ParticleGrow: Event by event simulation of heavy-ion collisions via autoregressive point cloud generation

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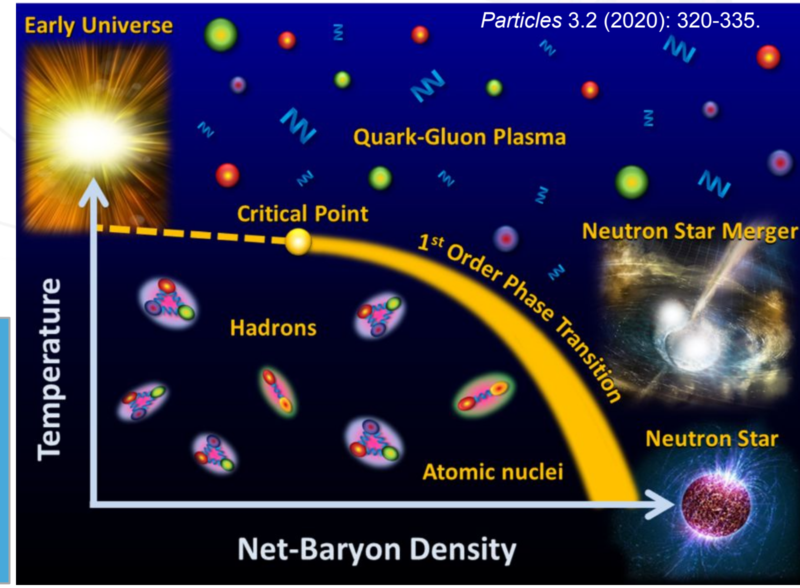
Studying strongly interacting matter

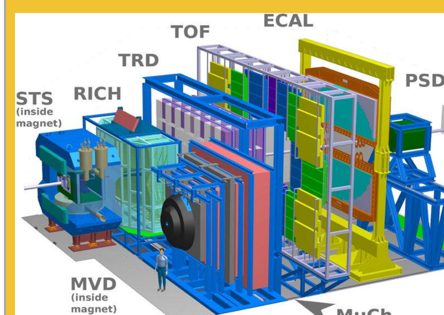
- Heavy-ion collisions probe the QCD phase diagram
- creates matter with extreme temperatures and/or densities



Experiments

e.g. CBM @ FAIR

- SIS-100, Darmstadt
- 10^7 events/ s



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Model simulations

- microscopic models eg: UrQMD
- hydrodynamics
- hybrid models
  - **~1 event/hr**

Observables

e.g. collective flow, fluctuations

Physics inference

- Multi-param fits, bayesian inference
- e.g. EoS, Phase transitions

Fast model simulations are necessary to fully exploit future experiments

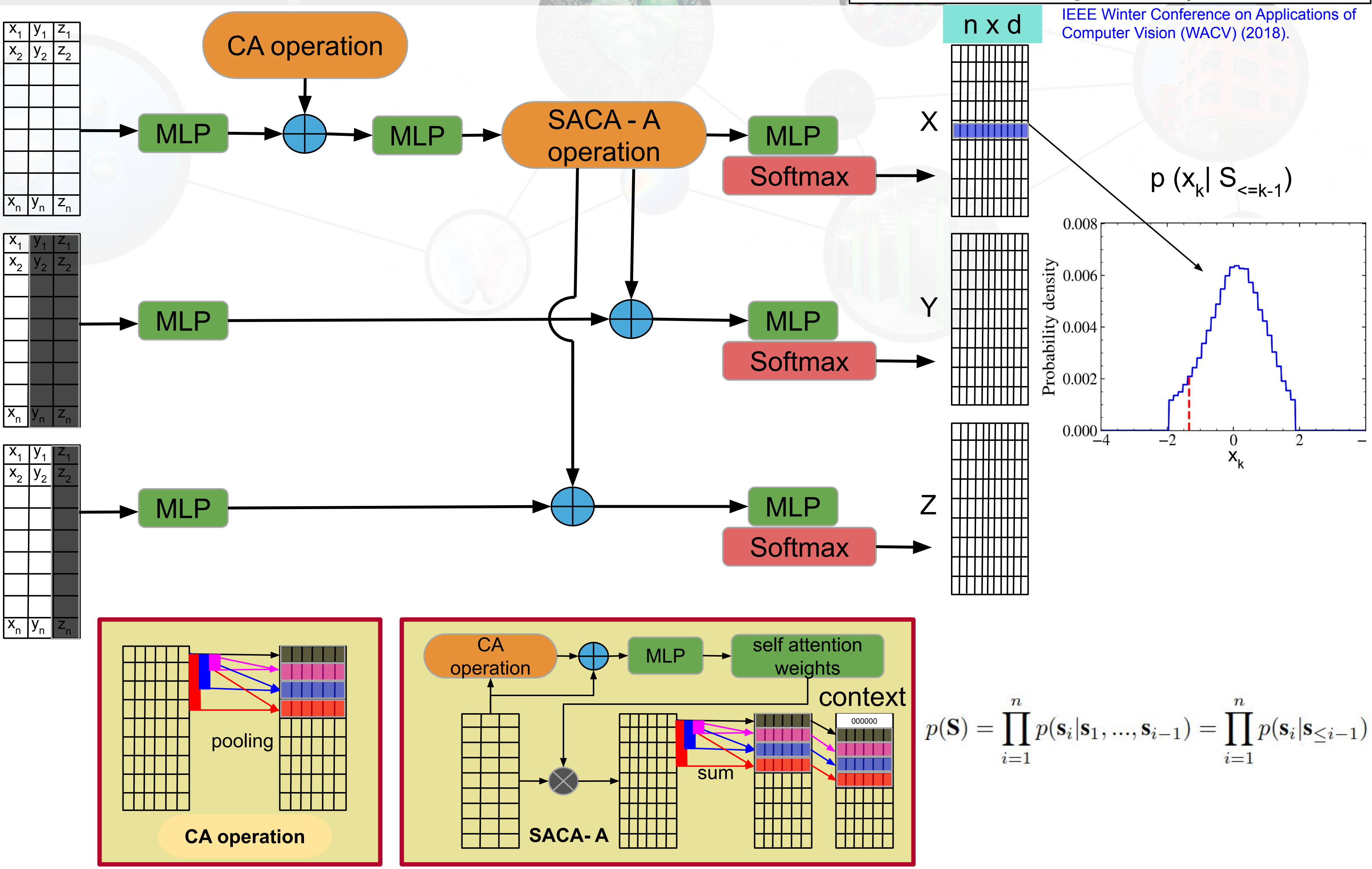
Autoregressive point cloud generation

PointGrow: Autoregressively Learned Point Cloud Generation with Self-Attention

Yongbin Sun[1], Yue Wang[1], Ziwei Liu[2]*, Joshua E Siegel[3] & Sanjay E Sarma[1]

1. Massachusetts Institute of Technology 2. The Chinese University of Hong Kong 3. Michigan State University

IEEE Winter Conference on Applications of Computer Vision (WACV) (2018).



$$p(\mathbf{S}) = \prod_{i=1}^{n} p(\mathbf{s}_i|\mathbf{s}_1, ..., \mathbf{s}_{i-1}) = \prod_{i=1}^{n} p(\mathbf{s}_i|\mathbf{s}_{\leq i-1})$$

Generating “UrQMD like events”

ityp	nucleon	ityp	delta	ityp	lambda	ityp	sigma	ityp	xi	ityp	omega
1	N_{938}	17	Δ_{1232}	27	Λ_{1116}	40	Σ_{1192}	49	Ξ_{1317}	55	Ω_{1672}
2	N_{1440}	18	Δ_{1600}	28	Λ_{1405}	41	Σ_{1385}	50	Ξ_{1530}		
3	N_{1520}	19	Δ_{1620}	29	Λ_{1520}	42	Σ_{1660}	51	Ξ_{1690}		
4	N_{1535}	20	Δ_{1700}	30	Λ_{1600}	43	Σ_{1670}	52	Ξ_{1820}		
5	N_{1650}	21	Δ_{1900}	31	Λ_{1670}	44	Σ_{1775}	53	Ξ_{1950}		
6	N_{1675}	22	Δ_{1905}	32	Λ_{1690}	45	Σ_{1790}	54	Ξ_{2025}		
7	N_{1680}	23	Δ_{1910}	33	Λ_{1800}	46	Σ_{1915}				
8	N_{1700}	24	Δ_{1920}	34	Λ_{1810}	47	Σ_{1940}				
9	N_{1710}	25	Δ_{1930}	35	Λ_{1820}	48	Σ_{2030}				
10	N_{1720}	26	Δ_{1950}	36	Λ_{1830}						
11	N_{1900}			37	Λ_{1890}						
12	N_{1990}			38	Λ_{2100}						
13	N_{2080}			39	Λ_{2110}						
14	N_{2190}										
15	N_{2200}										
16	N_{2250}										

UrQMD

Table 1: Baryon-itypes used in **UrQMD**. Antibaryons carry a negative sign.

ityp	0^{-+}	ityp	1^{--}	ityp	0^{++}	ityp	1^{++}	ityp	charmed
101	π	104	ρ	111	a_0	114	a_1	133	D
106	K	108	K^*	110	K_0^*	113	K_1^*	134	D^*
102	η	103	ω	105	f_0	115	f_1	135	J/Ψ
107	η'	109	ϕ	112	f_0^*	116	f_1'	136	χ_c
ityp	1^{+-}	**ityp**	2^{++}	**ityp**	$(1^{--})^*$	**ityp**	$(1^{--})^{**}$	137	Ψ'
122	b_1	118	a_2	126	ρ_{1450}	130	ρ_{1700}	138	D_s
121	K_1	117	K_2^*	125	K_{1410}^*	129	K_{1680}^*	139	D_s^*
123	h_1	119	f_2	127	ω_{1420}	131	ω_{1662}		
124	h_1'	120	f_2'	128	ϕ_{1680}	132	ϕ_{1900}		

Table 2: Meson-itypes in **UrQMD**, sorted with respect to spin and parity, included into the **UrQM** model. Mesons with strangeness -1 (or charm -1 for itypes > 132) carry a negative sign. See Table

ParticleGrow

N Λ Σ Ξ

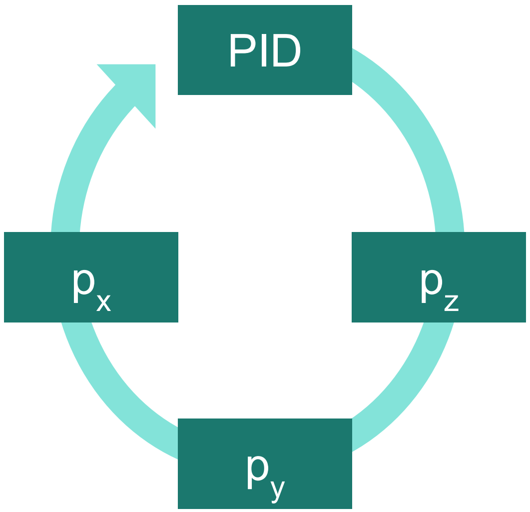
π K η

The data

- UrQMD cascade
- Au- Au , E_{lab}= 10 AGeV, b= 1 fm
- Training: 4000 events
- testing: 6400 events
- We fix the event multiplicity to be 1100
  - 7 particle species
- A particle:
  - PID, p_x, p_y, p_z
- Events with less particles are filled with zeros
  - empty/ dummy particle
- Loss: cross entropy
  - 100 bins for momentum distributions
  - 8 bins for PID

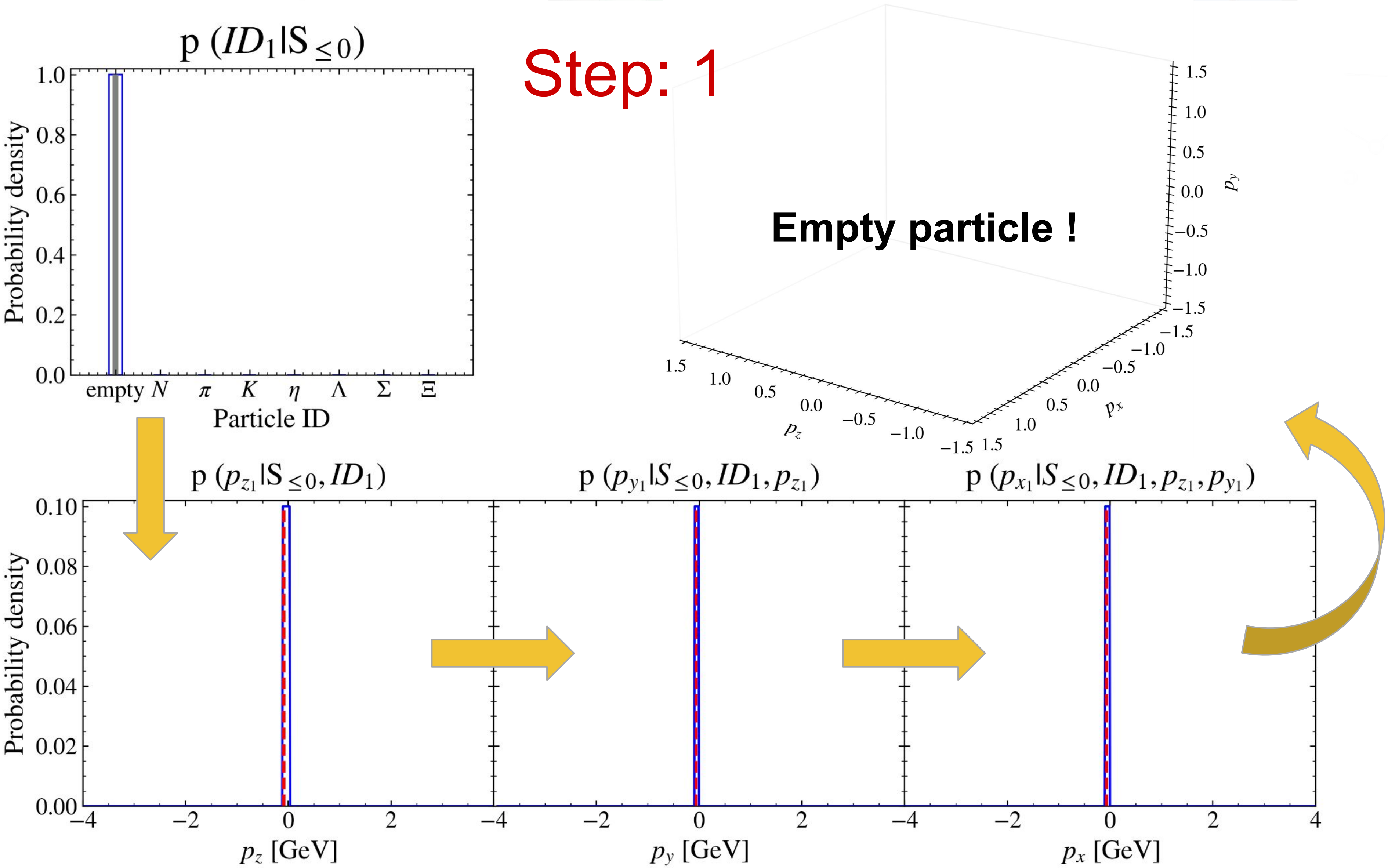
An event in point cloud representation

ID_1	p_{z1}	p_{y1}	p_{X1}
ID_2	p_{z2}	p_{y2}	p_{X2}
ID_3	p_{z3}	p_{y3}	p_{X3}
ID_4	p_{z4}	p_{y4}	p_{X4}
. .			
ID_{1100}	p_{z1100}	p_{y1100}	p_{X1100}



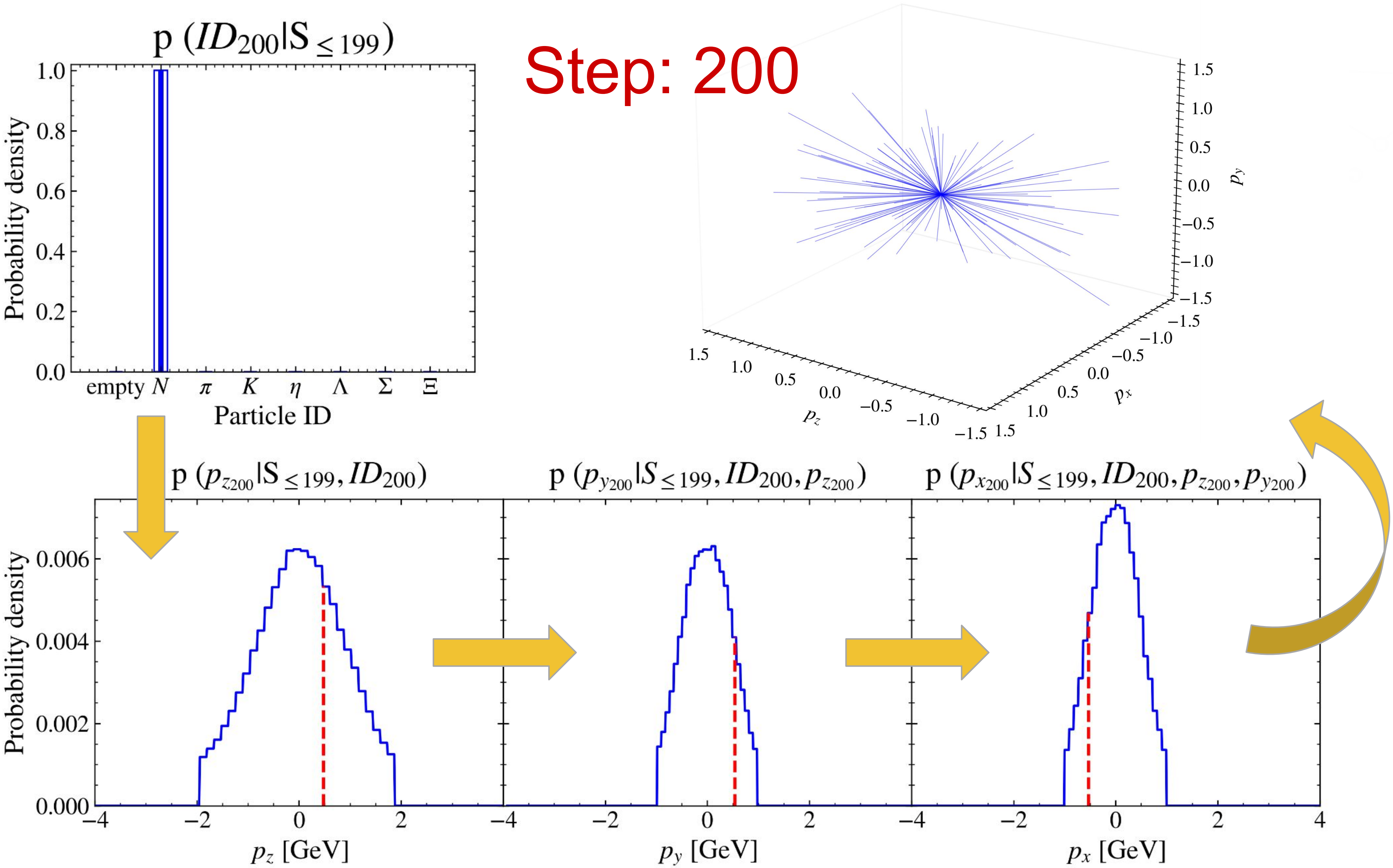
Generation

Step: 1

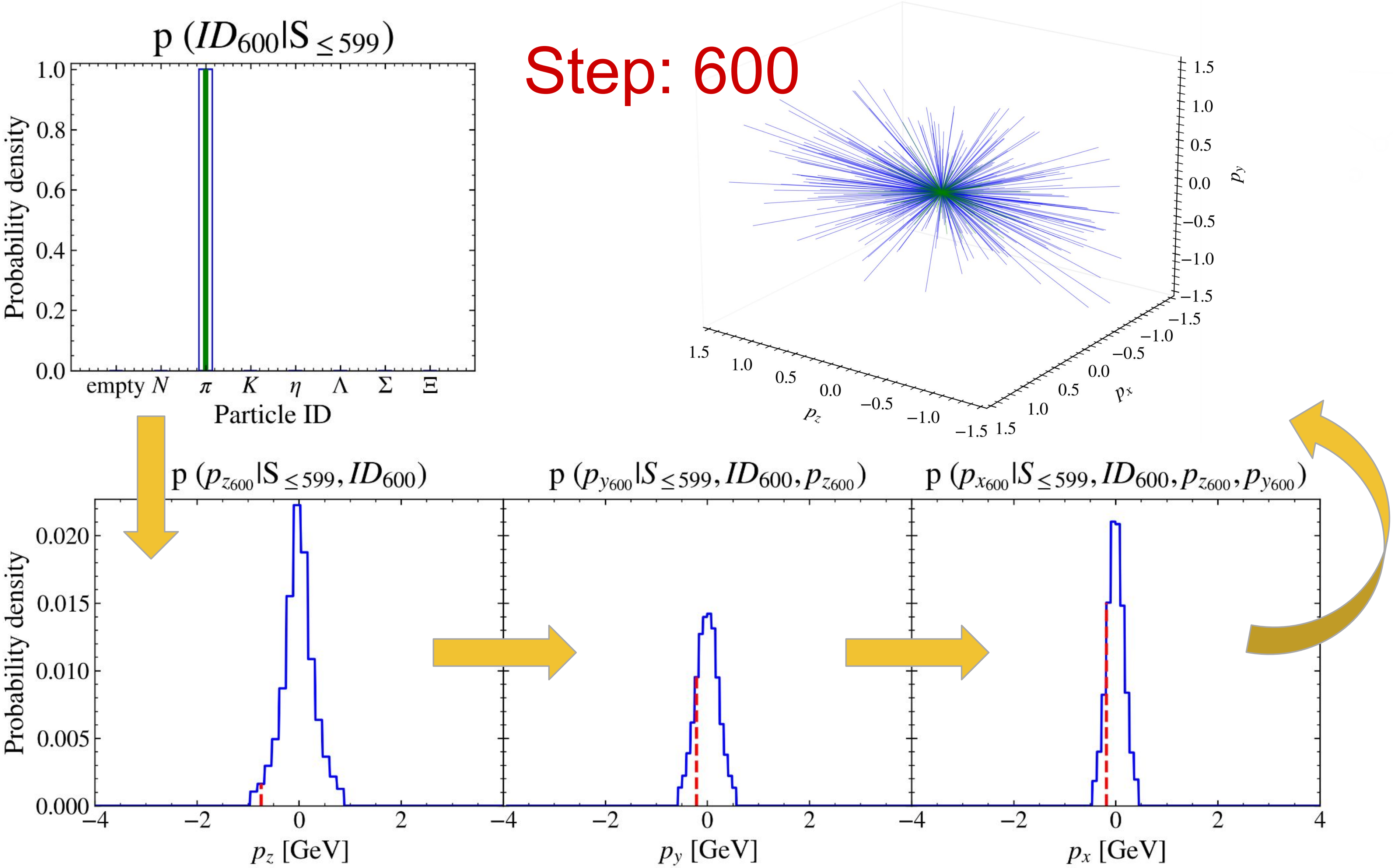


Generation

Step: 200

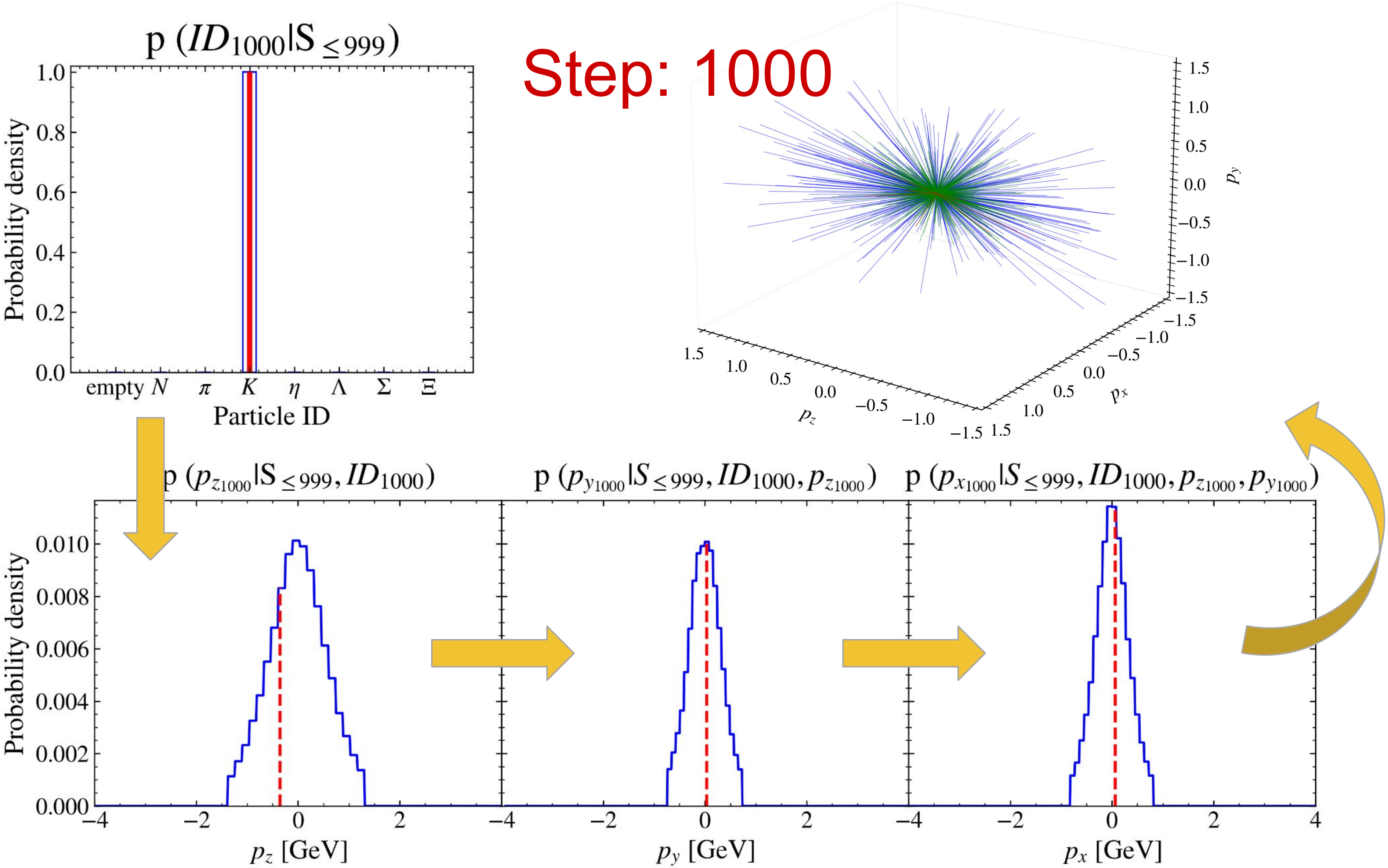


Generation



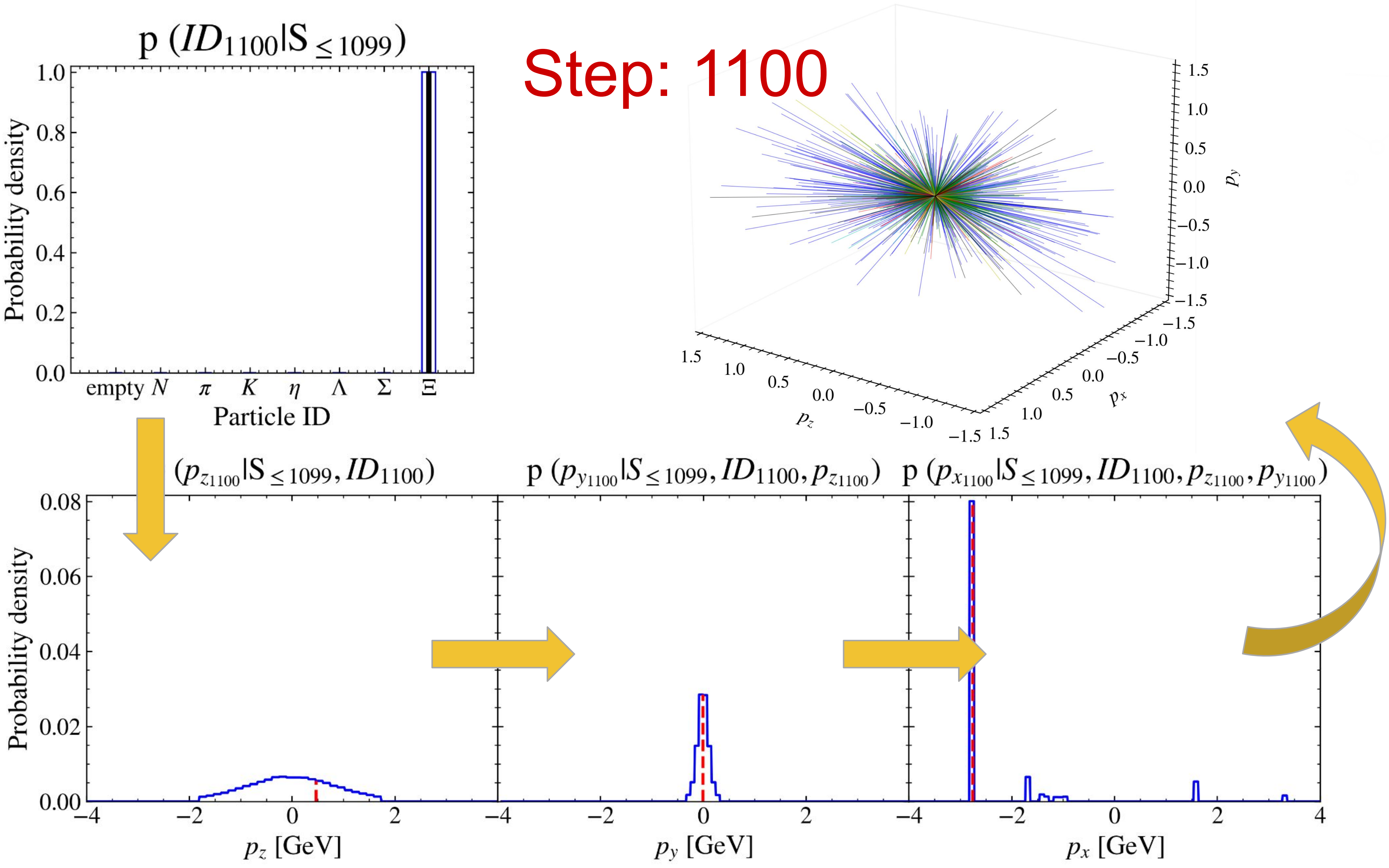
$p\,(ID_{600}|S_{\leq 599})$
Step: 600
Probability density
Particle ID
empty N π K η Λ Σ Ξ
p_z
p_x
p_y
$p\,(p_{z_{600}}|S_{\leq 599}, ID_{600})$
$p\,(p_{y_{600}}|S_{\leq 599}, ID_{600}, p_{z_{600}})$
$p\,(p_{x_{600}}|S_{\leq 599}, ID_{600}, p_{z_{600}}, p_{y_{600}})$
p_z [GeV]
p_y [GeV]
p_x [GeV]

Generation



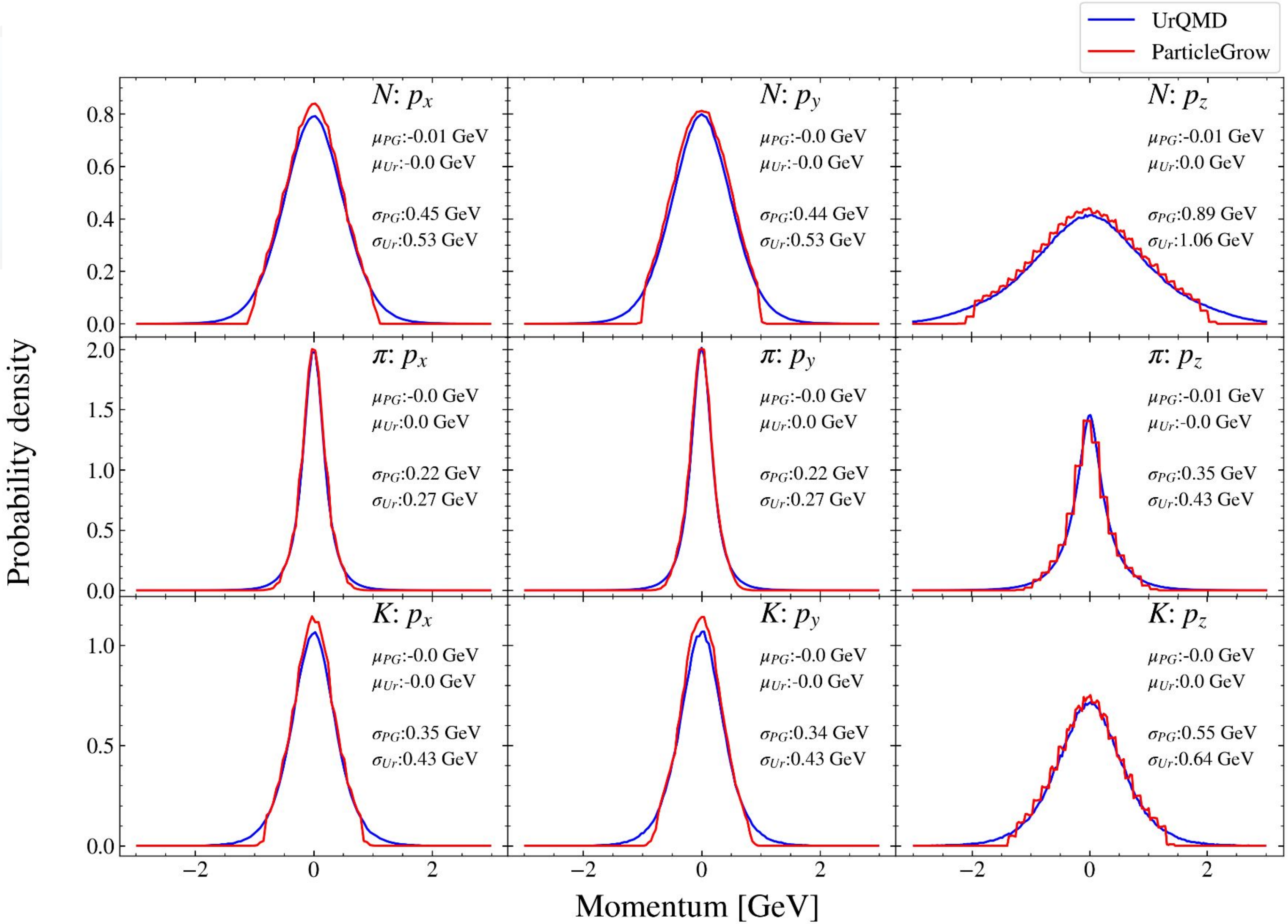
Step: 1000
p $(ID_{1000}|S_{\leq 999})$
Probability density
Particle ID
empty N π K η Λ Σ Ξ
p_x
p_y
p_z
p $(p_{z_{1000}}|S_{\leq 999}, ID_{1000})$
p $(p_{y_{1000}}|S_{\leq 999}, ID_{1000}, p_{z_{1000}})$
p $(p_{x_{1000}}|S_{\leq 999}, ID_{1000}, p_{z_{1000}}, p_{y_{1000}})$
p_z [GeV]
p_y [GeV]
p_x [GeV]

Generation



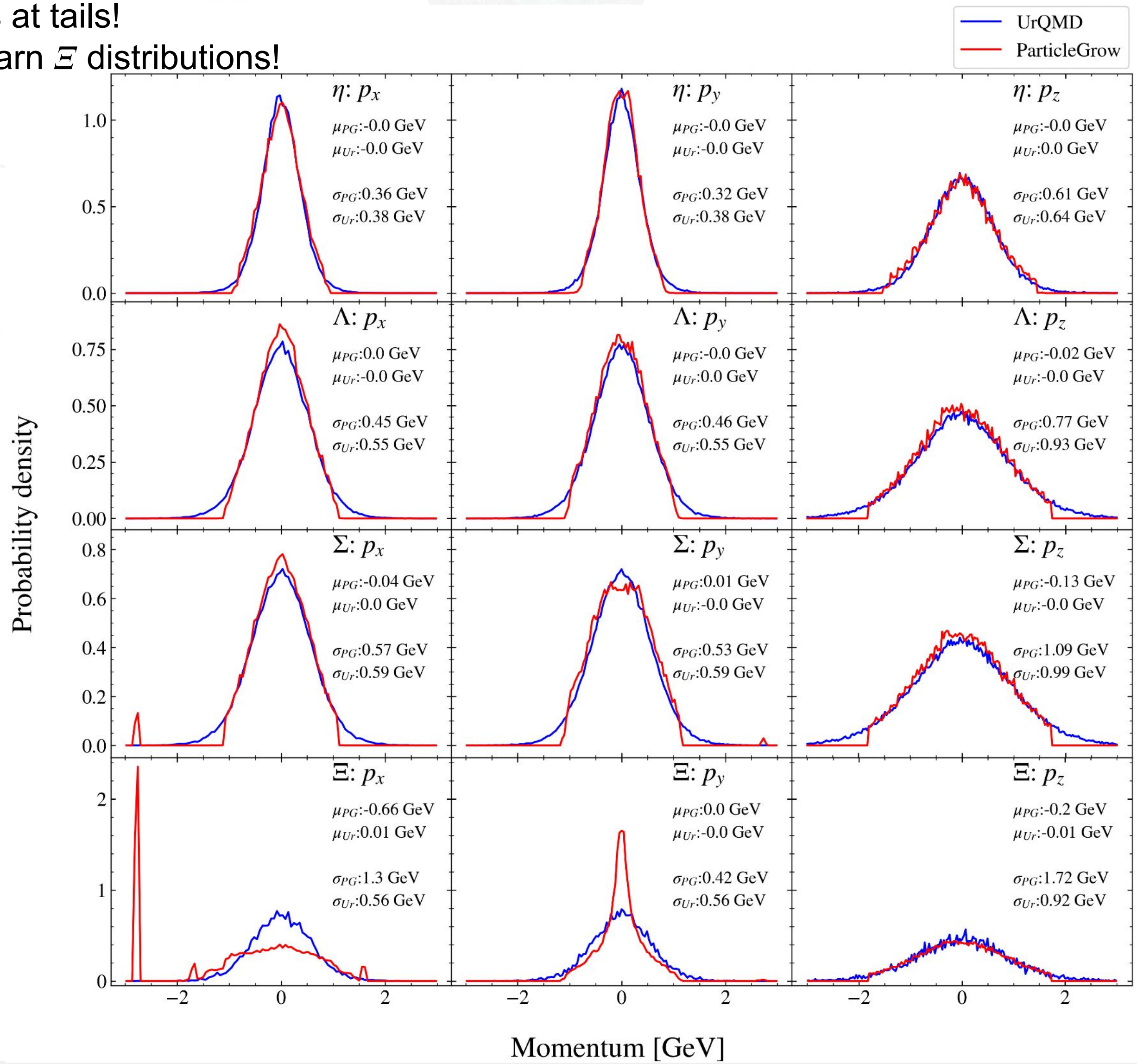
Step: 1100
p $(ID_{1100}|S_{\leq 1099})$
Probability density
Particle ID
empty N π K η Λ Σ Ξ
$(p_{z_{1100}}|S_{\leq 1099}, ID_{1100})$
p $(p_{y_{1100}}|S_{\leq 1099}, ID_{1100}, p_{z_{1100}})$
p $(p_{x_{1100}}|S_{\leq 1099}, ID_{1100}, p_{z_{1100}}, p_{y_{1100}})$
p_z [GeV]
p_y [GeV]
p_x [GeV]
p_x
p_y
p_z

Performance: Momentum distributions

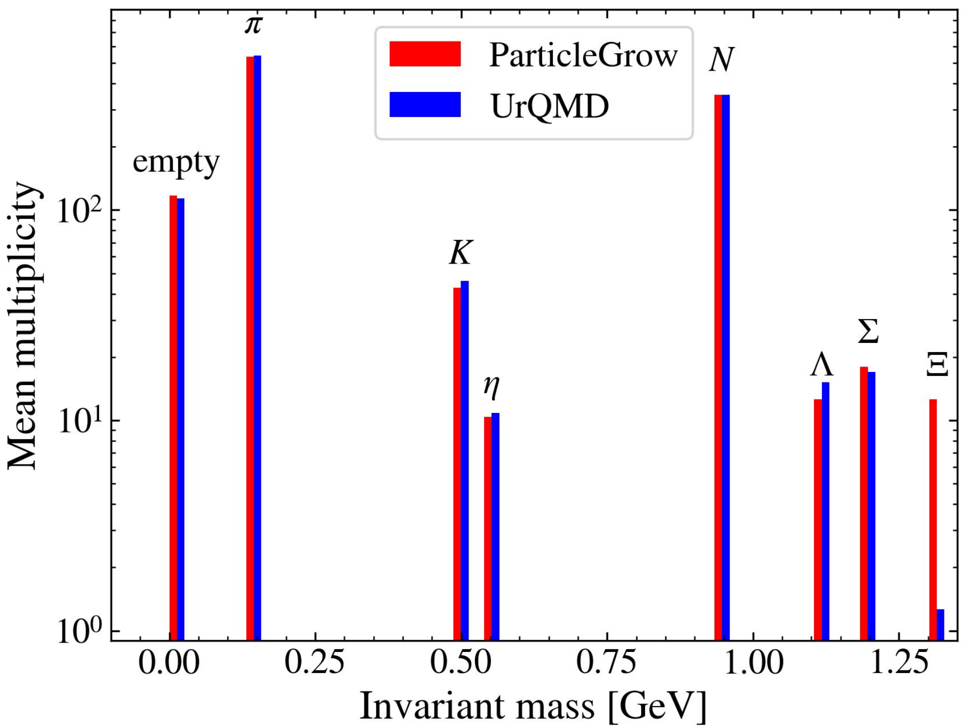


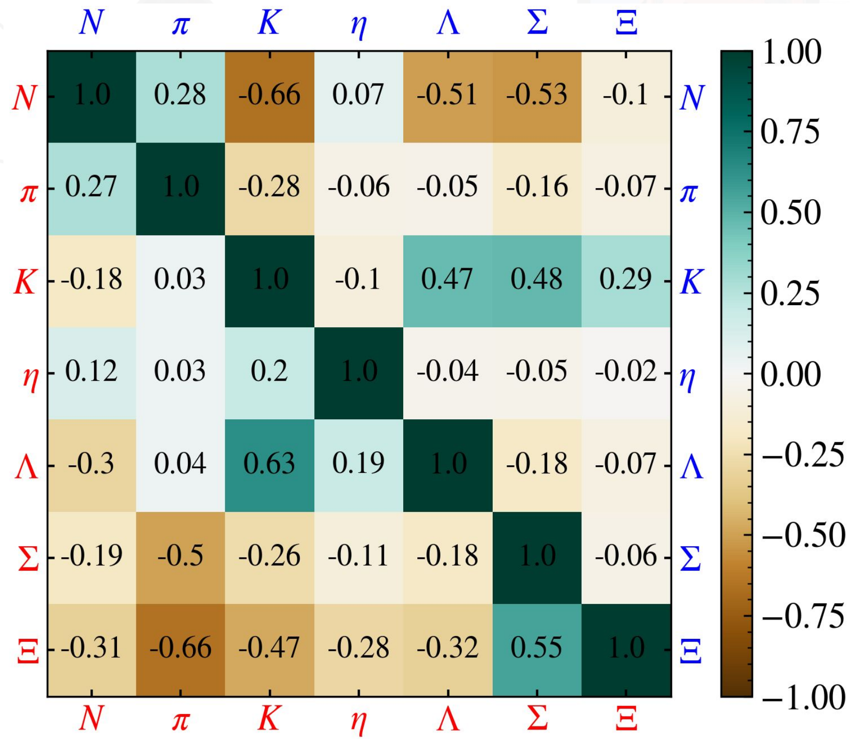
Performance: Momentum distributions

- Well captured for most species
- Deviations at tails!
- Doesn't learn Ξ distributions!



Particle Multiplicity

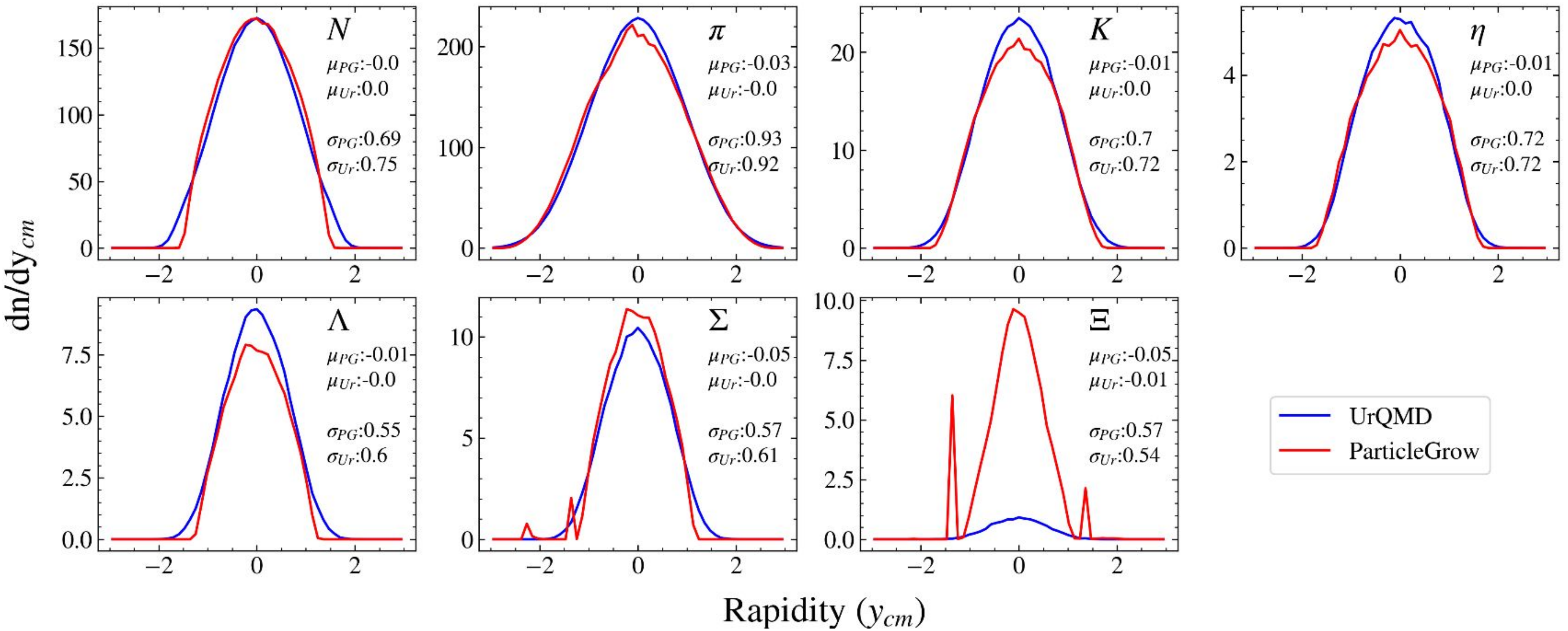




- everything except *Ξ* agrees well to ground truth

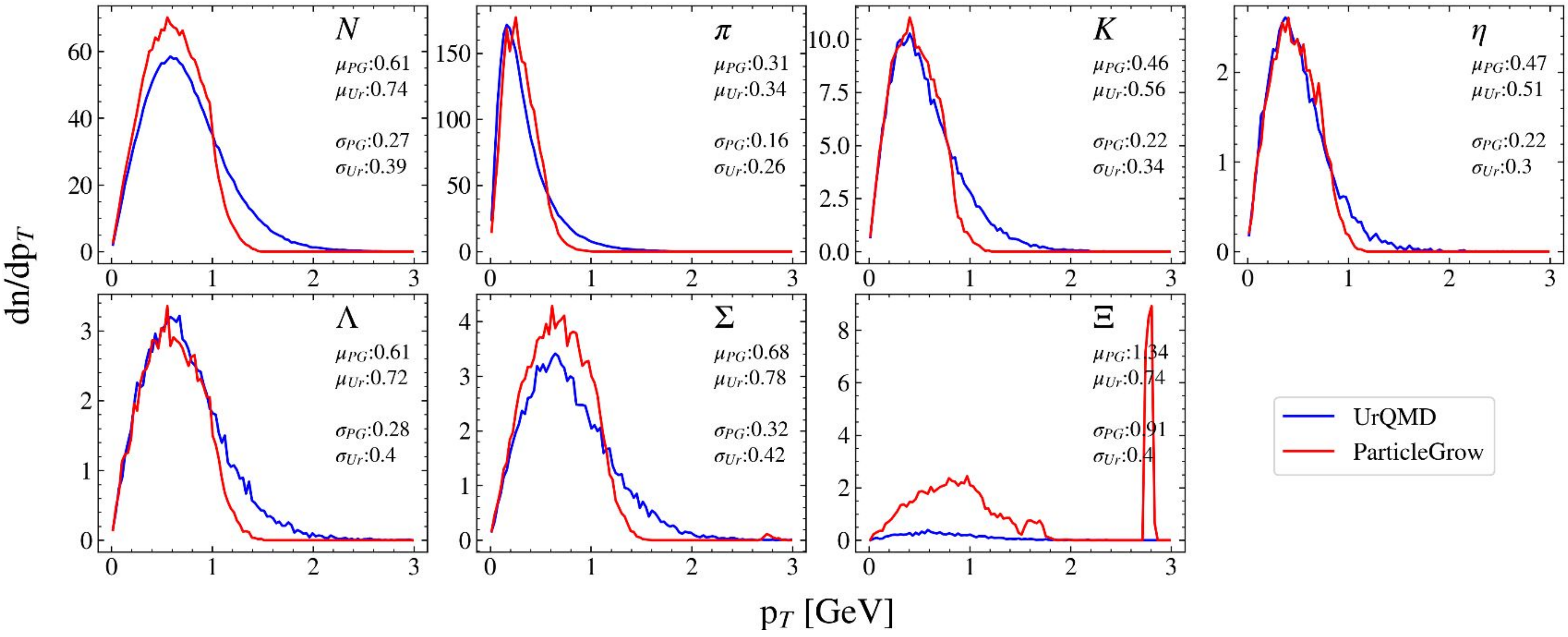
- learns certain correlations of abundant particles
- Also creates several non existent correlations
  - Σ - *Ξ*

Rapidity distributions



- Agrees well to the data except for *Ξ* !

p_T distributions: mid rapidity



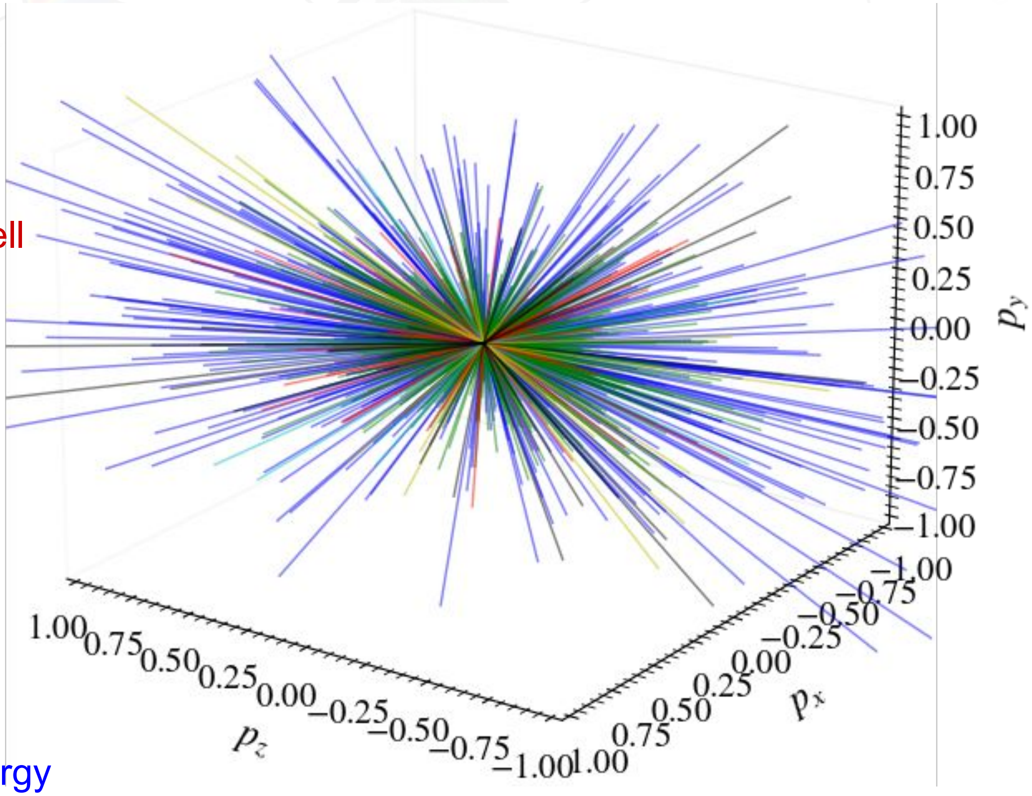
- Deviates at tails but reproduces the mean p_T well for most particles

Outlook

- Learns the mean and variance of the distributions well
- Averaged observables are well reproduced
- certain correlations are well captured

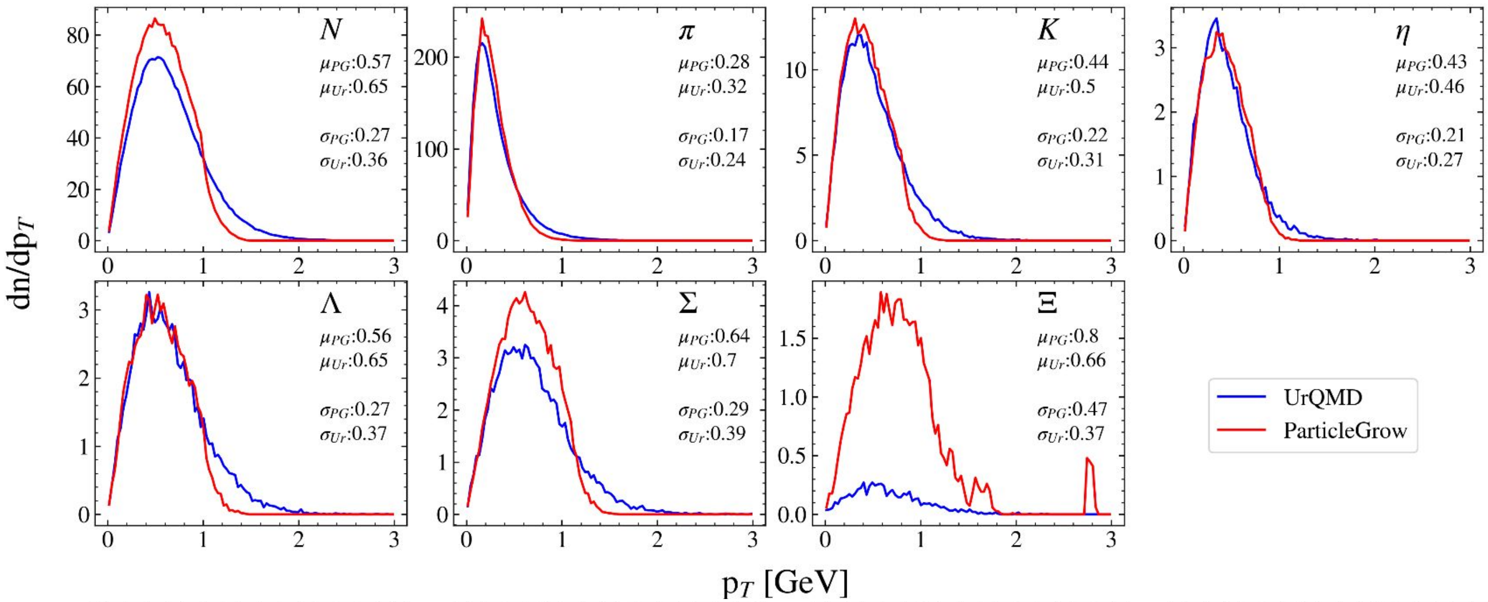
- Also learns also fictitious correlations
- Low multiplicity particles are not learned well
  - only 4000 training events!

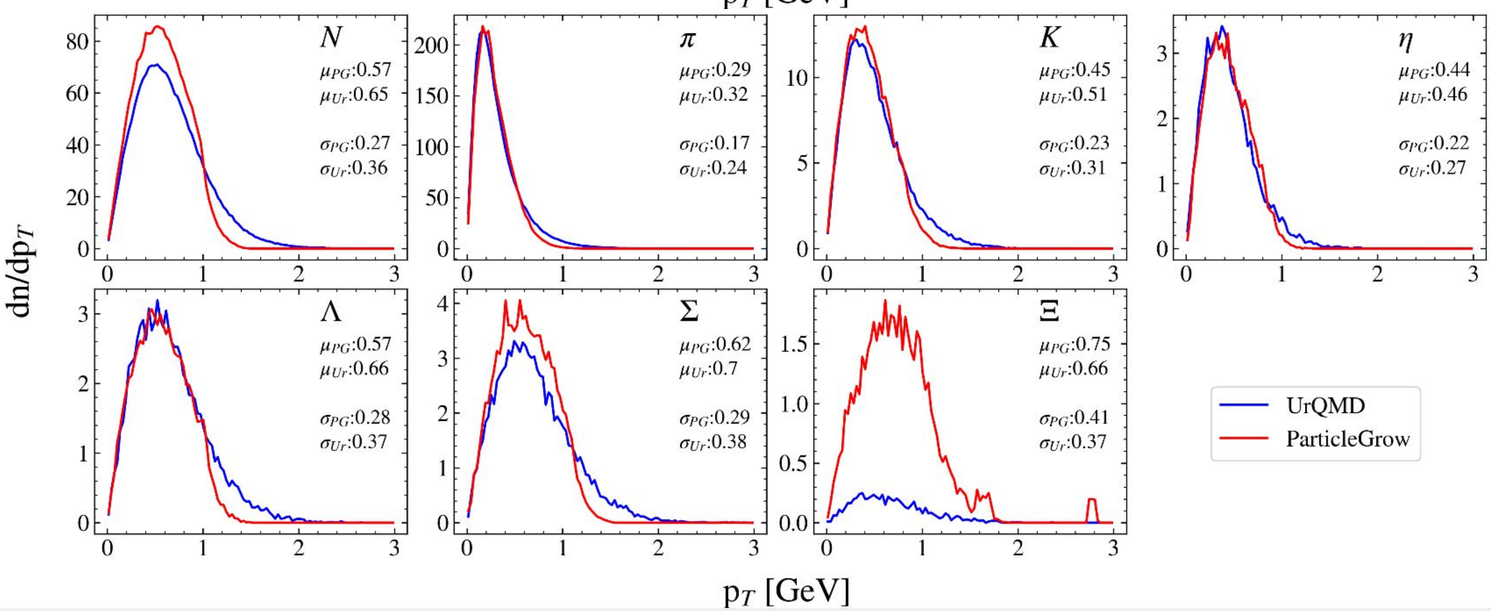
- Increase training dataset
- train on hydro/ hybrid model data
- train for detector response simulation
- conditional generation :
  - centrality, collision system, beam energy



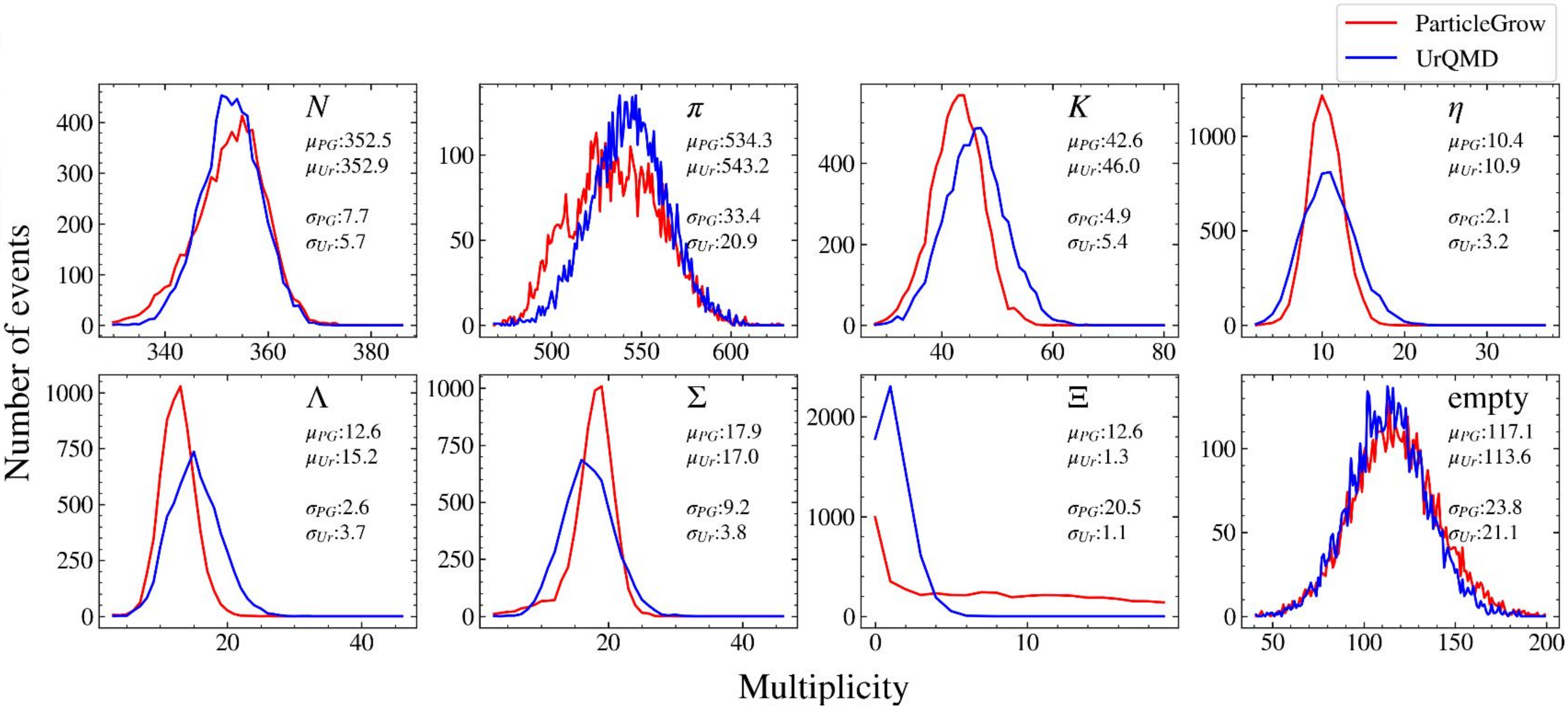
Backup slides

p_T distributions: Forward and backward rapidity





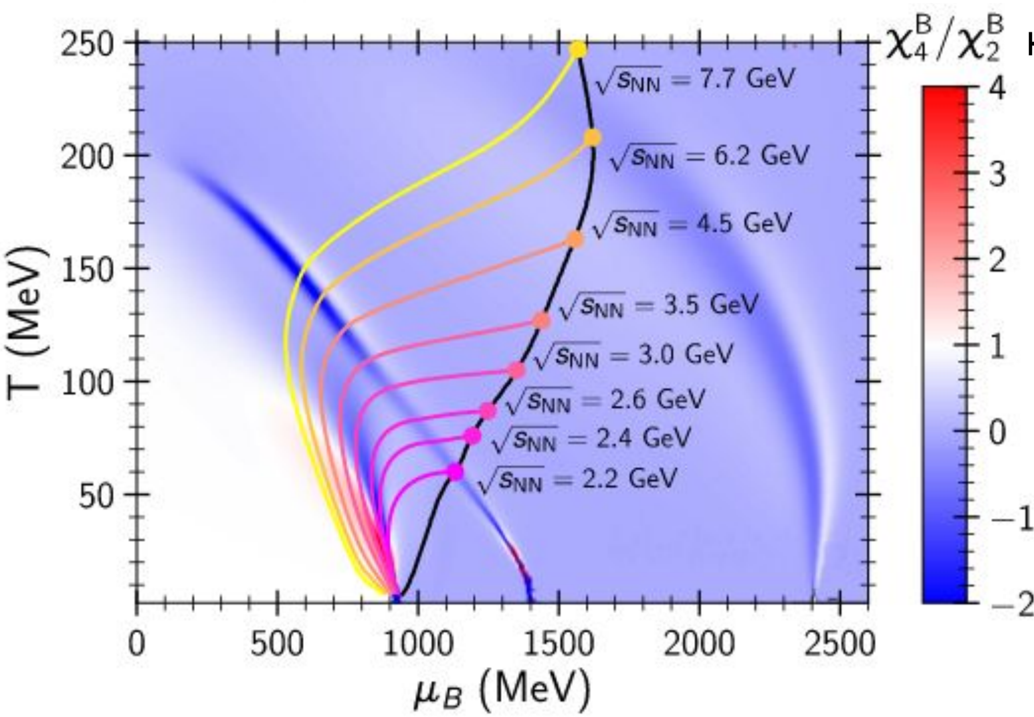
Multiplicity distributions



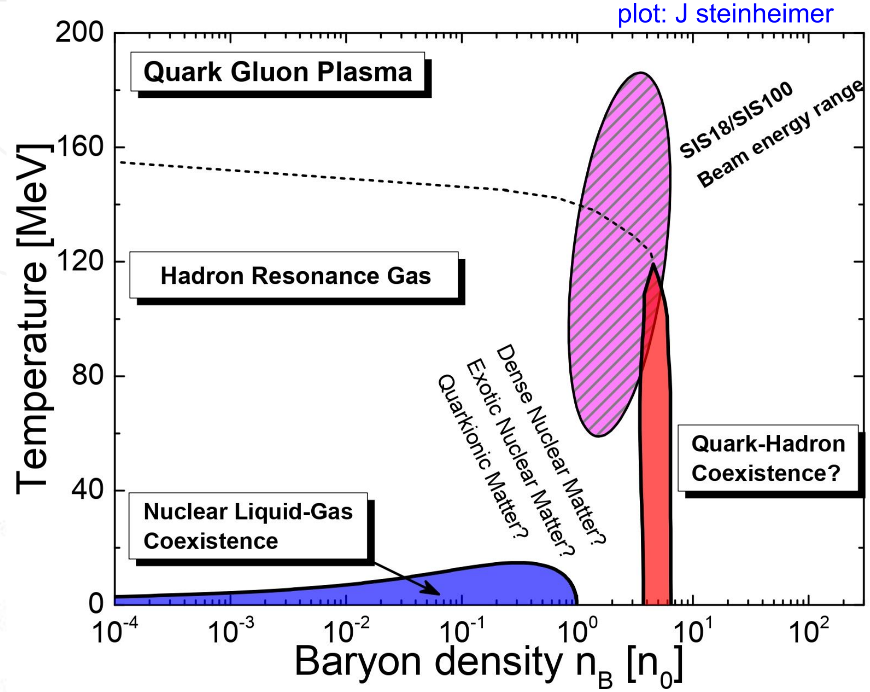
- Event multiplicity matches UrQMD data well
- The means of individual distributions are close to ground truth
- However, the variance and higher moments deviate from true values

The Phase Diagram

PhysRevC.101.034904



plot: J steinheimer



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Sun, Yongbin et al. 2020 IEEE Winter Conference on Applications of Computer Vision (WACV) (2018): 61-70.

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