October 1, 2014

Development of a monitoring tool to validate trigger level analysis in the ATLAS experiment

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Abstract

This report summarizes my thirteen week summer student project at CERN from June 30th until September 26th of 2014. My task was to contribute to a monitoring tool for the ATLAS experiment, comparing jets reconstructed by the trigger to fully offline reconstructed and saved events by creating a set of insightful histograms to be used during run 2 of the Large Hadron Collider, planned to start in early 2015. The motivation behind this project is to validate the use of data taken solely from the high level trigger for analysis purposes. Once the code generating the plots was completed, it was tested on data collected during run 1 up to the year 2012 and Monte Carlo simulated events with center-of-mass energies $\sqrt{s} = 8\,\text{TeV}$ and $\sqrt{s} = 14\,\text{TeV}$.

With special thanks to my supervisors Caterina Doglioni and Dag Gillberg.

Contents

1 Introduction

At the Large Hadron Collider, researchers have spent years studying high energy particle collisions that were hoped to (and indeed did) yield new insights into the microscopic structures of matter and significantly contributed to our understanding of the visible universe. Colliding particles at even higher energies, the LHC could result in yet many more fundamental discoveries, though the physics signatures potentially leading to these are extremely rare. For example, with the LHC running at around 10 TeV, the recently discovered Higgs Boson is only created once in every ten billion proton-proton interactions [1]. During Run II, physicists now hope to find clues for "new physics" by colliding protons with a center-of-mass energy of up to 13 TeV.

One big challenge in collecting data using one of the four detectors set up around the LHC, for instance ATLAS, lies in the sheer amount of potentially interesting information collected in the different parts of the detector while running the collider. Working at its design luminosity of $10^{34}\,\mathrm{cm}^{-2}\mathrm{s}^{-1}$, the LHC produces 40 million bunch crossings per second with each bunch containing around 10^{11} protons. This results in a proton collision rate lying in the order of $10^7 - 10^9$ Hz inside of the detector [1]. Since the cross sections of interactions relevant for current research are typically very small compared to soft interactions such as simple diffraction, the great majority of collision events are not interesting to physicists for analysis.

The low probability of producing interesting events and the subsequent need for a high collision rate result in the need for some sort of filter, sorting out interesting events from collisions that only involve already well understood phenomena. This is exactly what the *triggers* are used for. Each detector has its unique trigger system and in this report, the focus will be placed on the jet triggers used for the ATLAS experiment.

This particular system consists of three levels of triggers. The level 1 trigger is hardware-based and located near the detector, just far enough away to protect the electronics from radiation damage. It has around 2.5 μs to scan the calorimeter for objects with high transverse momentum p_T, a strong indicator for a hard interaction having taken place in the collision. With a course granularity two-dimensional scan using sliding windows, so called trigger towers, indicating the energy deposited in a certain region of the detector, are used to cut the rate of potentially important events down from 40 MHz to 75 kHz.

The level 2 and 3 triggers, the latter also called the *high level trigger* (HLT) or *event filter*, are both software utilities, reconstructing jets from the energy deposits in the hadronic calorimeter to filter events based on more specific criteria. The second level cuts the event rate from 75 kHz down to 3 kHz with a decision time of about 40 ms. Within 4 s for each crossing, the last level reduces the rate further down to 200 events per second being saved for later analysis offline [3].

Each trigger level reconstructs the jets detected in the calorimeter with increasing detail, peaking in the HLT, which uses the same algorithms found in the offline reconstruction (usually Anti-kT, cf. [2]). This fact raises the question of how reliable the jet information merely reconstructed by the trigger system is and whether it could be used for analysis. The advantage of this would be that these so called *trigger jets* are stored in much smaller files, as opposed to jets intended for offline analysis (*offline jets*), which are reconstructed additionally considering all other information collected by the experiment, such as tracker data and cleaning variables.

If the trigger jet data, reconstructed only from the hadronic calorimeter measurements, can be shown to match the offline jet data well enough, many more events can be saved during Run II alongside the 200 events being stored already, right from the event filter. This would significantly boost statistics overall and additionally allow groups studying exotic phenomena, that possibly aren't granted high priority in the trigger criteria, to do research using trigger jet data.

To continuously ensure the quality of the HLT data, a monitoring tool is needed, comparing the jets from the so called trigger data to the jets reconstructed offline for the same events. My task consisted of writing C++ code to use `Root` to generate histograms that efficiently display the quality of the trigger jets with the offline-reconstructed jets (short *reco-jets*) as a reference.

2 Timeline

During the first few weeks of my stay at CERN, I read about jets, jet substructure and jet reconstruction. Among others, I worked through a lecture series by Gavin Salam on jet substructure and reconstruction algorithms [2], which was very helpful to understand what I was going to be working with. I also learned about how calorimeters work and how they are calibrated, mostly with the help of a review by Peter Loch [4] and a presentation by M. Weber [5].

In parallel, I started getting acquainted with `Root`. Since I had never worked with the program before, it took some time to learn the basics through tutorials and simple practice tasks. At first, I was supposed to use the `TTreeReader` and `TSelector` for my preliminary code. After the upgraded version we used of `Root 5` turned out to have a bug in generating the `TSelector` framework, my supervisors decided to have me use the `MakeClass` command on a tree. This gave me a C++ frame to loop over all events in a `TTree`.

On July 25$^{\text{th}}$, I held my first presentation in front of my supervisor Caterina Doglioni's colleagues from the University of Geneva. There I presented the motivation and goals of my project and showed the first plots I had made with `Root` (similar to the inclusive p_T distribution shown later). At this time, I used a small set of data from an 8 TeV Monte Carlo simulation just to write and test the code.

After this, I continued writing a program to run over `TTrees` from `.root`-files to generate histograms proposed by my supervisors, their colleagues and myself. The goal at this point was to be able to present final results at the annual Hadronic Calibration Workshop in Munich during the week of September 8$^{\text{th}}$, 2014. At this point, I should have run the finished code over large data files from Monte Carlo simulations and possibly actual data collected during run 1. The 5$^{\text{th}}$ of September was the deadline for turning in material to be presented.

On August 11$^{\text{th}}$, I held a talk in a meeting of the Exotic Dijets Analysis group to present my progress and new plots I had made. After a positive feedback and input from the group, including Dr. Lee Sawyer, I continued to work on the code to implement the changes suggested. A week later, on the 18$^{\text{th}}$ of August, I held my third talk for the Trigger Monitoring group during a meeting over `Vidyo`, where the full set of plots to be included in the monitoring tool, as well as details concerning the placement of the plots were proposed and discussed in the group.

Once I had all the histograms implemented in the code, my supervisor Dag Gillberg and I had noticed some flaws, which were slowing down the program. During the last two weeks before the Hadronic Calibration Workshop I spent a lot of time improving the efficiency of the program and rewrote the code. In the end, I was able to make the histogram sets fairly fast using big data sets generated by Monte Carlo simulation at both 8 TeV and 14 TeV center-of-mass energies. During the first September week, I worked on making the plots look better and prepared slides for a presentation of my work to be held by the organizers of the workshop in Munich. On September 5$^{\text{th}}$, I submitted my final presentation including the plots shown and described on the following pages. All my presentations can be found on indico under indico.cern.ch/search?categId=0&sortOrder=d&p=artur+hahn&f=&startDate=&endDate=.

For the rest of my stay, I was originally supposed to help with the implementation of my code into the existing monitoring software. Since the trigger monitoring framework was undergoing transitional work for Run II, I could not insert my code there directly, but instead wrote it in a more general and flexible way such that it could easily be moved at a later stage.

3 Results

After some feedback from different groups, my supervisors and I decided to make the following plots for the trigger jet monitoring tool. The histograms are complementary and taken together, they allow a detailed assessment of the trigger jet quality in different detector regions and for different jet types (differentiating in p_{T}). The histograms can be ordered as follows:

I. Histograms before jet matching

1. Inclusive distributions, displaying all jets found in both data sets
   i. Inclusive spatial distribution
   ii. Inclusive p_{T} distribution

II. Histograms after jet matching

2. Unmatched jet histograms
   i. Unmatched spatial distribution
   ii. Unmatched p_{T} distribution

3. Kinematic reconstruction histograms
   i. Histograms displaying the p_{T} response
   ii. Histograms displaying the matched p_{T} distribution (alternative to 3.i)
   iii. Histograms displaying the η reconstruction quality
   iv. Histograms displaying the ϕ reconstruction quality.

The plots can also be divided into a *spatial family*, focusing on angular information, and a p_{T} *family*, displaying transverse momentum variables. All the plots displaying angular variables are binned in p_{T}. Respectively, ten identically structured plots include only jets in specified p_{T} ranges, making it easier to pinpoint different phenomena occurring for certain jet types. The binning is logarithmic, with ten bins ranging from the p_{T}-cut of 20 GeV up to 6 TeV. With these parameters, the transverse momenta used as bin edges to separate different histograms lie at p_{T} [GeV] $\in \{20, 35, 63, 111, 196, 346, 613, 1084, 1917, 3392, 6000\}$. The code was written so that the user could easily adjust all the binning parameters, including these. The histograms in the p_{T} family are binned in the jet pseudorapidity η. Here, twelve bins have been chosen to separate the different sectors of the ATLAS calorimeters with edges at $\eta \in \{0, \pm 0.8, \pm 1.2, \pm 2.1, \pm 2.8, \pm 3.2, \pm 4.5\}$.

In the following, I have included some exemplary histograms that were produced from an inclusive, high statistics `Pythia` QCD Monte Carlo sample generated with $\sqrt{s} = 8$ TeV (seven "JZXW" samples were merged, weighted according to their cross sections). The offline jets were calibrated according to `JES_Full2012dataset_Preliminary_Jan13.config`. In the appendix, I have added a link to the final code along with instructions on how to use it.

Histograms for the monitoring tool

1.i) Inclusive spatial distribution

As the name suggests, these histogram pairs include all jets reconstructed both offline and in the trigger. With simple two-dimensional histograms, displaying all jets reconstructed in all the events, one can make a first rough comparison to see if something went wrong in a certain detector region (the vertical black dashed lines mark the edges of the calorimeter sections). In order to see the distributions of specific jet types, ten additional p_{T} binned histogram pairs of this sort are made using the logarithmic binning introduced before. In the lower two plots of the example in fig. 1, a dead calorimeter module can be seen at $0 < \eta < 0.8$, $\phi \approx 0.5$.

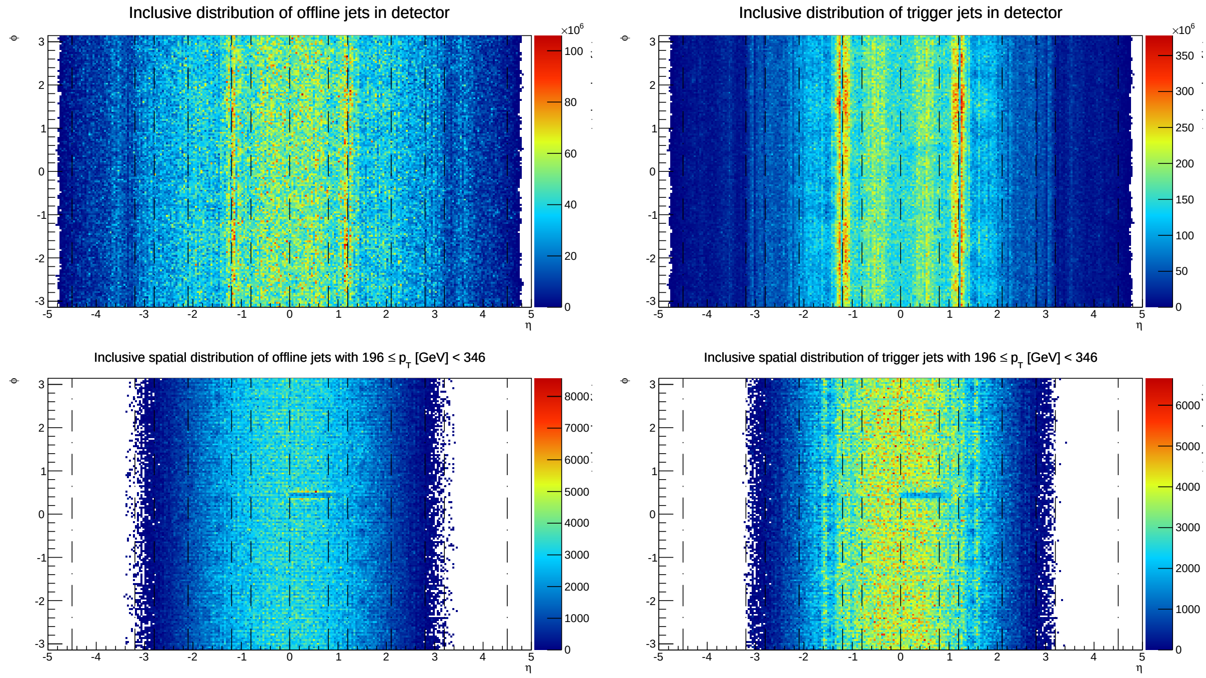

Figure 1: Scatter plots of the spatial jet distribution in η and ϕ for offline (left) and trigger jets (right), integrated over all p_{T} (top) and for jets with p_{T} in the range of 196-346 GeV (bottom).

1.ii) Inclusive p_{T} distribution

These plots also include every jet found in both data sets. The number of jets reconstructed with a certain p_{T} from both files is shown with logarithmic axes to better display the distribution in absolute numbers. Each of the twelve histograms is specific to a certain sector of the calorimeter, binned in η. In fig. 2, an example from the central part of the detector is presented.

At this point it can be noted that all p_{T} based histograms have a range corresponding to the η-section in the detector that they are made from. Assuming the hardest jets of a 14 TeV collision to mostly have an absolute momentum below $|p| = 6\,\mathrm{TeV}$, the highest transverse momentum p_{T} possible at a certain pseudorapidity η is determined by $|p| = p_{\mathrm{T}} \cdot \cosh \eta$. The ranges are corrected with this equation using the η edge with the smaller absolute value.

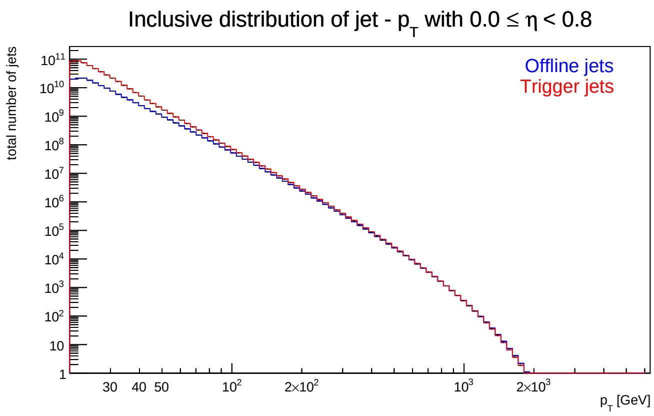

Figure 2: Inclusive p_{T} histogram considering all trigger and offline jets with certain η separately. The difference at low p_{T} is due to the lack of pileup correction for the trigger jets (see below).

In order to get an insight into how well the jets are reconstructed in the high level trigger, it is necessary to compare the two data sets event by event, jet by jet and determine how much the defining jet variables vary from trigger to offline jets. In the code I wrote to generate the monitoring histograms, for each offline jet in an event, every trigger jet from the same event is compared to it to find the best match based on spatial proximity. The same is done in vice versa, finding matching offline jets for each trigger jet. After loading the jets from their `TTrees` into `TLorentzVectors`, the `DeltaR` function of the `TLorentzVector` class is used for this. Since an Anti-kT4 algorithm was used for both reconstructions, two jets are considered matched if the angular separation $\Delta R = \sqrt{\Delta\eta^2 + \Delta\phi^2}$ is smaller than 0.4. In the following, I present the histograms made after the jet matching process.

2.i) Unmatched spatial distribution

These two-dimensional histograms show the percentage of jets from one data set in a certain η-ϕ-area, that did not find a match in the other set through spatial requirements. These plots would show anomalies in the calorimeter, such as faults that may have been corrected in the offline reconstruction or for instance areas of great misplacement of the jets in the trigger reconstruction. As in all the plots, the binning can be changed easily in a list of variables to be altered by the user. Again, dashed black lines mark the edges of the calorimeter sectors.

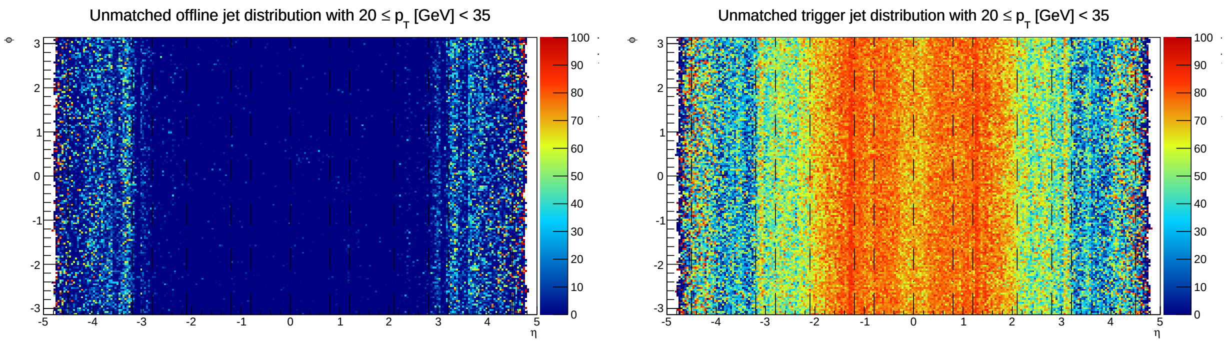

Figure 3: Spatial detector reconstruction (η,ϕ) showing the percentage of unmatched offline (left) and trigger jets (right) in each 2D-bin with a p_{T} of 20-35 GeV.

One may think the example in fig. 3 gives reason to worry, but taking a look at the preceding p_{T} slices (or the next histogram presented), it turns out that the high percentage of unmatched trigger jets is limited to low transverse momentum jets ($p_{\mathrm{T}} \lesssim 40\,\mathrm{GeV}$). This makes sense because the offline reconstruction incorporates pile-up subtraction, while the HLT data includes all jets. The eventshape variable ρ, stating the average energy density deposited in the detector by pile-up, can be used to determine a p_{T} limit for unmatched jets due to pile-up correction.

2.ii) Unmatched p_{T} distribution

These one-dimensional histograms simply display the percentage of jets found in a certain p_{T} range that remained unmatched (both offline jets and trigger jets). The x-axis, displaying the transverse momentum has logarithmic binning, while the y-axis, giving the unmatched percentage, is linear. Again an individual histogram is made for each sector of the calorimeter, giving twelve plots of this type in total. Below, two examples are shown from the central detector region and the forward direction.

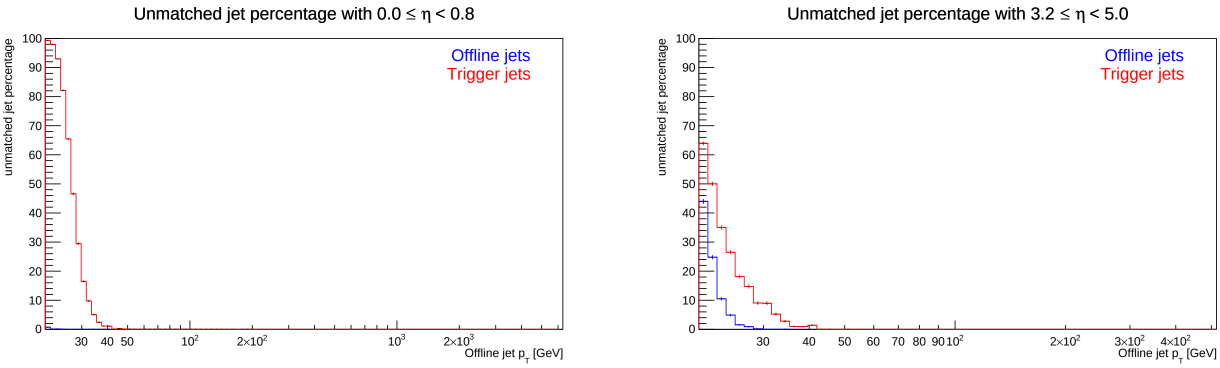

Figure 4: Percentage of unmatched jets by p_{T} from a central calorimeter sector (left) and the most forward direction (right). The effect of pile-up subtraction in just the offline data is visible.

Combining the information displayed in the unmatched jet distribution plots, it is possible to determine fundamental errors in the event reconstruction of the HLT as compared to the full reconstruction offline. The following histograms shed light on the precision of the reconstruction of the trigger jets that were matched with an offline jet.

3.i) Histograms displaying the p_{T} response

Once a trigger jet is matched to an offline jet, the generating code fills one of these histograms (the offline jet η is used to choose the right histogram). The two-dimensional plots display the ratio of the trigger jet p_{T} to the offline jet p_{T} in different p_{T} ranges (with the offline jets as the reference). For each offline jet p_{T} bin on the x-axis, the response is normalized to 100 over the y-axis in order to give a percentile distribution for each p_{T} bin. The range on the y-axis is fixed but can be altered by the user easily. The contents of every overflow and underflow bin are added to the highest and lowest bins on the y-axis respectively. This way, one can see if there is a high percentage being matched outside of the range of 0.6 to 1.4.

On top of the two-dimensional histograms, I have added profiles in magenta to show the average p_{T} response for every bin on the x-axis. This shows trends more clearly, especially for p_{T} intervals with a high spread on the response (as for low p_{T} in fig. 5). Ideally, the matching percentage should peak closely around 1 with a small spread in the y-direction. Calibration errors, for instance, would appear as horizontal lines deviating from 1 in these plots. An example from the central detector region is shown in fig. 5.

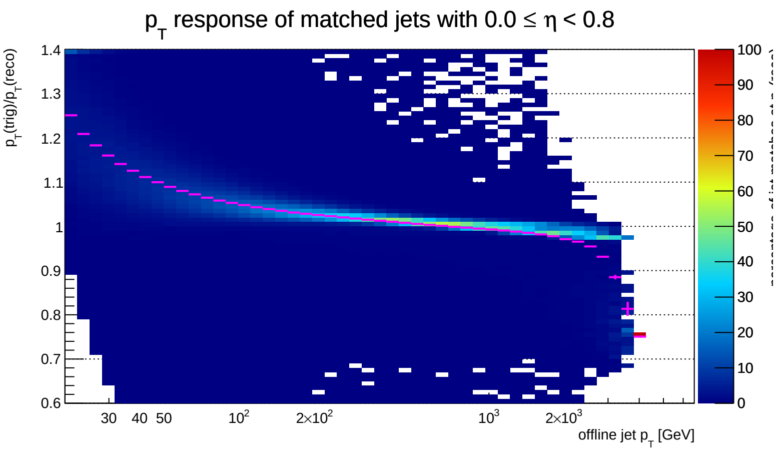

Figure 5: Histogram displaying the p_{T} response for different p_{T} in a central calorimeter section.

3.ii) Histograms displaying the matched p_T distribution

These histograms are an alternative to the p_T response plots just introduced. They basically yield the same information in a different form. At the Hadronic Calibration Workshop it was decided to include both histogram forms in the monitoring software, since the p_T reconstruction monitoring is of fundamental importance and there are some differences in the representation, making them useful for different purposes.

With the trigger jet p_T on the x-axis and the offline jet p_T on the y-axis (both with logarithmically scaled bins), for each trigger jet that is matched to an offline jet, the bin corresponding to the matched transverse momenta is incremented (in the left plot). The z-axis is also logarithmic on the left since it displays absolute numbers and low p_T jets strongly dominate due to high cross sections.

The right plot shows the same histogram, but normalized to 100 in the y-direction for every bin on the x-axis. This shows, for each trigger jet p_T interval, the percentage of matched offline jets in the corresponding p_T range on the y-axis. Combined, these histogram pairs show how much the p_T of a trigger jet can be trusted in a certain region. The left histogram with absolute numbers can be used to determine the statistical significance of a possible high deviation of matching percentage from the optimal diagonal (marked by the dashed black line).

A useful feature of these plots over the 3,i-histograms is the double logarithmic binning. For higher p_T, the bins (including the y-axis) grow in size, increasing the tolerance on the absolute deviation from the diagonal. This representation displays more of an error ratio $\Delta p_T / p_T$ rather than just the absolute deviation Δp_T.

Another advantage of these histogram pairs is the direct display of the absolute numbers of matches in certain p_T regions. In general, the percentile distribution is more useful for determining the reconstruction quality in all p_T ranges but as already mentioned, the left plot holds information on the statistical significance of what is seen on the right. This is a missing feature in the response plots (3.i).

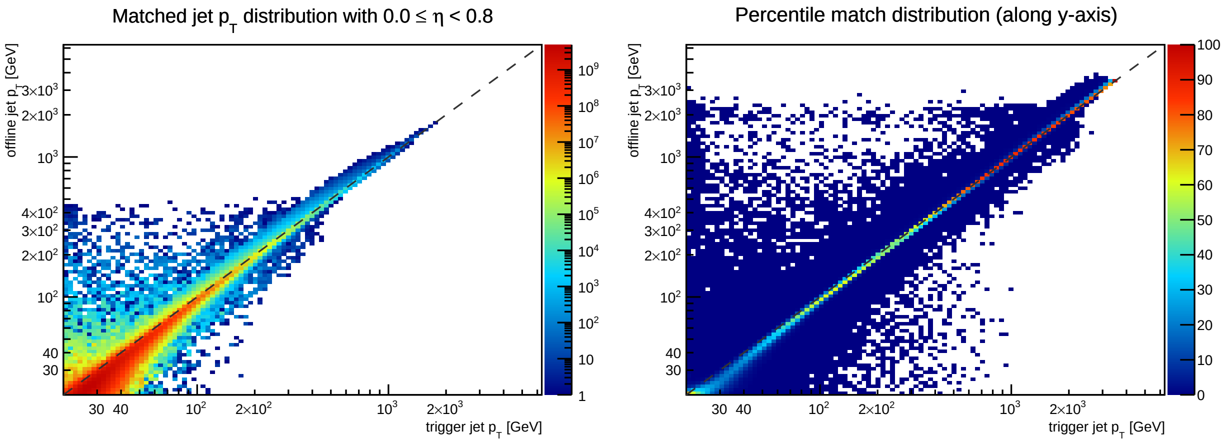

Figure 6: Histogram pair displaying the p_T matching quality in absolute numbers (left) and in percent for each trigger jet p_T bin (right). Only jets with an offline η of 0-0.8 are included here.

In the example in fig. 6 from the central barrel area, the appearing jet matches are obviously different in the two plots. The reason for this lies in the logarithmic scaling of the z-axis in the left plot, combined with the data being displayed. As already mentioned, what is being shown here is a merging of seven Monte Carlo samples. To combine the different JZXW slices, multiple weights had to be applied (effectively filter efficiency·cross section·luminocity).[1] Because of this,

[1]twiki.cern.ch/twiki/bin/viewauth/AtlasProtected/Dijet14TeVECFAStudies#Pythia_QCD_JZW_samples

the z-axis of the plot on the left actually does not display the matches in natural numbers, but scaled down. Setting the lower limit of the logarithmic scale to 1 makes sense for experimental data, where the matches are counted in absolute numbers, but it is somewhat problematic for scaled down Monte Carlo samples, resulting in events of too little statistical significance to land in the underflow bin. In the percentile distribution on the right, all jet matches can be seen.

3.iii) Histograms displaying the η reconstruction quality

These two-dimensional plots are similar to the p_{T} response histograms (3.i). On the x-axis, the offline jet η is linearly binned (with dashed vertical lines marking calorimeter sectors) and the y-axis displays the difference between the trigger and the offline jet η of a match. Again, the distributions are normalized to 100 along the y-axis for every bin on the x-axis to display the percentage of matches in a certain η range with a certain reconstruction accuracy. The magenta profile shows the average η difference for matched jets in every η interval. Jet matches with an η deviation outside the range of -0.04 to 0.04 are added into the edge bins of the y-axis.

In the examples in fig. 7, a slight inconsistency in the η calibration of the trigger and offline jets can be seen. Compared to the average jet radius of 0.4 and and the size of a calorimeter cell (0.1), the deviations seen here are very well acceptable. It is nonetheless interesting to see that there are different trends dominating at different p_{T} ranges.

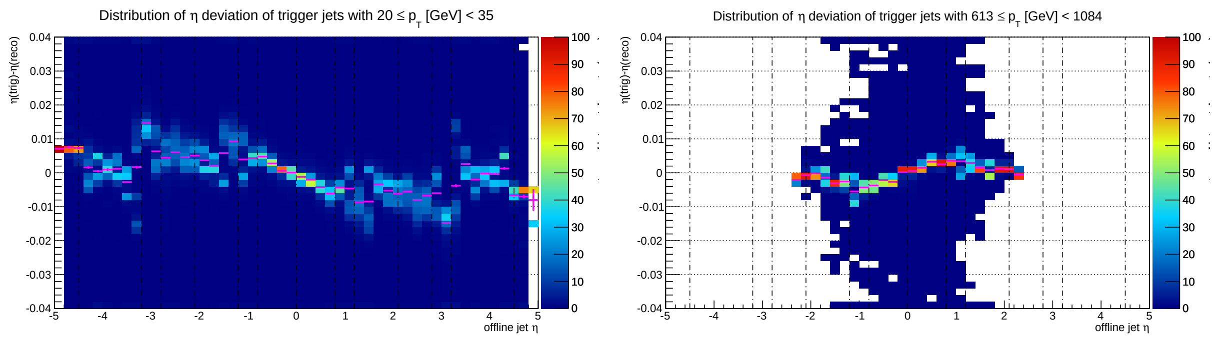

Figure 7: Percentile distributions (along y-axis) of the matched η deviation at different offline reconstructed η values for low p_{T} jets (left) and jets with a p_{T} of 613-1064 GeV (right).

3.iv) Histograms displaying the ϕ reconstruction quality

These histograms are structured just like the previous set for the η reconstruction monitoring (3.iii). The difference $\Delta\phi$ on the y-axis is plotted against the offline jet ϕ on the x-axis with adjustable resolution and range. To get the azimuthal separation $\Delta\phi$ of the jets, the `DeltaPhi` function of the `TLorentzVector` class is used. This method takes into account that the scale is connected at $\pm\pi$, determining the shorter of the two possible paths between the jets.

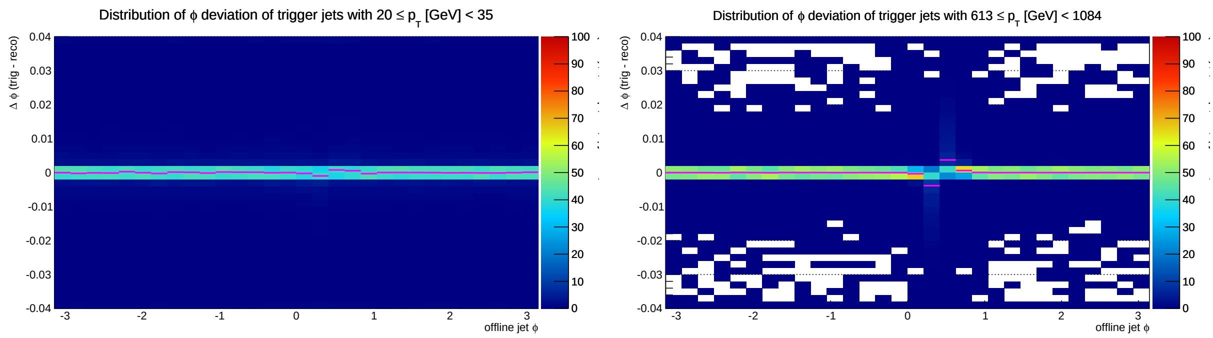

Figure 8: Percentile distributions (along y-axis) of the matched ϕ deviation at different offline reconstructed ϕ values for low p_{T} jets (left) and jets with a p_{T} of 613-1064 GeV (right).

Of course the deviation of matched η and ϕ variables is limited by the matching process itself, but it is still insightful to monitor the reconstruction differences at a high resolution. Trends and faults can be seen in these plots, such as for instance the jump in $\Delta\phi$ at $\phi_{\text{offline}} \approx 0.5$ in fig. 8 or the slightly higher η differences around $\eta_{\text{offline}} = \pm 3.2$ near the edge between two sectors of the calorimeter (fig. 7). With the y-axis in the examples of plots (3.iii) and (3.iv), the resolution on the difference between the angular variables of matched trigger and offline jets is very high. A real spatial reconstruction problem would only manifest itself in a high percentage of matches showing up at the highest or lowest bins on the y-axis (containing the overflow and underflow bin contents respectively). In such a case, the range on this axis could be extended by the user in the histogram specifications to create new plots that would show the problematic match distribution at bigger scale.

4 Conclusion

During my stay at CERN, I created a program that generates the plots to be included in the trigger monitoring software to be used for Run II of the LHC. After my results were approved at the Hadronic Calibration Workshop 2014 in Munich, it was confirmed that the histograms my code creates will be tied into the monitoring software of the ATLAS experiment. This will help to spot problems with the trigger, and hence aid the collection of high quality data at the LHC. Perhaps even more importantly, it will make a validated trigger level analysis possible, enabling the researches at ATLAS to use larger datasets, containing key physics observables reconstructed and recorded by the high level trigger system. Such data can be used in the search of new physics, boosting statistics reliably and allowing focus on new signatures, that possibly lacked collision data previously.

Beyond the knowledge I have gained in `C++` coding, especially in the `Root` environment, and what I have learned about jet substructure, reconstruction algorithms and detector functions, the summer at CERN was an incredible personal experience. Working in such an international environment and having to do with people from so many different backgrounds has been a great pleasure and honor. I sincerely thank my supervisors Caterina Doglioni and Dag Gillberg for being great mentors and guiding me through this project.

Appendix

The finished code can be found on SVN under the following link:
https://svnweb.cern.ch/trac/atlasperf/browser/CombPerf/JetETMiss/JetPerformanceScripts/TriggerToOfflineComparisonCode/.
The `.cxx` files are in the `Root` directory. In the `TriggerToOfflineComparisonCode` directory, I have placed the header files with instructions on how to use the program I ran in `makeclass_tla_validation.h` and instructions on how to make the histograms in other environments in `monitoring_class.h`. In the following, instructions for the implementation of the histograms into an existing framework using (exemplarily) the xAOD data format and a guide for the program used with D3PD data are given.

A Instructions on how to use the monitoring class

Before leaving CERN, I made my code more modular, in order to make the implementation into other existing frameworks easier. For this purpose, I created a class, which I called the `monitoring_class` (see `monitoring_class.cxx` and `monitoring_class.h` in SVN). It can be included in any existing code, where then, just a few member functions of that class need to be called to create the histogram set. To use this class, the offline reconstructed, as well as the trigger jets have to be passed as `TLorentzVectors`. An example on how the class can be implemented into a code running with xAOD data is presented below.

```
**********How to use the tool with xAOD (or any other EDM):**********

During initialization
--------------
*Creation of the montioring object:*
m_trigMon = new monitoring_class(output_file_name);

*Initalization:*
m_trigMon->MakeTheHistos();
--------------

For each event
---------
*Code to convert xAOD containers to vectors of TLorentzVector:*
vector<TLorentzVector> recoJets, trigJets;
for ( auto jet :  xAODofflineJets ) recoJets.push_back( jet.p4() );
for ( auto tjet :  xAODtrigJets ) trigJets.push_back( tjet.p4() );

*Event weight - if applicable, e.g.  prescale dependent:*
double eventWeight = 1.0;

*Call the histogram filling:*
m_trigMon -> FillTheHistos( trigJets, recoJets, eventWeight );
---------

*Post processing and writing to output_file_name.root:*
m_trigMon -> FinalizeAndSaveOutput();
```

```
**************How to use produce the plots in pdf files**************

*Done by standalone program from the .root file saved as output*
*with the binary produced when compiling with RootCore.*
*To run the program to produce 8 pdf documents*
*(one for each plot type), call the following:*

make_tla_plots INPUTFILE [OUTPUT_PDF_SUFFIX]

*If last argument is skipped, the input file name is used for suffix.*
```

B Instructions on how to use the makeclass code

```
***************How to use the makeclass code on TChains**************
*Compile makeclass_tla_validation.cxx and monitoring_class.cxx*
*using RootCore, it produces the binary to execute:*

run_tla_monitor INPUT_FILE_DIRECTORY OUTPUT_FILE_NAME.root COLLISION_-
ENERGY

*The last argument (COLLISION_ENERGY), which should be 8 or 14,*
*is used for the offline jet calibration.*
*It determines which config file to use.*
*If it is left out or an integer other than 8 or 14 is passed,*
*the program runs without the calibration tool.*
*The plots are produced with the standalone make_tla_plots program.*
```

References

[1] Bryan Dahmes, *Triggers for LHC Physics Lecture*, CERN Summer School lectures 2014.

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[3] Imma Riu, *Performance of the ATLAS Trigger with Proton Collisions at the LHC*, ATLAS collaboration, CERN, Journal of Physics: Conference Series 331 (2011) 032027, IOP Publishing, CHEP 2010.

[4] Peter Loch, *A brief Introduction into Principles of and Data Analysis for Sampling Calorimeters in High Energy Physics Experiments*, Dept. of Physics, University of Arizone, April, 1999.

[5] M. Weber, *Calorimeter and Jet Reconstruction* presentation, http://www.becher.itp.unibe.ch/LHC/.