



Multiplicity Dependence of Two-Particle Angular Correlations in Proton-Proton Collisions

Eva Sicking on behalf of the ALICE Collaboration

MPI@LHC 2012
MB & UE Working Group

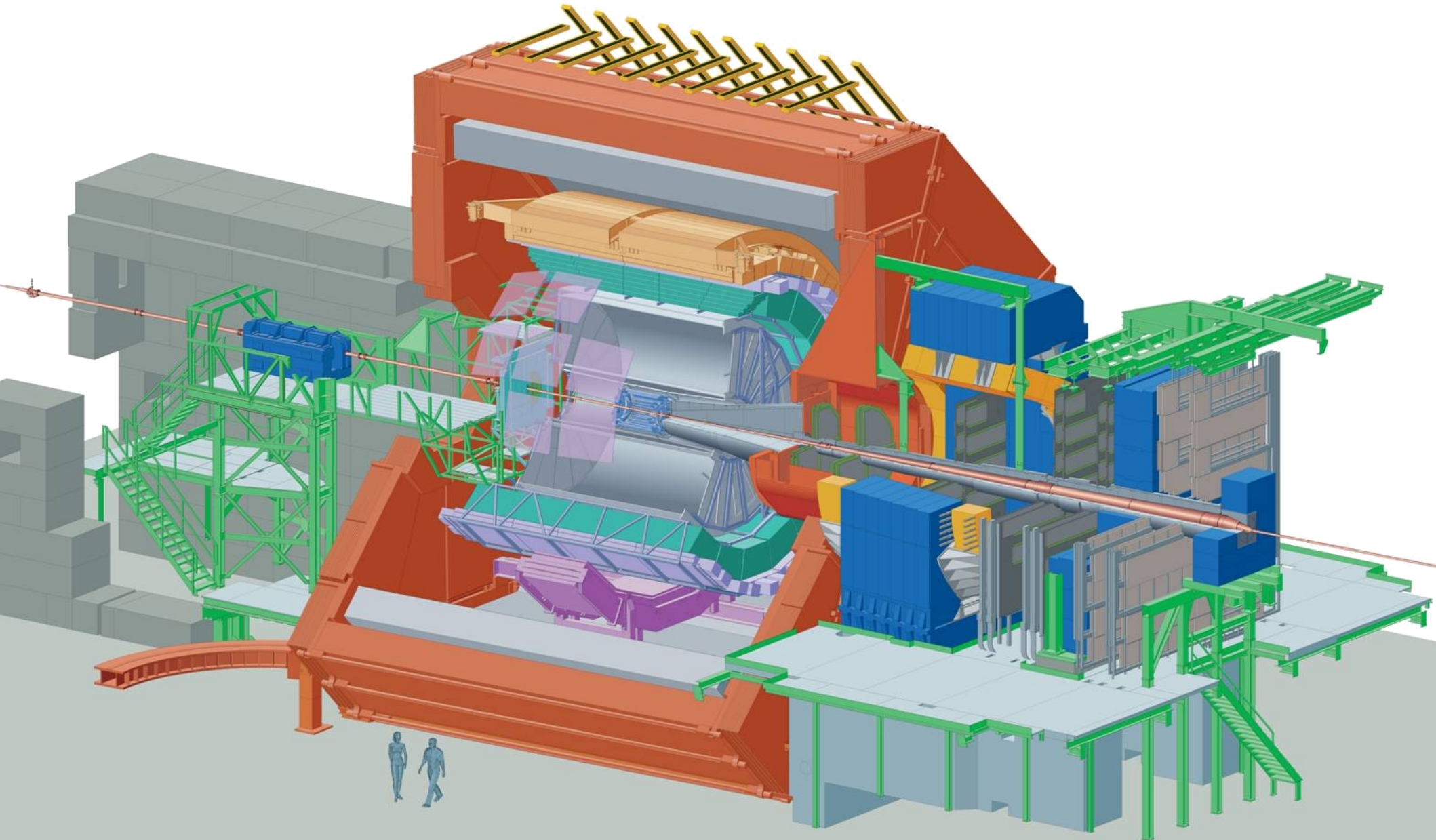
CERN, 03-12-2012

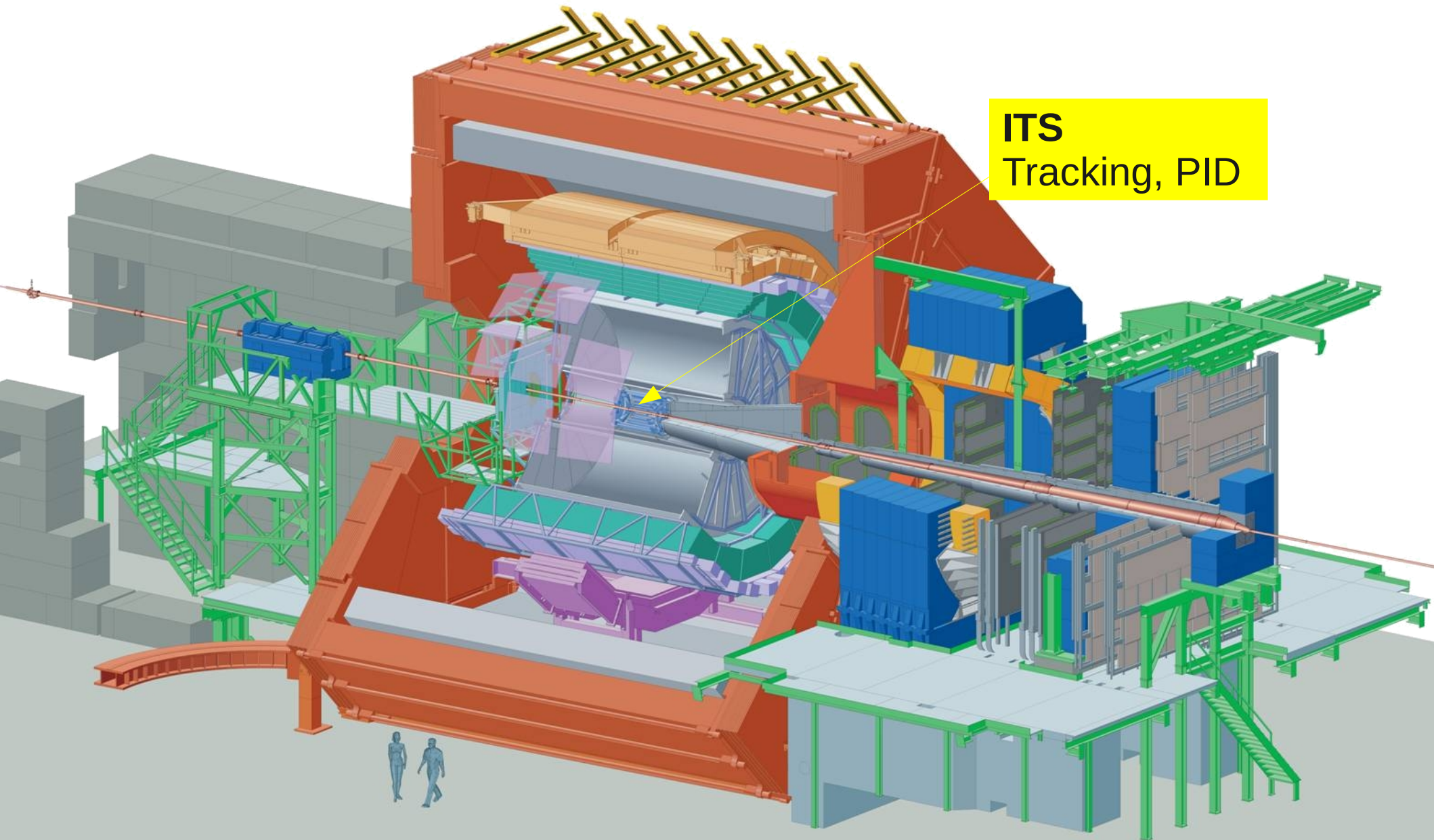


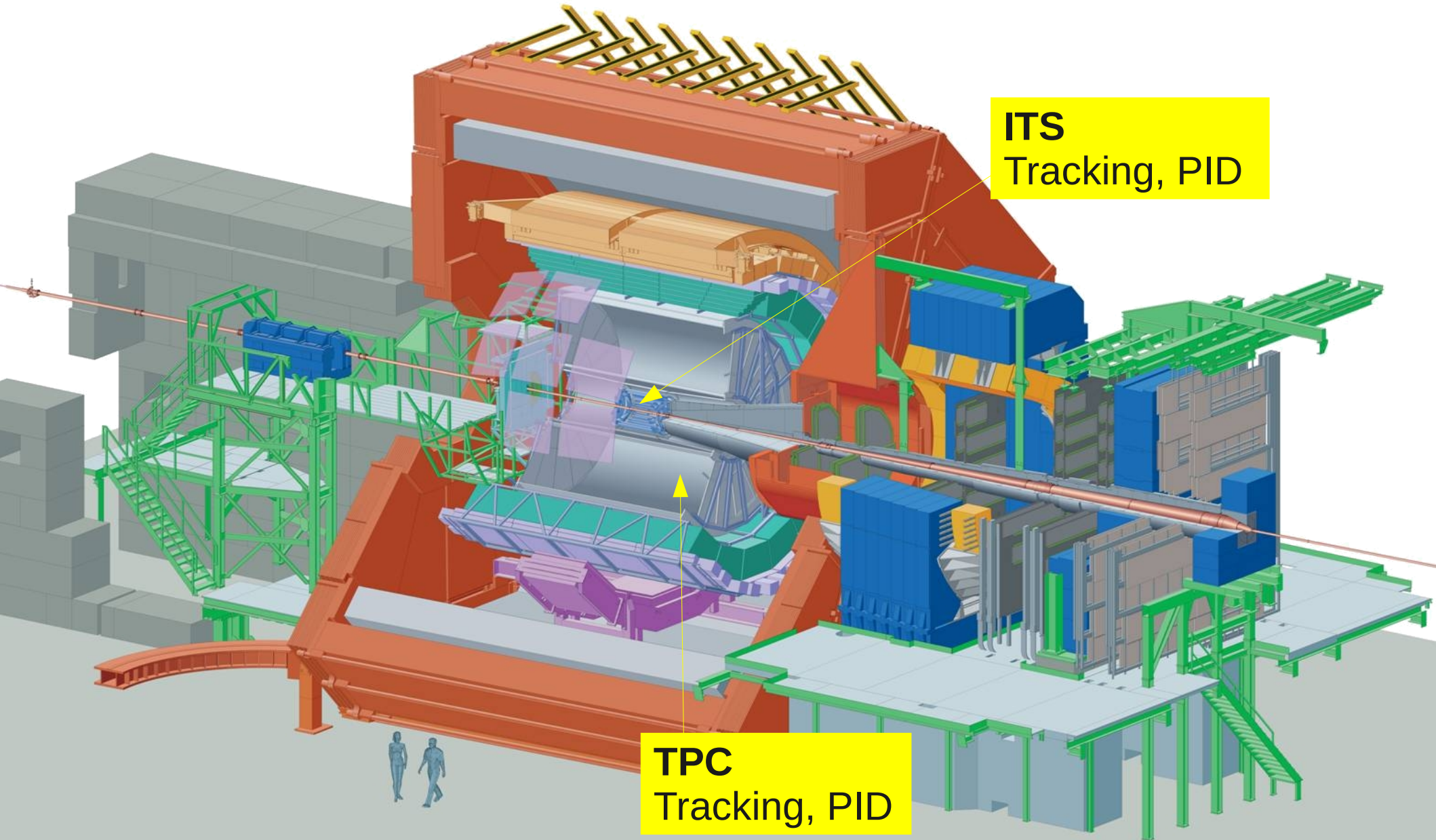
A Large Ion Collider Experiment



- ALICE is designed to study heavy-ion (Pb-Pb) collisions and also proton-proton (pp) collisions
 - Several signals in heavy-ion collisions are measured relative to pp
 - ALICE also has a rich pp program
- ALICE special features for pp minimum bias physics
 - Low momentum sensitivity due to low material budget and low magnetic field
 - Excellent primary and secondary vertex resolution
 - Excellent Particle Identification (PID) capability
- ALICE can give important input to pp studies
 - Rare signals need good description of soft underlying event
 - Tuning of MC generators in low- p_T region
 - Study of high-multiplicity collisions

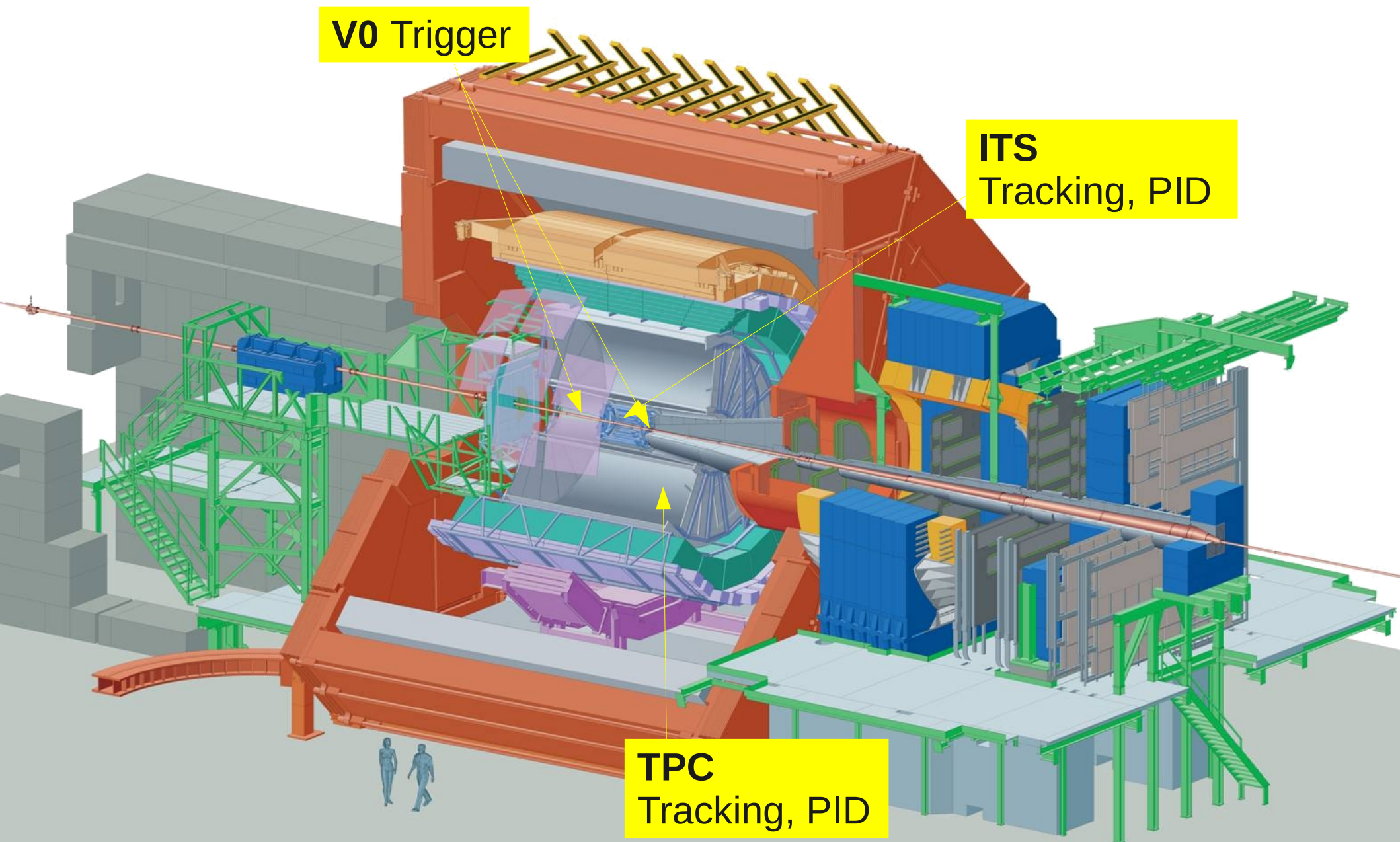




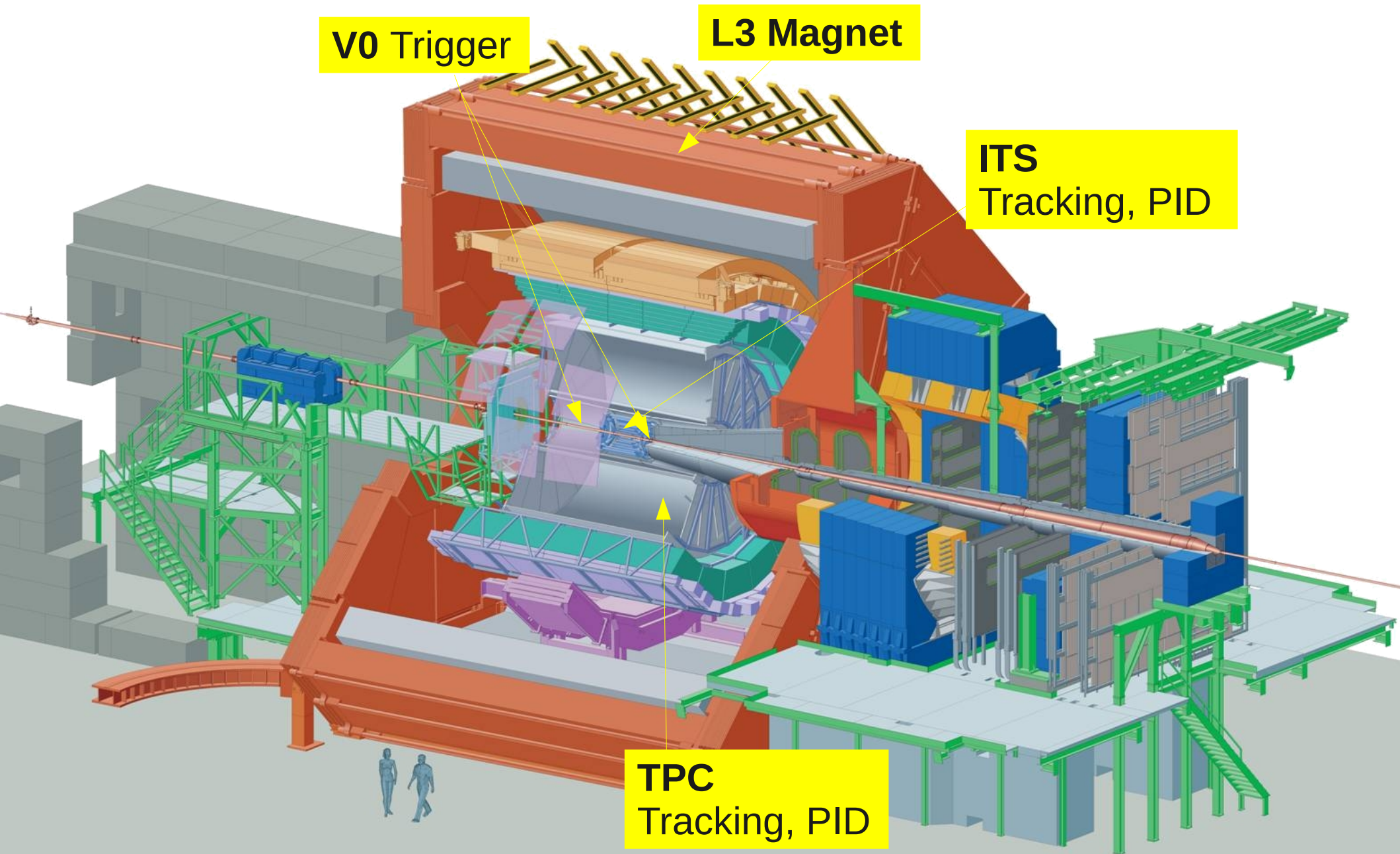


ITS
Tracking, PID

TPC
Tracking, PID

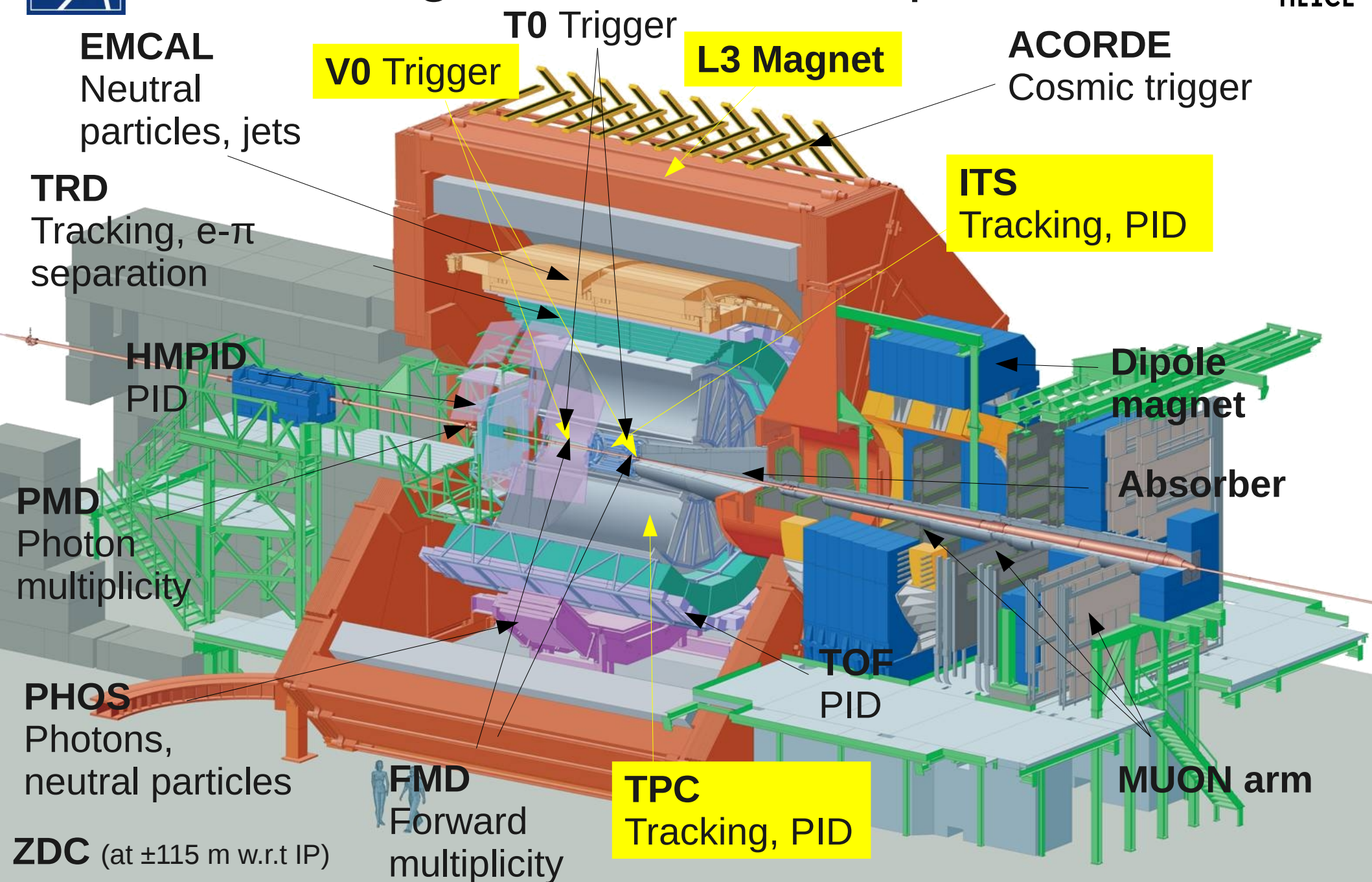


A Large Ion Collider Experiment





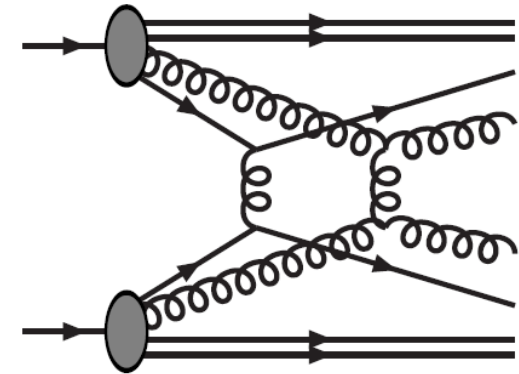
A Large Ion Collider Experiment



Analysis Motivation

- High-energy proton-proton collisions can be interpreted as collisions of two “bunches of partons”
- → when two protons collide, it is possible that multiple distinct pairs of partons collide with each other

→ Multiple parton interactions (MPI)



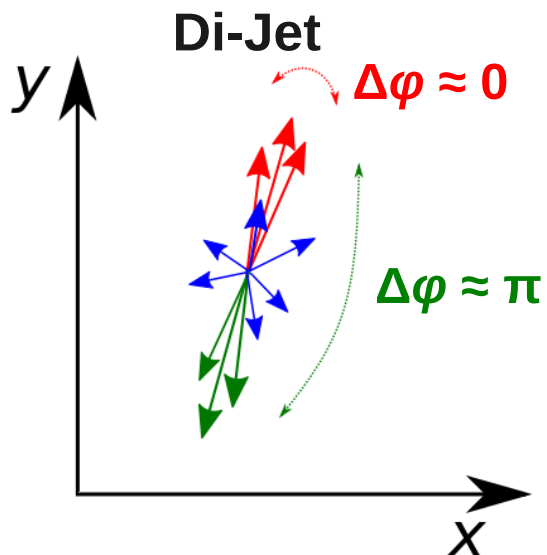
- MPIs presumably have impact on multiplicity distribution, jets, and the underlying event
- Is it possible to measure multiple parton interactions, e.g. the number and the corresponding particle yield?
 - Possible access to MPI via measurement of **di-jets**

Motivation of Analysis Procedure

- Investigate properties of **jets** and low energetic “**mini-jets**” and their contribution to the event multiplicity
 - “Mini-Jets” are particles from “hard scattering”, which have too low energy in comparison to the underlying event, and which therefore can not be reconstructed event-by-event
 - But, there is a possibility to access mini-jet properties via two particle correlations averaged over many events

- Different correlation approaches:
 1. Correlation with one leading particle, particles with highest transverse momentum
 - Bias to hard momentum scale (growth of $p_{T,max}$ with N_{ch})
 2. Triggered, inclusive correlations between all tracks with $p_T > p_{T,trig}$ and $p_T > p_{T,assoc}$ using $p_{T,trig} > p_{T,assoc}$
 - Attention: possible bias due to unwanted combinatorics of correlated trigger particles
- Both methods have drawbacks for mini-jet measurements

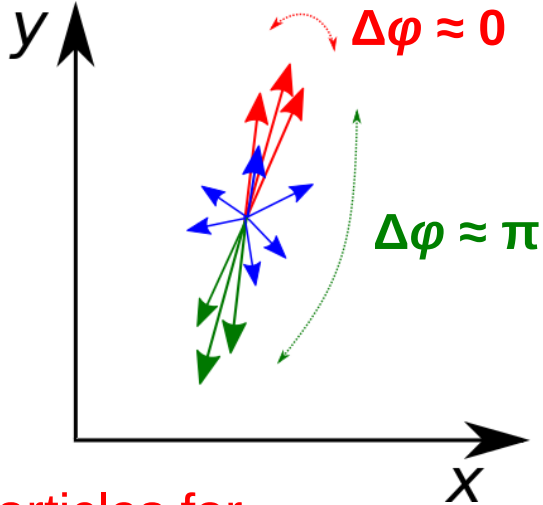
Two-Particle Angular Correlations



- Measure distances between particle pairs of trigger particles ($p_T > p_{T, \text{trig}}$ with $p_{T, \text{trig}} \gg \Lambda_{\text{QCD}}$) and associated particles ($p_T > p_{T, \text{assoc}}$)
- Distance in terms of azimuthal angle φ and pseudorapidity η

Two-Particle Angular Correlations

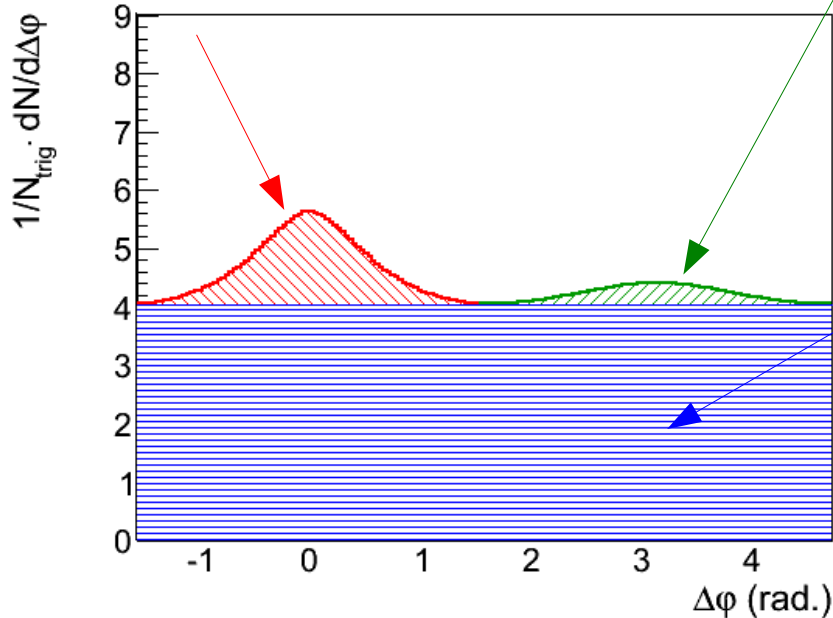
Di-Jet



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Particles for same jet

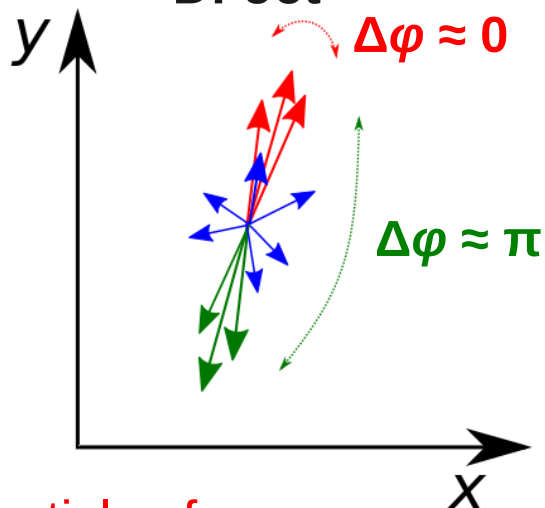
Particles from away side jet



Particles from processes uncorrelated to trigger particle

Two-Particle Angular Correlations

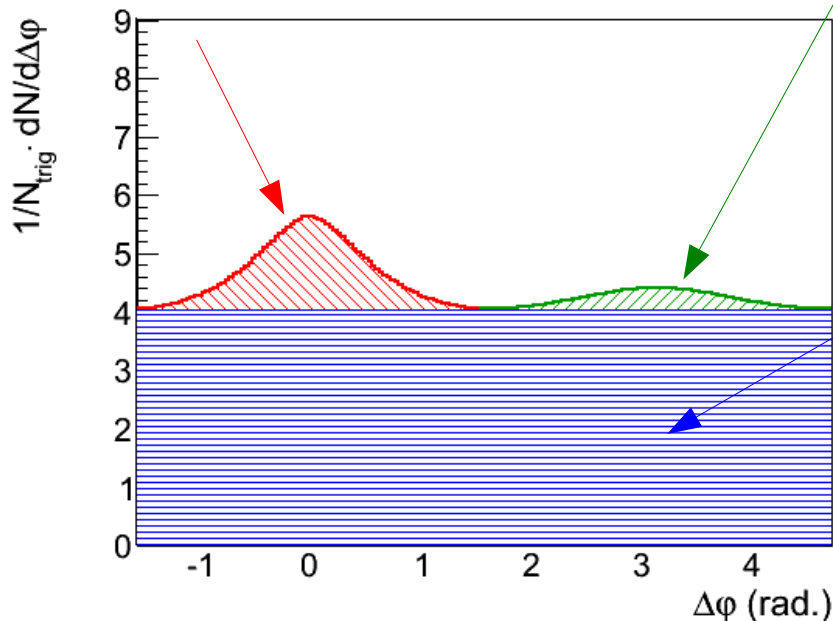
Di-Jet



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Particles for same jet

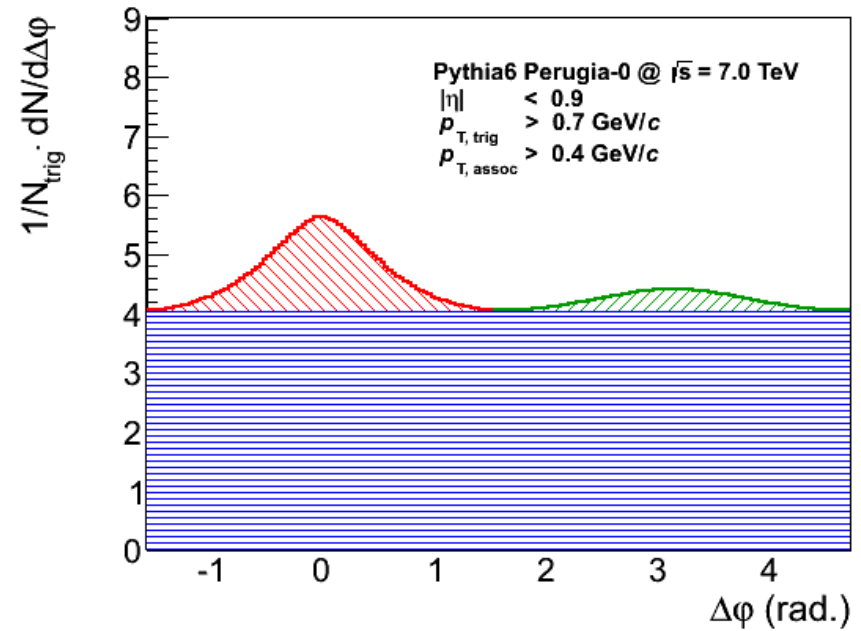
Particles from away side jet



Particles from processes uncorrelated to trigger particle

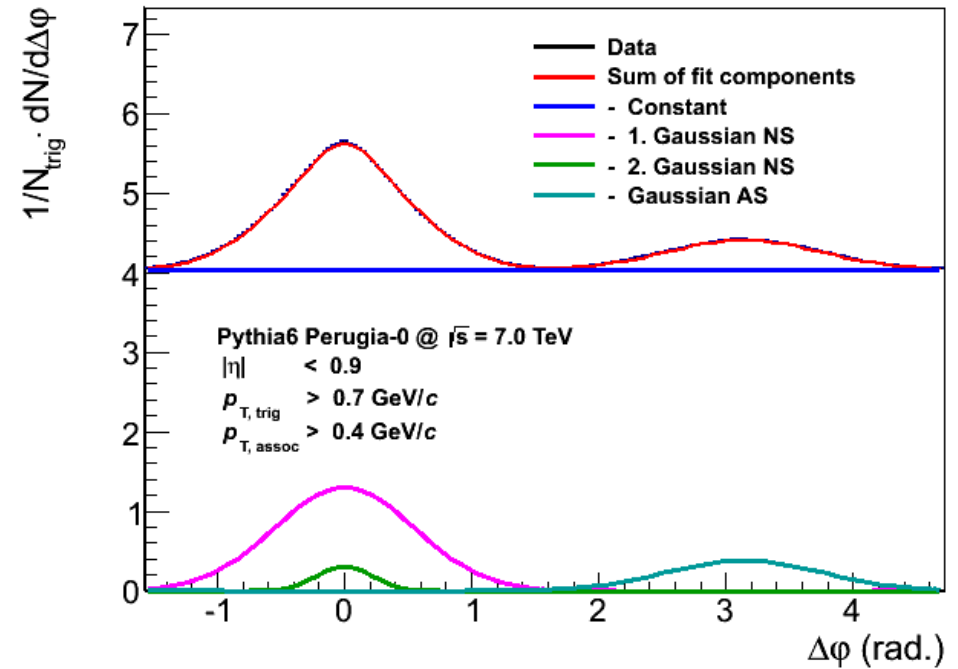
- Further possible contributions can be neglected when choosing $p_{T, \text{trig}}^{\text{max}} > 0.7 \text{ GeV}/c$
 - Particle decay ($< 10\%$)
 - Photon conversion
 - Hanbury Brown and Twiss effect (HBT)

- Azimuthal correlation can be divided into three contributions: background and two peaks



- Azimuthal correlation can be divided into three contributions: background and two peaks
- Fit function: Combination of constant and Gaussian functions

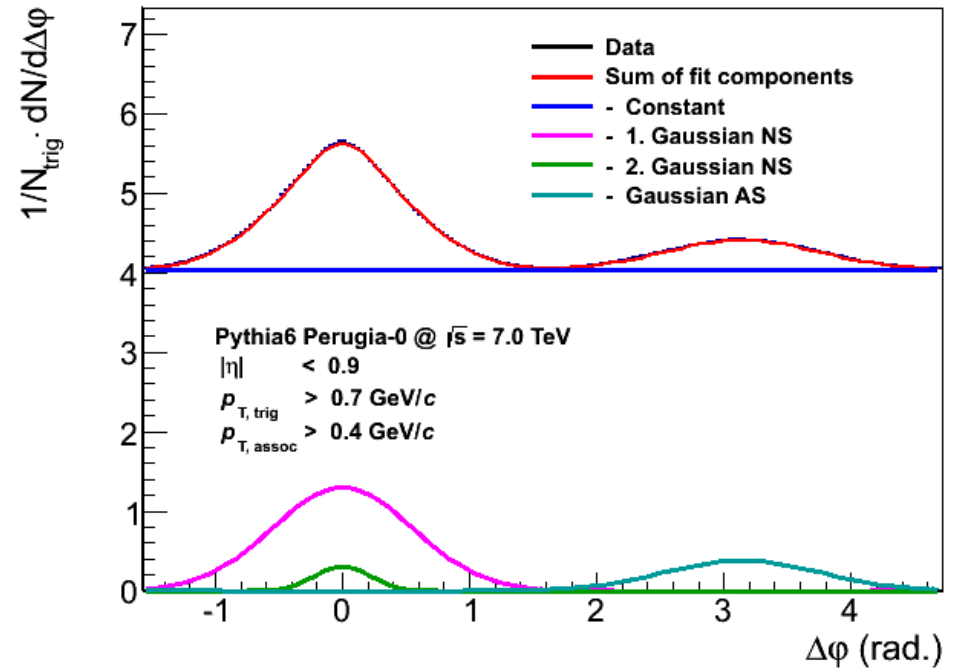
$$\begin{aligned}
 f(\Delta\varphi) = & C + A_1 e^{-\frac{\Delta\varphi^2}{2\sigma_1^2}} + A_1 e^{-\frac{(\Delta\varphi - 2\pi)^2}{2\sigma_1^2}} \\
 & + A_2 e^{-\frac{\Delta\varphi^2}{2\sigma_2^2}} + A_2 e^{-\frac{(\Delta\varphi - 2\pi)^2}{2\sigma_2^2}} \\
 & + A_3 e^{-\frac{(\Delta\varphi - \pi)^2}{2\sigma_3^2}} + A_3 e^{-\frac{(\Delta\varphi + \pi)^2}{2\sigma_3^2}}
 \end{aligned}$$



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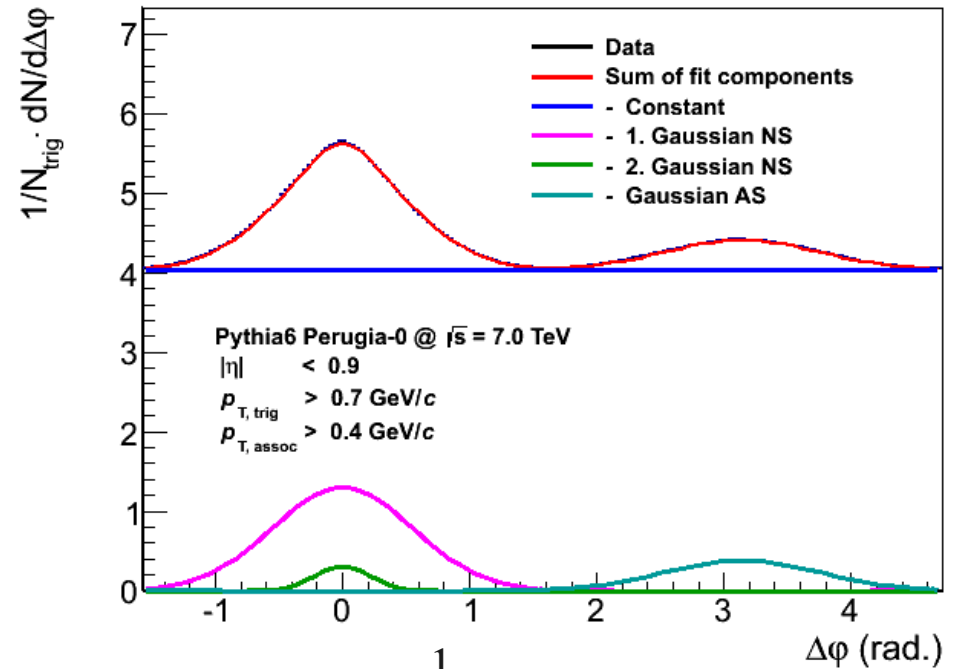
- Data and fit are in excellent agreement, fit is stable



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$$\langle N_{isotrop} \rangle = \frac{1}{N_{trig}} \cdot C$$

$$\langle N_{assoc, \text{near side}} \rangle = \frac{1}{N_{trig}} \sqrt{2\pi} (A_1 \sigma_1 + A_2 \sigma_2)$$

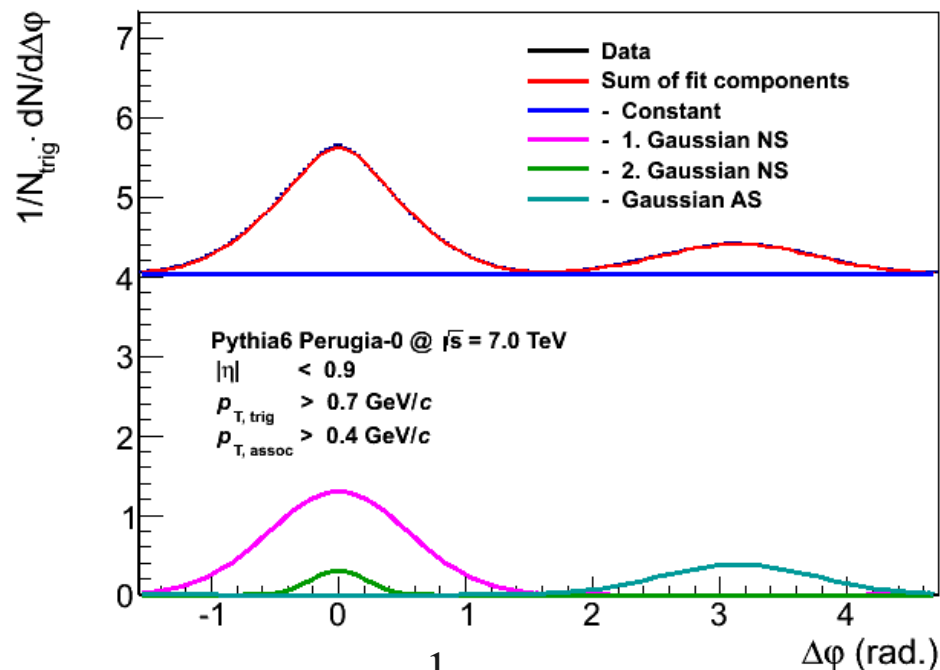
$$\langle N_{assoc, \text{away side}} \rangle = \frac{1}{N_{trig}} \sqrt{2\pi} (A_3 \sigma_3)$$

$$\langle N_{trigger} \rangle = \frac{N_{trigger}}{N_{event}}$$

- Azimuthal correlation can be divided into three contributions: background and two peaks
- Fit function: Combination of constant and Gaussian functions

$$f(\Delta\varphi) = C + A_1 e^{-\frac{\Delta\varphi^2}{2\sigma_1^2}} + A_1 e^{-\frac{(\Delta\varphi - 2\pi)^2}{2\sigma_1^2}} + A_2 e^{-\frac{\Delta\varphi^2}{2\sigma_2^2}} + A_2 e^{-\frac{(\Delta\varphi - 2\pi)^2}{2\sigma_2^2}} + A_3 e^{-\frac{(\Delta\varphi - \pi)^2}{2\sigma_3^2}} + A_3 e^{-\frac{(\Delta\varphi + \pi)^2}{2\sigma_3^2}}$$

- Data and fit are in excellent agreement, fit is stable
- Compute number of sources of particle production → possibility to access information about MPI



$$\langle N_{isotrop} \rangle = \frac{1}{N_{trig}} \cdot C$$

$$\langle N_{assoc, \text{near side}} \rangle = \frac{1}{N_{trig}} \sqrt{2\pi} (A_1 \sigma_1 + A_2 \sigma_2)$$

$$\langle N_{assoc, \text{away side}} \rangle = \frac{1}{N_{trig}} \sqrt{2\pi} (A_3 \sigma_3)$$

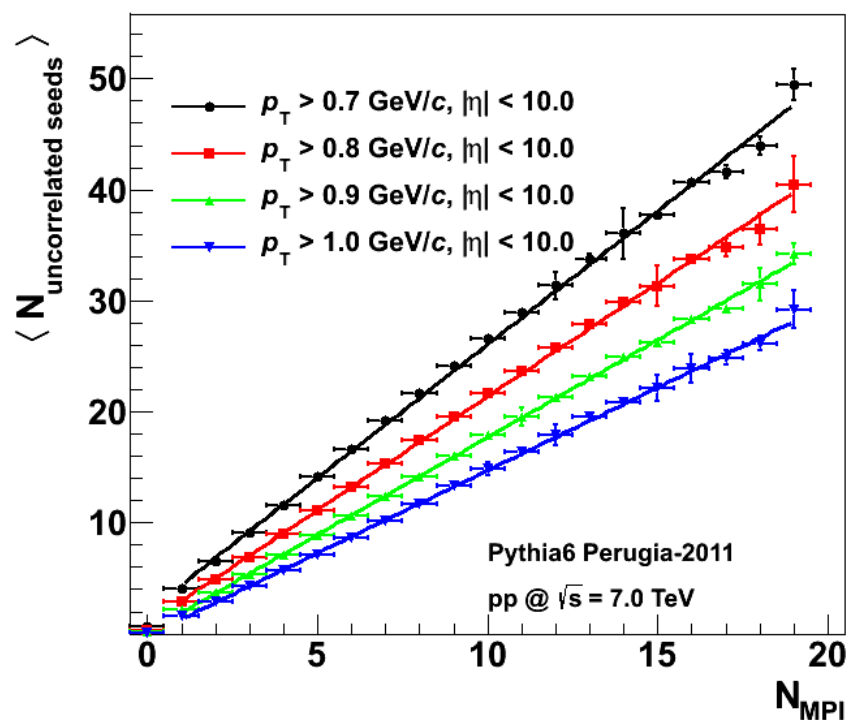
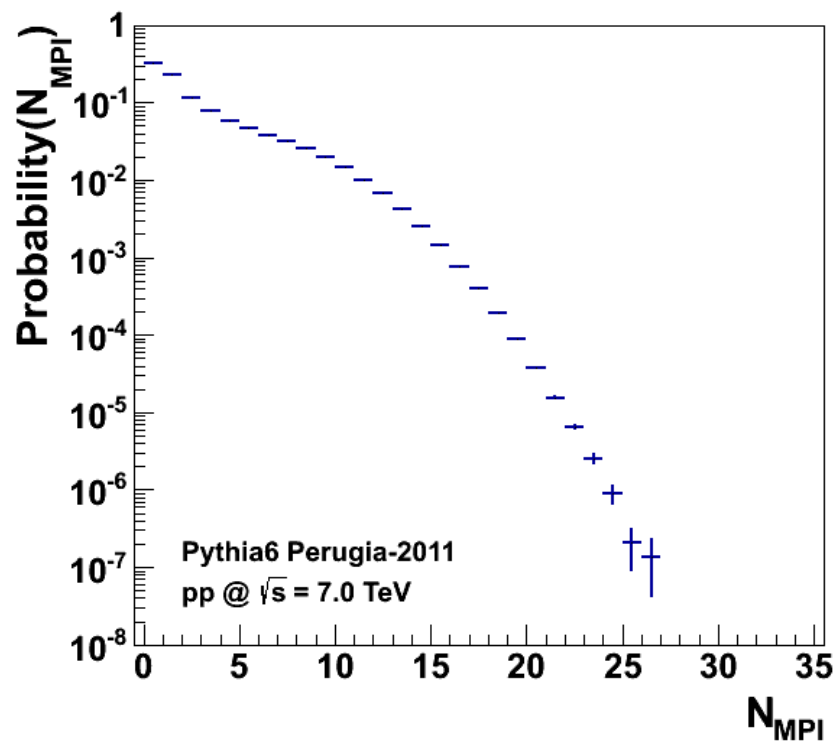
$$\langle N_{trigger} \rangle = \frac{N_{trigger}}{N_{event}}$$

$$\langle N_{uncorrelated\ seeds} \rangle = \frac{\langle N_{trigger} \rangle}{\langle 1 + N_{assoc, \text{near} + \text{away}}(p_T > p_{T, trig}) \rangle}$$

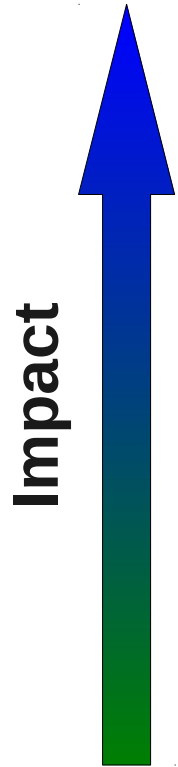
- Pythia has a phenomenological model of multiple parton interactions (MPI)

$$N_{MPI}(p_{T, min}) = \frac{\sigma_{interaction}(p_{T, min})}{\sigma_{non-diffractive}}$$

- Within the Pythia model, N_{MPI} is proportional to the number of uncorrelated seeds $N_{uncorrelated\ seeds}$
- Possibility to access N_{MPI} using presented analysis method



- Data (including ITS and TPC)
 - pp @ $\sqrt{s} = 0.9$ TeV:
 - 7 million events
 - pp @ $\sqrt{s} = 2.76$ TeV:
 - 27 million events
 - pp @ $\sqrt{s} = 7.0$ TeV:
 - 204 million events
- Event cuts
 - Minimum bias trigger: hit in V0 or SPD
 - One distinct reconstructed vertex within $|z_{\text{vertex}}| < 10$ cm of good quality
 - At least one track in ITS-TPC acceptance ($p_{\text{T}} > 0.2$ GeV/c, $|\eta| < 0.9$)
- Track cuts
 - Full refit procedure during the tracking in ITS and TPC
 - At least 1 hit per track in one of the first 3 ITS layers (first 3 out of 6)
 - At least 70 clusters per track in the TPC drift volume (out of 159)
 - $\chi^2/\text{TPC cluster} < 4$
 - Reject tracks with kink topology
 - p_{T} -dependent DCA_{xy} cut corresponding to 7σ of track distribution ($\text{DCA}_{xy,\text{max}} = 0.3$ cm)
 - $\text{DCA}_z < 2$ cm

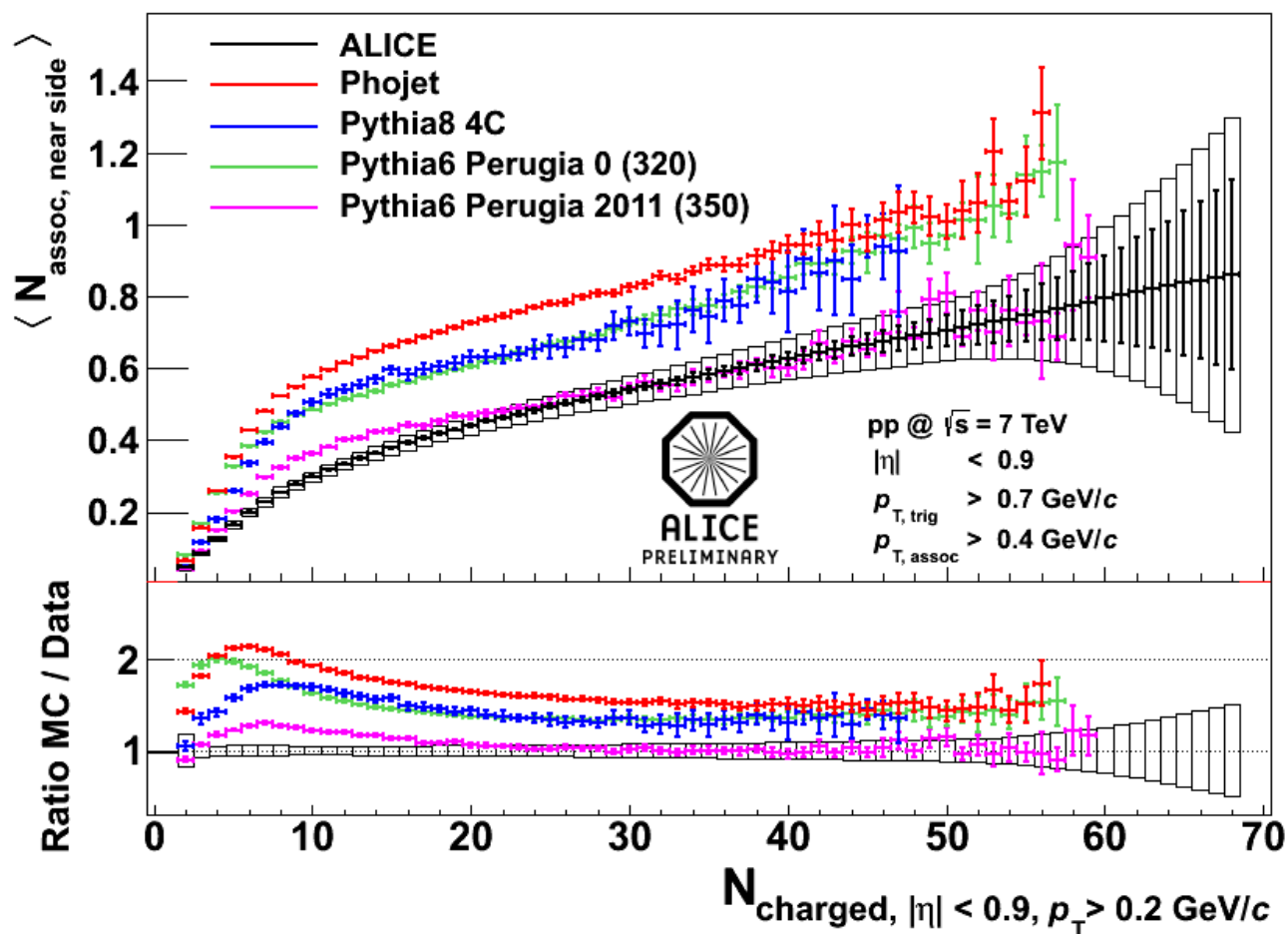


- Correction chain

- Reconstruction efficiency
- Contamination with tracks from secondary particles
- Two-track and detector effects
- Multiplicity correction
- Contamination from strange particles
- Vertex reconstruction efficiency
- Trigger efficiency

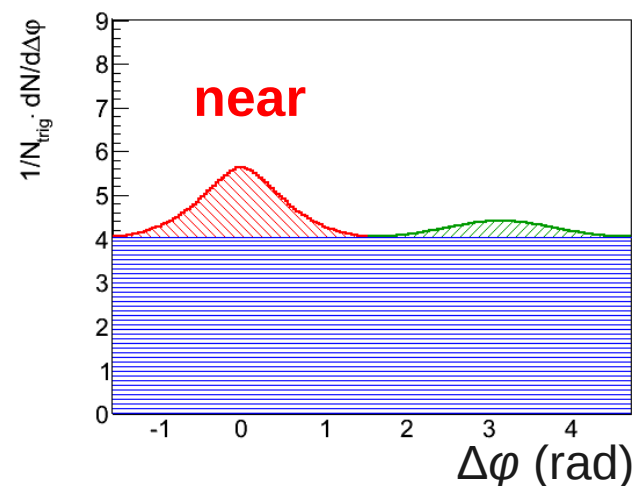
- Sources of systematic uncertainties

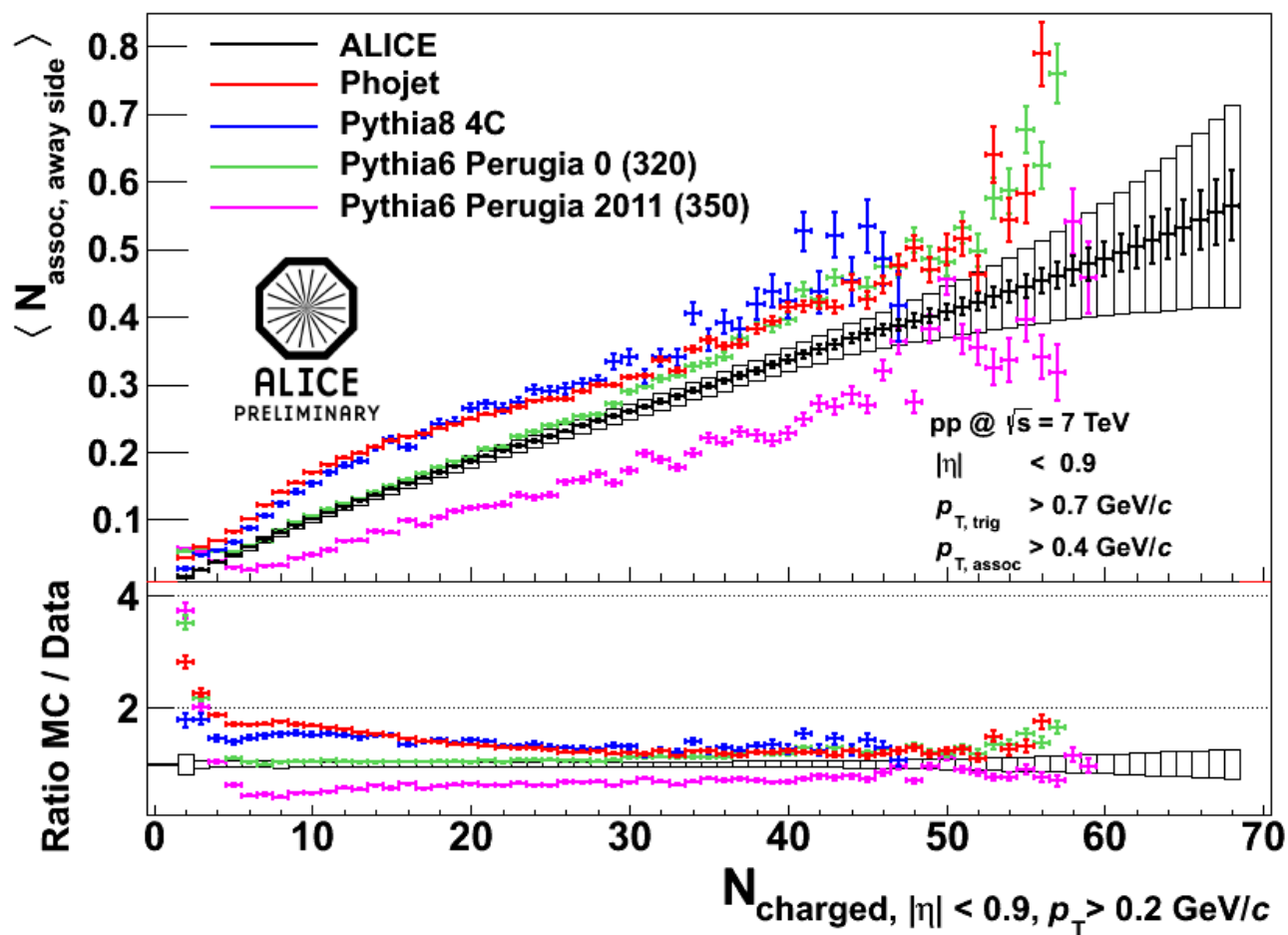
- Uncertainty of ITS-TPC efficiency
- Particle composition in MC
- Track cut dependence
- Correction procedure
- Event generator dependence
- Transport MC dependence
- Signal extraction
- Vertex quality cut dependence
- Pileup events
- Influence of resonances
- Material budget
- Strangeness correction



- Particle production in near side peak is dominated by jet fragmentation

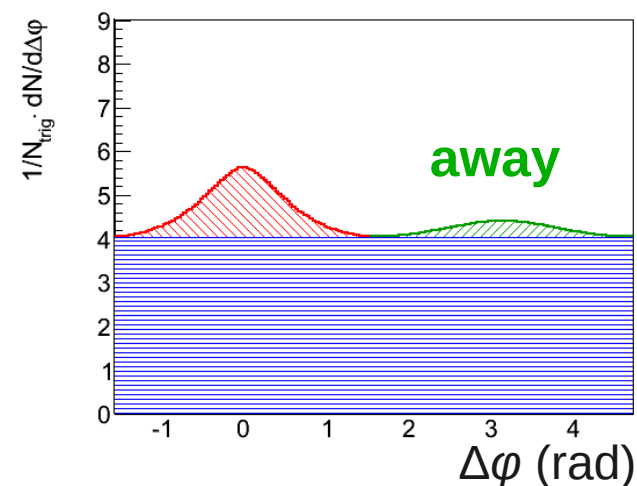
- Per-trigger near side pair yield grows with N_{ch}
- Near side is overestimated by Phojet, Pythia8, and Pythia6 Perugia-0 by up to 100%, Pythia6 Perugia-2011 gives best agreement with only small deviations

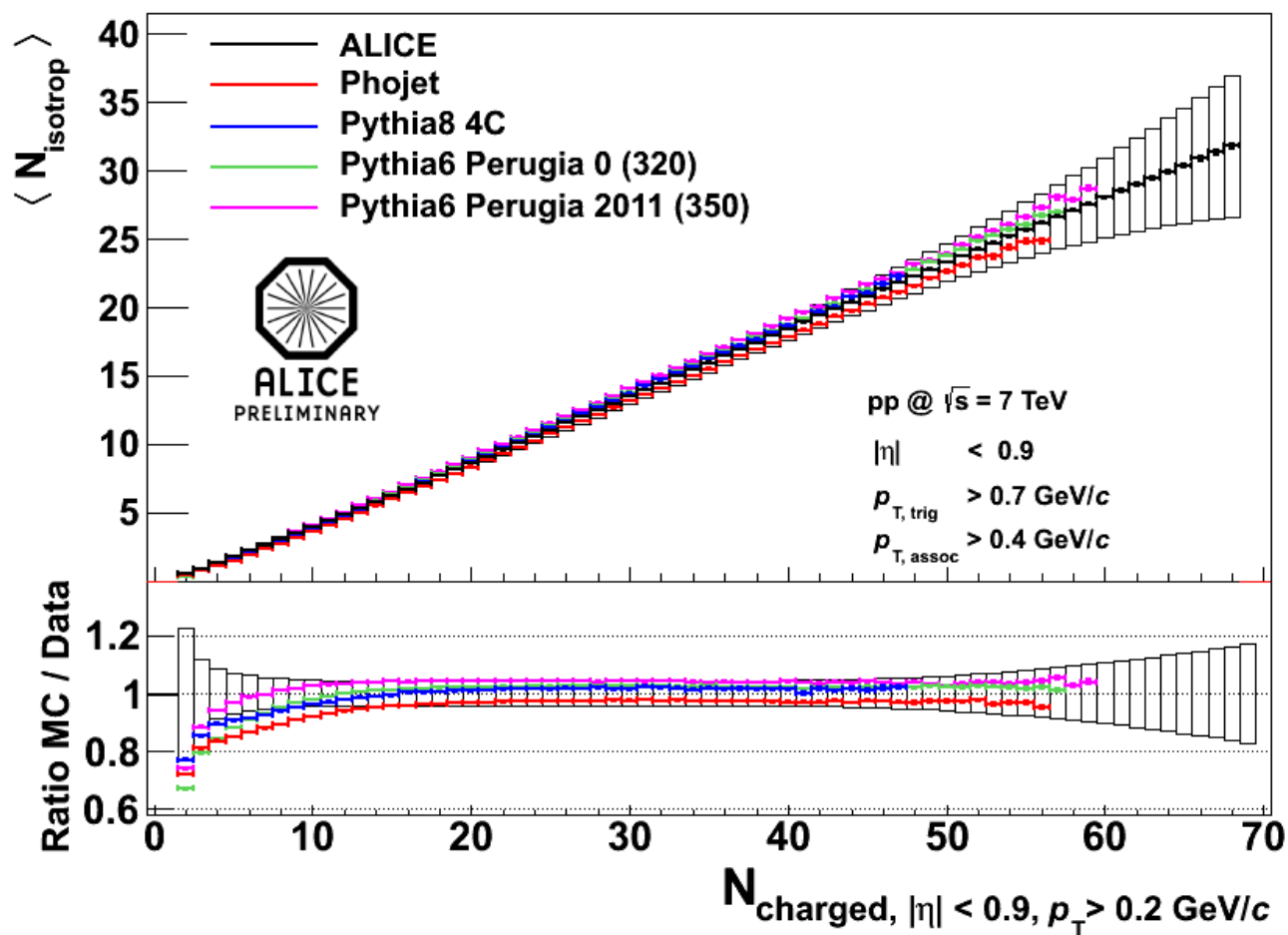




- Particles in away side peak are produced in recoiling jets

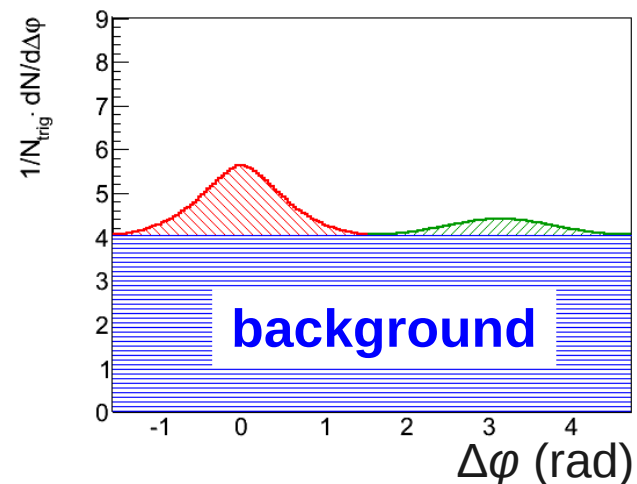
- Per-trigger away side pair yield grows with N_{ch}
- Pythia6-Perugia-0 gives best agreement with ALICE results



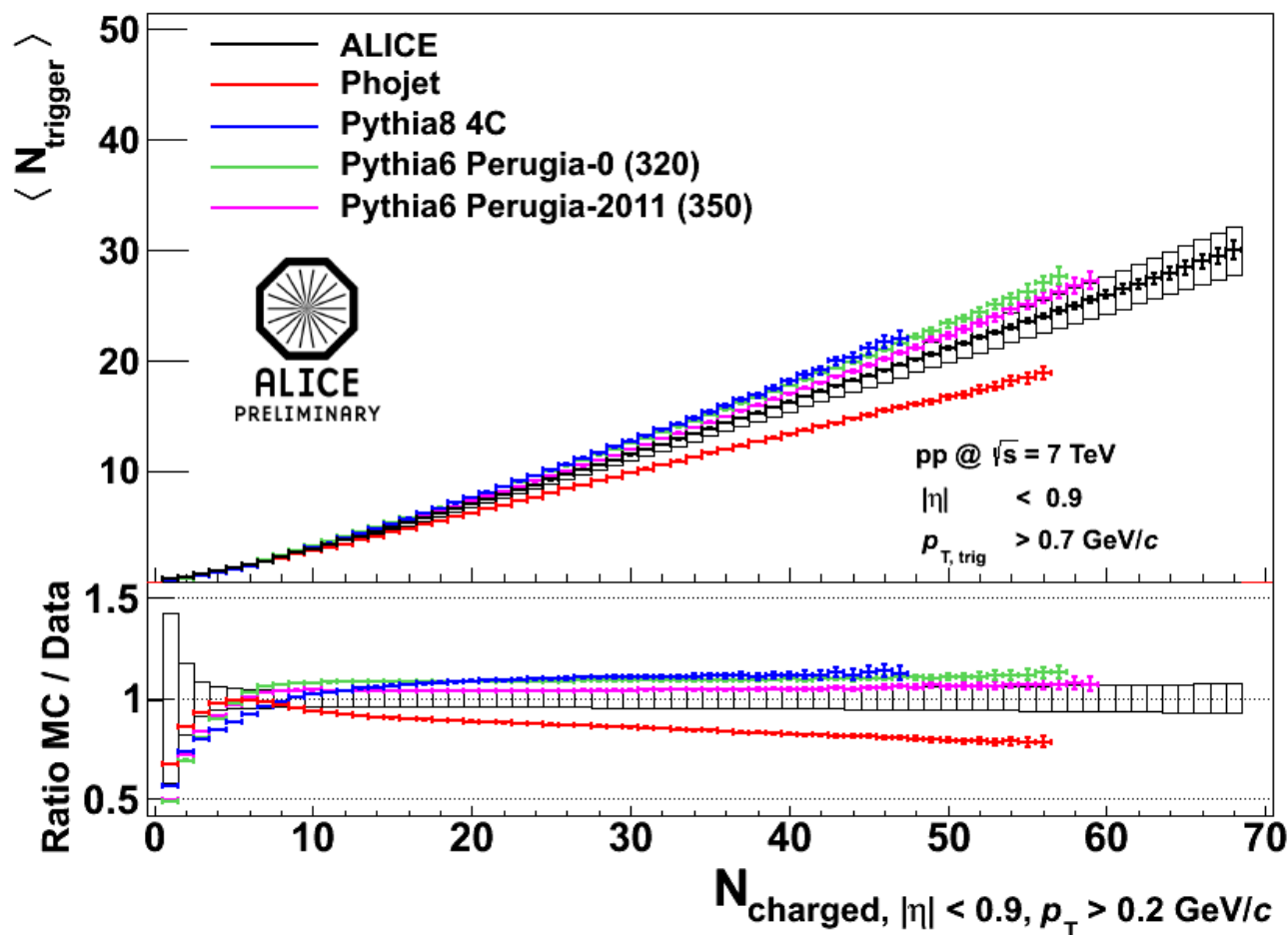


- Particles from processes which are uncorrelated to production process of trigger particle

- Pair yield in uncorrelated background is well reproduced by all models within the systematic uncertainties



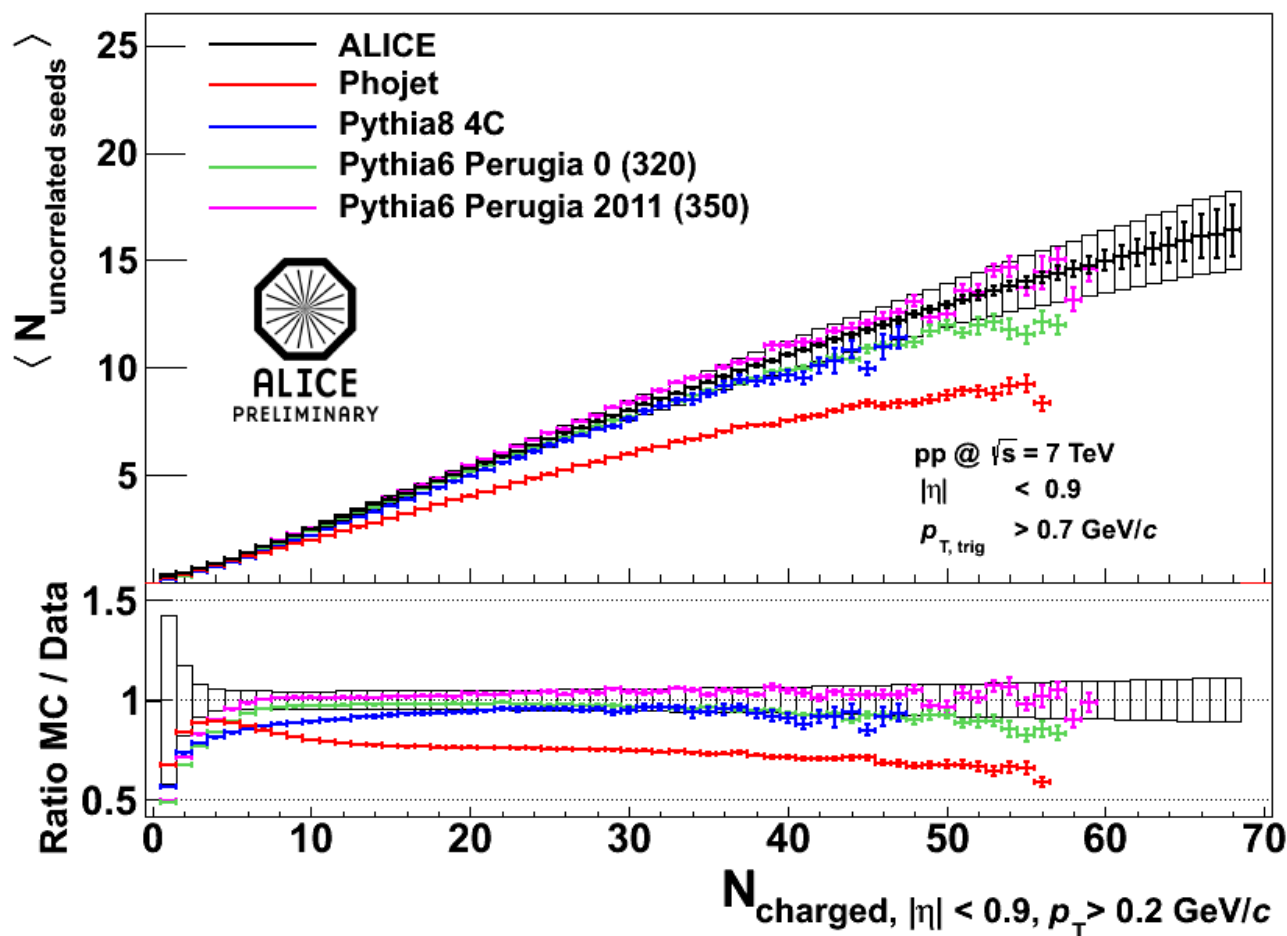
Average Number of Trigger Particles



- Average number of trigger particle contains information about MPI and fragmentation
- N_{trigger} grows slightly faster than linear, growth of mean- p_T with N_{ch}

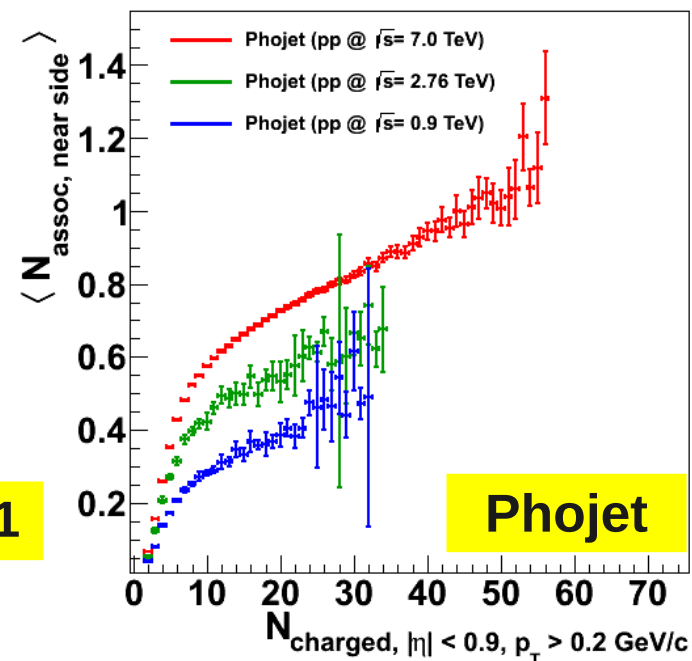
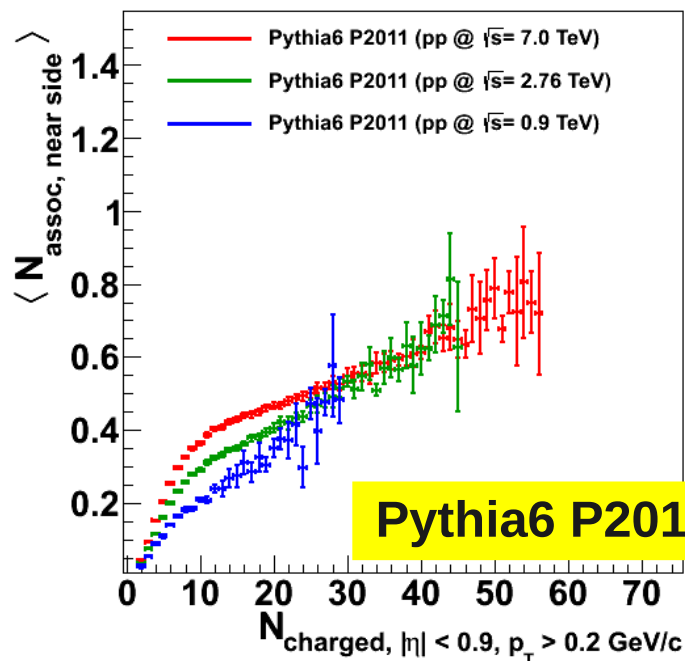
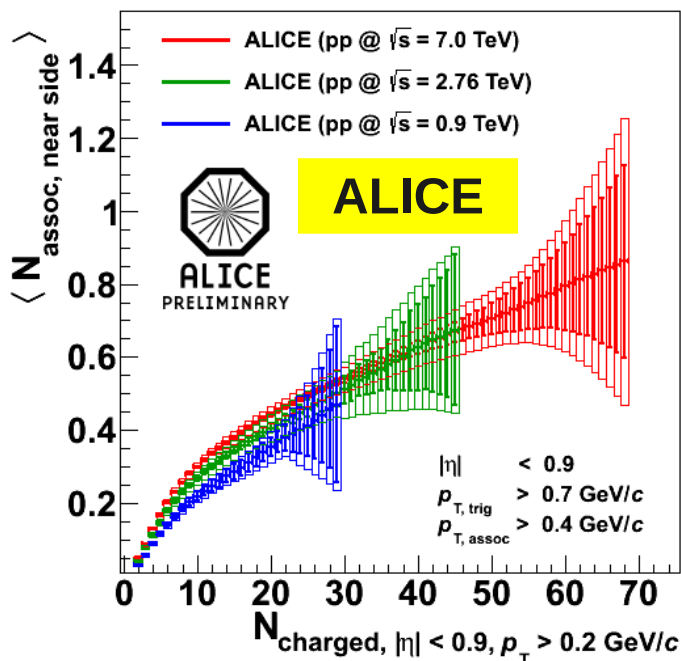
- All Pythia tunes slightly overestimate the ALICE results
- Phojet underestimated the ALICE results

Number of Uncorrelated Seeds

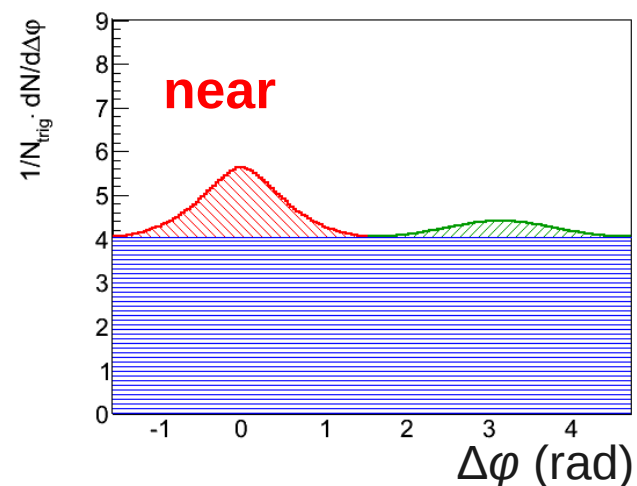


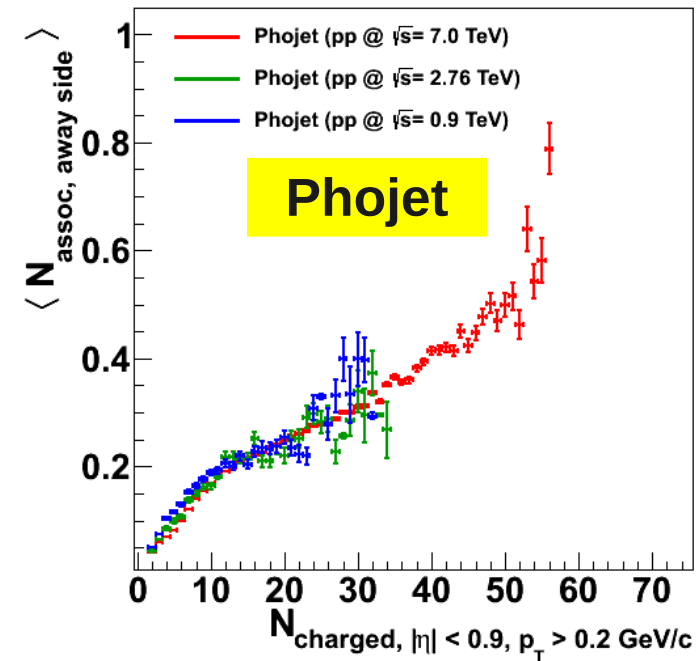
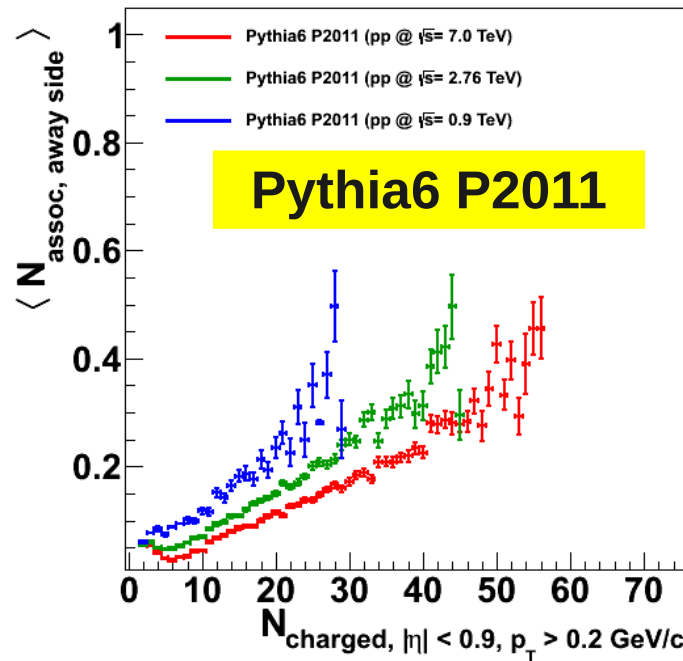
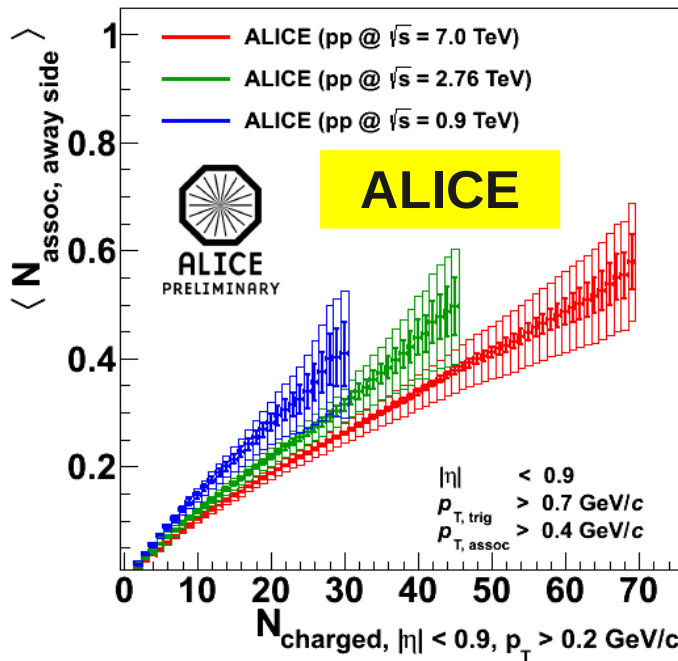
- The number of uncorrelated seeds contains information about MPI: In Pythia N_{MPI} and $N_{\text{uncorrelated seeds}}$ are proportional
- All Pythia tunes reproduced the ALICE results fairly well
- Phojet underestimates the ALICE results

$$\langle N_{\text{uncorrelated seeds}} \rangle = \frac{\langle N_{\text{trigger}} \rangle}{\langle 1 + N_{\text{assoc, near+away}}(p_T > p_{T, \text{trig}}) \rangle}$$

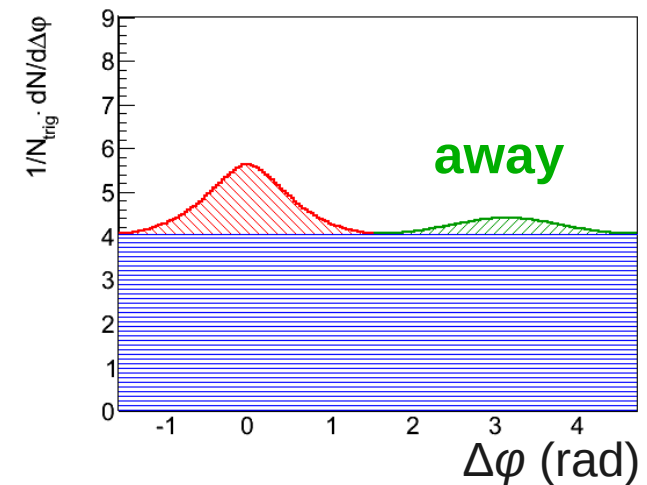


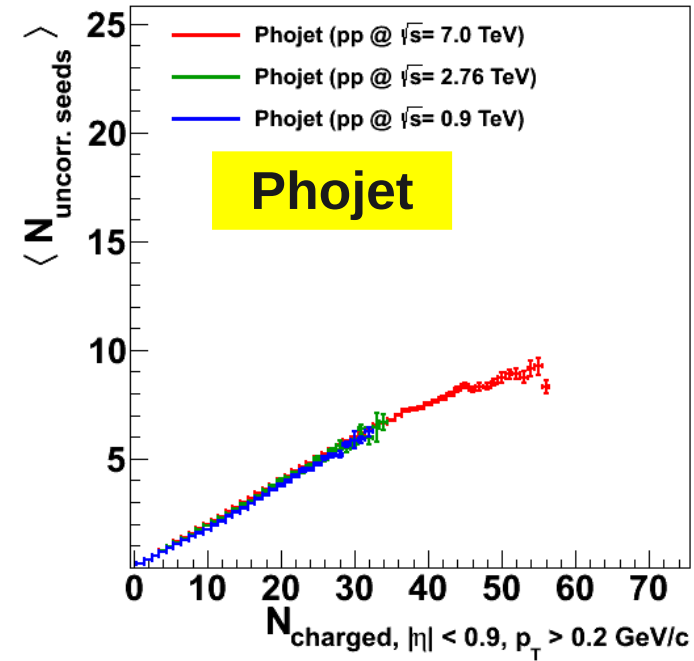
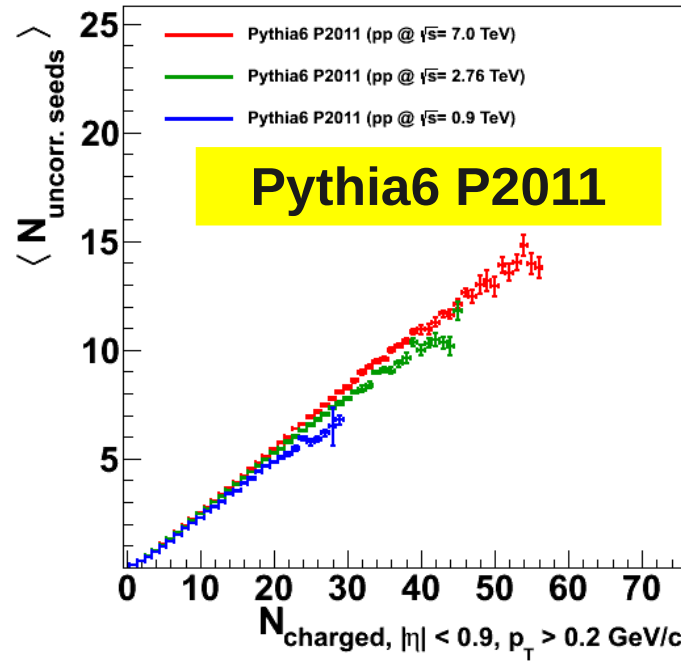
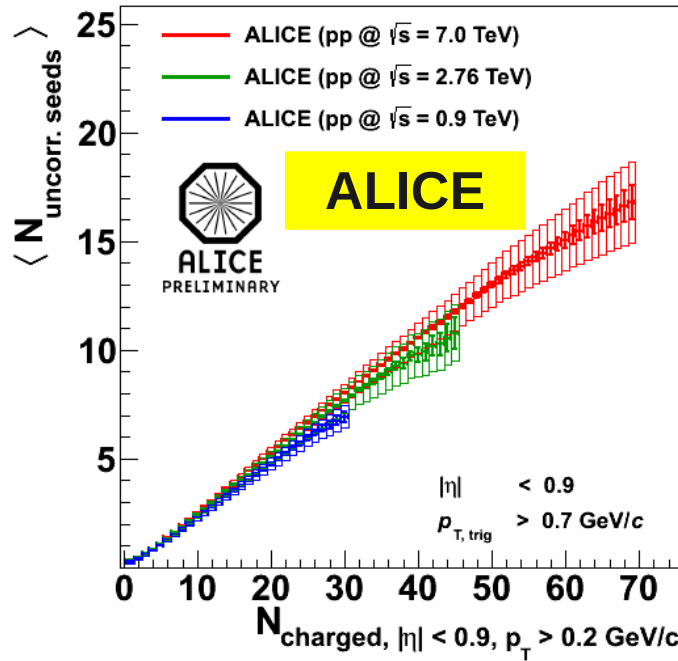
- Center-of-mass energy $\sqrt{s} = 0.9, 2.76, 7.0$ TeV
- Near side pair yield at same multiplicity bin grows with increasing center-of-mass energy
- Splitting between slopes for different \sqrt{s} is largest for Phojet





- Away side yield at same multiplicity bin shrinks with increasing \sqrt{s}
- Pythia6 Perugia-2011 underestimates ALICE data
- Phojet shows almost no \sqrt{s} dependence

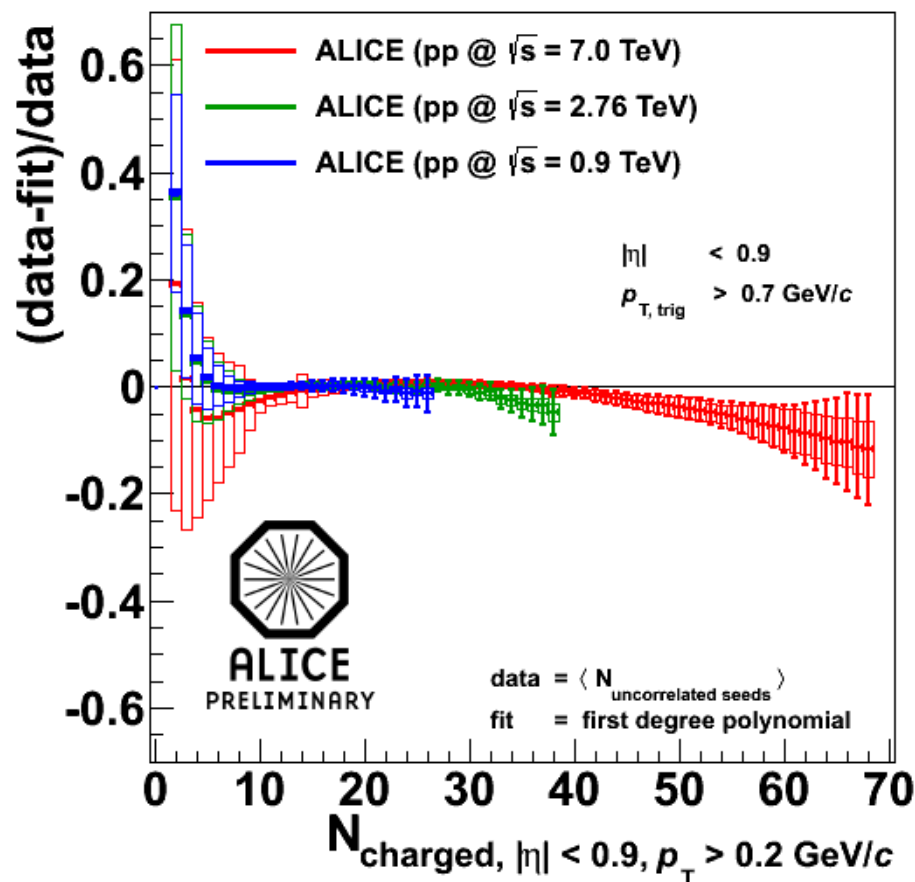
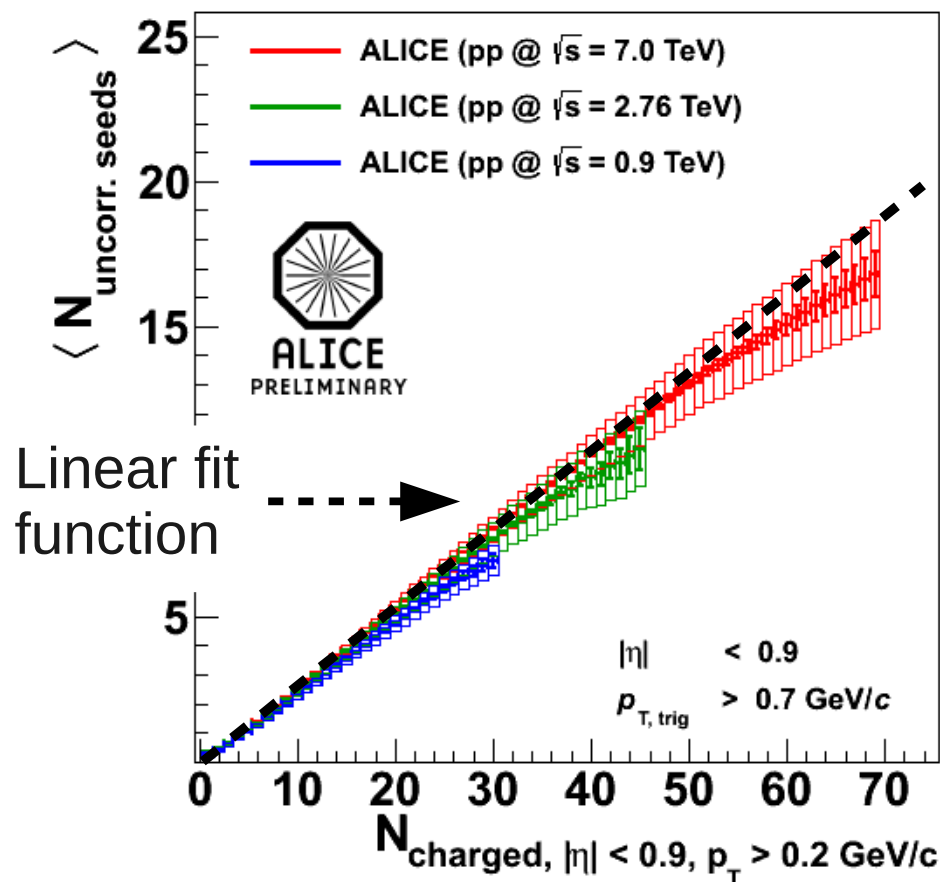




$$\langle N_{\text{uncorrelated seeds}} \rangle = \frac{\langle N_{\text{trigger}} \rangle}{\langle 1 + N_{\text{assoc, near+away}}(p_T > p_{T, \text{trig}}) \rangle}$$

- Only small \sqrt{s} dependence
- In low and intermediate multiplicity region: $N_{\text{uncorrelated seeds}}$ grows linearly with N_{ch}
- At high multiplicities, the number of $N_{\text{uncorrelated seeds}}$ stagnates \rightarrow Multiplicity increase only by selecting events with highly populated jets, limit in N_{MPI}

$\langle N_{\text{uncorrelated seeds}} \rangle$ and Linear Fit



- Compare distribution with linear fit in intermediate N_{ch} range
- At high multiplicities, hint of deviation from linear dependence - this would indicate a limit in MPI

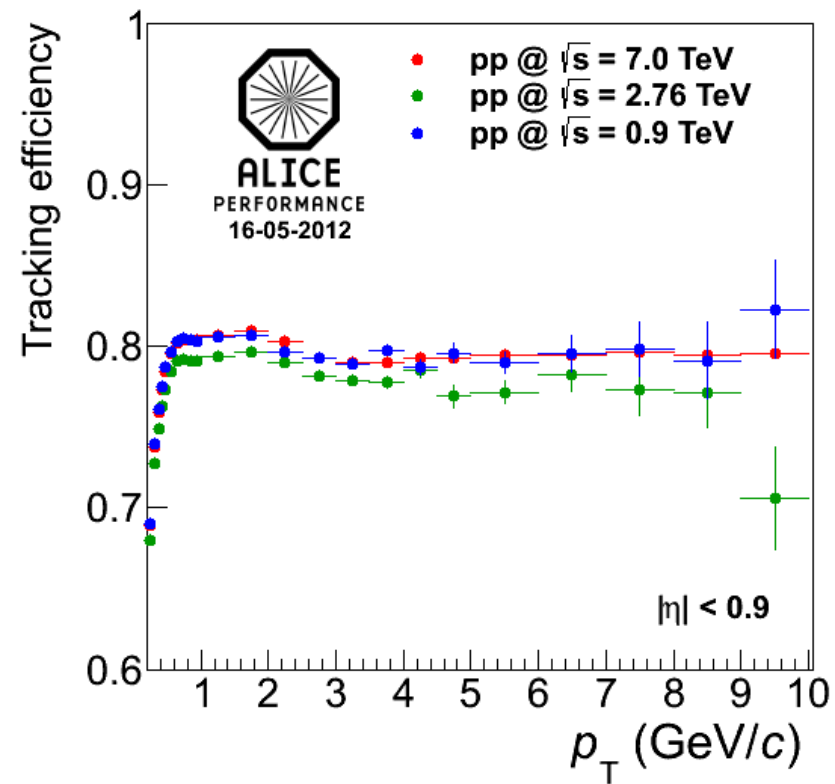
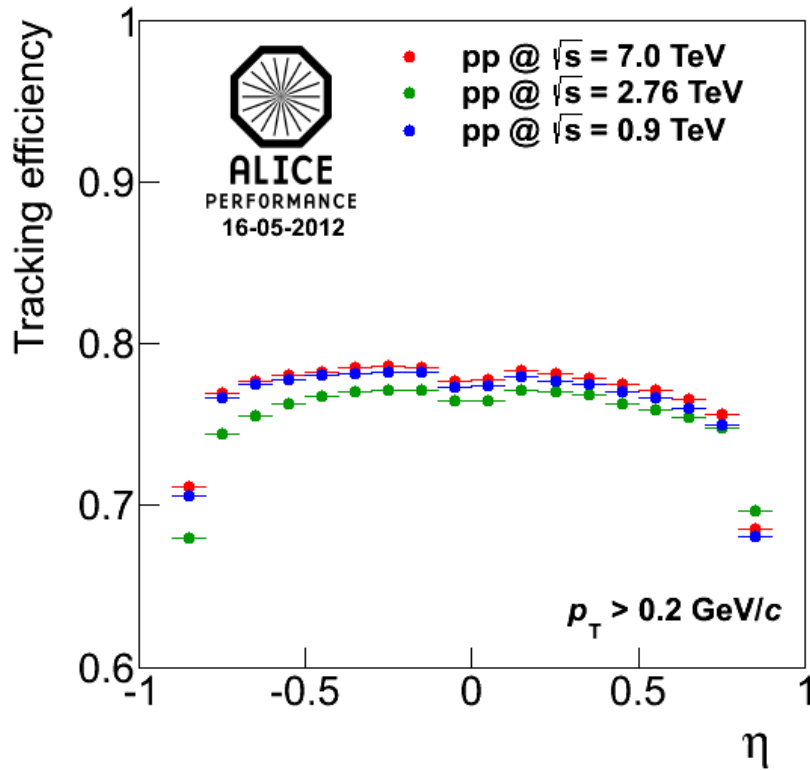
Summary

- Study of the per-trigger pair yield at the near side and the away side as well as the number of uncorrelated seeds using a two-particle correlation analysis
 - Information about jet fragmentation and MPI
- Analysis of ALICE data at $\sqrt{s} = 0.9, 2.76, \text{ and } 7.0 \text{ TeV}$
- At high multiplicities, the number of uncorrelated seeds show a hint of a deviation from linear dependence with multiplicity - this would indicate a limit in MPI
- Pythia studies show that the analysis approach can probe number of multi parton interactions (MPI)
- Pythia Perugia-2011 gives best description of ALICE results
 - However, at intermediate N_{ch} , the away side yield is underestimated by 50%
- Phojet, Pythia6-Perugia-0, and Pythia8 show large discrepancies to ALICE results
 - e.g. per-trigger near side yield is overestimated by all Monte Carlos by 100% at low and intermediated N_{ch}

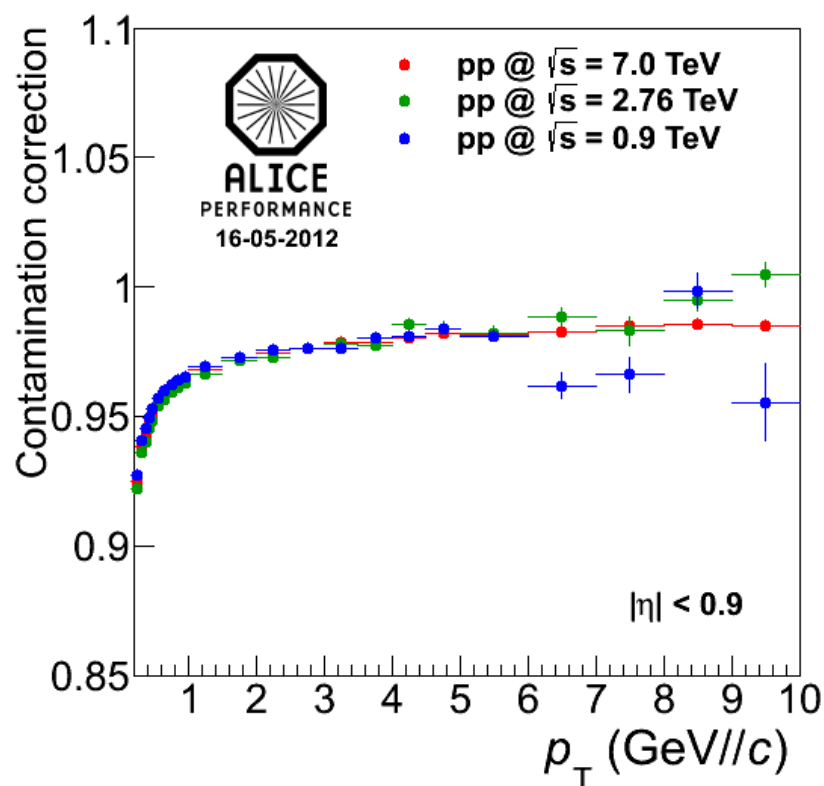
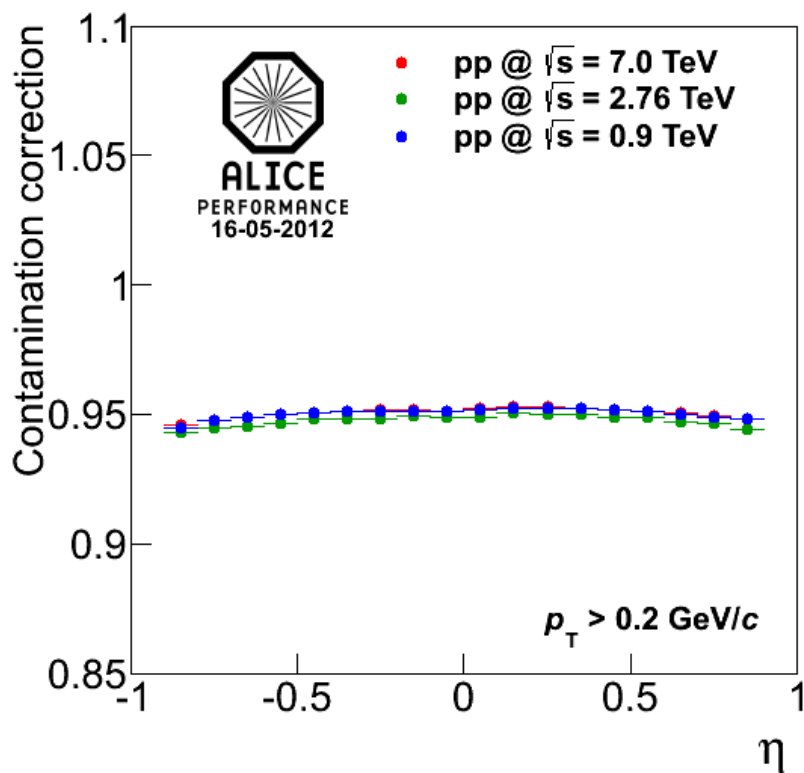


Backup



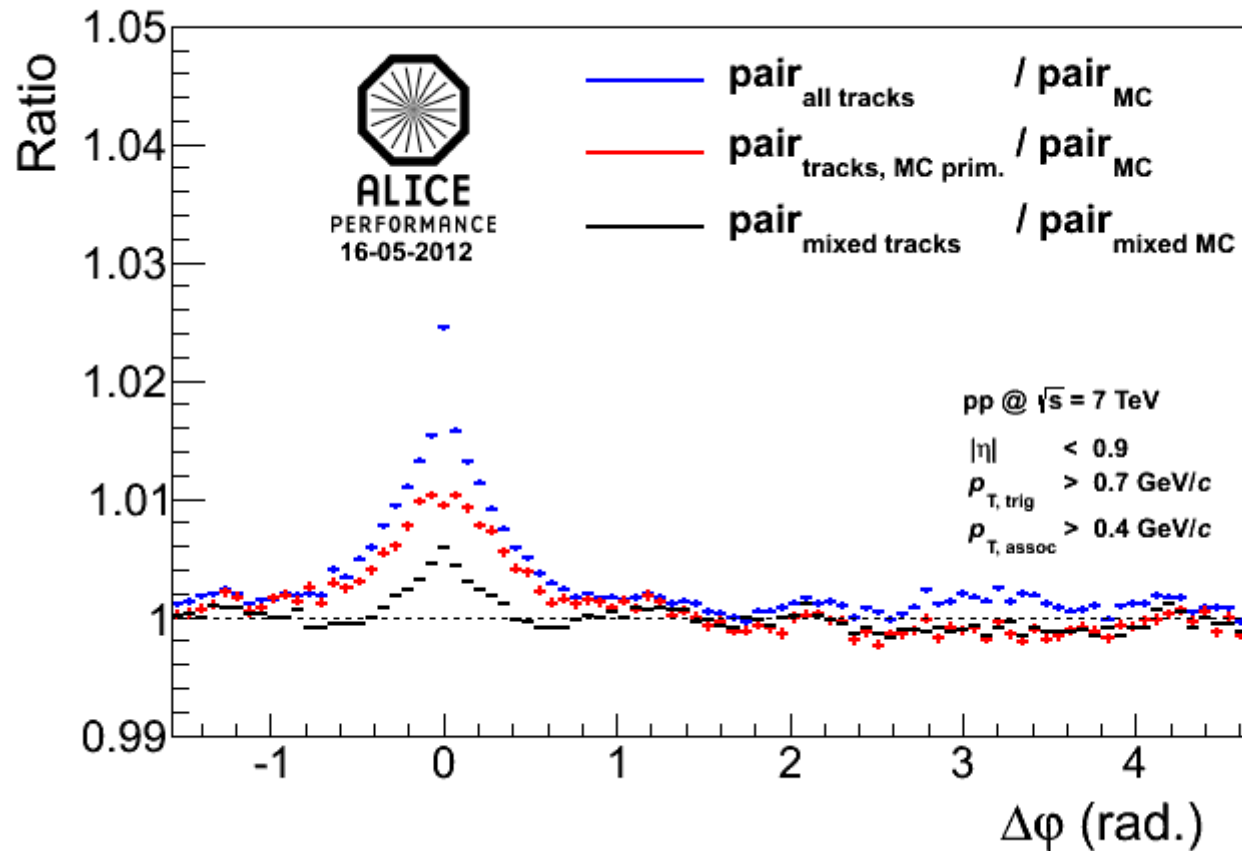


- *Reconstruction efficiency*: Ratio of the number reconstructed and accepted particles tracks of primary particles to number of primary particles
- 78% of all primary particles (at $p_T > 0.2$ GeV/c, $|\eta| < 0.9$) are found in the reconstruction → **Loss of 22%**



- *Contamination*: Ratio of number of all reconstructed tracks to number of reconstructed tracks of primary particles → Contamination from decay products of strange particles, photon conversion, hadronic interaction with the detector material
- Contamination of 6% (at $p_T > 0.2$ GeV/c, $|\eta| < 0.9$)

Correction: Two Track and Detector Effects



- A fraction of the near side peak after single track correction is due to detector effects (black) → limited flatness in φ distribution give rise to structures in $\Delta\varphi$
- Remaining peak comes from split tracks, resonances, gamma conversion
- Correction on total yield is very small

- Multiplicity correction via normalized and extended correlation matrix

- Normalization:

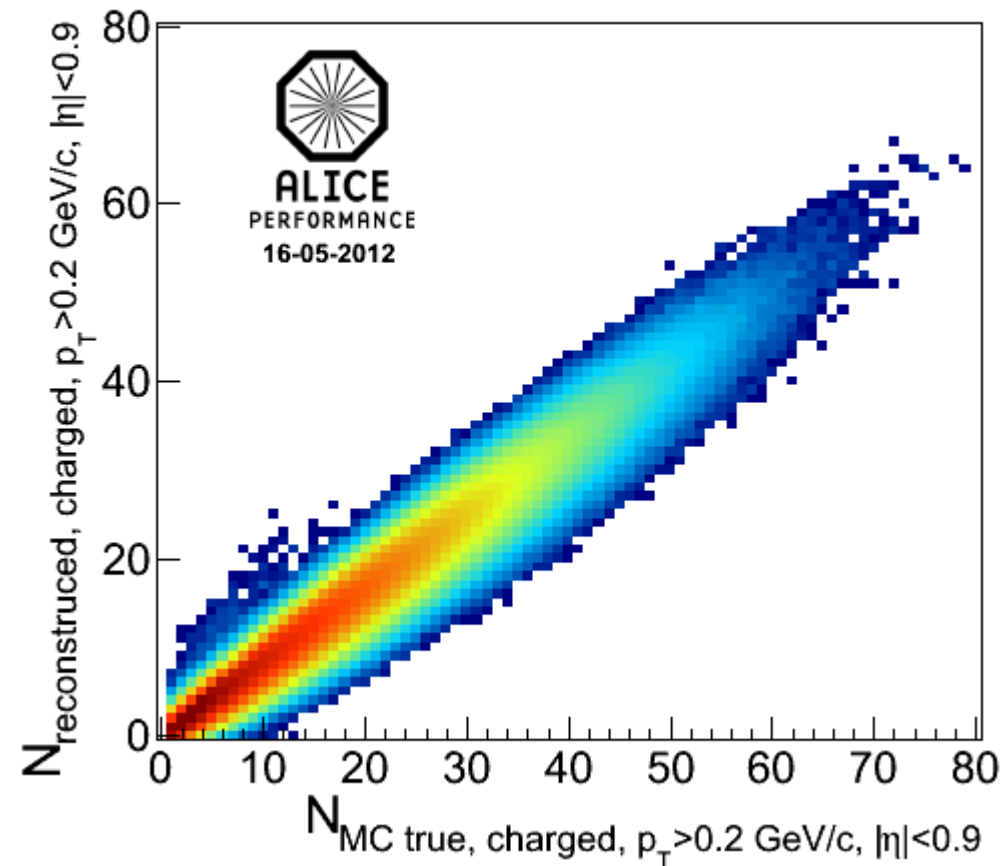
$$- \sum_{N_{rec}} R(N_{mc}, N_{rec}) = 1$$

- Extension:

- Fit slice of correlation matrix with Gaussian function and extract sigma and mean
- Used extrapolated sigma and mean for extended correlation matrix

- Correction:

$$Observable(N_{mc}) = \sum_{N_{rec}} Observable(N_{rec}) \cdot R_{1,extended}(N_{mc}, N_{rec})$$

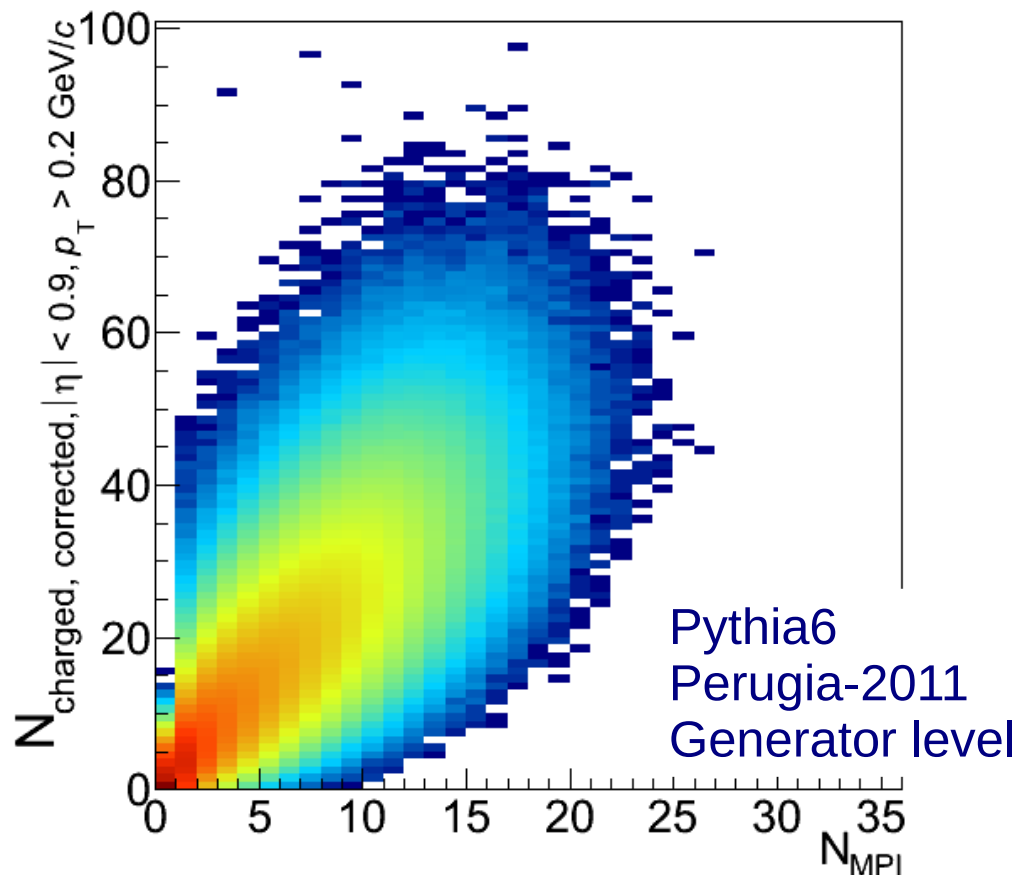
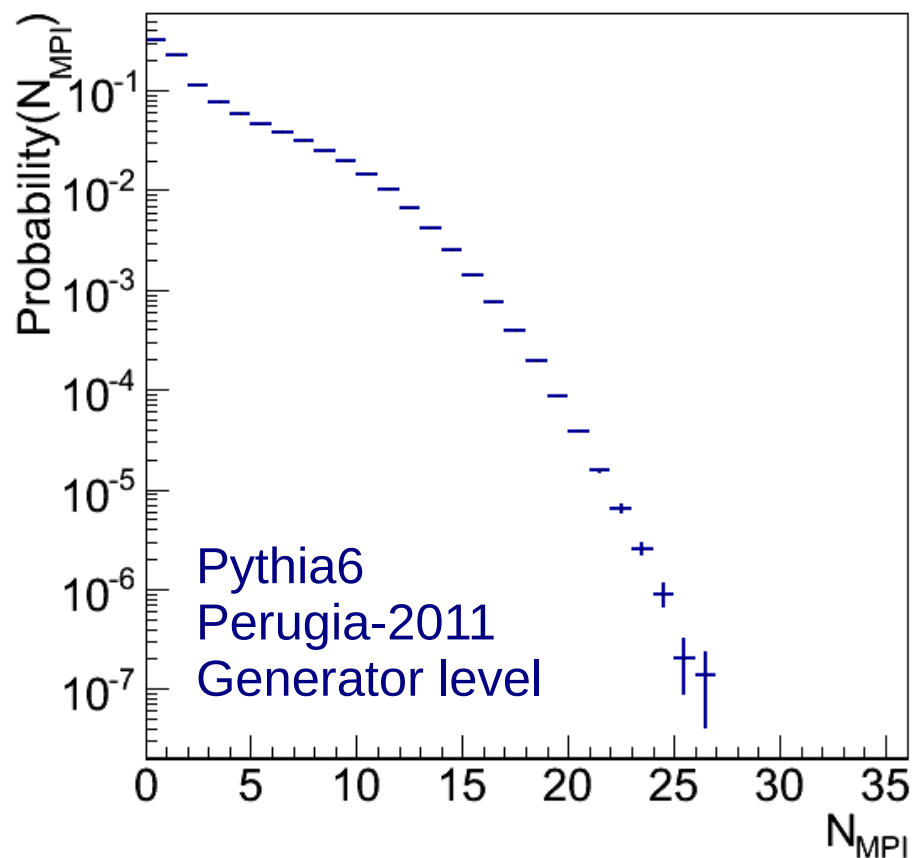


Assumption: $N_{\text{uncorrelated seeds}} \rightarrow N_{\text{MPI}}$

- We measure $N_{\text{uncorrelated seeds}}$

$$\langle N_{\text{uncorrelated seeds}} \rangle = \frac{\langle N_{\text{trigger}} \rangle}{\langle 1 + N_{\text{assoc, near, } p_T > p_{T, \text{trig}}} + N_{\text{assoc, away, } p_T > p_{T, \text{trig}}} \rangle}$$

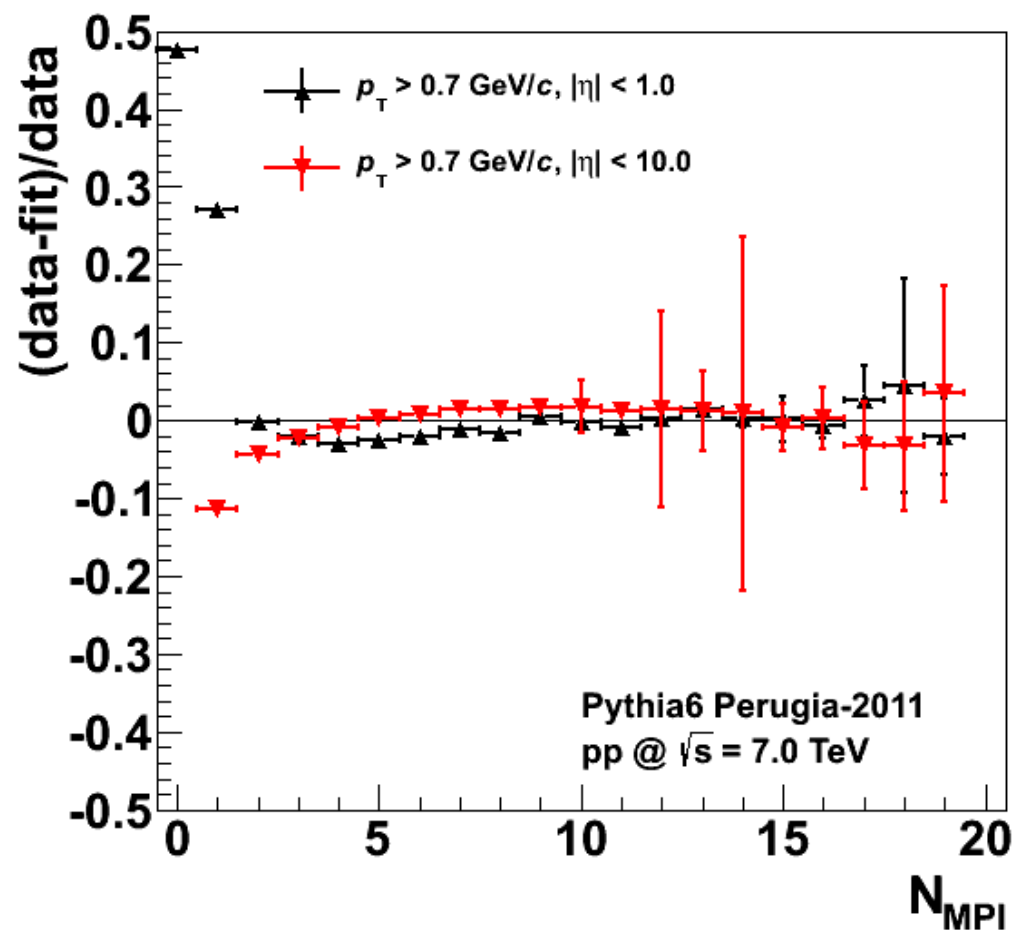
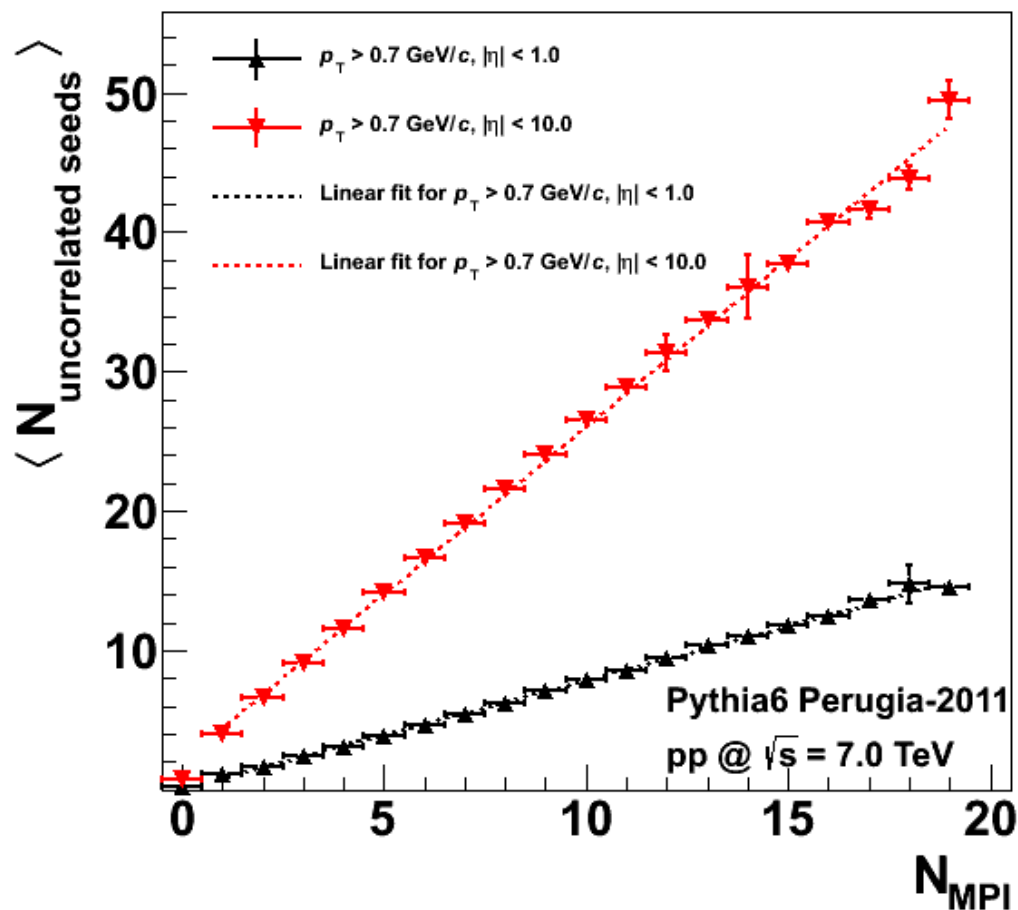
- We assume that $N_{\text{uncorrelated seeds}}$ scales with the number of multiple parton interactions
- Can we demonstrate a direct dependence in Pythia simulations
 - Perform two-particle correlation analysis of Pythia6 simulations as function of N_{MPI} = number of multiple parton interactions
 - N_{MPI} (Pythia definition) = number of hard or semi-hard scatterings that occurred in the current event in the multiple interaction scenario; is 0 for a low- p_T event



- Spectrum of multiple parton interactions in Pythia6 Perugia-2011

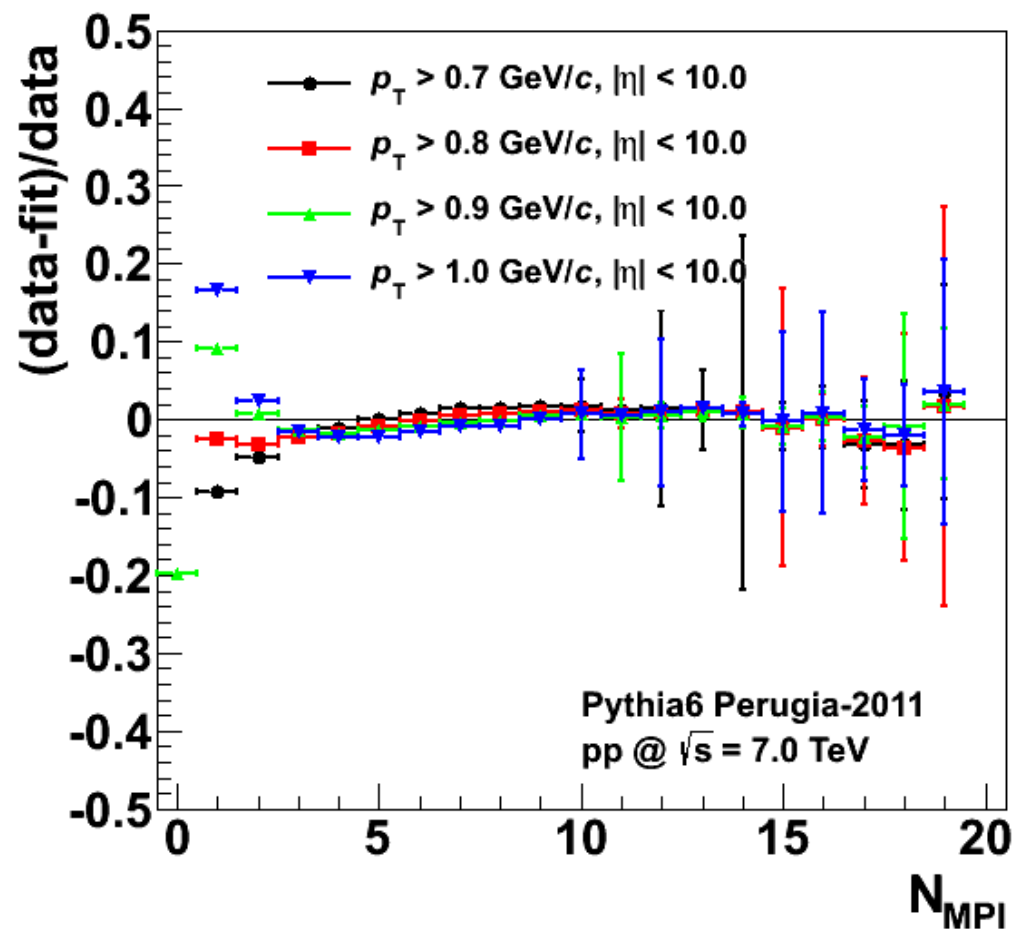
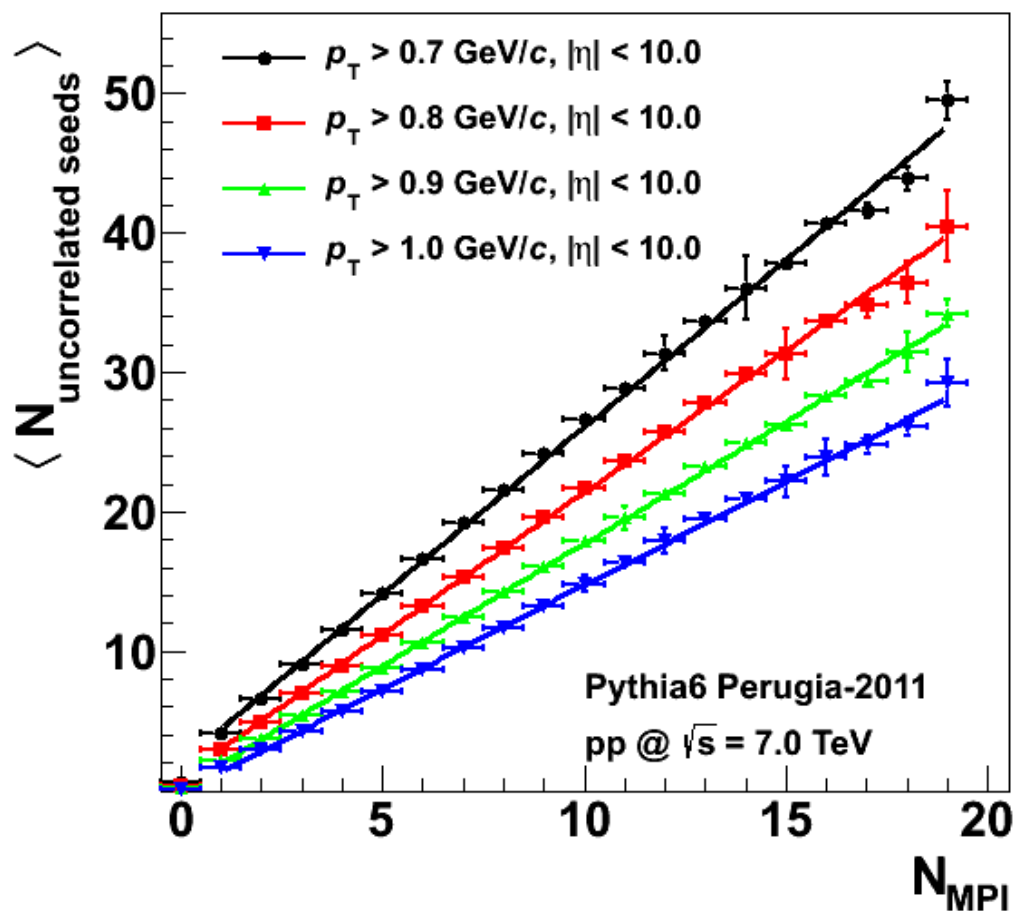
- Correlation of measured multiplicity to number of multiple parton interactions

$$N_{\text{uncorrelated seeds}} \sim N_{\text{MPI}}$$

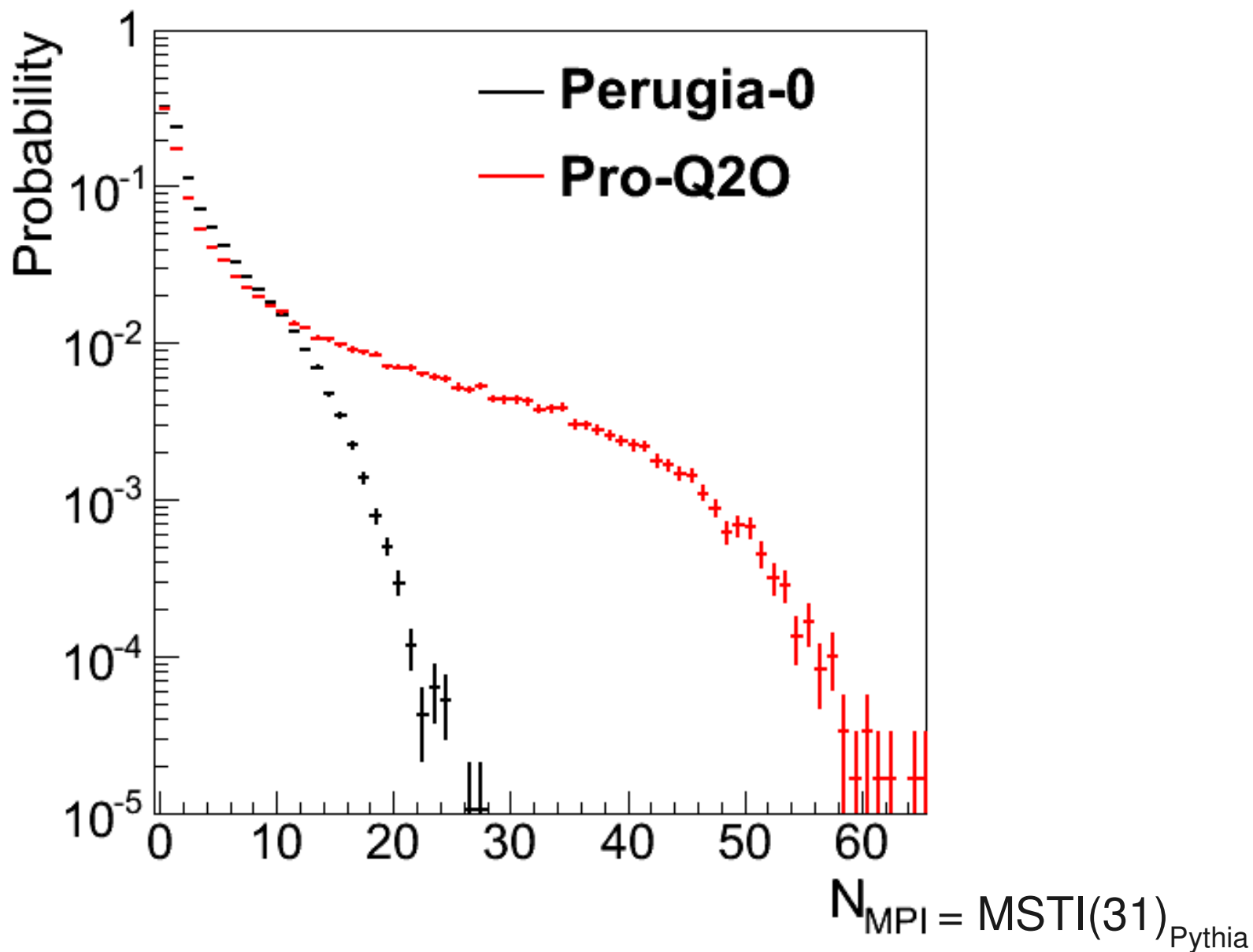


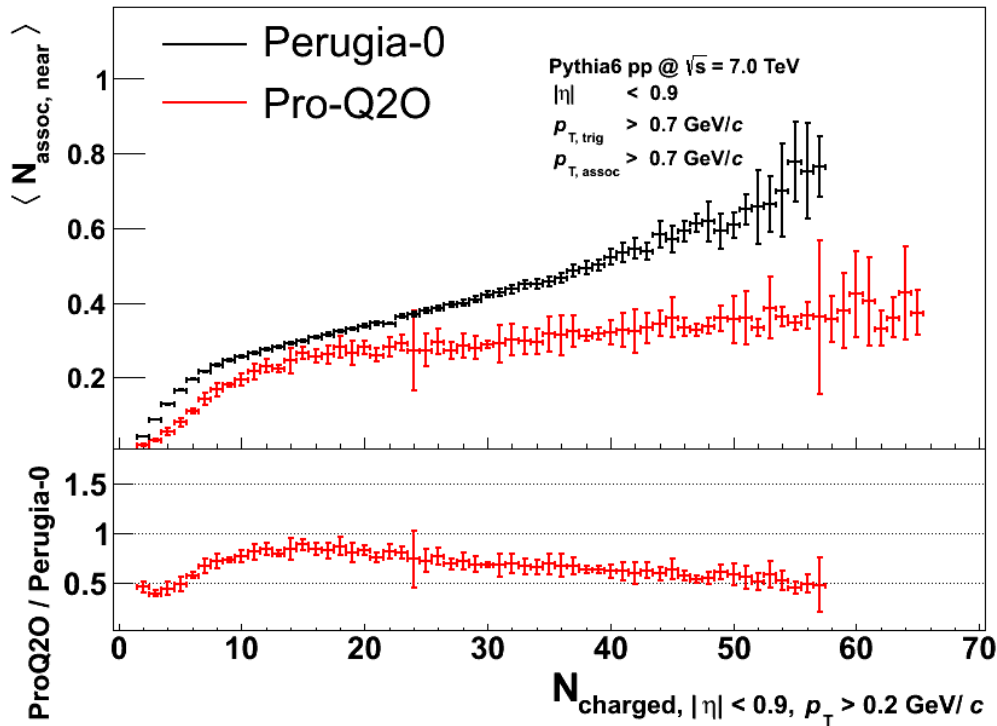
- Agreement with linear fit is better when accepting tracks at full η acceptance and not only the tracks in the ALICE acceptance

$$N_{\text{uncorrelated seeds}} \sim N_{\text{MPI}}$$

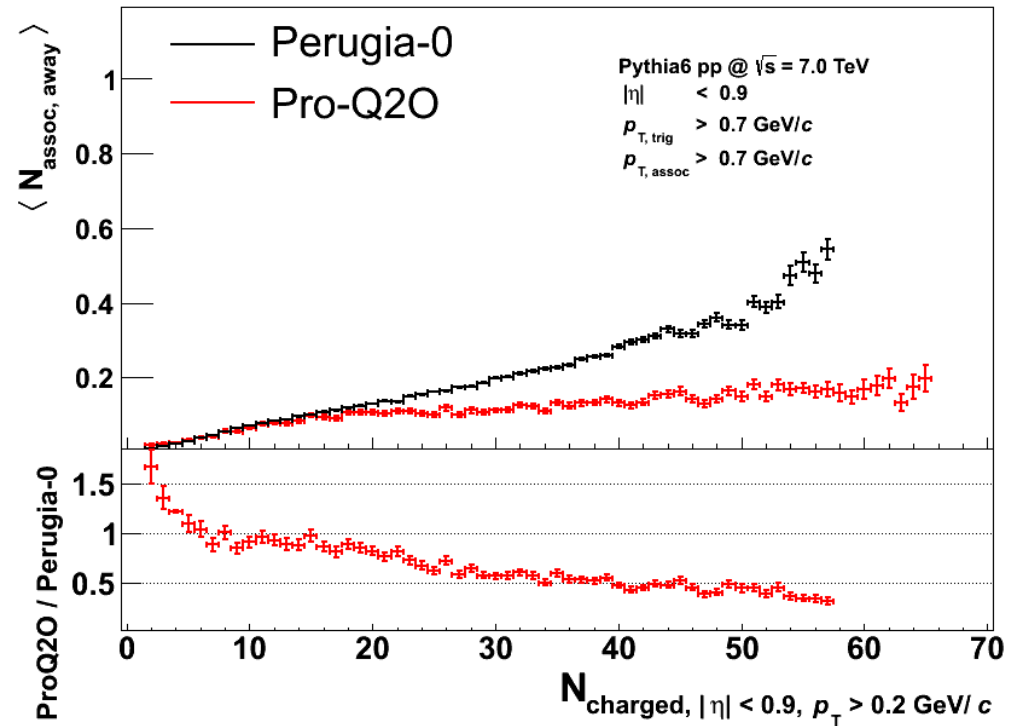


- Linear dependence is given for several p_T thresholds

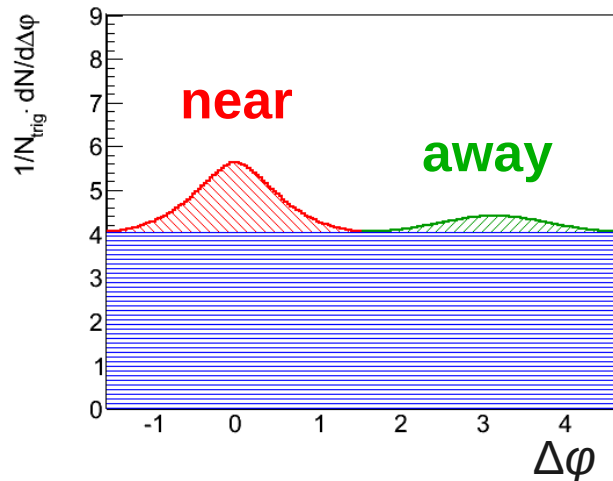


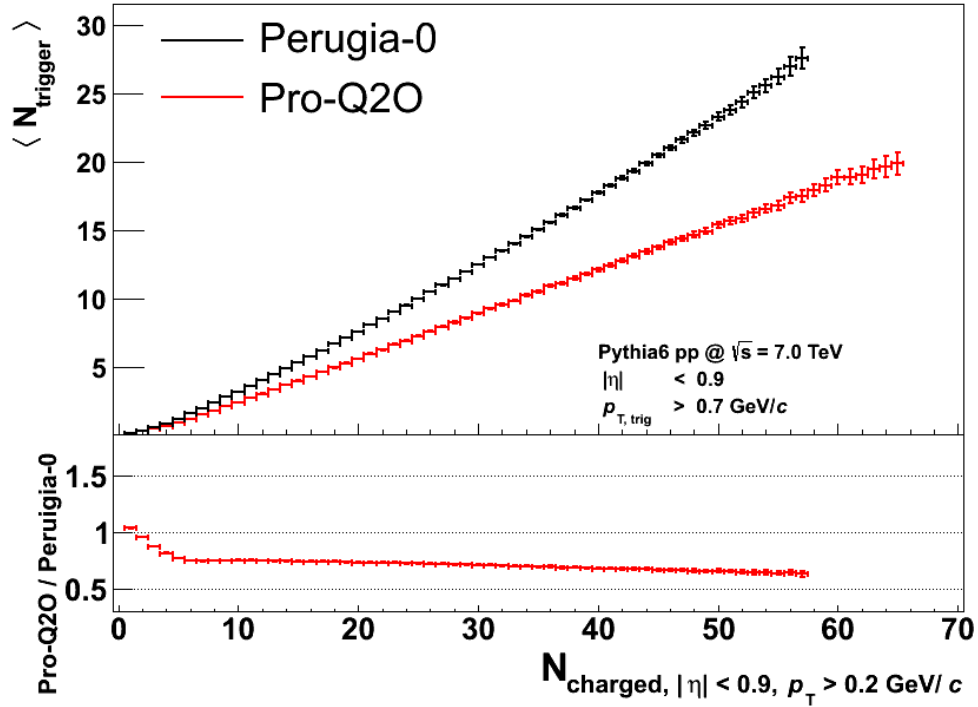


Near side

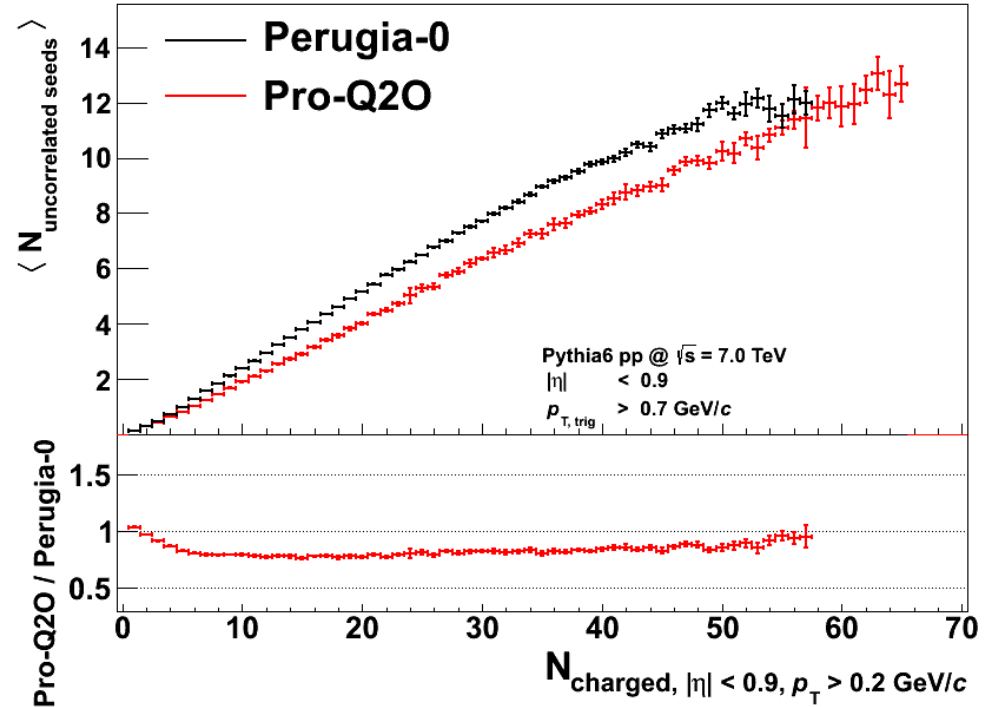


Away side





$\langle N_{\text{trigger}} \rangle$



$\langle N_{\text{uncorrelated seeds}} \rangle$

$$\langle N_{\text{uncorrelated seeds}} \rangle = \frac{\langle N_{\text{trigger}} \rangle}{\langle 1 + N_{\text{assoc}, \text{near} + \text{away}}(p_T > p_{T, \text{trig}}) \rangle}$$

For an a priori unknown multiplicity distribution $P(n)$ of the mini-jet, we measure

$$\frac{\langle n(n-1) \rangle}{2\langle n \rangle} = \frac{1}{2} \left(\frac{\langle n^2 \rangle}{\langle n \rangle} - 1 \right)$$

For steadily falling $P(n)$ and small $\langle n \rangle$ this is in good approximation:

$$\frac{1}{2} \left(\frac{\langle n^2 \rangle}{\langle n \rangle} - 1 \right) \rightarrow \frac{\langle n \rangle}{1 - P(0)} - 1 \quad (= \langle n \rangle \text{ with trigger condition} - 1)$$

Which is the mean number of associated particles.

Example 1 (geom. row):

$$P(n) = (1-q)q^n$$

$$\langle n \rangle = \frac{q}{1-q}$$

$$\langle n^2 \rangle = 2\langle n \rangle^2$$

$$\frac{1}{2} \left(\frac{\langle n^2 \rangle}{\langle n \rangle} - 1 \right) = \langle n \rangle$$

$$\frac{\langle n \rangle}{1 - P(0)} - 1 = \langle n \rangle$$

Relation is exact !

Example 2 (Poisson):

$$P(n) = \frac{\mu^n e^{-\mu}}{n!}$$

$$\langle n \rangle = \mu$$

$$\langle n^2 \rangle = \mu^2 + \mu$$

$$\frac{1}{2} \left(\frac{\langle n^2 \rangle}{\langle n \rangle} - 1 \right) = \frac{\mu}{2}$$

$$\frac{\langle n \rangle}{1 - P(0)} - 1 = \frac{\mu}{1 - e^{-\mu}} - 1 = \frac{\mu}{2} + \frac{\mu^2}{12} + \dots$$

Example 3 (Log Series):

$$P(n) = \frac{-1}{\ln(1-p)} \frac{p^n}{n}$$

$$\langle n \rangle = \frac{-1}{\ln(1-p)} \frac{p}{(1-p)}$$

$$\langle n^2 \rangle = \frac{\langle n \rangle}{(1-p)}$$

$$\frac{1}{2} \left(\frac{\langle n^2 \rangle}{\langle n \rangle} - 1 \right) = \frac{p}{2(1-p)}$$

$$\frac{\langle n \rangle}{1 - P(0)} - 1 = \frac{p}{2(1-p)} + \frac{p^2}{12(1-p)} + p^3 \dots$$

Expect $P(n)$ to be steadily falling, choose $p_{T,\text{trig}}$ such that $\langle n \rangle$ is low