

## Automatic Bad Channel Classification (Plots for APR)

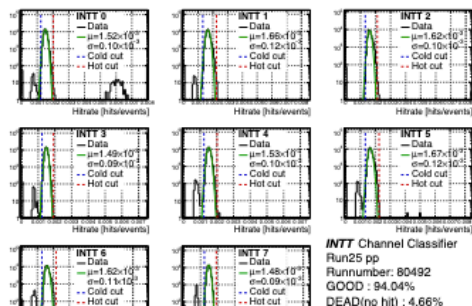
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## Validation of Automated Channel Classification for Intermediate Silicon Tracker at sPHENIX

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sPHENIX<sup>1)</sup> is a state-of-the-art detector system at RHIC that enables measurements of heavy-ion and polarized proton collisions to explore QCD matters. During the 2025 run, sPHENIX recorded both Au+Au and  $p + p$  data sets. The Intermediate Silicon Tracker (INTT) has roughly 370,000 channels read out in eight servers, and we built an automated decoding-stage pipeline to classify bad channels (hot/cold/dead) using Gaussian fits to hit-rate distributions per server.

Figure 1 shows an example of the Gaussian fitting procedure used for channel classification. The hit-rate distributions and fits illustrate how the pipeline extracts mean and width to tag bad channels.



data show comparable run-by-run behavior, supporting that the automated classification framework operates universally across beam species.

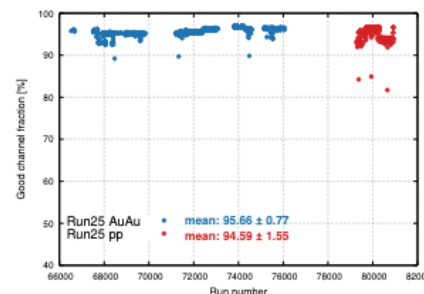


Fig. 2. Good-channel fraction versus run number for Run25 Au+Au and Run25  $p + p$  data.

Figure 3 shows the hit rate evolution for the eight readout servers during Run25  $p + p$  data (run range 80665–80825). Within a fill, the hit rate shows an overall decreasing trend as the beam intensity decays, and the consistent behavior across servers indicates that the automated mean values track the expected beam

3 Plots considered to be added in APR

1) Hitrate distribution with Gaussian Fit

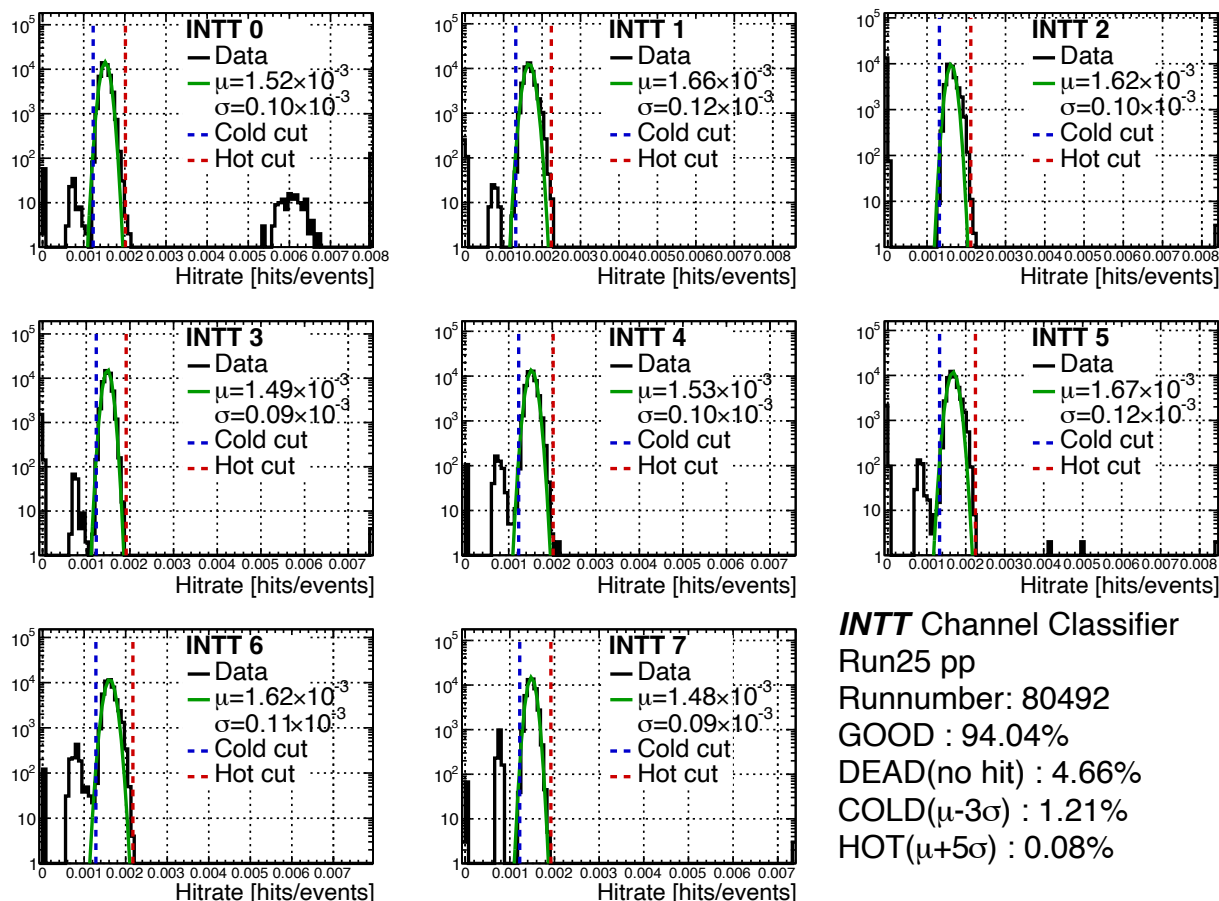
2) Good Channel Ratio for Run25 AuAu, pp

3) Hitrate vs runnumber to see the lumi. effect

Automatic channel classification

: We've implemented the calibration modules at decoding stage, so we can make bad channel CDBTTree during the decoding/production

APR about : How the calibration results looks like



## INTT Channel Classifier

Run25 pp  
 Runnumber: 80492  
 GOOD : 94.04%  
 DEAD(no hit) : 4.66%  
 COLD( $\mu-3\sigma$ ) : 1.21%  
 HOT( $\mu+5\sigma$ ) : 0.08%

3 Plots considered to be added in APR

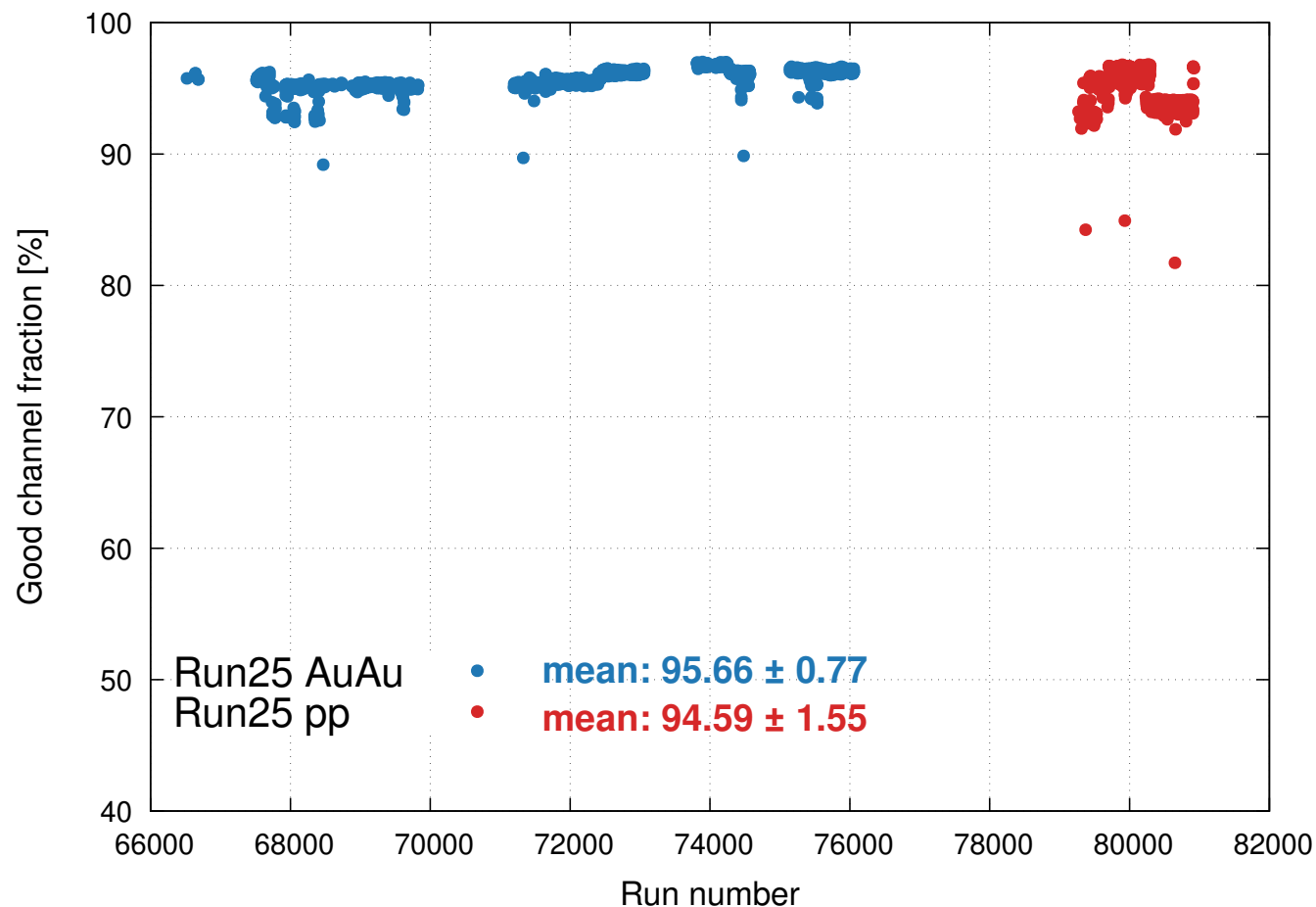
1) Hitrate distribution with Gaussian Fit

2) Good Channel Ratio for Run25 AuAu, pp

3) Hitrate vs runnumber to see the lumi. effect

Hit rate distribution per each server  
 with its **Gaus fit result**

**BLUE/RED** dashed line indicating **cold/hot** cut respectively



3 Plots considered to be added in APR

1) Hitrate distribution with Gaussian Fit

**2) Good Channel Ratio for Run25 AuAu, pp**

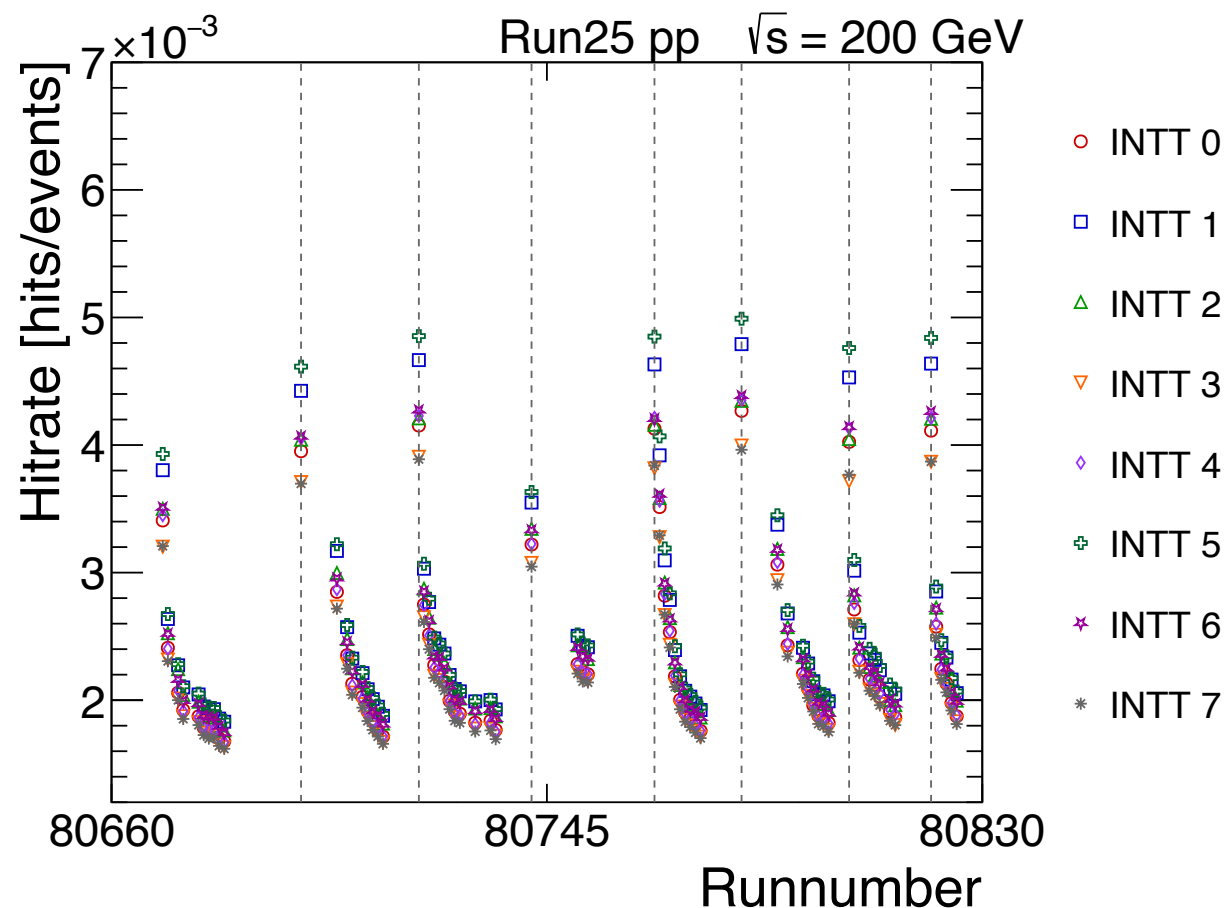
3) Hitrate vs runnumber to see the lumi. effect

GOOD channel fration[%] for physics run selection

1)BCO alignment GOOD

2)10kevents> runs only

BLUE/RED dots indicating AuAu/pp data respectively



3 Plots considered to be added in APR

1) Hitrate distribution with Gaussian Fit

2) Good Channel Ratio for Run25 AuAu, pp

**3) Hitrate vs runnumber to see the lumi. effect**

Dashed line indicating first run of the fill

Within a fill, the hit rate shows an over-all decreasing trend as the beam intensity decays, and the consistent behavior across servers indicates that the automated mean values track the expected beam