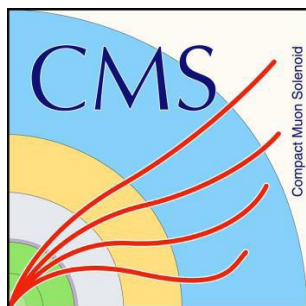


# Electrons and Photons

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什么是高能物理


大型强子对撞机上的实验如何运行

上帝粒子如何被发现

第三届  
中国CMS冬令营

<https://indico.ihep.ac.cn/event/24586/>

时间: 2025年1月16日-20日  
地点: 北航物理学院

  
中国科学院高能物理研究所  
Institute of High Energy Physics  
Chinese Academy of Sciences



# Welcome to $e/\gamma$ + Hands-on

- Physics motivations
- $e/\gamma$  reconstruction and identification
- Exercises

## Goal

- Learn basics of  $e/\gamma$  reconstruction and ID
  - ✓ Variables used in ID/discrimination
- Efficiency studies with  $Z \rightarrow ee$  TnP
- Make comparison and performance plots

## Some useful links

CMS Offline WorkBook : <https://twiki.cern.ch/twiki/bin/view/CMSPublic/WorkBook>

CMS DAS: <https://lpc.fnal.gov/programs/schools-workshops/cmsdas.shtml>

E/gamma POG twiki : <https://twiki.cern.ch/twiki/bin/view/CMS/EgammaPOG>

2025 CMSDAS

• LPC, \*IN PERSON at FERMILAB\* (January 13-17, 2025) - [Indico Agenda](#)

# Importance of $e$ and $\gamma$ in CMS

## ➤ Standard Model (SM) physics

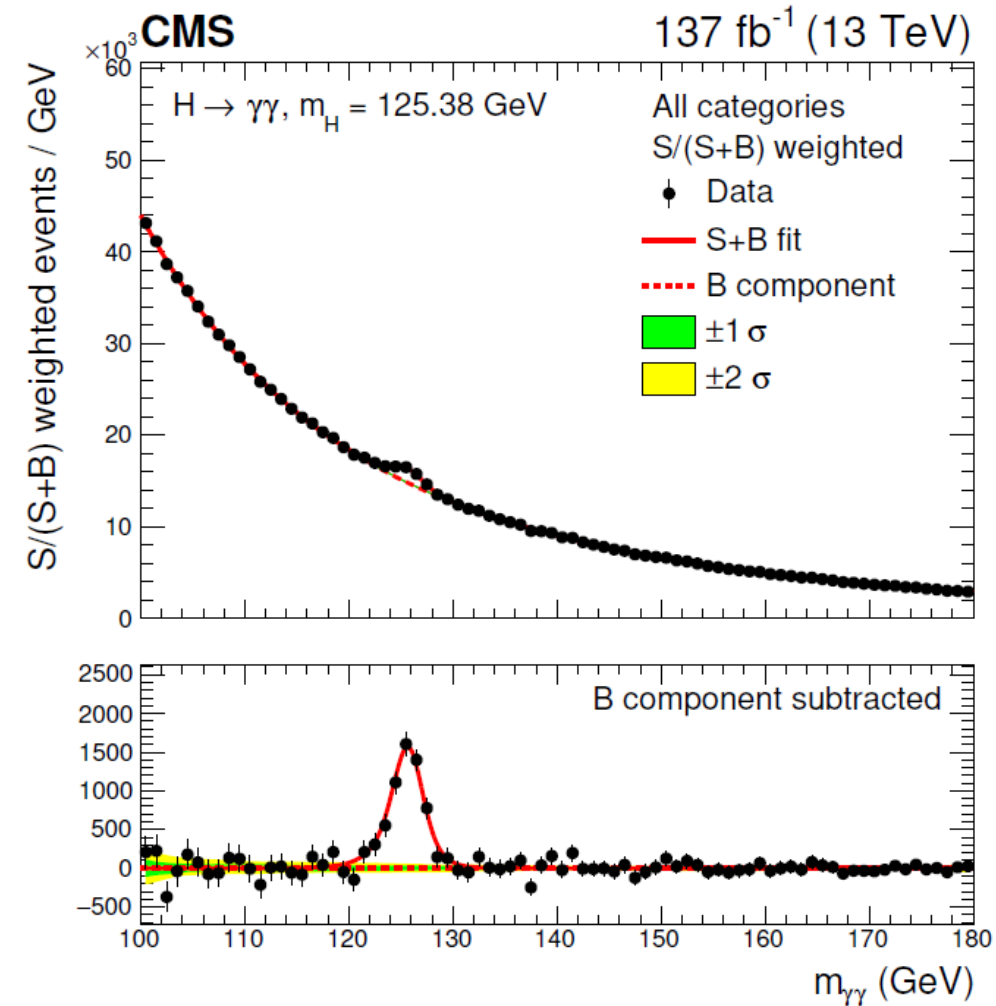
- ✓  $H \rightarrow \gamma\gamma$
- ✓  $W \rightarrow e\nu$
- ✓  $Z \rightarrow ee$ 
  - Standard candle of particle physics
  - Detector calibration

## ➤ Beyond the Standard Model (BSM) physics

- ✓  $Z'$  and  $W'$  decay directly to the SM leptons (i.e. electrons)
  - **Any BSM with  $W/Z$  in final state**
- ✓ Photons important to BSM searches: Dark Matter and SUSY etc.
  - Low-mass or high-mass  $X \rightarrow \gamma\gamma$
  - Anything with a Higgs in the final state :  $X \rightarrow HH/HY$ , with  $H/Y \rightarrow \gamma\gamma$

## ➤ Trigger

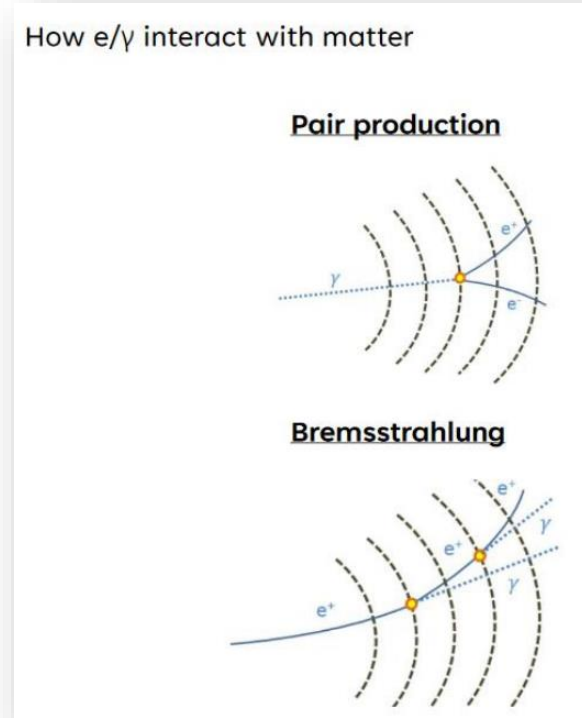
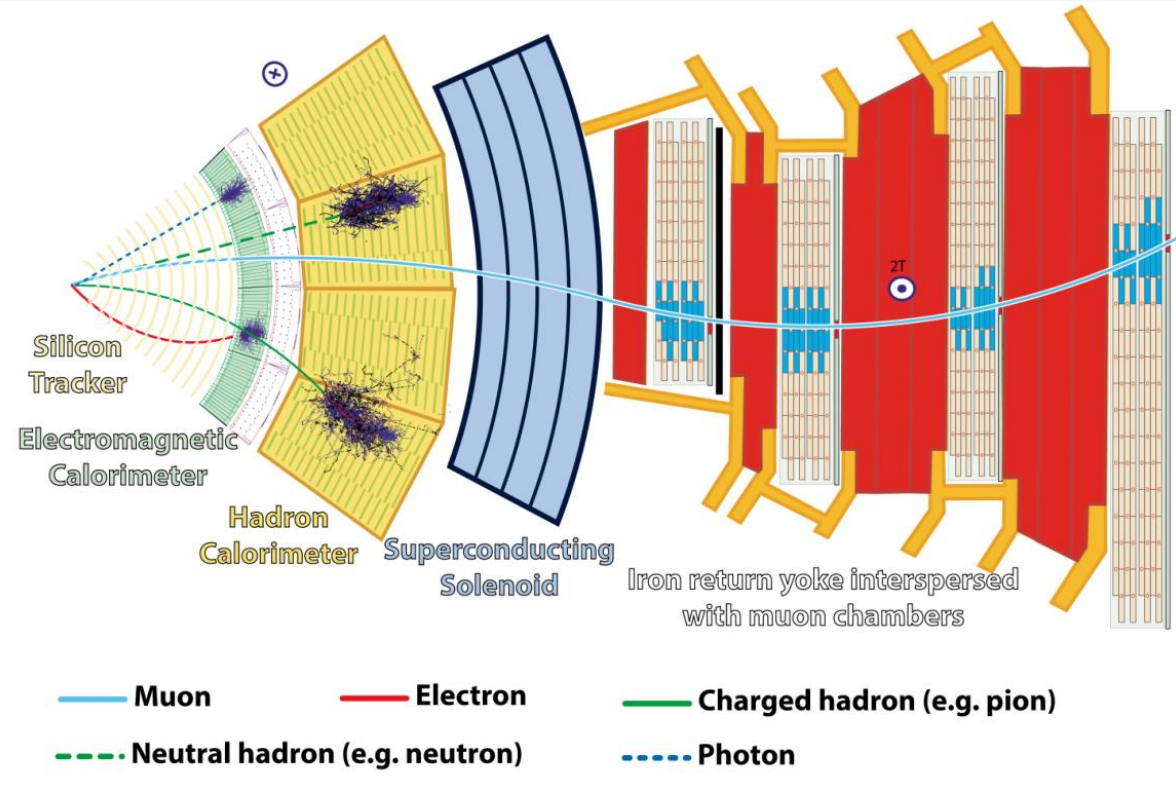
- ✓ Electron/Photons used to trigger events like those listed above
- ✓ Their standard model production rate is significantly lower than hadrons produced from QCD



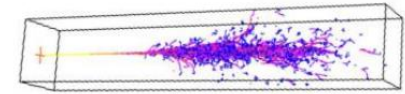
JHEP07(2021)027

# e and $\gamma$ interactions in CMS

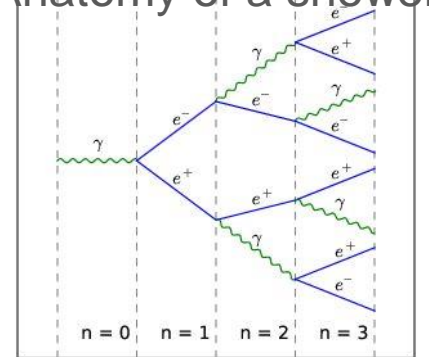
Both create electromagnetic showers in electromagnetic calorimeter (ECAL)



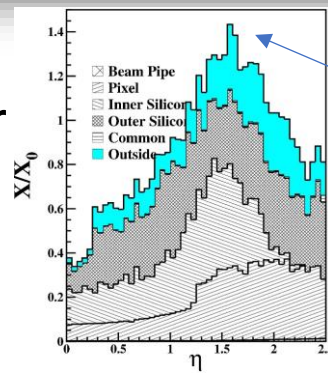
These two processes form the basis of the “electromagnetic shower”



### Anatomy of a shower



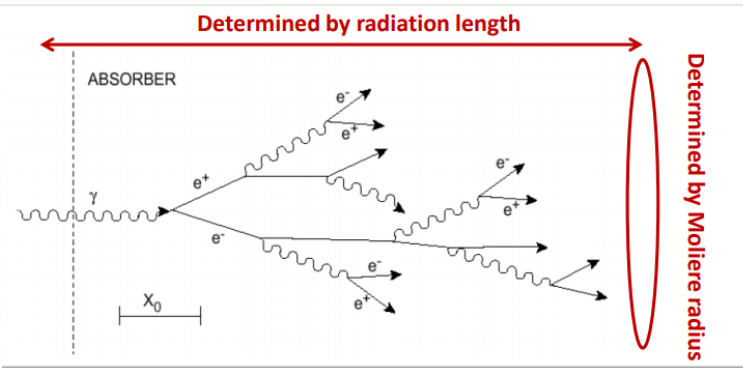
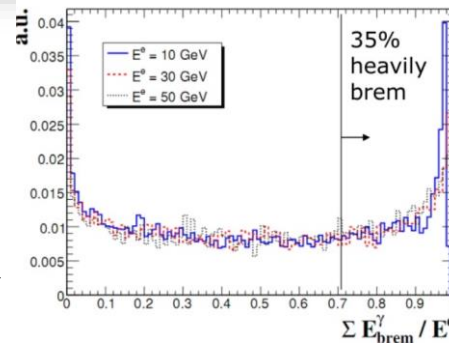
- ✓ **e**: Tracker + **ECAL**
  - ✓  **$\gamma$** : **ECAL** + Tracker
- for converted photons + **HCAL** for fake rejection



Conversion as high as  $\sim 70\%$

Material before ECAL radiation length  $X_0$

$$P_{conv} = 1 - e^{-\frac{7x}{9x_0}}$$

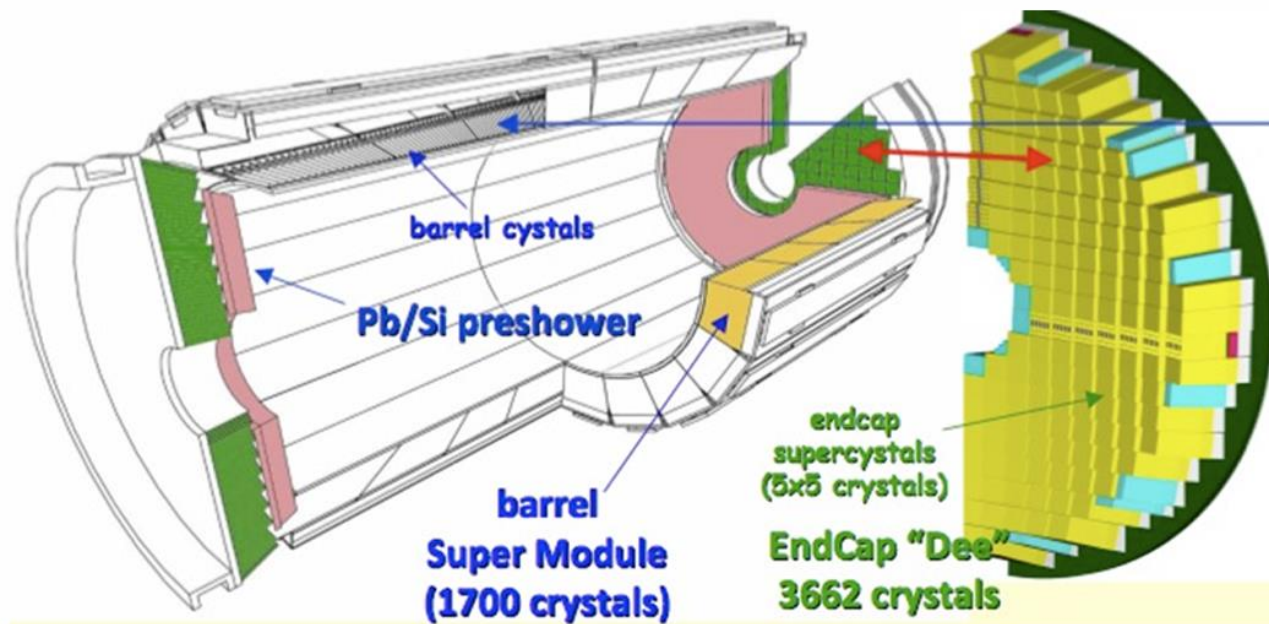


Longitudinal extension  $\sim \ln(E_0/E_c)$

Lateral extension: Moliere radius ( $M_R$ )

90% (95%) of its energy in 1 (2)  $M_R$

# CMS ECAL



Tapered crystals to provide off-pointing of  $\sim 3^\circ$  from vertex

## Lead Tungstate ( $\text{PbWO}_4$ ) scintillator

- 80% of light released in 25ns
- Has a density of  $8.28 \text{ g/cm}^3$
- A radiation length of  $0.89\text{cm}$  and a Molière radius of  $2.2\text{cm}$
- Total weight of the ECAL is 88.7 tonnes

### Barrel:

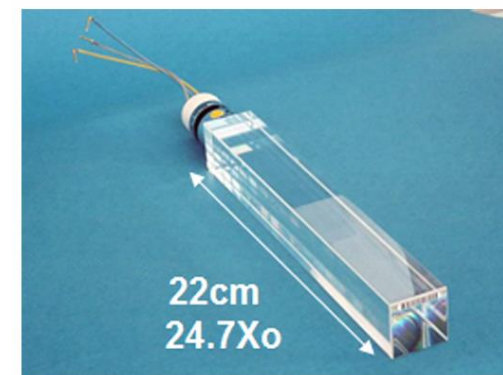
36 Supermodules (18 per half barrel);  
61200 crystals;  
Total crystal mass 67.4t;  
Avalanche PhotoDiode readout;  
coverage:  $|\eta| < 1.48$ ,  $\sim 26X_0$ .



Barrel crystal, tapered 34 types,  $\sim 2.6 \times 2.6 \text{ cm}^2$  at rear

### Endcaps:

4 Dees (2 per endcap);  
14648 crystals;  
Total crystal mass 22.9t;  
Vacuum PhotoTriode readout;  
coverage:  $1.48 < |\eta| < 3$ ,  $\sim 25X_0$ .

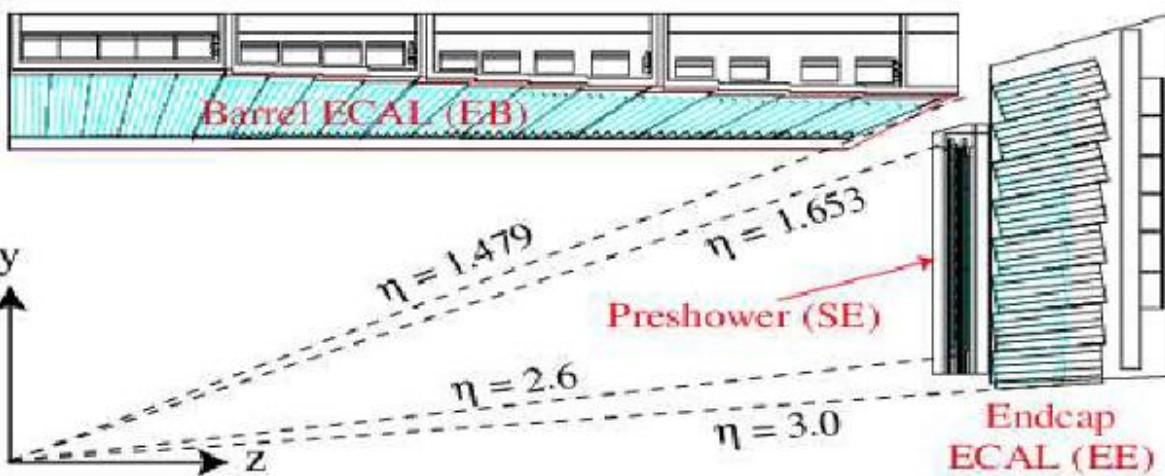


Endcap crystal, tapered 1 type,  $3 \times 3 \text{ cm}^2$  at rear

### Endcap Preshower:

Pb ( $2X_0$ ,  $1X_0$ )/Si;  
4 Dees (2 per endcap);  
4300 Si strips;  
1.8 mm x 63 mm;  
coverage:  $1.65 < |\eta| < 2.6$ .

Two crystal producers: BTCP (Russia) and SIC (China)

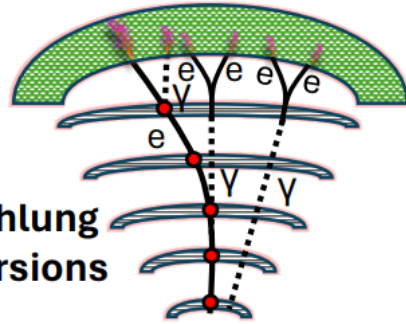


# e and $\gamma$ reconstruction

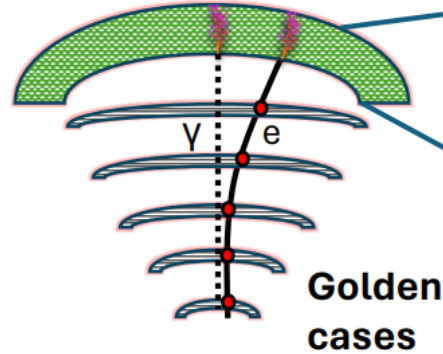
At CMS, **Reconstruction & Identification** of e &  $\gamma$  is done primarily using information from silicon tracker & electromagnetic calorimeter (ECAL)

## Tracker + ECAL

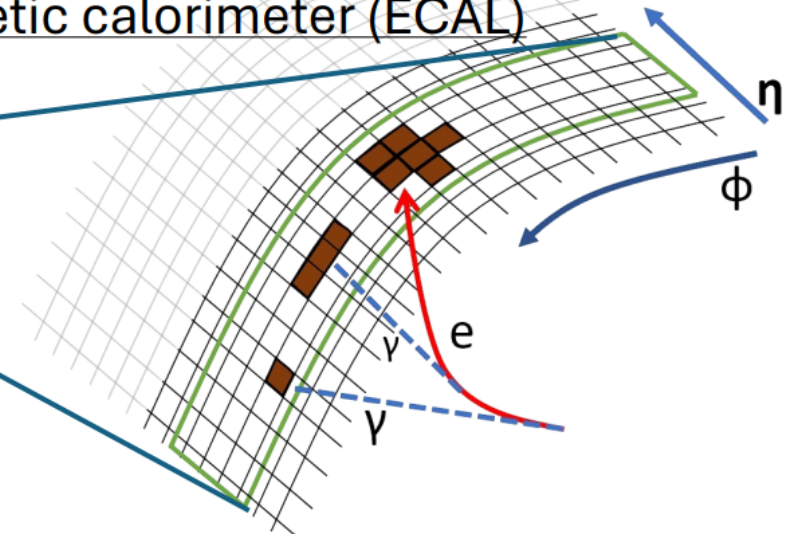
With  
bremsstrahlung  
and conversions



Tracker



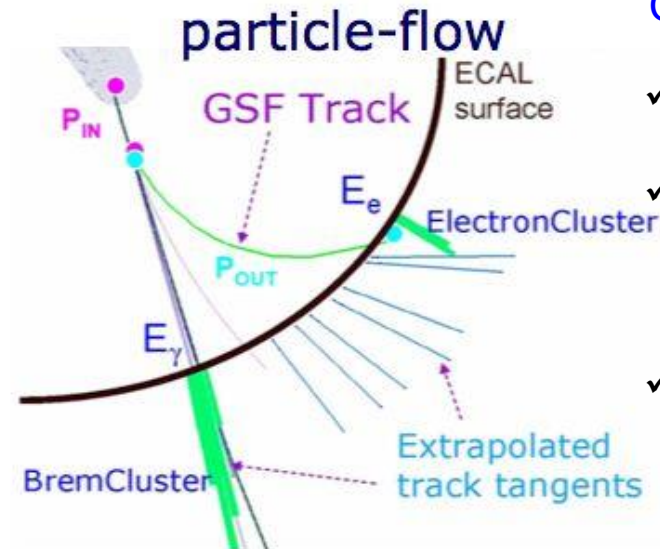
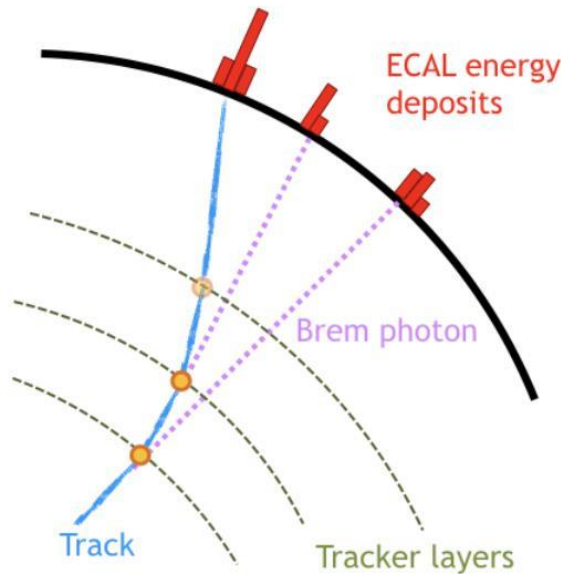
Golden cases



What does an electron look like?

**Electron emits bremsstrahlung photons**

- ✓ **multiple energy deposits in ECAL**: take into account energy of brems
- ✓ **Electron track can have “kinks”**: special tracking needed for electrons to take care of that



## Gaussian Sum Filter (GSF)

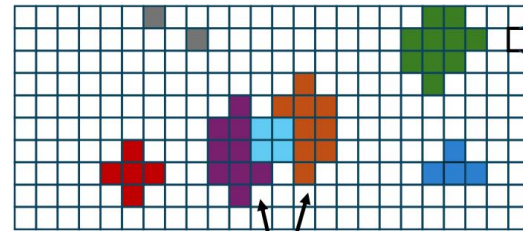
- ✓ For all other charged particle tracking, **Kalman Filter** is used
- ✓ Electrons use a dedicated tracking algorithm known as **Gaussian Sum Filter (GSF)**. It is a non-linear extension of KF
- ✓ GSF track connected to superclusters via the PF algorithm

# ECAL/Energy Reconstruction

- ECAL **RecHit** energy is calculated by a multifit from ECAL Digis
- RecHits are clustered into **Particle Flow (PF) clusters**
- **PF Mustache Algorithm** creates **superclusters**
  - ✓ Groups clusters wide in  $\phi$  and narrow in  $\eta$
  - ✓ This is to catch bremsstrahlung
- **Refined supercluster** adds soft brem and accounts for photon conversions using tracker info

## Clustering

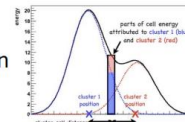
- Clustering of ECAL clusters



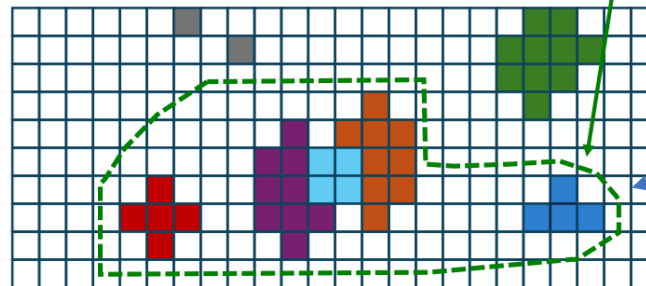
Clusters corresponding to electrons / photons

found 5 Clusters

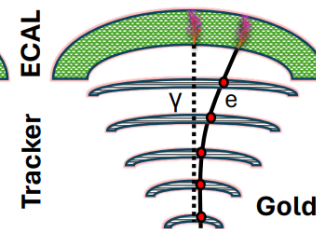
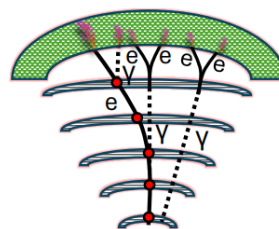
these two clusters overlap, clustering algo shares energy of rec-hits between the two clusters according to a Gaussian energy profile, each gets a fraction of the rec-hit energy



## Refined Supercluster



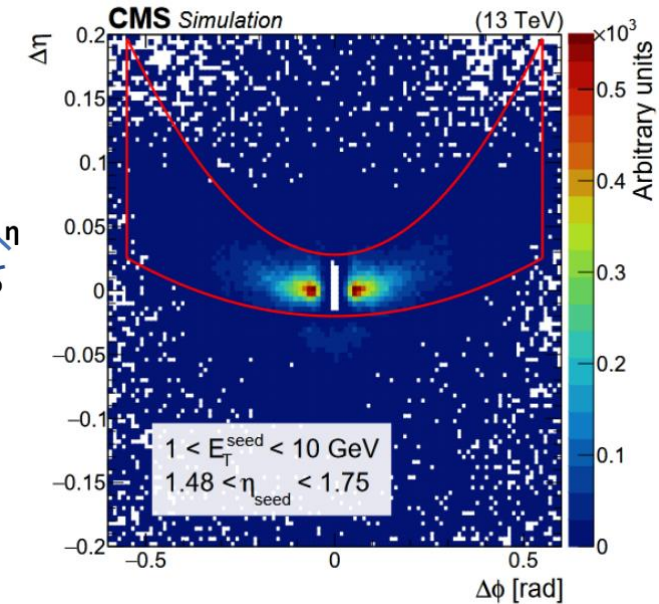
With bremsstrahlung and conversions



Tracker ECAL Golden cases

## Moustache supercluster

a cluster of clusters



Refined superclusters use the **information from the tracker**, to be able to link bremsstrahlung emissions to missed ECAL deposits

There is also dedicated photon conversion recovery algorithm

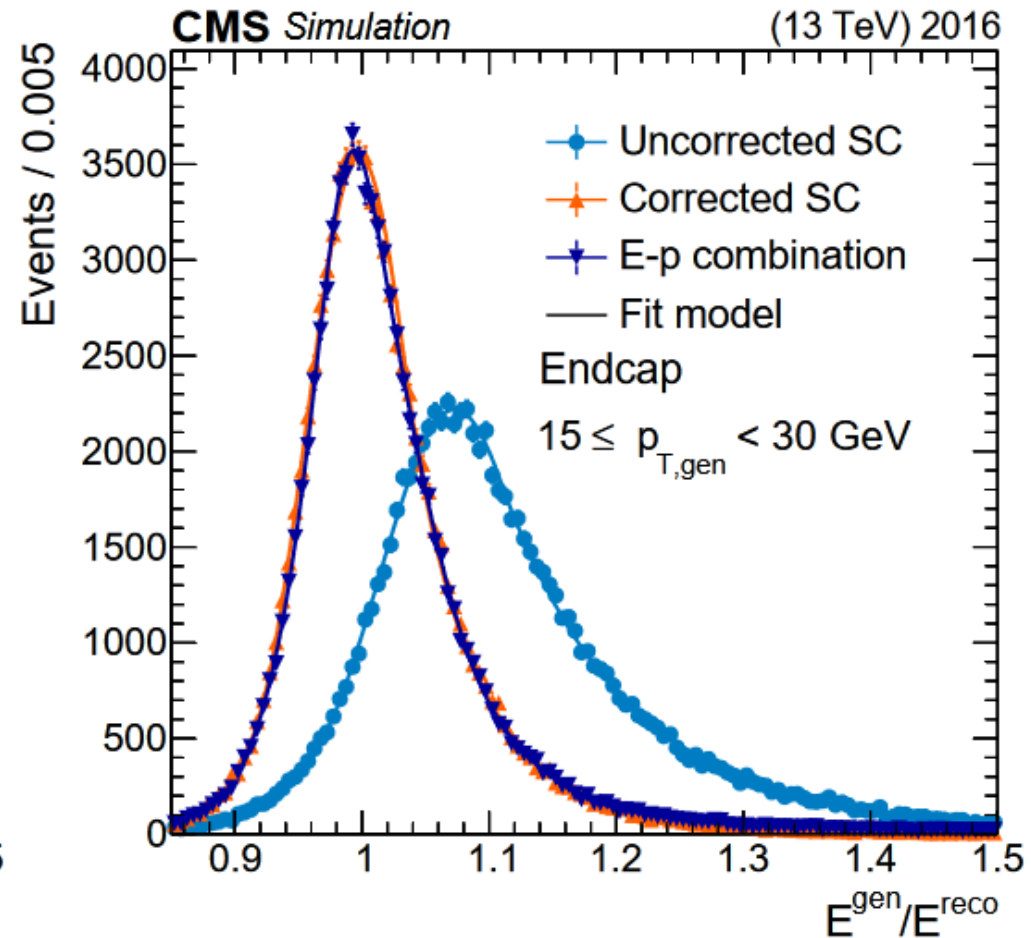
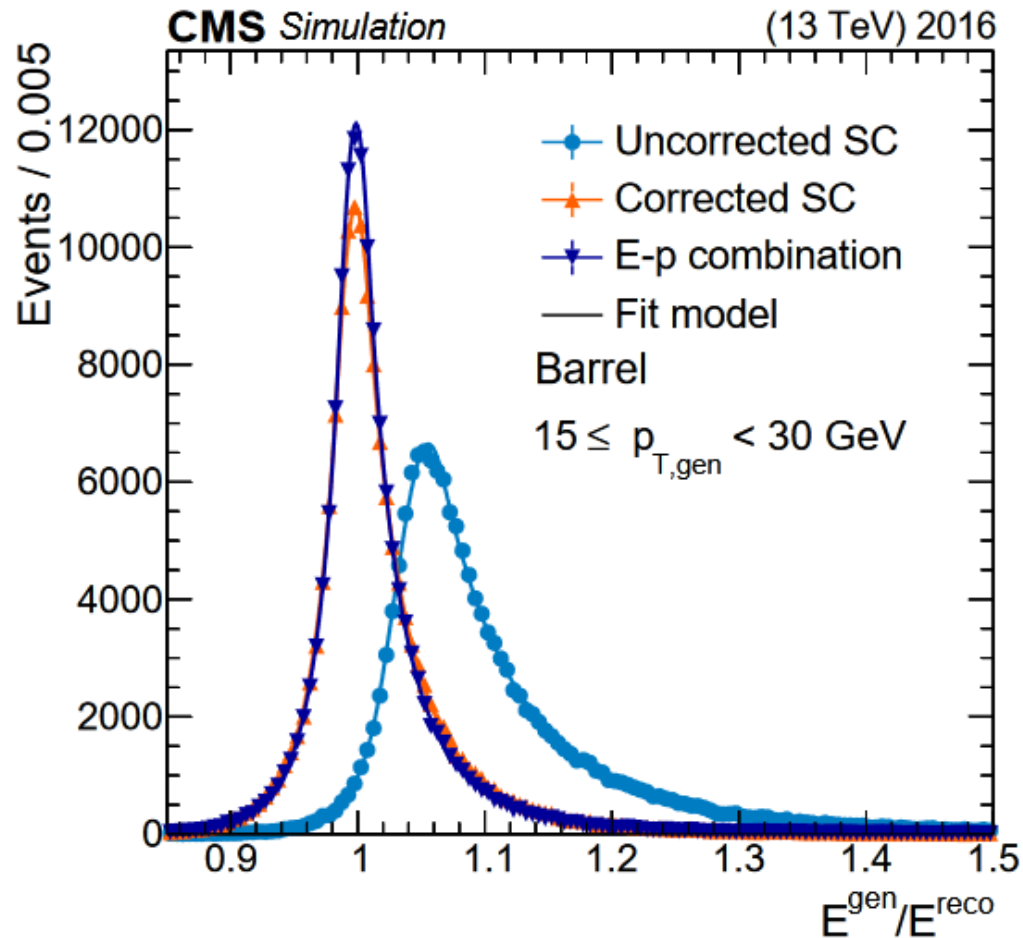
**Conversion reconstruction is challenging:**

- Displaced tracks to be reconstructed (issues with resolution and combinatorics)
- Trailing conversion leg may be very soft <sup>7</sup>
- Conversion legs can radiate photon

# Energy corrections

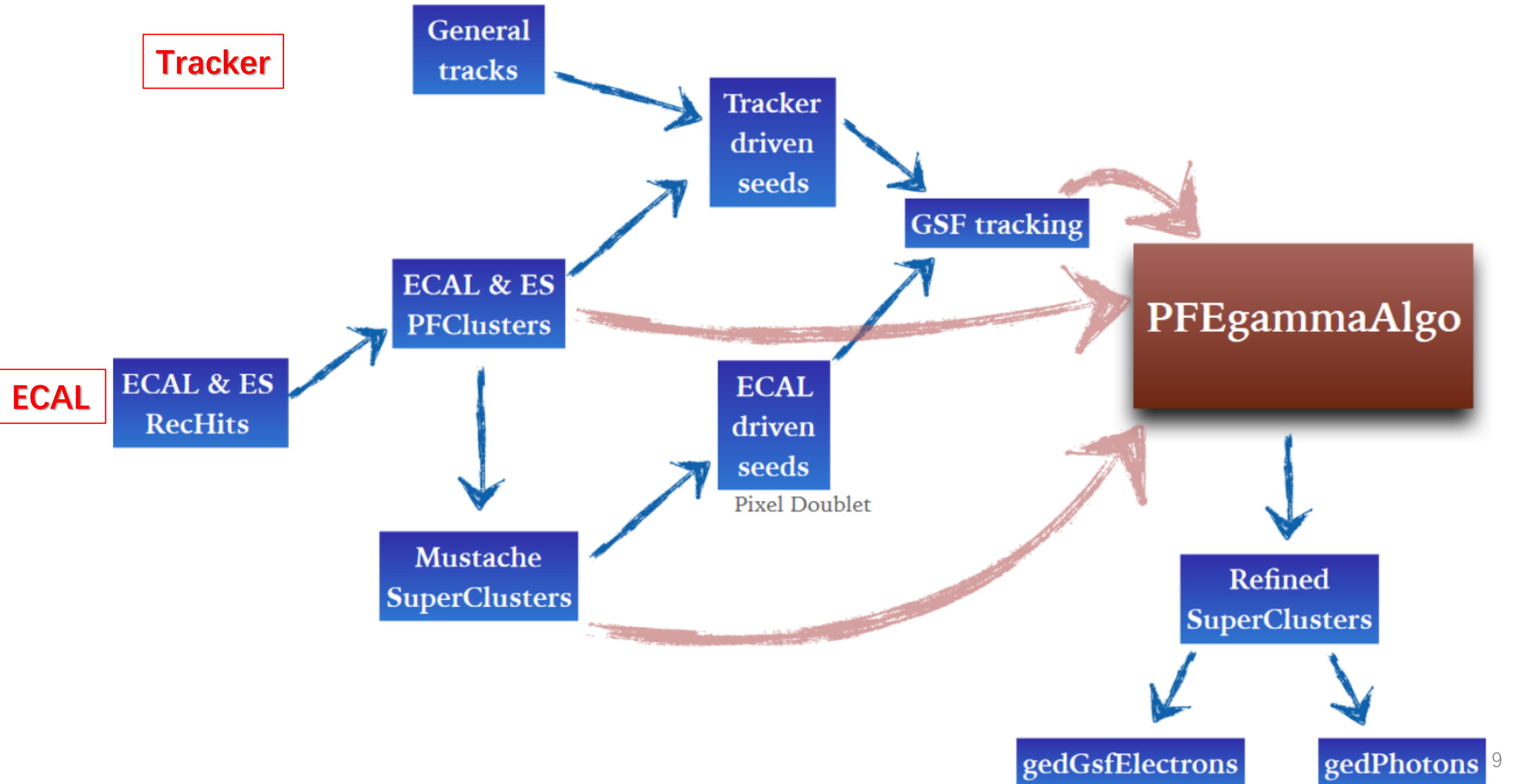
Several **losses** occur before electrons and photons deposit energy in the ECAL

- We **calibrate the reconstructed energy** back to the expected original energy using **correction** procedures
- Employ **machine learning (Regression)** in tandem with algorithmic approaches
- **Tracker information** used for E-p combination





# e and $\gamma$ reconstruction



# Electron and photon identifications

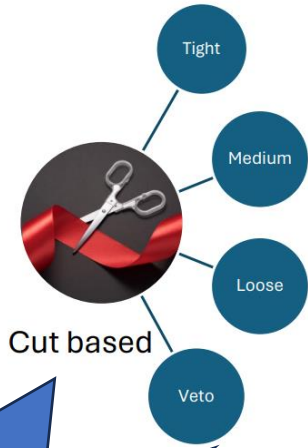
## [CutBasedElectronIdentificationRun3](#)

Two schemes are primarily used for identification:

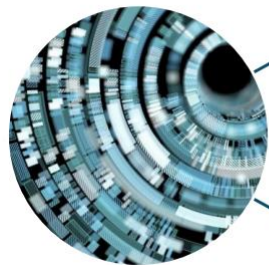
- **Cut-based selections** on various high-level properties
- **Machine learning** based classifiers trained on these high level properties

122X-tuned selection, barrel cuts ( $|\eta_{\text{supercluster}}| \leq 1.479$ )

	Veto (122X)	Loose (122X)	Medium (122X)	Tight (122X)	Access in
full5x5_sigmaletaleta <	0.0117	0.0107	0.0103	0.0101	<a href="#">link</a>
abs(dEtaSeed) <	0.0071	0.00691	0.00481	0.00411	<a href="#">link</a>
abs(dPhiIn) <	0.208	0.175	0.127	0.116	<a href="#">link</a>
H/E <	$0.05+1.28/E_{\text{SC}}+0.0422p/E_{\text{SC}}$	$0.05+1.28/E_{\text{SC}}+0.0422p/E_{\text{SC}}$	$0.0241+1.28/E_{\text{SC}}+0.0422p/E_{\text{SC}}$	$0.02+1.16/E_{\text{SC}}+0.0422p/E_{\text{SC}}$	<a href="#">link</a>
rellsoWithEA <	$0.406+0.535/p_T$	$0.194+0.535/p_T$	$0.0837+0.535/p_T$	$0.0388+0.535/p_T$	<a href="#">link</a>
abs(1/E-1/p) <	0.178	0.138	0.0966	0.023	<a href="#">link</a>
expected missing inner hits <=	2	1	1	1	<a href="#">link</a>
pass conversion veto	yes	yes	yes	yes	<a href="#">link</a>



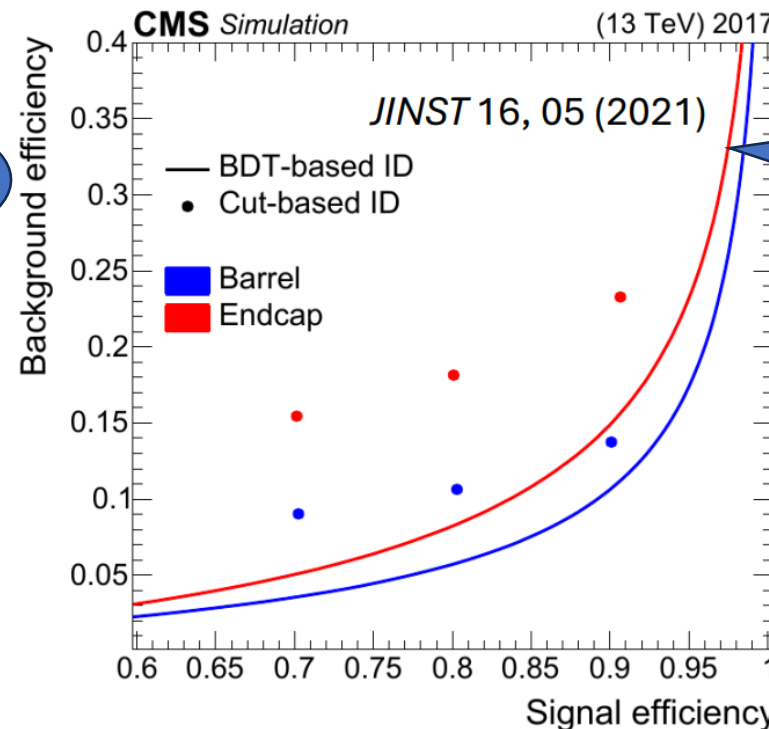
Exercise 1 : photon identifications with machine learning (TMVA BDT)



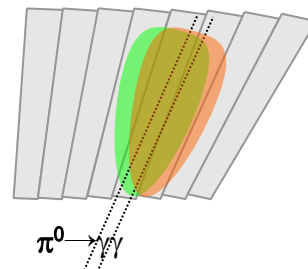
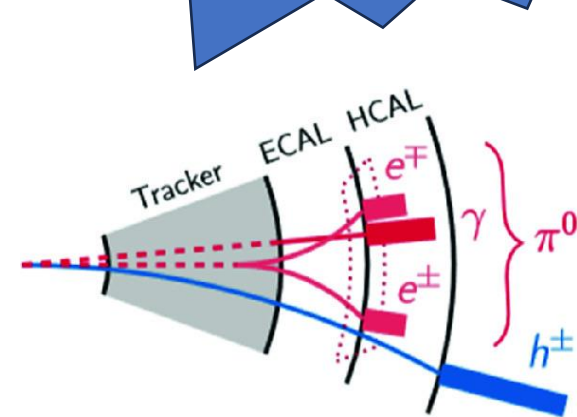
MVA based

80% Signal efficiency

90% Signal efficiency

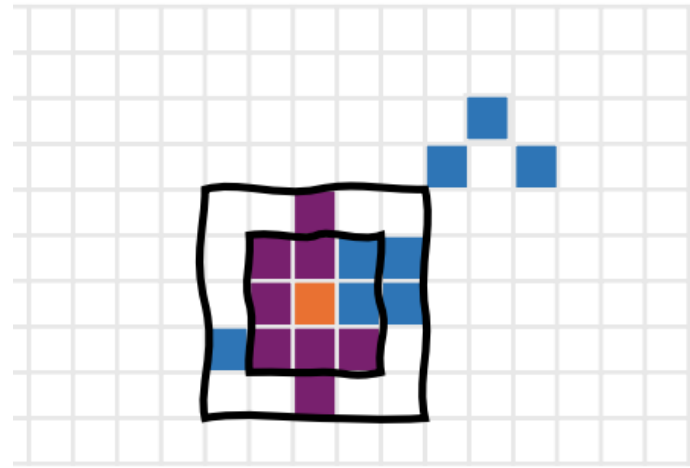


Exercise 2 : selection efficiencies and data/MC scale factors with Z→ee tag-and-probe (TnP)



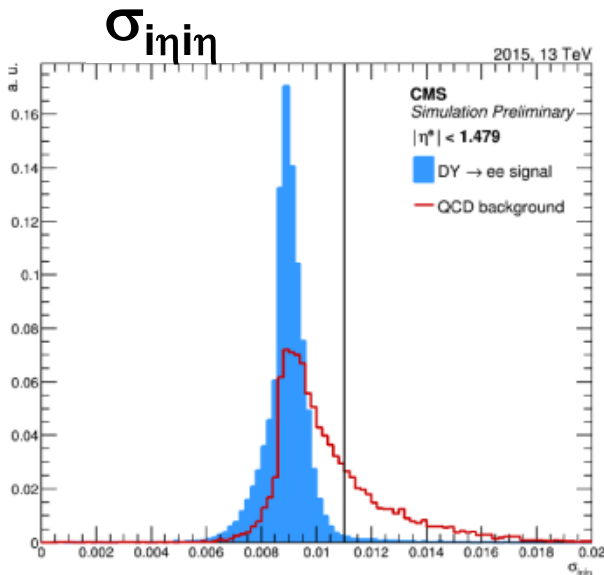
# Variables in $e/\gamma$ id : EM shower

- Description of the **electromagnetic shower** (energy deposit pattern, lateral and longitudinal spread etc.)
- **Tracking and clustering matching parameters** (momentum trajectory extrapolated to ECAL considering the magnetic field etc.)
- Quantification of **isolation** of these objects (Energy sums of crystals in ECAL in a defined area, leakage in HCAL etc.)



- $E_{sc}$  : Energy of supercluster
- $E_{2 \times 2}$  : Energy contained in 2X2 crystals
- $E_{3 \times 3}$  : Energy contained in 3X3 crystals
- $E_{5 \times 5}$  : Energy contained in 5X5 crystals
- $E_{1 \times 5}$  : Energy contained in 1X5 crystals
- $d\eta_{sc}$  :  $\eta$  width of supercluster
- $d\Phi_{sc}$  :  $\Phi$  width of supercluster

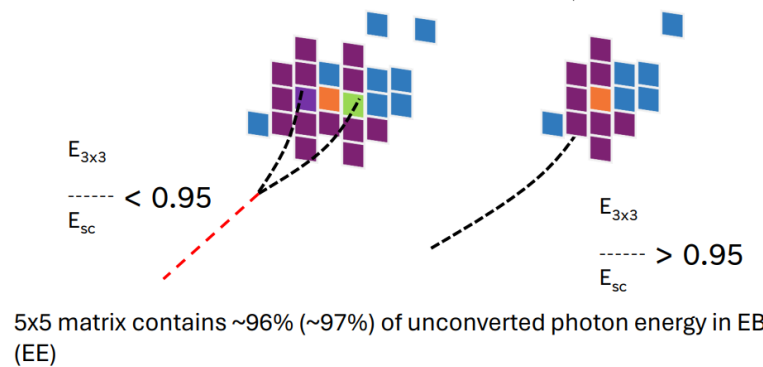
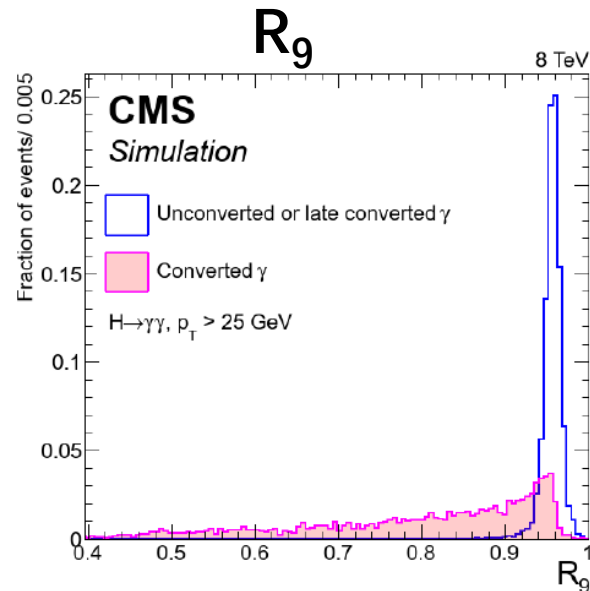
## Description of the EM shower shape



Lateral extension in terms of crystal cells

$$\sigma_{\eta\eta} = \sqrt{\left( \frac{\sum_i^{5 \times 5} w_i (\eta_i - \bar{\eta}_{5 \times 5})^2}{\sum_i^{5 \times 5} w_i} \right)} \quad w_i = 4.7 + \ln \frac{E_i}{E_{5 \times 5}}$$

Used as template in for example  $V\gamma/VV\gamma$  measurements for yields extraction

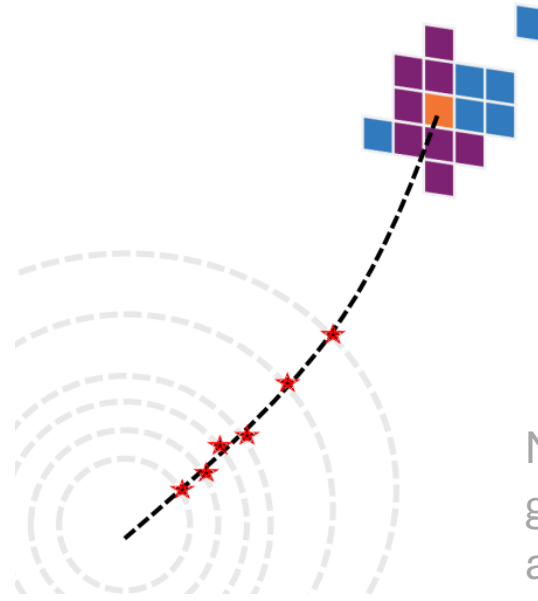


5x5 matrix contains ~96% (~97%) of unconverted photon energy in EE

$$S_4 = E_{2 \times 2} / E_{5 \times 5}$$

# Variables in $e/\gamma$ id : tracking + clustering

- Description of the **electromagnetic shower** (energy deposit pattern, lateral and longitudinal spread etc.)
- **Tracking and clustering matching parameters** (momentum trajectory extrapolated to ECAL considering the magnetic field etc.)
- Quantification of **isolation** of these objects (Energy sums of crystals in ECAL in a defined area, leakage in HCAL etc.)



$N_{hits}^{gsf}$  : Hits in the “gsf” track  
 $N_{hits}^{kf}$  : Hits in the “kf” track  
 $E/p$  : Energy of supercluster/ momentum  
 $\chi^2$ : Track quality

$\Delta\phi$  between track and supercluster

Not just for electrons, even for photons: good ones should not have a “track at all” or would have converted

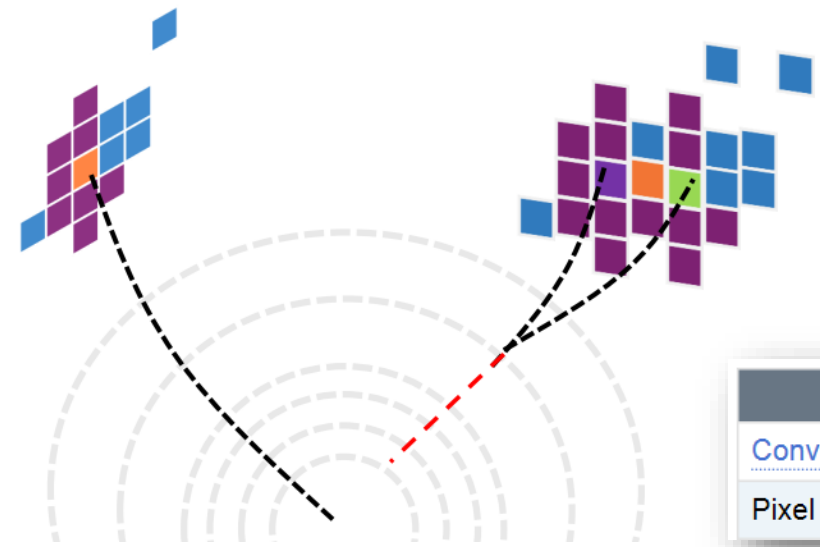
## Conversion ID variables

### Conversion Safe Electron Veto

If a secondary vertex is found, this is not an electron!

### Pixel Veto

Track in pixel detector, this is not a photon



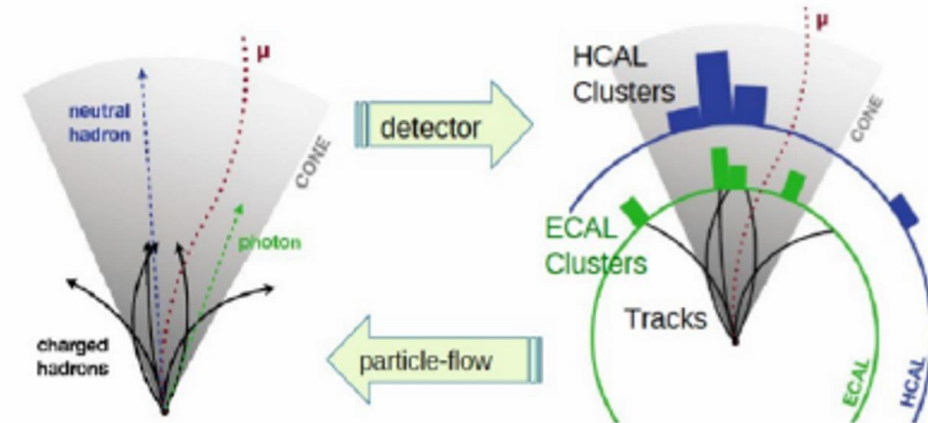
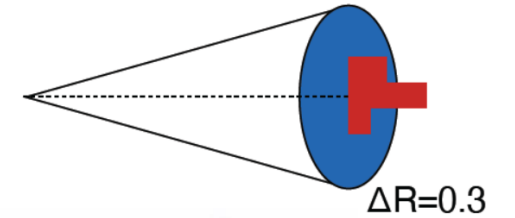
Electron veto	Use case	How to access the variable
Conversion safe electron veto	analysis not sensitive to electron -> photon fake rate	pat::photon->passElectronVeto()
Pixel seed veto	analysis sensitive to electron -> photon fake rate	pat::photon->hasPixelSeed() <sup>12</sup>

# Variables in $e/\gamma$ id : isolations

- Description of the **electromagnetic shower** (energy deposit pattern, lateral and longitudinal spread etc.)
- **Tracking and clustering matching parameters** (momentum trajectory extrapolated to ECAL considering the magnetic field etc.)
- Quantification of **isolation** of these objects (Energy sums of crystals in ECAL in a defined area, leakage in HCAL etc.)

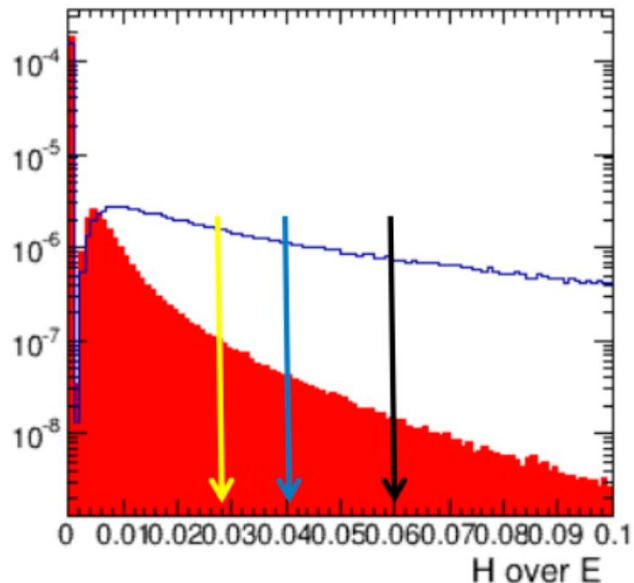
**Isolation cone** around  $e/\gamma$

$$\Delta R = \text{sqrt}(\Delta\eta^2 + \Delta\phi^2) = 0.3/0.4$$



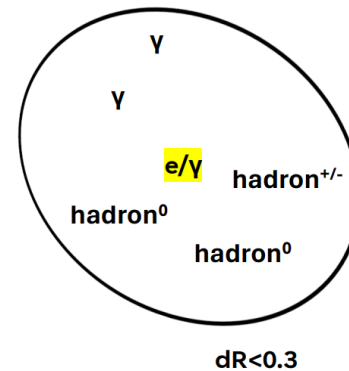
**H/E**: Energy leaked into HCAL / Energy in ECAL

-- HCAL energy within  $\Delta R = 0.15$  from the  $e/\gamma$  supercluster



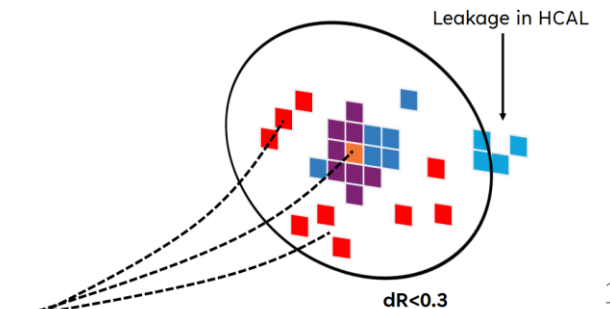
**PF Particle Isolations**

- Charged hadrons
- Neutral hadrons
- Photons



**PF Cluster+Tracker isolations**

- HCAL clusters
- ECAL clusters
- Tracks



# Two exercises

- Exercise 1 (~15min) -- **Photon identifications with machine learning (TMVA BDT)** with photon candidates in EB and EE separately
  - ✓ `/publicfs/cms/user/taojq/README_PhotonIDMVA_ForRun2Hgg`
  - ✓ ML techniques: MVA, Xgboost, ... (more ML in [Congqiao Li](#))
  - ✓ Run3: ID MVA trained and provided by EGamma POG
  
- Exercise 2 (~15min) –  **$e/\gamma$  selection efficiencies and data/MC scale factors with  $Z \rightarrow ee$  tag-and-probe (TnP) technique**
  - ✓ `/publicfs/cms/user/taojq/README_Zee_TnP`
  - ✓ Example: selection efficiency with a cut on the photon ID MVA score ( $>-0.7$ )
  - ✓ Efficiency of any selections on  $e/\gamma$

# Exercise 1 : photo ID with TMVA

- 1) Produce **comparison plots** of the discriminating variables for prompt and fake photons
- 2) Photon identification **training** with Machine Learning “TMVA BDTG”  
Toolkit for Multivariate Analysis (TMVA)
- 3) **Application** of photon ID MVA : evaluate the photon id MVA scores of the photon candidates in any samples (data,  $H \rightarrow \gamma\gamma$  MC, ...)

# Environment setup

```
cd /publicfs/cms/user/taojq/ (or your home dir) ← Your working area
#setenv SCRAM_ARCH slc7_amd64_gcc700 (Bash: export SCRAM_ARCH=slc7_amd64_gcc700) (echo $SHELL)
Bash: export SCRAM_ARCH=el9_amd64_gcc12      Csh/TCsh: setenv SCRAM_ARCH el9_amd64_gcc12 (echo $SHELL)
Bash: source /cvmfs/cms.cern.ch/cmsset_default.sh  Csh/TCsh: source /cvmfs/cms.cern.ch/cmsset_default.csh
cmsrel CMSSW_14_1_0
cd CMSSW_14_1_0/src/ ← Can test with any CMSSW version you have checked out (OS9)
cmsenv
mkdir PhotonIDMVA_ForRun2Hgg
cd PhotonIDMVA_ForRun2Hgg
cp /publicfs/cms/user/taojq/PhotonIDMVA_ForRun2Hgg/* .
#just put a soft link to the input file, since it's a large file
ln -s /publicfs/cms/user/taojq/PhotonIDMVA_ForRun2Hgg/InputFile .
```

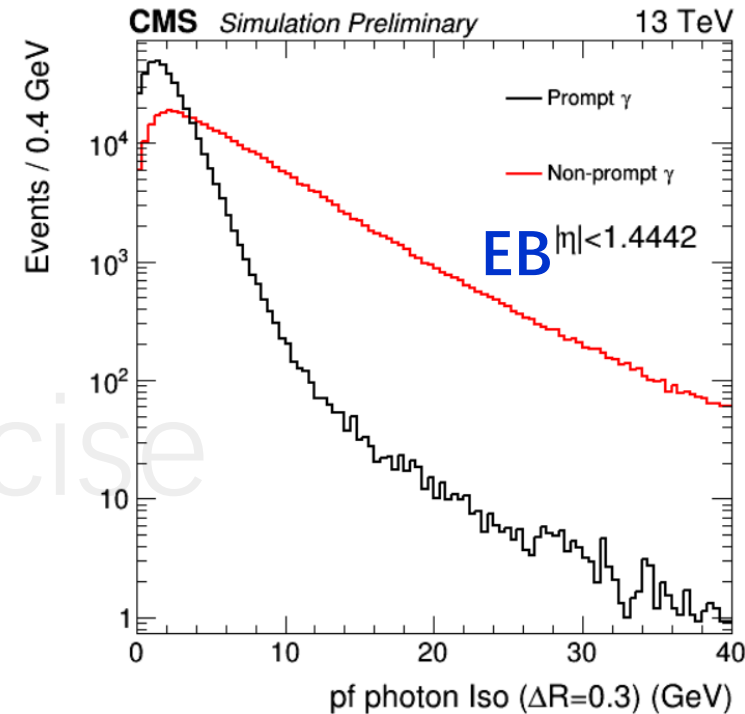
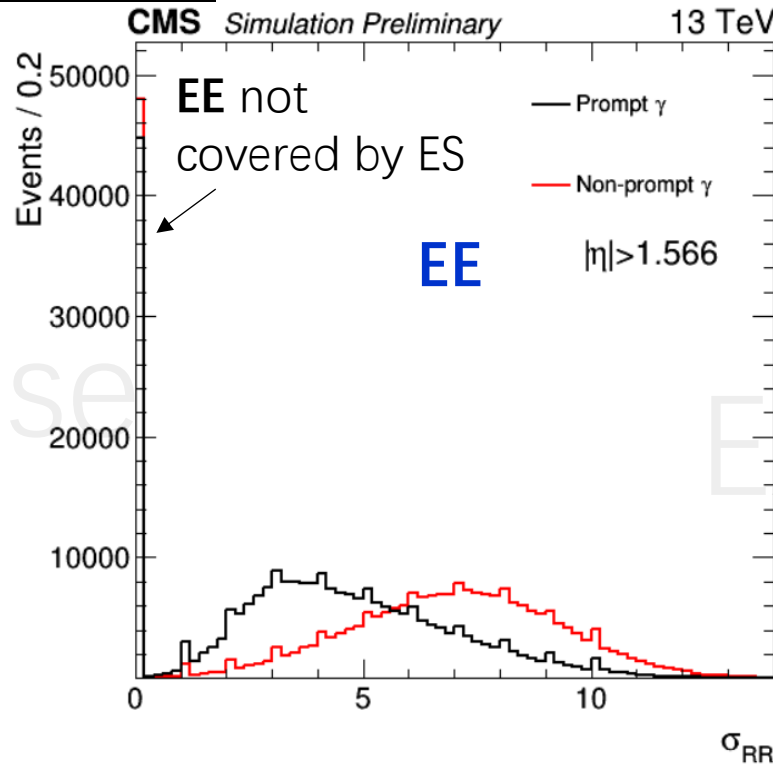
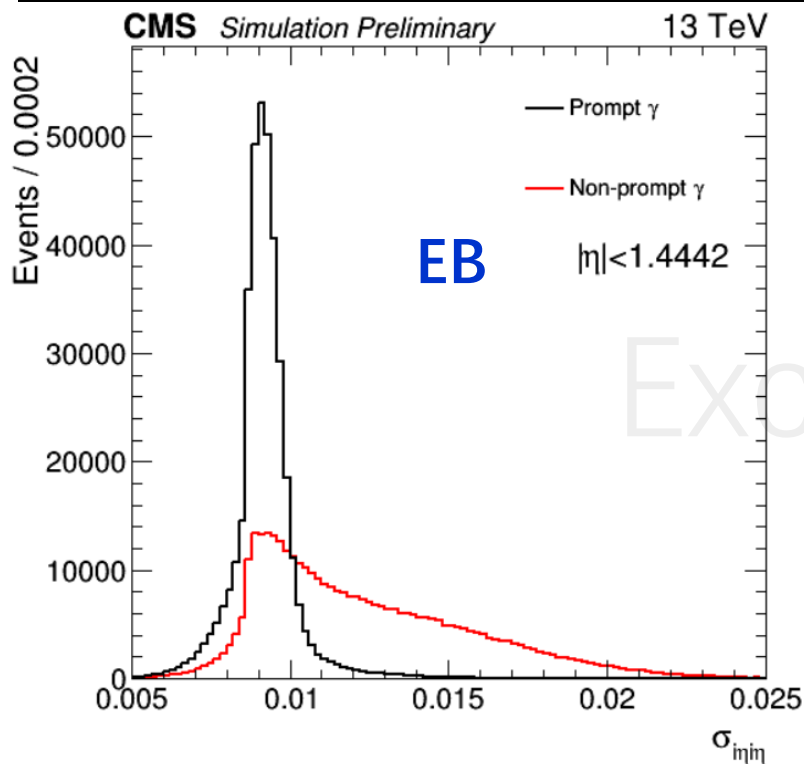
ROOT (+TMVA)



# Excise 1 : Produce plots of the identification variables for prompt and fake photons

```
> mkdir SigBkgComparisonsPlots
> root -l -b -q DrawComparisonPlots.C
--> output plots under SigBkgComparisonsPlots/
```

Both prompt and non-prompt photons selected from GJet MC



$\sigma_{\eta\eta}$ : can be directly used in for example  $V\gamma/VV\gamma$  cross section measurements for yields extraction

**Preshower  $\sigma_{RR}$** : the standard deviation of the shower spread in the x and y planes of the preshower (only defined in the endcap)

$$\sigma_{xx}^2 \equiv \frac{\sum E_i (X_i - \bar{X})^2}{\sum E_i} \quad \sigma_{RR, \text{Eff.}} \equiv \sqrt{\sigma_{\text{Eff.}}^2_{XX} + \sigma_{\text{Eff.}}^2_{YY}} \quad \text{link}$$

Also **PF photon iso** in  $\Delta R=0.4$  used in  $\gamma\gamma$  XS measurement (*IHEP...Eur. Phys. J. C (2014) 74:3129*)

# Excise 1 : Photon identification with TMVA “BDTG”

➤ TMVA – BDTG (Gradient Boosting Decision Trees) : could try more ML methods ([TMVAClassification.C](#))

➤ Train  $\gamma$ -ID MVA for EB and EE separately

✓ Shower shape variables:  $E_{2 \times 2} / E_{5 \times 5}$ ,  $\text{cov}_{i\eta\phi}$ ,  $\sigma_{i\eta\eta}$ ,  $R_9$ ,  $\sigma_\eta$ ,  $\sigma_\phi$   
Preshower  $\sigma_{RR}$  and  $E_{ES} / E_{SC}$  (EE)

✓ Isolation variables: PF Photon ISO, PF Charged ISO (selected vertex), PF Charged ISO (worst vertex)

✓ Other variables:  $\rho$ , Supercluster  $\eta$ , Supercluster  $E_{RAW}$

```
> root -l -b -q TMVAClassification_EB.C &
> root -l -b -q TMVAClassification_EE.C
```

>& t\_tmva\_eb.log &

→ **weight files**: PhotonID\_Weight/weights/PhoID\*\_Train\_GJetMC\_BDTG.weights.xml (\*=barrel/endcap) (for later application)  
→ **output root files**: PhoID\*\_Train\_GJetMC.root (\*= barrel/endcap)

➤ Once training done, “TMVAGui”

```
>root -l
>TMVA::TMVAGui("PhoID_barrel_Train_GJetMC.root")
--> comparisons of inputs, correlation matrix, output, eff., ....
```

```
IdTransformation : Ranking input variables (method unspecific)...
                  : Ranking result (top variable is best ranked)
                  :-----
                  : Rank : Variable           : Separation
                  :-----
                  : 1 : pho_PFChWorstIso   : 2.605e-01
                  : 2 : pho_SigmaIEtaIEtaFull5x5 : 2.066e-01
                  : 3 : pho_FFPhoIso      : 2.056e-01
                  : 4 : s4                 : 1.737e-01
                  : 5 : pho_SigmaIEtaIPhiFull5x5 : 1.688e-01
                  : 6 : pho_SCEtaWidth   : 1.077e-01
                  : 7 : pho_PFChIso       : 1.045e-01
                  : 8 : pho_R9Full5x5    : 8.418e-02
                  : 9 : pho_SCPHiWidth   : 4.673e-02
                  : 10 : pho_SCRawE       : 7.673e-03
                  : 11 : pho_SCEta        : 6.271e-03
                  : 12 : evt_rho          : 1.460e-03
                  :-----
Factory           : Train method: BDTG for Classification
                  :
BDTG              : Events with weight == 0 are going to be simply ignored
                  : #events: (reweighted) sig: 513110 bkg: 513110
                  : #events: (unweighted) sig: 534514 bkg: 491705
                  : Training 2000 Decision Trees ... patience please
                  : ..... (1%, time left: 54 mins min)
```

Half for training and the rest half for testing (**homework**)

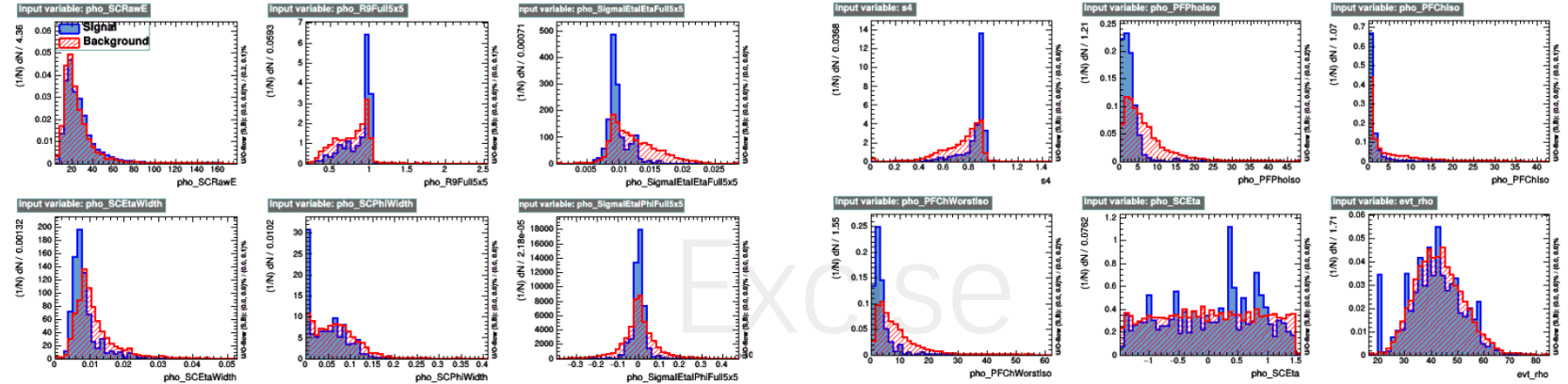
10k of each sig/bkg for **training** (~2min) and 100k of each sig/bkg for testing (~2min)

```
dataLoader->PrepareTrainingAndTestTree( mycuts, mycutb,
//                                     "nTrain_Signal=0:nTrain_Background=0
:SplitMode=Random:NormMode=EqualNumEvents:!V" ); //NumEvents
                                     "nTrain_Signal=10000:nTrain_Background
=10000:nTest_Signal=100000:nTest_Background=100000:SplitMode=Random:NormMode=E
qualNumEvents:!V" ); //test only 10000 events forbkg/sig
```

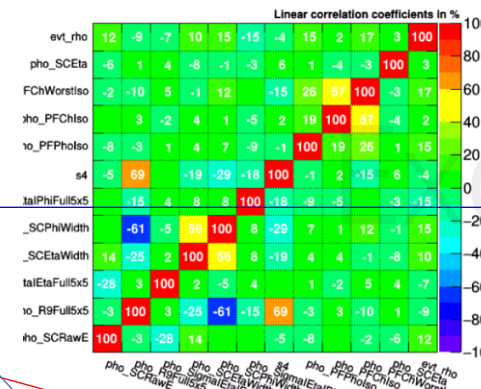
# Information in the output root

TMVA::TMVAGui("PhoID\_barr  
el\_Train\_GJetMC.root")

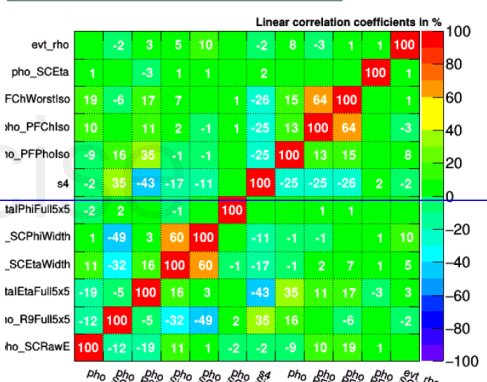
- TMVA Plotting Macros for Classification**
- (1a) Input variables (training sample)
  - (1b) Input variables 'Deco'-transformed (training sample)
  - (1c) Input variables 'PCA'-transformed (training sample)
  - (1d) Input variables 'Gauss\_Deco'-transformed (training sample)
  - (2a) Input variable correlations (scatter profiles)
  - (2b) Input variable correlations 'Deco'-transformed (scatter profiles)
  - (2c) Input variable correlations 'PCA'-transformed (scatter profiles)
  - (2d) Input variable correlations 'Gauss\_Deco'-transformed (scatter profiles)
  - (3) Input Variable Linear Correlation Coefficients
  - (4a) Classifier Output Distributions (test sample)
  - (4b) Classifier Output Distributions (test and training samples superimposed)
  - (4c) Classifier Probability Distributions (test sample)
  - (4d) Classifier Rarity Distributions (test sample)
  - (5a) Classifier Cut Efficiencies
  - (5b) Classifier Background Rejection vs Signal Efficiency (ROC curve)
  - (5b) Classifier 1/(Backgr. Efficiency) vs Signal Efficiency (ROC curve)
  - (6) Parallel Coordinates (requires ROOT-version >= 5.17)
  - (7) PDFs of Classifiers (requires "CreateMVAPdfs" option set)
  - (8) Likelihood Reference Distributions
  - (9a) Network Architecture (MLP)
  - (9b) Network Convergence Test (MLP)
  - (10) Decision Trees (BDT)
  - (11) Decision Tree Control Plots (BDT)
  - (12) Plot Foams (PDEFoam)
  - (13) General Boost Control Plots
  - (14) Quit



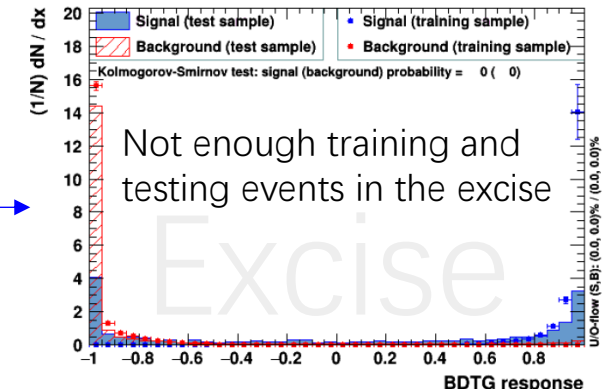
Correlation Matrix (signal)



Correlation Matrix (background)

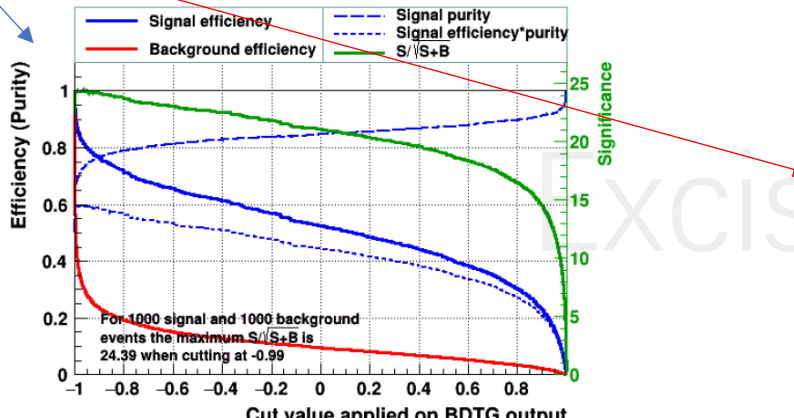


TMVA overtraining check for classifier: BDTG

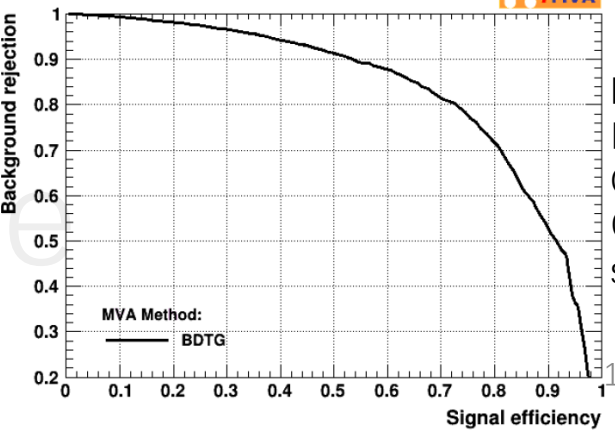


Not enough training and testing events in the excise

Cut efficiencies and optimal cut value



Background rejection versus Signal efficiency



ROC: Receiver Operations Characteristic

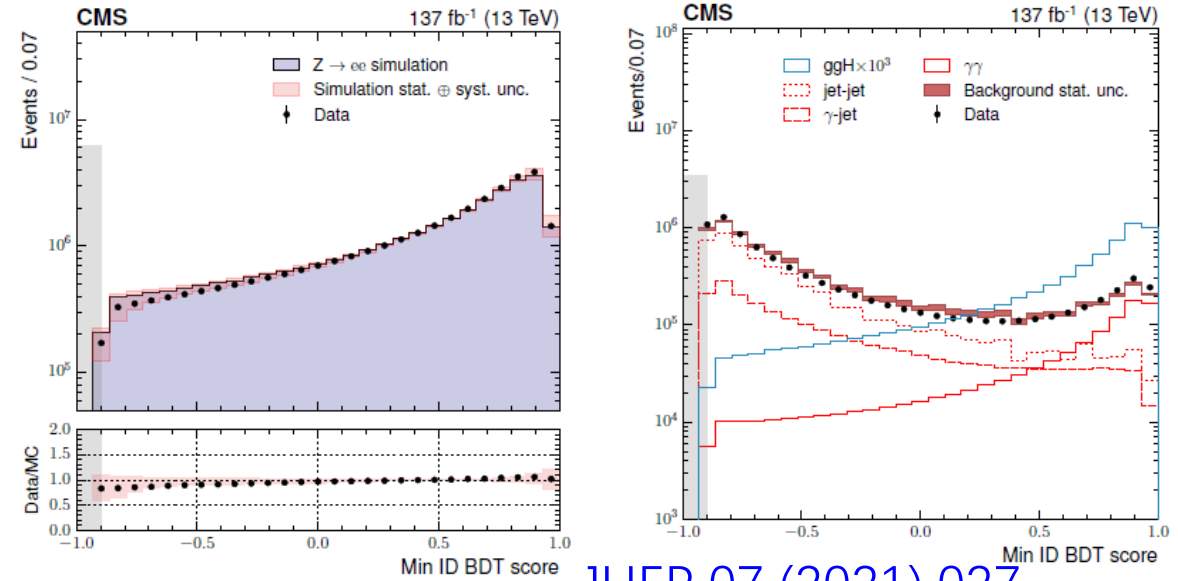
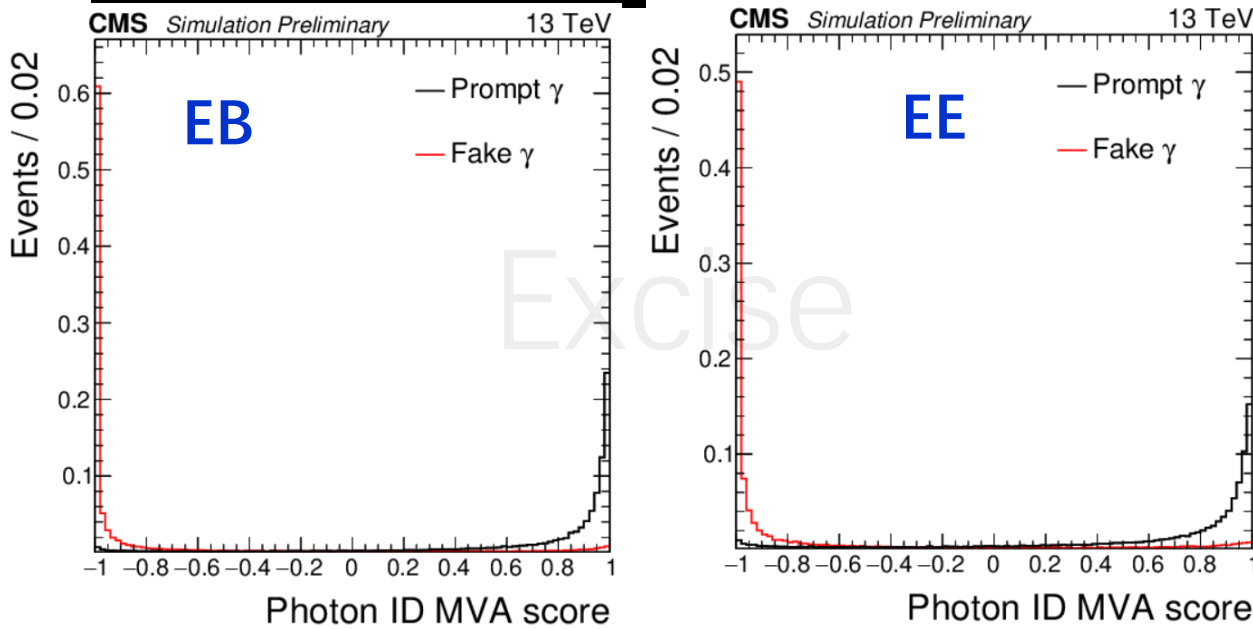
# Excise 1 : Application of photon ID MVA

- Evaluate the photon id MVA scores of the photon candidates in any samples ( $Z \rightarrow ee$  data/MC,  $Z \rightarrow \mu\mu\gamma$  data/MC, diphoton data/MC for **validations**, data and  $H \rightarrow \gamma\gamma$  MC for **analysis**)

```
> root -l -b -q evaluateMVA_AnySample.C
--> Output_mvares_included.root
--> Cut on "idmva_res" to suppress bkg on analyses
```

- To obtain **comparison plots** of photon ID MVA between signal photons and fake photons, in EB and EE separately

```
> root -l -b -q DrawComparisonPlots_IDMVA.C
#together with plotting style hggPaperStyle.C
--> *.png / *.pdf plots
```



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Applications in  $H \rightarrow \gamma\gamma$  analyses:

- After **looser cut** ( $> -0.9$ ), photon ID MVA scores of leading and subleading photons are used as two of inputs of **diphoton BDT** (for event categorization targeting untagged event classes with signal mainly from ggH production mode)
- Tighter cut** in some dedicated event classes, such as  $> -0.2$  in VBF tagged events

# EGamma POG $\gamma$ -ID MVA : Run2 vs Run3

➤ Some update on the input features

Run2 <a href="#">EGamma <math>\gamma</math> ID MVA</a>	Variables	<a href="#">NanoAOD</a>
For both EB and EE	$R_9$	Photon_r9 (full5x5)
	$E_{2 \times 2} / E_{5 \times 5}$	Photon_s4 (full5x5)
	$Cov_{\eta\phi}$	Photon_sieip
	$\sigma_{\eta\eta}$	Photon_sieie
	$\eta_{width}$	Photon_etaWidth
	$\phi_{width}$	Photon_phiWidth
	PF Photon Isolation	Photon_pfPhoIso03
	PF charged Isolation wrt chosen vertex	Photon_pfChargedIsoPFPV
	PF Charged Isolation wrt Worst vertex	Photon_pfChargedIsoWorstVtx
	Super cluster raw energy	Photon_energyRaw
	Super cluster eta	Photon_scEta
Energy density $\rho$	fixedGridRhoAll (event-level)	
EE-only	ES effective sigma	Photon_esEnergyOverRawE
	ES energy/ SC raw energy	Photon_esEffSigmaRR

**Current Run3 EGamma  $\gamma$ -ID MVA: similar as Run2**

- ✓ “PF photon isolation” removed
- ✓ Adding **H/E, Track Iso** (hollow cones 0.3) and Track Iso (solid cone 0.4), **PF ECAL cluster Iso, PF HCAL Cluster Iso** (EE-only)
- ✓ Keeping the rest the same as Run2

Same inputs as Run2  $H \rightarrow \gamma\gamma$  photon ID MVA: dedicated MVA for vertex determination in  $H \rightarrow \gamma\gamma \rightarrow$  “pf Charged Iso wrt chosen vertex”

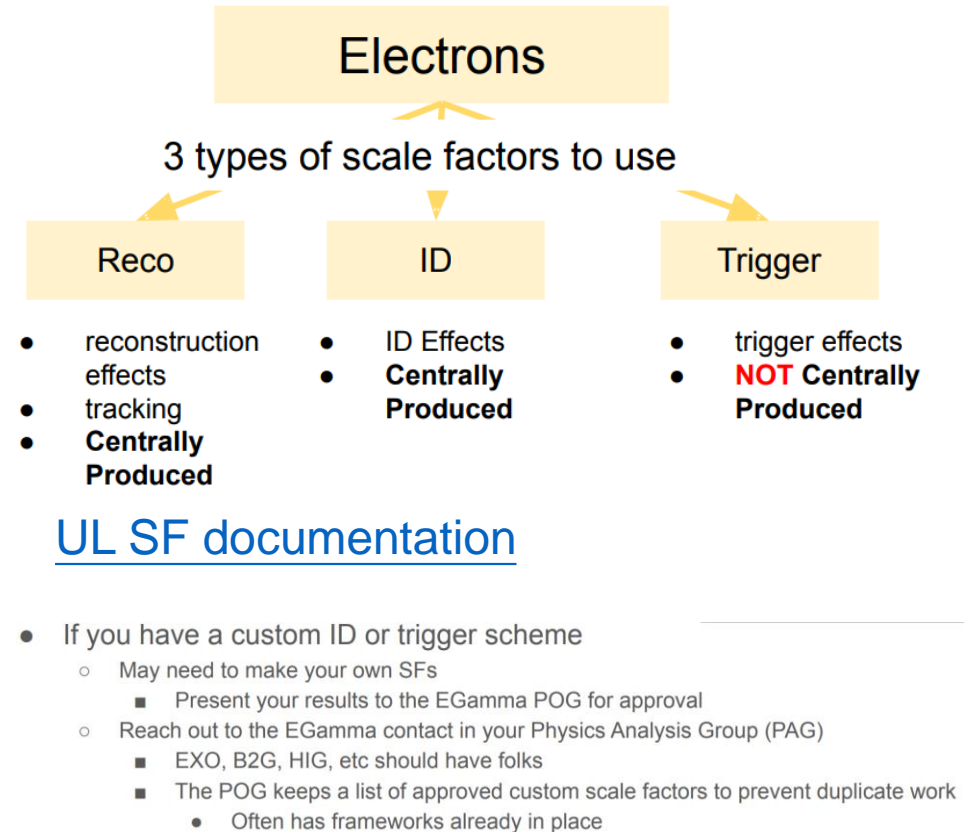
# Exercise 2: selection eff with $Z \rightarrow ee$ TnP

- Selection efficiencies and trigger efficiencies can differ in data and MC
  - ✓ If using MC (signal), want the MC to behave like data

- Scale Factors (SF) are made to match MC efficiencies to Data efficiencies
  - ✓ Defined as the ratio of data efficiencies to MC efficiencies
  - ✓ usually applied as an event weight

- Efficiency-type SF measured via Tag And Probe\* OR a different dataset
  - ✓ High  $p_T$ :  $Z \rightarrow \mu^+ \mu^-$ ,  $Z \rightarrow e^+ e^-$
  - ✓ Low- $p_T$ :  $J/\psi \rightarrow \mu^+ \mu^-$ ,  $J/\psi \rightarrow e^+ e^-$

One leg as Tag with tighter selections (ID, HLT ..), the other leg as Probe with looser selections to study the selection efficiencies: peaks in  $ee/\mu\mu$  invariant mass spectrum



- ❑ Exercise: selection with a cut on the customized photon ID MVA score ( $>-0.7$ ): [/publicfs/cms/user/taojq/README\\_Zee\\_TnP](/publicfs/cms/user/taojq/README_Zee_TnP)
- ❑ Efficiency of any selections you plan to study

# Environment setup

Useful links: [https://github.com/cms-egamma/egm\\_tnp\\_analysis](https://github.com/cms-egamma/egm_tnp_analysis)  
<https://twiki.cern.ch/twiki/bin/view/CMS/ElectronScaleFactorsRun2>

```
#To a container with OS7
/cvmfs/container.ihep.ac.cn/bin/hep_container shell CentOS7
cd /publicfs/cms/user/taojq/
export SCRAM_ARCH=slc7_amd64_gcc700
source /cvmfs/cms.cern.ch/cmsset_default.sh
cmsrel CMSSW_10_6_29
```

OS7 (OS9 in testing)

## Zee TnP package

```
cd /publicfs/cms/user/taojq/CMSSW_10_6_29/src/
cmsenv
#git clone git@github.com:cms-egamma/egm_tnp_analysis.git
cp -r /publicfs/cms/user/taojq/Zee_TnP/egm_tnp_analysis .
cd egm_tnp_analysis
make
#Note: if you modify anything in histUtils.pyx then you need to run make cython-build before make
```

# Configurations and modifications

Skip this step, all modifications included in  
/publicfs/cms/user/taojq/Zee\_TnP/egm\_tnp\_analysis

- 1) **settings.py**: etc/config/settings\_Tao2017.py  
--> **example with UL2017 Zee TnP**
- 2) **Input samples**: etc/inputs/**tnpSampleDef.py**
- 3) Tree name, mass range and binning defined in **tnpEGM\_fitter.py**
- 4) Other modifications: "minPtForSwitch" related in libPython/fitUtils.py, initial values and ranges of "nBkgF" and "nSigF" in libCpp/histFitter.C,...

etc/inputs/tnpSampleDef.py

etc/config/settings\_Tao2017.py

```
# flag to be Tested
flags = { Any selections/cuts you plan to study
          'passingIDMVACut' : '(ph_mvaID_Mod > -0.7)'
        }
baseOutDir = 'results UL2017/'
```

```
### not: you can setup another sampleDef File in inputs
import etc.inputs.tnpSampleDef as tnpSamples
tnpTreeDir = ' Data and MC samples

samplesDef = {
  'data' : tnpSamples.TaoInp2017['Data_2017'].clone(),
  'mcNom' : tnpSamples.TaoInp2017['DY_MC_NLO'].clone(),
  'mcAlt' : None,
  'tagSel' : None
}
```

```
##### binning definition [can be nD binning]
##### pT and  $\eta$  bins
binningDef = [
#   { 'var' : 'ph_sc_eta', 'type': 'float', 'bins': [-2.5,-2.0,-1.566,-1.4442, -0.8, 0.0,
0.8, 1.4442, 1.566, 2.0, 2.5] },
#   { 'var' : 'ph_et', 'type': 'float', 'bins': [20.0,35.0,50.0,100.0,200.,1000.0] },
  { 'var' : 'ph_sc_eta', 'type': 'float', 'bins': [-2.5, -1.566, 0.0, 1.566, 2.5] },
  { 'var' : 'ph_et', 'type': 'float', 'bins': [20.0, 50.0, 1000.0] },
]
```

**Homework: test with more bins**

```
##### Cuts definition for all samples
##### Some preselections
## cut
#cutBase = 'mass>60. && mass<120. && tag_Ele_et>35. && ph_et>20. && ph_hoe<0.08'
cutBase = 'mass>60. && mass<120. && tag_Ele_et>35. && ph_et>20. && ph_hoe<0.08 &&
mcTrue>0.5' ##data mcTrue always ==1
#cutBase = 'mass>60. && mass<120. && tag_Ele_et>35. && ph_et>20. && mcTrue>0.5' ##
data mcTrue always ==1
```

```
##
TaoEos2017 = '/publicfs/cms/data/Publics/taojq/ZeeTnP/UL17/' #'/eos/cms/store/user/jtao/ZeeTnP/UL17/'
TaoInp2017 = {
'DY_MC_NLO' : tnpSample('DY_MC_NLO',
                        TaoEos2017 + 'TnPtree_DYJetsToLL_M-50_TuneCP5_13TeV-amcatnloFXFX-
pythia8_UL2017_DY_NLO_EvalIDMVA_Wgt.root',
                        isMC = True, nEvts = -1 ),
'DY_MC_LO' : tnpSample('DY_MC_LO',
                        TaoEos2017 + 'TnPtree_DYJetsToLL_M-50_TuneCP5_13TeV-madgraphMLM-p
pythia8_UL2017_DY_LO_EvalIDMVA.root',
                        isMC = True, nEvts = -1 ),
'Data_2017' : tnpSample('Data_2017', TaoEos2017 + 'TnPtree_SingleElectron_UL2017_EvalIDMVA_Wgt.root',
                        lumi = 41.5 ),
}
```



# Nominal fits, skip the systematics (homework)

```
##### fitting params to tune fit by hand if necessary
#####
tnpParNomFit = [
    "meanP[-1.0,-2.0,0.1]", "sigmaP[0.8,0.1,2.0]",
    "meanF[-1.0,-2.0,0.1]", "sigmaF[1.0,0.1,3.0]",
    "acmsP[60.,40.,80.]", "betaP[0.03,0.01,0.5]", "gammaP[0.05, -0.5, 0.2]", "peakP[90.0]",
    "acmsF[60.,40.,80.]", "betaF[0.09,0.01,0.5]", "gammaF[0.04, -0.5, 0.2]", "peakF[90.0]",
]

tnpParAltSigFit = [
    "meanP[-2.0,-4.0,0.1]", "sigmaP[0.5,0.1,3.0]", "alphaP[2.0,0.5,3.5]", 'nP[3,-5,5]', "sigmaP_2[1.5,0.5,5.0]", "sosP[1.5,0.5,3.0]",
    "meanF[-1.0,-4.0,0.1]", "sigmaF[0.5,0.1,3.0]", "alphaF[2.0,0.5,3.5]", 'nF[3,-5,5]', "sigmaF_2[2.5,0.5,5.0]", "sosF[2.0,0.5,3.5]",
    "acmsP[60.,40.,90.]", "betaP[0.2,0.01,0.5]", "gammaP[0.05, -0.3, 0.5]", "peakP[90.0]",
    "acmsF[60.,40.,100.]", "betaF[0.1,0.01,0.3]", "gammaF[-0.03, -0.3,0.5]", "peakF[90.0]",
]

tnpParAltSigFit_addGaus = [
    "meanP[-0.0,-5.0,5.0]", "sigmaP[1,0.7,6.0]", "alphaP[2.0,1.2,3.5]", 'nP[3,-5,5]', "sigmaP_2[1.5,0.5,6.0]", "sosP[1,0.5,5.0]",
    "meanF[-0.0,-5.0,5.0]", "sigmaF[2,0.7,6.0]", "alphaF[2.0,1.2,3.5]", 'nF[3,-5,5]', "sigmaF_2[2.0,0.5,6.0]", "sosF[1,0.5,5.0]",
    "meanGF[90.0,70.0,100.0]", "sigmaGF[10,1.0,20.0]",
    "acmsP[60.,40.,80.]", "betaP[0.03,0.01,0.5]", "gammaP[0.05, -1, 1]", "peakP[90.0]",
    "acmsF[60.,40.,80.]", "betaF[0.03,0.01,0.5]", "gammaF[0.03, -1, 1]", "peakF[90.0]",
]

tnpParAltBkgFit = [
    "meanP[0.3,0.01,1.0]", "sigmaP[0.3,0.01,1.0]",
    "meanF[0.3,0.01,1.0]", "sigmaF[0.3,0.01,1.0]",
    "alphaP[-0.5,-1.,0.01]",
    "alphaF[-0.5,-1.,0.01]",
]
```

S and B parameters

[etc/config/settings\\_Tao2017.py](#)

## Fitting

- Signal
  - Template from MC and smear with Gaussian
- Background
  - [RooCMSShape](#)
- Mass window : 60-120 [GeV](#)
- MC efficiencies : MC truth matching and tau rejection and then evaluated by counting

## Systematics

- Variation tag selection criteria: tight/medium WP, change of tag pT (e.g. 25 to 35)
- Signal model: use a fully parametric model (Double Crystall Ball convoluted with Breit-Wigner + exponential for low pT bins). The usage of the Double CB allows to properly fit also the high pT bins.
- Background modelling: [RooCMSShape](#) vs Exponential (keep signal model as the nominal one)
- Different generator: use [aMC@NLO](#) (see MC table above)
- Additional sources may be considered in case of photon ID e.g. electron/photon R9 difference, Higgs to Z pT spectrum difference...

## Remarks:

- Generator systematics affect only MC so they are derived from a simple counting method.
- In most of the analysis a PU reweigh is already applied thus it is not needed to account for an additional systematic contribution in the scale factor(i.e. double counting).If data/MC corrections for different

than the nominal PU reweighing are needed it is possible to recompute the scale factors with three simple steps:

- recompute the target PU distribution varying the minbias xsec
- update the puTarget in the configuration
- rerun the MC counting fit

# Exercise 2: binned histograms

## ➤ Check bins

```
python tnpEGM_fitter.py
etc/config/settings_Tao2017.py --flag
passingIDMVACut --checkBins
```

## ➤ Create the binning

```
python tnpEGM_fitter.py
etc/config/settings_Tao2017.py --flag
passingIDMVACut --createBins
--> results_UL2017//passingIDMVACut//bining.pkl
```

## ➤ Create the histograms of Zee invariant mass

```
python tnpEGM_fitter.py
etc/config/settings_Tao2017.py --flag
passingIDMVACut --createHists
--> results_UL2017/passingIDMVACut/*.root
--> N_eta*N_pt "Pass" and "Fail" TH1D hists
```

Time-consuming step, depending on the binning (N\_eta\*N\_pt) and input root files

```
====> Output directory:
results_UL2017//passingIDMVACut/
bin00_ph_sc_eta_m2p50Tom1p57_ph_et_20p00To50p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= -2.500000 && ph_sc_eta < -1.566000 && ph_et >= 20.000000 && ph_et < 50.000000')
bin01_ph_sc_eta_m1p57To0p00_ph_et_20p00To50p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= -1.566000 && ph_sc_eta < 0.000000 && ph_et >= 20.000000 && ph_et < 50.000000')
bin02_ph_sc_eta_0p00To1p57_ph_et_20p00To50p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= 0.000000 && ph_sc_eta < 1.566000 && ph_et >= 20.000000 && ph_et < 50.000000')
bin03_ph_sc_eta_1p57To2p50_ph_et_20p00To50p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= 1.566000 && ph_sc_eta < 2.500000 && ph_et >= 20.000000 && ph_et < 50.000000')
bin04_ph_sc_eta_m2p50Tom1p57_ph_et_50p00To1000p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= -2.500000 && ph_sc_eta < -1.566000 && ph_et >= 50.000000 && ph_et < 1000.000000')
bin05_ph_sc_eta_m1p57To0p00_ph_et_50p00To1000p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= -1.566000 && ph_sc_eta < 0.000000 && ph_et >= 50.000000 && ph_et < 1000.000000')
bin06_ph_sc_eta_0p00To1p57_ph_et_50p00To1000p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= 0.000000 && ph_sc_eta < 1.566000 && ph_et >= 50.000000 && ph_et < 1000.000000')
bin07_ph_sc_eta_1p57To2p50_ph_et_50p00To1000p00
(' - cut: ', 'mass>60. && mass<120. && tag Ele_et>35. && ph_et>20. && ph_hoe<0.08 && mcTrue>0.5 &&
ph_sc_eta >= 1.566000 && ph_sc_eta < 2.500000 && ph_et >= 50.000000 && ph_et < 1000.000000')
```

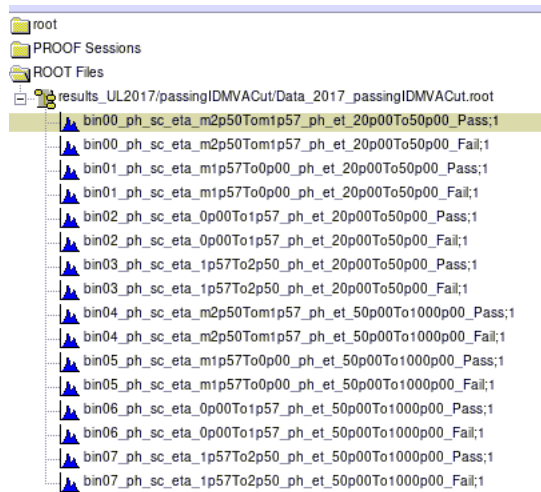
```
Starting event loop to fill histograms..
0 % Data 2017
5 % Data 2017
10 % Data 2017
15 % Data 2017
20 % Data 2017
25 % Data 2017
30 % Data 2017
35 % Data 2017
40 % Data 2017
45 % Data 2017
50 % Data 2017
55 % Data 2017
60 % Data 2017
65 % Data 2017
70 % Data 2017
75 % Data 2017
80 % Data 2017
85 % Data 2017
90 % Data 2017
95 % Data 2017
100 % Data 2017
```

results\_UL2017/passingIDMVACut/Data\_2017\_passingIDMVACut.root and DY\_MC\_NLO\_passingIDMVACut.root

```
TFile* results_UL2017/passingIDMVACut/Data_2017_passingIDMVACut.root
KEY: TH1D bin00_ph_sc_eta_m2p50Tom1p57_ph_et_20p00To50p00 Pass;1
KEY: TH1D bin00_ph_sc_eta_m2p50Tom1p57_ph_et_20p00To50p00 Fail;1
KEY: TH1D bin01_ph_sc_eta_m1p57To0p00_ph_et_20p00To50p00 Pass;1
KEY: TH1D bin01_ph_sc_eta_m1p57To0p00_ph_et_20p00To50p00 Fail;1
KEY: TH1D bin02_ph_sc_eta_0p00To1p57_ph_et_20p00To50p00 Pass;1
KEY: TH1D bin02_ph_sc_eta_0p00To1p57_ph_et_20p00To50p00 Fail;1
KEY: TH1D bin03_ph_sc_eta_1p57To2p50_ph_et_20p00To50p00 Pass;1
KEY: TH1D bin03_ph_sc_eta_1p57To2p50_ph_et_20p00To50p00 Fail;1
KEY: TH1D bin04_ph_sc_eta_m2p50Tom1p57_ph_et_50p00To1000p00 Pass;1
KEY: TH1D bin04_ph_sc_eta_m2p50Tom1p57_ph_et_50p00To1000p00 Fail;1
KEY: TH1D bin05_ph_sc_eta_m1p57To0p00_ph_et_50p00To1000p00 Pass;1
KEY: TH1D bin05_ph_sc_eta_m1p57To0p00_ph_et_50p00To1000p00 Fail;1
KEY: TH1D bin06_ph_sc_eta_0p00To1p57_ph_et_50p00To1000p00 Pass;1
KEY: TH1D bin06_ph_sc_eta_0p00To1p57_ph_et_50p00To1000p00 Fail;1
KEY: TH1D bin07_ph_sc_eta_1p57To2p50_ph_et_50p00To1000p00 Pass;1
KEY: TH1D bin07_ph_sc_eta_1p57To2p50_ph_et_50p00To1000p00 Fail;1
```

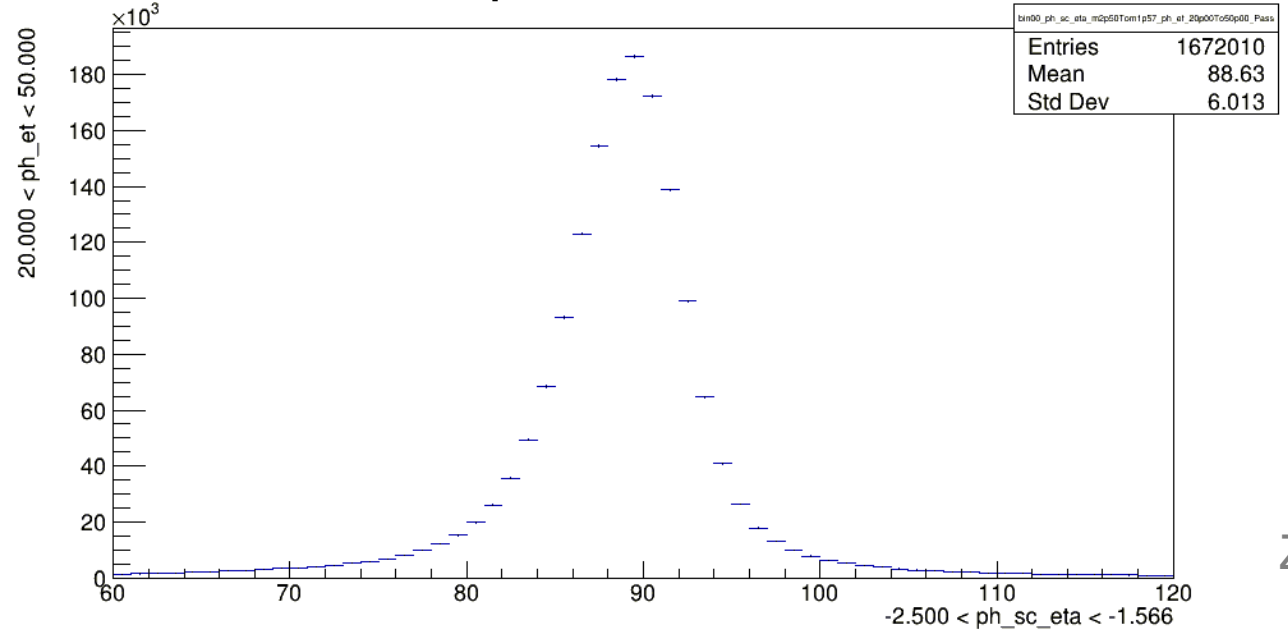
```
root -l
results_UL2017/passingIDMVACut/Data_2017_passingIDMVACut.root
```

```
c=new TBrowser()
```



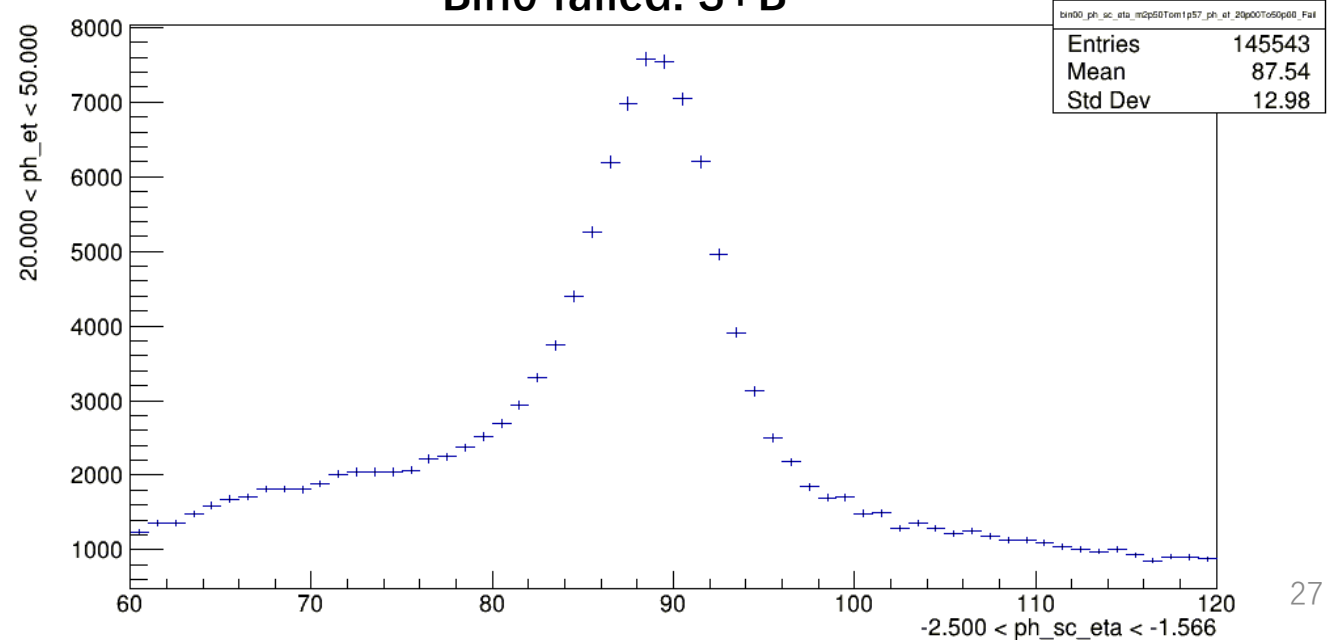
Invariant mass with tag + passed probe,  
tag + failed probe

Bin0 passed: S+B



$Z \rightarrow e^+e^-$

Bin0 failed: S+B



# Exercise 2: nominal fitting

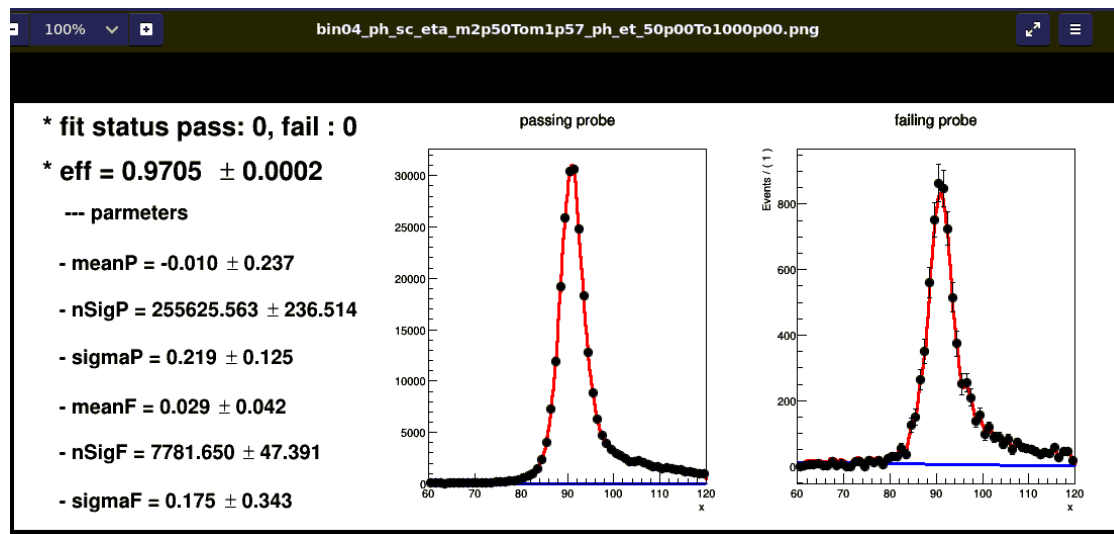
$$\text{eff} = \frac{N_{S_{\text{passed}}}}{N_{S_{\text{passed}}} + N_{S_{\text{failed}}}}$$

MC: `python tnpEGM_fitter.py`  
`etc/config/settings_Tao2017.py --flag`  
`passingIDMVACut --doFit -mcSig`  
 --> plots:  
`results_UL2017/passingIDMVACut/plots/DY_MC_NLO/nominalFit/*.png`  
 --> rootuples:  
`results_UL2017/passingIDMVACut/DY_MC_NLO_passingIDMVACut.nominalFit-bin*.root`

Data: `python tnpEGM_fitter.py`  
`etc/config/settings_Tao2017.py --flag`  
`passingIDMVACut --doFit`  
 --> plots:  
`results_UL2017/passingIDMVACut/plots/Data_2017/nominalFit/*.png`  
 --> rootuples:  
`results_UL2017/passingIDMVACut/Data_2017_passingIDMVACut.nominalFit-bin*.root`

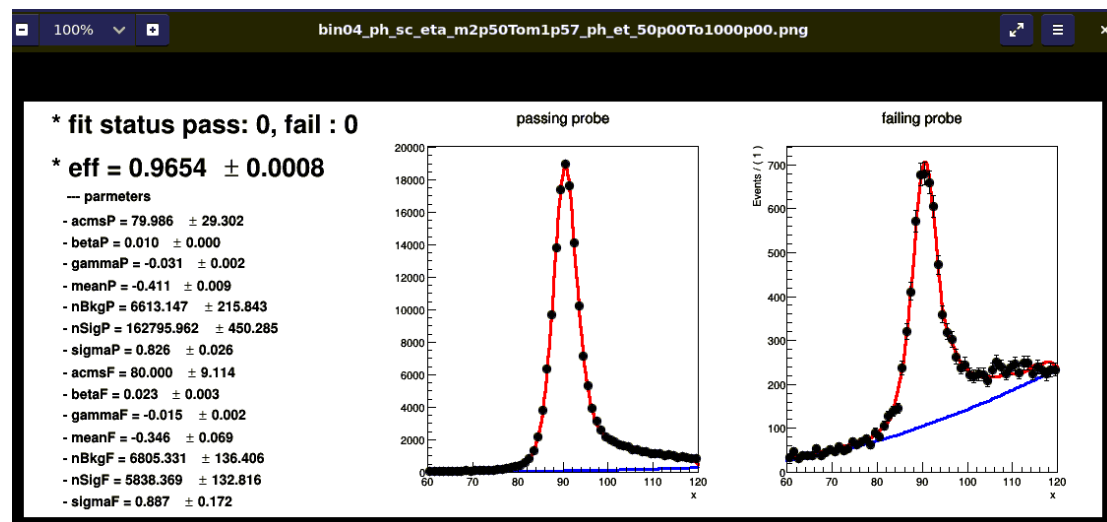
Note: may need to tune parameters for some bins

results\_UL2017/passingIDMVACut/plots/DY\_MC\_NLO/nominalFit/



DY MC:  
only Sig

results\_UL2017/passingIDMVACut/plots/Data\_2017/nominalFit/



Data:  
S+B

# Exercise 2: data/MC scale factors

Once all fits are fine, put everything in the egm format txt file, and get the **plots of eff and SFs with unc.**

```
python tnpEGM_fitter.py  
etc/config/settings_Tao2017.py --flag  
passingIDMVACut --sumUp
```

-->

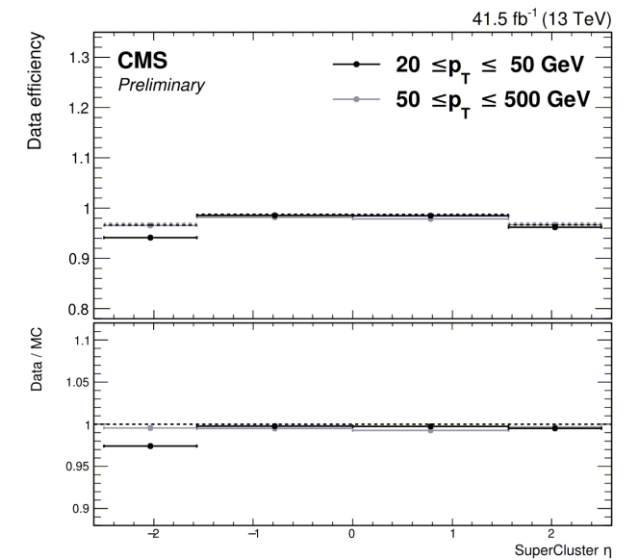
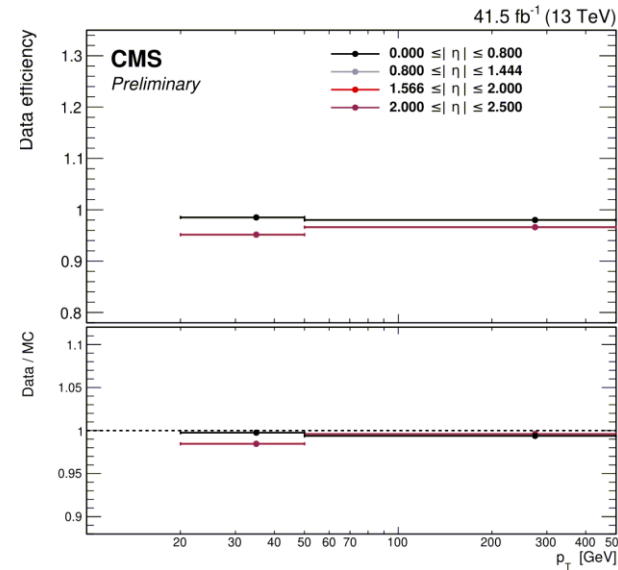
```
results_UL2017/passingIDMVACut//egammaEffi.txt
```

```
--> results_UL2017//passingIDMVACut/*.png
```

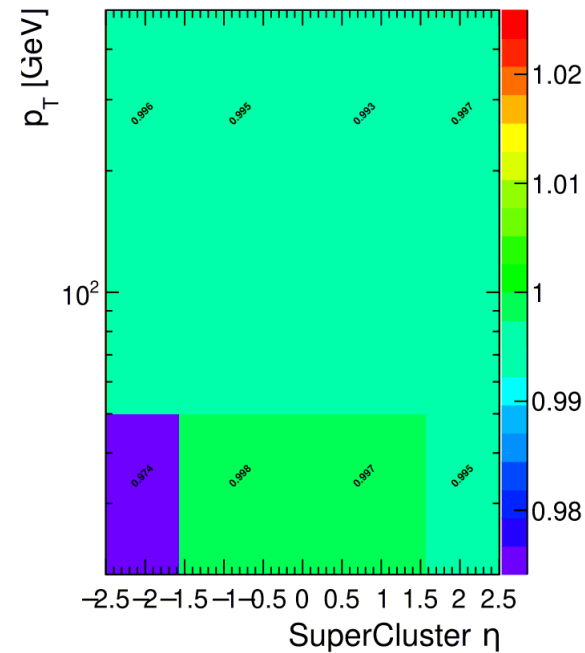
```
--> results_UL2017//passingIDMVACut/*.pdf
```

**Note: systematics plots are empty  
(skip the fitting, homework)**

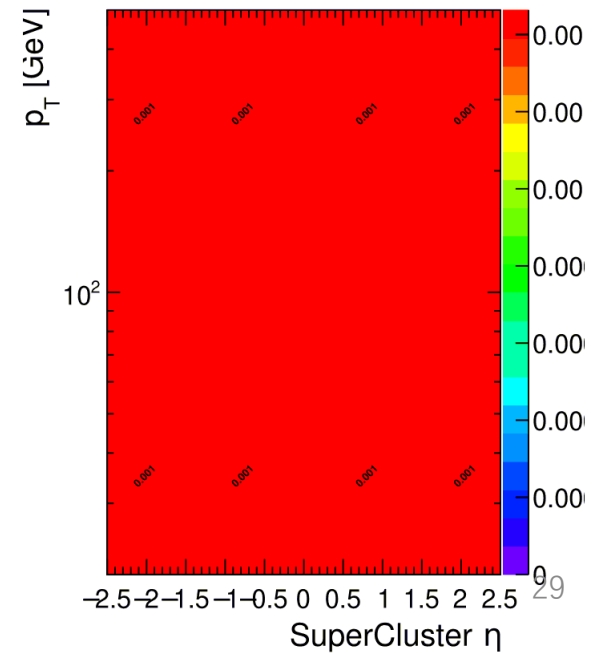
SFs are usually applied as an event weight, to correct your MC signal with the cut/selections employed in your analysis



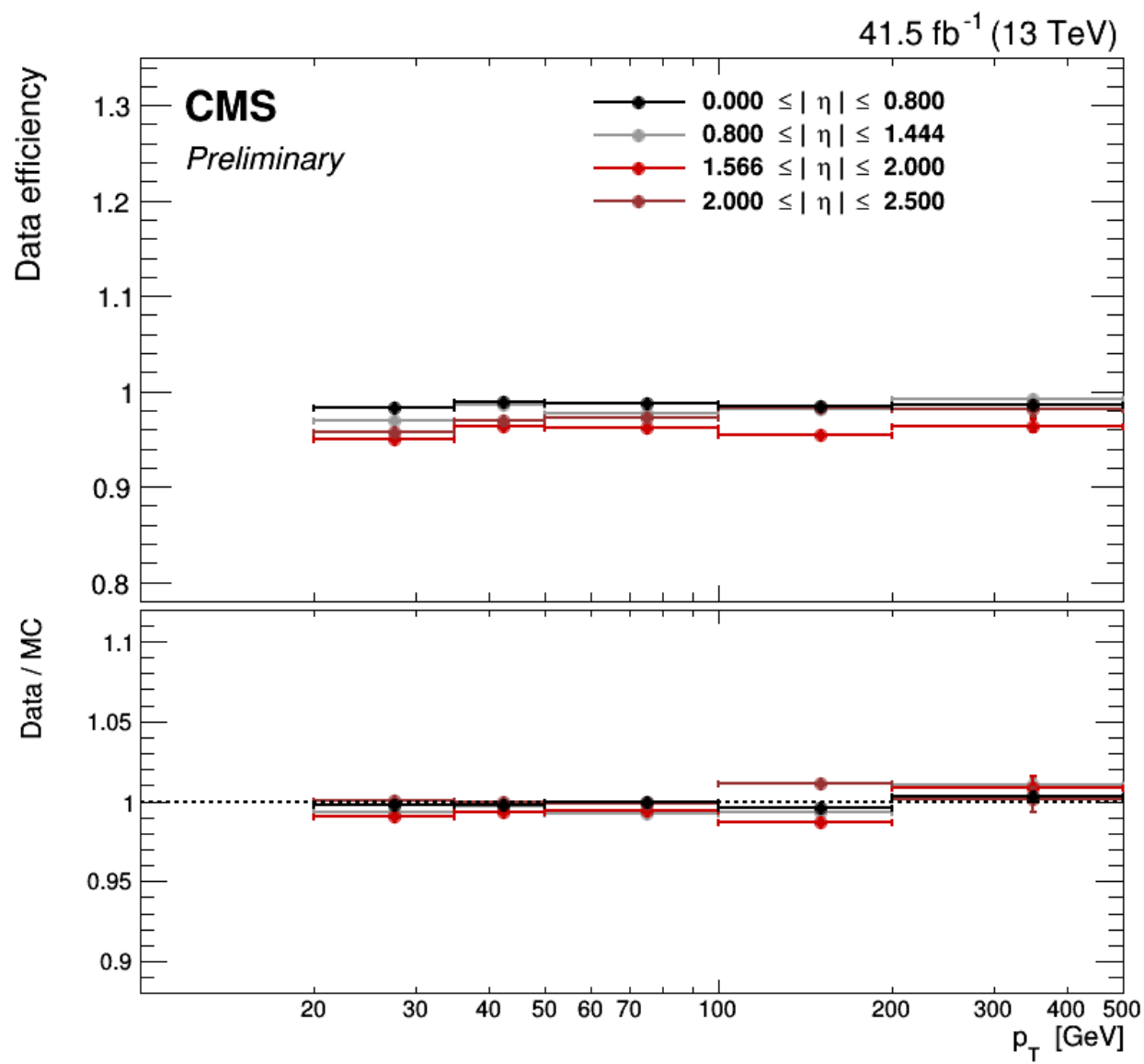
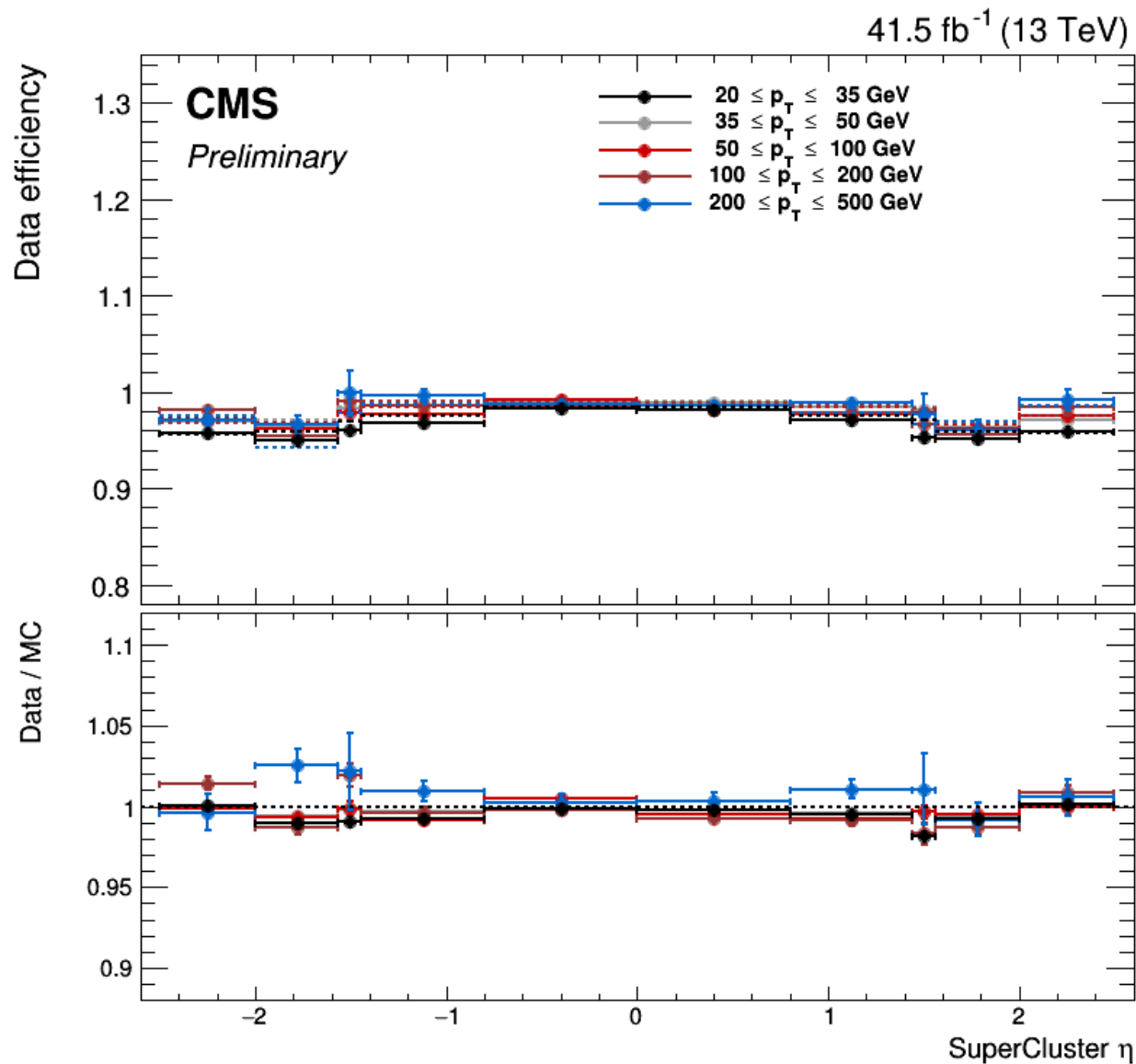
**e/gamma scale factors**



**e/gamma uncertainties**



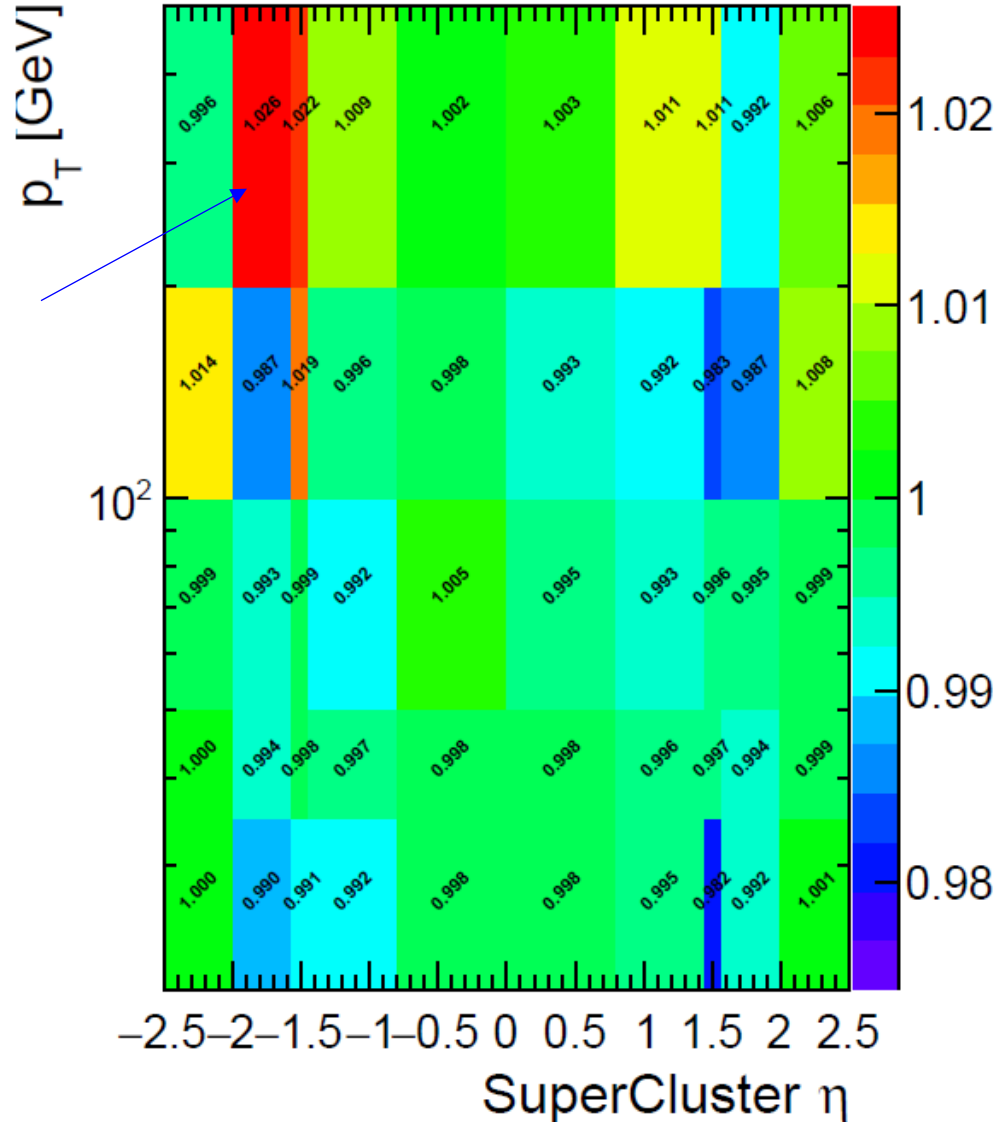
# UL2017 data eff. and data/MC SF (stat. unc.)



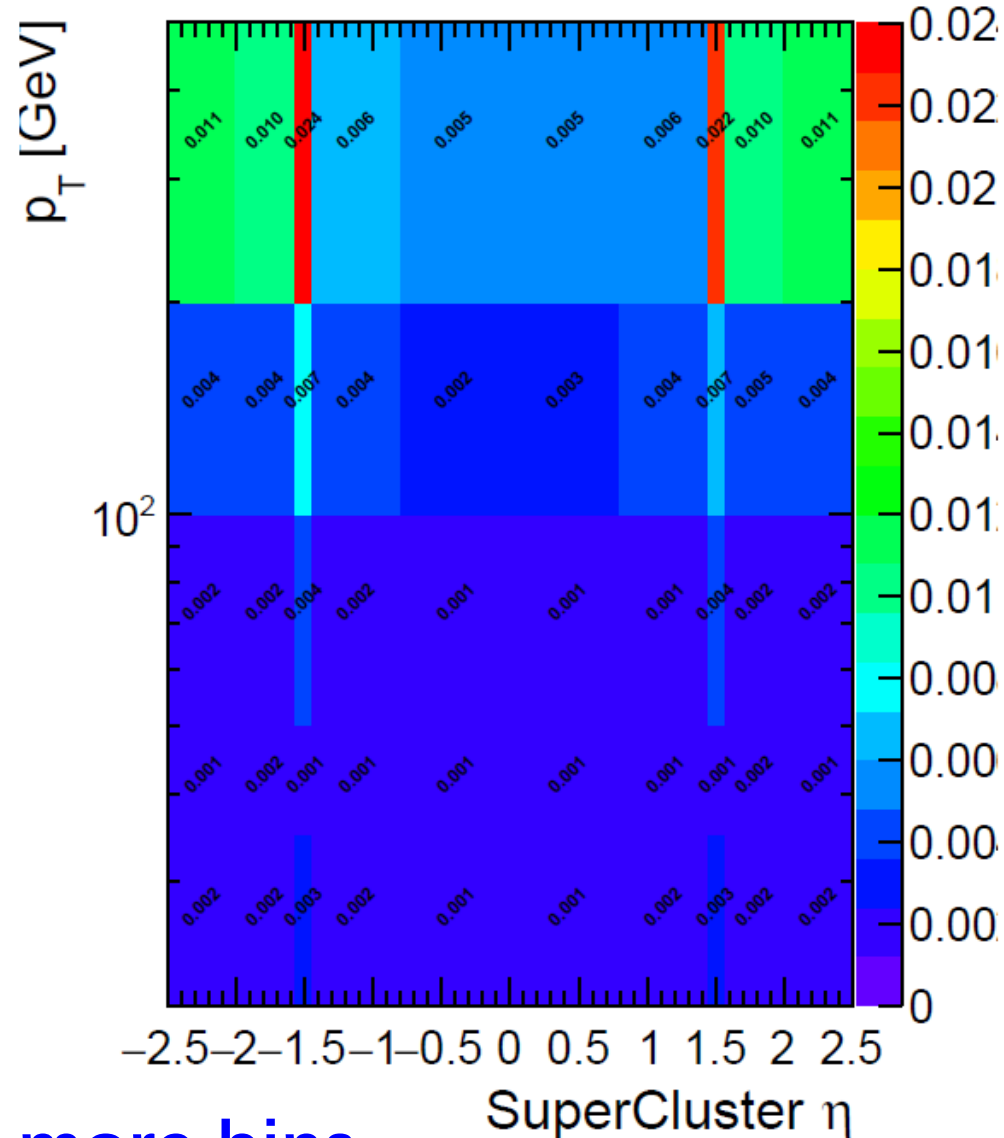
more bins

# UL2017 SF and stat. unc. : 2D

$e/\gamma$  scale factors



$e/\gamma$  uncertainties



SF : <3% different from 1

Except EB/EE gaps, typically stat. unc. <~1%

My [presentation](#) at EGamma meeting on 15 Mar 2024

more bins

# THE END ...MANY THANKS!



# Enjoy your CMS analyses!