

REU Program

SJY Group

Cyclotron Institute

National Science Foundation

Department of Energy

DETERMINATION OF IMPACT PARAMETER FOR FERMI ENERGY HEAVY ION COLLISIONS USING THE HIPSE EVENT GENERATOR

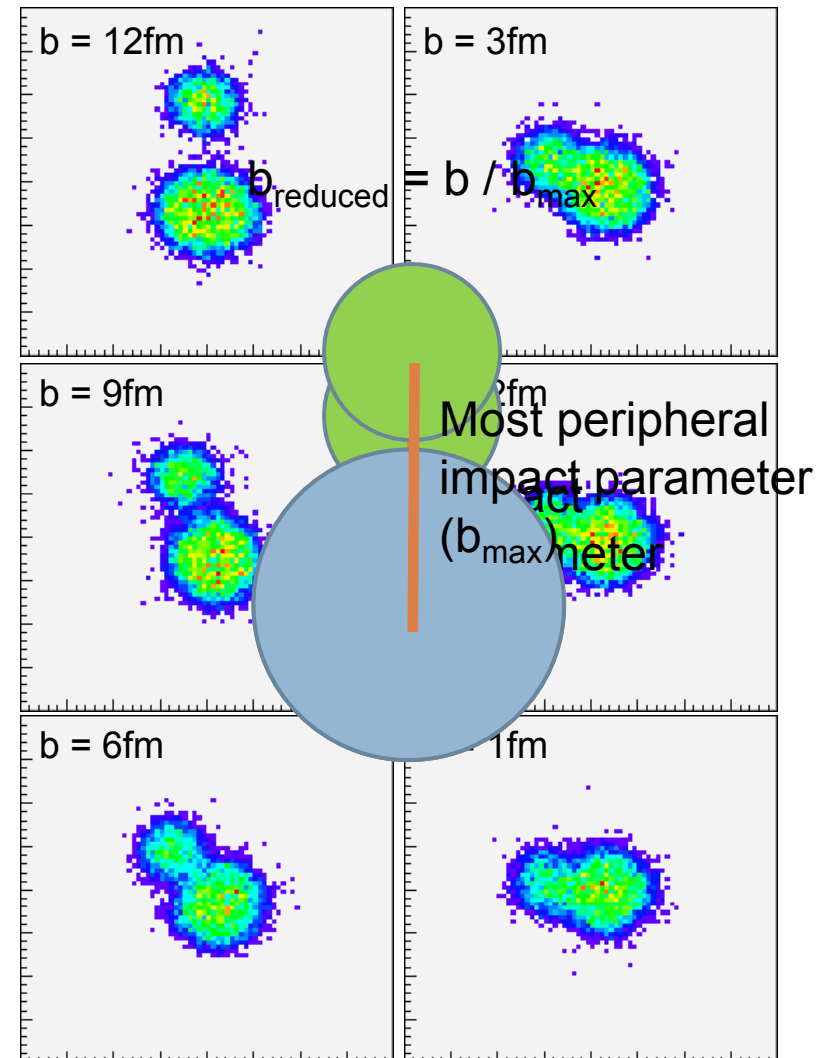
Mike Mehlman, Rice University – August 1, 2008

Mentors: Sherry Yennello & Zach Kohley, Texas A&M Cyclotron Institute

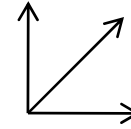
Objective

- What is impact parameter
- Impact parameter is an important quantity (for making cuts, determining event mechanism, etc.)
- Cannot be experimentally observed
- Seek to deduce event impact parameter from knowable quantities

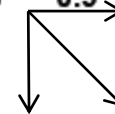
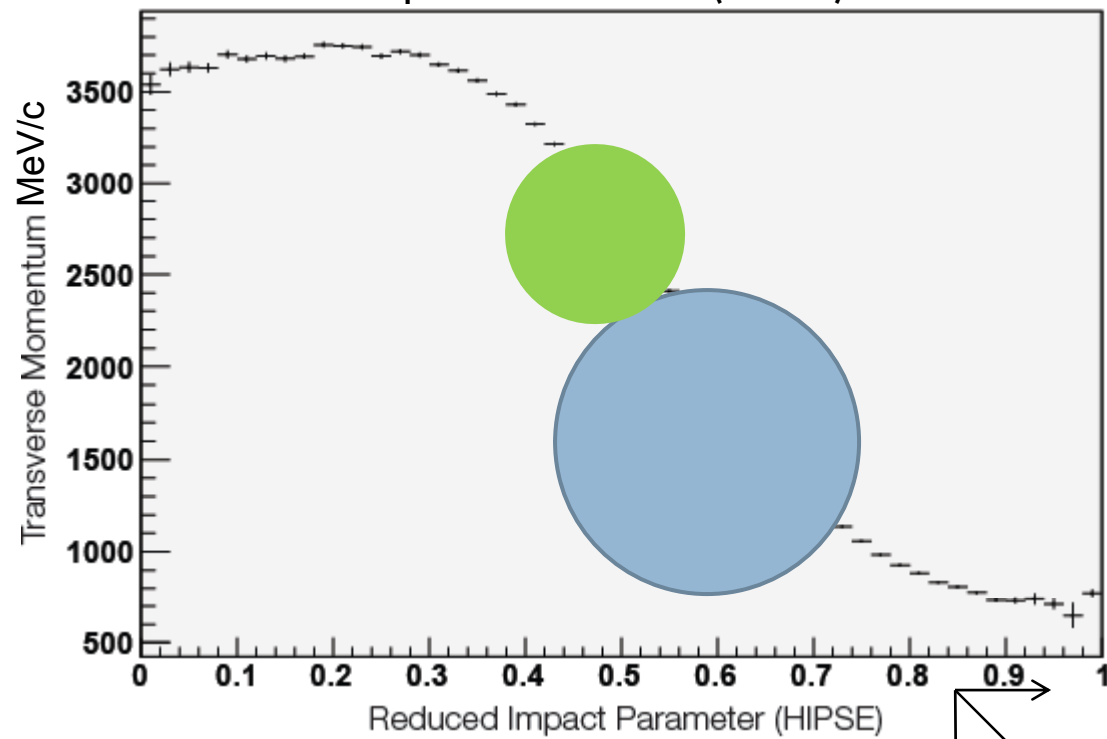
Video clip courtesy of August Keksis,
32 MeV/u $^{48}\text{Ca} + ^{124}\text{Sn}$, BUU Code



Objective



Event Transverse Momentum versus Reduced Impact Parameter (HIPSE)



Outline



- Introduction
 - ▣ HIPSE
 - ▣ NIMROD Filter
 - ▣ Neural Network
- Bin Mapping Approach
 - ▣ Method
 - ▣ Results
- Neural Network
 - ▣ Method
 - ▣ Results

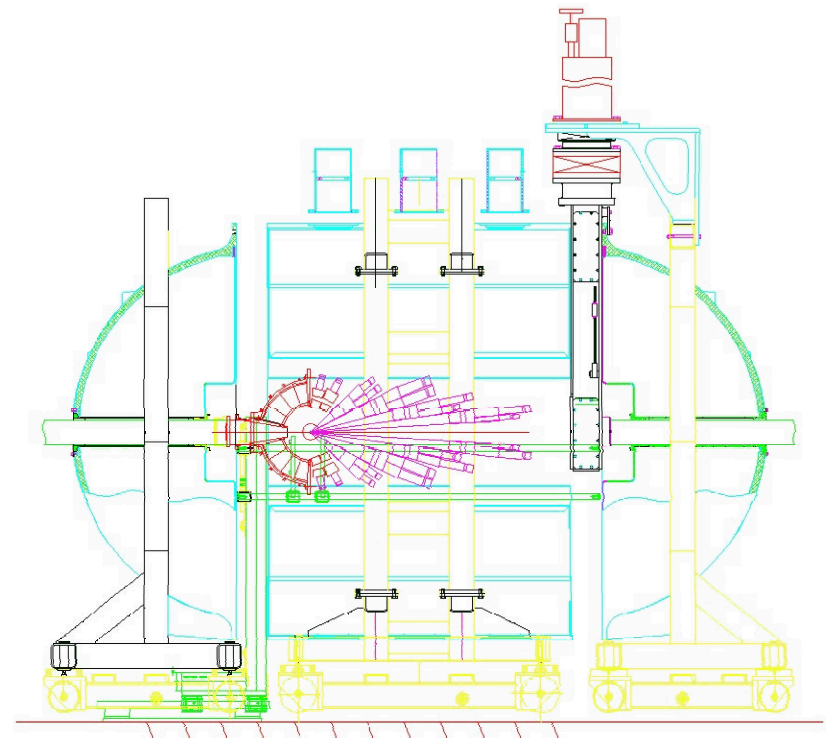
Introduction - HIPSE

- HIPSE event generator
- Heavy-Ion Phase-Space Exploration
- Parameterized to replicate experimental data taken on the INDRA detector
- Hot fragments de-excited with statistical model SIMON
- Allows for correlation of impact parameter with different observables (since HIPSE provides impact parameter)

D. Lacroix *et al.*, *Phys. Rev. C* 69, 1 (2004).

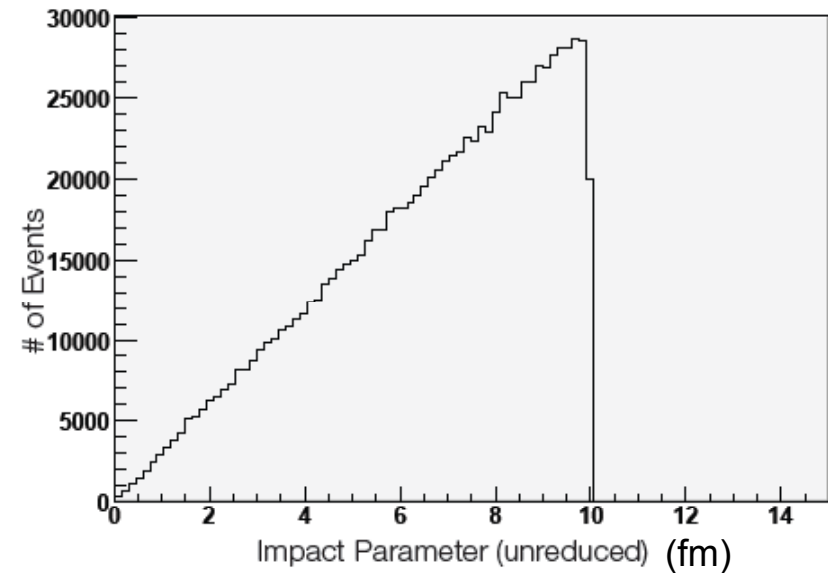
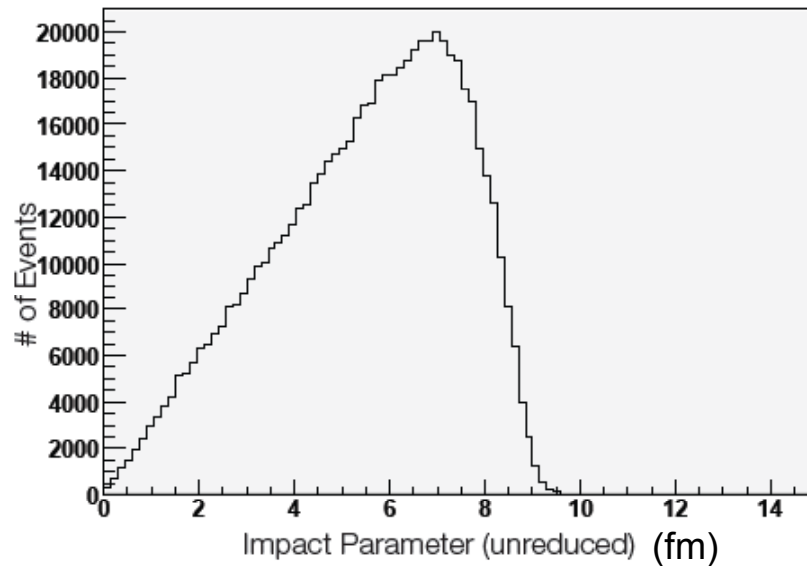
Introduction – NIMROD Filter

- NIMROD filter
- Filters data to approximate experimental data taken on NIMROD
 - ▣ For example, angular resolution becomes discrete, some particles don't have enough energy to be detected
- Because we want to use this method for data taken on NIMROD (July-August 2008)



Introduction – NIMROD Filter

Distribution of events sorted by impact parameter with
(left) and without (right) NIMROD filter



Introduction – Neural Network

- Neural Network allows for multiple correlations to be considered for estimating the output for a given set of inputs
- Trained using simulated data
- Can then applied to experimental data

A simple neural network

input layer hidden layer output layer

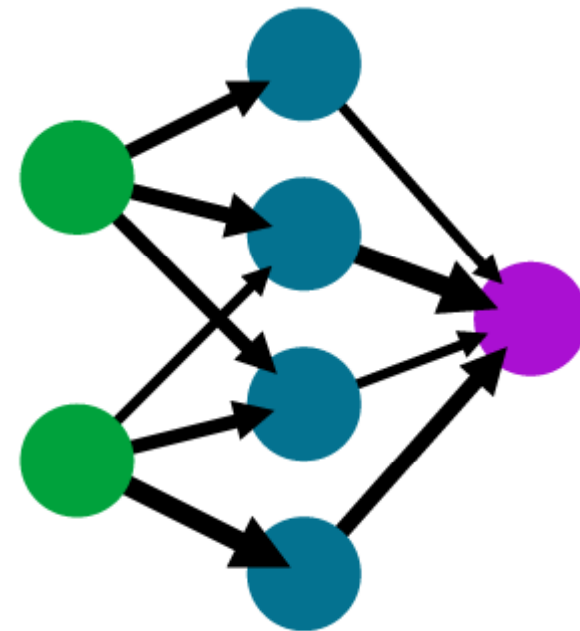
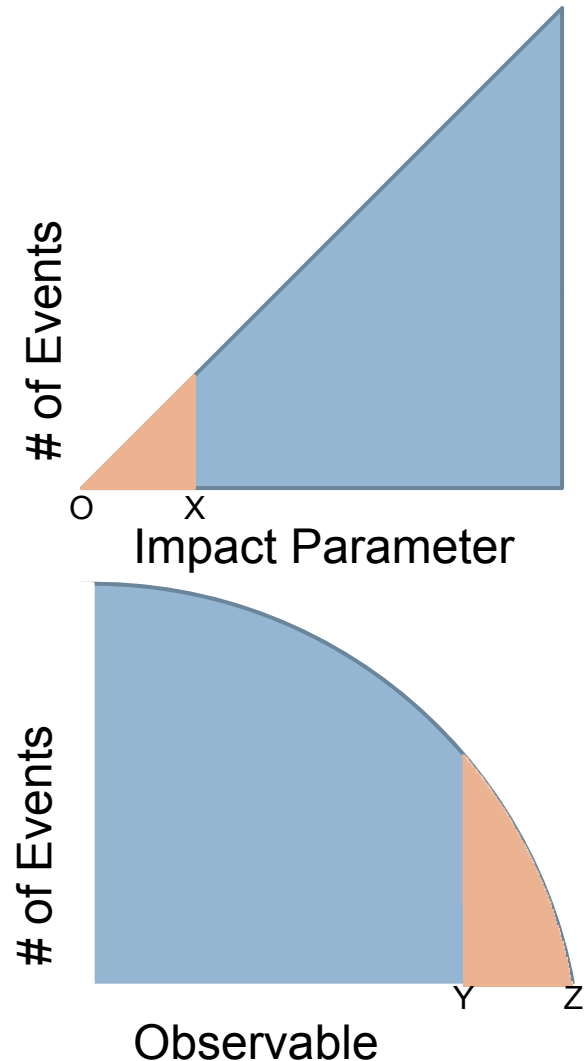


Image courtesy of Wikipedia:

http://en.wikipedia.org/wiki/Image:Neural_network_example.png

Bin Mapping Approach – Method

- Geometrical impact parameter distribution separated into portions
- Percentage of each portion calculated
- Distribution of the global observable is binned such that the integral percentage of each bin is equal to the corresponding percentage of the impact parameter portion
- Bins from the observable distribution now mapped to distinct impact parameter ranges



Bin Mapping Approach – Method



- Three approaches:
 - ▣ Impact parameter distribution is separated into four or five evenly spaced portions to which observable distributions are mapped.
 - ▣ Observable distribution is separated into four or five evenly spaced portions to which impact parameter distribution is mapped.
 - ▣ Observable distribution is binned by hand to avoid discontinuities. Impact parameter distribution is then mapped to these bins.
- Estimates compared with HIPSE values

Bin Mapping Approach – Method

□ Systems

- ^{70}Zn on ^{70}Zn at 35MeV/u
- ^{64}Zn on ^{64}Zn at 35MeV/u
- ^{64}Ni on ^{64}Ni at 35MeV/u
- ^{64}Zn on ^{64}Ni at 35MeV/u

Bin Mapping Approach – Method

□ Quantities examined

□ All quantities examined with Z-V cut: $\sum Z_{\text{frag}} \times V_{||\text{frag}} > \frac{1}{2} Z_{\text{proj}} \times V_{\text{proj}}$

- ▣ Event transverse momentum* and velocity (avg. and total)
- ▣ Event parallel momentum and velocity (avg. and total)
- ▣ Transverse energy
- ▣ Average detector angle (theta)
- ▣ Neutron multiplicity*
- ▣ Charged particle multiplicity*
- ▣ Total particle multiplicity
- ▣ Mid-rapidity charge (amount of charge per event with $-V_{\text{proj}} < V_{\text{particle}} < V_{\text{proj}}$ in center of mass frame)
- ▣ Forward charge (theta < 35°)
- ▣ Backward charge (theta > 70°)*
- ▣ Heavy (Z > 2) / light (Z ≤ 2) fragment ratio
- ▣ Intermediate (6 > Z > 2) / light (Z ≤ 2) fragment ratio

*marked quantities also examined without the cut

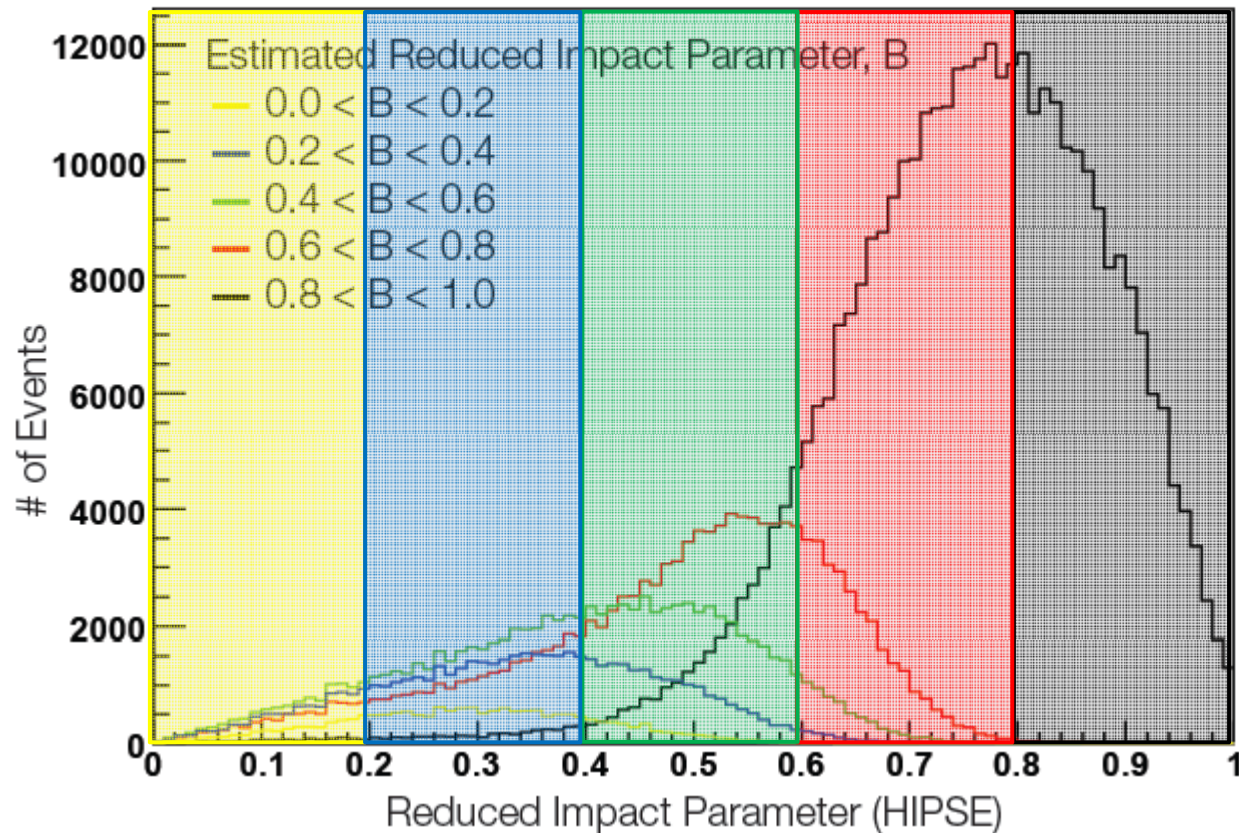
Bin Mapping Approach – Results



- Examples of poor separation:
 - ▣ Mid-rapidity charge
 - ▣ Total parallel momentum
- Examples of good separation:
 - ▣ Total particle multiplicity
 - ▣ Neutron multiplicity
 - ▣ Charged particle multiplicity
 - ▣ Event total transverse momentum

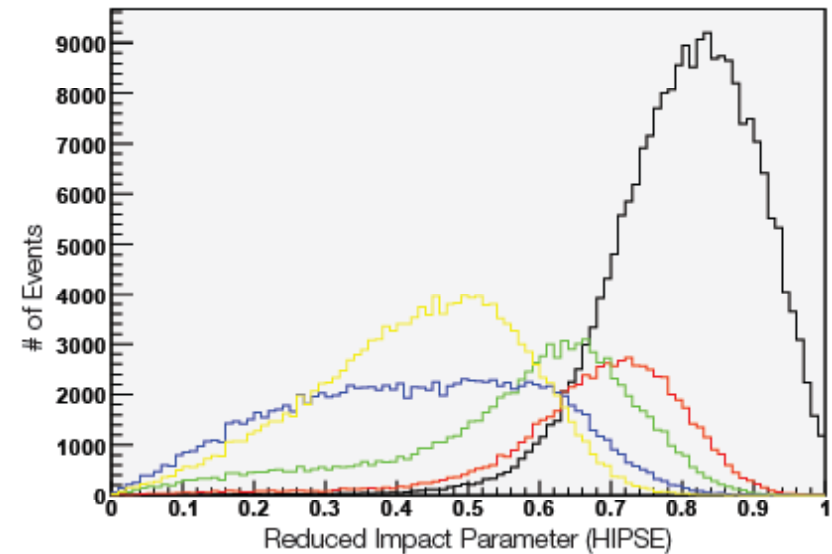
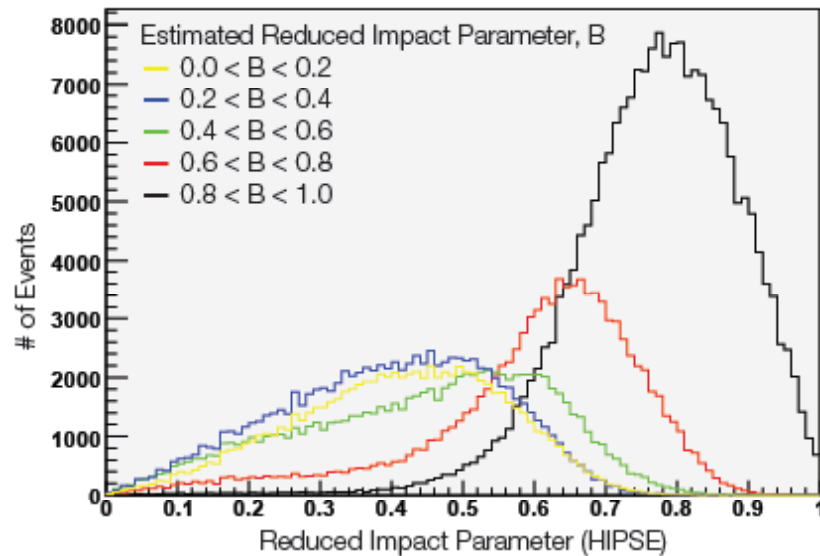
Bin Mapping Approach – Results

Example - Separation of impact parameter by total transverse momentum without Z-V cut



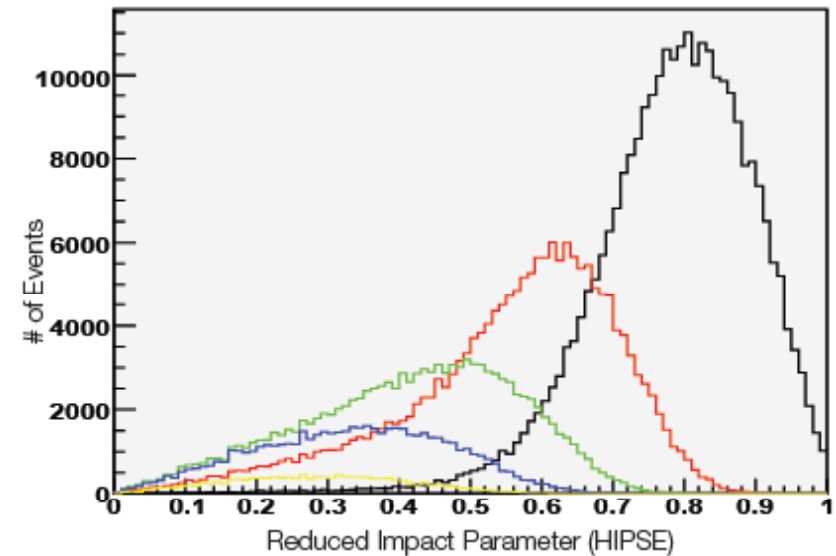
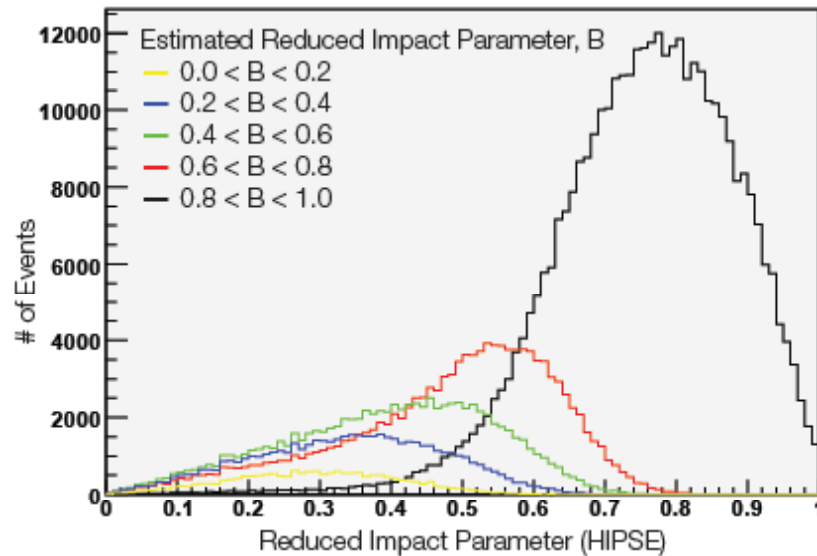
Bin Mapping Approach – Results

Separation of impact parameter by mid-rapidity charge
(left) and total parallel momentum (right)



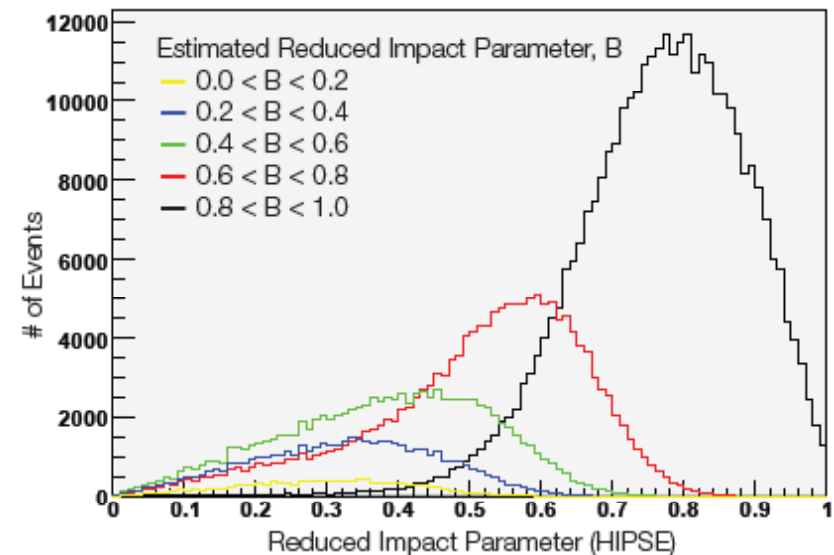
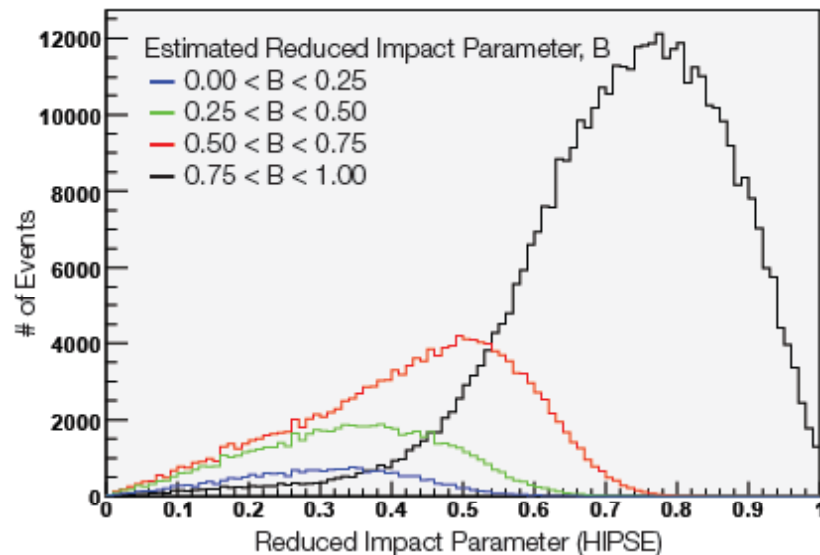
Bin Mapping Approach – Results

Separation of impact parameter by total particle multiplicity (left) and neutron multiplicity (right)



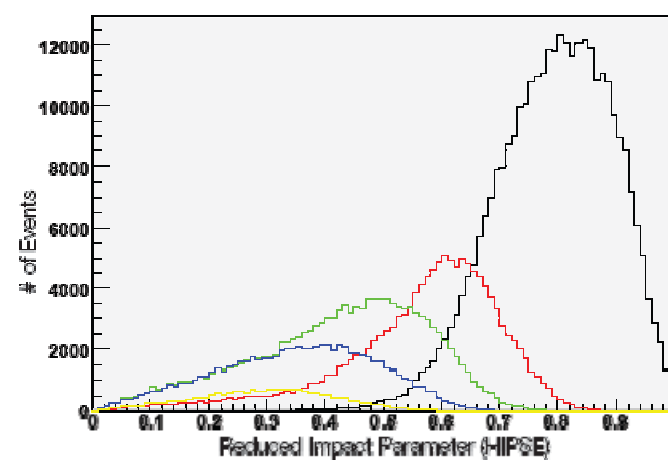
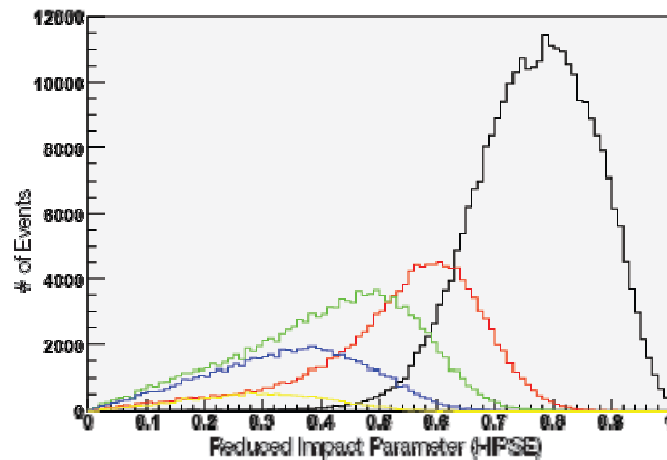
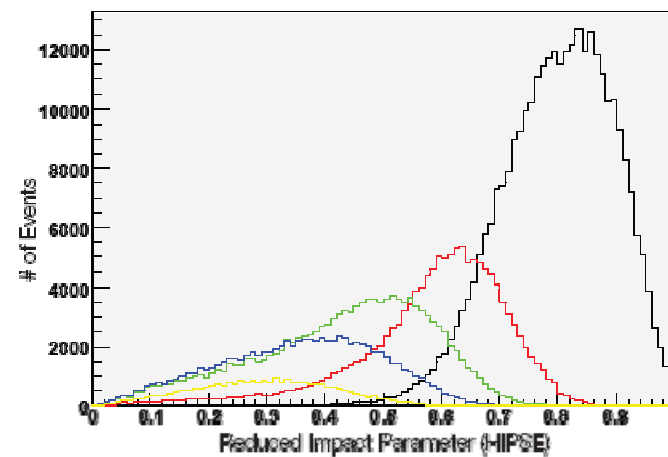
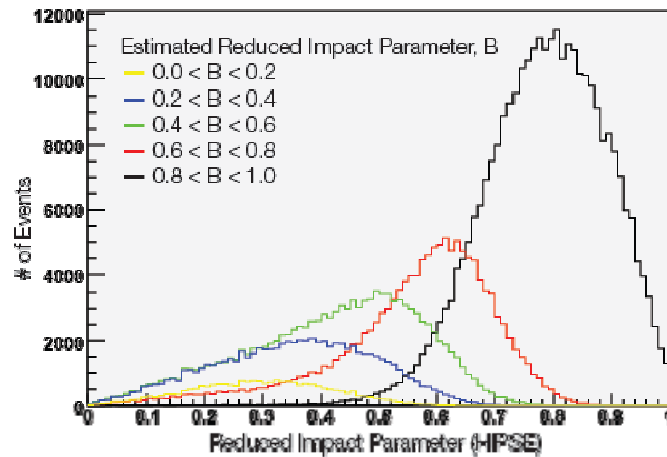
Bin Mapping Approach – Results

Separation of impact parameter by charged particle multiplicity using four bins (left) and five bins (right)



Bin Mapping Approach – Results

Separation of impact parameter by total transverse momentum without Z-V cut ^{70}Zn on ^{70}Zn (top left), ^{64}Zn on ^{64}Zn (top right), ^{64}Ni on ^{64}Ni (bottom left), ^{64}Zn on ^{64}Ni (bottom right), all at 35MeV/u



Neural Net Approach – Method

- Trained with:
 - ▣ Charged particle multiplicity
 - ▣ Neutron multiplicity
 - ▣ Event total transverse momentum
 - ▣ Intermediate / light fragment ratio
- Set up to yields most probable bin number to be compared to binned HIPSE values

<http://cern.root.ch> , Class: TMultiLayerPerceptron

<https://twiki.cern.ch/twiki/bin/view/Atlas/PhysicsAnalysisWorkBookNeuralNetwork>

Neural Net Approach – Results

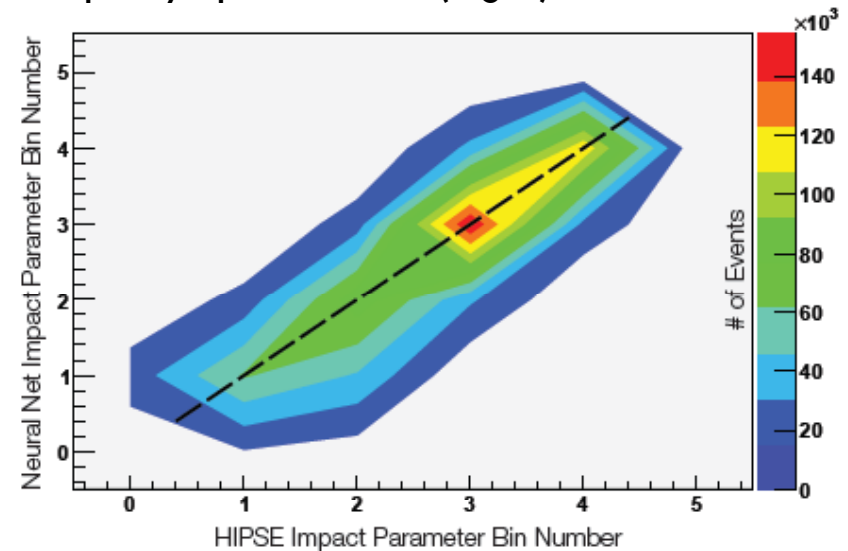
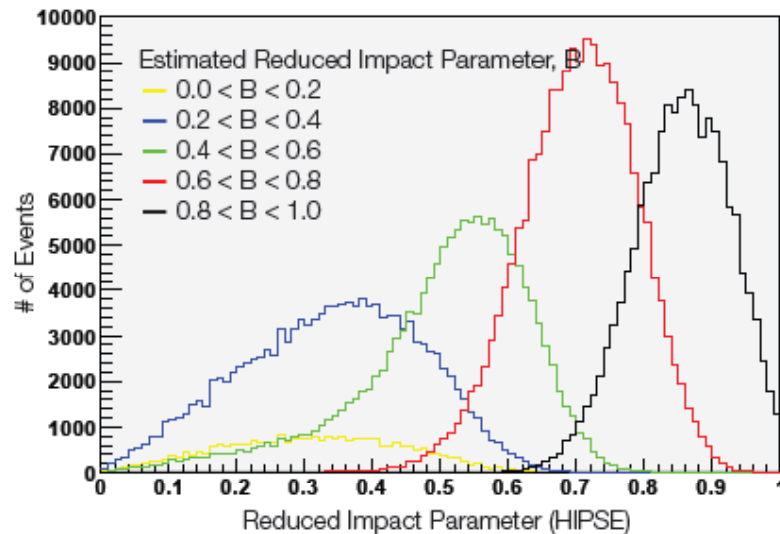


□ Neural Net

- Separation proved better than previous method
- Still some overlap at low impact parameter (understandable)
- Values placed in one of five equally spaced bins (due to the nature of this net) and compared with similarly binned HIPSE values

Neural Net Approach – Results

Separation of impact parameter using the Neural Net(left) and distribution of Neural Net generated impact parameters versus HIPSE generated impact parameters (both divided into five equally spaced bins (right))



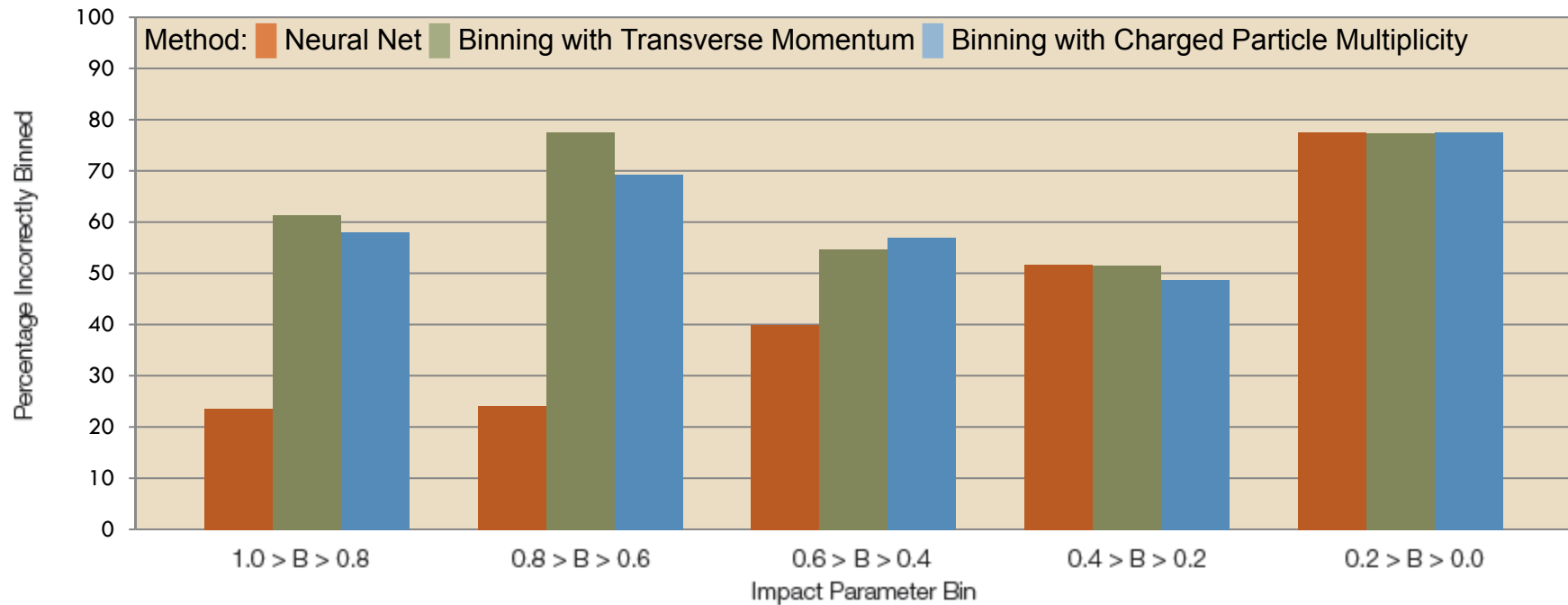
Conclusions



- Total transverse momentum and charged particle, neutron, and total particle multiplicities suitable for impact parameter determination via binning method
- Neural Net useful tool to better impact parameter determination
- Continuing research would allow for additional quantities to be examined, and for promising quantities to be integrated into the training of the neural net

Conclusions

Percentage of events incorrectly binned (by bin) for: the Neural Net, mapping with transverse momentum, and mapping with charged particle multiplicity



Acknowledgements



□ References:

- C. Ogilvie *et al.*, *Phys. Rev. C* 40, 654 (1989).
- D. Lacroix *et al.*, *Phys. Rev. C* 69, 1 (2004).
- F. Haddad *et al.*, *Phys. Rev. C* 55, 1371 (1997).

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