

Data ex Machina

Machine Learning with Public Collider Data

AI & Physics, Applied Machine Learning Days 2020

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Patrick
Komiske



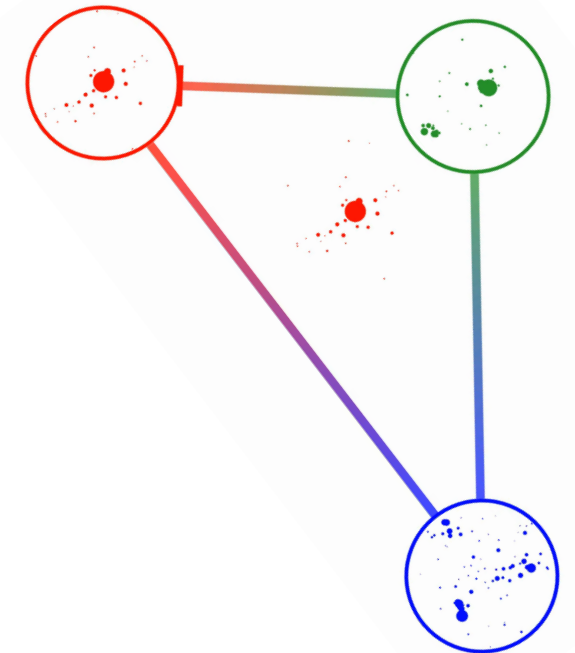
Radha
Mastandrea



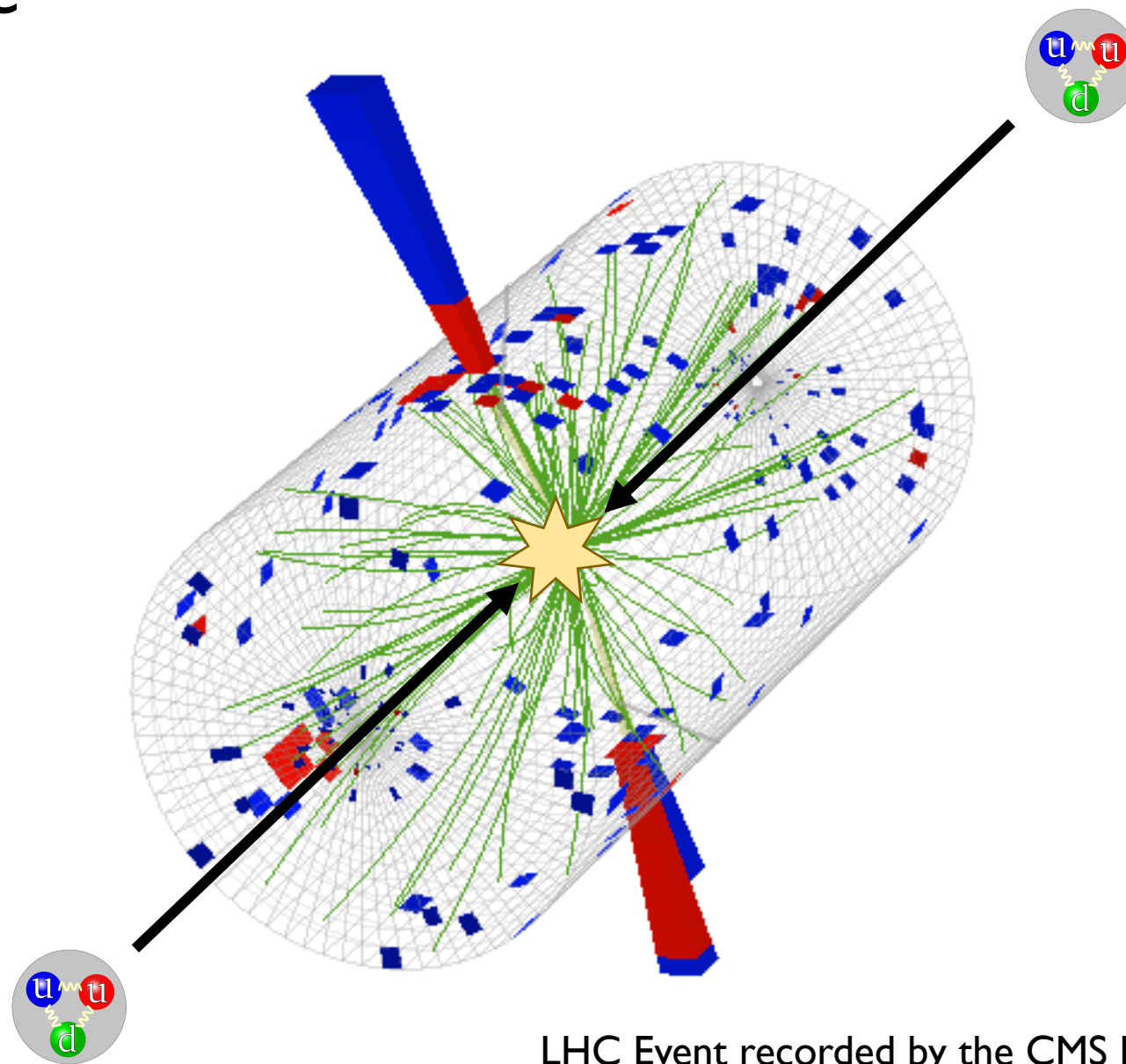
Preksha
Naik



Jesse
Thaler

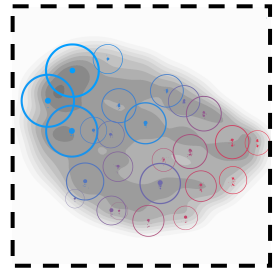


Collision Course

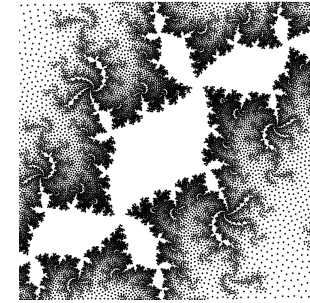


LHC Event recorded by the CMS Experiment at CERN

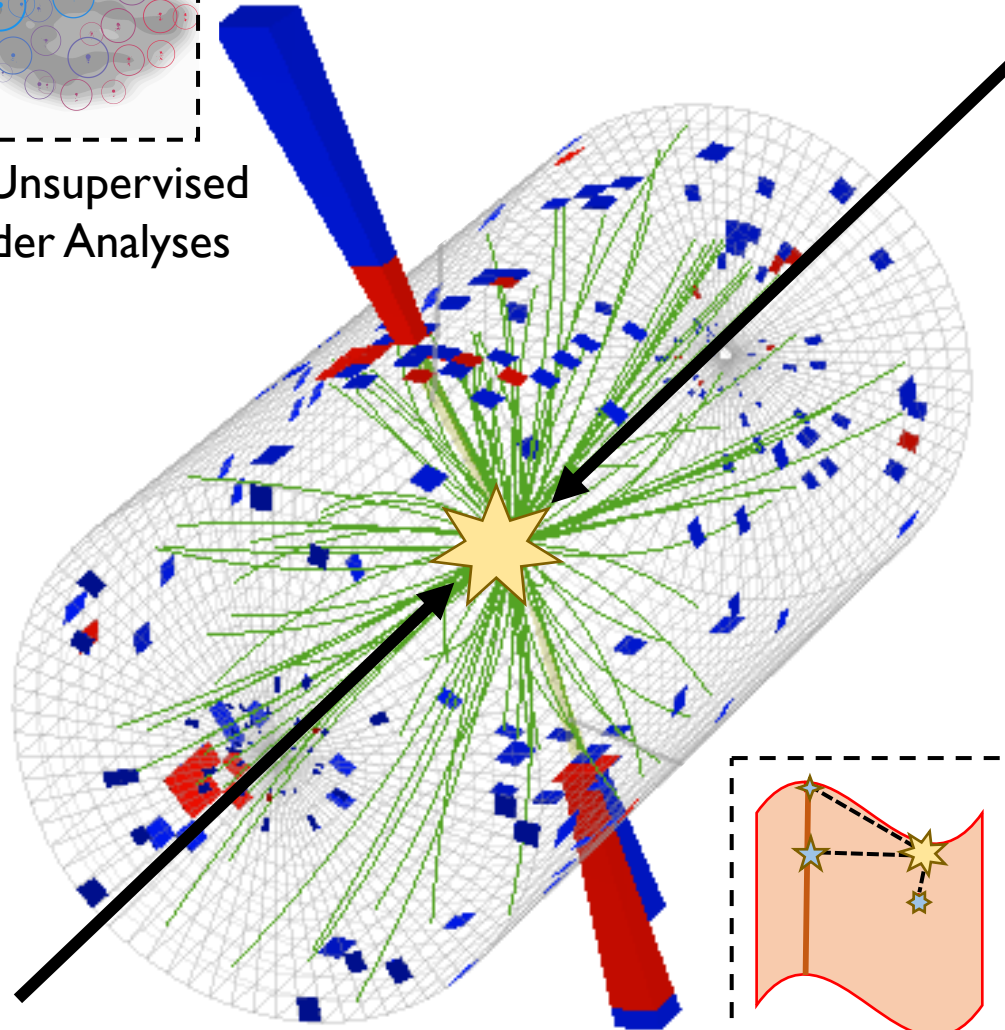
Collision Course



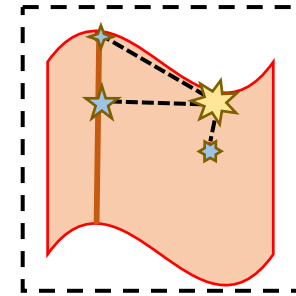
New Unsupervised
Collider Analyses



Optimal Transport
[\[OTML Workshop, NeurIPS 2019\]](#)



Public Collider Data
[\[opendata.cern.ch\]](https://opendata.cern.ch)



New Insights into
Quantum Field Theory

[\[h/t Jesse Thaler\]](#)

opendata.cern.ch

Explore more than **two petabytes**
of open data from particle physics!

jet primary dataset

Search

search examples: [collision datasets](#), [keywords:education](#), [energy:7TeV](#)

Explore

- [datasets](#)
- [software](#)
- [environments](#)
- [documentation](#)

Focus on

- [ATLAS](#)
- [ALICE](#)
- [CMS](#)
- [LHCb](#)
- [OPERA](#)
- [Data Science](#)

▾ Get started ▾

CMS Open Data

Download a CMS “AOD” file: [2011A Jet Primary Dataset](#)

04913DA0-8B3F-E311-924F-0025901AD38A.root

966.3 MB



Fifteen lines of code later...

```
import uproot
# Load in the specified file with uproot
file = uproot.open('~Downloads/04913DA0-8B3F-E311-924F-0025901AD38A.root')
events = file[b'Events;1']

# read particle transverse momenta (pts), pseudorapidity (eta), and azimuth (phi)
PFCKey = b'recoPFCandidates_particleFlow_RECO.obj'
pts = events[PFCKey + b'.pt_'].array()
etas = events[PFCKey + b'.eta_'].array()
phis = events[PFCKey + b'.phi_'].array()
```

```
import numpy as np
import matplotlib.pyplot as plt

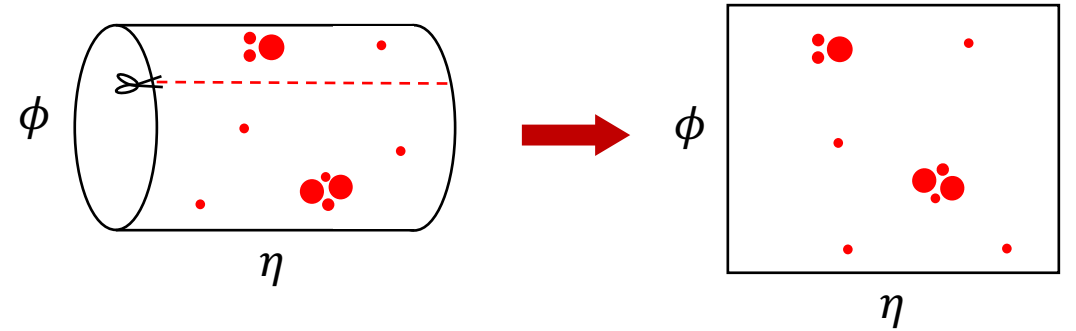
# choose an event
ind = 6457

# plot the collision event of interest
plt.scatter(etas[ind], phis[ind], s=pts[ind], lw=0, color='red')

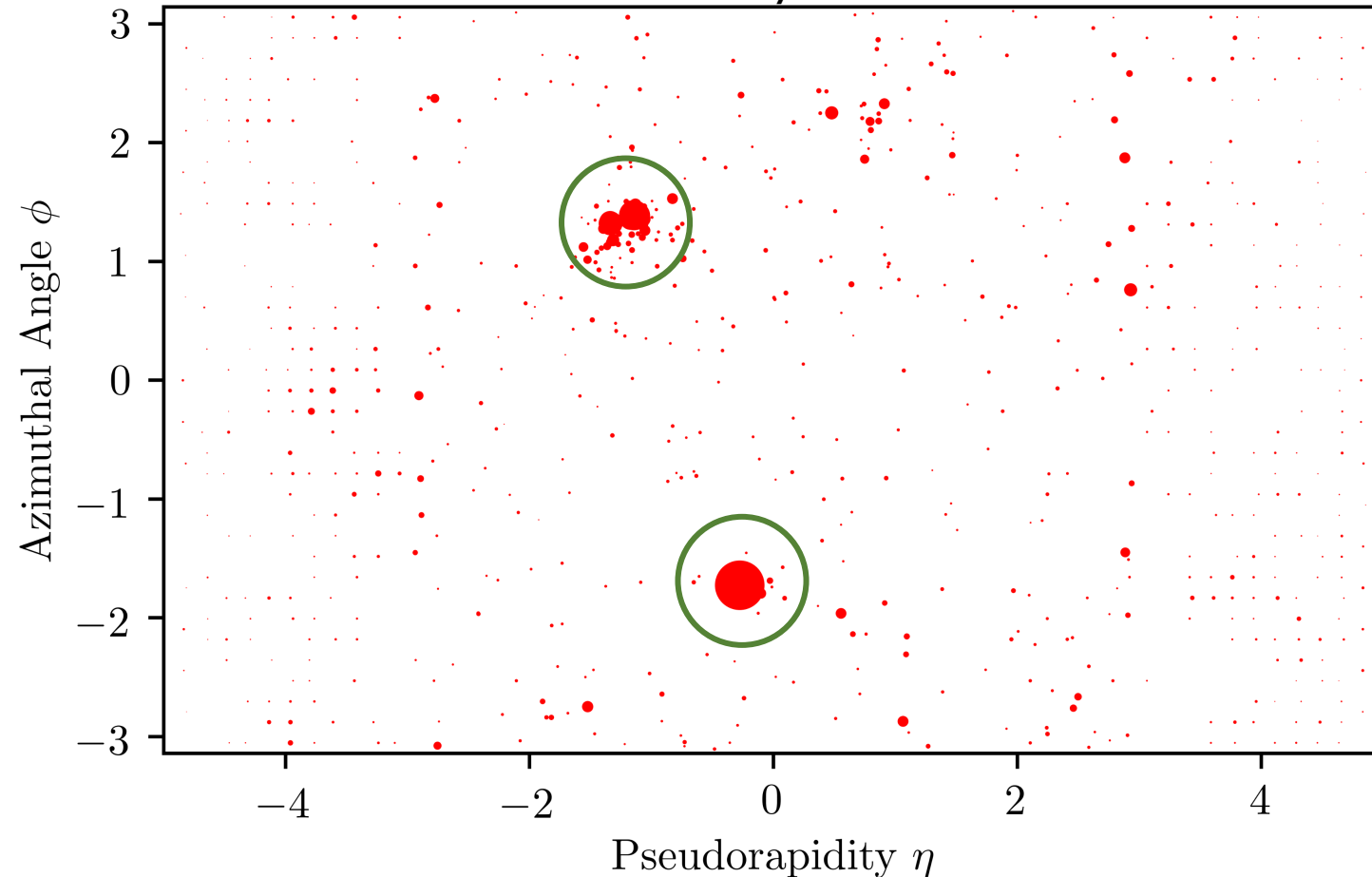
# plot settings
plt.xlim(-5, 5)
plt.ylim(-np.pi, np.pi)
plt.xlabel('Pseudorapidity  $\eta$ ')
plt.ylabel('Azimuthal Angle  $\phi$ ')

plt.show()
```

Thanks to the [uproot](#) package!



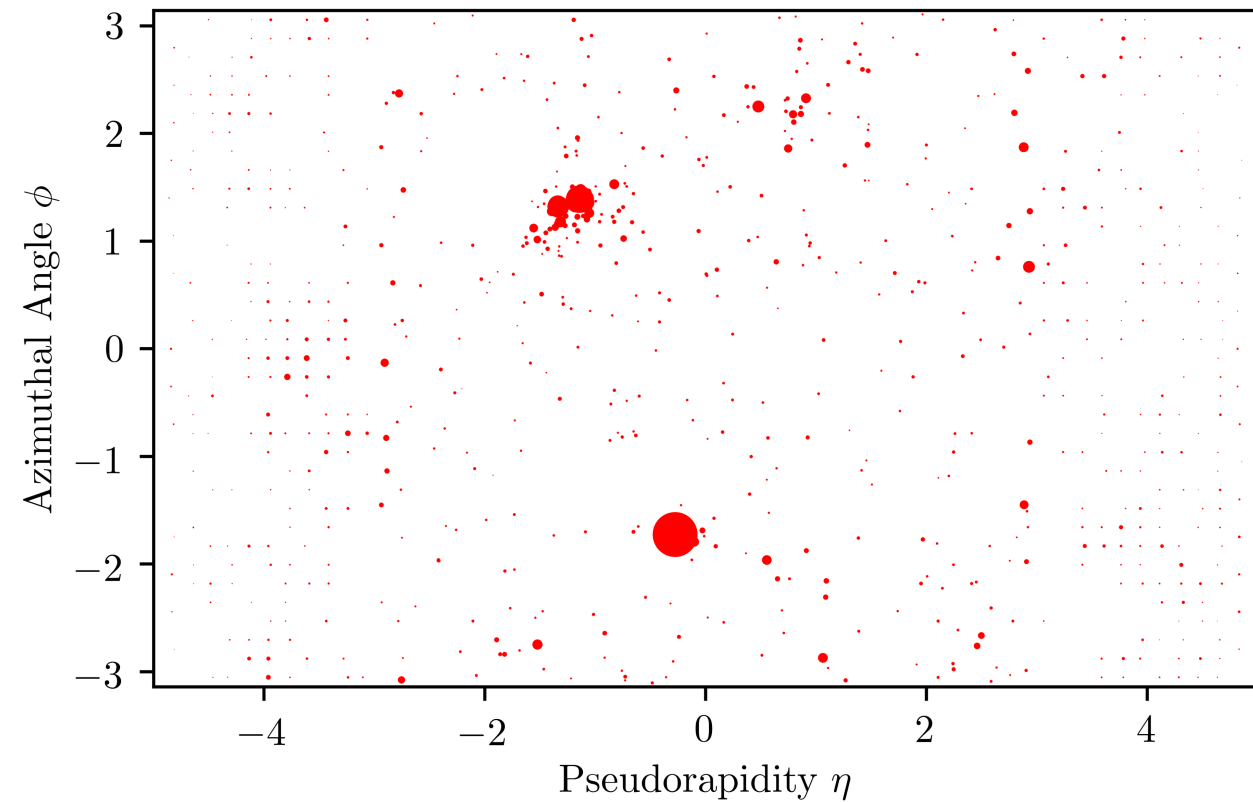
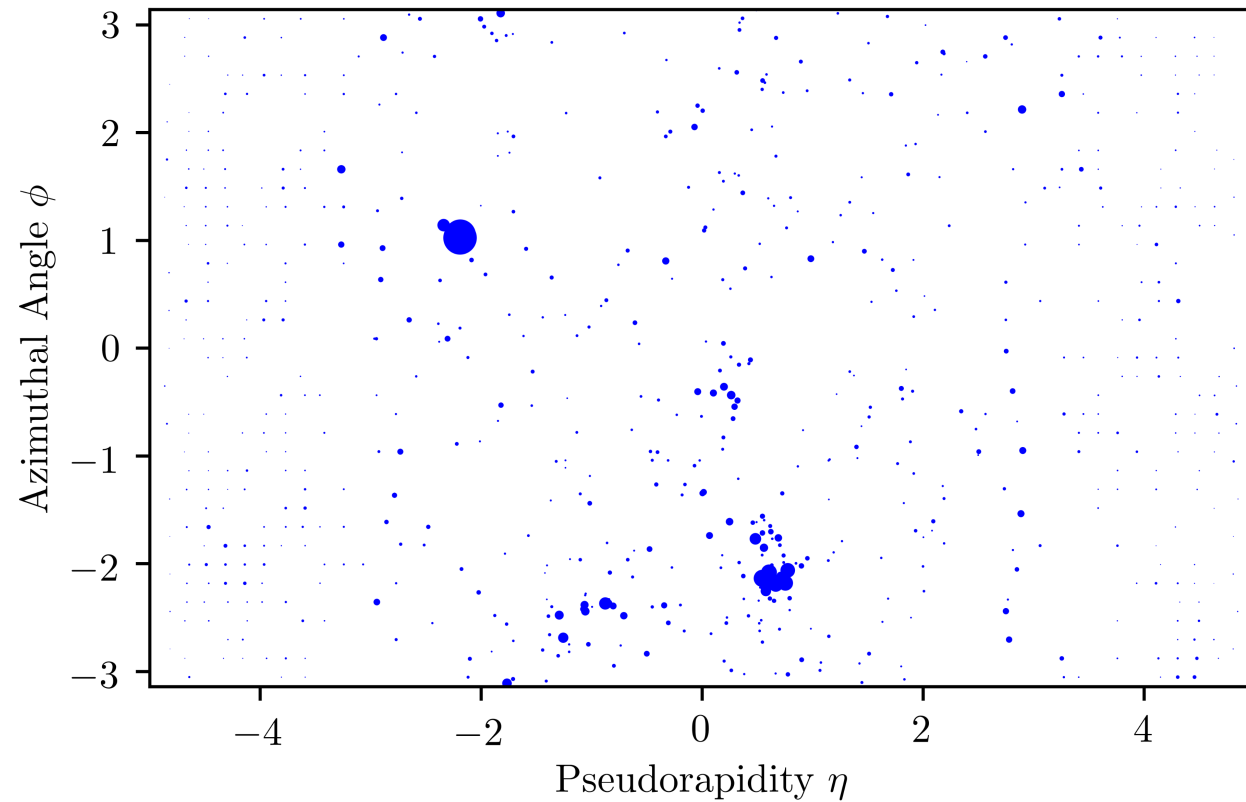
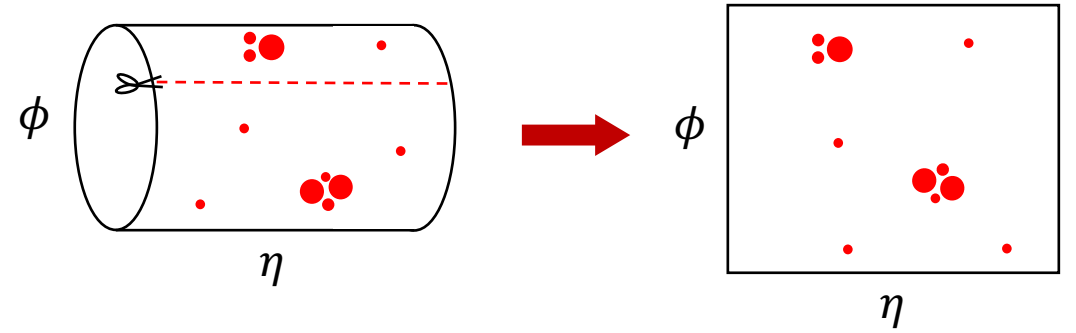
A real collision event recorded by CMS!



When are two collisions similar?

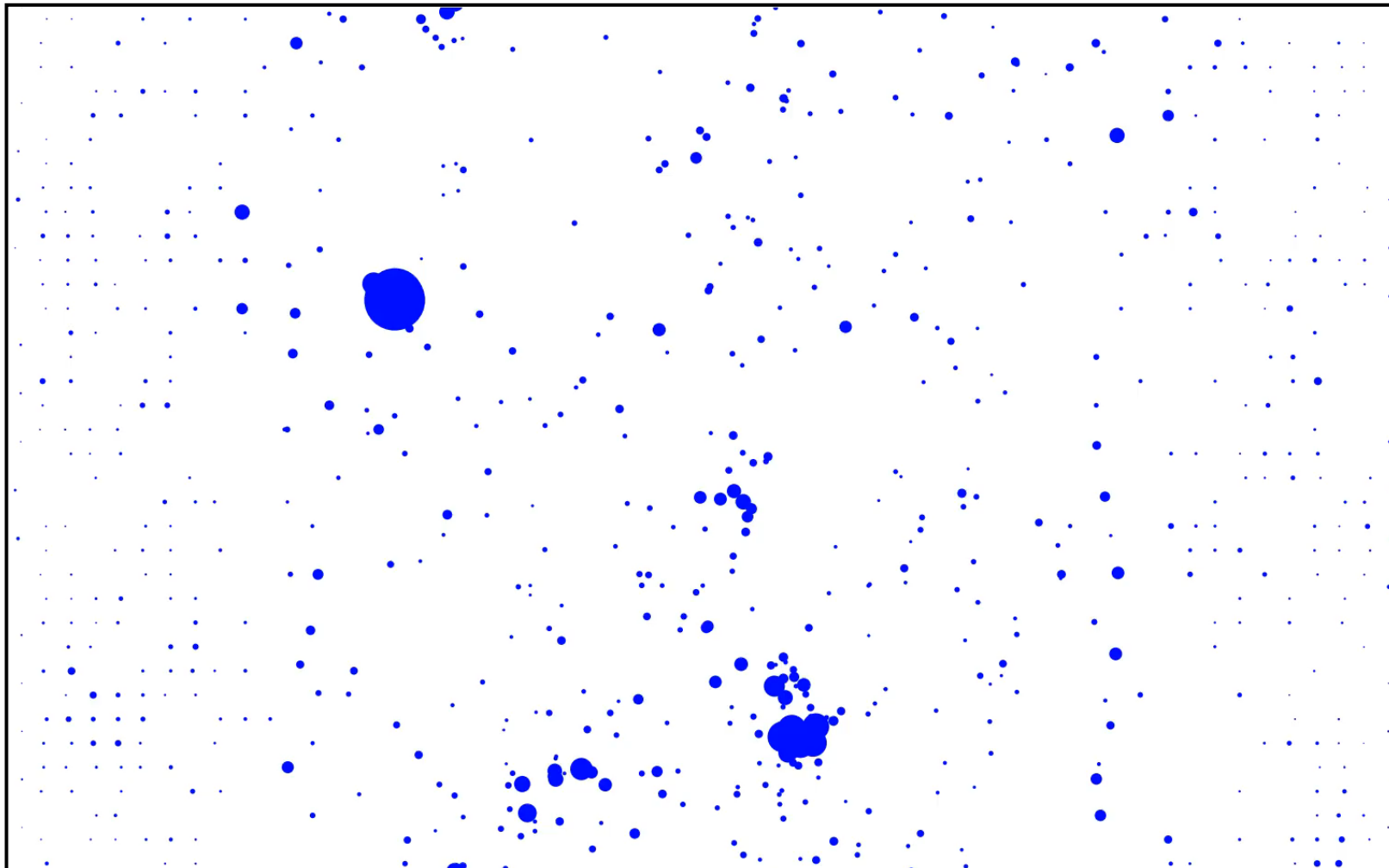
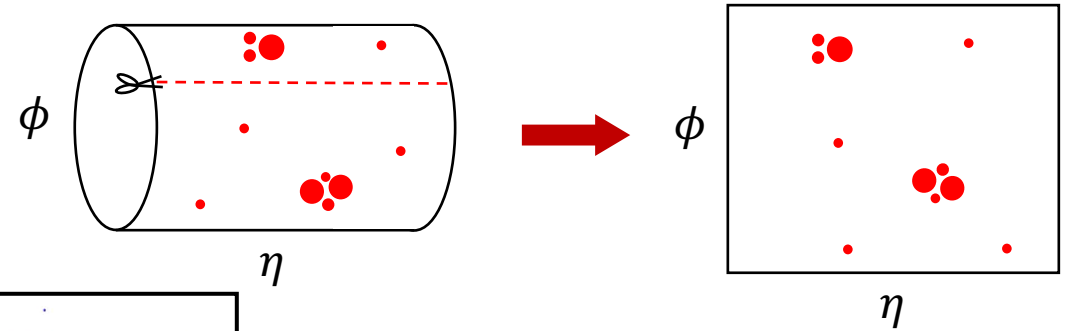
Many unsupervised methods rely on a **distance matrix**.

Need a physically-sensible **metric** between events!



When are two collisions similar?

The Earth Mover's (or Wasserstein) Distance



The “work” required to rearrange one collision event into another!

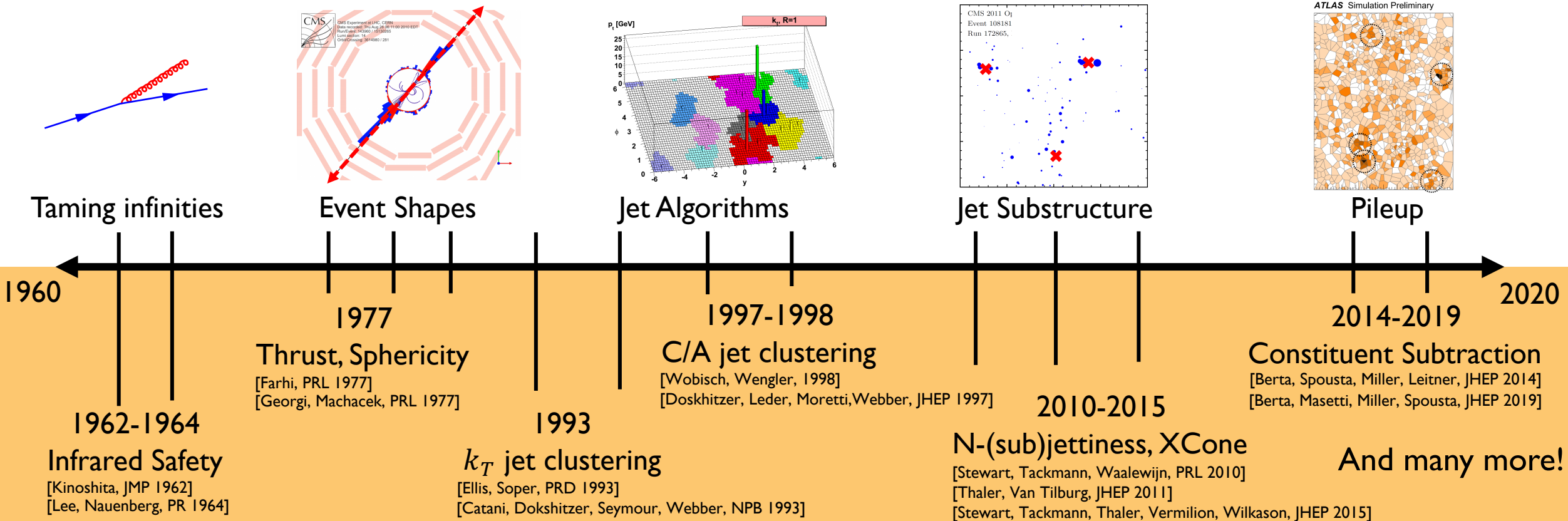
Plus a cost to create or destroy energy.

Optimal Transport Problem

Here using [python optimal transport](#)

[Komiske, **EMM**, Thaler, PRL 2019]

Six Decades of Collider Techniques



Six Decades of Collider Techniques as Optimal Transport!

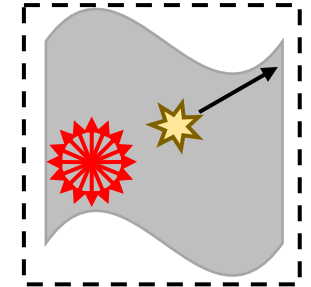
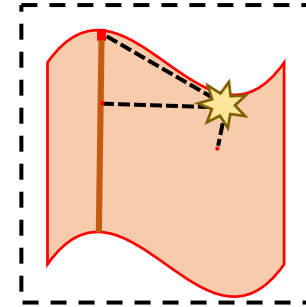
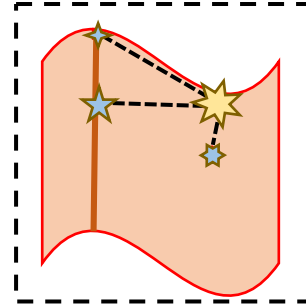
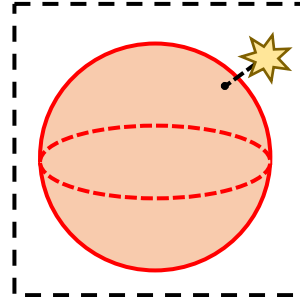
[Komiske, **EMM**, Thaler, *to appear*]

Smooth function of energy distribution are finite in QFT

Event shapes as distances to the 2-particle manifold

Jets are N-particle event approximations

Subtract a pileup as a uniform distribution



$$\text{EMD}(\mathcal{E}, \mathcal{E}') < \delta \rightarrow |\mathcal{O}(\mathcal{E}) - \mathcal{O}(\mathcal{E}')| < \epsilon$$

$$t(\mathcal{E}) = \min_{|\mathcal{E}'|=2} \text{EMD}(\mathcal{E}, \mathcal{E}')$$

$$\mathcal{J}(\mathcal{E}) = \operatorname{argmin}_{|\mathcal{E}'|=N} \text{EMD}(\mathcal{E}, \mathcal{E}')$$

$$\mathcal{E} - \mathcal{U}$$

Taming infinities

Event Shapes

Jet Algorithms

Jet Substructure

Pileup

1960

1962-1964

Infrared Safety

[Kinoshita, JMP 1962]
[Lee, Nauenberg, PR 1964]

1977

Thrust, Sphericity

[Farhi, PRL 1977]
[Georgi, Machacek, PRL 1977]

1993

k_T jet clustering

[Ellis, Soper, PRD 1993]
[Catani, Dokshitzer, Seymour, Webber, NPB 1993]

1997-1998

C/A jet clustering

[Wobisch, Wengler, 1998]
[Doskhitzer, Leder, Moretti, Webber, JHEP 1997]

2010-2015

N-(sub)jettiness, XCone

[Stewart, Tackmann, Waalewijn, PRL 2010]
[Thaler, Van Tilburg, JHEP 2011]
[Stewart, Tackmann, Thaler, Vermilion, Wilkason, JHEP 2015]

2014-2019

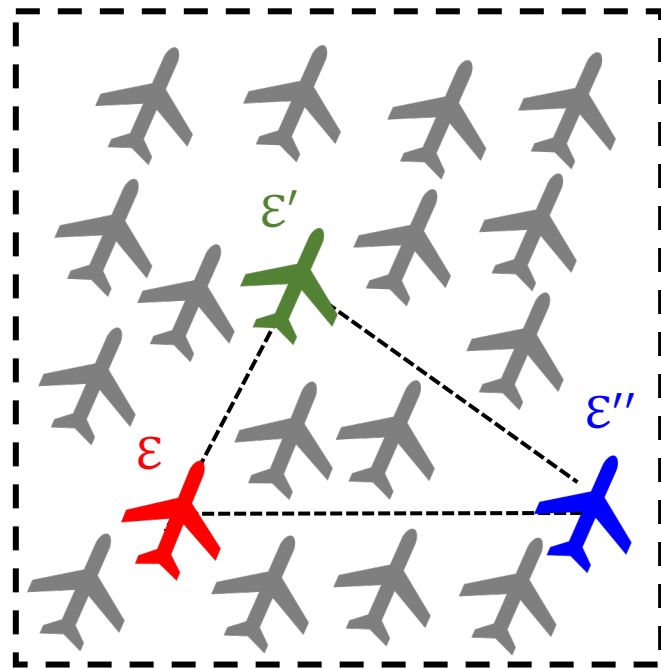
Constituent Subtraction

[Berta, Spousta, Miller, Leitner, JHEP 2014]
[Berta, Masetti, Miller, Spousta, JHEP 2019]

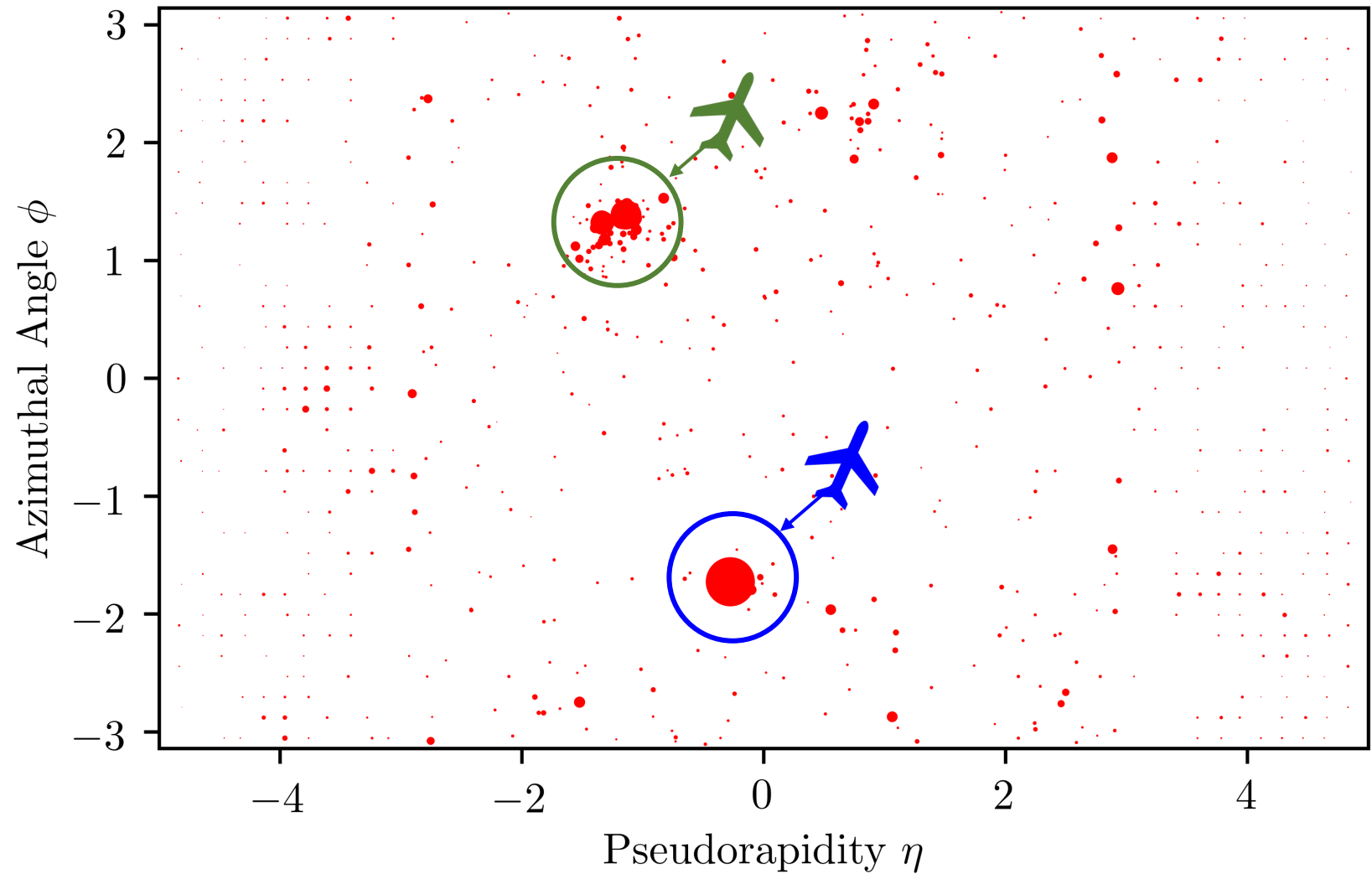
And many more!

2020

Exploring the Space of Jets



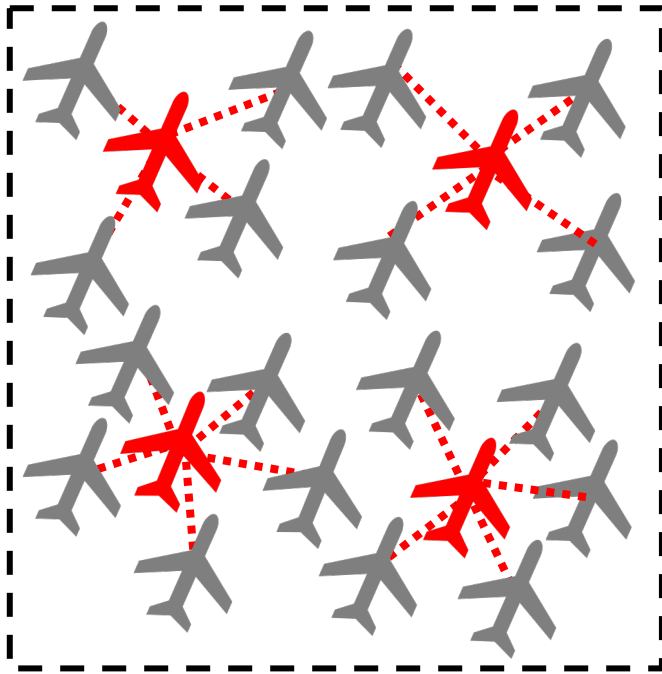
$$\text{EMD}(\mathcal{E}, \mathcal{E}') + \text{EMD}(\mathcal{E}', \mathcal{E}'') \geq \text{EMD}(\mathcal{E}, \mathcal{E}'')$$



Most Representative Jets

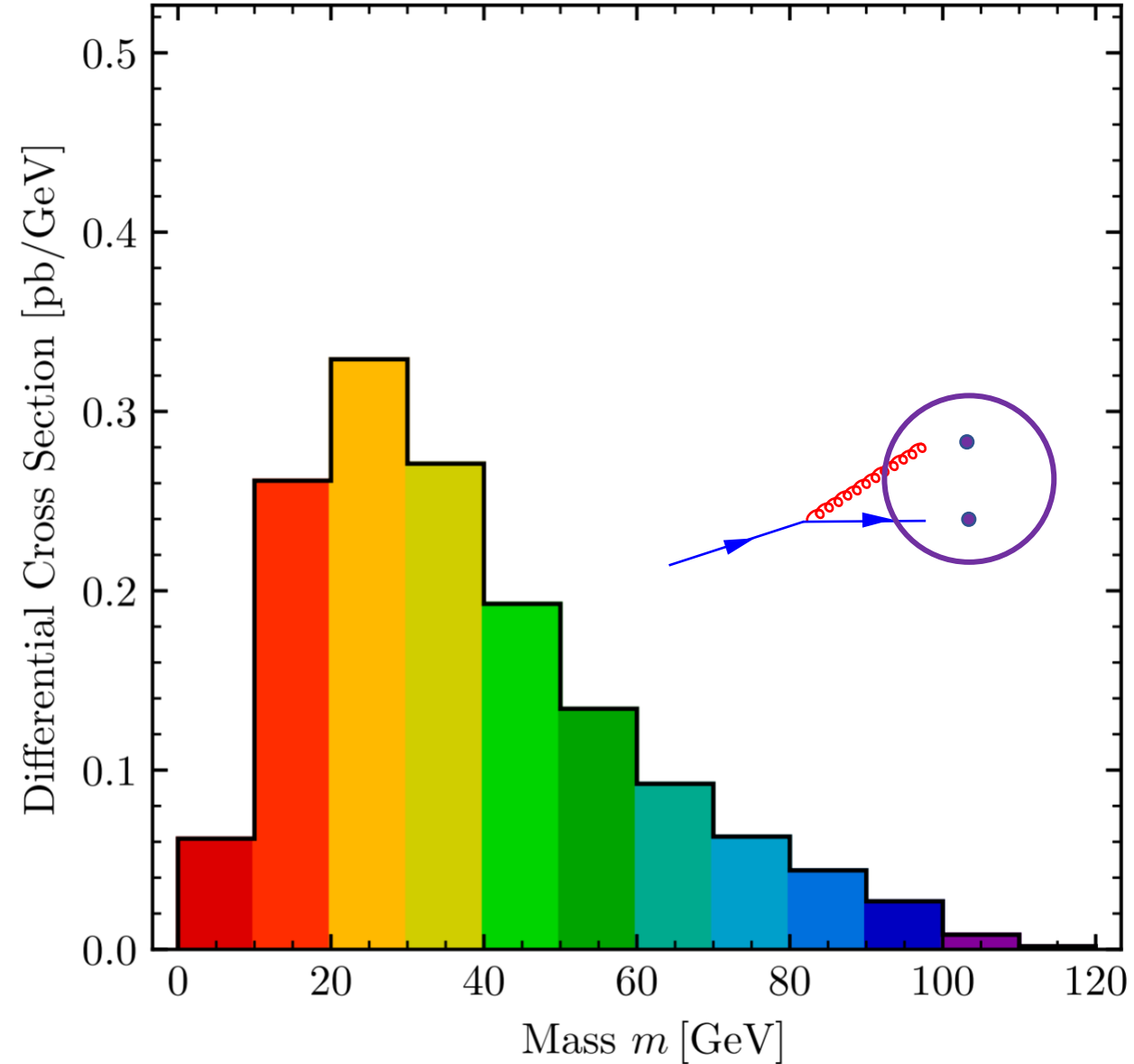
$$\text{Jet Mass: } m = \left(\sum_{i=1}^M p_i^\mu \right)^2$$

Measures how “wide” the jet is.



MOD

Jet Mass Histogram

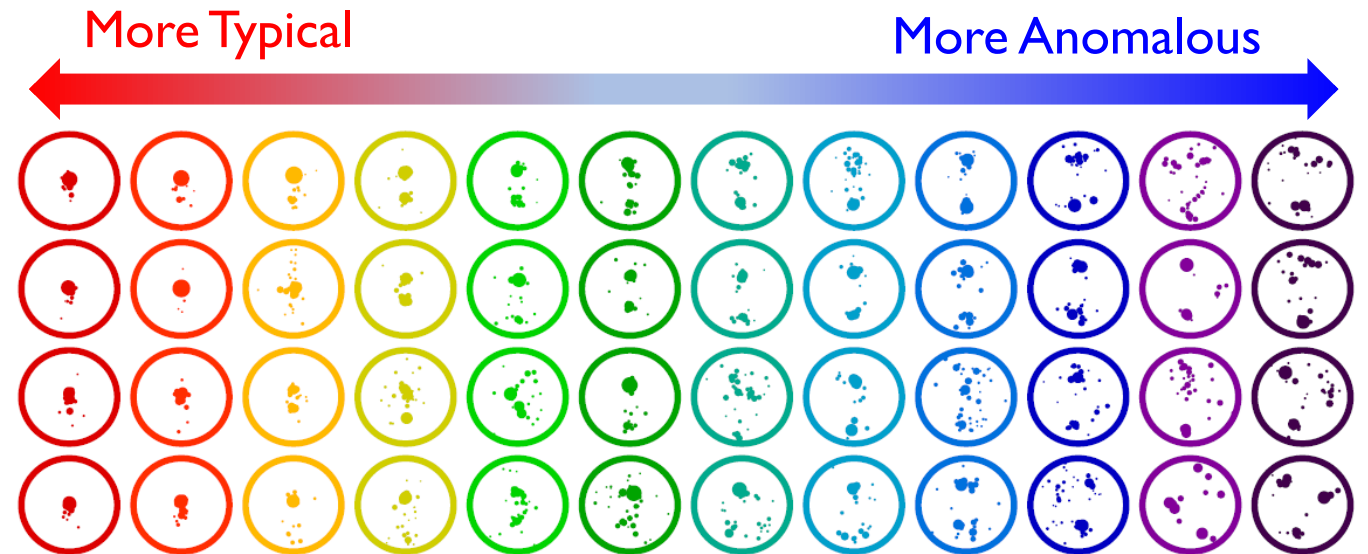
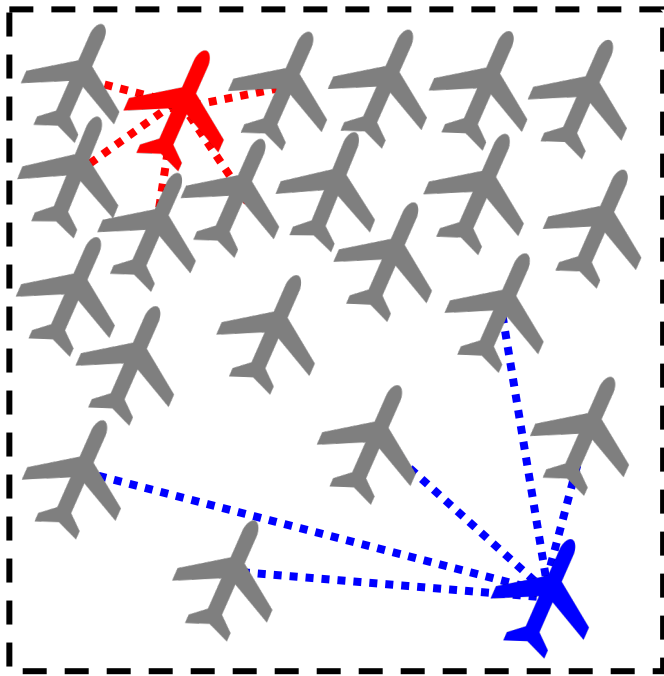


[Komiske, Mastandrea, EMM, Naik, Thaler, 1908.08542]

Towards Anomaly Detection

Mean EMD to Dataset:

$$\bar{Q}(\mathcal{E}) = \sum_{i=1}^N \text{EMD}(\mathcal{E}, \mathcal{E}_i)$$



Complements recent developments in anomaly detection for collider physics.

[\[Collins, Howe, Nachman, 1805.02664\]](#)

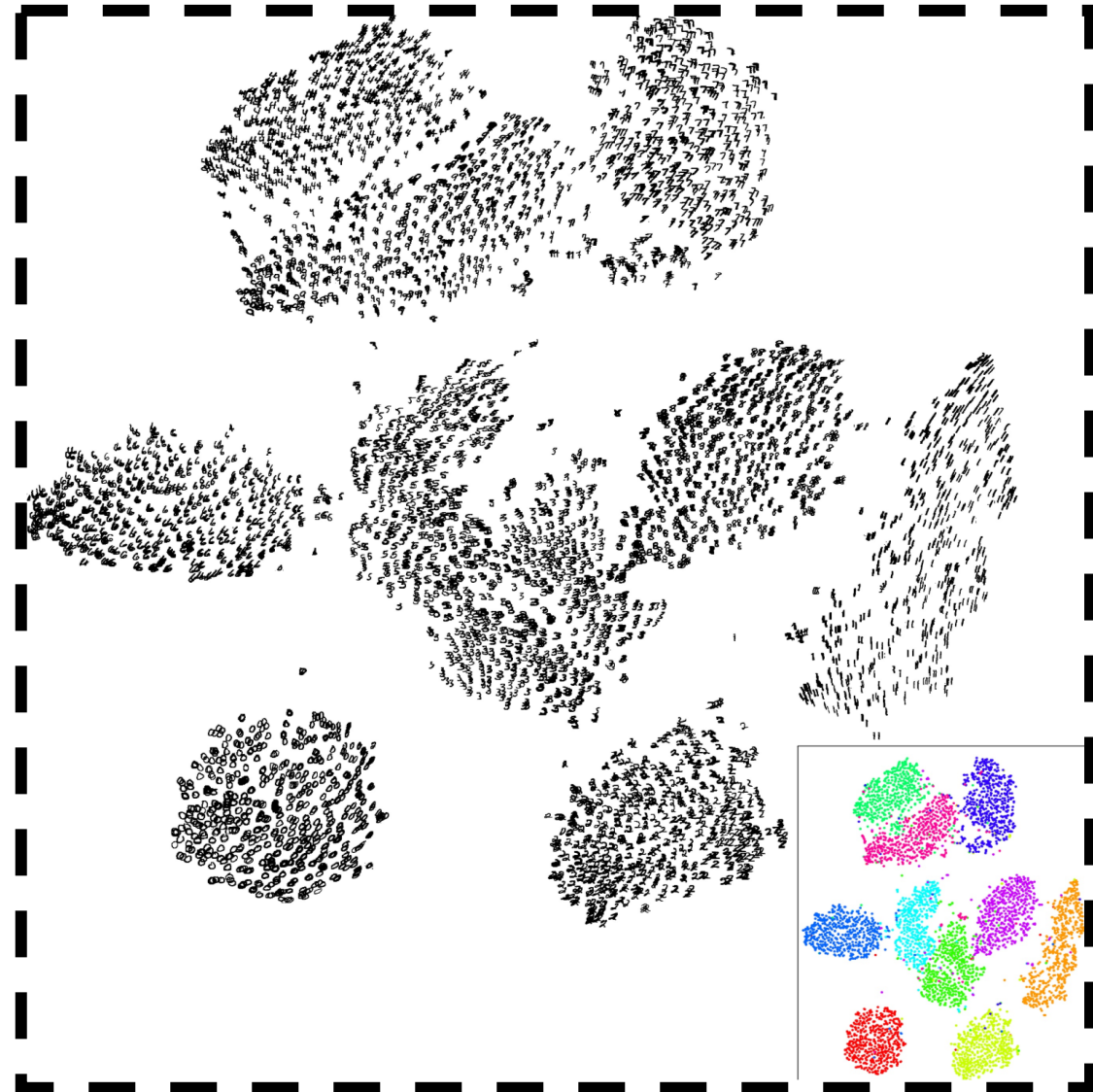
[\[Heimel, Kasieczka, Plehn, Thompson, 1808.08979\]](#)

[\[Farina, Nakai, Shih, 1808.08992\]](#)

[\[Cerri, Nguyen, Pierini, Spiropulu, Vlimant, 1811.10276\]](#)

Visualizing the Manifold

What does the space of jets look like?

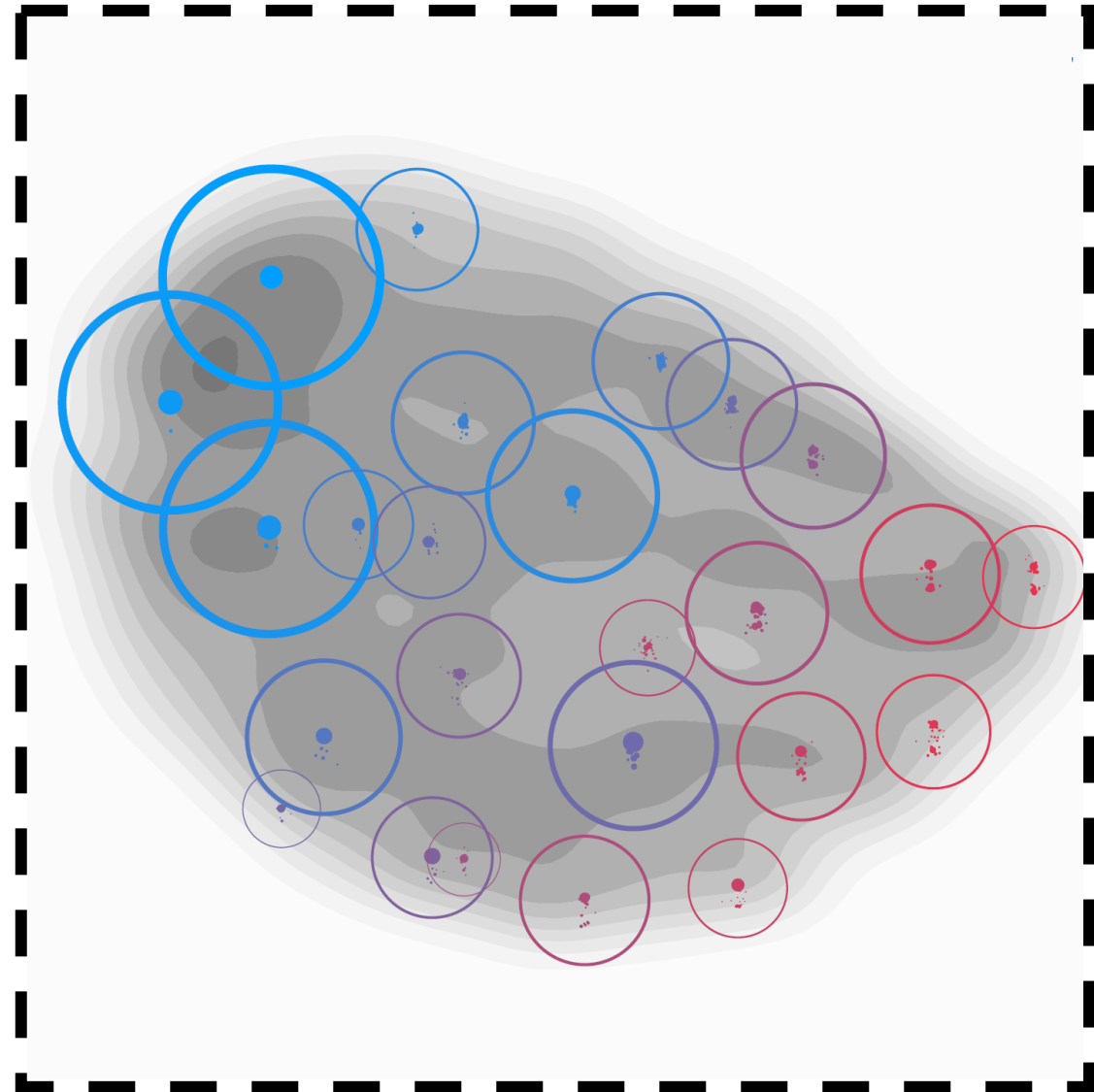
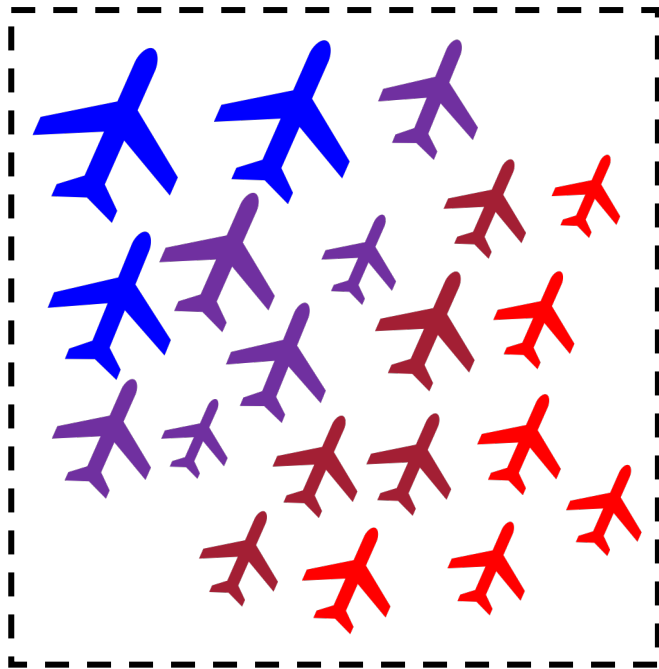


t-SNE embedding

[van der Maaten, Hinton, JMLR 2008]

Visualizing the Manifold

What does the space of jets look like?



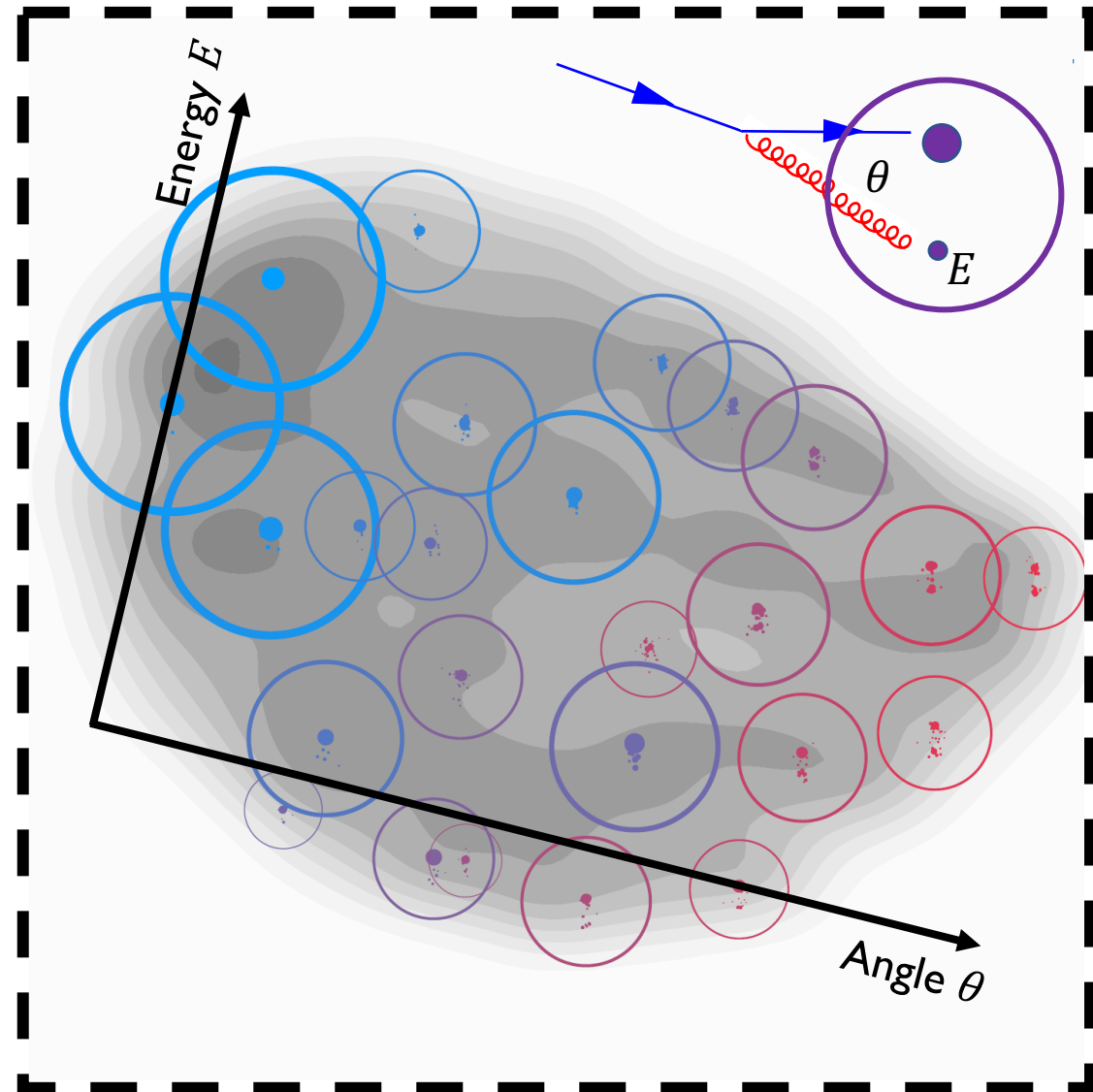
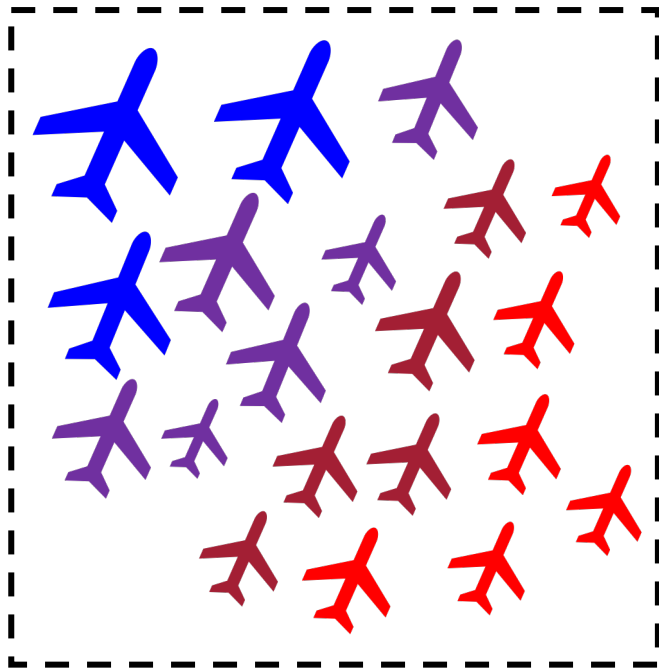
t-SNE embedding: 25-medoid jets shown

[van der Maaten, Hinton, JMLR 2008]

[[Komiske, Mastandrea, EMM, Naik, Thaler, 1908.08542](#)]

Visualizing the Manifold

What does the space of jets look like?



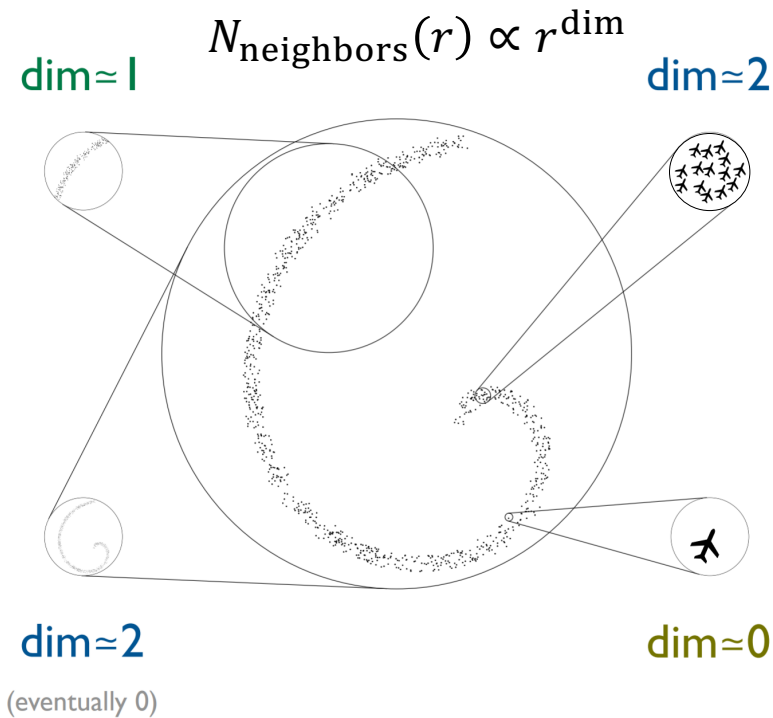
t-SNE embedding: 25-medoid jets shown

[van der Maaten, Hinton, JMLR 2008]

[[Komiske, Mastandrea, EMM, Naik, Thaler, 1908.08542](#)]

Correlation Dimension

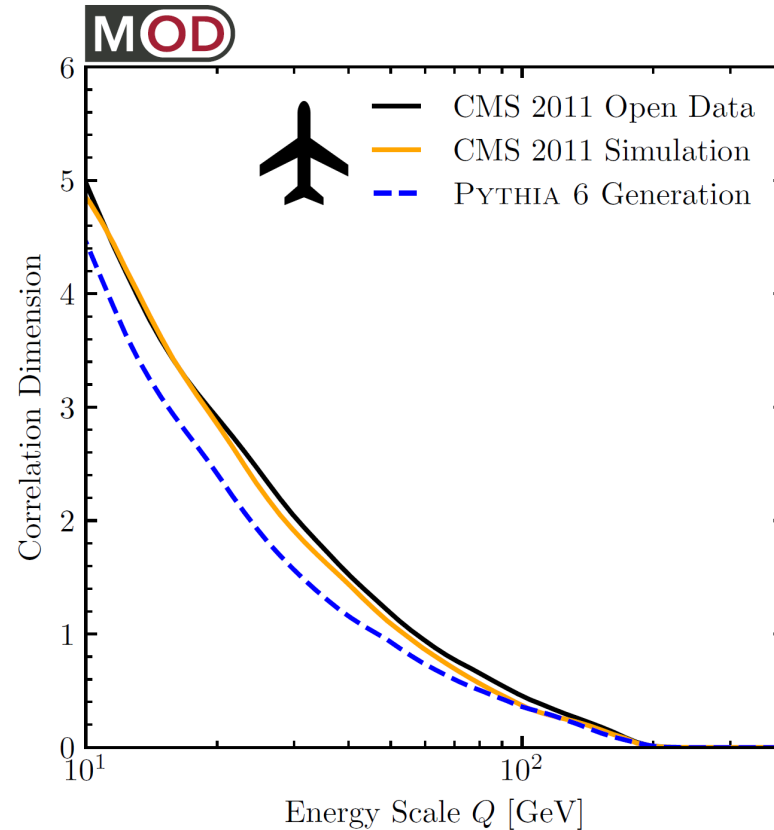
Conceptual Idea



$$\text{dim}(Q) = Q \frac{\partial}{\partial Q} \ln \sum_{i=1}^N \sum_{j=1}^N \Theta[\text{EMD}(\epsilon_i, \epsilon_j) < Q]$$

[Grassberger, Procaccia, PRL 1983] [Kegl, NeurIPS 2002]

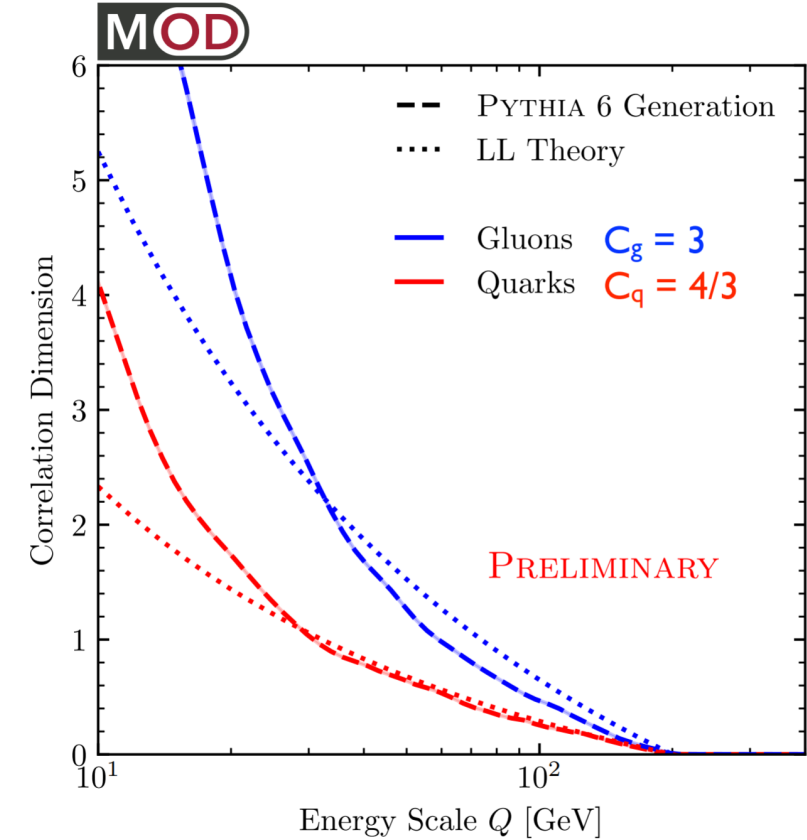
Experimental Data



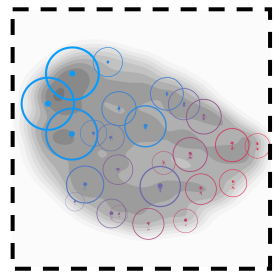
Dimension blows up at low energies.

[Komiske, Mastandrea, EMM, Naik, Thaler, 1908.08542]

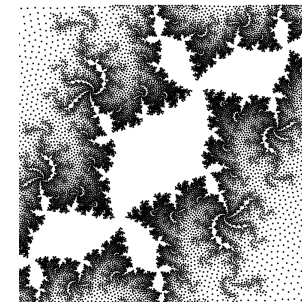
Theoretical Calculation



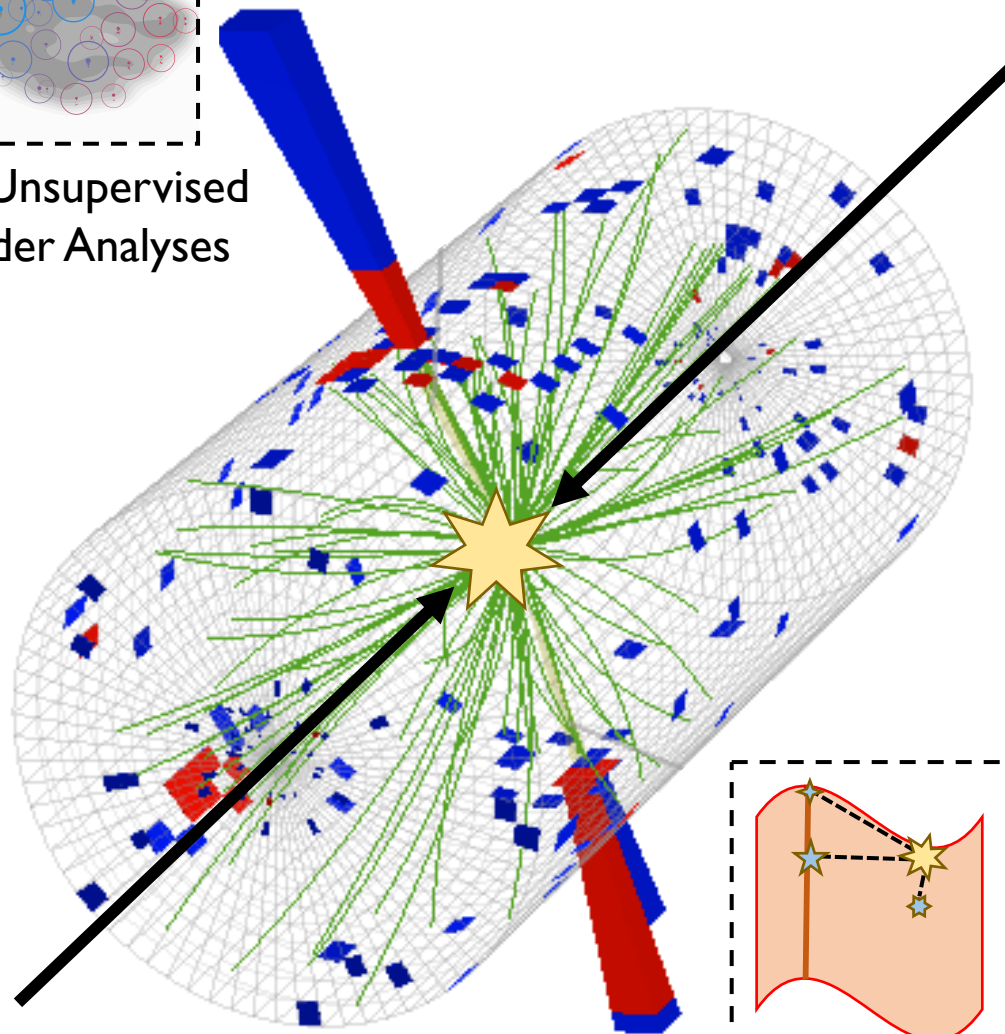
Thank You!



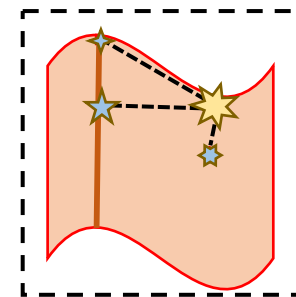
New Unsupervised
Collider Analyses



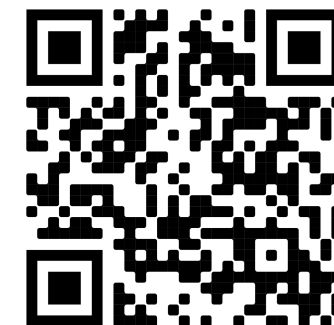
Optimal Transport
[\[OTML Workshop, NeurIPS 2019\]](#)



Public Collider Data
[\[opendata.cern.ch\]](https://opendata.cern.ch)

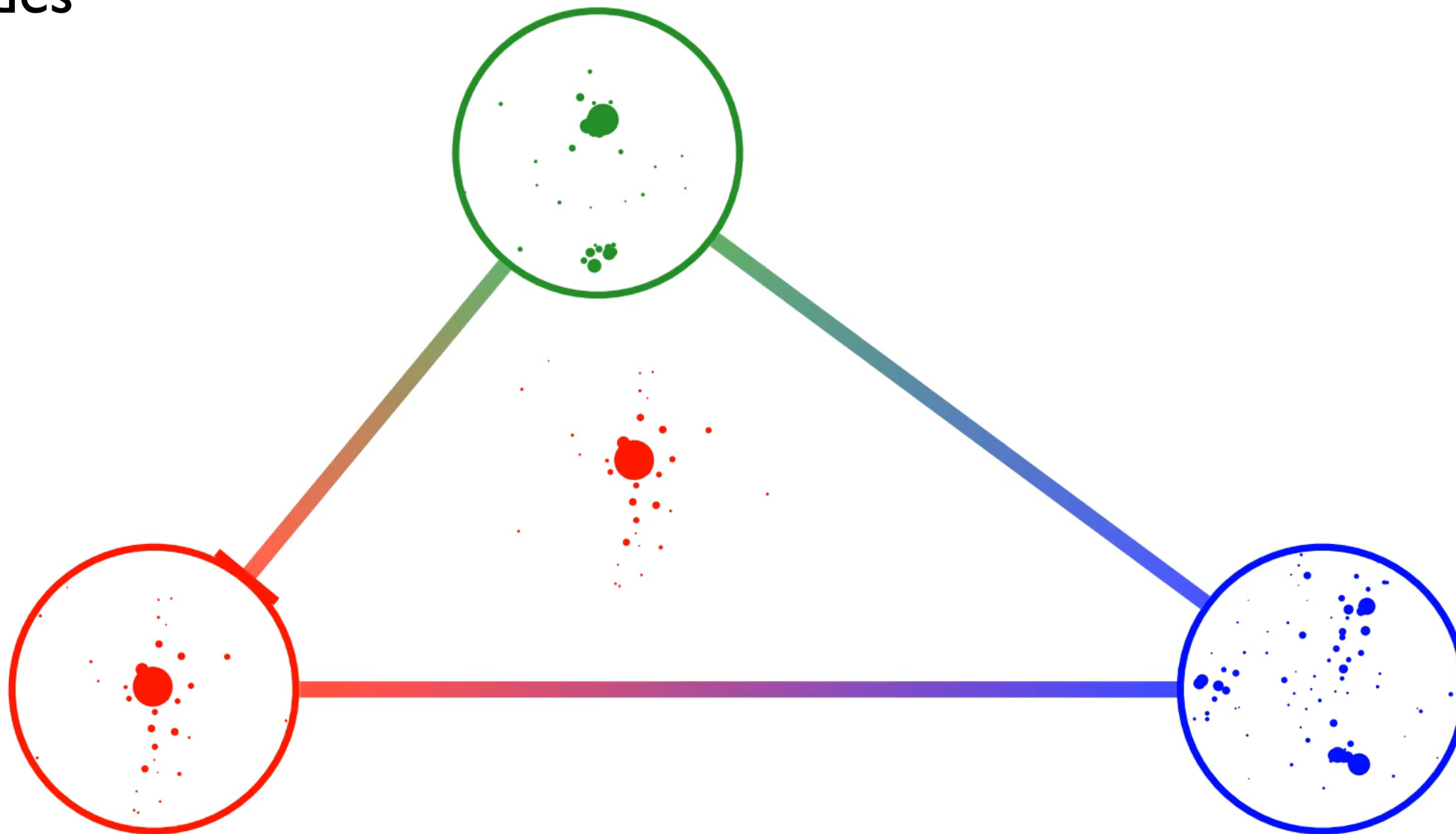


New Insights into
Quantum Field Theory

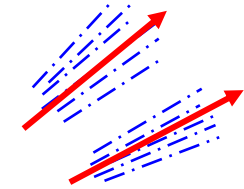


[Publicly released
jet dataset](#)

Extra Slides



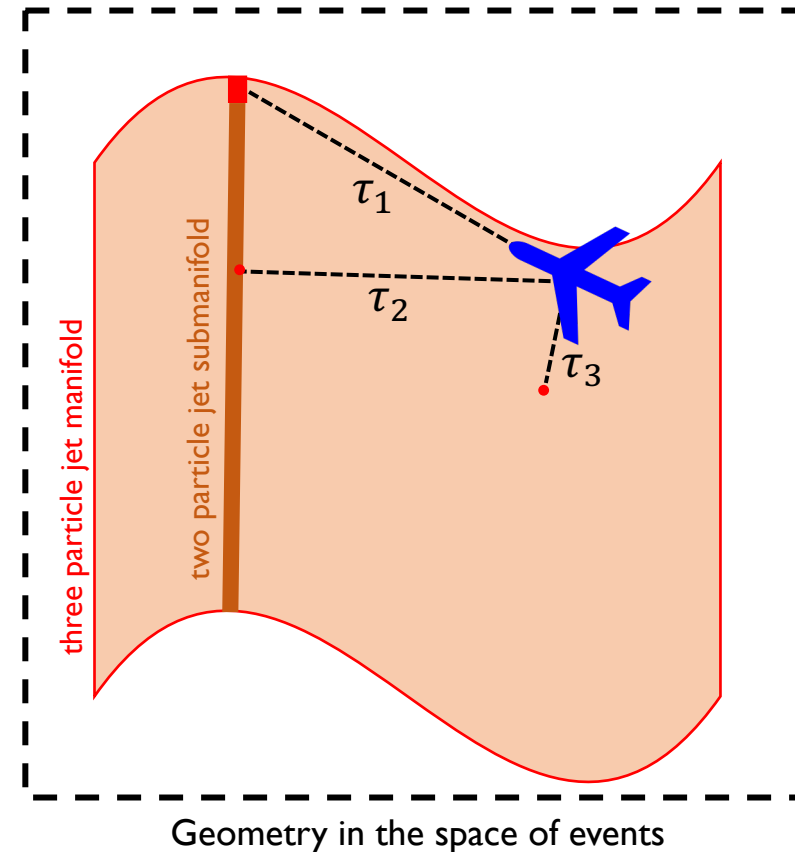
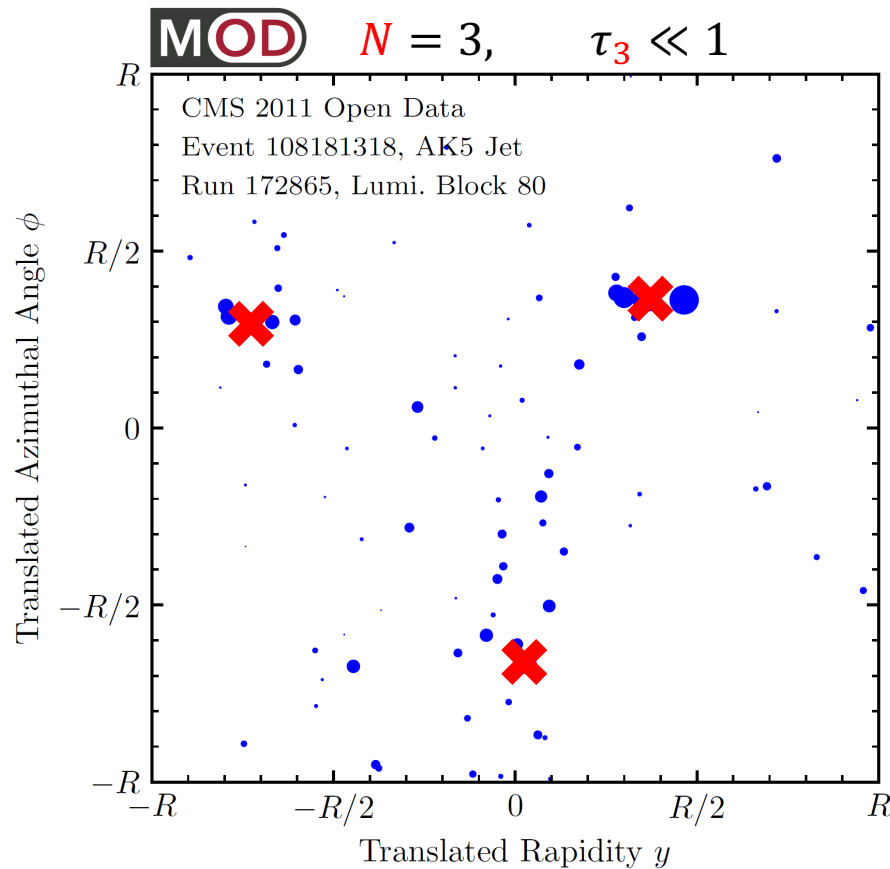
A Geometric Language for Observables



N -(sub)jettiness is the EMD between the **event** and the closest N -particle event.

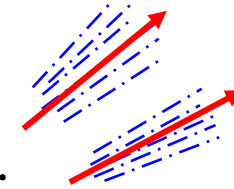
$$\tau_N(\mathcal{E}) = \min_{N \text{ axes}} \sum_{i=1}^M E_i \min\{\theta_{1,i}^\beta, \theta_{2,i}^\beta, \dots, \theta_{N,i}^\beta\} \longrightarrow \tau_N(\mathcal{E}) = \min_{|\mathcal{E}'|=N} \text{EMD}(\mathcal{E}, \mathcal{E}').$$

β -Wasserstein distance



A Geometric Language for Observables

Thrust is the EMD between the **event** and the closest **two-particle** event.



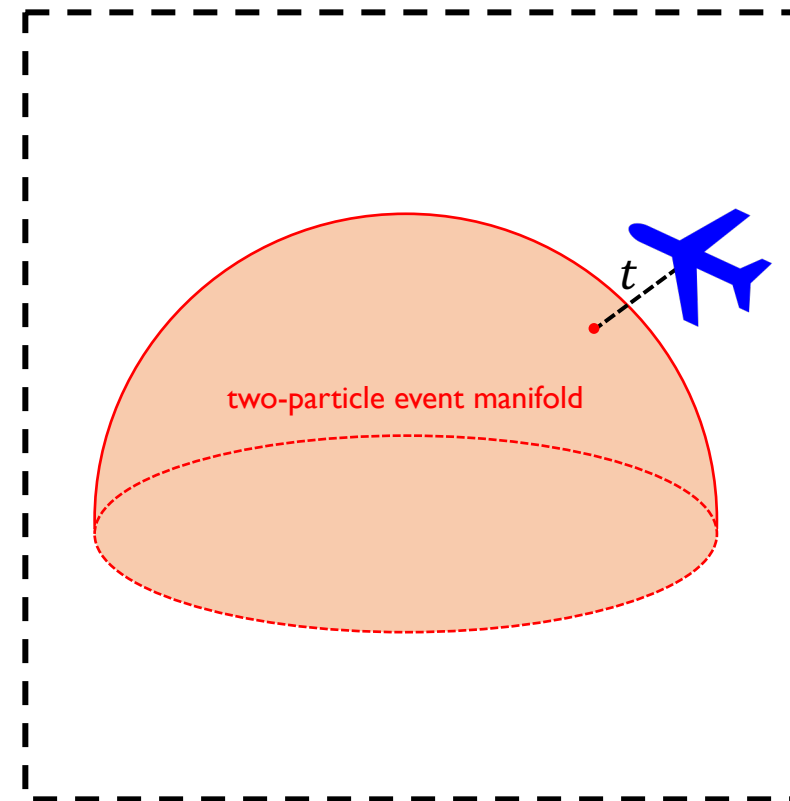
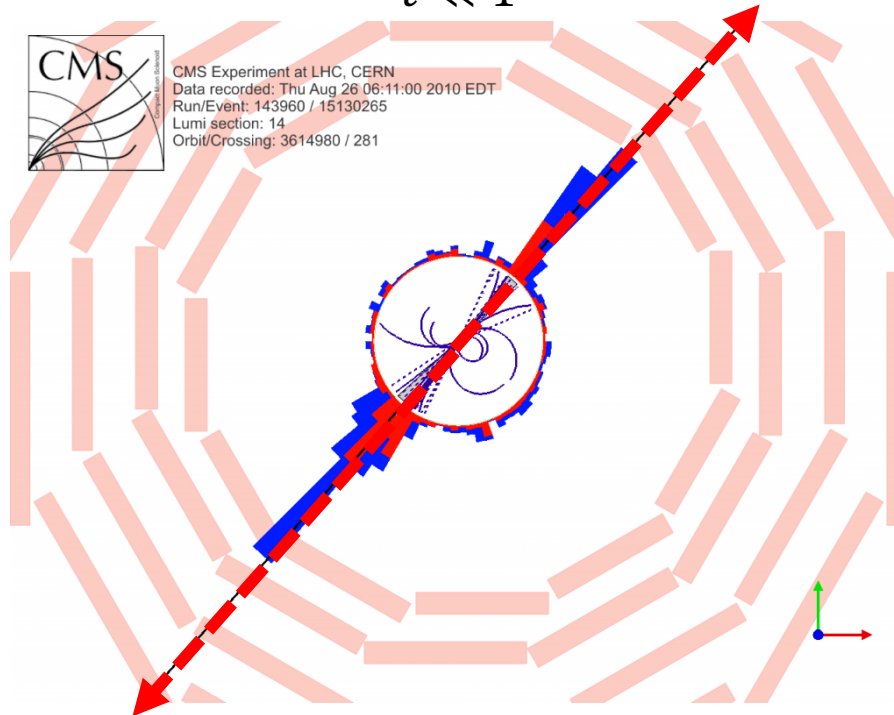
$$t(\mathcal{E}) = E - \max_{\hat{n}} \sum_i |\vec{p}_i \cdot \hat{n}|$$



$$t(\mathcal{E}) = \min_{|\mathcal{E}'|=2} \text{EMD}(\mathcal{E}, \mathcal{E}')$$

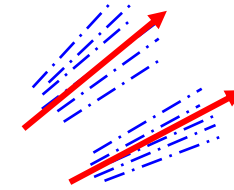
$$\text{with } \theta_{ij} = \hat{n}_i \cdot \hat{n}_j, \quad \hat{n} = \vec{p}/E$$

$$t \ll 1$$



Geometry in the space of events

A Geometric Language for Observables

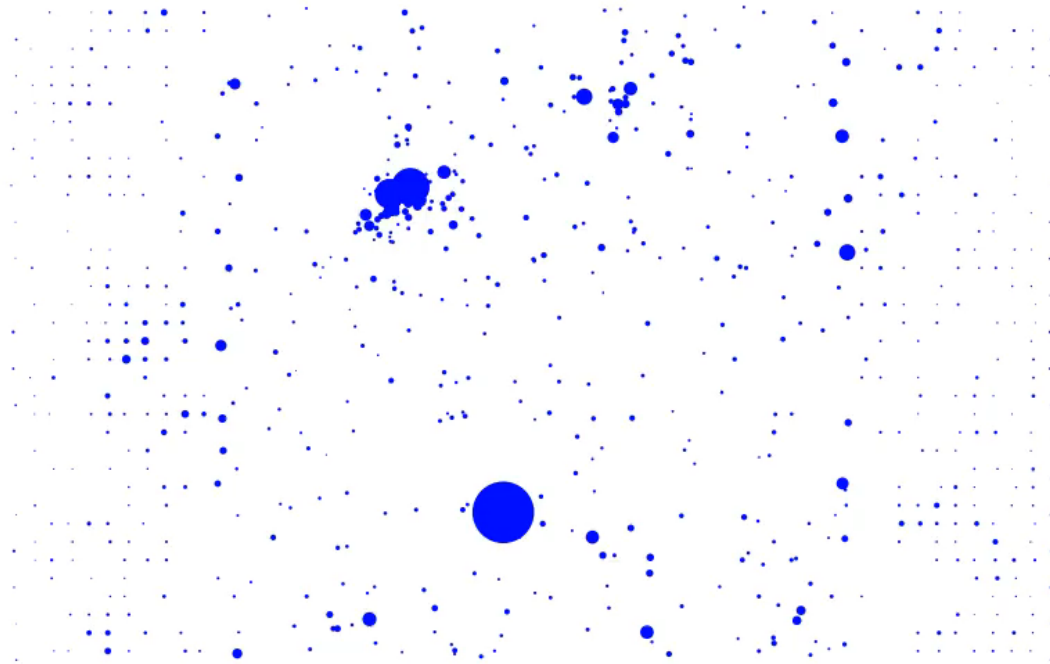


Isotropy is a new observable to probe how “uniform” an event is.

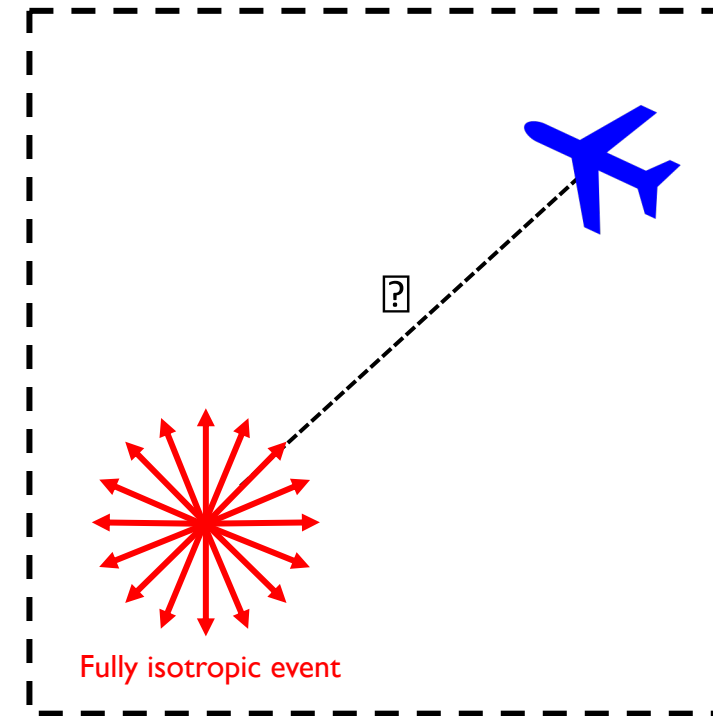
It is sensitive to very different new physics signals than existing event shapes.

e.g. uniform radiation from micro black holes [\[Cari Cesarotti and Jesse Thaler, coming soon!\]](#)

$$\mathcal{I}(\mathcal{E}) = \text{EMD}(\mathcal{E}, \mathcal{E}_{\text{iso}}) \text{ where } \mathcal{E}_{\text{iso}} \text{ is a fully isotropic event}$$

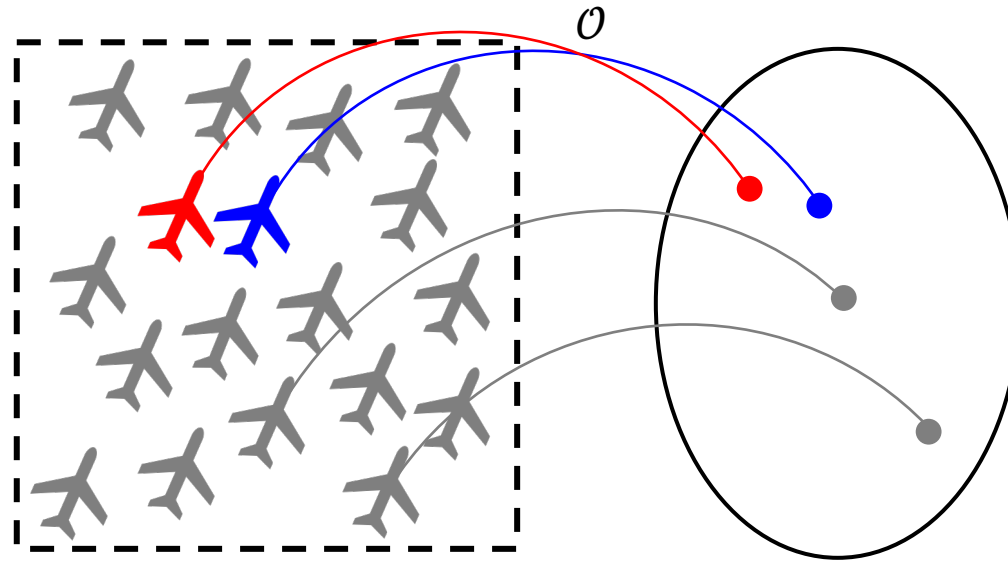


dijet event from CMS Open Data



A Geometric Language for Observables

Events close in EMD are close in any infrared and collinear safe observable!



Additive IRC-safe observables:
$$\mathcal{O}(\mathcal{E}) = \sum_{i=1}^M E_i \Phi(\hat{n}_i)$$

Energy Mover's
Distance

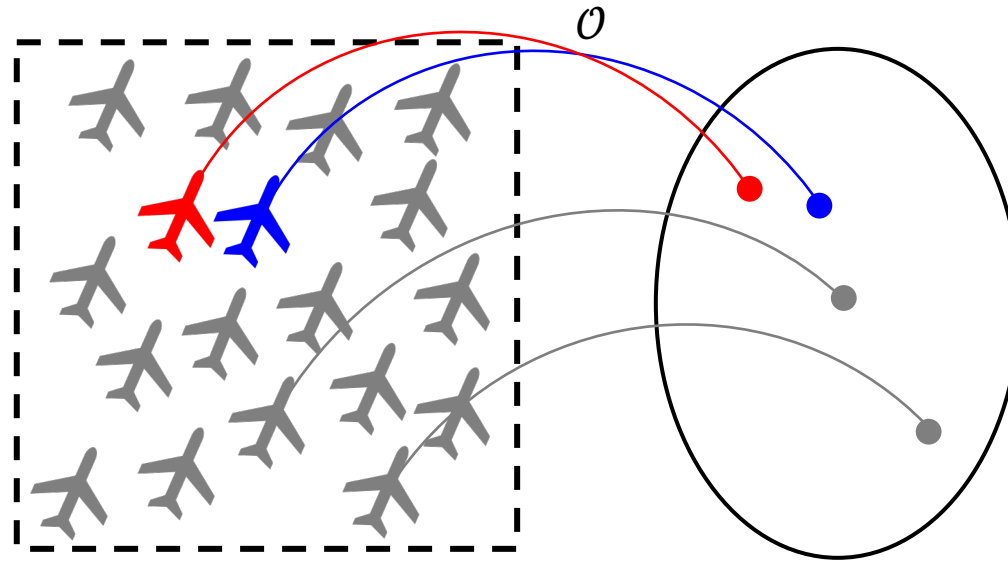
$$\text{EMD}(\mathcal{E}, \mathcal{E}') \geq \frac{1}{RL} |\mathcal{O}(\mathcal{E}) - \mathcal{O}(\mathcal{E}')|$$

Difference in
observable values

↑
“Lipschitz constant” of Φ
i.e. bound on its derivative

A Geometric Language for Observables

Events close in EMD are close in any infrared and collinear safe observable!



Jet angularities with $\beta \geq 1$:

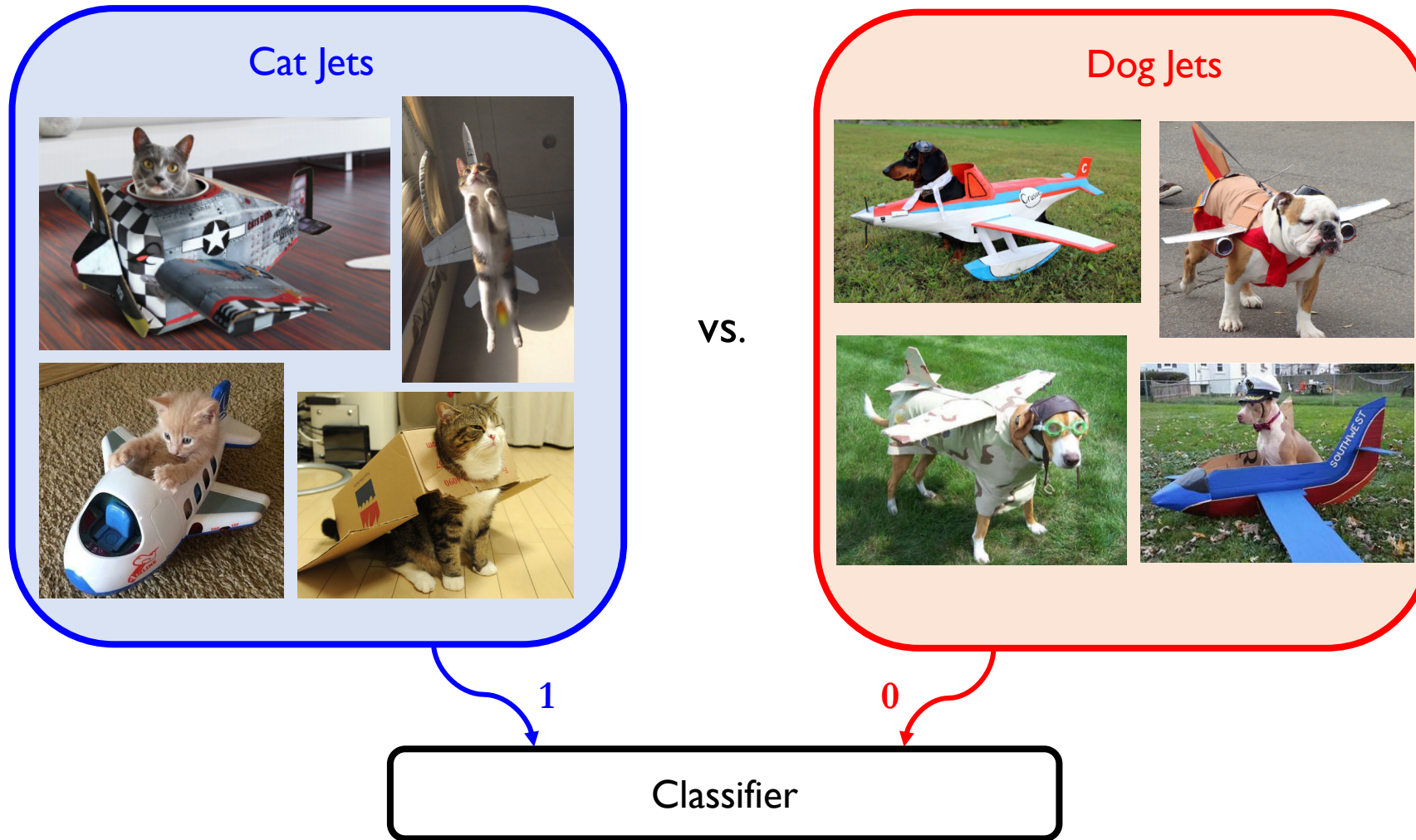
[\[C. Berger, T. Kucs, and G. Sterman, 0303051\]](#)

[\[A. Larkoski, J. Thaler, and W. Waalewijn, 1408.3122\]](#)

$$\lambda^{(\beta)} = \sum_{i=1}^M E_i \theta_i^\beta$$

$$|\lambda^{(\beta)}(\mathcal{E}) - \lambda^{(\beta)}(\mathcal{E}')| \leq \beta \text{EMD}(\mathcal{E}, \mathcal{E}')$$

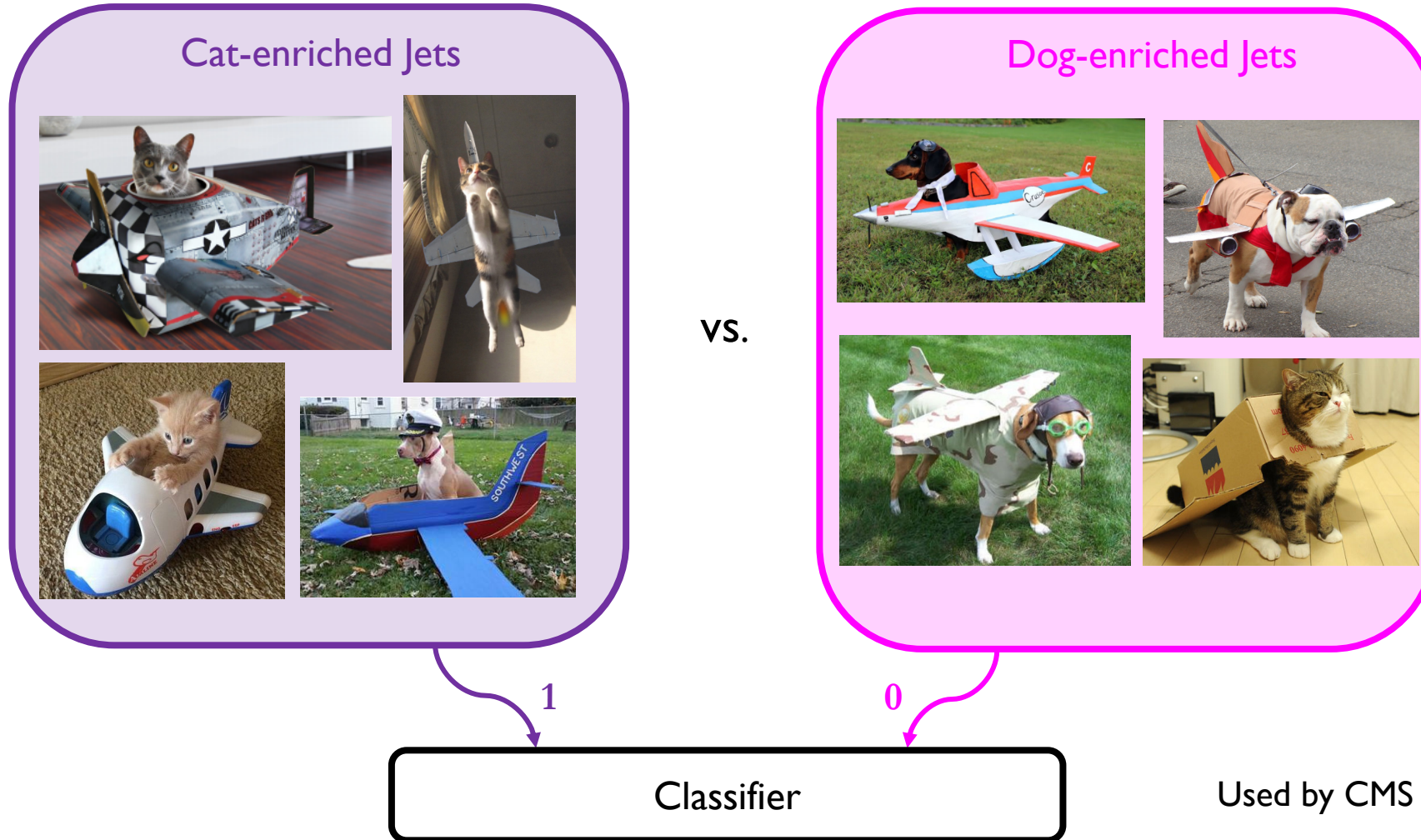
Training on pure samples: Cat jets vs. Dog jets



Training on mixed samples: Cat jets vs. Dog jets

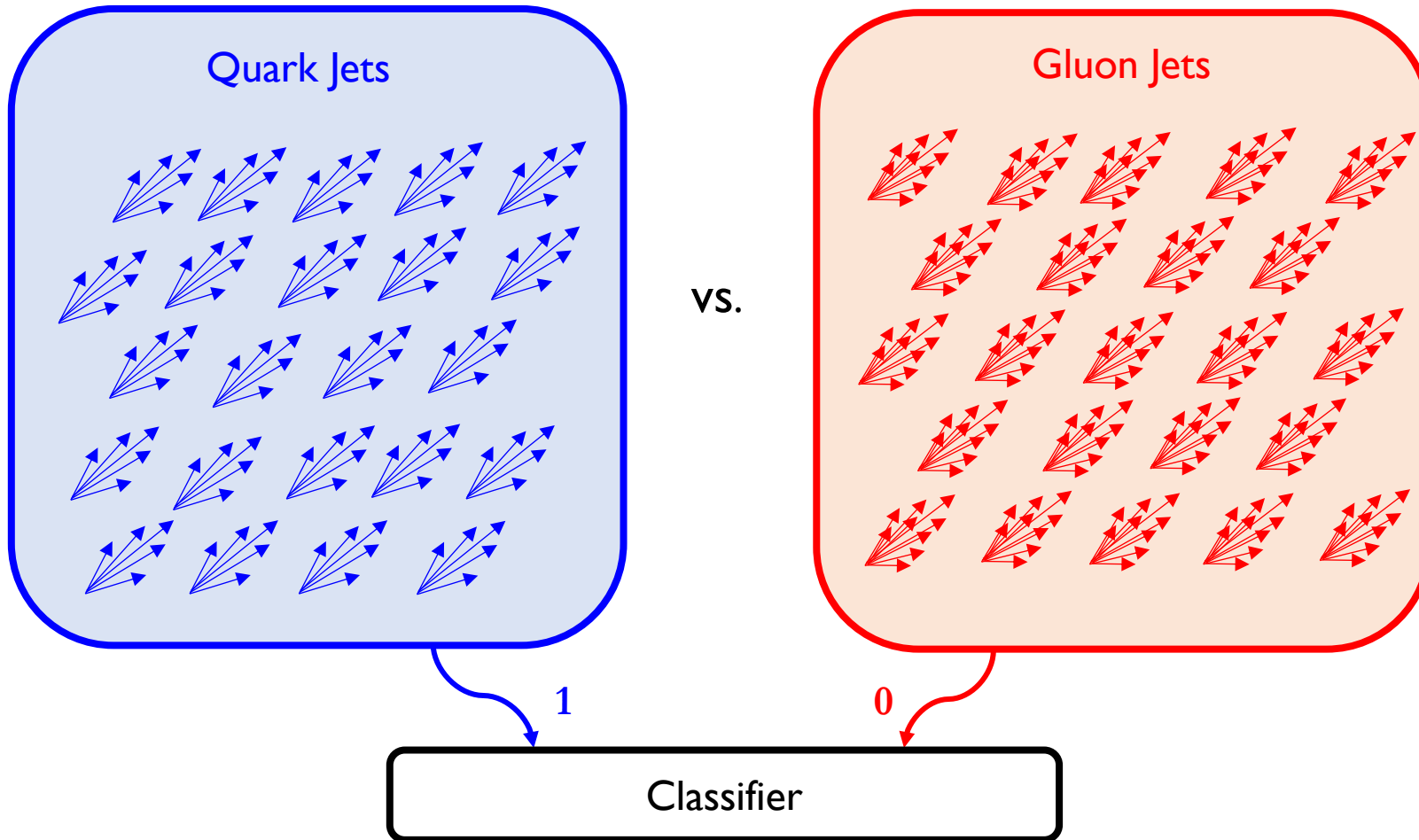


Classification Without Labels (CWoLa)



This defines an equivalent classifier to the pure case!

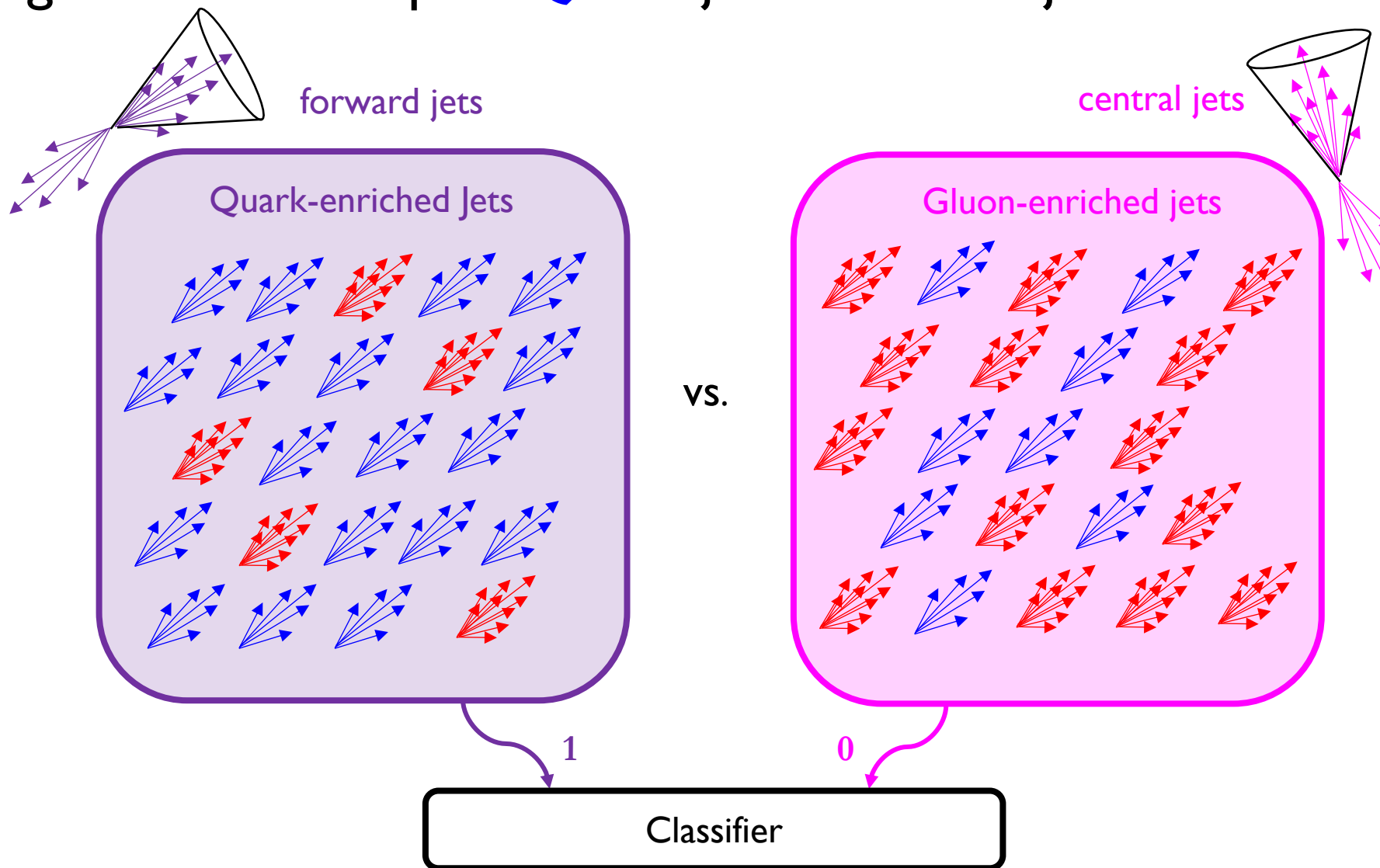
Training on pure samples: Quark jets vs. Gluon jets



Training on mixed samples: Quark jets vs. Gluon jets



Classification
Without Labels
(CWoLa)



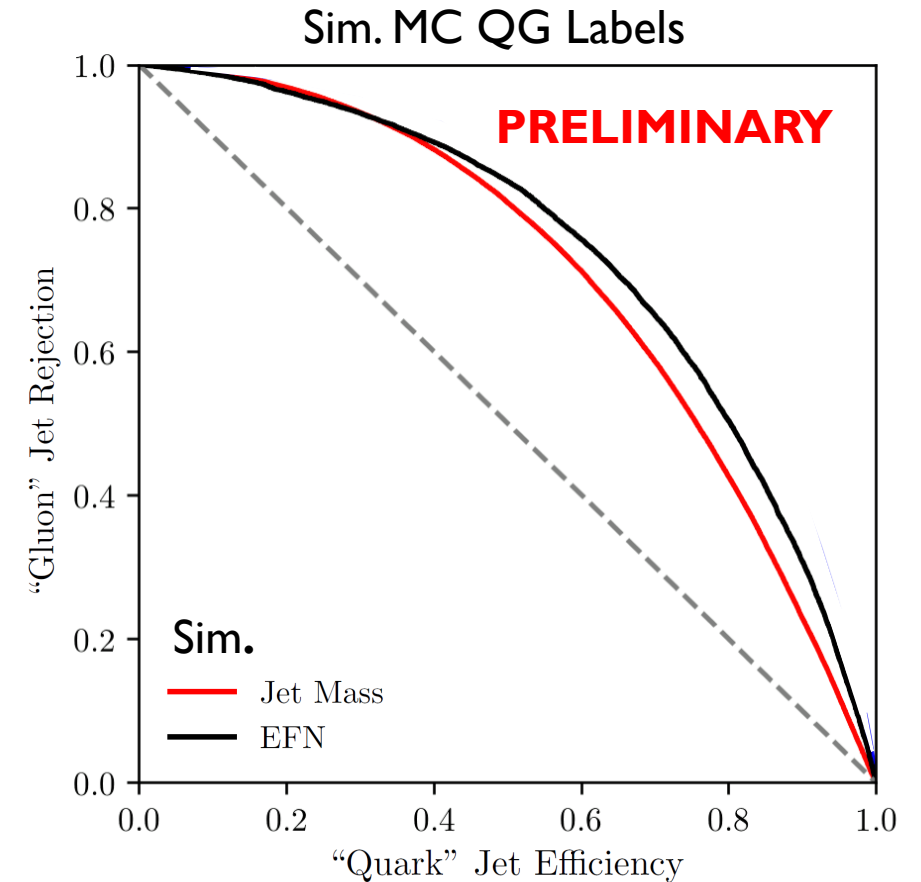
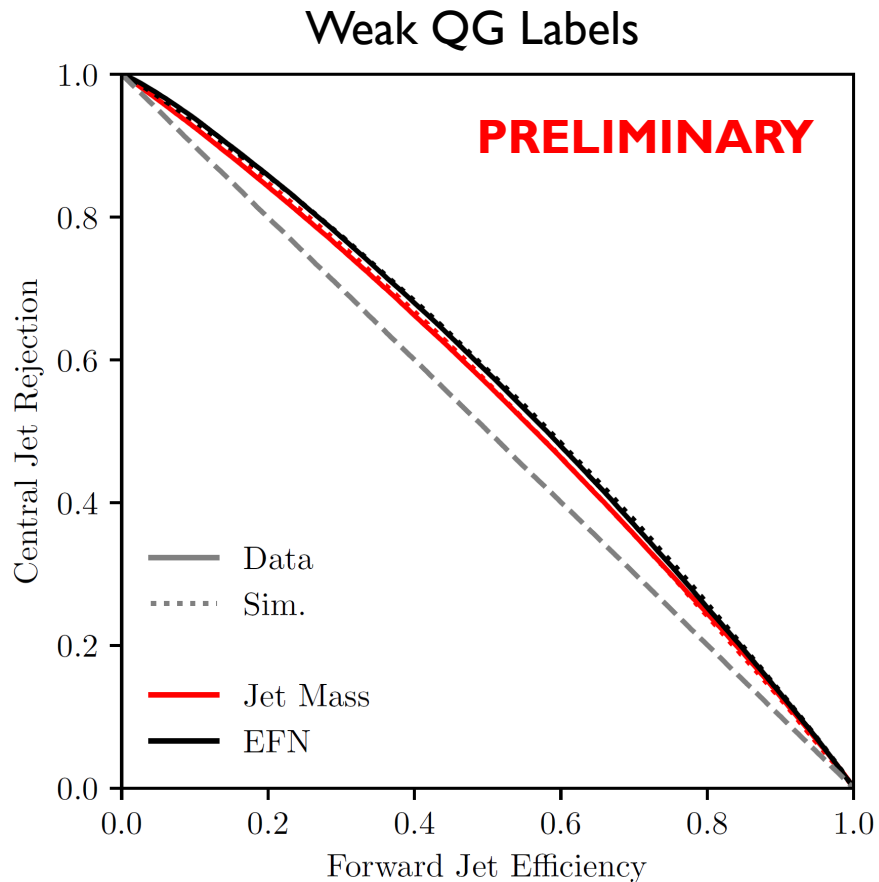
[[EMM, B. Nachman, J. Thaler, 1708.02949](#)]

[[P.T. Komiske, EMM, B. Nachman, M.D. Schwartz, 1801.10158](#)]

[[L. Dery, B. Nachman, F. Rubbo, A. Schwartzman, 1702.00414](#)] [[T. Cohen, M. Freytsis, B. Ostdiek, 1706.09451](#)]

Training on Data!

Central Jets ($|\eta^{\text{jet}}| < 0.7$): ~45% quark jets
Forward Jets ($|\eta^{\text{jet}}| > 0.7$): ~65% quark jets



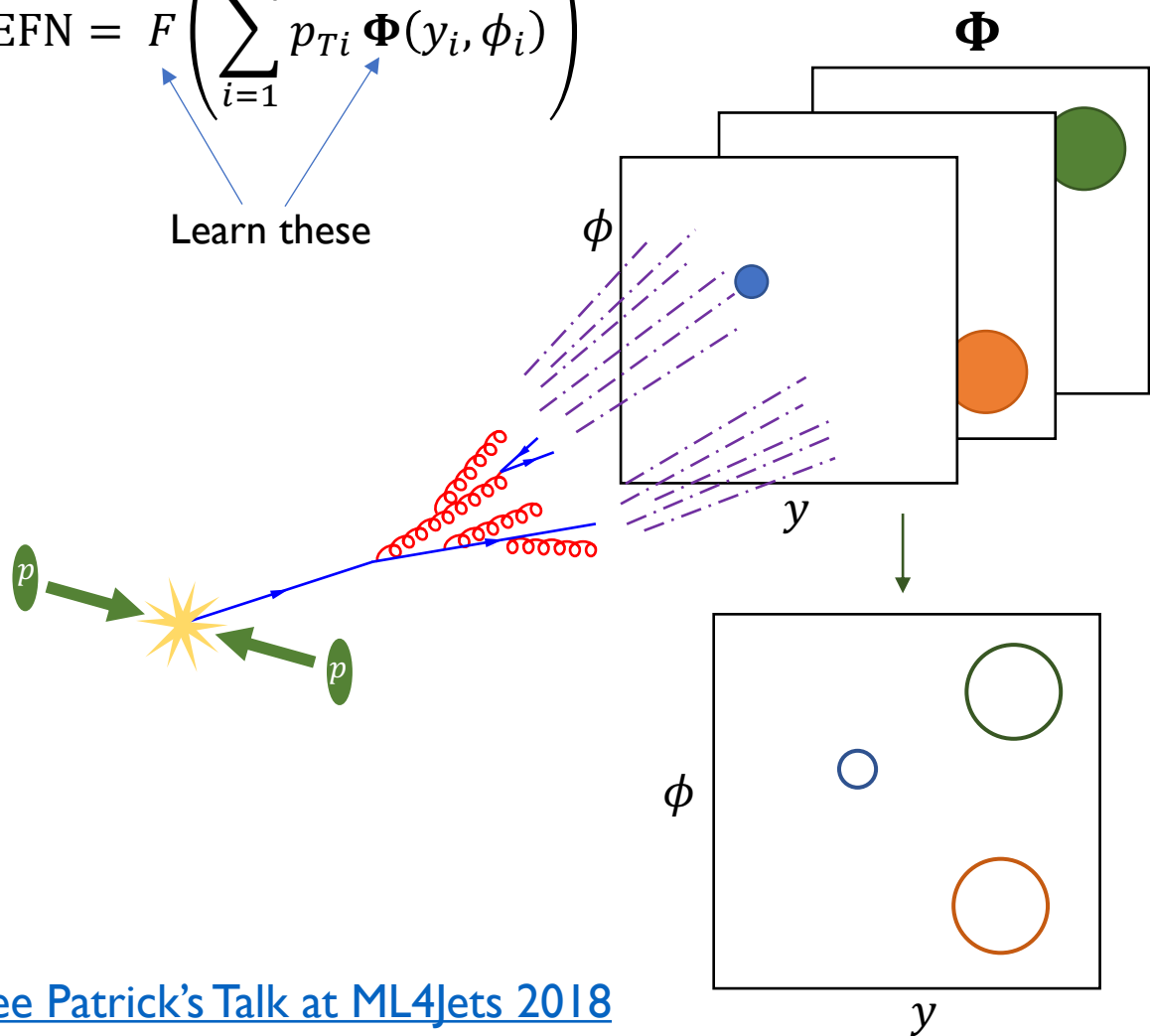
To reduce sample dependence, we train an EFN on tracks with $p_T^{\text{PFC}} > 1$ GeV and remove pileup.

Or high-dimensional unfolding? [See Patrick's Talk](#)

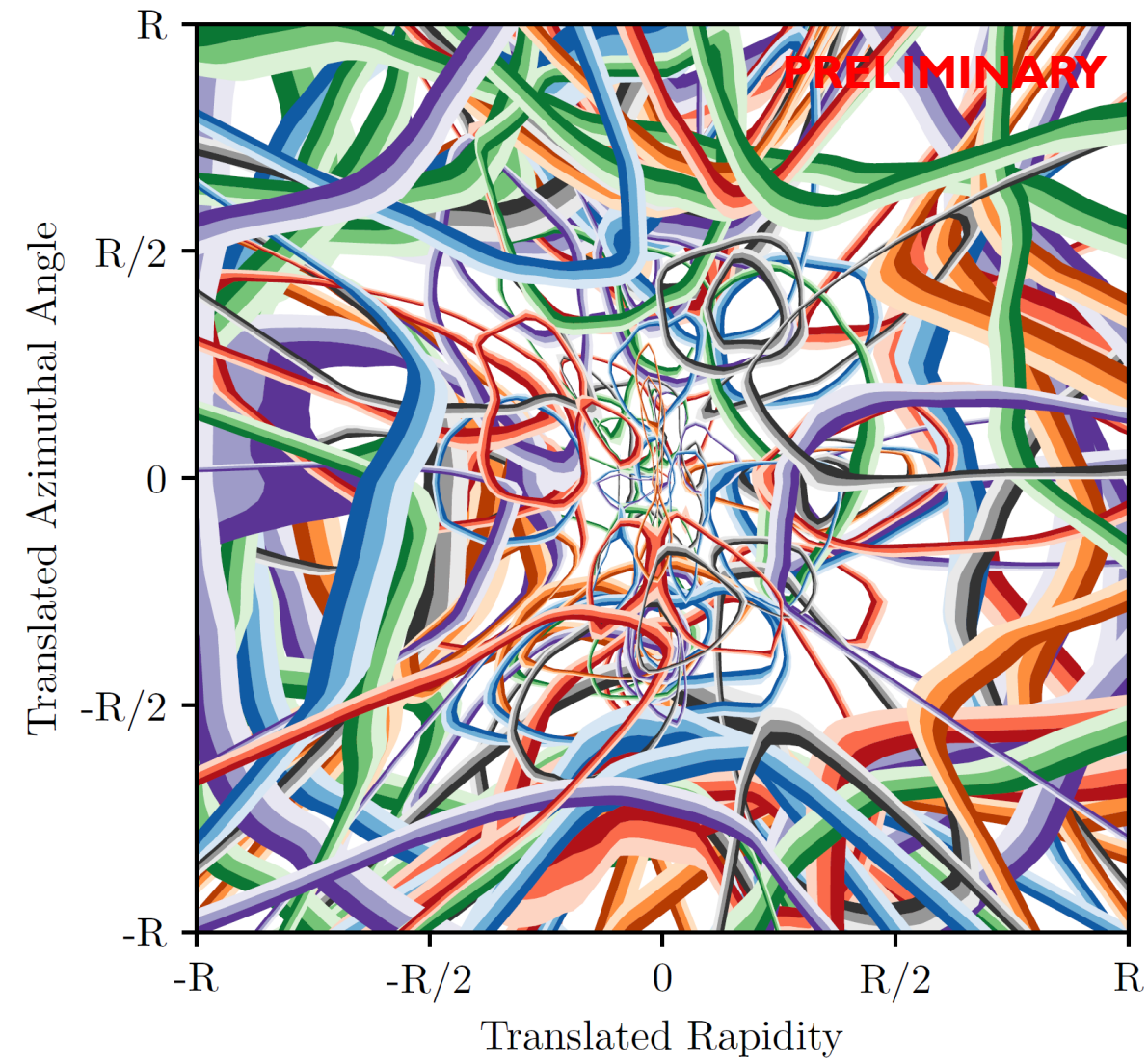
What is the model learning?

$$\text{EFN} = F \left(\sum_{i=1}^M p_{Ti} \Phi(y_i, \phi_i) \right)$$

Learn these



$$dP_{i \rightarrow ig} \approx \frac{2\alpha_s C_i}{\pi} \frac{d\theta}{\theta} \frac{dz}{z}$$



Visualizing 256 filters for EFN (weakly) trained on data

[See Patrick's Talk at ML4jets 2018](#)

Exploring the Space of Jets: Correlation Dimension

Sketch of leading log (one emission) calculation:

$$\dim_{q/g}(Q) = Q \frac{\partial}{\partial Q} \ln \sum_{i=1}^N \sum_{j=1}^N \Theta[\text{EMD}(\epsilon_i, \epsilon_j) < Q]$$

$$= Q \frac{\partial}{\partial Q} \ln \text{Pr} [\text{EMD} < Q]$$

$$= Q \frac{\partial}{\partial Q} \ln \text{Pr} [\lambda^{(\beta=1)} < Q; C_{q/g} \rightarrow 2 C_{q/g}]$$

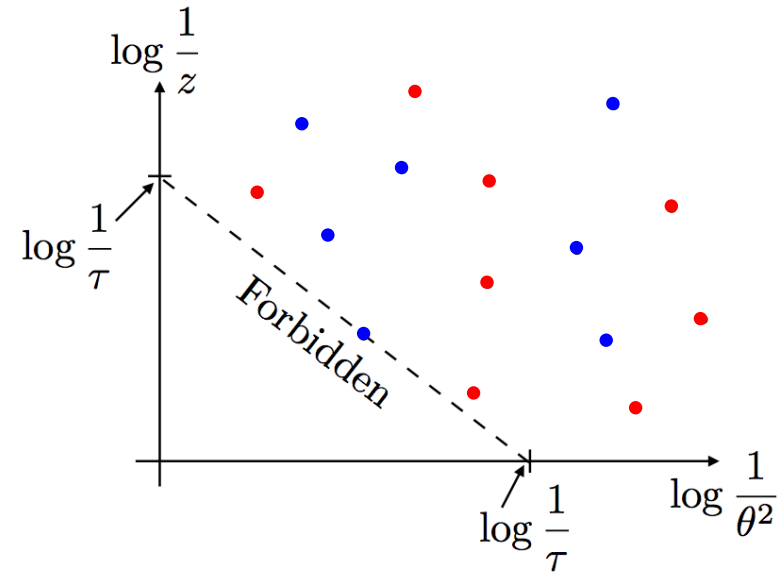
$$= Q \frac{\partial}{\partial Q} \ln \exp \left(-\frac{4\alpha_s C_{q/g}}{\pi} \ln^2 \frac{Q}{p_T/2} \right)$$

$$= -\frac{8\alpha_s C_{q/g}}{\pi} \ln \frac{Q}{p_T/2}$$

+ 1-loop running of α_s

$$C_q = C_F = \frac{4}{3}$$

$$C_g = C_A = 3$$



[A. Larkoski, 1709.06195]

