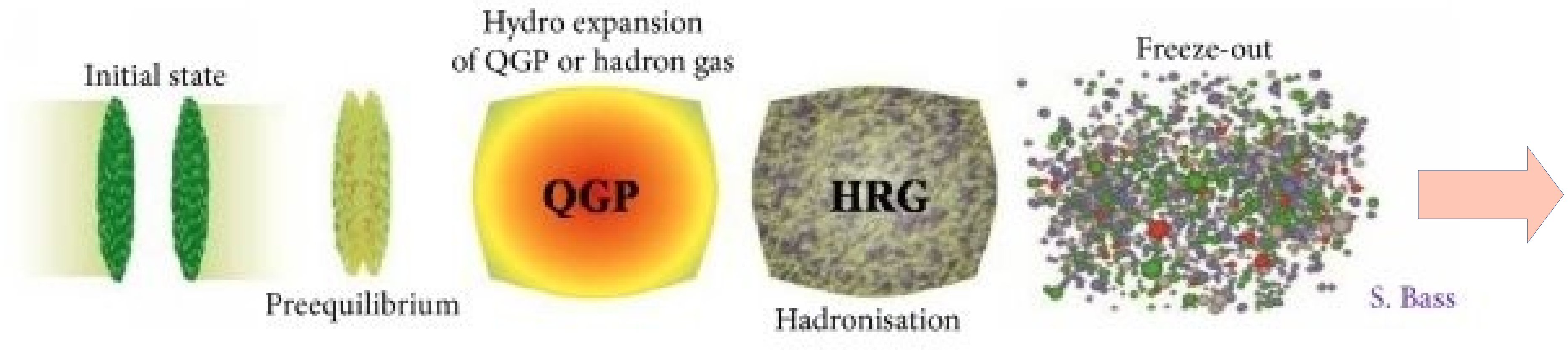
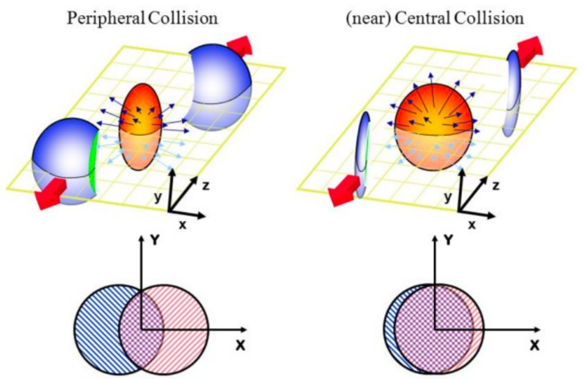
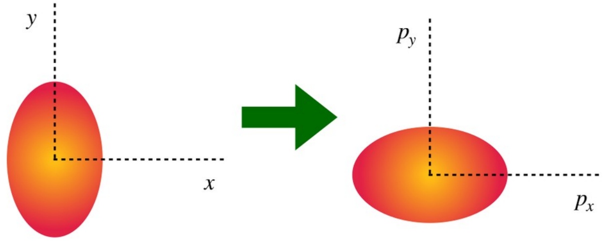
QGP signature: elliptic flow (v_2) in HIC





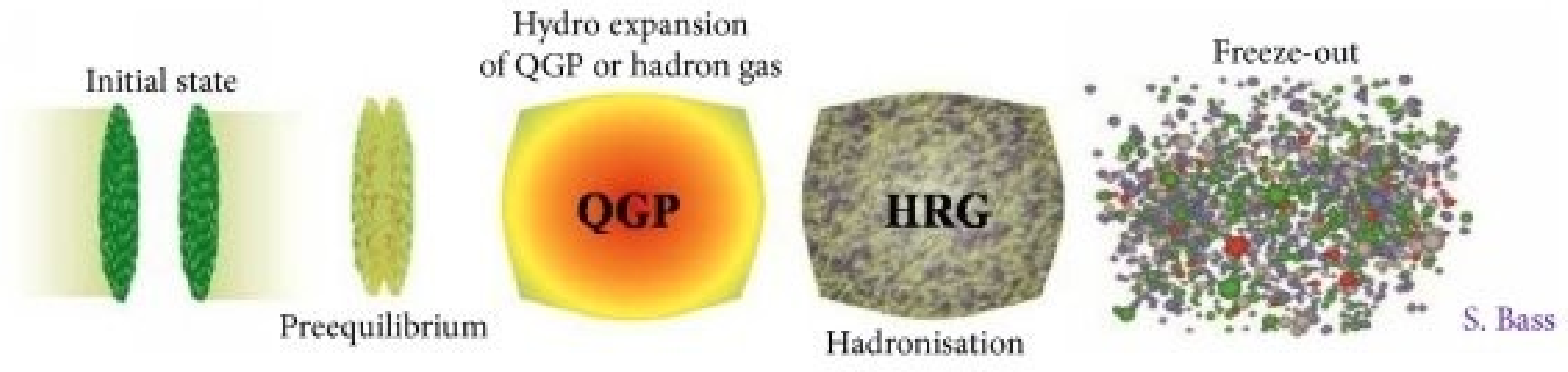
Elliptic flow describes the azimuthal momentum space anisotropy of particle emission for a non-central heavy-ion collision.

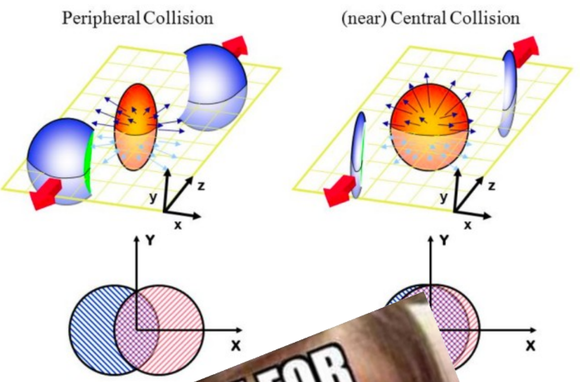
$$E\frac{d^3N}{dp^3} = \frac{d^2N}{p_T dp_T dy}\frac{1}{2\pi}\left(1 + 2\sum_{n=1}^{\infty} v_n \cos[n(\phi - \psi_n)]\right)$$



The 2nd harmonic coefficient of the Fourier expansion of azimuthal momentum distribution: $v_2(p_T, y) = \langle\cos(2(\phi - \psi_2))\rangle$

QGP signature: elliptic flow (v_2) in HIC





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The 2^{nd} harmonic coefficient of the Fourier expansion of azimuthal momentum distribution: $v_2(p_T, y) = \langle \cos(2(\phi - \psi_2)) \rangle$

Results: how ML can help with this?

- **It is possible to estimate the elliptic flow by ML**
  - Get best Min. Bias. Monte Carlo simulation data and train the well-designed DNN system…
    - → AMPT & DNN correlates well for all centrality
    - → Best correlation is for the highest statistic
    - → Energy scaling is well preserved (non-linear)
    - → The $v_2(p_T)$ is also preserved with PID & NCQ
- **See more on poster #105**

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Refs.: PRD 105, 114022 (2022) PRD 107, 094001(2023)