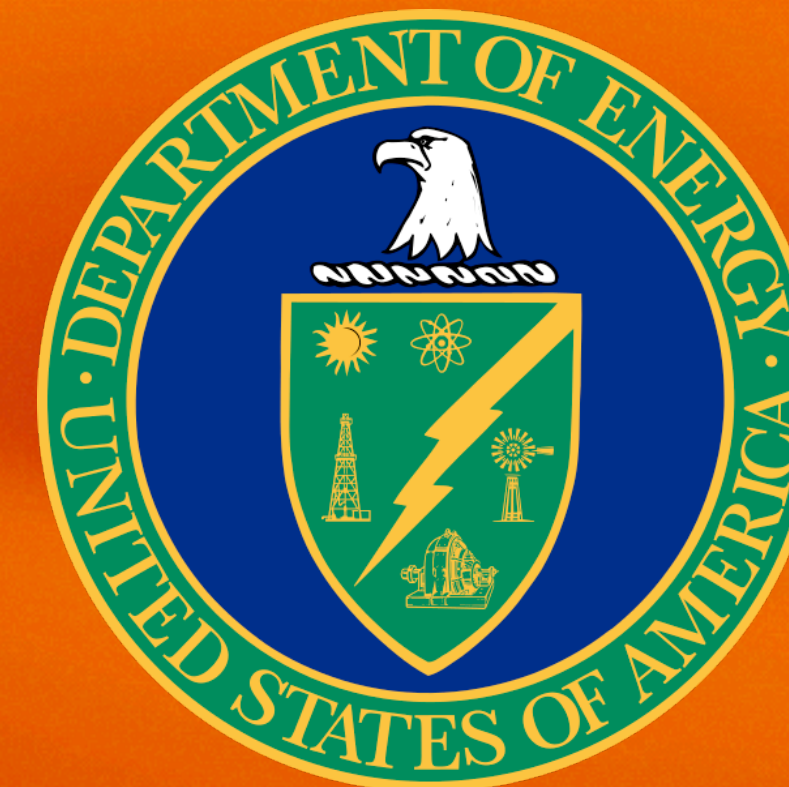


# Boosting Simulations of Hot Nuclear Matter with Machine Learning

**Brandon Boudreaux**

Department of Physics and Astronomy  
Wayne State University

*A special thanks to to The Gordon and Betty Foundation and the American Physical Society to present at the GHP 2023 workshop!*



**WAYNE STATE**  
UNIVERSITY

# Summer 2022 REU

**Chun Shen**

Wayne State University  
Department of Physics  
and Astronomy

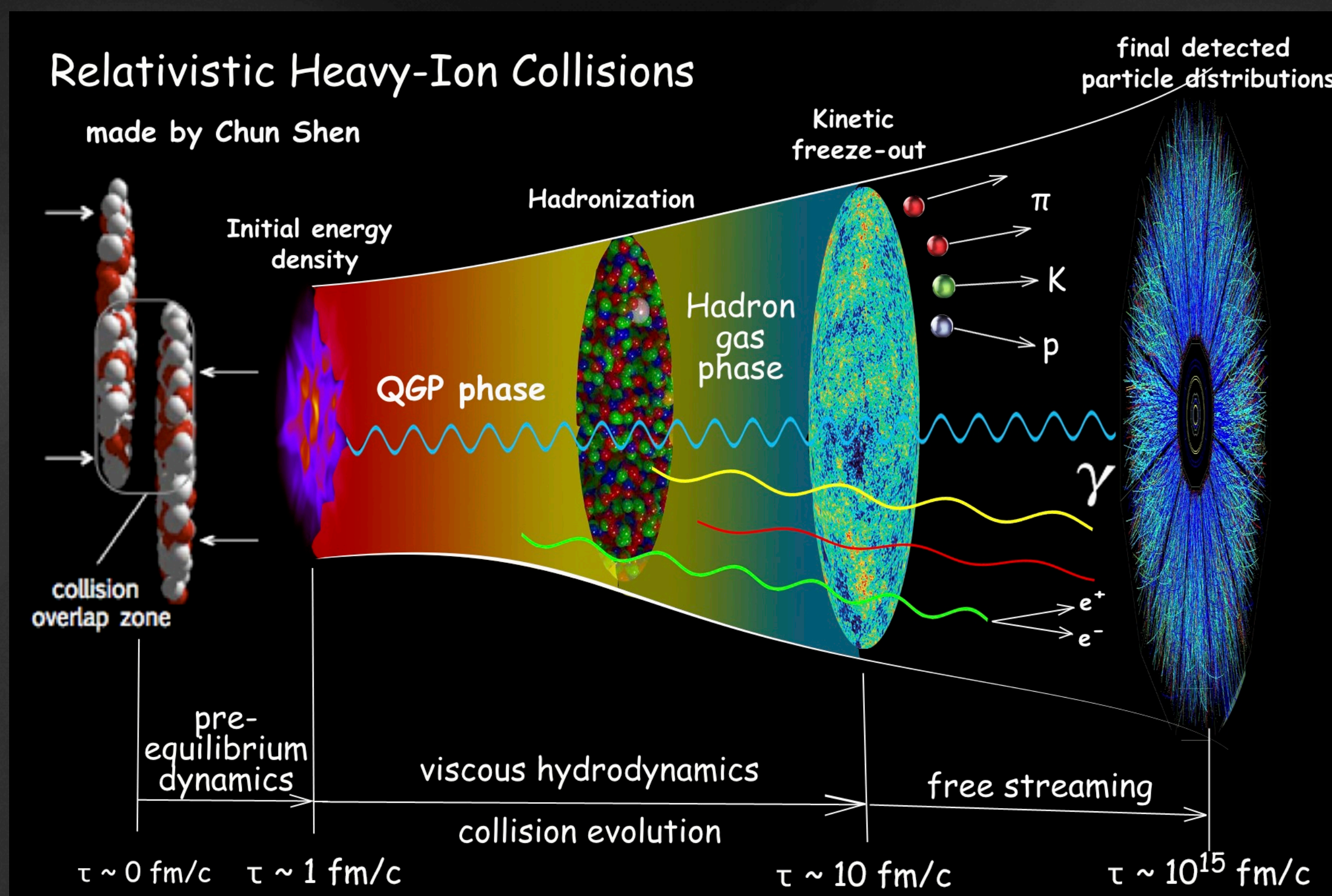
**Wenbin Zhao**

Wayne State University  
Department of Physics  
and Astronomy

Along with

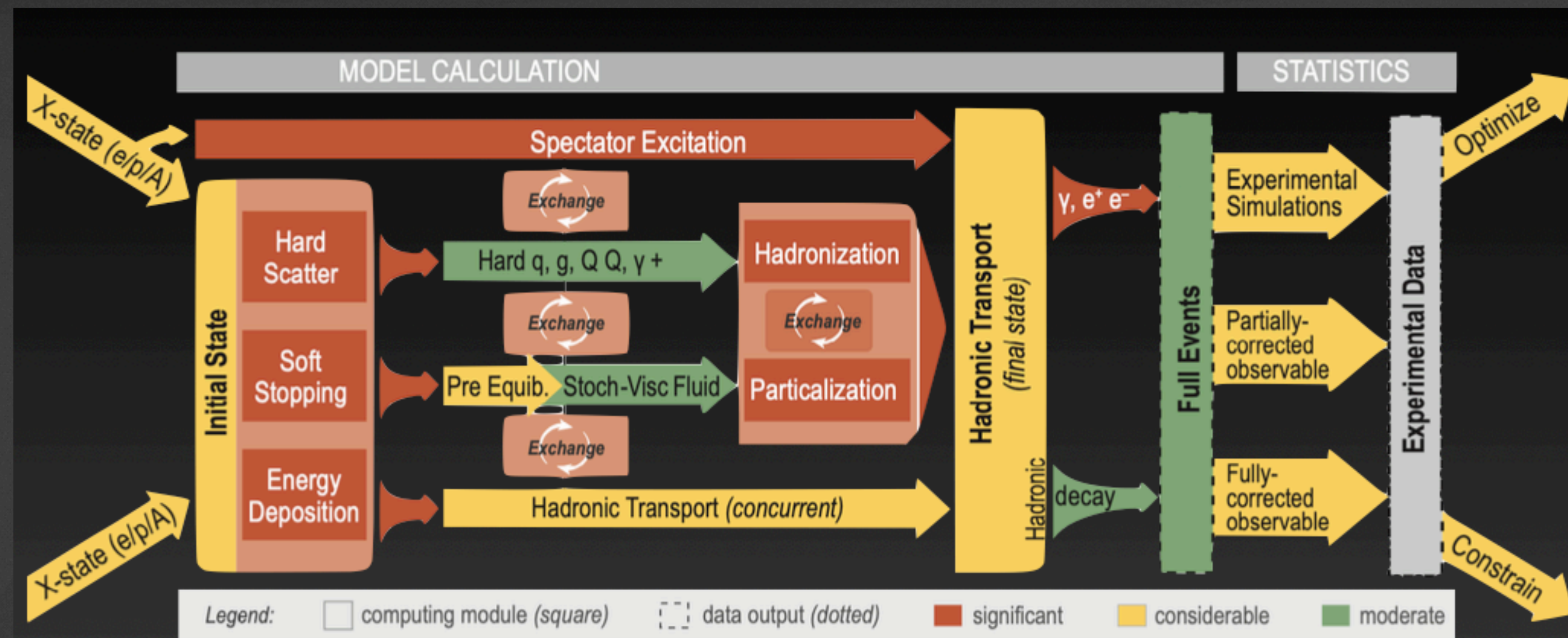


## Numerical Simulations of (3+1)D Hydrodynamics + hadronic transport hybrid model

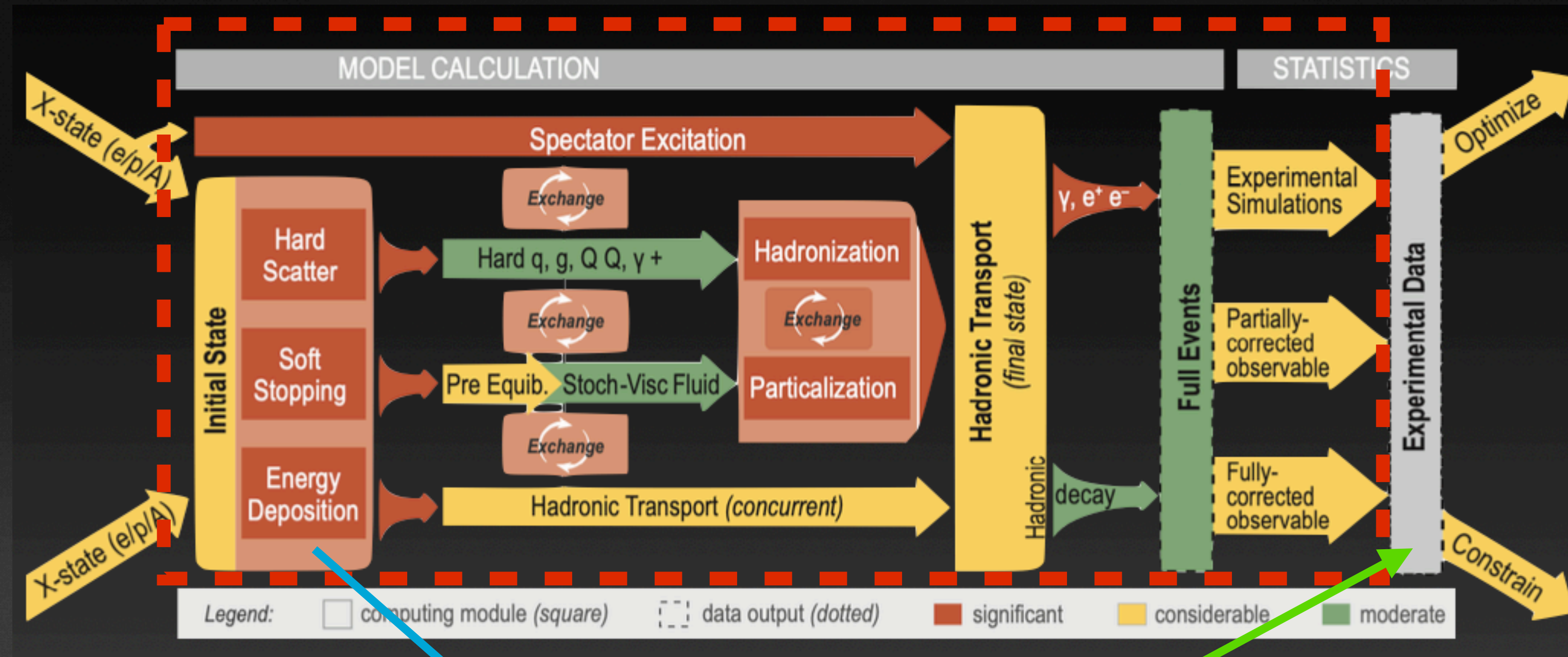


# The problem

- Computationally expensive
- Time expensive; a single batch run can take 30+ hours to complete
- 10-100 million events are required to ensure enough statistics for observables
- It is **critical** to find ways to reduce computational costs



# The problem



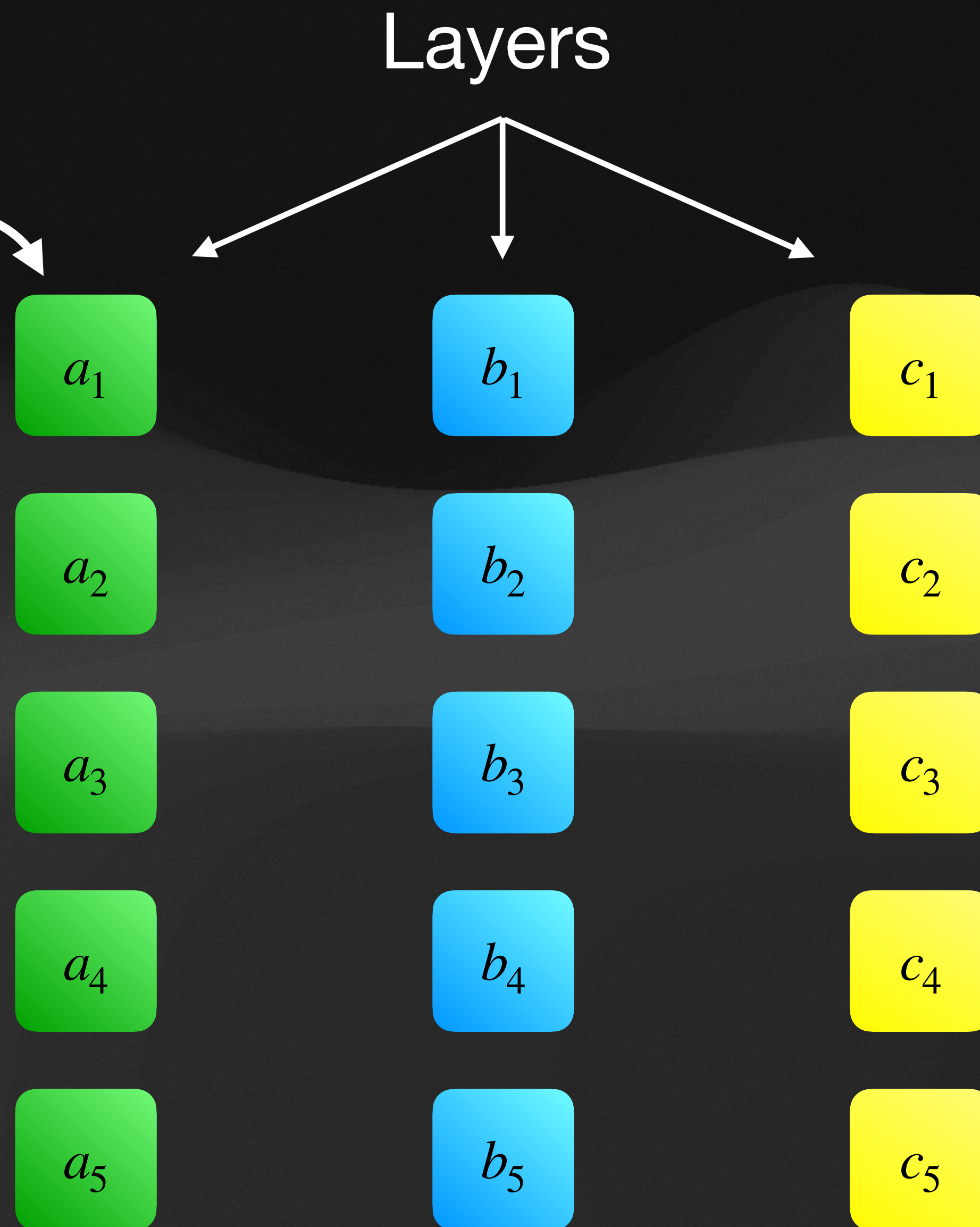
ML Model

Can we create a machine learning model that can learn the correlation between the initial state and the final state?

# Network Structure

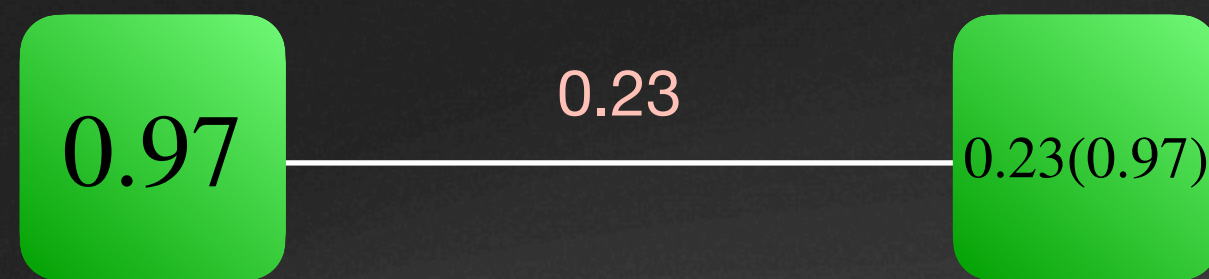
The Neuron

- Represents a data point
- When you combine more than one, you can represent an array of data.
- Placing multiple sets of neurons together forms the layers of the network

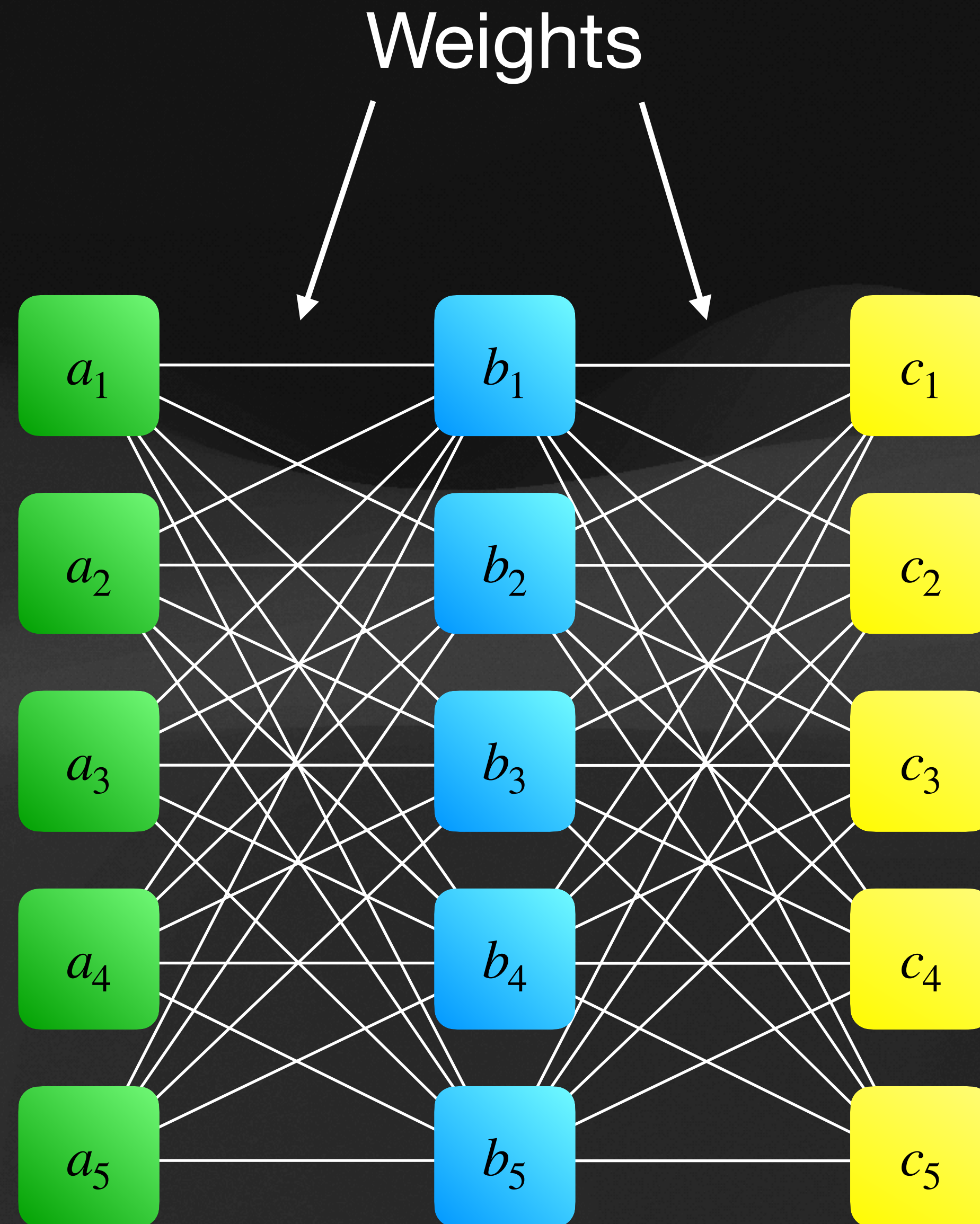


# Network Structure

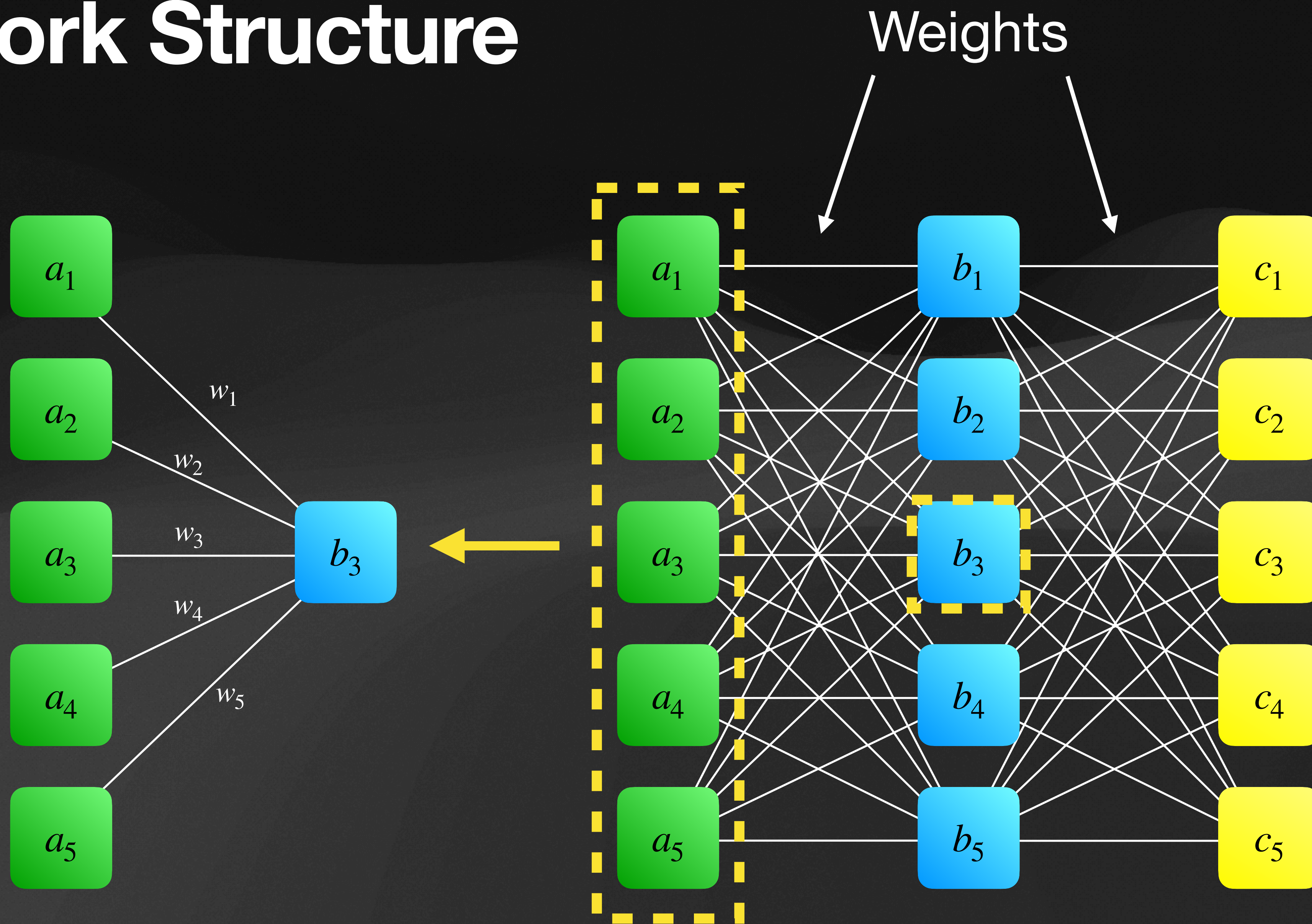
Each neuron is connected by a weight



*The weights are the parameters that we are training!*

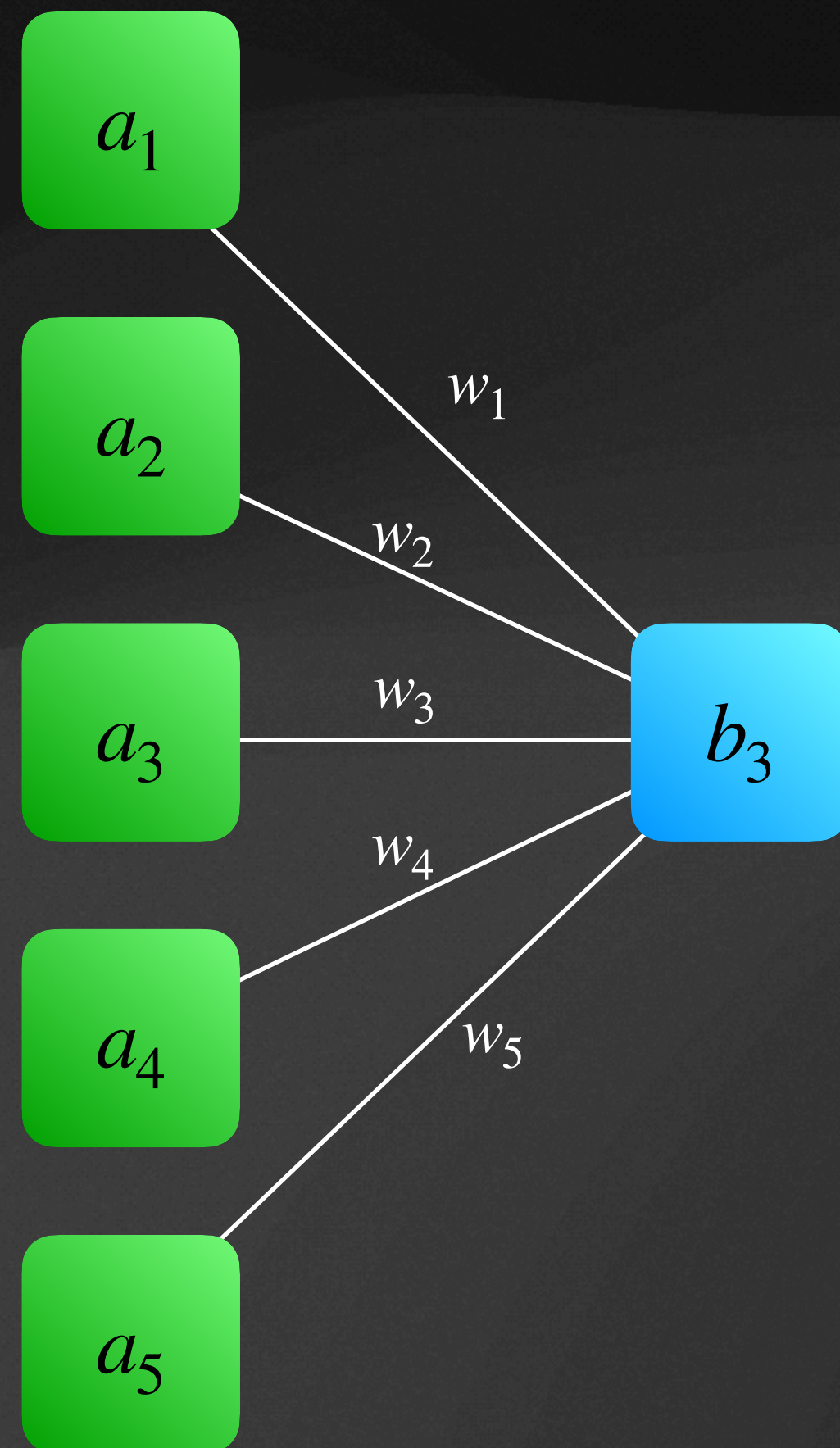


# Network Structure



# Network Structure

$b_j$  is the linear combinations of all of its weights and connections

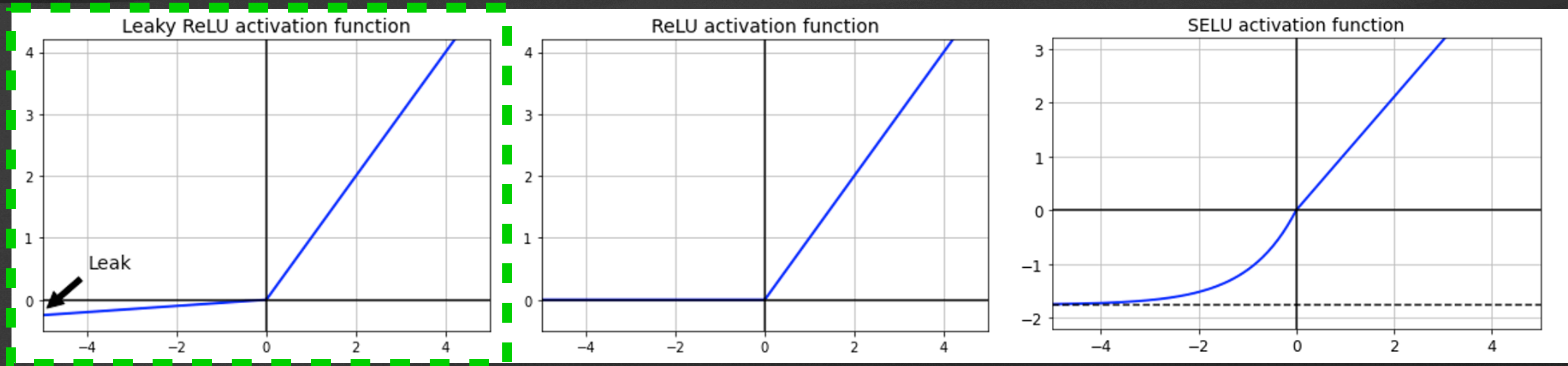


$$b_j = \sum_{i=1}^n a_i w_i$$

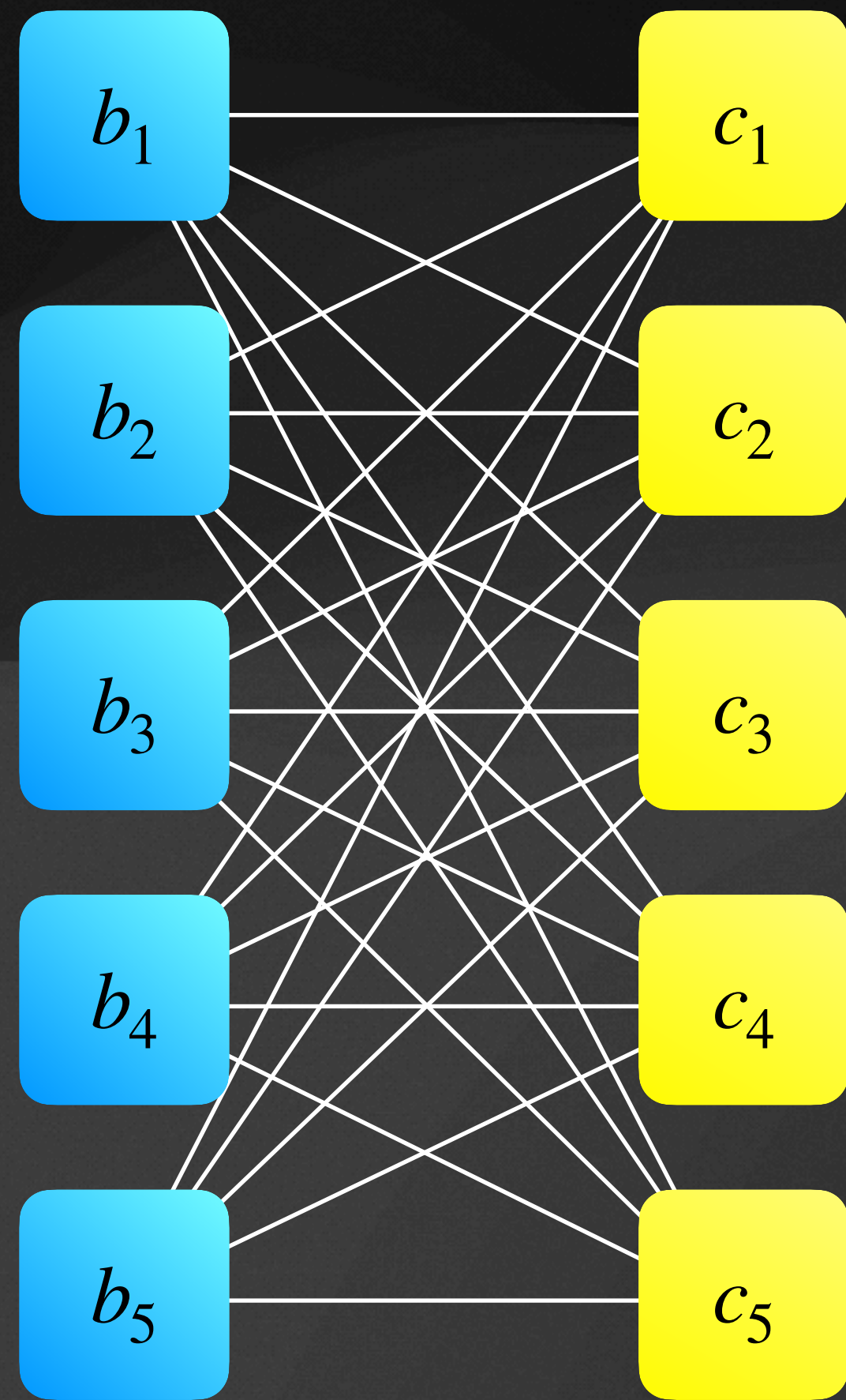


# Non-linearity

$$b_j = \text{ReLU} \left( \sum_{i=1}^n a_i w_i \right)$$



# Error Calculation



$$l_n = (x_n - y_n)^2$$

Model Output      Real Data

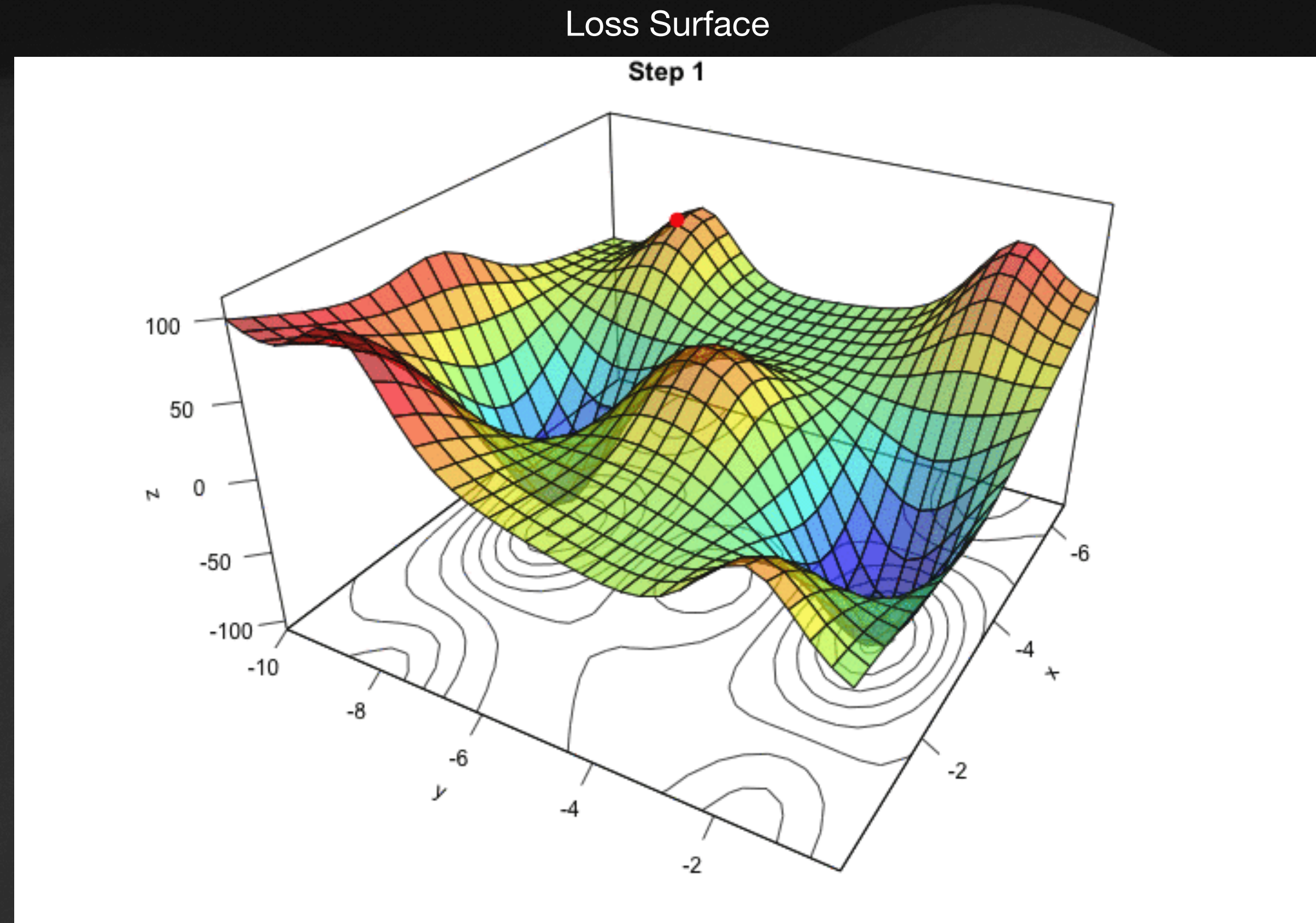
$$l(x, y) = L = \{l_1, l_2, \dots, l_N\}^T$$

# Traversing the 'loss surface'

Optimization Algorithms traverse the 'loss surface' to look for the global minimum over  $L$

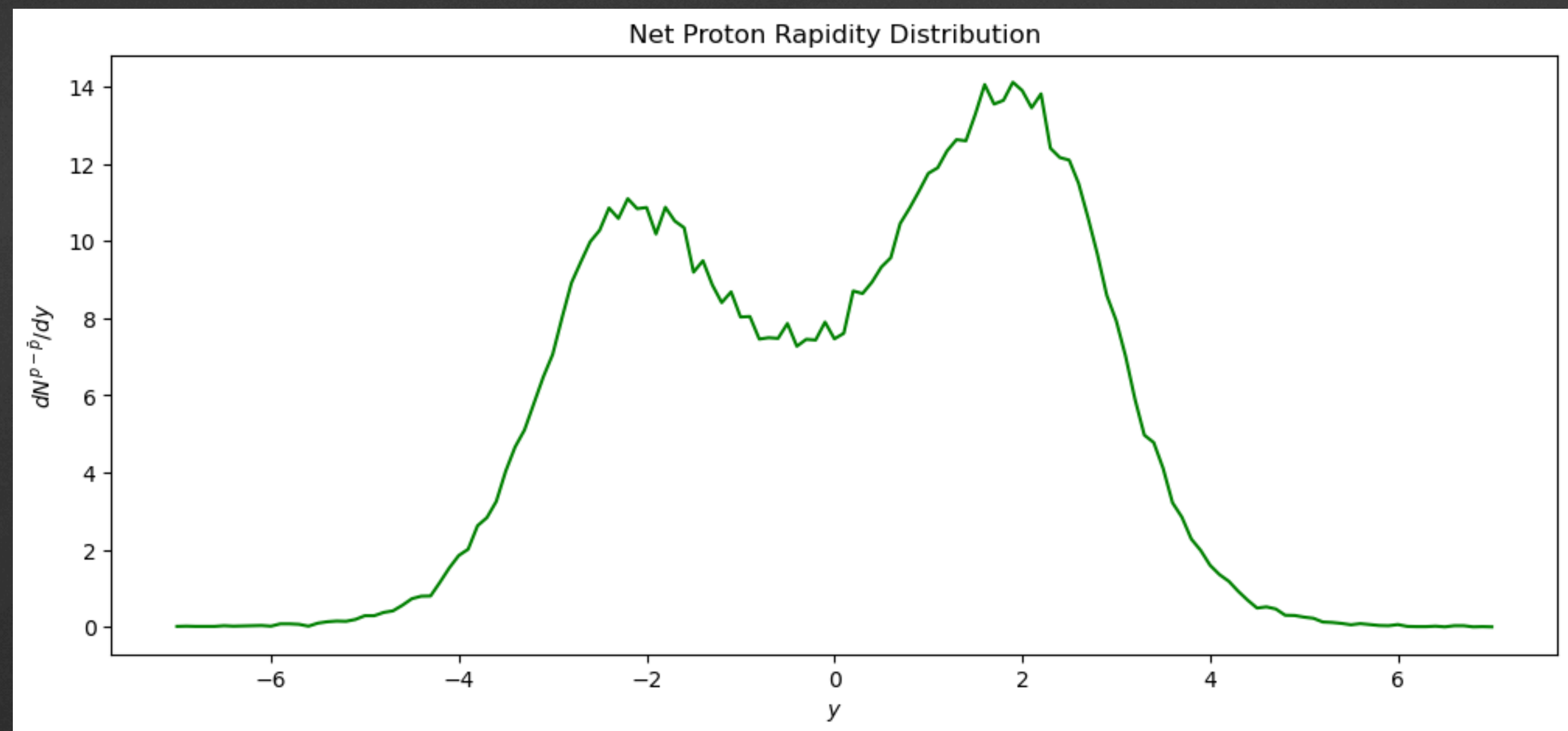
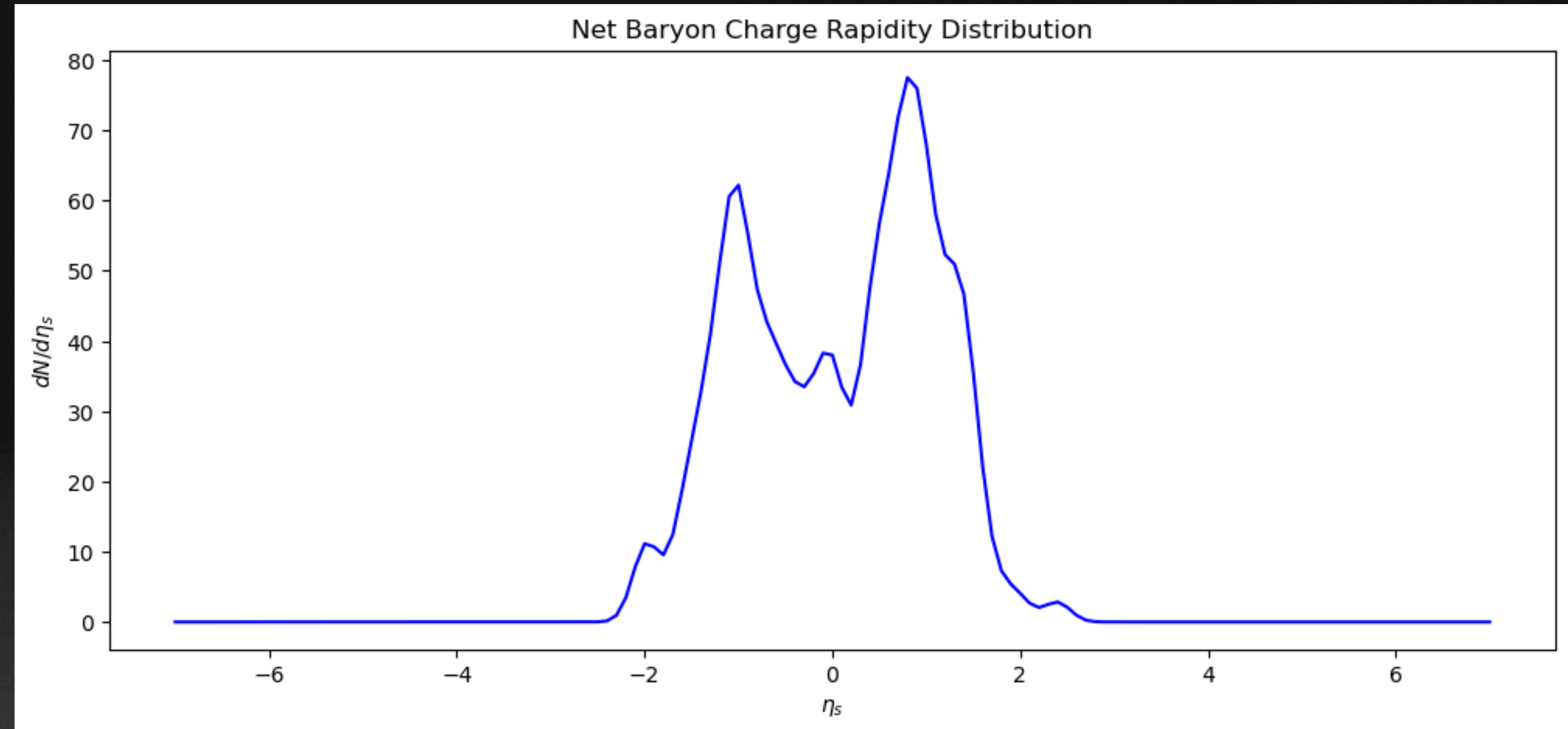
Common Optimizers:

- Gradient Decent (Depicted)
- Stochastic Gradient Decent
- Adam
- Adamax



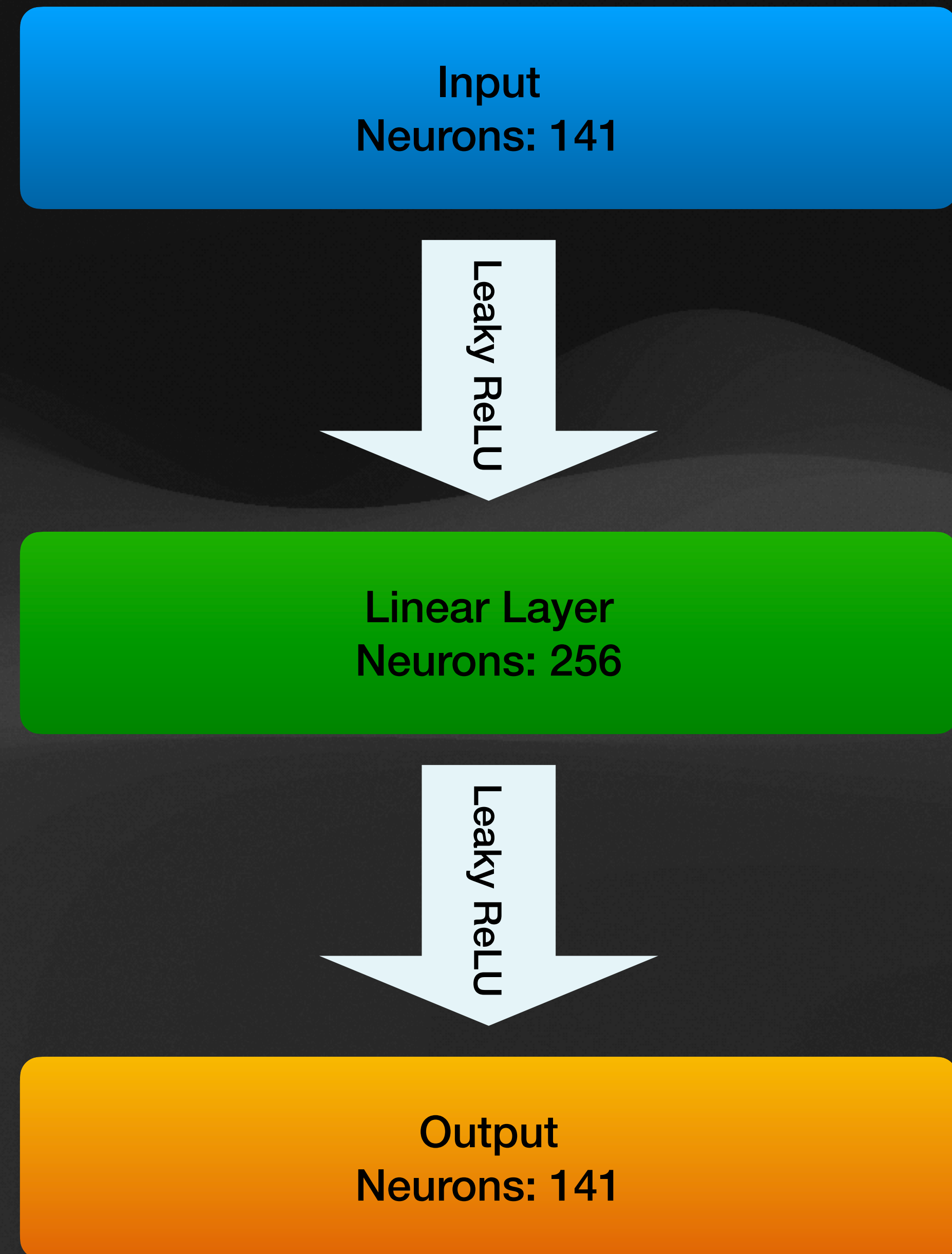
# It starts here

- Au + Au collisions
- 19.6 GeV



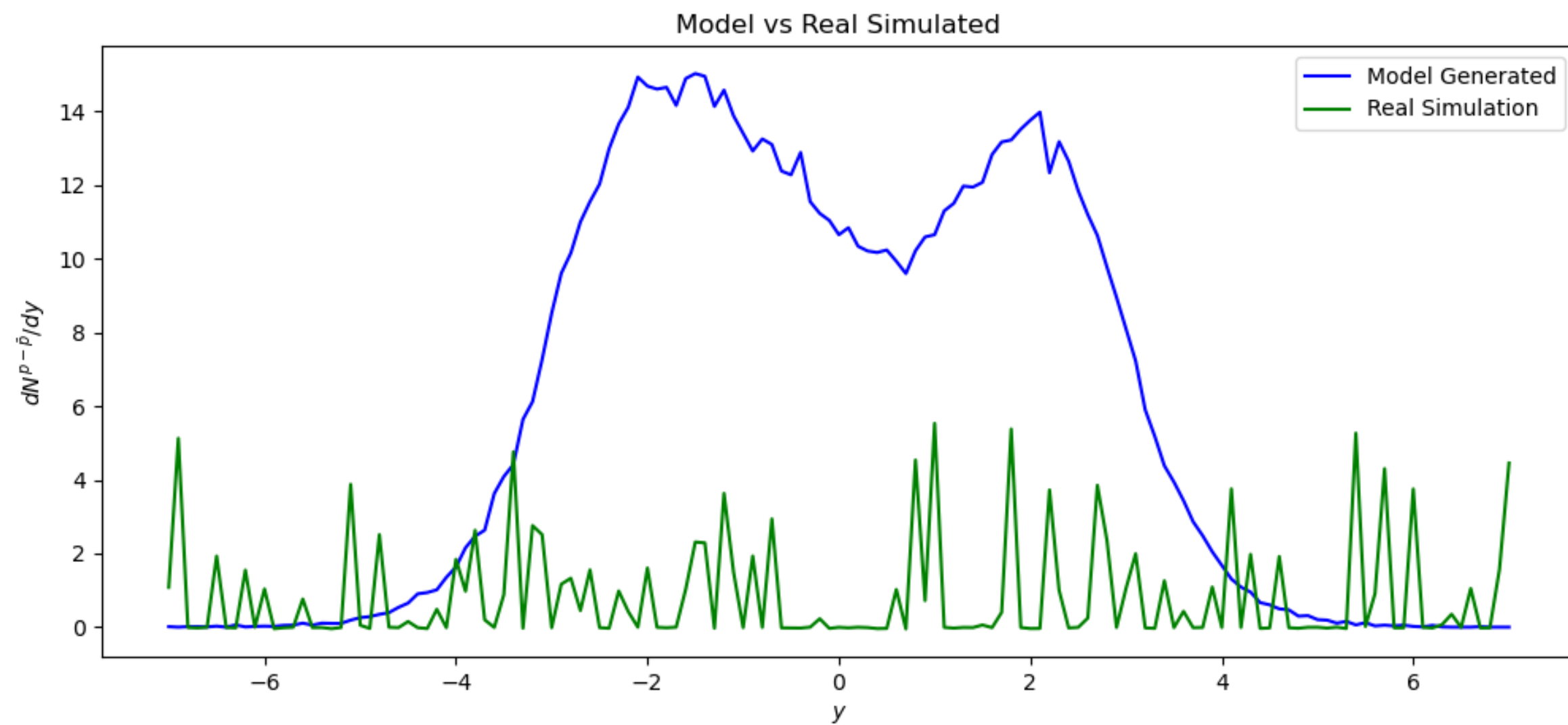
# Structure

- Trained on 5,000 pre-simulated initial and final states
- 3 fully connected layers
- Leaky ReLU reduces 'dead neurons'
- Roughly analogous to a polynomial regression

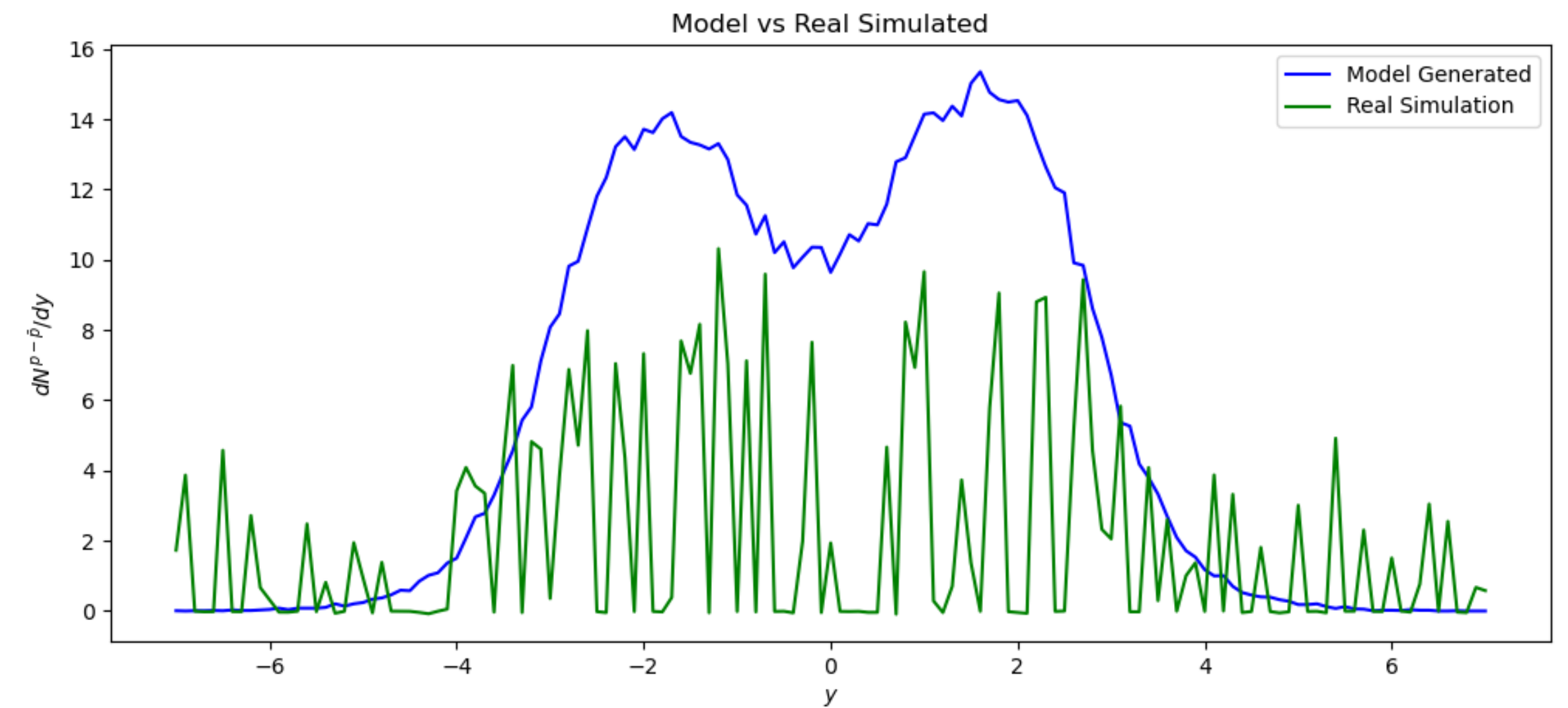


# Training iterations

Step 1

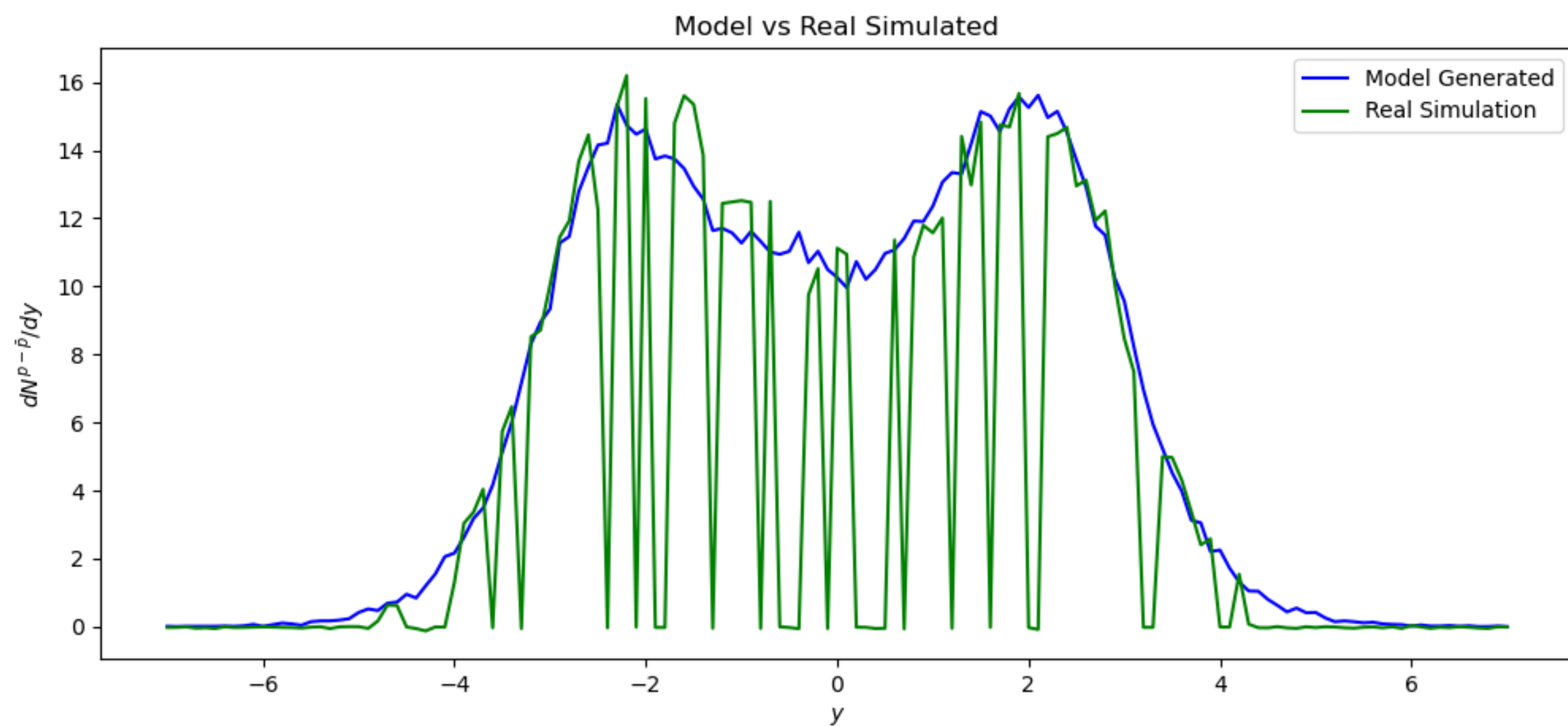


Step 17

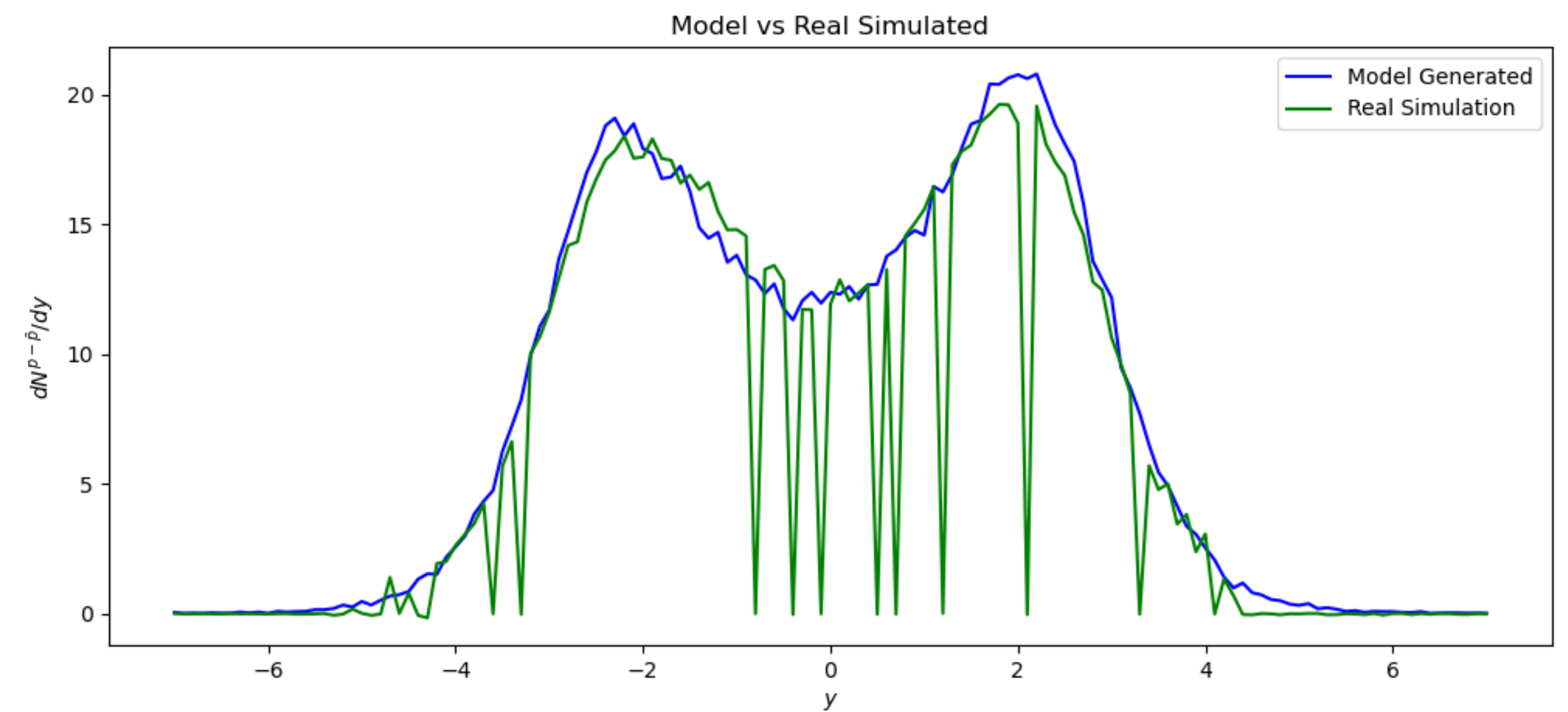


# Training iterations

Step 58

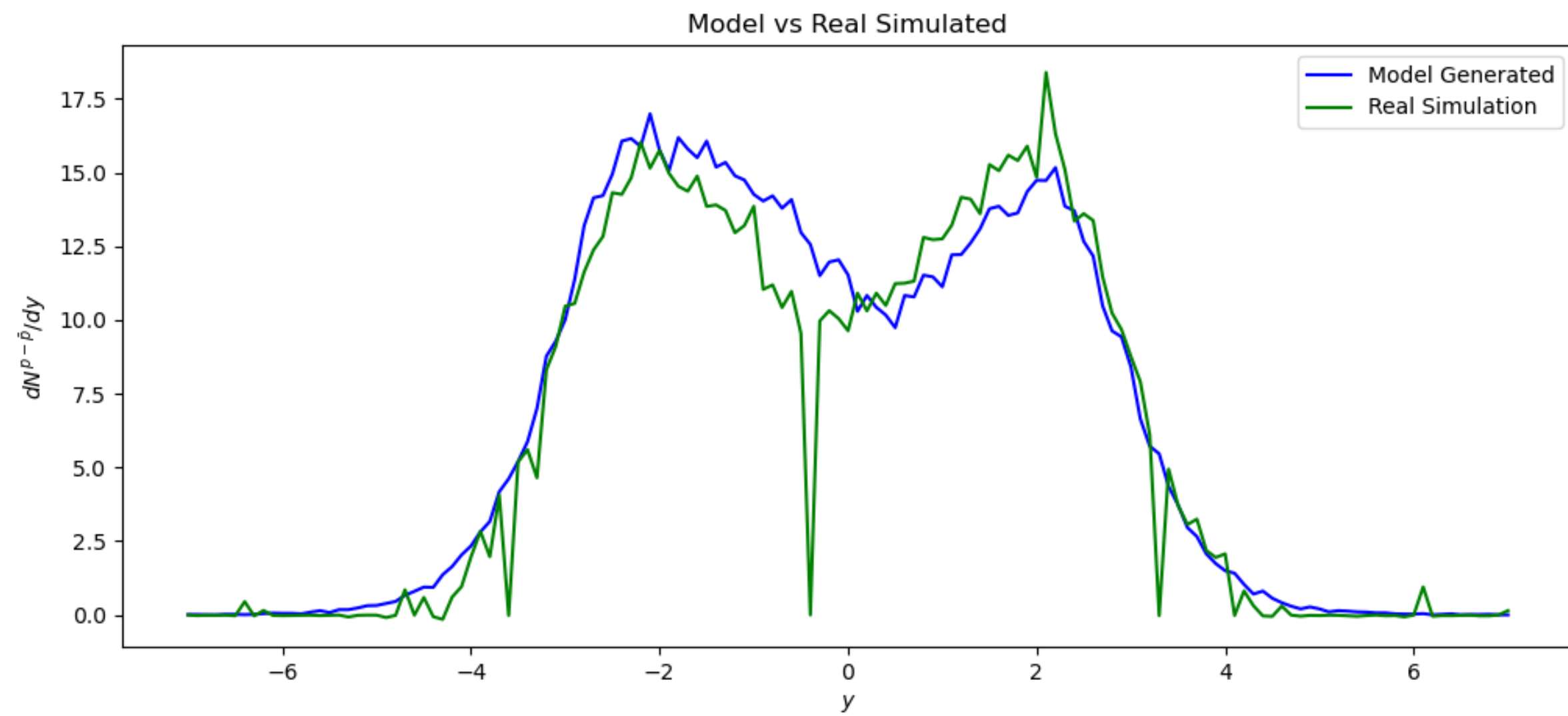


Step 433

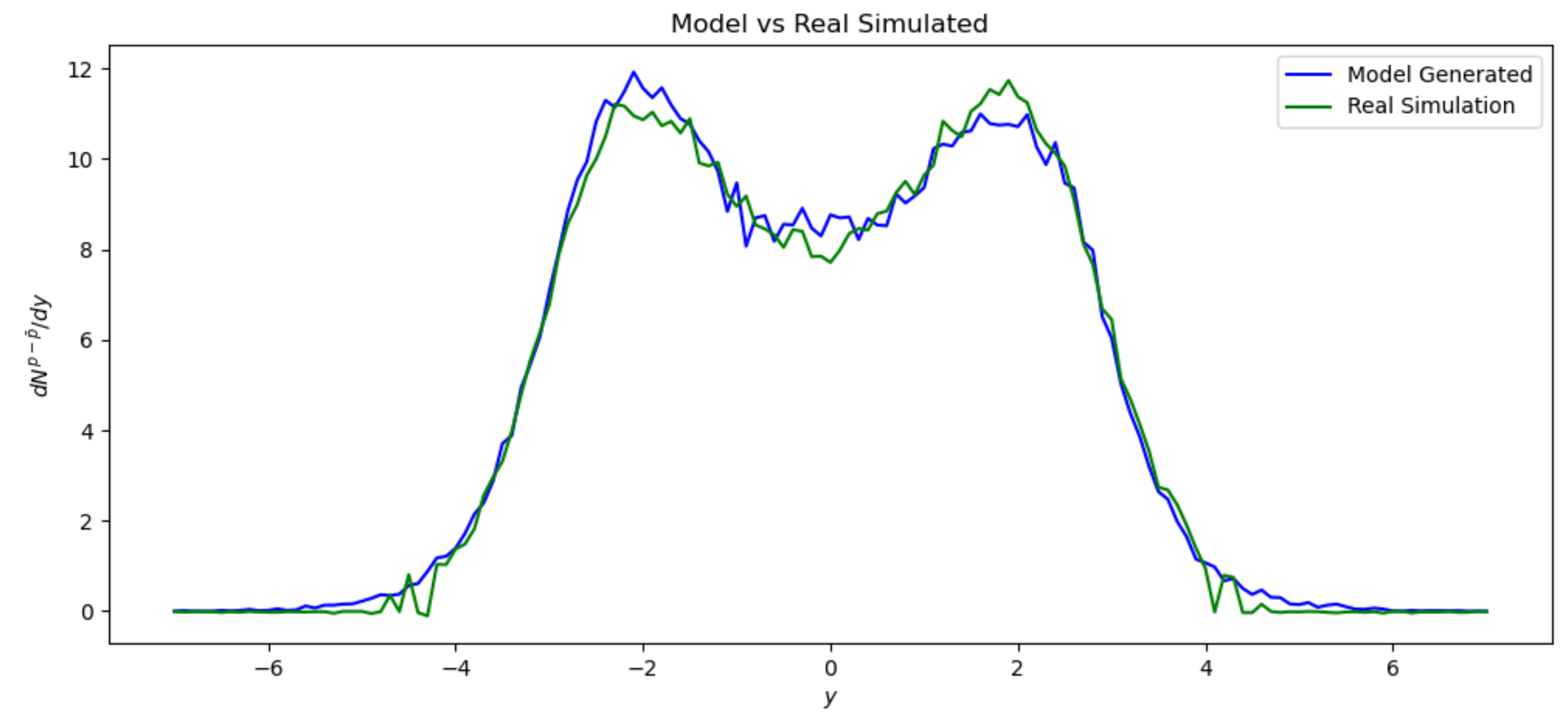


# Training iterations

Step 603



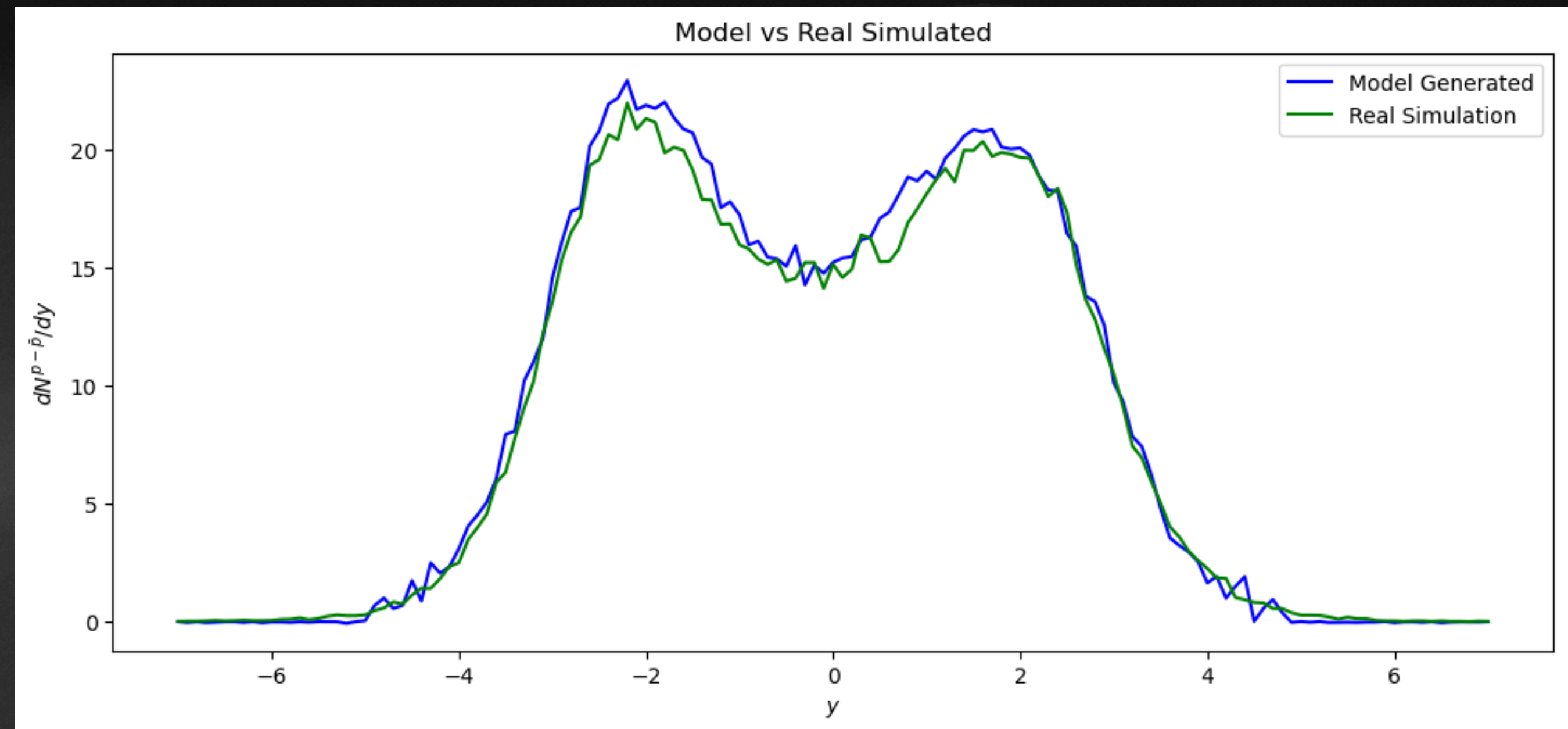
Step 942





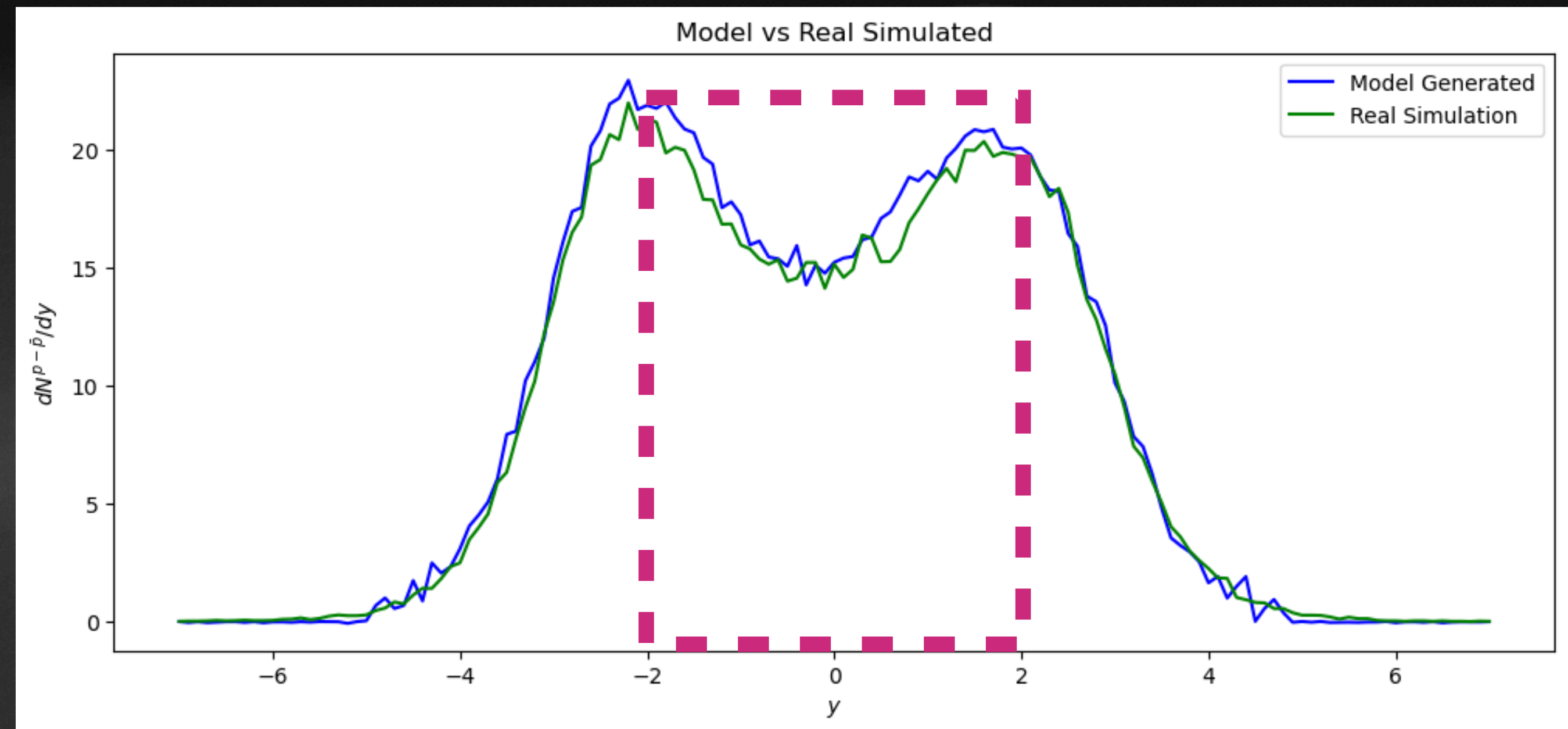
# Model Validation

- Model is shown new initial states that it was not trained on
- We can compare the expected output versus the generated output
- Spikes/noise is already accounted for as statistical fluctuations

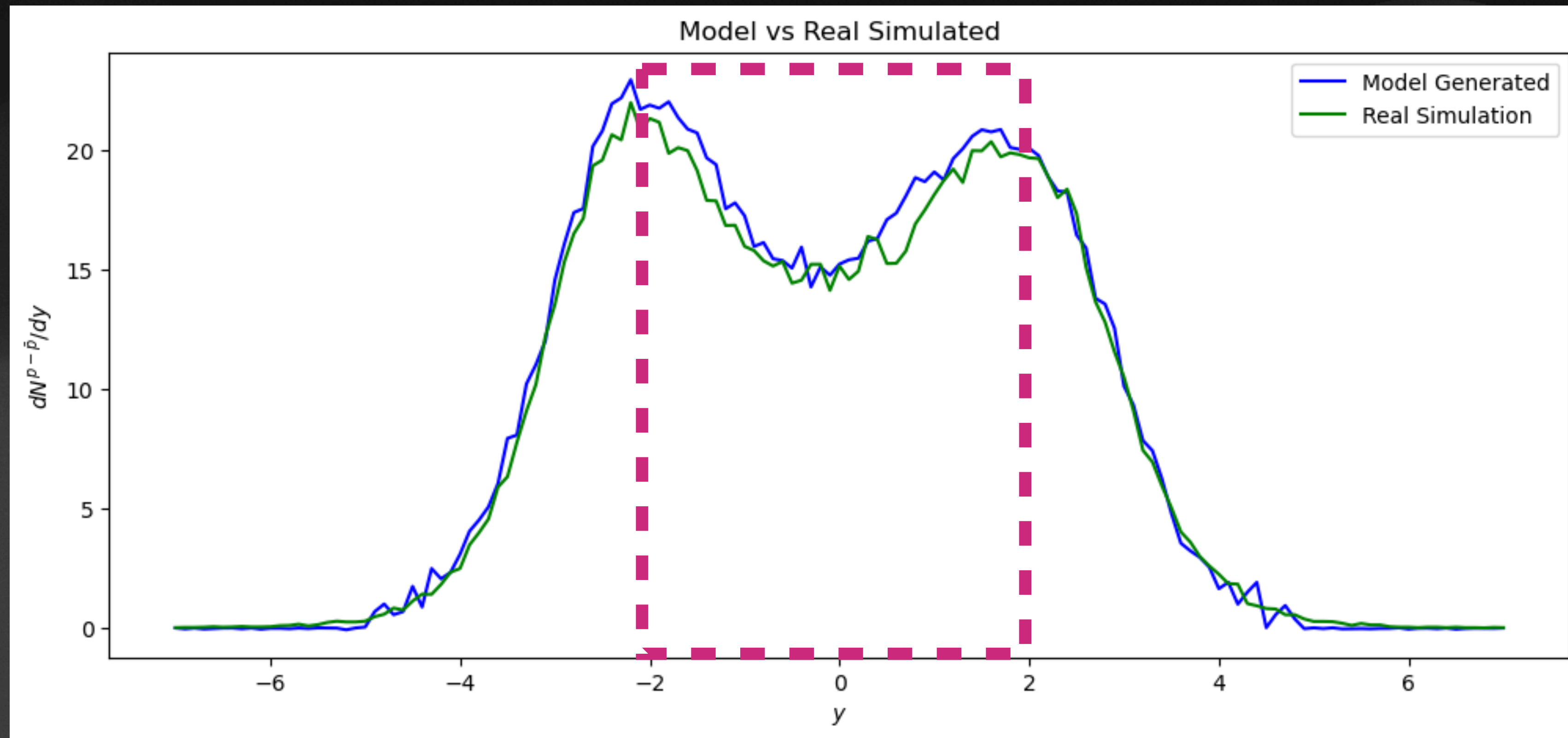


# Model Validation

- Model is shown new initial states that it was not trained on
- 5,000 validation events
- We can compare the expected output versus the generated output
- Spikes/noise is already accounted for as statistical fluctuations

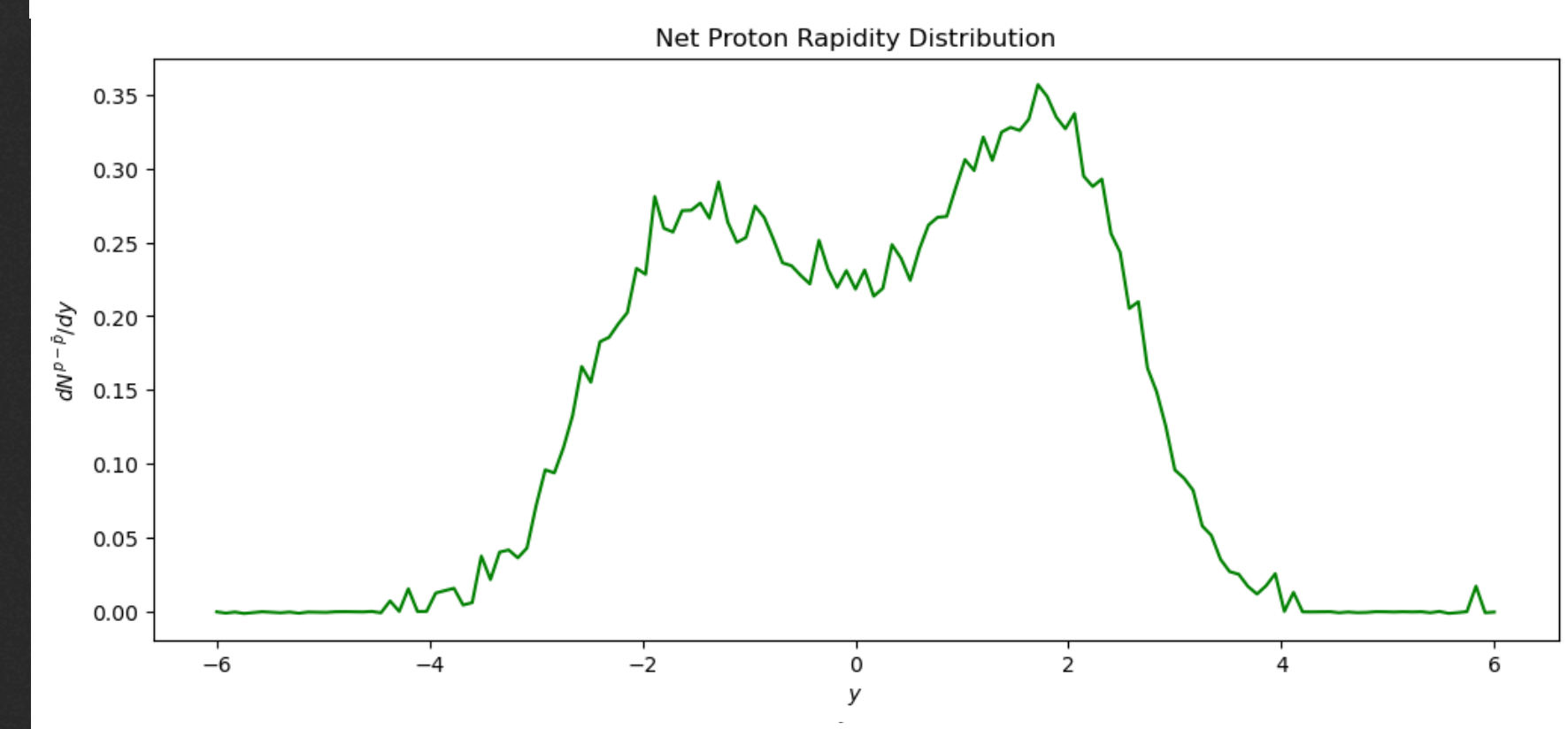
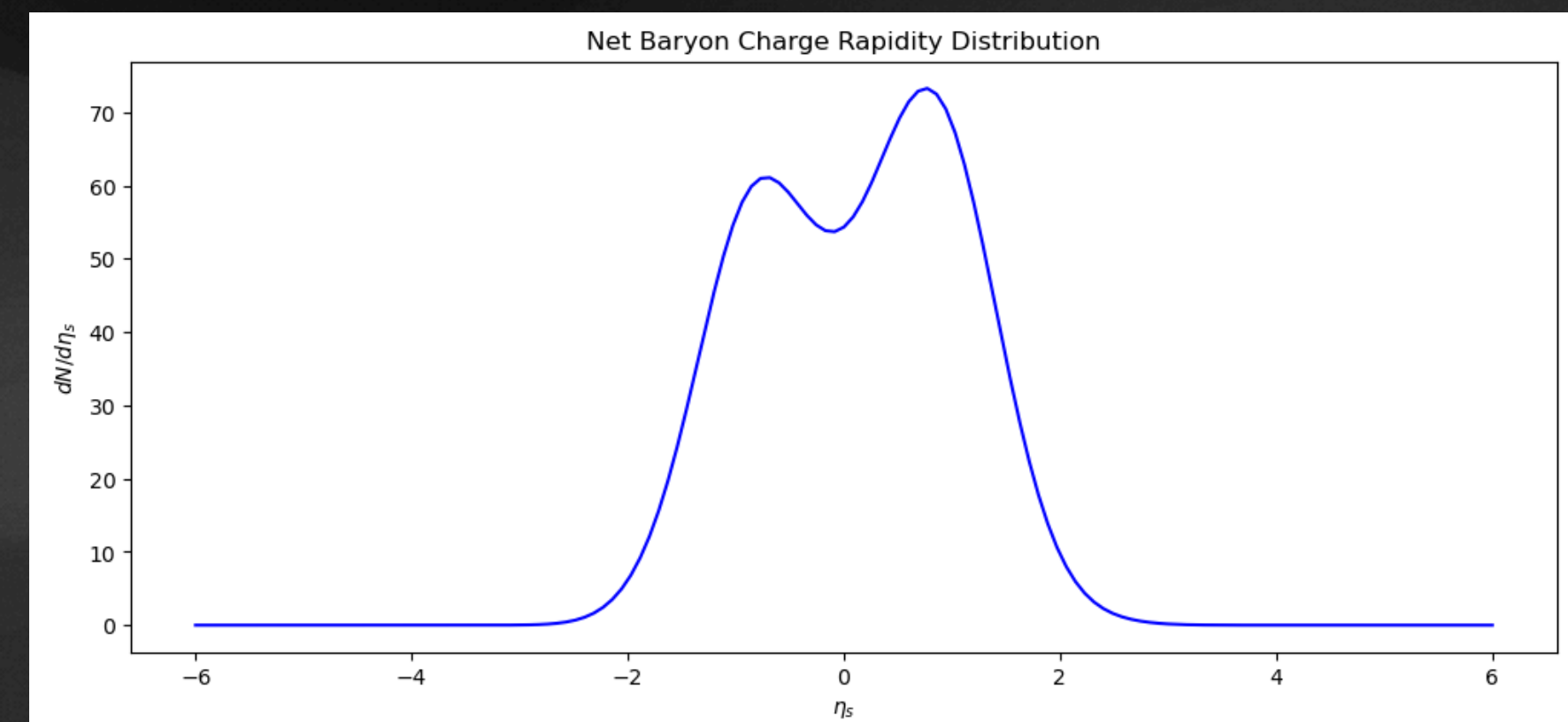
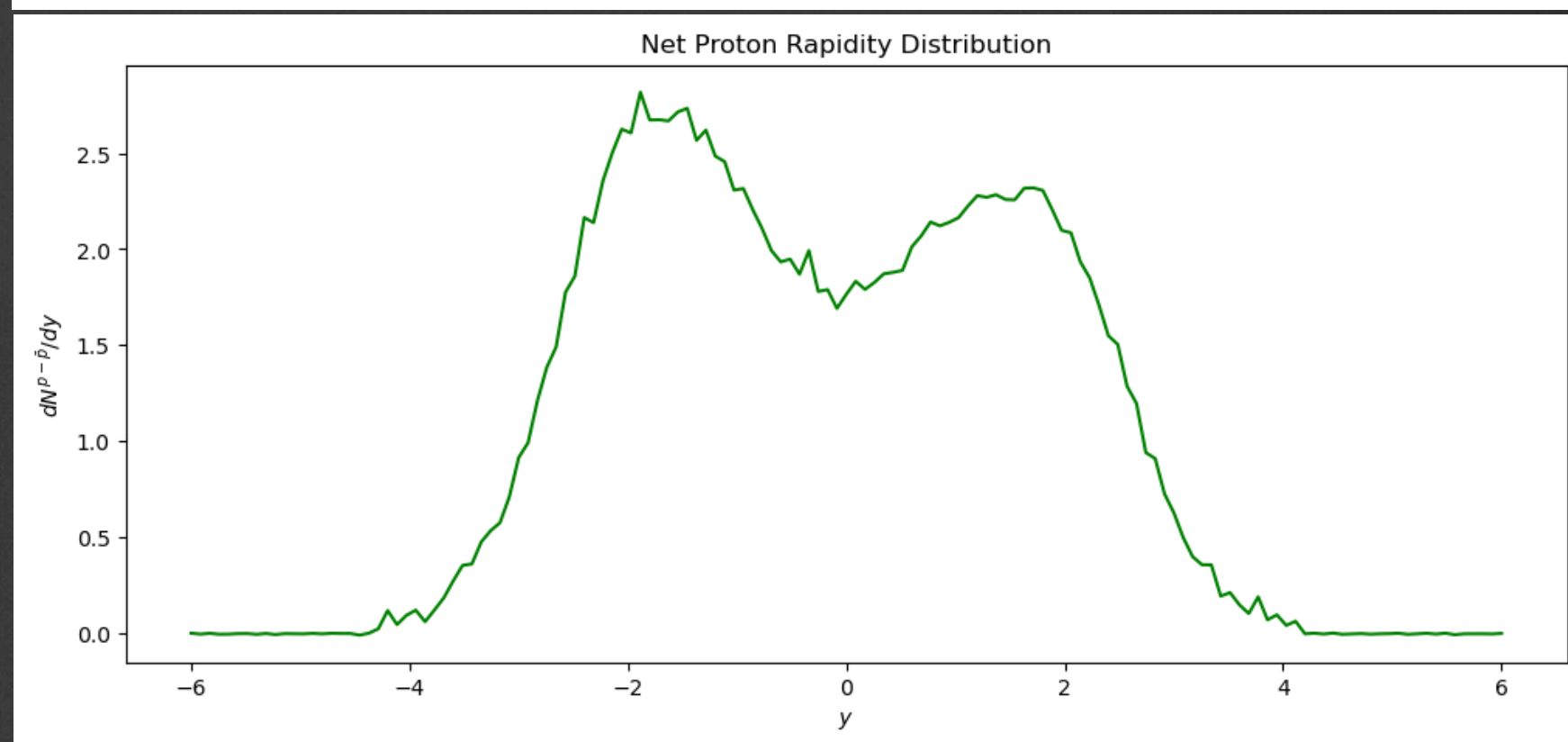
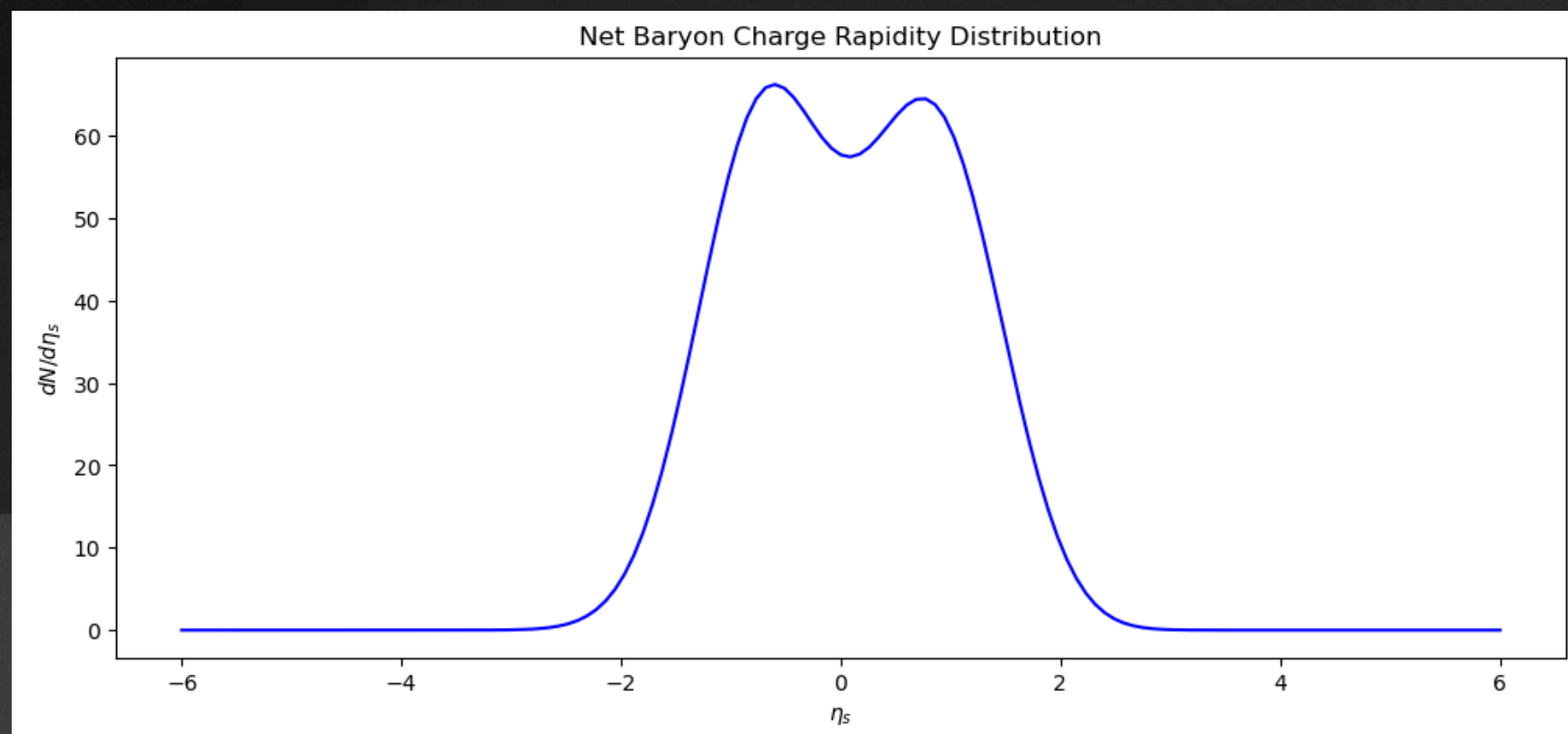


# Model Validation



# Results

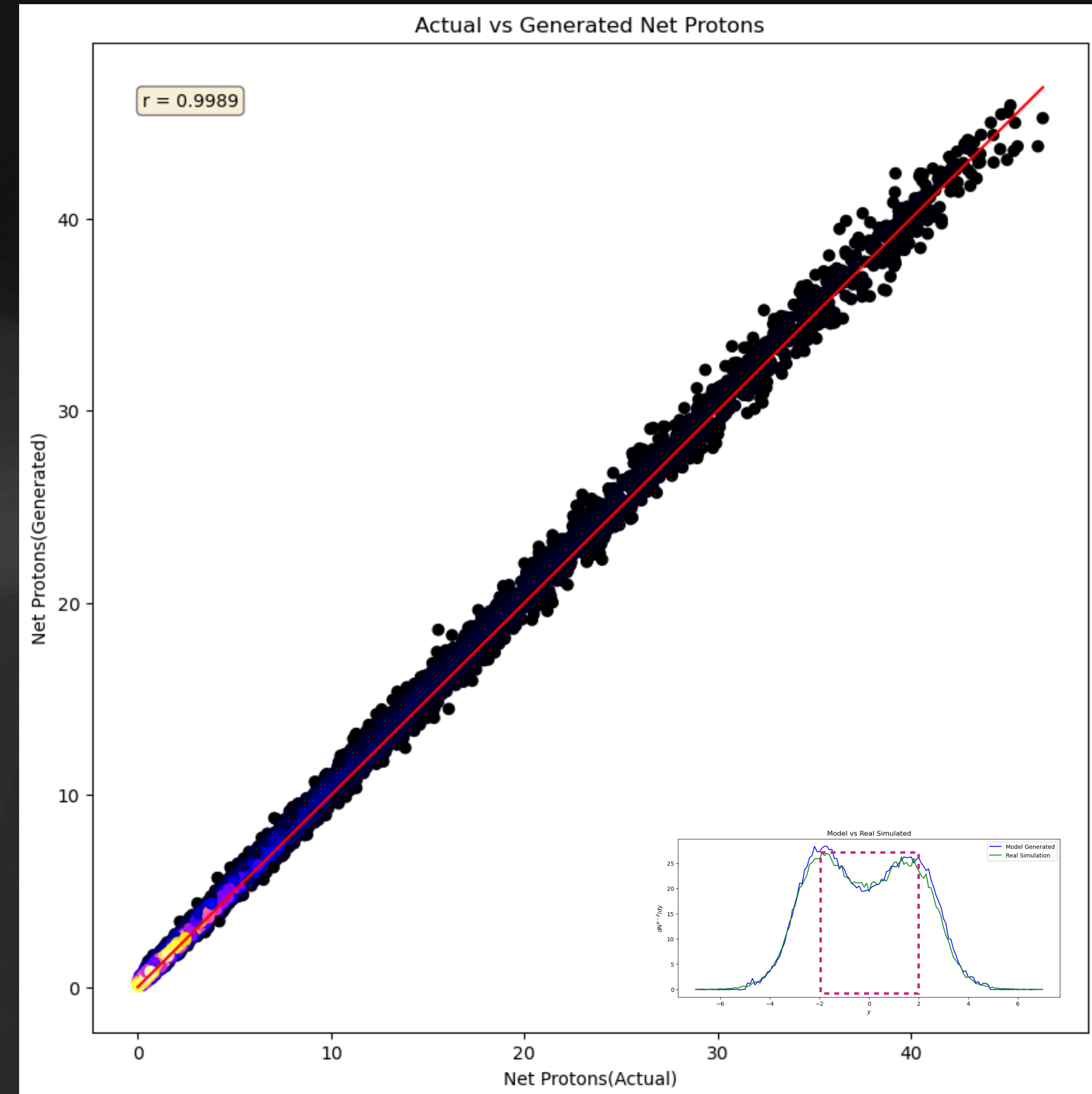
```
└─$ python main.py -d datasets/nB_etas_distribution_N_141.dat  
{'gridNx': 141, 'model': 'baryon_model_19.6gev.pt'}  
(100000, 1, 141)  
Run time: 7.484050035476685 seconds
```



# Model Validation

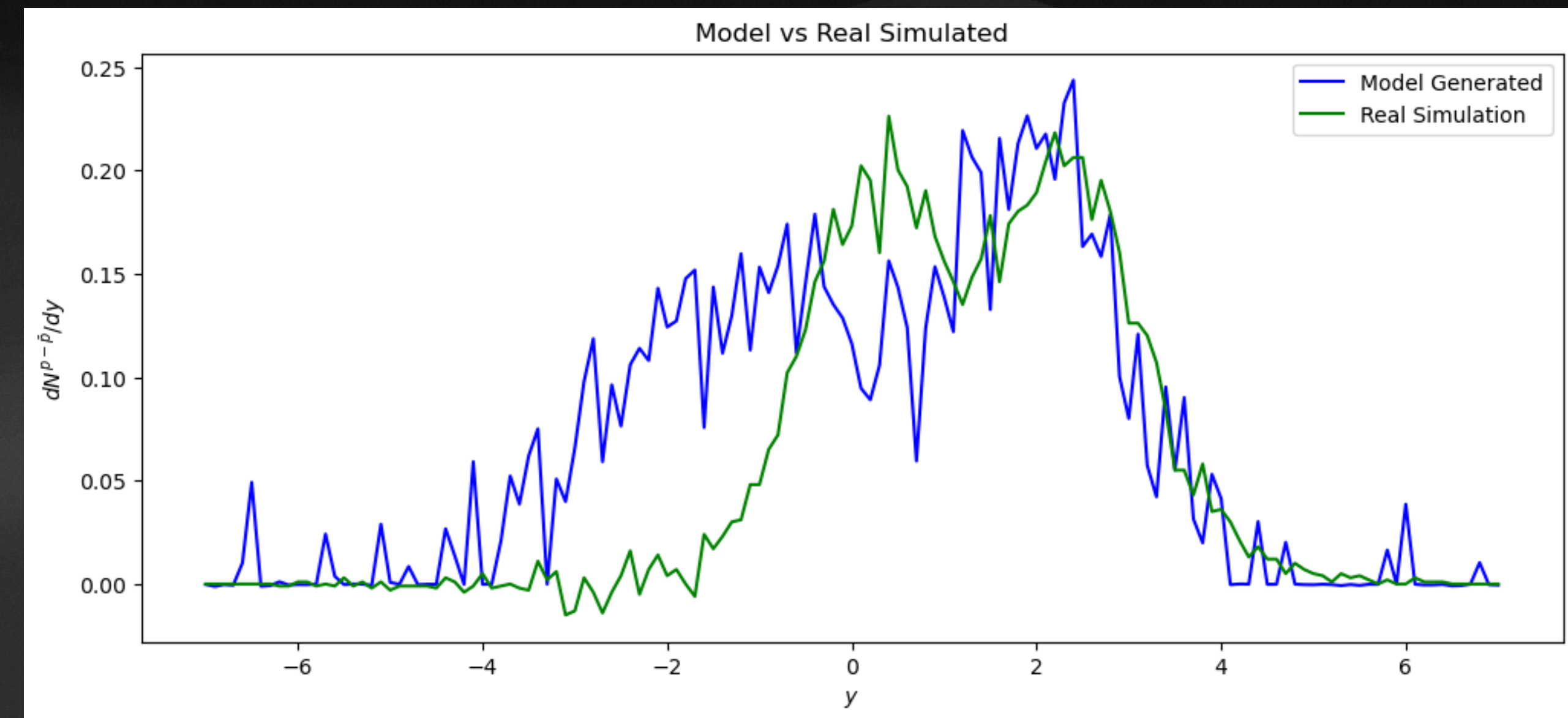
Real simulations vs model generated area for  $[-2,2]$

	Real Final State	Generated Final State
Mean	3.17 +- 0.35	3.23 +- 0.36
Variance	14.22 +- 0.50	13.51 +- 0.44
Skew	1.25 +- 0.74	1.14 +- 0.61
Kurtosis	3.60 +- 4.05	3.20 +- 2.90



# A note on model generalization

- Minimum Bias — Peripheral collisions get worse
- May not be a significant problem outside of model generalization



# Conclusion

- 1,000,000 final states can be generated in less than 30 seconds
- $O(10^5)$  speed up from 30 hours to a few seconds on an event-by-event basis

## Future Plans:

- Calculate high-order cumulants for net protons at the RHIC BES program
- Expand neural network emulation for anisotropic flow vector  $v_n(\eta)$ 
  - A more complex design may be needed
- Deploy neural network emulation as low fidelity simulations for Bayesian Interface analysis

# Questions?