

Tagging Quark/Gluon Initiated Jets at ATLAS

Boston Jets 2014

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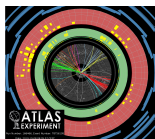
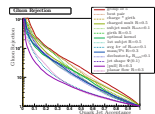
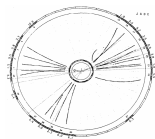
21 January, 2014



History and Motivation



- Quark-initiated and gluon initiated jets have long been known to have different properties
 - Well measured at PETRA, SLAC, LEP, others
- Two papers from Schwartz and Gallicchio in 2011, along with previous efforts in ATLAS, led to a push for creating and commissioning a quark-gluon tagger at ATLAS
 - Theory paper ([here](#)) investigated the best variables to use to train a tagger, in parallel to our own efforts
- Many potential applications in searches for new physics and standard model measurements
 - Separate hadronically decaying bosons from gluon dominated backgrounds (diboson searches, Higgs, etc.), improve discrimination in dijet searches, monojet characterization, many more



Today's Talk



- Today, we are showing for the first time the full results of the 2011 ATLAS q/g tagger
- Results not yet publicly available: will be published in a paper (very soon)

① Constructing of a Tagger
Variable Selection
Purified Samples
Defining the Likelihood

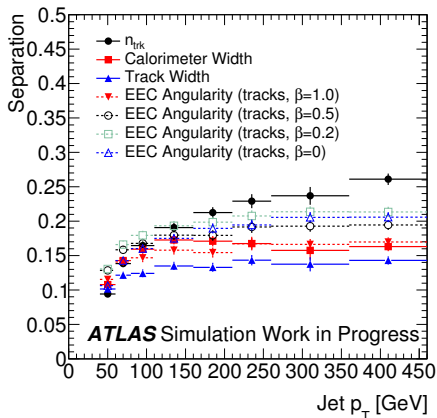
② Tagging Performance
Systematic Uncertainties
Overview of Performance
Angularities

Constructing a Tagger

Variable Selection

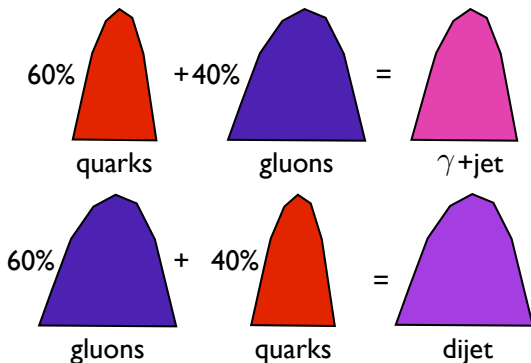


- Important to choose pileup robust variables: **use only tracking**
- Need strong performance across wide range of p_T : n_{trk} has best performance at highest, track width better at low
- EEC variables have good separation as well– but have systematic issues we will describe later
- We use a **likelihood** combining n_{trk} and track width



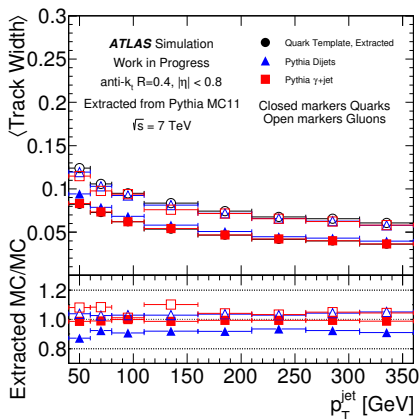
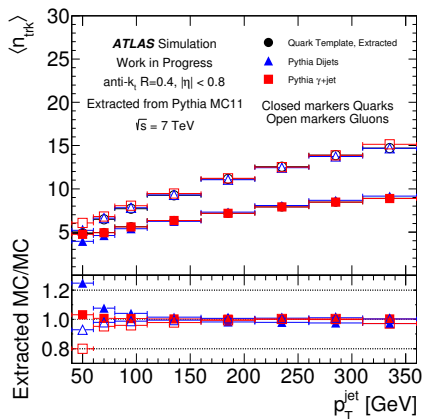
Template Methods

- Significant data/MC disagreement for the input variables required the use of a data-driven template technique



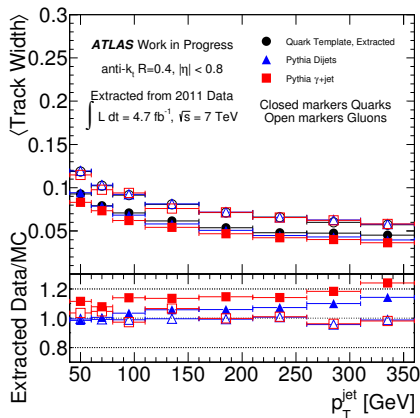
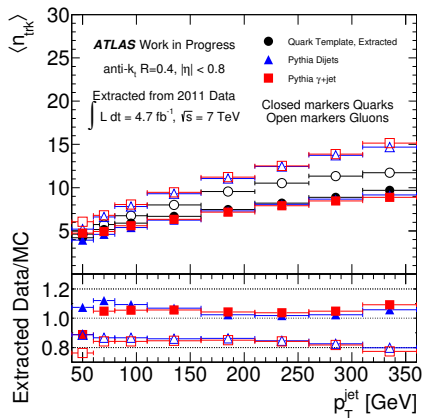
- Take percentages from MC, measure γ +jet and dijet in data: solve for quark and gluon distributions in data
- More information on method in [▶ backup](#)

Testing Method in MC



- MC-labeled distributions in γ +jet and dijets agree very well with templates derived in MC
 - Disagreement at low p_T will be discussed at length soon
- Gives us confidence that the algorithm is doing something sensible

Templates with Data



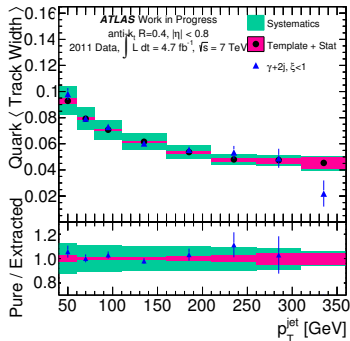
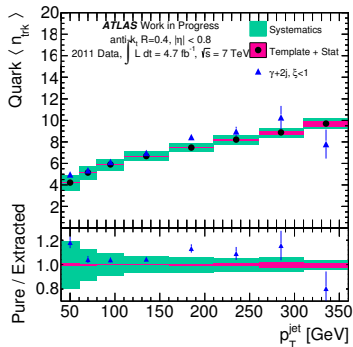
- But data disagrees with Pythia in n_{trk} , leading to worse separation than expected
- Track Width has better agreement, though not good at high p_T

Purified Samples



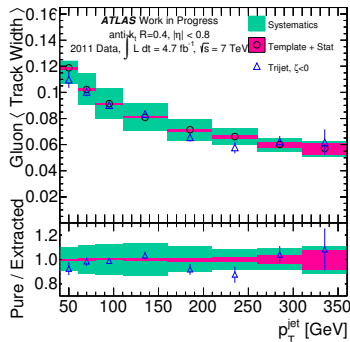
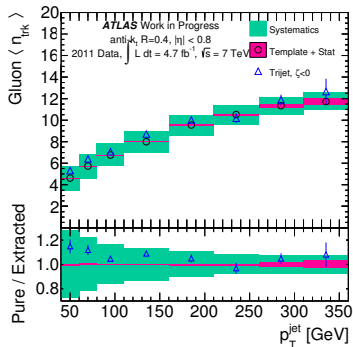
- Are the data templates correct? How can we test these derived shapes?
- Define **topological/kinematic regions** where jets are more likely to be quark-initiated or gluon-initiated
 - Trijet sample, with $\zeta = |\eta_3| - |\eta_1| - |\eta_2| < 0$ is gluon-like
 - $\gamma+2$ jet sample, with $\xi = \eta_{jet1} \times \eta_\gamma + \Delta R(jet2, \gamma) < 1$ is quark-like
 - See [arXiv:1104.1175](https://arxiv.org/abs/1104.1175) for more details
- These regions have purity of $\sim 90\%$ – good regions for **validation of templates!**
 - Not enough statistics to derive 2D templates, but enough to be useful for validation

Pure Shapes: Quarks



- Shapes from topologically purified samples **generally agree** with extracted templates to 1σ

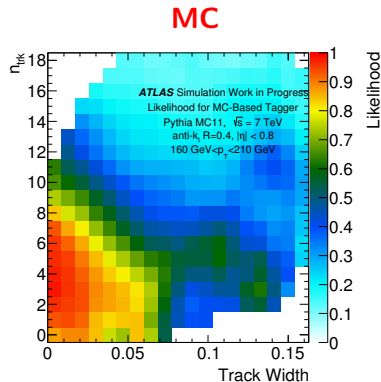
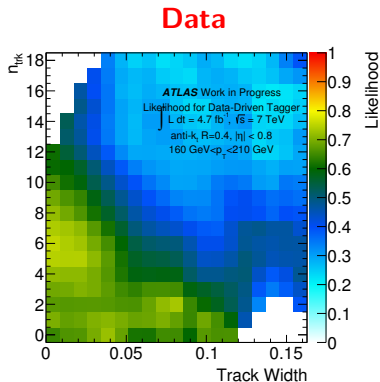
Pure Shapes: Gluons



- **Similar levels of agreement** with gluon shapes
- **Completely independent** data samples verify our template shapes

Likelihood

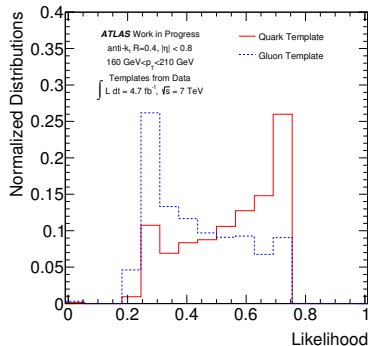
- Define $L = q/(q + g)$ separately in data and MC



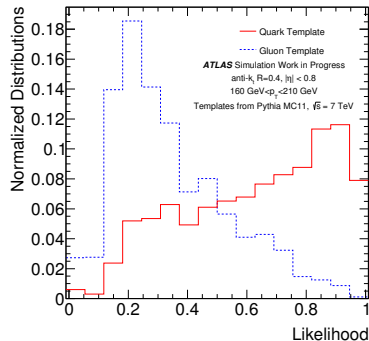
- Immediately can see that while **shapes are similar**, performance is **much worse** in data

Likelihood Output

Data



MC



- **Significantly reduced** performance in data
 - But enough to still make something useful!
- We will define a tagger at **4 operating points**: 0.3, 0.5, 0.7, and 0.9 quark efficiency

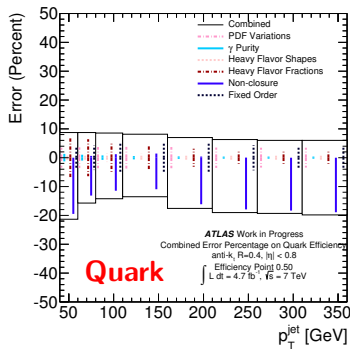
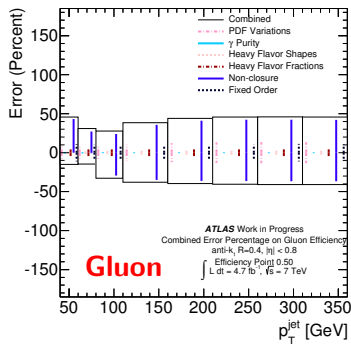
Tagging Performance

Systematic Uncertainties



- Many different sources of error considered for the tagger:
 - 1 PDF variations– affect q/g fractions
 - 2 γ purity– affects data input
 - 3 Heavy flavor shapes/fraction– affects MC inputs
 - 4 Madgraph/Pythia fraction differences– affect q/g fractions
 - 5 Non-closure/ sample dependence– affects data inputs

Systematics Summary



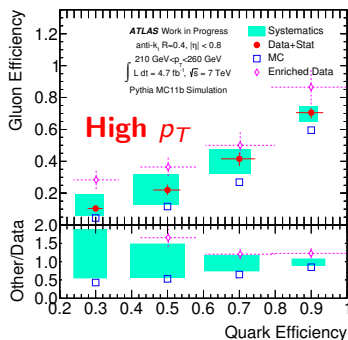
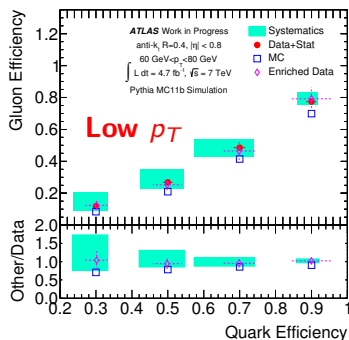
- Here, show **breakdown of systematics** for 50% quark-like o.p.
- **Sample dependence** is by far the largest effect
 - Quarks/gluons from γ +jet do not look exactly like quarks/gluons from dijets (in both Pythia and Herwig)
 - Need to understand this effect to apply this tagger to other topologies
- More operating points, and details on non-closure, in [▶ backup](#)

Overview of Performance

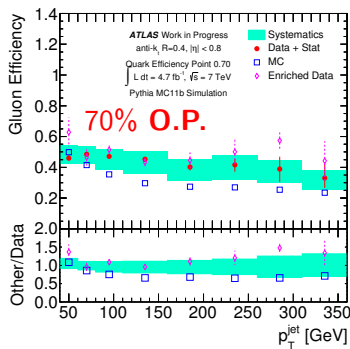
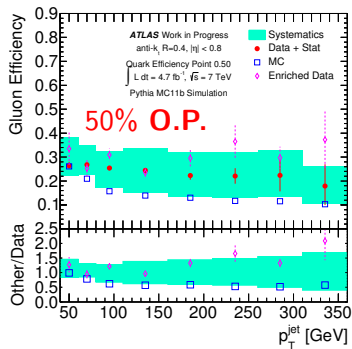


- For measuring performance, we will show several different tests together:
 - **Red points** indicate performance of data tagger, tested on data templates
 - **Red lines** on those points indicate statistical uncertainties
 - **Teal band** indicates systematic uncertainties
 - **Blue points** indicate performance of pythia tagger, tested on pythia templates
 - **Magenta points** indicate performance of data tagger, tested on **pure data samples**

Gluon Efficiency vs. Quark Efficiency



- Purified samples show slightly worse gluon efficiency than data, but **agreement within 1σ**
- Data shows worse performance than MC– **generally greater than 1σ disagreement**

Performance vs. Jet p_T 

- Left shows 50% quark point, right shows 70%
- Results are consistent across p_T : purified samples measurement **generally agree with data, but MC significantly overestimates performance**
- Other operating points in [▶ backup](#)

Angularities

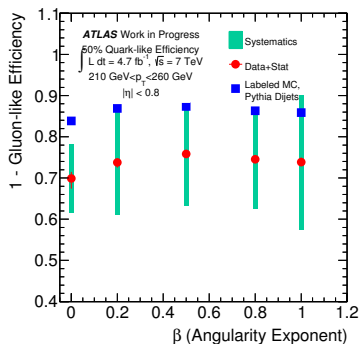
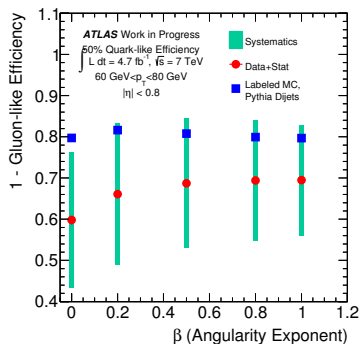


- New class of variables, called “Energy Correlation Angularities,” described in [arXiv:1305.0007](https://arxiv.org/abs/1305.0007)
- Interestingly: possible to show that these variables contain **maximum** discriminatory power between q/g
- Defined with free parameter β :

$$Ang = \frac{\sum_i \sum_j p_{T,i} p_{T,j} (\Delta R(i,j))^\beta}{(\sum p_{T,i})^2} \quad (1)$$

- How does gluon efficiency change with β , and how large are the systematics?

Angularity Performance



- **NB:** 1 - Gluon Efficiency shown
- **Significant differences** between data and MC performance, and **systematics are larger** than for the likelihood
 - Sample dependence is **very large** for angularities, at least with $\beta < 1$
- $\beta = 0.2$ is slightly optimal in MC, but difficult to tell trend in data

Conclusions

Summary



- Much effort has gone into studying the properties of quark and gluon initiated jets (see existing conf note, [ATLAS-CONF-2012-138](#))
- Since then, work has focused on deriving a tagger, calibrating it to data, and determining the systematics
- Data/MC disagreements make tagger derivation difficult– use **templates from data**
- Systematics need to be carefully assessed– **large sample dependencies observed**
 - Angularities in particular seem sensitive to these effects
- Final paper, with all these results and more, should be out soon!

Thank You For Your Attention!

Backup

Defining Quark/Gluon Initiated Jets



- Need to use a consistent definition across generators for defining a quark/gluon initiated jet
- We use: “a jet is defined by the flavor of the highest energy parton inside the jet”
 - This labelling is studied in Madgraph to determine how often it matches the Matrix Element: 95 – 99% of the time

Extracting Templates

- Goal: to better understand quark/gluon shapes in data, extrapolate **data** to 100% purity with fractions from MC
- Ideally, solve for q/g on bin-per-bin basis from:

$$h^{\gamma+j} = P_Q^{\gamma+j} q + P_G^{\gamma+j} g$$

$$h^{dijet} = P_Q^{dijet} q + P_G^{dijet} g$$

P_Q = percentage quark

h = histogram value

q/g = templates

$(\gamma + jet)/(dijet)$ = different sample

- But, need to account for b and c fractions (for now, taken from MC):

$$h^{\gamma+jet} = P_Q^{\gamma+jet} q + P_G^{\gamma+jet} g + P_B^{\gamma+jet} b + P_C^{\gamma+jet} c$$

$$h^{dijet} = P_Q^{dijet} q + P_G^{dijet} g + P_B^{dijet} b + P_C^{dijet} c$$

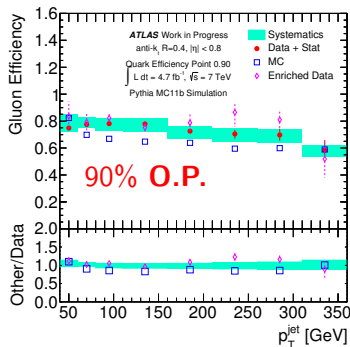
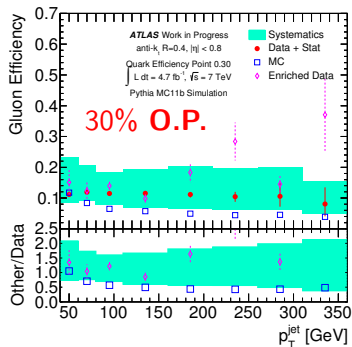
From Data

From MC

Solving for This

- Then, compare pure data shapes to pure MC shapes (used for training tagger)

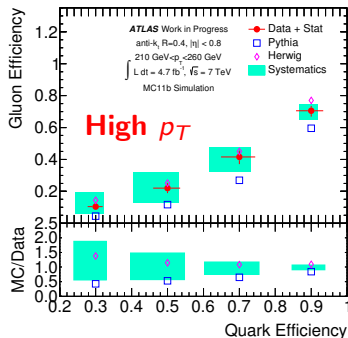
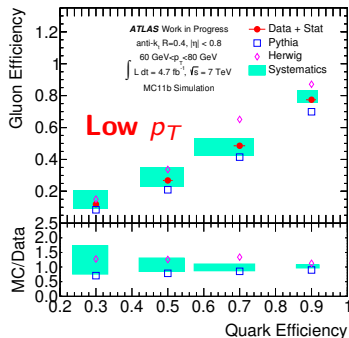
Performance vs. Jet p_T



- Results are consistent across p_T : purified samples measurement **generally agree with data**, but **MC significantly overestimates performance**

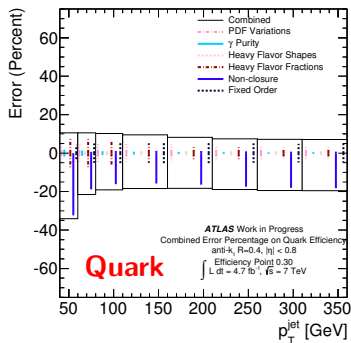
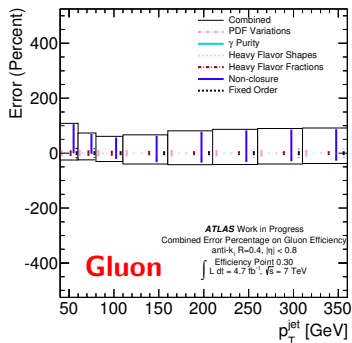


Gluon Efficiency vs. Quark Efficiency, with Herwig++



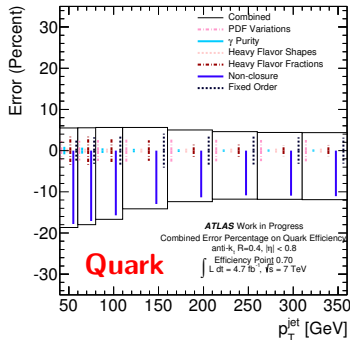
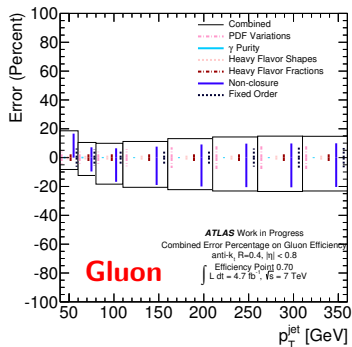
- Herwig++ generally agrees with data better: sometimes even under-predicts performance

Systematics Summary: 30% Operating Point



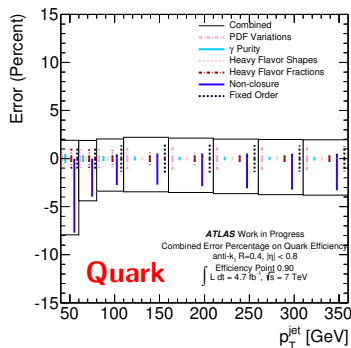
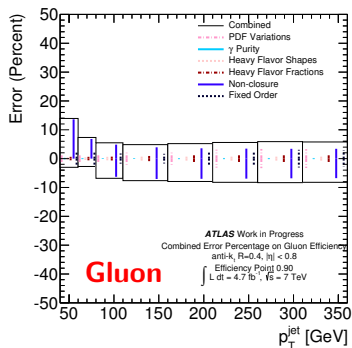
- Similar effects as at other operating points: largest here at low efficiency

Systematics Summary: 70% Operating Point



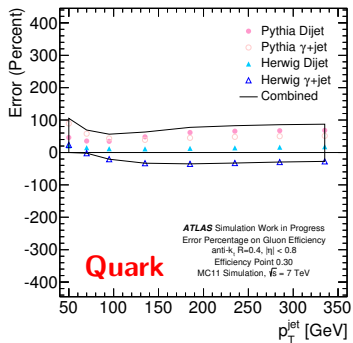
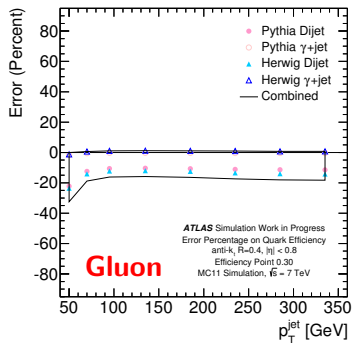
- Similar effects as at other operating points

Systematics Summary: 90% Operating Point



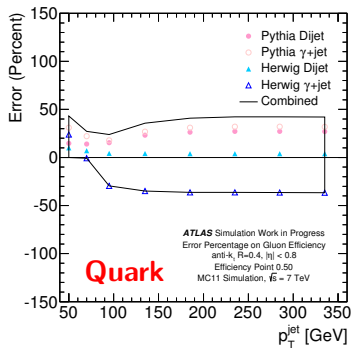
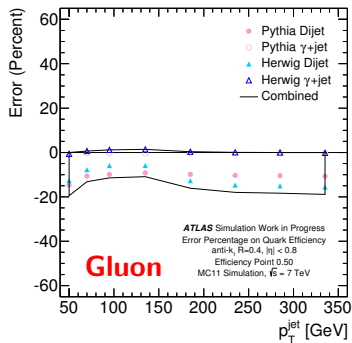
- Similar effects as at other operating points

Nonclosure: 30% Operating Point



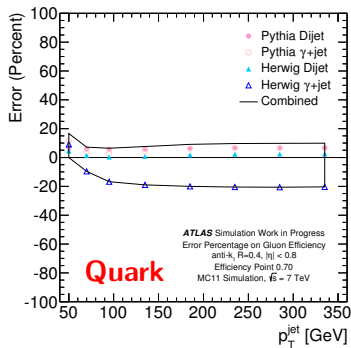
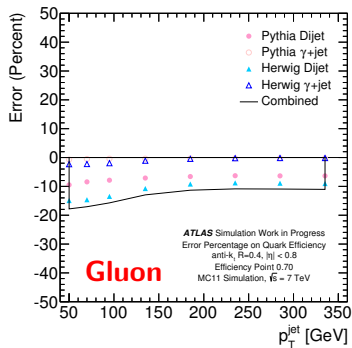
- Breakdown of Pythia/Herwig++ disagreements with their respective templates

Nonclosure: 50% Operating Point



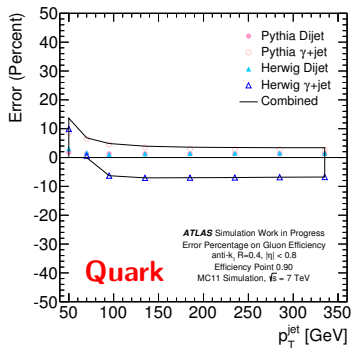
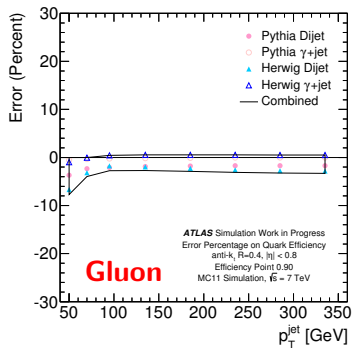
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Nonclosure: 70% Operating Point



- Breakdown of Pythia/Herwig++ disagreements with their respective templates

Nonclosure: 90% Operating Point



- Breakdown of Pythia/Herwig++ disagreements with their respective templates