### End-to-end Jet ID for quark/gluon discrimination using CMS Open Data

<u>M. Andrews</u><sup>1</sup>, J. Alison<sup>1</sup>, S. An<sup>1</sup>, P. Bryant<sup>1</sup>, M. Paulini<sup>1</sup>, B. Poczos<sup>1</sup> S. Gleyzer<sup>2</sup> B. Burkle<sup>3</sup>, M. Narain<sup>3</sup>, E. Usai<sup>3</sup> <sup>1</sup>Carnegie Mellon University, <sup>2</sup>University of Florida, <sup>3</sup>Brown University

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## E2E | Outline

- Motivation
- The CMS Detector
- The End-to-end Approach
- Quark vs. Gluon Jet Identification
- Di-quark vs. Di-gluon Event Identification
- Conclusions

### **Motivation** Typical Jet ID

Break down classification into different sub-steps which are optimized separately



## Jet ID | Images

#### Jet images for quark vs gluon discrimination not new:

- See P. Komiske et al.: https://arxiv.org/abs/1612.01551
- See ATLAS: http://cds.cern.ch/record/2275641



Translated Pseudorapidity n

after Pixel Standardization





0.15

0.05

0.15 🕺

0.05

0.4

0.2

0.4

0.2

### Jet ID | Images vs High-level features

#### **RecNN**, Jet ID for QCD vs boosted W jet

- K. Cranmer et al.: https://arxiv.org/pdf/1702.00748.pdf
- **DELPHES** detector simulation

RecNN

- Applied to quark vs gluon by T. Cheng: https://arxiv.org/pdf/1711.02633.pdf
- Traditional jet images perform less well than 4-momenta

	Projected into images			
Traditional	towers	MaxOut	0.8418	-
	towers	$k_t$	$0.8321 \pm 0.0025$	$12.7\pm0.4$
Jet images	towers	$k_t \ (\text{gated})$	$0.8277 \pm 0.0028$	$12.4\pm0.3$

	with gating (see Appendix A)				
towers	$k_t$	$0.8822 \pm 0.0006$	$25.4\pm0.4$		
towers	C/A	$0.8861 \pm 0.0014$	$26.2\pm0.8$		
towers	anti- $k_t$	$0.8804 \pm 0.0010$	$24.4\pm0.4$		
towers	$\operatorname{asc-}p_T$	$0.8849 \pm 0.0012$	$27.2\pm0.8$		
towers	$\operatorname{desc}-p_T$	$\textbf{0.8864} \pm \textbf{0.0007}$	$\textbf{27.5} \pm \textbf{0.6}$		
towers	random	$0.8751 \pm 0.0029$	$22.8 \pm 1.2$		

With goting (coo Appendix A)

### Jet ID | Images vs High-level features

CMS DeepJet, Jet ID for quark vs gluon jet

- CMS: <u>https://cds.cern.ch/record/2275226</u>
- Jets from QCD dijet, with PU,  $|\eta| < 1.3$  or  $1.3 < |\eta| < 2.4$
- CMS GEANT4 full detector simulation
- DeepJet comparable to RecNN\*

			Area under ROC	$\epsilon$ (tight)	$\epsilon$ (medium)	$\epsilon$ (loose)
		QCD	$\hat{p}_T = 80 - 120 \mathrm{GeV}$	, jet $p_{\mathrm{T}} > 7$	'0 GeV	
	0.796	DeepJet central	0.204	0.17	0.51	0.65
	0.797	DeepJet forward	0.203	0.15	0.50	0.65
ROC	0.789	Convolution central	0.211	0.15	0.49	0.64
AUC*	0.785	Convolution forward	0.215	0.13	0.47	0.63
	0.795	Recurrent central	0.205	0.16	0.51	0.65
	0.795	Recurrent forward	0.205	0.14	0.49	0.65

**\*NOTE:** "In addition, the  $p_T$  and  $\eta$  of the jet, the number of charged and neutral candidates, and the number of secondary vertices within the jet are given to the following dense layer with 128 nodes."

### **CMS** | Geometry & Particle ID



### **CMS** | Detector Segmentation





**HCAL Endcap** (iφ, iη)

Image Credit: CERN

### **CMS** | Detector Geometry



### End-to-end Event ID

Optimize for the final classification objective

Detector data as fundamental (maximum?) measured information



### Detector Data

### **Event Class**

(e.g. digluon vs. diquark)

### **End-to-end** Jet ID

Optimize for the final classification objective

Detector data as fundamental (maximum?) measured information



### Jet ID | Traditional vs E2E Image

Traditional jet image

E2E jet image



Note: Not the same jet.

#### CMS OpenData QCD Samples

- Leading jet from QCD dijet qq' (*uds*) or gg, EMenriched @ 8 TeV
- CMS GEANT4 full detector simulation, PTYHIA 6
- β<sub>T</sub>: 80-170 GeV, reco p<sub>T</sub> > 70 GeV, |η| < 1.8</li>
- Run-dependent (PU): 18-21
- Produced and ntuplized with CMSSW 5\_3\_32
- Sample split:
  - Training set: 576k jets (of which, 26k jets for validation)
  - Test set: 139k jets
  - Balanced samples per class
  - Balanced PU representation per class
- Architecture: ResNet-15 trained from scratch on an NVIDIA Titan X/p using Pytorch 0.4

1 px = 0.0174 x 0.0174 Δη x Δφ

Tracks

ECAL

HCAL

## E2E Image | gluon

Radiation pattern more dispersed (top: overlays, bottom: single jet)

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1 px = 0.0174 x 0.0174 Δη x Δφ

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Tracks

ECAL

HCAL

## E2E Image | quark

Radiation pattern more focused (top: overlays, bottom: single jet)



15







	ROC AUC
E2E jet image, Tracks	0.782
E2E jet image, ECAL	0.760
E2E jet image, HCAL	0.682

#### • E2E Results, Jet ID

- Provides insight into detector performance / particle ID
- Spatial resolution important: track info more valuable than shower/energy information from any one calorimeter
- Handles sparsity well



	ROC AUC
E2E jet image, ECAL+Tracks	0.804
E2E jet image, Tracks	0.782
E2E jet image, ECAL+HCAL	0.781

#### • E2E Results, Jet ID

- Combine two subdetector images
- Spatial resolution important: charged hadron info from Tracks more valuable than from HCAL
- Track info alone as valuable as combined calo info





	ROC AUC
E2E jet image, ECAL+HCAL+Tracks	0.808
E2E jet image, ECAL+Tracks	0.804

#### • E2E Results, Jet ID

- Combine ECAL+HCAL+Tracks images
- ECAL+Tracks sufficient for strong discrimination: HCAL info not so important
- Track info supplemented with calo info works best.

	ROC AUC
E2E image, ECAL+HCAL+Tracks	0.8077 ± 0.0003*
<b>RecNN,</b> ascending-p <sub>T</sub>	$0.8017 \pm 0.0003^*$
RecNN, descending-pT	0.802
<b>RecNN,</b> anti-k <sub>T</sub>	0.801
RecNN, Cambridge/Aachen	0.801
RecNN, no rotation/reclustering	0.800
RecNN, k <sub>T</sub>	0.800
<b>RecNN,</b> k <sub>T</sub> -colinear10-max	0.799
RecNN, random	0.797

#### RecNN Results, Jet ID

- Use 4-momenta derived from CMS Particle Flow
- Perform boost/rotation, then reclustering with different algos
- E2E jet images perform well

- Classify the full event as either QCD di-quark or di-gluon
- In addition to local jet physics, global event-level physics factors in: jet 4-momenta, qq spin-correlations and polarization
- Problem becomes much richer!



• Scenario A: 2 x jet images



Fully-connected, 128 x 2

• Scenario B: 2 x jet images + jet 4-momenta



Fully-connected, 128 x 2

Scenario C: Fully end-to-end detector image



	ROC AUC
Scenario A	0.876
Scenario B	0.878
Scenario C	0.889

#### • Local or global physics? Part I.

- Performance dominated by jet-level differences (Scenario A vs. B or C)
- Both dijets are non-resonant decays, so jet 4-momenta doesn't hold much discrimination power (Scenario B vs. A)
- Fully E2E approach (Scenario C) picking up on subtle, event-level effects not captured by either B or A?

- Is the E2E relying on the underlying event/PU?
  - Try Scenario C-Zero: zero out all pixels outside of the two jet windows



	ROC AUC
Scenario C	0.889
Scenario C-Zero	0.887
Scenario C, evaluated on C-Zero	0.883
Scenario C-Zero, evaluated on C	0.884

#### Is the E2E relying on the underlying event/PU?

 E2E event classifier not sensitive to underlying event and PU outside of jet region of interest

- Local or global physics? Part II.
  - Scenario C-Zero-Graft: Graft jets from different events onto a new image with fake event-level info but otherwise real jets



#### • Local or global physics? Part II.

 Use model trained on Scenario C-Zero and evaluate on grafted events, Scenario C-Zero-Graft

	ROC AUC
Scenario C-Zero	0.887
Scenario C-Zero, evaluated on C-Zero-Graft	0.877
Scenario A	0.876

#### Consistent with findings from Part I:

- Performance from jet-level differences preserved
- The subtle event-level info is lost in Scenario C-Zero-Graft score now similar to 2 x jet images (Scenario A)
- E2E learns event-level correlations

## E2E | Conclusions

#### E2E Jet ID:

- Achieves quark vs. gluon discrimination competitive with existing state-of-the-art jet ID classifiers
- Not all jet images are created equally: E2E techniques help to optimize full detector performance

#### E2E Event ID:

- Able to capturesubtle, event-level correlations not present at jetlevel that may otherwise be difficult to model by hand
  - Capable of learning particle phenomenology
  - Can be be "reversed-engineered" to understand what deep physics is being learned
- Smart enough to know what is noise/irrelevant in the image without any human intervention

## E2E | Outlook

#### • How far can we take E2E approach?

- Use the full Tracker information?
- Add Muon Trackers
- Effects of higher pile-up?
- Apply to boosted topologies

### BACKUP

### HCAL | Segmentation



### **ECAL** | Hit Reconstruction

http://iopscience.iop.org/article/10.1088/1742-6596/1085/4/042022

**Scale:** 1 pixel = 1 crystal



Scintillating<br/>CrystalSignal<br/>PulseDigitized Hit<br/>("DIGI")Reconstructed<br/>Hit ("RecHit")

# Jet ID | q vs g

#### RecNN, Jet ID for quark vs gluon jet

- *T. Cheng:* <u>https://arxiv.org/pdf/1711.02633.pdf</u>
- Jets from QCD dijet gg or qq events, no PU,  $|\eta| < 2.5$
- DELPHES detector simulation

Recursive Neural Networks in Quark/Gluon Tagging

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ROC AUC   $R_{\epsilon=80\%}$   $R_{\epsilon=50\%}$	200 GeV	300 GeV	500 GeV	1000 GeV
BDT	0.8164   3.1   10.5	0.8443   3.8   16.5	0.8385   3.5   14.1	0.8421   3.6   16.1
RecNN without pflow identification	0.8344   3.4   12.9	0.8390   3.6   14.4	0.8505   3.9   16.9	0.8623   4.2   21.9
RecNN with categorical pflow	0.8392   3.6   14.0	0.8443   3.8   16.5	0.8517   4.0   17.8	0.8637   4.4   22.0
RecNN with pt-weighted charge	0.8340   3.5   12.8	0.8453   3.9   14.5	0.8525   4.0   18.6	0.8616   4.3   20.4

**Table 2** AUCs and background rejection rates for different jet  $p_T s$ . The baseline BDT and three scenarios concerning particle flow identification are considered. The largest AUCs and  $R_{\epsilon=50\%}$ s are highlighted in bold.