

Studies for the measurement of the $tt+\gamma$ process with ATLAS at LHC

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Motivation



Why is $pp \rightarrow t\bar{t}\gamma$ interesting?

- sensitive to the electromagnetic coupling of the top quark \rightarrow direct charge measurement
- sensitive to vertex structure (in differential measurements) → test of the Standard Model and possible clues to physics beyond the Standard Model

$$\begin{split} \Gamma^{\mu}\left(q^{2}\right) &= -iQ_{t}e\gamma^{\mu}\left(F_{1}^{V}\left(q^{2}\right)+F_{1}^{A}\left(q^{2}\right)\gamma_{5}\right)\\ &-iQ_{t}ei\frac{\sigma^{\mu\nu}}{2m_{t}}q_{\nu}\left(F_{2}^{V}\left(q^{2}\right)+F_{2}^{A}\left(q^{2}\right)\gamma_{5}\right) \end{split}$$

Precision measurements:

• possible background: charged hadrons that are misidentified as photons and photons from hadron decays



Photons at ATLAS

Reconstruction and identification

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photons deposit energy mostly in the electromagnetic calorimeter:

- searching for energy clusters in the electromagnetic calorimeter
- reconstruction and matching of the tracks, photon conversion?
- possibly: reconstruction of conversion vertex
- depending on the matching: (un)converted photon or electron

Photon identification with hight signal efficiency and hight background rejection is required. Photon identification is based on cuts on discriminating variables that characterize:

- hadronic leakage
- lateral and longitudinal shower development
- energy ratios







Prompt Photons and Hadron Fakes



Prompt Photons

A prompt photons is a photon originating from the matrix element, the parton shower or the hadronisation.

Hadron fake

A hadron fake is either a hadron misidentified as photon or a photon from the hadron decay.

Data modelling

hadron fakes:

- based on dijet events
- e.g. $g + g \rightarrow g + g$
- final state gluons create jets
- some hadrons of these jets will be detected as photons

prompt photons:

- based on inclusive photon samples
- primarily events where $g + q \rightarrow \gamma + q$ via t-channel scattering (QCD-Compton)

Hadron Fakes



High amount of hadronic fakes for $t\bar{t}\gamma$ -processes (about 30 % at $\sqrt{s} = 7$ TeV). At $\sqrt{s} = 7$ TeV discrimination using discriminating variables e.g. $p_{\rm T}^{\rm iso}$.

The photon track-isolation variable $p_{\rm T}^{\rm iso}$...

... is defined as the scalar sum of the transverse momenta of selected tracks in a cone of $\Delta R = 0.2$ around the photon candidate.

 $p_{\rm T}^{\rm iso}$ -distribution of signal and background is simulated with templates. The templates are fitted to the data using a likelihood fit.



Figure: ²Results of the combined likelihood fit using the track-isolation (p_T^{iso}) distributions as the discriminating variable for the electron channel.

²Phys.Rev.D 91:072007

Shower Shape Studies



- check distributions of the shower shape variables for differences
- use differences to discriminate between hadron fakes and prompt photons
- use information about conversion

$$s = \frac{1}{2} \sum_{i \in \text{bins}} \frac{\left(s_i - b_i\right)^2}{\left(s_i + b_i\right)}$$





Table: Comparison of separations between prompt photons and hadron fakes for different variables and conversion types.

	all	converted	unconverted	$N_{\rm bins}$	<i>x</i> _{min}	x _{max}
R_{η}	0.0531	0.0462	0.0279	30	0.85	1.05
R_{ϕ}	0.0764	0.0344	0.0507	30	0.5	1.1
$W_{\eta 2}$	0.0232	0.0153	0.0091	30	0.004	0.016
$f_{\rm side}$	0.0778	0.0332	0.0809	30	0	0.7
$w_{\eta 1}$	0.0464	0.0262	0.0321	30	0.4	0.85
Wstot	0.0484	0.0350	0.0391	30	0	4
$R_{\sf had}$	0.0310	0.0354	0.0238	30	-0.2	0.25
R_{had_1}	0.0291	0.0368	0.0224	30	-0.05	0.06
E_{ratio}	0.0234	0.0286	0.0209	30	0.75	1.02
ΔE	0.0029	0.0052	0.0016	30	-25~GeV	300 GeV

BDT-Algorithm



BDT uses an ensemble of weak learners to create one strong learner. Models have form:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$$

 $h_m(x)$ are called weak learners, we use decision trees. The model is build iterative:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

 $h_m(x)$ is chosen so that the loss function L will be minimized:

$$F_m(x) = F_{m-1}(x) + \arg\min_{h} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) - h(x))$$

Use learning rate ν to scale step length:

$$F_m(x) = F_{m-1}(x) + \nu \gamma_m h_m(x)$$

BDT Kolmogorov-Smirnov Test





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Table: Comparison of AUC-values

	no conversion	converted	unconverted	conversion as feature
AUC-test	0.8829	0.8780	0.8761	0.8838
AUC-train	0.8840	0.8803	0.8805	0.8864

Table: Comparison AUC-values for exponential loss function

	no conversion	converted	unconverted	conversion as feature
AUC-test	0.8829	0.8784	0.8774	0.8846
AUC-train	0.8839	0.8811	0.8798	0.8853



Summary

- can use differences in shower shapes to discriminate between prompt photons and hadron fakes
- training two different BDTs for converted and unconverted photons does not improve performance
- increase in performance when using conversion as feature

Outlook

- studies of systematics
- optimization of BDT parameters
- comparison with other MVA-algorithms (e.g. neural network)



Thank you for your attention.



Backup



Gradient Tree Boosting

- number of single trees = 120, maximum depth of trees = 3, learning rate = 0.1, subsample = 0.5
- loss function: $L = -2(yP \log(1 + \exp(P)))$, where P is the log-odds
- train size: 0.8, test size: 0.2
- features: R_{η} , R_{ϕ} , $w_{\eta 2}$, f_{side} , $w_{\eta 1}$, w_{stot} , R_{had} , R_{had_1} , E_{ratio} , ΔE , (see appendix)

Decision Tree



- uses a set of decision rules to perform classification on a dataset
- training vectors $x_i \in \mathbb{R}^l$, i = 1, ..., n
- label vector $y_i \in \mathbb{R}, \ i = 1, ..., n$
- *n* samples and *l* features
- data at node m represented by Q
- split candidates $\theta = (j, t_m)$ with feature j and threshold t_m
- data is split into two subsets $Q_{\text{left}}(\theta)$ and $Q_{\text{right}}(\theta)$:

$$egin{aligned} \mathcal{Q}_{\mathsf{left}}(heta) &= \left\{ (x_i, y_i) | x_i^j \leq t_m
ight\} \ \mathcal{Q}_{\mathsf{right}}(heta) &= \mathcal{Q} \setminus \mathcal{Q}_{\mathsf{left}} \end{aligned}$$

- x_i^j is the value of the *i*-th sample for the *j*-th feature
- impurity at node m is calculated for impurity function H():

$$G(Q, \theta) = \frac{n_{\text{left}}}{N_m} H(Q_{\text{left}}(\theta)) + \frac{n_{\text{right}}}{N_m} H(Q_{\text{right}}(\theta))$$





• the parameters that minimize the impurity are chosen:

$$\theta^* = \arg\min_{\theta} G(Q, \theta)$$

- recuse for $Q_{\text{left}}(\theta^*)$ and $Q_{\text{right}}(\theta^*)$.
- possible measure for impurity is GINI:

$$egin{aligned} \mathcal{H}(X_m) &= \sum_k p_{mk}(1-p_{mk}), \ p_{mk} &= rac{1}{N_m} \sum_{x_i \in R_m} I(y_i = k). \end{aligned}$$

• p_{mk} is the proportion of class k in node m.

Example for a decision tree using the iris dataset





BDT-Algorithm



BDT uses an ensemble of decision trees. Models have form:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$$

 $h_m(x)$ are called weak learners, we use decision trees. The model is build iterative:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

 $h_m(x)$ is chosen so that the loss function L will be minimized:

$$F_m(x) = F_{m-1}(x) + \arg\min_h \sum_{i=1}^n L(y_i, F_{m-1}(x_i) - h(x))$$

Use learning rate ν to scale step length:

$$F_m(x) = F_{m-1}(x) + \nu \gamma_m h_m(x)$$



General idea of MVA implementation and training procedure

- learn some properties of a data set and apply them to new data
- split data into training set and testing set
- train MVA algorithm using the training set
- test algorithm on testing set

Data



Signal

- · based on inclusive photon samples
- primarily events where $g + q \rightarrow \gamma + q$ via t-channel scattering (QCD-Compton)
- /eos/atlas/atlascerngroupdisk/perf-egamma/InclusivePhotons/ v12/v12_01/PyPt17_inf_mc15c_v12_PIDuse.root

Background

- · based on dijet events
- e.g. $g + g \rightarrow g + g$
- final state gluons create jets
- some hadrons of these jets will be detected as photons
- /eos/atlas/atlascerngroupdisk/perf-egamma/InclusivePhotons/ v12/v12_01/Py8_jetjet_mc15c_v12_PIDuse.root



Normalised hadronic leakage

$$R_{
m had} = rac{E_{
m T}^{
m had}}{E_{
m T}}$$

The transverse energy deposited in the hadronic calorimeter $E_{\rm T}^{\rm had}$ in a window of $\Delta\eta\times\Delta\phi=0.24\times0.24$ behind the photon cluster, normalized to the total transverse energy $E_{\rm T}$

Normalised hadronic leakage in first layer

$$R_{had_1} = \frac{E_{T}^{had,1}}{E_{T}}$$

The transverse energy deposited in the first layer of the hadronic calorimeter $E_{\rm T}^{\rm had,1}$ in a window of $\Delta\eta\times\Delta\phi=0.24\times0.24$ behind the photon cluster, normalized to the total transverse energy $E_{\rm T}$

Definitions from Eur. Phys. J. C 76 (2016) 666



Middle η energy ratio

$$R_{\eta} = \frac{E_{3\times7}^{S2}}{E_{7\times7}^{S2}}$$

The ratio of the sum of the energy $E_{3\times7}^{S2}$ in a rectangle of 3×7 calorimeter cells in the second layer, to the sum of the energies $E_{7\times7}^{S2}$ in a 7×7 rectangle, centred around the cluster seed.

Middle ϕ energy ratio

$$\mathsf{R}_{\phi} = \frac{E_{3\times3}^{S2}}{E_{3\times7}^{S2}}$$

The ratio of the sum of the energy $E_{3\times3}^{S2}$ in a rectangle of 3×3 calorimeter cells in the second layer, to the sum of the energies $E_{3\times7}^{S2}$ in a 3×7 rectangle, centred around the cluster seed.



Middle lateral width

$$w_{\eta 2} = \sqrt{\frac{\sum E_i \eta_i^2}{\sum E_i} - \left(\frac{\sum E_i \eta_i}{\sum E_i}\right)^2}$$

Measures the lateral width of the shower in the second layer of the electromagnetic calorimeter in a window of $\eta \times \phi = 3 \times 5$ cells. E_i is the energy deposited in each cell and η_i the η position of the cell.

Front side energy ratio

$$F_{\rm side} = \frac{E(\pm 3) - E(\pm 1)}{E(\pm 1)}$$

Measures the lateral containment of the shower in η . $E(\pm n)$ is the energy in the $\pm n$ strips around the strip with the highest energy.



Front lateral width (3 strips)

$$w_{s3} = \sqrt{\frac{\sum E_i \left(i - i_{\max}\right)^2}{\sum E_i}}$$

Measures the width of the shower in η using three strip cells centred on the strip with the highest energy. *i* is the strip identification number, i_{max} identifies the strip with the highest energy and E_i is the energy deposited in each strip.

Front lateral width (total)

 $w_{s tot}$ measures the width of the shower in η using alls cells in a window of $\Delta \eta \times \Delta \phi = 0.0625 \times 0.196$, approximately 20×2 strip cells. $w_{s tot}$ is computed as w_{s3} .



Front second maximum energy difference

$$\Delta E = \begin{bmatrix} E_{2^{nd}max}^{S1} - E_{min}^{S1} \end{bmatrix}$$

The difference between the energy of the strip cell with the second largest energy $E_{2^{nd}max}$ and the energy of the cell with the lowest energy found between the largest and the second largest energy E_{min}^{S1} . If there is no second maximum $\Delta E = 0$.

Front maxima relative energy ratio

$$E_{\rm ratio} = \frac{E_{1^{\rm st}max}^{S\,1} - E_{2^{\rm nd}max}^{S\,1}}{E_{1^{\rm st}max}^{S\,1} + E_{2^{\rm nd}max}^{S\,1}}$$

The relative difference between the energy of the strip with the highest energy $E_{1^{st}max}^{S1}$ and the energy of the strip with the second highest energy $E_{2^{nd}max}^{S1}$. If there is no second maximum $E_{ratio} = 1$



Table: Comparison of separations between converted and unconverted photons for different variables for all photons, prompts and hadron fakes

	all	prompt	fake	$N_{\rm bins}$	X _{min}	X _{max}
R_{η}	0.0891	0.0608	0.0830	30	0.85	1.05
R_{ϕ}^{\cdot}	0.4148	0.3930	0.4035	30	0.5	1.1
$W_{\eta 2}$	0.0996	0.0831	0.0974	30	0.004	0.016
$f_{\rm side}$	0.1195	0.1643	0.0748	30	0	0.7
$w_{\eta 1}$	0.1266	0.1288	0.1091	30	0.4	0.85
W _{stot}	0.0820	0.0808	0.0707	30	0	4
$R_{\sf had}$	0.0104	0.0051	0.0087	30	-0.2	0.25
R_{had_1}	0.0060	0.0030	0.0052	30	-0.05	0.06
$E_{\rm ratio}$	0.0059	0.0060	0.0060	30	0.75	1.02
ΔE	0.0033	0.0035	0.0034	30	-25~GeV	300 GeV

Separation



Separation:

$$s = rac{1}{2}\sum_{i\in ext{bins}}rac{\left(s_i-b_i
ight)^2}{\left(s_i+b_i
ight)}$$

 R_{η}





Figure: Comparison of R_η between tight-ID converted and unconverted photons.





 R_{η}





Figure: Comparison of R_η between tight-ID converted and unconverted fake photons.





 R_{η}





Figure: Comparison of R_{η} between tight-ID converted prompt photons and fake photons.





 R_{ϕ}





Figure: Comparison of R_{ϕ} between tight-ID converted and unconverted photons.





 R_{ϕ}





Figure: Comparison of R_{ϕ} between tight-ID converted and unconverted fake photons.



1.1 R_o R_{ϕ}





Figure: Comparison of R_{ϕ} between tight-ID converted prompt photons and fake photons.





 $W_{\eta 2}$





Figure: Comparison of $w_{\eta 2}$ between tight-ID converted and unconverted photons.





 $W_{\eta 2}$





Figure: Comparison of $w_{\eta 2}$ between tight-ID converted and unconverted fake photons.





 $W_{\eta 2}$





Figure: Comparison of $w_{\eta 2}$ between tight-ID converted prompt photons and fake photons.





 $f_{\rm side}$





Figure: Comparison of f_{side} between tight-ID converted and unconverted photons.





 $f_{\rm side}$





Figure: Comparison of f_{side} between tight-ID converted and unconverted fake photons.





 $f_{\rm side}$





Figure: Comparison of f_{side} between tight-ID converted prompt photons and fake photons.





 $w_{\eta 1}$





Figure: Comparison of $w_{\eta 1}$ between tight-ID converted and unconverted photons.





 $W_{\eta 1}$





Figure: Comparison of $w_{\eta 1}$ between tight-ID converted and unconverted fake photons.





 $w_{\eta 1}$





Figure: Comparison of $w_{\eta 1}$ between tight-ID converted prompt photons and fake photons.





Wtot,s1





Figure: Comparison of $w_{tot,s1}$ between tight-ID converted and unconverted photons.



Figure: Comparison of $w_{tot,s1}$ between tight-ID converted and unconverted prompt photons.

Wtot,s1





Figure: Comparison of $w_{tot,s1}$ between tight-ID converted and unconverted fake photons.





Wtot,s1





Figure: Comparison of $w_{tot,s1}$ between tight-ID converted prompt photons and fake photons.



Figure: Comparison of $w_{tot,s1}$ between tight-ID unconverted prompt photons and fake photons.

 R_{had}





Figure: Comparison of R_{had} between tight-ID converted and unconverted photons.

Figure: Comparison of \mathcal{R}_{had} between tight-ID converted and unconverted prompt photons.

0.2 0.25 R_{had} R_{had}





Figure: Comparison of R_{had} between tight-ID converted and unconverted fake photons.

Figure: Comparison of R_{had} between tight-ID prompt photons and fakes.

0.2 0.25 R_{had} R_{had}





Figure: Comparison of R_{had} between tight-ID converted prompt photons and fake photons.





 R_{had_1}





Figure: Comparison of R_{had_1} between tight-ID converted and unconverted photons.





 R_{had_1}





Figure: Comparison of R_{had_1} between tight-ID converted and unconverted fake photons.





 R_{had_1}





Figure: Comparison of R_{had_1} between tight-ID converted prompt photons and fake photons.



Figure: Comparison of R_{had_1} between tight-ID unconverted prompt photons and fake photons.

Eratio





Figure: Comparison of E_{ratio} between tight-ID converted and unconverted photons.





 E_{ratio}





Figure: Comparison of E_{ratio} between tight-ID converted and unconverted fake photons.





Eratio





Figure: Comparison of E_{ratio} between tight-ID converted prompt photons and fake photons.





 ΔE





Figure: Comparison of ΔE between tight-ID converted and unconverted photons.

Figure: Comparison of ΔE between tight-ID converted and unconverted prompt photons.

300 4 E

250

 ΔE





Figure: Comparison of ΔE between tight-ID converted and unconverted fake photons.

Figure: Comparison of ΔE between tight-ID prompt photons and fakes.

300 ∆ E

250

 ΔE





Figure: Comparison of ΔE between tight-ID converted prompt photons and fake photons.



Figure: Comparison of ΔE between tight-ID unconverted prompt photons and fake photons.