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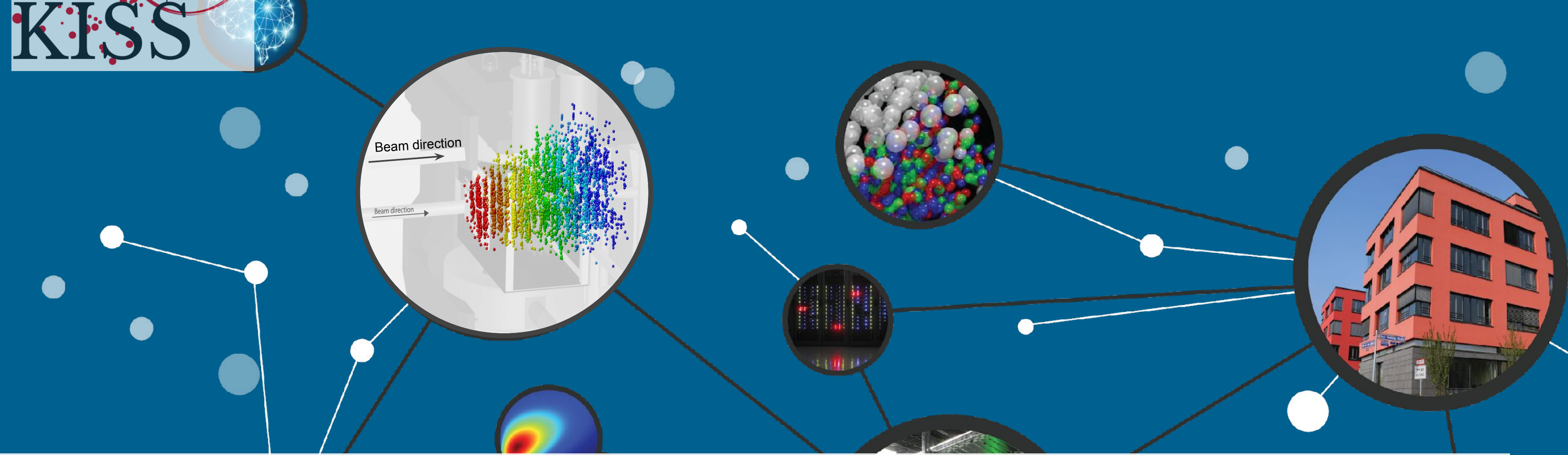
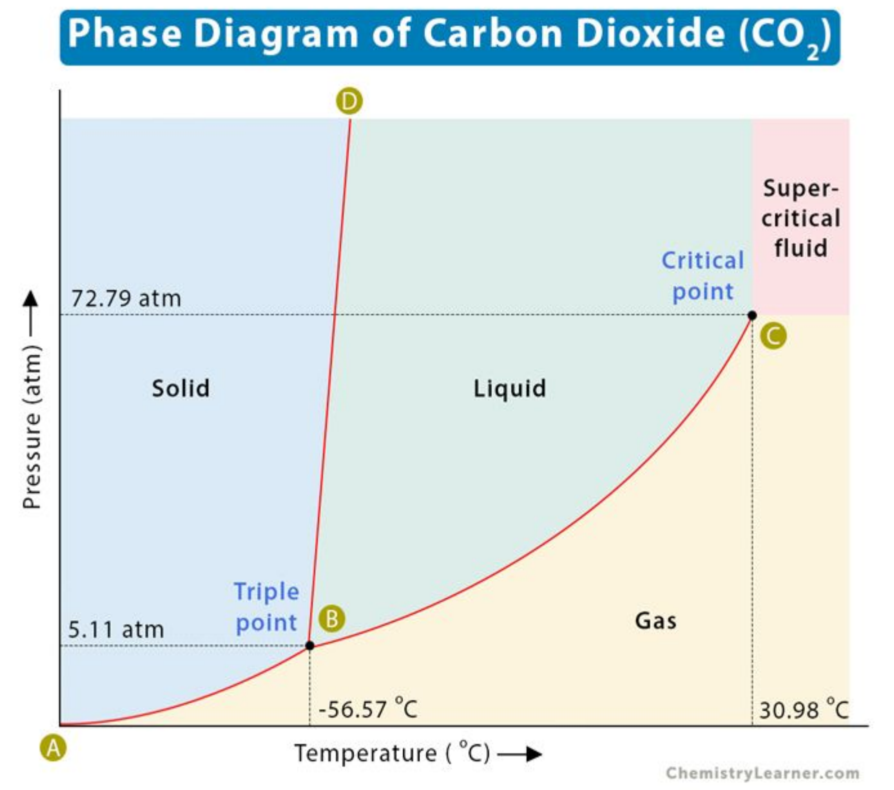
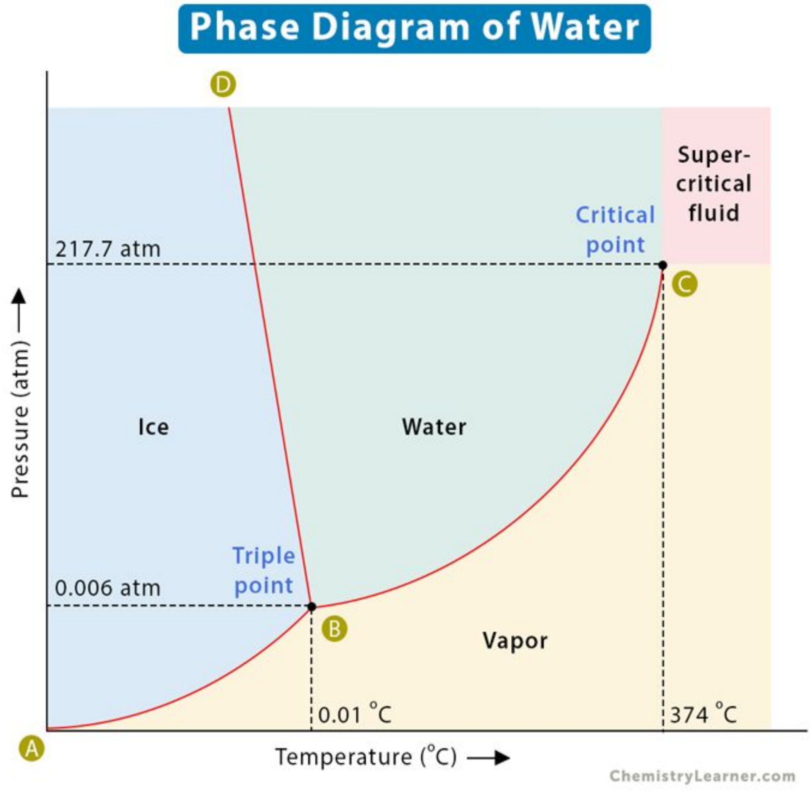


AI-Driven Exploration of Strongly Interacting Nuclear Matter under Extreme Conditions

Manjunath Omana Kuttan, Kai Zhou, Jan Steinheimer,
Horst Stoecker

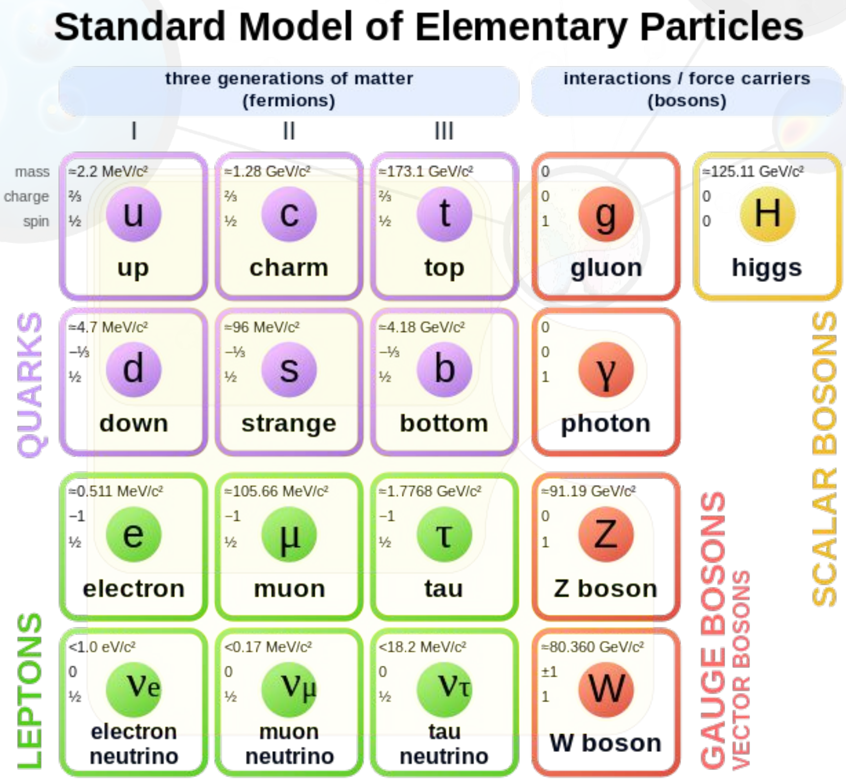
Few phase diagrams we know …





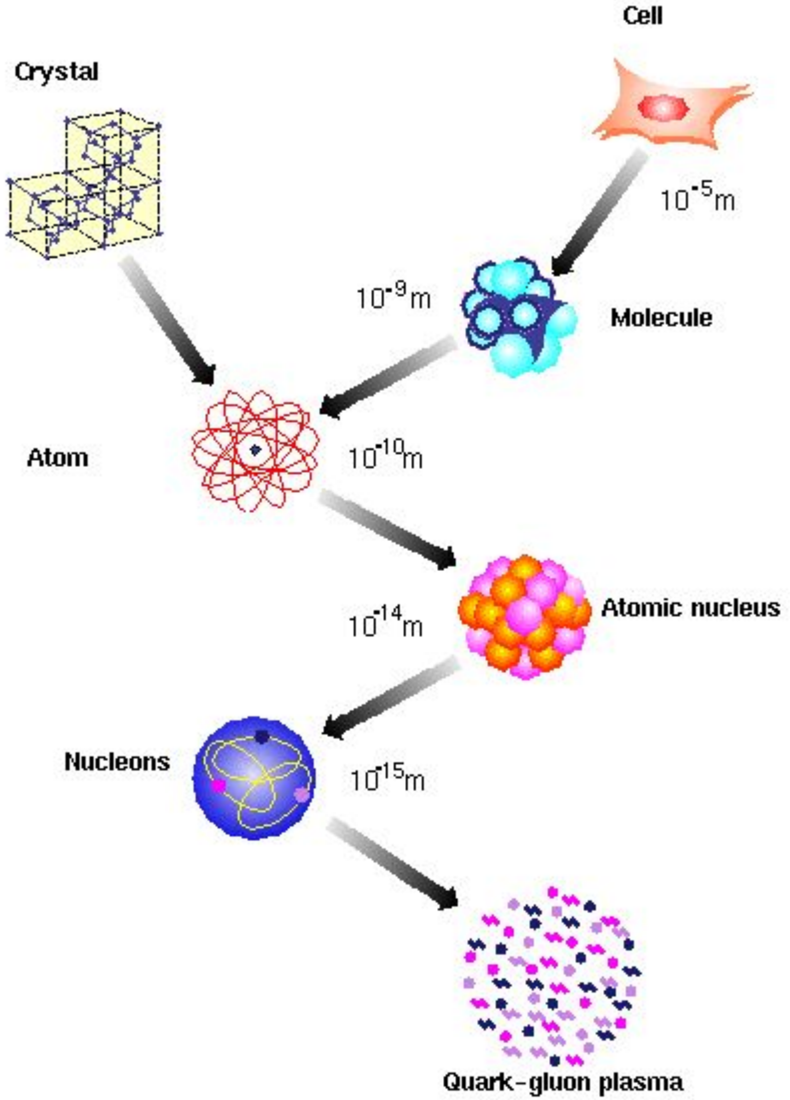
Phase diagrams portray the behaviour of a substance with varying thermodynamic conditions

A phase diagram of fundamental matter?



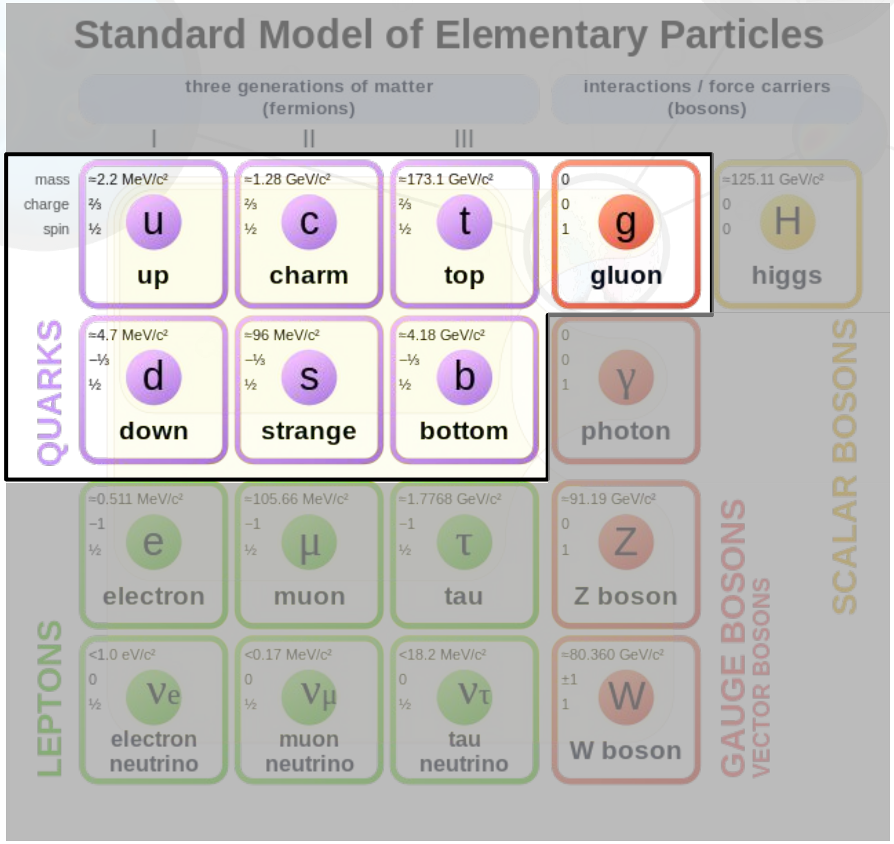
Standard Model of Elementary Particles

	three generations of matter (fermions) I	II	III	interactions / force carriers (bosons)	
mass charge spin	≈2.2 MeV/c² ⅔ ½ u up	≈1.28 GeV/c² ⅔ ½ c charm	≈173.1 GeV/c² ⅔ ½ t top	0 0 1 g gluon	≈125.11 GeV/c² 0 0 H higgs
QUARKS	≈4.7 MeV/c² −⅓ ½ d down	≈96 MeV/c² −⅓ ½ s strange	≈4.18 GeV/c² −⅓ ½ b bottom	0 0 1 γ photon	SCALAR BOSONS
	≈0.511 MeV/c² −1 ½ e electron	≈105.66 MeV/c² −1 ½ μ muon	≈1.7768 GeV/c² −1 ½ τ tau	≈91.19 GeV/c² 0 1 Z Z boson	
LEPTONS	<1.0 eV/c² 0 ½ ν_e electron neutrino	<0.17 MeV/c² 0 ½ ν_μ muon neutrino	<18.2 MeV/c² 0 ½ ν_τ tau neutrino	≈80.360 GeV/c² ±1 1 W W boson	GAUGE BOSONS VECTOR BOSONS



https://www.wattpad.com/404853180-science-for-thought-quark-gluon-plasma

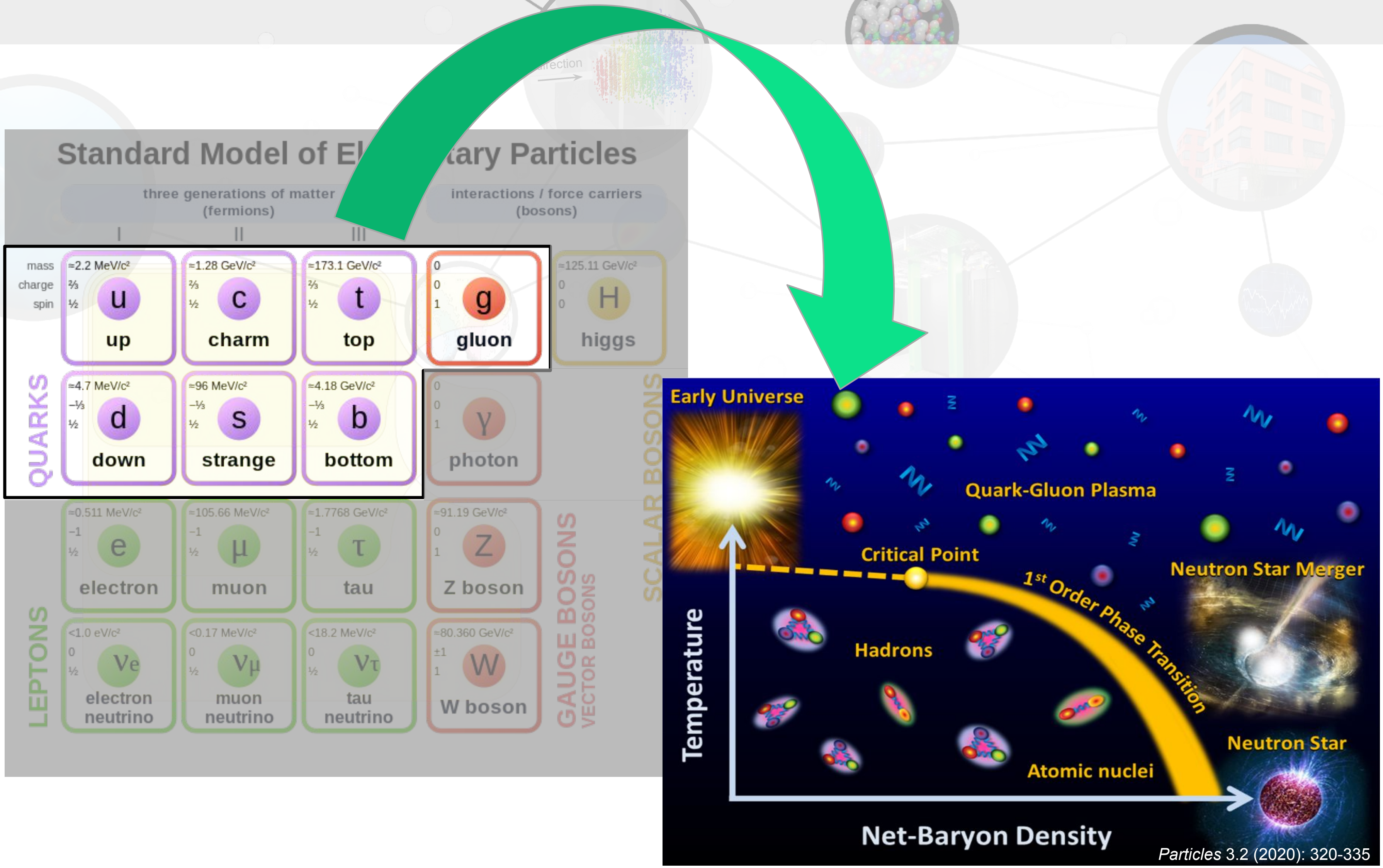
A phase diagram of fundamental matter?



➔ ordinary matter: confined quarks
  - ◆ only protons and neutrons

➔ How does nuclear matter behave at high temperatures/ densities?

A phase diagram for fundamental matter?



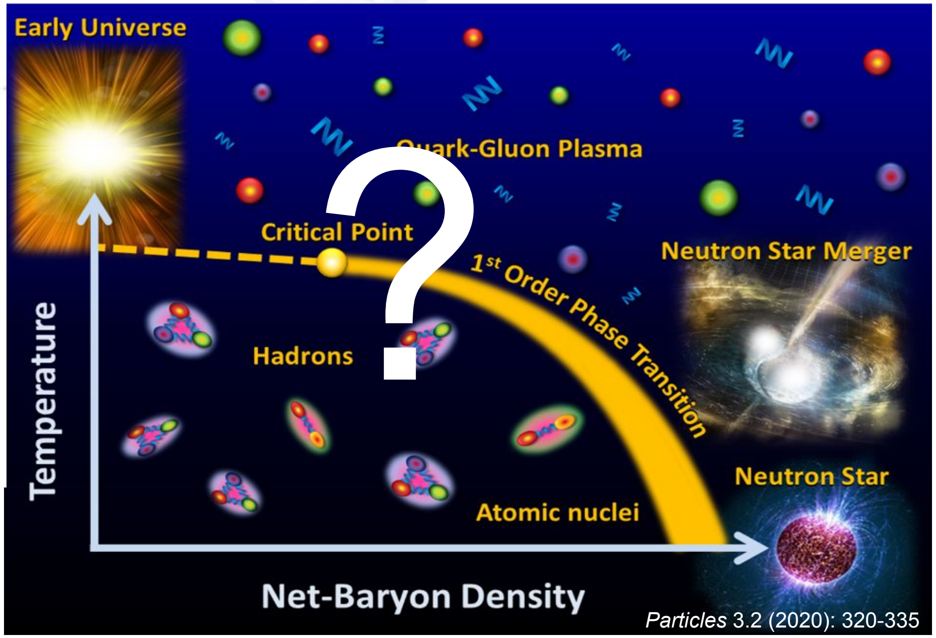
Particles 3.2 (2020): 320-335

Can we construct a phase diagram of strongly interacting, nuclear matter?

The QCD phase diagram

The QCD phase diagram is highly conjectured

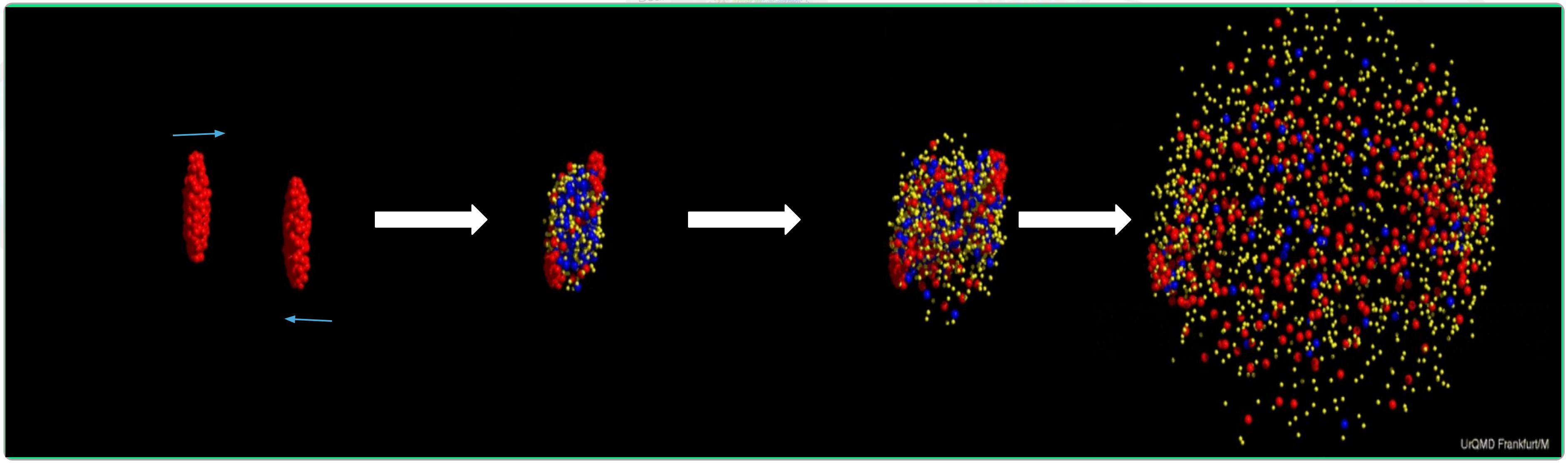
https://www.wattpad.com/404853180-science-for-thought-quark-gluon-plasma



Particles 3.2 (2020): 320-335

How can we explore the phase diagram?

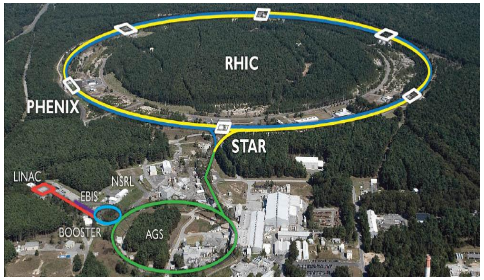
Creating hot-dense QCD matter in a lab



Heavy-ion collisions can create systems with extremely high temperatures and densities

CERN

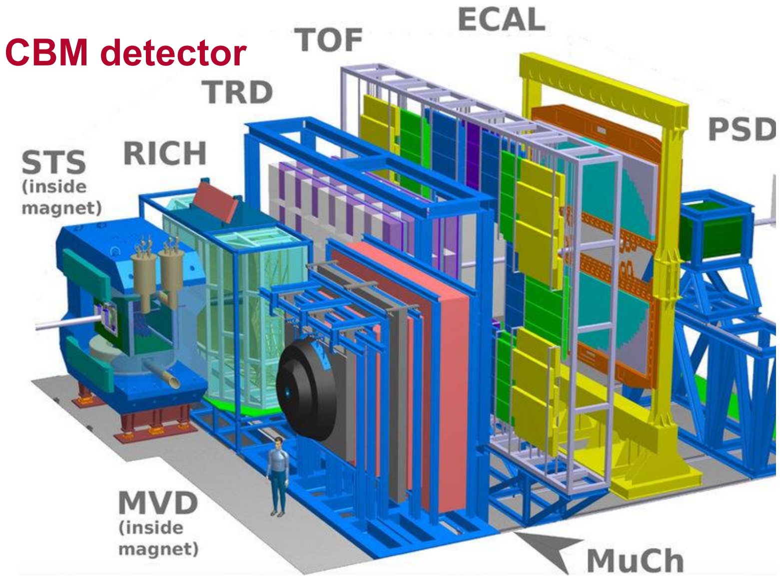
RHIC



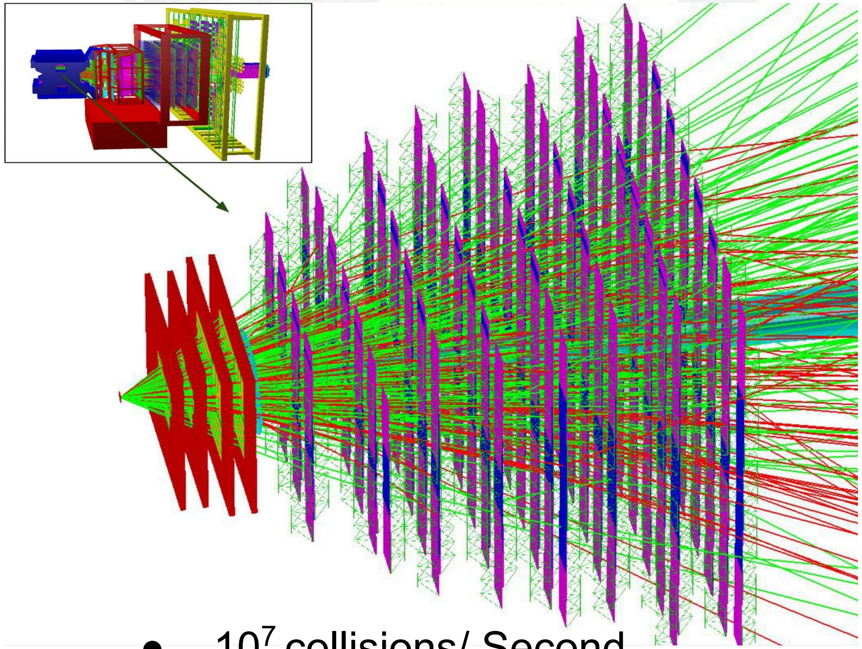
FAIR, Darmstadt

The CBM experiment at FAIR

- CBM studies Intermediate beam energies
  - moderate temperatures and high densities
  -
- Similar n_b, T found in neutron star mergers, supernova explosion etc.



- explore high density QCD EoS
- search for phase transitions
- in medium hadronic properties



- 10^7 collisions/ Second
- 1000 tracks/ collision
- **1 TB/s raw data**

The challenges

- ➔ Limited first principle calculations
  - ◆ Effective models for high density

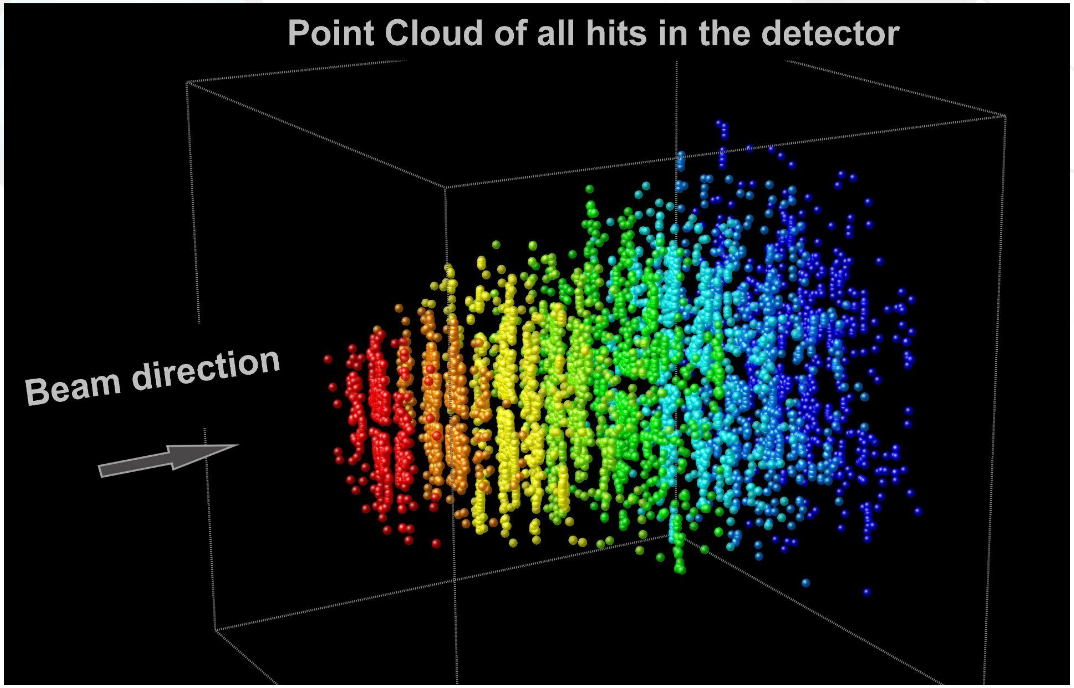
- ➔ State of the art effective models are often slow
  - ◆ upto 1 hour/event at FAIR energies

How can AI be used to address these issues?

- ➔ No smoking gun signals
  - ◆ multiple observables with limited sensitivity
  - ◆ bayesian inference, multi-param fits

- ➔ Experimental uncertainties
  - ◆ collision centrality
  - ◆ high model dependencies in analysis

Deep Learning on experimental data

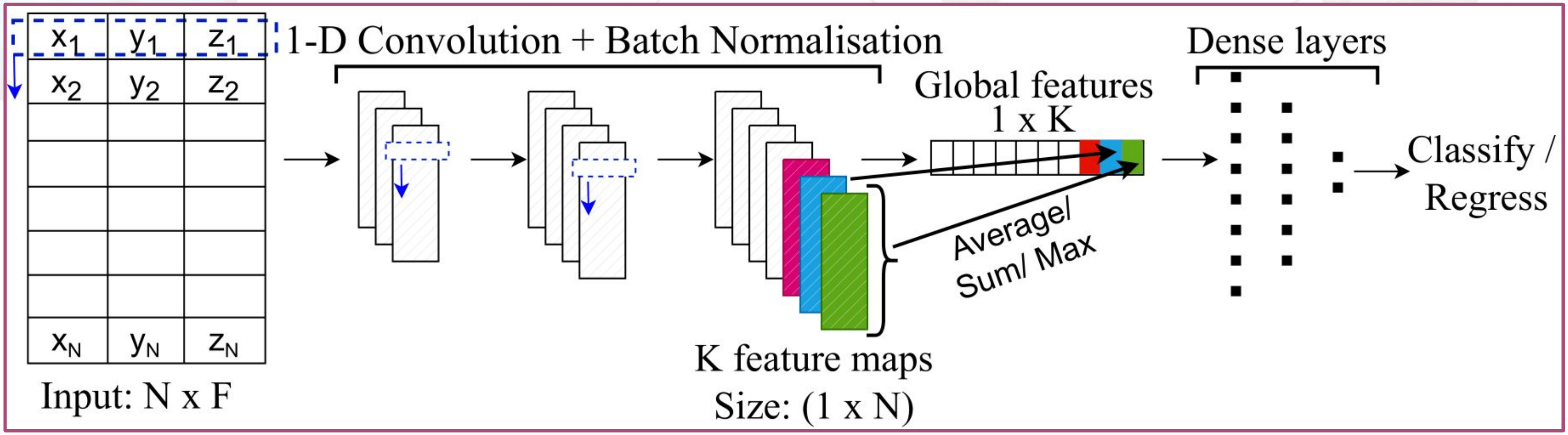


- Point cloud: set of data points
    - No ordering
    - sensors, detector data
    - tabular representation

- Electronic data: point cloud structure

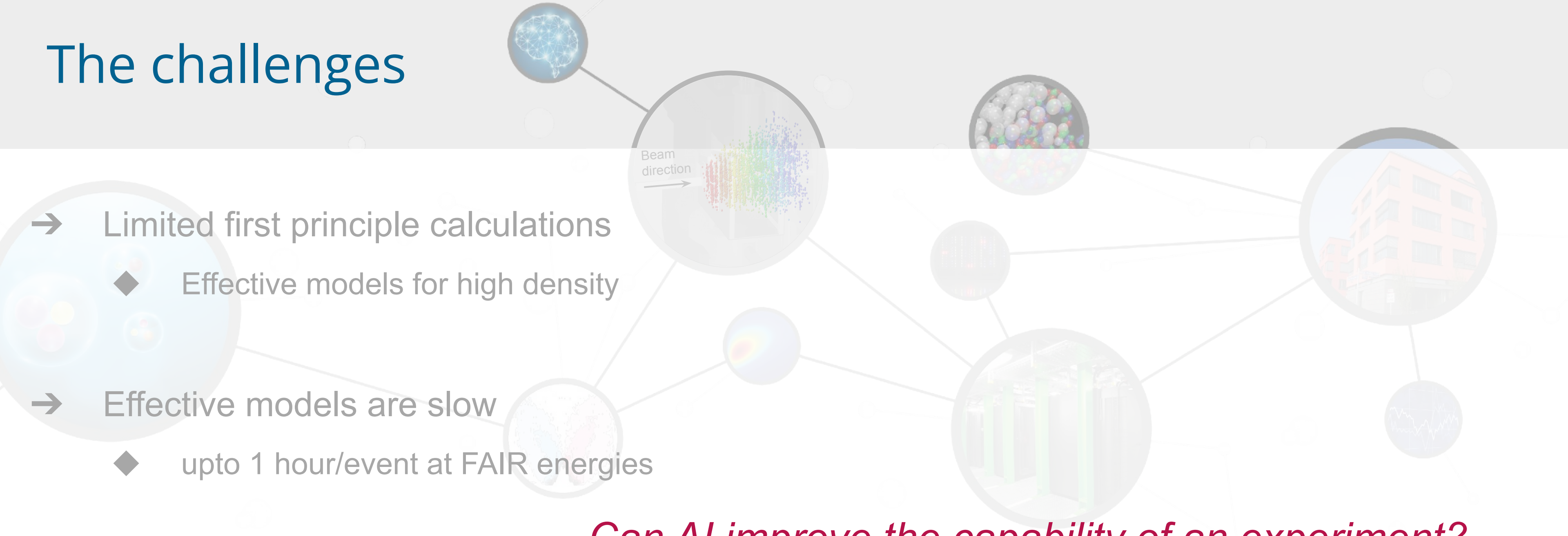
Experimental data are point clouds !

Deep Learning on experimental data



PointNet based models learn global event features from experimental data

The challenges



- ➔ Limited first principle calculations
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Can AI improve the capability of an experiment?

- ➔ No smoking gun signals
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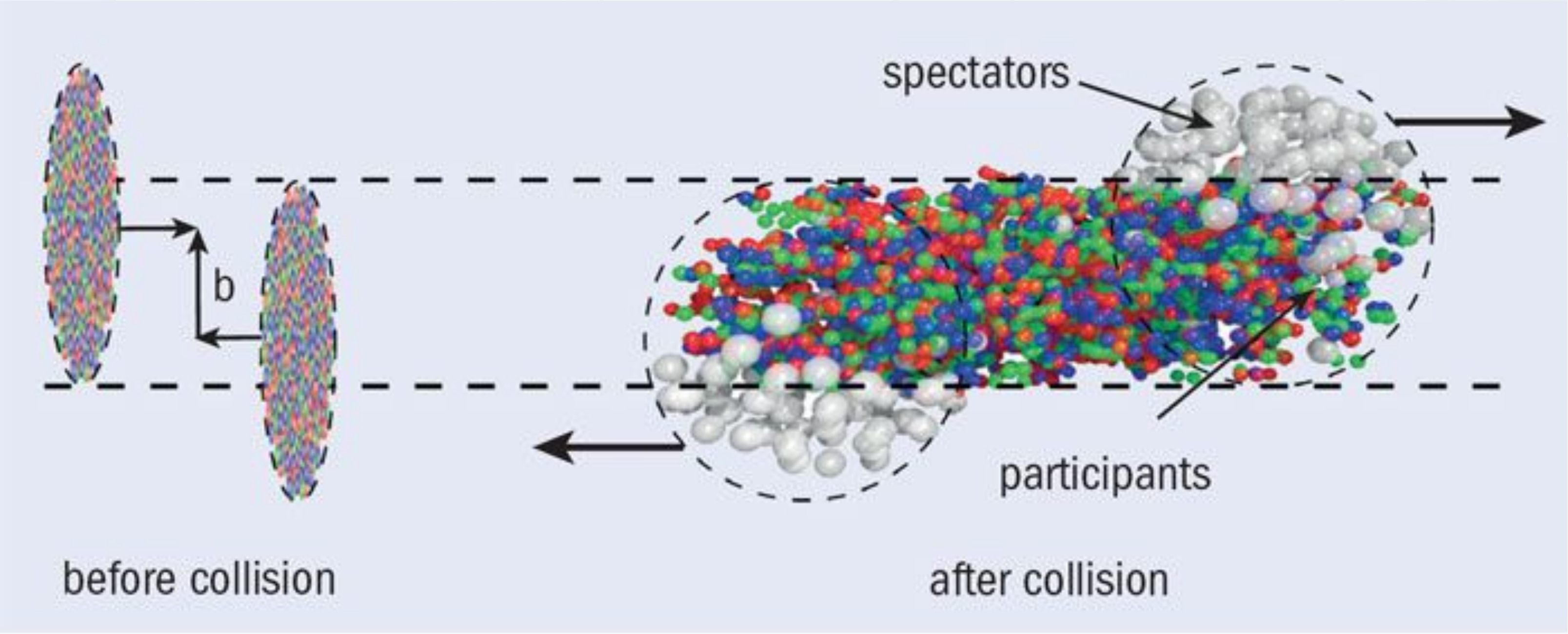
PointNet based impact parameter determination

Phys.Lett.B 811 (2020) 135872
Particles 2021, 4(1), 47-52

Observables often depend strongly on collision centrality



Estimating the impact parameter directly is not possible experimentally

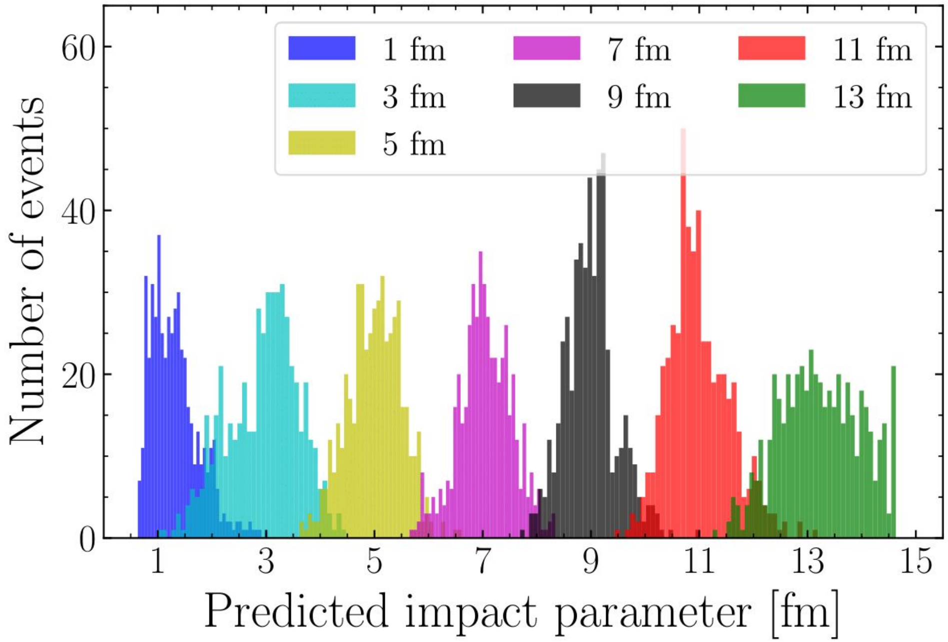
Experiments use N_{chg} to estimate centrality

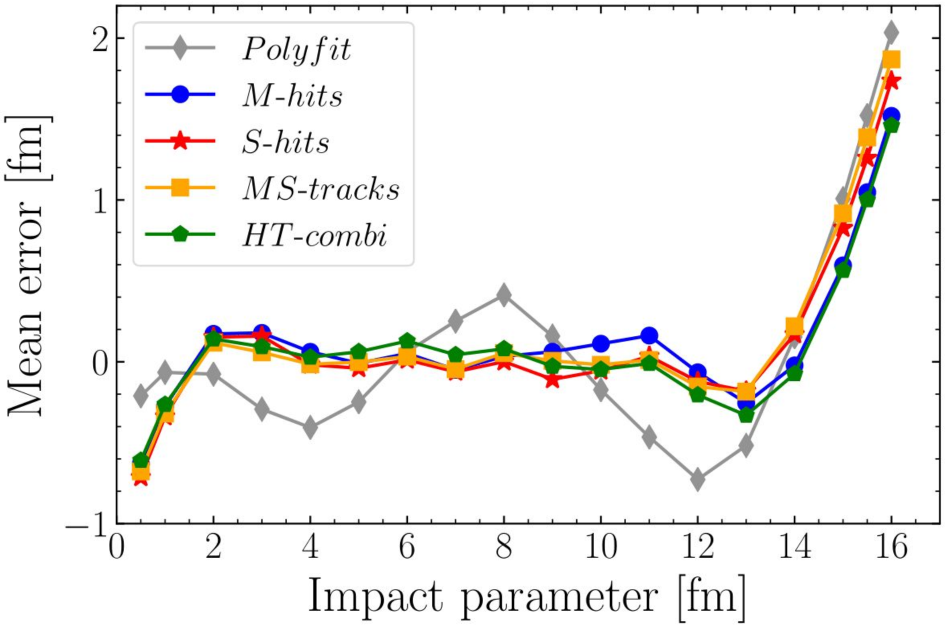
No event by event impact parameter available

PointNet based impact parameter determination

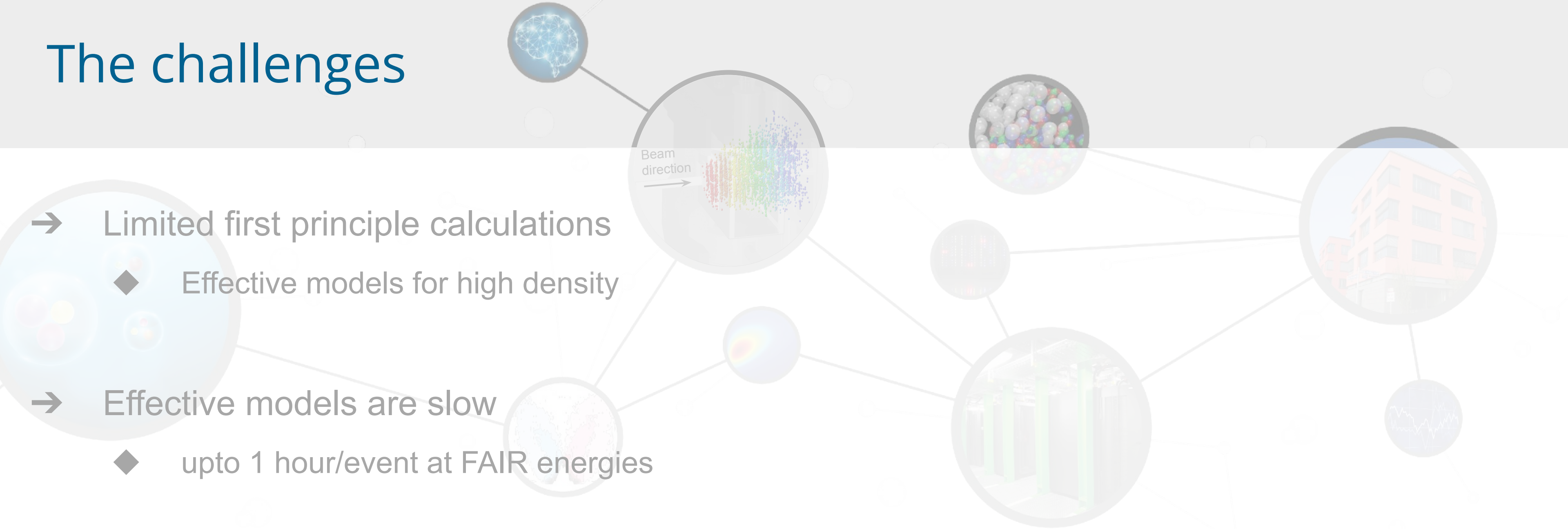
Phys.Lett.B 811 (2020) 135872
Particles 2021, 4(1), 47-52

- precise and accurate prediction over wide range of impact parameters
- outperforms non-ML method (Polyfit)
- Fast event-by-event predictions : ~1 ms/ event
  - online event characterisation





The challenges



- ➔ Limited first principle calculations
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Can AI find better ways to analyse data?

- ➔ No smoking gun signals
  - ◆ multiple observables with limited sensitivity
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- ➔ Experimental uncertainties
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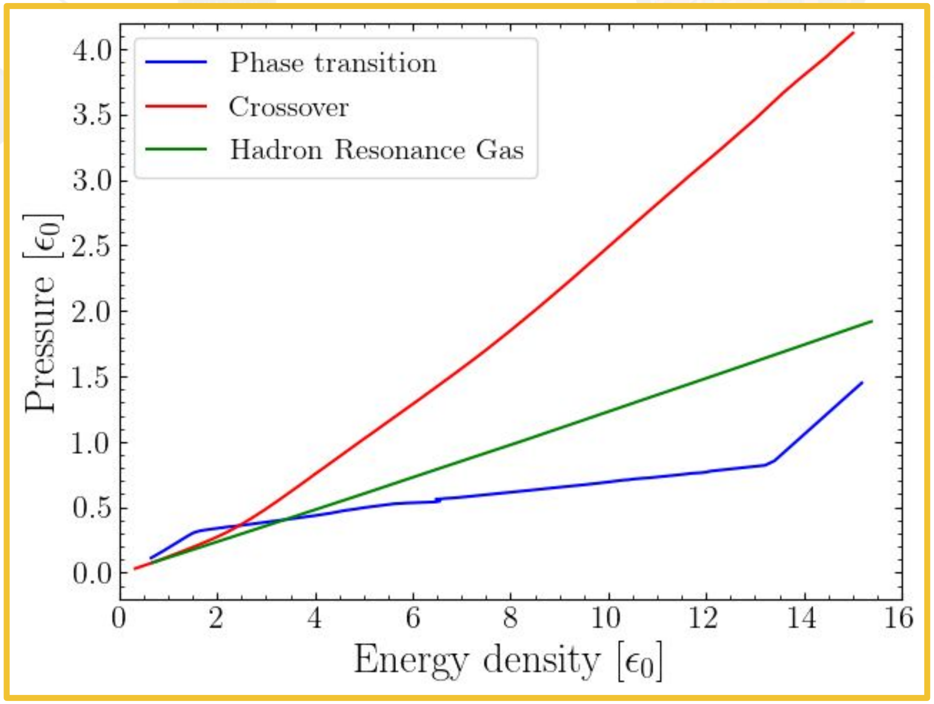
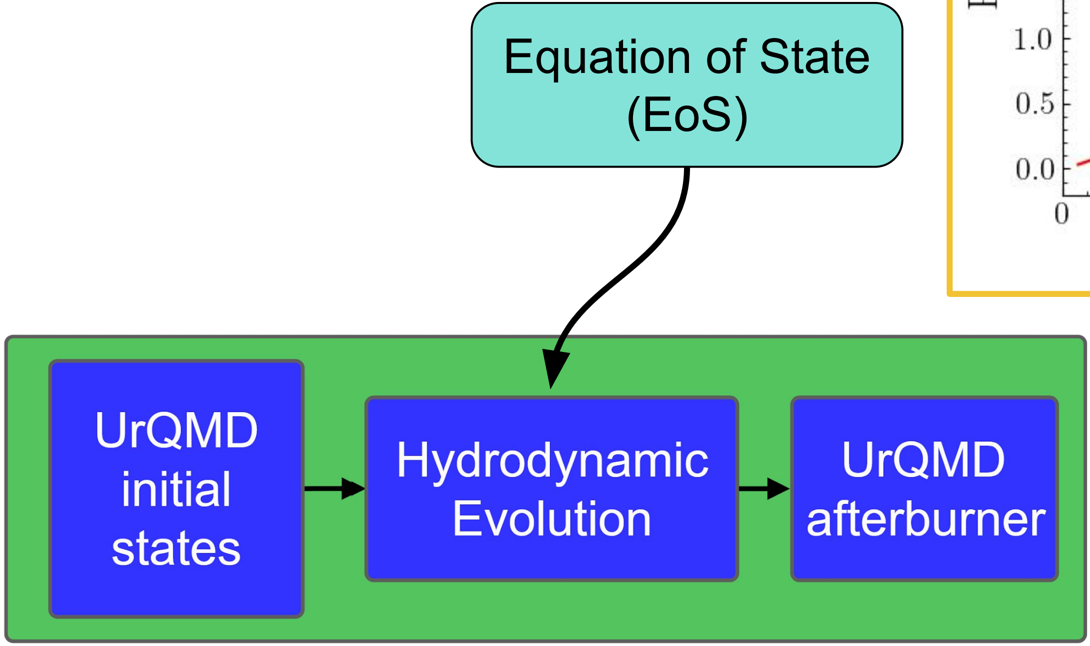
Identiying phase transitions with PointNet

JHEP 10 (2021) 184
PoS FAIRness2022 (2023) 040

- ➔ The EoS gives the pressure as function energy densities and densities
- ➔ Pressure gradients drive the evolution
- ➔ Mandatory input to models

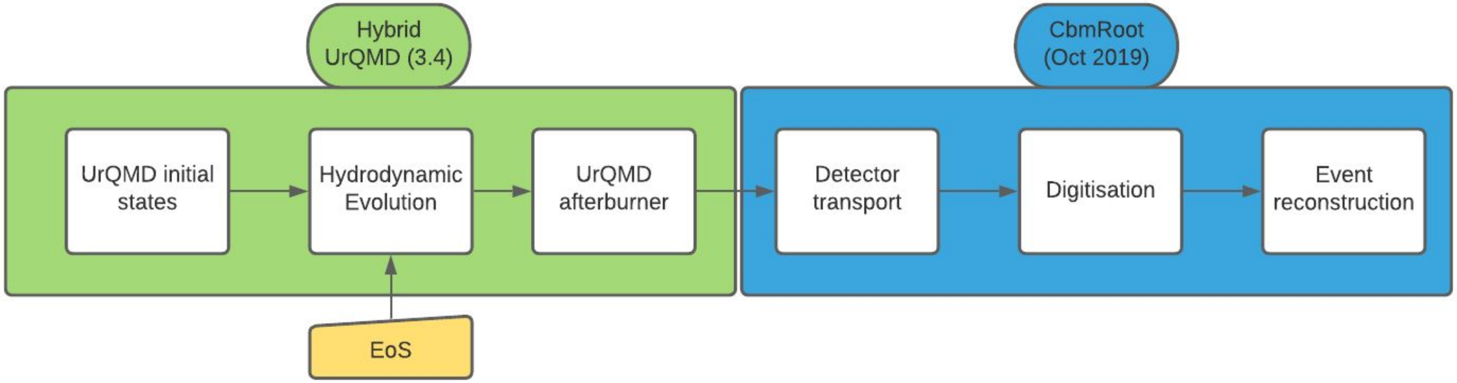




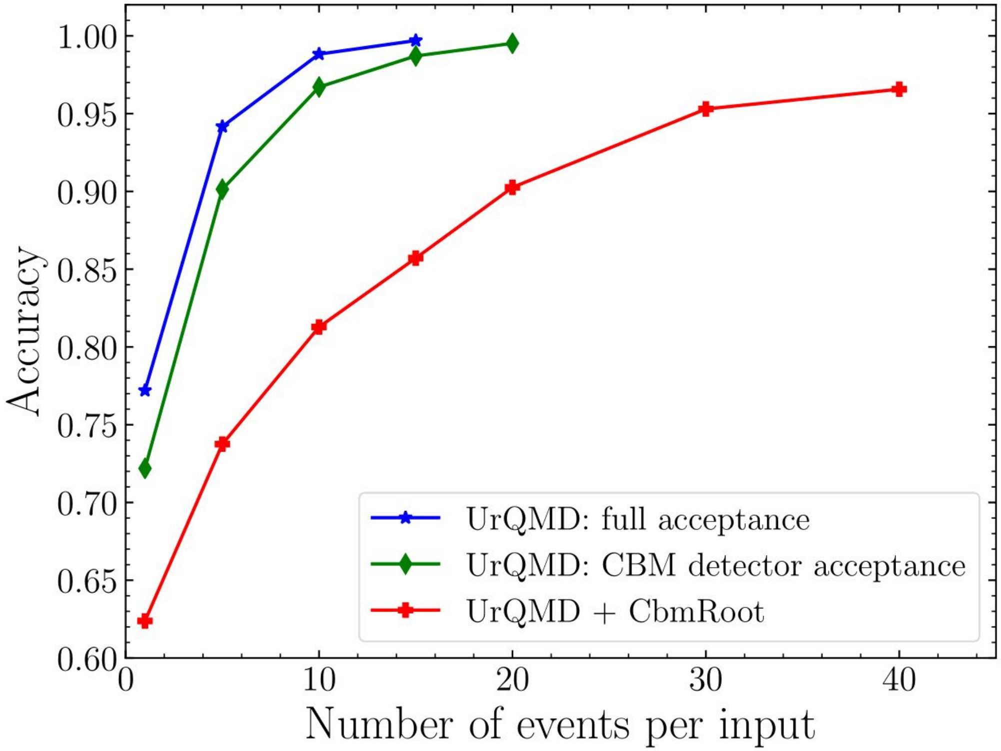
Determination of QCD EoS: fundamental goal for Heavy-ion experiments

Identifying phase transition with PointNet

JHEP 10 (2021) 184
PoS FAIRness2022 (2023) 040



- >95 % accuracy with just 40 events!
  - realistic scenario



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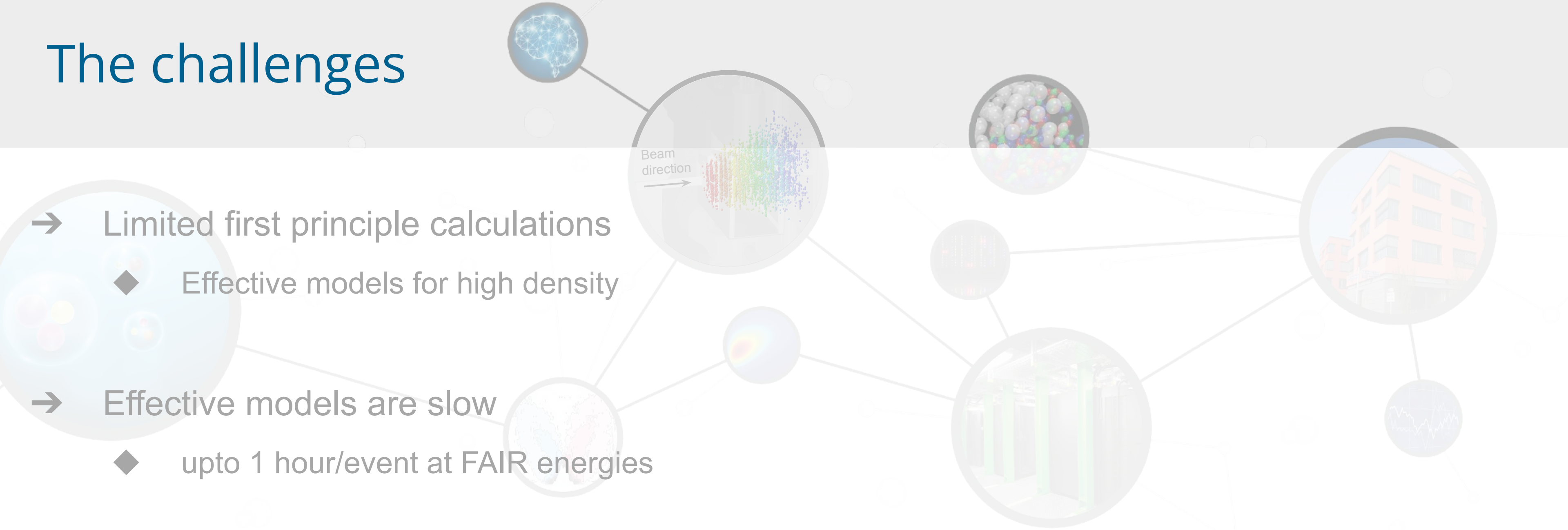

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AI based surrogate models for faster analysis?

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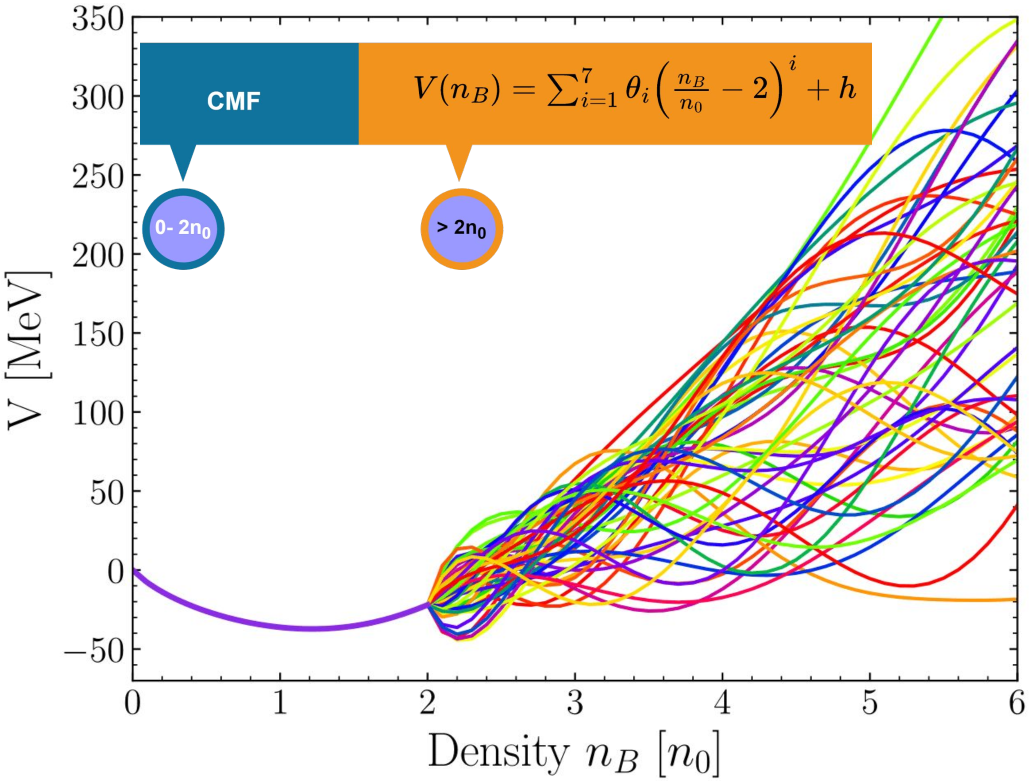
Bayesian inference of the EoS

PRL 131 (20), 202303

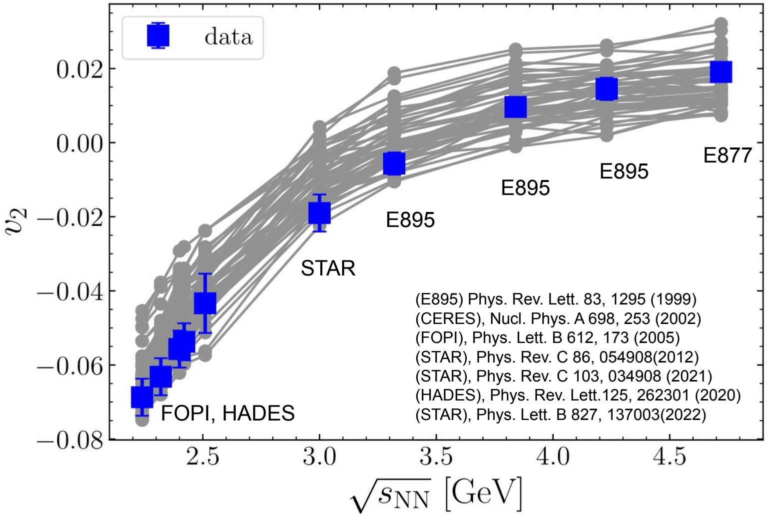
- EoS as density dependent potentials
- 7th degree polynomial for potential above $2n_0$

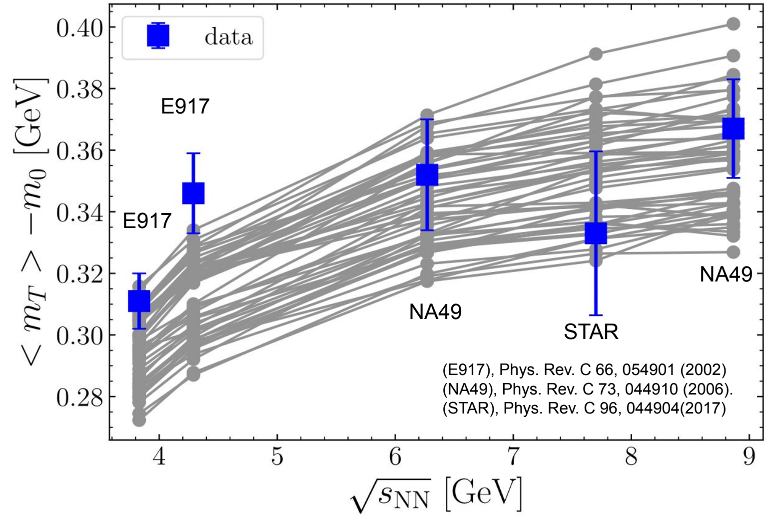


We constrain the polynomial coefficients

$$\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_7\}$$

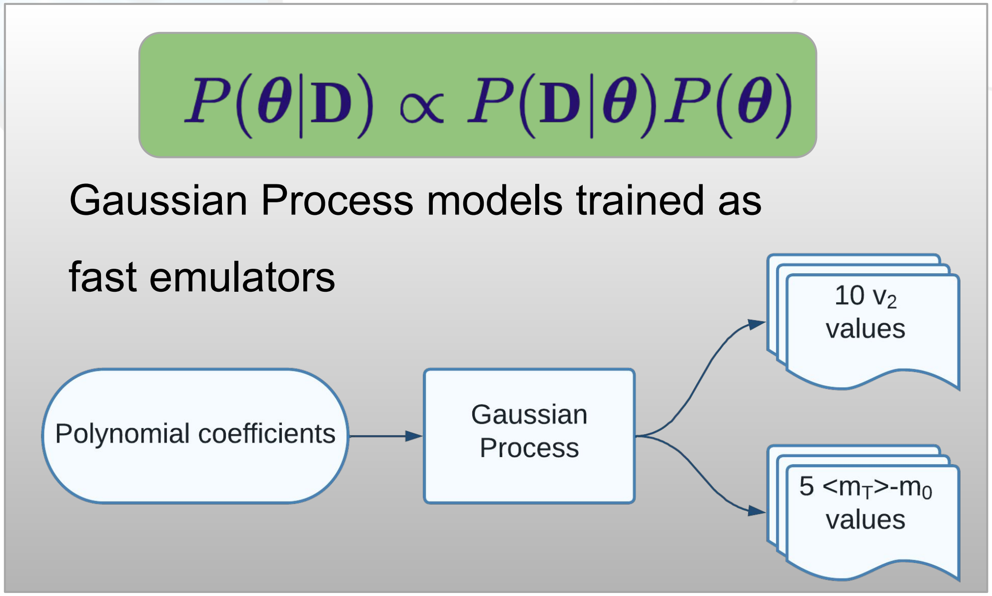
The data, $\mathbf{D} = \{v_2^{exp}, \langle m_T \rangle^{exp} - m_0\}$ is used to constrain the parameters $\boldsymbol{\theta}$





The inferred posteriors

PRL 131 (20), 202303



$$P(\boldsymbol{\theta}|\mathbf{D}) \propto P(\mathbf{D}|\boldsymbol{\theta})P(\boldsymbol{\theta})$$

Gaussian Process models trained as fast emulators

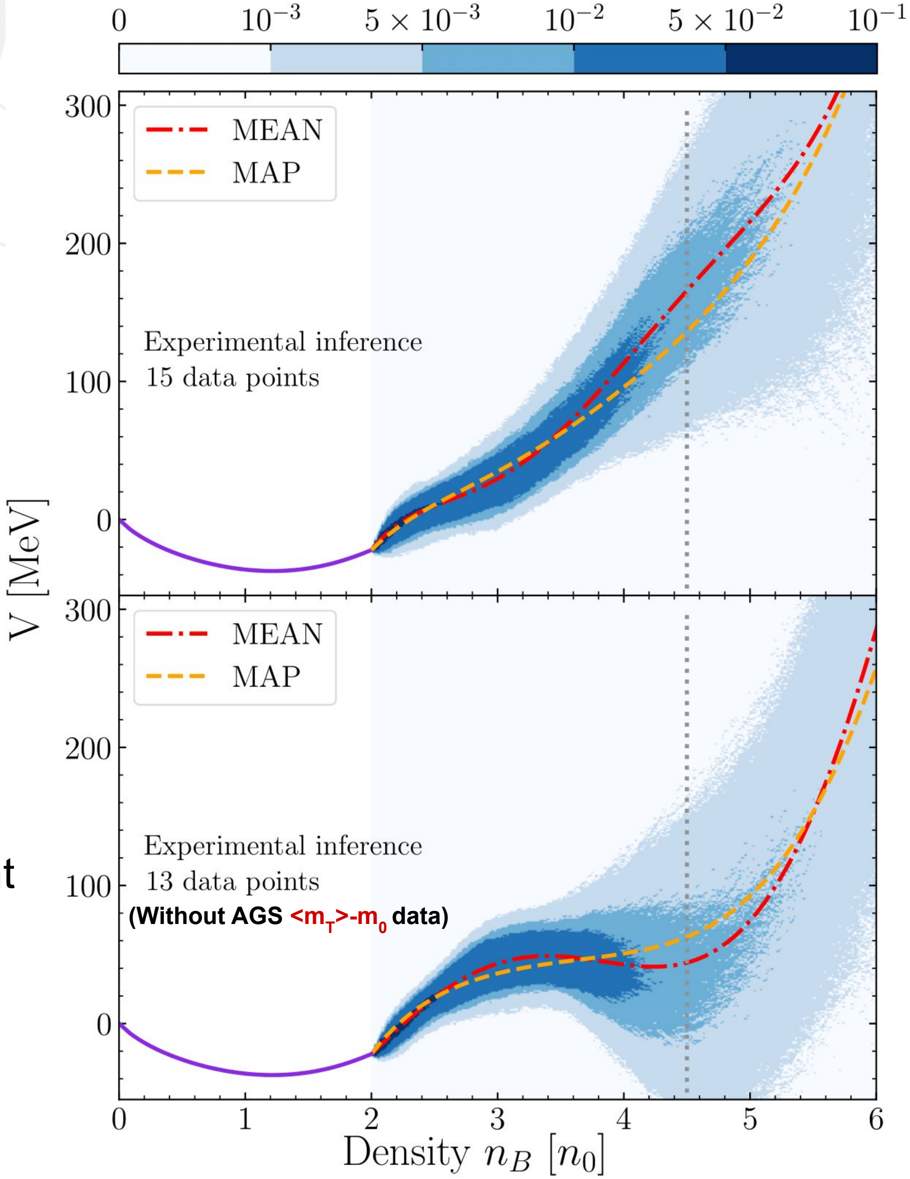
Polynomial coefficients

Gaussian Process

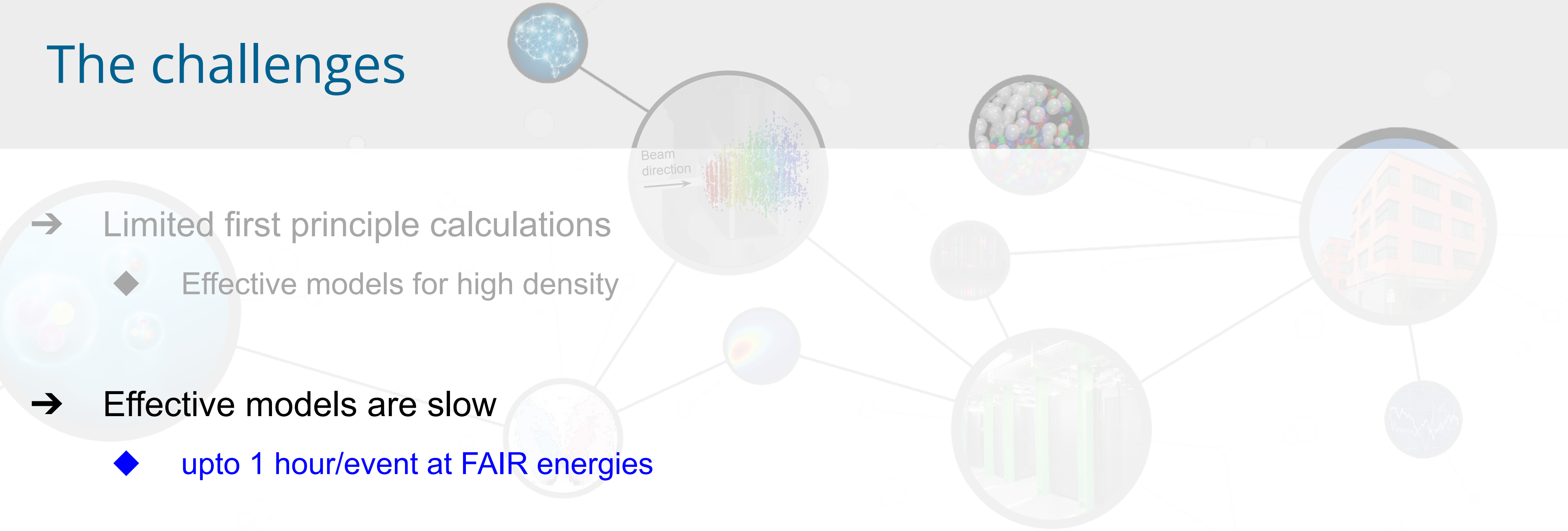
10 v_2 values

5 $\langle m_T \rangle - m_0$ values

- Good constraints up to 4 n_0
- Constraints above 3 n_0 is strongly data dependent



The challenges



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Realistic, Fast, AI based emulators?

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Generating collisions with DL

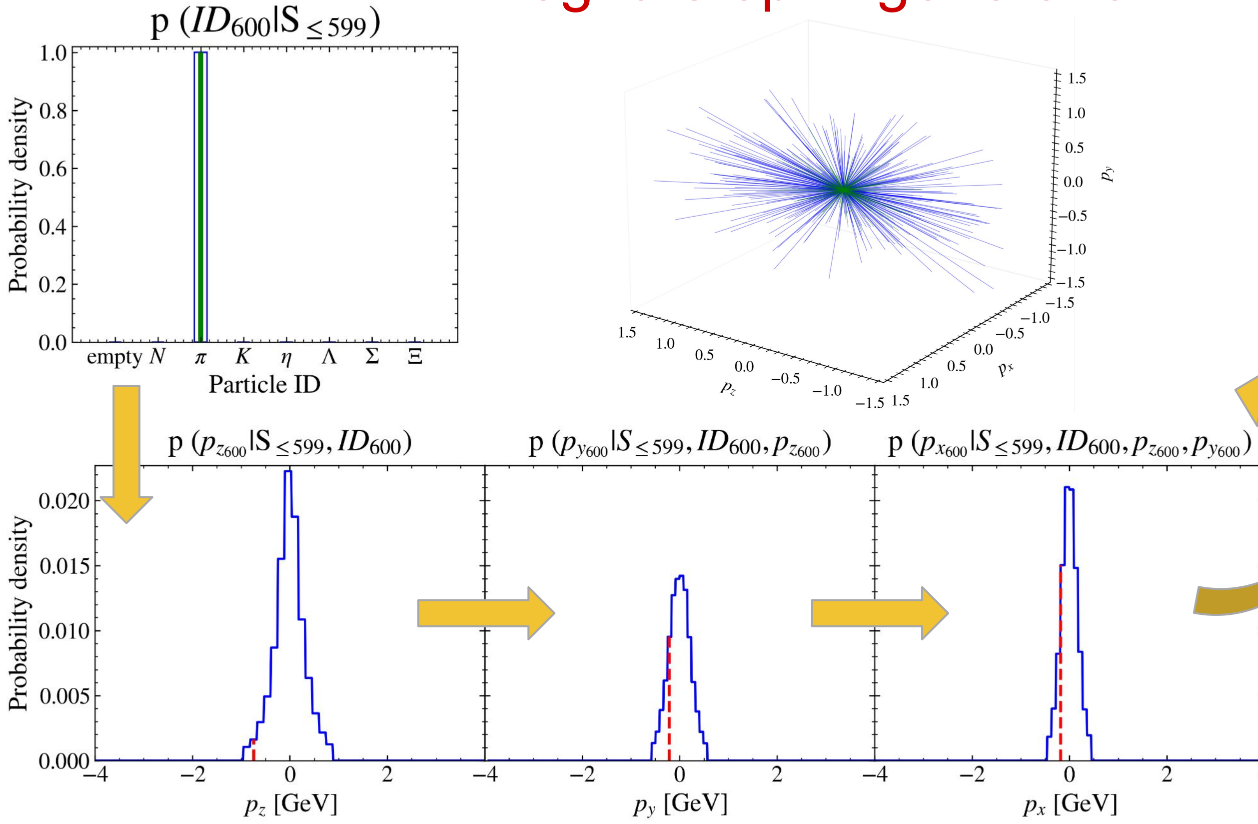
What’s necessary:

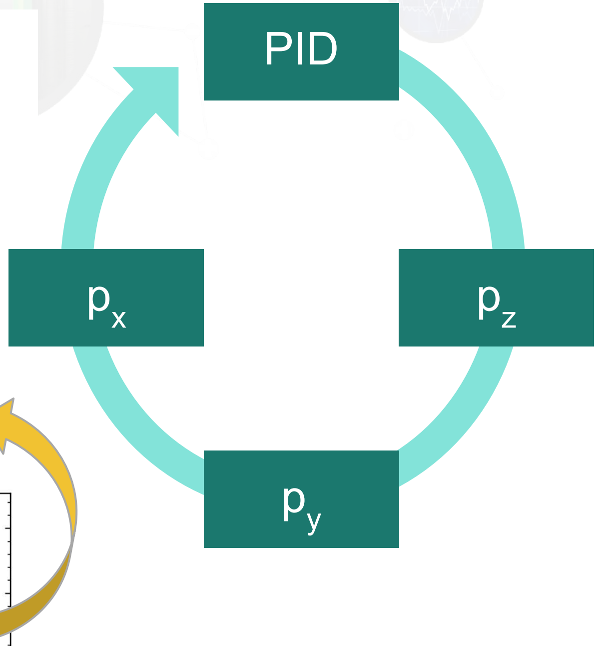
- event by event generation
- generate large multiplicity ~1000
- capture correlations

Autoregressive point cloud generation

- 7 particle species
- A particle:
  - PID, p_x, p_y, p_z

eg: a step in generation





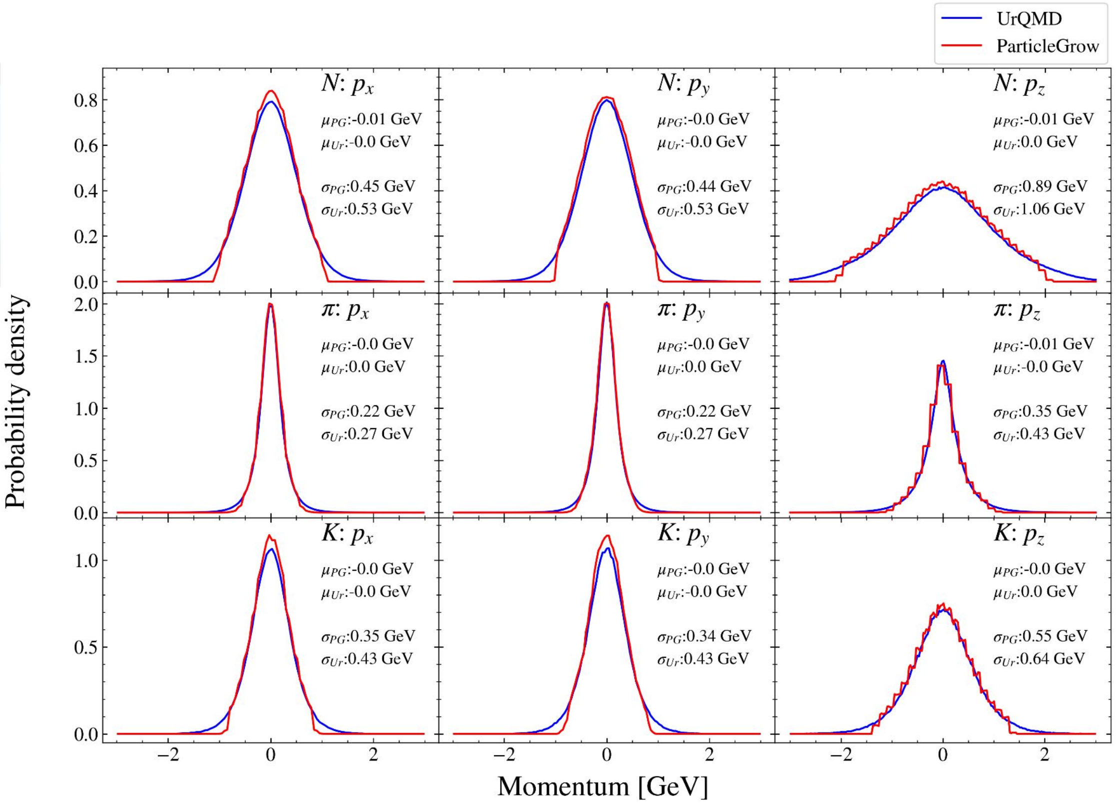
PID

p_z

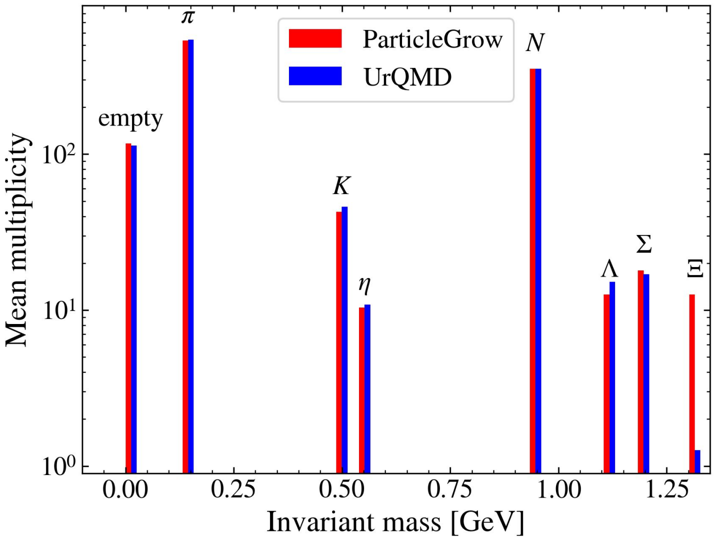
p_y

p_x

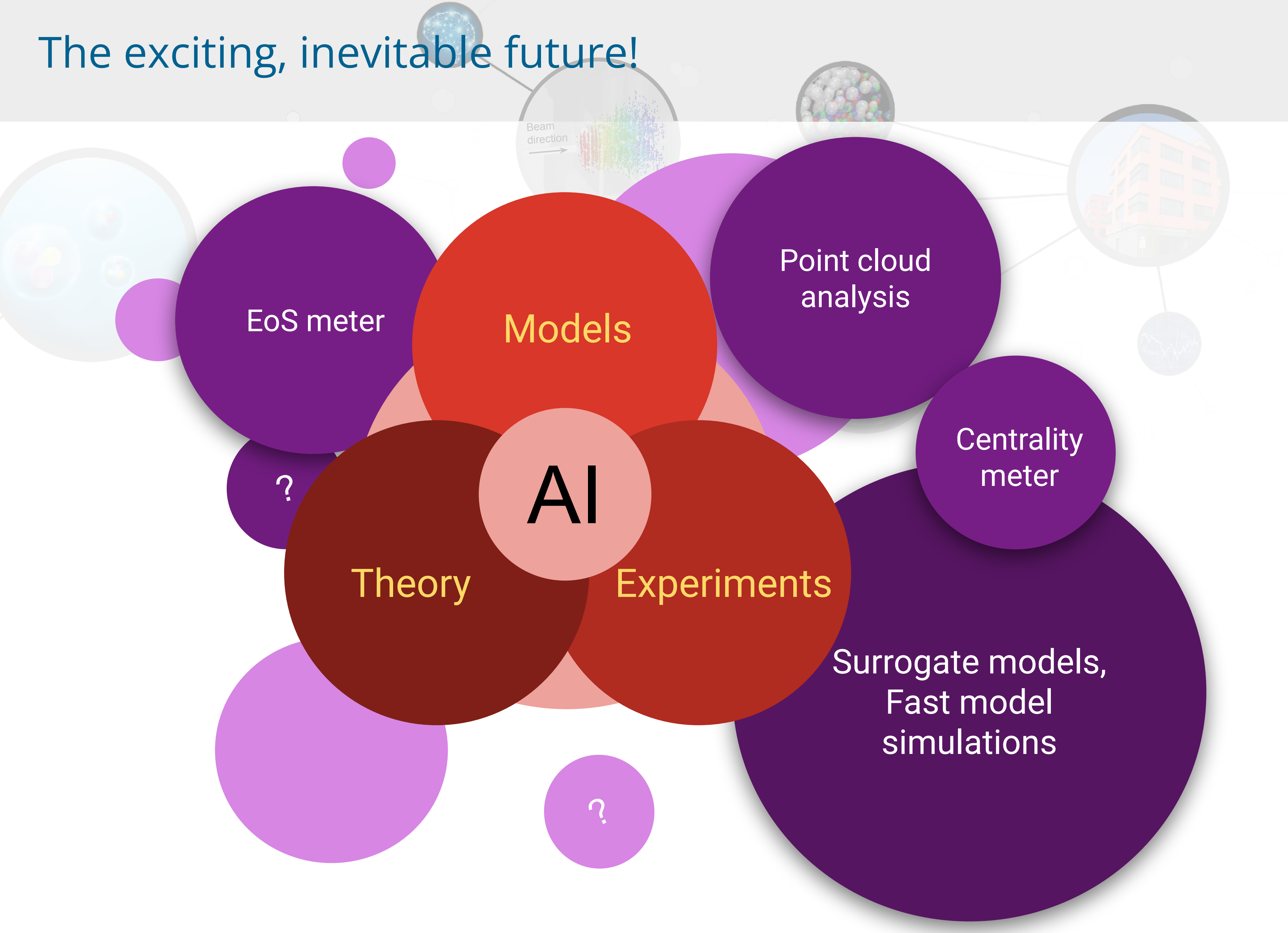
Performance of the model



- Momentum distributions are well captured
- everything except *Ξ* agrees well to ground truth



The exciting, inevitable future!



EoS meter

Models

Point cloud analysis

Centrality meter

?

AI

Theory

Experiments

Surrogate models, Fast model simulations

?